# Package 'bnRep'

October 26, 2025

Title A Repository of Bayesian Networks from the Academic Literature

Version 0.0.6

**Description** A collection of Bayesian networks (discrete, Gaussian, and conditional linear Gaussian) collated from recent academic literature. The 'bnRep\_summary' object provides an overview of the Bayesian networks in the repository and the package documentation includes details about the variables in each network. A Shiny app to explore the repository can be launched with 'bnRep\_app()' and is available online at <a href="https://manueleleonelli.shinyapps.io/bnRep">https://manueleleonelli.shinyapps.io/bnRep</a>>. Reference: 'M. Leonelli' (2025) <a href="https://manueleleonelli.network.network.">doi:10.1016/j.neucom.2025.129502</a>>.

License MIT + file LICENSE

**Encoding UTF-8** 

RoxygenNote 7.3.2

LazyData true

**Imports** bnlearn, dplyr, DT, Rgraphviz, qgraph,shiny, shinyjs, shinythemes

URL https://github.com/manueleleonelli/bnRep

BugReports https://github.com/manueleleonelli/bnRep/issues

**Depends** R (>= 3.5)

Suggests knitr, rmarkdown, ggplot2, scales, stringr, RColorBrewer

VignetteBuilder knitr

NeedsCompilation no

**Author** Manuele Leonelli [aut, cre, cph] (ORCID: <a href="https://orcid.org/0000-0002-2562-5192">https://orcid.org/0000-0002-2562-5192</a>)

Maintainer Manuele Leonelli <manuele.leonelli@ie.edu>

Repository CRAN

**Date/Publication** 2025-10-26 18:50:09 UTC

cachexia1	47
cachexia2	48
cardiovascular	49
case	50
catchment	51
charleston	52
chds	53
cng	54
compaction	57
conasense	57
	58
	59
	59 59
concrete3	
concrete4	60
concrete5	61
concrete6	61
concrete7	62
consequenceCovid	63
constructionproductivity	64
corall	65
coral2	66
coral3	66
coral4	67
coral5	68
corical	69
corrosion	70
corticosteroid	71
covid1	71
covid2	72
covid3	73
covidfear	74
covidrisk	75
covidtech	75
covidtest	77
crimescene	78
	79
	80
criminal2	
criminal3	81
criminal4	81
crypto	82
curacaol	83
curacao2	84
curacao3	85
curacao4	86
curacao5	87
darktriad	88
diabetes	89
diagnosis	89

dioxins	
lisputed1	
disputed2	92
disputed3	93
disputed4	94
dragline	95
drainage	97
dustexplosion	98
earthquake	
ecosystem	
electric vehicle	
electrolysis	
emergency	
engines	
enrollment	
estuary	
ets	
expenditure	
fingermarks1	
fingermarks2	
ire	
firealarm	
firerisk	
flood	
fluids1	
fluids2	
fluids3	
foodallergy1	
foodallergy2	
foodallergy3	
foodsecurity	
forest	
fundraising	
gasexplosion	
gasifier	
GDIpathway1	
GDIpathway2	
get_network_list	
gonorrhoeae	
greencredit	
grounding	
nealthinsurance	
numanitarian	
nydraulicsystem	
ncome	
ntensification	
ntentionalattacks	
nverters	
	137

knowledge	139
kosterhavet	139
lawschool	141
lexical	142
lidar	143
liquefaction	144
liquidity	145
lithium	146
load_network	147
macrophytes	148
medicaltest	149
megacities	149
metal	151
moodstate	151
mountaingoat	152
nanomaterials1	153
nanomaterials2	155
navigation	157
nuclearwaste	157
nuisancegrowth	158
oildepot	159
onlinerisk	161
orbital	163
oxygen	164
parkinson	166
perioperative	167
permaBN	168
phdarticles	169
pilot	169
pneumonia	171
polymorphic	174
poultry	175
project	177
projectmanagement	178
propellant	179
rainstorm	181
rainwater	183
realestate1	183
realestate2	185
realestate3	186
redmeat	187
resilience	188
ricci	190
rockburst	190
rockquality	191
ropesegment	
safespeeds	
sallyclark	194

salmonella1																							 						194
salmonella2																							 						195
seismic																							 						196
shipping																							 						197
simulation																							 						198
softwarelogs1																							 						199
softwarelogs2																													
softwarelogs3																													
softwarelogs4																							 						201
soil																							 						202
soillead																													
soilliquefaction1																							 						204
soilliquefaction2																							 						204
soilliquefaction3																							 						205
soilliquefaction4																							 						206
stocks																													
student1																													
student2																													
suffocation																													
tastingtea																													
tbm																													
theft1																													
theft2																													
titanic																													
trajectories																													
transport																													
tubercolosis																													
turbine1																													
turbine2																													
twinframework .																													
urinary																													
vaccine																													
vessel1																													
vessel2																													
volleyball																													
waterlead																													
wheat																													
windturbine																													
witness																													
yangtze	•	٠	•	•	•	٠	•	•	•	 •	•	•	•	•	•	•	 •	•	•	•	 •	•	 •	•	•	•	 •	•	231
																													234

Index

.onAttach 7

.onAttach Message for the User

### **Description**

Prints out a friendly reminder message to the user.

accidents

accidents Bayesian Network

# **Description**

Analysis of maritime transport accidents using Bayesian networks.

# **Format**

A discrete Bayesian network to provide transport authorities and ship owners with useful insights for maritime accident prevention. Probabilities were given within the referenced paper. The vertices are:

**AccidentType** (Collision, Grounding, Flooding, Fire/Explosion, Capsize, Contact/Crush, Sinking, Overboard, Others);

**EquipmentDevice** (Devices and equipment on board operate correctly, Devices and equipment not fully utilised or operated correctly);

ErgonomicDesign (Ergonomic friendly, Ergonomic impact of innovative bridge design);

FairwayTraffic (Good, Poor);

GrossTonnage (Less than 300, 300-1000, More than 1000, NA);

HullType (Steel, Wood, Aluminium, Others);

Information (Effective and updated information provided, Insufficient or lack of updated information);

**Length** (Less than 100, More than 100, NA);

SeaCondition (Good, Poor);

**ShipAge** (0,5, 6-10, 11-15, 16-20, More than 20, NA);

**ShipOperation** (Towing, Loading/Unloading, Pilotage, Manoeuvring, Fishing, At anchor, On passage, Others);

**ShipSpeed** (Normal, Fast);

**ShipType** (Passenger vessel, Tug, Barge, Fishing vessel, Container ship, Bulk carrier, RORO, Tanker or chemical ship, Cargo ship, Others);

TimeOfDay (7am to 7pm, Other);

**VesselCondition** (Good, Poor);

**VoyageSegment** (In port, Departure, Arrival, Mid-water, Transit, Others);

WeatherCondition (Good, Poor);

8 adhd

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Fan, S., Yang, Z., Blanco-Davis, E., Zhang, J., & Yan, X. (2020). Analysis of maritime transport accidents using Bayesian networks. Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability, 234(3), 439-454.

adhd

adhd Bayesian Network

# **Description**

Development of a computerized adaptive testing for ADHD using Bayesian networks: An attempt at classification.

#### **Format**

A discrete Bayesian network to classify ADHD symptom. Probabilities were given within the referenced paper. The vertices are:

**ADHD** ADHD symptom severity (No, Few, Moderate, Risk);

Carelessness Carelessness (Never, Sometimes, Often, Very Often);

**DifficultySustainingAttention** Difficulty sustaining attention in activities (Never, Sometimes, Often, Very Often);

**DoesntListen** Doesn't listen (Never, Sometimes, Often, Very Often);

NoFollowThrough No follow through (Never, Sometimes, Often, Very Often);

CantOrganize Can't organize (Never, Sometimes, Often, Very Often);

**AvoidsTasks** Avoids/dislikes tasks requiring sustained mental effort (Never, Sometimes, Often, Very Often);

**LosesItems** Loses important items (Never, Sometimes, Often, Very Often);

EasilyDistractible Easily distractible (Never, Sometimes, Often, Very Often);

**Forgetful** Forgetful in daily activities (Never, Sometimes, Often, Very Often);

SquirmsAndFidgets Squirms and fidgets (Never, Sometimes, Often, Very Often);

CantStaySeated Can't stay seated (Never, Sometimes, Often, Very Often);

RunsExcessively Runs/climbs excessively (Never, Sometimes, Often, Very Often);

CantPlayQuietly Can't play/work quietly (Never, Sometimes, Often, Very Often);

**OnTheGo** On the go, "driven by a motor" (Never, Sometimes, Often, Very Often);

TalksExcessively Talks excessively (Never, Sometimes, Often, Very Often);

**BlurtsOutAnswers** Blurts out answers (Never, Sometimes, Often, Very Often);

**CantWaitForTurn** Can't wait for turn (Never, Sometimes, Often, Very Often);

**IntrudesOthers** Intrudes/interrupts others (Never, Sometimes, Often, Very Often);

adversarialbehavior 9

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Jiang, Z., Ma, W., Flory, K., Zhang, D., Zhou, W., Shi, D., ... & Liu, R. (2023). Development of a computerized adaptive testing for ADHD using Bayesian networks: An attempt at classification. Current Psychology, 42(22), 19230-19240.

adversarialbehavior

adversarialbehavior Bayesian Network

# **Description**

Inferring adversarial behaviour in cyber-physical power systems using a Bayesian attack graph approach.

#### **Format**

A discrete Bayesian network to define and solve the inference problem of adversarial movement in the grid infrastructure towards targets of physical impact. Probabilities were given within the referenced paper. The vertices are:

RemoteAdversary (TRUE, FALSE);

RootAccessFTPServer (TRUE, FALSE);

FTPBasedBufferOverflow (TRUE, FALSE);

RemoteBufferOverflowOnSSHDaemon (TRUE, FALSE);

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Sahu, A., & Davis, K. (2023). Inferring adversarial behaviour in cyber-physical power systems using a Bayesian attack graph approach. IET Cyber-Physical Systems: Theory & Applications, 8(2), 91-108.

10 aerialvehicles

aerialvehicles

aerialvehicles Bayesian Network

# Description

Analysis and assessment of risks to public safety from unmanned aerial vehicles using fault tree analysis and Bayesian network.

# **Format**

A discrete Bayesian network to analyze critical risks associated with unmanned aerial vehicles. Probabilities were given within the referenced paper. The vertices are:

- **X1** Mechanical failures (yes, no);
- X2 Battery failures (yes, no);
- X3 Flight control system failures (yes, no);
- X4 Gust (yes, no);
- X5 Rain and snow (yes, no);
- X6 Thunderstorm (yes, no);
- X7 Visibility (yes, no);
- X8 Communication link failures (yes, no);
- X9 GPS failures (yes, no);
- X10 Ostacles (yes, no);
- **X11** Route planning issues (yes, no);
- X12 Unclear airspace division (yes, no);
- X13 Unqualified knowledge and skills (yes, no);
- **X14** Weak safety awareness (yes, no);
- **X15** Lack of experience (yes, no);
- X16 Careless (yes, no);
- X17 Fatigue (yes, no);
- **X18** Violations (yes, no);
- **X19** Lack of legal awareness (yes, no);
- **X20** Psychological problems (yes, no);
- **X21** Undefined subject of supervision responsibility (yes, no);
- **X22** Lack of unified industry standard (yes, no);
- **X23** Unclear airworthiness certification procedures (yes, no);
- **X24** Long flight approval cycle (yes, no);
- **X25** Weak laws and regulations (yes, no);
- **X26** Inadequate training system (yes, no);
- X27 Lack of supervision system (yes, no);

agropastoral1 11

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Xiao, Q., Li, Y., Luo, F., & Liu, H. (2023). Analysis and assessment of risks to public safety from unmanned aerial vehicles using fault tree analysis and Bayesian network. Technology in Society, 73, 102229.

agropastoral1

agropastoral Bayesian Networks

# **Description**

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach.

# **Format**

A discrete Bayesian network to explore the influence of the environment on subsistence strategies (Fig. 5 of the paper). The structure of the BN was given within the referenced paper together with a dataset. Probabilities were learned using the dataset and the discretization mentioned in the paper. The vertices are:

```
Agriculture (None, <55, >=55);
Anumal_Husbandry (None, <25, >=25);
Annual_Temperature (low, medium, high);
CV_Annual_Precipitation (low, medium, high);
CV_Annual_Productivity (low, medium, high);
CV_Annual_Temperature (low, medium, high);
Distance_Coast (low, medium, high);
Elevation (low, medium, high);
Fishing (None, <25, >=25);
Gathering (None, <25, >=25);
Hunting (None, <25, >=25);
Landscape (Aquatic, Tundra, Desert, Forest, Grassland);
Monthly_Precipitation (low, medium, high);
Monthly_Productivity (low, medium, high);
Slope (low, medium, high);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

12 agropastoral2

# References

Palacios, O., Barceló, J. A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. Plos One, 17(10), e0276088.

agropastoral2

agropastoral Bayesian Networks

# **Description**

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach.

### **Format**

A discrete Bayesian network to explore the relationship between the environment and social organisation (Fig. 6 of the paper). The structure of the BN was given within the referenced paper together with a dataset. Probabilities were learned using the dataset and the discretization mentioned in the paper. The vertices are:

```
Annual_Temperature (low, medium, high);

Community_Size (<200, >=200)

CV_Annual_Precipitation (low, medium, high);

CV_Annual_Productivity (low, medium, high);

CV_Annual_Temperature (low, medium, high);

Distance_Coast (low, medium, high);

Elevation (low, medium, high);

Landscape (Aquatic, Tundra, Desert, Forest, Grassland);

Monthly_Precipitation (low, medium, high);

Monthly_Productivity (low, medium, high);

Slope (low, medium, high);
```

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Palacios, O., Barceló, J. A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. Plos One, 17(10), e0276088.

agropastoral3 13

agropastoral3

agropastoral Bayesian Networks

# **Description**

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach.

### **Format**

A discrete Bayesian network to explore the relationship between the environment and social decisions (Fig. 7 of the paper). The structure of the BN was given within the referenced paper together with a dataset. Probabilities were learned using the dataset and the discretization mentioned in the paper. The vertices are:

```
Annual_Temperature (low, medium, high);

CV_Annual_Precipitation (low, medium, high);

CV_Annual_Productivity (low, medium, high);

CV_Annual_Temperature (low, medium, high);

Distance_Coast (low, medium, high);

Elevation (low, medium, high);

Exchange_InSettlement (No, Yes);

Landscape (Aquatic, Tundra, Desert, Forest, Grassland);

Monthly_Precipitation (low, medium, high);

Monthly_Productivity (low, medium, high);

Slope (low, medium, high);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Palacios, O., Barceló, J. A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. Plos One, 17(10), e0276088.

14 agropastoral4

agropastoral4

agropastoral Bayesian Networks

# **Description**

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach.

# **Format**

A discrete Bayesian network to explore the relationship between the environment and social decisions (Fig. 8 of the paper). The structure of the BN was given within the referenced paper together with a dataset. Probabilities were learned using the dataset and the discretization mentioned in the paper. The vertices are:

```
Annual_Temperature (low, medium, high);
Crop_Specialisation (No, Yes);
CV_Annual_Precipitation (low, medium, high);
CV_Annual_Productivity (low, medium, high);
CV_Annual_Temperature (low, medium, high);
Distance_Coast (low, medium, high);
Elevation (low, medium, high);
Exchange_InSettlement (No, Yes);
Exchange_OutSettlement (No, Yes);
Foraging_Intensification (No, Yes);
Landscape (Aquatic, Tundra, Desert, Forest, Grassland);
Monthly Precipitation (low, medium, high);
Monthly_Productivity (low, medium, high);
None (No, Yes);
Permanent_Migration (No, Yes);
Reciprocity (No, Yes);
Resource_Diversification (No, Yes);
Slope (low, medium, high);
Storage (No, Yes);
Temporal_Migration (No, Yes);
Transhumance (No, Yes);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

agropastoral5 15

# References

Palacios, O., Barceló, J. A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. Plos One, 17(10), e0276088.

agropastoral5

agropastoral Bayesian Networks

# **Description**

Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach.

### **Format**

A discrete Bayesian network to explore the relationship between social organisation and subsistence strategies. The structure of the BN was given within the referenced paper together with a dataset. Probabilities were learned using the dataset and the discretization mentioned in the paper. The vertices are:

Community\_Organisation (Clan communities, Missing, No exogamous clans);

**Community\_Size** (<200, >=200);

**Gathering** (None, <25, >=25);

Household\_Organisation (Small extended, Large extended, Nuclear);

**Settlement\_Types** (Camp, Hamlet, Homesteads, Village);

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Palacios, O., Barceló, J. A., & Delgado, R. (2022). Exploring the role of ecology and social organisation in agropastoral societies: A Bayesian network approach. Plos One, 17(10), e0276088.

16 airegulation1

aircrash

aircrash Bayesian Network

# **Description**

Application of a Bayesian network to aid the interpretation of blood alcohol (ethanol) concentrations in air crashes.

### **Format**

A discrete Bayesian network to model the relationships between analytical results, circumstantial evidence and the concentration of alcohol at the time of death in cases of air crash. Probabilities were given within the referenced paper. The vertices are:

**5HTOL5HIAARatio** (Above 20, Below 20);

**BACAtTimeOfDeath** (a101plus, a80-100, a50-80, a40-49, a30-39, a20-29, a10-19, Negative);

EthanolConsumptionWithin8hrsOfDeath (Yes, No);

MeasuredBAC (a101plus, a80-100, a50-80, a40-49, a30-39, a20-29, a10-19, Negative);

**PMAlcoholFormation** (PMF, No PMF);

**UACPositive** (UPositive, UNegative);

**VACPositive** (Positive, Negative);

VOCDetected (Detected, Not Detected);

WitnessEvidenceOfETOHConsumption (Positive, Negative);

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Maskell, P. D., & Jackson, G. (2020). Application of a Bayesian network to aid the interpretation of blood alcohol (ethanol) concentrations in air crashes. Forensic Science International, 308, 110174.

airegulation1

airegulation Bayesian Networks

# Description

Understanding support for AI regulation: A Bayesian network perspective.

airegulation1 17

A discrete Bayesian network to understand public perceptions towards AI (full BN of the paper).

# **Format**

```
The BN was learned from data. The vertices are:
Age (14-29, 30-44, 45-59, 60+);
AIEasierLife (Strongly_disagree, Somewhat_disagree, Somewhat_agree, Strongly_agree);
AIFalseInfo (Strongly_disagree, Somewhat_disagree, Somewhat_agree, Strongly_agree);
AIFieldBenefit (Strongly_disagree, Somewhat_disagree, Somewhat_agree, Strongly_agree);
AIHealthcareBenefit (Strongly_disagree, Somewhat_disagree, Somewhat_agree, Strongly_agree, Don_t_know);
AIReduceShortageWorkers (Strongly_disagree, Somewhat_disagree, Somewhat_agree, Strongly_agree);
AIRegulations (No, Yes);
AIUncontrollable (Strongly disagree, Somewhat disagree, Somewhat agree, Strongly agree);
AIvsHuman (Strongly_disagree, Somewhat_disagree, Somewhat_agree, Strongly_agree);
DevelopAI (Risk, Opportunity, Both);
Education (Low, Medium, High);
EUAppropriateRegulation (Appropriate, Too_strict, Not_strict_enough, Don_t_know);
FriendsAI (No, Yes);
HeardEURegulation (No, Yes);
Income (Low, Medium, High, Not_reported);
InformedAI (Very_poor, Rather_poor, Rather_good, Very_good);
InterestAI (Not_at_all, Less_strongly, Strongly, Very_strongly);
MediaAI (No, Yes);
Municipality (<5k, 5k-19k, 20k-99k, 100k-499k, 500k+);
SearchAI (No, Yes);
Sex (Female, Male);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

VoteIntent (Left, Right, Other);

Cremaschi, A., Lee, D. J., & Leonelli, M. (2025). Understanding support for AI regulation: A Bayesian network perspective. International Journal of Engineering Business Management, 17, 18479790251383310.

18 airegulation2

airegulation2

airegulation Bayesian Networks

# Description

Understanding support for AI regulation: A Bayesian network perspective.

### **Format**

A discrete Bayesian network to understand public perceptions towards AI (risk BN of the paper). The BN was learned from data. The vertices are:

```
Age (14-29, 30-44, 45-59, 60+);
AI_Risk_data (Not_mentioned, Mentioned);
AI_Risk_Jobs (Not_mentioned, Mentioned);
AI_Risk_LossOfControl (Not_mentioned, Mentioned);
AI_Risk_Misuse_Regulation (Not_mentioned, Mentioned);
AI_Risk_Society (Strongly_disagree, Somewhat_disagree, Somewhat_agree, Strongly_agree);
AIRegulations (No, Yes);
Education (Low, Medium, High);
EUAppropriateRegulation (Appropriate, Too_strict, Not_strict_enough, Don_t_know);
FriendsAI (No, Yes);
HeardEURegulation (No, Yes);
Income (Low, Medium, High, Not_reported);
InformedAI (Very_poor, Rather_poor, Rather_good, Very_good);
InterestAI (Not_at_all, Less_strongly, Strongly, Very_strongly);
MediaAI (No, Yes);
Municipality (<5k, 5k-19k, 20k-99k, 100k-499k, 500k+);
SearchAI (No, Yes);
Sex (Female, Male);
VoteIntent (Left, Right, Other);
```

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Cremaschi, A., Lee, D. J., & Leonelli, M. (2025). Understanding support for AI regulation: A Bayesian network perspective. International Journal of Engineering Business Management, 17, 18479790251383310.

airegulation3

airegulation3

airegulation Bayesian Networks

# **Description**

Understanding support for AI regulation: A Bayesian network perspective.

### **Format**

A discrete Bayesian network to understand public perceptions towards AI (opportunity BN of the paper). The BN was learned from data. The vertices are:

```
Age (14-29, 30-44, 45-59, 60+);
AI_Risk_data (Not_mentioned, Mentioned);
AI_Risk_Jobs (Not_mentioned, Mentioned);
AI_Risk_LossOfControl (Not_mentioned, Mentioned);
AI_Risk_Misuse_Regulation (Not_mentioned, Mentioned);
AI_Risk_Society (Strongly_disagree, Somewhat_disagree, Somewhat_agree, Strongly_agree);
AIRegulations (No, Yes);
Education (Low, Medium, High);
EUAppropriateRegulation (Appropriate, Too_strict, Not_strict_enough, Don_t_know);
FriendsAI (No, Yes);
HeardEURegulation (No, Yes);
Income (Low, Medium, High, Not_reported);
InformedAI (Very_poor, Rather_poor, Rather_good, Very_good);
InterestAI (Not_at_all, Less_strongly, Strongly, Very_strongly);
MediaAI (No, Yes);
Municipality (<5k, 5k-19k, 20k-99k, 100k-499k, 500k+);
SearchAI (No, Yes);
Sex (Female, Male);
VoteIntent (Left, Right, Other);
```

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Cremaschi, A., Lee, D. J., & Leonelli, M. (2025). Understanding support for AI regulation: A Bayesian network perspective. International Journal of Engineering Business Management, 17, 18479790251383310.

20 algal2

algal1

algal Bayesian Networks

# **Description**

Seasonal forecasting of lake water quality and algal bloom risk using a continuous Gaussian Bayesian networks.

### **Format**

A discrete Bayesian network to to forecast, in spring, mean total phosphorus and chlorophyll a concentration, mean water colour, and maximum cyanobacteria biovolume for the upcoming growing season (May–October) in Vansjø. Probabilities were given within the referenced paper. The vertices are:

ChiA Mean lake chl a concentration - Current (Low, High);

ChiA\_PS Mean lake chl a concentration - Previous (Low, High);

Colour Mean lake colour (Low, Medium, High);

Cyanobacteria Mean lake cyanobacterial biovolume (Low, High);

RainSum Precipitation sum (Low, High);

**TP** Mean lake TP concentration - Current (Low, High);

**TP\_PS** Mean lake TP concentration - Previous (Low, High);

WindSpeed Mean daily mean wind speed (Low, High);

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Jackson-Blake, L. A., Clayer, F., Haande, S., Sample, J. E., & Moe, S. J. (2022). Seasonal forecasting of lake water quality and algal bloom risk using a continuous Gaussian Bayesian network. Hydrology and Earth System Sciences, 26(12), 3103-3124.

algal2

algal Bayesian Networks

# Description

Seasonal forecasting of lake water quality and algal bloom risk using a continuous Gaussian Bayesian networks.

algalactivity1 21

### **Format**

A Gaussian Bayesian network to to forecast, in spring, mean total phosphorus and chlorophyll a concentration, mean water colour, and maximum cyanobacteria biovolume for the upcoming growing season (May–October) in Vansjø. Probabilities were given within the referenced paper. The vertices are:

ChiA Mean lake chl a concentration - Current;

ChiA\_PS Mean lake chl a concentration - Previous;

Colour Mean lake colour;

Cyanobacteria Mean lake cyanobacterial biovolume;

RainSum Precipitation sum;

**TP** Mean lake TP concentration - Current;

**TP PS** Mean lake TP concentration - Previous;

WindSpeed Mean daily mean wind speed;

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Jackson-Blake, L. A., Clayer, F., Haande, S., Sample, J. E., & Moe, S. J. (2022). Seasonal forecasting of lake water quality and algal bloom risk using a continuous Gaussian Bayesian network. Hydrology and Earth System Sciences, 26(12), 3103-3124.

algalactivity1

algalactivity Bayesian Networks

# **Description**

Influence of resampling techniques on Bayesian network performance in predicting increased algal activity.

### **Format**

A discrete Bayesian network to to predict chlorophyll-a (chl-a) using a range of water quality parameters as predictors (Fig. 6 of the referenced paper). Probabilities were given within the referenced paper (a uniform was given to the vertex Chl\_a since it was missing). The vertices are:

```
C (0, 1);

Chl_a (0, 1);

DO (0, 1);

N (0, 1);

P (0, 1);

pH (0, 1);

Te (0, 1);

Tu (0, 1);
```

22 algalactivity2

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Rezaabad, M. Z., Lacey, H., Marshall, L., & Johnson, F. (2023). Influence of resampling techniques on Bayesian network performance in predicting increased algal activity. Water Research, 244, 120558.

algalactivity2

algalactivity Bayesian Networks

# **Description**

Influence of resampling techniques on Bayesian network performance in predicting increased algal activity.

# **Format**

A discrete Bayesian network to to predict chlorophyll-a (chl-a) using a range of water quality parameters as predictors (Fig. 7 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

```
C (0, 1);

Chl_a (0, 1);

DO (0, 1);

N (0, 1);

P (0, 1);

pH (0, 1);

Te (0, 1);

Tu (0, 1);
```

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Rezaabad, M. Z., Lacey, H., Marshall, L., & Johnson, F. (2023). Influence of resampling techniques on Bayesian network performance in predicting increased algal activity. Water Research, 244, 120558.

algorithms1 23

algorithms1

algorithms Bayesian Networks

# **Description**

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

### **Format**

A Gaussian Bayesian network to illustrate the algorithms developed in the associated paper (Figure 1, top). The probabilities were available from a repository. The vertices are:

**X1** 

**X2** 

**X3** 

**X4** 

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. Algorithms, 17(1), 24.

algorithms2

algorithms Bayesian Networks

# Description

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

# **Format**

A Gaussian Bayesian network to illustrate the algorithms developed in the associated paper (Figure 1, bottom). The probabilities were available from a repository. The vertices are:

**X1** 

**X2** 

**X3** 

**X4** 

24 algorithms3

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. Algorithms, 17(1), 24.

algorithms3

algorithms Bayesian Networks

# **Description**

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

# **Format**

A discrete Bayesian network to illustrate the algorithms developed in the associated paper (Figure 2, top). The probabilities were available from a repository. The vertices are:

**X1** (a, b);

**X2** (c, d);

**X3** (e, f);

**X4** (g, h);

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. Algorithms, 17(1), 24.

algorithms4 25

algorithms4

algorithms Bayesian Networks

# **Description**

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

### **Format**

A discrete Bayesian network to illustrate the algorithms developed in the associated paper (Figure 2, bottom). The probabilities were available from a repository. The vertices are:

**X1** (a, b);

X2 (c, d);

**X3** (e, f);

**X4** (g, h);

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. Algorithms, 17(1), 24.

algorithms5

algorithms Bayesian Networks

# **Description**

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

# **Format**

A conditional linear Gaussian Bayesian network to illustrate the algorithms developed in the associated paper (Figure 3, top). The probabilities were available from a repository. The vertices are:

**X1** (a, b);

**X2** (c, d);

**X3** (e, f);

**X4** 

X5

**X6** 

26 algorithms6

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. Algorithms, 17(1), 24.

algorithms6

algorithms Bayesian Networks

# Description

Entropy and the Kullback-Leibler divergence for Bayesian networks: Computational complexity and efficient implementation.

### **Format**

A conditional linear Gaussian Bayesian network to illustrate the algorithms developed in the associated paper (Figure 3, bottom). The probabilities were available from a repository. The vertices are:

**X1** (a, b);

**X2** (c, d);

**X3** (e, f);

**X4** 

**X5** 

**X6** 

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Scutari, M. (2024). Entropy and the Kullback-Leibler Divergence for Bayesian Networks: Computational Complexity and Efficient Implementation. Algorithms, 17(1), 24.

APSsystem 27

**APSsystem** 

APSsystem Bayesian Network

# **Description**

An ERP data quality assessment framework for the implementation of an APS system using Bayesian networks.

#### **Format**

A discrete Bayesian network for data quality assessment. Probabilities were given within the referenced paper. The vertices are:

```
QPlanDeliveryTime (Complete, Incomplete);
QSetupTime (Complete, Incomplete);
PlanDeliveryTime (Complete, Incomplete);
SetupTime (Complete, Incomplete);
NNTransactionData (Complete, Incomplete);
NNMasterData (Complete, Incomplete);
NNValues (High, Low);
Completeness (High, Low);
Consistency (High, Low);
DataQuality (High, Low);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Herrmann, J. P., Tackenberg, S., Padoano, E., Hartlief, J., Rautenstengel, J., Loeser, C., & Böhme, J. (2022). An ERP Data Quality Assessment Framework for the Implementation of an APS system using Bayesian Networks. Procedia Computer Science, 200, 194-204.

28 arcticwaters

arcticwaters

arcticwaters Bayesian Network

# Description

An object-oriented Bayesian network model for the quantitative risk assessment of navigational accidents in ice-covered Arctic waters.

### **Format**

A discrete Bayesian network for the quantitative risk assessment of multiple navigational accidents in ice-covered Arctic waters. Probabilities were given within the referenced paper. The vertices are:

```
AidNavigationFailure (No, Yes);
AirTemperature (<0 degrees, >0 degrees);
C_BesettingInIce (Significant, Severe, Catastrophic);
C_Collision (Significant, Severe, Catastrophic);
C_Grounding (Significant, Severe, Catastrophic);
C_ShipIceCollision (Significant, Severe, Catastrophic);
ChannelDepth (Inadequate, Adequate);
ChartUpdating (No, Yes);
CommunicationEquipmentFailure (No, Yes);
DriftIce (No, Yes);
EnvironmentalObstacles (No, Yes);
Fatigued (No, Yes);
Fog (No, Yes);
GrossTonnage ((0,500], (500,3000], (3000,10000], >10000);
IceConcentration (<3/10, 4/10-6/10, >7/10);
IceCondition (Poor, Good);
IceStrength (Low, Medium, High);
IceThickness (<0.5m, >0.5m);
IceType (Thin Ice, Medium Ice, Old Ice);
InadequateKnowledge (No, Yes);
JudgmentFailure (No, Yes);
LackCommunication (No, Yes);
LackSafetyMeasures (No, Yes);
LackSituationalAwareness (No, Yes);
MechanicalEquipmentFailure (No, Yes);
NavigatorFailure (No, Yes);
```

argument 29

```
Negligence (No, Yes);
P_BesettingInIce (No, Yes);
P_Collision (No, Yes);
P_Grounding (No, Yes);
P_ShipIceCollision (No, Yes);
PowerFailure (No, Yes);
PropellerFailure (No, Yes);
RadarFailure (No, Yes);
Rain (No, Yes);
SeaCurrent (No, Yes);
SeaTemperature (<0 degrees, >0 degrees);
ShipType (Oil Tanker, General Cargo Ship, Passenger Ship, Icebreaker, Others);
SteeringFailure (No, Yes);
StrongWind (No, Yes);
UnsafeAct (No, Yes);
UnsafeCondition (No, Yes);
UnsafeSpeed (No, Yes);
Visibility (Poor, Good);
WaterwayCondition (Poor, Good);
WeatherCondition (Poor, Good);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Fu, S., Zhang, Y., Zhang, M., Han, B., & Wu, Z. (2023). An object-oriented Bayesian network model for the quantitative risk assessment of navigational accidents in ice-covered Arctic waters. Reliability Engineering & System Safety, 238, 109459.

argument

argument Bayesian Network

# **Description**

Towards an empirically informed normative Bayesian scheme-based account of argument from expert opinion.

30 asia

# **Format**

A discrete Bayesian network formalizing Walton's re-constructed set of critical questions. Probabilities were given within the referenced paper. The vertices are:

**DecisionProcess** (Not based on evidence, Integrative complexity, Absence of integrative complexity);

```
DeliberativePractice (FALSE, TRUE);
ExpertAssertsHypothesis (FALSE, TRUE);
Feedback (FALSE, TRUE);
GenuineExpertise (FALSE, TRUE);
Hypothesis (FALSE, TRUE);
ObjectiveEvidence (FALSE, TRUE);
RegularPractice (FALSE, TRUE);
Validity (High, Medium, High);
```

WellInformedPractice (FALSE, TRUE);

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Pei, K. N., & Chin, C. S. A. (2023). Towards an empirically informed normative Bayesian scheme-based account of argument from expert opinion. Thinking & Reasoning, 29(4), 726-759.

asia

asia Bayesian Network

# **Description**

Local computation with probabilities on graphical structures and their application to expert systems.

# **Format**

A synthetic discrete Bayesian network to model the relationships between lung diseases and visits to Asia. Probabilities were given within the referenced paper. The vertices are:

```
Bronchitis (True, False);

Dyspnea (True, False);

Lung_Cancer (True, False);

Smoker (True, False);

Tubercolosis (True, False);

TubercolosisOrCancer (True, False);

Visit_To_Asia (True, False);

XRay_Result (True, False);
```

aspergillus 31

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Lauritzen, S. L., & Spiegelhalter, D. J. (1988). Local computations with probabilities on graphical structures and their application to expert systems. Journal of the Royal Statistical Society: Series B (Methodological), 50(2), 157-194.

aspergillus

aspergillus Bayesian Network

# **Description**

Using staged tree models for health data: Investigating invasive fungal infections by aspergillus and other filamentous fungi.

# **Format**

A discrete Bayesian network modelling the relationship between risk factors and death by Aspergillus. The original dataset was used to learn the Bayesian network. The vertices are:

```
CMV CMV Infection (No, Si);
```

**DT** Diagnostic Time (<16 days, >=16 days);

**DTH** Death (No, Si);

**GR** Immunosuppresion Groups (Neutropenia, IS-convencional, IS-non-convencional);

ICU Accessed the ICU (No, Si);

IM Immunotherapy (No, Si);

MN Malnutrition (No, Si);

RP Radiological Pattern (No, Si);

SC Systemic Corticoids (No, Si);

**SOT** Solid Organ Transplant (No, Si);

**VP** Viral Pneumonia (No, Si);

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Filigheddu, M. T., Leonelli, M., Varando, G., Gómez-Bermejo, M. Á., Ventura-Díaz, S., Gorospe, L., & Fortún, J. (2024). Using staged tree models for health data: Investigating invasive fungal infections by aspergillus and other filamentous fungi. Computational and Structural Biotechnology Journal, 24, 12-22.

32 bank

augmenting

augmenting Bayesian Network

# **Description**

Augmenting learning components for safety in resource constrained autonomous robots.

### **Format**

A discrete Bayesian network to estimate the probability that the car will remain on track, given its current state and control actions. Probabilities were given within the referenced paper. The vertices are:

```
CmdSteeringOnTurn (Leaf, Straight, Right);

CurrentPosition (Near, On , Far);

CurrentSteering (Straight, Left, Right);

CurrentVelocity (Slow, Medium, Fast);

InTrack (Yes, No);

SafeTurnRegion (Yes, No);
```

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Ramakrishna, S., Dubey, A., Burruss, M. P., Hartsell, C., Mahadevan, N., Nannapaneni, S., ... & Karsai, G. (2019, May). Augmenting learning components for safety in resource constrained autonomous robots. In 2019 IEEE 22nd International Symposium on Real-Time Distributed Computing (ISORC) (pp. 108-117). IEEE.

bank

bank Bayesian Network

# **Description**

Structural learning of simple staged trees.

bankruptcy 33

# **Format**

A discrete Bayesian network to model whether customers subscribe to a product after being contacted by direct marketing campaigns of a Portuguese banking institution. The Bayesian network is learned via data as stated in the paper. The vertices are:

```
marital Marital status (divorced, married, single, unknown);
education Education (no_uni, uni);
contact Type of direct marketing contact (cellular, telephone);
subscription (no, yes);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Leonelli, M., & Varando, G. (2024). Structural learning of simple staged trees. Data Mining and Knowledge Discovery, 38(3), 1520-1544.

bankruptcy

bankruptcy Bayesian Network

# Description

Using Bayesian networks for bankruptcy prediction: Some methodological issues.

### **Format**

A discrete Bayesian network for bankruptcy prediction. Probabilities were given within the referenced paper. The vertices are:

```
BankruptcyStatus (FALSE, TRUE);
AuditorsOpinion (FALSE, TRUE);
StockReturn (Low, Medium, High);
NetIncomeRate (Low, Medium, High);
IndustryFailureRate (Low, Medium, High);
MarketableSecurities (Low, Medium, High);
FirmSize (Low, Medium, High);
NetIncomeNegative (FALSE, TRUE);
CashAssets (Low, Medium, High);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

34 beam1

# References

Sun, L., & Shenoy, P. P. (2007). Using Bayesian networks for bankruptcy prediction: Some methodological issues. European Journal of Operational Research, 180(2), 738-753.

beam1

beams Bayesian Network

# **Description**

Bayesian networks and their application to the reliability of FRP strengthened beams.

# **Format**

A discrete Bayesian network assess the structural reliability of bridge systems (Figure 2). Probabilities were given within the referenced paper. The vertices are:

```
BeamShearSpan (Low, High);
FRPSheetsSpacing (Low, High);
ModelOfFailure (Rupture, Debonding, Pass);
ProbabilityOfFailure (Fail, Pass);
ShearGain (Low, Medium, High);
```

**WrappingScheme** (Grooving, Side Bonding, Three Side Bonding, Three Side Bonding With Anchoring, Full Wrapping);

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Obaid, O., & Leblouba, M. (2022, March). Bayesian Networks and Their Application to the Reliability of FRP Strengthened Beams. In International Civil Engineering and Architecture Conference (pp. 277-284). Singapore: Springer Nature Singapore.

beam2 35

beam2

beams Bayesian Network

### **Description**

Bayesian networks and their application to the reliability of FRP strengthened beams.

### **Format**

A discrete Bayesian network assess the structural reliability of bridge systems (Figure 3). Probabilities were given within the referenced paper. The vertices are:

```
BeamWidth (Low, High);
ConcreteStrength (Low, High);
ProbabilityOfFailure (Fail, Pass);
Reinforcement (Low, High);
TempAndHumidity (Low, High);
WaterCementRatio (Low, High);
```

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Obaid, O., & Leblouba, M. (2022, March). Bayesian Networks and Their Application to the Reliability of FRP Strengthened Beams. In International Civil Engineering and Architecture Conference (pp. 277-284). Singapore: Springer Nature Singapore.

beatles

beatles Bayesian Network

# Description

Measuring coherence with Bayesian networks.

# **Format**

A discrete Bayesian modelling a situation where a member of the Beatles band might be dead. Probabilities were given within the referenced paper. The vertices are:

```
ExactlyOneBeatlesIsDead (TRUE, FALSE);
GeorgeIsAlive (TRUE, FALSE);
JohnIsAlive (TRUE, FALSE);
PaulIsAlive (TRUE, FALSE);
RingoIsAlive (TRUE, FALSE);
```

36 blacksea

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Kowalewska, A., & Urbaniak, R. (2023). Measuring coherence with Bayesian networks. Artificial Intelligence and Law, 31(2), 369-395.

blacksea

blacksea Bayesian Network

# Description

Analyzing collision, grounding, and sinking accidents occurring in the Black Sea utilizing HFACS and Bayesian networks.

# **Format**

A discrete Bayesian network to analyze the marine accidents. The probabilities were given within the referenced paper. The vertices are:

AnchorageAreaSelection (Appropriate, Inappropriate);

CargoShiftingOrInappropriateStability (Yes, No);

CollisionAndContact (Yes, No);

**COLREG** (Not Violated, Violated);

CompanyManningStrategy (Optimum Safe Manning, Minimum Safe Manning);

**CrewAssignment** (Qualified Crew, Unqualified Crew);

DepartureFromPortInHeavyWeatherAndSeaCondition (Yes, No);

ExternalInternalCommunication (Adequate, Inadequate);

ExternalOperationalConditionsForCollisionAndContact (Observed, Unobserved);

ExternalOperationalConditionsForGrounding (Observed, Unobserved);

ExternalOperationalConditionsForSinking (Observed, Unobserved);

Fatigue (Yes, No);

Grounding (Yes, No);

HeavyWeatherAndSeaConditions (Yes, No);

**InadequateManning** (Yes, No);

InlandVessel (Yes, No);

InternalOperationalConditionsForCollisionAndContact (Observed, Unobserved);

InternalOperationalConditionsForGrounding (Observed, Unobserved);

InternalOperationalConditionsForSinking (Observed, Unobserved);

Malfunction (Observed, Unobserved);

blacksea 37

ManoeuvreOfBridgeTeamMembers (Appropriate, Inappropriate);

```
ManoeuvreOfCaptain (Appropriate, Inappropriate);
ManoeuvreOfPilot (Appropriate, Inappropriate);
ManoeuvreOfWatchkeepingOfficer (Appropriate, Inappropriate);
NavigationArea (Narrow Water, Port, Coastal Water, Open Sea, Anchorage);
NavigationOnStorm (Yes, No);
ObservationDuringOperation (Clear, Unclear);
OversightAndControl (Adequate, Inadequate);
PilotOperationManagement (Safe, Unsafe);
PlannedMaintenance (Completed, Uncompleted);
PortCompanyPressure (Yes, No);
PortOperationManagement (Safe, Unsafe);
PortOperationPlanning (Adequate, Inadequate);
Procedure (Appropriate, Inappropriate);
Sinking (Yes, No);
Situational Awareness (Sufficient, Insufficient);
TrainingAndFamiliarization (Sufficient, Insufficient);
TriggeringEventForCollisionAndContact (Observed, Unobserved);
TriggeringEventForGrounding (Observed, Unobserved);
TriggeringEventForSinking (Observed, Unobserved);
TugboatOperation (Operational, Faulty);
UseOfVesselInConditionOfExceedingDesignLimit (Yes, No);
VesselAge (Old, New);
VesselCargoOperationManagement (Safe, Unsafe);
VesselCargoOperationPlanning (Adequate, Inadequate);
VesselNavigationOperationManagement (Safe, Unsafe);
VesselNavigationOperationPlanning (Unsafe, Safe);
Visibility (Poor, Good);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Ugurlu, O., Yildiz, S., Loughney, S., Wang, J., Kuntchulia, S., & Sharabidze, I. (2020). Analyzing collision, grounding, and sinking accidents occurring in the Black Sea utilizing HFACS and Bayesian networks. Risk analysis, 40(12), 2610-2638.

38 blockchain

blockchain

blockchain Bayesian Network

# **Description**

A machine learning based approach for predicting blockchain adoption in supply chain.

#### **Format**

A discrete Bayesian network to predict the probability of blockchain adoption in an organization. Probabilities were given within the referenced paper. The vertices are:

```
BA Blockchain adoption (Low, High);

COMPB Compatibility (Low, High);

COMPX Complexity (Low, High);

CP Competitive pressure (Low, High);;

PEOU Perceived ease of use (Low, High);

PFB Perceived financial benefits (Low, High);

PR Partner readiness (Low, High);

PU Perceived usefulness (Low, High);

RA Relative advantage (Low, High);

TE Training and education (Low, High);

TKH Technical know-how (Low, High);

TMS Top management support (Low, High);
```

@return An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Kamble, S. S., Gunasekaran, A., Kumar, V., Belhadi, A., & Foropon, C. (2021). A machine learning based approach for predicting blockchain adoption in supply chain. Technological Forecasting and Social Change, 163, 120465.

bnRep 39

bnRep

bnRep: A Repository of Bayesian Network Models

### Description

A repository of discrete, Gaussian, and conditional linear Gaussian Bayesian networks from the recent academic literature.

### **Details**

The package includes over 200 Bayesian networks which appeared in recent academic papers. They can be accessed by their name, as provided in this documentation.

They are stored as bn.fit objects from the bnlearn package. Recall that in order to plot them, the function bn.net must be used to convert them into a graph object.

The package includes two handy functionalities:

- The bnRep\_summary object: a dataframe including a lot of details about the Bayesian networks in the repository;
- The bnRep\_app function, which launchs a Shiny app to explore the Bayesian networks in the repository.

Thanks to the interface with bnlearn, functions from that package can be used to export the networks in other formats and use them in other platforms, such as Netica, Hugin, or Python.

bnRep\_app

Launch the Bayesian Network Viewer App

# Description

This function launches the Shiny app that allows users to interactively view and filter the Bayesian networks repository.

#### Usage

bnRep\_app()

### Value

The function calls a Shiny app to plot networks in bnRep and explore the database of networks stored in bnRep\_summary.

40 bnRep\_summary

bnRep\_summary

BnRep Summary

## **Description**

Summary of the Bayesian networks in bnRep reporting various graph, definition and application details.

#### **Usage**

bnRep\_summary

#### **Format**

A data frame with a row for each BN in bnRep and the following columns:

Name Name of the R object storing the BN;

**Type** Type of Bayesian network (Discrete, Gaussian, Hybrid);

**Structure** How the graph of the BN was defined (Data, Expert, Fixed, Knowledge, Mixed, Synthetic);

**Probabilities** How the probabilities of the BN were defined (Data, Expert, Knowledge, Mixed, Synthetic);

**Graph** Type of graph of the BN (Generic, K-Dep, Naive Bayes, Reverse Naive Bayes, Reverse Tree, TAN, Tree);

**Area** Subject area of the Bayesian network using the SJR classification (Agricultural Sciences, Business, Chemical Engineering, etc.);

**Nodes** Number of nodes in the BN;

**Arcs** Number of arcs in the BN;

Parameters Number of free parameters in the BN;

Avg. Parents Average number of parents;

Max Parents Maximum number of parents;

Avg. Levels Average number of discrete variables' levels;

Max Levels Max number of discrete variables' levels:

Average Markov Blanket Average size of a node's Markov blanket;

**Year** Year of the publication where the BN appeared;

Journal Journal where the BN appeared;

**Reference** Reference of the paper where the BN appeared.

### **Examples**

summary(bnRep\_summary)

BOPfailure1 41

BOPfailure1

BOPfailure Bayesian Networks

### **Description**

Providing a comprehensive approach to oil well blowout risk assessment.

### **Format**

A discrete Bayesian network for risk assessment of oil well blowout (Fig. 5 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

```
BOP_System_Failure (F, S);
```

- **X1** BOP stack failure (F, S);
- **X2** Valve failure (F, S);
- **X3** BOP control system failure (F, S);
- **X4** Line failure (F, S);
- **X5** Choke manifold failure (F, S);
- **X6** Annular preventer (F, S);
- **X7** Ram preventer (F, S);
- **X8** Kill valve fail (F, S);
- **X9** Choke valve fail (F, S);
- **X10** Choke line fail (F, S);
- X11 Kill line fail (F, S);
- **X12** Upper annular preventer fails (F, S);
- **X13** Lower annular preventer fails (F, S);
- **X14** Upper pipe ram fail (F, S);
- **X15** Middle pipe ram fail (F, S);
- **X16** Lower pipe ram failure (F, S);
- **X17** Blind shear ram failure (F, S);
- **X18** Power system failure (F, S);
- X19 4Way valve failure (F, S);
- **X20** Remote panel valve failure (F, S);
- **X21** Signal line failure (F, S);
- **X22** Accumulator line failure (F, S);
- **X23** Air-driven pump failure (F, S);
- **X24** Electric pump failure (F, S);
- **X25** Choke valve failure (F, S);
- **X26** Hydraulic choke valve failure (F, S);
- **X27** Gate valve failure (F, S);
- **X28** Choke remote panel failure (F, S);
- **X29** Hydraulic choke valve failure (F, S);

42 BOPfailure2

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Satiarvand, M., Orak, N., Varshosaz, K., Hassan, E. M., & Cheraghi, M. (2023). Providing a comprehensive approach to oil well blowout risk assessment. Plos One, 18(12), e0296086.

BOPfailure2

BOPfailure Bayesian Networks

### **Description**

Providing a comprehensive approach to oil well blowout risk assessment.

#### **Format**

A discrete Bayesian network for risk assessment of oil well blowout (Fig. 3 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

```
Kick (F, S);
```

- **X1** Efficient hydrocarbon formation (F, S);
- **X2** Negative diffraction pressure (F, S);
- **X3** Sufficient permeability (F, S);
- **X4** Low hydrostatic pressure (F, S);
- **X5** Low and lost Annular Pressure Loss (F, S);
- **X6** Surface line failure (F, S);
- **X7** Power failure (F, S);
- **X8** Pump failure (F, S);
- **X9** Operator failure to notice adjustment (F, S);
- **X10** Pump control failure (F, S);
- **X11** Leakage from the pump's fluid side (F, S);
- X12 Blowing (F, S);
- **X13** Density reduction (F, S);
- **X14** Volume reduction (F, S);
- **X15** Inadequate holes fill up (F, S);
- **X16** Mud loss (F, S);
- **X17** Gas-cut mud (F, S);
- **X18** Abnormal pressurize (F, S);
- **X19** Swabbing while tripping (F, S);
- **X20** Mud weight reduction (F, S);

BOPfailure2 43

- **X21** Failure in Mud treatment equipment (F, S);
- **X22** Formation (F, S);
- **X23** Increasing mud weight (F, S);
- **X24** Annular losses (F, S);
- **X25** Bad cementing (F, S);
- **X26** Casing failure (F, S);
- **X27** Surging-piston effect (F, S);
- **X28** Failure in centrifuge (F, S);
- **X29** Failure in degasser (F, S);
- **X30** Mud cleaner equipment in adjustment (F, S);
- **X31** Power failure (F, S);
- **X32** Agitator(mixer) failure (F, S);
- **X33** Settlement of mud-weight substance (F, S);
- **X34** Pulling the pipe too fast (F, S);
- **X35** Using Mud with high viscosity and high gel strength (F, S);
- **X36** Having balled up a bit (F, S);
- X37 Having thick wall cake (F, S);
- **X38** Having a small clearance between the string and the hole (F, S);
- **X39** Having and plugged drill string (F, S);
- **X40** Directing the pipes at the speed inside the well (F, S);
- **X41** Using mud of high viscosity & and high gel strength (F, S);
- **X42** Having balled up (F, S);
- X43 Having Thick wall cake (F, S);
- **X44** Having a small clearance between the string and the hole (F, S);
- **X45** Using the float valve /nonreturn safety valve (F, S);

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Satiarvand, M., Orak, N., Varshosaz, K., Hassan, E. M., & Cheraghi, M. (2023). Providing a comprehensive approach to oil well blowout risk assessment. Plos One, 18(12), e0296086.

44 BOPfailure3

BOPfailure3

BOPfailure Bayesian Networks

## **Description**

Providing a comprehensive approach to oil well blowout risk assessment.

#### **Format**

A discrete Bayesian network for risk assessment of oil well blowout (Fig. 4 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

```
Kick_Detection_Failure (F, S);
```

- **X1** Mud volume/ flow change (F, S);
- **X2** Circulation pressure change (F, S);
- X3 Gas-cut (F, S);
- **X4** Mud property change (F, S);
- **X5** Rate of Penetration (ROP) change Failure (F, S);
- **X6** Mud tank (F, S);
- **X7** Flow Failure (F, S);
- **X8** Pump Failure (F, S);
- **X9** Pump Rate (Stroke Per Minute: SPM) (F, S);
- X10 Mud density (F, S);
- **X11** Mud conductivity (F, S);
- **X12** Failure of tank level indicator (float system) (F, S);
- **X13** Failure of an operator to notice the tank level change (F, S);
- X14 Failure of flow meter (F, S);
- **X15** Failure of an operator to notice the flow meter (F, S);
- **X16** Failure of pressure gage (F, S);
- **X17** Failure of an operator to notice a change in SPM (F, S);
- X18 Failure of stroke meter (F, S);
- X19 Failure of an operator to notice a change in P.R (F, S);
- **X20** Failure of gas detector (F, S);
- **X21** Failure of an operator to notice the gauge (F, S);
- **X22** Failure of the density meter (F, S);
- **X23** Failure of an operator to the density meter (F, S);
- **X24** Failure of resistivity (F, S);
- **X25** Failure of an operator to notice the conductivity change (F, S);
- **X26** Failure of the ROP indicator (F, S);
- **X27** Failure of the ROP change (F, S);

building 45

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Satiarvand, M., Orak, N., Varshosaz, K., Hassan, E. M., & Cheraghi, M. (2023). Providing a comprehensive approach to oil well blowout risk assessment. Plos One, 18(12), e0296086.

building

building Bayesian Network

### **Description**

Sensitivity analysis in Gaussian Bayesian networks using a symbolic-numerical technique.

#### **Format**

A Gaussian Bayesian network to assess the damage of reinforced concrete structures of buildings. Probabilities were given within the referenced paper. The vertices are:

- X1 Damage assessment;
- X2 Cracking state;
- **X3** Cracking state in shear domain;
- X4 Steel corrosion;
- **X5** Cracking state in flexure domain;
- **X6** Shrinkage cracking;
- X7 Worst cracking in flexure domain;
- X8 Corrosion state;
- **X9** Weakness of the beam;
- **X10** Deflection of the beam;
- X11 Position of the worst shear crack;
- **X12** Breadth of the worst shear crack;
- **X13** Position of the worst flexure crack;
- X14 Breadth of the worst flexure crack;
- **X15** Length of the worst flexure cracks;
- X16 Cover;
- X17 Structure age;
- X18 Humidity;
- X19 pH value in the air;
- **X20** Content of chlorine in the air;
- X21 Number of shear cracks;
- X22 Number of flexure cracks;
- X23 Shrinkage;
- X24 Corrosion;

46 bullet

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Castillo, E., & Kjærulff, U. (2003). Sensitivity analysis in Gaussian Bayesian networks using a symbolic-numerical technique. Reliability Engineering & System Safety, 79(2), 139-148.

bullet

bullet Bayesian Network

### **Description**

Combined interpretation of objective firearm evidence comparison algorithms using Bayesian network.

### Usage

bullet

#### **Format**

A discrete Bayesian network to leverage the strengths of individual approaches to evaluate the similarity of features on two bullets. The network was available in a repository. The vertices are:

Conclusion (NotSource, Source);

CCF Cross-correlation function (CCF\_0\_1, CCF\_1\_2, CCF\_2\_3, CCF\_3\_4, CCF\_4\_5, CCF\_5\_6, CCF\_6\_7, CCF\_7\_8, CCF\_8\_9, CCF\_9\_10);

CMPS Congruent matching profile segments (CMPS\_0, CMPS\_1, CMPS\_2, CMPS\_3, ..., CMPS\_27);

**RF** Random forest (RF\_0\_1, RF\_1\_2, RF\_2\_3, RF\_3\_4, RF\_4\_5, RF\_5\_6, RF\_6\_7, RF\_7\_8, RF\_8\_9, RF\_9\_10);

CMS Consecutively matching striae (CMS\_0, CMS\_1, ...., CMS\_29);

### **Details**

@usage NULL

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Spaulding, J. S., & LaCasse, L. S. (2024). Combined interpretation of objective firearm evidence comparison algorithms using Bayesian networks. Journal of Forensic Sciences.

burglar 47

burglar

burglar Bayesian Network

# **Description**

Strategies for selecting and evaluating information.

#### **Format**

A discrete Bayesian network modeling a simple burglary scenario (Model 1, Table 2). The network was available from an associated repository. The vertices are:

```
Burglar (Suspect 1, Suspect 2, Suspect3);
PrimaryItemStolen (Jewellery, Electronics, Money);
```

BurglaryTime (Day, Night);

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Liefgreen, A., Pilditch, T., & Lagnado, D. (2020). Strategies for selecting and evaluating information. Cognitive Psychology, 123, 101332.

cachexia1

cachexia Bayesian Networks

### **Description**

Model-preserving sensitivity analysis for families of Gaussian distributions.

### **Format**

A Gaussian Bayesian networks comparing the dependence of metabolomics for people who suffer of Cachexia. The Bayesian network is learned as in the referenced paper. The vertices are:

A Adipate;

B Betaine;

F Fumarate:

GC Glucose;

GM Glutamine;

V Valine;

48 cachexia2

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Gorgen, C., & Leonelli, M. (2020). Model-preserving sensitivity analysis for families of Gaussian distributions. Journal of Machine Learning Research, 21(84), 1-32.

cachexia2

cachexia Bayesian Networks

### **Description**

Model-preserving sensitivity analysis for families of Gaussian distributions.

#### **Format**

A Gaussian Bayesian networks comparing the dependence of metabolomics for people who do not suffer of Cachexia. The Bayesian network is learned as in the referenced paper. The vertices are:

A Adipate;

B Betaine:

F Fumarate;

GC Glucose;

GM Glutamine;

V Valine;

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Gorgen, C., & Leonelli, M. (2020). Model-preserving sensitivity analysis for families of Gaussian distributions. Journal of Machine Learning Research, 21(84), 1-32.

cardiovascular 49

cardiovascular

cardiovascular Bayesian Network

### **Description**

A Bayesian network model for predicting cardiovascular risk.

### **Format**

A discrete Bayesian network allowing for making inferences and predictions about cardiovascular risk factors. Probabilities were given within the referenced paper. The vertices are:

```
Age (18-24", 24-34, 34-44, 44-54, 54-64, 64-74);

Anxiety (No, Yes);

BodyMassIndex (Normal, Obese, Overweight, Underweight);

Depression (No, Yes);

Diabetes (No, Yes);

EducationLevel (1, 2, 3);

Hypercholesterolemia (No, Yes);

Hypertension (No, Yes);

PhysicalActivity (Insufficiently Active, Regularly Active);

Sex (Female, Male);

SleepDuration (6-9hours, <6hours, >9hours);

SmokerProfile (Ex_Smoker, Non_Smoker, Smoker);

SocioeconomicStatus (1, 2, 3);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Ordovas, J. M., Rios-Insua, D., Santos-Lozano, A., Lucia, A., Torres, A., Kosgodagan, A., & Camacho, J. M. (2023). A Bayesian network model for predicting cardiovascular risk. Computer Methods and Programs in Biomedicine, 231, 107405.

50 case

case

case Bayesian Network

# **Description**

Building a stronger case: Combining evidence and law in scenario-based Bayesian networks.

# **Format**

A discrete Bayesian network for concrete legal fact idioms that qualify events in a narrative Bayesian network. The network was available from a public repository. The vertices are:

```
Body (f, t);
ComplicityMurder (f, t);
DebtFightFK (f, t);
FBarn (f, t);
FightBarn (f, t);
FStenGun (f, t);
Help (f, t);
Intent (f, t);
KBarn (f, t);
Killed (f, t);
KKilled (f, t);
Murder (f, t);
Murdered (f, t);
PlanBarnF (f, t);
Premed (f, t);
Prov (f, t);
SBarn (f, t);
ShootStenGun (none, F, Not F);
TMathus (f, t);
TSF1 (f, t);
TSF2 (f, t);
TSLocation (f, t);
TStenGun (f, t);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

catchment 51

#### References

Van Leeuwen, L., Verbrugge, R., Verheij, B., & Renooij, S. (2024, June). Building a Stronger Case: Combining Evidence and Law in Scenario-Based Bayesian Networks. In 3rd International Conference on Hybrid Human-Artificial Intelligence, HHAI 2024 (pp. 291-299). IOS Press.

catchment

catchment Bayesian Network

### **Description**

A framework to diagnose the causes of river ecosystem deterioration using biological symptoms.

#### **Format**

A discrete Bayesian network to estimate the probability of individual stressors being causal for biological degradation at the scale of individual riverine ecosystems (Catchment BN). The network was available from an associated repository. The vertices are:

```
Arable (Low, Enhanced, Intermediate, High);
N (Low, Intermediate, High);
Urban (None, Enhanced, High);
Fines (Normal, Enhanced);
Nitrate (Low, Enhanced);
Grazer (Low, Medium, High);
oPO4 (Low, High);
BufForest (Low, High);
BOD5 (Low, Enhanced, High);
WaterQ (Low, Fair, Good);
OrgMatter (Low, High);
Stagnant (No, Yes);
HabitatQ (Low, Fair, Good);
Straight (No, Yes);
FlowQ (Low, High);
EPT (Low, Medium, High);
ASPT (Low, Medium, High);
SI (Low, Medium, High);
Shredder (Low, Medium, High);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

52 charleston

#### References

Feld, C. K., Saeedghalati, M., & Hering, D. (2020). A framework to diagnose the causes of river ecosystem deterioration using biological symptoms. Journal of Applied Ecology, 57(11), 2271-2284.

charleston

charleston Bayesian Network

### **Description**

Parameterization framework and quantification approach for integrated risk and resilience assessments.

#### **Format**

A discrete Bayesian network for risk and resilience assessment of climate change impacts within the Charleston Harbor Watershed of South Carolina (Region 3). The probabilities were given within the referenced paper. The vertices are:

AbilityToEvacuate (Zero, Low, Medium, High);

ActiveHurricane (No, Yes);

**DrowningMortality** (Zero, Low, Medium, High);

EvacuationRequired (Zero, Low, Medium, High);

ExtremePrecipitation (Zero, Low, Medium, High);

ExtremePrecipitationNonHurricane (Zero, Low, Medium, High);

FloodExposure (Zero, Low, Medium, High);

FloodHazard (Zero, Low, Medium, High);

FloodPreparedness (No, Yes);

HurricaneCategory (Zero, Low, Medium, High);

NuisanceFloodExposure (Zero, Low, Medium, High);

NuisanceFloodFrequency (Zero, Low, Medium, High);

NuisanceFloodHazard (Zero, Low, Medium, High);

Personal Vehicle (No, Yes);

PhysicalFloodProtection (No, Yes);

PopulationLocation (Zero, Low, Medium, High);

RegionWithCoastline (No, Yes);

RiskToHumanHealth (Zero, Low, Medium, High);

RoadwayAccessibility (Zero, Low, Medium, High);

RoadwayLocation (Zero, Low, Medium, High);

SeaLevelRise (Zero, Low, Medium, High);

StormSurge (Zero, Low, Medium, High);

**StormSurgeProtection** (No, Yes);

TideLevelAboveHighTide (Zero, Low, Medium, High);

chds 53

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Cains, M. G., & Henshel, D. (2021). Parameterization framework and quantification approach for integrated risk and resilience assessments. Integrated Environmental Assessment and Management, 17(1), 131-146.

chds

chds Bayesian Network

### **Description**

Refining a Bayesian network using a chain event graph.

### **Format**

A discrete Bayesian network looking at the effect the family's social background, the economic status and the number of family life events have on the child's health which is measured by rates of hospital admission. The Bayesian network is learned as in the referenced paper. The vertices are:

Social Social background (High, Low);

**Economic** Economic status (High, Low);

**Events** Number of life events (High, Average, Low);

**Admission** Rate of hospital admissions (Yes, No);

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Barclay, L. M., Hutton, J. L., & Smith, J. Q. (2013). Refining a Bayesian network using a chain event graph. International Journal of Approximate Reasoning, 54(9), 1300-1309.

54 cng

cng

cng Bayesian Network

### Description

Quantitative risk estimation of CNG station by using fuzzy bayesian networks and consequence modeling.

#### **Format**

A discrete Bayesian network for risk assessment in compressed natural gas (CNG) stations. The probabilities were given within the referenced paper. The vertices are:

```
X1 Not up-to-date technology (T, F);
```

- **X2** Lack of maintenance (T, F);
- **X3** Unsafe equipment (T, F);
- **X4** Type of ignition material (T, F);
- **X5** The nature of the chemical substance (T, F);
- **X6** Inspection defect in wear detection (T, F);
- **X7** Improper use of the equipment (T, F);
- X8 Leakage (T, F);
- **X9** High temperature (T, F);
- **X10** Low temperature (T, F);
- **X11** Horizontal wind speed (T, F);
- **X12** Vertical wind speed (T, F);
- **X13** Environmental stability and instability (T, F);
- **X14** Sunny hours (T, F);
- **X15** Relative humidity and evaporation rate (T, F);
- **X16** Lighting (T, F);
- X17 Landslide (T, F);
- **X18** Flood (T, F);
- **X19** Earthquake (T, F);
- **X20** Land settlement (T, F);
- **X21** Deliberate vandalism (T, F);
- **X22** Incidents related to the missile site (T, F);
- **X23** Military attack (T, F);
- **X24** Explosion of other equipment (T, F);
- **X25** Deliberate error in the execution of the recipe (T, F);
- **X26** Accidental collision valves (T, F);

cng 55

```
X27 Failure to issue a work permit (T, F);
X28 Artificial lighting (T, F);
X29 Natural lighting (T, F);
X30 Lack of cost (T, F);
X31 Requirements for conducting training classes by managers (T, F);
X32 Fatigue (T, F);
X33 Shift work (T, F);
X34 Stress - internal causes) (T, F);
X35 Stress - external causes (T, F);
X36 Not having enough experience and skills (T, F);
X37 Hearing loss - non-occupational causes (T, F);
X38 Hearing loss - occupational causes (T, F);
X39 Failure to notify the control room in time (T, F);
X40 Fear of explosion and fire by operator (T, F);
X41 Operator performance - temperature and humidity (T, F);
X42 Chemical pollutants - particles (T, F);
X43 Chemical pollutants - gas and steam (T, F);
X44 Solid waste (T, F);
X45 Liquid waste (T, F);
X46 Adjacent commercial use (T, F);
X47 Adjacent residential use (T, F);
X48 Adjacent industrial use (T, F);
X49 Land uses changes (T, F);
X50 Room metering - measurement of changes (T, F);
X51 Room metering - operator error (T, F);
X52 Lack of standard dryer quality (T, F);
X53 Disturbance in the electricity flow of the dryer (T, F);
X54 Fire dryer heaters (T, F);
X55 Leakage of tank (T, F);
X56 Adjacent tanks (T, F);
X57 Dispenser leakage and damage (T, F);
X58 Disregarding dispenser safety signs (T, F);
X59 Dispenser malfunction (T, F);
X60 Improper management performance (T, F);
AdjacentLandUses (T, F);
AnticipatedEvents (T, F);
ChemicalContaminants (T, F);
```

56 cng

```
ClimateChanges (T, F);
Dispenser (T, F);
Dryer (T, F);
EnvironmentChanges (T, F);
Exhaustion (T, F);
FailureToInspectAndOperateEquipment (T, F);
FortuitousEvents (T, F);
HearingLoss (T, F);
HumanReasons (T, F);
ImproperOperatorPerformance (T, F);
InadequateTraining (T, F);
LeakOfCNG (T, F);
Lighting (T, F);
MilitaryIncidents (T, F);
NaturalDisasters (T, F);
ProcessProblems (T, F);
RoomMetering (T, F);
Storage (T, F);
Stress (T, F);
TankStructure (T, F);
Temperature (T, F);
Wastes (T, F);
WindSpeed (T, F);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Abbasi Kharajou, B., Ahmadi, H., Rafiei, M., & Moradi Hanifi, S. (2024). Quantitative risk estimation of CNG station by using fuzzy bayesian networks and consequence modeling. Scientific Reports, 14(1), 4266.

compaction 57

compaction

compaction Bayesian Network

# **Description**

A Bayesian approach toward the use of qualitative information to inform on-farm decision making: The example of soil compaction.

#### **Format**

A discrete Bayesian network to highlight the financial consequences of failing to adopt controlled traffic farming management for a particular agricultural enterprise. The probabilities were given within the referenced paper. The vertices are:

ClayContent (Very Low, Low, Medium, High, Very High);

CompactionRisk (Low, Medium, High);

CompactionVulnerability (Low, Medium, High);

InherentSusceptibility (Low, Medium, High);

SoilWetness (Dry, Moist, Wet);

TotalExposure (Low, Medium, High);

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Roberton, S. D., Lobsey, C. R., & Bennett, J. M. (2021). A Bayesian approach toward the use of qualitative information to inform on-farm decision making: the example of soil compaction. Geoderma, 382, 114705.

conasense

conasense Bayesian Network

## **Description**

Bayesian neural networks for 6G CONASENSE services.

### **Format**

A discrete Bayesian network to support to optimization of the CONASENSE network. Probabilities were given within the referenced paper. The vertices are:

Communication (Bandwidth, CoverageArea, Latency, PacketLoss);

Navigation (Accuracy, Mobility, Speed);

**Sensing** (TransmissionRange, Angle, Uplink);

Services (Good, Moderate, Poor);

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Henrique, P. S. R., & Prasad, R. (2022, October). Bayesian Neural Networks for 6G CONASENSE Services. In 2022 25th International Symposium on Wireless Personal Multimedia Communications (WPMC) (pp. 291-296). IEEE.

concrete1

concrete Bayesian Networks

## **Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

### **Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Model 1.1 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

Basement (False, True);

BlueConcrete (False, True);

BuildingClass (Single Family House, MultiFamily House, School Building, Other Building);

FloorArea (0-150, 150-220, 220-360, 360-1500, >1500);

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. Expert Systems with Applications, 222, 119812.

concrete2

concrete Bayesian Networks

### **Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

### **Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Model 2.1 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

Basement (False, True);

BlueConcrete (False, True);

BuildingClass (Single Family House, MultiFamily House, School Building, Other Building);

ConstructionYear (1930-1955, 1955-1960, 1960-1968, 1968-1975, 1975-1980);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. Expert Systems with Applications, 222, 119812.

concrete3

concrete Bayesian Networks

### **Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

# Format

A discrete Bayesian network for evaluating the presence probability of blue concrete (Model 3.1 of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

**AverageDistance** (0-150, 150-220, 220-360, 360-1500, >1500)

BlueConcrete (False, True);

FloorArea (0-150, 150-220, 220-360, 360-1500, >1500);

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. Expert Systems with Applications, 222, 119812.

concrete4

concrete Bayesian Networks

### **Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

#### **Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Fig. E1 - Single-Family Houses, of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

```
AverageDistance (0-300, 300-600, >600);

Basement (False, True);

BlueConcrete (False, True);

ConstructionYear (1930-1955, 1955-1960, 1960-1968, 1968-1975, 1975-1980);
```

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. Expert Systems with Applications, 222, 119812.

concrete5

concrete Bayesian Networks

### Description

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

#### **Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Fig. E1 - Multi-Family Houses, of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

```
AverageDistance (0-300, 300-600, >600);

BlueConcrete (False, True);

FloorArea (0-150, 150-220, 220-360, 360-1500, >1500);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. Expert Systems with Applications, 222, 119812.

concrete6

concrete Bayesian Networks

### **Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

### **Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Fig. E1 - School Buildings, of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

```
AverageDistance (0-300, 300-600, >600);

BlueConcrete (False, True);

FloorArea (0-150, 150-220, 220-360, 360-1500, >1500);
```

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. Expert Systems with Applications, 222, 119812.

concrete7

concrete Bayesian Networks

# **Description**

Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks.

#### **Format**

A discrete Bayesian network for evaluating the presence probability of blue concrete (Fig. E1 - Other Buildings, of the referenced paper). Probabilities were given within the referenced paper. The vertices are:

```
AverageDistance (0-300, 300-600, >600);
```

BlueConcrete (False, True);

ConstructionYear (1930-1955, 1955-1960, 1960-1968, 1968-1975, 1975-1980);

**FloorArea** (0-150, 150-220, 220-360, 360-1500, >1500);

NumberOfStairwells (0, 1, 2, 3, 4);

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Wu, P. Y., Johansson, T., Mangold, M., Sandels, C., & Mjornell, K. (2023). Estimating the probability distributions of radioactive concrete in the building stock using Bayesian networks. Expert Systems with Applications, 222, 119812.

consequenceCovid 63

consequenceCovid

consequenceCovid Bayesian Network

### **Description**

Global sensitivity analysis of uncertain parameters in Bayesian networks.

#### **Format**

A discrete Bayesian network including demographic information of the respondents of the Eurobarometer 93.1 together with their opinion about how the COVID-19 emergency was handled by local authorities and its consequences in the long term. The Bayesian network was learned as in the referenced paper. The vertices are:

**AGE** How old are you? (18-30, 30-50, 51-70, 70+);

**LIFESAT** On the whole, are you satisfied with the life you lead? (Yes, No);

**TRUST** Do you trust or not the people in your country? (Yes, No);

**SATMEAS** In general, are you satisfied with the measures taken to fight the Coronavirus outbreak by your government? (Yes, No);

**HEALTH** Thinking about the measures taken by the public authorities in your country to fight the Coronavirus and its effects, would you say that they... (Focus too much on health, Focus too much on economives, Are balanced);

**JUSTIFIED** Thinking about the measures taken by the public authorities in your country to fight the Coronavirus and its effects, would you say that they were justfied? (Yes, No);

**PERSONALFIN** The Coronavirus outbreak will have serious economic consequences for you personally (Agree, Disagree, Don't know);

**COUNTRYFIN** The Coronavirus outbreak will have serious economic consequences for your country (Agree, Disagree, Don't know);

**INFO** Which of the following was your primary source of information during the Coronavirus outbreak? (Television, Written press, Radio, Websites, Social networks);

**COPING** Thinking about the measures taken to fight the Coronavirus outbreak, in particular the confinement measures, would you say that it was an experience...? (Easy to cope with, Both easy and difficult to cope with, Difficult to cope with);

**POLITICS** In political matters people talk of 'the left' and 'the right'. How would you place your views on this scale? (Left, Centre, Right, Don't know);

**OCCUPATION** Are you currently working? (Yes, No);

**GENDER** What is your sex? (Male, Female);

**COMMUNITY** Would you say you live in a... (Rural area or village, Small or middle sized town, Large town);

**CLASS** Do you see yourself and your household belonging to...? (Working class, Lower class, Middle class, Upper class);

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Ballester-Ripoll, R., & Leonelli, M. (2024). Global Sensitivity Analysis of Uncertain Parameters in Bayesian Networks. arXiv preprint arXiv:2406.05764.

constructionproductivity

constructionproductivity Bayesian Network

# Description

Construction productivity prediction through Bayesian networks for building projects: case from Vietnam.

#### **Format**

A discrete Bayesian network to identify causal relationship and occurrence probability of critical factors affecting construction productivity. Probabilities were given within the referenced paper. The vertices are:

```
Accidents (Yes, No);
AdverseWeather (Yes, No);
Age (Yes, No);
Attitude (Yes, No);
EngineerQualification (Yes, No);
Experience (Yes, No);
HealthStatus (Yes, No);
MaterialPresence (Yes, No);
OwnerFinance (Yes, No);
PlanningAndMethod (Yes, No);
Productivity (Yes, No);
Sex (Yes, No);
SkilledWorkers (Yes, No);
TaskComplexity (Yes, No);
TechnologyLevel (Yes, No);
WorkingFrequency (Yes, No);
WorkingTools (Yes, No);
Workmanship (Yes, No);
```

@return An object of class \code{bn.fit}. Refer to the documentation of \code{bnlearn} for details.

coral1 65

### References

Khanh, H. D., & Kim, S. Y. (2022). Construction productivity prediction through Bayesian networks for building projects: Case from Vietnam. Engineering, Construction and Architectural Management, 30(5), 2075-2100.

coral1

coral Bayesian Networks

# **Description**

Assessing coral reef condition indicators for local and global stressors using Bayesian networks.

#### **Format**

A discrete Bayesian network for the evaluation of threats to reef condition globally (colony bleaching). The probabilities were given within the referenced paper. The vertices are:

**CoralColonyBleached** (Less than 0, 0-0.145, 0.145-0.374, 0.374-0.680, More than 0.680);

AcidificationThreat (Low, High);

CoastalDevelopmentThreat (Low, Medium, High);

ManagementEffectiveness (Ineffective, Partial, Effective);

MarineBasedPollutionThreat (Low, Medium, High);

Overfishing (Low, Medium, High);

ThermalStress (None, Severe);

WatershedBasedPollutionThreat (Low, Medium, High);

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Carriger, J. F., Yee, S. H., & Fisher, W. S. (2021). Assessing coral reef condition indicators for local and global stressors using Bayesian networks. Integrated Environmental Assessment and Management, 17(1), 165-187.

66 coral3

coral2

coral Bayesian Networks

# **Description**

Assessing coral reef condition indicators for local and global stressors using Bayesian networks.

#### **Format**

A discrete Bayesian network for the evaluation of threats to reef condition globally (recently killed corals). The probabilities were given within the referenced paper. The vertices are:

**KilledCoralCover** (Less than 0, 0-0.075, 0.075-0.212, 0.212-0.450, More than 0.450);

AcidificationThreat (Low, High);

CoastalDevelopmentThreat (Low, Medium, High);

ManagementEffectiveness (Ineffective, Partial, Effective);

MarineBasedPollutionThreat (Low, Medium, High);

Overfishing (Low, Medium, High);

ThermalStress (None, Severe);

 $Watershed Based Pollution Threat \ (Low, Medium, High);\\$ 

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Carriger, J. F., Yee, S. H., & Fisher, W. S. (2021). Assessing coral reef condition indicators for local and global stressors using Bayesian networks. Integrated Environmental Assessment and Management, 17(1), 165-187.

coral3

coral Bayesian Networks

### **Description**

Assessing coral reef condition indicators for local and global stressors using Bayesian networks.

coral4 67

#### **Format**

A discrete Bayesian network for the evaluation of threats to reef condition globally (live coral index). The probabilities were given within the referenced paper. The vertices are:

**ReefHealthIndex** (Less than 0, 0-0.118, 0.118-0.330, 0.330-0.683, More than 0.683);

AcidificationThreat (Low, High);

CoastalDevelopmentThreat (Low, Medium, High);

ManagementEffectiveness (Ineffective, Partial, Effective);

MarineBasedPollutionThreat (Low, Medium, High);

Overfishing (Low, Medium, High);

ThermalStress (None, Severe);

WatershedBasedPollutionThreat (Low, Medium, High);

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Carriger, J. F., Yee, S. H., & Fisher, W. S. (2021). Assessing coral reef condition indicators for local and global stressors using Bayesian networks. Integrated Environmental Assessment and Management, 17(1), 165-187.

coral4

coral Bayesian Networks

### **Description**

Assessing coral reef condition indicators for local and global stressors using Bayesian networks.

#### **Format**

A discrete Bayesian network for the evaluation of threats to reef condition globally (live coral cover). The probabilities were given within the referenced paper. The vertices are:

 $\textbf{LiveCoralCover} \;\; (Less \; than \; 0, \, 0\text{-}0.040, \, 0.040\text{-}0.122, \, 0.122\text{-}0.241, \, 0.241\text{-}0.417, \, More \; than \; 0.417); \\$ 

AcidificationThreat (Low, High);

CoastalDevelopmentThreat (Low, Medium, High);

ManagementEffectiveness (Ineffective, Partial, Effective);

MarineBasedPollutionThreat (Low, Medium, High);

Overfishing (Low, Medium, High);

ThermalStress (None, Severe);

WatershedBasedPollutionThreat (Low, Medium, High);

68 coral5

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Carriger, J. F., Yee, S. H., & Fisher, W. S. (2021). Assessing coral reef condition indicators for local and global stressors using Bayesian networks. Integrated Environmental Assessment and Management, 17(1), 165-187.

coral5

coral Bayesian Networks

### **Description**

Assessing coral reef condition indicators for local and global stressors using Bayesian networks.

#### **Format**

A discrete Bayesian network for the evaluation of threats to reef condition globally (population bleaching). The probabilities were given within the referenced paper. The vertices are:

**CoralPopulationBleached** (Less than 0, 0-0.086, 0.086-0.265, 0.265-0.507, More than 0.507);

AcidificationThreat (Low, High);

CoastalDevelopmentThreat (Low, Medium, High);

ManagementEffectiveness (Ineffective, Partial, Effective);

MarineBasedPollutionThreat (Low, Medium, High);

Overfishing (Low, Medium, High);

ThermalStress (None, Severe);

WatershedBasedPollutionThreat (Low, Medium, High);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Carriger, J. F., Yee, S. H., & Fisher, W. S. (2021). Assessing coral reef condition indicators for local and global stressors using Bayesian networks. Integrated Environmental Assessment and Management, 17(1), 165-187.

corical 69

corical

corical Bayesian Network

### **Description**

Risk-benefit analysis of the AstraZeneca COVID-19 vaccine in Australia using a Bayesian network modelling framework.

#### **Format**

A discrete Bayesian network to perform risk-benefit analysis of vaccination. The probabilities were given in the referenced paper. The vertices are:

**Age** (0-9, 10-19, 20-29, 30-39, 40-49, 50-59, 60-69, 70+);

**AZVaccineDoses** (One, Two, Three, Four);

BackgroundCSVTOver6Weeks (Yes, No);

BackgroundPVTOver6Weeks (Yes, No);

Covid19AssociatedCSVT (Yes, No);

Covid19AssociatedPVT (Yes, No);

DieFromBackgroundCSVT (Yes, No);

DieFromBackgroundPVT (Yes, No);

DieFromCovid19 (Yes, No);

DieFromCovid19AssociatedCSVT (Yes, No);

DieFromCovid19AssociatedPVT (Yes, No);

DieFromVaccineAssociatedTTS (Yes, No);

IntensityOfCommunityTransmission (None, ATAGI Low, ATAGI Med, ATAGI High, One Percent, Two Percent, NSW 200 Daily, NSW 1000 Daily, VIC 1000 Daily, QLD 1000 Daily);

**RiskOfSymptomaticInfection** (Yes, No);

 $\textbf{RiskOfSymptomaticInfectionUnderCurrentTransmissionAndVaccinationStatus} \ \ (Yes, No);$ 

**SARSCoV2Variant** (Alpha Wild, Delta);

Sex (Male, Female);

VaccineAssociatedTTS (Yes, No);

VaccineEffectivenessAgainstDeathIfInfected (Effective, Not Effective);

VaccineEffectivenessAgainstSymptomaticInfection (Effective, Not Effective);

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Lau, C. L., Mayfield, H. J., Sinclair, J. E., Brown, S. J., Waller, M., Enjeti, A. K., ... & Litt, J. (2021). Risk-benefit analysis of the AstraZeneca COVID-19 vaccine in Australia using a Bayesian network modelling framework. Vaccine, 39(51), 7429-7440.

70 corrosion

corrosion

corrosion Bayesian Network

# **Description**

Dynamic Bayesian network model to study under-deposit corrosion.

#### **Format**

A discrete Bayesian network to understand different risk factors and their interdependencies in under-deposit corrosion and how the interaction of these risk factors leads to asset failure due to under-deposit corrosion. Probabilities were given within the referenced paper. The vertices are:

```
BurstPressure (High, Low);
Chloride (High, Moderate, Low);
DefectDepth (Yes, No);
DefectLength (Yes, No);
FlowVelocity (High, Moderate, Low);
InorganicDeposits (Absent, Present);
MEG (Absent, Present);
MixedDeposits (Absent, Present);
OD (High, Low);
OperatingPressure (High, Moderate, Low);
OperatingTemperature (High, Moderate, Low);
OrganicDeposits (Absent, Present);
PartialPressureCO2 (High, Moderate, Low);
pH (Acid, Neutral, Basic);
PipeFailure (Yes, No);
ShearingForce (High, Moderate, Low);
SolidDeposits (High, Moderate, Low);
SteelGrade (High, Low);
SuspendedDeposits (High, Moderate, Low);
UDCCorrRate (High, Moderate, Low);
UnderDepositGalvanicCell (Poor, Fair, Good, Excellent);
WallThicknessLoss (Yes, No).
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Dao, U., Sajid, Z., Khan, F., & Zhang, Y. (2023). Dynamic Bayesian network model to study under-deposit corrosion. Reliability Engineering & System Safety, 237, 109370.

corticosteroid 71

corticosteroid

corticosteroid Bayesian Network

### **Description**

Corticosteroid discontinuation, complete clinical response and remission in juvenile dermatomyositis.

#### **Format**

A discrete Bayesian network to compute the conditional probability of complete clinical response and remission. The probabilities were given within the referenced paper. The vertices are:

```
FinalCSDCAchieved (Achieved, Not Achieved);
CCRAchieved (Achieved, Not Achieved);
RemissionAchieved (Achieved, Not Achieved);
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Kishi, T., Warren-Hicks, W., Bayat, N., Targoff, I. N., Huber, A. M., Ward, M. M., ... & with the Childhood Myositis Heterogeneity Study Group. (2021). Corticosteroid discontinuation, complete clinical response and remission in juvenile dermatomyositis. Rheumatology, 60(5), 2134-2145.

covid1

covid Bayesian Networks

# **Description**

Uncovering hidden and complex relations of pandemic dynamics using an AI driven system.

# Format

A discrete Bayesian network to classify the severity of covid-19 given different symptoms (Naive Bayes). The probabilities were available from a repository. The vertices are:

```
CovidSeverity (1. 1, 2. 2, 3. 3, 4. 4, 5. 5, 6. 6);

Cough (1. 0, 2. 1);

Diarrhea (1. 0, 2. 1);

Fatigue (1. 0, 2. 1);

Fever (1. 0, 2. 1);
```

72 covid2

```
Headache (1. 0, 2. 1);
LossOfSmell (1. 0, 2. 1);
LossOfTaste (1. 0, 2. 1);
MuscleSore (1. 0, 2. 1);
RunnyNose (1. 0, 2. 1);
Sob (1. 0, 2. 1);
SoreThroat (1. 0, 2. 1);
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Demirbaga, U., Kaur, N., & Aujla, G. S. (2024). Uncovering hidden and complex relations of pandemic dynamics using an AI driven system. Scientific Reports, 14(1), 15433.

covid2

covid Bayesian Networks

## **Description**

Uncovering hidden and complex relations of pandemic dynamics using an AI driven system.

#### **Format**

A discrete Bayesian network to classify the severity of covid-19 given different symptoms (TAN structure). The probabilities were available from a repository. The vertices are:

```
CovidSeverity (1. 1, 2. 2, 3. 3, 4. 4, 5. 5, 6. 6);
Cough (1. 0, 2. 1);
Diarrhea (1. 0, 2. 1);
Fatigue (1. 0, 2. 1);
Fever (1. 0, 2. 1);
Headache (1. 0, 2. 1);
LossOfSmell (1. 0, 2. 1);
LossOfTaste (1. 0, 2. 1);
MuscleSore (1. 0, 2. 1);
RunnyNose (1. 0, 2. 1);
Sob (1. 0, 2. 1);
SoreThroat (1. 0, 2. 1);
```

covid3 73

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Demirbaga, U., Kaur, N., & Aujla, G. S. (2024). Uncovering hidden and complex relations of pandemic dynamics using an AI driven system. Scientific Reports, 14(1), 15433.

covid3

covid Bayesian Networks

# Description

Uncovering hidden and complex relations of pandemic dynamics using an AI driven system.

#### **Format**

A discrete Bayesian network to classify the severity of covid-19 given different symptoms (Generic BN). The probabilities were available from a repository. The vertices are:

```
CovidSeverity (1. 1, 2. 2, 3. 3, 4. 4, 5. 5, 6. 6);
Cough (1. 0, 2. 1);
Diarrhea (1. 0, 2. 1);
Fatigue (1. 0, 2. 1);
Fever (1. 0, 2. 1);
Headache (1. 0, 2. 1);
LossOfSmell (1. 0, 2. 1);
LossOfTaste (1. 0, 2. 1);
MuscleSore (1. 0, 2. 1);
RunnyNose (1. 0, 2. 1);
Sob (1. 0, 2. 1);
SoreThroat (1. 0, 2. 1);
```

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Demirbaga, U., Kaur, N., & Aujla, G. S. (2024). Uncovering hidden and complex relations of pandemic dynamics using an AI driven system. Scientific Reports, 14(1), 15433.

74 covidfear

covidfear

covidfear Bayesian Network

# **Description**

Learning and interpreting asymmetry-labeled DAGs: a case study on COVID-19 fear.

#### **Format**

A discrete Bayesian network to understand the effect of demographic factors on the answers to the COVID-19 fear scale and the relationship between the scale items. The Bayesian network was learned as in the referenced paper. The vertices are:

Age (Young, Adult);

Gender (Female, Male);

Fear I am most afraid of COVID-19 (Disagree, Neither, Agree);

**Think** It makes me uncomfortable to think about COVID-19 (Disagree, Neither, Agree);

Hands My hands become clammy when I think about COVID-19 (Disagree, Neither, Agree);

Life I fear losing my life because of COVID-19 (Disagree, Neither, Agree);

**News** I become nervous or anxious when watching news and stories about COVID-19 on social media (Disagree, Neither, Agree);

Sleep I cannot sleep because I am worried about getting COVID-19 (Disagree, Neither, Agree);

**Hearth** My heart races or palpitates when I think about getting COVID-19 (Disagree, Neither, Agree);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Leonelli, M., & Varando, G. (2024). Learning and interpreting asymmetry-labeled DAGs: a case study on COVID-19 fear. Applied Intelligence, 54(2), 1734-1750.

covidrisk 75

covidrisk	covidrisk Bayesian Network	

## **Description**

Highly efficient structural learning of sparse staged trees.

#### **Format**

A discrete Bayesian network to to investigate how various country risks and risks associated to the COVID-19 epidemics relate to each other. The Bayesian network is learned as in the referenced paper. The vertices are:

```
HAZARD (low, high);

VULNERABILITY (low, high);

COPING (low, high);

RISK (low, high);

ECONOMIC (low, high);

BUSINESS (low, high);

POLITICAL (low, high);

COMMERCIAL (low, high);

FINANCING (low, high);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Leonelli, M., & Varando, G. (2022, September). Highly efficient structural learning of sparse staged trees. In International Conference on Probabilistic Graphical Models (pp. 193-204). PMLR.

# **Description**

The YODO algorithm: An efficient computational framework for sensitivity analysis in Bayesian networks.

76 covidtech

#### **Format**

A discrete Bayesian network to model the relationship between the use of technology and the psychological effects of forced social isolation during the COVID-19 pandemic. The Bayesian network is learned as in the referenced paper. The vertices are:

**AGE** Age of respondent ( $\langle 25, \rangle = 25$ );

**GENDER** Gender of respondent (Male, Female);

**BELONGINGNESS** How often the word we is used (Low, Medium, High);

ANG\_IRR Perceived level of anger/irritability (Low, Medium, High);

SOCIAL Perceived social support (Low, Medium, High);

**ANXIETY** Level of anxiety (Low, Medium, High);

**BOREDOM** Level of boredom (Low, Medium, High);

**LONELINESS** Perceived loneliness (Low, Medium, High);

**TECH\_FUN\_Q** Use of communication technology for fun in quarantine (Low, Medium, High);

**TECH\_FUN\_PQ** Use of communication technology for fun pre-quarantine (Low, Medium, High);

**TECH\_WORK\_Q** Use of communication technology for work in quarantine (Low, High);

**TECH\_WORK\_PQ** Use of communication technology for work pre-quarantine (Low, High);

**OUTSIDE** Times outside per week  $(0, 1, \ge 2)$ ;

**SQUARE\_METERS** Home square meters (<80, >=80);

**FAMILY\_SIZE** Number of individuals at home (1, 2, >=3);

**DAYS\_ISOLATION** Days since lockdown (0-10, 11-20, >20);

**REGION** Region of residence (Lombardy, Other);

**OCCUPATION** Occupation (Other, Smartworking, Student, Office work);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Ballester-Ripoll, R., & Leonelli, M. (2023). The YODO algorithm: An efficient computational framework for sensitivity analysis in Bayesian networks. International Journal of Approximate Reasoning, 159, 108929.

covidtest 77

covidtest

covidtest Bayesian Network

## **Description**

Discrete latent variables discovery and structure learning in mixed Bayesian networks.

### **Format**

A conditional linear-Gaussian Bayesian network to predict the outcome of a covid test. The DAG structure was taken from the referenced paper and the probabilities learned from data (earliest version in the repository, missing data dropped). The vertices are:

```
asthma (FALSE, TRUE);
autoimmune_dis (FALSE, TRUE);
cancer (FALSE, TRUE);
covid19_test_results (Negative, Positive);
ctab (FALSE, TRUE);
diabetes (FALSE, TRUE);
diarrhea (FALSE, TRUE);
fever (FALSE, TRUE);
htn (FALSE, TRUE);
labored_respiration (FALSE, TRUE);
loss_of_taste (FALSE, TRUE);
pulse
sob (FALSE, TRUE);
sore_throat (FALSE, TRUE);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Peled, A., & Fine, S. (2021). Discrete Latent Variables Discovery and Structure Learning in Mixed Bayesian Networks. In 20th IEEE International Conference on Machine Learning and Applications (pp. 248-255). IEEE.

78 crimescene

crimescene

crimescene Bayesian Network

# **Description**

How did the DNA of a suspect get to the crime scene? A practical study in DNA transfer during lock-picking.

#### **Format**

A discrete Bayesian network to study DNA transfer during lock-picking. Probabilities were given within the referenced paper. The vertices are:

```
Hypothesis (Prosecutor, Defense);
SuspectCutTheFoil (Yes, No);
SuspectDNAOnFoilFromCutting (Yes, No);
SuspectDNAOnFoilFromPicking (Yes, No);
SuspectPickedLock (Yes, No);
UnknownPickedLock (Yes, No);
UnknownCutTheFoil (Yes, No);
UnknownDNAOnFoil (Yes, No);
DNAFoundOnFoil (Suspect DNA On Foil, Suspect And Unknown DNA On Foil, Unknown DNA On Foil, No DNA On Foil);
```

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Mayuoni-Kirshenbaum, L., Waiskopf, O., Finkelstein, N., & Pasternak, Z. (2022). How did the DNA of a suspect get to the crime scene? A practical study in DNA transfer during lock-picking. Australian Journal of Forensic Sciences, 54(1), 15-25.

criminal 1

criminal1

criminal Bayesian Networks

# **Description**

Using agent-based simulations to evaluate Bayesian networks for criminal scenarios.

#### **Format**

A discrete Bayesian network describing a criminal scenario (top-left of Figure 3). Probabilities were given within the referenced paper. The vertices are:

```
Motive (0,1);
Sneak (0,1);
Stealing (0,1);
EPsychReport (0,1);
ObjectDroppedAccidentally (0,1);
ECameraSeenStealing (0,1);
EObjectGone (0,1);
ECamera (0,1);
Scenario1 (0,1);
Scenario2 (0,1);
Scenario3 (0,1);
Constraint (Scenario1, Scenario2, Scenario3, NA);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023, June). Using agent-based simulations to evaluate Bayesian Networks for criminal scenarios. In Proceedings of the Nineteenth International Conference on Artificial Intelligence and Law (pp. 323-332).

80 criminal2

criminal2

criminal Bayesian Networks

# **Description**

Using agent-based simulations to evaluate Bayesian networks for criminal scenarios.

### **Format**

A discrete Bayesian network describing a criminal scenario (bottom-left of Figure 3). Probabilities were given within the referenced paper. The vertices are:

```
Motive (0,1);
Sneak (0,1);
Stealing (0,1);
EPsychReport (0,1);
ObjectDroppedAccidentally (0,1);
ECameraSeenStealing (0,1);
EObjectGone (0,1);
ECamera (0,1);
Scenario1 (0,1);
Scenario2 (0,1);
Scenario3 (0,1);
Constraint (Scenario1, Scenario2, Scenario3, NA);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023, June). Using agent-based simulations to evaluate Bayesian Networks for criminal scenarios. In Proceedings of the Nineteenth International Conference on Artificial Intelligence and Law (pp. 323-332).

criminal3 81

criminal3

criminal Bayesian Networks

# **Description**

Using agent-based simulations to evaluate Bayesian networks for criminal scenarios.

#### **Format**

A discrete Bayesian network describing a criminal scenario (top-right of Figure 3). Probabilities were given within the referenced paper. The vertices are:

```
Motive (0,1);

Sneak (0,1);

Stealing (0,1);

EPsychReport (0,1);

ObjectDroppedAccidentally (0,1);

ECameraSeenStealing (0,1);

EObjectGone (0,1);

ECamera (0,1);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023, June). Using agent-based simulations to evaluate Bayesian Networks for criminal scenarios. In Proceedings of the Nineteenth International Conference on Artificial Intelligence and Law (pp. 323-332).

criminal4

criminal Bayesian Networks

## **Description**

Using agent-based simulations to evaluate Bayesian networks for criminal scenarios.

82 crypto

## **Format**

A discrete Bayesian network describing a criminal scenario (bottom-right of Figure 3). Probabilities were given within the referenced paper. The vertices are:

```
Motive (0,1);

Sneak (0,1);

Stealing (0,1);

EPsychReport (0,1);

ObjectDroppedAccidentally (0,1);

ECameraSeenStealing (0,1);

EObjectGone (0,1);

ECamera (0,1);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023, June). Using agent-based simulations to evaluate Bayesian Networks for criminal scenarios. In Proceedings of the Nineteenth International Conference on Artificial Intelligence and Law (pp. 323-332).

crypto

crypto Bayesian Network

# Description

Dynamic evolution of causal relationships among cryptocurrencies: an analysis via Bayesian networks.

### **Format**

A discrete Bayesian modelling to exam- ine the causal interrelationships among six major cryptocurrencies. Probabilities were given within the referenced paper. The vertices are:

```
Bitcoin (Down, Up);
Binance_Coin (Down, Up);
Ethereum (Down, Up);
Tether (Down, Up);
Litecoin (Down, Up);
Ripple (Down, Up);
```

curacao1 83

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Amirzadeh, R., Thiruvady, D., Nazari, A., & Ee, M. S. (2024). Dynamic evolution of causal relationships among cryptocurrencies: an analysis via Bayesian networks. Knowledge and Information Systems, 1-16.

curacao1

curacao Bayesian Networks

# Description

Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao.

### **Format**

A discrete Bayesian network to determine land use suitability and potential conflicts for emerging land uses (Conservation BN). The probabilities were given in the referenced paper (input nodes are given a uniform distribution). The vertices are:

CulturalSiteProximity (low, med, high);

FloraRichness (low, med, high);

KeySpeciesPresence (no, yes);

**NeighborhoodConservationValue** (low, high);

NeighborhoodNaturalLandCover (low, med, high);

SpeciesRelatedConservationValue (low, high);

SuitabilityForConservation (no, yes);

VisitorDemand (low, med, high);

WatershedConservationValue (low, high);

WSAboveMarineProtectedArea (no, yes);

WSIncludesOtherKeyDesignations (no, yes);

WSIncludesRAMSARArea (no, yes);

WSLandscapeVariability (low, med, high);

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

84 curacao2

curacao2

curacao Bayesian Networks

# Description

Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao.

### **Format**

A discrete Bayesian network to determine land use suitability and potential conflicts for emerging land uses (Tourism BN). The probabilities were given in the referenced paper (input nodes are given a uniform distribution). The vertices are:

```
CoastalView (no, yes);
DistanceToTourismCore (distant, nearby, inside);
ImmediateBeachAccess (no, yes);
NaturalAmenities (low, high);
NeighborhoodSafetyScore (low, medium, high);
ProximityToPOIs (far, near, immediate);
ProximityToSouthernCoast (far, near, immediate);
RoadsWithin1KM (no, yes);
SiteInfrastructure (low, high);
SuitabilityForTourism (no, yes);
UtilityAccess (no, yes);
ViewExtent (low, medium, high);
ViewQuality (low, high);
```

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

curacao3 85

curacao3

curacao Bayesian Networks

## **Description**

Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao.

### **Format**

A discrete Bayesian network to determine land use suitability and potential conflicts for emerging land uses (Urban fabric BN). The probabilities were given in the referenced paper (input nodes are given a uniform distribution). The vertices are:

```
AccessToPublicTransportation (no, yes);
AirNuisance (no, yes);
CoastalView (no, yes);
LuxuryAmenities (low, high);
NearbySupportingFunctions (low, medium, high);
NeighborhoodFactors (low, high);
NeighborhoodSafetyScore (low, medium, high);
NoiseNuisance (no, yes);
PollutedSoils (no, yes);
PrimaryRoads (no, yes);
ProximityToBeach (no, yes);
ProximityToCoast (far, near, immediate);
SiteFavorability (low, high);
SlopeLimited (no, yes);
SmallRoads (no, yes);
SuitabilityForUrbanFabric (no, yes);
TransportationAccess (low, high);
ViewExtent (low, medium, high);
ViewQuality (low, high);
```

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

86 curacao4

curacao4

curacao Bayesian Networks

# **Description**

Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao.

## **Format**

A discrete Bayesian network to determine land use suitability and potential conflicts for emerging land uses (Conventional agriculture BN). The probabilities were given in the referenced paper (input nodes are given a uniform distribution). The vertices are:

```
AgriculturalDensity (low, med, high);
AllRoadAccess (no, yes);
BuiltUpDensity (low, med, high);
CoUserInteractionConstraints (low, high);
EnvironmentalConstraints (yes, no);
Geology (colluvial clay, diabase or other, limestone bare rock);
GroundwaterDepth (less than 25m, between 25 and 60m, over 60m);
InfrastructureConstraints (low, high);
ProductivityConstraints (low, high);
SiteConstraints (low, high);
SiteConstraints (low, high);
Slope (flat, moderate, steep);
SuitabilityConventionalAgriculture (no, yes);
UtilitiesAccess (no, planned, yes);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

curacao5 87

curacao5

curacao Bayesian Networks

# **Description**

Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao.

### **Format**

A discrete Bayesian network to determine land use suitability and potential conflicts for emerging land uses (Structural agriculture BN). The probabilities were given in the referenced paper (input nodes are given a uniform distribution). The vertices are:

```
AgriculturalDensity (low, med, high);
AllRoadAccess (no, yes);
BuiltUpDensity (low, med, high);
CoUserInteractionConstraints (low, high);
EnvironmentalConstraints (yes, no);
Geology (colluvial clay, diabase or other, limestone bare rock);
GroundwaterDepth (less than 25m, between 25 and 60m, over 60m);
InfrastructureConstraints (low, high);
ProductivityConstraints (low, high);
SiteConstraints (low, high);
SiteConstraints (low, high);
Slope (flat, moderate, steep);
SuitabilityStructuralAgriculture (no, yes);
UtilitiesAccess (no, planned, yes);
```

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

88 darktriad

darktriad

darktriad Bayesian Network

# **Description**

Bayesian Network modeling for Dark Triad, aggression, and empathy.

# **Format**

A conditional linear Gaussian Bayesian network to examine the validity of the constructed models as predictable. The probabilities were given within the referenced paper. The vertices are:

Age

Gender (Male, Female);

Machiavellianism

**Fantasy** 

**Emotional Susceptibility** 

Narcissism

**Psychopathy** 

SelfOrientedEmotionalReactivity

VerbalAggression

**Perspective Taking** 

OtherOrientedEmotional

PhysicalAggression

**Hostility** 

Anger

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Zaitsu, W. (2024). Bayesian Network modeling for Dark Triad, aggression, and empathy. Personality and Individual Differences, 230, 112805.

diabetes 89

diabetes

ciabetes Bayesian Network

# **Description**

Sensitivity and robustness analysis in Bayesian networks with the bimonitor R package.

# **Format**

A discrete Bayesian network to predict whether or not a patient has diabetes, based on certain diagnostic measurements. The Bayesian network is learned as in the referenced paper. The vertices are:

AGE Age (Low, High);

**DIAB** Test for diabetes (Neg, Pos);

GLUC Plasma glucose concentration (Low, High);

**INS** 2-hour serum insulin (Low, High);

MASS Body mass index (Low, High);

**PED** Diabetes pedigree function (Low, High);

**PREG** Number of times pregnant (Low, High);

PRES Diastolic blood pressure (Low, High);

**TRIC** Triceps skin fold thickness (Low, High);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Leonelli, M., Ramanathan, R., & Wilkerson, R. L. (2023). Sensitivity and robustness analysis in Bayesian networks with the bimonitor R package. Knowledge-Based Systems, 278, 110882.

diagnosis

diagnosis Bayesian Network

# Description

An interpretable unsupervised Bayesian network model for fault detection and diagnosis.

### **Format**

A discrete Bayesian network to support the process monitoring scheme. Probabilities were given within the referenced paper, although the variances were not clearly specified. The vertices are X1, X2, ..., X16.

90 dioxins

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Yang, W. T., Reis, M. S., Borodin, V., Juge, M., & Roussy, A. (2022). An interpretable unsupervised Bayesian network model for fault detection and diagnosis. Control Engineering Practice, 127, 105304.

dioxins

dioxins Bayesian Network

# Description

Designing optimal food safety monitoring schemes using Bayesian network and integer programming: The case of monitoring dioxins and DL-PCBs.

#### **Format**

A discrete Bayesian network to optimize the use of resources for food safety monitoring. The Bayesian network is learned as in the referenced paper. The vertices are:

screeningResults The results from the screening DR CALUX method (negative, suspect);

**year** The monitoring year (2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017);

**trimester** The quarter of the year (1, 2, 3, 4);

**animalSpecies** The animal species monitored (bovine animal, bovine animal for fattening, broiler, calf for fattening, cow, deer, duck, eel, fishm goat, goose, hen, horse, pig, poultry, rabbit, sheep, trout);

**product** The food product type (egg, liver, meat, milk);

sampling place The control points (aquaculture, farm, slaughterhouse);

**euMonitoring** The number of samples analyzed for EU monitoring to estimate background contamination in different products (0, 1, ..., 31);

**gcResults** The results from the GC/MS method (0, n, p);

**sampleSize** The number of samples collected during the monitoring period (196, 226, 254, 340, 352, 358, 365, 366, 379, 425).

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Wang, Z., van der Fels-Klerx, H. J., & Oude Lansink, A. G. J. M. (2023). Designing optimal food safety monitoring schemes using Bayesian network and integer programming: The case of monitoring dioxins and DL-PCBs. Risk Analysis, 43(7), 1400-1413.

disputed1 91

disputed1

disputed Bayesian Networks

### **Description**

A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities.

### **Format**

A discrete Bayesian network for the evaluation of transfer evidence given activity level propositions considering a dispute about the relation of an item to one or more activities (Figure 2). The probabilities were given in the referenced paper. The vertices are:

**BGU** Background DNA U on sweater (false, true);

**DNAfind** DNA findings on sweater (false, true);

**DNAU** DNA U present on sweater (false, true);

**DNAX** DNA X present on sweater (false, true);

**Prop** Who strangled person Y? (H1, H2);

**TPRaltactX** Transfer of DNA X from X to sweater via X wearing sweater two weekd before incident (false, true);

**TPRUstrangledY** Transfer of DNA U from U to sweater via U strangling Y (false, true);

**TPRXstrangledY** Transfer of DNA X from X to sweater via X strangling Y (false, true);

**UstrangledY** Unknown person strangled person Y (false, true);

**Xaltact** X wore sweater two weeks before incident (false, true);

**XstrangledY** Mr. X strangled person Y (false, true);

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Vink, M., de Koeijer, J. A., & Sjerps, M. J. (2024). A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities. Forensic Science International: Synergy, 9, 100546.

92 disputed2

disputed2

disputed Bayesian Networks

# **Description**

A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities.

#### **Format**

A discrete Bayesian network for the evaluation of transfer evidence given activity level propositions considering a dispute about the relation of an item to one or more activities (Figure 3). The probabilities were given in the referenced paper. The vertices are:

**BGFibers** Background on fibers matching Y top on sweater (false, true);

**BGU** Background DNA U on sweater (false, true);

CaseFind Case findings on sweater (false, true);

**DNAfind** DNA findings on sweater (DNA X, DNA U, DNA X + U, No DNA);

**DNAU** DNA U present on sweater (false, true);

**DNAX** DNA X present on sweater (false, true);

**FiberFind** Fiber findings on sweater(false, true);

**FibersSweater** Fibers matching Y garment on sweater (false, true);

**ItemProposition** Sweater worn by offender during incident (false, true);

**Prop** Who strangled person Y? (H1, H2);

**TPRaltactX** Transfer of DNA X from X to sweater via X wearing sweater two weekd before incident (false, true);

**TPRUstrangledY** Transfer of DNA U from U to sweater via U strangling Y (false, true);

**TPRXstrangledY** Transfer of DNA X from X to sweater via X strangling Y (false, true);

**TPRYtoSweater** Transfer of fibers from Y top to sweater during incident (false, true);

**UstrangledY** Unknown person strangled person Y (false, true);

**Xaltact** X wore sweater two weeks before incident (false, true);

**XstrangledY** Mr. X strangled person Y (false, true);

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Vink, M., de Koeijer, J. A., & Sjerps, M. J. (2024). A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities. Forensic Science International: Synergy, 9, 100546.

disputed3 93

disputed3

disputed Bayesian Networks

## Description

A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities.

#### **Format**

A discrete Bayesian network for the evaluation of transfer evidence given activity level propositions considering a dispute about the relation of an item to one or more activities (Figure 9). The probabilities were given in the referenced paper. The vertices are:

**BGFibers** Background fibers present on Y top (false, true);

**BGM** Background fibers matching sweater present on Y top (false, true);

**BGMnotM** Background fibers not matching sweater present on Y top (false, true);

C52 Fibers matching Y top on sweater (false, true);

**C61** Background of fibers matching Y top on sweater (false, true);

C7 Background DNA u on sweater (false, true);

CaseFindSweater Case findings on sweater (false, true);

**DNAfind** DNA findings on sweater (DNA X, DNA U, DNA X + U, No DNA);

**DNAU** DNA U present on sweater (false, true);

**DNAX** DNA X present on sweater (false, true);

**FiberfindSweater** Fiber findings on Sweater (false, true);

**FiberfindYtop** Fiber findings on Y top (matching, not matching, both matching and not matching, no fibers);

**FibersM** Fibers matching sweater on Y top (false, true);

**FibresnotM** Fibers not matching sweater on Y top (false, true);

**Prop** Who strangled person Y? (H1, H2);

Sworn Sweater worn by offender during incident (false, true);

**TPRaltactX** Transfer of DNA X from X to sweater via X wearing sweater two weekd before incident (false, true);

**TPRStoY** Transfer of fibers from sweater to Y top during incident (false, true);

**TPRUstrangledY** Transfer of DNA U from U to sweater via U strangling Y (false, true);

**TPRUtoY** Transfer of fibers from unknown garment to Y top during incdient (false, true);

**TPRXstrangledY** Transfer of DNA X from X to sweater via X strangling Y (false, true);

**TPRYtoS** Transfer of fibers from Y top to sweater during incident (false, true);

**UstrangledY** Unknown person strangled person Y (false, true);

**Uworn** Unknown garment worn by offender during incident (false, true);

94 disputed4

**WhichGarment** Which garment was worn by offender during incident? (sweater, unknown garment);

**Xaltact** X wore sweater two weeks before incident (false, true);

**XstrangledY** Mr. X strangled person Y (false, true);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Vink, M., de Koeijer, J. A., & Sjerps, M. J. (2024). A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities. Forensic Science International: Synergy, 9, 100546.

disputed4

disputed Bayesian Networks

#### **Description**

A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities.

### Format

A discrete Bayesian network for the evaluation of transfer evidence given activity level propositions considering a dispute about the relation of an item to one or more activities (Figure 10). The probabilities were given in the referenced paper. The vertices are:

**BGFibersYtop** Backgroun fibers present on Y top (false, true);

**BGM** Background fibers matching sweater present on Y top (false, true);

**BGMnotM** Background fibers not matching sweater present on Y top (false, true);

**BGYonS** Background of fibers matching Y top on sweater (false, true);

**CaseFind** Case findings on sweater (false, true);

**DNAfind** DNA findings on sweater (DNA X, DNA U, DNA X + U, No DNA);

**DNAX** DNA X present on sweater (false, true);

**FiberfindSweater** Fiber findings on Sweater (false, true);

**FiberfindYtop** Fiber findings on Y top (matching, not matching, both matching and not matching, no fibers):

**FibersMSonY** Fibers matching sweater on Y top (false, true);

**FibersnotMSonY** Fibers not matching sweater on Y top (false, true);

**Fibers Yons** Fibers matching Y top on Sweater (false, true);

**Prop** Who strangled person Y? (H1, H2);

dragline 95

**Sweater** Sweater worn by Mr. X during incident (false, true);

**TPRaltactX** Transfer of DNA X from X to sweater via X wearing sweater two weekd before incident (false, true);

**TPRStoYtop** Transfer of fibers from sweater to Y top during incident (false, true);

TPRUtoYtop Transfer of fibers from unknown garment to Y top during incident (false, true);

**TPRXstrangledY** Transfer of DNA X from X to sweater via X strangling Y (false, true);

**TPRYtoptoS** Transfer of fibers from Y top to sweater during incident (false, true);

**Unknown** Unknown garment worn by offender during incident (false, true);

**WhichGarment** Which garment was worn by offender during incident? (sweater, unknown garment);

**Xaltact** X wore sweater two weeks before incident (false, true);

**XstrangledY** Mr. X strangled person Y (false, true);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Vink, M., de Koeijer, J. A., & Sjerps, M. J. (2024). A template Bayesian network for combining forensic evidence on an item with an uncertain relation to the disputed activities. Forensic Science International: Synergy, 9, 100546.

dragline

dragline Bayesian Network

## **Description**

Bayesian network approach for dragline reliability analysis: A case study.

## **Format**

A discrete Bayesian network for the evaluation of the reliability of a draglines system. Probabilities were given within the referenced paper. The vertices are:

- **X1** Teeth Failure (True, False);
- **X2** Adapter failure (True, False);
- **X3** Equalizer pins (True, False);
- **X4** Anchor pins (True, False);
- **X5** Hitch shackle pins (True, False);
- **X6** Drag motor failure (True, False);
- **X7** Drag motor failure2 (True, False);
- **X8** Control system failure (True, False);

96 dragline

```
X9 Drag rope failure (True, False);
```

- X10 Gearbox failure (True, False);
- X11 Drag drum failure (True, False);
- **X12** Drag chain failure (True, False);
- **X13** Drag brake failure (True, False);
- **X14** Drag socket failure (True, False);
- **X15** Drag pulley failure (True, False);
- **X16** Dump rope failure (True, False);
- **X17** Dump socket failure (True, False);
- X18 Dump pulley failure (True, False);
- **X19** Hoist motor 1 failure (True, False);
- **X20** Hoist motor 2 failure (True, False);
- **X21** Hoist rope failure (True, False);
- **X22** Control system failure (True, False);
- **X23** Hoist chain failure (True, False);
- **X24** Hoist brake failure (True, False);
- **X25** Rotate frame failure (True, False);
- **X26** Roller failure (True, False);
- X27 Gearbox failure (True, False);
- X28 Control system failure (True, False);
- X29 Swing motor failure (True, False);
- **X30** Swing motor failure (True, False);
- **X31** Exciter failure (True, False);
- **X32** M.G. set failure (True, False);
- **X33** Synchronous motor failure (True, False);
- **X34** DC problem failure (True, False);
- **X35** Power failure (True, False);
- **X36** Trailing cable failure (True, False);
- X37 Compressor failure (True, False);
- **X38** Lubrication system failure (True, False);
- **X39** Guide pulley failure (True, False);
- **X40** Boom light failure (True, False);
- A1 (True, False);
- A2 (True, False);
- A3 (True, False);
- **S1** Bucket and accessories (True, False);
- **S2** Drag mechanism (True, False);

drainage 97

```
S3 Rigging mechanism (True, False);
S4 Hoisting mechanism (True, False);
S5 Swing mechanism (True, False);
S6 Electrical auxiliary (True, False);
S7 Other subsystem (True, False);
Dragline (True, False);
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Kumar, D., Jana, D., Gupta, S., & Yadav, P. K. (2023). Bayesian network approach for dragline reliability analysis: A case study. Mining, Metallurgy & Exploration, 40(1), 347-365.

drainage

drainage Bayesian Network

# **Description**

Fuzzy Bayesian network fault diagnosis method based on fault tree for coal mine drainage system.

#### **Format**

A discrete Bayesian network for fault diagnosis of a coal mine drainage system. The probabilities were available from a repository. The vertices are:

```
AbnormalFlow (T, F);
AirLeakageOfShaftSeal (T, F);
GetValveFailure (T, F);
ImpellerDamaged (T, F);
LowSpeed (T, F);
LowVoltage (T, F);
MotorFault (T, F);
PipelineFailure (T, F);
PipelineRupture (T, F);
Silting (T, F);
WaterPumpFailure (T, F);
```

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

98 dustexplosion

## References

Shi, X., Gu, H., & Yao, B. (2024). Fuzzy Bayesian Network Fault Diagnosis Method Based on Fault Tree for Coal Mine Drainage System. IEEE Sensors Journal.

dustexplosion

dustexplosion Bayesian Network

### **Description**

Scenario derivation and consequence evaluation of dust explosion accident based on dynamic Bayesian network.

#### **Format**

A discrete Bayesian network for the accurate solution of scenario state probability. Probabilities were given within the referenced paper. The vertices are:

```
AccidentDoNotOccur (True, False);
AccidentUnderControl (True, False);
BlastWavesThroughPipes (True, False);
BuildingDamage (I, II, III, IV);
Casualties (I, II, III, IV);
CombustibleDustAccumulates (True, False);
DirectEconomicLosses (I, II, III, IV);
DustAccumulationUnderControl (True, False);
DustCloudDisappearance (True, False);
DustExplosionIntensityCoefficient (I, II, III, IV, V);
EndOfRescue (True, False);
EnvironmentalImpact (I, II, III, IV);
EquipmentDamage (I, II, III, IV);
ExplosionPreventionMeasures (True, False);
ExtinctionOfSpark (True, False);
IgnitingTheDustCloud (True, False);
InitiateEmergencyResponse (True, False);
Misoperation (True, False);
NoExplosionControlMeasures (True, False);
OpenFireExtinguished (True, False);
PreventFurtherExpansion (True, False);
RestrictedSpace (True, False);
SparkDetectorExtinguishSparks (True, False);
SparkOccurence (True, False);
StrengthenDustControl (True, False);
```

TriggerSecondaryExplosion (True, False);

earthquake 99

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Pang, L., Zhang, M., Yang, K., & Sun, S. (2023). Scenario derivation and consequence evaluation of dust explosion accident based on dynamic Bayesian network. Journal of Loss Prevention in the Process Industries, 83, 105055.

earthquake

earthquake Bayesian Network

## **Description**

A Bayesian Network risk model for estimating coastal maritime transportation delays following an earthquake in British Columbia.

#### **Format**

A discrete Bayesian network for estimating the delays in maritime transportation to island communities in British Columbia, resulting from a major earthquake in the region. Probabilities were given within the referenced paper. The vertices are:

- **AD** Arrival-related delays (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);
- **BSA** Bridge safety assessment required (Yes, No);
- **BSD** Bathymetric survey required destination (Yes, No);
- **BSO** Bathymetric survey required origin (Yes, No);
- **BVOR** Bridge over navigation route (Yes, No);
- CIDD Communication infrastructure damage destination (Low, Medium, High);
- CIDO Communication infrastructure damage origin (Low, Medium, High);
- **CN** Community needs (Low, Medium, High);
- **CSR** Communication system restauration required (Yes, No);
- **DAC** Delay due to arranging crew members (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);
- **DD** Departure-related delays (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);
- **DDG** Delay in dangerous goods reporting (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);
- **DGR** Dangerous good reporting required (Yes, No);
- **DL** Destination location (V\_Isl\_W, V\_Isl\_E, V\_Isl\_S);
- DTWD Delay due to tsunami warning destination (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);
- **DTWO** Delay due to tsunami warning origin (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);
- **EEL** Earthquake epicentre location (V\_Isl\_W\_offshore, V\_Isl\_E\_offshore, V\_Isl\_Inland, BC\_ML);
- **ESD** Earthquake severity destination (VI\_or\_less, VII, VIII, IX, X\_or\_more);

100 earthquake

**ESO** Earthquake severity - origin (VI\_or\_less, VII, VIII, IX, X\_or\_more);

**ESR** Earthquake severity - regional (VI\_or\_less, VII, VIII, IX, X\_or\_more);

**MMSC** Mandatory minimum ship crew required (Yes, No);

**OL** Origin location (V\_Isl\_W, V\_Isl\_E, V\_Isl\_S, BC\_ML);

**PAD** Personnel availability - destination (Low, Medium, High);

PAO Personnel availability - origin (Low, Medium, High);

**RD** Route delay (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TBS** Time required for bridge safety assessment (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TBSD** Time required for bathymetric survey - destination (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

TBSO Time required for bathymetric survey - origin (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TCSD** Time required for communication system restauration - destination (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TCSO** Time required for communication system restauration - origin (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TIDD** Terminal infrastructure damage - destination (Low, Medium, High);

**TIDO** Terminal infrastructure damage - origin (Low, Medium, High);

**TTRD** Time required for terminal recovery ops - destination (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TTRO** Time required for terminal recovery ops - origin (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**TWD** Tsunami warning - destination (Yes, No);

**TWO** Tsunami warning - origin (Yes, No);

**VD** Voyage-related delays (L0, B0\_6, B6\_12, B12\_24, B24\_48, M48);

**VT** Vessel type (BC\_Ferries, Seaspan, Barge);

WIDD Waterway infrastructure damage - destination (Low, Medium, High);

WIDO Waterway infrastructure damage - origin (Low, Medium, High);

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Goerlandt, F., & Islam, S. (2021). A Bayesian Network risk model for estimating coastal maritime transportation delays following an earthquake in British Columbia. Reliability Engineering & System Safety, 214, 107708.

ecosystem 101

ecosystem

ecosystem Bayesian Network

# **Description**

Evaluating the supply-demand balance of cultural ecosystem services with budget expectation in Shenzhen, China.

#### **Format**

A discrete Bayesian network to infer the supply and demand match for cultural ecosystem services. Probabilities were given within the referenced paper. The vertices are:

Bus Density of bus and subway stations (Low, High);

Road Road density (Low, High);

Lot Density of public parking lots (Low, High);

**Traffic** Convenience for tourists to arrive (Low, Medium, High);

**Park** Convenience for visitors after arrival (Low, Medium, High);

**Green** Green space coverage rate (Low, Medium, High);

Water Whether there is a water body or not (No, Yes);

**Opportunity** Recreational convenience (Low, Medium, High);

**Potential** Aesthetic value of landscape (Low, Medium, High);

People Population density (Low, Medium, High);

Supply CES supply of communities (Low, Medium, High);

**Demand** CES demand of communities (Low, Medium, High);

Budget Balance of supply and demand (Deficit, Balance, Surplus).

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Wu, J., Jin, X., Wang, H., & Feng, Z. (2022). Evaluating the supply-demand balance of cultural ecosystem services with budget expectation in Shenzhen, China. Ecological Indicators, 142, 109165.

102 electric vehicle

electricvehicle

electricvehicle Bayesian Network

## Description

Electric vehicle fire risk assessment based on WBS-RBS and fuzzy BN coupling.

#### **Format**

A discrete Bayesian network to evaluate the risk of electric vehicle fire accidents. Probabilities were given within the referenced paper. The vertices are:

```
ACF Air conditioning equipment failure (yes, no);
```

**AM** Artificial modification (yes, no);

**AWE** Not aware of early fire (yes, no);

**BEP** Blocked exhaust pipe (yes, no);

BF Battery failure (yes, no);

**BO** Battery overcharge (yes, no);

**CBI** The car body is ignited (yes, no);

CEF Charging equipment fault (yes, no);

CI Collision ignition (yes, no);

**DTH** Defroster temperature too high (yes, no);

**EC** Electrical circuit failure (yes, no);

ECF Electronic component failure (yes, no);

**FFE** The vehicle is not equipped with fire-fighting equipment (yes, no);

HF Human factor (yes, no);

**IS** Ignition source (yes, no);

**ISC** Risk of internal spontaneous combustion of electric vehicles (yes, no);

MMA Man made arson (yes, no);

**OFE** The early open fire was not extinguished (yes, no);

**REI** Risk of external ignition (yes, no);

SBB (yes, no);

**SCB** Short circuit in battery (yes, no);

**TLD** Transmission line damage (yes, no);

**VFD** Electric vehicle fire disaster (yes, no);

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Chen, J., Li, K., & Yang, S. (2022). Electric vehicle fire risk assessment based on WBS-RBS and fuzzy BN coupling. Mathematics, 10(20), 3799.

electrolysis 103

electrolysis

electrolysis Bayesian Network

# **Description**

Safety analysis of proton exchange membrane water electrolysis system.

#### **Format**

A discrete Bayesian network to analyze evolving hazard scenarios, such as gas permeation/crossover during proton exchange membrane water electrolysis based on fluid dynamics and electrochemistry of electrolysis. Probabilities were given within the referenced paper. The vertices are:

C Operating current density (High, Low);

F Formation of hazardous H2/O2 gas mixture (Yes, No);

**FPR** Formation of peroxide radicals which can cause membrane degradation (Yes, No);

**GP** Gas permeation (Yes, No);

**GRE** Gas recombiner employed (Yes, No);

**H** Relative humidity (High, Low);

**HCF** Hazardous condition formation (Yes, No);

HOR H2 and O2 recombination at catalyst/membrane surface (Yes, No);

**IOA** Inhibiting oxygen accumulation (Yes, No);

**IRF** Inhibiting reaching flammability range (Yes, No);

**P** Operating pressure (High, Low);

**RGP** Reduction in gas purity (Yes, No);

SBT Surface/bulk treatments of the polymeric membrane (Yes, No);

**SMT** Sufficient membrane thickness (Yes, No);

T Operating temperature (High, Low);

V Operating cell voltage (High, Low);

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Liu, Y., Amin, M. T., Khan, F., & Pistikopoulos, E. N. (2023). Safety analysis of proton exchange membrane water electrolysis system. Journal of Environmental Chemical Engineering, 11(5), 110772.

104 emergency

emergency

emergency Bayesian Network

## **Description**

A risk evaluation method for human-machine interaction in emergencies based on multiple mental models-driven situation assessment.

#### **Format**

A discrete Bayesian network to evaluate risk in human-machine interaction in emergencies. The probabilities were given within the referenced paper. The vertices are:

**TS** Trim state (normal, abnormal);

FP Flap position (retracted, extended);

**CPMS** Cabin pressurization mode setting (automatic, manual);

**ECFS** Equipment cooling fan state (normal, failure);

**TC** Takeoff configuration (correct, wrong);

**CP** Cabine pressure (normal, low);

ECA Equipment cooling airflow (normal, low);

OMD Oxygen mask deployment (yes, no);

**TSI** Trim state indication (normal, abnormal);

FPI Flap position indication (retracted, extended);

**CPMSI** Cabin pressurization mode setting indication (automatic, manual);

ECFCBI Equipment cooling fan circuit break indication (on, off);

**CAW** Cabine altitued warning (yes, no);

CLPL Cabin low pressure light (illuminated, extinguished);

**OMDL** Oxygen mask deployment light (illuminated, extinguished);

**ECOL** Equipment cooling OFF light (illuminated, extinguished);

ECFOL Equipment cooling fan OFF light (illuminated, extinguished);

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Guo, J., Ma, S., Zeng, S., Che, H., & Pan, X. (2024). A risk evaluation method for human-machine interaction in emergencies based on multiple mental models-driven situation assessment. Reliability Engineering & System Safety, 110444.

engines 105

engines

engines Bayesian Network

# **Description**

A fuzzy Bayesian network risk assessment model for analyzing the causes of slow-down processes in two-stroke ship main engines.

# **Format**

A discrete Bayesian network to assess the factors contributing to the engine's slow-down processes. The probabilities were given in the referenced paper. The vertices are:

- **H1** Oil mist high density (yes, no);
- H2 Scavenge air box fire (yes, no);
- H3 Piston cooling oil non flow (yes, no);
- **H4** Cylinder lube oil non flow (yes, no);
- **H5** Cylinder cooling fresh water low pressure (yes, no);
- **H6** Cylinder cooling fresh water high temperature (yes, no);
- **H7** Main lube oil low pressure (yes, no);
- H8 Thrust pad high temperature (yes, no);
- **H9** Piston cooling oil high temperature (yes, no);
- H10 Exhaust gas high temperature (yes, no);
- H11 Stern tube bearing high temperature (yes, no);
- H (yes, no);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Bashan, V., Yucesan, M., Gul, M., & Demirel, H. (2024). A fuzzy Bayesian network risk assessment model for analyzing the causes of slow-down processes in two-stroke ship main engines. Ships and Offshore Structures, 19(5), 670-686.

106 estuary

enrollment

enrollment Bayesian Network

# Description

Research on evaluation methods for sustainable enrollment plan configurations in Chinese universities based on Bayesian networks.

#### **Format**

A discrete Bayesian network for sustainable enrollment plan configurations aimed at enhancing the advanced education rate. The probabilities were given in the referenced paper. The vertices are:

```
AdvancedEducationRate (0, 1);
AverageAdmissionScore (0, 1, 2);
CoursePassRate (0, 1, 2);
EmploymentRate (0, 1, 2);
FirstTimeGraduationRate (0, 1, 2);
StudentTeacherRatio (0, 1, 2);
TransferRate (0, 1, 2);
EnrollmentQuota (-2, -1, 0, 1, 2);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Wang, K., Wang, T., Wang, T., & Cai, Z. (2024). Research on Evaluation Methods for Sustainable Enrollment Plan Configurations in Chinese Universities Based on Bayesian Networks. Sustainability, 16(7), 2998.

estuary

estuary Bayesian Network

## **Description**

Predicting and scoring estuary ecological health using a Bayesian belief network.

estuary 107

#### **Format**

A discrete Bayesian network to calculate an Estuary Trophic Index (ETI) score ranging between 0 (no symptoms of eutrophication) to 1 (grossly eutrophic) for estuaries in Aotearoa New Zealand. The probabilities were given within the referenced paper. The vertices are:

EstuaryType (Coastal lake, Tidal lagoon, Tidal river);

**Intertidal** (0 to 5, 5 to 40, 40 to 100);

**Flushing** (0 to 3, 3 to 6, 6 to 10, More than 10);

**Salinity** (0 to 5, 5 to 30, More than 30);

**PotentialTNConcentration** (0 to 50, 50 to 100, 100 to 150, 150 to 200, 200 to 300, 300 to 400, 400 to 500, 500 to 600, 600 to 700, 700 to 1000, 1000 to 2000);

**Seasonality** (Less than 0.5, 0.5 to 0.65, More than 0.65);

WaterColStratification (Yes, No);

ClosureDuration (Open, Short close, Long close);

**SedimentLoad** (0 to 1, 1 to 5, 5 to 10, 10 to 20, 20 to 50, 50 to 100, More than 100);

**SedTrappingEfficiency** (0 to 0.1, 0.1 to 0.5, 0.5 to 0.85, 0.85 to 0.95, 0.95 to 1);

**SedDeposition** (0 to 0.1, 0.1 to 0.5, 0.5 to 1, 1 to 2, 2 to 5, 5 to 10, More than 10);

**SedMud** (0 to 12, 12 to 25, 25 to 34, 34 to 100);

**Macroalgae** (0.8 to 1, 0.6 to 0.8, 0.4 to 0.6, 0 to 0.4);

**Phytoplankton** (0 to 5, 5 to 10, 10 to 15, 15 to 25, 25 to 60, 60 to 100);

**MacroalgaeStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**PhytoplanktonStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**ETIPrimaryScore** (0 to 0.1, 0.1 to 0.2, 0.2 to 0.3, 0.3 to 0.4, 0.4 to 0.5, 0.5 to 0.6, 0.6 to 0.7, 0.7 to 0.8, 0.8 to 0.9, 0.9 to 1.0);

**Oxygen** (7 to 8, 6 to 7, 5 to 6, 4 to 5);

**OxygenStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**SedToc** (0 to 0.5, 0.5 to 1.2, 1.2 to 2, 2 to 10);

**SedARPD** (More than 4, 2.5 to 4, 1 to 2.5, Less than 1);

**SedARPDStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**SedTocStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**SeagrassDecline** (Extreme, Severe, Moderate, Minor);

**SeagrassStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**Macrobenthos** (0 to 1.2, 1.2 to 3.3, 3.3 to 4.3, 4.3 to 7);

**MacrobenthosStandardised** (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1);

**ETISecondaryScore** (0 to 0.1, 0.1 to 0.2, 0.2 to 0.3, 0.3 to 0.4, 0.4 to 0.5, 0.5 to 0.6, 0.6 to 0.7, 0.7 to 0.8, 0.8 to 0.9, 0.9 to 1.0);

**ETIScore** (0 to 0.1, 0.1 to 0.2, 0.2 to 0.3, 0.3 to 0.4, 0.4 to 0.5, 0.5 to 0.6, 0.6 to 0.7, 0.7 to 0.8, 0.8 to 0.9, 0.9 to 1.0);

**ETIBand** (A, B, C, D);

108 ets

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Zeldis, J. R., & Plew, D. R. (2022). Predicting and scoring estuary ecological health using a Bayesian belief network. Frontiers in Marine Science, 9, 898992.

ets

ets Bayesian Network

## **Description**

Uncovering drivers of EU carbon futures with Bayesian networks.

#### **Format**

A discrete Bayesian network to model the influence of financial, economic, and energy-related factors on EUA futures prices. The model was given in the referenced paper. The vertices are:

```
CAC (High, Low, Neutral);
CO1 (High, Low, Neutral);
DAX (High, Low, Neutral);
ECO (High, Low, Neutral);
EURCHF (High, Low, Neutral);
EURCNY (High, Low, Neutral);
EURGBP (High, Low, Neutral);
EURRUB (High, Low, Neutral);
EURUSD (High, Low, Neutral);
LBEATREU (High, Low, Neutral);
LB01TREU (High, Low, Neutral);
MO1 (High, Low, Neutral);
MXEU0EN (High, Low, Neutral);
NG1COMB (High, Low, Neutral);
SPGTCED (High, Low, Neutral);
SPX (High, Low, Neutral);
SXXP (High, Low, Neutral);
VIX (High, Low, Neutral);
XA1 (High, Low, Neutral);
XAU (High, Low, Neutral);
```

expenditure 109

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Maciejowski, J., & Leonelli, M. (2025). Uncovering Drivers of EU Carbon Futures with Bayesian Networks. arXiv preprint arXiv:2505.10384.

expenditure

expenditure Bayesian Network

## **Description**

The FEDHC Bayesian network learning algorithm.

#### **Format**

A Gaussian Bayesian network modeling the monthly credit card expenditure of individuals. The code to learn the Bayesian network was given within the referenced paper (Figure 12.c). The vertices are:

Card Whether the application for a credit card was accepted or not;

**Reports** The number of major derogatory reports;

Age The age in years plus twelfths of a year;

**Income** The yearly income in \$10,000s;

**Share** The ratio of monthly credit card expenditure to yearly income;

**Expenditure** The average monthly credit card expenditure;

Owner Whether the person owns their home or they rent;

**Selfemp** Whether the person is self employed or not;

**Dependents** The number of dependents + 1;

**Months** The number of months living at current address;

**Majorcards** The number of major credit cards held;

Active The number of active credit accounts.

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Tsagris, M. (2022). The FEDHC Bayesian network learning algorithm. Mathematics, 10(15), 2604.

110 fingermarks1

fingermarks1

fingermarks Bayesian Networks

## **Description**

Using case specific experiments to evaluate fingermarks on knives given activity level propositions.

#### **Format**

A discrete Bayesian network for the evaluation of fingermarks given activity level propositions. The probabilities were given within the referenced paper. The vertices are:

- C1 Propositions (Hp, Hd);
- C2 Suspect stabbed the victime with the knife (True, False);
- C3 Suspect cut food with the knife (True, False);
- C4 Marks on handle stabbing (FM S present, FM S absent);
- C5 Marks on back stabbing (FM S present, FM S absent);
- **C6** Marks on blade stabbing (FM S present, FM S absent);
- C7 Marks on handle cutting (FM S present, FM S absent);
- **C8** Marks on back cutting (FM S present, FM S absent);
- C9 Marks on blade cutting (FM S present, FM S absent);
- C10 Findings Marks on handle (FM S present, FM S absent);
- C11 Findings Marks on blade (FM S present, FM S absent);
- C12 Findings Marks on back (FM S present, FM S absent);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

de Ronde, A., Kokshoorn, B., de Puit, M., & de Poot, C. J. (2021). Using case specific experiments to evaluate fingermarks on knives given activity level propositions. Forensic Science International, 320, 110710.

fingermarks2

fingermarks2

fingermarks Bayesian Networks

## **Description**

Using case specific experiments to evaluate fingermarks on knives given activity level propositions.

#### **Format**

A discrete Bayesian network for the evaluation of fingermarks given activity level propositions. The probabilities were given within the referenced paper. The vertices are:

- C1 Propositions (Hp, Hd);
- C2 Suspect stabbed the victime with the knife (True, False);
- C3 Suspect cut food with the knife (True, False);
- C4 Marks on handle stabbing (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C5 Marks on back stabbing (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- **C6** Marks on blade stabbing (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C7 Marks on handle cutting (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- **C8** Marks on back cutting (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C9 Marks on blade cutting (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C10 Findings Marks on handle (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C11 Findings Marks on blade (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);
- C12 Findings Marks on back (P, F, P\_F, P\_T, F\_T, P\_F\_T, Undetermined, None);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

de Ronde, A., Kokshoorn, B., de Puit, M., & de Poot, C. J. (2021). Using case specific experiments to evaluate fingermarks on knives given activity level propositions. Forensic Science International, 320, 110710.

fire

fire fire Bayesian Network

# Description

Psychological response in fire: A fuzzy Bayesian network approach using expert judgment.

#### **Format**

A discrete Bayesian network to model causal relationship of psychological response at the initial stage of fire events. The probabilities were given within the referenced paper. The vertices are:

```
AudioFireCues (Yes, No);
EmotionalStability (Stable, Unstable);
Escape (True, False);
FireCues (Consistent, Not consistent);
FireKnowledge (Yes, No);
LayoutFamiliarity (Yes, No);
PerceivedHazard (Risky, Not risky);
PsychologicalIncapacitation (Mild, Severe);
Stress (Low, High);
TimePressure (Low, High);
VisualFireCues (Yes, No);
```

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Ramli, N., Ghani, N. A., Ahmad, N., & Hashim, I. H. M. (2021). Psychological response in fire: a fuzzy Bayesian network approach using expert judgment. Fire Technology, 57, 2305-2338.

firealarm 113

firealarm

firealarm Bayesian Network

## Description

When do numbers really matter?.

#### **Format**

A discrete Bayesian network to model a simple fire alarm system. Probabilities were given within the referenced paper. The vertices are:

```
Fire (true, false);
Tampering (true, false);
Smoke (true, false);
Alarm (true, false);
Leaving (true, false);
Report (true, false);
```

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Hei Chan, Adnan Darwiche (2002). "When do numbers really matter?". Journal of Artificial Intelligence Research 17 (265-287).

firerisk

firerisk Bayesian Network

## **Description**

Predictive study of fire risk in building using Bayesian networks.

## **Format**

A discrete Bayesian network to calculate the probability of fire ignition in buildings (root nodes were given a uniform distribution). The probabilities were available from a repository. The vertices are:

- **A1** Deficient electrical installation (T, F);
- **A2** Bad quality of electical equipment (T, F);
- **A3** Contact between incompatible products (T, F);

114 flood

- B1 Mishandling of electrical devices (T, F);B2 Electrical overload (T, F);
- **B3** Power cut (T, F);
- **B4** Degradation of electrical wires (T, F);
- **B5** Excessive heating in the conductors (T, F);
- **B6** Insulation fault (T, F);
- **B7** Short circuit (T, F);
- **B8** Strong intensity electric (T, F);
- **B9** Combustion of electrical equipment (T, F);
- **B10** Appearance of electric arcs (T, F);
- **B11** Appearence of sparks (T, F);
- **B12** Chemical reactions (T, F);
- **B13** Heat release (T, F);
- **B14** Appearance of new products (T, F);
- **C1** Electrical equipment malfunction (T, F);
- C2 Electrocution (T, F);
- **C3** Fire ignition (T, F);
- C4 Poisoning (T, F);
- C5 Asphyxia (T, F);
- **C6** Explosion (T, F);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Issa, S. K., Bakkali, H., Azmani, A., & Amami, B. (2024). Predictive study of fire risk in building using Bayesian networks. Journal of Theoretical and Applied Information Technology, 102(7).

flood

flood Bayesian Network

# **Description**

A trade-off between farm production and flood alleviation using land use tillage preferences as a natural flood management (NFM) strategy.

flood 115

#### **Format**

A discrete Bayesian network to analyse land use tillage practices for flood management, considering climate, soilscape, slope, and farming systems. Probabilities were given within the referenced paper. The vertices are:

```
Bulk_Density (0 to 0.25, 0.25 to 0.5, 0.5 to 0.75, 0.75 to 1, 1 to 1.25, 1.25 to 1.5);
Daily_Runoff (0 to 18, 18 to 36, 36 to 54, 54 to 72);
Erosion (High, Low);
Farm_Yield (Positive, Negative);
Flood Alleviation (Positive, Negative);
Land_Use (Arable, Arable With Grass, Grassland, Woodland);
Nutrients (High, Low);
Product_Weight (0 to 2550, 2550 to 5100, 5100 to 7650, 7650 to 10200);
Rainfall (0 to 0.4, 0.4 to 0.8, 0.8 to 1.2, 1.2 to 1.6, 1.6 to 2, 2 to 2.4, 2.4 to 2.8);
Runoff (0 to 7.7, 7.7 to 15.4);
Senesced (0 to 77.5, 77.5 to 155, 155 to 232.5, 232.5 to 310);
Slope (Flat, Sloped);
SOMC (0 to 1.833e5, 1.833e5 to 3.666e5, 3.666e5 to 5.499e5, 5.499e5 to 7.322e5, 7.322e5 to
     9.165e5);
Temperature (7.5 to 8.54, 8.54 to 9.06, 9.06 to 9.58, 9.58 to 10.1, 10.1 to 10.62);
Texture (Loamy, Clay);
Tillage (Conservational, Conventional);
VESS (Fragile, Intact, Firm, Compact, Very Compact);
Water (0 to 159, 159 to 318, 318 to 477, 477 to 636);
Water Stress (0 to 3.66, 3.66 to 7.32, 7.32 to 10.98, 10.98 to 14.64);
Weeds (Present, Absent);
Weight (0 to 5000, 5000 to 10000, 10000 to 15000, 15000 to 20000, 20000 to 25000);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

**Yield** (Decrease, Increase):

Ali, Q. (2023). A trade-off between farm production and flood alleviation using land use tillage preferences as a natural flood management (NFM) strategy. Smart Agricultural Technology, 6, 100361.

116 fluids2

fluids1

fluids Bayesian Networks

## **Description**

Use of Bayesian Networks for the investigation of the nature of biological material in casework.

#### **Format**

A discrete Bayesian network to assess the presence of blood in the recovered material and combine potentially contradictory observations. The network was available from an associated repository. The vertices are:

**OBTI** Blood test (Positive, Negative, Weak positive);

Visual (Red, Light red, Other);

**Concentration** Concentration of total DNA (0-0.0002, 0.0002-0.0005, 0.0005-0.001, 0.001-0.002, 0.002-0.004, 0.004-0.01, 0.01-0.01, 0.02-inf);

**Blood** (Yes, No);

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Samie, L., Champod, C., Delemont, S., Basset, P., Hicks, T., & Castella, V. (2022). Use of Bayesian Networks for the investigation of the nature of biological material in casework. Forensic Science International, 331, 111174.

fluids2

fluids Bayesian Networks

## **Description**

Use of Bayesian Networks for the investigation of the nature of biological material in casework.

## **Format**

A discrete Bayesian network to assess the presence of saliva in the recovered material and combine potentially contradictory observations. The network was available from an associated repository. The vertices are:

**Risk** Risk of false positive for saliva detection (High, Low);

Saliva (Yes, No);

**RSID** Saliva test (Positive, Negative, Weak positive);

fluids3

**Concentration** Concentration of total DNA (0-0.0002, 0.0002-0.0005, 0.0005-0.001, 0.001-0.002, 0.002-0.004, 0.004-0.01, 0.01-0.01, 0.02-inf);

**Nature\_of\_stain** (Saliva, Fecal matter/vaginal secretion/sperm/breat milk/urine, Other);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Samie, L., Champod, C., Delemont, S., Basset, P., Hicks, T., & Castella, V. (2022). Use of Bayesian Networks for the investigation of the nature of biological material in casework. Forensic Science International, 331, 111174.

fluids3

fluids Bayesian Networks

### **Description**

Use of Bayesian Networks for the investigation of the nature of biological material in casework.

#### **Format**

A discrete Bayesian network to assess the presence of sperm in the recovered material and combine potentially contradictory observations. The network was available from an associated repository. The vertices are:

**Concentration\_EPI** Total concentration of male DNA in non sperm fraction (0-0.0002, 0.0002-0.0005, 0.0005-0.001, 0.001-0.002, 0.002-0.004, 0.004-0.01, 0.01-0.01, 0.02-inf);

Sperm (Yes, No);

Nature\_of\_stain (At least Sperm, Lubricant/urine/vaginal secretion);

Location (Vaginal/condom/panties, Other);

**Concentration\_Total** Total concentration of male DNA (0-0.0002, 0.0002-0.0005, 0.0005-0.001, 0.001-0.002, 0.002-0.004, 0.004-0.01, 0.01-0.01, 0.02-inf);

**AZO** (Azoospermic, Non azoospermic);

**CT** Spermatozoa detection (Positive, Negative, 1 spz, Possible spz);

**PSA** Seminal fluid test (Positive, Negative, Weak positive);

**Concentration\_SP** Total concentration of male DNA in sperm fraction (0-0.0002, 0.0002-0.0005, 0.0005-0.001, 0.001-0.002, 0.002-0.004, 0.004-0.01, 0.01-0.01, 0.02-inf);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

118 foodallergy1

## References

Samie, L., Champod, C., Delemont, S., Basset, P., Hicks, T., & Castella, V. (2022). Use of Bayesian Networks for the investigation of the nature of biological material in casework. Forensic Science International, 331, 111174.

foodallergy1

foodallergy Bayesian Networks

## **Description**

Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling.

#### **Format**

A discrete Bayesian network to to estimate conditional probabilities of each food allergy when other food allergies are present (full population). Probabilities were given within the referenced paper. The vertices are:

```
Cereals (T, F);
Eggs (T, F);
Fruits (T, F);
Milk (T, F);
Nuts (T, F);
Peanuts (T, F);
Seafood (T, F);
Veg_Leg (T, F);
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Belmabrouk, S., Abdelhedi, R., Bougacha, F., Bouzid, F., Gargouri, H., Ayadi, I., ... & Rebai, A. (2023). Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling. World Allergy Organization Journal, 16(9), 100813.

foodallergy2

foodalle	ergy2	foodallergy Bayesian Networks	

# Description

Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling.

## **Format**

A discrete Bayesian network to to estimate conditional probabilities of each food allergy when other food allergies are present (adults only). Probabilities were given within the referenced paper. The vertices are:

```
Cereals (T, F);

Eggs (T, F);

Fruits (T, F);

Milk (T, F);

Nuts (T, F);

Peanuts (T, F);

Seafood (T, F);

Veg_Leg (T, F);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Belmabrouk, S., Abdelhedi, R., Bougacha, F., Bouzid, F., Gargouri, H., Ayadi, I., ... & Rebai, A. (2023). Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling. World Allergy Organization Journal, 16(9), 100813.

foodallergy Bayesian Networks
-------------------------------

## **Description**

Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling.

120 foodsecurity

## **Format**

A discrete Bayesian network to to estimate conditional probabilities of each food allergy when other food allergies are present (children only). Probabilities were given within the referenced paper. The vertices are:

```
Cereals (T, F);
Eggs (T, F);
Fruits (T, F);
Milk (T, F);
Nuts (T, F);
Peanuts (T, F);
Seafood (T, F);
Veg_Leg (T, F);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Belmabrouk, S., Abdelhedi, R., Bougacha, F., Bouzid, F., Gargouri, H., Ayadi, I., ... & Rebai, A. (2023). Prevalence of self-reported food allergy in Tunisia: General trends and probabilistic modeling. World Allergy Organization Journal, 16(9), 100813.

foodsecurity

foodsecurity Bayesian Network

## **Description**

Coherent combination of probabilistic outputs for group decision making: an algebraic approach.

## **Format**

A discrete Bayesian network modelling a food security scenario. Probabilities were given within the referenced paper. The vertices are:

Cost

EducationalAttainment

Health

**SocialCohesion** 

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

forest 121

#### References

Leonelli, M., Riccomagno, E., & Smith, J. Q. (2020). Coherent combination of probabilistic outputs for group decision making: an algebraic approach. OR Spectrum, 42(2), 499-528.

forest

forest Bayesian Network

## **Description**

Forest biodiversity and structure modulate human health benefits and risks.

#### **Format**

A discrete Bayesian network modelling the relationships between forest biodiversity, structure, and human health outcomes across 164 European forest stands. The full model was provided by the authors in a repository. The vertices are:

```
BasalArea (0 to 20, 20 to 90.3);
```

BirdBiophonyPerDay (Silence prevails, Intermediate, Biophony prevails);

**BirdSpeciesDiversity** (4 to 7, 7 to 9, 9 to 12);

CanopyRoughness (Low, Medium, High);

Condition (low, high);

**CoolingCapacity** (<-10, -10 to -5, -5 to 0, >=0);

**DecidousProportion** (EvergreenOrMixed, DecidousDominated);

**DeerAbundance** (0 to 2, 2 to 4, 4 to 8);

DeltaPhysiologicalStress (Increase, Small decrease, Large decrease);

**DeltaPhysStressControl** (0.6 to 1.5);

**DeltaPosAffControl** (-35 to -8, -8 to 0, 0 to 8);

**DeltaPositiveAffectA1** (Decrease, Small increase, Large increase);

**DominantCanopyHeight** (0 to 20, 20 to 39);

**DIN** (0, 0 to 0.25, 0.25 to 1, >=1);

**DON** (0, 0 to 1, 1 to 3, 3 to 14.3);

**DONCorrection** (-0.5 to 0, 0 to 0.5);

**EdibleMushroomProductivity** (0 to 4, 4 to 40, 40 to 270);

ForestStandType (Mature and Natural, Young and Planted);

**HeatMortalityForest** (-5 to 0, 0 to 5, 5 to 10, >= 10);

**HeatMortalityMacro** (-5 to 0, 0 to 5, 5 to 10, >= 10);

**HeatStressForest** (None, Slight, Moderate, Strong, Extreme);

**HeatStressMacro** (Slight, Moderate, Strong, Extreme);

ImprovementAnxiety (Large, Small, Decline);

122 forest

```
ImprovementNegativeAffect (Large, Small, Decline);
ImprovementPhysiologicalStress (Large, Small, Decline);
ImprovementPositiveAffect (Large, Small, Decline);
LeafAreaIndex (0 to 1, 1 to 3, 3 to 7.2);
LymeBorreliosisRisk (No risk, Low, Medium, High);
MeanLeafSize (0 to 1500, 1500 to 3000, 3000 to 10500);
MedicinalPlantDiversity (0 to 0.1, 0.1 to 0.24, 0.24 to 0.8);
MedicinalPlantProductivity (0 to 3.8, 3.8 to 15, 15 to 102);
MidFrequencyCoverBiophony (Little diverse, Intermediate, Highly diverse);
MortalityReduction (-5 to 0, 0 to 5, 5 to 10, \geq 10);
MouseAbundance (0 to 10, 10 to 20, 20 to 30);
MushroomProductivity (0 to 10, 10 to 80, 80 to 400);
MushroomRelatedHealthBenefits (Low, Medium, High);
MushroomSpeciesDiversity (0 to 15, 15 to 30, 30 to 72);
NIP (0, 0 to 0.5, 0.5 to 1);
NIPCorrection (-1 to -0.75, -0.75 to -0.25, -0.25 to 0.25, 0.25 to 0.75, 0.75 to 1.05);
PerceivedAcousticDiversity (1 to 2, 2, 2 to 5);
PerceivedArtificialness (Low, Medium, High);
PerceivedBiodiversity (Low, Medium, High);
PerceivedDensity (Low, Medium, High);
PlotLevelPolyphenolContent (0 to 34, 34 to 600, 600 to 6000);
PM100Deposition (0 to 0.05, 0.05 to 0.15, 0.15 to 0.95);
PM10Deposition (0 to 0.035, 0.035 to 0.1, 0.1 to 0.35);
PM10InsideForest (4.77137 to 15, 15 to 20, 20 to 30);
PM10OutsideForest (10 to 15, 15 to 20, 20 to 30);
PM2.5Deposition (0 to 0.02, 0.02 to 0.07, 0.07 to 0.25);
PM2.5InsideForest (1.24706 to 7.5, 7.5 to 10, 10 to 15);
PM2.5OutsideForest (5 to 7.5, 7.5 to 10, 10 to 15);
PolyphenolRelatedHealthBenefits (Negligible, LowToMedium, High);
RelativeHumidity (0 to 80, 80 to 100);
RestorativenessA1 (Low, Medium, High);
RestorativenessA2 (Low, Medium, High);
RiskInsideForestPM10 (1 to 1.05, 1.05 to 1.1, 1.1 to 1.15);
RiskInsideForestPM2.5 (1 to 1.1, 1.1 to 1.15, 1.15 to 1.2);
RiskMitigationPM10 (Low, Medium, High);
RiskMitigationPM2.5 (1 to 1.05, 1.05 to 1.1, 1.1 to 1.15);
RiskOutsideForestPM10 (1 to 1.05, 1.05 to 1.1, 1.1 to 1.15);
```

fundraising 123

```
RiskOutsideForestPM2.5 (1 to 1.1, 1.1 to 1.15, 1.15 to 1.2);
SoilFertility (Mull - fertile, Rich moder, Poor model or mor - infertile);
StemDensity (50 to 500, 500 to 2500, 2500 to 12200);
ThermalComfortForest (Cold, Cool, sCool, Neutral, sWarm, Warm);
ThermalComfortMacro (Cool, sCool, Neutral, sWarm, Warm, Hot);
ThermalPreferenceForest (Warmer, No Change, Colder);
ThermalPreferenceMacro (Warmer, No Change, Colder);
TreeSpeciesDiversity (Monospecific, Polyspecific);
UnderstoryProductivity (0 to 25, 25 to 75, 75 to 100);
VocalizingBirdSpeciesDiversity (4 to 10, 10 to 15, 15 to 25);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Gillerot, L., Landuyt, D., Bourdin, A., Rozario, K., Shaw, T., Steinparzer, M., ... & Verheyen, K. (2025). Forest biodiversity and structure modulate human health benefits and risks. Nature Sustainability, 1-13.

fundraising

fundraising Bayesian Network

# **Description**

A coupled mathematical model of the dissemination route of short-term fund-raising fraud.

## **Format**

A discrete Bayesian network to analyze the dissemination, identification, and causation of fundraising fraud. Probabilities were given within the referenced paper. The vertices are:

```
FailureInvest (Yes, No);
FinancialFraud (Yes, No);
LackAwareness (Yes, No);
LackKnowledge (Yes, No);
LackRegulation (Yes, No);
OverTrust (Yes, No);
PatsyInvestment (Yes, No);
PromotionalMessages (Yes, No);
```

@return An object of class bn.fit. Refer to the documentation of bnlearn for details.

124 gasexplosion

#### References

Yang, S., Su, K., Wang, B., & Xu, Z. (2022). A coupled mathematical model of the dissemination route of short-term fund-raising fraud. Mathematics, 10(10), 1709.

gasexplosion

gasexplosion Bayesian Network

## **Description**

Risk assessment of unsafe acts in coal mine gas explosion accidents based on HFACS-GE and Bayesian networks.

#### **Format**

A discrete Bayesian network to analyze unsafe human acts in coal mine gas explosion accidents. Probabilities were given within the referenced paper. The vertices are:

Accidental Violations (Non-occurence, Occurence);

 $\label{lem:converged} \textbf{CreateAFalseImpressionToDeceiveTheRegulators} \hspace{0.2cm} \textbf{(Non-occurence, Occurence);}$ 

**DecisionErrors** (Non-occurence, Occurence);

 $Deparments And Institutions Are Not Complete \ (Non-occurence, Occurence);$ 

HabitualViolations (Non-occurence, Occurence);

**IllegalCommand** (Non-occurence, Occurence);

InadequateEmergencyPlan (Non-occurence, Occurence);

InsufficientCracdownOnIllegalActivities (Non-occurence, Occurence);

InsufficientSupervisionOfWorkSafety (Non-occurence, Occurence);

MentalStates (Non-occurence, Occurence);

OrganizeProductionInViolationOfLawsAndRegulations (Non-occurence, Occurence);

PerceptualErrors (Non-occurence, Occurence);

PhysicalIntellectualDisability (Non-occurence, Occurence);

SafetyEducationAndTraning (Non-occurence, Occurence);

SafetySupervisionIsInadequate (Non-occurence, Occurence);

SecurityManagementConfusion (Non-occurence, Occurence);

SafetySupervisionIsInadequate (Non-occurence, Occurence);

**SecurityManagementConfusion** (Non-occurence, Occurence);

 ${\bf Skill Based Errors} \ \ ({\bf Non-occurence}, {\bf Occurence});$ 

TechnicalEnvironment (Non-occurence, Occurence);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

gasifier 125

#### References

Niu, L., Zhao, J., & Yang, J. (2023). Risk assessment of unsafe acts in coal mine gas explosion accidents based on HFACS-GE and Bayesian networks. Processes, 11(2), 554.

gasifier

gasifier Bayesian Network

## **Description**

Failure risk assessment of coal gasifier based on the integration of bayesian network and trapezoidal intuitionistic fuzzy number-based similarity aggregation method (TpIFN-SAM).

#### **Format**

A discrete Bayesian network for the failure-risk assessment of process system. Probabilities were given within the referenced paper. The vertices are:

AbnormalCoalWater Abnormal flow rate of coal water (Occurred, NotOccured);

AbnormalLiquidLevel Abnormal liquid level (Occurred, NotOccured);

AbnormalQuenchWater Abnormal flow rate of quench water (Occurred, NotOccured);

AbnormalTemperature Abnormal temperature (Occurred, NotOccured);

AntiCorrosion Anti-corrosion layer damaged (Occurred, NotOccured);

**BurnerDamaged** Burner damaged (Occurred, NotOccured);

CorrosionFailure Corrosion failure (Occurred, NotOccured);

**Cracking** Cracking in the quench ring or vertical pipe (Occurred, NotOccured);

**DeliberateDestruction** Deliberate destruction (Occurred, NotOccured);

External Corrosion (Occurred, NotOccured);

**FurnaceBricks** Slag opening blocked by molten furnace bricks (Occurred, NotOccured);

**GasifierAbnormality** Gasifier abnormality (Occurred, NotOccured);

GasifierFailure Gasifier failure (Occurred, NotOccured);

GaugeDamaged Liquid-level gauge damaged by blockage (Occurred, NotOccured);

**HighCO2** High CO2 content (Occurred, NotOccured);

**HighConcentration** High concentration of coal slurry (Occurred, NotOccured);

**HighFlow** High flow rate (Occurred, NotOccured);

**HighFlowRate** High flow rate of coal slurry (Occurred, NotOccured);

HighH2O High H2O content (Occurred, NotOccured);

**HighH2S** High H2S content (Occurred, NotOccured);

**HighOxygen** High oxygen-flow rate (Occurred, NotOccured);

**HumanOrganization** Human organization factors (Occurred, NotOccured);

ImproperOperation Improper operation (Occurred, NotOccured);

126 GDIpathway1

Insulation Insulation layer damaged (Occurred, NotOccured);

**Internal Corrosion** Internal corrosion (Occurred, NotOccured);

Leakage Leakage of drain valve of quench water (Occurred, NotOccured);

LowConcentration Low concentration of coal slurry (Occurred, NotOccured);

**LowFlowRate** Low flow rate of coal slurry (Occurred, NotOccured);

LowLiquidLevel Low liquid rate in quench chamber (Occurred, NotOccured);

LowOxygen Low oxygen-flow rate (Occurred, NotOccured);

MediumContent Medium content (Occurred, NotOccured);

**PiecesOfSlag** Slag opening blocked by large pieces of slage (Occurred, NotOccured);

PreJobTraining Pre-job training is not up to standard (Occurred, NotOccured);

**PressureFluctuation** Pressure fluctuation (Occurred, NotOccured);

SensorDamaged1 Temperature sensor damaged (Occurred, NotOccured);

TemperatureSensor Temperature sensor damaged (Occurred, NotOccured);

TooHighTemperature Too-high temperature (Occurred, NotOccured);

**TooLowTemperature** Too-low temperature (Occurred, NotOccured);

**Unattended** Unattended/unsafe supervision (Occurred, NotOccured);

Unintentional Destruction Unintentional destruction (Occurred, NotOccured);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Liu, Y., Wang, S., Liu, Q., Liu, D., Yang, Y., Dan, Y., & Wu, W. (2022). Failure risk assessment of coal gasifier based on the integration of bayesian network and trapezoidal intuitionistic fuzzy number-based similarity aggregation method (TpIFN-SAM). Processes, 10(9), 1863.

GDIpathway1

GDIpathway Bayesian Networks

## **Description**

Integrative network modeling highlights the crucial roles of Rho-GDI signaling pathway in the progression of non-small cell lung cancer.

GDIpathway1

## **Format**

A discrete Bayesian network to pinpoint key cellular factors and pathways likely to be involved with the onset and progression of non-small cell lung cancer (healthy patients). The network was available from an associated repository. The vertices are:

```
ARHGAP6 (Above, Below);
ARHGEF19 (Above, Below);
CD44 (Above, Below);
CDC42-IT1 (Above, Below);
CDH1 (Above, Below);
CFL2 (Above, Below);
DAGLB (Above, Below);
DGKZ (Above, Below);
DLC1 (Above, Below);
ECM1 (Above, Below);
ERMAP (Above, Below);
ERMP1 (Above, Below);
GNA11 (Above, Below);
GNG11 (Above, Below);
GPRC5A (Above, Below);
ITGB2 (Above, Below);
LACTB (Above, Below);
LIMK2 (Above, Below);
PAAF1 (Above, Below);
PAK1 (Above, Below);
PAK1 (Above, Below);
PIP (Above, Below);
PIP4K2A (Above, Below);
PIP5K1B (Above, Below);
RAC2 (Above, Below);
RHOJ (Above, Below);
ROCK2 (Above, Below);
RTKN (Above, Below);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Gupta, S., Vundavilli, H., Osorio, R. S. A., Itoh, M. N., Mohsen, A., Datta, A., ... & Tripathi, L. P. (2022). Integrative network modeling highlights the crucial roles of rho-GDI signaling pathway in the progression of non-small cell lung cancer. IEEE Journal of Biomedical and Health Informatics, 26(9), 4785-4793.

128 GDIpathway2

GDIpathway2

GDIpathway Bayesian Networks

## **Description**

Integrative network modeling highlights the crucial roles of Rho-GDI signaling pathway in the progression of non-small cell lung cancer.

#### **Format**

A discrete Bayesian network to pinpoint key cellular factors and pathways likely to be involved with the onset and progression of non-small cell lung cancer (unhealthy patients). The network was available from an associated repository. The vertices are:

```
ARHGAP6 (Above, Below);
ARHGEF19 (Above, Below);
CD44 (Above, Below);
CDC42-IT1 (Above, Below);
CDH1 (Above, Below);
CFL2 (Above, Below);
DAGLB (Above, Below);
DGKZ (Above, Below);
DLC1 (Above, Below);
ECM1 (Above, Below);
ERMAP (Above, Below);
ERMP1 (Above, Below);
GNA11 (Above, Below);
GNG11 (Above, Below);
GPRC5A (Above, Below);
ITGB2 (Above, Below);
LACTB (Above, Below);
LIMK2 (Above, Below);
PAAF1 (Above, Below);
PAK1 (Above, Below);
PAK1 (Above, Below);
PIP (Above, Below);
PIP4K2A (Above, Below);
PIP5K1B (Above, Below);
RAC2 (Above, Below);
RHOJ (Above, Below);
ROCK2 (Above, Below);
RTKN (Above, Below);
```

get\_network\_list 129

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Gupta, S., Vundavilli, H., Osorio, R. S. A., Itoh, M. N., Mohsen, A., Datta, A., ... & Tripathi, L. P. (2022). Integrative network modeling highlights the crucial roles of rho-GDI signaling pathway in the progression of non-small cell lung cancer. IEEE Journal of Biomedical and Health Informatics, 26(9), 4785-4793.

get\_network\_list

Get the list of available Bayesian network files

## **Description**

This function lists all the .rda files in the data directory.

## Usage

```
get_network_list()
```

#### Value

A character vector of network file names.

gonorrhoeae

gonorrhoeae Bayesian Network

### Description

Policy, practice, and prediction: model-based approaches to evaluating N. gonorrhoeae antibiotic susceptibility test uptake in Australia.

## **Format**

A discrete Bayesian network to simulate the clinician-patient dynamics influencing antibiotic susceptibility test initiation. The probabilities were given within the referenced paper. The vertices are:

**ASTTest** (Initiated, Not initiated);

ClinicianExperience (Experienced, Unexperienced);

EpidemiologicalFactors (High risk group, Low risk group);

InitialTreatmentFailure (Treatment success, Treatment failure);

MedicationAdherence (Proper Adherence, Improper Adherence);

130 greencredit

```
NumberPartners (One, Two to five, More than six);
PastDiagnoses (One, Two to four, five to nine, More than ten);
PersistingSymptoms (Symptoms persist, Symptoms resolve);
SexualOrientation (Heterosexual, Homosexual);
```

UnpromptedTest (Initiated, Not initiated);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Do, P. C., Assefa, Y. A., Batikawai, S. M., Abate, M. A., & Reid, S. A. (2024). Policy, practice, and prediction: model-based approaches to evaluating N. gonorrhoeae antibiotic susceptibility test uptake in Australia. BMC Infectious Diseases, 24(1), 498.

greencredit

greencredit Bayesian Network

## Description

The coupling relationships and influence mechanisms of green credit and energy-environment-economy under China's goal of carbon neutrality.

#### **Format**

A discrete Bayesian network nvestigate the coupling relationships and influence mechanisms of green credit and 3E system. Probabilities were given within the referenced paper (missing distributions were set as uniform). The vertices are:

**ECS** Energy consumption structure (High, Medium, Low);

EI Energy intensity (High, Medium, Low);

EPI Environment (High, Medium, Low);

**GCI** Interest expense proportion (High, Medium, Low);

**GDP** Economy sharing (High, Medium, Low);

IS Green economy (High, Medium, Low);

**OU** Economy opening up (High, Medium, Low);

**PEC** Per capita energy consumption (High, Medium, Low);

TP Economy innovation (High, Medium, Low);

UR Economy coordination (High, Medium, Low);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

grounding 131

## References

Chai, J., Wang, Y., Hu, Y., Zhang, X., & Zhang, X. (2023). The Coupling Relationships and Influence Mechanisms of Green Credit and Energy-Environment-Economy Under China's Goal of Carbon Neutrality. Journal of Systems Science and Complexity, 36(1), 360-374.

grounding

grounding Bayesian Network

# **Description**

A framework for quantitative analysis of the causation of grounding accidents in arctic shipping.

#### **Format**

A discrete Bayesian network to for quantitative analysis of the causation of grounding accidents in Arctic shipping. Probabilities were given within the referenced paper (some information appeared incorrect). The vertices are:

**BW** Bad Weather (No, Yes);

**DAM** Damage (No, Yes);

**DE** Dependent equipment (No, Yes);

**GRO** Grounding (No, Yes);

ICC Insufficient communication and collaboration (No,Yes);

IER Imperfect emergency (No, Yes);

**ILC** Improper labeling of the chart (No,Yes);

**INE** Inefficient use of navigation equipment (No, Yes);

**IO** Improper operation (No, Yes);

**IPS** Insufficient preparation for sailing (No, Yes);

**IRP** Improper route planning (No,Yes);

IRR Irregularities (No,Yes);

IS Insufficient supervision (No, Yes);

ISL Inconsistent standardization and language (No, Yes);

**ISS** Insufficient supervision system, rules and regulations (No,Yes);

**IWP** Insufficient work plan (No,Yes);

**LID** Limited information dissemination channels (No, Yes);

LNE Lack of navigation equipment (No, Yes);

LSM Lack of safety management system (No, Yes);

LT Lack of training (No, Yes);

**MIJ** Misjudgment (No, Yes);

**OD** Outdated data (No, Yes);

healthinsurance

```
PC Poor communication at high latitudes (No,Yes);
PEC Poor external communication (No,Yes);
PF Psychological factors (No,Yes);
PFC Poor traffic conditions (No,Yes);
PSA Poor situational awareness (No,Yes);
PSM Poor safety management (No,Yes);
PSQ Poor service quality (No,Yes);
SMS Ship SMS conflict (No,Yes);
UCD Unupdated chart data (No,Yes);
UDL Unclear division of labour (No,Yes);
UPA Unreasonable planning and arrangement (No,Yes);
UR Underestimate the risk (No,Yes);
US Unsafe speed (No,Yes);
WD Wrong decision (No,Yes);
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Fu, S., Yu, Y., Chen, J., Xi, Y., & Zhang, M. (2022). A framework for quantitative analysis of the causation of grounding accidents in arctic shipping. Reliability Engineering & System Safety, 226, 108706.

healthinsurance

healthinsurance Bayesian Network

# Description

Discrete latent variables discovery and structure learning in mixed Bayesian networks.

## **Format**

A conditional linear-Gaussian Bayesian network to predict health insurance charges. The DAG structure was taken from the referenced paper and the probabilities learned from data. The vertices are:

```
age
bmi
charges
children (0, 1, 2, 3, 4, 5)
region (northeast, northwest, southeast, southwest);
sex (female, male);
smoker (no, yes);
```

humanitarian 133

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Peled, A., & Fine, S. (2021). Discrete Latent Variables Discovery and Structure Learning in Mixed Bayesian Networks. In 20th IEEE International Conference on Machine Learning and Applications (pp. 248-255). IEEE.

humanitarian

humanitarian Bayesian Network

### **Description**

You only derive once (YODO): Automatic differentiation for efficient sensitivity analysis in Bayesian networks.

#### **Format**

A discrete Bayesian network to assess the country-level risk associated with humanitarian crises and disasters. The Bayesian network is learned as in the referenced paper. The vertices are:

```
RISK (low, medium, high);
```

**EARTHQUAKE** (low, medium, high);

**FLOOD** (low, medium, high);

TSUNAMI (low, medium, high);

TROPICAL\_CYCLONE (low, medium, high);

**DROUGHT** (low, medium, high);

**EPIDEMIC** (low, medium, high);

**PCR** Projected conflict risk (low, medium, high);

**CHVCI** Current highly violent conflict intensity (low, medium, high);

**D\_AND\_D** Development and deprivation (low, medium, high);

ECON\_DEP Economic dependency (low, medium, high);

**UNP\_PEOPLE** Unprotected people (low, medium, high);

**HEALTH\_COND** Health conditions (low, medium, high);

CHILDREN\_U5 (low, medium, high);

**RECENT\_SHOCKS** (low, medium, high);

**FOOD\_SECURITY** (low, medium, high);

OTHER\_VULN\_GROUPS Other vulnerable groups (low, medium, high);

GOVERNANCE (low, medium, high);

**COMMUNICATION** (low, medium, high);

**PHYS INFRA** Physical infrastructure (low, medium, high);

ACCESS\_TO\_HEALTH (low, medium, high);

hydraulicsystem

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Ballester-Ripoll, R., & Leonelli, M. (2022, September). You only derive once (YODO): automatic differentiation for efficient sensitivity analysis in Bayesian networks. In International Conference on Probabilistic Graphical Models (pp. 169-180). PMLR.

hydraulicsystem

hydraulicsystem Bayesian Network

## **Description**

Analysis and assessment of risks to public safety from unmanned aerial vehicles using fault tree analysis and Bayesian network.

## **Format**

A discrete Bayesian network to to analyze time series hydraulic system operation reliability. Probabilities were given within the referenced paper. The vertices are:

```
YellowHydraulicSystem (True, False);
GreenHydraulicSystem (True, False);
BlueHydraulicSystem (True, False);
HydraulicSystem (True, False);
```

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Pan, W. H., Feng, Y. W., Liu, J., & Lu, C. (2023). Operation reliability monitoring towards fault diagnosis of airplane hydraulic system using quick access recorder flight data. Measurement Science and Technology, 34(5), 055111.

income 135

income

income Bayesian Network

## **Description**

The FEDHC Bayesian network learning algorithm.

## **Format**

A discrete Bayesian network modeling the factors affecting the income of individuals. The code to learn the Bayesian network was given within the referenced paper (Figure 13.c) The vertices are:

```
Income (0-40'000, 40'000+);
Sex (male, female);
Marriage (married, cohabitation, divorced, widowed, single);
Age (14-34, 35+);
Education (college graduate, no college graduate);
Occupation (professional/managerial, sales, laborer, clerical/service, homemaker, student, military, retired, unemployed);
Bay Number of years in bay area (1-9, 10+);
No of people Number of people living in the house (1, 2+);
Children (0, 1+);
Rent (own, rent, live with parents/family);
Type (house, condominuim, apartment, mobile home, other);
Ethnicity (American Indian, Asian, black, east Indian, hispanic, white, pacific islander, other);
Language (english, spanish, other);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Tsagris, M. (2022). The FEDHC Bayesian network learning algorithm. Mathematics, 10(15), 2604.

136 intensification

intensification

intensification Bayesian Network

## **Description**

Modeling intensification decisions in the Kilombero Valley floodplain: A Bayesian belief network approach.

## **Format**

A discrete Bayesian network to or identifying determinants of intensification and their interrelationships. The Bayesian network is learned as in the referenced paper. The vertices are:

AccessToCredi (No, Yes);

**AgeofHHHead** (25-35, 35-45, 45-55, >55);

**Choice\_Of\_Intensification\_Strategy** (ApplyFertilizer, ApplyImprovedSeed, CropMultipleTimes, None, UseIrrigation, UseIrrigationAndFertilizerApplication);

**CommercializationIndex** (<30%, 30-60%, >60%);

**CropChoice** (Maize, Rice, RiceAndMaize, RiceMaizeAndVegit, Vegitables, VegitAndMaize, VegitAndRice);

**DistanceToBigMarket** (<15km, 15-30km, >30km);

**ExpectedPriceOfMaize** (0, 0-800, 800-861.111, 861.111-1111.11);

**ExpectedPriceOfRice** (0 to 1000, 1000 to 1200, 1200 to 1500, 1500 to 1900);

**FarmerType** (AgroPastoralist, Diversifier, Subsistence);

**Income** (0-160, 160-280, 280-600, 600-15800);

**LabourInManDays** (<120, 120-220, 220-400, >400);

**PercentOfNonFarmIncome** (None, <30%, >30%);

**ShareOfHiredLabour** (<10%, 10-60%, >60%);

SizeOfCropLand (<3Ha, 3-6Ha, 6-9Ha, >9Ha);

**SizeOfHousehold** (<4, 4-7, >7);

TopographicWetnessIndex (14-18, 18-23, 23-32);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Gebrekidan, B. H., Heckelei, T., & Rasch, S. (2023). Modeling intensification decisions in the Kilombero Valley floodplain: A Bayesian belief network approach. Agricultural Economics, 54(1), 23-43.

intentionalattacks 137

intentionalattacks intentionalattacks Bayesian Network

## **Description**

Probability elicitation for Bayesian networks to distinguish between intentional attacks and accidental technical failures.

#### **Format**

A discrete Bayesian network modeling a floodgate in the Netherlands. Probabilities were given within the referenced paper. The vertices are:

- X1 Weak physical access-control (True, False);
- X2 Sensor data integrity verification (True, False);
- U1 Lack of physical maintenance (True, False);
- **U2** Well-written maintenance procedure (True, False);
- Y Major cause for sensor sends incorrect water level measurements (Intentional Attack, Accidental Technical Failure);
- **Z1** Abnormalities in the other locations (True, False);
- **Z2** Sensor sends correct water level measurements after cleaning the sensor (True, False)
- **Z3** Sensor sends correct water level measurements after recalibrating the sensor (True, False);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Chockalingam, S., Pieters, W., Teixeira, A. M., & van Gelder, P. (2023). Probability elicitation for Bayesian networks to distinguish between intentional attacks and accidental technical failures. Journal of Information Security and Applications, 75, 103497.

inverters

inverters Bayesian Network

## Description

Intelligent fault inference of inverters based on a three-layer Bayesian network.

inverters inverters

#### **Format**

A discrete Bayesian network to infer the probable uncertain faults. Probabilities were given within the referenced paper. The vertices are:

```
AbnormalPulseVoltageWaveform (TRUE, FALSE);
APhaseFailure (TRUE, FALSE);
APhaseNegativeWaveFormDistortion (TRUE, FALSE);
APhasePositiveWaveFormDistortion (TRUE, FALSE);
BPhaseFailure (TRUE, FALSE);
BPhaseNegativeWaveFormDistortion (TRUE, FALSE);
BPhasePositiveWaveFormDistortion (TRUE, FALSE);
C1Failure (TRUE, FALSE);
C1VoltageAnomaly (TRUE, FALSE);
C2Failure (TRUE, FALSE);
C2VoltageAnomaly (TRUE, FALSE);
CapacitanceParameterWeakening (TRUE, FALSE);
CPhaseFailure (TRUE, FALSE);
CPhaseNegativeWaveFormDistortion (TRUE, FALSE);
CPhasePositiveWaveFormDistortion (TRUE, FALSE);
DCLinkFailure (TRUE, FALSE);
G1PulseMissing (TRUE, FALSE);
G2PulseMissing (TRUE, FALSE);
G3PulseMissing (TRUE, FALSE);
G4PulseMissing (TRUE, FALSE);
G5PulseMissing (TRUE, FALSE);
G6PulseMissing (TRUE, FALSE);
T1OC (TRUE, FALSE);
T2OC (TRUE, FALSE);
T3OC (TRUE, FALSE);
T4OC (TRUE, FALSE);
T5OC (TRUE, FALSE);
T6OC (TRUE, FALSE);
VoltageWaveFormAsymmetry (TRUE, FALSE);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Han, S., He, Y., Zheng, S., & Wang, F. (2019). Intelligent Fault Inference of Inverters Based on a Three-Layer Bayesian Network. Mathematical Problems in Engineering, 2019(1), 3653746.

knowledge 139

knowledge

knowledge Bayesian Network

## **Description**

Dynamic knowledge inference based on Bayesian network learning.

#### **Format**

A discrete Bayesian network to predict whether students would pass specific courses. Probabilities were given within the referenced paper. The vertices are:

```
Math (Pass, Fail);
C (Pass, Fail);
Java (Pass, Fail);
Database (Pass, Fail);
Android (Pass, Fail);
Web (Pass, Fail);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Wang, D., AmrilJaharadak, A., & Xiao, Y. (2020). Dynamic knowledge inference based on Bayesian network learning. Mathematical Problems in Engineering, 2020(1), 6613896.

kosterhavet

kosterhavet Bayesian Network

## **Description**

A Bayesian network to inform the management of key species in Kosterhavet National Park under contrasting storylines of environmental change.

#### **Format**

A discrete Bayesian network to predict the consequences of human activities for coastal ecosystems and identify areas for directed abatement measures. Probabilities were given within the referenced paper (missing probabilities were given a uniform distribution). The vertices are:

**LeisureBoating** Boats per year in marinas and natural harbors (for natural harbors only high season from Jul. 01 to Aug. 07 considered) within Kosterhavet National Park (Low, Medium, High);

140 kosterhavet

**TrawlingFrequency** Number of trawling events per area and year within Kosterhavet National Park (Low, High);

**MusselCultivation** Extent of oysters and blue mussels farms within Kosterhavet National Park (Low, Medium, High, Very high);

**DevelopedLand** Proportion of developed land in the catchments of marine water bodies (Low, High);

**AgriculturalLand** Proportion of agricultural land in the catchments of marine water bodies (Low, Medium, High);

**TNExchange** Annual net total nitrogen exchange between marine water bodies (Low, Medium, High);

**TPExchange** Annual net phosphorus exchange between marine water bodies (Low, Medium, High);

RadiativeForcing Scenarios of radiative forcing till the end of 2100 (Current, RF45, RF85);

**Precipitation** Annual mean precipitation on land within the catchments of marine water bodies (Low, High);

**Discharge** Sum of discharges from rivers and runoff from land into marine water bodies (Low, Medium, High);

Wind Maximum summer (Jun.-Aug.) offshore wind speed (Low, Medium, High);

**DIN** Mean winter (Dec.-Feb.) dissolved inorganic nitrogen concentration in surface waters (Low, Medium, High);

**DIP** Mean winter (Dec.-Feb.) dissolved inorganic phosphorus concentration in surface waters (Low, Medium, High);

**POM** Annual mean concentration POM (POC - chl-a) (Low, High);

**NutrientEnrichmentRisk** Dependent on combination of states of DIN, DIP and POM (Low, Medium, High);

Noise Noise from leisure boats (Low, Medium, High);

**AnchorDamageRisk** Risk of seafloor in shallow bays being impacted by anchor damage of leisure boats (Low, High);

**WaterTemperatureShallow** Mean summer (Jun.- Aug.) sea surface temperature - depth < 10m (Low, Medium, High);

Transparency Mean summer (Jun-Aug) Secchi depth (Low, Medium, High);

OxygenShallow Lowest percentile of summer (Jun.-Aug.) oxygen concentration of surface water - depth < 10m (Low, Medium, High);

**OxygenDeep** Lowest percentile of summer (Jun.-Aug.) oxygen concentration of surface water - depth < 60m (Low, Medium, High);

**Turbidity** Amount of dry weight (Low, Medium, High);

**BottomSubstrate** Type of bottom substrate (Soft, Hard);

**SeafloorDisturbance** Benthic quality index (Low, High);

**WaterTemperatureDeep** Mean summer (Jun.- Aug.) sea surface temperature - depth < 60m (Low, High);

**TNLoad** Annual load of total nitrogen to marine water bodies (Low, Medium, High);

**TPLoad** Annual load of total phosphorus to marine water bodies (Low, Medium, High);

lawschool 141

**SedimentLoad** Annual sediment load to marine water bodies (Low, Medium, High);

**HabitatQuality** Dependent on combination of states of oxygen (deep), turbidity (deep), seafloor disturbance (Low, Medium, High);

Cod Catch per unit effor (Low, Medium, High);

**IntermediateFishPredators** Abundance of intermediate fish predators (e.g. Gobiidae, three-spined stickleback) (Low, Medium, High);

Mesograzers Abundance of mesograzers (e.g. amphipods, isopods)(Low, Medium, High);

**FilamentousAlgae** Maximum summer (May-Aug.) cover of filamentous algae in eelgrass meadows (Low, Medium, High);

**Phytoplankton** Mean summer (Jun.-Aug.) chl-a concentration (Low, Medium, High);

**Zooplankton** Strongly responds to phytoplankton with weaker links to temperature and oxygen concentration (Low, Medium, High);

**Prey** Dependent on combination of states of zooplankton and seafloor disturbance (Low, Medium, High);

**Eelgrass** Extent of eelgrass meadows within Kosterhavet National Park (Decrease, No change, Increase);

**NorthernShrimp** Catch per unit effort (Decrease, No change, Increase);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Rettig, K., Hansen, A. S., Obst, M., Hering, D., & Feld, C. K. (2023). A Bayesian network to inform the management of key species in Kosterhavet National Park under contrasting storylines of environmental change. Estuarine, Coastal and Shelf Science, 280, 108158.

lawschool

lawschool Bayesian Network

## **Description**

A survey on datasets for fairness-aware machine learning.

#### **Format**

A discrete Bayesian network modeling law school admission records. The DAG was taken from the referenced paper and the probabilities learned from the associated dataset. The vertices are:

**fam\_inc** The student's family income bracket (1, 2, 3, 4, 5);

**fulltime** Whether the student will work full-time or part-time (1, 2);

**lsat** The student's LSAT score (<=37, 37);

male Whether the student is male or female (female, male);

142 lexical

```
pass_bar Whether the student passed the bar exam on the first try (negative, positive);
racetxt Race (non-white, white);
tier Tier (1, 2, 3, 4, 5, 6);
ugpa The student's undergraduate GPA (<3,3, >=3.3);
zfygpa The first year law school GPA (<=0, >0);
zgpa The cumulative law school GPA (<=0, >0);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Le Quy, T., Roy, A., Iosifidis, V., Zhang, W., & Ntoutsi, E. (2022). A survey on datasets for fairness-aware machine learning. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 12(3), e1452.

lexical

lexical Bayesian Network

## **Description**

Accounting for the relationship between lexical prevalence and acquisition with Bayesian networks and population dynamics.

## **Format**

A Gaussian Bayesian network to analyze various measures of lexical dispersion and assess the extent to which they are linked to age of acquisition. Probabilities were given within the referenced paper. The vertices are:

```
aoa Age of aquisition;
area Area in which the word is known;
genre_disp Dispersion across genres;
log_freq Logarithm of word frequency;
log_range Logarithm of dispersion across texts;
prev_heard Fraction of speakers that have already heard a word;
prev_used Fraction of speakers that have already used a word;
social_disp Entropy of educational status per word;
```

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

lidar 143

## References

Baumann, A., & Sekanina, K. (2022). Accounting for the relationship between lexical prevalence and acquisition with Bayesian networks and population dynamics. Linguistics Vanguard, 8(1), 209-224.

lidar

lidar Bayesian Network

## **Description**

Decision support using SAR and LiDAR machine learning target classification and Bayesian belief networks.

## **Format**

A discrete Bayesian network to compute posterior event probabilities for sample analyst scenarios. Probabilities were given within the referenced paper. The vertices are:

```
ActivityIndustrialArea (Routine, Unusual);
ActivitySiteA (Routine, Unusual);
ActivitySiteB (Routine, Unusual);
ThunderstormsA (High, Low);
ThunderstormsB (High, Low);
TrafficUnusualEvent (True, False);
UsualRushHourTraffic (True, False);
VehicleDensityA (High, Low);
VehicleDensityB (High, Low);
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Bogart, C., Solorzano, L., & Lam, S. (2022, May). Decision support using SAR and LiDAR machine learning target classification and Bayesian belief networks. In Geospatial Informatics XII (Vol. 12099, pp. 28-36). SPIE.

144 liquefaction

liquefaction

liquefaction Bayesian Network

# Description

A continuous Bayesian network regression model for estimating seismic liquefaction-induced settlement of the free-field ground.

#### **Format**

A Gaussian Bayesian network to predict seismic liquefaction-induced settlement. The Bayesian network is learned using the data available from the referenced paper. The vertices are:

Ds

**GWT** 

**Inamax** 

lnR

lnt

 $\mathbf{M}\mathbf{w}$ 

N160

 $\mathbf{S}$ 

**Sigmav** 

Ts

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Hu, J., Xiong, B., Zhang, Z., & Wang, J. (2023). A continuous Bayesian network regression model for estimating seismic liquefaction-induced settlement of the free-field ground. Earthquake Engineering & Structural Dynamics, 52(11), 3216-3237.

liquidity 145

liquidity	liquidity Bayesian Network	

## **Description**

An artificial neural network and Bayesian network model for liquidity risk assessment in banking.

### **Format**

A discrete Bayesian network demonstrate applicability and exhibit the efficiency, accuracy and flexibility of data mining methods when modeling ambiguous occurrences related to bank liquidity risk measurement. Probabilities were given within the referenced paper. The vertices are:

```
X1 (FALSE, TRUE);
X2 (FALSE, TRUE);
X3 (FALSE, TRUE);
X4 (FALSE, TRUE);
X5 (FALSE, TRUE);
X6 (FALSE, TRUE);
X7 (FALSE, TRUE);
X8 (FALSE, TRUE);
X9 (FALSE, TRUE);
X10 (FALSE, TRUE);
```

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Tavana, M., Abtahi, A. R., Di Caprio, D., & Poortarigh, M. (2018). An Artificial Neural Network and Bayesian Network model for liquidity risk assessment in banking. Neurocomputing, 275, 2525-2554.

146 lithium

lithium

lithium Bayesian Network

## Description

Fire accident risk analysis of lithium battery energy storage systems during maritime transportation.

### **Format**

A discrete Bayesian network to o evaluate the fire accident risk of lithium battery energy storage system in the process of maritime transportation. Probabilities were given within the referenced paper. The vertices are:

- **X1** Bad weather condition (True, False);
- **X2** Improper storage (True, False);
- **X3** Improper ballast (True, False);
- **X4** High ship speed (True, False);
- **X5** Defect of binding equipment (True, False);
- **X6** Improper maintenance of binding equipment (True, False);
- X7 Improper binding (True, False);
- X8 Contact accident (True, False);
- **X9** Collision accident (True, False);
- X10 Direct sunlight (True, False);
- **X11** Stowage adjacent to engine room (True, False);
- **X12** Stowage adjacent to oil tank (True, False);
- **X13** High ambient temperature (True, False);
- **X14** Cargo hold flooding (True, False);
- **X15** No installation of short-circuit prevention device (True, False);
- **X16** High humidity (True, False);
- X17 Lack of insulation (True, False);
- X18 Overcharge (True, False);
- X19 Over discharge (True, False);
- **X20** Defect of separate (True, False);
- **X21** Burrs on the electrode surface (True, False);
- **X22** No installation of monitoring devices (True, False);
- **X23** Monitoring equipment cannot cover all goods (True, False);
- X24 Damage of monitoring equipment (True, False);
- **X25** The monitoring equipment does not have real-time alarm function (True, False);
- **X26** The crew does not patrol according to regulations (True, False);

load\_network 147

**X27** Insufficient firefighting equipment (True, False);

```
X28 Failure of firefighting equipment (True, False);
X29 Firefighting equipment is not suitable for putting out lithium battery fires (True, False);
X30 Crew members are not trained in lithium battery firefighting (True, False);
X31 (True, False);
X1 The crew did not know the correct way to put out the lithium battery fire (True, False);
BindingFailure (True, False);
ExternalShortCircuit (True, False);
HighTemperature (True, False);
Impact (True, False);
ImproperOperation (True, False);
InsufficientFirefightingCapacity (True, False);
InsufficientFireMonitoring (True, False);
InternalShortCircuit (True, False);
LBESSCatchFire (True, False);
LBESSFireAccident (True, False);
PoorShipStability (True, False);
ShortCircuit (True, False);
UnableToPutOutFire (True, False);
ViolentRolling (True, False);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Zhang, C., Sun, H., Zhang, Y., Li, G., Li, S., Chang, J., & Shi, G. (2023). Fire accident risk analysis of lithium battery energy storage systems during maritime transportation. Sustainability, 15(19), 14198.

load\_network

Load a Bayesian network

## **Description**

This function loads a selected Bayesian network file.

## Usage

load\_network(network\_name)

148 macrophytes

## Arguments

network\_name The name of the network file to load.

### Value

A bn.fit object representing the Bayesian network.

macrophytes

macrophytes Bayesian Network

## **Description**

Mechanical removal of macrophytes in freshwater ecosystems: Implications for ecosystem structure and function.

## **Format**

A discrete Bayesian network o assess the implications of macrophyte removal on interrelated ecosystem properties across a wide range of environmental conditions. The probabilities were given within the referenced paper (missing probabilities were given a uniform distribution). The vertices are:

```
BenthicFishForaging (Low, Moderate, High);
```

**Disturbance** (Low, Moderate, High);

**Ecosystem** (Standing floating, Standing submerged, Flowing submerged);

**EcosystemServices** (Flooding, Birds, Nutrient retention, Angling, Swimming, Boating, Hydropower, Irrigation, Invasive species);

EpiphyticInvertebrates (Low, Moderate, High);

**Flow** (Low, Moderate, High);

Light (Low, High);

**NutrientLoading** (Low, Moderate, High);

Phytoplankton (Low, Moderate, High);

PiscivorousFish (Present, Absent);

PiscivorousFishPredation (Low, High)

PlanktivorousFish (Low, High);

PlantRemoval (None, Partial, Full;)

Resources (Low, Moderate, High);

**Zooplankton** (Low, Moderate, High);

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

medicaltest 149

## References

Thiemer, K., Schneider, S. C., & Demars, B. O. (2021). Mechanical removal of macrophytes in freshwater ecosystems: Implications for ecosystem structure and function. Science of the Total Environment, 782, 146671.

medicaltest

medicaltest Bayesian Network

## **Description**

Global sensitivity analysis of uncertain parameters in Bayesian networks.

### **Format**

A discrete Bayesian network representing a synthethic example of two medical tests. Probabilities were given within the referenced paper. The vertices are:

```
Test1 (no, yes);
Test2 (no, yes);
Disease (no, yes);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Ballester-Ripoll, R., & Leonelli, M. (2024). Global Sensitivity Analysis of Uncertain Parameters in Bayesian Networks. arXiv preprint arXiv:2406.05764.

megacities

megacities Bayesian Network

## **Description**

Air pollution risk assessment related to fossil fuel-driven vehicles in megacities in China by employing the Bayesian network coupled with the fault tree method.

150 megacities

### **Format**

A discrete Bayesian network to quantitatively assess the risk factors of excess vehicle emissions and their impact on air quality for China's typical megacities. Probabilities were given within the referenced paper (the model refers to Beijing in 2014). The vertices are:

- **X1** Lack of supervision and policy guide (True, False);
- **X2** Excess vehicles (True, False);
- **X3** Severe traffic jam (True, False);
- X4 Aging of catalytic unit and combustor (True, False);
- **X5** Vehicle desing defect (True, False);
- **X6** Examination defect (True, False);
- X7 Non-strict supervision (True, False);
- **X8** Oil refinery capability defect (True, False);
- X9 Market demand (True, False);
- **X10** Excess heavy trucks (True, False);
- X11 Excess yellow label cars (True, False);
- M1 Consumption of unqualified oil (True, False);
- M2 Bad traffic situation (True, False);
- M3 Emission by vehicles with defects (True, False);
- M4 Severe emission of high pollution vehicles (True, False);
- **M5** Production of inferior oil (True, False);
- M6 Excess high pollution vehicles using (True, False);
- ExcessVehicleEmission (True, False);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Li, H., Huang, W., Qian, Y., & Klemes, J. J. (2023). Air pollution risk assessment related to fossil fuel-driven vehicles in megacities in China by employing the Bayesian network coupled with the Fault Tree method. Journal of Cleaner Production, 383, 135458.

metal 151

metal

metal Bayesian Network

# Description

Bayesian belief network modeling of accident occurrence in metal lathe machining operations.

## **Format**

A discrete Bayesian network to model the uncertainty surrounding the occurrence of a fly-out accident during metal lathe machining operations and its corresponding consequences. Probabilities were given within the referenced paper. The vertices are:

**CAF** Chuck association fault (Okay, Faulty);

WHF Workpiece holding failure (N-Fail, FLRE);

**TPF** Tool-post fault (Okay, Faulty);

CF Coolant fault (Okay, Faulty);

**OS** Operating speed (Proper, Improper);

**SGF** Safety guards faul (Okay, Faulty);

IFR Wrong feed rate (HR, HE);

FlyOutAccident (Fatal, Major, Minor).

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Akinyemi, O. O., Adeyemi, H. O., Olatunde, O. B., Folorunsho, O., & Musa, M. B. (2022). Bayesian belief network modeling of accident occurrence in metal lathe machining operations. Mindanao Journal of Science and Technology, 20(2).

moodstate

moodstate Bayesian Network

## **Description**

Inference of mood state indices by using a multimodal high-level information fusion technique.

152 mountaingoat

### **Format**

A discrete Bayesian network to perform high-level information fusion. Probabilities were given within the referenced paper (one node is not included). The vertices are:

```
Anxiety (0-2, 3-5);

DepressiveState (TRUE, FALSE);

EEG (>0, <0);

Energy (0-2, 3-5);

Irritability (0-3, 4-5);

MoodState (+3, +2, +1, 0, -1, -2, -3);

Sleep (<6 Hours, >6 Hours;
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Tai, C. H., Chung, K. H., Teng, Y. W., Shu, F. M., & Chang, Y. S. (2021). Inference of mood state indices by using a multimodal high-level information fusion technique. IEEE Access, 9, 61256-61268.

mountaingoat

mountaingoat Bayesian Network

## **Description**

Using Bayesian networks to map winter habitat for mountain goats in coastal British Columbia, Canada.

### **Format**

A discrete Bayesian network to predict the suitability of habitats for mountain goats. Probabilities were given within the referenced paper. The vertices are:

```
Distance_Escape_Terrain (On Escape Terrain, <=150m away, <=300m away, >300m away);
Elevation (<=500m, <=900m, <=1300m, <=1700m, >1700m);
Forest_Age_Class (Early, Mid, Mature, Old, Non-Forested);
Location (Observations, Random));
Slope (Shallow, Moderate, Steep);
Snow_Zone (Shallow, Moderate, Deep, Very Deep);
Solar_Insolation (Very Low, Low, Moderate, High, Very High));
```

nanomaterials1 153

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Wilson, S. F., Nietvelt, C., Taylor, S., & Guertin, D. A. (2022). Using Bayesian networks to map winter habitat for mountain goats in coastal British Columbia, Canada. Frontiers in Environmental Science, 10, 958596.

nanomaterials1

nanomaterial Bayesian Networks

## **Description**

Probabilistic model for assessing occupational risk during the handling of nanomaterials.

### **Format**

A discrete Bayesian network for the assessment of the occupational risk associated with the handling of nanomaterials in research laboratories (before expert opinion). Probabilities were given within the referenced paper. The vertices are:

Risk (High, Medium, Low);

Hazard (High, Medium, Low);

ClassificationGHS (1, 2, 3, 4, 5);

VariablesPhysicoChemical (High, Medium, Low);

RiskControl (High, Medium, Low);

Exposure (High, Medium, Low);

PersonalProtectiveEquipment (High, Medium, Low);

AdministrativeMeasures (High, Medium, Low);

**ProtectionByUsingCollectiveProtectiveEquipment** (Full containment/isolation, Enclosed ventilation, Local ventilation, General mechanical ventilation);

**BodyProtection** (No use, Cotton lab coats, Synthetic material lab coats, Chemical protection coveralls);

**HandProtection** (No use, Rubber gloves, Nitrile gloves - 1 pair, Nitrile gloves - 2 pairs);

EyesProtection (No use, Safety glasses, Safety goggles, Face shields);

**RespiratoryProtection** (No use, Safety mask without selection criteria, Respiratory mask according to the respiratory protection program);

FootProtection (Open shoes, Work shoes, Safety shoes for chemical agents);

OccupationalEnvironmentRiskProgram (No, Yes, Yes - consider NMs);

**MedicalSurveillance** (No, Yes, Yes - consider NMs);

**RespiratoryProtectionProgram** (No, Yes, Yes - consider NMs);

154 nanomaterials1

**PeriodicMaintenanceOfCPE** (No, Yes - less than 12 months, Yes - more than 12 months);

**StandardOperatingProcedureOfTask** (No, Yes);

RiskTrainingInvolvingNMs (No, Yes);

Frequency (Daily, Weekly, Monthly, Semiannual, Yearly);

**DustFormation** (With, Without);

AerosolFormation (With, Without);

**Amount** (<10mg, 10-100mg, >100mg);

**Duration** (<30min, 30-240min, >240min);

**SurfaceArea** (< 10 m2g, 10-49 m2g, >50 m2g);

**Agglomeration** (With, Without);

Morphology (Spherical, Plates, Rods);

CrystallineStructure (With, Without);

**SolubilityInWater** (Dissolution pH 5 to 9, Insoluble);

SizeOfAtLeastOneDimension (Less than 100, More than 100);

SuspensionStability (Less than 30, More than 30);

SurfaceChargeInSolution (Charged, Neutral);

SurfaceModificationWithHydrophilicGroups (Without, With);

**AcuteToxicityDermalExposure** (Less than 50, 50-200, 200-1000, 1000-2000, 2000-5000, No effect);

ChronicToxicityExposureByDustInhalation (Less than 0.02, 0.02-0.2, No effect);

**AcuteToxicityExposureByGasInhalation** (Less than 100, 100-500, 500-2500, 2500-20000, No effect);

ChronicToxicityByTheExposureRouteInhalationGas (Less than 50, 50-200, No effect);

**Potentially Carcinogenic** (Confirmed for humans, Possibly toxic to humans, No effect);

AcuteToxicityExposureByDustInhalation (Less than 0.5, 0.5-2, 2-10, 10-20, No effect);

**ChronicToxicityByTheExposureRouteInhalationDust** (Less than 0.5, 0.5-2, 2-10, 10-20, No effect);

**RespiratorySensitization** (There is evidence for humans, There are positive tests for animal testing, No effect);

ChronicToxicityInTheAquaticEnvironment (Less than 0.01, 0.01-0.1, 0.1-1, No effect);

**SkinIrritation** (Skin corrosion, Skin irritation, ILskin irritation, No effect);

**ChronicToxicityDermalExposure** (Less than 20, 20-200, No effect);

**EyeIrritation** (No effect, Reversible irritation, Irreversible damage);

AcuteToxicityInTheAquaticEnvironment (Less than 1, 1-10, 10-100, No effect);

AcuteToxicityByTheExposureRouteOral (Less than 5, 5-50, 50-300, 300-2000, 2000-5000, No effect);

ChronicToxicityExposureOral (Less than 10, 10-100, No effect);

nanomaterials2 155

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Schmidt, J. R. A., Nogueira, D. J., Nassar, S. M., Vaz, V. P., da Silva, M. L. N., Vicentini, D. S., & Matias, W. G. (2020). Probabilistic model for assessing occupational risk during the handling of nanomaterials. Nanotoxicology, 14(9), 1258-1270.

nanomaterials2

nanomaterial Bayesian Networks

## **Description**

Probabilistic model for assessing occupational risk during the handling of nanomaterials.

### **Format**

A discrete Bayesian network for the assessment of the occupational risk associated with the handling of nanomaterials in research laboratories (after expert opinion). Probabilities were given within the referenced paper. The vertices are:

Risk (High, Medium, Low);

Hazard (High, Medium, Low);

ClassificationGHS (1, 2, 3, 4, 5);

VariablesPhysicoChemical (High, Medium, Low);

RiskControl (High, Medium, Low);

Exposure (High, Medium, Low);

PersonalProtectiveEquipment (High, Medium, Low);

AdministrativeMeasures (High, Medium, Low);

**ProtectionByUsingCollectiveProtectiveEquipment** (Full containment/isolation, Enclosed ventilation, Local ventilation, General mechanical ventilation);

**BodyProtection** (No use, Cotton lab coats, Synthetic material lab coats, Chemical protection coveralls);

**HandProtection** (No use, Rubber gloves, Nitrile gloves - 1 pair, Nitrile gloves - 2 pairs);

EyesProtection (No use, Safety glasses, Safety goggles, Face shields);

**RespiratoryProtection** (No use, Safety mask without selection criteria, Respiratory mask according to the respiratory protection program);

FootProtection (Open shoes, Work shoes, Safety shoes for chemical agents);

OccupationalEnvironmentRiskProgram (No, Yes, Yes - consider NMs);

MedicalSurveillance (No, Yes, Yes - consider NMs);

**RespiratoryProtectionProgram** (No, Yes, Yes - consider NMs);

156 nanomaterials2

**PeriodicMaintenanceOfCPE** (No, Yes - less than 12 months, Yes - more than 12 months);

**StandardOperatingProcedureOfTask** (No, Yes);

RiskTrainingInvolvingNMs (No, Yes);

Frequency (Daily, Weekly, Monthly, Semiannual, Yearly);

**DustFormation** (With, Without);

AerosolFormation (With, Without);

**Amount** (<10mg, 10-100mg, >100mg);

**Duration** (<30min, 30-240min, >240min);

**SurfaceArea** (< 10 m2g, 10-49 m2g, >50 m2g);

**Agglomeration** (With, Without);

Morphology (Spherical, Plates, Rods);

CrystallineStructure (With, Without);

**SolubilityInWater** (Dissolution pH 5 to 9, Insoluble);

**SizeOfAtLeastOneDimension** (Less than 100, More than 100);

SuspensionStability (Less than 30, More than 30);

SurfaceChargeInSolution (Charged, Neutral);

SurfaceModificationWithHydrophilicGroups (Without, With);

**AcuteToxicityDermalExposure** (Less than 50, 50-200, 200-1000, 1000-2000, 2000-5000, No effect);

ChronicToxicityExposureByDustInhalation (Less than 0.02, 0.02-0.2, No effect);

AcuteToxicityExposureByGasInhalation (Less than 100, 100-500, 500-2500, 2500-20000, No effect);

ChronicToxicityByTheExposureRouteInhalationGas (Less than 50, 50-200, No effect);

Potentially Carcinogenic (Confirmed for humans, Possibly toxic to humans, No effect);

AcuteToxicityExposureByDustInhalation (Less than 0.5, 0.5-2, 2-10, 10-20, No effect);

**ChronicToxicityByTheExposureRouteInhalationDust** (Less than 0.5, 0.5-2, 2-10, 10-20, No effect);

**RespiratorySensitization** (There is evidence for humans, There are positive tests for animal testing, No effect);

ChronicToxicityInTheAquaticEnvironment (Less than 0.01, 0.01-0.1, 0.1-1, No effect);

SkinIrritation (Skin corrosion, Skin irritation, ILskin irritation, No effect);

**ChronicToxicityDermalExposure** (Less than 20, 20-200, No effect);

EyeIrritation (No effect, Reversible irritation, Irreversible damage);

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Schmidt, J. R. A., Nogueira, D. J., Nassar, S. M., Vaz, V. P., da Silva, M. L. N., Vicentini, D. S., & Matias, W. G. (2020). Probabilistic model for assessing occupational risk during the handling of nanomaterials. Nanotoxicology, 14(9), 1258-1270.

navigation 157

navigation

navigation Bayesian Network

## **Description**

Safety analysis of RNP approach procedure using fusion of FRAM model and Bayesian belief network.

### **Format**

A discrete Bayesian network to demonstrate the existing variability in functions that are part of the complex navigation system. Probabilities were given within the referenced paper. The vertices are:

ToAcquireGPSsignal (Accurate, Acceptable, Inaccurate);

ToCheckAircraftPositionExecutingRNPProcedure (Accurate, Acceptable, Inaccurate);

ToKeepAircraftOnProgrammedRoute (Accurate, Acceptable, Inaccurate);

ToShowAircraftPositionBasedOnGPSSignal (Accurate, Acceptable, Inaccurate);

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Oliveira, D., Moraes, A., Junior, M. C., & Marini-Pereira, L. (2023). Safety analysis of RNP approach procedure using fusion of FRAM model and Bayesian belief network. The Journal of Navigation, 76(2-3), 286-315.

nuclearwaste

nuclearwaste Bayesian Network

## **Description**

Comprehensiveness of scenarios in the safety assessment of nuclear waste repositories.

## **Format**

A discrete Bayesian network to obtain bounds on the probability that the reference safety threshold is violated. Probabilities were given within the referenced paper. The vertices are:

BarrierDegradation (Fast, Slow);

ChemicalDegradation (Fast, Slow);

CrackAperture (Micro, Macro);

DiffusionCoefficient (Low, High);

158 nuisancegrowth

```
DistributionCoefficient (Low, High);
Earthquake (BDBE, Major);
HydraulicConductivity (Low, Medium, High);
MonolithDegradation (Very Fast, Fast, Slow);
WaterFlux (Low, High);
DoseRate (Violated, Not Violated);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Tosoni, E., Salo, A., Govaerts, J., & Zio, E. (2019). Comprehensiveness of scenarios in the safety assessment of nuclear waste repositories. Reliability Engineering & System Safety, 188, 561-573.

nuisancegrowth

nuisancegrowth Bayesian Network

## Description

Drivers of perceived nuisance growth by aquatic plants.

### **Format**

A discrete Bayesian network approach to integrate the perception of nuisance with the consequences of plant removal. Probabilities were given within the referenced paper (missing entries were given uniform probabilities). The vertices are:

Activity (Swimming, Boating, Angling, Biodiversity, Aesthetics, Bird-watching);

**BenthicFishForaging** (Low, Moderate, High);

**Disturbance** (Low, Moderate, High);

Ecosystem (Standing floating, Standing submerged, Flowing submerged);

EpiphyticInvertebrates (Low, Medium, High);

Flow (Low, Medium, High);

**Light** (Low, High);

**MacrophyteGrowth** (Very low, Low, Medium, High, Very high);

MacrophyteRemoval (None, Partial Full);

**MacrophyteSpecies** (Elodea nuttallii, Pontederia crassipes, Ludwigia, Juncus bulbosus, Sagittaria sagittifolia);

NutrientLoading (Low, Moderate, High);

Perception (Nuisance, No nuisance);

oildepot 159

```
Phytoplankton (Low, Moderate, High);
PiscivorousFish (Absent, Present);
PiscivorousFishPredation (Low, High);
PlanktivorousFish (Low, High);
Resources (Low, Moderate, High);
RespondentType (Resident, Visitor);
Zooplankton (Low, Moderate, High);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Thiemer, K., Immerzeel, B., Schneider, S., Sebola, K., Coetzee, J., Baldo, M., ... & Vermaat, J. E. (2023). Drivers of perceived nuisance growth by aquatic plants. Environmental Management, 71(5), 1024-1036.

oildepot

oildepot Bayesian Network

## **Description**

Dynamic risk analysis of oil depot storage tank failure using a fuzzy Bayesian network model.

## **Format**

A discrete Bayesian network for failure risk analysis of oil storage tank leakage. Probabilities were given within the referenced paper. The vertices are:

```
X1 (True, False);
X2 (True, False);
X3 (True, False);
X4 (True, False);
X5 (True, False);
X6 (True, False);
X7 (True, False);
X8 (True, False);
X9 (True, False);
X10 (True, False);
X11 (True, False);
```

X12 (True, False);

160 oildepot

```
X13 (True, False);
X14 (True, False);
X15 (True, False);
X16 (True, False);
X17 (True, False);
X18 (True, False);
X19 (True, False);
X20 (True, False);
X21 (True, False);
X22 (True, False);
X23 (True, False);
X24 (True, False);
X25 (True, False);
M1 Internal corrosion (True, False);
M2 External corrosion (True, False);
M3 Liquid level exceeded safe level (True, False);
M4 Equipment failure (True, False);
M5 Personnel issue (True, False);
M6 Not found in time (True, False);
M7 Corrosion (True, False);
M8 Overfill (True, False);
M9 Environment (True, False);
M10 Design defect (True, False);
M11 Equipment ageing (True, False);
M12 Tank hazard (True, False);
M13 Lax supervision (True, False);
M14 Rules and regulation (True, False);
M15 Inadequate management (True, False);
TankLeakage (True, False);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Zhou, Q. Y., Li, B., Lu, Y., Chen, J., Shu, C. M., & Bi, M. S. (2023). Dynamic risk analysis of oil depot storage tank failure using a fuzzy Bayesian network model. Process Safety and Environmental Protection, 173, 800-811.

onlinerisk 161

onlinerisk

onlinerisk Bayesian Network

## **Description**

Online risk modeling of autonomous marine systems: Case study of autonomous operations under sea ice.

### **Format**

A discrete Bayesian network to develop online risk models for an autonomous marine system. Probabilities were given in an associated GitHub repository. The vertices are:

```
Acoustic_Link_Quality (Acceptable, Unacceptable);
```

Acoustic\_Link\_Quality\_buoy (Acceptable, Unacceptable);

**Altitude\_of\_AUV** (High, Medium, Low);

**Control\_algorith\_is\_flawed** (Acceptable, Unacceptable);

Copy\_2\_of\_Control\_algorith\_is\_flawed (Acceptable, Unacceptable);

Copy\_2\_SoftwareFailure (Yes, No);

Copy\_of\_Air\_temperature (Yes, No);

Copy\_of\_Control\_algorith\_is\_flawed (Acceptable, Unacceptable);

Copy\_of\_Environmental\_constraint (High, Medium, Low);

Copy\_of\_Flawed\_algorithm (Acceptable, Unacceptable);

Copy\_of\_Operator\_effectiveness (High, Medium, Low);

Copy\_of\_Research\_vessel\_effectiveness (High, Medium, Low);

Copy\_of\_RIF2Waypoint (Yes, No);

Copy\_of\_Salvage (Yes, No);

Copy of SoftwareFailure (Yes, No);

Copy\_of\_Strong\_wind (Yes, No);

Copy\_of\_Training\_level (High, Medium, Low);

Copy\_of\_Weather\_condition (Good, Poor);

Copy\_RIF5 (Yes, No);

Current\_speed (High, Medium, Low);

Depth\_of\_AUV (High, Medium, Low);

**Difficulty\_of\_AUV\_salvage** (High, Medium, Low);

Difficulty\_of\_salvage\_operation (High, Medium, Low);

**Difficulty\_to\_pinpoint\_the\_vehicle** (High, Medium, Low);

**Dist\_to\_home** (High, Medium, Low);

Environmental\_complexity (High, Medium, Low);

162 onlinerisk

```
Failure_of_ADCP_DVL (Acceptable, Unacceptable);
Failure_of_CTD_sensor (Acceptable, Unacceptable);
Failure_of_IMU_module (Acceptable, Unacceptable);
Failure_of_temperature_sensor (Acceptable, Unacceptable);
Fins (Reliable, Failure);
Flawed_algorithm_of_waypoint_generation (Acceptable, Unacceptable);
GNSS_accuracy (Acceptable, Unacceptable);
H1 (Yes, No);
H2 (Yes, No);
H5 (Yes, No);
H6 (Yes, No);
H7 (Yes, No);
Ice_concentration (High, Medium, Low);
Ice_Environment (Good, Poor);
Ice_Ruggnes (High, Medium, Low);
Ice_thickness (High, Medium, Low);
Improper_handling_of_navigation_errors (Yes, No);
InaccurateWaypoint (Yes, No);
Loss_of_AUV (Loss, Damage, No);
Loss_of_mission (Yes, No);
Multipath_From_Ice (Good, Medium, Poor);
Position_Measurement_Quality (Yes, No);
Power_capacity (High, Medium, Low);
Power_system (Yes, No);
Propulsion_system_fails_to_provide_necessary_motion (Yes, No);
Range_to_buoy (Long, Medium, Close);
Reliability_GPS_Module (Reliable, Failure);
Reliability_of_acoustic_module_in_AUV (Reliable, Failure);
Reliability_of_the_propulsion_system (Reliable, Failure);
ReliabilityAcousticNavigation (Reliable, Failure);
RIF_Range_Quality (Yes, No);
RIF2Propulsion (Yes, No);
RIF2Waypoint (Yes, No);
RIF3 (Yes, No);
RIF3Collision (Yes, No);
RIF3Inaccurate (Yes, No);
RIF4 (Yes, No);
```

orbital 163

```
RIF5 (Yes, No);
RSSI_commu (Acceptable, Unacceptable);
RSSI_ranging (Acceptable, Unacceptable);
SIL_commu (Acceptable, Unacceptable);
SIL_ranging (Acceptable, Unacceptable);
SoftwareFailure (Yes, No);
Speed_of_AUV (High, Medium, Low);
Steering_system_fails_to_provide_necessary_motion (Yes, No);
Time_left_to_salvage_the_vehicle_if_it_losts (Plenty, Enough, Not Enough);
Tool_effectiveness (High, Medium, Low);
UCA17_N_1 (Yes, No);
UCA17_P_1 (Yes, No);
UCA18_N_1 (Yes, No);
UCA18_P_1 (Yes, No);
UCA5_P_1 (Yes, No);
UCA6_N_1 (Yes, No);
UCA6_N_2 (Yes, No);
UCA6_N_3 (Yes, No);
Vessel_constraint (High, Medium, Low);
Visibility (High, Medium, Low);
Water_Environment (Good, Poor);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Yang, R., Bremnes, J. E., & Utne, I. B. (2023). Online risk modeling of autonomous marine systems: case study of autonomous operations under sea ice. Ocean Engineering, 281, 114765.

orbital

orbital Bayesian Network

## Description

Approaching ntention prediction of orbital maneuver based on dynamic Bayesian network.

164 oxygen

### **Format**

A (dynamic) discrete Bayesian network to to help operators recognize the approaching intention quickly and systemically. Probabilities were given within the referenced paper. Ten time slices of the dynamic network are constructed. The vertices in the first time slice are:

```
ApproachingIntentionT1 (Hover, Attach, Capture, Approach);
LocationT1 (Within the threat range, Outside the threat range);
ManeuverT1 (Maneuver, Non-maneuver);
RelativeVelocityT1 (Fast, Slow);
HeadingT1 (0-110 degress, 110 degrees);
RelativeDistanceT1 (Far, Near);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Shibo, C. H. E. N., Jun, L. I., Yaen, X. I. E., Xiande, W. U., Shuhang, L. E. N. G., & Ruochu, Y. A. N. G. (2023). Approaching Intention Prediction of Orbital Maneuver Based on Dynamic Bayesian Network. Transactions of Nanjing University of Aeronautics & Astronautics, 40(4).

oxygen

oxygen Bayesian Network

# Description

Providing an approach to analyze the risk of central oxygen tanks in hospitals during the COVID-19 pandemic.

### **Format**

A discrete Bayesian network to calculate failure rates of oxygen tanks in hospitals during the COVID-19 pandemic. Probabilities were given within the referenced paper. The vertices are:

```
CorrosionCausedByTheEnvironment (True, False);
CorrosiveEnvironment (True, False);
DefectInTheTankDryer (True, False);
DefectInTheTankPressureGauge (True, False);
DefectInTheTankReliabilityGauge (True, False);
DefectsInConnectingTankFastenersF1 (True, False);
DefectsInConnectingTankFastenersF2 (True, False);
DefectsInConnectionsAndGauges (True, False);
```

DefectsInInletAndOutletValvesV1 (True, False);

oxygen 165

```
DefectsInInletAndOutletValvesV2 (True, False);
DefectsInTankEquipmentRepairs (True, False);
DefectsInTheExternalCoatingSystemOfTheTank (True, False);
DefectsInTheInspectionAndTestingProgramOfTankDevices (True, False);
DefectsInTheTankCoating (True, False);
ExternalCorrosionOfTheTank (True, False);
FailureInProtectiveMeasures (True, False);
FailureInRepairsAndMaintenance (True, False);
FailureOfConnectionsAndFasteners (True, False);
FailureOfGauges (True, False);
FailureToUseStandardAndUpdatedInstructions (True, False);
HumanError (True, False);
InadequacyOfPeopleSkills (True, False);
InternalCorrosionOfTheTank (True, False);
OperationalError (True, False);
OrganizationalWeakness (True, False);
OxygenLeakage (True, False);
TankCorrosion (True, False);
ValveLeakage (True, False);
WeakEducationSystem (True, False);
WeaknessInPurchasingTankEquipment (True, False);
WeaknessInTheInstallationOfTankEquipment (True, False);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Laal, F., Hanifi, S. M., Madvari, R. F., Khoshakhlagh, A. H., & Arefi, M. F. (2023). Providing an approach to analyze the risk of central oxygen tanks in hospitals during the COVID-19 pandemic. Heliyon, 9(8).

parkinson

parkinson

parkinson Bayesian Network

# Description

AI reveals insights into link between CD33 and cognitive impairment in Alzheimer's disease.

### **Format**

A Gaussian Bayesian network to simulate a down-expression of the putative drug target CD33, including potential impact on cognitive impairment and brain pathophysiology. Probabilities were given within the referenced paper. The vertices are:

- Cluster\_1
- Cluster\_2
- Cluster\_3
- Cluster\_4
- Cluster\_6
- Cluster\_7
- Cluster\_8
- Cluster\_9
- Cluster\_11
- Cluster\_14
- Cluster\_15
- Cluster\_16
- Cluster\_17
- $Cluster\_18$
- Cluster\_19
- Cluster\_20
- Cluster\_21
- Cluster\_25
- Cluster\_26
- Cluster\_27
- cognition
- PatDemo\_educ
- PatDemo\_sex
- PatDemo\_apoe
- PatDemo\_age
- PatDemo\_brainregion

perioperative 167

**REL** 

**PPARG** 

TRAF1

**GRIN1** 

CASP7

NAV3

DLG4

**CD33** 

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Raschka, T., Sood, M., Schultz, B., Altay, A., Ebeling, C., & Frohlich, H. (2023). AI reveals insights into link between CD33 and cognitive impairment in Alzheimer's Disease. PLOS Computational Biology, 19(2), e1009894.

perioperative

perioperative Bayesian Network

## **Description**

Development of a perioperative medication suspension decision algorithm based on Bayesian networks.

## **Format**

A discrete Bayesian network for the estimation of the drug suspension period even in the presence of competing risks. The probabilities were available from a repository. The vertices are:

```
DrugSuspension (0 days, 5 days, 7 days);
ThromboticRisk (High, Medium, Low);
BleedingRisk (High, Null);
PlateletCount (High, Medium, Low);
AbnormalAPTT (High, Medium, Low);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

168 permaBN

## References

Kawaguchi, S., Fukuda, O., Kimura, S., Yeoh, W. L., Yamaguchi, N., & Okumura, H. (2024, January). Development of a Perioperative Medication Suspension Decision Algorithm Based on Bayesian Networks. In 2024 IEEE/SICE International Symposium on System Integration (SII) (pp. 7-12). IEEE.

permaBN

permaBN Bayesian Network

## **Description**

PermaBN: A Bayesian Network framework to help predict permafrost thaw in the Arctic.

### **Format**

A discrete Bayesian network to simulate permafrost thaw in the continuous permafrost region of the Arctic. The probabilities were given within the referenced paper. The vertices are:

```
ActiveLayerIceContent (Low, Medium, High);
AirTemperature (Low, Medium, High);
Aspect (North, East, South, West);
Insulation (Low, Medium, High);
Rain (Low, Medium, High);
Season (Snow free, Snow);
Snow (Low, Medium, High);
SnowDepth (None, Low, Medium, High);
SoilDensity (Low, Medium, High);
SoilMoisture (Low, Medium, High);
SoilTemperature (Low, Medium, High);
SoilWaterInput (Low, Medium, High);
ThawDepth (Low, Medium, High);
VegetationHeight (Low, Medium, High);
```

### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

### References

Beall, K., Loisel, J., & Medina-Cetina, Z. (2022). PermaBN: A Bayesian Network framework to help predict permafrost thaw in the Arctic. Ecological Informatics, 69, 101601.

phdarticles 169

phdarticles

phdarticles Bayesian Network

## **Description**

The R package stagedtrees for structural learning of stratified staged trees.

### **Format**

A discrete Bayesian network modeling factors affecting the number of publications of PhD students. The Bayesian network is learned as in the referenced paper. The vertices are:

**Articles** Number of articles during the last three years of PhD (0, 1-2, >2);

Gender (male, female);

**Kids** If the student has at least one kid 5 or younger (yes, no);

Married (yes, no));

Mentor Number of publications of the student's mentor (low, medium, high);

Prestige Prestige of the university (high, low);

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Carli, F., Leonelli, M., Riccomagno, E., & Varando, G. (2022). The R Package stagedtrees for Structural Learning of Stratified Staged Trees. Journal of Statistical Software, 102, 1-30.

pilot

pilot Bayesian Network

## **Description**

Dynamic analysis of pilot transfer accidents.

### **Format**

A discrete Bayesian network to classify ADHD symptom. Probabilities were given within the referenced paper. The vertices are:

AdverseSeaSwell (Yes, No);

AdverseWind (Yes, No);

CommercialPressure (Yes, No);

ExcessiveEnvironmentFactors (Yes, No);

pilot pilot

```
ExcessiveMotionVessel (Yes, No);
ExcessiveShipSpeed (Yes, No);
FailureHandholds (Yes, No);
HeavyRain (Yes, No);
HumanFailures (Yes, No);
ImproperShipHandling (Yes, No);
InappropriateAngle (Yes, No);
IncorrectHeigth (Yes, No);
IncorrectRigging (Yes, No);
IndividualFailure (Yes, No);
LackOfSafetyCulture (Yes, No);
LackOfSupervision (Yes, No);
ManeouveringFailures (Yes, No);
NonCertifiedPilotLadder (Yes, No);
NonComplyTrapdoor (Yes, No);
OperationalFailures (Yes, No);
OrganizationalFailure (Yes, No);
PilotLadder (Yes, No);
PilotTransferAccident (Yes, No);
PoorCombinationLadder (Yes, No);
PoorCommunicationWithPilotBoat (Yes, No);
PoorConditionPTA (Yes, No);
PoorIllumination (Yes, No);
PoorISMSystem (Yes, No);
PoorPilotLadder (Yes, No);
PTAEquipmentFailure (Yes, No);
PTAFailure (Yes, No);
PTAPreparedWindward (Yes, No);
RestrictedVisibility (Yes, No);
RetrievalLine (Yes, No);
RiggingFailure (Yes, No);
SecuringFailure (Yes, No);
SecuringFailurePilot (Yes, No);
SecuringFailurePTA (Yes, No);
ShipSideObstructed (Yes, No);
StructuralFailure (Yes, No);
SubstandardActs (Yes, No);
SubstandardConditions (Yes, No);
```

pneumonia 171

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Sakar, C., & Sokukcu, M. (2023). Dynamic analysis of pilot transfer accidents. Ocean Engineering, 287, 115823.

pneumonia

pneumonia Bayesian Network

### **Description**

Predicting the causative pathogen among children with pneumonia using a causal Bayesian network.

#### **Format**

A discrete Bayesian network to predict causative pathogens for childhood pneumonia. Probabilities were given within the referenced paper. The vertices are:

**Age Group** Age group of study participant. In the model, we define each group as follow: Infant (<=2yo), PreSchool (2-5yo), School (5-18yo);

**Ethnicity** Australian Indigenous status of participant, including Aboriginal, Pacific Islander, and Maori (Indigenous, NonIndigenous);

SmokerInHousehold (Yes, No);

**Prematurity** Born <37 weeks gestation (Yes, No);

**ChildcareDays** Childcare or school attendance, day/s per week (Five or more, Two to four, One or less);

**ImpairedImmunity** Primary immunodeficiencies, immunocompromising, or use of immunosuppressive drug (Reported, Unknown);

ChronicRespiratoryDisease (Reported, Unknown);

**PreviousSignificantInfection** Previous episode of confirmed significant infection e.g. bacteraemia, meningitis, osteomyelitis, urinary infection, and etc (Reported, Unknown);

**InfluenzaSeason** Participant was enrolled (present to hospital) during the influenza season in Australia, which is defined as June to September (No, Yes);

PneumococcalVaccine The number of pneumococcal vaccine received, according to Australian Childhood Immunisation Register (ACIR); a child is defined as fully vaccinated if three or more doses were recorded, and under vaccinated if less than three doses (UnderVax, Fully-Vax);

**Influenza Vaccine** Influenza vaccine received within one year prior to this presentation/enrolment, according to ACIR (No, Yes);

**LevelOfExposure** This refers to the child's exposure to pathogens with more transient and transmissible characteristics (High, Low);

172 pneumonia

**SusceptibilityToColonisation** This summarises the level of a child's susceptibility to nasopharyngeal colonisation by typical bacterial pathogens that can be responsible for the presenting case of pneumonia (High, Low);

- **SusceptibilityToProgression** This describes the extent of the child to progress to more severe manifestation of pneumonia if infected (High, Low);
- **RSVInNasopharynx** Any detection of RSV from nasopharyngeal swab or aspiration via either the prospective study or routine clinical investigation (Positive, Negative);
- **HMPVInNasopharynx** Any detection of HMPV from nasopharyngeal swab or aspiration via either the prospective study or routine clinical investigation (Positive, Negative);
- **InfluenzaInNasopharynx** Any detection of influenza from nasopharyngeal swab or aspiration via either the prospective study or routine clinical investigation (Positive, Negative);
- **ParainfluenzaInNasopharynx** Any detection of parainfluenza from nasopharyngeal swab or aspiration via either the prospective study or routine clinical investigation (Positive, Negative);
- **MycoplasmaInNasopharynx** Any detection of mycoplasma from nasopharyngeal swab or aspiration via either the prospective study or routine clinical investigation (Positive, Negative);
- **TypicalBacteriaInNasopharynx** Any detection of typical bacteria is present in nasopharynx via either the prospective study or routine clinical investigation (Yes, No);
- **ViralNasopharyngealInfection** Replication of viral-like pathogens is occurring in the nasopharyngeal tissues (Present, Absent);
- **ThroatInfection** Replication of viral-like pathogens is occuring in the laryngeal tissues (Present, Absent);
- **ViralLikePneumonia** Replication of viral-like pathogens is occurring in the terminal air spaces of the respiratory tract (Present, Absent);
- **TypicalBacterialPneumonia** Typical bacteria is invading the terminal air spaces of the respiratory tract (Present, Absent);
- **CausativePathogenForPneumonia** The cause of presenting pneumonia (TypicalBac, ViralLike, NoPneumonia);
- **UpperAirwayInvolvment** Involvement of other site/s of respiratory tract concurrent with the presenting pneumonia episode (NP, Throat, NPAndThroat, No);
- **SubjectGroup** X-ray confirmed pneumonia (Case, Control);
- **DiagnosisBacterialPneumonia** In this study, baterial pneumonia is clinically diagnosed based on clinical diagnosis of pleural effusion or positive blood culture result (Yes, No);

```
Cough (Recorded, Unknown);

Headache (Recorded, Unknown);

Rhinorrhoea (Recorded, Unknown);

SoreThroat (Recorded, Unknown);

Earache (Recorded, Unknown);

Fever (Recorded, Unknown);

Irritability (Recorded, Unknown);

OtherPain (Recorded, Unknown);

HighestTemperature (Above 39, Between 38 and 39, Below 38);
```

pneumonia 173

ChillSweat (Recorded, Unknown);

Vomiting (Recorded, Unknown);

Diarrhoea (Recorded, Unknown);

ReducedOralIntake (Recorded, Unknown);

EnergyLoss (Recorded, Unknown);

Wheezing (Recorded, Unknown);

Crackles (Recorded, Unknown);

**DurationOfSymptomsOnset** (More than one week, Three to seven days, One or two days);

**PleuralEffusion** The build-up of excess fluid between the layers of the pleura outside the lungs. The true status of pleural effusion can not be directly observed, therefore is latent. Clinical diagnosis of pleural effusion is used as a surrogate for the true status (thus classified as signs and is observable) (Yes, No);

AbdominalPain (Recorded, Unknown);

ChestPain (Recorded, Unknown);

**BreathingDifficulty** (Recorded, Unknown);

**RespiratoryRate** (Above 50, Between 30 and 50, Below 30);

Rash (Recorded, Unknown);

**CurrentPhenotype** This was introduced as a summary node of patient presentation phenotypes based on signs and symptoms relevant to pneumonia (Type1, Type2);

**BloodCultureResult** Detection of any (non-contaminant) bacteria from blood culture via routine clinical investigation (Positive, Negative, NotDone);

**PleuralFluidResult** Detection of any bacteria from pleural fluid via either PCR or culture (Positive, Negative, NotDone);

**CReactiveProtein** (Above 70, Between 30 and 70, Below 30);

WhiteCellCount (Above 18, Between 10 and 18, Below 10);

NeutrophilProportion (Above 80, Between 50 and 80, Below 50);

OxygenSaturation (Below 92, Between 92 and 95, Above 95);

HospitalTransfer Transferred from another hospital/facility (Yes, No);

**AntibioticExposure** Any antibiotic use in the 7 days or 24 hours prior to this presentation/admission (LastDay, LastWeek, No);

BloodCulturePerformed (Yes, No);

**O2Type** If the child has been put on supplementary oxygen when measuring oxygen saturation (SuppO2, RoomAir);

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Wu, Y., Mascaro, S., Bhuiyan, M., Fathima, P., Mace, A. O., Nicol, M. P., ... & Blyth, C. C. (2023). Predicting the causative pathogen among children with pneumonia using a causal Bayesian network. PLoS Computational Biology, 19(3), e1010967.

174 polymorphic

polymorphic

polymorphic Bayesian Network

## **Description**

Reliability analysis of high-voltage drive motor systems in terms of the polymorphic Bayesian network.

### **Format**

A discrete Bayesian network to depict the high-voltage drive motor system's miscellaneous fault states. Probabilities were given within the referenced paper. The vertices are:

PresenceAbrasiveParticles (Normal, Degradation, Failed);

ExcessiveSpeed (Normal, Degradation, Failed);

PoorLubrification (Normal, Degradation, Failed);

InappropriateClearance (Normal, Degradation, Failed);

HighTemperatureGluing (Normal, Degradation, Failed);

**ScratchVibration** (Normal, Degradation, Failed);

Indentation (Normal, Degradation, Failed);

ImproperLubrification (Normal, Degradation, Failed);

ImproperAssembly (Normal, Degradation, Failed);

Moisture (Normal, Degradation, Failed);

ExcessiveInterShaftCurrent (Normal, Degradation, Failed);

ChemicalCorrosion (Normal, Degradation, Failed);

HighFrequencyPulseVoltage (Normal, Degradation, Failed);

**LocalizedHighTemperatures** (Normal, Degradation, Failed);

**PoorCooling** (Normal, Degradation, Failed);

SeverePartialDischarges (Normal, Degradation, Failed);

SurfaceCorrosion (Normal, Degradation, Failed);

PlasticDeformation (Normal, Degradation, Failed);

**CorrosionFailure** (Normal, Degradation, Failed);

**InsulationDeterioration** (Normal, Degradation, Failed);

WearFault (Normal, Degradation, Failed);

SystemDegradation (Normal, Degradation, Failed);

### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Zheng, W., Jiang, H., Li, S., & Ma, Q. (2023). Reliability Analysis of High-Voltage Drive Motor Systems in Terms of the Polymorphic Bayesian Network. Mathematics, 11(10), 2378.

poultry 175

poultry

poultry Bayesian Network

# Description

Practical application of a Bayesian network approach to poultry epigenetics and stress.

### **Format**

A discrete Bayesian network to provide further insights into the relationships among epigenetic features and a stressful condition in chickens. The Bayesian network is learned as in the referenced paper. The vertices are:

```
ARHGAP26 (0,1);
BOP1 (0,1);
CANX (0,1);
CWC25 (0,1);
DGKD (0,1);
DMR1 (0,1);
DMR2 (0,1);
DMR5 (0,1);
DMR6 (0,1);
DMR7 (0,1);
DOCK5 (0,1);
EEPD1 (0,1);
EFR3B (0,1);
ENS10218 (0,1);
ENS27231 (0,1);
ENS46425 (0,1);
ENS47746 (0,1);
ENS50012 (0,1);
ENS50641 (0,1);
ENS51236 (0,1);
ENS53725 (0,1);
FBN1 (0,1);
GNAO1 (0,1);
GRP141 (0,1);
LOC101750642 (0,1);
LOC770074 (0,1);
```

176 poultry

```
LRP5 (0,1);
MFSD4A (0,1);
MIP (0,1);
OCLN (0,1);
PAPK2 (0,1);
PLXNA2 (0,1);
POP5 (0,1);
RP1_27O5_3 (0,1);
SCHIP1 (0,1);
SELENOI (0,1);
SHISA2 (0,1);
SKOR2 (0,1);
STAT3 (0,1);
Stress (0,1);
TPST2 (0,1);
TRMT10A (0,1);
TTLL9 (0,1);
VGLL4 (0,1);
XRCC4 (0,1);
ZBTB48 (0,1);
ZDHHC18 (0,1);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

### References

Videla Rodriguez, E. A., Pertille, F., Guerrero-Bosagna, C., Mitchell, J. B., Jensen, P., & Smith, V. A. (2022). Practical application of a Bayesian network approach to poultry epigenetics and stress. BMC Bioinformatics, 23(1), 261.

project 177

project Bayesian Network

# Description

A collective efficacy-based approach for bi-objective sustainable project portfolio selection using interdependency network model between projects.

### **Format**

A discrete Bayesian network to analyze the criticality and possible impact of a project's failure on each other and on the entire portfolio. Probabilities were given within the referenced paper. The vertices are:

- **P1** (F, T);
- **P2** (F, T);
- **P3** (F, T);
- **P4** (F, T);
- **P5** (F, T);
- **P6** (F, T);
- **P7** (F, T);
- **P8** (F, T);
- **P9** (F, T);
- **P10** (F, T);
- **P11** (F, T);
- **P12** (F, T);
- **P13** (F, T);
- **P14** (F, T);
- **P15** (F, T);
- ( , , , ,
- **P16** (F, T);
- **P17** (F, T);
- **P18** (F, T);
- **P19** (F, T);
- **P20** (F, T);
- **P21** (F, T);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

178 projectmanagement

### References

Ebnerasoul, M., Ghannadpour, S. F., & Haeri, A. (2023). A collective efficacy-based approach for bi-objective sustainable project portfolio selection using interdependency network model between projects. Environment, Development and Sustainability, 25(12), 13981-14001.

projectmanagement

projectmanagement Bayesian Network

## **Description**

Project Complexity and Risk Management (ProCRiM): Towards modelling project complexity driven risk paths in construction projects.

#### **Format**

A discrete Bayesian network to identify critical risks and selecting optimal risk mitigation strategies at the commencement stage of a project. Probabilities were given within the referenced paper (uniform priors were given to root nodes). The vertices are:

- C1 Lack of experience with the involved team (YES, NO);
- C2 Use of innovative technology (YES, NO);
- C3 Lack of experience with technology (YES, NO);
- C4 Strict quality requirements (YES, NO);
- C5 Multiple contracts (YES, NO);
- C6 Multiple stakeholders and variety of perspectives (YES, NO);
- C7 Political instability (YES, NO);
- **C8** Susceptibility to natural disasters (YES, NO);
- **R1** Contactor's lack of experience (YES, NO);
- **R2** Suppliers' default (YES, NO);
- R3 Delays in design and regulatory approvals (YES, NO);
- **R4** Contract related problems (YES, NO);
- **R5** Economic issues in country (YES, NO);
- **R6** Major design changes (YES, NO);
- **R7** Delays in obtaining raw material (YES, NO);
- **R8** Non-availability of local resources (YES, NO);
- **R9** Unexpected events (YES, NO);
- **R10** Increase in raw material price (YES, NO);
- R11 Changes in project specifications (YES, NO);
- R12 Conflicts with project stakeholders (YES, NO);
- **R13** Decrease in productivity (YES, NO);

propellant 179

- **R14** Delays/interruptions (YES, NO);
- O1 Decrease in quality of work (YES, NO);
- O2 Low market share/reputational issues (YES, NO);
- O3 Time overruns (YES, NO);
- **O4** Cost overruns (YES, NO);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Qazi, A., Quigley, J., Dickson, A., & Kirytopoulos, K. (2016). Project Complexity and Risk Management (ProCRiM): Towards modelling project complexity driven risk paths in construction projects. International Journal of Project Management, 34(7), 1183-1198.

propellant

propellant Bayesian Network

## **Description**

A Bayesian network-based safety assessment method for solid propellant granule-casting molding process.

### **Format**

A discrete Bayesian network to assess the safety of the solid propellant granule-casting molding process. Probabilities were given within the referenced paper. The vertices are:

AbsorptionAnomaly (True, False);

CalenderingRepellentWaterTimesAnomaly (True, False);

CalenderingRepellingWaterTemperatureAnomaly (True, False);

CalenderingRollDistanceAnomaly (True, False);

CastingAnomaly (True, False);

CastingDifferentialPressureAnomaly (True, False);

CastingTimeAnomaly (True, False);

CatalystGrindingAnomaly (True, False);

CentrifugalRunningTimeAnomaly (True, False);

 ${\bf Circulating Water Temperature Anomaly \ (True, False);}$ 

CirculationWaterTemperatureAnomaly (True, False);

CuringAnomaly (True, False);

CuringTemperatureAnomaly (True, False);

180 propellant

```
CuringTimeAnomaly (True, False);
CuttingAnomaly (True, False);
DryingOfMedicineGranulesAnomaly (True, False);
DryingRepellentWaterAnomaly (True, False);
DryingRepellingWaterTemperatureAnomaly (True, False);
DryingRepellingWaterTimeAnomaly (True, False);
DryingSolventRemovingAnomaly (True, False);
DryingTemperatureAnomaly (True, False);
DryingTimeAnomaly (True, False);
ExtrusionAnomaly (True, False);
ExtrusionStrengthAnomaly (True, False);
FloodingTimeAnomaly (True, False);
FrequencyOfWaterChangeAnomaly (True, False);
GranuleCastingMoldingAnomaly (True, False);
GrindingTimeAnomaly (True, False);
HoldingPressureAnomaly (True, False);
HoldingTimeAnomaly (True, False);
JacketTemperatureAnomaly (True, False);
KneadingAnomaly (True, False);
KneadingTimeAnomaly (True, False);
LengthSettingValueAnomaly (True, False);
LiquidPreparationAnomaly (True, False);
MedicineGranulesDryingTemperatureAnomaly (True, False);
MedicineGranulesDryingTimeAnomaly (True, False);
PolishAnomaly (True, False);
PolishTimeAnomaly (True, False);
RepellentWaterAnomaly (True, False);
ShineAnomaly (True, False);
ShineTimeAnomaly (True, False);
SolventRemovingAnomaly (True, False);
TemperatureAnomaly (True, False);
VacuumDegreeAnomaly1 (True, False);
VacuumDegreeAnomaly2 (True, False);
VacuumTimeAnomaly1 (True, False);
VacuumTimeAnomaly2 (True, False);
WaterAdditionAnomaly (True, False);
```

rainstorm 181

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Bi, Y., Wang, S., Zhang, C., Cong, H., Gao, W., Qu, B., & Li, J. (2023). A bayesian network-based safety assessment method for solid propellant granule-casting molding process. Journal of Loss Prevention in the Process Industries, 83, 105089.

rainstorm

rainstorm Bayesian Network

# **Description**

Deduction of sudden rainstorm scenarios: integrating decision makers' emotions, dynamic Bayesian network and DS evidence theory.

#### **Format**

A discrete Bayesian network to simulate the dynamic change process of scenario deduction. Probabilities were given within the referenced paper. The vertices are:

- **EmAct1** Activate the flood prevention emergency plan; organize emergency rescue teams to garrison key safety points and increase the intensity of inspections; each site is equipped with sufficient special flood prevention materials and equipment (Effective, Void);
- **EmAct2** Improve the level of flood prevention emergency response; organize the maintenance of houses; restrict people's travel; clean up the water outlet in time; and do a good job in popularizing flood prevention emergency measures (Effective, Void);
- **EmAct3** Vigorous dredging of drainage channels, all personnel involved in flood control (Effective, Void);
- **EmAct4** Strengthen inspections and inspections of rivers, reservoirs, geological disasters, urban infrastructure, etc.; force all factories with hidden dangers (enterprises that may have water inlets and hot furnaces, etc.) to stop work and production (Effective, Void);
- **EmAct5** Enterprises continue to close down and add infrastructure (Effective, Void);
- **EmAct6** Arrange professional personnel to guide the dangerous situation of the reservoir on the spot; excavate the drainage trough as soon as possible to reduce the water level, add hydrological stations, and strengthen supervision and early warning (Effective, Void);
- **EmAct7** Extensive excavation of emergency drainage channels; transfer of personnel in hazardous areas; and increase of emergency equipment and medical teams (Effective, Void);
- **EmAct8** Accelerate the transfer of personnel from disaster areas, add high-tech rescue equipment (Effective, Void);
- Scenario1 Rainstorm (True, False);
- **Scenario2** Precipitation continues to increase (True, False);
- **Scenario3** The ground area is reduced by water (True, False);

182 rainstorm

Scenario4 The weather continued to deteriorate and heavy rainstorms occurred (True, False);

**Scenario5** Secondary disasters occur (True, False);

Scenario6 Heavy rains trigger small floods (True, False);

Scenario7 Heavy rains triggered large flooding (True, False);

Scenario8 Floods trigger landslides (True, False);

Scenario9 All stagnant water is discharged (True, False);

**Scenario10** The flood disappeared (True, False);

Scenario11 The danger was completely controlled and the rainstorm disappeared (True, False);

Sent1 Optimistic/pessimistic (Optimism, Gloomy);

Sent2 Optimistic/pessimistic (Optimism, Gloomy);

Sent3 Optimistic/pessimistic (Optimism, Gloomy);

**Sent4** Optimistic/pessimistic (Optimism, Gloomy);

**Sent5** Optimistic/pessimistic (Optimism, Gloomy);

**Sent6** Optimistic/pessimistic (Optimism, Gloomy);

**Sent7** Optimistic/pessimistic (Optimism, Gloomy);

**Sent8** Optimistic/pessimistic (Optimism, Gloomy);

**Target1** The normal living order of the people, and make all the preparations for the deterioration of heavy rains (Attain, Miss);

**Target2** Ensure that all the water outlets are unblocked, and all the rest are protected at home except for the necessary travel personnel (Attain, Miss);

**Target3** Water in the ground area is accelerating and decreasing (Attain, Miss);

**Target4** Ensure that all hidden factories are shut down, avoid other accidents such as explosions, and ensure that all infrastructure is operating normally (Attain, Miss);

Target5 The whole society is subordinate to the unified organization of the state (Attain, Miss);

**Target6** Ensures reservoir danger is under control and casualties continue to decrease (Attain, Miss);

**Target7** Ensure that the water level is controlled, all personnel in the danger area are evacuated, and there is no increase in the number of casualties (Attain, Miss);

**Target8** The supply of medical supplies is timely, the efficiency of search and rescue is guaranteed, and the number of casualties is no longer increasing (Attain, Miss);

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Xie, X., Tian, Y., & Wei, G. (2023). Deduction of sudden rainstorm scenarios: integrating decision makers' emotions, dynamic Bayesian network and DS evidence theory. Natural Hazards, 116(3), 2935-2955.

rainwater 183

rainwater

rainwater Bayesian Network

# **Description**

Short-term instead of long-term rainfall time series in rainwater harvesting simulation in houses: An assessment using Bayesian Network.

## **Format**

A discrete Bayesian network to predict if a given short-term time series leads to results similar to those obtained using a long-term time series. Probabilities were given within the referenced paper. The vertices are:

Representativeness (Yes, No);

**SeriesLength** (One Year, Two Year, Three Year, Four Year, Five Year, Six Year, Seven Year, Eigth Year, Nine Year, Ten Year, Fifteen Year, Twenty Year);

SeasonalityIndex (High, Medium, Low);

RainwaterDemand (Demand 20, Demand 30, Demand 40, Demand 50);

AverageAnnualRainfall (High, Medium, Low);

AverageNumberOfDryDaysPerYear (High, Medium, Low);

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Geraldi, M. S., & Ghisi, E. (2019). Short-term instead of long-term rainfall time series in rainwater harvesting simulation in houses: An assessment using Bayesian Network. Resources, Conservation and Recycling, 144, 1-12.

realestate1

realestate Bayesian Networks

# Description

Disentangling spatial and structural drivers of housing prices through Bayesian networks: A case study of Madrid, Barcelona, and Valencia.

184 realestate1

## **Format**

A discrete Bayesian network modeling both spatial and structural drivers of house prices in the city of Madrid. The Bayesian network is learned as in the referenced paper. The vertices are:

AC Air conditioning available (Yes, No);

**AGE** Age of the building (New Development, Modern, Mid-Age, Historic);

**AREA** Constructed area in square meters (Small, Medium, Large, Luxury);

**BATHS** Number of bathrooms binned (Few, Moderate, Many));

**CENTRE** Distance to city centre (Very Near, Near, Medium, Far);

**CONDITION** Property condition (New Construction, Second Hand Renovation, Second Hand Good Condition);

**DENSITY** Number of dwellings in the building (Low Medium, High, Very High-Density);

**DMAN** Doorman service present (Yes, No);

**FLOOR** Floor level in the building (Lower, Mid, Upper, Top);

**GARDEN** Garden present (Yes, No);

GREEN Distance to green space (Very Near, Near, Medium, Far);

HEIGHT Maximum building height (Low-Rise, Mid-Rise, High-Rise, Skyscraper);

LIFT Lift presente (Yes, No);

MARKET Distance to supermaket (Very Near, Near, Medium, Far);

METRO Distance to metro station (Very Near, Near, Medium, Far);

NHBD Neighborhood frequency - quartile rank (Most Common, Frequent, Less Frequent, Rare);

**POOL** Swimming pool present (Yes, No);

**PRICE** Asking price per square meter - binned (Very Low, Low, Medium Low, Medium High, High, Luxury);

PRKG Parking space available (Yes, No);

**QUALITY** Cadastral building quality index (Low Value, Moderate Value, High Value, Very High Value);

**ROOMS** Number of rooms - binned (Few, Moderate, Many);

**STREET1** Distance to primary avenue (Very Near, Near, Medium, Far);

STREET2 Distance to secondary avenue (Very Near, Near, Medium, Far);

**STRG** Storage room available (Yes, No);

TRRC Terrace present (Yes, No);

**TYPE** Property type (Studio, Duplex, Penthouse, Standard);

**WRDRB** Built-in wardrobes (Yes, No);

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Murga, A. G., & Leonelli, M. (2025). Disentangling Spatial and Structural Drivers of Housing Prices through Bayesian Networks: A Case Study of Madrid, Barcelona, and Valencia. arXiv preprint arXiv:2506.09539.

realestate2 185

realestate2

realestate Bayesian Networks

# Description

Disentangling spatial and structural drivers of housing prices through Bayesian networks: A case study of Madrid, Barcelona, and Valencia.

## **Format**

A discrete Bayesian network modeling both spatial and structural drivers of house prices in the city of Barcelona. The Bayesian network is learned as in the referenced paper. The vertices are:

AC Air conditioning available (Yes, No);

AGE Age of the building (New Development, Modern, Mid-Age, Historic);

**AREA** Constructed area in square meters (Small, Medium, Large, Luxury);

**BATHS** Number of bathrooms binned (Few, Moderate, Many));

**CENTRE** Distance to city centre (Very Near, Near, Medium, Far);

**CONDITION** Property condition (New Construction, Second Hand Renovation, Second Hand Good Condition);

**DENSITY** Number of dwellings in the building (Low Medium, High, Very High-Density);

**DMAN** Doorman service present (Yes, No);

**FLOOR** Floor level in the building (Lower, Mid, Upper, Top);

**GARDEN** Garden present (Yes, No);

**GREEN** Distance to green space (Very Near, Near, Medium, Far);

HEIGHT Maximum building height (Low-Rise, Mid-Rise, High-Rise, Skyscraper);

**LIFT** Lift presente (Yes, No);

**MARKET** Distance to supermaket (Very Near, Near, Medium, Far);

**METRO** Distance to metro station (Very Near, Near, Medium, Far);

NHBD Neighborhood frequency - quartile rank (Most Common, Frequent, Less Frequent, Rare);

**POOL** Swimming pool present (Yes, No);

**PRICE** Asking price per square meter - binned (Very Low, Low, Medium Low, Medium High, High, Luxury);

**PRKG** Parking space available (Yes, No);

**QUALITY** Cadastral building quality index (Low Value, Moderate Value, High Value, Very High Value);

**ROOMS** Number of rooms - binned (Few, Moderate, Many);

STREET1 Distance to primary avenue (Very Near, Near, Medium, Far);

**STREET2** Distance to secondary avenue (Very Near, Near, Medium, Far);

**STRG** Storage room available (Yes, No);

TRRC Terrace present (Yes, No);

**TYPE** Property type (Studio, Duplex, Penthouse, Standard);

WRDRB Built-in wardrobes (Yes, No);

186 realestate3

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Murga, A. G., & Leonelli, M. (2025). Disentangling Spatial and Structural Drivers of Housing Prices through Bayesian Networks: A Case Study of Madrid, Barcelona, and Valencia. arXiv preprint arXiv:2506.09539.

realestate3

realestate Bayesian Networks

# **Description**

Disentangling spatial and structural drivers of housing prices through Bayesian networks: A case study of Madrid, Barcelona, and Valencia.

## **Format**

A discrete Bayesian network modeling both spatial and structural drivers of house prices in the city of Valencia. The Bayesian network is learned as in the referenced paper. The vertices are:

AC Air conditioning available (Yes, No);

**AGE** Age of the building (New Development, Modern, Mid-Age, Historic);

**AREA** Constructed area in square meters (Small, Medium, Large, Luxury);

**BATHS** Number of bathrooms binned (Few, Moderate, Many));

**CENTRE** Distance to city centre (Very Near, Near, Medium, Far);

**CONDITION** Property condition (New Construction, Second Hand Renovation, Second Hand Good Condition);

**DENSITY** Number of dwellings in the building (Low Medium, High, Very High-Density);

**DMAN** Doorman service present (Yes, No);

**FLOOR** Floor level in the building (Lower, Mid, Upper, Top);

GARDEN Garden present (Yes, No);

**GREEN** Distance to green space (Very Near, Near, Medium, Far);

HEIGHT Maximum building height (Low-Rise, Mid-Rise, High-Rise, Skyscraper);

LIFT Lift presente (Yes, No);

MARKET Distance to supermaket (Very Near, Near, Medium, Far);

METRO Distance to metro station (Very Near, Near, Medium, Far);

NHBD Neighborhood frequency - quartile rank (Most Common, Frequent, Less Frequent, Rare);

**POOL** Swimming pool present (Yes, No);

**PRICE** Asking price per square meter - binned (Very Low, Low, Medium Low, Medium High, High, Luxury);

redmeat 187

PRKG Parking space available (Yes, No);

**QUALITY** Cadastral building quality index (Low Value, Moderate Value, High Value, Very High Value);

**ROOMS** Number of rooms - binned (Few, Moderate, Many);

STREET1 Distance to primary avenue (Very Near, Near, Medium, Far);

**STREET2** Distance to secondary avenue (Very Near, Near, Medium, Far);

STRG Storage room available (Yes, No);

TRRC Terrace present (Yes, No);

**TYPE** Property type (Studio, Duplex, Penthouse, Standard);

WRDRB Built-in wardrobes (Yes, No);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Murga, A. G., & Leonelli, M. (2025). Disentangling Spatial and Structural Drivers of Housing Prices through Bayesian Networks: A Case Study of Madrid, Barcelona, and Valencia. arXiv preprint arXiv:2506.09539.

redmeat

redmeat Bayesian Network

# **Description**

Framing and tailoring prefactual messages to reduce red meat consumption: Predicting effects through a psychology-based graphical causal model.

## **Format**

A discrete Bayesian network to predict the potential effects of message delivery from the observation of the psychosocial antecedents. Probabilities were given within the referenced paper. The vertices are:

Baseline\_Intention (high, medium, low);

Desensitization (high, medium, low);

**Diffused\_Responsibility** (high, medium, low);

Food\_Involvment (high, medium, low);

Future\_Intention (high\_positive, low\_positive, neutral, low\_negative, high\_negative);

Message (gain, nonloss, nongain, loss);

Perceived Control (high, medium, low);

Perceived\_Severity (high, medium, low);

Prevention\_Focus (high, medium, low);

**Promotion Focus** (high, medium, low);

Systematic\_Processing (high, medium, low);

188 resilience

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Catellani, P., Carfora, V., & Piastra, M. (2022). Framing and tailoring prefactual messages to reduce red meat consumption: Predicting effects through a psychology-based graphical causal model. Frontiers in Psychology, 13, 825602.

resilience

resilience Bayesian Network

# Description

Quantifying resilience of socio-ecological systems through dynamic Bayesian networks.

## **Format**

A discrete Bayesian network for the evaluation and modeling of socio-ecological systems structure. Probabilities were given within the referenced paper. The vertices are:

Absorption 1920-1960 (false, true); Absorption1 1960-1980 (false, true); Absorption2 1980-2019 (false, true); Adaptation 1920-1960 (false, true); Adaptation1 1960-1980 (false, true); Adaptation2 1980-2019 (false, true);

**Autonomy** Development of subsistence means and a market economy in which inhabitants own the means of production and influence the dynamics of production processes: 1920-1960 (deficient, low);

**Autonomy1** As Autonomy: 1960-1980 (deficient, low); **Autonomy1** As Autonomy: 1989-2019 (low, moderate);

**Connectivity** The concept refers to a device's availability to be connected to another or a network. The connectivity emphasizes communicational, social and infrastructural dimensions: 1920-1960 (deficient, low);;

Connectivity1 As Connectivity: 1960-1980 (low, moderate);

Connectivity2 As Connectivity: 1980-2019 (high, moderate);

**Density** Average number of inhabitants of a country, region, urban or rural area in relation to a given unit area of the territory where that country, region or area is located: 1920-1960 (low, moderate);

**Density1** As Density: 1960-1980 (low, moderate); **Density2** As Density: 1980-2019 (high, moderate);

resilience 189

**Diversity** Palynological diversity calculated using the palynological richness from the Monquentiva pollen record. This variable indicates the diversity of vegetation represented in the pollen record: 1920-1960 (low, moderate)

**Diversity1** As Diversity: 1960-1980 (high, low, moderate);

**Diversity2** As Diversity: 1980-2019 (high, moderate);

**FCover** Percentage of tree taxa calculated from the Monquentiva pollen record: 1920-1960 (low, moderate);

FCover1 As FCover: 1960-1980 (low, moderate);

FCover2 As FCover: 1980-2019 (high, low, moderate);

**Fires** Fire activity at local and regional levels from the Monquentiva charcoal record. The fire record is obtained from the analysis of charcoal in the Monquentiva sediments: 1920-1960 (high, moderate);

Fires1 As Fires: 1960-1980 (high, low, moderate);

Fires2 As Fires: 1980-2019 (low, moderate);

**Function** 1920-1960 (false, true); **Function1** 1960-1980 (false, true); **Function2** 1980-2019 (false, true);

Organization: 1920-1960 (deficient, low);

**Organization1** As Organization: 1960-1980 (low, moderate); **Organization2** As Organization: 1980-2019 (high, moderate);

**Precipitation** Annual precipitation recorded at the meteorological station No3506029, Embalse Tominé, Guatavita, Colombia: 1920-1960 (high, low, moderate);

Precipitation1 As Precipitation: 1960-1980 (low, moderate);

Precipitation2 As Precipitation: 1980-2019 (high, low, moderate);

Transformation 1920-1960 (true, false); Transformation1 1960-1980 (true, false); Transformation2 1980-2019 (true, false);

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Franco-Gaviria, F., Amador-Jimenez, M., Millner, N., Durden, C., & Urrego, D. H. (2022). Quantifying resilience of socio-ecological systems through dynamic Bayesian networks. Frontiers in Forests and Global Change, 5, 889274.

190 rockburst

ricci

ricci Bayesian Network

# **Description**

A survey on datasets for fairness-aware machine learning.

## **Format**

A discrete Bayesian network modeling the results of a promotion exam within a fire department. The DAG was taken from the referenced paper and the probabilities learned from the associated dataset (the variable Promoted was constructed manually). The vertices are:

Combine The combined score (<70, >=70);

**Oral** The oral exam schore (<70, >=70);

Position The desired promotion (Lieutenant, Captain);

**Promoted** Whether an individual obtains a promotion (FALSE, TRUE);

Race (White, Non-White);

**Written** The written exam score (<70, >=70);

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Le Quy, T., Roy, A., Iosifidis, V., Zhang, W., & Ntoutsi, E. (2022). A survey on datasets for fairness-aware machine learning. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 12(3), e1452.

rockburst

rockburst Bayesian Network

# **Description**

Dynamic early warning of rockburst using microseismic multi-parameters based on Bayesian network.

rockquality 191

# **Format**

A Gaussian Bayesian network to give early-warning of rockbursts. The probabilities were given within the referenced paper. The vertices are:

```
Rockburst (No, Yes);
MMAV (Sligth, Medium, Strong);
SRAV (Small, Medium, Big);
ASAV (Small, Medium, Big);
DSDAV (Small, Medium, Big);
SEAV (Low, Medium, High);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Li, X., Mao, H., Li, B., & Xu, N. (2021). Dynamic early warning of rockburst using microseismic multi-parameters based on Bayesian network. Engineering Science and Technology, an International Journal, 24(3), 715-727.

rockquality

rockquality Bayesian Network

## **Description**

A probability prediction method for the classification of surrounding rock quality of tunnels with incomplete data using Bayesian networks.

# **Format**

A discrete Bayesian network to predict the probability for the classification of surrounding rock quality of tunnel with incomplete data. Probabilities were given within the referenced paper. The vertices are:

BQ Basic quality of rock mass (Num1, Num2, Num3, Num4, Num5);

Groundwater (DryWet, MoistDripping, RainlikeDripping, TubularGushing);

InSituStress (Low, Medium, High, ExtremelyHigh);

RockHardness (Hard, SlightlyHard, SlightlySoft, Soft, ExtremelySoft);

RockMassIntegrity (Complete, SlightlyComplete, SlightlyBroken, Broken, ExtremelyBroken);

RockMassStructure (State1, State2, State3, State4, State5);

**RockQuality** (I, II, III, IV, V);

StructuralPlaneIntegrity (Good, Ordinary, Bad, VeryBad);

WeatheringDegree (Fresh, Slight, Medium, Severe, Extreme).

192 ropesegment

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Ma, J., Li, T., Li, X., Zhou, S., Ma, C., Wei, D., & Dai, K. (2022). A probability prediction method for the classification of surrounding rock quality of tunnels with incomplete data using Bayesian networks. Scientific Reports, 12(1), 19846.

ropesegment

ropesegment Bayesian Network

# Description

Availability optimization of a dragline subsystem using Bayesian network.

# **Format**

A discrete Bayesian network to analyze the availability of the rope segment. Probabilities were given within the referenced paper. The vertices are:

```
DragRopeFault (TRUE, FALSE);
DragChainLinkBroken (TRUE, FALSE);
DragHitchShacklePinOut (TRUE, FALSE);
DumpRopeFault (TRUE, FALSE);
DumpSocketPinOut (TRUE, FALSE);
HoistRopeSystem (TRUE, FALSE);
HoistChainPinOut (TRUE, FALSE);
DragSubsystem (TRUE, FALSE);
DumpSubsystem (TRUE, FALSE);
HoistSubsystem (TRUE, FALSE);
RopeSegment (TRUE, FALSE);
```

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Jana, D., Kumar, D., Gupta, S., & Gupta, K. K. (2024). Availability optimization of a dragline subsystem using Bayesian network. Journal of The Institution of Engineers (India): Series D, 105(1), 77-88.

safespeeds 193

safespeeds

safespeeds Bayesian Network

## **Description**

Modelling driver expectations for safe speeds on freeway curves using Bayesian belief networks.

#### **Format**

A discrete Bayesian network to model driver expectations using measured speeds in 153 curves and data on the characteristics of the curve approaches. The probabilities were given in the referenced paper. The vertices are:

**Angle** (A010-100, A100-200, A200-310);

CurveSign (Present, Not Present);

**Direction** (Left, Right);

**ExpectedSafeSpeed** (S060-069, S070-079, S080-089, S090-099, S100-109, S110-119, S120-129, S130-140);

NumberOfLanes (One, Two, Three, Four);

**PrecedingCurveSpeed** (S060-080, S080-100, S100-120, S120-140, Tangent);

**PrecedingRoadwayType** (Connector Road, Deceleration Lane, Fork, Main Carriageway, Merge, Weaving Section);

**SpeedSign** (AdvSpeed50, AdvSpeed60, AdvSpeed70, AdvSpeed80, AdvSpeed90, SpeedLimit50, SpeedLimit60, SpeedLimit70, SpeedLimit80, SpeedLimit90, NoSpeedLimit);

WarningSign (Present, Not Present);

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Vos, J., Farah, H., & Hagenzieker, M. (2024). Modelling driver expectations for safe speeds on free-way curves using Bayesian belief networks. Transportation Research Interdisciplinary Perspectives, 27, 101178.

194 salmonella1

sallyclark

sallyclark Bayesian Network

# Description

Measuring coherence with Bayesian networks.

#### **Format**

A discrete Bayesian modelling the evidence from the Sally Clark trial. Probabilities were given within the referenced paper. The vertices are:

```
ABrusing (TRUE, FALSE);
ADisease (TRUE, FALSE);
AMurder (TRUE, FALSE);
BBruising (TRUE, FALSE);
BDisease (TRUE, FALSE);
BMurder (TRUE, FALSE);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Kowalewska, A., & Urbaniak, R. (2023). Measuring coherence with Bayesian networks. Artificial Intelligence and Law, 31(2), 369-395.

salmonella1

salmonella Bayesian Networks

# **Description**

Patterns of antimicrobial resistance in Salmonella isolates from fattening pigs in Spain.

# **Format**

A discrete Bayesian network to show the existence of dependencies between resistance to antimicrobials. Probabilities were given within the referenced paper. The vertices are (s stands for susceptible, r for resistant):

```
CHL Chloramphenicol (s, r);CIP Ciprofloxacin (s, r);CTX Cefotaxime (s, r);
```

salmonella2 195

```
FFC Florfenicol (s, r);GEN Gentamicin (s, r);NAL Nalidixic acid (s, r);TET Tetracycline (s, r);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Teng, K. T. Y., Aerts, M., Jaspers, S., Ugarte-Ruiz, M., Moreno, M. A., Saez, J. L., ... & Alvarez, J. (2022). Patterns of antimicrobial resistance in Salmonella isolates from fattening pigs in Spain. BMC Veterinary Research, 18(1), 333.

salmonella2

salmonella Bayesian Networks

# Description

Patterns of antimicrobial resistance in Salmonella isolates from fattening pigs in Spain.

# Format

A discrete Bayesian network to show the existence of dependencies between resistance to antimicrobials. Probabilities were given within the referenced paper. The vertices are (s stands for susceptible, r for resistant):

```
AMP Ampicillin (s, r);

CAZ Ceftazidime (s, r);

CHL Chloramphenicol (s, r);

CIP Ciprofloxacin (s, r);

CTX Cefotaxime (s, r);

GEN Gentamicin (s, r);

NAL Nalidixic acid (s, r);

SMX Sulfamethoxazole (s, r);

TET Tetracycline (s, r);

TMP Trimethoprimn (s, r);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

196 seismic

## References

Teng, K. T. Y., Aerts, M., Jaspers, S., Ugarte-Ruiz, M., Moreno, M. A., Saez, J. L., ... & Alvarez, J. (2022). Patterns of antimicrobial resistance in Salmonella isolates from fattening pigs in Spain. BMC Veterinary Research, 18(1), 333.

seismic

seismic Bayesian Network

# **Description**

Probabilistic seismic risk assessment of a reinforced concrete building considering hazard level and the resulting vulnerability using Bayesian Belief Network.

# **Format**

A discrete Bayesian network for the identification of the seismic risk associated with a particular building which can be utilised to guide stakeholders, policymakers and designers in the efficient planning of emergency response, rescue operations and recovery activities. The probabilities were given in the referenced paper. The vertices are:

```
ConstructionQuality (Low, Medium, High);
Distance (Short, Medium, Long);
Fragility (Low, Medium, High);
LiveLoad (Low, Medium, High);
Magnitude (Low, Medium, High);
SeismicHazard (Low, Medium, High);
SeismicRisk (Low, Medium, High);
ShakingIntensity (Low, Medium, High);
StrengthDegradation (Low, Medium, High);
Vulnerability (Low, Medium, High);
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Roy, G., Sen, M. K., Singh, A., Dutta, S., & Choudhury, S. (2024). Probabilistic seismic risk assessment of a reinforced concrete building considering hazard level and the resulting vulnerability using Bayesian Belief Network. Asian Journal of Civil Engineering, 25(3), 2993-3009.

shipping 197

shipping

shipping Bayesian Network

# **Description**

Leverage Bayesian Network and Fault Tree Method on Risk Assessment of LNG Maritime Transport Shipping Routes: Application to the China–Australia Route.

## **Format**

A discrete Bayesian network to evaluate the occurrence likelihood of risk of transporting liquefied natural gas on the China–Australia Route. Probabilities were given within the referenced paper. The vertices are:

```
AirlineInherentRisks (Yes, No);
CoastalPortsRisk (Yes, No);
DeepChannel (Yes, No);
DifficultHandlingLNG (Yes, No);
FewerPorts (Yes, No);
FireRiskLNG (Yes, No);
HeavyFog (Yes, No);
HeavyTraffic (Yes, No);
HighCurrent (Yes, No);
HighWaves (Yes, No);
ImpactEpidemic (Yes, No);
InfluencePoliticalGame (Yes, No);
InfluenceWeather (Yes, No);
LNGLoadingRisk (Yes, No);
LNGTransportRisk (Yes, No);
LongDistance (Yes, No);
LowVisibility (Yes, No);
MaritimeSecurity (Yes, No);
MilitaryConflict (Yes, No);
NonTraditionalThreat (Yes, No);
ObjectiveFactors (Yes, No);
PiracyAttack (Yes, No);
PoorDraftLevel (Yes, No);
PoorOrganization (Yes, No);
SafetyPerformanceLNG (Yes, No);
```

198 simulation

```
SafetyRoutes (Yes, No);
SeaBreezeEffect (Yes, No);
SovereignityDispute (Yes, No);
StrongSeaBreeze (Yes, No);
StrongWinds (Yes, No);
SubjectiveFactors (Yes, No);
Thunderstorms (Yes, No);
TransportLNGRisk (Yes, No);
UncertainNavigablePeriod (Yes, No);
UnsafePersonnel (Yes, No);
VesselRisk (Yes, No);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Chang, Z., He, X., Fan, H., Guan, W., & He, L. (2023). Leverage Bayesian network and fault tree method on risk assessment of LNG maritime transport shipping routes: Application to the China-Australia route. Journal of Marine Science and Engineering, 11(9), 1722.

simulation

simulation Bayesian Network

# **Description**

Integration of fuzzy reliability analysis and consequence simulation to conduct risk assessment.

## **Format**

A discrete Bayesian network to assist asset managers in evaluating the risk arising from the operations. Probabilities were given within the referenced paper. The vertices are:

```
JointFailure (True, False);
PressureRegulatorLeakage (True, False);
SealFailure (True, False);
ValveActivation (True, False);
```

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Leoni, L., & De Carlo, F. (2023). Integration of fuzzy reliability analysis and consequence simulation to conduct risk assessment. Journal of Loss Prevention in the Process Industries, 83, 105081.

softwarelogs1

softwarelogs1

softwarelogs Bayesian Networks

## Description

Bayesian Network analysis of software logs for data-driven software maintenance.

#### **Format**

A discrete Bayesian network to discover poor performance indicators in a system and to explore usage patterns that usually require temporal analysis. The networks are given in the referenced paper. The vertices are:

```
error Error that has occured (com.mysql, etc.);
class Class that throws the error (chessleague.db, etc.);
severity Severity of the entry (SEVERE, WARNING, INFO);
method Method where the error has occured (deleteAccount, etc.);
thread name Name of the thread (AutoDeployer, etc.);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

del Rey, S., Martinez-Fernandez, S., & Salmeron, A. (2023). Bayesian Network analysis of software logs for data-driven software maintenance. IET Software, 17(3), 268-286.

softwarelogs2

softwarelogs Bayesian Networks

# **Description**

Bayesian Network analysis of software logs for data-driven software maintenance.

# Format

A discrete Bayesian network to discover poor performance indicators in a system and to explore usage patterns that usually require temporal analysis. The networks are given in the referenced paper. The vertices are:

page\_t\_0 (A128GCM, dir, HS512, SunJSSE version 1.8, AdminCron, AdminLeagues, AdminMarket, AdminNotices, AdminSuggestion, AdminSuggestions, AdminUser, AdminUsers, AllLeagues, Bid, Calendar, Classification, Cron, DirectorOfChess, ErrorPage, Finance, Help, Index, Invite, LastMovements, League, Lineup, Market, MarketOperations, NewAccount, NewPassword, NewSuggestion, OfferPlayer, OldSeasons, Play, Player, Privacy, Results, Search-Player, Start, Team, Trainer, Transactions, UserConfiguration, ViewOffers);

200 softwarelogs3

```
user_type_t_0 (active, ocasional, regular, very active);
load_time_t_0 (high, low, medium, optimal);
time_on_page_t_0 (high, low, medium, very low).
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

del Rey, S., Martinez-Fernandez, S., & Salmeron, A. (2023). Bayesian Network analysis of software logs for data-driven software maintenance. IET Software, 17(3), 268-286.

softwarelogs3

softwarelogs Bayesian Networks

# **Description**

Bayesian Network analysis of software logs for data-driven software maintenance.

## **Format**

A discrete Bayesian network to discover poor performance indicators in a system and to explore usage patterns that usually require temporal analysis. The networks are given in the referenced paper. The vertices are:

**load\_time** (high, low, medium, optimal);

**language** (bg, ca, cw, de, en, es, eu, fr, gl, it, jwe content encryption algorithms, jwe key management algorithms, jws signature algorithms, nl, pl, pt, ru, sr, unknown, zh);

user (high, low, medium, optimal);

page (high, low, medium, very low);

action (A128KW, A192GCM, ES256, SunJCE version 1.8, bad capthca, bad email, bad recapthca, bonus, bonus introduced is not a number, cancelBid, contract-sponsor, correctBPIOL, create, create division, create offer, createLeague, createLeagues, cronDiariom cronDiarioAuto, cronEVO, cronJorunada, cronJornadaAuto, cronSemanaAuto, cronTemporada, deleteAccount, deleteMessage, edit, fire player, fire trainer, hire trainer, load market page, load page, load round, logout, pay bonus, prepare team, publish a suggestion, redirect, search player, search top players, sendNotice, set new password, successful-search-players, successful bid, successfully send invitation, successfully create account, tried to create an offer, unsuccessful-search-players, unsuccessful bid-already invested, unsuccessful bid-amount too low, unsuccessful bid-less than initial price, unsuccessful bid-negative amount, unsuccessful bid-not enough available money, unsuccessful bid-wrong number format, update account, updateRatingList, username in use, wrongcaptcha send invitation);

day (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday);
action\_duration (high, low, medium, optimal);

softwarelogs4 201

```
time_on_page (high, medium, low, very low);
num_petitions (1-3, 3-6, 6-59);
```

**country** (Argentina, Austria, Belgium, Canada, China, Czechia, France, Germany, Italy, Mexico, Peru, Portugal, Russia, Saudi Arabia, Slovakia, Spain, Turkey, Uganda, Ukraine, United Arab Emirates, United States, unknown, Venezuela);

**browser** (Mozilla, not set, Android Webview, Chrome, Edge, Firefox, Opera, Safari, Safari in-app, Samsung Internet, UC Browser, unknown);

```
device (desktop, mobile, tablet, unknown);
num_errors (high, low, medium, none);
user_type (ocasional, regular, very active);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

del Rey, S., Martinez-Fernandez, S., & Salmeron, A. (2023). Bayesian Network analysis of software logs for data-driven software maintenance. IET Software, 17(3), 268-286.

softwarelogs4

softwarelogs Bayesian Networks

# Description

Bayesian Network analysis of software logs for data-driven software maintenance.

## **Format**

A discrete Bayesian network to discover poor performance indicators in a system and to explore usage patterns that usually require temporal analysis. The networks are given in the referenced paper. The vertices are:

```
load_time (high, low, medium, optimal);
```

**language** (bg, ca, cw, de, en, es, eu, fr, gl, it, jwe content encryption algorithms, jwe key management algorithms, jws signature algorithms, nl, pl, pt, ru, sr, unknown, zh);

user (high, low, medium, optimal);

page (high, low, medium, very low);

action (A128KW, A192GCM, ES256, SunJCE version 1.8, bad capthca, bad email, bad recapthca, bonus, bonus introduced is not a number, cancelBid, contract-sponsor, correctBPIOL, create, create division, create offer, createLeague, createLeagues, cronDiariom cronDiarioAuto, cronEVO, cronJorunada, cronJornadaAuto, cronSemanaAuto, cronTemporada, deleteAccount, deleteMessage, edit, fire player, fire trainer, hire trainer, load market page, load page, load round, logout, pay bonus, prepare team, publish a suggestion, redirect, search player, search

202 soil

top players, sendNotice, set new password, successful-search-players, successful bid, successfully send invitation, successfully create account, tried to create an offer, unsuccessful-search-players, unsuccessful bid-already invested, unsuccessful bid-amount too low, unsuccessful bid-less than initial price, unsuccessful bid-negative amount, unsuccessful bid-not enough available money, unsuccessful bid-wrong number format, update account, updateRatingList, username in use, wrongcaptcha send invitation);

```
day (Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday);
action_duration (high, low, medium, optimal);
time_on_page (high, medium, low, very low);
num_petitions (1-3, 3-6, 6-59);
country (Argentina, Austria, Belgium, Canada, China, Czechia, France, Germany, Italy, Mexico, Peru, Portugal, Russia, Saudi Arabia, Slovakia, Spain, Turkey, Uganda, Ukraine, United Arab Emirates, United States, unknown, Venezuela);
browser (Mozilla, not set, Android Webview, Chrome, Edge, Firefox, Opera, Safari, Safari in-app, Samsung Internet, UC Browser, unknown);
device (desktop, mobile, tablet, unknown);
num_errors (high, low, medium, none);
user_type (ocasional, regular, very active);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

del Rey, S., Martinez-Fernandez, S., & Salmeron, A. (2023). Bayesian Network analysis of software logs for data-driven software maintenance. IET Software, 17(3), 268-286.

soil

soil Bayesian Network

# **Description**

Characteristic study of some parameters of soil irrigated by magnetized waters.

## **Format**

A discrete Bayesian network to display the water treatment impact on soil characteristics. Probabilities were given within the referenced paper. The vertices are:

```
Depth (0-20, 20-40);
EC (Less than 1.4, More than 1.4);
Intensity (Less than 0.3, More than 0.3);
Length (Less than 20, More than 20);
pH (Less than 7.7, More than 7.7);
W (Less than 10, More than 10);
```

soillead 203

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Ben Amor, H., Elaoud, A., Ben Hassen, H., Ben Salah, N., Masmoudi, A., & Elmoueddeb, K. (2020). Characteristic study of some parameters of soil irrigated by magnetized waters. Arabian Journal of Geosciences, 13, 1-11.

soillead

soillead Bayesian Network

# **Description**

Lead distribution in urban soil in a medium-sized city: household-scale analysis.

## **Format**

A discrete Bayesian network to classify residential parcels by risk of exceeding residential gardening standards. The probabilities were given within the referenced paper. The vertices are:

```
SoilPbAbove100ppm (0,1);
```

**BlackPercentage** (Below 0.355, 0.355-0.727, Above 0.727);

**DistanceToMajorRoad** (Below 500, 500-1000, Above 1000);

**HouseAge** (Below 4.2, 4.2-7.9, Above 7.9);

HouseValue (Below 1.292, 1.292-2.859, Above 2.859);

MedianHouseholdIncome (Below 0.255, 0.255-0.470, Above 0.470);

**SoilClay** (Below 26.14, 26.14-33.125, Above 33.125);

**SoilPH** (Below 5.316, 5.316-5.974, Above 5.974);

SoilSamplingLocation (Dripline, Streetside, Yard);

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Obeng-Gyasi, E., Roostaei, J., & Gibson, J. M. (2021). Lead distribution in urban soil in a medium-sized city: household-scale analysis. Environmental Science & Technology, 55(6), 3696-3705.

204 soilliquefaction2

soilliquefaction1

soilliquefaction Bayesian Networks

# Description

Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential.

## **Format**

A discrete Bayesian network to evaluate the earthquake-induced liquefaction potential of soil based on the cone penetration test field case history records (Fig. 1.a). The data was available in the reference paper and was discretized as suggested in the paper. The DAGs were given in the paper and probabilities were learned using the Bayes method with imaginary sample size of one. The vertices are:

```
ConePenetrationResistance (small, medium, big, super);
```

EartquakeMagnitude (medium, strong, big, super);

LiquefactionPotential (no, yes);

MeanGrainSize (medium, strong, big, super);

PeakGroundAcceleratione (low, medium, high, super);

**TotalVerticalStress** (small, medium, big, super);

VerticalEffectiveStress (small, medium, big, super);

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Ahmad, M., Tang, X. W., Qiu, J. N., Ahmad, F., & Gu, W. J. (2021). Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential. Frontiers of Structural and Civil Engineering, 15, 490-505.

soilliquefaction2

soilliquefaction Bayesian Networks

# Description

Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential.

soilliquefaction3 205

## **Format**

A discrete Bayesian network to evaluate the earthquake-induced liquefaction potential of soil based on the cone penetration test field case history records (Fig. 1.b). The data was available in the reference paper and was discretized as suggested in the paper. The DAGs were given in the paper and probabilities were learned using the Bayes method with imaginary sample size of one. The vertices are:

```
ConePenetrationResistance (small, medium, big, super);
EartquakeMagnitude (medium, strong, big, super);
LiquefactionPotential (no, yes);
MeanGrainSize (medium, strong, big, super);
PeakGroundAcceleratione (low, medium, high, super);
TotalVerticalStress (small, medium, big, super);
VerticalEffectiveStress (small, medium, big, super);
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Ahmad, M., Tang, X. W., Qiu, J. N., Ahmad, F., & Gu, W. J. (2021). Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential. Frontiers of Structural and Civil Engineering, 15, 490-505.

soilliquefaction3

soilliquefaction Bayesian Networks

# Description

Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential.

# Format

A discrete Bayesian network to evaluate the earthquake-induced liquefaction potential of soil based on the cone penetration test field case history records (Fig. 1.c). The data was available in the reference paper and was discretized as suggested in the paper. The DAGs were given in the paper and probabilities were learned using the Bayes method with imaginary sample size of one. The vertices are:

```
ConePenetrationResistance (small, medium, big, super);
EartquakeMagnitude (medium, strong, big, super);
LiquefactionPotential (no, yes);
MeanGrainSize (medium, strong, big, super);
PeakGroundAcceleratione (low, medium, high, super);
TotalVerticalStress (small, medium, big, super);
VerticalEffectiveStress (small, medium, big, super);
```

206 soilliquefaction4

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Ahmad, M., Tang, X. W., Qiu, J. N., Ahmad, F., & Gu, W. J. (2021). Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential. Frontiers of Structural and Civil Engineering, 15, 490-505.

soilliquefaction4

soilliquefaction Bayesian Networks

# Description

Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential.

#### **Format**

A discrete Bayesian network to evaluate the earthquake-induced liquefaction potential of soil based on the cone penetration test field case history records (Fig. 1.d). The data was available in the reference paper and was discretized as suggested in the paper. The DAGs were given in the paper and probabilities were learned using the Bayes method with imaginary sample size of one. The vertices are:

ConePenetrationResistance (small, medium, big, super);

EartquakeMagnitude (medium, strong, big, super);

LiquefactionPotential (no, yes);

MeanGrainSize (medium, strong, big, super);

PeakGroundAcceleratione (low, medium, high, super);

TotalVerticalStress (small, medium, big, super);

VerticalEffectiveStress (small, medium, big, super);

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Ahmad, M., Tang, X. W., Qiu, J. N., Ahmad, F., & Gu, W. J. (2021). Application of machine learning algorithms for the evaluation of seismic soil liquefaction potential. Frontiers of Structural and Civil Engineering, 15, 490-505.

stocks 207

stocks

stocks Bayesian Network

# Description

Gaussian Bayesian network model of healthcare, food and energy sectors in the pandemic: Turkiye case.

## **Format**

A Gaussian Bayesian network to explore the causal relations between the healthcare, food, and energy sectors. The probabilities were given in the paper. The vertices are:

**AEFES** 

**AKSEN** 

**CCOLA** 

**ENJSA** 

**KERVT** 

LKMNH

MPARK

**ODAS** 

**PENGD** 

**TUKAS** 

ULKER

**ULUUN** 

**ZOREN** 

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Sener, E., & Demir, I. (2024). Gaussian Bayesian network model of healthcare, food and energy sectors in the pandemic: Turkiye case. Heliyon, 10(1).

208 student1

student1

student Bayesian Networks

# Description

than 1 hour);

A survey on datasets for fairness-aware machine learning.

## **Format**

A discrete Bayesian network modeling students' achievement in the secondary education of two Portuguese schools in 2005–2006 in the Portuguese subject. The DAG was taken from the referenced paper and the probabilities learned from the associated dataset. The vertices are:

```
activities Extra-curricular activities (yes, no);
address Student's home address type (Rural, Urban);
age Student's age (15, 16, 17, ..., 22);
class Final grade (< 10, >= 10);
failures Number of past class failures (0, 1, 2, 3);
famsize Race (non-white, white);
famsup Family size (Less or equal to 3, Greater than 3);
Fedu Father's education (None, Primary Education, 5th to 9th Grade, Secondary Education, Higher
     Education);
Fjob Father's job (At Home, Healthcare Related, Other, Civil Services, Teacher);
G1 First period grade (< 10, >= 10);
G2 Second period grade (< 10, >= 10);
goout Going out with friends (Very Low, Low, Medium, High, Very High);
guardian Student's guardian (Mother, Father, Other);
higher Wants to take higher education (yes, no);
internet Internet access at home (yes, no);
Medu Mother's education (None, Primary Education, 5th to 9th Grade, Secondary Education,
     Higher Education);
Mjob Mother's job (At Home, Healthcare Related, Other, Civil Services, Teacher);
nursery Attended nursery school (yes, no);
paid Extra paid classes within the course subject (yes, no);
Pstatus Parent's cohabitation status (Living together, Apart);
reason Reason to choose this school (Close to Home, School Reputation, Course Preference,
     Other);
romantic With a romantic relationship (yes, no);
school Student's school (Gabriel Pereira, Mousinho da Silveira);
schoolsup Extra educational support (yes, no);
sex Student's sex (Female, Male);
traveltime Home to school travel time (Less than 15min, 15 to 30 mins, 30 mins to 1 hour, More
```

student2 209

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Le Quy, T., Roy, A., Iosifidis, V., Zhang, W., & Ntoutsi, E. (2022). A survey on datasets for fairness-aware machine learning. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 12(3), e1452.

student2

student Bayesian Networks

# **Description**

A survey on datasets for fairness-aware machine learning.

## **Format**

A discrete Bayesian network modeling students' achievement in the secondary education of two Portuguese schools in 2005–2006 in the Mathematics subject. The DAG was taken from the referenced paper and the probabilities learned from the associated dataset. The vertices are:

```
activities Extra-curricular activities (yes, no);
```

address Student's home address type (Rural, Urban);

age Student's age (15, 16, 17, ..., 22);

class Final grade (< 10, >= 10);

failures Number of past class failures (0, 1, 2, 3);

famsize Race (non-white, white);

**famsup** Family size (Less or equal to 3, Greater than 3);

**Fedu** Father's education (None, Primary Education, 5th to 9th Grade, Secondary Education, Higher Education);

**Fjob** Father's job (At Home, Healthcare Related, Other, Civil Services, Teacher);

**G1** First period grade (< 10, >= 10);

**G2** Second period grade (< 10, >= 10);

goout Going out with friends (Very Low, Low, Medium, High, Very High);

guardian Student's guardian (Mother, Father, Other);

higher Wants to take higher education (yes, no);

internet Internet access at home (yes, no);

**Medu** Mother's education (None, Primary Education, 5th to 9th Grade, Secondary Education, Higher Education);

**Mjob** Mother's job (At Home, Healthcare Related, Other, Civil Services, Teacher);

nursery Attended nursery school (yes, no);

210 suffocation

paid Extra paid classes within the course subject (yes, no);

**Pstatus** Parent's cohabitation status (Living together, Apart);

**reason** Reason to choose this school (Close to Home, School Reputation, Course Preference, Other);

**romantic** With a romantic relationship (yes, no);

school Student's school (Gabriel Pereira, Mousinho da Silveira);

schoolsup Extra educational support (yes, no);

sex Student's sex (Female, Male);

**traveltime** Home to school travel time (Less than 15min, 15 to 30 mins, 30 mins to 1 hour, More than 1 hour);

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Le Quy, T., Roy, A., Iosifidis, V., Zhang, W., & Ntoutsi, E. (2022). A survey on datasets for fairness-aware machine learning. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 12(3), e1452.

suffocation

suffocation Bayesian Network

# **Description**

Human-related hazardous events assessment for suffocation on ships by integrating Bayesian network and complex network.

# Format

A Gaussian Bayesian network to investigate the human-related factors associated with suffocation on ships during docking repair. The probabilities were given within the referenced paper. The vertices are:

- **N4** The safety supervisor on board the ship did not perceive the unsafe actions of the operators and failed to correct the inappropriate operations;
- N5 The representative of the ship owner was absent during the operation;
- N8 Nitrogen leakage
- **N10** The safety management department of the shipyard failed to strictly implement all safety measures during the holiday season;
- **N11** The safety management department of the shipyard did not attach great importance to the safety of the operation on site, and the safety issues were not paid much attention;

suffocation 211

**N12** The quality management system in the safety management department was found be defective in the aspect of the required process guidance documents;

- **N13** The shipyard failed to effectively supervise the operators on site to strictly implement the safety management system and the operation instruction;
- **N14** The safety management department of the shipyard did not strictly implement the safety management regulations there was no confirmation of the key operation;
- **N16** The superintendent of the civil marine project failed to effectively supervise the issues in risk prevention;
- **N17** The managers and officers in the civil marine project failed to pay much attention to the preventive measures in the field of safety when formulating the operation plan;
- **N18** The superintendent of the civil marine project did not eliminate the potential dangers for the common operation in time;
- N20 The nitrogen accumulated in the enclosed space on site;
- **N22** The person in charge of the operation on site did not implement safety-related regulations, such as confirmation, lighting, and supervision;
- **N23** The person in charge of the operation on site failed to give input on the operation environment and provide caution to the operators;
- N24 The person in charge of the on-site operation did not confirm the ventilation;
- **N25** The operators on site did not implement the required risk-prevention measures for the operation in the limited space;
- **N26** The operator on site did not apply for a permit for the operation procedures;
- **N27** The person in charge of the operation on site failed to check the operation permit in the limited space before the operation;
- **N28** The person in charge of the operation on site did not confirm the implementation of gas detection;
- **N29** The person in charge of the operation on site did not effectively perform their designated responsibility during the operation;
- **N30** The work associated with risk identification before the operation was not performed by the person in charge of the operation;
- **N32** The removing of the U pipe containing nitrogen in the enclosed space is usually characterized by high risk, which was not did not receive due attention from the operators on site;
- **N33** The risk-prevention measures applicable for the enclosed space were not in place before the operation, and various potential risks were not effectively identified;
- **N34** The process guidance documents for the officers in the general assembly department were absent;
- **N35** The officers in the general assembly department failed to identify all the risks associated with the temporary operation;
- **N36** The officers in the general assembly department failed to implement the safety-related measures designed for the holiday season;
- **N37** The person on duty in the general assembly department did not perform their responsibilities effectively;

212 tastingtea

**N38** The officers in the general assembly department failed to implement the safety training for the temporary operators in relation to operative environments and the potential risks;

- **N39** The officers in the general assembly department did not effectively perform their supervision and risk monitoring responsibilities;
- **N40** Most of the people involved in the accident were found to have low awareness of the safety-related issues during the May 1st Labor Day;
- **UA** Unsafe acts;
- **UP** Precondition for unsafe acts;
- **US** Unsafe supervision;
- OI Organizational influence;

## PersonnelSuffocation

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Qiao, W., Guo, H., Huang, E., Deng, W., Lian, C., & Chen, H. (2022). Human-Related Hazardous Events Assessment for Suffocation on Ships by Integrating Bayesian Network and Complex Network. Applied Sciences, 12(14), 6905.

tastingtea

tastingtea Bayesian Network

# **Description**

A Bayesian network for modelling the Lady tasting tea experiment.

## **Format**

A discrete Bayesian network for modelling the Lady Tasting Tea experiment. The probabilities were given in the referenced paper. The vertices are:

```
AbilityToTaste (0.5, 0.75, 1);
Cup1 (tea, milk);
Cup2 (tea, milk);
Cup3 (tea, milk);
Cup4 (tea, milk);
Cup5 (tea, milk);
Cup6 (tea, milk);
Cup7 (tea, milk);
Cup8 (tea, milk);
```

tbm 213

```
TestOutcome1 (tea, milk);
TestOutcome2 (tea, milk);
TestOutcome3 (tea, milk);
TestOutcome4 (tea, milk);
TestOutcome5 (tea, milk);
TestOutcome6 (tea, milk);
TestOutcome7 (tea, milk);
TestOutcome8 (tea, milk);
```

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Xie, G. (2024). A Bayesian network for modelling the Lady tasting tea experiment. PloS one, 19(7), e0307866.

tbm

tbm Bayesian Network

## Description

Risk assessment of TBM jamming based on Bayesian networks.

## **Format**

A discrete Bayesian network to assess the risk of tunnel boring machine jamming. The Bayesian network was learned as in the referenced paper. The vertices are:

```
Expansive_Surrounding_Rock (High, Low, Medium, None);
Fault_Zone (High, Low, Medium, None);
In.Situ_Stress (High, Low, Medium, None);
Large_Deformation_Surrounding_Rock (Serious, Slight);
Rock_Mass_Classes (High, Low, Medium, None);
Soft.Hard_Interbedded_Rock (High, Low, Medium, None);
TBM_Jamming (No, Yes);
Tunnell_Collapse (Serious, Slight);
Underground_Water (High, Low, Medium, None);
Water.And.Mud_Inrush (Serious, Slight);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

214 theft2

# References

Lin, P., Xiong, Y., Xu, Z., Wang, W., & Shao, R. (2022). Risk assessment of TBM jamming based on Bayesian networks. Bulletin of Engineering Geology and the Environment, 81, 1-15.

theft1

theft Bayesian Networks

# Description

Evaluating methods for setting a prior probability of guilt.

# **Format**

A discrete Bayesian network representing a legal scenario. Probabilities were given within the referenced paper. The vertices are:

```
EredHanded (F, T);
EseenCS (F, T);
EWallet (F, T);
Guilty (F, T);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023). Evaluating Methods for Setting a Prior Probability of Guilt. In Legal Knowledge and Information Systems (pp. 63-72). IOS Press.

theft2

theft Bayesian Networks

# **Description**

Evaluating methods for setting a prior probability of guilt.

## **Format**

A discrete Bayesian network representing a legal scenario. Probabilities were given within the referenced paper. The vertices are:

```
AtCrimeScene (F, T);
EredHanded (F, T);
EseenCS (F, T);
EWallet (F, T);
Guilty (F, T);
```

titanic 215

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

van Leeuwen, L., Verheij, B., Verbrugge, R., & Renooij, S. (2023). Evaluating Methods for Setting a Prior Probability of Guilt. In Legal Knowledge and Information Systems (pp. 63-72). IOS Press.

titanic

titanic Bayesian Network

# **Description**

The R Package stagedtrees for Structural Learning of Stratified Staged Trees.

## **Format**

A discrete Bayesian network modeling the survival of the Titanic passengers. The Bayesian network was learned as in the referenced paper. The vertices are:

```
Class (1st, 2nd, 3rd, Crew);
Sex (Male, Female);
Age (Child, Adult);
Survived (No, Yes).
```

# Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Carli, F., Leonelli, M., Riccomagno, E., & Varando, G. (2022). The R Package stagedtrees for Structural Learning of Stratified Staged Trees. Journal of Statistical Software, 102, 1-30.

216 transport

trajectories

trajectories Bayesian Network

## **Description**

Context-specific causal discovery for categorical data using staged trees.

## **Format**

A discrete Bayesian network modeling the trajectory of patients hospitalized due to COVID. The Bayesian network is learned as in the referenced paper. The vertices are:

```
SEX (male, female);
ICU (0, 1);
OUT (death, survived);
AGE (child, adult, elder);
RSP (intub, mask, no);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

# References

Leonelli, M., & Varando, G. (2023, April). Context-specific causal discovery for categorical data using staged trees. In International Conference on Artificial Intelligence and Statistics (pp. 8871-8888). PMLR.

transport

transport Bayesian Network

# **Description**

Bayesian networks: with examples in R.

## **Format**

A discrete Bayesian network modeling transport choices of a population. Probabilities were given within the referenced paper. The vertices are:

```
A Age (young, adult, old);
```

- **S** Sex (M, F);
- E Education (high uni);
- O Occupation (emp, self);
- **R** Residence (small, big);
- T Transport (car, train, other);

tubercolosis 217

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Scutari, M., & Denis, J. B. (2014). Bayesian networks: with examples in R. Chapman and Hall/CRC.

tubercolosis

tubercolosis Bayesian Network

## Description

A decision support system for tuberculosis prevalence in South Africa.

#### **Format**

A discrete Bayesian network to educate, inform, and prescribe measures to take when visiting a high prevalence location. The probabilities were given within the referenced paper. The vertices are:

```
Location (Nkangala, Gert Sibande, Ehlanzeni);
Gender (Male, Female);
AgeGroup (0 to 35, 35 to 65, More than 65);
Tubercolosis (Pulmonary, ExtraPulmonary);
TreatmentOutcome (Alive, Died);
```

# Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Razwiedani, M., & Kogeda, O. P. (2021). A Decision Support System for Tuberculosis Prevalence in South Africa. In Computational Science and Its Applications. Springer International Publishing.

218 turbine1

turbine1

turbine Bayesian Networks

## **Description**

Potential use of Bayesian Networks for estimating relationship among rotational dynamics of floating offshore wind turbine tower in extreme environmental conditions.

#### **Format**

A Gaussian Bayesian network for the estimation of technical relationships among structural dynamic responses of the tower of a floating spar-type offshore wind turbine. Probabilities were given within the referenced paper. The vertices are:

PtfmPitch Platform pitch tilt angular (rotational) displacement;

PtfmRoll Platform roll tilt angular (rotational) displacement;

PtfmSurge Platform horizontal surge (translational) displacement;

PtfmSway Platform horizontal sway (translational) displacement;

**TTDspFA** Tower-top/yaw bearing fore-aft (translational) deflection (relative to the undeflected position);

**TTDspPtch** Tower-top/yaw bearing angular (rotational) pitch deflection (relative to the undeflected position);

**TTDspRoll** Tower-top/yaw bearing angular (rotational) roll deflection (relative to the undeflected position);

**TTDspSS** Tower-top/yaw bearing side-to-side (translation) deflection (relative to the undeflected position);

TwrBsFxt Tower base fore-aft shear force;

TwrBsFyt Tower base side-to-side shear force;

**TwrBsMxt** Nonrotating tower-top/yaw bearing roll moment;

**TwrBsMyt** Nonrotating tower-top/yaw bearing pitch moment;

YawBrFxp Tower-top/yaw bearing fore-aft (nonrotating) shear force;

**YawBrFyp** Tower-top/yaw bearing side-to-side (nonrotating) shear force;

YawBrMxp Nonrotating tower-top/yaw bearing roll moment;

YawBrMyp Nonrotating tower-top/yaw bearing pitch moment;

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Rostam-Alilou, A. A., Zhang, C., Salboukh, F., & Gunes, O. (2022). Potential use of Bayesian Networks for estimating relationship among rotational dynamics of floating offshore wind turbine tower in extreme environmental conditions. Ocean Engineering, 244, 110230.

turbine2 219

turbine2

turbine Bayesian Networks

## **Description**

Potential use of Bayesian Networks for estimating relationship among rotational dynamics of floating offshore wind turbine tower in extreme environmental conditions.

#### **Format**

A Gaussian Bayesian network for the estimation of technical relationships among structural dynamic responses of the tower of a floating spar-type offshore wind turbine. Probabilities were given within the referenced paper. The vertices are:

PtfmPitch Platform pitch tilt angular (rotational) displacement;

PtfmRoll Platform roll tilt angular (rotational) displacement;

PtfmSurge Platform horizontal surge (translational) displacement;

PtfmSway Platform horizontal sway (translational) displacement;

**TTDspFA** Tower-top/yaw bearing fore-aft (translational) deflection (relative to the undeflected position);

**TTDspPtch** Tower-top/yaw bearing angular (rotational) pitch deflection (relative to the undeflected position);

**TTDspRoll** Tower-top/yaw bearing angular (rotational) roll deflection (relative to the undeflected position);

**TTDspSS** Tower-top/yaw bearing side-to-side (translation) deflection (relative to the undeflected position);

TwrBsFxt Tower base fore-aft shear force;

TwrBsFyt Tower base side-to-side shear force;

**TwrBsMxt** Nonrotating tower-top/yaw bearing roll moment;

**TwrBsMyt** Nonrotating tower-top/yaw bearing pitch moment;

YawBrFxp Tower-top/yaw bearing fore-aft (nonrotating) shear force;

**YawBrFyp** Tower-top/yaw bearing side-to-side (nonrotating) shear force;

YawBrMxp Nonrotating tower-top/yaw bearing roll moment;

YawBrMyp Nonrotating tower-top/yaw bearing pitch moment;

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Rostam-Alilou, A. A., Zhang, C., Salboukh, F., & Gunes, O. (2022). Potential use of Bayesian Networks for estimating relationship among rotational dynamics of floating offshore wind turbine tower in extreme environmental conditions. Ocean Engineering, 244, 110230.

220 urinary

twinframework

twinframework Bayesian Network

## Description

Sustainable operation and maintenance modeling and application of building infrastructures combined with digital twin framework.

#### **Format**

A discrete Bayesian network to identify critical factors during the in-service phase and achieve sustainable operation and maintenance for building infrastructures. Probabilities were given within the referenced paper. The vertices are:

```
Weather (Fine weather, Bad weather);
SocialActivities (Active, No activity);
Time (Non-working hours, Working hours);
CampusActivities (Campus activities, No campus activities);
PersonnelType (Student, Social personnel);
EquipmentStatus (Good equipment, Equipment abnormality)
UsingPlayground (Use, Not in use);
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

# References

Jiao, Z., Du, X., Liu, Z., Liu, L., Sun, Z., & Shi, G. (2023). Sustainable Operation and Maintenance Modeling and Application of Building Infrastructures Combined with Digital Twin Framework. Sensors, 23(9), 4182.

urinary

urinary Bayesian Network

# **Description**

Urinary tract infections in children: building a causal model-based decision support tool for diagnosis with domain knowledge and prospective data.

urinary 221

## **Format**

A discrete Bayesian network to describe the causal relationships among variables relevant to paediatric urinary tract infections. Probabilities were given within the referenced paper. The vertices are:

```
AbdoPain (Yes, Unknown);
AgeGroup (LessThan6Mon, Btw6MonAnd2Yr, Btw2And5Yr, Above5Yr);
CauseUTI (EColi, OtherGramNeg, GramPos, None);
CollMethod (CleanCatch, Catheter, SupraAsp);
ContaminationRisk (High, Low);
CRPLevel (Above70, Btw15And70, Below50, NotDone)
CurrPhenotype (Type1, Type2, Type3);
Diarrhea (Yes, No);
EColi (Positive, Negative);
EColiPresence (High, Low);
EmpricAbxGroup3 (Narrow, Broader);
Epithelials (Low, Moderate);
FeverPR (Yes, No);
GramPos (Positive, Negative);
GramPosPresence (High, Low);
Irritable (Yes, No);
Lethargy (Yes, No);
Microscopy bacts (Many, Moderate, Few, NotSeen);
NauseaOrVomit (Yes, No);
NeutLevel (Above15, Btw8And15, Below8, NotDone);
OnAbxEDGroup3 (No, Narrow, Broader);
OtherGramNeg (Positive, Negative);
OtherGramNegPresence (High, Low);
PoorIntake (Yes, No);
PrevUriKidProbs (Reported, Unknown);
RespSymp (Yes, No);
Sex (Female, Male);
TemperatureLvl2 (Abv385, Btw375and385, Btw365and375, Below365);
UltraSound (Abnormal, Unknown, NotDone);
Urin_Leuc (High, Moderate, Low);
Urin_LeucEst (High, Moderate, Low, NotDetected);
Urin_Nitrite (Detected, NotDetected);
UrinSym_haematuria (Yes, Unknown);
UrinSym_PainOrDiscomf (Yes, Unknown);
UrinSym_smelly (Yes, Unknown);
WCCLevel (Above18, Btw10And18, Below10, NotDone);
```

222 vessel1

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Ramsay, J. A., Mascaro, S., Campbell, A. J., Foley, D. A., Mace, A. O., Ingram, P., ... & Wu, Y. (2022). Urinary tract infections in children: building a causal model-based decision support tool for diagnosis with domain knowledge and prospective data. BMC Medical Research Methodology, 22(1), 218.

vaccine

vaccine Bayesian Network

# Description

Sensitivity analysis in multilinear probabilistic models.

#### **Format**

A (synthetic) discrete Bayesian network modeling a vaccine scenario. Probabilities were given within the referenced paper. The vertices are:

**Screening\_Test** (Negative, Positive);

Disease (Healthy, Mildly, Severly);

Vaccine (No, Yes);

@return An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Leonelli, M., Gorgen, C., & Smith, J. Q. (2017). Sensitivity analysis in multilinear probabilistic models. Information Sciences, 411, 84-97.

vessel1

vessel Bayesian Networks

## **Description**

Analysis of fishing vessel accidents with Bayesian network and Chi-square methods.

vessel2 223

## **Format**

A discrete Bayesian network to understand the occurrence of accidents in fishing vessels and to estimate the occurrence of accidents in variable conditions (Sinking, Fig. 1). Probabilities were given within the referenced paper. The vertices are:

```
CarryingLoadAboveTransportLimits (Yes, No);
DesignDefect (Yes, No);
HuntingEquipmentOverload (Yes, No);
LossOfBuoyancy (Yes, No);
LossOfStability (Yes, No);
LossOfWaterTightness (Present, Absent);
Overload (Yes, No);
PlannedMaintenance (Completed, Uncompleted);
Sinking (Yes, No);
UnstableLoading (Yes, No);
UsedHuntingEquipment (Proper, Improper);
VesselAge (Old, New);
VesselPipelines (Corroded, Normal);
VesselStructure (Worn, Normal);
WaterIntake (Yes, No);
WeatherAndSeaConditions (Bad, Good);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Ugurlu, F., Yildiz, S., Boran, M., Ugurlu, O., & Wang, J. (2020). Analysis of fishing vessel accidents with Bayesian network and Chi-square methods. Ocean Engineering, 198, 106956.

vessel2

vessel Bayesian Networks

## **Description**

Analysis of fishing vessel accidents with Bayesian network and Chi-square methods.

224 volleyball

#### **Format**

A discrete Bayesian network to understand the occurrence of accidents in fishing vessels and to estimate the occurrence of accidents in variable conditions (Collision, Fig. 2). Probabilities were given within the referenced paper. The vertices are:

```
AlcoholDrugUse (Yes, No);
BridgeWithoutAWatchkeeper (Yes, No);
Collision (Yes, No);
Fatigue (Yes, No);
IntentionOfTargetVessel (Understood, Not understood);
InterShipCommunication (Proper, Improper);
Lookout (Proper, Improper);
Manning (Minimum num, Optimum num);
OccupationWithOtherTasks (Yes, No);
PresenceOfTargetVessel (Not Detected, Detected);
RestrictedVisibility (No, Yes);
TypeOfNavigation (Coastal Waters, Off Shore, Port);
UseOfNavigationEquipment (Adequate, Inadequate);
```

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Ugurlu, F., Yildiz, S., Boran, M., Ugurlu, O., & Wang, J. (2020). Analysis of fishing vessel accidents with Bayesian network and Chi-square methods. Ocean Engineering, 198, 106956.

volleyball

volleyball Bayesian Networks

# Description

Modeling psychological profiles in volleyball via mixed-type Bayesian networks.

## **Format**

A discrete Bayesian network to model the psychological profiles of volleyball athletes. Probabilities are estimated from data. The vertices are:

```
agreeableness (One, Two, Three, Four, Five);
concentration_disruption (One, Two, Three, Four, Five, Six);
conscientiousness (One, Two, Three, Four, Five);
```

waterlead 225

```
emotional_arousal (One, Two, Three, Four, Five, Six);
extraversion (One, Two, Three, Four, Five);
goal_setting (One, Two, Three, Four, Five, Six);
match_preparation (One, Two, Three, Four, Five, Six);
mental_practice (One, Two, Three, Four, Five, Six);
neuroticism (One, Two, Three, Four, Five);
openness (One, Two, Three, Four, Five);
self_confidence (One, Two, Three, Four, Five, Six);
self_esteem (One, Two, Three, Four, Five, Six);
worry (One, Two, Three, Four, Five, Six);
```

## Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

#### References

Iannario, M., Lee, D. J., & Leonelli, M. (2025). Modeling Psychological Profiles in Volleyball via Mixed-Type Bayesian Networks. arXiv preprint arXiv:2509.22111.

waterlead

waterlead Bayesian Network

## **Description**

Improved decision making for water lead testing in U.S. child care facilities using machine-learned Bayesian networks.

#### **Format**

A discrete Bayesian network to predict building-wide water lead risk in over 4,000 child care facilities in North Carolina according to maximum and 90th percentile lead levels from water lead concentrations at 22,943 taps. The Bayesian network was learned using the code in the referenced paper. The vertices are:

```
Target (0, 1);

PER_FREE ((-Inf, 0.505], (0.505,0.956],(0.956, Inf]);

PER_NON_WHITE ((-Inf, 0.0996], (0.0996,0.958], (0.958, Inf]);

TOTAL_ENROLL ((-Inf, 2.69], (2.69, 22.8], (22.8, Inf]);

nsamples ((-Inf, 4.1], (4.1, 23], (23, Inf]);

perc_filtered ((-Inf, 0.169], (0.169, 0.725], (0.725, Inf]);

head_start (0, 1);
```

226 wheat

```
school (0, 1);
home_based (0, 1);
Y_N_FIXTURE_CHG (dk, no, yes);
fixture_year_cat (1988to2014, after2014, pre1988);
year_began_operating_cat (1988to2014, after2014, pre1988);
type_binary (GW, SW);
ph_binary (0, 1);
chloramines (0, 1);
connections_cat ((1e+04,Inf], (3.3e+03, 1e+04], (1, 3.3e+03]);
ruca_cat (Metropolitan, Micropolitan, Rural, Small town);
```

#### Value

An object of class bn.fit. Refer to the documentation of bnlearn for details.

## References

Mulhern, R. E., Kondash, A. J., Norman, E., Johnson, J., Levine, K., McWilliams, A., ... & Hoponick Redmon, J. (2023). Improved decision making for water lead testing in US child care facilities using machine-learned Bayesian networks. Environmental Science & Technology, 57(46), 17959-17970.

wheat

wheat Bayesian Network

## **Description**

Embedding expert opinion in a Bayesian network model to predict wheat yield from spring-summer weather.

## Format

A discrete Bayesian network to predict wheat yield. Probabilities were given within the referenced paper. The vertices are:

```
MaximumTemperature (Low, Medium, High);
MeanTemperature (Moderate, Other);
NDVIinMarch (Low, Medium, High, Very High);
Rainfall (Dry, Average, Very Wet, Drought and Very Wet);
Yield (Very Low, Low, Average, High, Very High).
```

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Mahmood, S. A., Karampoiki, M., Hammond, J. P., Paraforos, D. S., Murdoch, A. J., & Todman, L. (2023). Embedding expert opinion in a Bayesian network model to predict wheat yield from spring-summer weather. Smart Agricultural Technology, 4, 100224.

windturbine

windturbine Bayesian Network

## **Description**

Reliability analysis of a floating offshore wind turbine using Bayesian Networks.

#### **Format**

A discrete Bayesian network to model and analyze the reliability of a floating offshore wind turbine. The probabilities were given within the referenced paper. The vertices are:

- **B01** Human error (Yes, No);
- **B02** Resonance (Yes, No);
- **B03** Faulty welding (Yes, No);
- **B04** Material fatigue (Yes, No);
- **B05** Pillar damage (Yes, No);
- **B06** Capsize (Yes, No);
- **B07** Anchor failure (Yes, No);
- **B08** Poor operation environment (Yes, No);
- **B09** Insufficient emergency measurement (Yes, No);
- **B10** Strong wave (Yes, No);
- **B11** Lightning strike (Yes, No);
- **B12** Storm (Yes, No);
- B13 Typhoon (Yes, No);
- **B14** Planes crash (Yes, No);
- **B15** Biological collision (Yes, No);
- **B16** Inefficient detection (Yes, No);
- **B17** Pipe joint corrosion (Yes, No);
- **B18** Pipe joint weld defect (Yes, No);
- **B19** Pipe joint fatigue (Yes, No);
- **B20** Fairlead corrosion (Yes, No);
- **B21** Fairlead fatigue (Yes, No);
- **B22** Transitional chain wear (Yes, No);
- B23 Friction chain wear (Yes, No);

- **B24** Mooring winch failure (Yes, No);
- **B25** Buoys friction chain wear (Yes, No);
- **B26** Anchor pickup device damage (Yes, No);
- **B27** Abnormal stress (Yes, No);
- **B28** Invalid maintenance (Yes, No);
- B29 Mooring lines wear (Yes, No);
- **B30** Mooring lines fatigue (Yes, No);
- **B31** Mooring lines corrosion (Yes, No);
- **B32** Hydraulic motor failure (Yes, No);
- **B33** Over pressure (Yes, No);
- **B34** Accumulation failure (Yes, No);
- **B35** Lighting protection failure (Yes, No);
- **B36** Limit switch fails (Yes, No);
- **B37** Abnormal vibration (Yes, No);
- **B38** Oil leakage (Yes, No);
- **B39** Filters failure (Yes, No);
- **B40** Power 1 failure (Yes, No);
- **B41** Power 2 failure (Yes, No);
- **B42** Vane damage (Yes, No);
- **B43** Anemometer damage (Yes, No);
- **B44** Abnormal filter (Yes, No);
- **B45** Poor quality lubrication oil (Yes, No);
- **B46** Dirt lubrication oil (Yes, No);
- **B47** Abnormal vibration (Yes, No);
- **B48** Glued (Yes, No);
- **B49** Pitting (Yes, No);
- **B50** Corrosion of pins (Yes, No);
- **B51** Abrasive wear (Yes, No);
- **B52** Pitting gear bearing (Yes, No);
- **B53** Gear tooth deterioration (Yes, No);
- **B54** Excessive pressure (Yes, No);
- **B55** Excess temperature (Yes, No);
- **B56** Fatigue gear (Yes, No);
- **B57** Poor design of teeth gears (Yes, No);
- **B58** Tooth surface defects (Yes, No);
- **B59** Measurement facilities failure (Yes, No);
- **B60** Wire fault (Yes, No);

- **B61** Leak (Yes, No);
- **B62** Asymmetry (Yes, No);
- **B63** Structural deficiency (Yes, No);
- **B64** Abnormal vibration (Yes, No);
- **B65** Abnormal instrument reading (Yes, No);
- **B66** Fail to synchronize (Yes, No);
- **B67** Broken bars (Yes, No);
- **B68** Fail to start on demands (Yes, No);
- **B69** Sensor failure (Yes, No);
- **B70** Temperature abovel limitation (Yes, No);
- **B71** Yaw subsytem failure (Yes, No);
- **B72** Drive train failure (Yes, No);
- **B73** Brake failure (Yes, No);
- **B74** Controller failure (Yes, No);
- **B75** Transformer failure (Yes, No);
- **B76** Sensors failure (Yes, No);
- **B77** Converter failure (Yes, No);
- **B78** Blades structure failure (Yes, No);
- **B79** Hub failure (Yes, No);
- **B80** Bearings failure (Yes, No);
- A01 Mooring subsystem failure (Yes, No);
- **A02** Tower failure (Yes, No);
- **A03** Floating fundation failure (Yes, No);
- A04 Devices failure (Yes, No);
- A05 Extreme sea condition (Yes, No);
- A06 Collapse due to environment (Yes, No);
- A07 Hit by dropped objects (Yes, No);
- A08 Watertight fault (Yes, No);
- A09 Other devise failure (Yes, No);
- A10 Pipe joint failure (Yes, No);
- **A11** Fairlead failure (Yes, No);
- **A12** Mooring lines broken (Yes, No);
- A13 Mooring line breakage (Yes, No);
- A14 Mooring lines wear (Yes, No);
- A15 Accumulating wear (Yes, No);
- A16 Hydraulic system failure (Yes, No);
- A17 Alarm facilities failure (Yes, No);

- **A18** Wrong pitch angle (Yes, No);
- A19 Hydraulic oil failure (Yes, No);
- A20 Power failure (Yes, No);
- A21 Meteorological unit failure (Yes, No);
- A22 Lubrication failure (Yes, No);
- A23 Abnormal gear (Yes, No);
- A24 Bearings fault (Yes, No);
- A25 Tooth wear gears (Yes, No);
- A26 Cracks in gears (Yes, No);
- A27 Offset of teeth gears (Yes, No);
- A28 Rotor and stator failure (Yes, No);
- A29 Bearing failure (Yes, No);
- A30 Abnormal signals (Yes, No);
- A31 No centricity generation (Yes, No);
- A32 Overheating (Yes, No);
- A33 Speed train failure (Yes, No);
- A34 Electric component failure (Yes, No);
- A35 Blades failure (Yes, No);
- A36 Rotor failure (Yes, No);
- S1 Support structure failure (Yes, No);
- **S2** Pitch system failure (Yes, No);
- S3 Gearbox failure (Yes, No);
- S4 Generator failure (Yes, No);
- **S5** Auxiliary system failure (Yes, No);
- **FOWTMalfunctions** Flowing offshore wind turbine malfunctions (Yes, No);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

## References

Li, H., Soares, C. G., & Huang, H. Z. (2020). Reliability analysis of a floating offshore wind turbine using Bayesian Networks. Ocean Engineering, 217, 107827.

witness 231

witness

witness Bayesian Network

## **Description**

Measuring coherence with Bayesian networks.

## **Format**

A discrete Bayesian modelling a situation where equally reliable witnesses try to identify a criminal. Probabilities were given within the referenced paper. The vertices are:

**W1SteveDidIt** Witness 1 report: Steve did it (True, False);

**W2SteveDidIt** Witness 2 report: Steve did it (True, False);

W3SteveMartinOrDavidDidIt Witness 3 report: Steve, Martin, or David did it (True, False);

W4SteveJohnOrJamesDidIt Witness 4 report: Steve, John, or James did it (True, False);

**W5SteveJohnOrPeterDidIt** Witness 5 report: Steve, John, or Peter did it (True, False);

WhoCommittedTheDeed Who is the criminal (Steve, Martin, David, John, James, Peter);

#### Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

#### References

Kowalewska, A., & Urbaniak, R. (2023). Measuring coherence with Bayesian networks. Artificial Intelligence and Law, 31(2), 369-395.

yangtze

yangtze Bayesian Network

# Description

Towards system-theoretic risk management for maritime transportation systems: A case study of the yangtze river estuary.

## Format

A discrete Bayesian network to determine the probabilities and consequences of accident scenarios in maritime transportation systems. Probabilities were given within the referenced paper (some inconsistencies in the numbers provided). The vertices are:

**AssessmentFailure** Assessment failure (Yes, No);

**AvoidanceRules** Strengthen the study of international maritime ship collision avoidance rules (Adopted, Unadopted);

232 yangtze

**CautiousDriving** Cautious driving to keep lookout in the cautionary area of YRE (Adopted, Unadopted);

Collision Collision probability (Yes, No);

CompetentCrew Failure to have a competent crew (Yes, No);

Consequence Collision Collision consequence (Serious, Moderate, Minor);

ConsequenceContact Contact consequence (Serious, Moderate, Minor);

ConsequenceSinking Sinking consequence (Serious, Moderate, Minor);

Contact Contact probability (Yes, No);

**CrewTraining** Strengthen crew training on operation in narrow and crowded waters (Adopted, Unadopted);

**EarlyMeasures** Failure to take early measures (Yes, No);

**EquipmentFailure** Operation equipment failure (Yes, No);

**GrossTonnage** Gross tonnage (< 3000 tons, 3000-10000 tons, > 10000 tons);

**HardwareMaintenance** Strengthen ship hardware maintenance and management (Adopted, Unadopted);

ImproperStowage Improper stowage (Yes, No);

InadequateCommunication Inadequate communication (Yes, No);

NegligentLookout Negligent lookout (Yes, No);

NoGiveWay No give way (Yes, No);

**QualifiedCrew** Strengthen the supervision of competent crew according to law (Adopted, Unadopted);

**ResourceManagement** Enhance teamwork resource management training on the bridge (Adopted, Unadopted);

SafetyTraining Strengthening crew safety awareness training (general) (Adopted, Unadopted);

**ShipAge** Ship age (<10 years, 10-20 years, > 20 years);

**ShipTracking** Strengthen ship tracking management (Adopted, Unadopted);

**ShipType** Ship type (Carrier/Container, Tanker, Other ship);

Sinking Sinking probability (Yes, No);

**SupervisingCompanies** Strengthen the inspection of the effectiveness of safety management of supervising shipping companies (Adopted, Unadopted);

**SupervisionVessel** Strengthen the supervision of inland river vessel companies by the YRE port and navigation department (Adopted, Unadopted);

**TrafficFlow** Traffic flow (Heavy, NormalOrLow);

UnsafeSpeed Unsafe speed (Yes, No);

Visibility Visibility (Poor, Good);

**Wind** Wind (>= Category 5, < Category 5).

## Value

An object of class bn. fit. Refer to the documentation of bnlearn for details.

yangtze 233

# References

Fu, S., Gu, S., Zhang, Y., Zhang, M., & Weng, J. (2023). Towards system-theoretic risk management for maritime transportation systems: A case study of the yangtze river estuary. Ocean Engineering, 286, 115637.

# **Index**

* CLGBN	theft1, 214
algorithms5, 25	witness, 231
algorithms6, 26	* ReverseNaiveBayes
covidtest, 77	beatles, 35
darktriad, 88	hydraulicsystem, 134
healthinsurance, 132	medicaltest, 149
* Datasets	metal, 151
$bnRep\_summary, 40$	simulation, 198
* GBN	soilliquefaction1, 204
algal2, <u>20</u>	wheat, 226
algorithms1, 23	* ReverseTree
algorithms2, 23	beam1, 34
building, 45	beam2, 35
cachexia1,47	BOPfailure1,41
cachexia2,48	BOPfailure2,42
diagnosis, 89	BOPfailure3,44
expenditure, 109	cng, 54
foodsecurity, 120	compaction, 57
lexical, 142	curacao1,83
liquefaction, 144	curacao2, 84
parkinson, 166	curacao3, 85
stocks, 207	curacao4, 86
suffocation, 210	curacao5, 87
turbine1, 218	dragline, 95
turbine2, 219	drainage, 97
* KDep	ecosystem, 101
mountaingoat, 152	electricvehicle, 102
* NaiveBayes	fluids2, 116
accidents, 7	gasifier, 125
adhd, 8	gonorrhoeae, 129
agropastoral5, 15	lithium, 146
bankruptcy, 33	megacities, 149
burglar, 47	navigation, 157
concrete6, 61	oildepot, 159
covid1,71	pilot, 169
enrollment, 106	polymorphic, 174
moodstate, 151	propellant, 179
perioperative, 167	rockquality, 191
softwarelogs3, 200	ropesegment, 192
	_

INDEX 235

shipping, 197	algorithms2, 23
soilliquefaction2, 204	algorithms3, 24
soilliquefaction4, 206	algorithms4, 25
suffocation, 210	algorithms5,25
tubercolosis, 217	algorithms6, 26
* TAN	APSsystem, 27
bullet, 46	arcticwaters, 28
coral1, 65	argument, 29
coral2,66	asia, 30
coral3,66	aspergillus, 31
coral4, <del>67</del>	augmenting, 32
coral5, <u>68</u>	
covid2, <b>72</b>	bank, 32
dioxins, 90	bankruptcy, 33
rainwater, 183	beam1, 34
rockburst, 190	beam2, 35
safespeeds, 193	beatles, 35
waterlead, 225	blacksea, 36
* Tree	blockchain, 38
chds, 53	bnRep, 39
concrete3, 59	bnRep_app, 39
concrete4, 60	bnRep_summary, 40
concrete5, 61	BOPfailure1,41
concrete7, 62	BOPfailure2, 42
nanomaterials1, 153	BOPfailure3,44
nanomaterials2, 155	building, 45
orbital, 163	bullet, 46
sallyclark, 194	burglar, 47
theft2, 214	bi-1 47
.onAttach, 7	cachexia1, 47
ancidanta 7	cachexia2, 48
accidents, 7	cardiovascular, 49
adhd, 8	case, 50 catchment, 51
adversarialbehavior, 9	charleston, 52
aerialvehicles, 10	chds, 53
agropastoral1, 11	
agropastoral2, 12 agropastoral3, 13	cng, 54 compaction, 57
agropastoral4, 14	conasense, 57
agropastoral5, 15	concrete1, 58
aircrash, 16	concrete2, 59
airegulation1, 16	concrete3, 59
airegulation, 10 airegulation2, 18	concrete4, 60
airegulation3, 19	concrete5, 61
_	concrete6, 61
algal1, 20 algal2, 20	concrete, 62
algalactivity1, 21	consequenceCovid, 63
algalactivity, 21 algalactivity2, 22	constructionproductivity, 64
algorithms1, 23	corall, 65
01501 1 UIIII31, 4J	COI at 1, UJ

236 INDEX

coral2, 66	fingermarks1,110
coral3,66	fingermarks2,111
coral4, 67	fire, 112
coral5, 68	firealarm, 113
corical, 69	firerisk, 113
corrosion, 70	flood, 114
corticosteroid, 71	fluids1, <u>116</u>
covid1, 71	fluids2, 116
covid2, 72	fluids3, 117
covid3,73	foodallergy1, 118
covidfear, 74	foodallergy2, 119
covidrisk, 75	foodallergy3, 119
covidtech, 75	foodsecurity, 120
covidtest, 77	forest, 121
crimescene, 78	fundraising, 123
criminal1, 79	
criminal2, 80	gasexplosion, 124
criminal3,81	gasifier, 125
criminal4,81	GDIpathway1, 126
crypto, 82	GDIpathway2, 128
curacao1, 83	<pre>get_network_list, 129</pre>
curacao2, 84	gonorrhoeae, 129
curacao3, 85	greencredit, 130
curacao4, 86	grounding, 131
curacao5, 87	h 14h 122
cui acaos, or	healthinsurance, 132
darktriad, 88	humanitarian, 133
diabetes, 89	hydraulicsystem, 134
diagnosis, 89	income, 135
dioxins, 90	intensification, 136
disputed1, 91	intentionalattacks, 137
	inverters, 137
disputed2, 92	111701 101 3, 137
disputed3, 93	knowledge, 139
disputed4, 94	kosterhavet, 139
dragline, 95	,
drainage, 97	lawschool, 141
dustexplosion, 98	lexical, 142
	lidar, 143
earthquake, 99	liquefaction, 144
ecosystem, 101	liquidity, 145
electricvehicle, 102	lithium, 146
electrolysis, 103	load_network, 147
emergency, 104	
engines, 105	macrophytes, 148
enrollment, 106	medicaltest, 149
estuary, 106	megacities, 149
ets, 108	metal, 151
expenditure, 109	moodstate, 151

INDEX 237

mountaingoat, 152	soillead, 203
nanomaterials1, 153	soilliquefaction1, 204 soilliquefaction2, 204
nanomaterials2, 155	
navigation, 157	soilliquefaction3, 205
	soilliquefaction4, 206
nuclearwaste, 157	stocks, 207
nuisancegrowth, 158	student1, 208
.: 1 down to 150	student2, 209
oildepot, 159	suffocation, 210
onlinerisk, 161	
orbital, 163	tastingtea, 212
oxygen, 164	tbm, 213
	theft1, 214
parkinson, 166	theft2, 214
perioperative, 167	titanic, 215
permaBN, 168	trajectories, 216
phdarticles, 169	transport, 216
pilot, 169	tubercolosis, 217
pneumonia, 171	turbine1, 218
polymorphic, 174	turbine2, 219
poultry, 175	twinframework, 220
project, 177	ewitti amework, 220
projectmanagement, 178	urinary, 220
propellant, 179	J,
properrant, 179	vaccine, 222
noineterm 101	vessel1, 222
rainstorm, 181	vessel2, 223
rainwater, 183	volleyball, 224
realestate1, 183	voricybarr, 22 i
realestate2, 185	waterlead, 225
realestate3, 186	wheat, 226
redmeat, 187	windturbine, 227
resilience, 188	witness, 231
ricci, 190	withe33, 231
rockburst, 190	yangtze, 231
rockquality, 191	yag = 20, 201
ropesegment, 192	
safespeeds, 193	
sallyclark, 194	
salmonella1, 194	
salmonella2, 195	
seismic, 196	
shipping, 197	
simulation, 198	
softwarelogs1, 199	
softwarelogs2, 199	
softwarelogs3, 200	
softwarelogs4, 201	
soil, 202	