Package ‘bnRep’

May 24, 2025

Title A Repository of Bayesian Networks from the Academic Literature

Version 0.0.4

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 <https://manueleleonelli.shinyapps.io/bnRep>. Reference: 'M. Leonelli' (2025) <doi:10.1016/j.neucom.2025.129502>.

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 (>= 2.10)

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

VignetteBuilder knitr

NeedsCompilation no

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

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

Repository CRAN

Date/Publication 2025-05-24 18:00:02 UTC

Contents

`.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);

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);

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.

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);

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.

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` *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.

`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.

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.

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.

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.

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);

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` *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

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` *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

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` *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.

`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);
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.

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);

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.

`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.

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.

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` *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);

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);

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);

SituationalAwareness (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.

`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` *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`.

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` *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);

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);

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.

`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);

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;

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` *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;

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` *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.

---

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.

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.

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);

PersonalVehicle (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);

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.

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);

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);

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 *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` *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 economivcs, 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.
```

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.

`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);

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.

`coral3` *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 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:

LiveCoralCover (Less than 0, 0-0.040, 0.040-0.122, 0.122-0.241, 0.241-0.417, 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);

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` *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);

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.

`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` *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);

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);

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.

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` *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.

`covidtech` *covidtech Bayesian Network*

Description

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

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 (<25, >=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, >=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 *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);

temperature

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.

`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.

`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);

Scenari3 (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).

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);

Scenari3 (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` *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.

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);

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

Steward, R., Chopin, P., & Verburg, P. H. (2024). Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao. Environmental Science & Policy, 156, 103733.

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

Steward, R., Chopin, P., & Verburg, P. H. (2024). Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao. Environmental Science & Policy, 156, 103733.

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

Steward, R., Chopin, P., & Verburg, P. H. (2024). Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao. Environmental Science & Policy, 156, 103733.

`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);

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

Steward, R., Chopin, P., & Verburg, P. H. (2024). Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao. Environmental Science & Policy, 156, 103733.

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);

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

Steward, R., Chopin, P., & Verburg, P. H. (2024). Supporting spatial planning with a novel method based on participatory Bayesian networks: An application in Curacao. Environmental Science & Policy, 156, 103733.

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

EmotionalSusceptibility

Narcissism

Psychopathy

SelfOrientedEmotionalReactivity

VerbalAggression

PerspectiveTaking

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 *ciabetes Bayesian Network*

Description

Sensitivity and robustness analysis in Bayesian networks with the bnmonitor 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 bnmonitor 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.

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` *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.

`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 *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);

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);

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

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

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);

Unkown 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);

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);

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.

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);

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);

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 *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.

`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` *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.

`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 *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.

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.

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);

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);

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.

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 *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 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` *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);

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.

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);

Yield (Decrease, Increase);

Value

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

References

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.

`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);

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.

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` *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.

`foodallergy3` *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 (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.

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.

`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 fund-raising 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.

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:

AccidentalViolations (Non-occurence, Occurence);

CreateAFalseImpressionToDeceiveTheRegulators (Non-occurence, Occurence);

DecisionErrors (Non-occurence, Occurence);

DeparmentsAndInstitutionsAreNotComplete (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);

SkillBasedErrors (Non-occurence, Occurence);

TechnicalEnvironment (Non-occurence, Occurence);

Value

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

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);

ExternalCorrosion 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);

Insulation Insulation layer damaged (Occurred, NotOccured);

InternalCorrosion 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);

UnintentionalDestruction 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.

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.

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);

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);

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.

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);

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);

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);

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` *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.

`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 *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.

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` *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);

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);

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);

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.

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.

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

lnamax

lnR

lnt

Mw

N160

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 *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.

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);

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)
```

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.

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.

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` *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.

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));

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);

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);

PotentiallyCarcinogenic (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);

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);

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);

PotentiallyCarcinogenic (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 *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);

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);

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);

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 *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);

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);

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.

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);

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 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

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.

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 *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);

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);

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, FullyVax);

InfluenzaVaccine 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);

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 occuring 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 occuring 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);

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.

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 *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);

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 *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.

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);

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);

CirculatingWaterTemperatureAnomaly (True, False);

CirculationWaterTemperatureAnomaly (True, False);

CuringAnomaly (True, False);

CuringTemperatureAnomaly (True, False);

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);

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);

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` *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.

`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);

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);

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.

`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.

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).

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` *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 freeway curves using Bayesian belief networks. Transportation Research Interdisciplinary Perspectives, 27, 101178.

`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);

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.

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` *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);

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 — *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, SearchPlayer, Start, Team, Trainer, Transactions, UserConfiguration, ViewOffers);

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, unsuccessuful 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.

`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 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, unsuccessuful 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);

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.

---

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);

PeakGroundAccelerationе (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.

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);

PeakGroundAccelerationе (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);

PeakGroundAccelerationе (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.

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);

PeakGroundAccelerationе (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 *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).

`student1` *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 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 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.

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);

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;

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;

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);

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.

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);

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.

`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);

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.

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` *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.

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.

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);

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.

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.

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.

`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);

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` *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);

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);

ConsequenceCollision 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.

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