Package 'CoOL'

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Type Package

Title Causes of Outcome Learning

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Description Implementing the computational phase of the Causes of Outcome Learning approach as described in Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <doi:10.1093/ije/dyac078>. The optional 'ggtree' package can be obtained through Bioconductor.

URL https://bioconductor.org

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Imports Rcpp, data.table, pROC, graphics, mltools, stats, plyr, ggplot2, ClustGeo, wesanderson, grDevices

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R topics documented:

`CoOL_0_binary_encode_exposure_data`

Binary encode exposure data

Description

This function binary encodes the exposure data set so that each category is coded 0 and 1 (e.g. the variable sex will be two variables men (1/0) and women (0/1)).

Usage

```
CoOL_0_binary_encode_exposure_data(exposure_data)
```

Arguments

`exposure_data` The exposure data set.

Value

Data frame with the expanded exposure data, where all variables are binary encoded.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

`CoOL_0_common_simulation` *Common example*

Description

To reproduce the common causes example.

Usage

```
CoOL_0_common_simulation(n)
```

Arguments

`n`	number of observations for the synthetic data.

Value

A data frame with the columns Y, A, B, C, D, E, F and n rows.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

CoOL_0_complex_simulation

Complex example

Description

To reproduce the complex example.

Usage

```
CoOL_0_complex_simulation(n)
```

Arguments

n	number of observations for the synthetic data.

Value

A data frame with the columns Y, Physically_active, Low_SES, Mutation_X, LDL, Night_shifts, Air_pollution and n rows.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

CoOL_0_confounding_simulation

Confounding example

Description

To reproduce the confounding example.

Usage

```
CoOL_0_confounding_simulation(n)
```

Arguments

n	number of observations for the synthetic data.

Value

A data frame with the columns Y, A, B, C, D, E, F and n rows.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

`CoOL_0_mediation_simulation` *Mediation example*

Description

To reproduce the mediation example.

Usage

```
CoOL_0_mediation_simulation(n)
```

Arguments

`n`	number of observations for the synthetic data.

Value

A data frame with the columns Y, A,B ,C, D, E, F and n rows.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

`CoOL_0_working_example` *CoOL working example with sex, drug A, and drug B*

Description

To reproduce the CoOL working example with sex, drug A, and drug B.

Usage

```
CoOL_0_working_example(n)
```

Arguments

n number of observations for the synthetic data.

Value

A data frame with the columns Y, sex, drug_a, drug_b and rows equal to n.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
while (FALSE) {
 library(CoOL)
 set.seed(1)
 data <- CoOL_0_working_example(n=10000)
 outcome_data <- data[,1]
 exposure_data <- data[,-1]
 exposure_data <- CoOL_0_binary_encode_exposure_data(exposure_data)
 model <- CoOL_1_initiate_neural_network(inputs=ncol(exposure_data),
 output = outcome_data,hidden=5)
 model <- CoOL_2_train_neural_network(lr = 1e-4,X_train=exposure_data,
 Y_train=outcome_data,X_test=exposure_data, Y_test=outcome_data,
 model=model, epochs=1000,patience = 200, input_parameter_reg = 1e-3
 ) # Train the non-negative model (The model can be retrained)
 model <- CoOL_2_train_neural_network(lr = 1e-5,X_train=exposure_data,
 Y_train=outcome_data,X_test=exposure_data, Y_test=outcome_data, model=model,
 epochs=1000,patience = 100, input_parameter_reg = 1e-3)
 # Train the non-negative model (The model can be retrained)
 model <- CoOL_2_train_neural_network(lr = 1e-6,X_train=exposure_data,
 Y_train=outcome_data,X_test=exposure_data, Y_test=outcome_data, model=model,
 epochs=1000,patience = 50, input_parameter_reg = 1e-3
 ) # Train the non-negative model (The model can be retrained)
 plot(model$train_performance,type='l',yaxs='i',ylab="Mean squared error",
 xlab="Epochs",main="A) Performance during training\n\n",
 ylim=quantile(model$train_performance,c(0,.975))) # Model performance
 CoOL_3_plot_neural_network(model,names(exposure_data),5/max(model[[1]]),
 title = "B) Model connection weights\nand intercepts") # Model visualization
 CoOL_4_AUC(outcome_data,exposure_data,model,
 title = "C) Receiver operating\ncharacteristic curve") # AUC
 risk_contributions <- CoOL_5_layerwise_relevance_propagation(exposure_data,model
 ) # Risk contributions
 CoOL_6_number_of_sub_groups(risk_contributions = risk_contributions,
 low_number = 1, high_number = 5)
 CoOL_6_dendrogram(risk_contributions,number_of_subgroups = 3,
 title = "D) Dendrogram with 3 sub-groups") # Dendrogram
 sub_groups <- CoOL_6_sub_groups(risk_contributions,number_of_subgroups = 3
 ) # Assign sub-groups
```

```
 CoOL_6_calibration_plot(exposure_data = exposure_data,
 outcome_data = outcome_data, model = model, sub_groups = sub_groups)
 CoOL_7_prevalence_and_mean_risk_plot(risk_contributions,sub_groups,
 title = "E) Prevalence and mean risk of sub-groups") # Prevalence and mean risk plot
 results <- CoOL_8_mean_risk_contributions_by_sub_group(risk_contributions,
 sub_groups,outcome_data = outcome_data,exposure_data = exposure_data,
 model=model,exclude_below = 0.01) #  Mean risk contributions by sub-groups
CoOL_9_visualised_mean_risk_contributions(results = results,  sub_groups = sub_groups)
CoOL_9_visualised_mean_risk_contributions_legend(results = results)
}
```

`CoOL_1_initiate_neural_network`

Initiates a non-negative neural network

Description

This function initiates a non-negative neural network. The one-hidden layer non-negative neural network is designed to resemble a DAG with hidden synergistic components. With the model, we intend to learn the various synergistic interactions between the exposures and outcome. The model needs to be non-negative and estimate the risk on an additive scale. Neural networks include hidden activation functions (if the sum of the input exceeds a threshold, information is passed on), which can model minimum threshold values of interactions between exposures. We need to specify the upper limit of the number of possible hidden activation functions and through model fitting, the model may be able to learn both stand-alone and synergistically interacting factors.

Usage

```
CoOL_1_initiate_neural_network(inputs, output, hidden = 10)
```

Arguments

`inputs`	The number of exposures.
`output`	The outbut variable is used to calcualte the mean of it used to initiate the baseline risk.
`hidden`	Number of hidden nodes.

Details

The non-negative neural network can be denoted as:

$$P(Y=1|X^+) = \sum_j \Big(w^+_{j,k} ReLU_j \big(\sum_i (w^+_{i,j} X^+_i) + b^-_j \big) \Big) + R^b$$

Value

A list with connection weights, bias weights and meta data.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

CoOL_2_train_neural_network *Training the non-negative neural network*

Description

This function trains the non-negative neural network. Fitting the model is done in a step-wise procedure one individual at a time, where the model estimates individual's risk of the disease outcome, estimates the prediction's residual error and adjusts the model parameters to reduce this error. By iterating through all individuals for multiple epochs (one complete iterations through all individuals is called an epoch), we end with parameters for the model, where the errors are smallest possible for the full population. The model fit follows the linear expectation that synergism is a combined effect larger than the sum of independent effects. The initial values, derivatives, and learning rates are described in further detail in the Supplementary material. The non-negative model ensures that the predicted value cannot be negative. The model does not prevent estimating probabilities above 1, but this would be unlikely, as risks of disease and mortality even for high risk groups in general are far below 1. The use of a test dataset does not seem to assist deciding on the optimal number of epochs possibly due to the constrains due to the non-negative assumption. We suggest splitting data into a train and test data set, such that findings from the train data set can be confirmed in the test data set before developing hypotheses.

Usage

```
CoOL_2_train_neural_network(
  X_train,
  Y_train,
  X_test,
  Y_test,
  C_train = 0,
  C_test = 0,
  model,
  lr = c(1e-04, 1e-05, 1e-06),
  epochs = 2000,
  patience = 100,
  monitor = TRUE,
  plot_and_evaluation_frequency = 50,
```

```
    input_parameter_reg = 0.001,
    spline_df = 10,
    restore_par_options = TRUE,
    drop_out = 0,
    fix_baseline_risk = -1,
    ipw = 1
  )
```

Arguments

`X_train`	The exposure data for the training data.
`Y_train`	The outcome data for the training data.
`X_test`	The exposure data for the test data (currently the training data is used).
`Y_test`	The outcome data for the test data (currently the training data is used).
`C_train`	One variable to adjust the analysis for such as calendar time (training data).
`C_test`	One variable to adjust the analysis for such as calendar time (currently the training data is used).
`model`	The fitted non-negative neural network.
`lr`	Learning rate (several LR can be provided, such that the model training will train for each LR and continue to the next).
`epochs`	Epochs.
`patience`	The number of epochs allowed without an improvement in performance.
`monitor`	Whether a monitoring plot will be shown during training.
`plot_and_evaluation_frequency`	The interval for plotting the performance and checking the patience.
`input_parameter_reg`	Regularisation decreasing parameter value at each iteration for the input parameters.
`spline_df`	Degrees of freedom for the spline fit for the performance plots.
`restore_par_options`	Restore par options.
`drop_out`	To drop connections if their weights reaches zero.
`fix_baseline_risk`	To fix the baseline risk at a value.
`ipw`	a vector of weights per observation to allow for inverse probability of censoring weighting to correct for selection bias

Value

An updated list of connection weights, bias weights and meta data.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

`CoOL_3_plot_neural_network` *Plotting the non-negative neural network*

Description

This function plots the non-negative neural network

Usage

```
CoOL_3_plot_neural_network(
  model,
  names,
  arrow_size = NA,
  title = "Model connection weights and intercepts",
  restore_par_options = TRUE
)
```

Arguments

`model`	The fitted non-negative neural network.
`names`	Labels of each exposure.
`arrow_size`	Define the arrow_size for the model illustration in the reported training progress.
`title`	Title on the plot.
`restore_par_options`	Restore par options.

Value

A plot visualizing the connection weights.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

`CoOL_4_AUC` *Plot the ROC AUC*

Description

Plot the ROC AUC

Usage

```
CoOL_4_AUC(
  outcome_data,
  exposure_data,
  model,
  title = "Receiver operating\ncharacteristic curve",
  restore_par_options = TRUE
)
```

Arguments

`outcome_data`	The outcome data.
`exposure_data`	The exposure data.
`model`	The fitted the non-negative neural network.
`title`	Title on the plot.
`restore_par_options`	Restore par options.

Value

A plot of the ROC and the ROC AUC value.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

CoOL_4_predict_risks — *Predict the risk of the outcome using the fitted non-negative neural network*

Description

Predict the risk of the outcome using the fitted non-negative neural network.

Usage

```
CoOL_4_predict_risks(X, model)
```

Arguments

X	The exposure data.
model	The fitted the non-negative neural network.

Value

A vector with the predicted risk of the outcome for each individual.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

CoOL_5_layerwise_relevance_propagation — *Layer-wise relevance propagation of the fitted non-negative neural network*

Description

Calculates risk contributions for each exposure and a baseline using layer-wise relevance propagation of the fitted non-negative neural network and data.

Usage

```
CoOL_5_layerwise_relevance_propagation(X, model)
```

Arguments

`X`	The exposure data.
`model`	The fitted the non-negative neural network.

Details

For each individual:

$$P(Y = 1|X^+) = R^b + \sum_i R_i^X$$

The below procedure is conducted for all individuals in a one by one fashion. The baseline risk, R^b, is simply parameterised in the model. The decomposition of the risk contributions for exposures, R^X_i, takes 3 steps:

Step 1 - Subtract the baseline risk, R^b:

$$R_k^X = P(Y = 1|X^+) - R^b$$

Step 2 - Decompose to the hidden layer:

$$R_j^X = \frac{H_j w_{j,k}}{\sum_j (H_j w_{j,k})} R_k^X$$

Where H_j is the value taken by each of the $ReLU()_j$ functions for the specific individual.

Step 3 - Hidden layer to exposures:

$$R_i^X = \sum_j \left(\frac{X_i^+ w_{i,j}}{\sum_i (X_i^+ w_{i,j})} R_j^X \right)$$

This creates a dataset with the dimensions equal to the number of individuals times the number of exposures plus a baseline risk value, which can be termed a risk contribution matrix. Instead of exposure values, individuals are given risk contributions, R^X_i.

Value

A data frame with the risk contribution matrix [number of individuals, risk contributors + the baseline risk].

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

CoOL_6_calibration_plot
Calibration curve

Description

Shows the calibration curve e.i. the predicted risk vs the actual risk by subgroups.

Usage

```
CoOL_6_calibration_plot(
  exposure_data,
  outcome_data,
  model,
  sub_groups,
  ipw = 1,
  restore_par_options = TRUE
)
```

Arguments

exposure_data	The exposure dataset.
outcome_data	The outcome vector.
model	The fitted non-negative neural network.
sub_groups	The vector with the assigned sub_group numbers.
ipw	a vector of weights per observation to allow for inverse probability of censoring weighting to correct for selection bias
restore_par_options	Restore par options.

Value

A calibration curve.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

CoOL_6_dendrogram *Dendrogram and sub-groups*

Description

Calculates presents a dendrogram coloured by the pre-defined number of sub-groups and provides the vector with sub-groups.

Usage

```
CoOL_6_dendrogram(
  risk_contributions,
  number_of_subgroups = 3,
  title = "Dendrogram",
  colours = NA,
  ipw = 1
)
```

Arguments

`risk_contributions`
: The risk contributions.

`number_of_subgroups`
: The number of sub-groups chosen (Visual inspection is necessary).

`title`
: The title of the plot.

`colours`
: Colours indicating each sub-group.

`ipw`
: a vector of weights per observation to allow for inverse probability of censoring weighting to correct for selection bias

Value

A dendrogram illustrating similarities between individuals based on their risk contributions.

Examples

```
#See the example under CoOL_0_working_example
```

`CoOL_6_individual_effects_matrix`

Risk contribution matrix based on individual effects (had all other exposures been set to zero)

Description

Estimating the risk contribution for each exposure if each individual had been exposed to only one exposure, with the value the individual actually had.

Usage

```
CoOL_6_individual_effects_matrix(X, model)
```

Arguments

`X`	The exposure data.
`model`	The fitted the non-negative neural network.

Value

A matrix [Number of individuals, exposures] with the estimated individual effects by each exposure had all other values been set to zero.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

`CoOL_6_number_of_sub_groups`

Number of subgroups

Description

Calculates the mean distance by several number of subgroups to determine the optimal number of subgroups.

Usage

```
CoOL_6_number_of_sub_groups(
  risk_contributions,
  low_number = 1,
  high_number = 5,
  ipw = 1,
  restore_par_options = TRUE
)
```

Arguments

`risk_contributions`
: The risk contributions.

`low_number`
: The lowest number of subgroups.

`high_number`
: The highest number of subgroups.

`ipw`
: a vector of weights per observation to allow for inverse probability of censoring weighting to correct for selection bias

`restore_par_options`
: Restore par options.

Value

A plot of the mean distance by the number of subgroups. The mean distance converges when the optimal number of subgroups are found.

Examples

```
#See the example under CoOL_0_working_example
```

`CoOL_6_sub_groups` *Assign sub-groups*

Description

Calculates presents a dendrogram coloured by the pre-defined number of sub-groups and provides the vector with sub-groups.

Usage

```
CoOL_6_sub_groups(risk_contributions, number_of_subgroups = 3, ipw = 1)
```

Arguments

`risk_contributions`
: The risk contributions.

`number_of_subgroups`
: The number of sub-groups chosen (Visual inspection is necessary).

`ipw`
: a vector of weights per observation to allow for inverse probability of censoring weighting to correct for selection bias

Value

A vector [number of individuals] with an assigned sub-group.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

CoOL_6_sum_of_individual_effects

Predict the risk based on the sum of individual effects

Description

By summing the through the risk as if each individual had been exposed to only one exposure, with the value the individual actually had.

Usage

```
CoOL_6_sum_of_individual_effects(X, model)
```

Arguments

`X`
: The exposure data.

`model`
: The fitted the non-negative neural network.

Value

A value the sum of indivisual effects, had there been no interactions between exposures.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

`CoOL_7_prevalence_and_mean_risk_plot`
Prevalence and mean risk plot

Description

This plot shows the prevalence and mean risk for each sub-group. Its distribution hits at sub-groups with great public health potential.

Usage

```
CoOL_7_prevalence_and_mean_risk_plot(
  risk_contributions,
  sub_groups,
  title = "Prevalence and mean risk\nof sub-groups",
  y_max = NA,
  restore_par_options = TRUE,
  colours = NA,
  ipw = 1
)
```

Arguments

`risk_contributions`
The risk contributions.

`sub_groups` The vector with the sub-groups.

`title` The title of the plot.

`y_max` Fix the axis of the risk of the outcome.

`restore_par_options`
Restore par options.

`colours` Colours indicating each sub-group.

`ipw` a vector of weights per observation to allow for inverse probability of censoring weighting to correct for selection bias

Value

A plot with prevalence and mean risks by sub-groups.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

CoOL_8_mean_risk_contributions_by_sub_group

Mean risk contributions by sub-groups

Description

Table with the mean risk contributions by sub-groups.

Usage

```
CoOL_8_mean_risk_contributions_by_sub_group(
  risk_contributions,
  sub_groups,
  exposure_data,
  outcome_data,
  model,
  exclude_below = 0.001,
  restore_par_options = TRUE,
  colours = NA,
  ipw = 1
)
```

Arguments

`risk_contributions`	The risk contributions.
`sub_groups`	The vector with the sub-groups.
`exposure_data`	The exposure data.
`outcome_data`	The outcome data.
`model`	The trained non-negative model.
`exclude_below`	A lower cut-off for which risk contributions shown.

restore_par_options
: Restore par options.

colours
: Colours indicating each sub-group.

ipw
: a vector of weights per observation to allow for inverse probability of censoring weighting to correct for selection bias

Value

A plot and a dataset with the mean risk contributions by sub-groups.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

CoOL_9_visualised_mean_risk_contributions

Visualisation of the mean risk contributions by sub-groups

Description

Visualisation of the mean risk contributions by sub-groups. The function uses the output

Usage

```
CoOL_9_visualised_mean_risk_contributions(
  results,
  sub_groups,
  ipw = 1,
  restore_par_options = TRUE
)
```

Arguments

results
: CoOL_8_mean_risk_contributions_by_sub_group.

sub_groups
: The vector with the sub-groups.

ipw
: a vector of weights per observation to allow for inverse probability of censoring weighting to correct for selection bias

restore_par_options
: Restore par options.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

CoOL_9_visualised_mean_risk_contributions_legend

Legend to the visualisation of the mean risk contributions by sub-groups

---

Description

Legend to the visualisation of the mean risk contributions by sub-groups. The function uses the output

Usage

```
CoOL_9_visualised_mean_risk_contributions_legend(
  results,
  restore_par_options = TRUE
)
```

Arguments

`results`	CoOL_8_mean_risk_contributions_by_sub_group.
`restore_par_options`	Restore par options.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
#See the example under CoOL_0_working_example
```

`CoOL_default` *The default analysis for computational phase of CoOL*

Description

The analysis and plots presented in the main paper. We recommend using View(CoOL_default) and View() on the many sub-functions to understand the steps and modify to your own research question. 3 sets of training will run with a learning rate of 1e-4 and a patience of 200 epochs, a learning rate of 1e-5 and a patience of 100 epochs, and a learning rate of 1e-6 and a patience of 50 epochs.

Usage

```
CoOL_default(
  data,
  sub_groups = 3,
  exclude_below = 0.01,
  input_parameter_reg = 0.001,
  hidden = 10,
  monitor = TRUE,
  epochs = 10000
)
```

Arguments

`data`	A data.frame(cbind(outcome_data,exposure_data)).
`sub_groups`	Define the number of expected sub-groups.
`exclude_below`	Risk contributions below this value are not shown in the table.
`input_parameter_reg`	The regularization of the input parameters.
`hidden`	The number of synergy-functions.
`monitor`	Whether monitoring plots will be shown in R.
`epochs`	The maximum number of epochs.

Value

A series of plots across the full Causes of Outcome Learning approach.

References

Rieckmann, Dworzynski, Arras, Lapuschkin, Samek, Arah, Rod, Ekstrom. 2022. Causes of outcome learning: A causal inference-inspired machine learning approach to disentangling common combinations of potential causes of a health outcome. International Journal of Epidemiology <https://doi.org/10.1093/ije/dyac078>

Examples

```
# Not run
while (FALSE) {
#See the example under CoOL_0_working_example for a more detailed tutorial
library(CoOL)
data <- CoOL_0_working_example(n=10000)
CoOL_default(data)
}
```

---

cpp_train_network_relu

Function used as part of other functions

Description

Non-negative neural network

Usage

```
cpp_train_network_relu(
  x,
  y,
  c,
  testx,
  testy,
  testc,
  W1_input,
  B1_input,
  W2_input,
  B2_input,
  C2_input,
  ipw,
  lr = 0.01,
  maxepochs = 100,
  input_parameter_reg = 1e-06,
  drop_out = 0L,
  fix_baseline_risk = -1
)
```

Arguments

x	A matrix of predictors for the training dataset of shape (nsamples, nfeatures)
y	A vector of output values for the training data with a length similar to the number of rows of x
c	A vector of the data to adjust the analysis for such as calendar time (training data) with the same number of rows as x.

testx	A matrix of predictors for the test dataset of shape (nsamples, nfeatures)
testy	A vector of output values for the test data with a length similar to the number of rows of x
testc	A vector the data to adjust the analysis for such as calendar time (training data) with the same number of rows as x.
W1_input	Input-hidden layer weights of shape (nfeatuers, hidden)
B1_input	Biases for the hidden layer of shape (1, hidden)
W2_input	Hidden-output layer weights of shape (hidden, 1)
B2_input	Bias for the output layer (the baseline risk) af shape (1, 1)
C2_input	Bias for the data to adjust the analysis for
ipw	a vector of weights per observation to allow for inverse probability of censoring weighting to correct for selection bias
lr	Initial learning rate
maxepochs	The maximum number of epochs
input_parameter_reg	Regularisation decreasing parameter value at each iteration for the input parameters
drop_out	To drop connections if their weights reaches zero.
fix_baseline_risk	To fix the baseline risk at a value.

Value

A list of class "SCL" giving the estimated matrices and performance indicators

Author(s)

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random *Function used as part of other functions*

Description

Function used as part of other functions

Usage

```
random(r, c)
```

Arguments

r	rows in matrix
c	columns in matrix

`rcpprelu` *Function used as part of other functions*

Description

relu-function

Usage

```
rcpprelu(x)
```

Arguments

`x`	input in the relu function

`rcpprelu_neg` *Function used as part of other functions*

Description

negative relu-function

Usage

```
rcpprelu_neg(x)
```

Arguments

`x`	input in the negative relu-function

`relu` *Function used as part of other functions*

Description

Function used as part of other functions

Usage

```
relu(input)
```

Arguments

`input`	input in the relu function

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