

Package ‘dosearch’

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Type Package

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Title Causal Effect Identification from Multiple Incomplete Data Sources

Description Identification of causal effects from arbitrary observational and experimental probability distributions via do-calculus and standard probability manipulations using a search-based algorithm.

Allows for the presence of mechanisms related to selection bias (Bareinboim, E. and Tian, J. (2015)

<http://ftp.cs.ucla.edu/pub/stat_ser/r445.pdf>), transportability (Bareinboim, E. and Pearl, J. (2014)

<http://ftp.cs.ucla.edu/pub/stat_ser/r443.pdf>), missing data (Mohan, K. and Pearl, J. and Tian., J. (2013) <http://ftp.cs.ucla.edu/pub/stat_ser/r410.pdf>) and arbitrary combinations of these.

License GPL (>= 2)

Imports Rcpp (>= 0.12.19)

LinkingTo Rcpp

SystemRequirements C++11

NeedsCompilation yes

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dosearch-package	<i>Causal Effect Identification from Multiple Incomplete Data Sources</i>
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Description

Solves causal effect identifiability problems from arbitrary observational and experimental data using a heuristic search. Allows for the presence of advanced data-generating mechanisms. See the Vignette for further details.

Author(s)

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References

- J. D. Angrist, G. W. Imbens, and D. B. Rubin. Identification of causal effects using instrumental variables. *Journal of the American Statistical Association*, 91(434):444–455, 1996.
- E. Bareinboim and J. Pearl. Controlling selection bias in causal inference. In *Proceedings of the 15th International Conference on Artificial Intelligence and Statistics*, 22:100–108, 2012a.
- E. Bareinboim and J. Pearl. Causal inference by surrogate experiments: z-identifiability. In *Proceedings of the 28th Conference on Uncertainty in Artificial Intelligence*, 113–120, 2012b.
- E. Bareinboim and J. Pearl. A general algorithm for deciding transportability of experimental results. *Journal of Causal Inference*, 1:107–134, 2013.
- E. Bareinboim and J. Pearl. Transportability from multiple environments with limited experiments: Completeness results. In *Proceedings of the 27th Annual Conference on Neural Information Processing Systems*, 280–288, 2014.
- E. Bareinboim and J. Tian. Recovering causal effects from selection bias. In *Proceedings of the 29th AAAI Conference on Artificial Intelligence*, 3475–3481, 2015.
- E. Bareinboim, J. Tian, and J. Pearl. Recovering from selection bias in causal and statistical inference. In *Proceedings of the 28th AAAI Conference on Neural Information Processing Systems*, 2014.
- N. E. Breslow. Statistics in epidemiology: The case-control study. *Journal of the American Statistical Association*, 91(433):14–28, 1996.
- B. Chen, D. Kumor, and E. Bareinboim. Identification and model testing in linear structural equation models using auxiliary variables. In *Proceedings of the 34th International Conference on Machine Learning*, 70:757–766, 2017.
- J. Correa and E. Bareinboim. Causal effect identification by adjustment under confounding and selection biases. In *Proceedings of the 31st AAAI Conference on Artificial Intelligence*, 2017.

- J. Correa, J. Tian, and E. Bareinboim. Generalized adjustment under confounding and selection biases. In *Proceedings of the 32nd AAAI Conference on Artificial Intelligence*, 2018.
- D. Danks, C. Glymour, and R. E. Tillman. Integrating locally learned causal structures with overlapping variables. In *Advances in Neural Information Processing Systems*, 1665–1672, 2009.
- A. P. Dawid. Influence diagrams for causal modelling and inference. *International Statistical Review*, 70(2):161–189, 2002.
- D. Entner, P. Hoyer, and P. Spirtes. Data-driven covariate selection for nonparametric estimation of causal effects. In *Proceedings of the 16th International Conference on Artificial Intelligence and Statistics*, 31:256–264, 2013.
- S. Greenland, J. M. Robins, and J. Pearl. Confounding and collapsibility in causal inference. *Statistical Science*, 14(1):29–46, 1999.
- Y. Huang and M. Valtorta. Pearl’s calculus of intervention is complete. In *Proceedings of the 22nd Conference on Uncertainty in Artificial Intelligence*, 217–224, 2006.
- A. Hyttinen, F. Eberhardt, and P. O. Hoyer. Causal discovery of linear cyclic models from multiple experimental data sets with overlapping variables. In *Proceedings of the 28th Conference on Uncertainty in Artificial Intelligence*, 387–396, 2012.
- A. Hyttinen, F. Eberhardt, and M. Jarvisalo. Do-calculus when the true graph is unknown. In *Proceedings of the 31st Conference on Uncertainty in Artificial Intelligence*, 395–404, 2015.
- A. Jaber, J. Zhang, and E. Bareinboim. Causal identification under Markov equivalence. In *Proceedings of the 34th Conference on Uncertainty in Artificial Intelligence*, 978–987, 2018.
- J. Karvanen. Study design in causal models. *Scandinavian Journal of Statistics*, 42(2):361–377, 2015.
- D. Koller and N. Friedman. *Probabilistic Graphical Models: Principles and Techniques*, 2009.
- S. L. Lauritzen. Causal inference from graphical models. In *Complex Stochastic Systems*, 67–107, 2000.
- R. J. A. Little and D. B. Rubin. *Statistical Analysis with Missing Data*, 1986.
- M. H. Maathuis, M. Kalisch, and P. Buhlmann. Estimating high-dimensional intervention effects from observational data. *The Annals of Statistics*, 37(6A):3133–3164, 2009.
- D. Malinsky and P. Spirtes. Estimating bounds on causal effects in high-dimensional and possibly confounded systems. *International Journal of Approximate Reasoning*, 88:371–384, 2017.
- K. Mohan and J. Pearl. Graphical models for processing missing data. 2018. Forthcoming, <https://arxiv.org/abs/1801.03583>.
- K. Mohan, J. Pearl, and J. Tian. Graphical models for inference with missing data. In *Advances in Neural Information Systems*, 26:1277–1285, 2013.
- J. M. Pena and M. Bendtsen. Causal effect identification in acyclic directed mixed graphs and gated models. *International Journal of Approximate Reasoning*, 90:56–75, 2017.
- J. Pearl. Causal diagrams for empirical research. *Biometrika*, 82(4):669–688, 1995.
- J. Pearl. *Causality: Models, Reasoning, and Inference*, 2009.
- E. Perkovic, J. Textor, M. Kalisch, and M. Maathuis. A complete generalized adjustment criterion. In *Proceedings of the 31st Conference on Uncertainty in Artificial Intelligence*, 682–691, 2015.
- J. Peters, J. M. Mooij, D. Janzing, and B. Scholkopf. Causal discovery with continuous additive noise models. *Journal of Machine Learning Research*, 15:2009–2053, 2014.

- I. Shpitser and J. Pearl. Identification of joint interventional distributions in recursive semi-Markovian causal models. In *Proceedings of the 21st National Conference on Artificial Intelligence – Volume 2*, 1219–1226, 2006a.
- I. Shpitser and J. Pearl. Identification of conditional interventional distributions. In *Proceedings of the 22nd Conference on Uncertainty in Artificial Intelligence*, 437–444, 2006b.
- I. Shpitser and J. Pearl. Complete identification methods for the causal hierarchy. *Journal of Machine Learning Research*, 9:1941–1979, 2008.
- I. Shpitser, K. Mohan, and J. Pearl. Missing data as a causal and probabilistic problem. In *Proceedings of the 31st Conference on Uncertainty in Artificial Intelligence*, 802–811, 2015.
- P. Spirtes, C. Glymour, and R. Scheines. *Causation, Prediction, and Search*, 1993.
- S. Tikka and J. Karvanen. Identifying causal effects with the R package causaleffect. *Journal of Statistical Software*, 76(12):1–30, 2017a.
- S. Tikka and J. Karvanen. Simplifying probabilistic expressions in causal inference. *Journal of Machine Learning Research*, 18(36):1–30, 2017b.
- S. Tikka and J. Karvanen. Enhancing identification of causal effects by pruning. *Journal of Machine Learning Research*, 18(194):1–23, 2018a.
- S. Tikka and J. Karvanen. Surrogate outcomes and transportability. Submitted manuscript, <http://arxiv.org/abs/1806.07172>, 2018b.
- R. Tillman and P. Spirtes. Learning equivalence classes of acyclic models with latent and selection variables from multiple datasets with overlapping variables. In *Proceedings of the 14th International Conference on Artificial Intelligence and Statistics*, 3–15, 2011.
- S. Triantafillou and I. Tsamardinos. Constraint-based causal discovery from multiple interventions over overlapping variable sets. *Journal of Machine Learning Research*, 16:2147–2205, 2015.
- S. Triantafillou, I. Tsamardinos, and I. Tollis. Learning causal structure from overlapping variable sets. In *Proceedings of the 13th International Conference on Artificial Intelligence and Statistics*, 860–867, 2010.
- B. van der Zander and M. Liskiewicz. On searching for generalized instrumental variables. In *Proceedings of the 19th International Conference on Artificial Intelligence and Statistics*, 2016.

bivariate_missingness *Systematic Analysis of Bivariate Missing Data Problems*

Description

This data set contains the results of a systematic analysis of all missing data problems of two variables. Each problem is associated with a graph containing two vertices, X and Y , and their response indicators, R_X and R_Y .

Usage

```
data(bivariate_missingness)
```

Format

A data frame with 6144 rows and 8 variables:

graph the graph of the instance, see [get_derivation](#) for more details on the syntax

nedges number of edges in the graph (directed and bidirected)

arrowXtoY whether the graph contains an arrow from X to Y or not

jointXY identifiability of the joint distribution of X and Y

marginX identifiability of the marginal distribution of X

marginY identifiability of the marginal distribution of Y

YcondX identifiability of the conditional distribution of Y given X

YdoX identifiability of the causal effect of X on Y

Source

See the Vignette, Section 5.1.

get_derivation	<i>Identify a causal effect from arbitrary experiments and observations</i>
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Description

Identify a causal query from available data in a causal model described by a semi-Markovian graph. Special mechanisms related to transportability of causal effects, recoverability from selection bias and identifiability under missing data can also be included in the model.

Usage

```
get_derivation(data, query, graph, transportability = NULL, selection_bias = NULL,
  missing_data = NULL, control = list())
```

Arguments

data	a character string describing the available distributions in the package syntax. See ‘Details’
query	a character string describing the target distribution in the package syntax. See ‘Details’
graph	a character string describing the graph in the package syntax. See ‘Details’
transportability	a character string describing the transportability nodes of the model in the package syntax. See ‘Details’
selection_bias	a character string describing the selection bias nodes of the model in the package syntax. See ‘Details’
missing_data	a character string describing the missing data mechanisms of the model in the package syntax. See ‘Details’
control	a list of control parameters. See ‘Details’.

Details

data is used to list the available input distributions of the form

$$P(A_i|do(B_i), C_i).$$

Individual variables within sets should be separated by a comma. For example, three input distributions

$$P(Z|do(X)), P(W, Y|do(Z, X)), P(W, Y, X|Z),$$

should be given as follows:

```
> data <- "
+ P(Z|do(X))
+ P(W, Y|do(Z, X))
+ P(W, Y, X|Z)
+"
```

The use of multiple do-operators is not permitted. Furthermore, when both conditioning variables and a do-operator are present, every conditioning variable must either precede the do-operator or follow it.

query is the target distribution of the search. It has the same syntax as data, but only a single distribution should be given.

graph is a description of a directed acyclic graph where directed edges are denoted by `->` and bidirected arcs corresponding to unobserved confounders are denoted by `--`. As an example a graph with two directed edges and one bidirected arc is constructed as follows:

```
> graph <- "
+ X -> Z
+ Z -> Y
+ X -- Y
+"
```

transportability enumerates the nodes that should be understood as transportability nodes responsible for discrepancies between domains. Individual variables should be separated by a comma. See e.g., Bareinboim and Pearl (2014) for details on transportability.

selection_bias enumerates the nodes that should be understood as selection bias nodes responsible for bias in the input data sets. Individual variables should be separated by a comma. See e.g., Bareinboim and Pearl (2014) for details on selection bias recoverability.

missing_data enumerates the missingness mechanisms of the model. The syntax for a single mechanism is $M_X : X$ where M_X is the mechanism for X . Individual mechanisms should be separated by a comma. Note that both M_X and X must be present in the graph if the corresponding mechanism is given as input. Proxy variables should not be included in the graph, since they are automatically generated based on missing_data. By default, a warning is issued if a proxy variable is present in an input distribution but its corresponding mechanism is not present in any input. See e.g., Mohan, Pearl and Tian (2013) for details on missing data as a causal inference problem.

The control argument is a list that can supply any of the following components:

- benchmark** A logical value. If TRUE, the search time is recorded and returned (in milliseconds). Defaults to FALSE.
- draw_derivation** A logical value. If TRUE, a string representing the derivation steps as a DOT graph is returned. The graph can be exported as an image for example by using [dot](#). Defaults to FALSE.
- draw_all** A logical value. If TRUE and if `draw_derivation = TRUE`, the derivation will contain every step taken by the search. If FALSE, only steps that resulted in an identifiable target are returned. Defaults to FALSE.
- formula** A logical value. If TRUE, a string representing the identifiable query is returned. If FALSE, only a logical value is returned that takes the value TRUE for an identifiable target and FALSE otherwise. Defaults to TRUE.
- heuristic** A logical value. If TRUE, new distributions are expanded according to a search heuristic (see the vignette for details). Otherwise, distributions are expanded in the order in which they were identified. Defaults to TRUE unless missing data mechanisms are provided in `missing_data`.
- improve** A logical value. If TRUE, various improvements are applied to the search to make it more efficient (see the vignette for details). Defaults to TRUE.
- md_sym** A single character describing the symbol to use for active missing data mechanisms. Defaults to "1".
- replace** A logical value. If TRUE, the search will continue deriving new distributions after the target has been reached in order to possibly find a shorter search path. Defaults to FALSE.
- rules** A numeric vector describing a subset of the search rules to be used. Must be a subset of `c(-1, -2, -3, 1, 2, 3, 4, 5, -6, 6, -7, 7, 8, 9)` (see the vignette for details).
- verbose** A logical value. If TRUE, diagnostic information is printed to the console during the search. Defaults to FALSE.
- warn** A logical value. If TRUE, a warning is issued for possibly unintentionally misspecified but syntactically correct input distributions.

Value

A list with the following components by default. See the options of `control` for how to obtain a graphical representation of the derivation or how to benchmark the search.

identifiable A logical value that attains the value TRUE if the target quantity is identifiable and FALSE otherwise.

formula A character string describing a formula for an identifiable query or an empty character vector for an unidentifiable effect.

Author(s)

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Examples

```
# Multiple input distributions (both observational and interventional)
```

```

data1 <- "
  p(z_2,x_2|do(x_1))
  p(z_1|x_2,do(x_1,y))
  p(x_1|w_1,do(x_2))
  p(y|z_1,z_2,x_1,do(x_2))
  p(w|y,x_1,do(x_2))
"

query1 <- "p(y,x_1|w,do(x_2))"

graph1 <- "
  x_1 -> z_2
  x_1 -> z_1
  x_2 -> z_1
  x_2 -> z_2
  z_1 -> y
  z_2 -> y
  x_1 -> w
  x_2 -> w
  z_1 -> w
  z_2 -> w
"

get_derivation(data1, query1, graph1)

# Selection bias

data2 <- "
  p(x,y,z_1,z_2|s)
  p(z_1,z_2)
"

query2 <- "p(y|do(x))"

graph2 <- "
  x -> z_1
  z_1 -> z_2
  x -> y
  y -- z_2
  z_2 -> s
"

get_derivation(data2, query2, graph2, selection_bias = "s")

# Transportability

data3 <- "
  p(x,y,z_1,z_2)
  p(x,y,z_1|s_1,s_2,do(z_2))
  p(x,y,z_2|s_3,do(z_1))
"

query3 <- "p(y|do(x))"

```



```
graph3 <- "  
  z_1 -> x  
  x   -> z_2  
  z_2 -> y  
  z_1 -- x  
  z_1 -- z_2  
  z_1 -- y  
  t_1 -> z_1  
  t_2 -> z_2  
  t_3 -> y  
  "  
  
get_derivation(data3, query3, graph3, transportability = "t_1, t_2, t_3")  
  
# Missing data  
  
data4 <- "  
  p(x*,y*,z*,m_x,m_y,m_z)  
  "  
  
query4 <- "p(x,y,z)"  
  
graph4 <- "  
  z -> x  
  x -> y  
  x -> m_z  
  y -> m_z  
  y -> m_x  
  z -- y  
  "  
  
get_derivation(data4, query4, graph4, missing_data = "m_x : x, m_y : y, m_z : z")  
  
# Export the DOT diagram of the derivation as an SVG file  
# to the working directory via the DOT package  
# PostScript format is also supported  
  
## Not run:  
d <- get_derivation(data1, query1, graph1, control = list(draw_derivation = TRUE))  
DOT::dot(d$derivation, "derivation.svg")  
  
## End(Not run)
```

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