Package ‘multibias’

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Type Package

Title Simultaneous Multi-Bias Adjustment

Version 1.5.0

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Description Quantify the causal effect of a binary exposure on a binary outcome with adjustment for multiple biases. The functions can simultaneously adjust for any combination of uncontrolled confounding, exposure/outcome misclassification, and selection bias. The underlying method generalizes the concept of combining inverse probability of selection weighting with predictive value weighting. Simultaneous multi-bias analysis can be used to enhance the validity and transparency of real-world evidence obtained from observational, longitudinal studies. Based on the work from Paul Brendel, Aracelis Torres, and Onyebuchi Arah (2023) <doi:10.1093/ije/dyad001>.

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LazyData true

Depends R (>= 2.10)

Imports dplyr (>= 1.1.3), magrittr (>= 2.0.3), rlang (>= 1.1.1)

Suggests knitr, rmarkdown, testthat (>= 3.0.0)

URL https://github.com/pcbrendel/multibias

BugReports https://github.com/pcbrendel/multibias/issues

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Description

adjust_emc returns the exposure-outcome odds ratio and confidence interval, adjusted for exposure misclassification.

Usage

```r
adjust_emc(
  data,
  exposure,
  outcome,
  confounders = NULL,
  x_model_coefs,
  level = 0.95
)
```

Arguments

- **data**  
  Dataframe for analysis.
- **exposure**  
  String name of the exposure variable.
- **outcome**  
  String name of the outcome variable.
- **confounders**  
  String name(s) of the confounder(s). A maximum of three confounders are allowed.
- **x_model_coefs**  
  The regression coefficients corresponding to the model: 
  \[
  logit(P(X = 1)) = \delta_0 + \delta_1 X^* + \delta_2 Y + \delta_{2+j} C_j,
  \]
  where X represents the binary true exposure, \(X^*\) is the binary misclassified exposure, Y is the binary outcome, C represents the vector of binary measured confounders (if any), and j corresponds to the number of measured confounders. The number of parameters is therefore 3 + j.
- **level**  
  Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).
adjust_emc_omc

Examples

```r
adjust_emc(
  evans,
  exposure = "SMK",
  outcome = "CHD",
  confounders = "HPT",
  x_model_coefs = c(qlogis(0.01), log(6), log(2), log(2))
)
```

Description

`adjust_emc_omc` returns the exposure-outcome odds ratio and confidence interval, adjusted for exposure misclassification and outcome misclassification.

Usage

```r
adjust_emc_omc(
  data,
  exposure,
  outcome,
  confounders = NULL,
  x_model_coefs,
  y_model_coefs,
  level = 0.95
)
```

Arguments

data  Dataframe for analysis.
exposure  String name of the exposure variable.
outcome  String name of the outcome variable.
confounders  String name(s) of the confounder(s). A maximum of three confounders are allowed.
x_model_coefs  The regression coefficients corresponding to the model: \( \logit(P(X = 1)) = \delta_0 + \delta_1 X^* + \delta_2 Y^* + \delta_2 + jC_j \), where \( X \) represents the binary true exposure, \( X^* \) is the binary misclassified exposure, \( Y^* \) is the binary misclassified outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders. The number of parameters is therefore 3 + j.
The regression coefficients corresponding to the model: $\logit(P(Y = 1)) = \beta_0 + \beta_1 X + \beta_2 Y* + \beta_3 + jC_j$, where $Y$ represents the binary true exposure, $X$ is the binary exposure, $Y$ is the binary misclassified outcome, $C$ represents the vector of binary measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters is therefore $3 + j$.

**Details**

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

**Value**

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

**Examples**

```r
adjust_emc_omc(
  df_emc_omc,
  exposure = "Xstar",
  outcome = "Ystar",
  confounders = "C1",
  x_model_coefs = c(-2.15, 1.64, 0.35, 0.38),
  y_model_coefs = c(-3.10, 0.63, 1.60, 0.39)
)
```

**Description**

`adjust_emc_sel` returns the exposure-outcome odds ratio and confidence interval, adjusted for exposure misclassification and selection bias.

**Usage**

```r
adjust_emc_sel(
  data,
  exposure,
  outcome,
```

---

**Adjust for exposure misclassification and selection bias.**

- Description:
  - `adjust_emc_sel` returns the exposure-outcome odds ratio and confidence interval, adjusted for exposure misclassification and selection bias.

- Usage:
  - `adjust_emc_sel(data, exposure, outcome, y_model_coefs, x_model_coefs, level = 0.95)`
confounders = NULL,
x_model_coefs,
s_model_coefs,
level = 0.95
)

Arguments

- **data**
  - Dataframe for analysis.

- **exposure**
  - String name of the exposure variable.

- **outcome**
  - String name of the outcome variable.

- **confounders**
  - String name(s) of the confounder(s). A maximum of three confounders are allowed.

- **x_model_coefs**
  - The regression coefficients corresponding to the model: 
    \[
    \logit(P(X = 1)) = \delta_0 + \delta_1 X^* + \delta_2 Y + \delta_2 + jC_j,
    \]
    where \(X\) represents the binary true exposure, \(X^*\) is the binary misclassified exposure, \(Y\) is the binary outcome, \(C\) represents the vector of binary measured confounders (if any), and \(j\) corresponds to the number of measured confounders. The number of parameters is therefore \(3 + j\).

- **s_model_coefs**
  - The regression coefficients corresponding to the model: 
    \[
    \logit(P(S = 1)) = \beta_0 + \beta_1 X^* + \beta_2 Y + \beta_2 + jC_j,
    \]
    where \(S\) represents binary selection, \(X^*\) is the binary misclassified exposure, \(Y\) is the binary outcome, \(C\) represents the vector of binary measured confounders (if any), and \(j\) corresponds to the number of measured confounders. The number of parameters is therefore \(3 + j\).

- **level**
  - Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: \(rnorm(1, mean = 2, sd = 1)\)). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples

```r
adjust_emc_sel(
  df_emc_sel,
  exposure = "Xstar",
  outcome = "Y",
  confounders = "C1",
  x_model_coefs = c(-2.78, 1.62, 0.58, 0.34),
```

Description

adjust_multinom_emc_omc returns the exposure-outcome odds ratio and confidence interval, adjusted for exposure misclassification and outcome misclassification.

Usage

adjust_multinom_emc_omc(
  data,
  exposure,
  outcome,
  confounders = NULL,
  x1y0_model_coefs,
  x0y1_model_coefs,
  x1y1_model_coefs,
  level = 0.95
)

Arguments

data Dataframe for analysis.

exposure String name of the exposure variable.

outcome String name of the outcome variable.

confounders String name(s) of the confounder(s). A maximum of three confounders are allowed.

x1y0_model_coefs The regression coefficients corresponding to the model: \( \log(P(X = 1, Y = 0)/P(X = 0, Y = 0)) = \gamma_{1,0} + \gamma_{1,1}X^* + \gamma_{1,2}Y^* + \gamma_{1,2+j}C_j \), where X is the binary true exposure, Y is the binary true outcome, X* is the binary misclassified exposure, Y* is the binary misclassified outcome, C represents the vector of binary measured confounders (if any), and j corresponds to the number of measured confounders.

x0y1_model_coefs The regression coefficients corresponding to the model: \( \log(P(X = 0, U = 1)/P(X = 0, U = 0)) = \gamma_{2,0} + \gamma_{2,1}X^* + \gamma_{2,2}Y^* + \gamma_{2,2+j}C_j \), where X is the binary true exposure, Y is the binary true outcome, X* is the binary misclassified exposure, Y* is the binary misclassified outcome, C represents the vector of binary measured confounders (if any), and j corresponds to the number of measured confounders.
The regression coefficients corresponding to the model: 
$log(P(X = 1, Y = 1)/P(X = 0, Y = 0)) = \gamma_{3,0} + \gamma_{3,1}X^* + \gamma_{3,2}Y^* + \gamma_{3,2+j}C_j$, where X is the binary true exposure, Y is the binary true outcome, $X^*$ is the binary misclassified exposure, $Y^*$ is the binary misclassified outcome, C represents the vector of binary measured confounders (if any), and j corresponds to the number of measured confounders.

level Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

Details

This function uses one bias model, a multinomial logistic regression model, to predict the exposure (X) and outcome (Y). If separate bias models for X and Y are desired, use `adjust_emc_omc`.

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples

```r
adjust_multinom_emc_omc(
  df_emc_omc,
  exposure = "Xstar",
  outcome = "Ystar",
  confounders = c("C1", "C2", "C3"),
  x1y0_model_coefs = c(-2.86, 1.63, 0.23, 0.37, -0.22, 0.87),
  x0y1_model_coefs = c(-3.26, 0.22, 1.60, 0.41, -0.93, 0.28),
  x1y1_model_coefs = c(-5.62, 1.83, 1.83, 0.74, -1.15, 1.19)
)
```

---

**adjust_multinom_uc_emc**

Adjust for uncontrolled confounding and exposure misclassification.

Description

`adjust_multinom_uc_emc` returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding and exposure misclassification.
adjust_multinom_uc_emc

Usage

adjust_multinom_uc_emc(
  data,
  exposure,
  outcome,
  confounders = NULL,
  x1u0_model_coefs,
  x0u1_model_coefs,
  x1u1_model_coefs,
  level = 0.95
)

Arguments

data Dataframe for analysis.
exposure String name of the exposure variable.
outcome String name of the outcome variable.
confounders String name(s) of the confounder(s). A maximum of three confounders are allowed.
x1u0_model_coefs The regression coefficients corresponding to the model: \[ \log(P(X = 1, U = 0)/P(X = 0, U = 0)) = \gamma_{1,0} + \gamma_{1,1}X^* + \gamma_{1,2}Y + \gamma_{1,2+j}C_j, \]
where X is the binary true exposure, U is the binary unmeasured confounder, X* is the binary misclassified exposure, Y is the binary outcome, C represents the vector of binary measured confounders (if any), and j corresponds to the number of measured confounders.
x0u1_model_coefs The regression coefficients corresponding to the model: \[ \log(P(X = 0, U = 1)/P(X = 0, U = 0)) = \gamma_{2,0} + \gamma_{2,1}X^* + \gamma_{2,2}Y + \gamma_{2,2+j}C_j, \]
where X is the binary true exposure, U is the binary unmeasured confounder, X* is the binary misclassified exposure, Y is the binary outcome, C represents the vector of binary measured confounders (if any), and j corresponds to the number of measured confounders.
x1u1_model_coefs The regression coefficients corresponding to the model: \[ \log(P(X = 1, U = 1)/P(X = 0, U = 0)) = \gamma_{3,0} + \gamma_{3,1}X^* + \gamma_{3,2}Y + \gamma_{3,2+j}C_j, \]
where X is the binary true exposure, U is the binary unmeasured confounder, X* is the binary misclassified exposure, Y is the binary outcome, C represents the vector of binary measured confounders (if any), and j corresponds to the number of measured confounders.
level Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

Details

This function uses one bias model, a multinomial logistic regression model, to predict the uncontrolled confounder (U) and exposure (X). If separate bias models for X and U are desired, use adjust_uc_emc.
Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

**Value**

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

**Examples**

```r
adjust_multinom_uc_emc(
  df_uc_emc,
  exposure = "Xstar",
  outcome = "y",
  confounders = "C1",
  x1u0_model_coefs = c(-2.82, 1.62, 0.68, -0.06),
  x0u1_model_coefs = c(-0.20, 0.00, 0.68, -0.05),
  x1u1_model_coefs = c(-2.36, 1.62, 1.29, 0.27)
)
```

---

`adjust_multinom_uc_emc_sel`  
*Adjust for uncontrolled confounding, exposure misclassification, and selection bias.*

**Description**

`adjust_multinom_uc_emc_sel` returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding, exposure misclassification, and selection bias.

**Usage**

```r
adjust_multinom_uc_emc_sel(
  data,
  exposure,
  outcome,
  confounders = NULL,
  x1u0_model_coefs,
  x0u1_model_coefs,
  x1u1_model_coefs,
  s_model_coefs,
  level = 0.95
)
```
Arguments

- **data**: Dataframe for analysis.
- **exposure**: String name of the exposure variable.
- **outcome**: String name of the outcome variable.
- **confounders**: String name(s) of the confounder(s). A maximum of three confounders are allowed.

**x1u0_model_coefs**

The regression coefficients corresponding to the model: \( \log(P(X = 1, U = 0)/P(X = 0, U = 0)) = \gamma_{1,0} + \gamma_{1,1}X^* + \gamma_{1,2}Y + \gamma_{1,2+j}C_j \), where \( X \) is the binary true exposure, \( U \) is the binary unmeasured confounder, \( X^* \) is the binary misclassified exposure, \( Y \) is the binary outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders.

**x0ul_model_coefs**

The regression coefficients corresponding to the model: \( \log(P(X = 0, U = 1)/P(X = 0, U = 0)) = \gamma_{2,0} + \gamma_{2,1}X^* + \gamma_{2,2}Y + \gamma_{2,2+j}C_j \), where \( X \) is the binary true exposure, \( U \) is the binary unmeasured confounder, \( X^* \) is the binary misclassified exposure, \( Y \) is the binary outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders.

**x1ul_model_coefs**

The regression coefficients corresponding to the model: \( \log(P(X = 1, U = 1)/P(X = 0, U = 0)) = \gamma_{3,0} + \gamma_{3,1}X^* + \gamma_{3,2}Y + \gamma_{3,2+j}C_j \), where \( X \) is the binary true exposure, \( U \) is the binary unmeasured confounder, \( X^* \) is the binary misclassified exposure, \( Y \) is the binary outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders.

**s_model_coefs**

The regression coefficients corresponding to the model: \( \logit(P(S = 1)) = \beta_0 + \beta_1X^* + \beta_2Y + \beta_{2+j}C_j \), where \( S \) represents binary selection, \( X^* \) is the binary misclassified exposure, \( Y \) is the binary outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders.

**level**: Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

Details

This function uses one bias model, a multinomial logistic regression model, to predict the uncontrolled confounder (U) and exposure (X). If separate bias models for X and U are desired, use `adjust_uc_emc_sel`.

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (e.g., `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.
adjust_multinom_uc_omc

Value
A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples
adjust_multinom_uc_emc_sel(
  df_uc_emc_sel,
  exposure = "Xstar",
  outcome = "y",
  confounders = c("C1", "C2", "C3"),
  x1u0_model_coefs = c(-2.78, 1.62, 0.61, 0.36, -0.27, 0.88),
  x0u1_model_coefs = c(-0.17, -0.01, 0.71, -0.08, 0.07, -0.15),
  x1u1_model_coefs = c(-2.36, 1.62, 1.29, 0.25, -0.06, 0.74),
  s_model_coefs = c(0.00, 0.26, 0.78, 0.03, -0.02, 0.10)
)

Adjust for uncontrolled confounding and outcome misclassification.

Description
adjust_multinom_uc_omc returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding and outcome misclassification.

Usage
adjust_multinom_uc_omc(
  data,
  exposure,
  outcome,
  confounders = NULL,
  u1y0_model_coefs,
  u0y1_model_coefs,
  u1y1_model_coefs,
  level = 0.95
)

Arguments
data Dataframe for analysis.
exposure String name of the exposure variable.
outcome String name of the outcome variable.
confounders String name(s) of the confounder(s). A maximum of three confounders are allowed.
The regression coefficients corresponding to the model: \( \log(P(U = 1, Y = 1)/P(U = 0, Y = 0)) = \gamma_{1,0} + \gamma_{1,1}X + \gamma_{1,2}Y^* + \gamma_{1,2+j}C_j \), where \( U \) is the binary unmeasured confounder, \( Y \) is the binary true outcome, \( X \) is the binary exposure, \( Y^* \) is the binary misclassified outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders.

The regression coefficients corresponding to the model: \( \log(P(U = 0, Y = 1)/P(U = 0, Y = 0)) = \gamma_{2,0} + \gamma_{2,1}X + \gamma_{2,2}Y^* + \gamma_{2,2+j}C_j \), where \( U \) is the binary unmeasured confounder, \( Y \) is the binary true outcome, \( X \) is the binary exposure, \( Y^* \) is the binary misclassified outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders.

The regression coefficients corresponding to the model: \( \log(P(U = 1, Y = 1)/P(U = 0, Y = 0)) = \gamma_{3,0} + \gamma_{3,1}X + \gamma_{3,2}Y^* + \gamma_{3,2+j}C_j \), where \( U \) is the binary unmeasured confounder, \( Y \) is the binary true outcome, \( X \) is the binary exposure, \( Y^* \) is the binary misclassified outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders.

Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

Details

This function uses one bias model, a multinomial logistic regression model, to predict the uncontrolled confounder (\( U \)) and outcome (\( Y \)). If separate bias models for \( X \) and \( U \) are desired, use adjust_uc_omc.

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: \( \text{rnorm}(1, \text{mean} = 2, \text{sd} = 1) \)). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples

adjust_multinom_uc_omc(
    df_uc_omc,
    "X",
    "Ystar",
    "C1",
    uly0_model_coefs = c(-0.19, 0.61, 0.00, -0.07),
    uly1_model_coefs = c(-0.19, 0.61, 0.00, -0.07),
    u0y1_model_coefs = c(-0.19, 0.61, 0.00, -0.07),
    level = 0.95)
adjust_multinom_uc_omc_sel

Adjust for uncontrolled confounding, outcome misclassification, and selection bias.

Description

adjust_multinom_uc_omc_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding, outcome misclassification, and selection bias.

Usage

adjust_multinom_uc_omc_sel(
  data,
  exposure,
  outcome,
  confounders = NULL,
  u0y1_model_coefs,
  u1y0_model_coefs,
  u1y1_model_coefs,
  s_model_coefs,
  level = 0.95
)

Arguments

data
  Dataframe for analysis.

exposure
  String name of the exposure variable.

outcome
  String name of the outcome variable.

confounders
  String name(s) of the confounder(s). A maximum of three confounders are allowed.

u0y1_model_coefs
  The regression coefficients corresponding to the model: \( \log(P(U = 0, Y = 1)/P(U = 0, Y = 0)) = \gamma_{2,0} + \gamma_{2,1}X + \gamma_{2,2}Y^* + \gamma_{2,2+j}C_j \), where \( U \) is the binary unmeasured confounder, \( Y \) is the binary true outcome, \( X \) is the binary exposure, \( Y^* \) is the binary misclassified outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders.

u1y0_model_coefs
  The regression coefficients corresponding to the model: \( \log(P(U = 1, Y = 0)/P(U = 0, Y = 0)) = \gamma_{1,0} + \gamma_{1,1}X + \gamma_{1,2}Y^* + \gamma_{1,2+j}C_j \), where \( U \) is
the binary unmeasured confounder, Y is the binary true outcome, X is the bi-
nary exposure, Y* is the binary misclassified outcome, C represents the vector
of binary measured confounders (if any), and j corresponds to the number of
measured confounders.

\( u1y1_model_coefs \)

The regression coefficients corresponding to the model: 
\[ \log\left( \frac{P(U = 1, Y = 1)}{P(U = 0, Y = 0)} \right) = \gamma_{3,0} + \gamma_{3,1}X + \gamma_{3,2}Y* + \gamma_{3,2+j}C_j \], 
where U is the binary unmeasured confounder, Y is the binary true outcome, X is the bi-
nary exposure, Y* is the binary misclassified outcome, C represents the vector
of binary measured confounders (if any), and j corresponds to the number of
measured confounders.

\( s_model_coefs \)

The regression coefficients corresponding to the model: 
\[ \logit(P(S = 1)) = \beta_0 + \beta_1X + \beta_2Y* + \beta_{2+j}C_j \], 
where S represents binary selection, X is the binary exposure, Y* is the binary misclassified outcome, C represents the vector
of binary measured confounders (if any), and j corresponds to the number of
measured confounders.

\( level \)

Value from 0-1 representing the full range of the confidence interval. Default is
0.95.

Details

This function uses one bias model, a multinomial logistic regression model, to predict the uncontrol-
ted confounder (U) and outcome (Y). If separate bias models for U and Y are desired, use
\texttt{adjust_uc_omc_sel}.

Values for the regression coefficients can be applied as fixed values or as single draws from a prob-
ability distribution (ex: \texttt{rnorm(1, mean = 2, sd = 1)}). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty
in the estimate and confidence interval, this function should be run in loop across bootstrap samples
of the dataframe for analysis. The estimate and confidence interval would then be obtained from
the median and quantiles of the distribution of odds ratio estimates.

Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and
the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples

\begin{verbatim}
adjust_multinom_uc_omc_sel(
  df_uc_omc_sel, 
  exposure = "X", 
  outcome = "Ystar", 
  confounders = c("C1", "C2", "C3"),
  u1y0_model_coefs = c(-0.20, 0.62, 0.01, -0.08, 0.10, -0.15),
  u0y1_model_coefs = c(-3.28, 0.63, 1.65, 0.42, -0.85, 0.26),
  u1y1_model_coefs = c(-2.70, 1.22, 1.64, 0.32, -0.77, 0.09),
  s_model_coefs = c(0.00, 0.74, 0.19, 0.02, -0.06, 0.02)
)
\end{verbatim}
adjust_omc returns the exposure-outcome odds ratio and confidence interval, adjusted for outcome misclassification.

**Usage**

```r
adjust_omc(
  data,
  exposure,
  outcome,
  confounders = NULL,
  y_model_coefs,
  level = 0.95
)
```

**Arguments**

- **data**: Dataframe for analysis.
- **exposure**: String name of the exposure variable.
- **outcome**: String name of the outcome variable.
- **confounders**: String name(s) of the confounder(s). A maximum of three confounders are allowed.
- **y_model_coefs**: The regression coefficients corresponding to the model: \( \logit(P(Y = 1)) = \delta_0 + \delta_1 X + \delta_2 Y^* + \delta_2 + j C_j \), where Y represents the binary true outcome, X is the binary exposure, Y* is the binary misclassified outcome, C represents the vector of binary measured confounders (if any), and j corresponds to the number of measured confounders. The number of parameters is therefore \( 3 + j \).
- **level**: Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

**Details**

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.
adjust_omc_sel

Value
A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples
adjust_omc(
  evans,
  exposure = "SMK",
  outcome = "CHD",
  confounders = "HPT",
  y_model_coefs = c(qlogis(0.01), log(1.5), log(5), log(1.5))
)

adjust_omc_sel
Adjust for outcome misclassification and selection bias.

Description
adjust_omc_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for outcome misclassification and selection bias.

Usage
adjust_omc_sel(
  data,
  exposure,
  outcome,
  confounders = NULL,
  y_model_coefs,
  s_model_coefs,
  level = 0.95
)

Arguments
data          Dataframe for analysis.
exposure      String name of the exposure variable.
outcome       String name of the outcome variable.
confounders   String name(s) of the confounder(s). A maximum of three confounders are allowed.
y_model_coefs The regression coefficients corresponding to the model: \( \logit(P(Y = 1)) = \delta_0 + \delta_1 X + \delta_2 Y^* + \delta_{2+j} C_j \), where \( Y \) represents the binary true outcome, \( X \) is the binary exposure, \( Y^* \) is the binary misclassified outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders. The number of parameters is therefore \( 3 + j \).
The regression coefficients corresponding to the model: \( \logit(P(S = 1)) = \beta_0 + \beta_1 X + \beta_2 Y^* + \beta_{2+j} C_j \), where \( S \) represents binary selection, \( X \) is the binary exposure, \( Y^* \) is the binary misclassified outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders. The number of parameters is therefore \( 3 + j \).

**Details**

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (e.g., `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

**Value**

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

**Examples**

```r
adjust_omc_sel(
  df_omc_sel,
  exposure = "X",
  outcome = "Ystar",
  confounders = "C1",
  y_model_coefs = c(-3.24, 0.58, 1.59, 0.45),
  s_model_coefs = c(0.03, 0.92, 0.12, 0.05)
)
```

---

**Description**

`adjust_sel` returns the exposure-outcome odds ratio and confidence interval, adjusted for selection bias.

**Usage**

```r
adjust_sel(
  data,
  exposure,
  outcome,
  level = 0.95,
  s_model_coefs = c(0.03, 0.92, 0.12, 0.05),
  y_model_coefs = c(-3.24, 0.58, 1.59, 0.45)
)
```
Arguments

data
exposure
outcome
confounders
s_model_coefs
level

Details

Value

Examples
adjust_uc

Adjust for uncontrolled confounding.

Description

adjust_uc returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding.

Usage

adjust_uc(
  data, exposure, outcome, confounders = NULL, u_model_coefs, level = 0.95
)

Arguments

data Dataframe for analysis.
exposure String name of the exposure variable.
outcome String name of the outcome variable.
confounders String name(s) of the confounder(s). A maximum of three confounders are allowed.
u_model_coefs The regression coefficients corresponding to the model: \( \text{logit}(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y + \alpha_2 + j C_j \), where \( U \) is the (binary) unmeasured confounder, \( X \) is the (binary) exposure, \( Y \) is the (binary) outcome, \( C \) represents the vector of (binary) measured confounders (if any), and \( j \) corresponds to the number of measured confounders. The number of parameters therefore equals 3 + \( j \).
level Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: \( \text{rnorm}(1, \text{mean} = 2, \text{sd} = 1) \)). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).
Examples

```r
adjust_uc(
  evans,
  exposure = "SMK",
  outcome = "CHD",
  confounders = "HPT",
  u_model_coefs = c(qlogis(0.25), log(0.5), log(2.5), log(2)),
)
```

**Description**

`adjust_uc_emc` returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding and exposure misclassification.

**Usage**

```r
adjust_uc_emc(
  data,
  exposure,
  outcome,
  confounders = NULL,
  u_model_coefs,
  x_model_coefs,
  level = 0.95
)
```

**Arguments**

- **data**: Dataframe for analysis.
- **exposure**: String name of the exposure variable.
- **outcome**: String name of the outcome variable.
- **confounders**: String name(s) of the confounder(s). A maximum of three confounders are allowed.
- **u_model_coefs**: The regression coefficients corresponding to the model: \(\text{logit}(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y\), where \(U\) is the binary unmeasured confounder, \(X\) is the binary true exposure, \(Y\) is the binary outcome. The number of parameters therefore equals 3.
- **x_model_coefs**: The regression coefficients corresponding to the model: \(\text{logit}(P(X = 1)) = \delta_0 + \delta_1 X^* + \delta_2 Y + \delta_{2+j} C_j\), where \(X\) represents the binary true exposure, \(X^*\) is the binary misclassified exposure, \(Y\) is the binary outcome, \(C\) represents the vector of binary measured confounders (if any), and \(j\) corresponds to the number of measured confounders. The number of parameters therefore equals \(3 + j\).
- **level**: Value from 0-1 representing the full range of the confidence interval. Default is 0.95.
Details
This function uses two separate logistic regression models to predict the uncontrolled confounder (U) and exposure (X). If a single bias model for jointly modeling X and U is desired use adjust_multinom_uc_emc. Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: rnorm(1, mean = 2, sd = 1)). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

Value
A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples
adjust_uc_emc(
  df_uc_emc,
  exposure = "Xstar",
  outcome = "Y",
  confounders = "C1",
  u_model_coefs = c(-0.23, 0.63, 0.66),
  x_model_coefs = c(-2.47, 1.62, 0.73, 0.32)
)

adjust_uc_emc_sel
Adjust for uncontrolled confounding, exposure misclassification, and selection bias.

Description
adjust_uc_emc_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding, exposure misclassification, and selection bias.

Usage
adjust_uc_emc_sel(
  data,
  exposure,
  outcome,
  confounders = NULL,
  u_model_coefs,
  x_model_coefs,
  s_model_coefs,
  level = 0.95
)
Arguments

**data**
Dataframe for analysis.

**exposure**
String name of the exposure variable.

**outcome**
String name of the outcome variable.

**confounders**
String name(s) of the confounder(s). A maximum of three confounders are allowed.

**u_model_coefs**
The regression coefficients corresponding to the model: \( \logit(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y \), where \( U \) is the binary unmeasured confounder, \( X \) is the binary true exposure, and \( Y \) is the binary outcome. The number of parameters therefore equals 3.

**x_model_coefs**
The regression coefficients corresponding to the model: \( \logit(P(X = 1)) = \delta_0 + \delta_1 X^* + \delta_2 Y + \delta_{2+j} C_j \), where \( X \) represents binary true exposure, \( X^* \) is the binary misclassified exposure, \( Y \) is the binary outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders. The number of parameters therefore equals 3 + \( j \).

**s_model_coefs**
The regression coefficients corresponding to the model: \( \logit(P(S = 1)) = \beta_0 + \beta_1 X^* + \beta_2 Y + \beta_{2+j} C_j \), where \( S \) represents binary selection, \( X^* \) is the binary misclassified exposure, \( Y \) is the binary outcome, \( C \) represents the vector of binary measured confounders (if any), and \( j \) corresponds to the number of measured confounders. The number of parameters therefore equals 3 + \( j \).

**level**
Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

Details

This function uses two separate logistic regression models to predict the uncontrolled confounder (\( U \)) and exposure (\( X \)). If a single bias model for jointly modeling \( X \) and \( U \) is desired use `adjust_multinom_uc_emc_sel`.

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples

```r
adjust_uc_emc_sel(
  df_uc_emc_sel,
  exposure = "Xstar",
  outcome = "Y",
  confounders = c("C1", "C2", "C3"),
  u_model_coefs = c(-0.32, 0.59, 0.69),
```
adjust_uc_omc

```r
x_model_coefs = c(-2.44, 1.62, 0.72, 0.32, -0.15, 0.85),
s_model_coefs = c(0.00, 0.26, 0.78, 0.03, -0.02, 0.10)
```

---

**adjust_uc_omc**  
Ajust for uncontrolled confounding and outcome misclassification.

**Description**

`adjust_uc_omc` returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding and outcome misclassification.

**Usage**

```r
adjust_uc_omc(
  data,
  exposure,
  outcome,
  confounders = NULL,
  u_model_coefs,
  y_model_coefs,
  level = 0.95
)
```

**Arguments**

- `data`  
  Dataframe for analysis.

- `exposure`  
  String name of the exposure variable.

- `outcome`  
  String name of the outcome variable.

- `confounders`  
  String name(s) of the confounder(s). A maximum of three confounders are allowed.

- `u_model_coefs`  
  The regression coefficients corresponding to the model:  
  \[ \logit(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y, \]  
  where U is the binary unmeasured confounder, X is the binary true exposure, Y is the binary true outcome. The number of parameters therefore equals 3.

- `y_model_coefs`  
  The regression coefficients corresponding to the model:  
  \[ \logit(P(Y = 1)) = \delta_0 + \delta_1 X + \delta_2 Y^* + \delta_{2+j} C_j, \]  
  where Y represents binary true outcome, X is the binary exposure, Y* is the binary misclassified outcome, C represents the vector of binary measured confounders (if any), and j corresponds to the number of measured confounders. The number of parameters therefore equals 3 + j.

- `level`  
  Value from 0-1 representing the full range of the confidence interval. Default is 0.95.
Details

This function uses two separate logistic regression models to predict the uncontrolled confounder (U) and outcome (Y). If a single bias model for jointly modeling Y and U is desired use adjust_multinom_uc_omc.

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: rnorm(1, mean = 2, sd = 1)). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples

adjust_uc_omc(
  df_uc_omc,
  "X",
  "Ystar",
  "C1",
  u_model_coefs = c(-0.22, 0.61, 0.70),
  y_model_coefs = c(-2.85, 0.73, 1.60, 0.38)
)

Description

adjust_uc_omc_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding, outcome misclassification, and selection bias.

Usage

adjust_uc_omc_sel(
  data, exposure, outcome, confounders = NULL, u_model_coefs, y_model_coefs, s_model_coefs, level = 0.95
)
Arguments

**data** Dataframe for analysis.

**exposure** String name of the exposure variable.

**outcome** String name of the outcome variable.

**confounders** String name(s) of the confounder(s). A maximum of three confounders are allowed.

**u_model_coefs** The regression coefficients corresponding to the model: $\logit(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y$, where $U$ is the binary unmeasured confounder, $X$ is the binary exposure, and $Y$ is the binary true outcome. The number of parameters therefore equals 3.

**y_model_coefs** The regression coefficients corresponding to the model: $\logit(P(Y = 1)) = \delta_0 + \delta_1 X + \delta_2 Y^* + \delta_{2+j} C_j$, where $Y$ represents binary true outcome, $X$ is the binary exposure, $Y^*$ is the binary misclassified outcome, $C$ represents the vector of binary measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters therefore equals $3 + j$.

**s_model_coefs** The regression coefficients corresponding to the model: $\logit(P(S = 1)) = \beta_0 + \beta_1 X + \beta_2 Y^* + \beta_{2+j} C_j$, where $S$ represents binary selection, $X$ is the binary exposure, $Y^*$ is the binary misclassified outcome, $C$ represents the vector of binary measured confounders (if any), and $j$ corresponds to the number of measured confounders. The number of parameters therefore equals $3 + j$.

**level** Value from 0-1 representing the full range of the confidence interval. Default is 0.95.

Details

This function uses two separate logistic regression models to predict the uncontrolled confounder ($U$) and outcome ($Y$). If a single bias model for jointly modeling $Y$ and $U$ is desired use adjust_multinom_uc_omc_sel.

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (e.g., `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples

```r
adjust_uc_omc_sel(
  df_uc_omc_sel,
  exposure = "X",
  outcome = "Ystar",
  confounders = c("C1", "C2", "C3"),
  u_model_coefs = c(-0.32, 0.59, 0.69),
  y_model_coefs = c(-0.6, 0.8, 0.7),
  s_model_coefs = c(-0.5, 0.3, 0.7),
  level = 0.95)
```
adjust_uc_sel

\[
\begin{align*}
y\text{-model\_coefs} & = c(-2.85, 0.71, 1.63, 0.40, -0.85, 0.22), \\
s\text{-model\_coefs} & = c(0.00, 0.74, 0.19, 0.02, -0.06, 0.02)
\end{align*}
\]

Description

adjust_uc_sel returns the exposure-outcome odds ratio and confidence interval, adjusted for uncontrolled confounding and exposure misclassification.

Usage

\[
\text{adjust\_uc\_sel}( \\
data, \\
exposure, \\
oncome, \\
confounders = \text{NULL}, \\
u\text{-model\_coefs}, \\
s\text{-model\_coefs}, \\
level = 0.95)
\]

Arguments

data | Dataframe for analysis.
exposure | String name of the exposure variable.
oncome | String name of the outcome variable.
confounders | String name(s) of the confounder(s). A maximum of three confounders are allowed.
u\text{-model\_coefs} | The regression coefficients corresponding to the model: \( \text{logit}(P(U = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 Y + \alpha_2 + j C_j \), where U is the binary unmeasured confounder, X is the binary exposure, Y is the binary outcome, C represents the vector of binary measured confounders (if any), and j corresponds to the number of measured confounders. The number of parameters therefore equals \( 3 + j \).
s\text{-model\_coefs} | The regression coefficients corresponding to the model: \( \text{logit}(P(S = 1)) = \beta_0 + \beta_1 X + \beta_2 Y \), where S represents binary selection, X is the binary exposure, and Y is the binary outcome. The number of parameters therefore equals 3.
level | Value from 0-1 representing the full range of the confidence interval. Default is 0.95.
Details

Values for the regression coefficients can be applied as fixed values or as single draws from a probability distribution (ex: `rnorm(1, mean = 2, sd = 1)`). The latter has the advantage of allowing the researcher to capture the uncertainty in the bias parameter estimates. To incorporate this uncertainty in the estimate and confidence interval, this function should be run in loop across bootstrap samples of the dataframe for analysis. The estimate and confidence interval would then be obtained from the median and quantiles of the distribution of odds ratio estimates.

Value

A list where the first item is the odds ratio estimate of the effect of the exposure on the outcome and the second item is the confidence interval as the vector: (lower bound, upper bound).

Examples

```r
adjust_uc_sel(
  df_uc_sel,
  exposure = "X",
  outcome = "Y",
  confounders = c("C1", "C2", "C3"),
  u_model_coefs = c(-0.19, 0.61, 0.72, -0.09, 0.10, -0.15),
  s_model_coefs = c(-0.01, 0.92, 0.94)
)
```

Simulated data with exposure misclassification

Description

Data containing one source of bias, three known confounders, and 100,000 observations. This data is obtained from `df_emc_source` by removing the column `X`. The resulting data corresponds to what a researcher would see in the real-world: a misclassified exposure, `Xstar`, and no data on the true exposure. As seen in `df_emc_source`, the true, unbiased exposure-outcome odds ratio = 2.

Usage

`df_emc`

Format

A dataframe with 100,000 rows and 5 columns:

- **Xstar**: misclassified exposure, 1 = present and 0 = absent
- **Y**: outcome, 1 = present and 0 = absent
- **C1**: 1st confounder, 1 = present and 0 = absent
- **C2**: 2nd confounder, 1 = present and 0 = absent
- **C3**: 3rd confounder, 1 = present and 0 = absent
df_emc_omc

Simulated data with exposure misclassification and outcome misclassification

Description

Data containing two sources of bias, three known confounders, and 100,000 observations. This data is obtained from df_emc_omc_source by removing the columns X and Y. The resulting data corresponds to what a researcher would see in the real-world: a misclassified exposure, Xstar, and a misclassified outcome, Ystar. As seen in df_emc_omc_source, the true, unbiased exposure-outcome odds ratio = 2.

Usage

df_emc_omc

Format

A dataframe with 100,000 rows and 5 columns:

- **Xstar** misclassified exposure, 1 = present and 0 = absent
- **Ystar** misclassified outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **C2** 2nd confounder, 1 = present and 0 = absent
- **C3** 3rd confounder, 1 = present and 0 = absent

df_emc_omc_source

Data source for df_emc_omc

Description

Data with complete information on the two sources of bias, three known confounders, and 100,000 observations. This data is used to derive df_emc_omc and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df_emc_omc. With this source data, the fitted regression \( \logit(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3 \) shows that the true, unbiased exposure-outcome odds ratio = 2.

Usage

df_emc_omc_source
Format

A dataframe with 100,000 rows and 7 columns:

**X** true exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent

**Xstar** misclassified exposure, 1 = present and 0 = absent

**Ystar** misclassified outcome, 1 = present and 0 = absent

---

**df_emc_sel**

Simulated data with exposure misclassification and selection bias

Description

Data containing two sources of bias, three known confounders, and 100,000 observations. This data is obtained by sampling with replacement with probability = S from *df_emc_sel_source* then removing the columns X and S. The resulting data corresponds to what a researcher would see in the real-world: a misclassified exposure, Xstar, and missing data for those not selected into the study (S=0). As seen in *df_emc_sel_source*, the true, unbiased exposure-outcome odds ratio = 2.

Usage

*df_emc_sel*

Format

A dataframe with 100,000 rows and 5 columns:

**Xstar** misclassified exposure, 1 = present and 0 = absent

**Y** outcome, 1 = present and 0 = absent

**C1** 1st confounder, 1 = present and 0 = absent

**C2** 2nd confounder, 1 = present and 0 = absent

**C3** 3rd confounder, 1 = present and 0 = absent
df_emc_sel_source

Data source for df_emc_sel

Description

Data with complete information on the two sources of bias, three known confounders, and 100,000 observations. This data is used to derive df_emc_sel and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df_emc_sel. With this source data, the fitted regression $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3$ shows that the true, unbiased exposure-outcome odds ratio $= 2$.

Usage

df_emc_sel_source

Format

A dataframe with 100,000 rows and 7 columns:

- X true exposure, 1 = present and 0 = absent
- Y outcome, 1 = present and 0 = absent
- C1 1st confounder, 1 = present and 0 = absent
- C2 2nd confounder, 1 = present and 0 = absent
- C3 3rd confounder, 1 = present and 0 = absent
- Xstar misclassified exposure, 1 = present and 0 = absent
- S selection, 1 = selected into the study and 0 = not selected into the study

df_emc_source

Data source for df_emc

Description

Data with complete information on one source of bias, three known confounders, and 100,000 observations. This data is used to derive df_emc and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df_emc. With this source data, the fitted regression $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3$ shows that the true, unbiased exposure-outcome odds ratio $= 2$.

Usage

df_emc_source
Format

A dataframe with 100,000 rows and 6 columns:

- X  exposure, 1 = present and 0 = absent
- Y  true outcome, 1 = present and 0 = absent
- C1 1st confounder, 1 = present and 0 = absent
- C2 2nd confounder, 1 = present and 0 = absent
- C3 3rd confounder, 1 = present and 0 = absent
- Xstar misclassified exposure, 1 = present and 0 = absent

Description

Data containing one source of bias, three known confounders, and 100,000 observations. This data is obtained from df_omc_source by removing the column Y. The resulting data corresponds to what a researcher would see in the real-world: a misclassified outcome, Ystar, and no data on the true outcome. As seen in df_omc_source, the true, unbiased exposure-outcome odds ratio = 2.

Usage

df_omc

Format

A dataframe with 100,000 rows and 5 columns:

- X  exposure, 1 = present and 0 = absent
- Ystar misclassified outcome, 1 = present and 0 = absent
- C1 1st confounder, 1 = present and 0 = absent
- C2 2nd confounder, 1 = present and 0 = absent
- C3 3rd confounder, 1 = present and 0 = absent
### df_omc_sel

**Simulated data with outcome misclassification and selection bias**

**Description**

Data containing two sources of bias, a known confounder, and 100,000 observations. This data is obtained by sampling with replacement with probability = S from df_omc_sel_source then removing the columns Y and S. The resulting data corresponds to what a researcher would see in the real-world: a misclassified outcome, Ystar, and missing data for those not selected into the study (S=0). As seen in df_omc_sel_source, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df_omc_sel

**Format**

A dataframe with 100,000 rows and 3 columns:

- **X** exposure, 1 = present and 0 = absent
- **Ystar** misclassified outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent

### df_omc_sel_source

**Data source for df_omc_sel**

**Description**

Data with complete information on the two sources of bias, a known confounder, and 100,000 observations. This data is used to derive df_omc_sel and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df_omc_sel. With this source data, the fitted regression logit(P(Y = 1)) = α₀ + α₁X + α₂C1 shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

df_omc_sel_source

**Format**

A dataframe with 100,000 rows and 5 columns:

- **X** exposure, 1 = present and 0 = absent
- **Y** true outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **Ystar** misclassified outcome, 1 = present and 0 = absent
- **S** selection, 1 = selected into the study and 0 = not selected into the study
Description

Data with complete information on one sources of bias, three known confounders, and 100,000 observations. This data is used to derive df_omc and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df_omc. With this source data, the fitted regression logit(P(Y = 1)) = α0 + α1X + α2C1 + α3C2 + α4C3 shows that the true, unbiased exposure-outcome odds ratio = 2.

Usage

df_omc_source

Format

A dataframe with 100,000 rows and 6 columns:

<table>
<thead>
<tr>
<th></th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>X</td>
<td>exposure, 1 = present and 0 = absent</td>
</tr>
<tr>
<td>Y</td>
<td>true outcome, 1 = present and 0 = absent</td>
</tr>
<tr>
<td>C1</td>
<td>1st confounder, 1 = present and 0 = absent</td>
</tr>
<tr>
<td>C2</td>
<td>2nd confounder, 1 = present and 0 = absent</td>
</tr>
<tr>
<td>C3</td>
<td>3rd confounder, 1 = present and 0 = absent</td>
</tr>
<tr>
<td>Ystar</td>
<td>misclassified outcome, 1 = present and 0 = absent</td>
</tr>
</tbody>
</table>

Description

Data containing one source of bias, three known confounders, and 100,000 observations. This data is obtained by sampling with replacement with probability = S from df_sel_source then removing the S column. The resulting data corresponds to what a researcher would see in the real-world: missing data for those not selected into the study (S=0). As seen in df_sel_source, the true, unbiased exposure-outcome odds ratio = 2.

Usage

df_sel
df_sel_source

Format

A dataframe with 100,000 rows and 5 columns:

- **X** exposure, 1 = present and 0 = absent
- **Y** outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **C2** 2nd confounder, 1 = present and 0 = absent
- **C3** 3rd confounder, 1 = present and 0 = absent

---

df_sel_source

Data source for df_sel

---

Description

Data with complete information on study selection, three known confounders, and 100,000 observations. This data is used to derive df_sel and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df_sel. With this source data, the fitted regression $\logit(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3$ shows that the true, unbiased exposure-outcome odds ratio = 2.

Usage

df_sel_source

Format

A dataframe with 100,000 rows and 6 columns:

- **X** true exposure, 1 = present and 0 = absent
- **Y** outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **C2** 2nd confounder, 1 = present and 0 = absent
- **C3** 3rd confounder, 1 = present and 0 = absent
- **S** selection, 1 = selected into the study and 0 = not selected into the study
### df_uc

**Simulated data with uncontrolled confounding**

**Description**

Data containing one source of bias, three known confounders, and 100,000 observations. This data is obtained from df_uc_source by removing the column U. The resulting data corresponds to what a researcher would see in the real-world: information on known confounders (C1, C2, and C3), but nothing for confounder U. As seen in df_uc_source, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

`df_uc`

**Format**

A dataframe with 100,000 rows and 5 columns:

- **X** exposure, 1 = present and 0 = absent
- **Y** outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **C2** 2nd confounder, 1 = present and 0 = absent
- **C3** 3rd confounder, 1 = present and 0 = absent

### df_uc_emc

**Simulated data with uncontrolled confounding and exposure misclassification**

**Description**

Data containing two sources of bias, a known confounder, and 100,000 observations. This data is obtained from df_uc_emc_source by removing the columns X and U. The resulting data corresponds to what a researcher would see in the real-world: a misclassified exposure, Xstar, and missing data on a confounder U. As seen in df.uc_emc_source, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

`df.uc_emc`
**Format**

A dataframe with 100,000 rows and 3 columns:

- **Xstar** misclassified exposure, 1 = present and 0 = absent
- **Y** outcome, 1 = present and 0 = absent
- **C1** confounder, 1 = present and 0 = absent

---

**df_uc_emc_sel**

*Simulated data with uncontrolled confounding, exposure misclassification, and selection bias*

---

**Description**

Data containing three sources of bias, three known confounders, and 100,000 observations. This data is obtained by sampling with replacement with probability = $S$ from `df_uc_emc_sel_source` then removing the columns X, U, and S. The resulting data corresponds to what a researcher would see in the real-world: a misclassified exposure, Xstar; missing data on a confounder U; and missing data for those not selected into the study ($S=0$). As seen in `df_uc_emc_sel_source`, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

`df_uc_emc_sel`

**Format**

A dataframe with 100,000 rows and 5 columns:

- **Xstar** misclassified exposure, 1 = present and 0 = absent
- **Y** outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **C2** 2nd confounder, 1 = present and 0 = absent
- **C3** 3rd confounder, 1 = present and 0 = absent
df uc_emc_sel_source  Data source for df uc_emc_sel

Description

Data with complete information on the three sources of bias, three known confounders, and 100,000 observations. This data is used to derive df uc_emc_sel and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df uc_emc_sel. With this source data, the fitted regression $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3 + \alpha_5 U$ shows that the true, unbiased exposure-outcome odds ratio = 2.

Usage

df uc_emc_sel_source

Format

A dataframe with 100,000 rows and 8 columns:

X  true exposure, 1 = present and 0 = absent
Y  outcome, 1 = present and 0 = absent
C1 1st confounder, 1 = present and 0 = absent
C2 2nd confounder, 1 = present and 0 = absent
C3 3rd confounder, 1 = present and 0 = absent
U unmeasured confounder, 1 = present and 0 = absent
Xstar misclassified exposure, 1 = present and 0 = absent
S selection, 1 = selected into the study and 0 = not selected into the study

df uc_emc_source  Data source for df uc_emc

Description

Data with complete information on the two sources of bias, a known confounder, and 100,000 observations. This data is used to derive df uc_emc and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df uc_emc. With this source data, the fitted regression $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 U$ shows that the true, unbiased exposure-outcome odds ratio = 2.

Usage

df uc_emc_source
**df_uc_omc**

**Format**

A dataframe with 100,000 rows and 5 columns:

- **X** true exposure, 1 = present and 0 = absent
- **Y** outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **U** unmeasured confounder, 1 = present and 0 = absent
- **Xstar** misclassified exposure, 1 = present and 0 = absent

---

**df_uc_omc**

*Simulated data with uncontrolled confounding and outcome misclassification*

---

**Description**

Data containing two sources of bias, a known confounder, and 100,000 observations. This data is obtained from *df_uc_omc_source* by removing the columns Y and U. The resulting data corresponds to what a researcher would see in the real-world: a misclassified outcome, Ystar, and missing data on a confounder U. As seen in *df_uc_omc_source*, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

*df_uc_omc*

**Format**

A dataframe with 100,000 rows and 3 columns:

- **X** exposure, 1 = present and 0 = absent
- **Ystar** misclassified outcome, 1 = present and 0 = absent
- **C1** confounder, 1 = present and 0 = absent
df\_uc\_omc\_sel 

Simulated data with uncontrolled confounding, outcome misclassification, and selection bias

Description

Data containing three sources of bias, three known confounders, and 100,000 observations. This data is obtained by sampling with replacement with probability = S from df\_uc\_omc\_sel\_source then removing the columns Y, U, and S. The resulting data corresponds to what a researcher would see in the real-world: a misclassified outcome, Ystar; missing data on a confounder U; and missing data for those not selected into the study (S=0). As seen in df\_uc\_omc\_sel\_source, the true, unbiased exposure-outcome odds ratio = 2.

Usage

df\_uc\_omc\_sel

Format

A dataframe with 100,000 rows and 5 columns:

- **X** exposure, 1 = present and 0 = absent
- **Ystar** misclassified outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **C2** 2nd confounder, 1 = present and 0 = absent
- **C3** 3rd confounder, 1 = present and 0 = absent

---

df\_uc\_omc\_sel\_source 

Data source for df\_uc\_omc\_sel

Description

Data with complete information on the three sources of bias, three known confounders, and 100,000 observations. This data is used to derive df\_uc\_omc\_sel and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df\_uc\_omc\_sel. With this source data, the fitted regression $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3 + \alpha_5 U$ shows that the true, unbiased exposure-outcome odds ratio = 2.

Usage

df\_uc\_omc\_sel\_source
Format

A dataframe with 100,000 rows and 8 columns:

- **X**: exposure, 1 = present and 0 = absent
- **Y**: true outcome, 1 = present and 0 = absent
- **C1**: 1st confounder, 1 = present and 0 = absent
- **C2**: 2nd confounder, 1 = present and 0 = absent
- **C3**: 3rd confounder, 1 = present and 0 = absent
- **U**: unmeasured confounder, 1 = present and 0 = absent
- **Ystar**: misclassified outcome, 1 = present and 0 = absent
- **S**: selection, 1 = selected into the study and 0 = not selected into the study

Data source for df_uc_omc

Description

Data with complete information on the two sources of bias, a known confounder, and 100,000 observations. This data is used to derive df_uc_omc and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df_uc_omc. With this source data, the fitted regression $\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 U$ shows that the true, unbiased exposure-outcome odds ratio = 2.

Usage

df_uc_omc_source

Format

A dataframe with 100,000 rows and 5 columns:

- **X**: true exposure, 1 = present and 0 = absent
- **Y**: outcome, 1 = present and 0 = absent
- **C1**: 1st confounder, 1 = present and 0 = absent
- **U**: unmeasured confounder, 1 = present and 0 = absent
- **Ystar**: misclassified outcome, 1 = present and 0 = absent
**df_uc_sel**

*Simulated data with uncontrolled confounding and selection bias*

**Description**

Data containing two sources of bias, three known confounders, and 100,000 observations. This data is obtained by sampling with replacement with probability = S from df_uc_sel_source then removing the columns U and S. The resulting data corresponds to what a researcher would see in the real-world: missing data on confounder U; and missing data for those not selected into the study (S=0). As seen in df_uc_sel_source, the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

`df_uc_sel`

**Format**

A dataframe with 100,000 rows and 3 columns:

- **X** exposure, 1 = present and 0 = absent
- **Y** outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **C2** 2nd confounder, 1 = present and 0 = absent
- **C3** 3rd confounder, 1 = present and 0 = absent

**df_uc_sel_source**

*Data source for df_uc_sel*

**Description**

Data with complete information on the two sources of bias, a known confounder, and 100,000 observations. This data is used to derive df_uc_sel and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df_uc_sel. With this source data, the fitted regression \( \text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3 + \alpha_5 U \) shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

`df_uc_sel_source`
**Format**

A dataframe with 100,000 rows and 5 columns:

- **X** true exposure, 1 = present and 0 = absent
- **Y** outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **C2** 2nd confounder, 1 = present and 0 = absent
- **C3** 3rd confounder, 1 = present and 0 = absent
- **U** unmeasured confounder, 1 = present and 0 = absent
- **S** selection, 1 = selected into the study and 0 = not selected into the study

---

**df_uc_source**

**Data source for df_uc**

---

**Description**

Data with complete information on one source of bias, three known confounders, and 100,000 observations. This data is used to derive df uc and can be used to obtain bias parameters for purposes of validating the simultaneous multi-bias adjustment method with df uc. With this source data, the fitted regression 

\[
\text{logit}(P(Y = 1)) = \alpha_0 + \alpha_1 X + \alpha_2 C1 + \alpha_3 C2 + \alpha_4 C3 + \alpha_5 U
\]

shows that the true, unbiased exposure-outcome odds ratio = 2.

**Usage**

**df_uc_source**

**Format**

A dataframe with 100,000 rows and 6 columns:

- **X** exposure, 1 = present and 0 = absent
- **Y** true outcome, 1 = present and 0 = absent
- **C1** 1st confounder, 1 = present and 0 = absent
- **C2** 2nd confounder, 1 = present and 0 = absent
- **C3** 3rd confounder, 1 = present and 0 = absent
- **U** uncontrolled confounder, 1 = present and 0 = absent
Description

Data from a cohort study in which white males in Evans County were followed for 7 years, with coronary heart disease as the outcome of interest.

Usage

evans

Format

A dataframe with 609 rows and 9 columns:

- **ID**: subject identification
- **CHD**: outcome variable; 1 = coronary heart disease
- **AGE**: age (in years)
- **CHL**: cholesterol, mg/dl
- **SMK**: 1 = subject has ever smoked
- **ECG**: 1 = presence of electrocardiogram abnormality
- **DBP**: diastolic blood pressure, mmHg
- **SBP**: systolic blood pressure, mmHg
- **HPT**: 1 = SBP greater than or equal to 160 or DBP greater than or equal to 95

Source

<http://web1.sph.emory.edu/dkleinb/logreg3.htm#data>
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