

Package ‘SimpleTable’

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Title Bayesian Inference and Sensitivity Analysis for Causal Effects
from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding

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Depends R (>= 2.5.1), hdrcde, locfit, MCMCpack, tcltk

Description SimpleTable provides a series of methods to conduct
Bayesian inference and sensitivity analysis for causal effects
from 2 x 2 and 2 x 2 x K tables when unmeasured confounding is present or suspected.

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Description

analyze2x2 performs a causal Bayesian analysis of a 2 x 2 table in which it is assumed that unmeasured confounding is present. The binary treatment variable is denoted $X = 0$ (control), 1 (treatment); and the binary outcome variable is denoted $Y = 0$ (failure), 1 (success). The notation and terminology are from Quinn (2008).

Usage

```
analyze2x2(C00, C01, C10, C11, a00, a01, a10, a11,
           b00, b01, b10, b11, c00, c01, c10, c11, nsamp = 50000)
```

Arguments

C00	The number of observations in $(X = 0, Y = 0)$ cell of the table. In other words, the number of observations that received control and failed.
C01	The number of observations in $(X = 0, Y = 1)$ cell of the table. In other words, the number of observations that received control and succeeded.
C10	The number of observations in $(X = 1, Y = 0)$ cell of the table. In other words, the number of observations that received treatment and failed.
C11	The number of observations in $(X = 1, Y = 1)$ cell of the table. In other words, the number of observations that received treatment and succeeded.
a00	One of four parameters (with a01, a10, and a11 governing the Dirichlet prior for θ (the joint probabilities of X and Y)). This prior has the effect of adding a00 - 1 observations to the $(X = 0, Y = 0)$ cell of the table.
a01	One of four parameters (with a00, a10, and a11 governing the Dirichlet prior for θ (the joint probabilities of X and Y)). This prior has the effect of adding a01 - 1 observations to the $(X = 0, Y = 1)$ cell of the table.
a10	One of four parameters (with a00, a01, and a11 governing the Dirichlet prior for θ (the joint probabilities of X and Y)). This prior has the effect of adding a10 - 1 observations to the $(X = 1, Y = 0)$ cell of the table.
a11	One of four parameters (with a00, a01, and a10 governing the Dirichlet prior for θ (the joint probabilities of X and Y)). This prior has the effect of adding a11 - 1 observations to the $(X = 1, Y = 1)$ cell of the table.
b00	One of two parameters (with c00) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing b00 - 1 Helped units in the $(X = 0, Y = 0)$ cell of the table.
b01	One of two parameters (with c01) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing b01 - 1 Always Succeed units in the $(X = 0, Y = 1)$ cell of the table.

b10	One of two parameters (with c10) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing b10 - 1 Hurt units in the $(X = 1, Y = 0)$ cell of the table.
b11	One of two parameters (with c11) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing b11 - 1 Always Succeed units in the $(X = 1, Y = 1)$ cell of the table.
c00	One of two parameters (with b00) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing b00 - 1 Never Succeed units in the $(X = 0, Y = 0)$ cell of the table.
c01	One of two parameters (with b01) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing c01 - 1 Hurt units in the $(X = 0, Y = 1)$ cell of the table.
c10	One of two parameters (with b10) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing c10 - 1 Never Succeed units in the $(X = 1, Y = 0)$ cell of the table.
c11	One of two parameters (with b11) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing b11 - 1 Helped units in the $(X = 1, Y = 1)$ cell of the table.
nsamp	Size of the Monte Carlo sample used to summarize the posterior.

Details

analyze2x2 performs the Bayesian analysis of a 2 x 2 table described in Quinn (2008). summary and plot methods can be used to examine the output.

Value

An object of class SimpleTable.

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

[ConfoundingPlot](#), [analyze2x2xK](#), [ElicitPsi](#), [summary.SimpleTable](#), [plot.SimpleTable](#)

Examples

```
## Not run:
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   ‘‘Jury Aversion and Voter Registration.’’
##   American Political Science Review. 93: 147-152.)
##
##           Y=0       Y=1
## X=0      19        143
## X=1     114        473
##
## uniform prior on the potential outcome distributions
S.unif <- analyze2x2(C00=19, C01=143, C10=114, C11=473,
                   a00=.25, a01=.25, a10=.25, a11=.25,
                   b00=1, c00=1, b01=1, c01=1,
                   b10=1, c10=1, b11=1, c11=1)

summary(S.unif)
plot(S.unif)

## a prior belief in an essentially negative monotonic treatment effect
S.mono <- analyze2x2(C00=19, C01=143, C10=114, C11=473,
                   a00=.25, a01=.25, a10=.25, a11=.25,
                   b00=0.02, c00=10, b01=25, c01=3,
                   b10=3, c10=25, b11=10, c11=0.02)

summary(S.mono)
plot(S.mono)

## End(Not run)
```

analyze2x2xK

Analyze 2 x 2 x K Table in the Presence of Unmeasured Confounding

Description

analyze2x2xK performs a causal Bayesian analysis of a 2 x 2 x K table in which it is assumed that unmeasured confounding is present. The binary treatment variable is denoted $X = 0$ (control), 1 (treatment); the binary outcome variable is denoted $Y = 0$ (failure), 1 (success); and the categorical measured confounder is denoted $W = 0, \dots, K - 1$. The notation and terminology are from Quinn (2008).

Usage

```
analyze2x2xK(SimpleTableList, Wpriorvector)
```

Arguments

SimpleTableList

A list of K SimpleTable objects formed by using analyze2x2 to analyze the K conditional (X, Y) tables given each level of the measured confounder W .

Wpriorvector

K -vector giving the parameters of the Dirichlet prior for ϕ where $\phi_k \equiv \Pr(W = k)$ for $k = 0, \dots, K - 1$. The k th element of Wpriorvector corresponds to the k th element of W .

Details

analyze2x2xK performs the Bayesian analysis of a $2 \times 2 \times K$ table described in Quinn (2008). summary and plot methods can be used to examine the output.

Value

An object of class SimpleTable.

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2×2 and $2 \times 2 \times K$ Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

[ConfoundingPlot](#), [analyze2x2](#), [ElicitPsi](#), [summary.SimpleTable](#), [plot.SimpleTable](#)

Examples

```
## Not run:
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   'Jury Aversion and Voter Registration.'
##   American Political Science Review. 93: 147-152.)
##
##
##           W=0
##       Y=0  Y=1
## X=0      1   21
## X=1     10   93
##
##
##           W=1
##       Y=0  Y=1
## X=0      5   32
## X=1     27   92
##
```

```

##
##           W=2
##           Y=0  Y=1
## X=0       4    44
## X=1      52   186
##
##
##           W=3
##           Y=0  Y=1
## X=0       7    20
## X=1      19   47
##
##
##           W=4
##           Y=0  Y=1
## X=0       2    26
## X=1       6    55
##

## a prior belief in an essentially negative monotonic treatment effect
## with the largest effects among those for whom W <= 2

S.mono.0 <- analyze2x2(C00=1, C01=21, C10=10, C11=93,
                      a00=.25, a01=.25, a10=.25, a11=.25,
                      b00=0.02, c00=10, b01=25, c01=3,
                      b10=3, c10=25, b11=10, c11=0.02)

S.mono.1 <- analyze2x2(C00=5, C01=32, C10=27, C11=92,
                      a00=.25, a01=.25, a10=.25, a11=.25,
                      b00=0.02, c00=10, b01=25, c01=3,
                      b10=3, c10=25, b11=10, c11=0.02)

S.mono.2 <- analyze2x2(C00=4, C01=44, C10=52, C11=186,
                      a00=.25, a01=.25, a10=.25, a11=.25,
                      b00=0.02, c00=10, b01=25, c01=3,
                      b10=3, c10=25, b11=10, c11=0.02)

S.mono.3 <- analyze2x2(C00=7, C01=20, C10=19, C11=47,
                      a00=.25, a01=.25, a10=.25, a11=.25,
                      b00=0.02, c00=10, b01=15, c01=1,
                      b10=1, c10=15, b11=10, c11=0.02)

S.mono.4 <- analyze2x2(C00=2, C01=26, C10=6, C11=55,
                      a00=.25, a01=.25, a10=.25, a11=.25,
                      b00=0.02, c00=10, b01=15, c01=1,
                      b10=1, c10=15, b11=10, c11=0.02)

S.mono.all <- analyze2x2xK(list(S.mono.0, S.mono.1, S.mono.2,
                               S.mono.3, S.mono.4),
                          c(0.2, 0.2, 0.2, 0.2, 0.2))

summary(S.mono.all)

```

```
plot(S.mono.all)

## End(Not run)
```

 ConfoundingPlot

Confounding Plot of Quinn (2008)

Description

ConfoundingPlot implements the "confounding plot" discussed in Quinn (2008). This plot displays, in the context of binary treatment ($X = 0$: control, 1: treatment) and binary outcome ($Y = 0$: failure, 1: success), all types of unmeasured confounding that would keep a true causal effect of interest within some user-defined tolerance of the estimated causal effect.

Usage

```
ConfoundingPlot(theta00, theta01, theta10, theta11,
                 conditioning = c("None", "Treated", "Control"),
                 PrY1.setX0 = NULL, PrY1.setX1 = NULL,
                 PrY1.setX0.withinTreated = NULL,
                 PrY1.setX1.withinControl = NULL,
                 epsilon = 0.025, color = "black", legend = FALSE)
```

Arguments

theta00	The <i>observed</i> joint probability that X is control and Y is failure ($\Pr(X = 0, Y = 0)$). In a 2 x 2 table in which C_{00} is the number of observations in the $(X = 0, Y = 0)$ cell and in which there are C total observations one can consistently estimate theta00 with C_{00}/C .
theta01	The <i>observed</i> joint probability that X is control and Y is success ($\Pr(X = 0, Y = 1)$). In a 2 x 2 table in which C_{01} is the number of observations in the $(X = 0, Y = 1)$ cell and in which there are C total observations one can consistently estimate theta01 with C_{01}/C .
theta10	The <i>observed</i> joint probability that X is treatment and Y is failure ($\Pr(X = 1, Y = 0)$). In a 2 x 2 table in which C_{10} is the number of observations in the $(X = 1, Y = 0)$ cell and in which there are C total observations one can consistently estimate theta10 with C_{10}/C .
theta11	The <i>observed</i> joint probability that X is treatment and Y is success ($\Pr(X = 1, Y = 1)$). In a 2 x 2 table in which C_{11} is the number of observations in the $(X = 1, Y = 1)$ cell and in which there are C total observations one can consistently estimate theta11 with C_{11}/C .
conditioning	A string detailing whether the post-intervention distribution, and hence the estimand of interest, is restricted to a particular subgroup. Possible values are: None, Treated, and Control. If <code>conditioning = None</code> then the post-intervention distribution is for all units. This is consistent with the causal estimand being the

average treatment effect (ATE). If `conditioning = Treated` then the post-intervention is calculated only for just the treated units. This is consistent with the causal estimand being the average treatment effect within the treated (ATT). Finally, if `conditioning = Control` then the post-intervention distribution is calculated for just the control units. this is consistent with the causal estimand being the average treatment effect within the controls (ATC). Default is `None`.

`PrY1.setX0` Optional value giving the *assumed* probability that a randomly chosen unit will have $Y = 1$ (success) if its X value is set to 0 (control) by outside intervention. If `PrY1.setX0 = NULL` (the default) then `PrY1.setX0` is set to the *observed* conditional probability that Y is 1 given that X is 0. In the terms of Quinn (2008), the reference distribution is the prima facie post-intervention distribution. Setting `PrY1.setX0` to some non-NULL value allows one to use reference distributions other than the prima facie post-intervention distribution. This is useful if one wants to start with a particular value for ATE (that is not the prima facie ATE) and see how unmeasured confounding might affect that inference. Only applicable if `conditioning = None`.

`PrY1.setX1` Optional value giving the *assumed* probability that a randomly chosen unit will have $Y = 1$ (success) if its X value is set to 1 (treatment) by outside intervention. If `PrY1.setX1 = NULL` (the default) then `PrY1.setX1` is set to the *observed* conditional probability that Y is 1 given that X is 1. In the terms of Quinn (2008), the reference distribution is the prima facie post-intervention distribution. Setting `PrY1.setX1` to some non-NULL value allows one to use reference distributions other than the prima facie post-intervention distribution. This is useful if one wants to start with a particular value for ATE (that is not the prima facie ATE) and see how unmeasured confounding might affect that inference. Only applicable if `conditioning = None`.

`PrY1.setX0.withinTreated` Optional value giving the *assumed* probability that a randomly chosen unit which received treatment would have $Y = 1$ (success) if its X value were set to 0 (control) by outside intervention. If `PrY1.setX0.withinTreated = NULL` (the default) then `PrY1.setX0.withinTreated` is set to the *observed* conditional probability that Y is 1 given that X is 0. In the terms of Quinn (2008), the reference distribution is the prima facie post-intervention distribution. Setting `PrY1.setX0.withinTreated` to some non-NULL value allows one to use reference distributions other than the prima facie post-intervention distribution. This is useful if one wants to start with a particular value for ATT (that is not the prima facie ATT) and see how unmeasured confounding might affect that inference. Only applicable if `conditioning = Treated`.

`PrY1.setX1.withinControl` Optional value giving the *assumed* probability that a randomly chosen unit which received control would have $Y = 1$ (success) if its X value were set to 1 (treatment) by outside intervention. If `PrY1.setX1.withinControl = NULL` (the default) then `PrY1.setX1.withinControl` is set to the *observed* conditional probability that Y is 1 given that X is 1. In the terms of Quinn (2008), the reference distribution is the prima facie post-intervention distribution. Setting `PrY1.setX1.withinControl` to some non-NULL value allows one to use reference distributions other than the prima facie post-intervention distribution. This is useful if one wants to start with a particular value for ATC (that is not the

	prima facie ATC) and see how unmeasured confounding might affect that inference. Only applicable if <code>conditioning = Control</code> .
<code>epsilon</code>	A scalar or array of tolerance values between 0 and 1. The plot depicts all regions of the space of confounders for which the absolute difference between the true post-intervention distribution and the assumed post-intervention distribution is less than <code>epsilon</code> . See Quinn (2008) for details. If <code>epsilon</code> is an array then <code>color</code> (see below) must also be an array and the various tolerance regions will be overlaid in color.
<code>color</code>	An array of colors for the plotting regions. <code>color</code> must have length equal to the length of <code>epsilon</code> (see above).
<code>legend</code>	Logical value indicating whether a legend should be printed.

Details

For full details see Quinn (2008).

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

[analyze2x2](#), [analyze2x2xK](#), [ElicitPsi](#),

Examples

```
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   "Jury Aversion and Voter Registration."
##   American Political Science Review. 93: 147-152.)
##
##       Y=0       Y=1
## X=0   19       143
## X=1  114       473
##
C <- 19 + 143 + 114 + 473
theta00 <- 19/C
theta01 <- 143/C
theta10 <- 114/C
theta11 <- 473/C

## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
```

```
theta10=theta10, theta11=theta11, legend=TRUE)

## same data but with various epsilons and a legend
## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
  theta10=theta10, theta11=theta11,
  epsilon=c(.01, .025, .05, .1),
  color=c("black", "darkblue", "blue", "cyan"),
  legend=TRUE)

## same data but reference distribution is now just within the treated
## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
  theta10=theta10, theta11=theta11,
  conditioning="Treated", legend=TRUE)

## set PrY1.setX0 and PrY1.setX1 in order to get a reference
## post-intervention distribution that is consistent with
## ATE = -0.2 (note there are many ways to do this)
## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
  theta10=theta10, theta11=theta11,
  PrY1.setX0=.9, PrY1.setX1=.7,
  legend=TRUE)

## another way to get ATE = -0.2
## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
  theta10=theta10, theta11=theta11,
  PrY1.setX0=.85, PrY1.setX1=.65,
  legend=TRUE)

## a way to get ATE = -0.2 that is impossible given the observed data
## (note the complete lack of any shaded regions in the left panel of plot)
## may have to adjust size of graphics device to make labels readable
ConfoundingPlot(theta00=theta00, theta01=theta01,
  theta10=theta10, theta11=theta11,
  PrY1.setX0=.5, PrY1.setX1=.3,
  legend=TRUE)
```

Description

ElicitPsi provides a Tcl/Tk graphical user interface that allows users to vary the parameters of the beta prior distributions over the ψ parameters (the potential outcome distributions within cells of the (X, Y) table) used by analyze2x2. See Quinn (2008).

Usage

```
ElicitPsi(C00, C01, C10, C11, maxvalue = 100,
          a00 = 0.25, a01 = 0.25, a10 = 0.25, a11 = 0.25,
          nsamp = 50000, output.object = "output.SimpleTable")
```

Arguments

C00	The number of observations in $(X = 0, Y = 0)$ cell of the table. In other words, the number of observations that received control and failed.
C01	The number of observations in $(X = 0, Y = 1)$ cell of the table. In other words, the number of observations that received control and succeeded.
C10	The number of observations in $(X = 1, Y = 0)$ cell of the table. In other words, the number of observations that received treatment and failed.
C11	The number of observations in $(X = 1, Y = 1)$ cell of the table. In other words, the number of observations that received treatment and succeeded.
maxvalue	The largest possible value for the parameters of the beta priors that are being elicited. This value is used to set the slider bars appropriately.
a00	One of four parameters (with a01, a10, and a11 governing the Dirichlet prior for θ (the joint probabilities of X and Y)). This prior has the effect of adding $a00 - 1$ observations to the $(X = 0, Y = 0)$ cell of the table.
a01	One of four parameters (with a00, a10, and a11 governing the Dirichlet prior for θ (the joint probabilities of X and Y)). This prior has the effect of adding $a01 - 1$ observations to the $(X = 0, Y = 1)$ cell of the table.
a10	One of four parameters (with a00, a01, and a11 governing the Dirichlet prior for θ (the joint probabilities of X and Y)). This prior has the effect of adding $a10 - 1$ observations to the $(X = 1, Y = 0)$ cell of the table.
a11	One of four parameters (with a00, a01, and a10 governing the Dirichlet prior for θ (the joint probabilities of X and Y)). This prior has the effect of adding $a11 - 1$ observations to the $(X = 1, Y = 1)$ cell of the table.
nsamp	Size of the Monte Carlo sample used to summarize the posterior.
output.object	String giving the name of the output object the result are sent to. Default is output.SimpleTable.

Details

See `analyze2x2` and Quinn (2008) for details regarding the model and prior specification used.

Value

While `ElicitPsi` does not formally have a return value, it does put a number of objects in the global environment. These objects are:

b00	One of two parameters (with c00) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing b00 - 1 Helped units in the $(X = 0, Y = 0)$ cell of the table.
b01	One of two parameters (with c01) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing b01 - 1 Always Succeed units in the $(X = 0, Y = 1)$ cell of the table.
b10	One of two parameters (with c10) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing b10 - 1 Hurt units in the $(X = 1, Y = 0)$ cell of the table.
b11	One of two parameters (with c11) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing b11 - 1 Always Succeed units in the $(X = 1, Y = 1)$ cell of the table.
c00	One of two parameters (with b00) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing c00 - 1 Never Succeed units in the $(X = 0, Y = 0)$ cell of the table.
c01	One of two parameters (with b01) governing the beta prior for the distribution of potential outcome types within the $(X = 0, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing c01 - 1 Hurt units in the $(X = 0, Y = 1)$ cell of the table.
c10	One of two parameters (with b10) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 0)$ cell of the table. This prior adds the same information as would be gained from observing c10 - 1 Never Succeed units in the $(X = 1, Y = 0)$ cell of the table.
c11	One of two parameters (with b11) governing the beta prior for the distribution of potential outcome types within the $(X = 1, Y = 1)$ cell of the table. This prior adds the same information as would be gained from observing c11 - 1 Helped units in the $(X = 1, Y = 1)$ cell of the table.

In addition, if the user presses the Calculate Effects button, `analyze2x2` is called with the current values of prior parameters. The output from `analyze2x2` is written to an object in the global environment with the name given by the `output.object` argument (see argument list above).

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

[ConfoundingPlot](#), [analyze2x2xK](#), [analyze2x2xK](#), [summary.SimpleTable](#), [plot.SimpleTable](#)

Examples

```
## Not run:
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   "Jury Aversion and Voter Registration."
##   American Political Science Review. 93: 147-152.)
##
##      Y=0      Y=1
## X=0   19      143
## X=1  114      473
##
ElicitPsi(C00=19, C01=143, C10=114, C11=473, output.object="output.2x2")

## End(Not run)
```

is.SimpleTable	<i>Is object of class SimpleTable?</i>
----------------	--

Description

Checks to see if object is of class SimpleTable.

Usage

```
is.SimpleTable(S)
```

Arguments

S An object to be checked.

Value

A logical value equal to TRUE if S is of class SimpleTable and FALSE otherwise.

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

[ConfoundingPlot](#), [analyze2x2xK](#), [ElicitPsi](#), [summary.SimpleTable](#), [plot.SimpleTable](#)

plot.SimpleTable *Summary plots of SimpleTable objects.*

Description

plot.SimpleTable summarizes a SimpleTable object by plotting the posterior density of the prima facie and sensitivity analysis causal effects.

Usage

```
plot.SimpleTable(x, estimand = c("ATE", "ATT", "ATC", "RR", "RRT", "RRC",
                                "logRR", "logRRT", "logRRC"),
                percent = 95, plot.bounds = TRUE, plot.pf = TRUE,
                plot.sens = TRUE, plot.prior = FALSE,
                color.bounds = "cyan",
                color1.pf = "lawngreen", color2.pf = "green",
                color1.sens = "magenta3", color2.sens = "purple4",
                color.prior = "lightgray", ymax = NULL, ...)
```

Arguments

x	An object of class SimpleTable produced by analyze2x2 or analyze2x2xK that is to be graphically summarized.
estimand	The causal estimand of interest. Options include: ATE (average treatment effect), ATT (average treatment effect on the treated), ATC (average treatment effect on the controls), RR (relative risk), RRT (relative risk on the treated), RRC (relative risk on the controls), logRR (log relative risk), logRRT (log relative risk on the treated), and logRRC (log relative risk on the controls).
percent	A number between 0 and 100 (exclusive) giving the size of the highest posterior density regions to be calculated and plotted. Default value is 95.
plot.bounds	Logical value indicating whether the large-sample nonparametric bounds should be plotted. Default value is TRUE.
plot.pf	Logical value indicating whether the posterior density of the prima facie causal effect should be plotted. Default value is TRUE.
plot.sens	Logical value indicating whether the posterior density of the sensitivity analysis causal effect should be plotted. Default value is TRUE.

plot.prior	Logical value indicating whether the prior density of the causal effect of interest should be plotted. Default value is FALSE.
color.bounds	The color of the line segment depicting the large-sample nonparametric bounds. Default value is cyan.
color1.pf	The color of the prima facie posterior density in regions outside the percent% highest posterior density region. Default value is lawngreen.
color2.pf	The color of the prima facie posterior density in regions inside the percent% highest posterior density region. Default value is green.
color1.sens	The color of the sensitivity analysis posterior density in regions outside the percent% highest posterior density region. Default value is magenta3.
color2.sens	The color of the sensitivity analysis posterior density in regions inside the percent% highest posterior density region. Default value is purple4.
color.prior	The color of the prior density of the causal effect of interest. Default value is lightgray.
ymax	The maximum height of the y -axis. If NULL (the default) then ymax is taken to be the maximum ordinate of the prima facie posterior density, the sensitivity analysis posterior density, and the prior density.
...	Other arguments to be passed.

Details

See Quinn (2008) for the a description of these plots along with the associated terminology and notation.

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

[ConfoundingPlot](#), [analyze2x2](#), [analyze2x2xK](#), [ElicitPsi](#), [summary.SimpleTable](#)

Examples

```
## Not run:
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   "Jury Aversion and Voter Registration."
##   American Political Science Review. 93: 147-152.)
##
##           Y=0       Y=1
## X=0      19        143
```

```
## X=1    114    473
##

## a prior belief in an essentially negative monotonic treatment effect
S.mono <- analyze2x2(C00=19, C01=143, C10=114, C11=473,
                    a00=.25, a01=.25, a10=.25, a11=.25,
                    b00=0.02, c00=10, b01=25, c01=3,
                    b10=3, c10=25, b11=10, c11=0.02)

## ATE (the default)
plot(S.mono)

## ATC instead of ATE
plot(S.mono, estimand="ATC")

## different colors
plot(S.mono, estimand="ATC", color1.pf="red", color2.pf="blue",
     color1.sens="gray", color2.sens="orange")

## End(Not run)
```

summary.SimpleTable *Summary of SimpleTable objects*

Description

summary.SimpleTable summarizes a SimpleTable object by printing the mode, mean, standard deviation, and percent% highest density region of the prima facie and sensitivity analysis posterior densities. Large-sample nonparametric bounds for the estimand of interest are also reported. Summaries of the prior distribution are also reported in situations where these summaries are numerically stable.

Usage

```
summary.SimpleTable(object, estimand = c("ATE", "ATT", "ATC",
                                         "RR", "RRT", "RRC",
                                         "logRR", "logRRT", "logRRC"),
                    percent = 95, ...)
```

Arguments

object	An object of class SimpleTable produced by analyze2x2 or analyze2x2xK that is to be summarized.
estimand	The causal estimand of interest. Options include: ATE (average treatment effect), ATT (average treatment effect on the treated), ATC (average treatment effect on the controls), RR (relative risk), RRT (relative risk on the treated), RRC (relative risk on the controls), logRR (log relative risk), logRRT (log relative risk on the treated), and logRRC (log relative risk on the controls).

percent A number between 0 and 100 (exclusive) giving the size of the highest posterior density regions to be calculated and printed. Default value is 95.

... Other arguments to be passed.

Details

See Quinn (2008) for the a description of these plots along with the associated terminology and notation.

Author(s)

Kevin M. Quinn

References

Quinn, Kevin M. 2008. "What Can Be Learned from a Simple Table: Bayesian Inference and Sensitivity Analysis for Causal Effects from 2 x 2 and 2 x 2 x K Tables in the Presence of Unmeasured Confounding." Working Paper.

See Also

[ConfoundingPlot](#), [analyze2x2](#), [analyze2x2xK](#), [ElicitPsi](#), [plot.SimpleTable](#)

Examples

```
## Not run:
## Example from Quinn (2008)
## (original data from Oliver and Wolfinger. 1999.
##   "Jury Aversion and Voter Registration."
##   American Political Science Review. 93: 147-152.)
##
##       Y=0       Y=1
## X=0   19       143
## X=1  114       473
##
## a prior belief in an essentially negative monotonic treatment effect
S.mono <- analyze2x2(C00=19, C01=143, C10=114, C11=473,
                   a00=.25, a01=.25, a10=.25, a11=.25,
                   b00=0.02, c00=10, b01=25, c01=3,
                   b10=3, c10=25, b11=10, c11=0.02)

## ATE (the default)
summary(S.mono)

## ATC instead of ATE
summary(S.mono, estimand="ATC")

## End(Not run)
```

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