

# Package ‘localIV’

October 13, 2022

**Type** Package

**Title** Estimation of Marginal Treatment Effects using Local  
Instrumental Variables

**Version** 0.3.1

**Description** In the generalized Roy model, the marginal treatment effect (MTE) can be used as a building block for constructing conventional causal parameters such as the average treatment effect (ATE) and the average treatment effect on the treated (ATT). Given a treatment selection equation and an outcome equation, the function mte() estimates the MTE via the semiparametric local instrumental variables method or the normal selection model. The function mte\_at() evaluates

MTE at different values of the latent resistance  $u$  with a given  $X = x$ , and the function mte\_tilde\_at()

evaluates MTE projected onto the estimated propensity score. The function ace() estimates population-level average causal effects such as ATE, ATT, or the marginal policy relevant treatment effect.

**Depends** R (>= 3.3.0)

**Imports** KernSmooth (>= 2.5.0), mgcv (>= 1.8-19), rlang (>= 0.4.4),  
sampleSelection (>= 1.2-0), stats

**Suggests** dplyr, ggplot2, tidyverse

**License** GPL (>= 3)

**Encoding** UTF-8

**LazyData** true

**RoxygenNote** 7.0.2

**URL** <https://github.com/xiangzhou09/localIV>

**BugReports** <https://github.com/xiangzhou09/localIV>

**NeedsCompilation** no

**Author** Xiang Zhou [aut, cre]

**Maintainer** Xiang Zhou <xiang\_zhou@fas.harvard.edu>

**Repository** CRAN

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ace	<i>Estimating Average Causal Effects from a Fitted MTE Model.</i>
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### Description

ace estimates Average Causal Effects (ACE) from a fitted MTE model. The estimand can be average treatment effect (ATE), average treatment effect on the treated (ATT), average treatment effect on the untreated (ATU), or the Marginal Policy Relevant Treatment Effect (MPRTE) defined in Zhou and Xie (2019).

### Usage

```
ace(model, estimand = c("ate", "att", "atu", "mprte"), policy = 1)
```

### Arguments

model	A fitted <code>mte</code> model returned by <code>mte</code> .
estimand	Type of estimand: "ate", "att", "atu", or "mprte".
policy	An <code>expression</code> written as a function of p. This is used only when <code>estimand="mprte"</code> .

### Value

Estimate of ATE, ATT, ATU, or MPRTE

### References

- Heckman, James J., Sergio Urzua, and Edward Vytlacil. 2006. "[Understanding Instrumental Variables in Models with Essential Heterogeneity](#)." *The Review of Economics and Statistics* 88:389-432.
- Zhou, Xiang and Yu Xie. 2019. "[Marginal Treatment Effects from A Propensity Score Perspective](#)." *Journal of Political Economy*, 127(6): 3070-3084.
- Zhou, Xiang and Yu Xie. 2020. "[Heterogeneous Treatment Effects in the Presence of Self-selection: a Propensity Score Perspective](#)." *Sociological Methodology*.

## Examples

```
mod <- mte(selection = d ~ x + z, outcome = y ~ x,
             data = toydata)

ate <- ace(mod, "ate")
att <- ace(mod, "att")
atu <- ace(mod, "atu")
mprte1 <- ace(mod, "mprte")
mprte2 <- ace(mod, "mprte", policy = p)
mprte3 <- ace(mod, "mprte", policy = 1-p)
mprte4 <- ace(mod, "mprte", policy = I(p<0.25))
c(ate, att, atu, mprte1, mprte2, mprte3, mprte4)
```

mte

*Fitting a Marginal Treatment Effects (MTE) Model.*

## Description

`mte` fits a MTE model using either the semiparametric local instrumental variables (local IV) method or the normal selection model (Heckman, Urzua, Vytlacil 2006). The user supplies a formula for the treatment selection equation, a formula for the outcome equations, and a data frame containing all variables. The function returns an object of class `mte`. Observations that contain NA (either in `selection` or in `outcome`) are removed.

## Usage

```
mte(
  selection,
  outcome,
  data = NULL,
  method = c("localIV", "normal"),
  bw = NULL
)
mte_localIV(mf_s, mf_o, bw = NULL)
mte_normal(mf_s, mf_o)
```

## Arguments

<code>selection</code>	A formula representing the treatment selection equation.
<code>outcome</code>	A formula representing the outcome equations where the left hand side is the observed outcome and the right hand side includes predictors of both potential outcomes.
<code>data</code>	A data frame, list, or environment containing the variables in the model.

method	How to estimate the model: either "localIV" for the semiparametric local IV method or "normal" for the normal selection model.
bw	Bandwidth used for the local polynomial regression in the local IV approach. Default is 0.25.
mf_s	A model frame for the treatment selection equations returned by <code>model.frame</code>
mf_o	A model frame for the outcome equations returned by <code>model.frame</code>

## Details

`mte_localIV` estimates  $MTE(x, u)$  using the semiparametric local IV method, and `mte_normal` estimates  $MTE(x, u)$  using the normal selection model.

## Value

An object of class `mte`.

coefs	A list of coefficient estimates: gamma for the treatment selection equation, beta10 (intercept) and beta1 (slopes) for the baseline outcome equation, beta20 (intercept) and beta2 (slopes) for the treated outcome equation, and theta1 and theta2 for the error covariances when <code>method = "normal"</code> .
ufun	A function representing the unobserved component of $MTE(x, u)$ .
ps	Estimated propensity scores.
ps_model	The propensity score model, an object of class <code>glm</code> if <code>method = "localIV"</code> , or an object of class <code>selection</code> if <code>method = "normal"</code> .
mf_s	The model frame for the treatment selection equation.
mf_o	The model frame for the outcome equations.
complete_row	A logical vector indicating whether a row is complete (no missing variables) in the original data
call	The matched call.

## References

Heckman, James J., Sergio Urzua, and Edward Vytlacil. 2006. "**Understanding Instrumental Variables in Models with Essential Heterogeneity.**" The Review of Economics and Statistics 88:389-432.

## See Also

`mte_at` for evaluating MTE at different values of the latent resistance  $u$ ; `mte_tilde_at` for evaluating MTE projected onto the propensity score; `ace` for estimating average causal effects from a fitted `mte` object.

## Examples

```
mod <- mte(selection = d ~ x + z, outcome = y ~ x, data = toydata, bw = 0.25)

summary(mod$ps_model)
hist(mod$ps)
```

```
mte_vals <- mte_at(u = seq(0.05, 0.95, 0.1), model = mod)
if(require("ggplot2")){
  ggplot(mte_vals, aes(x = u, y = value)) +
    geom_line(size = 1) +
    xlab("Latent Resistance U") +
    ylab("Estimates of MTE at Mean Values of X") +
    theme_minimal(base_size = 14)
}
```

**mte\_at***Evaluate Marginal Treatment Effects from a Fitted MTE Model.***Description**

`mte_at` evaluates marginal treatment effects at different values of the latent resistance  $u$  with a given  $X = x$ .

**Usage**

```
mte_at(x = NULL, u, model)
```

**Arguments**

- `x` Values of the pretreatment covariates at which  $\text{MTE}(x, u)$  is evaluated. It should be a numeric vector whose length is one less than the number of columns of the design matrix  $X$  in the outcome model. Default is the sample means.
- `u` A numeric vector. Values of the latent resistance  $u$  at which  $\text{MTE}(x, u)$  is evaluated. Note that the estimation involves extrapolation when the specified  $u$  values lie outside of the support of the propensity score.
- `model` A fitted MTE model returned by `mte`.

**Value**

`mte_at` returns a data frame.

- |                     |  |
|---------------------|--|
| <code>u</code>      | input values of $u$ .                                  |
| <code>x_comp</code> | the $x$ -component of the estimated $\text{MTE}(x, u)$ |
| <code>u_comp</code> | the $u$ -component of the estimated $\text{MTE}(x, u)$ |
| <code>value</code>  | estimated values of $\text{MTE}(x, u)$                 |

## Examples

```
mod <- mte(selection = d ~ x + z, outcome = y ~ x, data = toydata)

mte_vals <- mte_at(u = seq(0.05, 0.95, 0.1), model = mod)
if(require("ggplot2")){
  ggplot(mte_vals, aes(x = u, y = value)) +
    geom_line(size = 1) +
    xlab("Latent Resistance U") +
    ylab("Estimates of MTE at Mean Values of X") +
    theme_minimal(base_size = 14)
}
```

**mte\_tilde\_at**

*Evaluate Marginal Treatment Effects Projected onto the Propensity Score*

## Description

`mte_tilde_at` evaluates marginal treatment effects projected onto the estimated propensity score. The projection is done via the function `gam`.

## Usage

```
mte_tilde_at(p, u, model, ...)
```

## Arguments

<code>p</code>	A numeric vector. Values of the propensity score at which $\widetilde{MTE}(p, u)$ is evaluated.
<code>u</code>	A numeric vector. Values of the latent resistance at which $\widetilde{MTE}(p, u)$ is evaluated.
<code>model</code>	A fitted MTE model returned by <code>mte</code> .
<code>...</code>	Additional parameters passed to <code>gam</code> .

## Value

`mte_tilde_at` returns a list of two elements:

<code>df</code>	A data frame containing five columns: <ul style="list-style-type: none"> <li>• <code>p</code> input values of <code>p</code>.</li> <li>• <code>u</code> input values of <code>u</code>.</li> <li>• <code>p_comp</code> the <code>p</code>-component of the estimated <math>\widetilde{MTE}(p, u)</math></li> <li>• <code>u_comp</code> the <code>u</code>-component of the estimated <math>\widetilde{MTE}(p, u)</math></li> <li>• <code>value</code> estimated values of <math>\widetilde{MTE}(p, u)</math></li> </ul>
<code>proj</code>	Fitted <code>gam</code> model for $E[\mu_1(X) - \mu_0(X) P(Z) = p]$

## References

- Zhou, Xiang and Yu Xie. 2019. "Marginal Treatment Effects from A Propensity Score Perspective." Journal of Political Economy, 127(6): 3070-3084.
- Zhou, Xiang and Yu Xie. 2020. "Heterogeneous Treatment Effects in the Presence of Self-selection: a Propensity Score Perspective." Sociological Methodology.

## Examples

```

mod <- mte(selection = d ~ x + z, outcome = y ~ x, data = toydata)

u <- p <- seq(0.05, 0.95, 0.1)
mte_tilde <- mte_tilde_at(p, u, model = mod)

# heatmap showing MTE_tilde(p, u)
if(require("ggplot2")){
  ggplot(mte_tilde$df, aes(x = u, y = p, fill = value)) +
    geom_tile() +
    scale_fill_gradient(name = expression(widetilde(MTE)(p, u)), low = "yellow", high = "blue") +
    xlab("Latent Resistance U") +
    ylab("Propensity Score p(Z)") +
    theme_minimal(base_size = 14)
}

mprte_tilde_df <- subset(mte_tilde$df, p == u)

# heatmap showing MPRTE_tilde(p)
if(require("ggplot2")){
  ggplot(mprte_tilde_df, aes(x = u, y = p, fill = value)) +
    geom_tile() +
    scale_fill_gradient(name = expression(widetilde(MPRTE)(p)), low = "yellow", high = "blue") +
    xlab("Latent Resistance U") +
    ylab("Propensity Score p(Z)") +
    theme_minimal(base_size = 14)
}

# MPRTE_tilde(p) decomposed into the p-component and the u-component
if(require(tidyr) && require(dplyr) && require(ggplot2)){
  mprte_tilde_df %>%
    pivot_longer(cols = c(u_comp, p_comp, value)) %>%
    mutate(name = recode_factor(name,
      `value` = "MPRTE(p)",
      `p_comp` = "p(Z) component",
      `u_comp` = "U component")) %>%
    ggplot(aes(x = p, y = value)) +
    geom_line(aes(linetype = name), size = 1) +
    scale_linetype(name = "") +
    xlab("Propensity Score p(Z)") +
    ylab("Treatment Effect") +
    theme_minimal(base_size = 14) +
    theme(legend.position = "bottom")
}

```

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toydata

*A Hypothetical Dataset for Illustrative Purpose*

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### Description

A dataset containing 4 columns: *y* for a continuous outcome, *d* for a binary treatment, *x* for a pretreatment covariate, and *z* for an excluded instrument.

### Usage

toydata

### Format

An object of class `data.frame` with 10000 rows and 4 columns.

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