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rddtools: tools for Regression Discontinuity Design in R

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Abstract

The rddtools package implements functions for handling Regression Discontinuity Design in R.

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1. Introduction

The `rddtools` package attempts to provide a unified approach to using Regression Discontinuity Design (RDD) in R.

2. Design

A unified framework for RDD is implemented through the `rdd_data` class which inherits from the `R` `base` package's `data.frame` class. This functionality is made accessible through the associated `rdd_data` function, as well as the following associated methods.

- `summary.rdd_data()`
- `plot.rdd_data()`

The package is designed to leveredge of existing implementations of **Regression Discontinuity Design** in `R`, such as the `rdd` and `KernSmooth` packages. In addition to this, it implements several tools for RDD analysis that were previously unavailable.

- Simple visualisation of the data using binned-plot: `plot()`

2.1. Bandwidth Selection

Two new mehtods for Bandwidth selection are included. - MSE-RDD bandwidth procedure of (G. Imbens and Kalyanaraman 2012): `rdd_bw_ik()` - MSE global bandwidth procedure of (Ruppert, Sheather, and Wand 1995): `rdd_bw_rsw()`

2.2. Estimation

RDD parametric estimation: `rdd_reg_lm()` This includes specifying the polynomial order, including covariates with various specifications as advocated in (G. W. Imbens and Lemieux 2008).

RDD local non-parametric estimation: `rdd_reg_np()`. Can also include covariates, and allows different types of inference (fully non-parametric, or parametric approximation).

RDD generalised estimation: allows to use custom estimating functions to get the RDD coefficient. Could allow for example a probit RDD, or quantile regression.

2.3. Post-Estimation

A collection of Post-Estimation tools allow the robustness of the estimation results to be verified.

Various tools, to obtain predictions at given covariate values (`rdd_pred()`), or to convert to other classes, to lm (`as.lm()`), or to the package `np` (`as.npreg()`).

Function to do inference with clustered data: `clusterInf()` either using a cluster covariance matrix (`vcovCluster()`) or by a degrees of freedom correction (as in (Cameron, Gelbach, and Miller 2008)).

Contains functions to replicate the Monte-Carlo simulations of [Imbens and Kalyanaraman 2012]: `gen_mc_ik()`

2.4. Regression Sensitivity Analysis

Plot the sensitivity of the coefficient with respect to the bandwith: `plotSensi()`

Placebo plot using different cutpoints: `plotPlacebo()`

2.5. Design sensitivity analysis

McCrary test of manipulation of the forcing variable: wrapper `dens_test()` to the function `DCdensity()` from package `rdd`.

Test of equal means of covariates: `covarTest_mean()`

Test of equal density of covariates: `covarTest_dens()`

3. Data

A collection of typical data sets is included in the package.

- INDH, Arcand (2015): `indh`
- Seminal dataset of Lee (2008): `house`

Both data sets is made available as a `data.frame`. Using the previously discuss `rdd_data()` function we can transform a `data.frame` to an object of class `rdd_data`, which inherits from `data.frame`.

Here we can the data from the Initiative Nationale du Development Humaine (INDH), a development project in Morocco. The data is included with the package under the name `indh`.

```
[1] "indh"
```

Now that we have loading the data we can briefly inspect the structure of the data.

```
str(indh)
```

```
'data.frame':   720 obs. of  2 variables:
 $ choice_pg: int  0 1 1 1 1 1 0 1 0 0 ...
 $ poverty  : num  30.1 30.1 30.1 30.1 30.1 ...
 - attr(*, "na.action")=Class 'omit'  Named int [1:11] 58 289 290 291 292 293 294 295 296 2
  .. ..- attr(*, "names")= chr [1:11] "58" "289" "290" "291" ...
```

The `indh` object is a `data.frame` containing 720 observations (representing individuals) of two variables:

- `choice_pg`
- `poverty`

The variable of interest is `choice_pg`, which represent the decision to contibute to a public good or not. The observations are individuals choosing to contribute or not, these individuals are clustered by the variable `commune` which is the municiple structure at which funding was distributed as part of the INDH project. The forcing variable is `poverty` which represents the number of households in a commune living below the poverty threshold. As part of the INDH, commune with a proportion of household below the poverty threshhold greater than 30% were allowed to distribute the funding using a **Community Driven Development** scheme. The cutoff point for our analysis is therefore `30`.

We can now transform the `data.frame` to a special `rdd_data`-class object, inhereting from the `data.frame` class using the `rdd_data()` function.

```
rdd_dat_indh <- rdd_data(y=choice_pg,
                         x=poverty,
                         data=indh,
                         cutpoint=30 )
```

The `rdd_data()` can be used using the `data` argument, in which case the function will look for the values o `y` and `x` in this argument (before looking in the `.GlobalEnv`), if this argument is `NULL`, only the `.GlobalEnv` will be scanned. Additional exogenous variables can be included using the `covar` argument.

The structure is similar to the original `data.frame` object, but contains some additional information.

```
str(rdd_dat_indh)
```

```
Classes 'rdd_data' and 'data.frame':    720 obs. of  2 variables:
 $ x: num  30.1 30.1 30.1 30.1 30.1 ...
 $ y: int  0 1 1 1 1 1 0 1 0 0 ...
 - attr(*, "hasCovar")= logi FALSE
 - attr(*, "labels")= list()
 - attr(*, "cutpoint")= num 30
 - attr(*, "type")= chr "Sharp"
```

The `rdd_data` object has the classes `data.frame` and `rdd_data`. It contains two variables, `y` the explanandum or dependent variable and `x` the explanans or driving variable, which is also our discontinuous variable. Related to the discontinuous variable is the `attribute` called `cutpoint`, which describes where in the domain of `x` the discontinuity occurs. The `hasCover` attribute indicates if additional exogenous variables have been included using the `cover` argument to the `rdd_data()` function.

4. Analysis

In order to best understand our data, we start with an exploratory data analysis using tables…

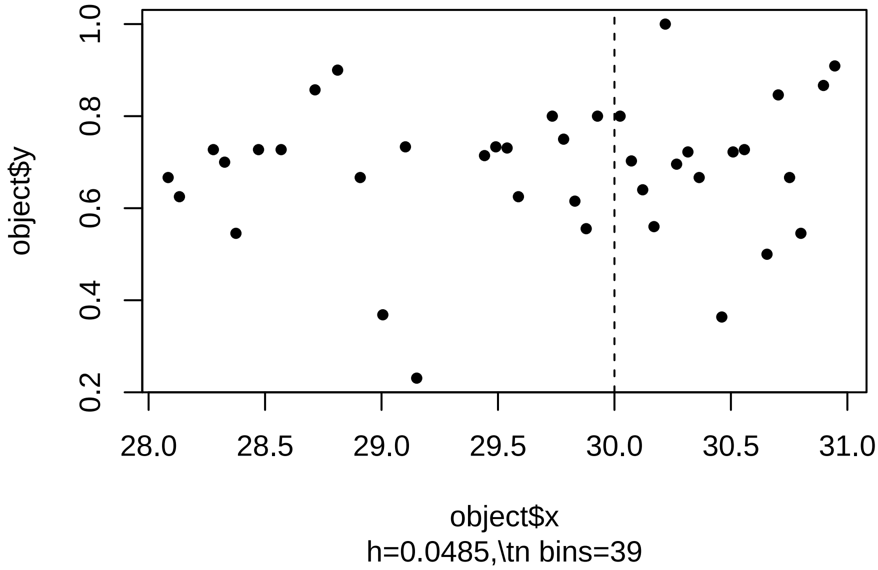
```
summary(rdd_dat_indh)
```

```
### rdd_data object ###

Cutpoint: 30
Sample size:
    -Full : 720
    -Left : 362
    -Right: 358
Covariates: no
```

…and plots.

```
plot(rdd_dat_indh)
```



We can now continue with a standard Regression Discontinuity Design estimation.

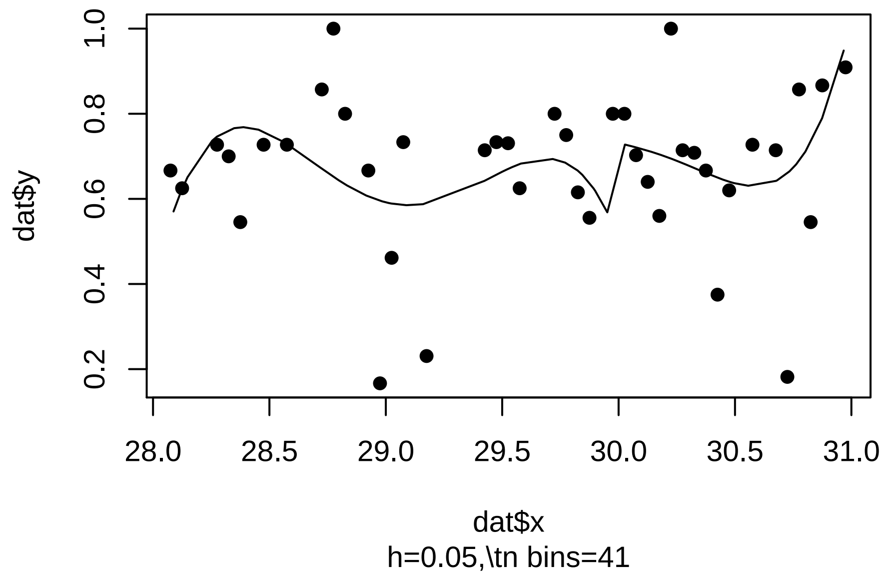
```
reg_para <- rdd_reg_lm(rdd_dat_indh, order=4)
print(reg_para) # uses print.rdd_data
```

```
### RDD regression: parametric ###
    Polynomial order:  4
    Slopes:  separate
    Number of obs: 720 (left: 362, right: 358)

    Coefficient:
  Estimate Std. Error t value Pr(>|t|)
D  0.22547    0.17696  1.2741    0.203
```

and visualising this estimation.

```
plot(reg_para)
```



In addition to the parametric estimation, we can also perform a non-parametric estimation.

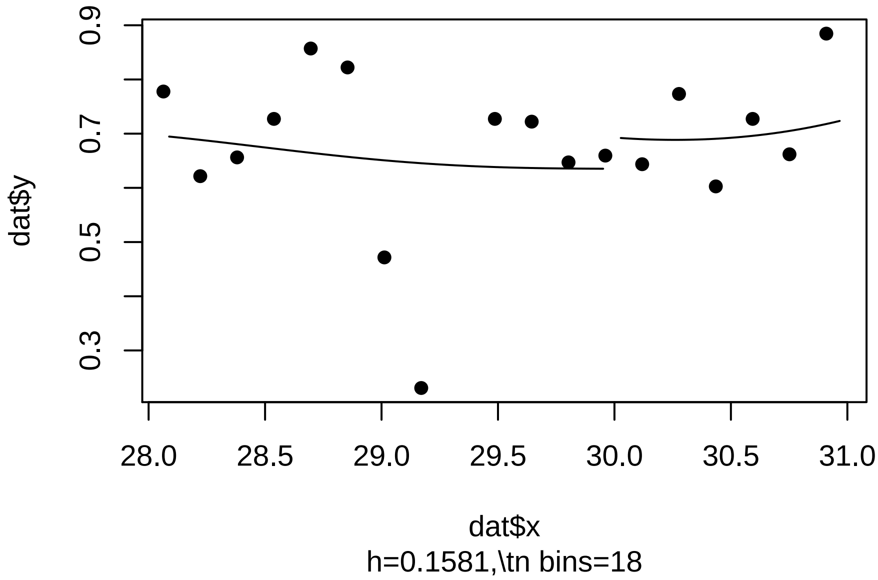
```
bw_ik <- rdd_bw_ik(rdd_dat_indh)
reg_nonpara <- rdd_reg_np(rdd_object=rdd_dat_indh, bw=bw_ik)
reg_nonpara
```

```
### RDD regression: nonparametric local linear###
    Bandwidth:  0.790526
    Number of obs: 460 (left: 139, right: 321)

    Coefficient:
  Estimate Std. Error z value Pr(>|z|)
D 0.144775   0.095606  1.5143     0.13
```

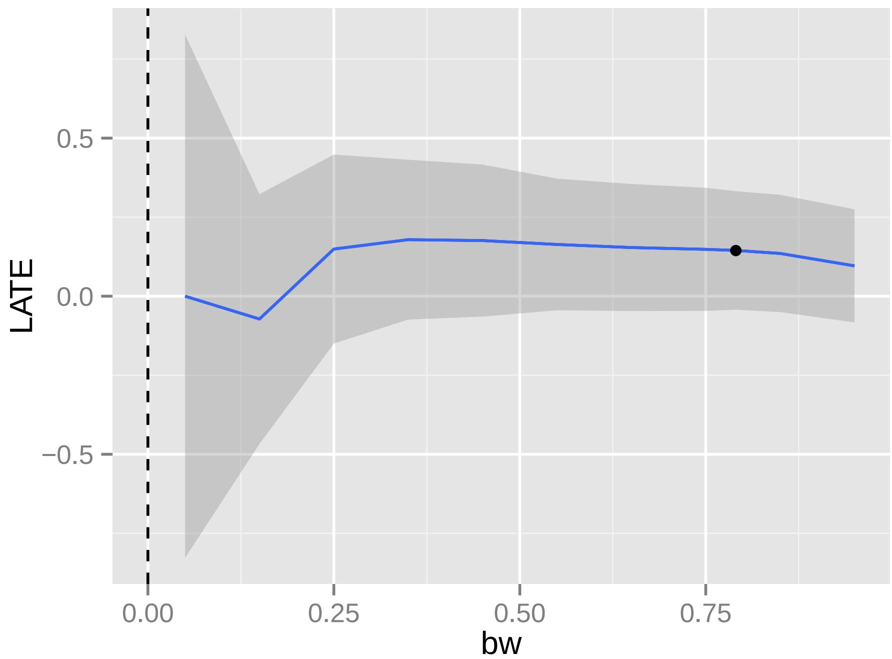
and visualising the non-parametric estimation.

```
plot(reg_nonpara)
```



Sensitity tests.

```
plotSensi(reg_nonpara, from=0.05, to=1, by=0.1)
```



5. Conclusion and Discussion

The package `rddtools` provides a unified framework for working with Regression Discontinuity Data in `R`. Functionality already available is several existing packages, such as `rdd` and `KernSmooth` can now easilty be utlised using the `rdd_data` framework, as well as several linking functions.

In addition to this, new tools and algorithms are also implement, as well as various post-estimation robustness checks.

Future packages implementing further RDD functionality can easily leverage the `rdd_data` framework, which allows users to quickly access new functionality through a familiar API.

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