# 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 the application of Regression Discontinuity Design (RDD) in R.

## 2. Design

A unified framework for RDD is implemented through the `rdd_data` class. This class 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.

- `[.rdd_data()` / `subset.rdd_data()`
- `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` (Dimmery 2013) and `KernSmooth` (M. Wand 2015)

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packages. Furthermore, general algorithms such as non-parametric regression from the `np` package (Hayfield and Racine 2008) is made accessible for RDD through the `rdd_data` framework.

In addition to this, it implements several tools for RDD analysis that were previously unavailable.

### 2.1. Bandwidth Selection

Two new methods 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.

- Initiative Nationale pour le Développement Humain (Arcand, Rieger, and Nguyen 2015): `indh`
- Voting in the U.S. House of Representatives (Lee 2008): `house`
- STAR dataset (Angrist and Pischke 2008): `STAR_MHE`

All three data sets are 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 pour le Développement Humain (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 ...
```

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 contribute 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 municipal 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 threshold 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, inheriting 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

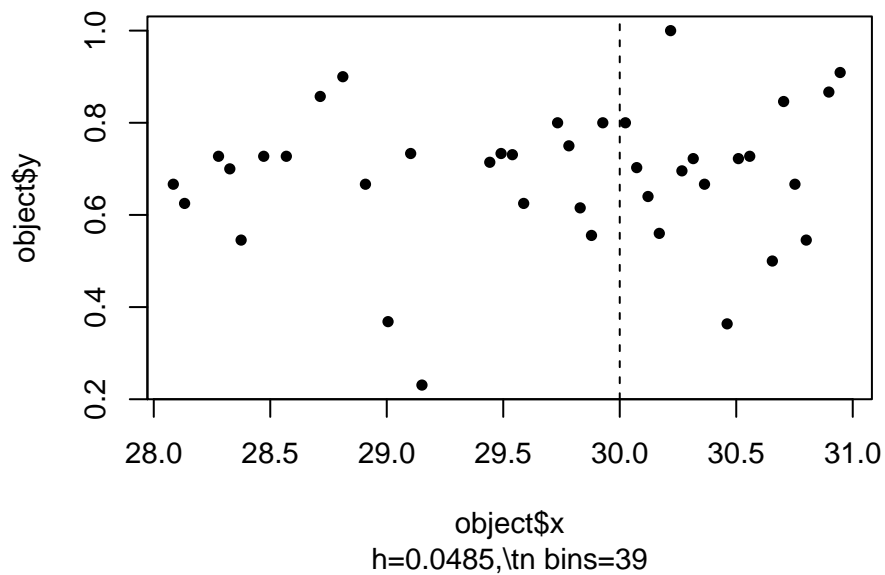In order to best understand our data, we start with an exploratory data analysis using tables. . .

```
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)
```



h=0.0485,\tn bins=39

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)
```

h=0.05,\tn bins=41
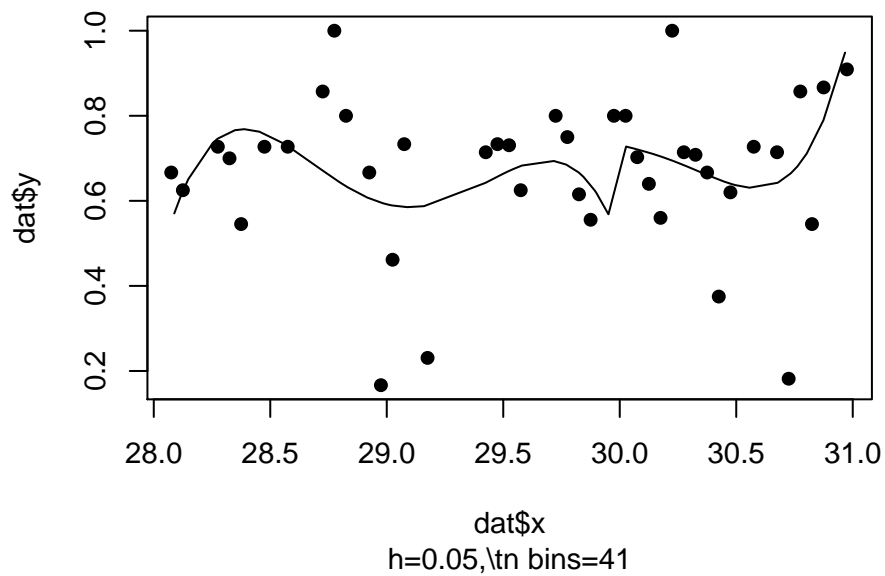
In addition to the parametric estimation, we can also perform a non-parametric estimation.
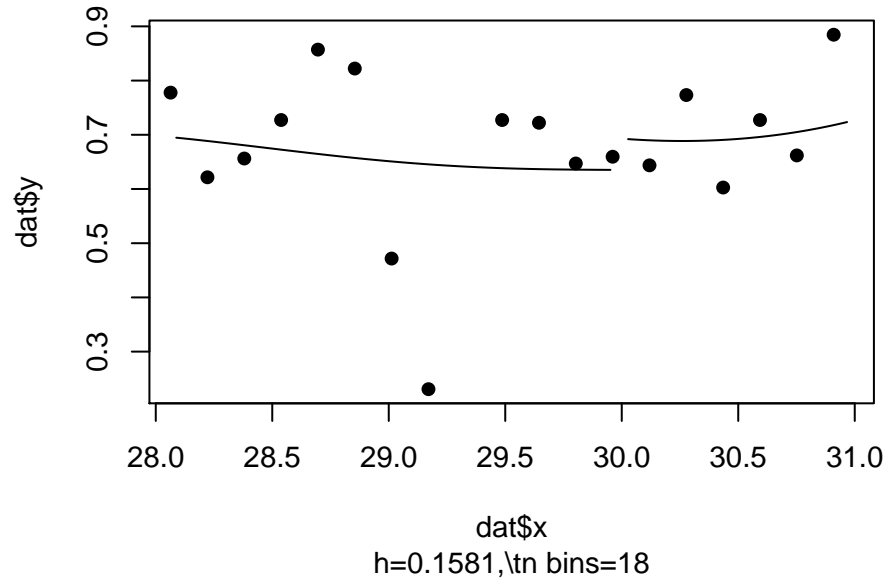
```
bw_ik <- rdd_bw_ik(rdd_dat_indh)
reg_nonpara <- rdd_reg_np(rdd_object=rdd_dat_indh, bw=bw_ik)
reg_nonpara
```

```
### 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
```
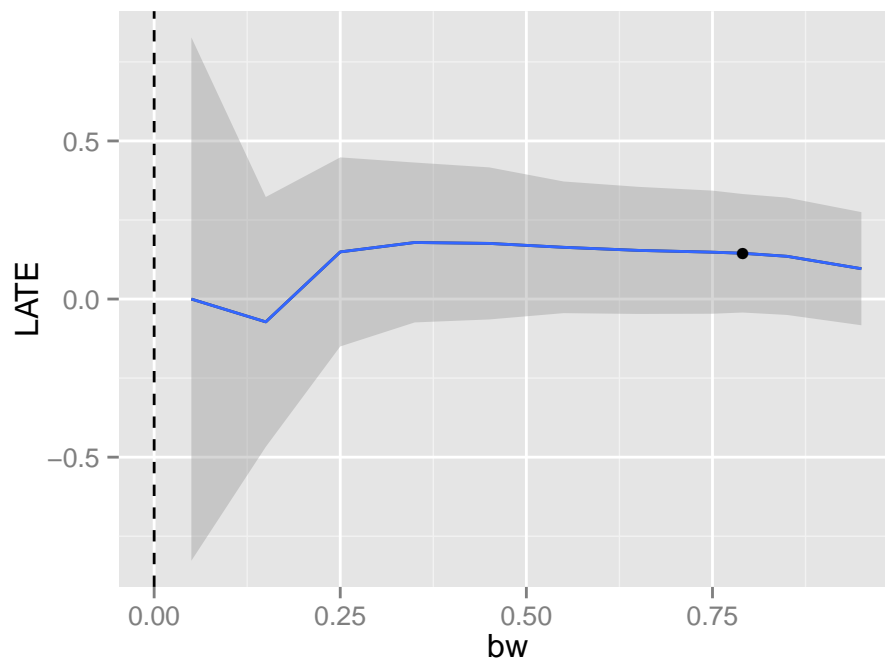
and visualising the non-parametric estimation.

```
plot(reg_nonpara)
```

Sensitivity 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 easily be utilised 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.

# References

Angrist, Joshua D, and Jörn-Steffen Pischke. 2008. *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton university press.

Arcand, Rieger, and Nguyen. 2015. "Development Aid and Social Dyanmics Data Set."

Cameron, A Colin, Jonah B Gelbach, and Douglas L Miller. 2008. "Bootstrap-Based Improvements for Inference with Clustered Errors." *The Review of Economics and Statistics* 90 (3). MIT Press: 414–27.

Dimmery, Drew. 2013. *Rdd: Regression Discontinuity Estimation.* http://CRAN.R-project.org/package=rdd.

Hayfield, Tristen, and Jeffrey S. Racine. 2008. "Nonparametric Econometrics: The Np Package." *Journal of Statistical Software* 27 (5). http://www.jstatsoft.org/v27/i05/.

Imbens, Guido W, and Thomas Lemieux. 2008. "Regression Discontinuity Designs: A Guide to Practice." *Journal of Econometrics* 142 (2). Elsevier: 615–35.

Imbens, Guido, and Karthik Kalyanaraman. 2012. "Optimal Bandwidth Choice for the Regression."

Lee, David S. 2008. "Randomized Experiments from Non-Random Selection in US House Elections." *Journal of Econometrics* 142 (2). Elsevier: 675–97.

Ruppert, David, Simon J Sheather, and Matthew P Wand. 1995. "An Effective Bandwidth Selector for Local Least Squares Regression." *Journal of the American Statistical Association* 90 (432). Taylor & Francis: 1257–70.

Wand, Matt. 2015. *KernSmooth: Functions for Kernel Smoothing Supporting Wand & Jones (1995).* http://CRAN.R-project.org/package=KernSmooth.

Wickham, Hadley. 2009. *Ggplot2: Elegant Graphics for Data Analysis.* Springer New York. http://had.co.nz/ggplot2/book.

Zeileis, Achim. 2004. "Econometric Computing with HC and HAC Covariance Matrix Estimators. Journal of Statistical Software." *Journal of Statistical Software* 11 (10). http://www.jstatsoft.org/v11/i10/.

———. 2006. "Object-Oriented Computation of Sandwich Estimators" 16 (9). Nournal os Statistical Software. http://www.jstatsoft.org/v16/i09/.

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