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rddtools: tools for Regression Discontinuity Design in R*

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Abstract

The rddtools package provides a framework for Regression Discontinuity Design (RDD) in R. In addtion to bringing together functionality from several different existing package, new functionality is implemented in terms of design and sensitivity test, as well as non parametric RDD.

Keywords: RDD, Regression, Discontinuity, Design, R.

1. Introduction

The `rddtools` package attempts to provide a unified approach to the application of Regression Discontinuity Design (RDD) in R. Functionality from several existing packages is brought together under one coherent API. Additionallity, the `rddtools` package implements new functionality in several aspects of regression discontinuity design.

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()`

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- `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) 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

The `rddtools` package implements two new methods for bandwidth selection. The first is the MSE-RDD bandwidth procedure of (G. Imbens and Kalyanaraman 2012). This procdure is implemented in the `rdd_bw_ik()` function. Secondly, the MSE global bandwidth procedure of (Ruppert, Sheather, and Wand 1995) is implemented in the `rdd_bw_rsw()` function.

2.2. Estimation

Various types of RDD estimation are supported. The functionality has been implemented in such a way, that the change from one estimation method to another is as small as possible.

Firstly, RDD parametric estimation though the `rdd_reg_lm()` function is implemented. The `rdd-reg_lm()` fnction includes functionality for specifying the polynomial order, including covariates with various specifications as advocated in (G. W. Imbens and Lemieux 2008).

Secondly, RDD local non-parametric estimation is available by means of the `rdd_reg_np()` function. The `rdd_reg_np()` function can also include covariates and allows different types of inference (such as fully non-parametric, or parametric approximation).

Lastly, RDD generalised estimation has been implemented. This allows to use custom estimating functions to get the RDD coefficient. For example a probit RDD, or quantile regression could be used here.

2.3. Post-Estimation

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

This includes various tools, such as the `rdd_pred()`, which is used to obtain predictions at given covariate values. As well as the `as.lm()` function, which is used to convert to the lm class. Furthermore there is the `as.npreg()` function, in order to convert to the `np` package.

Additional post-estmimation tools include `clusterInf()`, which can be used for inference with clustered data, using eithera covariance matrix (using the `vcovCluster()` function), or by a degrees of freedom corrention (as described in (Cameron, Gelbach, and Miller 2008)).

Finally, the package contains functions to replicate the Monte-Carlo simulations of [Imbens and Kalyanaraman 2012], using the `gen_mc_ik()` function.

2.4. Regression Sensitivity Analysis

Regression sensitivity analysis can be conducted using the `plotSense()` function, which test the sensitivity of the coefficient with respect to the bandwidth, or by means of **Placebo plot** using different cutpoints: `plotPlacebo()`

2.5. Design sensitivity analysis

Finally, methods for design sensitivity analysis are included.

The McCrary test of manipulation of the forcing variable is available by passing the wrapper `dens_test()` to the function `DCdensity()` from package `rdd`.

As well as, the test of equal means of covariates, which can be performed using the `covarTest_mean()` function.

In addition to this, the test of equal density of covariates is available via the `covarTest_dens()` function.

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 `data.frame` objects. Using the previously discussed `rdd_data()` function we can transform such a `data.frame` object to an object of class `rdd_data` (which inherits from the `data.frame` object class).

Here we take the data set 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`.

```
Warning: package 'car' was built under R version 3.2.2
```

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

After having loaded the data, we start with inspecting it's structure.

```
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 of 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.

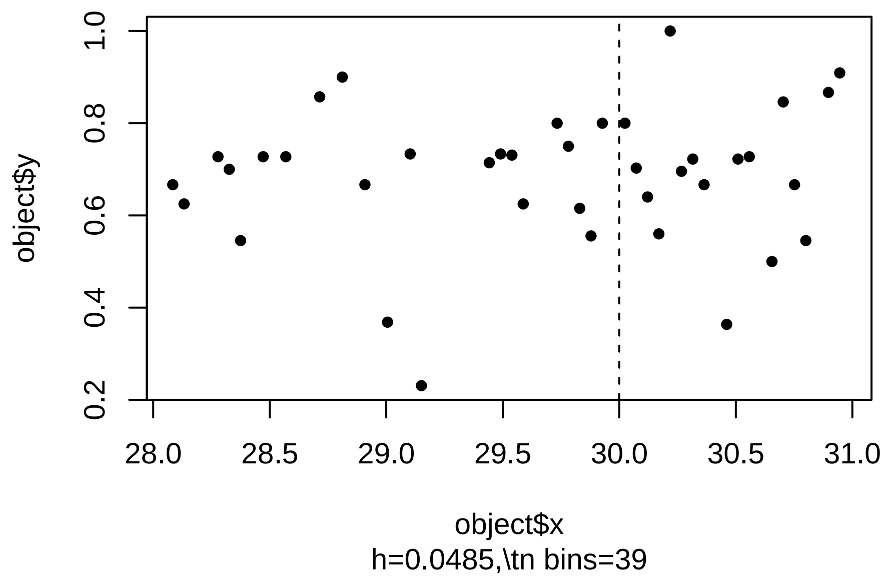
4. Analysis

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)
```



4.1. Parametric Estimation

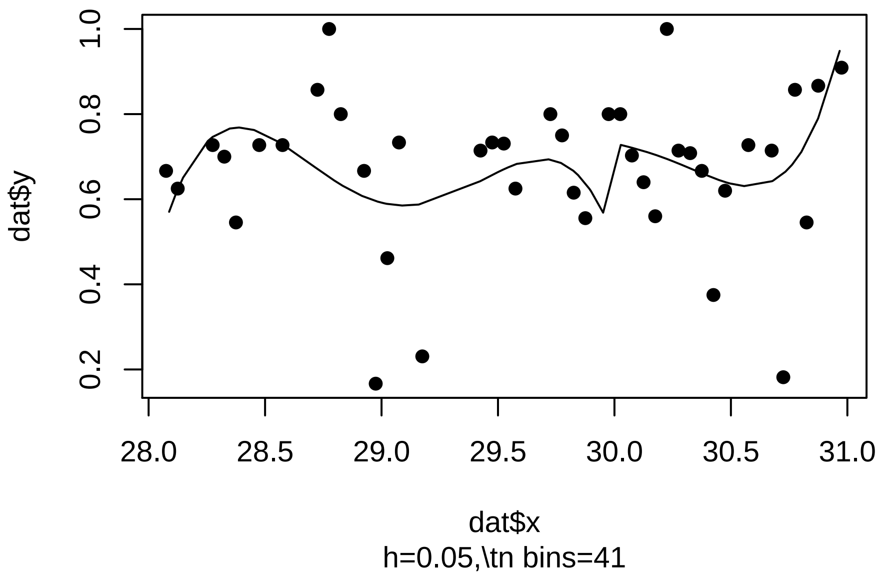
We can now continue with a standard Regression Discontinuity Design estimation.

```
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)
```



4.2. Non-parametric Estimation

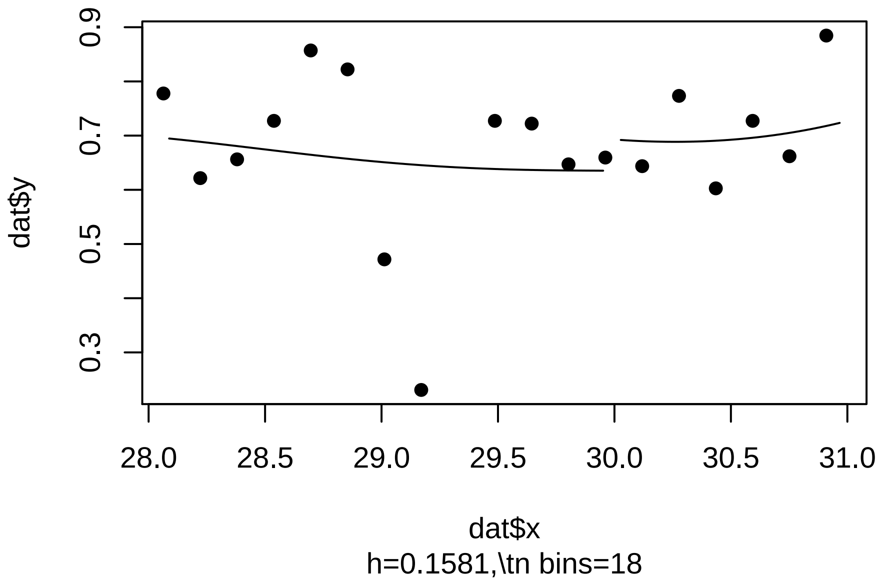
In addition to the parametric estimation, we can also perform a non-parametric estimation.

```
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.

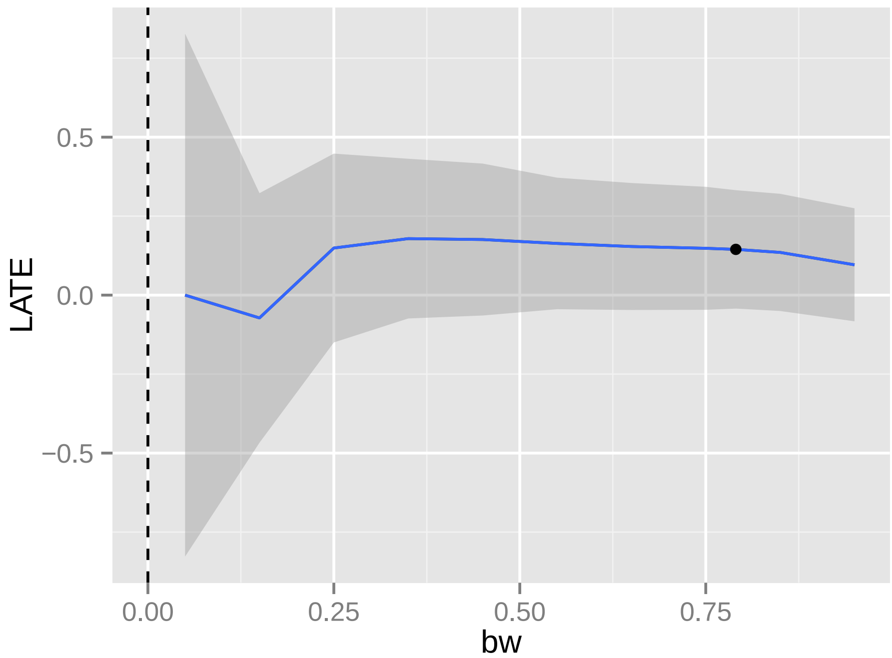
```
plot(reg_nonpara)
```



4.3. Sensitivity tests.

In addition to this, sepeveral sensitivity tests for the parametric and non-parametric estimation methods have been implemented.

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



In addition to the sensitivity test, we can also perform various other test such as a placebo test.

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 have also been implemented Furthermore, various post-estimation robustness checks are also included in the package.

In addition to the various procedures discussed here, future packages implementing further RDD functionality can easily leverage the `rdd_data` framework, which will allow users to quickly access this new functionality through a familiar API.

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