Journal of Statistical Software

MMMMMM YYYY, Volume VV, Issue II. http://www.jstatsoft.org/

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.

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.

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)

*This research was financed by the Swiss National Science Foundation (SNSF) under the grant 'Development Aid and Social Dynamics' (100018-140745) administered by the Graduate Institute's Centre on Conflict, Development and Peacebuilding (CCDP) and led by Jean-Louis Arcand. We thank Sandra Reimann and Oliver Jutersonke at the CCDP for their generous support.

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…

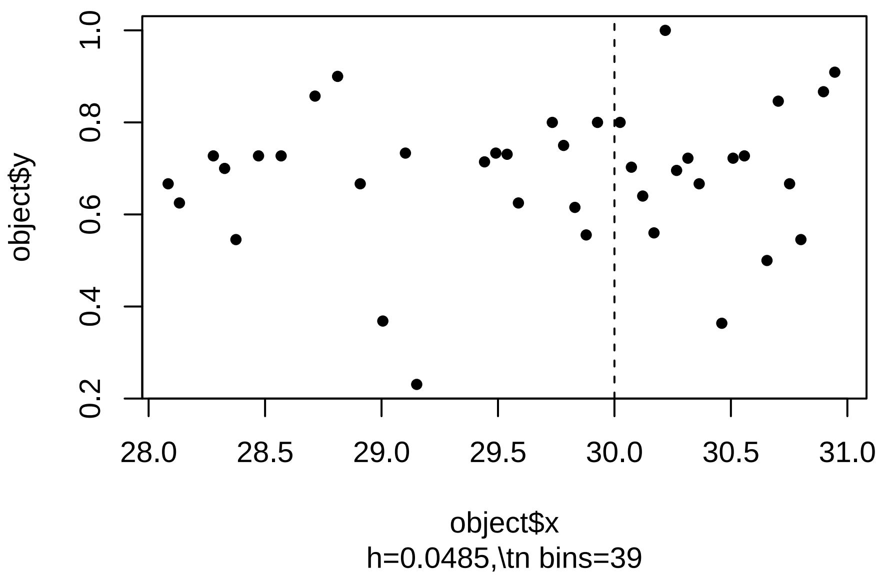
```
summary(rdd_dat_indh)
```

```
### 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.

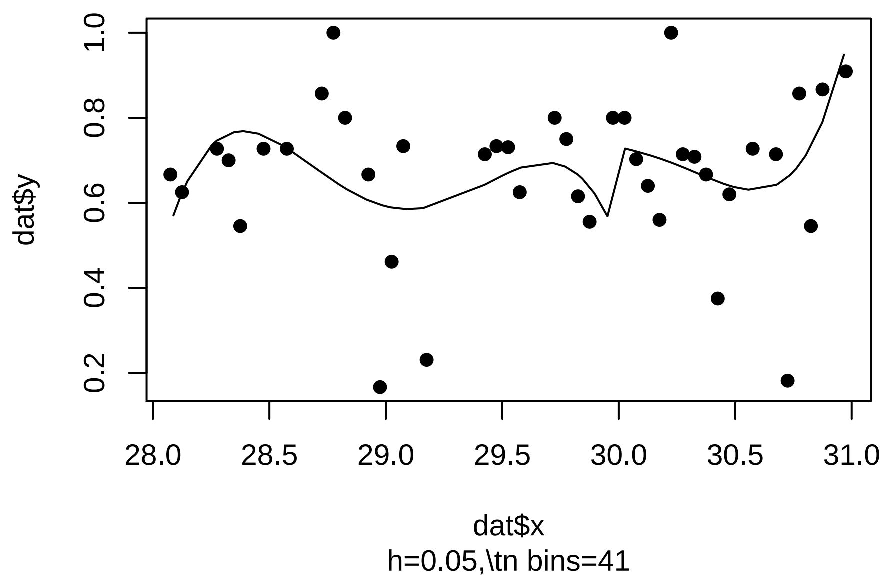
```
reg_para <- rdd_reg_lm(rdd_dat_indh, order=4)
print(reg_para) # uses print.rdd_data
```

```
### 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.

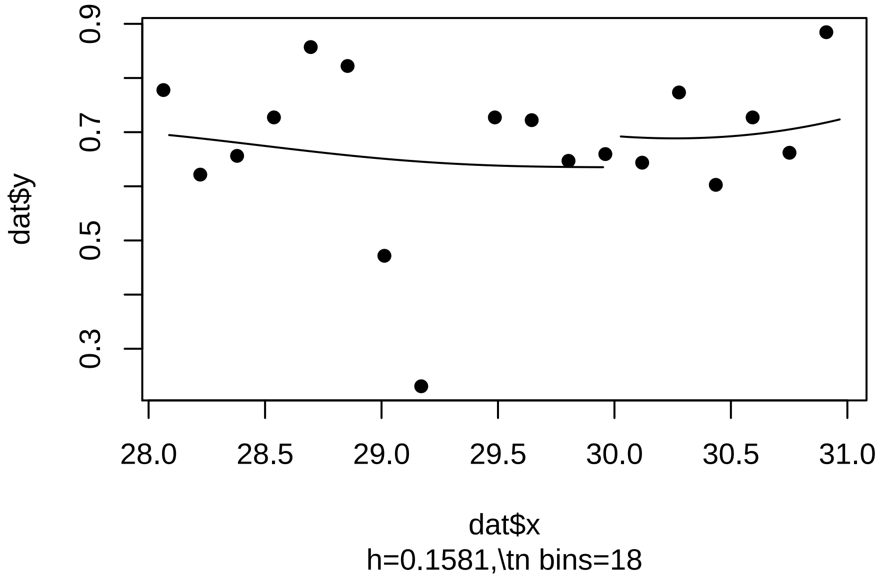
```
bw_ik <- rdd_bw_ik(rdd_dat_indh)
reg_nonpara <- rdd_reg_np(rdd_object=rdd_dat_indh, bw=bw_ik)
reg_nonpara

### 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.

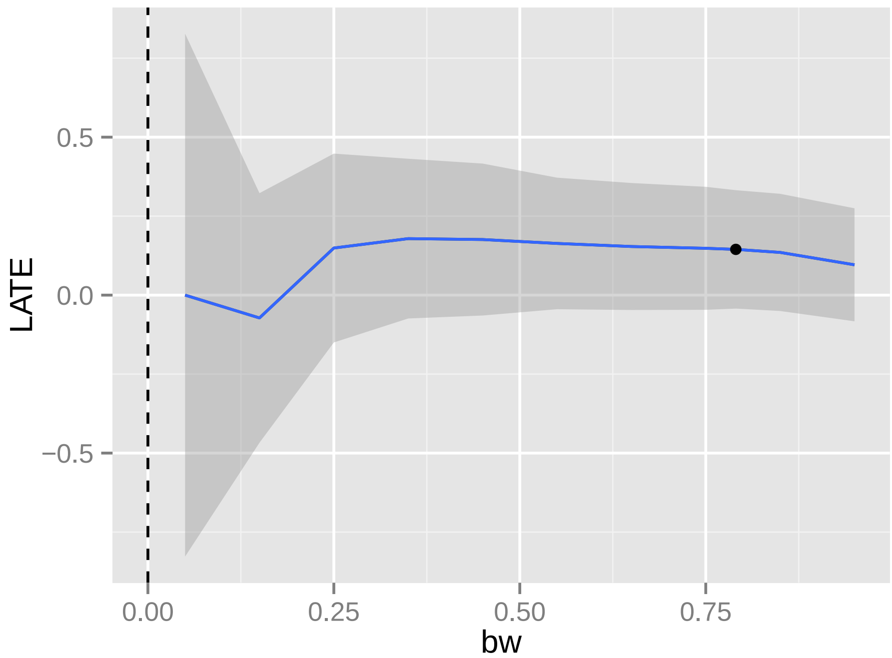
```
plot(reg_nonpara)
```



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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Journal of Statistical Software http://www.jstatsoft.org/
published by the American Statistical Association http://www.amstat.org/
Volume VV, Issue II *Submitted:* 2015-07-25
MMMMMM YYYY *Accepted:* yyyy-mm-dd