

PS630 Lab: RDD and Matching

Haohan Chen

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Disclaimer: I'm using lots of online resources for this tutorial...

Regression Discontinuity

The paper:

Carpenter, Christopher, and Carlos Dobkin. "The effect of alcohol consumption on mortality: regression discontinuity evidence from the minimum drinking age." *American Economic Journal: Applied Economics* 1, no. 1 (2009): 164-82.

Topic: The effect of alcohol consumption on mortality

Software Setup

```
#-----  
# Package  
#-----  
library(rdd)  
  
## Loading required package: sandwich  
## Loading required package: lmtest  
## Loading required package: zoo  
##  
## Attaching package: 'zoo'  
## The following objects are masked from 'package:base':  
##  
##   as.Date, as.Date.numeric  
## Loading required package: AER  
## Loading required package: car  
## Loading required package: carData  
## Loading required package: survival  
## Loading required package: Formula  
  
#-----  
# Package  
#-----  
library(readstata13)  
AEJfigs = read.dta13("AEJfigs.dta")  
  
#-----  
# Data cleaning  
#-----
```

```
# All = all deaths
AEJfigs$age = AEJfigs$agecell - 21
AEJfigs$over21 = ifelse(AEJfigs$agecell >= 21,1,0)
```

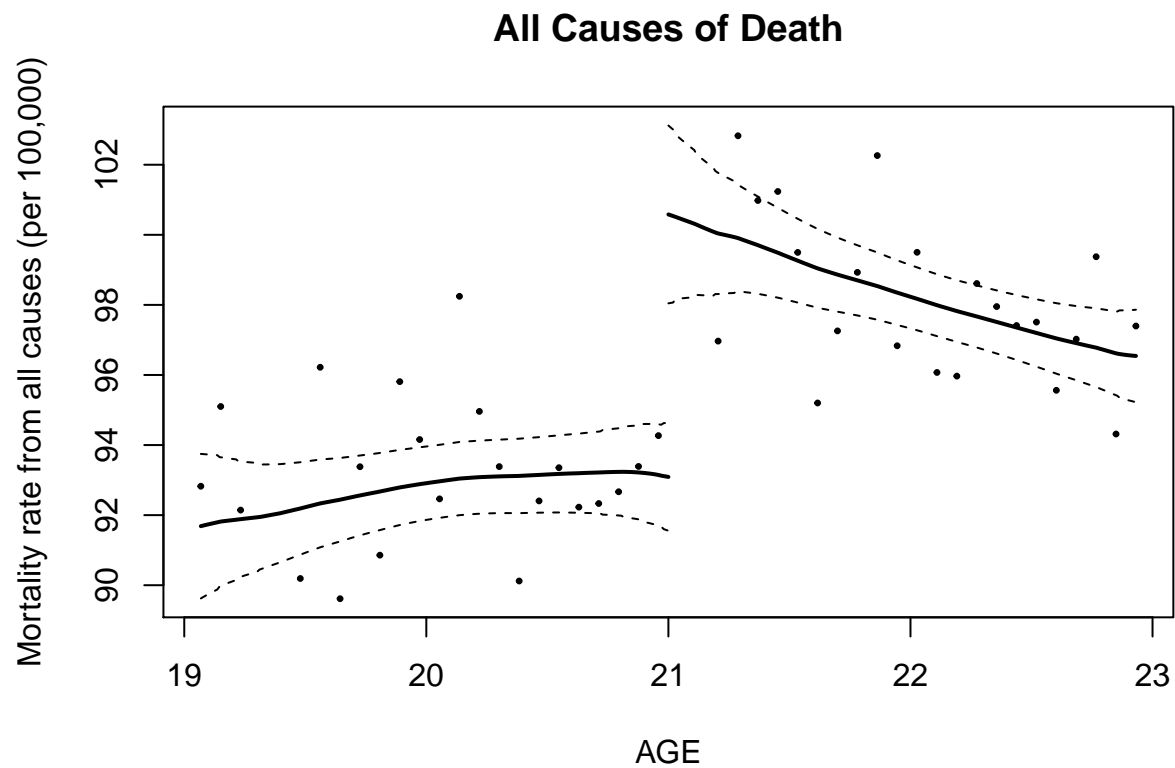
RD Model: Age cutpoint and Overall Mortality

Model Fit

```
#-----
# Fit RD model
#-----
reg.1=RDestimate(all~agecell,data=AEJfigs,cutpoint = 21)
```

Check Assumptions

```
plot(reg.1)
title(main="All Causes of Death", xlab="AGE",ylab="Mortality rate from all causes (per 100,000)")
```



Results

```
summary(reg.1)

##
## Call:
## RDestimate(formula = all ~ agecell, data = AEJfigs, cutpoint = 21)
```

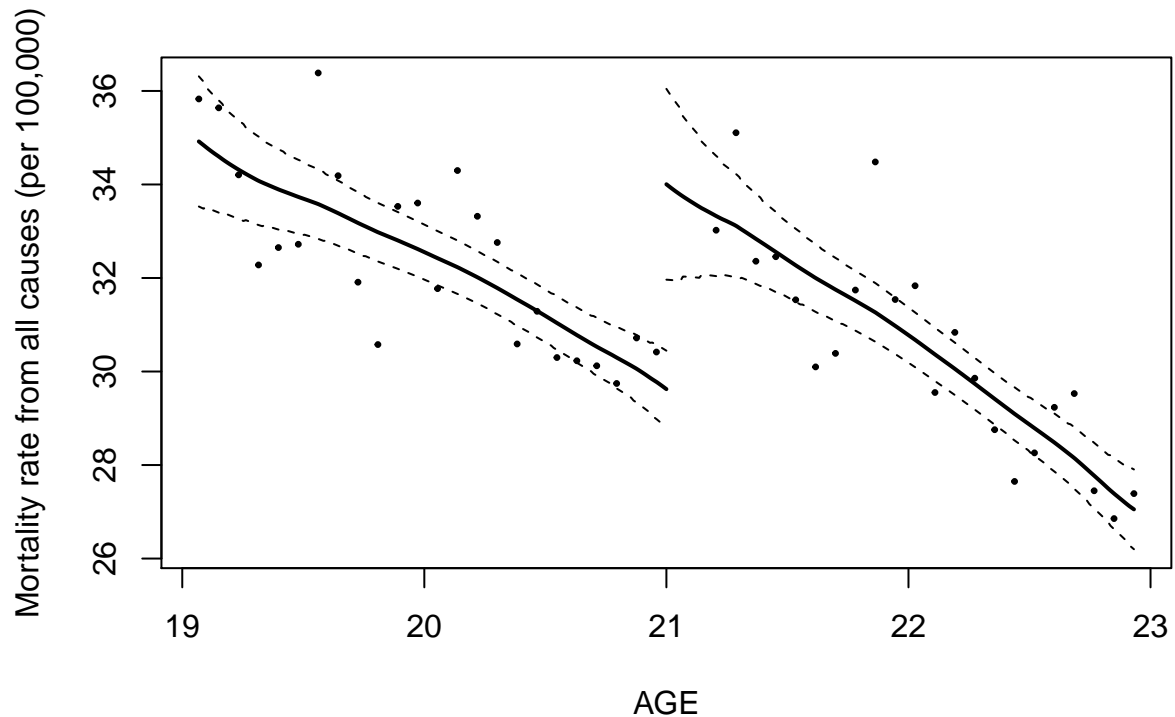
```
##
## Type:
## sharp
##
## Estimates:
##           Bandwidth  Observations  Estimate  Std. Error  z value
## LATE         1.6561      40          9.001    1.480      6.080
## Half-BW      0.8281      20          9.579    1.914      5.004
## Double-BW    3.3123      48          7.953    1.278      6.223
##           Pr(>|z|)
## LATE         1.199e-09 ***
## Half-BW      5.609e-07 ***
## Double-BW    4.882e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## F-statistics:
##           F      Num. DoF  Denom. DoF  p
## LATE        33.08    3         36      3.799e-10
## Half-BW     29.05    3         16      2.078e-06
## Double-BW   32.54    3         44      6.129e-11
```

Other DVs: Death

Motor Vehicle Accident

```
reg.2=RDestimate(mva~agecell,data=AEJfigs,cutpoint = 21)
plot(reg.2)
title(main="Motor Vehicle Accidents Death", xlab="AGE",ylab="Mortality rate from all causes (per 100,000)")
```

Motor Vehicle Accidents Death



```
summary(reg.2)
```

```
##
## Call:
## RDestimate(formula = mva ~ agecell, data = AEJfigs, cutpoint = 21)
##
## Type:
## sharp
##
## Estimates:
##      Bandwidth  Observations  Estimate  Std. Error  z value
## LATE          1.2109         30         4.977    1.0590    4.700
## Half-BW       0.6054         14         4.956    1.3767    3.600
## Double-BW     2.4218         48         4.566    0.7086    6.444
##      Pr(>|z|)
## LATE          2.607e-06 ***
## Half-BW       3.182e-04 ***
## Double-BW     1.162e-10 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## F-statistics:
##      F      Num. DoF  Denom. DoF  p
## LATE  13.32    3         26      3.692e-05
## Half-BW 12.76    3         10      1.879e-03
## Double-BW 26.99    3         44      9.322e-10
```

Internal Cause of Death

```
reg.3=RDestimate(internal~agecell,data=AEJfigs,cutpoint = 21)
plot(reg.3)
title(main="Internal Causes of Death", xlab="AGE",ylab="Mortality rate from all causes (per 100,000)")
```



```
summary(reg.3)
```

```
##
## Call:
## RDestimate(formula = internal ~ agecell, data = AEJfigs, cutpoint = 21)
##
## Type:
## sharp
##
## Estimates:
##           Bandwidth  Observations  Estimate  Std. Error  z value
## LATE           0.8809           22         1.4128    0.8206     1.722
## Half-BW        0.4405           10         1.8691    1.0203     1.832
## Double-BW      1.7618           42         0.7652    0.6179     1.239
##           Pr(>|z|)
## LATE           0.08513  .
## Half-BW        0.06698  .
## Double-BW      0.21553
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## F-statistics:
##           F      Num. DoF  Denom. DoF  p
## LATE      6.830    3          18      5.734e-03
## Half-BW   1.765    3           6      5.068e-01
## Double-BW 22.695    3          38      2.750e-08
```

Further reading: <https://rpubs.com/cuborican/RDD>

Matching

Example:

“Causal Effects in Non-Experimental Studies: Reevaluating the Evaluation of Training Programs,” Journal of the American Statistical Association, Vol. 94, No. 448 (December 1999), pp. 1053-1062.

Topic: The effect on trainee earnings of an employment program

Software Setup

```
#-----
# load packages
#-----
library(MatchIt)
# Political scientists package
# https://cran.r-project.org/web/packages/MatchIt/MatchIt.pdf

# Alternative packages: Matching, designmatch
# https://cran.r-project.org/web/packages/Matching/Matching.pdf
# https://cran.r-project.org/web/packages/designmatch/designmatch.pdf

library(tidyverse)
```

```
## -- Attaching packages ----- tidyverse 1.2.0

## v ggplot2 3.1.0      v purrr 0.2.5
## v tibble 1.4.2       v dplyr 0.7.8
## v tidyr 0.8.2        v stringr 1.3.1
## v readr 1.3.0        v forcats 0.3.0

## -- Conflicts ----- tidyverse_conflicts()

## x dplyr::filter() masks stats::filter()
## x dplyr::lag()     masks stats::lag()
## x dplyr::recode() masks car::recode()
## x purrr::some()    masks car::some()
```

```
#-----
# load dataset
#-----
data("lalonge")
names(lalonge)

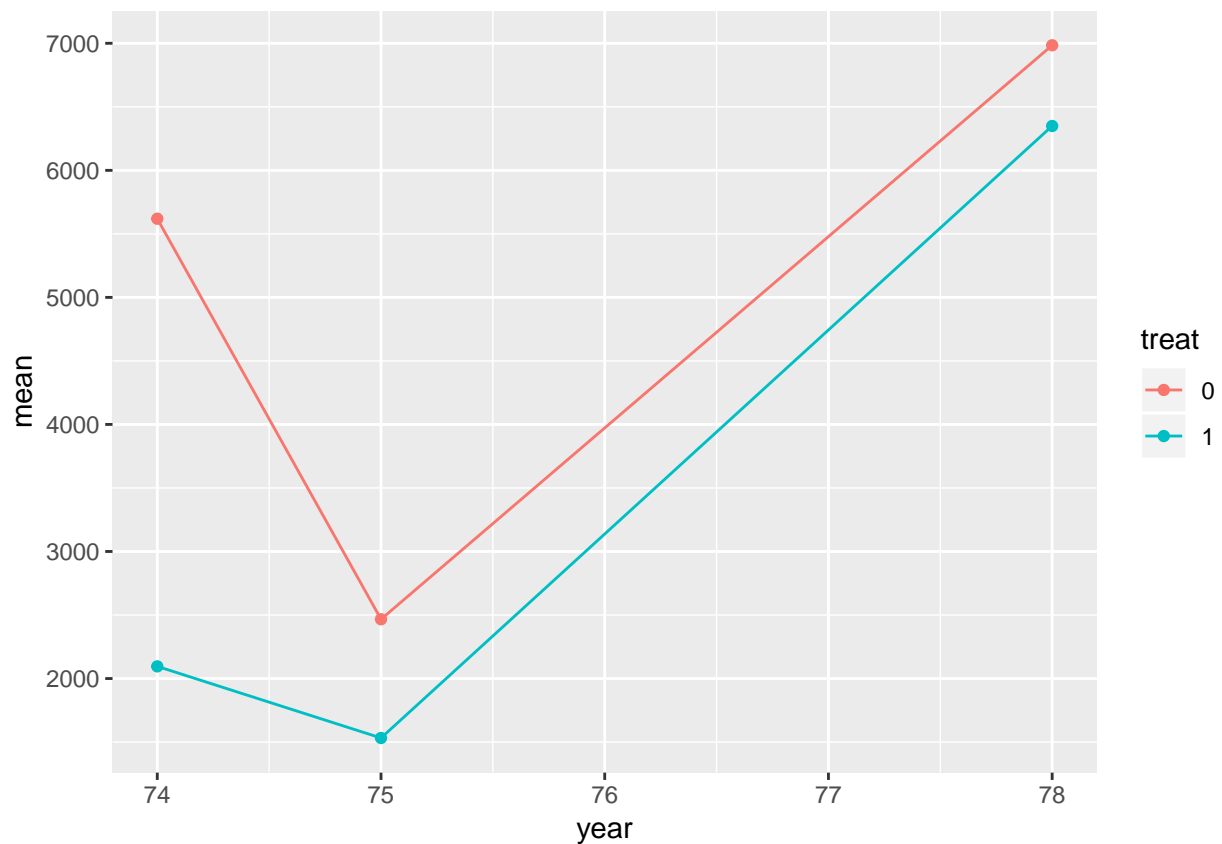
## [1] "treat"    "age"      "educ"     "black"    "hispan"   "married"
## [7] "nodegree" "re74"     "re75"     "re78"
```

Difference in Mean

```
# Table
lalonge %>%
  group_by(treat) %>%
  select(treat, re74, re75, re78) %>%
  summarise_all(funs(mean, sd))

## # A tibble: 2 x 7
##   treat re74_mean re75_mean re78_mean re74_sd re75_sd re78_sd
##   <int>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>    <dbl>
## 1     0      5619.     2466.     6984.     6789.     3292.     7294.
## 2     1      2096.     1532.     6349.     4887.     3219.     7867.

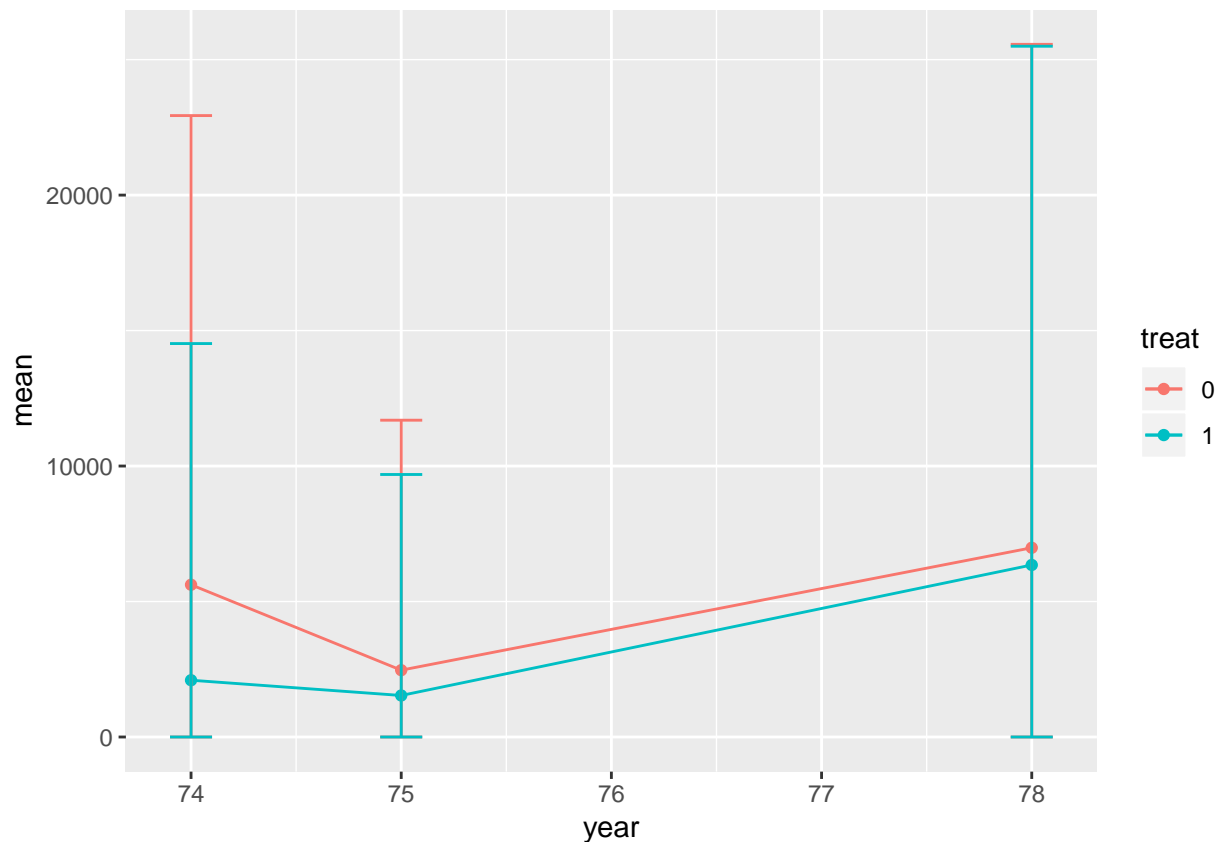
# Plot (without error)
lalonge %>%
  group_by(treat) %>%
  select(treat, re74, re75, re78) %>%
  summarise_all(funs(mean, lo = quantile(., 0.025), hi = quantile(., 0.975))) %>%
  gather(key, value, -treat) %>%
  mutate(year = as.integer(substr(key, 3, 4)),
         stat = substr(key, 6, 10),
         treat = as.factor(treat)) %>%
  select(-key) %>%
  spread(stat, value) %>%
  ggplot(aes(x = year, y = mean, color = treat)) + geom_point() + geom_line()
```



```

# Plot (with variance)
lalonge %>%
  group_by(treat) %>%
  select(treat, re74, re75, re78) %>%
  summarise_all(funs(mean, lo = quantile(., 0.025), hi = quantile(., 0.975))) %>%
  gather(key, value, -treat) %>%
  mutate(year = as.integer(substr(key, 3, 4)),
         stat = substr(key, 6, 10),
         treat = as.factor(treat)) %>%
  select(-key) %>%
  spread(stat, value) %>%
  ggplot(aes(x = year, y = mean, color = treat)) + geom_point() + geom_line() +
  geom_errorbar(aes(ymin = lo, ymax = hi), width=0.2)

```



Two-sample t-test

```

# Earning Growth
#-----
t.test(re78 - re75 ~ treat, data = lalonge)

##
## Welch Two Sample t-test
##
## data: re78 - re75 by treat
## t = -0.43138, df = 299.89, p-value = 0.6665

```



```
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -1665.248 1066.442
## sample estimates:
## mean in group 0 mean in group 1
##      4517.685      4817.088
```

```
# Remember what we did?
```

Checking Balance in Covariates

```
# Get a sense of the imbalance
lalonge %>%
  group_by(treat) %>%
  select(age, educ, black, hispan, married, nodegree) %>%
  summarise_all(funs(mean)) %>%
  gather(key, value, -treat) %>%
  spread(treat, value) %>%
  setNames(c("Covariate", "Control", "Treated")) %>%
  mutate(`T - C` = Treated - Control)

## Adding missing grouping variables: `treat`

## # A tibble: 6 x 4
##   Covariate Control Treated `T - C`
##   <chr>      <dbl>   <dbl>   <dbl>
## 1 age        28.0    25.8    -2.21
## 2 black       0.203    0.843    0.640
## 3 educ       10.2    10.3     0.111
## 4 hispan      0.142    0.0595 -0.0827
## 5 married     0.513    0.189   -0.324
## 6 nodegree    0.597    0.708    0.111

# A statistical summary of their difference
vars = c("age", "educ", "black", "hispan", "married", "nodegree")
ttests = apply(lalonge[, vars], 2, function(x) t.test(x ~ lalonge$treat))

# T statistics
sapply(ttests, function(x) x$statistic["t"])

##      age.t      educ.t      black.t      hispan.t      married.t      nodegree.t
## 2.991074 -0.546756 -19.344264  3.409136  8.596140 -2.712695

# p value
sapply(ttests, function(x) x$p.value)

##      age      educ      black      hispan      married
## 2.914274e-03 5.847977e-01 1.205890e-58 7.042071e-04 1.461278e-16
##      nodegree
## 6.982225e-03
```

Propensity Score Estimation

Fit PS Model

```
m_ps = glm(treat ~ age + educ + black + hispan + married + nodegree,
            family = binomial(link="logit"), data = lalonde)
summary(m_ps)
```

```
##
## Call:
## glm(formula = treat ~ age + educ + black + hispan + married +
##      nodegree, family = binomial(link = "logit"), data = lalonde)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.7709  -0.4606  -0.2963   0.7766   2.6384
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -4.67874    1.02120  -4.582 4.61e-06 ***
## age          0.01030    0.01329   0.775  0.43857
## educ         0.15161    0.06568   2.308  0.02098 *
## black        3.12657    0.28514  10.965 < 2e-16 ***
## hispan       0.99947    0.42191   2.369  0.01784 *
## married     -0.92969    0.27128  -3.427  0.00061 ***
## nodegree     0.78719    0.33507   2.349  0.01881 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 751.49  on 613  degrees of freedom
## Residual deviance: 494.70  on 607  degrees of freedom
## AIC: 508.7
##
## Number of Fisher Scoring iterations: 5
```

Predict PS Score

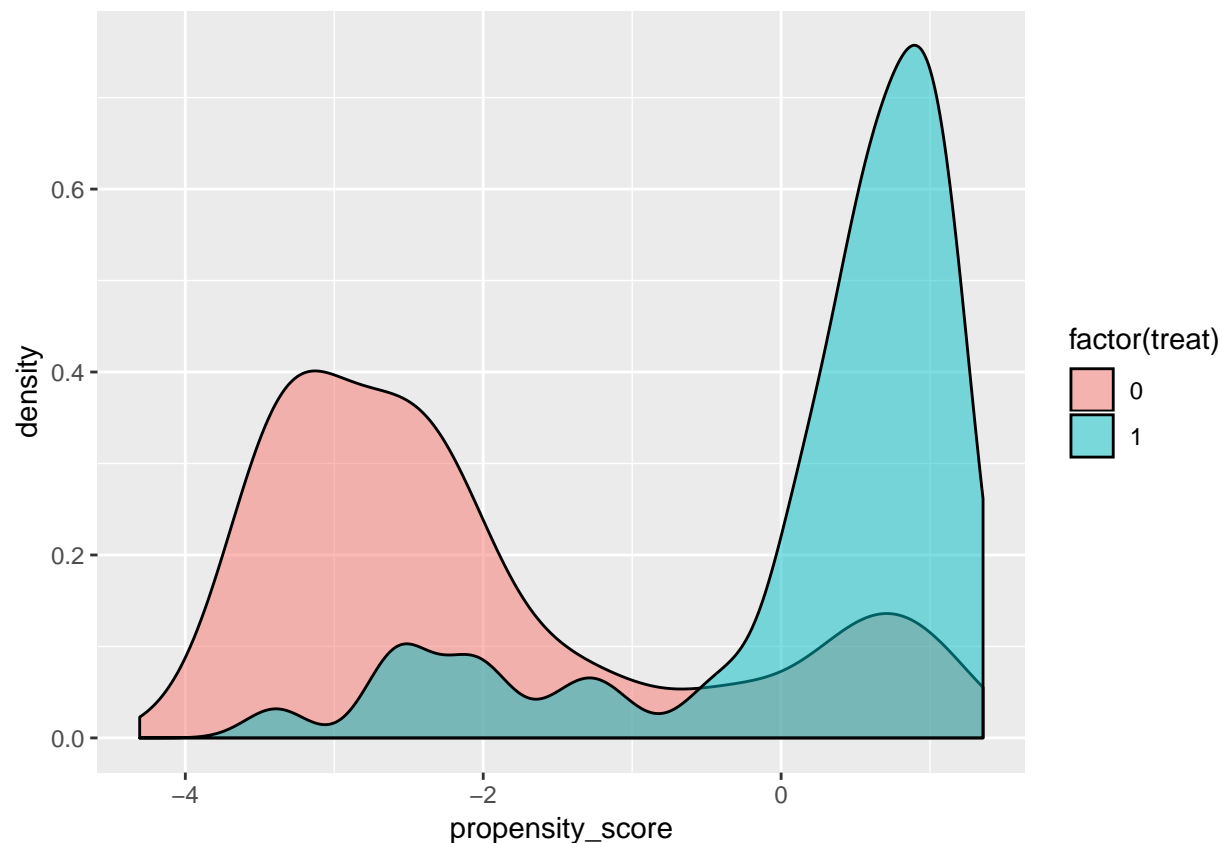
```
?predict
```

```
## starting httpd help server ... done
```

```
ps = predict(m_ps)
lalonde_ps = lalonde %>% mutate(propensity_score = ps)
```

Check overlap

```
lalonde_ps %>%
  ggplot(aes(x = propensity_score, fill = factor(treat))) +
  geom_density(alpha = 0.5)
```



Matching with the propensity score

Some more complication. Luckily, we have an one-stop solution!

One-Stop Solution

```
m_matchit =
  matchit(treat ~ age + educ + black + hispan + nodegree + married + re74 + re75,
    data = lalonde, method = "nearest", distance = "logit")

summary(m_matchit)
```

```
##
## Call:
## matchit(formula = treat ~ age + educ + black + hispan + nodegree +
## married + re74 + re75, data = lalonde, method = "nearest",
## distance = "logit")
##
## Summary of balance for all data:
```

	Means Treated	Means Control	SD Control	Mean Diff	eQQ Med
distance	0.5774	0.1822	0.2295	0.3952	0.5176
age	25.8162	28.0303	10.7867	-2.2141	1.0000
educ	10.3459	10.2354	2.8552	0.1105	1.0000
black	0.8432	0.2028	0.4026	0.6404	1.0000
hispan	0.0595	0.1422	0.3497	-0.0827	0.0000
nodegree	0.7081	0.5967	0.4911	0.1114	0.0000

```

## married          0.1892          0.5128          0.5004          -0.3236          0.0000
## re74             2095.5737          5619.2365          6788.7508          -3523.6628          2425.5720
## re75             1532.0553          2466.4844          3291.9962          -934.4291          981.0968
##               eQQ Mean      eQQ Max
## distance         0.3955      0.5966
## age              3.2649     10.0000
## educ             0.7027      4.0000
## black            0.6432      1.0000
## hispan           0.0811      1.0000
## nodegree         0.1135      1.0000
## married          0.3243      1.0000
## re74             3620.9240     9216.5000
## re75             1060.6582     6795.0100
##
##
## Summary of balance for matched data:
##               Means Treated Means Control SD Control Mean Diff eQQ Med
## distance         0.5774          0.3629          0.2533          0.2145          0.1646
## age              25.8162          25.3027          10.5864          0.5135          3.0000
## educ             10.3459          10.6054           2.6582         -0.2595          0.0000
## black            0.8432          0.4703          0.5005          0.3730          0.0000
## hispan           0.0595          0.2162          0.4128         -0.1568          0.0000
## nodegree         0.7081          0.6378          0.4819          0.0703          0.0000
## married          0.1892          0.2108          0.4090         -0.0216          0.0000
## re74             2095.5737          2342.1076          4238.9757         -246.5339          131.2709
## re75             1532.0553          1614.7451          2632.3533         -82.6898          152.1774
##               eQQ Mean      eQQ Max
## distance         0.2146      0.4492
## age              3.3892      9.0000
## educ             0.4541      3.0000
## black            0.3730      1.0000
## hispan           0.1568      1.0000
## nodegree         0.0703      1.0000
## married          0.0216      1.0000
## re74             545.1182     13121.7500
## re75             349.5371     11365.7100
##
## Percent Balance Improvement:
##               Mean Diff.      eQQ Med eQQ Mean eQQ Max
## distance         45.7140      68.1921     45.7536     24.7011
## age              76.8070     -200.0000     -3.8079     10.0000
## educ            -134.7737     100.0000     35.3846     25.0000
## black            41.7636     100.0000     42.0168      0.0000
## hispan          -89.4761      0.0000    -93.3333      0.0000
## nodegree         36.9046      0.0000     38.0952      0.0000
## married          93.3191      0.0000     93.3333      0.0000
## re74             93.0035      94.5880     84.9453    -42.3724
## re75             91.1508      84.4891     67.0453    -67.2655
##
## Sample sizes:
##               Control Treated
## All              429       185
## Matched           185       185
## Unmatched         244         0

```

Discarded 0 0

Further reading: <https://sejdemyr.github.io/r-tutorials/statistics/tutorial8.html>