WP9

Due Date: 11/12/21

1. Load the `rdrobust` package.

```
library(rdrobust)
library(readr)
```

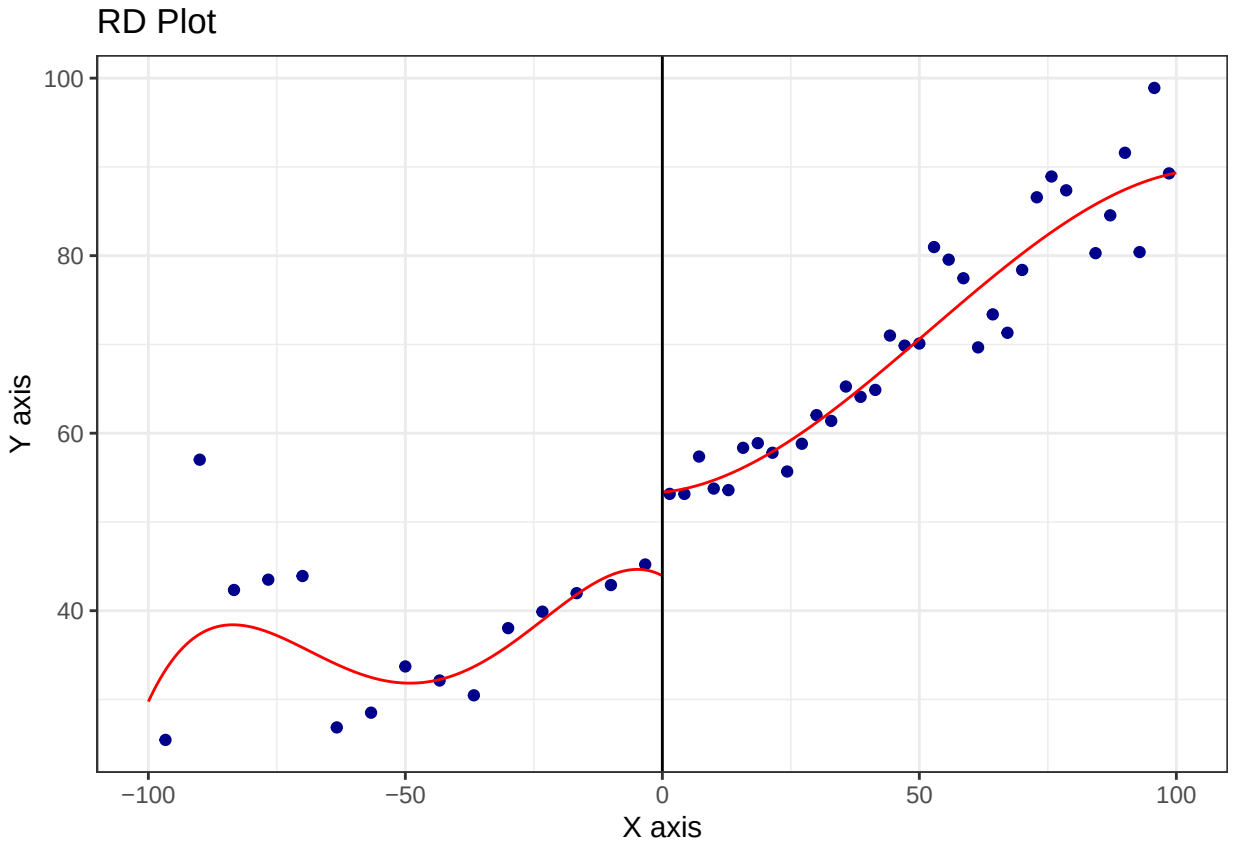
2. Load in the `senate.csv` dataset. Make a new dataset called `df` that has three variables:

- Y: made from demvoteshfor2
- Z: made from demmv
- D: a logical variable stating whether Z is greater than or equal to 0

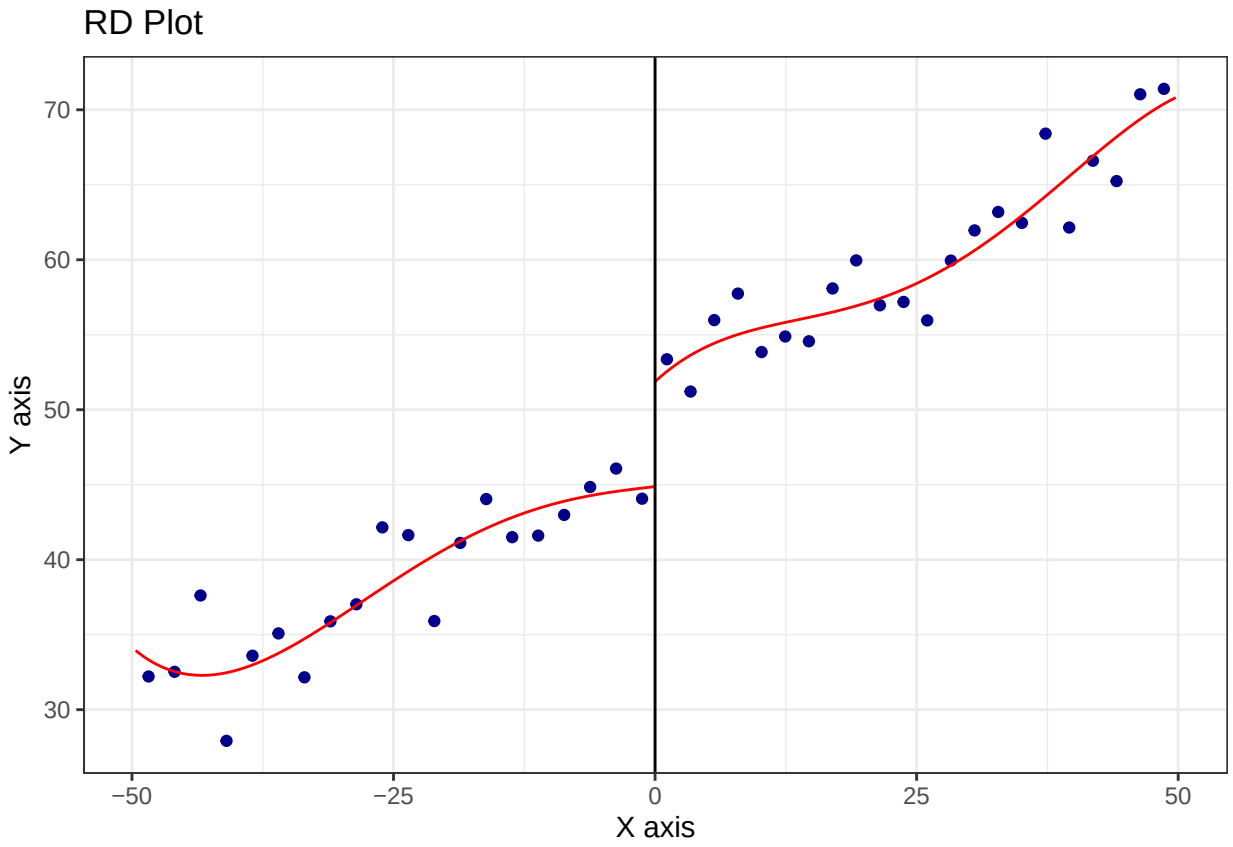
```
df <- read_csv("senate.csv") %>%
    select(Y = demvoteshfor2, Z = demmv) %>%
    mutate(D = Z >= 0)
```

3. Construct an RD plot of the Design. On the Y axis, plot the outcome variable. On the X axis, plot the score variable. Give this plot the title "RD Plot for Senate Elections Data"

```
## Raw comparison of means
rdplot(df$Y, df$Z)
```

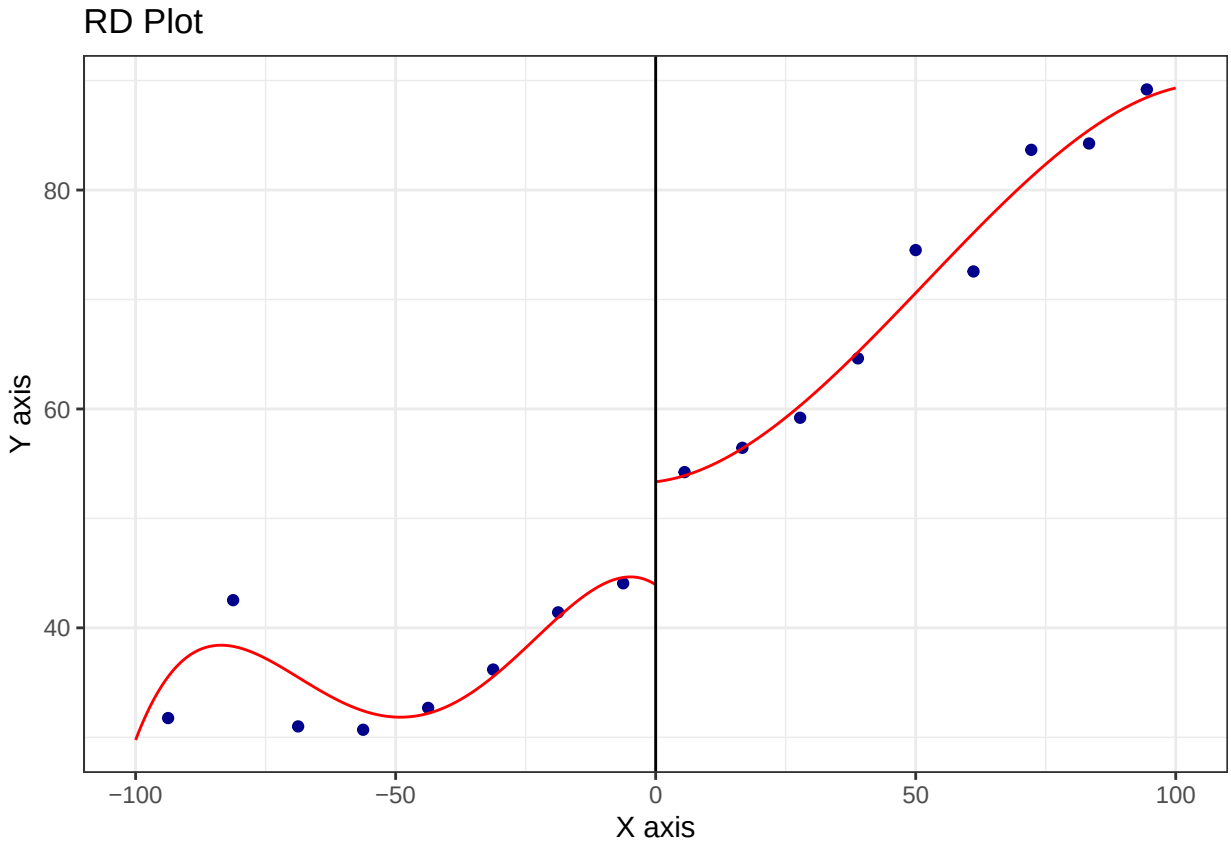


```
## local comparison of means
rdplot(df$Y[abs(df$Z) <= 50], df$Z[abs(df$Z) <= 50])
```



4. Construct an alternative RD plot with evenly spaced bins. Give this plot the same title and use the same variables.

```
# One way to do it without messing around with the number
# of bins
rdplot(df$Y, df$Z, binselect = "es")
```



5. Conduct an RD robust estimate with default options. Report the output and analyze whether there is a statistically significant effect.

```
default <- rdrobust(df$Y, df$Z)
summary(default)
```

```
## Call: rdrobust
##
## Number of Obs.                 1297
## BW type                       mserd
## Kernel                   Triangular
## VCE method                       NN
##
## Number of Obs.                 595         702
## Eff. Number of Obs.            360         323
## Order est. (p)                   1           1
## Order bias  (q)                  2           2
## BW est. (h)                 17.754      17.754
## BW bias (b)                 28.028      28.028
## rho (h/b)                    0.633       0.633
## Unique Obs.                    595         665
##
## ===============================================================================
##         Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
## ===============================================================================
##   Conventional     7.414     1.459     5.083     0.000     [4.555 , 10.273]
##         Robust         -         -     4.311     0.000     [4.094 , 10.919]
## ===============================================================================
```

6. Conduct an RD robust estimate with uniform weights and with triangular weights. Report both estimates. You will need to look at the options of the canonical function of `rdrobust` to do this.

```
# uniform weights
uniform <- rdrobust(df$Y, df$Z, kernel = "uniform")
summary(uniform)
```

```
## Call: rdrobust
##
## Number of Obs.                 1297
## BW type                       mserd
## Kernel                      Uniform
## VCE method                       NN
##
## Number of Obs.                  595          702
## Eff. Number of Obs.             271          235
## Order est. (p)                    1            1
## Order bias  (q)                   2            2
## BW est. (h)                  11.597       11.597
## BW bias (b)                  22.944       22.944
## rho (h/b)                     0.505        0.505
## Unique Obs.                     595          665
##
## ===============================================================================
##         Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
## ===============================================================================
##   Conventional     7.202     1.613     4.466     0.000     [4.041 , 10.364]
##         Robust         -         -     4.100     0.000     [3.963 , 11.224]
## ===============================================================================
```

```
# triangular weights
triangle <- rdrobust(df$Y, df$Z, kernel = "triangular")
summary(triangle)
```

```
## Call: rdrobust
##
## Number of Obs.                 1297
## BW type                       mserd
## Kernel                   Triangular
## VCE method                       NN
##
## Number of Obs.                  595          702
## Eff. Number of Obs.             360          323
## Order est. (p)                    1            1
## Order bias  (q)                   2            2
## BW est. (h)                  17.754       17.754
## BW bias (b)                  28.028       28.028
## rho (h/b)                     0.633        0.633
## Unique Obs.                     595          665
##
## ===============================================================================
##         Method     Coef. Std. Err.         z     P>|z|      [ 95% C.I. ]
## ===============================================================================
##   Conventional     7.414     1.459     5.083     0.000     [4.555 , 10.273]
##         Robust         -         -     4.311     0.000     [4.094 , 10.919]
## ===============================================================================
```

7. Do you think there is an effect of treatment in this RDD? If so what it is? What are the external validity limitations inherent in this design?

Yes, there is a treatment effect by our estimates. It's a strong treatment effect as well. The inherent limitations is that for any RDD is that we can only get a local effect. It is not clear that a design tells us anything about the general estimand of interest because RDD identify a LATE.