Politics Are Afoot!

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The Setup

There is *a lot* of money that is spent in politics in Presidential election years. So far, estimates have the number at about $11,000,000,000 (11 billion USD). For context, in 2019 Twitter's annual revenue was about $3,500,000,000 (3.5 billion USD).

The work

Install the package, `fec16`.

```
## install.packages('fec16')
```

This package is a compendium of spending and results from the 2016 election cycle. In this dataset are 9 different datasets that cover:

- `candidates`: candidate attributes, like their name, a unique id of the candidate, the election year under consideration, the office they're running for, etc.
- `results_house`: race attributes, like the name of the candidates running in the election, a unique id of the candidate, the number of `general_votes` garnered by each candidate, and other information.
- `campaigns`: financial information for each house & senate campaign. This includes a unique candidate id, the total receipts (how much came in the doors), and total disbursements (the total spent by the campaign), the total contributed by party central committees, and other information.

Your task

Describe the relationship between spending on a candidate's behalf and the votes they receive.

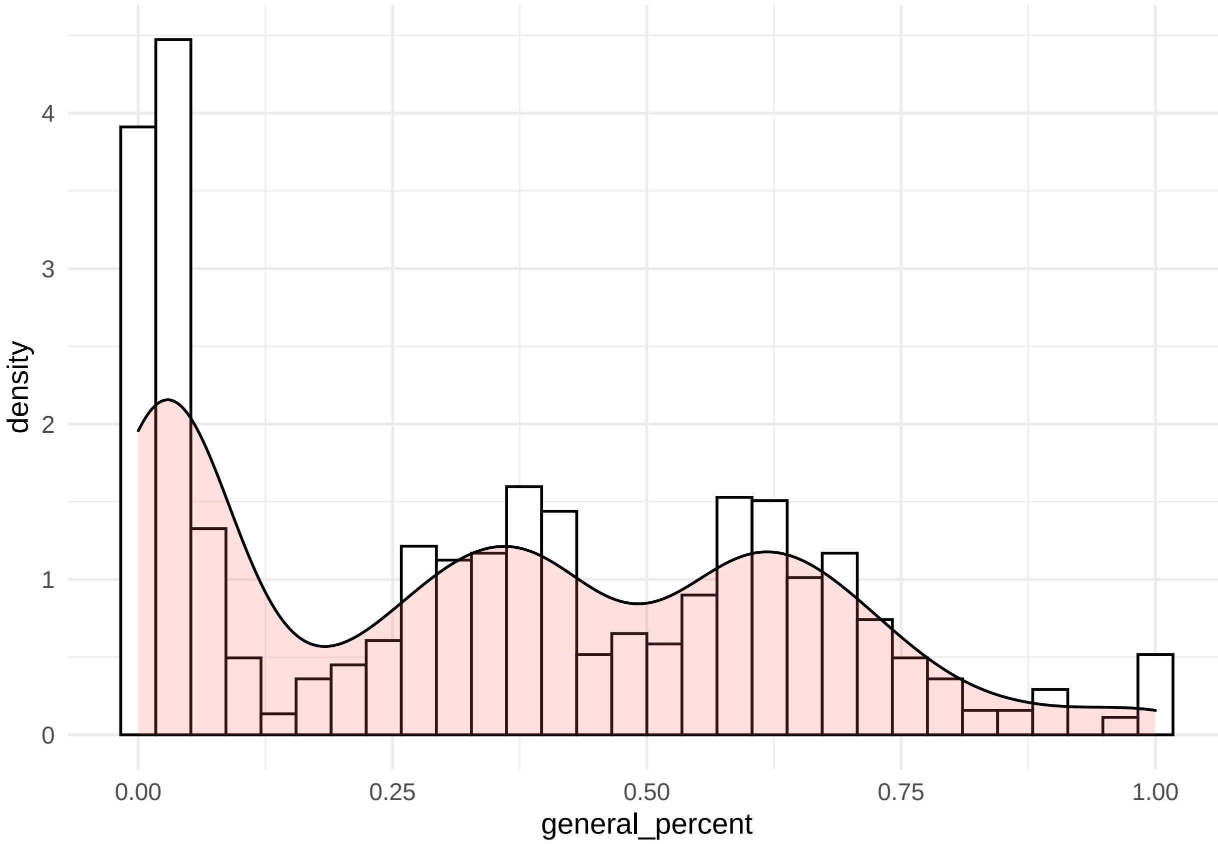
Your work

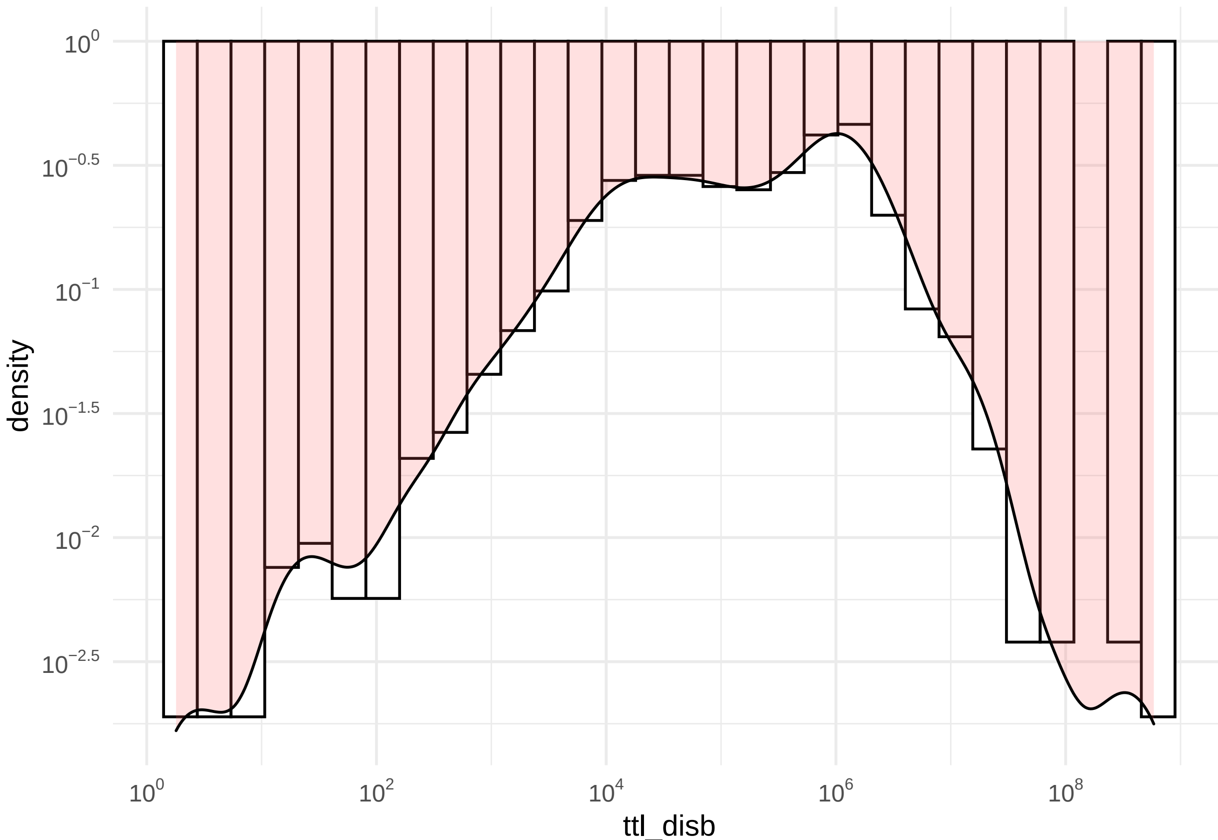
- We want to keep this work *relatively* constrained, which is why we're providing you with data through the `fec16` package. It is possible to gather all the information from current FEC reports, but it would require you to make a series of API calls that would pull us away from the core modeling tasks that we want you to focus on instead.
- Throughout this assignment, limit yourself to functions that are within the `tidyverse` family of packages: `dplyr`, `ggplot`, `patchwork`, and `magrittr` for wrangling and exploration and `base`, `stats`, `sandwich` and `lmtest` for modeling and testing. You do not *have* to use these packages; but try to limit yourself to using only these.

```r
candidates    <- fec16::candidates
results_house <- fec16::results_house
campaigns     <- fec16::campaigns
```

1. What does the distribution of votes and of spending look like?

1. (3 points) In separate histograms, show both the distribution of votes (measured in `results_house$general_percent` for now) and spending (measured in `ttl_disb`). Use a log transform if appropriate for each visualization. How would you describe what you see in these two plots?





2. Exploring the relationship between spending and votes.

2. (3 points) Create a new dataframe by joining `results_house` and `campaigns` using the `inner_join` function from `dplyr`. (We use the format `package::function` – so `dplyr::inner_join`.)

```
nrow(results_house)
```

```
## [1] 2110
```

```
nrow(campaigns)
```

```
## [1] 1898
```

```
d1 <- inner_join(results_house, campaigns, by = NULL)
```

```
## Joining, by = "cand_id"
```

```
#d1 <- merge(results_house, campaigns, by = "cand_id")
#d2 <- merge(results_house, campaigns)

nrow(d1)
```

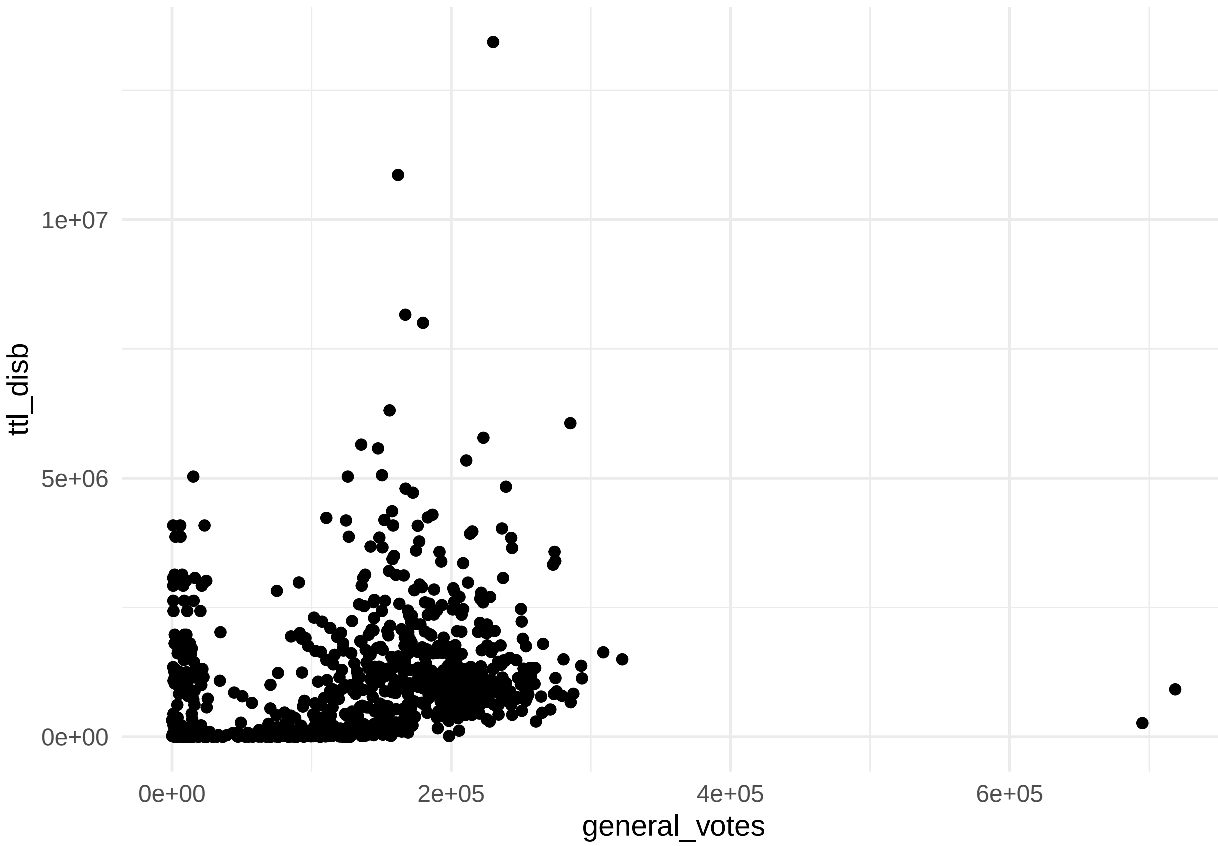
```
## [1] 1342
```

```r
#nrow(d2)

#comparison <- compare(d1,d2,allowAll=TRUE)
#comparison

#summary(d1)
#summary(d2)
```

3. (3 points) Produce a scatter plot of `general_votes` on the y-axis and `ttl_disb` on the x-axis. What do you observe about the shape of the joint distribution?

```r
ggplot(d1, aes(x=general_votes, y=ttl_disb)) + geom_point()
```

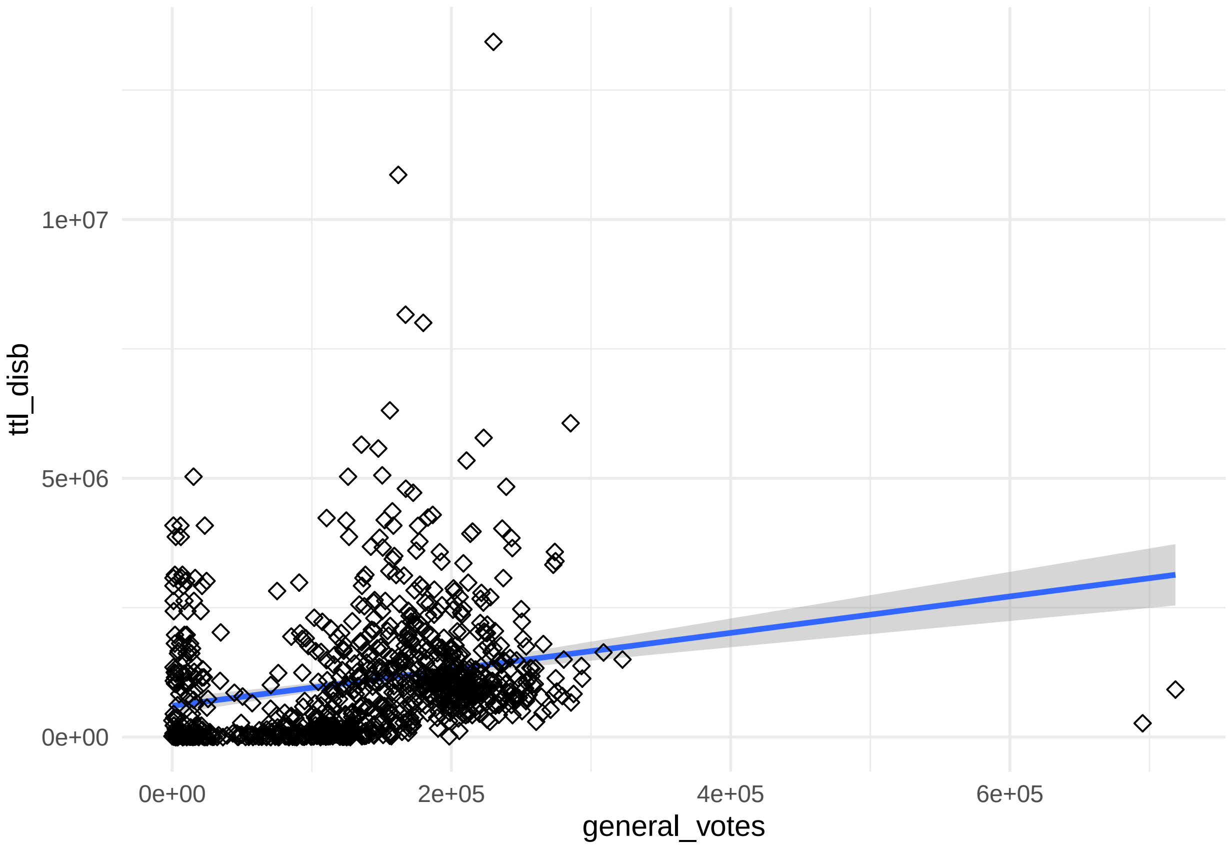
```
## Warning: Removed 462 rows containing missing values (geom_point).
```




```r
# Change the point size, and shape
sp <- ggplot(d1, aes(x=general_votes, y=ttl_disb  )) +
  geom_smooth(method=lm)+
  geom_point(size=2, shape=23)

sp
```

```
## `geom_smooth()` using formula 'y ~ x'
```

```
## Warning: Removed 462 rows containing non-finite values (stat_smooth).

## Warning: Removed 462 rows containing missing values (geom_point).
```




```
#sp + geom_density_2d()
```

4. (3 points) Create a new variable to indicate whether each individual is a "Democrat", "Republican" or "Other Party".

- Here's an example of how you might use `mutate` and `case_when` together to create a variable.

```
starwars %>%
  select(name:mass, gender, species) %>%
  mutate(
  type = case_when(
    height > 200 | mass > 200 ~ "large",
    species == "Droid"        ~ "robot",
    TRUE                      ~ "other"
    )
  )
```

Once you've produced the new variable, plot your scatter plot again, but this time adding an argument into the `aes()` function that colors the points by party membership. What do you observe about the distribution of all three variables?

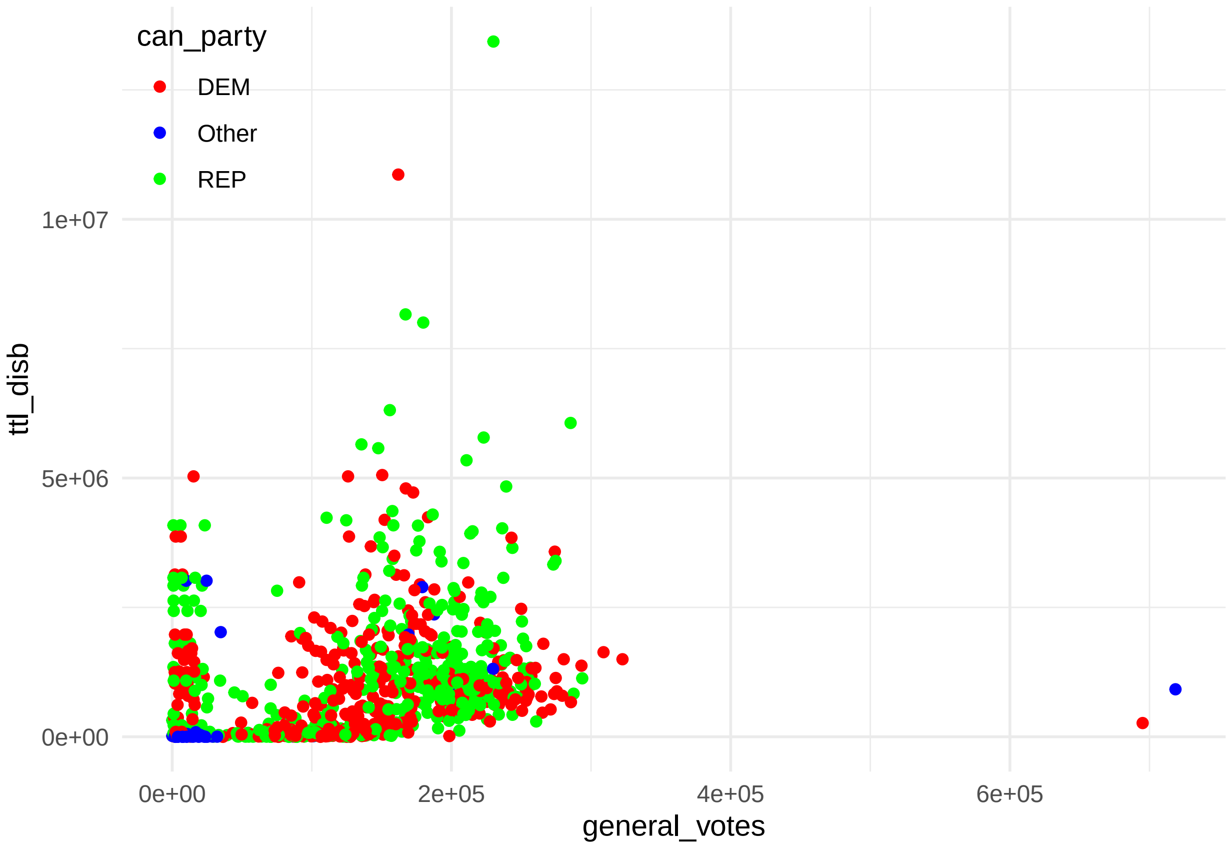
```r
d2<-d1 %>%
  select(cand_pty_affiliation, general_votes, ttl_disb) %>%
  na.omit() %>%
    mutate(
    can_party = case_when(
      cand_pty_affiliation=="REP" ~ "REP",
      cand_pty_affiliation=="DEM" ~ "DEM",
      TRUE ~ "Other"
    )
  )

write.csv(d2, "d2.csv")

#print(d2$general_votes)

#summary(d2)

#ggplot(d1, aes(x=general_votes, y=ttl_disb)) + geom_point()
# Change the point size, and shape

#d3 <- d2 %>% data.frame(can_party, general_votes, ttl_disb)


head(d2)
```

```
## # A tibble: 6 x 4
##   cand_pty_affiliation general_votes ttl_disb can_party
##   <chr>                        <dbl>    <dbl> <chr>
## 1 REP                         208083 1172750. REP
## 2 REP                         134886 1850536. REP
## 3 DEM                         112089   36844  DEM
## 4 REP                         192164 1071289. REP
## 5 DEM                          94549    7348  DEM
## 6 REP                         235925 1394461. REP
```

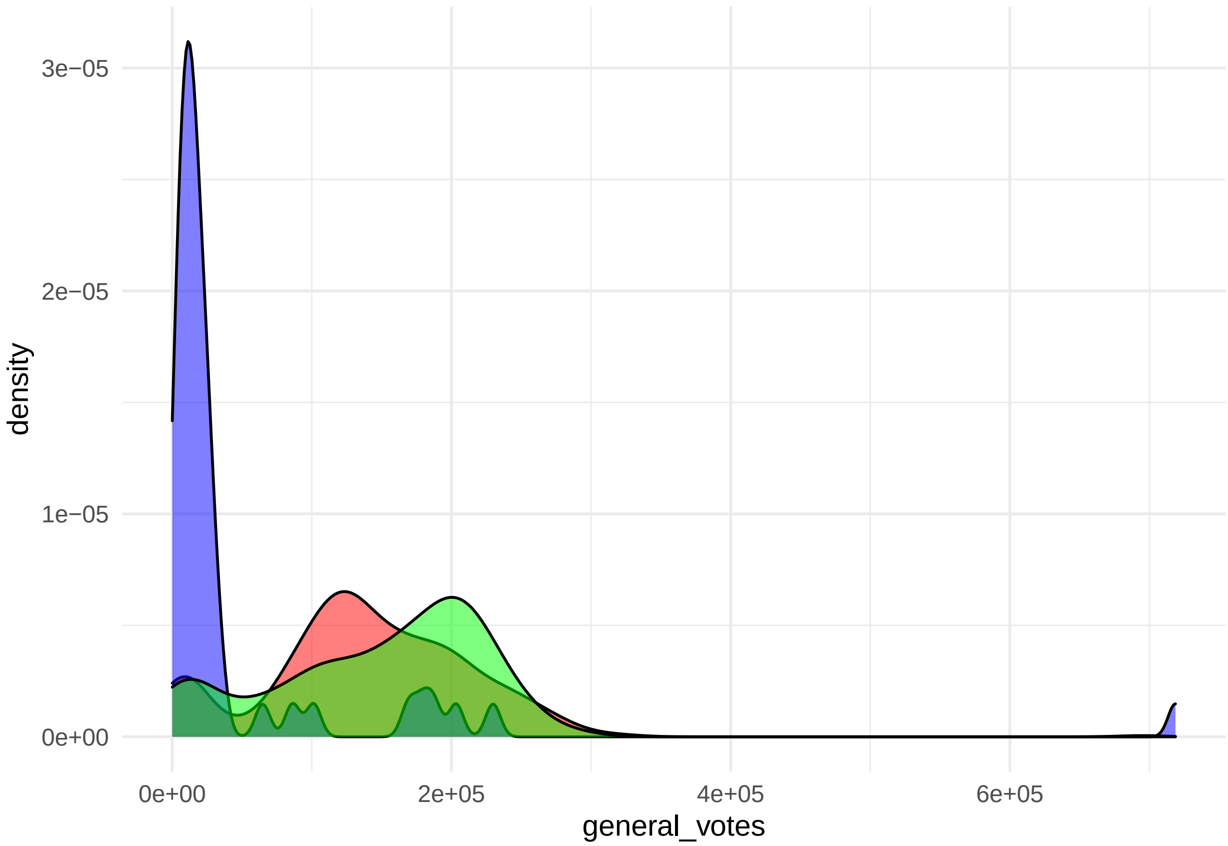
```r
sp <- ggplot(d2, aes(x=general_votes, y=ttl_disb, color=can_party)) +
  geom_smooth(method=lm)+
  geom_point(size=2, shape=23)
sp
```

```
## `geom_smooth()` using formula 'y ~ x'
```

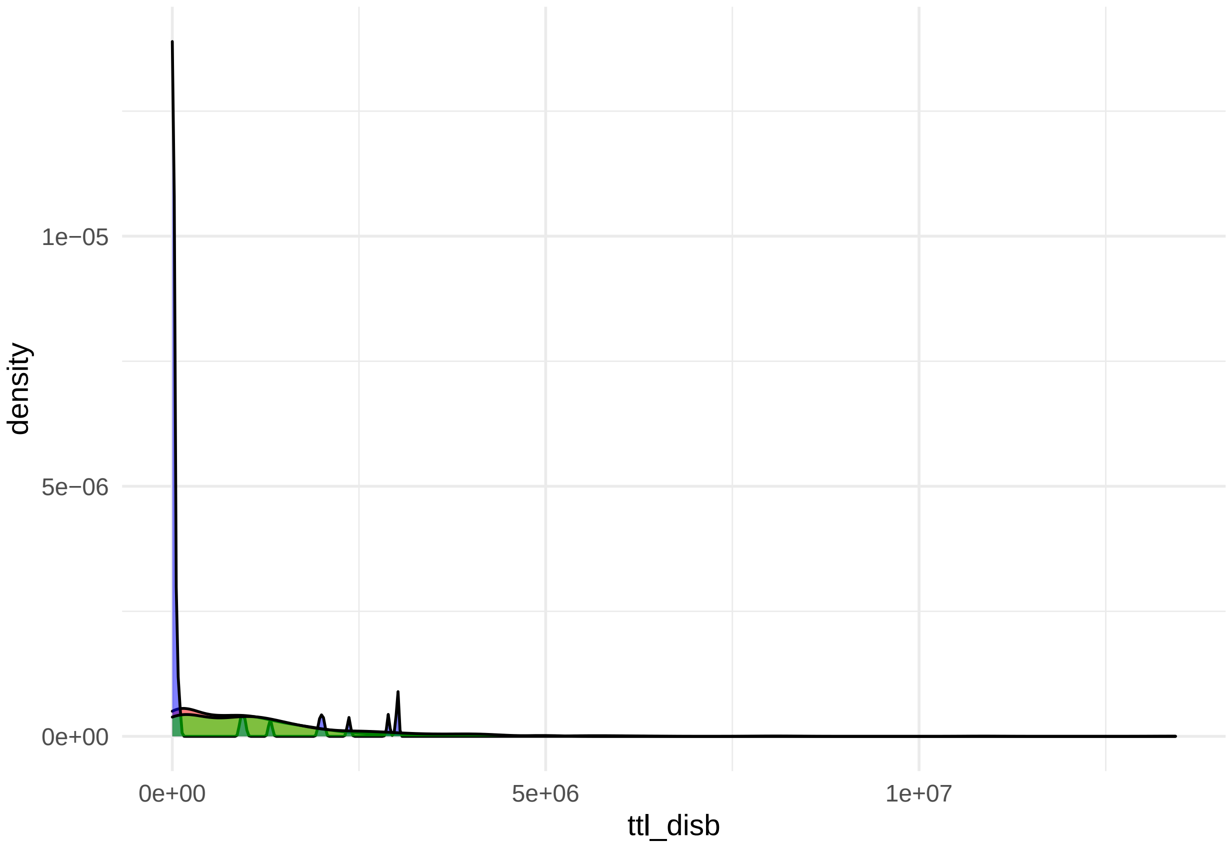

```r
p1<-ggplot(d2, aes(x=general_votes, y=ttl_disb, color=can_party)) +
  geom_point() +
  scale_color_manual(values = c("red", "blue", "green")) +
  theme(legend.position=c(0,1), legend.justification=c(0,1))
p1
```



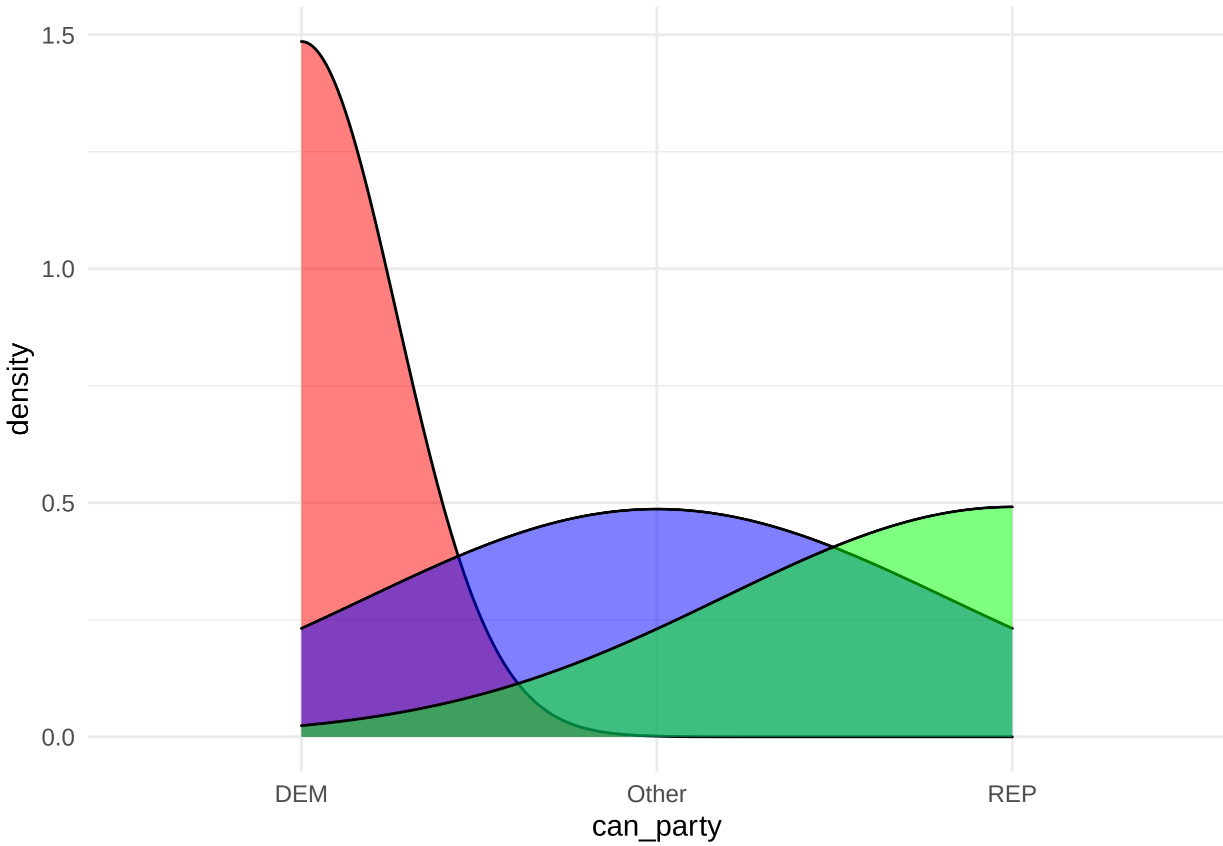

```
p2<-ggplot(d2, aes(x=general_votes, fill=can_party)) +
  geom_density(alpha=.5) +
  scale_fill_manual(values =  c("red", "blue", "green")) +
  theme(legend.position = "none")
p2
```




```
# Marginal density plot of y (right panel)
p3<-ggplot(d2, aes(x=ttl_disb, fill=can_party)) +
  geom_density(alpha=.5) +
  scale_fill_manual(values =  c("red", "blue", "green")) +
  theme(legend.position = "none")
p3
```




```
p3<-ggplot(d2, aes(x=can_party, fill=can_party)) +
  geom_density(alpha=.5) +
  scale_fill_manual(values =  c("red", "blue", "green")) +
  theme(legend.position = "none")
p3
```




```
#sp + geom_density_2d()


#summary(d1)
```

Produce a Descriptive Model

5. (5 Points) Given your observations, produce a linear model that you think does a good job at describing the relationship between candidate spending and votes they receive. You should decide what transformation to apply to spending (if any), what transformation to apply to votes (if any) and also how to include the party affiliation.

```
d2$disb <- log(d2$ttl_disb)
d2$votes <- log(d2$general_votes)

#d2$disb <- log(d2$ttl_disb)
#d2$votes <- log(d2$general_votes)

write.csv(d2, "d2.csv")

#d2[which(!is.finite(d2))] <- 0
#d2 <- d2[is.finite(rowSums(d2)),]
d2[d2 == -Inf] <- 0
```

```r
#data_new <- d2                                    # Duplicate data

#d2[is.na(d2$disb) | d2$disb == "Inf"] <- NA  # Replace NaN & Inf with NA

#d3 <- data_new

head(d2)
```

```
## # A tibble: 6 x 6
##   cand_pty_affiliation general_votes ttl_disb can_party  disb votes
##   <chr>                        <dbl>    <dbl> <chr>     <dbl> <dbl>
## 1 REP                         208083 1172750. REP       14.0   12.2
## 2 REP                         134886 1850536. REP       14.4   11.8
## 3 DEM                         112089   36844  DEM       10.5   11.6
## 4 REP                         192164 1071289. REP       13.9   12.2
## 5 DEM                          94549    7348  DEM        8.90  11.5
## 6 REP                         235925 1394461. REP       14.1   12.4
```

```r
head(d2$disb)
```

```
## [1] 13.974862 14.430986 10.514448 13.884374  8.902183 14.148019
```

```r
#d3<-d3%>%na.omit()

fit <- lm(d2$general_votes ~ d2$disb)

summary(fit)
```

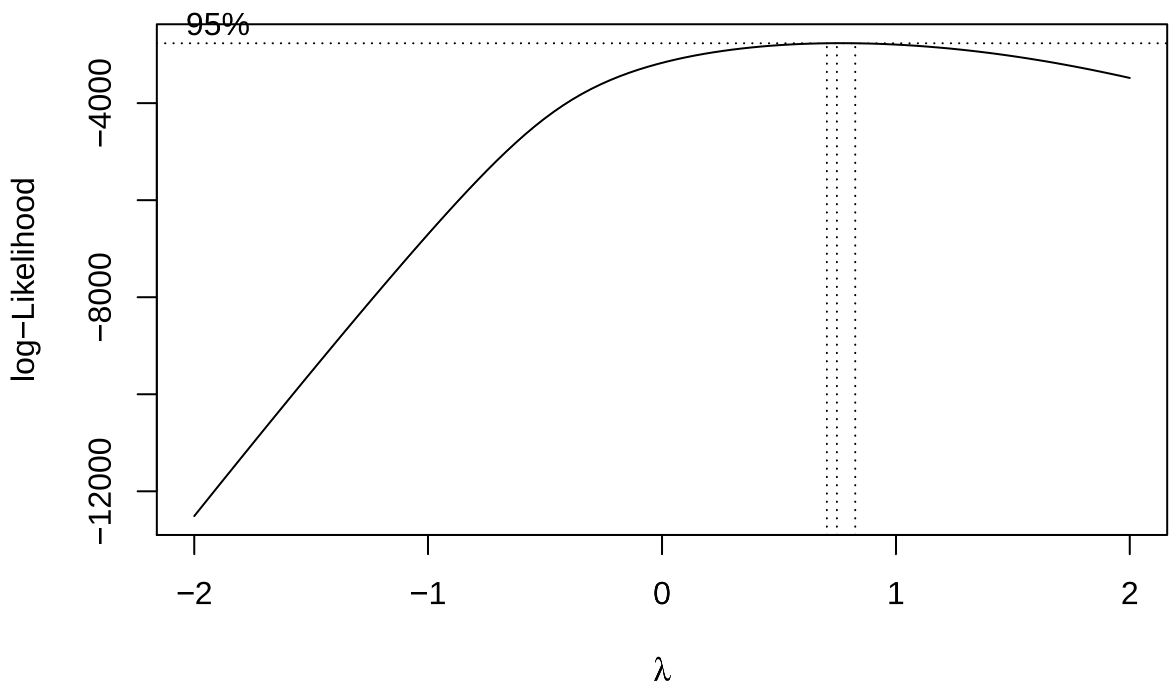
```
##
## Call:
## lm(formula = d2$general_votes ~ d2$disb)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -170750  -34066    7653   45029  568412
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -46697      14420  -3.238  0.00125 **
## d2$disb        14339       1109  12.928  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 73740 on 878 degrees of freedom
## Multiple R-squared:  0.1599, Adjusted R-squared:  0.159
## F-statistic: 167.1 on 1 and 878 DF,  p-value: < 2.2e-16
```

```r
## boxcox test
library(MASS)
```

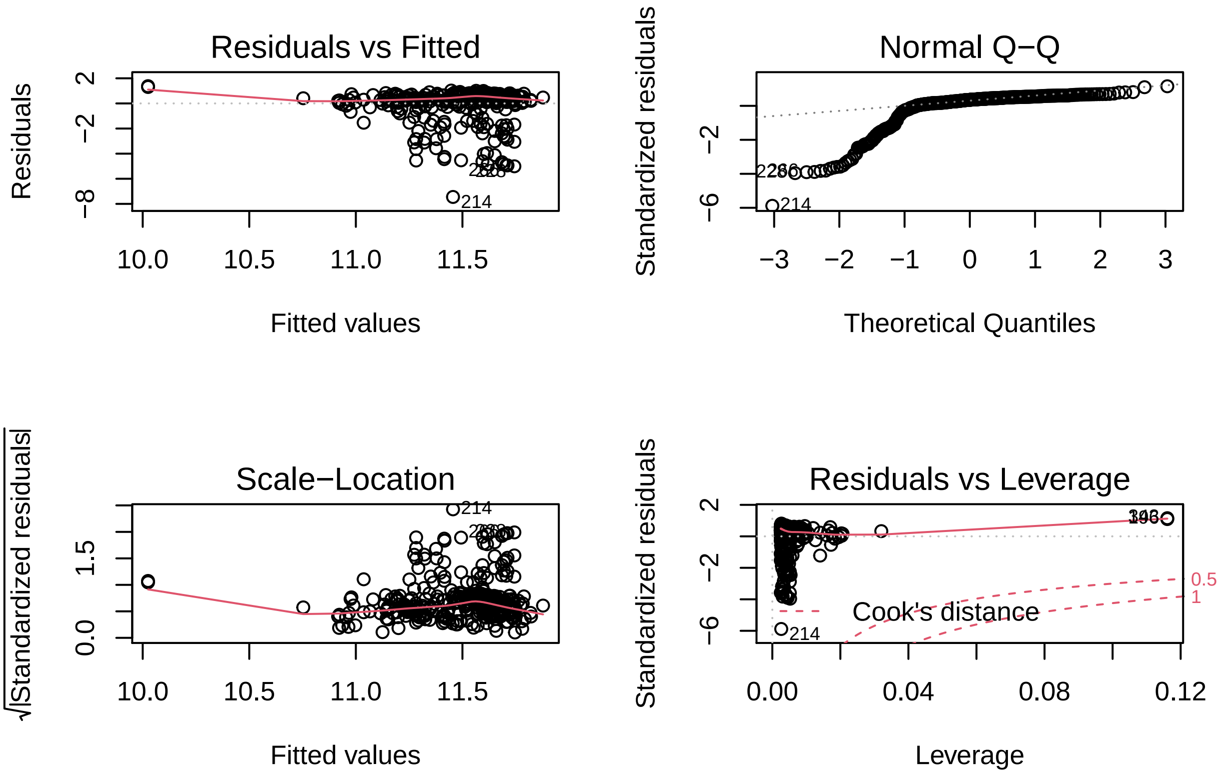
```
##
## Attaching package: 'MASS'
```

```
## The following object is masked from 'package:patchwork':
##
##     area

## The following object is masked from 'package:dplyr':
##
##     select
```

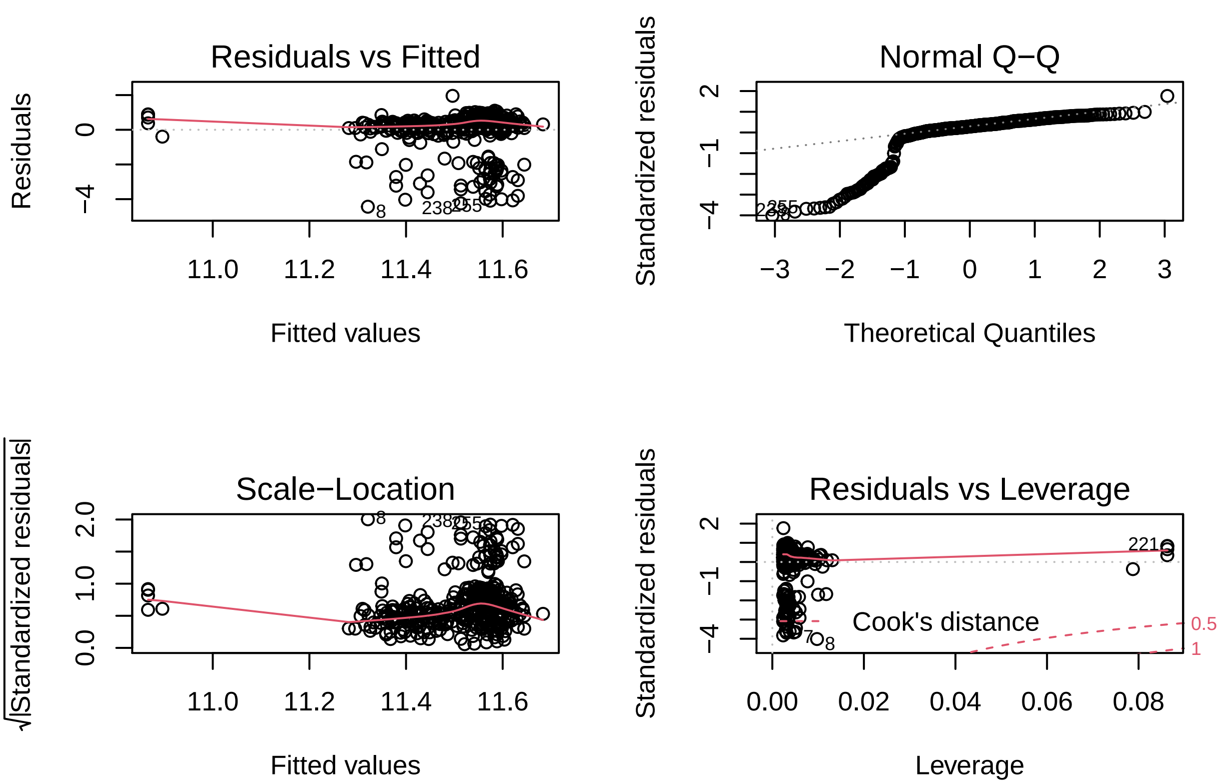
```
boxcox(general_votes~poly(disb,2),
          data = d2)
```



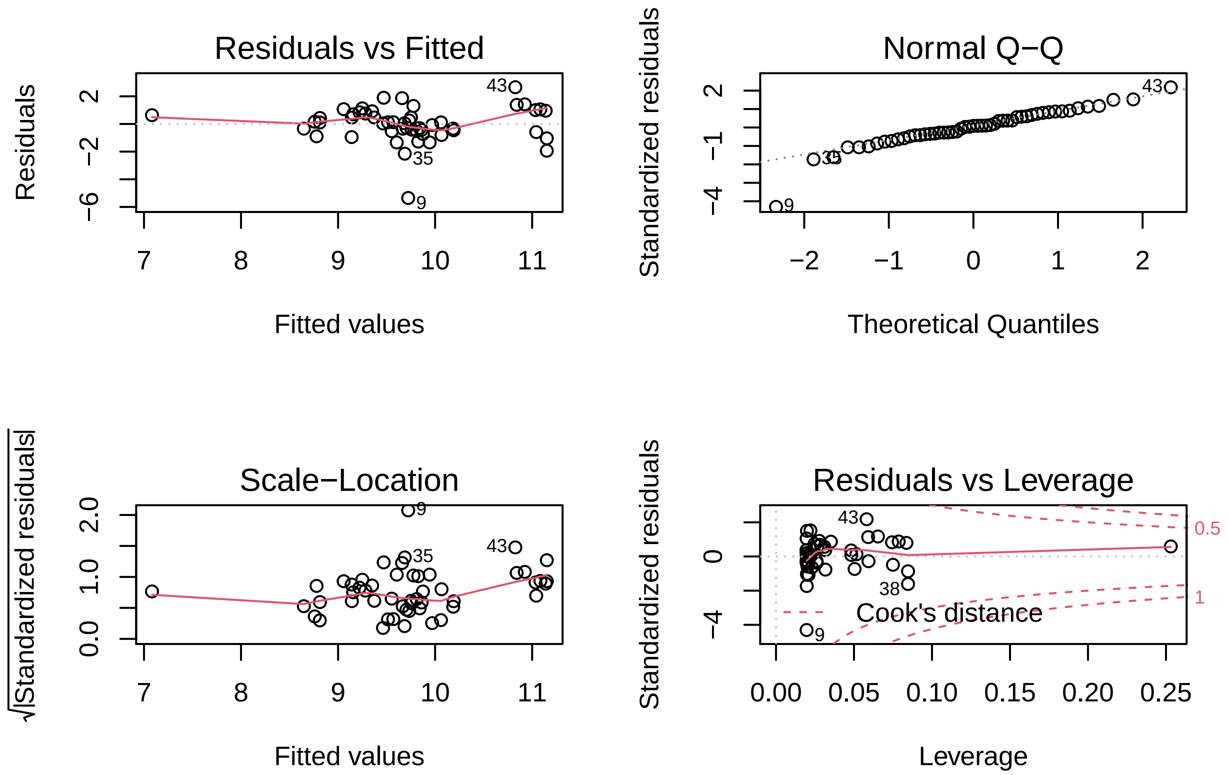

```
g1 <- filter(d2, can_party == "REP")
g2 <- filter(d2, can_party == "DEM")
g3 <- filter(d2, can_party == "Other")


fit <- lm(g1$votes ~ g1$disb)
par(mfrow=c(2,2))
plot (fit)
```




```r
fit1 <- lm(g2$votes ~ g2$disb)
par(mfrow=c(2,2))
plot (fit1)
```



```r
fit2 <- lm(g3$votes ~ g3$disb)
par(mfrow=c(2,2))
plot (fit2)
```




```r
summary(fit)
```

```
##
## Call:
## lm(formula = g1$votes ~ g1$disb)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -7.4485  0.1288  0.4484  0.6419  1.3730
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.02502    0.43189  23.212  < 2e-16 ***
## g1$disb      0.11290    0.03245   3.479 0.000557 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.268 on 404 degrees of freedom
## Multiple R-squared:  0.0291, Adjusted R-squared:  0.02669
## F-statistic: 12.11 on 1 and 404 DF,  p-value: 0.0005571
```

```r
summary(fit1)
```

```
##
## Call:
## lm(formula = g2$votes ~ g2$disb)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.4355  0.0615  0.3208  0.5981  1.9554
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.86598    0.32627  33.304   <2e-16 ***
## g2$disb      0.05047    0.02509   2.011   0.0449 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.111 on 421 degrees of freedom
## Multiple R-squared:  0.009519,   Adjusted R-squared:  0.007166
## F-statistic: 4.046 on 1 and 421 DF,  p-value: 0.04491
```

```
summary(fit2)
```

```
##
## Call:
## lm(formula = g3$votes ~ g3$disb)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.3535 -0.5197  0.1090  0.7988  2.6582
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  7.08213    0.63215  11.203 4.06e-15 ***
## g3$disb      0.27274    0.06218   4.387 6.10e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.257 on 49 degrees of freedom
## Multiple R-squared:  0.282,  Adjusted R-squared:  0.2673
## F-statistic: 19.24 on 1 and 49 DF,  p-value: 6.103e-05
```

```
#d2$disb <- log(d2$ttl_disb)
#d2$votes <- log(d2$general_votes)

write.csv(d2, "d2.csv")

#d2[which(!is.finite(d2))] <- 0
#d2 <- d2[is.finite(rowSums(d2)),]
d2[d2 == -Inf] <- 0

#data_new <- d2                                         # Duplicate data

#d2[is.na(d2$disb) | d2$disb == "Inf"] <- NA  # Replace NaN & Inf with NA
```

```r
#d3 <- data_new

head(d2)
```

```
## # A tibble: 6 x 6
##   cand_pty_affiliation general_votes ttl_disb can_party  disb votes
##   <chr>                        <dbl>    <dbl> <chr>     <dbl> <dbl>
## 1 REP                         208083 1172750. REP       14.0   12.2
## 2 REP                         134886 1850536. REP       14.4   11.8
## 3 DEM                         112089   36844  DEM       10.5   11.6
## 4 REP                         192164 1071289. REP       13.9   12.2
## 5 DEM                          94549    7348  DEM        8.90  11.5
## 6 REP                         235925 1394461. REP       14.1   12.4
```

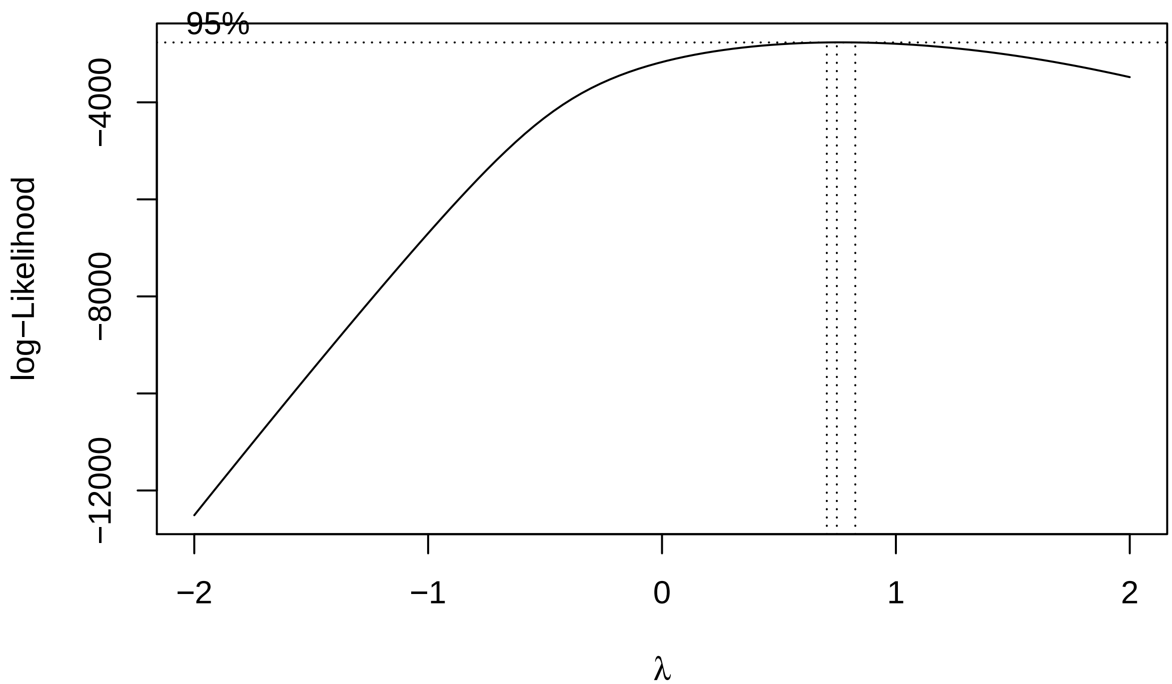
```r
head(d2$disb)
```

```
## [1] 13.974862 14.430986 10.514448 13.884374  8.902183 14.148019
```

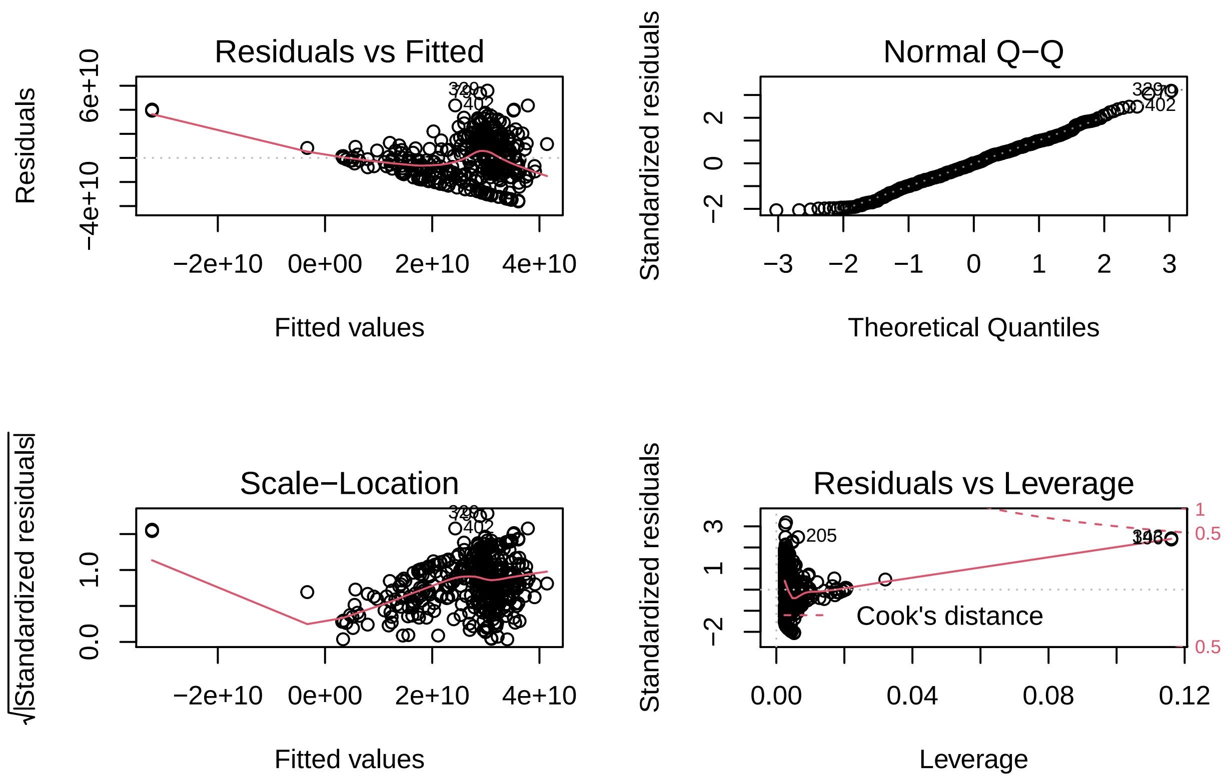
```r
#d3<-d3%>%na.omit()

fit <- lm(d2$general_votes ~ d2$disb)

summary(fit)
```

```
##
## Call:
## lm(formula = d2$general_votes ~ d2$disb)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -170750  -34066    7653   45029  568412
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -46697      14420  -3.238  0.00125 **
## d2$disb        14339       1109  12.928  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 73740 on 878 degrees of freedom
## Multiple R-squared:  0.1599, Adjusted R-squared:  0.159
## F-statistic: 167.1 on 1 and 878 DF,  p-value: < 2.2e-16
```

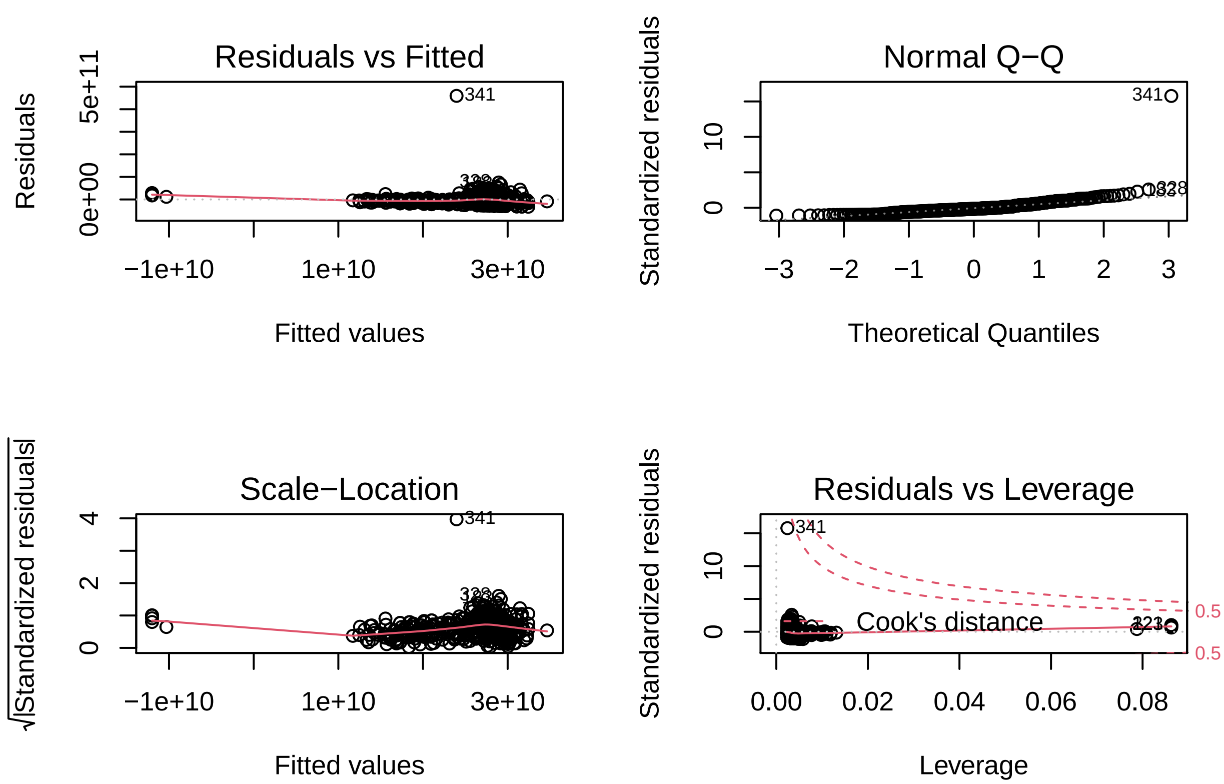
```r
## boxcox test
library(MASS)
boxcox(general_votes~poly(disb,2),
          data = d2)
```



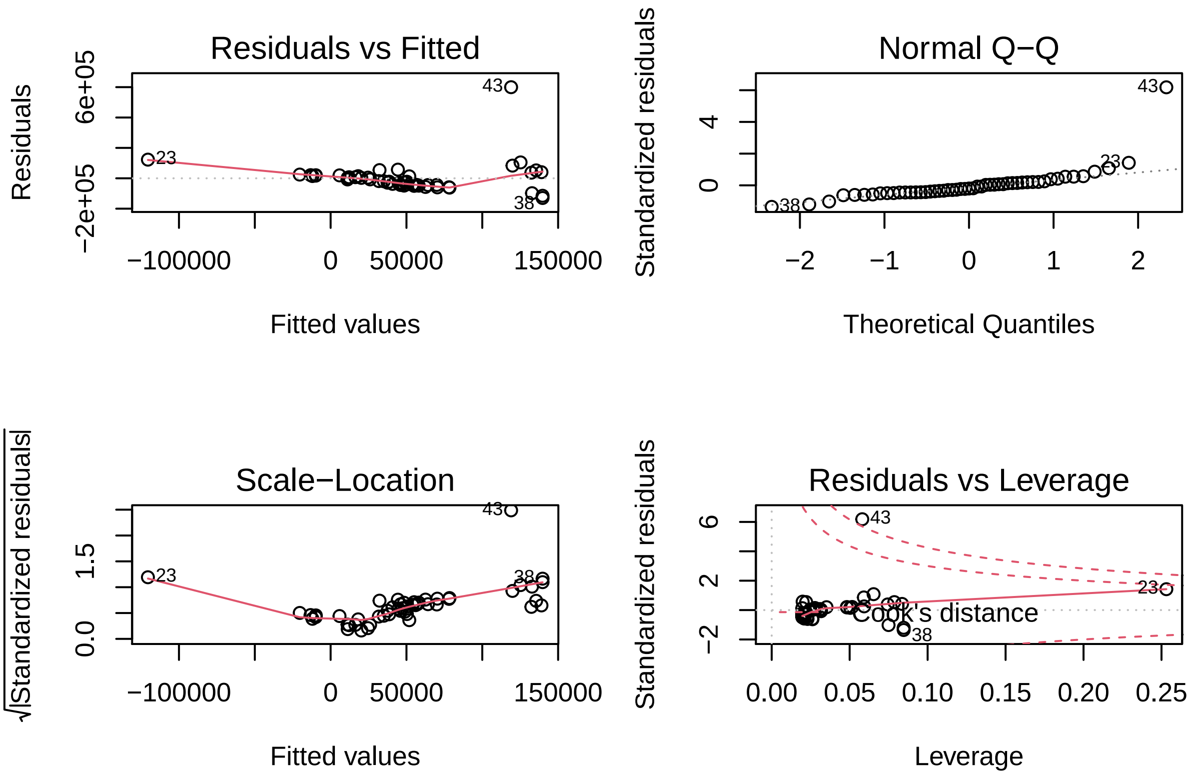

```
g1 <- filter(d2, can_party == "REP")
g1$votes <- g1$general_votes*g1$general_votes
g1$disb <- log(g1$ttl_disb)
g1[g1 == -Inf] <- 0


g2 <- filter(d2, can_party == "DEM")
g2$votes <- g2$general_votes*g2$general_votes
g2$disb <- log(g2$ttl_disb)
g2[g2 == -Inf] <- 0

g3 <- filter(d2, can_party == "Other")
g3$votes <- g3$general_votes
g3$disb <- log(g3$ttl_disb)
g3[g3 == -Inf] <- 0


write.csv(g1, "g1.csv")
write.csv(g2, "g2.csv")
write.csv(g3, "g3.csv")



fit <- lm(g1$votes ~ g1$disb)
par(mfrow=c(2,2))
plot (fit)
```




```r
fit1 <- lm(g2$votes ~ g2$disb)
par(mfrow=c(2,2))
plot (fit1)
```



```r
fit2 <- lm(g3$votes ~ g3$disb)
par(mfrow=c(2,2))
plot (fit2)
```




```r
summary(fit)
```

```
##
## Call:
## lm(formula = g1$votes ~ g1$disb)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -3.607e+10 -1.194e+10 -2.327e+07  1.201e+10  5.595e+10
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -3.227e+10  5.987e+09   -5.39  1.2e-07 ***
## g1$disb      4.489e+09  4.498e+08    9.98  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.757e+10 on 404 degrees of freedom
## Multiple R-squared:  0.1978, Adjusted R-squared:  0.1958
## F-statistic:  99.6 on 1 and 404 DF,  p-value: < 2.2e-16
```

```r
summary(fit1)
```

```
##
## Call:
## lm(formula = g2$votes ~ g2$disb)
##
## Residuals:
##        Min         1Q     Median         3Q        Max
## -3.220e+10 -1.267e+10 -4.690e+09  9.125e+09  4.592e+11
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.201e+10  8.562e+09  -1.403    0.161
## g2$disb      2.880e+09  6.584e+08   4.375 1.54e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.915e+10 on 421 degrees of freedom
## Multiple R-squared:  0.04348,    Adjusted R-squared:  0.04121
## F-statistic: 19.14 on 1 and 421 DF,  p-value: 1.535e-05
```

```r
summary(fit2)
```

```
##
## Call:
## lm(formula = g3$votes ~ g3$disb)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -129711  -44022  -19757   18234  599586
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -120489      50265  -2.397  0.02039 *
## g3$disb        17443       4944   3.528  0.00092 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 99910 on 49 degrees of freedom
## Multiple R-squared:  0.2026, Adjusted R-squared:  0.1863
## F-statistic: 12.45 on 1 and 49 DF,  p-value: 0.0009199
```

6. (3 points) Interpret the model coefficients you estimate.

- Tasks to keep in mind as you're writing about your model:
  - At the time that you're writing and interpreting your regression coefficients you'll be *deep* in the analysis. Nobody will know more about the data than you do, at that point. *So, although it will feel tedious, be descriptive and thorough in describing your observations.*
  - It can be hard to strike the balance between: on the one hand, writing enough of the technical underpinnings to know that your model meets the assumptions that it must; and, on the other hand, writing little enough about the model assumptions that the implications of the model can still be clear. We're starting this practice now, so that by the end of Lab 2 you will have had several chances to strike this balance.

```
#lm(d2$general_votes ~ b1*d2$ttl_disb + b2)
```