

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.

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 `t1l_disb`). Use a log transform if appropriate for each visualization. How would you describe what you see in these two plots?

ANSWER:

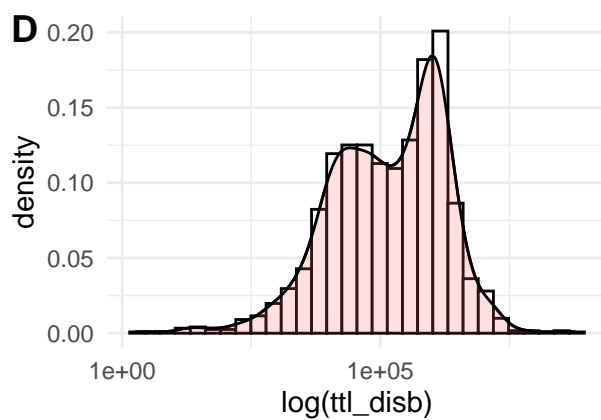
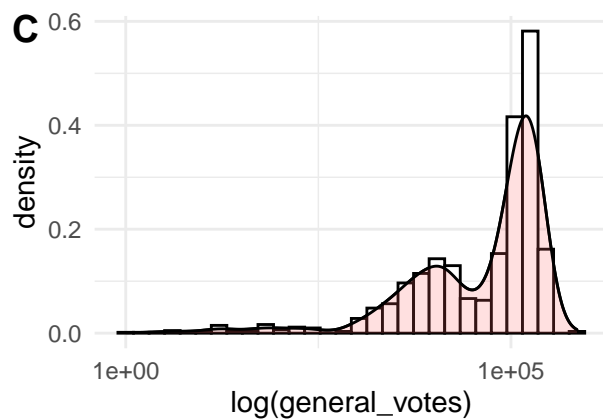
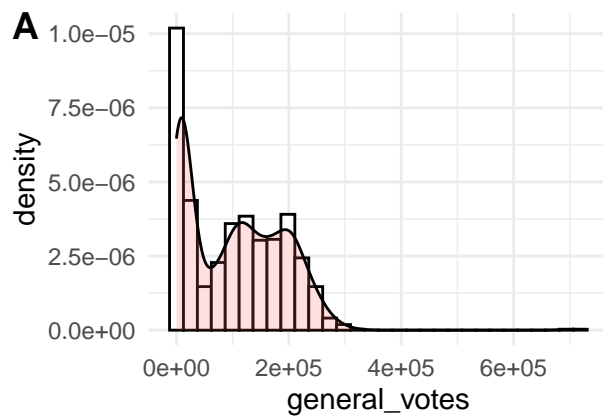
From my observation, the data `general_percent` and `t1l_disb` have the following problems:

- The original data of the 2 variables are not on the same scale (Fig. A-B) .
- Has skewness problems because the curve appears distorted and skewed to the left in a statistical distribution.
- The data are not centered.

At this stage, based on my finding, we need to perform data transforming including scaling, centering and skewness corrections.

I will perform Log transformation first, because log transform makes the data as “normal” as possible so that the statistical analysis results from this data become more valid, the log transformation reduces or removes the skewness of our original data. In detail I choose natural logarithm here for the purposes of linear modeling , i.e., using Log transformation replaces each variable x with a $\log(x)$. The results are shown in Fig. C-D, respectively. In C and D, after the transformation, the curves approximately follow normal distribution, the graph appears symmetry, there are about as many data values on the left side of the median as on the right side.

I will do other data transformations later in the following questions. Data transformation can make our model working efficiently: distance based models perform well when data is pre-processed and transformed; having all features scaled it speeds up the model; better accuracy and more generalized model.



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`.)

ANSWER:

Done the creation of new dataframe by joining `results_house` and `campaigns` using the `inner_join` function from `dplyr`. The new data frame is named “`d1`”. A discription of “`d1`” is as the follows:

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

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

```
nrow(d1)
```

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

```
summary(d1)
```

```
##      state      district_id      cand_id      incumbent
## Length:1342    Length:1342    Length:1342    Mode :logical
## Class :character Class :character Class :character FALSE:895
## Mode  :character Mode  :character Mode  :character TRUE :447
##
##
##
##      party      primary_votes  primary_percent  runoff_votes
## Length:1342    Min.      :      1    Min.      :0.00015    Min.      : 1096
## Class :character 1st Qu.: 8650    1st Qu.:0.19158    1st Qu.: 1464
## Mode  :character Median : 21299    Median :0.42257    Median : 8206
##              Mean  : 32227    Mean  :0.48844    Mean  :11274
##              3rd Qu.: 45638    3rd Qu.:0.78382    3rd Qu.:20082
##              Max.   :326988    Max.   :1.00000    Max.   :25322
##              NA's   :291      NA's   :292      NA's   :1330
## runoff_percent  general_votes  general_percent  won
## Min.      :0.3427    Min.      :    55    Min.      :0.0000    Mode :logical
## 1st Qu.:0.4624    1st Qu.: 88229    1st Qu.:0.3087    FALSE:850
## Median :0.5000    Median :142597    Median :0.4773    TRUE :492
## Mean      :0.5000    Mean      :136932    Mean      :0.4597
## 3rd Qu.:0.5376    3rd Qu.:198290    3rd Qu.:0.6406
## Max.      :0.6573    Max.      :718591    Max.      :1.0000
## NA's      :1330    NA's      :462     NA's      :463
## footnotes      cand_name      cand_ici      pty_cd
## Length:1342    Length:1342    Length:1342    Min.      :1.000
## Class :character Class :character Class :character 1st Qu.:1.000
## Mode  :character Mode  :character Mode  :character Median :2.000
##              Mean      :1.607
##              3rd Qu.:2.000
##              Max.      :3.000
##
```

```

## cand_pty_affiliation  ttl_receipts      trans_from_auth      ttl_disb
## Length:1342          Min.    :      0  Min.    :      0  Min.    :      0
## Class :character     1st Qu.:  46612  1st Qu.:      0  1st Qu.:  46147
## Mode  :character     Median : 398962  Median :      0  Median : 379570
##                      Mean   : 883177  Mean   :  26408  Mean   : 814754
##                      3rd Qu.:1290266  3rd Qu.:      0  3rd Qu.:1154148
##                      Max.   :19852221  Max.   :12374657  Max.   :13433669
##
## trans_to_auth        coh_bop          coh_cop          cand_contrib
## Min.    :      0  Min.    : -18681  Min.    : -32074  Min.    :      0
## 1st Qu.:      0  1st Qu.:      0  1st Qu.:      0  1st Qu.:      0
## Median :      0  Median :      0  Median :   3881  Median :      0
## Mean   :   7577  Mean   : 150271  Mean   : 218929  Mean   :   21879
## 3rd Qu.:      0  3rd Qu.:  85884  3rd Qu.: 170548  3rd Qu.:   1000
## Max.   :766500  Max.   :3750024  Max.   :9098873  Max.   :13414225
##
## cand_loans          other_loans      cand_loan_repay      other_loan_repay
## Min.    :      0  Min.    :      0  Min.    :      0  Min.    :      0.0
## 1st Qu.:      0  1st Qu.:      0  1st Qu.:      0  1st Qu.:      0.0
## Median :      0  Median :      0  Median :      0  Median :      0.0
## Mean   :   56809  Mean   :   1049  Mean   :  12579  Mean   :    638.7
## 3rd Qu.:   9000  3rd Qu.:      0  3rd Qu.:      0  3rd Qu.:      0.0
## Max.   :8050000  Max.   :350000  Max.   :1655854  Max.   :350000.0
##
## debts_owed_by      ttl_indiv_contrib  cand_office_st      cand_office_district
## Min.    :  -1786  Min.    :      0  Length:1342      Length:1342
## 1st Qu.:      0  1st Qu.:  21310  Class :character  Class :character
## Median :      0  Median : 207337  Mode  :character  Mode  :character
## Mean   :   42528  Mean   :  464597
## 3rd Qu.:  12903  3rd Qu.:  638629
## Max.   :2795000  Max.   :5975190
##
## other_pol_cmte_contrib  pol_pty_contrib  cvg_end_dt          indiv_refunds
## Min.    :      0  Min.    :      0  Min.    :2015-08-10  Min.    : -1150
## 1st Qu.:      0  1st Qu.:      0  1st Qu.:2016-12-31  1st Qu.:      0
## Median :  13700  Median :      0  Median :2016-12-31  Median :    200
## Mean   : 305670  Mean   :   1230  Mean   :2016-11-30  Mean   :    6617
## 3rd Qu.:506471  3rd Qu.:    150  3rd Qu.:2016-12-31  3rd Qu.:    5400
## Max.   :3279747  Max.   :   25400  Max.   :2017-01-31  Max.   :   227497
##
## cmte_refunds
## Min.    :      0
## 1st Qu.:      0
## Median :      0
## Mean   :   1093
## 3rd Qu.:    250
## Max.   :104758
##

```

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?

ANSWER:

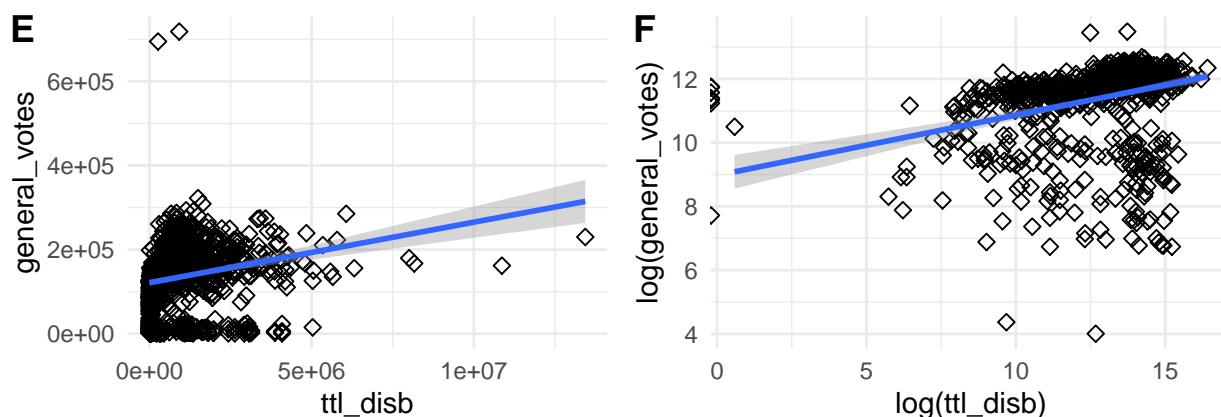
The scatter plot of `general_votes` on the y-axis and `ttl_disb` on the x-axis is shown below Fig.E. I also made a scatter plot using $y = \log(\text{general_votes})$ and $x = \log(\text{ttl_disb})$, as shown in Fig.F.

In general, a x-y scatter graph displays and compares values to show the numerical distribution of variables in a rectangular coordinate system. A two-dimensional scatter chart can show the data analysis of two variables to provide the relationship and correlation between the two. Scatter plots can provide three types of key information:

- Whether there is a quantitative correlation trend between variables;
- If there is a correlation trend, is it linear or non-linear;
- Observe whether there are outliers and analyze The influence of these outliers on the modeling analysis.

However, I couldn't find obvious correlation between variables since most of them look randomly distributed on the scatter plot. If there is a certain correlation, then most of the data points will be relatively dense and present in a certain trend, however I cannot figure it out it by simple observation.

By observing the distribution of data points on the scatter plot, I found there are some outliers.



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.

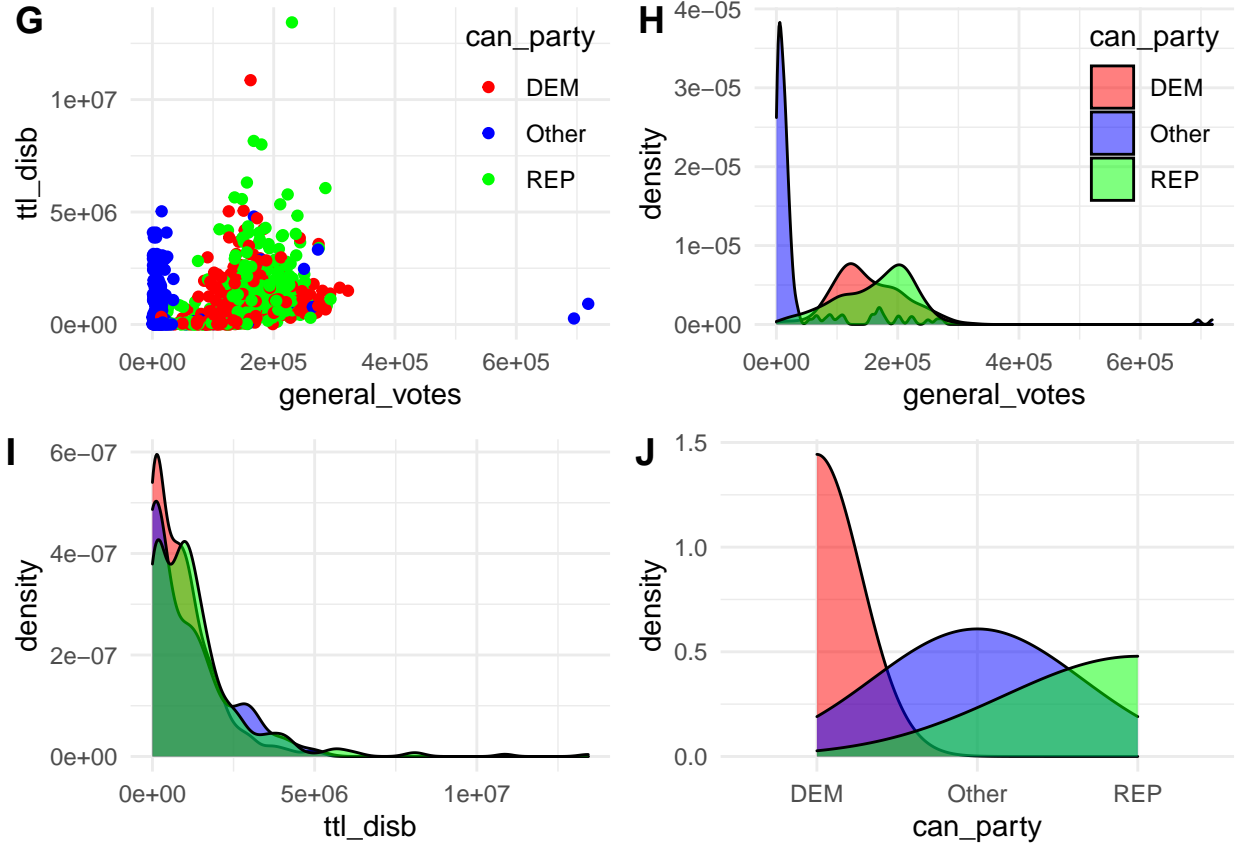
```
starwars %>%
  select(name:mass, gender, species) %>%
  mutate(
    type = case_when(
      height > 200 | mass > 200 ~ "large",
      species == "Droid"        ~ "robot",
      TRUE                      ~ "other"
    )
  )
```

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?

ANSWER:

The new variable has been produced, the new data frame is named “d2”, a discription is as the follows :

```
##   can_party      general_votes      ttl_disb
## Length:880      Min.   :    55  Min.   :    0
## Class :character 1st Qu.: 88229  1st Qu.: 102276
## Mode  :character Median :142597  Median : 830659
##              Mean   :136932  Mean   : 1084565
##              3rd Qu.:198290  3rd Qu.: 1527533
##              Max.   :718591  Max.   :13433669
```



From my observation in Fig H-J, the variable `general_percent`, `ttl_disb` and `can_party` have the following properties:

- The distribution of each of the three variables (i.e. `can_party`, `ttl_disb`, `general_vote`) are a combination of 3 different curves that are approximately following normal distributions.
- For each variable, the 3 curves in different color clustered by the 3 (i.e. DEM, REP, and Other) parties.
- Among the total 9 curves, each of the curves appears symmetry, there are about as many data values on the left side of the median as on the right side.
- Each of the curves has skewness problems because the curve appears distorted or skewed to the left or right in a statistical distribution.
- The data in each curve are not centered.

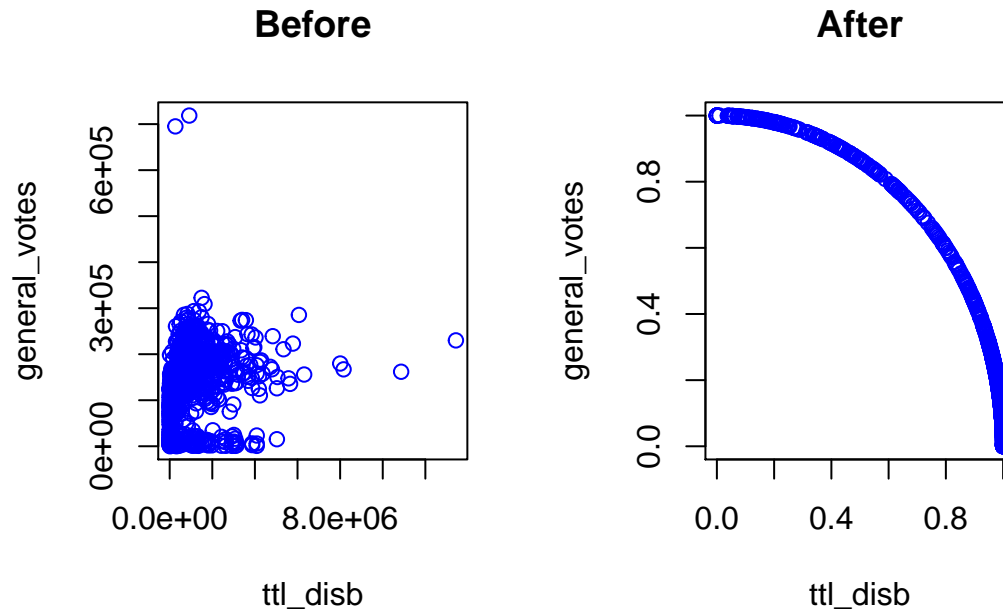
At this stage, based on my finding, the following decisions are made:

- A linear model can be created and fit the relationship between the `general_votes` and `ttl_disb` and `can_party`.
- Detailed analysis and pre-processing need to be done to the data using maths.
- further data transformations have to be performed.

Next, I will do the data pre-processing and model creation.

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.



```
##
## Call:
## lm(formula = d2$general_votes ~ d2$ttl_disb + d2$can_party)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -162812  -50839    -463    37128   645725
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.634e+05  4.080e+03  40.061  < 2e-16 ***
## d2$ttl_disb   1.163e-02  1.864e-03   6.238 6.88e-10 ***
## d2$can_party -5.062e+04  3.213e+03 -15.756  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 69240 on 877 degrees of freedom
## Multiple R-squared:  0.2602, Adjusted R-squared:  0.2585
## F-statistic: 154.2 on 2 and 877 DF, p-value: < 2.2e-16

##
## Call:
## lm(formula = d2$csvotes ~ d2$csdisb + d2$csparty)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

```

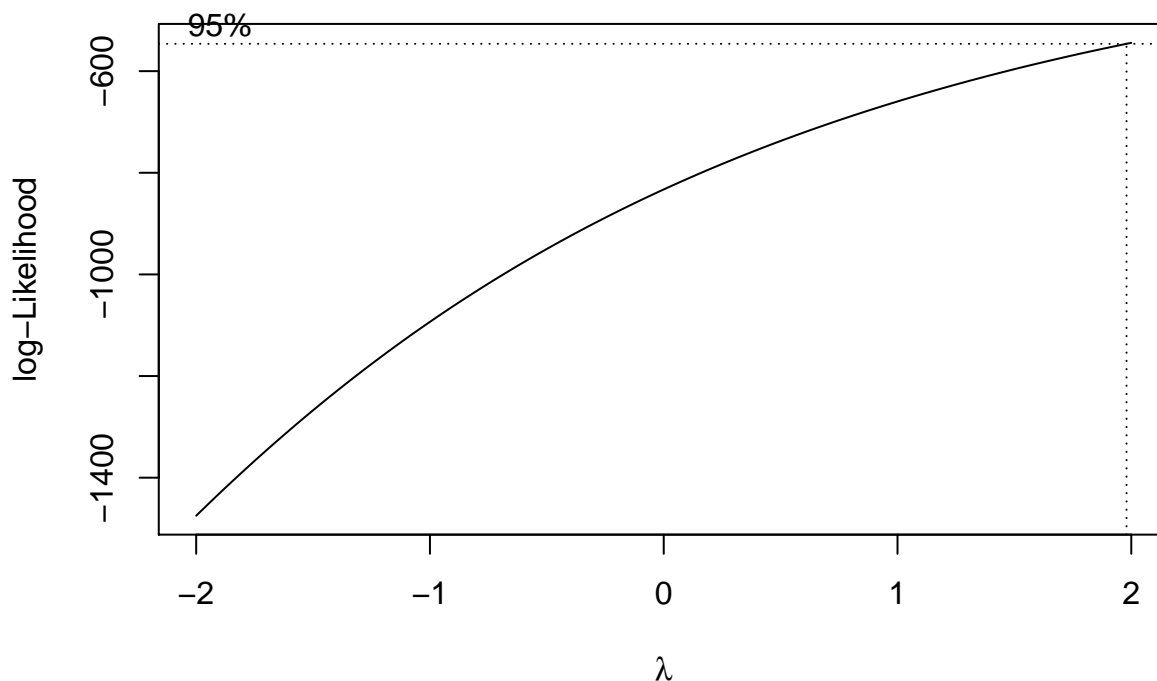
## -2.0249 -0.6323 -0.0058 0.4618 8.0309
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) -5.857e-16 2.903e-02 0.000      1
## d2$csdisb    1.820e-01 2.917e-02 6.238 6.88e-10 ***
## d2$csparty   -4.597e-01 2.917e-02 -15.756 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.8611 on 877 degrees of freedom
## Multiple R-squared: 0.2602, Adjusted R-squared: 0.2585
## F-statistic: 154.2 on 2 and 877 DF, p-value: < 2.2e-16

##
## Call:
## lm(formula = d2$novotes ~ d2$nodisb + d2$noparty)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.25036 -0.09079 -0.01375  0.08107  0.24505
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.25036    0.01271  98.38 <2e-16 ***
## d2$nodisb    -1.09452    0.01426 -76.76 <2e-16 ***
## d2$noparty   -80.80898   79.99695  -1.01  0.313
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.117 on 877 degrees of freedom
## Multiple R-squared: 0.8777, Adjusted R-squared: 0.8774
## F-statistic: 3146 on 2 and 877 DF, p-value: < 2.2e-16

##
## Call:
## lm(formula = d2$logvotes ~ d2$logdisb + d2$logparty)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -5.3555 -0.1927  0.0741  0.2940  4.1067
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 10.60108    0.16135 65.704 < 2e-16 ***
## d2$logdisb   0.09767    0.01226  7.968 5.01e-15 ***
## d2$logparty  -3.57205    0.10352 -34.507 < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.809 on 877 degrees of freedom
## Multiple R-squared: 0.6044, Adjusted R-squared: 0.6035
## F-statistic: 669.9 on 2 and 877 DF, p-value: < 2.2e-16

```

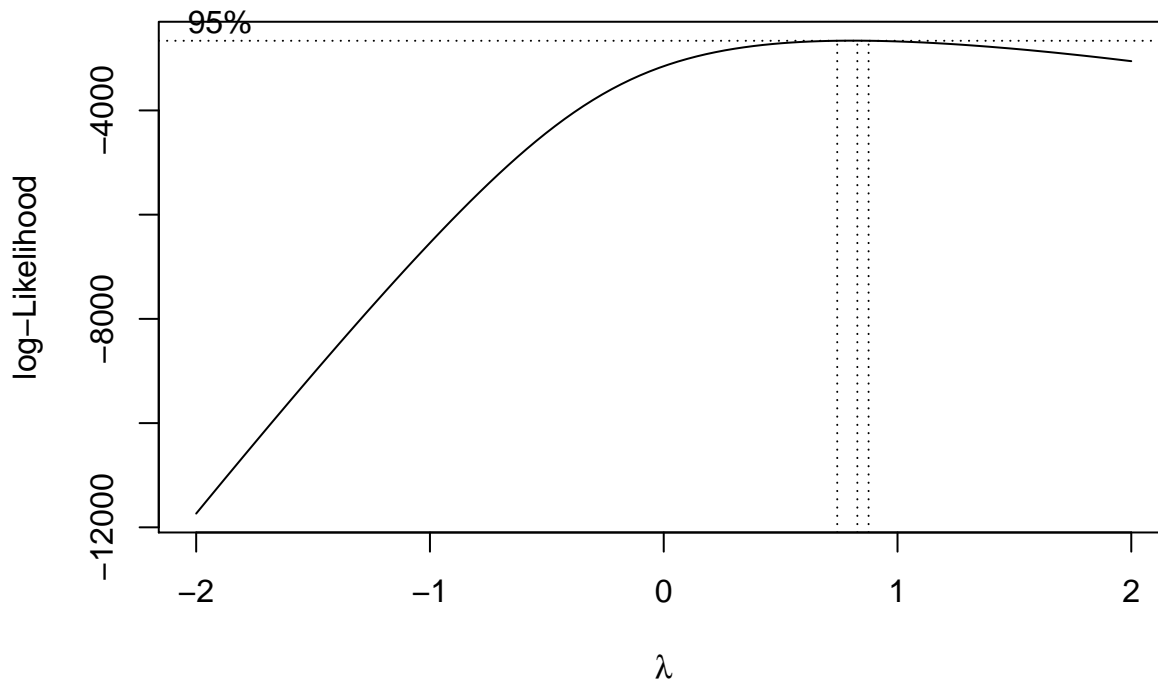
```
##
## Call:
## lm(formula = d2$general_votes ~ d2$logdisb + d2$can_party)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -164084  -42521    2037   33117  627966
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   20183.4   13565.1    1.488   0.137
## d2$logdisb     11935.7     999.7   11.939 <2e-16 ***
## d2$can_party  -46716.3    3070.3  -15.215 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 65620 on 877 degrees of freedom
## Multiple R-squared:  0.3354, Adjusted R-squared:  0.3339
## F-statistic: 221.3 on 2 and 877 DF, p-value: < 2.2e-16
```



```
##      lambda      lik
## [1,] -2.000000 -1474.865
## [2,] -1.959596 -1456.833
```

```
##
## Call:
## lm(formula = lamvotes ~ logdisb + logparty, data = d2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -103.727   -6.848    1.412    8.771   119.849
```

```
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)  118.737      4.067  29.192  <2e-16 ***
## logdisb       3.029      0.309   9.802  <2e-16 ***
## logparty    -91.757      2.610 -35.162  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.39 on 877 degrees of freedom
## Multiple R-squared:  0.6209, Adjusted R-squared:  0.62
## F-statistic: 718.1 on 2 and 877 DF, p-value: < 2.2e-16
```



```
##           lambda      lik
## [1,] -2.000000 -11735.61
## [2,] -1.959596 -11515.25
```

```
##
## Call:
## lm(formula = lam2votes ~ nodisb + noparty, data = d2)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.25036 -0.09079 -0.01375  0.08107  0.24505
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.25036    0.01271   19.70  <2e-16 ***
## nodisb      -1.09452    0.01426  -76.76  <2e-16 ***
## noparty     -80.80898   79.99695  -1.01   0.313
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.117 on 877 degrees of freedom
## Multiple R-squared:  0.8777, Adjusted R-squared:  0.8774
## F-statistic: 3146 on 2 and 877 DF,  p-value: < 2.2e-16
```

```
attach(d2)
```

```
c1 <- lm(lam2votes ~ nodisb + noparty)
summary(c1)
```

```
##
## Call:
## lm(formula = lam2votes ~ nodisb + noparty)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.25036 -0.09079 -0.01375  0.08107  0.24505
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.25036    0.01271   19.70  <2e-16 ***
## nodisb        -1.09452    0.01426  -76.76  <2e-16 ***
## noparty       -80.80898   79.99695   -1.01    0.313
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.117 on 877 degrees of freedom
## Multiple R-squared:  0.8777, Adjusted R-squared:  0.8774
## F-statistic: 3146 on 2 and 877 DF,  p-value: < 2.2e-16
```

```
e <- resid(c1)
c2 <- lm(e^2 ~ nodisb + noparty + I(nodisb^2) + I(noparty^2) + I(nodisb*noparty))
(R2 <- summary(c2)$r.sq)
```

```
## [1] 0.2223368
```

```
(n <- nrow(c2$model))
```

```
## [1] 880
```

```
(m <- ncol(c2$model))
```

```
## [1] 6
```

```
(W <- n*R2)
```

```
## [1] 195.6564
```

```
(P <- 1 - pchisq(W, m - 1))
```

```
## [1] 0
```

```
c3 <- lm(lam2votes ~ nodisb + noparty, weights = 1/abs(e))
summary(c3)
```

```
##
## Call:
## lm(formula = lam2votes ~ nodisb + noparty, weights = 1/abs(e))
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -0.49859 -0.29292 -0.09419  0.29253  0.50194
##
## Coefficients:
##              Estimate Std. Error  t value Pr(>|t|)
## (Intercept)   0.249475   0.008090   30.837  <2e-16 ***
## nodisb        -1.096230   0.008506  -128.871  <2e-16 ***
## noparty       -88.652739  28.156674   -3.149   0.0017 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3122 on 877 degrees of freedom
## Multiple R-squared:  0.9548, Adjusted R-squared:  0.9547
## F-statistic: 9270 on 2 and 877 DF, p-value: < 2.2e-16
```

```
##
## Call:
## lm(formula = lamvotes ~ logdisb + logparty)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -103.727  -6.848    1.412    8.771  119.849
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  118.737     4.067   29.192  <2e-16 ***
## logdisb       3.029     0.309    9.802  <2e-16 ***
## logparty     -91.757     2.610  -35.162  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 20.39 on 877 degrees of freedom
## Multiple R-squared:  0.6209, Adjusted R-squared:  0.62
## F-statistic: 718.1 on 2 and 877 DF, p-value: < 2.2e-16
```

```
## [1] 0.1645108
```

```
## [1] 880
```

```
## [1] 6
```

```
## [1] 144.7695

## [1] 0

##
## Call:
## lm(formula = lamvotes ~ logdisb + logparty, weights = 1/abs(e))
##
## Weighted Residuals:
##      Min       1Q   Median       3Q      Max
## -10.184  -2.701   1.057   2.873  10.958
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 118.10513    0.82784  142.67  <2e-16 ***
## logdisb      3.09811    0.06612   46.85  <2e-16 ***
## logparty    -92.24965    0.34882 -264.46  <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.571 on 877 degrees of freedom
## Multiple R-squared:  0.9881, Adjusted R-squared:  0.9881
## F-statistic: 3.635e+04 on 2 and 877 DF,  p-value: < 2.2e-16
```

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.

ANSWER

Interpreting a Coefficient as a Rate of Change in Y Instead of as a Rate of Change in the Conditional Mean of Y.

As pointed out in the discussion of overfitting, the computed regression equation estimates the true conditional mean function. How well it estimates the behavior of actual values of the random variable depends on the variability of the response variable Y. Thus, interpreting the computed coefficients in terms of the response variable is often misleading.

Illustration: In the graph shown below, the data are marked in green, the true line of conditional means is in violet, and the fitted (computed) regression line is in blue. Note that the fitted regression line is close to the true line of conditional means. The equation of the fitted regression line is (with coefficients rounded to a reasonable degree) $\hat{y} = 0.56 + 2.18x$. Thus it is accurate to say, "For each change of one unit in x, the average change in the mean of Y is about 2.18 units." It is not accurate to say, "For each change of one unit in x, Y changes about 2.18 units." For example, we can see from the graph that when x is 2, Y might be anywhere between a little below 4 to a little above 5.5; when x is 3, Y might be anywhere from a little more than 5.5 to a little more than 9. So when going from $x = 2$ to $x = 3$, the change in Y might be almost zero, or it might be as large as 5.5 units.

Interpreting a coefficient as a rate of change in Y instead of as a rate of change in the conditional mean of Y.

2. Not taking confidence intervals for coefficients into account.

Even when a regression coefficient is (correctly) interpreted as a rate of change of a conditional mean (rather than a rate of change of the response variable), it is important to take into account the uncertainty in the estimation of the regression coefficient. To illustrate, in the example used in item 1 above, the computed regression line has equation $\hat{y} = 0.56 + 2.18x$. However, a 95% confidence interval for the slope is (1.80, 2.56). So saying, "The rate of change of the conditional mean of Y with respect to x is estimated to be between 1.80 and 2.56" is usually preferable to saying, "The rate of change of the conditional mean Y with respect to x is about 2.18."

3. Interpreting a coefficient that is not statistically significant.²

Interpretations of results that are not statistically significant are made surprisingly often. If the t-test for a regression coefficient is not statistically significant, it is not appropriate to interpret the coefficient. A better alternative might be to say, "No statistically significant linear dependence of the mean of Y on x was detected."

4. Interpreting coefficients in multiple regression with the same language used for a slope in simple linear regression.

Even when there is an exact linear dependence of one variable on two others, the interpretation of coefficients is not as simple as for a slope with one dependent variable.

Example: If $y = 1 + 2x_1 + 3x_2$, it is not accurate to say “For each change of 1 unit in x_1 , y changes 2 units”. What is correct is to say, “If x_2 is fixed, then for each change of 1 unit in x_1 , y changes 2 units.”

Similarly, if the computed regression line is $\hat{y} = 1 + 2x_1 + 3x_2$, with confidence interval $(1.5, 2.5)$, then a correct interpretation would be, “The estimated rate of change of the conditional mean of Y with respect to x_1 , when x_2 is fixed, is between 1.5 and 2.5 units.”

For more on interpreting coefficients in multiple regression, see Section 4.3 (pp 161-175) of Ryan3.

5. Multiple inference on coefficients.