MSD 2019 Final Project

A replication and extension of Systematic Inequality and Hierarchy in Faculty Hiring Networks by Aaron Clauset, Samuel Arbesman, Daniel B. Larremore, Science Advances 12 Feb 2015, Vol. 1, No. 1

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2019-05-09 18:08:01

Contents

Introduction

This report represents a recreation and extension of the "Systematic inequality and hierarchy in faculty hiring networks" by Aaron Clauset, Samuel Arbesman and Daniel Larremore published in Science Advances in 2015. The paper explores the role of gender and institutional prestige in the faculty job market and finds that it is a deeply hierarchical and unequal system. Analyzing these effects is important as institutional hiring and faculty quality affects all aspects of university life both for the hired scholars as well as their undergraduate students. Furthermore, universities are often ideally seen as meritocracies with tests, grades, and journal publications allowing one's personal ability, as opposed to their networking ability, to shine. Debunking this myth will allow us to make the changes necessary to move closer to this ideal in the future.

The main contribution of the paper is the dataset, which has been painstakingly scraped and cleaned from a multitude of different sources. The data represents the placement of 18924 different faculty members at 461 academic institutions across the disciplines of Business, Computer Science and History. To explore the hierarchical structure of the departmental networks, the paper presents various figures and computations, which quantify and describe the inequality in different ways. For this report, we choose to recreate what we see as the most convincing of these results. Below we recreate, the visualization of the placement network for the top 10 schools in each department (Fig 1 top), the Lorentz curves for each department (Fig 2A), the network visualizations of the entire network for each department with the top 15% of schools highlighted (Fig 3A), and the probability distributions of the relative change in prestige rank for the top 15% of schools (Fig 3B) and all other institutions (Fig 3C). We also recreate the calculate the Gini Coefficient, which quantifies the social inequality in the network. For our extension, we attempt to predict . . .

```r
library(tidyverse)
```

```
## -- Attaching packages ---------------------------------------------------------------------------
## v ggplot2 2.2.1       v purrr   0.3.0
## v tibble  2.0.1       v dplyr   0.8.0.1
## v tidyr   0.8.1       v stringr 1.3.1
## v readr   1.1.1       v forcats 0.3.0
## Warning: package 'tibble' was built under R version 3.4.4
## Warning: package 'tidyr' was built under R version 3.4.4
## Warning: package 'purrr' was built under R version 3.4.4
## Warning: package 'dplyr' was built under R version 3.4.4
## -- Conflicts ------------------------------------------------------------------------------------
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```r
library(modelr)
```

```
## Warning: package 'modelr' was built under R version 3.4.4
```

```r
library(ggplot2)
library(igraph)
```

```
## Warning: package 'igraph' was built under R version 3.4.4
##
## Attaching package: 'igraph'
## The following object is masked from 'package:modelr':
##
##     permute
## The following objects are masked from 'package:dplyr':
##
##     as_data_frame, groups, union
## The following objects are masked from 'package:purrr':
##
##     compose, simplify
## The following object is masked from 'package:tidyr':
##
##     crossing
## The following object is masked from 'package:tibble':
##
##     as_data_frame
## The following objects are masked from 'package:stats':
##
##     decompose, spectrum
## The following object is masked from 'package:base':
##
##     union
```

```r
library(reldist)
```

```
## reldist: Relative Distribution Methods
## Version 1.6-6 created on 2016-10-07.
## copyright (c) 2003, Mark S. Handcock, University of California-Los Angeles
##  For citation information, type citation("reldist").
##  Type help(package="reldist") to get started.
```

```
library(here)
```

```
## here() starts at /Users/george/Desktop/msd2019-final-project-final-project-group-9
```

```
library(modelr)
```

Data Loading

```
fp_prefix <- "data/original/"

# Read by department data individually

business_edglist <- read.table(paste(fp_prefix, "Business_edgelist.txt", sep = ""),
  header = FALSE,
  col.names = c("u", "v", "rank", "gender")
)
business_vertexlist <- read.table(
  file = paste(fp_prefix, "Business_vertexlist.txt", sep = ""),
  sep = "   ", header = FALSE,
  col.names = c("u", "pi", "USN2009", "NRC2010", "Region", "institution")
)

computer_science_edglist <- read.table(paste(fp_prefix, "ComputerScience_edgelist.txt", sep = ""),
  header = FALSE,
  col.names = c("u", "v", "rank", "gender")
)
computer_science_vertexlist <- read.table(
  file = paste(fp_prefix, "ComputerScience_vertexlist.txt", sep = ""),
  sep = "   ", header = FALSE,
  col.names = c("u", "pi", "USN2009", "NRC2010", "Region", "institution")
)

history_edglist <- read.table(paste(fp_prefix, "History_edgelist.txt", sep = ""),
  header = FALSE,
  col.names = c("u", "v", "rank", "gender")
)
history_vertexlist <- read.table(
  file = paste(fp_prefix, "History_vertexlist.txt", sep = ""),
  sep = "   ", header = FALSE,
  col.names = c("u", "pi", "USN2009", "NRC2010", "Region", "institution")
)

# Store data in list structure for iterations

data_list <- list(
  "Buisness" = list("edge" = business_edglist, "vert" = business_vertexlist),
  "Computer_Science" = list("edge" = computer_science_edglist, "vert" = computer_science_vertexlist),
```

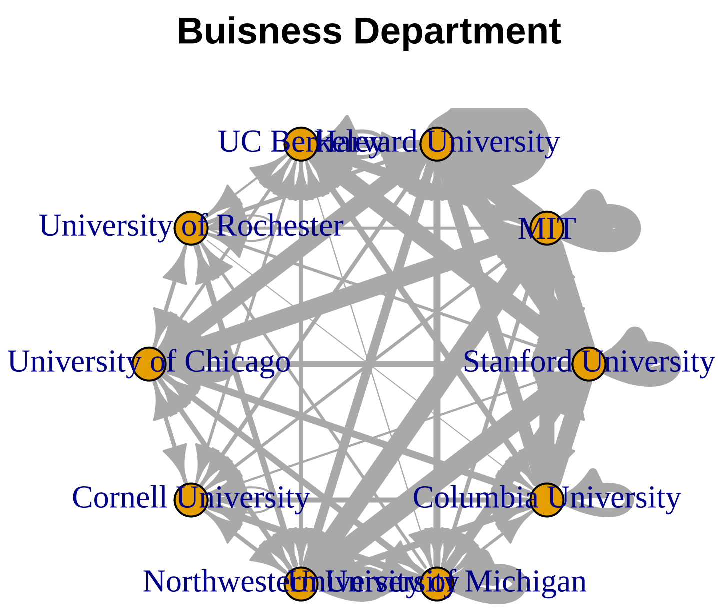
```
  "History" = list("edge" = history_edglist, "vert" = history_vertexlist)
)
```

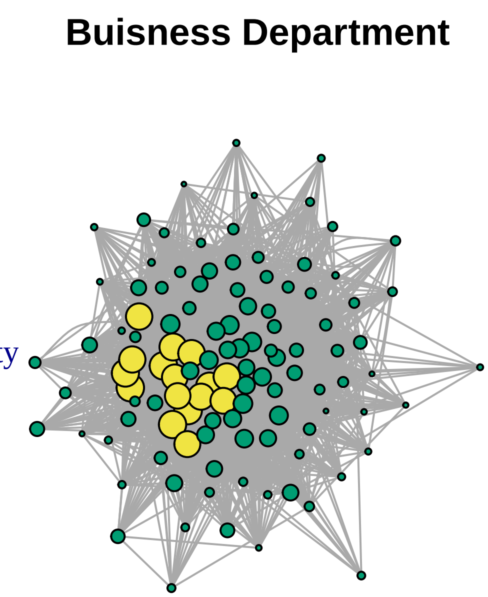
Produce Network Visualizations

```
top15 <- data.frame()
rest <- data.frame()
all_edgelists <- data.frame()
all_vertexes <- data.frame()
placement_data <- data.frame()


for (dep in names(data_list)) {
  edgelist <- data_list[[dep]]$edge
  vertex <- data_list[[dep]]$vert

  # making a table that includes the weight of each edge
  weighted_edgelist <- edgelist %>%
    group_by(v, u) %>%
    summarize(count = n()) %>%
    ungroup() %>%
    left_join(vertex, by = c("v" = "u")) %>%
    select(v, u, count, institution)


  # fitlering the weighted edgelist to make an easier to look at plot (like in Fig. 1)
  smaller <- weighted_edgelist %>%
    filter(u <= 10, v <= 10)

  # Then plotting this network of the top schools
  smaller_graph <- smaller %>%
    graph_from_data_frame(directed = TRUE)


  plot(smaller_graph,
    vertex_size = 2, edge.width = E(smaller_graph)$count / 2,
    layout = layout_in_circle(smaller_graph, order = V(smaller_graph)),
    vertex.label = unique(E(smaller_graph)$institution),
    main = paste(dep, "Department", sep = " ")
  )


  num_schools <- max(edgelist$u)

  # making another set of the full network to make a network plot like in Fig. 3
  prestige_list <- weighted_edgelist %>%
    filter(v != num_schools, u != num_schools) %>%
    group_by(v) %>%
    summarize(
      top_school = as.double(v <= 0.15 * num_schools)[1],
      prestige = num_schools - v[1]
```

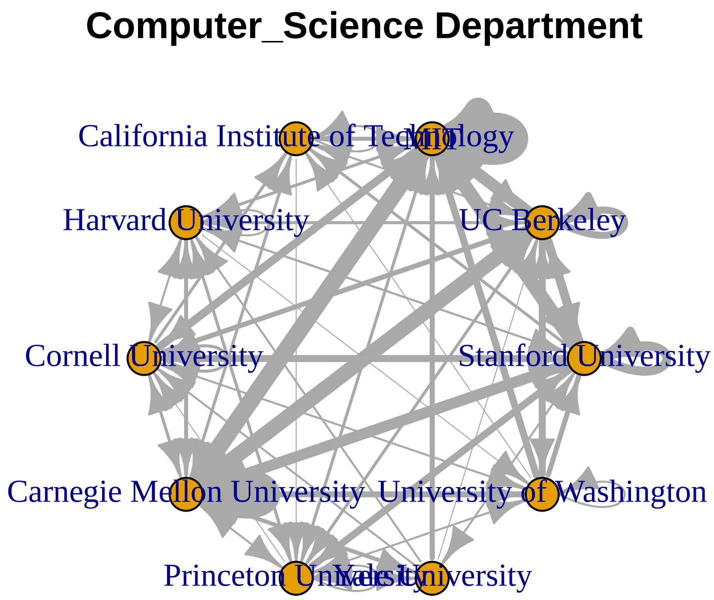
```
  ) %>%
  ungroup()


# Setting up the network to plot Fig. 3
graph <- weighted_edgelist %>%
  filter(u != v, u %in% prestige_list$v, v %in% prestige_list$v) %>%
  graph_from_data_frame(directed = FALSE, vertices = prestige_list)


plot(graph,
  vertex.size = 2 + 3 * V(graph)$top_school + V(graph)$prestige / 15,
  vertex.color = 3 + V(graph)$top_school,
  vertex.label = NA,
  main = paste(dep, "Department", sep = " ")
)


# making dataframes of the top 15 of institutions with the differences in prestige from phd to faculty
# This is to make the density plots in Fig. 3
# Am doing rbing to keep data from all the departments, but addign the label of department first

edgelist$dep <- dep
vertex$dep <- dep


top15 <- rbind(top15, edgelist %>%
  filter(u <= .15 * num_schools) %>%
  mutate(diff = (v - u) / num_schools) %>%
  select(diff, dep, rank))

# doing the same thing for the rest of the institutions
rest <- rbind(rest, edgelist %>%
  filter(u > .15 * num_schools) %>%
  filter(u < num_schools) %>%
  mutate(diff = (v - u) / num_schools) %>%
  select(diff, dep, rank))

# Finding the gini coefficient for each department, using the library reldist
school_counts <- edgelist %>%
  filter(v != num_schools) %>%
  group_by(v) %>%
  summarize(counts = n()) %>%
  ungroup()

# Here the coefficients look very small when looking at it split by department
G <- gini(school_counts$counts, runif(n = nrow(school_counts)))

cat("
", dep, "Gini Coefficient:", G)
```

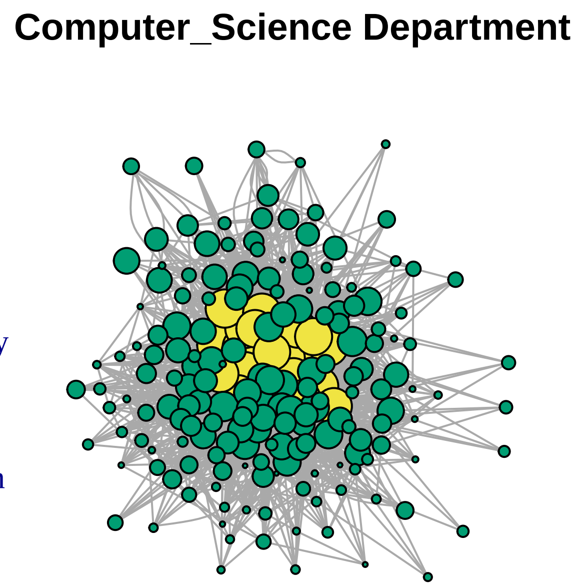
```r
  # save all the edgelists and vertex lists into one dataframe (with the department labels) so its easy
  all_edgelists <- rbind(all_edgelists, edgelist)
  all_vertexes <- rbind(all_vertexes, vertex)




  # Setting up Figure 2 plots
  total_placements <- edgelist %>%
    filter(u < n()) %>%
    summarise(rows = n())
  total_placements <- as.numeric(total_placements)



  placement_data <- rbind(placement_data, edgelist %>%
    filter(u < n()) %>%
    group_by(u) %>%
    summarise(
      faculty_produced = n(),
      fraction_placements = n() / total_placements
    ) %>%
    arrange(desc(fraction_placements)) %>%
    mutate(cum_place_percent = cumsum(fraction_placements)) %>%
    mutate(fraction_schools = row_number() / n()) %>%
    mutate(dep = dep) %>%
    ungroup(edgelist))
}
```



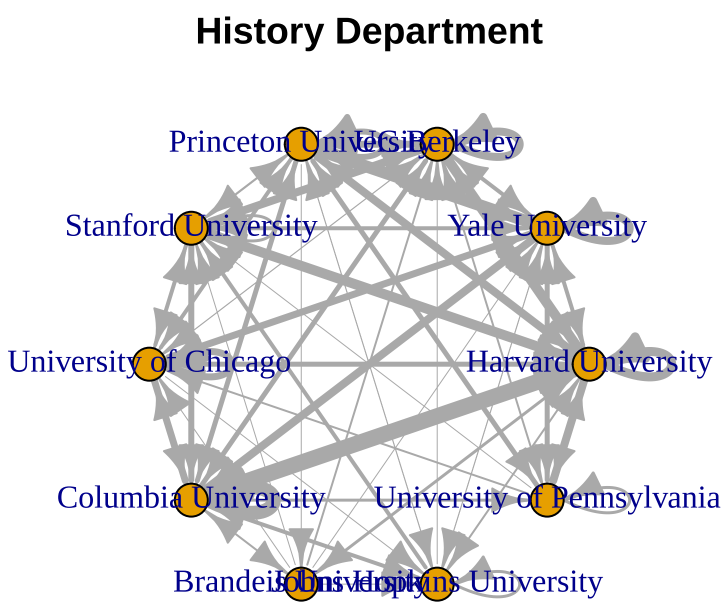



```
##
##  Buisness Gini Coefficient: 0.251649
```





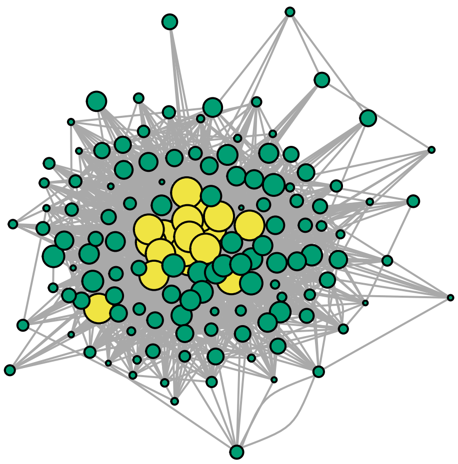

```
##
##  Computer_Science Gini Coefficient: 0.3130949
```




```
##
##  History Gini Coefficient: 0.2660275
```

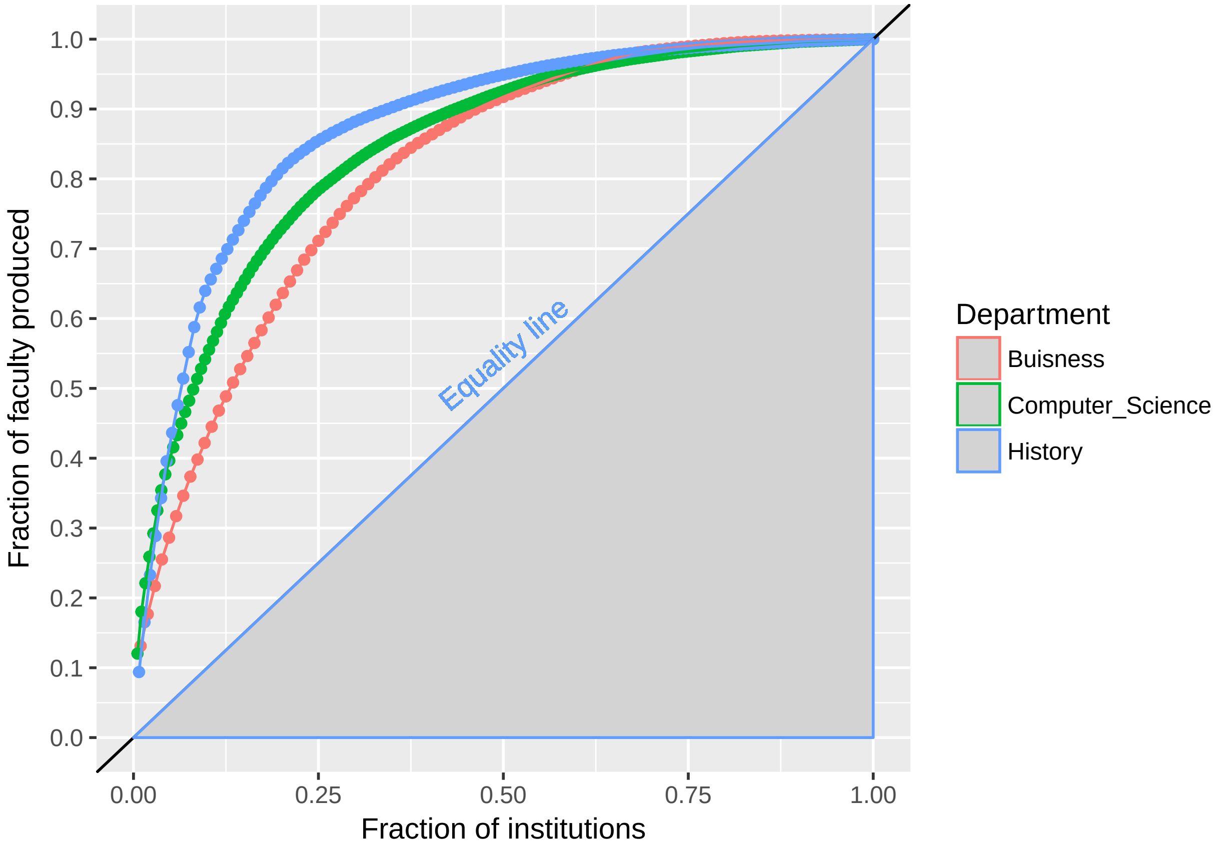
```
## Warning in `[<-.factor`(`*tmp*`, ri, value = c(1L, 12L, 14L, 1L, 9L, 4L, :
## invalid factor level, NA generated
```

History Department



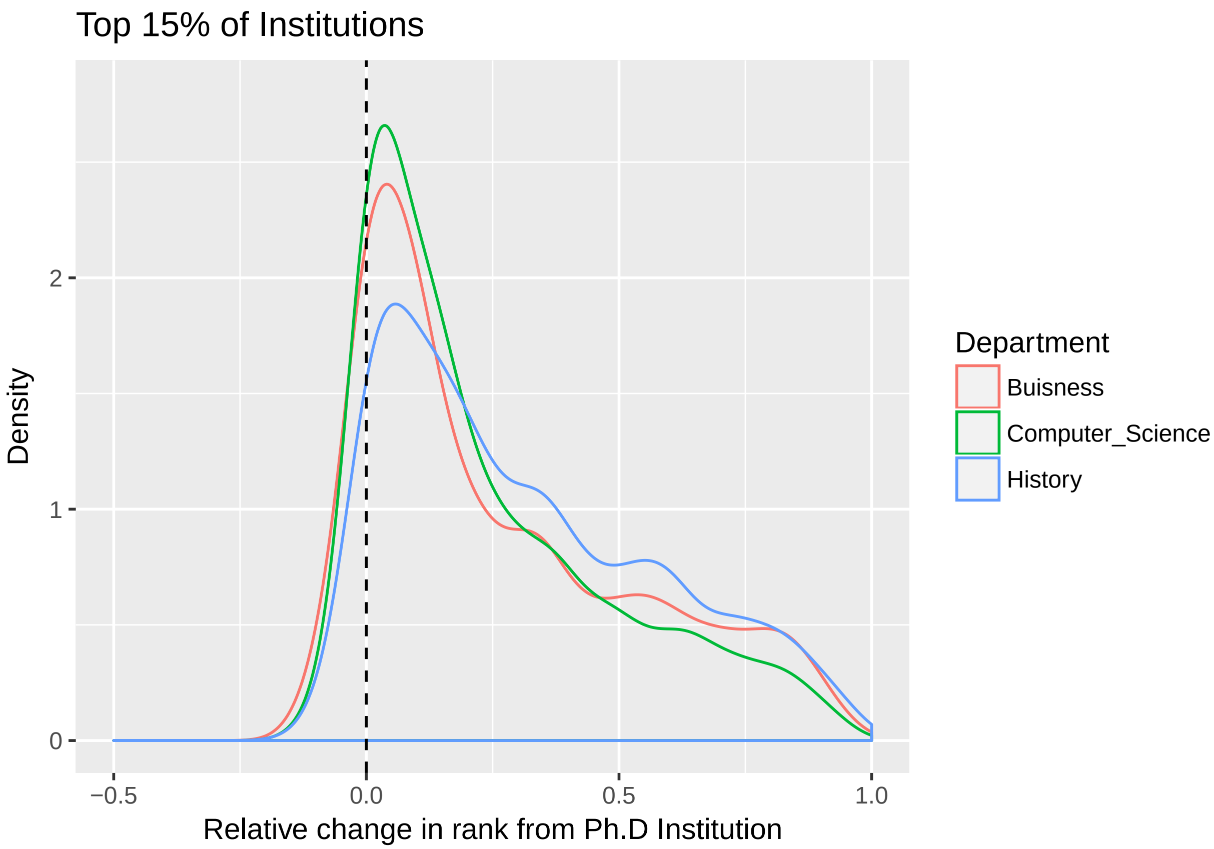
Plot Lorentz curves

```
x <- c(0, .5, 1)
y <- c(0, .5, 1)
equality_line <- data.frame(x, y)

placement_data %>%
  ggplot(aes(x = fraction_schools, y = cum_place_percent, color = dep)) +
  geom_point() +
  geom_line() +
  scale_x_continuous(breaks = seq(0, 1, by = 0.25)) +
  scale_y_continuous(breaks = seq(0, 1, by = 0.1)) +
  geom_abline(intercept = 0, slope = 1) +
  geom_text(aes(x = .5, y = .55, label = "Equality line", angle = 40)) +
  geom_area(data = equality_line, aes(x = x, y = y), fill = "#D3D3D3") +
  xlab("Fraction of institutions") +
  ylab("Fraction of faculty produced") +
  labs(color = "Department")
```



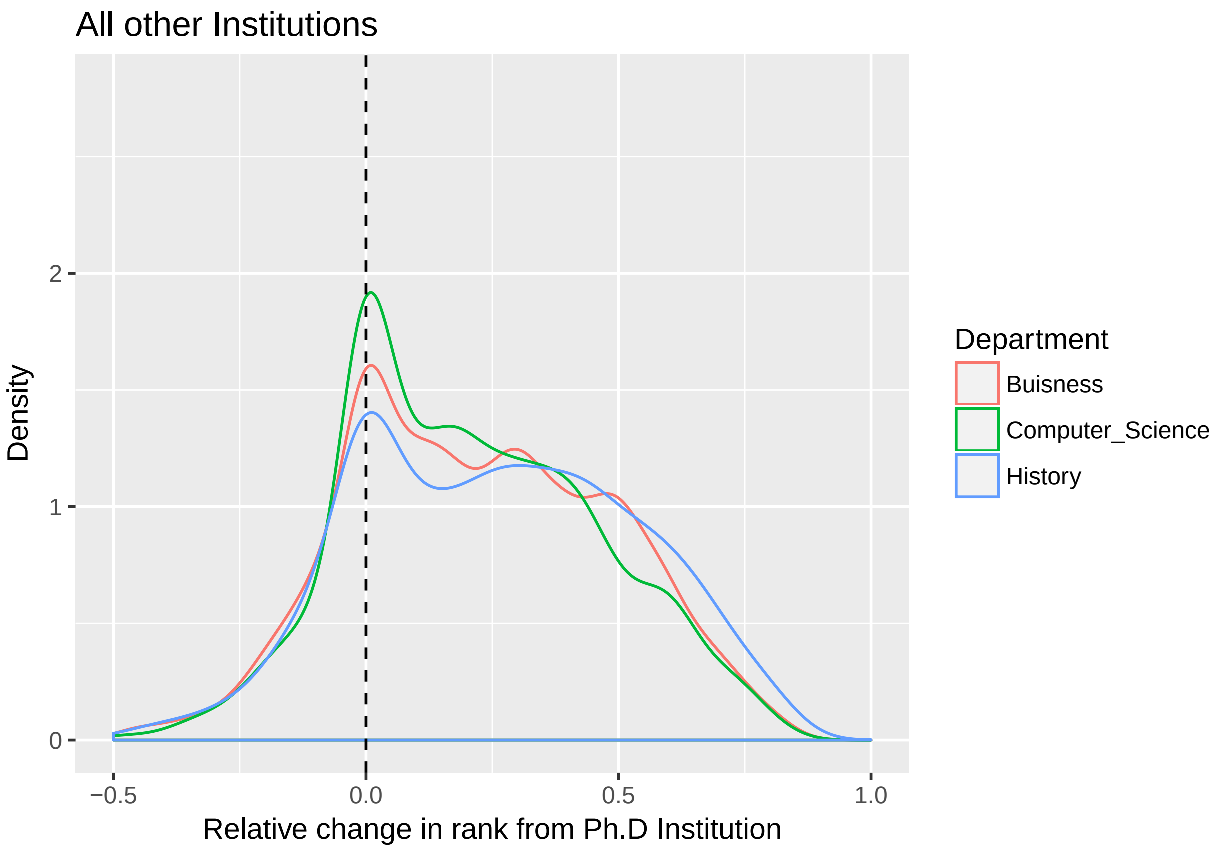
Faculty Placement PDFs

```r
# Making the density plots here

top15 %>%
  ggplot(aes(x = diff, color = dep)) +
  geom_density() +
  geom_vline(xintercept = 0, linetype = "dashed") +
  ylim(0, 2.8) +
  xlim(-.5, 1) +
  ggtitle("Top 15% of Institutions") +
  ylab("Density") +
  xlab("Relative change in rank from Ph.D Institution") +
  labs(color = "Department")
```




```
rest %>%
  ggplot(aes(x = diff, color = dep)) +
  geom_density() +
  geom_vline(xintercept = 0, linetype = "dashed") +
  ylim(0, 2.8) +
  xlim(-.5, 1) +
  ggtitle("All other Institutions") +
  ylab("Density") +
  xlab("Relative change in rank from Ph.D Institution") +
  labs(color = "Department")
```

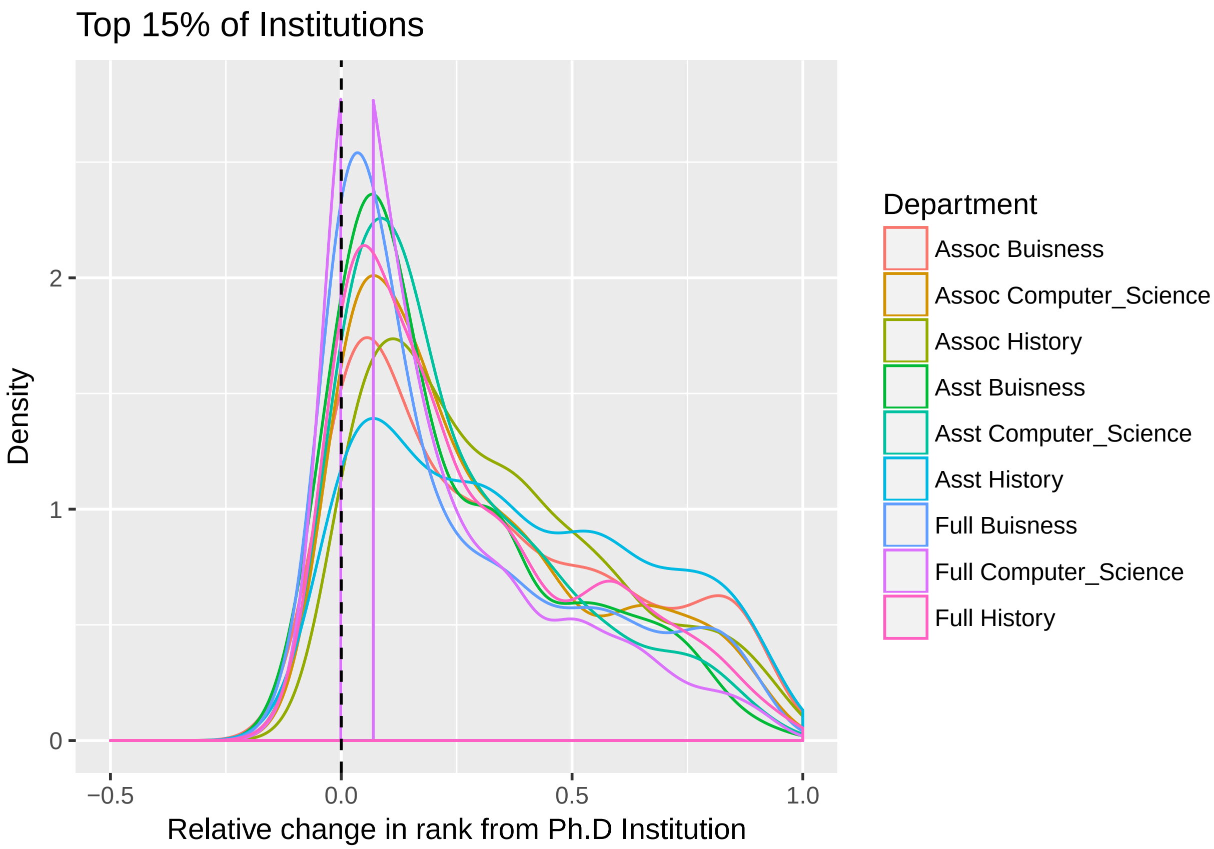
```
## Warning: Removed 36 rows containing non-finite values (stat_density).
```



Analyzing the mobility of prestige for different ranks

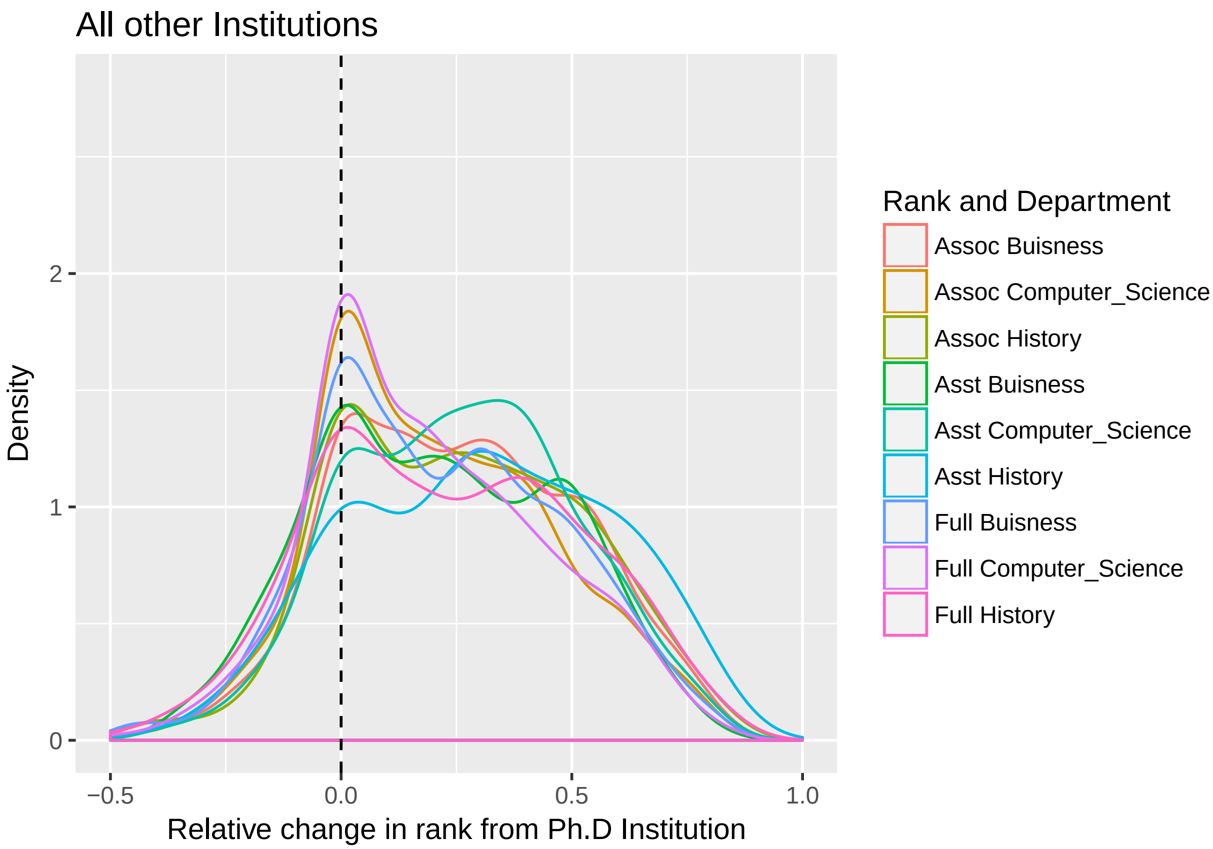
Below are density plots of prestige change for top15 and rest while splitting by both department and rank. Plots look pretty chaotic and we should probably bet rid of these eventually, but it doesn't hurt to see how small the differences are between the splits.

```
top15 %>%
  mutate(rankdep = paste(rank, dep)) %>%
  ggplot(aes(x = diff, color = rankdep)) +
  geom_density() +
  geom_vline(xintercept = 0, linetype = "dashed") +
  ylim(0, 2.8) +
  xlim(-.5, 1) +
  ggtitle("Top 15% of Institutions") +
  ylab("Density") +
  xlab("Relative change in rank from Ph.D Institution") +
  labs(color = "Department")
```




```
rest %>%
  mutate(rankdep = paste(rank, dep)) %>%
  ggplot(aes(x = diff, color = rankdep)) +
  geom_density() +
  geom_vline(xintercept = 0, linetype = "dashed") +
  ylim(0, 2.8) +
  xlim(-.5, 1) +
  ggtitle("All other Institutions") +
  ylab("Density") +
  xlab("Relative change in rank from Ph.D Institution") +
  labs(color = "Rank and Department")
```

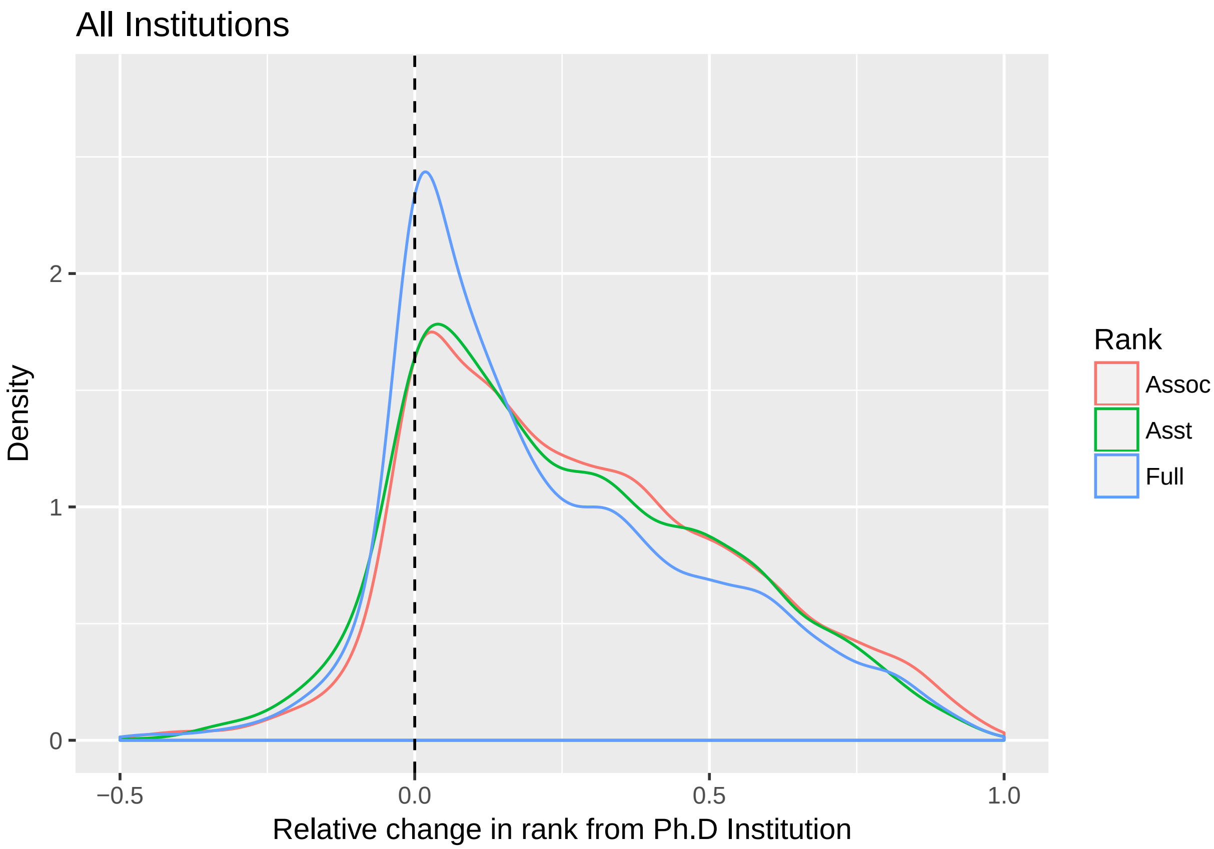
```
## Warning: Removed 36 rows containing non-finite values (stat_density).
```



Here is a plot of change in prestige density for the all the data, looking at splits by faculty rank. Can see a slightly larger portion of "full" faculy staying within their Ph.d institution's rank. Slightly more mobility fopr Assoc and Asst, but not by much.

```r
rbind(top15, rest) %>%
  ggplot(aes(x = diff, color = rank)) +
  geom_density() +
  geom_vline(xintercept = 0, linetype = "dashed") +
  ylim(0, 2.8) +
  xlim(-.5, 1) +
  ggtitle("All Institutions") +
  ylab("Density") +
  xlab("Relative change in rank from Ph.D Institution") +
  labs(color = "Rank")
```

```
## Warning: Removed 36 rows containing non-finite values (stat_density).
```



Total Gini Coefficient

still not able ot get the number they got in the original paper

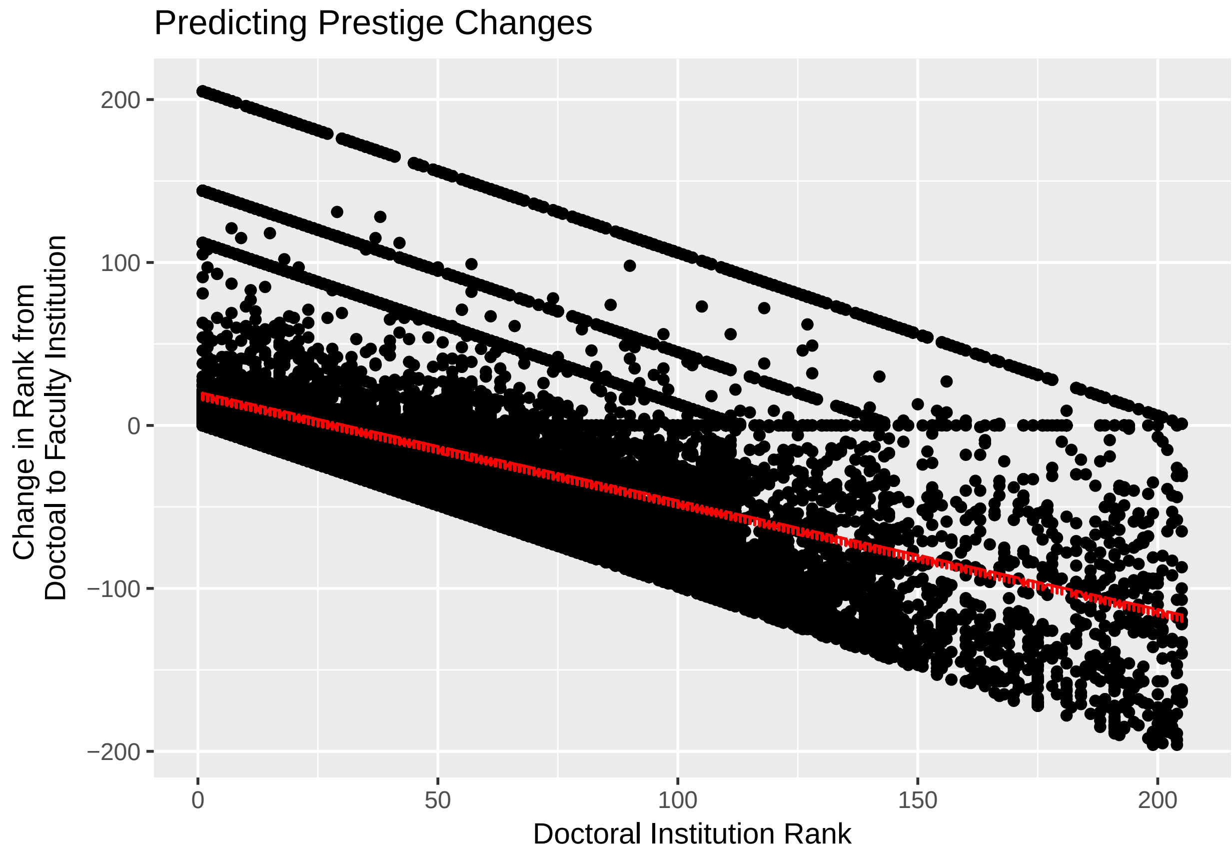
```
school_counts <- all_edgelists %>%
  left_join(all_vertexes, by = c("v" = "u", "dep" = "dep")) %>%
  select(v, u, institution) %>%
  filter(institution != "All others") %>%
  group_by(institution) %>%
  summarize(counts = n()) %>%
  ungroup()

# Here the coefficients look very small when looking at it split by department
G <- gini(school_counts$counts)

cat("Gini Coefficient for whole dataset:", G)
```

```
## Gini Coefficient for whole dataset: 0.4686504
```

Predicting rank of the hiring party from gender

```
regress <- all_edgelists %>%
  mutate(y = u - v) %>%
```

```r
  left_join(all_vertexes, by = c("v" = "u", "dep" = "dep")) %>%
  filter(institution != "All others") %>%
  mutate(num_gender = gender == "F") %>%
  select(y, v, num_gender)


# I could do train/test split, but the model's not very good, and we're really just doing thsi to inter
model <- lm(y ~ (v + num_gender), data = regress)
regress$pred <- predict(model, regress)

regress %>%
  ggplot(aes(x = v, y = y)) +
  geom_point() +
  geom_line(aes(y = pred), color = "red") +
  ylab("Change in Rank from
Doctoal to Faculty Institution") +
  xlab("Doctoral Institution Rank") +
  ggtitle("Predicting Prestige Changes")
```




```r
summary(model)
```

```
##
## Call:
## lm(formula = y ~ (v + num_gender), data = regress)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -83.725 -26.054 -15.387   7.889 188.557
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    20.386789   0.606901  33.592  < 2e-16 ***
## v              -0.666643   0.007396 -90.136  < 2e-16 ***
## num_genderTRUE -3.944168   0.799277  -4.935  8.1e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 46.27 on 18565 degrees of freedom
## Multiple R-squared:  0.3049, Adjusted R-squared:  0.3048
## F-statistic:  4071 on 2 and 18565 DF,  p-value: < 2.2e-16
```

We can see that the model predicts women to go to higher prestige schools relative to their doctoral school (the difference is statistically significant), although only by about 4 ranks, so not a very big difference. We can also see that as people go to lower prestige schools, the model predicts they will go to higher prestige schools. Of course, this doesn't really tell the full story, since by looking at the graph we can that there are more points for the higher prestige doctoral schools (x close to 1), and this model obviously doesn't capture the people who attended s these schools but didn't go on to become faculty professors.

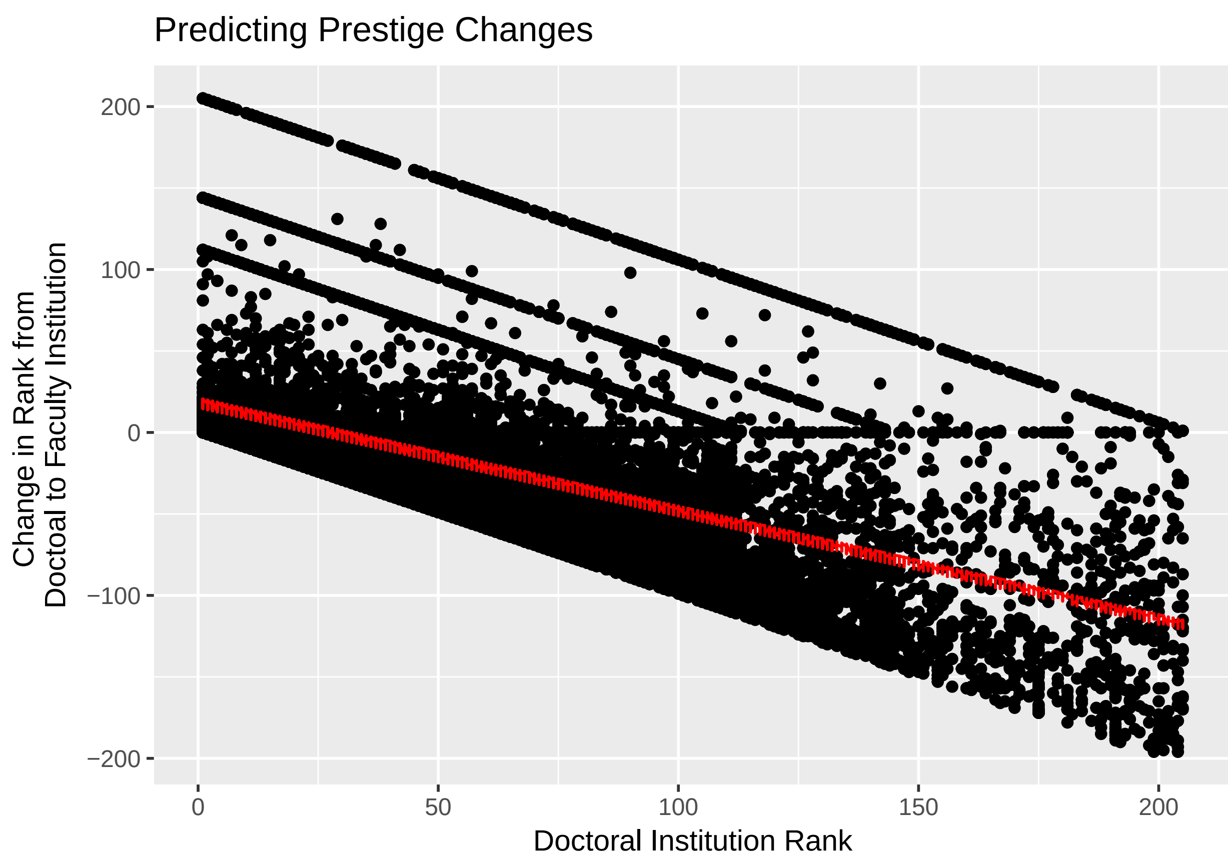
trying to predict school prestige and rank from doctoral school and gender

```r
#testing what how much prestige points yield the best, how to weigh k


for(k in c(0, 0.5, 1, 2, 4, 6, 8, 10, 50)){

cat('\nk =', k)

rank_regress = all_edgelists %>%
  mutate(asst  = as.double(rank == 'Asst') ) %>%
  mutate(full  = as.double(rank == 'Full') ) %>%
  mutate(assoc  = as.double(rank == 'Assoc') ) %>%
  mutate(y = (u - v) - k*( 3*full + 2*assoc + asst) ) %>%
  left_join(all_vertexes, by = c("v" = "u", "dep" = "dep")) %>%
  filter(institution != "All others") %>%
  mutate(num_gender = gender == "F") %>%
  select(y, v, num_gender)


# I could do train/test split, but the model's not very good, and we're really just doing thsi to inter
model <- lm(y ~ (v + num_gender), data = rank_regress)


cat("
R squared:", summary(model)$r.squared)

#We can see that scaling the change in prestige by the faculty rank doesn't help the predictive power a

}
```

```
##
## k = 0
## R squared: 0.3048886
## k = 0.5
## R squared: 0.3045917
## k = 1
## R squared: 0.3042663
## k = 2
## R squared: 0.3035302
## k = 4
## R squared: 0.3017194
## k = 6
## R squared: 0.2994642
## k = 8
## R squared: 0.296777
## k = 10
## R squared: 0.2936746
## k = 50
## R squared: 0.1873009
```

Using faculty ranks as predictors

```
rank_predictors =
  all_edgelists %>%
  mutate(asst  = as.double(rank == 'Asst') ) %>%
  mutate(full  = as.double(rank == 'Full') ) %>%
  mutate(assoc  = as.double(rank == 'Assoc') ) %>%
  mutate(y = (u - v) ) %>%
  left_join(all_vertexes, by = c("v" = "u", "dep" = "dep")) %>%
  filter(institution != "All others") %>%
  mutate(num_gender = gender == "F") %>%
  select(y, v, num_gender, full, assoc )


model <- lm(y ~ v + num_gender + assoc + full , data = rank_predictors)
rank_predictors$pred <- predict(model, rank_predictors)

rank_predictors %>%
  ggplot(aes(x = v, y = y)) +
  geom_point() +
  geom_line(aes(y = pred), color = "red") +
  ylab("Change in Rank from
Doctoal to Faculty Institution") +
  xlab("Doctoral Institution Rank") +
  ggtitle("Predicting Prestige Changes")
```




```r
cat("
coefficients:
")
```

```
##
## coefficients:
```

```r
summary(model)
```

```
##
## Call:
## lm(formula = y ~ v + num_gender + assoc + full, data = rank_predictors)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -84.861 -25.914 -15.178   7.731 189.736
##
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)    18.816342   0.895067  21.022  < 2e-16 ***
## v              -0.665045   0.007461 -89.132  < 2e-16 ***
## num_genderTRUE -3.557435   0.810498  -4.389 1.14e-05 ***
## assoc           0.875597   0.943187   0.928  0.35324
## full            2.388616   0.885013   2.699  0.00696 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 46.26 on 18563 degrees of freedom
```

```
## Multiple R-squared:  0.3052, Adjusted R-squared:  0.305 
## F-statistic:  2038 on 4 and 18563 DF,  p-value: < 2.2e-16
```

```r
cat("
R squared:", summary(model)$r.squared)
```

```
## 
## R squared: 0.3051953
```

We can see that faculty with a rank of full have a slightly bigger difference in prestige, going to less prestigious schools, although its such a small difference I don't believe it means very much. For that coefficient we do see a small p-value, and it makes intuitive sense that it is easier to get a full faculty position at a lower prestige school. Still, the difference is not nearly as big as I would have expected. As for Associate and Assistants, we see no statistically significant difference between the two coefficients.

The following is a list of all packages used to generate these results. (Leave at very end of file.)

```r
sessionInfo()
```

```
## R version 3.4.3 (2017-11-30)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS Sierra 10.12.6
## 
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/3.4/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.4/Resources/lib/libRlapack.dylib
## 
## locale:
## [1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8
## 
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base     
## 
## other attached packages:
##  [1] here_0.1        reldist_1.6-6   igraph_1.2.4    modelr_0.1.4   
##  [5] forcats_0.3.0   stringr_1.3.1   dplyr_0.8.0.1   purrr_0.3.0    
##  [9] readr_1.1.1     tidyr_0.8.1     tibble_2.0.1    ggplot2_2.2.1  
## [13] tidyverse_1.2.1
## 
## loaded via a namespace (and not attached):
##  [1] Rcpp_1.0.0          lubridate_1.7.4     lattice_0.20-35    
##  [4] assertthat_0.2.0    rprojroot_1.3-2     digest_0.6.15      
##  [7] R6_2.2.2            cellranger_1.1.0    plyr_1.8.4         
## [10] backports_1.1.2     acepack_1.4.1       evaluate_0.10.1    
## [13] httr_1.3.1          pillar_1.3.1        rlang_0.3.1        
## [16] lazyeval_0.2.1      readxl_1.1.0        rstudioapi_0.7     
## [19] data.table_1.11.4   rpart_4.1-11        Matrix_1.2-12      
## [22] checkmate_1.9.1     rmarkdown_1.10      labeling_0.3       
## [25] splines_3.4.3       foreign_0.8-69      htmlwidgets_1.2    
## [28] munsell_0.4.3       broom_0.5.0         compiler_3.4.3     
## [31] pkgconfig_2.0.2     base64enc_0.1-3     mgcv_1.8-22        
## [34] htmltools_0.3.6     nnet_7.3-12         tidyselect_0.2.5   
## [37] gridExtra_2.3       htmlTable_1.13.1    Hmisc_4.2-0        
## [40] crayon_1.3.4        grid_3.4.3          nlme_3.1-131       
## [43] jsonlite_1.5        gtable_0.2.0        magrittr_1.5       
## [46] scales_0.5.0        cli_1.0.1           stringi_1.2.2      
```

```
## [49] latticeExtra_0.6-28 xml2_1.2.0          Formula_1.2-3
## [52] RColorBrewer_1.1-2  tools_3.4.3         glue_1.3.0
## [55] hms_0.4.2           survival_2.41-3     yaml_2.1.18
## [58] colorspace_1.3-2    cluster_2.0.6       rvest_0.3.2
## [61] knitr_1.20          haven_1.1.2
```