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

George Austin (gia2105), Calvin Tong (cyt2113), Mia Fryer (mzf2106)

2019-05-11 18:46:44

Contents

Introduction

This report is a recreation and extension of the paper "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 introduce some predictive results to augment the primarily descriptive results from the paper. To do this, we attempt to predict the rank and prestige of the hiring party from different factors, focusing on gender and professor rank, and interpret the coefficients to decipher overall trends from the data.

```
library(tidyverse)
```

```
## -- Attaching packages ---------------------------------- tidyverse 1.2.1 --
## v ggplot2 3.1.0       v purrr   0.3.0
## v tibble  2.0.1       v dplyr   0.8.0.1
## v tidyr   0.8.2       v stringr 1.4.0
## v readr   1.3.1       v forcats 0.3.0
## -- Conflicts ------------------------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(modelr)
library(ggplot2)
library(igraph)
```

```
##
## 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
```

```
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/calvin/Documents/Columbia/msd2019-final-project-final-project-group-9
```

```
library(modelr)
```

Data Loading

The data provided by the authors required no additional cleaning to reproduce the results. Here we load the data individually and store it in a list to allow for exploration and efficient iteration.

```
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),
```

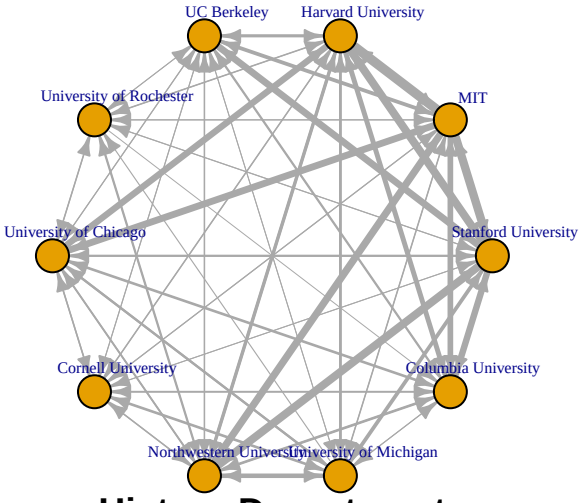
```
  "History" = list("edge" = history_edglist, "vert" = history_vertexlist)
)
```

Produce Network Visualizations (Fig 1 Top)

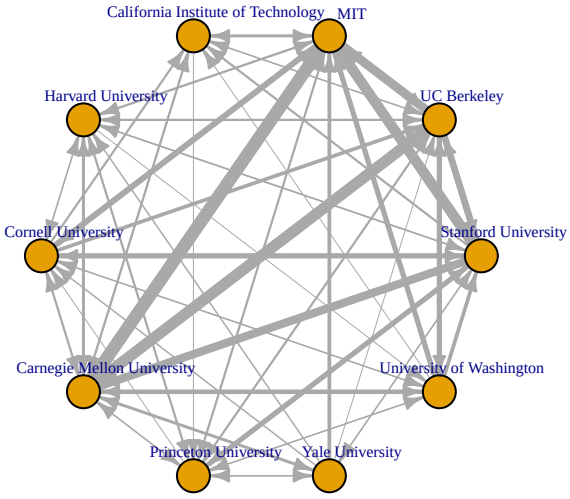
We begin by reproducing the network visualizations for each department. The paper does not report the graphs for all the departments, but we have created them below to allow for better understanding of the network shapes. Since we are plotting all the departments, we have to normalize the edge sizes to make the plots comparable. The paper did not mention any normalization as they were only showing a single department. We decided to normalize by dividing through by the total number of edges.

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

  # Making 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
  smaller <- weighted_edgelist %>%
    filter(u <= 10, v <= 10, u != v)

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

  plot(smaller_graph,
    vertex_size = 0.5,
    edge.width = E(smaller_graph)$count / sum(E(smaller_graph)$count) * 100,
    edge.arrow.size = 0.5,
    layout = layout_in_circle(smaller_graph, order = V(smaller_graph)),
    vertex.label = unique(E(smaller_graph)$institution),
    vertex.label.cex = c(0.5),
    vertex.label.dist = 2,
    main = paste(dep, "Department", sep = " ")
  )
}
```

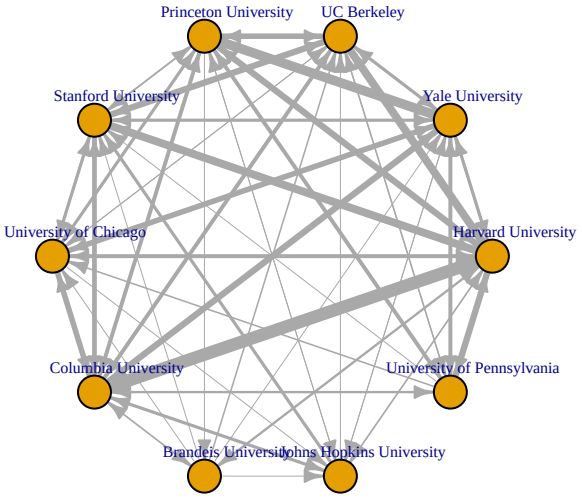
Buisness Department



Computer_Science Department



History Department

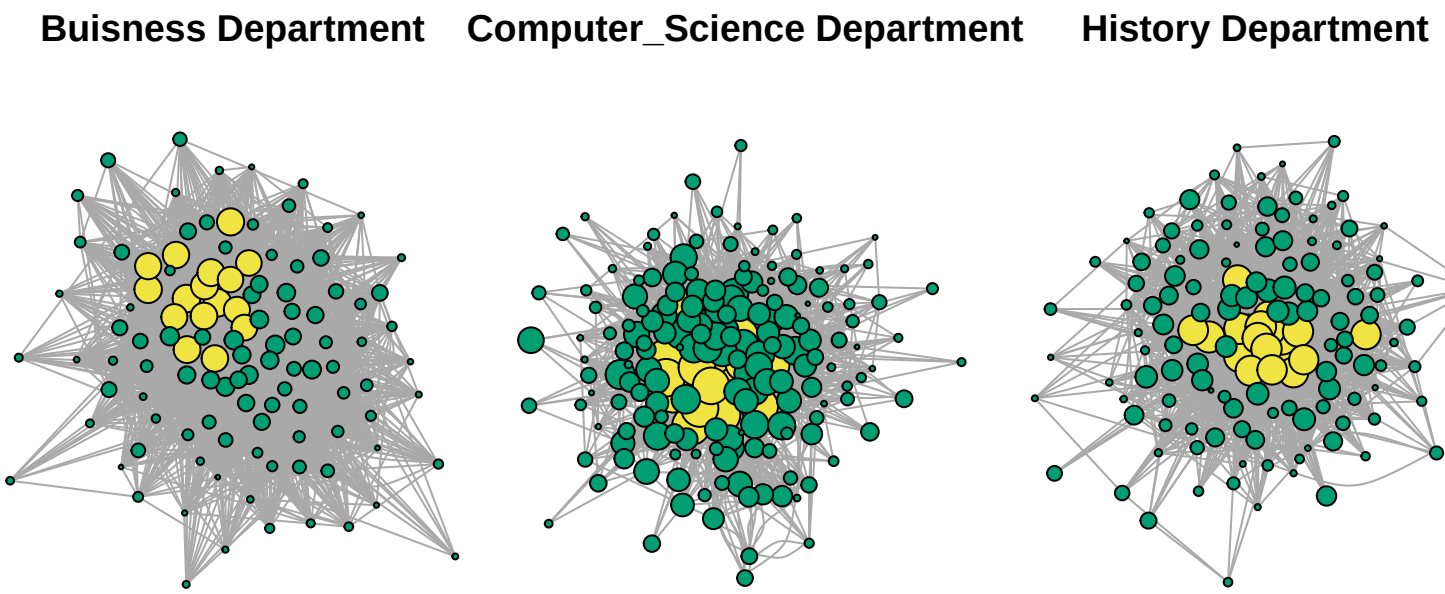


For comparison to the paper, we see that MIT's Computer Science department sends the most graduates to Carnegie Mellon. We see that for the history departments, there are strong ties between Harvard and Columbia and Princeton and Yale. We also see there is a strong ivy league network and dominance in the department, which we don't see in the Computer Science or Business networks. For Business schools, we see a much more balanced network with much less ivy league domination. It's also important to note that for each of these inferences it is assumed that becoming a professor is the ultimate goal of the candidates. The truth of this statement will vary from department to department, but is likely most true for the History department and less true for the Computer Science and Business departments as the industry opportunities will be more tempting in those areas. To get rid of this assumption, one would have to look at the percentage of applicants accepted instead of the net number hires. There was no data cleaning needed to produce these results indicating that the validity of the published data.

Full Network Visualizations (3A)

Below we reproduce full network visualizations with the top 15% of the institutions highlighted. The size of each vertex represents the school's prestige.

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

  # Make 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)


  num_schools <- max(edgelist$u)

  # Make full network to make a network plot
  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()


  # Set up the network to plot
  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 = " ")
  )
}
```



Just like in the paper, we see that the top 15 percent of schools (highlighted in yellow) tend to take up central positions in the graph, which indicates they have the best faculty production and placement. Similarly to the previous figure looking at placement directionality (figure 1), we see the History departments having a much more central bias than the other two discipline, with Business having the widest distribution of the three. There was no additional data processing needed to reproduce this result.

Faculty Placement PDFs (3B and 3C)

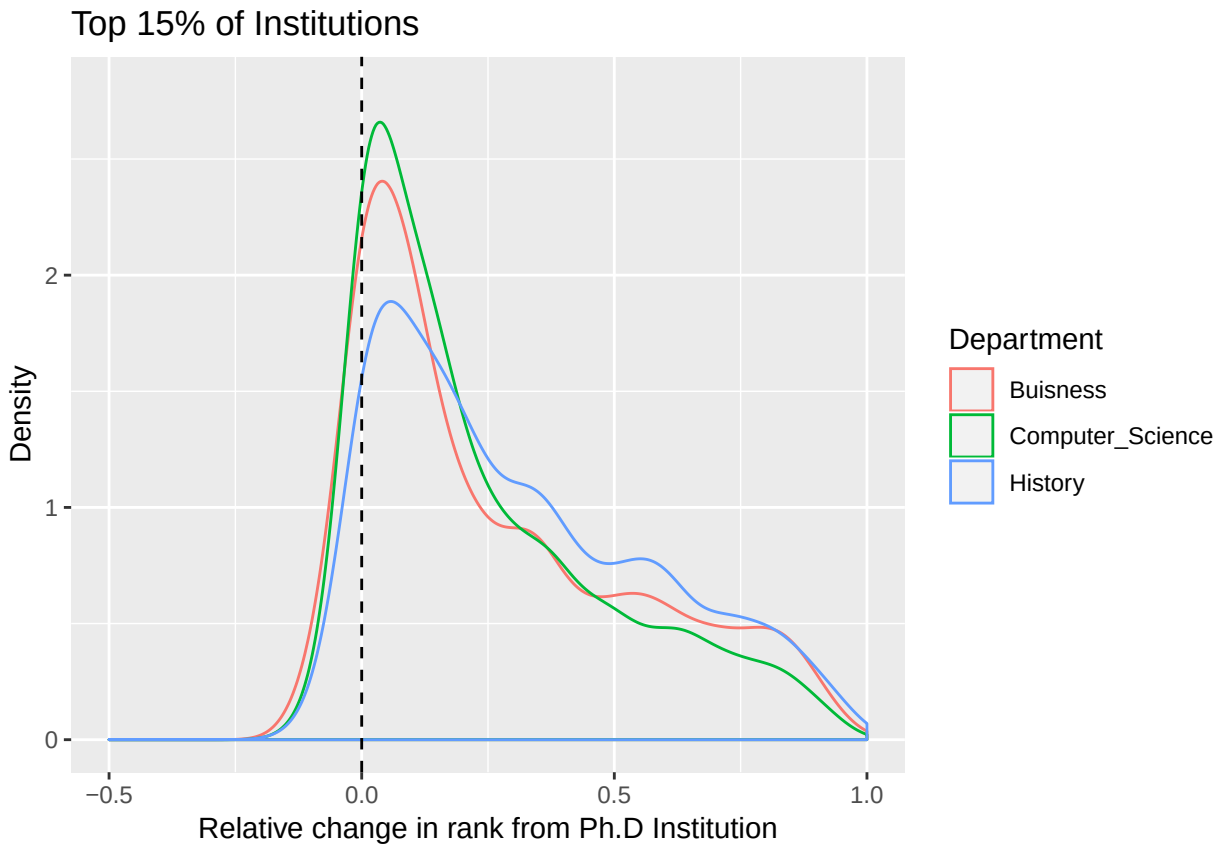
Here we reproduce the PDFs for the relative changes in rank for the top 15 schools and all other institutions.

```
# Dataframe of top 15 institutions and rest
top15 <- data.frame()
rest <- data.frame()

# All department edges and vertexes
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

  num_schools <- max(edgelist$u)

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

  # rbind to keep data from all the departments, adding the label of department first
  top15 <- rbind(top15, edgelist %>%
    filter(u <= .15 * num_schools) %>%
    mutate(diff = (v - u) / num_schools) %>%
    select(diff, dep, rank))
```

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


  # Save all the edgelists and vertex lists into one dataframe with dep labels
  all_edgelists <- rbind(all_edgelists, edgelist)
  all_vertexes <- rbind(all_vertexes, vertex)


  # Set placement dataframes
  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))
}
```

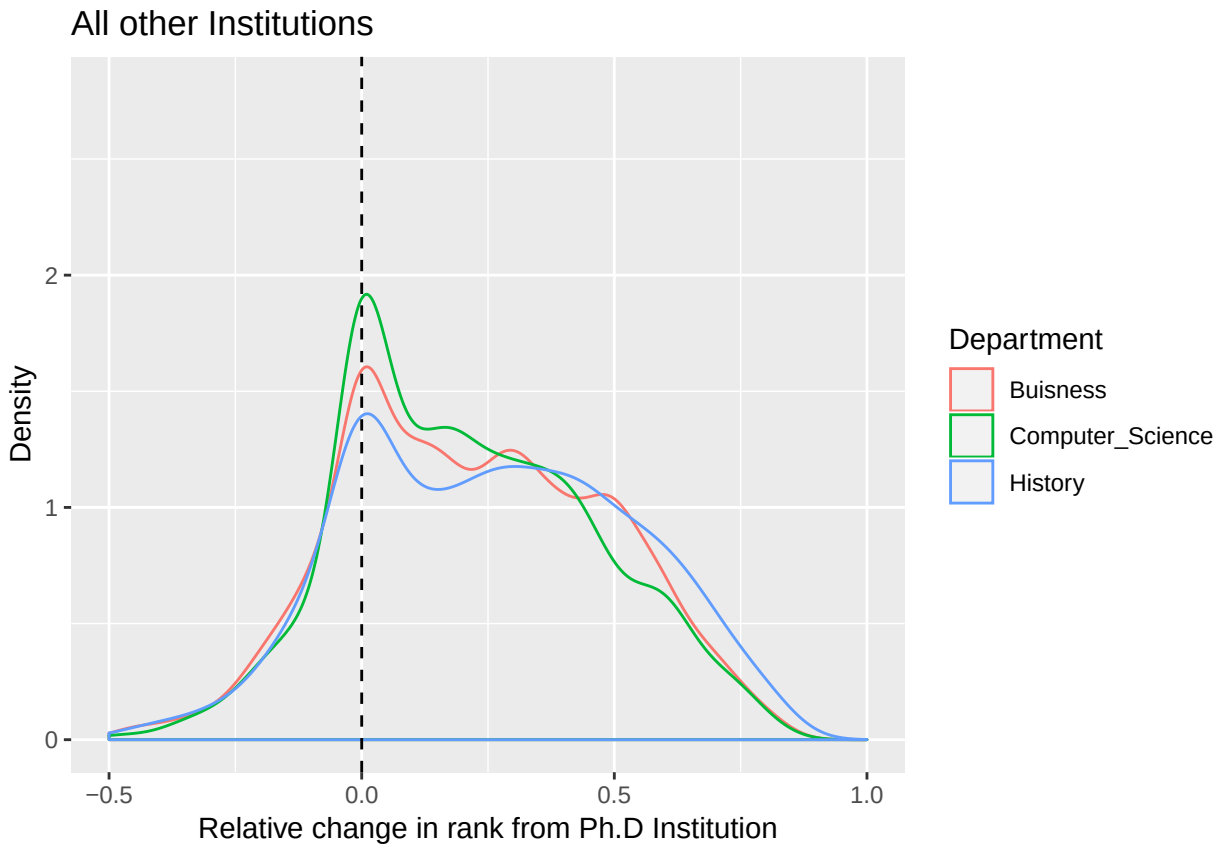
```
## Warning in `[<-.factor`(`*tmp*`, ri, value = c(1L, 12L, 14L, 1L, 9L, 4L, :
## invalid factor level, NA generated
```

```
# Making the density plots

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).
```



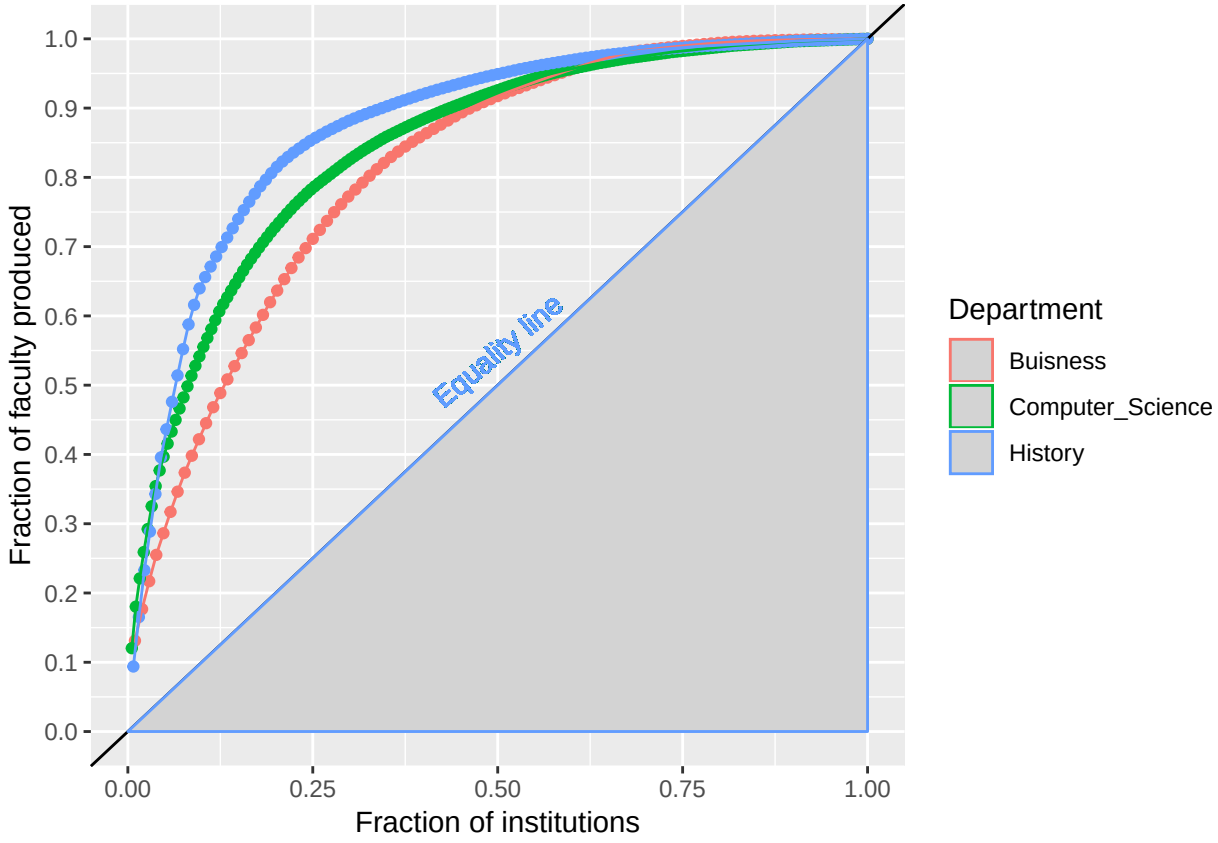
Just like in the paper, we see that candidates from the top 15% get much better placements than those in the rest of the institutions. One of the interesting observations here, however, was that the program with the highest spike was computer_science, followed by business and then history. This seems to correlate well with the high bias of the "prestigious" schools when it comes to history, meaning there is far less upward mobility in that space, whereas computer science seems to have the greatest upward mobility. There was no additional processing to achieve this result.

Plot Lorentz curves (Fig 2A)

Below we reproduce the Lorentz curve for the graphs. The Lorentz curve is normally used to show an income distribution, but here it is the fraction of faculty produced plotted as a function of the fraction of institutions. For this data, it shows that most of the hires come from a few select schools.

```
#Seting up the "line of equality"
x <- c(0, .5, 1)
y <- c(0, .5, 1)
equality_line <- data.frame(x, y)

#plotting each department as a seperate curve with fractions of instetutions plotted
#against fraction of faculty produced
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")
```



We see the same result as in the paper that all departments show strong inequality with History having the most and Business having the least. This is consistent with our network visualizations, which show the strongest ties in the History graph and the most equal ties in the Business graph. One possible reason for this could be that hiring methods in business rely more on the accomplishments in the world of business (a measurable statistic) while history on the other end of the spectrum does not have an easily measurable "success" metric which can be then used in faculty decisions. This also supports the theory of upward mobility, in history for example (the least upward mobile department) you have the greatest amount of inequality.

Total Gini Coefficient

Here we calculte the Gini Coefficient for all departments and the full dataset. The Gini Coefficient quantifies inequality in a distribution. If the distribution is uniform then the Gini coefficient is 0, if one person owns all the wealth then it is 1.

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

  # 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, "\n")
}
```

```
## Buisness Gini Coefficient:  0.2535513
## Computer_Science Gini Coefficient:  0.3301101
## History Gini Coefficient:  0.278643
```

```
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("Whole Dataset Coefficient:", G)
```

```
## Whole Dataset Coefficient: 0.4686504
```

We were unable to reproduce the Gini Coefficients reported in the paper. They report `G=0.62-0.76` indicating extremely strong inequality. Our values are much lower on the whole, but still indicate inequality.

Extension: Predicting Hiring Party Ranks and Prestige with Different Factors.

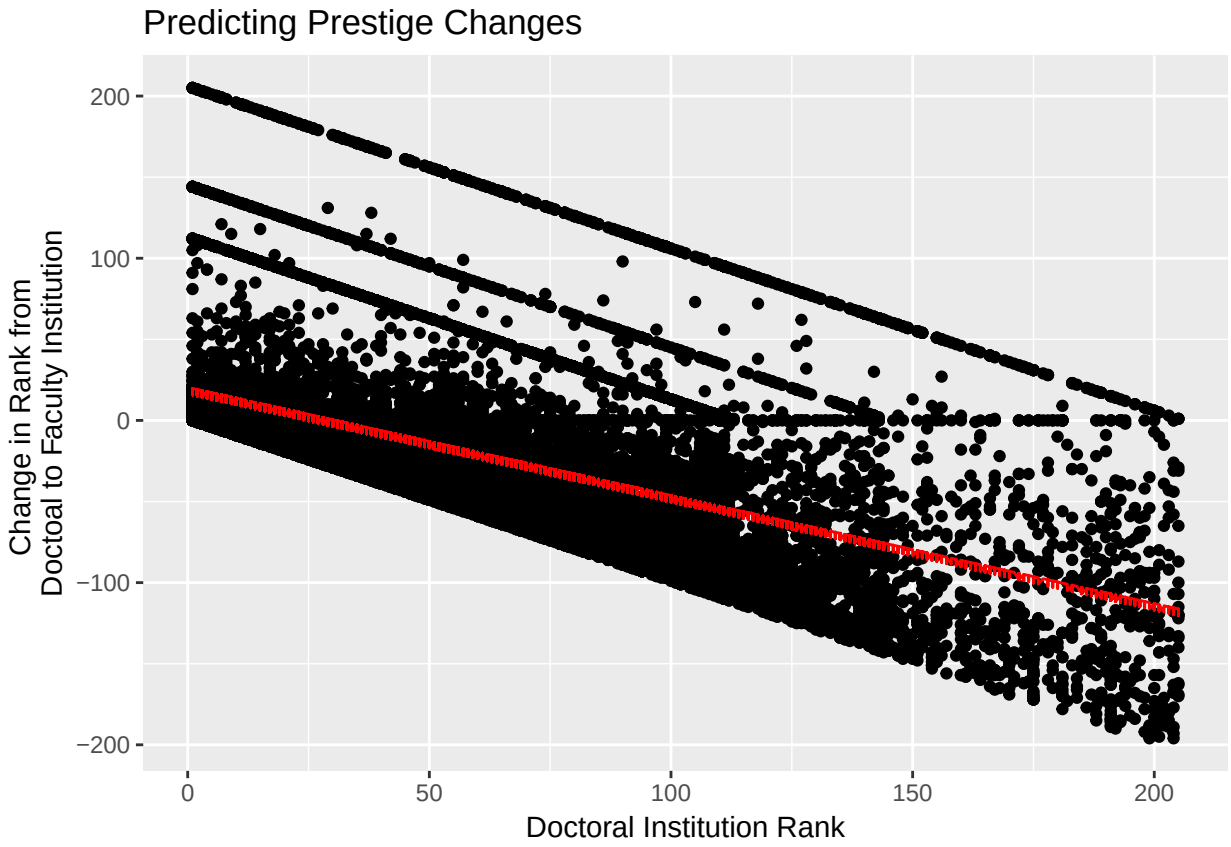
Most of the results in the paper are descriptive, some aspect of the graph is plotted and the authors appeal to the judgment of the reader to make the argument for inequality. For our extension, we aim to augment these results by introducing some more predictive results. Specifically, we use simple linear regression models to predict different properties of the hiring party. While we do not expect these simple models to be performant at predicting the future because the underlying distribution is expected to change in time, careful analysis of their coefficients will allow us to peel off general insights and trends for this particular dataset. We also further explore the Gini coefficients by computing it for full faculty and splitting by gender.

Predicting rank of the hiring party from gender

We begin by attempting to predict the rank of the hiring party from the gender of the candidate. This will allow us to draw some insights about the effect of gender on faculty hiring. We will be setting our level of statistical significance to be a p-value of 0.05.

```
regress <- all_edgelists %>%
  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)


# I could do train/test split, but the model's not very good, and we're really just doing thsi to interp
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")
```




```
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
```

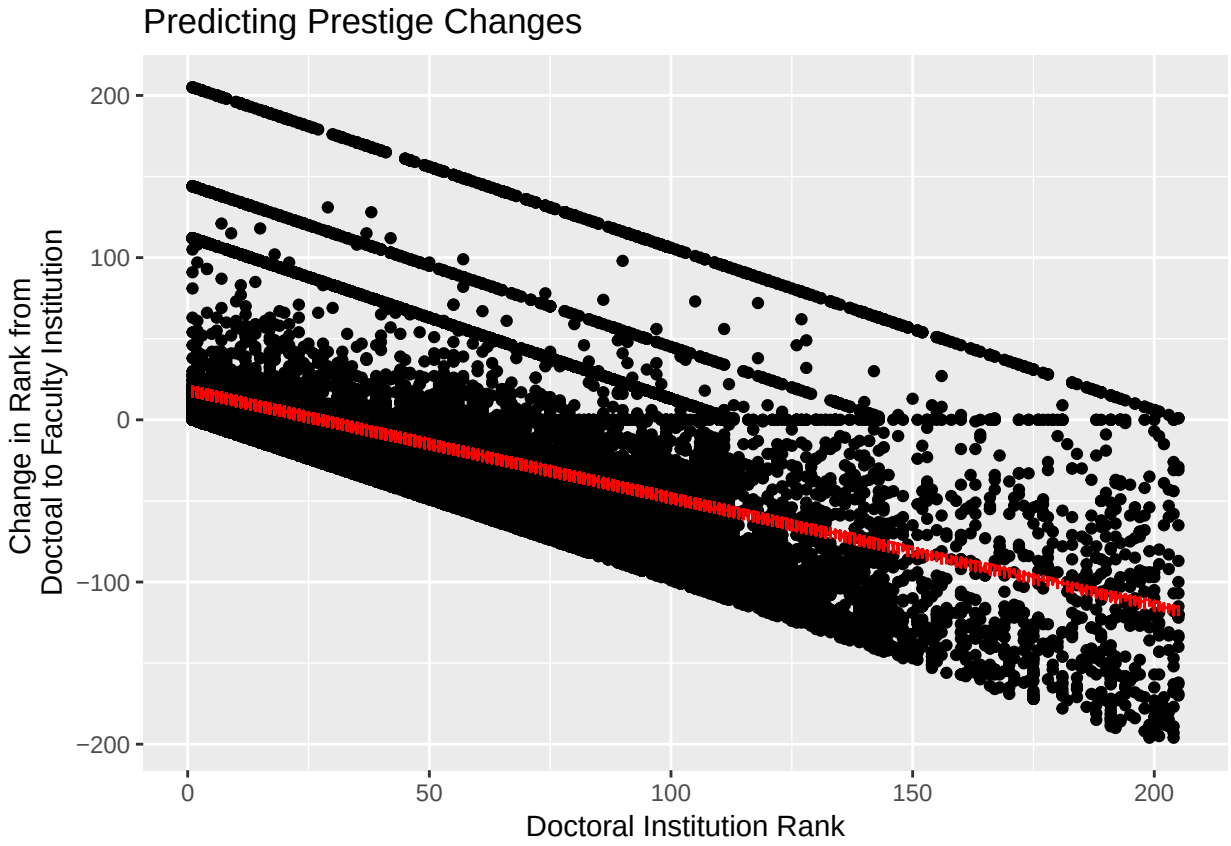
We can see that the model predicts that women go to higher prestige schools relative to their doctoral school (the difference is statistically significant), although only by about 4 ranks, so not a very big difference. We can also see that as people go to lower prestige schools, the model predicts they will work at relatively higher prestige schools. Part of the reason for this is also that there are more possible ranks to ascend by the lower rank you start at.

Of course, this doesn't really tell the full story, since by looking at the graph we can also see 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 the lower-rank schools but didn't go on to become faculty professors.

Using faculty ranks as predictors

He we add faculty ranks as predictors for the model. This allows us to estimate if there are differences in the hiring trends of schools for faculty of different ranks. Motivation for this step came from the assumption that hiring an associate or assistant faculty would be considered less of a commitment from the part of the hiring institution, and therefore it might be possible that schools are more or less willing to take a risk on hiring more associate or assistant professors coming from lower prestige institutions.

```
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")
```




```
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
```

We can see that faculty with a rank of full have a slightly bigger difference in prestige, going to less prestigious schools, although it's such a small difference we 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 we would have expected.

As for Associate and Assistants, we see no statistically significant difference between the two coefficients.

Predicting Hiring School Prestige from Doctoral Rank and Gender

From our last model, we saw a statistically significant difference in the hiring patterns for both women and full-time faculty members. We observe women going to relatively higher rank schools, while full-time faculty members go to relatively lower rank schools. Here we build on the previous model, including the binary coefficients for women and full-time faculty, but including one more variable for being both female and full-time. This will hopefully illustrate more about the universities' hiring patterns.

```
# testing what how much prestige points yield the best, how to weigh 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) ) %>%
    left_join(all_vertexes, by = c("v" = "u", "dep" = "dep")) %>%
    filter(institution != "All others") %>%
    mutate(num_gender = as.double( gender == "F") ) %>%
    select(y, v, full, assoc, num_gender)


  # No train test split as we want coef rather than predictions
  model <- lm(y ~ (v + num_gender + full + num_gender*full), data = rank_regress)


  summary(model)
```

```
##
## Call:
## lm(formula = y ~ (v + num_gender + full + num_gender * full),
##     data = rank_regress)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -85.259 -25.955 -15.244   7.728 188.489
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)     18.970899   0.748634  25.341  < 2e-16 ***
## v               -0.664598   0.007437 -89.363  < 2e-16 ***
## num_gender      -2.465689   1.011511  -2.438  0.01479 *
## full             2.543280   0.780314   3.259  0.00112 **
## num_gender:full -3.136150   1.686243  -1.860  0.06292 .
## ---
## 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:  0.3053, Adjusted R-squared:  0.3051
## F-statistic:  2039 on 4 and 18563 DF,  p-value: < 2.2e-16
```

```
cat('\nNumber of Male Full-time Faculty:', nrow(all_edgelists %>%
       filter(gender == 'M') %>%
       filter(rank == 'Full') ) )
```

```
##
## Number of Male Full-time Faculty: 7175
```

```
cat('\nNumber of Female Full-time Faculty:', nrow(all_edgelists %>%
       filter(gender == 'F') %>%
       filter(rank == 'Full') )  )
```

```
##
## Number of Female Full-time Faculty: 1406
```

```
#adding another model for just full professors to analyze the gender coefficient
rank_regress <- all_edgelists %>%
    filter(rank == 'Full') %>%
    mutate(y = (u - v) ) %>%
    left_join(all_vertexes, by = c("v" = "u", "dep" = "dep")) %>%
    filter(institution != "All others") %>%
    mutate(num_gender = as.double( gender == "F") ) %>%
    select(y, v, num_gender)

# No train test split as we want coef rather than predictions
model <- lm(y ~ (v + num_gender), data = rank_regress)


  summary(model)
```

```
##
## Call:
## lm(formula = y ~ (v + num_gender), data = rank_regress)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -85.653 -26.246 -16.186   5.914 188.211
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 21.35107    0.87965  24.272  < 2e-16 ***
## v           -0.66180    0.01151 -57.473  < 2e-16 ***
## num_gender  -5.59131    1.40519  -3.979 6.98e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 48.16 on 8578 degrees of freedom
## Multiple R-squared:  0.2783, Adjusted R-squared:  0.2781
## F-statistic:  1654 on 2 and 8578 DF,  p-value: < 2.2e-16
```

Here we see statistically significant differences for female associates and assistants, as well as male full-time faculty. Unfortunately, we do not see a statistically significant difference for female full-time faculty compared with the intercept, which denotes male associates and assistants. So when we look at the model predicting the difference on only the full-time faculty, we observe a statistically significant difference of women becoming full-time faculty 5.5 ranks higher than me, which corresponds to a drop of 15 ranks for women, vs 21 for me.

Part of the reason for the large p-value in the first model is the small number of female full-time faculty,

which is 1406, compared to 7175 for men. This is perhaps more telling, but from the data, it seems that the women are going to more prestigious schools. This is a bit reminiscent of the Berkely case where women claimed they were being systematically discriminated against, but further examinations showed that women were applying to more selective departments. While we cannot look at the applications, in this case, I still wouldn't expect them to fully explain the large difference in these two numbers. Still, it does seem like women are generally working at relatively higher prestige schools compared to where they get their doctorates, which could suggest they are also applying to more selective faculty ranks. However, from this data alone it wouldn't be appropriate to reach that conclusion.

From this research, we can really only say that women generally work at relatively higher prestige schools than men, while full-time faculty generally go to relatively lower prestige schools. Furthermore, we do observe a bigger difference between the hiring patterns of men and women when it comes to full-time faculty positions.

Gini Coefficient for Full faculty, split by Gender

```
male_full_counts <- all_edgelists %>%
  filter(rank == 'Full') %>%
  filter(gender =='M') %>%
  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()



fem_full_counts <- all_edgelists %>%
  filter(rank == 'Full') %>%
  filter(gender =='F') %>%
  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
MG <- gini(male_full_counts$counts)
FG <- gini(fem_full_counts$counts)

cat('\nGini Coefficient for Male Full-time Faculty:', MG)
```

```
##
## Gini Coefficient for Male Full-time Faculty: 0.5058606
```

```
cat('\nGini Coefficient for Femmale Full-time Faculty:', FG)
```

```
##
## Gini Coefficient for Femmale Full-time Faculty: 0.4894996
```

We can see that the Gini coefficient for full-time faculty is slightly higher than the dataset as a whole, further suggesting there is more observed inequality in the hiring process for faculty of rank full compared to assistants or associates. However, the Gini coefficient for male full-time faculty is actually larger than the Gini coefficient for female, suggesting that institutional prestige isn't a bigger factor for hiring women than

men. Still, these numbers are pretty large, implying that when it comes to both male and female full-time faculty, a small number of institutions produce a disproportionately large number of full-time faculty.

Also, it should be said that the coefficients we see here are still not as large as the reported coefficient in the original paper.

Conclusions

In this report, we reproduce several results from the paper "Systematic inequality and hierarchy in faculty hiring networks". We find, for the most part, that the results are easily reproducible with no extra guidance or data cleaning. The exception to this is the Gini coefficient, which we find to be much lower than reported in the paper. We were unable to reproduce the results in the paper as they did not go into detail about where they got their numbers.

For our extension, we augment the descriptive results in the paper with predictive results. We regress the gender of the candidate against the rank of the hiring party and find that our model predicts that women go to slightly higher prestige schools than their degree. Next, we regress faculty ranks against hiring rank and find that full professors go to slightly less prestigious schools. This is intuitive because some candidates would be willing to take a larger role at a smaller school, but the difference was smaller than we expected. We see the lower ranks go to less prestigious schools, having the intercept value indicate an average decrease in prestige of 19, while the full ranks' predicted drop is closer to 21. Finally, we combined the two regressions and regressed hiring school prestige against doctoral rank and gender. We also find a statistically significant difference between female and male full-time faculty, with men seeming to join schools of lower relative prestige. This difference is about 5 ranks, so it is also not very big. Another important observation is the low number of female professors in the dataset with the rank of full professor, with more than 4 times as many men as women in those positions. This is perhaps the greatest indicator of inequality, but this is under the assumption that there are the same number of men and women that want to become full professors, which isn't necessarily true. Still, the fact that this difference is so large indicates there are some underlying issues that need to be addressed.

Net-net, from this analysis we conclude that women generally work at relatively higher prestige schools and full-time faculty generally go to relatively lower prestige schools. Finally, we round out our analysis by exploring the Gini coefficient for full faculty when split by gender. We find that both the coefficients are larger than the coefficients for the whole dataset and that the male coefficient is higher than the female, but the difference is rather small. This indicates that the hiring process for full-time faculty is quite unique, favoring a select number of doctoral institutions, but it is more unequal for men than for women. That being said, this effect is quite small, and more study is required to confirm the effect.

Packages

The following is a list of all packages used to generate these results.

```
sessionInfo()
```

```
## R version 3.5.2 (2018-12-20)
## Platform: x86_64-apple-darwin15.6.0 (64-bit)
## Running under: macOS Mojave 10.14.4
##
## Matrix products: default
## BLAS: /Library/Frameworks/R.framework/Versions/3.5/Resources/lib/libRblas.0.dylib
## LAPACK: /Library/Frameworks/R.framework/Versions/3.5/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_0.1.3
##  [5] forcats_0.3.0   stringr_1.4.0   dplyr_0.8.0.1   purrr_0.3.0
##  [9] readr_1.3.1     tidyr_0.8.2     tibble_2.0.1    ggplot2_3.1.0
## [13] tidyverse_1.2.1
##
## loaded via a namespace (and not attached):
##  [1] Rcpp_1.0.0          lubridate_1.7.4     lattice_0.20-38
##  [4] rprojroot_1.3-2     assertthat_0.2.0    digest_0.6.18
##  [7] R6_2.4.0            cellranger_1.1.0    plyr_1.8.4
## [10] backports_1.1.3     acepack_1.4.1       evaluate_0.13
## [13] httr_1.4.0          pillar_1.3.1        rlang_0.3.1
## [16] lazyeval_0.2.1      readxl_1.3.0        data.table_1.12.2
## [19] rstudioapi_0.9.0    rpart_4.1-13        Matrix_1.2-15
## [22] checkmate_1.9.3     rmarkdown_1.11      labeling_0.3
## [25] splines_3.5.2       foreign_0.8-71      htmlwidgets_1.3
## [28] munsell_0.5.0       broom_0.5.1         compiler_3.5.2
## [31] xfun_0.4            pkgconfig_2.0.2     base64enc_0.1-3
## [34] mgcv_1.8-26         htmltools_0.3.6     nnet_7.3-12
## [37] tidyselect_0.2.5    gridExtra_2.3       htmlTable_1.13.1
## [40] Hmisc_4.2-0         crayon_1.3.4        withr_2.1.2
## [43] grid_3.5.2          nlme_3.1-137        jsonlite_1.6
## [46] gtable_0.2.0        magrittr_1.5        scales_1.0.0
## [49] cli_1.1.0           stringi_1.3.1       latticeExtra_0.6-28
## [52] xml2_1.2.0          generics_0.0.2      Formula_1.2-3
## [55] RColorBrewer_1.1-2  tools_3.5.2         glue_1.3.0
## [58] hms_0.4.2           survival_2.43-3     yaml_2.2.0
## [61] colorspace_1.4-0    cluster_2.0.7-1     rvest_0.3.2
## [64] knitr_1.21          haven_2.0.0
```