Exercise 3

Konstantin Volodin

2023-03-27

Summary Statistics

Workgroups 216 and 179 are evaluated.

- Workgroup 216 has 302 employees, and 179 has 829.
- Workgroup 216 is more male dominated with 73.5% vs 62.8% for 179.
- Both workgroup are mostly white and asian employees. With 179 having almost 80% white employees vs 60% for 216.
- Workgroup 216 generally has employees who have lower tenure than 179

Table 1: Gender Distribution

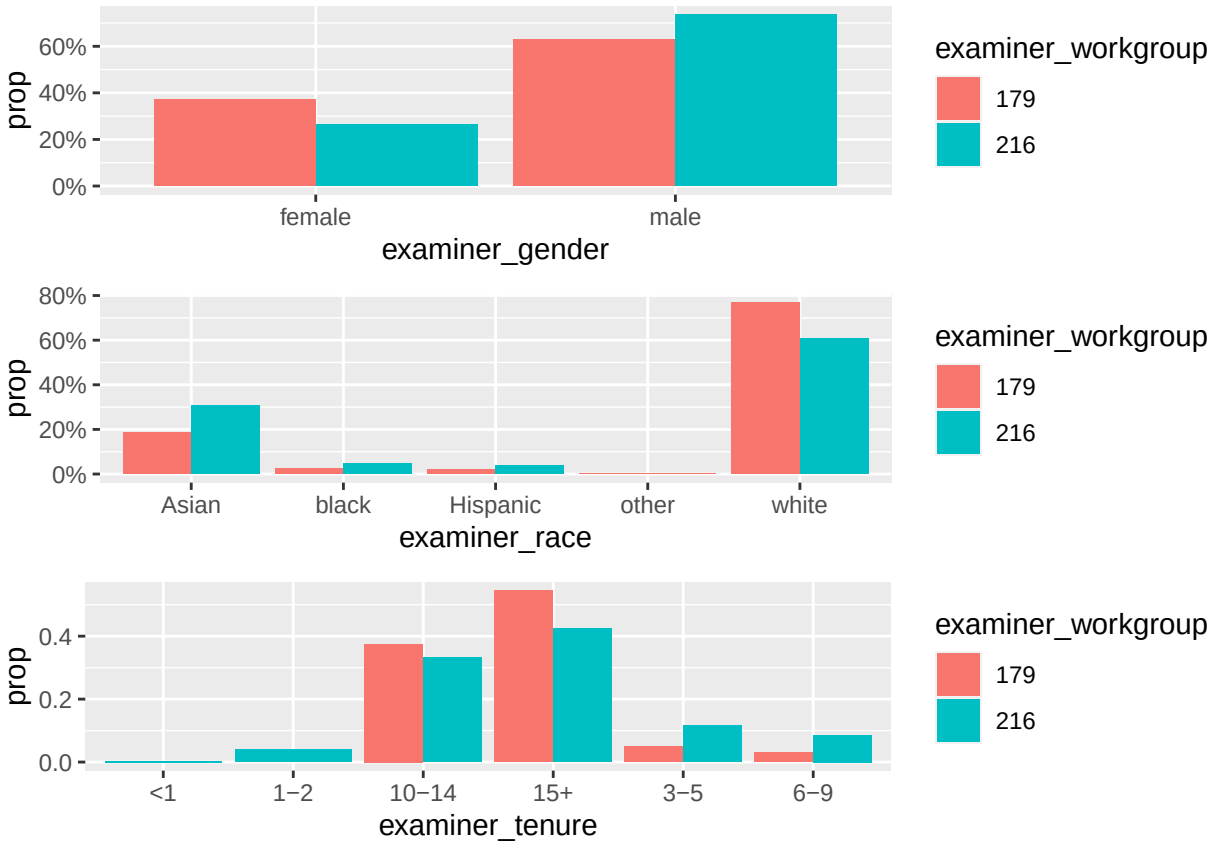
examiner_workgroup	female	male
179	37.15	62.85
216	26.49	73.51

Table 2: Race Distribution

examiner_workgroup	Asian	black	Hispanic	other	white
179	18.70	2.29	2.17	0.12	76.72
216	30.79	4.64	3.64	NA	60.93

Table 3: Tenure Distribution

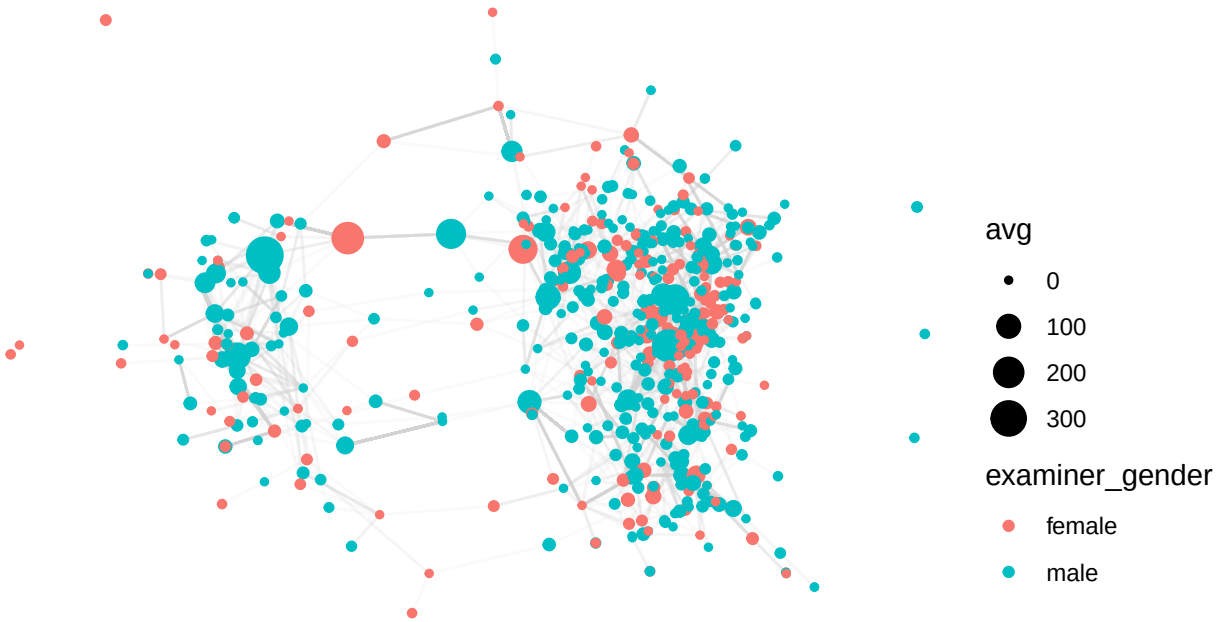
examiner_workgroup	10-14	15+	3-5	6-9	<1	1-2
179	37.52	54.40	5.07	3.02	NA	NA
216	33.11	42.38	11.59	8.61	0.33	3.97

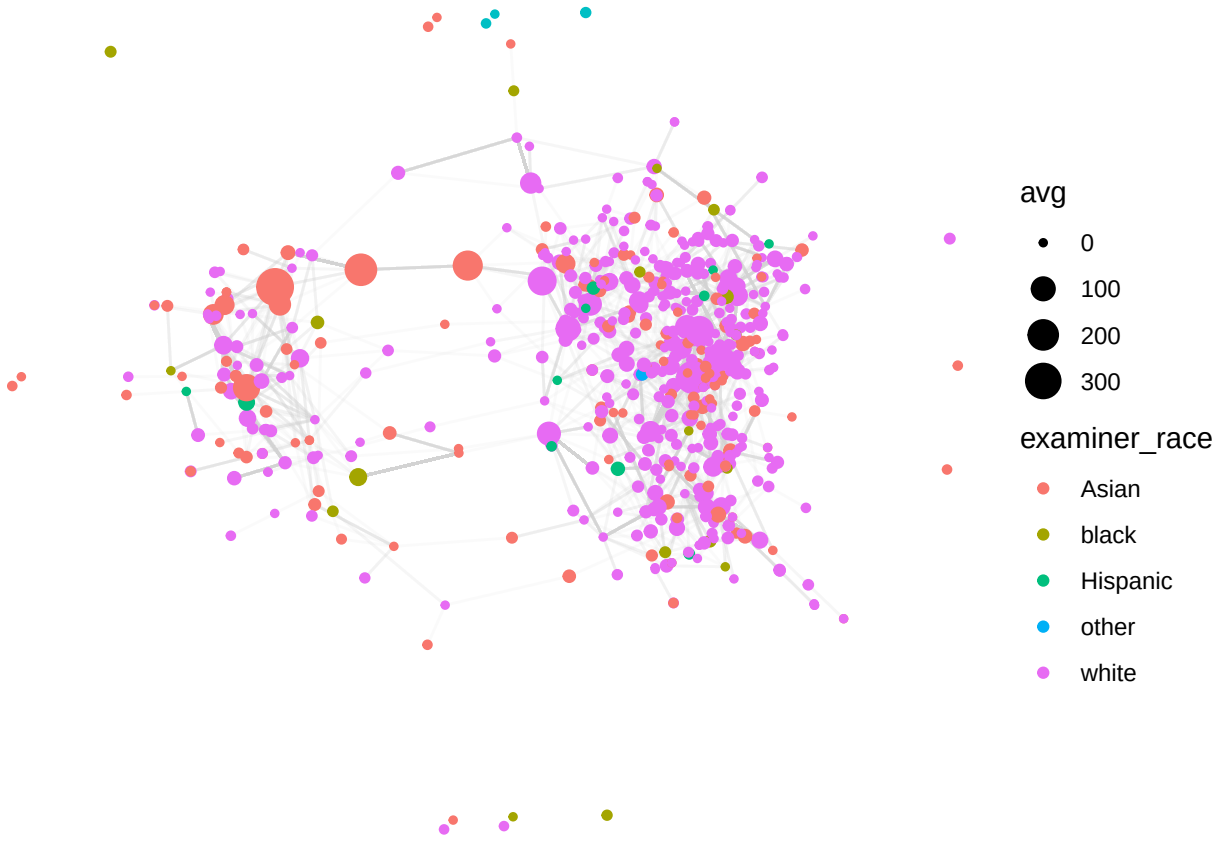


Network Visualization

There appears to be two distinct clusters. These clusters are likely base on workgroup.

- Within each of the 2 clusters there doesn't appear any segregation by gender or by race.
- This could be due to the non-dominant groups being too small to form their own cluster.
- It could also be because the employees are interested in maintaining diverse groups.





Discussion

Looking at degree and betweenness centrality for each gender and race the following are results.

- Gender generally performs very similarly in the centrality scores suggesting there is no discrimination based on that. The differences are likely due to women having a smaller population
- Race seems to play a larger role in clustering. It appears black and hispanic people tend to cluster together more. Whereas asian people tend to be the brokers in the network.

Table 4: Gender Centrality Scores

examiner_gender	top10_degree	top10_bet	mean_degree	mean_bet
female	30.79	74.14	5.010417	7.985249
male	32.53	82.61	5.674641	8.894336

examiner_race	top10_degree	top10_bet	mean_degree	mean_bet
Asian	24.46	161.74	4.352941	15.92577
black	60.00	5.00	7.222222	0.50000
Hispanic	45.00	0.00	7.000000	0.00000
white	35.16	67.26	5.686230	6.94378

Code

```
### LOAD DATA
applications <- read_parquet(here('assignments','assignment_3',"app_data_clean.parquet"))
edges <- read_csv(here('assignments','assignment_3',"edges_sample.csv"))

### CLEAN DATA
applications <- applications %>%
  select(-c('gender.y', 'race.y')) %>%
  rename(gender = gender.x, race = race.x) %>%
  mutate(tenure_years = tenure_days / 365) %>%
  mutate(tenure = case_when(
    tenure_years <= 1 ~ '<1',
    tenure_years <= 2 ~ '1-2',
    tenure_years <= 5 ~ '3-5',
    tenure_years <= 9 ~ '6-9',
    tenure_years <= 14 ~ '10-14',
    tenure_years <= 100 ~ '15+',
    TRUE ~ NA_character_
  ))


### WORKGROUPS
applications <- applications %>%
  mutate(examiner_workgroup = str_sub(examiner_art_unit, 1, -2))

### DROP NAs
applications <- applications %>% drop_na(gender, tenure, race)


### EXAMINER DATA
examiner_data <- applications %>%
  distinct(examiner_id, examiner_gender = gender,
           examiner_race = race, examiner_tenure = tenure)
```

```
### WORKGROUPS
examiner_subset <- applications %>%
  filter(examiner_workgroup %in% c(216, 179)) %>%
  distinct(examiner_id, examiner_workgroup) %>%
  left_join(examiner_data, by='examiner_id')


### COMPARE WORKGROUPS (STATISTICS)
t_gend <- examiner_subset %>% count(examiner_workgroup, examiner_gender) %>%
  group_by(examiner_workgroup) %>% mutate(freq = n / sum(n) * 100) %>%
  select(examiner_workgroup, examiner_gender, freq) %>%
  mutate(freq = round(freq, 2)) %>%
  pivot_wider(names_from = examiner_gender, values_from = freq)
t_race <- examiner_subset %>% count(examiner_workgroup, examiner_race) %>%
  group_by(examiner_workgroup) %>% mutate(freq = n / sum(n) * 100) %>%
  select(examiner_workgroup, examiner_race, freq) %>%
  mutate(freq = round(freq, 2)) %>%
  pivot_wider(names_from = examiner_race, values_from = freq)
t_tenure <- examiner_subset %>% count(examiner_workgroup, examiner_tenure) %>%
  group_by(examiner_workgroup) %>% mutate(freq = n / sum(n) * 100) %>%
  mutate(freq = round(freq, 2)) %>%
  select(examiner_workgroup, examiner_tenure, freq) %>%
  pivot_wider(names_from = examiner_tenure, values_from = freq)


### COMPARE WORKGROUPS (PLOTS)
p_gend <- ggplot(examiner_subset, aes(x=examiner_gender, y=..prop..,
                                      fill=examiner_workgroup,
                                      group=examiner_workgroup)) +
  geom_bar(aes(), stat='count', position='dodge') +
  scale_y_continuous(labels = scales::percent_format())
p_race <- ggplot(examiner_subset, aes(x=examiner_race, y=..prop..,
                                      fill=examiner_workgroup,
                                      group=examiner_workgroup)) +
  geom_bar(aes(), stat='count', position='dodge') +
  scale_y_continuous(labels = scales::percent_format())
p_tenure <- ggplot(examiner_subset, aes(x=examiner_tenure, y=..prop..,
                                        fill=examiner_workgroup,
                                        group=examiner_workgroup)) +
  geom_bar(aes(), stat='count', position='dodge')


### CREATE NETWORK
edge_subset <- edges %>%
  filter(ego_examiner_id %in% examiner_subset$examiner_id &
           alter_examiner_id %in% examiner_subset$examiner_id) %>%
  drop_na() %>%
  select(to = ego_examiner_id, from = alter_examiner_id)
node_subset <- edge_subset %>%
  pivot_longer(cols=c('from','to')) %>%
  distinct(examiner_id = value) %>%
  left_join(examiner_data, on='examiner_id') %>%
```

```
  distinct(examiner_id, examiner_gender, examiner_race, examiner_tenure) %>%
  rename(name = examiner_id) %>%
  mutate(name = as.character(name))
network <- graph_from_data_frame(edge_subset, directed = TRUE) %>%
  as_tbl_graph() %>%
  left_join(node_subset, by='name')


### ESTIMATE METRICS
network <- network %>%
  mutate(degree = centrality_degree(),
         betweenness = centrality_betweenness()) %>%
  mutate(avg = (degree + betweenness)/2) %>%
  mutate(label = paste0(name, '\n',
                        'Degree: ',round(degree,2), '\n',
                        'Betweenness: ',round(betweenness,2), '\n',
                        'Avg: ',round(avg,2)))


### PLOT NETWORK
set.seed(1)
net_gender <- network %>%
  ggraph(layout="mds") +
  geom_edge_link(edge_colour = "#d3d3d3", alpha=0.1) +
  geom_node_point(aes(color=examiner_gender, size=avg)) +
  theme_void()
set.seed(1)
net_race <- network %>%
  ggraph(layout="mds") +
  geom_edge_link(edge_colour = "#d3d3d3", alpha=0.1) +
  geom_node_point(aes(color=examiner_race, size=avg)) +
  theme_void()

### DISCUSSION
network_data <- network %>% as.data.frame() %>% as.tibble()

disc_gend_mean <- network_data %>%
  group_by(examiner_gender) %>%
  summarize(mean_degree = mean(degree),
            mean_bet = mean(betweenness))
disc_gend_top_degree <- network_data %>%
  arrange(desc(degree)) %>%
  group_by(examiner_gender) %>%
  top_frac(0.1, degree) %>%
  summarize(top10_degree = mean(degree)) %>%
  mutate(top10_degree = round(top10_degree, 2))
disc_gend_top_bet <- network_data %>%
  arrange(desc(betweenness)) %>%
  group_by(examiner_gender) %>%
  top_frac(0.1, betweenness) %>%
  summarize(top10_bet = mean(betweenness)) %>%
  mutate(top10_bet = round(top10_bet, 2))
disc_gend_top <- disc_gend_top_degree %>%
```

```
  left_join(disc_gend_top_bet, on='examiner_gender')
disc_gend <- disc_gend_top %>%
  left_join(disc_gend_mean, on='examiner_gender')



disc_race_mean <- network_data %>%
  group_by(examiner_race) %>%
  summarize(mean_degree = mean(degree),
            mean_bet = mean(betweenness))
disc_race_top_degree <- network_data %>%
  arrange(desc(degree)) %>%
  group_by(examiner_race) %>%
  top_frac(0.1, degree) %>%
  summarize(top10_degree = mean(degree)) %>%
  mutate(top10_degree = round(top10_degree, 2))
disc_race_top_bet <- network_data %>%
  arrange(desc(betweenness)) %>%
  group_by(examiner_race) %>%
  top_frac(0.1, betweenness) %>%
  summarize(top10_bet = mean(betweenness)) %>%
  mutate(top10_bet = round(top10_bet, 2))

disc_race_top <- disc_race_top_degree %>%
  left_join(disc_race_top_bet, on='examiner_race')
disc_race <- disc_race_top %>%
  left_join(disc_race_mean, on='examiner_race')
```