Exercise 4

Load data

```r
applications <- read_parquet("C:/Users/hedle/OneDrive/McGill - Summer 2022/ORGB 672 - Org Network Analys
edges <- read_csv("C:/Users/hedle/OneDrive/McGill - Summer 2022/ORGB 672 - Org Network Analysis/Data/edg
```

```
## Rows: 32906 Columns: 4
## -- Column specification --------------------------------------------------------
## Delimiter: ","
## chr  (1): application_number
## dbl  (2): ego_examiner_id, alter_examiner_id
## date (1): advice_date
##
## i Use `spec()` to retrieve the full column specification for this data.
## i Specify the column types or set `show_col_types = FALSE` to quiet this message.
```

```r
applications
```

```
## # A tibble: 2,018,477 x 16
##    application_number filing_date examiner_name_last examiner_name_first
##    <chr>              <date>      <chr>              <chr>
##  1 08284457           2000-01-26  HOWARD             JACQUELINE
##  2 08413193           2000-10-11  YILDIRIM           BEKIR
##  3 08531853           2000-05-17  HAMILTON           CYNTHIA
##  4 08637752           2001-07-20  MOSHER             MARY
##  5 08682726           2000-04-10  BARR               MICHAEL
##  6 08687412           2000-04-28  GRAY               LINDA
##  7 08716371           2004-01-26  MCMILLIAN          KARA
##  8 08765941           2000-06-23  FORD               VANESSA
##  9 08776818           2000-02-04  STRZELECKA         TERESA
## 10 08809677           2002-02-20  KIM                SUN
## # ... with 2,018,467 more rows, and 12 more variables:
## #   examiner_name_middle <chr>, examiner_id <dbl>, examiner_art_unit <dbl>,
## #   uspc_class <chr>, uspc_subclass <chr>, patent_number <chr>,
## #   patent_issue_date <date>, abandon_date <date>, disposal_type <chr>,
## #   appl_status_code <dbl>, appl_status_date <chr>, tc <dbl>
```

```r
edges
```

```
## # A tibble: 32,906 x 4
##    application_number advice_date ego_examiner_id alter_examiner_id
##    <chr>              <date>                <dbl>             <dbl>
##  1 09402488           2008-11-17            84356             66266
##  2 09402488           2008-11-17            84356             63519
```

```
##   3 09402488           2008-11-17              84356              98531
##   4 09445135           2008-08-21              92953              71313
##   5 09445135           2008-08-21              92953              93865
##   6 09445135           2008-08-21              92953              91818
##   7 09479304           2008-12-15              61767              69277
##   8 09479304           2008-12-15              61767              92446
##   9 09479304           2008-12-15              61767              66805
##  10 09479304           2008-12-15              61767              70919
## # ... with 32,896 more rows
```

Create a new variable which is a combination of both the issue date and the abandon date

```
# Create a new variable which is a combination of both the issue date and the abandon date
applications <- applications %>% mutate(combined = coalesce(patent_issue_date,abandon_date))

# compute difference in days
applications$app_proc_time<- as.numeric(difftime(applications$combined, applications$filing_date , unit
```

Feature engineering

Get gender for examiners

We'll get gender based on the first name of the examiner, which is recorded in the field `examiner_name_first`. We'll use library `gender` for that, relying on a modified version of their own example.

Note that there are over 2 million records in the applications table – that's because there are many records for each examiner, as many as the number of applications that examiner worked on during this time frame. Our first step therefore is to get all *unique* names in a separate list `examiner_names`. We will then guess gender for each one and will join this table back to the original dataset. So, let's get names without repetition:

```
# get a list of first names without repetitions
examiner_names <- applications %>%
  distinct(examiner_name_first)

# get a table of names and gender
examiner_names_gender <- examiner_names %>%
  do(results = gender(.$examiner_name_first, method = "ssa")) %>%
  unnest(cols = c(results), keep_empty = TRUE) %>%
  select(
    examiner_name_first = name,
    gender,
    proportion_female)

# remove extra columns from the gender table
examiner_names_gender <- examiner_names_gender %>%
  select(examiner_name_first, gender)

# joining gender back to the dataset
applications <- applications %>%
  left_join(examiner_names_gender, by = "examiner_name_first")

# cleaning up
```

```r
rm(examiner_names)
rm(examiner_names_gender)
gc()
```

```
##            used  (Mb) gc trigger  (Mb) max used  (Mb)
## Ncells  6038114 322.5    9786154 522.7  6296287 336.3
## Vcells 56150295 428.4  100969220 770.4 90503069 690.5
```

Guess the examiner's race

We'll now use package `wru` to estimate likely race of an examiner. Just like with gender, we'll get a list of unique names first, only now we are using surnames.

```r
# get a distinct dataframe of examiner surnames
examiner_surnames <- applications %>%
  select(surname = examiner_name_last) %>%
  distinct()

# apply the predict_race() function to determine examiner's race
examiner_race <- predict_race(voter.file = examiner_surnames, surname.only = T) %>%
  as_tibble()
```

```
## [1] "Proceeding with surname-only predictions..."
```

```
## Warning in merge_surnames(voter.file): Probabilities were imputed for 698
## surnames that could not be matched to Census list.
```

```r
# pick a race category with the highest probability for each last name and assign it respectively
examiner_race <- examiner_race %>%
  mutate(max_race_p = pmax(pred.asi, pred.bla, pred.his, pred.oth, pred.whi)) %>%
  mutate(race = case_when(
    max_race_p == pred.asi ~ "Asian",
    max_race_p == pred.bla ~ "black",
    max_race_p == pred.his ~ "Hispanic",
    max_race_p == pred.oth ~ "other",
    max_race_p == pred.whi ~ "white",
    TRUE ~ NA_character_))

# removing extra columns
examiner_race <- examiner_race %>%
  select(surname,race)

# join back to original dataframe
applications <- applications %>%
  left_join(examiner_race, by = c("examiner_name_last" = "surname"))

# cleaning up
rm(examiner_race)
rm(examiner_surnames)
gc()
```

```
##            used  (Mb) gc trigger  (Mb)  max used  (Mb)
## Ncells  6377649 340.7    9786154 522.7   7030517 375.5
## Vcells 59835972 456.6  100969220 770.4 100624811 767.8
```

Compute examiner's tenure

To figure out the timespan for which we observe each examiner in the applications data, let's find the first and the last observed date for each examiner. We'll first get examiner IDs and application dates in a separate table, for ease of manipulation. We'll keep examiner ID (the field `examiner_id`), and earliest and latest dates for each application (`filing_date` and `appl_status_date` respectively). We'll use functions in package `lubridate` to work with date and time values.

```
# consolidate examiner ID's and application dates in separate dataframe
examiner_dates <- applications %>%
  select(examiner_id, filing_date, appl_status_date)

# create new variables for examiners start and end date
examiner_dates <- examiner_dates %>%
  mutate(start_date = ymd(filing_date), end_date = as_date(dmy_hms(appl_status_date)))

# identify earliest and latest dates for examiners and compute the difference
examiner_dates <- examiner_dates %>%
  group_by(examiner_id) %>%
  summarise(
    earliest_date = min(start_date, na.rm = TRUE),
    latest_date = max(end_date, na.rm = TRUE),
    tenure_days = interval(earliest_date, latest_date) %/% days(1)
    ) %>%
  filter(year(latest_date)<2018)

# join back to original dataframe
applications <- applications %>%
  left_join(examiner_dates, by = "examiner_id")

# cleaning up
rm(examiner_dates)
gc()
```

```
##            used  (Mb) gc trigger   (Mb)  max used   (Mb)
## Ncells  6391719 341.4   21159077 1130.1  21159077 1130.1
## Vcells 72214697 551.0  145571676 1110.7 145292014 1108.5
```

```
# isolate the first three digits from examiner_art_unit variable to obtain working groups
applications$examiner_short <- floor(applications$examiner_art_unit/10)

# select the largest working group and a medium sized working group for comparisons
WG1 <- applications[applications$examiner_short == 162, ]
WG2 <- applications[applications$examiner_short == 219, ]
# for the sake of simplicity, workgroup 212 will be defined as WG1 and workgroup 162 will be defined as

# drop null observations
WG1 <- drop_na(WG1, gender)
```

```r
WG2 <- drop_na(WG2, gender)
WG1 <- drop_na(WG1, race)
WG2 <- drop_na(WG2, race)
WG1 <- drop_na(WG1, tenure_days)
WG2 <- drop_na(WG2, tenure_days)

# convert categorical variables to factor
WG1$gender <- as.factor(WG1$gender)
WG1$race <- as.factor(WG1$race)
WG2$gender <- as.factor(WG2$gender)
WG2$race <- as.factor(WG2$race)
```

Network Analysis

Nodes

Create node dataframe

We must first merge the edges dataframe with each respective work group and then define both node lists separately:

```r
# drop the nulls in the edges dataframe
edges <- drop_na(edges, ego_examiner_id)
edges <- drop_na(edges, alter_examiner_id)

# merge original edges dataframe with both workgroups
FULLWG1 <- inner_join(WG1, edges, by = "application_number", copy = FALSE)
FULLWG2 <- inner_join(WG2, edges, by = "application_number", copy = FALSE)

# remove extra nulls
FULLWG1 %>% skim()
```

Table 1: Data summary

Name	Piped data
Number of rows	326
Number of columns	27
Column type frequency:	
character	9
Date	7
factor	2
numeric	9
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
application_number	0	1.00	8	8	0	111	0
examiner_name_last	0	1.00	2	16	0	29	0
examiner_name_first	0	1.00	4	8	0	29	0
examiner_name_middle	39	0.88	1	9	0	19	0
uspc_class	0	1.00	3	3	0	12	0
uspc_subclass	0	1.00	6	6	0	82	0
patent_number	37	0.89	7	7	0	85	0
disposal_type	0	1.00	3	4	0	3	0
appl_status_date	0	1.00	18	18	0	94	0

Variable type: Date

skim_variable	n_missing	complete_rate	min	max	median	n_unique
filing_date	0	1.00	2000-11-01	2008-02-21	2005-03-31	105
patent_issue_date	37	0.89	2008-05-20	2016-04-05	2009-01-27	62
abandon_date	292	0.10	2008-04-17	2016-04-25	2009-06-27	23
combined	3	0.99	2008-04-17	2016-04-25	2009-02-19	83
earliest_date	0	1.00	2000-01-03	2004-01-30	2000-02-15	24
latest_date	0	1.00	2016-07-01	2017-11-08	2017-05-19	8
advice_date	0	1.00	2008-01-03	2008-12-29	2008-06-26	90

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
gender	0	1	FALSE	2	mal: 213, fem: 113
race	0	1	FALSE	3	whi: 287, Asi: 36, His: 3, bla: 0

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
examiner_id	0	1.00	73522.85	11499.17	60302	67690.00	67690	73364	99424	
examiner_art_unit	0	1.00	1623.96	1.69	1621	1623.00	1623	1625	1629	
appl_status_code	0	1.00	167.77	39.47	30	150.00	150	161	250	
tc	0	1.00	1600.00	0.00	1600	1600.00	1600	1600	1600	
app_proc_time	3	0.99	1657.88	723.27	421	1033.00	1623	2071	4261	
tenure_days	0	1.00	6132.29	359.92	4858	6060.75	6303	6339	6518	
examiner_short	0	1.00	162.00	0.00	162	162.00	162	162	162	
ego_examiner_id	0	1.00	75006.72	11749.52	60302	67690.00	67690	88832	99424	
alter_examiner_id	0	1.00	76105.59	12544.73	60377	66206.00	71259	87486	99191	

```
FULLWG2 %>% skim()
```

Table 6: Data summary

Name	Piped data
Number of rows	495

Table 6: Data summary

Number of columns	27
Column type frequency:	
character	9
Date	7
factor	2
numeric	9
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
application_number	0	1.00	8	8	0	277	0
examiner_name_last	0	1.00	2	10	0	42	0
examiner_name_first	0	1.00	2	8	0	41	0
examiner_name_middle	171	0.65	1	9	0	22	0
uspc_class	0	1.00	3	3	0	7	0
uspc_subclass	0	1.00	6	6	0	95	0
patent_number	134	0.73	7	7	0	209	0
disposal_type	0	1.00	3	3	0	2	0
appl_status_date	0	1.00	18	18	0	206	0

Variable type: Date

skim_variable	n_missing	complete_rate	min	max	median	n_unique
filing_date	0	1.00	2000-01-24	2008-06-30	2004-05-17	229
patent_issue_date	134	0.73	2008-03-25	2014-04-22	2009-06-09	124
abandon_date	361	0.27	2008-04-30	2015-09-10	2009-09-05	66
combined	0	1.00	2008-03-25	2015-09-10	2009-07-20	180
earliest_date	0	1.00	2000-01-03	2005-06-08	2001-07-23	38
latest_date	0	1.00	2013-04-19	2017-05-23	2017-05-19	15
advice_date	0	1.00	2008-01-02	2008-12-30	2008-06-09	160

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
gender	0	1	FALSE	2	mal: 309, fem: 186
race	0	1	FALSE	4	Asi: 327, whi: 158, bla: 6, His: 4

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
examiner_id	0	1	74737.83	10865.16	59491	65943.5	75399	76141	99346	
examiner_art_unit	0	1	2192.54	1.46	2191	2192.0	2192	2193	2199	

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
appl_status_code	0	1	173.22	38.58	150	150.0	150	163	250	
tc	0	1	2100.00	0.00	2100	2100.0	2100	2100	2100	
app_proc_time	0	1	2053.66	663.41	225	1672.0	1968	2546	4297	
tenure_days	0	1	5749.68	561.95	3133	5601.0	5780	6242	6349	
examiner_short	0	1	219.00	0.00	219	219.0	219	219	219	
ego_examiner_id	0	1	82263.11	12958.40	59491	71996.0	87028	96206	99346	
alter_examiner_id	0	1	79837.85	13100.27	59203	69002.0	82083	92028	99577	

```r
# generate a nodes dataframe for WG1 for both the ego_examiner_id and alter_examiner_id
WG1_nodes_ego <- FULLWG1 %>%
  distinct(ego_examiner_id) %>%
  rename(ID = ego_examiner_id)
WG1_nodes_alter <- FULLWG1 %>%
  distinct(alter_examiner_id) %>%
  rename(ID = alter_examiner_id)

# perform a union of both dataframes to create a final node list and filter for unique nodes only
WG1_FinalNodes <- union_all(WG1_nodes_ego, WG1_nodes_alter)
WG1_FinalNodes <- unique(WG1_FinalNodes)

# do the same for WG2
WG2_nodes_ego <- FULLWG2 %>%
  distinct(ego_examiner_id) %>%
  rename(ID = ego_examiner_id)
WG2_nodes_alter <- FULLWG2 %>%
  distinct(alter_examiner_id) %>%
  rename(ID = alter_examiner_id)

WG2_FinalNodes <- union_all(WG2_nodes_ego, WG2_nodes_alter)
WG2_FinalNodes <- unique(WG2_FinalNodes)
```

Edges

Create a clean edges dataframe

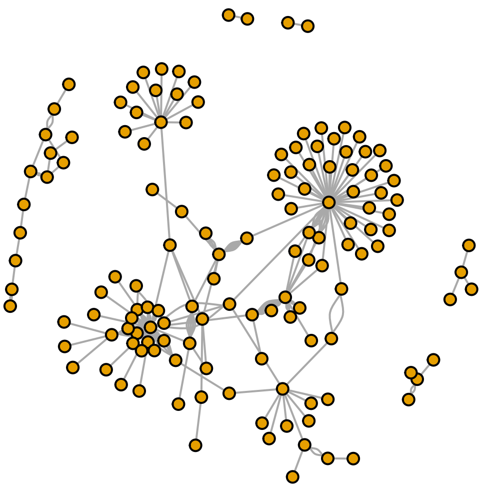
```r
# rename the applicants id variables in both groups
WG1_Edges <- FULLWG1 %>%
  select(ego_examiner_id, alter_examiner_id) %>%
  rename(From = ego_examiner_id, To = alter_examiner_id)

WG2_Edges <- FULLWG2 %>%
  select(ego_examiner_id, alter_examiner_id) %>%
  rename(From = ego_examiner_id, To = alter_examiner_id)
```

Initialize Graphs

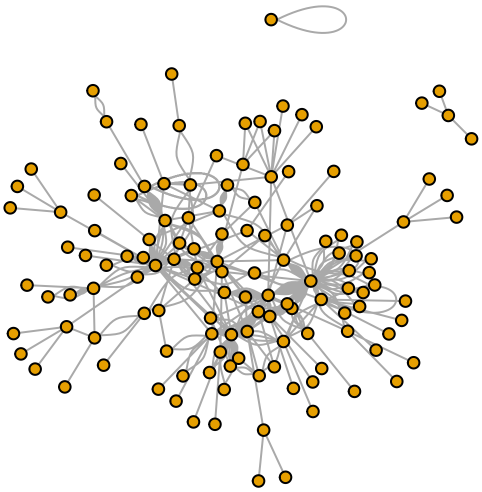
```r
# create graph objects for both workgroups
WG1_network <- graph_from_data_frame(d = WG1_Edges, vertices = WG1_FinalNodes, directed = FALSE)

WG2_network <- graph_from_data_frame(d = WG2_Edges, vertices = WG2_FinalNodes, directed = FALSE)
```

Visualize the Networks

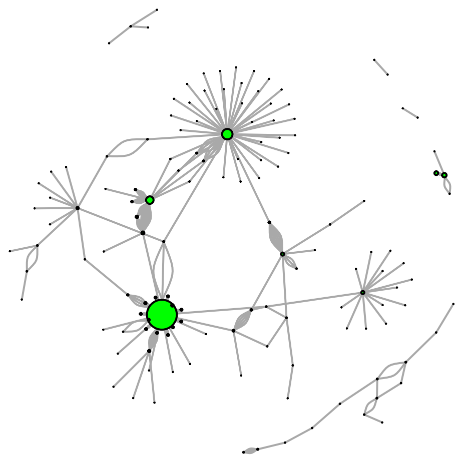
```r
# regular networks
plot(WG1_network, edge.arrow.size = 0.2, vertex.size= 5,vertex.label=NA)
```



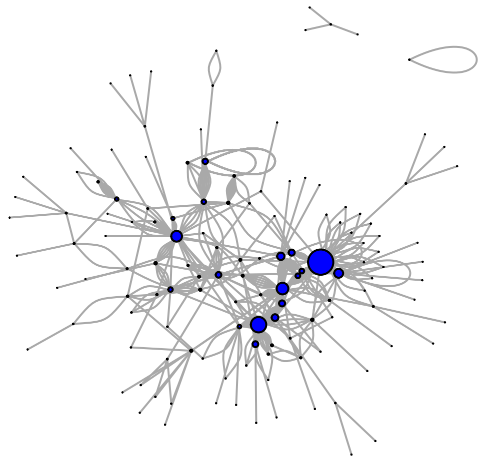
```r
plot(WG2_network, edge.arrow.size = 0.2, vertex.size= 5,vertex.label=NA)
```



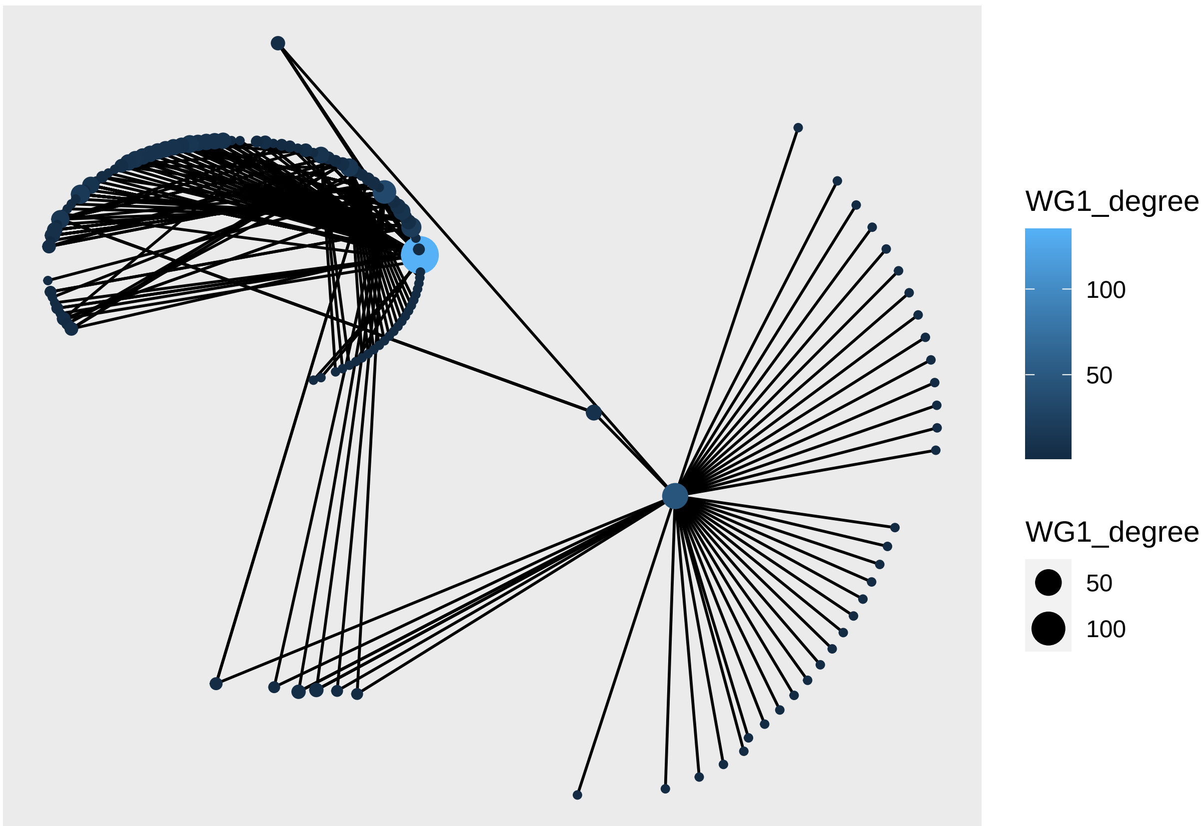
```
# visualize network based on degree
WG1_degree <- degree(WG1_network, v = V(WG1_network), mode = c("all"))
WG2_degree <- degree(WG2_network, v = V(WG2_network), mode = c("all"))

# assign degree value to nodes
V(WG1_network)$size <- (WG1_degree*0.1)
plot(WG1_network, edge.arrow.size = .5, vertex.color = "green", vertex.label=NA)
```



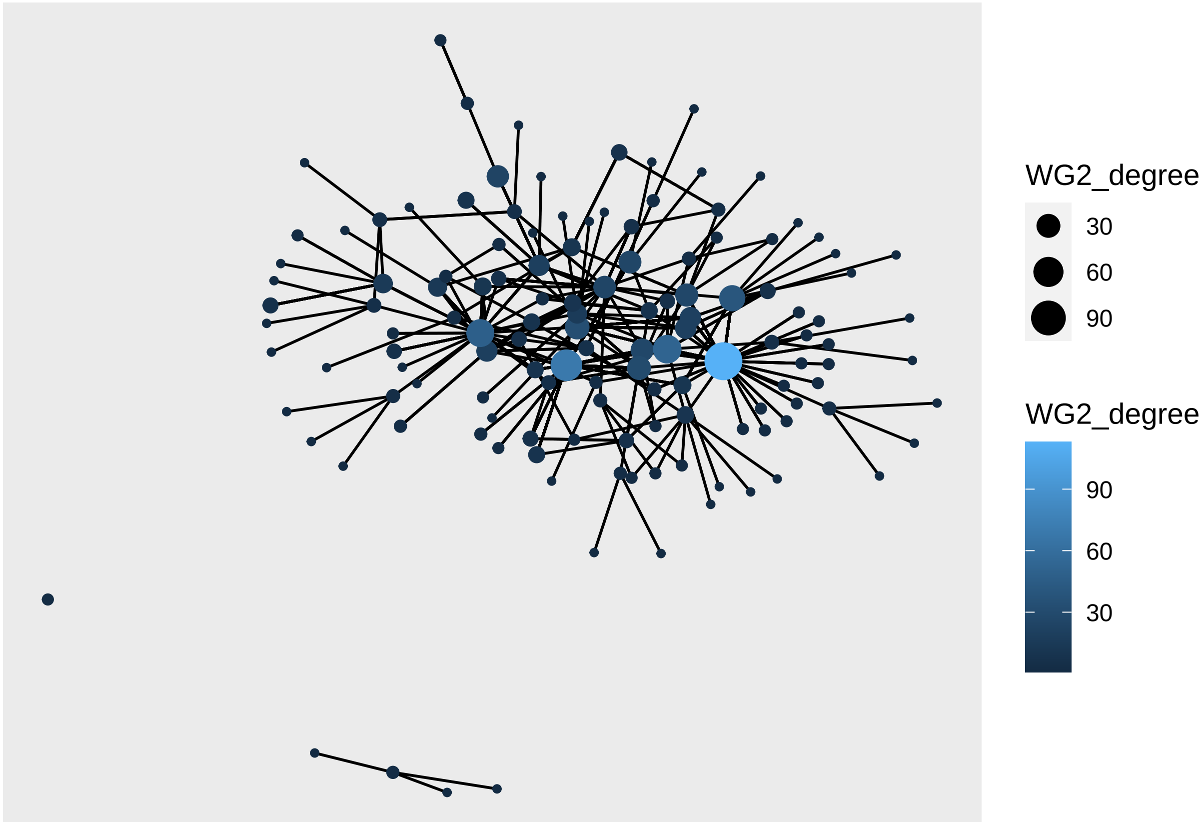
```
V(WG2_network)$size <- (WG2_degree*0.1)
plot(WG2_network, edge.arrow.size = .5, vertex.color = "blue",vertex.label=NA)
```



```
# another type of visualization using ggraph
ggraph(WG1_network, layout="kk")+
 geom_edge_link()+
  geom_node_point(aes(size = WG1_degree, colour = WG1_degree))
```




```
ggraph(WG2_network, layout="kk")+
 geom_edge_link()+
  geom_node_point(aes(size = WG2_degree, colour = WG2_degree))
```



Regression Analysis

Degree centrality join

```
# convert vector to dataframe
WG1_degree <- as.data.frame(WG1_degree)
WG2_degree <- as.data.frame(WG2_degree)

# assign index as a new column to merge with original WG dataframe
WG1_degree <- cbind(ego_examiner_id = rownames(WG1_degree), WG1_degree)
rownames(WG1_degree) <- 1:nrow(WG1_degree)
WG2_degree <- cbind(ego_examiner_id = rownames(WG2_degree), WG2_degree)
rownames(WG2_degree) <- 1:nrow(WG2_degree)
```

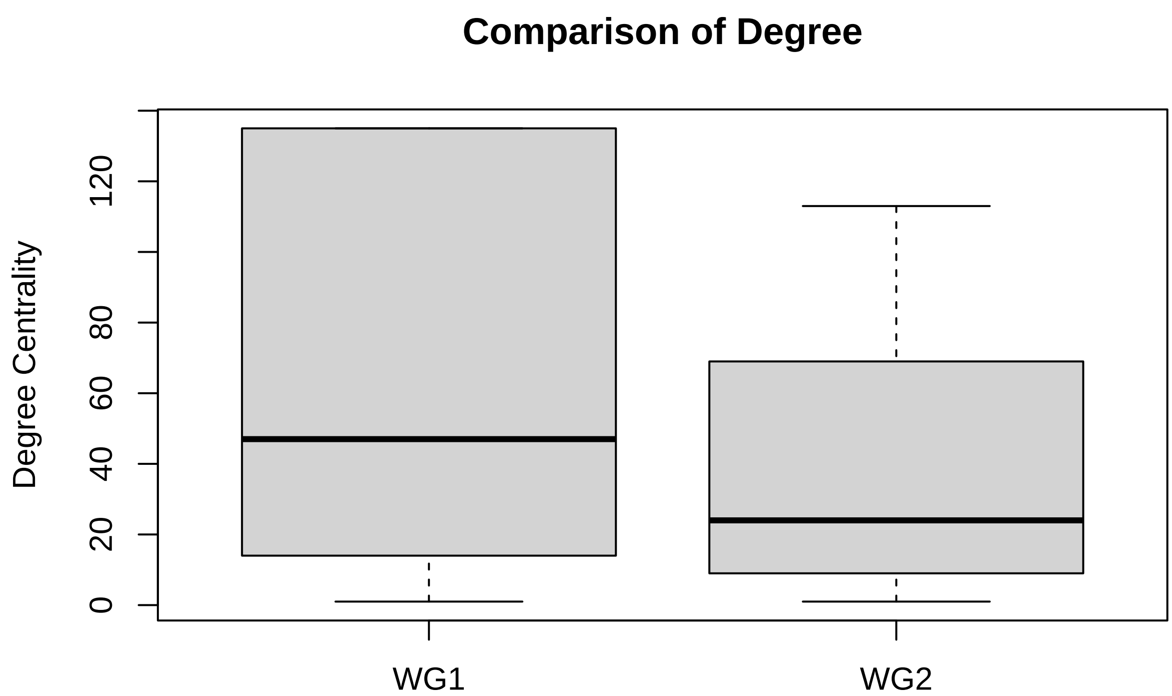
```
# convert examiner_id into numeric to perform merge with original dataframe
WG1_degree <- WG1_degree %>% mutate(across(where(is.character), as.numeric))
WG2_degree <- WG2_degree %>% mutate(across(where(is.character), as.numeric))
typeof(WG1_degree$ego_examiner_id)
```

```
## [1] "double"
```

```r
# merge degree centrality with WG dataframes
WG1Final <- left_join(FULLWG1, WG1_degree, by = "ego_examiner_id", copy = TRUE)
WG2Final <- left_join(FULLWG2, WG2_degree, by = "ego_examiner_id", copy = TRUE)
```

Overview of Degree Centrality for Both WG's

```r
boxplot(WG1Final$WG1_degree,WG2Final$WG2_degree,main = "Comparison of Degree", ylab = "Degree Centralit
```



Simple linear regression

Run linear regression to highlight patterns between centrality and app_proc_time:

```r
WG1_reg <- lm(app_proc_time~WG1_degree, data = WG1Final)
summary(WG1_reg)
```

```
##
## Call:
## lm(formula = app_proc_time ~ WG1_degree, data = WG1Final)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
```

```
## -1261.51  -599.33    -9.33   393.59  2576.53
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1685.2493    63.8644  26.388   <2e-16 ***
## WG1_degree    -0.3920     0.7096  -0.552    0.581
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 724 on 321 degrees of freedom
##   (3 observations deleted due to missingness)
## Multiple R-squared:  0.0009497,  Adjusted R-squared:  -0.002163
## F-statistic: 0.3051 on 1 and 321 DF,  p-value: 0.5811
```

```
WG2_reg <- lm(app_proc_time~WG2_degree, data = WG2Final)
summary(WG2_reg)
```

```
##
## Call:
## lm(formula = app_proc_time ~ WG2_degree, data = WG2Final)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1714.14  -371.14   -84.14   379.48  2276.53
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1915.9054    42.0278  45.587  < 2e-16 ***
## WG2_degree     3.8727     0.8488   4.563 6.39e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 650.5 on 493 degrees of freedom
## Multiple R-squared:  0.04051,    Adjusted R-squared:  0.03857
## F-statistic: 20.82 on 1 and 493 DF,  p-value: 6.385e-06
```

Control for other variables which may influence the relationship

Take a quick look at the dataset again:

```
str(WG1Final)
```

```
## tibble [326 x 28] (S3: tbl_df/tbl/data.frame)
##  $ application_number  : chr [1:326] "09704054" "09704054" "09714351" "09714351" ...
##  $ filing_date         : Date[1:326], format: "2000-11-01" "2000-11-01" ...
##  $ examiner_name_last  : chr [1:326] "ANDERSON" "ANDERSON" "STOCKTON" "STOCKTON" ...
##  $ examiner_name_first : chr [1:326] "JAMES" "JAMES" "LAURA" "LAURA" ...
##  $ examiner_name_middle: chr [1:326] "D" "D" "LYNNE" "LYNNE" ...
##  $ examiner_id         : num [1:326] 73364 73364 61417 61417 61417 ...
##  $ examiner_art_unit   : num [1:326] 1629 1629 1626 1626 1626 ...
##  $ uspc_class          : chr [1:326] "514" "514" "548" "548" ...
##  $ uspc_subclass       : chr [1:326] "323000" "323000" "537000" "537000" ...
```

```
##  $ patent_number       : chr [1:326] "8143283" "8143283" "7411075" "7411075" ...
##  $ patent_issue_date   : Date[1:326], format: "2012-03-27" "2012-03-27" ...
##  $ abandon_date        : Date[1:326], format: NA NA ...
##  $ disposal_type       : chr [1:326] "ISS" "ISS" "ISS" "ISS" ...
##  $ appl_status_code    : num [1:326] 250 250 250 250 250 250 250 250 250 250 ...
##  $ appl_status_date    : chr [1:326] "22apr2016 00:00:00" "22apr2016 00:00:00" "09sep2016 00:00:00"
##  $ tc                  : num [1:326] 1600 1600 1600 1600 1600 1600 1600 1600 1600 1600 ...
##  $ combined            : Date[1:326], format: "2012-03-27" "2012-03-27" ...
##  $ app_proc_time       : num [1:326] 4164 4164 2826 2826 2826 ...
##  $ gender              : Factor w/ 2 levels "female","male": 2 2 1 1 1 2 2 2 2 2 ...
##  $ race                : Factor w/ 4 levels "Asian","black",..: 4 4 4 4 4 4 4 4 4 4 ...
##  $ earliest_date       : Date[1:326], format: "2000-10-20" "2000-10-20" ...
##  $ latest_date         : Date[1:326], format: "2017-05-22" "2017-05-22" ...
##  $ tenure_days         : num [1:326] 6058 6058 6342 6342 6342 ...
##  $ examiner_short      : num [1:326] 162 162 162 162 162 162 162 162 162 162 ...
##  $ advice_date         : Date[1:326], format: "2008-06-12" "2008-06-12" ...
##  $ ego_examiner_id     : num [1:326] 73364 73364 61417 61417 61417 ...
##  $ alter_examiner_id   : num [1:326] 72814 98081 82244 72004 83224 ...
##  $ WG1_degree          : num [1:326] 5 5 10 10 10 135 135 135 135 135 ...
```

```
# since we do not have a clear data dictionary for this dataset, we can run a quick correlation check t
quantvars <- WG1Final[, c(7, 8, 9, 10,14,18,23,28)]
quantvars <- quantvars %>% mutate(across(where(is.character), as.numeric))
corr_matrix=cor(quantvars)
round(corr_matrix,2)
```

```
##                   examiner_art_unit uspc_class uspc_subclass patent_number
## examiner_art_unit              1.00       0.03          0.27            NA
## uspc_class                     0.03       1.00          0.21            NA
## uspc_subclass                  0.27       0.21          1.00            NA
## patent_number                    NA         NA            NA             1
## appl_status_code               0.12      -0.14         -0.11            NA
## app_proc_time                    NA         NA            NA            NA
## tenure_days                   -0.48      -0.01         -0.18            NA
## WG1_degree                    -0.50      -0.09         -0.62            NA
##                   appl_status_code app_proc_time tenure_days WG1_degree
## examiner_art_unit             0.12            NA       -0.48      -0.50
## uspc_class                   -0.14            NA       -0.01      -0.09
## uspc_subclass                -0.11            NA       -0.18      -0.62
## patent_number                   NA            NA          NA         NA
## appl_status_code              1.00            NA        0.13      -0.18
## app_proc_time                   NA             1          NA         NA
## tenure_days                   0.13            NA        1.00       0.41
## WG1_degree                   -0.18            NA        0.41       1.00
```

We can observe that there is no observable collinearity between the quantitative features within this dataset, so we can proceed to join and experiment with various combinations.

Random Forest Feature Importance

Let us run a random forest feature importance to observe which of the other variables may be helpful in explaining processing times and then experiment with different combinations, including interaction terms with degree centrality.

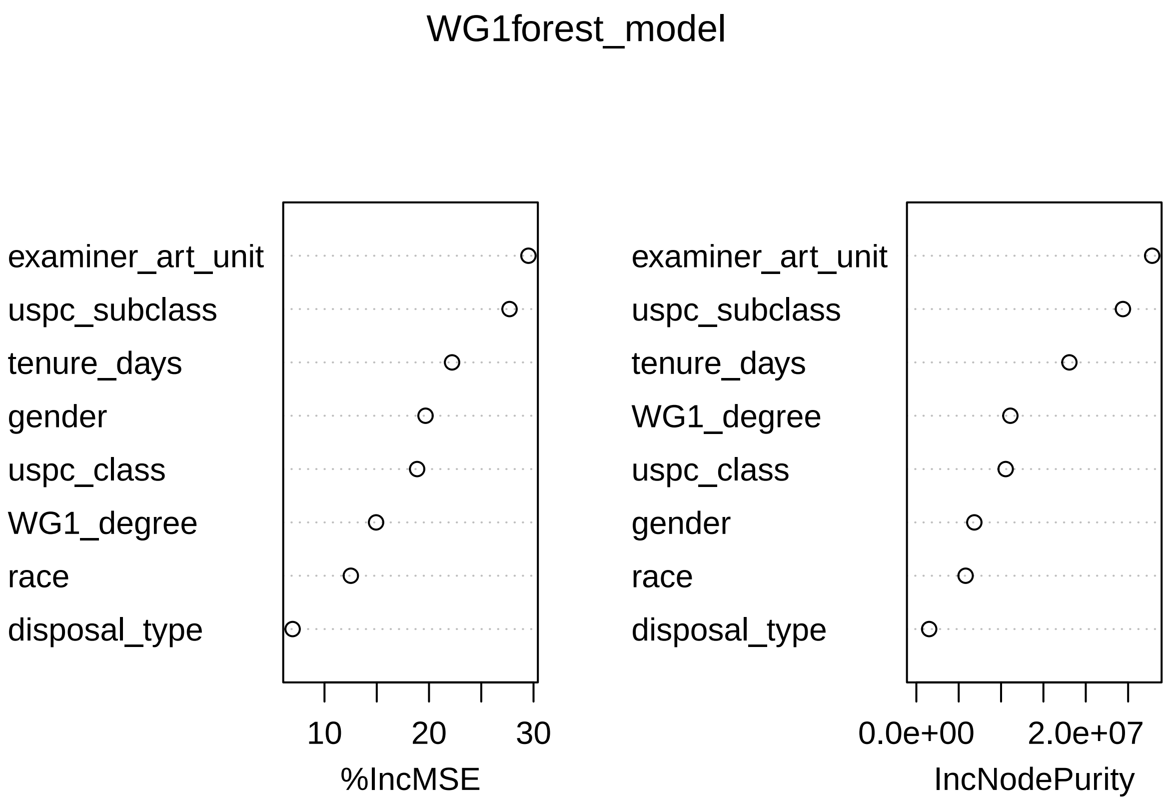
```r
# only focus on important variables
WG1forest_model <- randomForest(app_proc_time~examiner_art_unit+uspc_class+uspc_subclass+disposal_type +
WG1forest_model
```

```
##
## Call:
##  randomForest(formula = app_proc_time ~ examiner_art_unit + uspc_class +      uspc_subclass + disposa
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 2
##
##           Mean of squared residuals: 232044.1
##                     % Var explained: 55.5
```

```r
importance(WG1forest_model)
```

```
##                     %IncMSE IncNodePurity
## examiner_art_unit 29.513903      27838976
## uspc_class        18.861980      10542198
## uspc_subclass     27.705227      24386617
## disposal_type      6.950403       1511041
## gender            19.667650       6841770
## race              12.520187       5815244
## tenure_days       22.205852      18065141
## WG1_degree        14.934037      11097714
```

```r
varImpPlot(WG1forest_model)
```



We can see a large improvement in performance using this tree-based model for WG1 and including a few more features from with an r-squared value increasing from 0.0009497 to 55.85. From these results, it seems that broader technology centers under which certain working groups resides seem to have a larger influence in determining the number of days to abandon or finalize a patent, perhaps indicating that some TC's are more efficient at processing patents. The relative positioning of an examiner within the network, as expressed by their degree score is fourth most important when looking at trying to understand the features which influence processing times, which we will come back to in the final conclusions.

Looking at this increase in performance we can safely infer that the out-of-bag predictions for this random forest model explain the variance of app_proc_time of the training set much better than when running our initial simple regression. Let's look at WG2 and then include some of other terms back into our initial regression model:

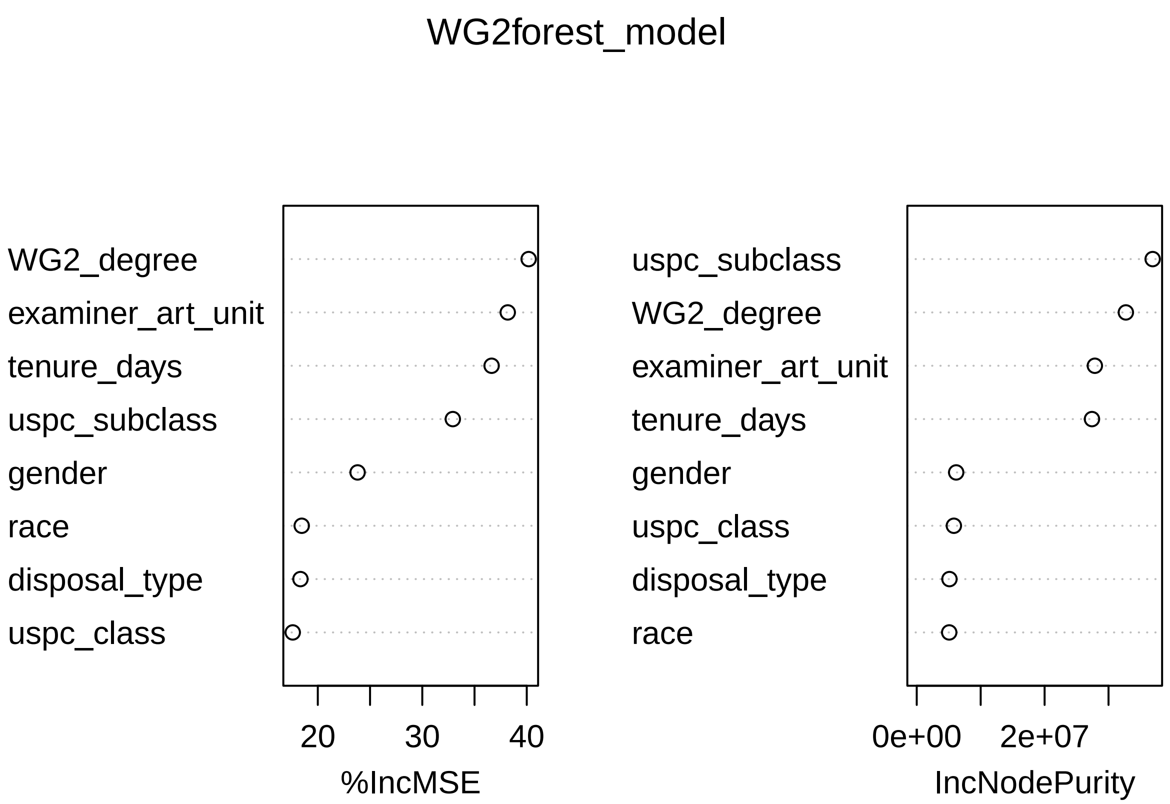
```
# only focus on important variables
WG2forest_model <- randomForest(app_proc_time~examiner_art_unit+uspc_class+uspc_subclass+disposal_type +
WG2forest_model
```

```
##
## Call:
##  randomForest(formula = app_proc_time ~ examiner_art_unit + uspc_class +      uspc_subclass + dispos
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 2
##
##           Mean of squared residuals: 231560.2
##                     % Var explained: 47.28
```

```
importance(WG2forest_model)
```

```
##                   %IncMSE IncNodePurity
## examiner_art_unit 38.18126      27861055
## uspc_class        17.60232       5805031
## uspc_subclass     32.92223      36903377
## disposal_type     18.33750       5114941
## gender            23.80848       6168466
## race              18.46236       5078630
## tenure_days       36.63549      27407454
## WG2_degree        40.18200      32711381
```

```
varImpPlot(WG2forest_model)
```



Multiple regression

Now lets run our multiple regression model and observe the results when including more features:

```
WG1_reg2 <- lm(app_proc_time~examiner_art_unit+uspc_class+uspc_subclass+as.factor(disposal_type) + gend
summary(WG1_reg2)
```

```
##
## Call:
```

```
## lm(formula = app_proc_time ~ examiner_art_unit + uspc_class +
##     uspc_subclass + as.factor(disposal_type) + gender + race +
##     tenure_days + WG1_degree, data = WG1Final)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -680.9    0.0    0.0    0.0 1084.1
##
## Coefficients: (9 not defined because of singularities)
##                               Estimate Std. Error t value Pr(>|t|)
## (Intercept)                 69161.3021 93301.3261   0.741 0.459274
## examiner_art_unit             -39.2186    57.0191  -0.688 0.492250
## uspc_class435                  26.4210   924.0271   0.029 0.977213
## uspc_class514                -531.7882   380.5630  -1.397 0.163625
## uspc_class540               -1474.5022   597.8490  -2.466 0.014368 *
## uspc_class546               -1013.9175   907.8870  -1.117 0.265230
## uspc_class548               -2241.7994   485.5215  -4.617 6.41e-06 ***
## uspc_class558               -2368.3283   790.4186  -2.996 0.003027 **
## uspc_class560               -1494.7767   900.1474  -1.661 0.098135 .
## uspc_class562               -1546.5398  1023.6677  -1.511 0.132193
## uspc_class564               -3537.5531   812.9258  -4.352 2.02e-05 ***
## uspc_class568               -2225.9689   711.9728  -3.126 0.001993 **
## uspc_class585               -2253.7802   669.7350  -3.365 0.000894 ***
## uspc_subclass008000           486.0000   528.2317   0.920 0.358494
## uspc_subclass023000           282.4724   804.4978   0.351 0.725817
## uspc_subclass025000           744.2092   842.3960   0.883 0.377903
## uspc_subclass027000           834.0811   797.9542   1.045 0.296975
## uspc_subclass032000                 NA         NA      NA       NA
## uspc_subclass042000          1481.2092   882.8297   1.678 0.094722 .
## uspc_subclass047000          1911.2092   806.1260   2.371 0.018558 *
## uspc_subclass049000          1054.6798   805.0345   1.310 0.191445
## uspc_subclass050000            -0.8241   743.8616  -0.001 0.999117
## uspc_subclass055000          1168.2092   842.3960   1.387 0.166832
## uspc_subclass058000          -985.7517   607.7601  -1.622 0.106162
## uspc_subclass070100         -1668.0333   487.4677  -3.422 0.000734 ***
## uspc_subclass111000           286.6832   772.7735   0.371 0.710988
## uspc_subclass112000           935.5958   860.3895   1.087 0.277975
## uspc_subclass119000          -471.4695   648.0834  -0.727 0.467658
## uspc_subclass125000          -779.0000   528.2317  -1.475 0.141629
## uspc_subclass129000         -1452.5401   672.5565  -2.160 0.031810 *
## uspc_subclass133000         -1314.7065   590.7823  -2.225 0.027011 *
## uspc_subclass134000                 NA         NA      NA       NA
## uspc_subclass159000          1106.5148   798.8316   1.385 0.167321
## uspc_subclass178000           -99.5223  1034.0430  -0.096 0.923408
## uspc_subclass183000          1008.2646   795.2655   1.268 0.206117
## uspc_subclass210000          -249.7065   528.4567  -0.473 0.636996
## uspc_subclass211130            62.5230   675.1524   0.093 0.926296
## uspc_subclass216000          -843.7140   504.7609  -1.672 0.095957 .
## uspc_subclass217000          -812.0000   528.2317  -1.537 0.125594
## uspc_subclass221000          -650.5469   462.9629  -1.405 0.161293
## uspc_subclass232000           -63.0000   528.2317  -0.119 0.905167
## uspc_subclass241000                 NA         NA      NA       NA
## uspc_subclass243000         -1892.5951   681.2456  -2.778 0.005911 **
## uspc_subclass247000           375.2092   882.8297   0.425 0.671222
```

```
## uspc_subclass250000                  NA         NA      NA       NA    
## uspc_subclass252100           -463.5761   710.6870  -0.652 0.514852    
## uspc_subclass253060          -2197.8701   571.7318  -3.844 0.000156 ***
## uspc_subclass253070          -2187.8701   571.7318  -3.827 0.000167 ***
## uspc_subclass254010             96.9523   946.0960   0.102 0.918466    
## uspc_subclass256000           -757.2428   421.8802  -1.795 0.073956 .  
## uspc_subclass257000           -674.7140   481.1769  -1.402 0.162176    
## uspc_subclass260000           1017.8482   680.3558   1.496 0.135987    
## uspc_subclass270000            180.2092   806.6013   0.223 0.823405    
## uspc_subclass274000             72.9291   613.3853   0.119 0.905460    
## uspc_subclass278000            -55.4461   726.0959  -0.076 0.939196    
## uspc_subclass279000            -55.4461   726.0959  -0.076 0.939196    
## uspc_subclass310000           1395.2646   795.2655   1.754 0.080660 .  
## uspc_subclass318000           -701.0918   622.8373  -1.126 0.261470    
## uspc_subclass322000          -1445.7498   691.0042  -2.092 0.037495 *  
## uspc_subclass323000           1615.4410   587.1029   2.752 0.006396 ** 
## uspc_subclass332000          -1676.8358   601.2793  -2.789 0.005726 ** 
## uspc_subclass338000            -58.0477   946.0960  -0.061 0.951129    
## uspc_subclass339000           -204.4695   648.0834  -0.315 0.752664    
## uspc_subclass342000          -1115.4965   470.9313  -2.369 0.018664 *  
## uspc_subclass343000          -1908.8358   618.4367  -3.087 0.002269 ** 
## uspc_subclass367000             96.2646   795.2655   0.121 0.903758    
## uspc_subclass369000           -446.3031   797.6910  -0.559 0.576360    
## uspc_subclass372000           2532.0054   748.4676   3.383 0.000841 ***
## uspc_subclass376000          -2124.5951   681.2456  -3.119 0.002044 ** 
## uspc_subclass400000            846.1727   773.9283   1.093 0.275365    
## uspc_subclass401000          -1406.4965   470.9313  -2.987 0.003121 ** 
## uspc_subclass405000            330.9515   944.9647   0.350 0.726484    
## uspc_subclass414000          -1622.6805   554.2619  -2.928 0.003752 ** 
## uspc_subclass423000            512.9277   895.0410   0.573 0.567143    
## uspc_subclass442000                  NA         NA      NA       NA    
## uspc_subclass458000           1049.7159   795.3513   1.320 0.188187    
## uspc_subclass464000           -154.8926   749.0336  -0.207 0.836354    
## uspc_subclass466000           1341.1647   998.3383   1.343 0.180445    
## uspc_subclass468000           -367.4461   726.0959  -0.506 0.613293    
## uspc_subclass483000            -86.8695   724.5611  -0.120 0.904671    
## uspc_subclass489000           1453.1647   998.3383   1.456 0.146848    
## uspc_subclass534000            746.2646   750.1267   0.995 0.320836    
## uspc_subclass535000            179.7630   589.2451   0.305 0.760581    
## uspc_subclass537000           1554.5148   738.3241   2.105 0.036317 *  
## uspc_subclass539000           1590.1190   681.0277   2.335 0.020396 *  
## uspc_subclass548000            493.0000   528.2317   0.933 0.351626    
## uspc_subclass557000            281.2370   344.0310   0.817 0.414488    
## uspc_subclass568000                  NA         NA      NA       NA    
## uspc_subclass593000                  NA         NA      NA       NA    
## uspc_subclass620000                  NA         NA      NA       NA    
## uspc_subclass649000          -1742.9289   784.9371  -2.220 0.027346 *  
## uspc_subclass769000           1154.0277   708.7711   1.628 0.104826    
## as.factor(disposal_type)ISS    392.2370   261.1151   1.502 0.134404    
## gendermale                    -741.6302   399.5635  -1.856 0.064696 .  
## raceHispanic                         NA         NA      NA       NA    
## racewhite                     1542.5274   464.7411   3.319 0.001047 ** 
## tenure_days                     -0.5818     0.2398  -2.426 0.016021 *  
## WG1_degree                     -12.3234     3.8554  -3.196 0.001583 ** 
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 373.5 on 234 degrees of freedom
##   (3 observations deleted due to missingness)
## Multiple R-squared:  0.8062, Adjusted R-squared:  0.7333
## F-statistic: 11.06 on 88 and 234 DF,  p-value: < 2.2e-16
```

```
WG2_reg2 <- lm(app_proc_time~examiner_art_unit+uspc_class+uspc_subclass+as.factor(disposal_type) + gende
summary(WG2_reg2)
```

```
##
## Call:
## lm(formula = app_proc_time ~ examiner_art_unit + uspc_class +
##     uspc_subclass + as.factor(disposal_type) + gender + race +
##     tenure_days + WG2_degree, data = WG2Final)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1704.7  -165.9     0.0   156.4  2068.2
##
## Coefficients: (2 not defined because of singularities)
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                -4.603e+05  4.882e+04  -9.430  < 2e-16 ***
## examiner_art_unit           2.100e+02  2.220e+01   9.458  < 2e-16 ***
## uspc_class707              -1.385e+03  7.424e+02  -1.866  0.06286 .
## uspc_class708              -2.048e+02  5.823e+02  -0.352  0.72527
## uspc_class709               1.908e+02  6.738e+02   0.283  0.77719
## uspc_class717               9.257e+01  6.355e+02   0.146  0.88425
## uspc_class718              -5.264e+02  5.829e+02  -0.903  0.36706
## uspc_class719              -1.363e+03  7.813e+02  -1.744  0.08194 .
## uspc_subclass004000         1.160e+03  6.315e+02   1.836  0.06711 .
## uspc_subclass005000         2.910e+02  5.242e+02   0.555  0.57909
## uspc_subclass017000                NA         NA      NA       NA
## uspc_subclass100000        -2.361e+01  3.751e+02  -0.063  0.94986
## uspc_subclass101000         5.216e+02  5.216e+02   1.000  0.31794
## uspc_subclass102000         9.127e+02  5.041e+02   1.811  0.07098 .
## uspc_subclass103000        -1.317e+02  4.332e+02  -0.304  0.76120
## uspc_subclass104000        -1.667e+02  3.618e+02  -0.461  0.64526
## uspc_subclass105000         2.760e+01  6.301e+02   0.044  0.96508
## uspc_subclass106000        -1.541e+01  3.975e+02  -0.039  0.96909
## uspc_subclass108000        -4.875e+02  4.297e+02  -1.134  0.25731
## uspc_subclass109000        -1.866e+02  4.162e+02  -0.448  0.65423
## uspc_subclass110000        -4.738e+02  4.829e+02  -0.981  0.32715
## uspc_subclass112000        -7.508e+02  4.829e+02  -1.555  0.12084
## uspc_subclass113000         4.667e+02  4.110e+02   1.135  0.25688
## uspc_subclass114000        -1.011e+02  5.184e+02  -0.195  0.84548
## uspc_subclass115000         6.070e+02  5.242e+02   1.158  0.24759
## uspc_subclass116000        -4.058e+02  6.312e+02  -0.643  0.52069
## uspc_subclass120000         7.420e+01  4.205e+02   0.176  0.86003
## uspc_subclass121000        -1.099e+02  4.235e+02  -0.260  0.79530
## uspc_subclass122000         1.587e+02  4.152e+02   0.382  0.70247
## uspc_subclass123000         3.732e+02  4.529e+02   0.824  0.41045
## uspc_subclass124000        -2.135e+02  3.901e+02  -0.547  0.58456
```

```
## uspc_subclass125000          6.203e+02  4.388e+02   1.414  0.15827
## uspc_subclass126000         -1.821e+02  3.937e+02  -0.463  0.64392
## uspc_subclass127000          2.090e+02  4.149e+02   0.504  0.61486
## uspc_subclass128000          3.228e+02  4.004e+02   0.806  0.42057
## uspc_subclass130000          3.034e+02  4.129e+02   0.735  0.46286
## uspc_subclass131000         -4.768e+02  4.760e+02  -1.002  0.31714
## uspc_subclass132000          2.252e+02  4.572e+02   0.493  0.62257
## uspc_subclass133000          1.826e+02  6.291e+02   0.290  0.77176
## uspc_subclass136000          1.473e+02  4.103e+02   0.359  0.71979
## uspc_subclass137000         -3.430e+02  5.200e+02  -0.660  0.50988
## uspc_subclass139000          9.721e+02  6.293e+02   1.545  0.12322
## uspc_subclass140000         -8.425e+00  4.259e+02  -0.020  0.98423
## uspc_subclass141000         -3.708e+02  6.321e+02  -0.587  0.55784
## uspc_subclass143000          1.784e+02  4.288e+02   0.416  0.67751
## uspc_subclass144000          3.440e+02  5.176e+02   0.665  0.50669
## uspc_subclass146000          8.662e+02  4.775e+02   1.814  0.07042 .
## uspc_subclass148000         -3.681e+02  4.848e+02  -0.759  0.44815
## uspc_subclass149000         -5.865e+02  4.456e+02  -1.316  0.18886
## uspc_subclass151000         -4.413e+02  3.939e+02  -1.120  0.26323
## uspc_subclass153000         -2.351e+02  4.274e+02  -0.550  0.58260
## uspc_subclass154000          1.282e+03  4.761e+02   2.693  0.00738 **
## uspc_subclass155000         -1.398e+03  5.186e+02  -2.695  0.00734 **
## uspc_subclass156000         -4.639e+01  6.291e+02  -0.074  0.94126
## uspc_subclass158000         -1.962e+02  4.085e+02  -0.480  0.63131
## uspc_subclass159000         -1.566e+02  4.214e+02  -0.372  0.71031
## uspc_subclass160000          2.695e+02  6.291e+02   0.428  0.66861
## uspc_subclass161000         -7.681e+01  4.109e+02  -0.187  0.85183
## uspc_subclass162000         -5.573e+02  4.558e+02  -1.223  0.22218
## uspc_subclass166000         -8.839e+01  6.291e+02  -0.141  0.88834
## uspc_subclass168000          1.851e+02  3.857e+02   0.480  0.63164
## uspc_subclass170000         -6.487e+01  4.552e+02  -0.143  0.88675
## uspc_subclass171000         -8.613e+01  4.219e+02  -0.204  0.83836
## uspc_subclass172000          1.286e+03  5.215e+02   2.466  0.01409 *
## uspc_subclass174000          3.950e+02  3.875e+02   1.019  0.30863
## uspc_subclass175000         -9.442e+02  5.325e+02  -1.773  0.07703 .
## uspc_subclass177000          3.892e+02  4.147e+02   0.939  0.34851
## uspc_subclass178000          1.441e+02  4.073e+02   0.354  0.72377
## uspc_subclass200000         -9.821e+01  4.115e+02  -0.239  0.81151
## uspc_subclass204000         -1.134e+02  4.741e+02  -0.239  0.81111
## uspc_subclass209000         -2.260e+02  5.819e+02  -0.388  0.69795
## uspc_subclass220000          7.443e+02  5.856e+02   1.271  0.20449
## uspc_subclass250000         -4.087e+01  4.293e+02  -0.095  0.92420
## uspc_subclass254000          4.043e+02  5.819e+02   0.695  0.48767
## uspc_subclass270000          4.868e+02  4.007e+02   1.215  0.22518
## uspc_subclass300000          3.273e+02  4.143e+02   0.790  0.42993
## uspc_subclass310000          1.198e+03  6.656e+02   1.799  0.07277 .
## uspc_subclass311000          5.897e+02  7.813e+02   0.755  0.45088
## uspc_subclass313000          1.746e+02  5.973e+02   0.292  0.77023
## uspc_subclass315000          1.378e+03  7.813e+02   1.763  0.07864 .
## uspc_subclass316000          1.598e+03  7.813e+02   2.045  0.04154 *
## uspc_subclass317000          8.086e+02  7.881e+02   1.026  0.30555
## uspc_subclass318000          9.273e+02  6.206e+02   1.494  0.13595
## uspc_subclass321000          1.288e+03  7.881e+02   1.634  0.10312
## uspc_subclass328000          1.679e+03  6.725e+02   2.497  0.01294 *
```

```
## uspc_subclass330000          7.959e+02  6.283e+02   1.267  0.20603
## uspc_subclass331000          9.486e+02  5.966e+02   1.590  0.11263
## uspc_subclass332000          1.775e+03  7.812e+02   2.272  0.02362 *
## uspc_subclass402000          5.964e+02  4.225e+02   1.412  0.15886
## uspc_subclass422000         -1.742e+03  5.819e+02  -2.994  0.00293 **
## uspc_subclass443000         -1.090e+02  5.995e+02  -0.182  0.85583
## uspc_subclass495000          1.030e+02  5.995e+02   0.172  0.86368
## uspc_subclass500000         -1.846e+03  5.821e+02  -3.171  0.00164 **
## uspc_subclass503000          7.492e+02  4.602e+02   1.628  0.10434
## uspc_subclass505000         -4.920e+02  5.821e+02  -0.845  0.39847
## uspc_subclass520000         -1.420e+02  4.657e+02  -0.305  0.76058
## uspc_subclass523000          1.611e+03  5.819e+02   2.768  0.00590 **
## uspc_subclass552000         -2.182e+01  4.602e+02  -0.047  0.96221
## uspc_subclass625000          1.900e+02  4.603e+02   0.413  0.68005
## uspc_subclass629000          1.057e+03  5.821e+02   1.816  0.07018 .
## uspc_subclass650000          2.051e+02  5.947e+02   0.345  0.73032
## uspc_subclass700000                 NA         NA      NA       NA
## as.factor(disposal_type)ISS  4.888e+01  6.741e+01   0.725  0.46884
## gendermale                   2.141e+02  8.604e+01   2.488  0.01325 *
## raceblack                   -2.583e+01  2.824e+02  -0.091  0.92716
## raceHispanic                 3.758e+02  3.454e+02   1.088  0.27722
## racewhite                   -2.582e+02  9.491e+01  -2.721  0.00681 **
## tenure_days                  2.859e-01  6.817e-02   4.194 3.41e-05 ***
## WG2_degree                   5.783e+00  1.056e+00   5.478 7.77e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 504 on 388 degrees of freedom
## Multiple R-squared:  0.5468, Adjusted R-squared:  0.4229
## F-statistic: 4.416 on 106 and 388 DF,  p-value: < 2.2e-16
```

There doesn't seem to be conclusive evidence that gender and race have a significant influence on app_proc_time but we can try to combine them with degree to see if there is any improvement in model performance:

Adding interaction terms

```
WG1_reg3 <- lm(app_proc_time~examiner_art_unit+uspc_class+uspc_subclass+as.factor(disposal_type) + gend
summary(WG1_reg3)
```

```
##
## Call:
## lm(formula = app_proc_time ~ examiner_art_unit + uspc_class +
##     uspc_subclass + as.factor(disposal_type) + gender + race +
##     tenure_days + WG1_degree * gender, data = WG1Final)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -680.9    0.0    0.0    0.0 1084.1
##
## Coefficients: (9 not defined because of singularities)
```

```
##                                 Estimate Std. Error t value Pr(>|t|)    
## (Intercept)                   69391.1324 97705.4789   0.710 0.478286    
## examiner_art_unit               -39.3634    59.8680  -0.658 0.511506    
## uspc_class435                    22.3706  1052.2160   0.021 0.983056    
## uspc_class514                  -533.9150   462.9121  -1.153 0.249935    
## uspc_class540                 -1486.7386  1624.0749  -0.915 0.360909    
## uspc_class546                 -1017.9359  1036.1139  -0.982 0.326894    
## uspc_class548                 -2240.6526   506.7139  -4.422 1.50e-05 ***
## uspc_class558                 -2373.1176   988.1920  -2.401 0.017114 *  
## uspc_class560                 -1500.7238  1162.7474  -1.291 0.198097    
## uspc_class562                 -1552.5120  1263.0099  -1.229 0.220231    
## uspc_class564                 -3539.4442   847.4133  -4.177 4.18e-05 ***
## uspc_class568                 -2229.7346   851.4035  -2.619 0.009400 ** 
## uspc_class585                 -2257.8355   837.1028  -2.697 0.007503 ** 
## uspc_subclass008000             486.0000   529.3639   0.918 0.359525    
## uspc_subclass023000             280.5488   840.4194   0.334 0.738816    
## uspc_subclass025000             742.2856   876.9190   0.846 0.398159    
## uspc_subclass027000             832.1493   834.4208   0.997 0.319664    
## uspc_subclass032000                   NA         NA      NA       NA    
## uspc_subclass042000            1479.2856   915.9932   1.615 0.107674    
## uspc_subclass047000            1909.2856   841.9849   2.268 0.024270 *  
## uspc_subclass049000            1052.7562   840.9354   1.252 0.211866    
## uspc_subclass050000              -4.5445   875.4178  -0.005 0.995862    
## uspc_subclass055000            1166.2856   876.9190   1.330 0.184825    
## uspc_subclass058000            -988.5507   700.1301  -1.412 0.159298    
## uspc_subclass070100           -1669.8302   536.4532  -3.113 0.002085 ** 
## uspc_subclass111000             285.5214   787.5813   0.363 0.717285    
## uspc_subclass112000             933.9357   886.2201   1.054 0.293047    
## uspc_subclass119000            -471.4447   649.4798  -0.726 0.468641    
## uspc_subclass125000            -779.0000   529.3639  -1.472 0.142484    
## uspc_subclass129000           -1455.2026   749.7732  -1.941 0.053482 .  
## uspc_subclass133000           -1314.6565   592.0806  -2.220 0.027354 *  
## uspc_subclass134000                   NA         NA      NA       NA    
## uspc_subclass159000            1100.9043  1058.2542   1.040 0.299278    
## uspc_subclass178000            -102.2272  1088.6590  -0.094 0.925268    
## uspc_subclass183000            1004.6601   912.6272   1.101 0.272101    
## uspc_subclass210000            -249.6565   529.6253  -0.471 0.637808    
## uspc_subclass211130              52.3882  1421.5941   0.037 0.970635    
## uspc_subclass216000            -853.8236  1345.8345  -0.634 0.526429    
## uspc_subclass217000            -812.0000   529.3639  -1.534 0.126407    
## uspc_subclass221000            -651.4463   477.0365  -1.366 0.173378    
## uspc_subclass232000             -63.0000   529.3639  -0.119 0.905369    
## uspc_subclass241000                   NA         NA      NA       NA    
## uspc_subclass243000           -1894.1049   707.6579  -2.677 0.007966 ** 
## uspc_subclass247000             373.2856   915.9932   0.408 0.684000    
## uspc_subclass250000                   NA         NA      NA       NA    
## uspc_subclass252100            -463.2240   713.5337  -0.649 0.516850    
## uspc_subclass253060           -2199.0852   592.2436  -3.713 0.000256 ***
## uspc_subclass253070           -2189.0852   592.2436  -3.696 0.000273 ***
## uspc_subclass254010              94.9826   978.7647   0.097 0.922775    
## uspc_subclass256000            -757.2633   422.7921  -1.791 0.074575 .  
## uspc_subclass257000            -684.8236  1337.1306  -0.512 0.609025    
## uspc_subclass260000            1016.5904   699.2467   1.454 0.147337    
## uspc_subclass270000             178.2856   842.4419   0.212 0.832581    
```

```
## uspc_subclass274000            70.5769   679.7478   0.104 0.917395    
## uspc_subclass278000           -58.4995   819.3667  -0.071 0.943144    
## uspc_subclass279000           -58.4995   819.3667  -0.071 0.943144    
## uspc_subclass310000          1391.6601   912.6272   1.525 0.128642    
## uspc_subclass318000          -702.7771   657.8884  -1.068 0.286522    
## uspc_subclass322000         -1447.6988   733.0398  -1.975 0.049457 *  
## uspc_subclass323000          1612.7763   673.9671   2.393 0.017506 *  
## uspc_subclass332000         -1678.6774   643.9736  -2.607 0.009730 ** 
## uspc_subclass338000           -60.0174   978.7647  -0.061 0.951157    
## uspc_subclass339000          -204.4447   649.4798  -0.315 0.753209    
## uspc_subclass342000         -1117.8333   553.0182  -2.021 0.044389 *  
## uspc_subclass343000         -1910.6774   660.0901  -2.895 0.004157 ** 
## uspc_subclass367000            92.6601   912.6272   0.102 0.919216    
## uspc_subclass369000          -448.9908   865.4341  -0.519 0.604390    
## uspc_subclass372000          2530.1821   783.0711   3.231 0.001411 ** 
## uspc_subclass376000         -2126.1049   707.6579  -3.004 0.002952 ** 
## uspc_subclass400000           840.3616  1056.1458   0.796 0.427024    
## uspc_subclass401000         -1408.8333   553.0182  -2.548 0.011493 *  
## uspc_subclass405000           327.4186  1042.4663   0.314 0.753741    
## uspc_subclass414000         -1624.8669   617.4758  -2.631 0.009069 ** 
## uspc_subclass423000           506.3527  1209.3074   0.419 0.675812    
## uspc_subclass442000                 NA         NA      NA       NA    
## uspc_subclass458000          1045.2677   967.6811   1.080 0.281180    
## uspc_subclass464000          -160.1754   994.0677  -0.161 0.872130    
## uspc_subclass466000          1334.5646  1289.9178   1.035 0.301923    
## uspc_subclass468000          -370.4995   819.3667  -0.452 0.651561    
## uspc_subclass483000           -88.3067   747.4458  -0.118 0.906055    
## uspc_subclass489000          1446.5646  1289.9178   1.121 0.263255    
## uspc_subclass534000           742.6601   873.4025   0.850 0.396027    
## uspc_subclass535000           179.7882   590.5163   0.304 0.761050    
## uspc_subclass537000          1548.9043  1013.1601   1.529 0.127674    
## uspc_subclass539000          1592.5021   743.1118   2.143 0.033148 *  
## uspc_subclass548000           493.0000   529.3639   0.931 0.352659    
## uspc_subclass557000           281.2118   344.7824   0.816 0.415550    
## uspc_subclass568000                 NA         NA      NA       NA    
## uspc_subclass593000                 NA         NA      NA       NA    
## uspc_subclass620000                 NA         NA      NA       NA    
## uspc_subclass649000         -1746.8241   921.7755  -1.895 0.059322 .  
## uspc_subclass769000          1150.4483   836.3549   1.376 0.170282    
## as.factor(disposal_type)ISS   392.2118   261.6932   1.499 0.135293    
## gendermale                   -738.7166   538.0754  -1.373 0.171107    
## raceHispanic                        NA         NA      NA       NA    
## racewhite                    1542.1566   467.9780   3.295 0.001136 ** 
## tenure_days                    -0.5805     0.2910  -1.995 0.047237 *  
## WG1_degree                    -12.1210    25.2607  -0.480 0.631794    
## gendermale:WG1_degree          -0.2148    26.5039  -0.008 0.993539    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 374.3 on 233 degrees of freedom
##   (3 observations deleted due to missingness)
## Multiple R-squared:  0.8062, Adjusted R-squared:  0.7322
## F-statistic: 10.89 on 89 and 233 DF,  p-value: < 2.2e-16
```

```r
WG2_reg3 <- lm(app_proc_time~examiner_art_unit+uspc_class+uspc_subclass+as.factor(disposal_type) + gend
summary(WG2_reg3)
```

```
##
## Call:
## lm(formula = app_proc_time ~ examiner_art_unit + uspc_class +
##     uspc_subclass + as.factor(disposal_type) + gender + race +
##     tenure_days + WG2_degree * gender, data = WG2Final)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1695.4  -162.8     0.0   153.5  1951.3
##
## Coefficients: (2 not defined because of singularities)
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                -4.813e+05  4.903e+04  -9.817  < 2e-16 ***
## examiner_art_unit           2.196e+02  2.230e+01   9.847  < 2e-16 ***
## uspc_class707              -1.346e+03  7.365e+02  -1.828  0.06835 .
## uspc_class708              -2.037e+02  5.776e+02  -0.353  0.72453
## uspc_class709               1.658e+02  6.683e+02   0.248  0.80423
## uspc_class717               4.709e+01  6.305e+02   0.075  0.94051
## uspc_class718              -5.834e+02  5.786e+02  -1.008  0.31389
## uspc_class719              -1.276e+03  7.756e+02  -1.645  0.10073
## uspc_subclass004000         1.199e+03  6.266e+02   1.914  0.05639 .
## uspc_subclass005000         3.545e+02  5.205e+02   0.681  0.49618
## uspc_subclass017000                NA         NA      NA       NA
## uspc_subclass100000        -8.689e+00  3.721e+02  -0.023  0.98138
## uspc_subclass101000         6.112e+02  5.183e+02   1.179  0.23910
## uspc_subclass102000         1.018e+03  5.015e+02   2.030  0.04304 *
## uspc_subclass103000        -1.783e+02  4.300e+02  -0.415  0.67871
## uspc_subclass104000        -9.126e+01  3.599e+02  -0.254  0.79995
## uspc_subclass105000         5.518e+01  6.250e+02   0.088  0.92969
## uspc_subclass106000        -2.455e+01  3.943e+02  -0.062  0.95039
## uspc_subclass108000        -4.969e+02  4.262e+02  -1.166  0.24434
## uspc_subclass109000        -8.954e+01  4.144e+02  -0.216  0.82902
## uspc_subclass110000        -5.410e+02  4.796e+02  -1.128  0.26001
## uspc_subclass112000        -8.180e+02  4.796e+02  -1.706  0.08890 .
## uspc_subclass113000         4.234e+02  4.080e+02   1.038  0.30006
## uspc_subclass114000        -9.939e+01  5.142e+02  -0.193  0.84682
## uspc_subclass115000         6.705e+02  5.205e+02   1.288  0.19841
## uspc_subclass116000        -4.038e+02  6.261e+02  -0.645  0.51929
## uspc_subclass120000         1.183e+02  4.174e+02   0.284  0.77692
## uspc_subclass121000        -1.803e+02  4.208e+02  -0.429  0.66847
## uspc_subclass122000         2.095e+02  4.123e+02   0.508  0.61165
## uspc_subclass123000         5.328e+02  4.531e+02   1.176  0.24031
## uspc_subclass124000        -1.741e+02  3.872e+02  -0.450  0.65322
## uspc_subclass125000         5.398e+02  4.362e+02   1.237  0.21669
## uspc_subclass126000        -2.295e+01  3.948e+02  -0.058  0.95367
## uspc_subclass127000         2.096e+02  4.116e+02   0.509  0.61088
## uspc_subclass128000         4.388e+02  3.994e+02   1.099  0.27262
## uspc_subclass130000         2.825e+02  4.096e+02   0.690  0.49069
## uspc_subclass131000        -4.398e+02  4.723e+02  -0.931  0.35231
## uspc_subclass132000         2.080e+02  4.536e+02   0.459  0.64677
```

```
## uspc_subclass133000           1.841e+02  6.240e+02   0.295  0.76817
## uspc_subclass136000           1.479e+02  4.070e+02   0.364  0.71643
## uspc_subclass137000          -3.302e+02  5.158e+02  -0.640  0.52240
## uspc_subclass139000           9.380e+02  6.242e+02   1.503  0.13376
## uspc_subclass140000          -1.508e+01  4.224e+02  -0.036  0.97153
## uspc_subclass141000          -3.880e+02  6.270e+02  -0.619  0.53638
## uspc_subclass143000           1.990e+02  4.253e+02   0.468  0.64012
## uspc_subclass144000           3.520e+02  5.133e+02   0.686  0.49336
## uspc_subclass146000           8.877e+02  4.736e+02   1.874  0.06164 .
## uspc_subclass148000          -3.504e+02  4.809e+02  -0.729  0.46665
## uspc_subclass149000          -5.877e+02  4.419e+02  -1.330  0.18438
## uspc_subclass151000          -4.131e+02  3.908e+02  -1.057  0.29116
## uspc_subclass153000          -2.786e+02  4.242e+02  -0.657  0.51167
## uspc_subclass154000           1.255e+03  4.723e+02   2.658  0.00819 **
## uspc_subclass155000          -1.432e+03  5.146e+02  -2.783  0.00565 **
## uspc_subclass156000          -4.495e+01  6.240e+02  -0.072  0.94261
## uspc_subclass158000          -3.513e+01  4.094e+02  -0.086  0.93167
## uspc_subclass159000          -6.405e+01  4.193e+02  -0.153  0.87867
## uspc_subclass160000           3.285e+02  6.243e+02   0.526  0.59904
## uspc_subclass161000          -7.962e+01  4.076e+02  -0.195  0.84522
## uspc_subclass162000          -5.093e+02  4.524e+02  -1.126  0.26094
## uspc_subclass166000          -8.695e+01  6.240e+02  -0.139  0.88925
## uspc_subclass168000           1.760e+02  3.826e+02   0.460  0.64575
## uspc_subclass170000          -7.044e+01  4.514e+02  -0.156  0.87609
## uspc_subclass171000          -1.116e+02  4.186e+02  -0.267  0.78984
## uspc_subclass172000           1.295e+03  5.172e+02   2.504  0.01270 *
## uspc_subclass174000           3.766e+02  3.844e+02   0.980  0.32787
## uspc_subclass175000          -8.976e+02  5.285e+02  -1.698  0.09022 .
## uspc_subclass177000           3.747e+02  4.113e+02   0.911  0.36295
## uspc_subclass178000           2.648e+02  4.064e+02   0.652  0.51501
## uspc_subclass200000          -8.620e+01  4.082e+02  -0.211  0.83286
## uspc_subclass204000          -1.542e+02  4.705e+02  -0.328  0.74323
## uspc_subclass209000          -2.260e+02  5.772e+02  -0.392  0.69559
## uspc_subclass220000           6.460e+02  5.820e+02   1.110  0.26770
## uspc_subclass250000          -3.983e+01  4.258e+02  -0.094  0.92552
## uspc_subclass254000           4.140e+02  5.772e+02   0.717  0.47361
## uspc_subclass270000           4.876e+02  3.974e+02   1.227  0.22065
## uspc_subclass300000           3.300e+02  4.109e+02   0.803  0.42237
## uspc_subclass310000           1.046e+03  6.626e+02   1.578  0.11537
## uspc_subclass311000           5.030e+02  7.756e+02   0.649  0.51701
## uspc_subclass313000          -2.958e+01  5.971e+02  -0.050  0.96052
## uspc_subclass315000           1.291e+03  7.756e+02   1.665  0.09681 .
## uspc_subclass316000           1.511e+03  7.756e+02   1.948  0.05211 .
## uspc_subclass317000           5.329e+02  7.882e+02   0.676  0.49942
## uspc_subclass318000           8.518e+02  6.161e+02   1.382  0.16765
## uspc_subclass321000           1.012e+03  7.882e+02   1.284  0.20000
## uspc_subclass328000           1.467e+03  6.716e+02   2.184  0.02958 *
## uspc_subclass330000           7.131e+02  6.239e+02   1.143  0.25377
## uspc_subclass331000           8.316e+02  5.932e+02   1.402  0.16176
## uspc_subclass332000           1.700e+03  7.753e+02   2.193  0.02889 *
## uspc_subclass402000           5.632e+02  4.192e+02   1.343  0.17990
## uspc_subclass422000          -1.742e+03  5.772e+02  -3.018  0.00271 **
## uspc_subclass443000          -1.009e+02  5.946e+02  -0.170  0.86530
## uspc_subclass495000           1.111e+02  5.946e+02   0.187  0.85194
```

```
## uspc_subclass500000         -1.823e+03  5.774e+02  -3.158  0.00171 **
## uspc_subclass503000          7.672e+02  4.565e+02   1.681  0.09363 .
## uspc_subclass505000         -4.693e+02  5.774e+02  -0.813  0.41684
## uspc_subclass520000         -1.380e+02  4.619e+02  -0.299  0.76531
## uspc_subclass523000          1.611e+03  5.772e+02   2.791  0.00551 **
## uspc_subclass552000         -3.803e+00  4.565e+02  -0.008  0.99336
## uspc_subclass625000          2.127e+02  4.566e+02   0.466  0.64160
## uspc_subclass629000          1.080e+03  5.774e+02   1.870  0.06225 .
## uspc_subclass650000          2.062e+02  5.898e+02   0.350  0.72686
## uspc_subclass700000                 NA         NA      NA       NA
## as.factor(disposal_type)ISS  5.589e+01  6.691e+01   0.835  0.40403
## gendermale                  -2.282e+01  1.219e+02  -0.187  0.85154
## raceblack                   -7.264e+00  2.802e+02  -0.026  0.97933
## raceHispanic                 2.440e+02  3.460e+02   0.705  0.48111
## racewhite                   -2.241e+02  9.497e+01  -2.359  0.01881 *
## tenure_days                  3.110e-01  6.824e-02   4.557 6.96e-06 ***
## WG2_degree                   1.160e+00  1.995e+00   0.582  0.56122
## gendermale:WG2_degree        6.272e+00  2.303e+00   2.723  0.00676 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 499.8 on 387 degrees of freedom
## Multiple R-squared:  0.5553, Adjusted R-squared:  0.4323
## F-statistic: 4.516 on 107 and 387 DF,  p-value: < 2.2e-16
```

Adjusted R-squared increased for WG2 with the introduction of this new interaction term increased and the new term still remained statistically significant, even though the magnitude of significance decreased by one order. The higher coefficient value tells us that we can reject our initial hypothesis that the relationship between degree and processing time is indeed different than degree in conjunction with the examiner being a male. This may be other confounding factors not included within this examination, but it is an interesting point to note nevertheless.

The dynamic between the interaction with gender and degree for WG1 was inconclusive.

Final Conclusions

We can see a very large improvement in performance from the original simple linear regression models which only incorporated degree when looking at the relationship between processing times and centrality, in which we saw the r-squared improve for WG1 from 0.0009497 to 0.8062 and 0.04051 to 0.5468 for WG2. Some interesting observations are that in both the simple regression model and multivariate models, for WG2, the examiners degree value was highly statistically significant. If we were to look at the *distribution* of degree scores we can see a lower average degree score indicating a more normalized and even distribution of centrality scores across all nodes. Additionally, the topography of the networks across both working groups varies and we can observe that WG2 is more densely connected with higher betweenness and has fewer disconnected components. WG1 has a few highly influential nodes within the center of the network but many sitting outside only connected by one or two connected short paths. We can infer that the negative relationship between processing time and degree for WG1 may be due to the fact that these few influential examiners are overworked and doing a majority of the work within their respective working groups. Furthermore, we can ascertain that the more connected a network is the faster the processing time will be for a patent, which will be further explained by exploring the coefficient values for degree below.

Random Forest Feature Importance

Looking at the feature importance for both WG1 and WG2, we can see a noticable difference in the positioning of the degree scores, wherein which degree for WG2 is ranked as being second most important in predicting processing times and for WG1 is ranked as fourth. This is further confirmation that the relative topological structure a network has influences the speed in which an examiner abandons or finalizes their respective patent.

Regression Degree Coefficient Values

Additionally, another interesting observation that provides for insightful inference is the value of the coefficients for degree centrality across both networks. For WG2 we can see a positive correlation between degree and processing times, with a coefficient value of 5.78. For WG1 we can see an inverse relationship with a stronger effect, with a degree centrality coefficient of -12.32 indicating that the longer it takes process the patent the smaller would be the extent of the connections between the edges within the network. This also could mean that with the passing of time the edges in the network for WG1 hit a plateau, saturate and remain stagnant over several months or years while with WG2 new examiners are consistently providing advice to new people as time passes.

Implications for USPTO

The organic chemistry workgroup seems to have two separate components and units working within the existing workgroup, while the software development workgroup has a greater degree of interconnectedness amongst the examiners providing advice. This may be due to the nature of the industries selected, in which the organic chemistry TC deals with distinct functions pertaining to completely different areas of research, as opposed to the software development workgroup where most of the innovations are confined to relatively similar domains.

Size of dataset for analysis

An important point to note is that the total size of the final datasets used for modelling in this exercise were quite small, with 326 observations for WG1 and 495 for WG2. With this in mind, it is prudent to examine other avenues to improve the reliability of the results through selecting workgroups in technology centers outside of organic chemistry (162) and Interprocess Communication and Software Development (219).