Final Project - USPTO Examination Analysis

2024-02-09

Introduction

This analysis aims to explore organizational and social factors affecting the length of patent application prosecution and examiner attrition at the U.S. Patent and Trademark Office (USPTO), with a particular focus on the role of gender, race, and ethnicity.

Data Loading

First, we need to load the dataset.

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## 13    2017-05-23        6343
## 14    2017-05-12        6335
## 15    2017-01-19        6225
## 16    2017-05-19        6335
## 17    2017-05-22        6340
## 18    2017-04-28        6325
## 19    2017-05-23        6335
## 20    2017-05-23        6347
## 21    2017-05-12        6328
## 22    2017-05-22        6341
## 23    2915-06-29      334352
## 24    2017-05-22        6347
## 25    2015-10-23        5769
## 26    2017-05-12        6337
## 27    2015-01-30        5504
## 28    2017-05-20        6337
## 29    2017-05-19        6329
## 30    2017-05-23        6340
## 31    2017-05-12        6339
## 32    2017-03-10        6276
## 33    2016-09-30        6099
## 34    2017-05-22        6331
## 35    2017-05-18        6343
## 36    2017-03-24        6282
## 37    2017-05-19        6343
## 38    2017-03-10        6276
## 39    2017-05-23        6342
## 40    2017-05-10        6322
## 41    2017-05-05        6332
## 42    2017-05-23        6349
## 43    2017-05-12        6332
## 44    2013-12-13        5082
## 45    2017-05-05        6328
## 46    2017-05-12        6335
## 47    2017-05-05        6330
## 48    2017-05-22        6349
## 49    2017-04-28        6309
## 50    2017-05-23        6349
## 51    2015-07-02        5657
## 52    2017-04-28        6324
## 53    2017-05-19        6315
## 54    2017-05-12        6324
## 55    2017-05-05        6323
## 56    2915-06-29      334373
## 57    2017-05-22        6347
## 58    2017-05-23        6347
## 59    2017-05-23        6348
## 60    2017-03-24        6283
## 61    2016-09-30        6099
## 62    2017-05-18        6336
## 63    2017-05-19        6330
## 64    2017-05-23        6342
## 65    2017-05-05        6328
## 66    2017-05-23        6348
## 67    2017-05-22        6348
## 68    2050-12-30       18610
## 69    2017-05-18        6327
## 70    2017-05-19        6342
## 71    2017-05-22        6338
## 72    2017-05-19        6338
## 73    2017-05-22        6349
## 74    2017-05-12        6337
## 75    2017-05-23        6342
## 76    2017-05-19        6245
## 77    2017-03-31        6296
## 78    2017-04-28        6324
## 79    2017-05-22        6349
## 80    2017-04-28        6324
## 81    2016-09-09        6084
## 82    2017-05-22        6347
## 83    2017-05-22        6341
## 84    2017-03-09        6265
## 85    2017-01-27        6224
## 86    2017-05-22        6341
## 87    2017-05-16        6049
## 88    2017-02-17        6254
## 89    2017-05-18        6323
## 90    2016-01-22        5860
## 91    2017-01-13        6209
## 92    2017-05-23        6350
## 93    2017-05-15        6321
## 94    2017-04-07        6288
## 95    2017-01-19        6226
## 96    2017-05-22        6347
## 97    2017-05-22        6342
## 98    2017-05-19        6339
## 99    2017-05-19        6338
## 100   2017-05-22        6347
## 101   2017-04-28        6318
## 102   2017-05-05        6321
## 103   2017-05-12        6336
## 104   2017-05-22        6349
## 105   2017-05-23        6347
## 4756  2016-11-18        6149
## 4757  2017-05-12        6335
## 4758  2017-05-19        6346
## 4759  2015-03-27        5561
## 4760  2017-03-31        6286
## 4761  2017-05-23        6350
##  [ reached 'max' / getOption("max.print") -- omitted 2013716 rows ]
```

Data Preparation

We need to prepare the data by ensuring correct data types and creating necessary features.

```
applications <- applications %>%
  mutate(filing_date = ymd(filing_date),
         patent_issue_date = ymd(patent_issue_date),
         abandon_date = ymd(abandon_date),
         prosecution_length = if_else(!is.na(patent_issue_date),
as.numeric(difftime(patent_issue_date, filing_date, units = "days")),
                                       as.numeric(difftime(abandon_date,
filing_date, units = "days"))))
```

Data Cleaning and Exploration We’ll examine the dataset for missing values and summarize its key statistics.

```
# Check for missing values
summary(applications)

##  application_number  filing_date         examiner_name_last
examiner_name_first
##  Min.   : 8284457   Min.   :2000-01-02   Length:2018477     Length:2018477
##  1st Qu.:10975476   1st Qu.:2005-03-30   Class :character   Class
:character
##  Median :12491809   Median :2009-07-23   Mode  :character   Mode
:character
##  Mean   :12477062   Mean   :2009-03-23
##  3rd Qu.:13892722   3rd Qu.:2013-05-22
##  Max.   :95002230   Max.   :2017-05-26
##
##  examiner_name_middle  examiner_id    examiner_art_unit  uspc_class
##  Length:2018477       Min.   :59012   Min.   :1600      Length:2018477
##  Class :character     1st Qu.:66476   1st Qu.:1671      Class :character
##  Mode  :character     Median :75243   Median :1773      Mode  :character
##                       Mean   :78712   Mean   :1928
##                       3rd Qu.:93754   3rd Qu.:2171
##                       Max.   :99990   Max.   :2498
##                       NA's   :9229
##  uspc_subclass      patent_number      patent_issue_date
##  Length:2018477     Length:2018477     Min.   :1997-03-04
##  Class :character   Class :character   1st Qu.:2008-04-29
##  Mode  :character   Mode  :character   Median :2012-05-22
##                                         Mean   :2011-06-20
##                                         3rd Qu.:2015-01-20
##                                         Max.   :2017-06-20
##                                         NA's   :931178
##   abandon_date         disposal_type      appl_status_code appl_status_date
##  Min.   :1965-07-20   Length:2018477     Min.   :  1.0    Length:2018477
##  1st Qu.:2008-06-23   Class :character   1st Qu.:150.0    Class :character
##  Median :2011-04-19   Mode  :character   Median :150.0    Mode  :character
##  Mean   :2011-01-28                      Mean   :145.9
##  3rd Qu.:2014-04-15                      3rd Qu.:161.0
##  Max.   :2050-06-30                      Max.   :865.0
##  NA's   :1417057                         NA's   :4609
##        tc          gender              race           earliest_date
##  Min.   :1600   Length:2018477     Length:2018477     Length:2018477
##  1st Qu.:1600   Class :character   Class :character   Class :character
##  Median :1700   Mode  :character   Mode  :character   Mode  :character
##  Mean   :1877
##  3rd Qu.:2100
##  Max.   :2400
##
##  latest_date         tenure_days      prosecution_length
##  Length:2018477     Min.   :     27   Min.   :-13636
##  Class :character   1st Qu.:   4963   1st Qu.:   765
##  Mode  :character   Median :   6094   Median :  1079
##                     Mean   :  10282   Mean   :  1190
##                     3rd Qu.:   6336   3rd Qu.:  1481
##                     Max.   :2727903   Max.   : 17898
##                                       NA's   :329761

# Quick summary of data columns
skim(applications)
```

Data summary

Name	applications
Number of rows	2018477
Number of columns	22
Column type frequency:	
character	12
Date	3
numeric	7
Group variables	None

Variable type: character

skim_variable	n_missing	complete_rate	min	max	empty	n_unique	whitespace
examiner_name_last	0	1	2	17	0	3806	0
examiner_name_first	0	1	1	12	0	2595	0
examiner_name_middle	0	1	0	12	471770	516	0
uspc_class	0	1	0	3	4	417	0
uspc_subclass	0	1	0	6	1677	6155	0
patent_number	0	1	0	7	931651	1086825	0
disposal_type	0	1	3	4	0	3	0
appl_status_date	0	1	0	18	4610	5706	0
gender	0	1	0	6	303859	3	0
race	0	1	5	8	0	5	0
earliest_date	0	1	10	10	0	2325	0
latest_date	0	1	10	10	0	888	0

Variable type: Date

skim_variable	n_missing	complete_rate	min	max	median	n_unique
filing_date	0	1.00	2000-01-02	2017-05-26	2009-07-23	6204
patent_issue_date	931178	0.54	1997-03-04	2017-06-20	2012-05-22	891
abandon_date	1417057	0.30	1965-07-20	2050-06-30	2011-04-19	5052

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
application_number	0	1.00	12477061.84	2198067.04	8284457	10975476	12491809	13892722	95002230	▇▁▁▁

skim_variable	n_missing	complete_rate	mean	sd	p0	p25	p50	p75	p100	hist
examiner_id	9229	1.00	78712.39	13606.61	59012	66476	75243	93754	99990	▁▇▇▂▂
examiner_art_unit	0	1.00	1928.02	304.38	1600	1671	1773	2171	2498	▇▇▂▁▂
appl_status_code	4609	1.00	145.94	51.72	1	150	150	161	865	▂▇▁▁▁
tc	0	1.00	1876.91	298.82	1600	1600	1700	2100	2400	▁▇▁▁▂
tenure_days	0	1.00	10282.35	87390.08	27	4963	6094	6336	2727903	▂▇▁▁▁
prosecution_length	329761	0.84	1190.22	620.88	-13636	765	1079	1481	17898	▁▁▇▁▁

Handling those missing values:

Imputation for prosecution_length:

For prosecution_length, since it’s numerical, using the median might be more robust to outliers than the mean.

```
median_prosecution_length <- median(applications$prosecution_length, na.rm =
TRUE)
```

```
applications$prosecution_length[is.na(applications$prosecution_length)] <-
median_prosecution_length
```

Examiner Gender and Race Estimation

```
library(gender)
library(dplyr)

# Step 1: Generate gender predictions
examiner_names <- applications %>%
  distinct(examiner_name_first)

# Use gender() on the unique list of first names
gender_predictions <- gender(examiner_names$examiner_name_first, method =
"ssa", years = c(1940, 2020))

## Warning in gender(examiner_names$examiner_name_first, method = "ssa",
years =
## c(1940, : The year range provided has been trimmed to fit within 1880 to
2012.

# Convert gender_predictions to a dataframe and prepare for join
gender_df <- as.data.frame(gender_predictions) %>%
  rename(examiner_name_first = name) %>%
  select(examiner_name_first, gender)

# Step 2: Join gender predictions back to applications
applications <- applications %>%
  left_join(gender_df, by = "examiner_name_first")

# Print the result to check the first few rows, including the newly added
gender column
head(applications)

##   application_number filing_date examiner_name_last examiner_name_first
## 1            8284457  2000-01-26             HOWARD          JACQUELINE
## 2            8413193  2000-10-11           YILDIRIM               BEKIR
## 3            8531853  2000-05-17           HAMILTON             CYNTHIA
## 4            8637752  2001-07-20             MOSHER                MARY
## 5            8682726  2000-04-10               BARR             MICHAEL
## 6            8687412  2000-04-28               GRAY               LINDA
##   examiner_name_middle examiner_id examiner_art_unit uspc_class
uspc_subclass
## 1                    V       96082              1764        508
273000
## 2                    L       87678              1764        208
179000
## 3                            63213              1752        430
271100
## 4                            73788              1648        530
388300
```

```
## 5                    E       77294              1762        427
430100
## 6                LAMEY       68606              1734        156
204000
##   patent_number patent_issue_date abandon_date disposal_type
appl_status_code
## 1       6521570        2003-02-18         <NA>           ISS
150
## 2       6440298        2002-08-27         <NA>           ISS
250
## 3       5607816        1997-03-04         <NA>           ISS
250
## 4       6927281        2005-08-09         <NA>           ISS
250
## 5                            <NA>   2000-12-27           ABN
161
## 6       6267836        2001-07-31         <NA>           ISS
150
##     appl_status_date   tc gender.x  race earliest_date latest_date
tenure_days
## 1 30jan2003 00:00:00 1700   female white    2000-01-10  2016-04-01
5926
## 2 27sep2010 00:00:00 1700          white    2000-01-04  2016-09-09
6093
## 3 30mar2009 00:00:00 1700   female white    2000-01-06  2017-05-20
6344
## 4 07sep2009 00:00:00 1600   female white    2000-01-04  2017-05-05
6331
## 5 19apr2001 00:00:00 1700     male white    2000-01-03  2017-05-05
6332
## 6 16jul2001 00:00:00 1700   female white    2000-01-04  2017-05-19
6345
##   prosecution_length gender.y
## 1               1119   female
## 2                685     <NA>
## 3              -1170   female
## 4               1481   female
## 5                261     male
## 6                459   female
```

Examiner Race Estimation

First, we need to start by predicting race based on surname using the WRU package:

```
library(dplyr)
library(wru)

# Step 1: Get unique surnames
examiner_surnames <- applications %>%
  distinct(examiner_name_last) %>%
```

```r
  rename(surname = examiner_name_last)

# Preparing the voter_file with surnames
#voter_file <- applications %>%
#  distinct(examiner_name_last) %>%
#  mutate(surname = tolower(examiner_name_last)) %>%
#  select(surname)

# Call to predict_race() adjusted for simplicity
#race_predictions <- predict_race(voter_file, census = "2010", surname.only =
TRUE)

# Step 2: Use predict_race() to estimate race
race_predictions <- predict_race(examiner_surnames, surname.only = TRUE)
```

```
## Proceeding with last name predictions...

## ℹ All local files already up-to-date!

## 701 (18.4%) individuals' last names were not matched.
```

```r
print(colnames(race_predictions))
```

```
## [1] "surname"  "pred.whi" "pred.bla" "pred.his" "pred.asi" "pred.oth"
```

```r
# Process the race predictions to identify the most probable race
race_predictions <- race_predictions %>%
  rowwise() %>%
  mutate(most_probable_race = case_when(
    pred.whi == max(c(pred.whi, pred.bla, pred.his, pred.asi, pred.oth),
na.rm = TRUE) ~ "White",
    pred.bla == max(c(pred.whi, pred.bla, pred.his, pred.asi, pred.oth),
na.rm = TRUE) ~ "Black or African American",
    pred.his == max(c(pred.whi, pred.bla, pred.his, pred.asi, pred.oth),
na.rm = TRUE) ~ "Hispanic",
    pred.asi == max(c(pred.whi, pred.bla, pred.his, pred.asi, pred.oth),
na.rm = TRUE) ~ "Asian",
    pred.oth == max(c(pred.whi, pred.bla, pred.his, pred.asi, pred.oth),
na.rm = TRUE) ~ "Other",
    TRUE ~ "Unknown"
  )) %>%
  ungroup()

# Join the race predictions back to the applications dataframe
# 'examiner_name_last' in 'applications' matches 'surname' in
'race_predictions'
applications_with_race <- applications %>%
  left_join(race_predictions %>% select(surname, most_probable_race), by =
c("examiner_name_last" = "surname"))

# Note: The above operation selects only the relevant columns ('surname' and
'most_probable_race')


# View the first few rows of the updated dataframe to check the join results
head(applications_with_race)

##   application_number filing_date examiner_name_last examiner_name_first
## 1            8284457  2000-01-26             HOWARD          JACQUELINE
## 2            8413193  2000-10-11           YILDIRIM               BEKIR
## 3            8531853  2000-05-17           HAMILTON             CYNTHIA
## 4            8637752  2001-07-20             MOSHER                MARY
## 5            8682726  2000-04-10               BARR             MICHAEL
## 6            8687412  2000-04-28               GRAY               LINDA
##   examiner_name_middle examiner_id examiner_art_unit uspc_class
uspc_subclass
## 1                    V       96082              1764        508
273000
## 2                    L       87678              1764        208
179000
## 3                            63213              1752        430
271100
## 4                            73788              1648        530
388300
## 5                    E       77294              1762        427
430100
## 6                LAMEY       68606              1734        156
204000
##   patent_number patent_issue_date abandon_date disposal_type
appl_status_code
## 1       6521570        2003-02-18         <NA>           ISS
150
## 2       6440298        2002-08-27         <NA>           ISS
250
## 3       5607816        1997-03-04         <NA>           ISS
250
## 4       6927281        2005-08-09         <NA>           ISS
250
## 5                            <NA>   2000-12-27           ABN
161
## 6       6267836        2001-07-31         <NA>           ISS
150
##     appl_status_date   tc gender.x  race earliest_date latest_date
tenure_days
## 1 30jan2003 00:00:00 1700   female white    2000-01-10  2016-04-01
5926
## 2 27sep2010 00:00:00 1700          white    2000-01-04  2016-09-09
6093
## 3 30mar2009 00:00:00 1700   female white    2000-01-06  2017-05-20
6344
## 4 07sep2009 00:00:00 1600   female white    2000-01-04  2017-05-05
```

```
6331
## 5 19apr2001 00:00:00 1700     male white    2000-01-03  2017-05-05
6332
## 6 16jul2001 00:00:00 1700   female white    2000-01-04  2017-05-19
6345
##   prosecution_length gender.y most_probable_race
## 1               1119   female              White
## 2                685     <NA>              White
## 3              -1170   female              White
## 4               1481   female              White
## 5                261     male              White
## 6                459   female              White
```

Dropping outliers

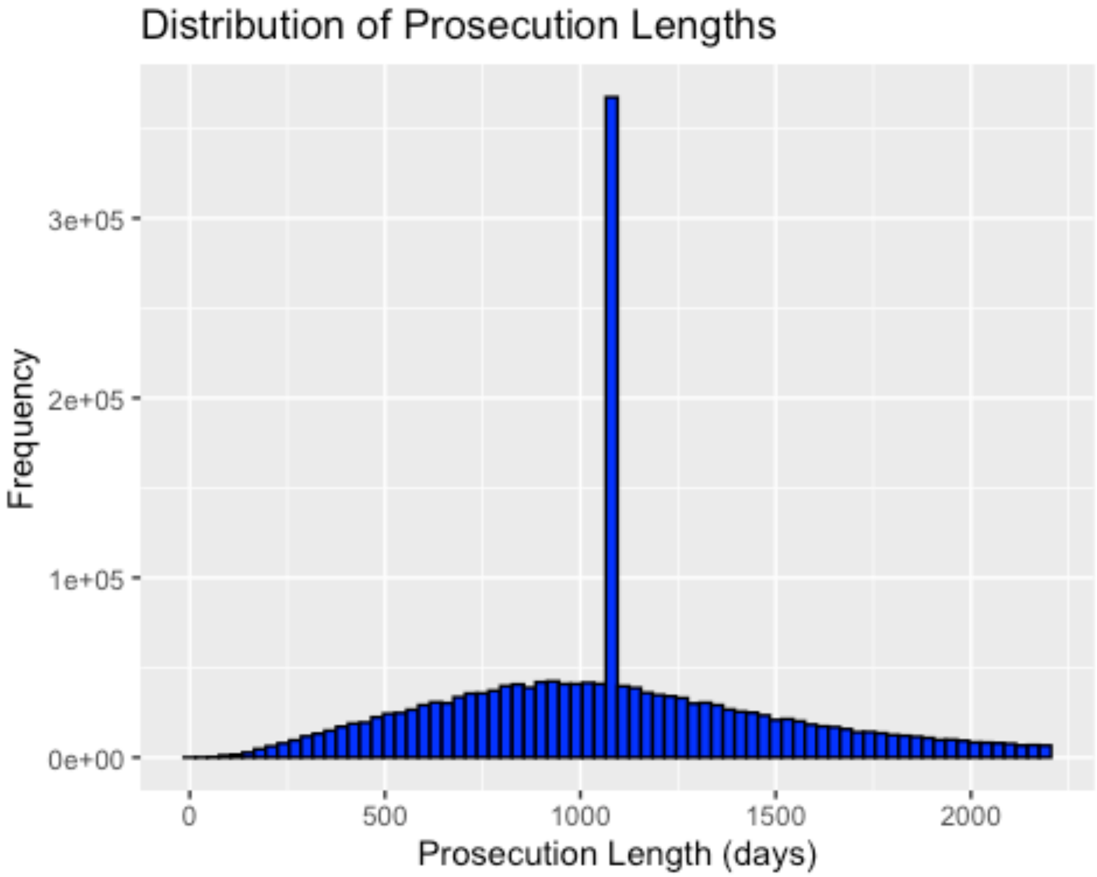
```
# Calculating the IQR for prosecution_length
Q1 <- quantile(applications_with_race$prosecution_length, 0.25, na.rm = TRUE)
Q3 <- quantile(applications_with_race$prosecution_length, 0.75, na.rm = TRUE)
IQR <- Q3 - Q1

# Defining the lower and upper bounds for what's considered an outlier
lower_bound <- Q1 - 1.5 * IQR
upper_bound <- Q3 + 1.5 * IQR

# Filtering out the outliers
applications_with_race <- applications_with_race %>%
  filter(prosecution_length >= lower_bound & prosecution_length <=
upper_bound)

# Checking the result after dropping outliers
summary(applications_with_race$prosecution_length)

##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##       5     807    1079    1076    1290    2205
```

Part 1 - 1 ##############

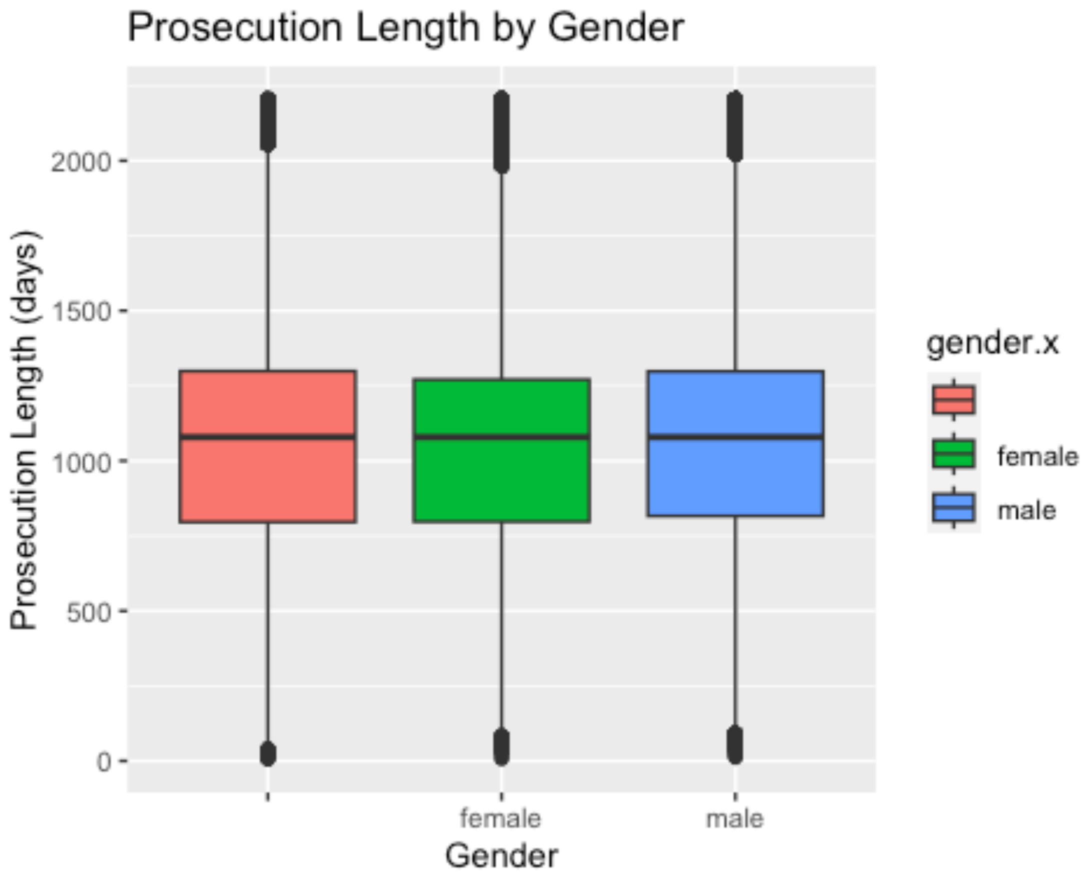
1. Organizational and Social Factors Associated with the Length of Patent Application Prosecution For this analysis, we consider factors such as examiner's art unit (examiner_art_unit), the USPC class/subclass, and demographic attributes (gender, most_probable_race).

Exploratory Analysis:

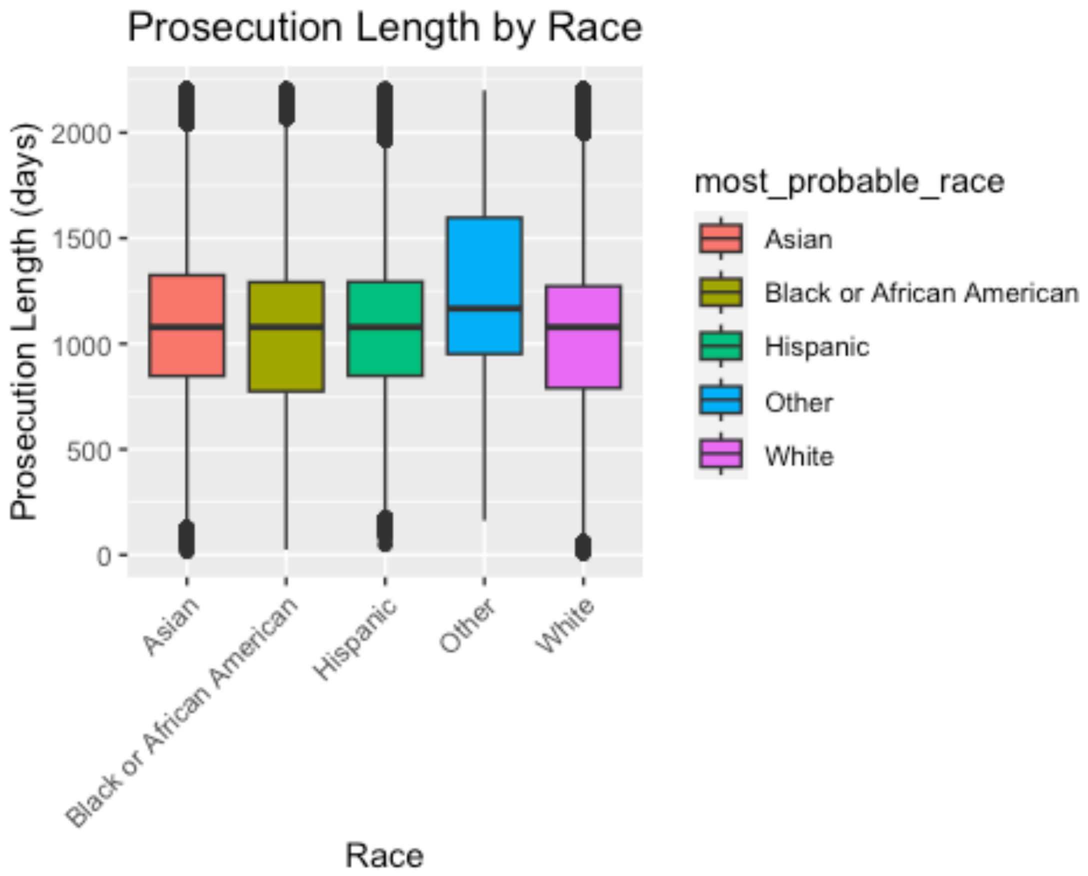
```
library(ggplot2)

# Distribution of prosecution lengths
ggplot(applications_with_race, aes(x = prosecution_length)) +
  geom_histogram(binwidth = 30, fill = "blue", color = "black") +
  labs(title = "Distribution of Prosecution Lengths", x = "Prosecution Length
(days)", y = "Frequency")
```



```
# Prosecution length by gender
ggplot(applications_with_race, aes(x = gender.x, y = prosecution_length, fill
= gender.x)) +
  geom_boxplot() +
  labs(title = "Prosecution Length by Gender", x = "Gender", y = "Prosecution
Length (days)")
```



```r
# Prosecution length by race
ggplot(applications_with_race, aes(x = most_probable_race, y =
prosecution_length, fill = most_probable_race)) +
  geom_boxplot() +
  labs(title = "Prosecution Length by Race", x = "Race", y = "Prosecution
Length (days)") +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Regression Analysis A linear regression can be used to quantify the impact of these factors on prosecution_length.

```
lm_result <- lm(prosecution_length ~ examiner_art_unit + uspc_class +
gender.x + most_probable_race, data = applications_with_race)
summary(lm_result)

##
## Call:
## lm(formula = prosecution_length ~ examiner_art_unit + uspc_class +
##     gender.x + most_probable_race, data = applications_with_race)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1327.83  -250.20   -25.74   212.57  1552.00
##
## Coefficients:
##                                                 Estimate Std. Error t value
## (Intercept)                                    6.513e+02  1.999e+02   3.257
## examiner_art_unit                             -2.200e-01  5.978e-03 -36.809
## uspc_class001                                  1.205e+03  4.465e+02   2.699
## uspc_class002                                  8.229e+02  2.078e+02   3.960
## uspc_class004                                  7.942e+02  2.283e+02   3.478
## uspc_class005                                7.874e+02  2.283e+02   3.449
## uspc_class007                                4.297e+02  3.458e+02   1.243
## uspc_class008                                6.964e+02  1.997e+02   3.487
## uspc_class012                                8.501e+02  2.824e+02   3.011
## uspc_class014                                6.043e+02  2.824e+02   2.140
## uspc_class015                                6.122e+02  1.998e+02   3.065
## uspc_class016                                8.461e+02  2.130e+02   3.972
## uspc_class019                                9.483e+02  2.824e+02   3.358
## uspc_class023                                7.056e+02  2.016e+02   3.499
## uspc_class024                                7.023e+02  2.503e+02   2.806
## uspc_class026                                9.367e+02  2.219e+02   4.221
## uspc_class027                                5.450e+02  3.050e+02   1.787
## uspc_class028                                7.784e+02  2.362e+02   3.295
## uspc_class029                                7.996e+02  2.000e+02   3.998
## uspc_class030                                8.307e+02  2.305e+02   3.603
## uspc_class033                                4.590e+02  3.458e+02   1.327
## uspc_class034                                7.602e+02  2.046e+02   3.716
## uspc_class036                                8.214e+02  2.445e+02   3.359
## uspc_class037                                1.267e+03  4.465e+02   2.837
## uspc_class038                                9.604e+02  4.465e+02   2.151
## uspc_class040                                7.826e+02  2.264e+02   3.457
## uspc_class042                                1.111e+03  2.400e+02   4.631
## uspc_class043                                5.311e+02  2.207e+02   2.406
## uspc_class044                                8.365e+02  1.998e+02   4.187
## uspc_class047                                7.242e+02  2.029e+02   3.568
## uspc_class048                                9.332e+02  1.998e+02   4.670
## uspc_class049                                9.764e+02  2.824e+02   3.458
## uspc_class051                                7.443e+02  1.999e+02   3.724
## uspc_class052                                7.648e+02  2.029e+02   3.769
## uspc_class053                                8.588e+02  2.122e+02   4.048
## uspc_class054                                6.218e+02  3.050e+02   2.039
## uspc_class055                                6.961e+02  1.997e+02   3.485
## uspc_class056                                6.091e+02  2.445e+02   2.491
## uspc_class057                                7.274e+02  2.163e+02   3.363
## uspc_class059                                7.940e+02  4.465e+02   1.779
## uspc_class060                                8.305e+02  2.049e+02   4.053
## uspc_class062                                7.227e+02  2.063e+02   3.503
## uspc_class063                                7.896e+02  3.050e+02   2.589
## uspc_class065                                8.383e+02  1.997e+02   4.197
## uspc_class066                                1.061e+03  3.458e+02   3.067
## uspc_class068                                9.143e+02  1.998e+02   4.576
## uspc_class069                                1.123e+03  3.458e+02   3.248
## uspc_class070                                7.022e+02  2.066e+02   3.400
## uspc_class071                                6.812e+02  2.000e+02   3.406
## uspc_class072                                8.449e+02  2.108e+02   4.009
## uspc_class073                                8.570e+02  2.031e+02   4.219
## uspc_class074                                1.025e+03  2.099e+02   4.883
## uspc_class075                                7.168e+02  1.997e+02   3.589
## uspc_class081                                9.655e+02  2.824e+02   3.419
## uspc_class082                                7.240e+02  2.080e+02   3.481
```

Part 1 -2 ##############

2. Organizational and Social Factors Associated with Examiner Attrition

As there's no straightforward attrition flag or direct indicator of examiner leaving, and considering attrition is meant to reflect whether an examiner has stopped working on applications (which from this dataset might not be directly inferable), we are considering alternative approaches to approximate this concept. Without a clear attrition indicator, we'll focus on what can be analyzed given the dataset.

Alternative Analysis Approach:

Since attrition directly cannot be assessed, let's pivot towards understanding the factors that influence application outcomes (e.g., issued patents vs. abandoned applications), which might provide insights into examiner behavior or organizational processes affecting application processing times or outcomes.

Analyzing Factors Influencing Application Outcomes:

We use the disposal_type as a proxy to differentiate between applications that were successfully issued a patent versus those abandoned or otherwise disposed of. This will allow us to analyze how different factors, including examiner demographics and organizational units, may influence these outcomes.

1- Preparing Data: First, we create a binary outcome variable based on disposal_type.

```
applications_with_race <- applications_with_race %>%
  mutate(outcome = ifelse(disposal_type == "ISS", 1, 0)) # "ISS" indicates
issued patents
```

2- Logistic Regression for Analyzing Influencing Factors: Since we don't have attrition_flag, we'll adjust the focus to the outcome variable just created.

```
# Logistic regression to explore factors influencing application outcomes
glm_outcomes <- glm(outcome ~ examiner_art_unit + tenure_days + gender.x +
race,
                    family = binomial(link = "logit"),
                    data = applications_with_race)

summary(glm_outcomes)

##
## Call:
## glm(formula = outcome ~ examiner_art_unit + tenure_days + gender.x +
##     race, family = binomial(link = "logit"), data =
applications_with_race)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)       -4.089e-01  1.110e-02 -36.841  < 2e-16 ***
## examiner_art_unit  3.068e-04  5.085e-06  60.328  < 2e-16 ***
## tenure_days       -3.982e-07  1.771e-08 -22.487  < 2e-16 ***
## gender.xfemale    -1.572e-01  4.849e-03 -32.416  < 2e-16 ***
## gender.xmale       5.963e-02  4.450e-03  13.400  < 2e-16 ***
## raceblack          2.526e-01  7.596e-03  33.260  < 2e-16 ***
## raceHispanic      -1.539e-01  8.968e-03 -17.163  < 2e-16 ***
## raceother          2.226e-01  4.981e-02   4.469 7.86e-06 ***
## racewhite         -6.838e-02  3.486e-03 -19.613  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2627056  on 1900660  degrees of freedom
## Residual deviance: 2613941  on 1900652  degrees of freedom
## AIC: 2613959
##
## Number of Fisher Scoring iterations: 4
```

3- Indirect Analysis for Examiner Attrition Given the limitations, we'll focus on exploring patterns that might suggest attrition-like behavior, such as examiners with shorter tenures possibly having different outcome patterns or being associated with specific organizational or social factors.

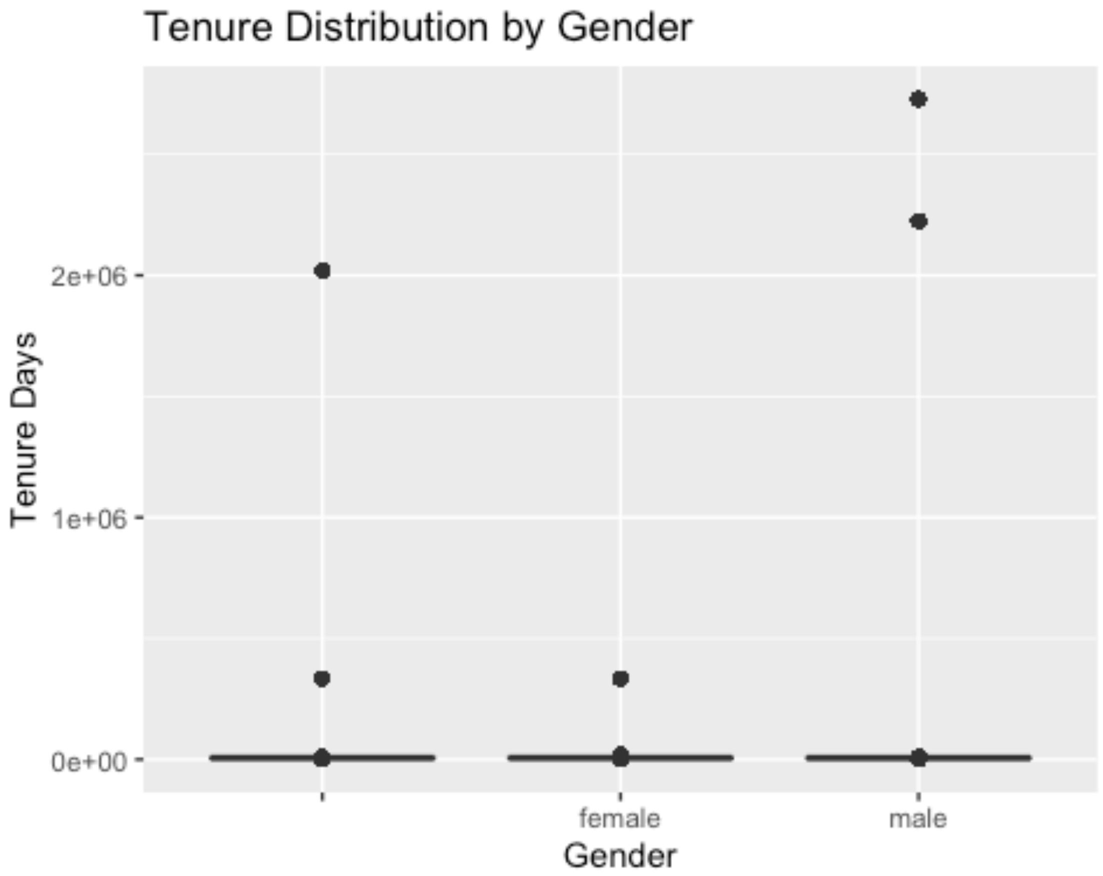
3 - 1 - Aggregate Analysis on Tenure and Outcomes First, we explore the relationship between tenure_days and application outcomes, assuming that changes in tenure_days distribution might reflect on engagement or attrition-like behavior.

```
# Aggregate analysis to explore tenure distribution across different
application outcomes
applications_with_race %>%
  group_by(outcome) %>%
  summarise(Average_Tenure = mean(tenure_days, na.rm = TRUE),
            Median_Tenure = median(tenure_days, na.rm = TRUE)) %>%
  print()
```

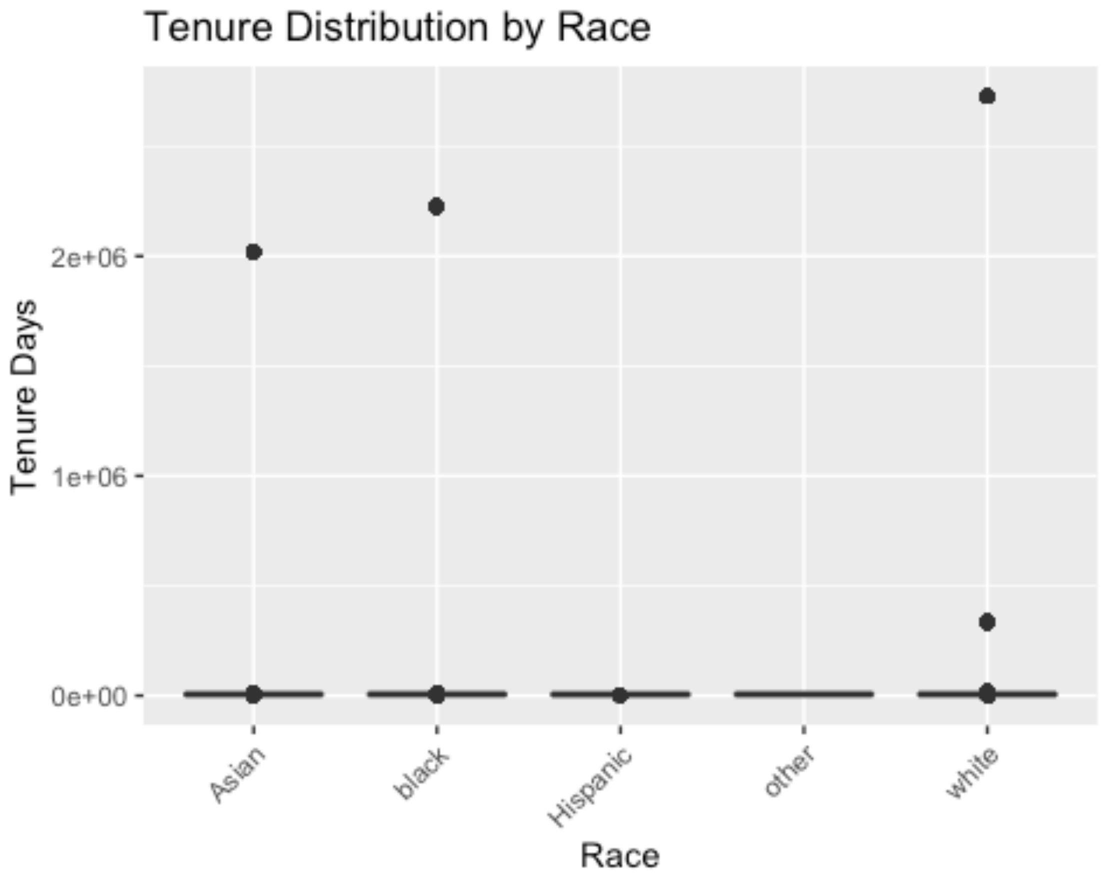
```
## # A tibble: 2 × 3
##   outcome Average_Tenure Median_Tenure
##     <dbl>          <dbl>         <dbl>
## 1       0         11608.          5849
## 2       1          9098.          6272
```

4. Exploratory Analysis on Tenure by Gender and Race Exploring tenure_days distribution across gender.x and race might also offer insights into differing patterns that could indirectly relate to attrition or engagement dynamics.

```
# Tenure distribution by gender
ggplot(applications_with_race, aes(x = gender.x, y = tenure_days)) +
  geom_boxplot() +
  labs(title = "Tenure Distribution by Gender", x = "Gender", y = "Tenure
Days")
```



```
# Tenure distribution by race
ggplot(applications_with_race, aes(x = race, y = tenure_days)) +
  geom_boxplot() +
  labs(title = "Tenure Distribution by Race", x = "Race", y = "Tenure Days")
+
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Part 1 - 3 ##############

3- Role of gender, race and ethnicity here in the processes

Analyzing the Impact of Gender, Race, and Ethnicity Given the results from your logistic regression model for application outcomes and the EDA conducted for tenure distributions, you can interpret the roles of gender, race, and ethnicity as follows:

1. Interpretation from Logistic Regression Model The coefficients from the logistic regression model (glm_outcomes) give us quantitative insights into how gender and race are associated with the likelihood of an application being issued a patent (outcome).

```
# Recap the summary of the logistic regression model for reference
summary(glm_outcomes)

##
## Call:
## glm(formula = outcome ~ examiner_art_unit + tenure_days + gender.x +
##     race, family = binomial(link = "logit"), data =
applications_with_race)
##
```

```
## Coefficients:
##                     Estimate Std. Error z value Pr(>|z|)    
## (Intercept)       -4.089e-01  1.110e-02 -36.841  < 2e-16 ***
## examiner_art_unit  3.068e-04  5.085e-06  60.328  < 2e-16 ***
## tenure_days       -3.982e-07  1.771e-08 -22.487  < 2e-16 ***
## gender.xfemale    -1.572e-01  4.849e-03 -32.416  < 2e-16 ***
## gender.xmale       5.963e-02  4.450e-03  13.400  < 2e-16 ***
## raceblack          2.526e-01  7.596e-03  33.260  < 2e-16 ***
## raceHispanic      -1.539e-01  8.968e-03 -17.163  < 2e-16 ***
## raceother          2.226e-01  4.981e-02   4.469 7.86e-06 ***
## racewhite         -6.838e-02  3.486e-03 -19.613  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
##     Null deviance: 2627056  on 1900660  degrees of freedom
## Residual deviance: 2613941  on 1900652  degrees of freedom
## AIC: 2613959
## 
## Number of Fisher Scoring iterations: 4
```

Part 1 - 3 - Interpretation ###########################

From the output of summary(glm_outcomes), we can interpret the coefficients related to gender.x and race as follows:

Gender (gender.x): Coefficients for gender variables (e.g., gender.xfemale, gender.xmale) indicate the influence of an examiner's gender on the likelihood of a patent application being issued. A positive coefficient suggests that being of that gender increases the likelihood of an application resulting in an issuance compared to the baseline gender category, while a negative coefficient suggests a decrease.

Race (race): Similarly, coefficients for different race categories show how the race of an examiner might impact the outcome of patent applications. Positive values indicate an increased likelihood of issuance for examiners of that race, while negative values indicate a decreased likelihood, both relative to the baseline race category.

```r
# Exploring interaction effects (example)
glm_interactions <- glm(outcome ~ examiner_art_unit * gender.x * race + 
tenure_days,
                        family = binomial(link = "logit"),
                        data = applications_with_race)
summary(glm_interactions)
```

```
## 
## Call:
## glm(formula = outcome ~ examiner_art_unit * gender.x * race + 
##     tenure_days, family = binomial(link = "logit"), data = 
applications_with_race)
## 
## Coefficients: (2 not defined because of singularities)
##                                                  Estimate Std. Error z 
value
## (Intercept)                                   -9.154e-01  3.064e-02 -
29.880
## examiner_art_unit                              5.788e-04  1.517e-05  
38.164
## gender.xfemale                                -3.133e-01  4.858e-02  -
6.450
## gender.xmale                                   6.356e-01  4.034e-02  
15.754
## raceblack                                      2.250e+00  7.855e-02  
28.647
## raceHispanic                                  -9.019e-01  1.824e-01  -
4.943
## raceother                                     -1.662e+01  5.312e+00  -
3.129
## racewhite                                     -2.277e-01  5.167e-02  -
4.407
## tenure_days                                   -3.672e-07  1.838e-08 -
19.984
## examiner_art_unit:gender.xfemale               1.147e-04  2.448e-05   
4.684
## examiner_art_unit:gender.xmale                -3.391e-04  1.969e-05 -
17.220
## examiner_art_unit:raceblack                   -9.262e-04  3.872e-05 -
23.920
## examiner_art_unit:raceHispanic                 3.862e-04  9.563e-05   
4.038
## examiner_art_unit:raceother                    6.966e-03  2.159e-03   
3.227
## examiner_art_unit:racewhite                    4.725e-07  2.583e-05   
0.018
## gender.xfemale:raceblack                      -1.856e+00  1.193e-01 -
15.552
## gender.xmale:raceblack                        -1.655e+00  1.220e-01 -
13.561
## gender.xfemale:raceHispanic                    1.301e+00  2.145e-01   
6.068
## gender.xmale:raceHispanic                      1.742e+00  1.997e-01   
8.724
## gender.xfemale:raceother                              NA         NA      
NA
## gender.xmale:raceother                        -1.031e+00  5.397e+00  -
0.191
## gender.xfemale:racewhite                       9.019e-01  6.928e-02  
13.018
```

```
## gender.xmale:racewhite                         2.573e-01  6.005e-02
4.284
## examiner_art_unit:gender.xfemale:raceblack     7.358e-04  6.120e-05
12.022
## examiner_art_unit:gender.xmale:raceblack       7.771e-04  5.820e-05
13.352
## examiner_art_unit:gender.xfemale:raceHispanic -6.718e-04  1.122e-04  -
5.989
## examiner_art_unit:gender.xmale:raceHispanic   -8.613e-04  1.035e-04  -
8.326
## examiner_art_unit:gender.xfemale:raceother            NA         NA
NA
## examiner_art_unit:gender.xmale:raceother       1.693e-03  2.207e-03
0.767
## examiner_art_unit:gender.xfemale:racewhite    -4.461e-04  3.545e-05 -
12.586
## examiner_art_unit:gender.xmale:racewhite      -7.557e-06  2.987e-05  -
0.253
##                                               Pr(>|z|)
## (Intercept)                                    < 2e-16 ***
## examiner_art_unit                              < 2e-16 ***
## gender.xfemale                                1.12e-10 ***
## gender.xmale                                   < 2e-16 ***
## raceblack                                      < 2e-16 ***
## raceHispanic                                  7.67e-07 ***
## raceother                                      0.00176 **
## racewhite                                     1.05e-05 ***
## tenure_days                                    < 2e-16 ***
## examiner_art_unit:gender.xfemale              2.81e-06 ***
## examiner_art_unit:gender.xmale                 < 2e-16 ***
## examiner_art_unit:raceblack                    < 2e-16 ***
## examiner_art_unit:raceHispanic                5.39e-05 ***
## examiner_art_unit:raceother                    0.00125 **
## examiner_art_unit:racewhite                    0.98541
## gender.xfemale:raceblack                       < 2e-16 ***
## gender.xmale:raceblack                         < 2e-16 ***
## gender.xfemale:raceHispanic                   1.30e-09 ***
## gender.xmale:raceHispanic                      < 2e-16 ***
## gender.xfemale:raceother                            NA
## gender.xmale:raceother                         0.84847
## gender.xfemale:racewhite                       < 2e-16 ***
## gender.xmale:racewhite                        1.83e-05 ***
## examiner_art_unit:gender.xfemale:raceblack     < 2e-16 ***
## examiner_art_unit:gender.xmale:raceblack       < 2e-16 ***
## examiner_art_unit:gender.xfemale:raceHispanic 2.11e-09 ***
## examiner_art_unit:gender.xmale:raceHispanic    < 2e-16 ***
## examiner_art_unit:gender.xfemale:raceother          NA
## examiner_art_unit:gender.xmale:raceother       0.44304
## examiner_art_unit:gender.xfemale:racewhite     < 2e-16 ***
## examiner_art_unit:gender.xmale:racewhite       0.80027
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 2627056  on 1900660  degrees of freedom
## Residual deviance: 2610065  on 1900632  degrees of freedom
## AIC: 2610123
##
## Number of Fisher Scoring iterations: 4
```