## **Project EDA**

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### Introduction

The data selected for this project consists of majors choosen by recent college graduates along with the salary that these graduates earn just after graduation. The data also consists of number of graduates that were men and women, their median salary etc.

I am keen on working with this data as I will also be a graduate soon and this data will help me know about the past trends that can be expected.

## About the data

#### **Data Source**

The data has been taken from a github repository which is maintained by Aaron Bycoff, Jay Boice, Neil Paine, Ryan Best. Citation: A.Bycoff, J.Boice, N.Paine, R.Best (Apr 3, 2018) special-elections. link: https://github.com/fivethirtyeight/data/blob/master/college-majors/recent-grads.csv

### **Data collection**

Data was collected using Ballotpedia and American Community Survey. Ballotpedia was used to compile the list of elections between Jan. 20, 2017 and March 27, 2018. Income and education data comes from the American Community Survey's five-year estimates for 2012–2016. Presidential results by district were collected from Daily Kos Elections (Florida results are from Matthew Isbell).

#### Units of observation

#### **Variables**

The variables present in the dataset are:
Rank - Rank by median earnings
Major\_code - Major code, FO1DP in ACS PUMS
xMajor - Major description
Major\_category - Category of major from Carnevale et al
Total - Total number of people with major
Sample\_size - Sample size (unweighted) of full-time, year-round ONLY (used for earnings)
Men - Male graduates

```
Women - Female graduates
ShareWomen - Women as share of total
Employed - Number employed (ESR == 1 or 2)
Full_time - Employed 35 hours or more
Part_time - Employed less than 35 hours
Full_time_year_round - Employed at least 50 weeks (WKW == 1) and at least 35 hours
(WKHP >= 35)
Unemployed - Number unemployed (ESR == 3)
Unemployment_rate - Unemployed / (Unemployed + Employed)
Median - Median earnings of full-time, year-round workers
P25th - 25th percentile of earnings
P75th - 75th percentile of earnings
College_jobs - Number with job requiring a college degree
Non_college_jobs - Number with job not requiring a college degree
Low_wage_jobs - Number in low-wage service jobs
```

I will be studying multiple variables like Major, Full\_time, Part\_time, Men, Women etc.

## Data cleanup

```
library("readxl")
library(tidyverse)
## — Attaching packages -
                                                                 tidyverse
1.3.2 -
                        ✓ purrr
## √ ggplot2 3.3.6
                                   0.3.4
## √ tibble 3.1.8
                        √ dplyr
                                   1.0.10
## √ tidyr

√ stringr 1.4.1

             1.2.1
## √ readr
             2.1.2

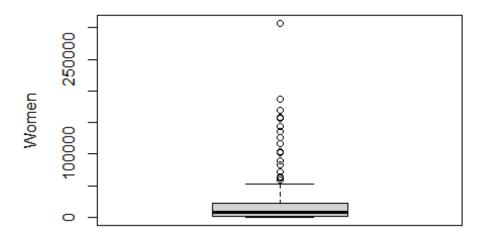
√ forcats 0.5.2

## — Conflicts
tidyverse conflicts() —
## X dplyr::filter() masks stats::filter()
## X dplyr::lag()
                     masks stats::lag()
setwd("C:\\Users\\Meghna\\OneDrive\\Documents\\Fall'22\\ISO-201\\project
proposal\\")
raw data <- read excel("data1.xlsx")</pre>
sum(is.na(raw data))
## [1] 4
```

Let's identify outliers and remove them

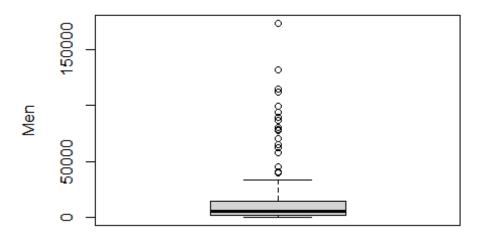
```
#finding outliers in women
women_outliers <- boxplot(raw_data$Women,
   ylab = "Women",
   main = "Boxplot of number of women in graduate studies")$out</pre>
```

# Boxplot of number of women in graduate studies



```
#finding outliers in men
men_outliers <- boxplot(raw_data$Men,
  ylab = "Men",
  main = "Boxplot of number of men in graduate studies")$out</pre>
```

# Boxplot of number of men in graduate studies



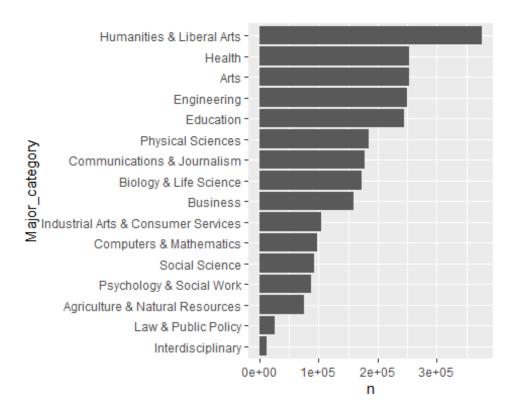
```
#removing women outliers
data <- raw_data
data <- data[-which(data$Women %in% women_outliers),]
#removing men outliers
data <- data[-which(data$Men %in% men_outliers),]</pre>
```

## **Exploratory Data Analysis**

#### **Data visualization**

Let's find out which is the most common major

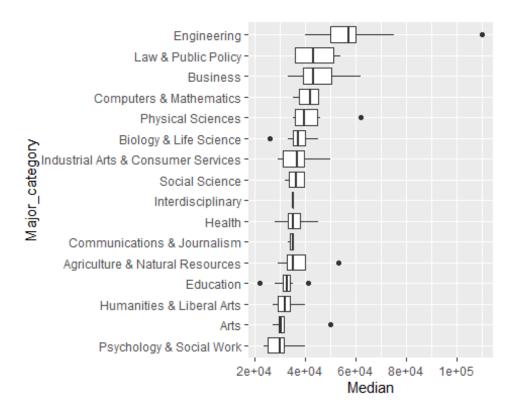
```
data %>%
  count(Major_category, wt = Total, sort = TRUE) %>%
  mutate(Major_category = fct_reorder(Major_category,n)) %>%
  ggplot(aes(Major_category,n)) +
  geom_col() +
  coord_flip()
```



We can see that Humanities & Liberal Arts is the most common major and Interdisciplinary is the least common major.

Now, let's see which major category has the highest salary

```
data %>%
  mutate(Major_category = fct_reorder(Major_category, Median)) %>%
  ggplot(aes(Major_category, Median)) +
  geom_boxplot() +
  coord_flip()
```



From the above plot we can understand that

- 1. Engineering students get the highest salary with median salary being around \$58,000.
- 2. Law & Public Policy students get second highest salary after Engineering students with median salary being \$42,000.
- 3. Psychology & Social work students get the lowest salary with median salary being around \$30,000.

Now, let's see which major has the highest salary

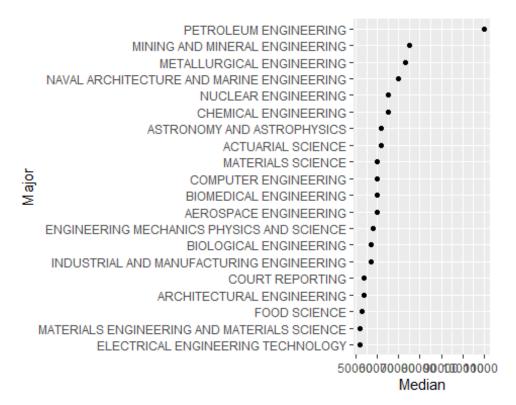
```
top_majors <- head(</pre>
  arrange(
     data,
     desc(data$Median)
  ), n=3
)
top_majors
## # A tibble: 3 × 21
       Rank Major ...¹ Major Total
                                           Men Women Major...<sup>2</sup> Share...<sup>3</sup> Sampl...<sup>4</sup> Emplo...<sup>5</sup>
##
Full ...6
                 <dbl> <chr> <dbl> <dbl> <dbl> <chr>
##
      <dbl>
                                                                    <dbl>
                                                                              <dbl>
                                                                                        <dbl>
<dbl>
## 1
                  2419 PETR... 2339
                                         2057
                                                  282 Engine...
                                                                    0.121
                                                                                  36
                                                                                          1976
1849
           2
                                                   77 Engine...
## 2
                  2416 MINI...
                                   756
                                           679
                                                                    0.102
                                                                                   7
                                                                                           640
556
```

```
## 3  3  2415 META... 856 725 131 Engine... 0.153  3  648
558
## # ... with 10 more variables: Part_time <dbl>, Full_time_year_round <dbl>,
## # Unemployed <dbl>, Unemployment_rate <dbl>, Median <dbl>, P25th <dbl>,
## # P75th <dbl>, College_jobs <dbl>, Non_college_jobs <dbl>,
## # Low_wage_jobs <dbl>, and abbreviated variable names ¹Major_code,
## # "Major_category, ³ShareWomen, ⁴Sample_size, ⁵Employed, ⁶Full_time
```

We can see that Petroleum engineering has the highest median salary followed by mining and mineral engineering and then metallurgical engineering.

We can also plot this

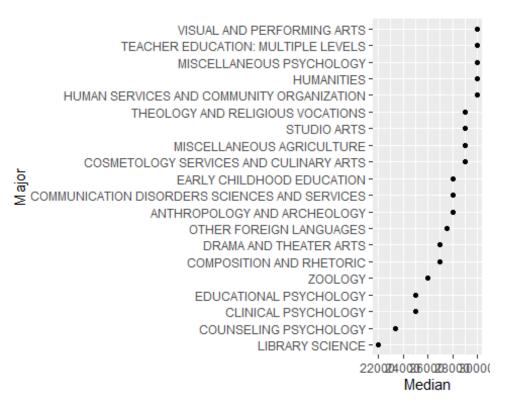
```
data %>%
    arrange(desc(data$Median)) %>%
    select(Major, Median) %>%
    head(20) %>%
    mutate(Major = fct_reorder(Major, Median)) %>%
    ggplot(aes(Major, Median)) +
    geom_point() +
    coord_flip()
```



From the above graph too we can see that Petroleum engineering has the highest median salary.

Now, let's see some of the lowest earning majors

```
data %>%
    arrange(desc(data$Median)) %>%
    select(Major, Median) %>%
    tail(20) %>%
    mutate(Major = fct_reorder(Major, Median)) %>%
    ggplot(aes(Major, Median)) +
    geom_point() +
    coord_flip()
```



From the above graph we can conclude that library science has the lowest earning.

# **Questions for next stage**

- 1. Does engineering has more graduated men than women?
- 2. Does engineering jobs require most number of college degrees?