STAT340 Final Report: Gender Base Salary Gap in STEM Field

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Abstract

Today, women earn approximately 82 cents for every dollar earned by a man(Carlton, G., 2021, The biggest barriers for women in STEM). However, a report from Scientific American shows that in the STEM field, males and females have approximately equal average base salaries (Ceci et al., 2015, Scientific American). Unlike other working fields, it seems that the gender salary gap in STEM fields is the least obvious. However, during our research and feedback from our friends, it seems that there still exists some salary gap in gender. Also, we found that in the STEM field, other factors such as regions, employee' education backgrounds, etc. also seem correlated with base salaries. Therefore, we want to figure out whether there truly exists gender differences in the STEM field, and if there exists, does such difference correlate with other factors like regions, job positions, different kinds of companies, etc? Based on these questions, our data is mainly focusing on the different personal situations and different salaries of employee in the STEM fields. Based on our research, we find that there still exists gender base salary gap in STEM field, and such gender base salary gap also depends on factors like regions (at state level), Job titles (positions) and Companies.

Dataset descriptions

We use two data sets in total for this project.

Dataset1: Data Science and STEM Salaries

The URL for this data set: https://www.kaggle.com/jackogozaly/data-science-and-stem-salaries

This data set was scraped off levels.fyi by Jack Ogozaly. levels.fyi is a website that lets you compare career levels & compensation packages across different tech companies, and is generally considered more accurate in terms of actual tech salaries relative to other compensation sites like glassdoor.com. We use this dataset because this dataset has most information we want: base salary, gender, company, location, races, and other useful features of an employee. We can easily use these information to compare median base salary differences in gender and compare such difference based on other factors. With this data set, we can answer our research questions more easily and efficiently.

Description of this dataset: This dataset contains 62,000 salary records from top STEM companies like Amazon, Apple, Google, SpaceX, etc. For each salary record, it contains the company that employee works for, job titles and positions, base salary, total year salary, gender, race, and other useful information. We can use this data set to analyze the base salary situation for workers in these companies based on all the features we have.

Variables :

- Timestamp: When the data was recorded.
- Company: The company name where the employee works (Google, Facebook, etc)
- Level: What level the employee is at.
- Title: Role title.
- Total yearly compensation: Total yearly compensation.
- Location: Job location.
- Years of experience: Years of Experience.
- Years at company: Years of experience at said company.
- Tag: Job type
- Base salary: Base salary an employee earned in a year
- Stock grant value: The equivalent value for the stocks the employee received.
- Bonus: These bonuses could be in the form of a lump sum cash payment, increment cash payments, stock options, or even an added vacation, we only count the bonus in dollar amounts here.
- Gender: gender identity of employee (male, female or other)
- Other details: Other details for the employee
- City id: The id for the city where the employee works
- Dmaid: Designated Market Areas (DMAs) delineate the geographic boundaries of 210 distinctive regions to assess TV penetration of audience counts within the U.S. for a viewership year.
- Row Number: row number of the data entry
- Masters_Degree: Whether the employee has a Master Degree (1: Yes, 0: No)
- Bachelors_Degree: Whether the employee has a Bachelor Degree (1: Yes, 0: No)
- Doctorate_Degree: Whether the employee has a Doctor Degree (1: Yes, 0: No)
- Highschool: Whether the employee has a High school Degree (1: Yes, 0: No)
- Some_College: if the employee has education limited to some college education.
- Race_Asian: if the employee is asian (1: Yes, 0: No)
- Race_White: if the employee is white (1: Yes, 0: No)
- Race_Two_Or_More: if the employee has two or more races. (1: Yes, 0: No)
- Race_Black: if the employee is black (1: Yes, 0: No)
- Race_Hispanic: if the employee is hispanic (1: Yes, 0: No)
- Race: Racial identity of the employee
- Education: the Education level of employee

Dataset2: Cost of Living Index by State 2021

The URL for this data set: https://worldpopulationreview.com/state-rankings/cost-of-living-index-by-state

This dataset is gathered by World Population Review website, which allows us to compare the cost of living index for different states. We used this dataset because the cost of living in some states like CA, WA, NY and MA are very expensive and many tech companies are based there. So, the base salaries in those regions will likely be higher, and this may negatively impact our regression model if we use state as one possible predictor. Therefore, to best predict base salary of different states and minimize such effects, we plan to add the cost of living index by state variable as an additional predictor.

Description of this dataset: This data set contains the cost-of-living-index for each state in America. It also contains the cost index in sub living categories like Grocery, Housing, Utilities, and etc.

Variables:

- Cost Index: The overall cost of living index for each state in America, the higher the index is, the higher overall living expense in that state.
- Grocery: The cost of index in Grocery category for each state in America
- Housing: The cost of index in Housing category for each state in America
- Utilities: The cost of index in Utilities category for each state in America
- Transportation: The cost of index in Transportation category for each state in America
- Misc: The cost of index in misc category for each state in America

Statistical Questions:

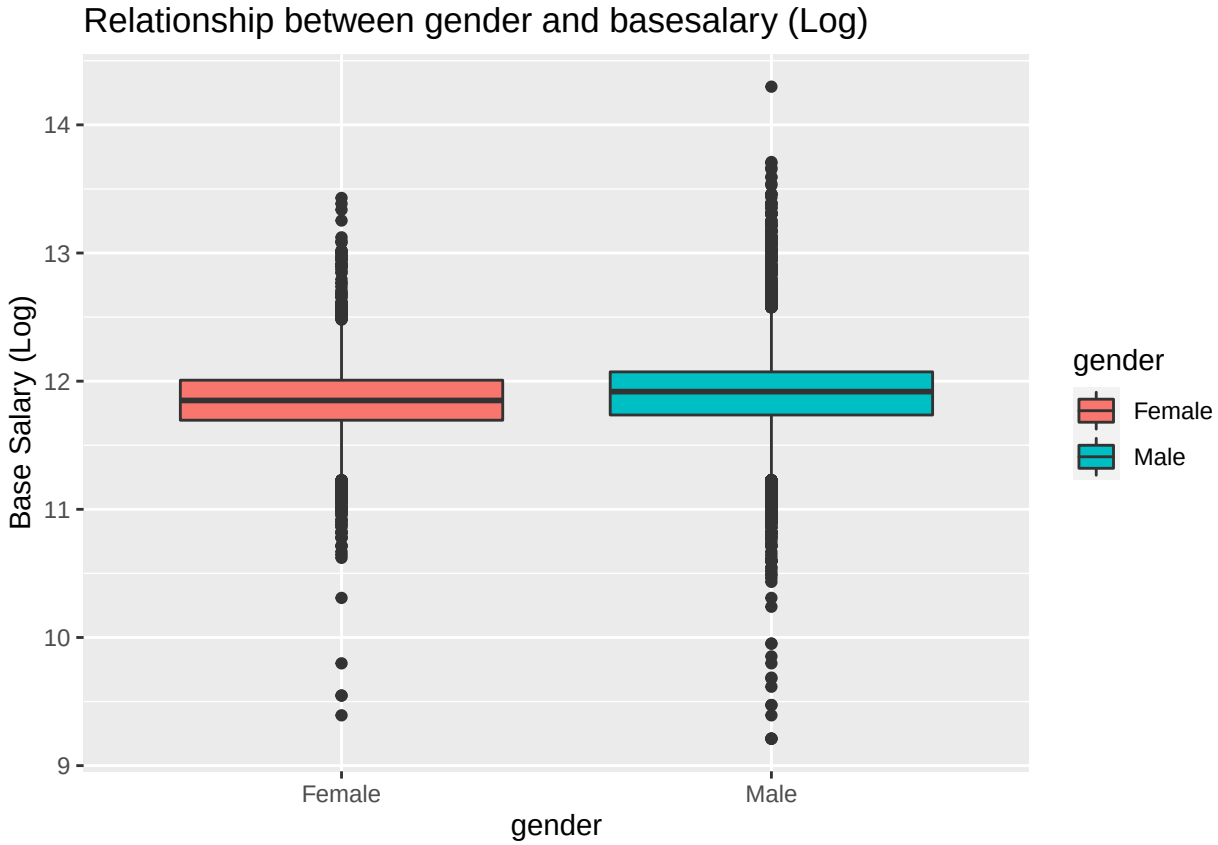
Main question: Is there a gender gap in income level(base salary) in the STEM fields? Does the difference vary depending on other factors (e.g., education, subfields, companies, regions, etc.)?

Process and part summaries:

Because our data set may contain outliers (i.e Some CEOs and employees may have extremely high base salaries), so instead of using average base salary, we focus on the median base salaries.

At first, we want to find out whether there truly exists gender gap in base salary, so we draw a box plot to show the median 'basesalary' (in logarithm) of males and females. We use logarithm to better visualize the difference

```
## Warning: Removed 823 rows containing non-finite values (stat_boxplot).
```



According to the above plot, It seems that the median base salary of females is only slightly lower than males' base salary. Therefore, we cannot tell whether males and females truly have different median base salary in STEM fields, so we conduct some hypothesis tests to verify what is shown in the plot.

Our null hypothesis is $H_0 : Median\_Salary_{male} = Median\_Salary_{female}$

The alternative hypothesis is $H_1 : Median\_Salary_{male} \neq Median\_Salary_{female}$

First, we conduct a two sample wilcoxon test, a test focus on testing the median of dataset, and the test result shows as follows:

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  basesalary by gender
```

```
## W = 78023286, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
```

The p value of the test result is smaller than 2.2e-16, which is much smaller than 0.01 and is highly significant. We have strong statistical evidence to reject the null hypothesis in favor of the conclusion that the median base salary for males and females are not the same.

We also apply the Monte carol testing to test the null hypothesis. Firstly, we adapt the permutation testing approach by randomly assign the base salary data into male group and female groups, and compare their medians, store the median base salary difference as an element in a list Replicate. Then we repeat the above step 1000 times and use all elements in Replicate to generate a 95% confidence interval. Finally we test whether the true median base salary difference is in the confidence interval.

Base on the Monte carol testing, our 95% confidence interval is

```
##       2.5%      97.5%
## -3736.0921  -335.7574
```

and the true median base salary difference is `-9000`, which is not in the confidence interval. Therefore, we can reject the null hypothesis that the median base salary of males and females are the same.

Based on the hypothesis tests, we find that in STEM fields, there truly exists gender base salary gap, which answers our first questions. So our next step is to consider whether the base salary difference vary depending on other factors.

Firstly, we want to figure out what factors are correlated to the base salary of employees in STEM field, so we fit a linear regression model to predict base salary of employees.

Throwing every state into the model as a predictor is not a great approach here, so we select some variables rather than just throwing them all into a model. Certainly, many of these states will have an effect– CA, WA, NY and MA have higher cost of living and many tech companies are based there, so the median base salary will be higher (both due to cost of living and to having more management roles).Therefore, we only include some states as predictors and include cost of living data about different states in our linear regression model.

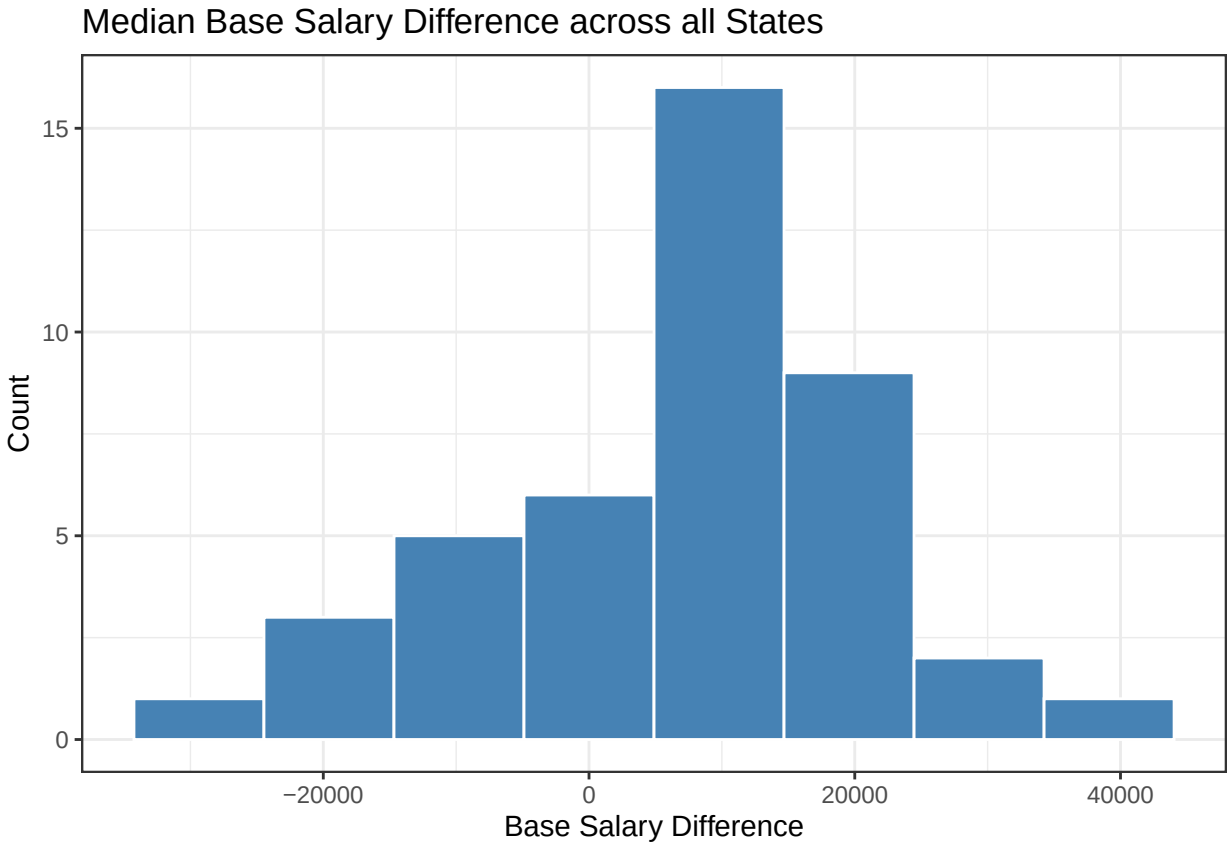
```
##
## Call:
## lm(formula = basesalary ~ 1 + gender + yearsofexperience + yearsatcompany +
##     title + costIndex + select_location, data = filted_data1)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -283438  -16751    -520   17545 1465795
##
## Coefficients:
##                                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)                       68076.34    6580.81  10.345  < 2e-16 ***
## genderMale                         4393.94     653.07   6.728 1.75e-11 ***
## yearsofexperience                  4164.22      50.35  82.705  < 2e-16 ***
## yearsatcompany                    -1172.31      84.91 -13.806  < 2e-16 ***
## titleData Scientist               37401.70    2518.52  14.851  < 2e-16 ***
## titleHardware Engineer            21948.06    2547.58   8.615  < 2e-16 ***
## titleHuman Resources               5517.14    4044.36   1.364   0.1725
## titleManagement Consultant        29899.03    3051.51   9.798  < 2e-16 ***
## titleMarketing                    13612.14    3214.42   4.235 2.29e-05 ***
## titleMechanical Engineer           7527.91    3501.60   2.150   0.0316 *
## titleProduct Designer             22879.43    2643.71   8.654  < 2e-16 ***
## titleProduct Manager              28902.10    2394.42  12.071  < 2e-16 ***
## titleRecruiter                    -3448.79    3649.02  -0.945   0.3446
```

```
## titleSales                           -2299.17    3945.52  -0.583   0.5601
## titleSoftware Engineer               28990.88    2246.74  12.904  < 2e-16 ***
## titleSoftware Engineering Manager    41936.64    2482.35  16.894  < 2e-16 ***
## titleSolution Architect              16420.17    2920.32   5.623 1.89e-08 ***
## titleTechnical Program Manager       23118.43    2762.72   8.368  < 2e-16 ***
## costIndex                              238.82      40.69   5.869 4.42e-09 ***
## select_locationMA                   -24172.87    1576.99 -15.329  < 2e-16 ***
## select_locationNY                    -1418.84    1015.19  -1.398   0.1622
## select_locationOther                -27458.47    2213.71 -12.404  < 2e-16 ***
## select_locationWA                    -7984.16    1777.23  -4.492 7.06e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 44800 on 34967 degrees of freedom
## Multiple R-squared:  0.2978, Adjusted R-squared:  0.2974
## F-statistic: 674.1 on 22 and 34967 DF,  p-value: < 2.2e-16
```

According to the regression model, males are more likely to have a higher base salary, and some job titles, years of experiences also affect the base salary of employees. Also, it seems like state location indeed affects the employees' salary (some state location is significant to the base salary, and cost of living also make the contribution of the base salary).

Based on the regression model, we want to figure out whether the gender base salary gap vary in factors like job titles, locations (in state level) and companies.

First we focused on the location factors, we want to figure out whether regions (at state level) influence the base salary difference of males and females. We compute the base salary difference for each state and make the following frequency plot.



The overall histogram shows that the values range from around -20000 to near 40000 with a normal distribution, which means for many states, median base salary for males is 10 thousand dollars greater than females, but there are also plenty of states that have larger base salary differences and some states have smaller base salary differences. Therefore, it seems that at the state level, there exists base salary differences of males and females.

To verify there exists base salary differences of males and females at state level, we conduct a chi-squared test to verify it. If there is no obvious gender base salary gap at state level, the standard deviation of the base salary difference should be very small (close to 0).

Our null hypothesis is H_0 : No obvious gender gap in base salary at state level.

and alternative hypothesis is H_1 : There exists gender gap in base salary at state level.

```
##
##  Chi-Squared Test on Variance
##
## data:  state_rela$sal_diff
## Chi-Squared = 8.5671e+13, df = 42, p-value < 2.2e-16
## alternative hypothesis: true variance is greater than 1e-04
## 95 percent confidence interval:
##  147393688       Inf
## sample estimates:
##  variance
## 203978959
```

According to the chi-squared test, the p-value is smaller than `2.2e-16`, which means that we can reject our null hypothesis that there is no obvious gender gap in base salary at state level.

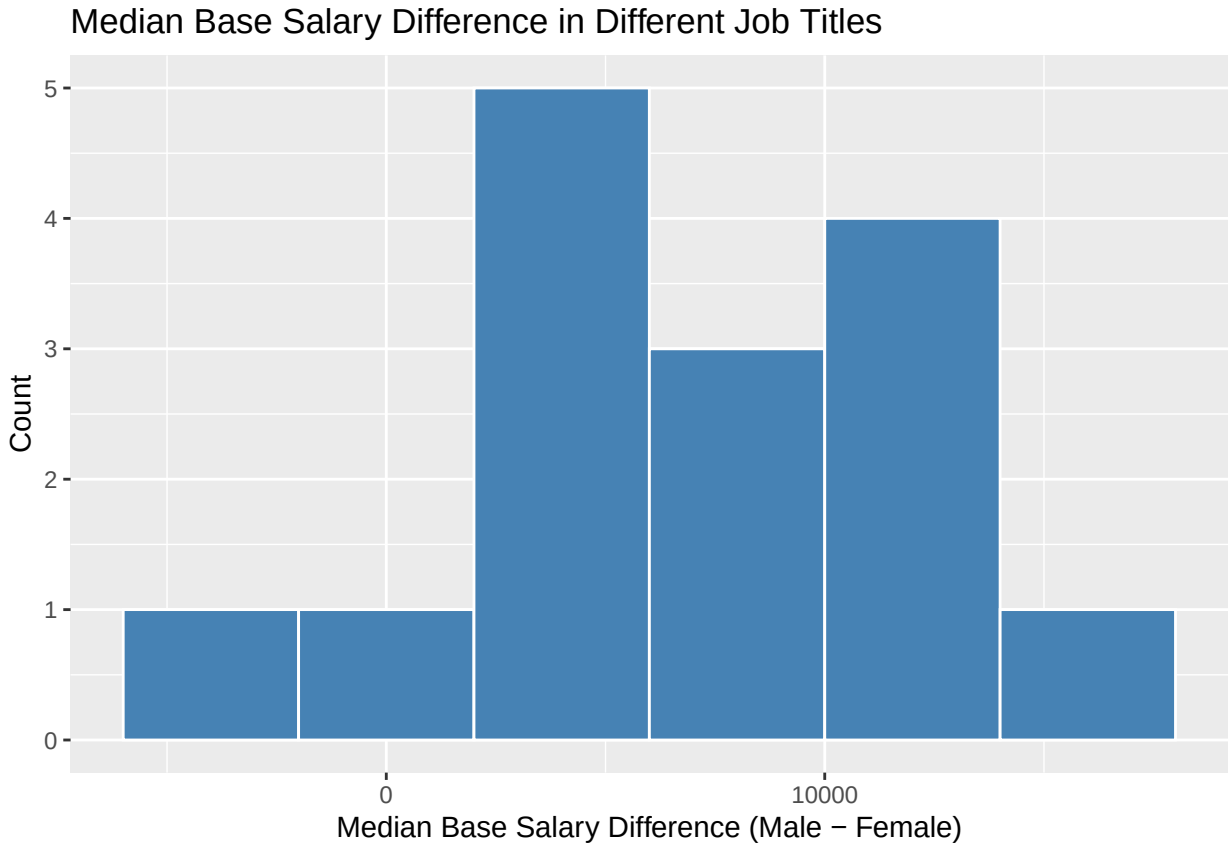
Then we want to figure out which states have gender gap in base salary, and which states do not. So for each state, we conduct a two sample wilcoxon test to test whether the median base salary of male and female in that state is equal.

According to the results of our wilcoxon test, we find that there are 9 tests for 9 states reject our null hypothesis that there are no base salary difference. And data from other 34 states cannot reject the null hypothesis. States that reject the null hypothesis are as follows:

```
##   Row State      P_Value significant
## 1   1    CA 8.330696e-38        TRUE
## 2   2    WA 3.004607e-33        TRUE
## 3   3    MA 1.390441e-05        TRUE
## 4   4    NY 2.182609e-19        TRUE
## 5   6    OR 4.728207e-04        TRUE
## 6  13    TX 1.493283e-02        TRUE
## 7  14    MN 3.346728e-02        TRUE
## 8  18    NC 4.118402e-03        TRUE
## 9  22    FL 9.473036e-03        TRUE
```

Therefore, at least based on our data and test results, there is obvious evidence that CA, WA, MA, NY, OR, TX, MN, NC, and FL have gender base salary gap, which means the the base salary difference in gender are vary related to location.

Secondly, we want to figure out whether job title is a factor of gender base salary gap in STEM field. Is there any difference in gender gaps for different job positions?



From this histogram, we can see that for most job titles, male workers have a higher median base salary than female workers. For some job titles like Data Scientist, Recruiter, the difference is very small. For Management Consultant, Human resources, and Sales, the difference is relatively large. Therefore, it seems that, within each job title, there exists base salary differences of males and females.

To verity that base salary differences of males and females in each job title is not the same, we conduct a chi-squared test to verity it. If there is no obvious gender base salary gap in each job level, the standard deviation of the base salary difference should be very small. And we consider the a standard deviation less than 500 to be small.

Our null hypothesis is H_0 : No obvious gender base salary gap difference between each job title

The alternative hypothesis is H_1 : There exists gender base salary gap difference between each job title

```
##
##  Chi-Squared Test on Variance
##
## data:  gap$basesalary
## Chi-Squared = 761000, df = 14, p-value < 2.2e-16
## alternative hypothesis: true variance is greater than 500
## 95 percent confidence interval:
##  16065162      Inf
## sample estimates:
## variance
## 27178571
```

According to the chi-squared test, because the p-value is smaller than `2.2e-16`, which means the we can reject the null hypothesis that there is no obvious gender base salary gap difference between each job title.

Then we want to figure out how big the gender gap in base salary for different job titles. So for each job title,

we conduct a two sample wilcoxon test to test whether the median base salary of male and female with that job title is equal. Then we show the test result as follows:

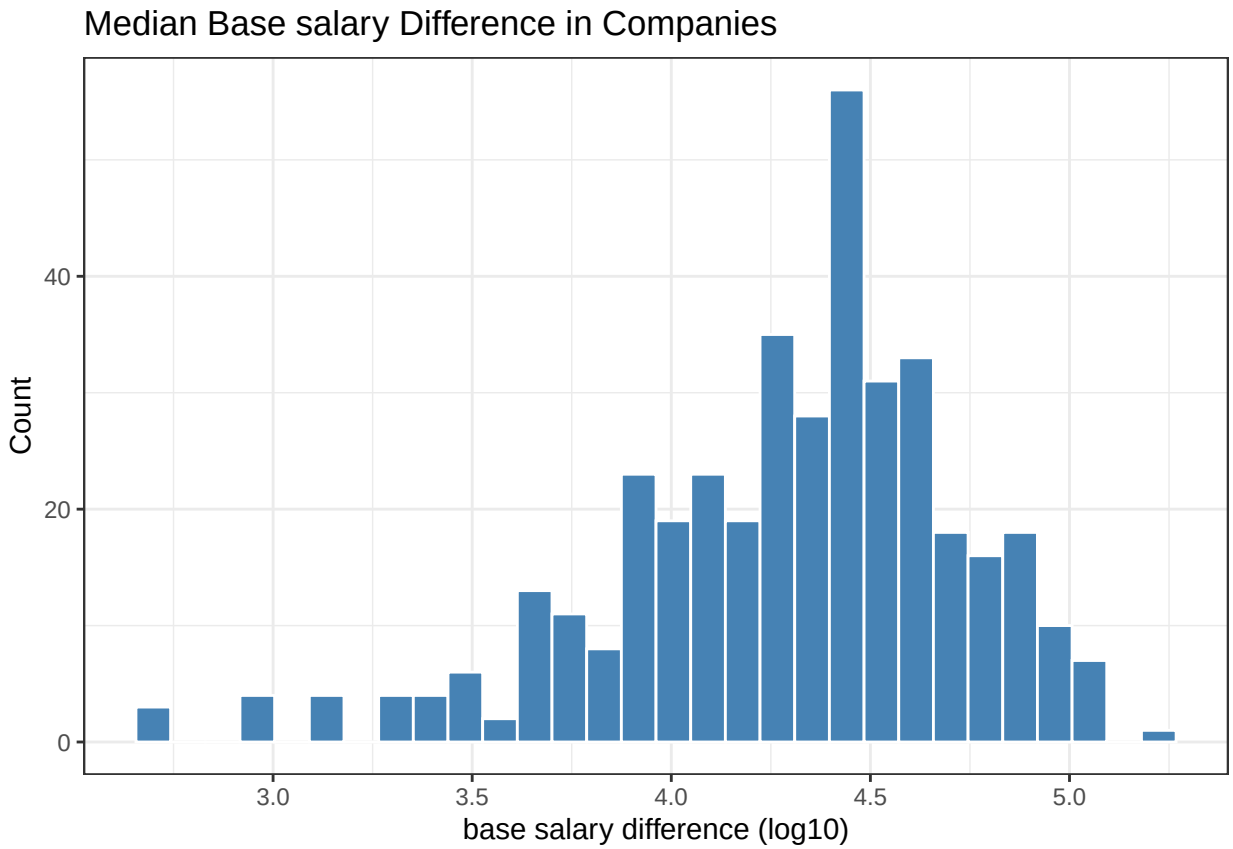
```
##    Row                    Job_Title      P_Value significant
## 1    1             Business Analyst 1.833379e-01       FALSE
## 2    2               Data Scientist 1.294007e-01       FALSE
## 3    3            Hardware Engineer 3.711855e-02       FALSE
## 4    4              Human Resources 5.569707e-02       FALSE
## 5    5        Management Consultant 1.796622e-02       FALSE
## 6    6                    Marketing 1.501460e-02       FALSE
## 7    7          Mechanical Engineer 7.165900e-01       FALSE
## 8    8             Product Designer 1.347460e-05        TRUE
## 9    9              Product Manager 2.052063e-13        TRUE
## 10  10                    Recruiter 5.036747e-01       FALSE
## 11  11                        Sales 5.107261e-01       FALSE
## 12  12            Software Engineer 2.458608e-26        TRUE
## 13  13 Software Engineering Manager 8.542828e-02       FALSE
## 14  14           Solution Architect 7.946010e-03        TRUE
## 15  15    Technical Program Manager 1.802876e-03        TRUE
```

According to the results of our wilcoxon test, we find that we can reject the null hypothesis (Male workers have the same median base salary as female workers with the same job title) for 5 job titles. For the rest 10 job titles, we cannot reject the null hypothesis.

```
##   Row                 Job_Title      P_Value significant
## 1   8          Product Designer 1.347460e-05        TRUE
## 2   9           Product Manager 2.052063e-13        TRUE
## 3  12         Software Engineer 2.458608e-26        TRUE
## 4  14        Solution Architect 7.946010e-03        TRUE
## 5  15 Technical Program Manager 1.802876e-03        TRUE
```

In conclusion, gender gap presents differently in different job titles and in some jobs, there might not be a gender gap. From the above histogram and wilcoxon test, we find that there is strong evidence that gender gap exists in employees with job title "Product Designer", "Product Manager", "Software Engineer", "Solution Architect", and "Technical Program Manager".

Furthermore, we focused on the companies factors, we want to discover whether companies have influence on the base salary difference of males and females. The plot follows the same logic as above-we count the number of companies which has base salary difference according to gender.



At this level, we can observe there are significant base salary differences between males and females in most companies. Next step we will test how many companies are in the confidence interval.

```
##    company              Male           Female          sal_diff
##  Length:614         Min.   :     0   Min.   :     0   Min.   :-174000
##  Class :character   1st Qu.:116625   1st Qu.:103000   1st Qu.:  -7375
##  Mode  :character   Median :138000   Median :129000   Median :  10000
##                     Mean   :139286   Mean   :128192   Mean   :  11094
##                     3rd Qu.:161000   3rd Qu.:150000   3rd Qu.:  28500
##                     Max.   :455000   Max.   :405000   Max.   : 167500
##        x           Sign_diff
##  Min.   :   2.00   Mode :logical
##  1st Qu.:   5.00   FALSE:568
##  Median :   9.00   TRUE :46
##  Mean   :  54.35
##  3rd Qu.:  27.00
##  Max.   :4612.00
```

First, we assume that the base salary difference between men and women is zero in all companies, which means that the base salary difference is closer to zero, the more fair the base salary between men and women is. Next, we let zero be central to the confidence interval because we want this confidence interval to capture the companies that have smaller salary differences of gender.

```
##        company    x Sign_diff
## 20      AMAZON 4612     FALSE
## 349  MICROSOFT 3101     FALSE
## 239     GOOGLE 2574     FALSE
## 201   FACEBOOK 1872     FALSE
## 32       APPLE 1309     FALSE
```

```
## 397     ORACLE  660     FALSE
## 273      INTEL  622     FALSE
## 463 SALESFORCE  597     FALSE
## 114      CISCO  549     FALSE
## 262        IBM  531      TRUE
```

```
## # A tibble: 2 x 2
##   Sign_diff     n
##   <lgl>     <int>
## 1 FALSE       568
## 2 TRUE         46
```

According to the first 10 result of our test, we can see most companies are not captured by a confidence interval("FALSE" in "Sign_diff"), which means they have gender bias base salaries. And the test summarize shows only about ten percent of companies in the America are "TRUE" for "Sign_diff",which means they have fair base salary for male and female

Summary

Based on the hypothesis test at the beginning, we find that in STEM fields, there still exists gender gap in base salary. Next we examined whether the gender base salary difference vary depending on other factors. Based on the regression model, we figured out that the gender base salary gap have relationship to factors like job titles and locations (at state level). We also figured out whether companies influence the gender base salary gap. After we applying chi-squared test and wilcoxon test, we found that all these three factors indeed influence the gender base salary gap in STEM field.

- For the `job title` factor, evidence shows that gender gap exists in employees with job title `Product Designer`, `Product Manager`, `Software Engineer`, `Solution Architect`, and `Technical Program Manager`, for other job title, there is no clear evidence showing that there exists salary difference based on our data.
- For the `location (state)` factor, employees working in places like CA, WA, MA, NY, OR, TX, MN, NC, and FL clearly experience base salary bias and for employees in other states, the gender base salary gap is not very obvious.
- For the `company` factor, we let zero be central to the confidence interval to capture the companies that have smaller salary differences of gender. We found that over 90% companies have gender bias salaries, only companies such as `IBM`, `VMWARE` and `PAYPAL`, etc have fair salaries.

In conclusion, there exists a gender gap in income level(base salary) in the STEM fields, and such difference vary depending on other factors such as job titles, working state locations, working companies, etc.

Known Problems

Our data has 29 columns, and each data entry may have NA value in different columns. If we simply drop all the rows containing NA value would make our dataset super small. So we decided to only drop the rows with NA value in the 'gender' column, and for other columns, we will have some extra data cleaning before using them for different purposes.

Another issue is that there are some outliers in our dataset (some people with extremely high salary), including these data in our dataset might lead to a worse performance for linear regression models and other models.

Since there are a lot more males than females in the data set (female sample is 2/3 of the male sample), it could influence the accuracy of our estimated model. Data imbalance is not only a problem in classification task, but also in regression tasks. The performance of a regression model may suffer from the fact that the distribution of the target variable is not normally distributed and skewed. Applying transformations on the target variable can boost the performance.

Possible Future Questions

So far, we only determine that there exists a gender gap in income level(base salary) in STEM fields the difference vary depending on different location(states level), different job titles and different companies. However, we haven't quantified the gender gap in base salary, and we need to solve the problem of sample imbalance in our dataset. To deal with imbalanced data using these models, we have two options: first is to increase the representation of the observations of interest vs. the other observations (or vice versa). The second one is to adapt the model itself by parameter tuning based on customized criteria.

Besides, we plan to quantify the influential factors of gender gap in base salary we found and also conduct research on gender gap in other industry.

Therefore, our future steps includes dealing with the imbalance of our data set and possible future questions will be: Considering factors that influences gender base salary gap that we discovered, which states/job titles/companies have the most severe salary gap? What is the gender salary gap situation in non-STEM fields?

Reference

Carlton, G. (2021, February 22). The biggest barriers for women in STEM: BestColleges. BestColleges.com. Retrieved November 12, 2021, from https://www.bestcolleges.com/blog/barriers-for-women-in-stem/.

Stephen J. Ceci, Donna K. Ginther, Shulamit Kahn, Wendy M. Williams. (2015, January 1). Do Women Earn Less Than Men in STEM Fields? Scientific American. Retrieved December 04, 2021, from https://www.scientificamerican.com/article/do-women-earn-less-than-men-in-stem-fields/