
Bias Analysis in Human Resource System

-for Blacksaber Software in 2021

Report prepared for Black Saber Software by Data Over Flow

2021-04-21

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Executive summary

First, we would like to thank your company (Black Saber Software) for providing another opportunity to us (Data Over Flow Co. Ltd.). It has always been a pleasure working with your company.

As requested from your side, we have formed a team of three experienced analysts to work on this project. Specifically, the team examined the structure of the human resource system of your company by analyzing the provided data on the hiring, promotion and salary information. Our examination yielded the final conclusion that the hiring and remuneration processes are fair and based on talent and value to the company.

The key findings are:

- Even though there exists differences between the average salaries of male and female employees, the difference is not evidence of gender bias because multiple variables act as significant confounding variables between gender and salary.
- Among the three phases of recruitments, the chance of successfully landing the job is mostly dependent on other variables such as gpa and work experience. Gender is not found as a significant predicting variable for the chance of success during any of these phases. In other words, candidates with stronger background, talent and potential are selected, regardless of gender.
- The chances of being promoted is higher for male employees than for female employees, however (...)

The difference of salary shown in Figure(x) is due to factors other than gender. For example, men on average have higher seniority levels and hence are compensated with higher salary based on this higher added-value to the company. Candidates hired have a much higher gpa than those who did not get hired, as shown in Figure(x).

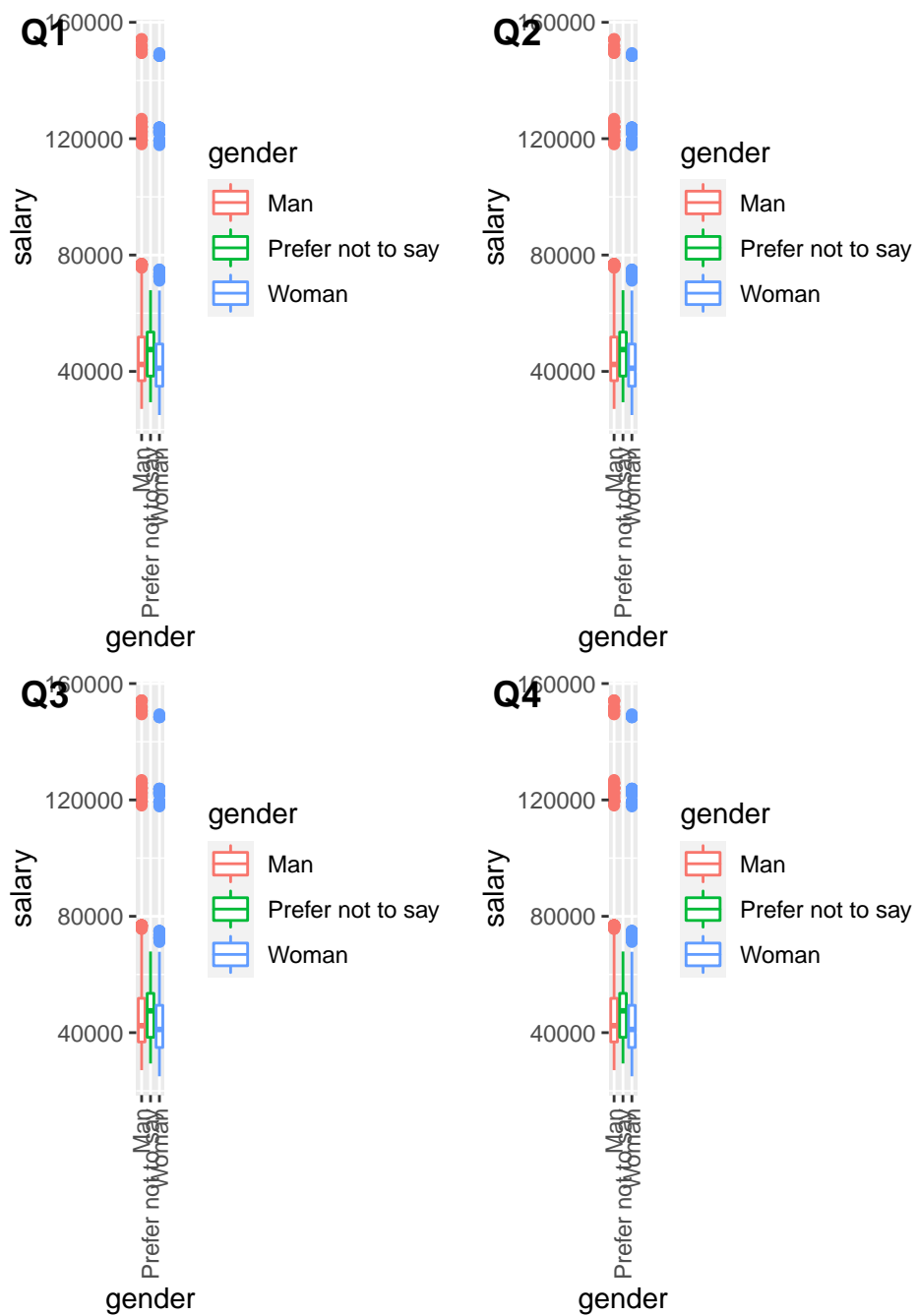


Figure 1: Salary Distribution for Men and Women in Each Quarter

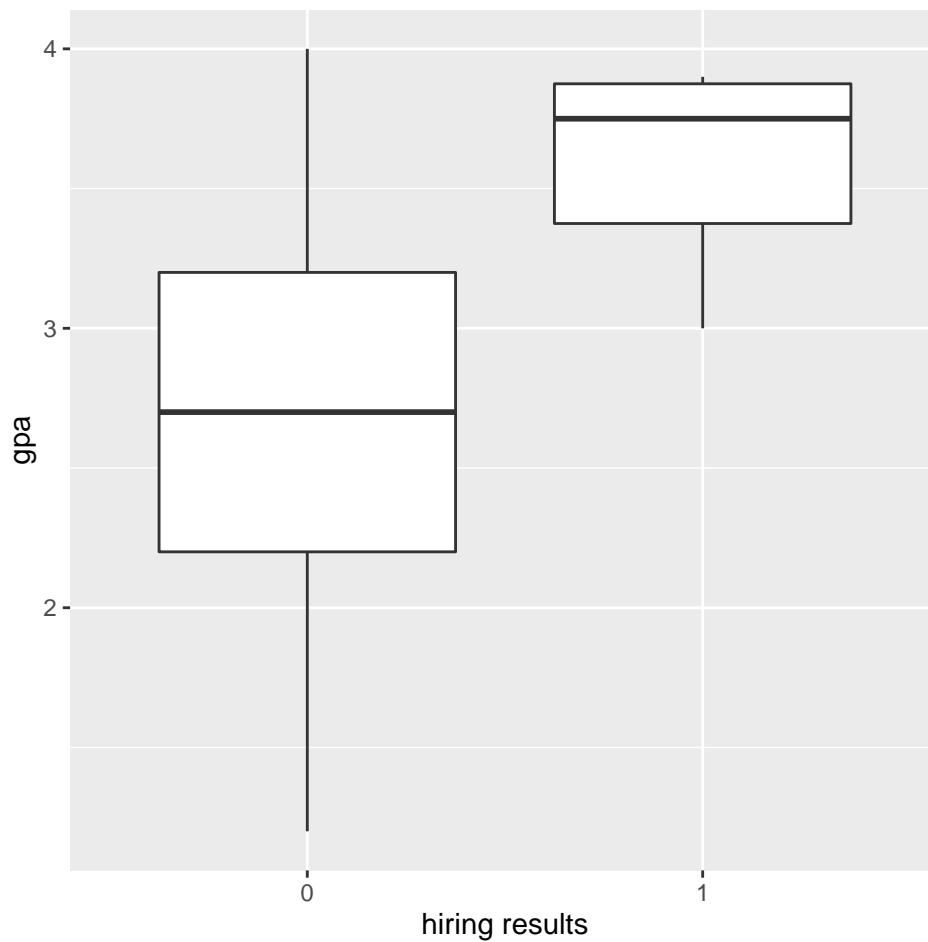


Figure 2: GPA Distribution Across Hiring Results

Based on our findings, we believe that the company is fair in terms of salary distributions for male and female employees. The hiring process empowered by the AI system is also recruiting the best talent without biasing on any gender. The promotion process is also determined by personal ability and contribution to the company. Any individual salary, promotion or hiring decision is made fairly based on non-gender and ability-related parameters only. Overall, Black Saber Software acts in accordance with the Ontario's Human Rights Code and Black Saber's policies.

Technical report

Introduction

We assessed the potential existence of bias from three different aspects: salary levels, hiring decisions, and promotions. We used a combination of model building and data visualization techniques to reach our conclusion that there is no bias in the company's hiring and remuneration processes. In the following report, "the company" refers to the Black Saber Software and "we" refers to the analysts from Data Over Flow. With no special notes, the assumed level of significance in this report is $\alpha = 0.05$.

Research questions

The three main research questions of the analysis are as follows:

- Is there a gender bias in the salary levels (remuneration) within the company?
- Is there a gender bias during the hiring processes of the company?
- Is there a gender bias in the promotion possibilities within the company?

Does there exist bias in current employee remuneration?

In order to analyze whether gender bias exists in the current employee remuneration, we fitted a linear mixed model as well as two general linear models on the dataset containing all current employees at the Black Saber Software. The dataset contains 6909 observations of 9 variables, including all 608 current employees of the Black Saber Software. Each observation records the information of a specific employee at a specific time (a given quarter in a given year). Based on data visualization outputs, the differences between different levels of juniors and seniors are not significant, thus we combined the positions "Entry-level", "Junior I", "Junior II" and "Junior III" into one category of "Junior" and combined "Senior I", "Senior II", "Senior III" into another category "Senior".

We consider salary as the key variable to measure employee remuneration and hence used it as the response variable. We want to assess whether an employee's salary is affected by his/her gender in order to detect the existence of bias. On top of that, we included other non-personal variables such as team information, financial quarter of the year and seniority of level which are key factors of salary level to reduce potential omitted variable bias between gender and salary. To incorporate both the fixed effects and the random effects of variables on the remuneration, we introduced the following linear mixed model:

$$y = X\beta + Zu + \epsilon \quad (1)$$

Linear mixed model considers the response variable y as a vector of observations with $E(y) = X\beta$. β is an unknown vector for the fixed effects and u is an unknown vector for the random effects. This model is appropriate when non-independence exists in the data. In our initial model, we consider gender, seniority, productivity, and the financial quarter as fixed effects. This is because we are interested in also observing each of these predictors' influence on salary. We treat team and leadership for level as random effects. This is because we are less interested in their effects on salary but we want to include them in the model to reduce influence caused by various groupings/levels. Note that random effects are included to work with multiple levels of correlated data. This allows the model to account for both the variability within random effect groups as well as between those groups, which is crucial because our data covers information across various time intervals and hierarchical corporate structure.

Given that our full model uses all factors, we tried to reduce the number of predictors to find the simplest model that incorporates all the relevant information. We first noticed that productivity is not a significant predictor in our full model, hence it is removed. Then, by attempting to drop predictors one by one and conducting likelihood ratio tests, we found that all other predictors beside "leadership" are significant. Thus, our final model dropped productivity and leadership_for_level as predictors and included all other predictors. The final model gives the following results:

Table 1: Statistics Summary for Reduced Salary Model

Variable	$\hat{\beta}$	Std. Error	p-value
intercept	116904.03	709.18	0.99
women	-2928.38	426.88	$6.06e^{-9}$
junior	-79703.19	342.56	$8.91e^{-7}$
manager	-50342.84	311.51	0.00
senior	-69910.72	323.8	0.01
vice-president	30024.17	498.25	$1.25e^{-12}$
quarter	74.31	28.28	0.01

Under this model, we predict a positive and statistically significant correlation between seniority level and salary. Given the baseline group as directors, it is reasonable to see any positions below director receives lower salaries and any positions above director receives higher salaries. There appears to be a difference between average salaries of males and females. More specifically holding all else constant, being female reduces the salary by 2953.78 on average. Prior to this model, we also considered the naive model that simply regresses gender on salary without

controlling for any variables. The effect found was that being women reduces one's salary by 2680.4. We see that this difference is larger now after eliminating many confounding variables. For further analysis, we fitted three general linear models to check the correlation amongst gender, productivity, and salary:

$$y_{productivity} = X\beta_{gender} + \epsilon \quad (2)$$

$$y_{salary} = X\beta_{gender} + \epsilon \quad (3)$$

$$y_{salary} = X\beta_{productivity} + \epsilon \quad (4)$$

According to 2, the average productivity of female employees is 1.46 times higher of male employees holding all other variables constant (p-value = 0.0001). 4 indicates a negative correlation between productivity score and salary level, or one unit increase in productivity leads to a decrease of 44.73 in salary. This is an interesting finding because it suggests that women tend to have higher productivity on average, which leads to lower salaries. This could be a potential sign of gender bias or compensation not in line with individual contribution. However, by analyzing the full model which takes multiple other variables into account, we realize that productivity is not a useful predictor for salary and hence this relationship between gender, productivity and salary is no longer valid considering other variables. Hence, there is no bias in which females work harder but get paid less.

Does there exist bias in the hiring process?

Moving on, we assessed the potential bias in the company's hiring process by using the hiring datasets. The hiring process contains three phases, where at each phase, different variables are examined by the human resources department to determine the successful applicants. Therefore we derived three different data sets from the original data provided and formed data of successful applicants at each phase. The response variable of interest is whether the candidate made it to the next phase, which is represented by a binary variable "final_hired", where 1 suggests hired and 0 suggests rejected. For this reason, we used general linear models with the family of binomials to model the hiring results. The model predicts p in ?? where p is the probability of event A that we are interested in, β_0 is the intercept, $x_1 \dots x_K$ are our variables of interest and $\beta_1 \dots \beta_k$ are parameters for each of these variables.

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k \quad (5)$$

At phase 1, we created the binary response variable “pass_phase1” to identify whether the candidate passed this phase or not. The predictor variables include gpa, whether the candidate has extracurricular experience, whether the candidate submitted a cover letter and whether the candidate has working experience. The results are summarized:

Table 2: Statistics Summary for Phase 1 Hiring Model

Variable	$\hat{\beta}$	Std. Error	p-value
intercept	-25.16	648.71	0.96
prefer not to say	0.16	0.85	0.84
women	-0.05	0.22	0.78
gpa	2.09	0.23	$< 2e^{-16}$
extra-curricular	0.29	0.21	0.17
cover letter	-18.68	648.7	0.97
work experience	0.76	0.27	0.01

According to $\alpha = 0.05$, only gpa and work experience are significant predictors to predicting whether the candidate passes the first phase, where both variables have a positive relationship with the chance of passing phase 1. It is expected that candidates with higher GPA and more work experience are selected because of higher talent. Notice that although the estimate is slightly negative for gender, it is not a significant predictor in this model.

At phase 2, we again created the binary response variable “pass_phase2” to indicate whether the candidate passed phase 2. The predicting variables include the team which candidate applied for, whether the candidate has extracurricular experience, whether the candidate has working experience, and three scores representing writing, speaking and technical skills. The results are summarized:

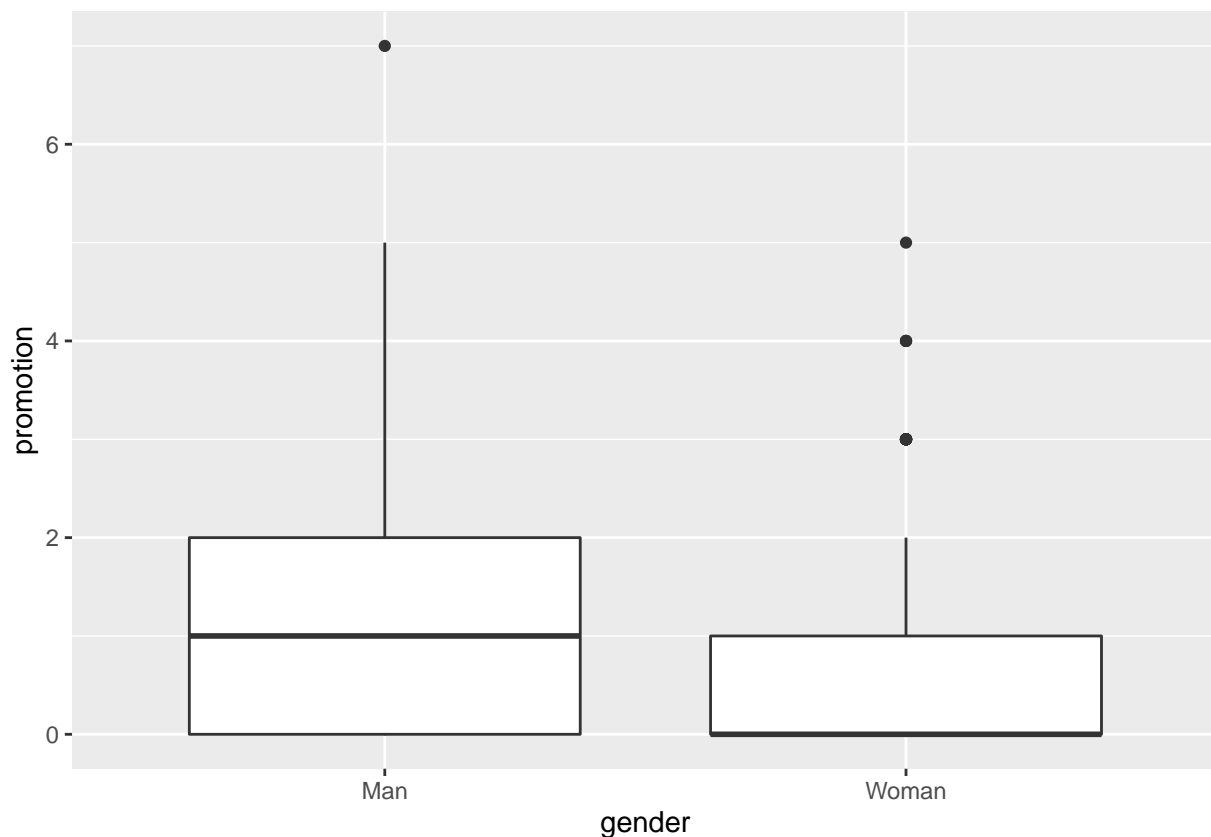
Table 3: Statistics Summary for Phase 2 Hiring Model

Variable	$\hat{\beta}$	Std. Error	p-value
intercept	-24.15	4.79	$4.77e^{-7}$
prefer not to say	1974.74	0.85	0.99
women	-0.63	0.79	0.42
team	1.4	0.76	0.06
extra-curricular	0.71	0.21	0.37
work experience	0.73	0.27	0.88
technical skills	0.02	0.27	$7.06e^{-5}$
writing skills	0.1	0.02	$9.93e^{-5}$
speaking skills	0.9	0.22	$9.13e^{-6}$
leadership presence	1.00	0.21	$3.73e^{-5}$

According to $\alpha = 0.05$, the significant predictors are technical skills, writing skills, speaking skills and leadership presence. We found that significant variables to pass-phase 1 are no longer significant. This is justified as candidates in this phase likely all have strong gpa and work experiences, hence the decision to move on will be based on the new information on skills and leadership. We notice that all three skills have positive and similar effect on the likelihood of passing this phase. Again, although the estimate for gender is negative, it is not statistically significant.

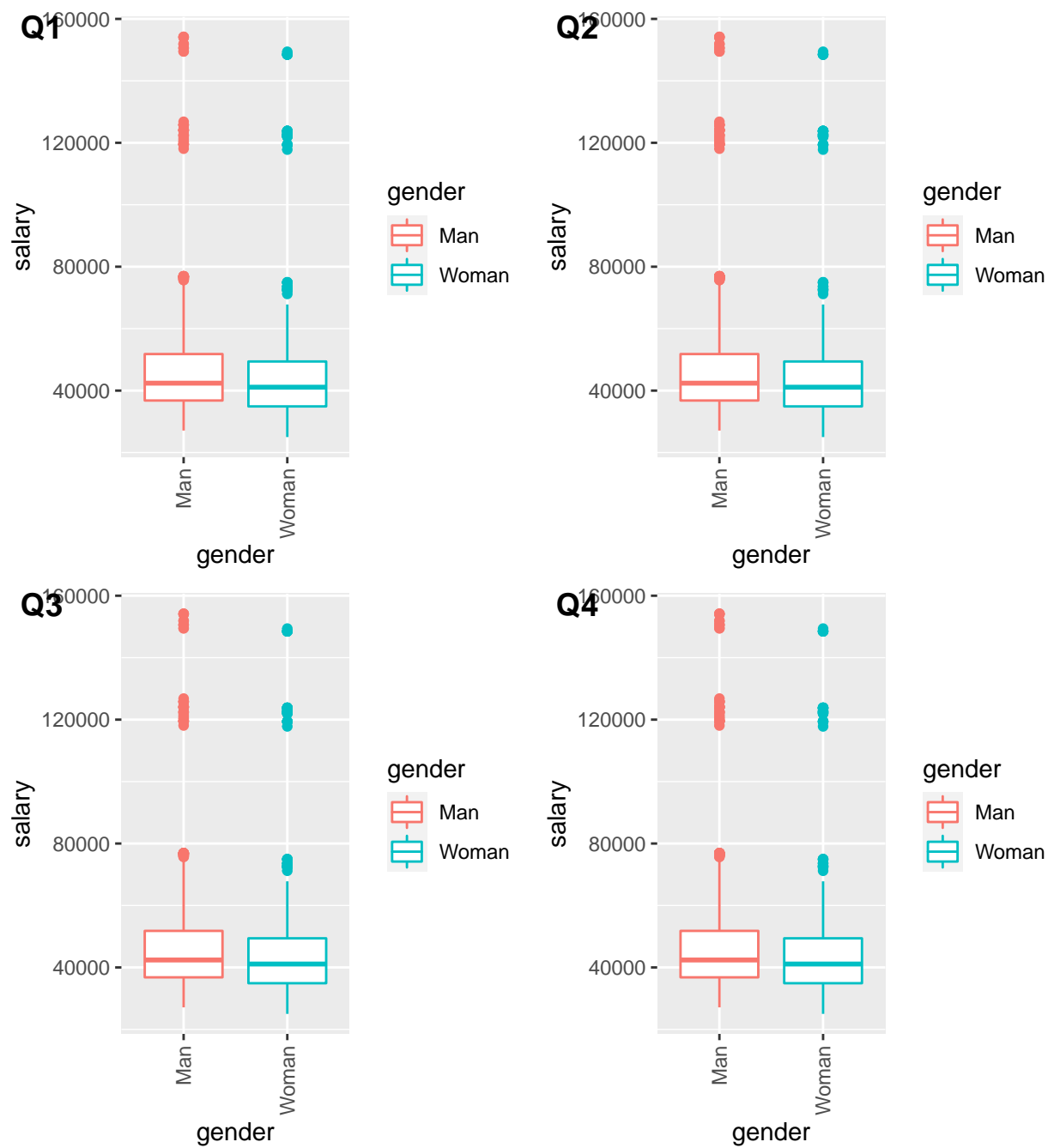
Last but not least, we use the phase 3 data to analyze the final hired candidates. “Final_hired” is the binary response variable indicating whether the candidate passed this phase or in other words, got hired. We also created the variable “avg” as the average of the candidate’s two interview ratings. Although the data size is limited, we still find that gender is not significant at this phase as well.

To conclude, we find that there is no gender bias during any of the phase of this hiring process. The candidates who pass each phase are the ones with stronger ability and talent, which is the fair decision to make during recruiting. We notice that the company is also not more biased on one skill out of writing, technical or speaking skills than others. This suggests Black Saber is also not having potential bias for candidates whose English may not be their first language and values talent equally.

Is there gender bias in the promotion process?**Figure 3:** The Number of Promotion By Gender

For the third research question, in order to examine the potential bias in promotion, we derived a promotion data set from the data on current employees. We counted the number of times each employee got promoted and made inference on this count using gender. We filtered out those who prefer not to disclose their gender in order to improve the accuracy of inference, which is fine because that is only 11 out of 608 employees. Figure 1 indicates the number of times being promoted across male and female employees. We observed that the median of promotion times for male is higher than the median for females: 1 for males and 0 for females. The employee being promoted the most is a male who got promoted 7 times.

We fitted a general linear model on the promotion data set using gender as a predictor for the number of times being promoted. The result indicates that female employees is promoted less than male employees, however(...)

Data Visualization**Figure 4:** Salary Distribution for Men and Women in Each Quarter

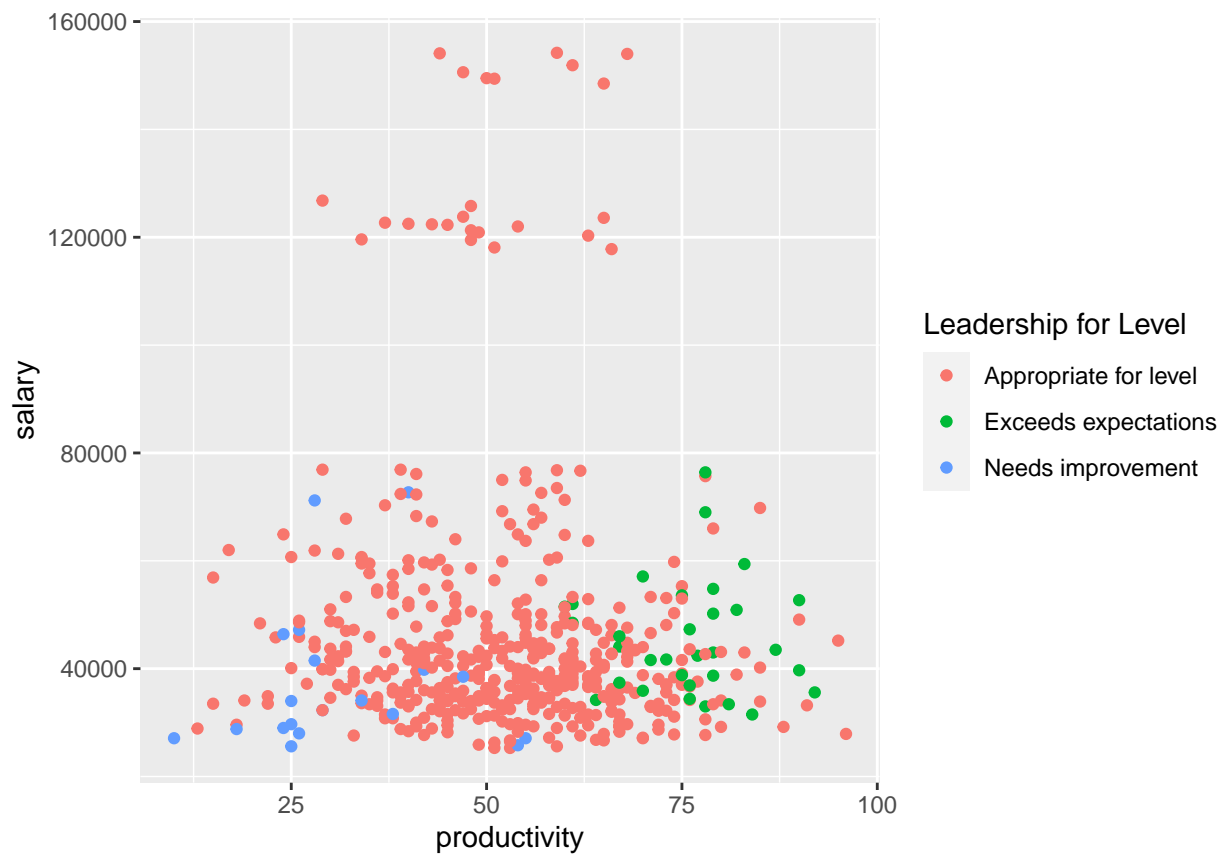


Figure 5: Salary Difference Across Leadership for Level Fixing Productivity

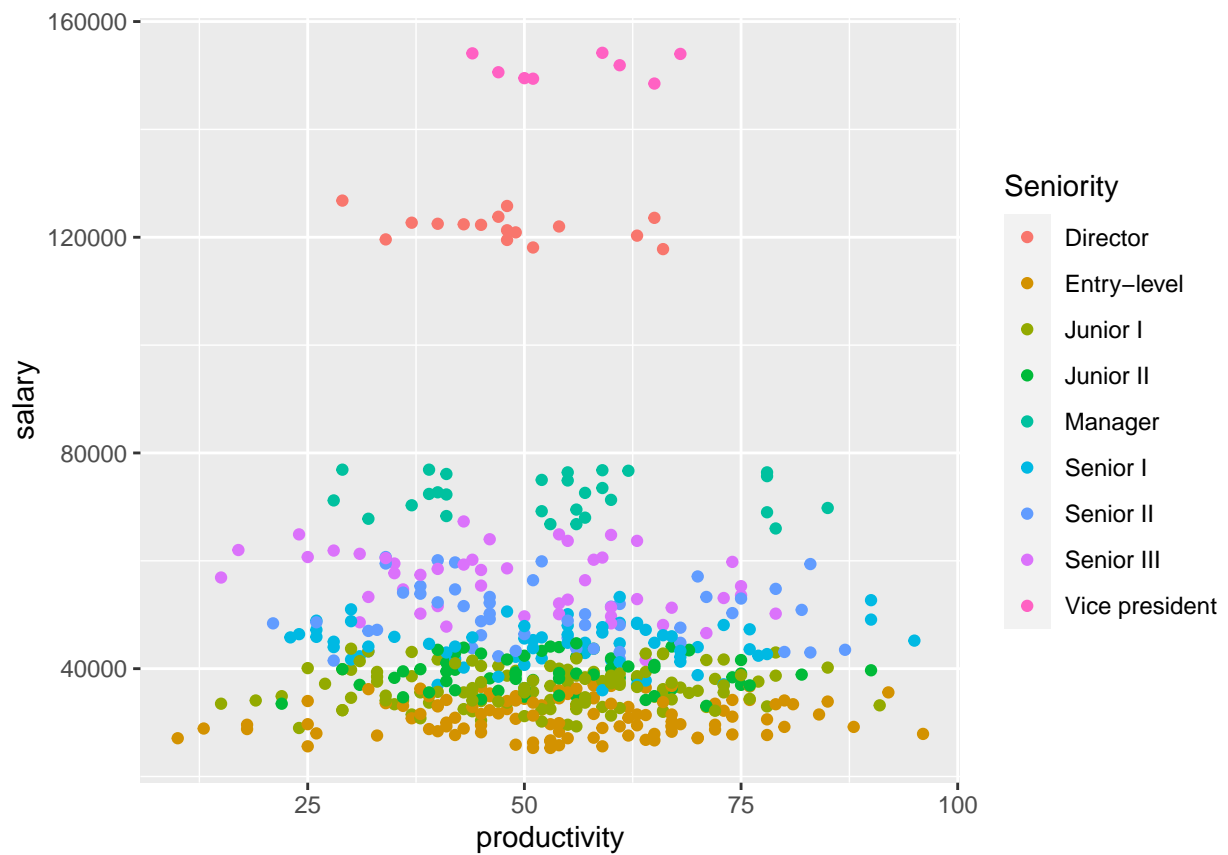


Figure 6: Salary Difference Across Role Seniority

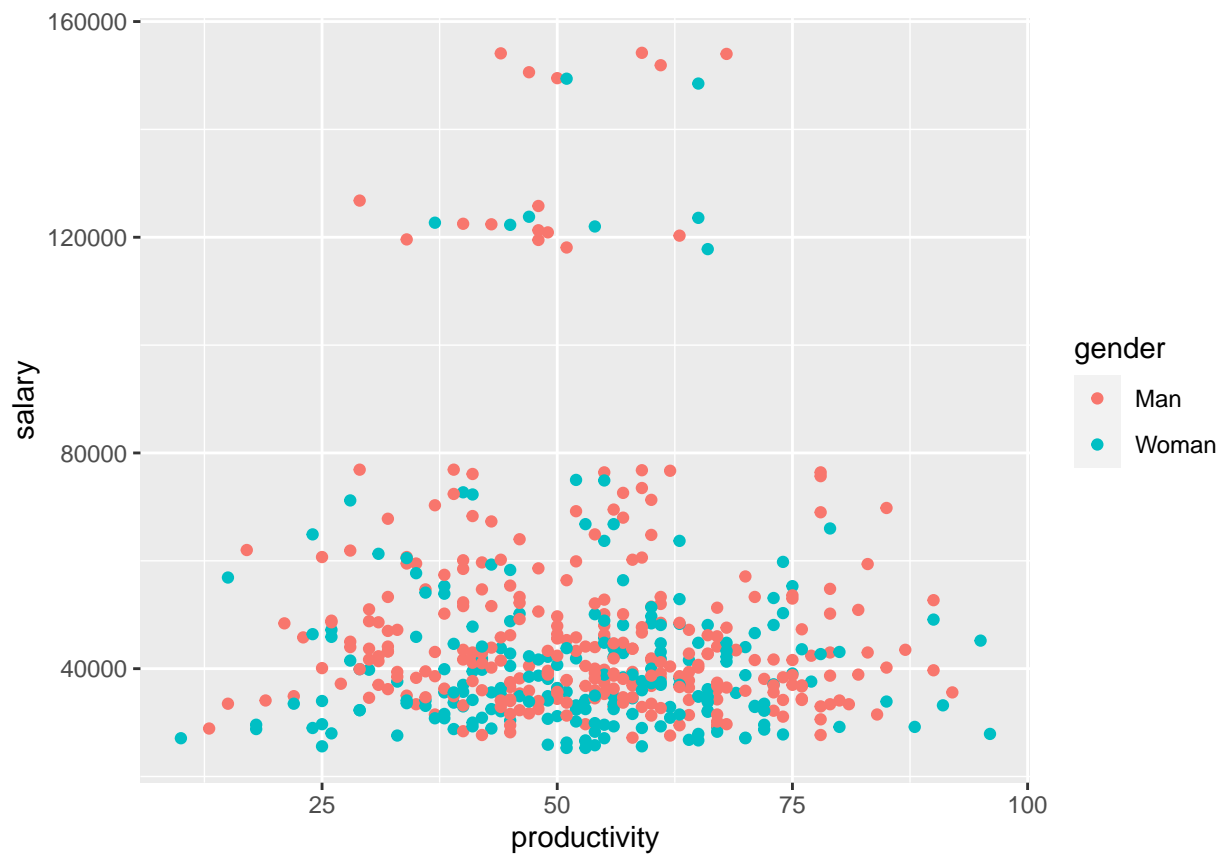


Figure 7: Salary Difference Across Leadership Levels

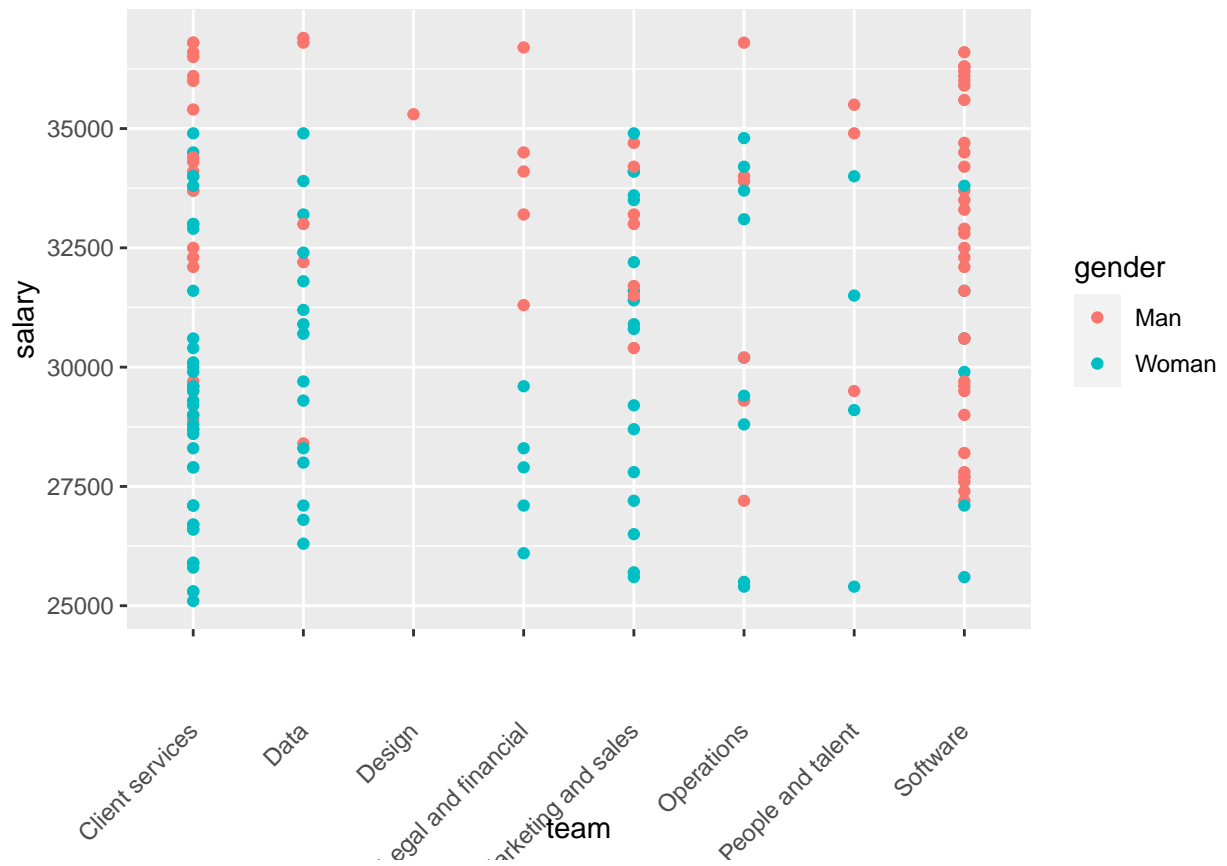


Figure 8: Salary Difference in Gender Across Teams, Fixing Quater and Seniority(Entry Level)

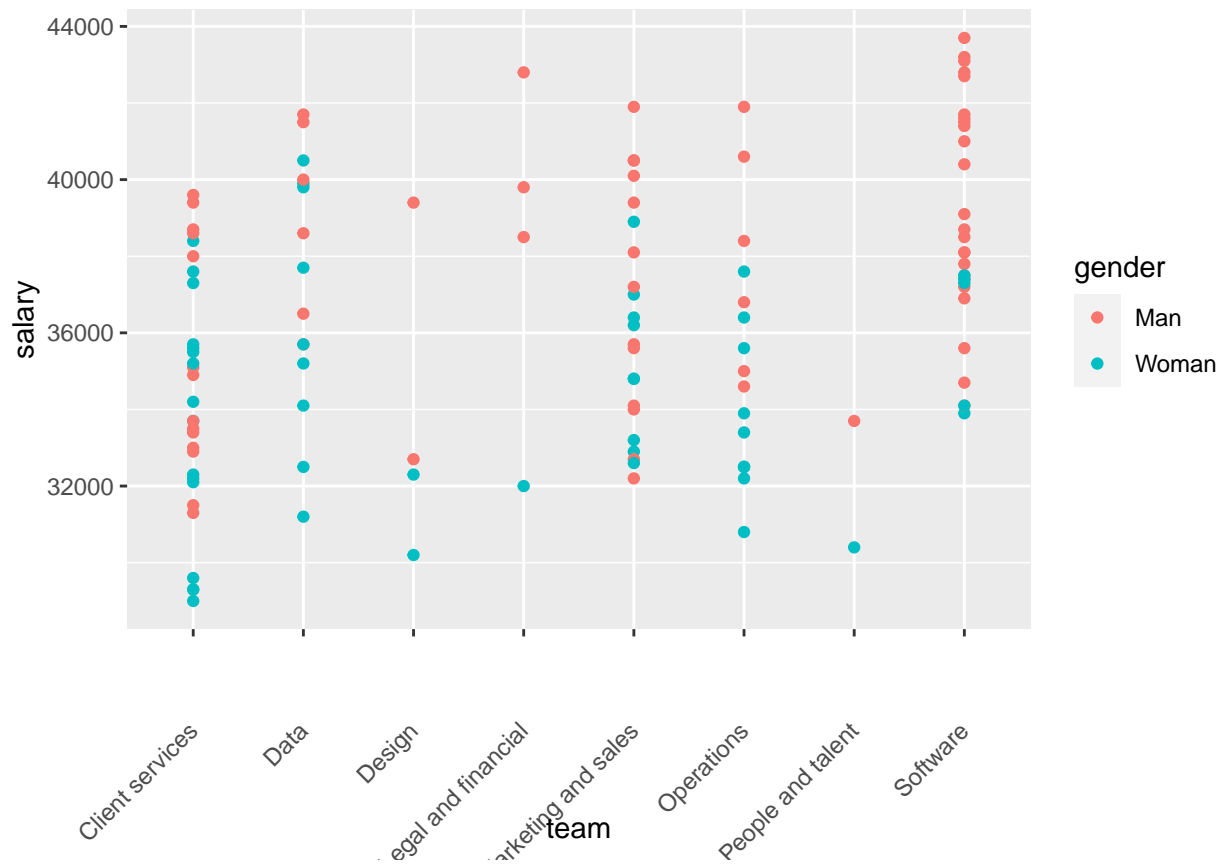


Figure 9: Salary Difference in Gender Across Teams, Fixing Quater and Seniority(Junior I)

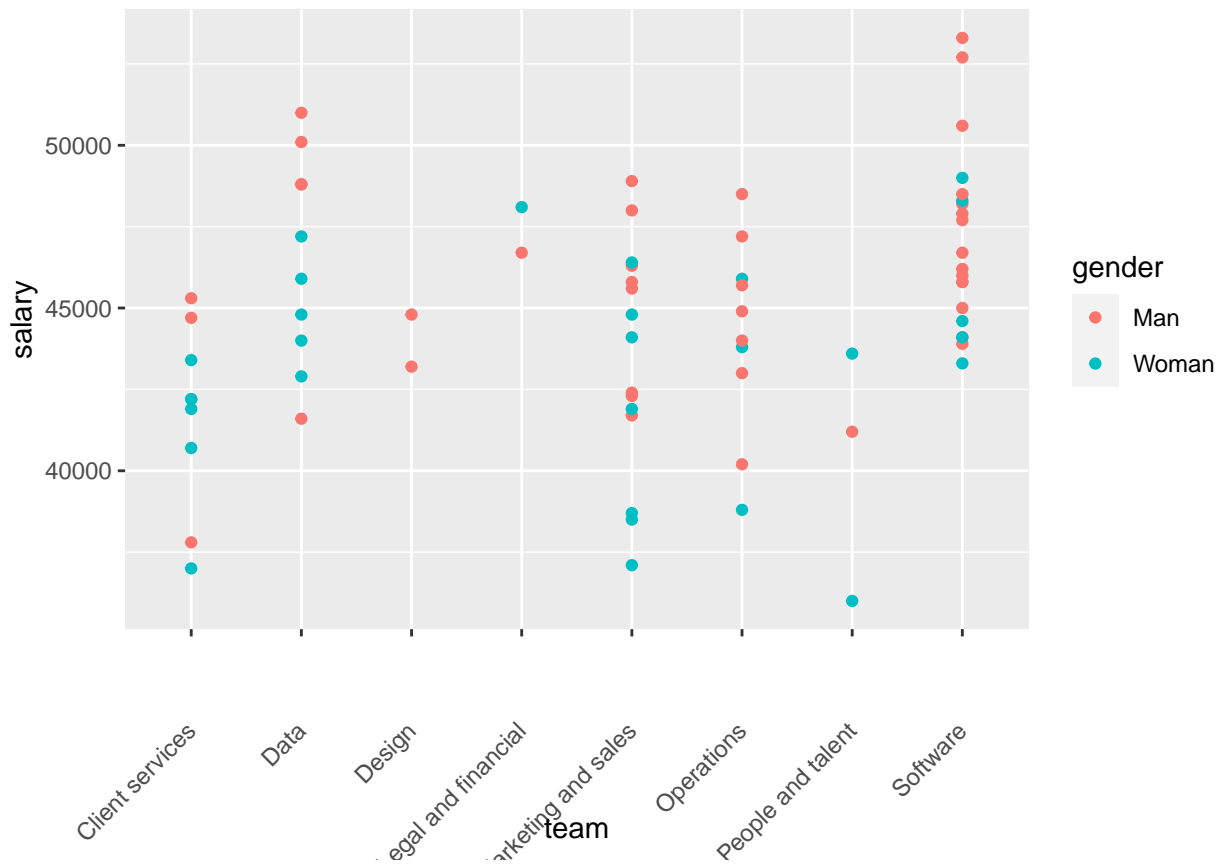


Figure 10: Salary Difference in Gender Across Teams, Fixing Quater and Seniority(Junior II)

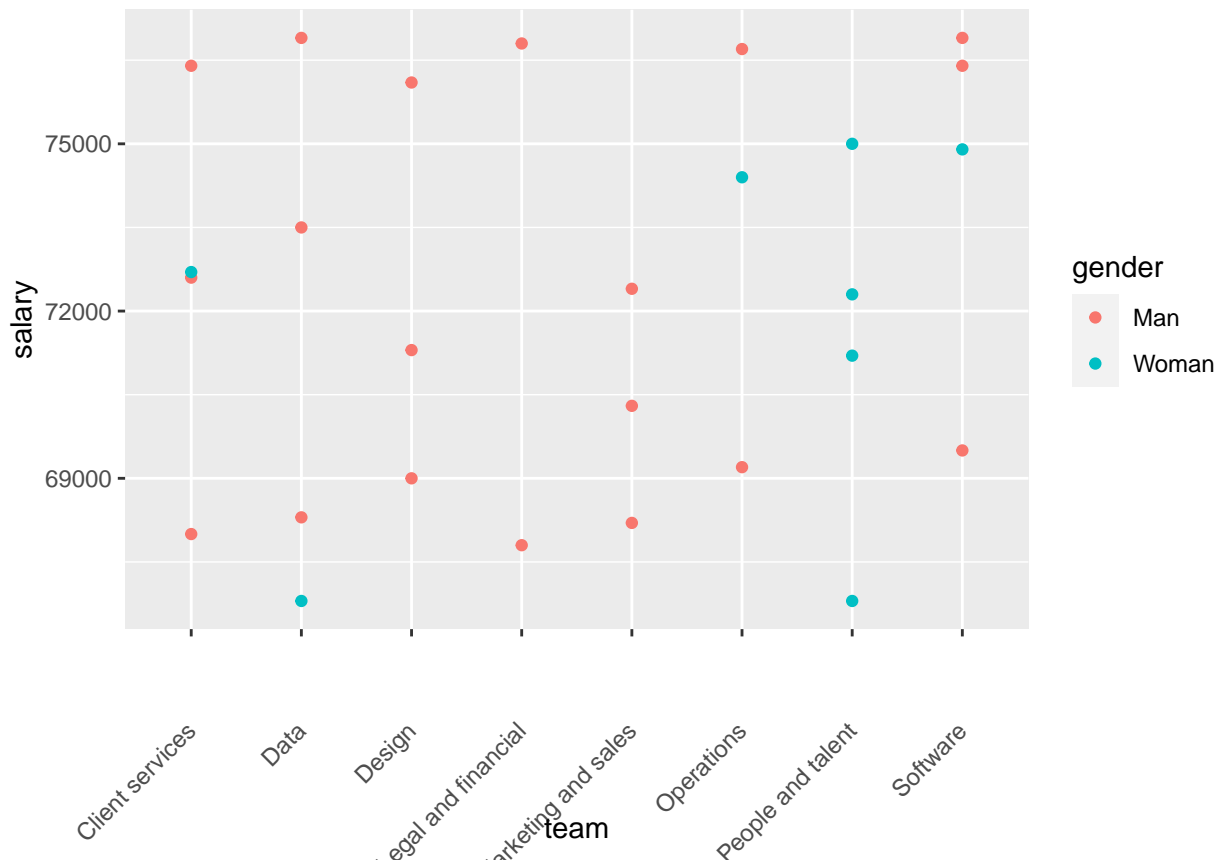


Figure 11: Salary Difference in Gender Across Teams, Fixing Quater and Seniority(Manager)

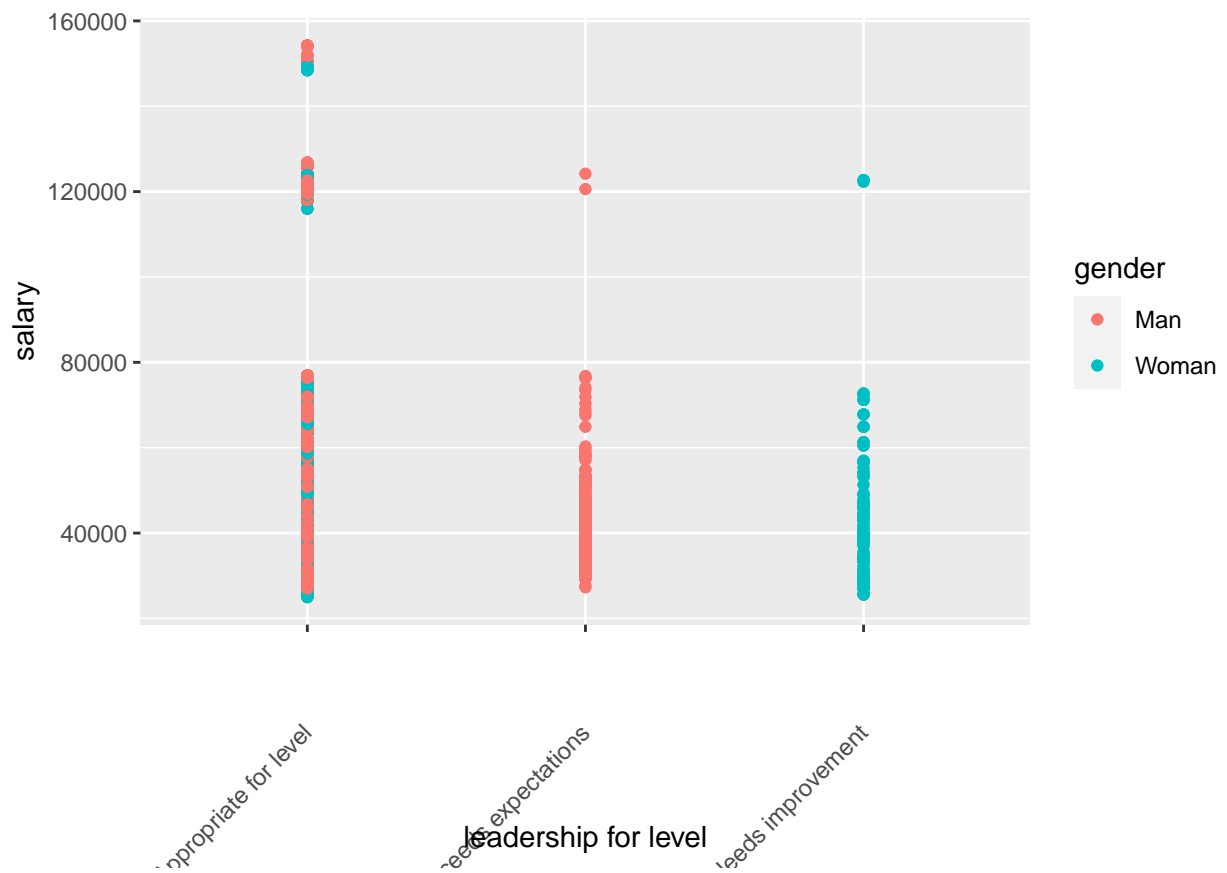


Figure 12: Salary Difference in Gender Across Leadership for Level

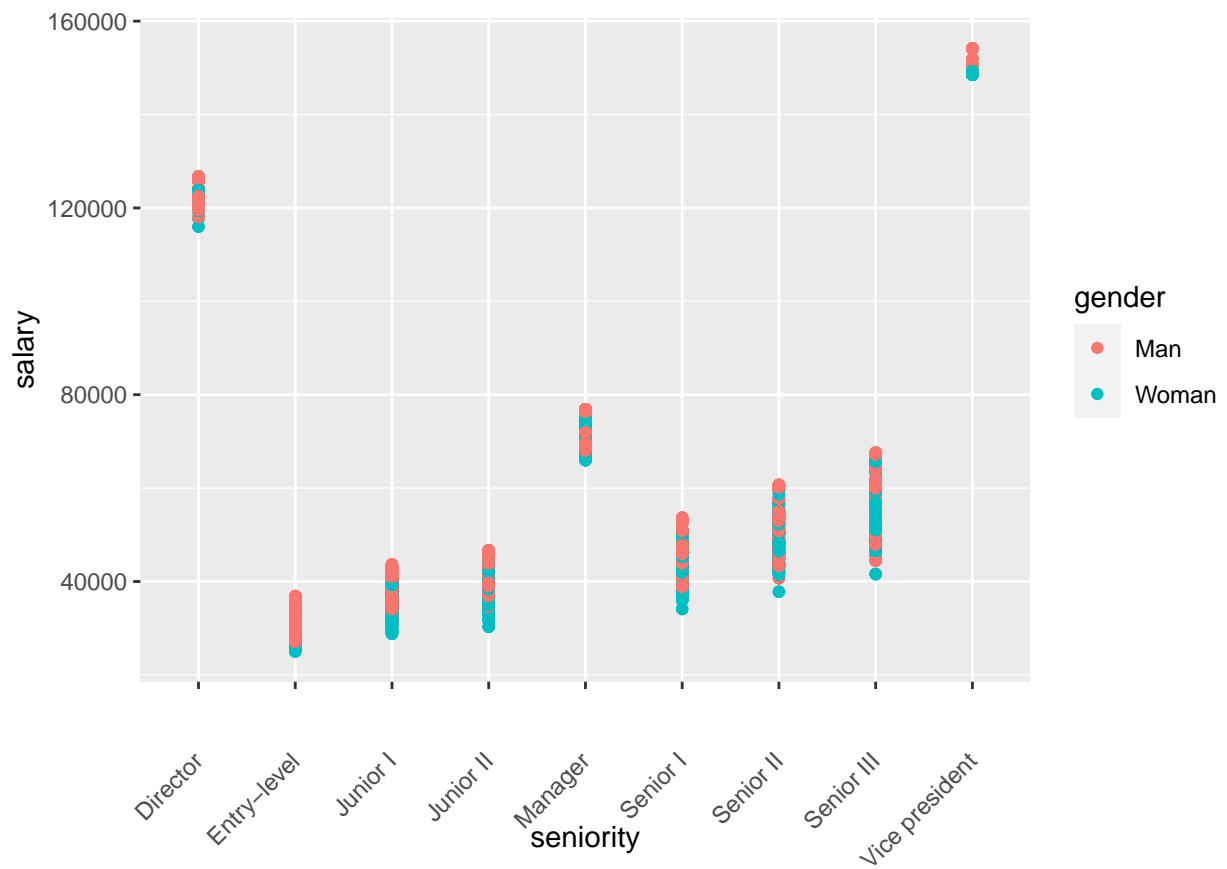


Figure 13: Salary Difference in Gender Across Seniority

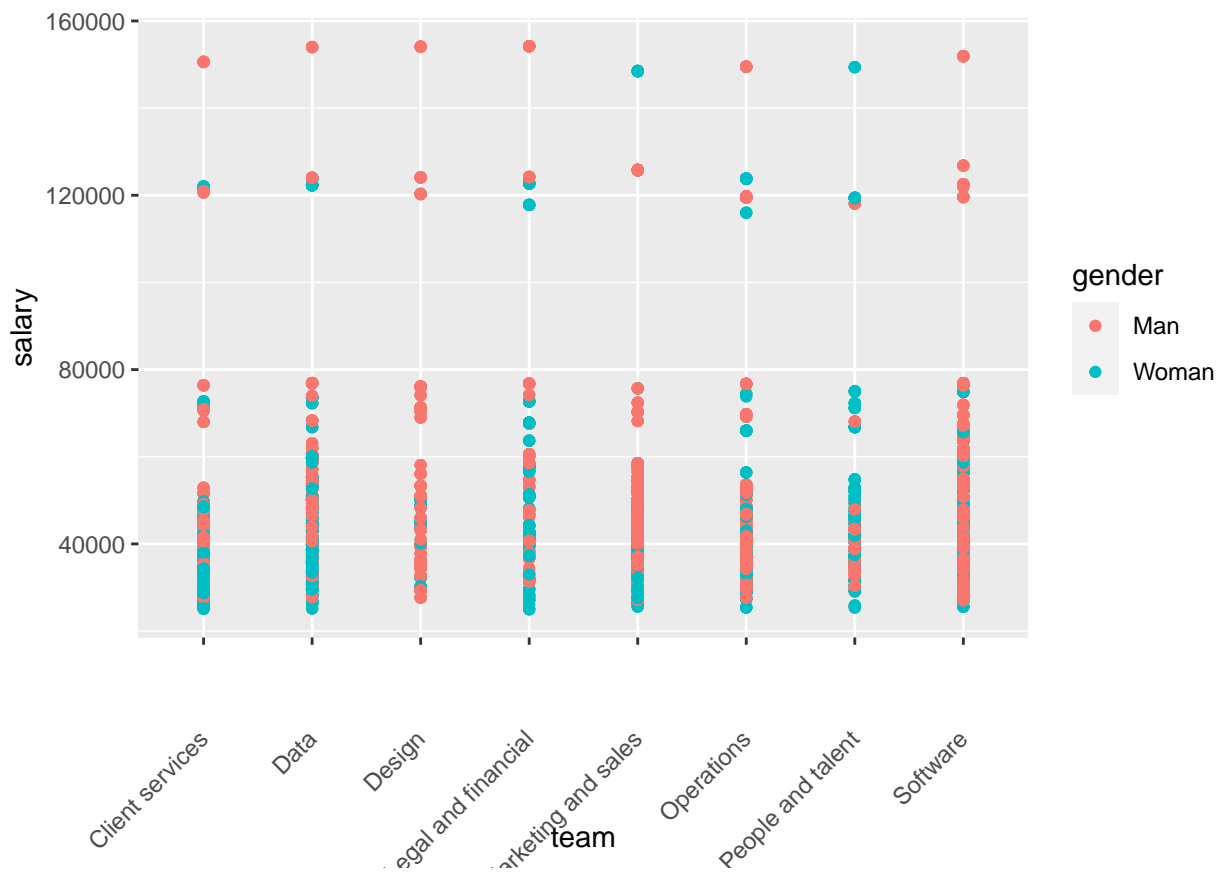


Figure 14: Salary Difference in Gender Across Teams

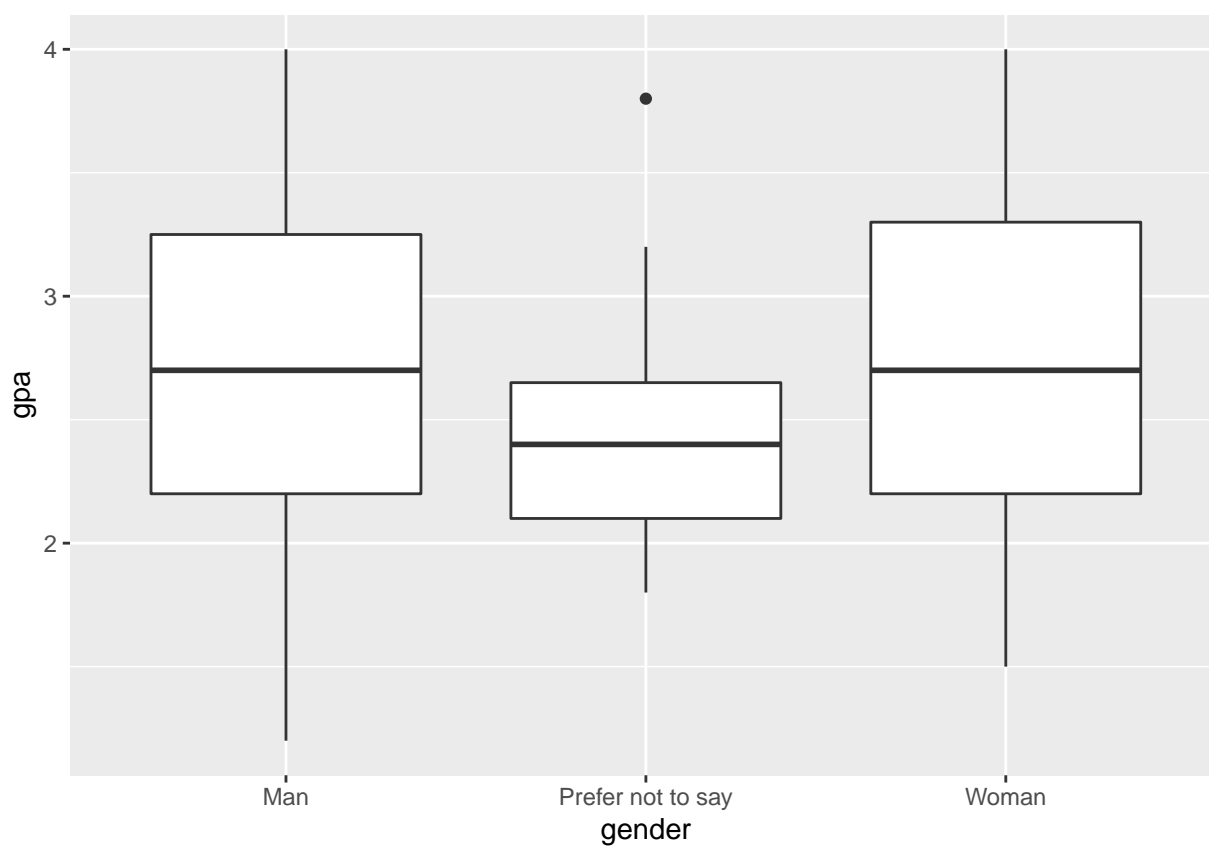


Figure 15: GPA Distribution Across Phase1 Applicants

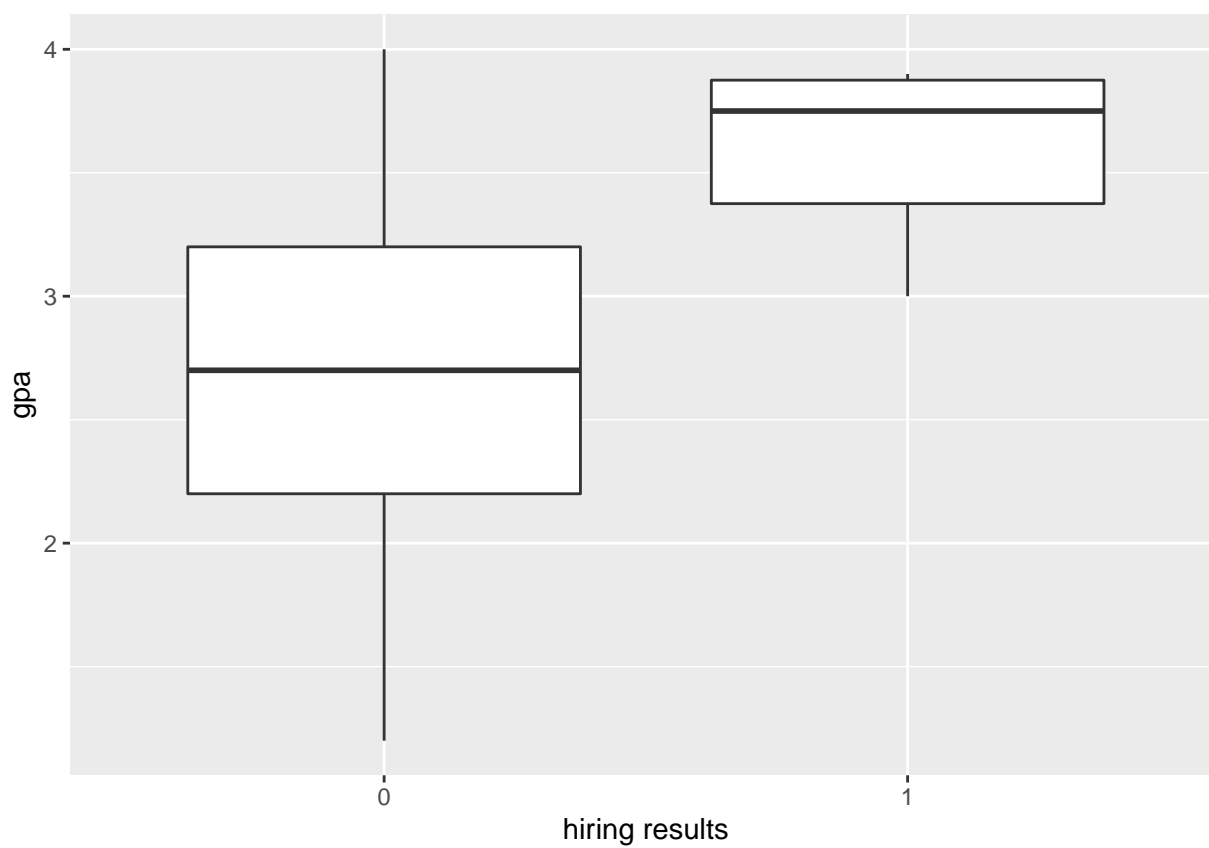
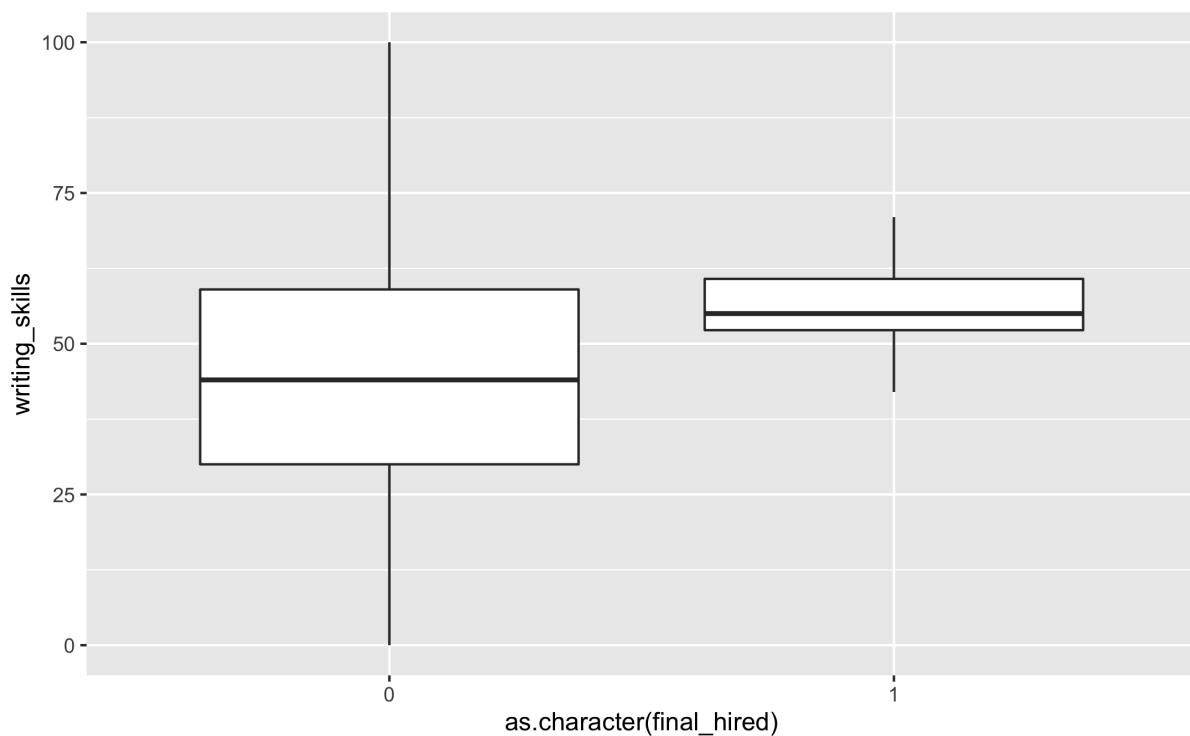


Figure 16: GPA Distribution Across Hiring Results



Discussion

In this section you will summarize your findings across all the research questions and discuss the strengths and limitations of your work. It doesn't have to be long, but keep in mind that often people will just skim the intro and the discussion of a document like this, so make sure it is useful as a semi-standalone section (doesn't have to be completely standalone like the executive summary).

Strengths and limitations

- The size of final hires data set is too small for inference. For data of this size(22 observations), inference of anykind is not meaningful. Alternatively, we rely on data visualization to come up with our conclusion.

Consultant information

Consultant profiles

Rain Wu. As the team leader, Rain is currently a senior consultant with Data OverFlow. She joined the company 6 years ago and specializes in data visualization. Rain earned her degree in Bachelor of Science, Specialist in Statistics Methods and Practice, from the University of Toronto in 2012. Before joining DataOverFlow, Rain has 3 year of working experience as a data engineer at Aviva in Markham, Toronto.

Tina Wang. Tina is currently a junior consultant with Data OverFlow who joined us 1 year ago. She specializes in reproducible analysis. Tina earned her degree in Bachelor of Science, Majoring in Computer Science and Statistics from the University of Toronto in 2018. Tina then pursued a Masters degree in Financial Insurance from the University of Toronto in 2020.

Yiqu Ding. Yiqu is a junior consultant with Data OverFlow who also joined us 1 year go. She specializes in statistical communication. Yiqu earned her degree in Bachelor of Science, specializing in mathematical application in finance and economics with a major in statistics from the University of Toronto in 2017. Yiqu has pursued a Masters degree in Financial Engineering at the University of Waterloo, during the time which she also gained research experience in machine learning algorithmns.

Code of ethical conduct

- At Data OverFlow, We respect and protect all confidential data obtained from, or relating to, clients and third parties, as well as personal data and information about employees from Data OverFlow. We only share information when there is a business purpose, and then do so in accordance with applicable laws and professional standards.
- We serve our clients with integrity and avoid any conflict of interest that may provide competitive advantages. We respect all intellectual properties of our clients and other consulting firms, and will not use proprietary information or methodologies without permission.
- We take proactive measures to safeguard our archives, computers and other data-storage devices containing confidential information or personal data. We promptly report any loss, damage or inappropriate disclosure of confidential information or personal data.
- We use social media and technology in a responsible way and respect everyone we work with. We obtain, develop and protect intellectual capital in an appropriate manner. We respect the restrictions on its use and reproduction.

- We work towards the goal of maximizing our positive impact on the people, the community and the environment. We are committed to meeting our social, environmental, economic, cultural, legal and ethical corporate responsibilities.