Gender Bias Analysis in Human Resource System

-for Black Saber Software in 2021

Report Prepared for Black Saber Software by Data OverFlow Operation

2021-04-21

Contents

Executive summary

We, Data Overflow Operation, have carefully examined the structure of the human resource system of your company, Black Saber Software, by analyzing the provided data on hiring, promotion and salary information. Our research questions focus on each of these three processes and whether gender bias exists in any of the processes. Our examination yielded the final conclusion that that the hiring process is fair and based on talent and value to the company, but the salary and promotion processes reveals potential gender bias.

The key findings are:

- After controlling for all necessary confounding variables, the difference between the average salaries of male and female employees remain significant with females on average earning 3428 dollars less than males.
- Among all three phases of recruitments involving the AI system, gender is not a significant indicator for passing each phase or getting hired. Candidates with stronger background, talent and potential are selected regardless of gender.
- With adjustments on the number of years worked at the company, the average rate of promotion for females is lower, at 0.7 of the average rate of promotion for men.

Table 1: Salary by gender

Variable	**Man**, N = 4,064	**Woman**, N = 2,725
salary	42,400 (36,800, 51,800)	40,000 (34,100, 48,500)

The overall median salary for men is 42,400, exceeding the median salary for women, which is 40,000. The plots below show that the salary for men is higher than female across all but the HR team, which is consistent across time. However, there exists many factors influencing gender and salary simultanerously,including role seniority and leadership. For example, we found that men are more likely to be in higher seniority positions with higher leadership ratings. Thus, they may be compensated higher based on higher value and contribution to the company, which is not any gender bias. However, later analysis will show that the salary gap exists even after taking all these factors into consideration.

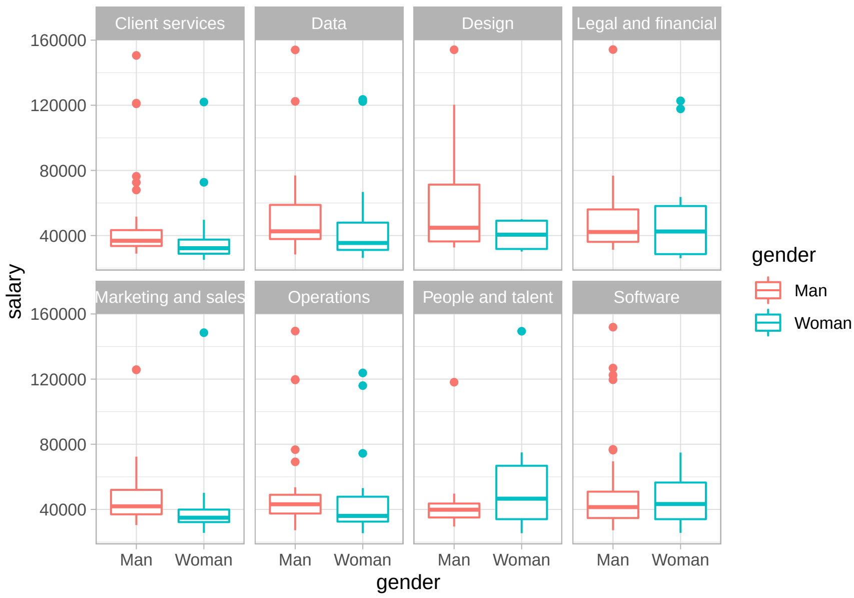


Figure 1: Most recent salary distribution across teams, by gender

Moving on to the hiring process, we conducted our analysis by going through each phase and test for gender bias. As shown below, we noticed that the male and female candidates had similar skill levels coming in, but the candidates who got hired have much better skills (higher GPA and skill scores) than ones who did not. Analysis suggests that the AI system selected candidates with stronger backgrounds and potential, unbiased by gender.

Table 2: Gpa and gender distribution

Variable	**Man**, N = 291	**Prefer not to say**, N = 11	**Woman**, N = 311
gpa	2.70 (2.20, 3.25)	2.40 (2.10, 2.65)	2.70 (2.20, 3.30)

Moreover, we extracted promotion information from the current employees dataset. On average, men tend to have more promotions then women. Even after adjusting for the number of years the employee has worked at the company, we found gender to be significant in determining the rate of promotions, which for women is only 0.7 times that of men.

Based on our findings, we believe that the company is fair in terms of the hiring process but exhibits gender bias in the salary and promotion processes. Controlling for many factors, candidates with higher value are hired to the company, but current female employees earn less than male employees and receive lower promotion rates than male employees. We will go through with greater details how we obtained the above findings in the report below.

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 renumeration 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 gender bias in current employee renumeration?

In order to analyze whether gender bias exists in the current employee renumeration, 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. We removed 117 observations where the employee preferred not to disclose their gender since these data does not offer valuable information to our analysis. Each observation records the corresponding 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 renumaration and hence used it as the response varible. 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 quater 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 remployee renumaration, we introduced the following linear mixed model:

$$y = X\beta + Zu + \epsilon \tag{1}$$

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, role 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. To account for quarterly differences and potential increase in salary due to inflation or deflation in the general industry, we created two variables: quarter that indicates the given quarter and year that indicates the given year. 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. We have also tested for random slopes but found the results insignificant and overly complicate our model.

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. Based on confidence interval intrepretations, we find that gender, role seniority, year, quarter and productivity are all significant predictors for salary. We attempted dropping predictors (including random effects) one by one and conducting likelihood ratio tests. We found that all other predictors besides leadership are significant. Hence, our final model included all othre predictors besides leadership.The final model gives the following results:

Table 3: Statistics Summary for Reduced Salary Model

Variable	$\hat{\beta}$	Std. Error
intercept	-2620956	50707.6
women	-3428.299	611.0878
junior	-70694.34	324.8482
manager	-47895.55	258.1007
senior	-64307.94	285.3001
vice-president	27747.96	409.2851
year	1352.881	25.05654
quarter	268.4411	23.30894
productivity	-26.40428	2.453329

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. We also observe positive and significant relationship between the time predictors quarter and year. This suggests some natural increase in salary over time unrelated to other variables. Interestingly, we observe a negative relationship between productivity and salary, which we will examine with closer detail later.

Most importantly, there appears to be a statistically significant difference between average salaries of males and females after controlling for all the necessary information. More specifically, holding all else constant, being female reduces the salary 3428.3 on average. The 95% confidence interval for gender is [-4638.331,-2238.205] which is strongly negative. Prior to this model, we also considered the naive linear regression 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. Moreover, we tried running the same final model but removing the gender variable. Then by the lmtest to compare the gender removed model versus the final model, we find a p-value significantly smaller than 0.05, suggesting that the fuller model is necessary. In other words, gender is a significant predictor for salaries. This is again evidence that there is gender bias in the salary levels.

Building on from the finding that higher productivity leads to lower salaries, we fitted three general linear models to check the correlation amongst gender, productivity, and salary:

$$y_{productivity} = X\beta_{gender} + \epsilon \tag{2}$$

$$y_{salary} = X\beta_{gender} + \epsilon \tag{3}$$

$$y_{salary} = X\beta_{productivity} + \epsilon \tag{4}$$

According to eqn1.2, the average productivity of female employees is 1.46 units higher as compared to male employees, holding all other variables constant(p-value = 0.0001). eqn1.4 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 then leads to lower salaries. This is another sign of a potential gender bias in the company, suggesting that compensation is not in line with individual value or contribution. Since both gender and productivity are significant predictors for salary, this bias holds even with other variables included.

In conclusion, we find statistically significant evidence to believe that there is gender bias in the current salaries levels within the company. Specifically, women's salary are on average more than 3000 lower than that of men after controlling for many crucial factors including seniority and productivity. This should be brought into attention to the board and decide on appropriate actions if necessary.

Does there exist genderbias in the hiring process?

Moving on, we assessed the potential gender 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 HR department using an AI system to determine the successfull applicants. Therefore we derived three different data sets from the original data provided and formed data of successful applicants at each phase. The response variables of interest are whether the candidate made it to the next phase at each stage as well as whether the candidate eventually gotemployed. Since the response variable is binary where 1 suggests passed/hired and 0 suggests rejected, we used general linear models with the family of binomials to model the hiring results. The model predicts p in equation where p is the probability of event A (eg.passing phase 1) that we are interested in, $\beta_0$is the intercept, $x_1...x_K$ are our variables of interest and $\beta_1...\beta_k$ are parameters for each of these variables.

$$log(\frac{p}{1-p}) = \beta_0 + \beta_1 x_1 + ... + \beta_k x_k \tag{5}$$

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

Table 4: 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. For example, holding all else constant, one unit increase in GPA increases the odds of passing phase 1 by 8.08% on average. It is expected that candidates with higher GPA and more work experience are selected because of higher talent. Notice that although the estimate is slighlty negative for gender, it is not a significant predictor in this model.

At phase 2, we again created a binary response variable 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 5: 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	$3.73e^{-5}$

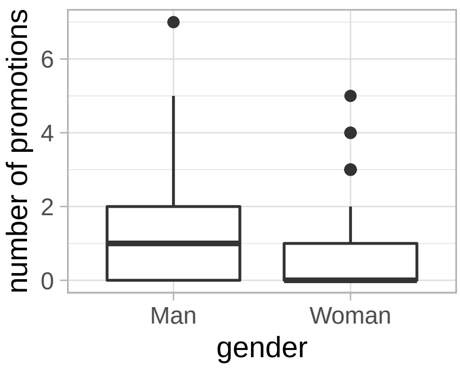
According to $\alpha = 0.05$, the significant predictors are technical skills, writing skills, speaking skills and leadership presence. We found that significant variables to pass phase 1 are no longer significant. This is justified as candidates in this phase likely all have strong gpa and work experiences, 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.For example, holding all else constant, one unit increase in speaking skills increases the odds of passing phase 2 by 2.47% on average. 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. We again have a binary response variable indicating whether the candidate passed this phase (got hired) or not. 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. We also attempted models that predicts if the candidate eventually got hired from phase 1 and phase 2 data, the results again show that gender is not a significant predictor.

To conclude, we believe that there is no gender bias during any of the phases of this hiring process. The candidates who pass each phase are the ones with stronger ability, 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. Thus, Black Saber can continue to trust the AI system in the hiring process to continue bringing the best talent to the company.

Is there gender bias in the promotion process?

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 these are only 11 out of 608 employees. We calculated the length of service of each employee in years and individual average productivity score over years. This is because it takes time to get promoted and hence employees should be compared adjusting for their years at the company. Similarly, individuals with higher productivity may be more likely to be promoted regardless of gender, and hence should also be controlled. Figure 1 below 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 male and 0 for female. The employee being promoted the most is a male who got promoted 7 times.



To model the promotion process, we considered basic Poisson model:

$$log(lambda_{promotion} = X\beta_{gender} + X\beta_{avg\_productivity} + X\beta_{service\_length} + \epsilon \quad (6)$$

In addition to the base model, we also modelled by offseting the log of service length instead of leaving it as a fixed effect predictor. This way all employees are put on the same scale to analyze their rate of promotion, as a count per unit of time.

According to the figure below, employees on average get promoted once every two years. It is also clear that the employees with more promotions are mostly men. Our first model regressed gender, service length, and average productivity together on the number of promotions. We found that the average productivity is not a significant predictor (p=0.059) and while the other two are significant (both below 0.05). To be more accurate, we used an offset term to offset the log of service years so that the count of promotions are all measured in same rates. The output from our second model suggests that the rate of promotions of women are on average 0.7 times that of men, revealing gender bias in the promotion system. This significant difference exists after taking other variables into consideration, such as team and leadership. We have also performed lmtest on a reduced model that drops the gender variable. With an extremely small p-value, we find that it is necessary to include this variable. In other words, gender is a significant indicator for promotions.

To address the potential problem that we see more zeros than expected in this promotion dataset due to the fact that many employees are new employees, we also considered a Zero-Inflated Poisson model (ZIP). We created a new binary variable setting the employee is a new employee if he or she has zero promotions and has been at the company for less than 2 years. The table below shows that 35.3% of the dataset, which is 211 employees fit under this category of new employee. By fitting a Zip model, we found that amongst old employees, the rate of promotion for women is 0.76 that of men, holding all else constant. This is similar to the 0.7 we observed before, indicating that our previous Poisson model is valid.

new_employee	n	prop
FALSE	386	0.647
TRUE	211	0.353

In conclusion, by creating a new dataset that focuses on the promotion information, we find that gender makes a significant difference in determining the number of promotions the employee gets after controlling for multiple factors. Specifically, the rate of promotions women get are only 0.7 of that of men, indicating gender bias in the promotion process.

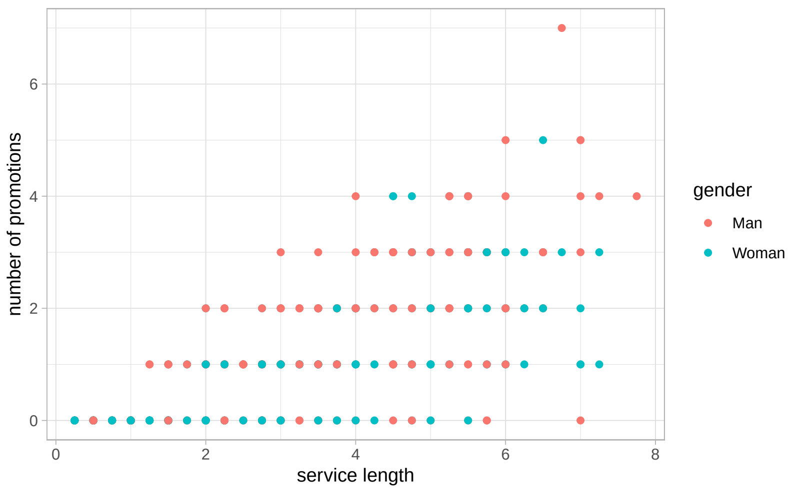


Figure 2: Number of promotions against service length

Data Visualization

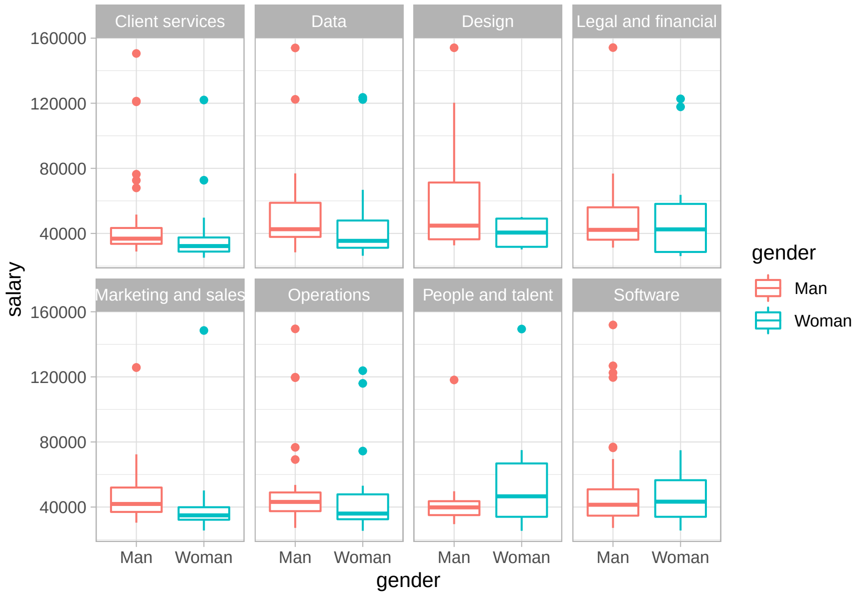


Figure 3: Most recent salary distribution across teams, by gender

Figure 4: Most recent salary distribution across levels, by gender

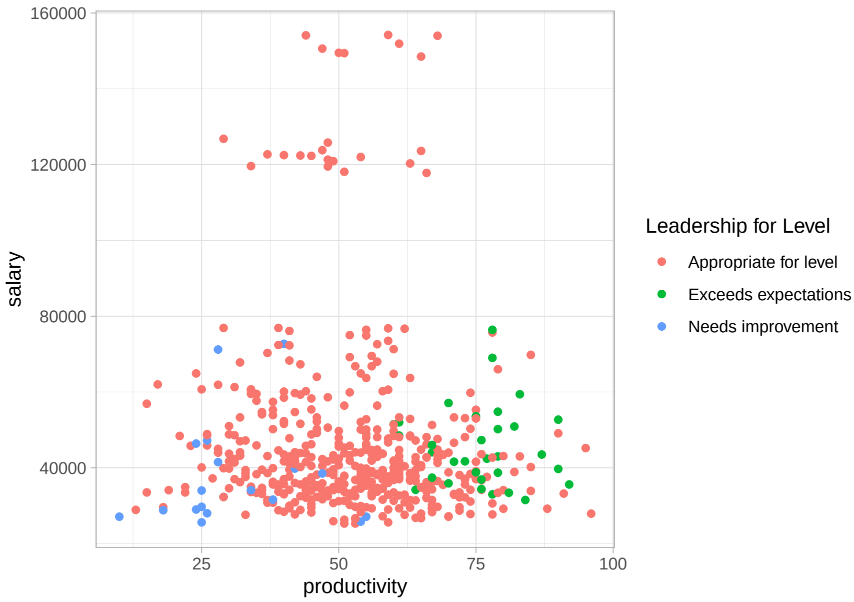


Figure 5: Salary Difference Across Leadership for Level Fixing Productivity

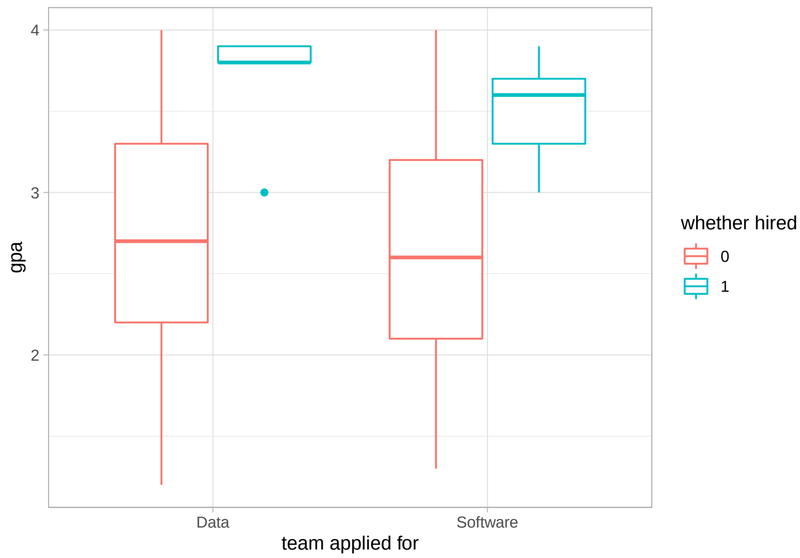


Figure 6: gpa comparison between applicants

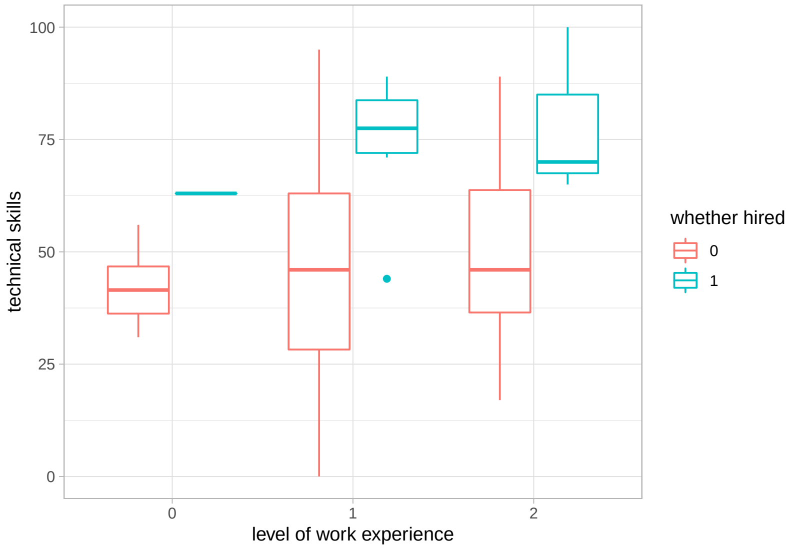


Figure 7: Hiring results compared between level of work experience and technical skills

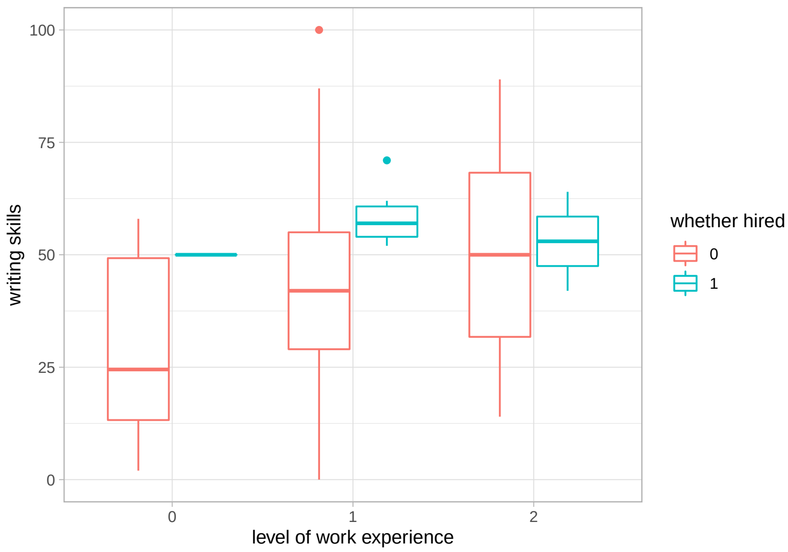


Figure 8: Hiring results compared between level of work experience and writing skills

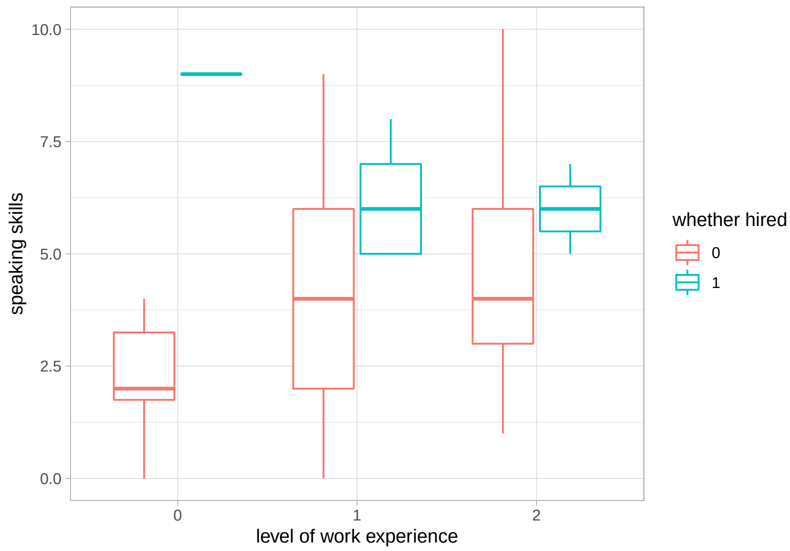


Figure 9: Hiring results compared between level of work experience and speaking skills

Discussion

To summarize, although we expect multiple variables including role seniority, productivity and team to confound the relationship between gender and salary, we in the end found a more negative relationship between the two, showing strong evidence of a gender bias in the salary levels. Amonge all three phases of recruitments, the AI system accurately selects the best talent by mostly depending on ability-related skills and not gender. There exists a positive relationshi between the number of times promoted and the length of service at the company, after controlling for these factors, we still observed females to receive lower promotion rates than male. Overall, there is bias in the salary and promotion processes but not in the hiring process.

Strengths and limitations

One strength of this analysis is that the provided data is representative of the employee and hiring information at Black Saber. Specifically, potential confounders including seniority, leadership, and productivity are all measured appropriately based on the scale provided by Black Saber. This way, we are able to find the most direct relationships between our variables of interest and reduce potential ommited variable bias to the minimum.

Extending from above, another strength of this analysis is that there are only around 1% of employees who are unwilling to disclose their gender. If this group was much larger, for example 30% of all employees, then our inference based on comparing men and women may be biased due to a significant lack of information that is important to the conclusion. However, we assumed in this report that the 11 employees who did not declare their gender are able to be represented by the rest. In other words, these 11 individuals can not be 11 women with extremely high salaries that would possibily distort our conclusion.

One limitation is that as we counted the number of promotions by the number of position changes in the employee, it may be possible that the employee went from a higher position to a lower one, which is infact not a promotion. We worked around this challenge by evaluating the corresponding time (quarter) of the data and found that all higher levels come later in time and hence there is no backward position change. Additionally, it is difficult to analyze the difference between one promotion from Entry to Manager versus two promotions from Entry to Junior I and then to Junior II. In this case we expect the salary increase to be larger for case 2 (since it is 2 promotions) while infact the greater jump in case 1 likely leads to a higher increase in salary. We faced this challenge by ignoring salary differences and just focus on the number of promotions and analyze whether male are promoted more frequently than female.

Another limitation for analyzing the hiring data is that the dataset is extremely small. Specifically, the phase 3 only contains 22 observations (with 10 being hired). Inference of anykind is difficult and hardly meaningful for data of this size. This is because the potential influence of one or a few outliers may be very disruptive to the overall model. With a larger dataset with at least 30 observations, our analysis results may be more reasonable and representative of future situations. Our team tried our best to overcome this limitation by conducting multiple data visualization processes to rule-out the appearance of outliers and conclude as much as possible from visualized outputs.

For future analysis, we would also be interested in analyzing potential racial biases in the company. Although we believe that this should not be an issue for Black Saber, it is useful information to analyze and justify to the board as a part of the EDI initiatives. If larger datasets with more observations (or variables) may be provided, we would love to redo our analysis to make more exact inferences.

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 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 ago. She specializes in statistical communication. Yiqu earned her degree in Bachelor of Science, specializing in mathmatical 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.

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- 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.