Potential Bias Analysis in Human Resource System

-for Blacksaber Software in 2021

Report prepared for Black Saber Software by Data Over Flow

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Contents

Executive summary

We 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 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.
- There is a positive relationship between the number of times being promoted and the length of service.

As shown by the table below, the median salary for men is 42,400, which exceeds the median salary for women which is 40,000. However, we observe that while men and women have a similar percentage of appropriate leadership for level, 6.6% of men exceed expection and 0% needs improvement. On the other hand, 0% of women exceeds expectation and 5.2% needs improvement. Hence, men on average have greater contribution and are likely compensated higher for appropriate reasons.

Table 1: **Leadership by gender**

Variable	**Man**, N = 4,064	**Woman**, N = 2,725
salary	42,400 (36,800, 51,800)	40,000 (34,100, 48,500)
leadership_for_level		
Appropriate for level	3,796 (93%)	2,583 (95%)
Exceeds expectations	268 (6.6%)	0 (0%)
Needs improvement	0 (0%)	142 (5.2%)

Moreover, the difference of salary by gender can also be explained by varying role seniority. On average, there are more men with higher positions than womeN. Since it is expected that higher positions receive hiher salaries, this reasonability brings up the average male salary as compared to female.

Salary for men is consistently higher than female no matter the financial quarter. Both the median and interquantile range appears to be shifted higher for men. Moreover, we notice that there is no significant increase of salary in Q4 where potentially bonuses are given.

Moving on to the hiring process, we find that the male and female candidates had similar levels of GPA coming in. However, the candidates who got hired have a much higher gpa than those who did not, which is reasonable and unrelated to gender. The same analysis is found for writing, speaking, and technical skills, where the plot for technical skills is shown as representation.

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)

Table 3: Skills score and gender

Variable	**Man**, N = 145	**Prefer not to say**, N = 3	**Woman**, N = 152
technical_skills	44 (31, 62)	67 (60, 73)	48 (32, 66)
writing_skills	41 (30, 57)	41 (36, 48)	46 (31, 61)
speaking_skills	5.00 (3.00, 7.00)	6.00 (5.50, 7.50)	3.00 (2.00, 4.00)

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 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 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. 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 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, 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 4: Statistics Summary for Reduced Salary Model

Variable	$\hat{\beta}$	Std. Error
intercept	116904.03	709.18
women	-2928.38	426.88
junior	-79703.19	342.56
manager	-50342.84	311.51
senior	-69910.72	323.8
vice-president	30024.17	498.25
quarter	74.31	28.28

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:

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

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

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

According to eqn1.2, the average productivity of female employees is 1.46 times higher of 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 leads to lower salaries. This could be a potential sign of gender bias or compensation not in line with individual contribution. However, by analzying 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 resourses department 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 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 equation where p is the probability of event A 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 5: 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 probability 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 6: 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 probability 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. "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?

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.

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. We considered three models:

$$y_{promotion} = X\beta_{gender} + X\beta_{avg\_productivity} + X\beta_{service\_length} + \epsilon \tag{6}$$

$$y_{salary} = X\beta_{gender} + X\beta_{service\_length} + \epsilon \tag{7}$$

$$y_{salary} = X\beta_{service\_length} + \epsilon \tag{8}$$

Model 7 indicates that the average profuctivity score does not have a siginifiant effect on the number of promotions(p=0.059). It shows that gender(p=$1.67e^{-5}$) and service length(p<$2e^{16}$) affects the number of promotions significantly. We further examined model 8 and 9 and compared them using a ratio test, the results suggests us dropping gender as a significant variable(p=$2.457e^{-5}$).

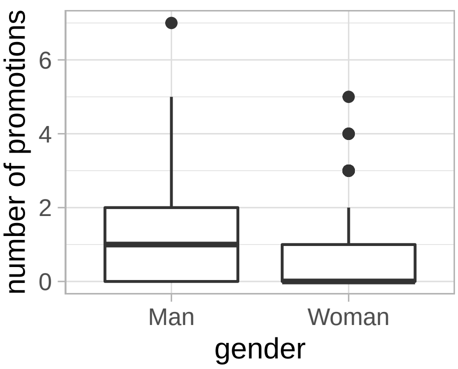

Figure 1: The Number of Promotion By Gender

We calculated the average productivity level for each employee and considered it as a variable affecting promotion. However, when regressing both gender and average productivity together on the number of promotions, we find that the average productivity is not a significant predictor and has no influence over the estimate for gender. According to 9, employees on average once every two years. However, as shown in figure(x), the number of promotions is not only related to the service length, which makes sense because there is a threshold to this positive relationship. That means, it is almost certain that under senior III, employees gets promoted every two year, however after that, promotion is likely dependent on other considerations which are hard to measure.

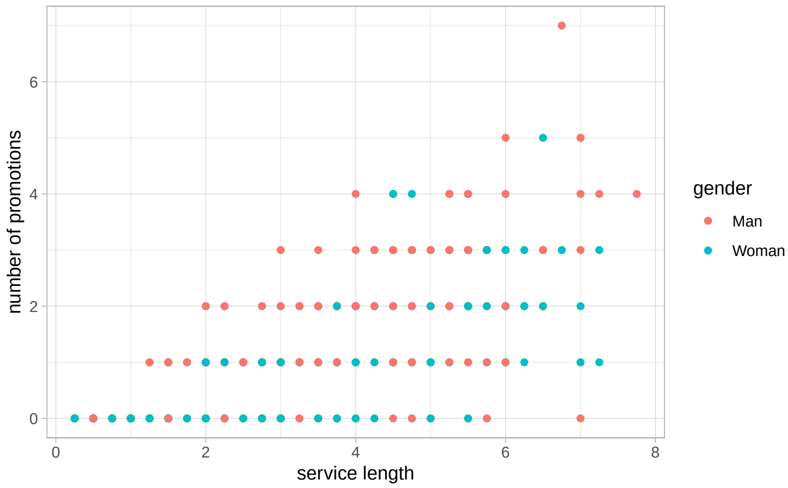

Figure 2: Number of promotios against service length

Data Visualization

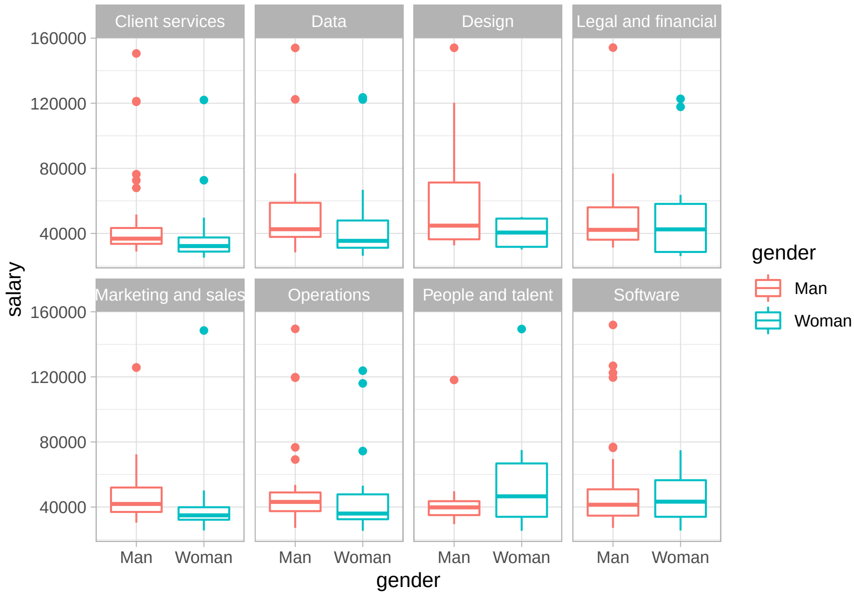

Figure 3: Most recent salary distribution across teams, by gender

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

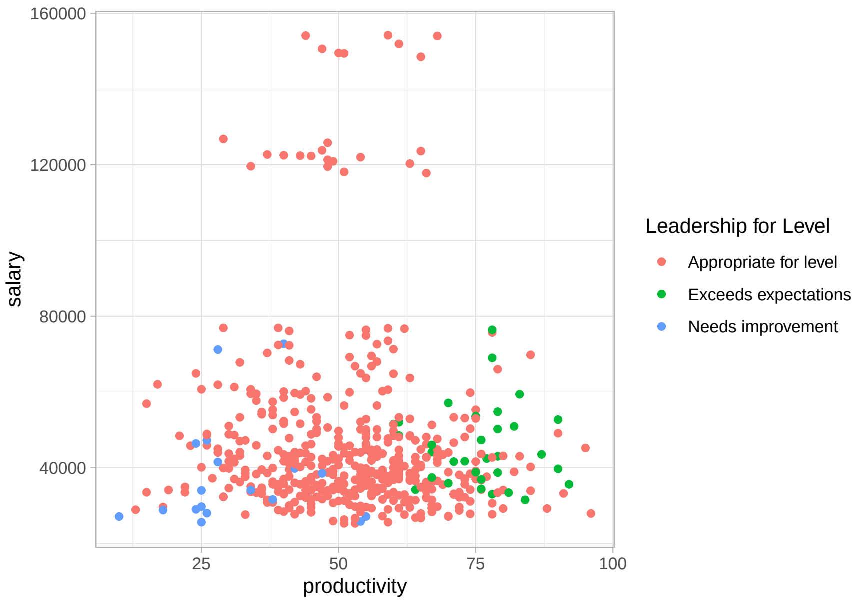

Figure 5: Salary Difference Across Leadership for Level Fixing Productivity

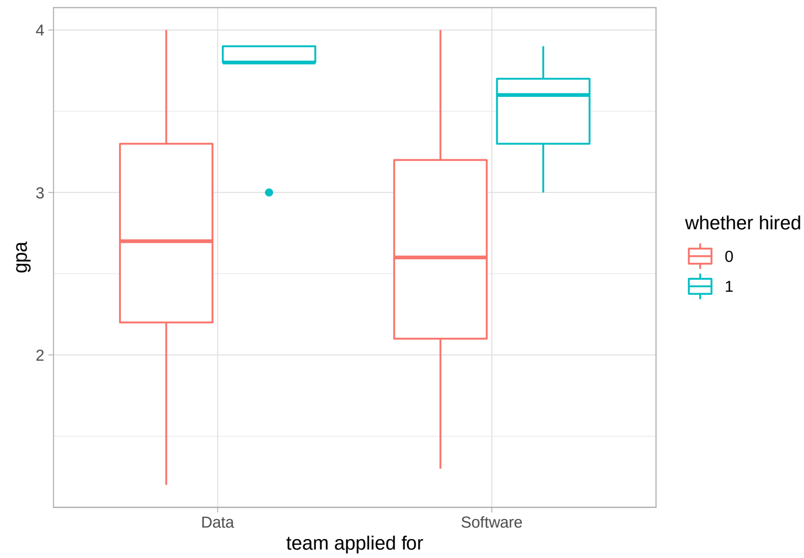

Figure 6: gpa comparison between applicants

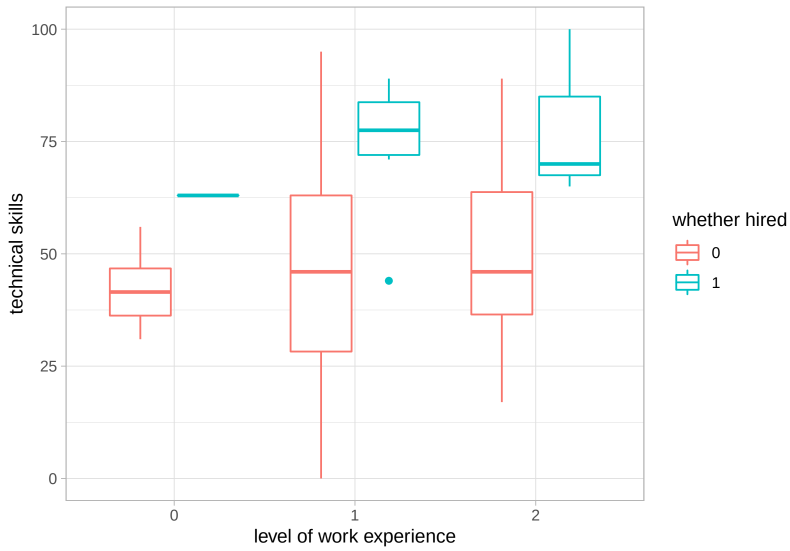

Figure 7: Hiring results compared between level of work experience and technical skills

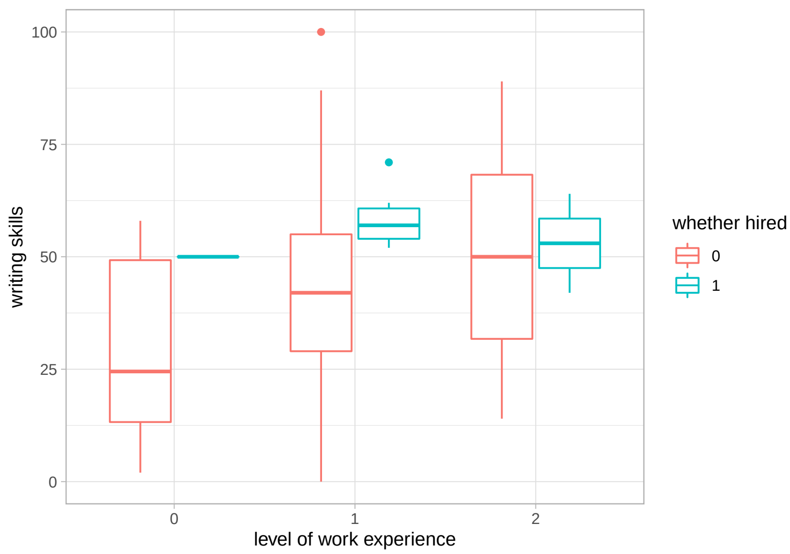

Figure 8: Hiring results compared between level of work experience and writing skills

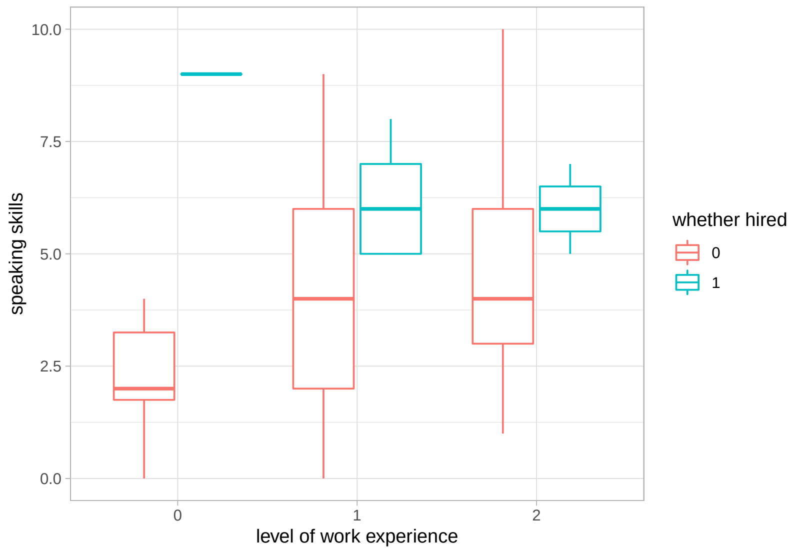

Figure 9: Hiring results compared between level of work experience and speaking skills

Discussion

To summarize, even though there exists differences between the average salaries of male and female employees, there exists multiple factors that affect the salary level such as productivity score, and the average salary increases as the seniority of role increases as it should. Gender is found to be a confounder of productivity, where productivity has a negative relationship with 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. There is a positive relationship between the number of times being promoted and the length of service, and ratio test between models shows that gender tend to induce over-parametrization for the number of times being promoted. Overall, the process of hiring, enumeration and promotion depends on non-personal factors of an employee such as talent and contribution to the firm, and therefore is not gender-biased.

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 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 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 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.