An Evaluation of Salary, Promotion, and Hiring Process at Black Saber Software

Evidence of Gender Bias in Salary

Report prepared for Black Saber Software by Calabash Brothers Solutions

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Contents

Executive summary

Over the past few months, several software companies had received bad press about their hiring and remuneration processes, during which human bias are present. As a consequence, people have been raising concerns about potential bias in the recruitment and promotion process of Black Saber Software. Experts in our advisory and consulting group are hired to ensure the client company is out ahead of any potential such issues. This study following set out to assess whether the client company exhibits a bias against female in hiring, as well as 2013-2020 salary and promotion.

The results of the study are summarized below.

*The gender bias are not present in the first two rounds of the hiring process. Females and males have equal opportunities to be selected in both the first round and the second round of the recruiting. Neither men nor women are more favorable.

*In the Phase I of the recruitment process, individuals who have higher GPA or those who have demonstrated some work experience in the past are more possible to be automatically selected by the AI to the next round. However, surprisingly, young professionals who have rich extracurricular experiences do not seem to have a notifiable advantage in the first round of the hiring.

*Only individuals who has provided sufficient material to the company, that is, only those who uploaded both CV and the cover letter are likely to pass the phase I recruiting process.

*In the Phase II of the hiring, GPA and work experience are no longer a factor that will have an effect on the selection process. Instead, the evaluation of individuals focus on technical skills as well as other soft skills such as writing skills, speaking skills and leadership skills.

*Overall, current male employees have higher salary compared to their female counterparts who has the same role seniority under the same department. Female employees are not well-paid even if they have the same amount of workloads as male employees.

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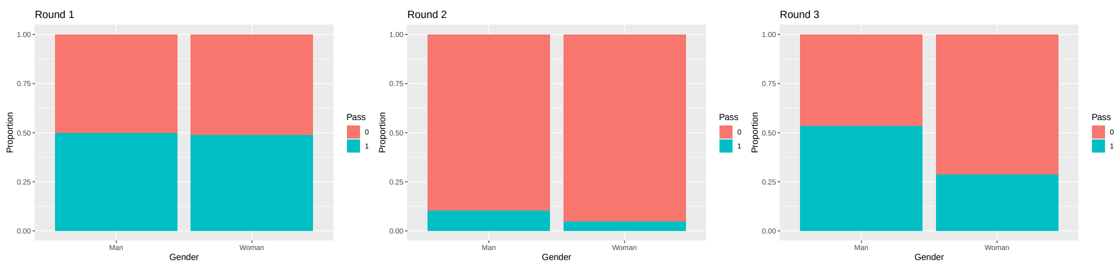
Key results of the study are summarized in the following tables.



team	man	woman	total	man_prop	woman_prop
Client services	553	579	1132	0.4885159	0.5114841
Data	458	450	908	0.5044053	0.4955947
Design	184	51	235	0.7829787	0.2170213
Legal and financial	172	182	354	0.4858757	0.5141243
Marketing and sales	802	400	1202	0.6672213	0.3327787
Operations	590	470	1060	0.5566038	0.4433962
People and talent	147	241	388	0.3788660	0.6211340
Software	1158	352	1510	0.7668874	0.2331126

Technical report

Introduction

Over the past few months, several companies in software have had bad press on people having complaints about their salaries, applicants having concerns about potenial bias in the hiring process. Chief People Officer | Black Saber Software had hired us and provided us with hiring data for new grad program, and data about promotion and salary for the entire staff. The report is to investigate whether there is potential bias in the hiring and remuneration processes, and to ensure that the company is out ahead of any potential issues.

Research questions

_ _ ## Informative title for section addressing a research question

Research Question 1: Is gender bias involved in the process of three-phases recruitment?

It is known that the recruitment process in Black Saber Software Company consists of three phases, so our examination of fairness of the hiring process will be focusing on analyzing hiring data in each phase respectively. By using the provided data sets containing information for applicants, we can construct statistical model (Logistics Regression in this report) using gender and other covariates to explain the probability of a given applicant being selected in each phase. Whether of not gender bias exists can be checked by its significance in the model we construct. This is the general methodology that we use to resolve this question. We will now go through the detailed process of model constructing for each phase as follows.

Phase 1 $\rightarrow$ Phase 2

We start by left joining applicants data in phase 2 into phase 1 by using function `left_join` in the `tidyverse` package in R with applicant ID and add binary variable `pass_phase1` to indicate whether the applicant is selected to the next phase.

In order to build model, some exploratory data analysis is performed as follows. Note that Figure 1 is the visualization for the contingency table that represents the proportion of applicants in each gender that are selected to the next phase. It can be seen that the proportion of men and women that are selected to the next phase is roughly the same. Out of those who apply for data team, 0.515625 are selected and out of those who apply for software tea,0.4705882 applicants are selected to move on. Figure 2 compares the proportion of applicants who are selected by their gender and the team they apply to work with. The plot suggests that for each gender group, their is a slightly higher proportion of acceptance if the applicant is willing to work in the data team compared to the software team. Therefore, a term for the team that applicants want to apply for will be considered in our model. It is also worth noting that no obvious difference can be observed between men and women group, which also agree with our previous plot.

Our outcome of interest is whether the applicant passes phase 1, and our predictors are GPA, work experience, extracurricular and team the applicant applies for, treated as a factor. As our outcome variable is binary, we are going to use logistic regression.The model can be written as:

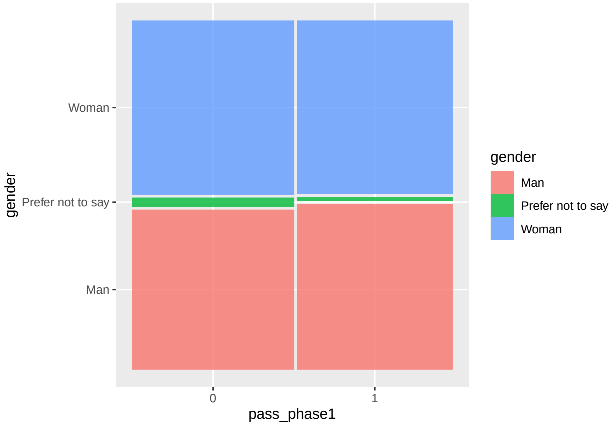
$$Y_i \sim Bernoulli(p_i)$$

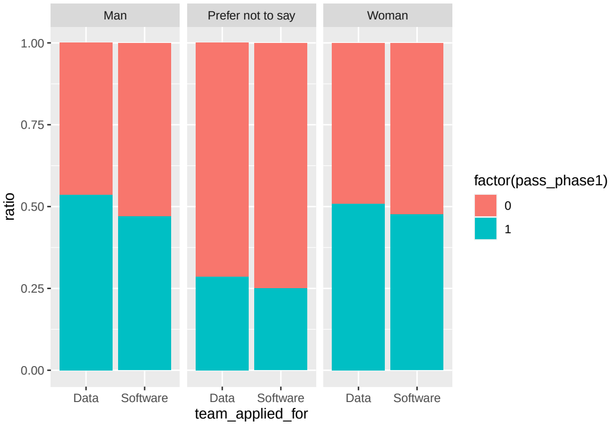
$$\log(\frac{p_i}{1-p_i}) = \beta_0 + \beta_1 GPA_i + \beta_2 \text{Extracurricular}_i + \beta_3 \text{Work Experience}_i + \beta_4 \text{Team applied for}_i$$

where Y_i is the acceptance of applicant i , X_is are explanatory variables.

The model is realized in R through the `glm` function. Result is shown in table 1. Not surprisingly, we find that GPA and work experiences are all significant at level 0.05. 1 unit increase of GPA is associated with the odds of being admitted increasing by 621%. Similarly, obtaining level 1 working experience will increase the odds of passing phase in by 335%. Most importantly, variable "gender: women" is highly insignificant with p-value 0.8576, which supports the nonexistence of gender bias in the first phase of hiring. Similar thing for the category where applicants are not willing to tell their gender.

	Estimate	Lower Limit	Upper Limit	p-value
Intercept	0	0	0	0.9638
GPA	7.21	4.78	11.18	0
Extracurriculars 1	8574079.7	2.23e+25	4.42e+92	0.9743
Extracurriculars 2	7877882.21	2.18e+38	1.88e+93	0.9744
Work Experience 1	4.35	2.12	9.87	0.0001
Work Experience 2	3.83	1.42	11.17	0.0103
Gender: Prefer Not To Say	0.5	0.08	2.33	0.4111
Gender: Women	0.96	0.64	1.45	0.8576
Team Applied for: Software	0.91	0.6	1.37	0.6457





Phase 2 $\rightarrow$ Phase 3

Similarly as the previous phase, we are going to check for gender bias from phase 2 to phase 3. See Figure 3 and 4 for comparison of proportion of passing phase 2 by gender and the team they apply to. In this case, we find less difference between employees that apply to data or software team than the previous phase, which may indicate the insignificance of this variable. Since applicants that are accepted from phase 1 should go through a series of tests online to check their technical skills, writing skills, we start our model by adding these variables with the predictor variables in the model we built in the previous phase.

Therefore, the outcome variable is whether or not the applicant passes phase 2 and for the first model we build, the explanatory variables are GPA, technical skills, writing skills, leadership presence, speaking skills and the team applicants want to join. See the mathematical formula:

$$Y_i \sim Bernoulli(p_i)$$

$$\log(\frac{p_i}{1-p_i}) = \beta_0 + \beta_1 GPA_i + \beta_2 \text{Technical Skills}_i + \beta_3 \text{Writing Skills}_i + \beta_4 \text{Speaking Skills}_i + \beta_5 \text{Leadership Presence}_i$$

See table 2 for the result of model coefficients after exponentiation realized by `glm` function. Notice that among these predictor variables, only skill related ones are significant under level 0.05. Therefore, we would like to remove some insignificant covariates to simplify our model. By removing GPA, working experience, extracurricular and team that the applicants want to join, we come up with the final logistic regression model, written as:

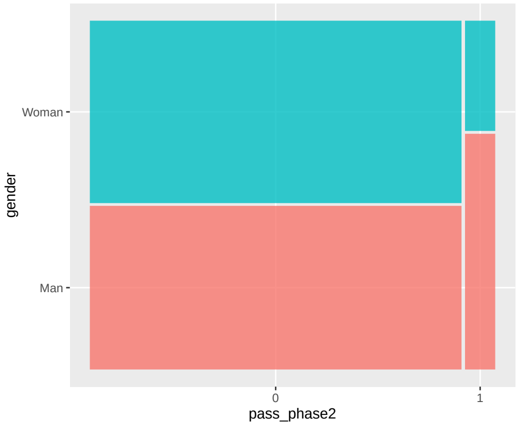
$$\log(\frac{p_i}{1-p_i}) = \beta_0 + \beta_1 GPA_i + \beta_2 \text{Technical Skills}_i + \beta_3 \text{Writing Skills}_i + \beta_4 \text{Speaking Skills}_i + \beta_5 \text{Leadership Presence}_i$$

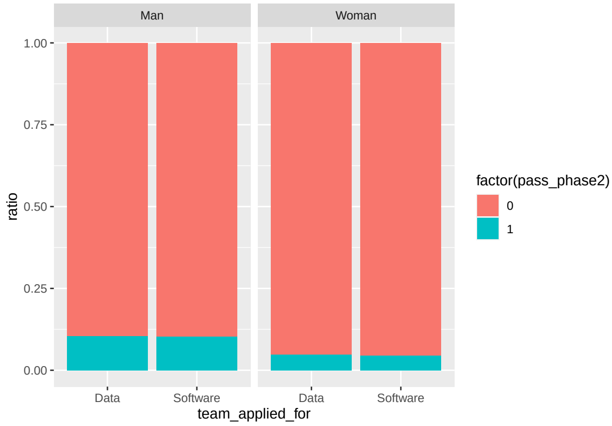
See table 3 for model results and this is a better model to fit since the AIC of the model drops from 87.527 to 83.574. The result table also suggests fairness between man and women since they are still insignificance with p-value 0.4205 > 0.01.

By conducting logistic regression, we find the algorithm for selecting applicant in phase 2 does not depend much on the significant variables in phase 1 but on the test scores for relevant skills and the selection process is also irrelevant with one's gender.

	Estimate	Lower Limit	Upper Limit	p-value
Intercept	0.00	0.00	0.00	0.0024
Gender: Woman	0.47	0.09	2.24	0.3503
GPA	0.47	0.09	2.19	0.3434
Technical Skills	1.11	1.06	1.18	0.0001
Writing Skills	1.12	1.06	1.20	0.0001
Leadship Presence	2.86	1.90	4.89	0.0000
Speaking Skills	2.46	1.68	4.05	0.0000
Team Applied For: Software	3.93	0.96	20.33	0.0743
Work Experience 1	0.30	0.00	193.38	0.8312
Work Experience 2	0.37	0.00	285.91	0.8593
Extracurriculars 2	0.65	0.14	2.78	0.5673

	Estimate	Lower Limit	Upper Limit	p-value
Intercept	0.00	0.00	0.00	0.0000
Gender: Woman	0.56	0.12	2.26	0.4205
GPA	0.42	0.10	1.55	0.2032
Technical Skills	1.10	1.05	1.16	0.0001
Writing Skills	1.11	1.06	1.17	0.0001
Leadship Presence	2.61	1.80	4.24	0.0000
Speaking Skills	2.12	1.55	3.12	0.0000





Phase 3 to Final Result

The methodology we use to deal with this phase is different from the first two phases. Since being listed as 'first' or 'second' interviewer is arbitrary, we create a new variable "sum" that is the sum of ratings by two interviewers. After sorting the sum of ratings for applicants who engaged in the interview and select top 10 applicants to match with the actual accepted interviewees, it is found that 9 of them is perfectly matched. Therefore, we can roughly make inference that the decision made in the last stage depends mostly on the interviewers' scores. Hence, we are going to test if there exists gender bias by modeling the factors that may influence the interviewer's score.

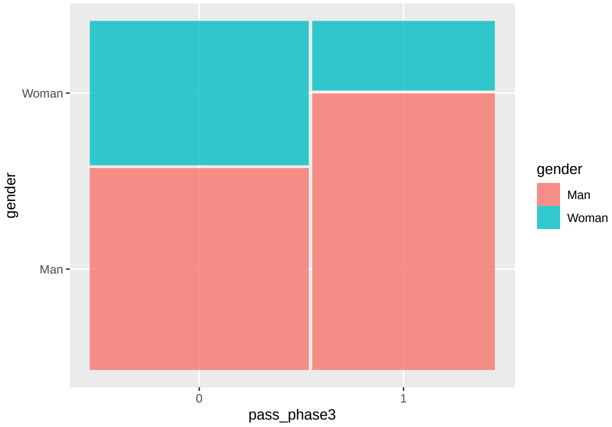
Here we are going to build the multiple linear regression model, where the outcome variable is the sum of two interviewers' score and the predictor variables are technical skills, writing skills, speaking skills, leadership presence and categorical variable gender, written as:

$$Y_i = \beta_0 + \beta_1 \text{gender}_i + \beta_2 \text{Technical Skills}_i + \beta_3 \text{Writing Skills}_i + \beta_4 \text{Speaking Skills}_i + \beta_5 \text{Leadership Presence}_i + \epsilon_i$$

Table 3 shows the results of the simple linear regression. All the skills related variables are significant except for the categorical variable gender with p value 0.6898, which supports the fairness of the hiring process.

Therefore, we conclude that there is no gender bias during the process of hiring in Black Saber Software Company.

	Estimate	Lower Limit	Upper Limit	p-value
Intercept	0.01	0.00	118491133073437.20	0.7786
Technical Skills	2.10	1.75	2.53	0.0000
Writing Skills	2.14	1.56	2.93	0.0001
Leadership Presence	139.52	20.04	971.60	0.0001
Speaking Skills	118.09	10.39	1341.59	0.0007
Gender: Woman	3.26	0.01	1557.75	0.6898



Research Question 2: Is there any gender bias in the remuneration processes?

Black Saber Software provides us with data about promotion and salary for the entire staff. The data we get consists information of the staff including annual salary, gender, job in the company, financial quarter salary, productivity, role seniority, and quality of demonstrated leadership. We use these data to investigate whether there is any gender bias in remuneration process. The general methodology that we use to is creating a boxplot of salary conditions on role seniority and gender setting, and then applying different types of regression models to see which one best serve our purpose. Boxplot:

From the graph, we can see that women have lower salaries across different role seniority.

In order to test whether gender bias truely exists, we need to first find the most appropriate model. We create a simple linear regression model:

$$y = x1 + x$$

, we find out that gender is statistically significant, which suggests gender has impacts on salaries. Moving on from SLR, we apply linear mixed model:

$$y =$$

, we add the variable “team”(job in the company) as the random intercept. We do such because we think there should be variations in salaries across different jobs in the company. The likelihood ratio test tells us including such does explain the data better. The results from the linear mixed model also show us that gender is significant. Next, we add a random slope to the previous model because the effect of the productivity may be different for different jobs in the company. After the likelihood ratio test, we find that slopes are an unnecessary complication to our model. Finally, we add role seniority as another random intercept because there should be variations in the salaries across different role seniority based on our histogram. For example, senior workers have higher salaries than junior workers. The likelihood ratio test tells us that including this random intercept does explain the model better. Thus, the final model is

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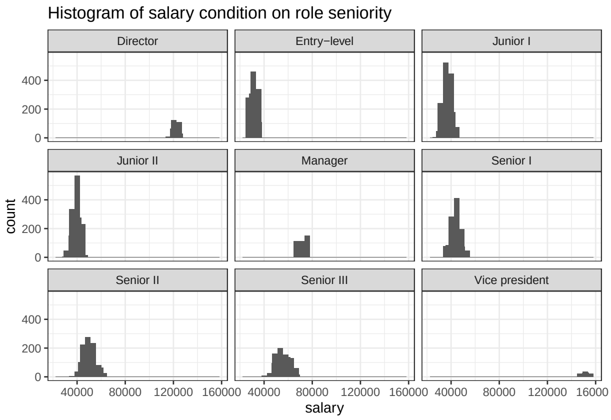
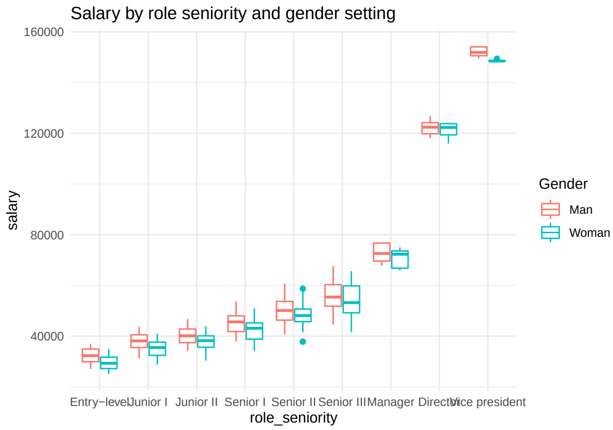
Based on interpretation, Woman has lower salary by an average of $1758 than man. This result indicates that there is gender bias in remuneration.

```
## Likelihood ratio test
##
## Model 1: salary ~ productivity + Gender + (1 | team)
## Model 2: salary ~ productivity + Gender + (1 | team) + (1 | role_seniority)
##   #Df LogLik Df Chisq            Pr(>Chisq)
## 1   5 -77184
## 2   6 -64769  1 24829 < 0.00000000000000022 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

	Estimates
Intecept	67253.17
Productivity	1.27
GenderWomen	-1757.64





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).

1 unit increase of GPA is associated with the odds of being admitted increasing by 621%. Similarly, obtaining level 1 working experience will increase the odds of passing phase in by 335%.

Strengths and limitations

Consultant information

Consultant profiles

Chengen Dong. Chengen is a senior consultant with Calabash Brothers Solutions. He specializes in data visualization. Daniel earned his Bachelor of Science, Specialist in Statistics Methods and Practice, from the University of Toronto in 2024.

Yuxuan Longt. Yuxuan is a senior consultant with Calabash Brothers Solutions. He specialize in reproducible analysis. Peter earned their Bachelor of Science, Majoring in Statistics from the University of Toronto in 2028.

Ran Li Ran is a junior consultant in Calabash Brothers Solutions. She is good at coding with software like R and Python. She specializes in Computer Science. Liran earned her Bachelor of Science, Majoring in Computer Science from the University of Toronto in 2028.

Peizhe Huang Peizhe is a senior consultant with Calabash Brothers Solutions. She specializes in Probability Statistics. Peizhe earned their Bachelor of Science, Majoring in Statistics from the University of Toronto in 2022.

Code of ethical conduct

Integrity: We maintained honest with our data and clear communication throughout the working process.

Teamwork: We worked together to get the job done.

Confidentiality: We maintained clients' condifence at all time

Growth: We always pursue professional growth Final advice: KNIT EARLY AND OFTEN!