Investigative Report of Black Saber Software Hiring and Renumeration

Examining potential gender bias

Report prepared for Black Saber Software by Eddie Moon Data

Contents

Executive summary

Background & Aim

This report aims to investigate and identify any existing potential biases in the hiring and renumeration processes at Black Saber Software. The goals are to effectively diagnose if there is any discrimination against the current and potential employees. More specifically, we are interested in whether there are key differences in the data between men and women. If all other factors are accounted for and employees are more favoured strictly based on their gender, then that implies unfairness existing in the company processes.

The main questions we will focus on answering, are whether or not these gender preferences already exist within the company, as well as in deciding new hires. For the new hiring system, we will focus on identifying any possible biases in regards to the AI's process, as well as the human process. The dataset used in this report was fully given by the company, and it includes anonymized information about the current employees, as well as applicants from the hiring process.

Key findings

- Proportions of different salary levels were similar for both men and women (Table 2)
- No obvious biases were observed in the hiring AI's decisions (Figures 2 & 3)
- Final interview stage with human interviewers had very similar results to the AI. (Figure 4)
- Overall, no apparent bias in any of the specific areas were found:
    - Black Saber Software does not employ any gender biases in their processes

Limitations

- More precision could have been added to the dataset (A single number depicting productivity at the company may not be the strongest reference)
- The integrity of this data is not confirmed, there was no way of determining if the values in the data were manipulated to alter outcomes
- Further characteristics of each employee and applicant could have also been included to be observed, such as age, ethnicity, religion, etc.

Technical report

Introduction

This section will attempt to display the process of investigation and answer the research questions at hand about Black Saber Software. We will dive deeper into each model specifically and technically to examine whether or not any biases may exist in the hiring and renumeration processes at the company. The current employee data holds key information such as gender, productivity score, salary, and role. The hiring data holds information about each applicant such as gender and gpa, as well as all of the scores given by the AI or the interviewers.

Research questions

1. Are there any existing biases in regards to salaries of the current employees?

2. Does the new AI hiring system have any built-in biases? Does it favour a specific gender over the other?

3. Do the human interviewers have any apparent gender bias? Was there any predilection in the last phase of the hiring process?

Current Employee Salaries

First, we can begin by looking at our original dataset, and we will remove the entries where gender is "Prefer not to say". This is because we are trying to find biases that may exist in regards to gender, so we are not interested in the cases where it is not specified. We also want to work with the salary variable. We want the value to be numeric so we need to remove the dollar sign and comma from the values in that column.

Now let's take a look at a basic scatterplot of our data as salary as the reponse variable.

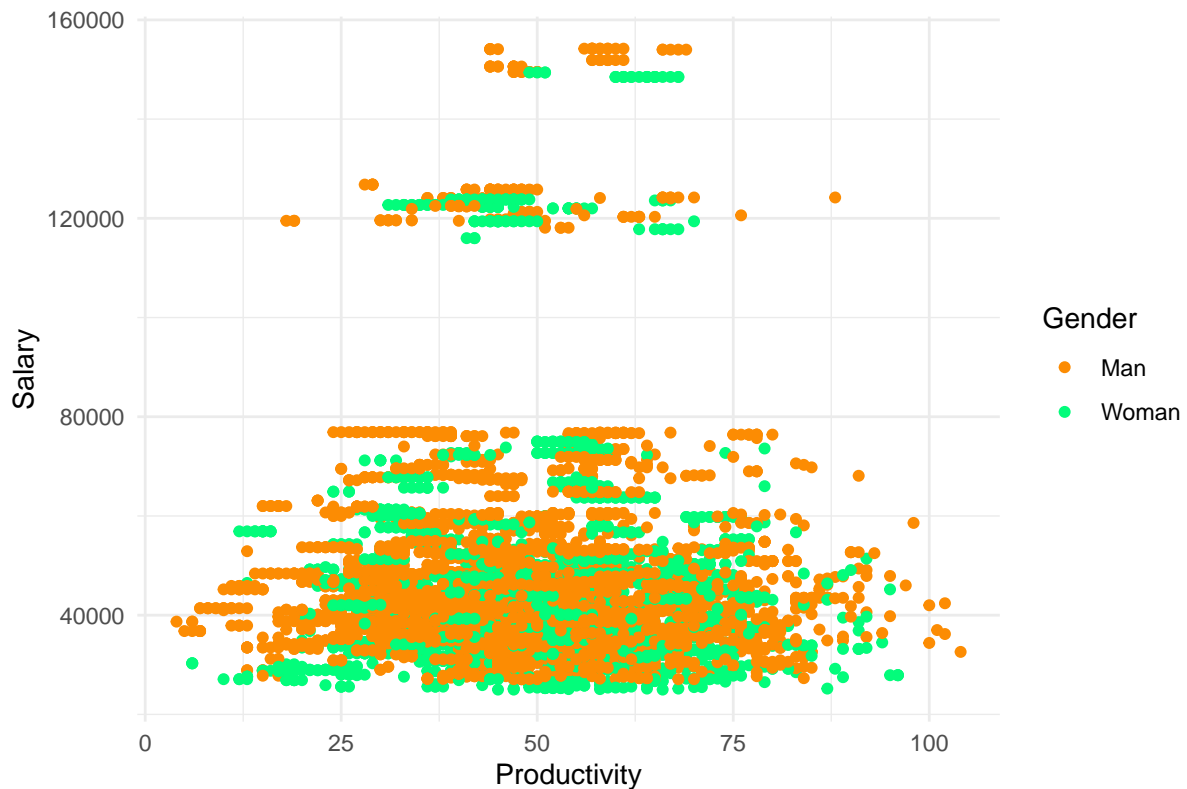Figure 1. Productivity vs Salary scatterplot categoried by Gender

We can see that the salary ranges vary, but it seems they are generally categorized into three different levels, so we can create a new variable that states the salary level: Low, Medium, or High. We can also see that productivity seems to vary greatly for all levels of salary, there are people from the productivity scale spread out fairly evenly.

Now let's look at some tables with proportions based on gender.

Table 1: Counts of gender

Var1	Freq
Man	4064
Woman	2725

Table 2: Conditional proportions of salaries for each gender

	High	Low	Medium
Man	0.013	0.952	0.035
Woman	0.010	0.953	0.038

We can see from Table 2 that for both Man and Woman, the proportions are almost identical, meaning there are similar proportions of salary levels for both of the men and women. This is one indicator that there is no bias based on gender for this specific case.

Hiring AI

Again, we can remove the cases where gender is "Prefer not to say". Firstly we can look at the phase 1 data, the initial applicants. We will create a new variable called total_score, which is the sum of all the numeric variables in the phase 1 data (these are the scores the AI gave to each applicant). This wil give us an easy way to compare different applicants. The higher the total_score means the more value an applicant should have in very general terms, based on the AI.

Then we can create another column passed_round that takes TRUE if they made it to phase 2, or FALSE if they were not selected by the AI for phase 2.

Finally, we can create a plot with the whether they passed or not as the response, and their score on the x-axis.

Let's separate our two graphs for each gender in our data, so we can easily visualize the comparisons.
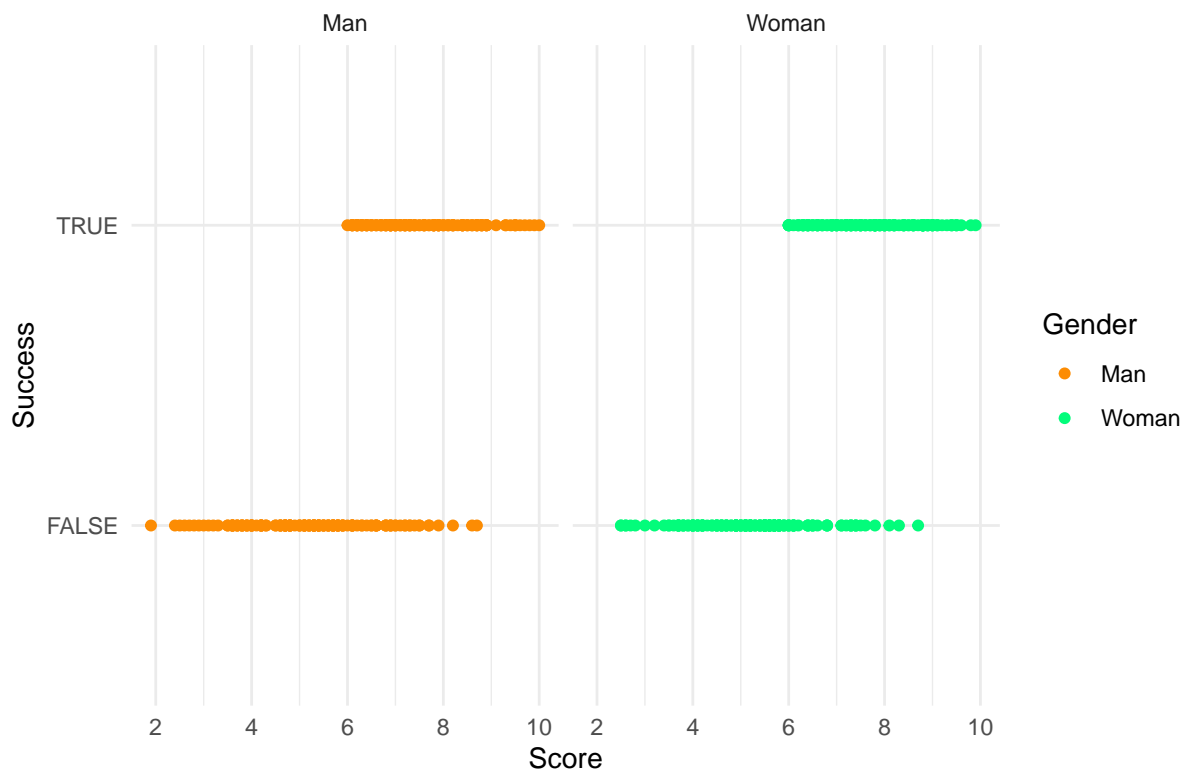
Figure 2. Applicant Score vs. Success (TRUE for passing to phase two, FALSE for not)

We can see quite clearly that the distributions for men vs women are similar. No applicant with a total score lower than ~6 passed the first stage. There does not seem to be any obvious biases here. This means that the AI likely made the decision to pass applicants based on their score only, regardless of gender. More importantly, the AI also seems to have given an equal distributions of scores to both men and women, which could be an indicator that there was no bias based on gender when grading the applicants.

Let's follow the same approach for applicants of phase two –> phase three. We will use the new variables from phase two to create a new score, and again compare men vs women to see who passed.
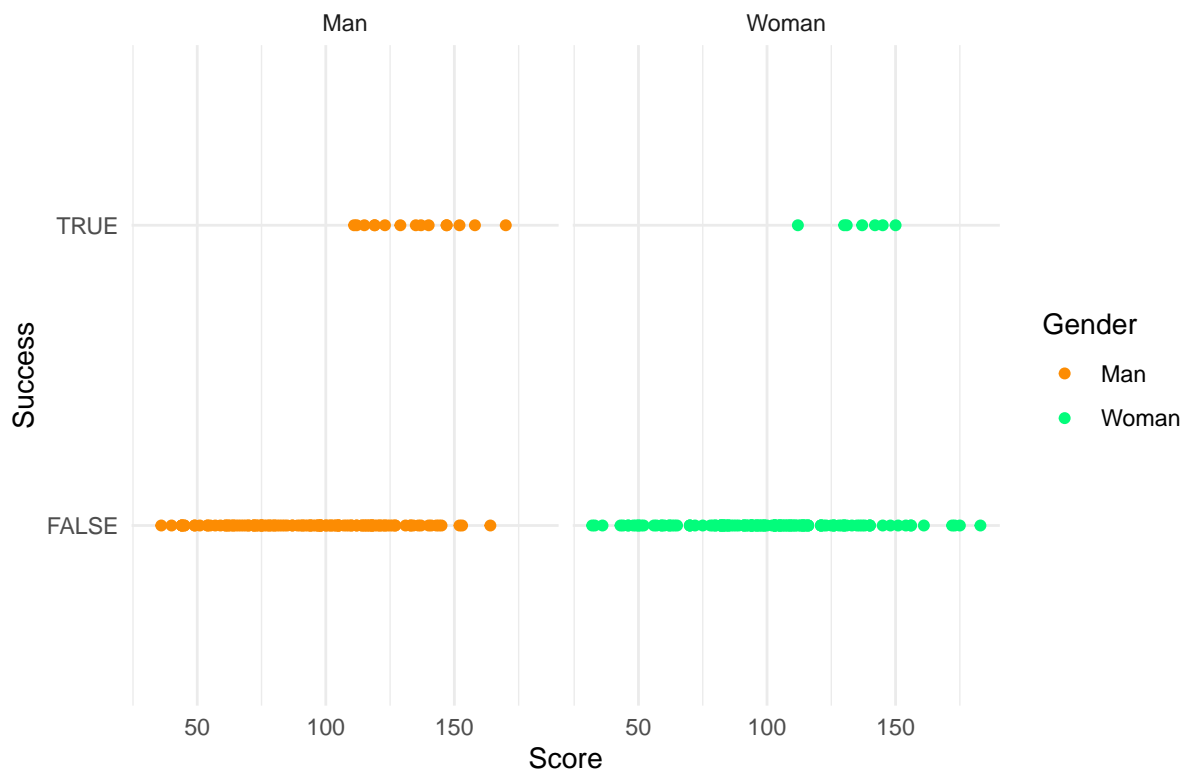
Figure 3. (Phase 2–>3) Applicant Score vs. Success (TRUE for passing to phase three, FALSE for not)

Similar as before, the distributions seem very similar between the men vs women. Applicants with a score under ~100 did not pass.

Human Interviewer

The final phase of the hiring process was by two human interviewers, who each gave the applicant a score. Again, we can take the sum of the scores from these two as the total score and visualize it similarly, based on who finally got hired and who did not.
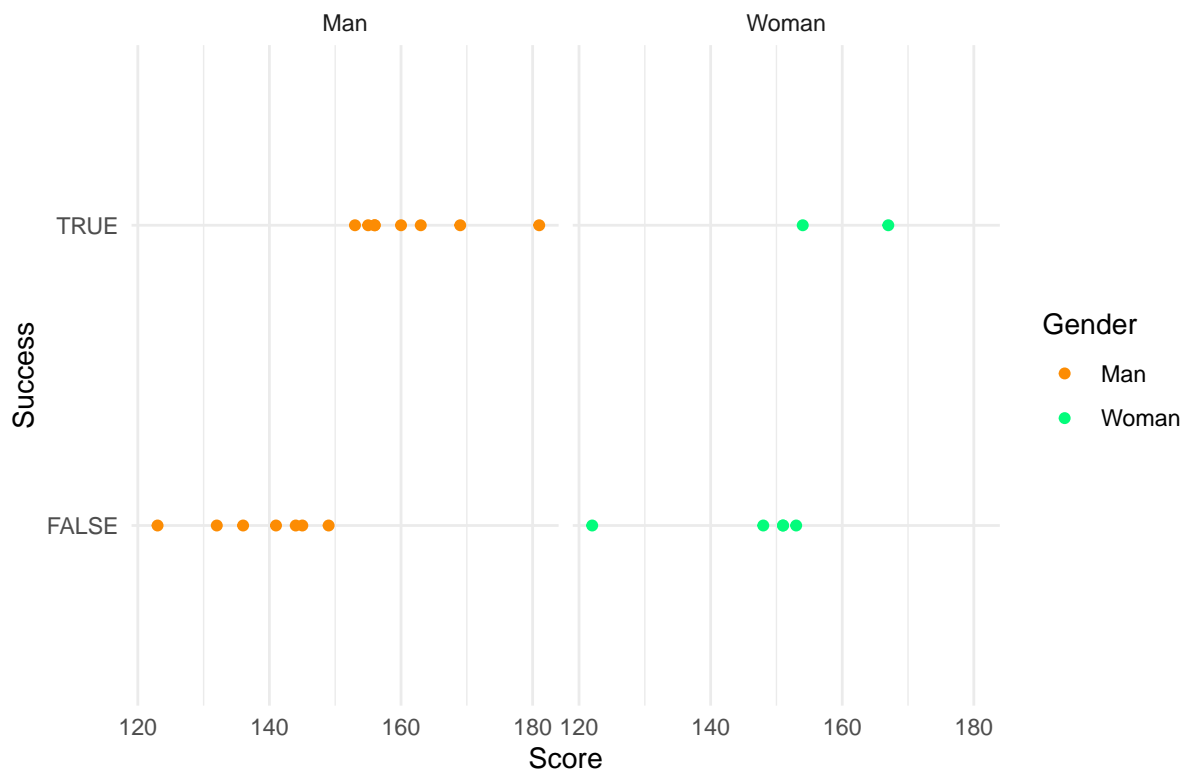
Figure 4. (Final phase) Applicant Score vs. Success (TRUE for hired, FALSE for not)

The data here is not large enough to make a concrete observation, but the pattern is again similar. There is a threshold of at least ~150 for being hired. The two interviewer scores were the only values taken during the final interview stage. This means that no other numeric value from testing affected the hiring results and we can see from Figure 4 that it seems that the score is a good predictor for being hired or not. It appears also that there were no human bias in gender differences in final hiring.

Discussion

Overall, looking at our tables and figures we can conclude that there is likely no bias based on gender in Black Saber Software. In the current employees, there seems to be no difference in salary and compensation between the genders. In the new hiring process managed by the AI, the grading and decisions of applicants seem to not be based on gender, and instead on the other characteristics and skills of the applicants. Similarly, the human interviewers in the final process follow the distributions of the AI.

Strengths and limitations

A strength of our investigation is that we are working with a large dataset with thousands of different cases. This allows us to build a model with a large enough sample size to make meaningful investigations and conclusions.

We are however, limited by the descriptions of each case in our data. The value of a current employee is mainly defined by their productivity, which is simply a numeric value in which we do not know how it was obtained. Additional mechanisms could be put into place to classify each employee to make the data even stronger, such as a score given by coworkers or managers, a dedication score, etc. Moreover, in our report we have only investigated the possibility of gender bias. Our conclusion does not eliminiate all potential bias in the company, there could still exist preferences based on age, race, ethnicity, etc. These variables could have been included in the data given to allow more opportunities for exploration and conclusions.

Consultant information

Consultant profiles

Eddie Moon. Eddie is the CEO and founder of Eddie Moon Data. He specializes in data manipulation and visualization. Eddie has earned his Bachelor of Science, Majoring in Statistics and Minoring in Computer Science and Mathematics at the University of Toronto in 2022.

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