

Gender Bias in Job Descriptions

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Theoretical background

Cultural and social constructions have been studied in relation to the labor market, with particular focus on the influence of gender. Gender, as a term, encompasses the cultural system of structural arrangements within the context of biological sex. Its meaning is shaped not only by the opposite gender but also by various societies, cultures, and fields. These gender-based constructions prevalent in society have been replicated in the labor market, resulting in inequalities. These inequalities manifest in wages, benefits, demands, expectations, and even in the perception of specific roles when performed by different genders.

In today's labor market, although there is a significant number of women, many organizations remain gender-dominated, with certain characteristics and qualities attributed primarily to one gender. Such cultural systems play a significant role in determining the roles expected to be fulfilled by men and women. One area where these gender inequalities are evident is the underrepresentation of women in science and engineering professions ([Women in Hi-tech industry 2022](#), Innovation Israel).

Gender bias is a pervasive issue that permeates various aspects of society. It is well known that women often experience discrimination in hiring, promotions, pay, and job assignments. Stereotypes and preconceived notions about gender roles influence how individuals are perceived and evaluated, leading to unequal treatment and limited opportunities. These biases can manifest subtly, including in the language used within job descriptions.

The software engineering industry, known for its historical male-dominated nature ([Technology Trends, Shubhomita Bose](#)), demonstrates significant gender bias. This bias is characterized by imbalances in the representation of men and women, which have persisted over time.

Job descriptions play a crucial role in shaping potential applicants' perceptions of a position and an organization. They serve as the initial point of contact between candidates and the job market. However, research suggests that gender bias can be embedded in the language and content of job descriptions, inadvertently deterring qualified women from applying.

This literature review aims to examine the gender-based differences in job descriptions within the software engineering industry, shedding light on the impact of job characteristics on women's job application decisions. Understanding these differences is crucial for promoting

gender equality and fostering diversity within the field. By identifying and addressing discriminatory language and practices in job descriptions, we can assist recruitment teams in creating more inclusive and welcoming environments that attract and retain talented women.

We drew significant inspiration from Moran Weber's post titled "[How to Attract More Women \(and not the way you think\)](#)", which offers practical suggestions for encouraging women to apply for jobs by addressing language characteristics. The recommendations include avoiding gender-related superlatives, refraining from describing a masculine environment, fostering a workplace that supports work-life balance for parents and more. These ideas align with the findings of "[Evidence That Gendered Wording in Job Advertisements Exists and Sustains Gender Inequality](#)" by Danielle Gaucher, Justin Friesen, and Aaron C. Kay.

In this workshop, our objective was to develop a tool that assists recruitment teams in avoiding practices that discourage women from applying for jobs, incorporating insights from the papers we have studied.

Upon completing our research and transitioning to the writing phase of this paper, we discovered that several tools have already been developed to address similar topics and assist recruitment teams. Notable examples include [Ongig](#) and [Textio](#), both of which aim to provide support in creating more inclusive and effective job descriptions. These tools align with our goal of aiding recruitment teams in developing gender-inclusive job descriptions that attract diverse candidates.

Research problem

The research problem addressed in this research is gender bias in job descriptions within the software engineering industry. Despite the significant number of women in the labor market, women are underrepresented in science and engineering professions.

This underrepresentation can be attributed to inequalities and biases in job descriptions, which deter qualified women from applying for positions. Therefore, there is a need to understand the gender-based differences in job descriptions and their impact on women's job application decisions in order to promote gender equality and diversity in the field.

Research target

1. To identify and analyze the gender-based differences in job descriptions within the software engineering industry.
2. To understand the role of language and content in job descriptions in perpetuating gender bias and limiting opportunities for women in software engineering.
3. To explore practical strategies and recommendations for creating more inclusive and gender-neutral job descriptions that attract diverse candidates.

Research questions

1. What are gender-based differences in software engineering job descriptions?
2. How does language and content in job descriptions contribute to gender bias and unequal treatment of women in software engineering?
3. What are the practical strategies and recommendations for creating more inclusive and gender-neutral job descriptions that attract diverse candidates?
4. What are the potential challenges and limitations in implementing gender-inclusive language in job descriptions, and how can these be addressed?
5. What are the implications of gender bias in job descriptions for promoting gender equality and fostering diversity within the software engineering industry?

Research methods

Population

The population for this research includes recruiters and hiring managers within the software engineering industry. These recruiters are responsible for creating and writing job descriptions and selecting candidates for interviews. They play a crucial role in shaping the language and content of job descriptions, and their awareness and understanding of gender bias can have a significant impact on promoting gender equality and diversity within the field. By examining the language and content of job descriptions created by these individuals, this research aims to identify and analyze gender-based differences and their impact on women's job application decisions and to provide valuable insights for recruiters and hiring managers to attract diverse candidates and promote gender equality within the software engineering industry.

Research process

1. **Problem identification:** The research problem addressed in this research is the presence of gender bias in job descriptions within the software engineering industry and its impact on women's job application decisions. The goal was to promote gender equality and diversity by understanding gender-based differences in job descriptions and exploring strategies for creating more inclusive and gender-neutral descriptions.
2. **Literature review:** We conducted a thorough review of existing literature on gender bias in job descriptions, gender-based differences in the software engineering industry, and strategies for promoting gender equality. This step helped in understanding the existing knowledge and identifying research gaps.
3. **Research questions:** We formulated research questions that addressed the objectives of the study, such as identifying gender-based differences, analyzing the role of language and content, exploring practical strategies, and understanding the implications of gender bias.
4. **Data collection:** Since labeled data was not available, alternative approaches needed to be employed. We initially considered a survey for labeling, but due to insufficient responses, an alternative approach was adopted.
5. **Labeling with a language model:** To label the data, a language model was utilized. It was trained on a large corpus of text and could generate coherent sentences. We used the language model to label the job descriptions based on the presence or absence of gender bias. However, this approach had its challenges, as the language model required careful adjustments and definition of ideal prompt to model language accurately.
6. **Defining an ideal prompt:** Generating unbiased labels with a language model required careful consideration of the prompt used to instruct the model. We experimented with different prompts to elicit accurate and unbiased responses. We aimed to provide clear instructions that would guide the model to identify gender bias effectively. We had to strike a balance between providing explicit instructions to the model without introducing any biases ourselves. We needed to avoid inadvertently influencing the model's output by unintentionally including biased language or assumptions in the prompt.

7. **Importance of human oversight:** Despite using a language model for data generation, human oversight remained crucial throughout the process. We carefully reviewed the generated labels, cross-checked them against established guidelines, and manually corrected any inaccuracies or biases. Human judgment and expertise played a vital role in ensuring the quality and reliability of the labeled data.
8. **Absence of gender-biased job description data:** Due to the unavailability of labeled data specifically addressing gender-biased job descriptions, we encountered a significant challenge. Without pre-existing examples to work with, alternative approaches were necessary to effectively tackle gender bias in job descriptions.
9. **Generating data with a language model:** To address the generation task, we employed a language model. However, this approach presented its own set of difficulties. The chosen language model was designed to prevent intentionally generating biased outputs. However, for the purpose of identifying gender bias in job descriptions, it was necessary to find ways to work around these guidelines without compromising the integrity of the results. This required careful consideration and experimentation to ensure that the language model could accurately generate the data while addressing the ethical concerns surrounding biased content.
10. **Sentence-level labeling approach:** To enhance the language model's understanding and labeling of gender bias, we segmented the job descriptions into individual sentences. This approach allowed for a more targeted analysis of potential biases within each sentence. By focusing on sentences rather than whole paragraphs, we aimed to provide more specific input to the language model, facilitating the identification and mitigation of biases.
11. **Model training on unbalanced data:** Another challenge we encountered was the unbalanced distribution of available training data. It is important to acknowledge that the language model's training could be influenced by the prevalence and distribution of biased or unbiased text in the training data. We made efforts to curate the training data carefully, ensuring a diverse representation of job descriptions. However, it is crucial to consider the potential bias inherent in the training data when interpreting the model's predictions.
12. **Training a classifier on unbalanced data:** One of the challenges we encountered was the unbalanced distribution of the data used to train the classifier. In our dataset, there was a

significant disparity in the number of biased and non-biased job descriptions. The majority of the job descriptions were non-biased, while the number of biased examples was relatively low. This class imbalance posed a challenge during the training process.

To address this issue, we employed various techniques such as oversampling, undersampling, and class-weighting to mitigate the impact of class imbalance on the classifier's performance. These techniques aimed to ensure that the classifier was not biased towards the majority class and could effectively learn patterns of bias from the limited biased examples available. However, it is important to note that despite these efforts, the inherent class imbalance could still affect the classifier's predictions, and this aspect needed to be taken into account when interpreting the results.

13. **Deciding on the classifier:** In order to classify job descriptions for gender bias, we extensively explored multiple machine learning algorithms. Some of the models we experimented with included logistic regression, support vector machines (SVM), and random forests. Each of these models has been widely used in text classification tasks and offered different advantages.

However, after thorough experimentation and evaluation, the Naive Bayes classifier emerged as the most suitable choice for our task. Naive Bayes classifiers have demonstrated strong performance in text classification tasks, particularly when dealing with natural language processing applications. Their simplicity and efficient computation make them well-suited for large-scale datasets, such as our job description dataset.

Furthermore, the Naive Bayes algorithm assumes independence between features given the class label, which aligns with the nature of text data where word occurrences are often treated as independent features. Although this assumption may not hold perfectly in practice, Naive Bayes classifiers have proven to be surprisingly effective in text classification scenarios.

Considering the performance, interpretability, and computational efficiency of the models we tested, the Naive Bayes classifier consistently yielded the best results for classifying job descriptions for gender bias. Its ability to handle high-dimensional text data, robust performance, and efficiency made it the optimal choice for our specific task.

Data collection tools

1. **Survey for labeling:** Initially, we conducted a survey to collect labeled data regarding gender bias in job descriptions. The survey aimed to gather insights from participants on their perceptions of bias in job descriptions and to identify specific examples. However, the number of survey responses we received was not sufficient for comprehensive analysis. Recognizing the need for a more extensive dataset, we explored alternative data collection methods.
2. **Kaggle database and manual LinkedIn scraping:** To augment our dataset, we turned to publicly available data sources. We leveraged a Kaggle database containing job descriptions from various industries, including software engineering. The Kaggle dataset provided us with a diverse range of job descriptions, enabling us to conduct a broader analysis of gender bias across different domains. Additionally, with the assistance of our colleagues from the labor study team, we manually collected job descriptions from professional networking platforms such as LinkedIn, with a specific emphasis on software engineering roles. This approach ensured access to real-world job descriptions, incorporating the latest trends and practices in the industry.

Data analysis methods

1. **Data pre-processing:** Before conducting the data analysis, it was essential to pre-process the job descriptions data. This step involved several preprocessing techniques, such as:
 - **Tokenization:** Splitting the job descriptions into individual tokens (words or subwords) to facilitate further analysis.
 - **Stop word removal:** Eliminating common and irrelevant words, such as "the," "is," and "and," that do not carry significant meaning.
 - **Normalization:** Applying techniques like stemming or lemmatization to reduce words to their base or root form for better representation.
2. **Feature extraction:** To analyze the job descriptions effectively, we needed to convert the text data into numerical features that machine learning algorithms could understand. The following techniques were employed for feature extraction:

- **TF-IDF** (Term Frequency-Inverse Document Frequency): Calculating the importance of words in the job descriptions by considering both their frequency in a particular description and their rarity across the entire dataset.
 - **Word embeddings**: Utilizing pre-trained word embeddings, such as Word2Vec or GloVe, to capture semantic relationships between words and represent them as dense numerical vectors.
3. **Model evaluation and interpretation**: After training the classifier, evaluating its performance and interpreting the results were crucial steps in the data analysis process. Key aspects included:
- **Accuracy and metrics**: Assessing the classifier's accuracy and other performance metrics such as precision, recall, and F1-score to measure its effectiveness in identifying gender bias.
 - **Confusion matrix analysis**: Analyzing the confusion matrix to understand the classifier's performance in terms of true positives, true negatives, false positives, and false negatives.
 - **Feature importance**: Investigating the importance of different features (words or phrases) in the classification process to gain insights into the key factors contributing to gender bias detection.
4. **Iterative refinement**: Data analysis often involves an iterative process of refinement and improvement. Based on the insights gained from the initial analysis, adjustments were made to the preprocessing steps, feature extraction techniques, or classifier parameters to enhance the accuracy and effectiveness of the model.

Ethical considerations

In conducting the workshop on gender bias in job descriptions, it is important to address specific ethical considerations that emerged during the research process. These considerations revolve around privacy concerns and the potential biases inherent in the methods used to analyze and generate gender-biased sentences. By recognizing these ethical issues, researchers can work towards mitigating any potential negative impacts and ensuring the integrity of the study. The following ethical considerations should be considered:

1. **Privacy protection:** In this research, we encountered a challenge in obtaining company-specific data regarding the number of male and female applicants for specific job descriptions. This lack of access to data compromised the research process and necessitated alternative approaches, such as using GPT as a judge to assess gender bias. However, it is essential to respect the privacy of organizations and individuals involved.
2. **Biases in labelling and sentence generation:** The workshop involved manual labelling of sentences to identify gender bias, as well as using GPT and BARD to generate gender-biased sentences. It is important to acknowledge that these methods can introduce biases themselves. We must be transparent about the limitations and potential biases in the labelling process, addressing any challenges and uncertainties associated with subjective judgment.
3. **Ethical use of findings:** The findings and recommendations derived from the workshop should be used responsibly and ethically. It is important to avoid misusing the results to perpetuate bias or discriminate against any gender. Instead, the findings should serve as a basis for raising awareness, fostering dialogue, and promoting positive change within the software engineering industry. Responsible application of the research can contribute to creating more inclusive job descriptions and recruitment practices.

By actively considering and addressing these ethical considerations, researchers can ensure that the workshop promotes fair and unbiased practices within the software engineering industry. Transparency, privacy protection, and responsible use of findings should guide the research process to facilitate a positive impact on gender equality and diversity.

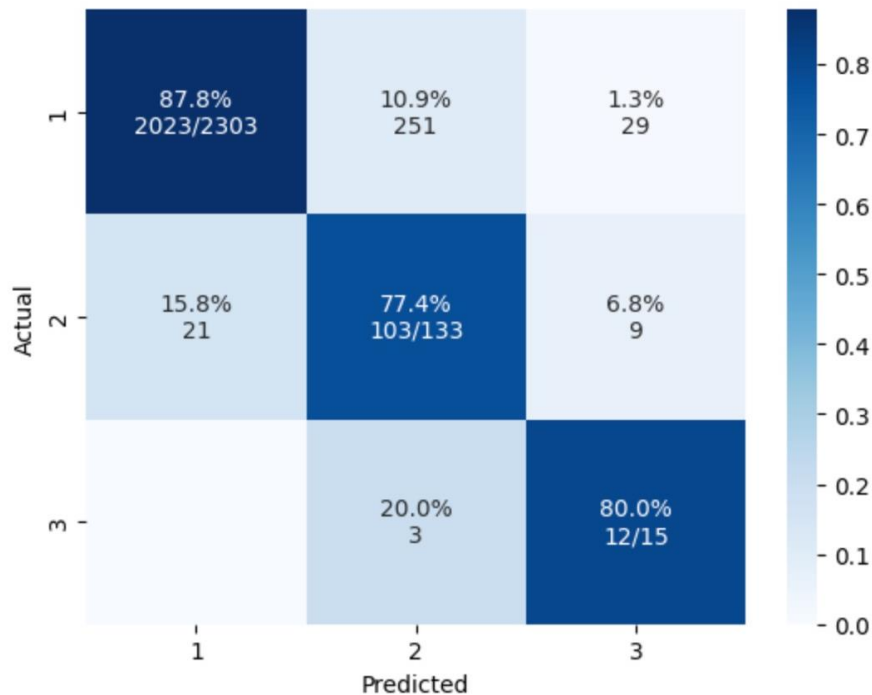
Research limitations

Some of the limitations in this research included the **unavailability of labeled data** specifically addressing discriminatory job descriptions, which required the use of alternative approaches such as a language model for data generation and labeling. Additionally, **the use of a language model** presented its own set of challenges, such as the need for careful defining an ideal prompt to accurately model the language and the task. The inherent **class imbalance in the data** used to train the classifier could also affect its predictions and needed to be taken into account when interpreting the results.

Findings

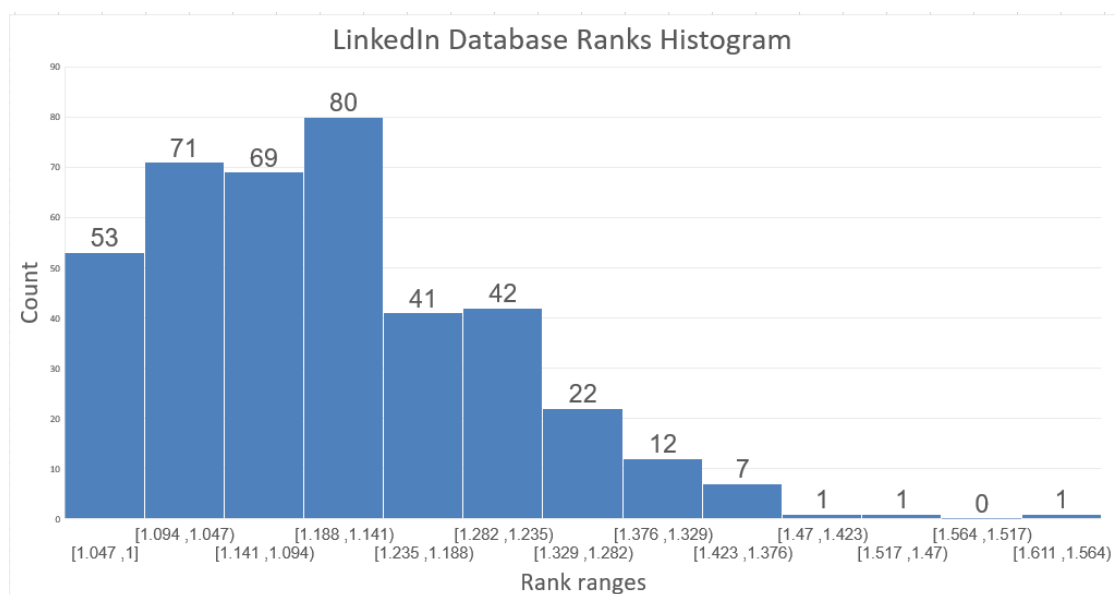
Our main program gets a job description, split it into main sentences, send them to our model and calculates a final grade to the job description as a whole.

Hereby is the confusion matrix of our classifier:



The classifier in our research achieved an accuracy of 0.87. This shows that the classifier was able to correctly identify gender bias in job descriptions with a high degree of accuracy.

We ran our program on our LinkedIn database, and received the following histogram:



As we can expect, all of the job descriptions we got from LinkedIn are in the range of 1-1.611 out of 3. This means that they are mostly gender neutral and a few tend to have mild gender biased. Here is an example for a job description ranked 1.57 out of 3, and the phrases that we think caused the classifier rank it in this grade:

XXXXXXX is looking for a **strong technical leader** to establish and manage a team of talented engineers within the Programs Team. As the leader of this new initiative, you'll work to build **mission-critical**, cross-company strategic projects from scratch (ex. internal apps, the builder certification program, video-on-demand site, and more).

We're looking for a **strategic leader** with an agile startup mindset, ambitious creativity, and strong mentorship skills.

About The Role

Leading innovative technical solutions for challenges across the company

Strategizing and developing new technical projects from A-Z

Owning the entire full-stack production process - from research and execution to optimization in production

Working closely with the product and design teams, **taking full responsibility from conception to post-deployment in a fast-paced, collaborative environment**

Scaling a development team - recruiting and mentoring top talent, building processes, building a team culture, etc.

Our stack: node.js, Ruby on Rails, React/Redux, AWS, GCP, Marketplace Apps, Elastic Search, MySQL, Redis, and WordPress

Requirements

7+ years of management experience

Experience in creating product roadmaps from conception to launch, driving product vision, and defining go-to-market strategy

Experience in complicated software architectures, preferably in web and SaaS environments

Passion for building great customer experience

A keen eye for details, UX, and design

Business-oriented with a passion for building high-end products

A soul of an entrepreneur, a passion for solving challenges, thrives in a fast-paced working environment

Strong mentorship and communication skills

As we can see, some of the phrases marked can discourage women from applying to this job, and we suggest refraining using them to make the job description more inclusive and encouraging for women to apply to the job.

In addition, the first part of our research included analysis of our LinkedIn job descriptions database. We extracted phrases that can discourage women from applying to jobs, and used an NLP model to enrich the list. We analyzed statistically the phrases per category (skills, work environment, coding languages, education, experience, advantages etc).

The results were as follows, where phrases that appear bigger repeated more in our database:



Discussion and conclusion

Our research has made some contributions to both the theoretical understanding and practical application of addressing gender bias in job descriptions within the software engineering industry. Theoretically, our research has advanced the understanding of gender-based differences in job descriptions and the role of language and content in perpetuating gender bias. Practically, our research has provided practical suggestions for creating more inclusive and gender-neutral job descriptions by refraining from using phrases that may discourage women from applying to the job. Our program was able to classify and grade job descriptions based on the level of gender-biased they are. Our classifier achieved an accuracy of 0.87, indicating its effectiveness in identifying gender bias. These findings have important implications for promoting gender equality and diversity within the software engineering industry. For future research, it would be valuable to explore additional strategies for creating inclusive job descriptions and to evaluate their effectiveness in attracting diverse candidates. Further research could also investigate the long-term impact of using inclusive job descriptions on the diversity of the workforce within the software engineering industry.

Personal reflections

Yuval Mor

Working as a team was an enriching experience that allowed us to leverage our diverse perspectives, knowledge, and skills to address the research problem effectively. By collaborating closely, we were able to divide tasks, support each other, and utilize our individual strengths to the fullest extent. Open and transparent communication played a pivotal role in our success, as we held regular meetings to discuss progress, share ideas, and provide feedback. Creating an inclusive environment where every team member's voice was valued fostered a strong sense of unity and alignment throughout the research process.

Through researching people analytics, specifically focusing on gender bias in job descriptions, I gained a deeper understanding of the pervasive inequalities that exist within the software engineering industry. This exploration highlighted the importance of addressing such biases and creating a more inclusive environment for underrepresented groups. Engaging in thorough literature reviews and analyzing case studies honed my analytical and research skills, enabling me to delve deeper into the complexities of gender bias in job descriptions. It was an eye-opening experience that broadened my perspective on the challenges faced by women pursuing careers in this field.

Working in an agile technique proved to be a refreshing and dynamic approach to project management. The iterative nature of the agile methodology allowed our team to adapt and respond to changing requirements and priorities throughout the research project. This fostered a collaborative environment that promoted flexibility, continuous learning, and quick decision-making. Efficient time management was facilitated through regular sprint planning and retrospectives, which helped us assess our progress, identify areas for improvement, and adjust our strategies accordingly. The iterative feedback loops kept us focused, accountable, and allowed us to deliver high-quality research outcomes within the given timeline.

Liron Cohen

As a female student and software engineer, I experience the gender gaps that exist between men and women in the high-tech field on a daily basis- starting with education at a young age, choosing science and technology majors in high school, recruitment for technological positions in the army, acceptance for scientific academic degrees, acceptance for workplaces and technological positions, and more.

The path of women to the high-tech industry begins at an early stage in their lives. Choices of high school majors greatly influence the continuation of their professional path and their chances of entering the field in the future. In order for women to become entrepreneurs or hold senior positions in high-tech companies they must acquire education and training relevant in order to progress within the industry.

As of 2022, at the beginning of the way, in the Bagrut exams at the level of 5 study units in mathematics, there is almost gender equality. But, the gender gap is starting to open in the army service, in the R&D and cyber positions in the IDF, which pave the way for those who serve in them to the arena of Israeli innovation, where women are only 23% from those serving in these positions.

In the scientific subjects in the academy it is better, but even though the number of female students increased by 64% within a decade, their relative share increased by a few percentages and we are less than a third of the students in these subjects in the academy.

Further down the road with senior levels, the share of women in the industry goes down. As of 2022, only 28% of employees in technological positions in Israeli high-tech are women.

On the personal side, I started to be active in the pursuit of equality between men and women in the technological professions during my military service. I decided that I wanted to take an active part and help girls and young women reach significant technological positions in their military service, in their academic career and in their work in high-tech after that. Therefore, I volunteered for a long time as an instructor and track coordinator in the organization she codes;

she codes is a technological community of women software developers, established with the aim of reaching 50% software developers in Israel. The members of the community are women

who wish to learn software development, developers who want to meet other developers, and high school-aged girls who study programming. The core values of the organization are belief in yourself, perseverance and community, values in which I also believe.

During my volunteering at the organization, I met a lot of girls and women with exciting and special stories, and I was moved when each community member succeeded in achieving her goal and was accepted for a technological position in one of the Israeli high-tech companies, as another step towards the long-awaited equality.

As part of the process, I was exposed to quite a few women who were afraid to submit their resumes for jobs, claiming that they do not meet all the criteria, they are not good enough, there are better candidates than them, and more. I wanted to act to eradicate this phenomenon, and during a conversation with Adva Regev, a recruiter in the group where I work at Microsoft, we decided to investigate the issue and contribute to the recruitment of women in the company in general.

After this conversation, we had the opportunity to participate in this workshop and put the idea into action. I was happy to cooperate with Adva and the other members of her team, and to get the human resources angle on this problem. Together with the members of our team, we held several joint meetings and thought about how to create tools that would help women in human resources create job descriptions accessible to women, which would not discourage women from applying but would encourage them to apply.

Of course, the more women submit resumes for the job, both the women will benefit and the companies themselves will benefit from diverse, specialized and more inclusive employees.

In conclusion, my connection to gender equality in the Israeli high-tech industry is both professional and personal. As a female student and software engineer, I experienced and continue to experience the advantages and challenges of being a woman in a field that is mostly made up of men. This workshop gave me an opportunity to learn about human resources and data analysis, to experience collaboration with different people and the research process in all its aspects.

I hope that this research will be one of many steps in the pursuit of gender equality in the Israeli high-tech and in general.

Ofer Tlusty

In the framework of the workshop, I had the opportunity to experience a completely different form of learning than what is commonly practiced in the university, especially in engineering and exact science faculties. The task was undefined, and so was the topic of the work. The lecturer spoke to us about emotions, feelings, and research (something amorphous?) instead of evidence, techniques, and algorithms- I won't lie, the confusion was significant.

Throughout my life, I have made sure to dedicate some of my time to volunteering, mostly in the field of education and occasionally in other areas. However, I have never delved into the field of gender and the disparities between women and men. Liron raised the topic, and along with the opportunity to work with students in occupational studies, we had a good feeling that it was an important and interesting subject worth investing time and effort in.

Embracing Modesty and Humility

The process began with reading articles and posts (with emphasis on the amazing blog by Moran Webber!). I always knew there was a gap, but the small details about how deeply it was ingrained in us, in our language, in the most basic habits, were both shocking and fascinating. The more I delved into it and shared my findings with my close surroundings, I discovered two things: first, even the women in my environment were not always aware of these hidden aspects (especially the men), and secondly, they identified with the feelings even when I somewhat belittled them because as a man, I didn't imagine they would resonate with some of the criticisms – from my perspective, it was an important lesson in modesty and humility.

After learning about the topic, we wanted to connect with the students' task in the parallel course. We held a synchronization and expectation coordination meeting and found that there was a good connection. We contributed our ability to provide value to them with automated tools and data analysis, and they guided us on where our impact would be expressed in the field of human resources. Due to the different schedules between the courses, we had to adjust and "jump in the water".

We formulated a relatively quick task without deep characterization of the broader research context we were required to adhere to, and we completed the task to enable the parallel group to continue their work. Later on, we used the basic output transferred to the parallel group as a "review" means for potential features in the model we developed, but collaboration with the

parallel group came to an end due to scheduling incompatibilities – I believe that if we had better alignment, we could have achieved more significant results and learned more from this unique collaboration.

Being Agile and Adaptive

Our next challenge was to obtain relevant data repositories for our task. My main effort was to try to obtain a tagged data repository from a private company or association that would reflect the distribution of women and men who submitted resumes for a job. I tried reaching out to recruiters at Apple (where I work), to companies of friends from the high-tech industry, and even to utilize a family member's connection who has been working for years in employment in the Arab sector in order to establish contact with the "Aluma" association (managers of a course that involves students in the employment world as part of their studies), but all my collaborative efforts fell due to the privacy policies of the companies.

Perseverance and Creativity in the Face of Challenges

The enlightening suggestion by Yuval to use language models like GPT and/or BARD as a tagging model for the job descriptions we found was no less than exciting. We knew there would be challenges in the process (we didn't realize how many), but thanks to perseverance, we managed to create a model that even produced good results in a short period.

From this moment, I felt like I returned to my comfort zone. We have a database, we found a suitable model that could deal with the received data, generate graphs and histograms, and analyze the results obtained. We went back to cleaning the data repository, improving the accuracy of the model, fine-tuning the graphs or the extracted results, and drawing conclusions from them.

This workshop allowed me to explore various aspects that I was not familiar with, from the research field of gender in the world of employment, through the research work itself, and even touching on the world of NLP and its practical application for solving real problems.

Thank you for the process, and good luck,

Ofer