Gender Bias in Job Advertisement Postings: Measuring Bias

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***Abstract*—Machine Learning algorithms have been used in the hiring process for job recommendations. The candidates are selected through resume and other personal information that are categorized as parameters for these ML models. Our aim is to find the biases that arise in such data during the preprocessing process to mitigate the errors in the further stages of the ML pipelines. Gender bias is an important area that caters to biases in the job recommendations. The proposed work helps to identify these patterns and relations for various recommendation algorithms.**

Keywords—Bias, recommendation, machine learning, word embeddings

I. INTRODUCTION

There has been a growing interest in using machine learning algorithms in the hiring process to make it easy for qualified candidates to find jobs that match their skillset and for companies to find employees that match their criteria. This is a task that can have a significant amount of bias both in the dataset and in the algorithm. A very problematic kind of bias that arises is that of gender discrimination. The study about Amazon's AI recruiting data tool that shows biases against women [8].

The company created a hiring tool that leveraged artificial algorithms to rate prospective job candidates on a scale of 1-5. The company realized the ratings were not gender neutral as the models were trained on data that came mostly from men in a male dominated industry. They realized that the resume's that mentioned a women's team or a women's college were rated poorly. The focus of filtering was not on skills but gender. We observed two different ways that gender bias is introduced into the recruitment process namely Gender bias in the job postings as well in resume screening.

II. RELEVANCE

A. Gender Bias in Job Posting Descriptions

Job advertisements haven't been allowed to advertise specifically for male or female or to use gendered pronouns such as he or she since 1973 in the US. Gender preferences can still be present in text through suggestive language about masculine or feminine traits and stereotypes. Words like competitive, dominant or leader are associated with male stereotypes or understand and supportive are associated with female stereotypes. Gendered language could make it less likely for candidates of the opposite gender to apply for these jobs. Different ways in which language can be gendered in job advertisements included -

Gendered words such aggressive or conscientious

- Superlative usage such as expert or superior
- Gendered pronouns
- Keywords containing man
- Words related to family and relationships

B. Gender Bias in Resume Selection

Natural language processing models are very capable of identifying gender in resumes. When training data is skewed towards a particular gender because of gender dominance in particular field, this has a reinforcing effect of recommending jobs to people of a particular gender. Our literature review led us to a troubling finding that resumes that have been effectively stripped of gender can still be segregated by gender by machine learning models. The authors of the paper [1] imply that there is no legitimate AI-based solution for 'de-gendering 'resumes in the recruitment pipeline, and that machine learning techniques that actively enforce fair treatment are a better approach to the problem of gender bias in the work marketplace. The paper concludes that job applicant resumes are effectively impossible to de-gender.

III. PROBLEM REPRESENTATION

The following section provides the description of the our work conducted in this area. A significant roadblock that was encountered was when none of the job recommendation resume datasets found online had the gender column explicitly mentioned for job applicants. Through our work, we have tried mapping the relevance of other columns that affect the biases in the recommendations. Our study helped us come up with a list that included job description, job listings, relocation, full time/part time, expected salary, and job title. Without the gender column it would be difficult to test our hypothesis on skewed job recommendations based on gender.

The datasets mentioned in the papers we read were private datasets. [2] used recruitment data set consisting of job vacancies and job seeker information provided by DPG Recruitment. The primary dataset used in [1] is a corpus of applicant resumes from 8 IT firms based in the U.S which were clients of an HR Recruitment Company that provided aggregated Applicant Tracking System (ATS) data as part of a research partnership. The data included resume text, the applicant's name, gender, years of experience, degree1, field of study2, the job posting to which they applied, and the outcome of the application

Gender is a sensitive attribute as it is personal data and we have not found it to be present in publicly available datasets.

We have currently studied various datasets that might contain gender biases for jobs and their recommendations. The LinkedIn dataset [9] that we started working on contains all the relevant information and parameters such as job category, title, salary expected as well as gender. However, this column was incomplete for many of the rows. Thus, we have performed manual tagging of the gender columns based on name as well as their LinkedIn profiles. The dataset is extensive with almost 10000 tuples and about 40 columns. The datasets are categorized for USA, India, Canada, Singapore, Brazil, Israel and Japan. We used Python tools and libraries to perform data preprocessing for the Indian Dataset. After processing a working dataset with relevant columns and rows was obtained with inclusion of manual tagging of gender column.

Parallelly, we also started working with textual data, based on job listings for Los Angeles city. The dataset contains various parameters such as Job profile, Education, Job designation, Driving license (Y/N) etc that may result in biases for recommendations. The writing style of the posts can be analyzed based on the tone and language. Keywords shall be analyzed for understanding the intensity of the posts.

We have seen in our research how job advertisements can show gender bias. The way a job advertisement is worded can have an impact on who is potentially more likely to apply for that job. Certain words such are associated with a particular gender and even removing those words sometimes does not have that big of an impact on mitigating this bias. Current algorithms focus on finding gender bias in job postings, but don't provide any ways to mitigate this problem. One potential solution to this that we saw in one of the papers[4] was finding alternative words that are closely related to the original gender biased words instead of removing them altogether.

Another approach to bias evaluation relies on word embeddings such as Word2Vec, GloVe in natural language processing. A word embedding model encodes each word in a vocabulary into a vector in high-dimensional space. Word embeddings can encode information about" gender direction" in vectors. For instance, the vector of he − she points to a similar direction as the vector father − mother. Thus, cosine similarity can be used to test if a word is biased toward a certain direction of gender (i.e., masculine/feminine)

IV. PROPOSED SOLUTION

The current research focuses on working with information retrieval systems and filtering systems at the root levels. Content based and collaborative based recommendation systems have been used by various researchers.

Heggo & Abdelbaki [4] provides information about various recommendation systems such as Collaborative Filtering,Content Based, Demographic based, Knowledge based. The authors observed five online recruitment portals CareerBuilder, LinkedIn from the United States, Proactive from England, eRecruiter from Austria and Wuzzuf. Based on the strengths of the above discussed models, the proposed hybrid model consists of content-based job recommendation (CBJR), collaborative filtering job recommendation (CFJR), demographics-based recommendation (DBJR), knowledge-based job recommendation (KBJR), reciprocal-based job recommendation (RBJR) and context-based job recommendation (CXJR) in addition to three developed modules which are behavioral-based job recommendation (BBJR), concept-based job recommendation (CPBJR) and ontology-based job recommendation (OBJR).Behavioral-based job recommender tracks the activities of job-seeker, it learns from user's previous actions. Reciprocal based approach used one way and two way analysis for job seekers as well as recruiters. The proposed hybrid job ranking algorithm (HJRA) is composed of relevancy, proximity and recency ranking methods. The results however are not documented as to how the feature selection process works.

Zhu et al [5] proposed a novel cross domain recommendation system for job seekers and employers. The paper provides a comparative study on user based , content based and collaborative filtering models. On the basis of study conducted, the authors propose a novel Graph community enabled approach to target career-education cross domain. The relevant details for the algorithm are obtained from the MOOCs , university courses and job advertisements of the IT industry. For cross domain approach, the work is conducted on collaborative filtering, semantic actions and deep learning techniques. The InfoMap algorithm was used in combination with a ranking function and the smallest path for the graph is found for recommendation.

Y. Cui [6] proposes a mathematical model for an intelligent recommendation system that is based on data mining techniques. It mainly uses the concept of association rule mining for analysis. The process is divided into three stages: data representation, model building and recommendations. Fuzzy clustering system with a euclidian distance metric is used to optimize the model. The result analysis is based on the MAE (Mean absolute errors) and provides system prediction accuracy for different subsets. More trails for user feedback shall be taken for better results.

Wang et al. [7] talk about how there is currently a rise in people working on mitigating discriminatory bias, in terms of age, gender, and race, in AI algorithms. In their paper, the authors look at the challenges that arise when human-fair-AI interact. They built a college major recommender system that applies gender debiasing machine learning techniques. From their results, they found out that the biased system was in fact preferred over the debiased one on average. Thus demonstrating, that we as a society first need to fix our own biases before we can focus on debiasing machine learning systems. The authors also touch on the topic of extending AI research from just focusing on debiasing to also include new persuasion and bias explanation technologies in order to achieve the intended societal impacts.

Based on the work conducted, we have completed processing of the dataset with the help of various Python libraries that can be used for the recommendation ML pipeline. We have identified the parameters that could impact the biasness in the results for the recommendations. The dataset contains 14 parameters such as skill, birthdate, gender, education, experience etc. that could impact the final accuracy of hiring. The proposed work consists of a hybrid model that shall include Content based filtering, similarity index matching, and collaborative filtering for recommendations.

V. LIMITATIONS

We encountered difficulties while finding the relevant datasets to be worked on. As a result of inconsistencies and missing columns, we handled the dataset with the help of manual tagging of columns. Care needs to be taken in the while handling the information for false positives and false negatives. This shall be taken care of during the iteration phases of the algorithms. The project helped to work with relevant information and help us understand the intricacies of the data itself. A lot of work went in the data preprocessing stage; however, this shall now be useful to handle the relations among the various parameters for the bias. The textual analysis carried out on the job listings has been significant in showing that gender biases can affect the recommendation and hiring process.

VI. FUTURE WORK

For future work, we plan to identify gendered language by look for gender direction in word embeddings. We are currently studying the relationship between gendered jobs and salary and gendered jobs and leadership roles or seniority. We shall perform statistical analysis and measure bias in the postings as well. Our goal is to create a model that shall help identify the biases in job recommendations.

ACKNOWLEDGMENT

We would like to thank our Professor Leilani Gilpin for providing the necessary guidance and support for our project.

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