Automated Search Bias Models & YouTube Gender Bias Analysis

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ABSTRACT
This work first presents our attempts to establish an automated model using state-of-the-art approaches for analysing bias in search results of Bing and Google. Secondly, in this paper we also aim to analyse YouTube video search results in terms of perceived gender bias, i.e. narrator’s gender from the viewer’s perspective. Experimental results indicate that the current class-wise F1-scores of our best model are not sufficient to establish an automated model for bias analysis. Thus, to evaluate YouTube video search results in terms of perceived gender bias, we use manual annotations.

KEYWORDS
search bias analysis, automated model, gender bias, online education

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1 PROBLEM STATEMENT
In our previous work [3], we achieved to show that there is ideological bias in search results of Bing and Google. It seems that both search engines are biased and they are biased towards the liberal side. Yet, we had fulfilled this study in the top-10 search engine result pages (SERPs) annotated via crowd-sourcing so these results do not help us to investigate the source of bias, i.e. if the bias comes from the dataset, or the ranking algorithm itself. Therefore, as the next step of this research study, we aimed to investigate the source of bias. For detecting the source of bias, we need to annotate the full SERPs of Bing and Google, note that we have 250 web documents for each controversial query and in total there are 57 queries which means that we need an automated model for the annotation phase.

For these reasons, we firstly extended our annotated dataset and then experimented with different models especially deep learning models to be able to annotate a given document with an acceptable level of accuracy. In the previous report, our models did not give satisfactory results which means that we could not use them for the annotation task, thereby to examine the source of bias in SERPs. Because of this, in this phase of our research we tried various approaches from literature to improve our BERT-based models as well as experimented with more traditional machine learning models such as XGBoost [1], Random Forest [4].

After we tried different approaches to improve our model, we observed a significant increase in class-wise model evaluation results. However, we believe that class-wise accuracies are still not sufficient for an automated model that will be used for bias analysis. Thus, we left the source of bias analysis part as unsolved and decided to apply our proposed bias measures for analysing gender bias in YouTube in the scope of education.

2 AUTOMATED BIAS ANALYSIS IN SEARCH

RESULTS
In this section, we aimed to establish an automated model for analysing search results using the state-of-the-art approaches.

2.1 Correcting the Annotation Dataset & Obtaining More Labels
We allocated some time for correcting the labels which were given by crowd-workers. Yet, in this stage we did not touch the annotations for the top-10 SERPs since we already published a journal manuscript that show our findings for the top-10 SERPs. Nonetheless, we experimented with the different versions of the dataset, i.e. removing the incorrect labels, keeping the incorrect labels with the corrected ones. Moreover, we annotated more documents to prevent overfitting and in total we have 3573 labelled documents, i.e. 829 pro instances, 693 agst instances, 1516 neut instances and 535 not-rel instances. For the model training phase, we generated more not-rel instances since our two-phase stance detection model works better when relevant instances exist almost equally to not-relevant instances in the dataset. After experimenting with these different approaches, unfortunately we could not see a sufficient improvement in evaluation results.

2.2 Examining the Model Errors & Cleaning the Dataset for Ambiguous Instances
In addition to correcting the labels and annotating more instances, we also examined the model errors. For the instances that the model labels wrongly, we looked at the textual content of the corresponding document and then the probability distribution that the model gave for the given instance. Our main aim here is to detect ambiguous instances which contain different opinions throughout the document. Based on this analysis, we discarded some ambiguous/difficult instances from the dataset and trained our model with this new dataset. Yet, we did not see a big improvement in model results.

2.3 Experimenting with Traditional Machine Learning Models
Apart from the BERT-based models, we also experimented with traditional machine learning models, namely Support Vector Machine (SVM) [2], Random Forest, and XGBoost. Among these, XGBoost gave the best class-wise results as displayed in Table 1 but still the model is not sufficiently good to be used for bias analysis.
2.4 Model Stacking

We also tried the approach of model stacking with the aim of creating a stronger classifier using the weak classifiers that are different from each other as depicted in Fig. ?? . This approach slightly improved our results that are not sufficient for bias analysis.

2.5 Language Model Fine-tuning On Our Stance Dataset

We also applied the steps of Universal Language Model Fine-Tuning (ULMFiT) with the aim of achieving a better domain adaptation. For this, we initially fine-tuned the pre-trained model of BERT on our dataset of query-document content pairs without any stance labels. For this intermediate step, we also experimented with slanted triangular rates, discriminative fine-tuning, and gradual unfreezing which are the proposed approaches in the original ULMFiT paper. Then, using the fine-tuned language model, we fine-tuned it on the stance classification tasks with stance labels. This approach helps to improve the classification performance in the last step on small datasets. However, we could not see a big improvement for our model.

2.6 Longformer: The Long-Document Transformer

Since transformer-based models, e.g. BERT, RoBERTa, are unable to process long sequences due to their self-attention mechanism, researchers proposed a new transformer to process long sequences. We also experimented with this transformer model and thought that this approach can improve our model results because we have very long documents in our stance dataset. Yet, the results did not show a big improvement.

2.7 Hyperparameter Tuning & Applying Mixout

Apart from the different methods we tried to improve our model results, finally we experimented with different hyperparameters. Despite the strong empirical performance of fine-tuned transformer models, fine-tuning is known to be an unstable process, different random seeds can result in large variance of the task performance. Thus, researchers reported the best hyper-parameter values for BERT, RoBERTa and ALBERT to alleviate the fine-tuning instability. Since we observed fine-tuning instability in our experiments, we experimented with the recommended hyper-parameter values. We observed that these values helped us to achieve a better fine-tuning stability regardless of the random seed, i.e. we obtained similar results with different training runs. However, the results were not sufficient.

Lastly, we applied the proposed technique of mixout to regularise the fine-tuning of a pretrained model motivated by another widely-used regularisation technique of dropout, especially for small datasets as displayed in Fig. 2. It has been observed that although BERT-large outperforms BERT-base generally, fine-tuning may fail if the target training dataset has less than 10,000 instances. We realised that as mixout helped us to achieve a better fine-tuning stability for transformed-based models and we used mixout with the recommended hyper-parameters. Although, we observed a significant improvement in fine-tuning stability, our models did not give sufficiently good results that can be used for obtaining stance labels. The best results we got using the approaches mentioned above can be seen in Table 2. As you can see that in comparison to our previous model results, we achieved better results – especially the decrease in loss value is quite high but our class-wise accuracies are still not good enough for annotation in bias analysis.

3 YOUTUBE GENDER BIAS ANALYSIS

In this section, our goal is to analyse YouTube video search results in terms of perceived gender bias.

3.1 Selecting the Framework for the YouTube Gender Bias Analysis

We simulated a real user search scenario in which the user is presumably an university student who studies one of the selected majors above, and uses YouTube for educational purposes. Initially, we crawled the modules of each selected major from TheUniGuide and each major has 10 modules in total. We opened the YouTube desktop version in incognito mode and set the region as US, language as English, and the other settings were left as default. Note that in the filter options at the top, by default only “sort by” option was selected as “relevance” which means that the search results will be ranked based on relevance. Then using these settings, we made a preliminary study to see what YouTube returns for a given query, in which format etc. to design our user study accordingly.

The preliminary study showed us that using the aforementioned settings, for a given query YouTube returns 12 search results in total as relevant to the given query. After these 12 relevant videos, the “people also watched” section shows up when one scrolls the page which in total contains 12 videos as well. Differently from the first 12 relevant videos in the first untitled section, these 12 videos of the section of “people also watched” can probably be seen as video recommendations by YouTube that might catch the user’s attention. The “people also watched” section is followed by the section of “for you” which also shows some videos but we did not include this section in our analysis. Note that since personalised search might highly affect the search results and complicate the

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Table 1: F1-scores for SVM, Random Forest, and XGBoost

|         | Pro  | Against | Neutral | Not-rel |
|---------|------|---------|---------|---------|
| SVM     | 0.50 | 0.19    | 0.55    | 0.59    |
| Random Forest | 0.53 | 0.10    | 0.46    | 0.43    |
| XGBoost | 0.49 | 0.34    | 0.61    | 0.84    |

1 https://yashuseth.blog/2018/06/17/understanding-universal-language-model-fine-tuning-ulmfit/
Table 2: Best Evaluation Results on the Stance Dataset with BERT-based Model

| Model                          | Pro | Against | Neutral | Not-rel | Loss |
|-------------------------------|-----|---------|---------|---------|------|
| Current Model (More Instances)| 0.58| 0.76    | 0.52    | 0.93    | 1.52 |
| Previous Model                | 0.65| 0.38    | 0.42    | 0.89    | 1.91 |

Figure 1: Universal Language Model Fine-Tuning (ULMFiT) Steps

Figure 2: The regularisation technique of mixout motivated by dropout

bias analysis more, in the scope of this work, we decided to design our analysis in unpersonalised search settings. Apart from these three main sections, there is one more section called "people also search for” popping up after the “for you” section while scrolling the search results which only provides query recommendations as a list for the user to follow up his/her search, or learning process.

3.2 Data Crawling & Annotation

We obtained all the educational topics from TheUniGuide\(^2\). TheUniGuide is a free university advice service which is part of The Student Room\(^3\) that helps students make more informed decisions about their higher education choices. The first reason why we chose TheUniGuide is that when we searched for queries like "university chemistry (university major) courses" in incognito mode to select educational queries for our study, TheUniGuide appears as the top result in Google search. The second reason is the pages for different majors from Science, Technology, Engineering, and Mathematics (STEM) as well as NON-STEM fields and observed that TheUniGuide website provides comprehensive information for a given major.

To illustrate the data crawling procedure, we can follow the above process for the major of "chemistry" from the STEM field as follows. Like other major fields of study, "chemistry" has 10 course modules in total, namely solid state chemistry, inorganic chemistry, etc. We initially searched for each of these 10 course modules in YouTube one by one to see if YouTube returns 12 relevant videos, then 12 videos as in the "people also watched" section, and lastly "people also search for” queries. We need all of these three sections to make a detailed bias analysis in relevant videos, recommended videos and also the relevant videos of the query recommendations in the "people also search for" section’s query list. For query recommendations of the main query which is a course module of a major, we only took top-3 recommendations and for each of these query recommendations, we only got top-12 relevant search results of each query recommendation for consistency. We note that for some of the course modules obtained from TheUniGuide, "people also search for” section did not show up, e.g. organic and biological chemistry, chemistry of materials, thus we discarded.

\(^1\)https://www.theuniguide.co.uk/
\(^2\)Free student discussion forum in UK
Table 3: Retrieval performance of YouTube, p-values of a two-tailed paired t-test computed between STEM and NON-STEM majors

|       | P@12     | DCG@12   | RBP     |
|-------|----------|----------|---------|
| STEM  | 0.9541   | 4.8979   | 0.9023  |
| NON-STEM | 0.9500   | 4.8725   | 0.8950  |
| p-value | > .5     | > .5     | > .5    |

Table 4: Gender (perceived) bias in YouTube for the top-12 relevant results, p-values of a two-tailed paired t-test computed between STEM and NON-STEM majors

|       | P@12     | DCG@12   | RBP     |
|-------|----------|----------|---------|
| MB    | 0.6083***| 3.1011***| 0.5596***|
| STEM  |          |          |         |
| NON-STEM | 0.3896***| 2.0519***| 0.3988***|
| p-value | .003     | .006     | .03     |
| effect size d | 0.73  | 0.62     | 0.50    |
| MAB   | 0.6083***| 3.1011***| 0.5596***|
| STEM  |          |          |         |
| NON-STEM | 0.4396***| 2.3961***| 0.4724***|
| p-value | .005     | .02      | .15     |
| effect size d | 0.65  | 0.49     | 0.32    |

Table 5: Gender (perceived) bias of YouTube for the top-12 results in people also watched section, p-values of a two-tailed paired t-test computed between STEM and NON-STEM majors

|       | P@12     | DCG@12   | RBP     |
|-------|----------|----------|---------|
| MB    | 0.5917***| 2.7716***| 0.4990**|
| STEM  |          |          |         |
| NON-STEM | 0.3250***| 1.7033***| 0.3640***|
| p-value | .0005    | .0197    | .0921   |
| effect size d | 0.87  | 0.60     | 0.45    |
| MAB   | 0.5917***| 2.7716***| 0.4990**|
| STEM  |          |          |         |
| NON-STEM | 0.3750***| 1.9587***| 0.3640***|
| p-value | .0015    | .0367    | .0921   |
| effect size d | 0.78  | 0.53     | 0.45    |

those modules and if a given major did not have at least 2 course modules which contain the aforementioned three sections, then we discarded those majors as well. Because of this, out of 10 course modules in 'chemistry', only 4 of them left for analysis namely, solid state chemistry, molecular pharmacology, states of matter, and inorganic chemistry. From these, we randomly selected 2 course modules as solid state chemistry and inorganic chemistry since we decided to obtain 2 course modules for each major. We note that for some majors, we obtained more than 2 course modules which contain query recommendations section and selected the course modules randomly as in the case of 'chemistry' major. Yet, some majors had exactly 2 course modules, and the NON-STEM majors of history, history of art, and philosophy had 1 course module or no course module at all with query recommendations.

Based on these, for each course module we crawled 120 video URLs, i.e. 12 relevant videos, 12 video recommendations, and 12 relevant videos for each top-3 query recommendations, so in total we obtained 1200 video URLs for 5 STEM and 5 NON-STEM majors, i.e. out of 8 NON-STEM majors we did not select the aforementioned NON-STEM majors deliberately but history, history of art, and philosophy were discarded as mentioned above for practical purposes. These 1200 videos are not all unique because of two main reasons: i. Same videos might show up for related queries, ii. Some modules share the same query recommendations in their top-3 so their video results are similar.

After the manual data crawling process, we annotated the video’s overall perception related to gender stereotypes as masculine, feminine, neutral, or NA from the viewer’s perspective using the gender of the narrator(s) in a given video. Note that our main aim in this study is only to detect the perception of the viewer related to perceived gender bias for the corresponding major that the video is about, i.e. if the given major is perceived by the viewer as more masculine or feminine which might help gender stereotypes, thereby gender imbalance in STEM/NON-STEM majors perpetuate.

Our annotation procedure has two phases. Firstly, a given video is annotated based on its relevancy to the given query as relevant, not-relevant, or NA. If the video is not English, or it cannot be reached because it has been removed then the video is annotated as NA, otherwise relevant, or not-relevant. If the relevancy of the video is not-relevant or NA, then we cannot include it in our gender
bias analysis. Only if the video is annotated as relevant to the given query, then its gender perceived by the viewer is annotated using the following procedure.

- If there is a male dominance in narration meaning that there are more male narrators than female ones, or the main narrator is male, or male narrators speak noticeably more than female narrators, then the video is annotated as masculine which denotes the viewer’s perception of the video related to gender bias.
- If the reverse case happens, then the video is annotated as feminine.
- If none of the previous cases happens, i.e. there are two main narrators as one male and one female, or male and female narrators speak almost equally, meaning that there
is no dominant male or female narrator then the video is annotated as neutral.

- If the video does not contain a narrator, then the video is annotated as NA.

### 3.3 Gender (Perceived) Bias Analysis via Bias Measures

After the data crawling and annotation process, we applied our bias measures published in our previous work to perceived gender bias problem in YouTube in the scope of educational queries. Before investigating the existence of bias in SERPs, we initially compared the retrieval performances of two search engines. In Table 3 we observe that the retrieval performance of the YouTube is high for both STEM and NON-STEM majors. The retrieval performance for the queries in STEM major seems to be slightly better than NON-STEM – but their difference is not statistically significant. This is verified across all three IR evaluation measures.

Next, we verify if YouTube return biased results in terms of narrator’s gender (perceived dominant gender in the video) and if so, we further investigate if YouTube top-12 relevant search results suffer from the same level of bias that the difference between the STEM and NON-STEM major queries are not statistically significant. In Table 4, all MB scores are positive, the STEM and NON-STEM categories seem to be biased towards the same perceived gender – male. We applied the one-sample t-test on MB scores to check the existence of perceived gender bias, i.e. if the true mean is different from zero. The results show that these biases are statistically significant with p-value < .001 denoted as *** in Table 4. Comparing the two majors on MB scores, we observe that their differences are statistically significant and it is shown with the two-tailed pair t-test on P@12, DCG@12, and RBP. Note that differences are statistically significant for P@12 and DCG@12 with difference confidence values, i.e. p-value = .002, .006, respectively; but statistically not significant for RBP. In addition to the p-values, we reported the corresponding effect sizes using Cohen’s d. Statistical significance, namely p-values in our analysis help us examine whether the findings show systematic bias or they are the result of noise, whereas effect sizes provide information about the magnitude of the differences which makes p-values and effect sizes are complementary.

Based on MAB scores, we can observe that both majors suffer from an absolute bias. The difference between the majors of STEM and NON-STEM which is shown with the two-tailed paired t-test is statistically significant for P@12 and DCG@12 with different confidence values, i.e. p-value = .004, .01 respectively; but statistically not significant for RBP. In Table 5 we show the perceived gender bias in Youtube’s top-12 recommended search results, namely people also watched section. Similarly to Table 4, lower is better since we use the same measures of bias. Unlike the Table 4, Table 5 shows the bias in YouTube’s recommendations rather than the relevant results. Similarly to Table 4, all MB and MAB scores are positive for all three IR evaluation measures; the one-sample t-test computed on MBs and MABs are statistically significant for all the measures p-value < .001 denoted as *** in Table 5. The two-tailed paired t-test computed on MBs to compare the difference in bias between STEM and NON-STEM majors, the results indicate that their differences are statistically significant only for P@12 with p-value = .0005 and statistically not significant for DCG@12, and RBP. Similarly, the two-tailed test on MABs is statistically significant only for the measure P@12 with p-value = .0015; but it is statistically not significant for the measures DCG@12 and RBP.

In Figure 3 we show how the topic-wise SERPs distribute over the male-female gender space for the measure DCG@12. The x-axis is the male gender (perceived) score (DCG_{male}@12) and the y-axis is the female gender (perceived) score (DCG_{female}@12). Each point corresponds to the overall SERP score of a topic. Black points are those SERPs retrieved by YouTube for STEM major and yellow points are those retrieved for NON-STEM major. We observe that topics are not uniformly distributed – topics are mostly on the male side. Moreover, STEM major has fewer points on the female side than NON-STEM major.

In Figure 4 we compare the overall gender (perceived) bias score ($\beta_{DCG@12}$), i.e. difference between the male and female gender (perceived) scores, of SERPs for each topic measured on the two corresponding majors. The x-axis is STEM and the y-axis is NON-STEM major. The points in positive coordinates denote the STEM vs. NON-STEM topics whose SERPs are overall biased towards the male (perceived) gender, negative coordinates are for the female (perceived) gender. The figures confirm the fact that both STEM and NON-STEM majors are biased toward male (perceived) gender but STEM major is more biased, i.e. all STEM major topic scores are positive.

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