Towards More Accountable Search Engines: 
Online Evaluation of Representation Bias

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ABSTRACT
Information availability affects people’s behavior and perception of the world. Notably, people rely on search engines to satisfy their need for information. Search engines deliver results relevant to user requests usually without being or making themselves accountable for the information they deliver, which may harm people’s lives and, in turn, society. This potential risk urges the development of evaluation mechanisms of bias in order to empower the user in judging the results of search engines. In this paper, we give a possible solution to measuring representation bias with respect to societal features for search engines and apply it to evaluating the gender representation bias for Google’s Knowledge Graph Carousel for listing occupations.

KEYWORDS
representation bias, rank bias measure, gender bias

1 INTRODUCTION
Nowadays, search engines are increasingly used as primary tools to access information. The information that search engines point their users too often helps people take decisions that guide them through their lives, while it may also affect their judgement and perception of the world [7]. Towards the end of the last century it has been observed that information systems can be biased [4] and that biased information (i.e., information that does not represent the reality of the world people live in) can be harmful to how people relate to each other and to how they evaluate their own decisions and opportunities [8]. The essential role that search engines have in influencing people’s access to information urges the need to design evaluation mechanisms to assess search systems for potential biases that may negatively impact society. This urge is further accentuated by the lack of transparency in how results to user searches are selected and displayed. Such a bias assessment process can be used as a diagnostic tool to monitor search systems results and make the systems more accountable, a desire that is raising to the attention of the research community [1].

Various measures to quantify bias in ranking have been previously proposed, e.g., Yang and Stoyanovich [9] define 3 measures starting from utility-based IR evaluation measures like RBP and nDCG; Zehlike et al. [10] define a statistical based method to evaluate and produce fair rankings. These metrics were then further discussed and improved by Gezici et al. [5]. In this short paper we focus on representation bias, also known as equality of opportunity [6] which is rank-independent, while the mentioned works focus on statistical parity, i.e. a fair ranking system retrieves the same proportion of individuals across groups. S. C. Geyik et al [3]

define a ratio based metric for the feature representation at cut-off $k$ but all experiments further on are wrt. ranking and not rank-free representation bias.

Many countries enforce legislation to protect people from discrimination, be it at work or in the wider society. More concretely, such legislation aims to protect individuals from being discriminated as to societal features like outer aspect, education, sexual orientation, or geographical location. In this context, search engines bias evaluation can also be used by regulatory bodies in order to combat potential discrimination during search for information.

Traditionally search engines are evaluated in terms of effectiveness and efficiency. An effective system retrieves relevant information while an efficient one is a system that does it fast and with few resources. We argue, here, that an orthogonal form of search engine evaluation is needed where the fair representation of relevant societal features in search results is assessed. In other words, we argue for a measure to assess a search system’s feature representation bias.

In this work we formalize the representation bias for categorical features and illustrate its use to analyze the gender representation bias in exponents of professions as displayed by the Knowledge Graph Carousel (KGC) featured by Google (Figure 1).

2 REPRESENTATION BIAS
The representation bias of a search system is the preference of the system for or against a group of results relevant to a user query, that manifest a specific feature value $c \in C$, with $C$ a set of categorical features like age, education, gender. For a given feature $c \in C$, we compute a system’s representation bias with respect to this feature as the difference between the proportion of result documents manifesting the $c$ feature value (the model $c$-ratio) and the proportion of all documents indexed by a search system that present the $c$ feature value (the target $c$-ratio).

We give, now, the definitions and rationale behind the representation bias and its two components, model and target $c$-ratios. In this work, and for the sake of formalization simplicity, we consider $C$ to be binary. The formalization can be generalized to any $C$ size.
\[ r = \text{with respect to } r \]

Since search engines, however, show only a lower size \( n \) subset \( U \) of the document set \( D \) found relevant to a query, we could define the target c-ratio at cut-off \( n \) similarly, as:

\[ \hat{\mu}_c @ n = \frac{|U^c|}{n}, \quad (2) \]

with \( n = |U| \) and \( U^c \) is the set of documents in \( U \) with feature \( c \).

To measure a search system’s representation bias our method compares the target c-ratio at cut-off \( n \) with the model c-ratio where the latter is defined as:

**Definition 2.2.** Given the set of documents, \( D \), relevant to a user’s input query, a binary feature set, \( C \), and a search result, \( r = [d_1, \ldots, d_m] \) with \( d_1, \ldots, d_m \in D \) of documents ranked by the search system, we define the model c-ratio at cut-off \( n \) with respect to \( r \) as:

\[ \hat{\mu}'_c @ n = \frac{|D^c r @ n|}{n}, \quad (3) \]

where \( r @ n \) is \( r \) cut at rank \( n \), \( D^c r @ n \) is the set of documents in \( r @ n \) that have the feature \( c \).

Ideally, \( \mu_c \) and \( \hat{\mu}_c @ n \) are the same, making a comparison between \( \mu_c @ n \) and \( \hat{\mu}_c @ n \), which we aim for with our method, straightforward. However, since \( |U| = n \) is usually much lower than \( |D| \), this is not always the case. Consider, for example, \( \mu_c = 0.5 \) and \( n = 11 \). Two result sets \( D r @ n \), one that contains 5 c-feature documents while the other displays 6 c-feature documents must be considered as equal from a representational bias point of view. Using the naive estimator in (2), in certain circumstances, we would be measuring an non existing bias. To this end, we define the unbiased version of the target c-ratio as follows:

**Definition 2.3.** For a given set of documents, \( D \), relevant to a user’s input query, a binary feature set, \( C \), and a search result, \( r \), the cut-off \( n \), let \( \delta_n = \mu_c - n - |\mu_c \cdot n| \). We define the target c-ratio at cut-off \( n \) with respect to \( r \) as:

\[
\mu'_c @ n = \frac{1}{n} \begin{cases} 
[|\mu_c \cdot n|] \\
\arg \min \{|[\mu_c \cdot n], [\mu_c \cdot n]| (|x - \mu'_c @ n|) \}
\end{cases} \quad \delta_n < 0.5
\]

\[
\delta_n = 0.5 \quad \delta_n > 0.5 \quad (4)
\]

The target c-ratio at cut-off \( n \) here defined is the ‘ideal’ model c-ratio, that is the observed \( r \) is free of representational bias. The way this is defined ensures that when computing the ideal c-ratio for a given \( r \), in case of ambiguity (\( \delta_n = 0.5 \)) the solution given by the search engine is accepted as correct.

**Definition 2.4.** The \( c \)-feature representation bias for a result set \( r \) is the difference between the model and the target c-ratios with respect to \( r \):

\[ \beta'_c @ n = \mu'_c @ n - \hat{\mu}'_c @ n \quad (5) \]

This equation is defined in the set \( \{k/n : k, n \in \mathbb{Z}, n > 0, |k| \leq n \} \).

When \( \beta'_c @ n = 0 \) we consider that \( r \) is bias-free with respect to the feature \( c \). When \( \beta'_c @ n > 0 \) the system result is biased towards \( c \), with maximal bias when \( \beta'_c @ n = 1 \). When \( \beta'_c @ n < 0 \) the system result is biased against \( c \), with maximal bias when \( \beta'_c @ n = -1 \).

We can now compute the Mean representation Bias (MB) and its Standard deviation (SB) over a set of user queries (topics) for each feature value \( c \). Note that when a search engine is biased towards one \( c \) value for one topic and towards the other value for another topic, these two topics may cancel each other out when computing MB. To compensate for this effect we compute also the Mean of the Absolute Bias (MAB).

### 3 CASE STUDY

Using the feature ratios defined in the previous section, we measure the representation bias for gender (a binary feature) at cut-off \( n = 10 \). The user topics we consider are professions. We measure the gender representation bias for Google’s KGs. The code used to collect the dataset and ran the analysis is available at the following web-link: https://github.com/aldolipani/TMASE. We note here that, as Google’s results are profile dependent - to say the least - we have crawled the KGC for professions using a United States location and an incognito browsing mode. Figure 1 shows an example of KG display, located between the Google search bar and the results list. Such a KG is displayed only when users give specific word patterns as input queries.

Though the list of word patterns that trigger the KG display is not disclosed, based on our tests, we found the following triggering patterns: ‘list of [professions’ noun]’, ‘top [professions’ noun]’, ‘important [professions’ noun]’. In this analysis we focus only on the first pattern that triggers the KG display, due to its (gender) neutral surface formulation. The connotative meaning of the ‘top’ or ‘important’ terms bring emotional and other associations we want to avoid. In this context, the neutral connotations for queries like ‘list of [professions’ noun]’ demonstrate a neutral intent to retrieve persons’ associated with the professions’. Although the search engine may return their results based on a predicted user preference, we believe that these queries in particular, due to their neutral intent, and based on the fact that Google does not make itself accountable by disclosing the feature used to rank these results (like ‘historical importance’, ‘yearly income’, etc.), give results free of bias.

During our initial experiments, we found out that not all queries to list persons with a certain occupations trigger the KG display. Therefore we extracted all professions available in Wikidata [2], together with their gender feature annotations. This gave us a list of 3,374 professions for which we generated Google word patterns, and retained 454 professions which did trigger the KG display. The analysis further on is done on these 474 professions. For cases where Google’s KG gender annotation did not match Wikidata’s, we did manual labelling.

As defined in the previous section, to calculate the target c-ratio for the results displayed in the KG we first compute the target c-ratio, \( \hat{\mu}_c \), for each profession. We select two document sets: (a) the full-length Google search result for professions, denoted by \( R; \)
we added a controlled jitter that makes them fall within a square
we would now observe two histograms centered on zero with no
est bias towards female gender was observed, respectively. The
gender was observed, no gender-ratio bias was observed, and high-
R
and model gender-ratios are equal, i.e. bias is null.

Figures 2 and 3 show the per gender histograms of KGC representation
bias values in relation to $R$ and $K$ target c-ratios. Considering the
binary characteristic of gender we expected these histograms to
be symmetric to each other, for each of the two cases. However,
these are not perfectly symmetric as for some queries the KGC has
shown less than 10 results. Still, had the KGC been free of bias,
we would now observe two histograms centered on zero with no
spread. Since this is not the case we may conclude that the KGC is
not free of gender representation bias. Additionally, the pair-wise
asymmetry of the histograms indicates that when the search result is
biased, it is more likely that the bias favours the male gender
over the female one. Looking at the distribution bias wrt. the $K$
target gender-ratio we observe a stronger bias than the one wrt. the
$R$ target gender-ratio of the full search result set. Moreover, we
also observe that when we base our target distribution based on
the KB we measure more bias than what we measure when the
target distribution is calculated over the full search results. Table 1
summarizes the data visualized in Figure 2.

Figure 3 compares the target (x-axis) and the model (y-axis)
gender-ratios for each profession in $K$ and $R$. To every data point
we added a controlled jitter that makes them fall within a square
of the grid surrounding the original data point. Looking at the dis-
perion of points along the x-axis, we note that the male gender
dominates many professions. The number of points per grid square
decreases when moving towards the center, these are those professions
equally represented by both genders. Only 4 professions are female-dominated. Would the KGC be free of bias, it would have
placed every profession within the green squares, where the target
and model gender-ratios are equal, i.e. bias is null.

Tables 2 and 3 show the top 11 professions extracted from $K$
and $R$ for which the highest representation bias towards the male
gender was observed, no gender-ratio bias was observed, and high-
est bias towards female gender was observed, respectively. The

$$\begin{array}{l|cccccc}
\text{Table 1: Summary of the data visualized in Fig. 2.}
\hline
\text{c} & \text{MB@10} & \text{SB@10} & \text{MAB@10} & \text{min} & \text{max} \\
\hline
K & \text{female} & 0.026 & 0.156 & 0.113 & -0.5 & 0.8 \\
 & \text{male} & -0.042 & 0.097 & 0.062 & -0.4 & 0.5 \\
R & \text{female} & 0.001 & 0.113 & 0.072 & -0.5 & 0.4 \\
 & \text{male} & -0.015 & 0.170 & 0.121 & -0.8 & 0.5 \\
\hline
\end{array}$$

and (b) the Wikidata collaboratively edited knowledge base (KB)
hosted by the Wikimedia Foundation, denoted by $K$.

The results shown by KGC, as many online systems, change
time over time, so the following analysis is relative to data crawled on
December 1st, 2019.

4 CONCLUSION

We have defined concepts to help evaluate the representation bias
with respect to specific societal features in online search engines.
Such evaluations, if provided together with search results, will allow
users to assess potential representation biases. In a concrete case
study, we have used the defined concepts to assess the rep-
presentation bias of the Google’s KGC with respect to gender and
professions. Assuming the correctness of the population frequency
of the documents available to KGC, we conclude that it suffers from
gender representation bias.

A key aspect of the method introduced in this paper is the as-
sumption of complete knowledge of the population frequency for
each feature value. In our case study, the feature ratios have been
calculated based on data that the search system provider made avail-
able and on a collaboratively knowledge base (Wikidata). However,
better statistics for c-ratios could be aimed for, e.g. official statistics
published by government agencies.

Finally, we have shown how such a representation bias evalua-
tion can be performed using a concrete case study. In this case study
we have analyzed the gender representation bias of the Google’s
KGC, and shown that, assuming the correctness of the population
means, it suffers from gender representation bias. We must be aware,
though, that the systems’ selection of documents to be displayed
(by KGC, for example), is most of the time not transparent, and
other features not openly accounted for, like ‘historical relevance’ or
‘yearly income’ may affect the final result shown to a user. At
the same time we must distinguish, between detecting the source
of bias and measuring a representation bias. The work described
in this paper may help a user hypothesize on sources of bias once
they have been detected by measuring the representation bias.


\footnote{Female- and male-ratio sum up to 1.}
Figure 3: Target vs. model gender-ratio for $\mathcal{K}$ (left) and $\mathcal{R}$ (right). Every point represents a profession. A jitter is added to every data point, i.e. points occurring in the same square of the grid have the same coordinates. The two sets of points for the male and female gender are symmetric. The points in the green squares are those free of bias.

Table 2: Values are calculated with $c = \text{female}$. The column $\text{Unbiased}$ spans across every target ratio, from 0.0 to 1.0. In this column, more than one profession is found with the same target ratio, we selected the one with the largest population in $\mathcal{K}$. The first and last columns are generated by ordering each profession based on its representation bias.

| Profession                  | $\mu_{c@10}$ | $\mu'_{c@10}$ | $\mu''_{c@10}$ | Profession                  | $\mu_{c@10}$ | $\mu'_{c@10}$ | $\mu''_{c@10}$ | Profession                  | $\mu_{c@10}$ | $\mu'_{c@10}$ | $\mu''_{c@10}$ |
|-----------------------------|--------------|---------------|----------------|-----------------------------|--------------|---------------|----------------|-----------------------------|--------------|---------------|----------------|
| announcer                   | 0.0          | 0.5           | -0.5           | american football player     | 0.0          | 0.0           | 0.0            | archivist                    | 0.9          | 0.1           | 0.8            |
| long jumper                 | 0.0          | 0.5           | -0.5           | historian                    | 0.1          | 0.1           | 0.0            | baker                       | 0.6          | 0.1           | 0.5            |
| high jumper                 | 0.0          | 0.5           | -0.5           | songwriter                  | 0.2          | 0.2           | 0.0            | school teacher              | 0.6          | 0.2           | 0.4            |
| science writer              | 0.1          | 0.6           | -0.5           | illustrator                  | 0.3          | 0.3           | 0.0            | modern pentathlete           | 0.5          | 0.1           | 0.4            |
| rugby sevens player         | 0.0          | 0.5           | -0.5           | choreographer                | 0.4          | 0.4           | 0.0            | church musician             | 0.4          | 0.0           | 0.4            |
| cell biologist              | 0.0          | 0.5           | -0.5           | badminton player             | 0.5          | 0.5           | 0.0            | drama teacher               | 0.7          | 0.3           | 0.4            |
| clinical psychologist       | 0.0          | 0.5           | -0.5           | artistic gymnast             | 0.5          | 0.5           | 0.0            | television presenter        | 0.7          | 0.4           | 0.3            |
| piano teacher               | 0.0          | 0.5           | -0.5           | model                       | 0.8          | 0.8           | 0.0            | scenographer                | 0.5          | 0.2           | 0.3            |
| water polo player           | 0.0          | 0.4           | -0.4           | flight attendant             | 0.9          | 0.9           | 0.0            | track cyclist               | 0.4          | 0.1           | 0.3            |
| middle-distance runner       | 0.0          | 0.4           | -0.4           | rhythmic gymnast             | 1.0          | 1.0           | 0.0            | skeleton racer               | 0.7          | 0.4           | 0.3            |
| botanical illustrator        | 0.3          | 0.7           | -0.4           | glamour model                | 1.0          | 1.0           | 0.0            | game author                 | 0.3          | 0.0           | 0.3            |

Table 3: Values are arranged as in Table 2 but selected using $\mathcal{R}$.

| Profession                  | $\mu_{c@10}$ | $\mu'_{c@10}$ | $\mu''_{c@10}$ | Profession                  | $\mu_{c@10}$ | $\mu'_{c@10}$ | $\mu''_{c@10}$ | Profession                  | $\mu_{c@10}$ | $\mu'_{c@10}$ | $\mu''_{c@10}$ |
|-----------------------------|--------------|---------------|----------------|-----------------------------|--------------|---------------|----------------|-----------------------------|--------------|---------------|----------------|
| librarian                   | 0.2          | 0.6           | -0.4           | officer of the french navy  | 0.0          | 0.0           | 0.0            | archivist                    | 0.9          | 0.4           | 0.5            |
| draughts player             | 0.0          | 0.4           | -0.3           | war photographer            | 0.1          | 0.1           | 0.0            | scenographer                | 0.5          | 0.2           | 0.3            |
| long jumper                 | 0.0          | 0.3           | -0.3           | table tennis player         | 0.2          | 0.2           | 0.0            | video blogger               | 0.7          | 0.4           | 0.3            |
| handball player             | 0.1          | 0.3           | -0.3           | fashion designer            | 0.3          | 0.3           | 0.0            | drama teacher               | 0.7          | 0.4           | 0.3            |
| translator                  | 0.1          | 0.4           | -0.3           | alpine skier                | 0.4          | 0.4           | 0.0            | sailor                      | 0.2          | 0.0           | 0.2            |
| classical archaeologist      | 0.0          | 0.2           | -0.2           | vj                          | 0.5          | 0.5           | 0.0            | lighting designer            | 0.3          | 0.1           | 0.2            |
| high jumper                 | 0.0          | 0.2           | -0.2           | sex educator                | 0.6          | 0.6           | 0.0            | chemist                     | 0.3          | 0.1           | 0.2            |
| talk show host              | 0.0          | 0.2           | -0.2           | beach volleyball player     | 0.6          | 0.6           | 0.0            | fighter pilot                | 0.2          | 0.0           | 0.2            |
| sound artist                | 0.0          | 0.2           | -0.2           | softball player             | 0.8          | 0.8           | 0.0            | musical theatre actor        | 0.6          | 0.4           | 0.2            |
| executive                   | 0.0          | 0.2           | -0.2           | domestic worker             | 0.9          | 0.9           | 0.0            | television presenter         | 0.7          | 0.5           | 0.2            |
| science journalist          | 0.1          | 0.3           | -0.2           | ballerina                   | 1.0          | 1.0           | 0.0            | skeleton racer               | 0.7          | 0.5           | 0.2            |

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