Gender and Racial Bias in Visual Question Answering Datasets

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ABSTRACT

Vision-and-language tasks have increasingly drawn more attention as a means to evaluate human-like reasoning in machine learning models. A popular task in the field is visual question answering (VQA), which aims to answer questions about images. However, VQA models have been shown to exploit language bias by learning the statistical correlations between questions and answers without looking into the image content: e.g., questions about the color of a banana are answered with *yellow*, even if the banana in the image is green. If societal bias (e.g., sexism, racism, ableism, etc.) is present in the training data, this problem may be causing VQA models to learn harmful stereotypes. For this reason, we investigate gender and racial bias in five VQA datasets. In our analysis, we find that the distribution of answers is highly different between questions about women and men, as well as the existence of detrimental gender-stereotypical samples. Likewise, we identify that specific race-related attributes are underrepresented, whereas potentially discriminatory samples appear in the analyzed datasets. Our findings suggest that there are dangers associated to using VQA datasets without considering and dealing with the potentially harmful stereotypes. We conclude the paper by proposing solutions to alleviate the problem before, during, and after the dataset collection process.

1 INTRODUCTION

The so-called vision-and-language tasks, which consist of applications that interact, process, and make decisions based on both visual and language content, present one of the greatest challenges in modern machine learning research. By construction, such applications not only need to deal with the challenges of image and text understanding but also overcome the modality gap between the visual and the language inputs. Such modality gap is non-trivial and has made tasks such as image captioning [51, 57] or visual question answering [4, 37] considerably popular within the computer vision (CV) [1, 16, 45, 55] and the natural language processing (NLP) [7, 40] communities. From classic CNN-based models [51] to the current self-attention multi-modal Transformers [33, 36], the rapid progression of the field has only been possible thanks to the collection, annotation, and public distribution of datasets and benchmarks [13, 32, 35, 44, 45] designed specifically to train and evaluate vision-and-language models.

The increased complexity of those models, which contain a high number of parameters to be trained, has made the availability of data a precious resource. At the same time, with the adoption of some of these models into real-world products, how this data represents the real world is of raising concern. For example, when minoritized groups are underrepresented in machine learning datasets, trained models can contribute to perpetuating social discrimination by producing potentially harmful outcomes. This has been the case for face recognition [8] as well as for object recognition [60]. With respect to vision-and-language, Burns et al. [9] and Zhao et al. [59] showed that image captioning models, i.e., models that aim to produce a descriptive sentence of a given image, perpetuate gender and racial bias. As crucial as this is, the depth of the problem has not been fully explored, and the question about whether other tasks within vision-and-language are also affected by unfair data representations remains open.

With the aim of raising awareness and starting an open discussion, this paper investigates societal bias in visual question answering (VQA), another of the foundational tasks within the vision-and-language community. The aim of VQA is to correctly answer questions about a given image (Figure 1), requiring understanding and associating the question and the image with potential candidate answers. One of the current challenges in VQA is that models tend to suffer from language bias [2], i.e., they exploit the

CCS CONCEPTS

- Social and professional topics → Gender; Race and ethnicity;
- Computing methodologies → Computer vision; Natural language processing.

KEYWORDS

visual question answering, gender stereotype, racial stereotype, datasets
superficial correlations between the questions and the answers in the training set, and produce answers without looking into the visual content. For example, in the VQA 1.0 dataset [4] questions starting with what sport are answered tennis on the 41% of the samples, which leads to models learning a shortcut to always produce tennis for this type of questions. This suggests that if societal bias, such as racism or sexism, is present in the training data, it will be highly likely perpetuated by VQA models. Moreover, as most of the VQA datasets are collected by crowdsourcing by showing human annotators a photo and asking them to freely write questions and answers about it, it is reasonable to think that the biases from the annotators may be leaked into the data.

Specifically, this paper analyzes gender and racial bias on five VQA datasets [19, 25, 32, 39, 61]. Our study is based on the compilation of statistics about the representation of different demographic groups, the correlation between demographic groups and answer and question distributions, and the exploration of harmful examples within each dataset. In Section 4, we analyze gender bias in terms of men and women representation, uncovering:

- There is a systematic imbalance on gender representation. Questions about men are about twice as frequent as those about women in all the analyzed datasets.
- Answer distributions are different between women and men questions. For example, in VQA 2.0 [19], the answer skateboarding appears 835 times for questions about men, but only 60 times for questions about women. Furthermore, we found that specific answers are co-related with each gender, e.g., the percentage of answers that are blonde is about 4 times higher in questions about women than in questions about men.
- We found multiple samples that reflect traditional gender stereotypes both in men and women images.
- Answers based on gender stereotypes tend to appear more frequently in samples where the answers cannot be grounded in the image content, such as What is the woman thinking?

In Section 5, we analyze VQA datasets in terms of racial bias. Specifically, we dig into samples that explicitly mentions race or ethnicity. Our analysis shows:

- All the VQA datasets contain questions related to race. However, the ratio of such questions is very small for GQA [25], whose questions and answers were automatically generated from the images, and for Visual7W [61], in which inappropriate samples were filtered.
- There is an imbalance on the representation of different demographic groups. For instance, in VQA 2.0, the answers White or Caucasian appear about 3.45 times more frequently than the answers Black or African.
- The correlation between race and nationality shows a US-centric viewpoint, with 65% of Black people being associated with American nationality in VQA 2.0.
- We found potential harmful examples related to race, ethnicity, or nationality. As in the case of gender, these samples tend to appear when answers cannot be grounded in the visual content of the image, leading annotators to answer the questions based on their own preconceptions of the world.

In Section 6, we identify two main sources of societal bias in VQA datasets, and propose mitigation strategies to alleviate them. The first problem is the underrepresentation of minoritized groups. We emphasize the importance of recognizing societal bias in VQA datasets and taking measures against it, as models trained on such datasets can learn to ignore minoritized attributes and lead to shortcut learning [18, 28]. The second problem is the presence of harmful samples in the datasets. We propose three simple tools to remove them while considering annotation costs: 1) automatically screening to identify unanswerable questions, 2) including ethical instruction in the annotation process, and 3) creating an open platform to allow user’s feedback, so that problematic samples can be easily addressed.

Finally, we would like to note that datasets are a crucial part for the development of the field, and all existing VQA datasets have been and will be necessary and important. This paper does not aim to diminish the contribution of such datasets, but to raise awareness within their users and potential dataset developers so that mitigation measures can be taken in the future.

2 BACKGROUND

Visual question answering (VQA) VQA is the task of answering a question about an image’s visual content, which has been commonly used to evaluate the ability of a model to understand and integrate visual and language information. In the seminal work by Agrawal et al. [4], the first large-scale dataset for VQA was created, commonly known as VQA 1.0 dataset. VQA 1.0 contained challenging reasoning questions involving a diverse set of
skills for the models to solve, such as object and activity recognition, counting, or space localization, among others. Since models became progressively better at VQA 1.0, new datasets and challenges were proposed [17, 19, 20, 25, 32, 39, 61], including VQA 2.0 [19], which partly addressed the existent language bias in VQA 1.0 by increasing the diversity of answers in similar types of questions, GQA [25], in which questions required various reasoning skills (e.g., spatial reasoning, logical inference) to find the correct answer, and OK-VQA [39], in which models needed to access external knowledge such as Wikipedia. As a result, the field has attracted a lot of attention from researchers all over the world, with a large number of models been proposed ever since [3–5, 10, 14, 22, 24, 27, 30, 33, 34, 36, 46, 53, 56, 58].

Although most of the effort has been focused on increasing the overall accuracy on the publicly available benchmarks, especially on the VQA 2.0 dataset, an important body of work [2, 11, 12, 15, 41] has been devoted to address language bias, which refers to the existence of skewed distributions of answers with respect to a certain type of question. Even though VQA is a multi-modal task, because of the language bias, models tend to learn and make inferences based on superficial correlations, such as questions about bananas are answered yellow with high probability [2]. This makes the models to ignore the visual information, which prevents generalization to out-of-distribution settings. Manjunatha et al. [30] further examined this tendency by utilizing rule mining algorithms to correlate the questions, answers, and regions in which a model focuses. The results showed that predictions tend to contain miscellaneous rules; for example, when what and brand are in a question and there is a laptop in the image, the answer tends to be Dell. It was also observed that in What is he/she doing? type of questions, answers for men were more diverse (skateboarding, snowboarding, surfing), than answers for women (texting). Although this evidence points at skewed distributions in terms of gender, societal bias in VQA datasets have not been explicitly studied yet.

**Societal bias in vision-and-language** It is only in recent years that societal bias has been investigated in CV and NLP tasks [6, 8, 26, 43, 49, 52, 54, 60]. One significant study is Buolamwini and Gebru’s work [8] on commercial face recognition applications. They demonstrated that the system’s performance varies depending on the gender and race of the individual, and in particular, misjudges women with darker skin. In vision-and-language tasks, there has been some recent advancements, especially for image captioning [9, 23, 47, 59]. In one of the first studies, Burns et al. [9] showed that, instead of looking into the appearance of people, captioning models predicted gender words based on gender stereotypes in the contextural information. For example, when an image had a laptop, models generated the word man, even when there was only a woman. Similarly, Zhao et al. [59] studied racial and gender bias. They found imbalances in gender and race representation in the COCO dataset [35], with more than twice images of men than of women and 9.2x more images of lighter-skinned than darker-skinned people. More recently, Hirota et al. [23] proposed a metric to quantify gender and racial bias amplification of image captioning models. Given this context, in order to raise awareness and mitigate the damage societal bias may be causing to underrepresented communities, it is only natural to investigate whether other tasks and datasets within vision-and-language are also affected by this problem.

### 3 PRELIMINARIES

We study gender and racial bias in VQA. We first describe the datasets under analysis in Section 3.1, and then, the methodology we followed in our experiments in Section 3.2.

#### 3.1 VQA datasets

We analyze five standard datasets, summarized in Table 1. Each dataset varies in the number of images, the number of questions, the annotation method, and the format of the answers; however, the images are from a common source, the COCO dataset [35]. A detailed description for each dataset is provided below.

**Visual Genome** [32] Visual Genome contains 108k images from the intersection of COCO [35] and YFCC100M [48] datasets, and 1.7 million question-answer pairs about the images. The answers are open-ended, which means they are freely written and their vocabulary is not restricted. Questions and answers were created by human annotators following three rules: 1) questions had to start with one of the six Ws: Who, Where, What, When, Why, and How, 2) ambiguous and speculative questions had to be avoided, and 3) questions had to be precise, unique, and relatable to the image, such that they had to be answerable if and only if the image was shown.

**Visual7W** [61] Visual7W is composed of 327k QA pairs and 1.3M human-generated multiple choice answers on top of 47k COCO images. The dataset is characterized by object-level rationales and multiple choice answers, which means several candidate answers are provided per question with only one being the correct one. Each question starts with one of the seven Ws: What, Where, When, Who, Why, How, and Which. Annotators instructed to create question-answer pairs while being concise and unambiguous to avoid wordy or speculative questions. After that, other annotators check the question-answer pairs to see if an average person can answer them.

**VQA 2.0** [19] The dataset is built on COCO images and contains 1.1M question-answer pairs. The questions are categorized by question types defined by the first few words of questions (e.g., *What is this, How many*). The dataset is divided into training (80k images and 44k questions), validation (40k images and 214k questions), and test (80k images and 448k questions) sets. VQA 2.0 is the de facto benchmark for natural image VQA. When making the questions, annotators freely create questions that people can answer while making questions not easy. Also, annotators are instructed to ask questions that require the image to answer. After that, ten different annotators answer each question. The answers of the test set are not published, so we use training and validation sets in our analysis.

**GQA** [25] GQA is a large-scale VQA dataset with 113k images from the Visual Genome dataset and 22.7M question-answer pairs. Questions require many types of reasoning which measure e.g., logical inference. The question-answer pairs are automatically generated using question templates and scene graph representing all the objects and relationships in the image. Hence, the answers are limited to the words in the scene graphs, which we called closed vocabulary. Due to its large-scale, we use a random subset of roughly 20 percent of the samples in our analysis.
We first analyze gender bias in VQA datasets. Following previous work, we define a list of words for women and men, e.g., woman, girl, she for women, man, boy, he for men. When a question only includes gender words in the questions (if any), we use a rule-based approach to detect such samples. Then, we analyze gender/racial bias by comparing different sets. Concretely, we run statistics on the number of samples, analyze trends in the answers, and visually inspect for potential harmful data.

### 3.2 Methodology

In Figure 2, we provide an overview of the methodology used to investigate gender and racial bias in VQA datasets. The first step is to select samples for each dataset with an explicit mention to gender (women/men questions) or race and ethnicity (racial questions). We use a rule-based approach to detect such samples. Then, we analyze gender/racial bias by comparing different sets. Concretely, we run statistics on the number of samples, analyze trends in the answers, and visually inspect for potential harmful data.

### 4 GENDER BIAS IN VQA

We first analyze gender bias in VQA datasets. Following previous work, we use a binary classification of gender, with the two gender categories being women and men. With a rule-based approach, we classify samples into women or men categories based on the gender words in the questions (if any). Specifically, we first define a list of words for women and men, e.g., woman, girl, she for women, man, boy, he for men. When a question only includes women words, the question is classified as a women question, and vice versa. Questions that are not classified either as women or men are excluded. Note that this analysis is based on the VQA annotator’s perceived gender, and not on gender identity. We report our findings below.

#### 4.1 Questions about men are dominant

The statistics of the number of women and men questions for each dataset are reported in Table 2. The number of questions about men is about twice as large as the number of questions about women in all the datasets. This tendency is consistent with the result in [59], which shows that there are more than twice as many men images as women images in the COCO dataset [35]. As all the datasets in Table 2 are based on COCO images, the root of the underrepresentation of women in VQA datasets may come from the original selection of images.

#### 4.2 Answer distributions are skewed toward each gender

In Figure 3, we show the top-20 answers for women (above) and men (below) questions in the VQA 2.0 dataset. We filter out yes/no and numeric answers. Each distribution is normalized by the number of questions for the corresponding gender. Comparing the two answer distributions, we can see that there are more frequent answers about sports in men questions (frisbee, skateboard, skateboarding, baseball, tennis, surfing, and surfboard) than in women questions (tennis). Also, the differences in the ratios about sport answers are larger between the two genders, perpetuating the stereotype that sport is an activity predominantly masculine. The top-20 answers for women questions with a notably higher ratio than men are pink, purple, blonde, and umbrella, most of them strongly associated with the traditional gender stereotype of femininity. We find these patterns are also exhibited in other datasets, e.g., Figure 1 in the appendix shows that the answers about sports are more frequent in men questions in the Visual7W dataset.

Figure 4 shows the women (above) and men (below) top-20 frequent answer distribution for the specific question type what is this in VQA 2.0 dataset, where the skew is more prominent. Answers for men questions include multiple sports words (e.g., surfing, skateboarding, skiing), with higher ratios than those of women. On the other hand, in women questions more motionless words appear (e.g., posing, sitting, smiling, talking on phone).

#### 4.3 Gender-answer correlations reflect gender stereotypes and discrimination

We calculate the correlation between answers and women/men questions by utilizing the bias score (BS) defined in [60]. We adapt the definition of BS to remove the influence of the difference of the number of women/men questions. Let $q_w$ and $q_m$ denote a women question and a men question respectively, and $a \in A$ the set of the answers. We filter answers that do not appear more than $n$ times in women/men questions. Our BS gives the degree to which answers are skewed toward each gender.

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The list of women/men words can be found in the appendix.

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### Table 1: Comparison of datasets under analysis

† denotes the images are from the intersection of COCO [35] and YFCC100M [48] datasets. The types of answers can be: Open ended, which means the answers are written freely without vocabulary restrictions; Multiple choice, which means several candidate answers, with only one correct answer, are provided per question; or Closed vocabulary, which means the words used as answers are taken from a limited list.

| Year | Dataset        | Num. Images | Source | Num. QA | QA Annotation | Answer Type         |
|------|----------------|-------------|--------|---------|---------------|---------------------|
| 2016 | Visual Genome  | 108k        | COCO†  | 1.7M    | Crowdsourcing | Open ended         |
| 2016 | Visual7W       | 47k         | COCO   | 327k    | Crowdsourcing | Multiple choice    |
| 2017 | VQA 2.0        | 204k        | COCO   | 1.1M    | Crowdsourcing | Open ended         |
| 2019 | GQA [25]       | 113k        | COCO†  | 22.7M   | Automatic     | Closed vocabulary  |
| 2019 | OK-VQA [39]    | 14k         | COCO†  | 14k     | Crowdsourcing | Open ended         |

OK-VQA [39] The dataset is built on a part of COCO images and contains 14k open-ended questions. Also, there are 10 knowledge categories into which each question is classified (e.g., Science and Technology, Cooking and Food). The dataset comprises questions that require external knowledge (e.g., Wikipedia) to answer. Questions are written by human annotators following the same instructions as VQA 2.0, but the annotators are also encouraged to make questions that require external knowledge. Later, five different annotators write the answers to those questions.

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1 $n$ is different among the datasets due to the size of each dataset. The detailed setting can be found in the appendix.
Figure 2: Overview of our methodology. For each VQA dataset, we automatically select the samples containing references to
gender and race/ethnicity, and proceed to perform statistical analysis, answer analysis, and visual inspection. Orange and
green circles represent samples with a gender reference. Blue circles are samples with a reference to race or ethnicity. Gray
circles are other samples.

Table 2: Statistics of women/men questions (Women Qs/Men Qs) in VQA datasets. MoW is the number of men questions over
the number of women questions. Ratio is the number of gender questions (Num. Women Qs + Num. Men Qs) over the total
number of questions (Num. Total Qs).

| Dataset         | Num. Men Qs | Num. Women Qs | MoW | Num. Gender Qs | Num. Total Qs | Ratio (%) |
|-----------------|-------------|---------------|-----|----------------|---------------|-----------|
| Visual Genome [32] | 111,286     | 56,013        | 2.0 | 167,299        | 1.7M          | 9.8       |
| Visual7W [61]   | 10,641      | 5,030         | 2.1 | 15,671         | 327K          | 4.8       |
| VQA 2.0 [19]    | 64,990      | 31,690        | 2.1 | 96,680         | 658K          | 14.7      |
| GQA [25]        | 296,242     | 178,518       | 1.7 | 474,760        | 4.3M          | 11.0      |
| OK-VQA [39]     | 868         | 443           | 2.0 | 1,311          | 14K           | 9.4       |

Figure 3: Top-20 frequent answers in VQA 2.0. Above: Frequent answers for women questions (orange). For the comparison,
we also show the ratio of the answers over men questions (green). Below: Frequent answers for men questions. As in above,
we also show the ratio of answers for women questions. A large difference in ratio indicates that the answer is skewed toward
certain gender.

answer $a$ is biased with respect to a men questions $q_m$:

$$BS(a, q_m) = \frac{c(a, q_m)}{c(a, q_m) + rc(a, q_w)}$$

where $c(a, q)$ is the number of co-occurrences of $a$ and $q_w$ or $q_m$, and $r$ is the ratio of the number of the men and women questions
(i.e., $r = \#$ men questions/$\#$ women questions). If $BS(a, q_m)$ is close
Figure 4: Top-20 frequent answers for the question type *what is this* in VQA 2.0. Above: Frequent answers for women questions (orange). Below: Frequent answers for men questions (green). As in Figure 3, we compare the answer ratios between the two genders.

Figure 5: Top-20 answers that are co-related with women questions (above) and men questions (below) in the VQA 2.0 dataset.

If \(BS(a, q_m)\) is close to 1, then the answer \(a\) is correlated with men questions. On the contrary, if \(BS(a, q_m)\) is close to 0, answer \(a\) is correlated with women questions. The difference between BS and Figure 3 and 4 is that the distribution of BS shows the answers that often appear only in questions of one gender. For example, in Figure 3, *black* is the most common answer for both gender questions, but it is not biased towards any gender, in which case the value of BS is close to 0.5.

The top-20 answers that are correlated with each gender based on BS in VQA 2.0 are shown in Figure 5. In a bias-free dataset, the distribution of BS would be flat, which reveals that the VQA 2.0 dataset contains strong gender bias in their answers. Again, many sport words (e.g., *skateboarding*, *baseball*, *snowboarding*) are strongly correlated toward men questions, while no answers about sports are highly related to women questions. On the other hand, food-related words (e.g., *wine*, *knife*, *cake*) are highly correlated to women questions. This trend is common in other datasets as well; for example, in GQA (Figure 2 in the appendix), sports or outdoor words (e.g., *skating*, *surfing*, *tan*) made up most of the top-20 answers for men questions, while there are no sports or activity-related answers in the case of women, and instead, static words (e.g., *umbrella*, *sofa*, and *posing*) are common. Similarly to the results in the previous section, these results are a reflection of the real-world stereotypes that leads to gender bias and discrimination.
which filters out not visually grounded samples, do not contain stereotypical answers such as girl and woman. The common denominator in these examples is that their questions are not visually grounded: there is no definite and unambiguous evidence in the image to answer.

Additionally, we find some inappropriate or directly harmful examples. For instance, the top-row middle question in Figure 7 has a sexual connotation about the woman in the image, and in the second-row left image in Figure 7, where a woman is just standing in front of a mirror with a camera, one of the ground truth answers to the question of what is she doing is flirt, implying that the mere fact that a woman is standing is to seduce someone.

4.6 Discussion

Biased distributions We have shown that the ratio of men questions over women questions and the answer distributions are biased in all datasets. Especially for the ratio of men questions over women questions, we know the real-world ratio of the men to women is roughly 1 : 1. Hence, the skew of the ratio of men questions over women questions in VQA datasets (i.e., men questions are about twice as numerous as women questions) is far from the real world distribution. That is unfair underrepresentation of women and could lead machine learning models trained on these datasets to potentially ignore women. This means that models perpetuate the underrepresentation of women unveiled in the dataset, which is very problematic from the perspective of gender equality.

As for the answer distributions, while we have shown that the answer distributions are highly skewed toward each gender, it is difficult to know the real-world distributions (e.g., the actual gender ratio among those who snowboard). Furthermore, realistically, the gender ratio for the answers cannot be aligned, and even if it could be, the gender bias in models might not disappear [8, 54]. However, machine learning models trained on these datasets without considering the biased distributions can learn to ignore underrepresented combinations in the datasets (e.g., a woman who snowboards) and lead to shortcut learning [18, 28]. Being aware of such bias toward each gender encourages the community to design better model architectures and training paradigms to mitigate the bias, which is a research direction to be further explored, as in [9].
Gender-stereotypical examples Compared to the skewed answer distributions, gender-discriminatory samples are undoubtedly harmful. Such samples are often found when the associated question is not visually grounded. For such questions, annotators may answer based on their gender stereotypes. Such harmful samples are found in datasets in which not visually grounded questions are not filtered (i.e., VQA 2.0, OK-VQA, and Visual Genome). Also, in VQA 2.0 and OK-VQA, the annotators who create the questions are different from those who answer them. This choice is to deal with the problem of multiple possible correct answers to the same question [4]. Although the process allows the datasets to have diverse answers, it does not require the annotators to answer to their own questions and gives room to make questions that are not visually grounded. On the other hand, in GQA and Visual7W, while not visually grounded questions hardly exist because of the datasets construction, the diversity of answers is limited. In conclusion, manual removal of potential harmful questions may be necessary to ensure ethical goodness. Thus, it may be a good practice to build an efficient mechanism to report potential ethical problems and review them on a regular basis to decide whether some samples should be removed.

5 RACIAL BIAS IN VQA

To study racial bias, we first identify samples in the dataset with a reference to race or ethnicity. We select all the samples whose questions explicitly contain the words race or ethnicity. We refer to these samples as racial samples or racial questions. Additionally, we elaborate a list of racial-related words (e.g., Asian, Caucasian, Black) and nationality-related words (e.g., American, Chinese, Indian) from the answers in VQA 2.0. Our findings are reported below.

5.1 Most datasets contain racial words

The number of racial samples per dataset is shown in Table 3. All datasets contain racial questions. However, the ratio of racial questions is very small for GQA, whose questions and answers were

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The complete list of words can be found in the appendix.
Table 3: Statistics of racial questions (Racial Qs) in VQA datasets. Ratio is the number of racial questions over the number of questions.

| Dataset          | Num. Racial Qs | Num. Total Qs | Ratio (%) |
|------------------|----------------|---------------|-----------|
| Visual Genome [32]| 619            | 1.7M          | 0.43      |
| Visual7W [61]    | 74             | 327K          | 0.05      |
| VQA 2.0 [19]     | 799            | 658K          | 0.12      |
| GQA [25]         | 85             | 4.3M          | 0.00      |
| OK-VQA [39]      | 30             | 14K           | 0.21      |

created automatically from the image’s scene graph, and for Visual7W, in which annotators had explicit instructions to write visually grounded questions, and inappropriate samples were filtered. In contrast, VQA 2.0, Visual Genome, and OK-VQA show higher ratios of racial questions. As the absolute number in OK-VQA is small, we conduct our analysis in the VQA 2.0 and Visual Genome.

5.2 White people are majority, and Black people are minority

First, we investigate the distribution of answers for racial questions. To remove answers that may not be related to race, ethnicity, or nationality, we filter yes, no, horse⁶ and answers to questions about colors⁷. In Figure 8, we show the top-10 answers to racial questions in VQA 2.0 and Visual Genome. In both datasets, the demographic group that occupies the largest amount of answers is related to White people (White, Caucasian), followed by Asian people related words (Asian, Chinese). On the contrary, words usually associated with Black people (Black, African American, African) and Hispanic people (Hispanic) appear less frequently, showing an underrepresentation of darker-skinned people on the analyzed samples. This tendency has also been observed in other computer vision datasets, such as facial recognition (e.g., 79.6% subjects are lighter-skinned in IJB-A [8, 31]), or in image captioning [59]. This imbalance can lead to poor performance on images of darker-skinned people in models trained on such datasets.

5.3 US-centric perspective of nationality and race

We next explore the relationship between race and nationality in the VQA 2.0 dataset. We examine the co-occurrence of nationality-related and racial-related words in the answers. We roughly categorize them into three races or ethnicities: African-oriented (with the words Black and African), Asian-oriented (with the words Asian and Oriental), and White-oriented (with the words White and Caucasian).⁸

Figure 9 shows the top-10 nationalities co-occurring with each racial category. Each racial category is strongly tied to a specific country. The result in Figure 9 (left) shows that about 65% of Black people are considered to be American (i.e., African American or American). As for Asian-oriented category, most of the nationality answers are Chinese with a 42% ratio, followed by Japanese and Indian with a 13% and 12% ratio, respectively (Figure 9 (middle)). Regarding the White-oriented category, American is the most frequent nationality answer with a 33% ratio (Figure 9 (right)). As the concept of race is highly tied to the social and cultural background of each individual [21], it is remarkable to note that the relationship between race and nationality in the analyzed datasets seems to be rooted in a United States point of view where White and Black people are associated with American nationality, and Asian people with Chinese nationality. This is probably the result of a US-centric annotation process.

5.4 Racial-stereotypical examples

We manually inspect all the racial samples for all the datasets to check whether they can be potentially harmful. In addition to this, we conduct an intersectional analysis and explore more than 300 samples of women and men questions for each dataset in terms of racial bias. We find that there are two types of samples with racial bias: 1) racial discriminatory samples, and 2) biased judgment samples. Such examples appear in the VQA 2.0, Visual Genome, and OK-VQA datasets, and some of them are shown in Figure 10. More can be found in the appendix.

Some samples that fall into the racial discriminatory category are shown in Figure 10. For example, in the top-row left example, the question What causes the skiing pigment of the girl in the blue shirt to be so dark? implies that lighter-skin is the standard. Another example is shown in Figure 10 second-row right image, whose question asks about the woman’s nationality. One of the answers, Oriental, is an outdated term that has not been used in US federal laws since 2016 [42]. Still, it appears 23 times as an answer in VQA 2.0. With respect to biased judgment samples, they often appear in questions that are not visually grounded. In other words, when there is no clue in the image to identify the race, ethnicity, or nationality. For example, in Figure 10 bottom-row left image, the answer is White even though we can only see the tips of the fingers. A similar case can be seen in the bottom-row right example.

5.5 Discussion

Biased distributions In VQA 2.0 and Visual Genome, the number of samples related to White people is much greater than samples related to Black and Hispanic people (e.g., there are 3.45x more samples related to White people than Black people in VQA 2.0). The skewed distribution of race can be problematic if models trained on those datasets are used in real world applications, as the underrepresentation of certain races or ethnicities may lead to biased answers. Although it seems ideal to have a uniform racial distribution, race
itself is a vague concept, which is strongly tied to the personal background of each individual [21]. Furthermore, aligning racial distributions alone is insufficient to remove racial bias from the models [8, 54]. For these reasons, it is essential to make an effort to have racial diversity in the datasets, but at the same time, it is vital to devise learning strategies that can debias the datasets.

**Biased samples** Even though the number of racial questions is relatively small, the stereotypical samples in terms of race are unquestionably harmful and should be removed from the datasets. Datasets that have not gone through manual screening to remove samples that are not visually grounded are the most affected ones (VQA 2.0, Visual Genome, and OK-VQA). Also, the problem is accentuated in VQA 2.0 and OK-VQA, which increased the diversity in their answer set by making different annotators to answer the written questions. As samples with racial discrimination or biased judgment of race/nationality may reflect the bias in the annotators, an unconstrained or less-constrained annotation process may be prone to contain such harmful samples. This is supported by the fact that, we could not find such samples in GQA, which automatically generates question-answer pairs, or Visual7W, which applies manual filtering to exclude questions that are not based visually grounded. Because of this, an additional cleansing process on the samples may be a necessary strategy to remove samples with racial discrimination and biased judgment.

**Necessity versus validity of asking questions about race**
We take a step back and cast doubt on asking about race in the first place. Although race has been used to categorize people for a long time, it is extremely hard to provide fixed categories in which people from different backgrounds fit together [29]. Moreover, visual information alone is hardly sufficient to identify one’s race, ethnicity, or nationality, so asking this type of question is prone to cause biased answers based on stereotypes. Thus, we believe that, at least in VQA datasets, questions about race should be discouraged.

**6 POSSIBLE SOLUTIONS**

In order to reduce the risks associated with gender and racial bias, we would like to encourage VQA researchers to increase their awareness to this problem and take steps to address it. We specifically discuss possible solutions to address the two major problems presented in this paper: skewed distributions and harmful samples.

**Skewed distributions** We have shown that the analyzed VQA datasets have distributional bias related to gender (Section 4) and, some of them, to race (Section 5). Aligning the distributions is tricky for many reasons, such as the existence of bias in the real-world and the ambiguity of race categorization. Furthermore, even if the distributions could be aligned, this is not sufficient for bias-free models; models can still amplify bias. Nevertheless, if the distributions are too skewed in gender and race, models are more likely to ignore underrepresented groups of people and increase the risk of shortcut learning. Therefore, efforts should be made to avoid this underrepresentation. More importantly, we encourage the users of the datasets to be aware of the distributional biases related to gender and race in VQA datasets and design models and training paradigms that can address these issues.

**Harmful samples** We have found that some of the VQA datasets contain harmful samples that exhibit gender or racial stereotypes. Such samples are often found when the associated question is unanswerable from the image content. Thus, datasets that have no filtering processes, such as VQA 2.0, Visual Genome, OK-VQA, are prone to contain such samples. Also, questions and answers themselves...
What causes the skiing pigment of the girl in the blue shirt to be so dark?
melanin, sun, genetic, melatonin

What is the ethnicity of that lady?
Asian, Chinese

What language do the people in this country speak?
Chinese, Japanese, Korean, English

What race is the woman?
White, Caucasian, American

What race is the man on the left?
Black, African, African American

What nationality is the woman that is sitting on bench?
Asian, Chinese, Japanese, Oriental, Mexican

What race is the person holding open the sandwich?
White

What race is the person?
Hispanic

What is the race of the people?
Caucasian

Figure 10: Racial samples in OK-VQA [39] (above), VQA 2.0 [19] (middle), and Visual Genome [32] (below).

can be discriminatory. The ideal solution is to remove harmful samples by conducting a manual filtering, but the cost for such a process can be extremely expensive, especially if the size of dataset is large. So, we propose three alternative solutions to address both the ethical and the cost problems: 1) automatic screening, 2) ethical instructions, and 3) a feedback platform for users.

For the automatic screening, we propose to train a model to identify unanswerable questions from images. To train such a model, a labeled dataset to identify whether a question is answerable from an image might be necessary. With a trained model, visually not grounded samples could be potentially filtered out. Although the model’s performance is not guaranteed, it could be used to ease the manual screening process as a pre-filtering step.

The second proposed solution is to incorporate ethical instruction in the dataset’s annotation process. Ethical instructions are not commonly provided to annotators when creating VQA datasets. Nevertheless, as we have shown, VQA datasets can contain harmful samples; so instruction for annotators to be aware of making ethical questions and answers could reduce the amount of harmful samples. In this paper, we only focused on gender and race as demographic attributes, but ethical instructions should be extended to make datasets fairer with respect to any other attributes.

The last solution is to create a platform to report potential ethical problems and review them to decide whether they should be removed. The platform should allow dataset users to report and share with dataset developers when they find harmful samples in their use or investigation of datasets. This platform would be based on the idea of shifting from the traditional developer-driven paradigm of dataset creation to a user-participatory paradigm. Incorporating a process that allows users to improve datasets can solve both cost and ethics issues at a high level.

7 CONCLUSION

We investigated gender and racial bias in VQA datasets through the compilation of statistics and the manual exploration of harmful samples. The results showed: 1) distributions are very skewed concerning gender or race, and 2) harmful samples, denoting annotators’ gender or racial stereotypes, exist in VQA datasets. Additionally, we discussed potential solutions. We proposed the automatic screening...
of samples, the inclusion of ethical instructions in the annotations process, and the creation of a platform for receiving user's feedback. Through the analysis and discussion in this paper, we hope to raise awareness and encourage the VQA research community to take measures to mitigate societal bias.

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