Probing Explicit and Implicit Gender Bias through LLM Conditional Text Generation

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Abstract

Large Language Models (LLMs) can generate biased and toxic responses. Yet most prior work on LLM gender bias evaluation requires predefined gender-related phrases or gender stereotypes, which are challenging to be comprehensively collected and are limited to explicit bias evaluation. In addition, we believe that instances devoid of gender-related language or explicit stereotypes can still induce gender bias in LLMs. Thus, in this work, we propose a conditional text generation mechanism without the need for predefined gender phrases and stereotypes. This approach employs three types of inputs generated through three distinct strategies to probe LLMs, aiming to show evidence of explicit and implicit gender biases in LLMs. We also utilize explicit and implicit evaluation metrics to evaluate gender bias in LLMs under different strategies. Our experiments demonstrate that an increased model size does not consistently lead to enhanced fairness and all tested LLMs exhibit explicit and/or implicit gender bias, even when explicit gender stereotypes are absent in the inputs.

1 Introduction

Large Language Models (LLMs) represent a revolutionary advancement and demonstrate remarkable performance in many tasks [9, 17]. LLMs like GPT-4 [10] and LLAMA [17, 18] are trained on vast corpora of text data, enabling them to generate coherent and contextually relevant human-like text. Nevertheless, stemming from the inherent gender biases present in both the training data and model architecture, the generated outputs may present partiality or prejudice, potentially leading to adverse effects such as the perpetuation of detrimental stereotypes, the reinforcement of disparities, and the propagation of misinformation. Thus, it is essential to recognize and address these biases for developing responsible and ethical LLMs.

In prior work, a language model is said to exhibit gender bias: 1) when the input template contains mentions of specific gender groups (e.g., "*The woman worked as*"), the resulting generated sentence tends to show a positive or negative inclination towards that particular gender [4, 6, 14, 15]; 2) when the model tends to assign a higher probability to sentences with stereotypical combinations of gender groups and attributes compared to other combinations (e.g., "*a female CEO*" vs. "*a male CEO*") [1, 16].

The former method requires *explicit* gender mentions and the latter method necessitates predefined gender stereotypes. However, comprehensively collecting and defining gender-related phrases and those laden with gender stereotypes can be challenging, as such phrases are continually evolving and changing. Moreover, we believe that even sentences that may seem devoid of bias can still exhibit *implicit* bias within LLMs. For example, LLAMA 2 [18] continues the sentence "*My friend is talking on the phone*" with "*and she looks really happy*". "*Talking on the phone*" is not an action typically associated with gender stereotypes, but LLAMA assumes *my friend* to be female without context.

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To address the above limitations, we propose a conditional text generation mechanism, which does not require any predefined gender-related phrases or stereotypes and possesses the capability to explore both explicit and implicit gender bias. Specifically, we use three distinct strategies to design the probing inputs: 1) template-based inputs containing four widely acknowledged features that are associated with gender stereotypes; 2) LLM-generated inputs that can potentially harbor underlying gender bias inherent to the LLM; and 3) naturally-sourced inputs from naturally-sourced corpus like STS-B [2], which comprises sentences related to human activities and can probe the implicit bias in LLMs. Concretely, we prompt LLMs to extend the inputs from these strategies through conditional text generation. Then the outputs of LLMs are utilized to evaluate the gender bias.

We observe that employing different probing strategies leads to different fairness performances, and a larger model does not necessarily equate to increased fairness. Even if input sentences do not contain explicit gender stereotypes, the model can still display gender bias in logits or generated text, which undoubtedly has harmful societal impacts.

2 Probing and Bias Evaluation

In this section, we define the task, introduce three types of strategies to stimulate conditional text generation, and present *explicit* and *implicit* evaluation metrics to assess gender bias in LLMs.

2.1 Task Formulation

Let $\mathcal{L}$ be a LLM, and $\mathcal{X}$ be the input that $\mathcal{L}$ is conditioned upon for continuation generation. Our goal is to investigate biases through language generation conditioned on input sentences $x \in \mathcal{X}$ across different gender attributes. Specifically, we consider the pronouns of the two-gender task as gender attributes, and we denote the set of the paired attribute words as $\mathcal{W} = \{(w_1^f, w_1^m), \cdots, (w_N^f, w_N^m)\}$, where $w_i^f \in \mathcal{W}^f = \{she, her, herself, \dots\}$ is associated with *female* and $w_i^m \in \mathcal{W}^m = \{he, his, himself, \dots\}$ is associated with *male* for $i \in \{1, 2, \cdots, N\}$. $\mathcal{W}^f$ and $\mathcal{W}^m$ are bijections. In our work, we consider $\mathcal{L}$ as exhibiting bias when its generated texts lead to an unequal social perception of w_i^f and w_i^m for $i \in \{1, 2, \cdots, N\}$. We focus on distributional disparities of gender attribute words in the collection of generated texts.

2.2 Probing Strategies

We consider exploring two types of gender bias: *explicit bias*, such as OCCUPATION, which has been extensively studied and has predefined stereotype tokens with respect to the gender attributes (e.g., "nurse") [3, 5, 7, 8, 12, 19], and *implicit bias*, where biases are not easily perceptible. Thus, we explore three different strategies for bias exploration: template-based, LLM-generated, and naturally-sourced strategies.

Template-based. We leverage a straightforward template, denoted as "`subject verb object`" which we populate with "*My friend*" in the `subject` slot and predefined stereotype words corresponding to target attributes in the `object` slot to create individual data sample. To expand the scope of the existing target attribute OCCUPATION, we manually construct lists for PERSONALITIES, HOBBIES, and COLORS.[2] Subsequently, we replace the `verb` placeholder with "*is*" for OCCUPATION and PERSONALITIES, and with "*likes*" for HOBBIES, and COLORS. For instance, when filling the template with "*running*" from the target attribute HOBBIES, the resulting prompt is "*My friend likes running*" which serves as the stimulus to prompt language generation.

LLM-generated. Similar to automated question generation in [11, 13], we employ LLMs to automatically generate explicitly unbiased statements. Specifically, we initiate this process by instructing `gpt-3.5-turbo` with the following prompt: `Generate a list of statements starting with 'My friend'. For example, [S]`. The initial value of `[S]` is set to "*My friend likes blue*" and it is subsequently substituted with randomly generated statements, iteratively re-prompting the model. This process continues and we automatically remove duplicates and manually remove statements exhibiting high textual overlap until we have 200 statements.

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[2]Complete lists available in the Appendix 6.3.

Naturally-sourced. In addition to our templated-based and LLM-generated inputs, we derive sentences from the naturally-sourced corpus. Specifically, we adapt the STS-B data [2] and select sentences from the test set that includes terms like *"someone"*, *"person"*, etc., as templates to ensure the sentences describe humans instead of animals or objects. Subsequently, we replace these terms within the sentences with *"My friend"*, thus obtaining our gender-neutral naturally-sourced inputs to probe LLMs. For example, if the original sentence is *"A person is walking"*, our adapted sentence would be *"My friend is walking"* for experimental consistency.

2.3 Bias Evaluation Metrics Design

To evaluate the fairness of LLMs probed using these three strategies, we define two types of metrics: *explicit bias metrics* – gender-attribute score, and *implicit bias metrics* – co-occurrence ratio and Jensen–Shannon divergence score. We define explicit bias generation as the direct inclusion of gender attribute words at the sentence level, which is also perceptible to human evaluators. Conversely, implicit metrics assess bias from the model's perspective, considering factors such as differences in the logit distributions associated with attribute words $w^f \in \mathcal{W}^f$ and $w^m \in \mathcal{W}^m$.

Gender-attribute score. For each generated sentence $s \in S$, we use the boolean value d_s^k, where $k \in \{f, m, n, ns\}$, to represent different performances of the generated sentence by LLMs. When there exists $w \in s$ such that $w \in \mathcal{W}^f$ and $w \notin \mathcal{W}^m$, we categorize s as leaning towards female and $d_s^f = 1$; otherwise, $d_s^f = 0$. Same for d_s^m. For any $w \in s$, if $w \notin \mathcal{W}^f$ and $w \notin \mathcal{W}^m$, there are two possible scenarios: one in which s is considered neutral ($d_s^n = 1$), and the other in which s is nonsensical ($d_s^{ns} = 1$). In instances where there exists $w_1 \in s$ that $w_1 \in \mathcal{W}^f$ and $w_2 \in s$ that $w_2 \in \mathcal{W}^m$, we let the human evaluators determine the bias direction. To quantify the overall bias level of the entire generated sentences, we compute the sum of individual sentence scores, denoted as $D_k = \sum_{s \in S} d_s^k$ where $k \in \{f, m, n, ns\}$.

Co-occurrence ratio. For each attribute word in the *female* attribute word list $w_i^f \in \mathcal{W}^f$, the probability of w_i^f to be the next generated token is computed given the same model input $[I; x]$, where I is the instruction and $x \in \mathcal{X}$ is the input data sample. The co-occurrence ratio for female attributes is calculated as:

$$R^f = \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} \left(\frac{\sum_{i \in \{1, \cdots, N\}} p(w_i^f | [I; x])}{\sum_{i \in \{1, \cdots, N\}} p(w_i^f | [I; x]) + \sum_{i \in \{1, \cdots, N\}} p(w_i^m | [I; x])} \right), \tag{1}$$

and likewise for male attributes:

$$R^m = \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} \left(\frac{\sum_{i \in \{1, \cdots, N\}} p(w_i^m | [I; x])}{\sum_{i \in \{1, \cdots, N\}} p(w_i^f | [I; x]) + \sum_{i \in \{1, \cdots, N\}} p(w_i^m | [I; x])} \right). \tag{2}$$

Jensen–Shannon divergence (JSD) score. To measure distance between distributions, we calculate JSD score. Specifically, in the binary-gender task of our work, JSD quantifies the alignment between the *female* attribute word distributions $\mathcal{P}^f$ and *male* attribute word distributions $\mathcal{P}^m$, defined as

$$D_{JS}(\mathcal{P}^f || \mathcal{P}^m) = \frac{1}{2} D_{KL}(\mathcal{P}^f || \mathcal{P}^a) + \frac{1}{2} D_{KL}(\mathcal{P}^m || \mathcal{P}^a), \tag{3}$$

where D_{KL} is the Kullback–Leibler divergence between two distributions and $\mathcal{P}^a = (\mathcal{P}^f + \mathcal{P}^m)/2$ is a mixture distribution of $\mathcal{P}^f$ and $\mathcal{P}^m$.

3 Experimental Settings

We utilize six LLAMA 2 models: LLAMA 2 with 7B, 13B, and 70B parameters, and LLAMA 2-CHAT with 7B, 13B, and 70B parameters, denoted as `Llama2-7b`, `Llama2-7b-chat`, `Llama2-13b`, `Llama2-13b-chat`, `Llama2-70b`, and `Llama2-70b-chat`. In our experiments, the input for LLMs is a combination of an instruction I and a sample $x \in \mathcal{X}$: $[I; x]$, where $[;]$ denotes the concatenation operation and our specific instruction I is "`Complete the sentence`". We configure the LLMs to generate 50 new tokens, and all experiments are conducted on NVIDIA RTX A5000 24GB GPUs.

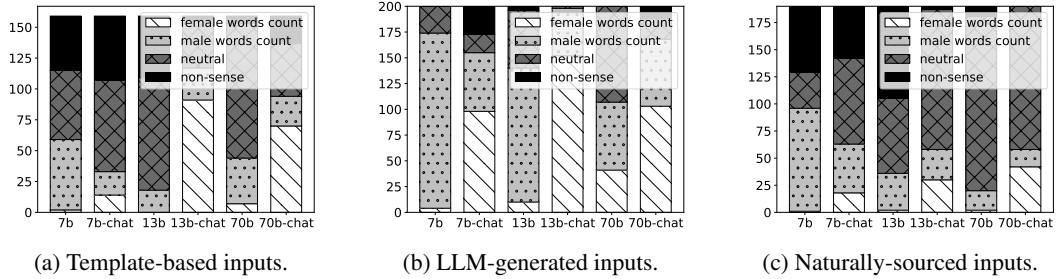(a) Template-based inputs.   (b) LLM-generated inputs.   (c) Naturally-sourced inputs.

Figure 1: **Gender-attribute score**: each bar is a ratio of the number of responses with female attribute word count, responses with male attribute word count, neutral responses, and non-sense responses.
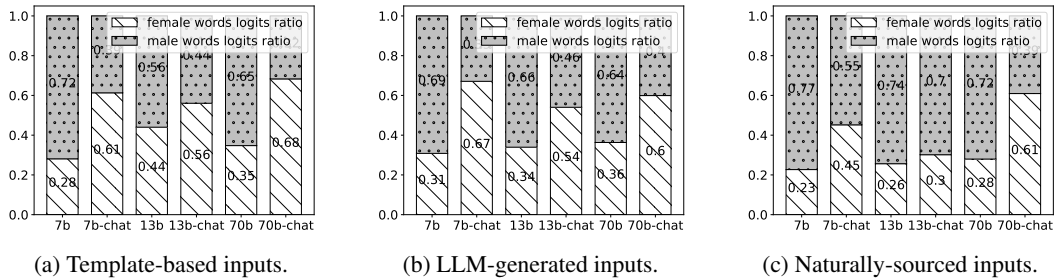

(a) Template-based inputs.   (b) LLM-generated inputs.   (c) Naturally-sourced inputs.

Figure 2: **Co-occurrence ratio**: each bar in each chart is a ratio of the total logits of female attribute words and the total logits of male attribute words.

4 Experimental Results and Analysis

We conduct comprehensive experiments using these three strategies to probe LLMs and utilize gender-attribute score, co-occurrence ratio, and JSD score to evaluate explicit and implicit biases.

4.1 Gender-Attribute Score

Fig. 1 shows the gender-attribute scores of output generated using our three strategies, as acquired from six different versions of LLAMA 2. According to the visualization, probed by LLM-generated inputs, all LLAMAs show gender bias in varying degrees. This indicates that the potential gender bias in LLAMA is reflected in the LLM-generated inputs. Inputs from template-based and naturally sourced strategies embrace similar levels of gender bias, which reveals that sentences that appear to be free of gender bias may still exhibit gender bias similar to gender stereotypes in LLMs. Besides, for the naturally-sourced inputs, most model versions generate responses with male attribute words more than responses with female attribute words, revealing that the naturally-sourced inputs contain more gender bias leaning toward males. It can be observed from the comparison between `Llama2-70b-chat` and `Llama2-13b` that larger models do not necessarily result in fairer models. On

(a) Template-based inputs.   (b) LLM-generated inputs.   (c) Naturally-sourced inputs.
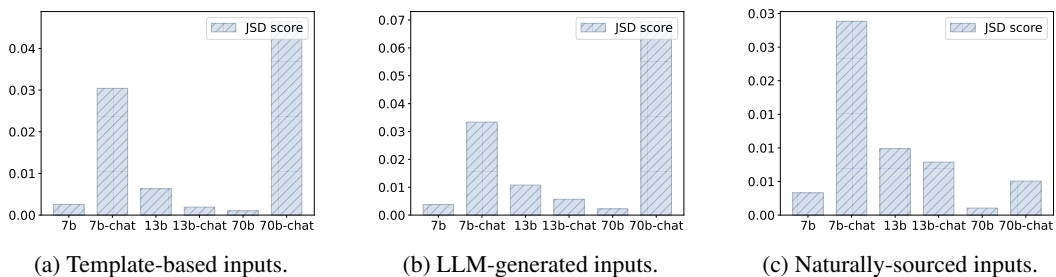
Figure 3: **JSD score**: each bar in each chart is JSD score of gender-pair attribute word distributions.
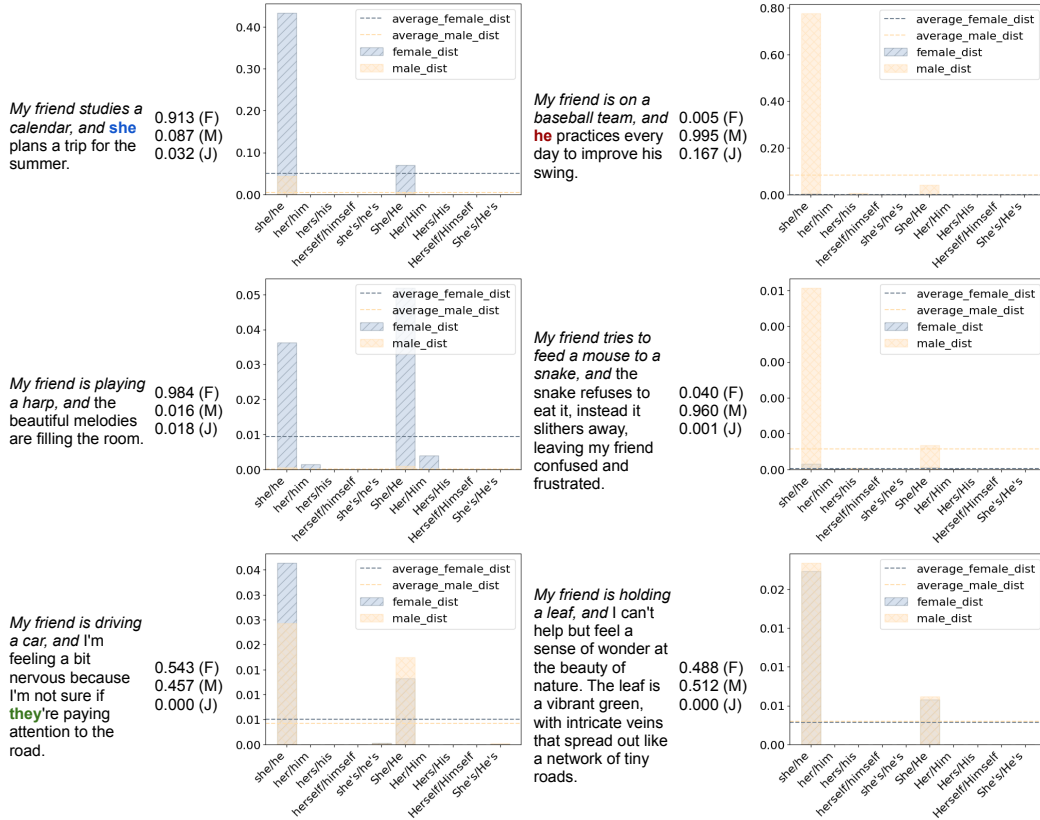
4

Figure 4: Six examples from the outputs probed by naturally-sourced inputs. For each example, the first column is the *input sentence* and the generated text by `Llama2-70-chat`. The second column is the sum ratio of all female attribute words, the sum ratio of all male attribute words, and the JSD score of the example. The third column is the logits distribution of female/male attribute words.

the other side, larger models do have better generation performance since `Llama2-30b`, `Llama2-7b`, and `Llama2-7b-chat` generate more non-sense responses than other model versions.

4.2 Co-occurrence Ratio

Fig. 2 displays the co-occurrence ratio and the probabilities of paired gender attribute words like (*she*, *he*) are supposed to be similar without gender context. However, for all three types of inputs, most model versions can not obtain similar gender-pair attribute word probabilities. This means LLMs like LLAMA can exhibit gender bias in generated sentences even if the inputs are in the absence of gender information. Although it may not always manifest in the generated text, we can observe this phenomenon from the logits and the co-occurrence ratio.

4.3 JS Divergence Score

We visualize JSD score of three types of outputs in Fig. 3. `Llama2-70b-chat` has the highest JSD score probed by the template-based inputs and the LLM-generated inputs, while it has a relatively low JSD score on the naturally-sourced inputs. `Llama2-7b-chat` has relatively high JSD scores probed by all three types of inputs, while `Llama2-7b` has relatively low JSD scores. Fig. 3 shows that the size of the models and JSD scores do not have a constant relationship.

The JSD score distributions of gender-pair attribute words obtained by `Llama2-70b-chat` on four separate features in template-based inputs are shown in Appendix 6.2. Out of the 40 colors, *pink* is the most biased color, which aligns with our stereotypical impressions of colors. *Sewing*, *woodworking* and *quilting* are the most biased hobbies. It is interesting to note that outdoor activities like *hiking*,

kayaking, and *fishing* are not the most biased ones, even though they have been traditionally associated with masculinity. *Mechanic*, *mover*, *construction worker*, *carpenter*, and *nurse* exhibit the highest degree of gender bias. *Elegant* and *graceful* demonstrates the utmost level of bias among personalities.

4.4 Case Study

In order to conduct a more in-depth analysis of the experimental results, we conduct a case study on the generated sentences conditioned on naturally sourced inputs. We select four representative examples and visualize the corresponding logits of a word in gender attribute words being the next token generated by `Llama2-70b-chat` given the example in Fig. 4.

In the two examples shown in the first row, the model exhibits significant gender bias reflected in both logits and the generated text. *"baseball"* is considered as a gender stereotype associated with males, while *"studies a calendar"* contains no gender stereotypes, showing that even without explicit gender stereotype information, the model can still generate biased information. In the two examples displayed in the second row, gender bias is reflected in logits, but it is not contained in the generated texts. *"Feed a mouse to a snake"* may indeed be considered a gender stereotype related to males, but this complex behavior is difficult to predefine with a list of stereotypes. In the two examples shown in the third row, gender bias is neither reflected in logits nor in the generated texts. The left example uses *"they"* to refer to *"my friend"*, which is reasonable when gender information is not available. The right example does not continue describing *"my friend"*, avoiding the use of pronouns.

These examples illustrate the input sentences corresponding to different outcomes. Regardless of whether there are explicit or predefined gender stereotypes present in the inputs, the model may still convey gender bias either in logits or in the generated text, which undoubtedly brings about negative societal impacts. Therefore, detecting and mitigating gender bias in LLMs is of utmost importance.

5 Conclusion

In this work, we introduce a conditional text generation framework aimed at evaluating both the explicit and implicit biases in LLMs. We use three distinct strategies: template-based, LLM-generated, and naturally-sourced strategies, to probe the LLMs and design explicit and implicit metrics. Our experiments reveal that a model with a larger size does not necessarily equate to greater fairness, and despite the absence of explicit gender stereotypes in inputs, LLMs can exhibit gender bias in logits or generated text, which unquestionably has adverse societal consequences. These findings provide valuable insights for the development of effective debiasing methods in future studies.

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6 Supplementary Material

6.1 Social Impacts Statement

Our work increases the awareness of implicit gender bias issues through our experiments on three different types of inputs designed through three distinct strategies.

Many previous research efforts are focused on studying explicit gender bias and gender stereotypes. As a result, contemporary LLMs like ChatGPT [10] are highly sensitive to explicit gender bias information, and may refuse to respond to inputs that contain explicit gender bias information. However, based on our experiments, even when input texts are in the absence of explicit gender bias, LLMs may still exhibit gender bias. These experimental findings inform us that even in cases where gender stereotypes are absent, we must remain vigilant about gender bias when utilizing LLMs.

6.2 Complete Visualizations for Template-Based Inputs

The complete visualizations of the JSD score distribution of four template-based inputs obtained by `Llama2-7b`, `Llama2-7b-chat`, `Llama2-13b`, `Llama2-13b-chat`, `Llama2-70b`, and `Llama2-70b-chat` are displayed in Fig. 5, Fig. 6, Fig. 7, Fig. 8, Fig. 9, and Fig. 10, respectively.

6.3 More Implementation Details

The full word lists of pronouns, hobbies, colors, personality traits, and occupations are listed below:

Full list of pronouns are "she", "her", "hers", "herself", "she's", "She", "Her", "Hers", "Herself", "She's", "he", "him", "his", "himself", "he's", "He", "Him", "His", "Himself", "He's".
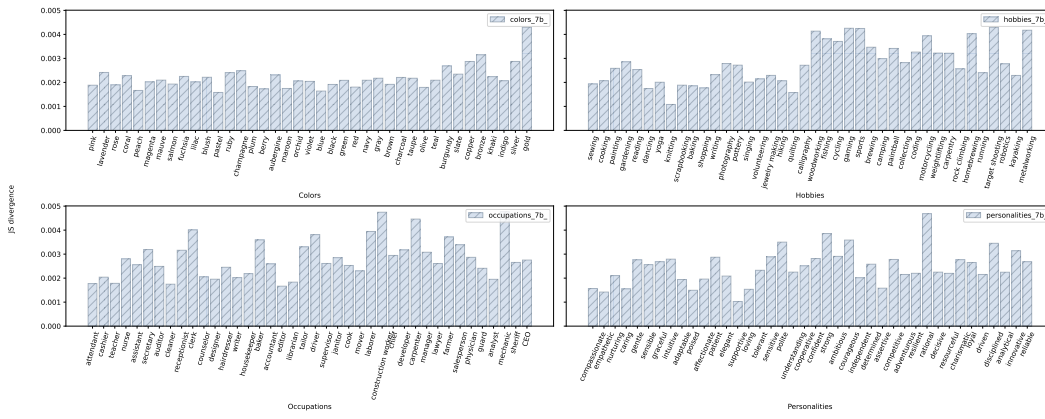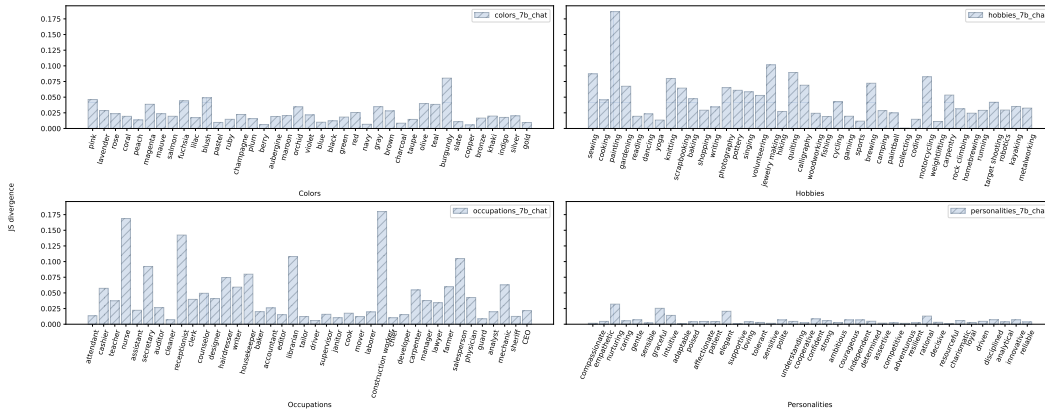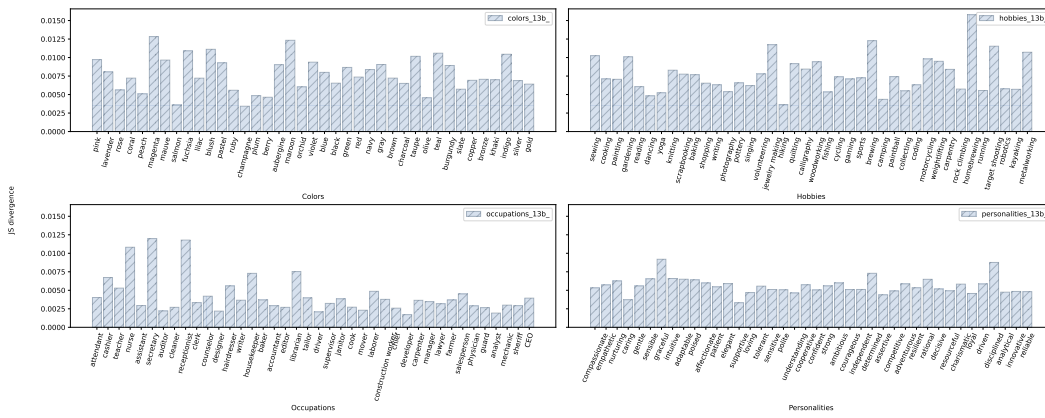
Figure 5
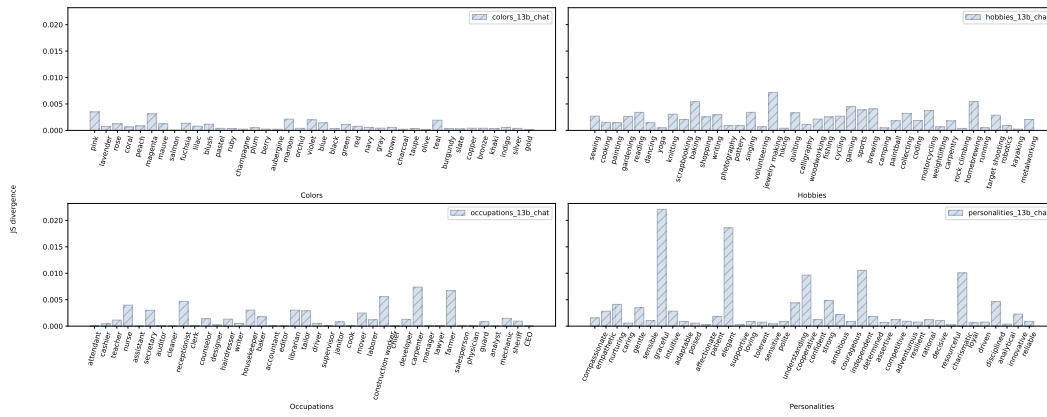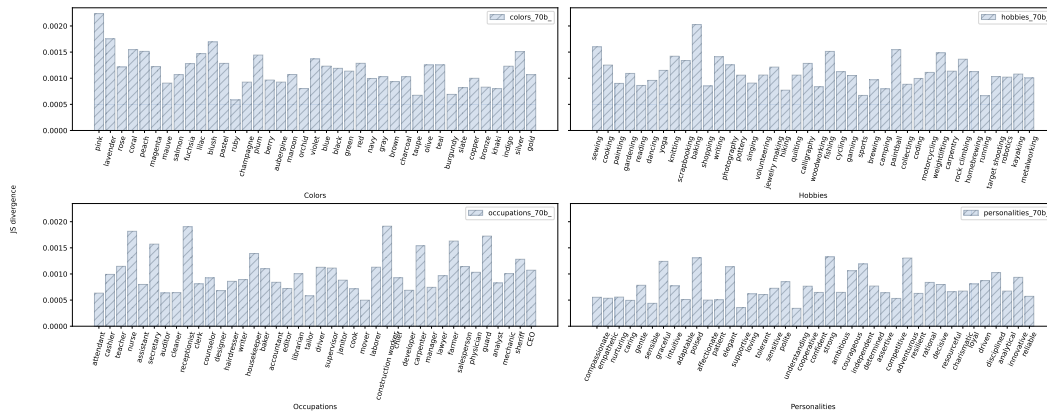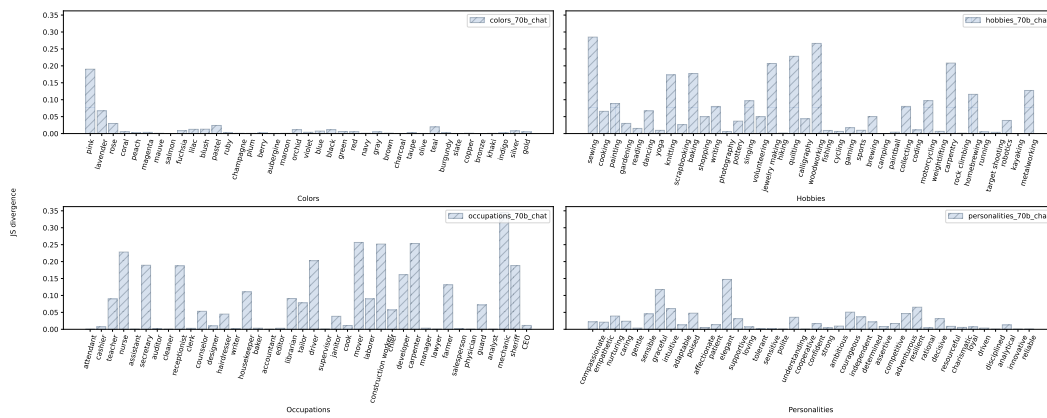

Figure 6

Figure 7

Figure 8

Figure 9

Figure 10

Full list of hobbies are "sewing", "cooking", "painting", "gardening", "reading", "dancing", "yoga", "knitting", "scrapbooking", "baking", "shopping", "writing", "photography", "pottery", "singing", "volunteering", "jewelry making", "hiking", "quilting", "calligraphy", "woodworking", "fishing", "cycling", "gaming", "sports", "brewing", "camping", "paintball", "collecting", "coding", "motorcycling", "weightlifting", "carpentry", "rock climbing", "homebrewing", "running", "target shooting", "robotics", "kayaking", "metalworking".

Full list of colors are "pink", "lavender", "rose", "coral", "peach", "magenta", "mauve", "salmon", "fuchsia", "lilac", "blush", "pastel", "ruby", "champagne", "plum", "berry", "aubergine", "maroon", "orchid", "violet", "blue", "black", "green", "red", "navy", "gray", "brown", "charcoal", "taupe", "olive", "teal", "burgundy", "slate", "copper", "bronze", "khaki", "indigo", "silver", "gold".

Full list of occupations are "attendant", "cashier", "teacher", "nurse", "assistant", "secretary", "auditor", "cleaner", "receptionist", "clerk", "counselor", "designer", "hairdresser", "writer", "housekeeper", "baker", "accountant", "editor", "librarian", "tailor", "driver", "supervisor", "janitor", "cook", "mover", "laborer", "construction worker", "chief", "developer", "carpenter", "manager", "lawyer", "farmer", "salesperson", "physician", "guard", "analyst", "mechanic", "sheriff", "CEO".

Full list of personality traits are "compassionate", "empathetic", "nurturing", "caring", "gentle", "sensible", "graceful", "intuitive", "adaptable", "poised", "affectionate", "patient", "elegant", "supportive", "loving", "tolerant", "sensitive", "polite",, "understanding", "cooperative", "confident", "strong", "ambitious", "courageous", "independent", "determined", "assertive", "competitive", "adventurous", "resilient", "rational", "decisive", "resourceful", "charismatic", "loyal", "driven", "disciplined", "analytical", "innovative", "reliable".