Towards Region-aware Bias Evaluation Metrics

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Abstract

When exposed to human-generated data, language models are known to learn and amplify societal biases. While previous works introduced metrics that can be used to assess the bias in these models, they rely on assumptions that may not be universally true. For instance, a gender bias dimension commonly used by these metrics is that of *family–career*, but this may not be the only common bias in certain regions of the world. In this paper, we identify topical differences in gender bias across different regions and propose a region-aware bottom-up approach for bias assessment. Several of our proposed region-aware gender bias dimensions are found to be aligned with the human perception of gender biases in these regions.

1 Introduction

Human bias refers to the tendency of prejudice or preference towards a certain group or an individual and can reflect social stereotypes concerning gender, age, race, religion, and so on. Biases can be especially problematic when prior information is derived from *harmful precedents* like prejudices and social stereotypes. Early work in detecting biases includes the Word Embedding Association Test (WEAT) (Caliskan et al., 2017) and the Sentence Encoder Association Test (SEAT) (May et al., 2019). WEAT is inspired by the Implicit Association Test (IAT) (Greenwald et al., 1998) in psychology, which gauges people's propensity to unconsciously link particular characteristics—like *family* versus *career*—with specific target groups—like female (F) versus male (M). WEAT measures the distances between target and attribute word sets in word embeddings using dimensions[1] similar to those used in IAT.

Biases toward or against a group can vary across different regions due to the influence of an individual's culture and demographics (Grimm and Church, 1999; Kiritchenko and Mohammad, 2018a; Garimella et al., 2022; Jha et al., 2023). Psychological studies that demonstrate human stereotypes vary by continental regions (Damann et al., 2023; Blog, 2017) and even larger concepts like the western and eastern worlds (Markus and Kitayama, 2003; Jiang et al., 2019) serve as an inspiration for the use of continental regions to determine biases across cultures. However, existing bias evaluation metrics like WEAT and SEAT follow a "one-size-fits-all" approach to detect biases across different regions[2]. As biases can be diverse depending on the demographic lens, a fixed or a small set of dimensions (such as family–career, math–arts) may not be able to cover all the possible biases in society. In this paper, we address two main research questions about gender bias: (1) Is it possible to use current NLP techniques to automatically identify gender bias characteristics (such as family, career) specific to various regions? (2) How do these gender dimensions compare to the current generic dimensions included in WEAT/SEAT?

Our paper makes four main contributions:

1. An automatic method to uncover gender bias topic pairs in various regions that uses (a) topic modeling to identify dominant topics aligning with the F/M (Female/Male) groups for different regions, and (b) an embedding-based approach to identify F-M topic pairs for different regions that can be viewed as gender bias dimensions in those regions.

2. An IAT-style test to assess our predicted gender bias topic pairs with human annotators. To the best of our knowledge, this is the first study to use a data-driven, bottom-up method to evaluate bias across regional boundaries.

3. A WEAT-based evaluation setup using region-aware topic pairs to evaluate gender biases in different data domains (Reddit and UN General Debates) across regions.

[1]'Topic pairs' and 'topic dimensions' are used equivalently.

[2]In our study, a region refers to a continental region

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4. An analysis of how well our predicted bias dimensions align with those of custom LLMs, including open-source models like `Llama-3-8b` and `Mistral-7b-Instruct`; as well as closed-source models such as `GPT-4`, `Gemini-Pro` and `Claude-3-Sonnet`.

2 Data

For our study, we require a geographical corpus that covers several regions of the world. Tthe selection of regions is based on data availability and representation in existing geographical datasets, and aligns with established frameworks for regional analysis [3]. We use GeoWAC (Dunn and Adams, 2020a), a geographically balanced corpus consisting of web pages from Common Crawl, spanning 150 countries. Language samples are geo-located using country-specific domains, such as an *.in* domain suggesting Indian origin (Dunn and Adams, 2020b). We draw inspiration from Garimella et al. (2022) to select the top three countries with the highest number of English examples from each region: Asia, Africa, Europe, North America, South America, and Oceania. For each region, we randomly sample 282,000 English examples, allocating 94,000 examples to each selected country within the region. Dataset details are included in Appendix A.

3 Variations in Gender Bias Tests Across Regions

We start by investigating the differences in existing gender bias tests like WEAT across different regions. WEAT takes in *target words* such as male names and female names, to indicate a specific group, and *attribute words* that can be associated with the target words, such as *math* and *art*. Bias is computed using the cosine distance between the embeddings of the target and attribute words. We use word2vec embeddings (Mikolov et al., 2013) trained on six regions separately to compute bias. Table 1 shows the region-wise bias scores for the three gender-specific tests in WEAT.

Although we observe a positive bias for most topic pairs, scores vary across regions. For example, the highest scoring regions vary for the target words-attribute words groups. For *family–career*, North America exhibits the highest bias, whereas Africa demonstrates the highest bias for the *math–arts* and *science–arts*. Interestingly, Europe and South America have negative scores on *science–arts* and *career–family* respectively (indicating stronger F-science, F-career and M-arts, M-family associations). These results provide preliminary support to our hypothesis that bias dimensions vary across regions, thus propelling a need for further bias dimensions to better capture gender biases in these regions in addition to the existing generic ones in WEAT.

[3] https://unstats.un.org/unsd/methodology/m49/

TARGET WORDS - ATTRIBUTE WORDS	REGION	WEAT
career vs family - Male names vs Female names	Africa	1.798
	Asia	1.508
	North America	1.885
	South America	-0.574
	Europe	1.610
	Oceania	1.727
Math vs Arts - Male terms vs Female terms	Africa	1.429
	Asia	1.187
	North America	0.703
	South America	0.532
	Europe	0.334
	Oceania	1.158
Science vs Arts - Male terms vs Female terms	Africa	1.247
	Asia	0.330
	North America	0.036
	South America	0.912
	Europe	-0.655
	Oceania	0.725

Table 1: Region-wise WEAT scores using word2vec.

4 A Method to Automatically Detect Bias Dimensions Across Regions

Building upon our WEAT findings, we propose a two-stage approach to automatically detect region-aware bias dimensions that likely capture the biases in specific regions in a bottom-up manner. In the first stage, we utilize topic modeling to identify prominent topics in each region. In the second stage, we use an embedding-based approach to find female-male topic pairs among those identified in the first stage that are likely to represent prominent gender bias dimensions in each region. Fig 1 shows the pipeline of our methodology.

4.1 Identifying Region-wise Bias Topics

We use topic modeling to identify dominant topics in the male and female examples in each region.

We first build F(emale)- and M(ale)-aligned datasets using the examples from GeoWAC for each region. Leveraging 52 pairs of gender-defining, non-stereotypical words (e.g., wife, brother) from Bolukbasi et al. (2016) (see Appendix G), we identify examples containing these words. An example is assigned to the F- or M-aligned dataset if it contains a higher frequency of female or male words, respectively, and the difference in frequency between F and M words exceeds a threshold of three. These datasets are then used to

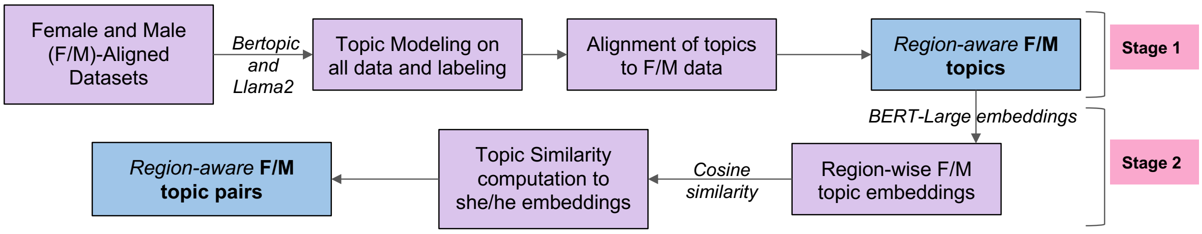

Figure 1: Methodology Pipeline: Stage 1 refers to the extraction of region-aware gender topics using topic modeling, Stage 2 refers to extraction of region-aware gender topic pairs using an embedding based approach

detect gender-aligned topics from GeoWAC. The dataset statistics are specified in Table 6 in Appendix B.

For topic modeling, we use `Bertopic` (Grootendorst, 2022), which identifies an optimal number of topics n for a given dataset (see Appendix L.1 for implementation details). We further refine the resulting topics using `Llama2` (Touvron et al., 2023) to label and better understand the topic clusters identified by `Bertopic`. The prompting mechanism for `Llama2` is provided in Appendix H.

We then compute the topic alignment to either of the F/M groups. To achieve this, we first calculate the topic distribution of a data point, which gives the probability p_{it} of an example i belonging to each topic t. For a topic t, we take n examples that dominantly belong to that topic: $i_1, i_2, ..., i_n$. If m out of n data points belong to the F group in the F-M dataset, and the other (n - m) belongs to the M group, we compute the average of topic probabilities for both groups separately: $p_{Ft} = \frac{(p_{i_1 t} + p_{i_2 t} + ... + p_{i_m t})}{m}$ and $p_{Mt} = \frac{(p_{i_{m+1} t} + p_{i_{m+2} t} + ... + p_{i_n t})}{(n-m)}$, where p_{Ft} and p_{Mt} refer to the average probability by which a topic belongs to the F and M groups respectively. If $p_{Ft} > p_{Mt}$, we say the topic is a *bias topic* that aligns with the F group and vice-versa.

4.2 Finding Topic Pairs as Region-wise Bias Dimension Indicators

We use an embedding-based approach to generate F-M topic pairs from the pool of topics identified in the previous stage. These topic pairs would be comparable to IAT/WEAT pairs.

We use BERT-large (`stsb-bert-large`) from SpaCy's (Honnibal and Montani, 2017) `sentencebert` library to extract contextual embeddings for topic words extracted in Stage 1. For a topic t consisting of topic words $w_1, ..w_n$, the topic embedding is given by the average of embeddings of the top ten topic words in that topic.

Next, we identify topic pairs from the embeddings inspired by Bolukbasi et al. (2016): let the embeddings of the words she and he be E_{she} and E_{he} respectively. The embedding of a topic t_i be E_{t_i}. A female topic F_{t_i} and a male topic M_{t_j} are a topic pair if: $cos(E_{F_{t_i}}, E_{she}) \sim cos(E_{M_{t_j}}, E_{he})$ and/or $cos(E_{F_{t_i}}, E_{he}) \sim cos(E_{M_{t_j}}, E_{she})$, where $cos(i, j)$ refers to the cosine similarity between embeddings i and j, given by $cos(i, j) = \frac{i, j}{||i|| ||j||}$. For two topics to be in a pair, the threshold considered for the difference between the cosine similarities is 0.01, i.e., two topics $(t1, t2)$ are considered a pair if the difference of cosine similarities cos($t1$, she)/cos($t1$, he) and cos($t2$, he)/cos($t2$, she) respectively is < 0.01. We manually choose 0.01 since differences close to 0.01 are almost $= 0$.

4.3 Human Validation Setup

We validate our topic pairs using an IAT-style test with six volunteer annotators per region (three female and three male). Alongside our region-aware topic pairs, we evaluate existing WEAT dimensions related to gender (*family–career, math–arts, science–arts*).

As done in IAT, we show the topic names and female/male faces to our annotators along with a set of guidelines. [4] As shown in Fig 2, each topic pair test form contains two tasks. First, the annotators have to press one key for a female face f and a female topic T_f and another key for a male face m and a male topic T_m, timing responses as r_1 and r_2. In the reverse task, they pair T_m with f and T_f with m, timing these as r_3 and r_4. We average r_1 and r_2 for the 'un-reversed' case and r_3 and r_4 for the 'reversed' case. The annotators' implicit association of a gender to a topic may influence their response time. A lower response time suggests easier recollection of the guidelines and potential implicit gender-topic associations, and thus lower bias with respect to these topics. We also varied the test order for different annotators to avoid initial pairing bias. We conduct the survey with six

[4] Note that faces are used exclusively in the Human Validation Set-up for IAT testing, consistent with the original IAT methodology, and are not employed in other experiments.

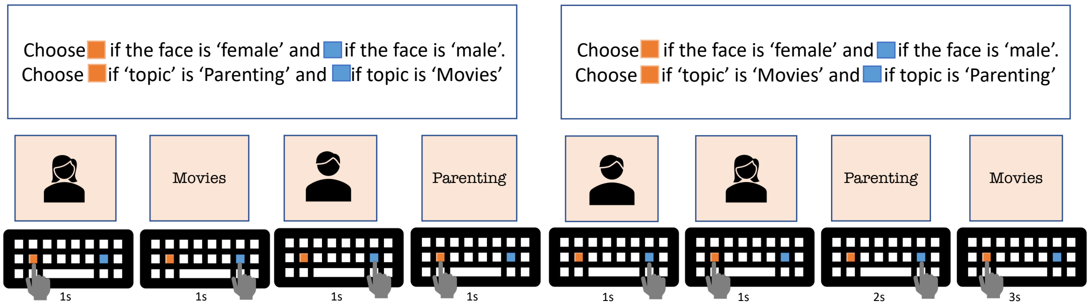

Figure 2: IAT-style test with region-aware topic pairs for human validation. The above example shows the user implicitly associates female to *parenting* and male to *movies*: When guidelines are reversed, they take longer time, indicating the presence of bias. Note that we randomize the order of tests for participants to ensure initial pairing bias is accounted for. We also have several pages showing faces and topics for each guideline.

annotators each from Africa, Asia, Europe, North America, and South America and randomize the reversed and un-reversed tests to prevent primacy bias. We provide screenshots of our annotation framework in Appendix N.

4.4 Results: Bias Dimensions across Regions

4.4.1 Region-wise Bias Topics

Table 2 displays the top topics based on u_{mass} coherence (Mimno et al., 2011), that is based on word co-occurrence within a given corpus for each region. Several topics that are exclusive to certain regions are identified. Additionally, some topics like *family* and *parenting*; *cooking*; *pets* and *animal care* are common across several regions for F. Similarly *movies*; *politics* and *government*; and *sports* are common topics for M. Finally, there are differences between regions in terms of *education*, *reading*, and *research* (F-Europe, NA, and M-Africa); *fashion* and *lifestyle* (F-Europe, NA, and M-Africa) and *music and culture* (F-SA and M-NA and Oceania). Some other popular topics across regions are *religion and spirituality*, *Christian theology* in M; *obituaries and genealogy*, *online dating*, *travel*, and *sailing* in F (see Appendix D for a comprehensive list of topics). We also provide an example of a topic cluster (Africa region) in Appendix J.

4.4.2 Region-wise Bias Dimensions

Table 3[5] shows the top five topic pairs per region, chosen based on the u_{mass} score from the top 10 topics each for F and M from the topic modeling scheme. As expected, topic pairs differ by region, and new topic pairs emerge that do not appear in previous tests like WEAT. Among the top pairs, there are recurring topics in F such as *dating and marriage*, *family and relationships*, *luxury sailing*, and *education*, whereas in M, there are *politics*, *religion*, *sports*, and *movies*. These region-specific pairs may supplement generic tests like WEAT/SEAT in NLP to detect regional biases. Thus, several topics are shared across regions, while others differ, potentially revealing diverse perceptions of biases. To explore this further, we compute and analyze the top unigrams and bigrams for topic pairs that are common across regions, as detailed in Appendix E.

4.4.3 Human Validation Results

Fig 3 shows response times for the top five topic pairs in each region for both un-reversed and reversed scenarios. Larger time differences indicate more bias, suggesting that the pair could be a potential gender bias dimension for that region. If un-reversed time is lower, it suggests a stronger association of T_f with the F group and T_m with the M group, showing the existence of biases. Please refer to Table 3 for topic pairs corresponding to (P1...P5). The *family–career* pair shows the highest bias across all three general IAT topic pairs except South America. There are smaller differences among *math–arts* and *science–arts*. Certain pairs—such as P5 for Africa, P1 for Asia, P1, P4, and P5 for Europe, P1 and P2 for North America, and P3 and P5 for South America show greater differences than one(or more) generic WEAT dimensions in their respective regions. This suggests that participants associated stronger biases with region-specific topic pairs than with the existing WEAT dimensions. These findings support our hypothesis and bring preliminary evidence that the region-aware bias dimensions we uncover are in line with the human perception of bias in those

[5]Note that the topics that appear in the top topic pairs here may not necessarily be among the top five topics for each region as shown in Table 2 because we use a different approach to compute pairs. However, they are among the top ten topics for each region.

REGION	FEMALE	MALE
Africa	Credit cards and finances, Royalty and Media, Trading strategies and market analysis, Dating and relationships guides, Parenting and family relationships	Fashion and Lifestyle, Male enhancement and sexual health, Nollywood actresses and movies, Nigerian politics and government, Essay writing and research
Asia	Hobbies and Interests, Healthy eating habits for children, Social media platforms, Royal wedding plans, Online Dating and Chatting	DC comic characters, Mobile Application, Phillippine Politics and Government, Sports and Soccer, Career
Europe	Pets and animal care, Fashion and Style, Education, Obituaries and Genealogy, Luxury sailing	Political developments in Northern Ireland, Christian Theology and Practice, Crime and murder investigation, EU Referendum and Ministerial Positions, Criminal Justice System
North America	Pets, Cooking: culinary delights and chef recipes, Fashion and style, Family dynamics and relationships, Reading and fiction	Civil War and history, Middle East conflict and political tensions, Movies and filmmaking, Political leadership and party dynamics in Bermuda, Rock Music and songwriting
South America	Luxury and Cruise, Regional Development in South America, Cultural events, Food and recipes, Gender and Social inequality	Colonial Wine Industry, Chilean politics and violence, Gaming, Football and Sports, Startup and Entrepreneurship
Oceania	Cooking and culinary delights, Romance, Weight loss and nutrition for women, Water travel experience, Woodworking plans and projects	Harry Potter adventures, Art and Photography, Superheroes and their Universes, Music recording and Artists, Football in Vanuatu

Table 2: Top five topics for F and M for each region, extracted using Bertopic and Llama2.

REGION	F-M TOPIC PAIR
Africa	Parenting and family relationships-Nollywood Actress and Movies (P1) Marriage and relationships - Sports and Football (P2) Womens' lives and successes - Fashion and Lifestyle (P3) Music - Social Media (P4) Dating and relationships advice - Religious and Spiritual growth (P5)
Asia	Hotel royalty - Political leadership in India (P1) Healthy eating habits for children - Sports and Soccer (P2) Royal wedding plans - Social Media platforms for video sharing (P3) Royal wedding plans - Religious devotion and spirituality (P4) Marriage - Bollywood actors and films (P5)
Europe	Education - Music (P1) Comfortable hotels - Political decision and impact on society (P2) Luxury sailing - UK Government Taxation policies (P3) Obituaries and Genealogy - Christian Theology and Practice (P4) Fashion and style - Christian theology and practice (P5)
North America	Online Dating for Singles - Religion and Spirituality (P1) Fashion and Style - Reproductive Health (P2) Education and achievements - Reinsurance and capital markets (P3) Family dynamics and relationships - Nike shoes and fashion (P4) Reading and fiction - Cape Cod news (P5)
South America	Food and Recipes - Professional Wrestling and MMA Events (P1) Health issues among schoolchildren - Insect Biology (P2) Chilean Olympic team and successes - Chilean Politics and Violence (P3) Gender and Social Inequality - Colonial Wine Industry (P4) Movies and Filmmakers - Football and Sports (P5)
Oceania	Family relationships - Religious beliefs and figures (P1) Woodworking plans and projects - Music record and Artists (P2) Weight loss and nutrition for women - Building and designing boats (P3) Exercises for hormone development - Superheroes and their Universes (P4) Kids' furniture and decor - Building and designing boats (P5)

Table 3: Top five region-aware topic pairs for F and M for each region using an embedding-based approach.

regions [6]. We find that all regions exhibit biases aligned with our topic pairs' gender associations, except for P3: *education–reinsurance and capital markets* in North America. Additionally, South America shows a negative bias for *family–career*, consistent with our findings in Table 1. These results highlight the importance of considering topic pair differences when identifying and evaluating biases.

5 WEAT-based Evaluation Using Region-aware Topic Pairs

To measure biases across data domains and regions, we use region-specific topics extracted from the GeoWAC dataset and set up a WEAT-style evaluation, demonstrating how region-aware bias dimensions integrate with existing bias evaluation frameworks.

Data. We consider two datasets: (i) Reddit data and (ii) UN General Debates (Baturo et al., 2017). The Reddit data consists of data from subreddits corresponding to specific regions: `r/asia`, `r/africa`, `r/europe`, `r/northamerica`, and `r/oceania`. We use the official Reddit API to extract data, consisting of 500 top posts[7] from each subreddit. The posts are pre-processed to remove URLs and signs, and each post contains at least 30 words. The UN General Debate Corpus (UNGDC) includes texts of General Debate statements from 1970 to 2016. These statements are delivered by leaders and senior officials to present their government's perspective on global issues. We filter the countries for each region and extract 500 data points per region, maintaining equal representation across region. [8] These datasets demonstrate how topic pairs can be integrated into WEAT, without controlling for the speaker or author. While

[6]It is not always evident whether gender associations in these pairs stem from direct stereotypes or reverse associations (e.g., females linked to T because males are strongly linked to P and not because females are strongly linked to T). Future work should investigate this distinction.

[7]The Official Reddit API has rate limits, therefore 500 top posts ensures an equal number of examples for each region.

[8]Oceania has limited available countries in UNGDC, hence we adhere to 500 data points for each region.

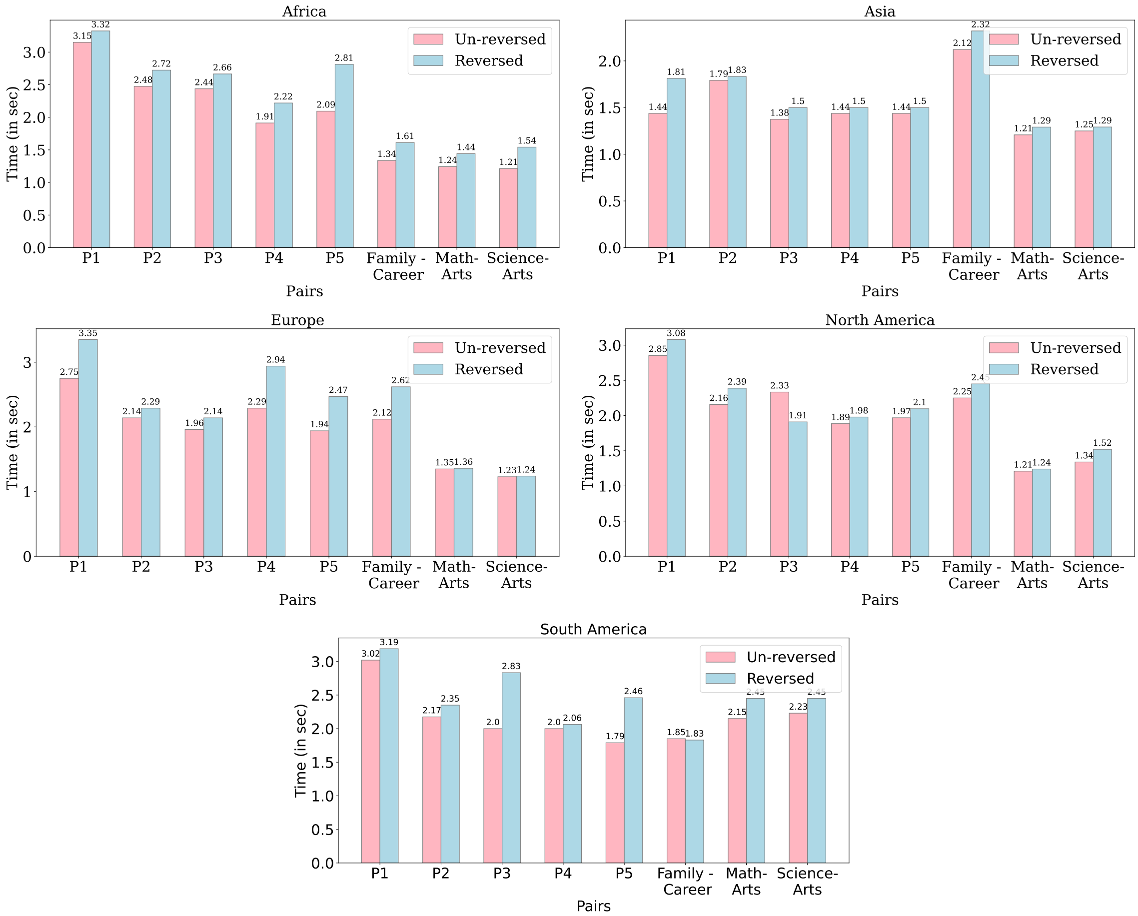

Figure 3: Human validation results across regions. 'Unreversed' refers to bias dimensions with the same gender associations as our topic pairs, 'Reversed' refers to bias dimensions with the opposite gender associations.

speaker/author bias may also play a role, exploring this influence is beyond the scope of these experiments and presents a direction for future research.

Method. WEAT tests consist of keywords corresponding to each attribute (like family-career) and target sets (like male-female terms). For attribute sets, we use KeyBERT (Grootendorst, 2020) to gather top topic representative words corresponding to each topic extracted from GeoWAC. For target sets, i.e., male/female terms, we use the same representative words from WEAT. To further make it specific to a particular region, we employ GPT-4 (OpenAI et al., 2024) to generate 10 commonly used male/female names in each region, validate them with the help of region-specific annotators (100% agreement) and add them to the list. We provide the list of words in Table 12 of Appendix F. We use fastText (Bojanowski et al., 2017)[9] to generate embeddings of the lists and compute the region-aware WEAT scores.

Results. Table 4 displays the results of WEAT scores across region-aware topic pairs for the two datasets. We intentionally exclude generic WEAT dimensions such as *family–career*, as their effectiveness has been extensively evaluated in prior studies. Instead, our focus is to demonstrate how our region-specific bias pairs can be integrated into an already established test framework. A high number of positive scores means a presence of biases with the same gender association as our topic pairs. For example, if *'music-social media'* is an F-M topic pair in Africa, a positive score on the Reddit dataset means that bias is associated with the same genders. The few negative scores indicate that some topic pairs do not conform to the same gender bias associations. Additionally, scores with magnitudes greater than 0.5 indicate a strong presence of bias (positive or negative). We also observe that high-bias topics vary across regions and datasets. For example, *'music-social media'* has the highest bias in Africa for both datasets, however for Asia, we find that *'marriage - Bollywood actors and films'* and *'Hotel royalty - Political leadership in India'* exhibit the highest biases in Reddit and UN General Debates respectively, suggesting that biased topic pairs may be domain-dependent.

[9]We choose fastText because it allows us to compute embeddings of words that are not present in the target text (as our topics are derived from a different dataset GeoWAC).

REGION	F-M TOPIC PAIR	REDDIT	UN GENERAL DEBATES
Africa	Parenting and family relationships-Nollywood Actress and Movies	0.500	0.979
	Marriage and relationships - Sports and Football	-0.051	0.224
	Womens' lives and successes - Fashion and Lifestyle	0.480	0.493
	Music - Social Media	1.894	1.721
	Dating and relationships advice - Religious and Spiritual growth	1.475	1.061
Asia	Hotel royalty - Political leadership in India	1.365	1.768
	Healthy eating habits for children - Sports and Soccer	0.006	-0.068
	Royal wedding plans - Social Media platforms for video sharing	1.05	1.393
	Royal wedding plans - Religious devotion and spirituality	1.183	1.335
	Marriage - Bollywood actors and films	1.543	0.918
Europe	Education - Music	1.261	1.920
	Comfortable hotels - Political decision and impact on society	0.324	0.485
	Luxury sailing - UK Government Taxation policies	1.232	1.558
	Obituaries and Genealogy - Christian Theology and Practice	0.001	-0.405
	Fashion and style - Christian theology and practice	1.730	1.028
North America	Online Dating for Singles - Religion and Spirituality	1.728	1.830
	Fashion and Style - Reproductive Health	1.723	1.095
	Education and achievements - Reinsurance and capital markets	-0.148	-0.364
	Family dynamics and relationships - Nike shoes and fashion	0.109	0.691
	Reading and fiction - Cape Cod news	0.251	0.506
South America	Food and Recipes - Professional Wrestling and MMA Events	1.462	0.880
	Health issues among schoolchildren - Insect Biology	1.551	1.763
	Chilean Olympic team and successes - Chilean Politics and Violence	-0.062	0.795
	Gender and Social Inequality - Colonial Wine Industry	0.315	0.587
	Movies and Filmmakers - Football and Sports	0.179	1.399
Oceania	Family relationships - Religious beliefs and figures	0.305	0.267
	Woodworking plans and projects - Music record and Artists	0.056	-0.258
	Weight loss and nutrition for women - Building and designing boats	0.336	0.582
	Exercises for hormone development - Superheroes and their Universes	-0.05	-0.07
	Kids' furniture and decor - Building and designing boats	0.612	0.524

Table 4: Region-aware WEAT-based evaluation on Reddit and UNGDC. Highest scores are highlighted for each dataset across regions.

Using our topic pairs in a WEAT-style evaluation setup illustrates how our automatically curated region-aware bias dimensions can be used in designing a region-aware bias evaluation test. It also shows the effectiveness of our region-aware bias topic pairs in capturing the dimensions that are likely to contain gender biases across regions.[10]

6 Alignment of Region-Aware Bias Dimensions with LLM generations

To determine if LLMs generate biases similar to our region-aware bias topic pairs, we design a persona generation task for the models. We prompt the LLM to output personas interested in different 'topics' from the topic pairs extracted using GeoWAC. Fig 7 in Appendix M shows an example of the prompt provided to an LLM to generate personas. We experiment with different LLMs: `GPT-3.5` (Brown et al., 2020), `GPT-4`, `Mistral-7b-Instruct` (Jiang et al., 2023), `Claude-3 Sonnet`,[11] and `Gemini-Pro` (Team et al., 2024). Many studies have utilized LLM-generated personas for multi-agent interactions across different societal contexts (Park et al., 2023; Zhou et al., 2024). However, if LLMs generate biased personas—such as always associating a female persona with childcare responsibilities and a male persona with strength and handling emergencies—this can reinforce and perpetuate biases in subsequent downstream tasks and interactions. Given this concern, we employ persona generation as a tool to assess whether any biases are present in the personas created by LLMs. To measure these biases, we compare the gender associations of the LLM-generated personas to the gender associations of our region-aware topic pairs. To ensure robustness, we average the results over seven runs.

Results. We plot the results of persona gender mismatch between LLMs and topic pairs in Fig 4. A

[10]Note that while our topic pairs are extracted from GeoWAC and may generalize to datasets like Reddit and UNGDC, we do not claim they are the optimal pairs, as topic pairs are data-dependent. However, our methodology can be used to identify bias-related topic pairs in specific datasets.

[11]https://claude.ai/

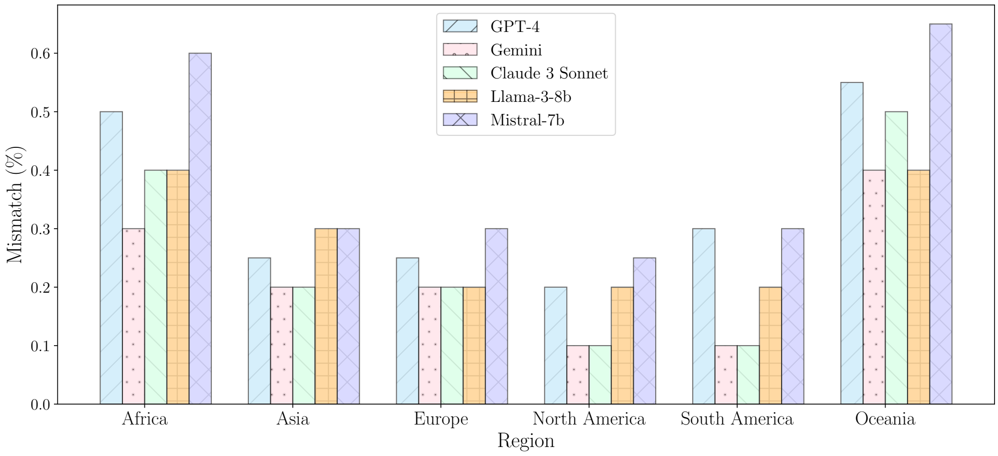

Figure 4: Bias Evaluation of LLM outputs using region-aware bias topic pairs through 'persona generation'.

mismatch occurs when an LLM generates a persona with a 'female' gender for a topic like Politics in Asia, which, according to our findings, is typically associated with a 'male' gender. Fewer mismatches mean the existence of region-aware biases. Regions with relatively higher representation: North America, South America, Europe, and Asia have fewer mismatches, with North America having the lowest mismatch. Conversely, regions like Africa and Oceania show higher mismatch rates. Among models, `Mistral-7b` (7B) has the highest mismatch rate while `Gemini-Pro` (50T) has the least, which may stem from varying model sizes. Overall, all the models exhibit similar mismatch trends for both highly-represented and other regions. Fewer mismatches in highly-represented regions show the importance of evaluation using region-specific topic pairs. Higher mismatches in regions like Africa and Oceania suggest LLMs do not mimic these regions' biases, which can be beneficial. However, due to growing research on LLM cultural alignment, a more precise, region-specific bias evaluation metric becomes essential.

7 Related Work

IAT (Greenwald et al., 1998) is one of the earliest method for measuring implicit social biases in humans. Inspired by the IAT, WEAT (Caliskan et al., 2017) and SEAT (May et al., 2019) use word and sentence embeddings respectively to measure biases in text. Additionally, various bias detection measures in NLP focus on post-training model predictions, such as gender swapping (Stanovsky et al., 2019). Moreover, there are specific gender bias evaluation test sets in tasks like coreference resolution (Rudinger et al., 2018; Zhao et al., 2018; Webster et al., 2018) and sentiment analysis (Kiritchenko and Mohammad, 2018b). Several studies have emphasized the significance of considering cultural awareness in the study of social phenomena. The demographics of individuals can shape their worldviews and thoughts (Garimella et al., 2016), potentially influencing their language preferences and biases in daily life. Notably, some studies have observed a bias towards Western nations in current LLMs (Dwivedi et al., 2023). Recent research has focused on cross-cultural aspects of LLMs, including aligning them with human values from different cultures (Glaese et al., 2022; Sun et al., 2023) and exploring them as personas representing diverse cultures (Gupta et al., 2024). To our knowledge, no prior work has proposed a data-driven approach to extract region-aware bias topics. Given the biases in LLMs, region-specific metrics can enable more accurate bias evaluations and enhance downstream tasks involving demographic-aware social simulations. This research is crucial for addressing cross-cultural biases effectively.

8 Conclusion

In this paper, we propose a bottom-up data-dependent approach to identify region-aware topic pairs that capture gender biases across different regions. Our human evaluation results demonstrate the validity of our proposed topic pairs.

We employ a region-aware WEAT-based evaluation setup to assess biases in two additional datasets: Reddit and UNGDC. The presence of region-specific biases in these datasets underscores the importance of a region-aware bias evaluation metric. Additionally, when examining LLM outputs against the gender associations in our region-aware topic pairs, we find that biases align closely for relatively highly represented regions such as North America, South America, Europe, and Asia. This emphasizes the value of region-aware topic pairs in LLM bias evaluation. Future work includes incorporating testing different model/dataset combinations and topic-pair dependency on data. We also intend to carry out a large-scale human validation experiment to further strengthen the validation of our approach. Finally, we aim to study biases in multiple languages and explore region-aware bias mitigation techniques. Our code and data are available at `https://github.com/MichiganNLP/DemographicAwareBiasEval`.

Limitations

Dataset limitations. We utilized the GeoWAC corpus as our sole data source for extracting topic pairs from various regions. However, we acknowledge the importance of incorporating additional datasets in our future work. It is important to note that the countries selected to represent each continent are based solely on data availability in GeoWAC. We do not claim that these three countries can fully encapsulate the diversity or complexity of an entire continent. This limitation should be considered when interpreting the results. Additionally, our WEAT-based evaluation was conducted on relatively smaller datasets. So, we intend to conduct further analysis on larger datasets to ensure a comprehensive evaluation based on WEAT.

Multilingualism and fine-grained bias evaluation. Our study did not account for different languages due to the diverse linguistic landscape of the regions (continents) included in our study. However, the significance of conducting a more detailed and multi-lingual analysis to examine variations among different countries would be interesting. Furthermore, we recognize that dividing the world by continent is an oversimplified approach, as it obscures nuanced regional differences. For example, Africa, with its large population and geographic diversity, is often condensed into a single category, while regions such as Oceania are treated similarly despite their smaller scale. This imbalance highlights the need for more granular or fine-grained frameworks for bias evaluation in future research.

Limited participants for human validation. In our study, we unfortunately encountered difficulties in finding participants from Oceania for human validation. Moving forward, we plan to include insights and findings from Oceania and also incorporate a larger population to ensure a more comprehensive human validation of our region-aware bias methodology.

Intersectional biases and gender diversity. We do not address intersectional biases, the overlapping systems of discrimination based on race, class, gender, ability, and so on, which are critical for understanding inequality (Lalor et al., 2022). Addressing these biases represents a valuable direction for future research. Additionally, our analysis is limited to a binary gender framework (female and male), excluding non-binary and gender non-conforming individuals. Future research directions can adopt diverse gender identities to ensure more inclusive and representative findings.

Ethical Considerations

When developing our region-aware topic pairs, it is essential to consider the ethical implications:

Broad cultural categorization: Since we utilize a much broader aspect of culture, i.e. continents to distinguish among cultures, the region-aware topic pairs we extract may not translate to cultures of communities that are not well-represented in models. Hence, it is important that we utilize topic pairs carefully.

Biases. AI models have been shown to frequently produce responses that align with Western, educated, industrialized, rich, and democratic (WEIRD) perspectives (Henrich et al., 2010; Mihalcea et al., 2025). Our findings also reveal that LLMs exhibit the strongest alignment with Western-centric biases. Therefore, it is essential to approach LLM-generated results with caution. Furthermore, it is important to note that in our persona experiment, we employ names generated by LLMs for various continents. Although these names were manually reviewed, they may still carry inherent LLM biases, therefore it is important to remain mindful of these biases when interpreting findings, and carefully consider their implications in future research. Such awareness is critical to ensuring more equitable and representative outcomes.

Offensive content. The Reddit data used for our region-aware evaluation metric may include offensive or inappropriate content, as it is sourced from a public platform with diverse user contributions. To mitigate privacy concerns, we have anonymized the data by removing usernames and any personally identifiable information. While this step helps protect user privacy, it does not eliminate the potential presence of offensive material. We emphasize the need for careful handling and interpretation of such data in research contexts.

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Harry Richardson, Mahmoud Alnahlawi, Christopher Yew, Priya Ponnapalli, Marco Tagliasacchi, Alex Korchemniy, Yelin Kim, Dinghua Li, Bill Rosgen, Kyle Levin, Jeremy Wiesner, Praseem Banzal, Praveen Srinivasan, Hongkun Yu, Çağlar Ünlü, David Reid, Zora Tung, Daniel Finchelstein, Ravin Kumar, Andre Elisseeff, Jin Huang, Ming Zhang, Ricardo Aguilar, Mai Giménez, Jiawei Xia, Olivier Dousse, Willi Gierke, Damion Yates, Komal Jalan, Lu Li, Eri Latorre-Chimoto, Duc Dung Nguyen, Ken Durden, Praveen Kallakuri, Yaxin Liu, Matthew Johnson, Tomy Tsai, Alice Talbert, Jasmine Liu, Alexander Neitz, Chen Elkind, Marco Selvi, Mimi Jasarevic, Livio Baldini Soares, Albert Cui, Pidong Wang, Alek Wenjiao Wang, Xinyu Ye, Krystal Kallarackal, Lucia Loher, Hoi Lam, Josef Broder, Dan Holtmann-Rice, Nina Martin, Bramandia Ramadhana, Mrinal Shukla, Sujoy Basu, Abhi Mohan, Nick Fernando, Noah Fiedel, Kim Paterson, Hui Li, Ankush Garg, Jane Park, DongHyun Choi, Diane Wu, Sankalp Singh, Zhishuai Zhang, Amir Globerson, Lily Yu, John Carpenter, Félix de Chaumont Quitry, Carey Radebaugh, Chu-Cheng Lin, Alex Tudor, Prakash Shroff, Drew Garmon, Dayou Du, Neera Vats, Han Lu, Shariq Iqbal, Alex Yakubovich, Nilesh Tripuraneni, James Manyika, Haroon Qureshi, Nan Hua, Christel Ngani, Maria Abi Raad, Hannah Forbes, Jeff Stanway, Mukund Sundararajan, Victor Ungureanu, Colton Bishop, Yunjie Li, Balaji Venkatraman, Bo Li, Chloe Thornton, Salvatore Scellato, Nishesh Gupta, Yicheng Wang, Ian Tenney, Xihui Wu, Ashish Shenoy, Gabriel Carvajal, Diana Gage Wright, Ben Bariach, Zhuyun Xiao, Peter Hawkins, Sid Dalmia, Clement Farabet, Pedro Valenzuela, Quan Yuan, Ananth Agarwal, Mia Chen, Wooyeol Kim, Brice Hulse, Nandita Dukkipati, Adam Paszke, Andrew Bolt, Kiam Choo, Jennifer Beattie, Jennifer Prendki, Harsha Vashisht, Rebeca Santamaria-Fernandez, Luis C. Cobo, Jarek Wilkiewicz, David Madras, Ali Elqursh, Grant Uy, Kevin Ramirez, Matt Harvey, Tyler Liechty, Heiga Zen, Jeff Seibert, Clara Huiyi Hu, Andrey Khorlin, Maigo Le, Asaf Aharoni, Megan Li, Lily Wang, Sandeep Kumar, Norman Casagrande, Jay Hoover, Dalia El Badawy, David Soergel, Denis Vnukov, Matt Miecnikowski, Jiri Simsa, Praveen Kumar, Thibault Sellam, Daniel Vlasic, Samira Daruki, Nir Shabat, John Zhang, Guolong Su, Jiageng Zhang, Jeremiah Liu, Yi Sun, Evan Palmer, Alireza Ghaffarkhah, Xi Xiong, Victor Cotruta, Michael Fink, Lucas Dixon, Ashwin Sreevatsa, Adrian Goedeckemeyer, Alek Dimitriev, Mohsen Jafari, Remi Crocker, Nicholas FitzGerald, Aviral Kumar, Sanjay Ghemawat, Ivan Philips, Frederick Liu, Yannie Liang, Rachel Sterneck, Alena Repina, Marcus Wu, Laura Knight, Marin Georgiev, Hyo Lee, Harry Askham, Abhishek Chakladar, Annie Louis, Carl Crous, Hardie Cate, Dessie Petrova, Michael Quinn, Denese Owusu-Afriyie, Achintya Singhal, Nan Wei, Solomon Kim, Damien Vincent, Milad Nasr, Christopher A. Choquette-Choo, Reiko Tojo, Shawn Lu, Diego de Las Casas, Yuchung Cheng, Tolga Bolukbasi, Katherine Lee, Saaber Fatehi, Rajagopal Ananthanarayanan, Miteyan Patel, Charbel Kaed, Jing Li, Shreyas Rammohan Belle, Zhe Chen, Jaclyn Konzelmann, Siim Põder, Roopal Garg, Vinod Koverkathu, Adam Brown, Chris Dyer, Rosanne Liu, Azade Nova, Jun Xu, Alanna Walton, Alicia Parrish, Mark Epstein, Sara McCarthy, Slav Petrov, Demis Hassabis, Koray Kavukcuoglu, Jeffrey Dean, and Oriol Vinyals. 2024. Gemini 1.5: Unlocking multimodal understanding across millions of tokens of context.

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Region	Country	#Examples
Africa	Nigeria Mali Gabon	3,153,761 660,916 645,769
Asia	India Singapore Philippines	12,327,494 6,130,047 3,166,971
Europe	Ireland United Kingdom Spain	8,689,752 7,044,434 465,780
North America	Canada United States Bermuda	7.965,736 8,521,094 244,500
South America	Chile Colombia Brazil	84,452,354 3,553,216 237,134
Oceania	New Zealand Palau Vanuatu	94,476 486,437 165,355

Table 5: Region-specific details in GeoWAC

A GeoWAC dataset details

Table 5 contain the total number of examples per country in a region. We consider the top three countries with the highest number of examples per region.

B F-M Dataset statistics

Table 6 displays the total number of examples from female and male groups per region for the region-specific F-M dataset.

Region	Total	#Female	#Male
Africa	57895	20153	37742
Asia	56877	21400	35477
Europe	59121	21049	38072
North America	70665	27627	43038
Oceania	62101	25951	36150

Table 6: F-M dataset statistics for regions (Total refers to the total number of examples in each region, therefore, total = #female + #male)

C Cultural differences in biases using WEAT

Table 7 shows the WEAT scores for all WEAT dimensions defined in (Caliskan et al., 2017). We find that scores and p-values differ across regions for different dimensions. High bias dimensions differ across regions, hence it is important to consider region-specific topic pairs.

D Region-wise topic lists in GeoWAC

Table 8 displays a comprehensive list of topics for female and male groups across all regions.

E Unigram/Bigram Analysis

Table 10 shows the unigrams and bigrams of common topics with different gender associations. We find that 'fashion' is highly associated with shoes when it is a male topic in Africa, whereas in Europe and North America, it is mostly associated with accessories like sunglasses, rings, etc. This shows the typical association of women with jewelry and men with shoes (Russell, 2010; Nichols, 2011). In the case of 'Music', we see that unigrams and bigrams pertaining to Africa contain words related to hip-hop music and artists. For Europe, we find location references and metal music. And finally, Oceania shows references of jazz and rock. We do not find any obvious gender associations in the analysis of the music topic. Table 11 provides a unigram/bigram analysis of topics that are commonly associated with a specific gender across regions. For *parenting and family relationships*, Africa has mentions of children, while Asia and Oceania contain mentions of family events, etc. In North America, we mostly find text about maintaining health in families. For *religion and spirituality*, the unigrams/bigrams are mostly about Jesus and Christianity across regions. For *politics*, we find mentions of specific regions, as expected. *Education* topic is more about being successful in Europe, where it is about degrees in North America. Finally, 'social media' trends are mostly similar. Overall for topics with same gender associations across regions, do not have stark differences.

F WEAT-based evaluation setup details

For male/female terms, we use the same representative words from WEAT: *brother, father, uncle, grandfather, son, he, his, him, man, boy, male* for male and *sister, mother, aunt, grandmother, daughter, she, hers, her, woman, girl, female for female*. We also utilize GPT-4 to output the ten most common male/female names specific to each region. We provide the lists of word belonging to each topic in Table 12.

G Paired-list for F-M datasets

Here is the list of the 52 pairs used to create the F-M datasets per region inspired from the foundational work on bias detection and mitigation in NLP using word embedding techniques (Bolukbasi et al., 2016):

Target words - Attribute words	Region	Region-specific p-value	Region-specific WEAT score	Original WEAT score, p-value
Male names vs Female names - career vs family	Africa	0.016	1.798	1.81, 0.001
	Asia	0.007	1.508	
	North America	0.04	1.885	
	South America	0.082	-0.574	
	Europe	$6 \cdot 10^{-4}$	1.610	
	Oceania	0.03	1.727	
Math vs Arts - Male vs Female terms	Africa	0.003	1.429	1.06, 0.018
	Asia	0.045	1.187	
	North America	0.007	0.703	
	South America	0.0006	0.532	
	Europe	0.005	0.334	
	Oceania	0.03	1.158	
Science vs Arts - Male vs Female terms	Africa	0.048	1.247	1.24, 0.01
	Asia	0.004	0.330	
	North America	$1 \cdot 10^{-5}$	0.036	
	South America	0.004	0.912	
	Europe	$1 \cdot 10^{-7}$	-0.655	
	Oceania	$2 \cdot 10^{-4}$	0.725	
Young people names vs old people names - pleasant vs unpleasant	Africa	$3 \cdot 10^{-5}$	0.855	1.21, 0.01
	Asia	$4 \cdot 10^{-4}$	0.917	
	North America	0.032	1.325	
	South America	0.0021	1.223	
	Europe	0.009	0.917	
	Oceania	0.014	0.947	
European American names vs African American names - pleasant vs unpleasant	Africa	$1 \cdot 10^{-5}$	0.008	1.28, 0.001
	Asia	$1 \cdot 10^{-6}$	-0.453	
	North America	0.009	1.29	
	South America	0.02	1.127	
	Europe	0.001	0.617	
	Oceania	$1 \cdot 10^{-4}$	0.492	
Instruments vs Weapons - pleasant vs unpleasant	Africa	0.03	1.443	1.53, $< 10^{-7}$
	Asia	0.009	1.001	
	North America	0.01	1.202	
	South America	0.045	0.672	
	Europe	0.02	1.21	
	Oceania	0.001	0.951	
Flowers vs Insects - pleasant vs unpleasant	Africa	0.002	0.312	1.5, $< 10^{-7}$
	Asia	0.009	0.869	
	North America	0.003	0.382	
	South America	0.009	0.412	
	Europe	0.001	0.332	
	Oceania	0.009	0.660	
Mental disease vs Physical disease - temporary vs permanent	Africa	0.008	0.835	1.38, 0.01
	Asia	0.02	1.201	
	North America	0.008	0.692	
	South America	0.01	1.123	
	Europe	0.04	1.382	
	Oceania	0.009	1.620	

Table 7: Region-wise WEAT scores and p-values across all dimensions specific in WEAT using word2vec. Negative scores are highlighted. We compare our region specific scores and p-values with the scores and p-values of the Original paper by (Caliskan et al., 2017)

Region	Female	Male
Africa	Credit cards and finances, Royalty and Media, Trading strategies and market analysis, Dating and relationships guides, Parenting and family relationships, Fashionable Ankara Styles, women's lives and successes, online dating	Fashion and Lifestyle, Male enhancement and sexual health, Nollywood actresses and movies, Nigerian politics and government, Essay writing and research, Medical care for children and adults, Journalism and Media Conference, Music industry news and releases, Football league standing and player performances, Academic success and secondary school education, Religious inspiration and spiritual growth, Economic diversification and Socio-economic development
Asia	Hobbies and Interests, Healthy eating habits for children, Social media platforms, Royal wedding plans, Online Dating and Chatting, Adult Services, Gift ideas for Valentine's Day	DC comic characters, Mobile Application, Philippine Politics and Government, Sports and Soccer, Career, Bike enthusiasts, Artists and their work, Youth Soccer Teams, Career in film industry, Political leadership in India, Bollywood actors and films, Religious devotion and spirituality, Phone accessories
Europe	Pets and animal care, Fashion and Style, Education, Obituaries and Genealogy, Luxury sailing, Traveling, Energy and climate change, Family and relationships, Pension and costs, Tech and business operations, Dating, Comfortable hotels, Government transportation policies	Political developments in Northern Ireland, Christian Theology and Practice, Crime and murder investigation, EU Referendum and Ministerial Positions, Criminal Justice System, Israeli politics and International relations, Cancer and medications, UK Government Taxation policies, Art Exhibitions, Political decision and impact on society, Music Gendres and artists, Medical specialties and university training, Political discourse and parliamentary debates
North America	Pets, Cooking: culinary delights and chef recipes, Fashion and style, Family dynamics and relationships, Reading and fiction, Scheduling and dates, Life and legacy of Adolf Hitler, Gender roles and inequality, Education and achievements, Online dating for singles, Luxury handbags, Footwear and Apparel brands, Essay writing and literature	Civil War and history, Middle East conflict and political tensions, Movies and filmmaking, Political leadership and party dynamics in Bermuda, Rock Music and songwriting, Wartime aviation adventures, Religion and Spirituality, Reproductive health, Reinsurance and Capital markets, Nike shoes and fashion, Cape Cod news, NHL players
South America	Luxury and Cruise, Regional Development in South America, Cultural events, Food and recipes, Gender and Social inequality, Immigrants lifestyles, Travel and Beauty essentials, yoga and fitness for women, family and school life, motherhood and family characteristics	Colonial Wine Industry, Chilean politics and violence, Gaming, Football and Sports, Startup and Entrepreneurship, movies and actors, men's health and sexual wellness, startup and entrepreneurship, Chilean business leaders and Innovation, Religious texts and figures, Superhero movies and TV shows
Oceania	Cooking and culinary delights, Romance, Weight loss and nutrition for women, Water travel experience, Woodworking plans and projects, Time management and productivity, Inspiring stories and books for alleges, Sexual violence and abuse, Car insurance, Exercises for hormone development, kid's furniture and decor	Harry Potter adventures, Art and Photography, Superheroes and their Universes, Music recording and Artists, Football in Vanuatu, Pet care and veterinary services, Building and designing boats, Religious beliefs and figures, Fashion, Classic movie stars, Men's hairstyle and fashion, Male sexual health and supplements

Table 8: Region-wise topics for female and male.

[monastery, convent], [spokesman, spokeswoman], [Catholic priest, nun], [Dad, Mom], [Men, Women], [councilman, councilwoman], [grandpa, grandma], [grandsons, granddaughters], [prostate cancer, ovarian cancer], [testosterone, estrogen], [uncle, aunt], [wives, husbands], [Father, Mother], [Grandpa, Grandma], [He, She], [boy, girl], [boys, girls], [brother, sister], [brothers, sisters], [businessman, businesswoman], [chairman, chairwoman], [colt, filly], [congressman, congresswoman], [dad, mom], [dads, moms], [dudes, gals], [ex girlfriend, ex boyfriend], [father, mother], [fatherhood, motherhood], [fathers, mothers], [fella, granny], [fraternity, sorority], [gelding, mare], [gentleman, lady], [gentlemen, ladies], [grandfather, grandmother], [grandson, granddaughter], [he, she], [himself, herself], [his, her], [king, queen], [kings, queens], [male, female], [males, females], [man, woman], [men, women], [nephew, niece], [prince, princess], [schoolboy, schoolgirl], [son, daughter], [sons, daughters], [twin brother, twin sister].
Each pair in the above is denoted as a [male, female] pair.

H Llama 2 prompt for topic modeling

The prompt scheme for `Llama2` consists of three prompts: (1) System Prompt: a general prompt that describes information given to all conversations, (2) Example Prompt: an example that demonstrates the output we are looking for, and (3) Main Prompt: describes the structure of the main question, that is with a given set of documents and keywords, we ask the model to create a short label for the topic. Fig 5 displays the three prompts as used in the code.

I Topic Cluster Labels using other LLMs

We use `Llama2` to fine-tune our topics to label them for better coherence in our paper. However, we also experiment with `GPT-4` and arrive at similar topics in Table 9. (see Table 2 for comparison with `Llama2` topic labels).

J Topic Word Clusters Example - Africa

Here, we provide an example of how topics look in our data. In Fig 6, we provide word clusters of topics from Africa. The word clusters contain the top 10 words from each topic in Africa. We find that topic labels by `Llama2` are coherent in terms of top topic words.

K Region specific BERTs to identify top words in F/M direction

To motivate our case to investigate differences in biases across regions, we use BERT to compute

```
[ ] # System prompt describes information given to all conversations
    system_prompt = """
    <s>[INST] <<SYS>>
    You are a helpful, respectful and honest assistant for labeling topics.
    <</SYS>>
    """
```

```
[ ] # Example prompt demonstrating the output we are looking for
    example_prompt = """
    I have a topic that contains the following documents:
    - Traditional diets in most cultures were primarily plant-based with a little meat on top, but with the rise of industrial style meat
    production and factory farming, meat has become a staple food.
    - Meat, but especially beef, is the word food in terms of emissions.
    - Eating meat doesn't make you a bad person, not eating meat doesn't make you a good one.

    The topic is described by the following keywords: 'meat, beef, eat, eating, emissions, steak, food, health, processed, chicken'.

    Based on the information about the topic above, please create a short label of this topic. Make sure you to only return the label and nothing more.

    [/INST] Environmental impacts of eating meat
    """
```

```
[ ] # Our main prompt with documents ([DOCUMENTS]) and keywords ([KEYWORDS]) tags
    main_prompt = """
    [INST]
    I have a topic that contains the following documents:
    [DOCUMENTS]

    The topic is described by the following keywords: '[KEYWORDS]'.

    Based on the information about the topic above, please create a short label of this topic. Make sure you to only return the label and nothing more.
    [/INST]
    """
```

Figure 5: `Llama2` prompt

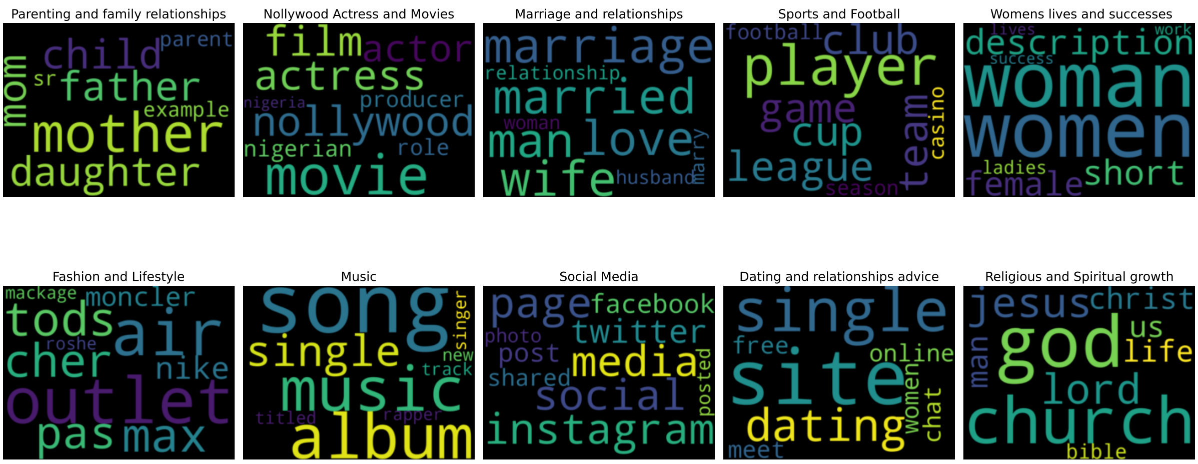


Figure 6: Topic Word Clusters - Africa

Region	Female topics	Male topics
Africa	Credit card-based financial services Royalty and femininity Financial trading Dating guides Motherhood and parenting	Fashion - footwear and celebrities Male enhancement and sexual health Nollywood Nigerian politics Academic writing
Asia	Hobbies Food and nutrition Social media platforms and content creation Royal weddings Online social interaction and dating	Superhero comic books Mobile applications Philippines politics and people Sports Career
Europe	Pets Fashion Education Deaths and funerals Luxury yachting and sailing	Irish politics Christianity Law enforcement and crime EU and Brexit Criminal justice system
North America	Pets Cooking and Food Fashion Family and relationships Reading novels	Civil War Military Middle Eastern politics and conflicts Movies and direction Bermuda politics Rock music
Oceania	Food and eating habits Romance and emotions Weight loss and nutrition Boat and sailing experience Woodworking and carpentry	Harry Potter Artistic expressions Superheroes of Marvel and DC Albums, songs and artists Vanuatu Football

Table 9: Topic labels by `gpt-4`, see Table 2 for comparison with `Llama2` topic labels

the top words corresponding to the *she-he* axis in the embedding space. BERT is a pre-trained transformer-based language model that consists of a set of encoders. As a motivation experiment to identify differences in the contextual embedding space for different regions, we fine-tune BERT with the masked language modeling task (no labels) for each region separately. For a given word, we compute its embeddings by averaging out all sentence embeddings where it occurs across the dataset.Similarly, we compute embeddings for all words in the dataset. The tokenized input goes through the BERT model and we take the hidden states at the end of the last encoder layer (in our case, BERT-base, i.e. 12 encoder layers) as sentence embeddings. We identify the top words with the highest projection across the *she-he* axis in the region-specific datasets. If we find differences in the top words across regions, it is possible that dominating bias topics vary by region as well. Fig 8 shows the top words closest to 'she' and 'he' contextual embeddings in our data for each region. We

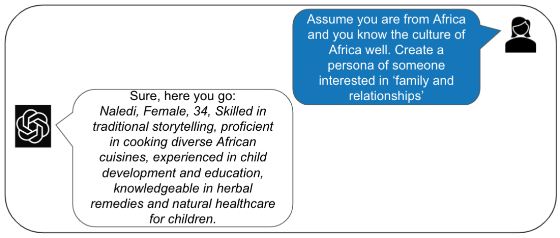


Figure 7: Example Prompt for Persona Generation

find that top words differ quite a bit across different regions. We find many differences in the top F (close to she) and M (close to he) words across regions. Some top F words are soprano, archaeological (Africa); graduate, secretary (Asia); innovative, graphics (Europe); poets, sentiments (NA); and arts, sleep (Oceania). Some top M words are history, leading (Africa); astronomer, commissioners (Asia); honorary, songwriters (Europe); owner, hospital (NA); and wrestlemania, orbits (Oceania). Gender-neutral words such as poets, secretaries, astronomers, commissioners, songwriters, owners, and so on are closer to either the she or he axes. Although comparable to the findings of (Bolukbasi et al., 2016), the variances among regions inspire us to look deeper into the data to arrive at culture-specific bias themes.

L Implementations details

For training our `Bertopic` model, we use `Google Colab's Tesla T4 GPU`, and it takes 15 min to run topic modeling for a region-specific F-M dataset. Region-specific BERTs are run on NVIDIA RTX2080 GPUs. Each BERT training experiment takes 1 GPU hour. For our LLM experiment, we used NVIDIA-A40 for `Mistral-7b-Instruct` and `Llama-3-8b` for an hour. We do not use any GPUs for `GPT-4`, `Claude-3-Sonnet` and `Gemini-Pro`.

L.1 Bertopic

We use Bertopic's default models: `SBERT` (Reimers and Gurevych, 2019) to contextually embed the dataset, `UMAP` (McInnes et al., 2018) to perform dimensionality reduction, `HDBSCAN` (Malzer and Baum, 2020) for clustering to perform topic modeling. We choose the embedding model `BAAI/bge-small-en` from *Huggingface* (Wolf et al., 2019). We set `top_n_words` to 10 and `verbose` as True and set the `min_topic_size` to 100 for the `Bertopic` model. Finally, we use Bertopic's official library to implement the model.

Topic	Region	Unigrams	Bigrams
Fashion and lifestyle	Africa (male)	march, outlet, air, max, tods, man, said, pas, cher, people	air max, pas cher, princess j, roshe run, nike air, tods outlet, j march, roger vivier, posts email, notify new
	Europe (female)	one, women, fashion, like, new, look, make, hair, girl, dress	oakley sunglasses, louis vuitton, red carpet, new york, fashion model, engagement rings, per cent, year old, christian louboutin, diamond ring
	North America (female)	one, love, like, little, new, made, time, get, make, women	s cooper, cooper main, t shirt, new york, little girl, men women, look good, main store, years ago, check out
Music	Africa (female)	music, song, album, new, video, single, one, singer, also, songs	music industry, hip hop, record label, single titled, new single, chris brown, tiwa savage, ice prince, kanye west, niegrian music
	Europe (male)	man, single, stage, years, world, many, metal, guitar, solo, irish	year shelfmark, black metal, time exercise, musical content, dundee repertory, singer songwriter, edinburgh year, zumba days, male vocalists, millions men
	Oceania (male)	music, album, new, songs, band, first, time, jazz, released, rock	new york, elizabth ii, debut album, years later, big band, rock roll, first time, studio album, los angeles, solo artist

Table 10: Common topics with different gender associations across regions

L.2 Llama2

We use `Llama2` to finetune the topics to give shorter labels for each topic. We set the `temperature` to 0.1, `max_new_tokens` to 500 and `repetition_penalty` to 1.1. We utilize Bertopic's built-in representation models to use `Llama2` in our topic model.

L.3 LLM experiment

For `GPT-4`, and `Mistral-7b-Instruct` and `Llama-3-8b`, we utilize the Microsoft Azure API[12], huggingface[13], and huggingface[14] for inference respectively. We use a temperature 0.8 for all models. For `Gemini-Pro` and `Claude-3-Sonnet`, we use the available chat interface.

L.4 Region-specific BERT

We use the uncased version BERT (Devlin et al., 2019) for our region-specific BERT model trained for the MLM objective. We use a batch size of 8, a learning rate of $1 \cdot 10^{-4}$, and an AdamW optimizer to train our BERT models for 3 epochs.

M Persona Generation Task

Figure 7 shows an example of the persona generation procedure for bias detection in LLMs.

N Human Validation

Students and staff from a college campus were recruited as annotators, who volunteered for the study. We have 6 annotators per region (3 male and 3 female) not necessarily from the same countries but belonging to the regions. Screenshots of the form are displayed in Fig 9.

O Reproducibility

We open-source our codes, which are uploaded to the submission system. We include commands with hyperparameters in our codes. This would help future work to reproduce our results.

[12] https://learn.microsoft.com/en-us/rest/api/azure/

[13] https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.1

[14] https://huggingface.co/meta-llama/Meta-Llama-3-8B

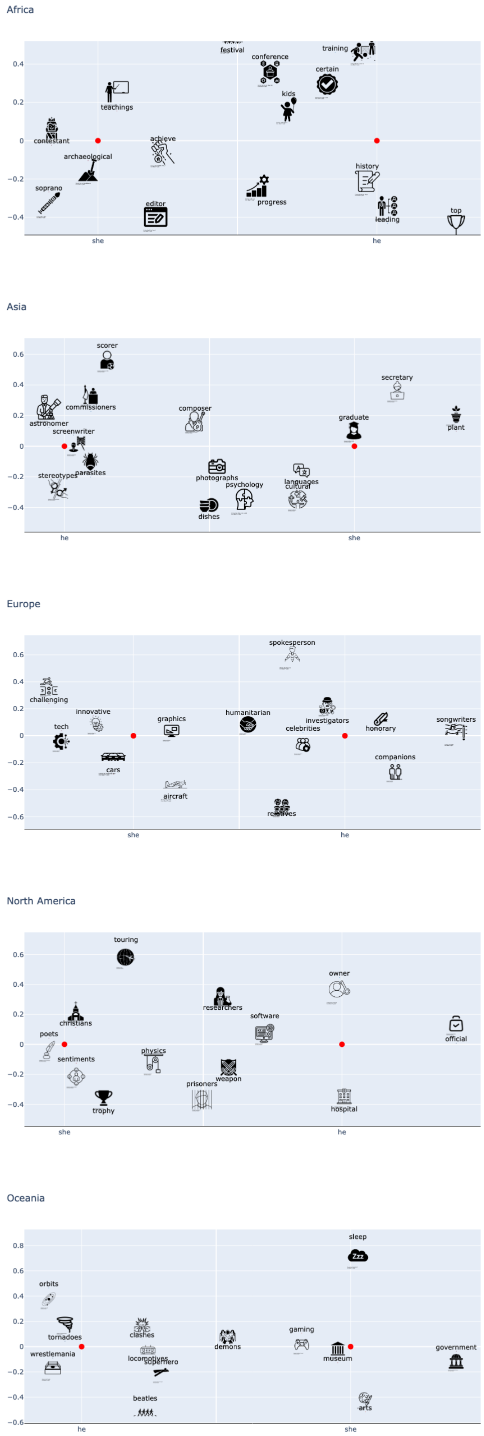
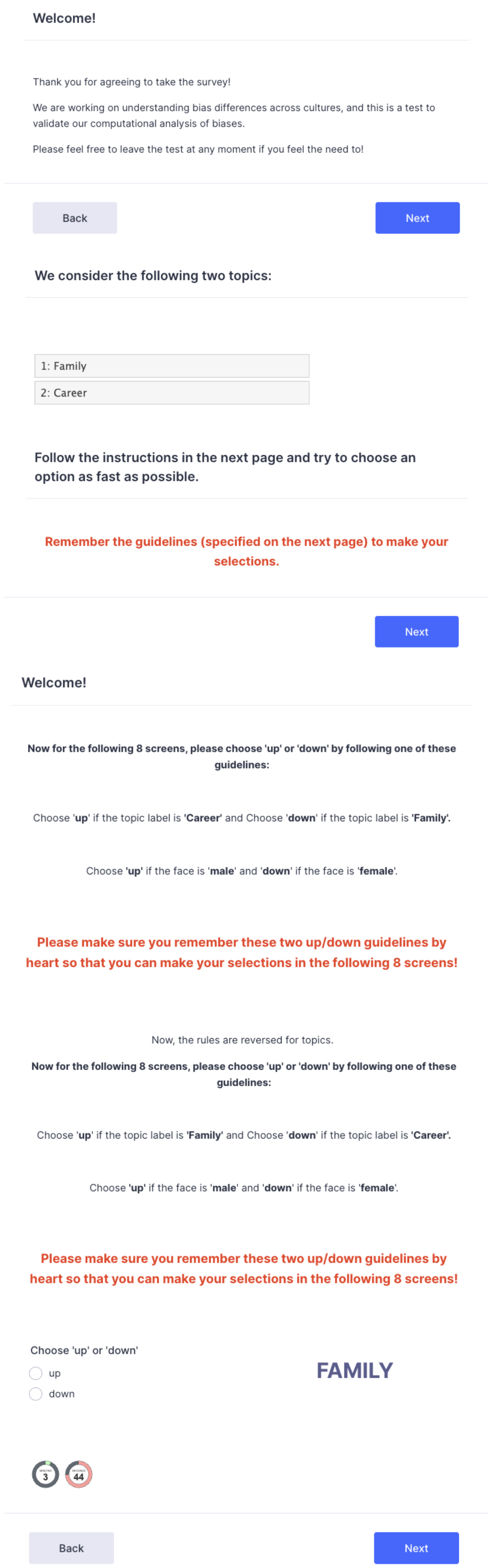


Figure 8: Top words for each region(Africa, Asia, Europe, North America and Oceania) using region-specific BERTs


Welcome!

Thank you for agreeing to take the survey!

We are working on understanding bias differences across cultures, and this is a test to validate our computational analysis of biases.

Please feel free to leave the test at any moment if you feel the need to!

Back

Next

We consider the following two topics:

1: Family

2: Career

Follow the instructions in the next page and try to choose an option as fast as possible.

Remember the guidelines (specified on the next page) to make your selections.

Next

Welcome!

Now for the following 8 screens, please choose 'up' or 'down' by following one of these guidelines:

Choose '**up**' if the topic label is '**Career**' and Choose '**down**' if the topic label is '**Family**'.

Choose '**up**' if the face is '**male**' and '**down**' if the face is '**female**'.

Please make sure you remember these two up/down guidelines by heart so that you can make your selections in the following 8 screens!

Now, the rules are reversed for topics.

Now for the following 8 screens, please choose 'up' or 'down' by following one of these guidelines:

Choose '**up**' if the topic label is '**Family**' and Choose '**down**' if the topic label is '**Career**'.

Choose '**up**' if the face is '**male**' and '**down**' if the face is '**female**'.

Please make sure you remember these two up/down guidelines by heart so that you can make your selections in the following 8 screens!

Choose 'up' or 'down'

up

down

FAMILY

3

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Back

Next

Figure 9: Annotation Form Screenshots (We do not include screenshots with faces to protect privacy)

TOPIC	REGION	UNIGRAMS	BIGRAMS
Parenting and family relationships	Africa (female)	child, registration, form, information, sent, women, foster, best, catholic, women	registration form, form information, child assigned, surgery doctors, new catholic, catholic women, contemporary challenge, best everything, foster short, doctors clinic
	Asia (female)	year, old, weekly, fortnightly, clicking, create, alert, state, 1, terms	year old, weekly fortnightly, create alert, stated agree, conditions acknowledge, finals appearances, together playing, dial guarded, came work, outlet jackets
	North America (female)	women, healthday, loss, three, worked, closely, together, she, elegant, dignified	three women, women worked, closely together, elegant dignified, very pleasant, soft spoken, women men, healthday reporter, tuesday march, participate more
	Oceania (female)	laurel, school, moved, one, day, royal, wedding, house, sister, hopefully	moved one, royal wedding, laurel school, 1 california, weeks dad, high school, one hopefully, nobody knew, sister means, fu school
Religion and Spirituality	Africa (male)	god, man, church, one, life, people, jesus, us, lord, christ,	short description, jesus christ, man god, holy spirit, god said, thank god, bible says, catholic church, today god, every man
	Asia (male)	life, jesus, us, church, one, man ,lord, said, father, christ	holu spirit, jesus christ, pope francis, brothers sisters, son god, men women, holy father, opus dei, eternal life, paul ii
	Europe (male)	god, one, jesus, church, life, people, father, man , said, christ	jesus christ, son man, catholic church, holy spirit, men women, said him, holy father, john paul, jesus said, word god
	North America (male)	god, jesus, one, man, us, life, would, christ, lord, people	recognizable cheering, section league, jesus christ, exact synonyms, past years, god said, years before, thanks mostly, mostly steph, father dell
	Oceania (male)	also, said, best, love, new, come, good, like, men, made	god said, jesus christ, holy spirit, lord krishna, temple god, father devil, eternal life, son god, son man, god father
Politics	Asia (male)	said, one, India, time, people, minister, government, years, state, police, court	indian congress, government plans, modi ministry, human rights, foreign politics, armed forces, international warfare, foreign ministry, middle east, united nations
	Europe (male)	government, said, minister, people, international, country, one, foreign, president, state	make statement, prime minister, human rights, armed forces, secretary state, middle east, united nations, hon friend, foreign secretary, united states
Education	Europe (female)	school, primary, teacher, founder, CEO, judgment, group, named, ranking, prestigious	as founder, founder CEO, judgment group, named fortune, ranking prestigious, world scientist, scientist women, students comprehend, program support, support students
	North America (female)	bachelor, years, student, leader, degree, animal, veterinary, music, taught, communication	bachelors degree, animal veterinary, bachelor music, alison taught, privately years, students ranging, development programmes, including leader, art communication, recent years
Social Media	Africa (male)	onigbinder, aura, pictures, first, gained, popularity, match, beaut, designed, music	aura pictures, gained popularity, match beaut, designed wonder, attending music, music festival, schomburg library, Instagram account, sugar coating, schedule tomorrow
	Asia (male)	time, later, latest, tracks, speedy, Zulfiqar, nasty, children, tweeted, guys	gets later, latest tracks, speedy zulfiqar, children pti, pti tweeted, taking long, long time, hosted pageant, time vincent, love fleeting

Table 11: Common topics with same-gender associations across regions

REGION	TOPICS: WORD LISTS
AFRICA	**Nollywood Actress and Movies**: nollywood, actress, actors, drama, celebrity, movie, acting, movies, producer, tv **Parenting and family relationships**: mother, mom, mothers, mum, moms, parent, her, child, momodu, parents **Sports and Football**: players, sports, fifa, team, player, football, mourinho, scored, league, champions **Marriage and relationships**: wives, marriage, husbands, marriages, married, wife, relationships, husband, marry, relationship **Fashion and lifestyle**: cher, nike, max, air, looked, face, love, tods, soldes, scarpe **Womens lives and successes**: women, ladies, woman, female, girls, men, gender, ones, employees, male **Social Media**: instagram, facebook, social, twitter, tweet, snapchat, tweets, tweeted, hashtag, followers **Music**: song, songs, album, hits, music, released, rap, singer, tracks, rapper **Religious and Spiritual Growth**: god, almighty, bible, christ, faith, believers, christian, jesus, prayer, religion **Dating and relationships advice**: dating, women, relationships, ladies, sites, singles, online, single, escorts, websites **Male terms**: male, man, boy, brother, he, him, his, son, Kwame, Mandela, Moyo, Jelani, Tariq, Keita, Obi, Simba, Ayo, Kofi, Jabari, Tunde, Mekonnen, Anwar, Chukwuemeka **Female terms**: sister, mother, aunt, grandmother, daughter, she, hers, her, Aisha, Zahara, Nia, Sade, Amara, Chinelo, Layla, Ayana, Nala, Zuri, Imani, Lola, Kamaria, Nyala, Kaya
ASIA	**Political Leardership in India**: modi, political, said, bjp, told, says, leader, congress, minister, public **Hotel Royalty**: visited, places, stayed, hotels, adventure, pictures, favourite, guest, hiking, hemingway **Sports and Soccer**: sports, team, basketball, players, nba, league, championship, coach, rebounds, finals **Healthy eating habits for children**: food, foods, eating, meals, nutrition, cuisine, diet, dishes, cooking, eat **Social Media platforms for video sharing**: instagram, video, videos, twitter, tweet, facebook, gifs, vlog, youtube, followers **Royal wedding plans**: meghan, duchess, engagement, england, royal, royalty, prince, kate, london, married **Religious devotion and spirituality**: god, bible, holy, faith, prayer, believe, christian, blessed, christ, spiritual **Royal wedding plans**: meghan, duchess, engagement, england, royal, royalty, prince, kate, london, married **Bollywood actors and films**: bollywood, bachchan, kapoor, actors, acting, kareena, actor, film, shahrukh, hindi **Marriage**: married, marriage, marriages, couple, couples, wife, marry, wedding, husband, divorced **Male terms**: male, man, boy, brother, he, him, his, son, Hiroshi, Ravi, Kazuki, Jin, Satoshi, Rohan, Haruki, Dai, Akira, Yuan **Female terms**: sister, mother, aunt, grandmother, daughter, she, hers, her, Sakura, Mei, Aiko, Yuna, Lina, Ji-hye, Mika, Nami, Anika, Rina
EUROPE	**Music**: music, songs, vocalists, album, albums, singing, vocals, singles, rock, song **Education**: school, schools, classroom, students, education, educational, pupils, boys, academy, college **Political decisions and impact on society**: government, public, minister, said, hon, people, first, the, column, committee **Comfortable hotels**: guests, staying, rooms, friendly, welcoming, stayed, hotel, beds, stay, comfortable **UK Government Taxation Policies**: corbyn, taxation, fiscal, tax, taxes, exchequer, labour, governments, government, deficit **Luxury Sailing**: yachts, yacht, boat, sailing, sails, cruising, sail, berths, cruiser, cabin **Christian Theology and Practice**: god, bible, christ, jesus, faith, christian, religious, religion, holy, gave **Obituaries and Genealogy**: died, edward, relatives, anne, lived, elizabeth, funeral, irish, mrs, galway **Christian Theology and Practice**: god, bible, christ, jesus, faith, christian, religious, religion, holy, gave **Fashion and style**: fashion, shoes, style, clothes, clothing, shoe, wear, nike, dress, stylish **Male terms**: male, man, boy, brother, he, him, his, son, Lukas, Matteo, Sebastian, Alexander, Gabriel, Nikolai, Maximilian, Leonardo, Daniel, Adrian **Female terms**: sister, mother, aunt, grandmother, daughter, she, hers, her, Emma, Sophia, Olivia, Isabella, Ava, Mia, Charlotte, Amelia, Lily, Emily
NORTH AMERICA	**Religion and Spirituality**: god, christ, jesus, bible, christian, holy, christians, scripture, faith, heaven **Online Dating for Singles**: dating, singles, hookup, single, relationships, dates, flirting, personals, date, mingle **Reproductive Health**: download, available, pdf, online, edition, manual, free, reprint, kindle, file **Fashion and style**: fashion, dresses, dress, wardrobe, clothes, clothing, style, outfit, vintage, wear **Reinsurance and capital markets**: reinsurance, reinsurers, insurers, insurance, securities, investors, investment, finance, trading, pension **Education and achievements**: school, schools, graduated, college, students, undergraduate, graduation, graduate, attended, education **Nike shoes and fashion**: nike, shoes, sneakers, jordans, jeans, tops, black, boys, men, casual **Family dynamics and relationships**: family, families, children, kids, grandchildren, relatives, grandparents, parents, child, parent **Cape Cod news**: lifeguard, drowned, drowns, newstweet, hospitalized, snorkeling, cape, reported, reuterstweet, pulled **Reading and fiction**: books, book, reading, novels, series, enjoyed, novel, romance, katniss, readers **Male terms**: male, man, boy, brother, he, him, his, son, Liam, Noah, Ethan, Jacob, William, Michael, James, Alexander, Benjamin, Matthew **Female terms**: sister, mother, aunt, grandmother, daughter, she, hers, her, Emma, Olivia, Ava, Sophia, Isabella, Mia, Charlotte, Amelia, Harper, Evelyn
OCEANIA	**Religious beliefs and figures**: god, gods, bible, mankind, faith, christ, spiritual, christian, religion, jesus **Family relationships**: mum, mother, mom, mums, parent, family, parents, baby, dad, father **Music record and Artists**: music, album, albums, jazz, songs, hits, musicians, artists, recordings, blues **Woordworking plans and projects**: plans, furniture, woodwork, wood, woodcraft, woodworking, plywood, carpentry, cabinets, wooden **Building and designing boats**: boatbuilder, boatbuilding, boats, plans, boat, sauceboat, sailboat, build, catamaran, kits **Weight loss and nutrition for women**: diet, workout, exercise, foods, weight, food, eating, healthy, pounds, fat **Superheroes and their Universes**: superhero, superheroes, avengers, marvel, comics, superman, aquaman, heroes, comic, hero **Exercises for hormone development**: hormones, weightlifting, workouts, deadlifts, hormonal, exercises, lifting, testosterone, fitness, squats **Building and designing boats**: boatbuilder, boatbuilding, boats, plans, boat, sauceboat, sailboat, build, catamaran, kits **Kids furniture and decor**: furniture, chairs, sofas, ikea, sofa, cushions, sectional, upholstered, couch, childrens **Male terms**: male, man, boy, brother, he, him, his, son, Manaia, Tane, Kai, Ariki, Mika, Koa, Rangi, Kane, Tama, Hemi **Female terms**: sister, mother, aunt, grandmother, daughter, she, hers, her, Aroha, Moana, Tui, Lani, Kahurangi, Ariana, Malie, Marama, Ava, Kaia

Table 12: Word lists corresponding to each topic for computing region-aware WEAT metric