Word Embedding Bias in Large Language Models

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BACKGROUND

The rapid development of large language models (LLMs) has expanded natural language processing (NLP) applications, from text generation to chatbots.

- Word embeddings are the core of these systems, converting words into numeric vectors based on their statistics usage patterns in text corpora..
- However, embeddings often reflect societal biases, reinforcing stereotypes [1].
- For instance, they may link professions like nurses to women and engineers to men.

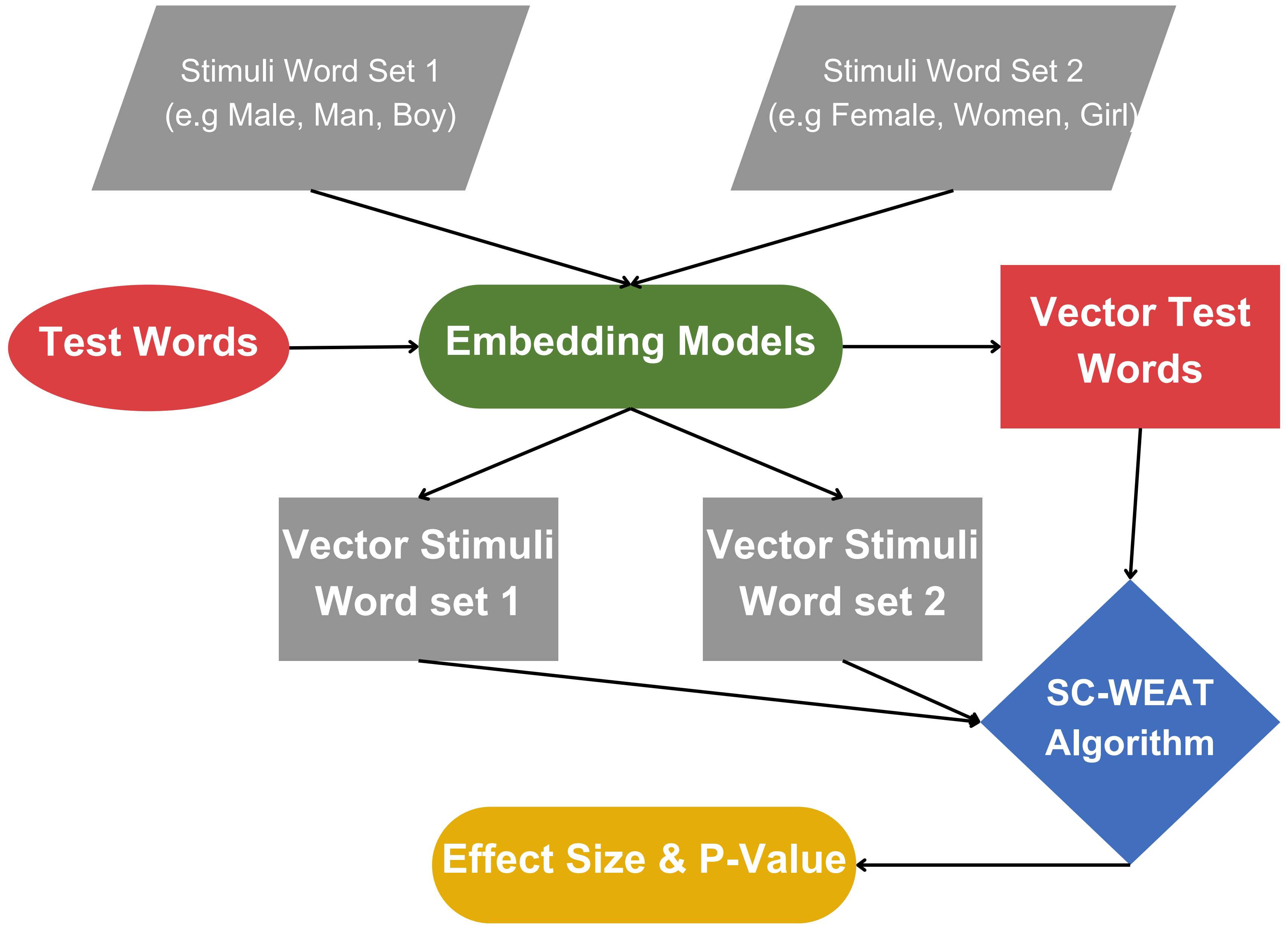
OBJECTIVES

- Analyze gender and race biases in modern LLMs.
  - OpenAI, Cohere, Google, Microsoft, and BGE
- Examine bias in word embeddings and their impact on real-world applications.
  - Tech Industry and Higher Education
- Address biases to ensure fairer and more ethical AI systems.

DATA SET

<table>
<tr><td><b>Test Word Sets</b></td><td>The most frequent 100,000 words from the GloVe embedding dataset</td></tr>
<tr><td><b>Word Embedding Models</b></td><td>OpenAI, Cohere, Google, Microsoft, and BGE embedding models.</td></tr>
<tr><td><b>Stimuli Words (Attribute Sets)</b></td><td>
<table>
<tr><th>Category</th><th>Stimuli Group</th><th>Stimuli Words</th></tr>
<tr><td rowspan="2">Gender</td><td>Female</td><td>Female, Woman, Girl, Hers, Sister, She, Her, Daughter</td></tr>
<tr><td>Male</td><td>Male, Man, Boy, Brother, He, Him, His, Son</td></tr>
<tr><td rowspan="3">Race</td><td>White</td><td>American, Australian, British, Canadian, White, Caucasian, European, French, German, Italian</td></tr>
<tr><td>Asian</td><td>Asian, Chinese, Japanese, Indonesian, Indian, Korean, Pakistani, Thai, Filipino, Brown</td></tr>
<tr><td>Black</td><td>African, African-American, Black, Congolese, Egyptian, Ethiopian, Haitian, Jamaican, Kenyan, Nigerian</td></tr>
</table>
</td></tr>
<tr><td><b>Big Tech Words</b></td><td>Big Tech companies based on [3]. Such as Google, Amazon, and Facebook</td></tr>
<tr><td><b>Top University Words</b></td><td>The top 50 universities from the 2024 Times Higher Education rankings</td></tr>
</table>

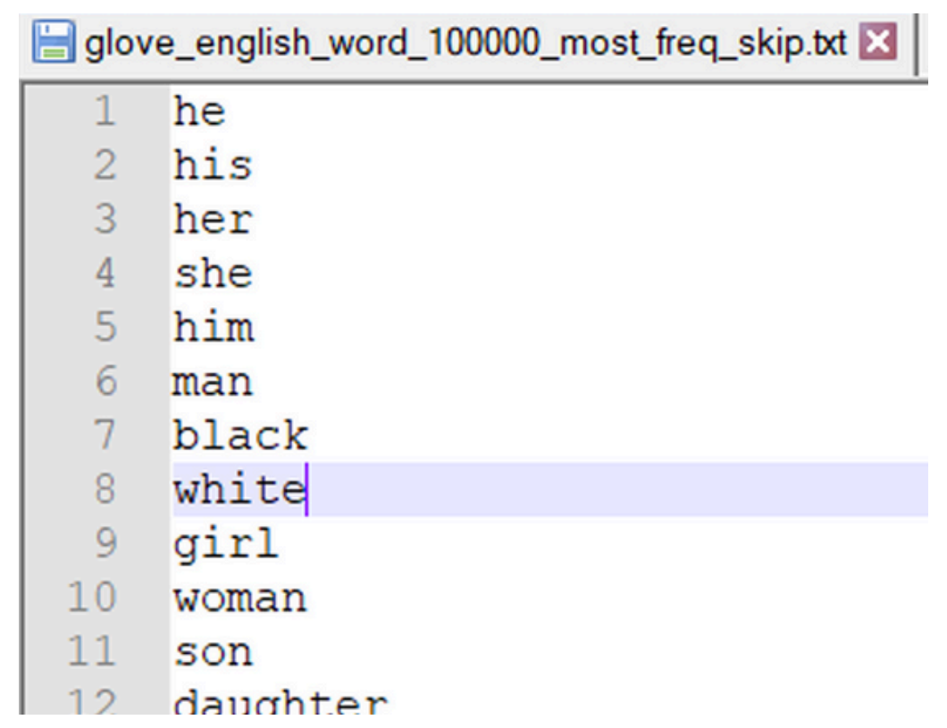
WORK FLOW



SC-WEAT [2]

- Measures bias using cosine similarity between word vectors.

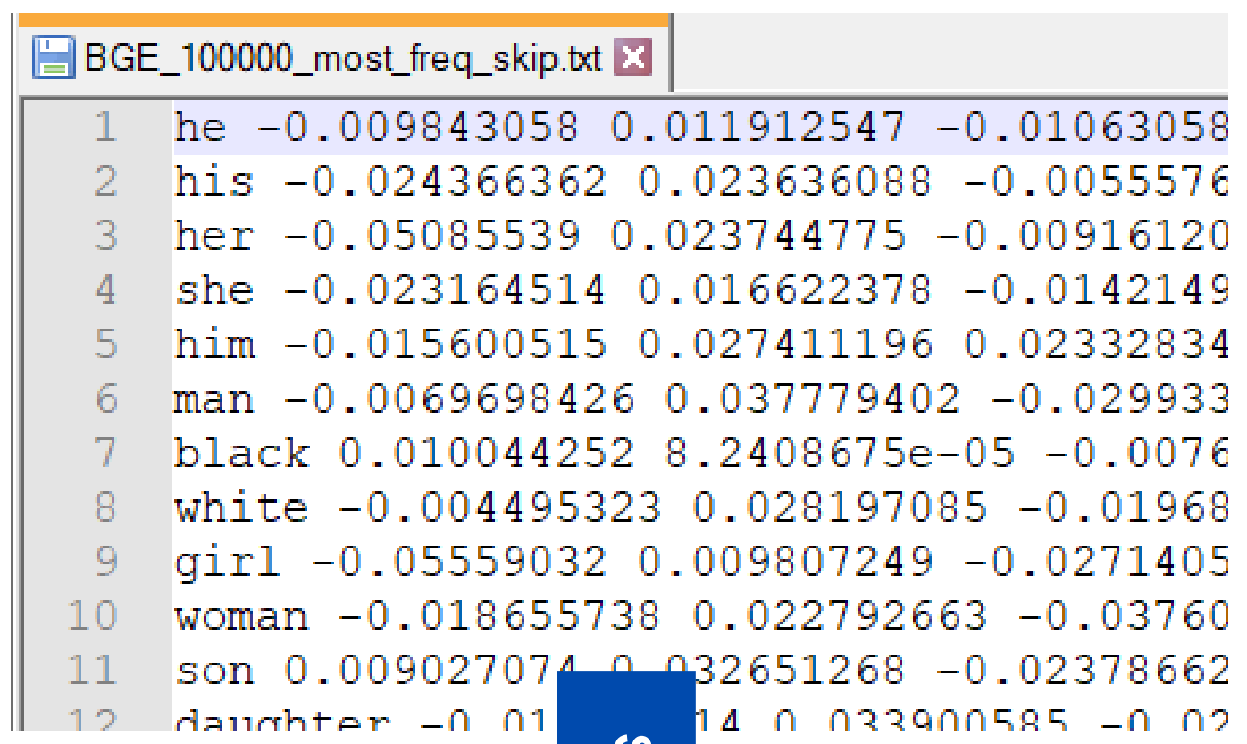
$$ES(\vec{w}, A, B) = \frac{\mathrm{mean}_{a \in A} \cos(\vec{w}, \vec{a}) - \mathrm{mean}_{b \in B} \cos(\vec{w}, \vec{b})}{\mathrm{std\_dev}_{x \in A \cup B} \cos(\vec{w}, \vec{x})}$$



glove_english_word_100000_most_freq_skip.txt

```
he
his
her
she
him
man
black
white
girl
woman
son
daughter
```

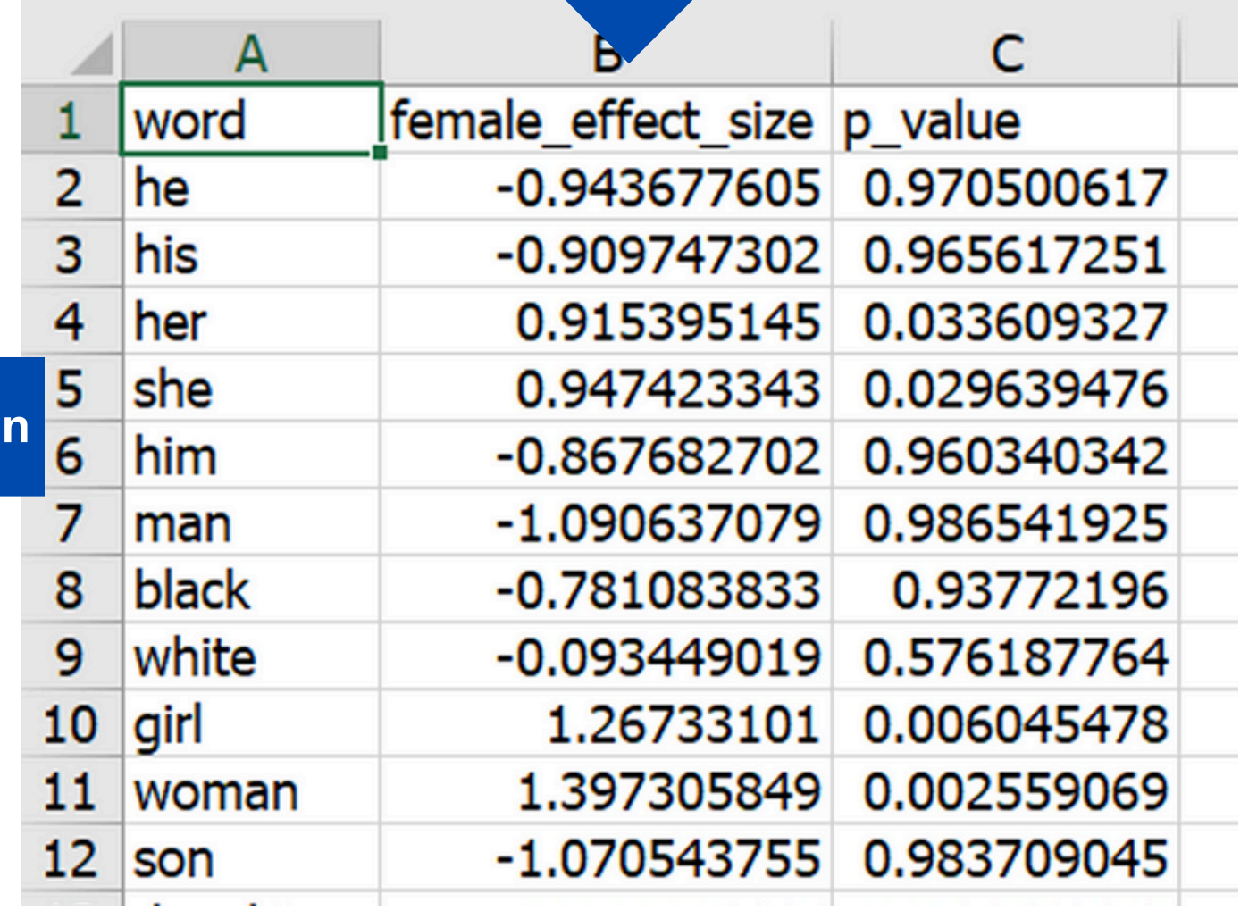
Embedding Models



BGE_100000_most_freq_skip.txt

```
he -0.009843058 0.011912547 -0.01063058
his -0.024366362 0.023636088 -0.0055576
her -0.05085539 0.023744775 -0.00916120
she -0.023164514 0.016622378 -0.0142149
him -0.015600515 0.027411196 0.02332834
man -0.0069698426 0.037779402 -0.029933
black 0.010044252 8.2408675e-05 -0.0076
white -0.004495323 0.028197085 -0.01968
girl -0.05559032 0.009807249 -0.0271405
woman -0.018655738 0.022792663 -0.03760
son 0.009027074 0.032651268 -0.02378662
daughter -0.01[illegible]14 0.033900585 -0.02
```

SC-WEAT Algorithm



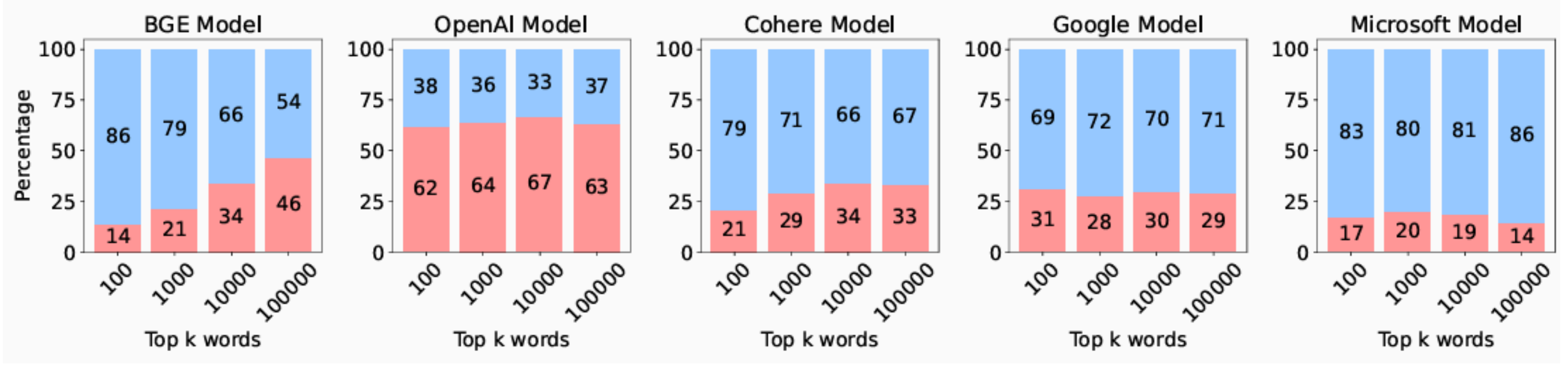
	A	B	C
1	word	female_effect_size	p_value
2	he	-0.943677605	0.970500617
3	his	-0.909747302	0.965617251
4	her	0.915395145	0.033609327
5	she	0.947423343	0.029639476
6	him	-0.867682702	0.960340342
7	man	-1.090637079	0.986541925
8	black	-0.781083833	0.93772196
9	white	-0.093449019	0.576187764
10	girl	1.26733101	0.006045478
11	woman	1.397305849	0.002559069
12	son	-1.070543755	0.983709045

Analysis & Virtualization

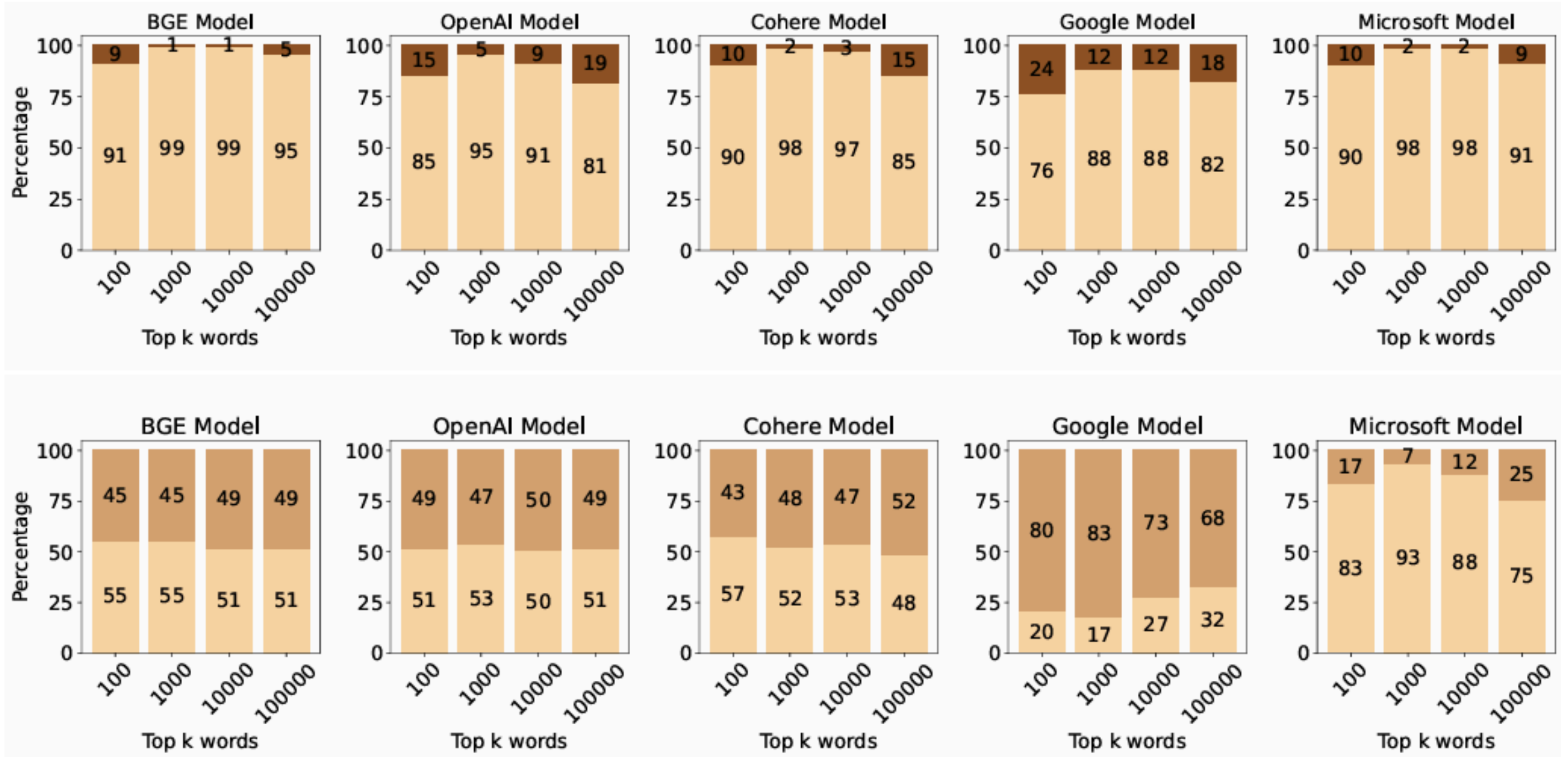
Analysis

- Bias Analysis by Frequency Range and Effect Size
- Semantic Categories of Gender- and Race-Associated Words
- Bias in Big Tech and Higher Education Contexts

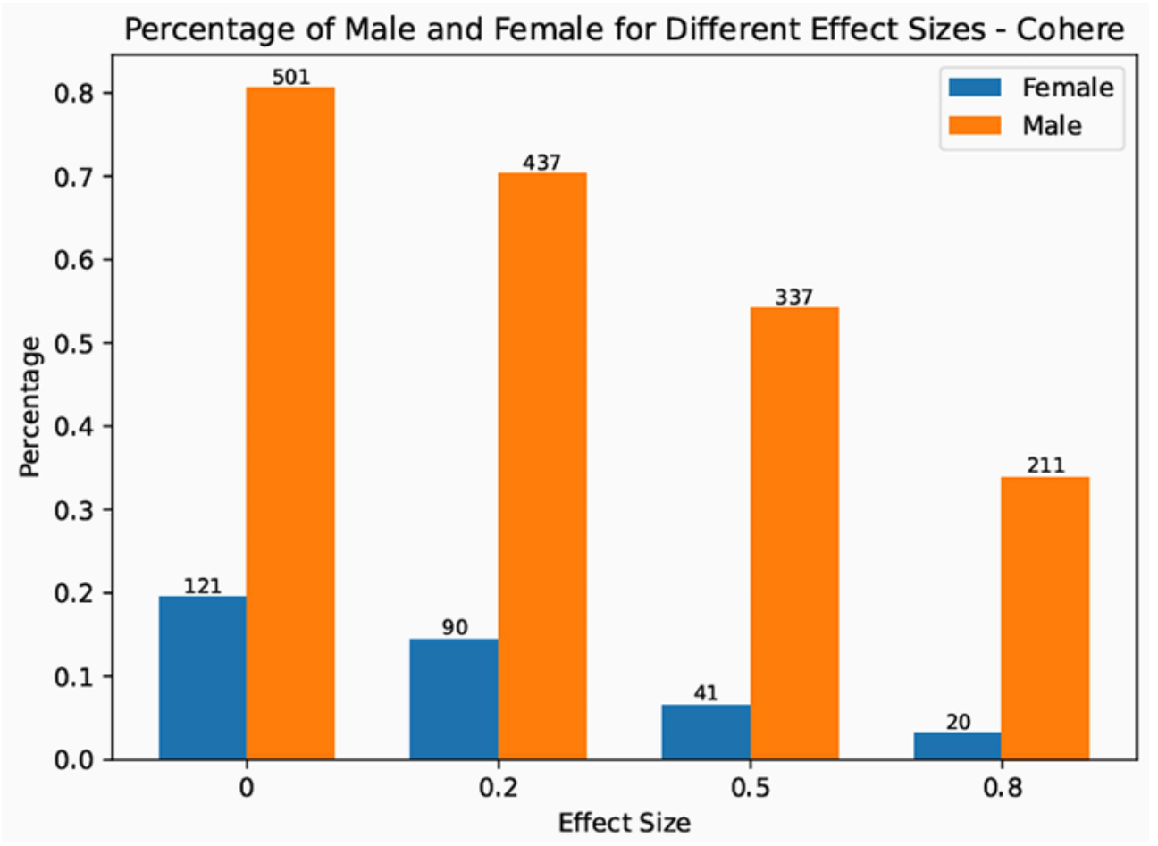
RESULTS



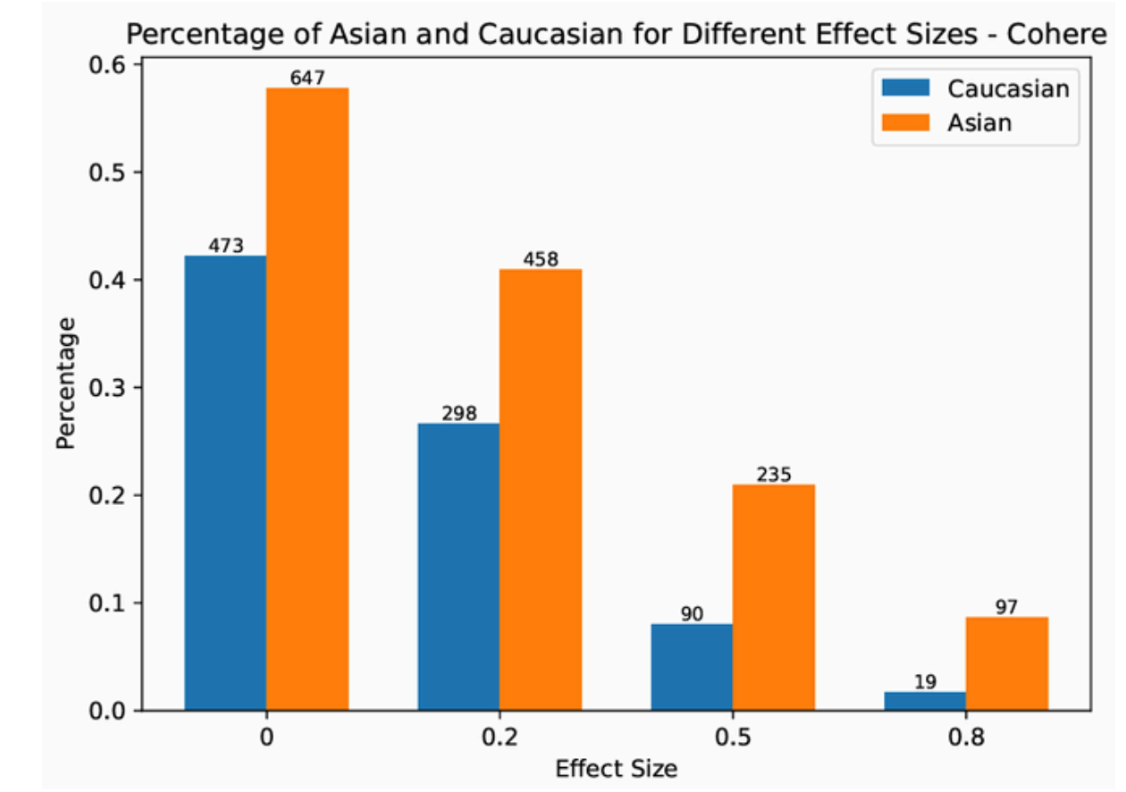
Gender Association of Top Words: Male is light blue, female is pink



Race Association of Top Words.1st row: White (lighter color) vs Black (darker color); 2nd row: White (lighter color) vs Asian (darker color)



Big Tech Association by Gender



Top University Association by Race

CONCLUSION

- **Male** group association dominates in most models
- **Black** group consistently underrepresented
- **Male** / **Asian** groups dominate in Big Tech
- **Male** / **Caucasian** groups dominate in Higher Education

REFERENCES

[1] Eric Michael Smith et al. ""I'm sorry to hear that": Finding new biases in language models with a holistic descriptor dataset". In: Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing. Abu Dhabi, United Arab Emirates: Association for Computational Linguistics, 2022, pp. 9180–9211.

[2] Aylin Caliskan et al. "Gender bias in word embeddings: A comprehensive anal ysis of frequency, syntax, and semantics". In: Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society. 2022, pp. 156–170.

[3] Mohamed Abdalla and Moustafa Abdalla. "The Grey Hoodie Project: Big to bacco, big tech, and the threat on academic integrity". In: Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society. 2021, pp. 287–297.

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