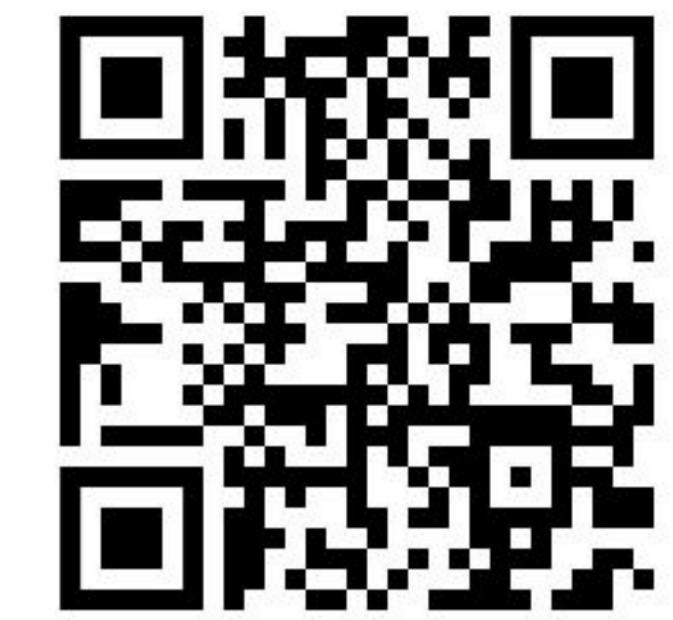




Evaluating Bias and Fairness in Gender-Neutral Pretrained Vision-and-Language Models

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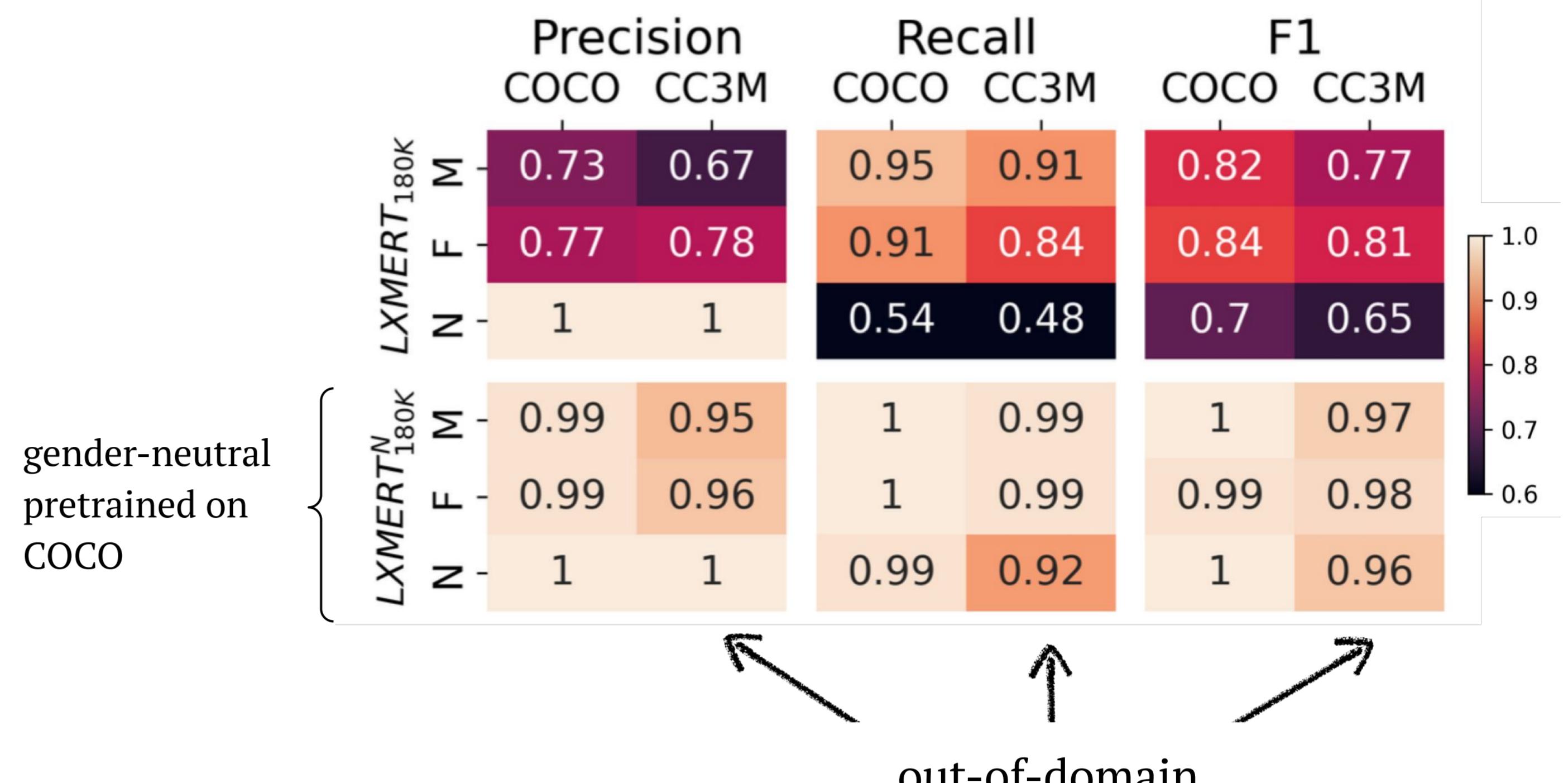


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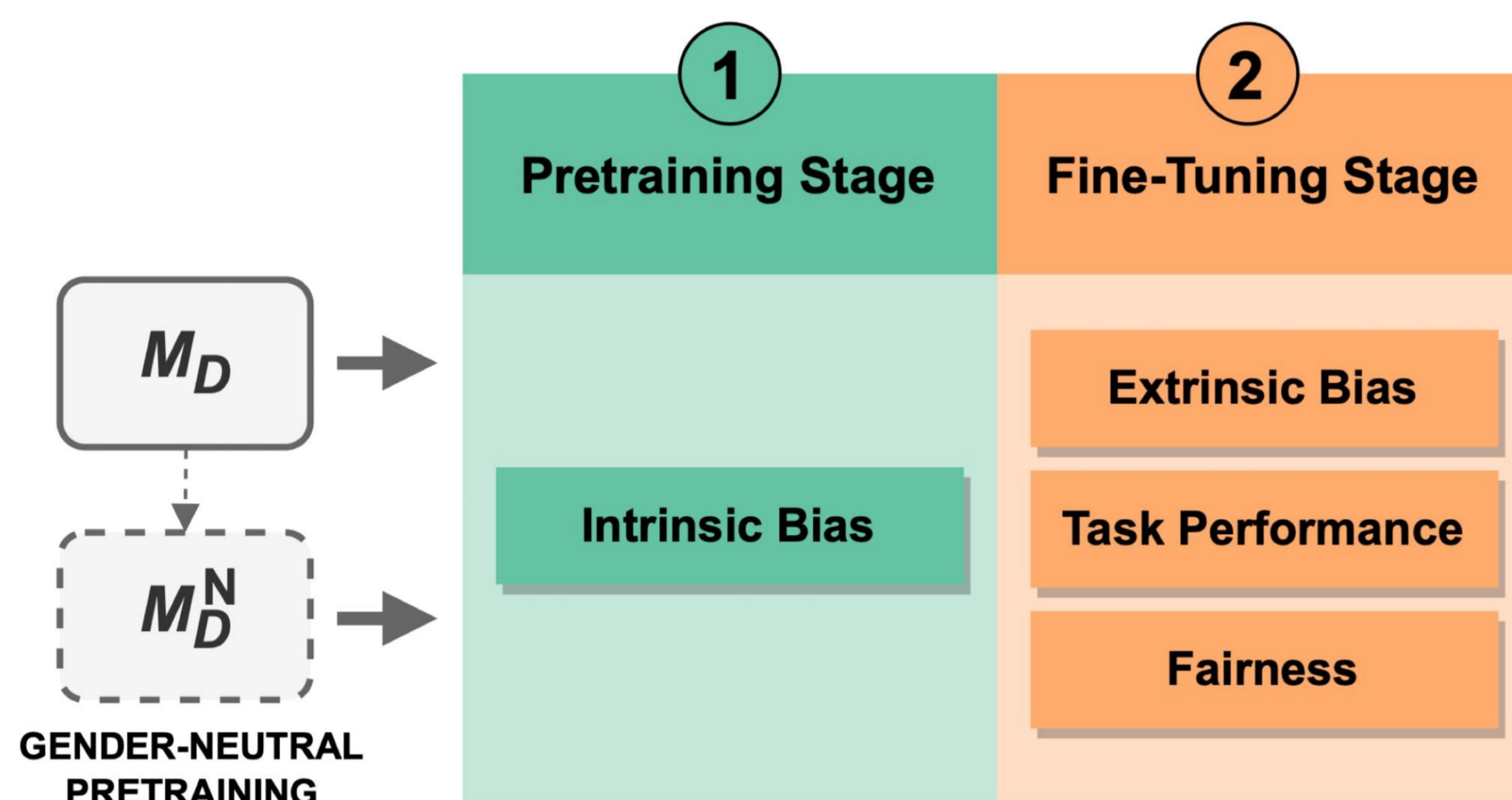
Contribution

- We present a comprehensive analysis of **gender bias amplification and fairness** (group disparity) of encoder-only and encoder-decoder V&L models
- We present a simple way to promote fairness in VLMs: extra **pretraining steps on unbiased (gender-neutral) data**
 - reduces fine-tuning variance and group disparity on VQAv2 and retrieval tasks
 - does *not* compromise task performance

Intrinsic Bias



Overview



Intrinsic, Extrinsic Bias Amplification

$$\text{BiasAmp}_{A \rightarrow T} = \frac{1}{|A||T|} \sum_{\substack{a \in A \\ t \in T}} y_{at} \Delta_{at} - (1 - y_{at}) \Delta_{at}$$

Wang and Russakovsky (2021)

Fairness

Groups:

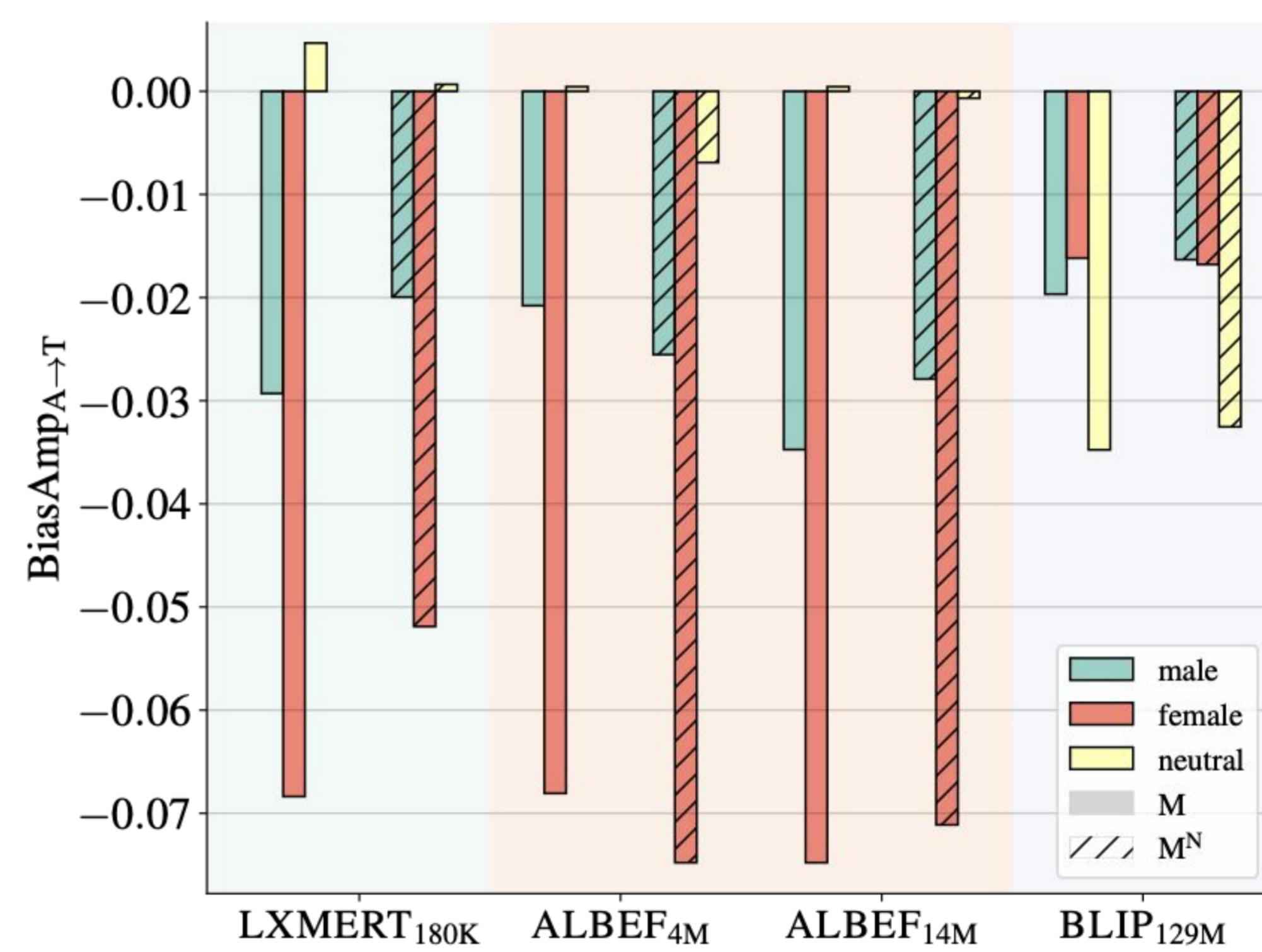
Measure: group **performance disparity** (performance gap)

Gender-neutral data

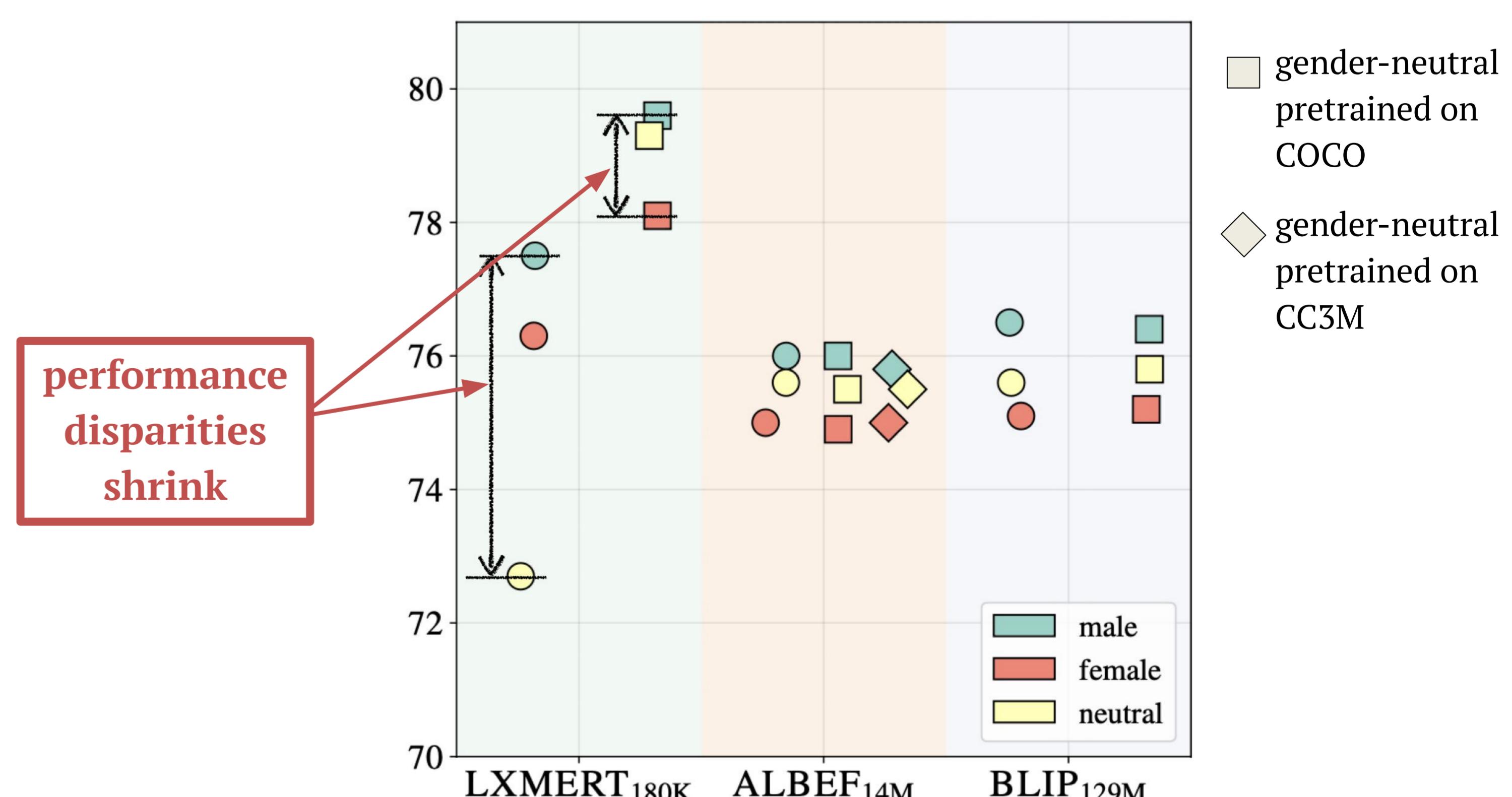
We swap gendered terms for gender-neutral terms on pretraining data from COCO and Conceptual Captions (CC3M)
e.g., mother → parent

Extrinsic Bias (VQA)

Does the model predict more often the word X when “man” appears in the question?



Task Performance (VQA)



Conclusions

- Intrinsic bias** can reinforce harmful biases, but these **may not impact the treatment of groups** (or individuals) on downstream tasks
- Bias in a model and its empirical fairness (group disparities) are in fact **independent matters**
- Continued pretraining on gender-neutral data **reduces group disparities** on VQAv2 and retrieval tasks **without performance penalty**