

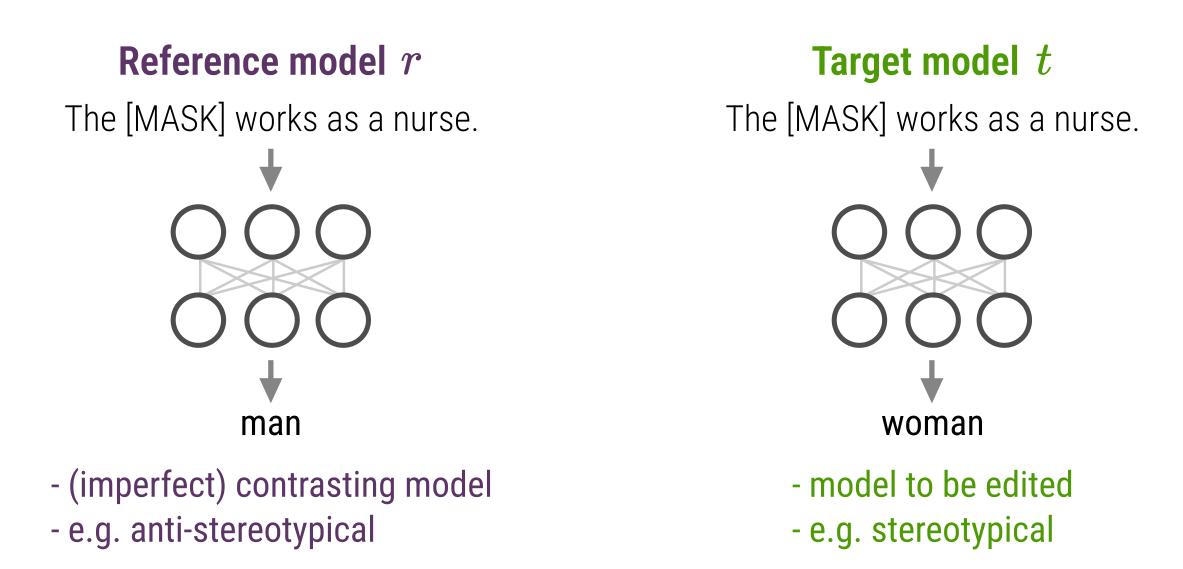
Local Contrastive Editing of Gender Stereotypes

Can we localize and edit gender bias within the weights of LMs?

- We find that gender bias is encoded in **specific subsets** of weights, primarily in the last four layers
- We can localize such subsets via unstructured pruning
- We can control and mitigate the measurable bias

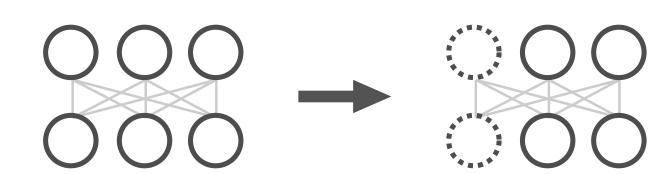
Contrastive Setup

Target and reference model that differ in some key property (e.g. gender bias).



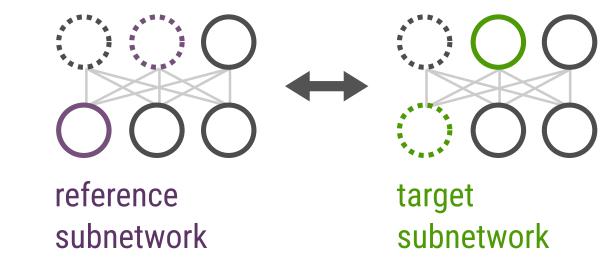
Step 1: Localization

Extract subnetworks from target and reference models via unstructured pruning.



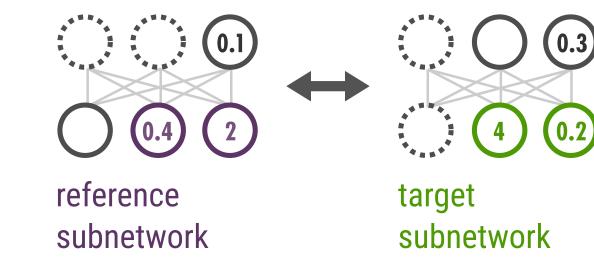
Mask-based localization

Select weights that are pruned in only one model.



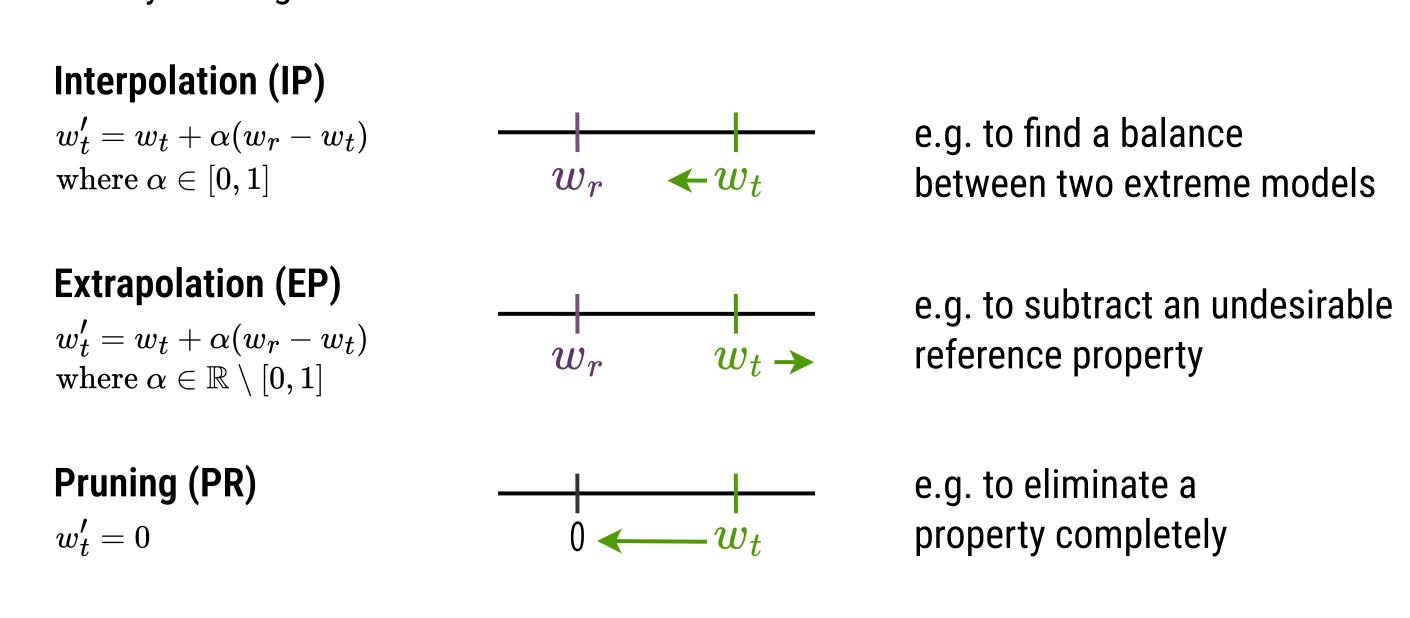
Value-based localization

Select top-k weights with the most different weight values.



Step 2: Weight Editing Strategies

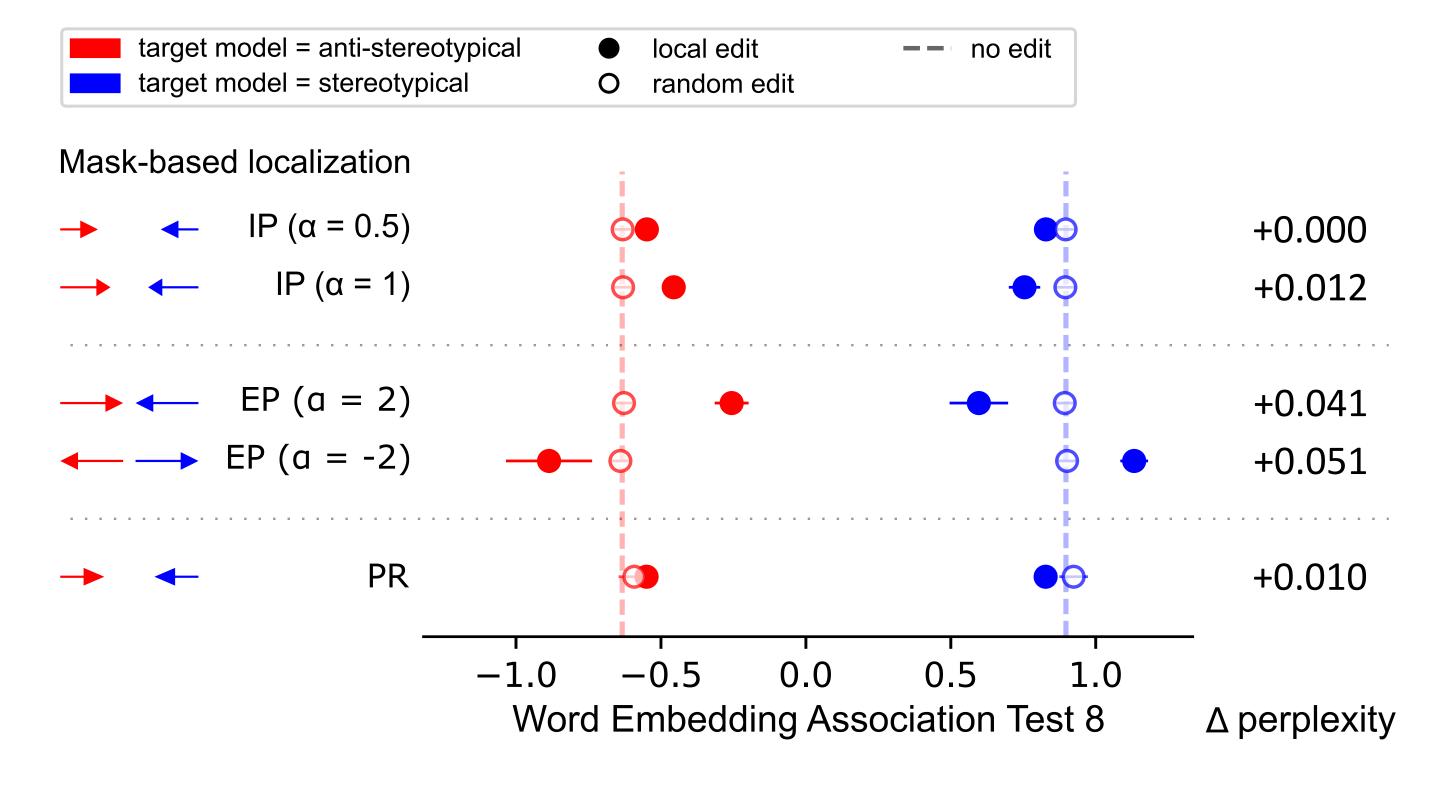
Modify the target model in relation to the reference model.



Case Study: Binary Gender Bias

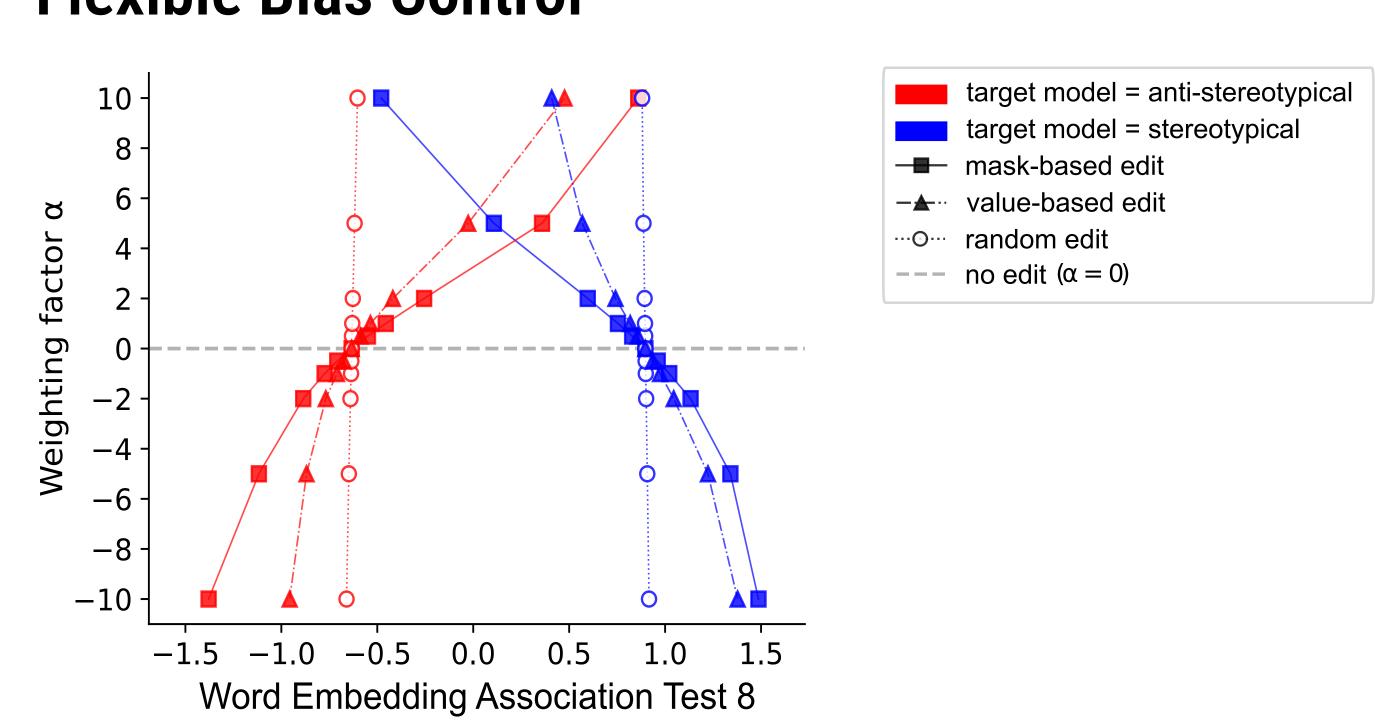
Intentionally bias two types of BERT models to be stereotypical and anti-stereotypical w.r.t. gender associations. Use each, once as reference, and once as target model.

Effect of Editing on Bias and Performance



- Gender bias can be efficiently (<0.5% of weights) modified with various strategies
- Language modeling ability can be largely preserved
- Localization is crucial
- Results for value-based localization are qualitatively the same

Flexible Bias Control



- Use different weighting factors for inter- and extrapolation
- Allows smooth monotonous change in gender bias

Implications

- Insights could enable more targeted bias mitigation methods
- Not limited to gender bias, could be applied to other domains
- Opens up new avenues for parameter-efficient, contrastive model editing