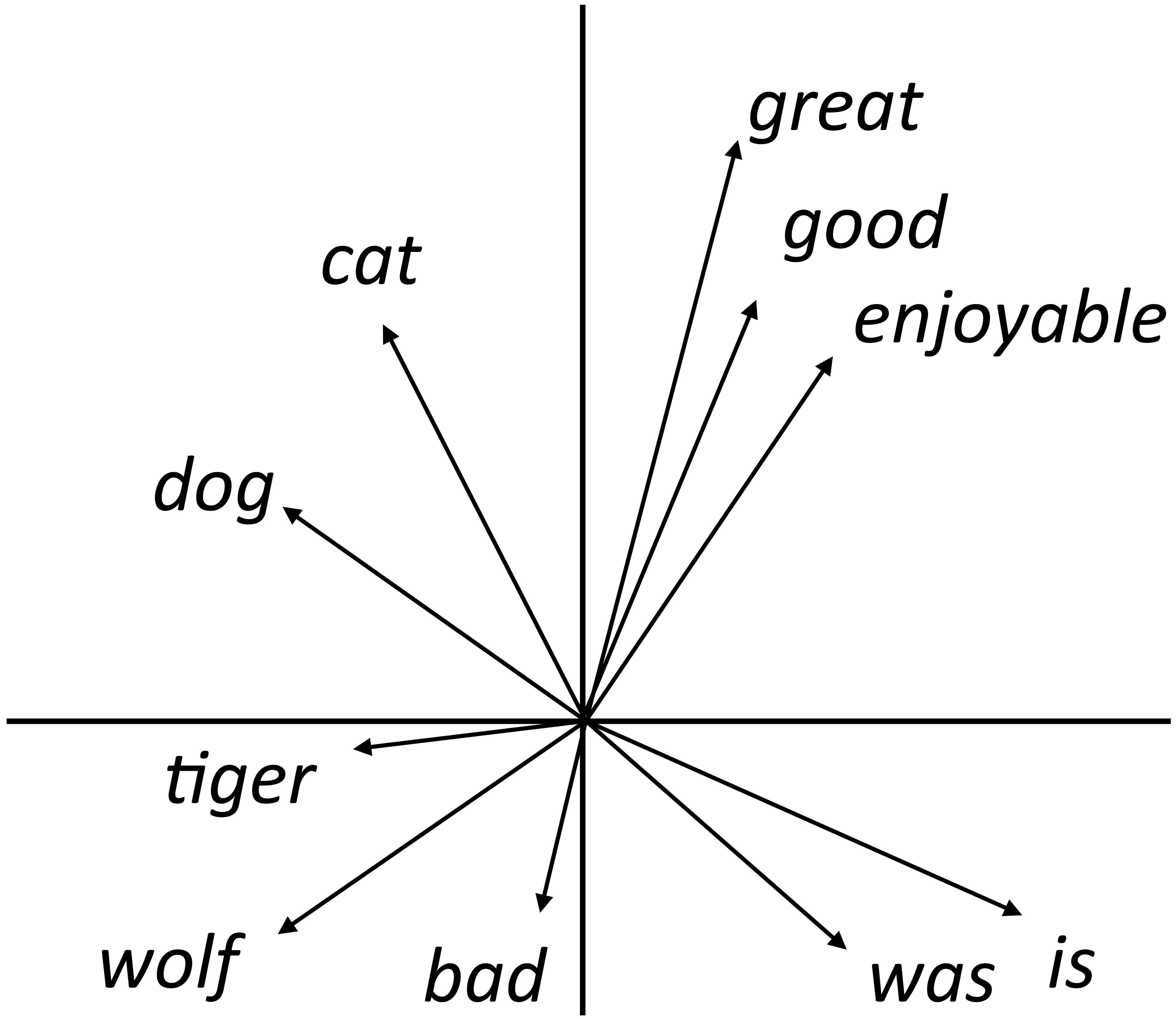
Word Embedding Evaluation

Evaluating Word Embeddings

- What properties of language should word embeddings capture?
- Similarity: similar words are close to each other
- Analogy:

  good is to best as smart is to ???

  Paris is to France as Tokyo is to ???
- Bias?



Similarity

Method	WordSim Similarity	WordSim Relatedness	Bruni et al. MEN	Radinsky et al. M. Turk	Luong et al. Rare Words	Hill et al. SimLex
PPMI	.755	**.697**	.745	.686	.462	.393
SVD	**.793**	.691	**.778**	.666	**.514**	.432
SGNS	**.793**	.685	.774	**.693**	.470	**.438**
GloVe	.725	.604	.729	.632	.403	.398

- SVD = singular value decomposition on PMI matrix
- GloVe does not appear to be the best when experiments are carefully controlled, but it depends on hyperparameters + these distinctions don't matter in practice

Levy et al. (2015)

Analogies

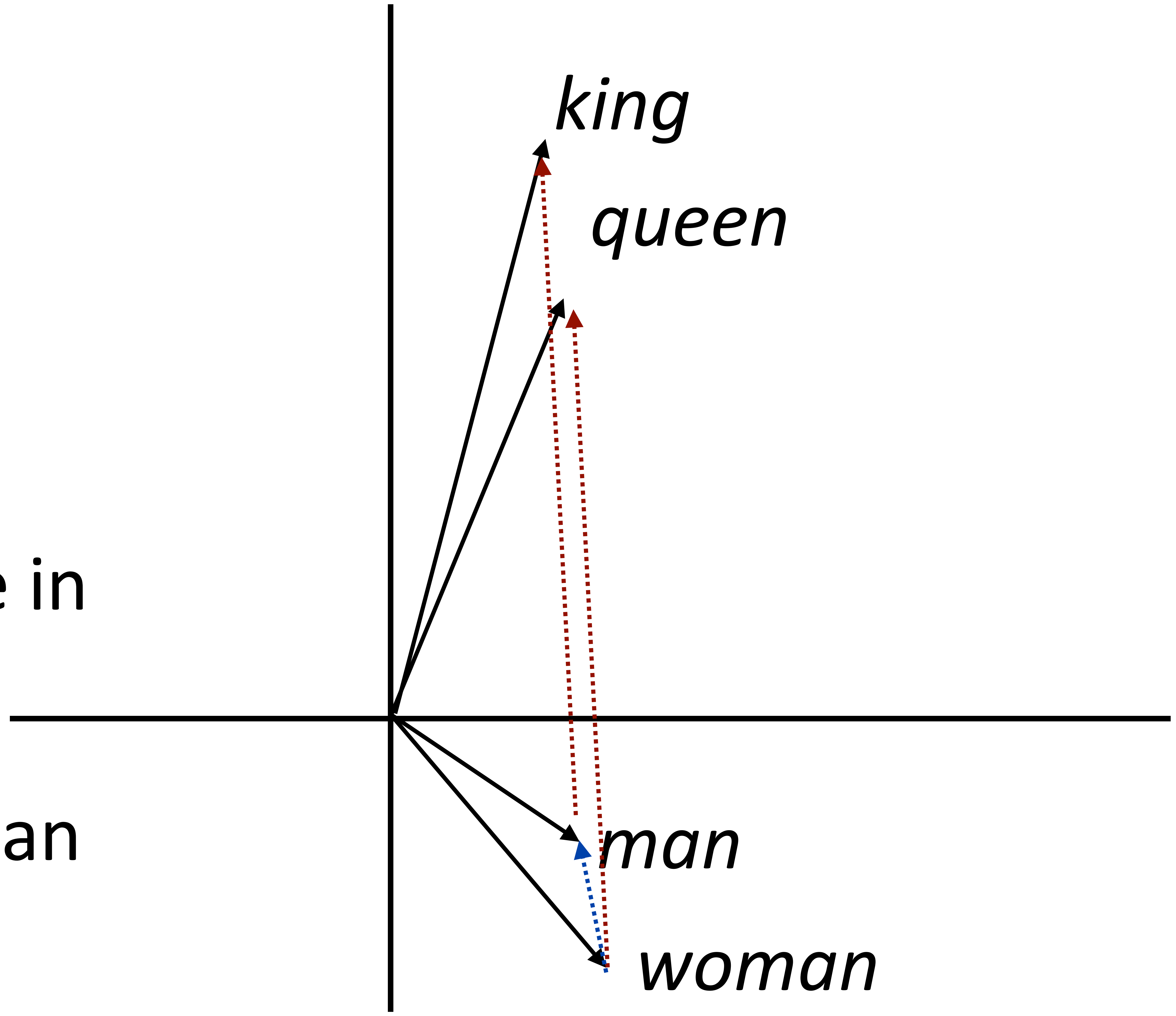
(king - man) + woman = queen

king + (woman - man) = queen

- Why would this be?

- woman - man captures the difference in the contexts that these occur in

- Dominant change: more “he” with man and “she” with woman — similar to difference between king and queen



Bias in Word Embeddings

- Identify *she* - *he* axis in word vector space, project words onto this axis

Extreme *she* occupations

1. homemaker	2. nurse	3. receptionist
4. librarian	5. socialite	6. hairdresser
7. nanny	8. bookkeeper	9. stylist
10. housekeeper	11. interior designer	12. guidance counselor

Extreme *he* occupations

1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. figher pilot	12. boss

Bolukbasi et al. (2016)

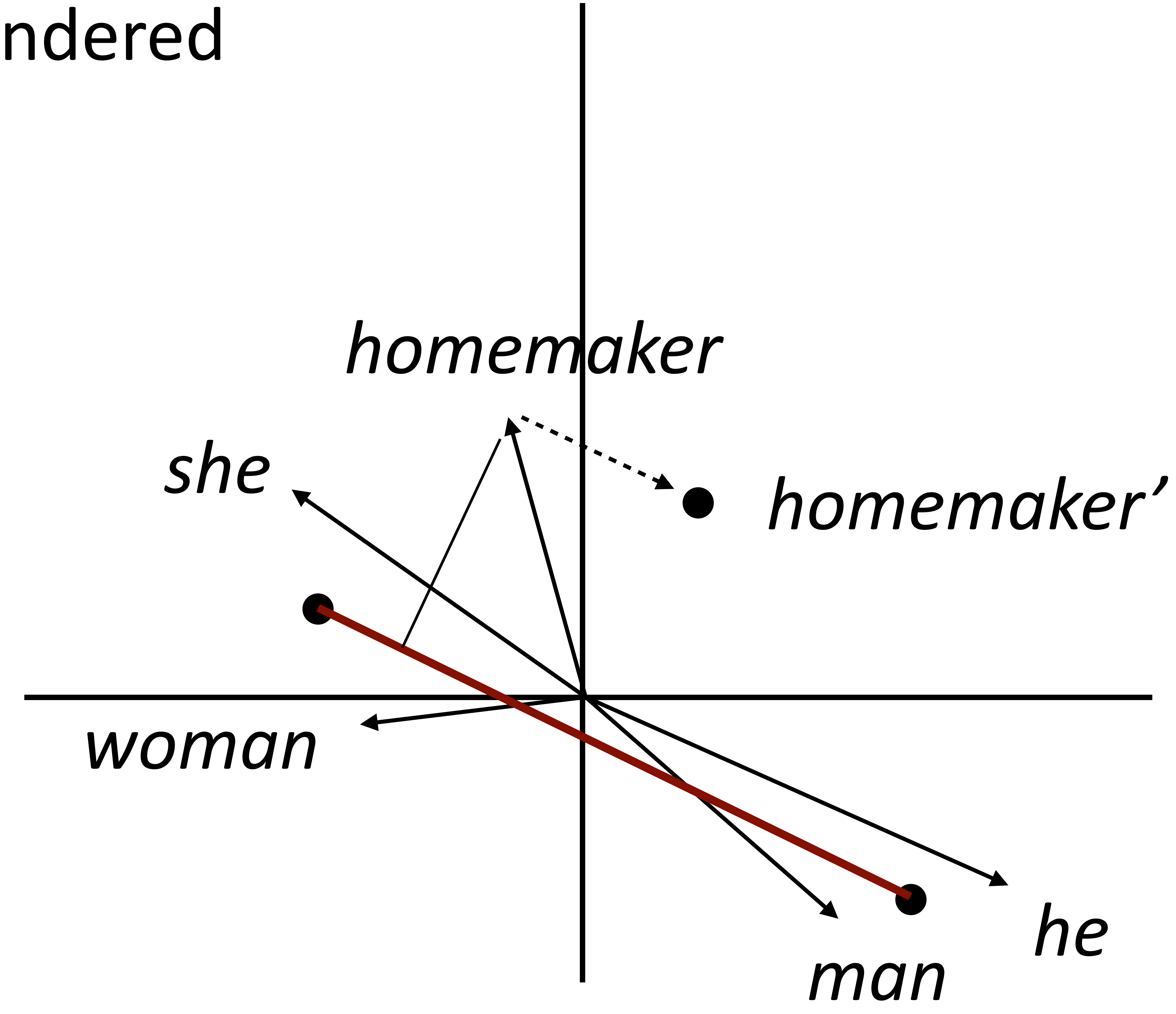
- Nearest neighbor of (b - a + c)

Racial Analogies	
black → homeless	caucasian → servicemen
caucasian → hillbilly	asian → suburban
asian → laborer	black → landowner
Religious Analogies	
jew → greedy	muslim → powerless
christian → familial	muslim → warzone
muslim → uneducated	christian → intellectually

Manzini et al. (2019)

Debiasing

- Identify gender subspace with gendered words
- Project words onto this subspace
- Subtract those projections from the original word

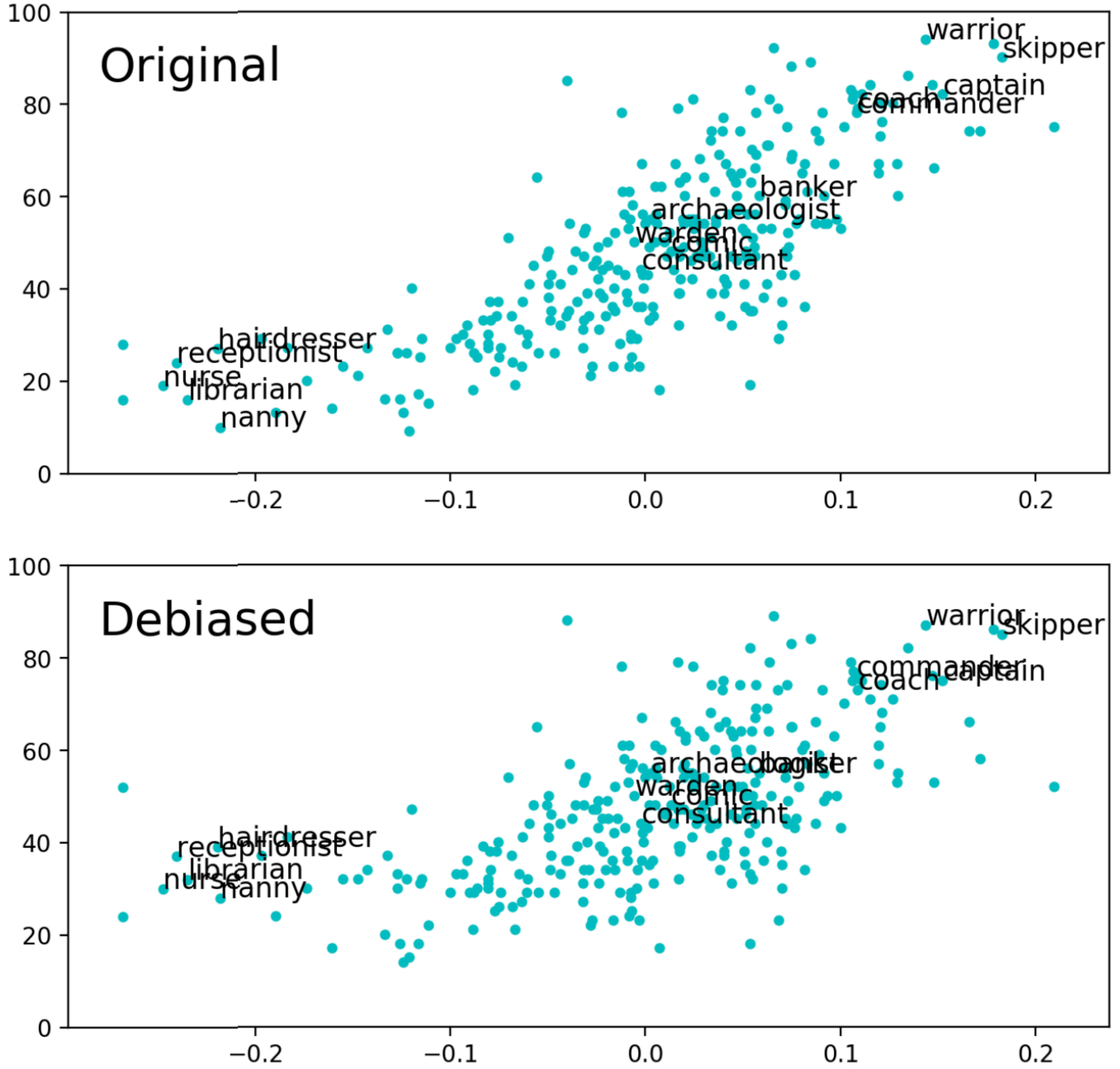


Bolukbasi et al. (2016)

Hardness of Debiasing

- Not that effective…and the male and female words are still clustered together

- Bias pervades the word embedding space and isn't just a local property of a few words



(a) The plots for HARD-DEBIASED embedding, before (top) and after (bottom) debiasing.

Gonen and Goldberg (2019)

Using Word Embeddings

- Approach 1: learn embeddings as parameters from your data
  - Often works pretty well, especially if data is large
- Approach 2: initialize using GloVe, keep fixed
  - Faster because no need to update these parameters
- Approach 3: initialize using GloVe, fine-tune
  - Usually works the best

Takeaways

- Continuous bag-of-words, Skip-gram, and Skip-gram with negative sampling are all similar ways to learn embeddings
- Matrix factorization approaches like GloVe are most standard
- Averaging inputs to feedforward networks can work well, will see other approaches later
- Later in the class: approaches to create “contextualized” word embeddings