



## What can go wrong with word embeddings?

- ▶ What's wrong with learning a word's "meaning" from its usage? Maybe some words are used in ways we don't want to replicate?
- ▶ What data are we learning from?
- ▶ What are we going to learn from this data?



## What do we mean by bias?

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

Extreme <i>she</i> 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 <i>he</i> occupations		
1. maestro	2. skipper	3. protege
4. philosopher	5. captain	6. architect
7. financier	8. warrior	9. broadcaster
10. magician	11. fighter pilot	12. boss

Bolukbasi et al. (2016)

- ▶ Nearest neighbor of (b - a + c)

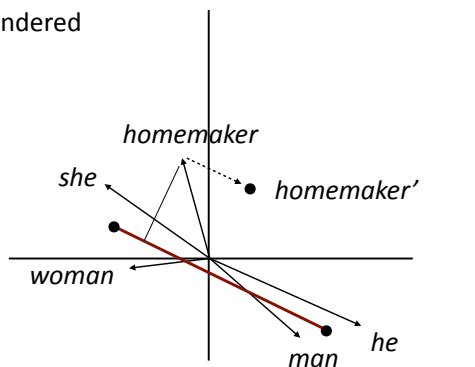
Racial Analogies	
black → homeless	caucasian → servicemen
caucasian → hillbilly	asian → suburban
asian → laborer	black → landowner
Religious Analogies	
jew → greedy	muslim → powerless
christian → familial	muslim → warzone
muslim → uneducated	christian → intellectually

Manzini et al. (2019)



## Debiasing

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

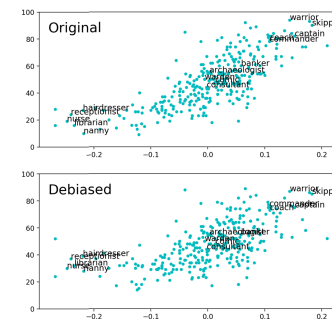


Bolukbasi et al. (2016)



## 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)