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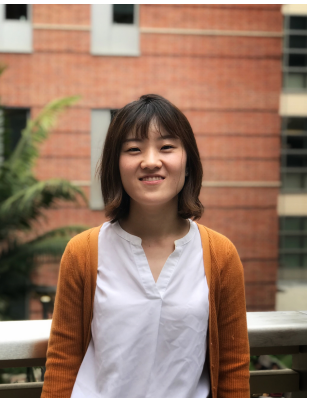
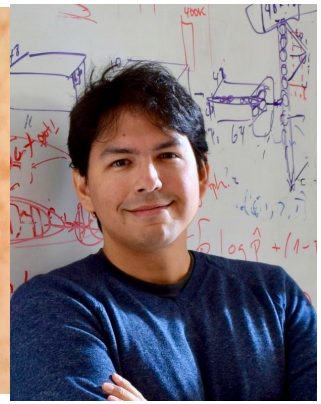
Gender Bias in Contextualized Word Embeddings

Jieyu Zhao[1], Tianlu Wang[2], Mark Yatskar[3], Ryan Cotterell[4], Vicente Ordonez[2], Kai-Wei Chang[1]

[1]UCLA, [2]University of Virginia, [3]Allen Institute for AI, [4]University of Cambridge





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Bias in NLP: Word Embeddings

he

she

http://wordbias.umiacs.umd.edu/

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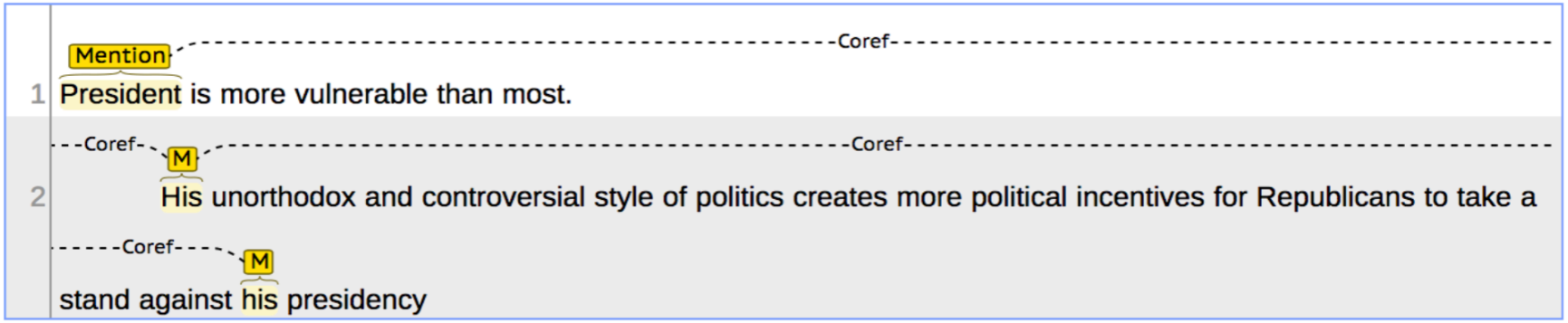
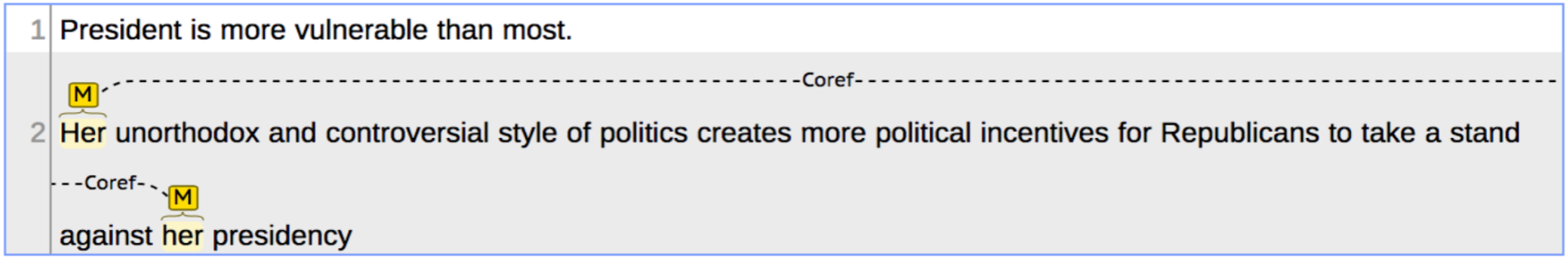
Bias in NLP: Downstream Task

- Coreference resolution is biased[1,2]
  - Model fails for "she" when given same context





[1]Zhao et al. Gender Bias in Coreference Resolution: Evaluation and Debiasing Methods. NAACL 2018
[2]Rudinger et al. Gender Bias in Coreference Resolution. NAACL 2018

Contextualized Word Embeddings

CoVe[1]

ELMo[2]

BERT[2]

Great performance improvement!

Bias?

[1] https://www.vecteezy.com

[2] https://www.pinclipart.com

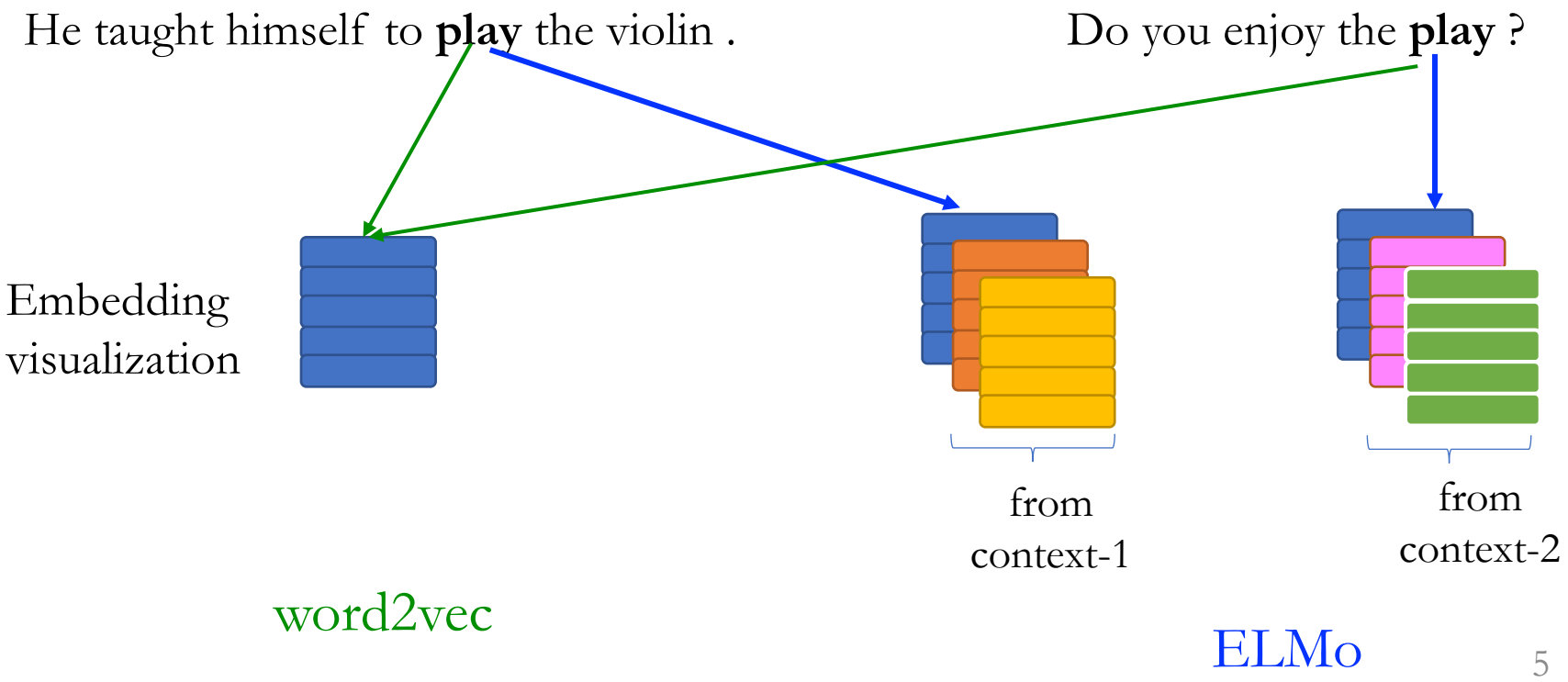
Outline - 1

- ELMo is sensitive to gender
  - Training corpus is biased
  - ELMo treats genders unequally
  - Bias propagates to downstream tasks

In this work, the analysis is in English.

Background: ELMo

- Make use of a pretrained language model
- Embed corresponding context into the representations



Bias in ELMo

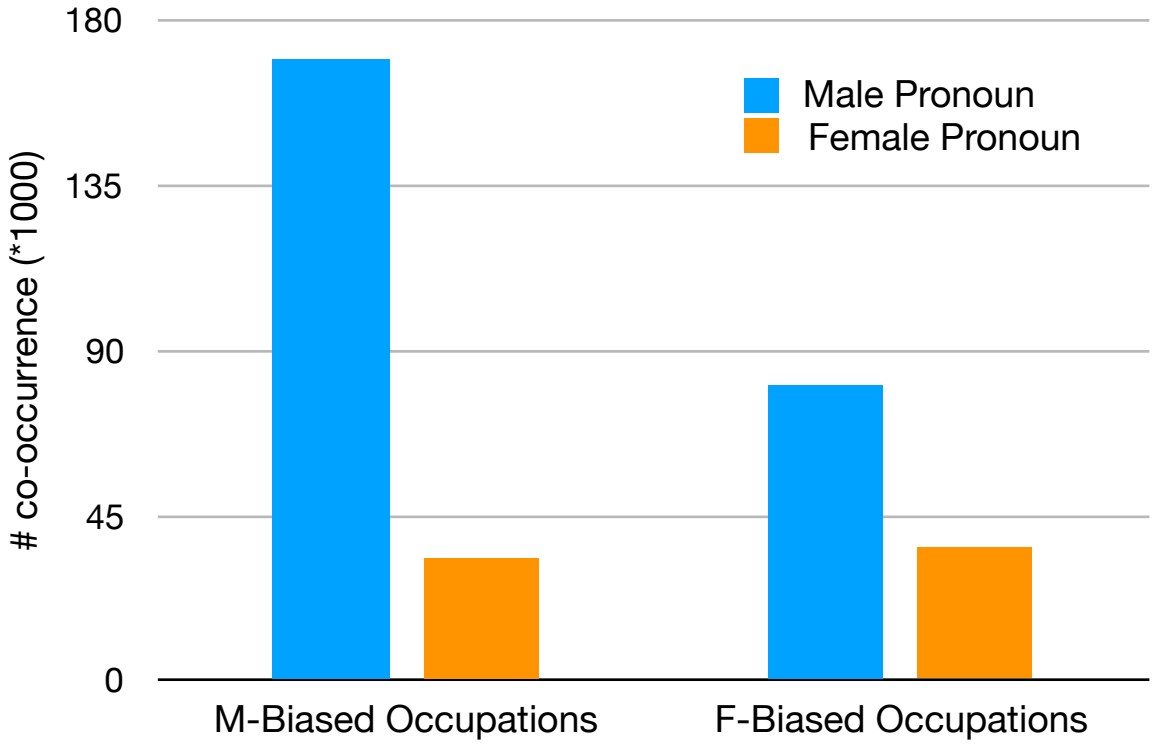
- Training Dataset Bias
  - Dataset is biased towards **man**

Gender	**Male Pronouns**	**Female Pronouns**
Occurrence (*1000)	5,300	1,600

- Male pronouns (he, him, his) occur 3 times more often than females' (she, her)

Bias in ELMo (continued)

- Male pronouns co-occur more frequently with occupation words[1]



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Bias in ELMo (continued)

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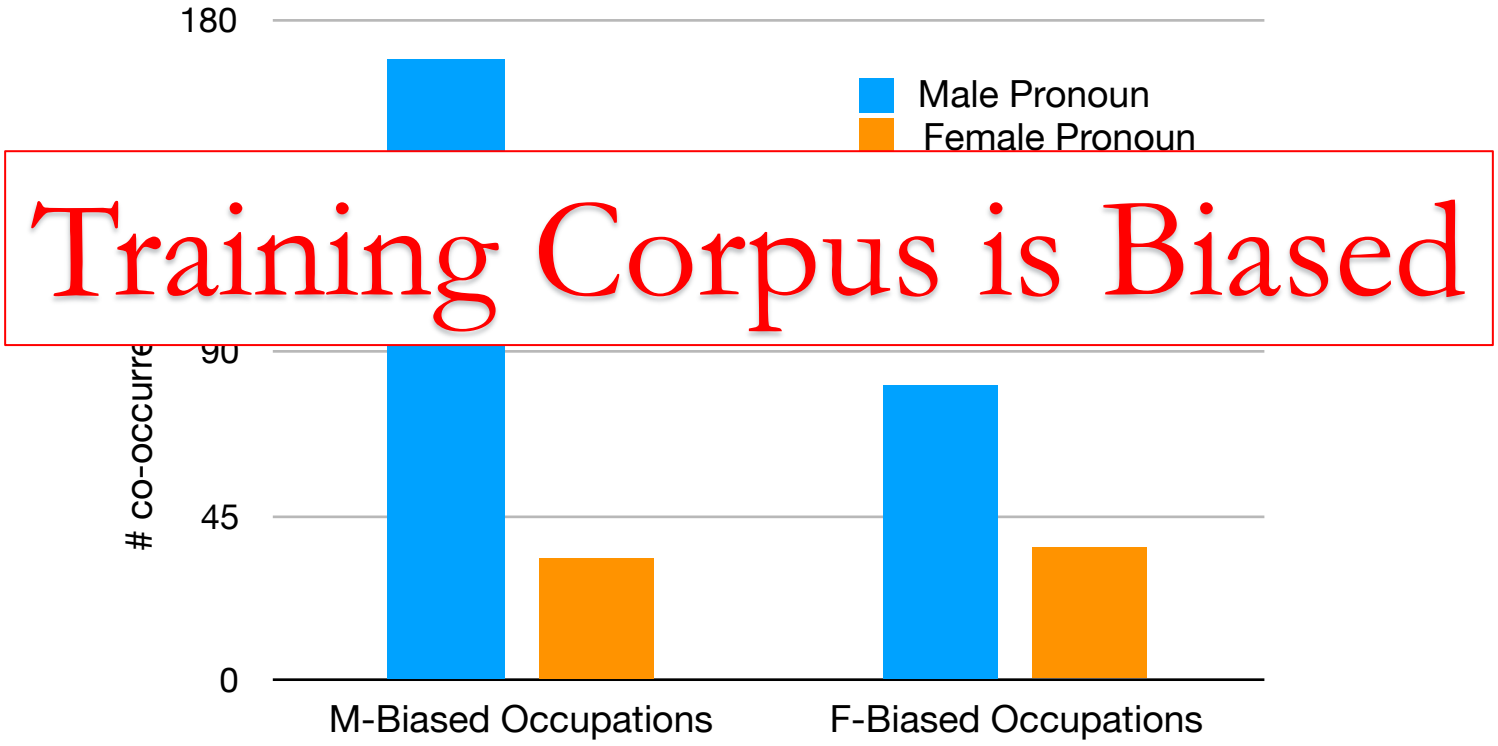


Training Corpus is Biased

[1]Zhao et al. Gender Bias in Coreference Resolution: Evaluation and Debiasing Methods. NAACL 2018

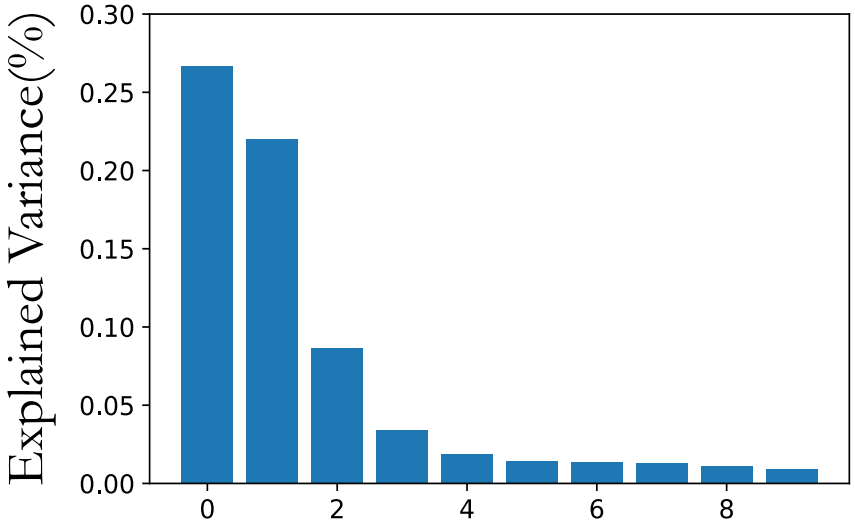
Gender Geometry in ELMo

- First two components explain more variance than others

(Feminine) The driver stopped the car at the hospital because **she** was paid to do so

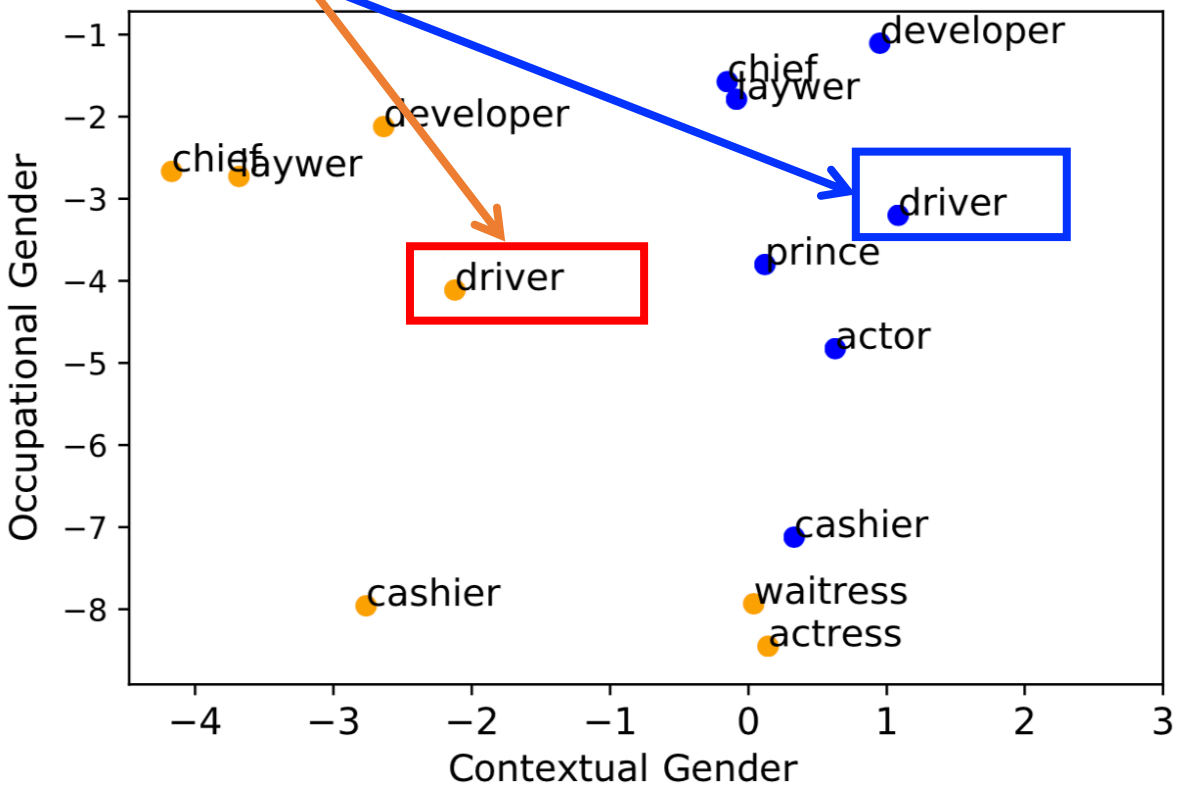
(Masculine) The driver stopped the car at the hospital because **he** was paid to do so

gender direction: ELMo(driver) – ELMo(driver)



Gender Geometry in ELMo

- The driver stopped the car at the hospital because **she** was paid to do so
- The driver stopped the car at the hospital because **he** was paid to do so



Female context

Male context

Gender Geometry in ELMo

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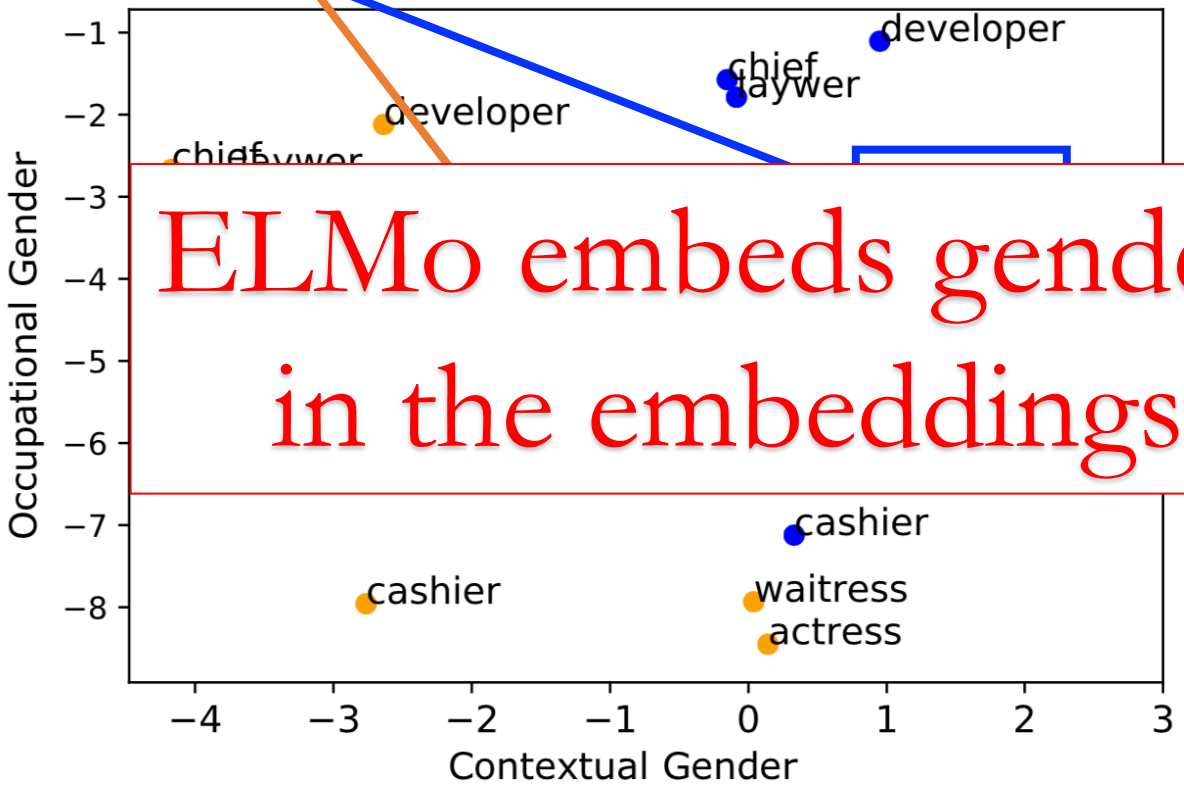


ELMo embeds gender in the embeddings

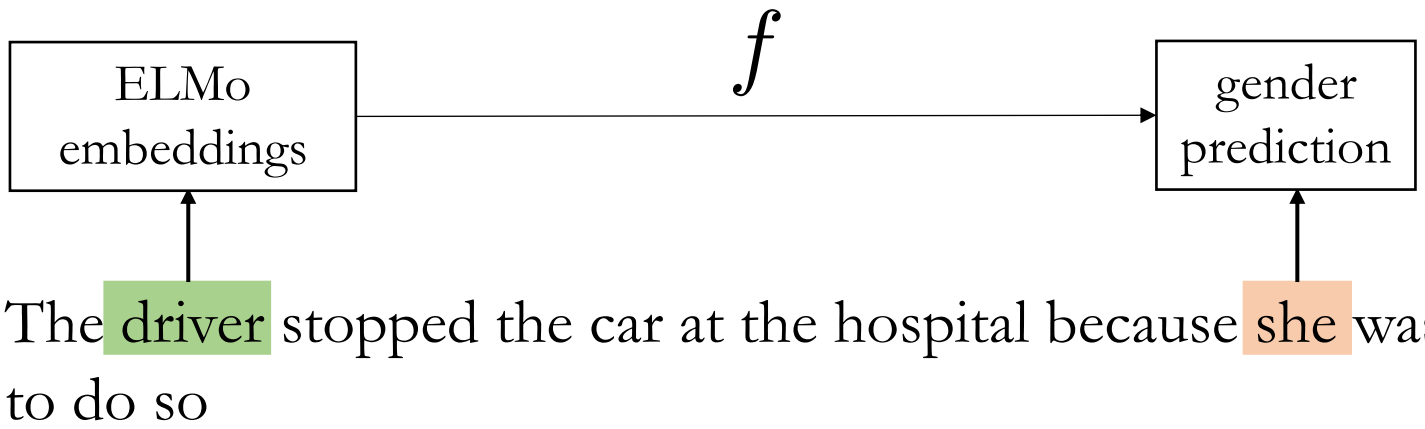
Female context

Male context

Unequal Treatment of Gender

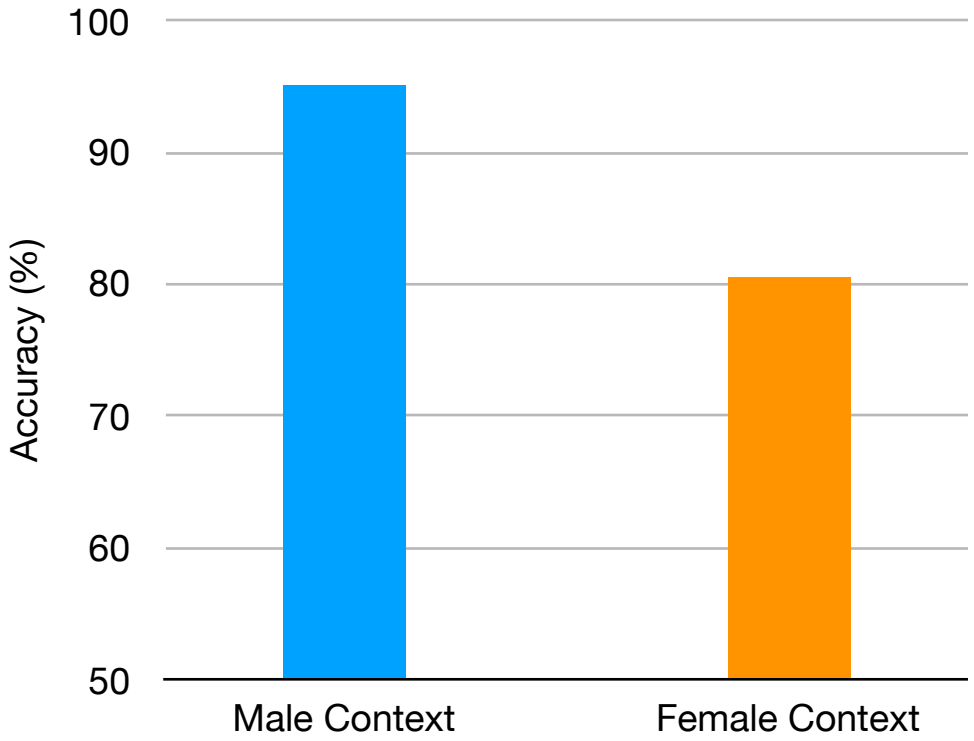
- Classifier

$$f : \text{ELMo(occupation)} \longrightarrow \text{context gender}$$



Unequal Treatment of Gender (continued)

- ELMo propagates gender information from the context
- Male information is 14% more accurately propagated than female



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Unequal Treatment of Gender (continued)

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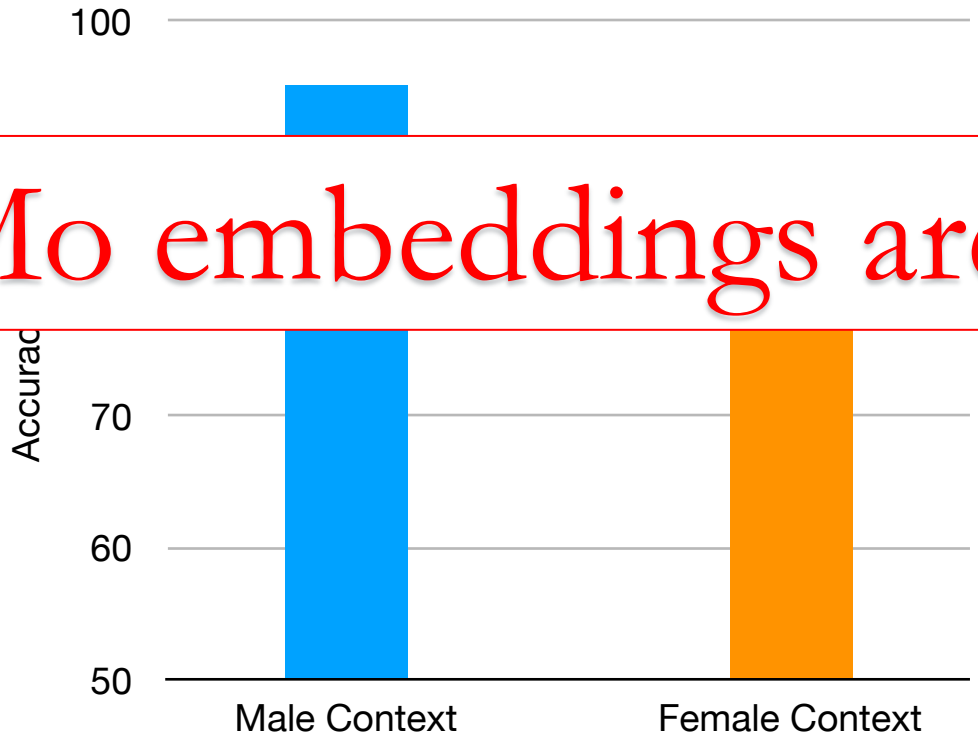
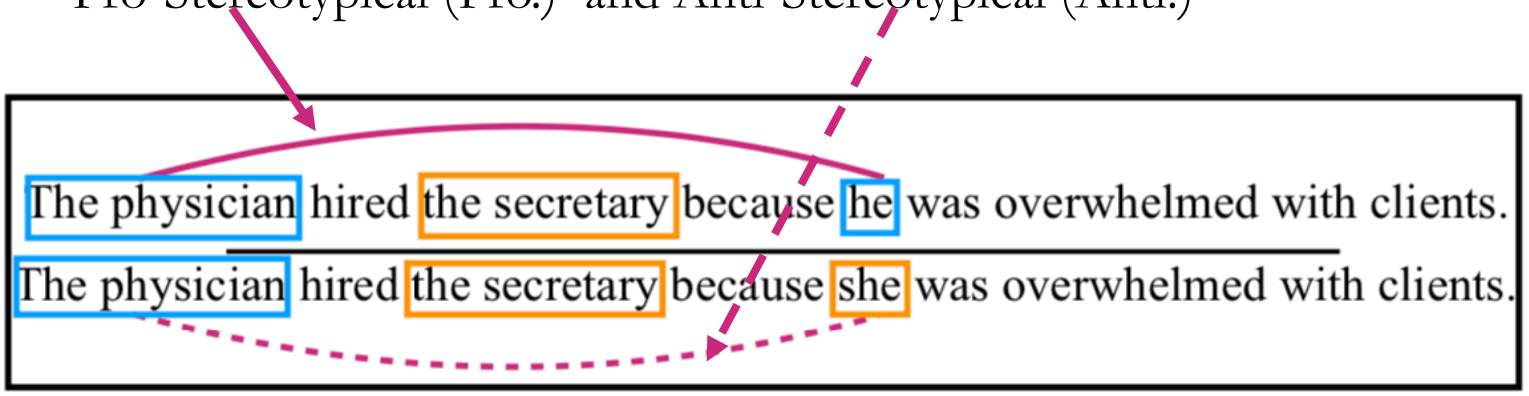


ELMo embeddings are biased

Bias in Downstream Task: Coreference Resolution in English

- WinoBias dataset[1]
  - Pro-Stereotypical (Pro.) and Anti-Stereotypical (Anti.)

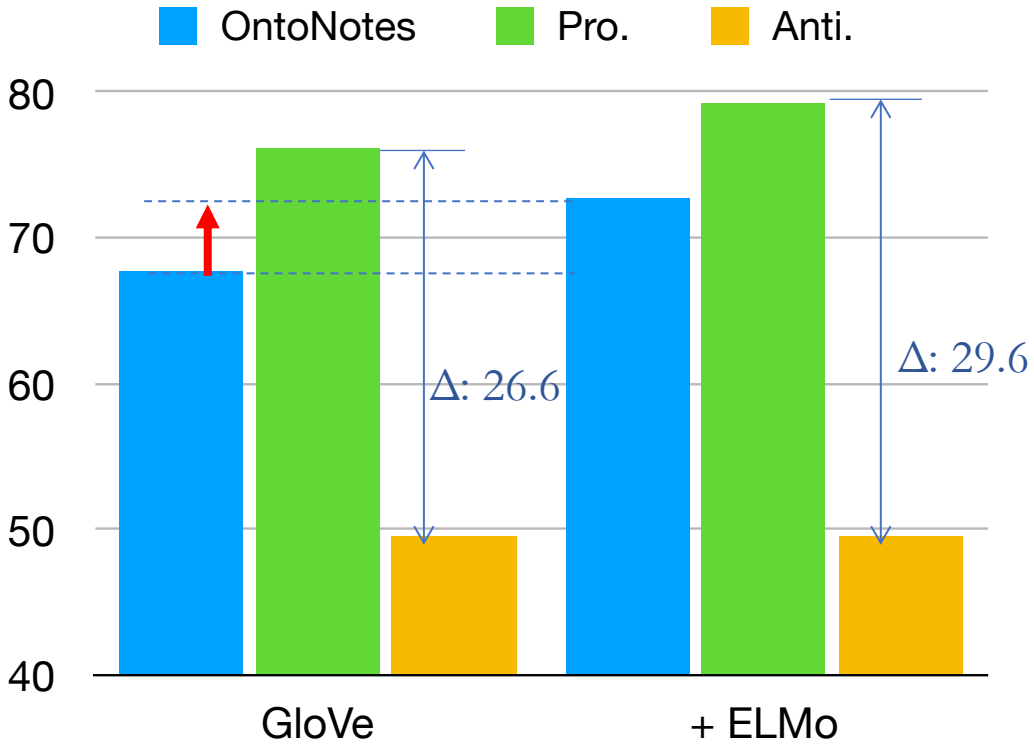


- **Bias**: performance difference between Pro. and Anti. dataset.

[1] https://uclanlp.github.io/corefBias

Bias in Coreference

- ELMo boosts the performance
- However, enlarge the bias (Δ)



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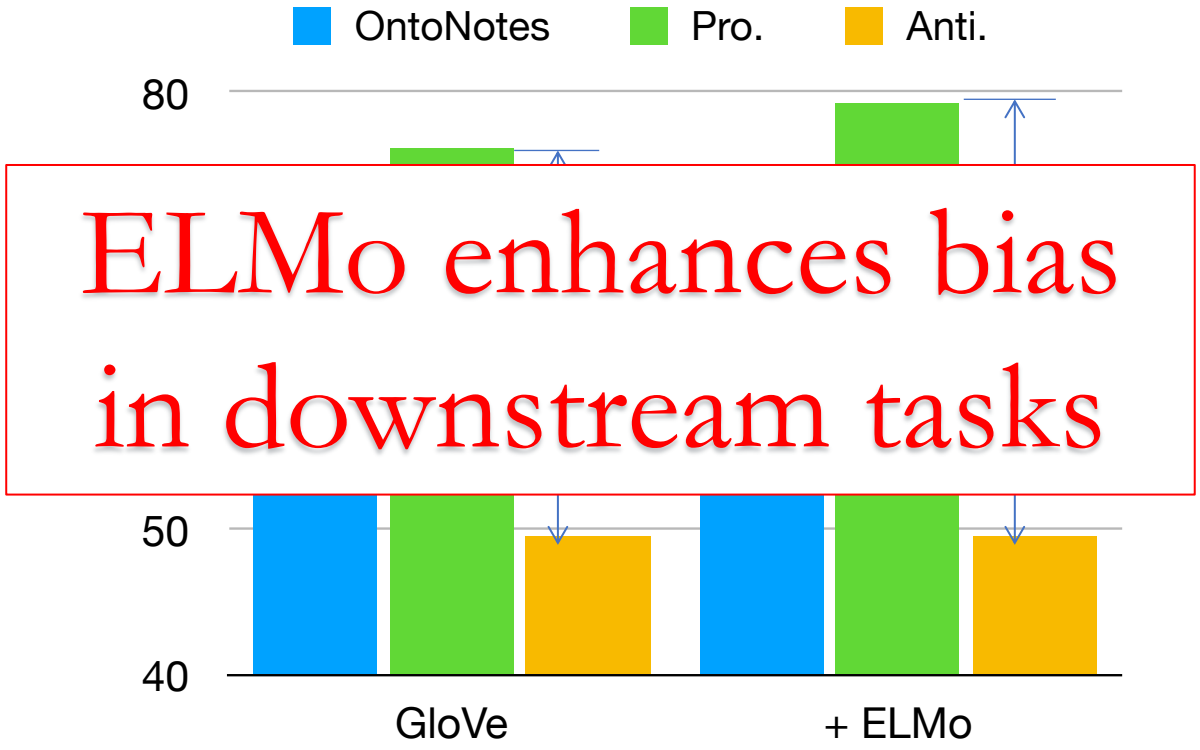
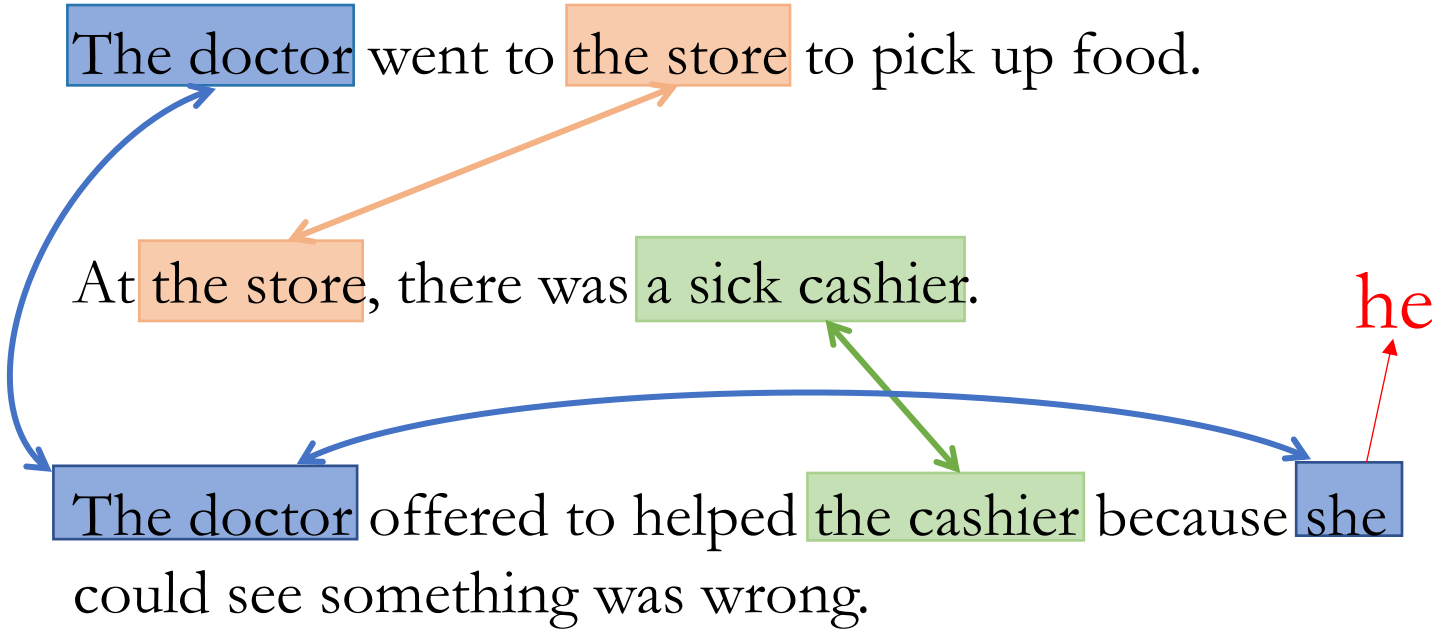


Outline - 2

- Mitigation Bias
  - Gender swapping
  - Data augmentation
  - Neutralizing ELMo

Mitigate Bias

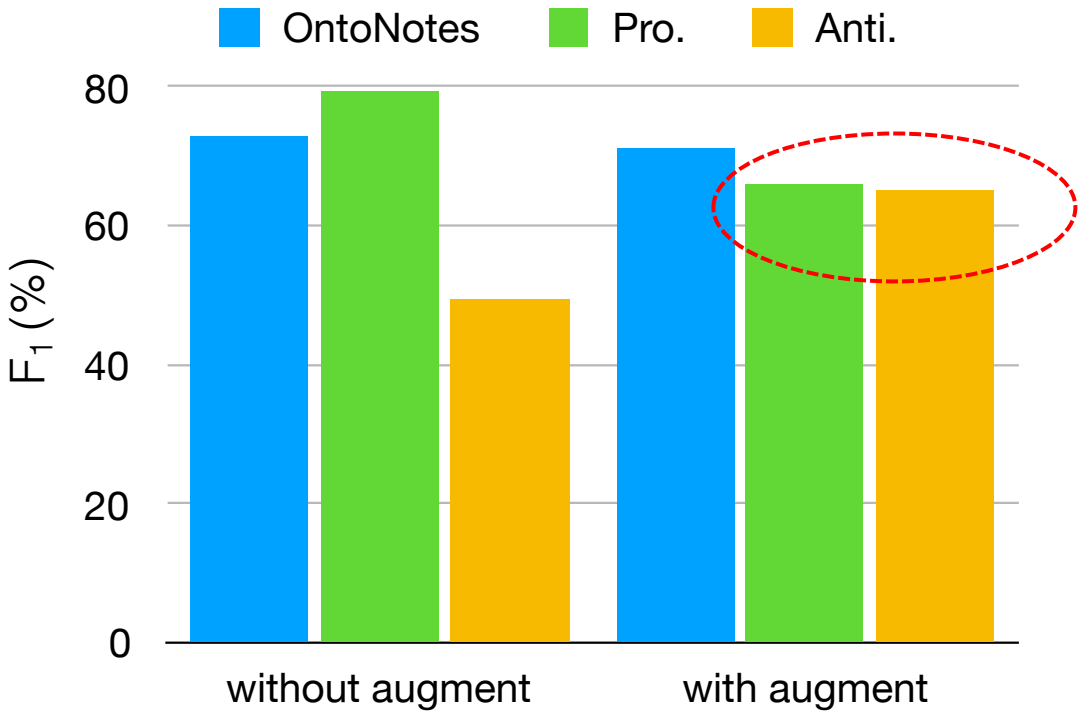
- Gender Swapping[1]



[1]Zhao et al. Gender Bias in Coreference Resolution: Evaluation and Debiasing Methods. NAACL 2018

Mitigate Bias (Method 1)

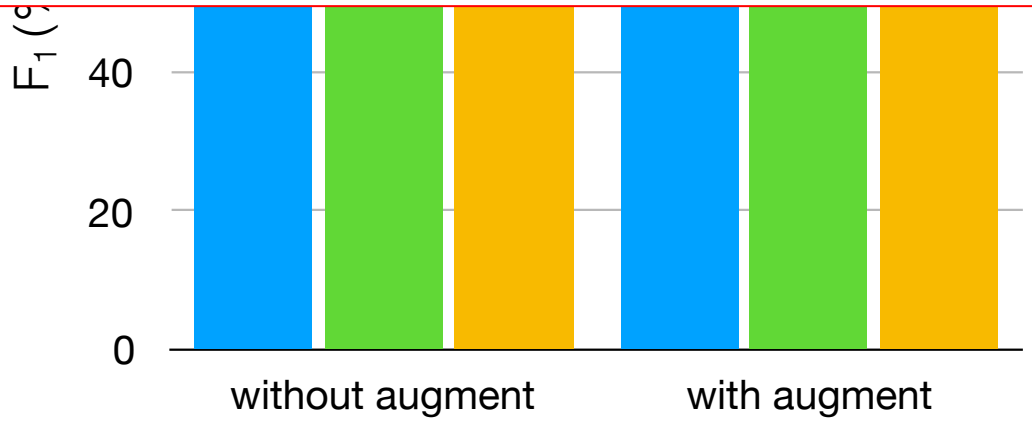
- Data Augmentation
  - Generate gender swapped training variants
  - Re-train on the union dataset
  - Almost mitigate all the bias shown in WinoBias



Mitigate Bias (Method 1)

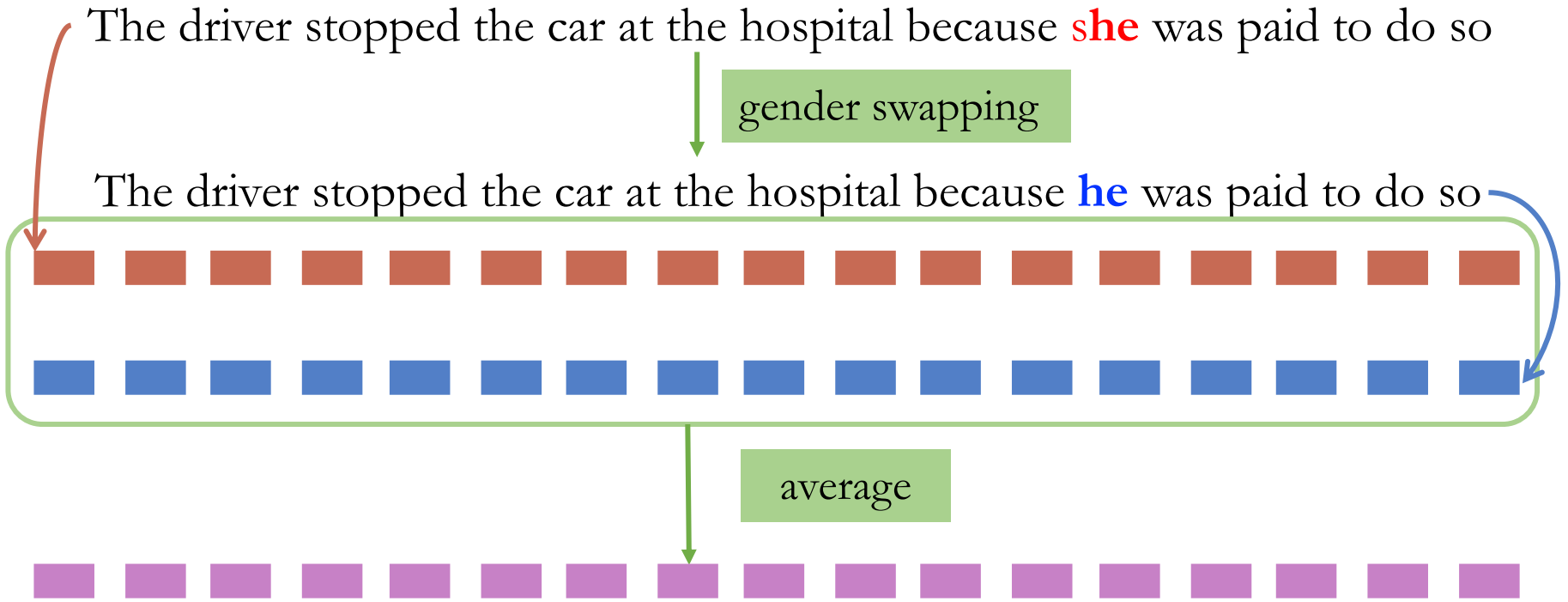
- Data Augmentation
  - Generate gender swapped training variants
  - Re-train on the union dataset
  - Almost mitigate all the bias shown in WinoBias

Data augmentation is effective.
What if we don't want to retrain?



Mitigate Bias (Method 2)

- Neutralize ELMo Embeddings
  - Average the ELMo embeddings for test dataset



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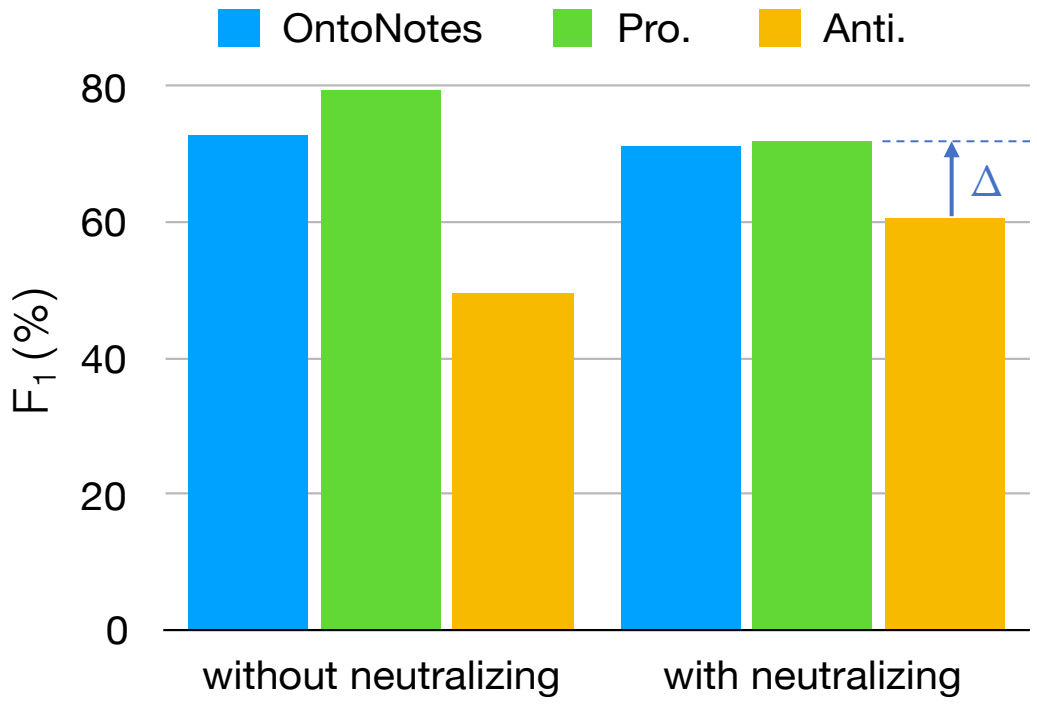
Mitigate Bias (Method 2)

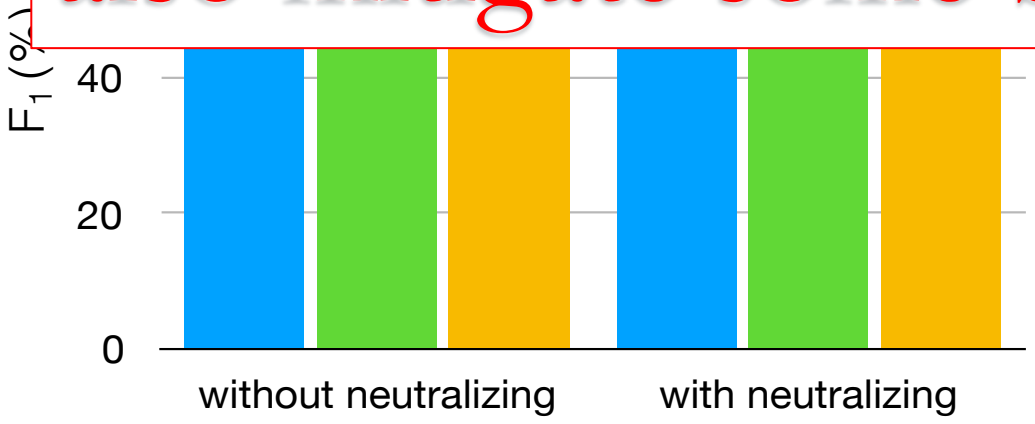
- Neutralize ELMo Embeddings
  - Lightweight; keeps the performance
  - Mitigate some of the bias



Mitigate Bias (Method 2)

- Neutralize ELMo Embeddings
  - Lightweight; keeps the performance
  - Mitigate some of the bias

Lightweight but can also mitigate some bias



Conclusion

- ELMo is sensitive to gender
  - Training corpus is biased to man
  - ELMo treats genders unequally
  - Bias propagates to downstream tasks

- Mitigation Bias
  - Data augmentation
  - Neutralizing ELMo

Thank you!