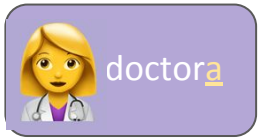
Evaluating Gender Bias in Machine Translation

Gabriel Stanovsky, Noah Smith and Luke Zettlemoyer

ACL 2019

Grammatical Gender

- Some languages encode *grammatical gender* (Spanish, Italian, Russian, …)



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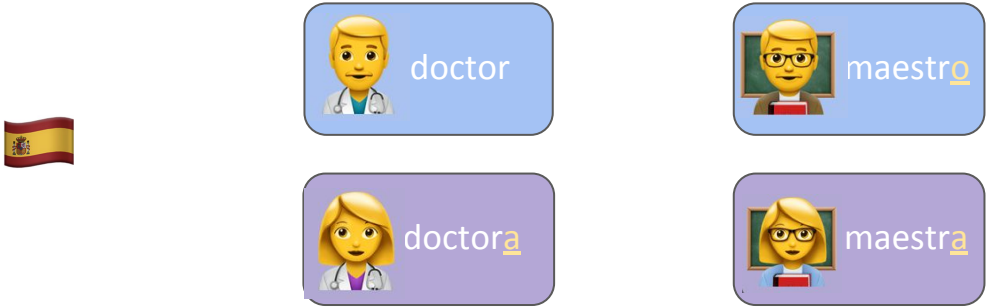
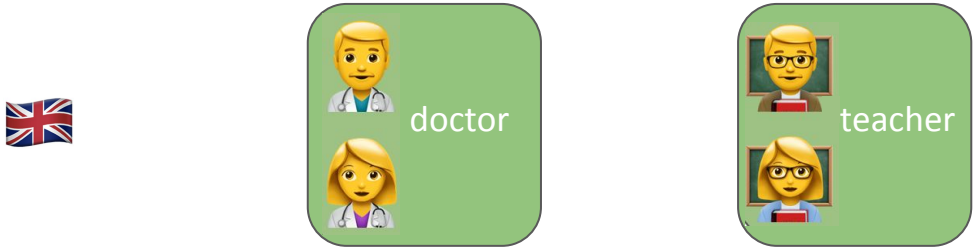


- Other languages *do not* (English, Turkish, Basque, Finnish, …)



Translating Gender

- Variations in gender mechanisms **prohibit one-to-one translations**

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La doctora le pidió a la enfermera que le ayudara con el procedimiento.

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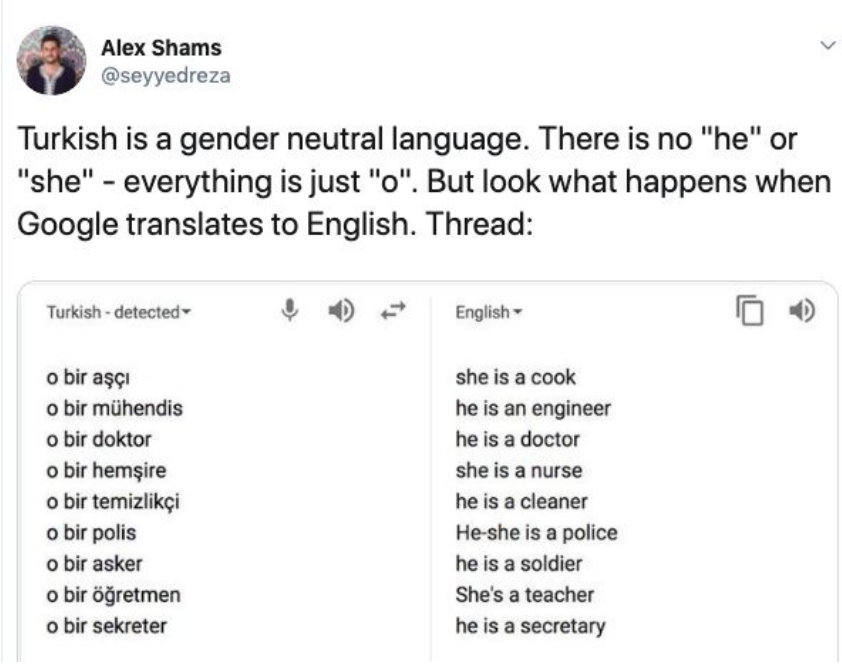

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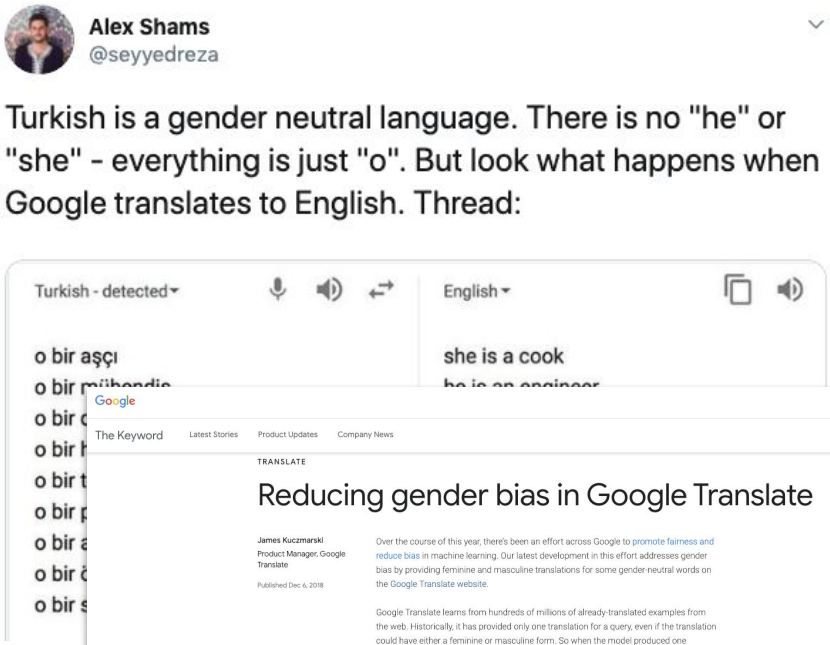

Is MT gender biased?

Alex Shams
@seyyedreza

Turkish is a gender neutral language. There is no "he" or "she" - everything is just "o". But look what happens when Google translates to English. Thread:

Turkish - detected

o bir aşçı

English

she is a cook

Google

The Keyword | Latest Stories | Product Updates | Company News

TRANSLATE

Reducing gender bias in Google Translate

James Kuczmarski
Product Manager, Google Translate

Published Dec 6, 2018

Over the course of this year, there's been an effort across Google to promote fairness and reduce bias in machine learning. Our latest development in this effort addresses gender bias by providing feminine and masculine translations for some gender-neutral words on the Google Translate website.

Google Translate learns from hundreds of millions of already-translated examples from the web. Historically, it has provided only one translation for a query, even if the translation could have either a feminine or masculine form. So when the model produced one translation, it inadvertently replicated gender biases that already existed. For example: it would skew masculine for words like "strong" or "doctor," and feminine for other words, like "nurse" or "beautiful."

Now you'll get both a feminine and masculine translation for a single word—like "surgeon"—when translating from English into French, Italian, Portuguese or Spanish. You'll also get both translations when translating phrases and sentences from Turkish to English. For example, if you type "o bir doktor" in Turkish, you'll now get "she is a doctor" and "he is a doctor" as the gender-specific translations.

Gretchen McCulloch @GretchenAMcC · 6 Dec 2018
I actually like this a lot.

Introduces the human back into the equation by acknowledging ambiguity, letting us decide which translation fits a particular circumstance better.

Google @Google
To reduce gender bias in #GoogleTranslate, we're providing feminine and masculine translations for queries that include gender neutral words → goo.gl/vgvt7v

GIF

7 78 289

(((ل)()ل() 'yoav))))
@yoavgo

Follow

Replying to @GretchenAMcC

almost working...

(but really, a very hard and interesting problem to solve.)

DETECT LANGUAGE | SPANISH | ENGLISH | FRENCH | ITALIAN | SPANISH | FRENCH

the smart surgeon met the smart nurse

le chirurgien intelligent a rencontré l'infirmière intelligente

37/5000

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English Source Texts

- Winogender (Rudinger et al., 2018) & WinoBias (Zhao et al., 2018)
  - 3888 English sentences designed to test gender bias in *coreference resolution*
  - Following the **Winograd schema**

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  - Equally split between stereotypical and non-stereotypical role assignments
  - Gold annotations for gender

Methodology: Automatic evaluation of gender bias

Input: MT model + target language
Output: Accuracy score for gender translation

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Quality estimated at > 85% vs. 90% IAA
Doesn't require reference translations!

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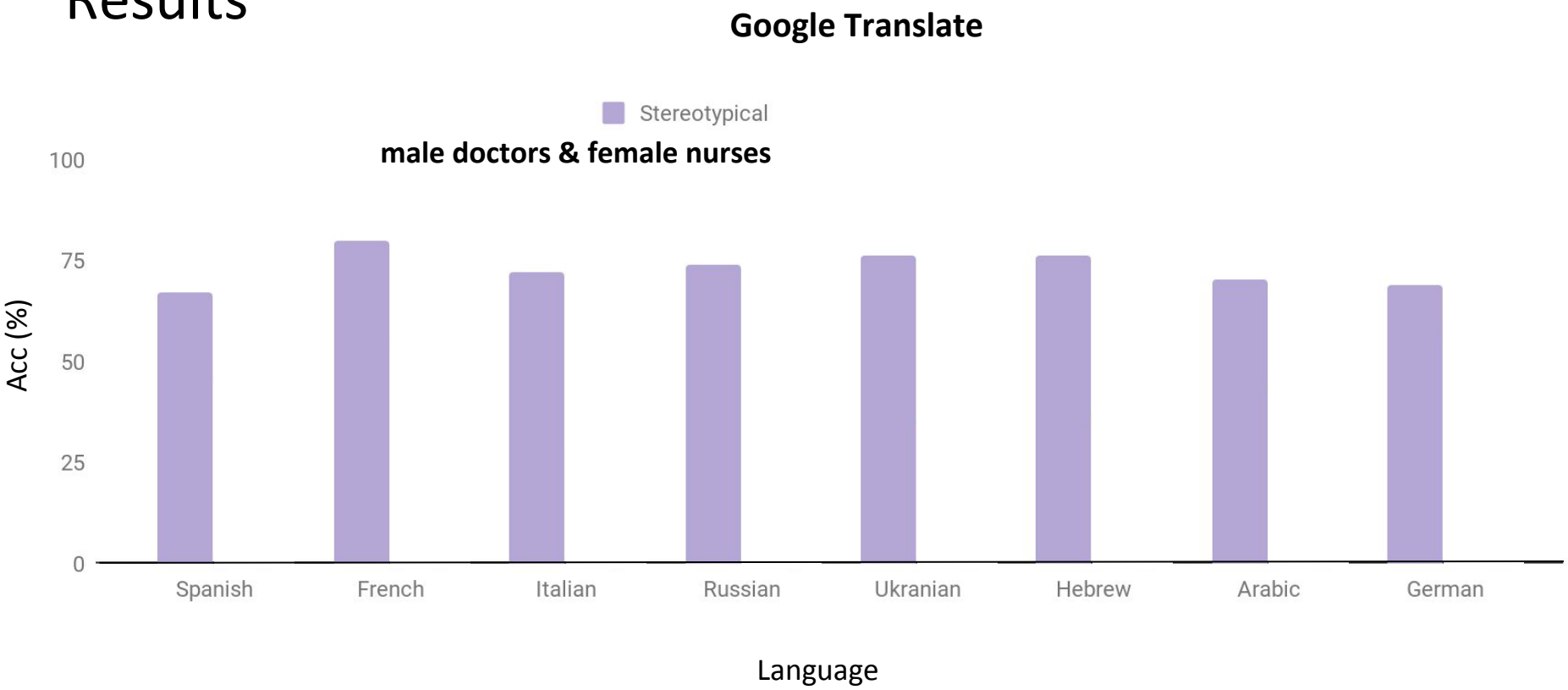
Results


Google Translate
Stereotypical
male doctors & female nurses
100
75
50
25
0
Acc (%)
Spanish
French
Italian
Russian
Ukranian
Hebrew
Arabic
German
Language

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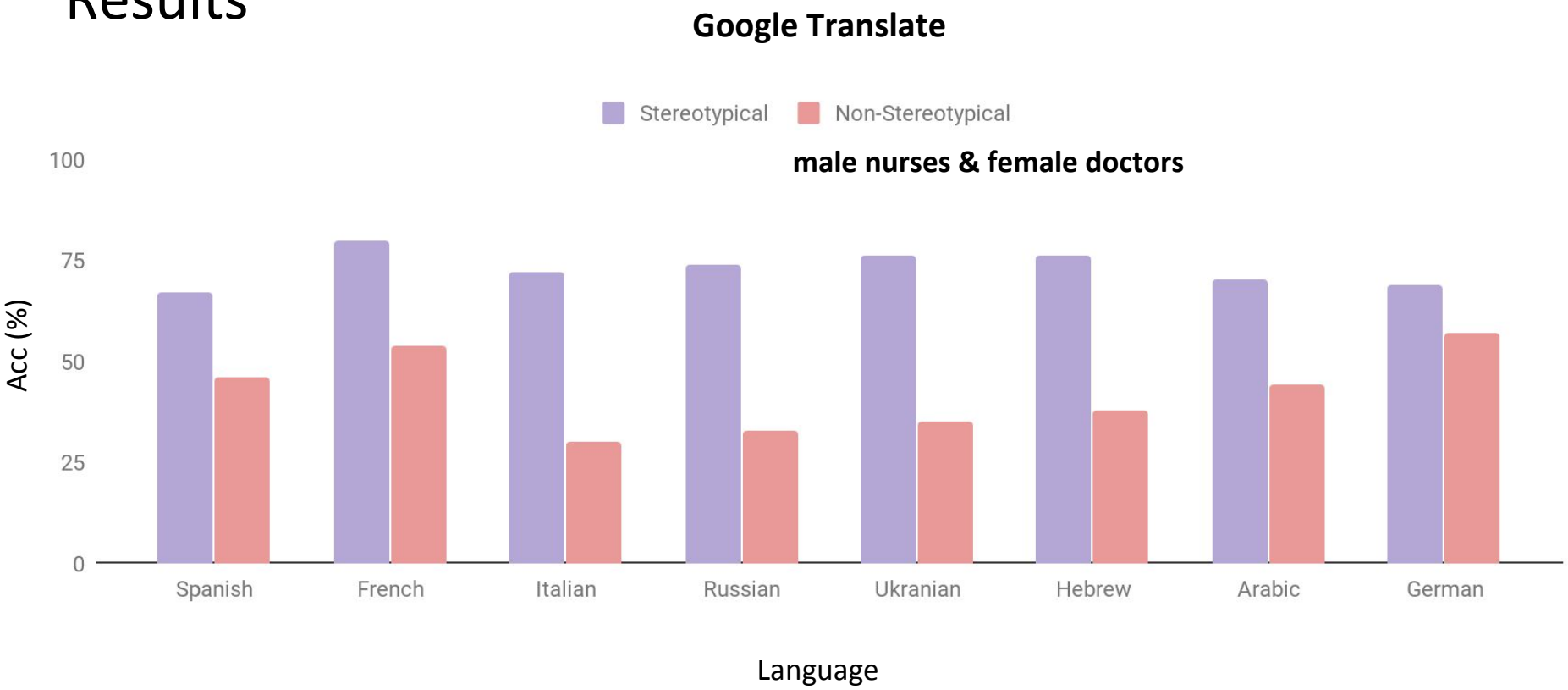
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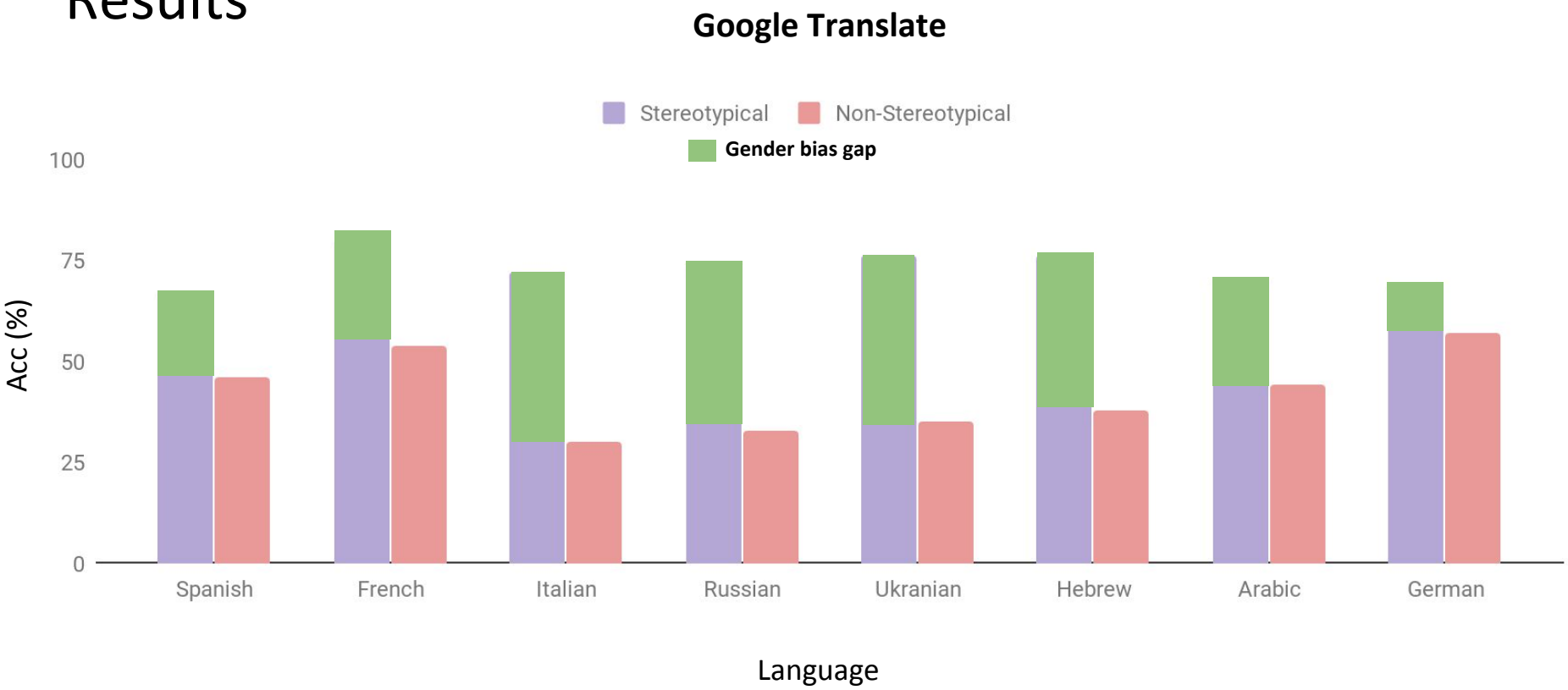
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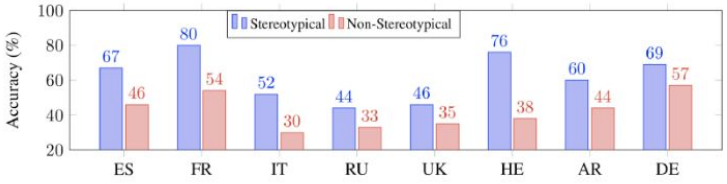
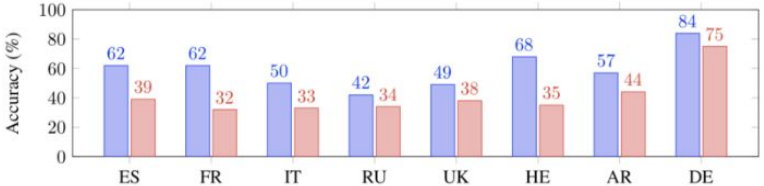
Results

- **MT struggles with non-stereotypical roles across languages and systems**
  - Often doing significantly worse than *random coin-flip*

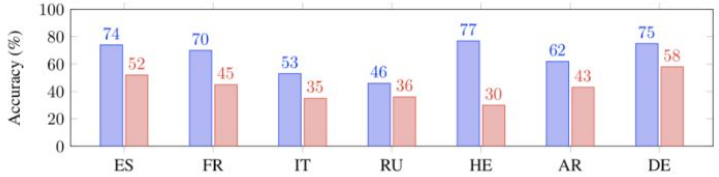
- **Academic models** (Ott et al., 2018; Edunov et al., 2018) **exhibit similar behavior**



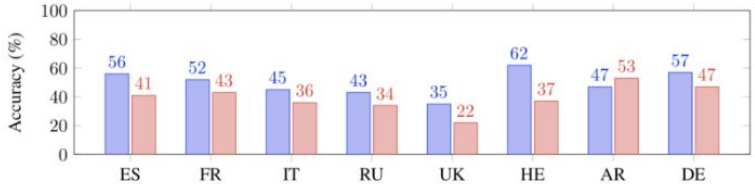
Google Translate performance on gender prediction.



Microsoft Translator

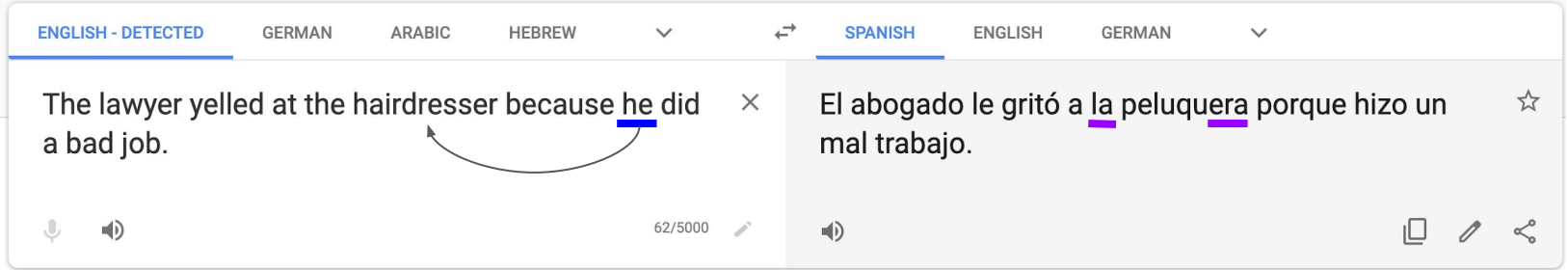


Amazon Translate



SYSTRAN

Examples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ARABIC
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62/5000
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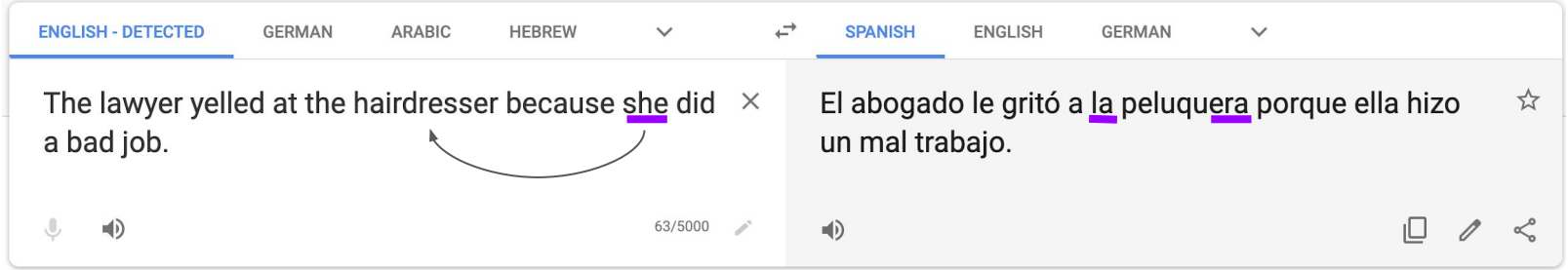
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Do Gendered Adjectives Affect Translation?

- Black-box injection of gendered adjectives (similar to Moryossef et al., 2019)
  - *the **pretty** doctor asked the nurse to help her in the operation*
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- Requires oracle coreference resolution!
  - Attests to the relation between coreference resolution and MT

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  - Allows for controlled experiment
  - Yet, might introduce its own annotation biases

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- Future work
  - **Collect naturally occurring samples on a large scale**

Conclusion

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  - 6 SOTA MT models on 8 diverse target languages
  - Doesn’t require reference translations

- **Significant gender bias found in all models in all tested languages**

- Code and data: https://github.com/gabrielStanovsky/mt_gender
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Come to the the **Gender Bias Workshop!** (Friday)

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Спасибі за слухання! Grazie per aver ascoltato! Danke fürs Zuhören!

תודה על ההקשבה!

Thanks for listening!

¡Gracias por su atención!

Merci pour l'écoute!

شكرا على الإنصات!

Спасибо за внимание!