





Screening Gender Transfer in Neural Machine Translation

universite PARIS-SACLAY





¹LLF, Université de Paris, F-75013 Paris, France ²CLILLAC-ARP, Université de Paris, F-75013 Paris, France ³LISN, Université Paris-Saclay & CNRS, 91403 Orsay, France

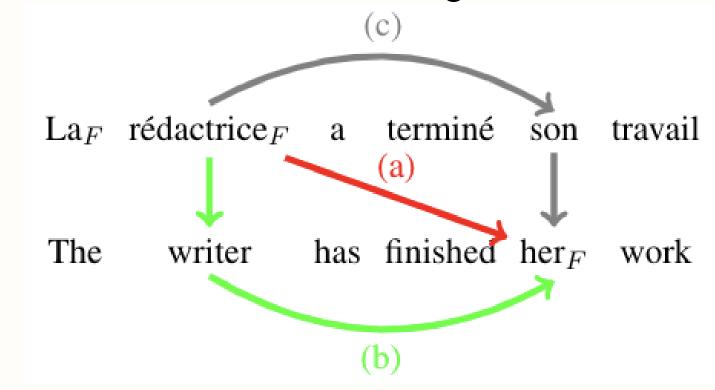
Guillaume Wisniewski¹, Lichao Zhu¹, Nicolas Ballier², François Yvon³

Information flow within an encoder/decoder architecture

- key steps in interpreting NMT systems
- which informations are captured by the decoder?
- which informations are captured by the encoder?
- how: study the transfer of gender information from French to English
- using probes to find where this information is represented;

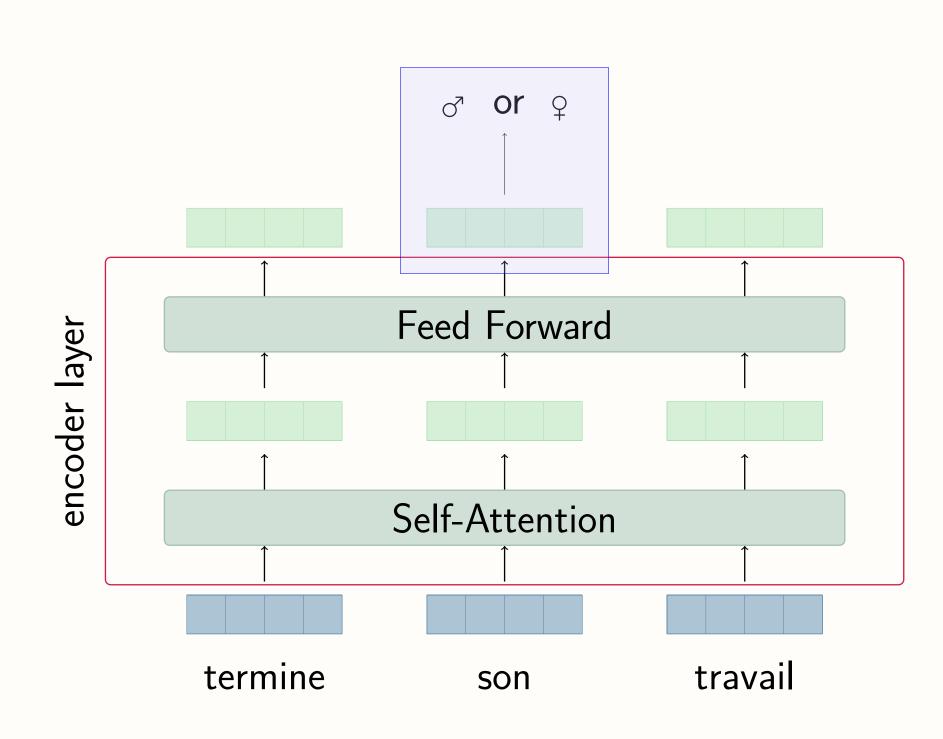
Gender Transfer between French and English

- challenge
- \hookrightarrow in French: gender = property of all nouns \oplus agreement rules within noun phrase
- focus on the following pattern:
 - [DET] [N] a terminé son travail.
 - \rightarrow The [N] has finished [PRO] work.
- \hookrightarrow [N] = occupational noun either feminine or masculine
- \hookrightarrow [DET] = French determiner in agreement with the noun
- \hookrightarrow [PRO] = English possessive pronoun
- Dataset of 3,394 parallel sentences following this pattern
- → perfectly balanced between genders
- Hypothetical paths for transferring gender information from French to English



- \hookrightarrow (a) direct influence \rightarrow cross-lingual attention;
- \hookrightarrow (b) indirect influence \rightarrow monolingual encoding of gender in the representation of the English noun;
- \hookrightarrow (c) indirect influence \rightarrow cross-lingual attention to the French possessive adjective.

Probing Representations



- linguistic probe: predict the gender of the French occupational noun from a source/target word representation

In the source

layer	а	terminé	son	travail	•	eos
1	80.4%	75.1%	80.6%	76.4%	59.5%	73.3%
2	85.8%	80.8%	81.6%	78.3%	87.6%	88.3%
3	89.5%	88.2%	89.2%	82.0%	86.5%	87.6%
4	90.8%	89.3%	90.6%	85.9%	85.7%	85.6%
5	90.4%	89.3%	90.4%	85.5%	86.4%	85.2%
6	91.0%	89.3%	90.0%	86.0%	86.4%	85.1%

Gender information

- → is more present in the deepest layer of the encoder
- \hookrightarrow spreads all over the representation of the source tokens
 - \Rightarrow and not only the tokens involved in our hypothesis

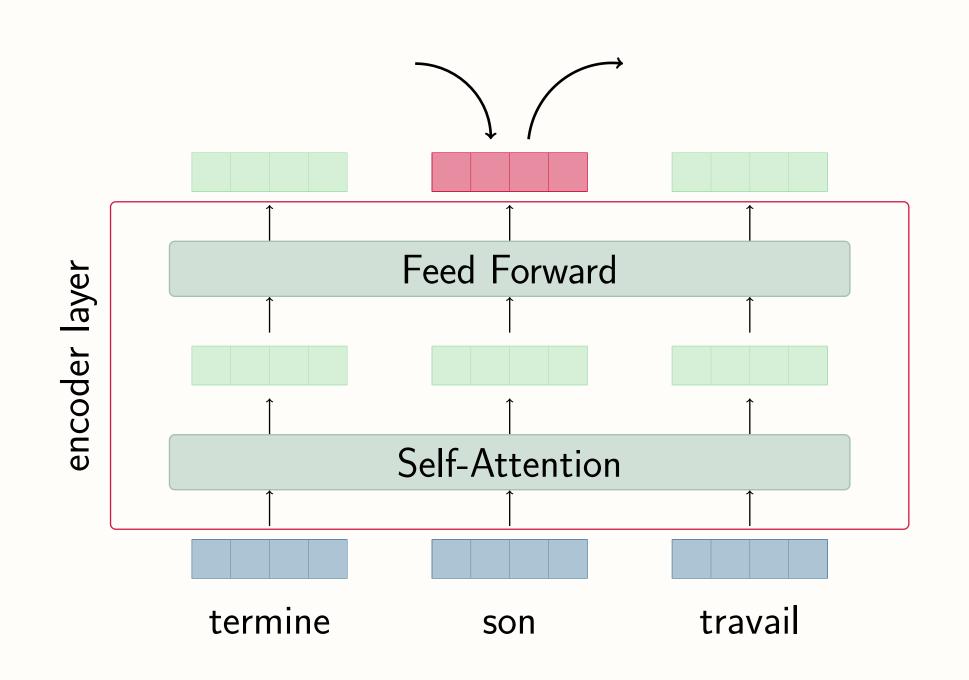
In the target

- target sentence not as 'regular' as source sentences (predicted by MT system)
 - \Rightarrow accuracy of the probe computed over all tokens of the translation hypothesis

	decoder			
layer	the	all tokens		
1	89.5%	71.6%		
2	92.0%	76.3%		
3	91.8%	78.1%		
4	90.9%	79.1%		
5	89.3%	82.4%		
6	87.7%	84.7%		

- gender information encoded in all target tokens
 - \Rightarrow even those for which the information is useless

Manipulating Representations



- goal: identify if and when gender information is used
- how: intervention → replace the embedding of 'son' by a representation that triggers

- → a neutral version of the embedding average of son representation over all sentences
- evaluation: distribution of pronoun in translation hypothesis

intervention	English pronoun	% sentences
none	her	13.4%
	his	57.1%
	other	29.5%
feminine	her	17.3%
	his	56.8%
	other	25.9%
gender-neutral	her	13.2%
	other	29.4%
	his	57.4%
masculine	her	13.8%
	other	29.2%
	his	57.0%

→ representations of son are not the only evidence used during the generation of the translation hypothesis
⇒ path (c) has only a limited influence

Conclusion

- Contributions: new dataset ⊕ two techniques (probing & manipulating)
- Conclusions:

- future work:
- → generalization to other language & syntactic divergences
- \hookrightarrow identify which information is used to choose the English pronoun

Code & Corpus

https://github.com/neuroviz/neuroviz/tree/main/blackbox2021

Acknowledgments

This work was partially funded by the NeuroViz project subsidized by the lle-de-France Region, and supported in part by the 2020 émergence research project SPEC-TRANS.

Contact information

guillaume.wisniewski@u-paris.fr