Screening Gender Transfer in Neural Machine Translation

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Information flow within an encoder/decoder architecture

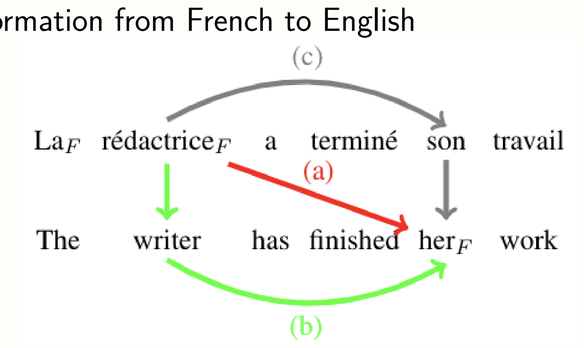
- key steps in interpreting NMT systems
  - ↪ which informations are captured by the encoder?
  - ↪ which informations are transferred from the source to the target?
- how: study the transfer of gender information from French to English
  - ↪ using probes to find where this information is represented;
  - ↪ using causal models to determine when this information is used.

Gender Transfer between French and English

- challenge
  - ↪ in French: gender = property of all nouns ⊕ agreement rules within noun phrase
  - ↪ in English: gender = only in rare constructs involving human agents and pronoun coreference
- focus on the following pattern:

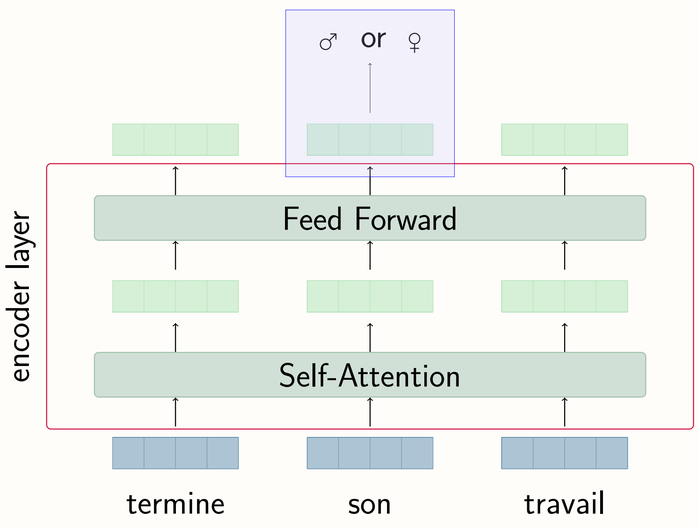
  [DET] [N] a terminé son travail.

  → The [N] has finished [PRO] work.
  - ↪ [N] = occupational noun either feminine or masculine
  - ↪ [DET] = French determiner in agreement with the noun
  - ↪ [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



  - ↪ (a) *direct influence* → cross-lingual attention;
  - ↪ (b) *indirect influence* → monolingual encoding of gender in the representation of the English noun;
  - ↪ (c) *indirect influence* → 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
  - ↪ simple binary classification problem
  - ↪ evaluation: accuracy

In the source

layer	a	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
- ↪ spreads all over the representation of the source tokens

  ⇒ and not only the tokens involved in our hypothesis

In the target

- target sentence not as 'regular' as source sentences

  (predicted by MT system)

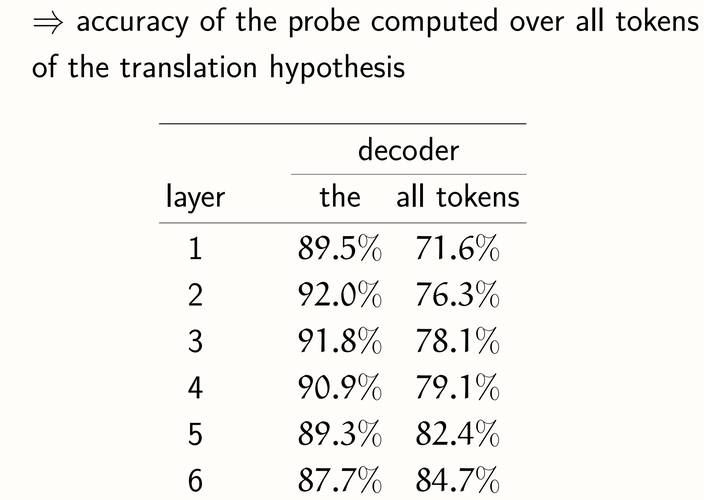
  ⇒ accuracy of the probe computed over all tokens of the translation hypothesis

	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

  ⇒ 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
  - ↪ the generation of '*her*' (feminine embedding)
  - ↪ the generation of '*his*' (masculine embedding)
  - ↪ 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:
  - ↪ gender information in the representation of all tokens representations built by the encoder and the decoder
  - ↪ choice of English pronoun distributed
- future work:
  - ↪ generalization to other language & syntactic divergences
  - ↪ identify which information is used to choose the English pronoun

Code & Corpus

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

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