

Large contexts in neural machine translation

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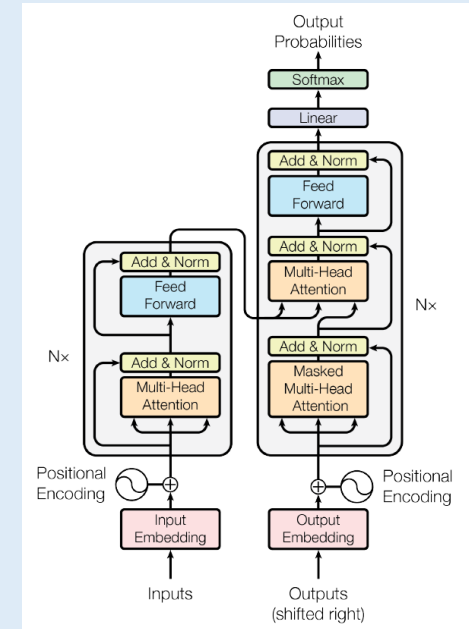
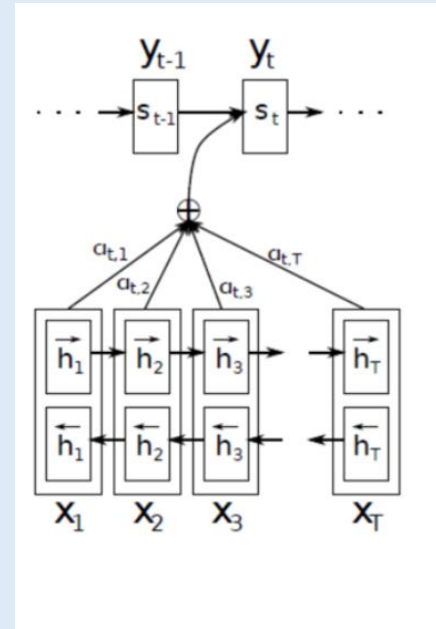
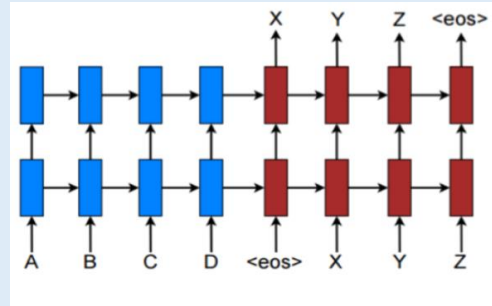
Quicker and quicker revolutions in MT

$$\operatorname{argmax}_{t \in \text{TARGET_LANGUAGE}} P(t|s) =$$

$t \in \text{TARGET_LANGUAGE}$

$$\operatorname{argmax}_{t \in \text{TARGET_LANGUAGE}} P(s|t) \times P(t)$$

$t \in \text{TARGET_LANGUAGE}$



Phrase-based statistical MT with a translation model and a language model (Koehn et al. 2007)

RNN encoder-decoder with LSTM units (Sutskever et al. / Cho et al. 2014)

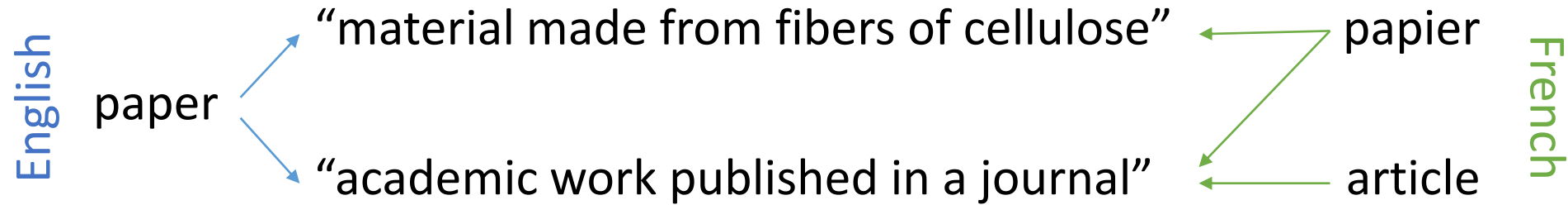
RNN encoder-decoder with attention model (Bahdanau et al. 2015)

The Transformer: self-attention networks with positional encoding (Vaswani et al. 2017)

Remaining challenges

- Many recent evaluation studies of neural MT [\[see my review on Arxiv\]](#)
 - NMT outperforms SMT, and Transformer outperforms RNN with attention
 - almost all participants at the WMT 2018 news translation used the Transformer
 - NMT still struggles with complex grammatical issues & word omission
- NMT cannot do better than random if a translation *needs a larger context* from other sentences (but neither did SMT)
 - **why context?** → pronouns, coherence, co-reference, style, politeness, etc.

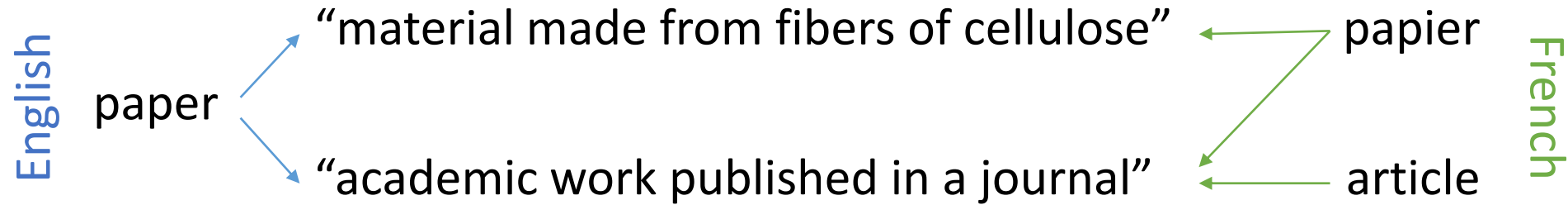
Case study: mistranslation of word senses (1)



Paper is a thin material produced from cellulose pulp. **Papers** are essential in legal documentation.
→ Le **papier** est un matériau fin fabriqué à partir de pâte de cellulose. Les **articles** sont essentiels dans la documentation juridique.

Incoherent translation: the meaning of **papers** (2nd occ.) is misunderstood
Maybe the system could have looked at the surrounding words?

Case study: mistranslation of word senses (2)



There are ten types of scientific papers. [...] Papers that carry specific objectives are: ...
→ Il existe dix types d'articles scientifiques. [...] Les papiers qui ont des objectifs spécifiques sont : ...

Inconsistent translation, the 2nd occurrence of papers should be rendered by the same word
Maybe the system could have looked at the first occurrence?

Contextually-correct lexical choices

1. Patch an NMT system with pre or post-processing
 - combine word sense disambiguation with MT
 - ensure consistency of repeated words in the source
2. Enable NMT to examine larger contexts
 - multiple-sentence or document-level encoder and decoder

Consistent translation of repeated nouns

(Pu, Mascarell and Popescu-Belis, EACL 2017)

- Learn whether two occurrences of the same noun must be translated identically or not, based on grammatical features

Example 1

Source: nach einföhrung dieser politik [...] die politik auf dem gebiet der informationstechnik [...]

Reference: once the policy is implemented [...] the information technology policy [...]

MT: after introduction of policy [...] the politics in the area of information technology [...]

Example 2

Source: 欺詐性旅行或身份證件系指有下列情形之一的任何旅行或身份證件

Reference: Fraudulent travel or identity document; shall mean any travel or identity document

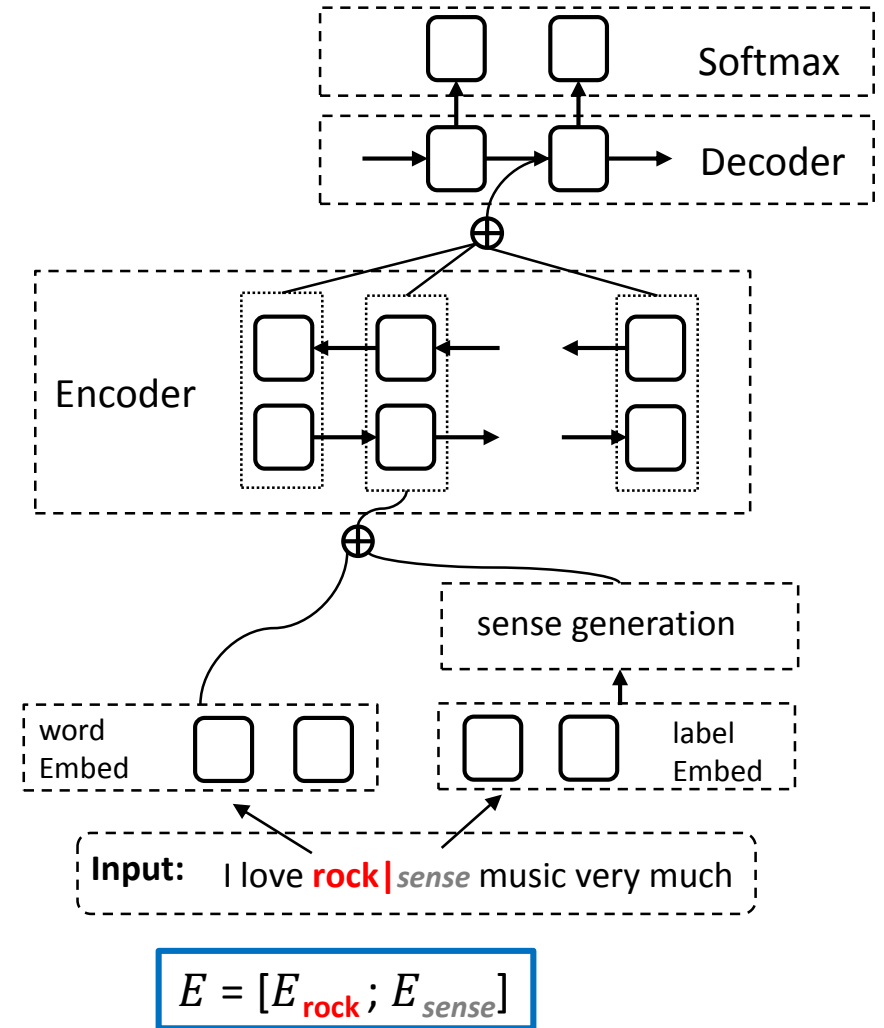
MT: 欺詐性 travel or identity papers. 系指 have under one condition; any travel, or identity document

1. Detect two close occurrences of the same noun in the source
2. Find their baseline translations by a PBSMT using word alignment
3. If they differ, decide if and how to edit: 1st replaces 2nd or vice-versa
4. Post-edit or re-rank the PBSMT output

Sense-aware neural MT

(Pu, Pappas, Henderson & Popescu-Belis, *to appear in TACL*)

- Add additional dimensions for sense embeddings (to word embeddings)
- How to train them? Three options:
 1. Add sense labels from WSD to words, then learn them just as words
 2. Represent senses by summing embeddings of WordNet definitions, then combine them for each token based on similarity with context
 3. Attention mechanism to compute similarity of context and sense embeddings



WSD in NMT: standard vs. large contexts

- Representations of ambiguous words: *right, like, last, case*
 - standard encoder-decoder RNNs with attention for EN/FR
 - the encoded context seems generally insufficient to enable WSD
 - Marvin R. and Koehn P. [Exploring WSD abilities of NMT systems](#). *AMTA 2018*.
- *Contrastive set*: test suite for lexical choice
 - manipulate context to see how system adapts the translation of an ambiguous and/or repeated lexical item: 100 “blocks” for EN/FR
 - Transformer encoding 2 sentences at the time gets 57% correct vs. 50% random
 - Bawden R., Sennrich R., Birch A., Haddow B. [Evaluating discourse phenomena in NMT](#). *NAACL 2018*.

Conclusion

- Open question: which one is better, to pre- or post-process discourse features separately or to consider a larger context?
- Evidence that large-context NMT implicitly learns pronoun resolution to some extent [Voita et al. [Context-Aware Neural Machine Translation Learns Anaphora Resolution](#). *ACL 2018*.]
- What about improving on several discourse phenomena? Integrate heterogeneous pre-/post-processors, or one large context to solve them all?
- New project: “On-demand Knowledge for Document-level MT”
- Upcoming DiscoMT 2019 workshop @EMNLP

References

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