Recent Advances In Document-level Neural Machine Translation

Lorenzo Lupo

Supervisors: Laurent Besacier, Marco Dinarelli

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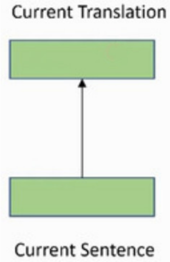
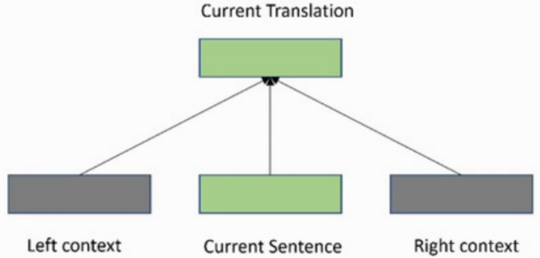
What is Document-level Machine Translation

Sentence-level MT

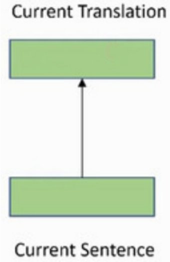


Document-level MT

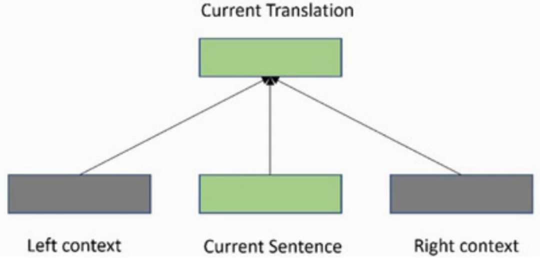


Document-level MT ↔ Context-aware MT

Context-agnostic MT



Context-aware MT



Sentence-level MT is inconsistent

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SENTENCE-LEVEL TRANSLATION

B: There they understood the importance of lexical cohesion.

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A: Nous avons refait l'exercice avec les mêmes etudiants.
Que pensez-vous qu'il est alors arrivé ?

B: Là, ils comprenaient l'importance de la cohésion lexicale.

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B: Là, ils comprenaient l'importance de la cohésion lexicale.

SENTENCE-LEVEL TRANSLATION

B: There they understood the importance of lexical cohesion.

CONTEXT-AWARE TRANSLATION

B: Now, they understood the importance of lexical cohesion.

How bad is it?

[Voita et al., 2019b] undertake a human study on context agnostic translation :

- 2000 pairs of consecutive English sentences (S1 + S2) from OpenSubtitles2018
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all	one/both bad	both good	
		bad pair	good pair
2000	211	140	1649
100%	11%	7%	82%

Which kind of inconsistencies?

type of phenomena	frequency
deixis	37%
ellipsis	29%
lexical cohesion	14%
ambiguity	9%
anaphora	6%
other	5%

Figure: Types of phenomena causing discrepancies in context-agnostic translation of consecutive sentences when placed in the context of each other.

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- **Evaluate such models** in a proper way;

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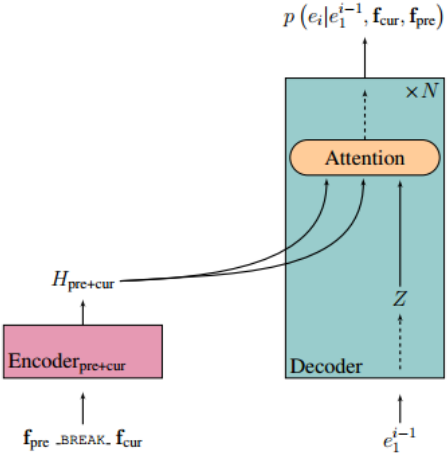
Concatenation Approaches

Concatenation approaches to DLNMT consist in feeding a standard encoder-decoder architecture with a concatenation of sentences.



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  - **2-TO-2**: the previous and the current sentences are translated together. The translation of the current sentence is then obtained by only retaining the tokens following the concatenation token.
  - **2-TO-1**: only the current sentence is translated.
- [Agrawal et al., 2018, Scherrer et al., 2019] investigated the concatenation approach with the Transformer as base model, extending the number of context sentences both on the source (s:-3,+1) and the target (t:-2) side.

Plan

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- **Two-pass approaches**, in which the encoder makes a first sentence-level encoding pass of the source, and a second in which it encodes contextual information too. See Slide 20.
  - Remark: a powerful feature of two-pass approaches is their ability to exploit **future** target-side context.

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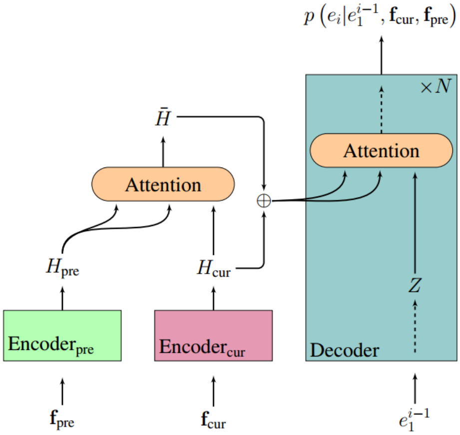
Once the encoding of the current and the context sentences has been carried out, they can be integrated in different ways:

- **Outside** the decoder.
  - $(+)$ symbol represents a gate, a sum or a concatenation.



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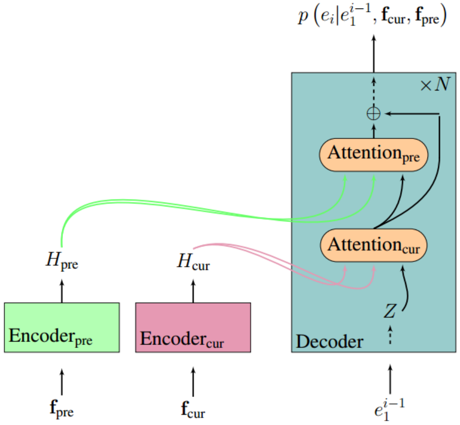

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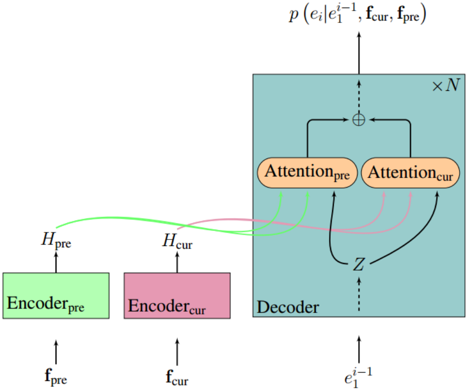

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The encoder-decoder architectures depicted above can be both RNN-based (until 2017) or Transfomer-based (after 2017), as for any approach to DLNMT. However, often some modifications are applied. For example:

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- Beside contextual representation of words, the context encoder can also generate higher level representations such as sentence or document embeddings. This representations can also be attended by the decoder [Miculicich et al., 2018, Maruf et al., 2019a] or added to the word-representations [Tan et al., 2019].

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- Parallel integration inside the decoder can also happen within a single multi-head attention that takes as values and queries the concatenations of the current and context sentence representations [Voita et al., 2019b]

Separate Encoding Approaches

Including target-side context

Despite some have considered including past target-side context harmful because of the *error propagation* problem [Zhang et al., 2018], most recent works have showed it to be of utmost importance for making the most out of context. Past works have successfully included target-side context information in different ways:

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- Translating past sentences (usually 1) along with the current one, and then discarding them, as in concatenation approaches [Bawden et al., 2018].
- By making the decoder attend the target-side hidden representations or embeddings of previously decoded sentences [Miculicich et al., 2018, Voita et al., 2019b, Maruf et al., 2019a, Zheng et al., 2020].

Separate Encoding Approaches

Reference	Context	Two-Pass Approach	Outside Integr.	Inside Integr.	Lang. Pair
[Wang et al., 2017]	s:-3		aut...	...aut	Zh→En
[Voita et al., 2018]	s:-1		yes		En→Ru
[Zhang et al., 2018]	s:-2		yes	sequential	Zh→En
[Miculicich et al., 2018]	s:-3; t:-3		yes		Zh/Es→En
[Maruf et al., 2019a]	s:all; t:all	optional	yes		En→De
[Zheng et al., 2020]	s:all; t:all	yes	yes		Zh/En→En/De
[Jean et al., 2017]	s:-1			parallel	En→De/Fr
[Bawden et al., 2018]	s:-1; t:-1			parallel	En→Fr
[Fu et al., 2019]	s:all	yes		parallel	En/Zh→De/En
[Voita et al., 2019b]	s:-3; t:-3	yes		parallel*	En→Ru
[Tan et al., 2019]	s:all	yes		parallel	Zh/De→En
[Wang et al., 2019]	s:2			sequential	Fr→En

Positional Embedding Schema

For many approaches to DNMT, the standard positional encoding proposed by [Vaswani et al., 2017] is insufficient because the DNMT system needs to tell context sentences from the current one. For this reason, many strategies have been proposed in the literature, such as:

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3. Adding a **segment embedding**, similar to classical positional encoding but for the position of the sentence/segment within the document [Zheng et al., 2020].

Plan

Cache Approaches

Cache approaches to DLNMT consist in encoder-decoder models that are equipped with one or more caches that store context information. The information stored can belong to both **source side or target side, past and future**.

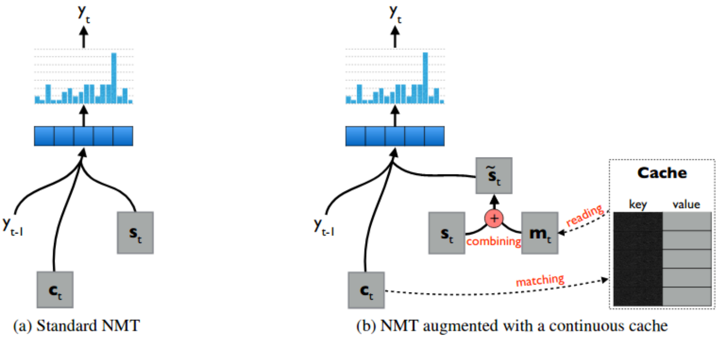
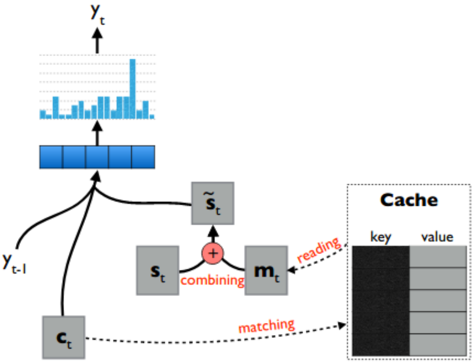
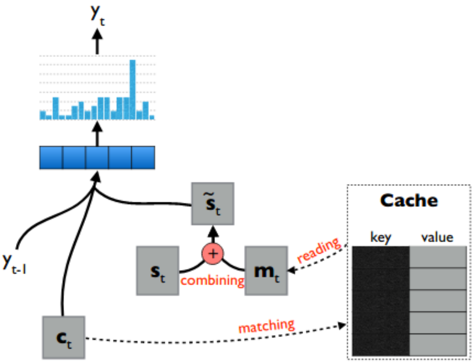


Figure: Continuous cache by [Tu et al., 2017]

Every cache slot is a **key-value-indicator** triplet (the key and the indicator are often the same thing). With these variables, we can **read** or **write** caches.



Cache reading involves:



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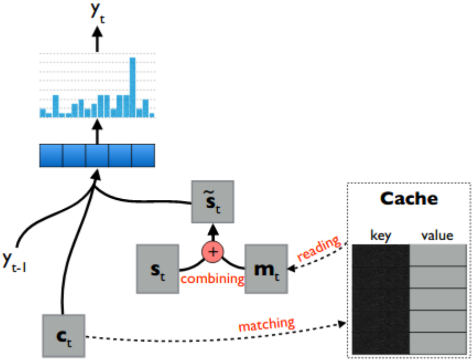

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Cache reading involves:

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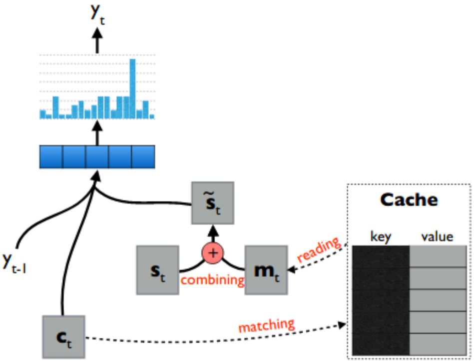

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Cache reading involves:

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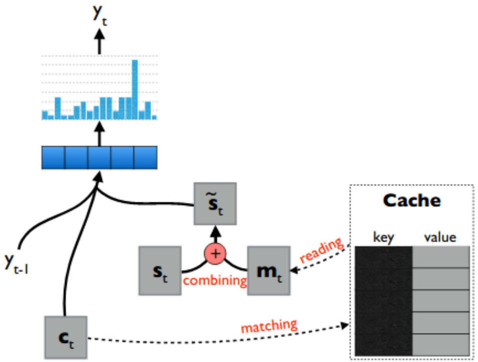
- Combining



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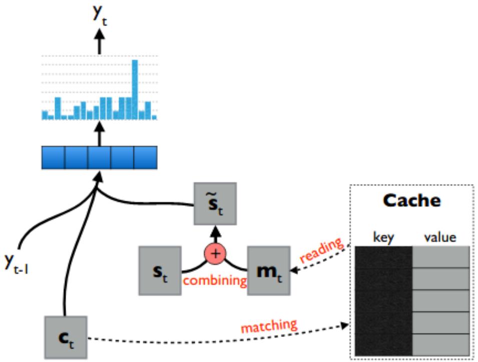

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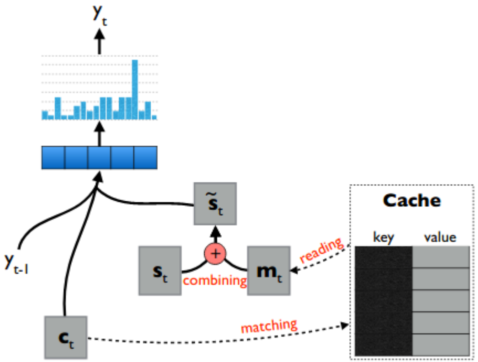

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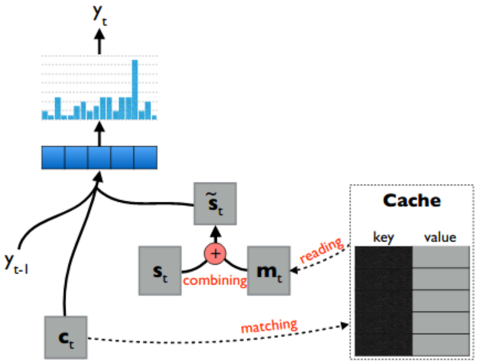
- Else, we write the triplet in an empty slot, after having emptied the oldest slot if the cache is full.



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Reference	Caches	Size	Key (Indic.)	Value	Lang. Pair
[Tu et al., 2017]	single	$\leqslant$ 500	$c_t(\ y_{k<t})$	$s_{k<t}$	Zh→En
[Kuang et al., 2018]	dynamic topic	100 200	c_t	$y_{k<t}$ topic emb.	Zh→En
[Maruf and Haffari, 2018]	source target	doc.size	h_t s_t	$sent.emb.$ $s_{k<t}$	Fr/De/Et→En

Plan

On Parallel Corpora for Training

DLNMT systems require training on **document-level parallel corpora**. These corpora are usually released during workshops on machine translation like IWSLT and WMT, and hosted on open source web inventories. The most common ones, are extracted from:

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  3. Train θ_D on a document-level parallel corpus C_D while fine-tuning θ_S, or freezing them [Zhang et al., 2018].

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Another solution to the lack of vast document-level parallel corpora is leveraging on huge *monolingual* document-level corpora like BookCorpus [Zhu et al., 2015] and PG-19 [Rae et al., 2019]. In the literature, we can find various approaches to leverage monolingual corpora:

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Exploiting Monolingual Corpora

Another solution to the lack of vast document-level parallel corpora is leveraging on huge *monolingual* document-level corpora like BookCorpus [Zhu et al., 2015] and PG-19 [Rae et al., 2019]. In the literature, we can find various approaches to leverage monolingual corpora:

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  - Initialize the econder (or decoder) of a DLNMT model [Li et al., 2019].
- Train **Automatic Post Editing** systems on target-side corpus (See next slide).

Automatic Post Editing (APE)
[Voita et al., 2019a] devised an APE system called DocRepair, that turns a sentence-level translation into a context-aware translation. DocRepair can work on top of whatever sentence-level MT system.

Cache Approaches

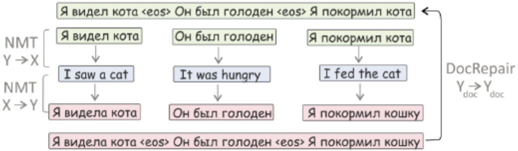

Figure 1: Training procedure of DocRepair. First, round-trip translations of individual sentences are produced to form an inconsistent text fragment (in the example, both genders of the speaker and the cat became inconsistent). Then, a repair model is trained to produce an original text from the inconsistent one.

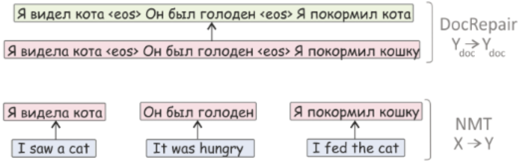

Figure 2: The process of producing document-level translations at test time is two-step: (1) sentences are translated independently using a sentence-level model, (2) DocRepair model corrects translation of the resulting text fragment.

Plan

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- Lexical chains of semantically similar words to promote word sense disambiguation [Rios Gonzales et al., 2017].
- Coreference chains to promote coreference resolution [Stojanovski and Fraser, 2018, Ohtani et al., 2019].

Learning Approaches
[Jean and Cho, 2019] looked at the problem from a learning perspective and designed a regularisation term to encourage a DLNMT model to exploit the additional context in a useful way . This regularisation term is applied at the token, sentence and corpus levels and is based on pair-wise ranking loss, that is, it helps to assign a higher log-probability to a translation paired with the correct context than to the translation without context.

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- Design automatic post-processing models that are lightweight and can be trained on little data [Kim et al., 2019].
- Study pre-trained language models for DLNMT decoder.
- Study other learning methods that foster document-level modeling [Jean and Cho, 2019].

Plan

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Evaluation

Evaluation Type	Discourse Phenomena	Dependency	Reference
Automatic Metric	Pronouns	Alignments, Pronoun lists	[29]
		Alignments, Pronoun lists	[77]
		English in target (anaphoric)	[43]
	Lexical Cohesion	Lexical cohesion devices	[120]
		Topic model, Lexical chain	[21]
	Discourse Connectives	Alignments, Dictionary	[26]
		Discourse parser	[25, 39]
		Discourse parser	[99]
Test Suites	Pronouns	En→Fr	[23]
		En→Fr (anaphora)	[7]
		En→De (anaphora)	[78]
	Cohesion	En→Fr	[7]
		En→Ru	[115]
	Coherence	En→Fr	[7]
		En↔De, Cs↔De, En→Cs	[117]
		En→Cs	[90]
	Conjunction	En/Fr→De	[85]
	Deixis, Ellipsis	En→Ru	[115]
	Grammatical Phenomena	En→De	[93]
		De→En	[2]
	Word Sense Disambiguation	De→En/Fr	[89, 88]
		En↔De/Fi/Lt/Ru, En→Cs	[86]

Figure: Overview of works on discourse phenomena evaluation in MT [Maruf et al., 2019b].

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- Focus on hard cases.
  - E.g., when translating English to French, **he** is easy whereas **it** is hard to translate because ambiguous.

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Plan

Automatic metrics

Accuracy of Pronoun Translation [Miculicich Werlen and Popescu-Belis, 2017]:

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- *Compatible languages*: conceived for English to French but it has also been extended to other language pairs.

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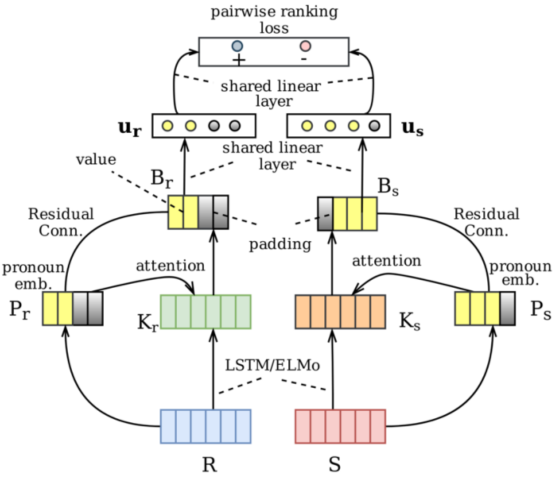

Figure: Pairwise ranking system by [Jwalapuram et al., 2019].

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- *Compatible languages*: all languages with stemmers and WordNets available.

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  - E.g. [Voita et al., 2018] build a specialized English → Russian test set by retrieving from OpenSubtitles2016 all the sentences containing pronouns that are coreferent to an expression in the previous sentence.
- **Contrastive test suites** consists in blocks of few candidate translations of a given source in which one translation is correct and the others are not. MT systems are assessed on their ability to rank correct translations higher than the incorrect ones.

Contrastive Test Suites

Pronomial Anaphora, Lexical Coherence and Cohesion [Bawden et al., 2018]

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- One test suite on **pronomial anaphora** comprised of 50 blocks.

Contrastive Test Suites

Source:

context:	Oh, I hate **flies**. Look, there's another one!
current sent.:	Don't worry, I'll kill **it** for you.

Target:

1	context:	Ô je déteste les **mouches**. Regarde, il y en a une autre !
	correct:	T'inquiète, je **la** tuerai pour toi.
	incorrect:	T'inquiète, je **le** tuerai pour toi.
2	context:	Ô je déteste les **moucherons**. Regarde, il y en a un autre !
	correct:	T'inquiète, je **le** tuerai pour toi.
	incorrect:	T'inquiète, je **la** tuerai pour toi.
3	context:	Ô je déteste les **araignées**. Regarde, il y en a une autre !
	semi-correct:	T'inquiète, je **la** tuerai pour toi.
	incorrect:	T'inquiète, je **le** tuerai pour toi.
4	context:	Ô je déteste les **papillons**. Regarde, il y en a un autre !
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Figure: Example block of the pronomial anaphora test suite.

Contrastive Test Suites

Pronomial Anaphora, Lexical Coherence and Cohesion [Bawden et al., 2018]

- *Language* English → French (OpenSubtitles2016).
- One test suite on **pronomial anaphora** comprised of 50 blocks.
- One on **lexical coherence and cohesion**, comprised of 100 blocks.

Contrastive Test Suites

Source:	
context:	So what do you say to £50?
current sent.:	It's a little **steeper** than I was expecting.
Target:	
context:	Qu'est-ce que vous en pensez de 50£ ?
correct:	C'est un peu plus **cher** que ce que je pensais.
incorrect:	C'est un peu plus **raide** que ce que je pensais.

Source:	
context:	How are your feet holding up?
current sent.:	It's a little **steeper** than I was expecting.
Target:	
context:	Comment vont tes pieds ?
correct:	C'est un peu plus **raide** que ce que je pensais.
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Figure: Example block of the lexical coherence and cohesion test suite.

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- *Language*: English → Russian (OpenSubtitles2018).
- *Design method*: manual design preceded by a human analysis on the most common translation errors in the target language pair.

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    - **Generate two contrastive translations for each** of the 12000 reference translations, by swapping the correct German pronoun with the two incorrect ones.

Plan

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– No existing metrics for coherence although it's very relevant for users.

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Test Suites

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– Contrastive evaluation has **limited guarantees**: only permits to conclude whether or not the reference translation is more probable than a contrastive variant. It is not guaranteed at all that the MT system will output such reference translation.[2]

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- New test suites for restricted scope.
  - Considering other documents other than movie subtitles for building test sets would be interesting for various reasons:
    - No multiple speakers, no unavailable context (the video), more phenomena related to future context.

Thank you for your attention!

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