-SOTA-
Document-level Neural Machine Translation

by Lorenzo Lupo

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Plan

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  - test suites.

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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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    - E.g. *it is difficult* → *il/ce/c' est difficile*.

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

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  - r, s are the positions of the pronouns to be compared in the translation R and S, respectively.

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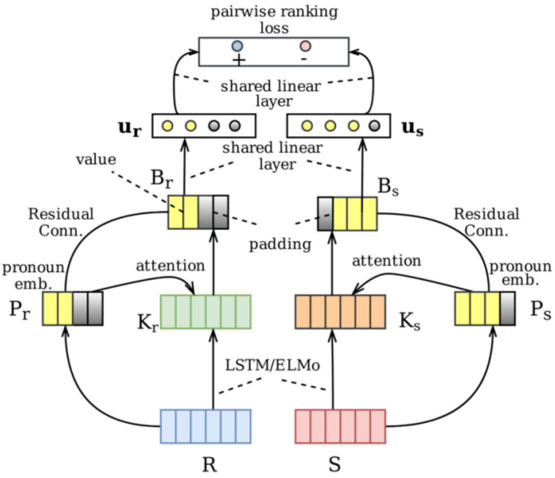

Figure: Pairwise ranking system by [Jwalapuram et al., 2019].

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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.

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- *Language* English $\longrightarrow$ French (OpenSubtitles2016).
- 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 !
	semi-correct:	T'inquiète, je **le** tuerai pour toi.
	incorrect:	T'inquiète, je **la** tuerai pour toi.

Figure: Example block of the pronomial anaphora test suite.

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- *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?
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context:	Comment vont tes pieds ?
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  - **Randomly sample** 4000 instances of each of the three translations of *it* under consideration: *er,sie,es*.
  - **Generate two contrastive translations for each** of the 12000 reference translations, by swapping the correct German pronoun with the two incorrect ones.

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

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- Excepts for specialized test sets (slide 13), test suites have a **limited scope**: fixed language pair, fixed number of context sentences (past and future).
- 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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  - Works on coherence and cohesion are particularly lacking.

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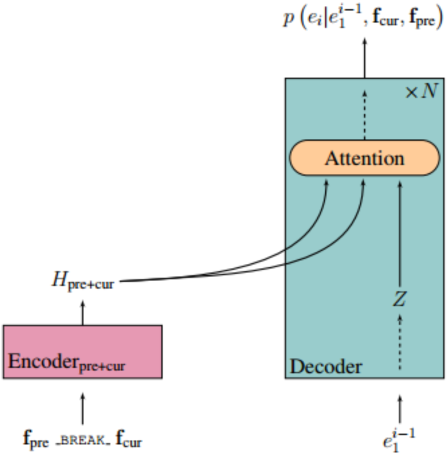
- New test suites for restricted scope.
  - Considering other documents other than movie subtitles for building test sets would be interesting for various reasons:
    - No multiple speakers, no unavailable context (the video), more phenomena related to future context.

Plan

Plan

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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    - 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:

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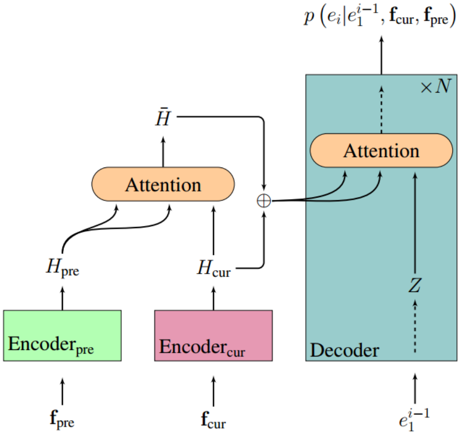

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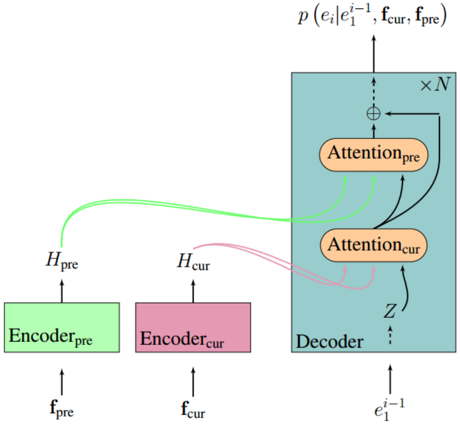

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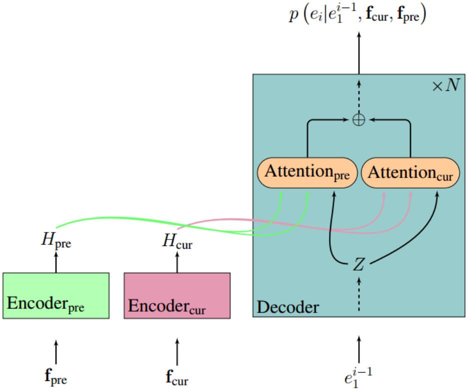

Architecture

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
[Tan et al., 2019]	s:all	yes		parallel	Zh/De→En
[Voita et al., 2019b]	s:-3; t:-3	yes		parallel*	En→Ru

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**.

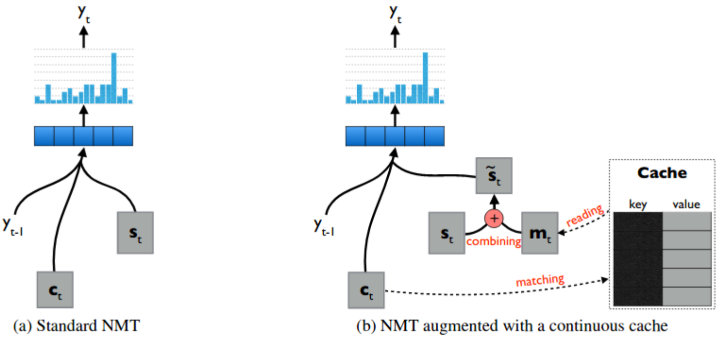
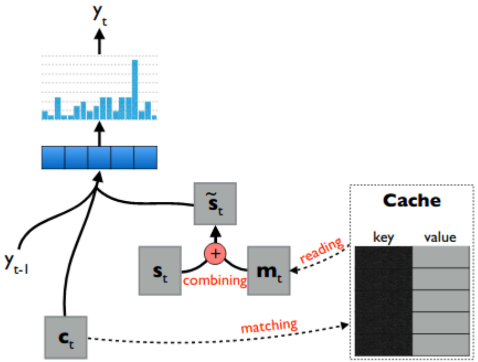


Figure: Continuous cache by [Tu et al., 2017]

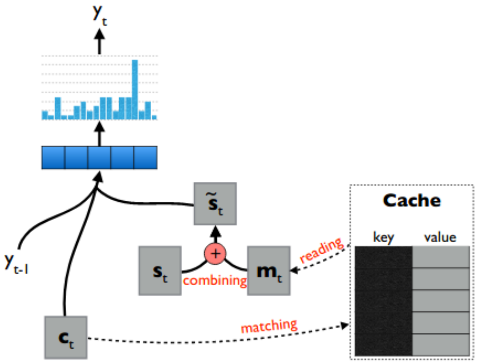
Cache Approaches

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 Approaches

Cache reading involves:



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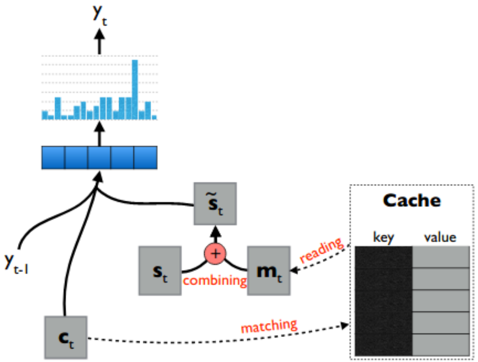

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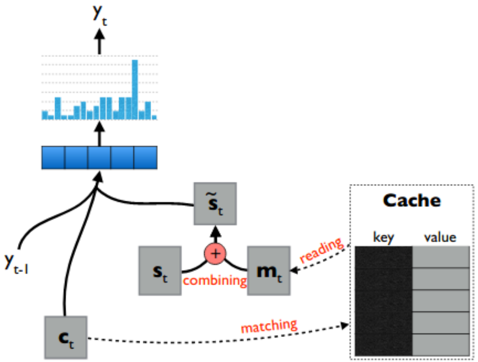

Cache Approaches

Cache reading involves:

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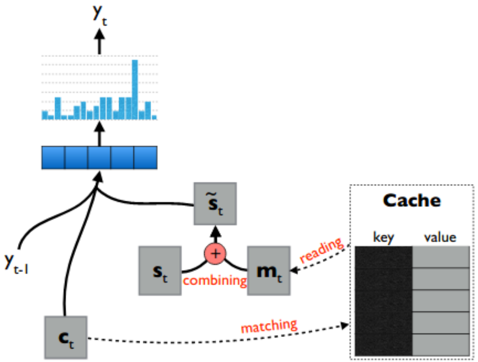
- Combining



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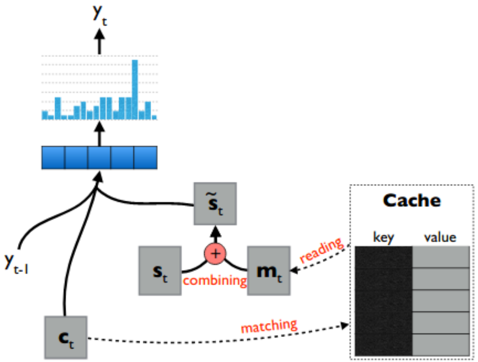

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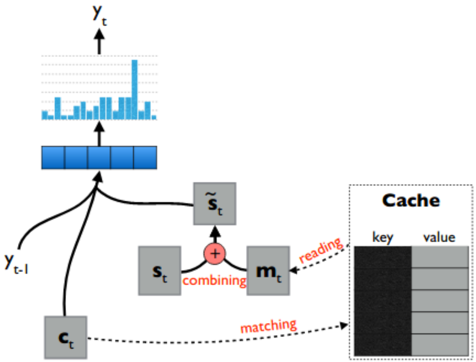

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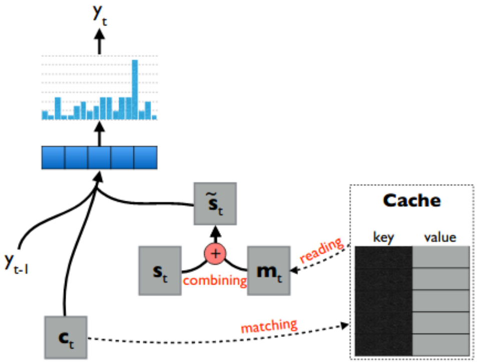
- Else, we write the triplet in an empty slot, after having emptied the oldest slot if the cache is full.



Cache Approaches

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

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  3. Train together θ_D and θ_S (finetune) on a document-level parallel corpus C_D.

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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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  - 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

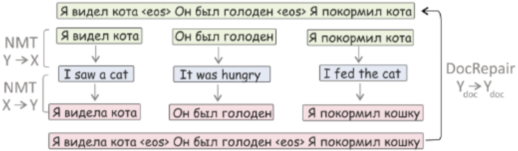

Figure 1: Training procedure of DocRepair. First, round-trip translations of individual sentences are produced to form an inconsistent text fragment (in the example, both genders of the speaker and the cat became inconsistent). Then, a repair model is trained to produce an original text from the inconsistent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

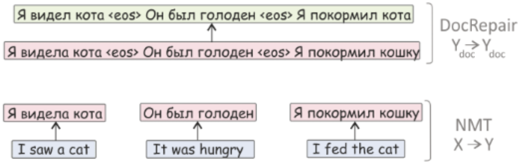

Figure 2: The process of producing document-level translations at test time is two-step: (1) sentences are translated independently using a sentence-level model, (2) DocRepair model corrects translation of the resulting text fragment.

Plan

Others

Approaches Including Additional Discourse Information as Input
These approaches consist in concatenation approaches or separate encoding approaches that also integrate discourse-related information as additional input features. Examples of extra features are:

Others

Approaches Including Additional Discourse Information as Input
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- 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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- Study pre-trained language models for DLNMT decoder.
- Study other learning methods that foster document-level modeling [Jean and Cho, 2019].

Thank you for your attention!

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