-SOTA-
Document-level Neural Machine Translation

by Lorenzo Lupo

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Plan

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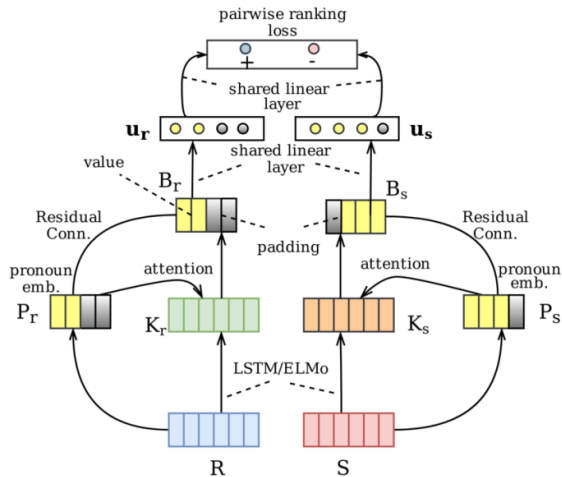
Figure: Pairwise ranking system by [Jwalapuram et al., 2019].

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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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- ‣ One test suite on **pronominal 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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- ‣ One test suite on **pronomial anaphora** comprised of 50 blocks.
- ‣ One on **lexical coherence and cohesion**, comprised of 100 blocks.

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.

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context: Comment vont tes pieds ?
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‣ *Design method*: manual design preceded by a human analysis on the most common translation errors in the target language pair.

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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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Remarks and conclusions

Automatic Metrics

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  - ‣ is the case of APT, for example, which has been shown by [Guillou and Hardmeier, 2018] not to be suitable to evaluate the translation of pronouns with certain functions.
- $-$ No existing metrics for coherence although it's very relevant for users.

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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 automatic metrics strongly tested against human judgment.
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- ‣ New test suites for restricted scope.

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- ▸ Semi-automatic metrics: use a high precision automatic metric and a human to evaluate negative cases.

- ▸ 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.
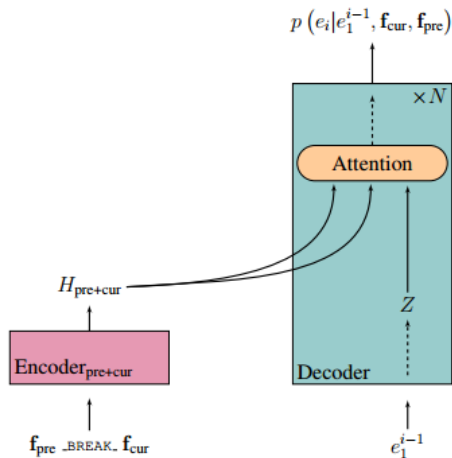
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  - **2-TO-2**: the previous and the current sentences are translated together. The translation of the current sentence is then obtained by only retaining the tokens following the concatenation token.
  - **2-TO-1**: only the current sentence is translated.
- [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:

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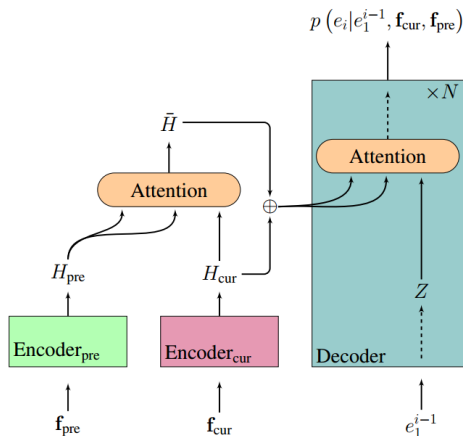
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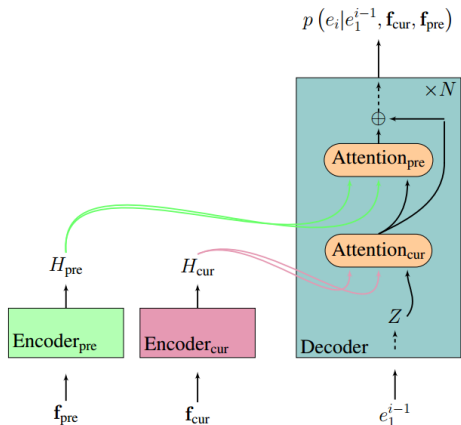
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The encoder-decoder architectures depicted above can be both RNN-based (until 2017) or Transfomer-based (after 2017), as for any approach to DLNMT. However, often some modifications are applied. For example:

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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]

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**.

(a) Standard NMT

(b) NMT augmented with a continuous cache
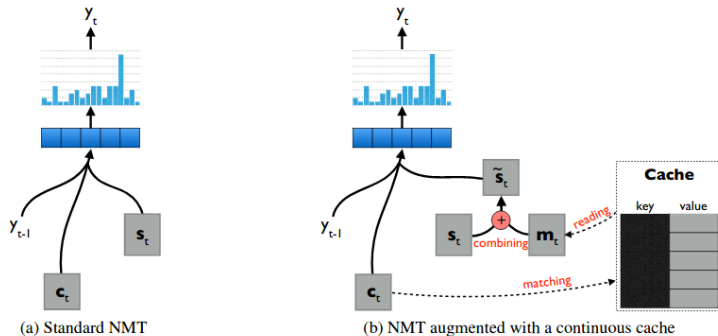
Figure: Continuous cache by [Tu et al., 2017]

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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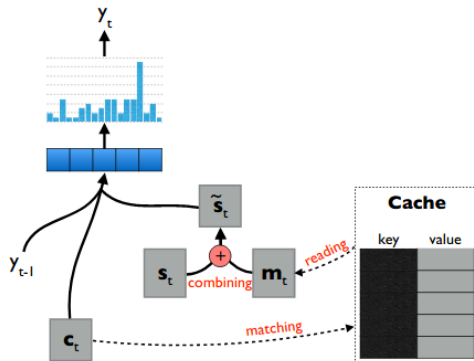
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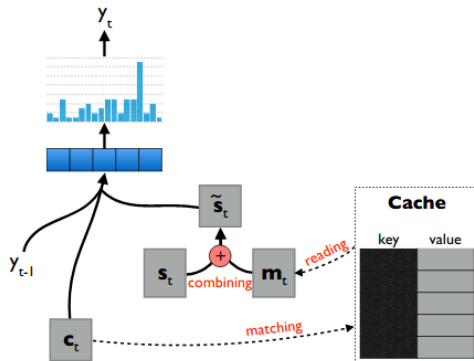
Cache writing can be undertaken after having translated one or more sentences. For every triplet:
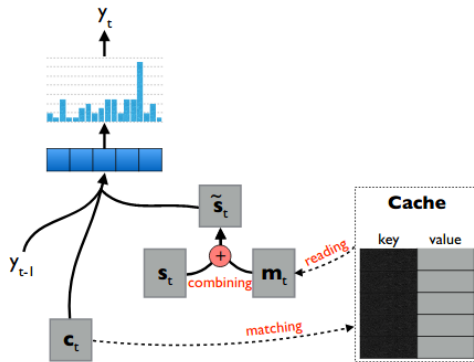
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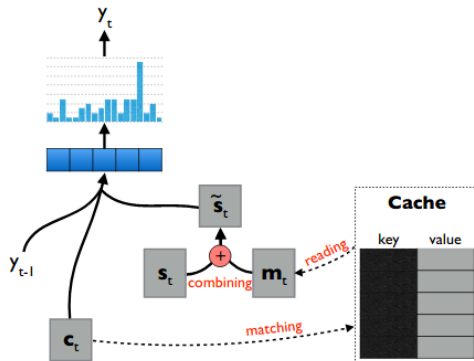
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- ‣ Else, we write the triplet in an empty slot, after having emptied the oldest slot if the cache is full.
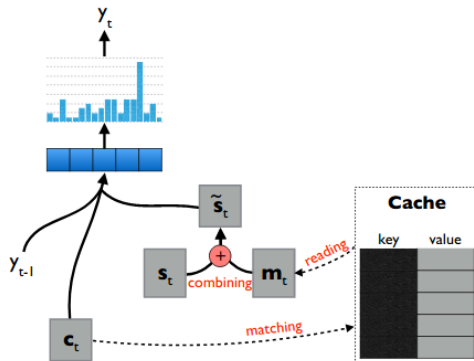
Cache Approaches

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

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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- ‣ Parliamentary interventions (Europarl)

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

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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- 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
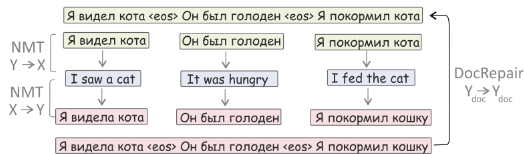
Figure 1: Training procedure of DocRepair. First, round-trip translations of individual sentences are produced to form an inconsistent text fragment (in the example, both genders of the speaker and the cat became inconsistent). Then, a repair model is trained to produce an original text from the inconsistent one.
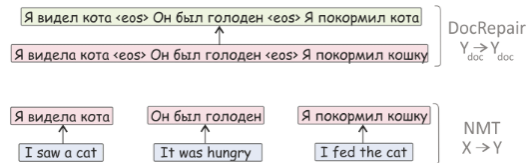
Figure 2: The process of producing document-level translations at test time is two-step: (1) sentences are translated independently using a sentence-level model, (2) DocRepair model corrects translation of the resulting text fragment.

Plan

Others

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  [Rios Gonzales et al., 2017].
- ‣ Coreference chains to promote coreference resolution
  [Stojanovski and Fraser, 2018, Ohtani et al., 2019].

Others

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.

Plan

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‣ Design models with good results on lexical cohesion [Voita et al., 2019b].

‣ Design models exploiting full context in a memory-efficient way:

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- ▸ Study other learning methods that foster document-level modeling [Jean and Cho, 2019].

Thank you for your attention!

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