Recent Advances In Document-level Neural Machine Translation

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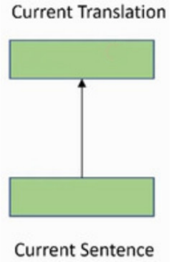
What is Document-level Machine Translation

Sentence-level MT



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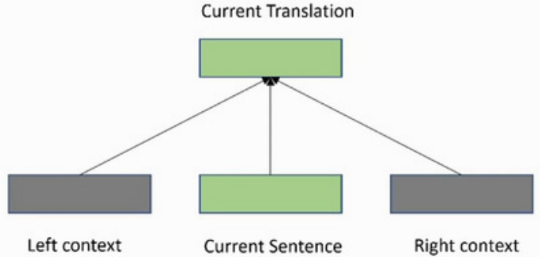
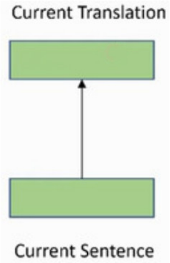


Document-level MT ↔ Context-aware MT

Context-agnostic MT



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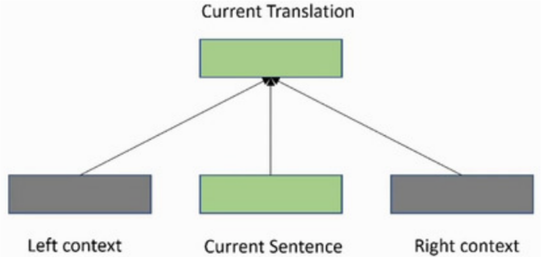

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- "In a pairwise ranking experiment, human raters assessing **adequacy** and **fluency** show a stronger preference for human over machine translation when evaluating documents as compared to isolated sentences." [Lubli et al., 2018]

Sentence-level NMT is inconsistent

B: How are you today?

Sentence-level NMT is inconsistent

B: How are you today?

SENTENCE-LEVEL TRANSLATION

B: Comment vas-tu aujourd'hui ?

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A: Good Morning, Mr. President.

B: How are you today?

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A: Good Morning, Mr. President.

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DOCUMENT-LEVEL TRANSLATION

B: Comment allez-vous aujourd'hui ?

How frequent are inconsistencies ?

[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 inconsistencies between English-Russian context-agnostic translations 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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  - they are not able to measure improvements over translations of discourse **phenomena that affect few words but heavily influence fluency and correctness** of the translation [Mller et al., 2018]. E.g. pronomial anaphora.
- Instead, we should evaluate DNMT with metrics that can **capture inter-sentential discourse phenomena**.

Desiderata of Document-level MT Evaluation

The evaluation of document-level MT should:

[1] in the remainder of this presentation, we refer to inter-sentential context simply as context.

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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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  - [Hajlaoui and Popescu-Belis, 2013] proposed new automatic and semi-automatic metrics for discourse connectives, referred to as **Accuracy of Connective Translation**.
  - [Wong and Kit, 2012] measure the abundance of lexical cohesion characterized by semantically related words with **Lexical Cohesion Devices**.

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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** allow to evaluate MT systems 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.

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 ?
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Figure: Example block of the lexical coherence and cohesion test suite.

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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.

Test Suites

[2]During scoring, the model is also provided with reference translations as target context (easier). Instead, during translation, the model needs to predict the full sequence, thus being subject to beam search failures and error propagation.

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– Excepts for specialized test sets (slide 17), 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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DNMT architectures

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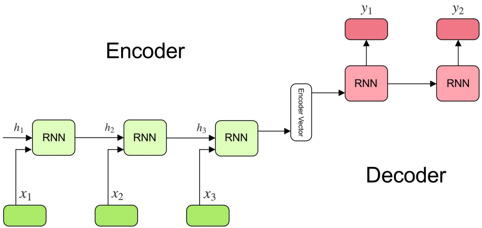
RNN-based (until 2017)



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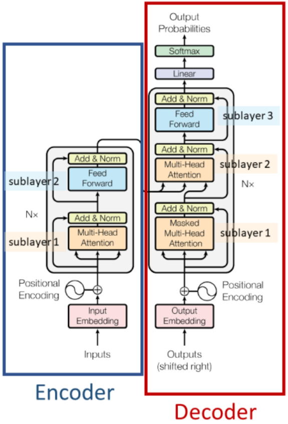
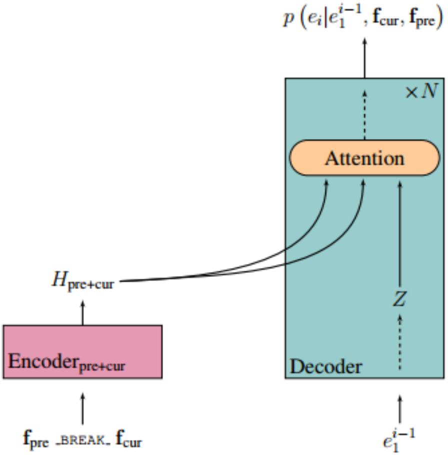
Transformer-based (afterwards)



Plan

Concatenation Approaches

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



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  - **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.

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- **Multiple encoders** working in parallel for the current and previous sentence. E.g. [Wang et al., 2017].
- **Multiple encoders with shared weights**. In this case, the parallel-working encoders not only have the same architecture, but also the same weights. E.g. [Voita et al., 2018].

Separate Encoding Approaches

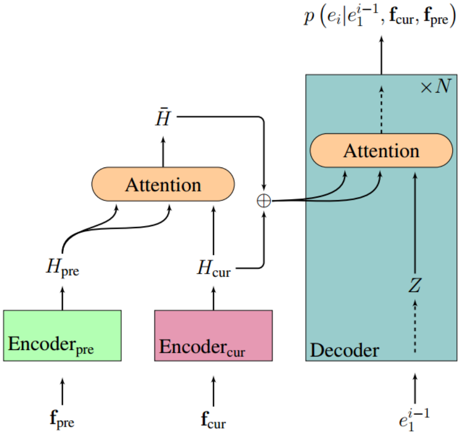
Separate encoding approaches to DNMT consist in encoder-decoder models that encode the current and context sentences separately. This can be undertaken by:

- **Multiple encoders** working in parallel for the current and previous sentence. E.g. [Wang et al., 2017].
- **Multiple encoders with shared weights**. In this case, the parallel-working encoders not only have the same architecture, but also the same weights. E.g. [Voita et al., 2018].
- **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 38.

Separate Encoding Approaches

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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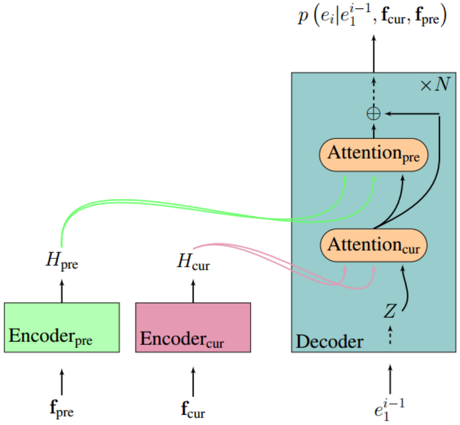

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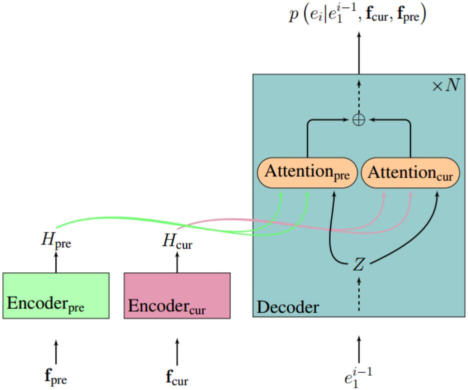

Separate Encoding Approaches

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., 2019, 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., 2019]	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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2. Assign **positional embeddings progressively** to the current sentence, then to the previous one, and so on, so that far away sentences have high values of positional embedding [Li et al., 2019].
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 DNMT 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**.

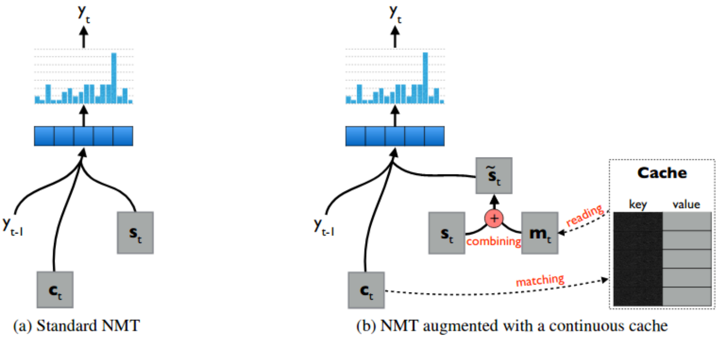
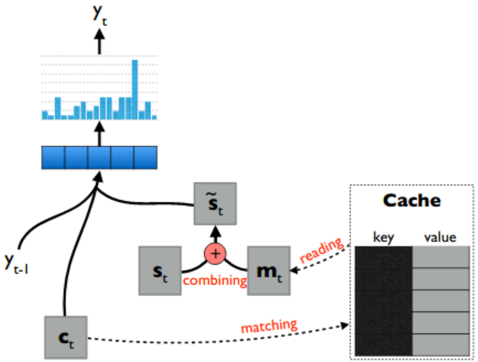
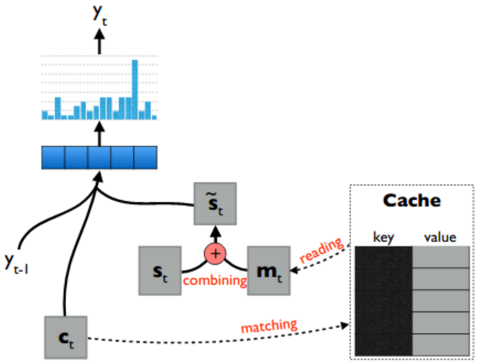


Figure: Continuous cache by [Tu et al., 2017]

Every cache slot is a **key-value** tuple.
With these variables, we can **read** or **write** caches.



Cache reading involves:



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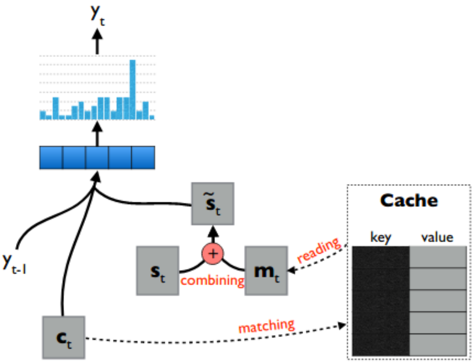

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- Soft key matching
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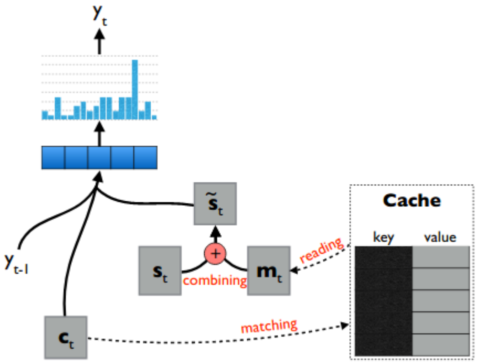

Cache Approaches

Cache reading involves:

- Soft key matching
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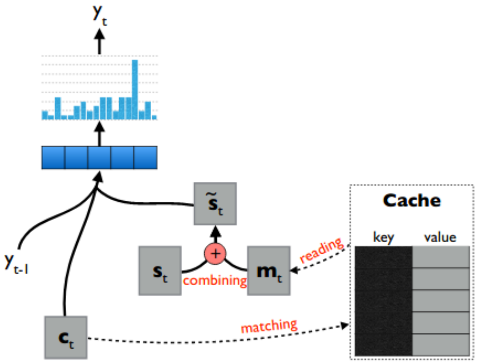

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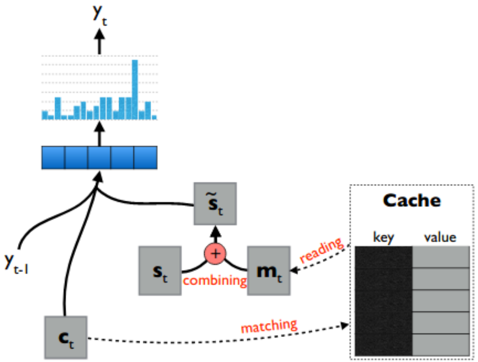

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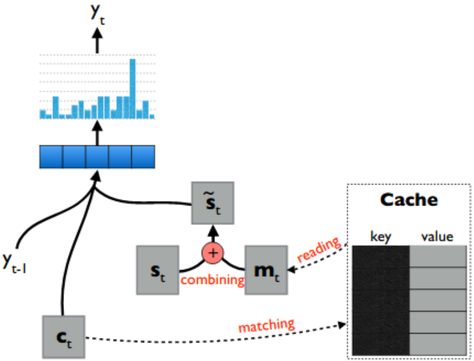

Cache Approaches

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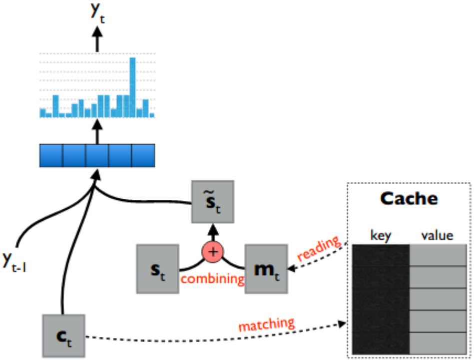
- If the **key** already exists in the cache, we just update its value.
- Else, we write the key-value tuple in an empty slot, after having emptied the oldest slot if the cache is full.



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

DNMT 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].

Exploiting Document-level 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 DNMT 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.

DocRepair

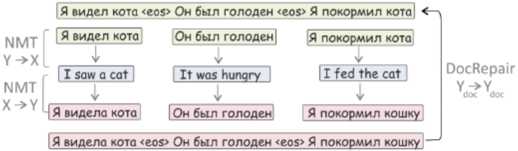

Figure 1: Training procedure of DocRepair. First, round-trip translations of individual sentences are produced to form an inconsistent text fragment (in the example, both genders of the speaker and the cat became inconsistent). Then, a repair model is trained to produce an original text from the inconsistent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

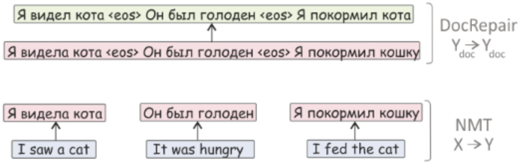

Figure 2: The process of producing document-level translations at test time is two-step: (1) sentences are translated independently using a sentence-level model, (2) DocRepair model corrects translation of the resulting text fragment.

Plan

Others

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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:

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

Thank you for your attention!

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