

-SOTA- Document-level Neural Machine Translation

by Lorenzo Lupo

April 2020

Plan

1. Evaluation
 - 1.2 Automatic metrics
 - 1.3 Test Suites
 - 1.4 Remarks and conclusions
2. Approaches to DLNMT
 - 2.5 Concatenation Approaches
 - 2.6 Separate Encoding Approaches
 - 2.7 Cache Approaches
 - 2.8 Exploiting Monolingual Corpora
 - 2.9 Others
 - 2.10 Remarks and conclusions

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 - ▶ automatic metrics.
 - ▶ test suites.

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]
Test Suites	Pronouns	Discourse parser	[25, 39]
		Discourse parser	[99]
		En→Fr	[23]
	Cohesion	En→Fr (anaphora)	[7]
		En→De (anaphora)	[78]
		En→Fr	[7]
	Coherence	En→Ru	[115]
		En→Fr	[7]
		En↔De, Cs↔De, En→Cs	[117]
	Conjunction	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.

Automatic metrics

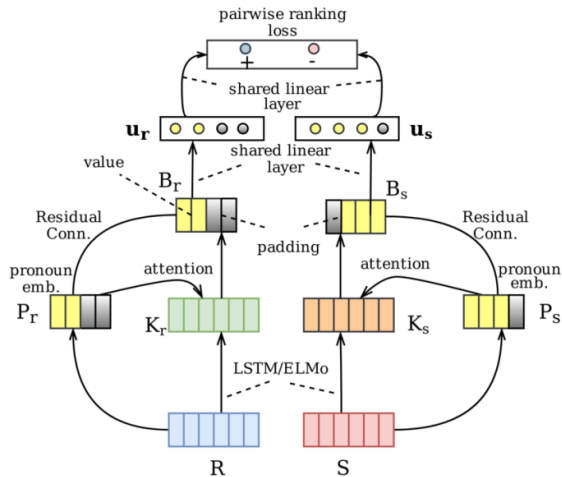


Figure: Pairwise ranking system by [Jwalapuram et al., 2019].

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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.

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- ▶ **Specialized test sets** are like normal MT test sets but consist of sentence pairs that are more densely populated with specific discourse phenomena. Translations are evaluated on such tests sets by means of average quality metrics like BLEU.
 - ▶ 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 → 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 mouchérons . Regarde, il y en a un autre ! |
| | correct: | T'inquiète, je le tuerai pour toi. |
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| | | |
| 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. |
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Figure: Example block of the pronomial anaphora test suite.

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- 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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 - ▶ **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.

Test Suites

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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).

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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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- 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

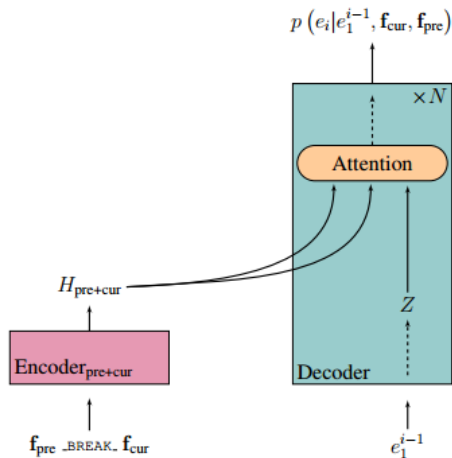
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Concatenation Approaches

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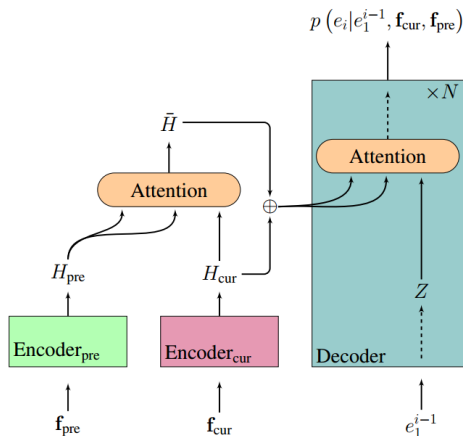
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Once the encoding of the current and the context sentences has been carried out, they can be integrated in different ways:

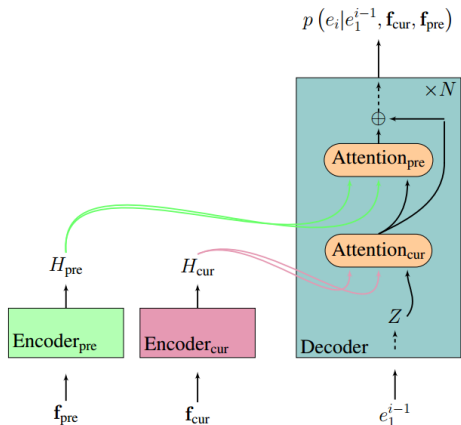
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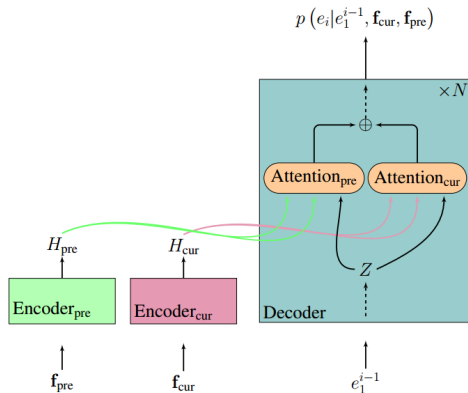
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- ▶ Parallel integration inside the decoder can also happen within a single multi-head attention that takes as values and queries the concatenations of the current and context sentence representations [Voita et al., 2019b]

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].

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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**.

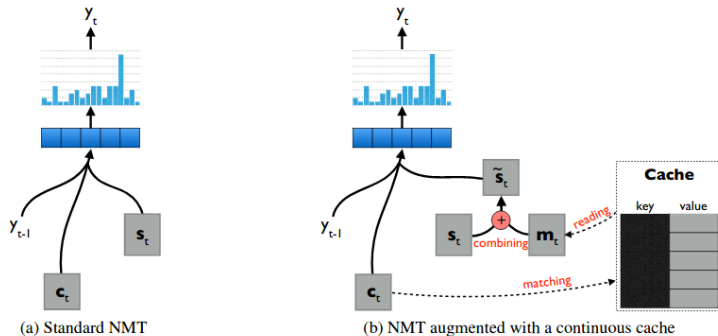
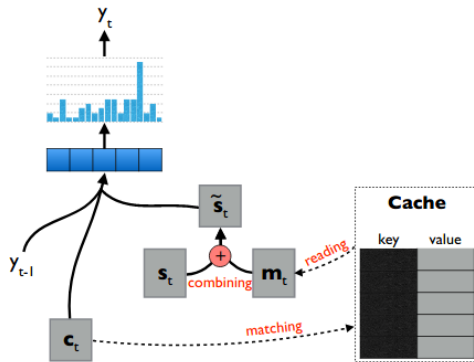


Figure: Continuous cache by [Tu et al., 2017]

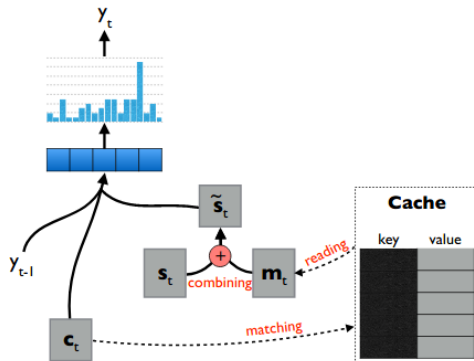
Cache Approaches

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

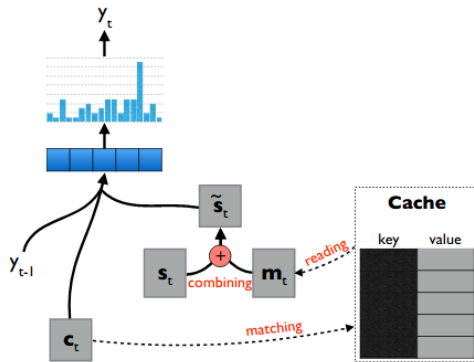
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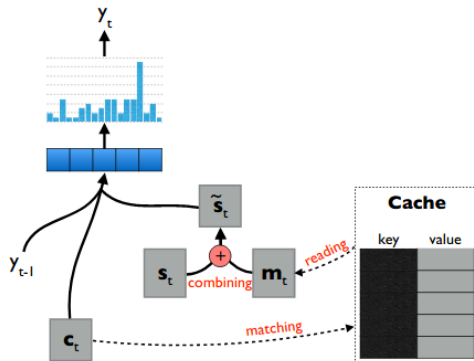
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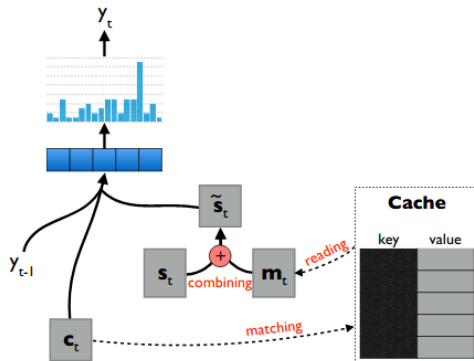
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Cache Approaches

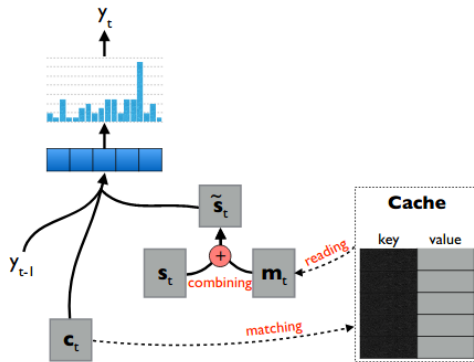
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Cache Approaches

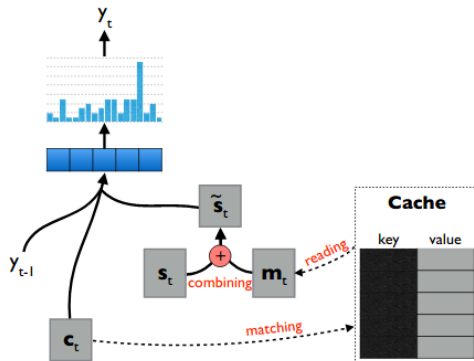
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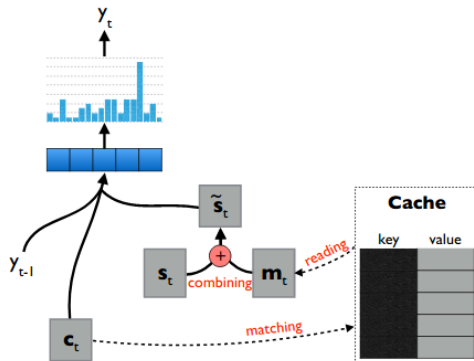
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- ▶ Else, we write the triplet in an empty slot, after having emptied the oldest slot if the cache is full.



Cache Approaches

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

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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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 - ▶ Initialize the encoder (or decoder) of a DLNMT model [Li et al., 2019].

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:

- ▶ **Back-translate** target-side corpus to augment dl corpus [Sugiyama and Yoshinaga, 2019].
- ▶ Train **context-aware language models** on target/source-side corpus, then:
 - ▶ Generate translations by fusing the decoder and the LM's scores to candidate words [Martnez Garcia et al., 2019].
 - ▶ Initialize the econdor (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

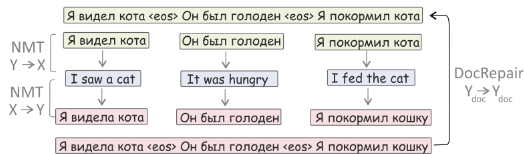


Figure 1: **Training procedure of DocRepair.** First, round-trip translations of individual sentences are produced to form an inconsistent text fragment (in the example, both genders of the speaker and the cat became inconsistent). Then, a repair model is trained to produce an original text from the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

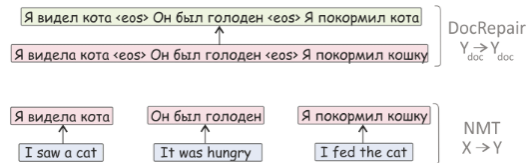


Figure 2: The process of producing document-level translations at **test time** is two-step: (1) sentences are translated independently using a sentence-level model, (2) DocRepair model corrects translation of the resulting text fragment.

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 - 1.4 Remarks and conclusions
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 - 2.7 Cache Approaches
 - 2.8 Exploiting Monolingual Corpora
 - 2.9 Others
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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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- 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!



References I

-  Agrawal, R. R., Turchi, M., and Negri, M. (2018).
Contextual Handling in Neural Machine Translation: Look Behind, Ahead and on
Both Sides.
pages 11–20.
00007 Accepted: 2018-08-08T15:15:28Z.
-  Bawden, R., Sennrich, R., Birch, A., and Haddow, B. (2018).
Evaluating Discourse Phenomena in Neural Machine Translation.
*In Proceedings of the 2018 Conference of the North American Chapter of the
Association for Computational Linguistics: Human Language Technologies,
Volume 1 (Long Papers)*, pages 1304–1313, New Orleans, Louisiana. Association
for Computational Linguistics.
00056.

References II

-  Fellbaum, C. (1998).
A Semantic Network of English: The Mother of All WordNets.
Computers and the Humanities, 32(2):209–220.
00194.
-  Fu, H., Liu, C., and Sun, J. (2019).
Reference Network for Neural Machine Translation.
In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 3002–3012, Florence, Italy. Association for Computational Linguistics.
00000.


References III


-  Guillou, L. and Hardmeier, C. (2018).
Automatic Reference-Based Evaluation of Pronoun Translation Misses the Point.
In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 4797–4802, Brussels, Belgium. Association for Computational Linguistics.
00008.
-  Jean, S., Bapna, A., and Firat, O. (2019).
Fill in the Blanks: Imputing Missing Sentences for Larger-Context Neural Machine Translation.
arXiv:1910.14075 [cs].
00000 arXiv: 1910.14075.

References IV



-  Jean, S. and Cho, K. (2019).
Context-Aware Learning for Neural Machine Translation.
arXiv:1903.04715 [cs].
00003 arXiv: 1903.04715.
-  Jean, S., Lauly, S., Firat, O., and Cho, K. (2017).
Does Neural Machine Translation Benefit from Larger Context?
arXiv:1704.05135 [cs, stat].
00039 arXiv: 1704.05135.
-  Jwalapuram, P., Joty, S., Temnikova, I., and Nakov, P. (2019).
Evaluating Pronominal Anaphora in Machine Translation: An Evaluation Measure
and a Test Suite.
arXiv:1909.00131 [cs].
00002 arXiv: 1909.00131.

References V




 Kim, Y., Tran, D. T., and Ney, H. (2019).
When and Why is Document-level Context Useful in Neural Machine Translation?
arXiv:1910.00294 [cs].
00001 arXiv: 1910.00294.

 Kuang, S., Xiong, D., Luo, W., and Zhou, G. (2018).
Modeling Coherence for Neural Machine Translation with Dynamic and Topic
Caches.
In Proceedings of the 27th International Conference on Computational Linguistics,
pages 596–606, Santa Fe, New Mexico, USA. Association for Computational
Linguistics.
00012.

References VI

-  Li, L., Jiang, X., and Liu, Q. (2019).
Pretrained Language Models for Document-Level Neural Machine Translation.
arXiv:1911.03110 [cs].
00001 arXiv: 1911.03110.
-  Martnez Garcia, E., Creus, C., and Espaa-Bonet, C. (2019).
Context-Aware Neural Machine Translation Decoding.
In Proceedings of the Fourth Workshop on Discourse in Machine Translation (DiscoMT 2019), pages 13–23, Hong Kong, China. Association for Computational Linguistics.
00000.

References VII

-  Maruf, S. and Haffari, G. (2018).
Document Context Neural Machine Translation with Memory Networks.
In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1275–1284, Melbourne, Australia.
Association for Computational Linguistics.
00000.
-  Maruf, S., Martins, A. F. T., and Haffari, G. (2019a).
Selective Attention for Context-aware Neural Machine Translation.
arXiv:1903.08788 [cs].
00012.
-  Maruf, S., Saleh, F., and Haffari, G. (2019b).
A Survey on Document-level Machine Translation: Methods and Evaluation.
arXiv:1912.08494 [cs].
00000 arXiv: 1912.08494.

References VIII



Miculicich, L., Ram, D., Pappas, N., and Henderson, J. (2018).
Document-Level Neural Machine Translation with Hierarchical Attention
Networks.

arXiv:1809.01576 [cs].



00029 arXiv: 1809.01576.



Miculicich Werlen, L. and Popescu-Belis, A. (2017).
Validation of an Automatic Metric for the Accuracy of Pronoun Translation
(APT).

In Proceedings of the Third Workshop on Discourse in Machine Translation, pages
17–25, Copenhagen, Denmark. Association for Computational Linguistics.
00000.



References IX

-  Mller, M., Rios, A., Voita, E., and Sennrich, R. (2018).
A Large-Scale Test Set for the Evaluation of Context-Aware Pronoun Translation
in Neural Machine Translation.
In Proceedings of the Third Conference on Machine Translation: Research Papers,
pages 61–72, Brussels, Belgium. Association for Computational Linguistics.
00010.
-  Ohtani, T., Kamigaito, H., Nagata, M., and Okumura, M. (2019).
Context-aware Neural Machine Translation with Coreference Information.
*In Proceedings of the Fourth Workshop on Discourse in Machine Translation
(DiscoMT 2019)*, pages 45–50, Hong Kong, China. Association for Computational
Linguistics.
00000.

References X

-  Porter, M. (1980).
An algorithm for suffix stripping.
Program, 40(3):211–218.
10830.
-  Rae, J. W., Potapenko, A., Jayakumar, S. M., and Lillicrap, T. P. (2019).
Compressive Transformers for Long-Range Sequence Modelling.
arXiv:1911.05507 [cs, stat].
00000 arXiv: 1911.05507.
-  Rios Gonzales, A., Mascarell, L., and Sennrich, R. (2017).
Improving Word Sense Disambiguation in Neural Machine Translation with Sense
Embeddings.
In Proceedings of the Second Conference on Machine Translation, pages 11–19,
Copenhagen, Denmark. Association for Computational Linguistics.
00030.

References XI

-  Rysov, K., Rysov, M., Musil, T., Polkov, L., and Bojar, O. (2019).
A Test Suite and Manual Evaluation of Document-Level NMT at WMT19.
In Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1), pages 455–463, Florence, Italy. Association for Computational Linguistics.
00001.
-  Scherrer, Y., Tiedemann, J., and Loiciga, S. (2019).
Analysing concatenation approaches to document-level NMT in two different domains.
In Proceedings of the Fourth Workshop on Discourse in Machine Translation (DiscoMT 2019), pages 51–61, Hong Kong, China. Association for Computational Linguistics.
00001.




References XII

-  Stojanovski, D. and Fraser, A. (2018).
Coreference and Coherence in Neural Machine Translation: A Study Using Oracle Experiments.
In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 49–60, Brussels, Belgium. Association for Computational Linguistics. 00003.
-  Sugiyama, A. and Yoshinaga, N. (2019).
Data augmentation using back-translation for context-aware neural machine translation.
In Proceedings of the Fourth Workshop on Discourse in Machine Translation (DiscoMT 2019), pages 35–44, Hong Kong, China. Association for Computational Linguistics. 00000.

References XIII



-  Tan, X., Zhang, L., Xiong, D., and Zhou, G. (2019).
Hierarchical Modeling of Global Context for Document-Level Neural Machine Translation.
In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 1576–1585, Hong Kong, China. Association for Computational Linguistics.
00002.
-  Tiedemann, J. and Scherrer, Y. (2017).
Neural Machine Translation with Extended Context.
In Proceedings of the Third Workshop on Discourse in Machine Translation, pages 82–92, Copenhagen, Denmark. Association for Computational Linguistics.
00040.

References XIV

-  Tu, Z., Liu, Y., Shi, S., and Zhang, T. (2017).
Learning to Remember Translation History with a Continuous Cache.
arXiv:1711.09367 [cs].
00041 arXiv: 1711.09367.
-  Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N.,
Kaiser, L., and Polosukhin, I. (2017).
Attention Is All You Need.
arXiv:1706.03762 [cs].
05728 arXiv: 1706.03762.
-  Voita, E., Sennrich, R., and Titov, I. (2019a).
Context-Aware Monolingual Repair for Neural Machine Translation.
arXiv:1909.01383 [cs].
00003 arXiv: 1909.01383.

References XV



-  Voita, E., Sennrich, R., and Titov, I. (2019b).
When a Good Translation is Wrong in Context: Context-Aware Machine Translation Improves on Deixis, Ellipsis, and Lexical Cohesion.
In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 1198–1212, Florence, Italy. Association for Computational Linguistics.
00007.
-  Voita, E., Serdyukov, P., Sennrich, R., and Titov, I. (2018).
Context-Aware Neural Machine Translation Learns Anaphora Resolution.
In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1264–1274, Melbourne, Australia. Association for Computational Linguistics.
00049.

-  Wang, L., Tu, Z., Way, A., and Liu, Q. (2017).
Exploiting Cross-Sentence Context for Neural Machine Translation.
In *Proceedings of the 2017 Conference on Empirical Methods in Natural Language Processing*, pages 2826–2831, Copenhagen, Denmark. Association for Computational Linguistics.
00048.
-  Wang, X., Weston, J., Auli, M., and Jernite, Y. (2019).
Improving Conditioning in Context-Aware Sequence to Sequence Models.
00002.

References XVII

-  Wong, B. T. M. and Kit, C. (2012).
Extending Machine Translation Evaluation Metrics with Lexical Cohesion to Document Level.
In Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning, pages 1060–1068, Jeju Island, Korea. Association for Computational Linguistics. 00044.
-  Zhang, J., Luan, H., Sun, M., Zhai, F., Xu, J., Zhang, M., and Liu, Y. (2018).
Improving the Transformer Translation Model with Document-Level Context.
In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 533–542, Brussels, Belgium. Association for Computational Linguistics. 00028.

References XVIII

-  Zheng, Z., Yue, X., Huang, S., Chen, J., and Birch, A. (2020).
Toward Making the Most of Context in Neural Machine Translation.
arXiv:2002.07982 [cs].
00000 arXiv: 2002.07982.
-  Zhu, Y., Kiros, R., Zemel, R., Salakhutdinov, R., Urtasun, R., Torralba, A., and Fidler, S. (2015).
Aligning Books and Movies: Towards Story-like Visual Explanations by Watching Movies and Reading Books.
arXiv:1506.06724 [cs].
00450 arXiv: 1506.06724.