Capturing Longer Context for Document-level Neural Machine Translation: A Multi-resolutional Approach

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Abstract

Discourse context has been proven useful when translating documents. It is quite a challenge to incorporate long document context in the prevailing neural machine translation models such as Transformer. In this paper, we propose multi-resolutional (MR) Doc2Doc, a method to train a neural sequence-to-sequence model for document-level translation. Our trained model can simultaneously translate sentence by sentence as well as a document as a whole. We evaluate our method and several recent approaches on nine document-level datasets and two sentence-level datasets across six languages. Experiments show that MR Doc2Doc outperforms sentence-level models and previous methods in a comprehensive set of metrics, including BLEU, four lexical indices, three newly proposed assistant linguistic indicators, and human evaluation.

Introduction

Neural machine translation (Bahdanau, Cho, and Bengio 2015; Wu et al. 2016; Vaswani et al. 2017) has achieved great progress and reached near human-level performance on several language pairs. However, most current sequence-to-sequence NMT models translate sentences individually. In such cases, discourse phenomena, such as pronominal anaphora, lexical consistency, and document coherence that depend on long-range context going further than a few previous sentences, are neglected (Bawden et al. 2017). As a result, Laubli, Sennrich, and Volk (2018) find human raters still show a markedly stronger preference for human translations when evaluating at the level of documents.

Many methods have been proposed to improve document-level neural machine translation (DNMT). Among them, the mainstream works focus on the model architecture modification, including hierarchical attention (Wang et al. 2017; Miculicich et al. 2018; Tan et al. 2019), additional context extraction encoders or query layers (Jean et al. 2017; Bawden et al. 2017; Zhang et al. 2018; Voita et al. 2018; Kuang and Xiong 2018; Maruf, Martins, and Haffari 2019; Yang et al. 2019; Jiang et al. 2019; Zheng et al. 2020; Yun, Hwang, and Jung 2020; Xu et al. 2020), and cache-like memory network (Maruf and Haffari 2018; Kuang et al. 2018; Yu et al. 2018).

These studies come up with different structures in order to include discourse information, specifically introducing adjacent sentences into the encoder or decoder as document contexts. Experimental results show effective improvements on universal translation metrics like BLEU (Papineni et al. 2002), METEOR (Banerjee and Lavie 2005), and TER (Shover et al. 2005) as well as document-level linguistic indices (Hedemann and Scherrer 2017; Bawden et al. 2017; Werlen and Popescu-Belis 2017; Múller et al. 2018; Voita et al. 2018; Voita, Sennrich, and Titov 2019).

Since the architecture adjustment has been fully explored in recent years, we take attempts to focus on the training paradigm. Instead of adding more model units with additional parameters, we head back to the original but concise way, tackling DNMT with the sequence-to-sequence training style, precisely, document-to-document (Doc2Doc). We leverage the full document information in such a training pattern, capturing much longer context in both source and target sides.

Though many studies report negative results of naive Doc2Doc translation (Zhang et al. 2018; Liu et al. 2020), we successfully activate it with multi-resolutional training, which involves multiple levels of sequences. It turns out that end-to-end document translation is not only feasible but also better functioning than sentence-level models and previous works. Furthermore, if assisted by extra sentence-level corpus, which can be much more easily obtained, our model can significantly improve the translation performance and achieve state-of-the-art results. It is worth noting that our method does not change the model architecture and needs no extra parameters.

Our experiments are conducted on nine document-level datasets, including TED (ZH-EN, EN-DE), News (EN-DE, ES-EN, FR-EN, RU-EN), Europarl (EN-DE), Subtitles (EN-RU), and a newly constructed News dataset (ZH-EN). Additionally, two sentence-level datasets are adopted in further experiments, including Wikipedia (EN-DE) and WMT (ZH-EN). Experiment results show that our strategy outperforms previous methods in a comprehensive set of metrics, including BLEU, four lexical indices, three newly proposed assistant linguistic indicators, and human evaluation. In addition to serving as improvement evidence, our newly proposed document-level datasets and metrics can also be a boosting contribution to the community.
Doc2Doc: End-to-End Document Translation

In this section, we attempt to explore a different training pattern to DNMT. Firstly, let us formulate the problem. Let $D_x = \{x(1), x(2), \ldots, x(M)\}$ be a source-language document containing $M$ source sentences. The goal of the document-level NMT is to translate the document $D_x$ in language $x$ to a document $D_y$ in language $y$. $D_y = \{y^{(1)}, y^{(2)}, \ldots, y^{(N)}\}$. We use $L_y^{(i)}$ to denote the sentence length of $y^{(i)}$.

Most previous works translate a document sentence-by-sentence, regarding DNMT as a step-by-step document-to-sentence (Doc2Sent) problem as:

$$
L_{\text{Doc2Sent}} = -\sum_{i=1}^{N} \sum_{j=1}^{L_y^{(i)}} \log p_{\theta}(y^{(i)}_{j} | y^{(i)}_{<j}, x^{(i)}, S^{(i)}, T^{(i)}),
$$

where $S^{(i)}$ is the context in the source side, depending on the model architecture and is usually comprised of only two or three sentences. Most current works focus on $S^{(i)}$, by utilizing hierarchical attention or extra encoders. And $T^{(i)}$ is the context in the target side, which is involved by only a couple of works. They usually make use of a topic model or word cache for around 100 words to form $T^{(i)}$.

Different from Doc2Sent, we propose to resolve document translation with the end-to-end, namely document-to-document (Doc2Doc) pattern as:

$$
L_{\text{Doc2Doc}} = -\sum_{i=1}^{N} \log p_{\theta}(y_i | y_{<i}, D_x),
$$

where $D_x$ is the complete context in the source side, and $y_{<i}$ is the complete historical context in the target side.

Why Doc2Doc is a Better Choice

Firstly, Doc2Sent does not utilize a full source-side context. Strictly speaking, the so-called Doc2Sent is more of “a couple of sentences to sentence” since most works only involve two or three preceding sentences as context. Some studies even show that more sentences beyond bring harmful effects in terms of BLEU. Therefore, the correct usage of long-range context is by Doc2Sent style. However, broader contexts shall provide more information and references, which lead to more improvements. Correspondingly, Doc2Doc is required to take account of all the source-side context.

Secondly, Doc2Sent does not utilize a full target-side context. Most previous works abandon the target-side historical context, and some even claim target-side information is harmful to translation quality. However, once the cross-sentence language model is discarded, some problems, such as tense mismatch (especially when the source language is tense-less like Chinese/Japanese) or pronoun dependency lost, may occur. Intuitively, a more extended language model can facilitate translating and maintain its coherence. A few works do attempt to utilize target-side history information but only make use of a limited context, like a 100-words cache. Longer dependency is neglected. On the contrary, Doc2Doc treats the whole document as a sequence and can naturally take advantage of all the target-side historical context.

Thirdly, Doc2Sent restricts the training scene. The previous works focus on adjusting the model structure to feed preceding source sentences, so the training data has to be in the form of consecutive sentences so as to meet the model entrance. As a result, it is hard to take advantage of large numbers of piecemeal parallel sentences. Such a rigid form of training data also greatly hinders the model potential because the scale of available parallel sentences can be tens of times of parallel documents. On the contrary, Doc2Doc can naturally absorb all kinds of sequences, including sentences as well as documents.

Lastly, Doc2Sent inevitably introduces extra model modules with extra parameters in order to capture contextual information. It complicates the model architecture, making it hard to renovate or generalize. On the contrary, Doc2Doc does not change the model structure and bring in no additional parameters.

Multi-resolutional Doc2Doc NMT

Although Doc2Doc seems more concise and better in multiple terms, it is not widely recognized. Therefore, the correct usage of long-range context is by Doc2Sent style. However, broader contexts shall provide more information and references, which lead to more improvements. Correspondingly, Doc2Doc is required to take account of all the source-side context.

Specifically, we split each document averagely into $k$ parts multiple times and collect all the sequences together, $k \in \{1, 2, 4, 8, \ldots\}$. For example, a document containing eight sentences will be split into two four-sentences segments, four two-sentences segments, and eight single-sentence segments. Finally, fifteen sequences are all gathered and fed into sequence-to-sequence training.

In this way, the model can acquire the ability to translate long documents since it is assisted by easier, shorter sentences and paragraphs. As a result, multi-resolutional Doc2Doc is able to translate all forms of sequences, including extremely long ones such as a whole document with more than 2000 tokens. In the following sections, we conduct the same experiments as the aforementioned studies by translating the whole document directly and atomically.
Table 1: The detailed information of the used datasets in this paper with downloading links on their names.

### Datasets

For our main experiments, we follow the datasets provided by [Maruf, Martins, and Haffari (2019)] and [Zheng et al. (2020)], including TED (ZH-EN/EN-DE), News (EN-DE), and Europarl (EN-DE). The Chinese-English and English-German TED datasets are from IWSLT 2015 and 2017 evaluation campaigns, respectively. For ZH-EN, we use dev2010 as the development set and tst2010-2013 as the test set. For TED (EN-DE), we use tst2016-2017 as the test set and the rest as the development set. For News (EN-DE), the training/test sets are: News Commentary v11, WMT newstest2015, and WMT newstest2016. For Europarl (EN-DE), the corpus is extracted from the Europarl v7 according to the method proposed in [Maruf, Martins, and Haffari (2019)].

Experiments on Spanish, French, Russian to English are also conducted, whose training sets are News Commentary v14, with the development sets and test sets are newstest2012 / newstest2013 (ES-EN), newstest2013 / newstest2014 (FR-EN), newstest2018 / newstest2019 (RU-EN), respectively.

Besides, two additional sentence-level datasets are also adopted. For EN-DE, we use Wikipedia, a corpus containing 2.4 million pairs of sentences. For ZH-EN, we extract one-tenth of WMT 2019, around 2 million sentence pairs.

Additionally, a document-level dataset with contrastive test sets in EN-RU ([Voita, Sennrich, and Titov 2019]) is used to evaluate lexical coherence.

Lastly, we propose a new document-level dataset in this paper, whose source, scales, and benchmark will be illustrated in the subsequent sections.

For sentences without any ending symbol inside documents, periods are manually added. For our Doc2Doc experiments, the development and test sets are documents merged by sentences. We list all the detailed information of used datasets in Table 1 including languages, scales, and downloading URLs for reproducibility.

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1 EN-DE datasets are from [https://github.com/sameenmaruf/selective-attn](https://github.com/sameenmaruf/selective-attn)

### Models

For the model setting, we follow the base version of Transformers ([Vaswani et al. 2017]), including 6 layers for both encoders and decoders, 512 dimensions for model, 2048 dimensions for ffn layers, 8 heads for attention. For all experiments, we use subword ([Sennrich, Haddow, and Birch 2016]) with 32K merge operations on both sides and cut out tokens appearing less than five times. The models are trained with a batch size of 32000 tokens on 8 Tesla V100 GPUs. Parameters are optimized by using Adam optimizer ([Kingma and Ba 2015]), with $\beta_1 = 0.9$, $\beta_2 = 0.98$, and $\epsilon = 10^{-9}$. The learning rate is scheduled according to the method proposed in [Vaswani et al. 2017], with warmup_steps = 4000. Label smoothing ([Szegedy et al. 2016]) of value=0.1 is also adopted. We set dropout = 0.3 for small datasets like TED and News, and dropout = 0.1 for larger datasets like Europarl, unless stated otherwise. Besides, we use Horovod library with RDMA inter-GPU communication ([Sergeev and Bals 2018]).

### Evaluation

For inference, we generate the translation hypothesis with a beam size of 5. Following previous works, we adopt tokenized case-insensitive BLEU ([Papineni et al. 2002]). Specifically, we follow the methods in [Liu et al. 2020], which calculate sentence-level BLEU (denoted as s-BLEU) and document-level BLEU (denoted as d-BLEU), respectively. For d-BLEU, the computing object is either the concatenated generated sentences or the directly generated documents. Since our documents are generated atomically and hard to split into sentences, we only report d-BLEU for Doc2Doc.

### Roadmap

For a full exploration of DNMT, we employ a series of experiments, including:

- Firstly, we verify the effectiveness of Doc2Doc translation, as aforementioned.
- Secondly, we explore the usage of the additional sentence-level corpus.
- Lastly, we deliver some analytical results on lexical coherence, context usage, and length influence.
Table 2: Experiment results of document translation. “-” means not provided. We choose the best hyper-parameters (specifically dropout) on the development sets for our models as well as baselines. “++” indicates using additional sentence corpus. From the upper part, though SR Doc2Doc yields disappointing translation, and even fails on TED, MR Doc2Doc achieves much better results, proving the feasibility of Doc2Doc. From the lower part, extra sentence-level corpus can activate SR Doc2Doc and boost MR Doc2Doc, yielding the best results.

| Models                        | ZH-EN s-BLEU | ZH-EN d-BLEU | EN-DE s-BLEU | EN-DE d-BLEU | Europarl s-BLEU | Europarl d-BLEU |
|-------------------------------|--------------|--------------|--------------|--------------|-----------------|-----------------|
| Sent2Sent (Zheng et al. 2020)| 17.0         | -            | 23.10        | -            | 22.40           | -               |
| Sent2Sent (Our implementation)| 19.2         | 25.8         | 25.19        | 29.16        | 27.03           | 31.70           |
| DocT (Zhang et al. 2018)     | -            | -            | 24.00        | -            | 23.08           | -               |
| HAN (Miculicich et al. 2018) | 17.9         | 24.58        | 25.03        | 29.40        | -               | -               |
| SAN (Marul, Martins, and Haffari 2019) | - | - | 24.42 | 24.84 | 29.75 | - |
| QCN (Yang et al. 2019)       | 25.19        | 22.37        | 29.82        | -            | -               | -               |
| MCN (Zheng et al. 2020)      | 19.1         | 29.09        | 26.97        | 30.40        | 32.63           | -               |
| SR Doc2Doc                   | -            | 4.70         | 21.18        | -            | 34.16           | -               |
| MR Doc2Doc                   | 25.9         | 29.27        | 26.71        | 31.37        | 32.59           | -               |
| Sent2Sent ++                  | 21.9         | 27.9         | 27.12        | 30.74        | 27.85           | 32.14           |
| SR Doc2Doc ++                | 27.0         | -            | 29.96        | -            | 30.61           | -               |
| MR Doc2Doc ++                | 28.4         | 31.37        | 32.59        | -            | -               | -               |

Table 3: Document translation experiments on more languages, showing the comprehensive effectiveness.

| Models | ES-EN | FR-EN | RU-EN |
|--------|-------|-------|-------|
| Sent2Sent | 29.55 | 28.69 | 23.22 |
| SR Doc2Doc | 26.79 | 23.86 | 16.47 |
| MR Doc2Doc | 29.37 | 28.85 | 23.98 |

Results and Analysis

MR Doc2Doc Improves Performance

It can be seen from the upper part of Table 2 that SR Doc2Doc indeed has a severe drop on News and even fails to generate normal results on TED, which accords with the findings of Zhang et al. (2018); Liu et al. (2020). It seems too hard for seq2seq models to learn long-range document translation directly.

However, once equipped with our training technique, MR Doc2Doc can yield the best results, outperforming our strong baseline and previous works on TED and Europarl. We suggest that NMT is able to acquire the capacity of translating long-range context, as long as it cooperates with some shorter segments as assistance. With the multi-resolutional help of easier patterns, the model can gradually master how to generate complicated sequences.

To show the universality of MR Doc2Doc, we also conduct the experiments on other language pairs: Spanish, French, Russian to English. As shown in Table 3, MR Doc2Doc can be successfully achieved on all language pairs and obtains comparable or better results compared with Sent2Sent.

Additional Sentence Corpus Helps

Furthermore, introducing extra sentence-level corpus is also an effective technique. This can be regarded as another form of multi-resolutional training, as it supplements more sentence-level information. This strategy makes an impact in two ways: activating SR Doc2Doc and boosting MR Doc2Doc.

We merge the datasets mentioned above and Wikipedia (EN-DE), WMT (ZH-EN), two out-of-domain sentence-level datasets to do experiments.

As shown in the lower part of Table 2, on the one hand, SR Doc2Doc models are activated and can reach comparable levels with Sent2Sent models as long as assisted with additional sentences. On the other hand, MR Doc2Doc obtains the best results on all datasets and further widens the gap with the sentence corpus’s boost. Even out-of-domain sentences can leverage the learning ability of document translation. It again proves the importance of multi-resolutional assistance.

In addition, as analyzed in the previous section, Doc2sent models are not compatible with sentence-level corpus since the model entrance is specially designed for consecutive sentences. However, Doc2Doc models can naturally draw on the merits of any parallel pairs, including piecemeal sentences. Considering the amount of parallel sentence-level data is much larger than the document-level one, MR Doc2Doc has a powerful application potential compared with Doc2Sent.

Sentences and documents in non-MR settings are oversampled for six times to keep the same data ratio with the MR settings, which is proved helpful to the performance in the Appendix. Due to the larger scale, we find the settings of dropout=0.2 for TED, News and dropout=0.1 for Europarl yield the best results for both Sent2Sent and Doc2Doc.
Further Analysis on MR Doc2Doc

Improved Discourse Coherence: Except for BLEU, whether Doc2Doc truly learns to utilize the context to resolve discourse inconsistencies has to be verified. We use the contrastive test sets proposed by [Voita, Sennrich, and Titov (2019)], which include deixis, lexicon consistency, elliptis (inflection), and ellipsis (verb phrase) on English-Russian. Each instance contains a positive translation and a few negative ones, whose difference is only one specific word. With force decoding, if the score of the positive one is the highest, then this instance is counted as correct.

As shown in Table 5, MR Doc2Doc achieves significant improvements and obtain the best results, which proves MR Doc2Doc indeed well captures the context information and maintain the cross-sentence coherence.

Compatible with Sentences: The performance with sequence length is also analyzed in this study. Taking Europarl as an example, we randomly split documents into shorter paragraphs in different lengths and evaluate them with our models, as shown in Figure 1. Obviously, the model trained only on sentence-level corpus has a severe drop when translating long sequences, while the model trained only on document-level corpus shows the opposite result, which reveals the importance of data distribution. However, the model trained with our multi-resolutioanal strategy can sufficiently cope with all situations, breaking the limitation of sequence length in translation. By conducting MR Doc2Doc, we obtain an all-in-one model that is capable of translating sequences of any length, avoiding deploying two systems for sentences and documents, respectively.

Strong Context Sensibility: [Li et al. (2020)] find the performance of previous context-aware systems does not decrease with intentional incorrect context and suspect the context usage of context encoders. To verify whether Doc2Doc truly takes advantage of the contextual information in the document, we also conduct the inference with the wrong context deliberately. If the model neglects discourse dependency, then there should be no difference in the performance.

Specifically, we firstly shuffle the sentence order inside each document randomly, marking it as Local Shuffle. Furthermore, we randomly swap sentences among all the documents to make the context more disordered, marking it as Global Shuffle. As shown in Table 5, the misleading context results in a significant drop for the Doc2Doc model in BLEU. Besides, Global Shuffle brings more harm than Local Shuffle, showing that more chaotic contexts tend to lead to more harm. After all, Local Shuffle still reserves some general information, like topic or tense. These experiments prove the usage of the context.

Table 4: Discourse phenomena evaluation on the contrastive test sets. Our Doc2Doc shows a much better capacity for building the document coherence.

| Models       | deixis | lex.c | ell.inf | ell.VP |
|--------------|--------|-------|---------|--------|
| Sent2Sent    | 51.1   | 45.6  | 55.4    | 27.4   |
| Zheng et al. (2020) | 61.3 | 46.1  | 61.0    | 35.6   |
| MR Doc2Doc   | 64.7   | 46.3  | 65.9    | 53.0   |

Table 5: Misleading contexts can bring negative effects to Doc2Doc, proving the dependent usage of the context information. And more chaotic contexts harm more (Global vs. Local).

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Further Evidence with Newly Proposed Datasets and Metrics

To further verify our conclusions and push the development of this field, we also contribute a new dataset along with new metrics. Specifically, we propose a package of a large and diverse parallel document corpus, three deliberately designed metrics, and correspondingly constructed test sets.

On the one hand, they make our conclusions more solid. On the other hand, they may benefit future researches to expand the comparison scenes.

Parallel Document Corpus

We crawl bilingual news corpus from two websites with both English and Chinese content provided. The detailed cleaning procedure is in the Appendix. Finally, 1.39 million parallel sentences within almost 60 thousand parallel documents are collected. The corpus contains large-scale data with internal dependency in different lengths and diverse domains, including politics, finance, health, culture, etc. We name it PDC (Parallel Document Corpus).

https://github.com/sunzewei2715/Doc2Doc_NMT
https://en.nytimes.com
https://en.ft.com
Metrics
To inspect the coherence improvement, we sum up three common linguistic features in document corpus that the Sent2Sent model can not handle:

**Tense Consistency (TC):** If the source language is tenseless (e.g. Chinese), it is hard for Sent2Sent models to maintain the consistency of tense.

**Conjunction Presence (CP):** Traditional models ignore cross-sentence dependencies, and the sentence-level translation may cause the missing of conjunctions like “And” (Xiong et al. 2018).

**Pronoun Translation (PT):** In pro-drop languages such as Chinese and Japanese, pronouns are frequently omitted. When translating from a pro-drop language into a non-pro-drop language (e.g., Chinese-to-English), invisible dropped pronouns may be missing (Wang et al. 2016b, 2018).

Afterward, we collect documents that contain abundant verbs in the past tense, conjunctions, and pronouns, as test sets. These words, as well as their positions, are labeled. Typical cases are in the Appendix.

For each word-position pair \( <w,p> \), we check whether \( w \) appears in the generated documents within a rough span. And we calculate the appearance percentage as the evaluation score, Specifically:

\[
\text{TC} / \text{CP} / \text{PT} = \frac{\sum_i^\text{n} \sum_j^{\text{W}_i} \mathbb{I}(y^{\text{span}}_i)}{\sum_i^\text{n} |W_i|} \quad (3)
\]

\[
\text{span} = [\alpha_i p_{ij} - d, \alpha_i p_{ij} + d] \quad (4)
\]

\( n \) indicates the number of sequences in the test set, \( W_i \) indicates the labeled word set of sequence \( i \), \( w \) indicates labeled words, \( y_i \) indicates output, \( p_{ij} \) indicates the labeled position of \( w_{ij} \) in the reference, \( \alpha_i \) indicates the length ratio of translation and reference, \( d \) indicates the span radius. We set \( d = 20 \) in this paper, and calculate the geometric mean as the overall score denoted as TCP.

Test Sets
Along with the filtration of the aforementioned coherence indices, the test sets are built based on websites that are totally different from the training corpus to avoid overfitting. Meanwhile, to alleviate the bias of human translation, the English documents are selected as the reference and manually translated to the Chinese documents as the source. Finally, a total of nearly five thousand sentences within 148 documents is obtained.

**Benchmark** Basic experiments with Sent2Sent and Doc2Doc are conducted based on our new datasets, along with full WMT ZH-EN corpus, a sentence-level dataset containing around 20 million pairs. \[\square\] We use WMT newest2019 as the development set and evaluate the models with our new test sets as well as metrics. The results are shown in Table [6].

| Systems     | d-BLEU | TC  | CP  | PT  | TCP | Man |
|-------------|--------|-----|-----|-----|-----|-----|
| Sent2Sent   | 27.05  | 54.0| 25.5| 62.5| 44.1| 2.89|
| SR Doc2Doc  | 24.33  | 46.7| 24.8| 61.5| 41.5| 2.87|
| MR Doc2Doc  | 27.80  | 56.9| 25.7| 63.9| 45.4| 3.02|
| Sent2Sent ++| 30.28  | 58.3| 34.1| 64.5| 50.4| 3.58|
| SR Doc2Doc ++| 31.20 | 59.7| 36.3| 65.9| 52.3| 3.61|
| MR Doc2Doc ++| 31.62 | 59.7| 36.3| 65.9| 52.3| 3.69|

Table 6: Benchmark of our new datasets. “++” indicates using additional WMT corpus. “Man” refers to human evaluation. Doc2Doc shows much better results in all terms.

**BLEU:** In terms of BLEU, MR Doc2Doc outperforms Sent2Sent, illustrating the positive effect of long-range context. Moreover, with extra sentence-level corpus, Doc2Doc shows significant improvements again.

**Fine-grained Metrics:** Our metrics show much clearer improvements. Considering the usage of contextual information, tense consistency is better guaranteed with Doc2Doc. Meanwhile, Doc2Doc is much more capable of translating the invisible pronouns by capturing original referent beyond the current sentence. Finally, the conjunction presence shows the same tendency.

**Human Evaluation:** Human evaluation is also conducted to illustrate the reliability of our metrics. One-fifth of translated documents are sampled and scored by linguistics experts from 1 to 5 according to not only translation quality but also translation consistency. As shown in Table [6], human evaluation shows a strong correlation with TCP. More specifically, the Pearson Correlation Coefficient (PCCs) between human scores and TCP is higher than that of BLEU (97.9 vs. 94.1).

**Case Study**
Table [7] shows an example of document translation. Sent2Sent model neglects the cross-sentence context and mistakenly translate the ambiguous word, which leads to a confusing reading experience. However, the Doc2Doc model can grasp a full picture of the historical context and make accurate decisions.

| Source | With majority of Europeans, the German chancellor is usually translated as "prime minister". | ... |
|--------|-----------------------------------------------|-----|
| Sent2Sent | Like most Europeans, the German chancellor has struggled to hide his disdain for the US president’s “America First” nationalism. | But she has entered her fourth and certainly final term as chancellor. |
| Doc2Doc | Like most Europeans, the German chancellor’s disdain for the US president’s “America First” nationalism is hard to hide. | But she has entered her fourth and certainly final term as prime minister. |

Table 7: Coherence problem in document translation. Without discourse contexts, the Chinese word “总理” is usually translated to “prime minister”, while in the context of “German”, it should be translated into “chancellor”.
Also, we manually switch the context information in the source side to test the model sensibility, as shown in Table 8. It turns out that Doc2Doc is able to adapt to different contexts.

| Country | Sent2Sent | Doc2Doc | Oracle |
|---------|-----------|---------|--------|
| Germany | prime minister | chancellor | chancellor |
| Italy   | prime minister | prime minister | prime minister |
| Austria | prime minister | chancellor | chancellor |
| France  | prime minister | prime minister | prime minister |

Table 8: Further study of Table 7. We switch the country information in the source side like German → Italian/Austrian/French, Berlin → Rome/Vienna/Paris. Doc2Doc model shows strong sensibility to the discourse context.

Discussion and Future Work

Limitation: Efficiency

Though multi-resolutional Doc2Doc achieves direct document translation and obtains better results, there still exists a big challenge: efficiency. The computation cost of self-attention in Transformer rises with the square of the sequence length. As we feed the entire document into the model, the memory usage will be a bottleneck for larger model deployment. Also, the training speed will inevitably be influenced. Recently, many studies focus on the efficiency enhancement on long-range sequence processing (Correia, Niculae, and Martins 2019; Child et al. 2019; Kitayev, Kaiser, and Levskaya 2020; Wu et al. 2020; Beltagy, Peters, and Cohan 2019; Rae et al. 2020). We leave reducing the computation cost to the future work.

Difficulty: Practical Improvements

Recently, a couple of researches raise doubts about DNMT studies. Kim, Tran, and Ney (2019) conclude that well-regularized or pre-trained sentence-level models can beat document-level models in the same settings. They check the translation and find that most improvements are not from coreference or lexical choice but “not interpretable”. Similarly, Jwalapuram et al. (2020) adopt a comprehensive evaluation and find that the existing context-aware models do not improve discourse-related translations consistently across languages and phenomena. Also, Li et al. (2020) find that the extra context encoders act more like a noise generator and the BLEU improvements mainly come from robust training instead of the leveraghe of contextual information. These conclusions fully illustrate the difficulty of document-level translation. The gap between existing indices and the actual improvements needs to be further studied and will be our following research objects.

Related Work

Document-level neural machine translation is an important task and has been abundantly studied with multiple datasets as well as methods.

The mainstream research in this field is the model architecture improvement. Specifically, several recent attempts extend the Sent2Sent approach to the Doc2Sent-like one. Wang et al. (2017); Miculicich et al. (2018); Tan et al. (2019) make use of hierarchical RNNs or Transformer to summarize previous sentences. Jean et al. (2017); Bawden et al. (2017); Zhang et al. (2018); Voita et al. (2018); Kuang and Xiong (2018); Maruf, Martins, and Haffari (2019); Yang et al. (2019); Jiang et al. (2019); Zheng et al. (2020); Yun, Hwang, and Jung (2020); Xu et al. (2020) introduce additional encoders or query layers with attention model and feed the history contexts into decoders. Maruf and Haffari (2018); Kuang et al. (2018); Yu et al. (2018) propose to augment NMT models with a cache-like memory network, which generates the translation depending on the decoder history retrieved from the memory.

Besides, some works intend to resolve this problem in other ways. Jean and Choi (2019) propose a regularization term for encouraging to focus more on the additional context using a multi-level pair-wise ranking loss. Yu et al. (2020) utilize a noisy channel reranker with Bayes’ rule. Garcia, Creus, and España-Bonet (2019) extends the beam search decoding process with fusing an attentional RNN with an SSLM by modifying the computation of the final score. Saunders, Stahlberg, and Byrne (2020) present an approach for structured loss training with document-level objective functions. Liu et al. (2020); Ma, Zhang, and Zhou (2020) combine large-scale pre-train model with document-level NMT.

There are also some works sharing similar ideas with us. Tiedemann and Scherrer (2017); Bawden et al. (2017) explore concatenating two consecutive sentences and generate two sentences directly. Obviously, we leverage greatly longer information and capture the full context. Junczys-Downmunt (2019) cut documents into long segments and feed them into training like BERT (Devlin et al. 2019). There are at least three main differences. Firstly, they need to add specific boundary tokens between sentences while we directly translate the original documents without any additional processing. Secondly, we propose a novel multi-resolutional training paradigm that shows consistent improvements compared with regular training. Thirdly, for extremely long documents, they restrict the segment length to 1000 tokens or make a truncation. Differently, we preserve entire documents and achieve literal document-to-document training as well as inference.

Finally, our work is also related to a series of works in long sequence generation like GPT (Radford 2018), GPT-2 (Radford et al. 2019), and Transformer-XL (Dai et al. 2019). We all suppose that deep neural generation models have the potential to process long-range sequences.

Conclusion

In this paper, we propose the literal document-to-document (Doc2Doc) translation and successfully activate it with multi-resolutional training. Different from traditional methods of modifying the model architectures, our approach introduces no extra parameters. A comprehensive set of experiments on various metrics show the advantage of MR Doc2Doc. In addition, we contribute a new document-level dataset as well as three new metrics to the community.
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Appendix

Oversampling Illustration

When combining document-level datasets with sentence-level datasets (especially out-of-domain corpus), we employ oversampling for non-MR settings. This can keep them the same data ratio with the MR setting and is helpful for their performance. Since the data size of MR is around 6 times of non-MR ($\approx \log_2 64$), as shown in Table 9, we mainly oversample for 6 times. The contrastive experiments are in Table 10. We attribute the improvements to the reduction of the proportion of out-of-domain data.

| Datasets       | Ratio |
|---------------|-------|
| TED (ZH-EN)   | 6.7   |
| TED (EN-DE)   | 7.6   |
| News (EN-DE)  | 5.9   |
| Europal       | 4.6   |
| News (ES-EN)  | 5.9   |
| News (FR-EN)  | 5.9   |
| News (RU-EN)  | 5.9   |
| PDC           | 5.3   |
| Mean          | 6.0   |

Table 9: Ratio of MR/non-MR in data size

Clean Procedure on PDC

We mainly crawl bilingual news corpus from two websites (https://cn.nytimes.com, https://cn.ft.com) with both English and Chinese content provided. Then three steps are followed to clean the corpus.

1. **Deduplication**: We deduplicate the documents that include almost the same content.

2. **Sentence Segmentation**: We use Pragmatic Segmenter\(^6\) to segment paragraphs into sentences.

3. **Filtration**: We use fast\_align\(^7\) to align sentence pairs and label the pairs as misaligned ones if the alignment scores are less than 40%. Documents are finally removed if they contain misaligned sentence pairs.

Finally, we obtain 1.39 million parallel sentences within almost 60 thousand cleaned parallel documents. The dataset contains diverse domains including politics, finance, health, culture, etc.

Cases of Our Test Sets

Apart from the statistic number in the main paper, we also provide some cases in our test sets to illustrate the value of our test sets and metrics, as shown in Table 11, 12, 13.

| Case | Example |
|------|---------|
| Ref  | Both parties had lodged applications with the tribunal in 2017. Templeton-Knight wanted his rent reimbursed. Burdett wanted to evict Templeton-Knight. |
| NMT  | Both parties filed applications with the court in 2017. Templeton-Knight wants to reimburse his rent. Burdett wants to get rid of Templeton-Knight. |

Table 11: Tense inconsistency problem in translating tenseless languages (e.g. Chinese) to tense-sensitive languages (e.g. English). Individual sentences are translated into present tense with sentence-level models while the history context has provided the signal of past tense.

| Case | Example |
|------|---------|
| Ref  | The type of insulin that my daughter uses — there are only two manufacturers worldwide of a similar type. They continue to increase their prices lockstep together. |
| NMT  | The type of insulin my daughter uses - there are only two manufacturers of similar types in the world. [conj miss] They continue to be consistent while raising prices. |

Table 12: Conjunction missing problem in sentence-level translation. The sentences have strong semantic connection but are translated without any conjunction.

| Case | Example |
|------|---------|
| Ref  | According to the city government, other proposed features at the Autry plant appear highly unlikely to be implemented according to the City Manager. Even though consultants and surveys recommended them. |
| NMT\(_A\) | According to the city government, other proposed features at the Autry plant appear highly unlikely to be implemented. Even if consultants and surveys recommend [pro miss]. |
| NMT\(_B\) | According to the municipal government, other proposed functions of the Autry plant seem highly impossible to implement. Even if consultants and surveys recommended it. |

Table 13: Pronoun drop problem in translating pro-drop languages (e.g. Chinese) to non-pro-drop languages (e.g. English). The pronoun is omitted or translated wrongly with sentence-level models.

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\(^6\)https://github.com/diasks2/pragmatic_segmenter
\(^7\)https://github.com/clab/fast_align

Table 10: The contrastive results of oversampling when combining sentence-level corpus.

| Dataset          | Sent2Sent non-OS | Sent2Sent OS | SR Doc2Doc non-OS | SR Doc2Doc OS |
|------------------|------------------|--------------|-------------------|----------------|
| TED (ZH-EN)+WMT  | 27.52            | 27.90        | 26.05             | 26.67          |
| TED (EN-DE)+Wiki | 29.19            | 30.74        | 29.81             | 29.96          |
| News+Wiki        | 27.77            | 29.41        | 30.15             | 30.61          |
| Europarl+Wiki    | 33.93            | 34.20        | 34.25             | 34.38          |
| PDC+WMT          | 29.52            | 30.28        | 29.60             | 31.20          |