Addressing Zero-Resource Domains Using Document-Level Context in Neural Machine Translation

Dario Stojanovski and **Alexander Fraser**
Center for Information and Language Processing
LMU Munich, Germany
{stojanovski,fraser}@cis.lmu.de

Abstract

Achieving satisfying performance in machine translation on domains for which there is no training data is challenging. Traditional domain adaptation is not suitable for addressing such zero-resource domains because it relies on in-domain parallel data. We show that document-level context can be used to capture domain generalities when in-domain parallel data is not available. We present two document-level Transformer models which are capable of using large context sizes and we compare these models against strong Transformer baselines. We obtain improvements for the two zero-resource domains we study. We additionally present experiments showing the usefulness of large context when modeling multiple domains at once.

1 Introduction

Training robust neural machine translation models for a wide variety of domains is an active field of work. NMT requires large bilingual resources which are not available for many domains and languages. When there is no data available for a given domain, e.g., in the case of web-based MT tools, this is a significant challenge. Despite the fact that these tools are usually trained on large scale datasets, they are often used to translate documents from a domain which was not seen during training. We call this scenario zero-resource domain adaptation and present an approach using document-level context to address it.

When an NMT model receives a test sentence from a zero-resource domain, it can be matched to similar domains in the training data. This is to some extent done implicitly by standard NMT. Alternatively, this matching can be facilitated by a domain adaptation technique such as using special domain tokens and features (Kobus et al., 2017; Tars and Fishel, 2018). However, it is not always easy to determine the domain of a sentence without larger context. Access to document-level context makes it more probable that domain signals can be observed, i.e., it is more likely to encounter words representative of a domain. We hypothesize this facilitates better matching of unseen domains to domains seen during training and provide experimental evidence supporting this hypothesis.

Recent work has shown that contextual information can provide for improvements in MT (Miculicich et al., 2018; Voita et al., 2019b; Maruf et al., 2019). They have shown that context-aware NMT provides for large improvements on anaphoric pronoun translation. However, in order to address discourse phenomena such as coherence and cohesion, access to larger context is preferable. Voita et al. (2019b,a) are the first to show large improvements on lexical cohesion in a controlled setting using challenge sets. However, it is unclear whether previous models can help with disambiguation of polysemous words where the sense used is dependent on the domain.

In this work, we study the usefulness of document-level context for zero-resource domain adaptation (which we think has not been studied in this way before). We propose two novel Transformer models which can efficiently handle large context and test their ability to model multiple domains at once. We show that document-level models trained on multi-domain datasets can provide improvements on zero-resource domains. We also study classical domain adaptation where access to in-domain data is allowed. However, our main focus is on addressing zero-resource domains. We evaluate on English→German translation using TED and PatTR (patent descriptions) as zero-resource domains.

Our first proposed model, which we call the domain embedding model (DomEmb) applies average or max pooling over all contextual embeddings and adds this representation to each source token-level embedding in the Transformer. The second model is conceptually similar to previous work on context-aware NMT (Voita et al., 2018; Stojanovski and Fraser, 2018; Miculicich et al., 2018; Zhang et al., 2018) and introduces additional multi-head attention components in the encoder and decoder in order to handle the contextual information. However, in order to facilitate larger context sizes, it creates a compressed context representation by applying average or max pooling with a fixed window and stride size. We compare our proposed models against previous context-aware NMT architectures and techniques for handling multi-domain setups. We show that our proposed document-level context methods improve upon strong baselines.

The contributions of our work can be summarized as follows: we (i) propose two NMT models which are able to handle large context sizes, (ii) show that document-level context in a multi-domain experimental setup is beneficial for handling zero-resource domains, (iii) show the effect of different context sizes and (iv) study traditional domain adaptation with access to in-domain data.

2 Related Work

Several previous works have addressed the problem that standard NMT may fail to adequately model all domains in a multi-domain setup even though the domains are known in advance. Kobus et al. (2017) introduced using domain tags for this problem, a similar method to the domain embedding model in our paper. These domain tags are mapped to corresponding embeddings and are either inserted at the beginning of the sentence or concatenated to the token-level embeddings. The domain embeddings are reserved for specific domains and are fixed for all sentences in a given domain. The number of distinct domain embeddings is limited to the number of known domains. Tars and Fishel (2018) defined a similar approach which uses oracle domain tags and tags obtained using supervised methods and unsupervised clustering. However, clustering limits how many domains can be taken into consideration. Furthermore, this approach assumes that sufficient domain information can be obtained from a single sentence alone. Document-level classifiers (Xu et al., 2007) address this problem, but they are not jointly trained with the MT model.

Zeng et al. (2018) use domain-specific and domain-shared annotations from adversarial and non-adversarial domain classifiers and Britz et al. (2017) use a discriminator to backpropagate domain signals. These works assume that the domains are known during training which is not always the case. Our proposed approaches model the domain implicitly by looking at document-level context.

Continued training is an established technique for domain adaptation if access to in-domain resources is possible. The method entails initially training on out-of-domain data, and then continuing training on in-domain data (Luong and Manning, 2015). Chen et al. (2017) and Zhang and Xiong (2018) improve upon this paradigm by integrating a domain classifier or a domain similarity metric into NMT and modifying the training cost based on weights indicating in-domain or out-of-domain data. Sajjad et al. (2017) and Farajian et al. (2017) use continued training in a multi-domain setup and propose various ways of fine-tuning to in-domain data. Standard continued training (Luong and Manning, 2015) leads to catastrophic forgetting, evident by the degrading performance on the out-of-domain dataset. Freitag and Al-Onaizan (2016) addressed this issue by ensembling the original and the fine-tuned model. We show that the model we propose obtains significant improvements compared to a baseline with the ensembling paradigm.

Bapna and Firat (2019) propose a retrieval-based method that adapts to unseen domains at inference time. They retrieve phrase pairs from a training set and use the encoded source and target phrases in the decoder. However, during inference-time adaptation to an unseen domain, they retrieve phrase pairs from the unseen domain's parallel training data. In contrast, at inference, we only assume access to the previous source sentences within the current document and we never use any monolingual or parallel data from the unseen domain.

A separate field of inquiry is context-aware NMT which proposes integrating cross-sentence context (Tiedemann and Scherrer, 2017; Bawden et al., 2018; Voita et al., 2018; Zhang et al., 2018; Stojanovski and Fraser, 2018; Miculicich et al., 2018; Tu et al., 2018; Maruf and Haffari, 2018; Voita et al., 2019b; Maruf et al., 2019; Yang et al., 2019; Voita et al., 2019a; Tan et al., 2019). These works have shown that context helps with discourse phenomena such as anaphoric pronoun translation, deixis, ellipsis and lexical cohesion. Kim et al. (2019) show that using context can improve topic-

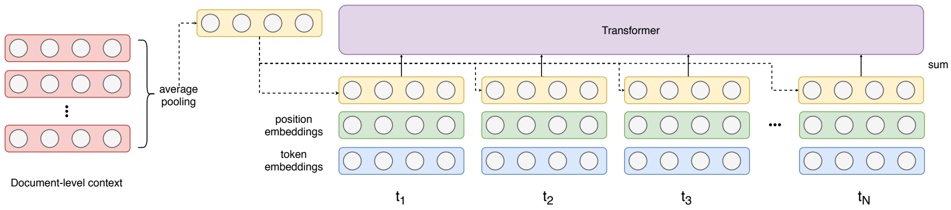

Figure 1: Domain embedding Transformer.

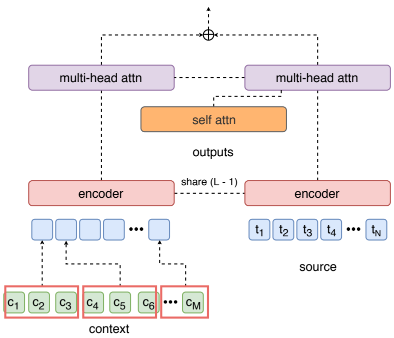

Figure 2: Context-aware Transformer with pooling.

aware lexical choice, but in a single-domain setup.

Previous work has mostly worked with limited context. Miculicich et al. (2018) addressed the problem by reusing previously computed encoder representations, but report no BLEU improvements by using context larger than 3 sentences. Zhang et al. (2018) found 2 sentences of context to work the best. Maruf and Haffari (2018) use a fixed pretrained RNN encoder for context sentences and only train the document-level RNN. Junczys-Dowmunt (2019) concatenate sentences into very large inputs and outputs as in (Tiedemann and Scherrer, 2017). Maruf et al. (2019) propose a scalable context-aware model by using sparsemax which can ignore certain words and hierarchical attention which first computes sentence-level attention scores and subsequently word-level scores. However, for domain adaptation, the full encoder representation is too granular and not the most efficient way to obtain domain signals, for which we present evidence in our experiments. Stojanovski and Fraser (2019a); Macé and Servan (2019) proposed a similar approach to our domain embedding model, but they did not investigate it from a domain adaptation perspective. Kothur et al. (2018) looked at the impact of using document-level post-edits.

Previous work has not studied using contextual information for domain adaptation. Our work is at the intersection of domain adaptation and context-aware NMT and studies if document-level context can be used to address zero-resource domains.

3 Model

The models we propose in this work are extensions of the Transformer (Vaswani et al., 2017). The first approach introduces separate domain embeddings applied to each token-level embedding. The second is conceptually based on previous context-aware models (Voita et al., 2018; Stojanovski and Fraser, 2018; Miculicich et al., 2018; Zhang et al., 2018). Both models are capable of handling document-level context. We modify the training data so that all sentences have access to the previous sentences within the corresponding source document. Access to the document-level context is available at test time as well. We train and evaluate our models with a 10 sentence context. Each sentence is separated with a special <SEP> token.

3.1 Domain Embedding Transformer

The first model is shown in Figure 1. It is inspired by Kobus et al. (2017) which concatenates a special domain tag to each token-level embedding. Kobus et al. (2017) assume access to oracle domain tags during training. However, at inference, perfect domain knowledge is not possible. Consequently, the domain has to be predicted in advance which creates a mismatch between training and inference. An additional problem is inaccurately predicted domain tags at test time. We modify this approach by replacing the predefined special domain tag with one inferred from the document context. A disadvantage of this approach as opposed to Kobus et al. (2017) is that there is no clear domain indicator. However, the model is trained jointly with the component inferring the domain which increases the capacity of the model to match a sentence from an unseen domain to a domain seen during training.

The main challenge is producing the domain embedding from the context. In this work we use maximum (DomEmb(max)) or average pooling

(DomEmb(avg)) over all of the token-level context embeddings, both resulting in a single embedding representation. We do not apply self-attention over the context in this model. The intuition is that the embeddings will contain domain knowledge in certain regions of the representation and that this can be extracted by max or average pooling. More domain-specific words will presumably increase the related domain signal. In contrast to a sentence-level model, large context can help to more robustly estimate the domain. We experimentally observed that adding a feed-forward neural network on the pooled embedding representation benefits the average pooling, but hurts the max pooling. Therefore, we use an FFNN for DomEmb(avg) and not for DomEmb(max). The Transformer represents each token as a sum of positional and token-level embeddings. We extend this by adding the inferred domain embedding to this representation. As the model only averages embeddings, the computational overhead is small. A computational efficiency comparison of the models is provided in the appendix.

3.2 Context-Aware Transformer with Pooling

The second approach (CtxPool) is similar to previous work on context-aware NMT (e.g., (Stojanovski and Fraser, 2018; Zhang et al., 2018)). The model is outlined in Figure 2. It first creates a compact representation of the context by applying max or average pooling over the context with certain window and stride sizes. The intuition is similar to DomEmb, but pooling over a window provides a more granular representation. We use the concatenation of all context sentences (separated by <SEP>) as input to CtxPool, essentially treating them as a single sentence.

The output of applying max or average pooling over time is used as a context representation which is input to a Transformer encoder. We share the first $L-1$ encoder layers between the main sentence and the context. L is the number of encoder layers. In the decoder, we add an additional multi-head attention (MHA) over the context. This attention is conditioned on the MHA representation from the main sentence encoder. Subsequently, these two representations are merged using a gated sum. The gate controls information flow from the context.

In contrast to DomEmb, CtxPool can be used to handle other discourse phenomena such as anaphora resolution. In this work, we use a window size of 10, suitable for domain adaptation. For anaphora, a large window size is problematic since ten neighboring words are summarized, so it is difficult to extract meaningful antecedent relationships. Careful tuning of these parameters may allow for modeling of both local and global context.

4 Experiments

4.1 Experimental Setup

We train models for English→German translation on 5 domains in total, Europarl, NewsCommentary, OpenSubtitles, Rapid and Ubuntu. TED and PatTR are considered as zero-resource domains for which we do not assume access to parallel data. We also consider classical domain adaptation where we do use parallel data in a continued training setup. The models are implemented in Sockeye (Hieber et al., 2017). Preprocessing details and model hyperparameters are presented in the appendix.

4.2 Datasets

The datasets for some domains are very large. For example, OpenSubtitles contains 22M sentences and PatTR 12M. In order to be able to scale the experiments given the computational resources we have available, we decided to randomly sample documents from these domains and end up with approximately 10% of the initial dataset size. We keep the original size for the remaining datasets. Dataset sizes for all domains are presented in Table 1. The development and test sets are also randomly sampled from the original datasets. We sample entire documents rather than specific sentences. For TED we use tst2012 as dev and tst2013 as test set.

domain	train	dev	test
Europarl	1.8M	3.2K	3.0K
NewsCommentary	0.3M	1.5K	1.5K
OpenSubtitles	2.2M	2.7K	3.3K
Rapid	1.5M	2.5K	2.5K
Ubuntu	11K	1.1K	0.6K
TED	0.2M	1.7K	1.0K
PatTR	1.2M	2.0K	2.2K

Table 1: Domain datasets sizes.

Europarl, NewsCommentary, OpenSubtitles, Rapid and TED are provided with document boundaries. Ubuntu lacks a clear discourse structure and PatTR is sentence-aligned, but provides document IDs. Previously it has been shown that context-aware NMT performance is not significantly degraded from lack of document boundaries (Müller et al., 2018; Stojanovski and Fraser, 2019b) or random context (Voita et al., 2018). To a large extent, both of these issues can be ignored, given the nature of our proposed models. DomEmb is oblivious to the sequential order of the sentences. CtxPool preserves some notion of sequentiality, but it should also be robust in this regard. Furthermore, we focus on obtaining domain signals. Even in an extreme case where the context comes from a different document (but from the same domain) we hypothesize similar performance. We later conduct an ablation study into whether arbitrary contextual information from the same domain has a negative effect on performance. The results partially support our hypothesis by either matching or exceeding sentence-level performance, but also show that correct document context is important to obtain the best results.

4.3 Baselines

We compare our proposed methods against a sentence-level baseline (SentBase) and the domain tag (TagBase) approach (Kobus et al., 2017). We train TagBase with oracle domain tags, while at test time, we use tags obtained from a document-level domain classifier. All sentences within a document are marked with the same predicted domain tag. The domain classifier is a two-layer feed-forward network and the documents are represented as a bag-of-words. The classifier obtains an accuracy of 98.6%. By design, documents from TED and PatTR were marked with tags from the remaining domains. Additionally, we compare with a context-aware model (CtxBase) which is similar to CtxPool, but we feed the full context to the context Transformer encoder, without applying max or average pooling beforehand. This model has token-level granular access to the context. We also train a concatenation model (ConcBase) (Tiedemann and Scherrer, 2017) using source-side context.

5 Results

5.1 Zero-Resource Domain Adaptation

In zero-resource domain adaptation experiments, we do not use any data from TED or PatTR, either as training or development data. The results are shown in Table 2. We compute statistical significance with paired bootstrap resampling (Koehn, 2004). Unless otherwise specified, we always compare the models against the sentence-level baseline.

SentBase achieves 16.7 and 32.9 BLEU on PatTR and TED respectively. The domains seen during training are more similar to TED in comparison to PatTR which is the reason for the large BLEU score differences. Our proposed models improve on PatTR by up to 0.4 BLEU and on TED by up to 1.0 BLEU. Improvements vary, but all models increase the BLEU score. The TagBase model does not improve significantly over SentBase.

	PatTR	TED
SentBase	16.7	32.9
TagBase	16.8	33.0
DomEmb(max)	**17.1**†	**33.9**†
DomEmb(avg)	**17.1**†	33.8†
CtxPool(max)	16.9	33.6‡
CtxPool(avg)	**17.1**†	**33.9**†

Table 2: Results on zero-resource domain adaptation for PatTR and TED. Best results in bold. †- statistical significance with $p < 0.01$, ‡- $p < 0.05$.

We see that our document-level models are robust across the two domains. These results confirm our assumption that access to document-level context provides for a domain signal. Of course, these models are oblivious to the actual characteristics of the domain since it was not seen during training, but presumably, they managed to match the zero-resource domain to a similar one. We assume that the reason for the larger improvements on TED in comparison to PatTR is that TED is a more similar domain to the domains seen during training. As a result, matching TED sentences to seen domains was easier for all models. Table 2 shows that our proposed models improve on PatTR and TED and provides evidence that document-level context is useful for addressing zero-resource domains.

5.2 Multi-Domain Setup

We assume that the observed improvements on zero-resource domains are because of document-level models having an increased capability to model all domains. As a result, we also evaluate these models on the other domains which were seen during training. We show average BLEU and the BLEU score on the concatenation of all test sets. This is a useful way of evaluation in a multi-domain setting because it is less sensitive to larger improvements on a smaller test set which can provide for higher average scores.

Table 3 shows the results. We first compare the baseline against DomEmb(avg). The smallest improvement is on NewsCommentary, only 0.2

domain	SentBase	TagBase	DomEmb(max)	DomEmb(avg)	CtxPool(max)	CtxPool(avg)
Europarl	31.3	31.4	32.3†	**32.5**†	32.4†	32.3†
NewsComm	32.8	32.6	32.7	33.0	**33.1**‡	32.8
OpenSub	26.6	27.1‡	27.0‡	**27.5**†	27.3†	27.4†
Rapid	40.7	40.9	41.1‡	41.5†	41.4†	**41.6**†
Ubuntu	31.5	**34.6**†	32.8‡	31.9	31.6	32.1
Average	30.4	30.9	**31.0**	**31.0**	30.9	**31.0**
Joint	29.1	29.2	29.5†	**29.8**†	29.7†	**29.8**†

Table 3: Results on the multi-domain dataset. Joint and average scores including PatTR and TED. Statistical significance computed for all scores except for Average. †- $p < 0.01$, ‡- $p < 0.05$.

BLEU. Improvements vary between 0.8 and 1.2 BLEU on Europarl, OpenSubtitles and Rapid. On Ubuntu, this model improves only by 0.4 BLEU. Joint and average BLEU improve by 0.7 and 0.6, respectively. Replacing average pooling with maximum pooling leads to slightly worse results on all domains except Ubuntu, but still improves upon the baseline. Our assumption is that averaging handles situations when there is a mix of domain signals because it can emphasize the more frequent domain signals. Max pooling is not able to differentiate between less and more frequent domain signals.

CtxPool(avg) and DomEmb(avg) perform similarly and have the same average and joint BLEU scores. Using maximum pooling provides slightly worse results as shown by the performance of CtxPool(max). TagBase is not very effective in our experiments, improving slightly on some domains and only performing well on Ubuntu. Our experiments show that document-level context is useful for modeling multiple known domains at the same time. In the appendix, we show translation examples from SentBase and DomEmb(avg).

5.3 Context Length

We also investigate the effect of context size on DomEmb(avg). Previous work (Zhang et al., 2018; Miculicich et al., 2018) has shown that large context fails to provide for consistent gains. This applies to more granular models which resemble the context-aware baseline CtxBase. In contrast, we observe that larger context does provide for improvements. We assume that this is because, for DomEmb, access to more context improves the likelihood of encountering domain-specific tokens.

We compare context sizes of 1, 5 and 10 and show the results in Table 4. A context size of 1 obtains the lowest scores on all domains. Context size of 5 performs either comparably or slightly worse than a context size of 10. Both *ctx=1* and *ctx=5* get higher scores on Ubuntu and obtain significant improvements over SentBase on the full test set. Significance indicators for *ctx=10* compared to SentBase already presented in Table 3.

domain	ctx=1	ctx=5	ctx=10
Europarl	31.5	32.0†‡	**32.5**†♣
NewsComm	32.7	32.9	**33.0**
OpenSub	26.8	27.2*‡	**27.5**†✧
Rapid	41.1‡	**41.5***‡	**41.5***
Ubuntu	32.5	**32.9***‡	31.9
PatTR	17.0‡	**17.2**‡	17.1
TED	33.5**	33.7‡	**33.8**
Average	30.7	**31.1**	31.0
Joint	29.3‡	29.7†‡	**29.8**†♣

Table 4: Results using the DomEmb(avg) model with different context sizes. Context size in number of previous sentences. ‡- $p < 0.01$, ** - $p < 0.05$, compared to SentBase. †- $p < 0.01$, * - $p < 0.05$, compared to *ctx=1*. ♣ - $p < 0.01$, ✧ - $p < 0.05$, compared to *ctx=5*.

5.4 Comparison to Context-Aware Baselines

Previous work on context-aware NMT has shown improvements in single-domain scenarios. In our work, we put two context-aware models to the test in a multi-domain setup. All models are trained with a 5 sentence context. The results in Table 5 show that all models improve to varying degrees. They perform similarly on NewsCommentary and OpenSubtitles. CtxBase and ConcBase obtain better results on Europarl than DomEmb(avg) and worse on Ubuntu. CtxBase is best on Rapid. Both baselines obtained better scores on TED, showing they have some capacity to transfer to unseen domains. However, both failed to improve on PatTR.

Scaling the baseline models to large context with regards to computational efficiency and memory usage is cumbersome which is the reason we trained models with 5 sentence context. In contrast,

domain	CtxBase	ConcBase	DomEmb(a)
Europarl	**32.4**†	**32.4**†	32.0†
NewsCo	32.8	32.7	**32.9**
OpenSub	27.2‡	**27.4**†	27.2†
Rapid	**41.8**†	40.8	41.5†
Ubuntu	31.6	29.1	**32.9**†
PatTR	16.6	14.8	**17.2**†
TED	**34.1**†	**34.1**†	33.7†
Average	30.9	30.2	**31.1**
Joint	**29.7**†	29.5	**29.7**†

Table 5: Comparison with the context-aware baseline CtxBase and the concatenation model ConcBase. †- p < 0.01, ‡- p < 0.05 compared to SentBase.

DomEmb scales easily to larger context. Furthermore, our analysis shows that DomEmb(avg) has the best average and joint score (CtxBase obtains the same joint score), improves on both unseen domains and consistently obtains significant improvements on all domains except NewsCommentary.

5.5 Translation of Domain-Specific Words

We also evaluated the translation of domain-specific words. We extracted the most important words from a domain based on TF-IDF scores and selected the top 100 with the highest scores which have more than 3 characters. Next, we follow Liu et al. (2018) and compute alignments using *fastalign* (Dyer et al., 2013) based on the training set and force align the test set source sentences to the references and generated translations. We then compute the F_1 score of the translation of the domain-specific words. Results are shown in Table 6. We compare SentBase with DomEmb(avg).

	SentBase	DomEmb(avg)
Europarl	0.661	**0.667**
NewsComm	0.649	**0.650**
OpenSub	0.435	**0.453**
Rapid	0.724	**0.730**
Ubuntu	0.434	**0.439**
PatTR	0.407	**0.409**
TED	0.551	**0.565**

Table 6: F_1 score for domain-specific words on the corresponding domains.

DomEmb(avg) improved the F_1 score across all domains with the largest improvements on OpenSubtitles and TED. The improvements on these domains are interesting because the words extracted based on TF-IDF are often not very ambiguous. Our assumption is that the baseline translation of these words is not optimal for the OpenSubtitles or TED domains. Unlike these domains, a large part of the multi-domain dataset contains more formal language (Europarl, NewsCommentary, Rapid). Lack of context seems to have biased SentBase to generate more formal translations.

5.6 Domain Adaptation with Available In-Domain Data

We also conduct a classical domain adaptation evaluation where access to in-domain data is allowed. We either use PatTR or TED as in-domain data and evaluate with SentBase and DomEmb(avg). In both cases we consider the concatenation of the remaining domains as out-of-domain. This setup differs from zero-resource domain adaptation because we assume access to in-domain training and dev data.

domain	SentBase	DomEmb(a)
TED	36.1	**36.6**‡
	ensemble	
Europarl	30.4	**30.8**†
NewsCommentary	31.9	**32.2**‡
OpenSubtitles	24.6	**25.4**†
Rapid	38.8	**39.5**†
Ubuntu	**32.7**	32.4
PatTR	16.9	**17.0**‡
TED	35.4	**35.8**‡
Average	30.1	**30.4**
Joint	28.4	**28.8**†

Table 7: Domain adaptation results on TED for SentBase and DomEmb(avg). †- p < 0.01, ‡- p < 0.05.

domain	SentBase	DomEmb(a)
PatTR	34.4	34.4
	ensemble	
Europarl	29.0	**29.6**†
NewsCommentary	28.7	**28.9**
OpenSubtitles	22.8	**23.4**†
Rapid	35.1	**35.7**†
Ubuntu	33.0	**33.4**
PatTR	29.2	**29.4**
TED	29.8	**30.4**‡
Average	29.7	**30.1**
Joint	30.2	**30.6**†

Table 8: Domain adaptation results on PatTR for SentBase and DomEmb(avg). †- p < 0.01, ‡- p < 0.05.

domain	Europarl	NewsComm	OpenSub	Rapid	Ubuntu	PatTR	TED	True
Europarl	**31.3**	30.1	30.6	30.3	30.7	30.7	30.7	32.5
NewsComm	30.6	**32.8**	31.9	30.1	32.3	31.5	32.1	33.0
OpenSub	22.2	23.1	**27.1**	22.0	25.4	24.4	26.7	27.5
Rapid	39.5	37.0	38.7	**41.3**	40.3	40.4	38.9	41.5
Ubuntu	29.3	29.1	29.2	29.6	**31.4**	31.1	30.1	31.9
PatTR	16.6	16.2	16.3	16.5	16.9	**17.1**	16.8	17.1
TED	30.0	33.0	33.1	28.8	33.4	31.5	**33.7**	33.8

Table 9: Results from the ablation study. Each row shows which domain is used as the test set and each column shows from which domain the context originates.

First, we train the baseline and DomEmb(avg) on out-of-domain data. Since these initial models are identical to the ones in the zero-resource setup, we reuse them. We then continue training on the corresponding in-domain data. Table 7 shows the results for TED domain adaptation. Fine-tuning the baseline and DomEmb(avg) on TED improves BLEU by 3.2 and 2.8 respectively. DomEmb(avg) performs better on TED than SentBase. Table 8 shows results for PatTR. Continued training on PatTR with SentBase obtains 34.4 BLEU, a large improvement over the out-of-domain model. Fine-tuning DomEmb(avg) on PatTR obtains the same score. The results are unsurprising because our model is tailored to multi-domain setups and is unlikely to contribute to large improvements in a single-domain scenario.

The strengths of our approach come to light by comparing it against SentBase in an ensembling scenario as in Freitag and Al-Onaizan (2016). We ensemble DomEmb(avg) trained on out-of-domain data with DomEmb(avg) fine-tuned on in-domain data and do the same for SentBase. The DomEmb(avg) ensemble is better than the SentBase ensemble on all domains. Table 7 and Table 8 show that the joint score improves by 0.4 BLEU.

5.7 Ablation

When designing the experimental setup, we hypothesized that our models will be able to benefit from contextual information from different documents within the same domain. We conduct an ablation study in order to test this assumption. For this experiment, we use the DomEmb(avg) model. The ablation study is similar to the one performed in (Kobus et al., 2017). They investigated the effect of giving the wrong domain tag to every sentence.

For our DomEmb(avg) model, we need to simulate this approach by giving contextual information representative of a domain. We achieve this by considering all contexts of the test set. We first compute the context representation by averaging the embeddings of the context tokens. We then define an intermediate domain representative contextual representation as the mean of all context representations from the corresponding domain. In order to end up with a context representation from the actual test set, we find the context whose mean embedding is closest to the domain representation as measured by cosine similarity. This context is used as the context for all test sentences.

Table 9 shows the results. On OpenSubtitles, Rapid, PatTR and TED, DomEmb(avg) improves on the sentence-level baseline if presented with context from the same domain (which is usually not from the same document). On Europarl, NewsCommentary and Ubuntu, it performs similarly to the baseline. In almost all cases, providing a mismatched context degrades the performance of the original DomEmb(avg). The results show that the model is relatively robust to incorrect, but closely related context which provides evidence for our hypothesis that DomEmb captures domain-relevant features. However, the correct context is important to obtain the best results across all domains.

6 Conclusion

We presented document-level context-aware NMT models and showed their effectiveness in addressing zero-resource domains. We compared against strong baselines and showed that document-level context can be leveraged to obtain domain signals. The proposed models benefit from large context and also obtain strong performance in traditional multi-domain scenarios. Our experimental results show that document-level context should be further explored in future work on domain adaptation and may also suggest that larger context would be beneficial for other discourse phenomena such as cohesion and coherence.

Acknowledgments

This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (grant agreement № 640550).

References

Ankur Bapna and Orhan Firat. 2019. Non-Parametric Adaptation for Neural Machine Translation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 1921–1931, Minneapolis, Minnesota. Association for Computational Linguistics.

Rachel Bawden, Rico Sennrich, Alexandra Birch, and Barry Haddow. 2018. Evaluating Discourse Phenomena in Neural Machine Translation. In *NAACL 2018*, New Orleans, USA.

Denny Britz, Quoc Le, and Reid Pryzant. 2017. Effective Domain Mixing for Neural Machine Translation. In *Proceedings of the Second Conference on Machine Translation*, pages 118–126. Association for Computational Linguistics.

Boxing Chen, Colin Cherry, George Foster, and Samuel Larkin. 2017. Cost Weighting for Neural Machine Translation Domain Adaptation. In *Proceedings of the First Workshop on Neural Machine Translation*, pages 40–46. Association for Computational Linguistics.

Chris Dyer, Victor Chahuneau, and Noah A. Smith. 2013. A Simple, Fast, and Effective Reparameterization of IBM Model 2. In *Proceedings of the 2013 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 644–648. Association for Computational Linguistics.

M. Amin Farajian, Marco Turchi, Matteo Negri, and Marcello Federico. 2017. Multi-Domain Neural Machine Translation through Unsupervised Adaptation. In *Proceedings of the Second Conference on Machine Translation*, pages 127–137. Association for Computational Linguistics.

Markus Freitag and Yaser Al-Onaizan. 2016. Fast Domain Adaptation for Neural Machine Translation. *CoRR*, abs/1612.06897.

Felix Hieber, Tobias Domhan, Michael Denkowski, David Vilar, Artem Sokolov, Ann Clifton, and Matt Post. 2017. Sockeye: A Toolkit for Neural Machine Translation. *ArXiv e-prints*.

Marcin Junczys-Dowmunt. 2019. Microsoft Translator at WMT 2019: Towards Large-Scale Document-Level Neural Machine Translation. In *Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1)*, pages 225–233, Florence, Italy. Association for Computational Linguistics.

Yunsu Kim, Thanh Tran, and Hermann Ney. 2019. When and why is document-level context useful in neural machine translation? In *DiscoMT@EMNLP*.

Catherine Kobus, Josep Crego, and Jean Senellart. 2017. Domain Control for Neural Machine Translation. In *Proceedings of the International Conference Recent Advances in Natural Language Processing, RANLP 2017*, pages 372–378. INCOMA Ltd.

Philipp Koehn. 2004. Statistical Significance Tests for Machine Translation Evaluation. In *Proceedings of the 2004 Conference on Empirical Methods in Natural Language Processing*, pages 388–395, Barcelona, Spain. Association for Computational Linguistics.

Sachith Sri Ram Kothur, Rebecca Knowles, and Philipp Koehn. 2018. Document-Level Adaptation for Neural Machine Translation. In *Proceedings of the 2nd Workshop on Neural Machine Translation and Generation*, pages 64–73. Association for Computational Linguistics.

Frederick Liu, Han Lu, and Graham Neubig. 2018. Handling Homographs 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 1336–1345.

Minh-Thang Luong and Christopher D Manning. 2015. Stanford Neural Machine Translation Systems for Spoken Language Domains. In *Proceedings of the International Workshop on Spoken Language Translation*, pages 76–79.

Valentin Macé and Christophe Servan. 2019. Using whole document context in neural machine translation. *arXiv preprint arXiv:1910.07481*.

Sameen Maruf and Gholamreza Haffari. 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.

Sameen Maruf, André F. T. Martins, and Gholamreza Haffari. 2019. Selective Attention for Context-aware Neural Machine Translation. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 3092–3102, Minneapolis, Minnesota. Association for Computational Linguistics.

Lesly Miculicich, Dhananjay Ram, Nikolaos Pappas, and James Henderson. 2018. Document-Level Neural Machine Translation with Hierarchical Attention

Networks. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 2947–2954. Association for Computational Linguistics.

Mathias Müller, Annette Rios, Elena Voita, and Rico Sennrich. 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, Volume 1: Research Papers*, pages 61–72, Brussels, Belgium. Association for Computational Linguistics.

Hassan Sajjad, Nadir Durrani, Fahim Dalvi, Yonatan Belinkov, and Stephan Vogel. 2017. Neural Machine Translation Training in a Multi-Domain Scenario. *CoRR*, abs/1708.08712.

Dario Stojanovski and Alexander Fraser. 2018. Coreference and Coherence in Neural Machine Translation: A Study Using Oracle Experiments. In *Proceedings of the Third Conference on Machine Translation, Volume 1: Research Papers*, pages 49–60, Brussels, Belgium. Association for Computational Linguistics.

Dario Stojanovski and Alexander Fraser. 2019a. Combining local and document-level context: The lmu munich neural machine translation system at wmt19. In *Proceedings of the Fourth Conference on Machine Translation (Volume 2: Shared Task Papers, Day 1)*, pages 400–406, Florence, Italy. Association for Computational Linguistics.

Dario Stojanovski and Alexander Fraser. 2019b. Improving Anaphora Resolution in Neural Machine Translation Using Curriculum Learning. In *Proceedings of Machine Translation Summit XVII Volume 1: Research Track*, pages 140–150, Dublin, Ireland. European Association for Machine Translation.

Xin Tan, Longyin Zhang, Deyi Xiong, and Guodong Zhou. 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.

Sander Tars and Mark Fishel. 2018. Multi-Domain Neural Machine Translation. *arXiv preprint arXiv:1805.02282*.

Jörg Tiedemann and Yves Scherrer. 2017. Neural Machine Translation with Extended Context. In *Proceedings of the Third Workshop on Discourse in Machine Translation*, pages 82–92.

Zhaopeng Tu, Yang Liu, Shuming Shi, and Tong Zhang. 2018. Learning to Remember Translation History with a Continuous Cache. *Transactions of the Association for Computational Linguistics*, 6:407–420.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is All you Need. In *Advances in Neural Information Processing Systems*, pages 6000–6010.

Elena Voita, Rico Sennrich, and Ivan Titov. 2019a. Context-Aware Monolingual Repair for 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 876–885, Hong Kong, China. Association for Computational Linguistics.

Elena Voita, Rico Sennrich, and Ivan Titov. 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.

Elena Voita, Pavel Serdyukov, Rico Sennrich, and Ivan Titov. 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.

Jia Xu, Yonggang Deng, Yuqing Gao, and Hermann Ney. 2007. Domain Dependent Statistical Machine Translation. In *MT Summit*.

Zhengxin Yang, Jinchao Zhang, Fandong Meng, Shuhao Gu, Yang Feng, and Jie Zhou. 2019. Enhancing Context Modeling with a Query-Guided Capsule Network for Document-level 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 1527–1537, Hong Kong, China. Association for Computational Linguistics.

Jiali Zeng, Jinsong Su, Huating Wen, Yang Liu, Jun Xie, Yongjing Yin, and Jianqiang Zhao. 2018. Multi-Domain Neural Machine Translation with Word-Level Domain Context Discrimination. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 447–457. Association for Computational Linguistics.

Jiacheng Zhang, Huanbo Luan, Maosong Sun, Feifei Zhai, Jingfang Xu, Min Zhang, and Yang Liu. 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. Association for Computational Linguistics.

Shiqi Zhang and Deyi Xiong. 2018. Sentence Weighting for Neural Machine Translation Domain Adaptation. In *Proceedings of the 27th International Con-

ference on Computational Linguistics, pages 3181–3190. Association for Computational Linguistics.

A Preprocessing and Hyperparameters

We tokenize all sentences using the script from Moses. We apply BPE splitting with 32K merge operations. We exclude TED and PatTR when computing the BPEs. The BPEs are computed jointly on the source and target data. Samples where the source or target are larger than 100 tokens are removed. We also apply a per-sentence limit of 100 tokens on the context, meaning that models trained on 10 sentences of context have a limit of 1000 tokens. A batch size of 4096 is used for all models.

We first train a sentence-level baseline until convergence based on early-stopping. All context-aware models are initialized with the parameters from this pretrained sentence-level baseline. Parameters that are specific to the models' architectures are randomly initialized. All proposed models in this work share the source, target, output and context embeddings. The models' architecture is a 6 layer encoder/decoder Transformer with 8 attention heads. The embedding and model size is 512 and the size of the feed-forward layers is 2048. The number of parameters for all models is shown in Table 10. We use label smoothing with 0.1. We use dropout in the Transformer with a value of 0.1. Models are trained on 2 GTX 1080 Ti GPUs with 12GB RAM.

Model	parameters
SentBase	61M
CtxBase	74M
CtxPool	74M
DomEmb(avg)	63M

Table 10: Number of model parameters. TagBase, ConcBase and DomEmb(max) have the same number of parameters as SentBase.

The initial learning rate for the document-level models is 10^{-4}. For the classical domain adaptation scenario with fine-tuning, we use a learning rate of 10^{-5} in order not to deviate too much from the well-initialized out-of-domain model. We lower the learning rate by a factor of 0.7 if no improvements are observed on the validation perplexity in 8 checkpoints. A checkpoint is saved every 4000 updates. We did not do any systematic hyperparameter search.

Before inference, we average the parameters of the 8 best checkpoints based on the validation perplexity. We use a beam size of 12. BLEU scores are computed on detokenized text using *multi-bleu-detok.perl* from the Moses scripts[1]. For the evaluation of translation of domain-specific words, we used the script from (Liu et al., 2018)[2].

B Computational Efficiency

In this section, we compare the computational efficiency of our proposed methods. We compare how many seconds on average are needed to translate a sentence from the test set. The average times are 0.2588, 0.2763 ± 0.0124, 0.3662 for SentBase, DomEmb and CtxPool, respectively. DomEmb is insignificantly slower than the sentence-level baseline, in contrast to CtxPool, which is to be expected considering the additional applying of self-attention over the compressed context.

C Validation performance

In Table 11, Table 12 and Table 13 we present BLEU scores on the development sets for all the experiments we ran. We only show results for the sets we actually used during training and therefore ignore TED and PatTR for which we had no access to data at training time. The results for TagBase are with oracle domain tags. For the experiments with continued training on TED and PatTR, we show results only on the development sets for TED and PatTR.

D Examples

In Table 14 we show some example translations from the sentence-level baseline and our DomEmb(avg) model. We show examples where our model corrected erroneous translations from the baseline. Some of the proper translations should be evident from the main sentence itself, but some can only be inferred from context.

In the first example, we can see that the sentence-level baseline translates "students" as "Studenten" (university students), but the correct translation in this case is "Schüler" (elementary or high school student). The main sentence itself is not informative enough for the sentence-level model to make this distinction. In contrast, the DomEmb model has access to more information which provides for the appropriate bias towards the correct translation.

The second sentence depicts an example where it's nearly impossible to make a correct prediction

[1] https://github.com/moses-smt/mosesdecoder/blob/master/scripts/generic/multi-bleu-detok.perl

[2] https://github.com/frederick0329/Evaluate-Word-Level-Translation

domain	SentBase	TagBase	DomEmb(max)	DomEmb(avg)	CtxPool(max)	CtxPool(avg)
Europarl	33.3	33.6	33.6	33.7	33.8	33.8
NewsComm	34.1	34.3	34.1	34.1	34.2	34.1
OpenSub	33.3	34.2	34.2	34.5	34.1	34.2
Rapid	39.4	39.7	39.5	39.7	39.8	39.9
Ubuntu	40.2	43.0	41.3	42.6	42.0	42.2

Table 11: BLEU scores on the development sets of the multi-domain dataset.

domain	ctx=1	ctx=5	ctx=10
Europarl	33.5	33.8	33.7
NewsComm	34.0	34.2	34.1
OpenSub	33.7	34.1	34.5
Rapid	39.7	39.8	39.7
Ubuntu	41.5	43.0	42.6
domain	**CtxBase**	**ConcBase**	**DomEmb(a)**
Europarl	34.0	34.1	33.7
NewsComm	34.0	33.9	34.1
OpenSub	33.9	34.5	34.5
Rapid	40.1	39.1	39.7
Ubuntu	42.3	42.3	42.6

Table 12: Results on the development sets using the DomEmb(avg) model with different context sizes and comparing DomEmb(avg) with *ctx=10* against CtxBase and ConcBase.

domain	SentBase	DomEmb(a)
TED	33.2	33.4
PatTR	36.4	36.3

Table 13: Domain adaptation results on PatTR and TED for SentBase and DomEmb(avg) on the development sets.

for the translation of “ambassador” because it depends on whether the person is male (Botschafter) or female (Botschafterin). In the third example, the sentence-level model translated “model” as in “a role model” (Vorbild), but the context indicates that the speaker talks about “fashion models”.

Examples 4 and 5 are relatively unintuitive because the main sentences themselves should be enough to infer the correct translation. In example 4, “reflect” refers to the physical process of reflection and should not be translated as in “to reflect on oneself” (“denken”), while in example 5, “raise” refers to the action of “lifting” or “elevating” (“aufwärtsbewegt” or “hochzuziehen”) some object instead of “raising” as in “growing a plant” (“züchten”).

The last example shows that the sentence-level model translates “springs” (“Federn” which is a part of the compound word “Druckfedern” in the reference) as in “water springs” (“Quellen” which is a part of the compound word “Kompressionsquellen”) while it should be translated instead as in the physical elastic device. However, in other test sentences, both SentBase and DomEmb(avg) translated “spring” as a season, even though this should be less likely in PatTR, showing that our model does not always succeed in capturing domain.

Source We all knew we were risking our lives – the teacher, the **students** and our parents. *Reference* Wir alle wussten, dass wir unser Leben riskierten: Lehrer, **Schüler** und unsere Eltern. *SentBase* Wir alle wussten, dass wir unser Leben riskieren... den Lehrer, die **Studenten** und unsere Eltern. *DomEmb(avg)* Wir wussten alle, dass wir unser Leben riskierten. Der Lehrer, die **Schüler** und unsere Eltern.
Source That's why I am a global **ambassador** for 10x10, a global campaign to educate women. *Reference* Deshalb bin ich globale **Botschafterin** für 10x10, einer weltweiten Kampagne für die Bildung von Frauen. *SentBase* Aus diesem Grund bin ich ein globaler **Botschafter** für 10x10, eine weltweite Kampagne zur Ausbildung von Frauen. *DomEmb(avg)* Deshalb bin ich eine globale **Botschafterin** für 10x10, eine weltweite Kampagne zur Ausbildung von Frauen.
Source And I am on this stage because I am a **model**. *Reference* Und ich stehe auf dieser Bühne, weil ich ein **Model** bin. *SentBase* Und ich bin auf dieser Bühne, weil ich ein **Vorbild** bin. *DomEmb(avg)* Und ich bin auf dieser Bühne, weil ich ein **Model** bin.
Source It's going to bounce, go inside the room, some of that is going to **reflect** back on the door ... *Reference* Es wird abprallen, in den Raum gehen, ein Teil davon wird wieder zurück auf die Tür **reflektiert** ... *SentBase* Es wird abprallen, ins Zimmer gehen, etwas davon wird wieder an die Tür **denken** ... *DomEmb(avg)* Es wird abprallen, ins Zimmer gehen, etwas davon wird wieder über die Tür **reflektieren** ...
Source Tie member 60 is driven to **raise** movable **cone** 58 ... *Reference* Mit dem Zugelement 60 wird durch den An der bewegliche **Kegel** 58 **aufwärtsbewegt** ... *SentBase* Tie-Mitglied 60 wird angetrieben, bewegliche **Konfitüre** 58 zu **züchten** ... *DomEmb(avg)* Teemitglied 60 wird angetrieben, bewegliche **Kegel** 58 **hochzuziehen** ...
Source It is only when a certain pressure level is reached that the pistons are pushed back against the action of the **compression springs** ... *Reference* Erst bei Erreichen eines bestimmten Druckniveaus werden die Kolben gegen die Wirkung der **Druckfedern** zurückgeschoben ... *SentBase* Erst wenn ein gewisses Druckniveau erreicht ist, werden die Pistonen gegen die Wirkung der **Kompressionsquellen** zurückgedrängt ... *DomEmb(avg)* Erst wenn ein bestimmtes Druckniveau erreicht ist, werden die Pistonen gegen die Wirkung der **Kompressionsfedern** zurückgedrängt ...

Table 14: Example translations obtained using sentence-level baseline and the DomEmb(avg) model. Relevant parts of the examples are in bold.