Domain Control for Neural Machine Translation

Catherine Kobus and Josep Crego and Jean Senellart

firstname.lastname@systrangroup.com SYSTRAN/5 rue Feydeau, 75002 Paris, France

Abstract

Machine translation systems are very sensitive to the domains they were trained on. Several domain adaptation techniques have been deeply studied. We propose a new technique for neural machine translation (NMT) that we call domain control which is performed at runtime using a unique neural network covering multiple domains. The presented approach shows quality improvements when compared to dedicated domains translating on any of the covered domains and even on out-ofdomain data. In addition, model parameters do not need to be re-estimated for each domain, making this effective to real use cases. Evaluation is carried out on English-to-French translation for two different testing scenarios. We first consider the case where an end-user performs translations on a known domain. Secondly, we consider the scenario where the domain is not known and predicted at the sentence level before translating. Results show consistent accuracy improvements for both conditions.

1 Introduction

Machine translation systems are very sensitive to the domain(s) they were trained on because each domain has its own style, sentence structure and terminology. There is often a mismatch between the domain for which training data are available and the target domain of a machine translation system. If there is a strong deviation between training and testing data, translation quality will be dramatically deteriorated. Word ambiguities are often an issue for machine translation systems. For instance, the English word "administer" has to be

translated differently if it appears in medical or political contexts. Our work is motivated by the idea that neural models could benefit from having domain information to choose the most appropriate terminology and sentence structure while using the information from *all* the domains to improve the base translation quality. Recently, (Sennrich et al., 2016) report on the neural network ability to control politeness through side constraints. We extend this idea to domain control. Our goal is to allow a model built from a diverse set of training data to produce in-domain translations.

The paper is structured as follows: Section 2 overviews related work. Details of our neural MT engine are given in Section 3. Section 4 describes the proposed approach. Experiments and results are detailed in Section 5. Finally, conclusions and further work are drawn in Section 6.

2 Related Work

A lot a work has already been done for domain adaptation in Statistical Machine Translation. The approaches vary from in-domain data selection based methods (Hildebrand et al., 2005) (Moore and Lewis, 2010) (Sethy et al., 2006) to in-domain models mixture-based methods (Foster and Kuhn, 2007) (Koehn and Schroeder, 2007) (Schwenk and Koehn, 2008).

Recent works have especially dealt with domain adaptation for NMT by providing meta-information to the Neural Network. Our work is in line with this kind of approach. (Chen et al., 2016) feeds Neural Network with topic information on the decoder side; topics are numerous and consist in human-labeled product categories. (Zhang et al., 2016) includes topic modelling on both encoder and decoder sides. A given number of topics are automatically inferred from the training data using LDA; each word in a sentence is assigned

its own vector of topics. In our work, we also provide meta-information about domain to the network. However, we introduce domain information at the sentence level.

3 Neural MT

Our NMT system follows the architecture presented in (Bahdanau et al., 2014). It is implemented as an encoder-decoder network with multiple layers of a RNN with Long Short-Term Memory hidden units (Zaremba et al., 2014).

The encoder is a bidirectional neural network that reads an input sequence $s=(s_1,...,s_J)$ and calculates a forward sequence of hidden states $(\overrightarrow{h_1},...,\overrightarrow{h_J})$, and a backward sequence $(\overleftarrow{h_1},...,\overleftarrow{h_J})$. The decoder is a RNN that predicts a target sequence $t=(t_1,...,t_I)$, being J and I respectively the source and target sentence lengths. Each word t_i is predicted based on a recurrent hidden state h_i , the previously predicted word t_{i-1} , and a context vector c_i . We employ the attentional architecture from (Luong et al., 2015). The framework is available on the open-source project $seq2seq-attn^1$. More details about our system can be found in (Crego et al., 2016).

4 Domain control

Two different techniques are implemented to integrate domain control: additional token and domain feature.

4.1 Additional Token

The additional token method, inspired by the politeness control technique detailed in (Sennrich et al., 2016) consists in adding an artificial token at the end of each source sentence in order to let the network pay attention to the domain of each sentence pair. For instance, consider the next English-French translation:

Src: Headache may be experienced
Tgt: Des céphalées peuvent survenir

The network reads off the sentence pair with the appropriate *Medical* domain tag **@MED**@:

Src: Headache may be experienced @MED@ Tgt: Des céphalées peuvent survenir

Domain tags are appropriately selected in order to avoid overlaps with words present in the source

language vocabulary. This method, though simple, has already proven to be effective to control the politeness level of a translation (Sennrich et al., 2016), or to support multi-lingual NMT models (Johnson et al., 2016).

4.2 Word Feature

We present a second technique to introduce domain control in our neural translation model. We use word-level features as described in (Crego et al., 2016). The first layer of the network is the word embedding layer. We adapt this layer to extend each word embedding with an arbitrary number of cells, designed to encode domain information. Figure 4.2 illustrates a word embedding layer extended with domain information.



Practically, the word feature is passed to the training script by annotating each word with the domain like:

Src: Headache|MED may|MED be|MED experienced|MED

Trg: Des céphalées peuvent survenir

Note that under this feature framework, the sentence-level domain information is added on a word-by-word basis to all the words in a sentence.

5 Experiments

We evaluate the presented approach on English-to-French translation. Section 5.1 describes the data used for the experiments and details training configurations. Finally, Section 5.2 reports on translation accuracy results.

5.1 Training Details

We used training corpora covering six different domains: *IT*, *Literature*, *Medical*, *News*, *Parliamentary* and *Tourism*. Statistics of the corpora used are given in Table 1.

All experiments employ the NMT system detailed in Section 3 and are performed on NVidia GeForce GTX 1080. We use BPE² with a total of 32,000 source and target tokens as vocabulary and word embedding size of 500 cells. During training, we use stochastic gradient descent, a minibatch size of 64 with dropout probability set to 0.3

http://nlp.seas.harvard.edu

²https://github.com/rsennrich/ subword-nmt

Domain	Lines	Src words	Tgt words
Train			
IT	399k	6.0M	7.3M
Literature	35k	881k	943k
Medical	923k	10.5M	12.3M
News	194k	5.4M	6.7M
Parliamentary	1.6M	37.6M	43.8M
Tourism	1.1M	23.3M	27.5M
Total	4,3M	83,7M	98.5M
Test			
IT	2k	36,8k	45,1k
Literature	2k	50.1k	54.0k
Medical	2k	35.6k	43.0k
News	2k	53.5k	66.4k
Parliamentary	2k	40.7k	49.4k
Tourism	2k	39.1k	45.5k

Table 1: Statistics for training and test sets of each domain corpus. Note that k stand for thousands and M for millions.

and bidirectional RNN. We train our models for 18 epochs. Learning rate is set to 1 and starts decaying after epoch 10 by 0.5. It takes about 10 days to train models on the complete training data set (4, 3M sentence pairs).

Four different training configurations are considered. The first includes six in-domain NMT models. Each model is trained using its corresponding domain data set (henceforth *Single* models). The *Join* network configuration is built using all the training data after concatenation. Note that this model does not include any information about domain. A *Token* network is also trained using all the available training data. It includes domain information through the additional token approach detailed in Section 4.1. Finally, *Feature* network is also trained on all available training data, it introduces domain information in the model by means of the feature framework detailed in Section 4.2.

5.2 Results

Table 2 shows translation accuracy results for the different training configurations. Accuracies are measured using BLEU³. As expected, the *Join* model outperforms all *Single* models on their corresponding test sets, showing that NMT engines benefit from additional training data. Differences in accuracy are lower for domains with a higher representation in the *Join* model, like Parliamentary and Tourism. No domain information is used on these first configurations (*none*). Results for models incorporating domain information are de-

tailed in columns Token and Feature. Oracle experiments indicate that the test set domains are known in advance, thus allowing to use the correct side-constraint. The model performing translations with the Token constraint performs similarly than the Join model, while incorporating domain information through the Feature approach seems to consistently improve translation quality. Using the feature framework on all the source words seems to be a good technique to convey domain side-constraint and to improve NMT target words choice consistency. Differences between the Feature and Join configurations are shown in parentheses. Note that an average improvement of 0.80 is observed on all test sets with the exception of Parliamentary translations, for which accuracy was only improved by 0.26. This can be explained by the fact that Parliamentary is the best represented domain in Join training set.

Translation examples are shown in Table 3 in a medical context. They show the impact on domain adaptation introduced by the *Feature* approach. The first example shows the preference of the *Feature* model for the French translation *suivies attentivement* of the English *carefully observed*. It seems more suitable than the hypothesis *soigneusement surveillées* output by the *Join* model. A similar effect is shown on the second example where the French *effectuées* is clearly more adapted as translation of *administered* than à *l'ordre du jour*.

Finally, we also evaluate the ability of our presented approach (*Feature*) to face test sets for which the domain is not known in advance. Hence, before translation, the domain tag is automatically detected using an in-house domain classification module based on basic TF-IDF (Salton et al., 1983) technology to disambiguate between the six different domains. The tool predicts the domain on a sentence-by-sentence basis, then translation is carried out using the predicted domain value in *Feature* model. Last row of Table 2 shows the accuracy of the domain classification tool for sentences on each of the predefined domains.

Results for this last condition are shown in column *tfidf*. Event though domain is wrongly predicted in some cases, translation accuracy is still improved when compared to the *Join* model. Notice that domain classification at sentence level is a challenging task as short context is considered. We also confront our approach with a final test

 $^{^3}$ multi-bleu.perl

set from a brand new domain, *Dialogs*, that is not present in our training data. Sentences are selected from TED Talks corpora. *TF-IDF* toolkit is able to assign each test sentence to one of the source domains, leading to outperform the *Join* model.

In order to better understand the influence of the predicted domain, we conduct a final set of experiments. Using the *Feature* model, we run each test set using all domain values. Results are detailed in Table 4 showing that translation quality can significantly be degraded when translating sentences with the wrong domain tag. It is especially the case for IT domain, where translating with the wrong domain tag dramatically reduces accuracy. Results also reveal proximities between different domains like, for example, News and Parliamentary. Translating the News test set with the Parliamentary domain tag (and vice versa) does not seem to hurt translation quality compared to other domain tag mismatches. Inversely, when translation and reference are provided, using BLEU as a similarity measure we observe that the model learned to classify: this is actually expected as RNN and word embeddings provide more powerful discriminant features.

6 Conclusions and Further Work

We have presented a method that incorporates domain information into a neural network. It allows to perform domain-adapted translations using a unique network that covers multiple domains. The presented method does not need to re-estimate model parameters when performing translations on any of the available domains.

We plan to further improve the feature technique detailed in this work. Rather than providing the network with a hard decision about domain, we want to introduce a vector of distance values of the given source sentence to each domain, thus allowing to smooth the proximity of each sentence to each domain.

Additionally, Table 4 shows indirectly that the neural network has learnt the ability to classify domains at the sentence level. We also plan to implement a joint approach for domain classification and translation, avoiding dependency with the TF-IDF classifier.

Finally, since domain classification is a document level task, it would be interesting to extend the current study to document level translation.

References

- [Bahdanau et al.2014] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2014. Neural machine translation by jointly learning to align and translate. *CoRR*, abs/1409.0473. Demoed at NIPS 2014: http://lisa.iro.umontreal.ca/mt-demo/.
- [Chen et al.2016] Wenhu Chen, Evgeny Matusov, Shahram Khadivi, and Jan-Thorsten Peter. 2016. Guided alignment training for topic-aware neural machine translation. *CoRR*, abs/1607.01628v1.
- [Crego et al.2016] Josep Crego, Jungi Kim, Guillaume Klein, Anabel Rebollo, Kathy Yang, Jean Senellart, Egor Akhanov, Patrice Brunelle, Aurelien Coquard, Yongchao Deng, Satoshi Enoue, Chiyo Geiss, Joshua Johanson, Ardas Khalsa, Raoum Khiari, Byeongil Ko, Catherine Kobus, Jean Lorieux, Leidiana Martins, Dang-Chuan Nguyen, Alexandra Priori, Thomas Riccardi, Natalia Segal, Christophe Servan, Cyril Tiquet, Bo Wang, Jin Yang, Dakun Zhang, Jing Zhou, and Peter Zoldan. 2016. Systran's pure neural machine translation systems. *CoRR*, abs/1610.05540.
- [Foster and Kuhn2007] George Foster and Roland Kuhn. 2007. Mixture-model adaptation for SMT. In Proceedings of the Second Workshop on Statistical Machine Translation, pages 128–135, Prague, Czech Republic, June. Association for Computational Linguistics.
- [Hildebrand et al.2005] Almut Silja Hildebrand, Matthias Eck, Stephan Vogel, and Alex Waibel. 2005. Adaptation of the translation model for statistical machine translation based on information retrieval. In *Proceedings of the 10th Conference of the European Association for Machine Translation (EAMT)*, Budapest, May.
- [Johnson et al.2016] Melvin Johnson, Mike Schuster, Quoc V.Le, Maxim Krikun, Yonghui Wu, Zhifeng Chen, and Nikkik Thorat. 2016. Google's multilingual neural machine translation system: Enabling zero-shot translation. arXiv:1611.04558v.
- [Koehn and Schroeder2007] Philipp Koehn and Josh Schroeder. 2007. Experiments in domain adaptation for statistical machine translation. In *Proceedings of the Second Workshop on Statistical Machine Translation*, pages 224–227, Prague, Czech Republic, June. Association for Computational Linguistics.
- [Luong et al.2015] Thang Luong, Hieu Pham, and Christopher D. Manning. 2015. Effective approaches to attention-based neural machine translation. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1412–1421, Lisbon, Portugal, September. Association for Computational Linguistics.
- [Moore and Lewis2010] Robert C. Moore and William Lewis. 2010. Intelligent selection of language model training data. In *Proceedings of the ACL*

- 2010 Conference Short Papers, pages 220–224, Uppsala, Sweden, July. Association for Computational Linguistics.
- [Salton et al.1983] Gerard Salton, Edward A. Fox, and Harry Wu. 1983. Extended boolean information retrieval. *Communications of the ACM*.
- [Schwenk and Koehn2008] Holger Schwenk and Philipp Koehn. 2008. Large and diverse language models for statistical machine translation. In *Proceedings of the 3rd International Joint Conference on Natural Language Processing (IJCNLP)*.
- [Sennrich et al.2016] Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Controlling politeness in neural machine translation via side constraints. In *Proceedings of the 15th Annual Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 35–40, San Diego, California, USA, June. Association for Computational Linguistics.
- [Sethy et al.2006] Abhinav Sethy, Panayiotis Georgiou, and Shrikanth Narayanan. 2006. Selecting relevant text subsets from web-data for building topic specific language models. In *Proceedings of the Human Language Technology Conference of the NAACL, Companion Volume: Short Papers*, pages 145–148, New York City, USA, June. Association for Computational Linguistics.
- [Zaremba et al.2014] Wojciech Zaremba, Ilya Sutskever, and Oriol Vinyals. 2014. Recurrent neural network regularization. *CoRR*, abs/1409.2329.
- [Zhang et al.2016] Jian Zhang, Liangyou Li, Andy Way, and Qun Liu. 2016. Topic-informed neural machine translation. In *COLING*.

Domain	Single	Join	Token Feature		Feature	
Domain	none		Oracle		tfidf	Acc
IT	52.73	53.81	53.76	54.56 (+0.75)	53.76	0.922
Literature	20.25	29.81	29.96	30.73 (+0.92)	30.47	0.854
Medical	33.97	41.83	42.02	42.51 (+0.68)	42.24	0.864
News	29.70	33.83	34.47	34.61 (+0.78)	34.54	0.804
Parl.	37.34	37.53	37.13	37.79 (+0.26)	37.55	0.663
Tourism	37.05	37.46	37.72	38.30 (+0.84)	37.61	0.776
Dialogs	-	19.25	-	-	19.84	-

Table 2: BLEU scores for the different systems.

Src:	Your doctor's instructions should be carefully observed .
Ref:	Vous devrez respecter scrupuleusement les instructions de votre médecin .
Join:	Les instructions de votre médecin doivent être soigneusement surveillées .
Feature:	Les instructions de votre médecin doivent être suivies attentivement.
Src:	All injections of Macugen will be administered by your doctor.
Ref:	Toutes les injections de Macugen doivent être réalisées par votre médecin.
Join:	Toutes les injections de Macugen seront à l'ordre du jour de votre médecin.
Feature:	Toutes les injections de Macugen seront effectuées par votre médecin.

Table 3: Translation examples of in-domain medical sentences with and without domain feature.

Test	Domain feature					
Test	IT	Literature	Medical	News	Parl.	Tourism
IT	54.56	-12.76	-10.25	-12.43	-13.83	-14.18
Literature	-5.96	30.73	-5.13	-2.89	-3.50	-3.03
Medical	-4.82	-6.23	42.51	-5.06	-5.39	-4.74
News	-3.36	-1.58	-3.04	34.61	-0.81	-2.48
Parliamentary	-4.14	-1.92	-3.09	-0.39	37.79	-3.01
Tourism	-6.72	-3.2	-4.16	-4.26	-4.35	38.30

Table 4: BLEU score decreases using different predefined domain tags.