NEURAL MACHINE TRANSLATION FRAMEWORK BASED CROSS-LINGUAL DOCUMENT VECTOR WITH DISTANCE CONSTRAINT TRAINING

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ABSTRACT

A universal cross-lingual representation of documents is very important for many natural language processing tasks. In this paper, we present a document vectorization method which can effectively create document vectors via self-attention mechanism using a neural machine translation (NMT) framework. The model used by our method can be trained with parallel corpora that are unrelated to the task at hand. During testing, our method will take a monolingual document and convert it into a “Neural machine Translation framework based cross-lingual Document Vector with distance constraint training” (cNTDV). cNTDV is a follow-up study from our previous research on the neural machine translation framework based document vector. The cNTDV can produce the document vector from a forward-pass of the encoder with fast speed. Moreover, it is trained with a distance constraint, so that the document vector obtained from different language pair is always consistent with each other. In a cross-lingual document classification task, our cNTDV embeddings surpass the published state-of-the-art performance in the English-to-German classification test, and, to our best knowledge, it also achieves the second best performance in German-to-English classification test. Comparing to our previous research, it does not need a translator in the testing process, which makes the model faster and more convenient.

Index Terms— cross-lingual text classification, distributed representation, neural machine translation model

1. INTRODUCTION

Distributed representation of text is very important for many natural language processing tasks. By projecting text into a continuous space, it embeds the syntactic or semantic relationship of words/sentences/documents into their relative position in the continues space. Therefore, the distributed representation can help us discover the relationship between words and sentences, categorizing documents and sharing the knowledge between related texts [1][2]. Comparing to text features in discrete spaces, distributed representations can include richer syntactic and semantic information [1][2][3][4][5].

A cross-lingual embedding of the texts from different languages to a unified space will enable comparison and knowledge-sharing between languages [6][7][8][9][10][11]. This is very useful in the case when we want to process the user input from a resource-scarce language. With cross-lingual embedding, we can use the data in the resource-rich language to help understand the inputs from the resource-scarce languages. Thus the studies on the cross-lingual distributed representation of multilingual texts have become increasingly important.

The existing research including cross-lingual word embeddings [12][13][7][9] and cross-lingual text sequence (document/sentence) embeddings [6][14][8]. The later can also be classified into several approaches. One is the multi-lingual extension of the original paragraph vector [14][9]. Among them, para_doc is currently the state-of-the-art cross-lingual document/sentence vector, achieving the best result in the cross-lingual document classification task on the Reuter’s RCV1/RCV2 dataset[12][15]. para_doc model is firstly trained on a parallel corpus, then the document vector (as the only free parameters) obtained by further optimizing the model on the monolingual test data. The other popular approaches include the extension of the multilingual/multi-task sequence to sequence/vector learning frameworks [6]. The document/sentence vector can be some intermediate state or the output of the model (often with a penalty term to minimize the distance between the vectors of the input sentence pair). After having been trained on some parallel corpus, the document or sentence vector of the test data can be obtained by a forward-pass running on the trained model.

In this study, we present a neural machine translation (NMT) framework based cross-lingual self-attentive document/sentence vectorization model with distance loss training (cNTDV) to convert a text sequence of variable length into a fix-sized vector. This is a follow-up research to our previous work: ‘Fast Cross-lingual Document Vectors from Self-attentive Neural Machine Translation Model (NTDV)’.

Both cNTDV and NTDV models are adapted from attention based neural machine translation framework and use a novel self-attentive layer designed to summarize sequential
information of viable length into a fixed matrix. As cNTDV only uses the forward-pass in the production mode, it is faster than methods that require training/optimization in producing document vectors. The cNTDV model achieves the best result among the fast vectorization methods (which do not require training in production mode), and it also surpasses the current state-of-the-art method in the English-to-German classification test.

Comparing to our previous research of NTDV model that obtain similar results, the cNTDV model is trained with a distance constraint to minimize the distance between vectors from different languages. Thus, it has the option to either use or not use the translator on the source language. In contrast, our previous NTDV model has to use a translator in order to balance the source and target language input and form a unified vector. Therefore the cNTDV is more flexible and light in usage. When it requires better performance, the translator can be used in the process. When it requires faster and simpler model, the translator can be discarded. Note that although cNTDV and NTDV model can use a translator, the said translator is trained within the same parallel corpus as in other researches without any outside information. It is therefore different from using a third-party translator or train with additional data.

2. MODEL ARCHITECTURE

2.1. The attention-based NMT model

Our cNTDV model is built upon the attention-based NMT framework [16]. The attention-based NMT framework adopts an encoder-decoder structure with an attention mechanism. The encoder is composed of a word embedding layer for the input language tokens and a bi-directional GRU layer, whereas the decoder is composed of a word embedding layer for previous output tokens and a conditional GRU (cGRU) layer [16].

The decoder state \( \hat{s}_j \) for generating the \( j \)th output token is determined by its previous state \( \hat{s}_{j-1} \), its previous output token \( y_{j-1} \) and the context vector \( \tilde{c}_j \) from the attention layer as follows:

\[
\hat{s}_j = cGRU_{att}(\hat{s}_{j-1}, y_{j-1}, \tilde{c}_j).
\] (1)

Let \( L_x \) be the length of an input sequence. The encoder output, which is the collection of the hidden states of its last layer from all \( L_x \) frames can be represented by the matrix \( H = [\hat{h}_1 \cdots \hat{h}_i \cdots \hat{h}_{L_x}] \). Then \( \tilde{c}_j \) is computed by the attention mechanism (ATT) as a weighted mean of the encoder’s hidden states \( H \):

\[
\tilde{c}_j = ATT(H, \hat{s}_j) = \sum_{i=1}^{L_x} \alpha_{ij} \hat{h}_i
\] (2)

\[
\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{n=1}^{L_x} \exp(e_{nj})}
\] (3)

\[ e_{ij} = \hat{v}_a^T \tanh(U_a \hat{s}_j^T + W_a \hat{h}_i^T) \] (4)

where \( \hat{s}_j \) is the intermediate hidden state in the conditional GRU; \( \alpha_{ij} \) is the normalized alignment weight between the \( i \)th source token and the \( j \)th target token; \( U_a, W_a, \hat{v}_a \) are the model parameters used in the attention mechanism.

2.2. The self-attentive cross-lingual document/sentence vectorization model

As pointed out by [17] [18], the information coming from below (the attention over the encoder’s states) helps to determine the content of word/sentence — the adequacy. On the other hand, the information propagating from the past (historical information in decoder LSTM/GRU) mainly helps to determine the function words and word order — the fluency. By taking advantage of the selective nature of self-attentive layer, this model uses a novel self-attentive mechanism to summarize the adequacy information from the encoder states. It could transform the sequential information of variable length into a fix-sized matrix as a primary form of the document/sentence representation [19].

We build the cNTDV model similar to the case of mul-

Fig. 1: The cross-lingual self-attentive document/sentence vectorization model (illustrated along time axis).

(a) Training mode

(b) Production mode

Fig. 2: The cross-lingual self-attentive document/sentence vectorization model.
tilingual NMT model, by creating shared layers between NMT\textsubscript{a→b} and NMT\textsubscript{b→a}, where a → b means translation from the source language a to the target language b. In details, we insert between the encoders and decoders of the NMT\textsubscript{a→b} and NMT\textsubscript{b→a} several shared layers: A GRU layer (GRU\textsubscript{shr1}), a self-attentive layer followed by another GRU layer (GRU\textsubscript{shr2}).

Figure 2(a) shows the cNTDV model in the training mode, with a being English (en) and b being German (de). During training, given a pair of English and German sentences, the English sentence will be processed through the encoder of NMT\textsubscript{en→de}, the shared layers, and its decoder resulting in the translation loss of \textit{l}\textsubscript{en→de}. Similarly, the German sentence in the pair will be processed through the encoder of NMT\textsubscript{de→en}, the same shared layers, and its decoder resulting in the translation loss of \textit{l}\textsubscript{de→en}.

NMT\textsubscript{a→b} and NMT\textsubscript{b→a}, are first trained. Their parameters are used in the cNTDV model without re-estimation. cNTDV model training only updates the parameters of the shared layers. We significantly reduce the training cost the cNTDV model by transferring knowledge from the NMT model to the latter.

We designed a novel self-attentive mechanism with multiple heads, inspired by the structured self-attentive sentence embedding and the transformer network \cite{vaswani2017attention}. Let \( \tilde{h}_i \) be the hidden state of the encoder, after the linear projection layer, it becomes

\[
\tilde{h}_i = \tilde{h}_i W_e + \tilde{b}_e ,
\]

where \( W_e \) is the weight matrix of the projection layer and \( \tilde{b}_e \) is the bias. \( \tilde{h}_i \) is the encoder state after the projection layer; Note that \( W_e \) is different for different language pairs.

After passing through the GRU\textsubscript{shr1} layer, the hidden states becomes

\[
\tilde{z}_i = \text{GRU}_{shr1}(\tilde{h}_i, \tilde{h}_{i-1}) ,
\]

The self-attention vector \( \tilde{p}_m \) produced by the \( m \)th attention head is:

\[
g_i^m = sf \left( \frac{(\tilde{z}_i W_q^m + \tilde{b}_q^m)(\tilde{z}_v W_k^m + \tilde{b}_v^m)^T}{\sqrt{d_h}} \right) ,
\]

\[
\tilde{p}_m = \sum_{i=1}^{L_e} g_i^m (\tilde{z}_i W_v^m + \tilde{b}_v^m) ,
\]

where \( i \) is the index of input frames; \( m \) is the index of different attention head; \( sf() \) is the softmax function; \( W_q^m, W_k^m, W_v^m \), and \( \tilde{b}_q^m, \tilde{b}_v^m \) are model parameters of the \( m \)th attention head, where the subscripts \( q, k, v \) refer to quantities related to the query, key and values in the attention mechanism \cite{vaswani2017attention}. In this study, although the same vectors are used for queries, keys and values, their projection weight matrices \( W_q^m, W_k^m, \) and \( W_v^m \) are different, and they all have the dimension \( d_h \times d_h \), where \( d_h \) is the number of hidden units in the self-attentive layer and the shared GRU layer. \( \tilde{b}_q^m, \tilde{b}_v^m, \) and \( \tilde{b}_d^m \) are vectors of dimension \( d_h \). Note also that compared with the the self-attentive mechanism in the transformer network, context states \( \tilde{z}_i \) in our case does not attend to other encoder states at different time frames. The reason is that our goal is to summarize the input sequence to a fixed-length vector, and the self-attentive layer, therefore, focuses only on the overall sequential pattern as in the case of the structured self-attentive sentence embedding \cite{vaswani2017attention}. Hence, our design of self-attention layer is novel and the mechanism is significantly different from that in the transformer network.

For an attention system with \( r \) heads, its \( r \) self-attention output vectors are grouped together in the context matrix \( \tilde{K} = \{ \tilde{p}_1, \ldots, \tilde{p}_m, \ldots, \tilde{p}_r \} \). If we set \( r = 1 \), then \( \tilde{P} \) will be a single context vector consisting of the weighted average information from the encoder. In general, the fixed-sized \( \tilde{P} \) is put through GRU\textsubscript{shr2} layer one row at a time to get an output from the GRU which is given by

\[
\tilde{k}_i = \text{GRU}_{shr2}(\tilde{p}_i, p_{i-1}) ,
\]

where \( \tilde{p}_i \) is the \( i \)th row of \( \tilde{P} \). \( \tilde{k}_i \) also goes through a projection layer as shown in Figure 2 before being input to the decoder part. The projected GRU\textsubscript{shr2} output is given by

\[
\tilde{c}_i = \tilde{k}_i W_p + \tilde{b}_p ,
\]

where \( W_p \) is the projection weight matrix, and \( \tilde{b}_p \) is the bias. The projected GRU\textsubscript{shr2} outputs from all the \( r \) context vectors are grouped together in the matrix \( \tilde{K} = \{ \tilde{k}_1, \ldots, \tilde{k}_i, \ldots, \tilde{k}_r \} \). \( \tilde{K} \) is then fed to an attention mechanism similar to the attention layer in the aforementioned NMT model to give the context vector for the decoder:

\[
\tilde{c}_j = \text{ATT}(\tilde{K}, \tilde{s}_j) ,
\]

where \( \tilde{c}_j \) and \( \tilde{s}_j \) are the same context vector and intermediate decoder state vector as in Eq. 2. In Figure 3 the input sentence has 3 words (or frames) and the output sentence has 4 words (or frames). The self-attentive layer has two heads (i.e., \( r = 2 \)). The self-attentive layer always selects and summarizes the information into the context matrix \( \tilde{P} \) of dimension \( 2 \times d_h \), no matter how long the sentence is.

### 2.3. Deriving the document vectors in production mode

Figure 2(b) shows how the cNTDV model works in the production mode when inputting a German document/sentence. In the production mode, only the encoder and the self-attentive layer is used, and either or both of the encoder of NMT\textsubscript{en→de} and NMT\textsubscript{de→en} may be used. If we want to use the encoder of NMT\textsubscript{en→de}, the German sentence is first translated to English using the NMT\textsubscript{de→en}, and the translated
The encoder of NMT directly feeds to the encoder of NMT (and $b$ used directly to produce the desired context vectors $P_{en}$). Therefore, if we only use the encoder of NMT on German documents/sentences and only use the encoder of NMT on English documents/sentences, no translator is needed. Otherwise, we can also use both encoders and the translator to form a combined vector for better performance. The output of the translator $NMT_{de-en}$ directly feeds to the encoder of the NMT, and is trained on the same corpus without other outside information, so it can be considered as a ‘preprocessing module’ of the model.

The proposed document vectors can be produced by only a forward-pass to the self-attention layer; no backward-propagation nor parameter updating is required. The costly computation of the softmax layer with a large vocabulary is avoided.

In this paper, we propose the following different document/sentence representation vectors in the form of summation or concatenation of the rows in $P^{(a)}$ and/or $P^{(b)}$, where $\overrightarrow{p_i}^{(a)}$ and $\overrightarrow{p_i}^{(b)}$ are the $i$th row of $P^{(a)}$ and $P^{(b)}$, respectively:

$$cNTDV_a = \sum_{i=1}^{r} \overrightarrow{p_i}^{(a)}$$

$$cNTDV_b = \sum_{i=1}^{r} \overrightarrow{p_i}^{(b)}$$

$$cNTDV^{(a)}_{con} = [\overrightarrow{p_1}^{(a)}, ..., \overrightarrow{p_i}^{(a)}, ..., \overrightarrow{p_r}^{(a)}]$$

$$cNTDV^{(b)}_{con} = [\overrightarrow{p_1}^{(b)}, ..., \overrightarrow{p_i}^{(b)}, ..., \overrightarrow{p_r}^{(b)}]$$

$$cNTDV_{a:b} = [cNTDV_a, cNTDV_b]$$

$$cNTDV_{a+b} = cNTDV_a + cNTDV_b$$

$$cNTDV_{con} = cNTDV^{(a)}_{con} + cNTDV^{(b)}_{con}$$

2.4. The stacked self-attentive cross-lingual document/sentence vectorization model

As shown in the Figure 3 we also tested a new structure with two stacked self-attentive model plus a GRU layer instead of a two GRU layer plus a self-attentive layer. Self-attentive layer is easier for parallel computation and faster to train due to the lack of recurrent structure and the gradient vanishing/explosion problem. This new model (we name this stack self-attentive model and the resulting vector as cNTDV$^2$ for the sake of convenience) also use only about half the size (500) in the shared layers comparing to the cNTDV model (1024). On the other hand, this model would use twice more heads as those in the cNTDV model. All in all, there are less parameter in cNTDV$^2$ than in cNTDV. We also suspect the stack self-attentive layer can be better trained at projecting the vectors from different source language into a unified space due to more attention heads and the stacked self-attentive layer. On the other hand, cNTDV may have better capability in capturing the sequential patterns with an additional GRU layer.

Apart from replacing the GRU layer with an self-attentive layer and the change in hidden layer size, the other aspects of the cNTDV$^2$ model is the same as those in the cNTDV model.

2.5. Distance constraint in training

In order to let the $P$ produced by the different languages as similar as possible, we adopt a new loss term which is the combination of the translation loss and the distance loss between the $P$ from NMT$_{a\rightarrow b}$ and NMT$_{b\rightarrow a}$ path. In specific, the machine translation cost is:

$$l_{mt} = l_{mt}^{a\rightarrow b} + l_{mt}^{b\rightarrow a}$$

where $l_{mt}^{a\rightarrow b}$ and $l_{mt}^{b\rightarrow a}$ is the cross-entropy loss of the NMT outputs from the NMT$_{a\rightarrow b}$ and NMT$_{b\rightarrow a}$ path respectively. The distance between two self attention matrix from NMT$_{a\rightarrow b}$ and NMT$_{b\rightarrow a}$ path is:

$$d_{ij}^{a-b} = |P^{(a)} - P^{(b)}|^2$$

where $||$ is function to retrieve the Frobenius norm of the matrix. To prevent the $P^{(a)}$ and $P^{(b)}$ from training to zero, we also add a term of negative sampling cost $[6]$

$$d_{ij}^{a-b} = |P^{(a)} - P^{(b_i)}|^2$$

where $P^{(b_i)}$ is a self-attention matrix from an randomly sampled $j$-th sentence (which is unrelated with the current sentence). The distance cost of one negative sample become:

$$l_{d_j} = \max(0, mrg + d_{ij}^{a-b} - d_{ij}^{a-b})$$

The idea is that we want to minimize the distance of $P^{(a)}$ and $P^{(b)}$ between the related sentence pair while maximizing...
the distance between the unrelated sentence pairs. With this arrangement, the tendency which drives the \( P(a) \) and \( P(b) \) to zero is compensated by the tendency to make \( P(c) \) and \( P(d) \) as large as possible. The \( \alpha \) is a margin constant to confine the numerical value in training. Finally, the total cost of the model is the distance cost of \( N_e \) samplings adding together, in combination with the translation cost:

\[
l_{c_{\text{com}}} = \beta \sum_{j=1}^{N_e} l_{d_j} + (1 - \beta) l_{mt}
\]

where \( \beta \) is a fixed parameter to balance the weight between the translation cost and the distance cost. \( N_e \) is the number of negative samples. This novel combination of the loss between translation and vector distance ensures that the document vectors produced contain ample information and are at the same time very similar between paralleled documents of different languages.

### 3. EXPERIMENTS

#### 3.1. Training and text processing

We train our models on the Europarl v7 parallel corpus. The English (en) and German (de) pair of the corpus consists of about 1.9M parallel sentences with 49.7M English tokens and 52.0M German tokens [21]. We segment words via byte-pair encoding (BPE) [22, 23]. Unless otherwise stated, we follow the default training and text processing settings in the NEMATUS toolkit [16], upon which our codes are built.

In training the attention-based NMT models, we use the default setting with mini-batches of size 80, a vocabulary size of 85,000, a maximum sentence length of 50, word embeddings of size 500, and hidden layers of size 1024. The models are trained with the Adam optimizer [24] using the cross-entropy loss. In current study, we set \( N_e \) to 20 while \( \beta \) to 0.5. We set the margin as \( 2 \sqrt{\alpha} \). In training the cNTDV model, we use mini-batches of size 40 and set the number of heads \( r \) to 4. The model parameters of cNTDV are initialized by the model parameters of the trained NMT model with the exception of the newly added shared layers. The training procedure of the cNTDV model is basically the same as that of the NMT model except that it always runs for 10 epochs with the original NMT parameters fixed. In this way, we transfer the knowledge from the attention-based NMT models to our cNTDV model and the training time of the cNTDV model is greatly reduced. In translation, the attention-based NMT model in the pipeline also uses the default setting of the NEMATUS toolkit except that the beam size is set to 1 (to increase the computation speed). Note that we did not use any validation set and we also did not use any information/vocabulary that is out of this parallel corpus, as our purpose is to develop a generalized model that can be directly used in the tasks without having to adapt or re-train the model.

We also experiment on a different structure with two self-attention layers stacking together (cNTDV\(^2\)). In this new structure, we use hidden layers of size 500 and set the number of attention heads \( r \) to 8 so that the number of parameters is about the same in this new model. We also remove the first GRU layer in the share layers to further increase the computation speed. Training procedure of this model is basically the same except that it only runs for 5 epochs. It may get better performance with more epochs in training.

#### 3.2. Cross-lingual document classification (CLDC) on RCV1/RCV2

The effectiveness of the cNTDs is evaluated on the cross-lingual document classification task on RCV1/RCV2 [12]. In this task, 1K English documents of four categories (Corporate/Industrial, Economics, Government/Social, and Market) are given to classify the category of the 5K German documents in the test set, and vice versa. The cNTDV model will produce a document representation vector for each document in either language. As a document in the corpus usually consists of several sentences, we treat the entire document as a continuous sequence of words and uses the cNTDV model to produce a single cNTDV for the document. We will re-name such document vectors simply as DV for the sake of brevity. Moreover, we also use DV\(^2\) to designate the vectors from the model that using two stacked self-attention layers from here on.

The produced cNTDV vectors are centered to zero and normalized to feed into a classifier. A linear SVM classifier from scikit-learn [25] is trained on the document vectors of one language produced from the training set. The default settings of SVM training in the scikit-learn toolkit are used except that the maximum number of iterations is set to 5000 and the class weight is set to ‘balanced’. After training, the SVM classifier will be used to classify the category of input document vectors of the opposite language in the test set.

The premise for our proposed method on the CLDC task is that when the document vectors of two languages (here, En-
English and German) are embedded into the same vector space, a classifier learned from document vectors of one language (English/German) can be used to classify document vectors of the other language (German/English).

4. RESULTS

Table 2: The classification accuracy on the CLDC task (%).

| Method      | en→de | de→en |
|-------------|-------|-------|
| para_doc *  | 92.7  | 91.5  |
| BAE #       | 91.8  | 74.2  |
| Unsup [26]  | 90.7  | 80.0  |
| BRAVE [8]   | 89.7  | 80.1  |
| MultiVec [9]| 88.2  | 79.1  |
| ADD [6]     | 86.4  | 74.7  |
| BI [6]      | 86.1  | 79.0  |
| MT_base [12]| 68.1  | 67.4  |
| NMT_base    | 92.89 | 70.84 |
| DV_en       | 93.10 | 82.84 |
| DV_de       | 93.24 | 81.43 |
| DV_{en→de}  | 93.56 | 82.33 |
| DV_{en+de}  | 94.10 | 82.98 |
| DV_{con}    | 94.26 | 83.28 |
| DV_{con→de} | 92.96 | 81.35 |
| DV_{con→ende}| 89.76 | 81.03 |
| DV_{ende}   | 88.92 | 79.09 |
| DV^2_{ende} | 91.12 | 80.93 |

Table 2 shows the performance of various methods on the CLDC task. The method para_doc marked with * is not considered as a fast method in production mode as it would require parameter optimization during testing. Methods marked with # uses additional monolingual data (from the CLDC datasets) during training [7]. MT_base is the machine translation baseline in the original study on the CLDC task [12].

As shown in the table, para_doc has currently the best performance among published results. All the other existing models fall very far behind para_doc in the de→en category. However, Our DVs from the cNTDV model give better performance than most of the existing methods with the only exception of para_doc. More specifically, our DV_{con} has the best en→de classification performance compared to existing publications. In the de→en task, our DV_{con} achieves the second best result and outperforms the third best method by a great margin.

Similar to the line of work that only use forward pass of the various neural network to produce document vectors, our cNTDV model does not require validation and hyper-parameter tuning on the monolingual data at test time. It can be directly applied to the text in the CLDC task after the model has been trained on the parallel data. More importantly, forward pass run of the encoder is much faster than parameter optimization. Therefore our model has better performance than all the fast model while faster in decoding than the para_doc. Nevertheless, we would like to mention that the para_doc model has a simpler structure and would be faster than ours in training with the paralleled corpora.

Although the cNTDV model requires training NMT models, it is trained on the same standard parallel data as in the previous studies and its parameters are reused in the larger part of the cNTDV model’s encoder and decoder framework, hence it can be seen as a part of the model. This approach is different from adopting an external translator (e.g., Google translator), which would bring in extra information and makes the comparison unfair.

Interestingly, the performance of DV derived from only one language (e.g., DV_{de}) is similar to DV_{en→de}. As they are produced by half of the cNTDV model, they can be produced faster. It is also easier to expand the cross-lingual framework into a multi-lingual framework by using a ‘pivot’ language with this ‘half-model’ approach.

In comparison with our previous work on NTDV, DV_{con→ende} and DV^2_{ende} are the results that use only the NMT_{de→en} encoder on the German documents/sentences and only use the NMT_{en→de} encoder on the English documents/sentences to produce the document vectors. Moreover, DV_{ende} uses cNTDV_{en} for English documents and cNTDV_{de} for German documents, DV_{con→ende} uses cNTDV_{con} for English documents and cNTDV^{(en)}_{con} for German documents, DV^2_{ende} uses cNTDV^2_{en} for English documents and cNTDV^2_{de} for German documents. Comparing to other fast models, DV_{ende}, DV^2_{ende}, DV_{con→ende} does not need the NMT translators and they also only use one encoder, so they have the simplest structure and the computational cost in decoding are lowest among cNTDV methods.

Comparing to other fast models that do not require training/adaptation on the monolingual data, DV^2_{ende} has the best performance in both en→de and de→en task. Note that as cNTDV^2 uses 8 attention heads, so we only use the summation form of the vector. Finally, the dimension of DV^2 is smaller than other DVs and they have better performances than other cNTDV vector without using the NMT translator (DV_{ende}, DV_{con→ende}).

The NMT_base is the classification performances achieved by the NMT models that we adapted our cNTDV model on. In the experiments, the testing documents are translated into the training language using the same NMT models and the same decoding setting as in the cNTDV model. And the classifier is then trained with the Turning-Frequency/Inverse-Turning-Frequency (TF/IDF) of the most frequent 50000-word features in the original and translated texts of the same language. Comparing with MT_base, it shows that we trained a superior baseline translator. Comparing with DV_{con}, it shows
that using the NMT translator in our cNTDV method and producing the document vector with both the English-to-German and the German-to-English paths is better than using NMT translator alone. Comparing to \(DV^2_{ende}\) (which does not involve a NMT translator in the production mode), the result from NMT\_base is better in the English-to-German test and worse in the German-to-English test. However, it also need to be considered that \(DV^2_{ende}\), \(DV_{ende}\), \(DV_{con-ende}\) would only use the encoding part of the cNTDV framework and are therefore much faster than the NMT decoding process (As the current production of word in the NMT need to be beam searched based on the previous results, the decoding part is the speed bottleneck in the translation process).

Therefore, we could conclude that \(DV^2_{ende}\) is the lighter and faster method during the production mode, with a good performance that is superior than those similar “forward propagation fast models” in the previous studies. On the other hand, \(DV_{con}\) is best performing model, with the NMT translator integrated into the framework to achieve a even better performance. And in our experience, albeit the model producing \(DV_{con}\) is more complicated than the NMT\_base model itself, the computation time from the additional encoder path is negligible.

5. CONCLUSION

The cNTDV model can produce good cross-lingual document vectors fast in a forward-pass of the model. Comparing to our previous work on NTDV, the cNTDV model has the flexibility (with the same trained model) impromptu to either use the translator to enhance performances or not use it to save computation cost and memory consumption. This is thanks to the distance constraint training adopted in this paper.
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