AN EFFICIENT CHARACTER-LEVEL NEURAL MACHINE TRANSLATION

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ABSTRACT

Neural machine translation aims at building a single large neural network that can be trained to maximize translation performance. The encoder-decoder architecture with an attention mechanism achieves a translation performance comparable to the existing state-of-the-art phrase-based systems on the task of English-to-French translation. However, the use of large vocabulary becomes the bottleneck in both training and improving the performance. In this paper, we propose an efficient architecture to train a deep character-level neural machine translation by introducing a decimator and an interpolator. The decimator is used to sample the source sequence before encoding while the interpolator is used to resample after decoding. Such a deep model has two major advantages. It avoids the large vocabulary issue radically; at the same time, it is much faster and more memory-efficient in training than conventional character-based models. More interestingly, our model is able to translate the misspelled word like human beings.

1 INTRODUCTION

Neural machine translation (NMT) attempts to build a single large neural network that reads a sentence and outputs a translation (Kalchbrenner and Blunsom, 2013; Cho et al., 2014a; Sutskever et al., 2014). Most of the extant neural machine translation models belong to a family of word-level encoder-decoders (Sutskever et al., 2014; Cho et al., 2014b). Bahdanau et al. (2014) recently proposed a model with attention mechanism which automatically searches the alignments and greatly improves the performance. However, the use of a large vocabulary seems necessary for the word-level neural machine translation models to improve performance (Sutskever et al., 2014; Cho et al.).

Chung et al. (2016) listed three reasons behind the wide adoption of word-level modeling: (i) word is a basic unit of a language, (ii) data sparsity, (iii) vanishing gradient of character-level modeling. Considering that a language itself is an evolving system, it is impossible to cover all words in the language. The problem of rare words that are out of vocabulary (OOV) is an important issue which can effect the performance of neural machine translation. Using larger vocabulary does improve performance (Sutskever et al., 2014; Cho et al.), but the training becomes much harder and the vocabulary is often filled with many similar words that share a lexeme but have different morphology.

There are many approaches to dealing with the out-of-vocabulary issue. Gulcehre et al. (2016); Luong et al. (2014); Cho et al. proposed to obtain the alignment information of target unknown words, after which simple word dictionary lookup or identity copy can be performed to replace the unknown words in translation. These approaches ignore several important properties of languages such as monolinguality and crosslinguality as pointed out by Luong and Manning (2016). Luong and Manning (2016) further proposed a hybrid neural machine translation model which leverages the power of both words and characters to achieve the goal of open vocabulary neural machine translation.

Intuitively, it is elegant to directly model pure characters. However, as the length of sequence grows significantly, character-level translation models have failed to produce competitive results compared with word-based models. In addition, they require more memory and computation resource. Especially, it is much difficult to train the attention component. Ling et al. (2015a) proposed a compositional character to word (C2W) model and applied to machine translation in Ling et al.
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However, they found that it is slow and difficult to train source character-level models and had to resort to layer-wise training the neural network and applying supervision for the attention component.

In order to address the training issue mentioned in (Ling et al., 2015b), we introduce a decimator before encoding as well as an interpolator after decoding. The decimator is based on a variant of the gate recurrent unit (GRU) (Cho et al., 2014b; Chung et al., 2014), which samples the character sequence according to the occurrence of delimiter (usually the space) and resets to the initial state accordingly. The interpolator also relies on a variant of GRU, which sets the state to the output of decoder and generates character sequence until generating a delimiter. In this way, we almost keep the same encoding length for encoder as word-based models but eliminate the use of a large vocabulary. Besides, the decoding step is much more natural compared with (Bahdanau et al., 2014) which uses a multi-layer network following a softmax function to compute the probability of each target word. Furthermore, we are able to efficiently train the deeper model which using multi-layer recurrent network and achieve higher performance.

In summary, we propose an efficient architecture to train a deep character-level neural machine translator. We show that the model achieves a higher translation performance compare to the word-level neural machine translation on the task of English-to-French translation. Furthermore, our model is able to translate the misspelled words and learn similar embeddings of the words with similar meanings.

2 Neural Machine Translation

Neural machine translation is often implemented as an encoder-decoder architecture. The encoder usually uses a recurrent neural network (RNN) or a bidirectional recurrent neural network (BiRNN) (Schuster and Paliwal, 1997) to encode the input sentence $x = \{x_1, \ldots, x_T\}$ into a sequence of hidden states $h = \{h_1, \ldots, h_T\}$:

$$h_t = f_1(e(x_t), h_{t-1}),$$

where $e(x_t) \in \mathbb{R}^m$ is an m-dimensional embedding of $x_t$. The decoder, another RNN, is often trained to predict next word $y_t$ given previous predicted words $\{y_1, \ldots, y_{t-1}\}$ and the context vector $c_t$:

$$p(y_t | \{y_1, \ldots, y_{t-1}\}) = g(e(y_{t-1}), s_t, c_t),$$

where

$$s_t = f_2(e(y_{t-1}), s_{t-1}, c_t)$$

and $g$ is a nonlinear and potentially multi-layered function that computes the probability of $y_t$. The context $c_t$ depends on the sequence of $\{h_1, \ldots, h_T\}$. Sutskever et al. (2014) encoded all information in the source sentence into a fixed-length vector, i.e., $c_t = h_T$. Bahdanau et al. (2014) computed $c_t$ by the alignment model which solves the bottleneck that the former approach meets.

The whole model is jointly trained to maximize the conditional log-probability of the correct translation given a source sentence with respect to the parameters of the model:

$$\theta^* = \arg\max_\theta \sum_{t=1}^{T} \log p(y_t | \{y_1, \ldots, y_{t-1}\}, x).$$

For the detailed description of the implementation, we refer the reader to the papers (Cho et al., 2014a; Sutskever et al., 2014; Bahdanau et al., 2014).

3 Deep Character-Level Neural Machine Translation

There are two problems in the word-level neural machine translation models. First, how can we map a word to a vector? It is usually done by a lookup table (embedding matrix) where the size of vocabulary is limited. Second, how do we map a vector to a word when predicting? It is usually done via a softmax function. However, the large vocabulary will make the softmax intractable computationally.

Ling et al. (2015a,b) proposed the C2W and V2C components to address these two problems, however, these components are less efficient. We correspondingly devise two novel operators that
we call \textit{decimator} and \textit{interpolator}. Accordingly, we propose a deep character-level neural machine translation model.

The decimator samples the input character sequence based on a delimiter (usually the space), which significantly reduces the length of input sequence. Thus the input of our bidirectional RNN encoder has the same length as the word-level encoder. The interpolator then takes the output of decoder to generate a sequence of characters ending with a delimiter. This further reduces the burden of generating process.

### 3.1 Decimator

We introduce a variant of the gate recurrent unit (GRU) (Cho et al., 2014b; Chung et al., 2014) that used in decimator and we denote it as DGRU (It is possible to use the LSTM (Hochreiter and Schmidhuber, 1997) units instead of the GRU described here). DGRU reads the sequence character by character. Once DGRU meets a delimiter, it will reset the state to the trainable initial state. Formally, given the input character sequence \( \{x_1, \ldots, x_t\} \), we first construct an auxiliary sequence \( \{a_1, \ldots, a_c\} \) which only contains 0 and 1 to indicate whether \( x_i \) is a delimiter. DGRU computes the state sequence \( \{h_1, \ldots, h_{t+1}\} \) by iterating the following updates:

\[
\begin{align*}
    r_t^j &= \sigma([W_r e(x_t)]^j + [U_r h_{t-1}]^j), \\
    z_t^j &= \sigma([W_z e(x_t)]^j + [U_z h_{t-1}]^j), \\
    \hat{h}_t^j &= \phi([W_e(x_t)]^j + [U (r_t \odot h_{t-1})]^j), \\
    h_t^j &= z_t^j h_{t-1}^j + (1 - z_t^j) \hat{h}_t^j, \\
    h_0 &= \text{initial state}.
\end{align*}
\]

where \( h_t^j \) is the \( j \)-th hidden unit of time \( t \), \( h_0 \) is the trainable initial state, \( \sigma \) is the sigmoid function and \( \phi \) is the activation function. Note that Steps 1 to 4 are the same as the conventional GRU (Cho et al., 2014b; Chung et al., 2014). The only difference is that \( h_t \) will set to the trainable initial state \( h_0 \) once a delimiter is met.

In our model, we regard the state of DGRU before it reads a delimiter as the summary of the previous character sequence (the previous word). Thus we need to sample \( \{h_1, \ldots, h_t\} \) which is the output of DGRU. In order to make the training more efficient, we construct a sampling matrix according to the delimiter in the source sequence. The sampling matrix \( S \) has \( t \) rows and \( c \) columns, and \( c \) is the number of the delimiters. \( S[i-1,j] \) is set to 1 if the \( j \)-th delimiter is the \( i \)-th character of the source sequence. For example, if the input character sequence is “a b c” and the output of DGRU is \( [h_1, h_2, h_3, h_4, h_5] \), then the corresponding sample step will be:

\[
\begin{bmatrix}
    h_1 & h_2 & h_3 & h_4 & h_5 \\
\end{bmatrix}
\begin{bmatrix}
    0 & 0 & 1 & 0 & 0 \\
    0 & 0 & 0 & 1 & 0 \\
\end{bmatrix} = [h_2, h_4].
\]

After sampling, \( [h_2, h_4] \) becomes the output of the decimator, thus the length of the sequence that needs to be encoded is significantly reduced, which can be handled efficiently by the bidirectional RNN encoder.

### 3.2 Interpolator

Our deep character-level neural machine translation also contains a variant of GRU in the interpolator that we call it IGRU. IGRU has a settable state and generates character sequence based on the given state until generating a delimiter. In our model, the state is initialized by the output of the decoder. Once IGRU generates a delimiter, it will set the state to the next output of the decoder. Given the previous output character sequence \( \{y_0, y_1, \ldots, y_{t-1}\} \) where \( y_0 \) is a token representing the start of sentence, and the auxiliary sequence \( \{a_0, a_1, \ldots, a_{t-1}\} \) which is the same as decimator (\( a_0 \) is set to
1. IGRU updates the state as follows:

\[ h_{t-1} = (1 - a_{t-1})h_{t-1} + a_{t-1}d_{i_t}, \]  
\[ r^i_t = \sigma([W_r e(y_{t-1})]^T + [U_r h_{t-1}]^T), \]  
\[ z^i_t = \sigma([W_z e(y_{t-1})]^T + [U_z h_{t-1}]^T), \]  
\[ \tilde{h}^i_t = \phi([W e(y_{t-1})]^T + [U(r_t \odot h_{t-1})]^T), \]  
\[ h^i_t = z^i_t \tilde{h}^i_{t-1} + (1 - z^i_t)\tilde{h}^i_t, \]

where \( d_{i_t} \) is the output of the decoder. We can compute the probability of each target character \( y_t \) based on \( h_t \) with a softmax function:

\[ p(y_t | \{ y_1, \ldots, y_{t-1} \}, x) = \text{softmax}(h_t). \]

The current problem is that the number of outputs of decoder is much fewer than the target character sequence. It will be intractable by conditionally picking outputs from the decoder when training in batch manner. In our model, we add a resampler to unfold the outputs of the decoder, which makes the training process more efficient. Like the sampler, the resampler contains a \( c \times t \) resampling matrix \( R \), where \( c \) is the number of delimiter of the target sequence and \( t \) is the length of the target. \( R[i, j_1 + 1] \) to \( R[i, j_2] \) are set as 1 if \( j_1 \) is the index of the \((i-1)\)-th delimiter and \( j_2 \) is the index of the \(i\)-th delimiter in the target character sequence. The index of the 0-th delimiter is set as 0. For example, when the target output is “<d> + <d> + <d>” and the output of the decoder is \( \{d_1, d_2\} \), the resample step will be:

\[ [d_1, d_2] \left[ \begin{array}{cc} 1 & 1 \\ 0 & 0 \\ 0 & 1 \\ 1 & 1 \end{array} \right] = [d_1, d_1, d_1, d_2, d_2], \]

therefore \( \{d_{i_1}, d_{i_2}, d_{i_3}, d_{i_4}, d_{i_5}\} \) is correspondingly set to \( \{d_1, d_1, d_1, d_2, d_2\} \) in IGRU iterations. After resampling, we can compute the probability of each target character by interpolator according to Eqns. 10 to 11. Compared with the two forward passes approach in [Luong and Manning 2016], our resampling approach is more efficient. Note that the resampling step is only necessary in training process. As explained in the Section 3.4 the generation procedure is different from the training procedure.

### 3.3 Model Architectures

There are totally five recurrent neural networks in our model, which can be divided into four layers as shown in Figure 1. Figure 1 illustrates the training procedure of a basic deep character-level neural machine translation. It is possible to use multi-layer recurrent neural networks to make the model deeper. The first layer contains a source sequence decimator which samples the character level sequence according to the delimiter (denoted as \(<d>\) in Figure 1). The second layer is a bidirectional RNN encoder which is identical to that of \((\text{Bahdanau et al.}, 2014)\). The third layer is the decoder. It takes the previous word representation as a feedback, which is produced by the target sequence decimator in our model. Then it combines the previous hidden state and the attention from the encoder to generate the next decoded vector. The last layer is the interpolator, which takes the decoded vector as the state of IGRU. Based on the information of previous generated character, the interpolator generates the next character until generating an end of sentence token (denoted as \(<\text{EOS}>\) in Figure 1). With the help of “sampler” and “resampler,” we can train our deep character-level neural translation model perfectly well in an end-to-end fashion.

### 3.4 Generation Procedure

We first encode the source sequence as in the training procedure, then we generate the target sequence character by character based on the decoded vector \( d_t \). Once we generate a delimiter, we should compute next decoded vector \( d_{i_{t+1}} \) through the decoder by combining feedback \( DY_t \) of the current generated word from the target decimator and the attention from the encoder. The generation procedure will terminate once an end of sentence (EOS) token is produced.
Figure 1: Basic deep character-level neural machine translation. The DGRUs with red border indicate that the state is reset to the initial state and the IGRUs with red border indicate that the state should be set to the next output of the decoder. We refer readers to the supplementary material for a detailed illustration.

4 EXPERIMENTS

We implement the model using Theano\cite{Bergstra10, Bastien12} and Blocks \cite{vanMerriënboer15}, the source code is available at github\footnote{https://github.com/SwordYork/DCNMT}. We train our model on a GTX Titan X. For fair comparison, we evaluate our deep character-level neural machine translation model (DCNMT) on the task of English-to-French translation, and conduct comparison with the basic word-level neural machine translation model (RNNsearch) \cite{Bahdanau14} and Ling et al.\cite{Ling15}'s model (CBNMT). We use the same dataset as RNNsearch which is the bilingual, parallel corpora provided by ACL WMT'14\footnote{http://www.statmt.org/wmt14/translation-task.html}.

4.1 DATASET

The English-French parallel corpus of WMT'14 contains totaling 850M words. Following the same procedure of \cite{Cho14b, Bahdanau14, Axelrod11}, we reduce the size of the corpus to 348M words. We use newstest2013 as the development set and evaluate the models on the newstest2014 which consists of 3003 sentences not present in the training data.

In terms of preprocessing, we only apply the usual tokenization. We choose a list of 120 most frequent characters for each language which covers nearly 100% of the training data. Those characters not included in the list are mapped to a special token (<unk>).
4.2 Training Details

We train two types of models with the sentences of length up to 50 words. We follow (Bahdanau et al., 2014) to use similar hyperparameters. The encoder of both the models consists of forward and backward RNN, each has 1024 hidden units; and the decoder also contains 1024 hidden units. We use 30,000 most frequent words for RNNsearch and the word embedding dimensionality is 620. We choose 120 most frequent characters for DCNMT and the character embedding dimensionality is 64. The DGRUs in both source decimator and target decimator have 512 hidden units. We test two models DCNMT-1 and DCNMT-2, which respectively contains a single-layer recurrent network and 2-layer recurrent network in the source decimator, bidirectional RNN encoder and decoder.

We use a stochastic gradient descent (SGD) with mini-batch of 80 sentences to train each model. We calculate an adaptive step rate using Adadelta (Zeiler, 2012). For fair comparison, we trained each model for approximately two weeks.

We use a beam search to find a translation that approximately maximizes the conditional log-probability which is a commonly used approach in neural machine translation (Sutskever et al., 2014; Bahdanau et al., 2014). In our DCNMT model, it is reasonable to search directly on character level to generate a translation.

5 Result and Analysis

We show the comparison of quantitative results on the English-French translation task in Section 5.1. Apart from measuring translation quality, we analyze the efficiency of our model and effects of character-level modeling in more details.

5.1 Quantitative Results

We illustrate the efficiency of the deep character-level neural machine translation by comparing with the basic neural machine translation model (RNNsearch) and CBNMT (Ling et al., 2015b). We test on the newstest2014 and measure the performance by BLEU score (Papineni et al., 2002) which is commonly used in translation tasks. It is possible to further improve the performance by using multi-layer deep RNNs, like the 4-layer LSTM used in (Sutskever et al., 2014; Luong et al., 2014).

Table 1: Model comparison

| Model     | Parameters | Max len | Max mem      | Updates per day | Epochs | BLEU  |
|-----------|------------|---------|--------------|----------------|--------|-------|
| RNNsearch | 85.6M      | 50      | 9690MiB      | ~ 58K          | 5.2    | 28.47 |
| CBNMT     | 34.8M      | 300     | 9680MiB      | ~ 54K/30K      | 5.1    | 28.67 |
| DCNMT-1   | 33.6M      | 300     | 9627MiB      | ~ 42K          | 4.3    | 30.49 |
| DCNMT-2   | 71.4M      | 300     | 11403MiB     | ~ 34K          | 3.8    | 31.76 |

As shown in Table 1, the number of parameters of RNNsearch is much large than character-based models and more than half of the parameters are in lookup table (55.8M) which is really redundant. CBNMT is layer-wise trained, thus the updates per day (54K) is similar to RNNsearch when training attention, but the updates per day is dramatically reduced to 30K when training the C2W component. Our models consume nearly the same memory as RNNsearch when the 6 times longer sequence length. It is commonly known that RNN is less efficient than a simple lookup table, and there are 3 additional RNNs in DCNMT which decrease the update rate of DCNMT, however, still more efficient than CBNMT. Compared with RNNsearch, both CBNMT and DCNMT achieves a higher BLEU score. However, DCNMT-1 is more efficient than CBNMT and achieves much higher BLEU score using the similar amount of parameters, despite the use of IBM model 4 in CBNMT to produce the word alignments as a supervision. Besides, the deeper model (DCNMT-2) further improves the performance within less epochs.

5.2 Efficiency Analysis

As shown in Figure 2(a), the training curves of the three models are similar (we subtract the minimum cost value from cost for comparison). The DCNMT models start from a higher-cost state because they
need to learn one more abstraction compared with the word based RNNsearch. Once they learnt some representation of words, they learn to translate just like the word-base models. Another evidence that DCNMT and RNNSearch have similar behavior is the similar change of BLEU scores on development set as shown in Figure 2(b). The DCNMT is able to perform as good as the RNNSearch when only trained by half of the epoch; in contrast to (Luong and Manning, 2016; Ling et al., 2015b), they found that the character-level neural machine translation is extremely slow and difficult to train. The comparison between DCNMT-1 and DCNMT-2 shows that the depth of recurrent network is critical for our model to achieve higher performance.

It indicates that DCNMT could outperform the word-level neural machine translation based on these analyses, and the out-of-vocabulary issue is solved at the cost of a small decrement of update rate.

5.3 Translate Misspelled Words and Word Embeddings

Another advantage of our deep character-level neural machine translation is the ability to translate the misspelled words. To the best of our knowledge, other extant neural machine translation models can not achieve this functionality. In Table 2, we list some examples where the source sentences are taken from newstest2013 but we change some words to misspelled words. We also list the translations from Google translate and online demo of LISA

As listed in Table 2, DCNMT is able to translate out the misspelled words correctly. For a word-based translator, this is never possible because the misspelled words are mapped into <unk> token before training. Thus, it will produce an <unk> token or just take the word from source sentence as Google (Le, 2016) and many other models (Gulcehre et al., 2016; Luong et al., 2014) do.

To investigate how DCNMT works to translate the misspelled word, we visualize representation, produced by DCNMT, of some frequent words in Figure 3, which is computed by the t-SNE algorithm (Van der Maaten and Hinton, 2008). We can conclude from Figure 3(a) that words share a similar representation in DCNMT. The *exercice* and *exercise* are extremely close as shown in Figure 3(a).

Finally, the most surprising thing is that the words with similar meanings but different structure like “April,” “February,” “January,” “June” and “July” are clustered together as shown in Figure 3(b). It suggests that DCNMT is able to learn the embedding of the word in vector space to cluster words of similar meanings (usages) together like the word-level neural machine translation (Cho et al., 2014b).

6 Conclusion

In this paper we have proposed an efficient architecture to train the deep character-level neural machine translation model by introducing a decimator and an interpolator. We have demonstrated the efficiency of the training process and the effectiveness of the model in comparison with the...
Table 2: Translation of misspelled words

| Example 1 |
|-----------|
| **Source** | Unlike in Canada, the American States are responsible for the organisation of federal elections in the United States. |
| **Reference** | Contrairement au Canada, les États américains sont responsables de l'organisation des élections fédérales aux États-Unis. |
| **Google translate** | Contrairement au Canada, les États américains sont responsable pour la organisation des élections fédérales aux États-Unis. |
| **LISA** | Contrairement au Canada, les États-Unis sont UNK pour la UNK des élections fédérales aux États-Unis. |
| **DCNMT** | Contrairement au Canada, les États américains sont responsables de l'organisation des élections fédérales aux États-Unis. |

| Example 2 |
|-----------|
| **Source** | As a result, 180 bills restricting the exercise of the right to vote in 41 States were introduced in 2011 alone. |
| **Reference** | En conséquence, 180 projets de lois restreignant l'exercice du droit de vote dans 41 États furent introduits durant la seule année de 2011. |
| **Google translate** | En conséquence, 180 projets de loi restreignant l'exercice du droit de vote dans 41 États ont été introduits en 2011 seulement. |
| **LISA** | Par conséquent, 180 projets de loi restreignant le droit de vote dans 41 États ont été UNK en 2011. |
| **DCNMT** | En conséquence, 180 projets de loi restreignant l'exercice du droit de vote dans 41 États ont été introduits en 2011 seuls. |

Figure 3: t-SNE visualization of source word representations. We zoom in the particular parts for illustration.

word-level models and [Ling et al. (2015b)]’s model. The higher BLEU score implies that our deep character-level neural machine translation model likely outperforms the word-level models and the conventional character-based models. It is possible to further improve performance by using deeper GRU recurrent networks or training longer [Sutskever et al. (2014)].

As a result of the character-level modeling, we have solved the out-of-vocabulary (OOV) issue that word-level models suffer from, and we have obtained a new functionality that never achieved by extant neural machine translation model to translate the misspelled words. More importantly, the deep character-level is able to learn the similar embedding of the words with similar meanings like the word-level models. Finally, it would be potentially possible that the idea behind our approach could be applied to many other tasks such as speech recognition and text classification.
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