Reducing Redundant Computations with Flexible Attention

Raphael Shu, Hideki Nakayama
shu@nlab.ci.i.u-tokyo.ac.jp, nakayama@ci.i.u-tokyo.ac.jp
The University of Tokyo

Abstract

Recently, attention mechanism plays a key role to achieve high performance for Neural Machine Translation models. It applies a score function to the encoder states to obtain alignment weights. However, as this computation is done for all positions in each decoding step, the attention mechanism greatly increases the computational complexity. In this paper we propose a novel attention model which can reduce redundant attentional computations in a flexible manner. The proposed mechanism tracks the center of attention in each decoding step, and computes position-based penalties. In the test time, the computations of the score function for heavily penalized positions are skipped. In our experiments, we found that the computations in the attention model can be reduced by 54% in average with almost no loss of accuracy.

Introduction

Recently, recurrent neural networks had shown success on various language pairs in machine translation. In some major language pairs such as English-French, Neural Machine Translation (NMT) has already achieved better performance compared with conventional Statistical Machine Translation (SMT) models (Luong et al., 2015).

NMT models are generally composed of an encoder and a decoder, which are also known as encoder-decoder framework (Sutskever et al., 2014). The encoder creates a vector representation of the input sentence, while the decoder generates the translations from this single vector. This simple encoder-decoder model suffers from a long backpropagation path, and thus prone to long input sentences.

For recent NMT models, soft attention mechanism (Bahdanau et al., 2014) is a key extension to achieve high performance. In each time step of the decoding, the attention model computes alignment weights for all encoder states. Then a context vector, which is a weighted summarization of all encoder states are computed and fed as an input to the decoder. The attention mechanism is illustrated in Figure 1 where \( a_t(s) \) is a function for computing an alignment weight for encoder-side position \( s \) in the decoding timestep \( t \). In contrast to the aforementioned simple encoder-decoder model, attention mechanism can shorten the backpropagation path.

Though the attention mechanism gives the NMT models a boost in performance, it also significantly increased the computational burden. As the attention model has to compute the alignment weights for all encoder states in each step, the...
Figure 2: An example of one-to-many and zero-to-many alignments in English-Japanese language pair

decoding process becomes time-consuming. Even worse, recent researches in NMT prefer to separate the texts to subwords (Sennrich et al., 2016) or even characters (Chung et al., 2016), which means more encoder states have to be considered in attention model, results in exponentially increased computational cost. On the other hand, the attention mechanism is becoming more complex. For example, the NMT model with recurrent attention modeling (Yang et al., 2016) maintains a dynamic memory of attentions for every encoder states. In this paper, we focus on reducing the computations in attention mechanism. As online translation is now switching to NMT (Wu et al., 2016), reducing the complexity of attention mechanism can enable the translation systems to process longer sequences in limited time or incorporate more expensive attention models.

Our proposed attention model is based on a simple intuition. For most language pairs, words inside a phrase will remain unbroken during translation. Even the words in a chunk will remain in the same chunk after translation, but not be mixed with the words outside. Hence, the information of far-away words is basically unnecessary when translating inside a phrase or chunk. For this reason, we argue that computing attention for all positions in each step is redundant. This is the case especially when dealing with one-to-many alignments, such as the example shown in Figure 2 where four Japanese words are translated from one English source word. If we can predict whether the next word to translate is in a local position, redundant computations of attention model can be reduced by controlling the range of attention. However, attending to distant positions is still important when dealing with long-range reorderings. This motivated us to propose a flexible attention model to optimize the computational cost according to the context.

To evaluate our proposed attention model, we choose conventional attention mechanism and Local Attention (Luong et al., 2015a) as our base-line models. We focus on comparing the minimum amount of computations these models can achieve without hurting the performance too much. We choose English-Japanese language pair for the evaluation as it involves long-range reordering, which means the attention model can not just look at a local range constantly. Through empirical evaluation, we found our proposed attention model can reduce the computations of the attention model by 54% in average with almost no loss of accuracy.

Our contributions can be summarized as two folds:

1. We proposed a novel attention model which controls the range of attention in a flexible manner in order to reduce computations. We found the amount of computations of attention model can be reduced by 54% with almost no harm to accuracy. This result confirms our hypothesis that conventional attention mechanism performs a significant amount of redundant computations.

2. The proposed attention mechanism is simple to implement, and able to be combined with other complex attention models which are expensive to compute for all positions in each step.

Attention Mechanism in NMT

Though the network architectures of NMT models differ among various previous works, they generally follow the encoder-decoder framework. In (Bahdanau et al., 2014), a bidirectional recurrent neural network is used as the encoder, the embeddings of input word are fed into it. The hidden states $h_1, ..., h_S$ of the encoder are then used in decoding phase. Basically, the decoder is composed of a recurrent neural network (RNN). The decoder RNN computes the next state based on the embedding of the previously generated word, and a context vector given by the attention mechanism. Finally, the probabilities of output words in each time step are predicted based on the decoder states $h_1, ..., h_N$.

In order to compute the context vector, soft attention mechanism introduced in (Bahdanau et al., 2014) computes a weighted summarization of all encoder states in each decoding step, as depicted in Figure 1.
\[ c_t = \sum_s a_t(s) \tilde{h}_s \] (1)

Where \( \tilde{h}_s \) is the \( s \)-th encoder state, \( a_t(s) \) is the alignment weight of \( \tilde{h}_s \) in decoding step \( t \). The calculation of \( a_t(s) \) is given by the softmax of weight scores:

\[ a_t(s) = \frac{\exp(\text{score}(h_{t-1}, \tilde{h}_s))}{\sum_{s'} \exp(\text{score}(h_{t-1}, \tilde{h}_{s'}))} \] (2)

The unnormalized weight scores are computed with a score function, defined as \( \text{score}(h_{t-1}, \tilde{h}_s) = v_a^\top \tanh(W_a[h_{t-1}; \tilde{h}_s]) \) (3)

Where \( v_a \) and \( W_a \) are the parameters of the score function, \([h_{t-1}; \tilde{h}_s]\) is a concatenation of an encoder state and the decoder state in previous step. Intuitively, the alignment weight indicates whether an encoder state is valuable for generating the next output word. Note that many discussions on alternative ways for computing the score function can be found in several existing researches (Luong et al., 2015a).

**Flexible Attention**

In this section, we present our main idea for reducing the computational cost in conventional attention model. In contrast to conventional attention model, we track the center of attention in each decoding step with

\[ p_t = \sum_s a_t(s) \cdot s \] (4)

The value of \( p_t \) provides a rough focus of attention in time step \( t \). Then we penalize the alignment weights for the encoder states far way from \( p_{t-1} \), which is the focus in the previous step. This is done by a position-based penalty function:

\[ \text{penalty}(s) = g_t \frac{(s - p_{t-1})^2}{2\sigma^2} \] (5)

Where \( g_t \) is a sigmoid function that adjusts the strength of penalty dynamically based on the previous decoder state. \((s - p_{t-1})^2\) gives the distance between position \( s \) and the focus in the previous step, so far-away positions will get exponentially large penalties. The denominator \( 2\sigma^2 \) is a hyperparameter controls the maximum of penalty when \( g_t \) outputs 1.

The position-based penalty function is finally integrated into the computation of alignment weights:

\[ a_t(s) = \frac{\exp(\text{score}(h_{t-1}, \tilde{h}_s) - \text{penalty}(s))}{\sum_{s'} \exp(\text{score}(h_{t-1}, \tilde{h}_{s'}) - \text{penalty}(s))} \] (6)

Note that the use of penalty function here is similar to Local Attention proposed in (Luong et al., 2015a) in appearance. The difference is that Local Attention predicts the center of attention in each step but the strength of position-based penalty is fixed in any context. Further discussion will be given in Related Work.

In order to adjust the strength of penalty according to the context, \( g_t \) is computed with:

\[ g_t = \text{sigmoid}(v_g^\top \tanh(W_g h_{t-1} + b_g)) \] (7)

This function is parameterized by \( v_g, W_g \) and a bias term \( b_g \). We refer our attention model as Flexible Attention in this paper, as the range of attention is adjusted by \( g_t \) in a flexible manner.

Intuitively, when the model is translating inside a phrase, the alignment weights for distant positions can be safely penalized with a large \( g_t \) value. If the next word is expected to be translated from a new phrase, \( g_t \) shall output a low value to allow attending on any position. Actually, the sampled output word in the previous step can greatly influence this decision, as the selection of output word can determine whether the translation of a phrase is finished. For this reason, we also consider to put the embedding of the previously sampled word into the computation of \( g_t \) as:

\[ g_t' = \text{sigmoid}(v_g^\top \tanh(W_g h_{t-1}; \tilde{i}_t) + b_g) \] (8)

Where \( \tilde{i}_t \) is the embedding of the feedback word in step \( t \), which is equivalent to previous sampled output word. Empirically, we find the attention model performs better with the feedback.

**Reducing Computations in Flexible Attention**

As we can see from Equation 6 if a position is heavily penalized, then it will get a low probability regardless of the value of score function. In the
Figure 3: An illustration of Flexible Attention. In each decoding step, only a portion of encoder states are selected by the position-based penalty function to compute alignment weights.

test time, we can set a threshold $\tau$, and only computes the score function for positions with penalties lower than $\tau$. Figure 3 provides an illustration of the selection process. Hence, we only computes the score function for positions in the range $[p_{t-1} - \sigma \sqrt{2\tau}/g_t, p_{t-1} + \sigma \sqrt{2\tau}/g_t]$.

As the strength term $g_t$ in Equation 5 needs only to be computed once in each step, the computational cost of the penalty function does not grow with increasing input length. By utilizing the penalty values to skip the computations of the score function, the totally cost can be reduced.

Though a low threshold leads to more reduction of computations, the performance may degrade with limited information from attention model. How can we find a good threshold to balance the tradeoff of performance and computational cost? Let $\bar{S}$ be the average input length, we practically find the “sweet spot” of good thresholds is near $\tau = -log \frac{1}{\bar{S}}$. Alternatively, we can also search for a good threshold $\tau$ on a validation set.

**Finetuning for Less Computations**

In order to reduce more computations in Flexible Attention, we want $g_t$ to output a large value to clearly differentiate valuable states from other states based on their positions. Thus, we can further finetune our model to encourage the model to decode with larger penalties with the following loss function:

$$J = \sum_{i=1}^{D} -\log p(y^{(i)}|x^{(i)}) - \beta \frac{1}{T} \sum_{t=1}^{T} g^{(i)}_t$$ (9)

Where $\beta$ is a hyperparameter to control the balance of cross-entropy and the average strength of penalty. In our experiments, we find that setting $\beta$ to 0.1 and finetuning for one epoch works well. If we train the model with this loss function from beginning, the value of $g_t$ saturates quickly, which slows down the training process.

**Related Work**

To the best of our knowledge, only a limit of related researches aim to reduce the computations of attention mechanism. Local Attention proposed in (Luong et al., 2015a) limit the range of attention to a fixed window size. In Local Attention, the center of attention $p_t$ is predicted in each time step $t$:

$$p_t = S \cdot \text{sigmoid}(v_{p}^\top \tanh(W_p h_t))$$ (10)

Where $S$ is the length of input sequence. Finally, the alignment weights are computed by:

$$a'_t(s) = a_t(s) \exp(-\frac{(s-p_t)^2}{2\sigma^2})$$

$$= \frac{\exp(\text{score}(h_{t-1}, h_s))}{\sum_{s'} \exp(\text{score}(h_{t-1}, h_{s'}))} \exp(-\frac{(s-p_t)^2}{2\sigma^2})$$ (11)

Where $\sigma$ is a hyper-parameter determined by the window size $D$ by $\sigma = D/2$. Local Attention only computes attention within the window $[p_t - D, p_t + D]$. In their work, the hyperparameter $D$ is empirically set to $D = 10$ for English-German task, which means a window of 21 words.

Out proposed attention model is different to Local Attention in two key points: (1) our proposed attention do not predict the center of attention but tracks it in each step (2) the position-based penalty in our attention model is adjusted flexibly rather than fixed. Note that in Equation 11 of Local Attention, the penalty term is applied outside the
softmax. In contrast, we integrate the penalty term with the score function (Eq. 6), so that the final probabilities still sum up to 1.

Recently, a cheap linear model (de Brébisson and Vincent, 2016) is proposed to replace the attention mechanism with a low-complexity function. The cheap linear attention mechanism achieves an accuracy in the middle of Global Attention and non-attention model on a question-answering dataset. This approach can be considered as another interesting way to balance the performance and computational complexity in sequence-generation tasks.

**Experiments**

In this section, we focus on evaluating the computational cost our proposed attention model can reduce with low performance loss. We measure the computational cost by an average of *computations per step (CPS)* of the score function. For conventional attention mechanism, as all positions have to be computed in each step, the CPS in this case is the average sentence length of the test corpus. Following (Luong et al., 2015a), we refer to the conventional attention mechanism as Global Attention in experiments.

**Experimental Settings**

We evaluate our models on English-Japanese translation task. As English-Japanese language pair has long-range reorderings, the attention model has to correctly predict it and look at far-away positions occasionally. Looking at a local range constently The training data contains 3M sentence pairs (Nakazawa et al., 2016), while test data contains 1812 sentences. The test data contains 24.4 input words in average. The vocabulary are cropped to 80k and 40k for English and Japanese respectively, while OOV words are replaced with a “UNK” symbol. We pick 1.5M sentence pairs according to automatically evaluated translation quality scores. Long sentences with more than 50 words in either source or target side are removed from training set. We use mini-batch in our training procedure, each batch contains 32 data samples. All sentence pairs are firstly sorted according to their length, then after we group them into mini-batches, the order of mini-batches are shuffled.

We adopt the network architecture described in (Bahdanau et al., 2014) and set it as our baseline model. The size of word embeddings are 1000 for both languages. For the encoder, we use a bidirectional RNN composed of two LSTMs with 1000 units. For the decoder, we use an one-layer LSTM with 1000 units, where the input in each step is a concatenated vector of the embedding of the previous output $i_t$ and the context vector $c_t$ given by attention mechanism. Before the final softmax layer, we insert a fully-connected layer with 600 units in order to boost the training speed.

To train the NMT models, we use Adam optimizer (Kingma and Ba, 2014) with an initial learning rate of 0.0001. We train the model for 6 epochs and start to halve the learning rate from the beginning of 4th epoch. The maximum norm of the gradients are clipped to 3. During test time, we use beam search with a beam size of 20.

We evaluate our implemented NMT models with BLEU. For English-Japanese task, RIBES scores (Isozaki et al., 2010) are also reported. The results are reported following standard post-processing procedures.

**Evaluations of Reduced Computations**

We evaluate our attention models to see the minimum CPS they can achieve with a modest loss of accuracy compared to Global Attention. The results evaluated on English-Japanese task are summarized in Table 1. The scores of Global Attention (conventional attention model) and Local Attention (Luong et al., 2015a) are listed for comparison. For Local Attention, we found a window size of 3 in the experiments.

| Model | CPS  | BLEU | RIBES  |
|-------|------|------|--------|
| Global Attention Baseline | 24.4 | 34.87 | 0.810  |
| Local Attention Baseline  | 18.4 | 34.52 | 0.809  |
| Flexible Attention ($\tau = \infty$) | 24.4 | 35.01 | 0.814  |
| Flexible Attention ($\tau = 1.38$) | 16.9 | 34.87 | 0.811  |
| + Finetuning ($\tau = 1.38$)      | **11.1** | 34.82 | 0.808  |

Table 1: Evaluation results on English-Japanese task. This tables provides a comparison of the minimum CPS the models can achieve with a modest loss of accuracy.

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2 We report the scores using Kytea tokenizer. The post-processing procedure for evaluation is described in [http://lotus.kuee.kyoto-u.ac.jp/WAT/evaluation/automatic_evaluation_systems/automaticEvaluationJA.html](http://lotus.kuee.kyoto-u.ac.jp/WAT/evaluation/automatic_evaluation_systems/automaticEvaluationJA.html)
size of 21 ($D = 10$) gives the best performance for English-Japanese task. In this setting, Local Attention gets a CPS of 18.4 in average, as some sentences in the test corpus are shorter than 21.

For Flexible Attention, we fixed threshold to 1.38 in the experiments. We can see from the results that Flexible Attention can achieve comparable scores even with greatly reduced computations. After finetuning, our proposed attention model further reduces 54% of the computations. The high reduction rate of computations confirms that the conventional attention model performs massive redundant computations. Flexible Attention can efficiently cut down redundant computations according to the context.

**Trade-off between Performance and Computational Cost**

![Figure 4: Trade off between computations and performance](image)

In order to figure out the minimum computational cost our attention model can achieve, we plot out the curve of the trade-off between BLEU score and average CPS on English-Japanese task, which is shown in Figure 4. The data points are collected by testing different thresholds with the finetuned Flexible Attention model. Interestingly, the NMT model with our proposed attention model suffers almost no loss in accuracy even the computations are half-reduced. Further trails to reduce the CPS beneath 10 words will result in drastically degradation in performance.

**Qualitative Analysis of Flexible Attention**

In order to inspect the behaviour of the penalty function in Flexible Attention when dealing with one-to-many and zero-to-many alignments, we let the model translate the sentence in Figure 2. The value of $g_t$ in Equation (5) is recorded in each decoding step, which is visualized in Figure 5.

![Figure 5: A visualization of the value of $g_t$ in each time step when translating the sentence in Figure 2](image)

We can see that the value of $g_t$ differs in different context. During the translation of “thyrotoxicosis”, which has one-to-many alignment, a high strength of penalty is given by $g_t$ to lock the attention to the same word. After finishing the translation of “thyrotoxicosis”, the attention model searches for the next word to translate globally.

**Conclusion: Implications and Limitations**

**Implications**

In this paper, we propose a novel attention model to reduce computations of score function in a flexible manner. In our experiments on English-Japanese task, we found the proposed attention model can safely reduce the amount of computations by 54% in test time.

The results confirm the existence of massive redundant computations in the conventional attention mechanism. By cutting down unnecessary computations, NMT models can translate extremely long sequence efficiently or incorporate more expensive score functions.

**Limitations**

Although Flexible Attention can greatly reduces the computations of the score function, the benefit may not be noticeable when measuring in real decoding speed due to implementation issues. When implementing the Beam Search algorithm with Flexible Attention, in order to select the encoder states in a specific range, we use advanced indexing in Theano. Unfortunately, as advanced indexing is a time-consuming operation, no significant difference in real decoding speed can be found in...
our experiments when comparing to Global Attention. To solve this problem, an efficient GPU-based implementation of Flexible Attention is required.

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