Modeling Coverage for Neural Machine Translation

Zhaopeng Tu†∗ Zhengdong Lu† Yang Liu‡ Xiaohua Liu† Hang Li†
†Huawei Noah’s Ark Lab, Hong Kong
‡Department of Computer Science and Technology, Tsinghua University, Beijing

Abstract

Attention mechanism advanced state-of-the-art neural machine translation (NMT) by jointly learning to align and translate. However, attention-based NMT ignores past alignment information, which often leads to over-translation and under-translation. In response to this problem, we maintain a coverage vector to keep track of the attention history. The coverage vector is fed to the attention model to help adjust future attention, which guides NMT to consider more about the untranslated source words. Experiments show that the proposed approach significantly improves both translation quality and alignment quality over traditional attention-based NMT.

1 Introduction

The past several years have witnessed the rapid development of end-to-end neural machine translation (NMT) (Sutskever et al., 2014; Bahdanau et al., 2015). Unlike conventional statistical machine translation (SMT) (Brown et al., 1993; Koehn et al., 2003; Chiang, 2007), NMT uses a single, large neural network instead of many sub-components to model the translation process. This leads to the following benefits. First, the use of distributed representations of words proves to alleviate the curse of dimensionality (Bengio et al., 2003). Second, there is no need to explicitly design features to capture translation regularities, which is quite difficult in SMT. Instead, NMT is capable of learning representations directly from the training data. Third, Long Short-Term Memory (Hochreiter and Schmidhuber, 1997) enables NMT to capture long-distance reordering, which is a notorious challenge in SMT.

However, there exists a serious problem with NMT, namely the lack of coverage. In phrase-based SMT (Koehn et al., 2003), a decoder maintains a coverage vector to indicate whether a source word is translated or not. This is important for ensuring that each source word is translated in decoding. The decoding process is completed when all source words are “covered” or translated. In NMT, there is no such coverage vector and the decoding process ends only when the end-of-sentence tag is produced. We believe that lacking coverage might result in the following problems in conventional NMT:

1. Over-translation: some words are unnecessarily translated for multiple times;
2. Under-translation: some words are mistakenly untranslated.

Specifically, in the state-of-the-art attention-based NMT model (Bahdanau et al., 2015), generating a target word heavily depends on the relevant parts on the source side. As each source word is involved in generating all target words, over-translation and under-translation inevitably happen because of no consideration of the “coverage” of source words (i.e., number of times a source word is translated to a target word). Figure 1(a) shows examples: the Chinese word “nide” is over translated to “your(s) twice (left panel), while “quxiao” (means “cancel”) is wrongly untranslated (right panel).

In this work, we propose a coverage mechanism to NMT (NMT-COVERAGE) to alleviate the over-translation and under-translation problems. Basically, we append coverage vectors to the intermediate representations of NMT models, which are sequentially updated after each attentive read during the decoding process, in order to keep track of the attention history. Those coverage vectors, when entering into attention model, can help adjust the future attention and significantly improve
the alignment between the source and target sentences. This design potentially contains many particular cases for coverage modeling with contrasting characteristics, which all share a clear linguistic intuition and yet can be trained in a data driven fashion. Notably, we achieve significant improvement even by simply using the sum of previous alignment probabilities as coverage for each word, as a successful example of incorporating linguistic knowledge into neural network-based NLP models. Experiments show that NMT-COVERAGE significantly outperforms conventional attention-based NMT on both translation and alignment tasks. Figure 1(b) shows an example, in which NMT-COVERAGE alleviates the over-translation and under-translation problems that NMT without coverage suffers from.

2 Background

Our work is built on attention-based NMT (Bahdanau et al., 2015), which simultaneously conducts dynamic alignment and generation of the target sentence, as illustrated in Figure 2. It produces the translation by generating one target word $y_i$ at every time step, which is conditioned on a source representation $s_i$, the decoding state $t_i$ and the previously generated word $y_{i-1}$. Given an input
In SMT, a coverage set is maintained to keep track of which source words have been translated ("covered") in the past. Take an input sentence $x = \{x_1, \ldots, x_{T_x}\}$ and previous generated words $\{y_1, \ldots, y_{i-1}\}$, the probability of next word $y_i$ is

$$P(y_i|y_1, \ldots, y_{i-1}, x) = g(y_{i-1}, t_i, s_i)$$  \hspace{1cm} (1)

where $t_i$ is a decoding state for time step $i$, computed by

$$t_i = f(t_{i-1}, y_{i-1}, s_i)$$  \hspace{1cm} (2)

Here the activation function $f(\cdot)$ is a gated recurrent unit (GRU) (Cho et al., 2014b), and $s_i$ is a distinct source representation for time $i$, calculated as a weighted sum of the source annotations $h$:

$$s_i = \sum_{j=1}^{T_x} \alpha_{i,j} \cdot h_j$$  \hspace{1cm} (3)

where $h_j = [h_j^T; h_j^T]^T$ is the annotation of $x_j$ from a bi-directional recurrent neural network (RNN) (Schuster and Paliwal, 1997), and its weight $\alpha_{i,j}$ is computed by

$$\alpha_{i,j} = \frac{\exp(e_{i,j})}{\sum_{k=1}^{T_x} \exp(e_{i,k})}$$  \hspace{1cm} (4)

and

$$e_{i,j} = a(t_{i-1}, h_j) = v_a^T \tanh(W_a t_{i-1} + U_a h_j)$$  \hspace{1cm} (5)

is an attention model that scores how well $y_i$ and $h_j$ match. With the attention model, it avoids the need to represent the entire source sentence with a fixed-length vector. Instead, the decoder selects parts of the source sentence to pay attention to, thus exploits an expected annotation $s_i$ over possible alignments $\alpha_{i,j}$ for each time step $i$.

However, the attention model misses the opportunity to take advantage of past alignment information, which proves useful to avoid over-translation and under-translation problems in conventional SMT (Koehn et al., 2003). For example, if a source word is translated in the past, it is less likely to be translated again, thus should be assigned a lower probability.

### 3 Coverage Model for NMT

In SMT, a coverage set is maintained to keep track of which source words have been translated ("covered") in the past. Take an input sentence $x = \{x_1, x_2, x_3, x_4\}$ as an example, the initial coverage set is $C = \{0, 0, 0, 0\}$ which denotes no source word is yet translated. When a translation rule $bp = (x_2x_3, y_my_{m+1})$ is applied, we produce one hypothesis labelled with coverage $C = \{0, 1, 1, 0\}$. It means that the second and third source words are translated. The goal is to generate translation with full coverage $C = \{1, 1, 1, 1\}$. A source word is translated when it is covered by one translation rule, and it is not allowed to be translated again in the future (i.e. hard coverage). In this way, each source word is guaranteed to be translated and only be translated once. As shown, coverage is essential for SMT since it avoids gaps and overlaps when translating source words.

Modeling coverage is also useful for attention-based NMT models, since they generally lack a mechanism to tell whether a certain segment of source sentence is translated, and therefore prone to the “coverage” mistakes: some part of source sentence is translated more than once or not translated. For NMT models, directly modeling coverage is less straightforward, but the problem can be significantly alleviated by keeping track of the attention signal during the decoding process. The most natural way for doing that is to append a coverage vector to the annotation of each source word (i.e. $h_j$), which is uniformly initialized but updated after every attention read of the corresponding annotation. This coverage vector will enter the soft attention model for alignment, as illustrated in Figure 3.

#### 3.1 Coverage Model

Roughly speaking, since the coverage vector summarizes the attention record for $h_j$ (and therefore for a small neighbour centering at the $j^{th}$
source word), it will discourage further attention to it if it has been heavily attended, and implicitly push the attention to the less attended segments of the source sentence since the attention weights are normalized to one. This could potentially solve both coverage mistakes mentioned above, when modelled and learned properly.

Formally, the coverage model is given by

\[ C_{i,j} = g_{update}(C_{i-1,j}, \alpha_{i,j}, \Phi(h_j), \Psi) \] (6)

where

- \( g_{update}(\cdot) \) is the function that updates \( C_{i,j} \) after the new attention at time step \( i \) in the decoding process;
- \( C_{i,j} \) is a \( d \)-dimensional coverage vector summarizing the history of attention till time step \( i \) on \( h_j \);
- \( \Phi(h_j) \) is a word-specific feature with its own parameters;
- \( \Psi \) are auxiliary inputs exploited in different sorts of coverage models;
- \( \Psi \) are auxiliary inputs exploited in different sorts of coverage models;

Equation (6) gives a rather general model, which could take different function forms for \( g_{update}(\cdot) \) and \( \Phi(\cdot) \), and different auxiliary inputs \( \Psi \) (e.g. previous decoding state \( t_{i-1} \)). In the rest of this section, we will give a number of representative implementations of the coverage model, which either resort to the flexibility of neural network function approximation (Section 3.1.1) or bear more linguistic intuition (Section 3.1.2).

### 3.1.1 Neural Network Based Coverage Model

When \( C_{i,j} \) is a vector \( (d \geq 1) \) and \( g_{update}(\cdot) \) takes a neural network (NN) form, we actually have a RNN model for coverage, as illustrated by Figure 4.

\[ C_{i,j} = f(C_{i-1,j}, \alpha_{i,j}, h_j, t_{i-1}) \]

where \( f(\cdot) \) is a nonlinear activation function and \( t_{i-1} \) is the auxiliary input that encodes past translation information. Note that we leave out the word-specific feature function \( \Phi(\cdot) \) and only take the input annotation \( h_j \) as the input to the coverage RNN. It is important to emphasize that the NN-based coverage model is able to be fed with arbitrary inputs, such as the previous attentional context \( s_{i-1} \). Here we only employ \( C_{i-1,j} \) for past alignment information, \( t_{i-1} \) for past translation information, and \( h_j \) for word-specific bias.

#### Gating

The neural function \( f(\cdot) \) can be either a simple activation function \( \tanh \) or a gating function that proves useful to capture long-distance dependencies. In this work, we adopt GRU for the gating activation since it is simple yet powerful (Chung et al., 2014). Please refer to (Cho et al., 2014b) for more details about GRU.

Although the NN-based coverage model enjoys the flexibility brought by the recurrent nonlinear form, its lack of clear linguistic meaning may render it hard to train: the coverage model can only be trained along with the attention model and get the supervision signal from it in back-propagation, which could be weak (relatively distant from the decoding process) and noisy (after the distortion from other under-trained components in the decoder RNN). Partially to overcome this problem, we also propose the linguistically inspired model which has much clearer interpretation but much less parameters.

### 3.1.2 Linguistic Coverage Model

While linguistically-inspired coverage in NMT is similar in spirit to that in SMT, there is one key difference: it indicates what percentage of source words have been translated (i.e. *soft coverage*). In NMT, each target word \( y_i \) is generated from all source words with probabilities \( \alpha_{i,j} \) for source word \( x_j \). In other words, the source word \( x_j \) involves in generating all target words and generates \( \alpha_{i,j} \) target word at time step \( i \). Note that unlike in SMT where each source word is *fully translated* at one decoding step, \( x_j \) is *partially translated* at each decoding step in NMT. Therefore, the coverage at time step \( i \) denotes the translated ratio of that each source word is translated.
We use a scalar \((d = 1)\) to represent linguistic coverage for each source word and employ an accumulate operation for \(g_{\text{update}}\). We iteratively construct linguistic coverages through an accumulation of alignment probabilities generated by the attention model, each of which is normalized by a distinct context-dependent weight. The coverage of source word \(x_j\) at time step \(i\) is computed by

\[
C_{i,j} \equiv \frac{1}{\Phi_j} \sum_{k=1}^{T_i} \alpha_{k,j}
\]

(7)

where \(\Phi_j\) is a pre-defined weight which indicates the number of target words \(x_j\) is expected to generate. The simplest way is to follow Xu et al. (2015) in image-to-translation to fix \(\Phi = 1\) for all source words, which means that we directly use the sum of previous alignment probabilities without normalization as coverage for each word, as done in (Cohn et al., 2016).

However, in natural languages, different types of source words contributes differently to the generation of translation. Take the sentence pairs in Figure\footnote{Fertility in SMT is a random variable with a set of fertility probabilities, \(n(\Phi_j|x) = p(\Phi_j^{-1}|x)\), which depends on the fertilities of previous source words. To simplify the calculation and adapt it to the attention model in NMT, we define the fertility in NMT as a constant number, which is independent of previous fertilities.} as an example, the noun on the source side “hangji” is translated into one target word “flights”, while the quantifier “liangqianduo” is translated into two words “over 2,000”. Therefore, we need to assign a distinct \(\Phi_j\) for each source word. Ideally, we expect \(\Phi_j = \sum_{k=1}^{T_j} \alpha_{k,j}\) with \(T_j\) be the total number of time steps in decoding. However, such desired value is not available before decoding, thus is not suitable in this scenario.

**Fertility** To predict \(\Phi_j\), we introduce the concept of **fertility**, which is firstly proposed in word-level SMT (Brown et al., 1993). Fertility of source word \(x_j\) tells how many target words \(x_j\) produces. In SMT, the fertility is a random variable \(\Phi_j\), whose distribution \(p(\Phi_j = \phi)\) is determined by the parameters of word alignment models (e.g. IBM models). In this work, we simplify and adapt fertility from the original model\footnote{Fertility in SMT is a random variable with a set of fertility probabilities, \(n(\Phi_j|x) = p(\Phi_j^{-1}|x)\), which depends on the fertilities of previous source words. To simplify the calculation and adapt it to the attention model in NMT, we define the fertility in NMT as a constant number, which is independent of previous fertilities.} and compute the fertility \(\Phi_j\) by

\[
\Phi_j = \mathcal{N}(x_j|x) = \mathcal{N}(h_j) = N \cdot \sigma(U_f h_j)
\]

(8)

where \(N \in \mathbb{R}\) is a predefined constant to denote the maximum number of target words one source word can produce, \(\sigma(\cdot)\) is a logistic sigmoid function, and \(U_f \in \mathbb{R}^{1 \times 2n}\) is the weight matrix. Here we use \(h_j\) to denote \((x_j|x)\) since \(h_j\) contains information about the whole input sentence with a strong focus on the parts surrounding \(x_j\) (Bahdanau et al., 2015). Since \(\Phi_j\) does not depend on \(i\), we can pre-compute it before decoding to minimize the computational cost.

### 3.2 Integrating Coverage into NMT

Although the introduction of attention model has advanced the state-of-the-art of NMT, it computes soft alignment probabilities without considering useful information in the past. For example, a source word that contributed a lot to the generated target words in the past should be assigned lower alignment probabilities in the following decoding.

Motivated by this observation, in this work, we propose to calculate the alignment probability by jointly taking into account past alignment information embedded in the coverage model.

Intuitively, at each time step \(i\) in the decoding phase, coverage from time step \((i - 1)\) serves as an additional input to the attention model, which provides complementary information of that how likely the source words are translated in the past. We expect the coverage information would guide the attention model to focus more on untranslated source words (i.e. assign higher probabilities). In practice, we find that the coverage model does come up to expectation (see Section\footnote{Fertility in SMT is a random variable with a set of fertility probabilities, \(n(\Phi_j|x) = p(\Phi_j^{-1}|x)\), which depends on the fertilities of previous source words. To simplify the calculation and adapt it to the attention model in NMT, we define the fertility in NMT as a constant number, which is independent of previous fertilities.}5). The translated ratios of source words from linguistic coverages negatively correlate to the corresponding alignment probabilities.

More formally, we rewrite the attention model in Equation\footnote{Fertility in SMT is a random variable with a set of fertility probabilities, \(n(\Phi_j|x) = p(\Phi_j^{-1}|x)\), which depends on the fertilities of previous source words. To simplify the calculation and adapt it to the attention model in NMT, we define the fertility in NMT as a constant number, which is independent of previous fertilities.}5 as

\[
e_{i,j} = a(t_{i-1}, h_j, C_{i-1,j})
\]

\[
= v_d^T \tanh(W_a t_{i-1} + U_a h_j + V_a C_{i-1,j})
\]

where \(C_{i-1,j}\) is the coverage of source word \(x_j\) before time \(i\). \(V_a \in \mathbb{R}^{n \times d}\) is the weight matrix for coverage with \(n\) and \(d\) being the numbers of hidden units and coverage units, respectively.

### 4 Training

In this paper, we take end-to-end learning for our NMT-COVERAGE model, which jointly learns not only the parameters for the “original” NMT (i.e., those for encoding RNN, decoding RNN, and attention model) but also the parameters for coverage modeling (i.e., those for annotation and its
role in guiding the attention) . More specifically, we choose to maximize the likelihood of reference sentences as most other NMT models (see, however (Shen et al., 2015)):

$$\arg \max N \sum_{n=1}^{N} \log P(y_n|x_n).$$ (9)

For the coverage model with a clearer linguistic interpretation (Section 3.1.2), it is possible to inject an auxiliary objective function on some intermediate representation. More specifically, we may have the following objective:

$$\arg \max N \sum_{n=1}^{N} (\log P(y_n|x_n)$$

$$- \lambda \sum_{j=1}^{T_y} (\Phi_j - \sum_{i=1}^{T_x} \alpha_{i,j})^2)$$ (10)

where the term $\sum_{j=1}^{T_y} (\Phi_j - \sum_{i=1}^{T_x} \alpha_{i,j})^2$ penalizes the discrepancy between the sum of alignment probabilities and the expect fertility for linguistic coverage. This is similar to the more explicit training for fertility as in Xu et al. (2015), which encourages the model to pay equal attention to every part of the image (i.e. $\Phi_j = 1$).

Our end-to-end training strategy poses less constraints on the dependency between $\Phi_j$ and the attention than a more explicit strategy taken in (Xu et al., 2015). We let the objective associated with the translation quality (i.e., the likelihood) drive the training. This strategy is arguably advantageous, since the attention weight on a hidden state $h_j$ cannot be interpreted as the proportion of the corresponding word being translated on the target side. For one thing, the hidden state $h_j$, after the transformation from encoding RNN, bear the contextual information from other parts of the source sentence and therefore lose the rigid correspondence with the corresponding words. Our empirical study shows that a combined objective as in Equation 1 -coverage-training consistently worsens the translation quality (BLEU score) while gaining slightly on the alignment.

5 Experiments

Dataset and Evaluation Metrics We report our empirical study on applying NMT-COVERAGE to Chinese-to-English translation. Our training data for the translation task consists of 1.25M sentence pairs extracted from LDC corpora, with 27.9M Chinese words and 34.5M English words respectively. We choose NIST 2002 dataset as our development set, and the NIST 2005, 2006 and 2008 datasets as our test sets. We carried out experiments of the alignment task on the evaluation dataset from (Liu and Sun, 2015), which contains 900 manually aligned Chinese-English sentence pairs. We use the case-insensitive 4-gram NIST BLEU score (Papineni et al., 2002) for the translation task, and the alignment error rate (AER) (Och and Ney, 2003) for the alignment task. To better estimate the quality of the soft alignment probabilities generated by NMT, we propose a variant of AER, naming SAER:

$$SAER = 1 - \frac{|M_A \times M_S| + |M_A \times M_P|}{|M_A| + |M_S|}$$

where $A$ is a candidate alignment, and $S$ and $P$ is the set of sure and possible links in the reference alignment respectively ($S \subseteq P$). $M$ denotes alignment matrix, and for both $M_S$ and $M_P$ we assign the elements that corresponds to the existing links in $S$ and $P$ with probabilities 1 while assign the other elements with probabilities 0. In this way, we are able to better evaluate the quality of the soft alignments produced by attention-based NMT. We use sign-test (Collins et al., 2005) for statistical significance test.

Training Neural Networks In training of the neural networks, we limit the source and target vocabularies to the most frequent 30K words in Chinese and English, covering approximately 97.7% and 99.3% of the two corpora respectively. We set $N = 2$ for the fertility model in the linguistic coverages. We train each model with the sentences of length up to 80 words in training data. The word embedding dimension is 620 and the size of a hidden layer is 1000. All the other settings are the same as in (Bahdanau et al., 2015).

We compare our method with two state-of-the-art SMT and NMT models:

- **Moses** (Koehn et al., 2007): an open source phrase-based translation system with default configuration and a 4-gram language model trained on the target portion of training data.

2The corpora include LDC2002E18, LDC2003E07, LDC2003E14, Hansards portion of LDC2004T07, LDC2004T08 and LDC2005T06.

3There are recent progress on aggregating multiple models or enlarging the vocabulary(e.g., in (Jean et al., 2015)), but here we focus on the generic models.
Table 1: Evaluation of translation quality. \( d \) denotes the dimension of NN-based coverages, and \( \dagger \) and \( \ddagger \) indicate statistically significant difference \((p < 0.01)\) from RNNSearch and Moses, respectively.

| #  | System                                | MT05   | MT06   | MT08   | Ave.   |
|----|---------------------------------------|--------|--------|--------|--------|
| 1  | Moses                                 | 31.37  | 30.85  | 23.01  | 28.41  |
| 2  | RNNSearch                             | 30.61  | 31.12  | 23.23  | 28.32  |
| 3  | + NN-based coverage w/o gating \((d = 1)\) | 31.94† | 32.11† | 23.31† | 29.12† |
| 4  | + NN-based coverage w/ gating \((d = 1)\) | 31.94† | 32.16† | 24.67† | 29.59† |
| 5  | + NN-based coverage w/ gating \((d = 10)\) | 32.73† | 32.47† | 25.23† | 30.14† |
| 6  | + Linguistic coverage w/o fertility    | 31.26† | 32.16† | 24.84† | 29.42† |
| 7  | + Linguistic coverage w/ fertility     | 32.36† | 32.31† | 24.91† | 29.86† |

Table 1: Evaluation of translation quality. \( d \) denotes the dimension of NN-based coverages, and \( \dagger \) and \( \ddagger \) indicate statistically significant difference \((p < 0.01)\) from RNNSearch and Moses, respectively.

5.1 Translation Quality

Table 1 shows the translation performances measured in BLEU score. Clearly the proposed NMT-COVERAGE significantly improves the translation quality in all cases, although there are still considerable differences among different variants. More specifically,

- **NN-based Coverages** (Rows 3-5 in Table 1):
  1. **Gating** (Rows 3 and 4): Both variants of NN-based coverages outperform RNNSearch with averaged gains of 0.8 and 1.3 BLEU points, respectively. Introducing gating activation function improves the performance of coverage models, which is consistent with the results in other tasks (Chung et al., 2014).
  2. **Coverage dimensions** (Rows 4 and 5): Increasing the dimension of coverage models further improves the translation performance by 0.6 point in BLEU score, at the cost of introducing more parameters (e.g. 100K)\(^4\).

- **Linguistic Coverages** (Rows 6 and 7): Two observations can be made. First, the simplest linguistic coverage (Row 6) already significantly improves translation performance by 1.1 BLEU points, indicating that coverage information is very important to the attention model. Second, incorporating fertility model boosts performance by better estimating the covered ratios of source words.

5.2 Alignment Quality

Table 2 lists the alignment performances. We find that coverage information improves attention model as expected by maintaining an annotation summarizing the log of previous attention on each source word. More specifically, linguistic coverage with fertility significantly reduces alignment errors under both metrics, in which fertility plays an important role. NN-based coverages, however, does not significantly reduce alignment errors until increasing the coverage dimension from 1 to 10. It indicates that NN-based models need more dimensions to encode the coverage information, which increases the computational complexity.

Table 2: Evaluation of alignment quality. The lower the score, the better the alignment quality.

| System                                | SAER | AER |
|---------------------------------------|------|-----|
| RNNSearch                             | 67.00| 54.67|
| + NN cov. w/o gating \((d = 1)\)      | 67.10| 54.46|
| + NN cov. w/ gating \((d = 1)\)       | 66.30| 53.51|
| + NN cov. w/ gating \((d = 10)\)      | 64.25| 50.50|
| + Ling. cov. w/o fertility            | 66.75| 53.55|
| + Ling. cov. w/ fertility             | 64.85| 52.13|

5.3 Effects on Long Sentences

We follow Bahdanau et al. (2015) to group sentences of similar lengths together and compute a BLEU score and an averaged length of translation per group, as shown in Figure 5. Cho et al. (2014a) shows that the performance of NMT drops rapidly when the length of input sentence increases. Our results confirm these findings. One main reason is that NMT produces much shorter translations on longer sentences (e.g. > 40, see right panel in Figure 5), thus faces a serious under-translation problem. NMT-COVERAGE alleviates this problem through incorporating coverage information into the attention model, which in general pushes the attention to untranslated parts of the input sentence and implicitly discourages the early stop of the de-
Coding process. It is worthy to emphasize that both NN-based coverages (with gating, $d = 10$) and linguistic coverages (with fertility) achieve similar performances on long sentences, reconfirming our claim that the two variants improve the attention model in their own ways.

6 Related Work

Our work is inspired by recent works on improving attention-based NMT with techniques that have been applied with success in SMT. Following the success of minimum risk training (MRT) in conventional SMT (Och, 2003), Shen et al. (2015) proposed MRT for end-to-end NMT to optimize model parameters directly with respect to evaluation metrics. Based on the observation that attention-based NMT only captures partial aspects of attentional regularities, Cheng et al. (2015) proposed an agreement-based learning (Liang et al., 2006) to encourage bidirectional attention models to agree on parameterized alignment matrices. Along the same direction, inspired by the essential coverage in SMT to avoid gaps and overlap when translating source words, we propose a coverage-based approach to NMT to alleviate the over-translation and under-translation problems.

Concurrent with our work, Cohn et al. (2016) and Feng et al. (2016) made use of the concept of “fertility” for the attention model, which is similar in spirit to our method for building the linguistically inspired coverage with fertility. Cohn et al. (2016) introduced a feature-based fertility that includes the total alignment scores for the surrounding source words. In contrast, we build a prediction of fertility before decoding, which works as a normalizer to better estimate the covered ratio of each source word. Feng et al. (2016) used the previous attentional context to represent implicit fertility and passed it to the attention model, which is in essence similar to the input-feed method proposed in (Luong et al., 2015). Comparatively, we predict explicit fertility for each source word based on its encoding annotation, and incorporate it into the linguistic-inspired coverage for attention model.

7 Conclusion

We have presented an approach to maintain a coverage vector for NMT to indicate whether each source word is translated or not. By encouraging NMT to pay more attention to untranslated words and less attention to translated words, our approach alleviates the serious over-translation and under-translation problems that attention-based NMT suffers. Specifically, we propose two variants of coverage models: NN-based coverage that resorts to the flexibility of neural network approximation and linguistic coverage that bears more linguistic intuition. Experimental results show that both variants achieve significant improvements in terms of translation quality and alignment quality over NMT without coverage.
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