Assessing the Bilingual Knowledge Learned by Neural Machine Translation Models

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Abstract

Machine translation (MT) systems translate text between different languages by automatically learning in-depth knowledge of bilingual lexicons, grammar and semantics from the training examples. Although neural machine translation (NMT) has led the field of MT, we have a poor understanding on how and why it works. In this paper, we bridge the gap by assessing the bilingual knowledge learned by NMT models with phrase table – an interpretable table of bilingual lexicons. We extract the phrase table from the training examples that a NMT model correctly predicts. Extensive experiments on widely-used datasets show that the phrase table is reasonable and consistent against language pairs and random seeds. Equipped with the interpretable phrase table, we find that NMT models learn patterns from simple to complex and distill essential bilingual knowledge from the training examples. We also revisit some advances that potentially affect the learning of bilingual knowledge (e.g., back-translation), and report some interesting findings. We believe this work opens a new angle to interpret NMT with statistical models, and provides empirical supports for recent advances in improving NMT models.

1 Introduction

Modern machine translation (MT) systems aim to produce fluent and adequate translations by automatically learning in-depth knowledge of bilingual lexicons, grammar and semantics from the training examples. Two technological advances solving this problem with statistical and neural techniques, statistical machine translation (SMT) and neural machine translation (NMT), have seen vast progress over the last two decades. SMT models generate translations on the basis of several statistical models that explicitly represent the knowledge bases, such as translation model for bilingual lexicons, reordering and language models for grammar and semantics (Koehn, 2009). Recently, NMT models have advanced the state-of-the-art by implicitly modeling the knowledge bases in a large neural network, which are trained jointly to maximize the translation performance (Bahdanau et al., 2015; Gehring et al., 2017; Vaswani et al., 2017). Despite their power with a massive amount of parameters, we have limited understanding of how and why NMT models work, which poses great challenges for error analysis and model refinement.

In this work, we bridge the gap by assessing the knowledge bases learned by NMT models with the statistical models of SMT systems. We believed (and in fact, provide some evidence to support the claim) that although using different forms (e.g., continuous vs. discrete) to represent the knowledge, NMT and SMT models are identical in modeling the essential knowledge. In the long-goal journey, we start with probing the bilingual knowledge with the translation model, also known as phrase table, which is one core component of SMT systems to represent the bilingual lexicons. Bilingual knowledge is at the core of adequacy modeling, which is a major weakness of the NMT models (Tu et al., 2016). Phrase table has proven its effectiveness for carrying useful bilingual knowledge, which can be seamlessly integrated to NMT models (Wang et al., 2018; Lample et al., 2018). For instance, Lample et al. (2018) have advanced the SOTA of unsupervised NMT by learning to align for phrase embeddings based on an external phrase table.

Specifically, we extract the phrase table from the predictions of NMT models, which is inspired by recent work on investigating the forgetting phenomenon of training examples in the image classification task (Toneva et al., 2019). Intuitively, if a trained NMT model can successfully recover (part of) a training example, the NMT model is more
likely to have learned the necessary bilingual lexicons for the recovery. Experimental results on three representative language pairs and random seeds show that the extracted phrase table correlates well with the NMT model performance, demonstrating that the phrase table can reasonably represent the bilingual knowledge learned by NMT models. Figure 1 shows an example, in which the phrase table extracted from a NMT model can well explain the generated output.

With the interpretable phrase table in hand, we are able to better understand behaviors of NMT models in many aspects. We start with investigating the learning dynamics of bilingual knowledge. We find that NMT tend to first learn simple patterns and then complex patterns, and the catastrophic forgetting phenomenon occurs during the training.\footnote{We follow Toneva et al. (2019) to define “forgetting event” to have occurred when a training example transitions from being predicted correctly to incorrectly during training.}

We also reveal that one of the strengths of NMT models over SMT models lie in their ability to distill high-quality bilingual knowledge from the training data.

We then revisit some advances in improving NMT models, which potentially affect the learning of bilingual knowledge. Though we cannot claim causality, we have several observations:

- **Model Capacity:** We thought it likely that increasing model capacity learns more bilingual lexicons. This turned out to be false. Transformer-Big outperforms Transformer-Base by 1.3 BLEU points, while the extracted phrase tables are almost the same. We conjecture that the strengths of larger models lie in a better learning of more complex knowledge, such as composition rules to combine the bilingual lexicons.

  - **Data Augmentation:** We investigate back-translation (Sennrich et al., 2016) and forward-translation (Zhang and Zong, 2016; He et al., 2020), which introduce additionally synthetic parallel corpus. Both techniques improve performance not only by introducing new bilingual knowledge, but also with a better quality estimation of existing knowledge.

  - **Domain Adaptation:** Fine-tune is a simple yet effective technique in domain adaptation, which learns to transfer out-domain knowledge to in-domain (Luong and Manning, 2015). As expected, by adapting to the target-domain, the fine-tune approach learns more and better bilingual knowledge from the target-domain data.

The key contributions of this paper are:

- Our study demonstrates the reasonableness and effectiveness of assessing the NMT knowledge with statistic models, which opens up a new angle to interpret NMT models.

- We report several interesting findings that can help humans better analyze and understand NMT models and some recent advances.

2 Related Work

**Evolution of MT Models.** The MT task has a long history, in which the techniques have evolved from rule-based MT (RBMT) (Hayes-Roth, 1985; Sato, 1992), through SMT (Brown et al., 1993; Och and Ney, 2004), to NMT (Sutskever et al., 2014; Bahdanau et al., 2015). RBMT methods require large sets of linguistic rules and extensive lexicons with morphological, syntactic, and semantic information, which are manually constructed by humans. Benefiting from the availability of large amounts of parallel data in 1990s, SMT approaches relieve the labor-intensive problem of RBMT by automatically learning the linguistic knowledge from bilingual corpora with statistic models. More recently, NMT models have taken the field of MT by building a single network that can be trained on the corpora in an end-to-end manner. Several studies have shown that representations learned by NMT
models contain a substantial amount of linguistic information on multiple levels: morphological (Belinkov et al., 2017), syntactic (Shi et al., 2016), and semantic (Hill et al., 2017).

In the development circle of each generation, MT models are generally improved with techniques that are essential in the last generation. For example, Chiang (2005) and Liu et al. (2006) relieved the nonfluent translation problem of SMT models by automatically learning syntactic rules from the parallel corpus, which are created manually by humans in RBMT systems. Tu et al. (2016) alleviated the inadequate translation problem of NMT models by introducing the coverage mechanism, which is a standard concept in SMT to indicate how many source words have been translated. Inspired by previous these studies, we hypothesize that MT models of different generations are possibly identical to model the essential knowledge. In this work, we propose to leverage the phrase table – a basic module of SMT system, to assess the bilingual knowledge learned by NMT models.

Exploiting Phrase Table for NMT. Phrase table is an essential component of SMT systems, which records the correspondence between bilingual lexicons (Koehn, 2009). Previous studies have incorporated phrase table as an external signal to guide the generation of NMT models (Wang et al., 2017; Zhang et al., 2017; Zhao et al., 2018; Guo et al., 2019). All these works show that the bilingual knowledge in phrase table can be identical to those in NMT models, and thereby can be seamlessly integrated to NMT models. Based on this observation, we employ the phrase table as an assessment tool of bilingual knowledge for NMT models.

Lample et al. (2018) have advanced the SOTA of unsupervised NMT by evolving from learning alignment of word embeddings to learning to align for phrase embeddings based on an external phrase table, which is identical to the evolution of SMT from word-based model (Brown et al., 1993) to phrase-based model (Koehn et al., 2003). This reconfirms our hypothesis that MT models of different generations are identical to model the essential knowledge, and thus share similar evolving trends.

Interpretability of NMT Models. The interpretability of NMT models has recently been approached mainly from two aspects (Alvarez-Melis and Jaakkola, 2017): (1) model interpretability, which aims to understand the internal properties of NMT models, such as layer representations (Shi et al., 2016; Belinkov et al., 2017; Yang et al., 2019; Voita et al., 2019a) and attention (Voita et al., 2019b; Jain and Wallace, 2019; Wiegreffe and Pinter, 2019; Li et al., 2018); and (2) behavior interpretability, which aims to explain particular behaviors of a NMT model, such as the input-output behavior (Alvarez-Melis and Jaakkola, 2017; Ding et al., 2017; He et al., 2019). In this paper, we focus on the second thread from a complementary viewpoint – assessing the bilingual knowledge learned by NMT models, which can provide explanations for model output, as shown in Figure 1.

Assessing Bilingual Knowledge with Phrase Table

In this section, we describe how to extract phrase table from the predictions of NMT models (Section 3.1), and verify our hypothesis by checking the correlation between the extracted phrase table and NMT performance (Section 3.3).

3.1 Methodology

There are many possible ways to implement the general idea of extracting phrase table from the predictions of NMT models. The aim of this paper is not to explore this whole space but simply to show that one fairly straightforward implementation works well and the proposed framework is reasonable. We leave the exploitation of more advanced forms of statistic models on bilingual knowledge such as syntax rules (Liu et al., 2006) and discontinuous phrases (Galley and Manning, 2010) for future work.

We follow the standard pipeline in SMT to construct the phrase table with a two-phase approach. The first phase, which is the focus of this paper, is phrase extraction where the bilingual phrase pairs are extracted from a word-aligned parallel data. Secondly, each phrase pair is assigned with some scores, which are estimated based on the occurrences of these phrases or their words on the same word-aligned training data. The key challenge lies in how to incorporate the prior of NMT predictions into the SMT pipeline. In this study, we model the NMT priors as a mask sequence, which is integrated into the standard SMT pipeline as a constraint, as listed in Algorithm 1.

Building Masked Word-Aligned Parallel Data. Inspired by Toneva et al. (2019), we define “memorized phrase pair” to be extracted from the associ-
Algorithm 1 Constructing Phrase Table

Input: training example \((x, y)\), alignment \(a\), mask \(m\)
Output: phrase set \(R\)

1: procedure \(\text{PHRASETABLE} \)
2: \(\text{EXTRACTION} \)
3: \(\text{ESTIMATION} \)
4: procedure \(\text{EXTRACTION} \)
5: \(\hat{R} \leftarrow \) extract candidates from \(\{(x, y), a\}\)
6: for each \(r \in \hat{R}\) do \(\triangleright \) priors of NMT predictions
7: \(\text{if } r \text{ is consistent with } m \text{ then} \)
8: \(R \leftarrow \text{append}(r)\)
9: procedure \(\text{ESTIMATION} \)
10: standard procedure

After (partial) training example, which is predicted correctly by the NMT model. To this end, we first decompose the sequence generation of NMT into a series of classification tasks. Given a training example \((x = \{x_1, \ldots, x_t\}, y = \{y_1, \ldots, y_j\})\) and a model \(M\), we use the model \(M\) to force-decode \(x\) to \(y\), and check whether each \(y_j\) is correctly predicted by \(M\):

\[
m_j = \begin{cases} 
1, & \text{if } y_j = \underset{y}{\arg \max} N_j[y] \\
0, & \text{otherwise}
\end{cases}
\]

where \(N_j\) is the probability distribution of model prediction at step \(j\). A token \(y_j\) is predicted correctly if it is assigned the highest probability by the model ("\(y_j = \underset{y}{\arg \max} N_j[y]\)").

Intuitively, a token \(y_j\) with mask \(m_j = 0\) denotes that this token is not correctly predicted by the model. Accordingly, any phrase pairs that contain the token \(y_j\) should not be extracted from the training example \((x, y)\), since these phrase pairs are not fully learned by the NMT model. A lightweight implementation is to replace these tokens with a special symbol "\$MASK\$", and run the standard phrase extraction phase as in the SMT pipeline. Then we remove all the phrase pairs that contain the symbol "\$MASK\$" (lines 6-8 in Algorithm 1), and feed the pruned phrase pairs to the second phase of parameter estimation.

3.2 Experimental Setup

Data and Models  We conduct experiments on both the widely-used WMT2014 English⇒German (En⇒De) and the syntactically-distant WAT2017 English⇒Japanese (En⇒Ja) (Neubig et al., 2015) datasets. We use 4-gram NIST BLEU score (Papineni et al., 2002) as the evaluation metric.

For SMT experiments, we follow the standard SMT pipeline and the setting of Edinburghs phrase-based system in WMT-2014 (Durrani et al., 2014) with as few human heuristics as possible. We use Moses (Koehn et al., 2007) with default system setting and the toolkit FastAlign (Dyer et al., 2013) for building word-aligned corpus, which is fast and automatic. Following Johnson et al. (2007) to reduce redundancy, we further remove phrase pairs that occur only once in the training data.

For NMT experiments, we use the toolkit Fairseq (Ott et al., 2019) to implement NMT models (Vaswani et al., 2017). We train the NMT models for 100,000 steps and save the checkpoint models at each epoch. In the first epoch, we save the model per 200 steps and extract phrase tables from training examples that have seen on so far only.

Evaluation Metrics  To verify our claim in this paper, we propose several metrics to quantitatively evaluate quality of the phrase table. If the metrics correlate well with NMT performance, then the phrase table is a reasonable assessment to represent the bilingual knowledge learned by NMT models. The metrics are as follows:

Phrase Table Size: As a straightforward metric, the size measures the number of distinct phrase pairs in a phrase table. A larger phrase table size indicates more abundant bilingual knowledge.

Recovery Percent: The phrase table size might be less accurate due to duplicate counting of compositions of existing phrase pairs. Accordingly, we propose another metric, recovery percent, to measure the distinct knowledge on data reconstruction. In detail, we use the phrase table to force decode the target sentence to recover as many target tokens as possible, and the ratio is denoted as the recovery percentage. A higher recovery percent indicates more distinct knowledge since more data can be reconstructed based on the phrase table.

Translation Quality: Finally, we directly evaluate the essential knowledge in the phrase table for the ultimate translation. Specifically, we train a SMT model with the extracted phrase table by the off-the-shelf Moses toolkit, and evaluate its BLEU score on the test set. For fair comparison, we keep other SMT components unchanged and only alter the phrase table, therefore the relative SMT BLEU values are our focus of interest.

3.3 Evaluating the Phrase Table

The extracted phrase table correlates well with the NMT performance. Figure 2a illustrates the results of the above metrics on the
English⇒German dataset. As seen, all three metrics are highly in line with the NMT performance (“NMT BLEU”) during the entire learning process. The Pearson correlations between NMT BLEU scores and phrase table size, recovery percent, and the translation quality are 0.975, 0.987, and 0.956, respectively, demonstrating very high correlations between the phrase table and NMT performance. This confirms our claim that phrase table is a reasonable assessment to represent the bilingual knowledge learned by NMT models.

The conclusion is robust across language pairs and random seeds. We also validate our approach on the English⇒Japanese dataset, as shown in Figure 2b. The Pearson correlations are respectively 0.988, 0.990, and 0.908, demonstrating the universality of our conclusions. To avoid the potential bias, we vary the initialization seed and analyze whether the extracted phrase table is robust. Figure 2c depicts the results. The phrase table size increases similarly in different seeds. Additionally, at each epoch, more than 85% phrase pairs are same among three seeds (“Overlap”), which shows that its robustness against random seeds.

Given the general applicability of the phrase table, we use the English⇒German translation as our test bed for further analyses. We will interchangeably use the terms “phrase table” and “bilingual knowledge” in the following sections.

4 Learning of Bilingual Knowledge

With the interpretable phrase table in hand, we attempt to understand how NMT models learn the bilingual knowledge from two perspectives:

- How do NMT models learn the bilingual knowledge during training? (Section 4.1)
- Does the trained NMT model sufficiently explore the bilingual knowledge embedded in the training examples? (Section 4.2)

4.1 Learning Dynamics

In this section, we investigate the evolvement of bilingual knowledge during the training. To this end, we first categorize the phrase pair into different complexity levels using several metrics that are widely used in the SMT research:

Phrase Length: A longer phrase is usually of more complexity (Lu, 2010). We categorize the phrase length into three types with increasing complexity: short (1-3) < middle (3-5) < long (5-7).

Reordering Type: This metric measures the order of two phrases with lexicalized reordering (Tillmann, 2004), and disordered phrases are often hard to translate (Koehn, 2009). We have three types with increasing complexity: monotone < swap < discontinuous.

Word Fertility: Word fertility measures the alignment relations between the words inside the phrase pair. Words with a complex fertility might indicate inherent translation difficulty (Brown et al., 1990). We have three fertility types with increasing difficulty: 1-1 align < M-1 align < 1-M align.

For each metric, we normalize the value by the maximum phrase pair size in each category.

NMT models tend to learn simple patterns first and complex patterns later. As shown in Figure 3a, NMT models learn short phrases faster than...
medium phrases and long phrases, embodied by a fastest convergence and a highest slope among three categories in the first epoch. As the learning continues, medium and long phrases start to converge to a relative stable state slowly. Besides, NMT BLEU scores show a very similar increasing trend as the short phrase, demonstrating a high correlation (Pearson correlation: 0.992) between the NMT performance and short phrases.

We can observe similar findings on the phrase reordering type (Figure 3b) and word fertility (Figure 3c). Simple patterns like monotone and 1-1 aligned phrase can be quickly learned by NMT models, while complex patterns are learned in a slower manner. This is in line with the findings of Rahaman et al. (2019): deep networks will first learn low-complexity functional components, before absorbing high-complexity features. These results also indicate that NMT models might by nature has the learning ability similar to the curriculum learning (Bengio et al., 2009; Kocmi and Bojar, 2017) without any explicit curriculum.

**Forgetting dynamics occur in the learning of bilingual knowledge.** As shown in Figures 2 and 3, the size of learned phrase table is monotonically increasing as the learning processes. One question naturally arises: *are the phrase pairs never forgotten once learnt?*

Figure 4 shows the result. Note that we only plot the first 15 epochs to ensure that the phrases are never forgotten for at least 6 epochs. Around 80% of learned phrase table is unforgettable phrases (always learned phrase pairs), while the rest phrase pairs are forgotten. This is consistent with the findings of Toneva et al. (2019) on the image classification tasks.

### 4.2 Learned Bilingual Knowledge

In this experiment, we evaluate whether NMT models have sufficiently explore the bilingual knowledge in the training examples, by comparing the phrase tables extracted from NMT predictions and from the raw training data. We use the latter to represent the full bilingual knowledge embedded in the training examples.

As shown in Table 1, the bilingual knowledge learned by NMT model (“NMT”) shows comparable translation quality with the full-data knowledge (“Full”) (17.90 vs. 17.91), but with only a *half of* phrases (9.0M vs. 17.5M).

2 In addition, NMT provides a better probability estimation for the distilled phrases (“Shared”, 17.90 vs. 17.32). In the “Non-Shared” table, 78.2% of the phrase pairs share the same source phrase with the “Shared” table, of which 83.2% have a lower translation probability. The results empirically confirm our hypothesis that NMT models distill the bilingual knowledge by discarding those low-quality phrase pairs.

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2When considering the filtered one-shot phrases, NMT phrase only takes 22.8% of the full table (76M vs. 335M).
Table 1: Comparison of the phrase table extracted from the full training data (“Full”) and NMT models (“NMT”). “All” denotes the whole phrase table, “Shared” denotes the intersection of two tables, and “Non-shared” denotes the complement. Note that the probabilities of “Shared” phrases are different for the two tables.

| Phrase Table | Shared | Non-Shared | All |
|--------------|--------|------------|-----|
|               | Size   | BLEU       | Size | BLEU  | Size  | BLEU |
| Full         | 9.0M   | 17.32      | 8.5M | 4.50  | 17.5M | 17.91|
| NMT          | 9.0M   | 17.90      | 0M   | 0     | 9.0M  | 17.90|

Table 2: Results of NMT models of different capacities.

| Model | NMT Phrase Table #Para | BLEU | Phrase Table Size | BLEU |
|-------|------------------------|------|-------------------|------|
| SMALL | 38M 25.45              | 7.7M 17.35 | SMALL Phrase Table | 7.0M 17.53 | 0.7M 2.37 |
| BASE  | 98M 27.11              | 9.0M 17.90 | BASE Phrase Table  | 7.0M 17.49 | 2.0M 3.57 |
| BIG   | 284M 28.40             | 9.2M 17.89 | BIG Phrase Table   | 7.0M 17.29 | 2.2M 3.47 |

Table 3: Comparison of phrases from three capacities.

| Model | Shared | Non-Shared |
|-------|--------|------------|
|       | Size   | BLEU       | Size | BLEU |
| SMALL | 7.0M   | 17.53      | 0.7M | 2.37 |
| BASE  | 7.0M   | 17.49      | 2.0M | 3.57 |
| BIG   | 7.0M   | 17.29      | 2.2M | 3.47 |

Table 4: Results of back-translation (“BT”) and forward-translation (“FT”).

| Model | NMT Phrase Table #Para | BLEU | Phrase Table Size | BLEU |
|-------|------------------------|------|-------------------|------|
| BASE  | 98M 27.11              | 9.0M 17.90 | BASE Phrase Table  | 8.4M 17.83 | 0.5M 1.21 |
| + BT  | 98M 29.75              | 20.9M 19.26 | + BT Phrase Table  | 8.4M 17.83 | 0.5M 1.21 |
| + FT  | 98M 28.43              | 28.0M 19.33 | + FT Phrase Table  | 8.4M 17.83 | 0.5M 1.21 |

Table 5: Comparison of phrases learned by BT and FT.

5 Revisiting Recent Advances

In this section, we revisit recent advances that potentially affect the learning of bilingual knowledge. Specifically, we investigate three types of techniques: (1) **model capacity** that indicates how complicated patterns a model can express (Section 5.1); (2) **data augmentation** that introduces additional knowledge with external data (Section 5.2); and (3) **domain adaptation** that transfers knowledge across different domains (Section 5.3).

5.1 Model Capacity

We vary the layer dimensionality of Transformer, and obtain three model variants: **SMALL** (256), **BASE** (512), and **BIG** (1024). As listed in Table 2, increasing model capacity consistently improves translation performance. However, the extracted phrase table is only marginally increased.

We compare the phrase tables learned by different models, as shown in Table 3. The phrases shared by all models take the overwhelming majority, which add most value to the translation performance. We conjecture that enlarging capacity improves NMT performance by better exploiting complex patterns beyond bilingual lexicons. This also confirms our intuition that bilingual lexicons can be a crucial early step in assessing the knowledge in NMT models.

5.2 Data Augmentation

In this experiment, we investigate two representative data augmentation approaches, back-translation (Sennrich et al., 2016) and forward-translation (Zhang and Zong, 2016), which differ at exploiting target or source-side monolingual data.

We select a same-size (around 4.5M) English and German monolingual dataset from the WMT website, and construct the synthetic corpus with **BASE** models that are trained on the parallel data.

Table 4 lists the results. Both techniques significantly improve the performance of NMT models by exploiting a larger and better phrase table.³ Table 5 shows the detailed comparison of the phrase tables. Both augmentation methods induce new knowledge and enhance existing knowledge over the baseline, and the newly introduced knowledge

³The different sizes of BT and FT phrase tables are due to the different monolingual datasets used for them, the averaged length of which are 24.8 and 28.4, respectively.
We extract the phrase table using the training data WMT14 dataset (News domain) for several epochs. We further analyze the characteristics of the newly introduced phrase pairs, as illustrated in Figure 5. One interesting finding is that the newly introduced phrase pairs are notably longer than the original ones. Besides, the new phrase pairs show less reordered patterns and more monotone patterns, which may explain the producing of longer phrases. The finding is consistent with previous studies, which show that the BT text is simpler than naturally occurring text (Edunov et al., 2019).

### 5.3 Domain Adaptation

In the last experiment, we analyze the transferability of the bilingual knowledge by directly applying it to another domain. To this end, we use the IWSLT14 English⇒German data (160,234 sentence pairs) as the target domain (Speech domain), and fine-tune the NMT model trained on the WMT14 dataset (News domain) for several epochs. We extract the phrase table using the training data of target domain, and the results are shown in Table 6. Clearly, the fine-tuned NMT model benefits from a larger and better phrase table, by adapting the model to the target domain. The analysis results in Table 7 further show that the fine-tuned phrase table improves performance with both more phrases (“Non-Shared”) and better estimation of original phrases (“Shared”).

In addition, we re-extract the phrase from the source domain (WMT data) with the fine-tuned model. The phrase table achieves only a BLEU score of 4.77 with 2.6M phrase pairs, while the original model without fine-tune shows a BLEU score of 17.90 with 9.0M phrase pairs. The fine-tune approach increases new knowledge of the target domain while forgets previous-learned knowledge of the source domain. The results provide an empirical validation of the phenomenon of catastrophic forgetting in domain adaptation (Kirkpatrick et al., 2017), which inversely demonstrate the reasonableness of our approach.

### 6 Discussion and Conclusion

In this work, we propose to assess the bilingual knowledge learned by NMT models with statistic models – phrase table. The reported results provide a better understanding of NMT models and recent technological advances in learning the essential bilingual lexicons, which also indicate several potential applications:

- **Error diagnosis** that debugs mistaken predictions by tracing associated phrase pairs (Ding et al., 2017);
- **Curriculum learning** that dynamically assigns more weights to instances associated with the unlearned knowledge (Platanios et al., 2019);
- **Phrase memory** that stores unlearned phrases in NMT to query when generating translations (Wang et al., 2017; Zhang et al., 2017).

Although the phrase table successfully explains many model behaviors, it cannot explain certain techniques such as enlarging model capacity. The explored bilingual lexicon is only one of the critical knowledge bases in the translation process. In the future, we will investigate more advanced forms of bilingual knowledge (Liu et al., 2006; Galley and Manning, 2010), as well as explore other types of knowledge bases such as grammar and semantics with statistic models (e.g., reordering and language models). This paper is the first step in what we hope will be a long and fruitful journey.
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