Sequence-Level Knowledge Distillation

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Abstract

Neural machine translation (NMT) offers a novel alternative formulation of translation that is potentially simpler than statistical approaches. However to reach competitive performance, NMT models need to be exceedingly large. In this paper we consider applying knowledge distillation approaches (Bucila et al., 2006; Hinton et al., 2015) that have proven successful for reducing the size of neural models in other domains to the problem of NMT. We demonstrate that standard knowledge distillation applied to word-level prediction can be effective for NMT, and also introduce two novel sequence-level versions of knowledge distillation that further improve performance, and somewhat surprisingly, seem to eliminate the need for beam search (even when applied on the original teacher model). Our best student model runs 10 times faster than its state-of-the-art teacher with only a decrease of 0.2 BLEU. It is also significantly better than a baseline model trained without knowledge distillation: by 4.2/1.7 BLEU with greedy decoding/beam search.

1 Introduction

Neural machine translation (NMT) (Kalchbrenner and Blunsom, 2013; Cho et al., 2014; Sutskever et al., 2014) is a deep learning-based method for translation that has recently shown promising results as an alternative to statistical approaches. NMT systems directly model the probability of the next-word in the target sentence, simply by conditioning a recurrent neural network on the source sentence and previously generated target words. Under this setup, the whole system can be directly trained end-to-end on a large set of supervised data.

While both simple and surprisingly accurate, NMT systems typically need to be very high capacity in order to perform well: Sutskever et al. (2014) used a 4-layer LSTM with 1000 hidden units per layer (herein 4 × 1000) and Zhou et al. (2016) obtained state-of-the-art results on English → French with a 16-layer LSTM with 512 units per layer. The sheer size of the models requires cutting-edge hardware for training and makes using the models on standard setups very challenging.

This issue of excessively large networks has been observed in several other domains, with much focus on fully-connected and convolutional networks for multi-class classification. Researchers have particularly noted that large networks seem to be necessary for training, but learn redundant representations in the process (Denil et al., 2013). Therefore compressing deep models into smaller networks has been an active area of research. As deep learning systems obtain better results on NLP tasks, compression also becomes an important practical issue with applications such as running deep learning models for speech and translation locally on cell phones.

Existing compression methods generally fall into two categories: (1) pruning and (2) knowledge distillation. Pruning methods (LeCun et al., 1990; Hinton et al., 1993; He et al., 2014; Han et al., 2016; Mariet and Sra, 2016), zero-out weights based

There has also been work on reducing the memory footprint of models through quantization of weights (Chen et al., 2015; Han et al., 2016; Courbariaux et al., 2016) as a postprocessing step.
on an importance criterion: [LeCun et al. (1990)] use (a diagonal approximation to) the Hessian to identify weights whose removal minimally impact the objective function, while [Han et al. (2016)] remove weights based on thresholding their absolute values. Knowledge distillation approaches (Bucila et al., 2006; Ba and Caruana, 2014; Li et al., 2014; Hinton et al., 2015; Romero et al., 2015; Mou et al., 2015) learn a smaller student network to mimic the original teacher network by minimizing the loss (typically $L_2$ or cross-entropy) between the student and teacher output.

In this work, we investigate knowledge distillation in the context of neural machine translation, with the goal of reducing the test-time computation burden (as opposed to memory footprint). We note that NMT differs from previous work which has mainly explored non-recurrent models in settings where the prediction is a single class. For NMT, while the model is trained on multi-class prediction at the word-level, it is tasked with predicting complete sequence outputs conditioned on previous decisions. With this difference in mind, we experiment with standard knowledge distillation for NMT and also propose two new versions of the approach that attempt to approximately match the sequence-level (as opposed to word-level) distribution of the teacher network. This sequence-level approximation leads to a simple training procedure wherein the student network is trained on the output of beam search from the teacher network.

To examine these approaches we run experiments to compress a large state-of-the-art $4 \times 1000$ LSTM model. With sequence-level knowledge distillation we are able to learn a $2 \times 500$ LSTM that roughly matches the performance of the full system. We see similar results compressing a $2 \times 500$ model down to $2 \times 100$ on a smaller data set. Furthermore, we find that our proposed approach has other benefits, such as not requiring any beam search at test-time. As a result we are able to perform greedy decoding on the $2 \times 500$ model 10 times faster than beam search on the $4 \times 1000$ model, with comparable performance. Our student models can even be run efficiently on a standard smart phone. We have released all code for the models described in this paper.

2 Background

For notation we denote vectors with bold lower-case (e.g. $h_i$, $b$), matrices with bold upper-case (e.g. $W$, $U$), and sets with cursive upper-case (e.g. $\mathcal{V}$, $\mathcal{T}$). We assume words are represented by their indices.

2.1 Sequence-to-Sequence with Attention

We begin by describing our baseline NMT model, which was proposed by [Luong et al. (2015)] and achieved state-of-the-art results on English $\rightarrow$ German translation. Let $s = [s_1, \ldots, s_I]$ and $t = [t_1, \ldots, t_J]$ be (random variable sequences representing) the source/target sentence, with $I$ and $J$ respectively being the source/target lengths. Machine translation involves finding the most probable target sentence given the source:

$$\argmax_{t \in \mathcal{T}} p(t \mid s)$$

where $\mathcal{T}$ is the set of all possible sequences. NMT models parameterize $p(t \mid s)$ with an encoder neural network which reads the source sentence and a decoder neural network which produces a distribution over the target sentence (one word at a time) given the source.

Encoder In attention-based models [Bahdanau et al., 2015; Luong et al., 2015], the encoder reads the source sentence and outputs a sequence of vectors (one vector for each time step) to be attended to during decoding. Concretely, we use a Long Short-Term Memory (LSTM) [Hochreiter and Schmidhuber, 1997] network to obtain the hidden states $h^s_i \in \mathbb{R}^m$ for each time step $i$,

$$h^s_i = \text{LSTM}(h^s_{i-1}, x^s_i)$$

where $x^s_i \in \mathbb{R}^m$ is the word embedding for $s_i$, the $i$-th word in the source sentence. Output of the encoder is the sequence of hidden state vectors $[h^s_1, \ldots, h^s_I]$. Initial hidden state of the encoder is set to zero (i.e. $h^s_0 \leftarrow 0$).

Decoder The decoder is another LSTM that produces a distribution over the next target word conditioned on the source vectors $[h^s_1, \ldots, h^s_I]$ and the previous target words $t_{<j} = [t_1, \ldots, t_{j-1}]$. Let

$$h^t_j = \text{LSTM}(h^t_{j-1}, x^t_j)$$

2.2 Knowledge Distillation as a New Form of Pretraining

Knowledge distillation is a way to train a student model to mimic the teacher model. The student model learns a parameterized distribution over the next word, conditioned on the previous words and the teacher model's output. This is done by minimizing the loss between the student and teacher model's distributions.

In this work, we propose two new versions of knowledge distillation for NMT. The first version is sequence-level knowledge distillation, where we approximate the teacher's distribution over the next word by minimizing the loss between the student and teacher model's distributions over the entire sequence. The second version is word-level knowledge distillation, where we approximate the teacher's distribution over the next word by minimizing the loss between the student and teacher model's distributions over individual words.

2.2.1 Sequence-Level Knowledge Distillation

Sequence-level knowledge distillation is a way to train a student model to mimic the teacher model's distribution over the entire sequence. This is done by minimizing the loss between the student and teacher model's distributions over the entire sequence. In this work, we propose two new versions of sequence-level knowledge distillation for NMT. The first version is the standard version, where we approximate the teacher's distribution by minimizing the loss between the student and teacher model's distributions over the entire sequence. The second version is the proposed version, where we approximate the teacher's distribution by minimizing the loss between the student and teacher model's distributions over the entire sequence.
be the hidden state of the target sentence at the \( j \)-th time step (with \( x^j_t \) being the word embedding for \( t_j \)). The current target hidden state \( h^j_t \) is combined with each of the source vectors to produce attention weights as follows,

\[
\begin{align*}
    u_{j,i} &= h^j_t \cdot W^s_{\alpha} h^s_i \\
    \alpha_{j,i} &= \frac{\exp u_{j,i}}{\sum_{k \in [1,I]} \exp u_{j,k}}
\end{align*}
\]

where \( W_{\alpha} \) are learnable parameters. The source vectors are multiplied with the respective attention weights, summed, and interacted with the current decoder hidden state \( c_j \) to produce a context vector \( v_j \),

\[
    v_j = \sum_{i \in [1,I]} \alpha_{j,i} h^s_i
\]

\[
    c_j = \tanh(W[v_j; h^j_t])
\]

Probability distribution over the next word is obtained by applying an affine transformation to \( c_j \) followed by a softmax,

\[
p(t_{j+1} | s, t_{<j+1}) = \text{softmax}(Uc_j + b)
\]

where \( t_j \) is the random variable for the \( j \)-th word in the target sentence, whose support is the vocabulary set \( V \). Finally, as in \( \text{Luong et al. (2015)} \) we feed \( c_j \) as additional input to the decoder for the next time step by concatenating it with \( x^j_t \), so the decoder equation is modified to,

\[
h^T_j = \text{LSTM}(h^T_{j-1}, [x^j_t; c_{j-1}])
\]

The decoder hidden state is initialized with the final hidden state of the encoder (i.e. \( h^0_0 \leftarrow h^*_{j} \)).

### 2.2 Knowledge Distillation

Knowledge distillation describes a class of methods for training a smaller student network to perform better by learning from a larger teacher network (in addition to learning from the training data set). We generally assume that the teacher has previously been trained, and that we are estimating parameters for the student.

Knowledge distillation suggests training by matching the student’s predictions to the teacher’s predictions. For classification this usually means matching the probabilities either via \( L_2 \) on the log scale \( \text{Ba and Caruana, 2014} \) or by cross-entropy \( \text{Li et al., 2014; Hinton et al., 2015} \).

Concretely, assume we are learning a multi-class classifier over a data set of examples of the form \((x, y)\) with possible classes \( V \). The usual training criteria is to minimize NLL for each example from the training data,

\[
    L_{\text{NLL}}(\theta) = -\sum_{k=1}^{|V|} 1\{y = k\} \log p(y = k | x; \theta)
\]

where \( 1\{ \cdot \} \) is the indicator function and \( p \) the distribution from our model (parameterized by \( \theta \)). This objective can be seen as minimizing the cross entropy between the degenerate data distribution (which has all of its probability mass on one class) and the model distribution \( p(y | x; \theta) \).

In knowledge distillation, we assume access to a learned teacher distribution \( q(y | x; \theta_T) \), possibly trained over the same data set. Instead of minimizing cross entropy with the observed data, we instead minimize the cross entropy with the teacher’s probability distribution,

\[
    L_{\text{KD}}(\theta; \theta_T) = -\sum_{k=1}^{\left| V \right|} q(y = k | x; \theta_T) \times \log p(y = k | x; \theta)
\]

where \( \theta_T \) parameterizes the teacher distribution and remains fixed. Note the cross entropy setup is identical, but the target distribution is no longer a sparse distribution.

Training on \( q(y | x; \theta_T) \) is attractive since it gives more information about other classes for a given data point (e.g. similarity between classes) and has less variance in gradients \( \text{Hinton et al., 2015} \).

Since the latter objective has no direct term for the training data, it is common practice to interpolate between the two losses,

\[
    L(\theta; \theta_T) = (1 - \alpha) L_{\text{NLL}}(\theta) + \alpha L_{\text{KD}}(\theta; \theta_T)
\]

where \( \alpha \) is a mixture parameter combining the one-hot distribution and the teacher distribution.

\[\text{In some cases the entropy of the teacher/student distribution is increased by annealing it with a temperature term } \tau > 1 \]

\[\tilde{p}(y | x) \propto p(y | x)^{\frac{1}{\tau}} \]

After testing \( \tau \in \{1, 1.5, 2\} \) we found that \( \tau = 1 \) worked best.
Figure 1: Overview of the different knowledge distillation approaches. In word-level knowledge distillation (left) cross entropy is minimized between the student/teacher distributions (yellow) for each word in the actual target sequence (ECD), as well as between the student distribution and the degenerate data distribution, which has all of its probability mass on one word (black). In sequence-level knowledge distillation (center) the student network is trained on the output from beam search of the teacher network that had the highest score (ACF). In sequence-level interpolation (right) the student is trained on the output from beam search of the teacher network that had the highest sim with the target sequence (ECE).

3 Knowledge Distillation for NMT

The large sizes of neural machine translation systems make them an ideal candidate for knowledge distillation approaches. In this section we explore three different ways this technique can be applied to NMT.

3.1 Word-Level Knowledge Distillation

NMT systems are trained directly to minimize word NLL, \( \mathcal{L}_{\text{WORD-NLL}} \), at each position. Therefore if we have a teacher model, standard knowledge distillation for multi-class cross entropy can be applied. We define this distillation for a sentence as,

\[
\mathcal{L}_{\text{WORD-KD}} = -\sum_{j=1}^{J} \sum_{k=1}^{|V|} q(t_j = k \mid s, t_{<j}) \times \\
\log p(t_j = k \mid s, t_{<j})
\]

and the student can be trained to optimize the mixture of \( \mathcal{L}_{\text{WORD-KD}} \) and \( \mathcal{L}_{\text{WORD-NLL}} \). In the context of NMT, we refer to this approach as word-level knowledge distillation and illustrate this in Figure 1 (left).

3.2 Sequence-Level Knowledge Distillation

Word-level knowledge distillation allows transfer of these local word distributions. Ideally however, we would like the student model to mimic the teacher’s actions at the sequence-level. The sequence distribution is particularly important for NMT, because wrong predictions can propagate forward at test-time.

First, consider the sequence-level distribution specified by the model over all possible sequences \( t \in \mathcal{T} \),

\[
p(t \mid s) = \prod_{j=1}^{J} p(t_j \mid s, t_{<j})
\]

with \( J \in \mathbb{N} \). The sequence-level negative log-likelihood for NMT then involves matching the one-hot distribution over all complete sequences,

\[
\mathcal{L}_{\text{SEQ-NLL}} = -\sum_{t \in \mathcal{T}} 1\{t = y\} \log p(t \mid s)
\]

\[
= -\sum_{j=1}^{J} \sum_{k=1}^{|V|} 1\{y_j = k\} \log p(t_j = k \mid s, t_{<j})
\]

\[
= \mathcal{L}_{\text{WORD-NLL}}
\]

where \( y = [y_1, \ldots, y_J] \) is the observed sequence. Of course, this just shows that from a negative log likelihood perspective, minimizing word-level NLL and sequence-level NLL are equivalent.

But now consider the case of sequence-level knowledge distillation. As before, we can simply replace the distribution from the data with a probability distribution derived from our teacher model.
However, instead of using a single word prediction, we use \( q(t \mid s) \) to represent the teacher’s sequence distribution, over the sample space of all possible sequences,

\[
\mathcal{L}_{\text{SEQ-KD}} = - \sum_{t \in T} q(t \mid s) \log p(t \mid s)
\]

Interestingly, \( \mathcal{L}_{\text{SEQ-KD}} \) is inherently different from \( \mathcal{L}_{\text{WORD-KD}} \), as the sum is over an exponential number of terms.

Despite its intractability, we posit that this sequence-level objective is worthwhile. It allows the teacher the chance to assign probabilities to complete sequences and therefore transfer a broader range of knowledge. We thus consider an approximation of this objective.

Our simplest approximation is to replace the teacher distribution \( q \) with its mode,

\[
q(t \mid s) \sim \mathbb{1}\{t = \hat{y}\}
\]

where \( \hat{y} = \arg\max_{t \in T} q(t \mid s) \). Observing that finding the mode is itself intractable, we use beam search to find an approximation. The loss is then

\[
\mathcal{L}_{\text{SEQ-KD}} \approx - \sum_{t \in T} \mathbb{1}\{t = \hat{y}\} \log p(t \mid s) = - \log p(t = \hat{y} \mid s)
\]

where \( \hat{y} \) is now the output from running beam search with the teacher model.

Using the mode seems like a poor approximation for the teacher distribution \( q(t \mid s) \), as we are approximating an exponentially-sized distribution with a single sample. However, previous results showing the effectiveness of beam search decoding for NMT lead us to belief that a large portion of \( q \)’s mass lies in a single output sequence. In fact, in experiments we find that with beam of size 1, \( q(\hat{y} \mid s) \) (on average) accounts for 1.3% of the distribution for German \( \rightarrow \) English, and 2.3% for Thai \( \rightarrow \) English (Table 1)\(^4\)

To summarize, sequence-level knowledge distillation suggests to: (1) train a teacher model, (2) run beam search over the training set with this model, (3) train the student network with cross entropy on this new dataset. Step (3) is identical to the word-level NLL process except now on the newly-generated data set. This is shown in Figure 1 (center).

### 3.3 Sequence-Level Interpolation

Next we consider integrating the training data back into the process, such that we train the student model as a mixture of our sequence-level teacher-generated data (\( \mathcal{L}_{\text{SEQ-KD}} \)) with the original training data (\( \mathcal{L}_{\text{SEQ-NLL}} \)),

\[
\mathcal{L} = (1 - \alpha) \mathcal{L}_{\text{SEQ-NLL}} + \alpha \mathcal{L}_{\text{SEQ-KD}} = -(1 - \alpha) \log p(y \mid s) - \alpha \sum_{t \in T} q(t \mid s) \log p(t \mid s)
\]

where \( y \) is the gold target sequence.

Since the second term is intractable, we could again apply the mode approximation from the previous section,

\[
\mathcal{L} = -(1 - \alpha) \log p(y \mid s) - \alpha \log p(\hat{y} \mid s)
\]

and train on both observed \( y \) and teacher-generated \( \hat{y} \) data. However, this process is non-ideal for two reasons: (1) unlike for standard knowledge distribution, it doubles the size of the training data (2) it requires training on both the teacher-generated sequence and the true sequence, conditioned on the same source input. The latter concern is particularly problematic since we observe that \( y \) and \( \hat{y} \) are often quite different.

As an alternative, we propose a single-sequence approximation that is more attractive in this setting. This approach is inspired by local updating (Liang et al., 2006) and hopfelfear training (Chiang, 2012), which are commonly-used methods for discriminative training in statistical machine translation (although to our knowledge not for knowledge distillation). These approaches suggest selecting a training increase the training set by a factor of \( K \). A beam of size 5 captures 2.8% of the distribution for German \( \rightarrow \) English, and 3.8% for Thai \( \rightarrow \) English. Another alternative is to use a Monte Carlo estimate and sample from the teacher model (since \( \mathcal{L}_{\text{SEQ-KD}} = \mathbb{E}_{t \sim q(t \mid s)}[- \log p(t \mid s)] \)). However in practice we found the mode to work well.

\[^4\] Additionally there are simple ways to better approximate \( q(t \mid s) \). One way would be to consider a \( K \)-best list from beam search and renormalizing the probabilities,

\[
q(t \mid s) \sim \frac{q(t \mid s)}{\sum_{t \in T_K} q(t \mid s)}
\]

where \( T_K \) is the \( K \)-best list from beam search. This would
sequence which is close to \( y \) and has high probability under the teacher model,

\[
y = \arg\max_{t \in T} \sim(t, y)q(t \mid s)
\]

where \( \sim \) is a function measuring closeness (e.g. Jaccard similarity or BLEU (Papineni et al., 2002)). Following local updating, we can approximate this sequence by running beam search and choosing

\[
y = \arg\max_{t \in T_{K}} \sim(t, y)
\]

where \( T_{K} \) is the \( K \)-best list from beam search. We take \( \sim \) to be smoothed sentence-level BLEU (Chen and Cherry, 2014).

We justify training on \( y \) from a knowledge distillation perspective with the following generative process: suppose that there is a true target sequence (which we do not observe) that is first generated from the underlying data distribution \( D \). And further suppose that the target sequence that we observe (\( y \)) is a noisy version of the unobserved true sequence: i.e. (i) \( t \sim D \), (ii) \( y \sim \epsilon(t) \), where \( \epsilon(t) \) is, for example, a noise function that independently replaces each element in \( t \) with a random element in \( V \) with some small probability.\(^5\) In such a case, ideally the student’s distribution should match the mixture distribution,

\[
\mathcal{D}_{\text{SEQ-Inter}} \sim (1 - \alpha)D + \alpha q(t \mid s)
\]

The key difference with the previous setting is that, due to the noise assumption, \( D \) now has significant probability mass around a neighborhood of \( y \) (not just at \( y \)), and, with the correct noise distribution, this neighborhood corresponds to high values of \( \sim \). Therefore, the argmax of the noisy mixture distribution is likely something other than \( y \) (the observed sequence) or \( \hat{y} \) (the output from beam search). We can see that \( \hat{y} \) is a natural approximation to the argmax of this mixture distribution between \( D \) and \( q(t \mid s) \) for some \( \alpha \). We illustrate this

\(^5\)While we employ a simple (unrealistic) noise function for illustrative purposes, the generative story is quite plausible if we consider a more elaborate noise function which includes additional sources of noise such as phrase reordering, replacement of words with synonyms, etc. One could view translation having two sources of variance that should be modeled separately: variance due to the source sentence (\( t \sim D \)), and variance due to the individual translator (\( y \sim \epsilon(t) \)).

Figure 2: Visualization of sequence-level interpolation on an example training sentence with a German \( \rightarrow \) English model: Bis 15 Tage vor Anreise sind Zimmer-Annullationen kostenlos. We run beam search and plot the final hidden state of the hypotheses using t-SNE and show the corresponding (smoothed) probabilities with contours. In the above example, the sentence that is at the top of the beam after beam search (green) is quite far away from gold (red), so we train the model on a sentence that is on the beam but had the highest \( \sim \) to gold (purple).

4 Experimental Setup

To test out these approaches, we conduct two sets of NMT experiments: high resource (English \( \rightarrow \) German) and low resource (Thai \( \rightarrow \) English).

The English-German data comes from WMT 2014\(^6\). The training set has 4m sentences and we take newstest2012/newstest2013 as the dev set and newstest2014 as the test set. We keep the top 50k most frequent words, and replace the rest with UNK. The teacher model is a \( 4 \times 1000 \) LSTM (as in Luong et al. (2015)) and we train two student models: \( 2 \times 300 \) and \( 2 \times 500 \). The Thai-English data comes from IWSLT 2015\(^7\). There are 90k sentences in the training set and we take 2010/2011/2012 data as the dev set and 2012/2013 as the test set. We take the top 25k most frequent words. Size of the teacher model is \( 2 \times 500 \) (which performed better than \( 4 \times 1000, 3 \times 750, 2 \times 750 \) models). The student model is \( 2 \times 100 \).

\(^6\)http://statmt.org/wmt14

\(^7\)https://sites.google.com/site/iwsltevaluation2015/mt-track
Other training details include: parameter initialization over a uniform distribution with support $[-0.1, 0.1]$; gradient norm constraint at 5; training for 13 epochs with learning rate equal to 1 that decays by half starting on epoch 9 (or the first epoch at which loss does not improve on dev); early stopping on dev; dropout with probability 0.3 on the 4 × 1000 and 2 × 500 models. We evaluate on tokenized BLEU with `multi-bleu.perl`.

We experiment with the following variations:

- **Word-Level Knowledge Distillation (Word-KD):** Student is trained on the original data and additionally trained to minimize the cross-entropy of the teacher distribution at the word-level. We tested $\alpha \in \{0.5, 0.9\}$ and found $\alpha = 0.5$ to work better.

- **Sequence-Level Knowledge Distillation (Seq-KD):** Student is trained on the teacher-generated data, which is the result of running beam search and taking the highest-scoring sequence with the teacher model. We use beam size $K = 5$ (we did not see improvements with a larger beam).

- **Sequence-Level Interpolation (Seq-Inter):** Student is trained on the sequence on the teacher’s beam that had the highest BLEU (beam size $K = 35$). We further adopt a fine-tuning approach where we begin training from a pretrained model (either on original data or Seq-KD data) and train with a smaller learning rate (0.1). We found that fine-tuning from a pretrained model resulted in slightly better performance than training on Seq-Inter data from scratch.

The teacher model had a tendency to erroneously produce consecutive UNK tokens on some sentences and therefore we discard sentences that had more than 25% UNK tokens on the teacher-generated data (which corresponded to approximately 1% of the corpus). For English-German we generate Seq-Inter data on a smaller portion of the training set (~ 50%) for efficiency.

Note that the above methods are complementary and can be combined with each other. For example, we can train on teacher-generated data but still include a word-level cross-entropy term between the teacher/student (Seq-KD + Word-KD in Table 1), or fine-tune towards sequence-level interpolation starting from the baseline (Baseline + Seq-Inter in Table 1).

## 5 Results and Discussion

Results of our experiments are shown in Table 1. We find that while word-level knowledge distillation (Word-KD) does improve upon the baseline, sequence-level knowledge distillation (Seq-KD) does better on English $\rightarrow$ German and performs similarly on Thai $\rightarrow$ English. Combining them (Seq-KD + Word-KD) results in further gains for the 2 × 300 and 2 × 100 models (although not for the 2 × 500 model), indicating that these methods provide orthogonal means of transferring knowledge from the teacher to the student: Word-KD is transferring knowledge at the local (i.e. word) level while Seq-KD is transferring knowledge at the global (i.e. sequence) level.

Sequence-level interpolation (Seq-Inter), in addition to improving models trained via Word-KD and Seq-KD, also improves upon the original teacher model that was trained on the actual data but fine-tuned towards Seq-Inter data (Teacher Baseline + Seq-Inter). In fact, greedy decoding with this fine-tuned model has similar performance (19.6) as beam search with the original model (19.5), allowing for faster decoding even with an identically-sized model.

We hypothesize that sequence-level knowledge distillation is effective because it allows the student network to model parts of the teacher distribution that are reachable (i.e. around the teacher’s mode) instead of ‘wasting’ parameters on trying to fit the actual target sequence (which may be too hard). We confirm that this is indeed the case: student models trained on original data (baseline/Word-KD) have substantially lower perplexity (calculated on the test set) than Seq-KD models (Table 1: PPL), indicating that baseline models are able to assign higher probabilities to reference translations. However, the probability mass that Seq-KD models assign to the

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8 Difficulty of training on reference translations has also been observed in discriminative statistical machine translation [Liang et al., 2006]
A greedily-decoded sequence is much higher (Table 1: \( p(t = \hat{y}) \)). For example, on English \( \rightarrow \) German we find that perplexity of the 2 × 500 baseline model is 8.2 while perplexity for the corresponding Seq-KD model is 22.7, despite the fact that Seq-KD model does significantly better for both greedy (+4.2) and beam search (+1.4) decoding. The (approximate) argmax from greedy decoding for the Seq-KD model accounts for 16.9% of the total probability mass while the corresponding number is 0.9% for the baseline. This also explains the success of greedy decoding for Seq-KD models—since we are only modeling around the teacher’s mode, the student’s distribution is less multimodal and therefore the argmax is much easier to find. Seq-Inter offers a compromise between the two: the 2 × 500 student model trained on Seq-KD and fine-tuned with Seq-Inter (Seq-KD + Seq-Inter) has a perplexity of 15.8, in between the baseline (8.2) and Seq-KD (22.7) models. The greedily-decoded se-

| Model                                      | Params | PPL  | BLEU\(_{K=1}\) | \( \Delta K=1 \) | BLEU\(_{K=5}\) | \( \Delta K=5 \) | \( p(t = \hat{y}) \) |
|--------------------------------------------|--------|------|----------------|-----------------|----------------|-----------------|-------------------|
| **English \( \rightarrow \) German (WMT 2014)**                                    |
| Teacher Baseline (4 × 1000)                | 221 m  | 6.7  | 17.7           | −               | 19.5           | −               | 1.3%              |
| Seq-Inter                                  | 221 m  | 10.4 | 19.6           | (+1.9)          | 19.8           | (+0.3)          | 8.2%              |
| Student Baseline (2 × 500)                 | 84 m   | 8.2  | 14.7           | −               | 17.6           | −               | 0.9%              |
| Word-KD                                    | 84 m   | 8.0  | 13.9           | (−0.8)          | 17.7           | (+0.1)          | 1.0%              |
| Seq-KD                                     | 84 m   | 22.7 | 18.9           | (+4.2)          | 19.0           | (+1.4)          | 16.9%             |
| Seq-Inter                                  | 84 m   | 11.3 | 18.5           | (+3.6)          | 18.7           | (+1.1)          | 5.7%              |
| Word-KD + Seq-Inter                        | 84 m   | 11.8 | 18.3           | (+3.6)          | 18.5           | (+0.9)          | 6.3%              |
| Seq-KD + Seq-Inter                         | 84 m   | 15.8 | 18.9           | (+4.2)          | 19.3           | (+1.7)          | 7.6%              |
| Seq-KD + Word-KD                           | 84 m   | 10.9 | 18.7           | (+4.0)          | 18.9           | (+1.3)          | 4.1%              |
| Seq-KD + Word-KD + Seq-Inter               | 84 m   | 14.8 | 18.8           | (+4.1)          | 19.2           | (+1.6)          | 7.1%              |
| Student Baseline (2 × 300)                 | 49 m   | 10.3 | 14.1           | −               | 16.9           | −               | 0.6%              |
| Word-KD                                    | 49 m   | 10.9 | 14.9           | (+0.8)          | 17.6           | (+0.7)          | 0.7%              |
| Seq-KD                                     | 49 m   | 64.4 | 18.1           | (+4.0)          | 18.1           | (+1.2)          | 14.8%             |
| Seq-Inter                                  | 49 m   | 13.0 | 17.6           | (+3.5)          | 17.9           | (+1.0)          | 10.0%             |
| Word-KD + Seq-Inter                        | 49 m   | 14.5 | 17.8           | (+3.7)          | 18.0           | (+1.1)          | 4.3%              |
| Seq-KD + Seq-Inter                         | 49 m   | 40.8 | 18.2           | (+4.1)          | 18.5           | (+1.6)          | 5.6%              |
| Seq-KD + Word-KD                           | 49 m   | 44.1 | 17.9           | (+3.8)          | 18.8           | (+1.9)          | 3.1%              |
| Seq-KD + Word-KD + Seq-Inter               | 49 m   | 97.1 | 18.5           | (+4.4)          | 18.9           | (+2.0)          | 5.9%              |
| **Thai \( \rightarrow \) English (IWSLT 2015)**                                  |
| Teacher Baseline (2 × 500)                 | 47 m   | 22.9 | 14.3           | −               | 15.7           | −               | 2.3%              |
| Seq-Inter                                  | 47 m   | 55.1 | 15.6           | (+1.3)          | 16.0           | (+0.3)          | 6.8%              |
| Student Baseline (2 × 100)                 | 8 m    | 37.0 | 10.6           | −               | 12.7           | −               | 1.4%              |
| Word-KD                                    | 8 m    | 35.3 | 11.8           | (+1.2)          | 13.6           | (+0.9)          | 1.4%              |
| Seq-KD                                     | 8 m    | 125.4 | 12.8          | (+2.2)          | 13.4           | (+0.7)          | 6.9%              |
| Seq-Inter                                  | 8 m    | 52.8 | 12.9           | (+2.3)          | 13.1           | (+0.4)          | 2.5%              |
| Word-KD + Seq-Inter                        | 8 m    | 58.7 | 13.0           | (+2.4)          | 13.7           | (+1.0)          | 3.2%              |
| Seq-KD + Seq-Inter                         | 8 m    | 106.4 | 13.6          | (+3.0)          | 14.0           | (+1.3)          | 3.9%              |
| Seq-KD + Word-KD                           | 8 m    | 67.4 | 13.7           | (+3.1)          | 14.2           | (+1.5)          | 3.1%              |
| Seq-KD + Word-KD + Seq-Inter               | 8 m    | 117.4 | 14.2          | (+3.6)          | 14.4           | (+1.7)          | 3.2%              |

Table 1: Results on English-German (newstest2014) and English-Thai (2012/2013) test sets. Params: number of parameters in the model; PPL: perplexity on the test set; BLEU\(_{K=1}\): BLEU score with beam size \( K = 1 \) (i.e. greedy decoding); \( \Delta K=1 \): BLEU gain over the baseline model without any knowledge distillation with greedy decoding; BLEU\(_{K=5}\): BLEU score with beam size \( K = 5 \); \( \Delta K=5 \): BLEU gain over the baseline model without any knowledge distillation with beam size \( K = 5 \); \( p(t = \hat{y}) \): Probability of output sequence from greedy decoding (averaged over the test set).
Table 2: Number of source words translated per second across the GPU (GeForce GTX Titan X), CPU, and cell phone (Samsung Galaxy 6). We were unable to run the $4 \times 1000$ models on the cell phone.

| Model Size | GPU | CPU | Android |
|------------|-----|-----|---------|
| Greedy     |     |     |         |
| $4 \times 1000$ | 425.5 | 15.0 | -       |
| $2 \times 500$  | 1051.3 | 63.6 | 8.8     |
| $2 \times 300$  | 1267.8 | 104.3 | 15.8    |

| Beam = 5 |
|----------|
| $4 \times 1000$ | 101.9 | 7.9 | -       |
| $2 \times 500$  | 181.9 | 22.1 | 1.9     |
| $2 \times 300$  | 189.1 | 38.4 | 3.4     |

5.1 Decoding Speed

Computational complexity for beam search grows linearly with beam size. Therefore, the fact that sequence-level knowledge distillation allows for greedy decoding is significant, with practical implications for running NMT systems across various devices. To test the speed gains, we run the teacher/student models on GPU, CPU, and cell phone, and check the average number of source words translated per second (Table 2). We use a GeForce GTX Titan X for the GPU and a Samsung Galaxy 6 smart phone. We find that we can run the student model 10 times faster with greedy decoding than the teacher model with beam search (1051.3 vs 101.9 words/sec), with little loss in performance.

5.2 Further Observations

We report on some further experiments and observations:

- We tried training very small student models ($1 \times 100$, $2 \times 50$) and found that performance degraded considerably compared to the teacher model.

- For models trained with word-level knowledge distillation, we also tried regressing the student network’s top-most hidden layer at each time step to the teacher network’s top-most hidden layer as a pretraining step, noting that Romero et al. (2015) obtained improvements with a similar technique on feed-forward models. We found this to give comparable results to standard knowledge distillation and hence did not pursue this further.

- Number of parameters for the student models (Table 1: Params) is still somewhat large, as majority of the parameters is dominated by the input word embeddings, which scale linearly with the embedding size (versus RNN parameters which scale quadratically with the hidden dimension size). For instance, on the $2 \times 500$ English $\rightarrow$ German model the input word embeddings account for approximately 60% (50m) of all the parameters. There have been promising recent results on eliminating word embeddings completely and obtaining word representations directly from characters with character composition models, which have many fewer parameters than word embedding lookup tables (Ling et al., 2015a; Kim et al., 2016; Ling et al., 2015b; Jozefowicz et al., 2016; Costa-Jussa and Fonollosa, 2016). For example Jozefowicz et al. (2016) compress a state-of-the-art language model by a factor of 20 by replacing input/output word embeddings with a character model. Combining such methods with knowledge distillation to further reduce the memory footprint of NMT systems remains an avenue for future work.

6 Conclusion

In this work we have investigated existing knowledge distillation methods for NMT (which work at the word-level) and introduced two sequence-level variants of knowledge distillation. We demonstrate that our method is effective, providing improvements over the baseline model without any knowledge distillation as well as over models trained with word-level knowledge distillation. We observe that the methods are complementary and combining them results in further improvements.

We also find that models trained with sequence-level knowledge distillation seem to not require
beam search during inference, indicating significant practical implications for deploying NMT systems in the wild. Our method can even be used to improve the original teacher model and likewise eliminates the need to beam search with the teacher model.

We have chosen to focus on translation as this domain has generally required the largest capacity deep learning models, but sequence-to-sequence framework has been successfully applied to a wide range of tasks including parsing (Vinyals et al., 2015a), summarization (Rush et al., 2015), dialogue (Vinyals and Le, 2015), NER/POS-tagging (Gillick et al., 2016), image captioning (Vinyals et al., 2015b), Chun et al., 2015), and video generation (Srivastava et al., 2015). We anticipate that methods described in this paper can be used to similarly train smaller models in other domains.

Finally, much existing work on compressing deep learning models has focused on either pruning or knowledge distillation, but not both. It would be interesting to see if knowledge distillation can be combined with pruning methods to further compress deep learning models.

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