MULTI-TASK SEQUENCE TO SEQUENCE LEARNING

Minh-Thang Luong∗
Stanford
lmthang@stanford.edu

Quoc V. Le, Ilya Sutskever, Oriol Vinyals, Lukasz Kaiser
Google
{qvl, ilyasu, vinyals, lukaszkaiser}@google.com

ABSTRACT

Sequence to sequence learning has recently emerged as a new paradigm in supervised learning. To date, most of its applications focused on only one task and not much work explored this framework for multiple tasks. This paper examines three settings to multi-task sequence to sequence learning: (a) the one-to-many setting – where the encoder is shared between several tasks such as machine translation and syntactic parsing, (b) the many-to-one setting – useful when only the decoder can be shared, as in the case of translation and image caption generation, and (c) the many-to-many setting – where multiple encoders and decoders are shared, which is the case with unsupervised objectives and translation. Our results show that training on parsing and image caption generation improves translation accuracy and vice versa. We also present novel findings on the benefit of the different unsupervised learning objectives: we found that the skip-thought objective is beneficial to translation while the sequence autoencoder objective is not.

1 INTRODUCTION

Multi-task learning (MTL) is an important machine learning paradigm that aims at improving the generalization performance of a task using other related tasks. Such framework has been widely studied by Thrun (1996); Caruana (1997); Evgeniou & Pontil (2004); Ando & Zhang (2005); Argyriou et al. (2007); Kumar & III (2012), among many others. In the context of deep neural networks, MTL has been applied successfully to various problems ranging from language (Liu et al., 2015), to vision (Donahue et al., 2014), and speech (Heigold et al., 2013; Huang et al., 2013).

Recently, sequence to sequence (seq2seq) learning, proposed by Sutskever et al. (2014) and Cho et al. (2014), emerges as an effective paradigm for dealing with variable-length inputs and outputs. seq2seq learning, at its core, uses recurrent neural networks to map variable-length input sequences to variable-length output sequences. While relatively new, the seq2seq approach has achieved state-of-the-art results in machine translation (Luong et al., 2015b; Jean et al. 2015; Luong et al. 2015a), image caption generation (Vinyals et al., 2015b), and constituency parsing (Vinyals et al., 2015a).

Despite the popularity of multi-task learning and sequence to sequence learning, there has been little work in combining MTL with seq2seq learning. To the best of our knowledge, there is only one recent publication by Dong et al. (2015) which applies a seq2seq models for machine translation, where the goal is to translate from one language to multiple languages. In this work, we propose three MTL approaches that complement one another: (a) the one-to-many approach – for tasks that can have an encoder in common, such as translation and parsing; this applies to the multi-target translation setting in Dong et al. (2015) as well, (b) the many-to-one approach – which is useful for multi-source translation or tasks in which only the decoder can be easily shared, such as translation and image captioning, and lastly, (c) the many-to-many approach – which share multiple encoders and decoders through which we study the effect of unsupervised learning in translation. We show

∗Work done while the author was an intern at Google.
that syntactic parsing and image caption generation improves the accuracy of machine translation and vice versa. We also explore two unsupervised learning objectives in the MTL setting, the sequence autoencoders (Dai & Le, 2015) and the skip-thought vectors (Kiros et al., 2015). Our novel findings reveal that the skip-thought objective improves translation while the sequence autoencoders does not.

2 SEQUENCE TO SEQUENCE LEARNING

Sequence to sequence learning (seq2seq) aims to directly model the conditional probability $p(y|x)$ of mapping an input sequence, $x_1, \ldots, x_n$, into an output sequence, $y_1, \ldots, y_m$. It accomplishes such goal through the encoder-decoder framework proposed by Sutskever et al. (2014) and Cho et al. (2014). As illustrated in Figure 1, the encoder computes a representation $s$ for each input sequence. Based on that input representation, the decoder generates an output sequence, one unit at a time, and hence, decomposes the conditional probability as:

$$\log p(y|x) = \sum_{j=1}^{m} \log p(y_j|y_{<j}, x, s)$$ (1)

A natural model for sequential data is the recurrent neural network (RNN), which is used by most of the recent seq2seq work. These work, however, differ in terms of: (a) architecture – from unidirectional, to bidirectional, and deep multi-layer RNNs; and (b) RNN type – which are long-short term memory (LSTM) (Hochreiter & Schmidhuber, 1997) and the gated recurrent unit (Cho et al., 2014).

Another important difference between seq2seq work lies in what constitutes the input representation $s$. The early seq2seq work (Sutskever et al., 2014; Cho et al., 2014; Luong et al., 2015b; Vinyals et al., 2015b) uses only the last encoder state to initialize the decoder and sets $s =$ in Eq. (1). Recently, Bahdanau et al. (2015) proposes an attention mechanism, a way to provide seq2seq models with a random access memory, to handle long input sequences. This is accomplished by setting $s$ in Eq. (1) to be the set of encoder hidden states computed along the way. On the decoder side, at each time step, the attention mechanism will decide how much information to retrieve from that memory by learning where to focus, i.e., computing the alignment weights for all input positions. Recent work such as (Xu et al., 2015; Jean et al., 2015; Luong et al., 2015a; Vinyals et al., 2015a) has found that it is crucial to empower seq2seq models with the attention mechanism.

3 MULTI-TASK SEQUENCE-TO-SEQUENCE LEARNING

We generalize the work of Dong et al. (2015) to the multi-task sequence-to-sequence learning setting that includes the tasks of machine translation (MT), constituency parsing, and image caption generation. Depending which tasks involved, we propose to categorize multi-task seq2seq learning into three general settings. In addition, we will discuss the unsupervised learning tasks considered as well as the learning process.

3.1 ONE-TO-MANY SETTING

This scheme involves one encoder and multiple decoders for tasks in which the encoder can be shared, as illustrated in Figure 2. The input to each task is a sequence of English words. A separate decoder is used to generate each sequence of output units which can be either (a) a sequence of tags
3.2 MANY-TO-ONE SETTING

This scheme is the opposite of the one-to-many setting. As illustrated in Figure 3, it consists of multiple encoders and one decoder. This is useful for tasks in which only the decoder can be shared, for example, when our tasks include machine translation and image caption generation (Vinyals et al., 2015b). In addition, from a machine translation perspective, this setting can benefit from a large amount of monolingual data on the target side, which is a standard practice in machine translation system and has also been explored for neural MT by Gulcehre et al. (2015).

3.3 MANY-TO-MANY SETTING

Lastly, as the name describes, this category is the most general one, consisting of multiple encoders and multiple decoders. We will explore this scheme in a translation setting that involves sharing multiple encoders and multiple decoders. In addition to the machine translation task, we will include two unsupervised objectives over the source and target languages as illustrated in Figure 4.

3.4 UNSUPERVISED LEARNING TASKS

Our very first unsupervised learning task involves learning autoencoders from monolingual corpora, which has recently been applied to sequence to sequence learning (Dai & Le, 2015). However, in Dai & Le (2015)’s work, the authors only experiment with pretraining and then finetuning, but not joint training which can be viewed as a form of multi-task learning (MTL). As such, we are very interested in knowing whether the same trend extends to our MTL settings.

Additionally, we investigate the use of the skip-thought vectors (Kiros et al., 2015) in the context of our MTL framework. Skip-thought vectors are trained by training sequence to sequence models on pairs of consecutive sentences, which makes the skip-thought objective a natural seq2seq learning candidate. A minor technical difficulty with skip-thought objective is that the training data must
Figure 4: **Many-to-many setting** – multiple encoders, multiple decoders. We consider this scheme in a limited context of machine translation to utilize the large monolingual corpora in both the source and the target languages. Here, we consider a single translation task and two unsupervised autoencoder tasks.

consist of ordered sentences, e.g., paragraphs. Unfortunately, in many applications that include machine translation, we only have sentence-level data where the sentences are unordered. To address that, we split each sentence into two halves; we then use one half to predict the other half.

3.5 **Learning**

Dong et al. (2015) adopted an *alternating* training approach, where they optimize each task for a fixed number of parameter updates (or mini-batches) before switching to the next task (which is a different language pair). In our setting, our tasks are more diverse and contain different amounts of training data. As a result, we allocate different numbers of parameter updates for each task, which are expressed with the *mixing* ratio values $\alpha_i$ (for each task $i$). Each parameter update consists of training data from one task only. When switching between tasks, we select randomly a new task $i$ with probability $\frac{\alpha_i}{\sum_j \alpha_j}$.

Our convention is that the first task is the *reference* task with $\alpha_1 = 1.0$ and the number of training parameter updates for that task is prespecified to be $N$. A typical task $i$ will then be trained for $\alpha_i \cdot N$ parameter updates. Such convention makes it easier for us to fairly compare the same reference task in a single-task setting which has also been trained for exactly $N$ parameter updates.

When sharing an encoder or a decoder, we share both the recurrent connections and the corresponding embeddings.

4 **Experiments**

We evaluate the multi-task learning setup on a wide variety of sequence-to-sequence tasks: constituency parsing, image caption generation, machine translation, and a number of unsupervised learning as summarized in Table 1.

4.1 **Data**

Our experiments are centered around the translation task, where we aim to determine whether other tasks can improve translation and vice versa. We use the WMT’15 data (Bojar et al., 2015) for the English}$ \leftrightarrow $German translation problem. Following Luong et al. (2015a), we use the 50K most frequent words for each language form the training corpus. These vocabularies are then shared with other tasks, except for parsing in which the target “language” has a vocabulary of 104 tags.

For the unsupervised tasks, we use the English and German monolingual corpora from WMT’15. For constituency parsing, we experiment with two types of corpora:

1. a small corpus – the widely used Penn Tree Bank (PTB) dataset (Marcus et al., 1993) and,
2. a large corpus – the high-confidence (HC) parse trees provided by Vinyals et al. (2015a).

The two parsing tasks, however, are evaluated on the same validation and test sets from the PTB data. Note also that the parse trees have been linearized following Vinyals et al. (2015a). Lastly,

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1The corpus has already been tokenized using the default tokenizer from Moses. Words not in these vocabularies are represented by the token <unk>.
Table 1: Data & Training Details – Information about the different datasets used in this work. For each task, we display the following statistics: (a) the number of training examples, (b) the sizes of the vocabulary, (c) the number of training epochs, and (d) details on when and how frequent we halve the learning rates (finetuning).

for image caption generation, we use a dataset of image and caption pairs provided by Vinyals et al. (2015b). Detailed information on the train and test data sets are provided in Table 1.

4.2 Training Details

In all experiments, following Sutskever et al. (2014) and Luong et al. (2015b), we train deep LSTM models as follows: (a) we use 4 LSTM layers each of which has 1000-dimensional cells and embeddings, (b) parameters are uniformly initialized in [-0.06, 0.06], (c) we use a mini-batch size of 128, (d) dropout is applied with probability of 0.2 over vertical connections (Pham et al., 2014), (e) we use SGD with a fixed learning rate of 0.7, (f) input sequences are reversed, and lastly, (g) we use a simple finetuning schedule – after $x$ epochs, we halve the learning rate every $y$ epochs. The values $x$ and $y$ are referred as finetune start and finetune cycle in Table 1 together with the number of training epochs per task.

As described in Section 3, for each multi-task experiment, we need to choose one task to be the reference task (which corresponds to $\alpha_1 = 1$). The choice of the reference task helps specify the number of training epochs and the finetune start/cycle values which we also when training that reference task alone for fair comparison. To make sure our findings are reliable, we run each experimental configuration twice and report the average performance in the format mean (+/-stddev).

4.3 Results

We explore several multi-task learning scenarios by combining a large task (machine translation) with: (a) a small task – Penn Tree Bank (PTB) parsing, (b) a medium-sized task – image caption generation, (c) another large task – parsing on the high-confidence (HC) corpus, and (d) lastly, unsupervised tasks, such as autoencoders and skip-thought vectors.

4.3.1 Large Tasks with Small Tasks

In this setting, we want to understand if a small task such as PTB parsing can help improve the performance of a large task such as translation. Since the parsing task maps from a sequence of English words to a sequence of parsing tags (Vinyals et al., 2015a), only the encoder can be shared with an English → German translation task. As a result, this is a a one-to-many MTL scenario ($\Sigma 3$).

To our surprise, the results in Table 2 suggest that by adding a very small number of parsing mini-batches (one per 100 translation mini-batches, i.e., the mixing ratio of 0.01), we can achieve a notable average gain of +0.6 in terms of translation perplexities. At the same time, the results also indicate that MTL helps parsing as well.

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2The training sizes reported for the unsupervised tasks are only 10% of the original WMT’15 monolingual corpora which we randomly sample from. Such reduced sizes are for faster training time and already about three times larger than that of the parallel data. We consider using all of the monolingual data in future work.

3For image caption generation, we use 1024 dimensions, which is also the size of the image embeddings.
Table 2: **English→German translation & Penn Tree Bank parsing results** – shown are perplexities for translation and parsing tasks under both the single- and multi-task settings. *Reference* tasks are in italic; whereas, the mixing ratio is in parentheses. Best results are highlighted in boldface.

### 4.3.2 LARGE TASKS WITH MEDIUM TASKS

We investigate whether the same pattern carries over to a medium task such as image caption generation. Since the image caption generation task maps images to a sequence of English words (Vinyals et al., 2015b; Xu et al., 2015), only the decoder can be shared with a German→English translation task. Hence, this setting falls under the *many-to-one* MTL setting (§3.2).

The results in Table 3 show the same trend we observed before, that is, by training on another task for a very small fraction of time, the model improves its performance on its main task. Specifically, with 5 image caption generation parameter updates every 100 translation updates (so the mixing ratio of 0.05), we obtain a gain of +0.7 in terms of translation perplexities.

When the *reference* task is image caption generation, MTL is still useful. For every captioning parameter update, if the model also performs MTL with 2 translation minibatches (a mixing ratio of 2), a gain of +3.3 points in terms of image caption generation perplexity can be achieved.

Table 3: **German→English translation & captioning results** – shown are perplexities for translation and captioning tasks with similar format as in Table 2. *Reference* tasks are in italic. Numbers in mean (+/-stddev) format are the average results of 2 runs; others are for 1 run only.

### 4.3.3 LARGE TASKS WITH LARGE TASKS

This setting is the same as the setting in Section 4.3.1 except that we are using more parsing data provided by Vinyals et al. (2015a) and referred as the *high-confidence* (HC) parsing corpus. When translation is the reference task and with a small mixing ratio of 0.01, we obtain the same pattern as before, that is, MTL helps translation as shown in Table 4. For this case, it is expected that we do not get better parsing results since the multi-task model has seen very little parsing data compared to the single-task model.

When parsing is the main task and with a mixing ratio of 0.05, we obtain a very small gain in terms of parsing perplexities. This can be explained by the fact that parsing is a relatively easier task than translation with only a target vocabulary of 104 tags compared to 50K words in the translation case. As a result, with large training data, we can obtain very low perplexities (cf. results in Table 2 are comparable) and it is more challenging to obtain better results. It would be very interesting to study how MTL can be useful with the presence of the attention mechanism which has been successfully applied to parsing by Vinyals et al. (2015a). We leave this for future work.

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4. See Section 3.5 on the use of reference tasks for fair comparison.

5. Note that 1.0 is the theoretical lower bound.
Table 4: **English→German translation & Large-Corpus parsing results** – shown are perplexities for translation and parsing tasks with similar format as in Table 2. *Reference* tasks are in italic.

### 4.3.4 Multi-tasks and Unsupervised Learning

Our main focus in this section is determine whether unsupervised learning can help improve translation, specifically translating between English and German. We follow the *many-to-many* approach described in Section 3.3 to utilize both monolingual corpora, one per language.

The results in Tables 5 and 6 show that as we train more on the *autoencoder* task, translation performance gets worse. On the other hand, we obtain very encouraging results with *skip-thought* objectives which improve translation performance between English and German in both directions. In addition, we observe that better translation perplexities are achieved as we increase the portions of unsupervised parameter updates from 0.01 to 1. These results show that the skip-thought objective is better than the autoencoder as an unsupervised objective for language tasks.

| Task | Perplexity | English | German |
|------|------------|---------|--------|
| Translation | 8.8 (+/-0.3) | - | - |
| **Autoencoders** | | | |
| Translation + autoencoders (0.1x) | 9.0 | 1.37 | 3.85 |
| Translation + autoencoders (1.0x) | 10.0 | 1.09 | 2.78 |
| Translation + skip-thought (0.01x) | 8.6 (+/-0.4) | 64.1 (+/-1.7) | 150.9 (+/-1.3) |
| Translation + skip-thought (0.1x) | 8.8 (+/-0.3) | 46.5 (+/-0.5) | 72.7 (+/-9.1) |
| Translation + skip-thought (1x) | **8.4** (+/-0.2) | 35.0 (+/-0.6) | 43.1 (+/-1.5) |

Table 5: **English→German translation & unsupervised learning results** – shown are perplexities for translation and unsupervised learning tasks. We experiment with both *autoencoders* and *skip-thought vectors* for the unsupervised objectives. Numbers in *mean (+/-stddev)* format are the average results of 2 runs; others are for 1 run only.

| Task | Perplexity | German | English |
|------|------------|--------|---------|
| Translation | 11.0 (+/-0.0) | - | - |
| **Autoencoders** | | | |
| Translation + autoencoders (0.1x) | 11.4 | 1.19 | 1.75 |
| Translation + autoencoders (1.0x) | 12.3 | 1.04 | 2.75 |
| Translation + skip-thought (0.01x) | 11.0 (+/-0.1) | 69.5 (+/-0.4) | 165.3 (+/-3.6) |
| Translation + skip-thought (0.1x) | 10.7 (+/-0.0) | 51.0 (+/-0.2) | 64.2 (+/-0.4) |
| Translation + skip-thought (1x) | **10.4** (+/-0.1) | 39.0 (+/-0.2) | 38.1 (+/-0.1) |

Table 6: **German→English translation & unsupervised learning results** – shown are perplexities for translation and unsupervised learning tasks. We follow the same format as in Table 5.

## 5 Conclusion

In this paper, we showed that multi-task learning can improve the performance of the attention-free sequence to sequence model of Sutskever et al. (2014). We found it surprising that training on syntactic parsing improved our translation performance, given that the parsing dataset is orders of magnitude smaller than typical translation datasets. It is also notable that the skip-thought vector
model outperformed the sequence autoencoder as an unsupervised objective. A criticism of our work is that the sequence to sequence model that we used did not employ attention (Bahdanau et al., 2015). We leave the exploration of multitask learning with attention for future work.

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