Gradual Learning of Deep Recurrent Neural Networks

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Abstract

Deep Recurrent Neural Networks (RNNs) achieve state-of-the-art results in many sequence-to-sequence tasks. However, deep RNNs are difficult to train and suffer from overfitting. We introduce a training method that trains the network gradually, and treats each layer individually, to achieve improved results in language modelling tasks. Training deep LSTM with Gradual Learning (GL) obtains perplexity of 61.7 on the Penn Treebank (PTB) corpus. As far as we know, GL improves the best state-of-the-art performance by a single LSTM/RHN model on the word-level PTB dataset.

1 Introduction

Several forms of deep recurrent neural network (RNN) architectures, such as LSTM [13] and GRU [4], have achieved state-of-the-art results in many sequential classification tasks during the past few years [22, 5]. The number of stacked RNN layers, i.e. the network depth, has key importance in extending the ability of the architecture to express more complex dynamic systems [3, 17]. It has been shown that deeper networks have achieved better practical success in language modeling and other sequential tasks than the shallower architectures [20, 22, 9, 11, 19], though training deeper networks poses difficulties and problems that are yet to be solved.

Training a very deep RNN network to exploit its performance potential can be a very difficult task. One of the problems in training deep networks is the degradation problem, as studied in [10]. Moreover, deep architectures are exposed to exponential vanishing or exploding gradients through the backpropagation through time algorithm. Many studies have attempted to address those problems by regularizing the network [21, 8, 7], using different layer initialization methods [1, 12], or using shortcut connections between layers [10, 22, 19].

Multiple studies have suggested to deal with sequential tasks using hierarchical architectures [11, 6], showing that different layers within multi-layer networks tend to learn different hierarchical dependencies. A natural extension to the underlying idea of those architectures, would be treating each layer as an independent entity inside the network, and, therefore, adjusting a proper training scheme for each layer individually. This approach is also motivated by the curriculum learning

*As for the 20.05.2017, when the github project was uploaded to https://github.com/zivaharoni/gradual-learning-rnn
In the manner of gradually increasing the complexity of the model, rather than the order in which training examples are presented to the model.

In this paper, we suggest a new approach that breaks the optimization process into several learning phases. Each learning phase includes training an increasingly deeper architecture than the previous ones. In this way we gradually train and extend the network depth, decreasing the bad effects of degradation and backpropagation problems. Additionally, we present a different way of setting regularization hyper-parameters, for each layer separately. In order to evaluate our method performance we tested it by performing experiments over the word-level language modeling Penn Tree Bank (PTB) dataset. We demonstrated that combining the Gradual Learning (GL) method and layer-wise hyper-parameter adaptations can significantly improve the results over the traditional training method of LSTM.

2 Related Research

In the past years significant work has been done in the field of training deep RNNs. He et al. [10] introduced the degradation problem of deep architectures and proposed the architecture of Resnets. They proposed the use of short-cut connections between layers, which is a way to maintain the performance of the network in the case where a deeper layer yields a deteriorating validation score with respect to shallower layers. They reason that sometimes deeper layers do not need to perform further processing to their inputs and have difficulties in fitting an identity mapping. Zilly et al. [22] introduced Recurrent Highway Networks (RHNs), where gated shortcut connections were used to construct a RNN with deep transition depth. This architecture achieved impressive results on the PTB and Wikipedia datasets, holding the state-of-the-art results on the Wikipedia, and, until lately, also on the PTB. Smith et al. [19] introduced the method of gradually adding layers to the network by a Dropin layer. A Dropin layer is inserted after two successive layers in the network, and controls the trade-off between passing the outputs of the first layer and the outputs of the second layer, when initially preferring the outputs of the first layer, and, as the learning process progresses, switches to preferring the outputs of the second layer. This process is done uniformly over all layers simultaneously, which is its main difference to our proposed method.

Sutskever et al. [20] found that choosing a proper random initialization combined with an adjusted increasing schedule to the momentum parameter enables training deep RNNs with stochastic gradient descent (SGD). Bengio et al. [1] proposed that a proper initialization of the network parameters by a layer-by-layer greedy unsupervised initialization process could recognize features in the input structure that would be valuable to the classifier at the network’s output.

3 Gradual Learning

In this section, we describe how to train a deep LSTM gradually and explain intuitively why our training scheme works. Next we elaborate on adjusting hyper-parameters for every layer individually. Here, we concentrate on LSTM cells, but the method can be extended to any RNN model as well.

3.1 Training Layers Gradually

Let us represent a network with $L$ layers as a mapping from an input sequence $x \in X$ to an output sequence $y_L \in Y$ by

$$\hat{y}_L = S \circ f_L \circ f_{L-1} \circ \cdots \circ f_1(x; \theta) \quad (1)$$

$$J_L(\theta) = \text{cost}(\hat{y}_L, y) \quad (2)$$

where $f_i$ is the $i^{th}$ layer transformation such as $\text{dom}(f_i) = X$, $\text{dom}(f_i) = \text{range}(f_{i-1})$ for $i \in \{2, \ldots, L\}$, $S$ operates as a softmax layer such that $\text{dom}(S) = \text{range}(f_L)$, $\text{range}(S) = Y$. The term $\theta$ stands for the network parameters, $f_2 \circ f_1$ represents the composition of $f_2$ over $f_1$. The term $y_L$ stands for the estimated output sequence of a network with $L$ layers, and $J_L(\theta)$ is the cost function with respect to the target sequence $y$ associated with a network with $L$ layers.

When training Traditionally, one needs to compute the gradient of $J_L(\theta)$ with respect to $\theta$ and update $\theta$ adaptively until best results are reached over the validation data. Training the network Gradually
comprises a different approach for updating $\theta$. Let us denote the output sequence and cost of the $l^{th}$ layer by

\[
\hat{x}_l = f_l \circ f_{l-1} \circ \cdots \circ f_1(x; \theta^l)
\]  
(3)

\[
\hat{y}_l = S_l(\hat{x}_l; \theta_{S_l})
\]  
(4)

\[
J_l(\theta^l, \theta_{S_l}) = \text{cost}(\hat{y}_l, y)
\]  
(5)

where $\theta_i$ is the parameters of the $i^{th}$ layer and $\theta^l = \{\theta_1, \ldots, \theta_l\}$. The term $S_l$ stands for the softmax layer of the $l^{th}$ layer (every layer has its own softmax layer). The parameters of $S_l$ are denoted by $\theta_{S_l}$. The term $\hat{x}_l$ denotes the inner output sequence of the first $l$ hidden layers (except the softmax layer) and $\hat{y}_l$ is the output sequence of the the first $l$ layers after applying softmax mapping. Now, we can describe the optimization process by optimizing $J_l(\theta^l, \theta_{S_l})$ sequentially as $l$ increases from 1 to $L$, where the initial parameters at the beginning of the optimization of layer $l$ are $\theta^{l-1}$, which is obtained from optimizing $J_{l-1}(\theta^{l-1}, \theta_{S_{l-1}}), \ldots, J_1(\theta^1, \theta_{S_1})$ and $\theta_1, \theta_{S_1}$ that are initiated randomly.

An example for a training scheme is depicted in Figure 1.

Figure 1: Depiction of our training scheme for a 3 layered network. At phase 1 we optimize the parameters of layer 1 according to cost 1. At phase 2, we add layer 2 to the network, and then we optimize the parameters of layers 1,2, when layer 1 is copied from phase 1 and layer 2 is initialized randomly. At phase 3, we add layer 3 to the network, and then we optimize all of the network’s parameters, when layers 1,2 are copied from phase 2 and layer 3 is initialized randomly.

3.2 Addressing Deep Learning Problems

Training the network gradually can address some of the deep training problems that we surveyed earlier: the vanishing/exploding gradient problem and the degradation problem. Unlike in traditional training, where deep architectures face gradient propagation attenuation (by the derivative of the activation function) or blockage (by dropout) along the longest assignment paths, when training gradually, gradients could propagate easily through shorter assignment paths to the shallow layers. Also, training the network gradually exposes the shallow layers of the network to the targets early in the training process. By optimizing $J_l(\theta^l, \theta_{S_l})$ with $l$ increasing from 1 to $L$, we produce a new representation of the input sequence $x$ by the inner output sequence $\hat{x}_l$, which is the best representation of $x$ such that a softmax classifier could classify it correctly to $y$. The process of gradually
reproducing a new representation of \( x \) ensures (empirically) that the training cost will not deteriorate while adding layers.

### 3.3 Layer-wise Adjusted Dropout (LAD)

Training layers gradually implies referring to each layer individually. This means that, by understanding that each layer has a different role in the input processing task, we would like to adjust different hyper-parameters at each layer, and, hence, to enable them to perform their individual role successfully. For a network that is regularized with dropout, adjusting different keep probabilities between layers yielded successful outcomes in our experiments.

Since shallower layers are locally close to the inputs, we would expect them to recognize basic features in the inputs, while deeper layers are responsible of recognizing more abstract/complex features, based on the basic features recognized by the shallow layers. Intuitively, the ability to recognize basic features in the data does not demand generalization of the task, as the ability to make the correct classification is based on the basic features. Therefore, it is reasonable to assume that adjusting higher keep probability to the shallow layers and lower keep probability to the deeper layers could adjust the proper generalization level for each layer.

### 4 Experiments

We present results on a dataset from the field of natural language processing: the PTB conducted as a word-level dataset (section 4.2). All experiments were run with Tensorflow using CUDA 8.0 and Nvidia’s CuDNN 5.1, on a single Nvidia GTX 1080 Ti GPU.

#### 4.1 Implementation

We start by implementing our methods (GL and LAD) within the Tensorflow implementation of [21], which is a common reference implementation of deep LSTM. We also implemented variational dropout, as proposed by [8], and used the weight tying (WT) embedding regularization, as proposed by [18]. When using WT with GL, we tied all softmax layers to the embedding matrix (\( S_1 = \cdots = S_L = W_{emb} \)). Then, we tested GL and LAD on the large model, as suggested in [21]. Next we performed experiments on deeper LSTM models. Throughout the experiments we refer to LSTMs with WT and variational dropout as variational LSTMs.

#### 4.2 Penn Treebank

The PTB dataset presented by Marcus et al. [14], downloaded from Thomas Mikolov’s webpage†, contains 40k sentences from the Wall Street Journal newspaper. When conducting a word-level representation of the data, we obtain a dataset of 929k training words, 73k validation words, and 82k test words. It has 10k words in its vocabulary. We used the tensorflow implementation of [21] to pre-process the data.

We implemented two models in our experiments, a reference model that is similar to the variational LSTM+WT as proposed by [8, 18], and a deep LSTM that was used to check the performance of our methods when stacking more layers. The reference model is similar to the large model, as proposed by [21], except that 1) we decayed the learning rate only when the validation perplexity deteriorated, 2) the grad clipping norm was reduced to 5, 3) a bias term was added to the embedding matrices. After constructing the model, we evaluated its performance when training the model gradually by GL, when adjusting dropout layer-wisely (LAD) and when combining both of them. when evaluating GL, we trained the first layer for 80 epochs, then we trained the entire model 80 additional epochs. When evaluating LAD we performed a grid search to find the best dropout parameters for every layer and trained the model for 160 epochs. Lastly we performed an experiment combining GL and LAD. Here, we needed to adjust the dropout parameters, not only by their position in the network, but by the learning phase. The deep LSTM contains 5 layers of 1500 units each. We chose the same hyper-parameters as we used for the reference model, except that we adjusted different dropout parameter for each layer, and decreased the BPTT truncation to 25 time steps due memory constraints. We trained the model gradually by GL, running 80 training epochs per layer.

†http://www.fit.vutbr.cz/~imikolov/rnnlm/simple-examples.tgz
Results of the reference model and deep LSTM model are shown in Table 1. We compared our results to the results of [18] over the large model using both variational dropout [8] and WT [18]. In Figure 2, a comparison between training a variational LSTM traditionally and gradually is depicted. Our results clearly demonstrate that applying GL/LAD improved the perplexity result of the PTB dataset; combining those methods brought even greater improvement.

| Model                                          | Size | Test  |
|------------------------------------------------|------|-------|
| Variational LSTM (2×1500) + GL                | 51M  | 67.8  |
| Variational LSTM (2×1500) + LAD               | 51M  | 65.8  |
| Variational LSTM (2×1500) + GL + LAD          | 51M  | 65.0  |
| **Variational LSTM (5×1500) + GL + LAD**      | **105M** | **61.7** |
| Zaremba et al. [21]                            | 66M  | 78.4  |
| Variational LSTM MC dropout[8]                 | 66M  | 73.4  |
| Variational LSTM + WT [8, 18]                  | 51M  | 73.2  |
| Variational RHN [22]                           | 32M  | 68.5  |
| Neural Architecture Search with base 8 [23]    | 32M  | 67.9  |
| Variational RHN + WT [22]                      | 23M  | 65.4  |
| Neural Architecture Search with base 8 + WT [23]| 25M  | 64.0  |
| Neural Architecture Search with base 8 + WT [23]| 54M  | 62.4  |

5 Conclusions

We presented two techniques to train deep RNNs. The GL technique increases the network depth gradually as training progresses, and the LAD technique, which adjusts the dropout parameter in-
individually for each layer. Our techniques are implemented easily and do not involve increasing the amount of parameters of the network. We demonstrated the effectiveness of our techniques on the PTB dataset. We believe that our techniques would be useful for additional neural networks architectures, such as GRUs and RHNs, and in additional settings, such as in reinforcement learning. In our future work we plan to extend the layer-wise adaptations to more hyper-parameters, such as grad-clipping, and investigate its effectiveness on the model’s generalization. Also, we plan on investigating our methods on additional architectures and with other regularization methods.

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