Twin Networks: Using the Future as a Regularizer

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Abstract

Being able to model long-term dependencies in sequential data, such as text, has been among the long-standing challenges of recurrent neural networks (RNNs). This issue is strictly related to the absence of explicit planning in current RNN architectures. More explicitly, the RNNs are trained to predict only the next token given previous ones. In this paper, we introduce a simple way of encouraging the RNNs to plan for the future. In order to accomplish this, we introduce an additional neural network which is trained to generate the sequence in reverse order, and we require closeness between the states of the forward RNN and backward RNN that predict the same token. At each step, the states of the forward RNN are required to match the future information contained in the backward states. We hypothesize that the approach eases modeling of long-term dependencies thus helping in generating more globally consistent samples. The model trained with conditional generation for a speech recognition task achieved 12% relative improvement (CER of 6.7 compared to a baseline of 7.6).

Index Terms: recurrent neural networks, sequence generation, speech recognition, attention model

1. Introduction

Recurrent Neural Networks are the basis of state-of-art models for generative modeling of sequential data, such as speech recognition. For conditional generation, encoder-decoder [1] state-of-art models take advantage of content-based soft attention, e.g., for image captioning [2], speech recognition [3, 4], and machine translation [5]. The decoder model for an attention model is a generative recurrent neural network which has as additional input the convex combination of *contexts* (outputs of the encoder), each corresponding to a different focus of attention. The soft attention mechanism assigns different weights to each context vector providing their convex combination to the decoder.

Given a target sequence, RNNs are usually trained with *teacher forcing*: at each time-step, the hidden state of the RNN is trained to predict the next token given all the previously observed tokens. This corresponds to optimizing a one-step ahead prediction. Usually, samples from RNNs exhibit local coherence but lacks meaningful global structure [6]. As there is no explicit bias towards planning in the training objective, the model may prefer focusing on few previously generated tokens instead of capturing long-term dependencies in order to ensure global coherence.

The issue of capturing long-term dependencies was raised and explored in several works [7, 8]. Gated architectures such as

LSTMs [9] and GRUs [10] have been successful in easing the modeling of long term-dependencies. Recent work explicitly attempted to model planning by using a value function estimator during sequence decoding by biasing the decoding towards tokens that maximize the expected "success" at each step of the generation process [11].

In this paper, we propose *TwinNet*, a simple way of regularizing the recurrent network towards better implicit planning during the training phase. In addition to predicting the next token in the sequence, we require the hidden state to contain information about the whole future of the sequence. Succinctly, this is achieved as follows: we run a backward RNN that predicts the sequence in reverse and we encourage the forward hidden states to be close to the backward hidden states that predict the same token, i.e. we force overlap between past and future information about a specific token (Fig. 1). In our work, this is used as a decoder for the encoder-decoder attention model. Our model can be generalized to any conditional generative models for sequence-to-sequence tasks. Our model is specifically focused on conditional generation to model the conditioned probability of a sequence x given features f, P(x|f), which contains much less entropy than unconditional generation. To be more specific, this is to avoid the impossible challenge of making the first few tokens containing all the information of the future, which could have very high entropy in unconditional generative models. In this paper, we evaluate our model in the setting of conditional generation for speech recognition.

We describe the model in details in the next section. Then we discuss the related work in Section3, present our experiments in Section 4 and conclude in Section 5.

2. Model

Given a dataset $\mathcal{X} = \{\mathbf{x}^1, \dots, \mathbf{x}^n\}$, where each $\mathbf{x} = \{x_1, \dots, x_T\}$ is an observed sequence, an RNN models a density over the space of possible sequences $p(\mathbf{x})$ and is trained to maximize the log-likelihood of the observed data $\mathcal{L} = \sum_{i=1}^n \log p(\mathbf{x}^i)$. RNN factorizes the probability of the sequence as

$$p(\mathbf{x}) = p(x_1)p(x_2|x_1)... = p(x_1)\prod_{t=2}^{T} p(x_t|x_{< t}).$$
 (1)

In other words, it predicts the next element in the sequence given all the previous ones. At each step, the RNN updates a hidden state h_t^f , which iteratively summarizes the sequence values seen until time t, i.e. $h_t^f = \phi_f(x_{t-1}, h_{t-1}^f)$, where f symbolizes that the network reads the sequence in the forward

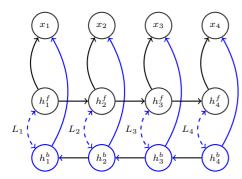


Figure 1: The forward and the backward networks predict the sequence $\{x_1,...,x_4\}$ independently. The penalty matches the forward (or a parametric function of the forward) and the backward hidden states. The forward network receives the gradient signal from the log-likelihood objective as well as L_i between states that predict the same token. The backward network is trained only by maximizing the data log-likelihood. During the evaluation part of the network colored with blue is discarded. The cost L_i is either a Euclidean distance or a learned metric $||g(h_i^f) - h_i^b||_2$ with an affine transformation g. Best viewed in color.

direction, and ϕ_f is typically a non-linear function such as an LSTM [9] cell. The prediction of x_t is performed using another non-linear transformation on top of h_t^f , i.e. $p_f(x_t|x_{< t}) = \psi_f(h_t^f)$. Therefore, h_t^f summarizes the information about the past in the sequence. The basic idea of our approach is to promote h_t^f to contain information that is useful to predict x_t but also compatible with the remaining upcoming symbols in the sequence. We run another network that predicts the sequence in reverse. Specifically, it updates its hidden state according to $h_t^b = \phi_b(x_{t+1}, h_{t+1}^b)$, and predicts $p_b(x_t|x_{>t}) = \psi_b(h_t^b)$ only using information about the future of the sentence. Then, we penalize the forward and backward hidden states for being far away according to some metric (see Fig. 1)

$$L_t(\mathbf{x}) = d_t \left(g(h_t^f), h_t^b \right), \tag{2}$$

where the dependence on ${\bf x}$ is implicit in the definition of h_t^f , h_t^b , and the loss d is the L2 loss. We introduce a class of functions g, where g can either be an identity matrix or a parametrized function. In our case, g is either an identity or a parametrized affine transformation. As we have shown experimentally, the affine transformation gives the model more flexibility and therefore leads to better results as shown in Section 4. The total loss incurred by the model for a sequence ${\bf x}$ is a weighted sum of the forward and backward negative log-likelihoods and the penalty term:

$$L(\mathbf{x}) = -\log p_f(\mathbf{x}) - \log p_b(\mathbf{x}) + \alpha \sum_t L_t(\mathbf{x}), \quad (3)$$

where α controls the importance of the penalty term. In our work we propagate the gradient of the penalty term through the forward network only.

The proposed method can be easily extended to the conditioned generation case. The hidden state transition is modified as

$$h_t^{\{f,b\}} = \phi_f \left(x_{t-1}, \left[h_{t-1}^{\{f,b\}}, c \right] \right),$$
 (4)

where c is task-dependent context information, the summarization of the input. The context c is usually the attention over the input sequence.

2.1. Regularization Loss

We first started experimenting with L2 loss to match the forward and backward hidden states. This gave us some improvements, however, we found this loss to be too strict and did not allow enough flexibility for the model to generate slightly different forward and backward hidden states. Therefore, we experimented with a parametric function to match the forward hidden and backward states. In this case, we simply used a parametric affine transformation that allows the forward path to not exactly match the backward path, but it merely allows the forward hidden states to contain the information about the backward hidden states. Experimentally, we found that a parametric loss gave our model big improvements for the conditional speech-to-text generation task. To be more specific, we first used L2 regularization term $d_t(h_t^f, h_t^b) = \left| \left| h_t^f - h_t^b \right| \right|_2$. The parametric regularization term we used is $d_t(h_t^f, h_t^b) = \left| \left| g(h_t^f) - h_t^b \right| \right|_2$, where $g(\cdot)$ is a simple affine transformation on h_t^f .

3. Related Work

Bidirectional neural networks [12] have been used as powerful feature extractors for sequence tasks. At each time step, the network makes use of both the information from past and future to perform the prediction. In other words, bidirectional RNNs have access to larger contexts, therefore act as better feature extractors than uniderictional ones. Unfortunately, they are almost only used for classification and feature extraction rather than generation. One of the reasons being that it is not trivial to detect the end of the sequence for a generation task if the forward and backward generations do not agree.

Bidirectional RNNs can also be seen as performing regularization for sequence tasks, which we have discussed in the earlier section 1. There have been many attempts on regularizing RNNs. We list some of the most influential ideas in this section.

One of the most popular methods for regularization of neural networks is dropout [13]. It is usually applied to feed-forward networks, and it is not straightforward to translate this to RNNs due to the recurrent connections. There have been several attempts in applying dropout to RNNs. Some works proposed (for example, [14]) to drop the feed-forward connections only, and several works proposed [15, 16] solutions allowing to drop the recurrent connections. The approach of Zoneout [22] modifies the hidden state to regularize the network. This technique randomly skips recurrent connections. This is equivalent to creating an ensemble of different length recurrent networks.

Exposure bias is a known issue for training sequence generation tasks. Overcoming exposure bias also helps with regularization, as it is easier for the network to memorize smaller chunks of sequences where it does not have to learn the underlying features, and since it is much more difficult for it to memorize longer sequences, that it helps to encourage the model to learn the underlying structure of the sequence. This implicitly helps with regularization of RNN training. Scheduled Sampling [17] is a popular RNN training method that helps to overcome exposure bias problem in sequence generation. During training, the generative RNN is fed with either a ground-truth or a generated input chosen with a sampling probability

that is annealed during the training procedure. Although this method works well in practice, [18] shows that the proposed loss is inconsistent in theory. Professor Forcing [19] is another attempt to solve the exposure bias problem using adversarial training [20]. Professor Forcing ensures that the distribution of the sampled output is similar to the teacher forcing output.

Other methods proposed to help with regularization of RNN training is to constraint the hidden states in RNNs. The work [21] introduces a "norm stabilization" regularization term that ensures that the consecutive hidden states of an RNN have similar Euclidean norm. Other RNN regularization methods include the weight noise [23], gradient clipping [8], gradient noise [24].

In comparison to the methods we discussed earlier, our model targets a particular type of regularization, which biases it towards planning for the future; and therefore could be combined with other regularization methods. Although, the inability to perform planning connected to the exposure bias problem, the TwinNet trained with the teacher forcing does not address it.

4. Experimental Setup and Results

In this section, we explore the difference in performance of the TwinNet with different loss, in this case a parametric loss and a fixed loss

We evaluated our approach on the conditioned generation for character-level speech recognition, where the model is trained to convert the speech audio signal to the sequence of characters. The forward and backward RNNs are trained as conditional generative models with soft-attention [3]. The context information c is an encoding of the audio sequence and the target sequence \mathbf{x} is the corresponding character sequence. We evaluate our model on the Wall Street Journal (WSJ) dataset closely following the setting described in [25]. We use 40 melfilter bank features with delta and delta-deltas with their energies as the acoustic inputs to the model, these features are generated according to the Kaldi s5 [26] recipe. The resulting input feature dimension is 123.

We observe the Character Error Rate (CER) for our validation set, and we early stop on the best CER observed so far. We report CER for both our validation and test sets. For all our models and the baseline, we pretrain the model for 1 epoch, we then let the context window look freely and perform main training for 15 epochs, we also then train with 2 different annealed learning rate for 3 epochs each. We use the AdaDelta optimizer for training. We weight the penalty by 1.0, 0.5, 0.25, and 0.1 (hyper-parameter α) and select the best one according to the CER on the validation set.

We summarize our findings in Table 1. The learned metric shows the best performance. We decode from the network without any external language model to emphasize the role of the proposed regularizer. Our model shows relative improvement of 12% comparing to the baseline.

5. Conclusion and Discussion

We present a generative recurrent model which is regularized to anticipate the future states computed via a second network running in the opposite direction. The experimental results show that the proposed regularization methods perform well.

The computation complexity of this is double of the unidirectional RNN for the decoder. However, for the conditioned

Table 1: Average character error rate (CER%) on WSJ dataset.

Experiment	Beam size	Test, %	Valid, %
Baseline	10	6.8	9.0
+ Twin (L2)	10	6.6	8.7
+ Twin (parametric)	10	6.2	8.4
Baseline	1	7.6	8.8
+ Twin (L2)	1	7.3	8.4
+ Twin (parametric)	1	6.7	9.2

case the encoder RNN is much larger than the decoder. Therefore, the additional time for training is negligible. The decoding speed stays the same since the second network is discarded for evaluation.

The future work includes more detailed exploration and visualization of the regularizer to understand better its internals. Other directions include experimental evaluation on different tasks and datasets.

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¹The best hyperparameter was 0.5.

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