Backbone Language Modeling for Constrained Sentence Generation

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Abstract

Recent language models, especially those based on recurrent neural networks (RNNs), make it possible to generate natural language from a learned probability. Language generation has wide applications including machine translation, summarization, question answering, conversation systems, etc. Existing methods typically learn a joint probability of words conditioned on additional information, which is (either statically or dynamically) fed to RNN's hidden layer. In many applications, we are likely to impose hard constraints on the generated texts, i.e., a particular word must appear in the sentence. Unfortunately, existing methods could not solve this problem. In this paper, we propose a backbone language model (backbone LM) for constrained language generation. Provided a specific word, our model generates previous words and future words simultaneously. In this way, the given word could appear at any position in the sentence. Experimental results show that the generated texts are coherent and fluent.

1 Introduction

Language modeling is aimed at minimizing the joint probability of a corpus. It has long been the core of natural language processing (NLP) [8], and has inspired a variety of other models, e.g., the n-gram model, smoothing techniques [4], as well as various neural networks for NLP [2, 6, 17]. In particular, the renewed prosperity of neural models has made groundbreaking improvement in many tasks, including language modeling *per se* [2], part-of-speech tagging, named entity recognition, semantic role labeling [17], etc.

The recurrent neural network (RNN) is a prevailing class of language models; it is suitable for modeling time-series data (e.g., a sequence of words) by its iterative nature. An RNN usually keeps one or a few hidden layers; at each time slot, it reads a word, and changes its state accordingly. Compared with traditional n-gram models, RNNs are more capable of learning long range features—especially with long short term memory (LSTM) units [7] or gated recurrent units (GRU) [5]—and hence are better at capturing the nature of sentences. On such a basis, it is even possible to generate a sentence from an RNN language model, which has wide applications in NLP, including machine translation [15], abstractive summarization [13], question answering [19], and conversation systems [18]. The sentence generation process is typically accomplished by choosing the most likely word at a time, conditioned on previous words as well as additional information depending on the task (e.g., the vector representation of the source sentence in a machine translation system [15]).

In many scenarios, however, we are likely to impose constraints on the generated sentences. For example, a question answering system may involve analyzing the question and querying an existing knowledge base, to the point of which, a candidate answer is at hand. A natural language generator is then supposed to generate a sentence, coherent in semantics, containing the candidate answer. Unfortunately, using existing language models to generate a sentence with a given word is non-trivial: adding additional information [16, 19] about a word does not guarantee that the wanted word will appear; generic probabilistic samplers (e.g., Markov chain Monte Carlo methods) hardly applies to RNN language models[1]; setting an arbitrary word to be the wanted word damages the fluency of a sentence; imposing the constraint on the first word restricts the form of generated sentences.

In this paper, we propose a novel backbone language model (backbone LM) to tackle the problem of constrained natural language generation. Rather than generate a sentence from the first word to the last in sequence as in traditional models, we use an RNN to generate previous words and subsequent words simultaneously conditioned on the given word, with two different output layers; the hidden layer is shared among the two output layers, so that each is aware of the other's state during sentence generation. The generative process terminates when both sides have generated a special token, <eos> (end of sequence). In this way, our model is complete in theory for generating a sentence with a wanted word, which can appear at an arbitrary position in the sentence.

The rest of this paper is organized as follows. Section 2 reviews existing language models and natural language generators. Section 3 describes the proposed backbone language model in detail. Section 4 presents experimental results. Finally, we have conclusion in Section 5.

2 Background and Related Work

2.1 Language Modeling

Given a corpus $\boldsymbol{w} = w_1, \cdots, w_m$, language modeling aims to minimize the joint distribution of $\boldsymbol{w}$, i.e. $p(\boldsymbol{w})$. Inspired by the observation that people always say a sentence from the beginning to the end, we would like to decompose the joint probability as[2]

$$p(\boldsymbol{w}) = \prod_{t=1}^{m} p(w_t|\boldsymbol{w}_1^{t-1}) \tag{1}$$

Parameterizing by multinomial distributions, we need to further simplify the above equation in order to estimate the parameters. Imposing a Markov assumption—a word is only dependent on previous $n-1$ words and independent of its position—results in the classic n-gram model, where the joint probability is given by

$$p(\boldsymbol{w}) \approx \prod_{t=1}^{m} p\left(w_t \middle| \boldsymbol{w}_{t-n+1}^{t-1}\right) \tag{2}$$

[1]With recent efforts in [3].

[2] $w_1, w_2, \cdots, w_t$ is denoted as $\boldsymbol{w}_1^t$ for short.

To mitigate the data sparsity problem, a variety of smoothing methods have been proposed to better estimate the probability. We refer interested readers to textbooks like [8] for n-gram models and their variants.

Bengio et al. [2] propose to use feed-forward neural networks to estimate the probability in Equation 2. In their model, a word is first mapped to a small dimensional vector, known as an *embedding*; then a feed-forward neural network propagates information to a softmax output layer, which estimates the probability of the next word.

An recurrent neural network (RNN) can also be used in language modeling. It keeps a hidden state vector ($\boldsymbol{h}_t$ at time t), dependent on the its previous state ($\boldsymbol{h}_{t-1}$) and the current input vector $\boldsymbol{x}$, the word embedding of the current word. An output layer estimates the probability that each word occurs at this time slot. Following are listed the formulas for a vanilla RNN.[3]

$$\boldsymbol{h}_t = \mathrm{RNN}(\boldsymbol{x}_t, \boldsymbol{h}_{t-1}) = f\left(W_{\mathrm{in}}\boldsymbol{x}_t + W_{\mathrm{hid}}\boldsymbol{h}_{t-1}\right) \tag{3}$$

$$p(w_t|\boldsymbol{w}_0^{t-1}) \approx \mathrm{softmax}\left(W_{\mathrm{out}}\boldsymbol{h}_t\right) \tag{4}$$

As is indicated from the equations, an RNN provides a means of direct parametrization of Equation 1, and hence has the ability to capture long term dependency, compared with n-gram models. In practice, the vanilla RNN is difficult to train due to the *gradient vanishing or exploding* problem; long short term (LSTM) units [7] and gated recurrent units (GRU) [5] are proposed to better balance between the previous state and the current input.

2.2 Language Generation

Using RNNs to model the joint probability of language makes it feasible to generate new sentences. An early attempt generates texts by a character-level RNN language model [14]; recently, RNN-based language generation has made breakthroughs in several real applications.

The sequence to sequence machine translation model [15] uses an RNN to encode a source sentence (in foreign language) into one or a few fixed-size vectors; another RNN then decodes the vector(s) to the target sentence. This model can be viewed as a language model, conditioned on the source sentence. At each time step, the RNN predicts the most likely word as the output; the embedding of the word is fed to the input layer at next step. The process continues until the RNN generates a special symbol <eos> indicating the end of the sequence. Beam search [15] or sampling methods [16] can be used to improve the quality and diversity of generated texts.

If the source sentence is too long to fit into one or a few fixed-size vectors, an attention mechanism [1] can be used to dynamically focus on different parts of the source sentence during target generation. In other studies, Wen et al. use an RNN to generate a sentence based on some abstract representations of semantics; they feed a one-hot vector, as additional information, to the RNN's hidden layer [16]. In a question answering system, Yin et al. leverage a soft logistic switcher to either generate a word from the vocabulary or copy the candidate answer [19].

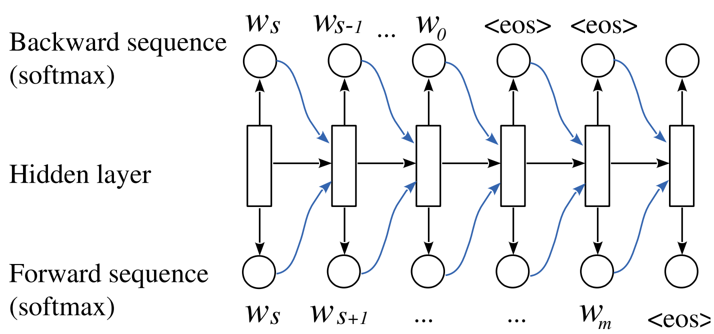

Figure 1: A backbone language model. At each time step, the input is a concatenation of word embeddings. During training, the words are those in the corpus; for generation, they are the words generated at the last time step. The embeddings are fed to a shared hidden layer. Two output layers then predict the words in the forward and backward sequences, respectively.

3 The Proposed backbone Language Model

In this part, we introduce our backbone language model in detail. The overall architecture is depicted in Figure 1.

For a sentence $\boldsymbol{w} = w_1, \cdots, w_m$, $w_s \in \boldsymbol{w}$ is chosen to split the sentence into two parts

- Forward sequence: $w_s, w_{s-1}, w_{s-2}, \cdots, w_1$ (s words)
- Backward sequence: $w_s, w_{s+1}, w_{s+2}, \cdots, w_n$ ($m - s + 1$ words)

The probability that the sentence $\boldsymbol{w}$ with the split word at position s decomposes as follows.

$$p\left(\frac{\boldsymbol{w}_s^1}{\boldsymbol{w}_s^n}\right) = \prod_{t=0}^{\max\{s,m-s+1\}-1} p\left(\frac{w_{s-t}}{w_{s+t}}\middle|\frac{\boldsymbol{w}_s^{s-t+1}}{\boldsymbol{w}_s^{s+t-1}}\right) \tag{5}$$

where the factor $p(=|=)$ refers to the conditional probability that current time step t generates w_{s-t}, w_{s+t} in the forward and backward sequences, respectively, given the middle part of the sentence, that is, $w_{s-t+1} \cdots w_s \cdots w_{s+t-1}$. If one part has generated <eos>, we pad the special symbol <eos> for this sequence until the other part also terminates.

To parametrize Equation 12, we also leverage a recurrent neural network (RNN) following the studies introduced in Section 2. Concretely,

$$p\left(\frac{w_{s-t}}{w_{s+t}}\middle|\frac{\boldsymbol{w}_s^{s-t+1}}{\boldsymbol{w}_s^{s+t-1}}\right) = p^{(\mathrm{bw})}\left(w_{s-t}|\boldsymbol{h}_t\right) \cdot p^{(\mathrm{fw})}\left(w_{s+t}|\boldsymbol{h}_t\right) \tag{6}$$

$$= \mathrm{softmax}\left(W_{\mathrm{out}}^{(\mathrm{bw})}\boldsymbol{h}_t\right) \cdot \mathrm{softmax}\left(W_{\mathrm{out}}^{(\mathrm{fw})}\boldsymbol{h}_t\right) \tag{7}$$

Here, $\boldsymbol{h}_t$ is the hidden layer, which is dependent on the previous state $\boldsymbol{h}_{t-1}$ and current

[3] W's refer to weights; biases are omitted.

input word embeddings $\tilde{\boldsymbol{x}} = \left[\boldsymbol{x}_t^{(\mathrm{fw})}; \boldsymbol{x}_t^{(\mathrm{bw})}\right]$. We use GRU [5] in our model, given by

$$\boldsymbol{r} = \sigma(W_r\tilde{\boldsymbol{x}} + U_r\boldsymbol{h}_{t-1}) \tag{8}$$
$$\boldsymbol{z} = \sigma(W_z\tilde{\boldsymbol{x}} + U_z\boldsymbol{h}_{t-1}) \tag{9}$$
$$\tilde{\boldsymbol{h}} = \tanh\left(W_x\tilde{\boldsymbol{x}} + U_x(\boldsymbol{r} \circ \boldsymbol{h}_{t-1})\right) \tag{10}$$
$$\boldsymbol{h}_t = (1-\boldsymbol{z}) \circ \boldsymbol{h}_{t-1} + \boldsymbol{z} \circ \tilde{\boldsymbol{h}} \tag{11}$$

where $\sigma(\cdot) = \frac{1}{1+e^{(-\cdot)}}$; $\circ$ denotes element-wise product. $\boldsymbol{r}$ and $\boldsymbol{z}$ are known as gates, $\tilde{h}$ the candidate hidden state at the current step.

Training Criteria. If we assume w_s is always given, the training criterion shall be the cross-entropy loss of all words in both chains except w_s. We can alternatively penalize the split word w_s in addition, which will make it possible to generate an entire sentence without w_s being provided. We do not deem the two criteria differ significantly, and adopt the latter one in our experiments.

Both labeled and unlabeled datasets suffice to train the backbone language model. If a sentence is annotated with a specially interesting word w_s, it is natural to use it as the split word. For an unlabeled dataset, we can randomly choose a word as w_s.

Notice that Equation 12 gives the joint probability of a sentence $\boldsymbol{w}$ with a particular split word w_s. To compute the probability of the sentence, we shall marginalize out different split words, i.e.,

$$p(\boldsymbol{w}) = \sum_{s=1}^{m} \prod_{t=0}^{\max\{s, m-s+1\}-1} p\left(\left.\frac{w_{s-t}}{w_{s+t}}\,\right|\, \frac{\boldsymbol{w}_s^{s-t+1}}{\boldsymbol{w}_s^{s+t-1}}\right) \tag{12}$$

In our scenarios, however, we always assume that w_s is given in practice. Hence, different from language modeling in general, the joint probability of a sentence is not the number one concern in our model.

4 Evaluation

4.1 The Dataset and Settings

To evaluate the backbone LM, we prefer a vertical domain corpus with interesting application nuggets instead of using generic texts like Wikipedia. In particular, we chose to build a language model upon scientific paper titles on arXiv.[4] Building a language model on paper titles may help researchers when they are preparing their drafts. Provided a topic (designated by a given word), constrained natural language generation could also acts as a way of brainstorming.[5]

We crawled computer science-related paper titles from January 2014 to November 2015.[6] Each word was decapitalized, but no stemming was performed. Rare words ($\leq$ 10 occurrences) were grouped as a single token, <unk>, (referring to *unknown*). We removed non-English

[4] http://arxiv.org
[5] The title of this paper is NOT generated by our model.
[6] Crawled from http://http://dblp.uni-trier.de/db/journals/corr/

Method	Overall PPL	First word's PPL	Subsequent words' PPL
Sequential LM	152.2	403.3	137.0
Backbone LM	187.0	539.4	165.5
Backbone LM (w_s oracle)	**97.5**	–	–

Table 1: Perplexity (PPL) of both sequential and backbone LMs.

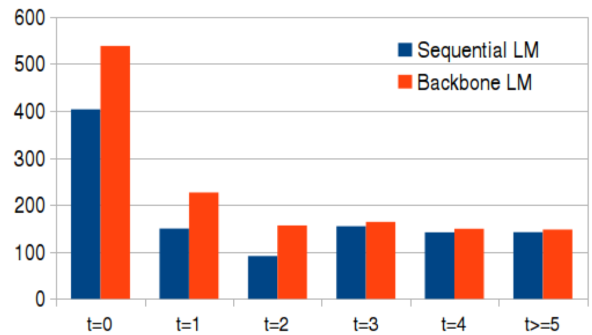

Figure 2: Perplexity versus word position t, which is the distance between the current word and the first / split word in sequential / backbone LMs, respectively.

titles, and those with more than three <unk>'s. We notice that <unk>'s may appear frequently, but a large number of them refer to acronyms, and thus are mostly consistent in semantics.

Currently, we have 25,000 samples for training, 1455 for validation and another 1455 for testing; our vocabulary size is 3380. Our network[7] has one hidden layer with 200 units; the embeddings are 50 dimensional, initialized randomly. These hyperparameters were set empirically. To train the model, we used standard backpropagation (batch size 50) with element-wise gradient clipping. Following [9], we applied rmsprop for optimization (embeddings excluded), which is more suitable for training RNNs than naïve stochastic gradient descent, and less sensitive to hyperparameters compared with momentum methods. Initial weights were uniformly sampled from $[-0.08, 0.08]$. Initial learning rate was 0.002, with a multiplicative learning rate decay of 0.97, moving average decay 0.99, and a damping term $\epsilon = 10^{-8}$. As word embeddings are sparse in use [12], they were optimized asynchronously by pure stochastic gradient descent with learning rate being divided by $\sqrt{\epsilon}$.

4.2 Results

We first use the perplexity measure to evaluate the learned language model. Perplexity is defined as $2^{-\ell}$, where ℓ is the log-likelihood (with base 2), averaged over each word.

$$\ell = \frac{1}{m}\sum_{i=1}^{m} \log p(w_i)$$

Note that <eos> is not considered when we compute the perplexity.

Table 1 summarizes the perplexity of both sequential LM and backbone LMs. We further plot the perplexity of a word with respect to its position when generation (Figure 2). In the

[7]The implementation was based on [10, 11].

Given word	Sequential LM	Backbone LM
convolutional	**convolutional** neural networks for <unk> - based image retrieval	**convolutional** neural networks for <unk> classification
tracking	**tracking** <unk> using convolutional neural networks	convolutional neural networks for object **tracking** and <unk>
systems	**systems** of <unk> - based cyber - physical systems with probabilistic <unk>	mult - output feedback control for <unk> **systems**
models	**models** and <unk> linear codes over finite fields	gaussian graphical **models**
:	**:** a <unk> - based approach for <unk> <unk> migration in cloud	<unk> **:** a <unk> - based approach to traffic analysis
to	**to** <unk> a pair - once game perspective	an <unk> approach **to** <unk> the <unk> problem

Table 2: Generated texts by the sequential and backbone LMs, with the word in bold being provided.

sequential LM, the hidden layer is 100 dimension, which is half of our model's. This makes a fair comparison because backbone LM should simultaneously learn implicit forward and backward LMs, which are completely different. Hence our hidden layer is twice as large as a one-directional LM.

From the results in Table 1, we have the following observations.

- Our model yields a larger perplexity than a sequantial LM. This makes much sense because randomly choosing a split word increases uncertainly. It should be also noticed that, in our model, the perplexity reflects the probability of a sentence with a specific split word, whereas the perplexity of the sequential LM assesses the probability of a sentence itself.

- Randomly choosing a split word cannot make use of position information in sentences. The titles of scientific papers, for example, oftentimes follow templates, which may begin with "*<unk> : an approach*" or "*<unk> - based approach.*" Therefore, sequential LM yields low perplexity when generating the second and third words ($t = 1, 2$), but such information is smoothed out in our backbone LM because the split word is chosen randomly.

- When t is large (e.g., $t \geq 3$), backbone LM yields almost the same perplexity as sequential LM. The long term behavior of backbone LM is similar to sequential LM, if we rule out the impact of choosing random words, which indicates that feeding two words' embeddings to the hidden layer does not add to confusion.

- In our applications, w_s is always given, which indicates $p(w_s) = 1$ (denoted as w_s *oracle* in Table 1). This reduces the perplexity to 97.3, showing that our backbone LM can well make use of such information that some word should appear in the generated text.

We then generate new paper titles from the learned language model with a specific word given, which can be thought of, in the application, as a particular interest of research topics. Table 2 illustrates examples generated from both sequential LM and our model. As we see, for words that are common at the beginning of a paper title—like the adjective *convolutional* and gerund *tracking*—both sequential LM and backbone LM can generate reasonable results. For plural nouns like *systems* and *models*, the titles generated by sequential LM are somewhat influent, but they basically comply with grammar rules. For words that are unlikely to be the initial word, sequential LM fails to generate grammatically correct sentences. By contrast, the backbone LM can handle all these scenarios flexibly, regardless of the position of the given word. In addition, empirical analysis shows no or little fluency degradation by simultaneously forward and backward generation.

5 Conclusion

In this paper, we proposed a backbone language model (backbone LM) for constrained natural language generation using a recurrent neural network. Given a particular word, our model can generate previous words and future words simultaneously. Experiments show a similar perplexity to sequential LM, if we disregard the perplexity introduced by random splitting. Our case study demonstrates that backbone LM can generate coherent, fluent sentences; that the given word can appear at any position in the sentence.

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