Language Modeling with Gated Convolutional Networks

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Abstract

The pre-dominant approach to language modeling to date is based on recurrent neural networks. In this paper we present a convolutional approach to language modeling. We introduce a novel gating mechanism that eases gradient propagation and which performs better than the LSTM-style gating of Oord et al. (2016b) despite being simpler. We achieve a new state of the art on WikiText-103 as well as a new best single-GPU result on the Google Billion Word benchmark. In settings where latency is important, our model achieves an order of magnitude speed-up compared to a recurrent baseline since computation can be parallelized over time. To our knowledge, this is the first time a non-recurrent approach outperforms strong recurrent models on these tasks.

1. Introduction

Statistical language models estimate the probability distribution of a sequence of words. This amounts to modeling the probability of the next word given the preceding words, i.e.

$$P(w_0, \dots, w_N) = P(w_0) \prod_{i=1}^{N} P(w_i | w_0, \dots, w_{i-1}),$$

where w_i are discrete word indices in a vocabulary. Language models are a critical part of systems for speech recognition (Yu & Deng, 2014) as well as machine translation (Koehn, 2010).

Recently, neural networks (Bengio et al., 2003; Mikolov et al., 2010; Jozefowicz et al., 2016) have been shown to outperform classical *n-gram* language models (Kneser & Ney, 1995; Chen & Goodman, 1996). Classical language models suffer under data sparsity that makes it difficult to represent large contexts and therefore long-range dependencies. Neural language models tackle this issue by embedding words in continuous space over which a neural network is applied. The current state of the art to language modeling is based on long short term memory networks (LSTM; Hochreiter et al., 1997) which can model potentially arbitrarily long dependencies.

In this paper, we introduce gated convolutional networks and apply them to language modeling. Convolutional networks can be stacked to represent large context sizes and extract hierarchical features over larger and larger contexts with more abstractive features (LeCun & Bengio, 1995). This allows to model long-term dependencies by applying $\mathcal{O}(\frac{N}{k})$ operations over a context of size N and kernel width k. In contrast, recurrent networks view the input as a chain structure and therefore require a linear number $\mathcal{O}(N)$ of operations.

Analyzing the input hierarchically bears resemblance to classical grammar formalisms which build syntactic tree structure of increasing granuality, e.g., sentences consist of noun phrases and verb phrases each comprising further internal structure (Manning & Schütze, 1999; Steedman, 2002). Hierarchical structure also eases learning since the number of non-linearities for a given context size is reduced compared to a chain structure, thereby mitigating the vanishing gradient problem (Glorot & Bengio, 2010).

Modern hardware is well suited to models that are highly parallelizable. In recurrent networks, the next output depends on the previous hidden state which does not enable parallelization over the elements of a sequence. Convolutional networks are very amenable to this computing paradigm since the computation of all input words can be performed simultaneously (§2).

Gating has been shown to be essential for recurrent neural networks to reach state-of-the-art performance (Jozefowicz et al., 2016). Our gated linear units reduce the vanishing gradient problem for deep architectures by providing a linear path for the gradients while retaining non-linear capabilities (§3)

We run experiments in a single GPU setup and show that gated convolutional networks outperform other recently published language models such as LSTMs trained in a similar setting on the Google Billion Word Benchmark (Chelba et al., 2013). We also evaluate the ability of our models to deal with long-range dependencies on the WikiText-103 benchmark for which the model is conditioned on an entire paragraph rather than a single sentence and we achieve a new state-of-the-art on this dataset (Merity et al., 2016). Finally, we show that gated linear units achieve higher accuracy and converge faster than the LSTM-style gating of Oord et al. (2016; §4, §5)

2. Approach

In this paper we introduce a new neural language model that replaces recurrent connections typically used in recurrent networks with gated temporal convolutions. Neural language models (Bengio et al., 2003) produce a representation $\mathbf{H} = [\mathbf{h}_0, \dots, \mathbf{h}_N]$ of the context for each word $w_0, \dots, w_N$ to predict the next word $P(w_i|\mathbf{h}_i)$. Recurrent neural networks compute $\mathbf{H}$ through a recurrent function $\mathbf{h}_i = f(\mathbf{h}_{i-1}, w_{i-1})$ which is an inherently sequential process that cannot be parallelized over i.[1]

The proposed approach convolves the inputs to obtain $\mathbf{H} = f * w$ and therefore has no temporal dependencies which makes it easier to parallelize over the individual words of a sentence. This process will compute each context as a function of a number of preceding words. Compared to recurrent networks, the context size is finite but we will demonstrate that we can represent large enough contexts to perform well in practice (§5).

Figure 1 illustrates the model architecture. Words are represented by a vector embedding stored in a lookup table $\mathbf{D}^{|\mathcal{V}|\times m}$ where $|\mathcal{V}|$ is the number of words in the vocabulary and m is the embedding size. The input to our model is a sequence of words $w_0, \dots, w_N$ which are represented by word embeddings $\mathbf{E} = [\mathbf{D}_{w_0}, \dots, \mathbf{D}_{w_N}]$. We compute the hidden layers $h_0, \dots, h_L$ as

$$h_l(\mathbf{X}) = (\mathbf{X} * \mathbf{W} + \mathbf{b}) \otimes \sigma(\mathbf{X} * \mathbf{V} + \mathbf{c}) \quad (1)$$

where $\mathbf{X} \in \mathbb{R}^{N\times m}$ is the input of layer h_l, that is either word embeddings or the outputs of previous layers, $\mathbf{W} \in \mathbb{R}^{k\times m\times n}$, $\mathbf{b} \in \mathbb{R}^n$, $\mathbf{V} \in \mathbb{R}^{k\times m\times n}$, $\mathbf{c} \in \mathbb{R}^n$ are learned parameters, σ is the sigmoid function and $\otimes$ is the element-wise product between matrices.

When convolving inputs, we take care that $\mathbf{h_i}$ does not contain information from future words. We address this by shifting the convolution inputs to prevent the kernels from seeing future context (Oord et al., 2016a). Specifically, we zero-pad the beginning of the sequence by $k/2$ elements, assuming the first input element is the beginning of sequence marker which we do not predict, where k is the width of the kernel.

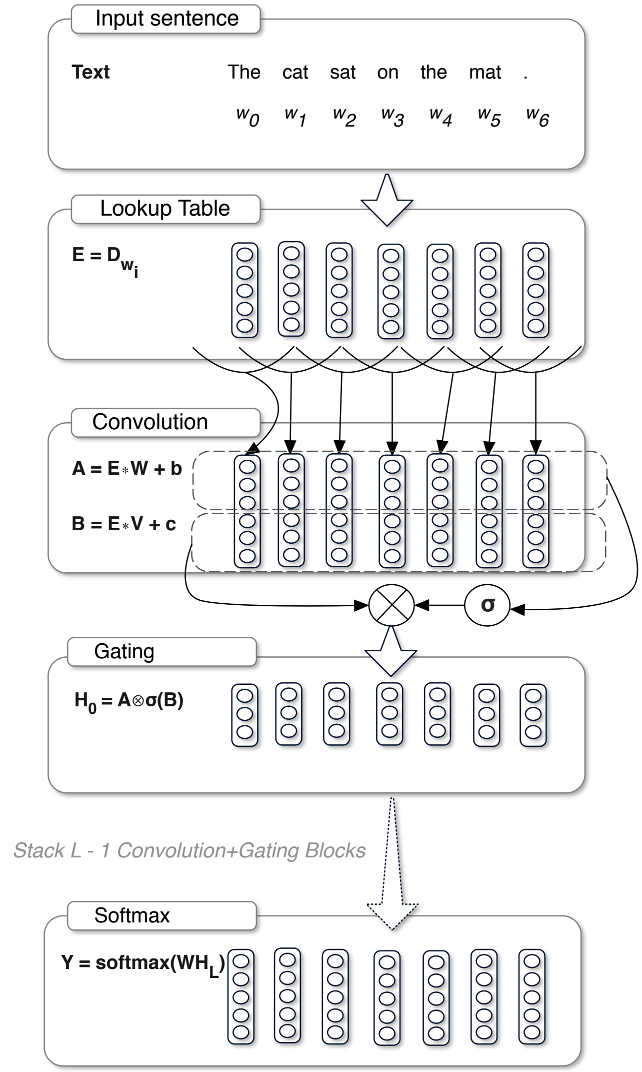

Figure 1. Architecture of the gated convolutional network for language modeling.

The output of each layer is a linear projection $\mathbf{X} * \mathbf{W} + \mathbf{b}$ modulated by the gates $\sigma(\mathbf{X} * \mathbf{V} + \mathbf{c})$. Similar to LSTMs, the gates multiply each element of the matrix $\mathbf{X} * \mathbf{W} + \mathbf{b}$ and control the information passed in the hierarchy. We dub this gating mechanism Gated Linear Units (GLU). Stacking multiple layers on top of the input $\mathbf{E}$ gives a representation of the context for each word $\mathbf{H} = h_L \circ \dots \circ h_0(\mathbf{E})$. We wrap the convolution and the gated linear unit in a pre-activation residual block that adds the input of the block to the output (He et al., 2015a). The blocks have a bottleneck structure for computational efficiency and each block has up to 5

[1] Parallelization is usually done over multiple sequences instead.

layers.

The simplest choice to obtain model predictions is to use a softmax layer, however, this choice is often computationally inefficient for large vocabularies and an approximation such as noise contrastive estimation (Gutmann & Hyvärinen) or hierarchical softmax (Morin & Bengio, 2005) is preferred. We choose an improvement of the latter known as *adaptive softmax* which assigns higher capacity to very frequent words and lower capacity to rare words (Grave et al., 2016a). This results in lower memory requirements as well as faster computation, both at training and at test time.

3. Gating Mechanisms

Gating mechanisms control the path through which information flows in the network and have proven to be useful for recurrent neural networks (Hochreiter & Schmidhuber, 1997). LSTMs enable long-term memory via a separate cell controlled by *input* and *forget* gates. This allows information to flow unimpeded through potentially many timesteps. Without these gates information could easily vanish through the transformations of each timestep. In contrast, convolutional networks do not suffer from the same kind of vanishing gradient and we find experimentally that they do not require forget gates.

Therefore, our gated linear units only possess output gates which allow the network to control which information should be propagated in the hierarchy of layers. We show this mechanism to be useful for language modeling as it allows the model to select which words or features are relevant to predict the next word. In parallel to our work, Oord et al. (2016b) have shown the effectiveness of an LSTM-style mechanism of the form $\tanh(\mathbf{X} * \mathbf{W} + \mathbf{b}) \otimes \sigma(\mathbf{X} * \mathbf{V} + \mathbf{c})$ for the convolutional modeling of images.

Gated linear units are a simplified gating mechanism based on the work of Dauphin & Grangier (2015) for non-deterministic gates that reduce the vanishing gradient problem by having linear units couple to the gates. This retains the non-linear capabilities of the layer while allowing the gradient to pass without scaling through the linear unit. The gradient of the LSTM-style gating of Oord et al. (2016b) is

$$\nabla[\tanh(\mathbf{X}) \otimes \sigma(\mathbf{X})] = \tanh'(\mathbf{X})\nabla\mathbf{X} \otimes \sigma(\mathbf{X}) + \sigma'(\mathbf{X})\nabla\mathbf{X} \otimes \tanh(\mathbf{X}). \quad (2)$$

Notice that it gradually vanishes as we stack layers because of the downscaling factors $\tanh'(\mathbf{X})$ and $\sigma'(\mathbf{X})$. In contrast, the gradient of the gated linear unit

$$\nabla[\mathbf{X} \otimes \sigma(\mathbf{X})] = \nabla\mathbf{X} \otimes \sigma(\mathbf{X}) + \mathbf{X} \otimes \sigma'(\mathbf{X})\nabla\mathbf{X} \quad (3)$$

has a path $\nabla\mathbf{X} \otimes \sigma(\mathbf{X})$ without downscaling for the activated gating units in $\sigma(\mathbf{X})$. This can be seen as a multiplicative skip connection which helps gradient flow through the layers. We find that gated linear units perform better in practice compared to LSTM-style gating which we dub gated tanh units (GTU; §5).

4. Experimental Setup

4.1. Datasets

We report results on two public large-scale language modeling datasets. First, the Google Billion Word dataset (GBW; Chelba et al., 2013) is considered one of the largest language modeling datasets with close to one billion tokens and a vocabulary of over 800K words. In this dataset, words appearing less than 3 times are replaced with a special unknown symbol. The data is based on an English corpus of $30,301,028$ sentences whose order has been shuffled. Second, WikiText-103 is a smaller dataset of over 100M tokens with a vocabulary of about 200K words (Merity et al., 2016). Different to GBW, sentences are consecutive which allows to condition the model on larger contexts than single sentences. For both datasets, we add a beginning of sequence marker <S > at the start of each line and an end of sequence marker </S> at the end of each line. On the Google Billion Word corpus each sequence is a single sentence, while on WikiText-103 a sequence is an entire paragraph. The model sees <S> and </S > as input but only predicts the end of sequence marker </S>. We evaluate models by computing the perplexity $e^{\frac{1}{N}\sum_i^N -\log p(w_i|\ldots,w_{i-1})}$ on the standard held out test portion of each dataset.

4.2. Training

We found Nesterov's momentum (Sutskever et al., 2013) to be worth the over-head compared to standard stochastic gradient descent. The cost in terms of memory is storing another vector of the size of the parameters but it increases the speed of convergence significantly with minimal computational over-head. The speed of convergence was further increased by clipping the gradients to 0.1 (Pascanu et al., 2013) and weight normalization (Salimans & Kingma, 2016). The combination of these methods allowed us to achieve stable and fast convergence with comparatively large learning rates such as 1.

Pascanu et al. (2013) argue for gradient clipping because it prevents the gradient explosion problem that characterizes RNNs. We argue that gradient clipping is not tied to RNNs since it can be derived from the more general concept of trust region methods. Gradient clipping is found using a

Model	Test PPL	Hardware
Sigmoid-RNN-2048 (Ji et al., 2015)	68.3	1 CPU
Interpolated KN 5-Gram (Chelba et al., 2013)	67.6	100 CPUs
Sparse Non-Negative Matrix LM (Shazeer et al., 2014)	52.9	-
RNN-1024 + MaxEnt 9 Gram Features (Chelba et al., 2013)	51.3	24 GPUs
LSTM-2048-512 (Jozefowicz et al., 2016)	43.7	32 GPUs
2-layer LSTM-8192-1024 (Jozefowicz et al., 2016)	30.6	32 GPUs
LSTM-2048 (Grave et al., 2016a)	43.9	1 GPU
2-layer LSTM-2048 (Grave et al., 2016a)	39.8	1 GPU
GCNN-13	38.1	1 GPU

Table 1. Results on the Google Billion Word test set.

spherical trust region

$$\Delta\theta^* = \underset{\text{s. t. } \|\Delta\theta\| \leq \epsilon}{\operatorname{argmin}} \; f(\theta) + \nabla f^T \Delta\theta$$
$$= -\max(\|\nabla f\|, \epsilon)\frac{\nabla f}{\|\nabla f\|}. \tag{4}$$

Our experiments run significantly faster with the use of gradient clipping even though we do not use a recurrent architecture.

We train on a single Tesla M40 GPU and implement our models in Torch (Collobert et al., 2011). While better performance could be achieved by training longer and on multiple GPUs, we focused on better exploring the hyper-parameter space of small models to identify a compact model with good generalization performance. This strategy is attractive to both understand architectual choices and to identify models with better efficiency at test time.

4.3. Hyper-parameters

We found good hyper-parameter configurations by cross-validation using random search on a validation set. In terms of the architecture of the model, we select the number of residual blocks between $\{1, \ldots, 10\}$, the size of the embeddings with $\{128, \ldots, 256\}$, the number of units between $\{128, \ldots, 2048\}$, the kernel width between $\{3, \ldots, 5\}$. In general, finding a good architecture is simple and the rule of thumb is that the larger the model, the better the performance. In terms of optimization, we initialize the layers of the model with the Kaiming initialization (He et al., 2015b), with the learning rate sampled uniformly in the interval $[1., 2.]$, the momentum set to 0.99 and clipping set to 0.1. Good hyper-parameter for the optimizer are quite straightforward to find and the optimal values do not seem to change very much between datasets.

5. Results

LSTMs and recurrent networks are able to capture long term dependencies and are fast becoming cornerstones in natural language processing. In this section, we compare strong LSTM and RNN models from the literature to our gated convolutional approach on two datasets.

Table 1 shows that our model outperforms all state-of-the-art approaches that have been trained on a single GPU on the Google Billion Word benchmark. Of the methods that use multiple GPUs, only the very large LSTM of Jozefowicz et al. (2016) achieves better results. However, this model was trained on 32 GPUs for 3 weeks while as our model trains on a single GPU in 2 weeks. The GCNN-13 model has 13 layers of 1268 units each and kernel width 4.

Model	Test PPL
LSTM-1024 (Grave et al., 2016b)	48.7
GCNN-8	44.9

Table 2. Results on the WikiText-103 dataset.

On Google Billion Word, the average sentence length is only 20 words which is relatively short. Next, we test on WikiText-103 to answer the question if our model can perform equally well in a setup were much larger contexts are possible. On WikiText-103, an input sequence is an entire Wikipedia article instead of an individual sentence. The results (Table 2) show that the gated convolutional model outperforms an LSTM on this problem as well. The GCNN-8 model has 8 layers with 800 units each and the LSTM has 1024 units.

5.1. Computational Efficiency

	Throughput (CPU)	Throughput (GPU)	Responsiveness (GPU)
LSTM-2048	169	45,622	2,282
GCNN-22	**179**	**45,878**	**45,878**

Table 3. Processing speed in tokens/s at test time for an LSTM with 2048 units and GCNN with 22 layers achieving 43.9 and 43.8 perplexity, respectively on Google Billion Word. The GCNN improves the responsiveness by 20 times while maintaining high throughput.

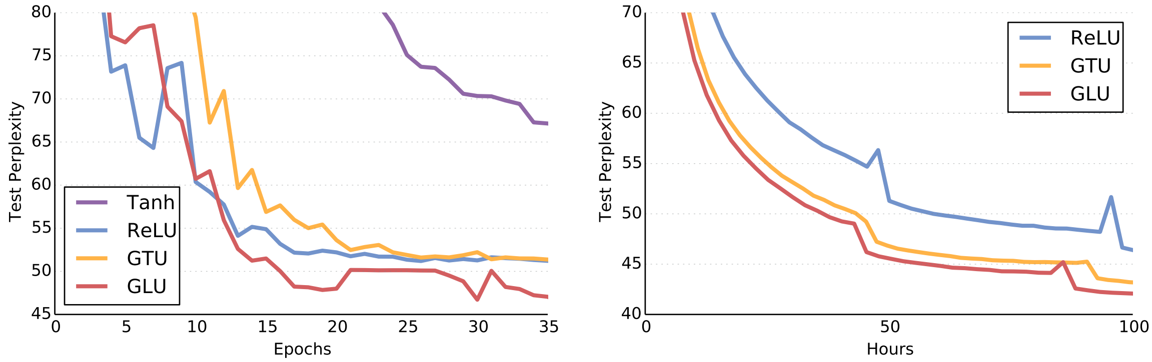

Figure 2. Learning curves on WikiText-103 (left) and Google Billion Word (right) for models with different activation mechanisms. Models with gated linear units (GLU) converge faster and to a lower perplexity.

Computational cost is an important consideration for language models. Depending on the application, there are a number of metrics to consider. We measure the *throughput* of a model as the number of tokens that can be processed per second. Throughput can be maximized by processing many sentences in parallel to amortize sequential operations. In contrast, *responsiveness* is the speed of processing the input sequentially, one token at a time. Throughput is important because it indicates the time required to process a corpus of text and responsiveness is an indicator of the time to finishing processing a sentence. A model can have low responsiveness but high throughput by evaluating many sentences simultaneously through batching. In this case, such a model is slow in finishing processing individual sentences, but can process many sentences at a good rate.

We evaluate the throughput and responsiveness for models that reach approximately 43.9 perplexity on the Google Billion Word benchmark. We consider the LSTM with 2048 units in Table 1 and a GCNN with 22 layers with Resnet blocks that have a bottleneck structure as described by (He et al., 2015a). The network has 3 bottleneck blocks of the form $128, 128, 512$ followed by a $256, 256, 512$ followed by a fully connected $1024, 1024, 2048$ block. Note that only the middle layer of these blocks is a convolution ($k = 5$). We found that this architecture is quite important to obtain good computational efficiency.

	Parameters	FLOPs/token
LSTM-2048	289M	19M
GCNN-22	**185M**	**14M**

Table 4. Number of parameters and FLOPs for the models of Figure 3. FLOPs exclude the operations required by the softmax layer which are identical.

The throughput of the LSTM is measured by using a large batch of 750 sequences of length 20, resulting in $15,000$ tokens per batch. Table 3 shows that the throughput for the LSTM and the GCNN are similar on CPU but not on GPU. The LSTM performs very well on GPU because the large batch size of 750 enables high parallelization. This is because the LSTM implementation has been thoroughly optimized and uses cuDNN while as the cuDNN implementation of convolutions is not been optimized for 1-D convolutions which we use in our model. We believe much better performance can be achieved by a more efficient 1-D cuDNN convolution. Unlike the LSTM, the GCNN can be parallelized both over sequences as well as across the tokens of each sequence. On the other hand, GCNN is 20 times faster in terms of responsiveness.

Table 4 shows that the convolutional model requires fewer parameters and floating point operations per token than a comparable LSTM.

5.2. Gating Mechanisms

In this section we compare the gated linear unit with other mechanisms as well as to models without gating. We consider the LSTM-style gating mechanism (GTU) $\tanh(\mathbf{X} * \mathbf{W} + \mathbf{b}) \otimes \sigma(\mathbf{X} * \mathbf{V} + \mathbf{c})$ of (Oord et al., 2016b) and networks that use regular ReLU or Tanh activations. Gating units add parameters and in order to make a fair comparison, we carefully cross-validate models with a comparable number of parameters. Figure 2 (left) shows that GLU networks converge to a lower perplexity than the other approaches on WikiText-103. Similar to gated linear units, the ReLU has a linear path that lets the gradients easily pass through the active units. In our experiments we observe that this translates to much faster convergence for both the ReLU and the GLU. On the other hand, neither Tanh nor GTU have a linear path and thus suffer from vanishing gradients.

Comparing the GTU and Tanh models allows us to measure the effect of gating since the Tanh model can be thought of as a GTU network with the sigmoid gating units removed. The results (Figure 2, left) show that the gating units make a vast difference. Both Tanh and GTU units suffer under vanishing gradients since in the GTU both the inputs as well as the gating units cut the gradients when the units saturate. We argue that the difference between GTU and Tanh indicates that gating units provide useful modeling capabilities. The ReLU unit is not an exact ablation of the gating units in the GLU, but it can be seen as a simplification $\text{ReLU}(\mathbf{X}) = \mathbf{X} \otimes (\mathbf{X} > 0)$ where the gates become active depending on the sign of the input. However, also in this case, GLU units lead to lower perplexity.

In Figure 2 (right) we repeat the same experiment on the larger Google Billion Words dataset. We consider a fixed time budget of 100 hours because of the considerable training time required for this task. Similar to WikiText-103 we see that gated linear units achieve the best results on this problem. There is a gap of about 5 perplexity points between the GLU and ReLU which is similar to the difference between the LSTM and RNN models measured by (Jozefowicz et al., 2016) on the same dataset.

5.3. Non-linear Modeling

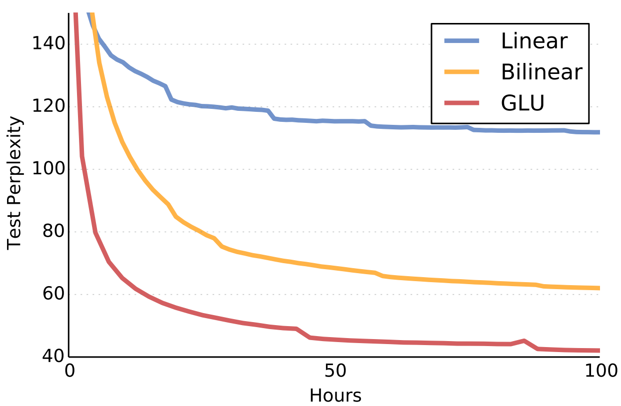

Figure 3. Learning curves on Google Billion Word for models with varying degrees of non-linearity.

The experiments so far have shown that the gated linear unit benefits from the linear path the unit provides compared to other non-linearities. Next, we compare networks with GLUs to purely linear networks and networks with bilinear layers in order to measure the impact of the non-linear path provided by the gates of the GLU. One motivation for this experiment is the success of linear models on many natural language processing tasks (Manning & Schütze, 1999).

We consider deep *linear* convolutional networks where the layers lack the gating units of the GLU and take the form $h_l(\mathbf{X}) = \mathbf{X} * \mathbf{W} + \mathbf{b}$. Stacking several layers on top of each other is simply a factorization of the model which remains linear up to the softmax, at which point it becomes log-linear. Another variation of GLUs are bilinear layers (Mnih & Hinton, 2007) which take the form $h_l(\mathbf{X}) = (\mathbf{X} * \mathbf{W} + \mathbf{b}) \otimes (\mathbf{X} * \mathbf{V} + \mathbf{c})$. This is similar to GLUs but with linear gating units instead.

Figure 3 shows that GLUs perform best, followed by bilinear layers and then linear layers. Bilinear layers improve over linear ones by more than 40 perplexity points, and the GLU improves another 20 perplexity points over the bilinear model. The linear model performs very poorly at perplexity 115 even compared to 67.6 of a Kneser-Ney 5-gram model, even though the former has access to more context. The linear gating units of the bilinear model provide a way for the model to modulate the flow of information in the network and the large reduction in perplexity shows that this is important. Surprisingly the introduction of the linear gating units is enough to allow reaching 61 perplexity on Google 1B which surpasses Kneser-Ney 5-gram models and the non-linear neural model of (Ji et al., 2015). However, the non-linear gating units of the GLU ultimately perform better.

5.4. Network Depth

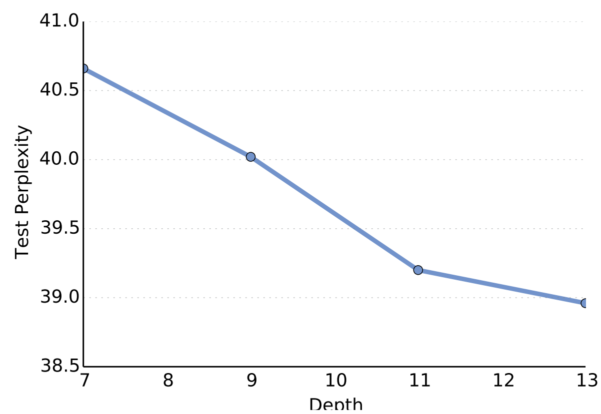

Figure 4. Impact of network depth on test perplexity for Google Billion Word. Deeper models perform better.

Next we turn to the question of how network depth effects the accuracy of our model. Figure 4 shows that perplexity on Google Billion Word improves as we increase the depth of the model. This also shows that good results are possible with a number of layers smaller than the average sentence length of 20 on GBW since we use 13 layers in this setting. The GCNN in Table 1 builds context representations by applying exactly 13 layers to each input while a recurrent model would pass information through 20 sequential layers on average on this corpus.

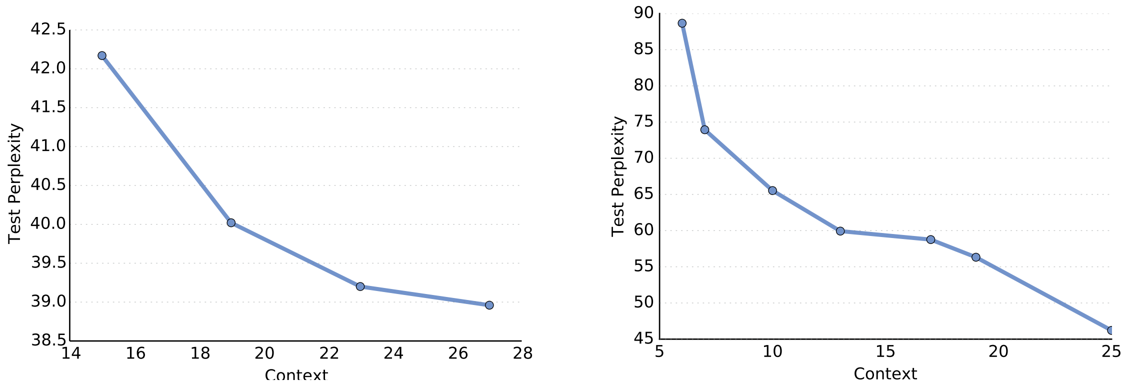

Figure 5. Test perplexity as a function of context for Google Billion Word (left) and Wiki-103 (right). We observe that models with bigger context achieve better results but the results start diminishing quickly after a context of 20.

5.5. Context Size

Figure 5 shows the impact of context size for the gated CNN. We tried different combinations of network depth and kernel widths for each context size and chose the best performing one for each size. Generally, larger contexts improve accuracy but returns drastically diminish with windows larger than 20 words, even for WikiText-103 where we may condition on an entire Wikipedia article. This means that the unlimited context offered by recurrent models is not strictly necessary for language modeling. Furthermore, this finding is also congruent with the fact that good performance with recurrent networks can be obtained by truncating gradients after only 20 timesteps using truncated back propgation through time. Figure 5 also shows that WikiText-103 benefits much more from larger context size than Google Billion Word as the performance degrades more sharply with smaller contexts. WikiText-103 provides much more context than Google Billion Word where the average sentence size is 20. However while the average size of the documents are close to 4000 tokens, we find that strong performance can be achieved with a context size as low as 30 tokens.

5.6. Training Algorithms

In this section, we perform an ablation of weight normalization and gradient clipping. We separately cross-validate the hyper-parameters of each configuration to make the comparison fair. Due to the high cost of each of these experiments we only consider a single iteration over the training data. Figure 6 shows that both methods significantly speed-up convergence. Weight normalization in particular improves the speed by over two times. This speed-up is partly due to the ability to use much larger learning rates (1 instead of 0.01) than would otherwise be possible. Both clipping and weight normalization add computational overhead but it is small compared to the large gains in convergence speed.

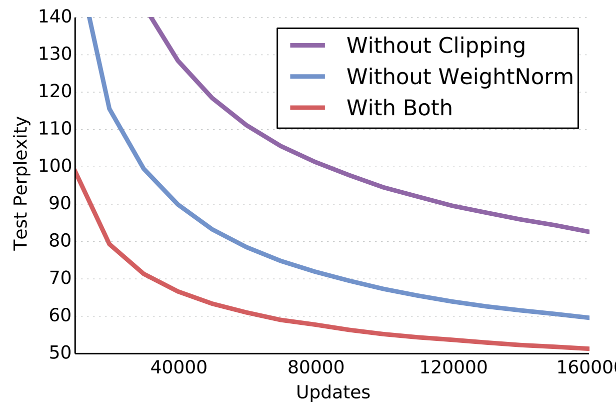

Figure 6. Effect of weight normalization and gradient clipping on Google Billion Word.

6. Conclusion

We introduce a convolutional neural network for language modeling with a novel gating mechanism. Compared to recurrent neural networks, our approach builds a hierarchical representation of the input words that makes it easier to capture long-range dependencies, similar in spirit to the tree-structured analysis of linguistic grammar formalisms. The same property eases learning since features are passed through a fixed number of layers and non-linearities, unlike for recurrent networks where the number of processing steps differs depending on the position of the word in the input. The results show that our gated convolutional network achieves a new state of the art on WikiText-103. On the larger Google Billion Word benchmark, we achieve a new best result for models trained on a single GPU, thereby outperforming several strong LSTM results.

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References

Bengio, Yoshua, Ducharme, Réjean, Vincent, Pascal, and Jauvin, Christian. A neural probabilistic language model. *journal of machine learning research*, 3(Feb):1137–1155, 2003.

Chelba, Ciprian, Mikolov, Tomas, Schuster, Mike, Ge, Qi, Brants, Thorsten, Koehn, Phillipp, and Robinson, Tony. One billion word benchmark for measuring progress in statistical language modeling. *arXiv preprint arXiv:1312.3005*, 2013.

Chen, Stanley F and Goodman, Joshua. An empirical study of smoothing techniques for language modeling. In *Proceedings of the 34th annual meeting on Association for Computational Linguistics*, pp. 310–318. Association for Computational Linguistics, 1996.

Collobert, Ronan, Kavukcuoglu, Koray, and Farabet, Clement. Torch7: A Matlab-like Environment for Machine Learning. In *BigLearn, NIPS Workshop*, 2011. URL http://torch.ch.

Dauphin, Yann N and Grangier, David. Predicting distributions with linearizing belief networks. *arXiv preprint arXiv:1511.05622*, 2015.

Glorot, Xavier and Bengio, Yoshua. Understanding the difficulty of training deep feedforward neural networks. *The handbook of brain theory and neural networks*, 2010.

Grave, E., Joulin, A., Cissé, M., Grangier, D., and Jégou, H. Efficient softmax approximation for GPUs. *ArXiv e-prints*, September 2016a.

Grave, E., Joulin, A., and Usunier, N. Improving Neural Language Models with a Continuous Cache. *ArXiv e-prints*, December 2016b.

Gutmann, Michael and Hyvärinen, Aapo. Noise-contrastive estimation: A new estimation principle for unnormalized statistical models.

He, Kaiming, Zhang, Xiangyu, Ren, Shaoqing, and Sun, Jian. Deep residual learning for image recognition. *arXiv preprint arXiv:1512.03385*, 2015a.

He, Kaiming, Zhang, Xiangyu, Ren, Shaoqing, and Sun, Jian. Delving deep into rectifiers: Surpassing human-level performance on imagenet classification. In *Proceedings of the IEEE International Conference on Computer Vision*, pp. 1026–1034, 2015b.

Hochreiter, Sepp and Schmidhuber, Jürgen. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.

Ji, Shihao, Vishwanathan, SVN, Satish, Nadathur, Anderson, Michael J, and Dubey, Pradeep. Blackout: Speeding up recurrent neural network language models with very large vocabularies. *arXiv preprint arXiv:1511.06909*, 2015.

Jozefowicz, Rafal, Vinyals, Oriol, Schuster, Mike, Shazeer, Noam, and Wu, Yonghui. Exploring the limits of language modeling. *arXiv preprint arXiv:1602.02410*, 2016.

Kneser, Reinhard and Ney, Hermann. Improved backing-off for m-gram language modeling. In *Acoustics, Speech, and Signal Processing, 1995. ICASSP-95., 1995 International Conference on*, volume 1, pp. 181–184. IEEE, 1995.

Koehn, Philipp. *Statistical Machine Translation*. Cambridge University Press, New York, NY, USA, 1st edition, 2010. ISBN 0521874157, 9780521874151.

LeCun, Yann and Bengio, Yoshua. Convolutional networks for images, speech, and time series. *The handbook of brain theory and neural networks*, 3361(10):1995, 1995.

Manning, Christopher D and Schütze, Hinrich. Foundations of statistical natural language processing, 1999.

Merity, S., Xiong, C., Bradbury, J., and Socher, R. Pointer Sentinel Mixture Models. *ArXiv e-prints*, September 2016.

Mikolov, Tomáš, Martin, Karafiát, Burget, Lukáš, Cernocký, Jan, and Khudanpur, Sanjeev. Recurrent Neural Network based Language Model. In *Proc. of INTERSPEECH*, pp. 1045–1048, 2010.

Mnih, Andriy and Hinton, Geoffrey. Three new graphical models for statistical language modelling. In *Proceedings of the 24th international conference on Machine learning*, pp. 641–648. ACM, 2007.

Morin, Frederic and Bengio, Yoshua. Hierarchical probabilistic neural network language model. In *Aistats*, volume 5, pp. 246–252. Citeseer, 2005.

Oord, Aaron van den, Kalchbrenner, Nal, and Kavukcuoglu, Koray. Pixel recurrent neural networks. *arXiv preprint arXiv:1601.06759*, 2016a.

Oord, Aaron van den, Kalchbrenner, Nal, Vinyals, Oriol, Espeholt, Lasse, Graves, Alex, and Kavukcuoglu, Koray. Conditional image generation with pixelcnn decoders. *arXiv preprint arXiv:1606.05328*, 2016b.

Pascanu, Razvan, Mikolov, Tomas, and Bengio, Yoshua. On the difficulty of training recurrent neural networks. In *Proceedings of The 30th International Conference on Machine Learning*, pp. 1310–1318, 2013.

Salimans, Tim and Kingma, Diederik P. Weight normalization: A simple reparameterization to accelerate training of deep neural networks. *arXiv preprint arXiv:1602.07868*, 2016.

Shazeer, Noam, Pelemans, Joris, and Chelba, Ciprian. Skip-gram language modeling using sparse non-negative matrix probability estimation. *arXiv preprint arXiv:1412.1454*, 2014.

Steedman, Mark. The syntactic process. 2002.

Sutskever, Ilya, Martens, James, Dahl, George E, and Hinton, Geoffrey E. On the importance of initialization and momentum in deep learning. 2013.

Yu, Dong and Deng, Li. *Automatic Speech Recognition: A Deep Learning Approach*. Springer Publishing Company, Incorporated, 2014. ISBN 1447157788, 9781447157786.