

Faster Transformer Decoding: N-gram Masked Self-Attention

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Abstract

Motivated by the fact that most of the information relevant to the prediction of target tokens is drawn from the source sentence $S = s_1, \dots, s_S$, we propose truncating the target-side window used for computing self-attention by making an N -gram assumption. Experiments on WMT EnDe and EnFr data sets show that the N -gram masked self-attention model loses very little in BLEU score for N values in the range $4, \dots, 8$, depending on the task.

1 Introduction

Transformers (Vaswani et al., 2017) are the most effective neural architectures for sequence modeling problems encountered in natural language, in particular language modeling and machine translation (MT). For MT in particular, the most successful modeling paradigm predicts a given target word using a conditional probability model leveraging all source words and the previous target words.

A first empirical observation is that the perplexity of a language model (LM) that predicts the target sentence using $P(t_k | t_1, \dots, t_{k-1}; \theta_{LM})$ is significantly higher than that of a conditional neural translation model (NMT): $P(t_k | t_1, \dots, t_{k-1}, s_1, \dots, s_S; \theta_{NMT})$. A transformer NMT model (6 layers, 8 attention heads, 512 model/embedding, 2048 hidden dimensionality, respectively, dropout 0.1) trained on the WMT EnDe data used for quality evaluation as described in Section 4.1.1 of (Wang et al., 2018) achieves conditional perplexity (PPL) 13.5 on the newstest2017 test data. An LSTM LM (2-layer, 1024 embedding and 2048 state dimensionality, respectively) trained on the De monolingual side of the parallel data, using the same word-piece model/vocabulary as the NMT model (32k, bilingual), achieves PPL 99.5.

Motivated by the fact that most of the information relevant to the prediction of target token t_k is drawn from the source sentence $S = s_1, \dots, s_S$, we propose truncating the target-side window used for computing self-attention by making an N -gram assumption. The self-attention mechanism in transformer models (Vaswani et al., 2017) already employs masking to make sure only target tokens prior to the current predicted position k are used when estimating $P(t_k | t_1, \dots, t_{k-1}; s_1, \dots, s_S; \theta_{NMT})$. Our proposed N -gram mask will restrict the self-attention mechanism to using only the previous $N - 1$ tokens.

A more detailed description of the N -gram self-attention mechanism is presented in Section 2. The experiments presented in Section 3 compare the baseline with the N -gram self-attention transformer.

2 N-gram Self-attention

The incremental computation of encodings for the target context t_1, \dots, t_{k-1} in a layered transformer decoder involves the following steps at each layer, after receiving the token embeddings (along with position encoding) or the encodings from the previous layer:

1. compute the self-attention query q_k and key k_k
2. compute softmax over the indexes $j = 1, \dots, k - 1$, and then the attention context for position k , of $\mathcal{O}(k)$
3. feed-forward computation of encoding for position k

For a target sentence of length T , the above steps need to be repeated $\forall k = 1, \dots, T$, resulting in computational complexity of $\mathcal{O}(T^2)$.

The N -gram self-attention mechanism reduces the context used for the prediction at position k , resulting in a computational complexity of $\mathcal{O}(N \cdot T)$. As shown in our experiments, see Section 3, $N = 8$ is a viable value for the N -gram order; for sentences of length $T \approx 16 - 25$ this promises a reduction in computational complexity on the order of $\mathcal{O}(T/N)$, or an $\approx 2 - 3X$ speed-up for the self-attention computation.

It remains to be seen to what extent this can be realized in practice in a given implementation and hardware platform (CPU, GPU or TPU), since the sibling feed-forward computation at step 3 may dominate the incremental computation at position k in the target sentence. The results in (Zhang et al., 2018) do show that optimizing the self-attention computation can have a significant impact on decoding speed.

Another potential computational advantage is the ability to store the context in a fixed size memory buffer of length $N - 1$, replacing context elements one by one as the decoder advances in the target sentence, e.g. by indexing the buffer modulo $N - 1$. This reduces the memory bandwidth required by the model at inference/beam-search time (a major bottleneck on TPU) by a factor of $\mathcal{O}(T/N)$.

We wish to emphasize that the N -gram self-attention mechanism *does not* result in a Markov model on the target side. Due to the convolutional nature of N -gram self-attention in a layered transformer decoder, the target side context used at position k directly spans the previous $1 + L \cdot (N - 2)$ tokens. However, even when the number of layers is $L = 1$, reusing the $N - 2$ previous values as stored in the context buffer for the computation of self-attention at context position $k - 1$ extends the memory of the model to the beginning of the target sequence.

3 Experiments

We implemented N -gram self-attention in lingvo (Shen et al., 2019) as a configuration option to TransformerAttentionLayer (lingvo/core/layers_with_attention.py). We perform experiments on two data sets: WMT’18 EnDe and WMT’14 EnFr; for EnDe we use newstest2012/2017 as dev/test data, respectively; for EnFr we concatenate newstest2012 and newstest2013 as dev data and use newstest2014 as test data.

The EnDe transformer model used is configured as follows: 6 layers, 8 attention heads, 512 model/embedding, 2048 hidden dimensionality, respectively, dropout 0.1. For EnFr we used 6 layers, 16 attention heads, 1024 model/embedding, 8192 hidden dimensionality, respectively, dropout 0.1. In both cases we used bilingual (source, target) word-piece models of size 32k.

The results are presented in Tables 1-2. Setting $N = 8$ or $N = 10$ achieves the best BLEU score on dev data and is within 0.3-0.4 BLEU from the baseline. Smaller N -gram orders are also a viable choice since performance degrades gracefully for $N \geq 3$.

4 Related Work

The use of local attention mechanism is not novel. It is used in LM and NMT experiments reported in (Shazeer, 2019), text summarization work in (Liu et al., 2018), image processing in (Parmar et al., 2018) and as well as automatic speech recognition as in (Povey et al., 2018). We wish to clarify that our use of local attention is restricted to the decoder component of the transformer model, unlike the image/speech processing use cases highlighted previously.

Unlike the blocking algorithm described in Section 4.2.4 of (Liu et al., 2018), we incrementally slide the attention window, just as also implemented in (Shazeer, 2019), see footnote on page 7 and results for $N = 32$ in Tables

Model	corpus BLEU		log_pplx		@steps
	dev	test	dev	test	(dev)
baseline	22.4	28.6	2.96	2.64	@151.6k
3-gram	22.1	28.0	3.12	2.76	@98.32k
4-gram	22.2	28.4	3.06	2.72	@93.62k
6-gram	22.2	28.3	3.01	2.68	@347.5k
8-gram	22.5	28.2	2.99	2.66	@467.8k
10-gram	22.5	28.3	2.98	2.65	@126.9k

Table 1: WMT’18 EnDe experiments: corpus BLEU and log-perplexity on the dev/test data, respectively at the best checkpoint picked according to the BLEU score on dev data.

Model	corpus BLEU		log_pplx		@steps
	dev	test	dev	test	(dev)
baseline	32.9	41.1/40.7+	2.52	2.16	@175.4k
2-gram	30.0	36.7	2.97	2.52	@176.4k
3-gram	32.2	40.3	2.58	2.21	@183.7k
4-gram	32.4	40.4	2.56	2.19	@180.3k
6-gram	32.7	41.1	2.53	2.17	@200.4k
8-gram	32.7	40.7	2.52	2.17	@176.5k
10-gram	32.8	40.8	2.52	2.17	@166.9k

Table 2: WMT’14 EnFr experiments: corpus BLEU and log-perplexity on the dev/test data, respectively at the best checkpoint picked according to the BLEU score on dev data; +: depending on the exact checkpoint on test data.

1 and 2, rows labeled with “-local” suffix. Our experiments show that significantly smaller values for the window length N are feasible.

A detailed performance analysis in both number of operations and memory footprint is presented in (Shazeer, 2019); particularly relevant is the one in Section 3.1 for incremental operation at inference time. Directly relevant to our proposed self-attention variant is the one in (Zhang et al., 2018) showing 4X improvements in decoding speed over the baseline transformer model.

5 Conclusion and Future Work

Experimental results show that N -gram self-attention is a viable alternative to full (one-sided/causal) self-attention in the decoder component of transformer models used in NMT. This slight model change promises run-time advantages in terms of memory footprint and speed that are yet to be investigated thoroughly, particularly at inference time.

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