Transformer++

Prakhar Thapak Machine Learning & AI Team American Express prakhar.thapak@aexp.com Prodip Hore Machine Learning & AI Team American Express prodip.hore@aexp.com

Abstract—Recent advancements in attention mechanisms have replaced recurrent neural networks and its variants for machine translation tasks. Transformer using attention mechanism solely achieved state-of-the-art results in sequence modeling. Neural machine translation based on the attention mechanism is parallelizable and addresses the problem of handling long-range dependencies among words in sentences more effectively than recurrent neural networks. One of the key concepts in attention is to learn three matrices, query, key, and value, where global dependencies among words are learned through linearly projecting word embeddings through these matrices. Multiple query, key, value matrices can be learned simultaneously focusing on a different subspace of the embedded dimension, which is called multi-head in Transformer. We argue that certain dependencies among words could be learned better through an intermediate context than directly modeling word-word dependencies. This could happen due to the nature of certain dependencies or lack of patterns that lend them difficult to be modeled globally using multi-head self-attention. In this work, we propose a new way of learning dependencies through a context in multi-head using convolution. This new form of multi-head attention along with the traditional form achieves better results than Transformer on the WMT 2014 English-to-German and English-to-French translation tasks. We also introduce a framework to learn POS tagging and NER information during the training of encoder which further improves results achieving a new state-of-the-art of 32.1 BLEU, better than existing best by 1.4 BLEU, on the WMT 2014 English-to-German and 44.6 BLEU, better than existing best by 1.1 BLEU, on the WMT 2014 English-to-French translation tasks. We call this Transformer++.

I. INTRODUCTION

Neural machine translation addresses the problem of translating one language into another language using neural networks. Typical encoder-decoder models read the entire sentence from the source language and encode it to a context vector. The task of the Decoder is to read this encoded vector and emit the words in the target language in a sequential fashion. Recurrent neural network and their variants have typically achieved state-of-the-art results in machine translation tasks [1, 2, 3, 4, 5]. Attention mechanism along with recurrent neural network has found usefulness to learn long term dependencies as it allows to establish alignment between words in input and output sequences directly irrespective of the distances [1, 6, 7, 8, 9, 10]. Recurrent neural networks are sequential in nature, which makes them difficult to parallelize and exploit GPU. It is also difficult to relate words separated by long distances using a recurrent neural network [11, 12, 13, 14].

Transformer[15] introduced in 2017 achieved state-of-the-art results on machine translation task using only attention mechanism eschewing recurrent neural networks. This was significant given attention mechanism based algorithms are parallelizable and can exploit GPU. Attention mechanism has proven to be useful as one can model dependencies of words in sequences irrespective of the distance between them.

In attention mechanism, three matrices query, key and value, are learned through backpropagation where global dependencies among words are learned through linearly projecting word embeddings through these matrices. Multiple query, key and value matrices can be learned through different representations, which allows the model to attend to information from different representation subspaces. This is called as multi-head attention in Transformer [15].

Along with learning global dependencies among words in self-attention [15], we argue that a machine translation task may also benefit from learning dependencies through an intermediate context than directly modeling word-word dependencies. This could happen due to the nature of certain dependencies that lend them difficult to be modeled globally in multi-head of self-attention or due to lack of patterns that makes these dependencies not obvious when modeled directly among words. In this work, we propose a new way of learning these dependencies in multi-head of self-attention [15] using convolution[14, 16, 17]. We explicitly model word-context dependencies, that is, which words are more relevant to a context. The context could be the summary of an entire sentence. This can be thought of as a novel way of computing alignments scores in the attention mechanism. In Transformer, the attention scores are being calculated modeling word-word dependencies, here we explicitly model word-context dependencies in multi-head. For example, consider the sentence 'There is a fire in the mountain'. For the query 'fire', we want a high attention score for the word 'mountain.' It is observed using proposed multi-head attention they are closer in the embedded space, and we believe this helps learn these kinds of dependencies better. Co-occurrences of words, such as 'fire' and 'mountain' may not be usual in a corpus; hence globally modeling as dependencies between words may be difficult. We also demonstrate that using POS tagging and NER information during the training of encoder helps in translation tasks and further improves results. Using POS and NER information has shown better results in recurrent neural networks in the past [18, 19]. We incorporate that in attention based encoder. To the best of our knowledge, this achieves a new state-of-the-art in machine translation tasks on the publicly available WMT 2014 English-to-German and WMT 2014 English-to-French translation tasks. We call it Transformer++.

II. BACKGROUND

Transformer achieved state-of-the-art results in neural machine translation without using recurrent neural networks and its variants. Sequential nature and difficulty in modeling long-range dependencies were drawbacks of recurrent neural networks and related algorithms [12]. There has been work to reduce sequential computational requirements in machine translation tasks, and most of them are based on using convolutional neural networks as building blocks [11, 13, 14]. Still modeling long-range dependencies is a challenge as the computational requirement grows linearly or logarithmically in these algorithms [12, 15]. In [20] using a simple lightweight convolution neural network, having a small number of parameters, they achieved comparable results to the Transformer, and using a dynamic convolutional network achieved better results than the Transformer. These models are also reported to be computationally faster than

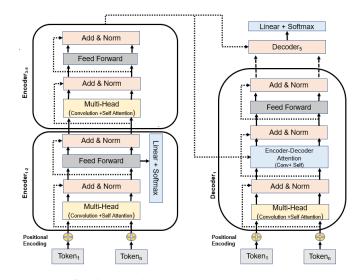
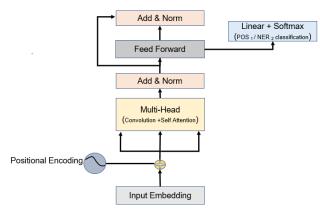


Fig. 1: Transformer++ model architecture

the Transformer. This shows that convolutional neural networks based algorithms also hold promise in neural translation tasks and also competitive in computation cost. In this work, we focus on improving the Transformer architecture which is based on self-attention and introduce the concept of modeling words-context dependencies in multi-head along with learning POS tagging and NER information. This achieves a new state-of-the-art of 32.1 BLEU on the WMT 2014 English-to-German and 44.6 BLEU on the WMT 2014 English-to-French translation.

III. MODEL ARCHITECTURE

We use an encoder-decoder architecture as shown in figure[1] for a sequence to sequence modeling following the architecture presented in Transformer [15]. We propose a new way to calculate attention function to learn both proposed new multi-head and traditional multi-head simultaneously. For a given H(total number of multi heads), we use self-attention in H/2 heads to capture global dependencies and use Convolution based attention in H/2 heads to capture dependencies through context. This explicitly models word-context dependencies using Convolution in H/2 heads. We demonstrate that word-context dependencies will complement traditional multi-head. Traditional multi-head can be thought of explicitly modeling word-word dependencies, linearly projecting words embeddings through three matrices query, key, and value.



Encoder 1,2 of multi task based context encoder

Fig. 2: Base Encoder

A. Encoder Stack

The encoder is composed of a base encoder followed by the standard encoder proposed as in Transformer [15]. The Base encoder is composed of a stack of N = 2 layers to accommodate the learning of POS tagging and NER, which we will explain later. These two encoders have three sub-layers. The first is a multi-head attention mechanism (self-attention + proposed context-word attention) layer, while the second layer is a simple position-wise fully connected feed-forward network followed by a linear + softmax layer to train on POS/NER labels as shown in figure[2]. We use residual connection [21] around each of the two multi-head and feed-forward layers followed by layer normalization [22]. The idea is to use multi-task learning to train encoder₁ for part of speech tagging as well as for machine translation. This allows the encoder layer to attending the syntactic functions of the input language. The encoder₂ is again trained in a multi-task manner. This encoder, along with machine translation, is used for learning named entity recognition forcing the encoder to attend to information extraction. The output from $encoder_2$ is connected to a minimum of 1 additional encoder, which is the same as proposed in the Transformer. This encoder takes the output produced by the base encoders to produce context encoder output. The labels for part of speech tagging and named entity recognition were obtained using the Spacy library.

B. Decoder Stack

We start with the decoder architecture in Transformer[15] and propose changes in the multi-head attention, which is a combination of self-attention and convolution as shown in figure[1]. The decoder also consists of N identical layers but doesn't have the extra linear and softmax layer used for POS and NER classification in the encoder. A multi-Head attention is also employed between the output of the final encoder layer and the output of each decoder layer after self-attention and feed-forward layer as in [15]. We use residual connections and layer normalization as employed in the encoder. The self-attention sub-layer in the decoder uses masking to avoid looking at the subsequent tokens. This masking ensures that the predictions for position i can depend only on the tokens less than *i*.

C. Attention

We use the scaled dot-product attention that takes care of hard softmax problem [15] along with the proposed contextword attention.

1) Scaled Dot-Product Attention: We used the Scaled Dot-Product Attention in H/2 heads. The input consists of queries (Q) and keys (K) of dimension d_k , and values (V) of dimension d_v [15].

$$Attention(K, Q, V) = softmax(QK^T / \sqrt{d_k})V \quad (1)$$

2) Convolution Attention: We propose two modules for convolution attention. First is the adaptive sequence module, which captures the local context for each word. The other being an adaptive query module, which captures the entire context for an input sequence as shown in figure[3]. Convolution has a fixed context window that helps in determining the importance of a word in a local context. The input sequence is first passed through a dilated causal convolution kernel[14, 16, 17] which is depth-wise separable. Causal convolution helps in ensuring that there is no information leak while the weights across temporal dimension F are softmax normalized so that a word representation is a weighted average of the words in a context. We use dilation [23] to increase the receptive field of the context window. Convolution being depth-wise helps in reducing the parameters from d^2F to dF where d is the dimension in word representation and F is the filter size. The output of

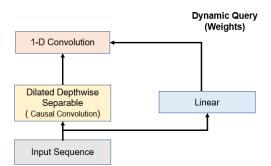


Fig. 3: Convolution Attention

the dilated depth-wise casual convolution is a token representation having a local context.

Adaptive sequence module calculates the following local context for t^{th} element in a sequence S across channels d.

$$LocalConv(S, W_{A}, t, d) = Conv(S, softmax(W_{A}), t, d) ; W_{A} \in \mathbb{R}^{F \times d}$$
(2)

The output from the adaptive sequence module represents the local context of a word across context F.

Adaptive query module: The input sequence S is passed through linear layers, W^{S} and W^{Q} , to obtain the Query matrix, which gets convolved with the output of the adaptive sequence module. This is conceptually similar to obtaining context using recurrent neural networks [1], hence the output of the linear layer after multiplying with W^{Q} is softmax normalized to obtain the weighted sum of the projection from the linear layer using W^{S} . For a sequence S with length T the dynamic query is given by :

$$Query = \sum_{t=1}^{T} (SW^S)_t \ softmax_t (S \times W^Q);$$
$$W^Q \in \mathbb{R}^d \ \& \ W^S \in \mathbb{R}^{d \times d} \quad (3)$$

$$DynamicConv(S, t, d) = Conv1D(LocalConv, Query) \quad (4)$$

In equation [4] above, Conv1 is simply computing the dot product between LocalConv and Query. In new multi-head, LocalConv is the word representation after convolution and Query represents the context of the entire sentence; hence attention score being computed in word-context relations. LocalConv is conceptually similar to the key matrix and DynamicConv as the value matrix in self-attention.

D. Multi-Head Attention

For a given H (total number of multi-head), we use H/2 self-attention heads to capture global dependencies directly among words and use H/2Convolution based heads to capture dependencies among words through a context. We demonstrate this novel way of capturing word-context dependencies will complement traditional multi-head and help model certain dependencies among words more meaningfully though a context rather directly. For $W^O \in \mathbb{R}^{d \times d}$.

$$MultiHead(S) = Concat(head_1...head_H)W^O$$
(5)

$$head_{i,1:H/2} = SelfAttn(QW_{i}^{Q}, KW_{i}^{K}, VW_{i}^{V})$$
$$head_{H/2:H} = DynamicConv(S, t, d)$$

Multi-head attention allows the model to attend different subspace of the embedded dimension simultaneously. In order to learn both the attention jointly, the output from the convolution attention and the self-attention, is concatenated and passed through a linear layer as in [15]. In Table III-D, we compare the complexities for different layer types where n is the sequence length, d is the embedding dimension and f refers to kernel size in convolution. Introducing word-context attention using depthwise separable convolution is of comparable cost.

IV. DATASETS AND TRAINING

We used the WMT 2014 English-German dataset and WMT 2014 English - French dataset for training while validating on newstest2013 and test on newstest2014. We replicate the setup of Transformer for training and used Adam optimizer [24] with the learning rate presented in Transformer. Tokens were encoded using byte-pair encoding [25]. Sentence pairs having same sequence length were batched together for faster computation.

We used a dropout [26] of 0.25 on the WMT En-De and 0.15 on the WMT En-Fr along with residual

Layer Type	Complexity per Layer	Sequential Operations	Minimum Path Length
Self-Attention	$O(n^2.d)$	O(1)	O(1)
Recurrent	$O(n.d^2)$	O(n)	O(n)
Convolution	$O(f.n.d^2)$	O(1)	$O(\log_{\mathbf{f}}(n))$
Depthwise Separable Convolution	O(f.n.d)	O(1)	$O(\log_{\rm f}(n))$

Table	III-D
-------	-------

dropout and token embedding dropout with value 0.10. We use DropConnect [27] as a regularizer for convolution operation. We train the WMT models on 4 GPUs for a total of 320K steps. We accumulate the gradient for 10 steps before applying an update [28]. The encoder and decoder both have N = 5 blocks to match the parameters of the Transformer with encoder_{1,2} trained on POS and NER in a multi-task manner. Both encoder and decoder have kernel size F = 3, 5, 7, 11, 15 for each block respectively and H = 16. We used stochastic weight averaging for the last 10 checkpoints with beam search of 5 and length penalty $\alpha = 0.5$ [29].

Performance of WMT on newstest2014 tests					
Model	Param	WMT En-De	WMT En-Fr		
Transformer [15]	213M	28.4	41.8		
Scaling Neural Machine Translation[28]	210M	29.3	43.2		
Lightweight and Dynamic convolution[20]	213M	29.7	43.2		
Data Diversification [30]	209M	30.7	_		
MUSE[31]	_	29.9	43.5		
Transformer++	212M	32.1	44.6		

V. RESULTS AND CONCLUSIONS

In Table[V], we compare the results of our algorithm

with other relevant state-of-the-art algorithms reported on the WMT 2014 English-German dataset and WMT 2014 English-French dataset. This new form of multi-head attention along with the traditional form achieves better results than Transformer by 1.8 BLEU score on the WMT 2014 English-to-German and 1.9 BLEU on the WMT 2014 English-to-French translation tasks. Training with POS tagging and NER information further improves results achieving new state-of-the-art of 32.1 BLEU, better than existing best [30] by 1.4 BLEU, on the WMT 2014 English-to-German and 44.6 BLEU, better than the existing best [31] by 1.1 BLEU, on the WMT 2014 English-to-French translation tasks. To get some insights, we computed the cosine similarity between the embedding of the words 'fire' and 'mountain' in the example sentence 'There is a fire in the mountain', where we anticipated word-context attention might help and bring 'fire' and 'mountain' closer in the embedded space. In self-attention, the cosine similarity is 0.21 while in the proposed method, computed from the embedding in equation[2], it is 0.39 indicating they came closer.

In this work, we proposed novel ways of creating word-context dependencies in multi-head self-attention demonstrating it complements traditional form of multi-head. We believe this will help the research community to explore other methods to learn dependencies in multi-head self-attention for neural machine translation tasks. Incorporating POS tagging and NER information in the training of encoder further improves results. To the best of our knowledge, it is the new state-of-the-art, and we call it Transformer++.

In the future, we plan to study more thoroughly the usefulness of various components in the encoder-decoder architecture, such as the optimal number of encoder and decoder stacks required, orthogonal value created from the proposed new way of creating multi-head attention, sensitivity to parameters, and explore learning word dependencies more effectively in multi-head attention for neural machine translation tasks.

REFERENCES

[1] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate. In Yoshua Bengio and Yann LeCun, editors, *3rd International Conference on Learning Representations, ICLR* 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, 2015.

- [2] Kyunghyun Cho, Bart van Merrienboer, Çaglar Gülçehre, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. Learning phrase representations using RNN encoder-decoder for statistical machine translation. *CoRR*, abs/1406.1078, 2014.
- [3] Junyoung Chung, Çaglar Gülçehre, KyungHyun Cho, and Yoshua Bengio. Empirical evaluation of gated recurrent neural networks on sequence modeling. *CoRR*, abs/1412.3555, 2014.
- [4] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8):1735–1780, 1997.
- [5] Noam Shazeer, Azalia Mirhoseini, Krzysztof Maziarz, Andy Davis, Quoc V. Le, Geoffrey E. Hinton, and Jeff Dean. Outrageously large neural networks: The sparsely-gated mixture-of-experts layer. *CoRR*, abs/1701.06538, 2017.
- [6] Yoon Kim, Carl Denton, Luong Hoang, and Alexander M. Rush. Structured attention networks. *CoRR*, abs/1702.00887, 2017.
- [7] Ankur P Parikh, Oscar Täckström, Dipanjan Das, and Jakob Uszkoreit. A decomposable attention model for natural language inference. arXiv preprint arXiv:1606.01933, 2016.
- [8] Minh-Thang Luong, Hieu Pham, and Christopher D. Manning. Effective approaches to attention-based neural machine translation. *CoRR*, abs/1508.04025, 2015.
- [9] Jan Chorowski, Dzmitry Bahdanau, Dmitriy Serdyuk, KyungHyun Cho, and Yoshua Bengio. Attention-based models for speech recognition. *CoRR*, abs/1506.07503, 2015.
- [10] Sainbayar Sukhbaatar, Arthur Szlam, Jason Weston, and Rob Fergus. Weakly supervised memory networks. *CoRR*, abs/1503.08895, 2015.
- [11] Jonas Gehring, Michael Auli, David Grangier, Denis Yarats, and Yann N. Dauphin. Convolutional sequence to sequence learning. *CoRR*, abs/1705.03122, 2017.
- [12] Sepp Hochreiter, Yoshua Bengio, Paolo Frasconi, Jürgen Schmidhuber, et al. Gradient flow in recurrent nets: the difficulty of learning long-term dependencies.
- [13] Ł ukasz Kaiser and Samy Bengio. Can active memory replace attention? In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, *Advances in Neural Information Processing Systems* 29, pages

3781–3789. Curran Associates, Inc., 2016.

- [14] Nal Kalchbrenner, Lasse Espeholt, Karen Simonyan, Aäron van den Oord, Alex Graves, and Koray Kavukcuoglu. Neural machine translation in linear time. *CoRR*, abs/1610.10099, 2016.
- [15] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *Advances in Neural Information Processing Systems 30*, pages 5998–6008. Curran Associates, Inc., 2017.
- [16] Lukasz Kaiser, Aidan N. Gomez, and François Chollet. Depthwise separable convolutions for neural machine translation. *CoRR*, abs/1706.03059, 2017.
- [17] François Chollet. Xception: Deep learning with depthwise separable convolutions. *CoRR*, abs/1610.02357, 2016.
- [18] Jan Niehues and Eunah Cho. Exploiting linguistic resources for neural machine translation using multi-task learning. *CoRR*, abs/1708.00993, 2017.
- [19] Zhongwei Li, Xuancong Wang, Ai Ti Aw, Eng Siong Chng, and Haizhou Li. Named-entity tagging and domain adaptation for better customized translation. In *Proceedings of the Seventh Named Entities Workshop*, pages 41–46, Melbourne, Australia, July 2018. Association for Computational Linguistics.
- [20] Felix Wu, Angela Fan, Alexei Baevski, Yann N. Dauphin, and Michael Auli. Pay less attention with lightweight and dynamic convolutions. *CoRR*, abs/1901.10430, 2019.
- [21] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.
- [22] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E. Hinton. Layer normalization, 2016.
- [23] Fisher Yu and Vladlen Koltun. Multi-scale context aggregation by dilated convolutions. In Yoshua Bengio and Yann LeCun, editors, 4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings, 2016.
- [24] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. In Yoshua Bengio and Yann LeCun, editors,

3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings, 2015.

- [25] Denny Britz, Anna Goldie, Minh-Thang Luong, and Quoc V. Le. Massive exploration of neural machine translation architectures. *CoRR*, abs/1703.03906, 2017.
- [26] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. *Journal* of Machine Learning Research, 15:1929–1958, 2014.
- [27] Li Wan, Matthew Zeiler, Sixin Zhang, Yann Le Cun, and Rob Fergus. Regularization of neural networks using dropconnect. In *International conference on machine learning*, pages 1058–1066, 2013.
- [28] Myle Ott, Sergey Edunov, David Grangier, and Michael Auli. Scaling neural machine translation. *arXiv preprint arXiv:1806.00187*, 2018.
- [29] Yonghui Wu, Mike Schuster, Zhifeng Chen, Quoc V Le, Mohammad Norouzi, Wolfgang Macherey, Maxim Krikun, Yuan Cao, Qin Gao, Klaus Macherey, et al. Google's neural machine translation system: Bridging the gap between human and machine translation. *arXiv preprint arXiv:1609.08144*, 2016.
- [30] Xuan-Phi Nguyen, Shafiq Joty, Wu Kui, and Ai Ti Aw. Data diversification: An elegant strategy for neural machine translation, 2019.
- [31] Guangxiang Zhao, Xu Sun, Jingjing Xu, Zhiyuan Zhang, and Liangchen Luo. Muse: Parallel multi-scale attention for sequence to sequence learning, 2019.
- [32] Jie Zhou, Ying Cao, Xuguang Wang, Peng Li, and Wei Xu. Deep recurrent models with fast-forward connections for neural machine translation. *CoRR*, abs/1606.04199, 2016.
- [33] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens, and Zbigniew Wojna. Rethinking the inception architecture for computer vision. *CoRR*, abs/1512.00567, 2015.
- [34] Oriol Vinyals, Łukasz Kaiser, Terry Koo, Slav Petrov, Ilya Sutskever, and Geoffrey Hinton. Grammar as a foreign language. In *Advances in neural information processing systems*, pages 2773–2781, 2015.
- [35] Ofir Press and Lior Wolf. Using the output

embedding to improve language models. *arXiv* preprint arXiv:1608.05859, 2016.

[36] Slav Petrov, Leon Barrett, Romain Thibaux, and Dan Klein. Learning accurate, compact, and interpretable tree annotation. In *Proceedings* of the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics, pages 433–440, Sydney, Australia, July 2006. Association for Computational Linguistics.