A Tensorized Transformer For Language Modeling

Xindian Ma[1], Peng Zhang[1*], Shuai Zhang[1], Nan Duan[2], Yuexian Hou[1], Dawei Song[3], Ming Zhou[2]

1 Tianjin University, China 2 Microsoft Research Asia, China

3 Beijing Institute of Technology, China

Introduction

Background

At present, Pre-training model plays an key role in many neural language processing tasks. However, Transformer, and its variant model BERT, limit the effective deployment of the model to limited resource setting.

- ◆ The compression of large nature pre-training language model has been an essential problem in NLP research.
- ◆ There are some compression methods only study the compression of embedding layers and some methods can not be integrated into the model after compressing.

Research Questions

- ◆ To linearly represent a self-attention by a group of basic vectors
- ◆ To compress multi-head attention in Transformer
- ◆ After compressing, it can be directly integrated into the encoder and decoder framework of Transformer

Our Methods

Basic Ideas

- ☐ **Low-rank decomposition**
- ☐ **Parameters sharing**

- ◆ Using Tucker decomposition formulation is to construct Single-block attention
- ◆ Using Block-term decomposition + Parameters sharing formulation is to construct multi-head mechanisms(Multi-linear attention)

Tensoried Transformer

- ■ Single-block Attention by Tucker Decomposition

$$Atten_{TD}(\mathcal{G};Q,K,V)=\sum_{i=1}^{I}\sum_{j=1}^{J}\sum_{m=1}^{M}\mathcal{G}_{i,j,m}Q_i\circ K_j\circ V_m$$

- ■ Multi-linear Attention by Block-term Decomposition

$$MultiLinear(\mathcal{G};Q',K',V')=SplitConcat\left(\frac{1}{h}\cdot(T_1+\cdots T_h)\right)W^O$$

$$where\ T_j=Atten_{TD}(\mathcal{G}_j;Q'W^q,K'W^k,V'W^v)$$

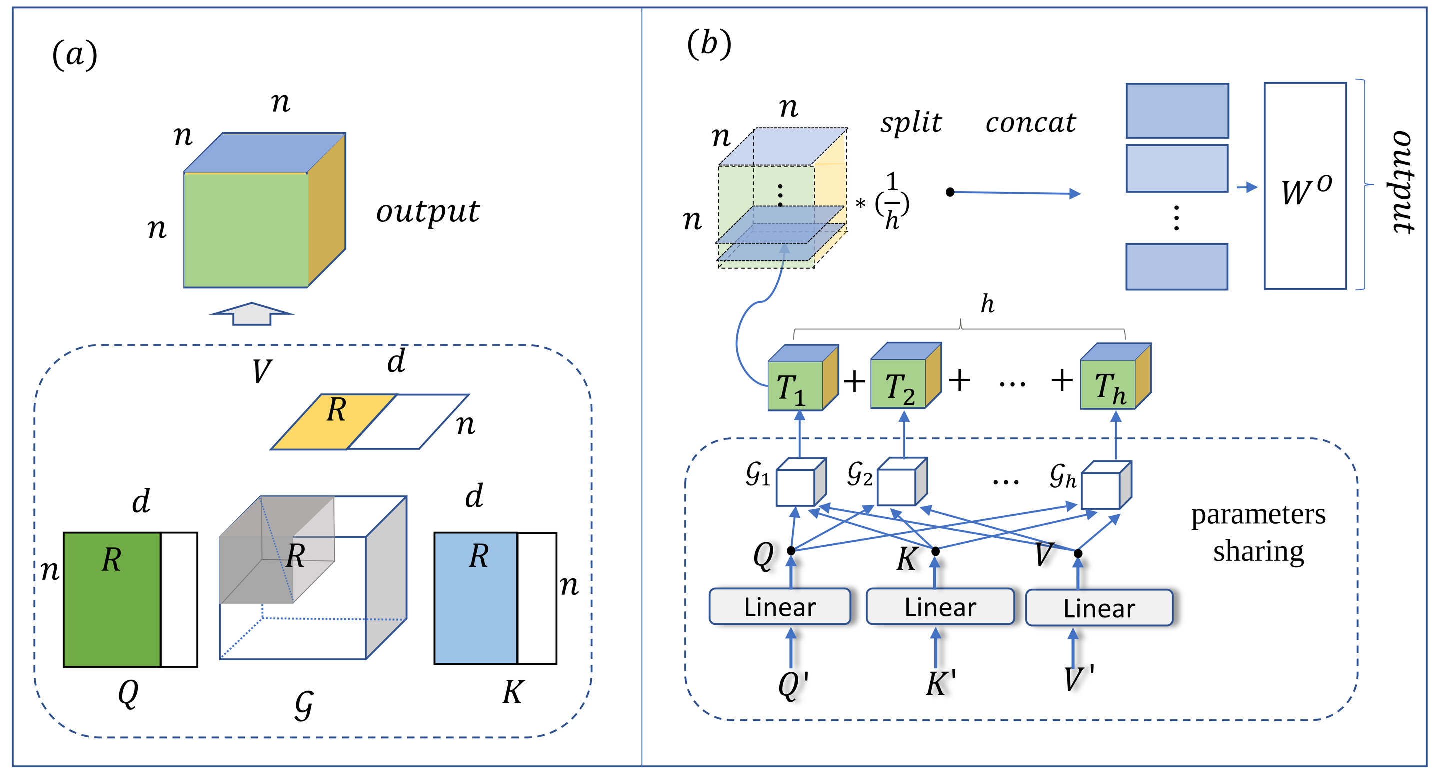


Figure: (a) is the Single-block attention using Tucker decomposition, (b) is the Multi-linear attention based on Block-term tensor decomposition.

Main Theorem

Let $e_1,\cdots,e_n$ be basis vectors from the vector S. Assume that Q,K,V can be linearly represented by this set of basis vector. The output of the attention function can be represented by a linear combination of the set of these basis vectors.

$$Attention(Q,K,V)=(e_1,\cdots,e_n)M$$

where $M\in\mathbb{R}^{N\times d}$is a coefficient matrix, and d is a dimension of these matrices.

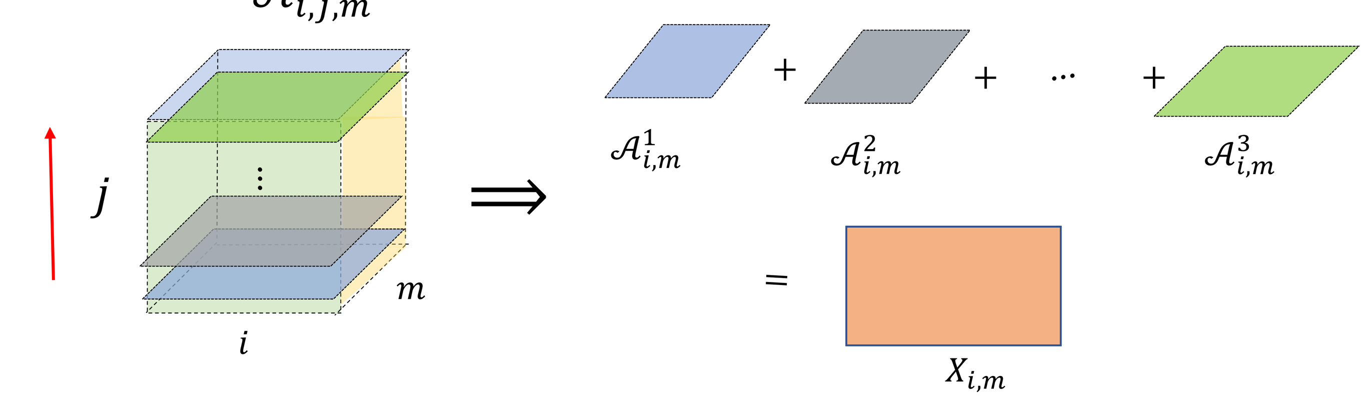
Conclusion

- ☐ Providing a novel self-attention method, namely Multi-linear attention.
- ☐ Combining two compression ideas, parameters sharing and low-rank decomposition.
- ☐ Achieving higher compression ratio and better experimental results in language modeling

Related Corollary

Single-block attention can reconstruct the self attention function by the summing over the tensor according to the second index.

$$Attention(Q,K,V)_{i,m}=\sum_{j=1}^{N}Atten_{TD}(\mathcal{G};Q,K,V)_{i,j,m}$$



Experimental Results

Model	PTB			WikiText-103		
	Params	Val PPL	Test PPL	Params	Val PPL	Test PPL
LSTM+augmented loss [15]	24M	75.7	48.7	–	–	48.7
Variational RHN [41]	23M	67.9	65.4	–	–	45.2
4-layer QRNN [21]	–	–	–	151M	–	33.0
AWD-LSTM-MoS [37]	22M	58.08	55.97	–	29.0	29.2
Transformer+adaptive input [1]	24M	59.1	57	247M	19.8	20.5
Transformer-XL-Base [7]	24M	56.72	54.52	151M	23.1	24.0
Transformer-XL-Large [7]	–	–	–	257M	–	**18.3**
Transformer-XL+TT [18]	18 M	57.9*	55.4*	130M	23.61*	25.70*
Sparse Transformer [28]	14M	74.0*	73.1*	174M	38.98*	40.23*
Tensorized Transformer core-1	12M	60.5	57.9	85.3M	22.7	20.9
Tensorized Transformer core-2	12M	**54.25**	**49.8**	85.3M	**19.7**	18.9

One-Billion

Model	Params	Test PPL
RNN-1024+9 Gram [4]	20B	51.3
LSTM-2018-512 [17]	0.83B	43.7
GCNN-14 bottleneck [8]	–	31.9
LSTM-8192-1024+CNN Input [17]	1.04B	30.0
High-Budget MoE [32]	5B	28.0
LSTM+Mos [37]	113M	37.10
Transformer+adaptive input [1]	0.46B	23.7
Transformer-XL Base [7]	0.46B	23.5
Transformer-XL Large [7]	0.8B	21.8
Tensorized Transformer core-1	0.16B	20.5
Tensorized Transformer core-2	0.16B	**19.5**

Language Modeling

- Our method is mainly experimented on three language model datasets, PTB, WikiText-103, and One-Billion, respectively. The lower the PPL, the better the model is.
- Our methods achieve a more better results with fewer parameters.

Main References

[1] Ashish et al., Attention is all you need. NeurIPS, 2017.

[2] Zihang et al., Transformer-xl: Attentive language models beyond a fixed-length context, 2019.

[3] Valentin et al, Tensorized embedding layers for efficient model compression,2019.