We highly appreciate the reviewers' invaluable comments and suggestions. Our responses are as follows.

To **Reviewer 1**: For Theorem 3.1, Q, K, and V can be linearly represented by a set of basis vectors. Such a relation is detailed in the supplementary material (in Eq.2). Under this condition, we prove Eq.4 in our paper. Theorem 3.1 provides a theoretical basis for building the proposed Multi-linear attention.

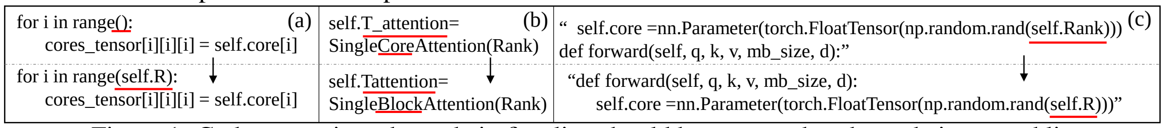
We used 3 or 4 cores to train our model. In the Future Work section of the paper, we mentioned that our model may suffer from overfitting when the number of cores becomes larger, and the issue will be explored in future. Furthermore, on PTB dataset, we have tested our model when increasing the number of layers from 3 to 7, and our model has approximately equal parameters (24M) as the original Transformer. However, our model gets a lower perplexity (PPL 52.7) than the original Transformer (PPL 59.1). We will add a more systematic evaluation in the revised version.

A detailed discussion about Sparse Transformer is given in the end of this response.

To **Reviewer 2**: According to your suggestion, during the response period we have tested the Transformer with reduced parameters by directly reducing the dimensions of Q, K, and V from 40 to 26. We have run the language modeling experiments on PTB dataset. This method achieves the same parameters (12M) as in our tensorized model, while obtaining a PPL 87.8, which is higher than the PPL 57.9 of our model. The result shows the better performance of our model. We will report a systematic comparison results in the revised paper.

Regarding the rationale for the improvements, besides the alleviation of overfitting by reducing parameters, another reason is that our method captures more information than the original Transformer. In Corollary 1, we prove that the output of the original attention can be represented by summing over the 3-order tensor (i.e., $output$(original)=$\sum_i^n T_i$, where T_i is matrix resulting from splitting the 3-order tensor(N×N×N), in Figure 2 of our paper). In our tensorized transformer, we use a concat function over these matrices ($ouput$(tensorized)=$concat(T_1, \ldots, T_i)$). The operation of concat models all values in the 3-tensor, and thus captures more information than the operation of sum.

To **Reviewer 3**: (1) For grammar issues, we will carefully check them and make changes accordingly.
(2) For the code link you mentioned, since the Author Response policy of NeurIPS2019 explicitly states "Author Responses must not contain external links", we can not provide such a link. Instead, we clarify the confusing aspects you mentioned and explain how to compile it as follows.


(a)
```
for i in range():
    cores_tensor[i][i][i] = self.core[i]
```
```
for i in range(self.R):
    cores_tensor[i][i][i] = self.core[i]
```
(b)
```
self.T_attention=
SingleCoreAttention(Rank)
```
```
self.Tattention=
SingleBlockAttention(Rank)
```
(c)
```
"  self.core =nn.Parameter(torch.FloatTensor(np.random.rand(self.Rank)))
def forward(self, q, k, v, mb_size, d):"
```
```
 "def forward(self, q, k, v, mb_size, d):
     self.core =nn.Parameter(torch.FloatTensor(np.random.rand(self.R)))"
```
Figure 1: Code correction: the code in first line should be corrected to the code in second line

(3) We apologize for the clerical errors we made when editing the code with Latex. We have corrected them in Figure 1.
#Confusing aspect of code 1: missing the variable "self.R" in parentheses. The revision is in Figure 1(a).
#Confusing aspect of code 2: the "self.Tattention" is not a pure function. It is the class named "SingleBlockAttention". The revision is in Figure 1(b). In addition, the True branch is not numerically identical to the False branch. In the class of "SingleBlockAttention", we define a variable "self.core" using a random function. The position for the definition of "self.core" should be adjusted. The revision is in Figure 1(c).

The code in supplementary file is the key code that aims to help readers understand the Multi-linear attention. This code can be compiled through the following steps. a) "SingleBlockAttention" replaces "ScaleDotProductAttention" in Transformer , and "MultiLinearAttention" replaces "MultiHeadAttention" in Transformer; b) Setting the parameter "head" in Transformer to 1. c) Changing the dimensions of the matrix in the fully connected layer.

We will add the experimental results for the total flops usage in comparison with the baseline in the next version.
We will add the following discussion on Sparse Transformer to the Related Work section in the revised version. We will also include the experimental results of Sparse Transformer in the language modeling task in comparison with ours.

Discussion of Sparse Transformer: Sparse Transformer is a recent work that adopts sparse techniques on the attention matrix and reduces its parameters. However, it differs from our Tensorized Transformer in the following aspects. (1) Sparse Transformer does not change the computation of original attention, but uses a sparse attention matrix by selecting the information on some positions in the attention matrix. Our paper proposes a new attention structure named Multi-linear attention. (2) Sparse Transformer does not outperform the original Transformer, as its sparse attention matrix only contains partial information of the original one. The Multi-linear attention we propose is based on tensor decomposition. It not only reduces parameters, but also improves the results. The improvements come from the use of the concat function in Multi-linear attention which captures more information. Please find detailed explanation in the response "To reviewer 2". (3) The target tasks in Sparse Transformer often involve processing of images, text (character predict) and audio. The target tasks of our model are language modeling and neural machine translation. When dealing with text, Sparse Transformer is trained at the character level, while language modeling task in our paper is typically on the word level.