Horizontal and Vertical Attention in Transformers

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Abstract
Transformers are built upon multi-head scaled dot-product attention and positional encoding, which aim to learn the feature representations and token dependencies. In this work, we focus on enhancing the distinctive representation by learning to augment the feature maps with the self-attention mechanism in Transformers. Specifically, we propose the horizontal attention to reweight the multi-head output of the scaled dot-product attention before dimensionality reduction, and propose the vertical attention to adaptively re-calibrate channel-wise feature responses by explicitly modelling inter-dependencies among different channels. We demonstrate the Transformer models equipped with the two attentions have a high generalization capability across different supervised learning tasks, with a very minor additional computational cost overhead. The proposed horizontal and vertical attentions are highly modular, which can be inserted into various Transformer models to further improve the performance. Our code is available in the supplementary material.

1 Introduction
Transformers have achieved significant progress in various machine learning tasks [Vaswani et al., 2017; Dosovitskiy et al., 2020; Dong et al., 2018; Cornia et al., 2020]. The power of the Transformer architecture relies on learning the dependencies of tokens, which are implemented by the multi-head self-attention mechanism. The sequential property of the word in Transformers is controlled by positional encoding, which is used in conjunction with self-attentions. These features are just weight sums and activations, so the learning process is highly parallelizable, making the Transformer model efficiently computed. When comes to the Vision Transformer (ViT) [Dosovitskiy et al., 2020], we can apply a similar learning architecture by using the image patches as tokens. At the input level, the tokens are formed by uniformly splitting the image into multiple patches, e.g., splitting a 224 × 224 image into 16 × 16 patches that are 14 × 14 pixels. At intermediate levels, the outputs from the previous layer become the tokens for the next layer. At the output level, Vit applies the global average pooling followed by a multi-layer perceptron (MLP) as the classification head. ViT attains excellent performance compared to the ConvNets, and has comparably low latency in computation. However, it requires pre-training on very large-scale image datasets.

The Transformer models adopt the self-attention mechanism with the Query-Key-Value (QKV) paradigm. Given the packed matrix representations of queries \( Q \in \mathbb{R}^{N \times D_k} \), keys \( K \in \mathbb{R}^{N \times D_k} \), and values \( V \in \mathbb{R}^{N \times D_v} \), where \( N \) is the length; \( D_k \) and \( D_v \) denote the dimensions of keys (or queries) and values, respectively. The self-attention is given by:

\[
\text{Attention}(Q, K, V) = \text{Softmax} \left( \frac{QK^T}{\sqrt{D_k}} \right) V. \tag{1}
\]

The dot-products of queries and keys are divided by \( D_k \) to alleviate the gradient vanishing problem of the softmax function.

A single SDPA is usually insufficient to learn distinctive features, even using the stacked Transformer blocks. Thus, the Transformer model uses multi-head attention, which is very similar to multi-view learning since each attention head focuses on a specific perspective of feature representation. Assume the input feature is \( X \in \mathbb{R}^{N \times D} \), where \( D \) is the dimensional original queries, keys and values are projected to \( D_k \), \( D_k \) and \( D_v \) dimensions, respectively, with \( M \) parallel learned projections. For each of the projected queries, keys and values, the output is computed via Eq. (1), then all outputs are concatenated and projected back to a \( D \)-dimensional feature representation:

\[
Y^M = \text{MultiHeadAttn}(X) = \text{Concat}(H_1, \ldots, H_M)W^M, \tag{2}
\]

where

\[
H_m = \text{Attention}(XW^Q_m, XW^K_m, XW^V_m), \quad \text{for } m = 1, \ldots, M, \tag{3}
\]

and \( W^M \in \mathbb{R}^{MD_k \times D}, W^Q_m \in \mathbb{R}^{D \times D_k}, W^K_m \in \mathbb{R}^{D \times D_k}, W^V_m \in \mathbb{R}^{D \times D_v} \) are all projection matrices.
machine translation, image classification and image captioning, on several public datasets. The results prove the effectiveness of the proposed methods, as well as their generalization capabilities in various Transformer models.

## 2 Related work

The Transformer model was first proposed as a sequence-to-sequence model for machine translation [Vaswani et al., 2017]. Later works show Transformers can also obtain very promising performance in computer vision [Dosovitskiy et al., 2020; Liu et al., 2021b; Touvron et al., 2021] and multi-model analysis [Cornia et al., 2020]. As a central piece of Transformer, the self-attention, i.e., multi-head SDPA, has the complexity and structural prior challenges. The computational complexity is mainly determined by the length of tokens, so in the long-sequence modelling, the global self-attention becomes a bottleneck for model optimization and inference. To deal with this problem, the Reformer model [Kitaev et al., 2020] applies the Local Sensitive Hashing (LSH) to efficiently compute the self-attention, and Linformer [Wang et al., 2020] utilizes linear projection to project keys and values to a smaller length, to simultaneously reduce the complexity and model size. Inspired by the kernel approximation, Performer [Choromanski et al., 2020] follows the Random Fourier feature map to approximate Gaussian kernels. The structural prior issue mainly appears in computer vision. Unlike the invariant word embedding in natural language processing, the high uncertainty of image patches lead to the inductive bias, making Transformer models less effective than the convolution counterparts in computer vision tasks [Liu et al., 2021a]. To obtain a comparable accuracy with ConvNet, using Vanilla Transformer as a backbone for image classification requires the pre-training on very large-scale datasets [Dosovitskiy et al., 2020]. This problem can be alleviated by applying some techniques such as token distillation [Touvron et al., 2021], multi-stage structures [Liu et al., 2021b; Yuan et al., 2021] and hybrid models [Wu et al., 2021]. For the improvement of multi-head attention in Transformers, Li et al. introduced an auxiliary disagreement regularization term into loss function to encourage diversity among different attention heads [Li et al., 2018]. Although some works also tried to restrict the attention spans [Sukhbaatar et al., 2019], or refine the aggregation [Gu and Feng, 2019] for multi-head attention, there is no mechanism to guarantee the distinct features in Transformers. Our work aims to design extra functions to explicitly re-weight the multi-head attention and re-calibrate the feature output, to effectively improve the performance without changing the overall Transformer architectures.

## 3 Method

In this section, we detail the two attention mechanisms that augment the feature representation of Transformers. The overall pipelines of the computation are illustrated in Figure 1. The proposed two methods are also based on self-attention. Considering the specific QKV paradigm with a residual connection, which is the key component in Transformer blocks,
we add several feature mapping functions for the multi-head re-weighting of SDPA and channel-wise calibration.

3.1 Horizontal attention: attention on the multi-head output of SDPA

Multi-head attention is an appealing property in Transformers to jointly attend to the information from different feature subspaces at multiple positions. In Vanilla Transformer, the multi-head SDPA is to learn the dependencies of each token. Just like the ensemble methods [Sagi and Rokach, 2018] in machine learning, the multi-head attention runs SDPA several times in parallel, and each attention head is optimized independently. Their attention outputs are then concatenated and linearly transformed into an expected dimension. Intuitively, multi-head attention allows for attending to parts of the sequence differently (e.g. long-term vs short-term dependencies). The feature learning procedure naturally raises the question that which SDPA heads provide “better” outputs, or are relatively more important than others. It would be beneficial to focus more on these feature outputs and suppress the less distinctive ones by employing a re-weighting function.

The horizontal attention is designed to auto-re-weight the multi-head outputs. Specifically, we introduce a re-weighting vector \( \alpha = [\alpha_1, \ldots, \alpha_M] \in \mathbb{R}^M \) that satisfies \( \sum_{m=1}^{M} \alpha_m = 1 \) and \( \alpha_m \geq 0 \). Thus, the multi-head SDPA with \( M \) attention heads in Eq.(2) becomes:

\[
Y^H = \text{MultiHeadAttn}(X) = \text{Concat}(\alpha_1H_1, \ldots, \alpha_MH_M)W^M. \tag{5}
\]

To compute the re-weighting vector \( \alpha \), we use the input \( X \) as the context variable, working with the multi-head SDPA outputs \( H_1, \ldots, H_M \), where \( H_m \in \mathbb{R}^{N \times D_v} \). In simple terms, the context variable \( X \) acts as a dynamic representation of the relevant attention head. For each head \( H_m \), the horizontal attention computes a positive weight \( \alpha_m \), which is interpreted as the relative importance that \( H_m \) provides the best output to focus for producing the feature for the subsequent computations. The pipeline to compute \( \alpha \) is formulated as follows:

\[
\begin{align*}
A_m &= \text{ReLU}(H_mW^{A1} + XW^{A2}), \\
B_m &= A_mW^B + b^B, \\
& \quad \text{for } m = 1, \ldots, M, \\
\alpha &= \text{Softmax}([B_1, \ldots, B_M]),
\end{align*}
\]

where \( W^{A1} \in \mathbb{R}^{D_v \times D_a}, W^{A2} \in \mathbb{R}^{D \times D_v}, W^B \in \mathbb{R}^{D_v} \) are projection matrices, and \( b^B \) is a bias term.

The horizontal attention for multi-head SDPA is essentially a deterministic attention function, which corresponds to feeding in a re-weighting vector \( \alpha \) to \( M \) learned feature representations. Similar to the Bahdanau attention used in image captioning [Xu et al., 2015], in each Transformer block, \( \alpha \) is approximated by using the expected context variable \( X \), which can be computed by a single feedforward computation with a softmax function. This suggests that the horizontal attention approximately maximize the marginal likelihood over all multi-head SDPA outputs. Note that the computation complexity of \( \alpha \) is only related to the dimension \( D_v \) but irrelevant to the length of token \( N \), so it can be efficiently computed even when handling the long sequences in Transformers.

3.2 Vertical attention: attention for feature re-calibration

The vertical attention can be viewed as a mechanism to bias the allocation of available feature channels towards the most informative components of an input signal, which is implemented by a gating function. It is specialized to model the channel-wise correlations in a computationally efficient way and designed to enhance the feature representation power of Transformer blocks throughout the whole network. Specifically, we aim to learn a channel weight vector \( \beta = [\beta_1, \ldots, \beta_D] \in \mathbb{R}^D \) to re-calibrate the feature map \( Y^M \) in Eq.(2) as:

\[
Y^V = \beta \ast Y^M, \tag{7}
\]

where \( \ast \) is the element-wise multiplication. The computation of vertical attention is similar to the above-mentioned horizontal attention that uses the input feature representation \( X \) as the context variable. The difference is the vertical attention aims to re-calibrate the dimensionality reduction of the multi-head output \( Y^M \) in Eq. (2). The computation of vertical attention is illustrated as follows:

\[
U = \text{ReLU}(XW^{U1} + Y^M W^{U2}), \\
\beta = \text{Sigmoid}(UW^U + b^U), \tag{8}
\]

where \( W^{U1}, W^{U2} \in \mathbb{R}^{D \times D_a}, W^U \in \mathbb{R}^{D_a \times D} \) are trainable mapping matrices, and \( b^U \in \mathbb{R}^D \) is a bias term.

The computation of \( \beta \) enables the increase of the sensitivity to the feature output \( Y^M \). \( D_a \) is a squeezed dimension that \( D_a < D \), and this setting is to embed the most informative feature component into a lower-dimensional space. Here we simply set \( D_a = D/4 \). The intermediate output \( U \) can be explained as a collection of the local descriptors whose statistics are expressive in the current context. To capture the channel-wise dependencies, it must learn a non-mutually-exclusive correlation since we need to ensure the multi-channels are allowed to be emphasized opposed to one-hot activation such as softmax activation. So in the vertical attention, we use the sigmoid activation as the gating function, which acts as the channel-weights adapted to the input-specific descriptor \( X \) and the learned feature representation \( Y^M \). The computation of vertical attention is similar to the squeeze-and-excitation (SE) module proposed in [Hu et al., 2018]. The differences are: (1) In the squeeze stage of SE module, it squeezes global spatial information into a channel descriptor, which is unnecessary in the vertical attention because the feature dependencies have already been embedded by SDPA; (2) The vertical attention considers the context information given by the input \( X \), which jointly consider the current feature output and the context information within the Transformer block. With this regard, the vertical attention intrinsically introduces dynamics conditioned on the input and multi-head SDPA, improving the discriminative ability of feature representations.
3.3 Complexity analysis

To illustrate the computational efficiency of the proposed methods, we analyze the core components in both horizontal and vertical attentions in Transformers. For the multi-head SDPA in Vanilla Transformer [Vaswani et al., 2017], we assume $D = D_k = D_v$, the length of the input sequence is $N$, and the number of heads is $M$. In the computation of multi-head SDPA, each head requires to store a $N \times N$ distribution matrix, so the complexity is $O(MN^2D)$. In the packed $Q$, $K$, and $V$ of $M$ attention heads, as well as the dimensionality reduction, each Transformer block requires $2MD^2$ trainable parameters. When applying the horizontal attention on the multi-head output, the computation of re-weighting vector $\alpha$ needs extra $O(MD)$ in Eq.(6). Similarly, the computation of re-calibration vector $\beta$ in Eq.(8) for vertical attention needs extra $O(MD)$ to compute the intermediate variables. To store the two mapping functions to compute $\alpha$ and $\beta$, the two attentions need extra $2D^2 + D$ and $3D^2$ parameters, respectively. The theoretical complexity and parameter counts are summarized in Table 1. From the analysis, we can see that the two proposed attentions are irrelevant to the query length $N$, which means they can be readily integrated into different Transformer variants such as Performer [Choromanski et al., 2020] and Linformer [Wang et al., 2020], without the change of their internal computation structures.

| Module          | Complexity     | #Params |
|-----------------|----------------|---------|
| Multi-head SDPA | $O(MN^2D)$    | $2MD^2$ |
| + Hor.          | $+O(MD)$      | $+2D^2 + D$ |
| + Ver.          | $+O(MD)$      | $+3D^2$ |

Table 1: Complexity and parameter counts analysis.

4 Experiments

We apply the proposed horizontal and vertical attentions in Transformer models then test them in three different learning tasks: machine translation, image classification and image captioning. We show that both attention methods can effectively boost the performance in supervised learning tasks.

4.1 Machine translation

Datasets and experimental settings

Machine translation is to map an input sentence representing a phrase in one language, to an output sentence representing the same phrase in a different language. In this task, we trained the Vanilla Transformer [Vaswani et al., 2017] on WMT-16 [Sennrich et al., 2016] and WMT-17 [Sennrich et al., 2017] English-German dataset. The relatively small WMT-16 dataset contains 29K, 1K and 1K sentence pairs for training, validation and testing, respectively. The average length of the testing target sentences is 12.4 words per sentence. The WMT-17 dataset is much larger, which has 1M, 3K and 3K sentence pairs for training, validation and testing, respectively. The testing ground truth of WMT-17 is not publicly available, so on this dataset, we report the performance on the validation split.

The attention functions were built based upon the public PyTorch implementation of Vanilla Transformer\footnote{https://github.com/jadore801120/attention-is-all-you-need-pytorch}, in which we added the horizontal and vertical attention, respectively, in the Transformer block. Note that the proposed two attention mechanisms can be either separately or jointly used in Transformer models. The word embedding dimension was set to 512 without the pre-training on extra data. The whole model is an encoder-decoder architecture, which contains 12 Transformer blocks in total. In each block, the number of SDPA heads was set to 8, and $D_k = D_v = 64$. We applied the label smoothing and categorical cross-entropy. The AdamW [Ilya and Frank, 2019] with the default learning rate 0.001 was used to optimize the model for 100 and 120 epochs on WMT-16 and WMT-17 datasets, respectively. The experiment was conducted on a server equipped with an NVIDIA Tesla V100 GPU card. Due to the memory restriction, the mini-batch size was set to 256.

We use the perplexity (PPL), which is the average per-word log-probability, to evaluate the machine translation quality and observe if the proposed two attention methods can bring the benefit to the Vanilla Transformer models in machine translation. The lower the PPL, the better the model is.

Experimental results

We plot the validation curves of different methods in Figure 2 for WMT-16 and Figure 3 for WMT-17 datasets, respectively. Considering the vocabulary size and number of data samples, both loss and accuracy curves in WMT-16 converge faster than in WMT-17. In terms of the validation loss and accuracy, inserting either horizontal or vertical attention, or
Table 2 shows the model sizes, FLOPs and PPL statistics on the two machine translation datasets. Here we assume the maximal length of the input sentence is $N = 64$. On the WMT-16 dataset, we can see that by adding the proposed horizontal and vertical attention functions to all Vanilla Transformer blocks, the number of trainable parameters is only increased by 0.4M and 3.4M, and the number of FLOPs is increased by 0.1G and 0.2G, respectively. Simultaneously applying the two attentions does not lead to significant computational burdens, which needs about 8.6% and 10.3% model parameters and FLOPs overhead. The model complexity on the WMT-17 dataset is comparably higher, due to the larger vocabulary size. However, the additional required resources of the two attentions are similar. The overall quality of machine translation is benefited by the two attention methods. On the WMT-16 dataset, horizontal and vertical attentions bring 0.99 and 1.13 PPL drops on the test split, respectively. Adding both of the two attention functions improves the baseline by 1.11 PPL, which is slightly worse than applying vertical attention. On the WMT-17 benchmark, the best validation PPL is obtained by the joint use of horizontal and vertical attentions.

4.2 Image classification

Dataset and baseline models

We use the ImageNet-100 [Wang and Isola, 2020], which is a subset of ImageNet-1K, to test the effectiveness of the proposed horizontal and vertical attentional visual Transformers. Compared to ConvNets, visual Transformers lack the inductive bias and the translation invariance, so they are usually required to pre-train on large-scale image datasets [Dosovitskiy et al., 2020] or use in conjunction with convolutions [Touvron et al., 2021]. Also, in our own practice, we found that on low-resolution images such as down-sampled ImageNet (e.g., $64 \times 64$) and CIFAR-100, training visual Transformers (e.g. Swin Transformer) from scratch achieves much inferior performance compared to ConvNets (e.g., ResNet38). So in our experiment, we use ImageNet-100 (100 classes) with the input size $224 \times 224$, where about 126K and 5K images are used for training and validation, respectively.

Here we apply two visual Transformer models as baselines: Swin Transformer [Liu et al., 2021b] and Tokens-to-token ViT [Yuan et al., 2021]. Swin Transformer builds hierarchical feature maps by merging feature patches in down-samplings and has a linear computation complexity to feature resolution due to self-attention being only computed within local windows. In the experiment, we use Swin-T as the baseline. The Token-to-token ViT (T2T-ViT) incorporates a layer-wise Token-to-Token transformation to progressively structurize the image to tokens by recursively aggregating neighbouring tokens into one token, and an efficient backbone with a deep-narrow structure. Here we use T2T-ViT-14 with the Performer implementation as the baseline of image classification. We inserted the proposed horizontal and vertical attention modules into the Transformer blocks, providing additional functions, then observe their effectiveness. We trained the baselines, both with and without the two additional attention modules, using the same data-augmentation protocol, and applied the hyper-parameter configuration suggested by the authors of Swin-T and T2T-VIT-14. We did not tune the specific hyperparameters when we used the proposed attention functions in all the experiments. All models were trained from scratch on a single GPU card and optimized by AdamW for 200 epochs, and the mini-batch size was set to 128.

Experimental results

In Table 3 we analyze the computational complexities and compare the classification accuracies of the two visual Transformer baselines and their extensions with horizontal or vertical attentions. In terms of model size and computational complexity, even applying both of the two proposed attentions in visual Transformers, it incurs less than 10% additional parameters and FLOPs, which proves the high computational efficiency without changing the overall network architectures. The Swin-T generally obtains slightly higher accuracies, but T2T-VIT-14 is more parameter efficient. The classification accuracies are shown in this table, and the confusion matrices on the validation set using Swin-T are illustrated in Figure 4. By observing these statistical results, we can see that the exception only occurs when applying the horizontal attention...
Table 4: Comparisons of $\mathcal{M}^2$ Transformer with its horizontal and vertical attention extensions on the Karpathy test split of MSCOCO dataset.

| Method            | BLEU-1 | BLEU-4 | METEOR | ROUGE-L | CIDEr  |
|-------------------|--------|--------|--------|---------|--------|
| $\mathcal{M}^2$ Transformer | 80.8   | 39.1   | 29.2   | 58.6    | 131.2  |
| + Hor.            | 80.9 ±0.1 | 39.0 ±0.1 | 29.1 ±0.1 | 58.7 ±0.1 | 132.4 ±1.2 |
| + Ver.            | 81.0 ±0.2 | 38.9 ±0.2 | 29.3 ±0.1 | 58.8 ±0.2 | 132.9 ±1.7 |
| + Hor. + Ver.     | 80.9 ±0.1 | 38.9 ±0.2 | 29.3 ±0.1 | 58.7 ±0.1 | 133.2 ±2.0 |

Experimental results

Table 4 summarizes the performance comparisons of image captioning on the testing split. From the statistics, we can see that by applying either horizontal or vertical attentions, the BLUE-4 score actually decreases slightly, while most other evaluation scores, especially the CIDEr score, improve in accordance with the use of the two proposed attention functions. When applying the horizontal attention in Transformer blocks, the BLUE-1, ROUGE-L and CIDEr scores obtain a 0.1, 0.1 and 1.2 improvement, respectively. Inserting the vertical attention for feature re-calibration, all testing scores are improved by a certain range, except the BLUE-4 score has a further drop of 0.2. Joint integrating horizontal and vertical attentions into $\mathcal{M}^2$ Transformer obtains the highest CIDEr score, a 2.0 improvement of the baseline model. However, all other evaluation metrics are not significantly benefited from the CIDEr fine-tuning, compared to the separate use of the two proposed attention methods. The experimental results can generally prove that both horizontal and vertical attentions are able to augment the feature representation by fully exploring the visual-semantic relationships between visual features and natural sentences in Transformers.

5 Conclusion

We have proposed two novel self-attention methods, namely horizontal and vertical attentions, to improve feature learning in various Transformer models. The horizontal attention aims to explicitly re-weight the multi-head output of SDPA, while the vertical attention tries to re-calibrate the feature output through a gating function. The proposed methods are highly modular, which can be readily pluggable to various Transformer models for many supervised learning tasks. The experimental results show that both attention methods can effectively improve the model accuracy while requiring very limited computational resources overhead.

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