Attention Augmented Convolution

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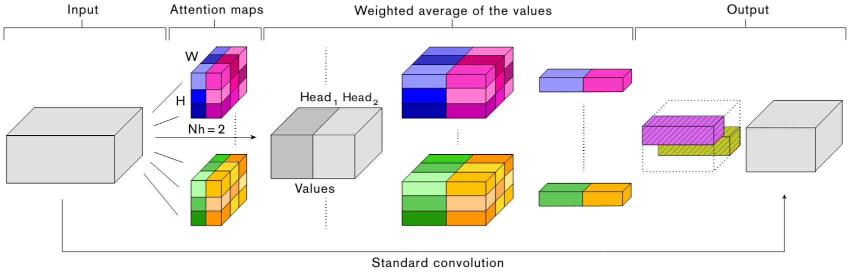
Motivation

- Convolutional Networks has been the go-to model architecture for image classification tasks, but it has local receptive field as it only operates on the local neighbourhood.
- To deal with this problem one has to either use a larger kernel size or make the network deeper or both which increases the model complexity.
- Self-Attention, on the other hand, has emerged as the choice of model architecture to capture long range interactions.
- Bello et al. [2020] has implemented Attention Augmented Convolutional Networks which combines both Convolutional Networks and Self-Attention.

Objective

- Bello et al. [2020] has used Vaswani et al. [2023]'s implementation of self attention (sdpa) which is quadratic in time and memory complexities.
- Over the years many sub-quadratic attention mechanisms have been proposed, we took Shen et al. [2024]'s implementation which is linear in time and space complexities.
- We indented to see how it affects the time and accuracy of the network.

What is Attention Augmented Convolutional Network



Attention Augmented Convolutional Network (AA-Conv)

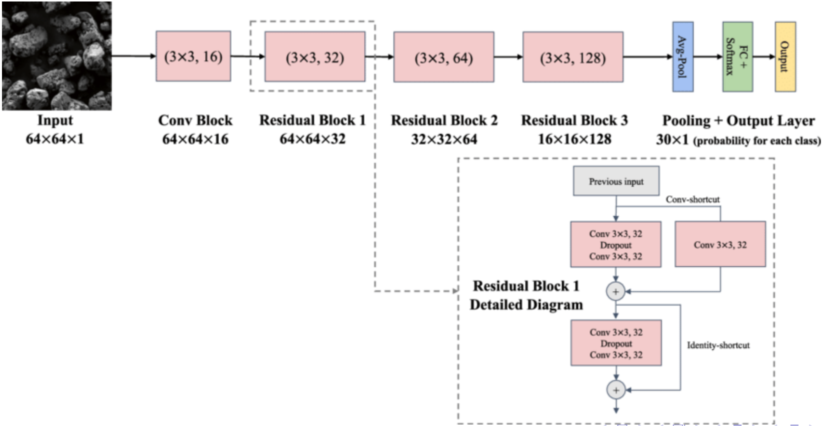
- For Vaswani et al. [2023]'s implementation given input $X \in \Re^{n \times m}$, we have 3 weight matrices $W_q \in \Re^{m \times d_k}, W_k \in \Re^{m \times d_k}, W_v \in \Re^{m \times d_v}$ that transforms the input as $Q = XW_q, K = XW_k, V = XW_v$ and the attention output as $O_h = \rho(\frac{QK^T}{\sqrt{d_k}})V$.
- We have input image to the AA-Conv with dimentions $F_{in} \times h\ w$, this is reshaped to dimensions $hw \times F_{in}$ and this is feed to the Attention Mechanism as input. Thus making the time and space complexities to be $O((hw)^2(d_k + d_v))$.

Linear Attention Augmented Convolutional Network (LAA-Conv)

- For Shen et al. [2024]'s implementation given input $X \in \Re^{n \times m}$, we have 3 weight matrices $W_q \in \Re^{m \times d_k}, W_k \in \Re^{m \times d_k}, W_v \in \Re^{m \times d_v}$ that transforms the input as $Q = XW_q, K = XW_k, V = XW_v$ and the attention output as $O_h = \rho_{col}(Q)(\rho_{row}(K))^T V$.
- We have input image to the LAA-Conv with dimentions $F_{in} \times h\ w$, this is reshaped to dimensions $hw \times F_{in}$ and this is feed to the Attention Mechanism as input. Thus making the time and space complexities to be $O(d_k d_v (hw))$.

Experiments

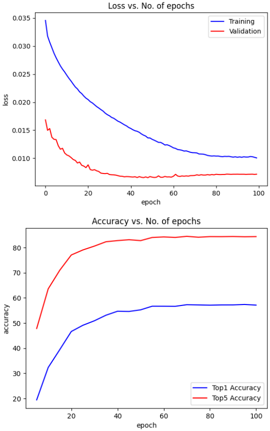
- We implemented 3 models viz Wide-ResNet, Wide-AAResNet and Wide-LAAResNet each for the two datasets viz CIFAR-100 and Tiny-Imagenet.
- Following is the architecture of the Wide-ResNet.



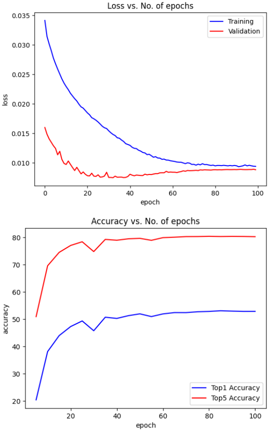
Experiments

- In each block of Wide-ResNet, we changed one conv layer to AA-conv layer (LAA-conv layer) to get Wide-AAResNet (Wide-LAAResNet).
- Bello et al. [2020] used learnt positional embeddings stating that they got bad results using sine-cosine positional embeddings used by Vaswani et al. [2023]. But in our experiments the later gave better results so we stuck with that.

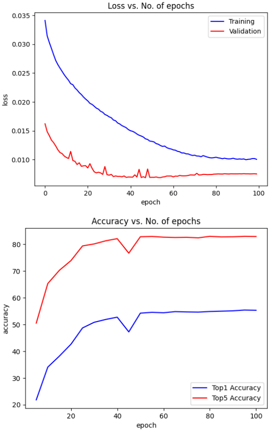
Experimental Results - CIFAR-100



Wide-ResNet

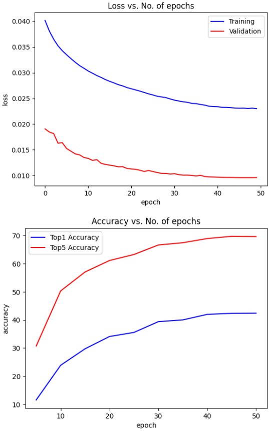


Wide-AAResNet

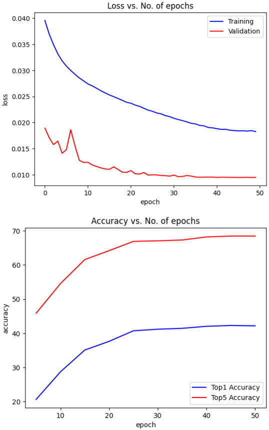


Wide-LAAResNet

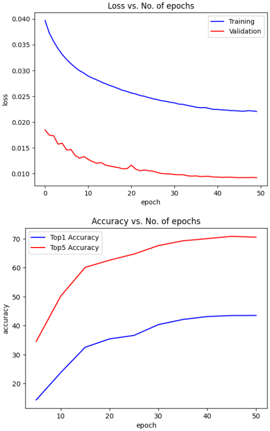
Experimental Results - Tiny-Imagenet



Wide-ResNet



Wide-AAResNet



Wide-LAAResNet

- Thanks You!
- You can find all the code and results of the experiments here.

References

I. Bello, B. Zoph, A. Vaswani, J. Shlens, and Q. V. Le. Attention augmented convolutional networks, 2020.

Z. Shen, M. Zhang, H. Zhao, S. Yi, and H. Li. Efficient attention: Attention with linear complexities, 2024.

A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin. Attention is all you need, 2023.