Attention Augmented Convolution

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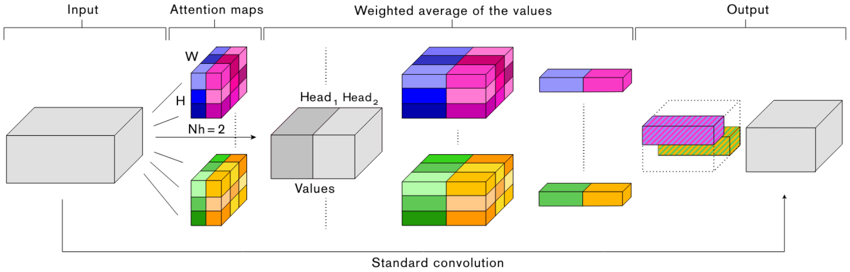
Motivation

- 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 space 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



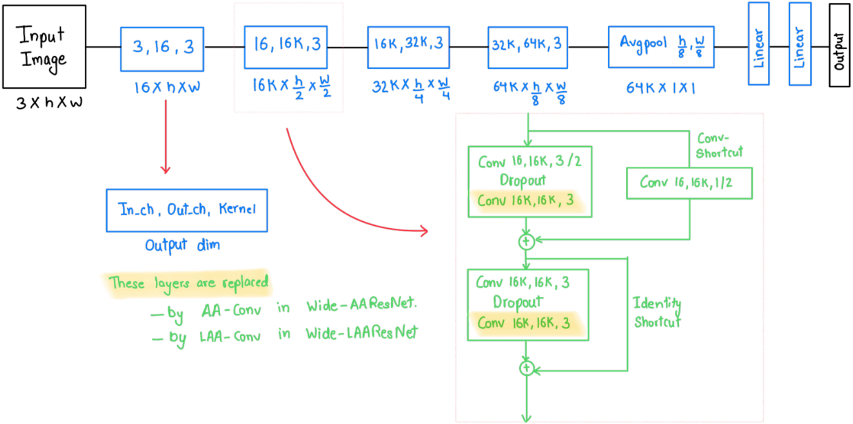
Attention Augmented Convolutional Network (AA-Conv)

- 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 $F_{in} \times h \times w$, 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 $F_{in} \times h \times w$, 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 $O(d_k d_v (hw))$.

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



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.

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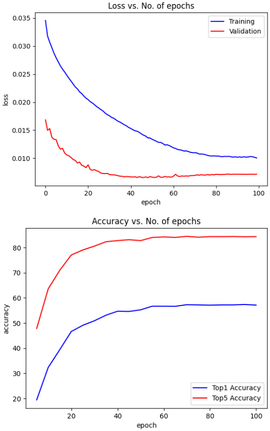
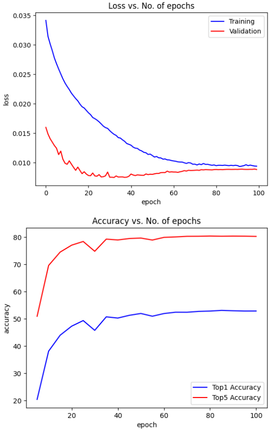
Experimental Results - CIFAR-100



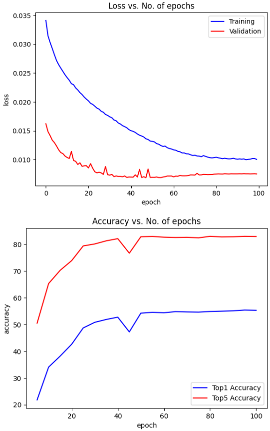
Wide-ResNet

57.11, 84.33



Wide-AAResNet

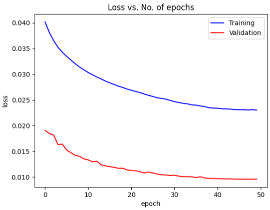
52.91, 80.31

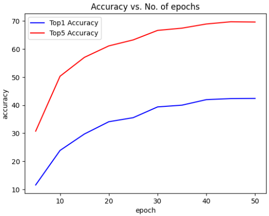


Wide-LAAResNet

55.32, 82.95

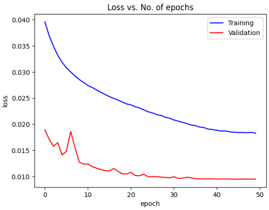
Experimental Results - Tiny-Imagenet

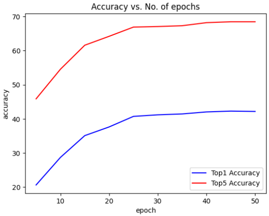




Wide-ResNet

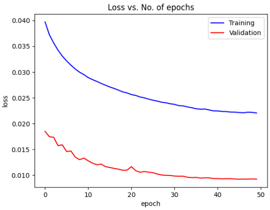
42.39, 69.61

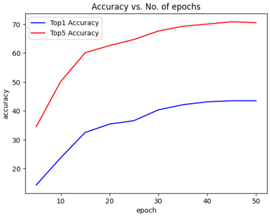




Wide-AAResNet

42.18, 68.44





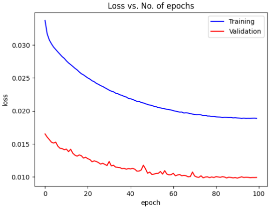
Wide-LAAResNet

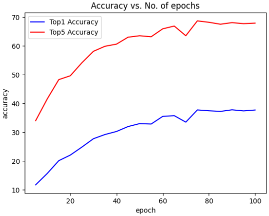
43.51, 70.52

Conclusion 1

- From the above experimental results, it seems that all 3 models perform similarly, which can be attributed to the fact that -
  - the models are already very deep and the Convolutional Layer's receptive field is covering the entire input image.
  - Moreover the attention approximation by linear attention is also compensated by the depth of the model.
- With this stated, an another experiment of training shallow networks can be performed to -
  - check whether the Attention Augmented Convolutional Layers truly capture global interactions,
  - check whether the approximation done by linear attention affects the accuracy or not.

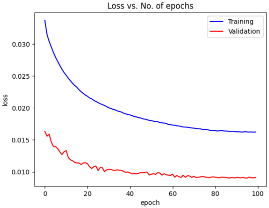
Experimental Results - CIFAR-100

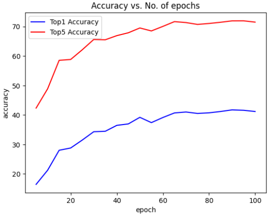




Simple-CNN

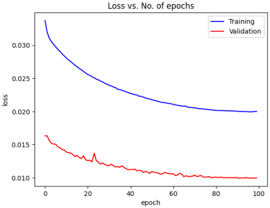
37.74, 67.94

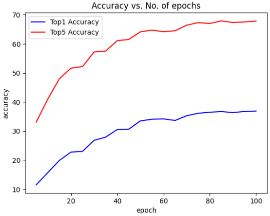




Simple-AACNN

41.19, 71.51





Simple-LAACNN

36.88, 67.81

Conclusion 2

- From the above experimental results we can conclude -
    - Higher Simple-AACNN's accuracy implies that the Attention Augmented Convolutional Networks does capture more information than the Convolutional Networks.
    - Lower Simple-AACNN's accuracy implies that the attention approximation by linear attention does looses information.
- Thank You!
- You can find all the code and results of the experiments here.

https://github.com/yoR-rihsihS/aip-andromeda

References

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

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