## Attention Augmented Convolution

Shishir Roy<sup>1</sup> Meghal<sup>2</sup>

 $^{1}\mathrm{M.Tech}$  A.I. Indian Institute of Science, Bangalore

<sup>2</sup>M.Tech A.I. Indian Institute of Science, Bangalore

Advanced Image Processing, May 2024





#### 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.

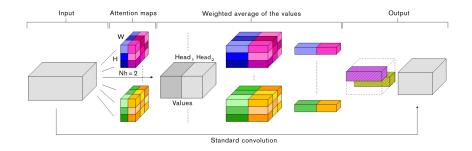


# Objective

- 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  $X \in \mathbb{R}^{n \times m}$ , we have 3 weight matrices  $W_a \in \mathbb{R}^{m \times d_k}$ ,  $W_k \in \mathbb{R}^{m \times d_k}$ ,  $W_v \in \mathbb{R}^{m \times d_v}$  that transforms the input as  $Q = XW_q$ ,  $K = XW_k$ ,  $V = XW_v$  and the attention output as  $O_h = \rho(\frac{QK^T}{\sqrt{d_i}})V$ .
- 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  $O((hw)^2(d_k + d_v))$ .



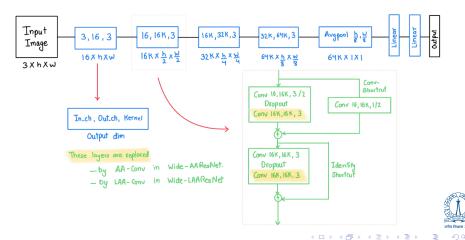
# Linear Attention Augmented Convolutional Network (LAA-Conv)

- For Shen et al. [2024]'s implementation given input  $X \in \mathbb{R}^{n \times m}$ , we have 3 weight matrices  $W_q \in \mathbb{R}^{m \times d_k}, W_k \in \mathbb{R}^{m \times d_k}, W_v \in \mathbb{R}^{m \times d_v}$  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  $O(d_k d_v(hw))$ .



### **Experiments**

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

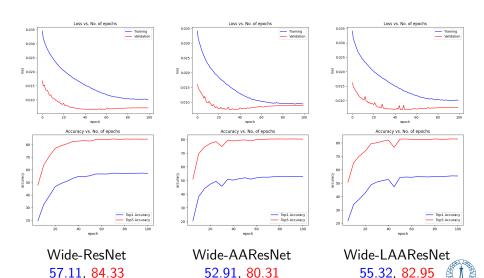


## Experiments

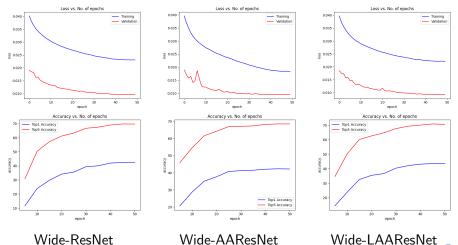
- In each block of Wide-ResNet, we changed one conv layer to AA-conv layer (LAA-conv layer) to get Wide-AAResNet (Wide-LAAResNet).
- Bello et al. [2020] used learnt positional embeddings stating that they
  got bad results using sine-cosine positional embeddings used by
  Vaswani et al. [2023]. But in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



## Experimental Results - CIFAR-100



## Experimental Results - Tiny-Imagenet



Wide-ResNet 42.39, 69.61

Vide-AAResNet 42.18, 68.44

43.51, 70.52



#### Conclusion

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

