# **Generalization by** Visual Attention?

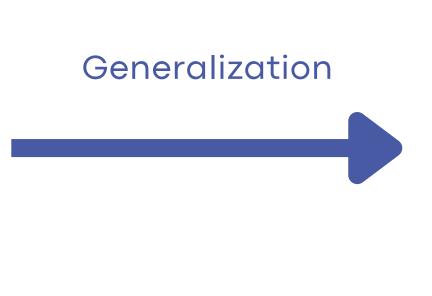
# CNNs vs Transformers on outof-distribution performance

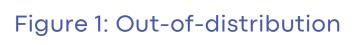
# **Background Information**

### **Out-of-distribution**

This research investigates if a neural network trained on specific distribution can generalize its world's understanding in a new distribution. We call this difference between training and test environment "out-of-distribution".



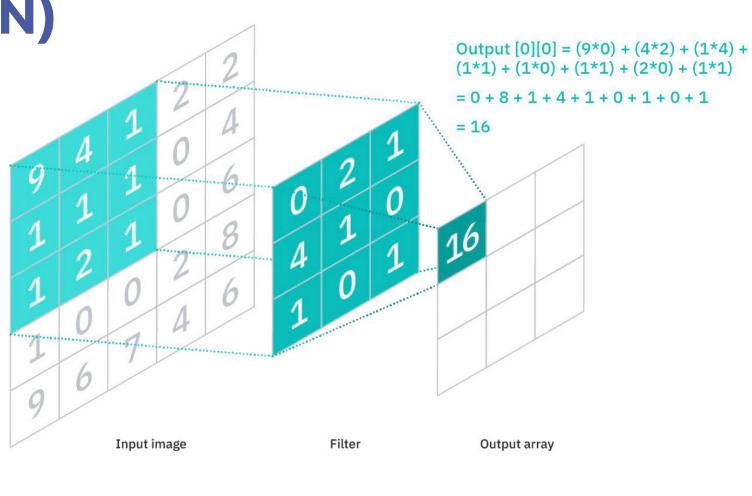


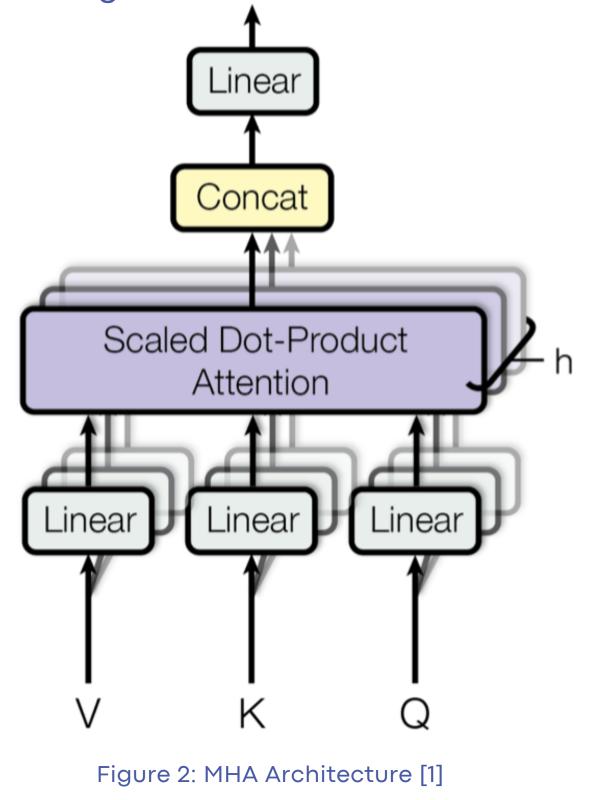


To illustrate our statement, as we can observe in figure 1 we wondered whether a network that has only seen the number "5" associated with trucks would still recognize the number "5" in a new environment like on top of a flower.

### **Convolutional neural network (CNN)**

The CNN architecture is the most common architecture in computer vision. It works by extracting features based on its kernel, which are a set of learnable weights. This kernel is then rolled over the image to produce an output, which allows the network to extract the meaningful feature out of the image.





### Transformer

The transformer is a novel alternative to CNNs for computer vision. Instead of being restricted by the association allowed inside the kernel, it can exploit the full input to make connections by using its attention mechanism (see figure 2). This attention is then duplicated and encapsulated into a single module that we call **multi-head attention** (MHA). We believed that the attention mechanism of the transformer should lead to better performance on out-of-distribution.



Figure 3: CNN Architecture [2]



### **Research Question**

Which network configurations have the largest impact on out-of-distribution performance in both architectures?



To investigate this question, we started by creating datasets with a customisable number of background per digit. I then implemented a custom module fully interchangeable with a convolution operation, named Mha2d. Lastly, I tested different network configuration for both models to see what configuration can improve outof-distribution performance.



### I. Baseline

I used the LeNet [3] architecture a baseline comparaison between both architecture by the convolutional swapping blocks with the Mha2d module. As we can see in figure 5, our multihead attention based model performed significantly better than CNNs for out-of-distribution

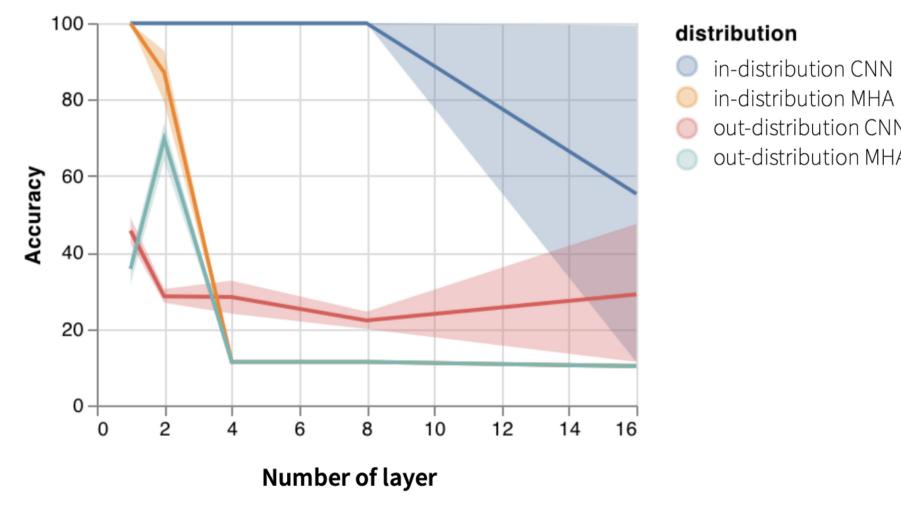


Figure 6: Accuracy of both models according to network depth

### **3. Number of heads**

The multi-head attention is controlled by a hyperparameter called the number of heads. This determines how many focal points (attention) the network has. We observed that for our task this parameter does not influence performance.

### **Author**

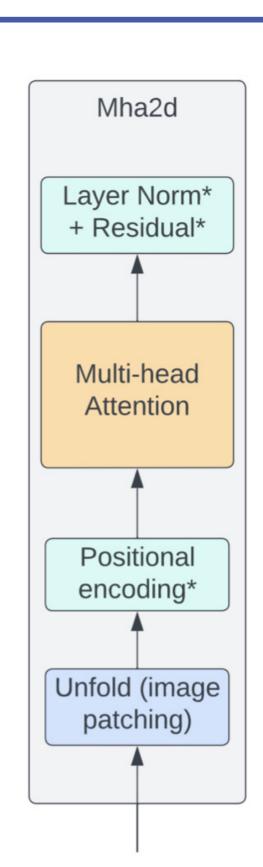


Figure 4: Custom mha2d module equivalent to conv2d

• [2] IBM Cloud Education, What are Convolutional Neural Networks? Oct. 20. [Online]. Available: https://www. ibm.com/cloud/learn/convolutional-neuralnetworks. • [3] Y. LeCun, B. Boser, J. S. Denker, et al., "Backpropagation Applied to

### **4. Transformer specific component**

Positional Encoding

After experimenting, I then came to the conclusion that only the layer normalization was shown to significantly improve out-of-distribution performance.

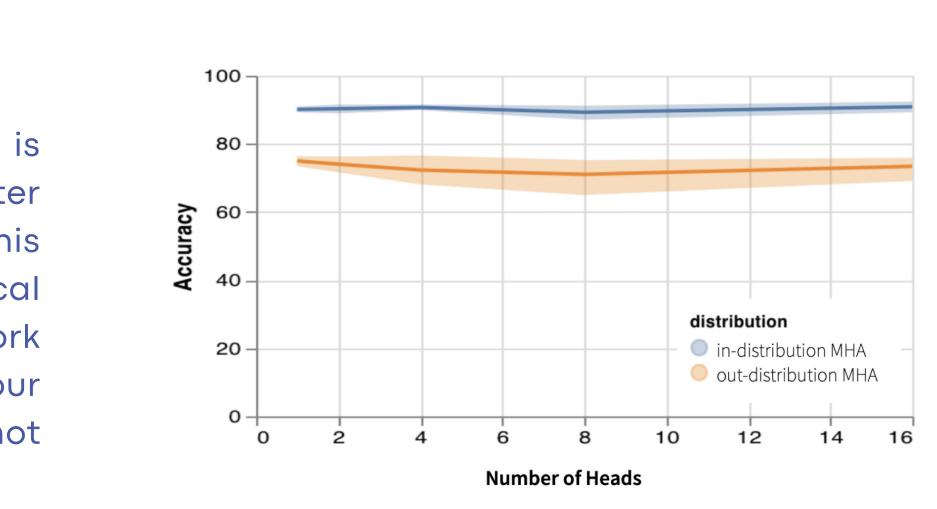
Bc Ne Nυ Pos Lay Re \_\_\_\_\_

Firstly, it would be interesting to investigate out-ofdistribution performance with images of bigger size (our experiment is only with 32x32 images). Secondly, stabilizing learning for depth network and studying the impact of residual connection on depth network could lead to more conclusions on the impact of network depth.

40 distribution in-distribution MHA in-distribution CNN out-distribution MHA out-distribution CNN 45 50 55 60 65 35 40 Number background per digit Figure 5: Baseline Performance

### 2. Network depth

In this experiment, I tested the impact of numbers of convolutional or attention layers on out-ofdistribution performance. We can see in figure 6 that with a higher number of layers the performance collapses, as the networks are not able to learn. However, CNNs are better able to train with more layer



compared to MHA.

Figure 7: Accuracy of MHA based on the number of heads

distribution

🔵 in-distribution MHA

out-distribution CNN

out-distribution MHA

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Bibliography

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### Want to learn more? Read the paper

• [1] A. Vaswani, N. Shazeer, N. Parmar, et al., "Attention is all you need," in Advances in Neural Information Processing Systems, vol. 2017-December, 2017.

Handwritten Zip Code Recognition," Neural Computation, vol. 1, no. 4, 1989, ISSN: 08997667. DOI: 10.1162/neco.1989.1.4.541.

This paper further investigated the below mentioned transformer-specific elements to see if they had an impact on out-of-distribution performance:

- This element adds locality information to the attention head.
- Layer Normalization
  - A regularisation technique used to normalize the output of a layer.

Residual Connection

• A connection between current and deeper layers, that allow us to skip these and add the input directly to a deeper layer.

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### Conclusion

	CNN	Transformer
Baseline		
Network Depth		
Number of Heads	X	
<b>Positional Encoding</b>	X	
Layer Normalization	X	
<b>Residual Connection</b>	X	
Conclusion		

### **Recommendation for further research**