Attention based Evolutionary Approach for Image Classification

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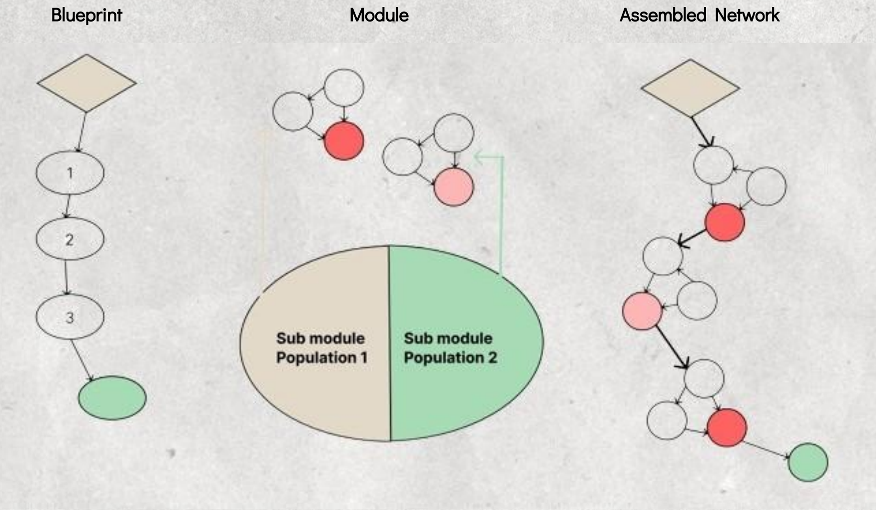
Introduction

- There is a need for increasingly complex neural network architectures.
- Neural networks are black boxes, which makes it difficult to design their topology for a specific task.
- Existing evolutionary methods are outdated and don't include advanced State-of-the-Art techniques that are guaranteed to improve performance.
- This paper explores the effect the addition of the Convolution Block Attention Module (CBAM) has on the performance of resulting topologies evolved using the CoDeepNEAT algorithm.

Past Approaches

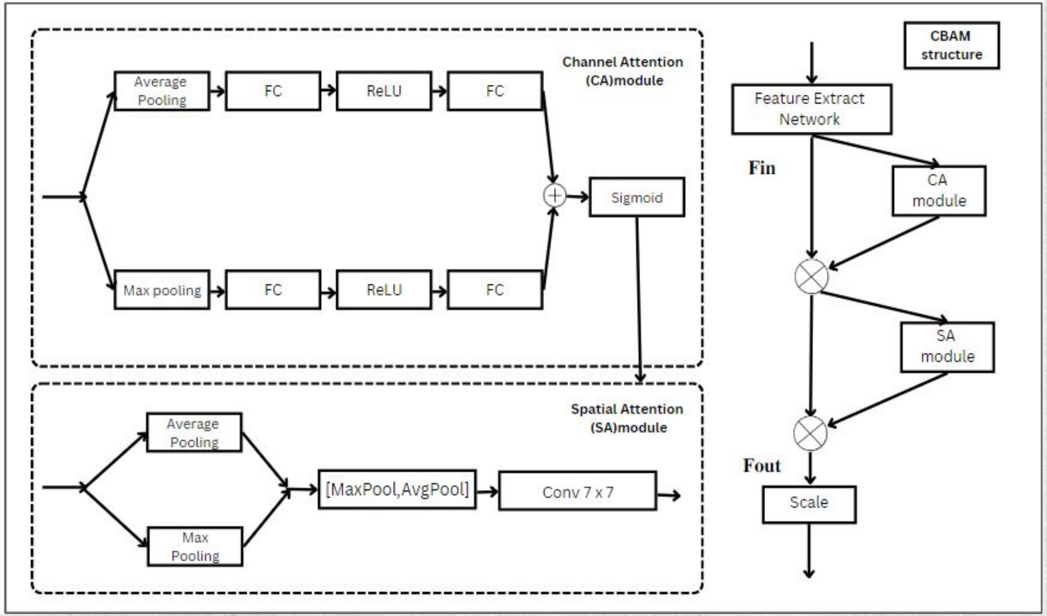
Theory	Description
NEAT	Genetic algorithm to evolve optimal neural networks
Hyper-NEAT	Specialized to evolve large scale structures through CPPNs
Deep-Hyper NEAT	CPPNs in HyperNEAT are augmented with new information, process of mutation is added to HyperNEAT
CoDeepNEAT	Takes advantage of the repetitive structure of DNNs, presence of modules in it allow for various extensions

CoDeepNEAT



- The CoDeepNEAT algorithm comprises of 2 sets of populations in every generation:
  1) Blueprint
  2) Module
- The Module represents the deep neural network.
- The Blueprint represents the connections between the modules.

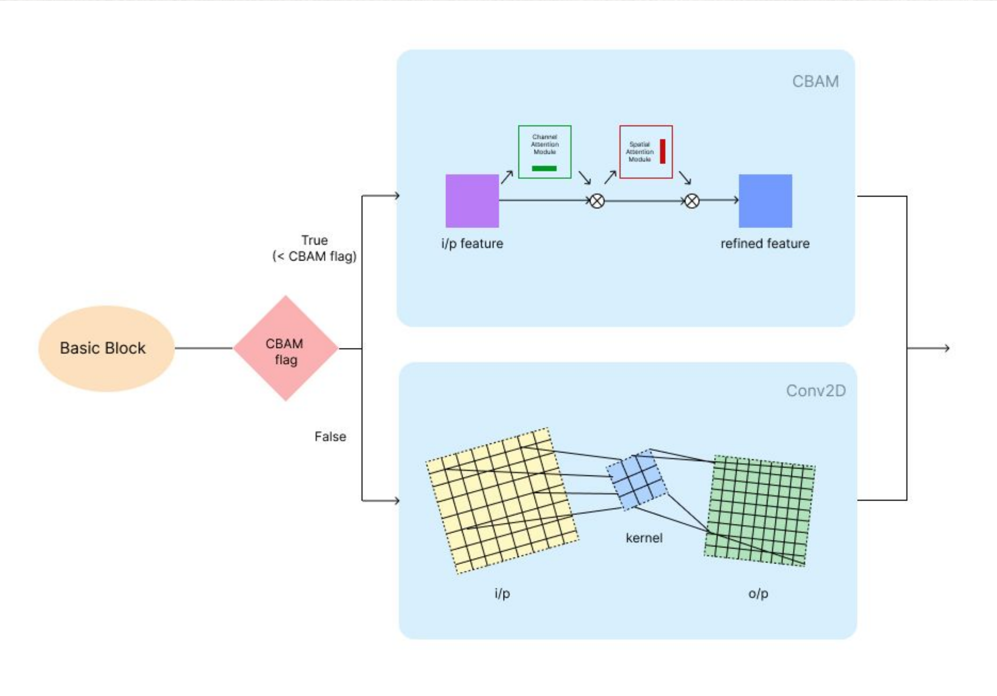
Convolution Block Attention Module



- Channel Attention Map: “What in the given image is meaningful?”
- Spatial Attention Map: “Where in the image the informative part lies?”

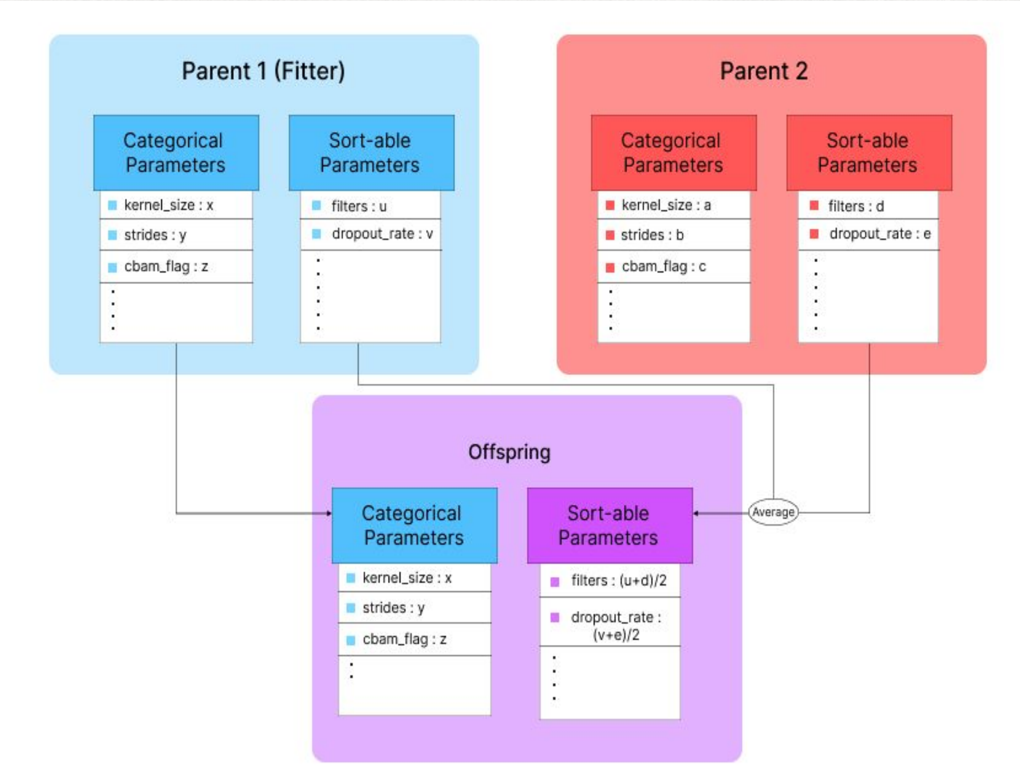
$$\mathbf{F}' = \mathbf{M_c}(\mathbf{F}) \otimes \mathbf{F},$$
$$\mathbf{F}'' = \mathbf{M_s}(\mathbf{F}') \otimes \mathbf{F}',$$

Methodology



CoDeepNEAT was given a choice between CBAM and the pre-existing Convolution module.

Crossover



During crossover the parameters of the modules were divided into two types, categorical and sort-able.

Experimental Setup

Dataset : CIFAR-10
Number of Generations : 30
Number of Genomes per Generation : 100
Batch Size : 512
Epochs : 8
Optimizer : SGD with Nesterov Momentum set to 0.69
CBAM Flag : 0.2
Platform : Google Colab
GPU's used : Tesla P100(16GiB) & Tesla A100(40 GiB)

Results

Work in Literature	Parameters	Accuracy	Hyperparameter Optimization	Data Augmentation
Aszemi et al.	-	80.62	YES	NO
Zhao et al.	-	86.33	NO	YES
Evangelista et al.	-	84.6	NO	NO
Thite et al.	-	75.59	YES	NO
Real et al.	5.4 M	94.6	-	-
Proposed Approach	**2.65 M**	**87.44**	**NO**	**NO**

Conclusion & Future Work

- Evolution can be guided!
- Addition of SOTA techniques to evolutionary algorithms results in better neural network architectures, possibly with fewer model parameters.
- As GPU's/TPU's become cheaper and more available, evolutionary algorithms are likely to be favoured.
- Testing this on Image Captioning tasks.
- Incorporating more SOTA techniques to further boost performance.
- Adapting the algorithm for NLP tasks.

Thank You For Listening!
Any Questions?