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On Growing Neural Networks with Multi-Agent Principles

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1 Introduction

Neural principles based on the biological template have become crucial in machine learning in recent years and artificial networks are indisputably SotA classifiers nowadays. Results in multiple specific domains are often fascinating, however, mainstream training methods are hardly ever capable of reaching the optimal behaviour and suboptimal solutions are accepted instead. The missing percents in performance cause unreliable behaviour of trained models and slow down their deployment in real world applications. As demonstrated in Fig. 1 (especially talking about the red box), the mainstream research procedure is based on an iterative tuning of hyper-parameters, collecting new data and increasing the computational power, while the core of the problem - the behaviour inside the trained model is usually kept shrouded in mystery.

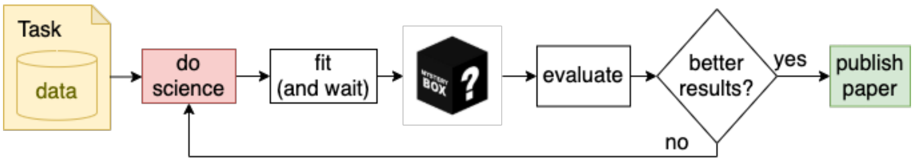

Figure 1: Mainstream research approach in machine learning.

On the way of developing reliable and meaningfully tunable AI solutions, I find the common approach tilting at windmills and therefore, this work suggests an alternative thinking of how to work with neural principles from scratch. Given a specific classification problem, the objective of the proposed method is to design a tailored (and purposefully tunable) neural network architecture. As illustrated in Fig. 2, the network generation process is based on the multi-agent theory supported by reinforcement learning, where parts of the network (neurons and synapses) are considered to be individual agents.

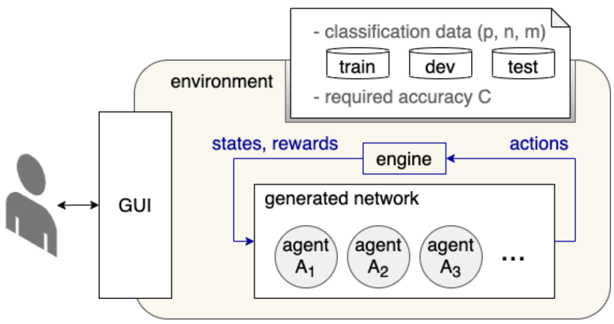

Figure 2: General view of the proposed method.

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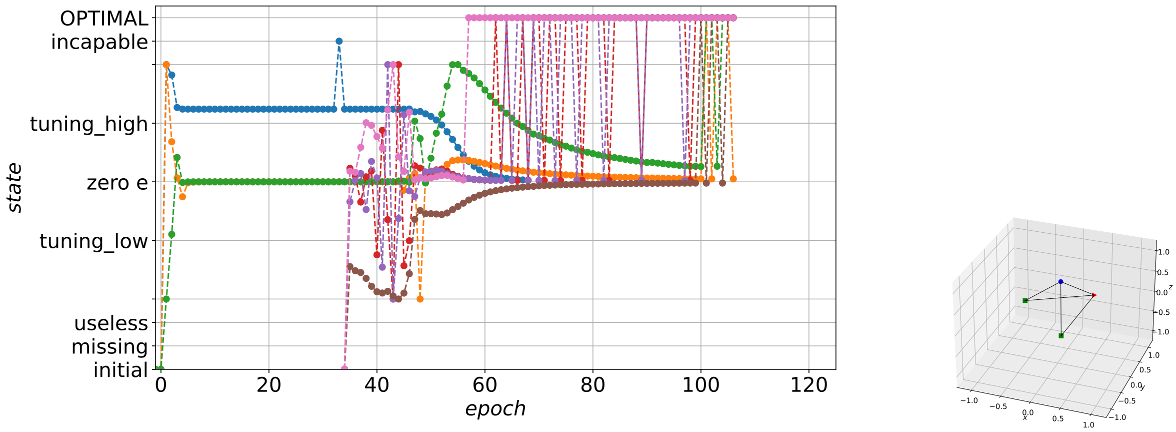
The key idea is to exploit the multi-agent analogy to the network parts and their primitive nature with a local point of view only, while they work together on a global task and emerge some intelligent-like behaviour as a whole (the classification capability).

2 Initial Experiments

The algorithm has already been compiled and initial 2D experiments were performed with expected results. Fig. 3a shows the evolution of states of individual agents, one by one gradually skipping into the *optimal* state. Defined deterministic rules ensure that once all of them reach the *optimal* state, the designed network structure (Fig. 3b) is optimal for the given classification problem (the XOR problem in this case).



(a) States of individual agents during the network generation process. **(b)** Generated net.

Figure 3: The XOR problem experiment - an algorithm verification in 2D.

Related methods including the *Badger* architecture (Rosa et al. (2019)), neural architecture search algorithms (Stanley and Miikkulainen (2002), Zoph and Le (2016)) and network growing algorithms (Mixter and Akoglu (2020)) are comparable, but different in their goals or basic principles. The project is currently at the phase of prooving the scalability on multidimensional data, hence the next step is to apply the method on the MNIST dataset and to reach the SotA performance with a multi-agent based network architecture.

References

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