CS7643

HW1 SP25

Adrian Kukla

Question 8

Briefly summarize the key contributions, strengths, and weaknesses of this paper.

The paper challenges the traditional belief that learning weight parameters via gradient descent is the primary driver of a neural network's predictive performance. It demonstrates that weight agnostic neural networks evolve architectures over time without relying on weight training.

Contributions

- Shows that specific architectures can perform well even with shared weights, highlighting the importance of network topology alongside weight optimization.
- Questions whether backpropagation is the only viable strategy for improving neural network performance, proposing a search-based alternative using NeuroEvolution of Augmented Topologies (NEAT).
- Suggests that genetic algorithms could identify architectures that generalize across tasks with minimal weight tuning.

Strengths

- The interactive version provides intuitive visualizations, making complex ideas more accessible.
- Innovatively challenges long-held assumptions, showing that architecture alone can encode strong inductive biases and improve performance, opening avenues for further research.
- Builds on principles inspired by natural behaviors, aligning with arguments like Zador's that backpropagation diverges from genetically inherited learning mechanisms.

Weaknesses

- The problems evaluated are narrow in scope, focusing on simple, structured environments, which may not translate well to unstructured tasks like speech recognition or image processing.
- Lacks a clear roadmap for integrating WANNs into modern deep learning frameworks for practical applications.
- No limitations section is included to critically analyze findings or address counterarguments.
- Discovered architectures might be computationally expensive and poorly suited for GPU acceleration.

Question 9

What is your personal takeaway from this paper? This could be expressed either in terms of relating the approaches adopted in this paper to your traditional understanding of learning parameterized models, or potential future directions of research in the area which the authors haven't addressed, or anything else that struck you as being noteworthy.

My personal takeaway has primarily to do with a life lesson, more than something specific to neural networks. It is that thinking out of the box, and not following a dogmatic world view is valuable and should be encouraged. To not blindly follow the standard practice inherited, and to be a conformist to traditional ways of thinking, but to evaluate new possibilities and be open minded.

In the context of neural networks I learned that it is also possible to tweak architectures and the neural network topology rather than sole use of the traditional backpropagation technique, which I personally thought was the' be-all end-all' of neural networks.

What interests me now is whether we can implement hybrid approaches investigating training weights combined with architectures that co-evolve with the trained weights.

NONE