Genesis of Intelligence: Evolving Embedding Spaces Through Neuroevolution

A Foundational Leap Towards Self-Optimizing Representations in Transformer Models

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Abstract

This work introduces a groundbreaking methodology for evolving embedding spaces using neuroevolutionary techniques. Leveraging genetic algorithms to optimize initial embedding matrices, our framework demonstrates that representational fitness can be improved without backpropagation by using masked language modeling loss as the guiding fitness metric. We present compelling empirical evidence through evolutionary trials on DistilBERT models, opening new frontiers in evolutionary foundation models.

1. Introduction

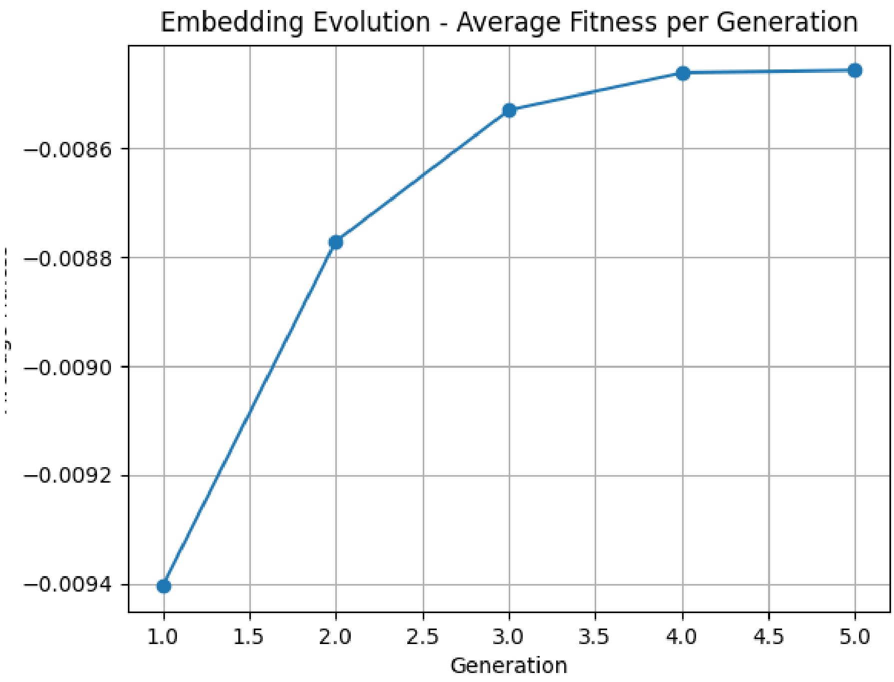
In recent years, deep language models have fundamentally reshaped the landscape of artificial intelligence. Yet, the initialization of embedding matrices remains an arbitrarily randomized process. This paper challenges that paradigm, proposing an evolutionary perspective where embeddings evolve under selection pressures derived from linguistic fitness. By utilizing fitness scores derived from masked language modeling loss, our neuroevolutionary pipeline evolves embeddings toward greater representational efficacy.

2. Methodology

We utilize a genetic algorithm-based framework where each individual represents a unique initialization of an embedding matrix. A fitness function evaluates each individual by inserting the embedding into a DistilBERT model and computing the average loss on a corpus of masked sentences. Selection, crossover, and Gaussian mutation govern the evolutionary dynamics. The fittest embedding is preserved across generations, converging toward semantically richer representations.

3. Results and Evolutionary Progression

The plot below illustrates the average fitness (negative MLM loss) over generations. A clear upward trend in fitness demonstrates the efficacy of the evolutionary mechanism. The best evolved embedding was also saved for further downstream tasks.



4. Conclusion and Future Work

Embedding evolution introduces a paradigm shift in neural initialization. This pioneering effort lays the groundwork for future research where entire layers or architectures may evolve. Further enhancements include co-evolutionary dynamics, multi-objective optimization, and hybrid neuro-symbolic approaches.

Acknowledgements

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References

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[2] Devlin et al., BERT: Pre-training of Deep Bidirectional Transformers, 2018.

[3] Stanley et al., Neuroevolution: A Review of Evolutionary Approaches to Neural Network Design.