Optimizing Neural Architectures with Dimensional Reduction via Neological Analysis

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Abstract

This research proposes a novel method for identifying complex surfaces within neural architectures and fine-tuning models using newly coined words, termed *neologisms*, to achieve optimal storage, improved training performance, and enhanced performance in symbolic reasoning. The term ”Logogenetic” can be used to encompass the creation of new words (Logos + Genesis) for the intent of more efficiently fitting tokens to a higher dimensional domain. We could also use the term ”neological” however, the derivation of words from semantic constituents should be understood as critical to this process as it is hypothesized that the familiarity of the word parts is a natural property of this approach; so by referencing genetics we hope to add weight to the hereditary nature of such emergent nominal abstractions. By replacing these complex surfaces with their corresponding neologisms, we reduce dimensional complexity through linguistic abstraction, enhancing both model performance and transfer learning capabilities.

1 Introduction

Language has long been recognized for its ability to abstract and simplify complex concepts. It is clear that over time, the inclusion of neologisms is critical both to collective innovation, but also in reasoning about complex concepts without having to saturate attentional context with ultimately abstractable semantic tedium. Adding terms to language is not a fast process, often words are coined in research papers such as this. Due to the requirement that collaborators have a common and dependable understanding of a new terms semantic applications, the rate at which neological augmentations can be realized is limited. This research proposes to move this capacity into either training or a pre-training process that is intended to align the tokenization implementation to consider new terms generated via detecting areas of slow loss reduction across several layers. This research explores the hypothesis that the coining of new words, or *neologisms*, can be leveraged to enhance the way information is leveraged to perform dimensional reduction in neural networks. By identifying and integrating these neologisms into neural architectures, we propose a method for optimizing model efficiency and performance.

2 Background

Previous work in linguistic economy and the Whorfian hypothesis suggests that language evolves to balance effort and clarity, influencing cognitive processes. In machine learning, algorithms are frequently tasked with processing complex data. Researchers have been proposing a linguistic approach to dimensional reduction by using simplified representations. This research builds on these foundations by proposing a method of identifying semantic stress or other situations where slow loss reduction indicates endemic issues stemming from from representational friction.

3 Methodology

3.1 Identifying Complex Surfaces

To identify complex surfaces within a neural architecture, we will:

1. Analyze the weight matrices and activation patterns of the network to identify regions of high dimensional complexity.
2. Apply topological data analysis (TDA) techniques to map these regions, identifying points of high structure and intricate structure.

3.2 Co-ining Neologisms

Using the identified complex surfaces, we will:

1. Develop a heuristic, the *Lexicogenetic Algorithm (LA)*, to detect terms and concepts with high usage frequency, contextual diversity, and cognitive load.
2. Coin new words (neologisms) to represent these complex terms, effectively reducing their dimensional complexity.

3.3 Fine-Tuning the Model

To integrate neologisms and optimize the neural architecture, we will:

1. Replace identified complex terms in the training data with their corresponding neologisms.
2. Retrain the model, allowing it to learn the new, simplified representations.
3. Evaluate model performance on standard benchmarks to assess improvements in storage efficiency and transfer learning capabilities.

4 Expected Outcomes

We anticipate that integrating neologisms into neural architectures will:

1. Reduce the dimensional complexity of the network, leading to more efficient storage and faster computation.
2. Enhance the model's ability to generalize across different domains, improving transfer learning performance.
3. Demonstrate the utility of linguistic abstraction in optimizing artificial intelligence systems.

5 Conclusion

This research aims to bridge the gap between linguistic evolution and neural network optimization, proposing a novel method for dimensional reduction through the coining of new words. By harnessing the power of neologisms, we hope to achieve new ways of measuring performance with respect to logogenetic agility and encourage its adoption as a means of optimizing neural architecture performance.

6 References

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