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Peer Review

Review of: "Ancestral Mamba: Enhancing Selective Discriminant Space Model with Online Visual Prototype Learning for Efficient and Robust Discriminant Approach"

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This paper presents a novel method for spatial discrete data modeling. The motivation for the method is well-defined, and all mathematical methods are theoretically sound and proven. The method in this article can solve catastrophic forgetting and contribute to continuous learning of deep learning. The combined use of prototype learning and adaptive feedback has certain innovative contributions, which are clearly demonstrated in the ablation experiment. Experiments have demonstrated that this method can outperform many baselines and SOTA methods after multiple tasks (using both synthesized and real-world data). This article not only mentions its advantages but also covers limitations such as closed set leaning and non-task-free continual learning.

This paper shows that there is a need in spatial discrete data modeling that is not being met before introducing the method that will solve the problem. In Section 3, for the instrument matrix G, it is unclear how q is selected. It is only stated that it is of order $O(\ln n)$; it would be beneficial to show how this is identified in practice. Additionally, guidance on how the candidate matrices in Section 4 (W_2, ..., W_S) are obtained would be useful. This is discussed for the examples in Section 6 and 7; however, a more general explanation and deep dive into the logic behind the choices would help with clarity and generalization. In Section 4, both model selection and model averaging methods are well-defined mathematically; however, there is no mention of when one should be used over the other. Should we always try model selection first, then use model averaging if it does not work? In section 5, the mathematical proofs are well-written in showing that the estimator delta is consistent with convergence

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and asymptotically normal. The experimental results in Section 6 and 7 align with the theoretical results, including the case for the zero matrix W_1. In the tables, it would be helpful to have a brief explanation about what the MS and MA columns contain. A final section for limitations/future work could also be added at the end of the paper. Revisions could also include adding in a discussion about how some model components such as candidate matrices are selected, and identifying the difference between the two techniques presented in real-world use cases (MS and MA). Areas for improvement include giving practical guidance for selecting candidate matrices/instrument matrix dimensions, adding in a discussion about the MS vs. MA techniques, and interpreting MS/MA columns in the experiment tables. Additionally, it would benefit from a direct comparison with existing methods on the same dataset to make the argument for the proposed approach stronger. Although the article focuses on the model learning of feature selection under the interaction of prototype learning and adaptive feedback, providing backbone descriptions and comparisons can help researchers build and learn models. In particular, the mention of keywords such as selective space model and Mamba in the model makes people guess whether the vision mamba based model is used to implement the method, but it is not clearly stated in the article. In addition, although the article clearly states that categories must be known, the impact of different categories and even the number of prototypes in each category under future model transfer can still be discussed.

Overall, the paper introduces a relevant novel approach to solve an issue, explains the motivation and theory behind the work with well-defined mathematical formulas and symbols, and contains evaluations with metrics.

Declarations

Potential competing interests: No potential competing interests to declare.