"TopoHyperDrive: Accelerating Meta-Search in Hyperparameter Optimization through Topological Analysis"

The author introduces an approach to optimize hyperparameters in neural networks by leveraging the topological structure of model embeddings. Traditional hyperparameter optimization methods often treat neural networks as black boxes, leading to lengthy and computationally expensive searches. TopoHyperDrive aims to address this by using Representation Topology Divergence (RTD), a metric that measures the dissimilarity between neural network embeddings based on their topological features.

By incorporating RTD into the optimization process, TopoHyperDrive can more efficiently navigate the hyperparameter space, potentially improving the convergence rate and overall performance of neural networks. The paper demonstrates the method's effectiveness through experiments on the CIFAR-100 dataset and compares it with existing optimization techniques, showing that TopoHyperDrive can achieve better convergence.

The abstract and introduction provide a clear overview of the problem, the limitations of existing hyperparameter optimization methods, and the proposed solution using topological analysis. This section effectively sets the context and motivates the research. However, the main points of the paper could have been stated more precisely, e.g. to emphasize the advantage of the proposed approach (whether the method is new, or whether it's comparatively better than others), also not very clear about metric-based and metric-free setups, the article does not comment on this further, and all three baselines consider the RTD score. The author has provided an in-depth review of the literature, existing methods. The description of the experimental setup, including the datasets, baseline methods, and specific hyperparameters being optimized, is well-organized and clear. I would recommend adding to the Results section more details about the One-to-Random method, which is only referred to in the plots, making it unclear that it is RTD-based method. Instead, the author briefly mentions it in the Discussion, highlighting its limitations while proposing separate subsections about alternative strategies that might only be used in the future.

This repository is well-structured, clear, and easy to navigate. The use of Lightning and Hydro templates makes it convenient to get started with the project. The author provided a detailed readme with examples of sequential installation and commands for reproducing. It was nice that the author also provided a colab that reproduced the results from the report. The code is nearly reproduced and demonstrates metrics at an intermediate point of learning. The author shared logs and checkpoints, so with access to checkpoints for results, I believe that it is possible to reproduce the plots with the final results.

The proposed method shows promising results, the author also discussed its limitations and suggested possible improvements in the future. It would help to include a more straightforward summary of key performance metrics and how they directly demonstrate the advantages of

TopoHyperDrive. It also would be interesting to try some more analysis of the relevance of the results since the metrics are not super high and it could add some insights for methods comparison. The effectiveness of the proposed method may depend heavily on the specific conditions and configurations of the neural networks being optimized, which might not generalize well across all types of models and datasets. Also, it would be interesting to try these methods, maybe, on well-known, traditional architectures.

No doubt, the article contributes valuable insights and opens new avenues for research in hyperparameter optimization.