Equivariant vs. Invariant Layers: A Comparison of Backbone and Pooling for Point Cloud Classification

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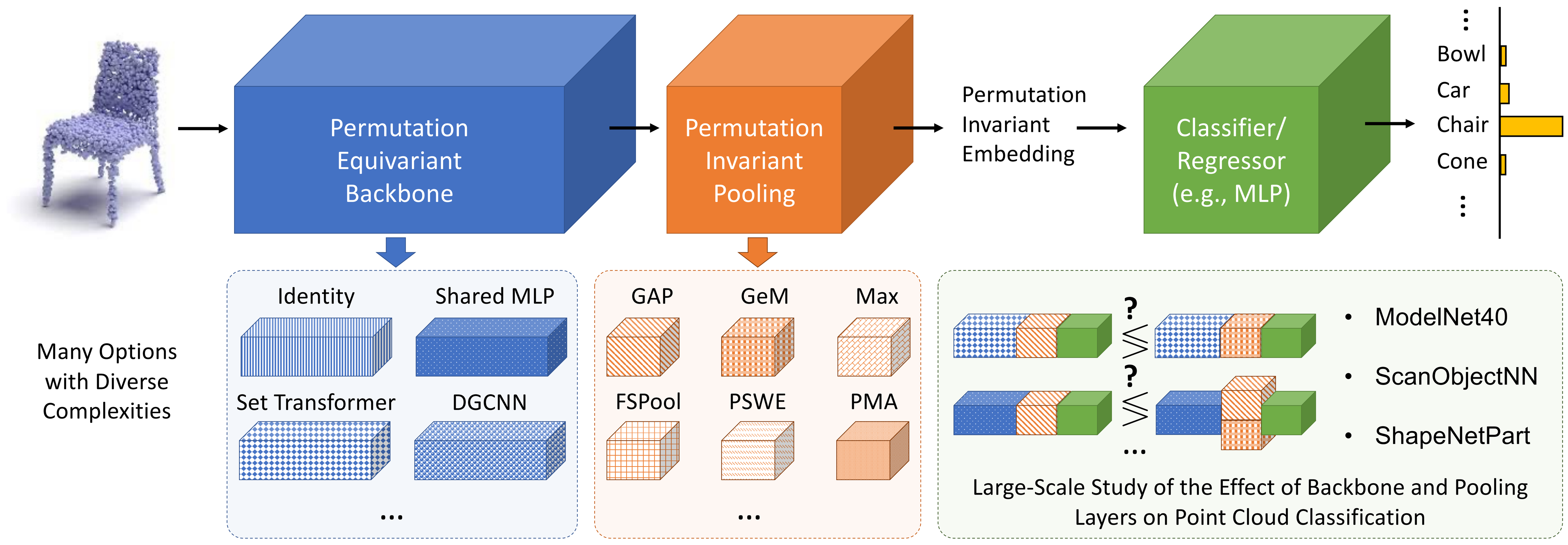
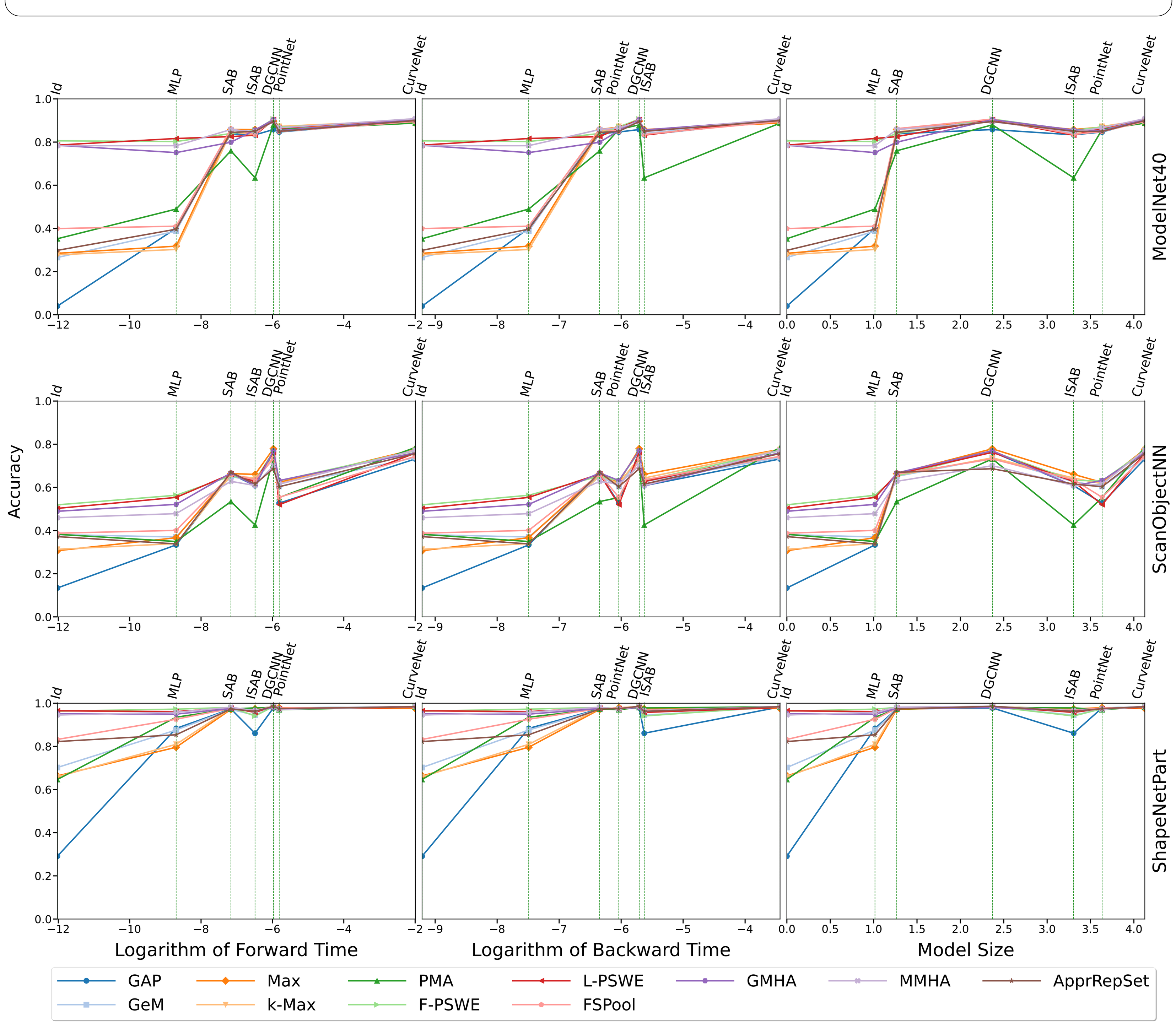


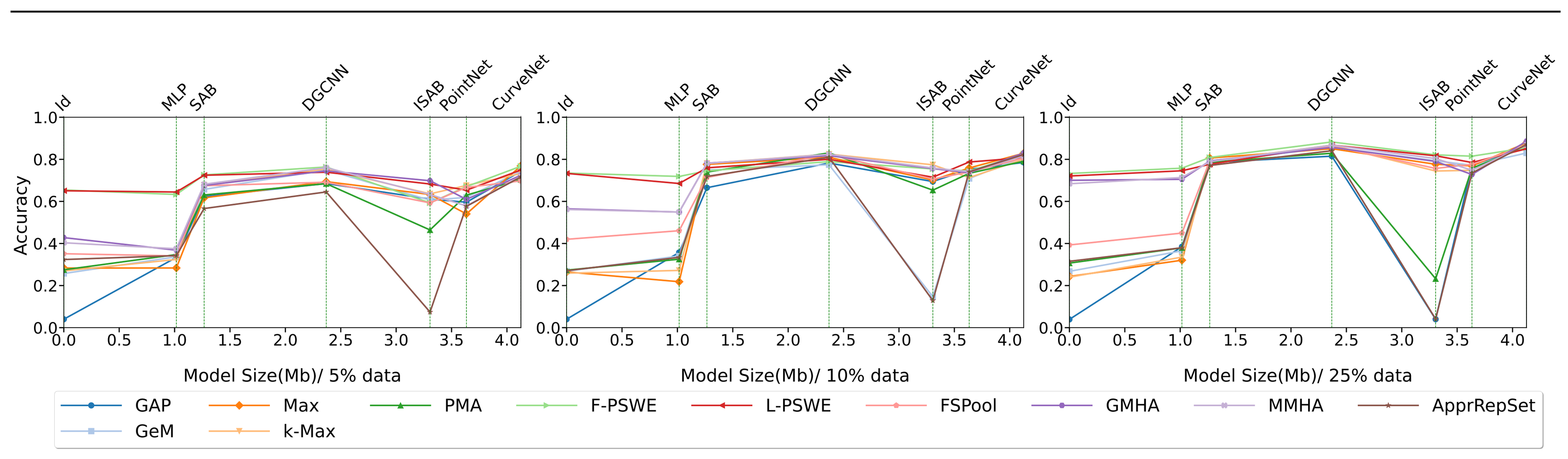
Motivation

- Geometric deep learning provides a blueprint for set neural networks that leverage the permutation symmetry of set-structured data (e.g. point clouds).
- In particular, we consider permutation invariant networks, composed of a permutation equivariant backbone, permutation invariant global pooling, and regression/classification head.
- Existing literature has extensively explored improving equivariant backbones, while the impact of the pooling layer is often overlooked.

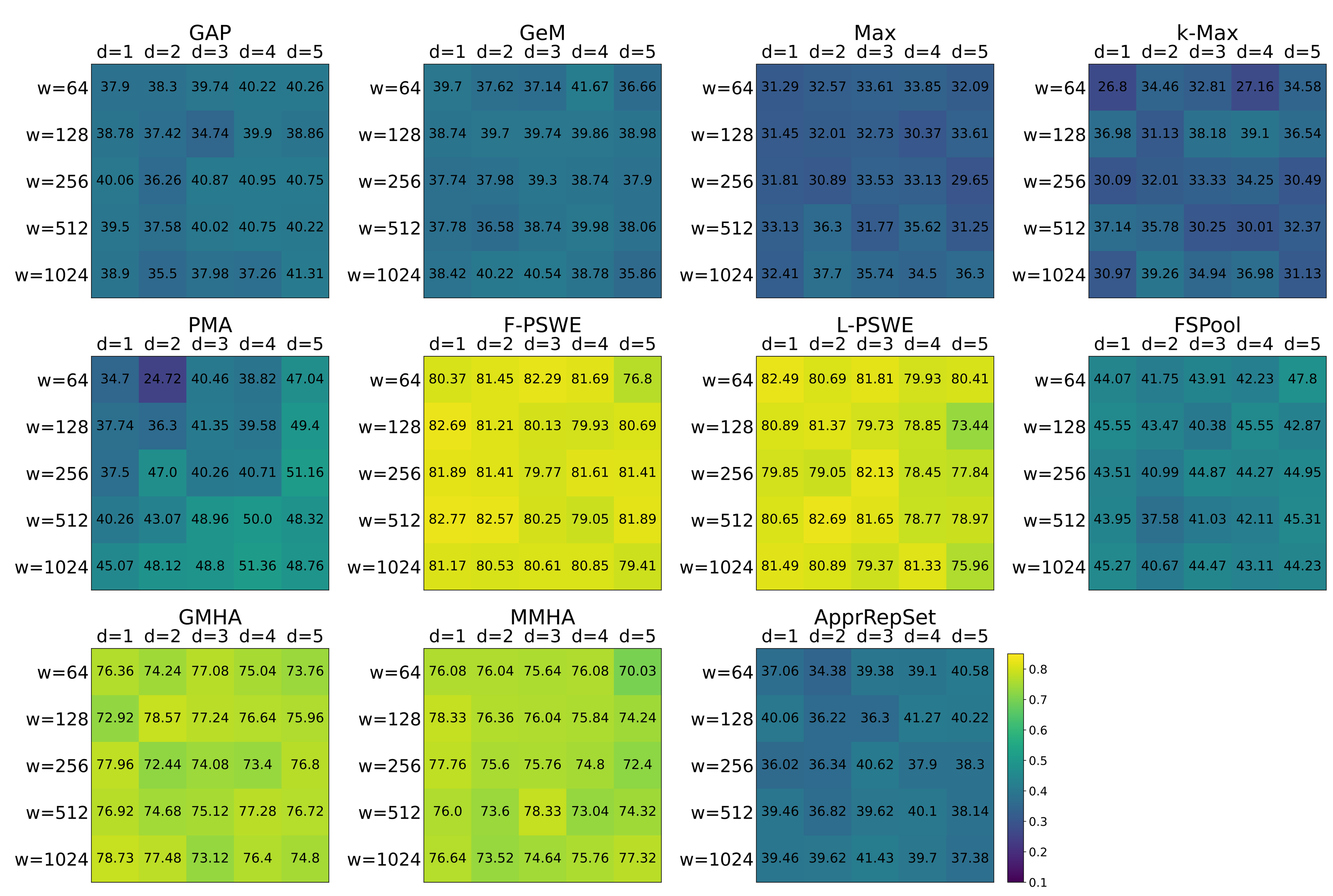
Objective: Explore the interplay between backbone architecture and pooling approach on model performance for point cloud classification.



Limited Training Data

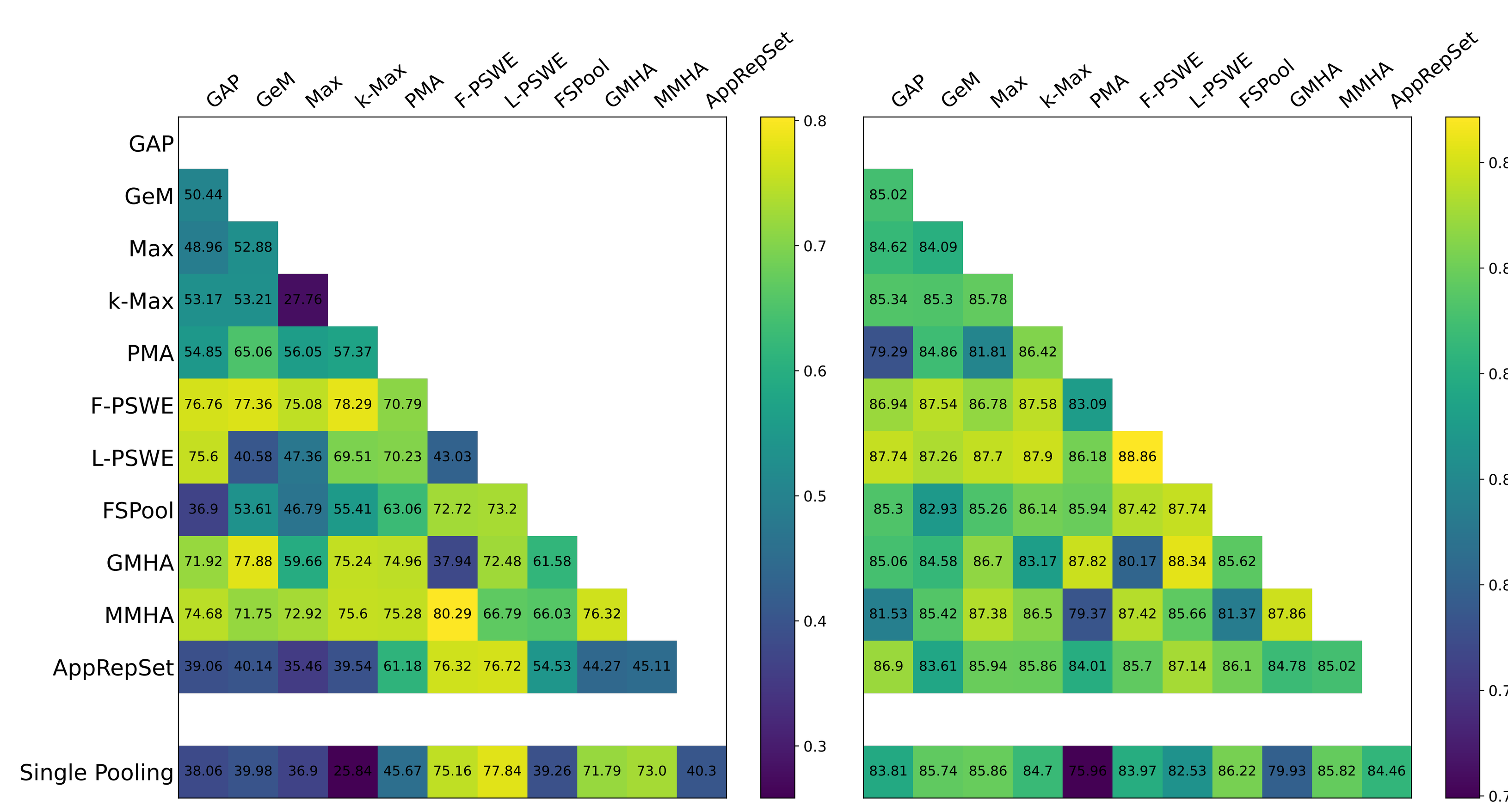


Depth vs. Width



Depth vs Width in MLP

Paired Poolings



Findings

- Complex pooling methods, such as transport-based or attention-based poolings, can significantly boost the performance of simple backbones, but the benefits diminish for more complex backbones.
- Even complex backbones can benefit from high-complexity pooling layers in low data scenarios.
- Surprisingly, the choice of pooling layers can have a more significant impact on the model's performance than adjusting the width and depth of the backbone.
- Pairwise combination of pooling layers can significantly improve the performance of a fixed backbone.