Adaptive Subspaces for Few-Shot Learning
Supplementary Material

In this supplementary material, we elaborate on the implementation details of the methods used in our experiments. Visualization of the subspace method against the prototype solution is provided to assess the robustness of the algorithms in the presence of outliers. Finally, additional ablation studies for the subspace dimensionality and the 1-shot case are discussed.

1. Implementation Details

4 Convolutional Layers (Conv-4). This backbone employs 4 convolutional blocks with 64 filters each, and batch normalization, ReLU, and max-pooling following the convolutional layer. To train our networks on this backbone, we employ episodes with the same number of class and shot as at the testing stage. Moreover, we do not apply any data augmentation for experiments that use this backbone.

ResNet-12. We follow the ResNet-12 architecture described in [1]. The CNN consists of 4 residual blocks (64, 160, 320, and 640 filters), each followed by 2×2 max-pooling, and DropBlock regularization [2]. We use label smoothing only for *mini*-ImageNet, and the smoothing coefficient equals 0.1. Data augmentation and episodic setting are applied to train the CNN backbone.

2. Robustness

In this section, we analyse the robustness of our approach on a toy data. We visualize how our subspace-based method compares to the prototype-based baseline under existence of the noise and/or outliers. Fig. A1 shows that the subspace classifier is more robust to outliers than the prototype-based baseline [3]. Outliers have a dramatic impact on prototypes resulting in large shifts and misclassification as a result. However, our subspace-based approach is less perturbed by the noise and outliers while exhibiting a better discriminative power due to its ability to capture second-order statistics.

3. Additional Ablation Study

Subspace Dimensionality. The impact of subspace dimensionality on the results is evaluated (ResNet-12 backbone) in Table A1. The analysis suggests that the subspace dimensionality does not affect the performance significantly. On a validation set, we observe that using $K-1$ subspaces yields the best results. Thus, we fix the number of subspaces to $K-1$ throughout experiments.

Model	**2**	**3**	**4**
DSN	78.42	78.44	78.83

Table A1: The impact of subspace dimensionality on the performance given the *mini*ImageNet and the ResNet-12. Evaluations are performed on the 5-way 5-shot protocol.

1-Shot Case. To create subspaces in the case of 1-shot learning, we require at least two samples per class. Therefore, we augmented training images by flipping images. To be fair in our comparisons, we also applied such an augmentation to other state-of-the-art approaches (given the ResNet-12 backbone and the *mini*-ImageNet). Table A2 shows that using image flips does not boost the performance of other approaches significantly.

Model	**w/o Aug.**	**w/ Aug.**
MetaOpt-Ridge* [1]	61.27	61.39
MetaOpt-SVM* [1]	61.38	61.24
DSN	–	62.64

Table A2: The accuracy without (w/o) and with (w/) image augmentation (for the 1-shot case). * is evaluated using our implementation.

References

[1] K. Lee, S. Maji, A. Ravichandran, and S. Soatto, "Meta-learning with differentiable convex optimization," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2019, pp. 10 657–10 665.

[2] G. Ghiasi, T.-Y. Lin, and Q. V. Le, "Dropblock: A regularization method for convolutional networks," in *Advances in Neural Information Processing Systems*, 2018, pp. 10 727–10 737.

[3] J. Snell, K. Swersky, and Z. Richard, "Prototypical networks for few-shot learning," in *Advances in Neural Information Processing Systems*, 2017.

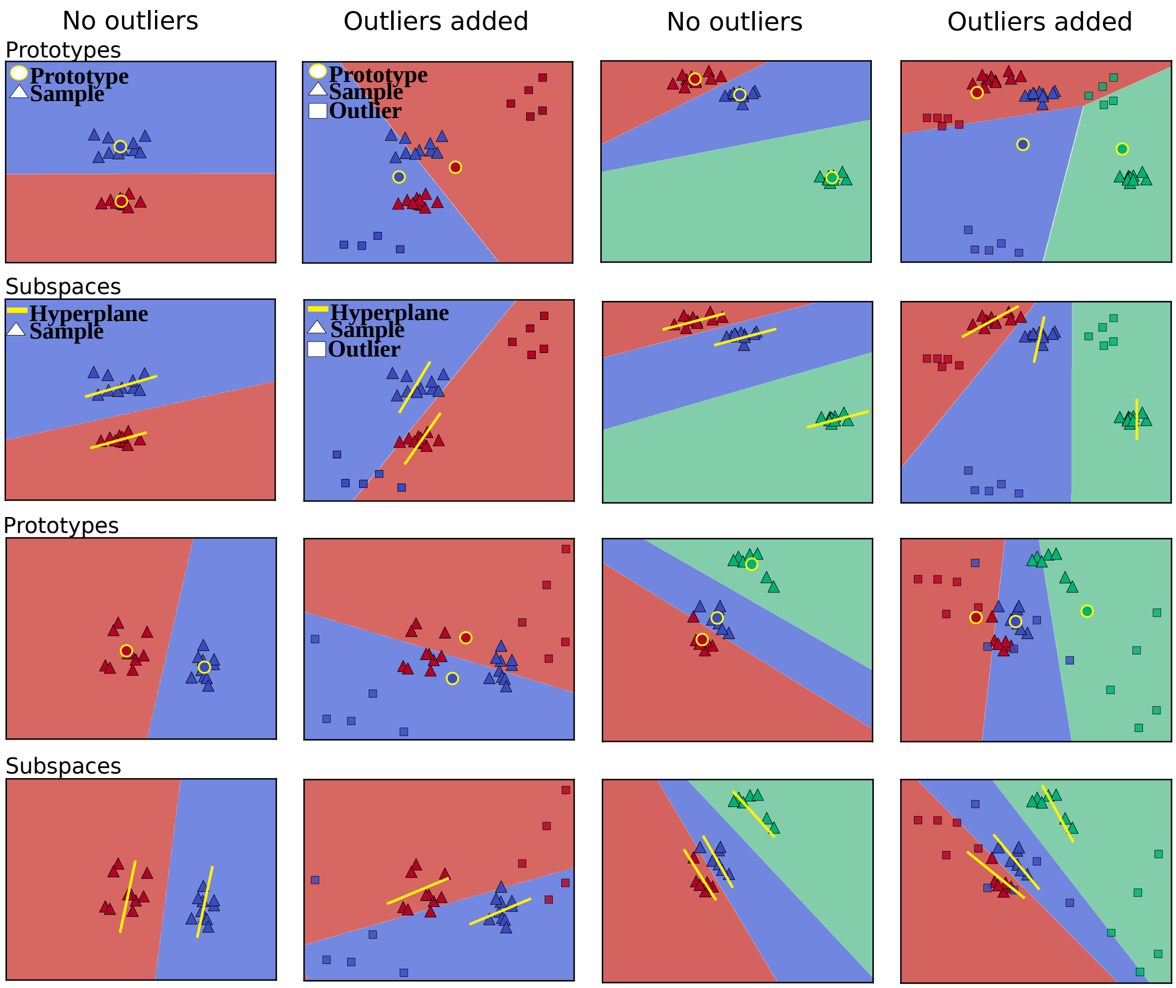

Figure A1: The impact of outliers on prototypes and subspaces. The odd rows show the decision boundaries obtained via prototypes (with and without outliers) for two- and three-class problems. The even rows depict how subspaces behave for the same problems. In general, subspaces show a better resilience to perturbations and attain higher discriminative power in comparison to prototypes. Best viewed in color.