

On Automatic Data Augmentation for 3D Point Cloud Classification (Supplementary Material)

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In this supplementary material, we further provide insight into augmentor designs and whether we can more efficiently learn the augmentor using only a subset of the data.

S1 Alternative augmentor designs

In this section, we explore the effect of alternative parameterizations of the augmentor. Specifically, we consider parametric probability distributions – uniform and Gaussian distributions – in our experiments. We first evaluate a uniform distribution augmentor where the lower bound lb and upper bound ub are the learnable parameters. Regularization is applied to encourage their mean to be close to a predefined constant $\hat{\theta}$: $\|(lb + ub)/2 - \hat{\theta}\|_2$. In addition, we evaluate a Gaussian distribution augmentor where μ and standard deviation σ are the learnable parameters. Regularization is applied only to the mean: $\|\mu - \hat{\theta}\|_2$. For fair comparison, we apply regularization with a weight of 0.5 for all augmentors. The results on ModelNet40 classification are presented in Tab. S1. We observe that AdaPC with Gaussian distribution and neural network augmentor outperforms the no-augmentor baseline. More importantly, only AdaPC with the neural network augmentor achieves better performance than predefined augmentations (second row in Tab. S1), suggesting that the more flexible neural network parametrization for the augmentor is essential to the success of learning stronger augmentations.

Augmentor	Augmentor params	Fixed ops	Learnable ops	Test accuracy
None	None	None	None	89.58
None	None	S, T, Ry	None	90.51
Uniform	lower and upper bound	None	S, T, Ry	89.46
Gaussian	mean and standard deviation	None	S, T, Ry	90.39
AdaPC	neural networks	None	S, T, Ry	91.61

Table S1: Alternative augmentor results on ModelNet40

Augmentor	Fixed ops	Learnable ops	Dataset for meta training	Test accuracy
None	None	None	None	82.14
None	Ry = 0.7	None	None	88.85
AdaPC	None	Ry	ModelNet40	85.89
AdaPC	None	Ry	10% ModelNet40	88.33

Table S2: Training the augmentor on a subset of ModelNet40.

S2 Learning the augmentor on a subset of data

In this section, we accelerate the learning process by training the augmentor using only a subset of the data. Concretely, we train the augmentor on a small subset (10% of all available data) of ModelNet40 and then use the learnt augmentor with the best validation accuracy to re-train a classifier with all available data. During re-training, the augmentor is fixed and only the classifier is trainable and we follow the same training protocol. In this experiment, both validation and test sets are rotated by 0.7 radian about the y-axis. We observe from Tab. S2 that AdaPC achieves a very competitive result (last row, 88.33%) when trained on 10% of ModelNet40 and transferred to the full dataset, suggesting that it is viable to use this strategy to accelerate augmentor learning. More specifically, we can train the augmentor 10 times faster with 10% ModelNet40, and the augmentor adds a negligible computational overhead in the re-training stage on the full dataset.