Interpretable3D: An Ad-Hoc Interpretable Classifier for 3D Point Clouds

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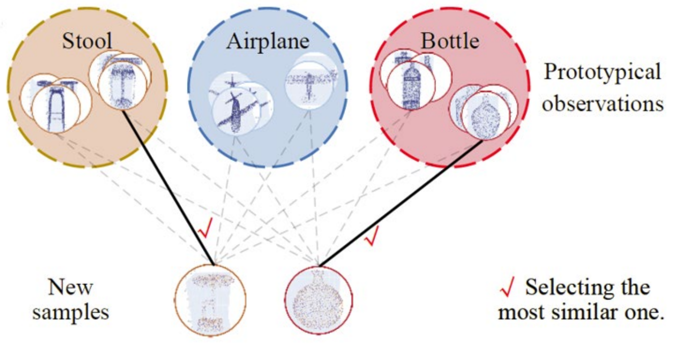
Problems of existing studies

1) Existing explanation studies on 3D models have been conducted with *post-hoc* explanations. However, *post-hoc* explanations are problematic:

- ☐ requiring **a separate modeling effort**
- ☐ **varying explanations** for different explanation models
- ☐ **cannot provide a reasoning process**
- ☐ **not interpretable to humans**

2) Parametric softmax classifier **learns highly abstract parameters** and **lacks a direct and intuitive interpretation**.

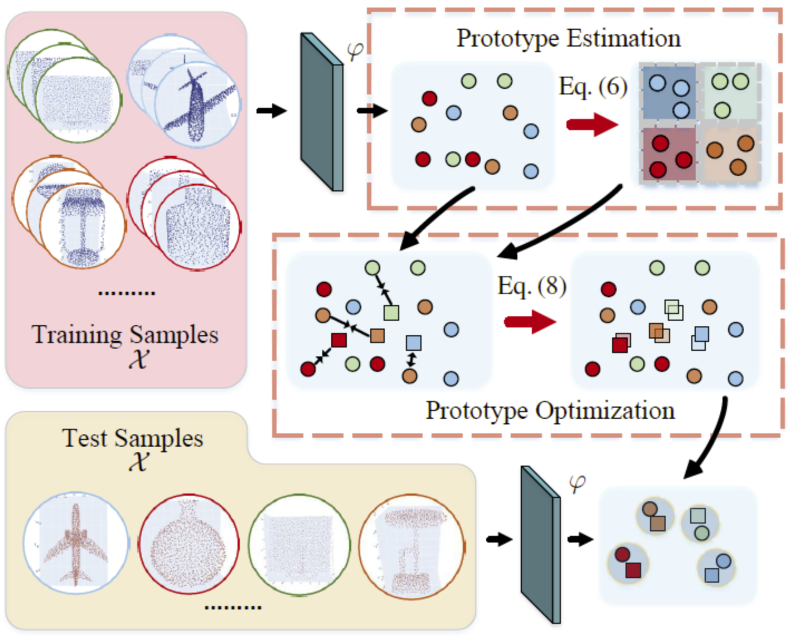
Why Interpretable3D



Interpretable3D

- ☐ provides **self-explanation** without *post-hoc* analysis and
- ☐ achieves **comparable performance** compared to softmax-based models.

The overview of our Interpretable3D



Case-based paradigm:
Prototypes can be interpreted as typical observations.

Training:
Two iterative training steps:

- ☐ Prototype Estimation
- ☐ Prototype Optimization

Testing:
Classifying new samples according to prototypes.

Prototype Estimation

Assignment matrix $\mathbf{A}^l$ is obtained by optimizing the similarity $\mathbf{Q}^l$ between the features and cluster centers:

$$\boldsymbol{A}^{l*} = \arg\min_{\boldsymbol{A}^l \geq 0} \langle \boldsymbol{Q}^l, \boldsymbol{A}^l \rangle_F,$$

The entropic regularization of this problem can be formulated as:

$$\min_{\boldsymbol{A}^l \geq 0} \langle \boldsymbol{Q}^l, \boldsymbol{A}^l \rangle_F - \zeta H(\boldsymbol{A}^l)$$

It can be solved by Sinkhorn-Knopp.

Prototype Optimization

To pursue more representative prototypes, the winning prototypes $\mathbf{M}^w$ are altered:

$$\boldsymbol{M}^w \leftarrow \boldsymbol{M}^w + \eta\,\psi(l, \hat{l}_w)(\boldsymbol{F}^l - \boldsymbol{M}^w),$$

$$\psi(l, \hat{l}_w) = \begin{cases} +1 & \text{if } l = \hat{l}_w \\ -1 & \text{else} \end{cases},$$

If $\mathbf{M}^w$ predicts correctly, it is rewarded with $\mathbf{F}^l$. Conversely, $\mathbf{M}^w$ is moved away from $\mathbf{F}^l$.

A momentum update strategy is applied to update the prototype, specifically, updating with the average of embeddings of each sub-class. In the last few epochs, we update prototypes with their most similar observations.

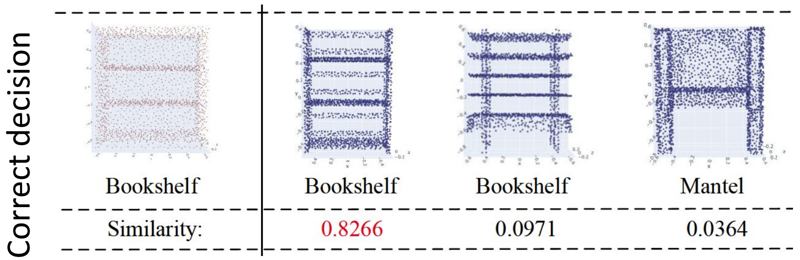
Classification results

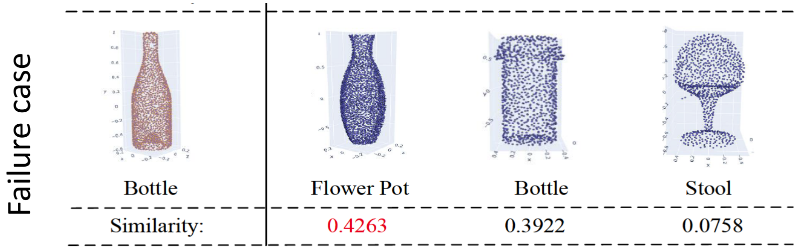
Our algorithm shows comparable performance:

Method	OA(%)	mAcc(%)
PointNet (Qi et al. 2017a)	89.2	86.0
PointNet++ (Qi et al. 2017b)	90.7	-
PointNet2 (Yan 2019)	92.2	-
PointNet2 + **Ours**	93.2	89.3
DGCNN (Phan et al. 2018)	92.9	90.2
DGCNN + **Ours**	93.5	90.3
PointMLP (Ma et al. 2021)	94.1	91.3
PointMLP + **Ours**	94.1	92.0
PointNeXt (Qian et al. 2022)	94.0	91.1
PointNeXt + **Ours**	94.3	91.8

How Interpretable3D makes decision

The decision-making mode is straightforward for users.





Codes and pre-trained models are at
https://github.com/FengZicai/ Interpretable3D