

# Exploiting Unlabeled Data, Cheaper Labels and Efficient Annotation for 3D Point Cloud Deep Learning



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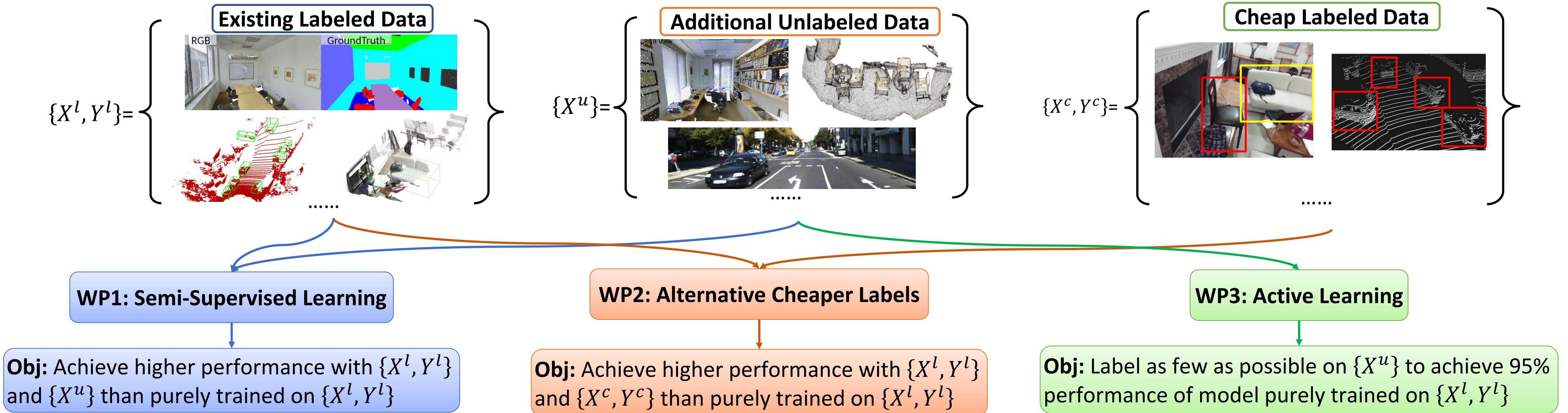
## Background

Environment sensing is key to the safety of autonomous driving and robotics. 3D point cloud deep learning[1] is the state-of-the-art techniques, however, requires substantial amount of labeled data. We aim to exploit unlabeled data, cheaper labels and efficient annotation to improve the efficacy of 3D point cloud deep learning.

## Key Challenges to Address

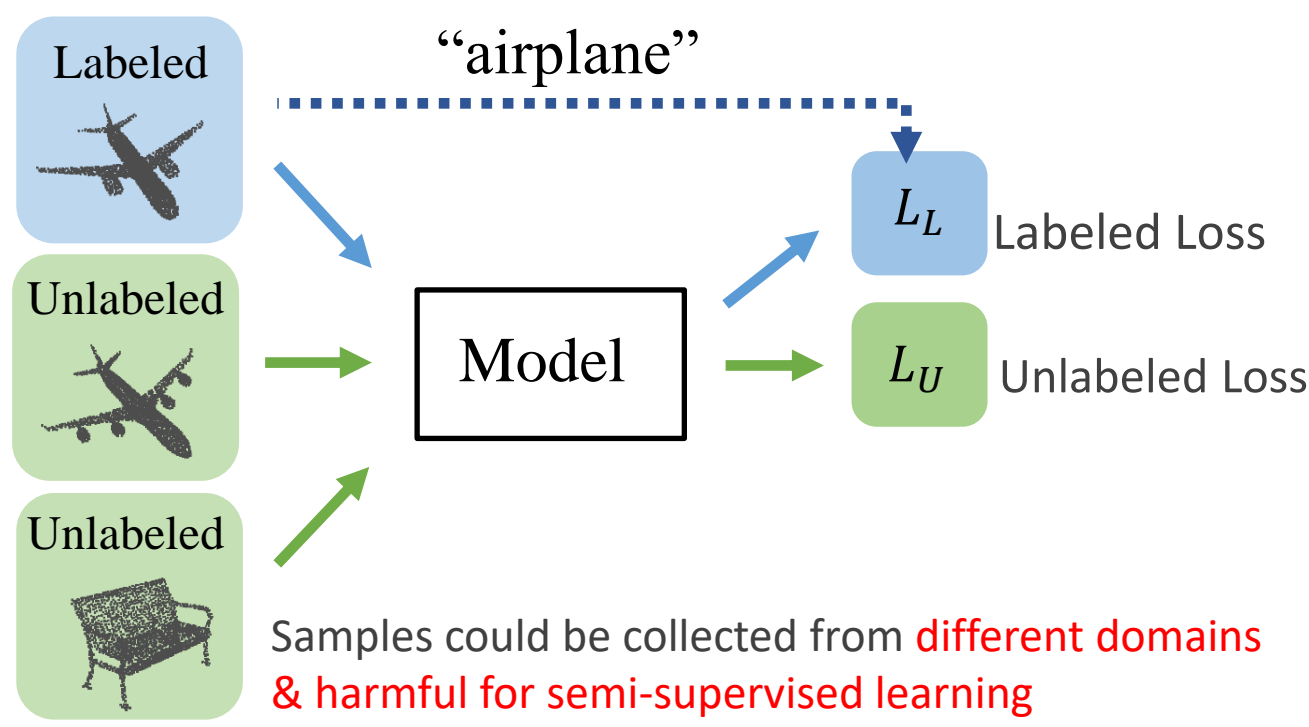
- ❑ Unlabeled data is abundant but hard to be used for training
- ❑ Cheap labeled data is easier to acquire but gives less precise supervision
- ❑ Annotation budget is precious and should be used wisely

## Our Solution



## WP1: Semi-Supervised Learning [2-3]

We develop the first open-set semi-supervised 3D point cloud semantic segmentation approach to exploit large uncured unlabeled data.



### Our Contributions:

- ❑ Formulate open-set semi-supervised learning as a bi-level optimization problem.
- ❑ A weight predictor network is introduced to estimate per-sample weights for unlabeled data.
- ❑ To address the instability issue of bi-level optimization, we introduce three regularization terms to further stabilize meta optimization loop.

### Our Results:

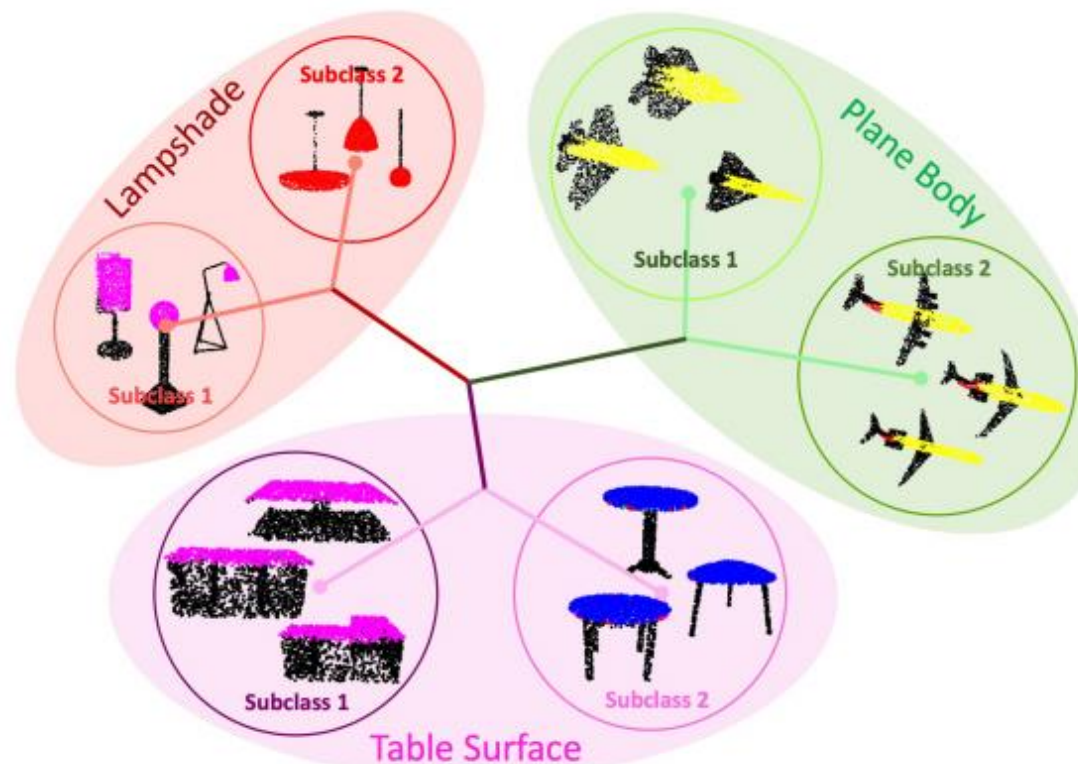
ModelNet40 ShapeNet weight > 0.9 weight < 0.1 (Out-of-distribution)



| Data      | Methods          | 1%          | 5%          |
|-----------|------------------|-------------|-------------|
| {L}       | SO-Net[12]       | 64.0        | 69.0        |
|           | PointCapsNet[36] | 67.0        | 70.0        |
|           | JointSSL[1]      | 71.9        | 77.4        |
|           | Multi-task[9]    | 68.2        | 77.7        |
| {L, N}    | PCont[31]        | 74.0        | 79.9        |
|           | ACD[7]           | 75.7        | 79.7        |
| {L, C}    | ReBO             | 76.2        | 80.1        |
| {L, U, M} | ReBO             | <b>76.9</b> | <b>80.3</b> |

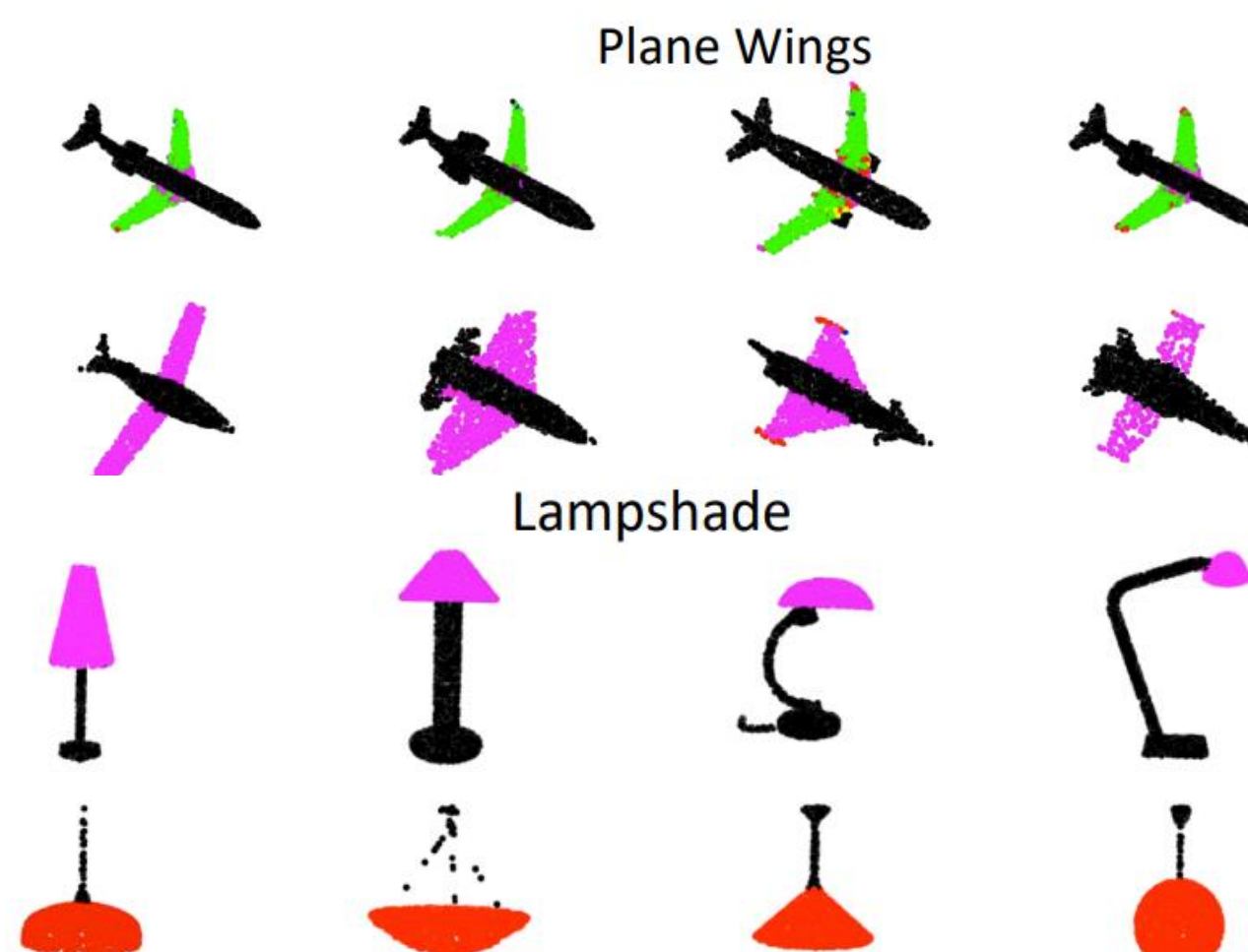
## WP2: Alternative Cheaper Labels [4]

We developed weakly supervised 3D point cloud segmentation approach by introducing multi-prototype learning.



### Our Contributions:

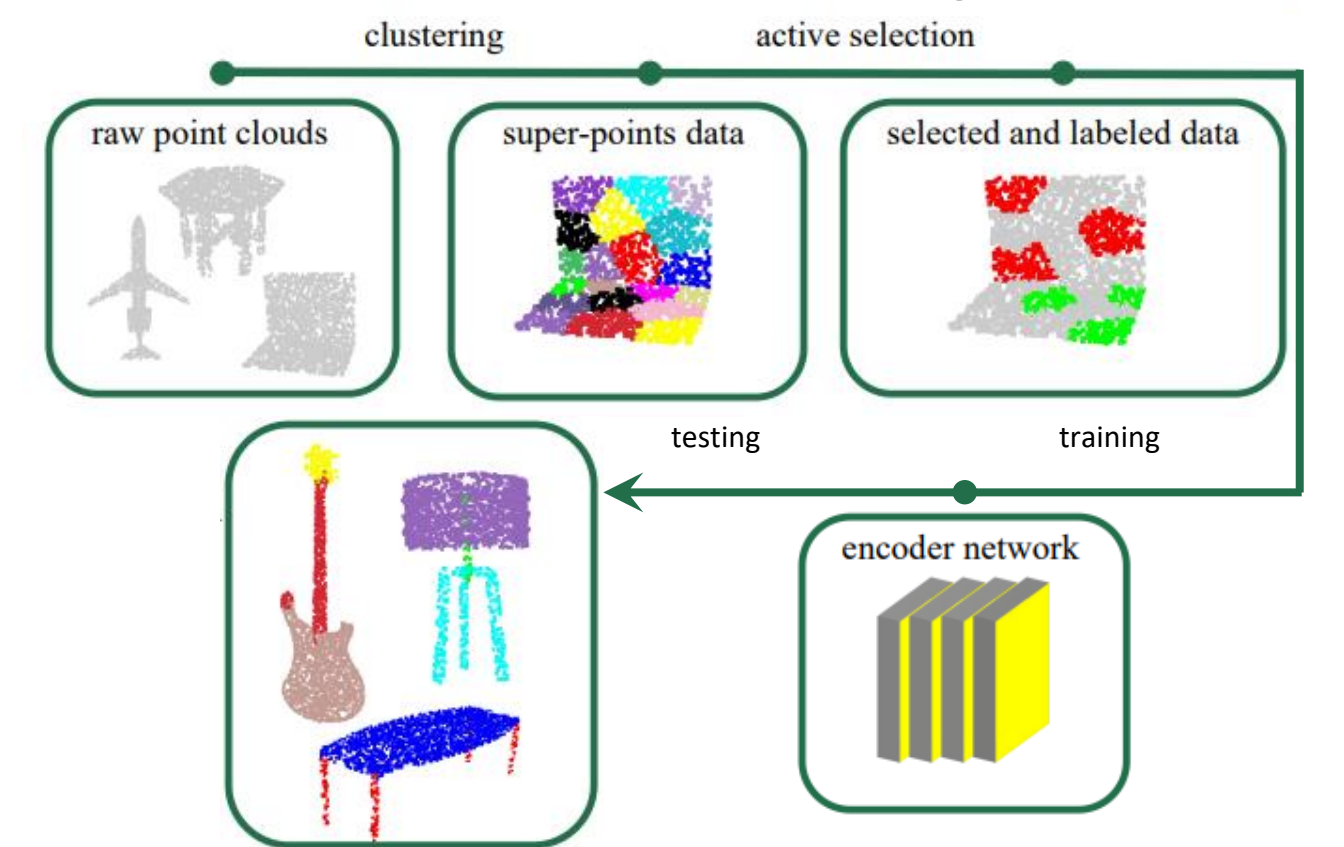
- ❑ Observing the clear sub-class structures in 3D point cloud data, we propose a multi-prototype classifier
- ❑ We propose a subclass averaging constraint to exploit both labeled and unlabeled data to supervise prototypes learning.
- ❑ We discover subclasses within each semantic category without any additional supervision.



| Method         | Annotation | SampAvg(%) | CatAvg(%) |
|----------------|------------|------------|-----------|
| DGCNN          | 1pt        | 72.6       | 72.2      |
| DGCNN          | 10%        | 84.5       | 81.5      |
| DGCNN          | 100%       | 85.1       | 82.3      |
| DGCNN + MulPro | 1pt        | 79.4       | 77.8      |
| DGCNN + MulPro | 10%        | 85.3       | 82.0      |
| DGCNN + MulPro | 100%       | 85.5       | 82.4      |

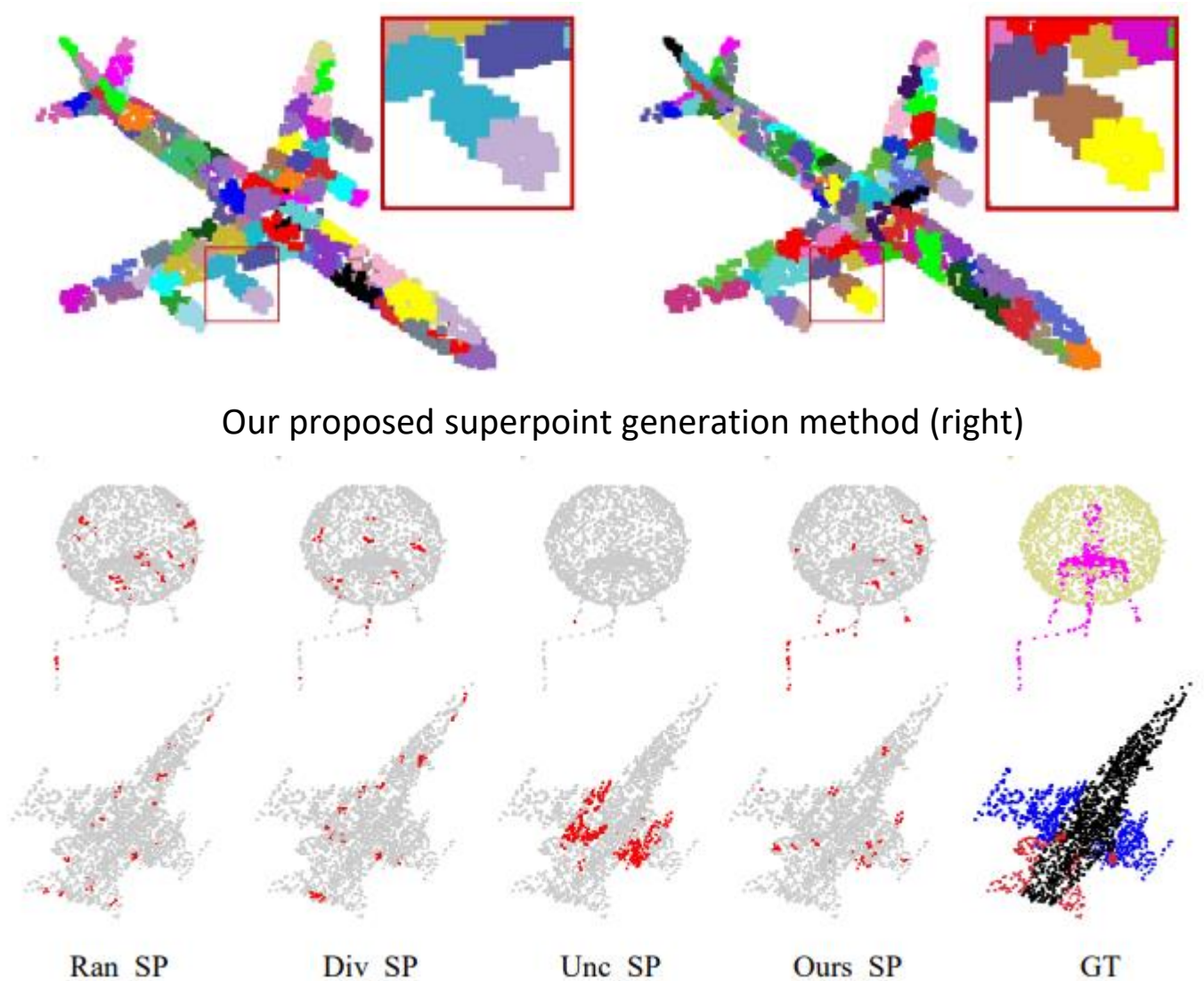
## WP3: Active Learning [5-6]

We developed one of the first active learning approach to 3D point cloud segmentation.



### Our Contributions:

- ❑ We demonstrate that active learning is effective for label-efficient 3D point cloud segmentation.
- ❑ We investigate the effectiveness of point-level, instance-level, polygon-level and superpoint-level selection schemes using realistic, click-based annotation cost.
- ❑ We propose to combine uncertainty and feature diversity for active selection.



Our proposed superpoint generation method (right)

| Methods         | mIoU (%) | #Clicks | #Points |
|-----------------|----------|---------|---------|
| SONet [46]      | 64.0     | ~ 250k  | ~ 250k  |
| 3DCNet [47]     | 67.0     | ~ 250k  | ~ 250k  |
| MUS [48]        | 68.2     | ~ 250k  | ~ 250k  |
| PTCT(HC) [7]    | 74.0     | ~ 250k  | ~ 250k  |
| PTCT(PINCE) [7] | 73.1     | ~ 250k  | ~ 250k  |
| PCWS [4]        | 74.4     | ~ 200k  | ~ 200k  |
| Ours            | 79.9     | 200k    | ~ 710k  |

## References (\* corresponding author; # equal contribution)

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- [2] Shi, X., Xu, X., Zhang, W., Zhu, X., Foo, C. S., & Jia, K. (2022, August). Open-set semi-supervised learning for 3d point cloud understanding. In *2022 26th International Conference on Pattern Recognition (ICPR)* (pp. 5045-5051). IEEE.
- [3] Deng, S., Xu, X., Wu, C., Chen, K., & Jia, K. (2021). 3d affordancenet: A benchmark for visual object affordance understanding. In *proceedings of the IEEE/CVF conference on computer vision and pattern recognition* (pp. 1778-1787).
- [4] Su, Y., Xu, X., & Jia, K. (2023). Weakly Supervised 3D Point Cloud Segmentation via Multi-Prototype Learning. *IEEE Transactions on Circuits and Systems for Video Technology*.
- [5] Liang, Z., Xu, X., Deng, S., Cai, L., Jiang, T., & Jia, K. (2024). Exploring diversity-based active learning for 3d object detection in autonomous driving. *Submitted to IEEE Transactions on Intelligent Transportation Systems*.
- [6] Shi, X., Xu, X., Chen, K., Cai, L., Foo, C. S., & Jia, K. (2024). Label-efficient point cloud semantic segmentation: An active learning approach. *Submitted to World Scientific Annual Review of Artificial Intelligence*.