# Enhanced Vote Network for 3D Object Detection in Point Clouds

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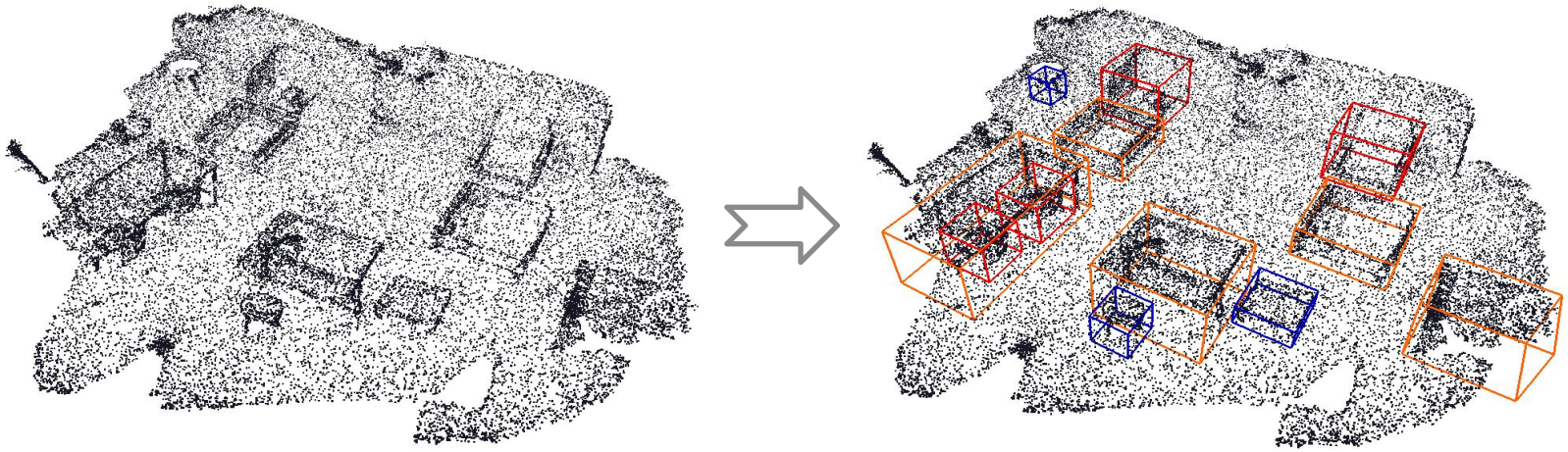
# Outline

- **Introduction**
- **Approach**
- **Experiments**

# Introduction: 3D point object detection



Input Point Cloud

Output 3D Bounding Box

- **3D point object detection** takes the point cloud as input and outputs the 3D bounding boxes and semantic classes of objects.
- Due to the sparse and unstructured nature of point clouds, encoding fine semantics and global context information are important for predicting the bounding boxes and its class.

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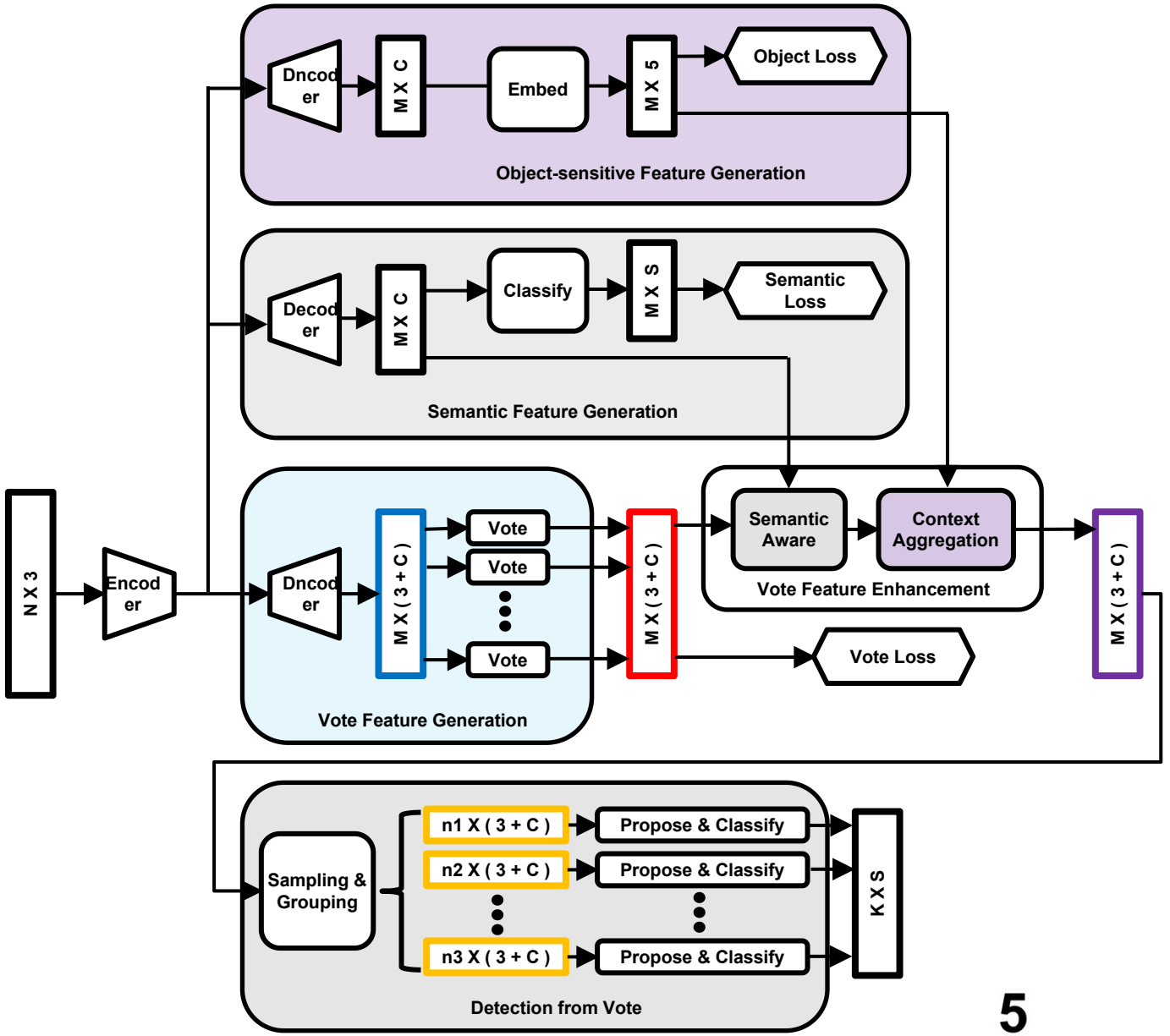
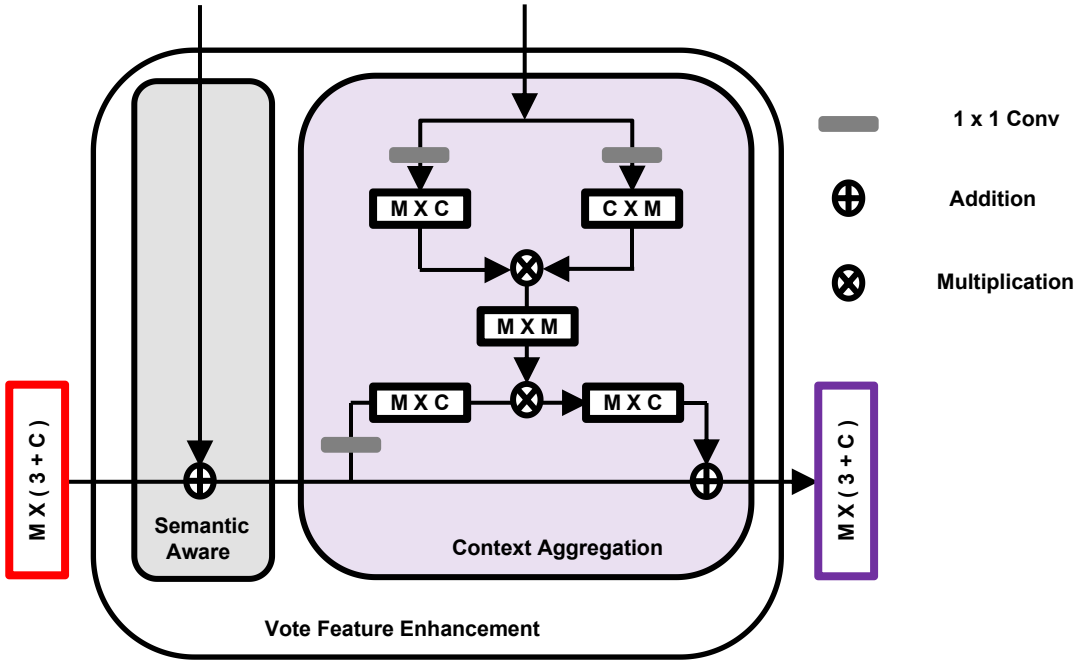
# Approach: The overall framework

- The feature encoder extract point features. Then, **Vote Feature Generation** module generates the vote features.
- To enhance vote features, **Semantic Feature Generation** module generates features with rich semantic information and **Semantic Aware** module combines it into the vote feature;
- **Object-sencetive Feature Generation** module outputs the object sensitive features that are used to aggregate the context for vote features by **Context Aggregation** module.
- Finally, the **Detection From Vote** module leverages the enhanced vote features to localize and classify the objects.



# Approach: Feature Enhancement

- **Semantic Aware.** Semantic Feature Generation module generates semantic aware feature with a semantic segmentation loss, and Semantic Aware module add it to the vote feature to obtain the semantic-aware vote feature.
- **Context Aggregation.** we learn object-sensitive embedding with a discriminative loss which encourages points belong to the same object to lie close with each other, otherwise, lie far away from each other. Then the Context Aggregation Module produces an attention map use the embeddings and applies to the vote feature to aggregate context information.



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# Comparison with Other Methods

| | Input | mAP@0.25 | mAP@0.5 |
|---|---|---|---|
| DSS [4] | Geo + RGB | 15.2 | 6.8 |
| MRCNN 2D-3D [2] | Geo + RGB | 17.3 | 10.5 |
| F-PointNet [8] | Geo + RGB | 19.8 | 10.8 |
| GSPN [30] | Geo + RGB | 30.6 | 17.7 |
| 3D-SIS [5] | Geo + 1 view | 35.1 | 18.7 |
| 3D-SIS [5] | Geo + 3 views | 36.6 | 19.0 |
| 3D-SIS [5] | Geo + 5 views | 40.2 | 22.5 |
| 3D-SIS [5] | Geo only | 25.4 | 14.6 |
| VoteNet | Geo only | 58.6 | 33.5 |
| **Ours** | Geo only | **60.3** | **36.8** |

Tab. 1: Compare with other methods on SUN RGB-D dataset.

- Evaluations on SUN RGB-D dataset show that our method can achieve outstanding results.

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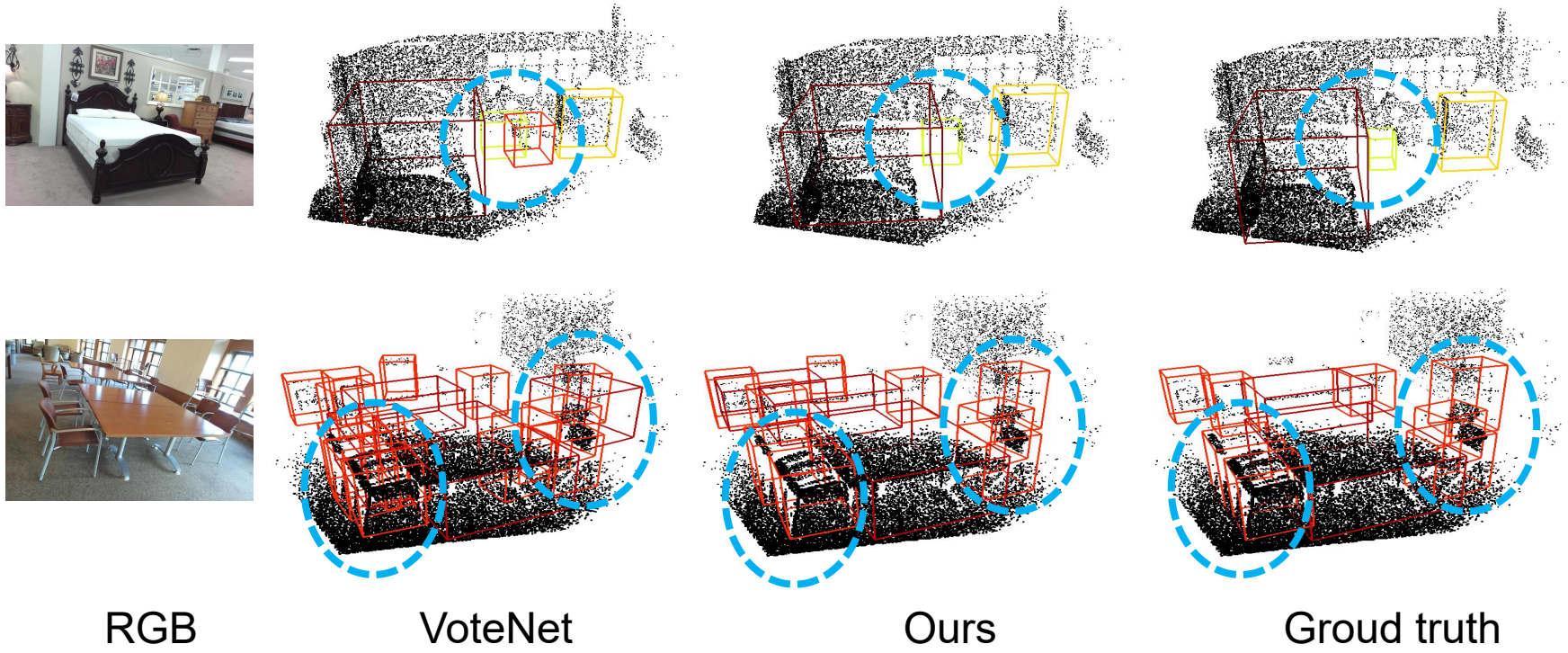


Fig. 4: Qualitative results on SUN RGB-D

- Since we encode the vote feature with some semantic information, the object class are better recognized by our method than VoteNet.
- As we take more global context into consideration, the objects are better distinguished compare to VoteNet.

# Ablation studies on two modules

| Method | +Context | +Semantic | mAP |
|---|---|---|---|
| Baseline | | | 58.6 |
| C-Module | ✓ | | 59.5 |
| S-Module | | ✓ | 60.0 |
| Full | ✓ | ✓ | **60.3** |

Tab. 2: Ablation studies on Scannetv2. C is Context Aggravation Module. S is Semantic-aware Feature Module.

- Only applying one of the modules, we can already outperform the VoteNet.
- By combining both modules. the improvement is better than applying only one of them.

# Thank You !