



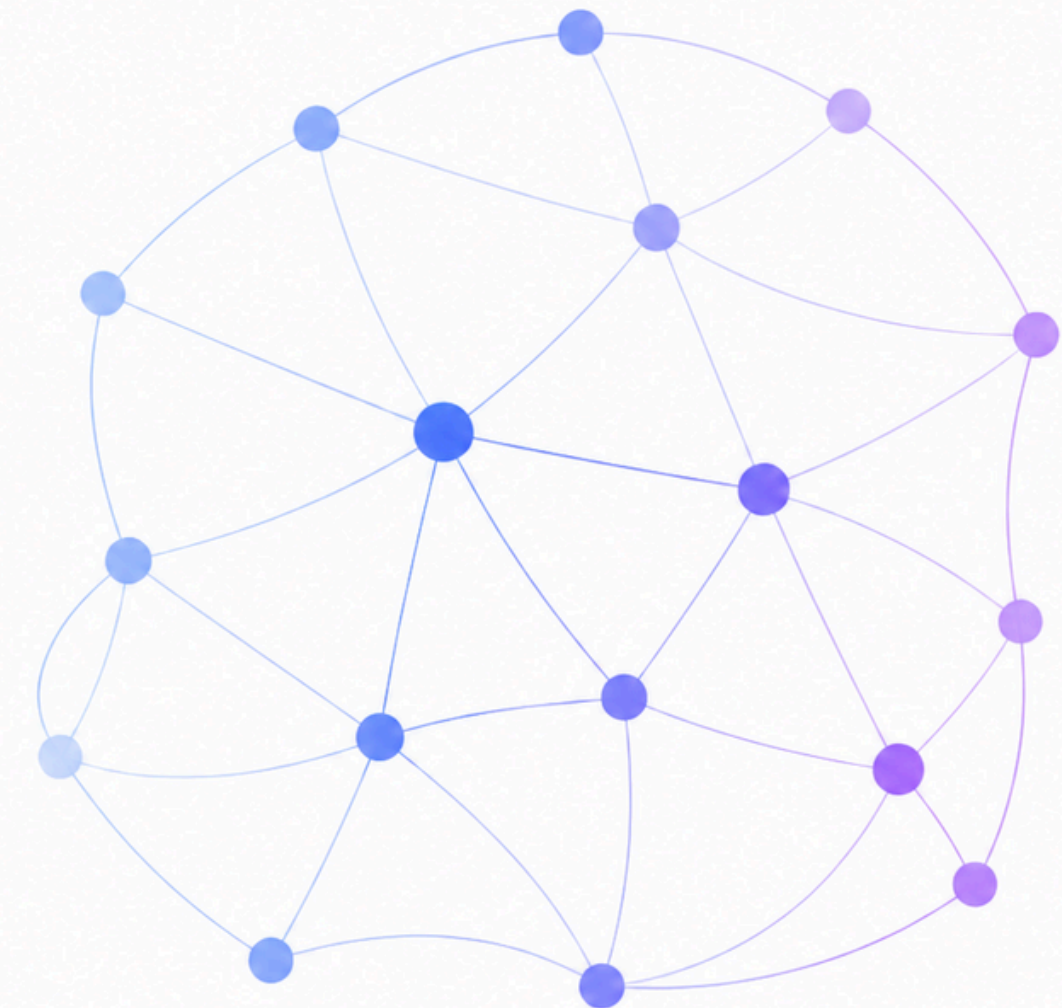
# GNNs FOR 3D MODELS GENERATION AND CLASSIFICATION

Applied Machine Learning 2026

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Tommaso Guarniera



# Can a GNN learn to classify and generate 3D objects?

In this project, we present:

1. **Dataset:** ModelNet40 3D objects represented as point clouds
2. **Methodology:** GNN-based classification and generative modeling pipeline
3. **Classification results:** comparison of baseline, AE-pretrained, and  $SO(3)$ -invariant models
4. **Generation results:** reconstruction and generation of 3D point-cloud objects - Conditional Variational Graph Autoencoder
5. **Real-world testing:** object scanning experiments and model performance on scanned data

# Why do we need models able to classify and generate 3D objects?

- **Navigation and mobility** - Spatial guidance and obstacle avoidance
- **Robotics** - object recognition and manipulation
- **Healthcare** - Medical imaging analysis
- **Industry & Manufacturing** - Industrial inspection
- **Entertainment & Content Creation** - gaming and virtual world

# Dataset: ModelNet40 Point Clouds

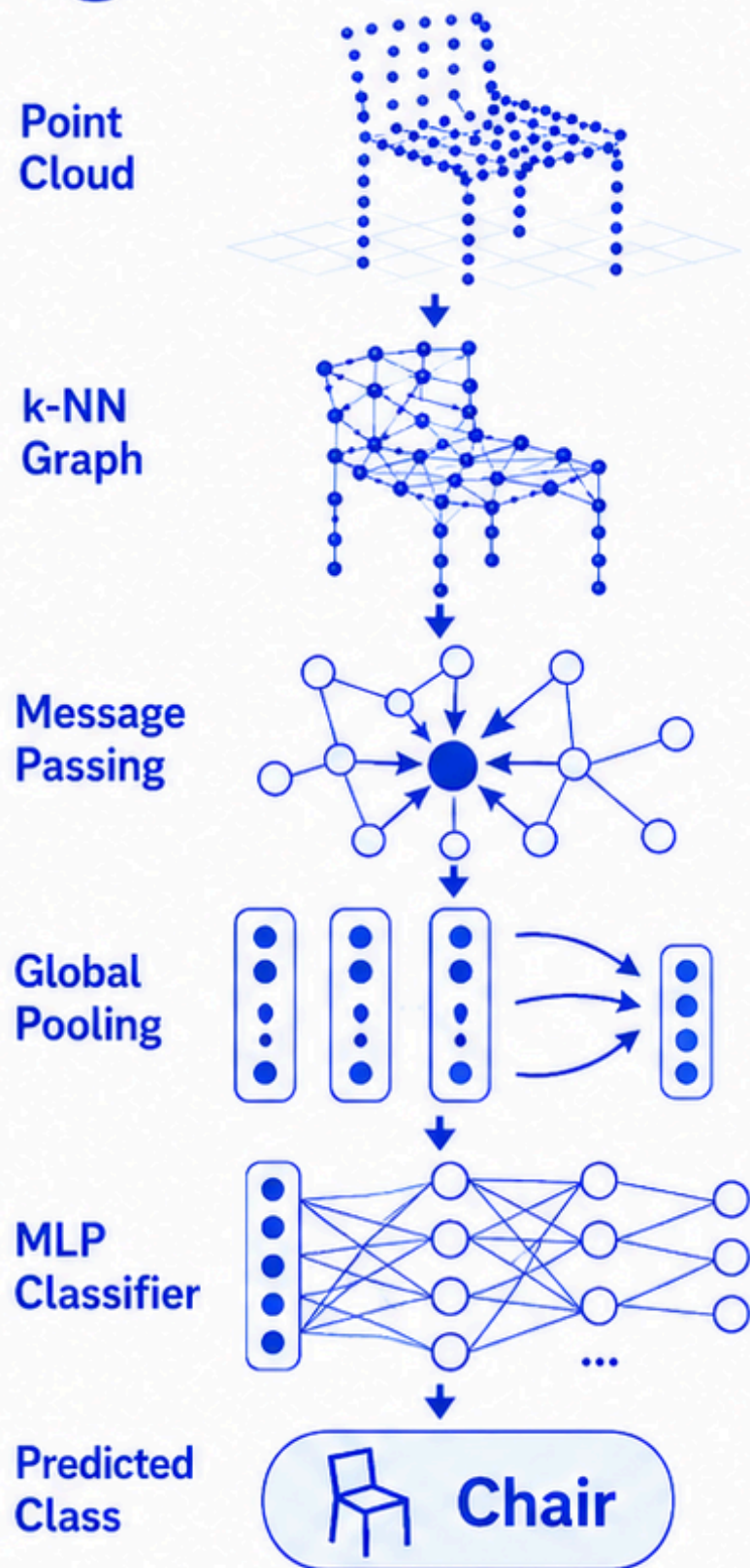


- 12,311 graphs
- 2,048 sampled nodes
- KNN edges

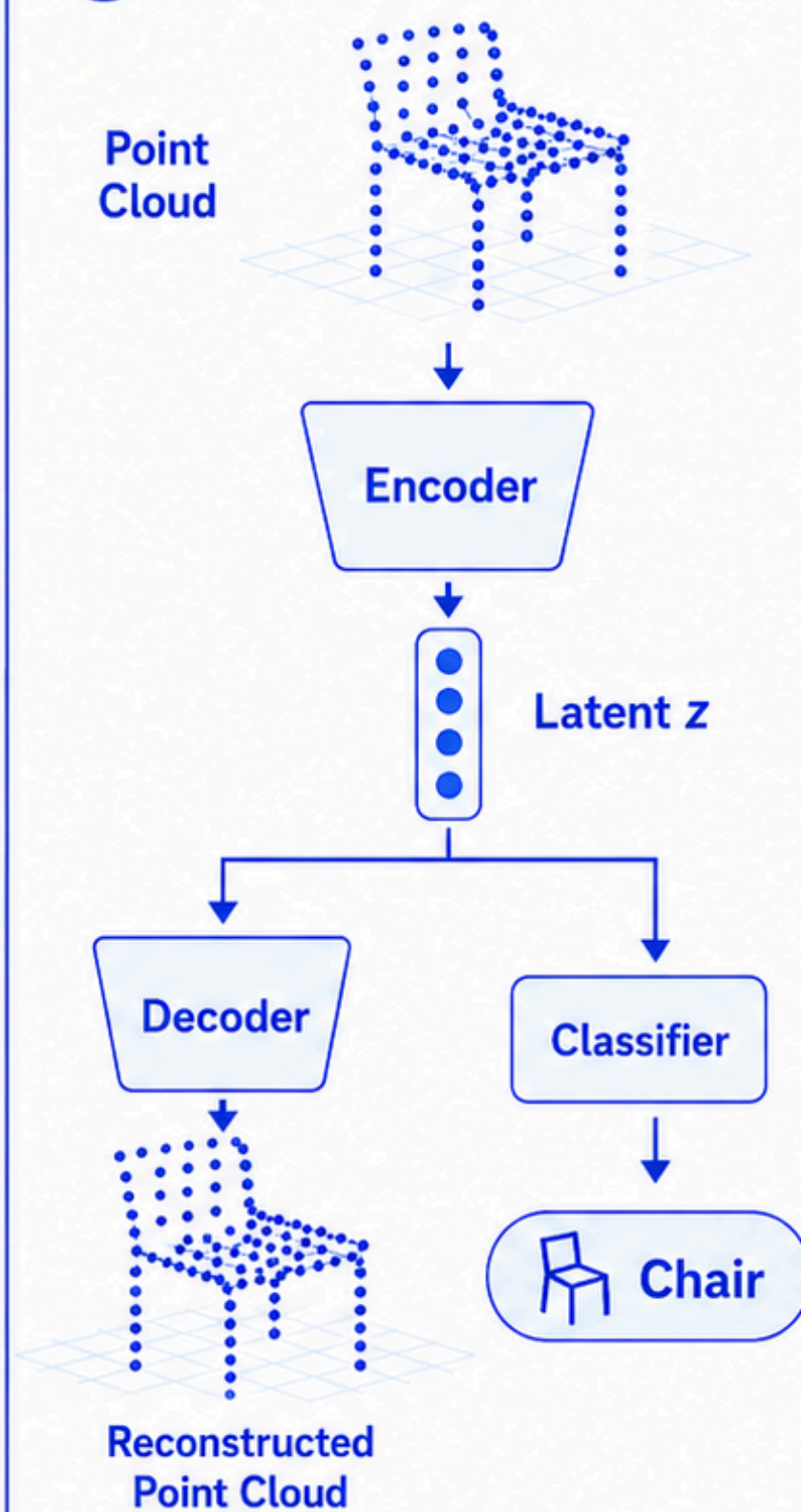
# Dataset: ModelNet40 Point Clouds



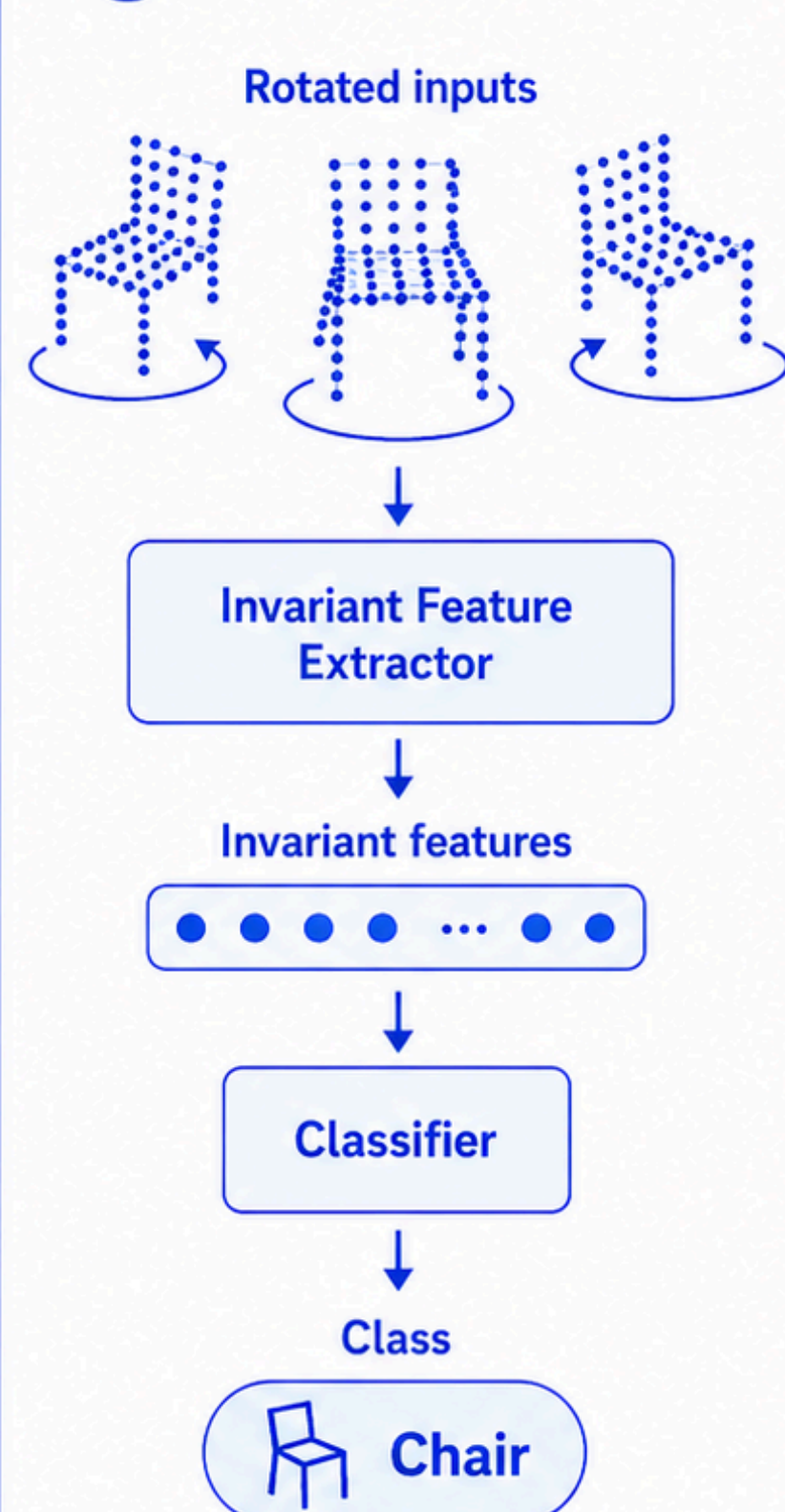
# 1 Vanilla GNN



# 2 Autoencoder Classifier



# 3 SO(3)-Invariant



# params:

851,624

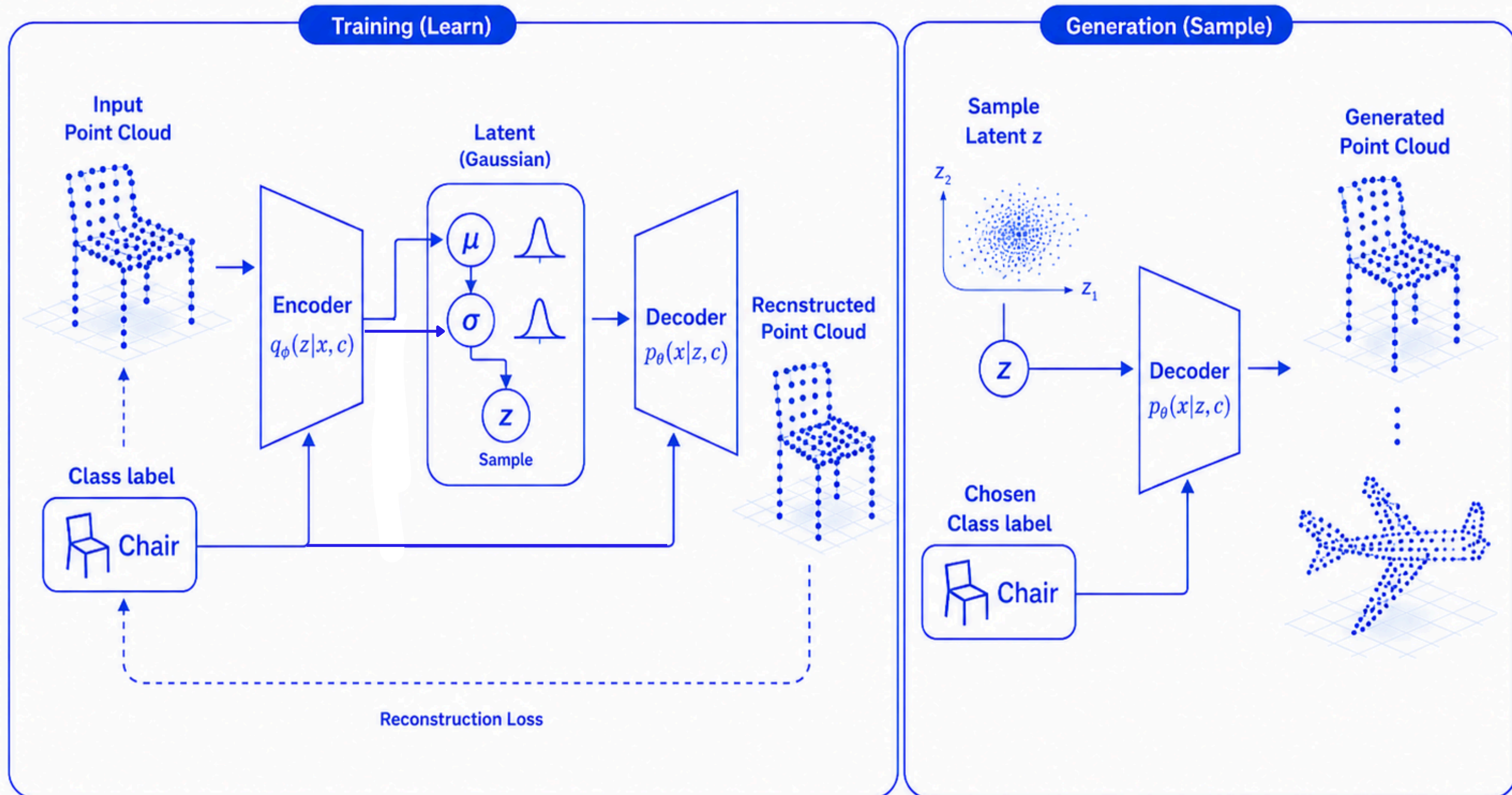
2,034,232

853,288

# Generation Method

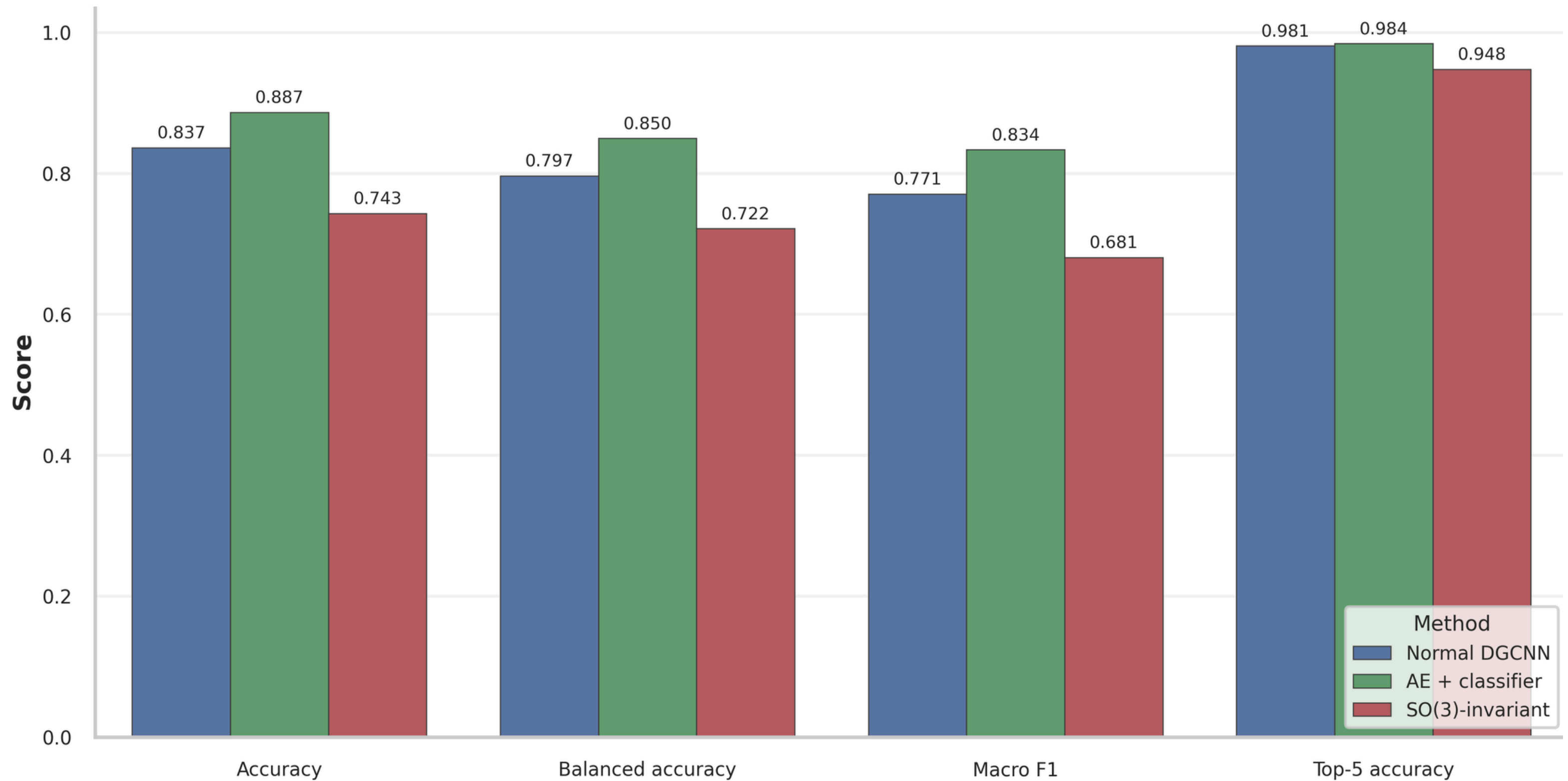
Conditional VAE (CVAE)

# params: 2,572,295



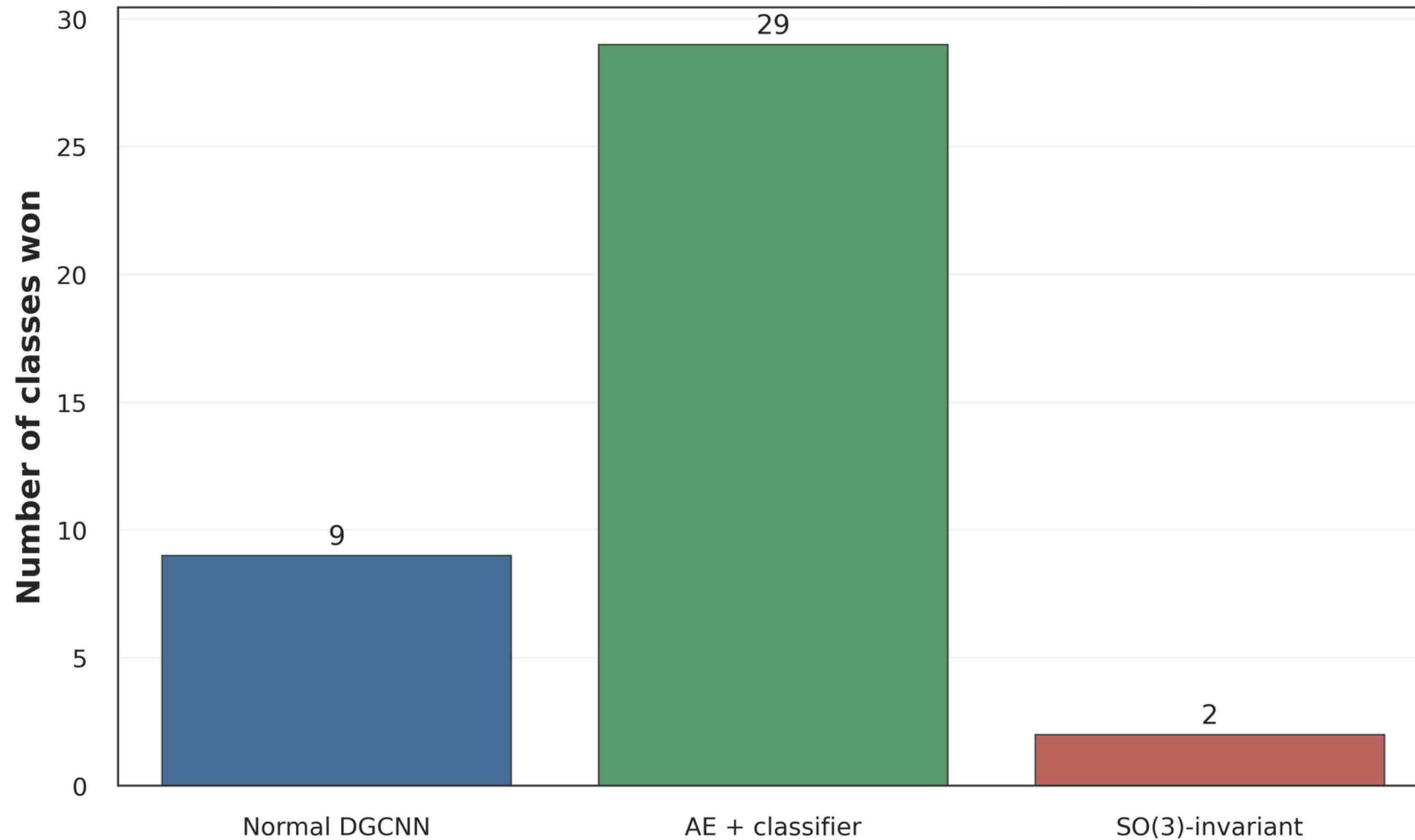
# Results: Classification

Classification performance comparison



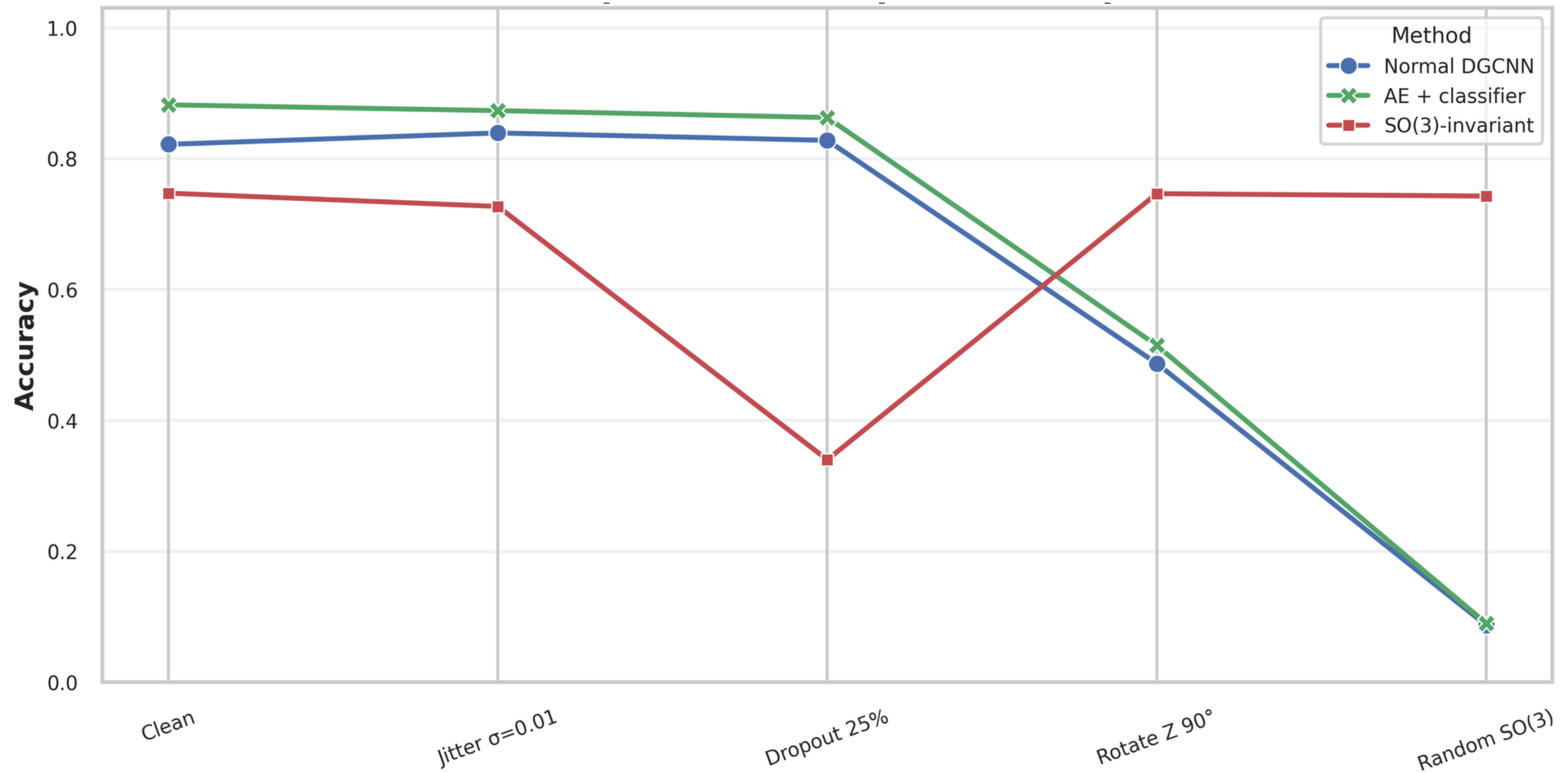
# Results: Classification

How many classes each method wins (per-class F1)



# Results: Classification

Robustness comparison under point-cloud perturbations

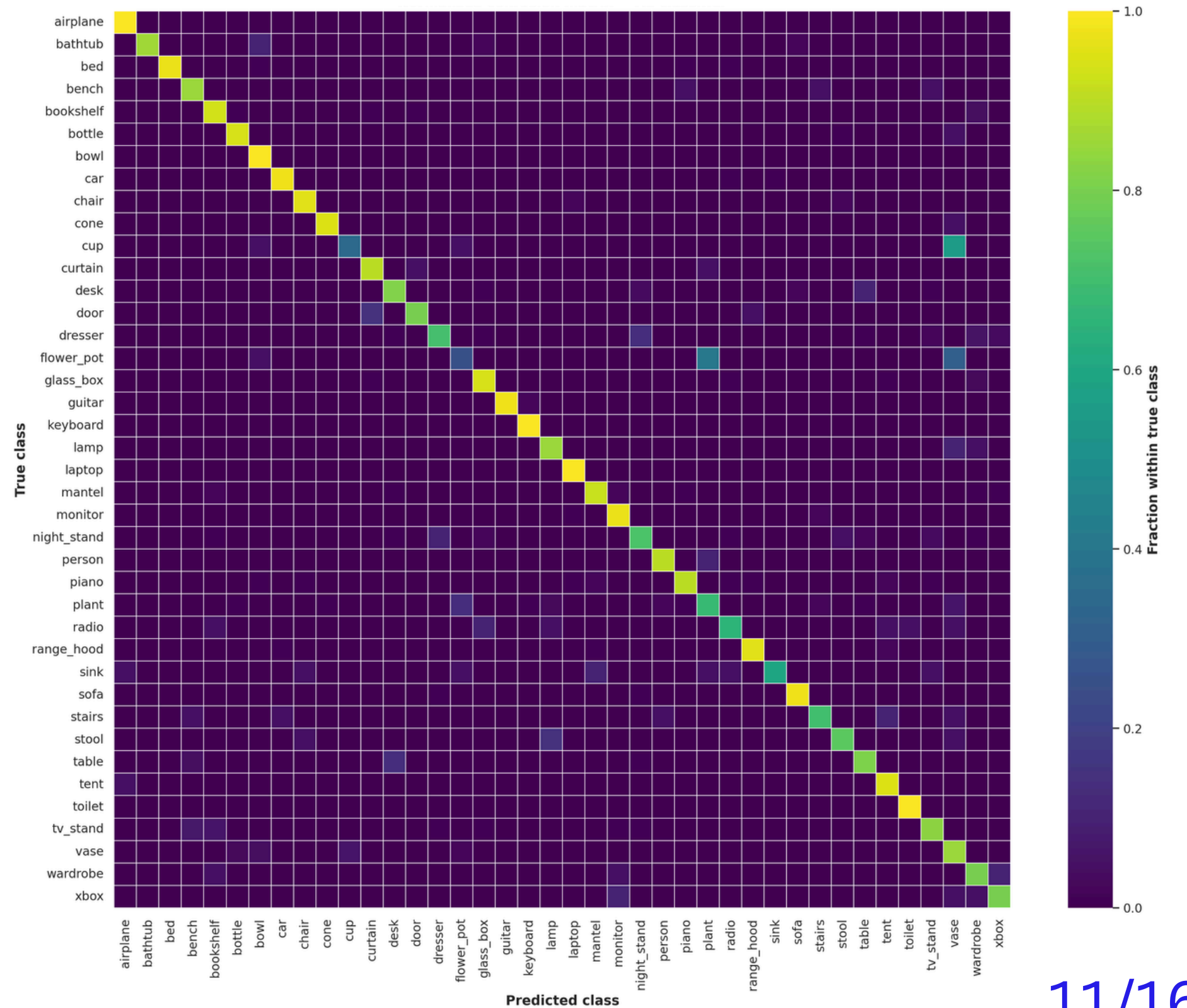


# Results: Classification

Normalized confusion matrix - AE classifier

## Top 5 misclassification pairs:

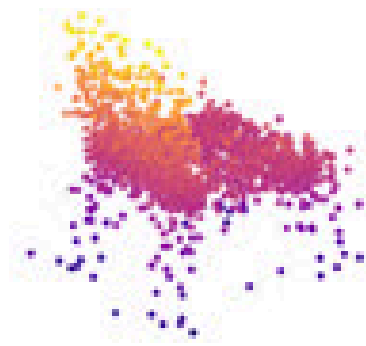
1. plant → flower\_pot
2. table → desk
3. dresser → night\_stand
4. cup → vase
5. night\_stand → dresser



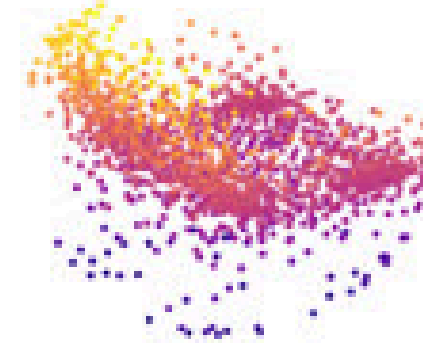
# Results: Generation

Gallery of generated  
samples using CVAE

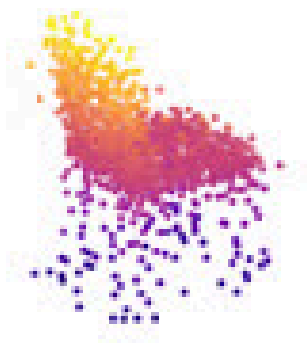
chair



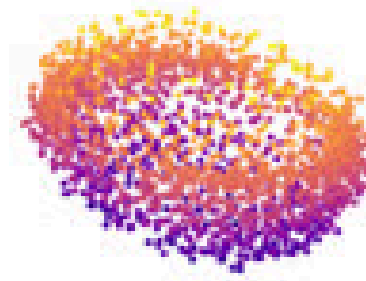
chair 2



chair 3



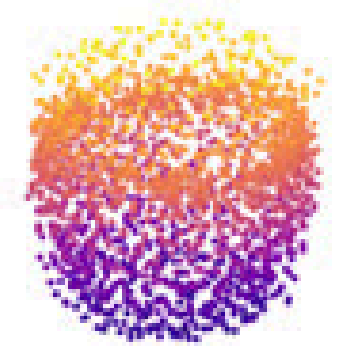
vase



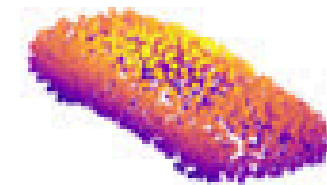
vase 2



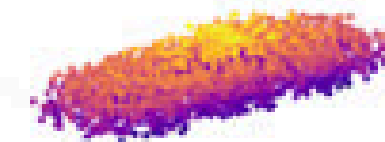
vase 3



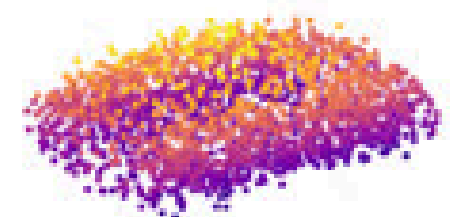
car



car 2

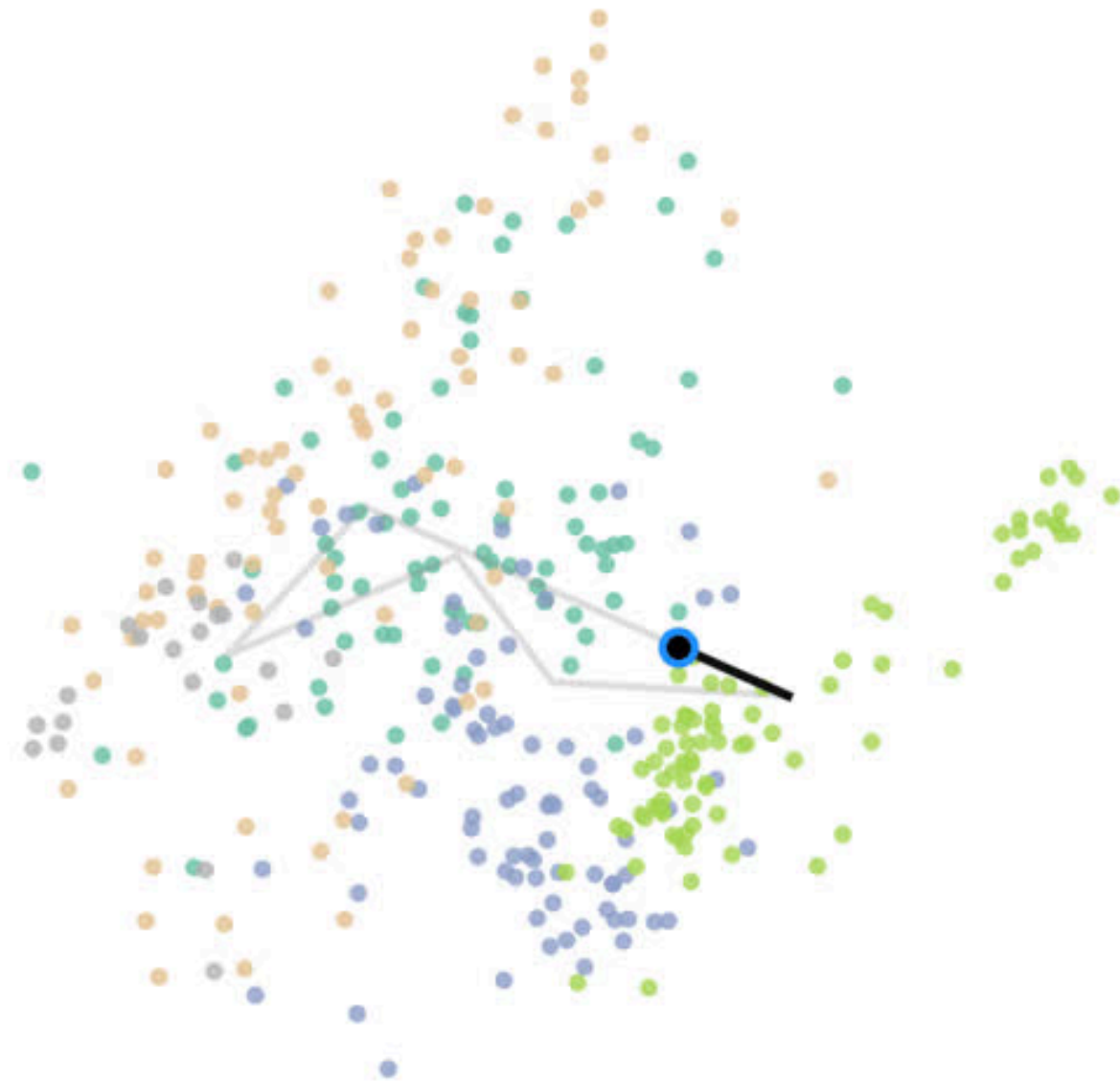


car 3



# Results: Generation

PCA latent trajectory

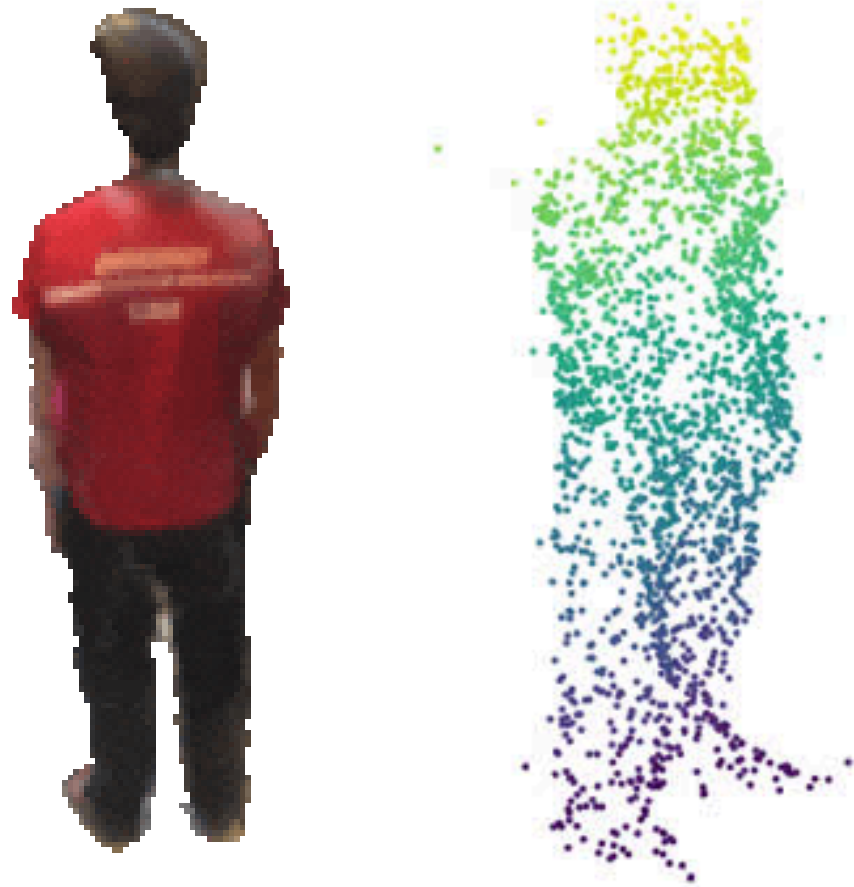


airplane → vase  
blend = 0.26



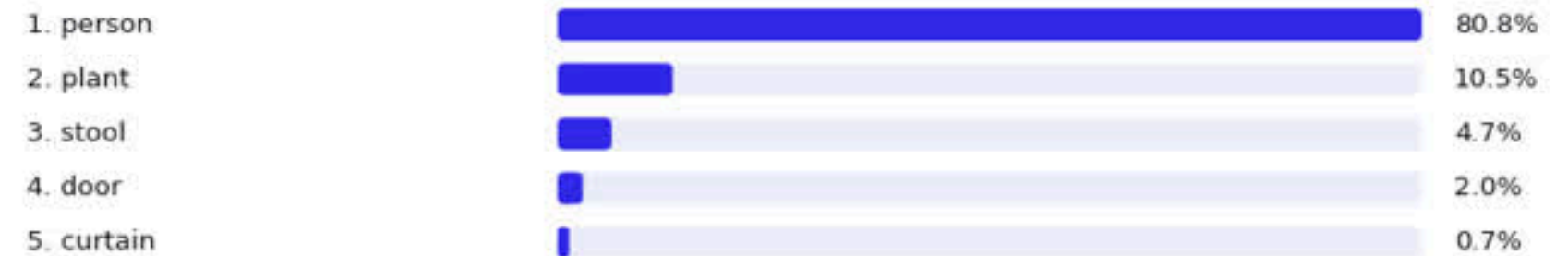
- chair
- airplane
- vase
- person
- table

# Results: Real world objects



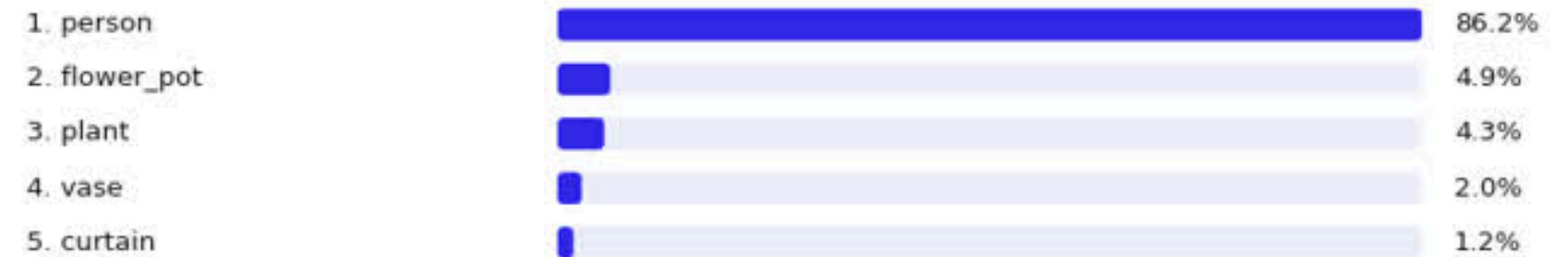
## Vanilla GNN Classifier

**Best: person (80.8%)**



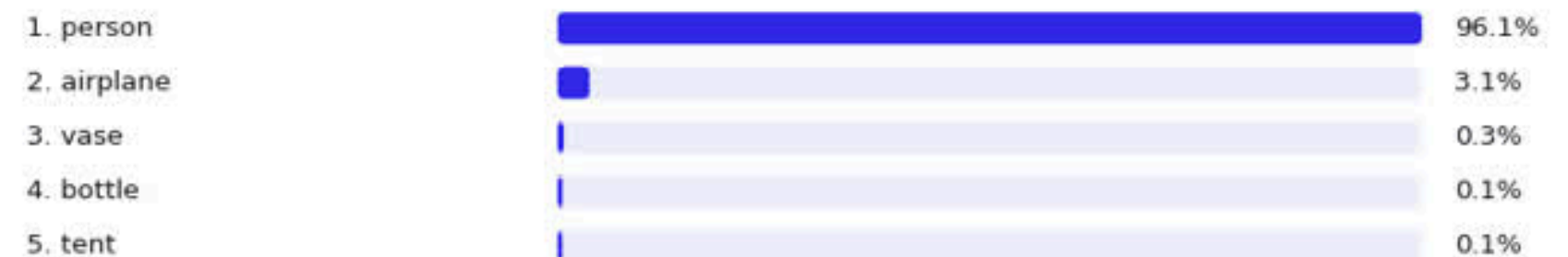
## Autoencoder Classifier

**Best: person (86.2%)**

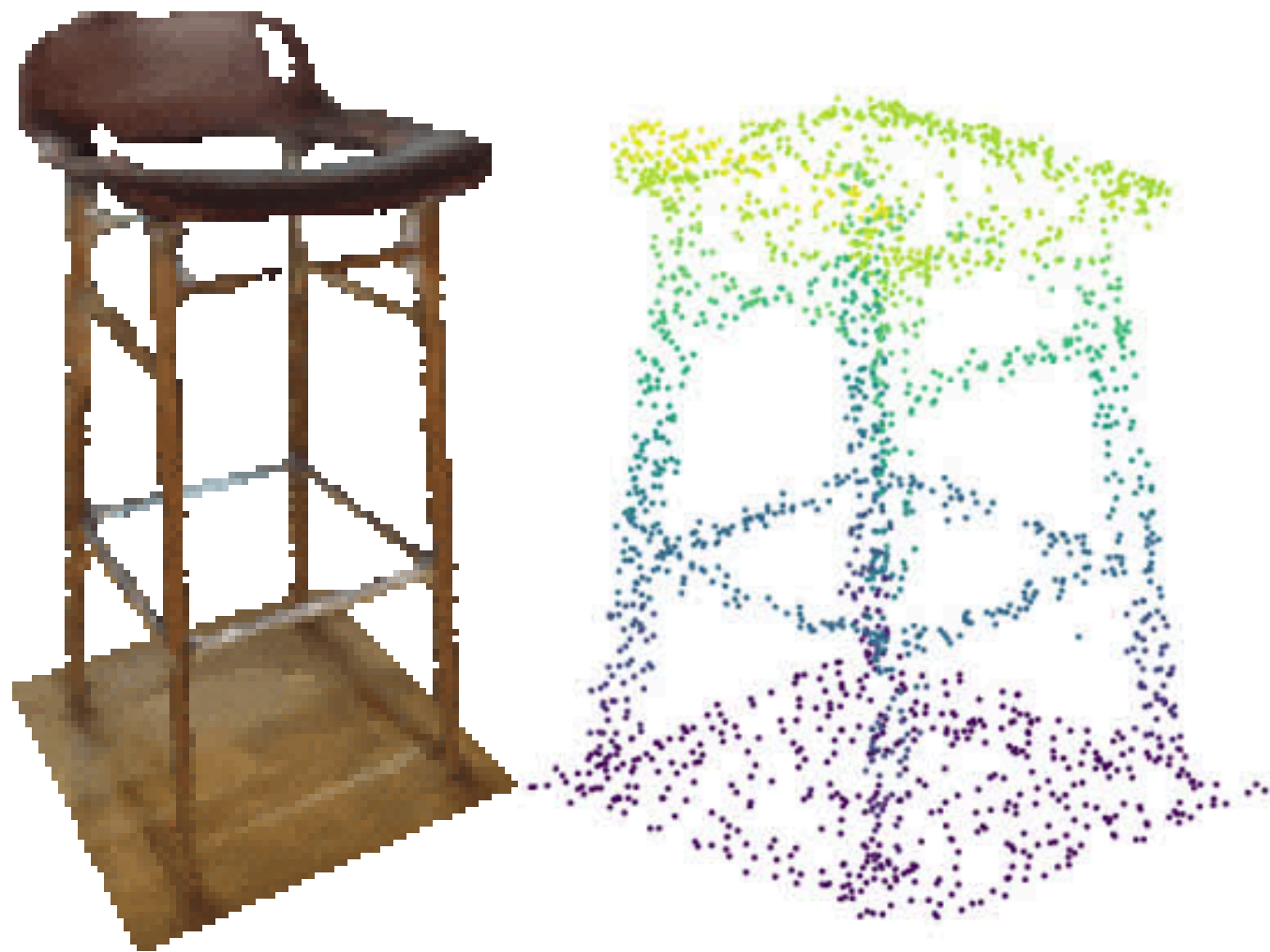


## SO(3) Invariant Classifier

**Best: person (96.1%)**

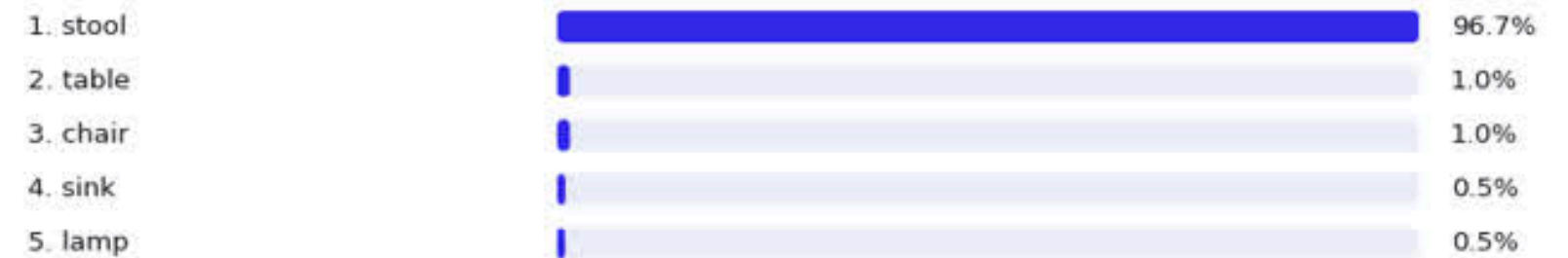


# Results: Real world objects



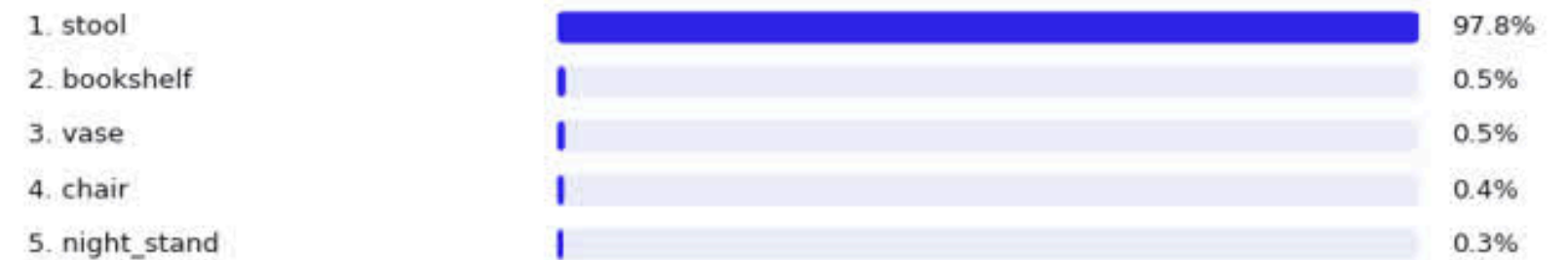
## Vanilla GNN Classifier

**Best: stool (96.7%)**



## Autoencoder Classifier

**Best: stool (97.8%)**



## SO(3) Invariant Classifier

**Best: stool (57.0%)**



# PROBLEMS AND DIRECTIONS

## Current problems:

1. Limited data for generation
2. Ambiguous object classes
3. High compute power needed

## Future directions:

1. Train on a larger and more diverse dataset
2. Improve Chamfer distance efficiency
3. Implement  $SO(3)$  invariance in autoencoders



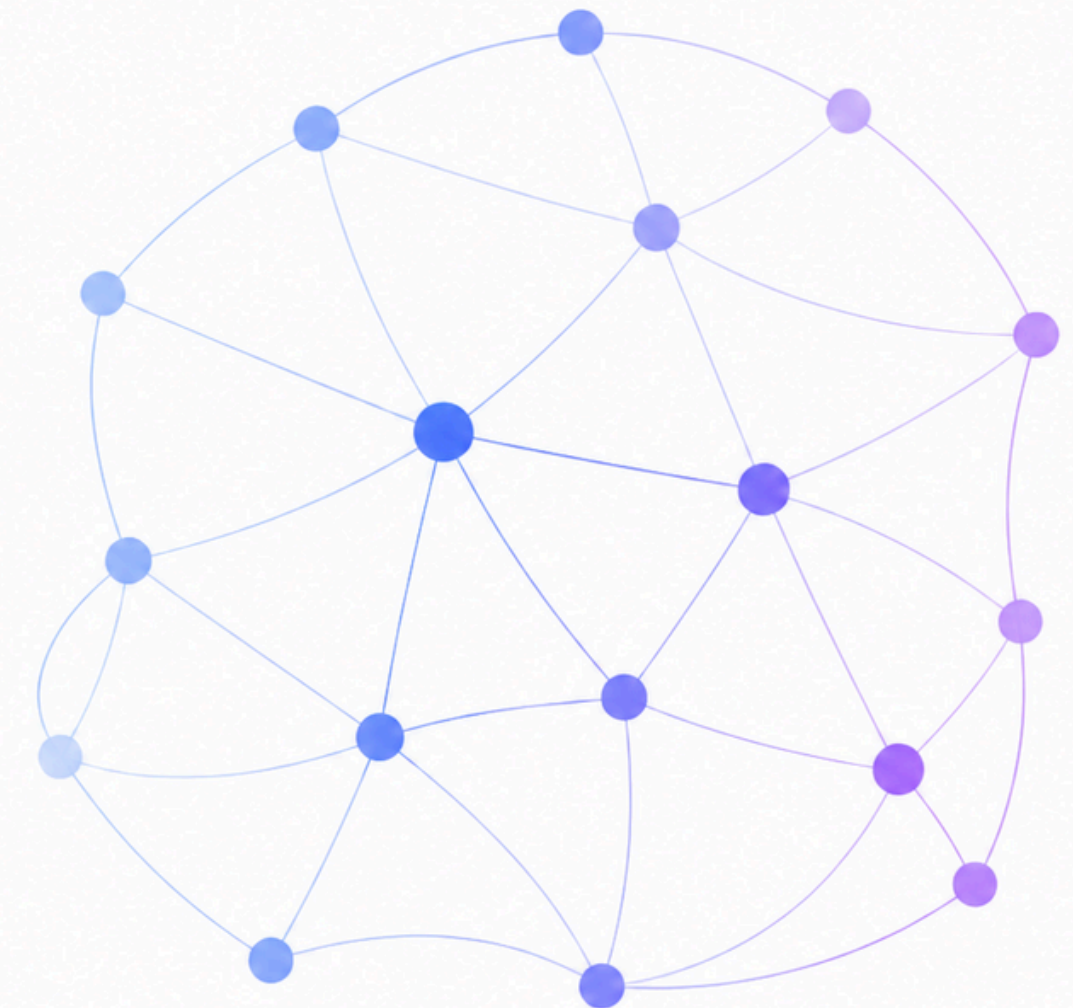
# THANKS!

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**PyG**

# APPENDIX

## 3D Point-Cloud Model Setup Details

- Dataset: ModelNet40-style point clouds
- Number of classes: 40
- Points per object: 2,048
- Point features: XYZ coordinates
- Graph construction: k-nearest neighbors
- K value: 20

# APPENDIX

## 1. Vanilla GNN Classifier

Total parameters: 851,624

### Architecture

- Input point cloud:  $2048 \times 3$
- Build dynamic KNN graph
- Apply DGCNN / EdgeConv blocks
- Concatenate learned point features
- Apply global mean pooling and max pooling
- Use classifier MLP
- Output: 40 class probabilities

# APPENDIX

## 2. Autoencoder Classifier

Total parameters: 2,034,232

### Architecture

- Input point cloud:  $2048 \times 3$
- DGCNN-style encoder extracts point-cloud features
- Bottleneck compresses the object into a latent vector
- Decoder reconstructs the point cloud
- Classification head uses the latent representation
- Output: 40 class probabilities

# APPENDIX

## 3. SO(3)-Invariant Classifier

Total parameters: 853,288

### Architecture

- Input point cloud:  $2048 \times 3$
- Center and normalize point cloud
- Build KNN graph
- Use rotation-invariant scalar features:
  - radius
  - radius<sup>2</sup>
  - distance between points
- Apply invariant message-passing blocks
- Apply global mean pooling and max pooling
- Use classifier MLP
- **Output: 40 class probabilities**

# APPENDIX

## 4. Graph CVAE

Total parameters: 2,572,295

### Architecture

- Input point cloud:  $2048 \times 3$
- Input class label: one of 40 classes
- Label embedding adds class information
- DGCNN-style encoder extracts object features
- Encoder predicts latent distribution:
  - mean
  - log variance
- Sample latent vector  $z$
- Decoder generates a point cloud conditioned on:
  - latent vector
  - class label