MsGT: Multi-scale Geometry and Topology Feature Extraction for Point Clouds

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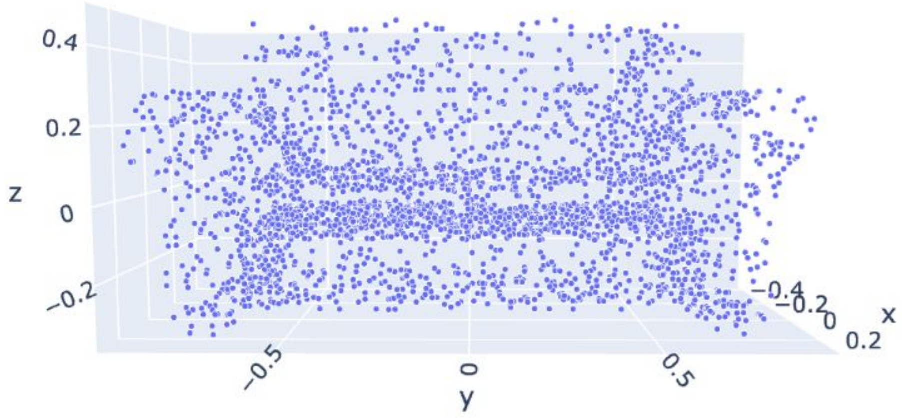
- Background
- MsGT Architecture: Our method
- Implementation
- Evaluation
- Future Work

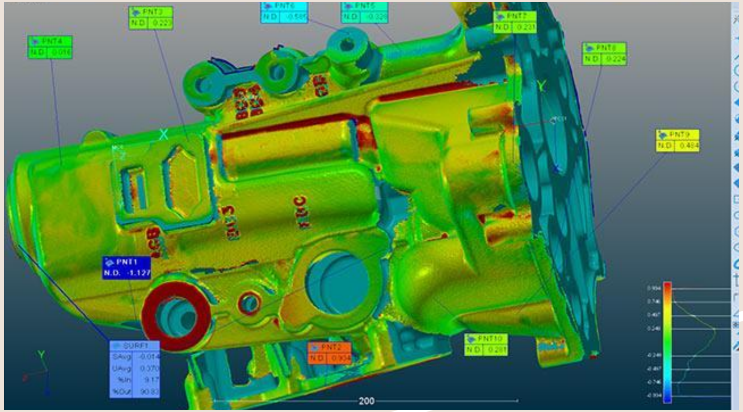
Outline

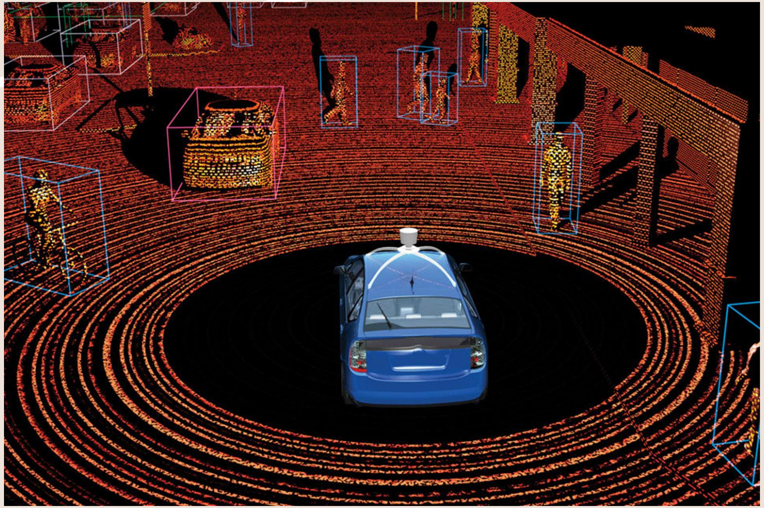
The Idea



Many Applications…

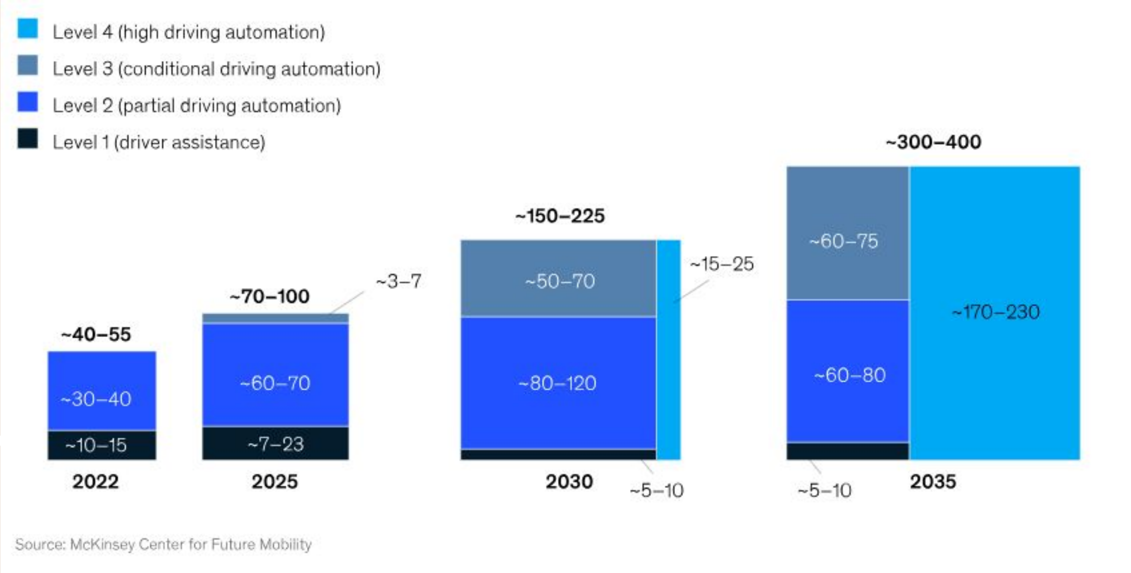
- Urban Planning and Infrastructure
- Construction and Design
- Manufacturing/Quality Control
- Autonomous Systems
- Data Collection





...Strong Economic Impact

- **New Business Opportunities**
- Cost Reduction
- Increased Efficiency
- Asset Management
- Risk Mitigation

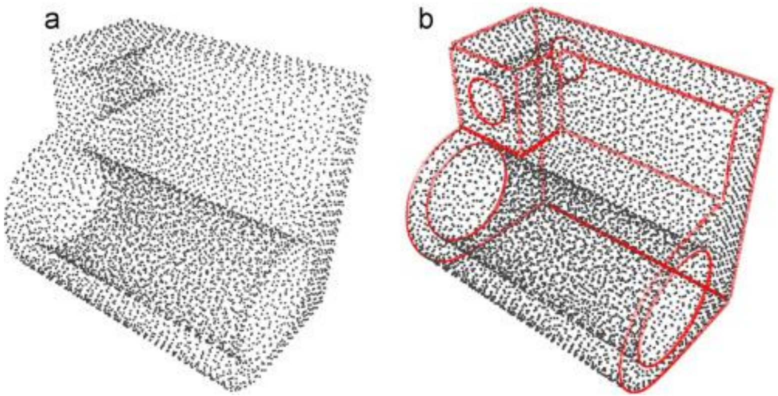


Automated driving: Projected size of industry in billions (USD)

Point Cloud Processing

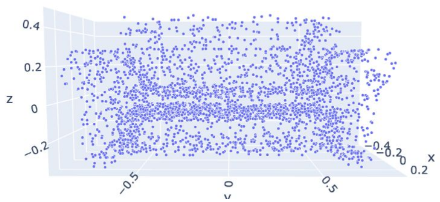
- Point Cloud = Data
- Point Cloud + Processing =

INFORMATION



INFORMATION ⇐ ***"FEATURES"***

How It Works



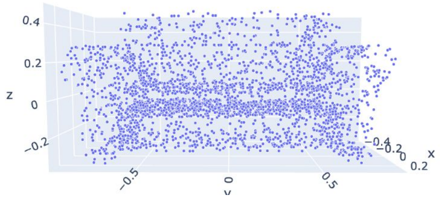
Point Cloud

Feature Extraction

Task

Information

How It Works



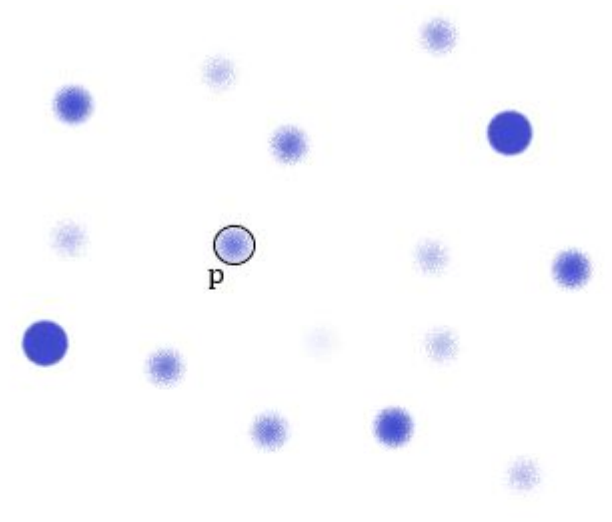
Point Cloud

Feature Extraction

Classification

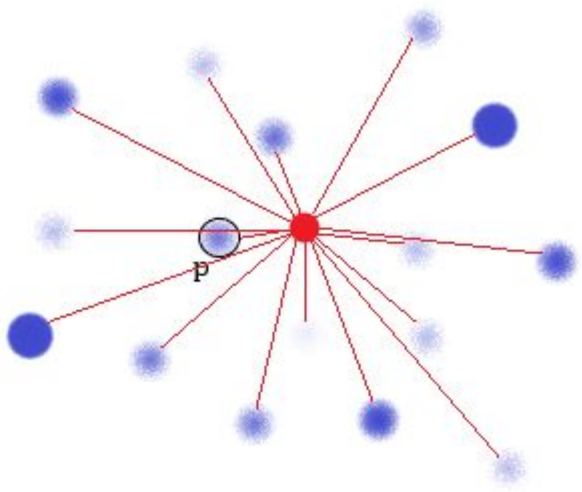
SOFA

Example



Feature Extraction

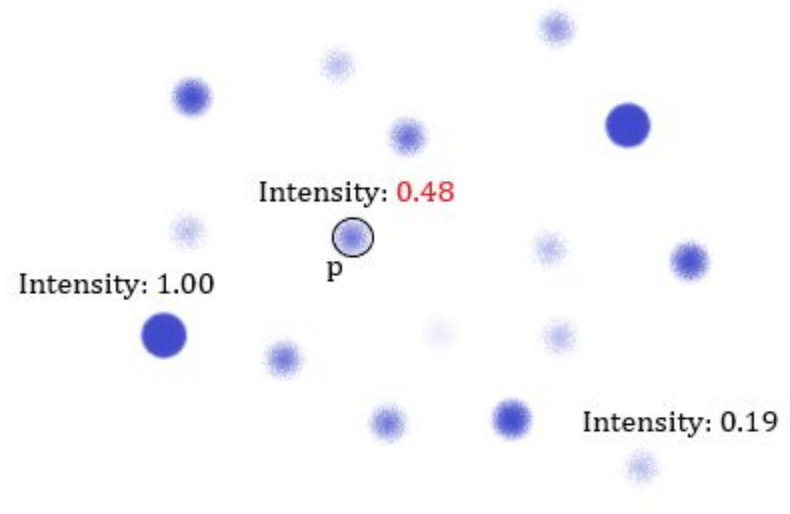
Example



Measurement 1

Feature Extraction

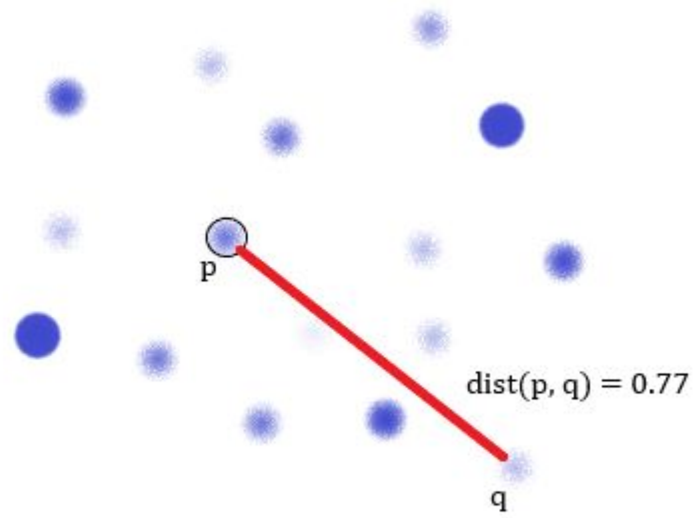
Example



Measurement 1 Measurement 2

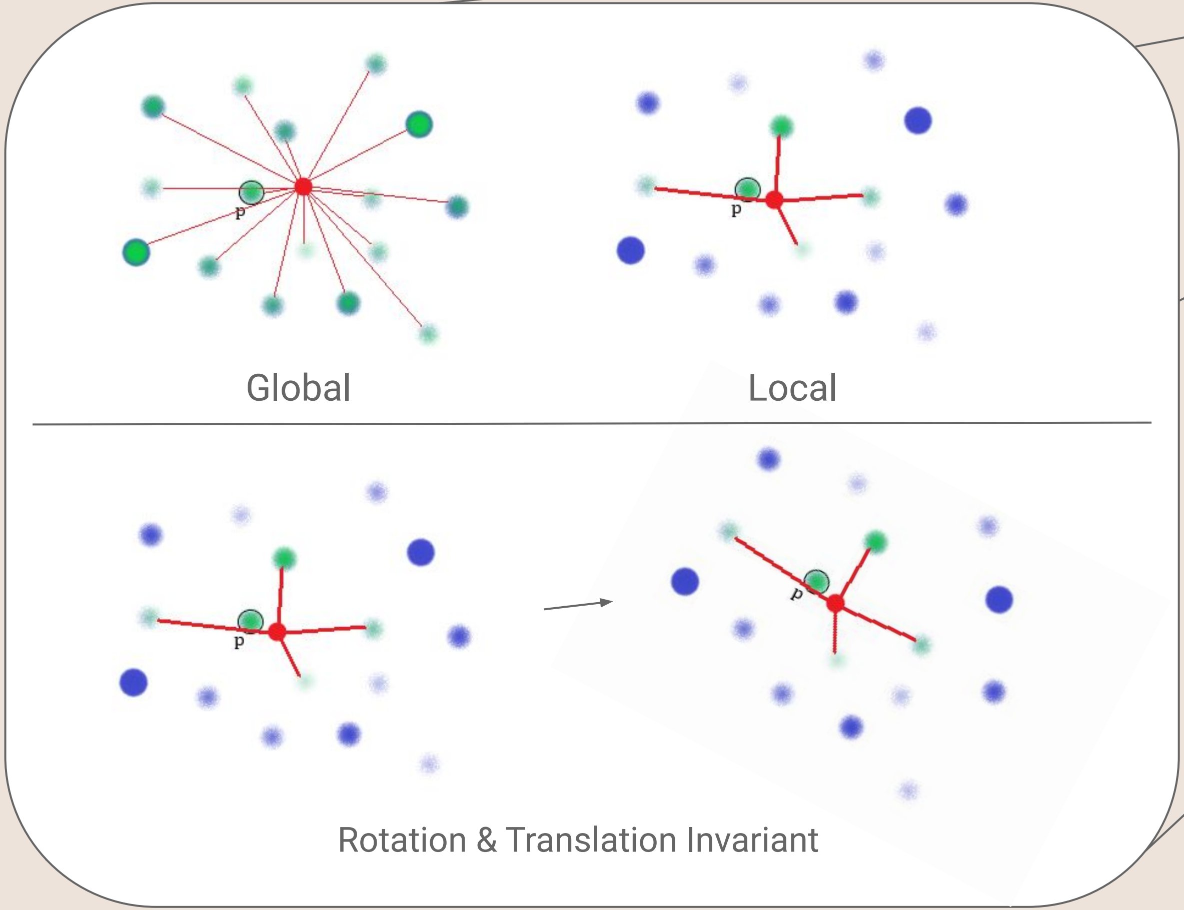
Feature Extraction

Example



Measurement 1 Measurement 2 Measurement 3

Feature Extraction



Feature Extraction

Two Ways

Hand-Crafted Methods

- First on the scene (Old)
- Mathematics and statistics
- Does some tasks well, but is **limited**

Deep Learning Methods

- New (**PointNet** 2017)
- Computer Science and Machine Learning
- Does many tasks **very well**, but is **expensive**

WHAT THIS TALK IS ABOUT:

MsGT: Feature Extraction Method

- Performs **better** than existing hand-crafted methods
- Introduces **novel mathematics** for point cloud processing
- **Strong accuracy** for several data classes
- **No deep learning**

- Background
- MsGT Architecture: Our method
- Implementation
- Evaluation
- Future Work

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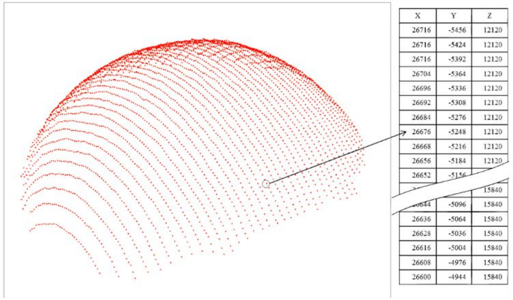
MultiScale Topology and Geometry

Point Clouds



X	Y	Z
26716	-5456	12120
26716	-5424	12120
26716	-5392	12120
26704	-5364	12120
26696	-5336	12120
26692	-5308	12120
26684	-5276	12120
26676	-5248	12120
26668	-5216	12120
26656	-5184	12120
26652	-5156	[illegible]
[illegible]	[illegible]	15840
[illegible]	-5096	15840
26636	-5064	15840
26628	-5036	15840
26616	-5004	15840
26608	-4976	15840
26600	-4944	15840

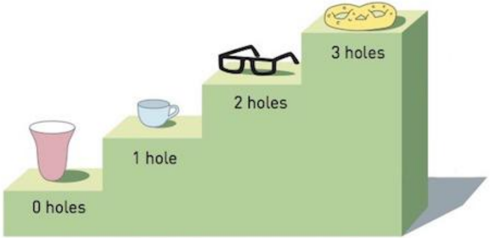
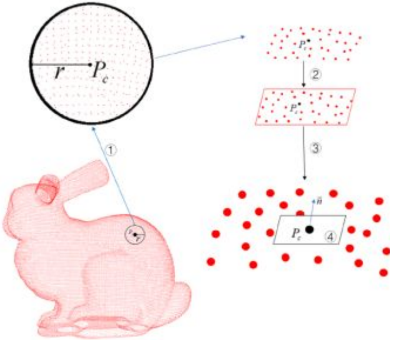


Illustration: ©Johan Jarnestad/The Royal Swedish Academy of Sciences

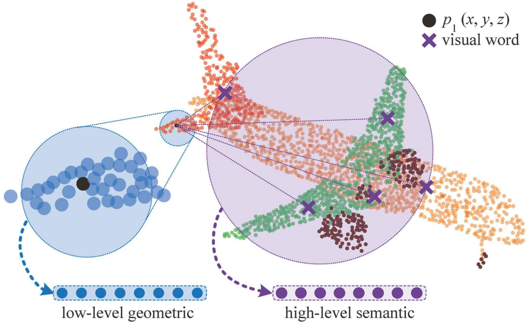
Topological features

MsGT Model

Geometric features

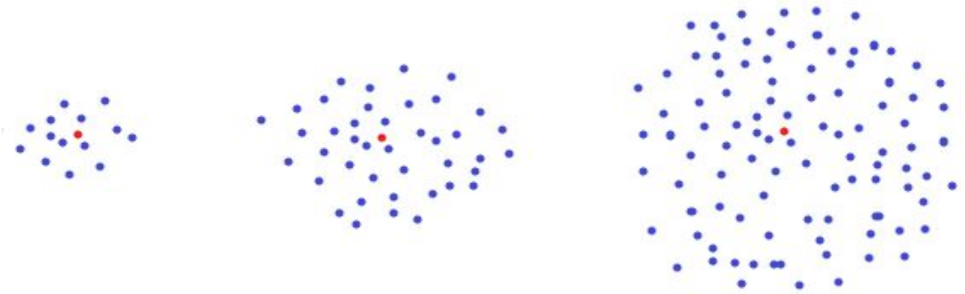


MultiScale Feature Extraction



Multi-scale Topology and Geometry

- Extract **global** features via **topology** (persistent homology, etc.)
- Extract **local** features via **geometry**
- Extract **local** features at **different scales**



Concatenate them:

$$\text{feature vector} = \left[\ \text{global} \mid \text{local}_1 \mid \cdots \mid \text{local}_n\ \right]^T$$

Significance: Most methods focus only on topology or geometry, **not both**.

Persistent Homology (TDA)

Persistent homology is the flagship tool of topological data analysis (TDA).
Definition: Persistent homology computes the topological features present in given data.

- Filtration

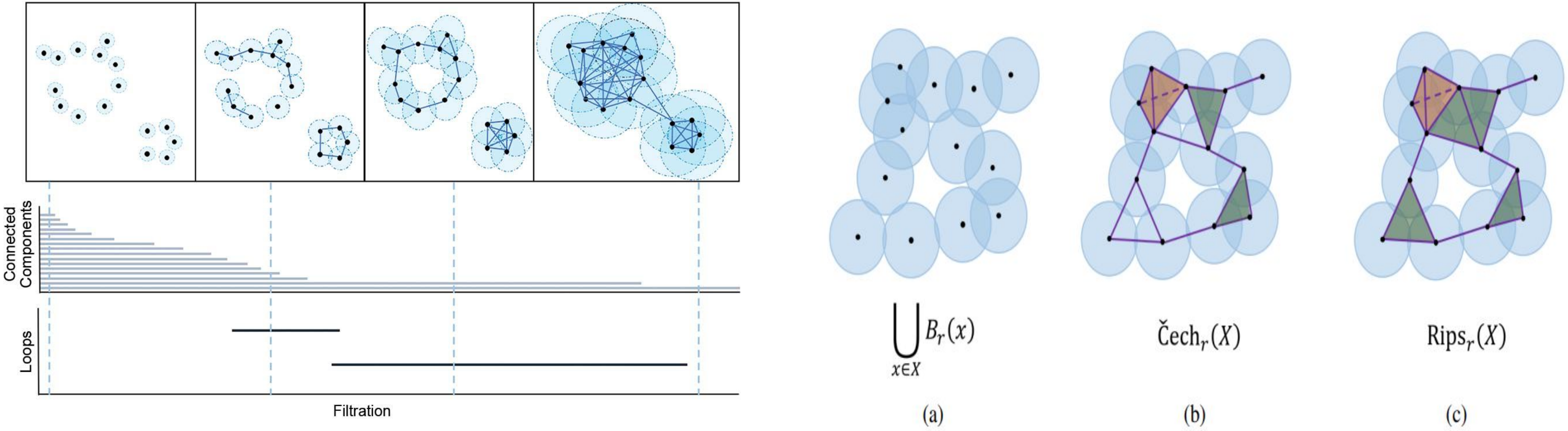


Figure: Filtration

Persistence Diagram (PD)

- **Persistence Diagrams (PD) = (birth, death)**

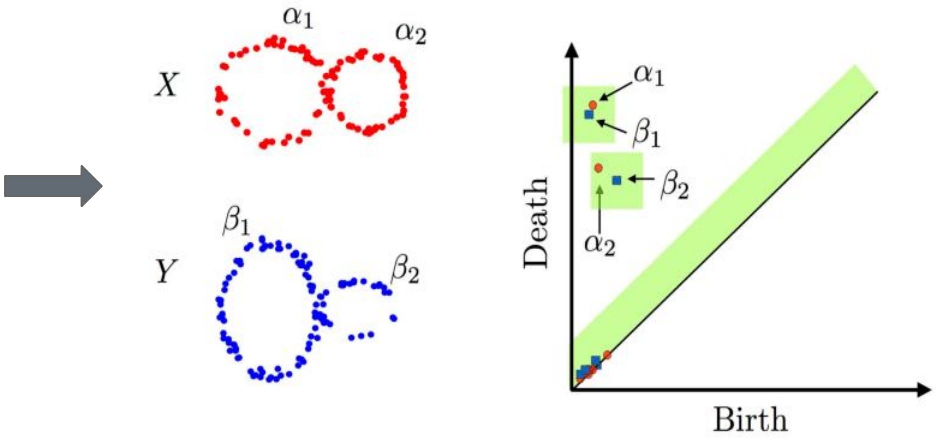
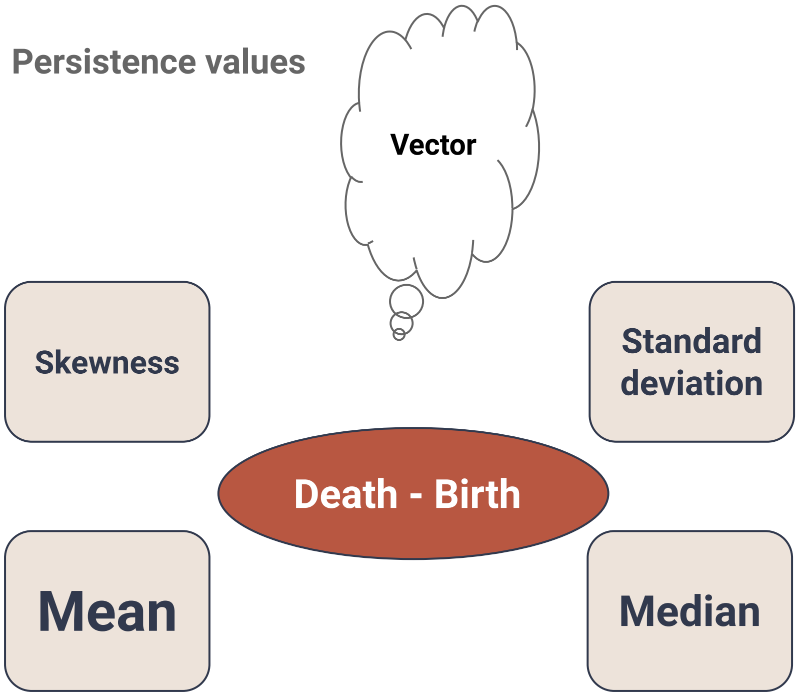


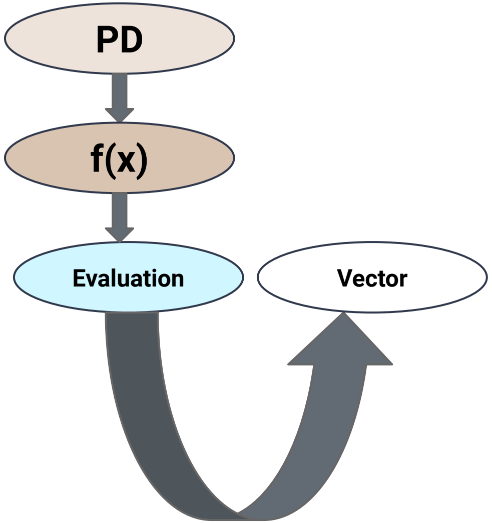
Figure: Persistence Diagram

Vectorization of the PD

Persistence values

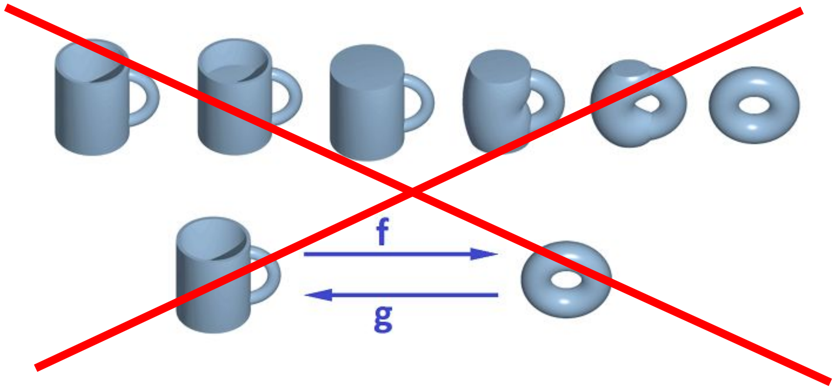


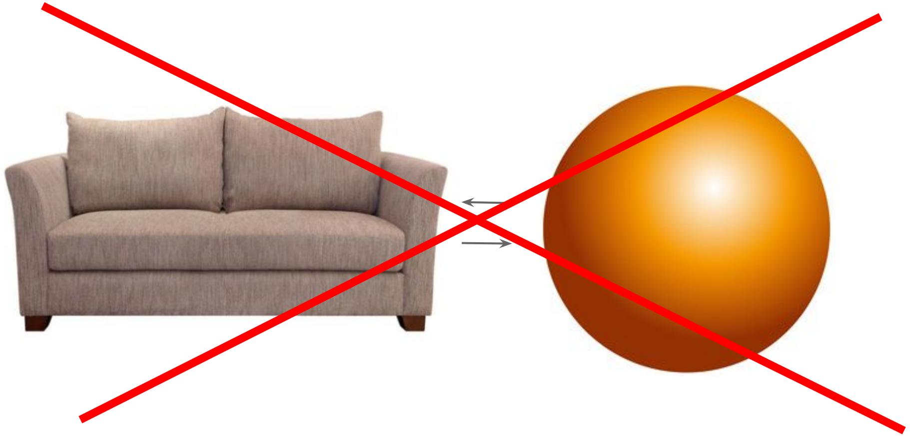
Persistent Landscape (PL)



Geometry: Local Features

In Geometry:



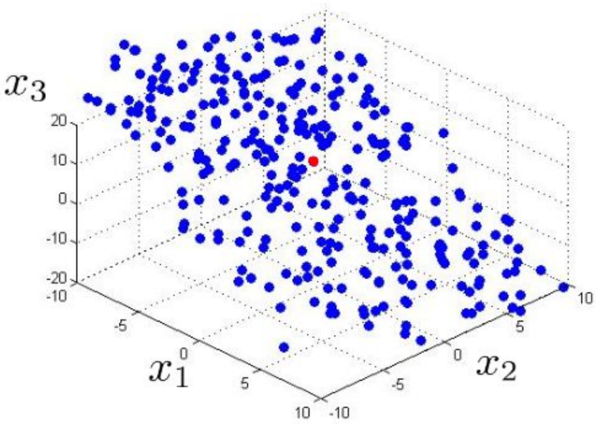


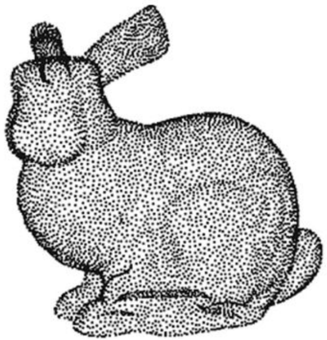
Geometry detects: **curvature, distances, etc.**

Geometry on point clouds ⟶ Local features

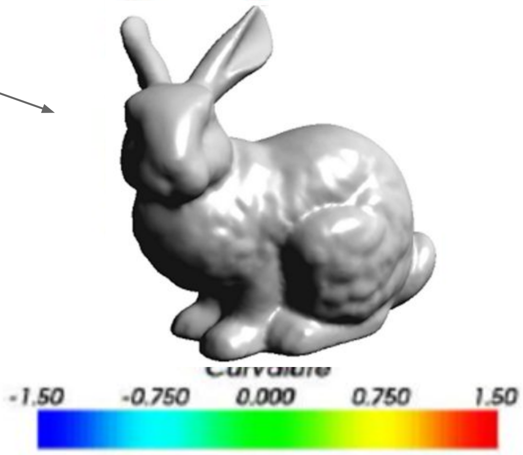
Geometry: Local Features

Point cloud $\approx$ Surface





Surface Fitting



$$(\lambda_0 \cdot \lambda_1 \cdot \lambda_2)^{\frac{1}{3}}$$

Ominivariance

↓

Spreadness

$$\frac{\lambda_0}{\lambda_0 + \lambda_1 + \lambda_2}$$

Surface variation

↓

Roundness

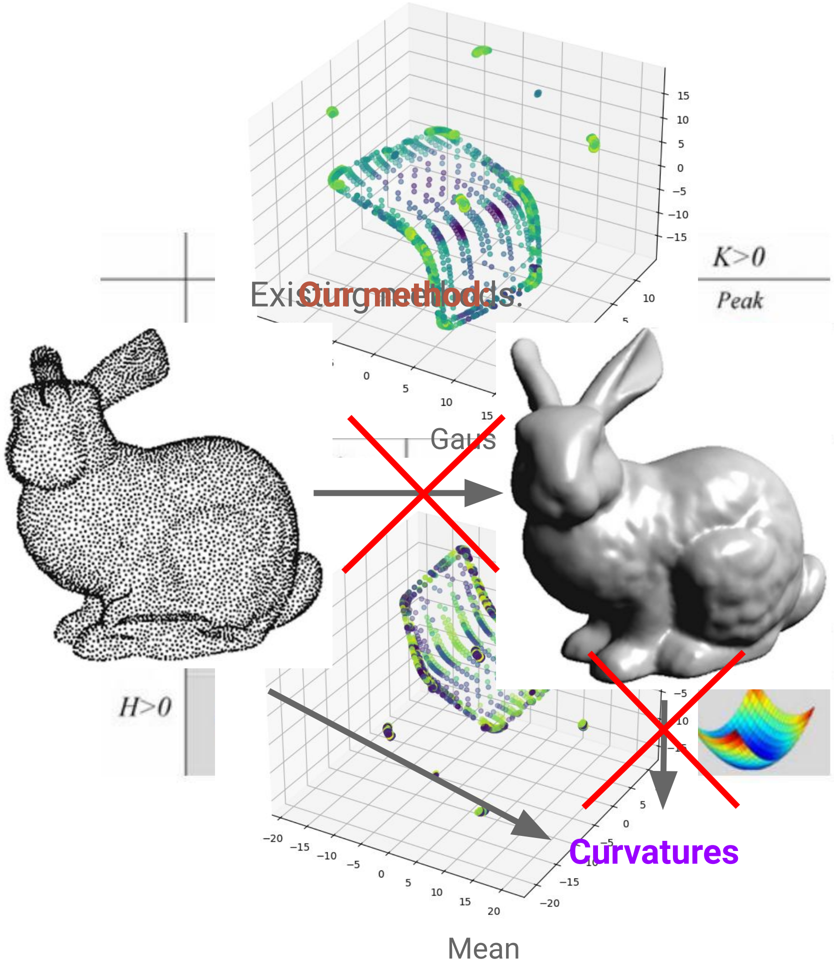
Geometry:
Local Features

Gaussian curvature & Mean curvature
=
Shape of a Surface

Our Gaussian and Mean curvature on pointcloud:

$$K_p = \left(\prod_{i=1}^{n} k(p, q_i) \right)^{\frac{1}{N}},$$

$$H_p = \frac{1}{n} \sum_{i=1}^{n} \left(k(p, q_i) \cdot \frac{\langle \mathrm{n}(q_i), (p - q_i) \rangle}{\|\mathrm{n}(q_i)\| \cdot \|p - q_i\|} \right).$$



Geometric features we used:

Our features

Gaussian curvature K
Mean curvature H

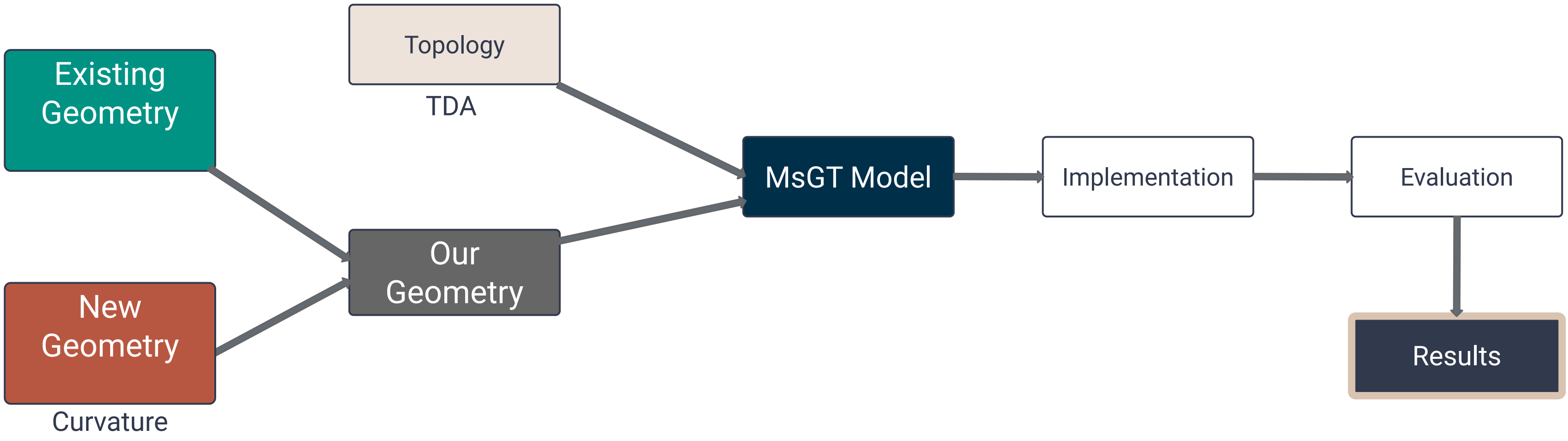
+

Existing features

Surface Variation
Omnivariance
Mean position

Our Geometry

Multi-scale Geometry Topology (MsGT)



- Background
- MsGT Architecture: Our method
- Implementation
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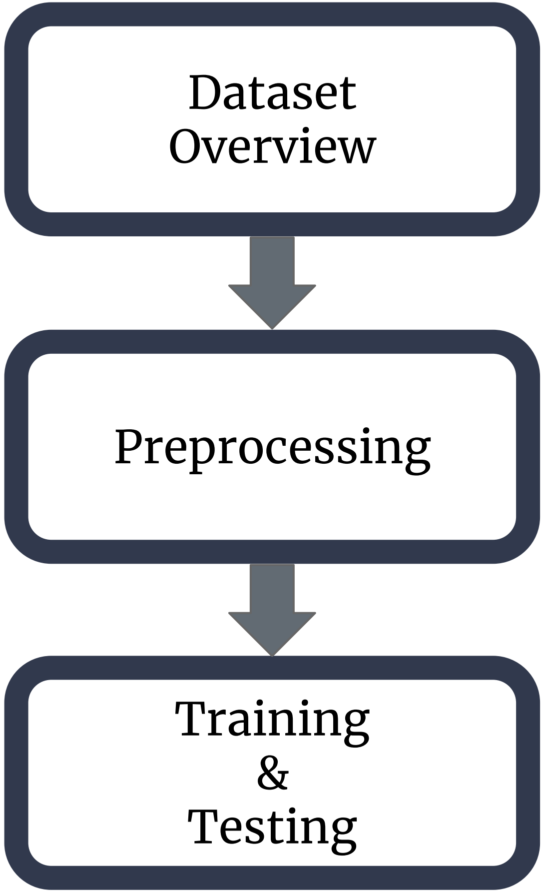
- Future Work

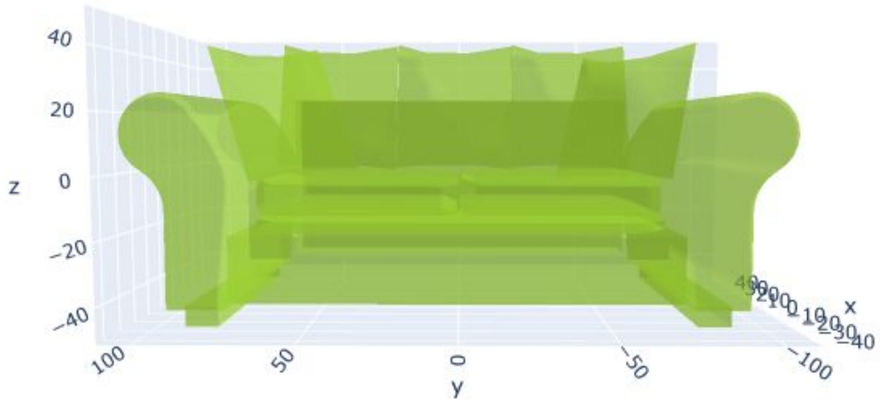
Outline

Implementation



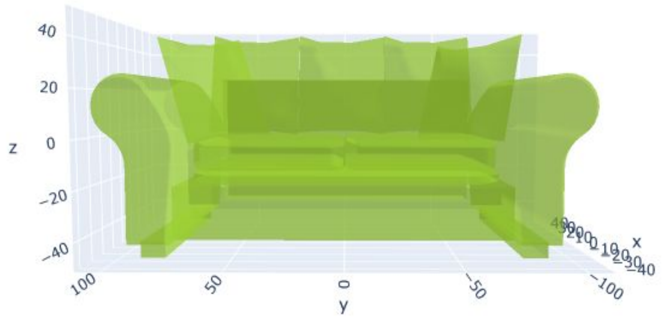
Dataset Overview

- ModelNet10 dataset
  - Training:
    - Size: 3991
    - Training classifiers
  - Testing:
    - Size: 908
    - Evaluating performance of extracted feature vectors
- A benchmark in 3D object recognition
- 10 object categories

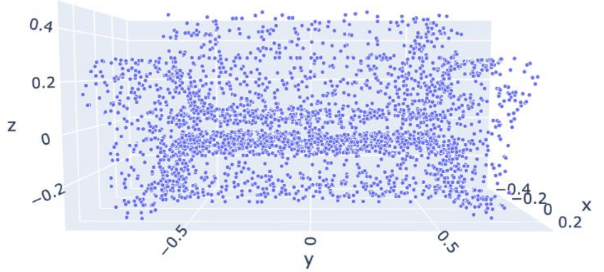


Preprocessing Steps

- Sampling:
  - 1024 points
  - ensure consistent input size



- Normalization:
  - rescale the point coordinates
  - lie within a common range



- Noise Addition:
  - introducing small variations
  - mimic real-world scenarios

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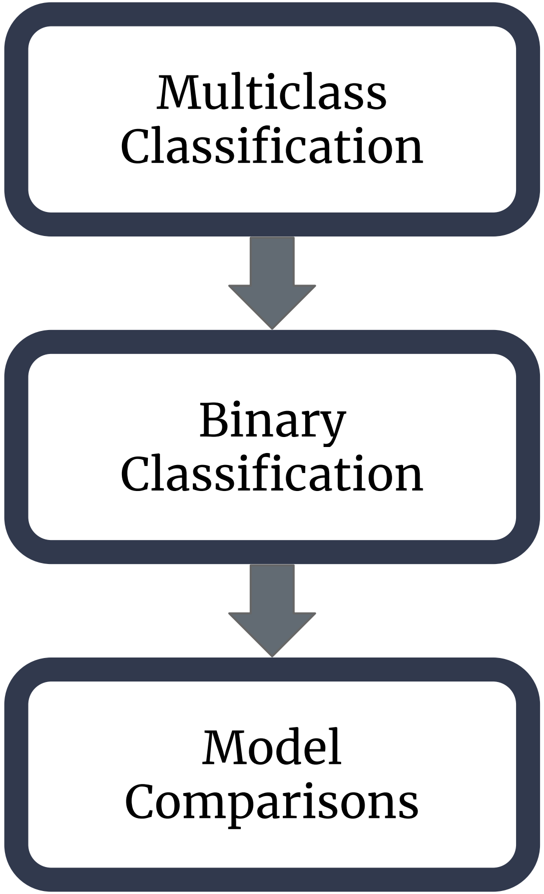
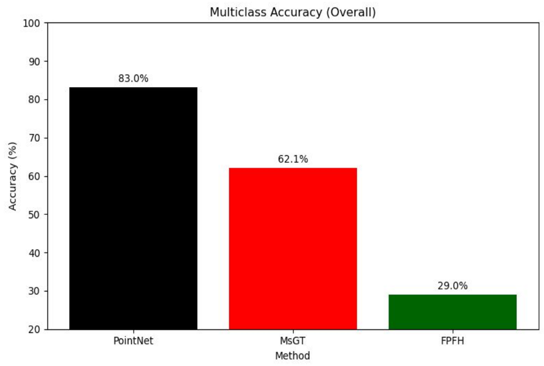
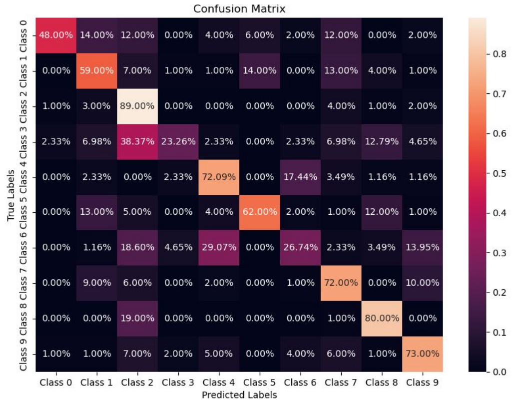
Model Evaluation



Multiclass Classification

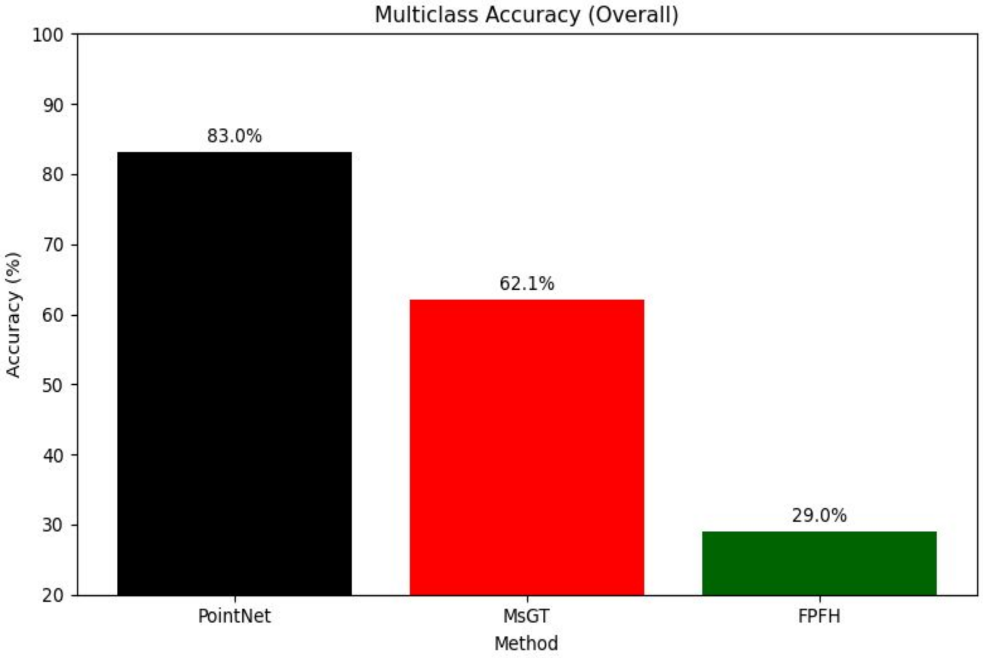


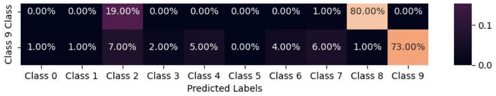


- MsGT stands out among other **handcrafted** methods
- MsGT lags behind **deep learning** approaches

- High Accuracy in Specific Classes
- Challenges with Low-Quality Data
- Insight into Misclassifications

Multiclass Classification





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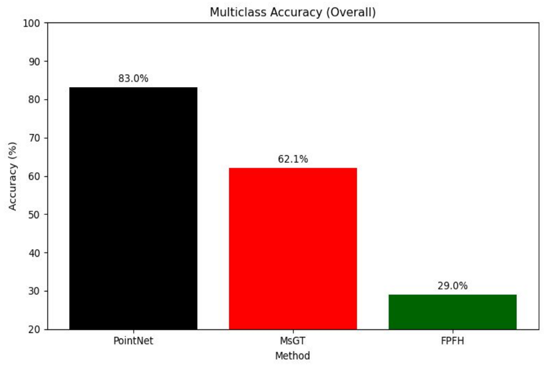

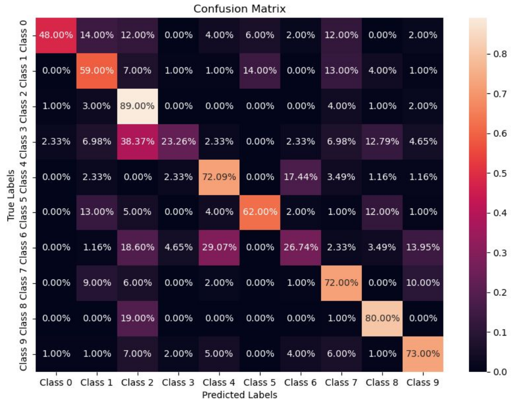

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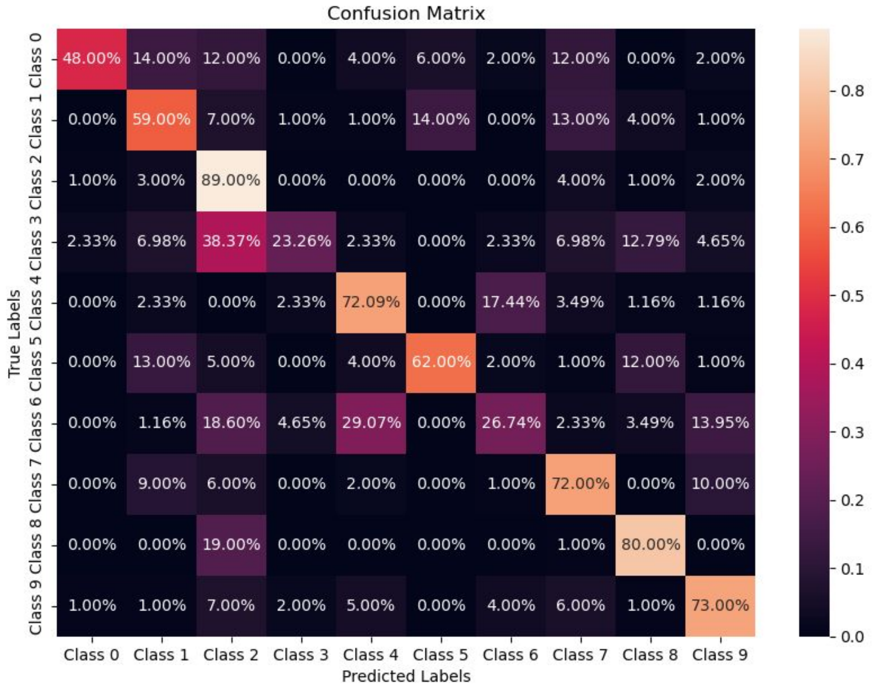

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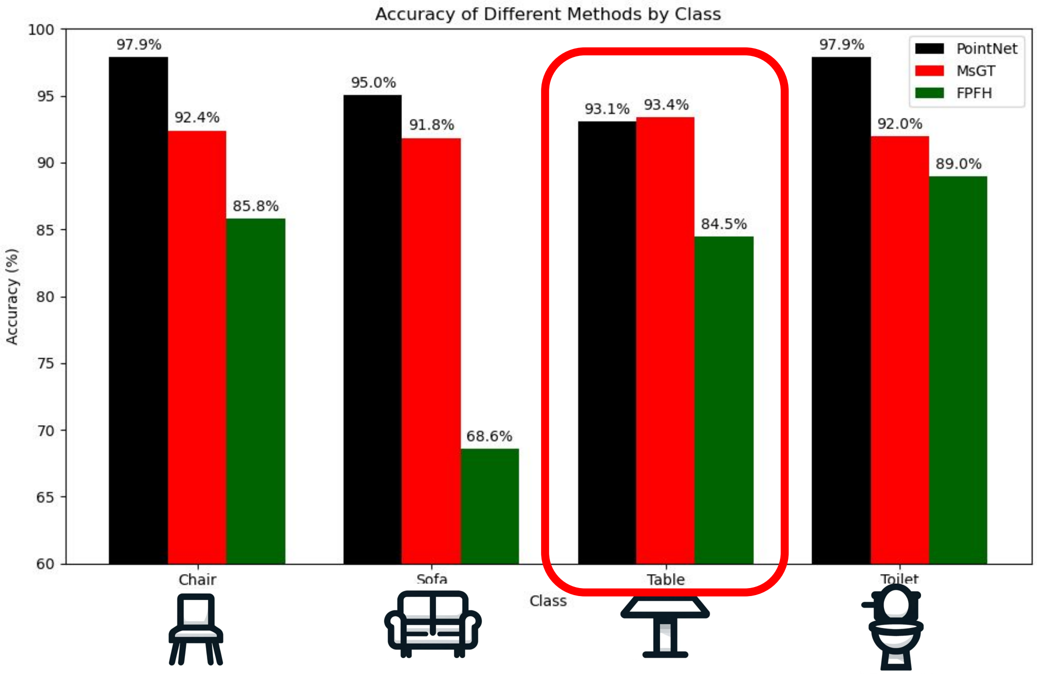
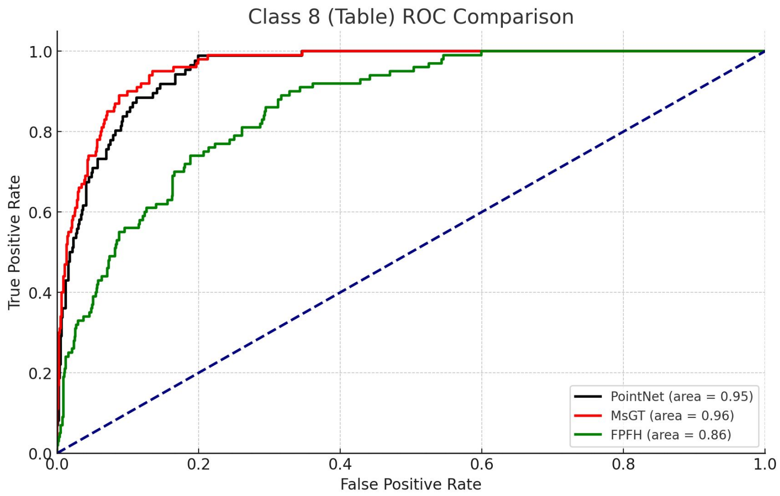
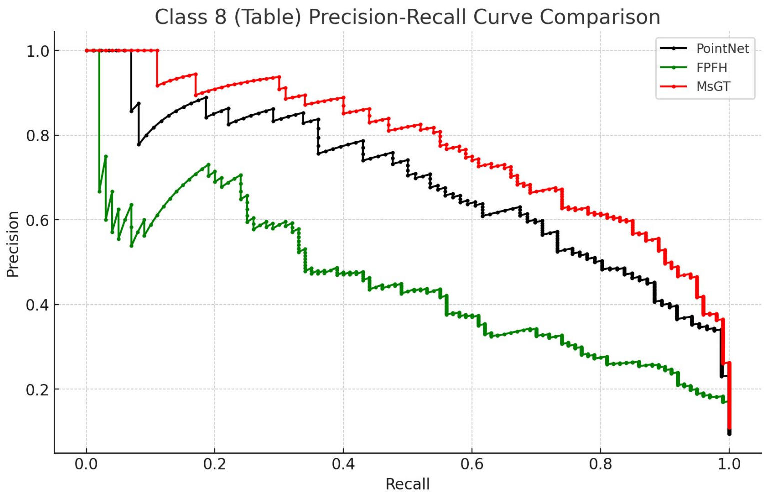
Binary Classification and Model Comparison



- High Accuracy Across Classes
- Superior to Other Handcrafted Methods
- Exceptional Performance in Table Class

Table Binary Classification: MsGT > PointNet > FPFH





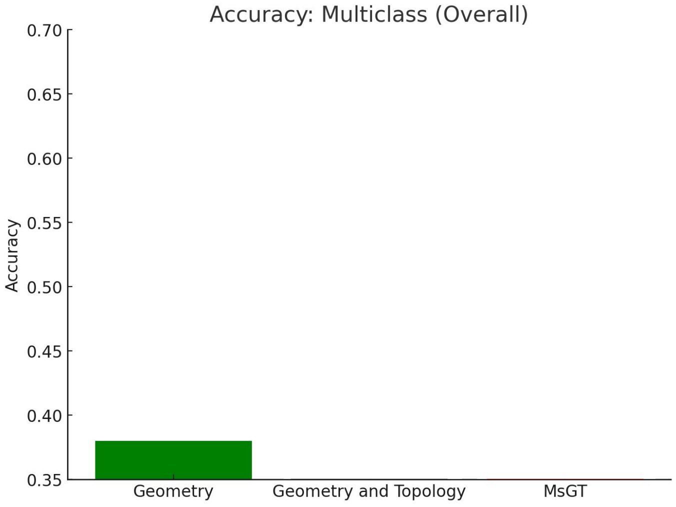
- The ROC curve for MsGT is close to the top left corner.
- AUC = 0.96: high effectiveness in distinguishing between positive and negative samples.

- MsGT Precision-Recall Performance

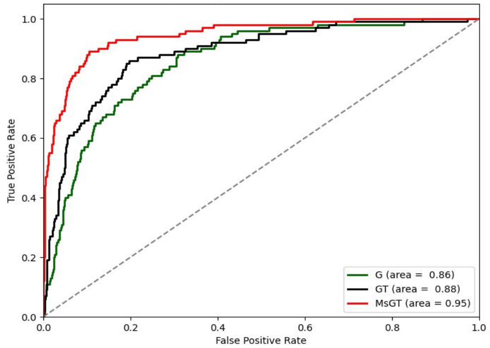
- Effectively detect the majority of positive samples while keeping false positives low

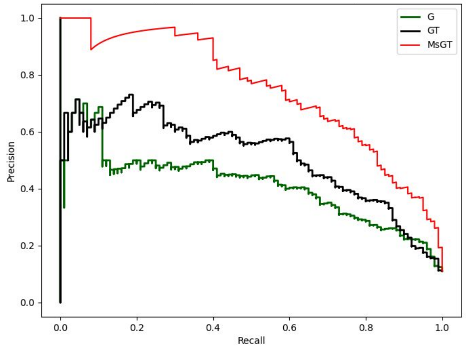
Geometry < Geom+Topo < MsGT Comparisons

Multiclass Accuracy



ROC and Precision-Recall Curve on Chair Binary Classification

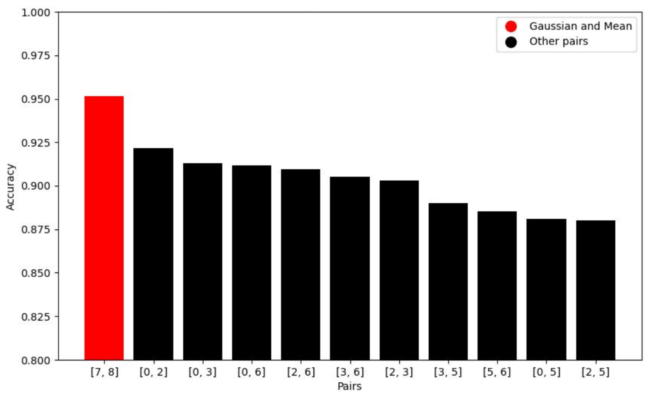




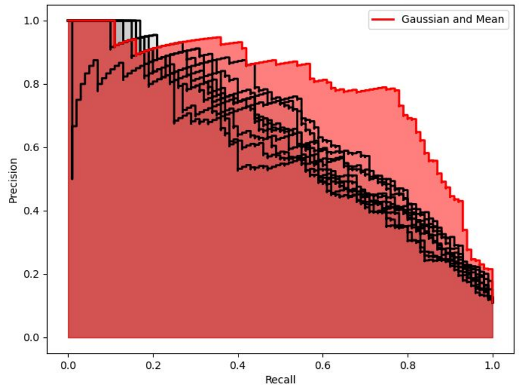
- MsGT model build-up
- Geometry (38%) ➡ Geometry+Topology (45%) ➡ MsGT (62%)

Geometry Features Comparison

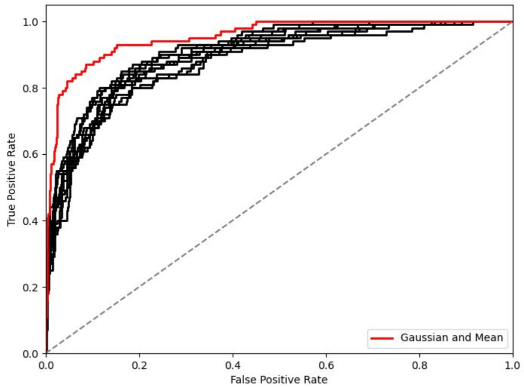
Chair Binary Classification



Precision-Recall Curve: Chair

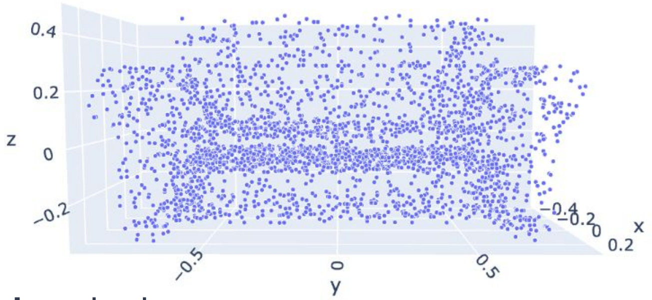


ROC Curve: Chair



- Our novel Geometric Feature (Red): Gaussian and Mean curvature
- Other pairs of some existing geometric features (Black)
- Gaussian and Mean > other geometry methods

Conclusion



- **MsGT Method:**
  - **Combines** topological and geometric features.
  - **Cost-effective** compared to deep learning.
- **Performance Comparison:**
  - Superior to **PointNet** in specific tasks.
  - Significantly better than FPFH and other **handcrafted** methods.
- **Key Advantages:**
  - **High accuracy**, especially in challenging categories (e.g., table classification).
  - Balanced **integration** of topological and geometric strengths.
- **Practical Implications:**
  - **Low cost** and **high efficiency** for various applications
- **Model Limitation:**
  - **Misclassifying** certain classes in multiclass classification
  - **Computational time**

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Future Work: Weighting

~~Normalization~~

[p. values | landscapes | Gauss | Mean | Omnivariance | ···]

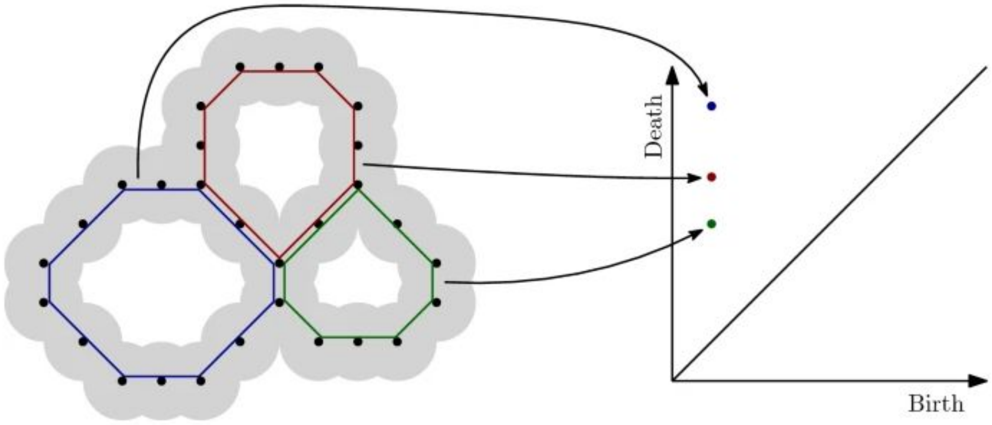
[p. values | landscapes | Gauss | Mean | Omnivariance | ···]

Based on accuracy correlation

Future Work: Topology Improvement

Vectorization of Persistence Diagram

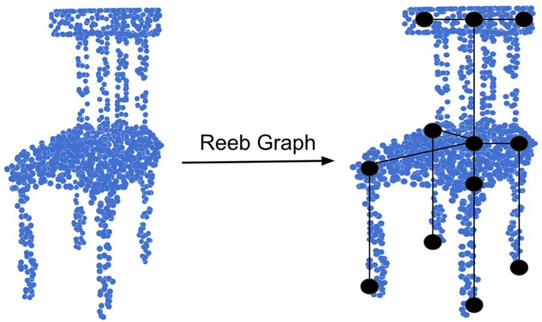
- Persistent Entropy
- Persistence Images

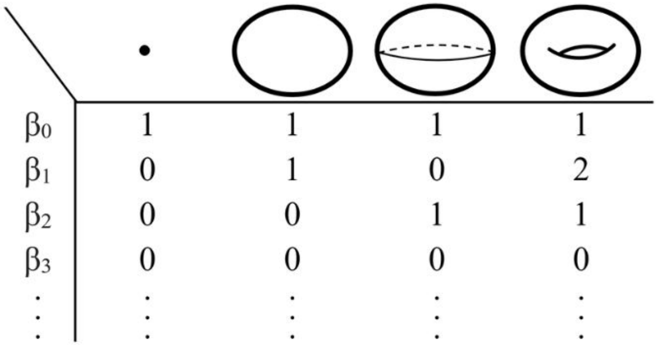


Future Work: Topology Improvement

Other Topological features

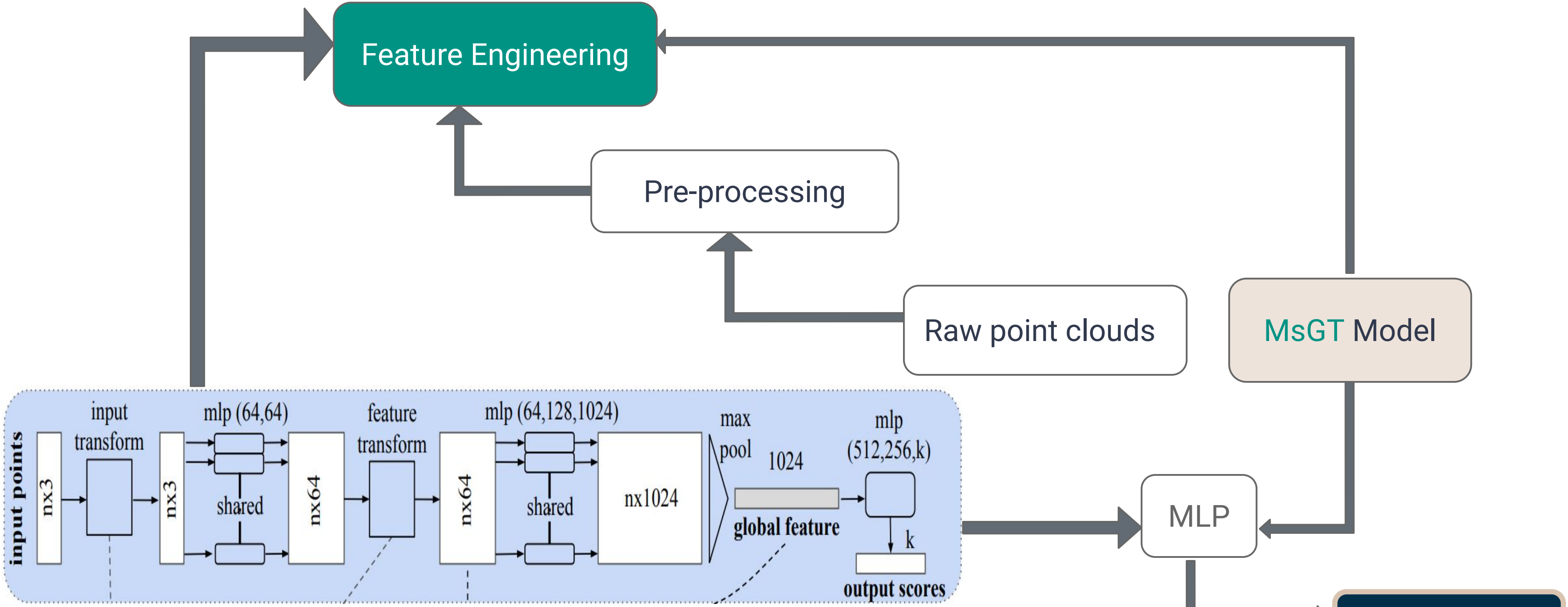
- Betti numbers
- Euler characteristics
- Reeb graphs





Name	Image	Vertices V	Edges E	Faces F	Euler characteristic: $V - E + F$
Tetrahedron		4	6	4	**2**
Hexahedron or cube		8	12	6	**2**
Octahedron		6	12	8	**2**
Dodecahedron		20	30	12	**2**
Icosahedron		12	30	20	**2**

Future Work: Combination with PointNet



PointNet

Thank you!

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AIMR

ipam

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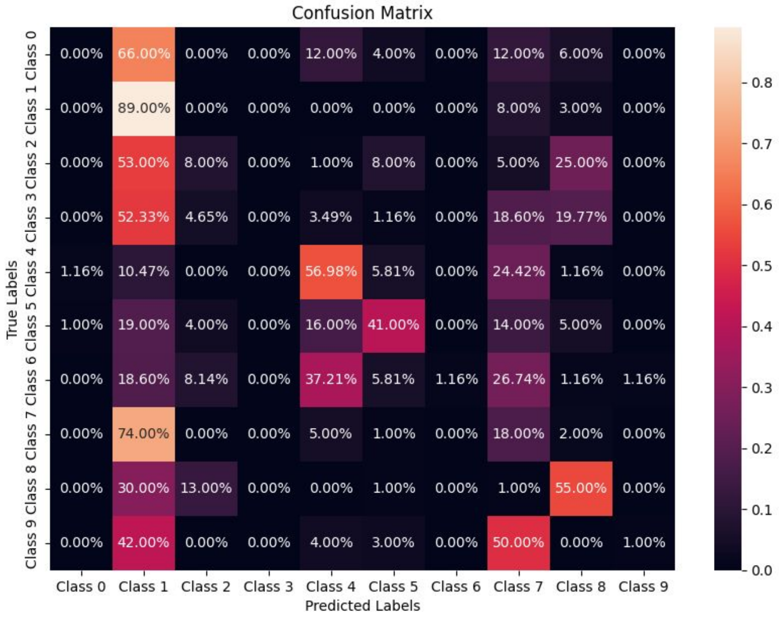
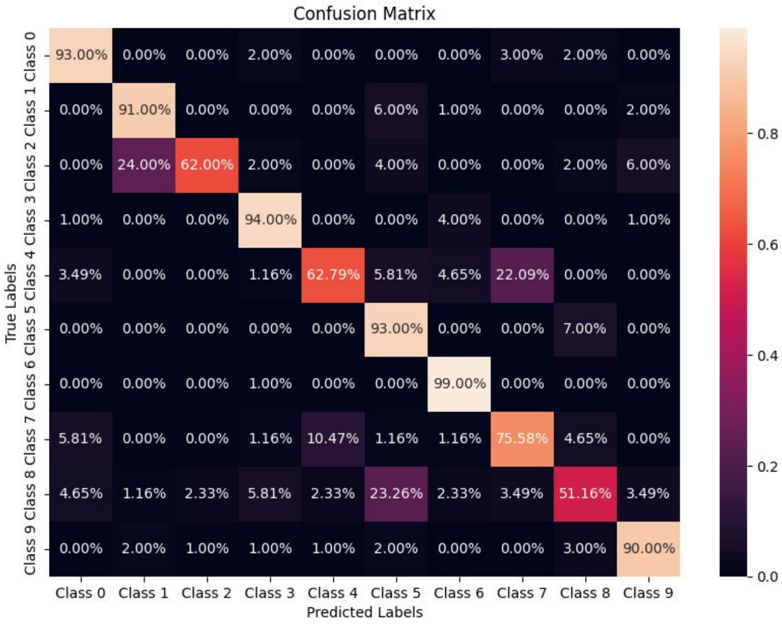
Questions?

Appendix

- FPFH Multiclass Classification



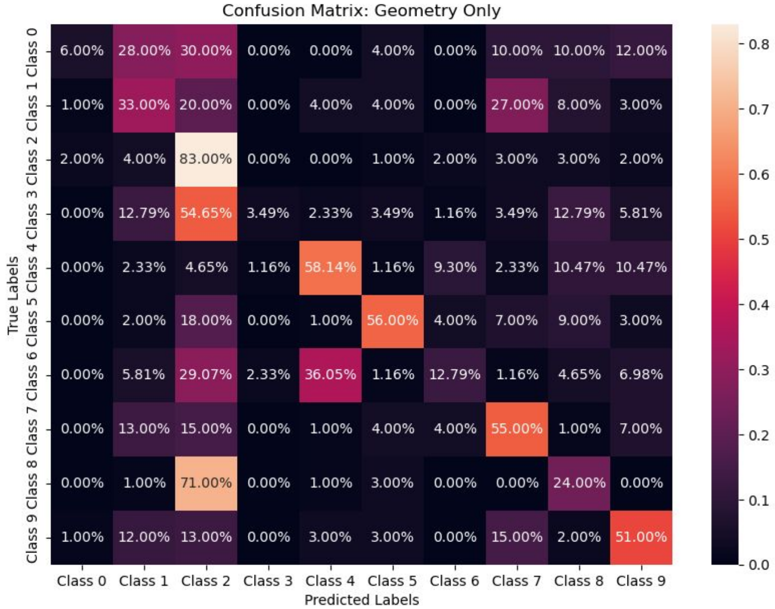
- PointNet Multiclass Classification

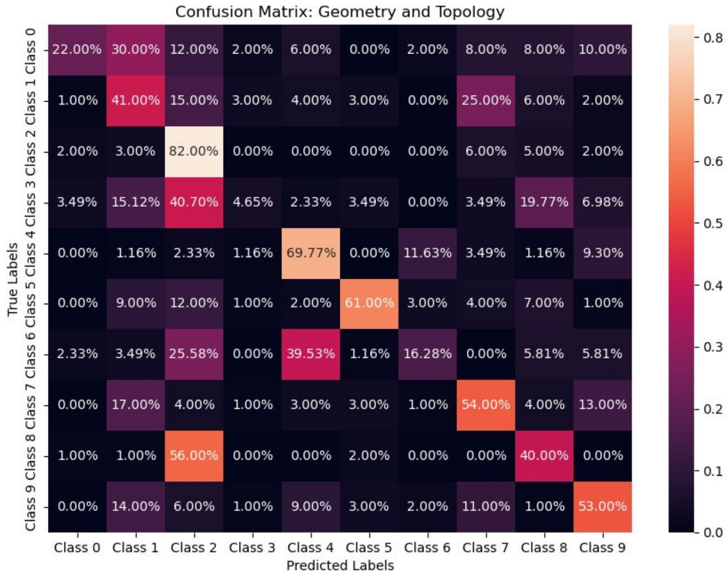


Appendix

- Geom Only Multiclass Classification

Geom + Topo Multiclass Classification





Appendix

Classifier	Multi-class	Binary			
		Chair	Sofa	Table	Toilet
MsGT	62.115%	92.401%	91.850%	93.392%	91.960%
PointNet	83.040%	97.907%	95.044%	93.062%	97.907%
FPFH	29.000%	85.793%	68.612%	84.471%	88.987%

Table 1: Classification Results for Different Classes and Feature Extraction Models

Classifier	**Accuracy**	**Recall**	**Prec.**	**F1**
Logistic Regression	0.6441	0.6441	0.6391	0.6300
Random Forest	0.5743	0.5743	0.5516	0.5407
Ridge	0.4894	0.4894	0.4669	0.4664
Naive Bayes	0.4715	0.4715	0.5206	0.4582
Support Vector Machine	0.4110	0.4110	0.4934	0.3432

Table 2: Performance comparison of classification models on MsGT features.