universität innsbruck

Point Clouds and Deep Learning

Martin Berger

Warm up

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Can you tell me a joke about 3D point clouds and AI?

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Why did the AI refuse to analyze the 3D point cloud?

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Can you tell me a joke about 3D point clouds and AI?

Why did the AI refuse to analyze the 3D point cloud?
Because it heard the data points were just "plane" boring!

Warm up

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That’s not really funny. Give me another one.

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Why did the AI become a master at processing 3D point clouds?

Warm up

That’s not really funny. Give me another one.

Why did the AI become a master at processing 3D point clouds?
Because it knew how to "point" out all the right features!

Overview

- Why point clouds?
- PointNet
- FoldingNet
- Cluster-Based Autoencoders for Volumetric Point Clouds

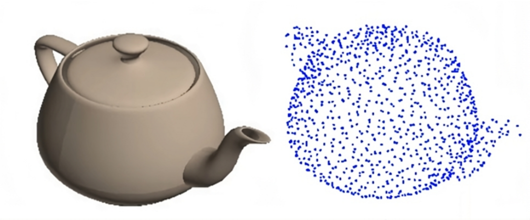
Point Clouds

What are 3D point clouds?

img source: https://shorturl.at/oHOZ8

Why though?

- Simplest representation: only points, no connections
- Collection of (x, y, z) coordinates



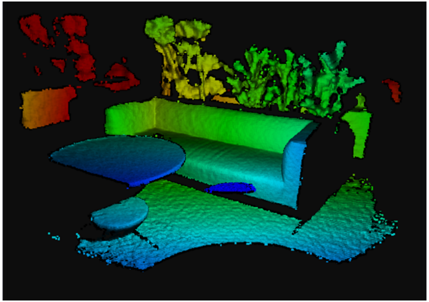
Why though?

- Laser (LIDAR, StreetView)

source: https://shorturl.at/hjnzK

Why though?

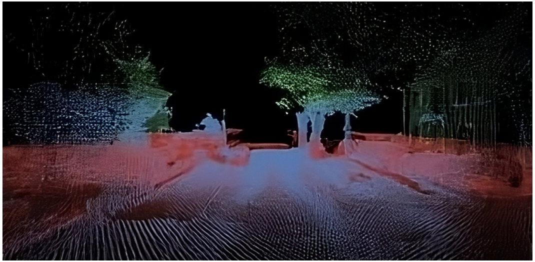
- Laser (LIDAR, StreetView)
- Infrared (Kinect)



source: https://shorturl.at/owEX9

Why though?

- Laser (LIDAR, StreetView)
- Infrared (Kinect)
- Stereo Cameras



source: https://shorturl.at/nvFP5

Challenges from a Data Science POV

- A point cloud is a set of sparse 3D points
- Irregular format is hard to handle

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First attempts:

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- A point cloud is a set of sparse 3D points
- Irregular format is hard to handle

First attempts:

- Transform data to regular 3D voxel grids (Volumetric CNNs)
- Turn point clouds into a collection of images (Multiview CNNs)

PointNet

https://arxiv.org/abs/1612.00593

Observation

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  $\rightarrow$ **invariance under permutations**

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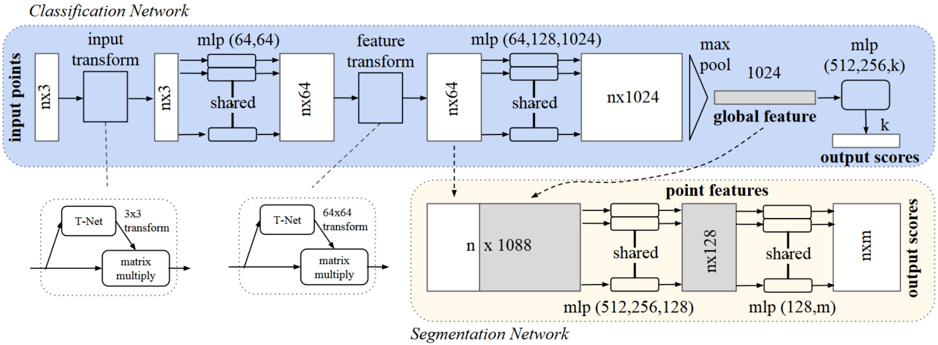
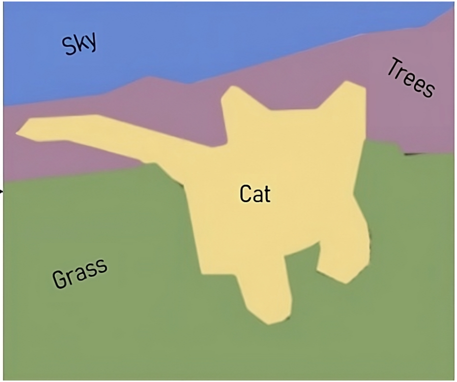
  $\rightarrow$ **invariance under transformations**

PointNet



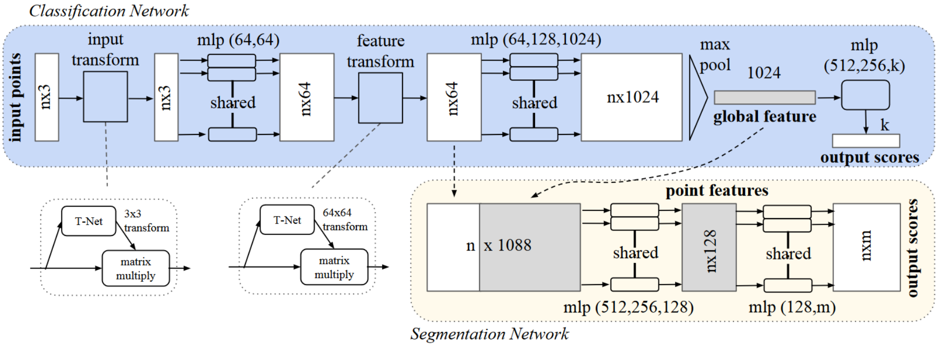
Classification Network
input points
nx3
input transform
nx3
mlp (64,64)
shared
nx64
feature transform
nx64
mlp (64,128,1024)
shared
nx1024
max pool
1024
global feature
mlp (512,256,k)
k
output scores
T-Net
3x3 transform
matrix multiply
T-Net
64x64 transform
matrix multiply
point features
n x 1088
shared
nx128
shared
nxm
output scores
mlp (512,256,128)
mlp (128,m)
Segmentation Network

Semantic Segmentation



source: https://shorturl.at/bvBQY

PointNet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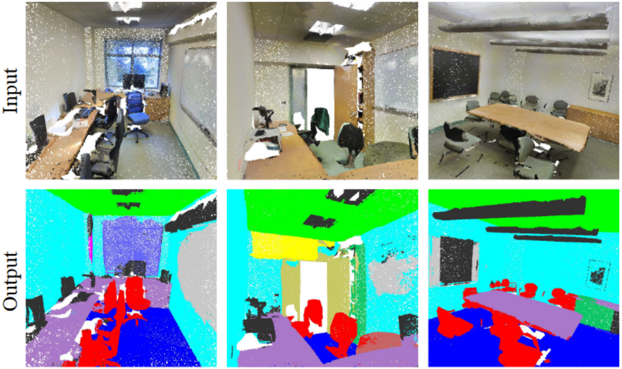
Segmentation Network

PointNet - Results Classification

	input	#views	accuracy avg. class	accuracy overall
SPH [11]	mesh	-	68.2	-
3DShapeNets [28]	volume	1	77.3	84.7
VoxNet [17]	volume	12	83.0	85.9
Subvolume [18]	volume	20	86.0	**89.2**
LFD [28]	image	10	75.5	-
MVCNN [23]	image	80	**90.1**	-
Ours baseline	point	-	72.6	77.4
Ours PointNet	point	1	86.2	**89.2**

PointNet - Results Segmentation

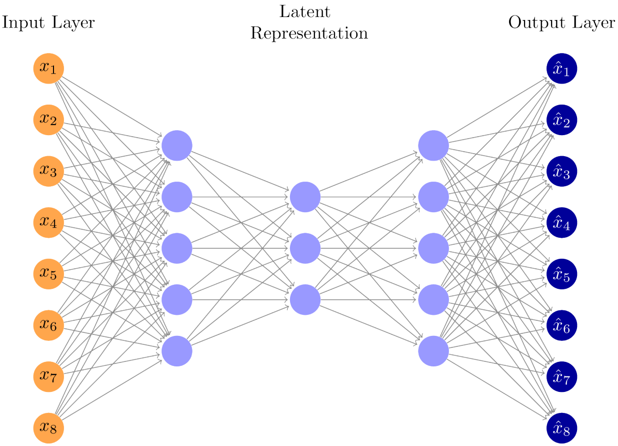
PointNet - Results Semantic Segmentation



FoldingNet

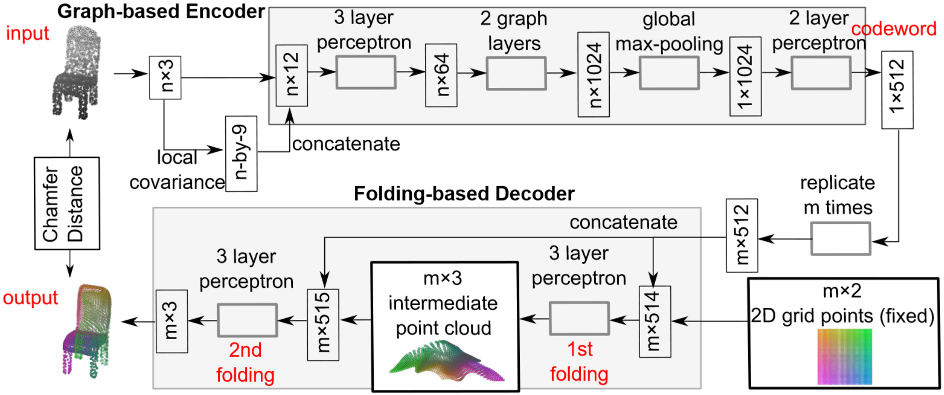
https://arxiv.org/abs/1712.07262

FoldingNet - Autoencoder for Point Clouds



source: https://shorturl.at/bhDP8

FoldingNet - Autoencoder for Point Clouds



FoldingNet - Local Covariance

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FoldingNet - Local Covariance

- Let P be a point in the given point cloud.
- Let $Q_1, \ldots, Q_K$ denote the K nearest neighbors of P.
- Compute the centroid C of the K points and set $\tilde{Q}_i = Q_i - C$
- Then

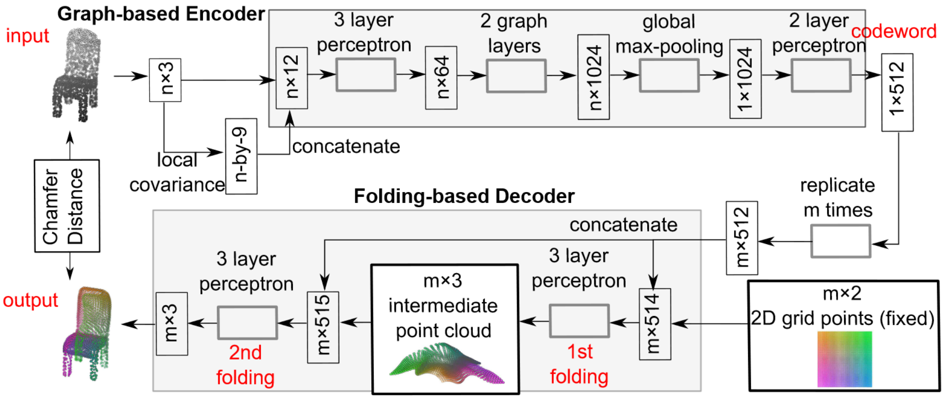
$$A = \begin{bmatrix} \tilde{Q}_1 \\ \vdots \\ \tilde{Q}_K \end{bmatrix} \in \mathbb{R}^{K \times 3}$$

and the covariance matrix is given by

$$A^T A = \begin{bmatrix} \sigma_{xx} & \sigma_{xy} & \sigma_{xz} \\ \sigma_{xy} & \sigma_{yy} & \sigma_{yz} \\ \sigma_{xz} & \sigma_{yz} & \sigma_{zz} \end{bmatrix} \in \mathbb{R}^{3 \times 3}$$

.

FoldingNet - Autoencoder for Point Clouds

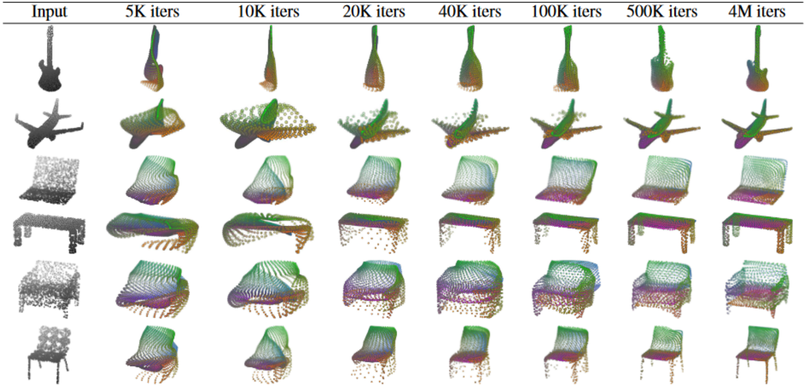


FoldingNet - Loss

Given two point clouds $\mathcal{X}, \mathcal{Y}$ their Chamfer distance is

$$d_{CH}(\mathcal{X}, \mathcal{Y}) = \max \left\{ \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} \min_{y \in \mathcal{Y}} \|x - y\|_2, \frac{1}{|\mathcal{Y}|} \sum_{y \in \mathcal{Y}} \min_{x \in \mathcal{X}} \|x - y\|_2 \right\}.$$

FoldingNet - Results



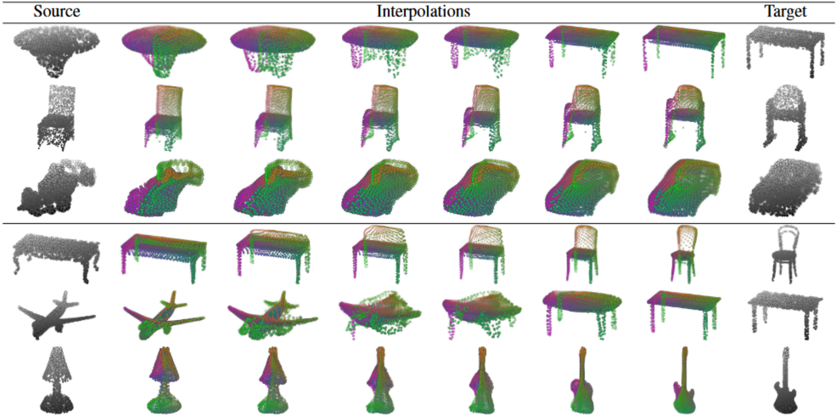
Blending between Datapoints

Given two point clouds P_1, P_2, encode them by codewords C_1, C_2 within the feature space then decode

$$\lambda C_1 + (1 - \lambda) C_2$$

for some $\lambda \in [0, 1]$ with the decoder.

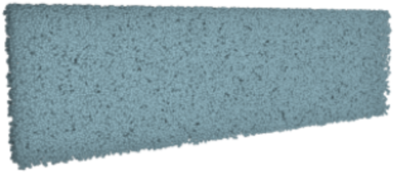
FoldingNet - Results

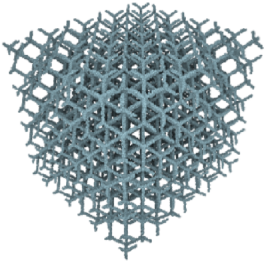


Cluster-Based Autoencoders for Volumetric Point Clouds

https://arxiv.org/abs/2211.01009

Density based Style Transfer

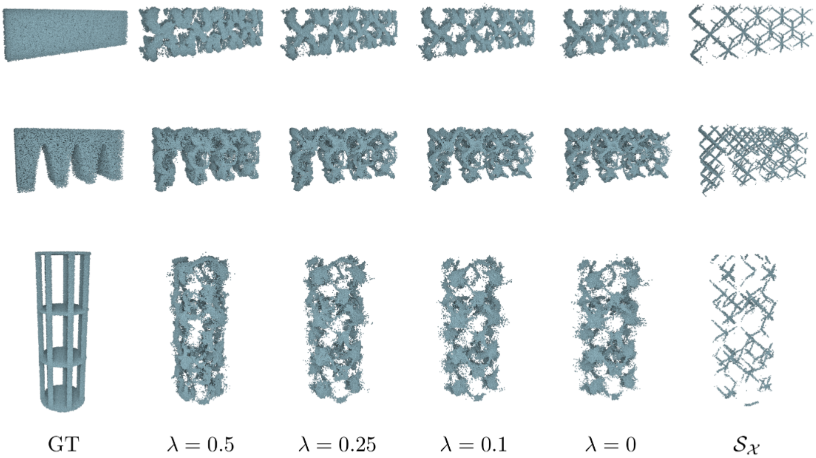




Density based Style Transfer

- Given a point cloud $\mathcal{X}$ and a style point cloud $\mathcal{S}$.
- Assume $\mathcal{X}$ was sampled according to the density $f_{\mathcal{X}}$.
- Sample a point cloud $\mathcal{S}_{\mathcal{X}}$ from $\mathcal{S}$ according to $f_{\mathcal{X}}$.
- Use the autoencoder to blend between $\mathcal{X}$ and $\mathcal{S}_{\mathcal{X}}$.

Density based Style Transfer



Cluster Based AC

- FoldingNet only works for small point clouds
- In practice resolution is much higher

Cluster Based AC

Idea:

Cluster Based AC

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- Split point clouds into smaller pieces

Cluster Based AC

Idea:

- Split point clouds into smaller pieces
- Feed the smaller point clouds into the autoencoder

Cluster Based AC

Idea:

- Split point clouds into smaller pieces
- Feed the smaller point clouds into the autoencoder
- Reassemble

Cluster Based AC

- Given two point clouds $\mathcal{X}$ and $\mathcal{Y}$

Cluster Based AC

- Given two point clouds $\mathcal{X}$ and $\mathcal{Y}$
- Cluster $\mathcal{X}$ into k clusters $\mathcal{X}_1, \ldots, \mathcal{X}_k$

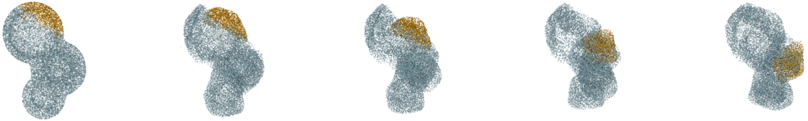
Cluster Based AC

- Given two point clouds $\mathcal{X}$ and $\mathcal{Y}$
- Cluster $\mathcal{X}$ into k clusters $\mathcal{X}_1, \ldots, \mathcal{X}_k$
- Cluster $\mathcal{Y}$ into k clusters $\mathcal{Y}_1, \ldots, \mathcal{Y}_k$

Cluster Based AC

- Given two point clouds $\mathcal{X}$ and $\mathcal{Y}$
- Cluster $\mathcal{X}$ into k clusters $\mathcal{X}_1, \ldots, \mathcal{X}_k$
- Cluster $\mathcal{Y}$ into k clusters $\mathcal{Y}_1, \ldots, \mathcal{Y}_k$
- Blend between $\mathcal{X}_i$ and $\mathcal{Y}_i$ for $i = 1, \ldots, k$

Cluster Based AC

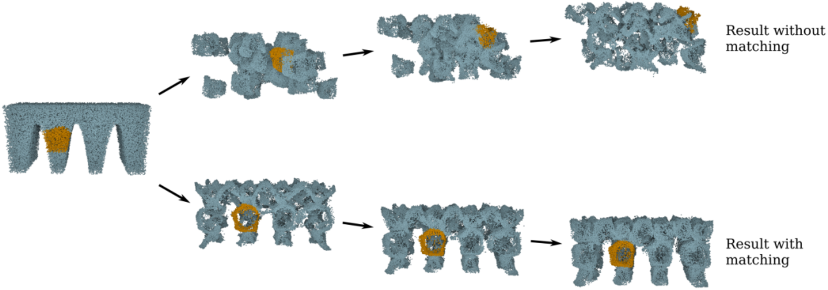


GT $\lambda = 0.1$ $\lambda = 0.25$ $\lambda = 0.5$ $\lambda = 0.75$

Cluster Based AC

- Given two point clouds $\mathcal{X}$ and $\mathcal{Y}$.
- Cluster $\mathcal{X}$ into k pieces and let $C_1, \ldots, C_k$ denote the centroids of these clusters.
- Cluster $\mathcal{Y}$ into k clusters with centers $C_1, \ldots, C_k$.
- Blend between $\mathcal{X}_i$ and $\mathcal{Y}_i$ for $i = 1, \ldots, k$

Cluster Based AC

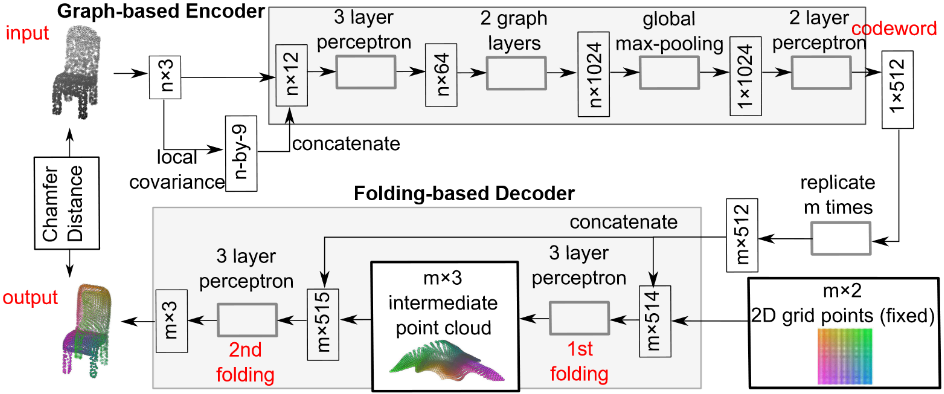


Thank you!

References I

- Stephan Antholzer, Martin Berger, and Tobias Hell.
  Cluster-based autoencoders for volumetric point clouds, 2022.
- Charles Ruizhongtai Qi, Hao Su, Kaichun Mo, and Leonidas J. Guibas.
  Pointnet: Deep learning on point sets for 3d classification and segmentation.
  CoRR, abs/1612.00593, 2016.
- Yaoqing Yang, Chen Feng, Yiru Shen, and Dong Tian.
  Foldingnet: Point cloud auto-encoder via deep grid deformation, 2018.

Appendix - Graph Layer



Appendix - Graph Layer

- Let X denote the input of the Graph layer.
- Create a matrix A via

$$A_{ij} = \mathrm{ReLU}(\max_{k \in \mathcal{N}(i)} x_{kj})$$

  where $\mathcal{N}(i)$ denotes the K nearest neighbors of ith row of X.
- Then the output is given via

$$A \cdot M$$

  where M is the feature mapping matrix.