L7: Single-Image to 3D

Hao Su

Slides prepared by Dr. Songfang Han

Agenda

- Task
- Synthesis-for-Learning Pipeline
- Single-image to Depth Map
- Single-image to Point Cloud
- Single-image to Mesh

Task

Review: Multi-View Stereo

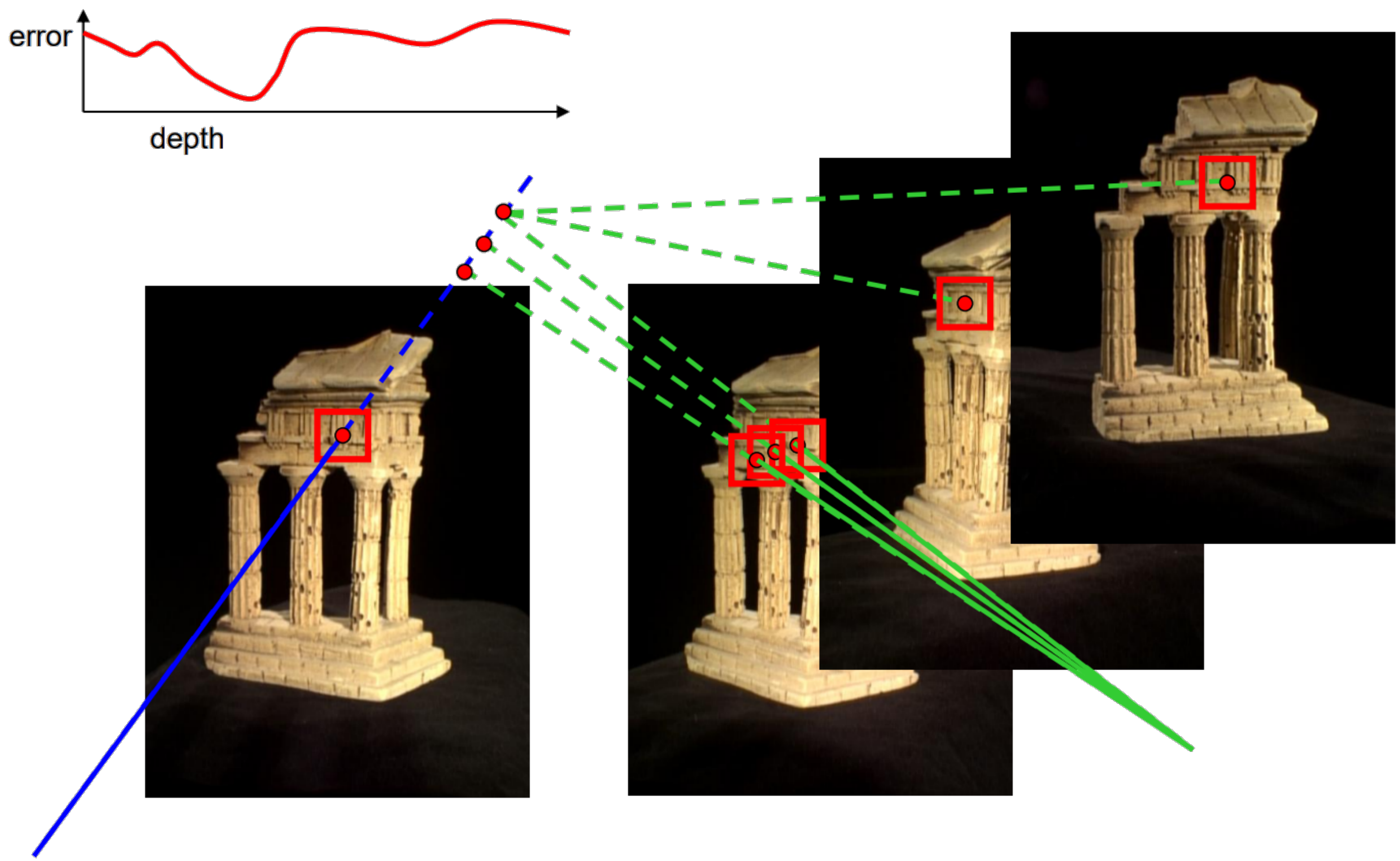


Image source: UW CSE455

Can We Infer 3D from just a **Single** Image?

Many Cues That Allow 3D Estimation

contrast

color

texture

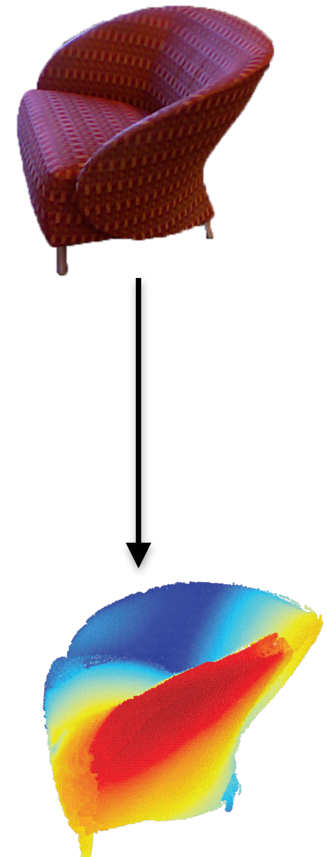
motion

symmetry

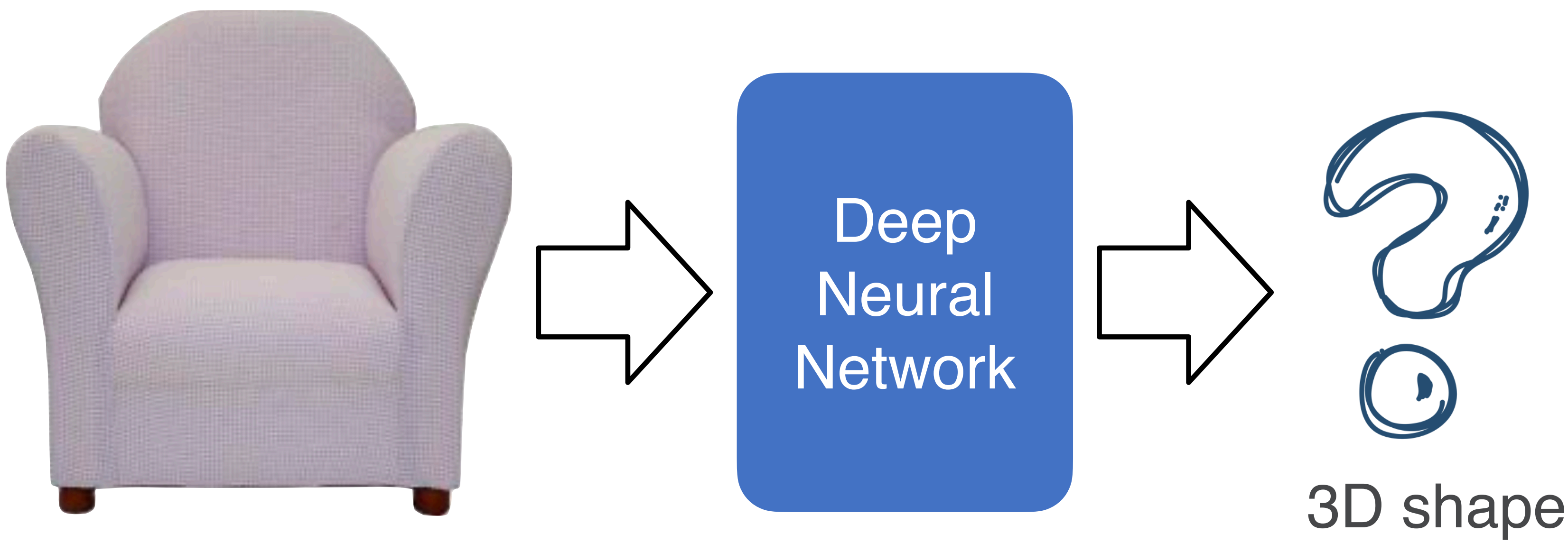
part

category-specific 3D knowledge

......



Learning-based 3D Reconstruction



Synthesis-for-Learning Pipeline

Where Are My Training Data?

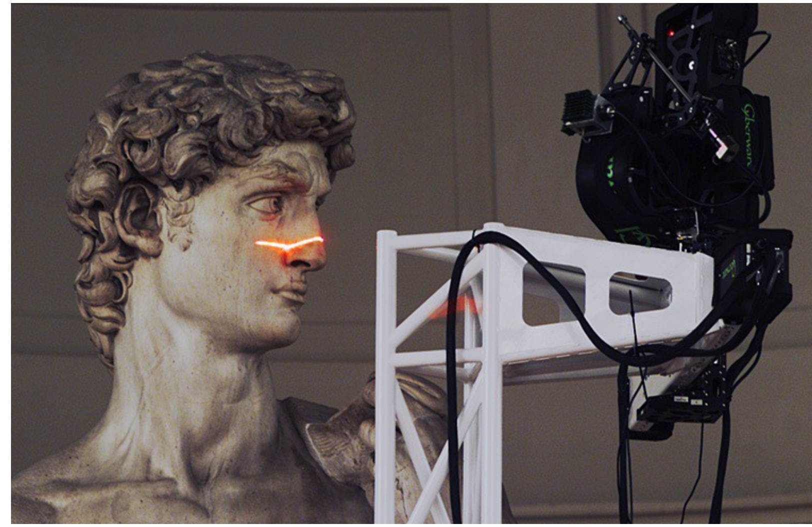
- In general, training deep networks needs **a lot of data with labels!**

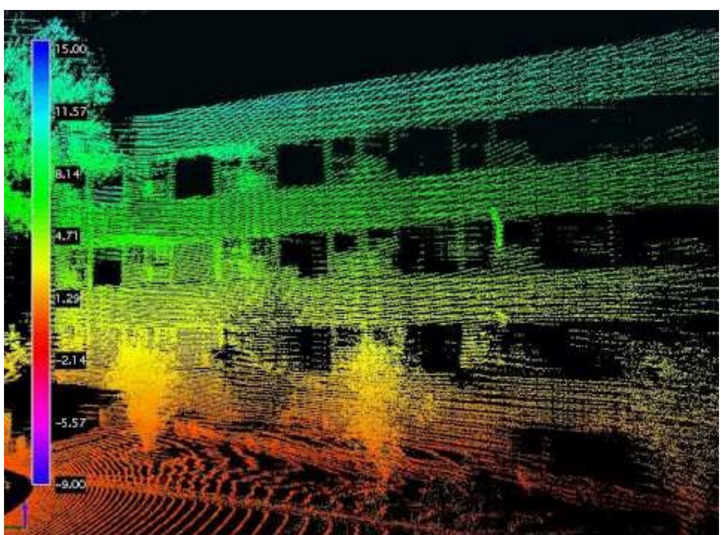
- In our case, we need many image-3D shape pairs…

- Before talking about learning algorithms, obtaining training data is already a challenge!

Source I: Real Data

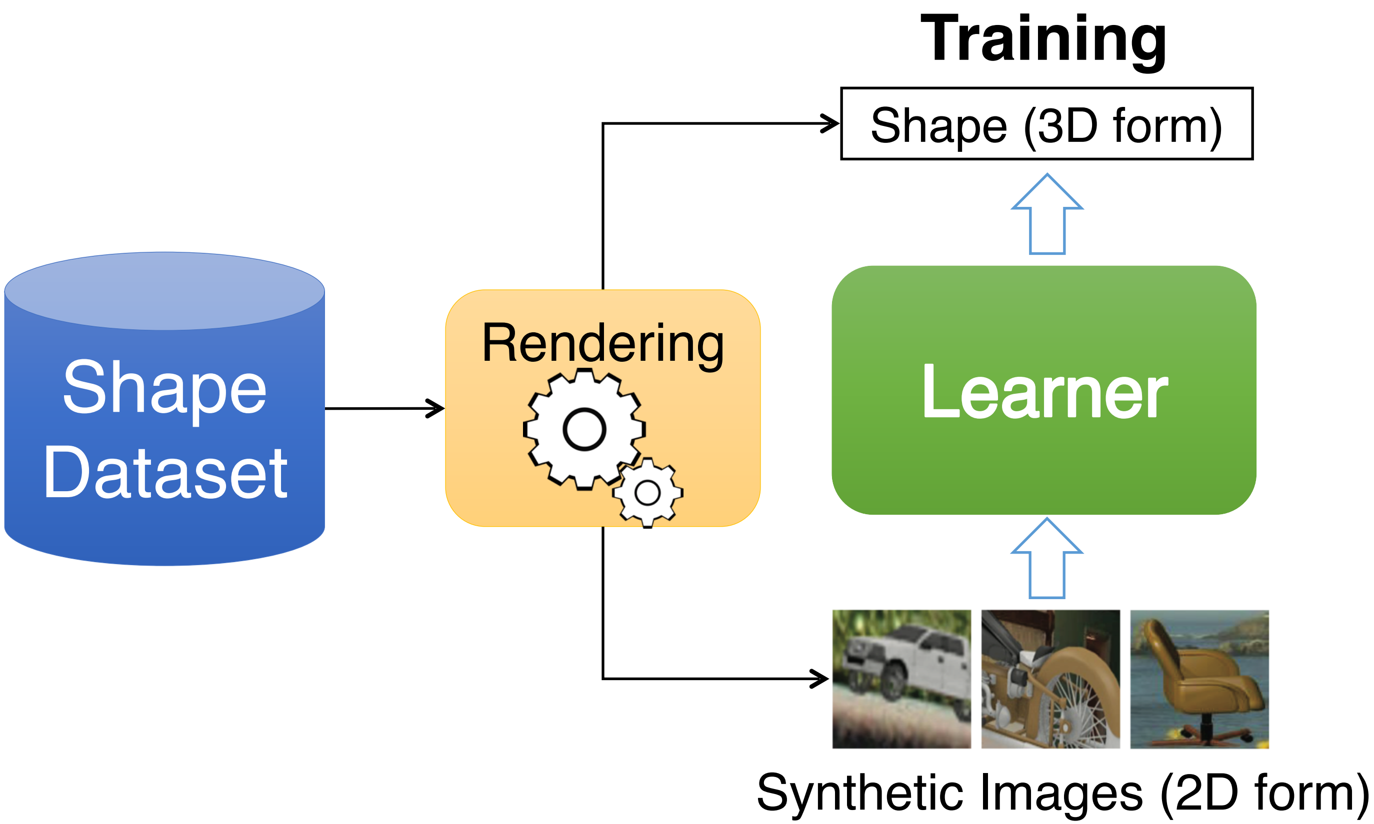
- Many techniques
  - Indoor: ToF or stereo sensors (Kinect, RealSense, …)
  - Outdoor: LiDAR





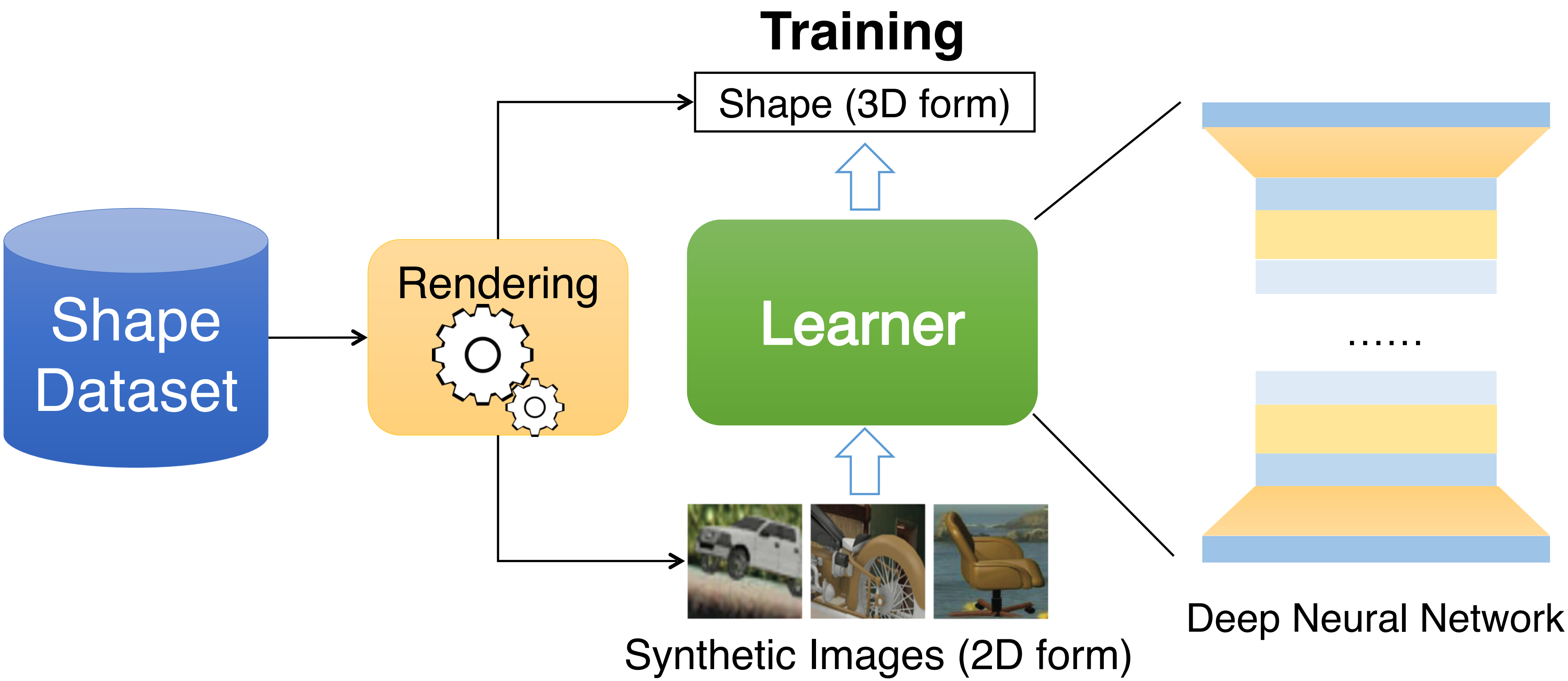
- The amount of real data is increasing quickly

Source II: Synthesis for Learning



[Su et al., RenderForCNN, ICCV15]

Source II: Synthesis for Learning



[Su et al., RenderForCNN, ICCV15]

Source II: Synthesis for Learning

- For example, image → point cloud

2D image (rendering)

3D model

3D point cloud (sampling)

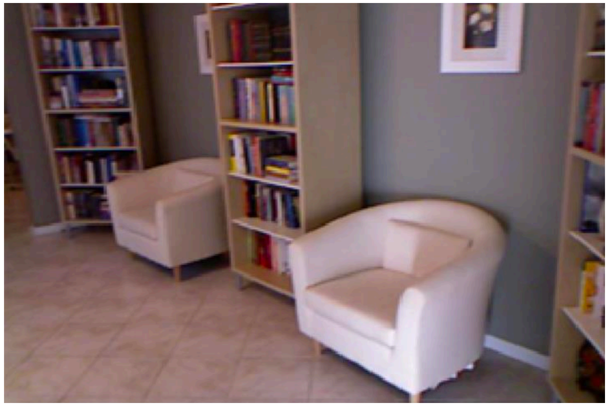
Large-Scale Synthetic 3D Dataset

- For example,
  - ShapeNet: http://www.shapenet.org

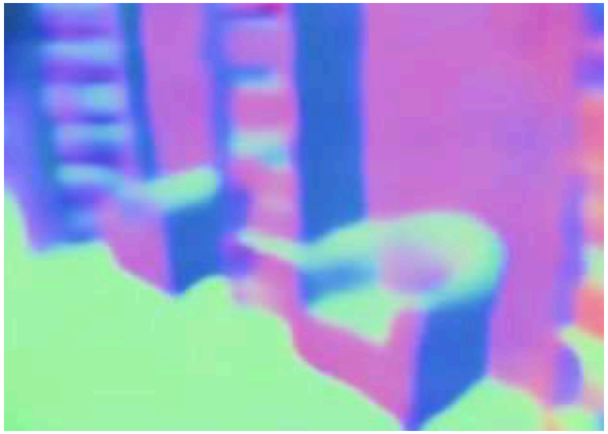
A Very Coarse Literature Review

Literature: to Depth Map

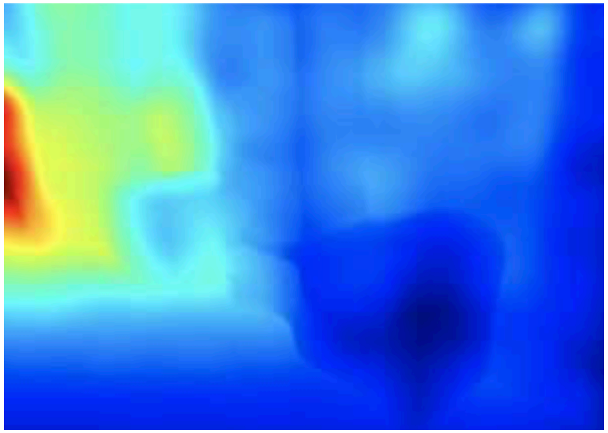
- Fully-convolutional



Input image



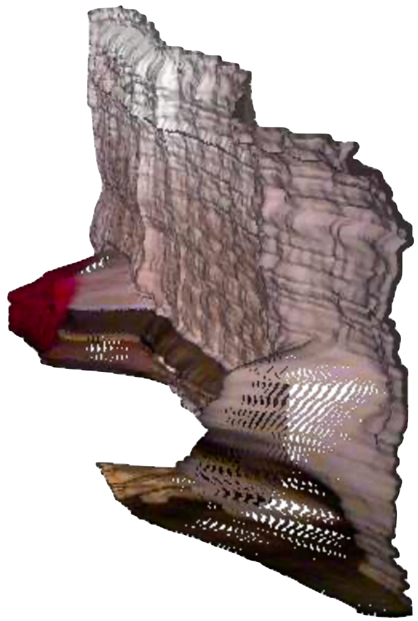
(a) Normal map



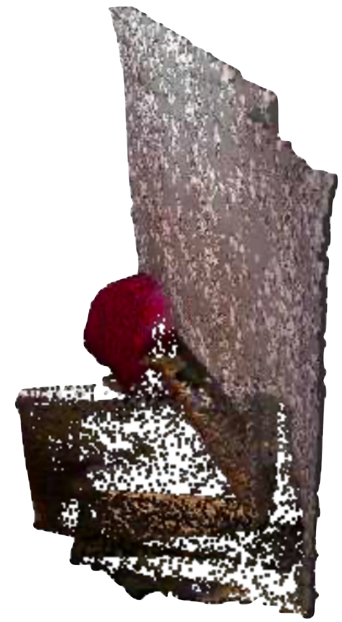
(b) Depth map

Qi et al., "**GeoNet: Geometric Neural Network for Joint Depth and Surface Normal Estimation**", *CVPR 2018*

Recall: Issue of L_p Depth Loss



Prediction



Groundtruth

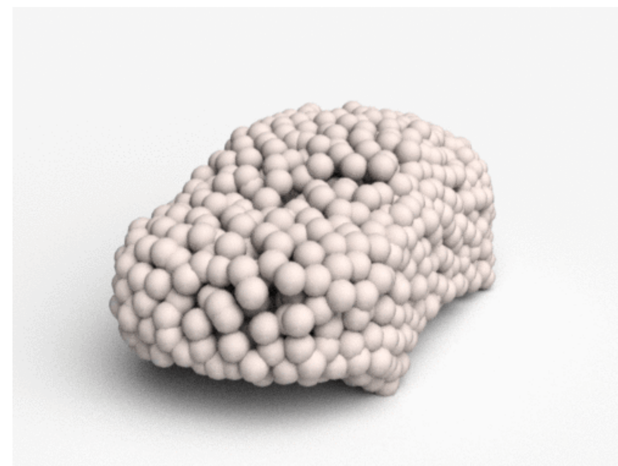
- Common strategy: Depth-Normal consistency
- Review last lecture
- Limitation: partial 3D info from camera view

Qi et al., "**GeoNet: Geometric Neural Network for Joint Depth and Surface Normal Estimation**", *CVPR 2018*

Literature: to Point Cloud

- From a single image to 3D point cloud generation.

Input image



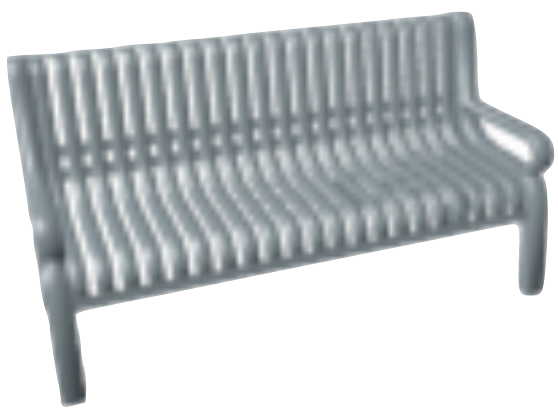
Reconstructed 3D point cloud

Fan et al., “**A Point Set Generation Network for 3D Object Reconstruction from a Single Image**”, *CVPR 2017*

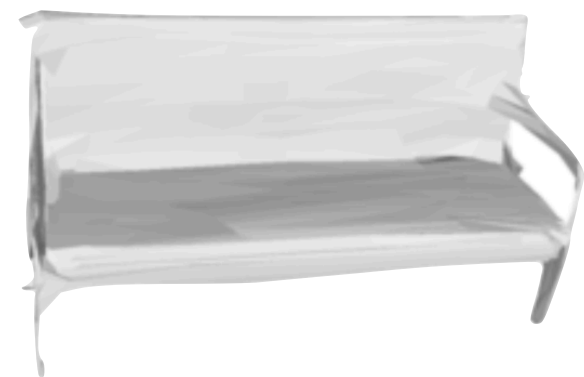
Explain with Details Later

Literature: to Mesh

- From a single image to mesh surface.



Input image



Reconstructed 3D mesh

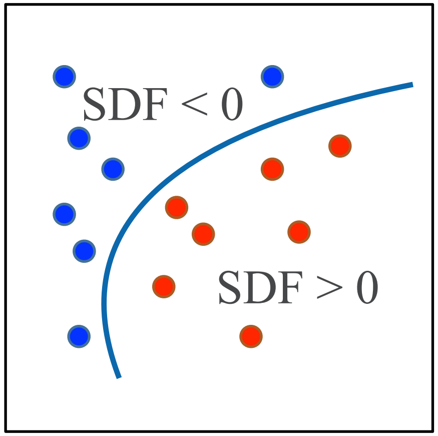
Groueix et al, **AtlasNet:A papier-mâché approach to learning 3d surface generation**, CVPR 2018

Explain with Details Later

Literature: to Implicit Field Function

- From a single image to implicit field function.

Input image



Implicit field function

$F(x) = 0$

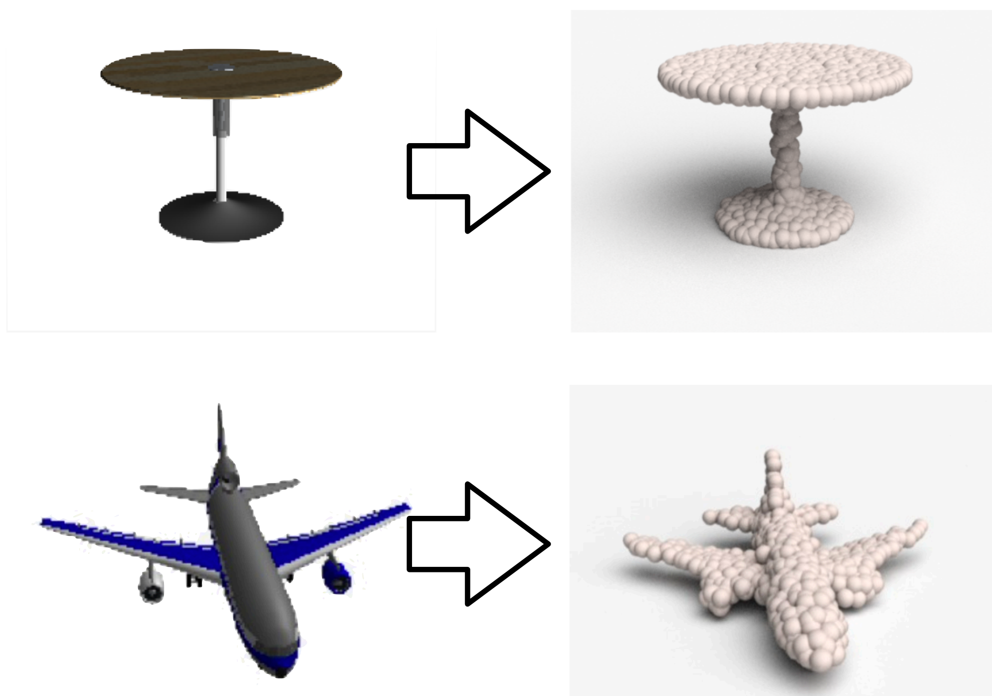
Mescheder et al., “**Occupancy networks: Learning 3d reconstruction in function space**”, *CVPR 2019*

Check by Yourself

Image to Point Cloud

Why Point Representation?

- Previous depth map covers only visible area.
- A flexible representation
  - A few thousands of points can model a great variety of shapes.



Point Cloud as a Set

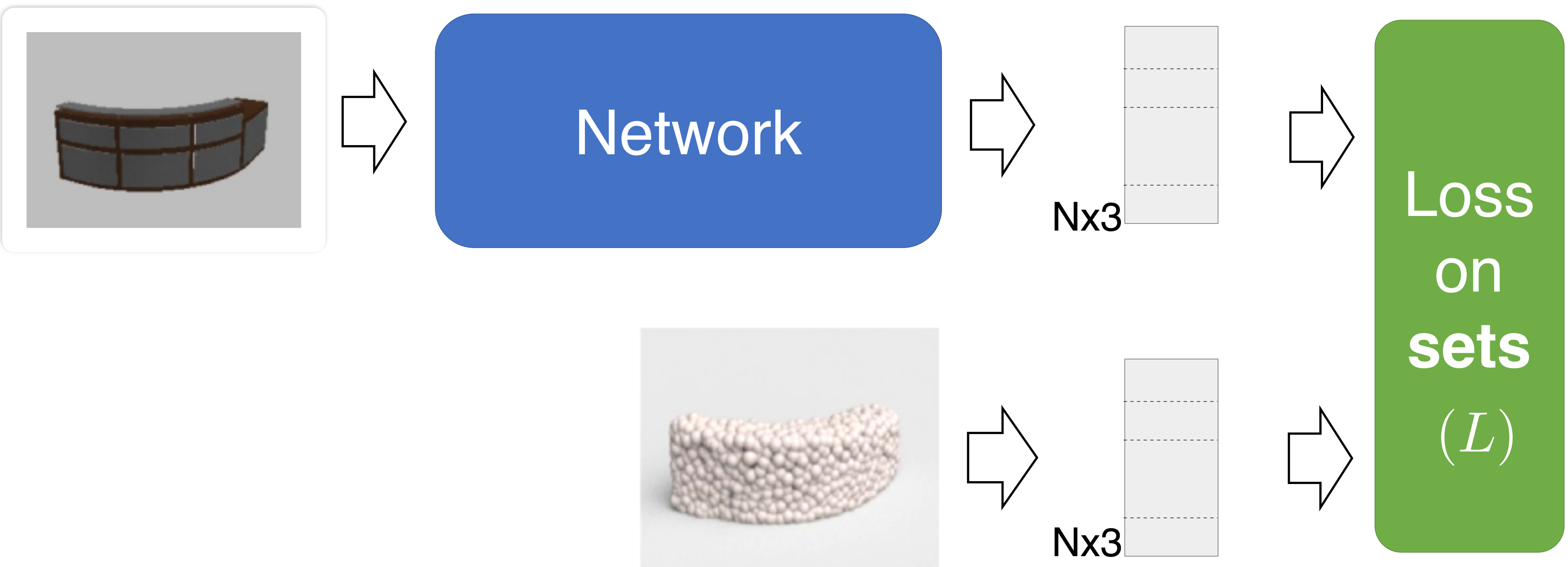
3D mesh

sampling

as

$$\left\{ \begin{array}{c} (x_1, y_1, z_1) \\ (x_2, y_2, z_2) \\ \ldots \\ (x_n, y_n, z_n) \end{array} \right\}$$

Pipeline



Fan et al., "**A Point Set Generation Network for 3D Object Reconstruction from a Single Image**", *CVPR 2017*

Real-world Results

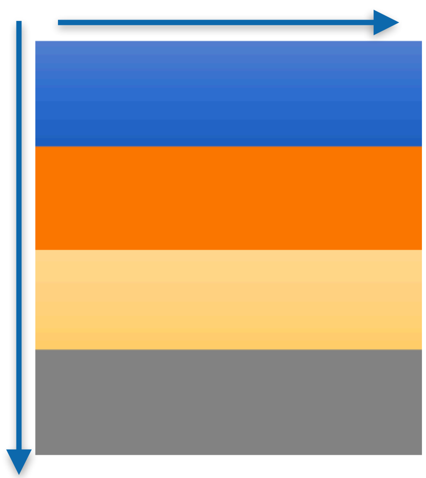
Some results

input | observed view | 90° | input | observed view | 90°

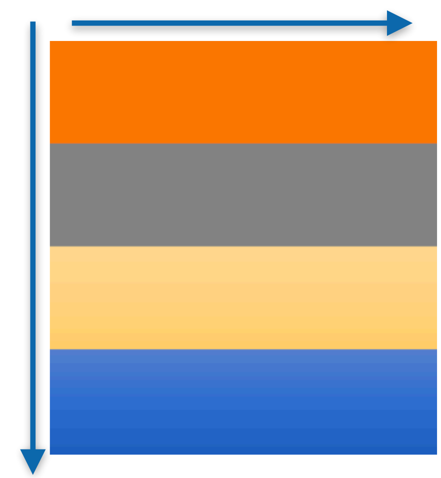
Differentiable Loss for Point Clouds

Permutation Invariance

- Point cloud: N orderless points, each represented by a D dim vector



represents the same **set** as



Permutation Invariance

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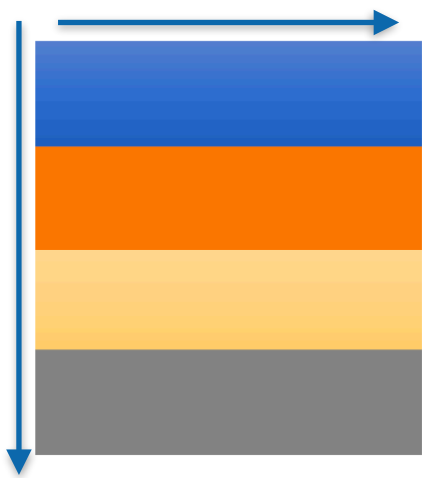

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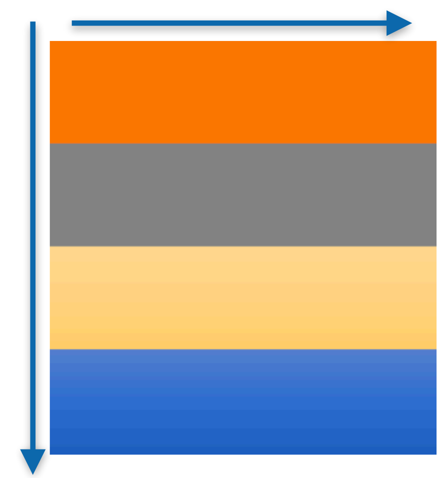


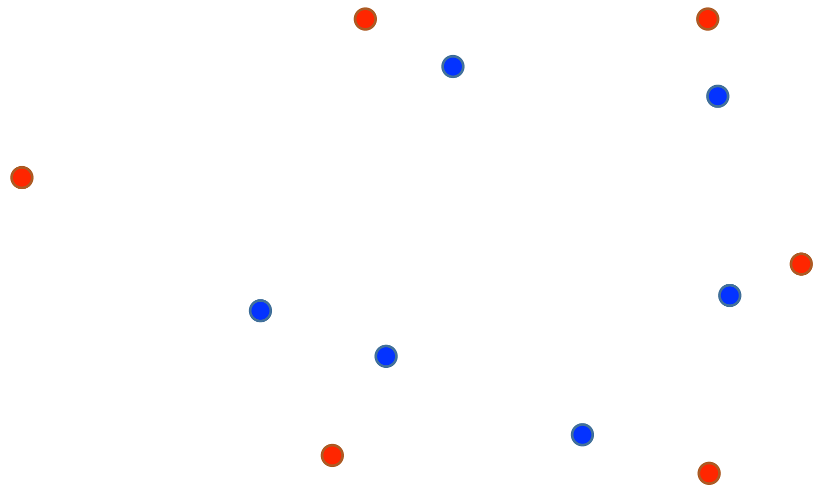
Loss needs to be invariant to ordering of points!

Metric for Point Clouds

- L2 loss does not work for point cloud.
- Need a metric to measure distance between two point sets
- Two popular choices
  - Earth Mover's Distance
  - Chamfer Distance

Earth Mover's Distance

- Find a 1-1 correspondence between point sets



Earth Mover's Distance

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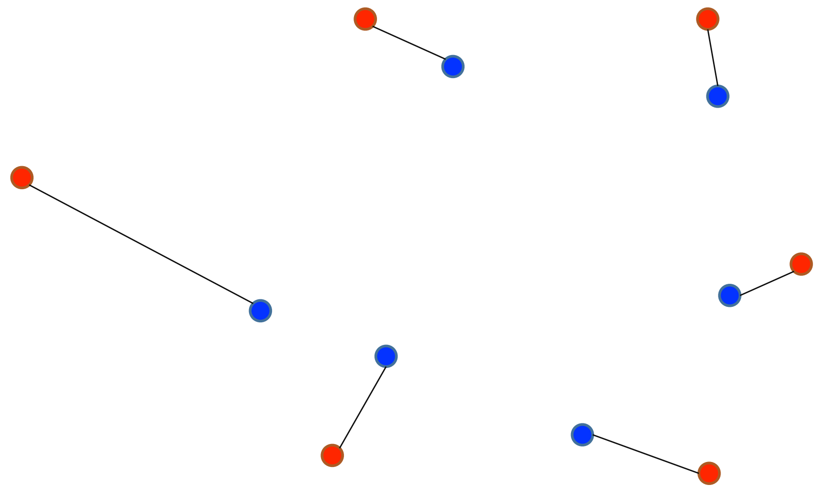

$$d_{EMD}(S_1, S_2) = \min_{\phi: S_1 \to S_2} \sum_{x \in S_1} \|x - \phi(x)\|_2$$

where $\phi : S_1 \to S_2$ is a bijection

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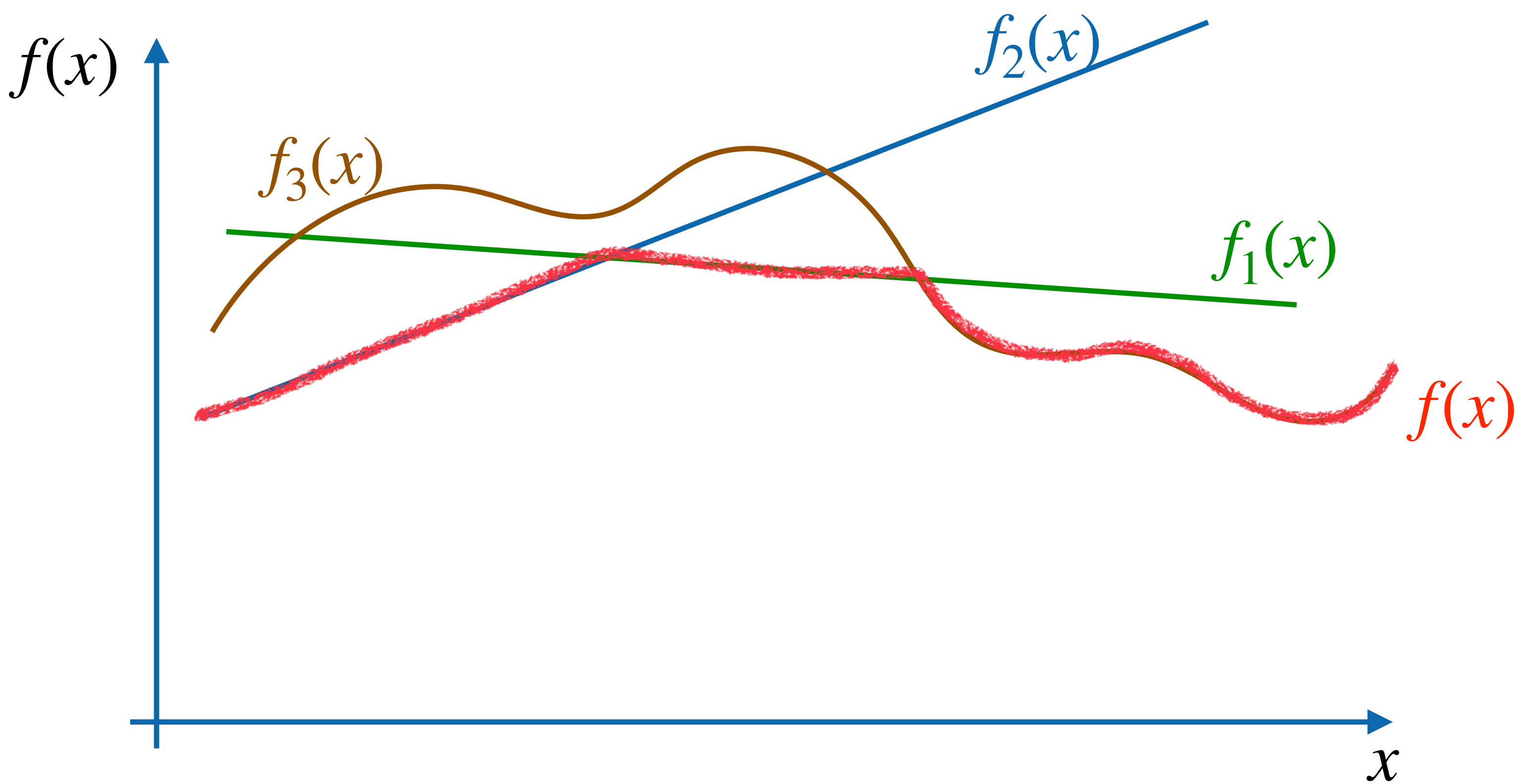
where $\phi : S_1 \to S_2$ is a bijection

Question:

Viewing $d_{EMD}(S_1, S_2)$ as a function of point coordinates in S_1, is this function **continuous**?

Lemma

- For a family of continuous functions $\{f_i(x)\}$, the point-wise minimum $f(x) = \min_i \{f_i(x)\}$ is continuous.



Continuity of $d_{EMD}(S_1, S_2)$

$$d_{EMD}(S_1, S_2) = \min_{\phi : S_1 \to S_2} \sum_{x \in S_1} \|x - \phi(x)\|_2$$

where $\phi : S_1 \to S_2$ is a bijection

- $\phi(x)$ defines a point-wise correspondence ($n!$ possibilities, $n =$ size of S_1).
- For a fixed ϕ, define $f_\phi(S_1) = \sum_{x \in S_1} \|x - \phi(x)\|_2$, and $f_\phi(S_1)$ is obviously continuous
- $d_{EMD}(S_1, S_2) = \min_{\phi : S_1 \to S_2} f_\phi(S_1)$ is thus continuous!

Differentiable?

$$d_{EMD}(S_1, S_2) = \min_{\phi:S_1 \to S_2} \sum_{x \in S_1} \|x - \phi(x)\|_2$$

where $\phi : S_1 \to S_2$ is a bijection

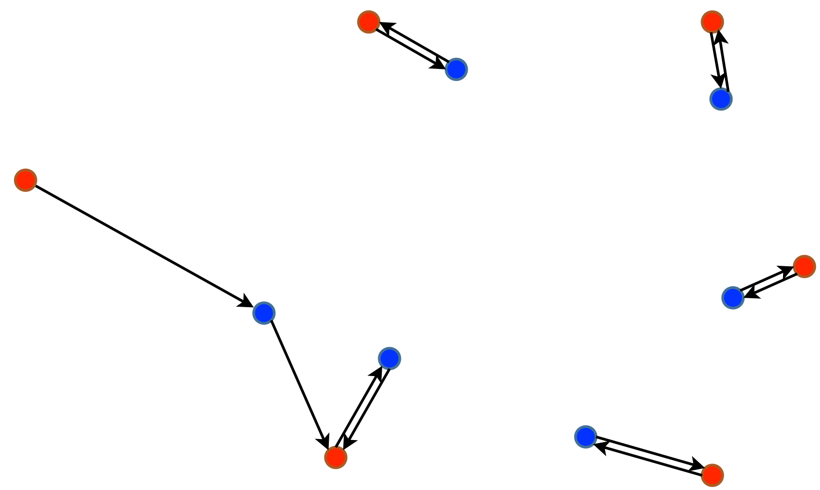
- From the example, we see that $d_{EMD}(S_1, S_2)$ can be constructed in a piece-wise manner
- Inside each piece, it is $f_{\phi_i}(S_1)$ by some ϕ_i, which is obviously differentiable (as $\phi_i(x)$ is a constant)
- $d_{EMD}(S_1, S_2)$ is differentiable except for zero-measure set!

Implementation

- Many algorithmic study on fast EMD computation (a specific bipartite matching problem)
- There exists parallelizable implementation of EMD on CUDA
- A fast implementation (approximated EMD): https://github.com/Colin97/MSN-Point-Cloud-Completion (by courtesy Minghua Liu)

Chamfer Distance

- Nearest neighbor correspondence for each point



Chamfer Distance

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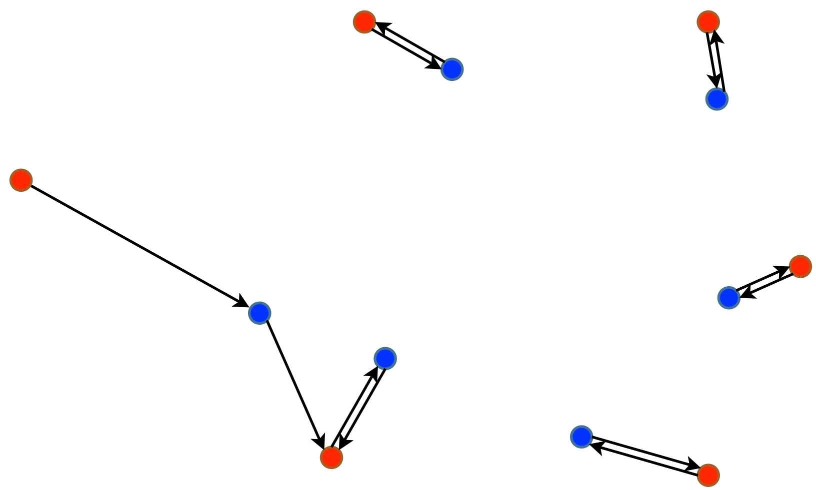


$$d_{CD}(S_1, S_2) = \sum_{x \in S_1} \min_{y \in S_2} \|x - y\|_2^2 + \sum_{y \in S_2} \min_{x \in s_1} \|x - y\|_2^2$$

Differentiability?

- Similar argument as EMD computation.

How Distance Metric Affect Learning?

- A fundamental issue: inherent ambiguity in 2D-3D dimension lifting.

How Distance Metric Affect Learning?

- A fundamental issue: inherent ambiguity in 2D-3D dimension lifting.

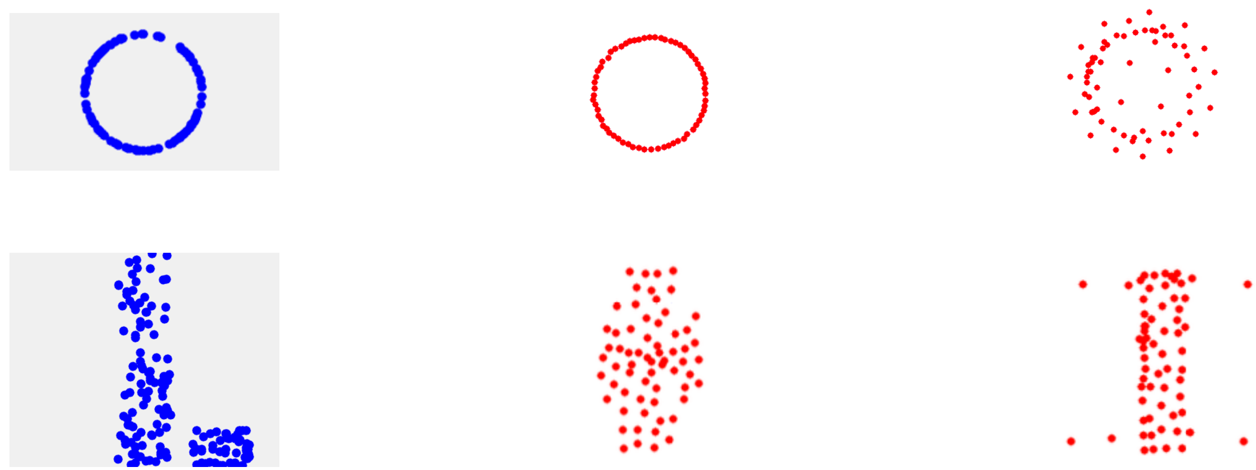
- By loss minimization, the network tends to predict a "**mean shape**" that averages out uncertainty

Distance Metrics Affect Mean Shapes

- The mean shape carries characteristics of the distance metric.

Continuous hidden variable (radius)

Discrete hidden variable (add-on location)

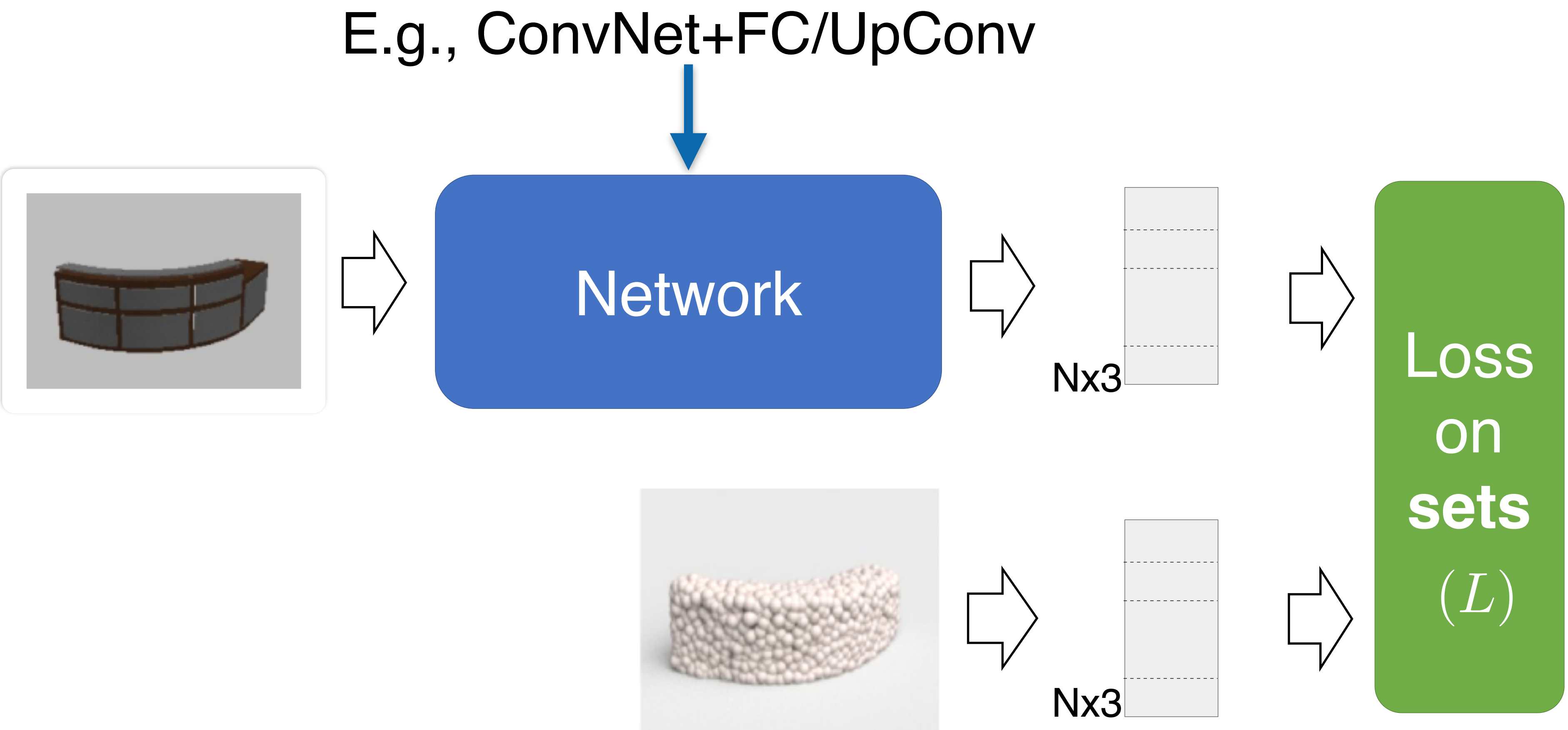


Input

EMD mean

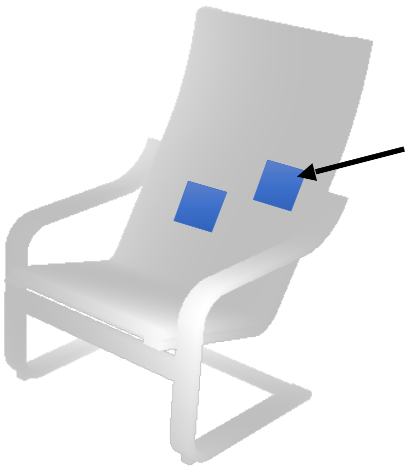
CD mean

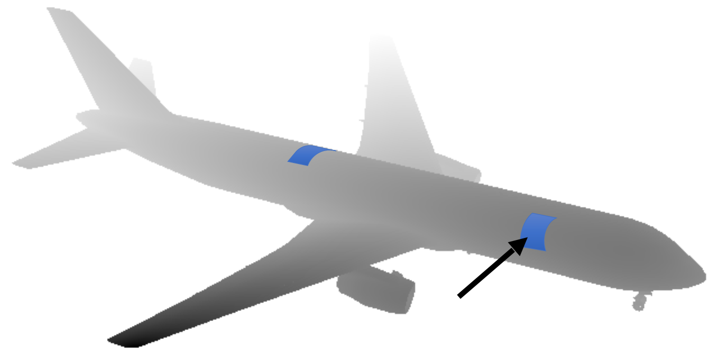
Network Choice: Certain Tricks



Fan et al., "**A Point Set Generation Network for 3D Object Reconstruction from a Single Image**", *CVPR 2017*

Network Design: Respect Natural Statistics of Geometry





- Many local structures are common

Read by Yourself

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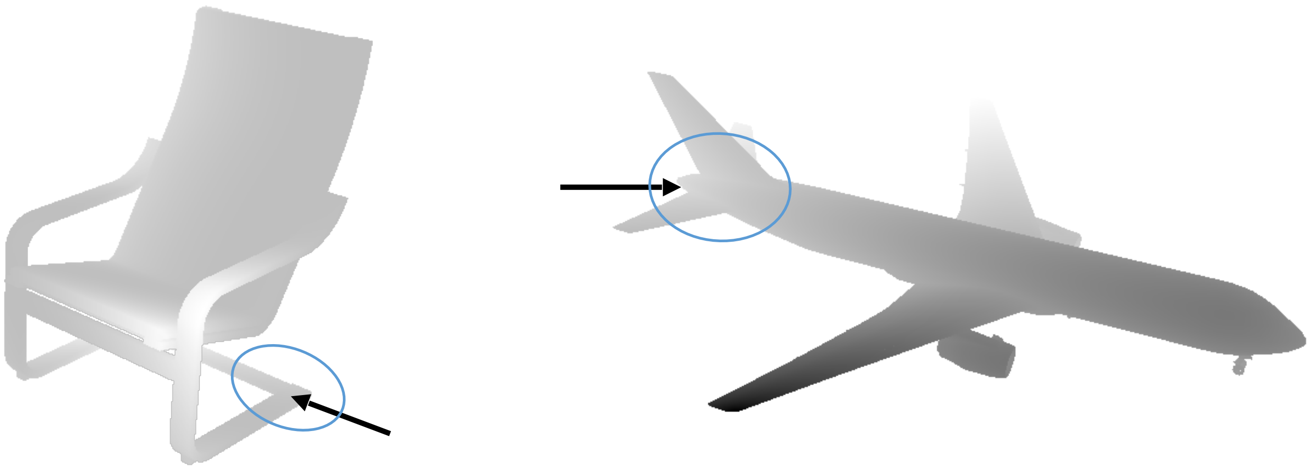
Network Design: Respect Natural Statistics of Geometry



- Many local structures are common
- Also some intricate structures

Read by Yourself

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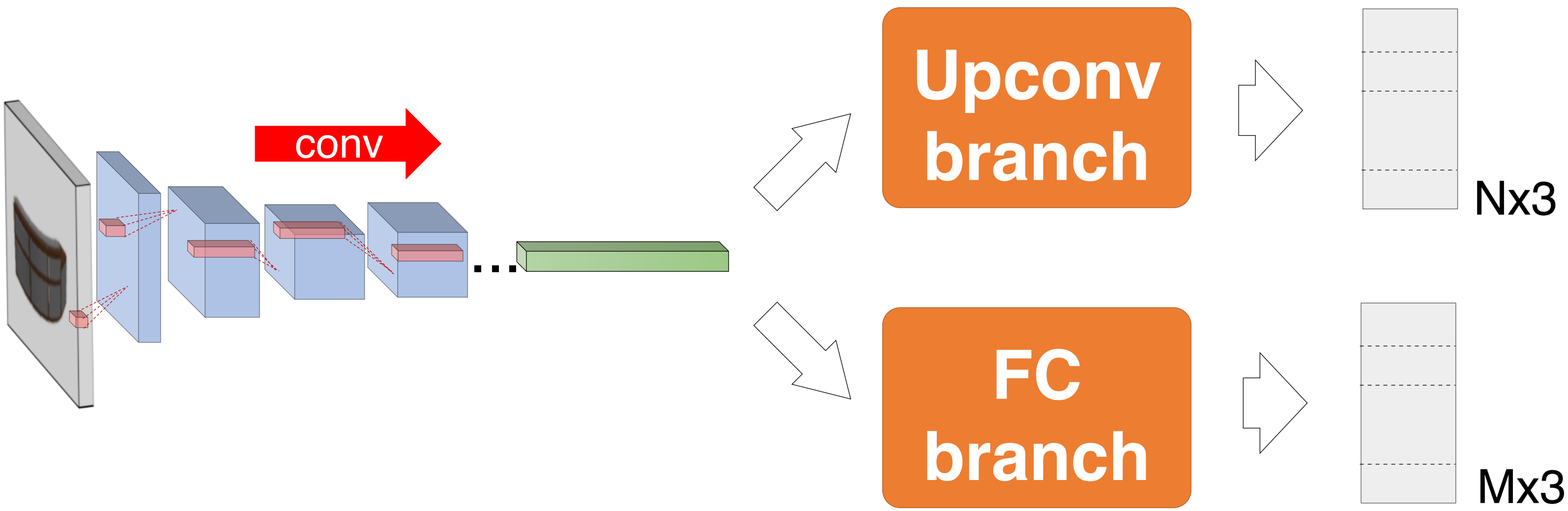
Two-Branch Architecture



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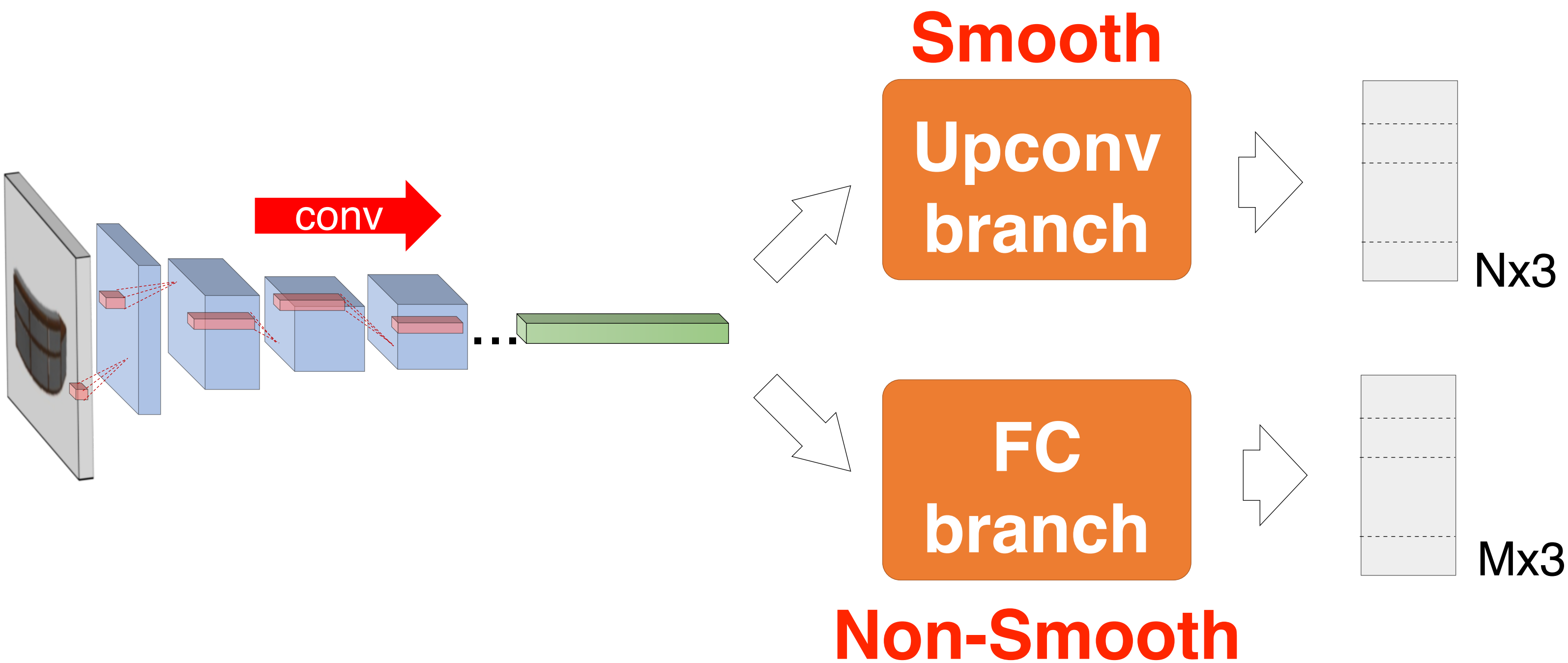

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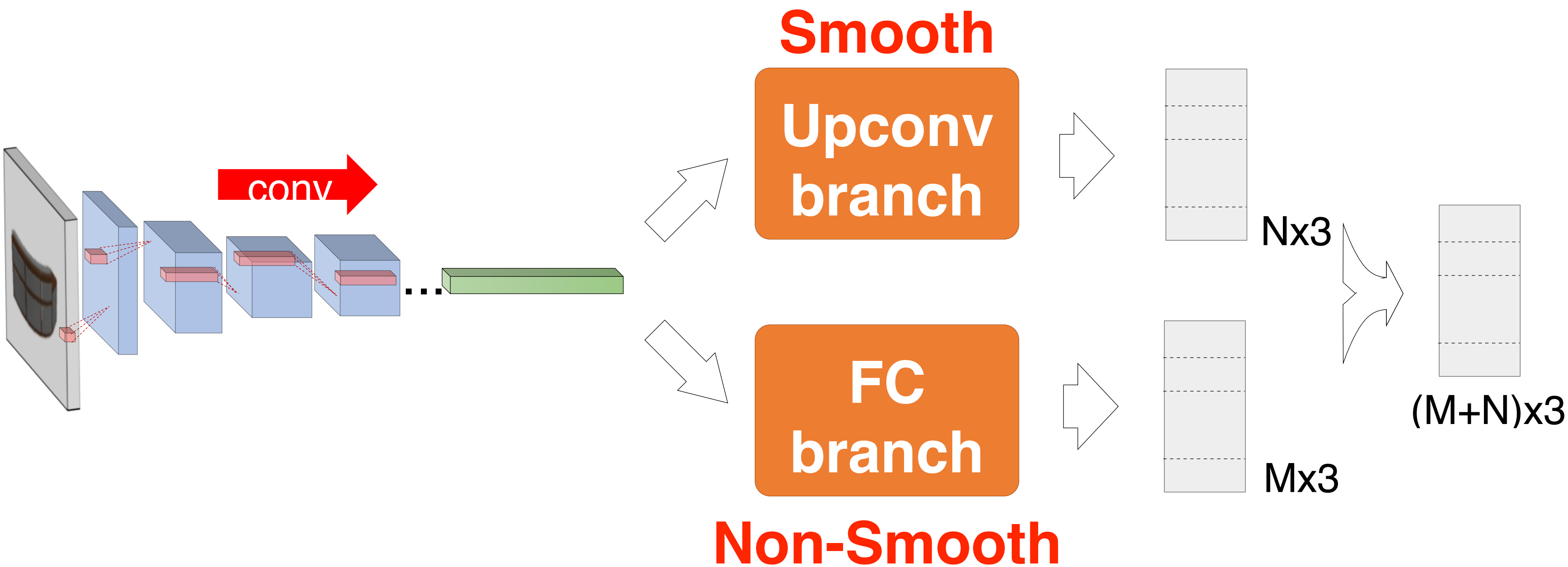


Set union by array concatenation

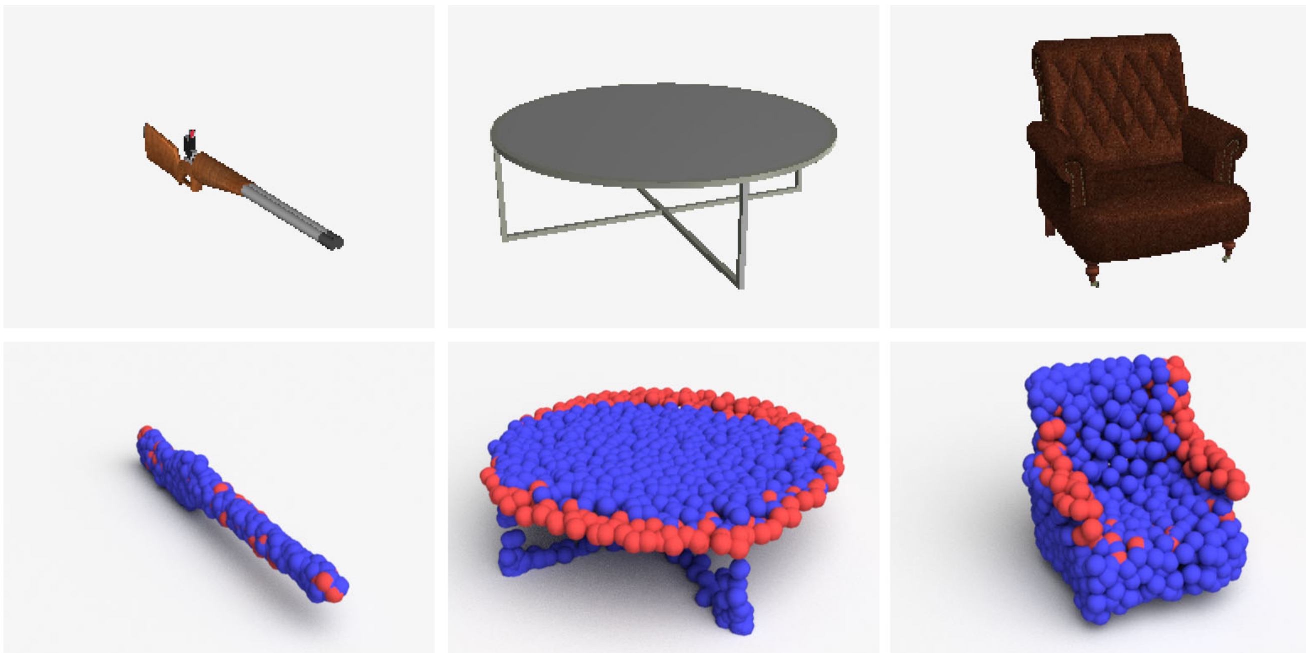
Read by Yourself

Fan et al., "**A Point Set Generation Network for 3D Object Reconstruction from a Single Image**", *CVPR 2017*

Which color corresponds to the upconv branch? FC branch?

Input

Prediction



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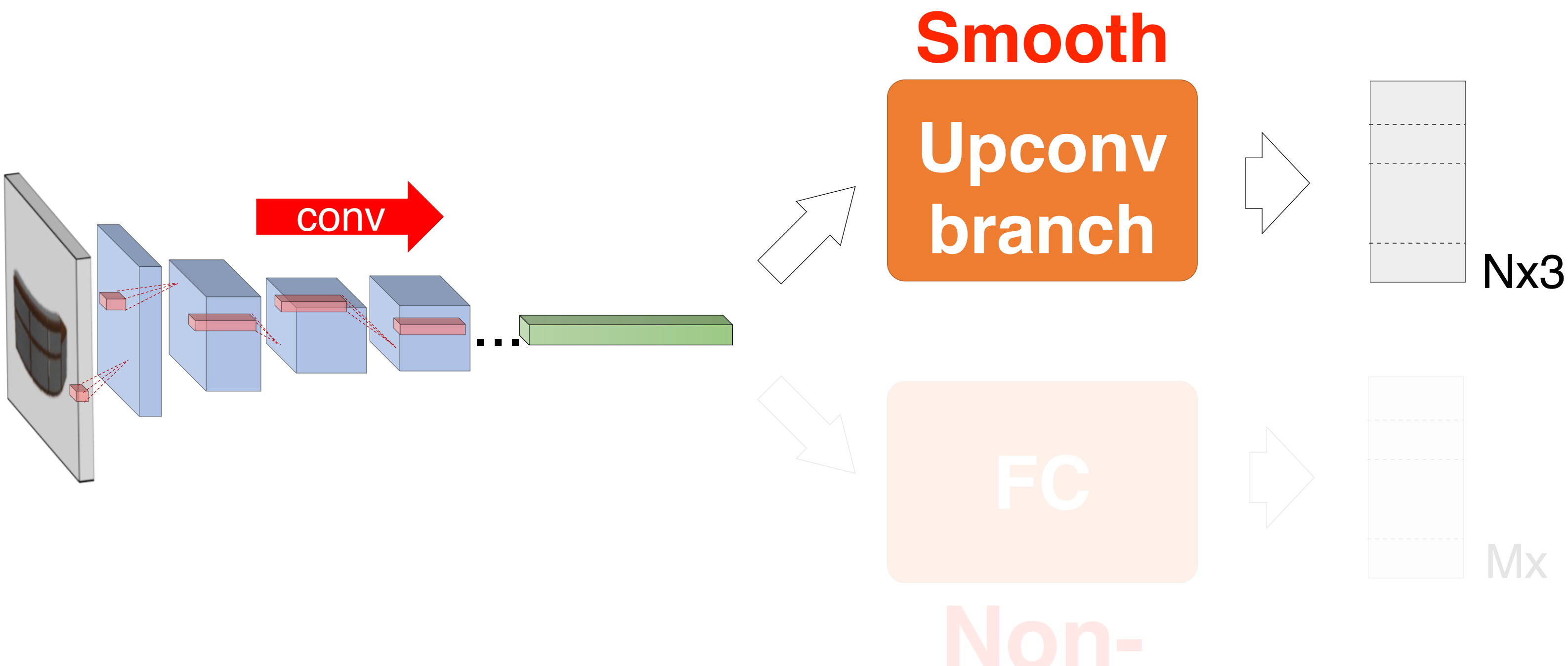
Design of Upconvolution Branch



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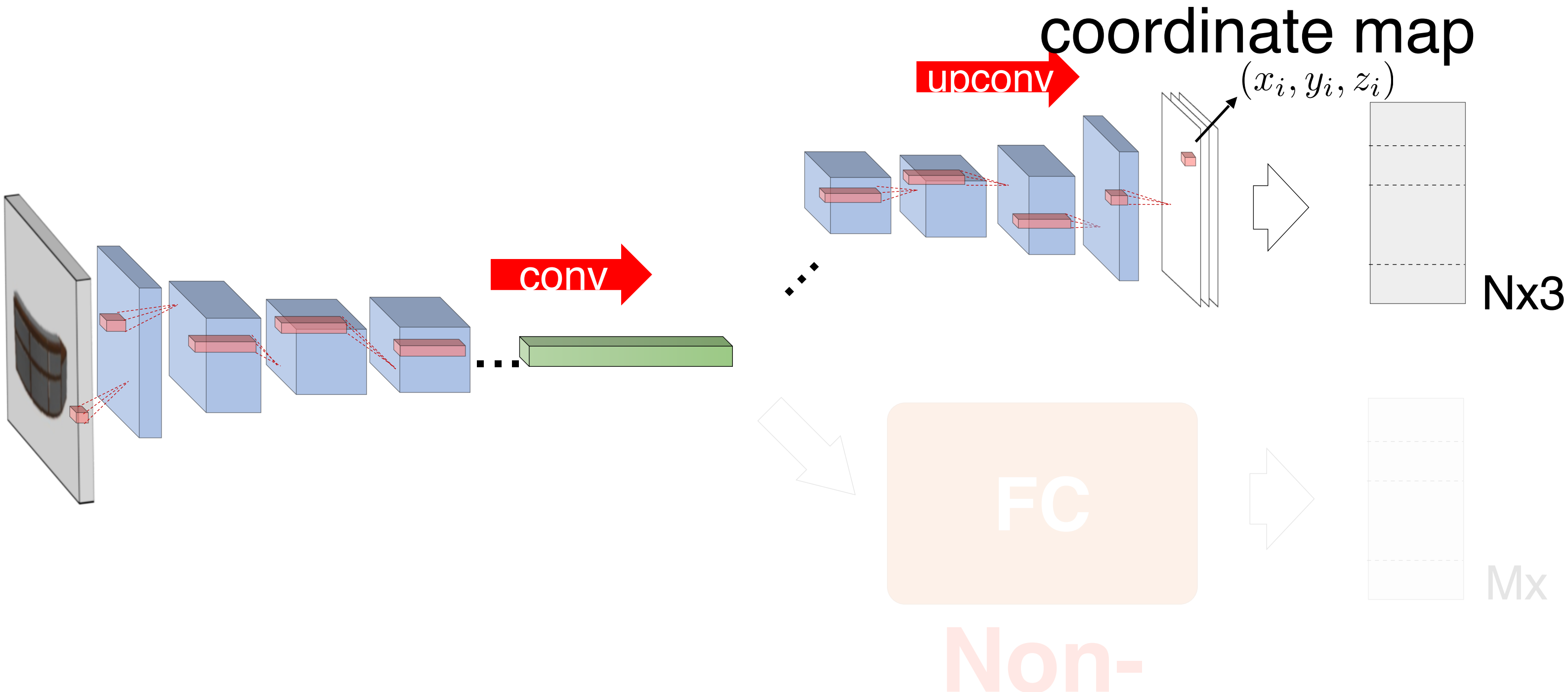

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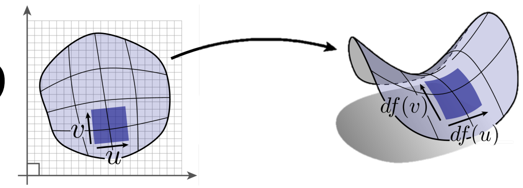
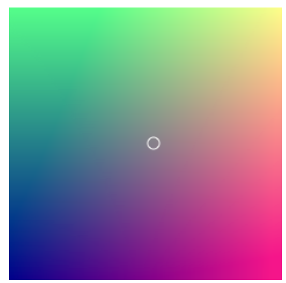
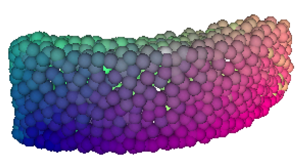
Learns a Surface Parameterization

Smooth parameterization from 2D to 

[image credit: Keenan Crane]

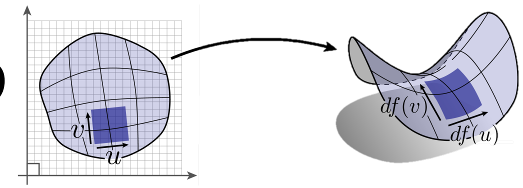




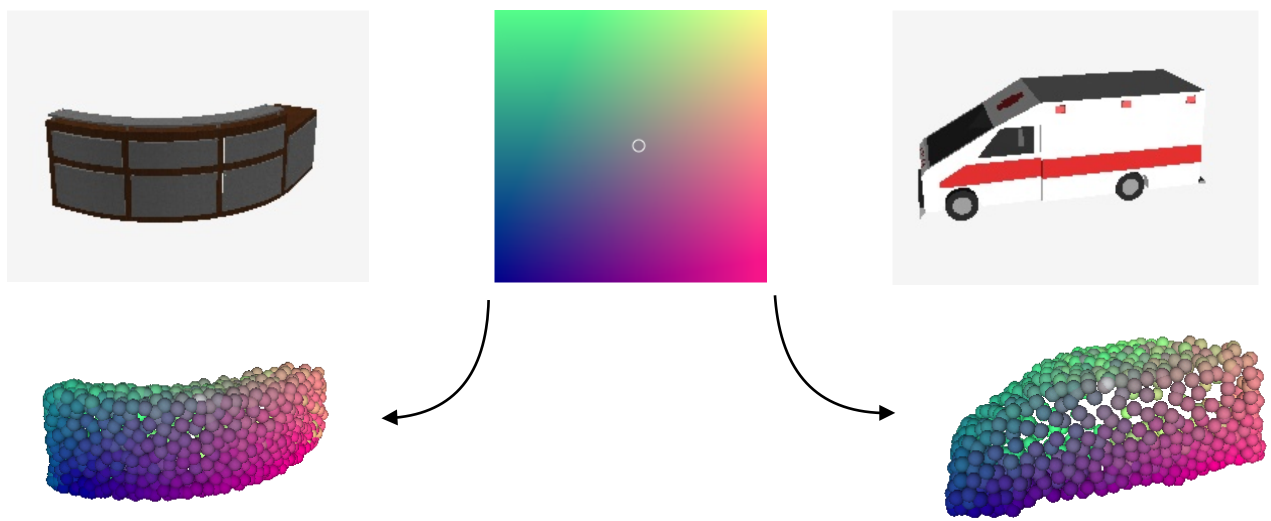
Read by Yourself

Learns a Surface Parameterization

Smooth parameterization from 2D to
Consistent across objects



[image credit: Keenan



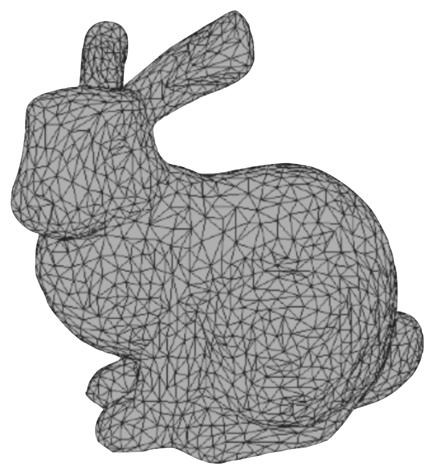
Read by Yourself

Image to Surfaces

Mesh Representation

- Previous point representation predicts only geometry without point connectivity.

- Mesh elements include mesh connectivity and mesh geometry $G = (V, E)$.



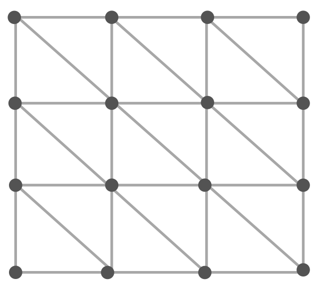
Mesh

Topology Ambiguity

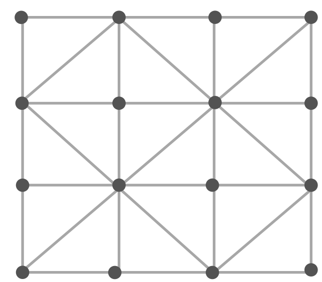
- Can we regress the vertices **and edges** from neural network?
  - Estimate vertices as a set of points. ✓
  - Estimate edges?

Designing Loss for Edge Prediction is Hard

- **Key observation**: given vertices, there are many possible ways to connect them and represent the same underlying surface:



$G = (V, E)$

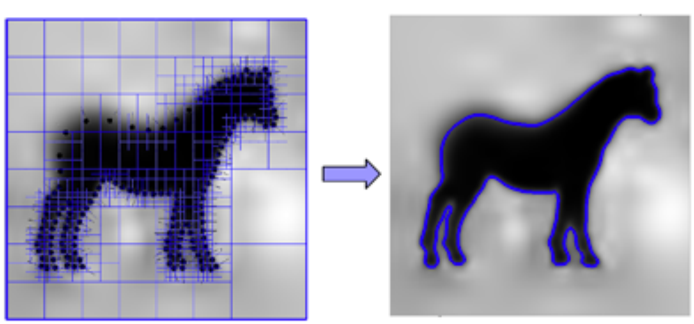


$G = (V, E')$

Image → Intermediate Repr. → Mesh

- One option is to first build a high-resolution intermediate representation, and then convert the point cloud to mesh

- Intermediate representations:
  - Voxel
  - Implicit surface
  - Point cloud



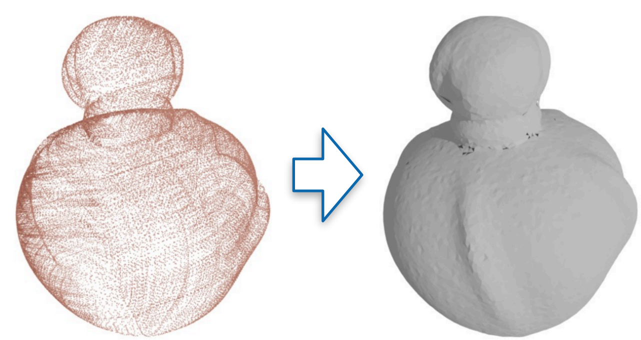


Image → Intermediate Repr. → Mesh

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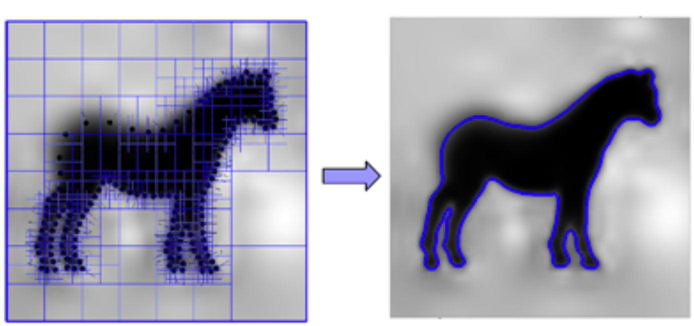
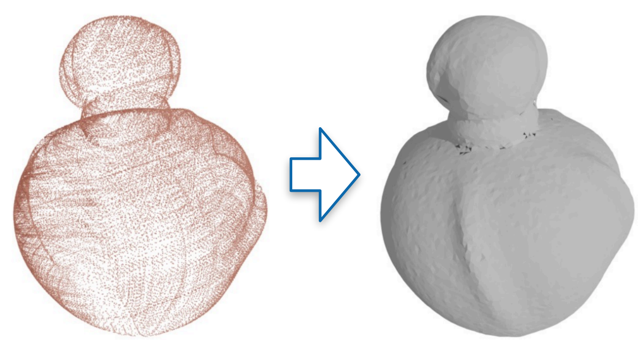
Defer to a later lecture!





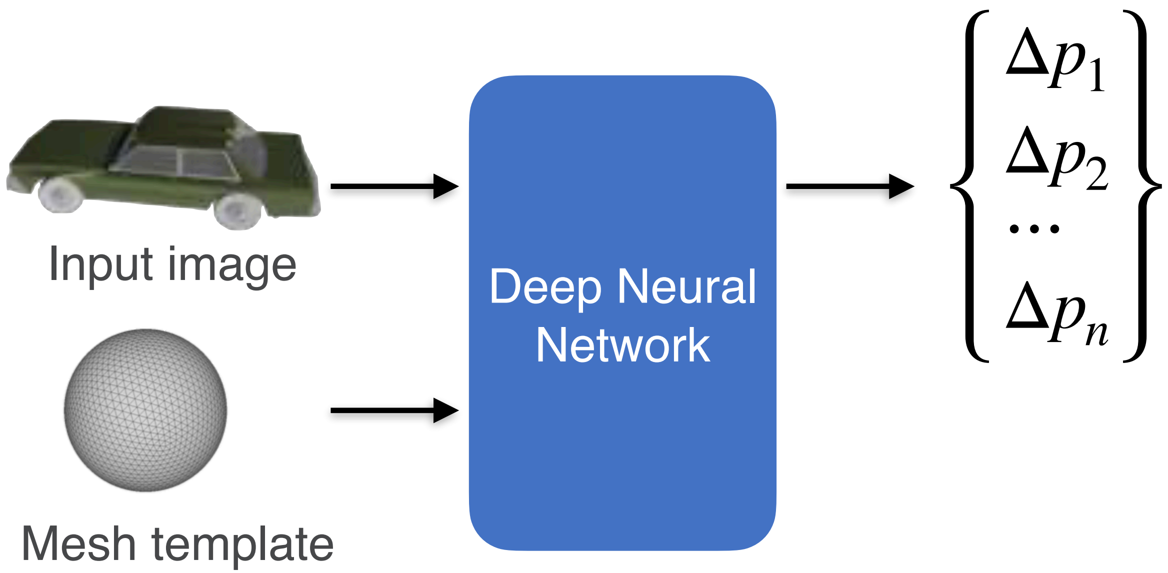
Editing-based Mesh Modeling

- Can we model mesh without predicting edges?

Mesh Editing-based Methods

Editing-based Mesh Modeling

- Key idea: starting from an established mesh and modify it to become the target shape



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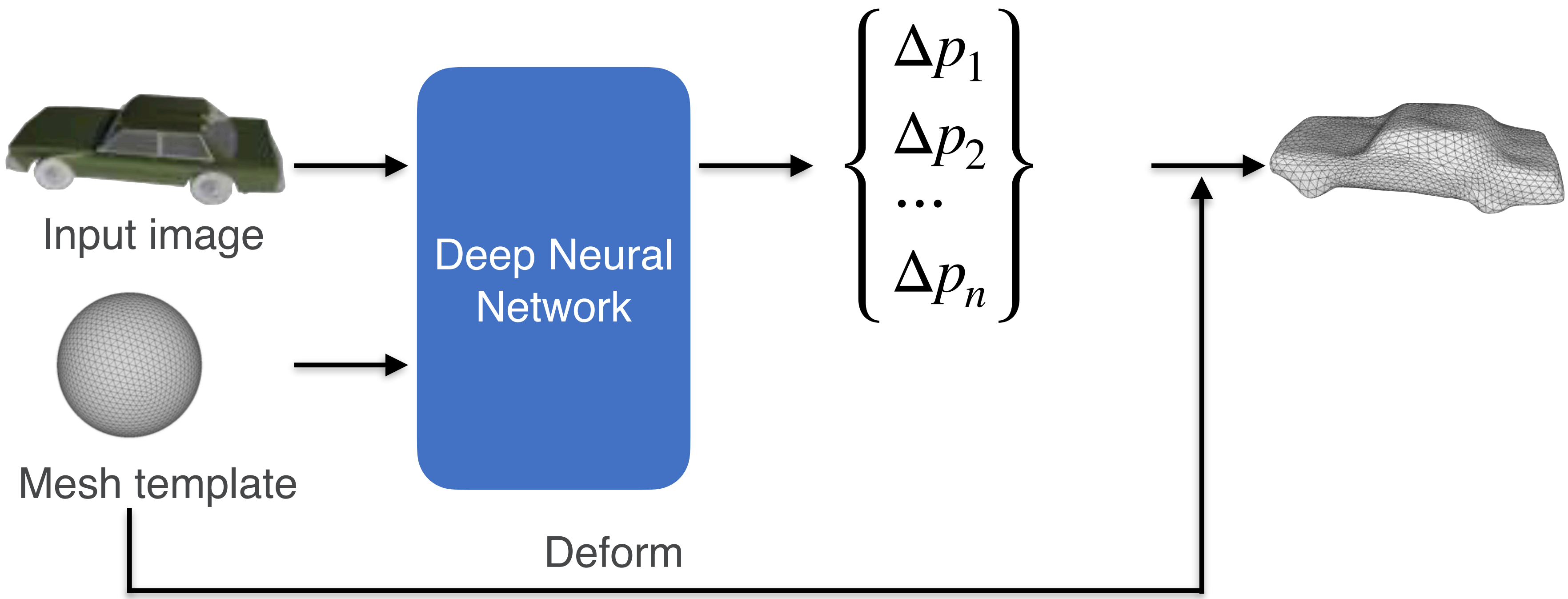
- Key idea: starting from an established mesh and modify it to become the target shape

For example, deformation-based modeling:



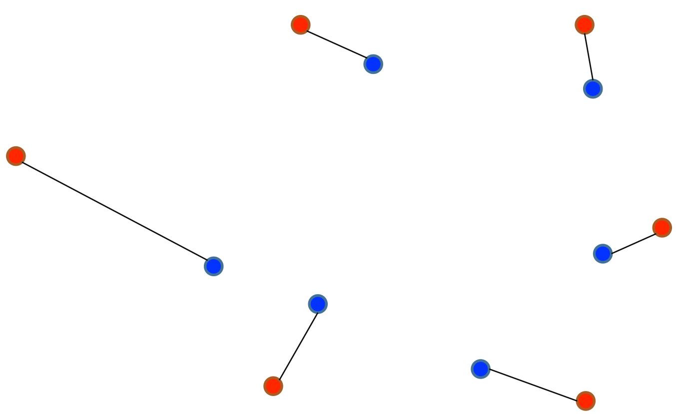
Losses for Mesh Editing

Some Example Losses

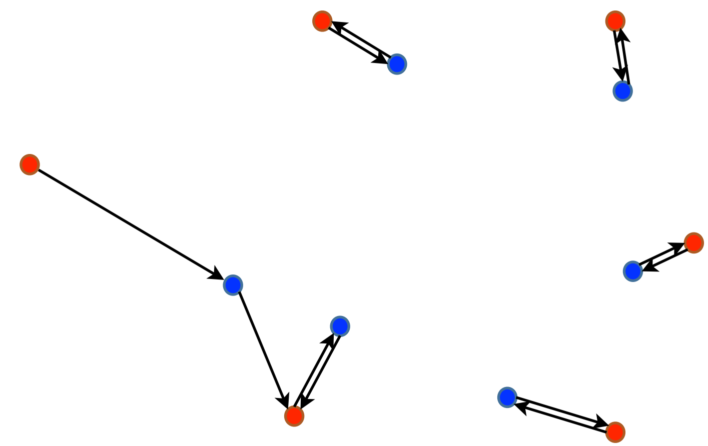
- Vertices distance.
  - Vertices point set distance.
- Uniform vertices distribution.
  - Edge length regularizer.
- Mesh surface smoothness.
- Normal Loss.

Loss I: Set Distance between Vertices

- Vertices are a set of points
- Recall the metrics for point clouds



Earth Mover's distance



Chamfer distance

$$d_{EMD}(S_1, S_2) = \min_{\phi: S_1 \to S_2} \sum_{x \in S_1} \|x - \phi(x)\|_2$$

$$d_{CD}(S_1, S_2) = \sum_{x \in S_1} \min_{y \in S_2} \|x - y\|_2^2 + \sum_{y \in S_2} \min_{x \in s_1} \|x - y\|_2^2$$

Loss II: Uniform Vertices Distribution

- Penalizes the flying vertices and overlong edges to guarantee the high quality of recovered 3D geometry
- Encourage equal edge length between vertices

$$L_{\text{unif}} = \sum_{p} \sum_{k \in N(p)} \|p - k\|_2^2$$

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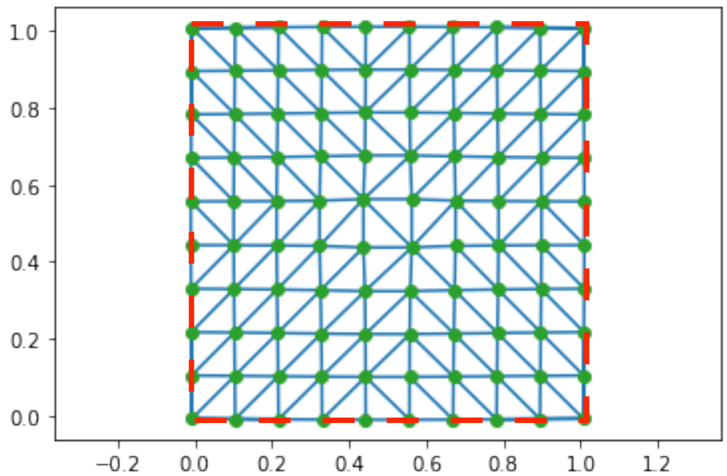
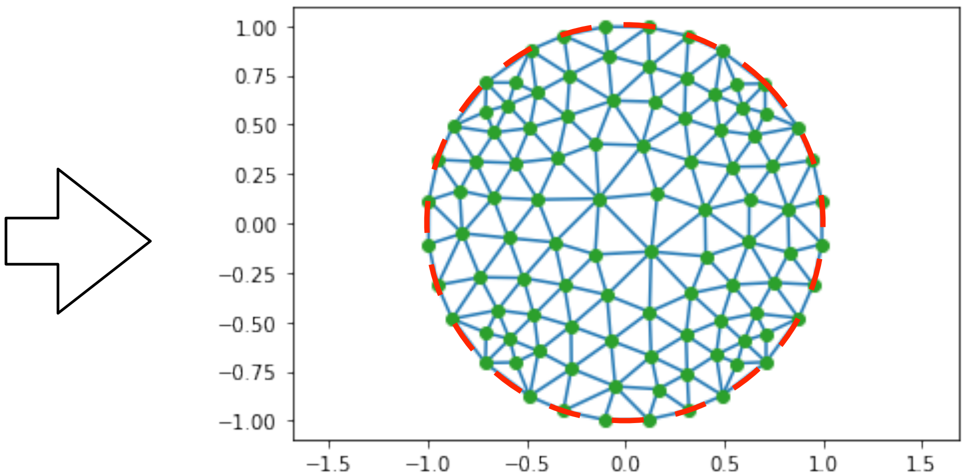
Effect of minimizing l when fixing topology and setting boundary points to the new positions

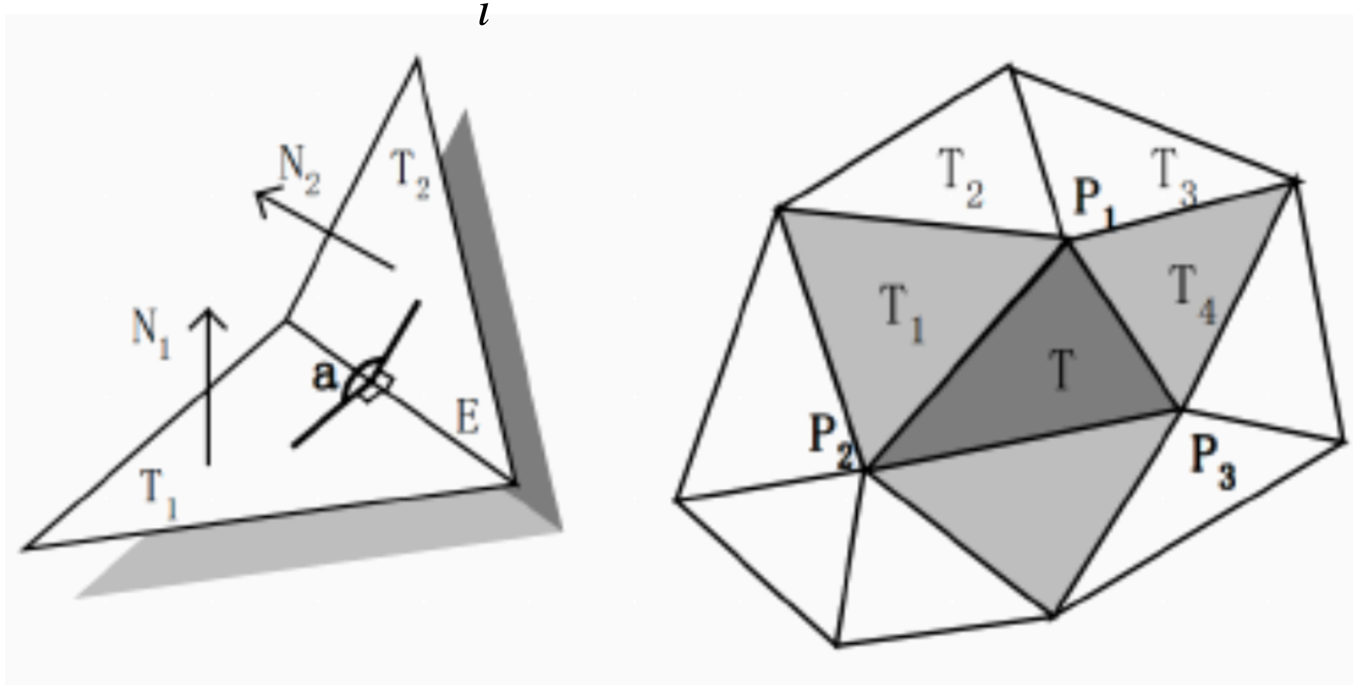




Loss III: Mesh Smoothness

- L_{smooth} encourages that intersection angles of faces are close to 180 degrees.

$$L_{smooth} = \sum_i (\cos\theta_i + 1)^2$$

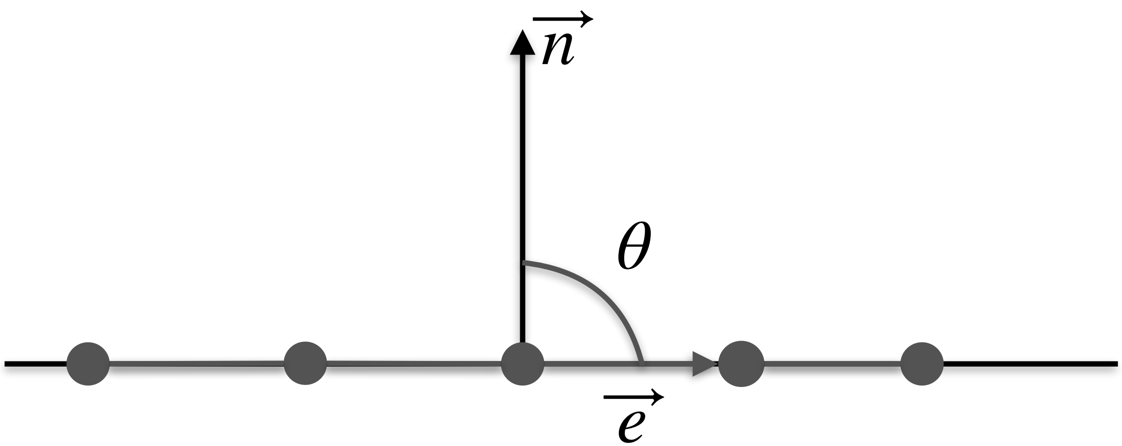


Read by Yourself

Loss IV: Normal Loss

- **Key assumption**: vertices within a local neighborhood lie on the same tangent plane.

- Regularize edge to be perpendicular to the underlying groundtruth surface normal



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Loss IV: Normal Loss

- But how to find the vertices normal?

- One approach: use the nearest ground truth point normal as current vertex normal.

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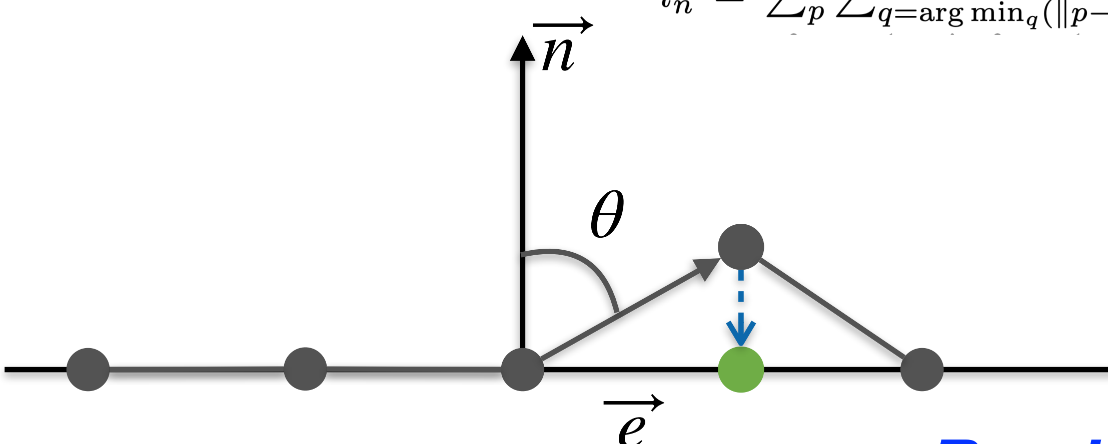
- But how to find the vertices normal?
- One approach: use the nearest ground truth point normal as current vertex normal.
- Penalize the edge direction to perpendicular to vertex normal.

$$l_n = \sum_p \sum_{q=\arg\min_q(\|p-q\|_2^2)} \|\langle p-k, \mathbf{n}_q \rangle\|_2^2$$



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