L15: Zero-shot 3D Understanding

Hao Su

Thank Dr. Songfang Han for helping to prepare slides

Many Successes of Machine Learning

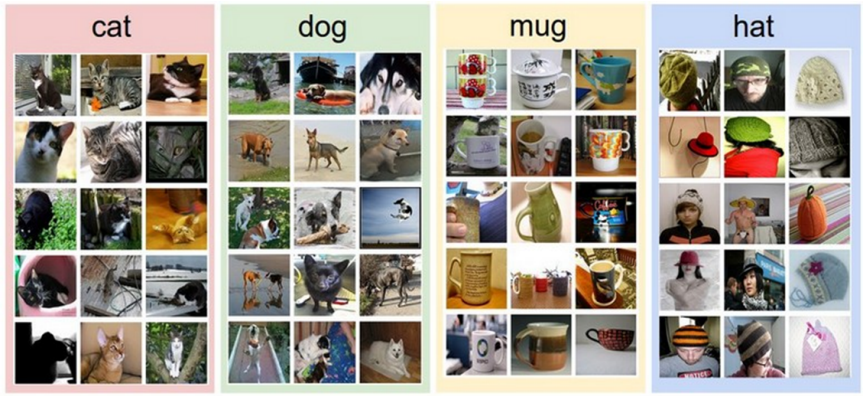
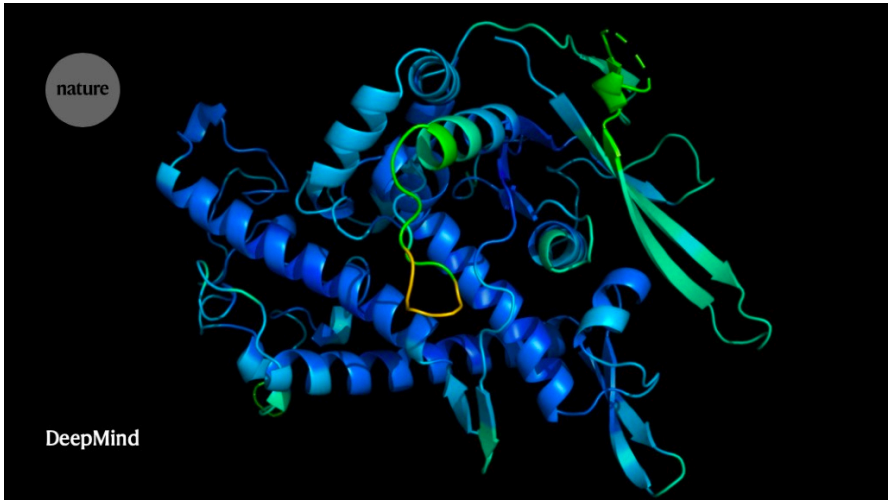
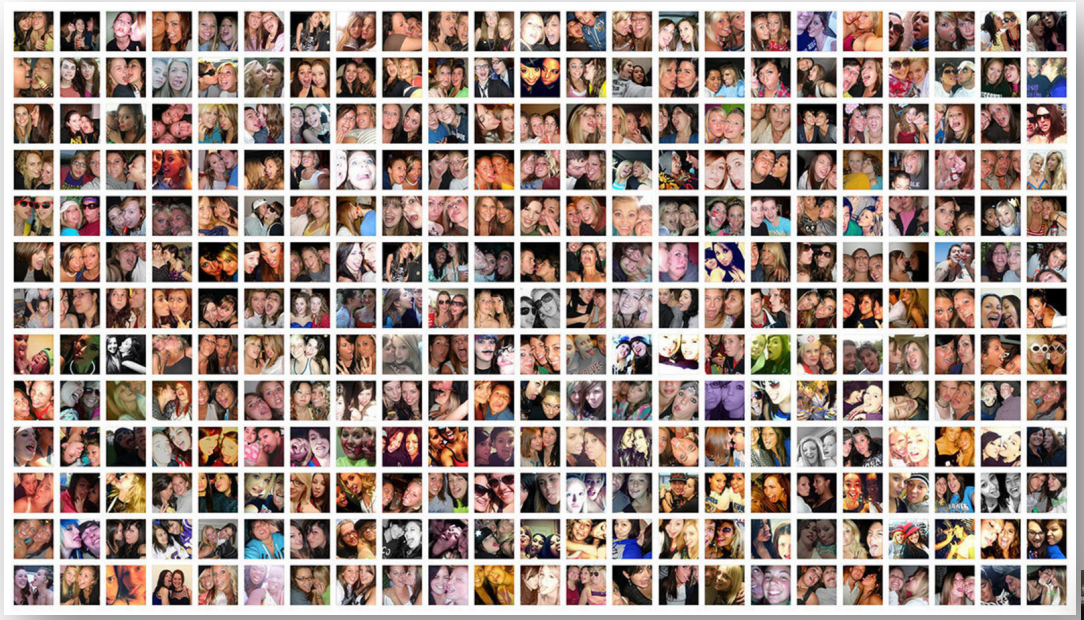


Image classification
Speech understanding
3D shape classification
…



Made Possible By ….



Lots of data

Lots of computing power

For i.i.d samples between train/ test sets, even generalize!

Common Framework

For each task:

Dataset: $\mathcal{T} = \{(x_i, y_i)\}_{i=1}^{n}$

Learner: $y = f(x;\theta)$

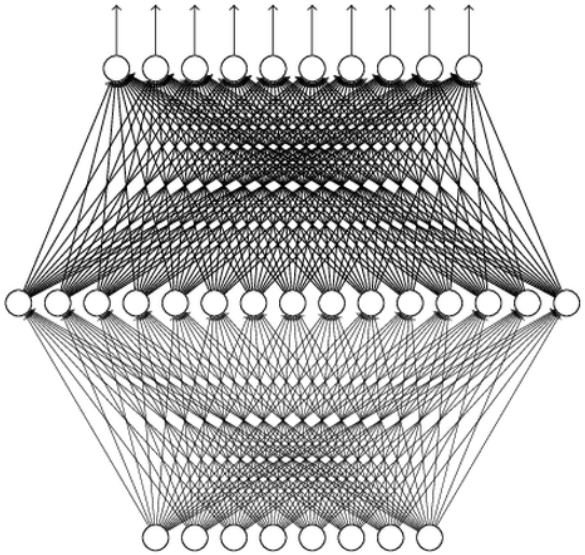
Referee (loss function): $L(y, y')$

Universality Theorem:

Any continuous function f

$$f : R^N \rightarrow R^{\mathrm{M}}$$

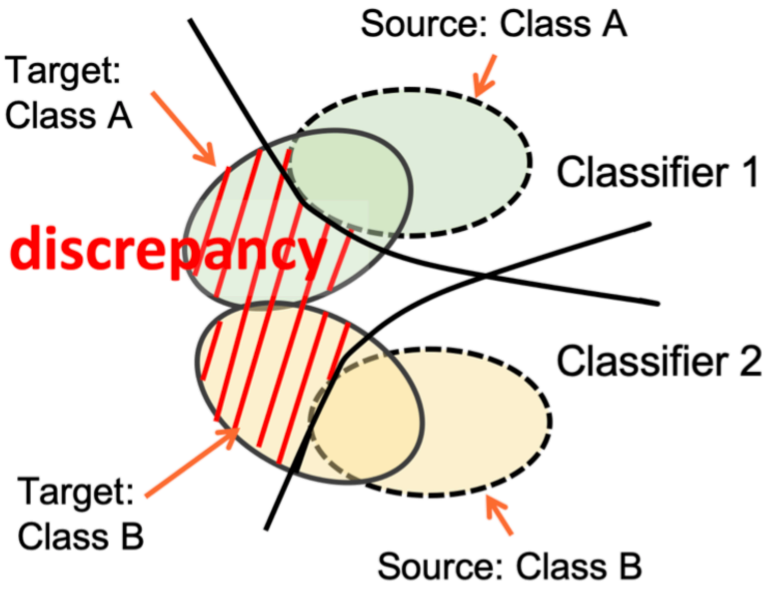
can be realized by a network



Discrepancy between Training and Test

- Source Domain ~ $P_S(X_S, Y_S)$, lots of labeled data
- Target Domain ~ $P_T(X_T, Y_T)$, unlabeled or limited labels

Discrepancy between training and test set causes bad performance.



Can We Transfer 3D Understanding from Training Category to **Unseen** Categories?

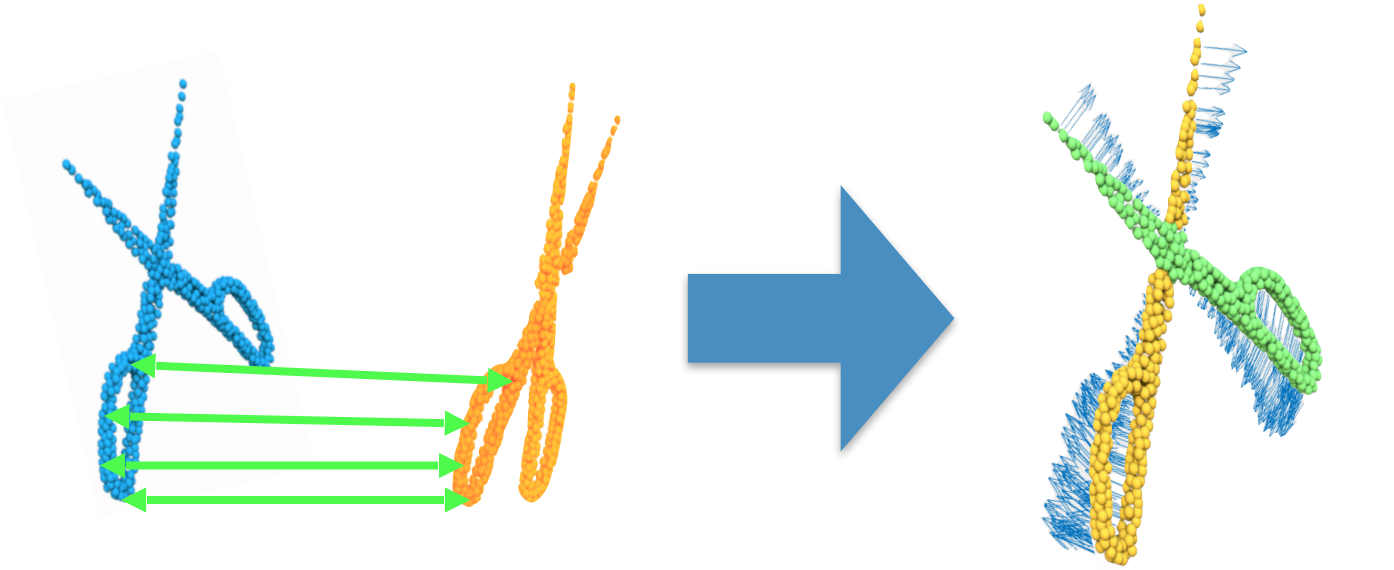
Agenda

- Correspondence-based Part Segmentation
- Compositional Generalizability View of Zero-shot Part Segmentation ***(read by yourself)***

Correspondence-based Part Segmentation

Motivation

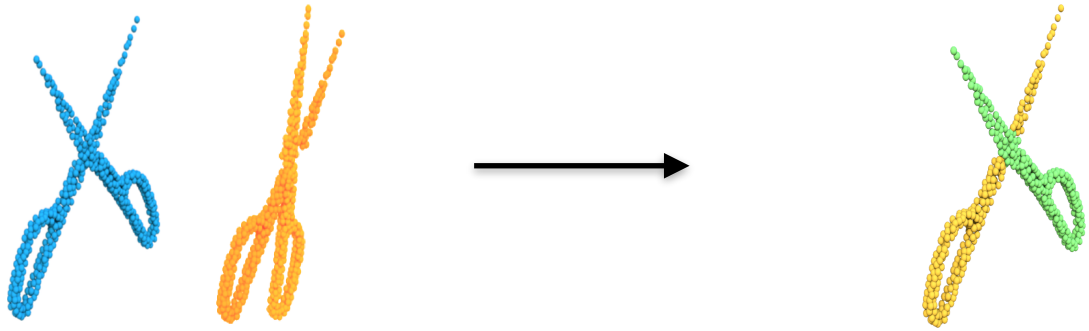
- **Key observation**: Correspondence assumes no object and categories information and focus on local regions.



Correspondence ***Segmentation***

Correspondence is more ***Generalizable*** to novel instances and novel object categories.

Problem Definition: Two Frame Reasoning

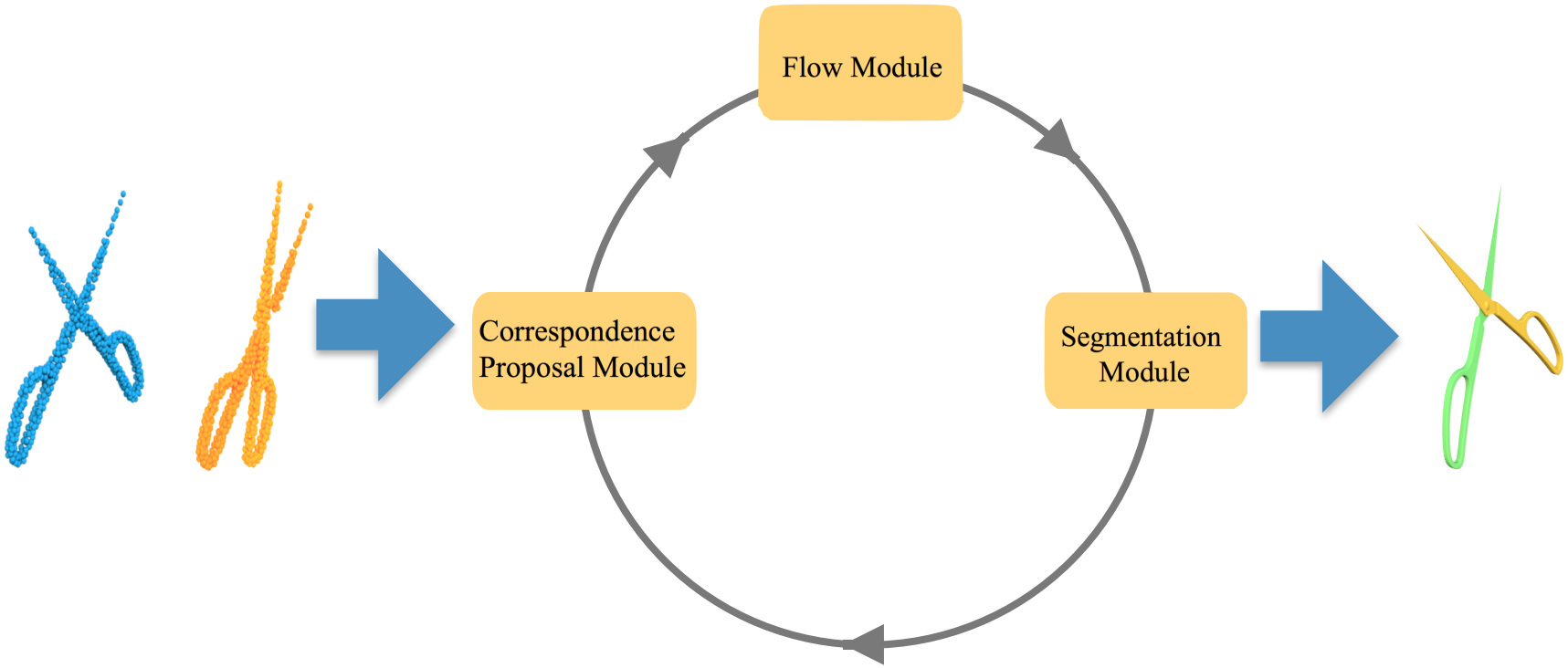


Input: two point sets with different articulation states

Output: part segmentation

Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

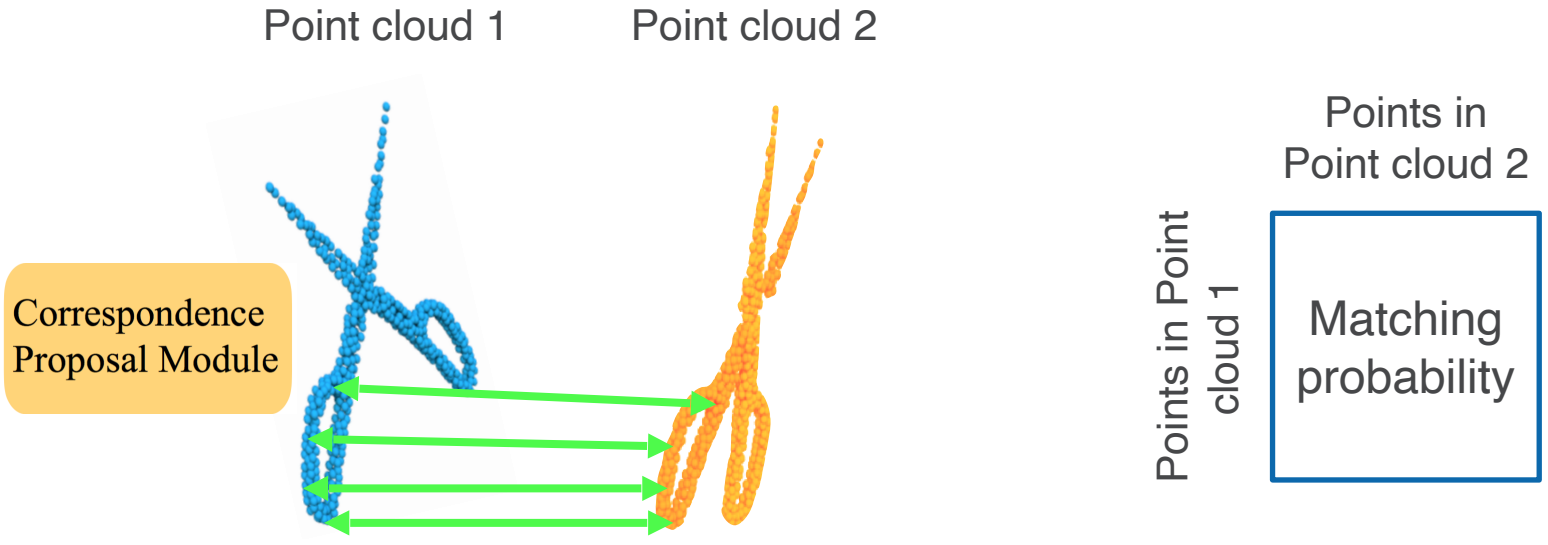
Overall Pipeline



Correspondence Proposal Module

Input

Output

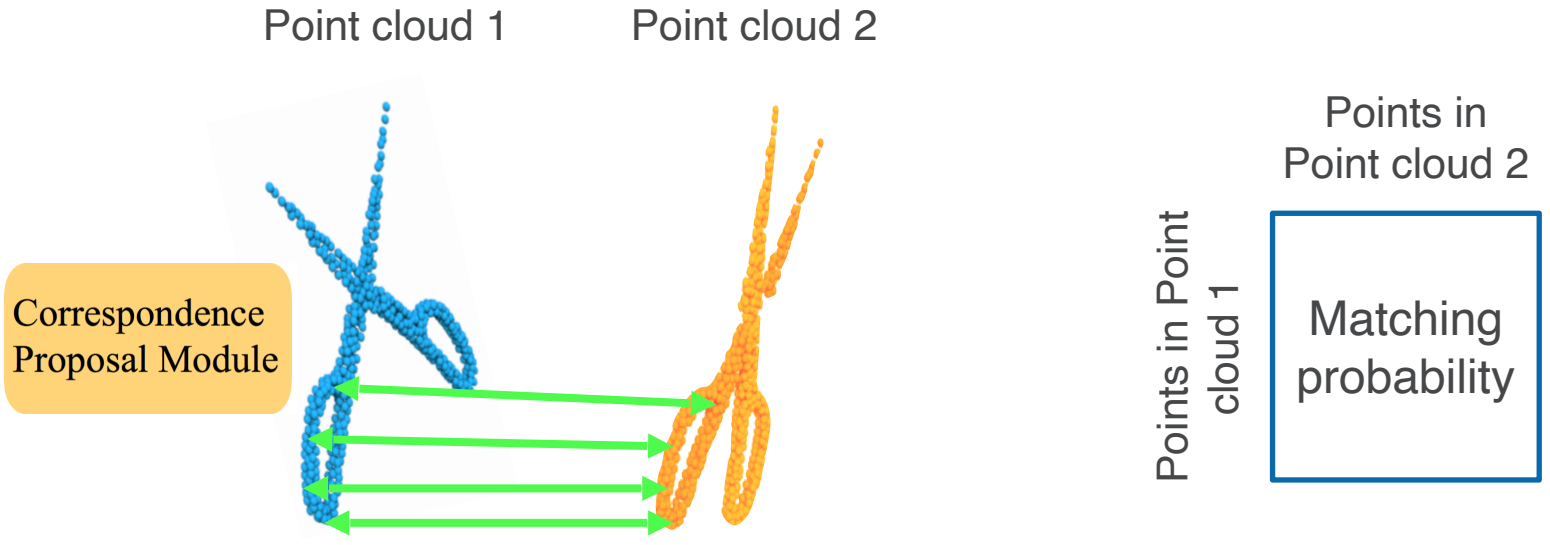


Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Correspondence Proposal Module

Input

Output



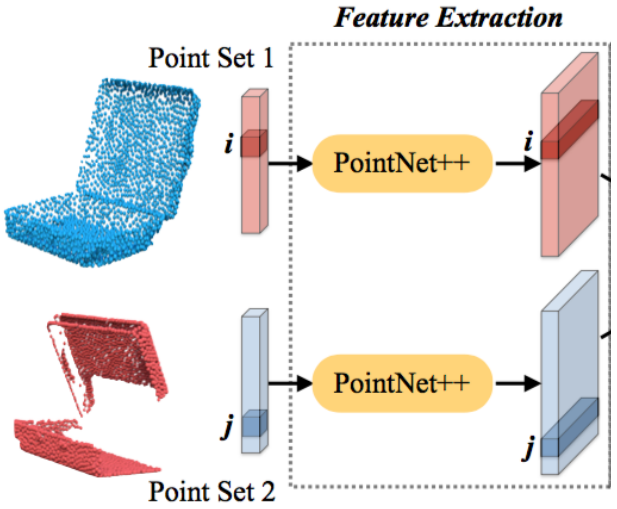
Idea:

- extract features of every point in p.c.1 & p.c.2
- compare each pair of points across p.c.1 & p.c.2

Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Correspondence Proposal Module

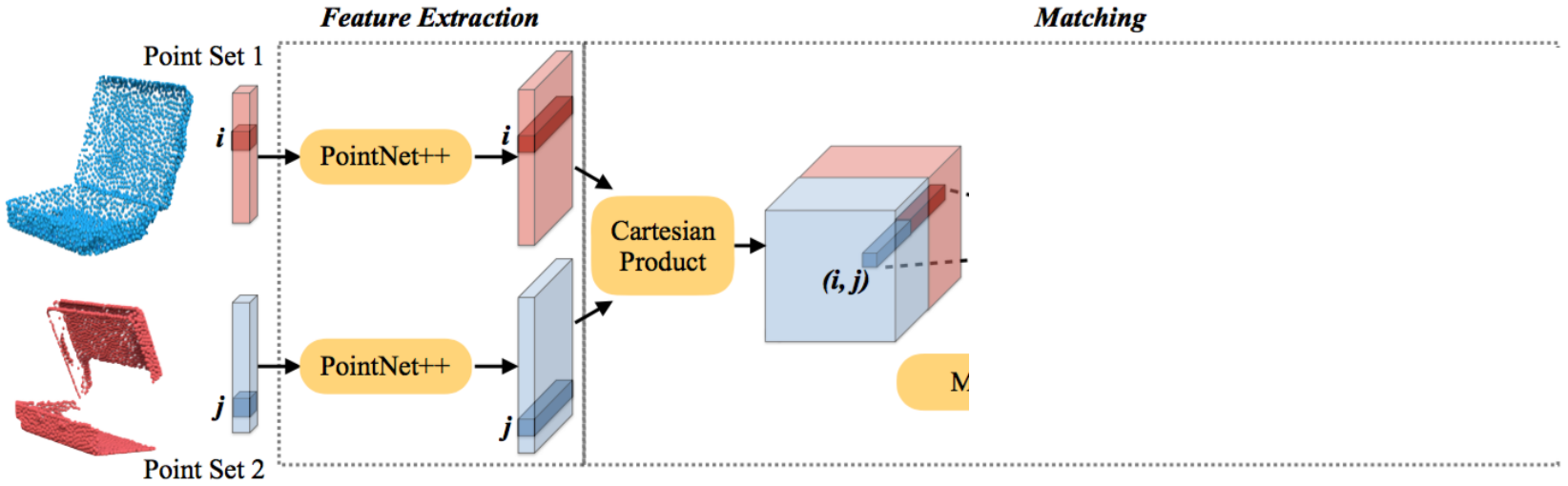
- Extract point feature with PointNet++ for point set 1 and point set 2 separately



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Correspondence Proposal Module

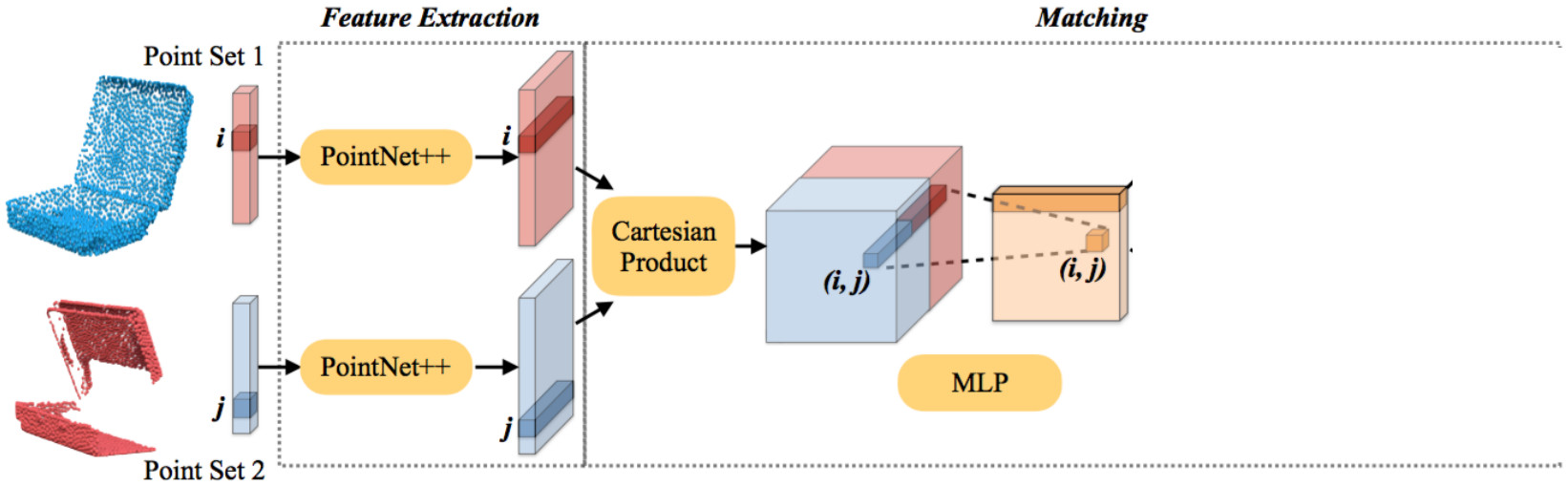
- For each pair, concatenate the extracted point feature



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Correspondence Proposal Module

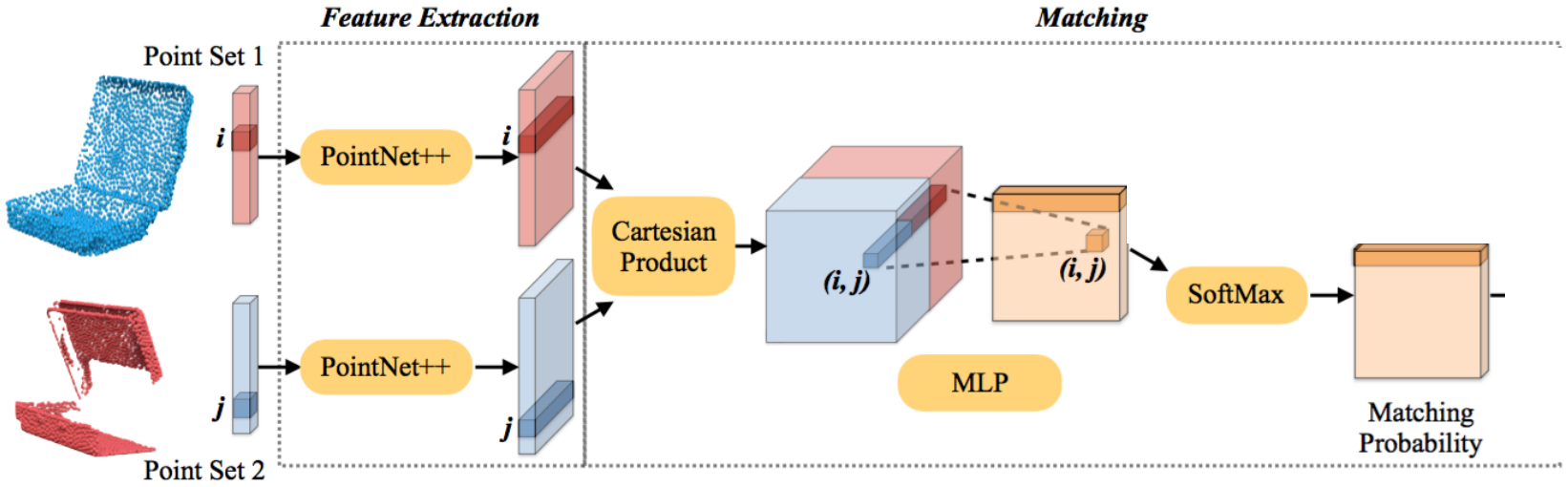
- For each pair, predict how likely the two points match



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Correspondence Proposal Module

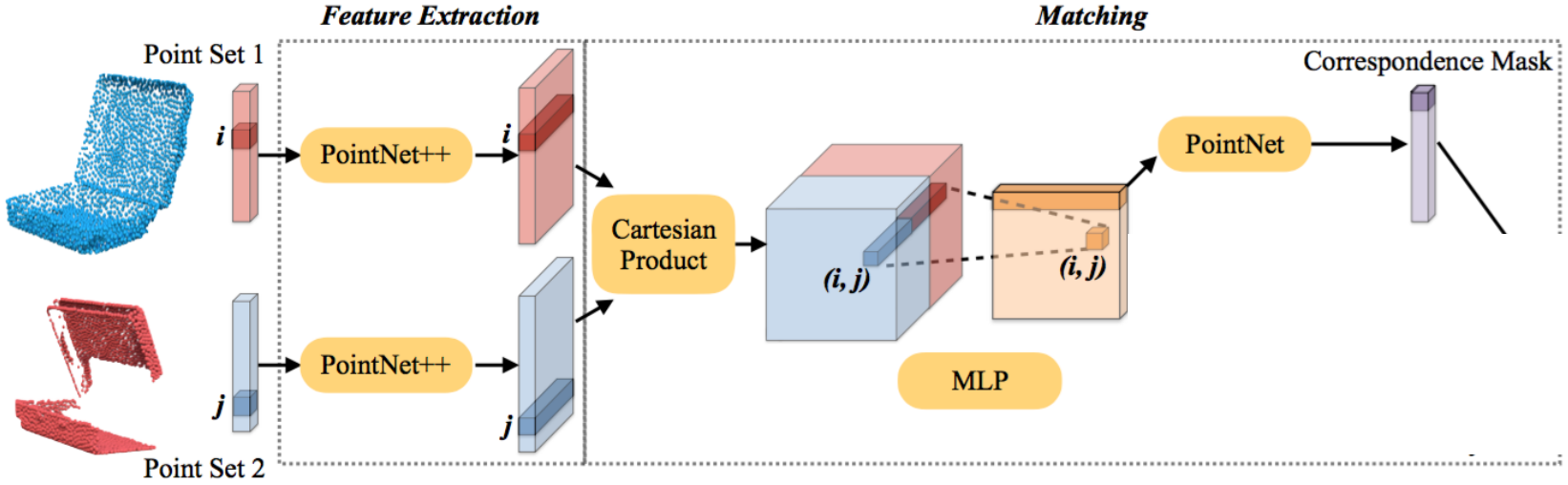
- Convert the confidence value into a probability with SoftMax operation along each row



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Correspondence Proposal Module

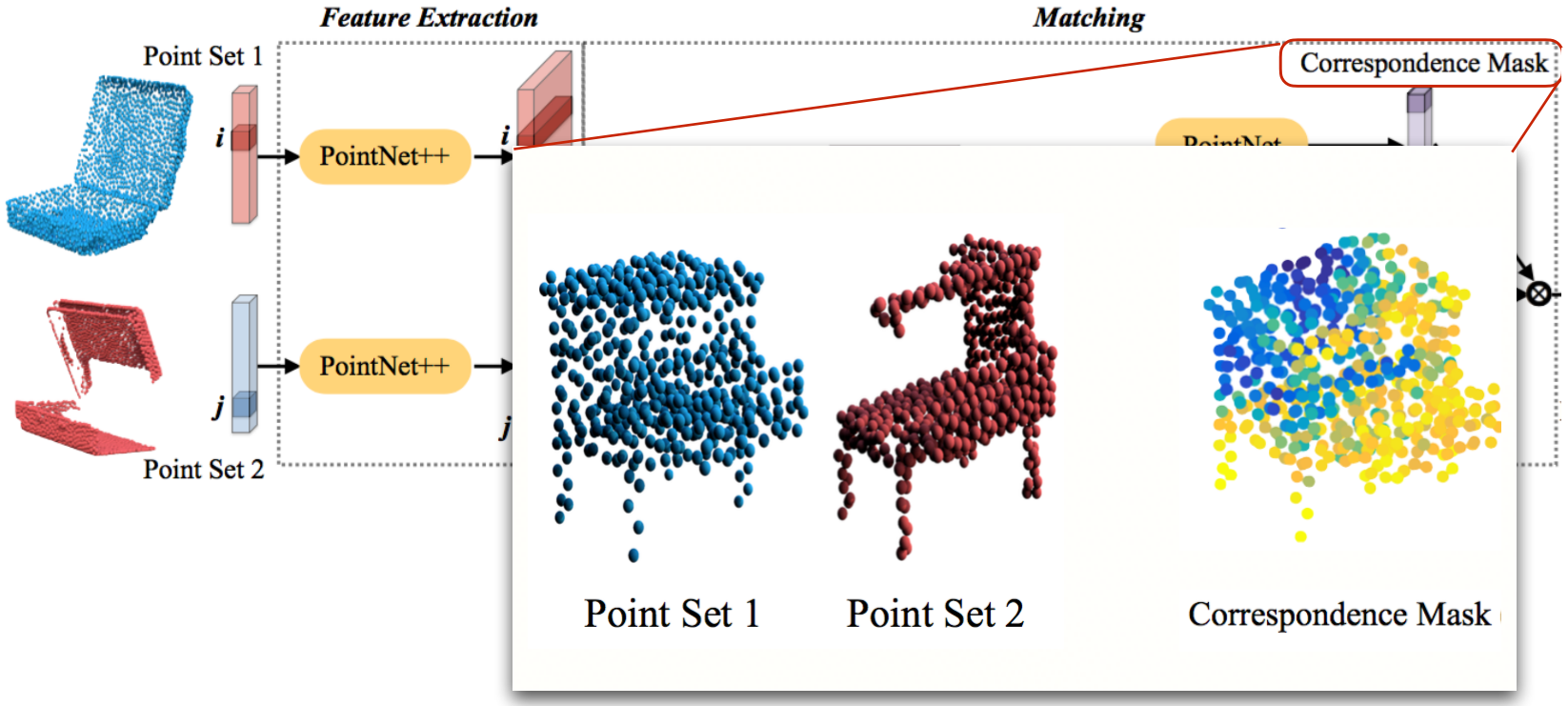
- Point cloud 1 may have points not in point cloud 2
- So we predict whether the corresponding point exists as a binary label



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Correspondence Proposal Module

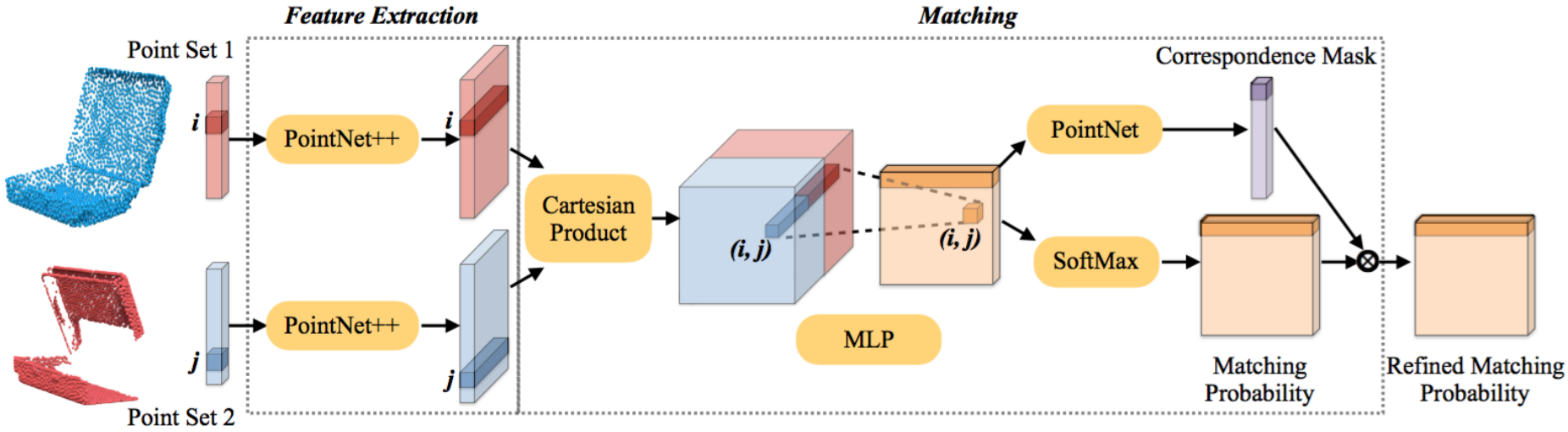
- Visualizing the existence prediction label as a mask



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Correspondence Proposal Module

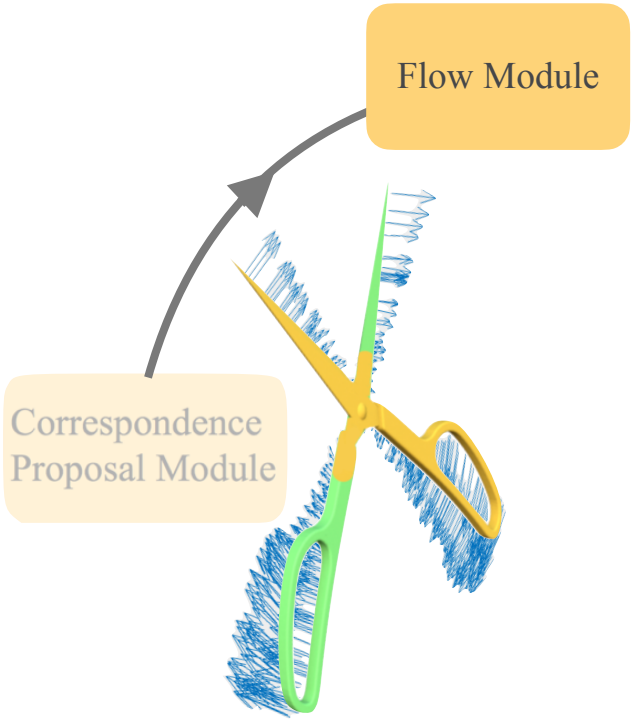
- Downweight those rows of matching probability if the corresponding point might be missing



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Flow Module

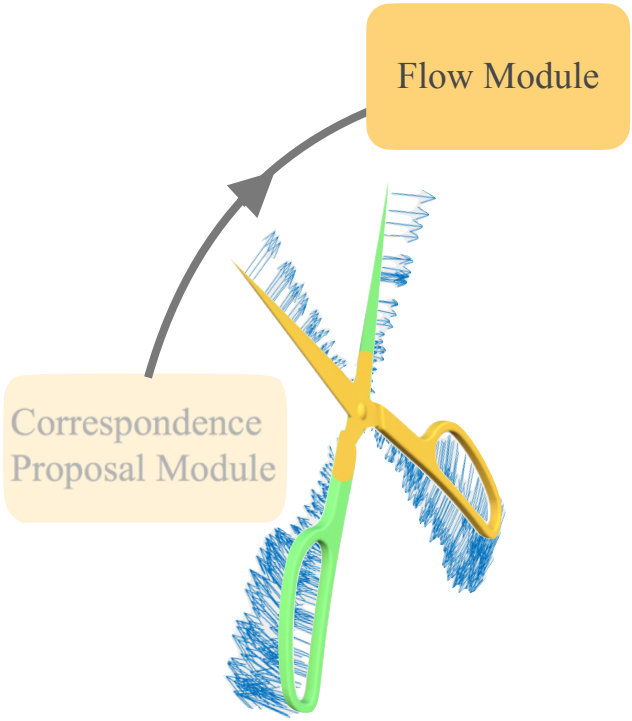
- Deformation flow:
  - At each point in point cloud 1 P,
  - Associate a vector denoting the offset to the corresponding point in point cloud 2 Q

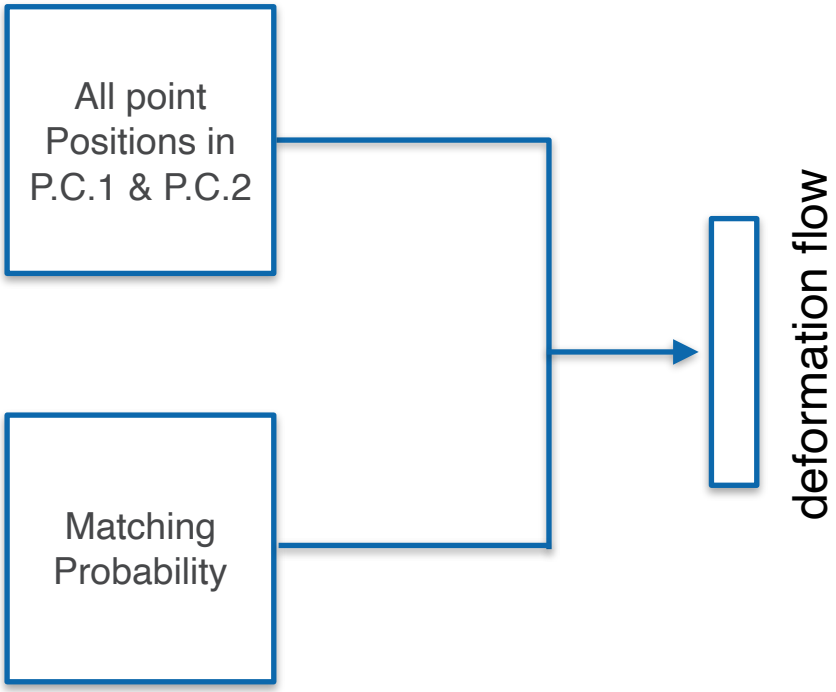


Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Flow Module

- Deformation flow:
  - At each point in point cloud 1 P,
  - Associate a vector denoting the offset to the corresponding point in point cloud 2 Q

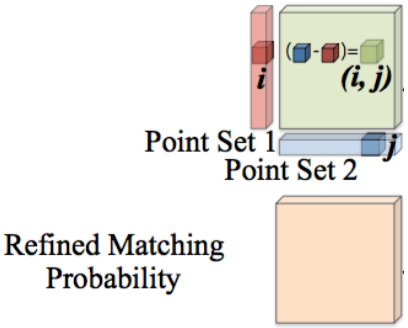




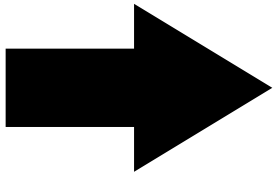
Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

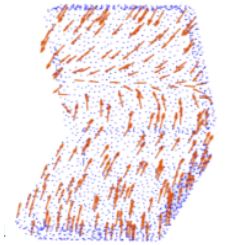
Input and Output

- Input:
  - Matching probability matrix
  - Pairwise 3D displacement matrix M, with $m_{i,j} = q_j - p_i$
- Output:
  - Displacement from point set1 to point set 2



Input



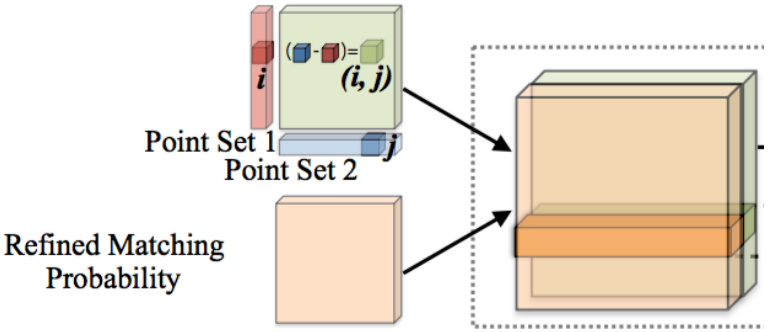


Output:
Deformation flow

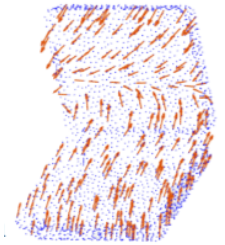
Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Flow Module Architecture

- Concatenate matching probability matrix with pairwise displacement matrix
- Each row corresponds to a point in point set 1:
  - all possible displacements
  - and correspondences



Input

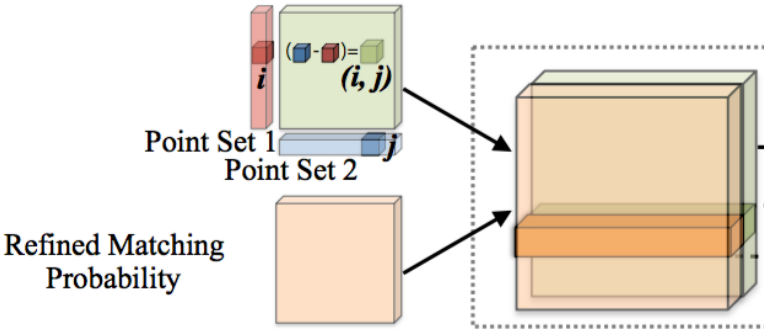


Output

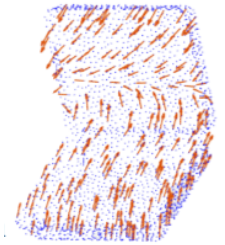
Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Flow Module Architecture

- Concatenate matching probability matrix with pairwise displacement matrix
- Each row corresponds to a point in point set 1:
  - all possible displacements
  - and correspondences
- **Let us vote for the deformation vector for each point in point set 1!**



Input

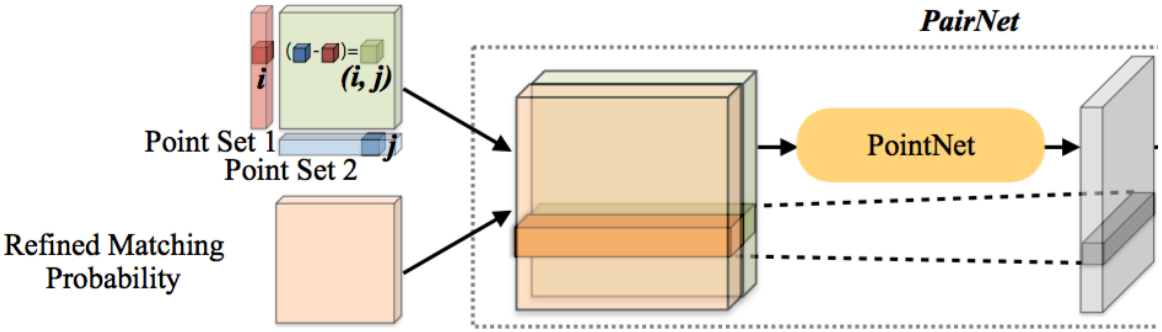


Output

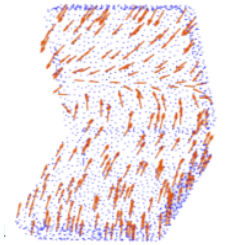
Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Vote for the Deformation Vector

- Correspondence information aggregation:
  - Aggregate the information for each point in point set 1 by PointNet and store as a row vector



Input

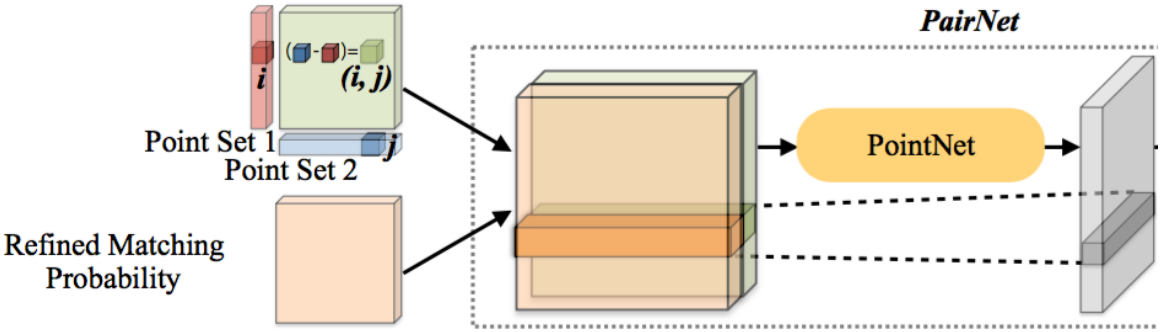


Output

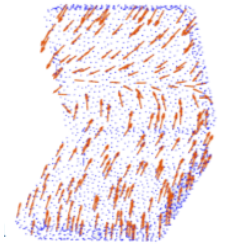
Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Denoising Correspondence Information

- Note that neighboring points in point set 1 should have similar displacements
- Recall that PointNet++ will form local groups and capture local correlations



Input

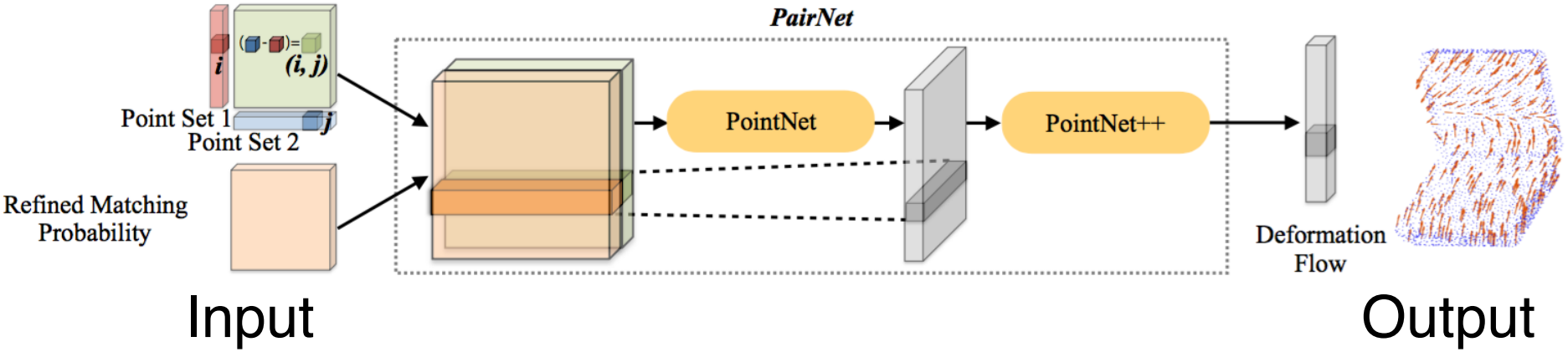


Output

Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

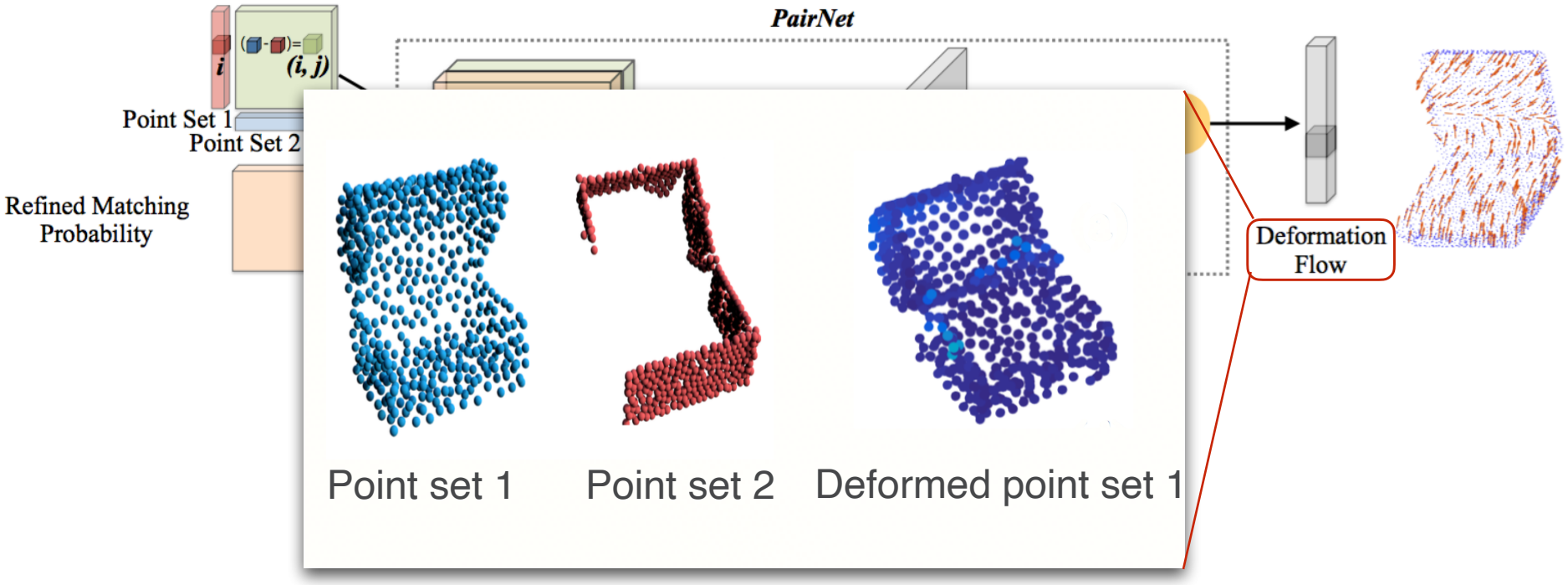
Denoising Correspondence Information

- In our correspondence information matrix
  - each row aggregates the correspondence information for each point in point set 1
- Treat each row as the features of a point, and use PointNet++ to predict a deformation vector for each point



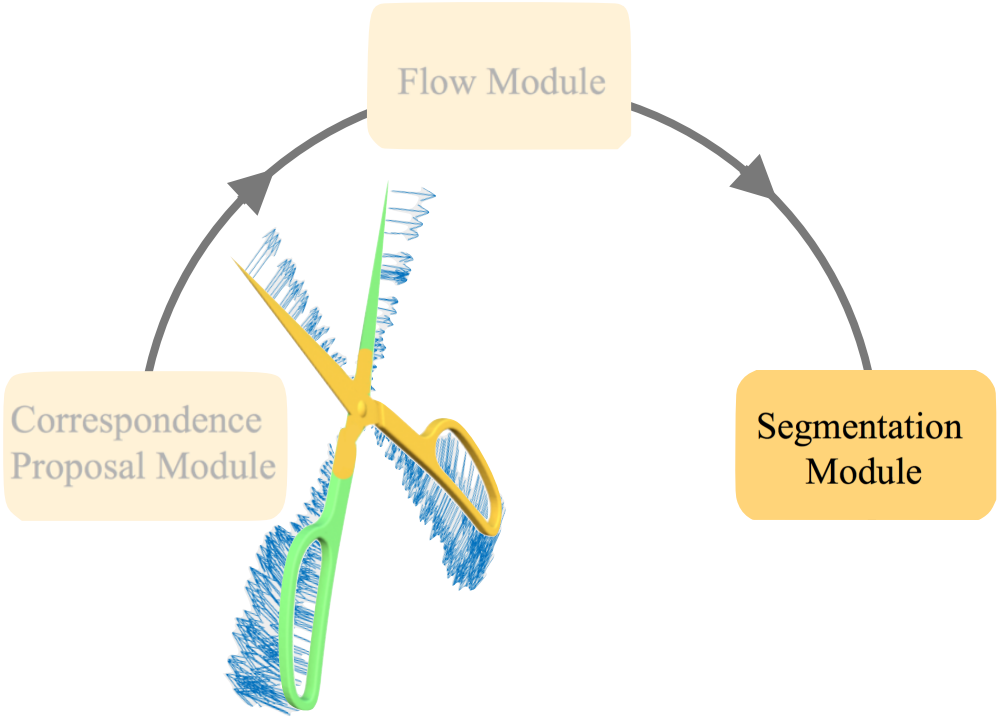
Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

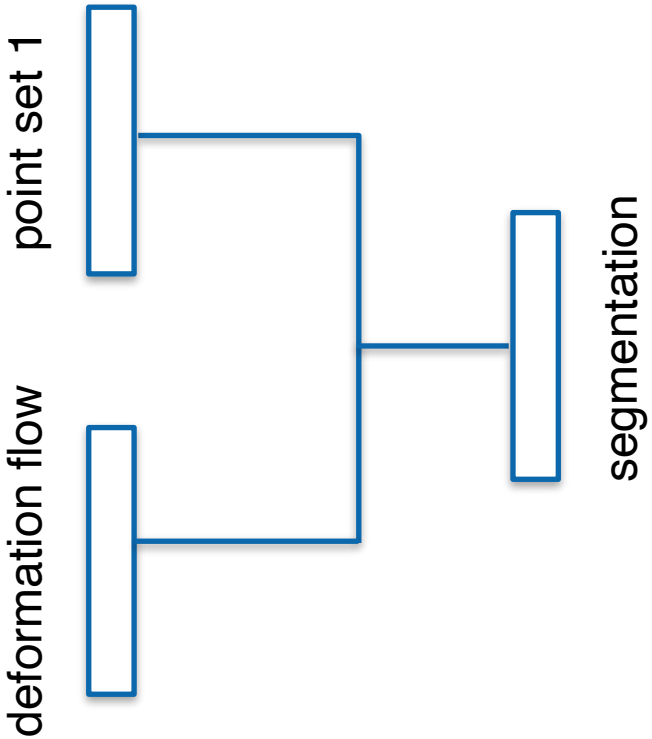
Visualization: Deforming Point Set 1 by Predicted Deformation Flow



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Segmentation Module

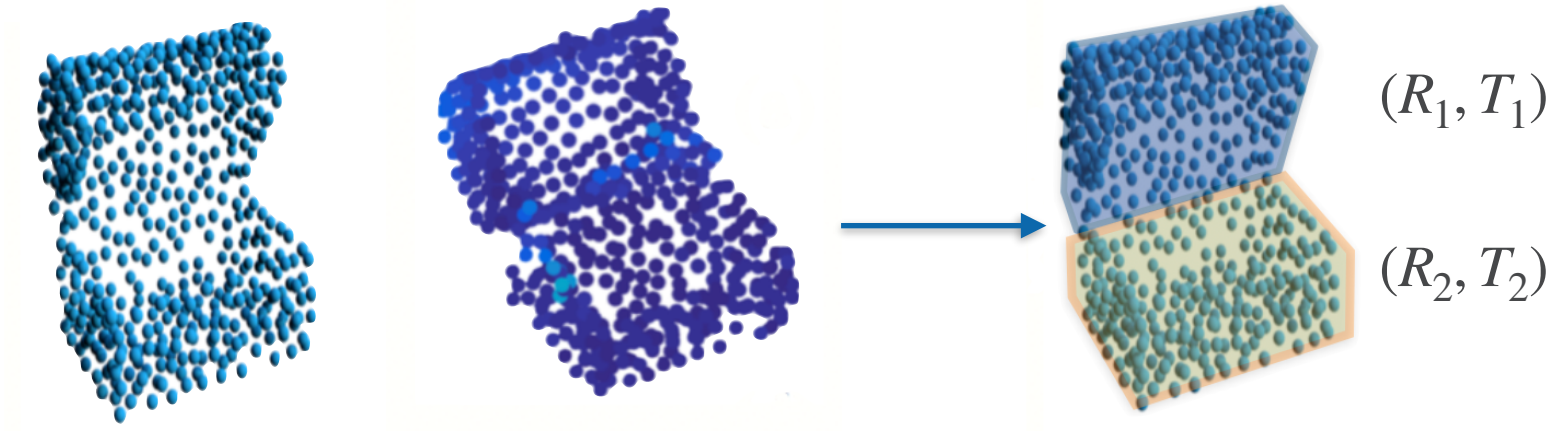




Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Segmentation Module

- How to segment parts from the deformation flow?
- Rigid part motion assumption: points from the same part share an identical transformation (R, T)



Point set 1 Deformed point set 1

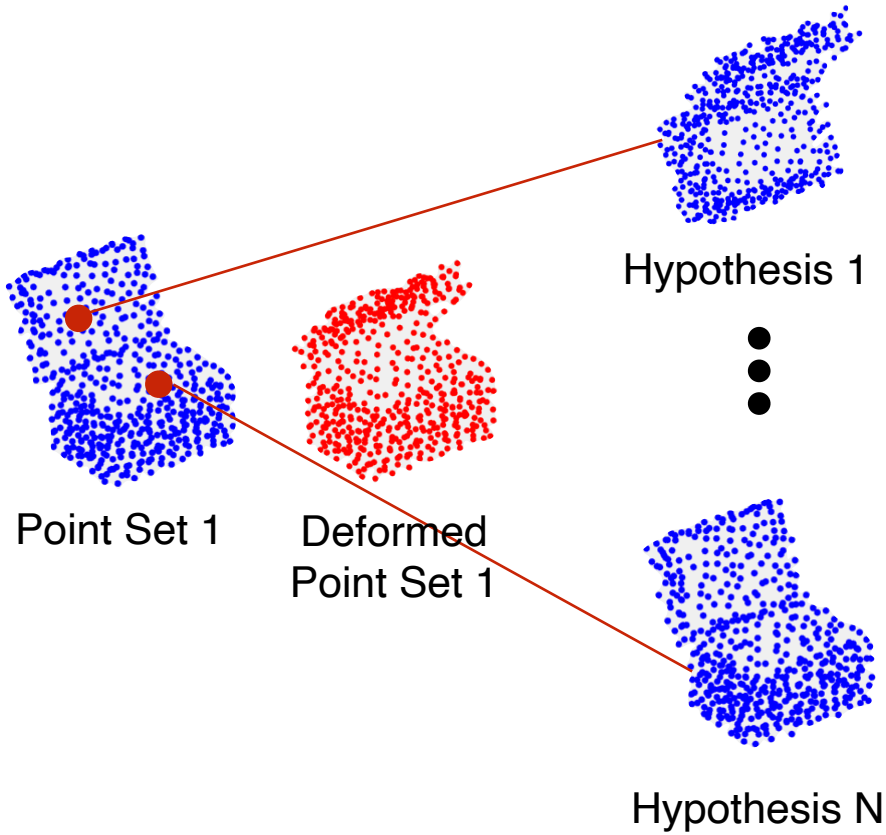
Segmentation Module

- A neural net-based differentiable sequential RANSAC
- Three steps:
  - Rigid motion hypothesis set generation
  - Support prediction for each rigid motion hypothesis
  - Recurrent part segmentation neural network

Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Rigid Motion Hypotheses Generation

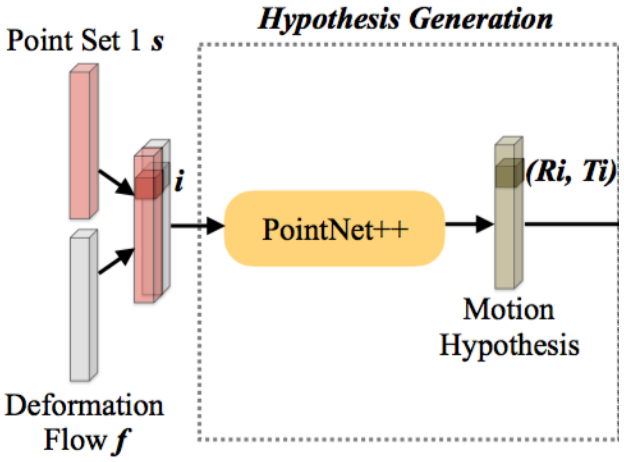
- Rigid motion hypothesis set generation
  - Compute the motion hypothesis (R_i, T_i) for each point p_i

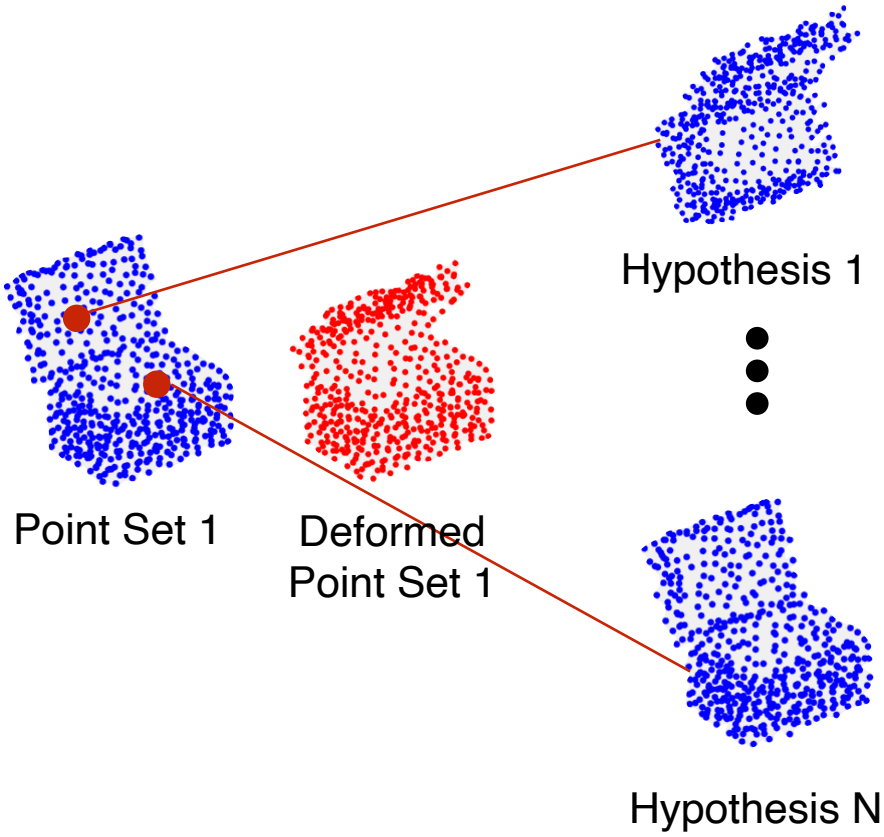


Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Rigid Motion Hypotheses Generation

- Rigid motion hypothesis set generation
  - Compute the motion hypothesis (R_i, T_i) for each point p_i

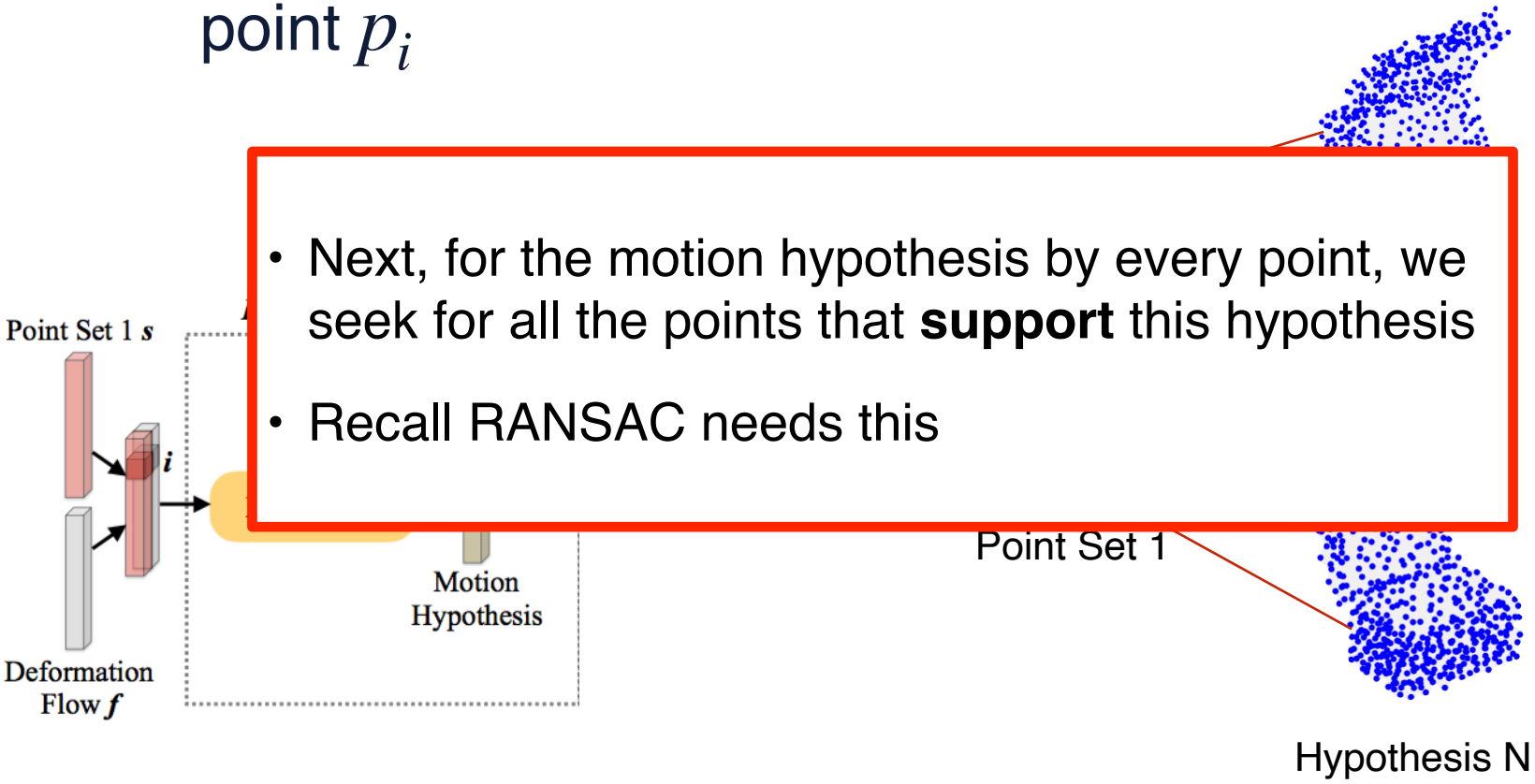




Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Rigid Motion Hypotheses Generation

- Rigid motion hypothesis set generation
  - Compute the motion hypothesis (R_i, T_i) for each point p_i



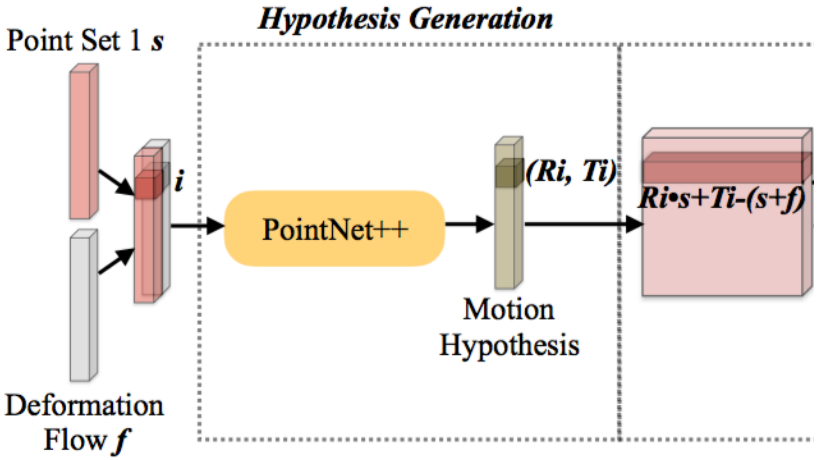
- Next, for the motion hypothesis by every point, we seek for all the points that **support** this hypothesis
- Recall RANSAC needs this

Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Build Error Matrix

- For each motion hypothesis (R_i, T_i), compute the difference between the transformed point set and the deformed point set with displacement f

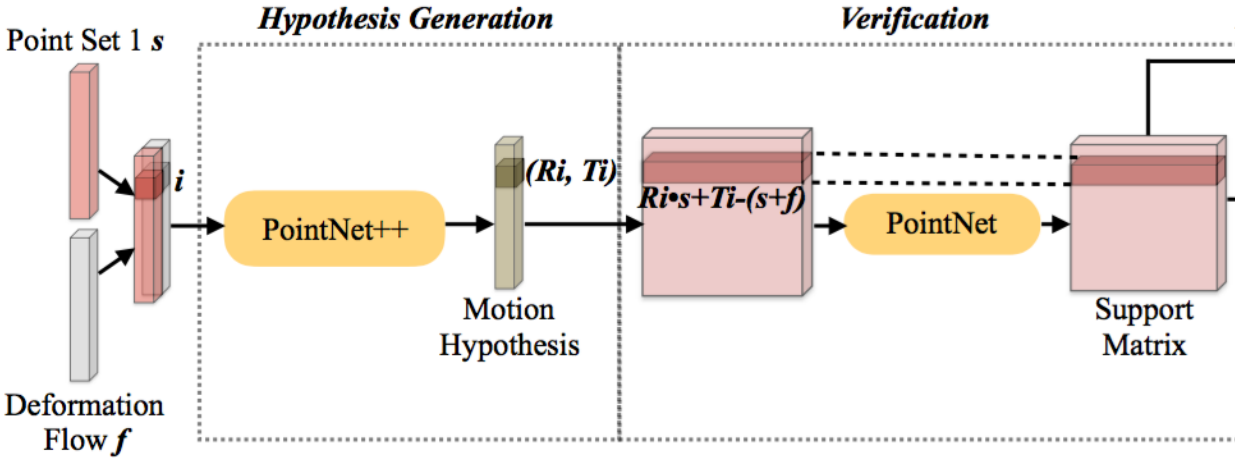
$$e_{i,j} = R_i p_j + T_i - (p_j + f_j)$$



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Support Prediction

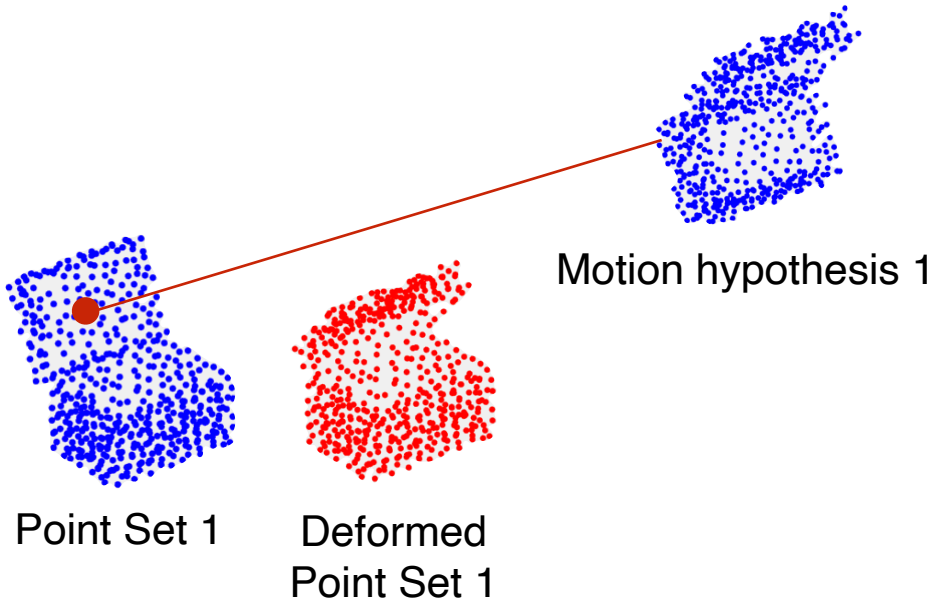
- Input: error matrix
- Output: support matrix
  - for each hypothesized rigid motion, the probability of every point under this rigid motion



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Support Prediction

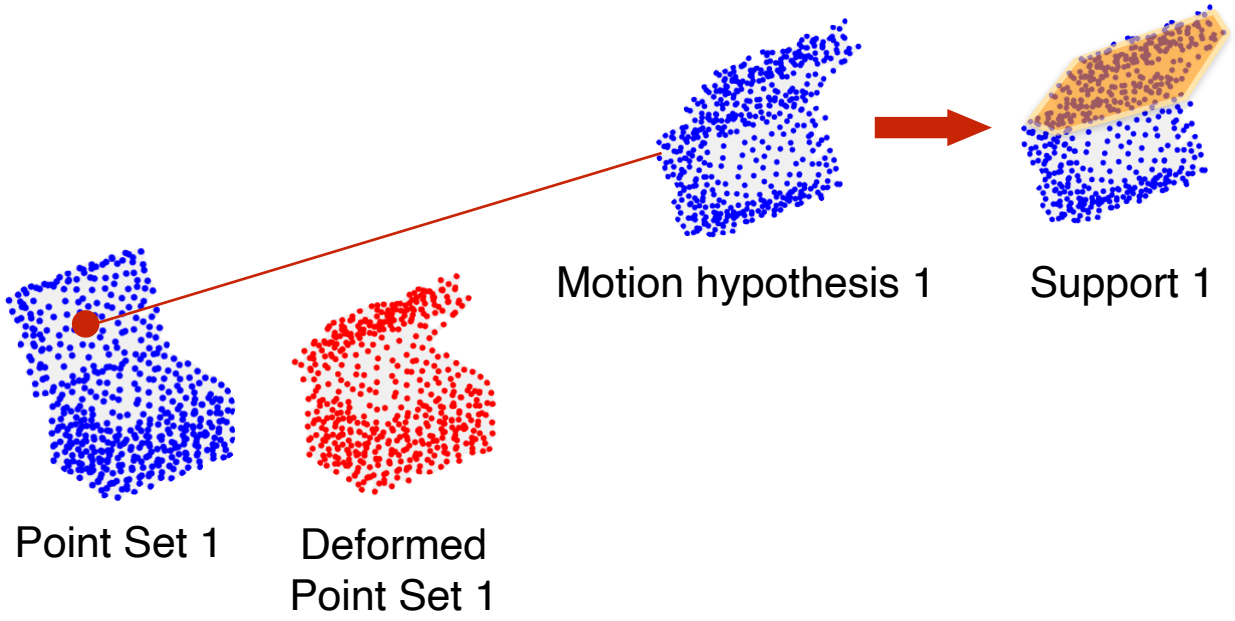
- Visualization



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Support Prediction

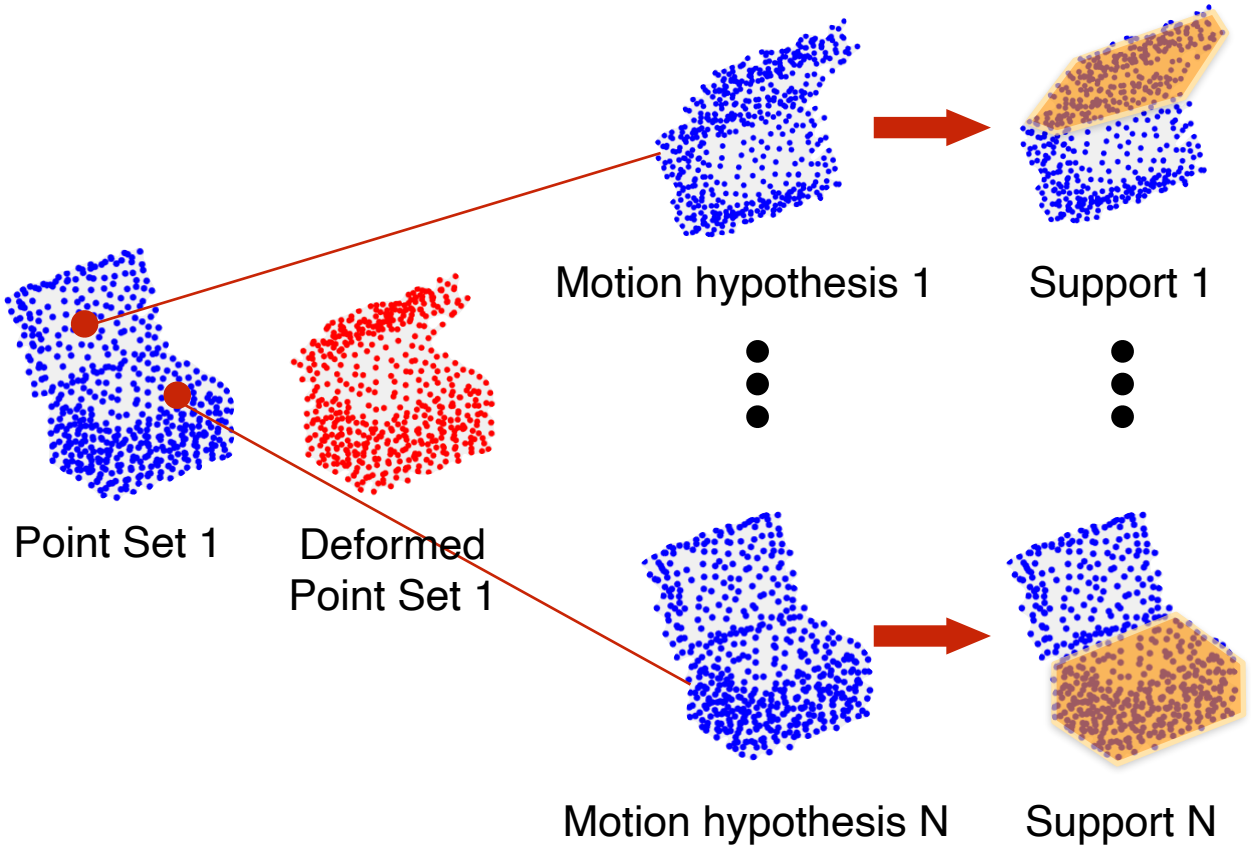
- Visualization



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Support Prediction

- Illustration



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

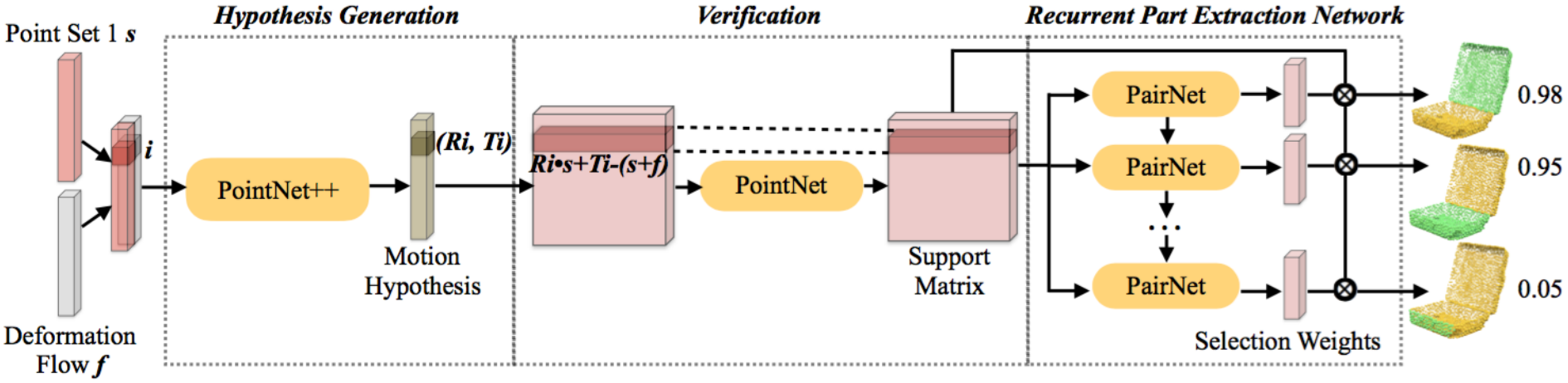
Part Segmentation from Support Prediction

- Support prediction gives points that conform to the same motion transformation
- Cluster support points of similar motion hypothesis into a group
- Use a weighted average of the supports, generating one segment.

Recurrent part segmentation network

Recurrent Part Segmentation Network

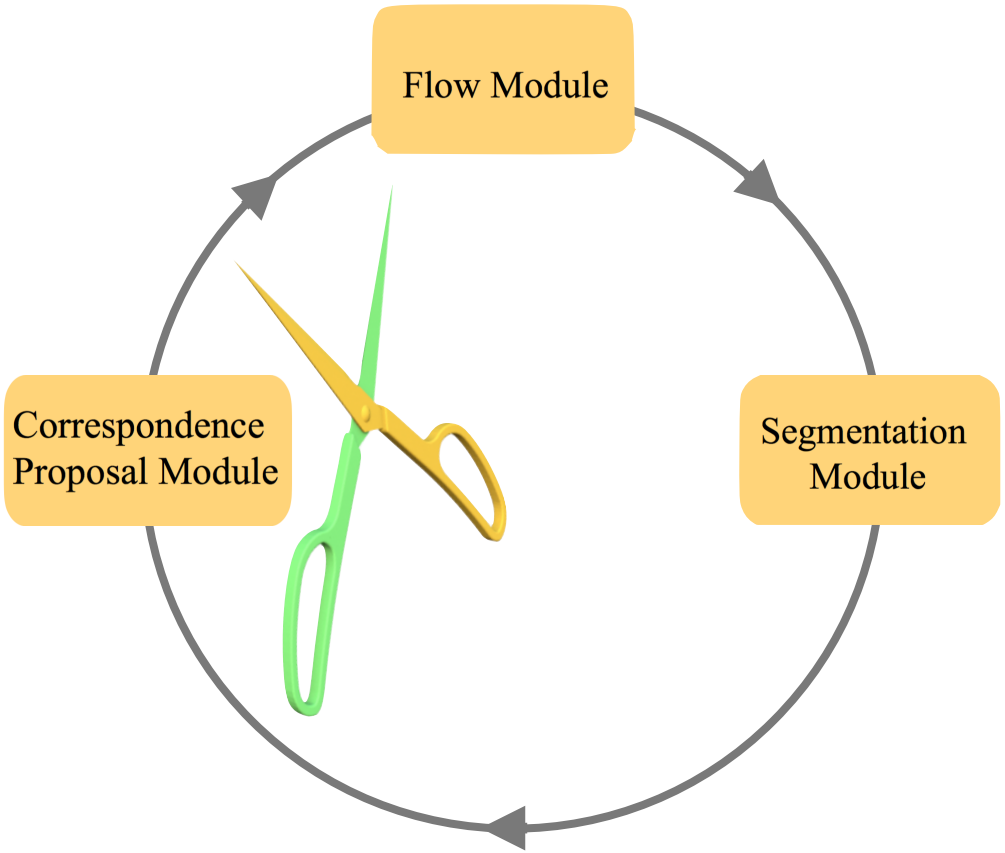
- Recurrent part segmentation neural network.
  - Spit a set of points (segmentation) with the same transformation
  - Adjust the internal hidden state to encode already spit regions



Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

Details omitted due to time constraints

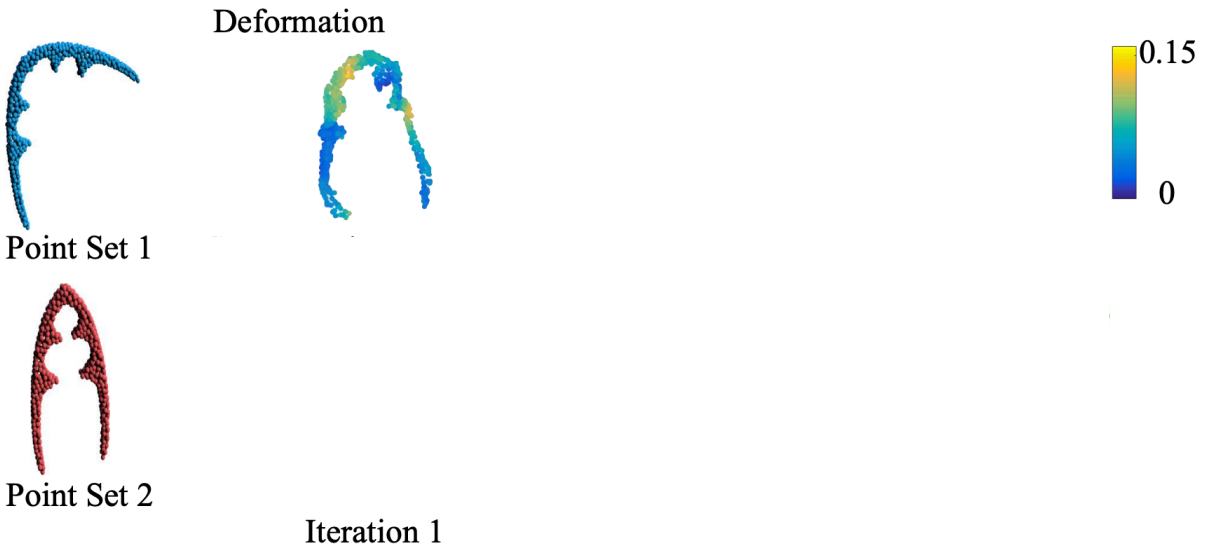
Iterative Mutual Reinforcement Procedure



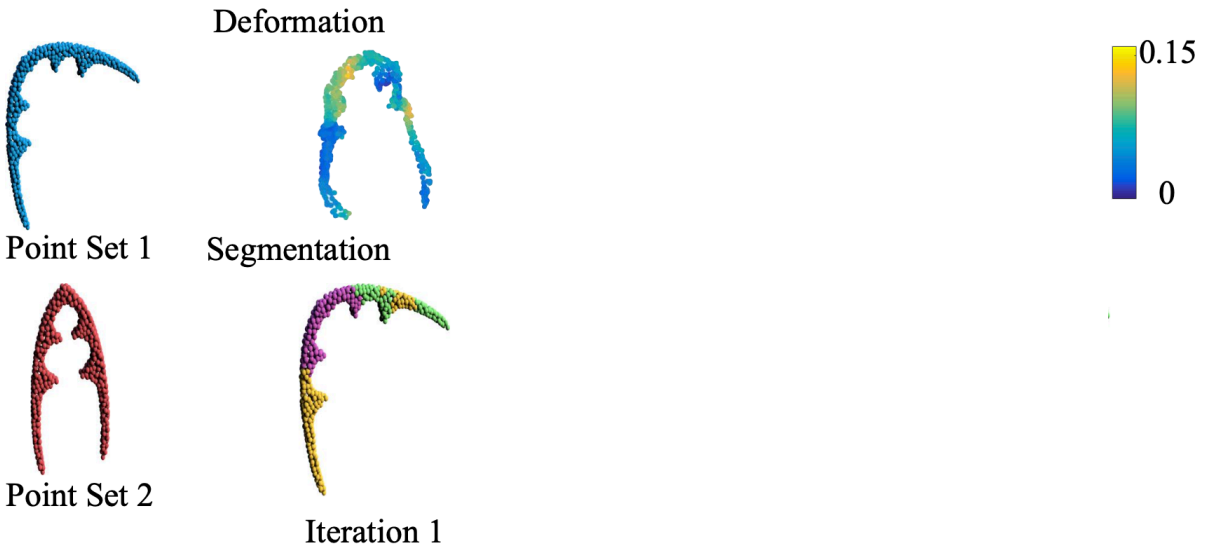
Segmentation mask helps to **restrict the possible regions** when estimating correspondences

Yi et al., "**Deep Part Induction from Articulated Object Pairs**", *SIGGRAPH Asia 2018*

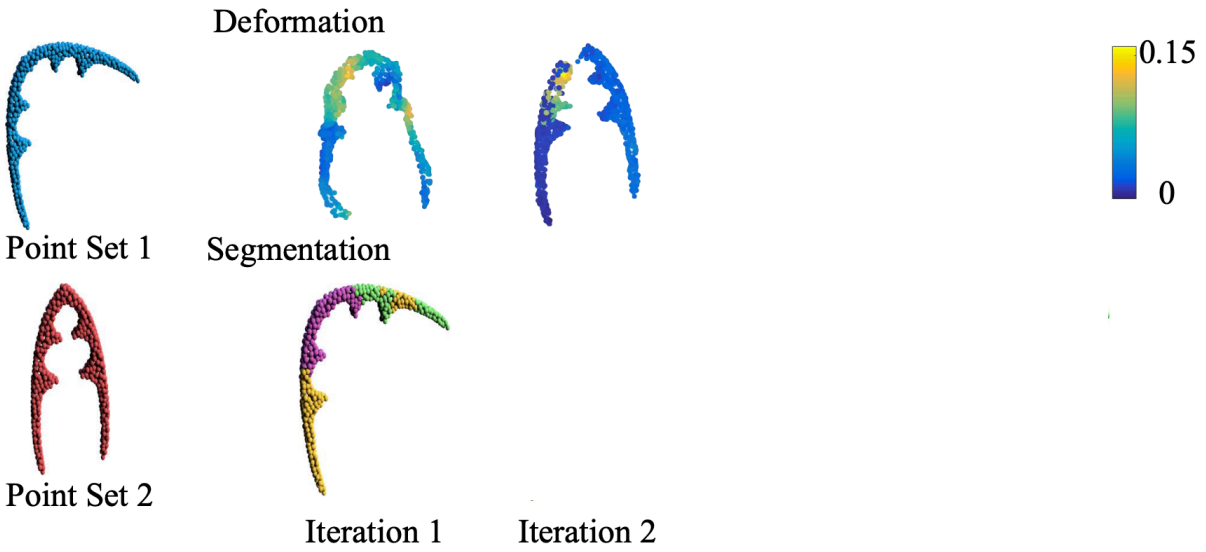
Iterative Mutual Reinforcement Procedure



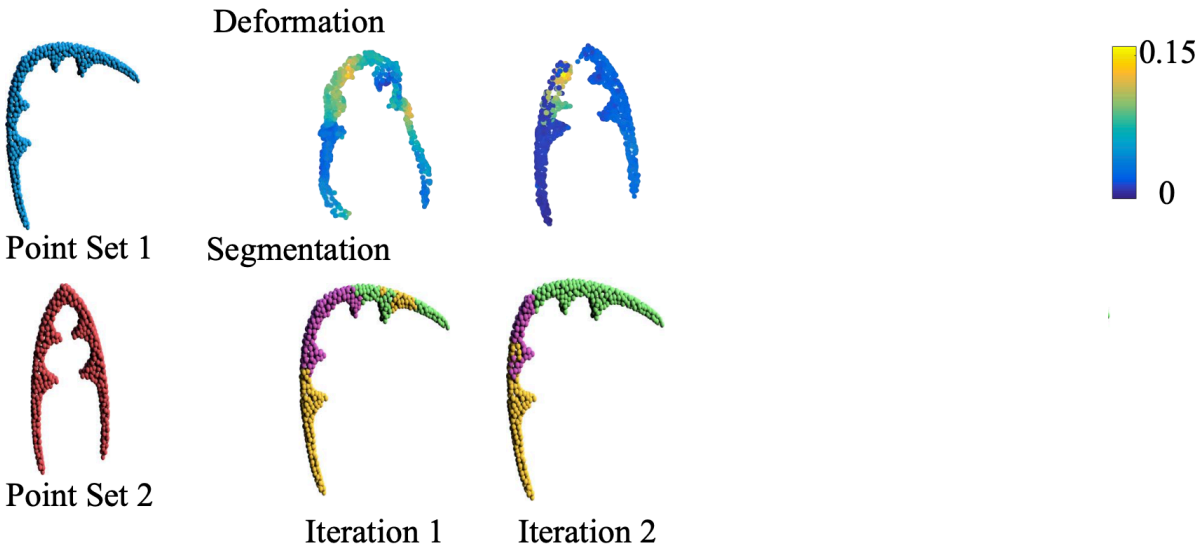
Iterative Mutual Reinforcement Procedure



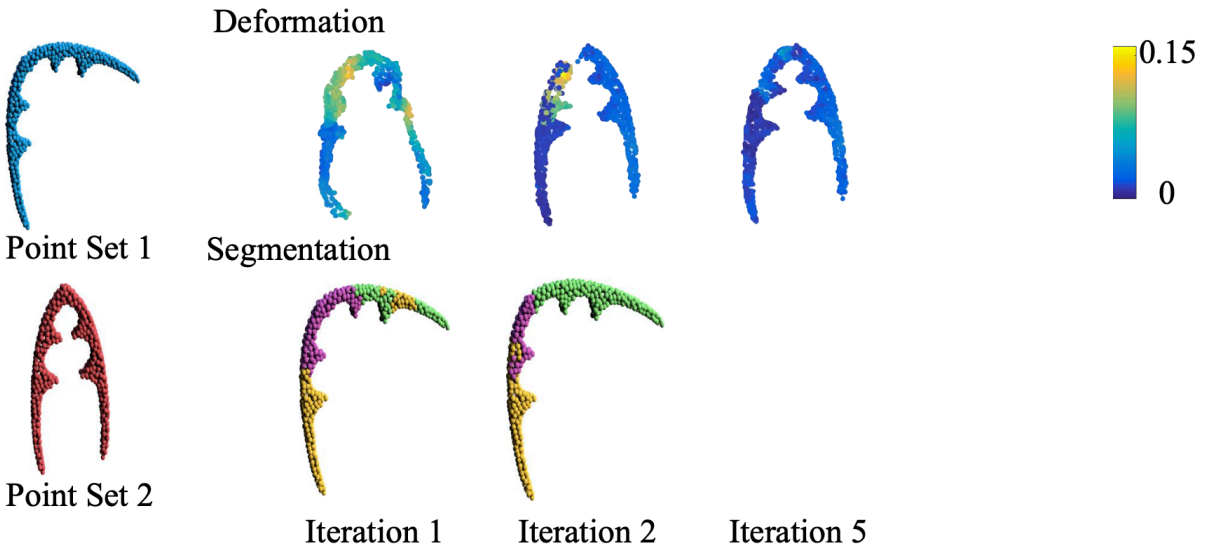
Iterative Mutual Reinforcement Procedure



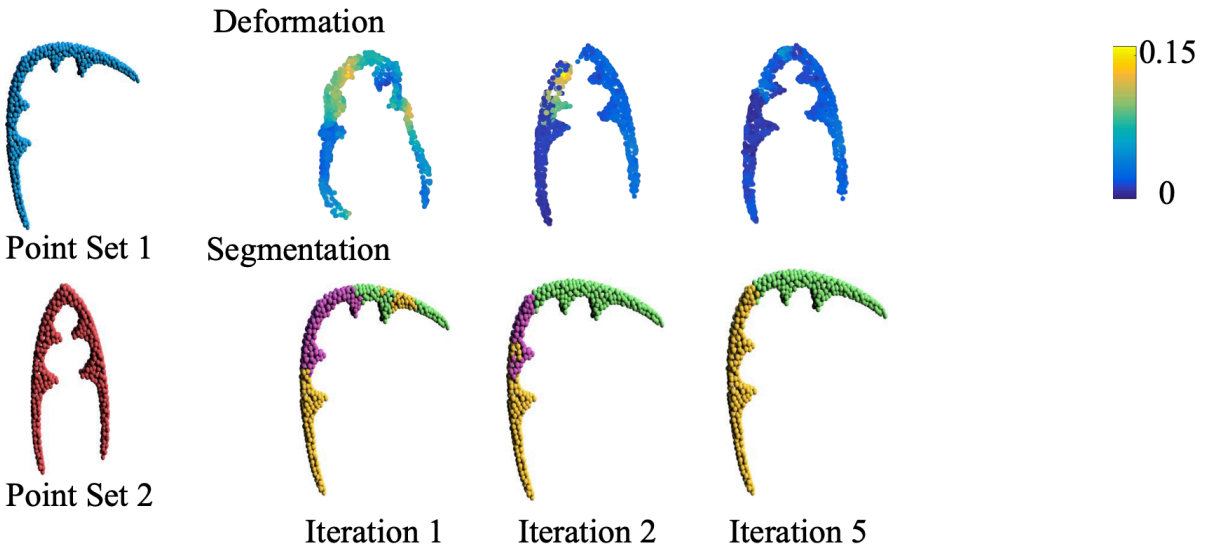
Iterative Mutual Reinforcement Procedure



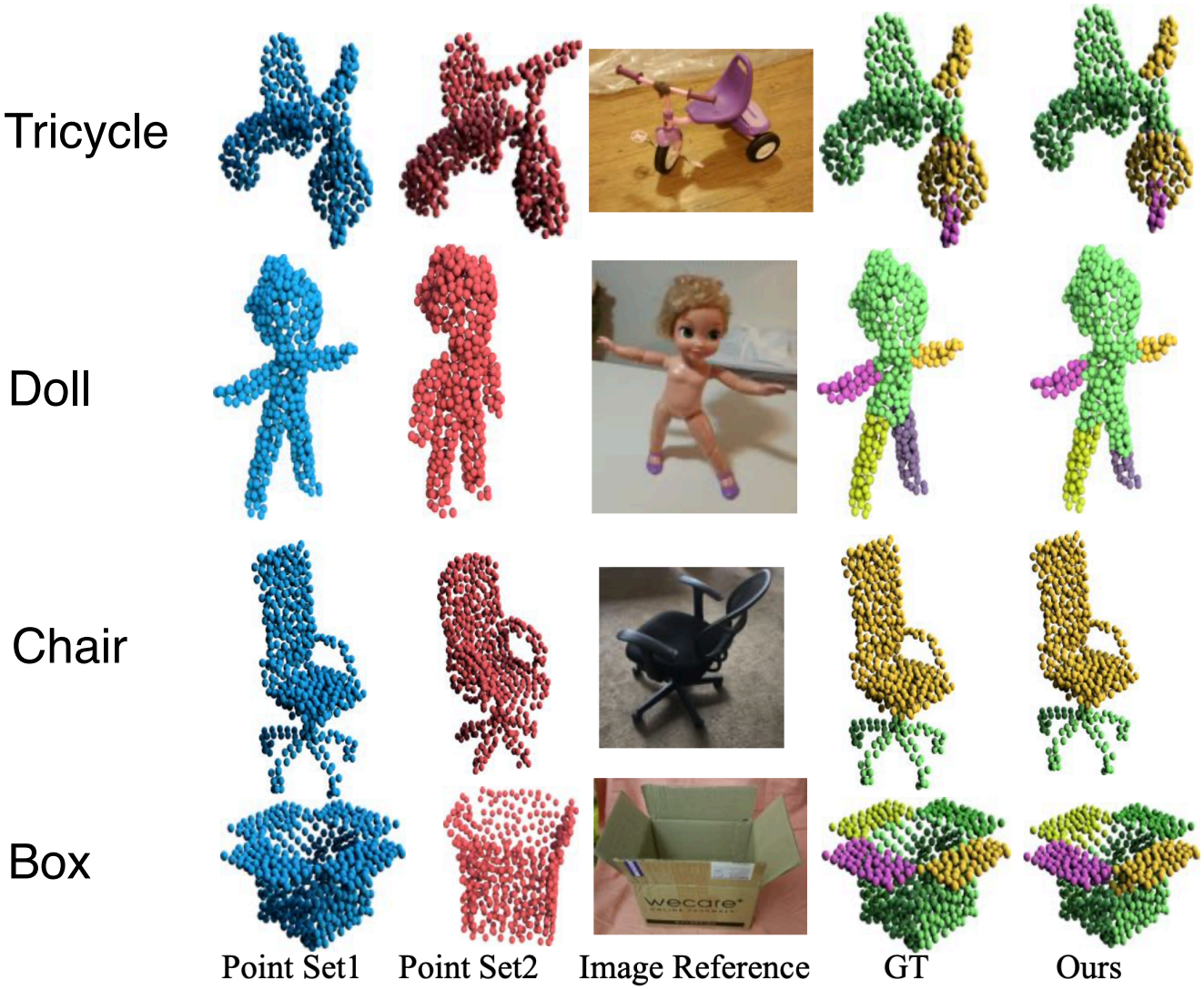
Iterative Mutual Reinforcement Procedure



Iterative Mutual Reinforcement Procedure



Segmentation Results on UnSeen Objects



Summary

- A **correspondence network** that predicts the matching probability, which can be applied to **object tracking**.

- A **flow network** that predicts the displacement between two point sets.

- A neural net-based **differentiable sequential RANSAC** which is a combination between algorithmic structure and learnable neural nets module.

Compositional Generalizability View of Zero-shot Part Segmentation *(read by yourself)*

Perspective: The World has Combinatorial Complexity

How to train a smart learner?

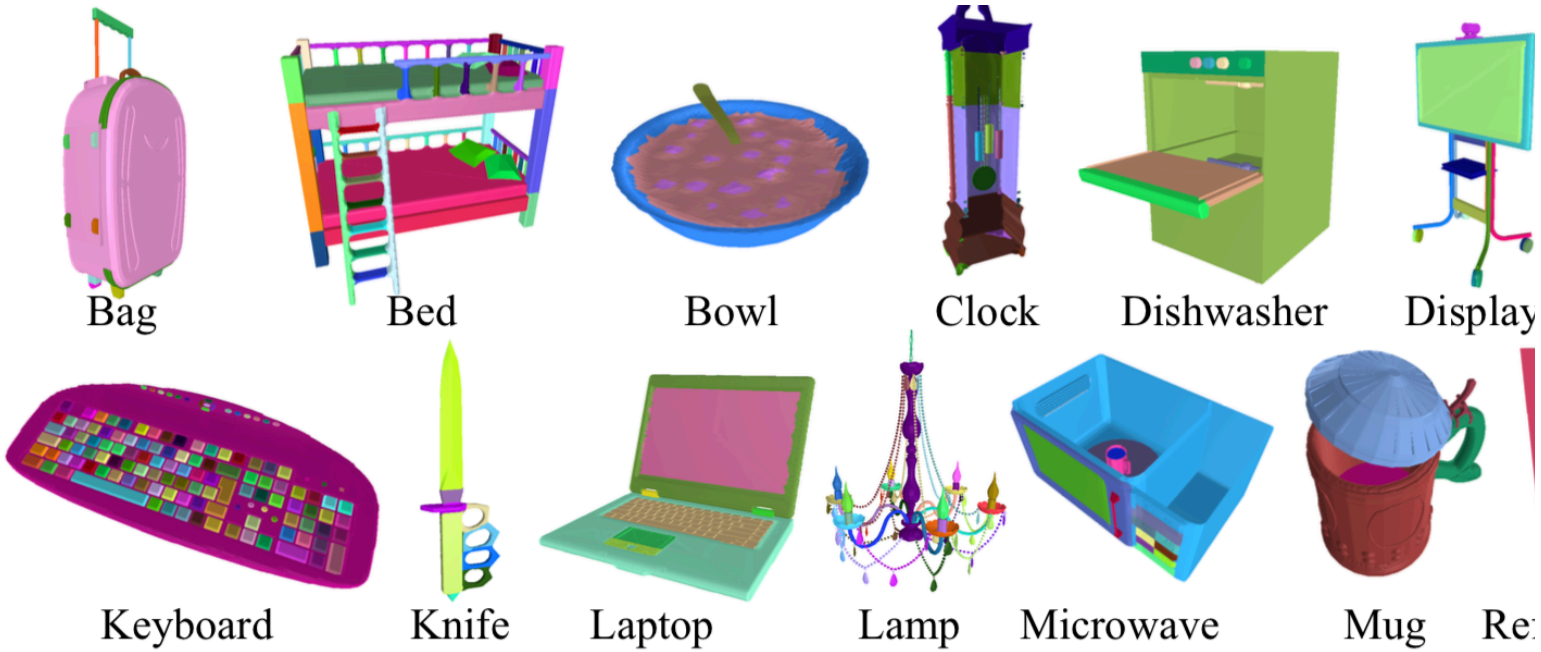
- However, human can learn unknown things from just a few examples .

- One character of human intelligence is **systematic compositionality**
  - the capacity to understand and produce a potentially infinite number of **novel combinations of known components**.

(Chomsky, Montague, Fodor, Marcus, Pinker, etc.)

PartNet Database

573,585 part instances over **26,671** 3D models covering **24** object categories

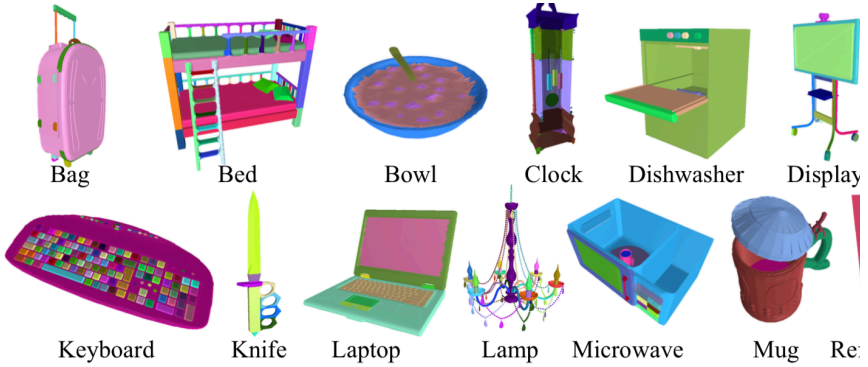


CVPR2019

Task: Zero-shot Part Segmentation

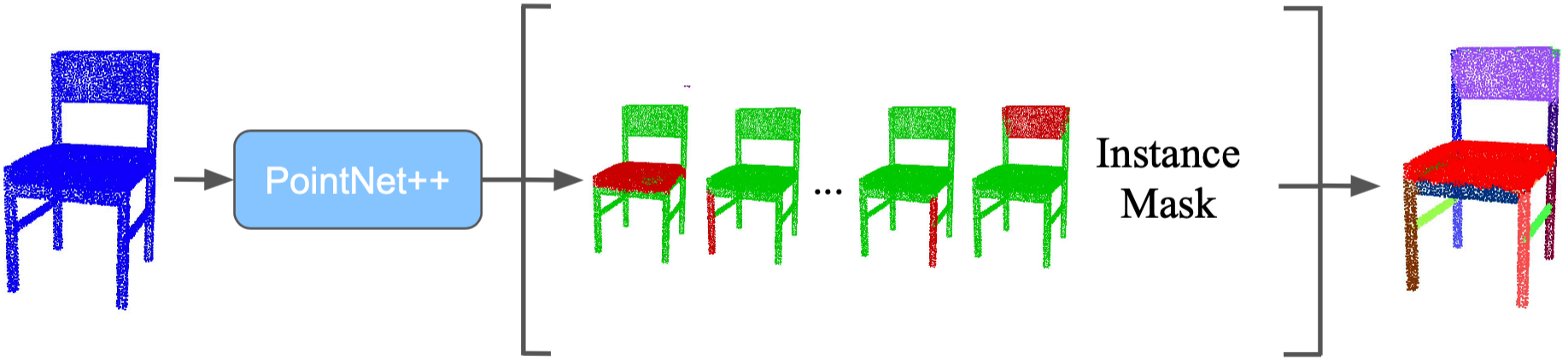
Train set
(Chair only)

Test set
(New categories)



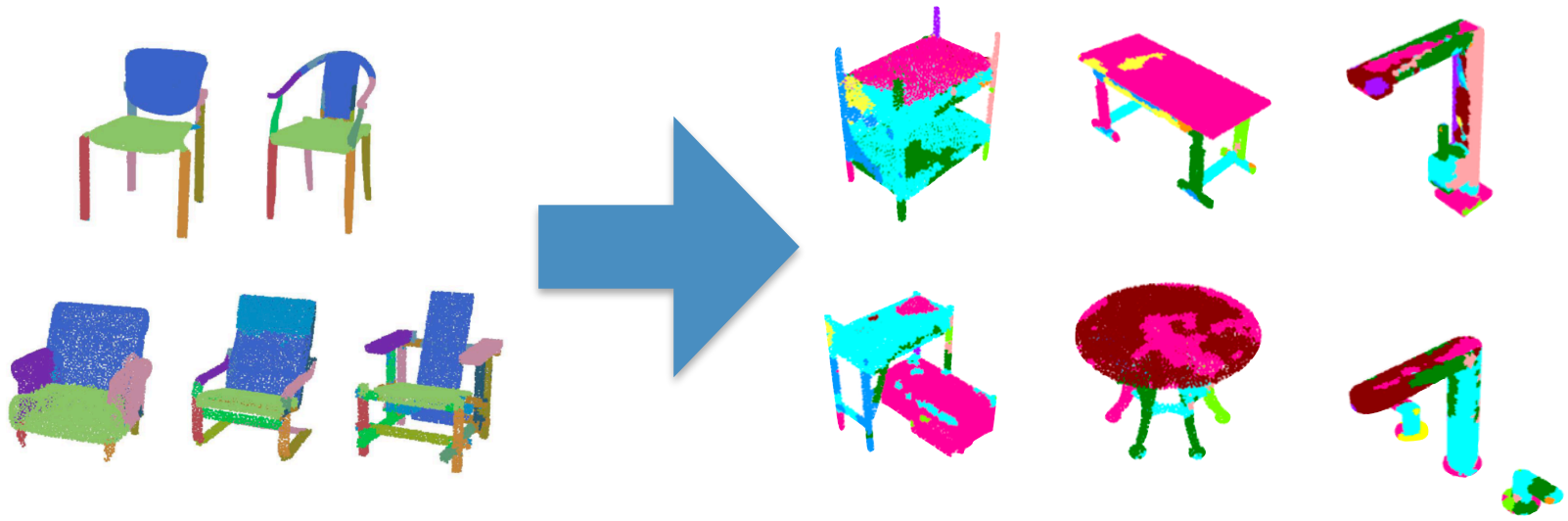
Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Literature: Top-down Segmentation Pipeline



Literature: Top-down Segmentation Pipeline

- Part segmentation



Training

Test: (Novel category)

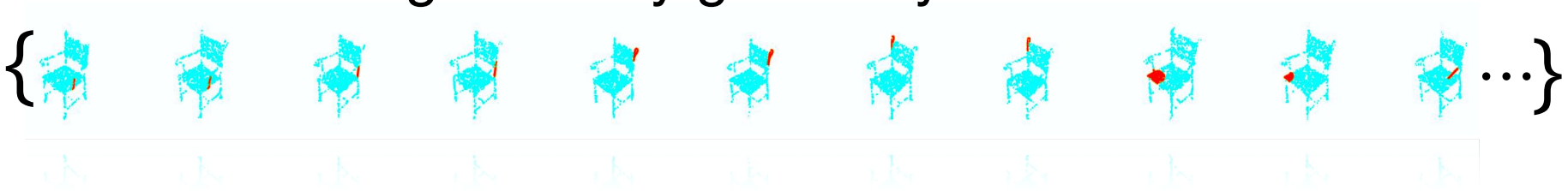
Fail to generalize to unseen categories due to the difference of global shapes

Learning to Group

- Design disciplines:
  - Restrict the field of view to local regions.
  - Bottom-to-up fashion. (Initial part segmentation)
  - A module to merge two parts at each time.

Basic Pipeline

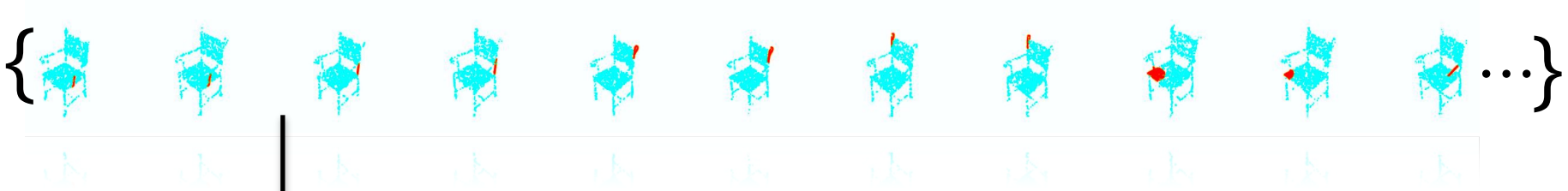
Cluster points into many small segments by geometry features



Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Basic Pipeline

Sub-Part Pool

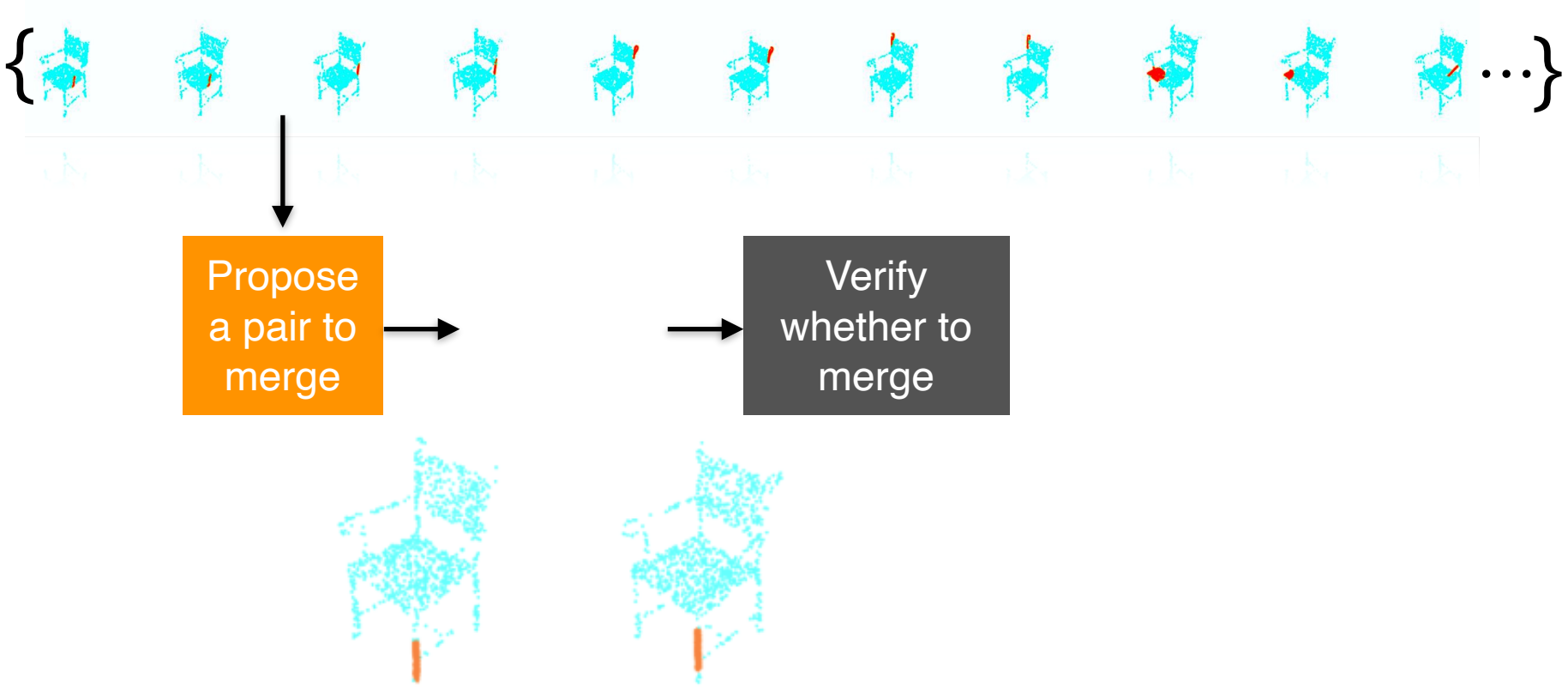


Propose a pair to merge

Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

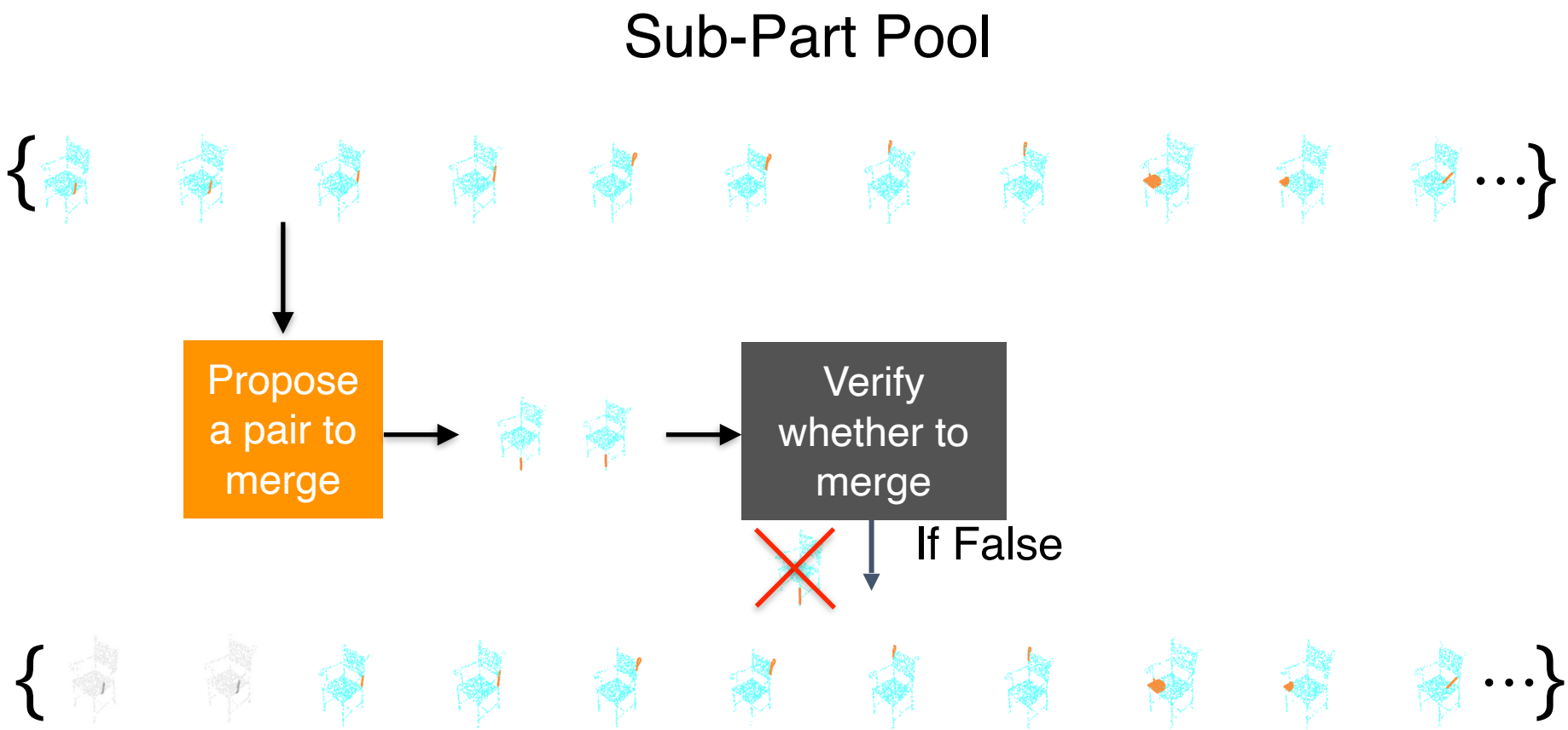
Basic Pipeline

Sub-Part Pool



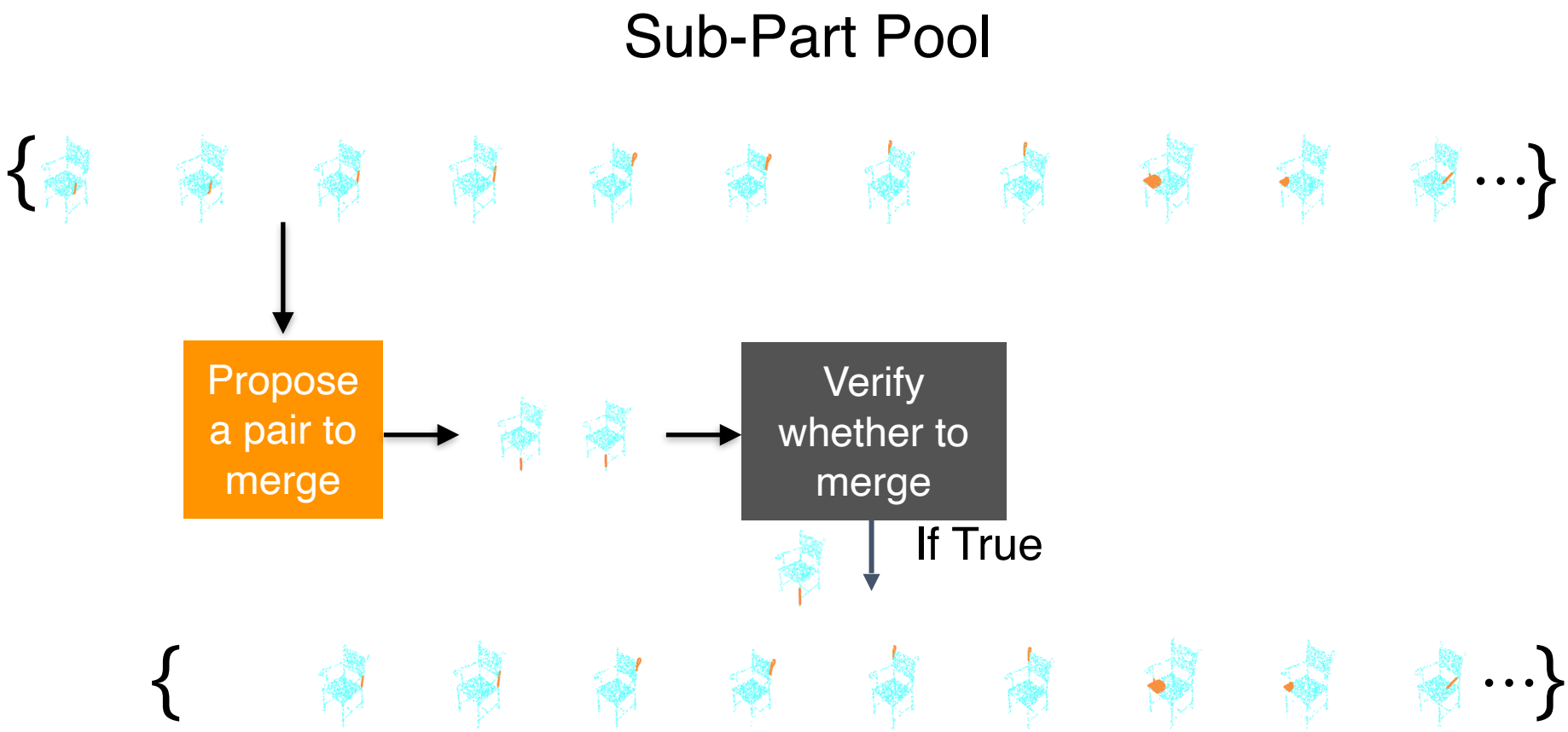
Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Learning to Group



Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Learning to Group



Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Learning to Group

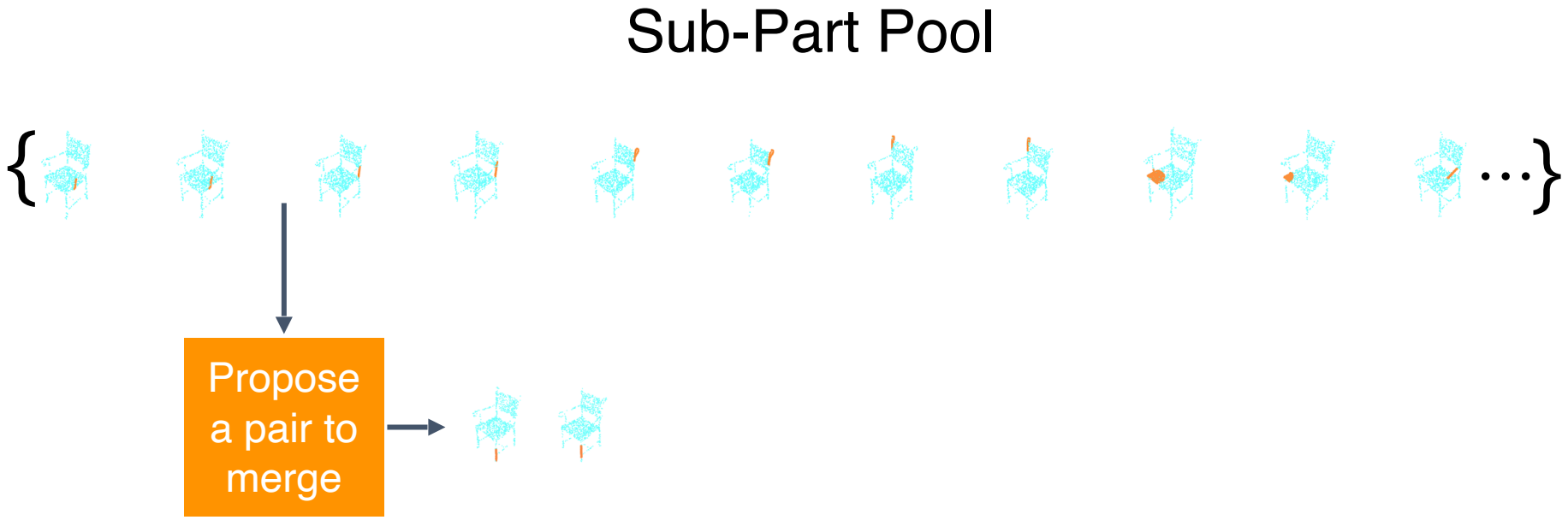
Sub-Part Pool

If all pairs verified to be false

Final

Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

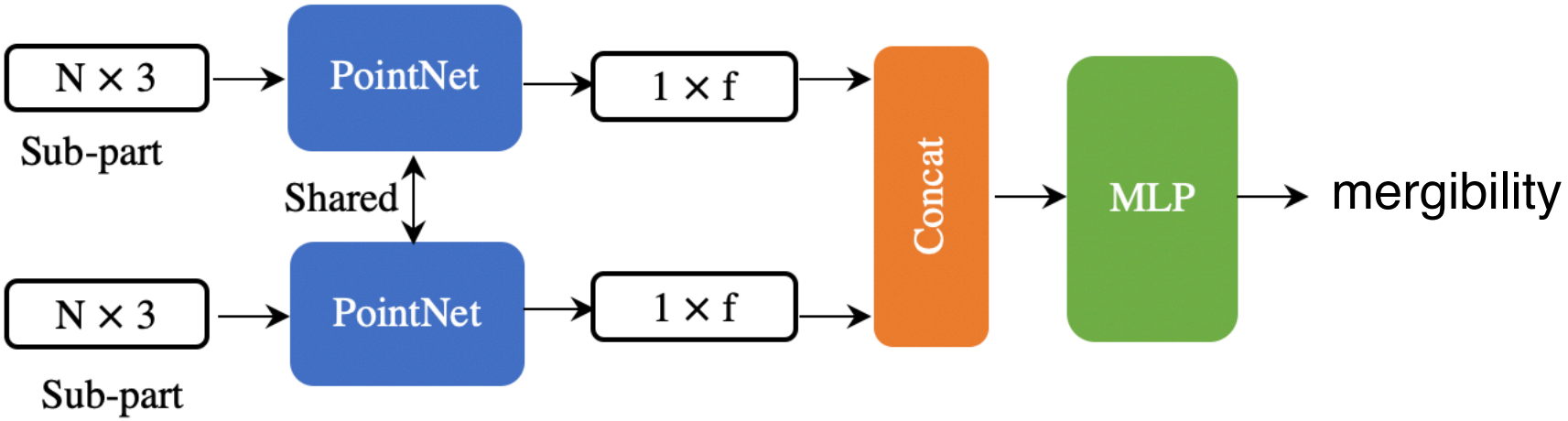
Details of Pair Proposals



Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Proposal Network

- Learn a network to predict the “mergibility”
- Architecture:



Training: RL Framework

- How to learn the proposal network?
- Proposal: about decisions of which parts to merge
- We are seeking to learn a “policy” network — Reinforcement learning!

Proposal Network as a Policy

- In the language of RL, a policy is denoted as a distribution π over possible actions $\mathscr{P}$. You can use the policy to sample an action:

$$a \sim \pi(\cdot \mid \mathscr{P})$$

- For our problem, $\mathscr{P}$ includes all the pairs, and $a_i = (P_{i_1}, P_{i_2})$ is a specific pair

Reward Design

- To learn the proposal policy π, we still need to know whether a proposal is good or bad.

- Let $M(a)$ be the score of a pair (reward):
  - $M(a) = 1$ if
    - (P_{i_1}, P_{i_2}) has the same part label, and
    - merging (P_{i_1}, P_{i_2}) would create a subpart overlaps with some groundtruth part $\geq 80\,\%$
  - $M(a) = 0$ otherwise

Policy Gradient

- We learn π as a network by optimizing the following problem:

$$\underset{\pi}{\text{maximize}}\ \mathbb{E}_{a\sim\pi(\cdot|\mathscr{P})}[M(a)]$$

Read by yourself

Policy Gradient

- We learn π as a network by optimizing the following problem:

$$\underset{\pi}{\text{maximize}}\ \mathbb{E}_{a\sim\pi(\cdot|\mathscr{P})}[M(a)]$$

- Gradient descent to update policy network
  - Note that:

$$\nabla_\pi L = \nabla \mathbb{E}_{a\sim\pi(\cdot)} M(a) = \nabla \int \pi(a) M(a)$$

$$= \int \nabla \pi(a) M(a) = \int \pi(a) \frac{1}{\pi(a)} \nabla \pi(a) M(a)$$

$$\approx \frac{1}{n} \sum_{a_i} \frac{1}{\pi(a_i)} \nabla \pi(a_i) M(a_i) = \frac{1}{n} \sum_{a_i} \nabla \log \pi(a_i) M(a_i)$$

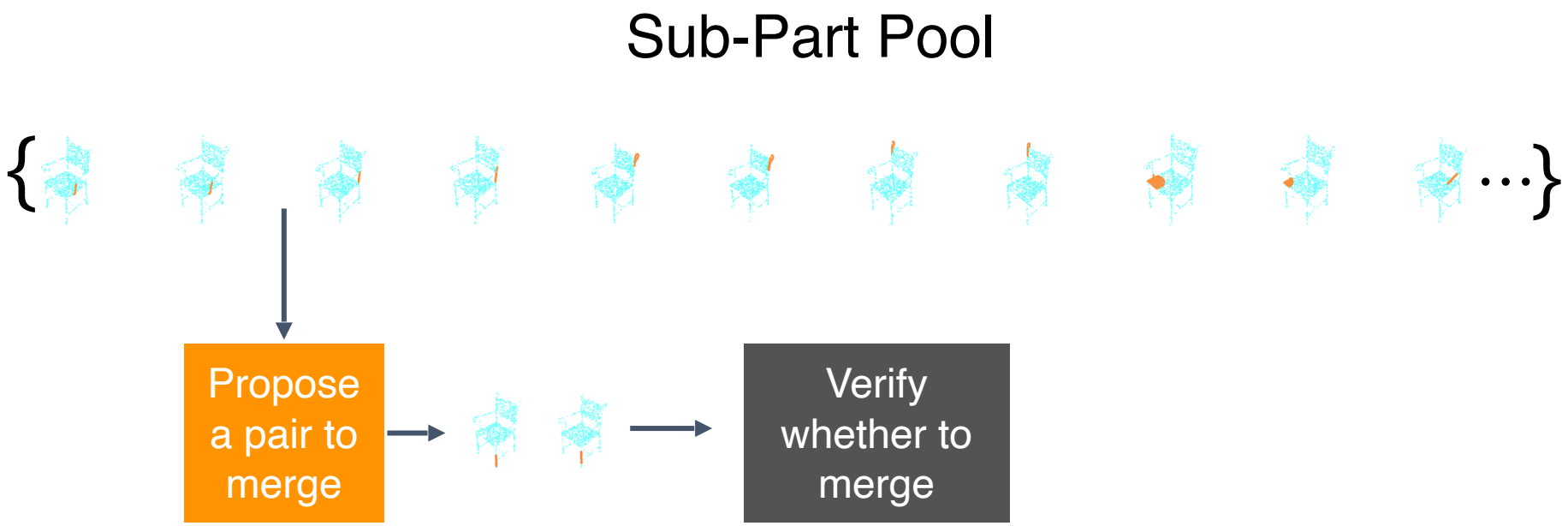
  - Network update by chain rule: $\nabla_\theta L = \nabla_\theta \pi \nabla_\pi L$

Read by yourself

Summary of Pair Proposal Training

- Proposal policy π to sample pairs of sub-parts to merge
- Reward M to sub-parts that belongs to the same part and have large overlap with ground-truth part
- Train the network by maximizing the expectation of reward

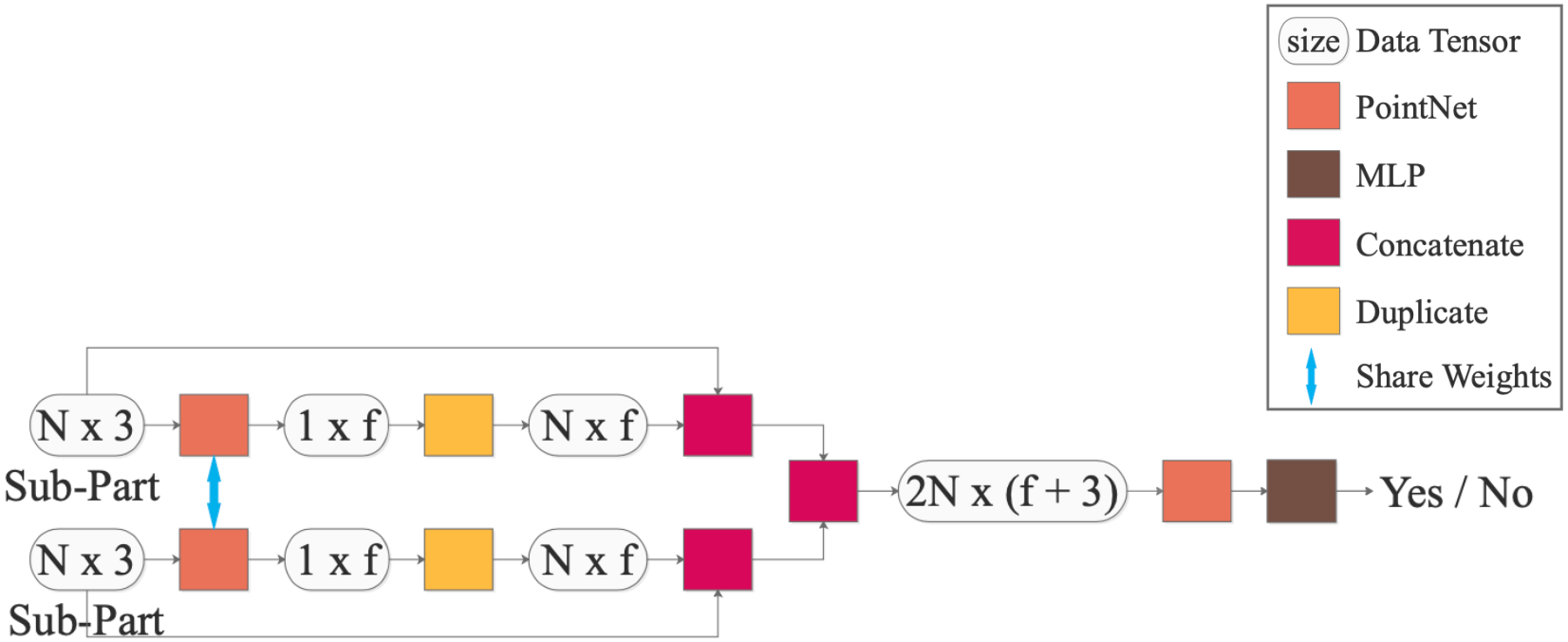
Details of Verification



Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

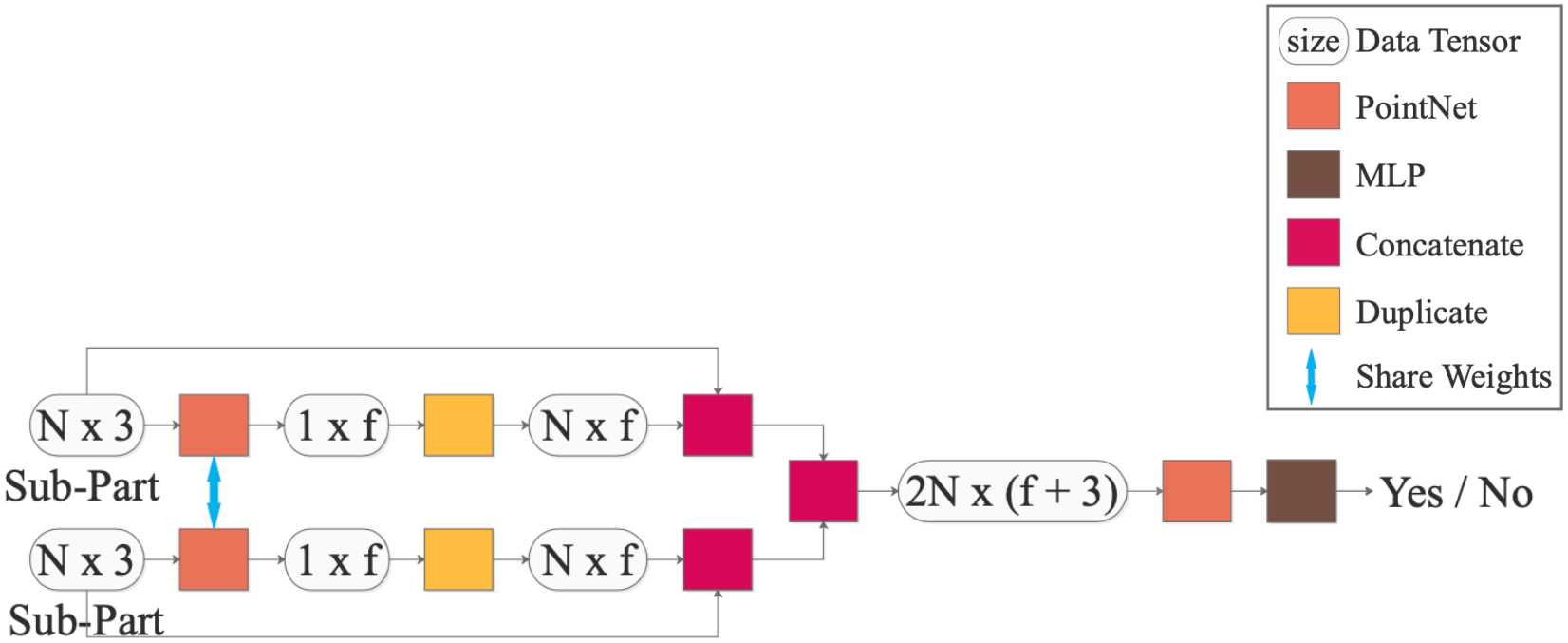
Network

- Verify whether the selected pair sub-parts should be merged or not.



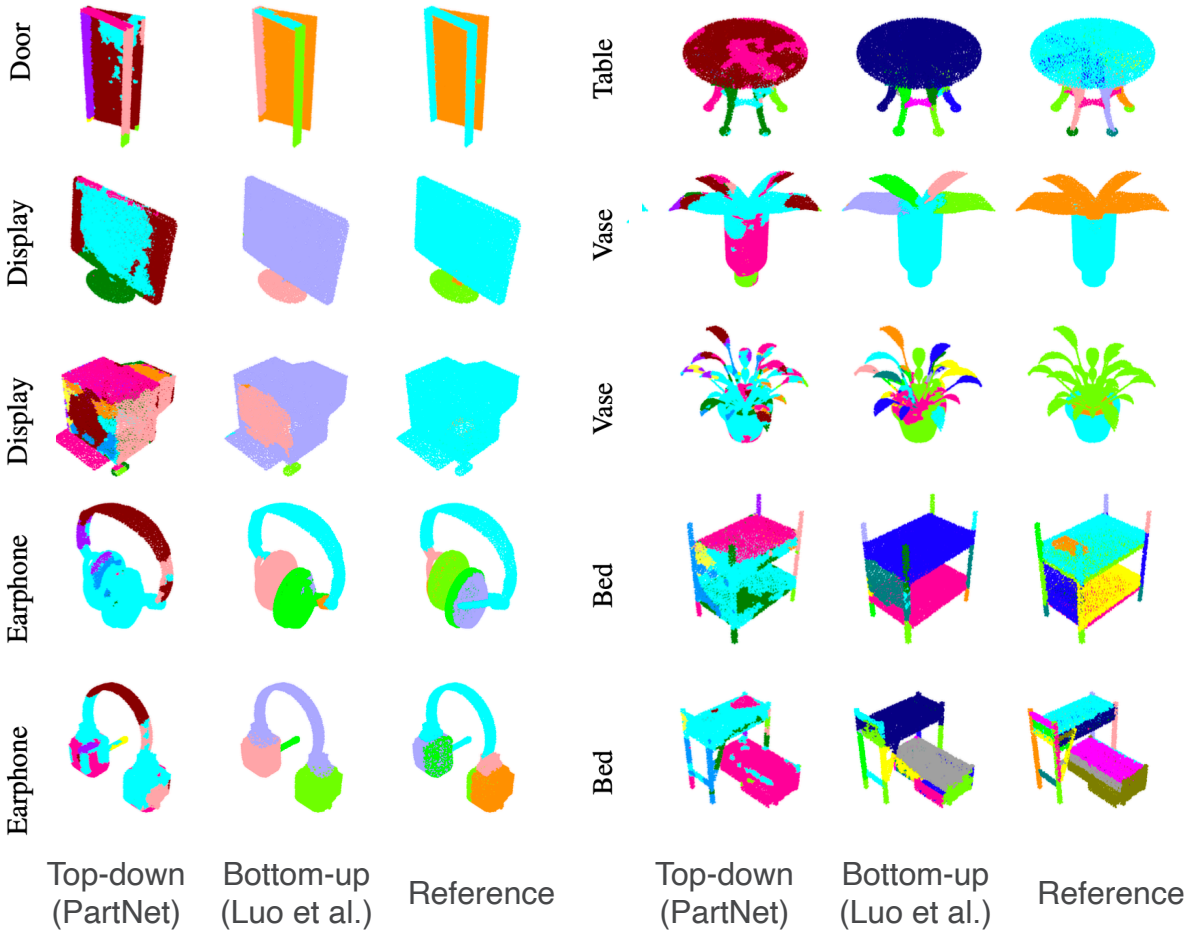
Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Training: Binary Classification



Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Results on Unseen Categories



Luo, Tiange, et al. **"Learning to Group: A Bottom-Up Framework for 3D Part Discovery in Unseen Categories."**, ICLR 2020.

Summary

- A **correspondence network** that predicts the matching probability between two point cloud in **Transformer** fashion.
- A neural net-based **differentiable sequential RANSAC** which is a combination between algorithmic structure and learnable neural nets module.
- A part discovery pipeline in **bottom-up** fashion.