Privacy Preserving Representations of 3D Point Clouds

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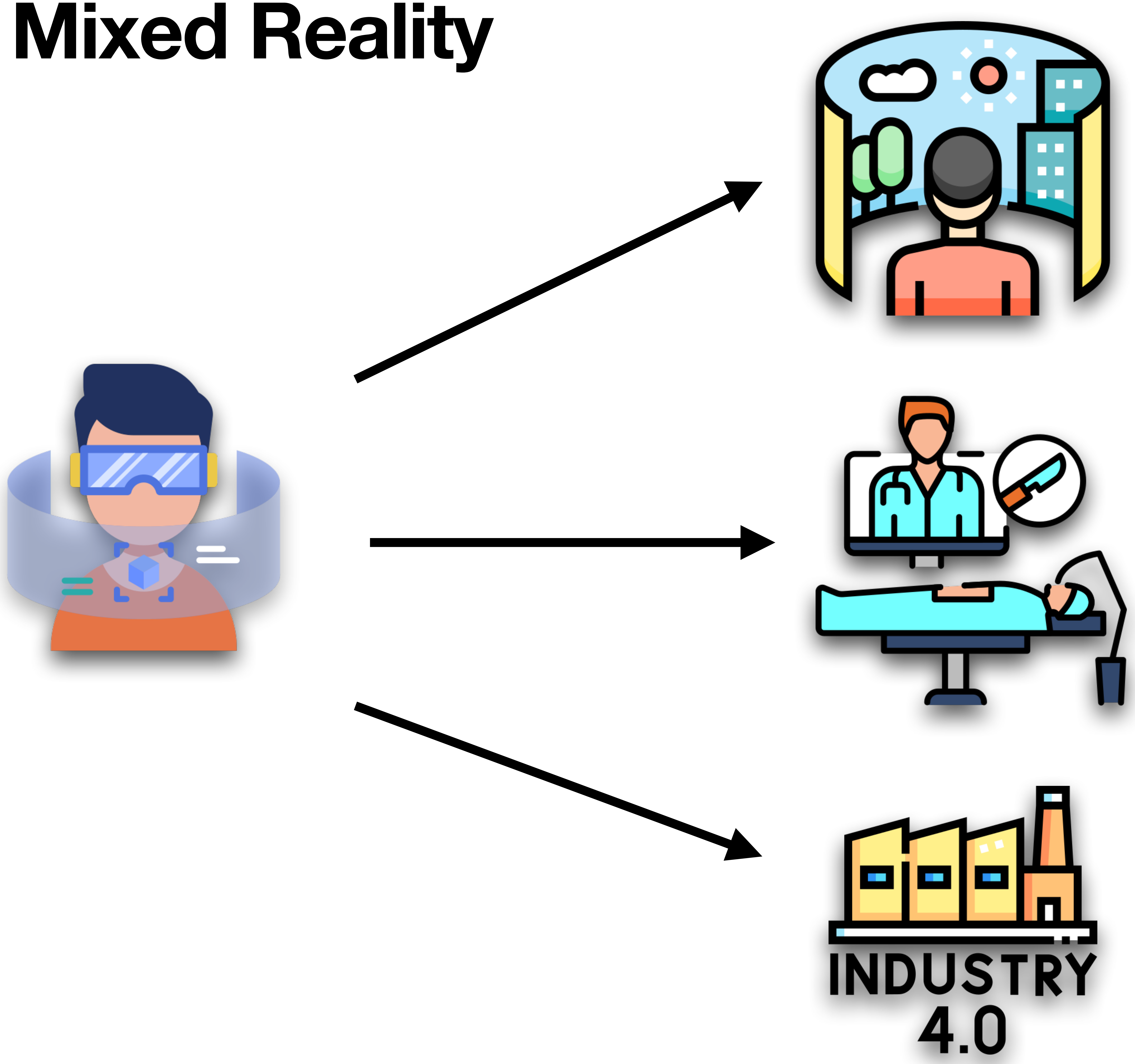
University of Sydney

Mixed Reality



FUTURE

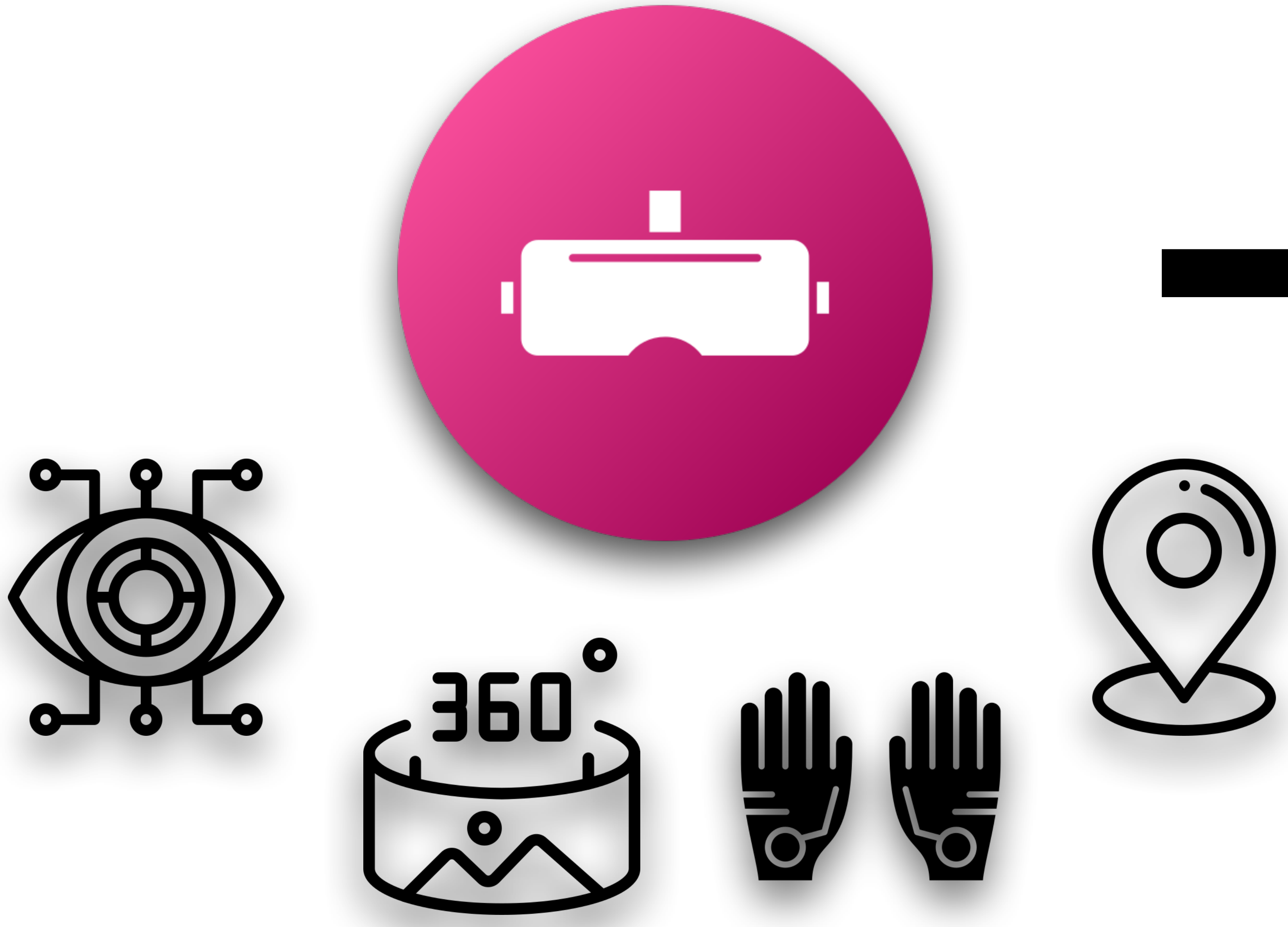
What if everyone wears MR glasses

everyday?

everywhere?

Mixed Reality : Spatial Data Privacy Risk

- Extract highly detailed 3D data with high accuracy



Multi camera visual sensing,
motion, hand gesture tracking……….

User space

Mixed Reality : Spatial Data Privacy Risk

- Sophisticated MR algorithms can infer knowledge about users

Wheelchair

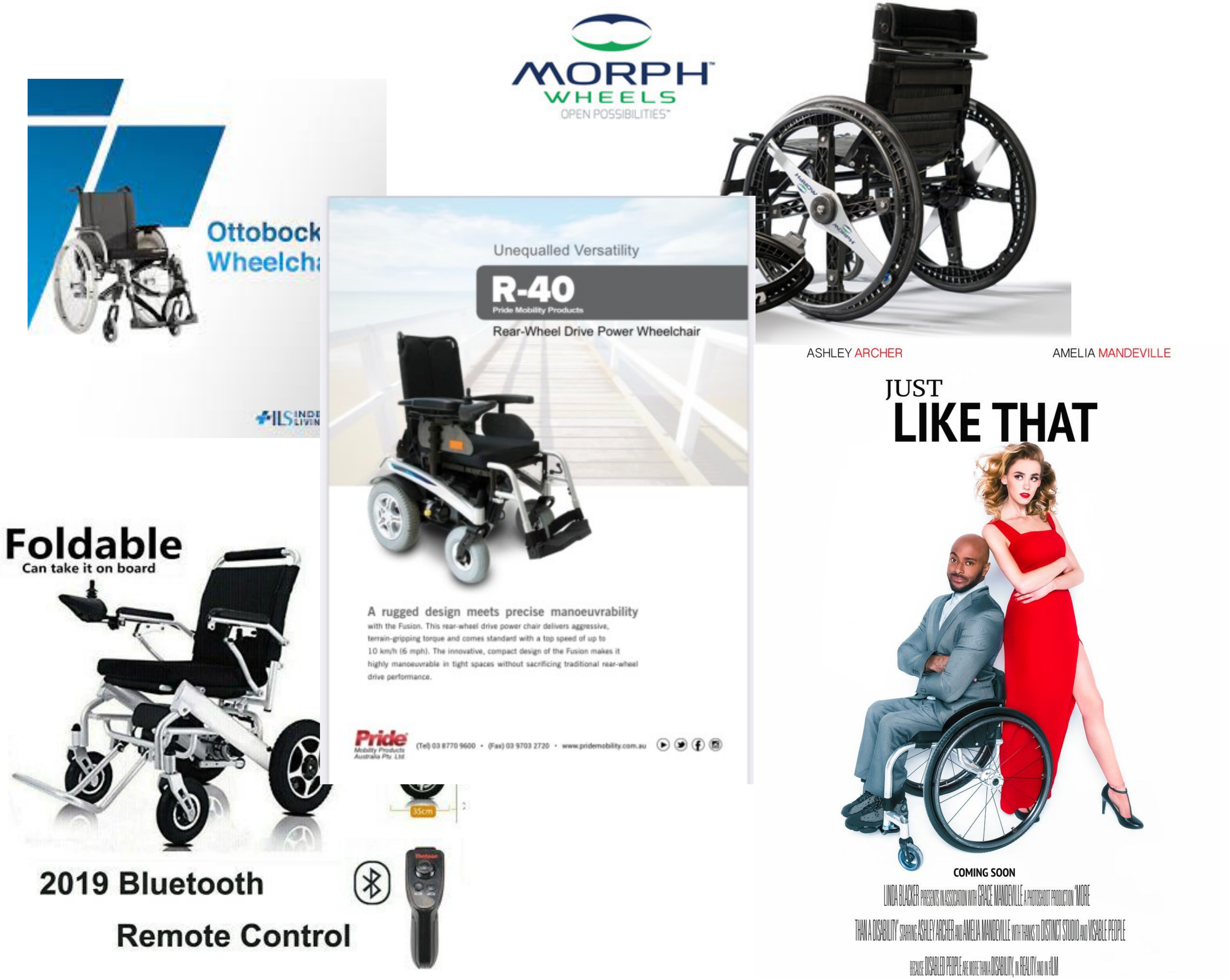
Inference :

There is a disabled person in this house

Mixed Reality : Spatial Data Privacy Risk

- Unintended manipulation of private details by third party applications

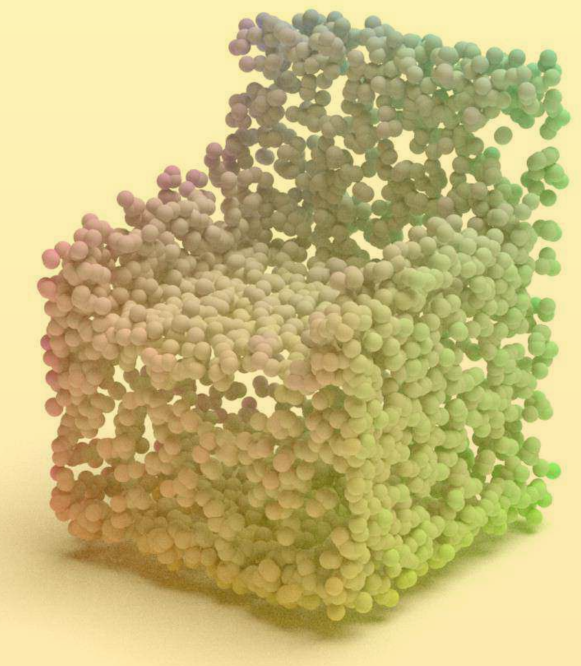
Advertisements



Mixed Reality : Spatial Data Privacy Risk

Privacy concerns

- Third parties
- Adversarial attackers



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Data breach

3D object/scene classification

Revealing location

Identifying movement/pose

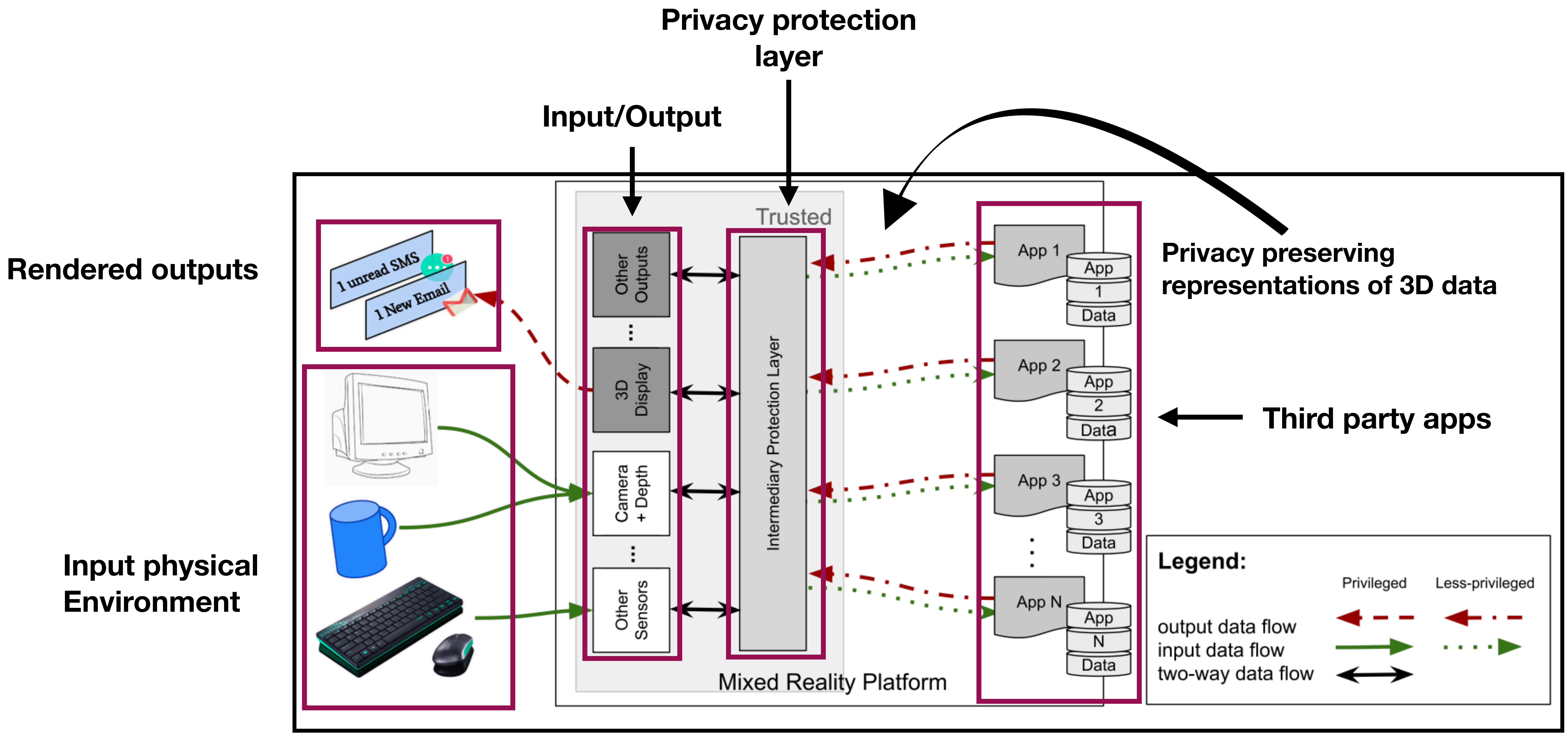
Aggressively targeted marketing

Security threats

Revealing personally identifiable information

Spatial Privacy in Mixed Reality : Literature Review

Privacy preserving framework

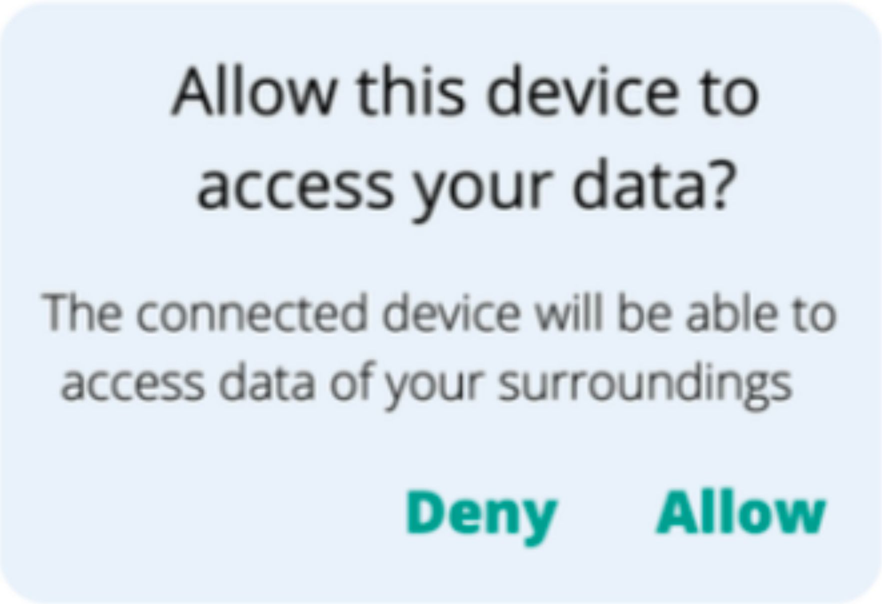


Introducing a protection layer to MR platform to hide sensitive information from 3D data before sending out for other third party applications. From Jaybie A. de Guzman, Kanchana Thilakarathna, and Aruna Seneviratne. 2019. Security and Privacy Approaches in Mixed Reality: A Literature Survey. ACM Comput. Surv. 52, 6, Article 110 (October 2019), 37 pages.

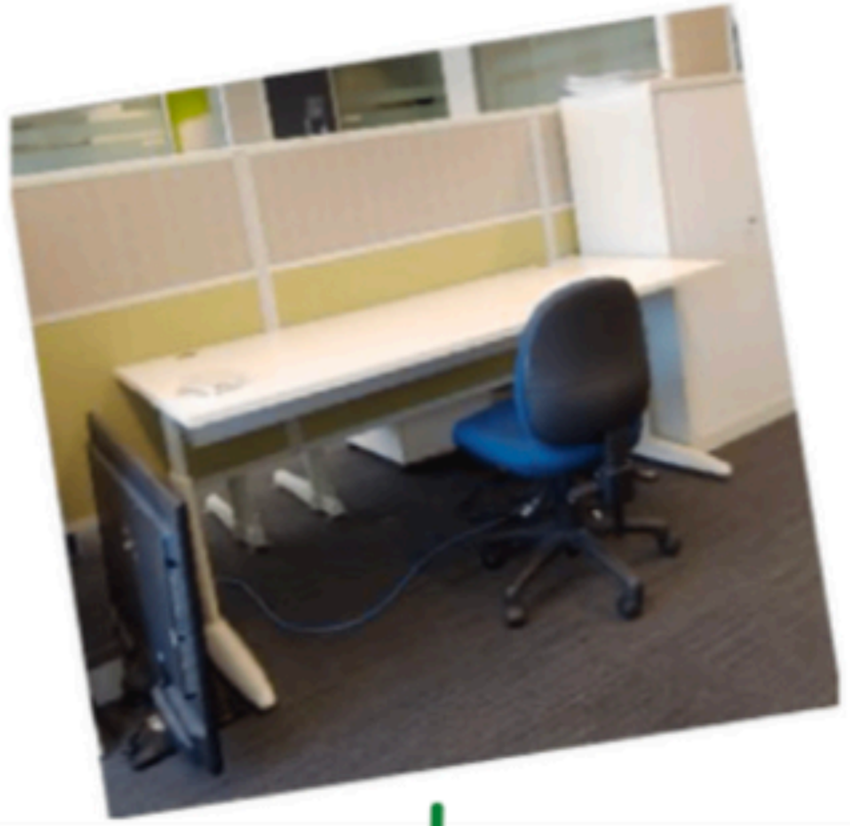
Privacy Preserving Transformations : Literature Review

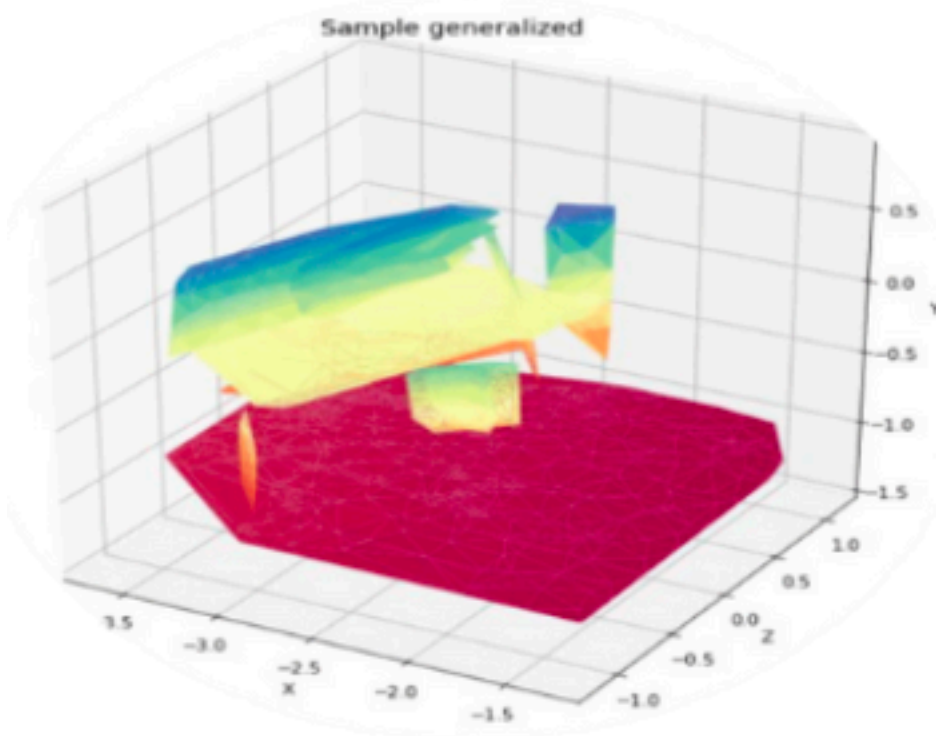
Input access controls

Allowing data release to applications

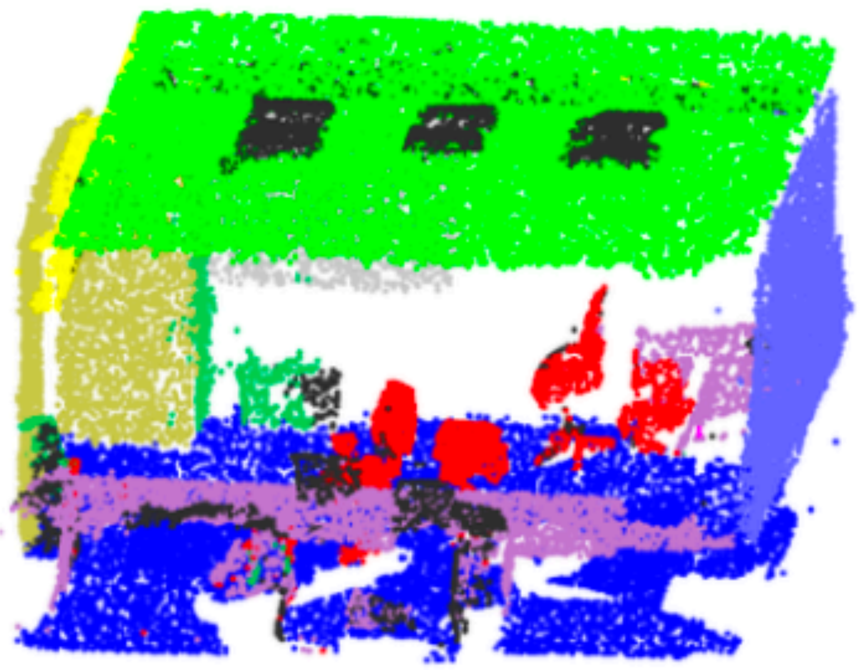


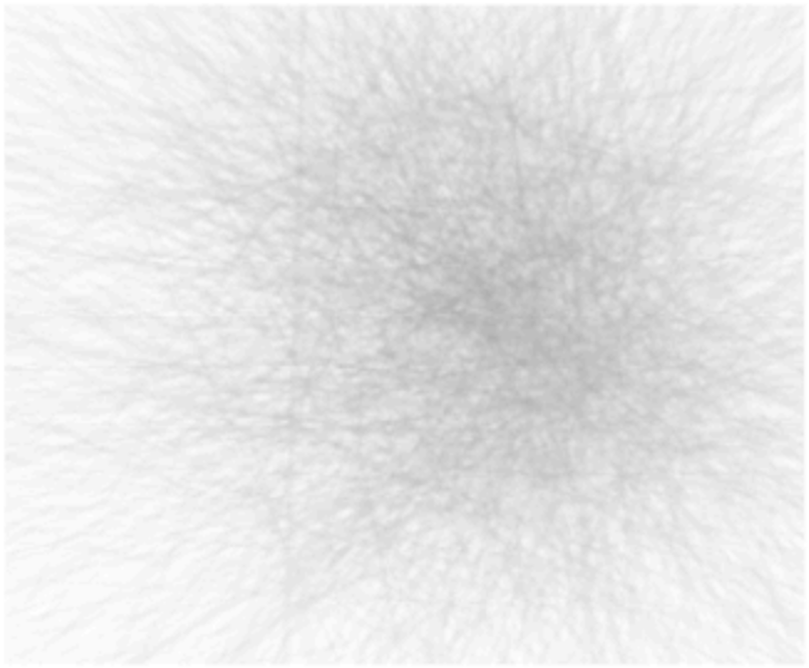
3D spaces to planes



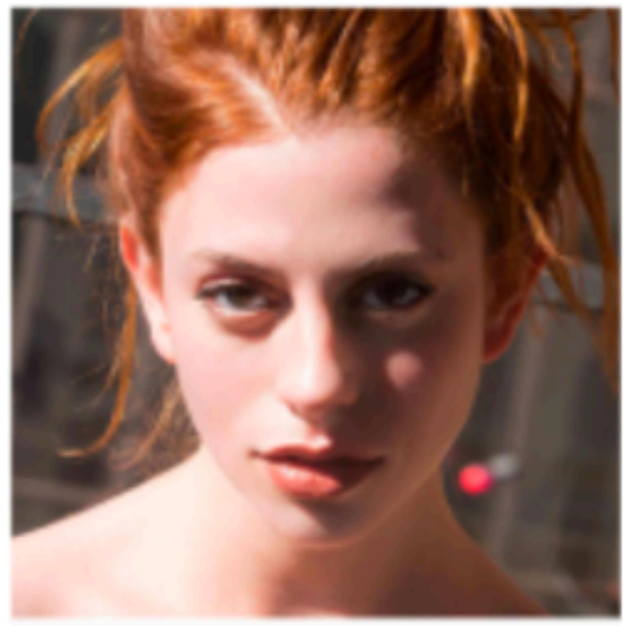


3D point clouds to Line clouds



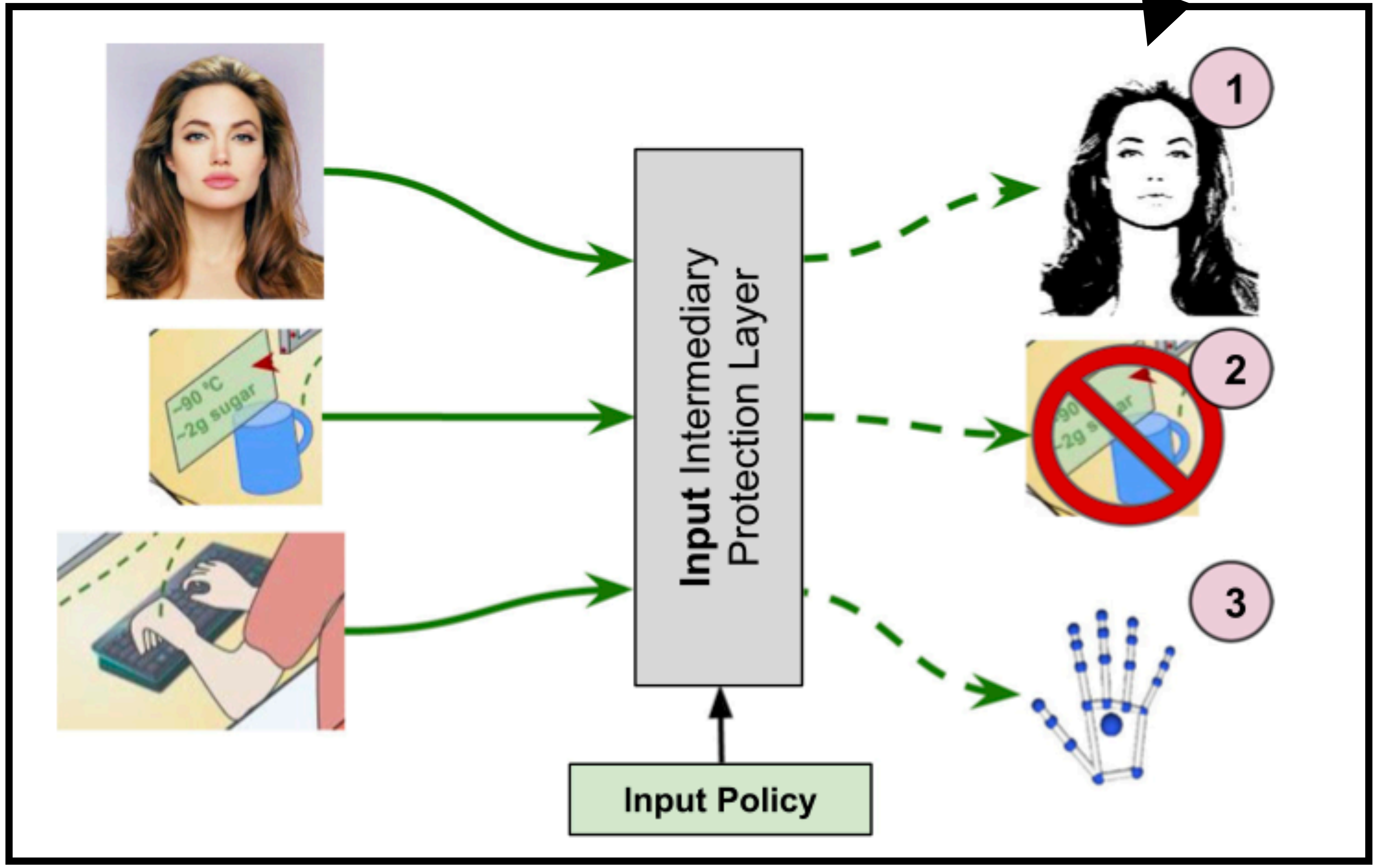


Generalised Differential Privacy



Privacy Preserving Transformations : Literature Review

User privacy preference not considered

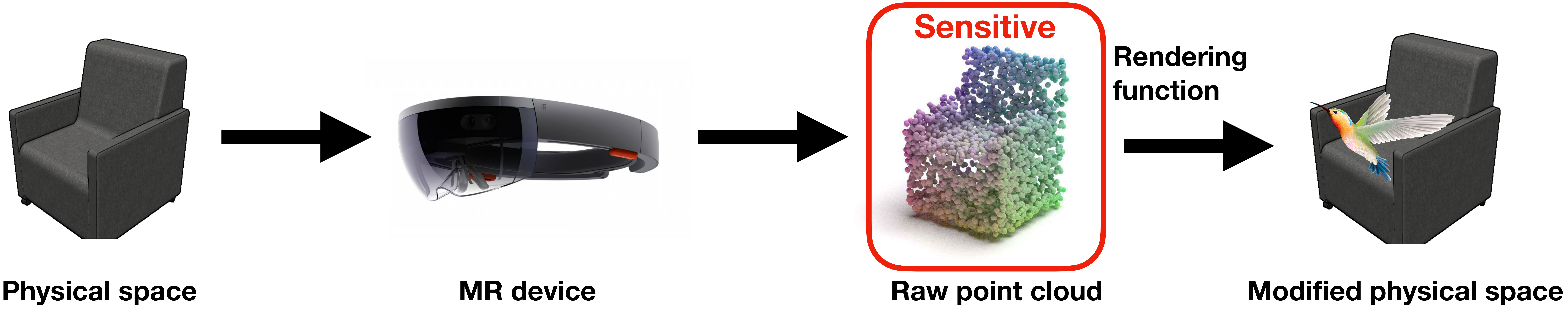


Privacy preserving representations of 2D data

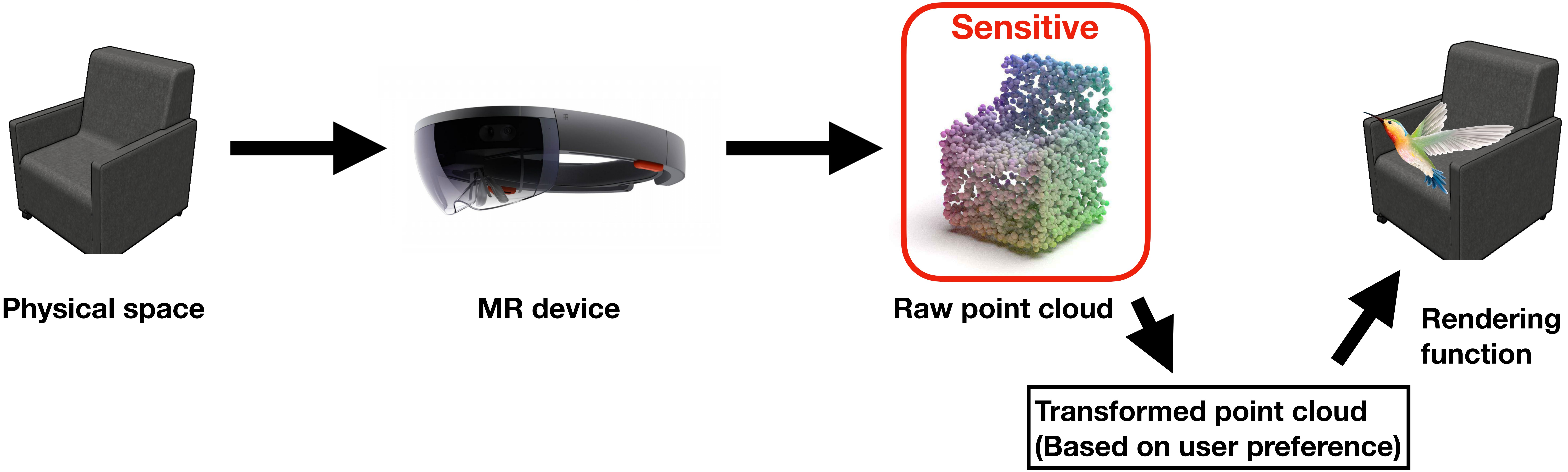
1. Information reduction
2. Complete blocking
3. Extracting only skeleton from hand gesture tracking

From Jaybie A. de Guzman, Kanchana Thilakarathna, and Aruna Seneviratne. 2019. Security and Privacy Approaches in Mixed Reality: A Literature Survey. ACM Comput. Surv. 52, 6, Article 110 (October 2019), 37 pages.

Spatial Privacy in Mixed Reality : User Preference



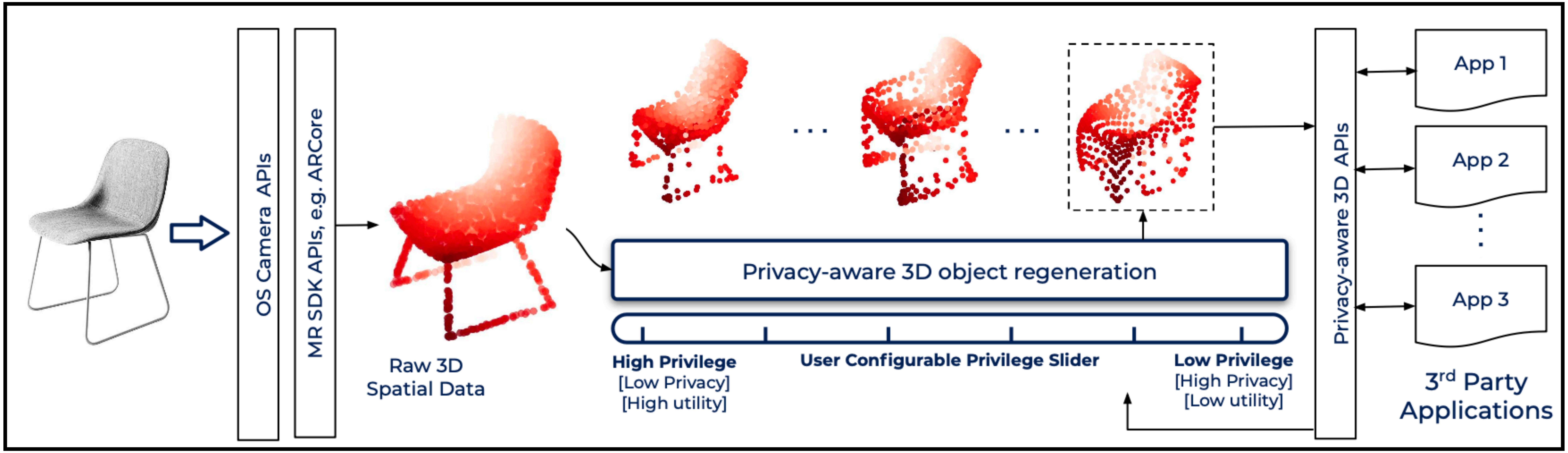
Controlled Transformations on 3D Point Clouds



Spatial Privacy in Mixed Reality : User Preference

Literature Review

Controlled Transformations on 3D Point Clouds



Nama, A., Dharmasiri, A., Thilakarathna, K., Zomaya, A., & de Guzman, J. A. (2021). User configurable 3D object regeneration for spatial privacy. arXiv preprint arXiv:2108.08273

Spatial Privacy in Mixed Reality : User Preference

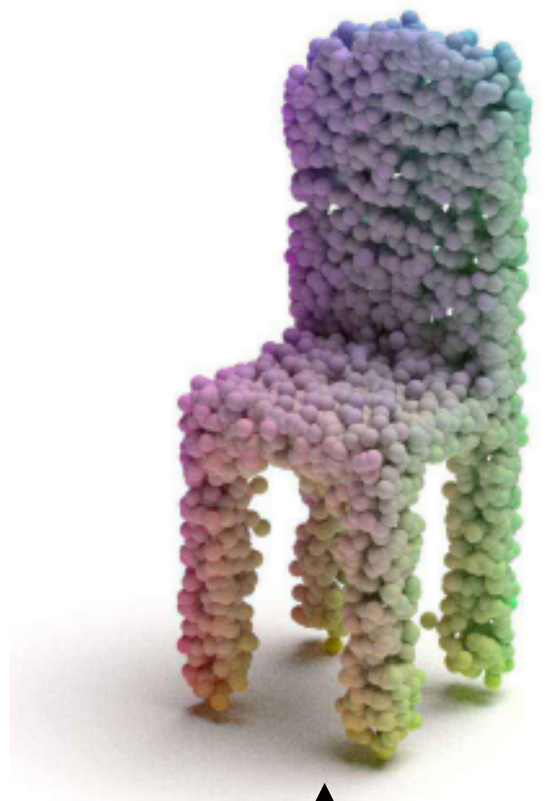
Literature Review

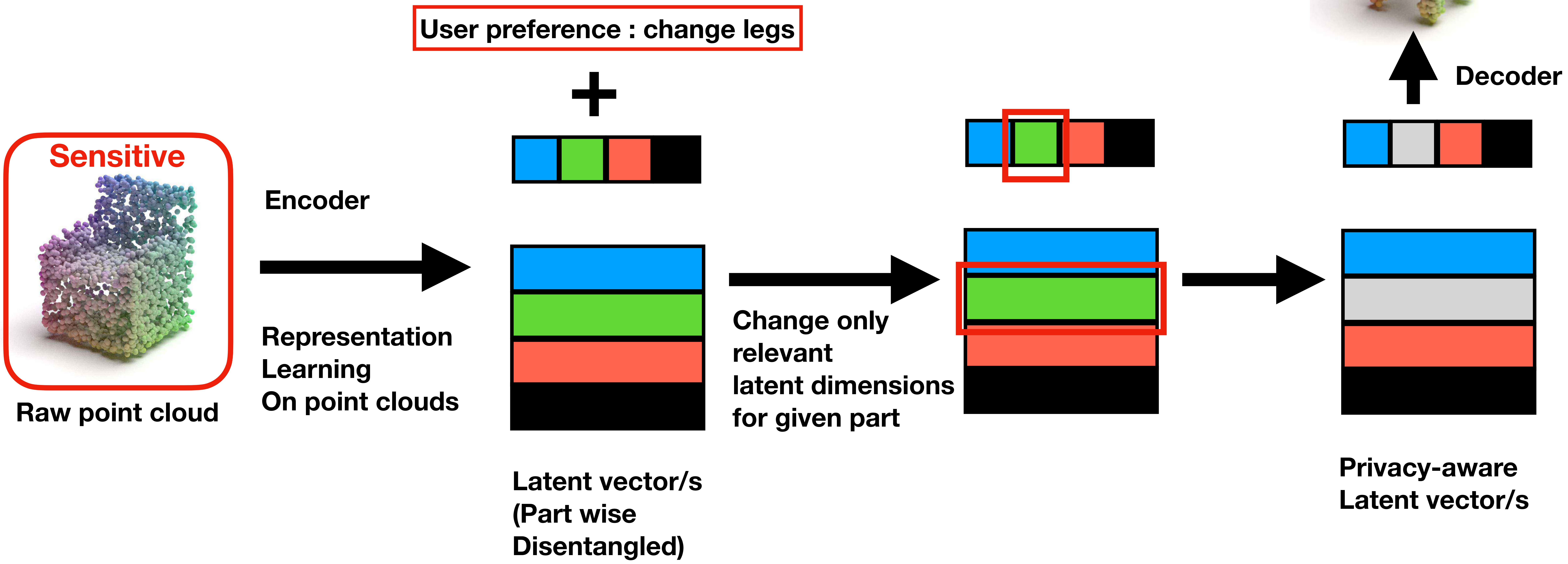
Controlled Transformations on 3D Point Clouds

- Privacy-utility trade off
- User privacy preference input : privilege level value (p)
- ‘p’ decides the transformation of entire object

No fine grained privacy permissions

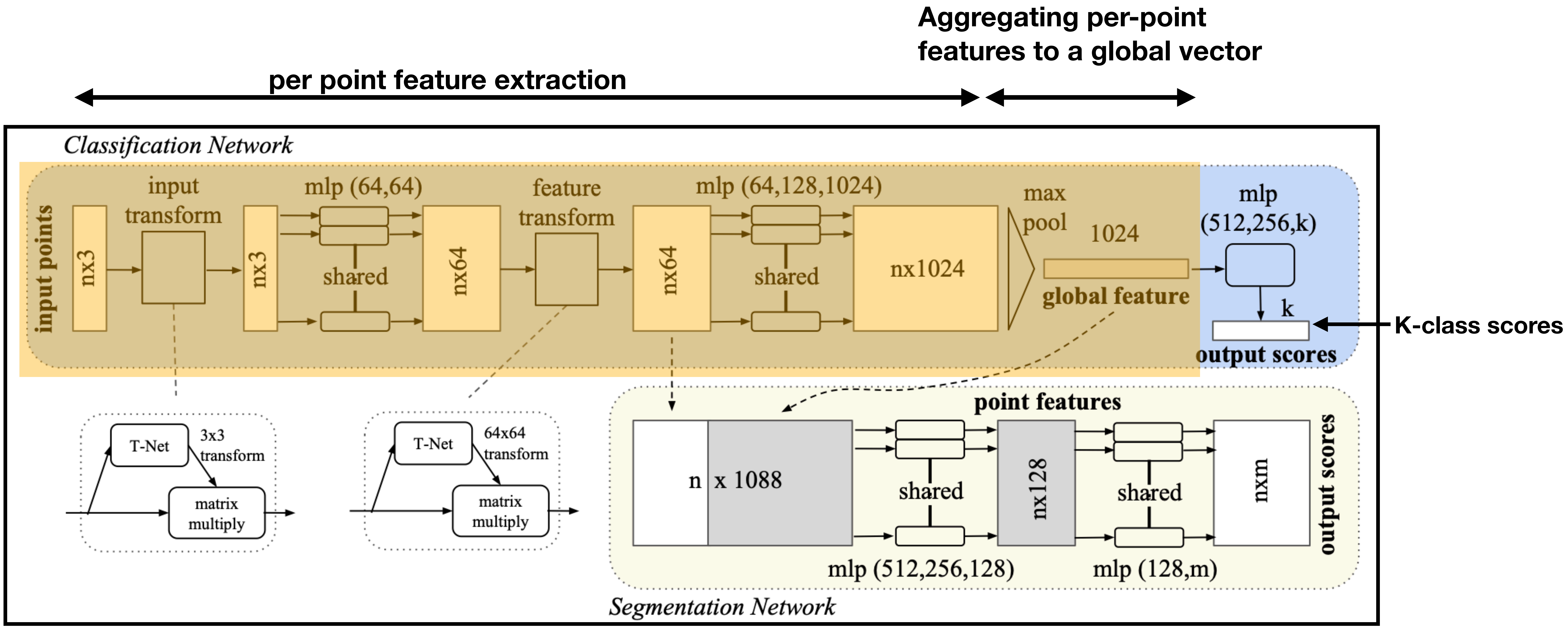
Our Approach to Spatial Privacy





Representation Learning on 3D Point Clouds

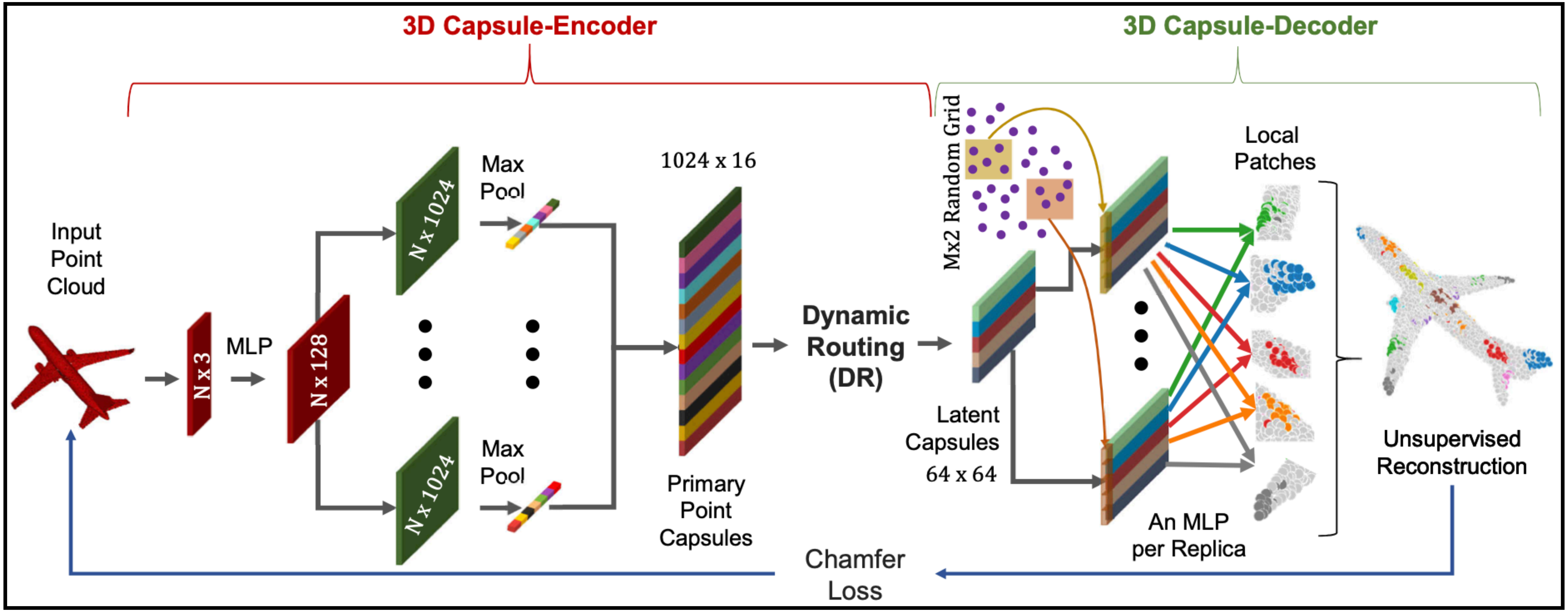
Convolutional Neural Networks



From Qi, Charles R and Su, Hao and Mo, Kaichun and Guibas, Leonidas J. "PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation". arXiv preprint arXiv:1612.00593 (2016).

Representation Learning on 3D Point Clouds

Capsule Networks

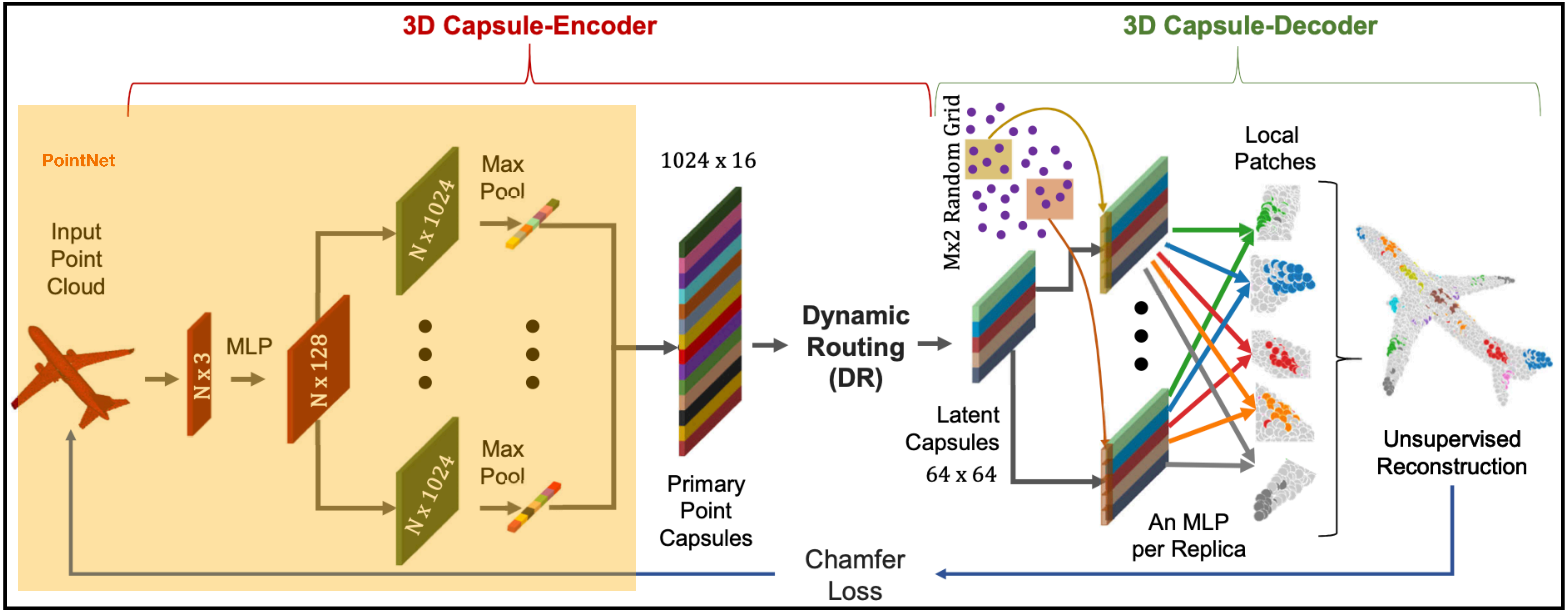


From Zhao, Yongheng and Birdal, Tolga and Deng, Haowen and Tombari. Conference on Computer Vision and Pattern Recognition (CVPR). "3D Point Capsule Networks". IEEE/CVF (2019).

Representation Learning on 3D Point Clouds

3D Capsule Encoder

First layers extracted from PointNet

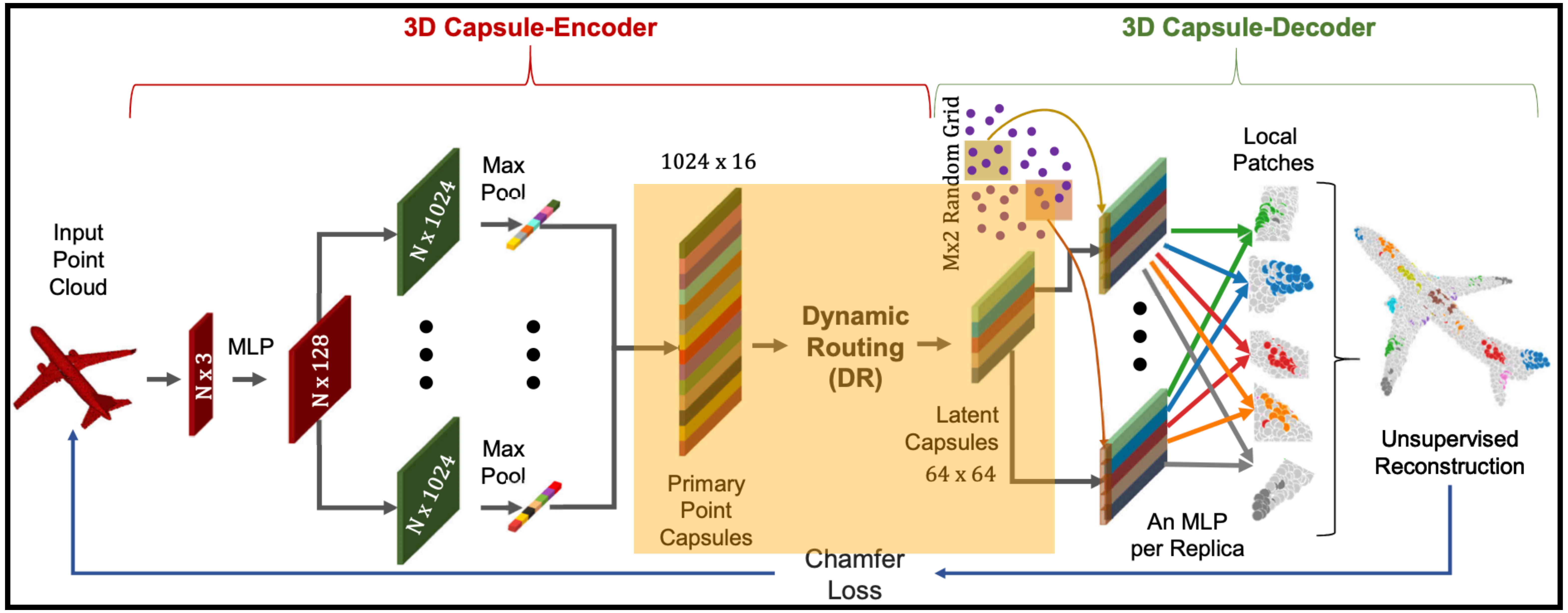


Representation Learning on 3D Point Clouds

3D Capsule Encoder

Dynamic routing preserves

part-whole relationships

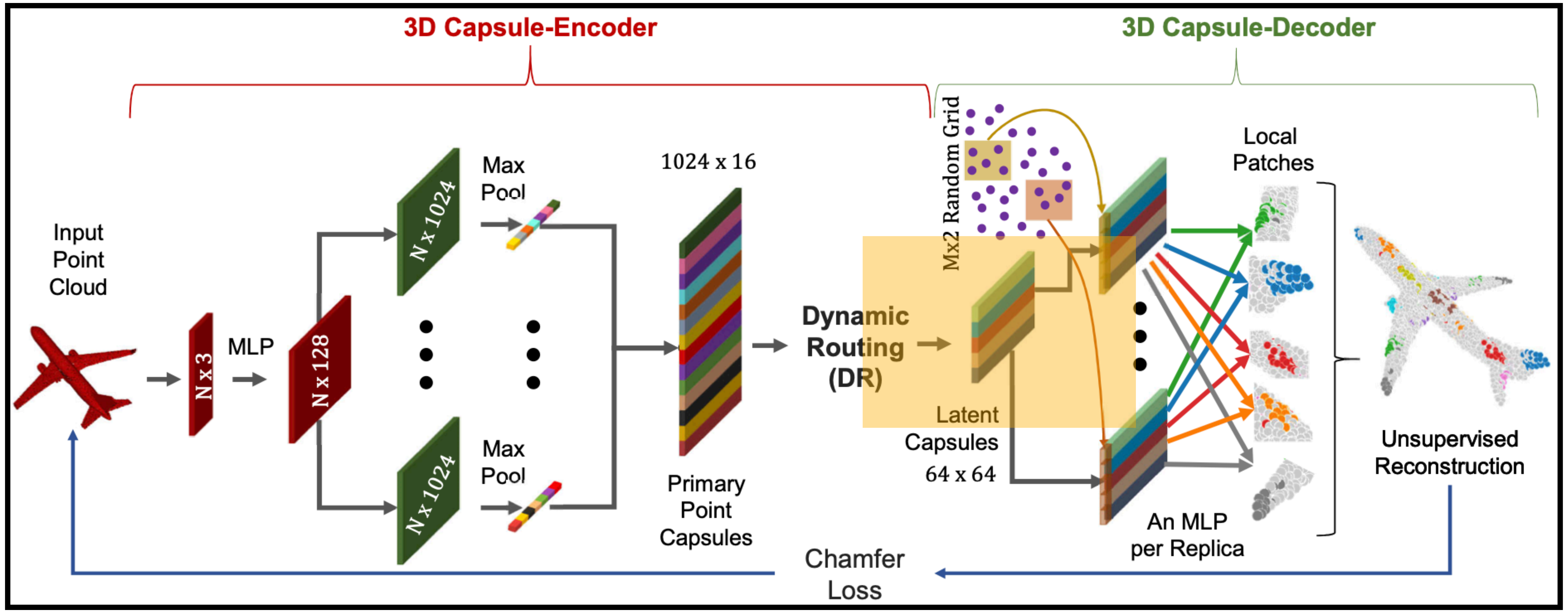


Representation Learning on 3D Point Clouds

3D Capsule Encoder

Multiple latent capsules

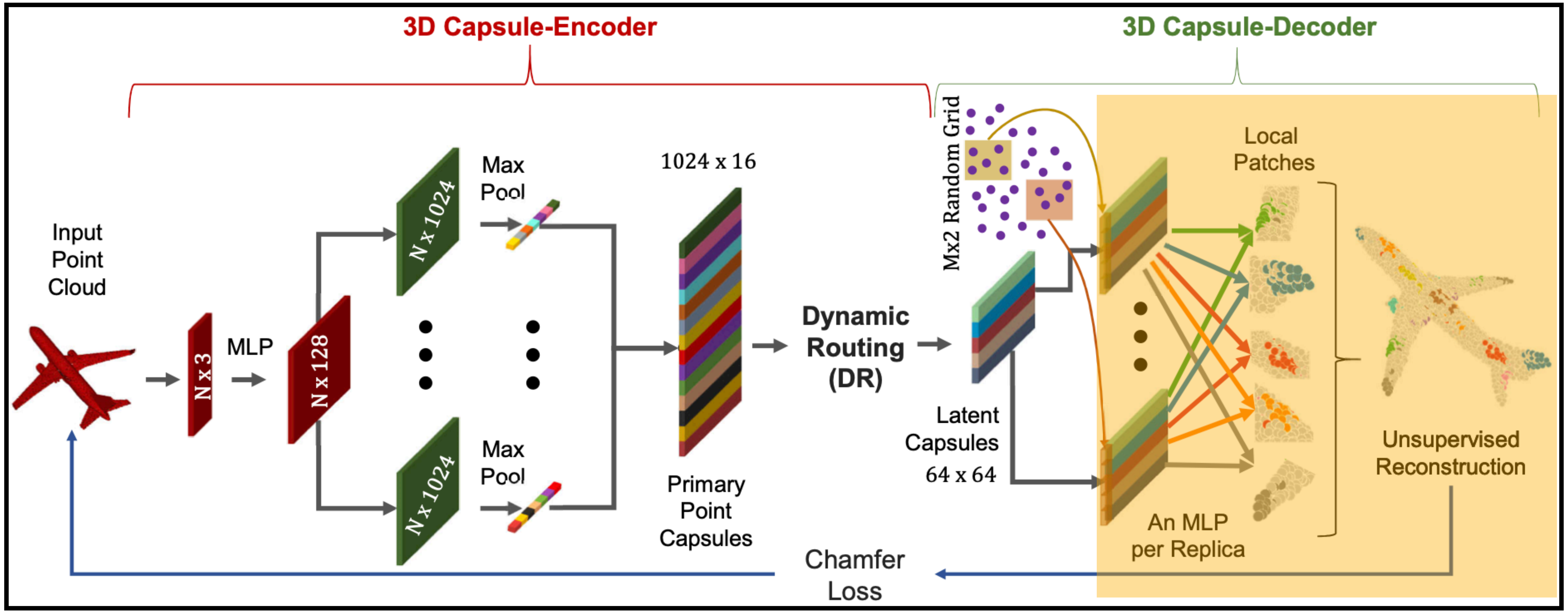
High dimensionality in latent space



Representation Learning on 3D Point Clouds

3D Capsule Decoder

- Due to dynamic routing, vectors in latent capsules act locally
- When transformed, each latent capsule forms a local patch of the 3D point cloud
- Local patches are glued together to get final reconstruction of the point cloud



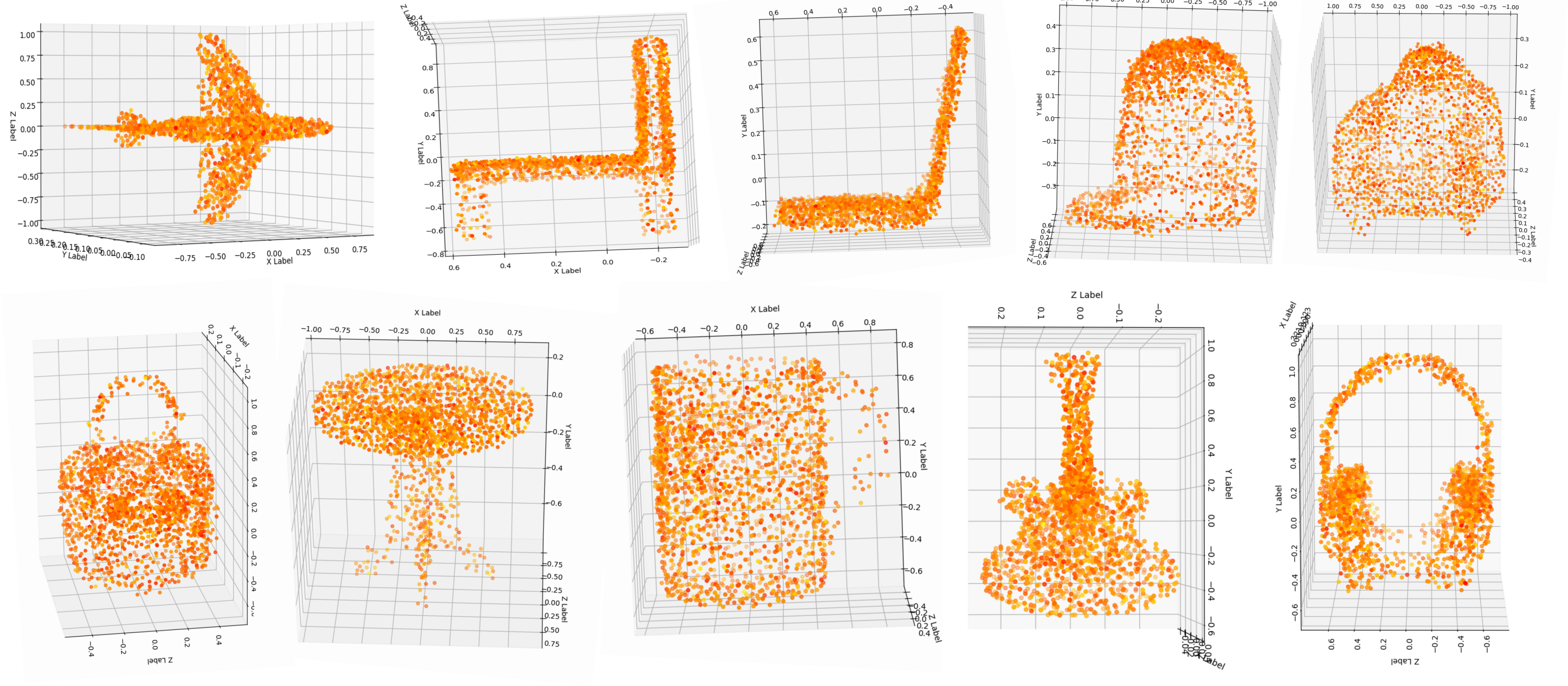
Our Experiments with Capsule Networks

Experimental Setup

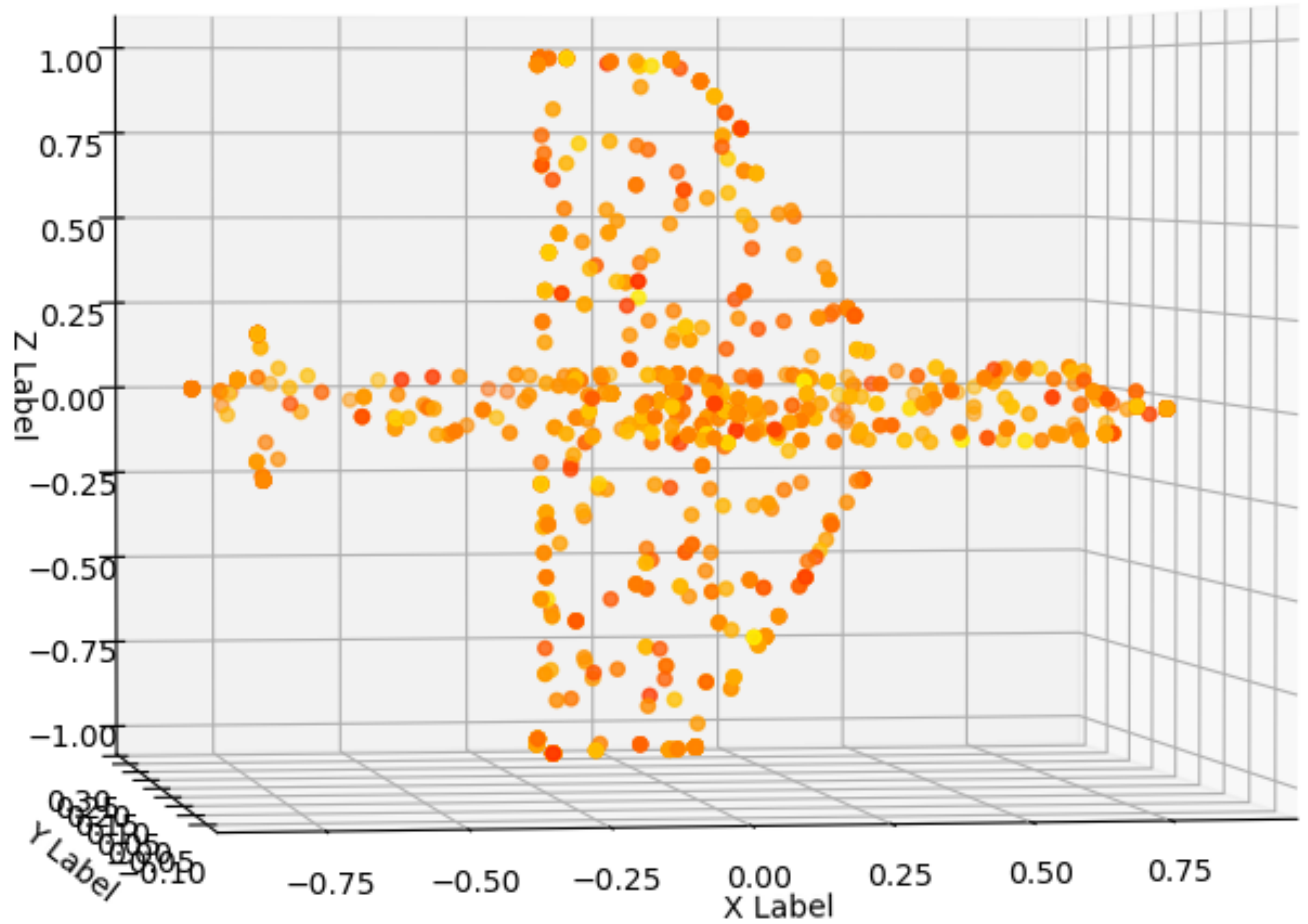
- Dataset : Shapenet Part
- Latent Dimensions : 64x64
- Trained on reconstruction loss
- No part wise supervision

Experiments :
Using a Capsule-based Point Cloud Representation Learning Network to Analyse Possibility of Privacy Preserving Transformations

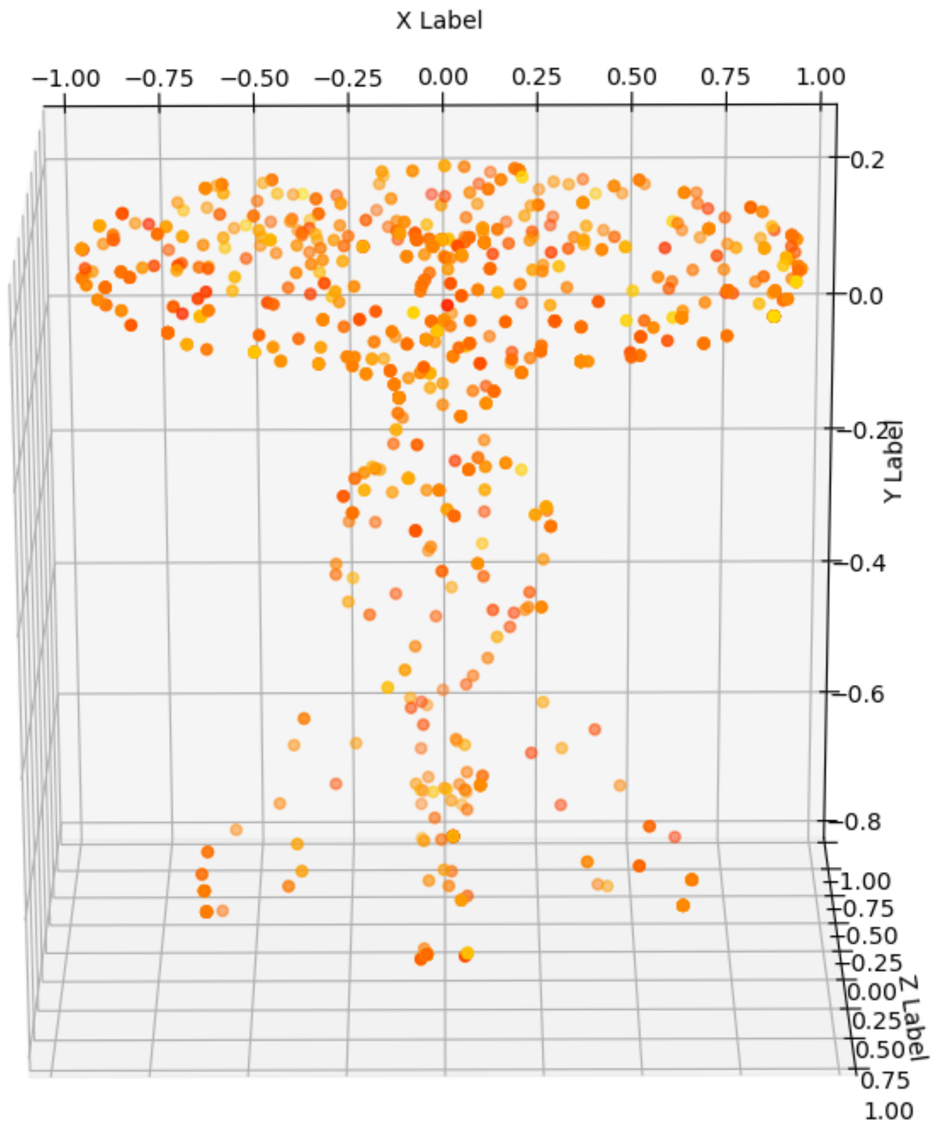
Reconstruction Results



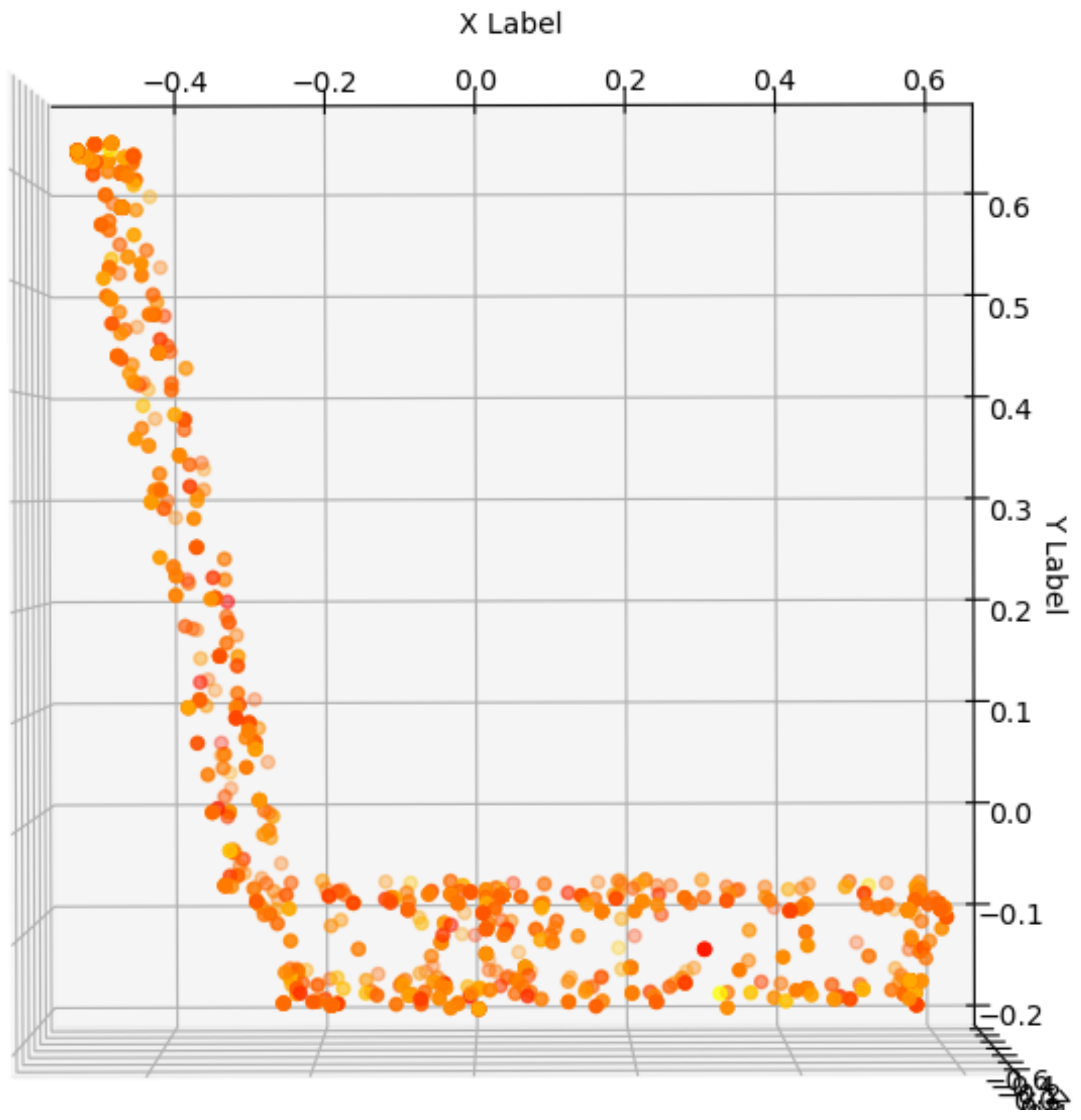
Experiments : Critical Point Analysis



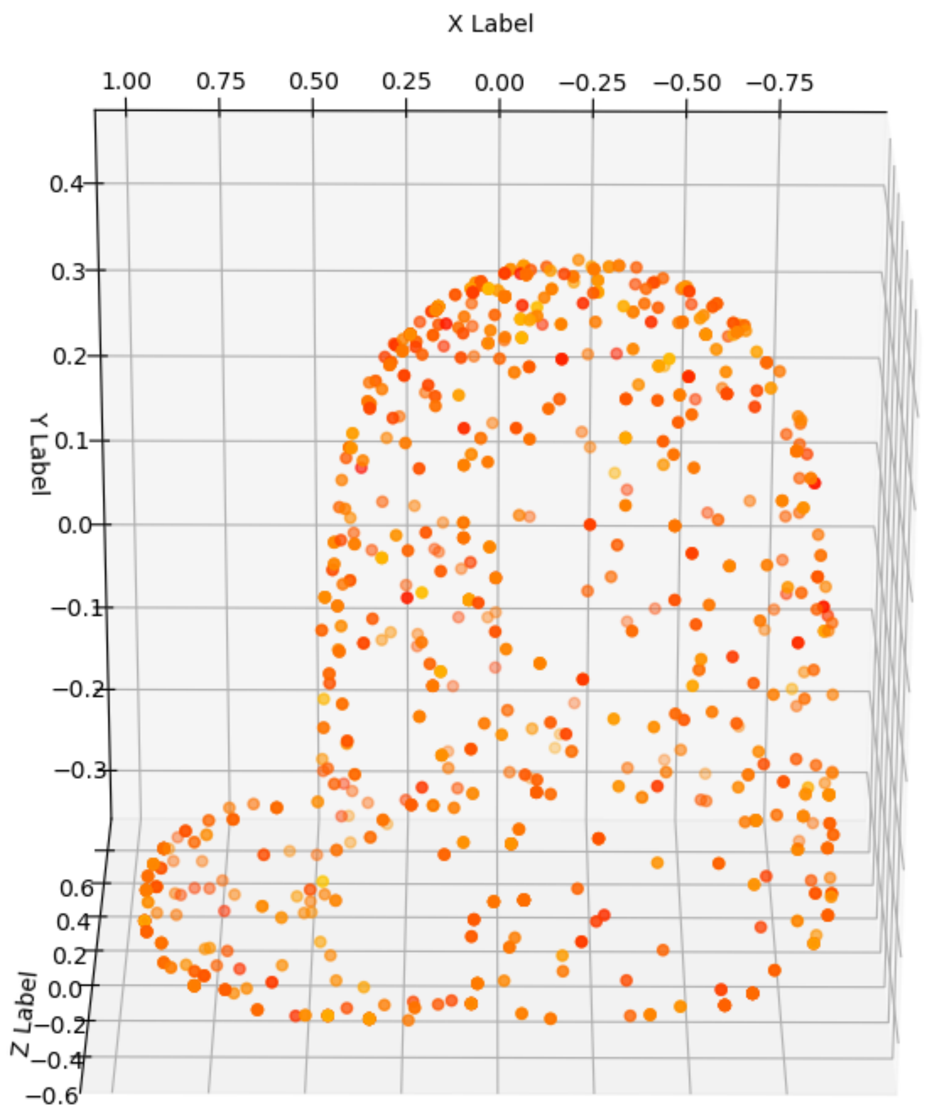
airplane



table



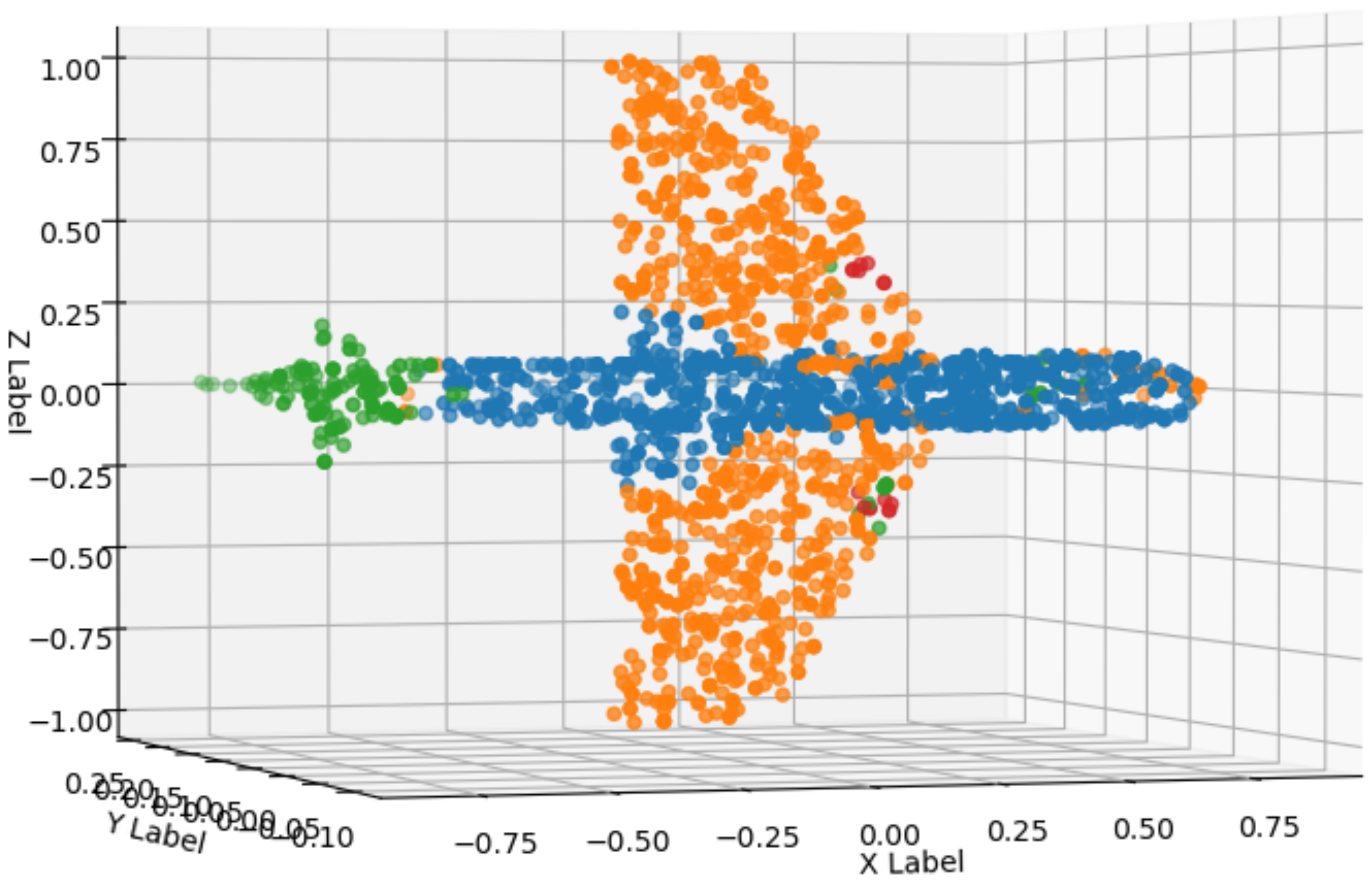
laptop



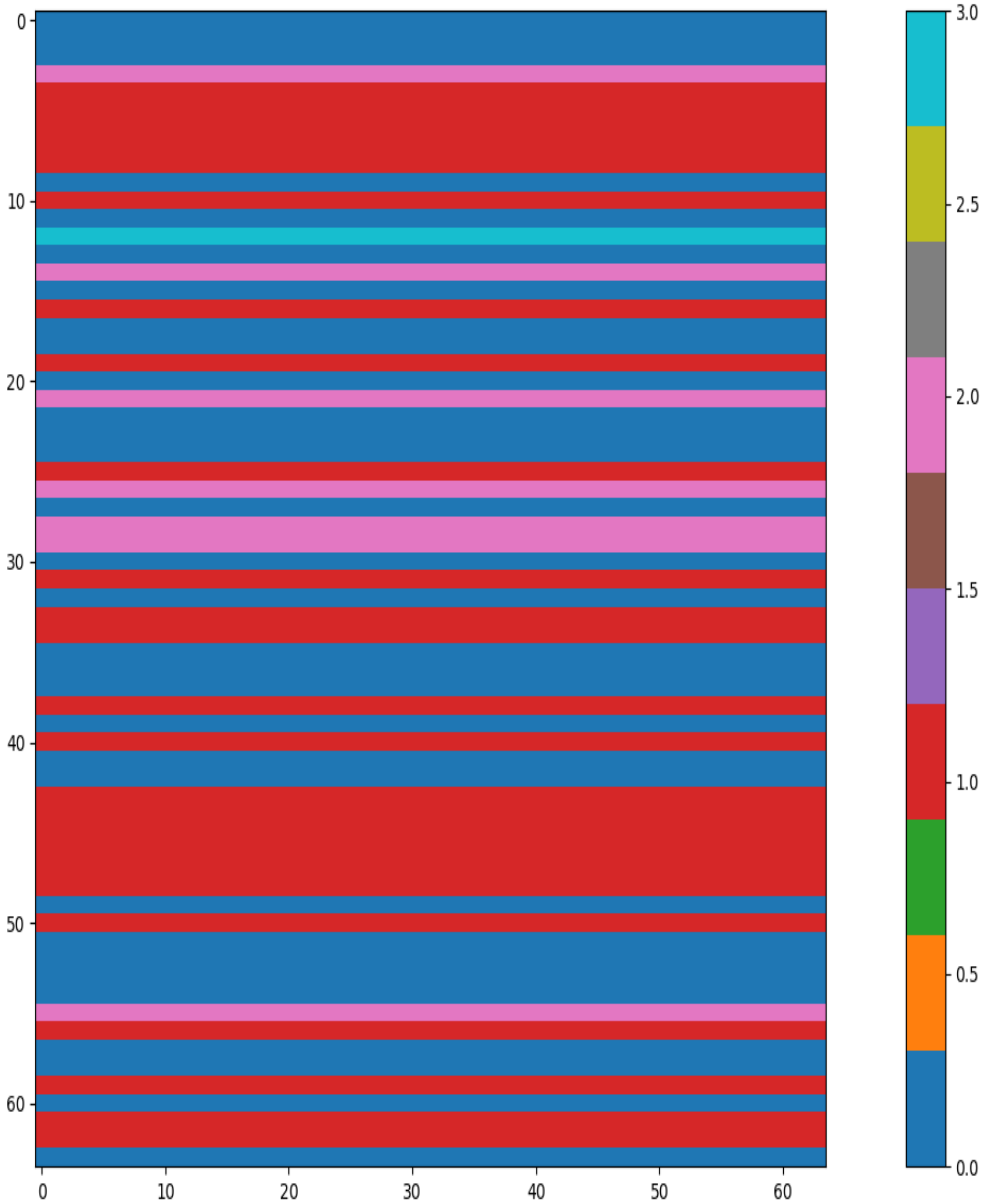
cap

Conclusion : Critical points identified by capsule network always lied in the skeleton of the point cloud

Experiments : 3D Point Cloud Part Segmentation & Part-wise Capsule Labelling



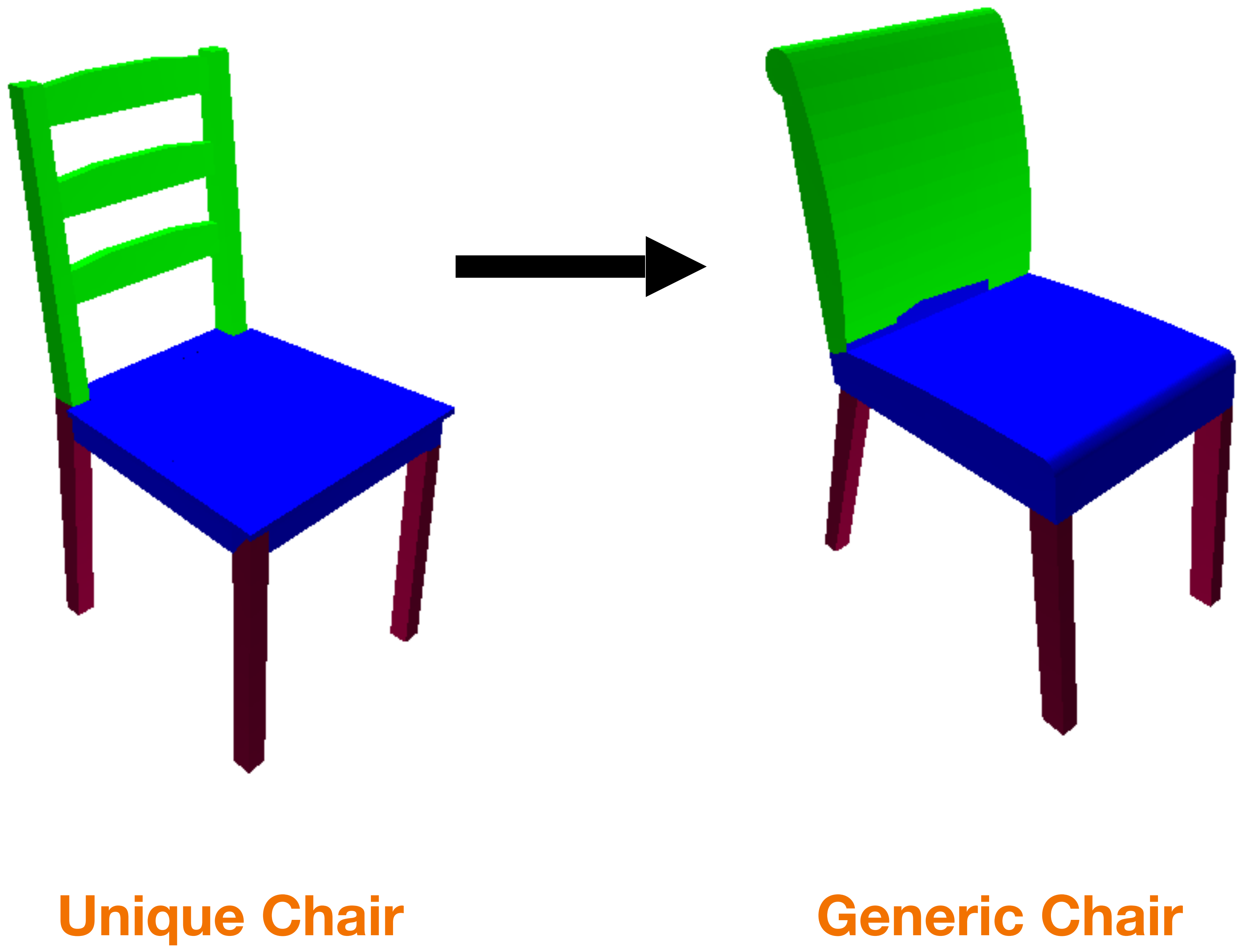
Part segmentation accuracy : 0.92

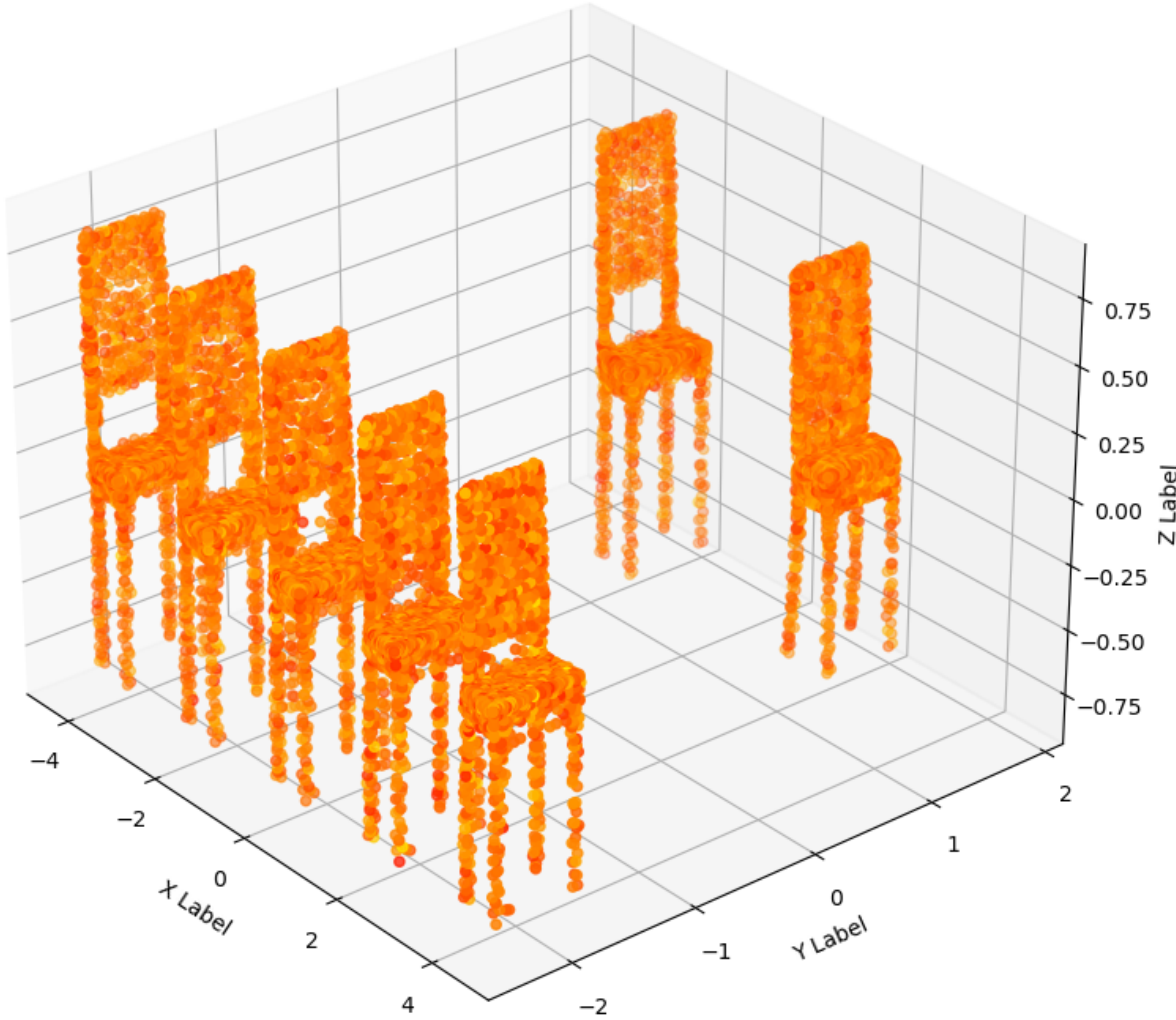


Part-wise capsule labelling

Possibility : changing only the capsules labels of part A to transform that part in point cloud

Experiments : Using Capsule-based Interpolation to Navigate a Point-Cloud towards a Generic representation





Conclusion and Future Work

- Capsules networks have the possibility to outperform traditional neural networks in point cloud learning
- We expect to improve part-wise capsule labelling accuracy
- Learn capsule labelling that can prioritise more unique parts
- Interpolation using capsules for preferred transformation
- Develop and end-to-end privacy preserving framework for MR

Thank You!

Any Questions ?

Contact me for any questions : hasindri98.hsw@gmail.com