# KAPLAN: A 3D Point Descriptor for Shape Completion

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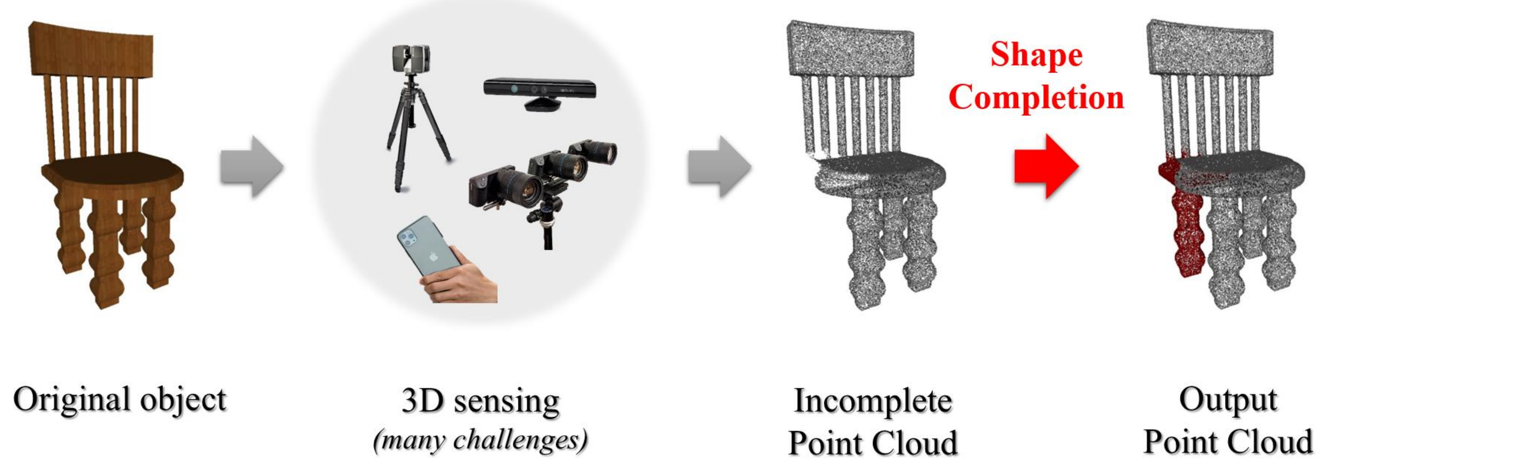
3DV 2020

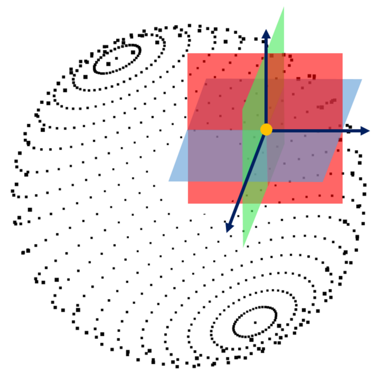
PRS Photogrammetry Remote Sensing — CVG Computer Vision and Geometry Lab — ETH zürich — Microsoft

## Motivation

Most 3D sensors deliver ***point clouds with holes*** due to deficiencies of the acquisition process (e.g. specularities, occlusions). Our goal is to fill these holes.

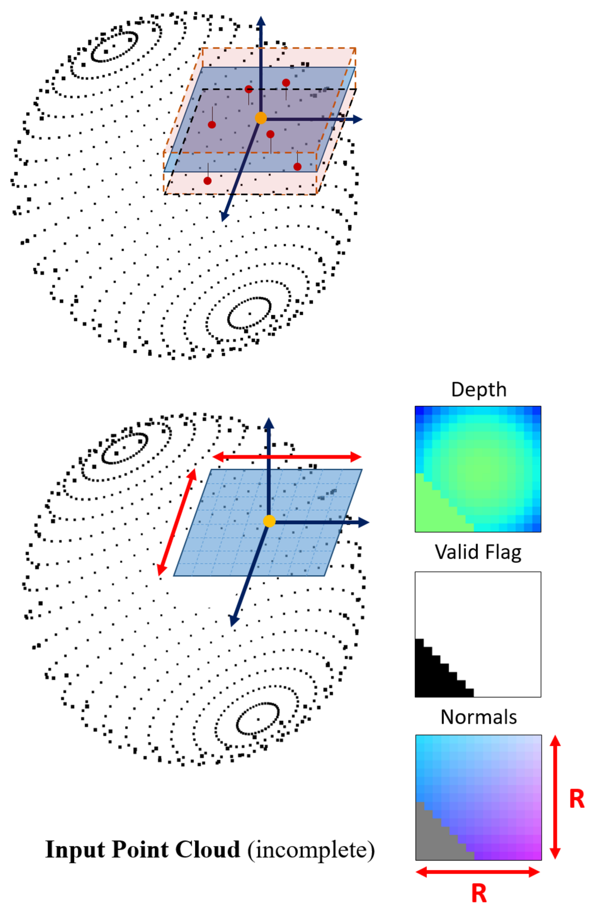



## Our Work



- ***Directly operates on the input point cloud***: no conversion into a memory-demanding representation
- ***Locally learn 2D descriptors:*** projection of the 3D geometry on selected K-planes
- ***Better complexity:*** we can do K-2d convolutions rather than volumetric convolutions

## KAPLAN: local 3D descriptor



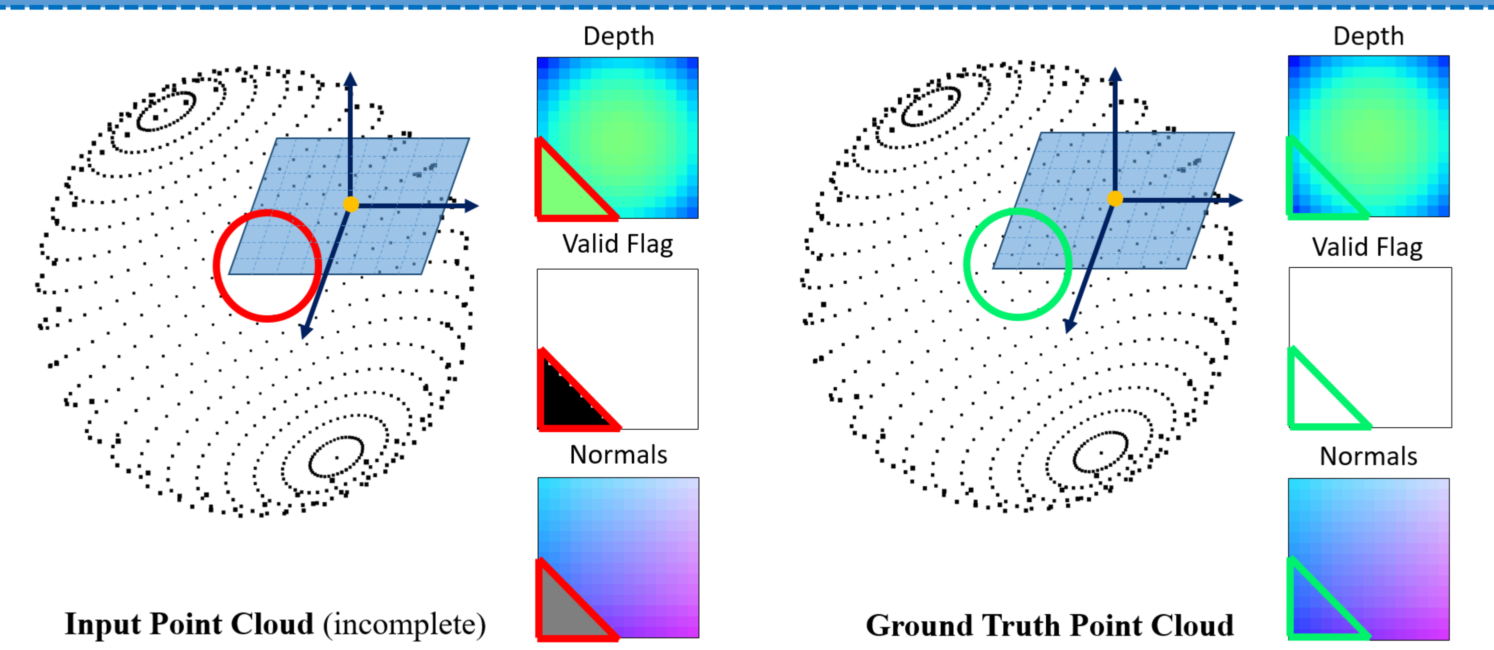

For a given plane of KAPLAN:

- Nearby points are first selected according to a box constraint, to ***preserve locality***.
- These points are then ***projected orthogonally*** onto the plane to form 2D images.

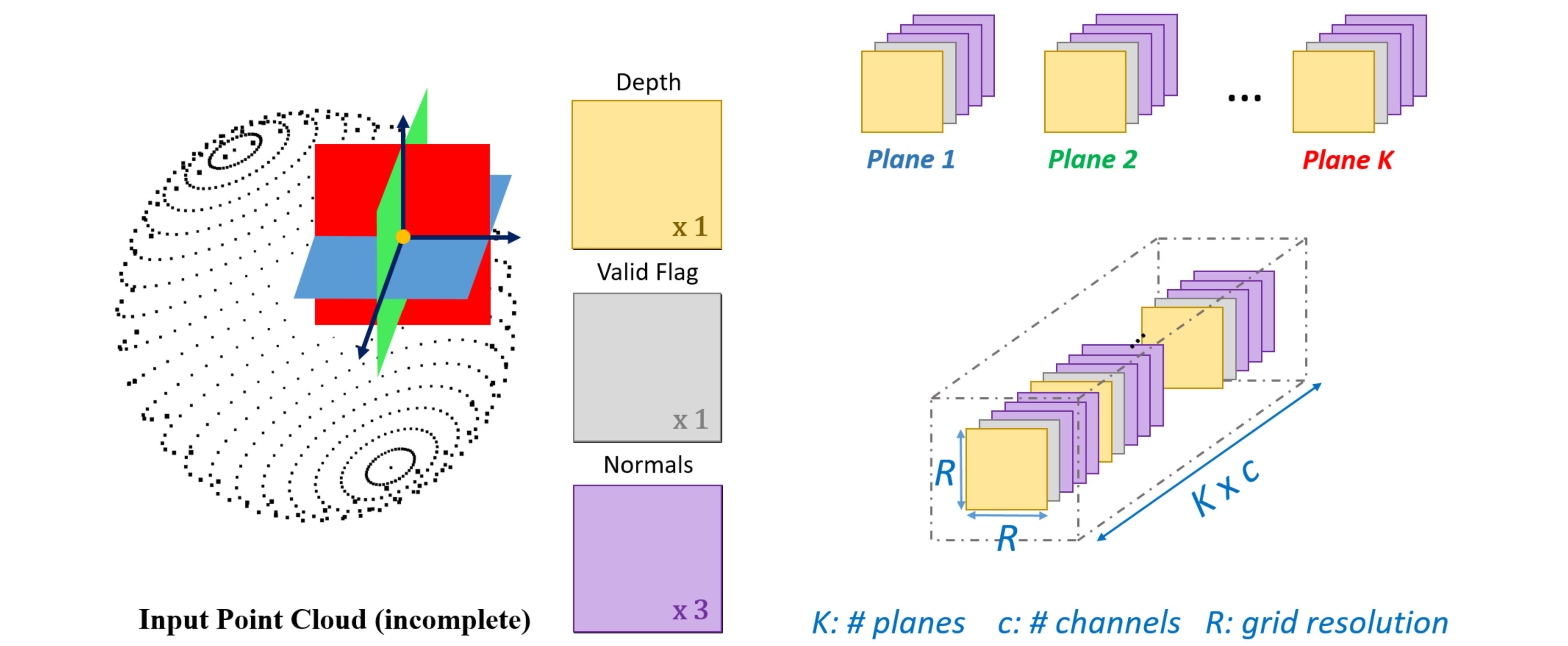
The plane is discretized into a grid of R x R cells:

- ***Each cell collects information*** about projected points that fall into it.
- We collect ***depth***, ***normals***, and a ***valid flag*** indicating if any points have been projected to a given cell.

## Learning to fill empty cells through Supervision

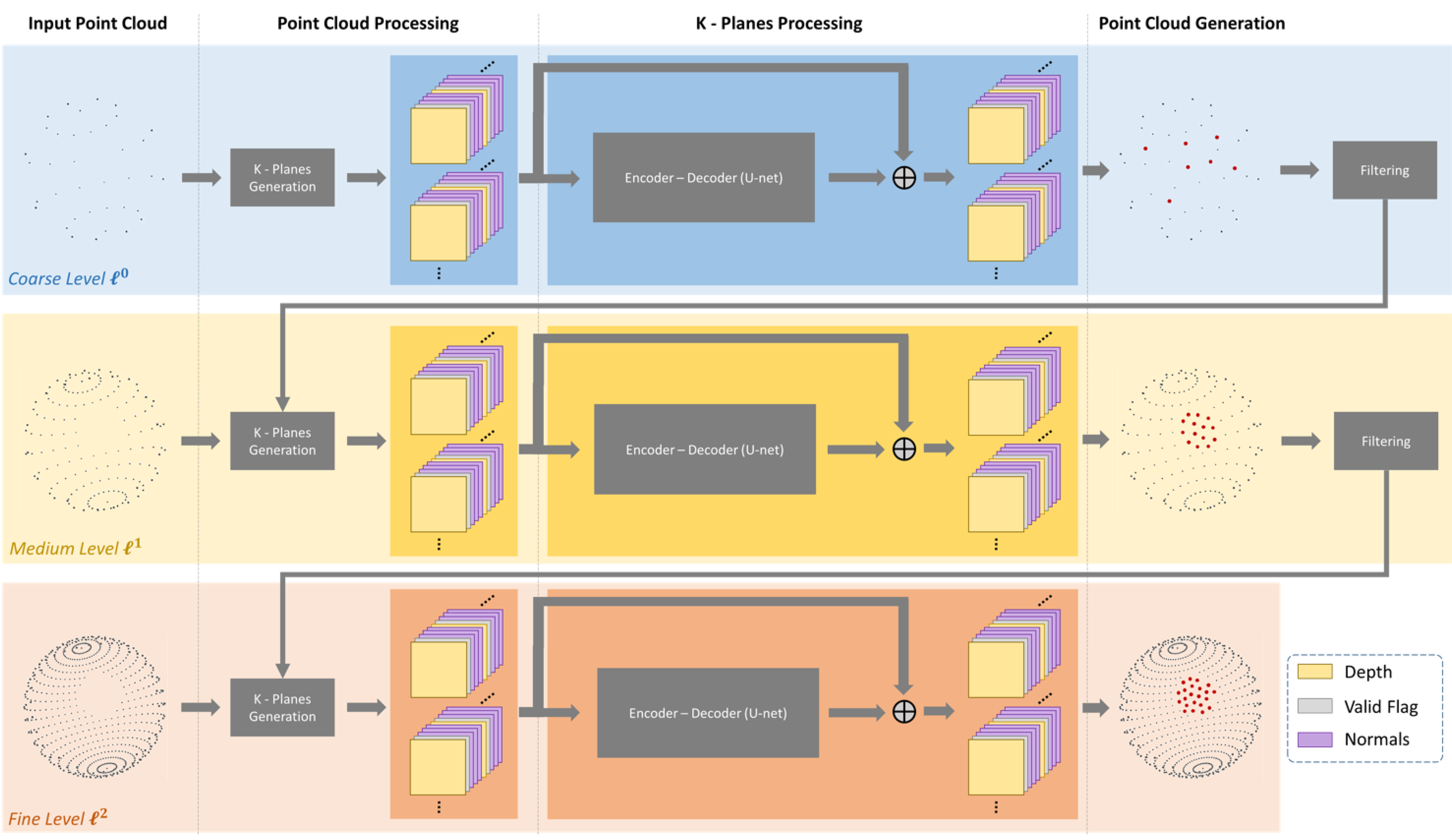



## KAPLAN structure

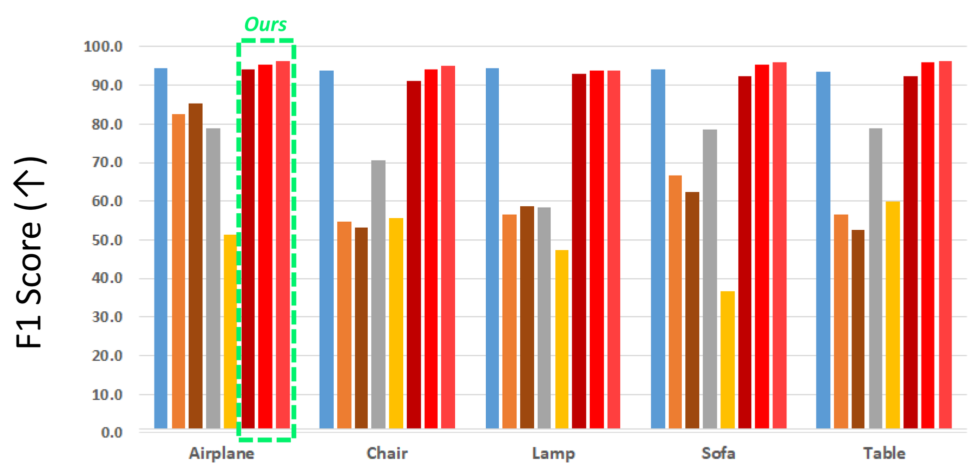



A few KAPLAN are then sampled at **selected query points** from the input cloud.

## Training setup



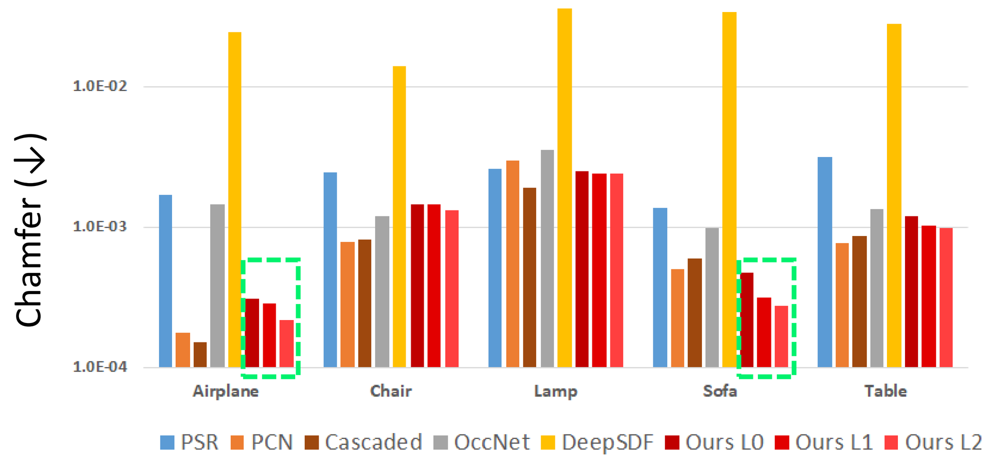

## Comparison with state-of-the-art - Quantitative




**F1 -Score**

Ours and PSR perform best.

Interpretation: the input points are not discarded and regenerated contrary to other methods.



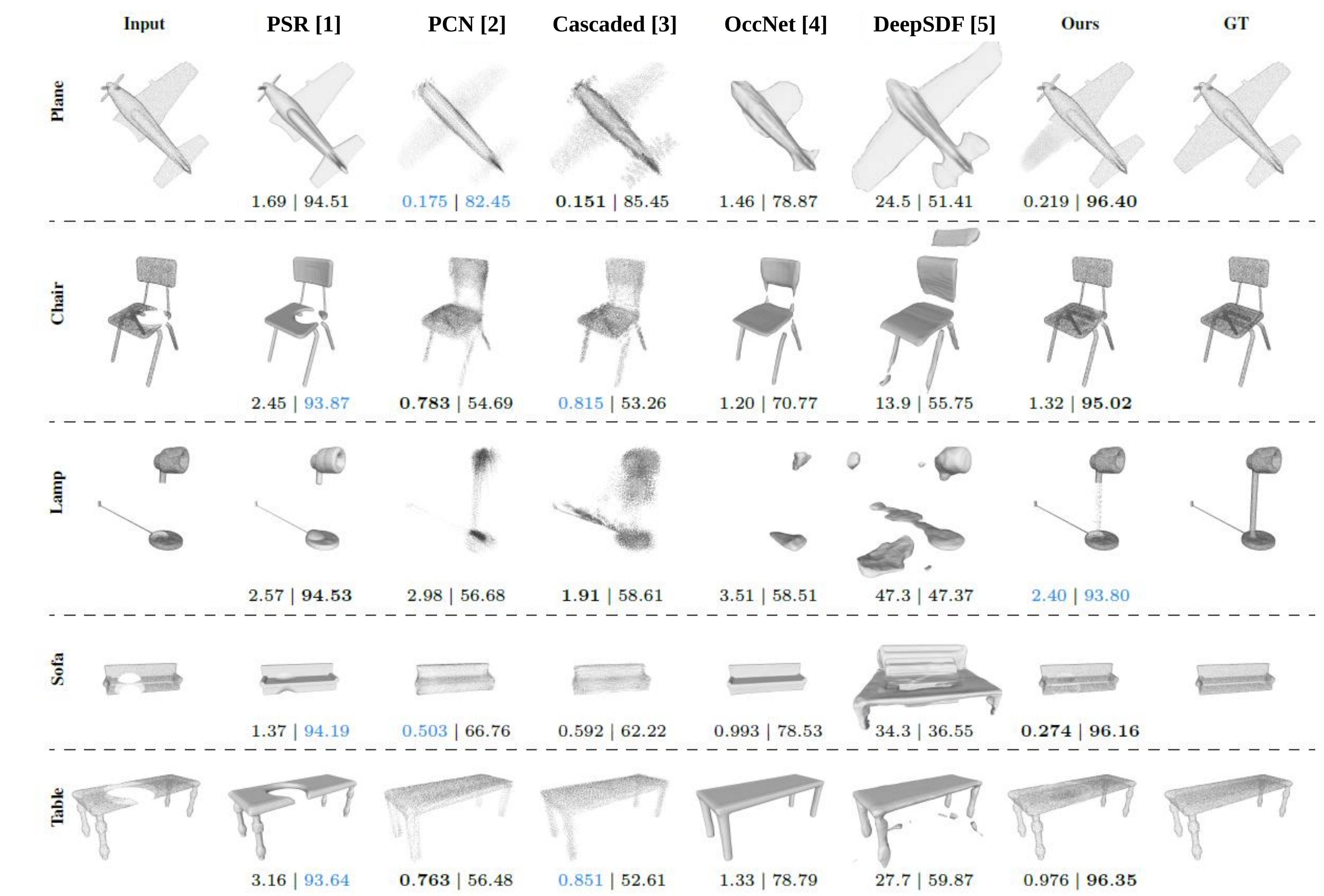

**Chamfer Distance**

Ours is on par with top baselines.

Airplane and Sofa clearly benefit from the coarse-to-fine scheme.

Interpretation: these categories possess large planar sufaces.

## Comparison with state-of-the-art - Qualitative




## Parameters study

| $R$ $(K=3)$ | $CD[\times 10^3] \downarrow$ | $F1 \uparrow$ |
|---|---|---|
| 15 × 15 | 0.46 | 93.50 |
| 35 × 35 | 0.31 | 94.29 |
| 49 × 49 | 0.26 | 94.41 |
| 65 × 65 | 0.17 | 95.33 |
| 85 × 85 | 0.13 | 95.51 |
| 105 × 105 | 0.12 | 95.60 |

Higher resolution appears beneficial. However a more significant gain from resolution *15 to 35*.

| $K$ $(R=35)$ | $CD[\times 10^3] \downarrow$ | $F1 \uparrow$ |
|---|---|---|
| 1 tangential | 1.56 | 93.15 |
| 2 random | 1.91 | 93.04 |
| 3 canonical | 0.31 | 94.29 |
| 5 random | 1.89 | 93.08 |
| 9 canonical | 0.28 | 94.39 |
| 12 random | 1.90 | 93.08 |
| 27 canonical | 0.27 | 94.50 |

***Canonical planes*** minimise redundancy while maximising the informative potential of KAPLAN descriptor

## Contributions

- A novel approach to shape completion for 3D point clouds that operates both locally and globally.
- KAPLAN, an efficient and scalable multi-view 3D representation.
- The combination of KAPLAN with a coarse-to-fine scheme allows the automatic detection of holes to be filled (no regeneration of the complete object).

## References

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