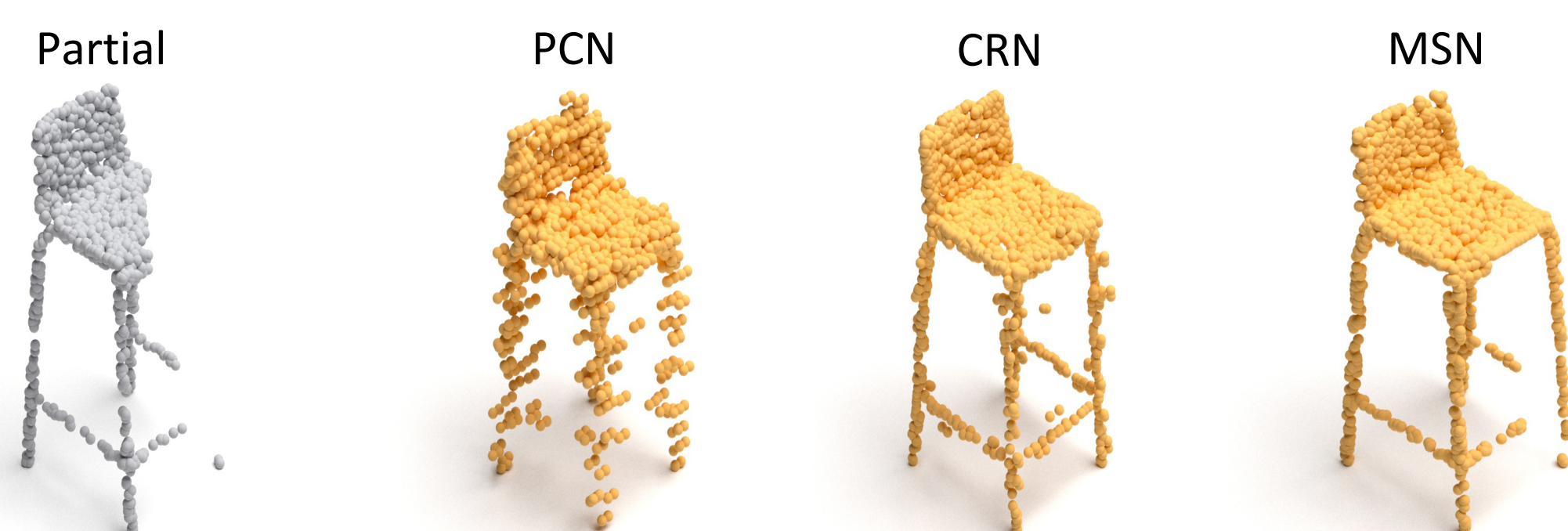


Shape Completion

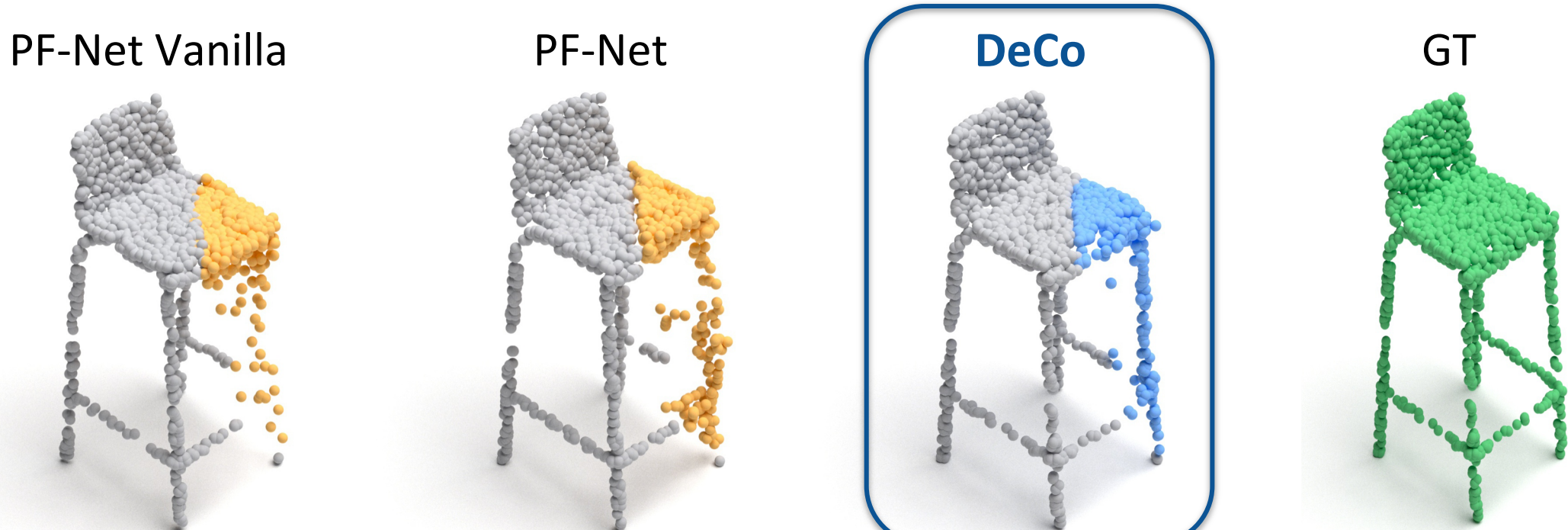
Point Cloud Completion aims to estimate the complete geometry of object from partial observation

- Preserving details from the partial observation
- Modelling the missing part with realistic structure

Existing models fail to meet both these requirements:

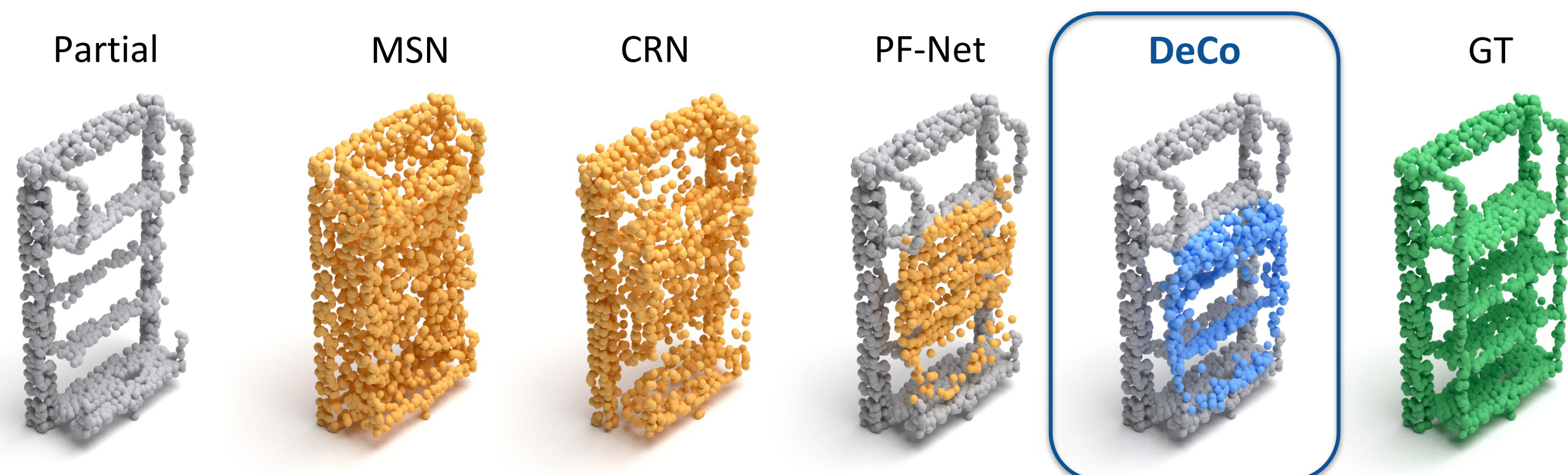


Partial preservation	✗	✗	✓
Missing part modelling	✗	✗	✗



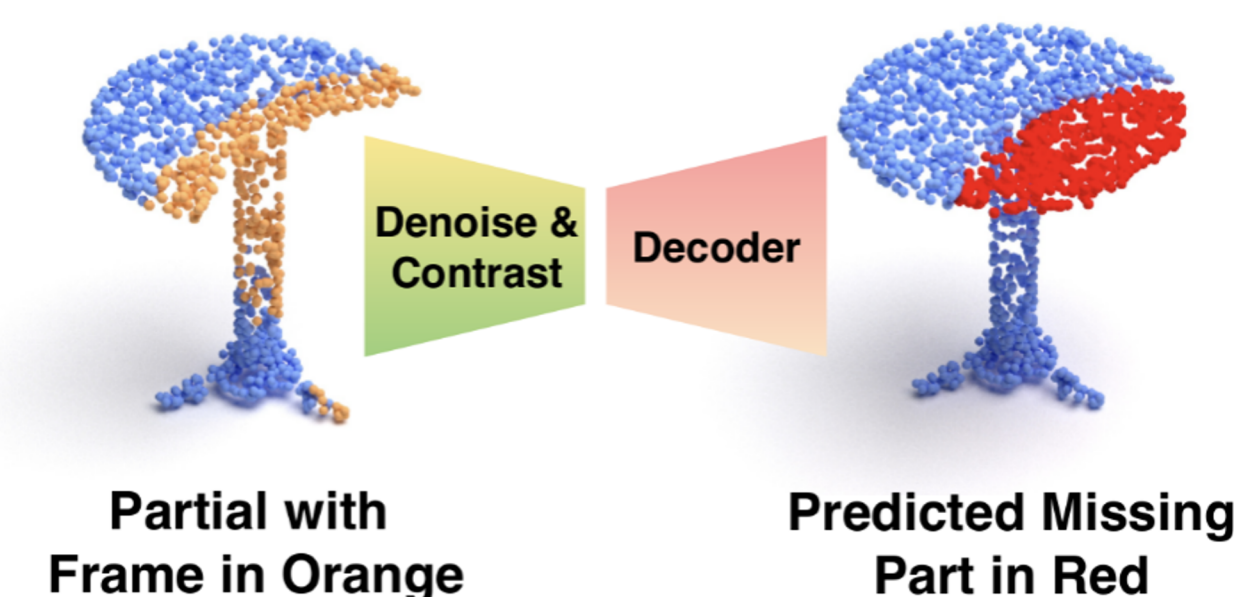
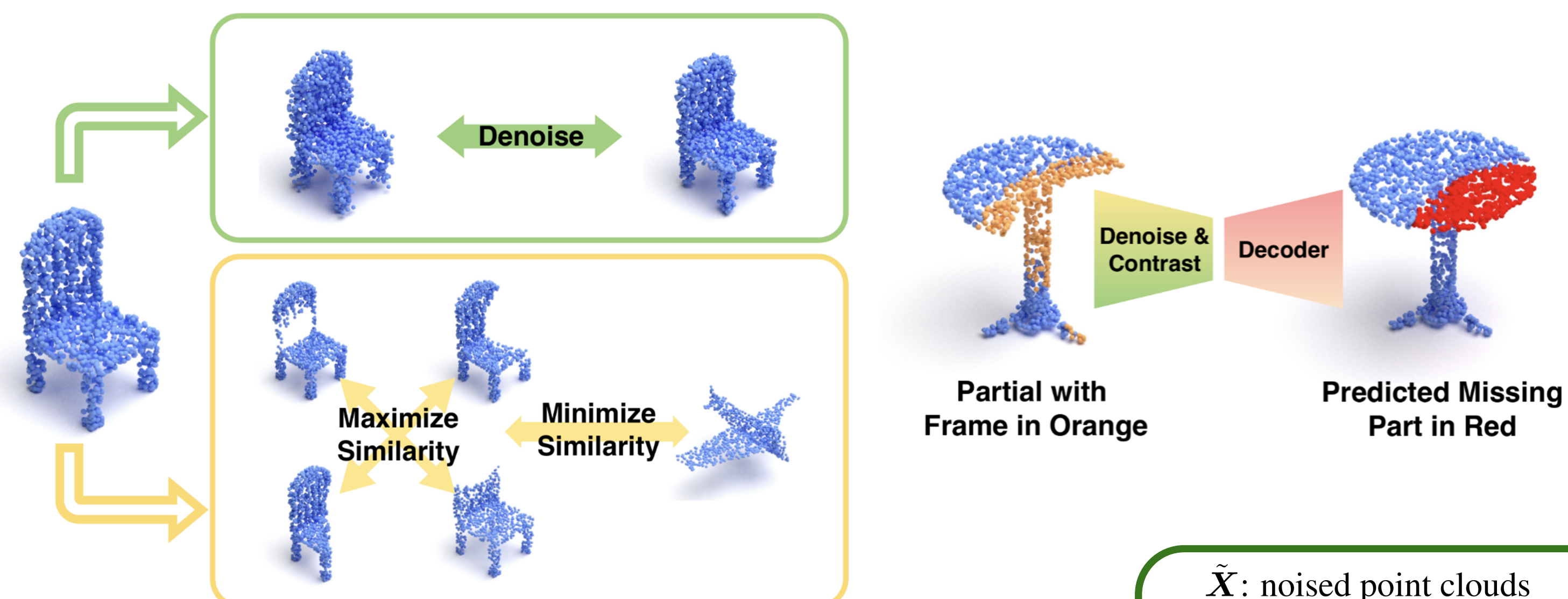
Partial preservation	✓	✓	✓
Missing part modelling	✗	✗	✓

What about completion of Unknown categories?



Partial preservation	✗	✗	✓	✓
Missing part modelling	✗	✗	✗	✓

Method



\tilde{X} : noised point clouds
 X : noiseless ground truths

$$\mathcal{L}_{MSE} = \frac{1}{N+M} \sum_{\substack{\tilde{x} \in \tilde{X} \\ x \in X}} \|\tilde{x} - x\|^2$$

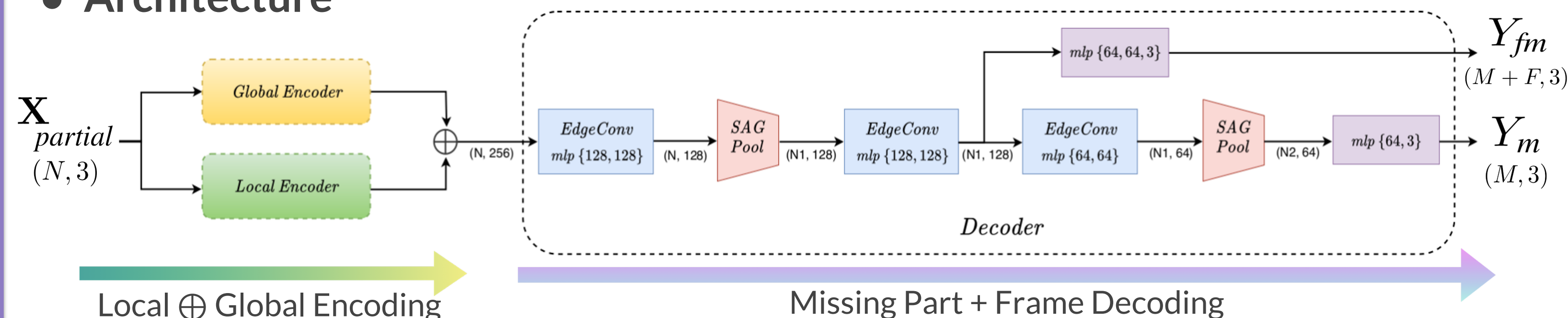
- Denoise
 - Accounting for local structures in the shape topology
 - Local features better generalize to Unknown classes

- Contrast
 - At a *global level*: the set $\mathcal{P}(i)$ of partial observations of the same i -th shape should encode similar information

$$\mathcal{L}_{NT-Xent} = \frac{-1}{|\mathcal{P}(i)|} \sum_{j \in \mathcal{P}(i)} \log \frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{4K} \mathbb{1}_{[k \neq i]} \exp(\text{sim}(z_i, z_k)/\tau)}$$

- Frame Regularization
 - Intermediate strategy between whole shape reconstruction and missing part prediction
 - Better blend the generated part with the partial observation

Architecture



Completion Training loss

X_m : missing part ground truths, X_{fm} : frame + missing ground truths

$$\mathcal{L}_{CD} = \frac{1}{2M} \left\{ \sum_{x \in X_m} \min_{y \in Y_m} \|x - y\|_2^2 + \sum_{y \in Y_m} \min_{x \in X_m} \|y - x\|_2^2 \right\} + \frac{1}{2(M+F)} \left\{ \sum_{x \in X_{fm}} \min_{y \in Y_{fm}} \|x - y\|_2^2 + \sum_{y \in Y_{fm}} \min_{x \in X_{fm}} \|y - x\|_2^2 \right\}$$

Results

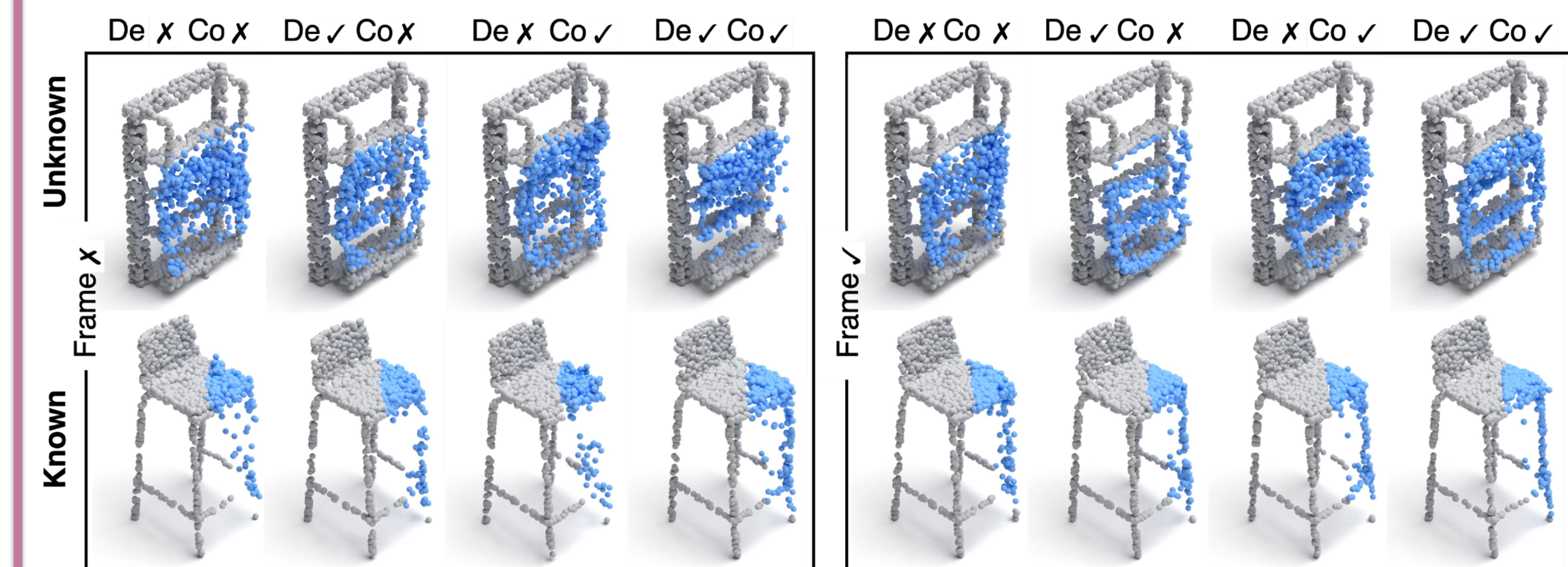
Known Categories

Category	PCN [39]	MSN [16]	CRN [30]	PF-Net vanilla [11]	PF-Net [11]	DeCo
Airplane	31.515	15.907	39.334	11.015	10.805	10.003
Bag	37.825	59.185	33.593	40.000	38.485	28.508
Cap	66.275	40.276	53.146	49.945	50.450	36.436
Car	24.320	24.176	39.537	21.925	21.640	22.963
Chair	31.265	20.751	28.688	19.130	19.490	16.428
Lamp	93.745	41.094	30.207	41.555	42.910	24.150
Laptop	22.460	11.718	26.393	11.520	11.220	12.706
Motorbike	34.420	21.276	41.292	20.525	19.905	19.136
Mug	35.905	57.007	41.153	32.800	31.880	34.239
Pistol	29.490	14.560	26.845	11.395	10.885	12.266
Skateboard	23.815	14.146	34.358	12.275	12.365	9.861
Table	24.775	22.103	23.953	20.560	20.845	17.120
Guitar	10.540	6.959	15.224	4.350	4.425	4.482
Overall	34.095	22.410	29.044	20.209	20.445	16.517

Unknown Categories

Categories	MSN [16]	CRN [30]	PF-Net vanilla [11]	PF-Net [11]	DeCo
Similar					
Bicycle	47.423	64.275	49.779	47.186	39.684
Basket	48.100	50.692	58.866	57.066	34.613
Helmet	71.161	57.851	63.742	69.849	47.412
Bowl	52.002	63.357	97.316	78.793	35.209
Rifle	34.712	47.239	25.438	28.684	12.004
Vessel	30.948	41.418	27.122	31.114	18.836
Overall	35.544	46.166	31.232	33.844	17.680
Dissimilar					
Piano	62.969	61.643	62.131	62.994	49.429
Bookshelf	48.397	44.738	58.920	55.123	34.681
Bottle	29.580	20.134	25.543	24.578	20.002
Clock	57.222	38.132	50.964	48.373	32.826
Microwave	53.354	56.259	61.702	56.152	41.877
Telephone	38.032	25.554	38.085	32.063	20.106
Overall	45.049	34.625	45.014	41.449	28.403

Visual Ablation



Conclusion

We propose **DeCo** for point cloud completion in which:

- Local and global feature encoding is enforced by (1) specific architectural choices and (2) the use of tailored pretext tasks
- Framing strategy allows us to blend the generated output with the partial obs.

Achieving SOTA for both Known and Unknown classes

