Supplementary

1 More Qualitative Results on Dense Embeddings

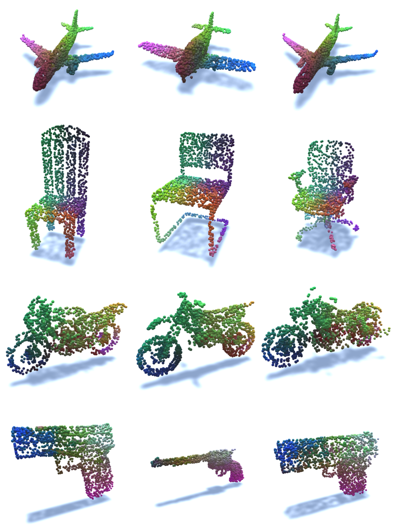

Fig. 1: GraphCNN.

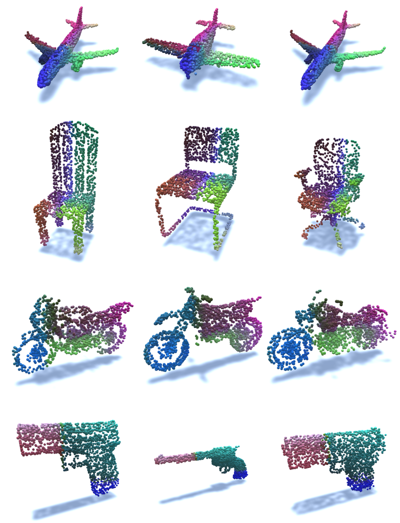

Fig. 2: RSNet.

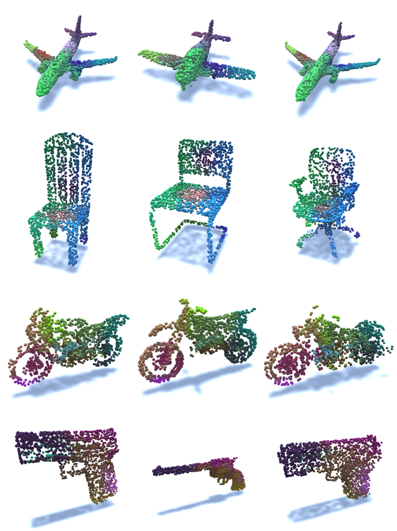

Fig. 3: PointNet++.

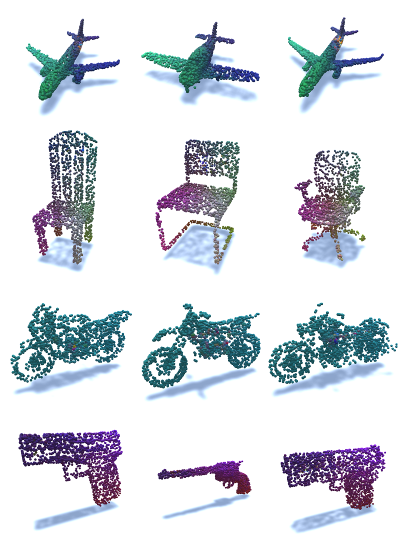

Fig. 4: Minkowski.

2 More Quantitative Results on Dense Embedding Evaluation

	Airplane	Bathtub	Bed	Bench	Bottle	Bus	Cap	Car	Chair	Dishwasher	Display	Earphone	Faucet
PointNet	0.055	0.123	**0.074**	0.062	0.086	**0.053**	0.091	0.067	**0.077**	**0.095**	**0.068**	0.132	0.106
PointNet++	0.049	0.152	0.111	0.065	0.129	0.112	0.120	0.071	0.098	0.142	0.106	0.117	0.125
RS-Net	0.048	0.136	0.114	0.086	**0.078**	0.057	0.099	**0.062**	0.083	0.137	0.077	0.107	0.115
PointConv	0.047	0.120	0.118	0.066	0.096	0.073	0.113	0.076	0.103	0.138	0.076	0.093	0.107
DGCNN	**0.042**	**0.106**	0.116	**0.054**	0.084	0.059	**0.083**	0.070	0.091	0.112	0.076	**0.081**	**0.103**
GraphCNN	0.061	0.137	0.118	0.083	0.155	0.095	0.119	0.102	0.122	0.151	0.076	0.122	0.117
Minkowski	0.077	0.134	0.140	0.102	0.139	0.109	0.150	0.096	0.134	0.170	0.153	0.106	0.122
SHOT	0.186	0.433	0.510	0.498	0.353	0.398	0.301	0.358	0.411	0.476	0.380	0.313	0.181
Random	0.277	0.434	0.491	0.477	0.391	0.381	0.399	0.376	0.420	0.450	0.415	0.371	0.254

	Guitar	Helmet	Knife	Lamp	Laptop	Motorcycle	Mug	Pistol	Rocket	Skateboard	Table	Vessel	Average
PointNet	0.061	0.145	0.062	0.191	0.153	0.071	0.069	**0.084**	0.140	**0.055**	**0.040**	**0.094**	0.090
PointNet++	0.078	0.156	0.075	0.192	0.174	0.075	0.101	0.110	0.143	0.081	0.090	0.130	0.112
RS-Net	**0.055**	0.143	0.061	0.210	0.164	**0.063**	**0.061**	0.091	0.124	0.067	0.099	0.111	0.098
PointConv	0.077	0.153	0.084	0.200	**0.112**	0.072	0.089	0.099	**0.115**	0.056	0.073	0.117	0.099
DGCNN	0.059	**0.138**	**0.049**	**0.189**	0.125	0.069	0.090	0.092	0.120	**0.055**	0.062	0.110	**0.089**
GraphCNN	0.108	0.153	0.110	0.209	0.152	0.097	0.125	0.105	0.160	0.077	0.093	0.174	0.121
Minkowski	0.113	0.169	0.095	0.212	0.195	0.111	0.142	0.116	0.145	0.088	0.105	0.142	0.131
SHOT	0.286	0.329	0.184	0.339	0.497	0.310	0.365	0.314	0.263	0.359	0.441	0.345	0.353
Random	0.310	0.343	0.404	0.379	0.511	0.330	0.426	0.366	0.300	0.368	0.449	0.346	0.387

Table 1: **Mean Euclidean error results**.

We also experiment with naive push-pull loss without geodesic consistency. For points in the same correspondence set, we pull them together. For points in different correspondence sets, we push them away with a fixed margin 1. All the networks quickly converge to a local minimum, with pull loss equal to 0 and push loss equal to 1. The predicted embedding are nearly a constant vector. This is because that there exists some annotations that are close to each other and naive push loss treats them as a hard negative sample, while geodesic consistency loss allows them to be close to each other in the embedding space. This verifies our design of geodesic consistency loss.

Besides, we evaluate predicted semantic embeddings by mean Euclidean error. Compared with mean Geodesic Error(mGE) in Algorithm 1, Euclidean error is less strict as the distance is measured in Euclidean space instead of on 2D object surfaces. The results are shown in Table 1. All deep learning based methods using our geodesic consistency loss achieve much smaller mean Euclidean error. Among them, DGCNN, PointNet, RS-Net and PointConv are relatively superior to the other nets on extracting semantic correspondence information. In contrast, local geometry based method SHOT fails to find correspondences between semantic points.

3 More Visualizations on Partial-Full Object Matching

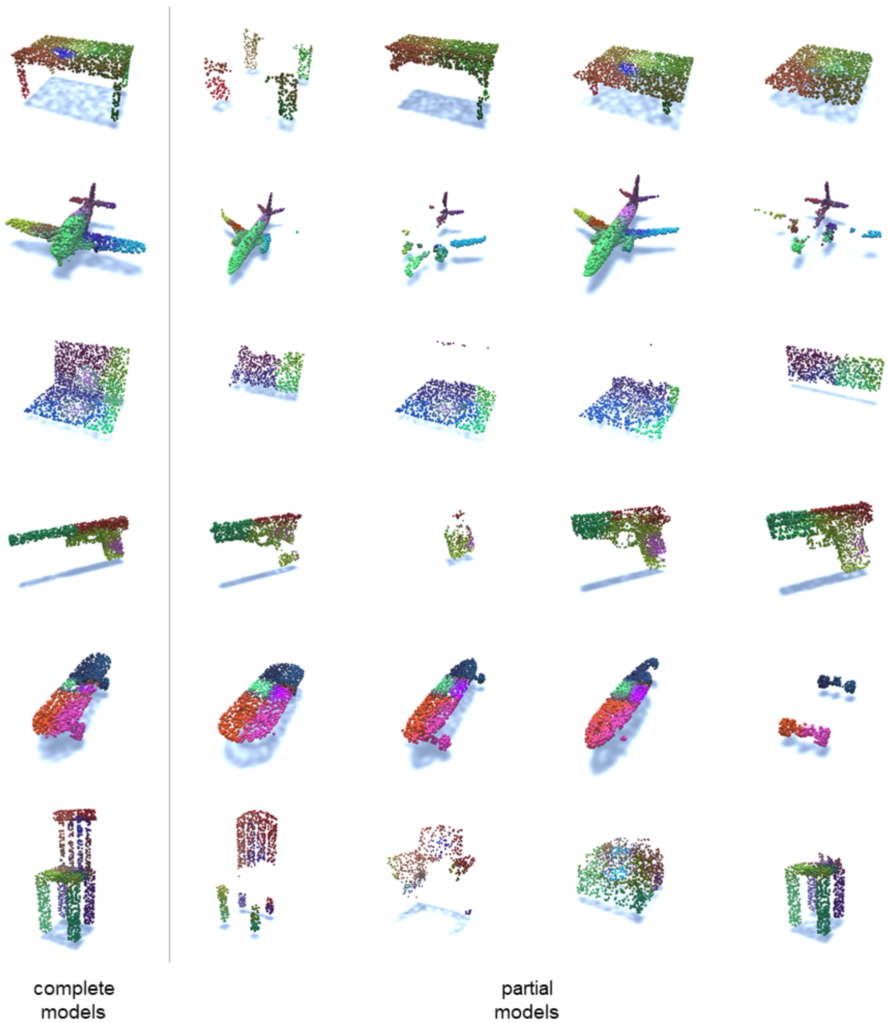

Fig. 5: Visualizations on Partial-Full Object Matching.

4 More Visualizations on Cross-Object Registration

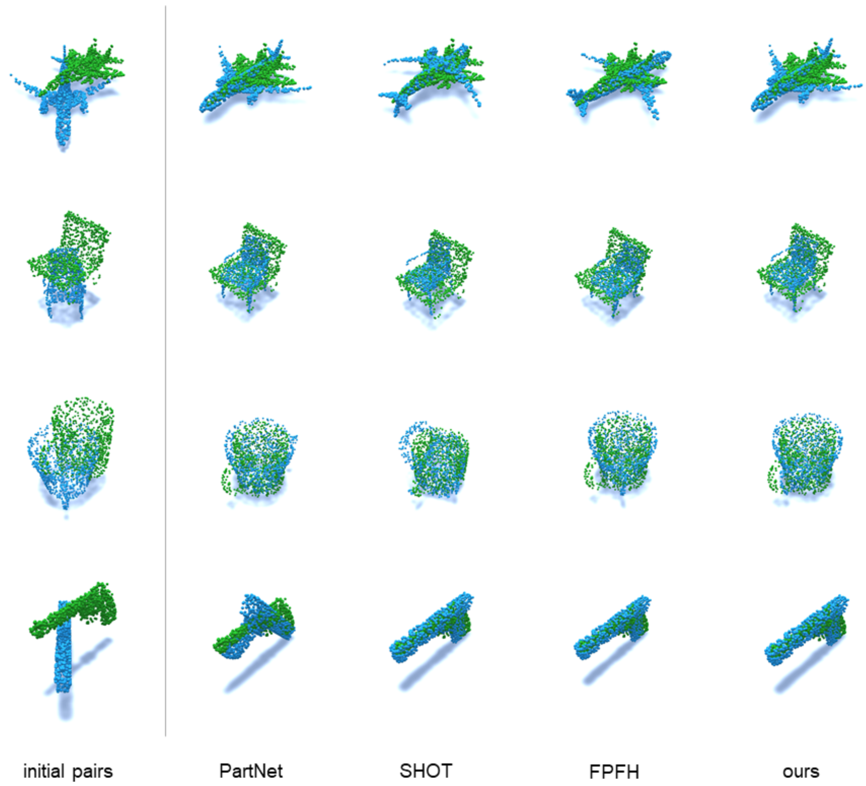

Fig. 6: Visualizations on cross-object registration.