Global Structure-from-Motion Meets Feedforward Reconstruction

Supplementary Material

6. Ablations

To understand the contribution of each component, we conduct ablation studies along three axes: the track types used in augmented bundle adjustment, the choice of feedforward backbone, and the covisibility filtering strategy.

6.1. Augmented Bundle Adjustment

Augmented bundle adjustment (A-BA) is ablated in Table 6, where all variants start from the same results after motion averaging. Three types of tracks are considered: SIFT tracks from classical feature matching, deep tracks (DT) obtained from VGGSfM [43] inference, and virtual tracks (VT) synthesized by reprojecting sampled rays across neighboring views. On ETH3D [36], SIFT tracks contribute most to accuracy at tight thresholds, confirming their precision for well-textured scenes. On SMERF [10], virtual tracks are essential for preventing drift across rooms with minimal overlap, while deep tracks provide complementary robustness under strong appearance changes, particularly for indoor scenes.

Table 6. Ablation results for Augmented Bundle Adjustment.

AUC@			ETH3D			SMERF (minimal)			SMERF (low)		
Components			1	3	5	1	5	20	1	5	20
DT	SIFT	VT	52.6	76.6	83.3	10.0	54.5	82.1	14.9	71.5	92.4
DT		VT	45.4	72.3	80.2	9.7	54.6	82.0	14.3	70.6	92.1
	SIFT	VT	46.6	72.8	80.5	9.2	54.6	82.0	12.5	70.0	92.0
DT	SIFT		54.8	77.7	84.0	7.2	32.6	68.3	9.9	47.2	79.5
DT			47.0	72.7	80.4	5.5	30.7	66.0	7.7	41.0	75.7
	SIFT		55.8	78.4	84.7	8.2	34.2	68.7	4.6	31.7	71.4

6.2. Different Backbones

End-to-end results with different feedforward backbones are shown in Table 7. Among the tested backbones, π^3 achieves the best overall performance, owing to its higher accuracy in local multi-view estimation. Importantly, our proposed pipeline generalizes across all backbones: motion averaging (init) and A-BA each provide consistent improvements over their respective baselines, regardless of the underlying feedforward model. This demonstrates that the gains from our global optimization are complementary to the local estimation quality.

6.3. Covisibility Filtering

An ablation of our two filtering steps can be found in Table 8, where *DG* stands for Doppelgangers++ and *VO* for visual overlap ratio. The results of all reported variants are after motion averaging. On ETH3D, filtering with Doppelgangers++ is sufficient for achieving high accuracy, while for more complex scenes, such as SMERF, it is essential to use our proposed visual overlap ratio filtering and weighting in the optimization.

Table 7. Ablation on different choices of backbones.

	ETH3D			SMERF (minimal)			SMERF (low)		
AUC@	1	3	5	1	5	20	1	5	20
π^3	13.2	36.1	48.9	3.2	18.0	51.7	1.5	14.3	49.8
VGGT	8.6	24.0	35.0	2.8	6.0	22.1	1.4	6.0	28.2
MA	5.1	11.1	18.3	3.0	14.5	42.7	1.7	17.7	56.1
π^3 (init)	20.3	49.0	61.9	9.8	55.5	82.3	12.9	70.2	92.1
VGGT (init)	15.8	38.3	50.5	6.7	45.4	76.7	11.3	59.9	87.3
MA (init)	5.3	12.3	19.7	4.2	33.7	70.5	3.2	39.7	78.7
π^3 (A-BA)	53.1	77.0	83.7	9.9	54.5	81.6	14.9	71.9	92.5
VGGT (A-BA)	53.7	76.9	83.3	7.2	45.6	76.4	12.0	60.2	87.2
MA (A-BA)	17.5	45.6	59.3	4.4	31.6	69.6	3.4	39.3	78.3

Table 8. Ablation results for covisibility filtering.

	ETH3D			SMERF (minimal)			SMERF (low)		
AUC@	1	3	5	1	5	20	1	5	20
DG+VO	20.3	49.0	61.9	9.8	55.5	82.4	12.9	70.2	92.1
DG	20.2	49.1	62.1	9.4	52.7	78.1	12.2	69.8	92.0
VO	13.5	37.0	49.9	3.2	17.2	46.8	1.8	13.6	32.3

7. Alternative System Designs

7.1. Different Radius for Local Estimation

The proposed method fixes the radius to 1 for local estimation, which maximizes the overlap between neighboring views within each star graph. Increasing the radius is not straightforward: it would require a graph expansion step, and feedforward tracking only works when frames pairs have visual overlap. Moreover, a larger radius increases computational cost and degrades local inference quality, as demonstrated in the main paper. We therefore rely on classical optimization to propagate consistency over large distances in the graph. For sequential inputs with high sampling rates or images captured from similar viewpoints, radius-1 stars may provide redundant coverage. We leave the exploration of adaptive or larger graph radii as future work.

7.2. Alternative Similarity Averaging Formulation

The similarity averaging problem in Eq. 13 can also be reformulated as

$$\min_{c,\tilde{s}} \sum_{l,(i,j)\in S_l} o_{ij} \cdot d\left(\tilde{s}_l \cdot R_{ij}^\top t_{ij} - (c_i - c_j)\right), \ \tilde{s}_0 = 1 \quad (16)$$

This formulation results in a convex optimization problem when d is convex. However, the error can be large and scale variant, while Eq. 13 is more constrained when the scale of each star is normalized. This is similar to the comparative advantage of BATA [54] over LUD [26] in translation averaging.

8. Runtime

Component-level runtime statistics are summarized in Table 9 and Table 10. All experiments are conducted on an Neoverse-V2 CPU with 856 GB RAM and an NVIDIA GH200 GPU with 96 GB memory. A *batch* refers to an image pair or a star. Because the number of retrieved pairs and the maximum number of neighbors per image are fixed, the runtime of Doppelgangers++ [49] and local inference (star reconstruction and tracking) scales linearly with the number of images. The global motion averaging and A-BA steps are comparatively inexpensive, especially when the number of images is small. If lower accuracy is acceptable for a downstream application, tracking and A-BA can be skipped entirely, significantly reducing the overall computation.

Table 9. Runtime (in seconds) of batch inference across datasets.

	Two View [49]		Star [47]		Tracking [43]	
Percentile @	50	90	50	90	50	90
Per batch	1.20	1.23	0.31	0.77	1.27	1.81

Table 10. Runtime (in seconds) for the global refinement

	Motion Averaging		Augmented Bundle Adjustement	
Percentile @	50	90	50	90
ETH3D	0.28	1.02	95.58	294.92
CO3D	0.09	0.42	8.58	45.92
IMC2021	0.07	0.35	4.91	28.64
SMERF	1.18	3.13	255.37	1142.33
LaMAR	177.5	280.00	19505.91	22578.51

9. Sampling Method for Analysis

We consider all sequences in the LaMAR [31] dataset. For each sequence, we select a random center frame every 200 images. Around each center frame, we extract subsequences at multiple temporal densities:

- Consecutive sampling (high density): subsequences of length 4, 8, 16, 32, 64, and 128 frames.
- Sampling every 2 frames (medium density): subsequences of 4, 8, 16, 32, and 64 frames.
- Sampling every 4 frames (low density): subsequences of 4, 8, 16, and 32 frames.

For example, from a 64-frame window, sampling at intervals of 2 or 4 yields subsequences of length 32 or 16, respectively. These subsequences observe the same scene but at different spatial-temporal densities.

The provided ground truth mesh is used to render depth maps, where sequences with inconsistent depths are discarded ($\approx 11.7\%$). The remaining sequences form the complete sample set.

10. Track Mixing Strategy

The three source of tracks, namely SIFT, feedforward tracks, and virtual tracks, are combined through a priority-based mixing strategy before being passed to the final bundle adjustment. The goal is to ensure that every image pair receives sufficient constraints while prioritizing SIFT tracks which have the highest accuracy and avoiding redundant tracks on pairs that are already well covered.

Concretely, we first include *all* SIFT tracks unconditionally. Next, we iterate over the deep tracks produced by the feedforward network. For each deep track, we check whether any image pair it spans is undercovered, which we define as having fewer than 512 existing matches. If at least one such under-covered pair exists, the deep track is added to the track set; otherwise it is discarded. Finally, the same procedure is applied to virtual tracks.

11. More Visualizations

To demonstrate the concrete challenges faced by Structure-from-Motion, we provide further visual examples.

In symmetric scenes, feedforward methods often have difficulty distinguishing visually similar structures, resulting in collapsed reconstructions where distinct parts of the scene are incorrectly merged. One such example with four-way symmetry can be found in Figure 5. By leveraging Doppelgangers++ [49] to filter non-covisible pairs, our proposed method can reliably distinguish between the different facades and produce a correct reconstruction.

Examples from the SMERF [10] benchmark as proposed by MP-SFM [28] can be found in Figure 6 and Figure 7. This benchmark is established by selecting a sparse subset of images from dense indoor captures, resulting in minimal to no multi-view overlap between consecutive frames, often compounded by low texture. The multi-room layout further introduces symmetry challenges, as structurally similar rooms can easily be confused. Fueled by feedforward methods for local reconstructions, our proposed method successfully reconstructs scenes even under minimal overlap, while maintaining high accuracy when overlap is abundant. In contrast, purely feedforward models struggle to distinguish visually similar rooms (*e.g.*, Berlin and London) and exhibit drastic scale drift across rooms. Furthermore, under low overlap, π^3 [47] lacks sufficient multi-view correspondences for bundle adjustment to be effective; in these cases, BA may fail to improve accuracy or even degrade it by overfitting to noisy observations. Consequently, π^3 achieves low scores even on scenes with high image density.

12. Detailed results

In this section, we provide per-scene and per-category breakdowns for ETH3D [36], CO3DV2 [29], and IMC2021 [15].

For ETH3D [36], per-scene results can be found in Table 11. ETH3D features high-resolution images with millimeter-accurate ground truth across diverse indoor and outdoor environments. The proposed method achieves the highest accuracy overall, benefiting from both the robustness of feedforward local estimation and the precision of classical global optimization.

For CO3D [29], per-category results can be found in Tables 12, 13, and 14. CO3D consists of object-centric video sequences that often exhibit low texture and limited multi-view overlap. With 10 images (Table 12), π^3 with bundle adjustment generally achieves higher accuracy than our method, as the feedforward model can observe nearly the entire scene in a single pass, reducing the need for global optimization. With 20 and 40 images, the proposed method matches or slightly exceeds π^3 + BA, as the larger scene coverage benefits from our global consistency enforcement.

For IMC2021 [15], per-scene results can be found in Table 15. IMC2021 consists of unordered internet photo collections with significant illumination and viewpoint variation. With only 5 images, π^3 + BA is slightly more accurate than the proposed method, though both significantly outperform classical methods that struggle with insufficient feature matches. With 10 images, the proposed method achieves the best accuracy among both classical and feedforward approaches. With 25 and full images, GLOMAP with SIFT features achieves the best accuracy as the denser sampling provides sufficient classical correspondences, while the proposed method remains competitive.

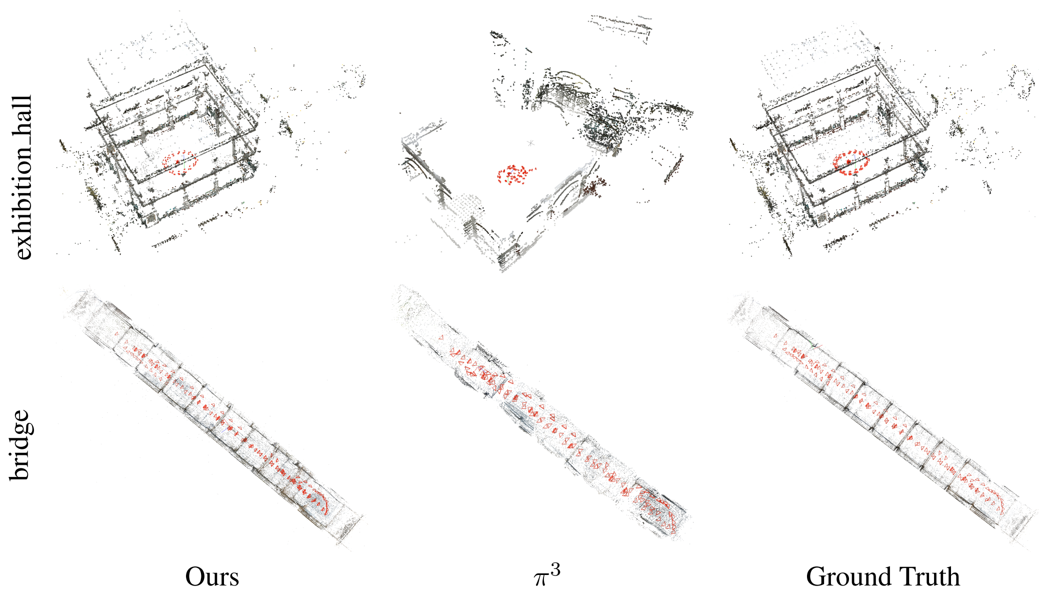

Figure 5. With the help of Doppelganger++ [49], our proposed method works well on scenes with high symmetry in ETH3D [36]. The result of feedforward methods like π^3 [47] collapses.

Table 11. Detailed results on ETH3D [36]. Results marked with * are with ground truth calibration.

	AUC@1							AUC@3							AUC@5						
	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	GLUEMAP*	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	GLUEMAP*	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	GLUEMAP*
botanical_garden	58.7	59.4	7.3	3.5	11.7	59.3	79.8	84.5	84.8	21.1	6.6	49.9	84.8	93.2	90.6	90.7	28.3	14.8	66.9	90.8	95.9
boulders	3.8	4.0	17.0	42.3	18.8	47.6	82.5	3.9	5.7	52.6	70.1	55.7	79.5	94.0	4.2	8.2	67.6	78.9	71.1	87.1	96.4
bridge	74.0	73.2	1.4	1.3	34.4	74.4	87.8	90.9	90.4	3.3	11.3	71.3	91.0	95.7	94.5	94.2	4.5	25.4	82.0	94.6	97.4
courtyard	29.7	45.9	16.0	40.5	32.3	52.8	80.1	42.2	76.4	51.4	73.6	69.1	82.1	93.4	45.6	85.4	66.4	83.7	81.1	89.3	96.0
delivery_area	19.9	47.8	6.7	9.4	28.0	43.9	68.6	25.5	69.9	32.7	34.4	60.3	68.9	78.5	27.1	75.0	47.9	47.5	68.9	74.7	80.5
door	79.6	70.7	21.9	47.8	21.8	80.2	86.9	90.5	87.5	46.2	78.7	46.1	90.7	92.9	92.7	90.9	64.7	85.6	64.6	92.8	94.1
electro	47.3	44.4	9.6	12.8	18.2	50.8	79.5	73.6	67.2	39.8	44.2	51.1	75.5	89.7	81.2	73.8	56.5	60.3	64.2	82.6	92.1
exhibition_hall	25.2	8.7	1.6	1.5	3.7	26.9	82.2	65.5	28.6	2.2	1.9	29.5	67.0	92.3	77.7	38.7	3.2	2.6	47.7	78.7	95.2
facade	71.4	68.8	19.7	21.7	21.8	70.4	88.8	88.7	87.8	51.8	53.7	57.9	88.7	96.2	93.0	92.5	65.5	67.4	72.7	93.1	97.7
kicker	54.1	55.2	34.8	60.6	36.6	56.6	90.7	77.1	81.6	71.7	85.2	71.6	82.7	96.9	83.2	88.4	81.7	90.9	81.6	89.1	98.1
lecture_room	44.5	58.3	18.0	49.9	42.4	55.7	78.1	62.8	80.2	51.0	76.3	75.0	79.1	91.7	71.0	87.2	66.5	84.2	84.3	86.4	95.0
living_room	70.3	50.8	14.7	16.8	29.1	66.2	77.0	88.4	66.8	48.2	50.1	66.9	86.7	91.4	92.7	70.7	64.2	64.9	78.1	91.6	94.6
lounge	34.0	28.1	20.3	34.0	18.9	37.1	42.3	38.0	36.0	56.8	66.3	37.9	47.0	48.8	38.8	37.6	72.8	76.7	44.6	49.9	51.1
meadow	16.1	33.1	29.1	42.6	24.2	43.2	48.5	31.0	75.7	69.1	74.8	65.6	76.7	79.4	35.1	85.2	80.2	84.2	78.2	85.9	87.6
observatory	43.0	21.2	5.5	33.4	9.4	42.8	68.1	74.5	26.2	17.8	64.2	27.1	74.4	88.2	84.0	27.2	30.1	76.2	43.1	84.0	92.9
office	24.3	21.9	8.0	25.1	8.7	24.7	41.7	42.6	36.9	18.4	41.6	20.6	41.4	54.4	51.2	44.7	26.2	51.5	27.6	49.0	58.5
old_computer	12.9	31.0	2.1	18.0	23.3	29.6	50.6	18.1	65.2	11.2	54.8	59.8	65.8	80.3	19.7	77.6	26.0	69.2	73.7	78.1	87.8
pipes	35.2	52.6	10.9	51.7	12.1	52.9	79.8	41.9	81.3	32.8	80.8	37.0	81.9	92.9	43.7	88.5	46.9	88.1	51.2	88.7	95.7
playground	67.4	55.4	4.3	23.7	9.2	68.0	87.6	88.2	83.1	16.1	53.0	38.6	88.6	95.8	92.9	89.6	26.8	66.9	53.9	93.1	97.5
relief	44.9	8.7	4.3	4.5	5.1	60.5	84.1	59.9	11.3	17.1	12.0	22.8	85.7	94.4	63.4	11.9	36.4	26.0	37.5	91.3	96.6
relief_2	32.8	12.5	5.8	3.8	8.5	37.3	53.5	44.9	13.9	18.2	13.6	26.9	62.5	61.9	47.5	14.2	29.1	24.3	42.5	74.6	69.4
statue	67.4	64.4	9.9	60.9	9.7	66.9	95.2	89.1	88.1	19.2	87.0	19.6	89.0	98.4	93.5	92.9	32.3	92.2	32.3	93.4	99.0
terrace	55.3	47.7	10.7	50.6	27.7	60.5	89.6	84.8	81.3	51.0	80.8	69.8	86.7	96.5	90.9	88.8	68.1	88.2	80.8	92.0	97.9
terrace_2	84.6	82.4	43.3	64.9	43.0	83.7	89.5	94.2	93.3	68.4	84.1	68.1	93.9	96.4	96.5	96.1	78.4	90.4	78.2	96.4	97.8
terrains	44.3	26.3	7.5	42.8	8.4	33.6	36.7	53.8	34.0	34.9	78.0	27.9	52.6	53.8	55.9	36.0	52.7	86.5	41.6	62.7	60.8

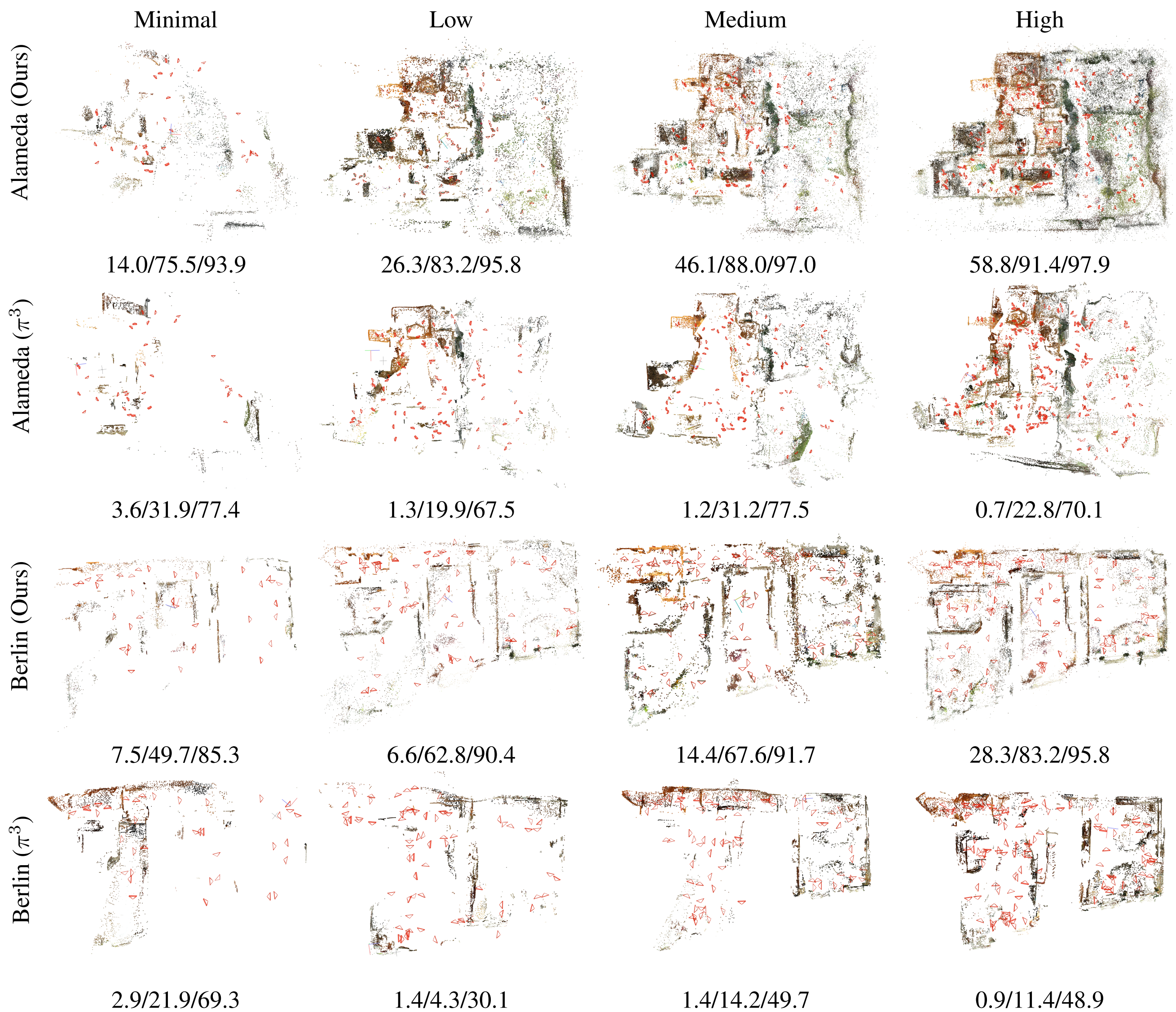

Figure 6. Our proposed method works well from minimal to high overlap on SMERF [10] using the benchmark setup by MP-SFM [28]. The AUC scores at 1/5/20 degrees are shown below the image. Our proposed method works well even under minimal overlap, while π^3 [47] has difficulty in generating accurate reconstructions.

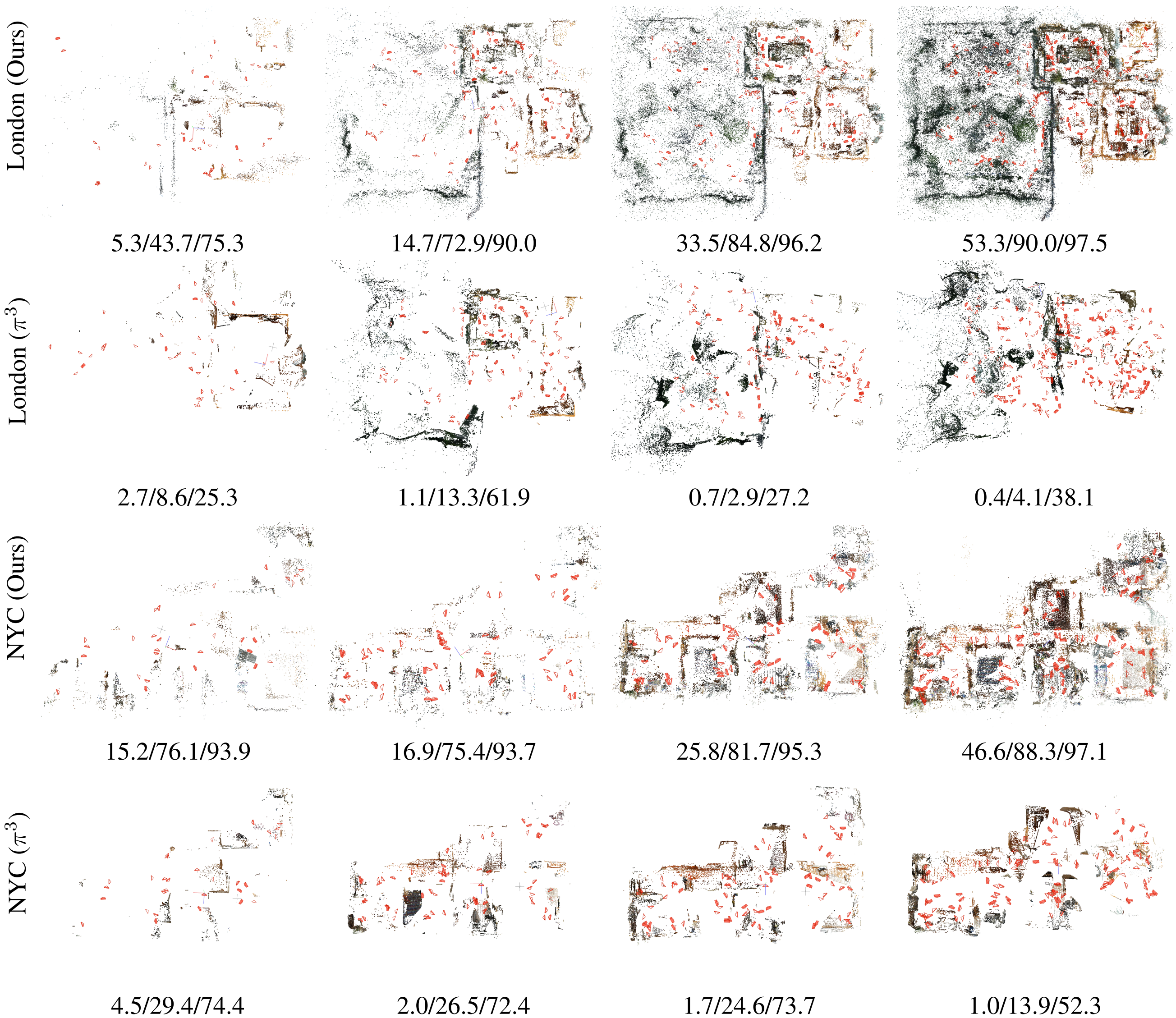

Figure 7. Continuation of Figure 6.

Table 12. Results per-category on CO3D [29] with 10 images per scene. The proposed method is on par with π^3 + BA.

	AUC@3						AUC@10						AUC@30					
	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP
apple (10)	26.0	22.7	49.9	61.1	47.6	57.4	34.9	30.2	78.7	82.5	77.8	81.2	39.6	35.0	90.8	91.6	90.2	91.3
backpack (10)	28.6	22.2	49.8	56.6	47.3	56.1	41.4	32.6	79.8	81.8	79.0	82.2	48.1	38.8	92.3	92.7	92.1	93.0
banana (10)	30.7	19.1	42.6	55.1	41.0	53.8	44.0	27.3	73.2	77.5	72.2	77.1	51.5	32.7	87.1	88.4	86.8	88.1
baseballbat (10)	26.8	18.8	37.5	48.7	34.4	48.0	41.3	27.4	68.3	73.0	67.7	73.3	50.6	35.0	84.7	86.2	84.1	86.0
baseballglove (10)	33.6	25.0	43.5	55.8	43.7	56.3	45.9	36.6	72.6	77.2	72.9	77.7	52.6	43.1	85.0	86.7	85.1	87.0
bench (10)	26.9	23.6	69.2	77.3	68.4	76.0	32.7	29.4	90.0	92.6	89.7	92.2	35.3	32.6	96.6	97.5	96.5	97.4
bicycle (10)	29.8	24.4	57.2	67.2	57.0	65.0	39.5	33.5	84.4	87.1	84.5	87.2	43.9	38.6	94.2	95.1	94.4	95.3
bottle (10)	28.3	16.3	50.6	57.2	47.9	56.2	40.1	22.3	78.2	80.0	77.7	80.3	45.3	26.6	90.0	91.2	90.1	91.1
bowl (10)	25.2	11.2	44.0	53.3	41.1	47.4	40.5	14.1	75.5	77.3	73.9	75.9	47.6	17.6	88.5	88.8	87.0	87.8
broccoli (10)	25.2	17.7	38.9	48.3	37.5	51.3	36.8	25.8	71.3	75.2	71.0	75.7	43.8	32.0	88.4	89.9	87.3	87.8
cake (10)	21.7	18.5	40.8	51.0	40.9	53.0	31.6	27.0	71.0	75.0	72.4	77.5	38.2	33.8	86.6	88.1	88.1	90.2
car (10)	22.4	24.0	60.7	60.3	62.4	65.9	28.2	29.4	83.4	81.5	84.0	84.9	31.4	33.9	92.2	90.6	92.4	92.6
carrot (10)	25.8	19.9	39.4	44.3	38.5	46.5	39.1	30.7	72.5	72.7	72.0	75.0	47.3	38.6	88.8	88.4	88.5	89.5
cellphone (10)	21.6	19.2	33.6	40.1	34.2	39.1	33.9	28.7	62.8	63.7	62.3	63.8	43.2	35.1	79.9	79.4	78.4	78.9
chair (10)	27.8	21.1	59.3	66.2	56.8	62.2	36.8	28.8	85.6	87.7	84.8	86.5	41.8	33.3	94.9	95.5	94.7	95.2
cup (10)	20.0	23.8	48.3	55.3	46.1	53.5	27.7	32.8	74.5	75.7	73.5	76.3	31.6	37.7	86.5	86.5	85.3	86.3
donut (10)	25.3	18.5	39.1	46.3	37.5	48.9	38.8	26.6	75.8	77.1	73.4	77.9	45.3	32.9	91.2	91.4	90.4	91.9
hairdryer (10)	23.9	20.5	50.1	61.2	49.0	58.9	32.9	30.5	80.9	85.1	80.4	84.5	37.7	36.3	93.0	94.4	92.9	94.2
handbag (10)	22.4	20.1	46.1	53.7	43.0	50.3	30.1	29.1	75.9	78.9	74.3	77.8	35.3	35.6	90.1	91.4	89.2	90.7
hydrant (10)	32.4	21.1	61.7	70.1	59.8	67.7	42.6	26.7	86.7	88.8	86.2	87.9	46.8	30.0	95.1	95.4	95.0	95.1
keyboard (10)	26.1	22.1	39.7	48.2	38.5	49.0	39.2	31.5	69.6	73.4	69.5	73.2	47.1	37.5	85.4	86.5	85.3	86.4
laptop (10)	29.0	26.1	45.5	53.2	44.5	51.3	42.2	37.5	72.6	74.3	72.1	74.3	50.5	44.7	87.1	86.5	86.7	87.0
microwave (10)	18.6	28.5	48.0	49.9	50.1	50.5	22.4	36.4	74.0	73.2	74.2	73.1	26.3	42.0	86.0	85.4	85.7	85.5
motorcycle (10)	24.3	25.3	63.7	69.7	61.5	69.1	31.7	34.8	88.2	89.3	87.7	90.3	35.5	39.2	96.0	96.3	95.8	96.7
mouse (10)	27.1	17.5	42.2	54.0	38.8	47.3	38.8	27.1	76.3	81.2	74.1	78.0	45.0	33.7	91.5	92.9	90.7	92.0
orange (10)	23.2	20.2	42.9	49.1	42.5	49.0	33.6	28.9	73.8	73.2	73.6	76.2	39.6	33.6	88.2	86.8	87.7	88.6
parkingmeter (10)	30.5	26.3	59.9	51.8	59.4	60.7	44.3	38.3	84.3	78.7	83.8	83.3	51.0	44.9	94.0	91.3	93.8	92.8
pizza (10)	36.0	17.6	36.4	53.0	38.6	53.1	52.6	28.3	69.1	74.8	69.8	74.4	62.4	33.4	86.5	87.7	85.2	85.6
plant (10)	30.0	16.7	52.7	64.6	51.2	59.9	40.3	22.7	82.6	86.0	82.3	85.6	44.3	26.1	93.9	94.6	93.9	95.0
stopsign (10)	18.7	20.6	42.5	42.8	39.6	46.6	27.4	29.9	78.0	71.1	76.0	77.9	32.7	35.8	91.5	87.4	90.8	91.7
teddybear (10)	25.9	26.8	53.1	58.2	50.7	57.7	34.2	37.0	81.1	82.1	79.9	82.6	39.1	42.6	92.4	92.8	92.0	93.2
toaster (10)	20.9	17.4	57.4	66.1	55.2	60.9	28.1	24.8	84.9	87.8	84.0	86.5	32.0	30.1	94.8	95.8	94.5	95.4
toilet (10)	28.3	31.6	39.0	41.7	39.9	42.5	41.5	48.6	65.8	66.1	66.3	65.5	51.6	61.3	81.9	81.3	82.0	81.4
toybus (10)	22.9	18.4	48.8	51.1	47.2	54.1	32.5	27.1	77.4	74.0	76.3	77.9	37.4	32.8	89.0	87.4	88.8	89.5
toyplane (10)	29.1	23.1	44.0	53.6	44.9	53.4	40.1	34.5	72.5	73.6	72.6	74.9	46.7	41.5	87.4	86.0	86.9	87.3
toytrain (10)	17.5	14.1	44.4	51.6	44.8	48.7	21.6	21.2	74.3	77.6	75.3	76.4	23.9	25.8	87.6	88.7	87.9	88.4
toytruck (10)	17.1	21.0	41.9	43.4	39.3	46.9	24.7	29.5	72.1	71.2	70.6	73.9	28.7	34.4	88.1	87.4	87.1	87.8
tv (10)	36.3	16.8	50.6	53.4	51.0	55.2	54.0	22.5	80.7	82.1	81.1	83.0	60.4	38.7	93.1	93.5	92.7	93.4
umbrella (10)	31.6	20.3	57.1	65.8	54.1	62.7	43.5	29.5	84.8	87.7	83.9	86.8	48.9	34.6	94.7	95.7	94.4	95.4
vase (10)	21.9	14.9	52.5	59.3	50.9	57.0	30.5	19.9	82.2	82.6	81.3	83.3	35.1	23.8	93.8	93.1	93.4	94.0
wineglass (10)	18.9	13.1	51.0	57.7	51.2	56.1	26.5	16.7	77.3	79.0	77.0	78.4	31.3	20.4	88.0	88.4	87.5	87.9

Table 13. Results per-category on CO3D [29] with 20 images per scene. The proposed method is on par with π^3 + BA.

	AUC@3						AUC@10						AUC@30					
	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP
apple (20)	32.4	53.1	55.8	67.0	58.5	64.1	39.9	68.3	82.9	87.3	85.4	86.4	44.0	76.0	94.0	95.7	94.9	94.1
apple (20)	32.4	53.1	52.8	67.0	57.4	69.3	39.9	68.3	81.1	87.3	83.9	87.9	44.0	76.0	93.2	95.7	94.2	95.6
backpack (20)	31.0	38.5	44.9	53.6	46.4	54.5	44.5	58.6	76.6	79.0	78.4	80.2	53.4	72.5	91.3	91.2	92.1	92.4
banana (20)	49.4	52.6	49.0	64.1	49.0	61.9	63.9	65.7	77.3	83.0	77.4	81.5	73.6	72.8	89.4	92.3	89.5	91.5
baseballbat (20)	27.1	39.3	35.1	48.8	33.9	50.8	43.5	55.2	66.7	72.1	66.4	71.4	53.9	66.7	81.7	84.0	81.6	82.5
baseballglove (20)	47.0	47.3	39.8	59.1	41.8	58.5	55.9	60.9	67.0	75.1	67.8	74.8	61.4	67.4	79.8	83.4	79.6	83.1
bench (20)	30.7	51.3	71.0	81.8	67.0	76.6	38.3	63.7	90.9	94.3	89.6	92.6	41.1	67.6	96.9	98.1	96.5	97.5
bicycle (20)	45.0	57.4	49.6	69.4	55.2	66.5	58.3	76.5	79.6	87.4	82.0	86.0	63.5	83.6	91.3	94.4	92.4	93.6
bottle (20)	35.9	21.7	43.7	56.2	40.8	48.2	50.2	31.7	77.2	80.7	76.7	78.7	56.1	36.5	91.9	93.1	91.8	92.4
bowl (20)	43.9	17.7	38.1	51.2	32.2	43.6	66.6	28.4	73.5	76.4	71.0	74.8	75.9	34.3	86.5	87.5	85.8	87.0
broccoli (20)	35.6	28.4	38.2	53.6	36.7	46.9	46.3	41.4	72.0	76.7	69.4	72.7	50.9	48.3	89.1	90.7	85.0	85.7
cake (20)	33.4	46.6	41.4	54.0	43.4	52.4	45.4	65.6	70.2	75.4	73.7	78.7	52.9	73.4	88.2	90.1	89.6	91.7
car (20)	22.0	44.5	52.8	57.2	55.0	59.7	31.9	61.2	79.2	79.3	81.1	82.7	39.1	72.8	91.2	91.1	91.8	92.3
carrot (20)	31.5	36.5	51.0	63.4	48.9	60.3	42.0	50.1	82.1	86.7	80.6	84.3	47.5	55.3	93.7	95.0	93.3	94.1
cellphone (20)	18.1	23.6	24.3	36.0	27.0	33.2	29.7	39.6	49.9	55.4	51.1	53.3	40.0	51.5	66.2	70.1	66.8	67.9
chair (20)	41.9	58.0	64.0	79.0	63.2	77.4	50.9	68.6	88.1	92.6	87.9	92.4	55.9	73.3	95.8	97.1	95.8	97.3
cup (20)	29.8	27.3	46.8	64.2	47.3	55.6	41.0	42.4	78.1	86.0	78.7	81.3	45.4	52.4	91.2	94.9	91.6	92.4
donut (20)	31.9	38.8	38.2	56.9	40.4	54.5	43.9	56.5	76.3	81.2	77.5	80.8	51.0	64.9	91.7	93.3	92.2	92.9
hairdryer (20)	31.7	43.3	41.3	60.5	43.4	55.0	46.5	67.6	77.6	85.7	77.2	83.9	54.6	77.8	91.9	94.7	91.7	94.2
handbag (20)	27.3	29.7	36.2	50.6	36.1	44.1	39.1	44.9	69.2	74.9	68.4	73.2	47.4	53.4	86.2	88.3	86.1	87.8
hydrant (20)	53.8	58.8	63.1	77.1	63.1	76.3	65.9	69.7	87.4	91.8	87.6	92.0	70.0	73.9	95.3	97.0	95.6	97.2
keyboard (20)	26.9	34.6	38.2	50.6	43.6	51.5	38.8	48.9	68.2	74.0	70.1	73.7	43.5	55.9	83.1	86.5	83.5	84.7
laptop (20)	46.4	46.2	50.0	62.7	51.5	60.4	56.9	64.1	77.7	81.8	78.9	81.4	64.0	74.3	91.1	91.8	91.6	91.5
microwave (20)	30.2	43.3	43.1	57.7	50.3	55.2	39.2	56.4	75.9	80.3	80.1	81.3	48.9	63.2	90.9	92.0	92.5	92.7
motorcycle (20)	48.8	65.5	67.6	81.1	66.8	76.9	57.3	79.3	89.7	93.9	89.5	92.6	60.0	84.2	96.5	97.8	96.4	97.5
mouse (20)	31.6	39.7	43.6	63.4	40.3	54.9	43.9	55.4	80.0	85.5	77.4	82.7	49.5	63.1	92.9	94.7	92.1	94.0
orange (20)	34.8	32.2	37.8	51.9	41.2	51.5	56.0	44.3	75.1	80.8	76.3	80.3	64.8	49.3	91.0	93.2	91.7	92.9
parkingmeter (20)	48.4	44.1	58.8	60.1	56.1	64.6	68.4	65.9	85.3	84.2	84.1	86.2	76.2	74.2	94.8	93.9	94.4	94.7
pizza (20)	34.2	36.6	28.4	50.5	33.5	46.2	52.3	51.8	63.0	72.1	65.4	69.5	63.2	59.8	84.6	85.3	83.7	85.4
plant (20)	52.3	50.4	61.0	71.4	61.2	71.2	66.1	65.7	87.0	90.4	87.1	90.4	70.8	72.3	95.6	96.7	95.6	96.7
stopsign (20)	24.3	35.9	47.6	56.3	42.5	50.0	36.0	52.0	81.3	85.0	78.4	79.6	41.2	61.1	93.4	94.9	92.6	92.9
teddybear (20)	29.8	46.2	56.0	62.9	50.2	58.2	40.1	63.9	84.7	87.4	82.9	85.6	44.4	72.8	94.6	95.7	94.0	95.0
toaster (20)	29.3	46.3	57.1	71.2	58.5	67.4	38.2	61.9	85.6	90.5	86.4	89.4	41.6	68.8	95.1	96.8	95.4	96.4
toilet (20)	33.1	33.2	31.7	43.9	34.1	39.0	44.0	47.6	57.1	61.9	57.6	59.3	52.7	57.0	71.8	72.4	72.3	72.9
toybus (20)	29.0	34.3	41.1	53.0	42.8	50.1	37.8	47.6	69.4	72.2	70.1	72.3	43.4	56.7	82.2	82.8	82.7	83.3
toyplane (20)	32.1	32.7	39.4	53.7	39.9	47.2	46.7	50.6	66.5	72.4	66.7	68.5	54.7	61.0	80.4	82.1	79.0	79.0
toytrain (20)	22.3	34.4	40.4	48.6	41.6	48.8	29.9	50.0	68.9	73.2	71.0	73.8	34.0	57.5	81.6	85.1	84.0	85.6
toytruck (20)	18.8	31.2	27.9	35.1	27.2	34.2	29.3	44.5	60.7	63.7	59.8	62.3	38.1	54.7	83.8	85.2	83.0	82.0
tv (20)	47.9	42.5	49.0	55.5	50.3	57.4	64.2	64.0	81.0	83.1	81.6	84.0	70.6	79.3	93.5	93.9	93.6	94.4
umbrella (20)	51.2	55.3	61.0	73.5	64.3	73.7	64.6	67.2	86.5	90.7	88.0	90.6	70.4	71.3	95.3	96.9	95.8	96.6
vase (20)	38.0	38.3	55.3	68.3	55.9	66.6	48.0	53.8	83.5	88.1	83.9	87.0	52.0	60.4	94.4	96.0	94.5	95.6
wineglass (20)	30.0	35.1	47.4	60.3	51.5	54.1	41.4	48.5	75.8	82.4	78.2	78.5	46.1	53.5	88.4	90.7	89.3	89.1

Table 14. Results per-category on CO3D [29] with 40 images per scene. The proposed method is on par with π^3 + BA.

	AUC@3						AUC@10						AUC@30					
	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP
apple (40)	58.6	63.3	53.5	68.9	58.5	71.2	70.2	79.6	80.9	87.2	84.1	88.4	75.1	85.7	92.7	95.5	94.1	95.5
backpack (40)	46.9	47.8	43.4	54.4	51.4	55.8	66.4	75.3	76.2	78.8	80.9	80.9	77.1	89.9	91.2	91.2	93.0	92.6
banana (40)	59.0	63.7	47.8	65.0	51.2	65.5	74.0	81.5	77.1	83.3	78.4	82.6	81.8	90.7	89.6	92.4	90.3	91.8
baseballbat (40)	46.6	45.0	37.0	52.3	36.0	51.1	67.3	61.5	67.2	73.3	67.3	71.4	78.4	77.5	82.1	84.5	82.3	82.6
baseballglove (40)	63.1	51.6	40.3	59.2	40.6	55.4	76.4	65.8	67.3	75.2	66.1	73.9	83.2	73.2	80.9	83.7	80.0	84.3
bench (40)	62.0	78.4	69.7	83.9	71.0	80.7	74.3	89.0	90.3	94.9	90.9	93.8	78.4	92.2	96.7	98.3	96.9	97.9
bicycle (40)	55.0	65.3	56.5	66.6	56.8	66.2	73.5	86.4	83.1	85.9	83.5	86.0	80.4	94.3	93.2	93.8	93.4	94.2
bottle (40)	32.3	37.8	43.5	55.2	43.2	52.0	42.6	56.1	77.6	80.5	78.0	80.5	46.8	64.7	91.8	93.0	92.2	92.9
bowl (40)	49.8	22.4	37.0	51.8	31.6	46.3	73.6	34.2	73.2	76.0	71.7	76.0	83.6	41.3	86.6	87.6	86.5	87.7
broccoli (40)	44.6	55.9	38.8	54.5	39.0	56.0	57.5	73.2	72.1	77.1	72.2	77.0	62.5	83.9	89.0	90.7	87.6	88.4
cake (40)	51.4	54.1	41.1	54.4	41.9	55.7	71.4	79.4	69.7	75.3	73.0	79.4	81.6	91.5	87.1	89.8	88.9	91.5
car (40)	38.9	61.2	51.8	58.8	55.4	60.9	51.6	80.5	77.6	81.1	79.6	81.2	58.8	90.2	88.9	91.6	89.6	89.7
carrot (40)	43.6	58.8	52.1	63.9	51.2	63.3	57.9	73.5	82.3	86.8	81.8	85.7	64.4	79.1	93.8	95.2	93.7	94.7
cellphone (40)	29.2	30.2	23.0	37.0	25.3	32.2	48.5	48.3	49.5	56.2	50.5	53.2	61.3	60.6	65.9	70.3	66.1	67.9
chair (40)	68.1	69.5	65.9	79.7	68.7	80.7	81.1	85.3	88.9	92.8	89.8	93.6	85.4	92.0	96.1	97.2	96.5	97.7
cup (40)	46.2	44.7	47.5	64.8	47.1	55.1	61.4	65.3	79.1	86.3	79.5	81.6	66.9	77.9	91.8	95.0	92.3	92.7
donut (40)	49.3	52.8	39.5	59.1	43.1	54.2	73.3	77.4	77.4	82.1	79.1	81.2	85.0	88.6	91.9	93.5	92.6	93.0
hairdryer (40)	50.9	55.7	42.0	61.0	45.7	54.5	70.0	80.0	78.3	86.0	79.8	84.0	77.3	91.6	92.1	94.8	92.8	94.3
handbag (40)	36.4	40.2	36.3	49.5	36.2	45.6	51.7	60.5	69.6	76.3	70.4	73.8	60.7	71.8	86.8	90.6	87.9	88.6
hydrant (40)	71.3	68.0	64.7	78.0	66.2	78.5	85.5	79.4	88.1	92.1	88.9	92.8	90.7	83.7	95.8	97.2	96.1	97.5
keyboard (40)	39.5	44.0	42.5	51.1	42.8	50.8	56.9	64.1	70.6	74.4	70.6	73.3	64.8	75.1	84.1	86.8	84.0	84.8
laptop (40)	56.4	59.6	49.1	62.0	53.6	63.4	72.5	78.8	77.1	81.7	79.4	82.1	81.5	88.8	90.6	92.0	91.7	91.7
microwave (40)	45.2	50.9	46.4	60.2	47.9	58.1	55.8	65.2	78.3	81.6	79.2	82.1	62.1	72.8	91.9	92.6	92.4	93.0
motorcycle (40)	75.2	81.3	68.7	82.0	69.2	81.1	87.7	93.8	90.0	94.2	90.3	93.9	91.8	97.8	96.6	97.9	96.7	97.9
mouse (40)	56.6	55.3	43.5	61.8	37.9	60.7	73.1	72.7	79.2	85.1	77.0	85.2	80.4	81.0	92.7	94.4	92.0	94.8
orange (40)	37.8	41.3	39.9	53.2	43.5	53.1	58.2	66.2	76.1	81.7	78.5	81.8	66.7	79.5	91.4	93.6	92.3	93.4
parkingmeter (40)	66.1	66.1	59.2	63.7	57.2	67.6	83.6	83.4	85.7	85.0	83.6	87.9	90.5	90.4	94.9	94.1	94.2	95.4
pizza (40)	47.4	45.3	29.7	50.8	32.7	44.8	70.6	65.6	64.4	74.5	65.2	70.1	83.3	75.9	85.1	90.0	85.0	86.4
plant (40)	67.1	66.0	58.3	77.6	60.0	74.8	80.7	82.8	86.2	92.8	86.3	91.4	85.3	88.1	95.3	97.5	95.3	97.0
stopsign (40)	48.6	55.5	47.7	60.9	41.1	57.2	72.5	80.1	81.4	87.0	76.2	83.8	82.7	88.8	93.5	95.6	91.8	94.4
teddybear (40)	46.2	47.2	56.6	66.7	52.3	58.1	63.4	65.1	84.7	88.4	83.6	85.5	72.1	76.8	94.6	96.0	94.2	94.9
toaster (40)	43.2	65.2	60.9	71.6	61.1	73.1	54.8	81.0	86.8	90.5	87.2	91.1	58.8	86.4	95.4	96.8	95.6	97.0
toilet (40)	39.5	35.5	29.7	43.5	31.8	37.6	52.3	54.3	54.7	62.0	55.7	57.3	61.1	65.4	69.7	72.7	70.0	71.0
toybus (40)	46.1	51.7	42.8	53.7	43.1	50.1	57.9	70.7	69.8	72.1	69.4	72.0	63.9	81.0	82.4	83.1	82.4	83.1
toyplane (40)	44.6	43.9	37.3	53.8	39.4	49.3	60.9	64.9	65.9	72.5	66.7	69.0	69.8	75.5	80.8	81.9	79.8	78.9
toytrain (40)	35.6	47.8	41.1	52.4	43.3	52.3	47.1	70.2	70.0	75.1	73.1	77.8	52.5	80.8	83.7	86.0	86.3	88.0
toytruck (40)	31.9	35.8	26.5	37.3	26.7	35.9	49.4	54.6	62.2	63.0	60.3	63.4	59.0	65.2	84.2	85.0	83.3	83.6
tv (40)	51.4	49.0	51.5	57.8	53.2	58.2	67.0	76.1	81.6	84.0	82.4	83.6	73.1	87.6	93.5	94.2	93.8	94.2
umbrella (40)	68.4	57.6	62.7	74.4	65.2	73.3	83.2	71.1	86.6	91.0	87.9	90.2	88.6	79.1	95.2	97.0	95.7	96.5
vase (40)	57.2	56.8	57.3	69.3	57.2	66.4	71.2	73.8	83.3	88.7	84.1	87.1	77.8	81.0	94.2	96.2	94.6	95.6
wineglass (40)	43.3	45.9	50.2	60.3	55.5	58.2	56.3	63.3	77.1	81.6	80.5	81.2	61.2	70.3	89.0	90.4	90.4	90.6

Table 15. Per-dataset results on IMC2021 [15].

	AUC@3						AUC@5						AUC@10					
	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP	SIFT	AL+LG	π^3	π^3+BA	GLUEMAP†	GLUEMAP
Bag 5																		
british_museum	31.6	41.5	40.9	41.9	40.9	39.7	38.6	52.0	52.7	52.3	52.8	50.2	51.0	66.4	67.8	67.7	67.9	65.1
florence_cathedral_side	58.1	61.4	57.5	68.1	57.7	67.7	67.5	71.6	70.0	77.5	70.1	77.2	77.8	81.8	82.4	86.7	82.5	86.8
lincoln_memorial_statue	40.6	52.5	61.1	68.8	61.1	68.1	48.3	62.2	73.8	79.4	73.8	78.9	57.4	71.9	85.6	89.1	85.6	88.8
london_bridge	34.9	51.2	42.0	52.3	41.8	51.8	41.9	62.5	54.7	64.7	54.3	64.5	50.6	75.2	71.9	78.1	71.6	78.1
milan_cathedral	41.3	41.3	40.2	43.4	40.1	46.7	51.2	52.2	53.1	55.1	53.0	58.3	63.7	67.3	69.8	70.5	69.6	73.2
mount_rushmore	30.1	31.9	32.7	42.9	32.7	43.8	35.2	38.2	40.5	52.6	40.5	53.0	42.6	48.1	53.8	66.0	53.7	65.8
piazza_san_marco	27.1	46.7	52.6	54.2	53.2	54.3	30.9	56.2	65.7	65.3	66.2	66.5	35.7	67.7	79.8	78.0	80.1	79.8
sagrada_familia	47.4	55.1	38.8	60.0	38.6	58.1	57.0	66.4	51.2	71.2	51.0	69.4	67.8	78.5	66.7	82.9	66.5	81.5
st_pauls_cathedral	45.4	54.2	50.1	54.3	50.1	58.6	54.8	65.5	64.0	66.1	63.8	69.7	66.1	78.2	78.9	79.3	78.8	81.4
Bag 10																		
british_museum	35.8	42.2	35.9	40.7	35.9	42.2	47.3	54.8	49.8	52.8	49.8	54.2	63.0	70.6	67.2	69.3	67.1	70.1
florence_cathedral_side	72.6	66.7	50.2	71.6	50.1	74.7	81.1	76.8	64.0	80.2	64.0	82.9	88.9	85.7	78.4	87.8	78.4	90.1
lincoln_memorial_statue	61.0	62.2	57.0	74.1	57.3	75.4	72.0	73.2	71.3	83.0	71.5	84.2	82.1	82.9	84.4	90.4	84.5	91.5
london_bridge	48.8	54.4	29.8	53.8	29.8	55.9	58.6	65.9	44.1	65.5	44.2	67.7	68.1	76.7	63.6	77.3	64.3	79.5
milan_cathedral	41.1	35.4	33.5	36.7	33.4	46.7	54.5	48.1	47.6	49.6	47.5	60.0	70.7	64.9	65.9	66.0	65.8	75.6
mount_rushmore	33.2	28.3	24.3	36.2	24.4	40.6	42.0	36.7	32.9	47.1	32.9	52.2	54.3	49.3	47.8	62.1	47.8	67.8
piazza_san_marco	43.3	49.5	47.4	58.0	47.6	56.9	52.8	61.3	62.0	69.8	62.1	70.4	63.0	73.1	77.6	81.5	77.7	83.5
sagrada_familia	56.8	60.7	35.8	60.1	35.9	65.3	68.8	71.8	50.2	72.0	50.4	76.4	80.7	82.3	67.5	83.2	67.6	86.9
st_pauls_cathedral	58.5	58.9	43.2	55.3	43.4	64.3	70.6	71.3	58.6	67.5	58.9	75.7	81.8	82.8	75.4	80.0	75.5	86.0
Bag 25																		
british_museum	42.8	41.4	31.3	40.9	31.3	41.9	56.2	55.0	46.1	54.1	46.1	55.1	72.6	71.6	64.5	70.8	64.5	71.1
florence_cathedral_side	79.2	69.6	47.1	73.3	47.2	75.1	86.0	77.3	61.6	81.7	61.7	83.1	92.1	84.6	76.8	89.2	76.8	90.1
lincoln_memorial_statue	78.5	58.7	56.3	80.6	56.5	82.5	85.5	66.7	70.9	87.9	71.0	89.0	91.2	74.5	84.3	93.8	84.3	94.4
london_bridge	68.0	59.3	26.9	51.0	26.7	62.8	76.5	68.6	42.7	63.1	43.0	72.8	84.1	77.1	63.1	75.4	64.0	82.0
milan_cathedral	49.6	42.7	27.6	38.8	27.5	55.2	62.7	56.0	42.5	52.2	42.4	67.7	77.1	71.8	62.4	69.3	62.3	81.2
mount_rushmore	53.4	31.5	21.0	43.6	21.0	52.6	65.3	40.5	30.3	55.9	30.3	64.6	78.4	52.9	46.7	71.0	46.7	78.1
piazza_san_marco	66.4	56.6	45.2	67.1	45.2	58.8	76.2	67.6	60.3	77.8	60.4	72.0	85.0	77.9	76.6	87.7	76.7	84.4
sagrada_familia	72.5	66.7	34.2	69.6	34.3	71.8	81.9	76.5	48.8	80.0	48.9	81.0	90.1	85.6	66.8	89.1	66.9	89.4
st_pauls_cathedral	69.0	65.4	40.0	55.9	40.3	71.2	78.7	75.5	56.8	69.2	57.1	80.3	87.3	84.6	74.4	82.2	74.6	88.5
Bag full																		
british_museum	54.5	41.3	29.8	4.4	29.2	50.5	66.8	53.5	45.1	8.2	44.1	63.0	79.9	69.1	64.2	17.4	63.1	76.4
florence_cathedral_side	89.0	81.1	47.1	73.3	46.2	83.6	92.9	86.8	61.3	80.9	60.9	89.0	96.2	92.1	76.5	88.0	76.2	93.7
lincoln_memorial_statue	85.7	72.4	56.1	84.6	55.1	85.1	89.0	79.4	70.6	90.1	70.3	90.7	92.2	86.3	84.0	94.9	84.0	95.2
london_bridge	74.8	60.9	18.5	20.6	35.2	79.3	81.4	70.4	29.1	31.5	52.4	85.8	87.2	80.0	45.6	48.2	71.6	91.6
milan_cathedral	73.9	56.7	27.7	47.5	25.6	68.2	81.8	68.0	43.2	60.3	41.1	77.5	89.4	79.7	63.3	75.0	61.9	87.0
mount_rushmore	76.1	47.3	18.8	52.5	18.2	62.8	83.3	59.3	27.6	63.4	27.9	74.0	89.6	74.6	44.0	77.2	44.7	84.5
piazza_san_marco	77.6	67.0	46.7	4.5	47.2	72.5	85.5	77.8	62.1	9.4	62.9	82.1	92.4	87.3	78.1	21.2	78.8	90.4
sagrada_familia	83.2	77.0	31.9	73.3	32.6	76.2	88.5	84.5	46.8	82.7	47.7	84.2	93.1	91.2	65.2	90.6	66.2	91.3
st_pauls_cathedral	77.8	61.6	40.4	51.9	40.9	78.5	84.6	72.0	57.2	66.4	57.7	85.5	90.7	82.5	74.8	80.5	75.1	91.7