

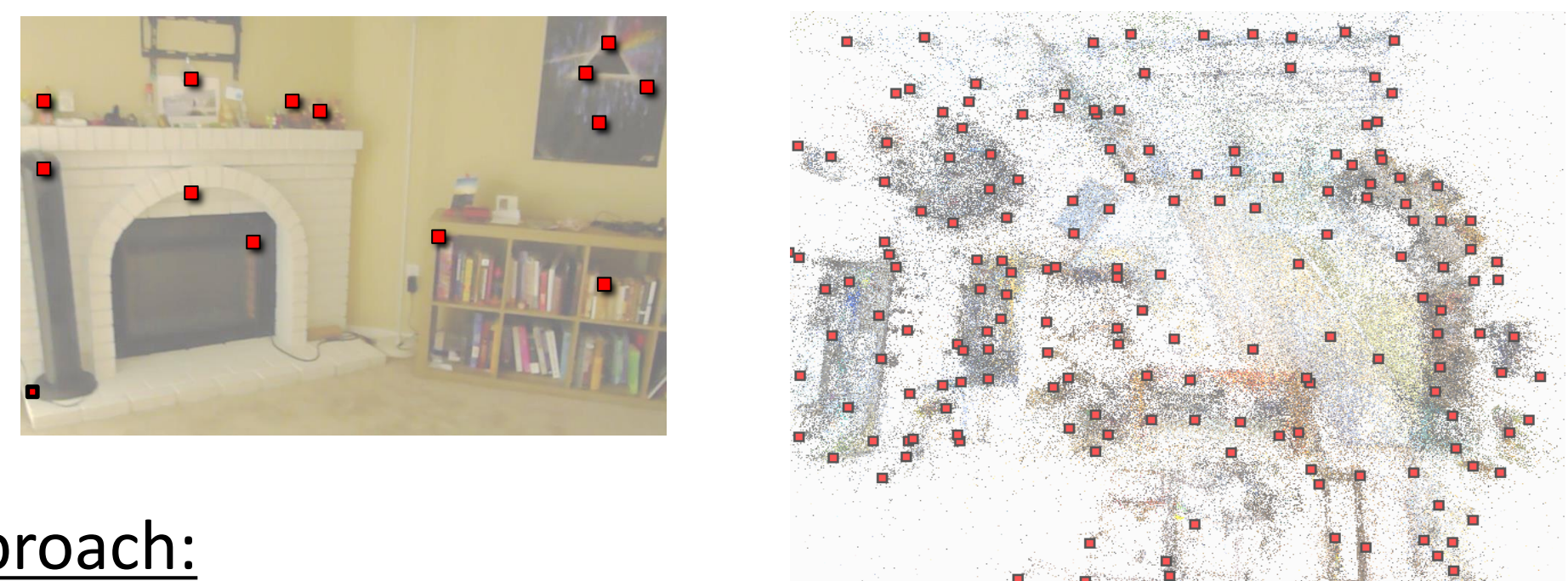
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* work done while author was at Microsoft.

Recap: Scene Landmarks Detection (SLD)

Scene landmarks are salient scene-specific 3D points, that can be used for 6-DoF camera localization in pre-mapped scenes.



Approach:

- Specify scene landmark points in 3D scene coordinates.
- Train detector (CNN-based heatmap predictor) to predict visible scene landmarks (2D pixel locations) in RGB images.
- Compute 6-DoF camera pose from the 2D--3D scene landmark correspondences.

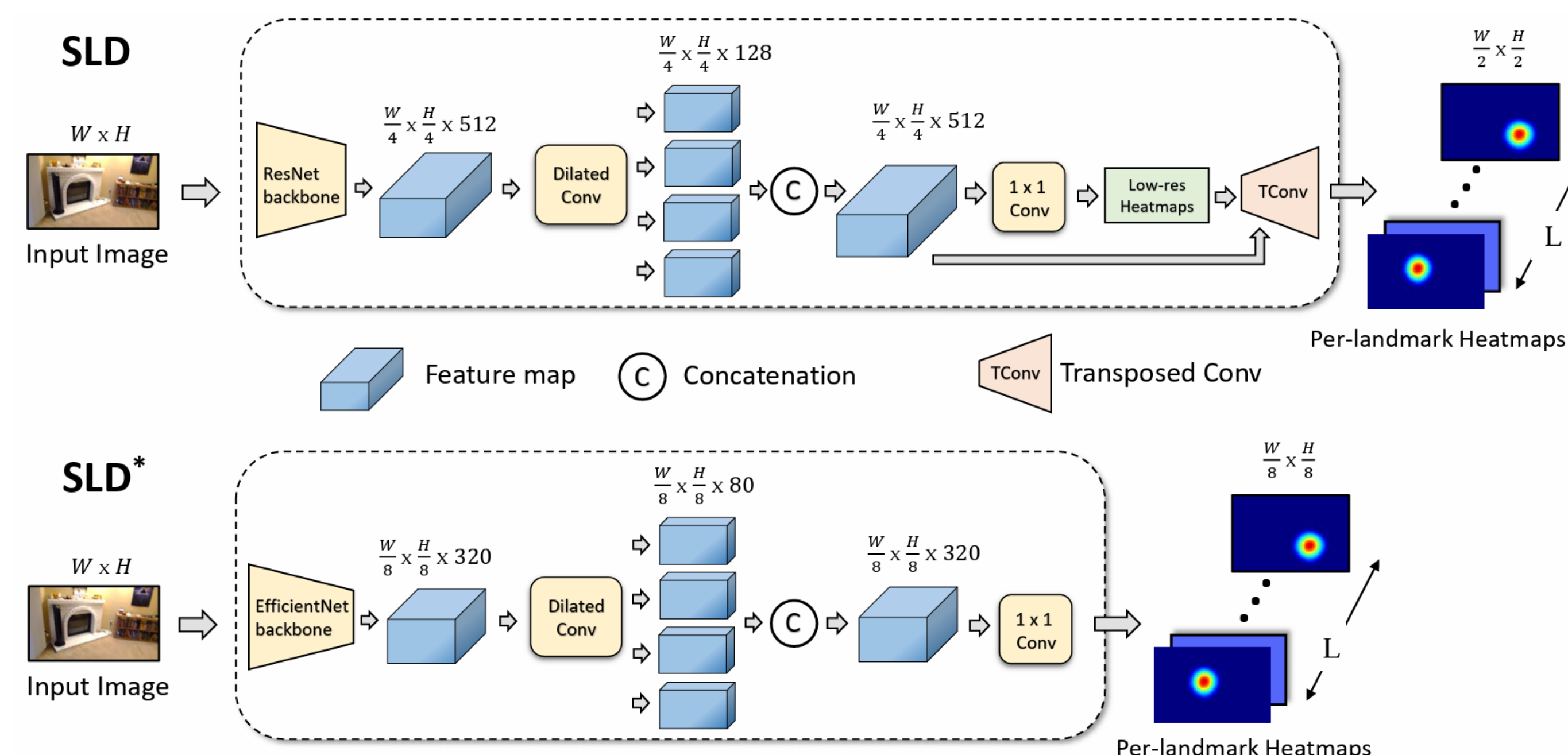
Our Contributions

- We show that the accuracy gap between **SLD [B]** and **hloc [A]** and **SLD's** inability to handle many scene landmarks was due to insufficient model capacity in the SLD architecture.
- We propose to partition the landmark set and train an ensemble of networks, one per subset of landmarks.
- We propose a compact architecture, and a method to generate better training labels for training **SLD** and **SLD***.
- SLD*** significantly outperforms **SLD [B]**. It is competitive with **hloc [A]** but 40X faster and 20X more storage efficient.

Related Work

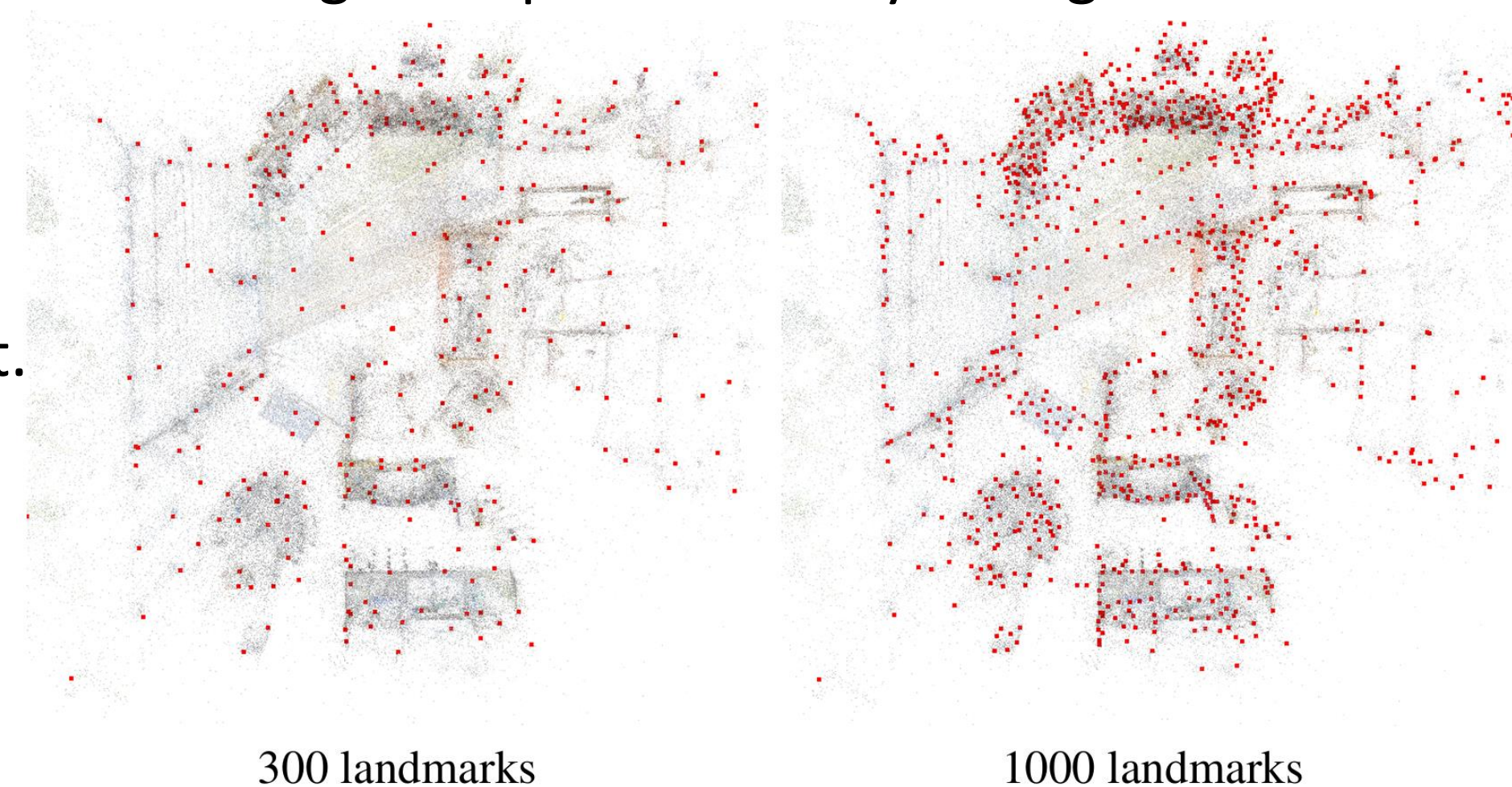
- [hloc]** Sarlin et al., From Coarse to Fine: Robust Hierarchical Localization at Large Scale, *CVPR 2019*.
- [SLD]** Do et al., Learning to Detect Scene Landmarks for Camera Localization, *CVPR 2022*.
- [DSAC*]** Brachmann and Rother, Visual Camera Re-Localization From RGB and RGB-D Images using DSAC, *T-PAMI 2022*.

1. Compact Network Architecture (SLD*)



2. Partitioning the Landmark Set

- Partition the landmark set into mutually exclusive subsets. Train an ensemble of networks, one per subset.
- Using more scene landmarks improves scene coverage and pose accuracy in larger scenes.



300 landmarks

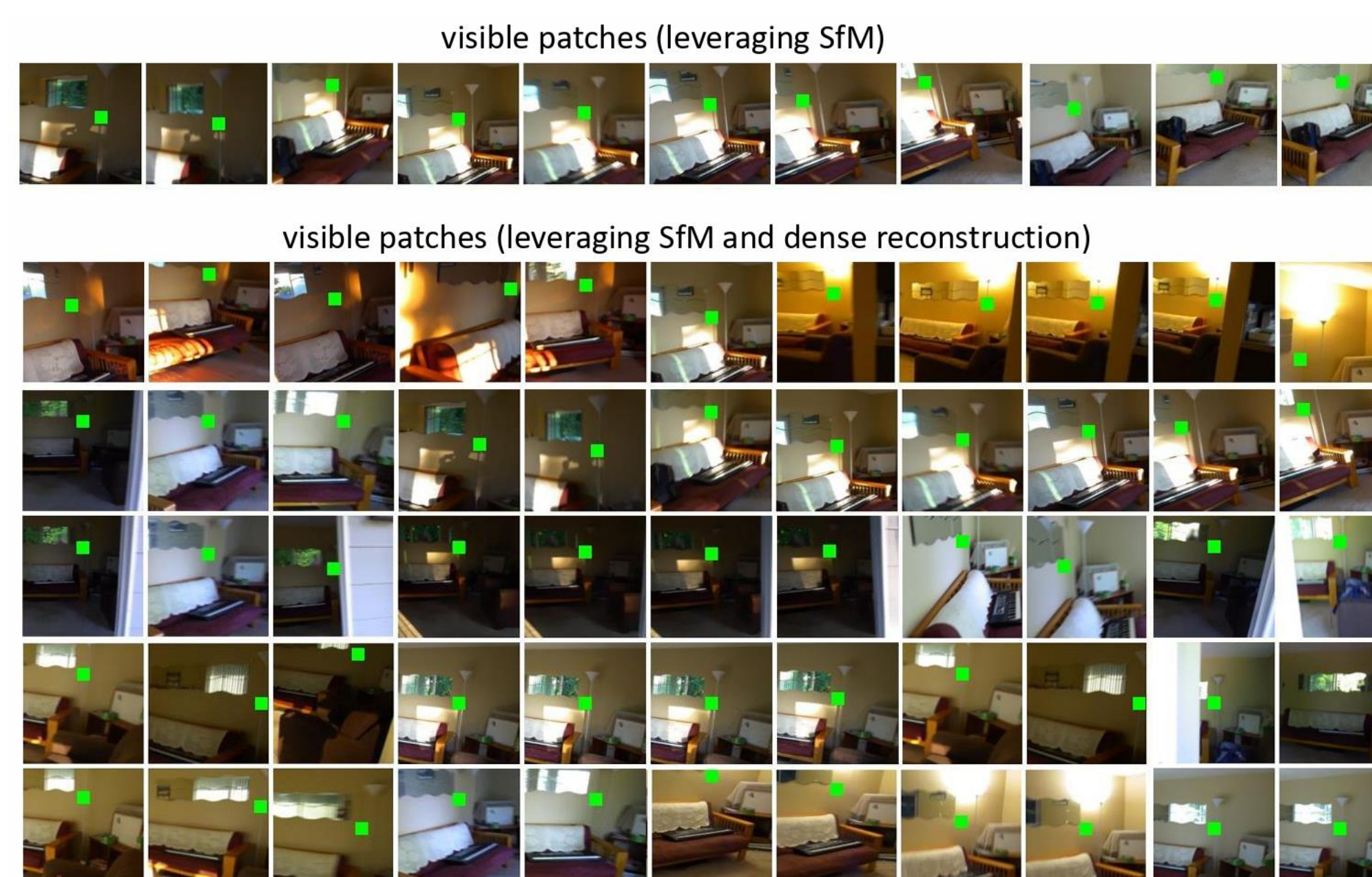
1000 landmarks

Indoor-6 Dataset (Do et al. 2022)

- Images span multiple days and times of day.
- Non-static geometry.
 - Dramatic lighting changes.

3. Improved Visibility Estimation

- Reconstruct 3D mesh and use it to infer visibility of scene landmarks. Generates better training labels.

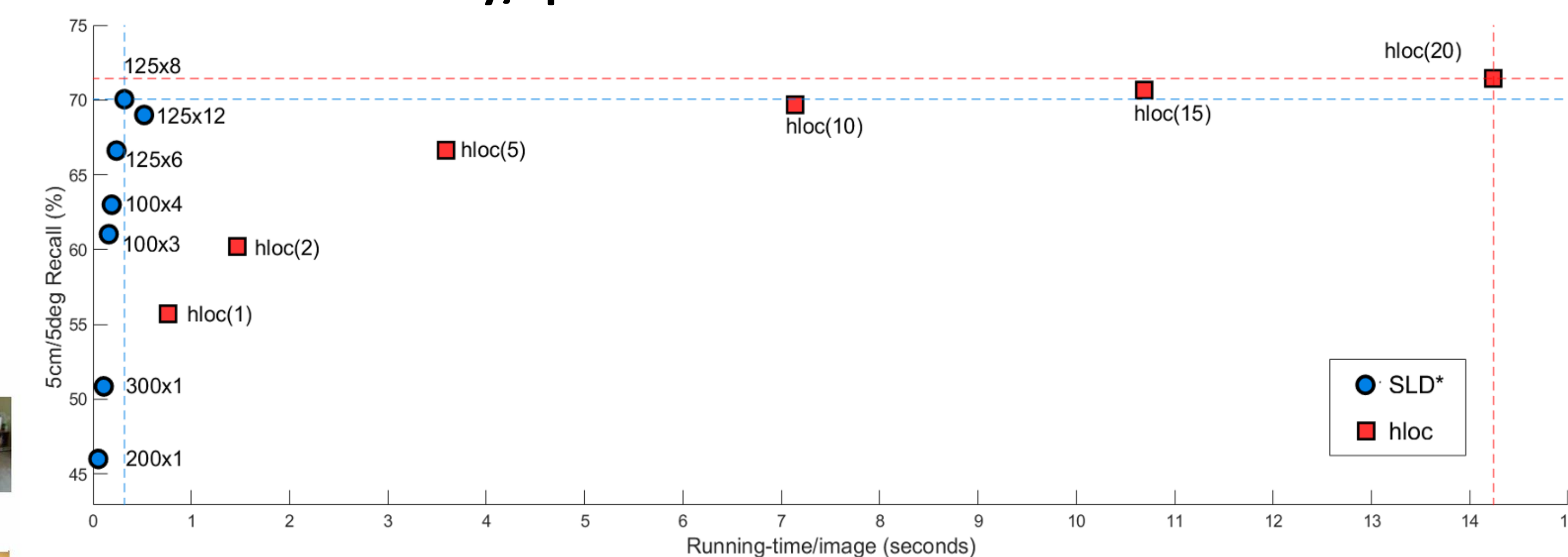


Results

	Scene	DSAC* [6]	NBE+SLD [11]	SLD [11]	SegLoc [21]	SLD* ours	hloc-1000 [11]	hloc-13000 [11]	hloc-A [11, 26]	hloc-B [26]	SLD* ours
#landmarks		n/a	300	300	n/a	300	1000	3000	n/a	n/a	1000
R@5cm/5° ↑	scene1	18.7	38.4	35.0	51.0	47.2	33.3	48.1	64.8	70.5	68.5
	scene2a	28.0	–	34.6	56.4	48.2	12.5	17.1	51.4	52.1	62.6
	scene3	19.7	53.0	50.8	41.8	56.2	48.3	61.9	81.0	86.0	76.2
	scene4a	60.8	–	56.3	33.8	67.7	34.8	39.2	69.0	75.3	77.2
	scene5	10.6	40.0	43.6	43.1	33.7	21.9	31.1	42.7	58.0	57.8
	scene6	44.3	50.5	48.9	34.5	52.0	47.4	59.1	79.9	86.7	78.0
	avg.	30.4	45.5	44.9	43.4	50.8	33.0	42.8	64.8	71.4	70.1
Size (GB) ↓		0.027	0.135	0.020	0.161	0.015	0.17–0.21	0.2–0.5	0.7–2.4	0.7–2.4	0.120
Mem. (GB) ↓		0.85	1.35	1.2	–	0.99	1.3	1.3	1.3	1.3	0.99

- Recall @ 5cm/5° (in %), storage used (Size), and in-memory footprint (Mem.).
- SLD*** is competitive with **hloc-B** (using latest code) but uses significantly less storage.

Accuracy/speed tradeoff of SLD* and hloc



- hloc's performance depends on the number of matched image pairs (1, 2, 5, ... 20). 20 pairs has the best recall (71.4%) but a high running time of 14.2 seconds/image.
- Amongst seven **SLD*** ensembles, $125 \times 8 = 1000$ landmarks has the best recall (70.1%) with running time of 0.3 sec./image. (40X faster than hloc).

Code & Data <https://github.com/microsoft/SceneLandmarkLocalization>