To Match or Not to Match: Revisiting Image Matching for Reliable Visual Place Recognition

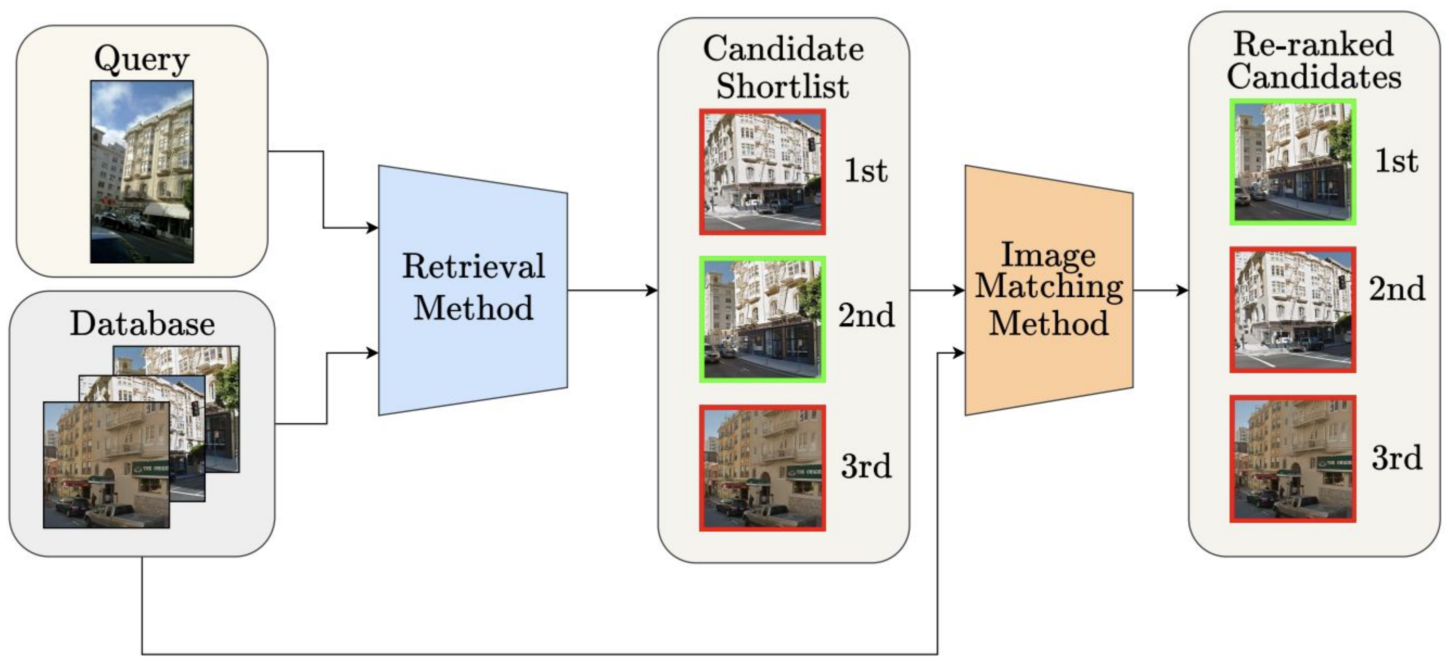
Davide Sferrazza[1], Gabriele Berton[1], Gabriele Trivigno[1], Carlo Masone[1,2]

[1]Politecnico di Torino, Italy [2]Focoos AI

Background

★ **Visual Place Recognition (VPR)** answers the question **"where was this picture taken?"** by comparing a query image against a database of reference images with known locations using global descriptors

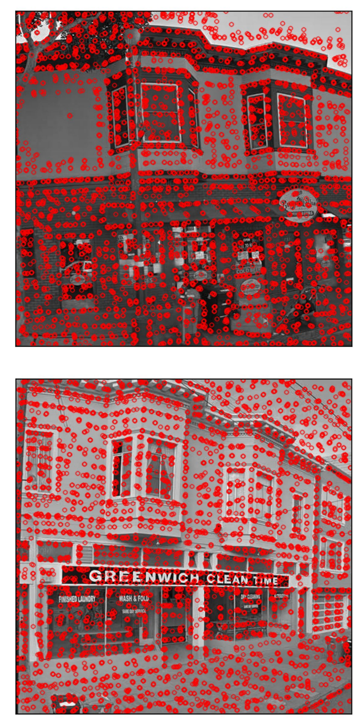
★ **Image Matching** methods are used as a means of **re-ranking** for the top-*K* retrieved results to trade-off computational cost for performance



★ **To date, does the re-ranking step still guarantee improved performance?**

Re-ranking via Image Matching

Local Features: keypoints coordinates and descriptors

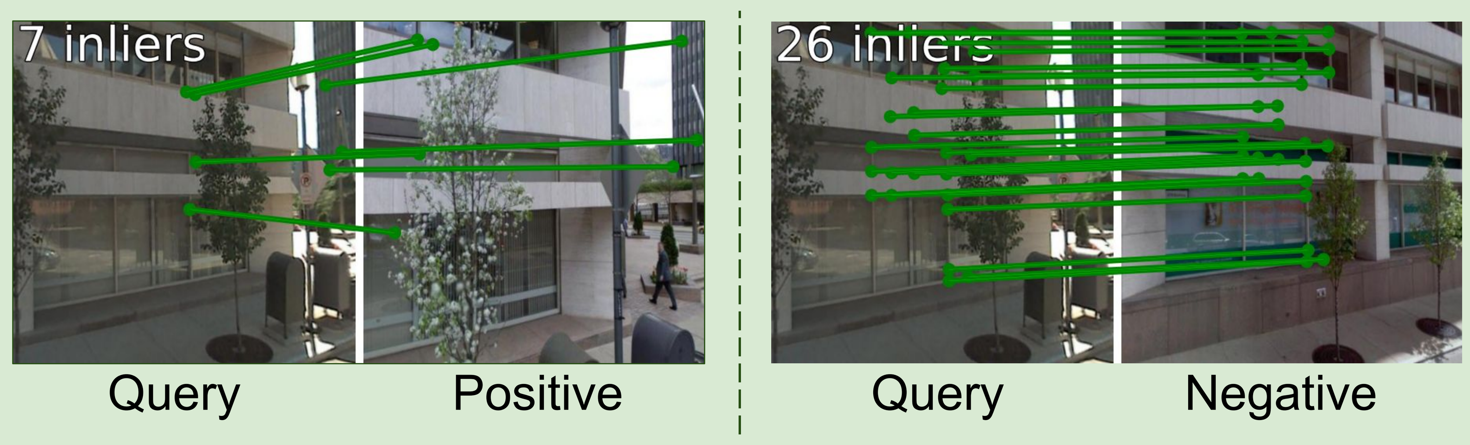


Spatial Verification matching: match keypoints between a query and a retrieved image

Re-ranking by number of matches

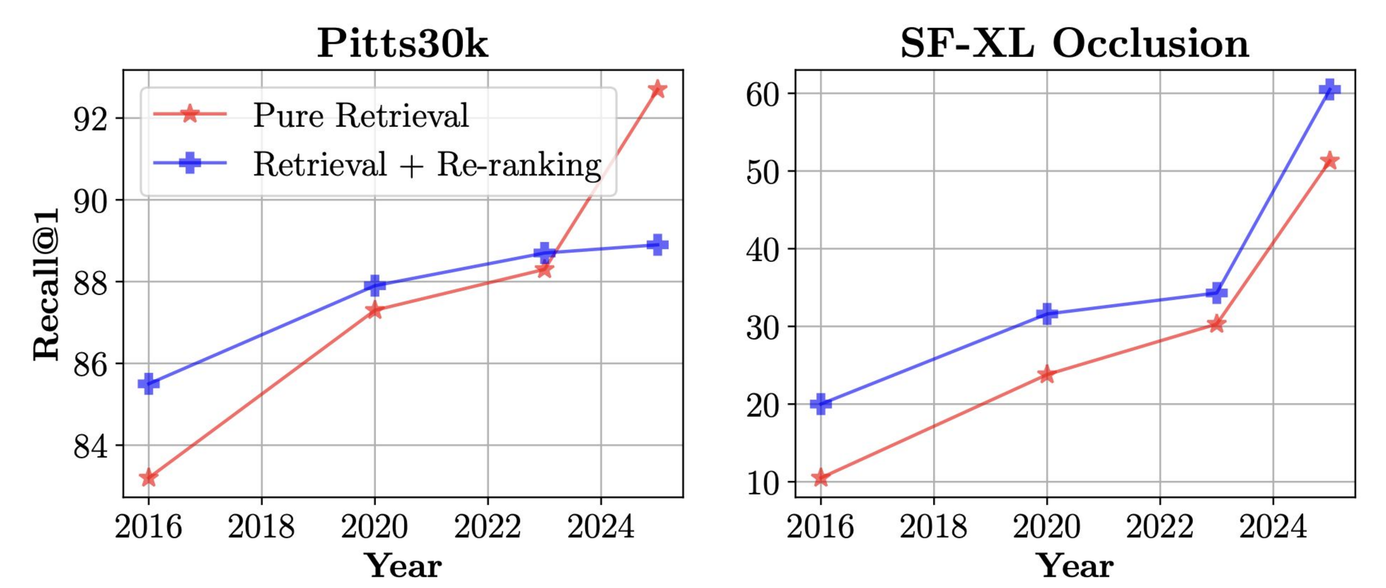
State-Of-The-Art VPR methods have reached a point where **re-ranking can degrade performance** in some scenarios

Employing **Image Matching methods** as a **verification step** to assess the **retrieval confidence** helps build more **robust VPR systems**

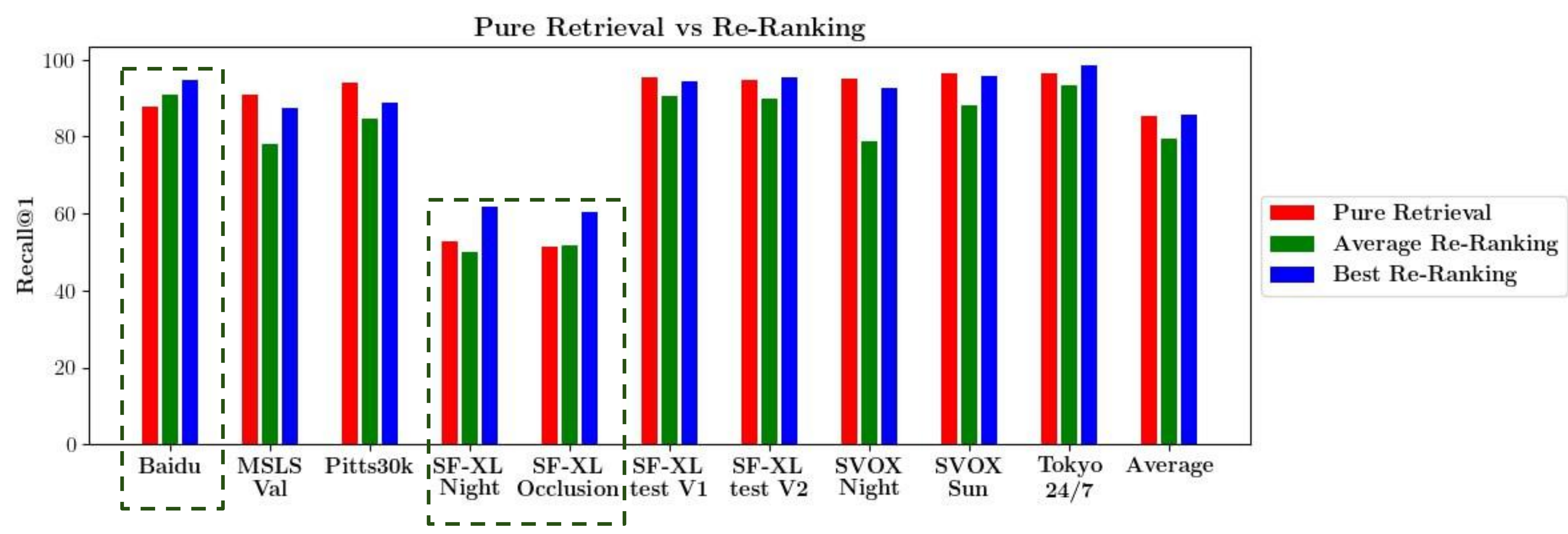


In the Era of Foundation Models

Performance of Retrieval + Re-ranking, as well as Retrieval only, over the years.



Re-ranking strategy **worsens performance** across datasets, with only a **few exceptions**



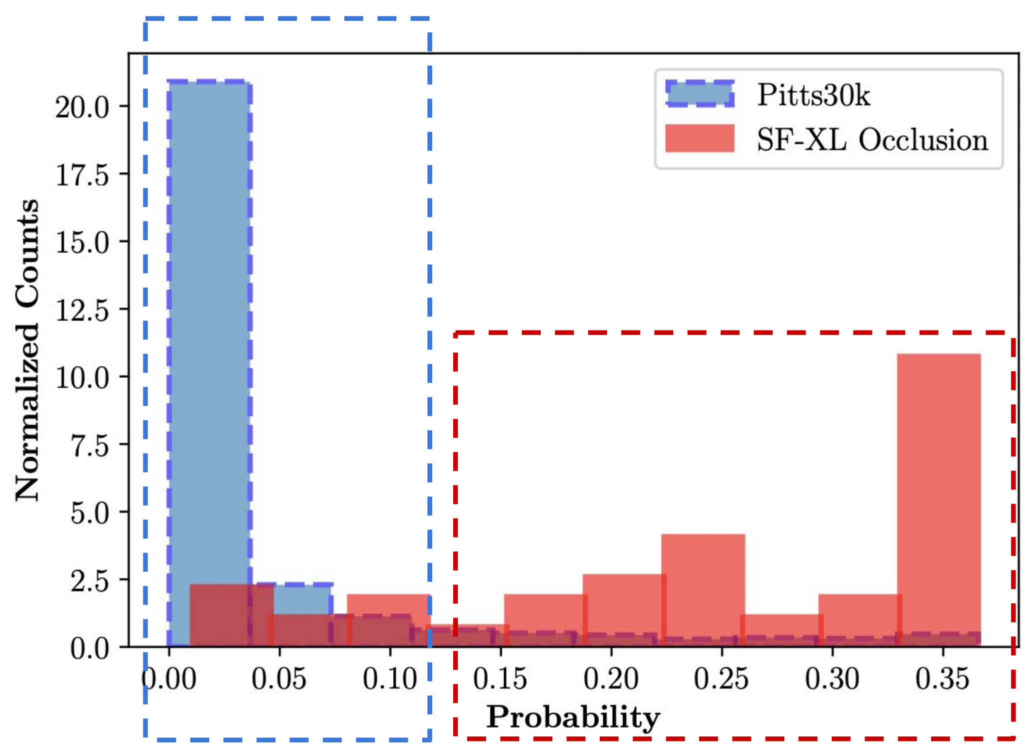
Towards Adaptive VPR Systems

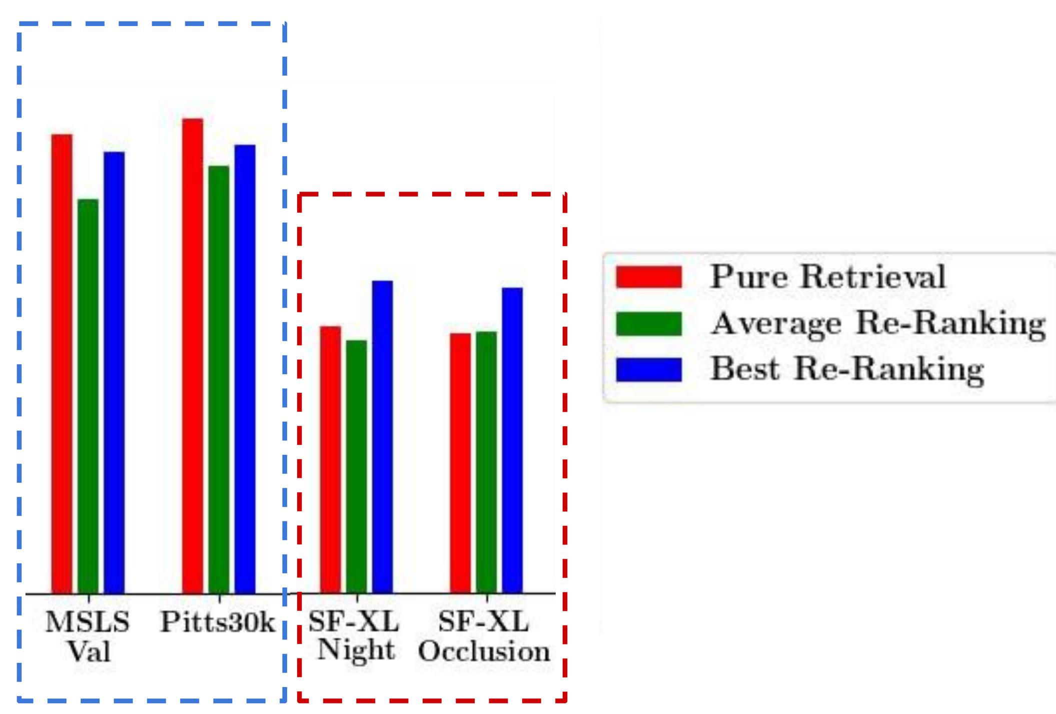
★ Use the **number of inliers** (*i.e.*, matches that survive the RANSAC post-processing) as a **measure of confidence** for the top-1 retrieved image

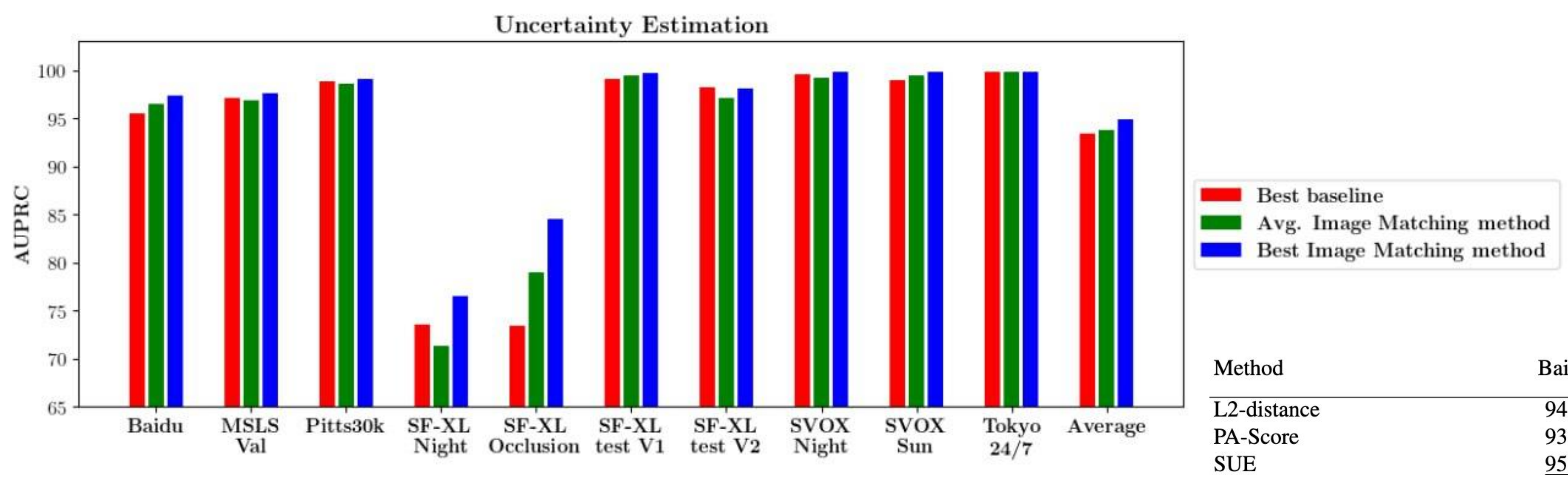
★ **Fewer inliers** suggests **greater uncertainty**, and thus **greater probability** of being a **wrongly localized query**

★ **Low uncertainty** leads to **re-ranking** being **detrimental**

★ **High uncertainty** allows for **improvement** through **re-ranking**







On **challenging datasets**, **Image Matching methods** provide **better uncertainty scores** than existing baselines. This highlights how the **number of inliers** provides a **reliable measure of uncertainty** and aids in creating **robust VPR systems**

Method	Baidu	MSLS Val	Pitts30k	SF-XL Night	SF-XL Occlusion	SF-XL test V1	SF-XL test V2	SVOX Night	SVOX Sun	Tokyo 24/7	Average
L2-distance	94.0	97.0	**99.1**	69.8	<u>77.5</u>	<u>99.5</u>	98.0	99.2	<u>99.1</u>	**99.9**	93.3
PA-Score	93.8	96.5	98.9	67.3	71.6	98.6	98.0	99.0	98.9	99.8	92.2
SUE	<u>95.5</u>	<u>97.1</u>	98.6	<u>73.6</u>	73.5	99.1	**98.2**	<u>99.6</u>	99.0	**99.9**	<u>93.4</u>
Random	88.0	90.8	94.3	53.2	45.9	94.7	96.0	94.8	97.6	96.9	85.2