HyperPose:
Hypernetwork-Infused Camera Pose Localization and an Extended Cambridge Landmarks Dataset

Ron Ferens Yosi Keller

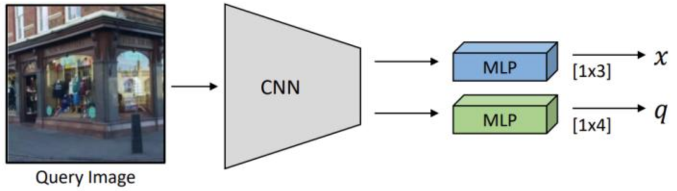
Faculty of Engineering, Bar Ilan University

Limitations of APR in Diverse Environments

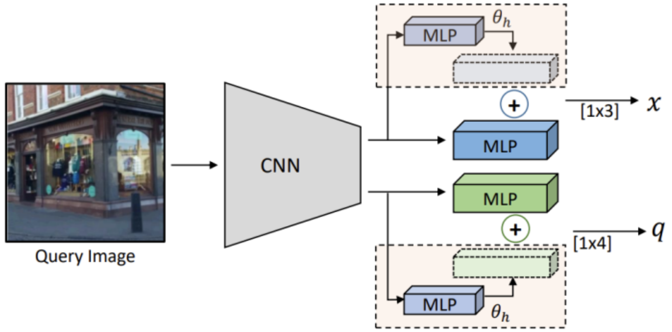
- Absolute Pose Regressors (APR) offer efficiency
- Lack generalization across diverse indoor and outdoor scenes
- Limited applicability in real-world settings

HyperPose

- We propose **HyperPose**, a hypernetwork based approach for absolute camera pose regression
- **The hypernetwork dynamically computes adaptive weights** for the localization regression heads based on the particular input image
- Enhancing feature focus and **improving performance across single- and multi-scene settings**.



(a) Baseline architecture.



(b) Baseline architecture with a hypernetwork.

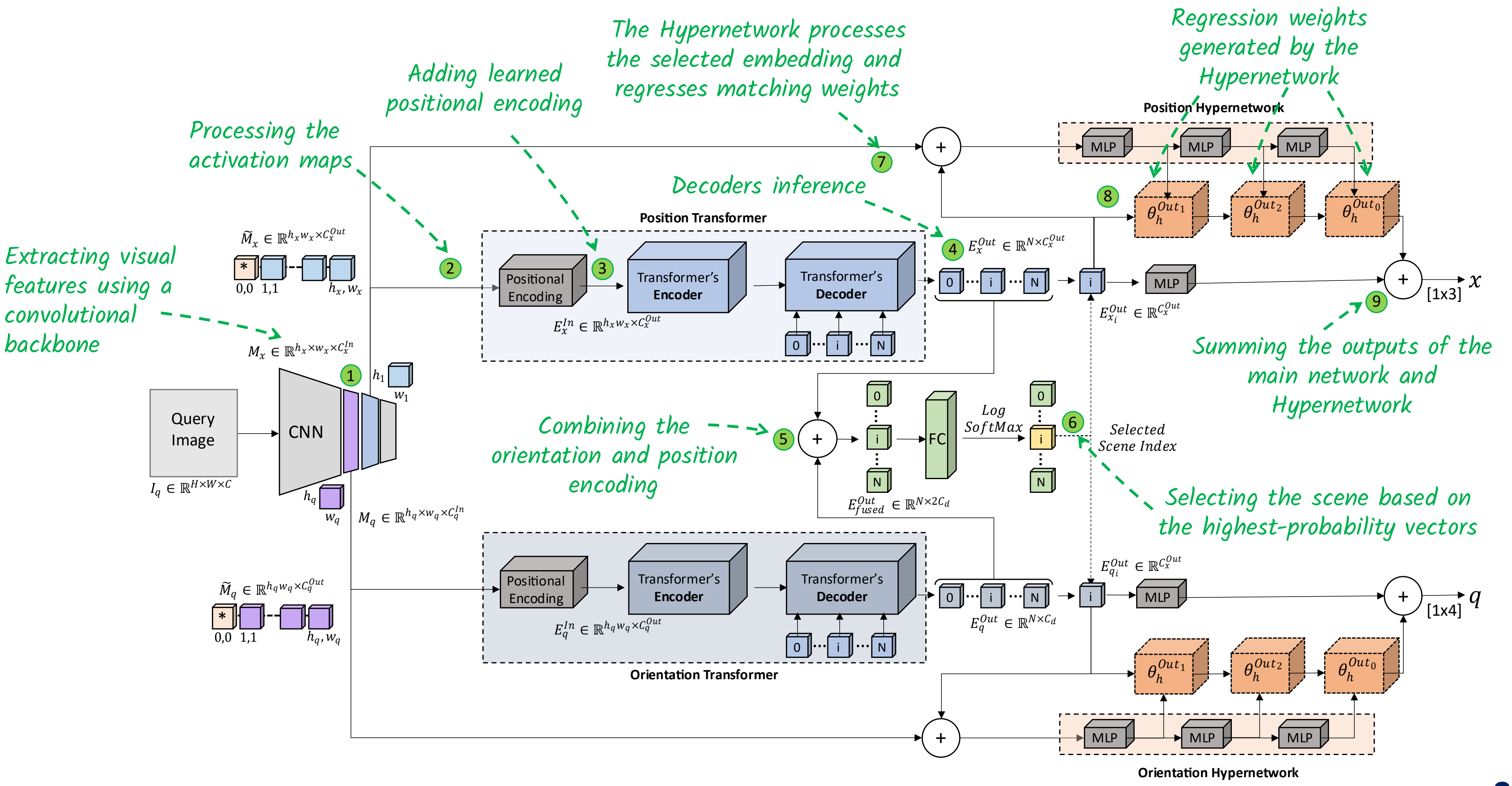
Model Robustness

- Hypernetwork-enhanced models outperform their original architectures:

Table 1. **Comparative analysis of APR architectures with and without the purposed hypernetwork addition using the Cambridge Landmarks dataset**. We report the median position/orientation error in meters/degrees. The best performance is marked in **bold**. (*) The authors of AtLoc did not report results on the Cambridge dataset, and we trained the AtLoc model on this dataset.

Method	K. College	Old Hospital	Shop Facade	St. Mary	Avg.
AtLoc* [61]	1.53,**3.21**	2.17,3.99	0.93,4.61	2.14,5.76	1.69,4.39
AtLoc w/ hypernet	**0.96**,3.43	**2.04,3.61**	**0.88,4.22**	**1.72,5.44**	**1.40,4.18**
Baseline APR	0.89,2.29	1.49,3.32	0.74,4.79	1.40,4.95	1.13,3.84
Baseline APR w/ hypernet	**0.77,2.07**	**1.47,3.29**	**0.72,4.01**	**1.37,4.90**	**1.08,3.57**

MS-HyperPose – Multi-Scene APR



CVPR Nashville JUNE 11-15, 2025

Results

Table 2. **Comparison to single-scene state-of-the-art methods - Cambridge Landmarks:** We report the median position/orientation error in meters/degrees. The most effective single and multi-scene APRs are marked in **bold**.

		K. College	Hospital	Shop Facade	St. Mary	Avg.
APR	PoseNet [25]	1.92,5.40°	2.31,5.38°	1.46,8.08°	2.65,8.48°	2.08,6.83°
	BayesianPN [23]	1.74,4.06°	2.57,5.14°	1.25,7.54°	2.11,8.38°	1.91,6.28°
	LSTM-PN [60]	0.99,3.65°	1.51,4.29°	1.18,7.44°	1.52,6.68°	1.30,5.57°
	SVS-Pose [33]	1.06,2.81°	1.50,4.03°	**0.63**,5.73°	2.11,8.11°	1.32,5.17°
	GPoseNet [11]	1.61,2.29°	2.62,3.89°	1.14,5.73°	2.93,6.46°	2.07,4.59°
	PoseNetLearn [24]	0.99,1.06°	2.17,**2.94°**	1.05,3.97°	1.49,3.43°	1.42,2.85°
	GeoPoseNet [24]	0.88,**1.04°**	3.20,3.29°	0.88,3.78°	1.57,**3.32°**	1.63,2.86°
	IRPNet [44]	1.18,2.19°	1.87,3.38°	0.72,**3.47°**	1.87,4.94°	1.41,3.50°
	Baseline APR w/ hypernet	**0.61**,1.84°	**1.44**,3.03°	0.70,3.62°	**1.37**,4.85°	**1.03**,**2.67°**
MS-APR	MSPN [3]	1.73,3.65°	2.55,4.05°	2.92,7.49°	2.67,6.18°	2.47,5.34°
	MS-Trans[46]	0.83,1.47°	**1.81**,2.39°	0.86,**3.07°**	1.62,3.99°	1.28,2.73°
	MS-HyperPose	**0.78**,**1.18°**	1.84,**2.11°**	**0.83**,3.13°	**1.61**,**3.22°**	**1.27**,**2.41°**

Table 3. **Comparison to single-scene SOTA methods - 7Scenes:** We report the median position/orientation error in meters/degrees. The most effective single and multi-scene APRs are distinguished in **bold**.

		Chess	Fire	Heads	Office	Pumpkin	Kitchen	Stairs	Avg.
APR	PoseNet [25]	0.32,8.12°	0.47,14.4°	0.29,12.0°	0.48,7.68°	0.47,8.42°	0.59,8.64°	0.47,13.8°	0.44,10.4°
	BayesianPN [23]	0.37,7.24°	0.43,13.7°	0.31,12.0°	0.48,8.04°	0.61,7.08°	0.58,7.54°	0.48,13.1°	0.47,9.81°
	LSTM-PN [60]	0.24,5.77°	0.34,11.9°	0.21,13.7°	0.30,8.08°	0.33,7.00°	0.37,8.83°	0.40,13.7°	0.31,9.85°
	GPoseNet [11]	0.20,7.11°	0.38,12.3°	0.21,13.8°	0.28,8.83°	0.37,6.94°	0.35,8.15°	0.37,12.5°	0.31,9.95°
	PoseNetLearn[24]	0.14,4.50°	0.27,11.8°	0.18,12.1°	0.20,5.77°	0.25,4.82°	0.24,5.52°	0.37,10.6°	0.24,7.87°
	GeoPoseNet[24]	0.13,4.48°	0.27,11.3°	0.17,13.0°	0.19,5.55°	0.26,4.75°	0.23,**5.35°**	0.35,12.4°	0.23,8.12°
	IRPNet[44]	0.13,5.64°	**0.25**,9.67°	**0.15**,13.1°	0.24,6.33°	0.22,5.78°	0.30,7.29°	0.34,11.6°	0.23,8.49°
	AtLoc[61]	0.10,**4.07°**	**0.25**,11.4°	0.16,11.8°	0.17,5.34°	0.21,**4.37°**	0.23,5.42°	**0.26**,10.5°	0.20,7.56°
	TransBoNet[49]	0.11,4.48°	**0.25**,12.5°	0.18,14.0°	0.20,**5.08°**	0.19,4.77°	0.17,**5.35°**	0.30,13.0°	0.20,8.45°
	Baseline APR w/ hypernet	**0.09**,4.47°	0.28,**9.44°**	**0.15**,**11.4°**	**0.16**,6.29°	**0.19**,4.62°	**0.18**,6.95°	0.28,**9.15°**	**0.19**,**7.48°**
MS-APR	MSPN[3]	**0.09**,4.76°	0.29,10.5°	0.16,13.1°	**0.16**,6.80°	0.19,5.50°	0.21,6.61°	0.31,11.6°	0.20,7.56°
	MS-Trans[46]	0.11,4.66°	0.24,9.60°	0.14,12.2°	0.17,**5.66°**	0.18,**4.44°**	**0.17**,**5.94°**	**0.26**,8.45°	0.18,7.28°
	MS-HyperPose	0.11,**4.34°**	**0.23**,9.79°	**0.13**,**10.7°**	0.17,6.05°	**0.16**,5.24°	**0.17**,6.86°	0.27,**6.00°**	**0.18**,**7.00°**

Outdoor

Cambridge Landmarks Dataset

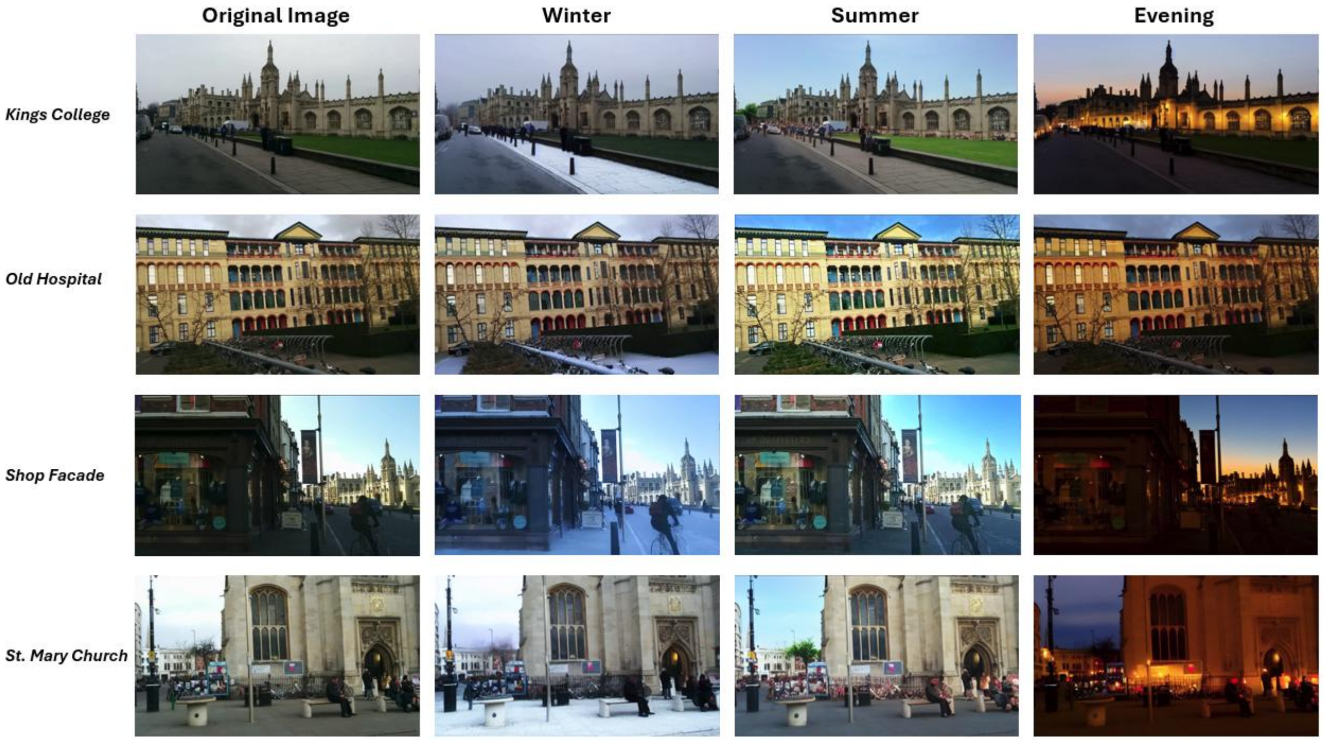
Indoor

7-Scenes Dataset

Extended Cambridge Landmarks Dataset

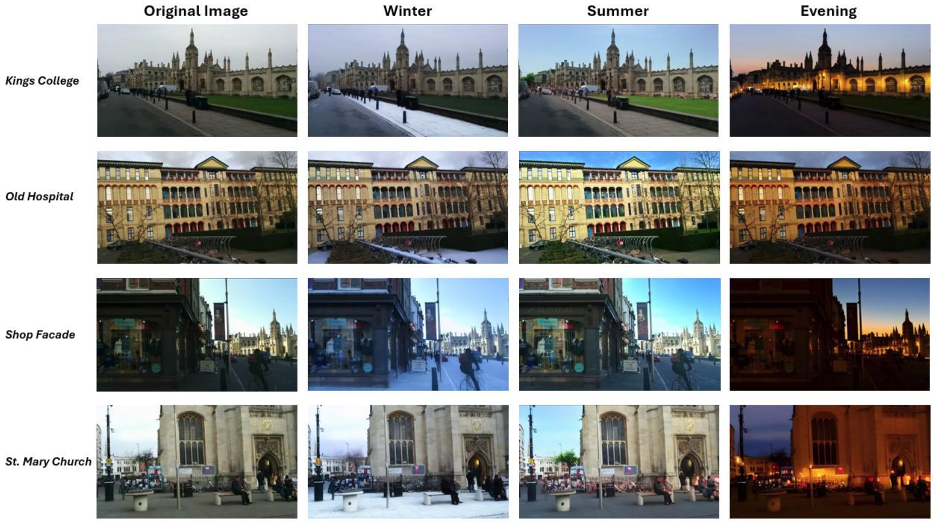
- An **augmented benchmark** introducing new localization challenges through synthetic seasonal and lighting variations

- Extending the original test scenes with three distinct variations: ***Summer***, ***Winter***, and ***Evening***.



CVPR Nashville JUNE 11-15, 2025

ECL Dataset – Model Robustness



Scene	Method	Flavor			
		original	winter	summer	evening
K. College	Baseline APR	0.89, 2.29	0.94, 2.14	1.03, 2.12	1.15, 2.59
	Baseline APR w/ hypernet	**0.61, 1.84**	**0.67, 2.03**	**0.69, 1.93**	**0.70, 2.52**
Old Hospital	Baseline APR	1.49, 3.30	1.84, 3.72	1.53, 3.77	2.03, 3.43
	Baseline APR w/ hypernet	**1.44, 3.03**	**1.39, 3.15**	**1.39, 3.36**	**1.77, 3.40**
Shop Facade	Baseline APR	0.74, 4.79	0.74, 5.06	0.76, 4.90	1.04, 4.99
	Baseline APR w/ hypernet	**0.70, 3.62**	**0.71, 4.26**	**0.75, 4.08**	**0.88, 4.90**
St. Mary	Baseline APR	1.40, 4.95	1.50, 5.26	1.52, 5.45	1.63, 5.55
	Baseline APR w/ hypernet	**1.37, 4.85**	**1.37, 5.07**	**1.48, 5.35**	**1.53, 5.34**

Model performance comparison on the ECL dataset **without retraining or fine-tuning** - models originally trained on the Cambridge Landmarks dataset

Summary

- We propose an approach to enhance any existing absolute camera pose regression models by integrating hypernetwork architectures.
- The proposed scheme achieves new SOTA accuracy on multi-scene APR benchmarks spanning diverse outdoor and indoor localization tasks.
- We introduce the Extended Cambridge Landmarks dataset, building upon the foundation of the original Cambridge Landmarks dataset

HyperPose on GitHub: https://ronferens.github.io/hyperpose/
ECL Dataset: https://ronferens.github.io/extcambridgelandmarks/

Thank You

HyperPose on GitHub: https://ronferens.github.io/hyperpose/
ECL Dataset: https://ronferens.github.io/extcambridgelandmarks/