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Sparse and topological coding for visual localization of autonomous vehicles

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Context

- Visual place recognition (VPR) for self-driving vehicles [1].
- Large-scale environment and computational cost.
- Neurocybernetics approach.

Contributions

- TSC, a new model of sparse coding for encoding visual information.
- SMP, a neurocybernetic model of visual localization model using TSC.

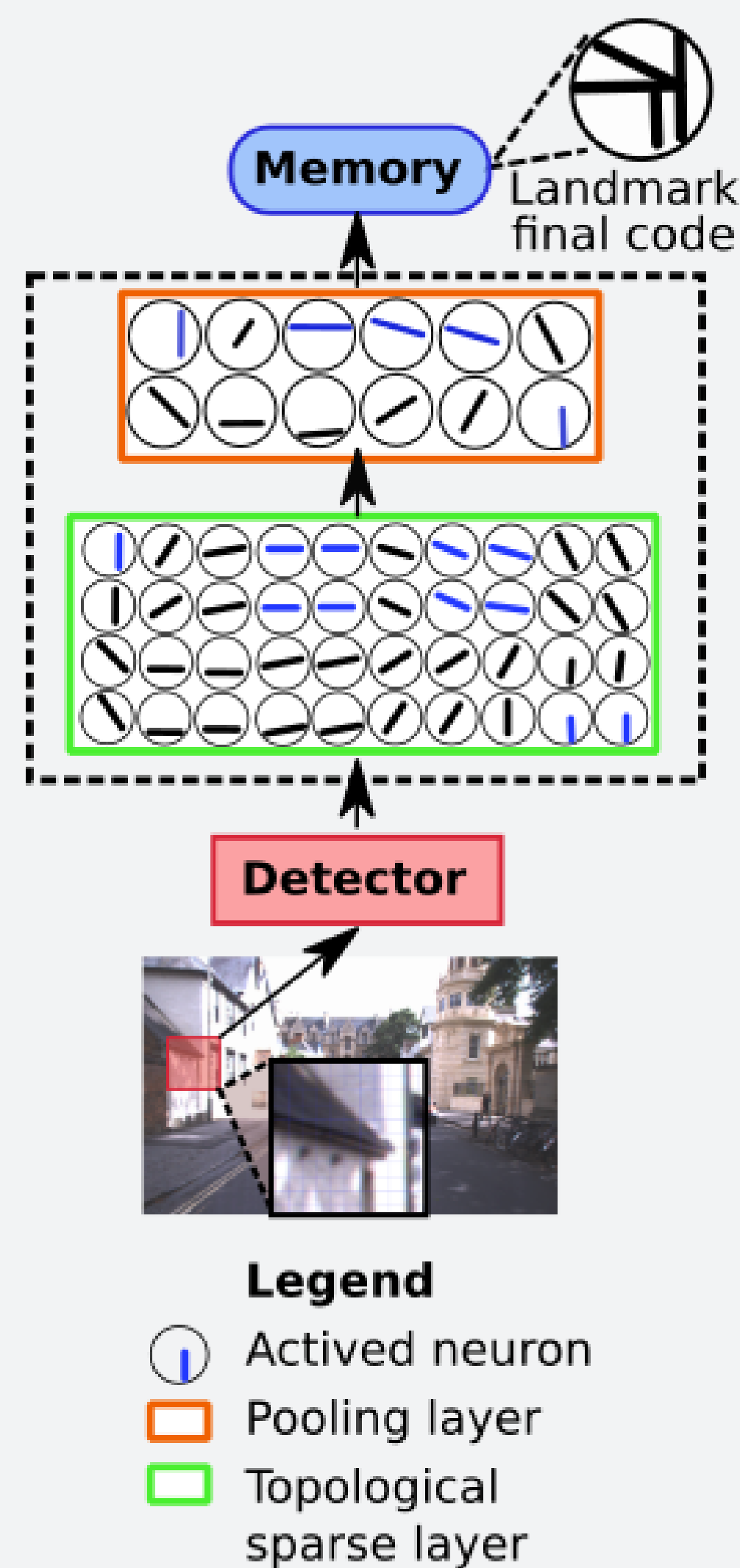
TSC: Topologic Sparse Coding

General overview of the TSC model

- New method of sparse coding aims to compress visual information, inspired by the visual cortex [3].
- Build a topological sparse dictionary: a sparse dictionary arranged on a 2D grid.
- Allows sparse code to be more consistent: contrarily to classic sparse coding methods, two close images have much similar codes.

Simplified operation

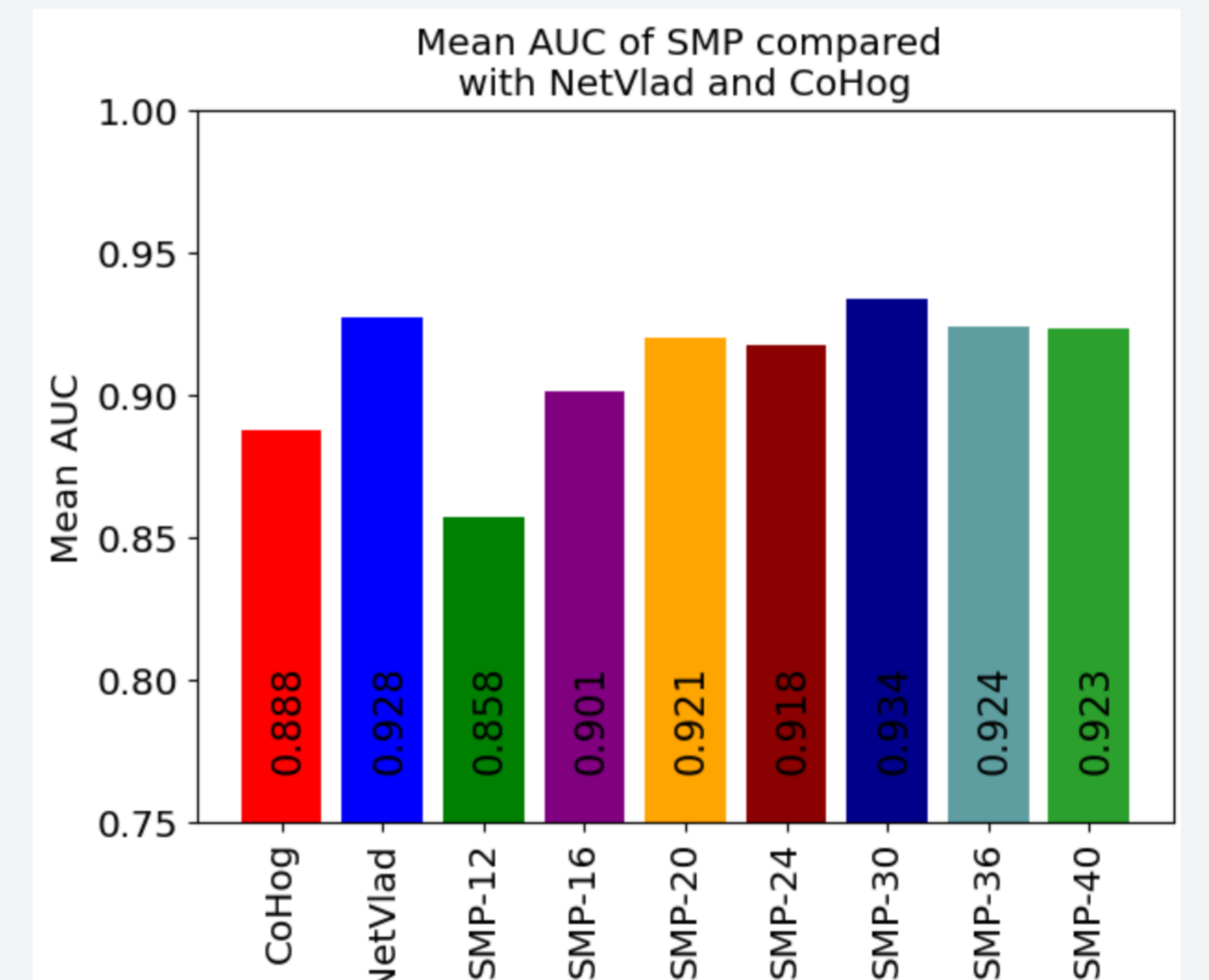
- Learns a sparse representation called a "dictionary" composed of $M \times N$ elements called "atoms".
- Alternation between two processes to learn a dictionary, given a sparsity and topology constraint:
 - ▶ An encoding stage where the current image is reconstructed with a limited number of atoms.
 - ▶ An update stage where the dictionary is modified to improve its reconstruction performance, depending of the encoding result.
- Based on the Sparse Hebbian Learning algorithm.



Results: configuration/performance

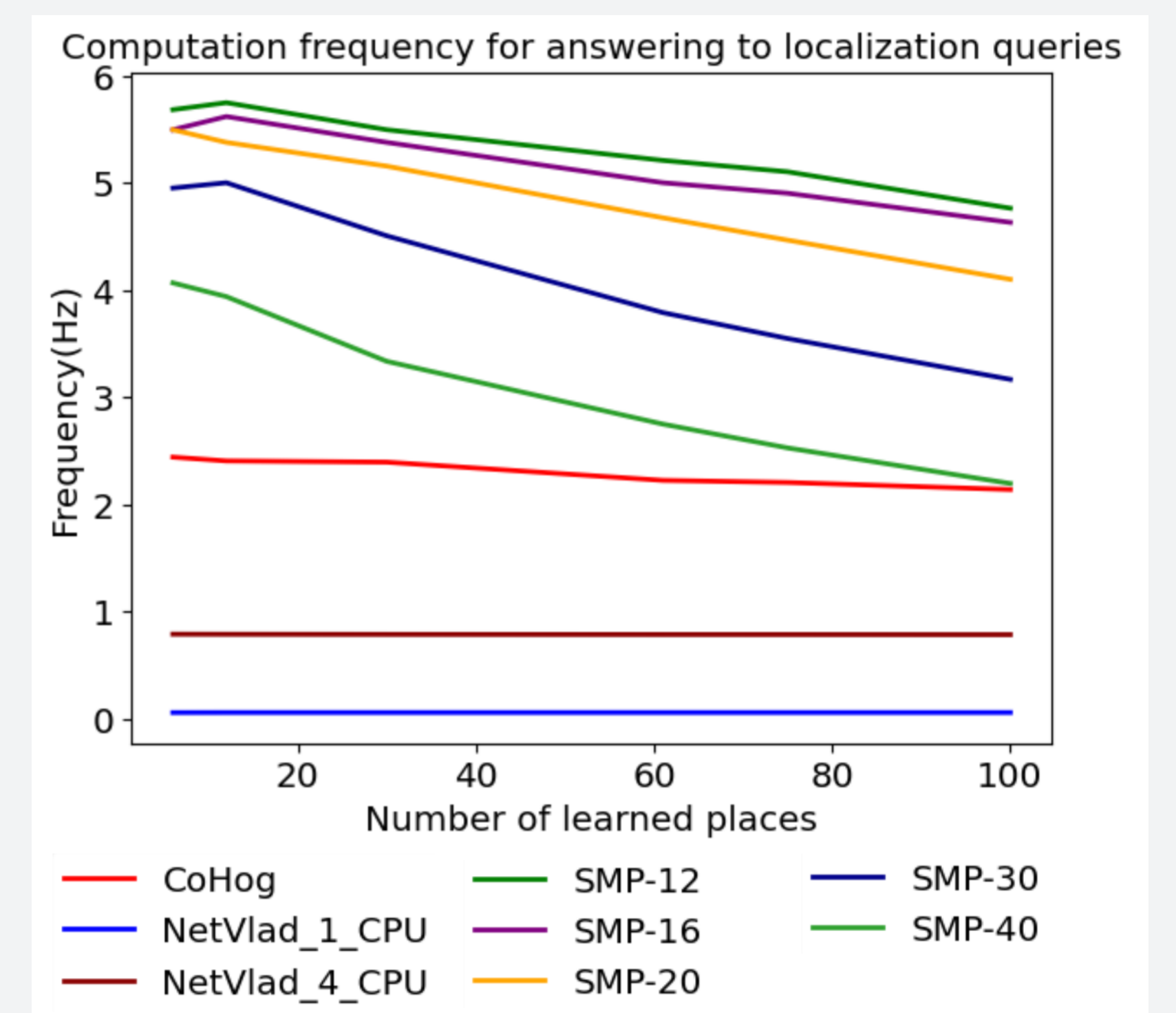
AUC by configuration

- Mean AUC increases with the size of TSC.
- SMP-30 has an average AUC equivalent to NetVlad.
- SMP-30 has a slightly better average AUC than CoHog, with a difference of 5%.
- Best performances with SMP-30.



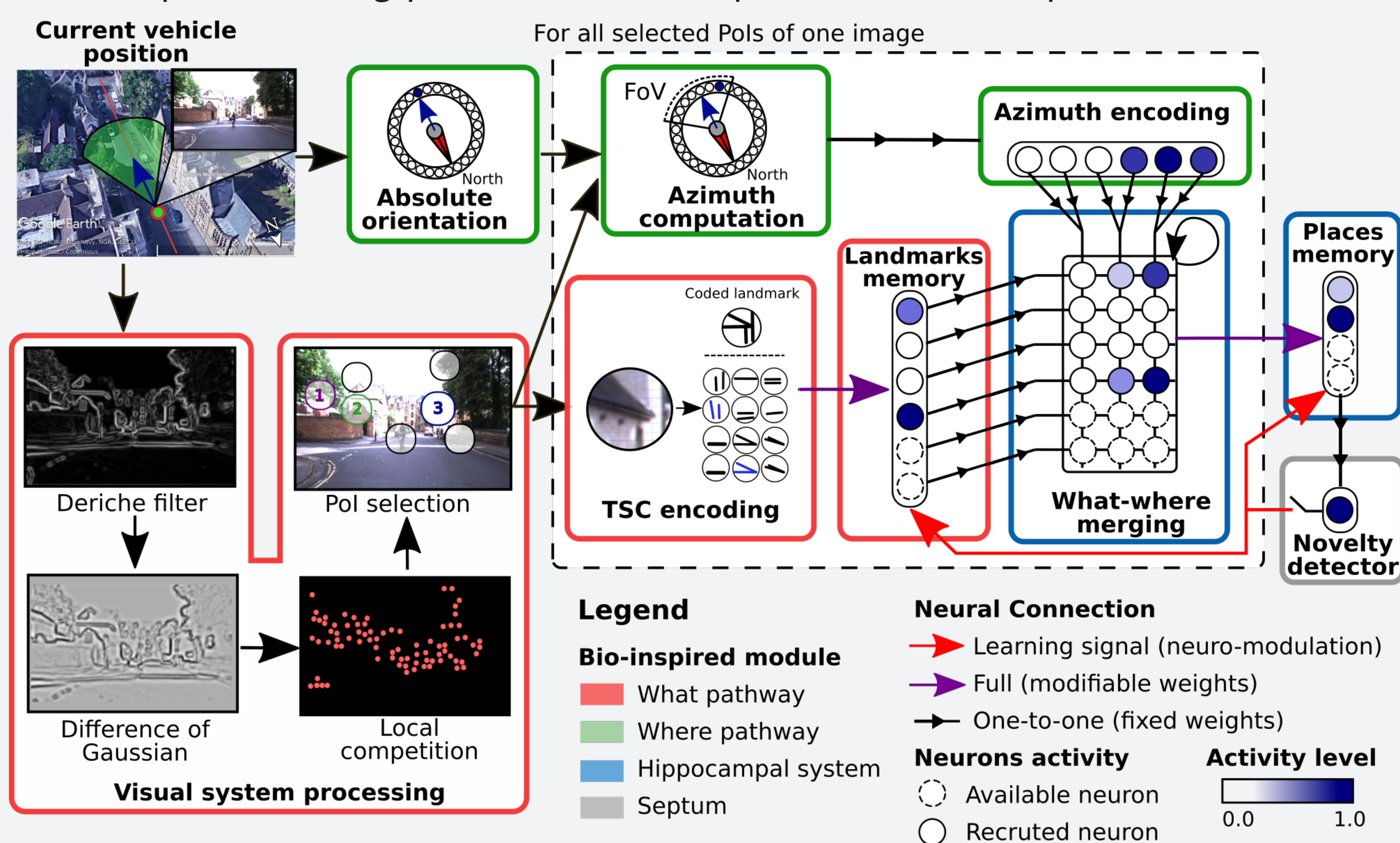
Mean frequency (Hz)

- Mean computation frequency decreases with the size of TSC.
- At equivalent AUC, SMP-30 allows to achieve a gain of $\times 60$ with NetVlad-1-CPU and a gain of $\times 3$ with NetVlad-4-CPU.
- At equivalent AUC, SMP-18 allows to achieve a gain of $\times 2$ with CoHog.



SMP: application to visual localization

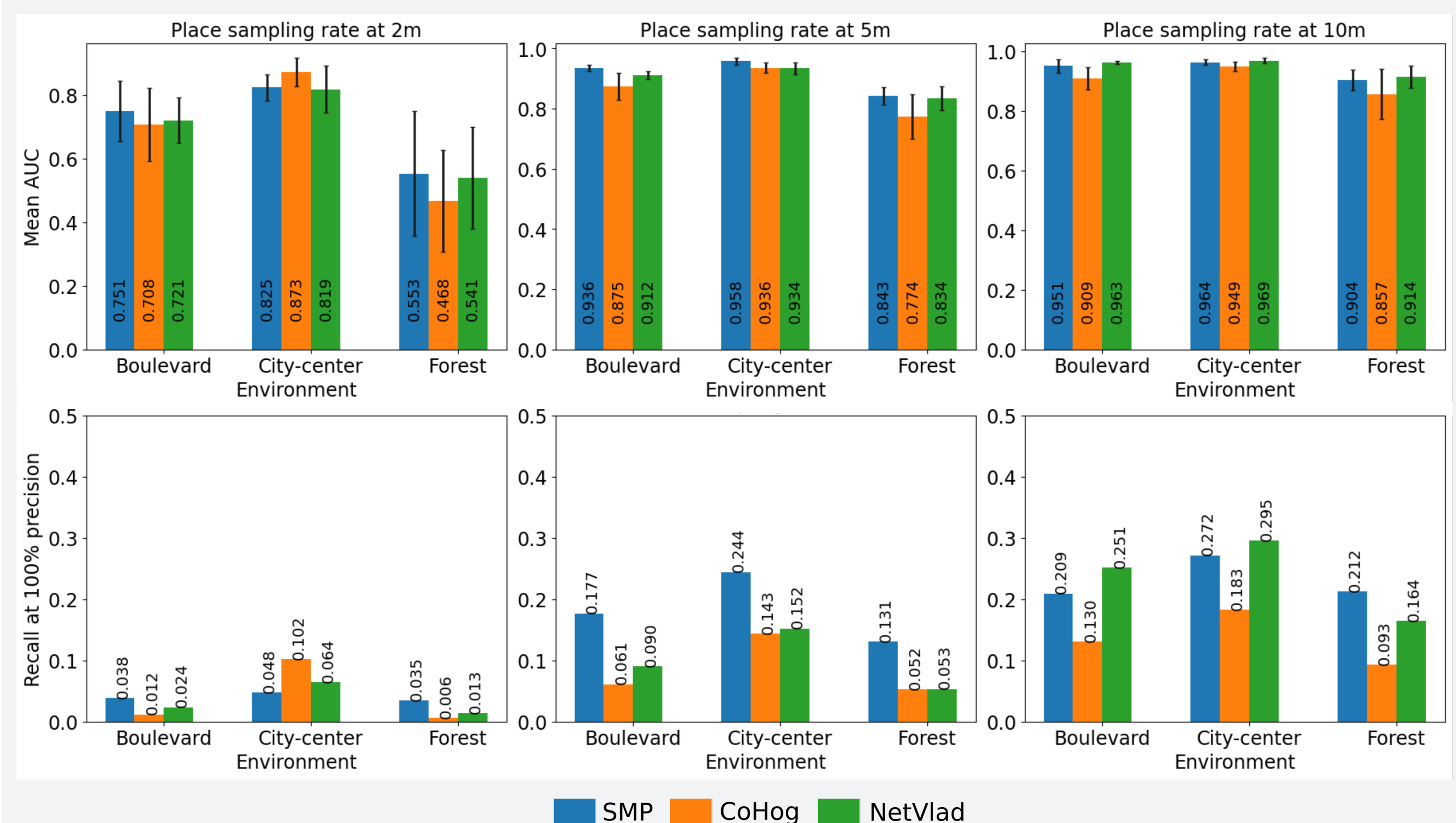
- Modification of LPMP, a bio-inspired model of VPR [2], to integrate TSC.
- TSC replaces the *log-polar* block to compress landmarks representation.



Results: state of the art comparison

Mean AUC and recall at 100% precision with SMP-30

- SMP-30 has better localization performance than the CoHog model in almost all cases.
- SMP-30 has competitive localization performance with the NetVlad model.



Conclusion

- TSC improves computation cost and localization accuracy of LPMP.
- Allows a trade-off between localization and time performance.
- Performs better than two state-of-the-art reference models.

References

- [1] Y. Espada, N. Cuperlier, G. Bresson, and O. Romain. From Neurobotic Localization to Autonomous Vehicles. *Unmanned Systems*, 07(03):183–194, July 2019.
- [2] P. Gauthier and S. Zreth. Perac: A neural architecture to control artificial animals. *Robotics and Autonomous Systems*, 16(2–4):291–320, Dec 1995.
- [3] B. Olshausen and D. Field. Sparse coding of sensory inputs. *Current Opinion in Neurobiology*, 14(4):481–487, Aug 2004.

Experiments

Dataset: Three routes with three distinct trajectories extracted from the OxfordCar dataset (total dataset distance: 4.2 km).

Evaluation methodology: Ability of models to recognize already visited places.

- Three distances of sampling on the learning dataset : 2m, 5m and 10m.
- Evaluation in cross-validation (for each routes).
- Comparison with state-of-the-art VPR models: Netvlad and CoHog.

Metrics: AUC (area under the curve) and recall at 100% of precision/recall curves; average processing frequency of an image.