

Introduction

- **Scope:** search in a large corpus of images and retrieve a specific object
- **Challenge:** reduce memory requirements without sacrificing performance
- **Bag-of-Words (BoW):** good performance at low cost, but indexes each local feature separately
- **Geometry verification:** constantly better performance than BoW, with roughly same memory requirements
- **Compact representations:** much lower memory requirements, e.g. Fisher vectors [Perronnin et al. 2010], not compatible with geometry verification
- **Feature Selection:** currently only from multiple views
- **Our solution:** selection from single views via symmetry and repeating pattern detection

Related work: Feature selection from multiple views

- **Supervised (by geo-tag):**
 - informative feature selection [Schindler et al. 2007] [Li & Kosecka 2006]
 - foreground object detection [Gammeter et al. 2009]
 - scene map construction [Avrithis et al. 2010].
- **Unsupervised:** Spatial verification of multiple views [Turcot & Lowe 2009]

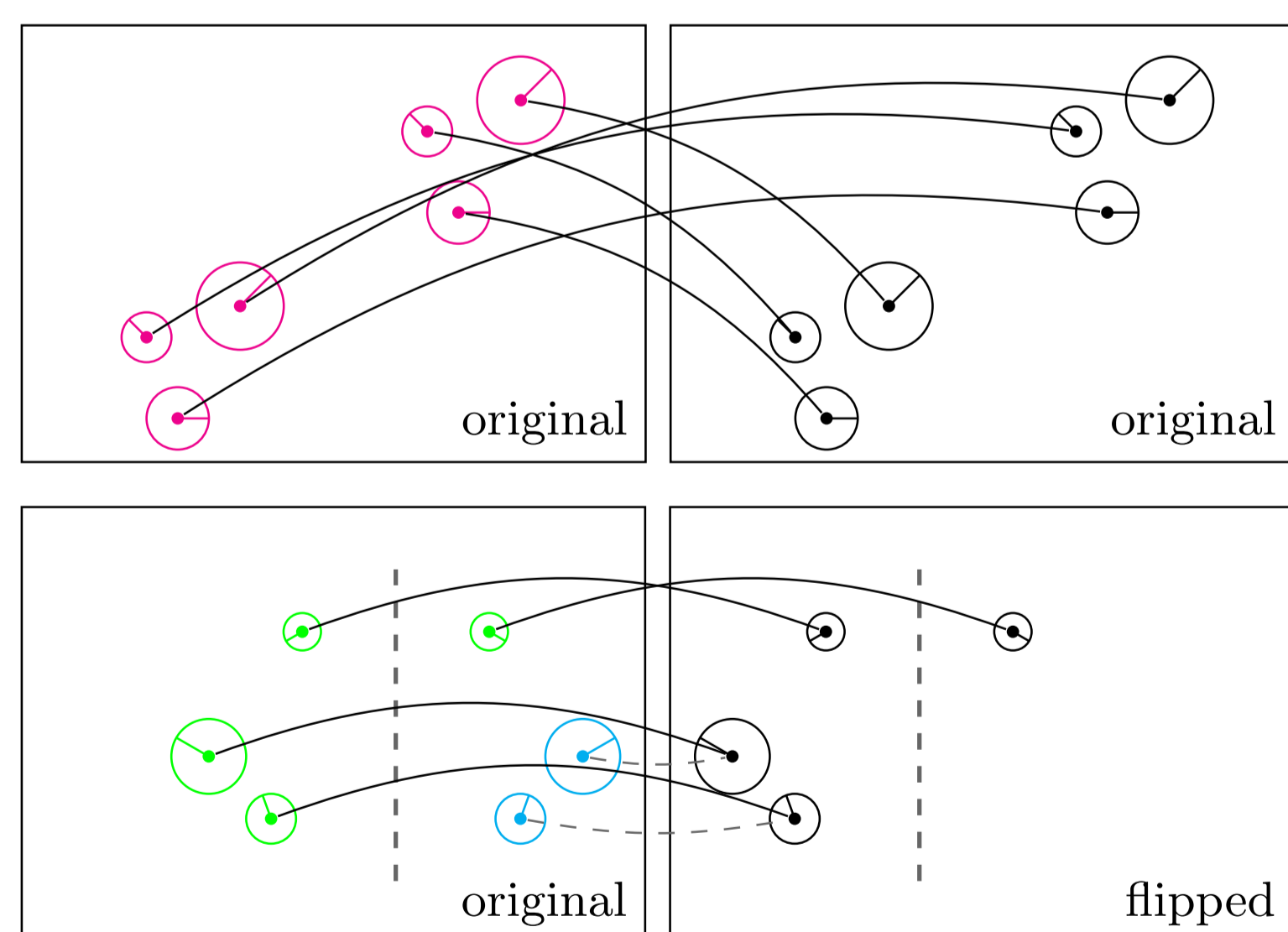


five different views matched by RANSAC

multiple view selection [Turcot & Lowe 2009]

single view selection (this work)

Feature selection from a single view



Self-matching

Flipped matching

Tentative Correspondences:

- Valid pairs: $C_v(X) = \{(x, y) \in X^2 : v(x, y)\}$
- Descriptor nearest neighbors: $N(x) = \{y \in X : y \in \mathcal{N}_X^k(x) \wedge d(x, y) \leq \delta\}$
- Tentative correspondences: $C_t(X) = C_d(X) \cap C_v(X)$
- **Flipped matching:** y' : flipped counterpart of feature y .

$$C_v(X, Y) = \{(x, y) \in X \times Y : v(x, y')\}$$

$$C_d(X, Y) = \{(x, y) \in X \times Y : y \in N(x)\}$$

$$C_t(X, Y) = C_d(X, Y) \cap C_v(X, Y)$$

Solution 1: Spatial self-matching (SSM)

- Inspired by fast spatial matching (FSM) [Philbin et al. 2007]
 - Hypothesis inliers: $I_C(h) = \{(x, y) \in C : \|p(y) - hp(x)\| < \epsilon\}$
 - Seek best hypothesis per correspondence
 - $H_C(x, y) = \{h \in t(C) : \|p(y) - hp(x)\| < \epsilon\}$
 - Strength: $\alpha_C(c) = \max\{|I_C(h)| : h \in H_C(c)\}$
 - Verified correspondences: $\alpha(C) = \{c \in C : \alpha_C(c) \geq \tau_\alpha\}$
 - Select features of verified correspondences
 - **Average running time on SymCity: 95ms**
- ```

1 procedure $\alpha \leftarrow$ SSM($C, t; \tau_\alpha$)
input : correspondences C , transformations t
parameter: inlier threshold τ_α
output : inlier strengths α
2 for $c \in C$ do
3 $inlier(c) \leftarrow$ FALSE
4 $\alpha(c) \leftarrow 0$
5 for $c \in C$ do
6 if $inlier(c)$ then continue
7 $h \leftarrow t(c)$
8 $I \leftarrow I_C(h)$
9 if $|I| < \tau_\alpha$ then continue
10 for $c' \in I$ do
11 $inlier(c') \leftarrow$ TRUE
12 $\alpha(c') \leftarrow \max(\alpha(c'), |I|)$
13 return α

```



Self-matching

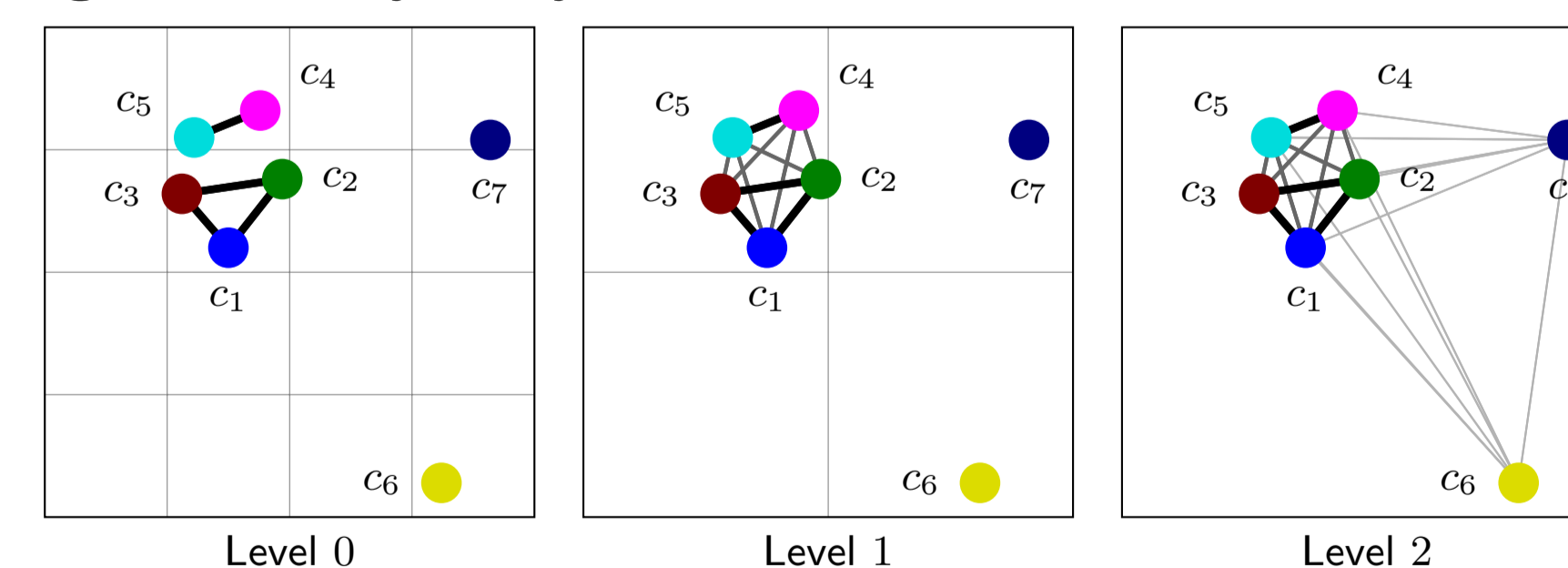
Flipped matching



Selected features: Original (red), flipped (green) and back-projected (blue)

## Solution 2: Hough pyramid self-matching (HPSM)

- Based on Hough pyramid matching [Tolias & Avrithis 2011]
- Same correspondences as in SSM but *linear* in the number of correspondences
- No inlier counting or transformation estimation
- Strength: geometrical consistency with all correspondences
- No one-to-one mapping as in original HPM
- **Average running time on SymCity: 16.2ms**



Correspondences in a single bin at level 0, All tentative correspondences, with red (yellow) being the strongest (weakest)

## Selection examples

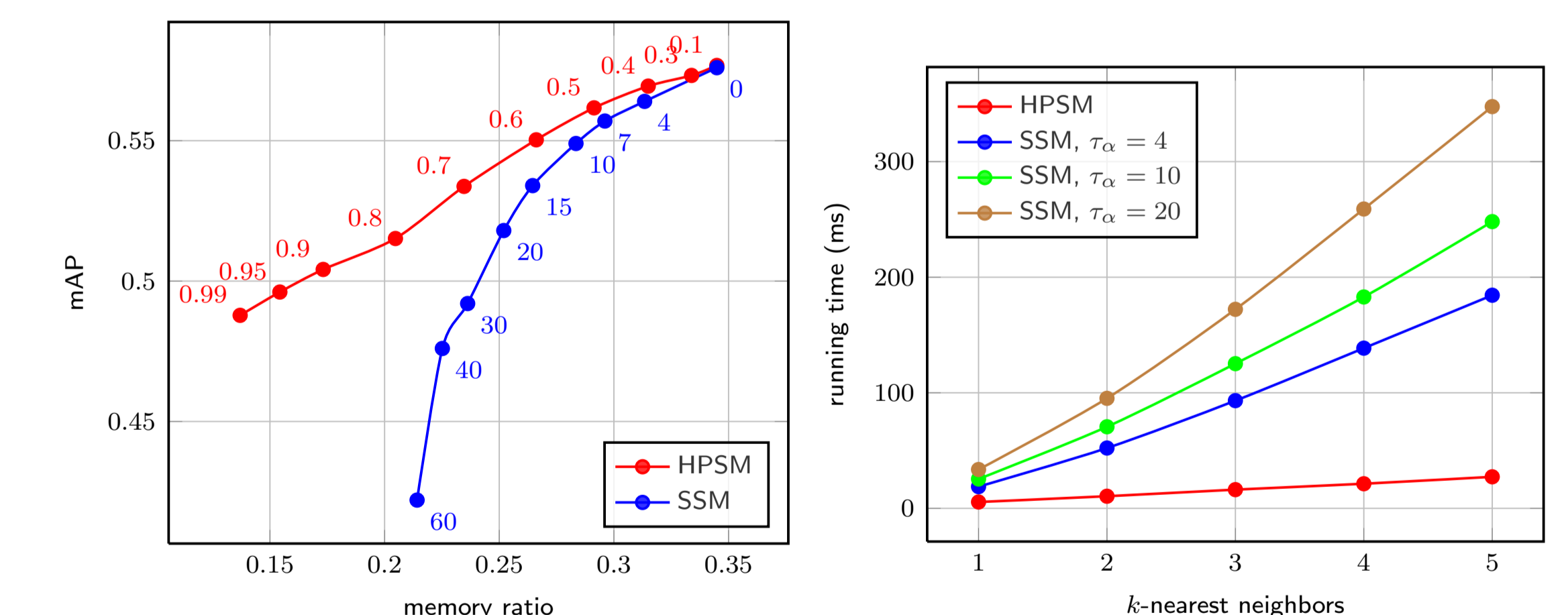


## Experiments

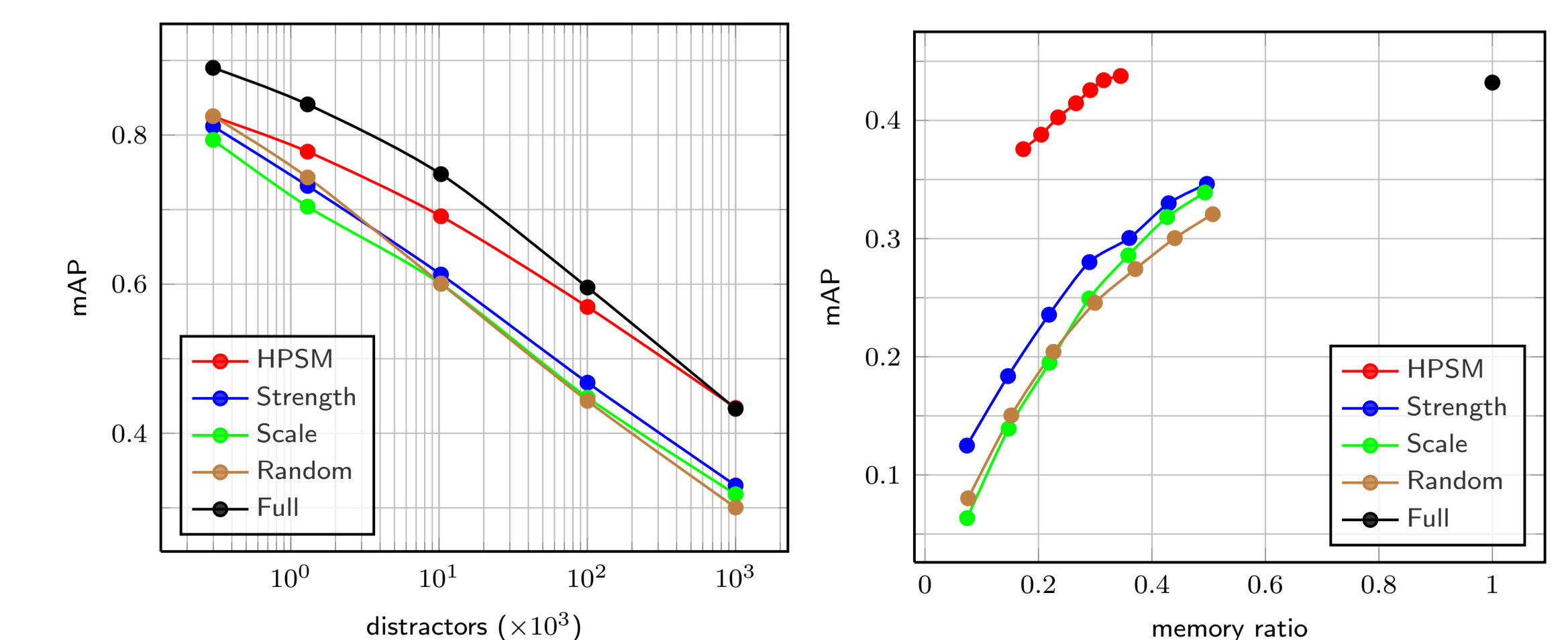
- **Datasets:** World Cities (WC) and new dataset SymCity
- **SymCity dataset:** 953 annotated photos from 299 groups; a single image from each group indexed in the database and the rest used as queries; publicly available



Sample images from the SymCity dataset



SSM vs HPSM using 100K distractors from WC



Large scale experiments using 1M distractors from WC