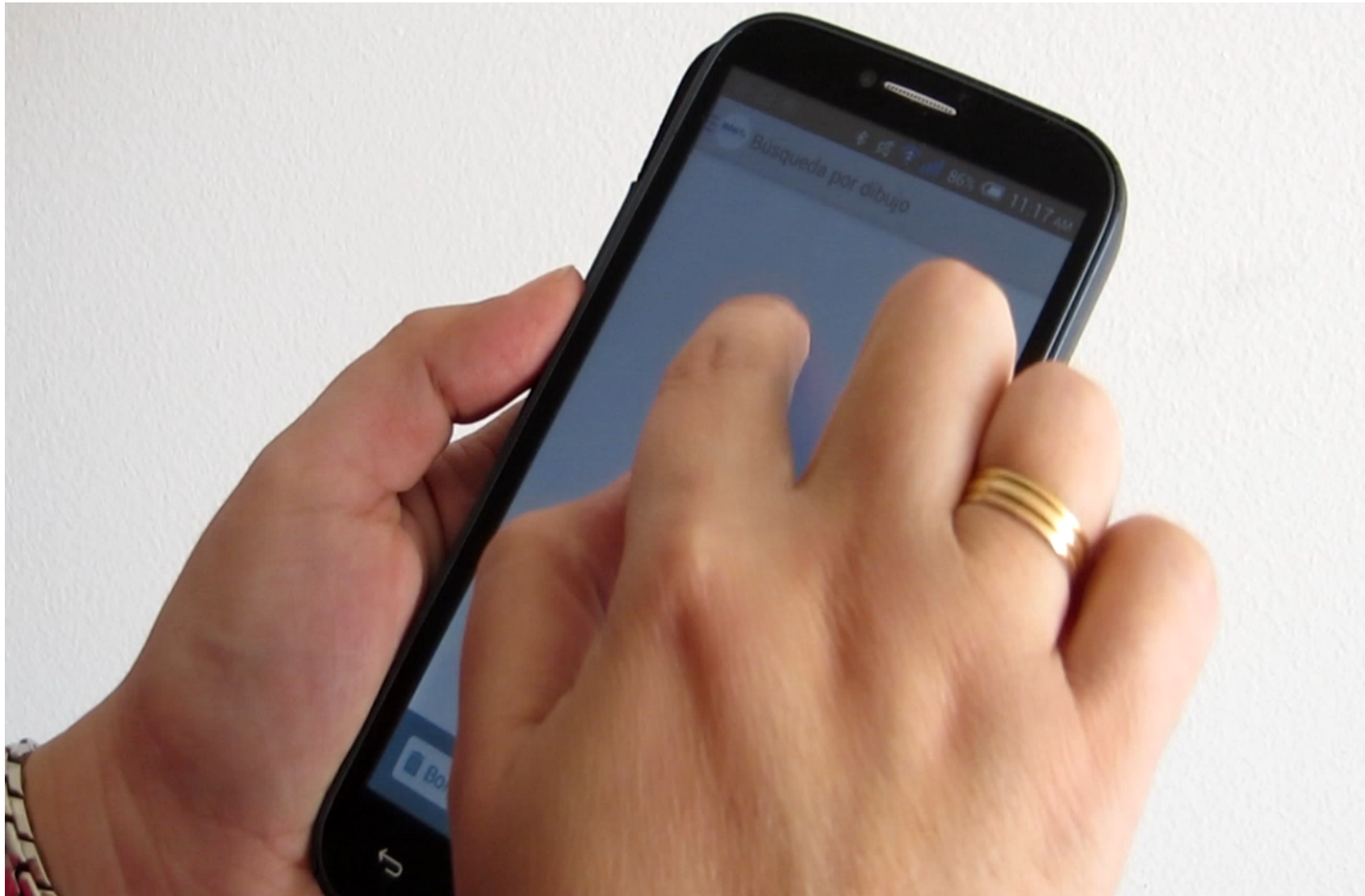


Sketch based Image Retrieval using Learned KeyShapes (LKS)

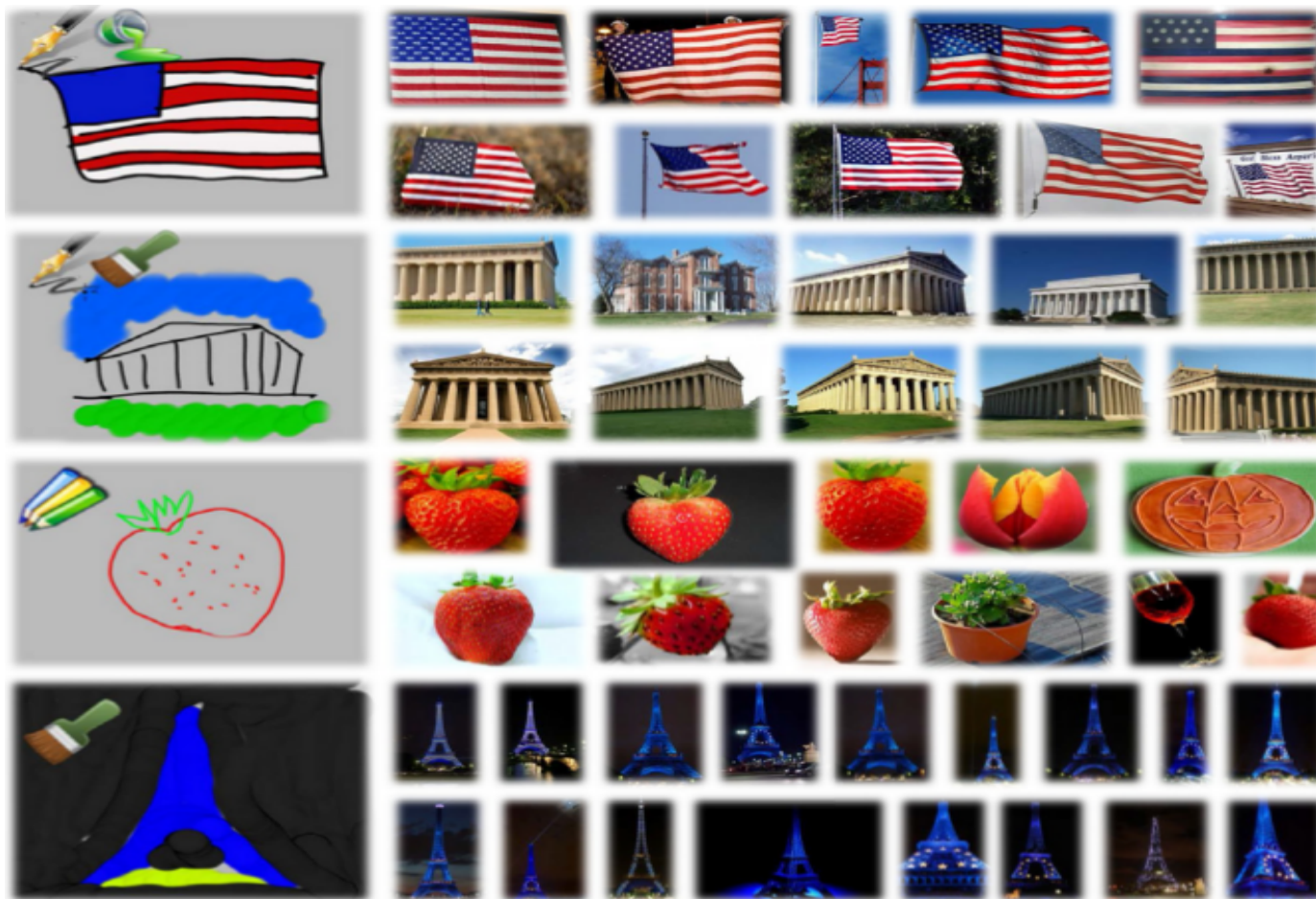
José M. Saavedra (PhD.)



Sketch Based Image Retrieval



Sketch Based Image Retrieval



Xinghai Sun, Changhu Wang, Avneesh Sud, Chao Xu, and Lei Zhang. 2013. MagicBrush: image search by color sketch. In Proceedings of the 21st ACM international conference on Multimedia (MM '13). ACM, New York, NY, USA

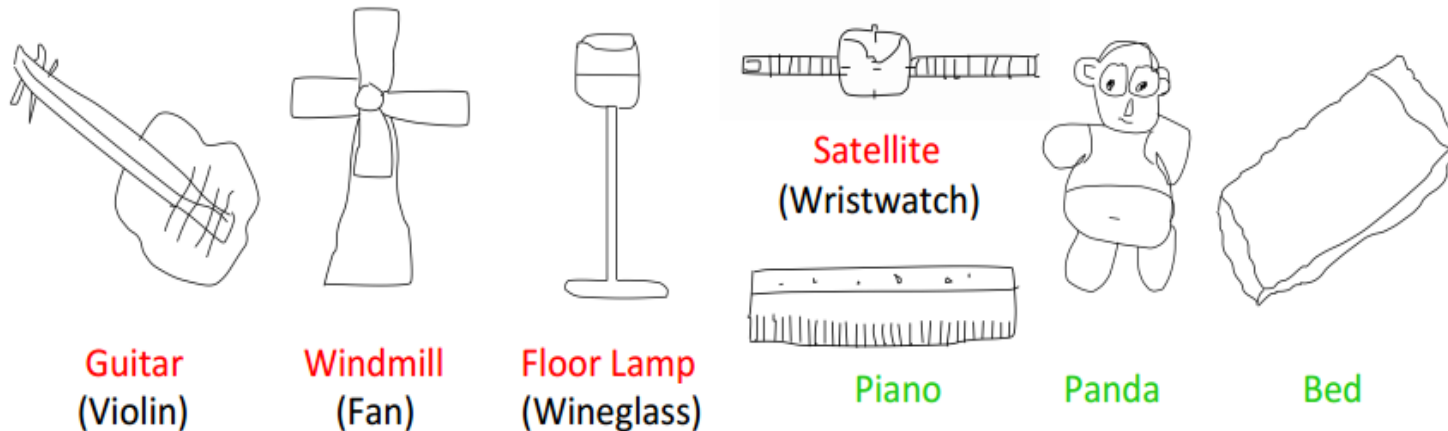
Sketch Based Image Retrieval

A sketch is a simple hand-made drawing composed of just a sequence of strokes. A sketch may lack of color and texture.



Sketch Based Image Retrieval

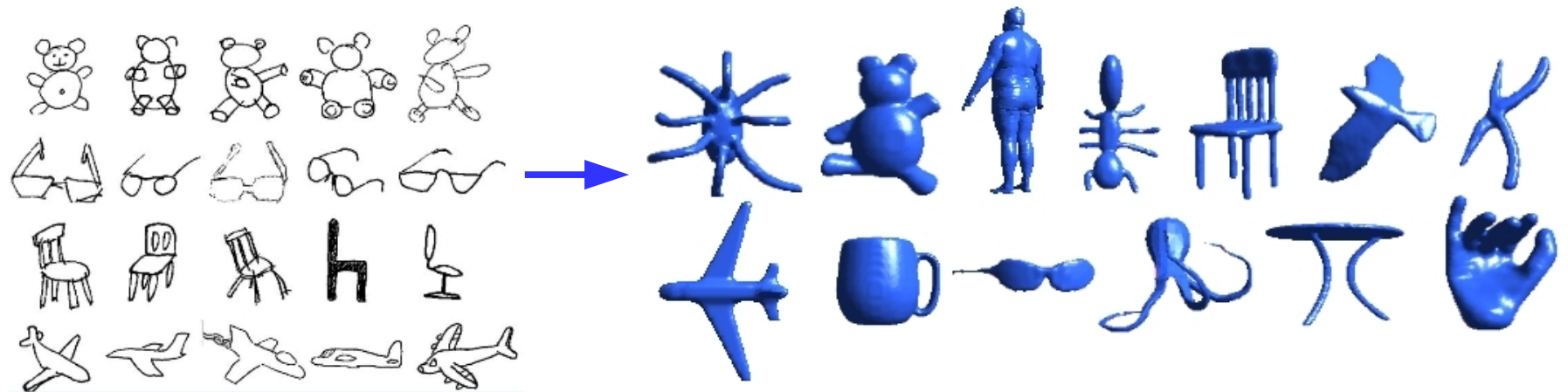
Related applications:



Sketch Classification

Sketch Based Image Retrieval

Related applications:

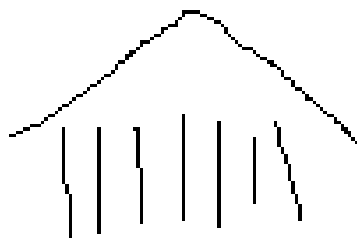


Sketch Classification

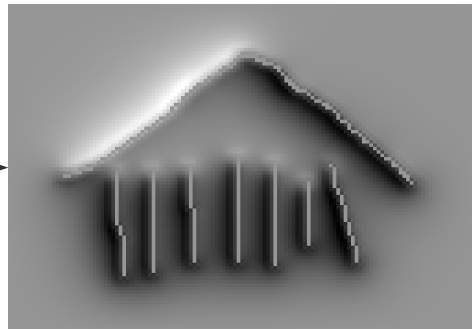
Sketch Based Image Retrieval

Related Work: Commonly using low-level features.

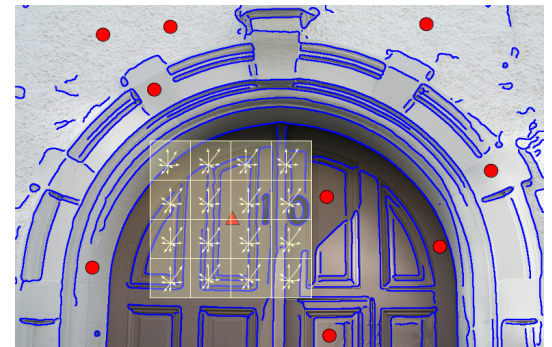
- Gradient Field [Hu et al. 2011, 2013]
- Spark Descriptor [Eitz et al. 2011]
- DoIGOH Descriptor [Eitz et al. 2011]



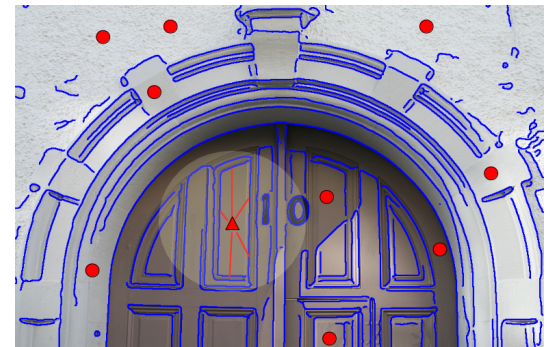
Sketch



Gradient field



DoIGOH

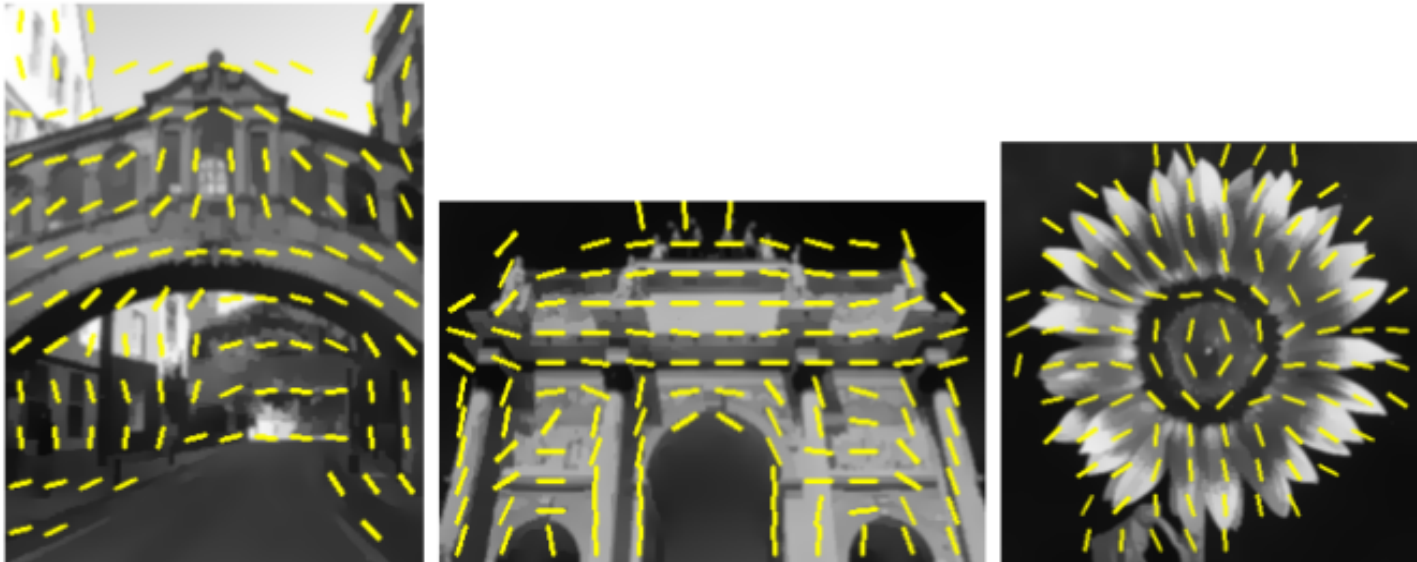


Spark

Sketch Based Image Retrieval

Related Work: Commonly using low-level features.

- HELO (Histogram of Edge Local Orientations) [Saavedra, 2010]
- SHELO (Soft HELO) [Saavedra, 2014]



Sketch Based Image Retrieval



Huebel and Wiesel cat experiment on Visual Perception

Sketch Based Image Retrieval

How can we apply MID-LEVEL
features in the SBIR problem?



KEYSHAPES

Sketch Based Image Retrieval

Related Work: Using keyshapes

- Sketch-based image retrieval using keyshapes [Saavedra, 2011(14)]

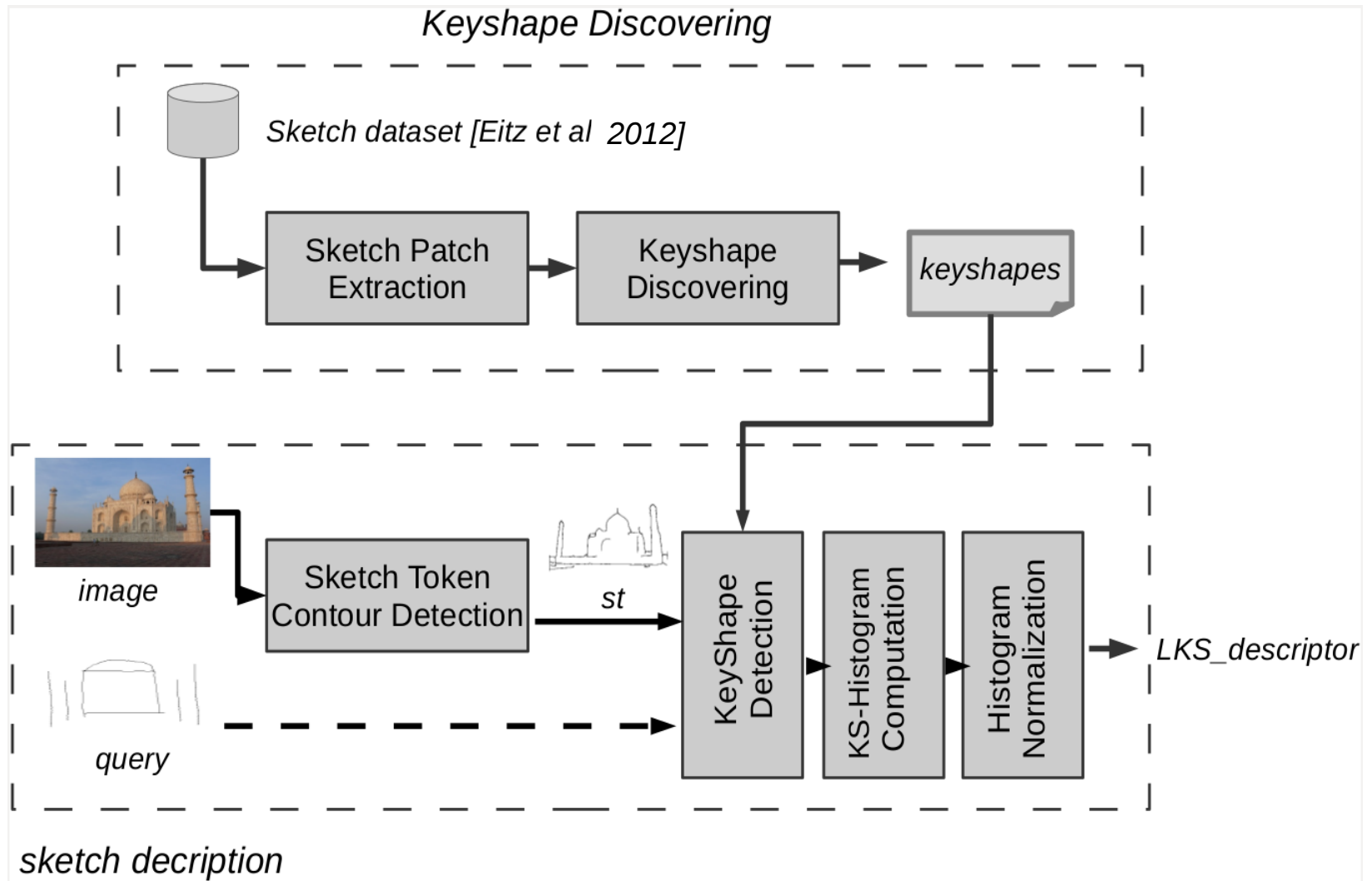


A set of shapes manually defined



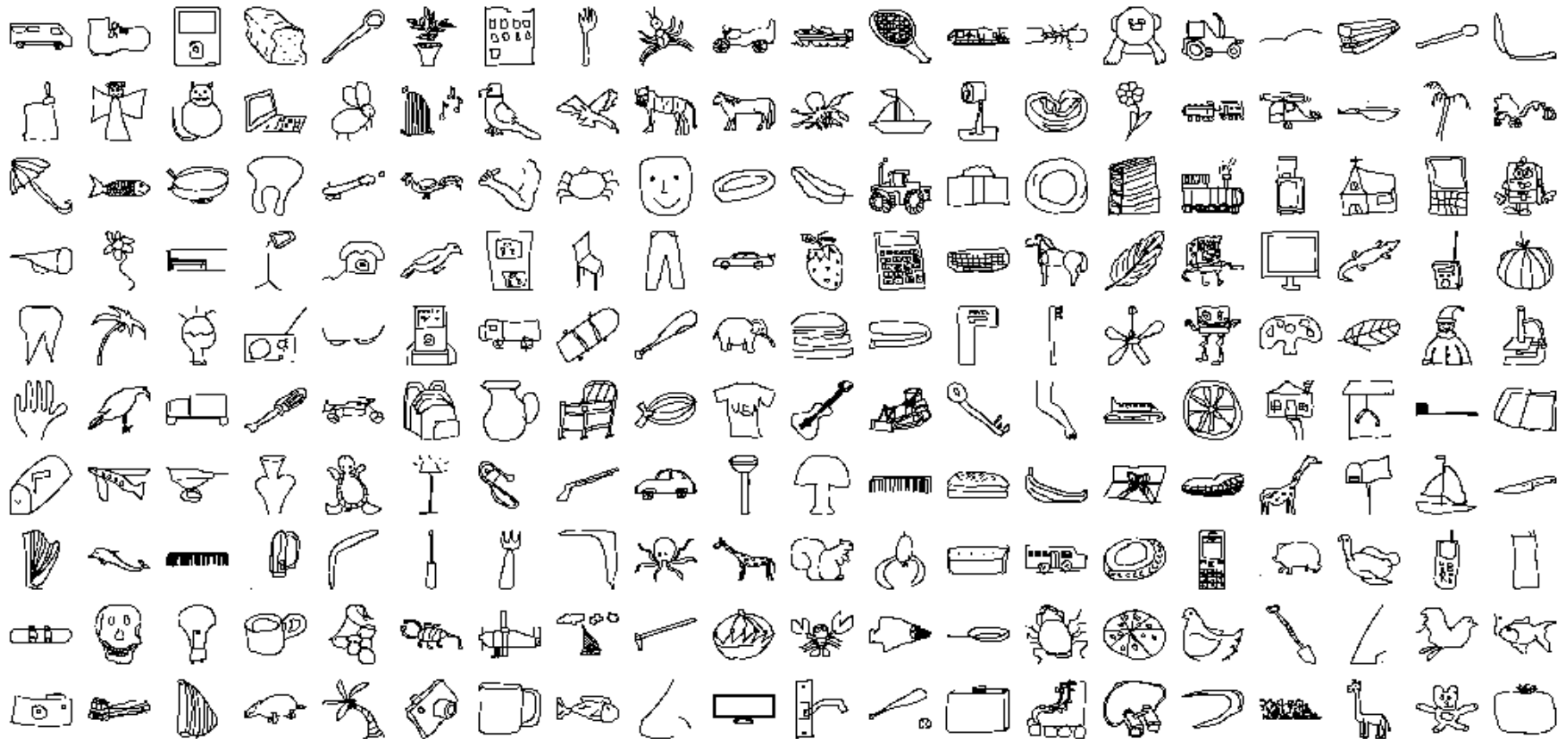
Sketch based Image Retrieval using Learned KeyShapes (LKS)

Scheme



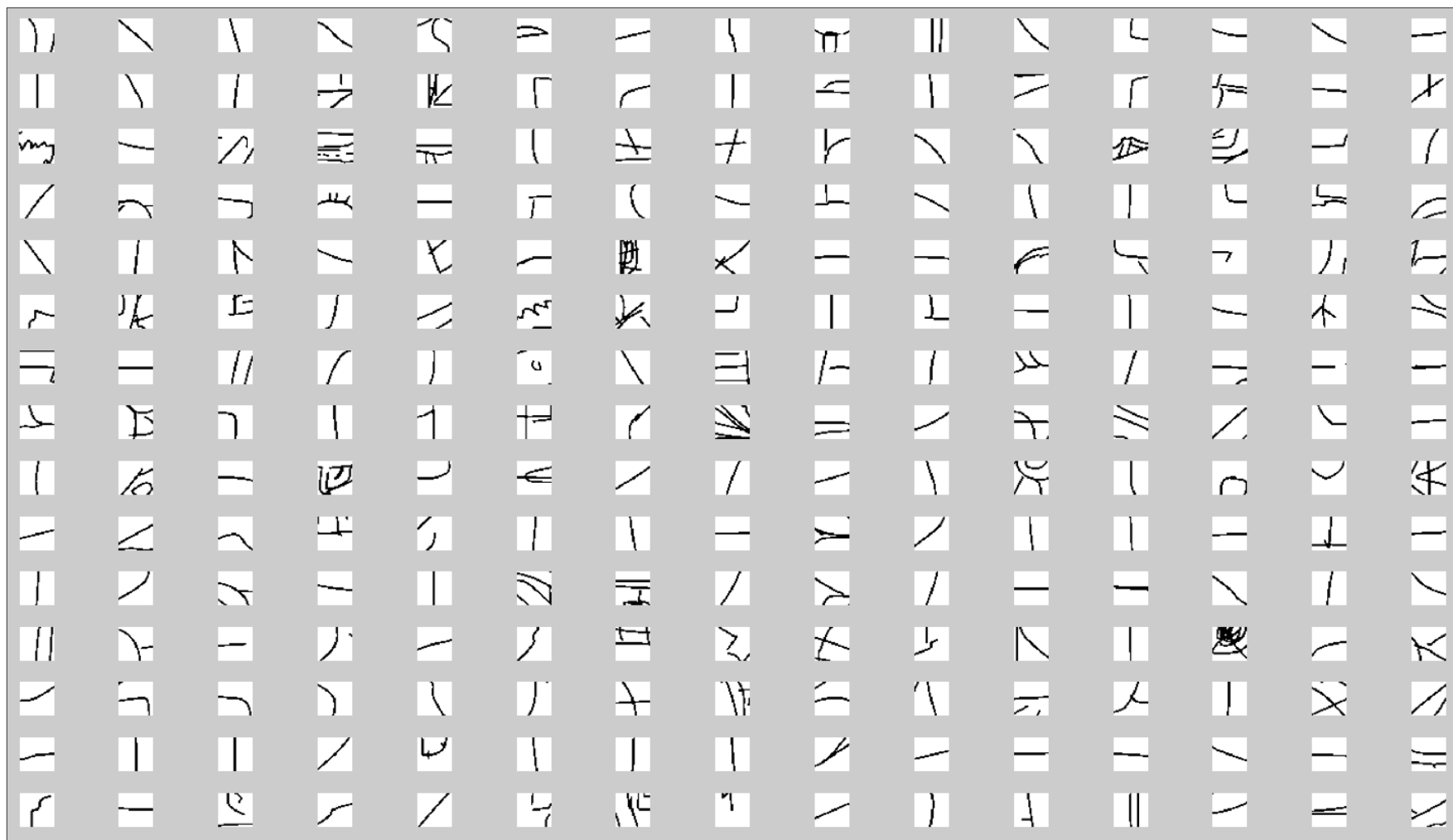
LKS-Keyshape Discovering

Training Dataset: 250 classes, 80 sketches/class,
total = 20K sketches.



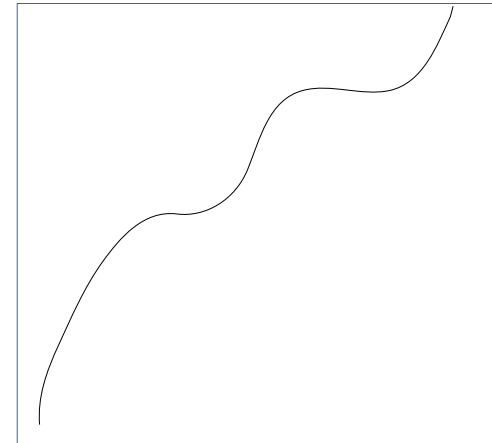
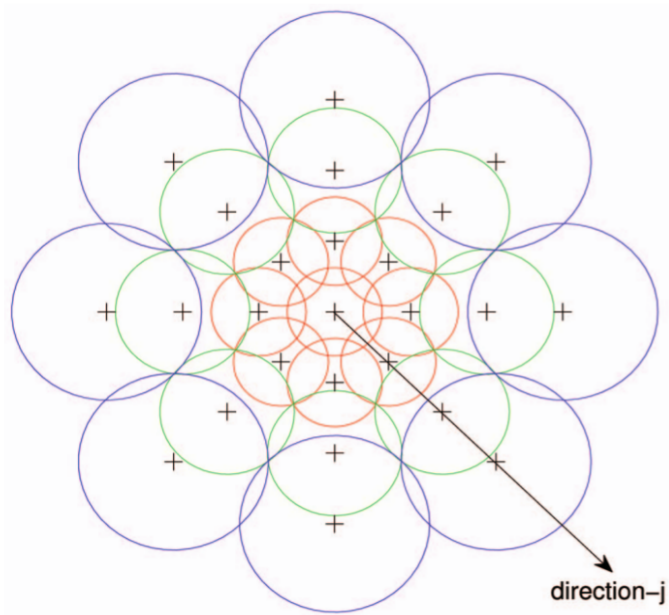
LKS-Keyshape Discovering

Patch Extraction



LKS-Keyshape Discovering Patch Description

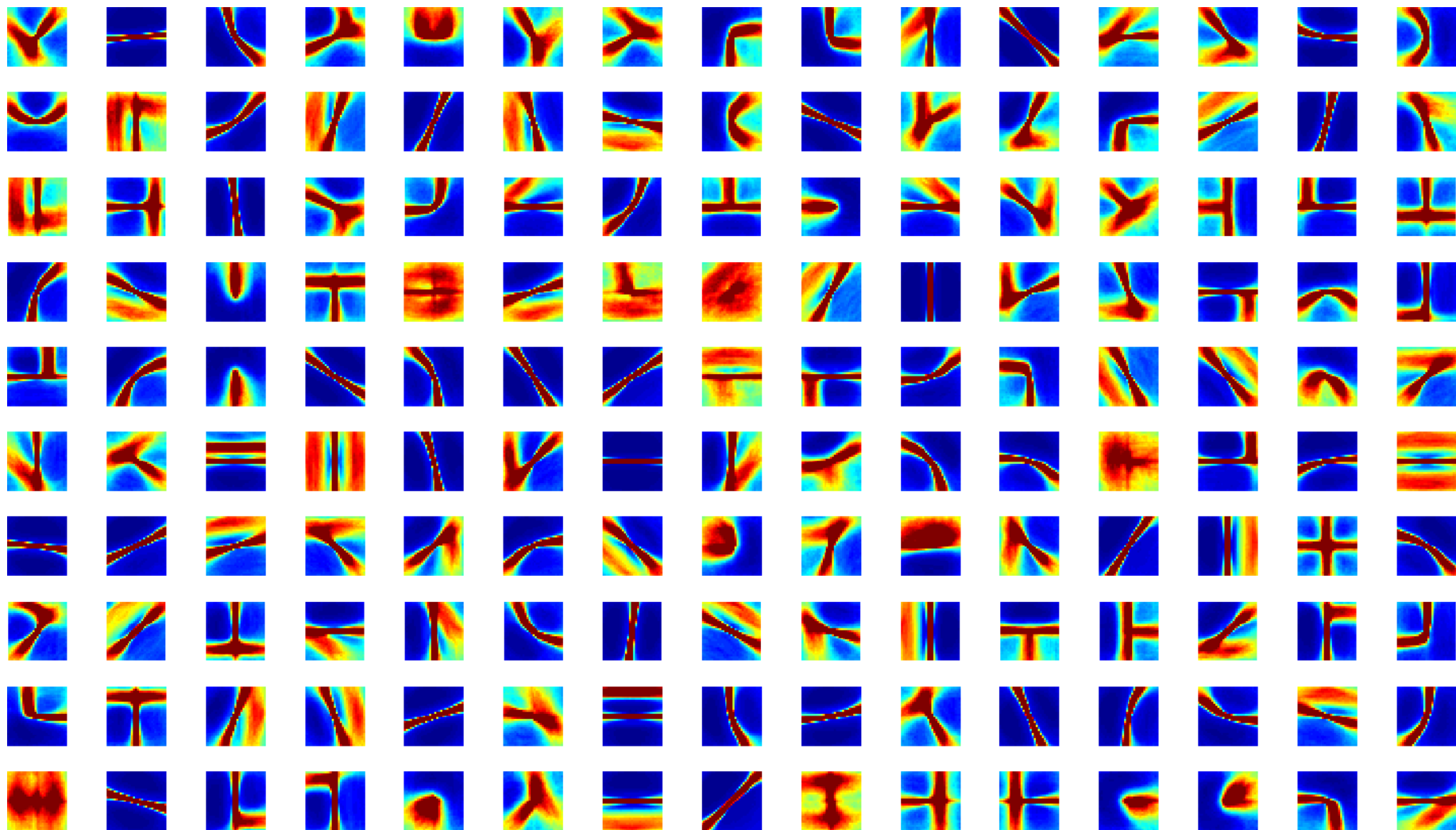
- ✓ Sketch patches are represented by DAISY descriptors



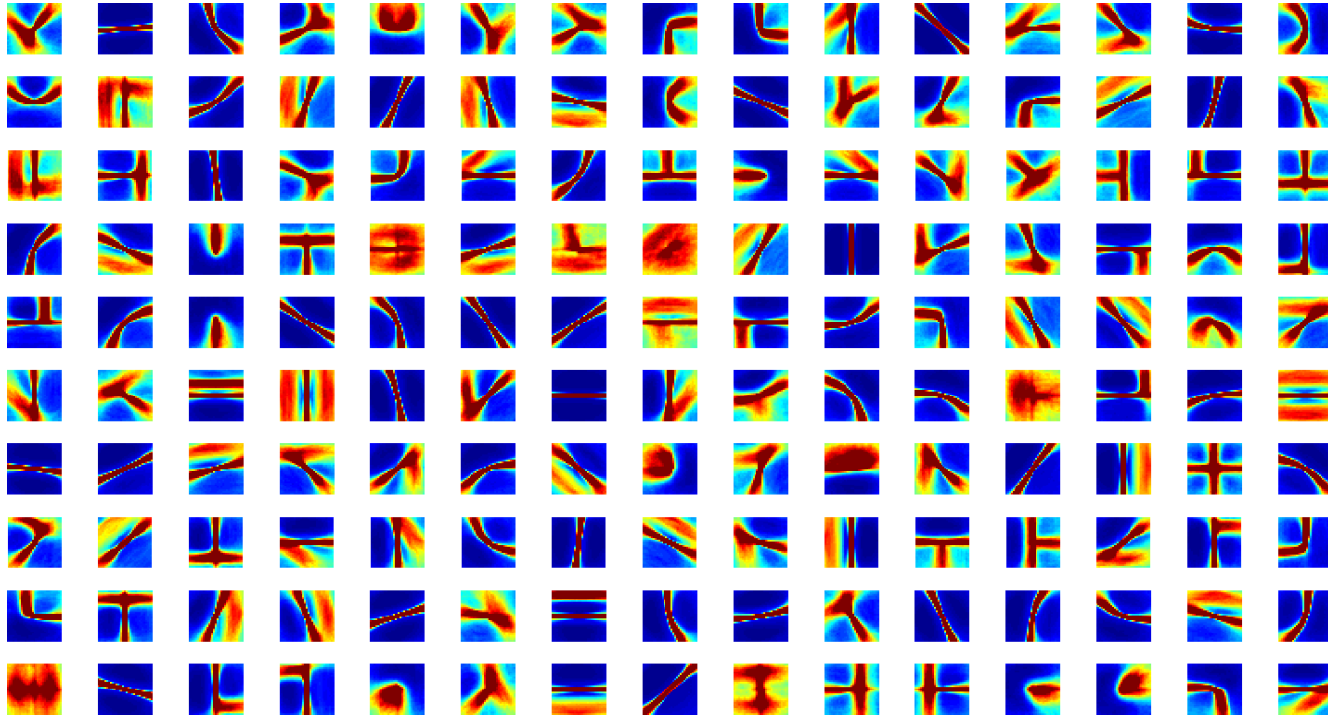
$$\mathcal{D}(u_0, v_0) = \left[\begin{aligned} &\tilde{\mathbf{h}}_{\Sigma_1}^\top(u_0, v_0), \\ &\tilde{\mathbf{h}}_{\Sigma_1}^\top(\mathbf{l}_1(u_0, v_0, R_1)), \dots, \tilde{\mathbf{h}}_{\Sigma_1}^\top(\mathbf{l}_T(u_0, v_0, R_1)), \\ &\tilde{\mathbf{h}}_{\Sigma_2}^\top(\mathbf{l}_1(u_0, v_0, R_2)), \dots, \tilde{\mathbf{h}}_{\Sigma_2}^\top(\mathbf{l}_T(u_0, v_0, R_2)), \\ &\dots \\ &\tilde{\mathbf{h}}_{\Sigma_Q}^\top(\mathbf{l}_1(u_0, v_0, R_Q)), \dots, \tilde{\mathbf{h}}_{\Sigma_Q}^\top(\mathbf{l}_T(u_0, v_0, R_Q)) \end{aligned} \right]^\top$$

LKS-Keyshape Discovering

Clustering (on 1M patches)

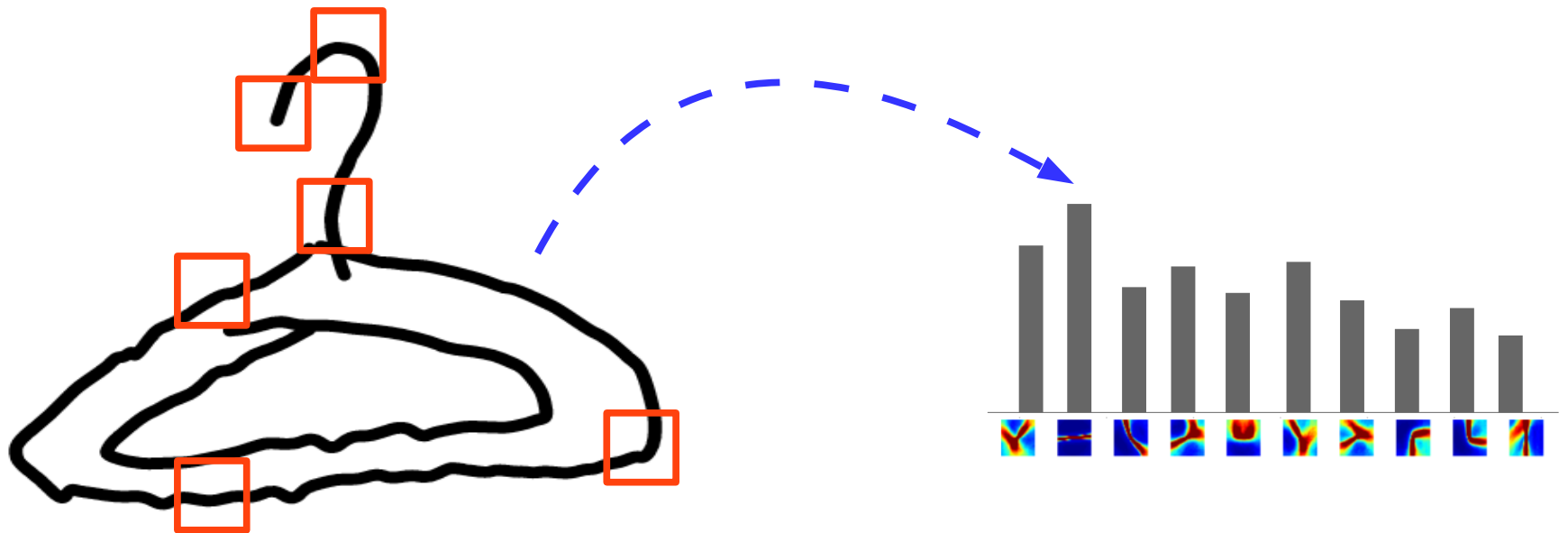


LKS-Keyshape Discovering Clustering



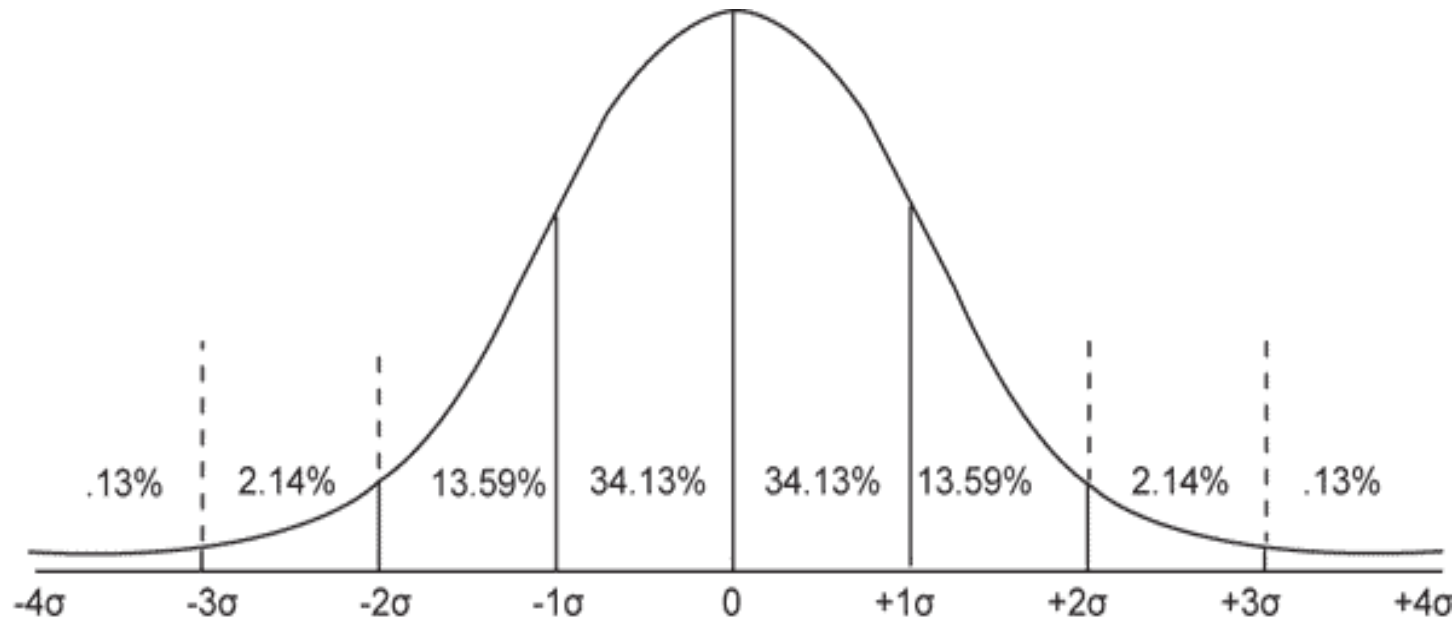
$$Clusters_K = \{(\mu_1, r_1), \dots, (\mu_K, r_K)\}$$

Sketch Representation



$$KS_P^i = \{(p_1^i, \delta_1^i), \dots, (p_P^i, \delta_P^i)\}$$

Voting Process

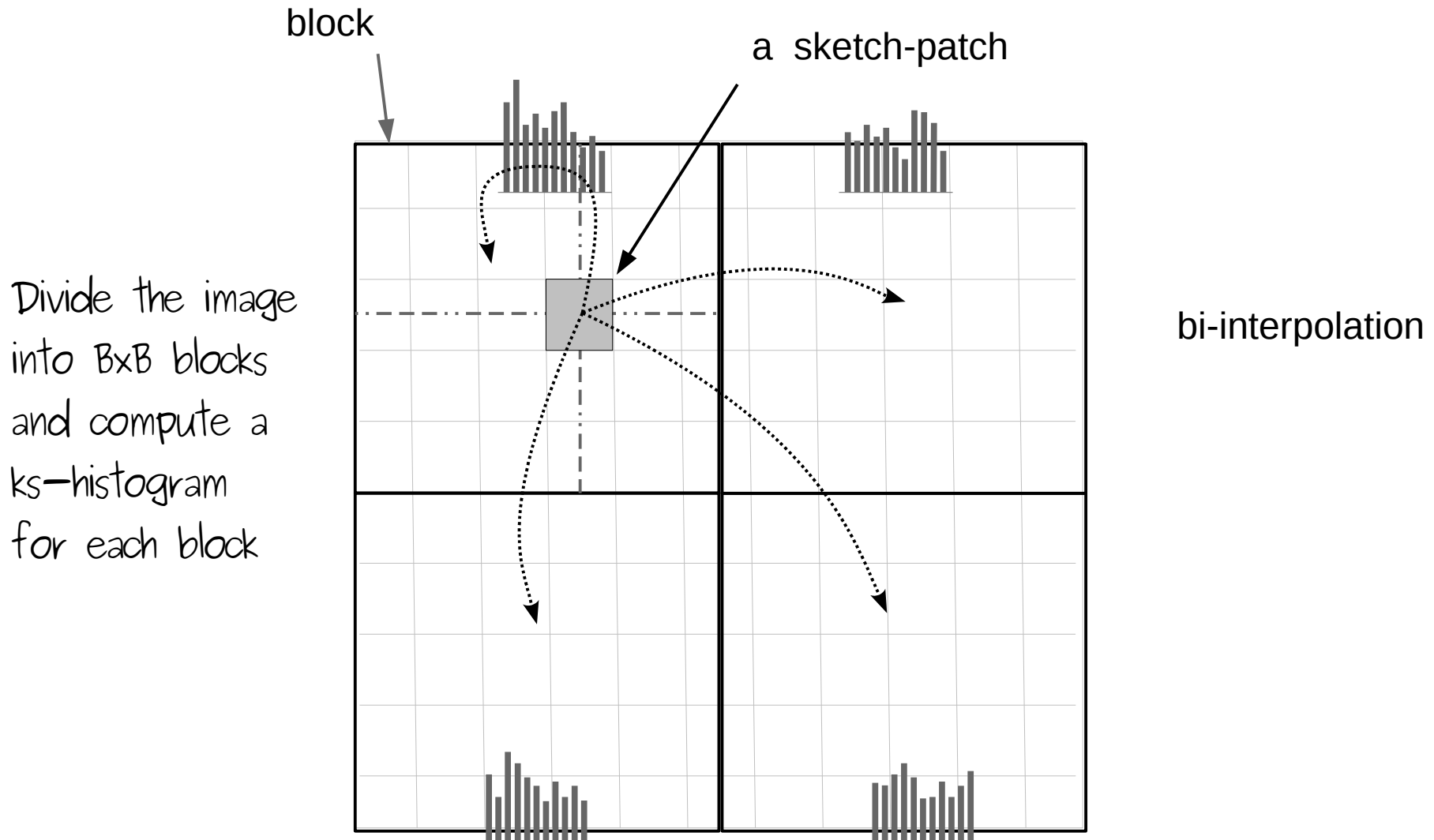


$$G(S_i, p_j^i) = \frac{1}{\sigma_{p_j^i} \sqrt{2\pi}} \exp \left(-0.5 \frac{\delta_j^{i2}}{\sigma_{p_j^i}^2} \right)$$

$$vote_j^i = \frac{G(S_i, p_j^i)}{\sum_{k=1}^P G(S_i, p_k^i)}$$

$$h_{LKS}(p_j^i) + = vote_j^i$$

Spatial Division



Experimental Evaluation

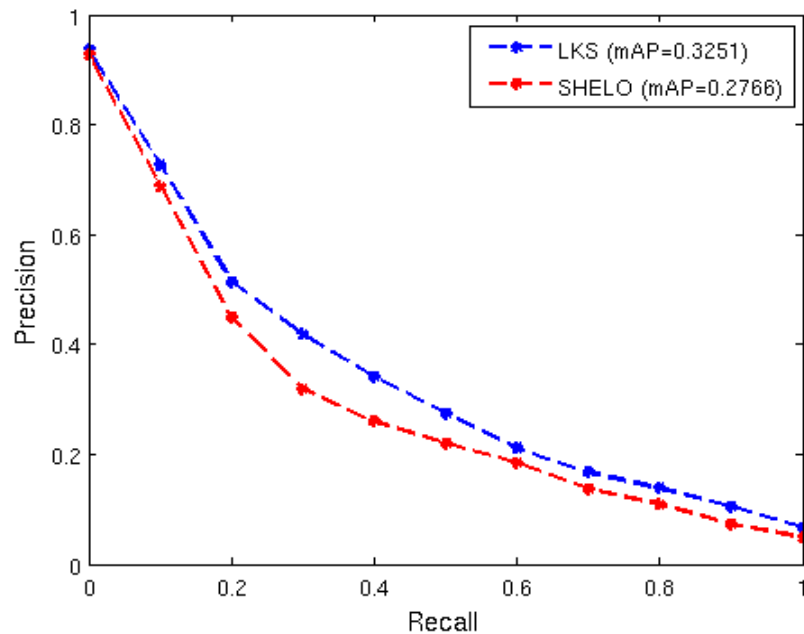
- Using two different datasets
 - Saavedra (1326 images, 53 queries)
 - Flickr 15K (14660 images, 330 queries)
- Evaluation Metrics
 - MAP: Mean Average Precision
 - Recall-Precision Graphic

Experimental Evaluation

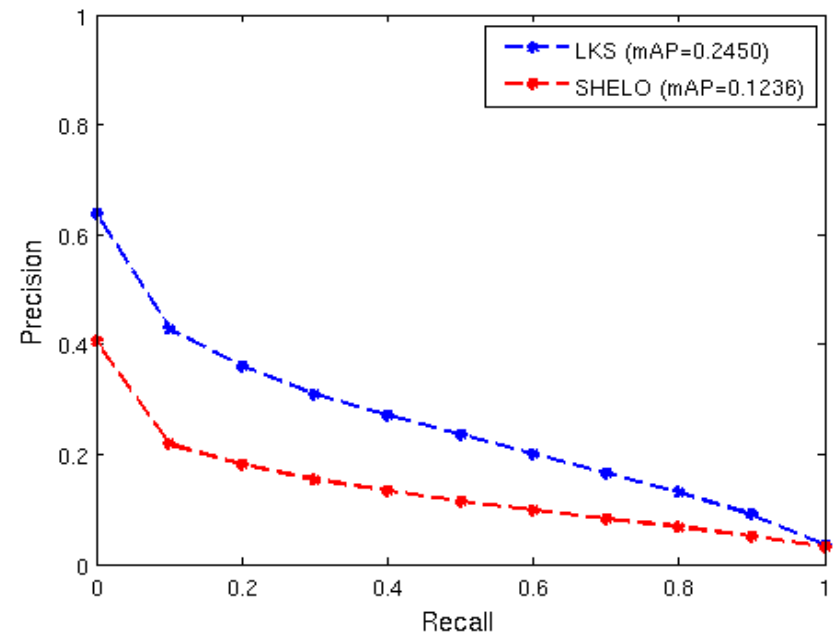
	HOG	GF-HOG[15]	SHELO[25]	LKS	gain
Saavedra's	0.2355	<i>unreported</i>	0.2766	0.3251	17.5%
Flickr15K	0.0771	0.1222	0.1236	0.2450	98.2%

mAP : Mean Average Precision

Experimental Evaluation



On Saavedra's dataset



On Flickr dataset

Experimental Evaluation

	K=50	K=100	K=150	K=200	K=300
B=3, P=10	0.2802	0.2901	0.2911	0.2908	0.2949
B=4, P=10	0.2925	0.3186	0.3251	0.3248	0.3180
B=3, P=15	0.2773	0.2888	0.2900	0.2911	0.2916
B=4, P=15	0.2828	0.3076	0.3210	0.3241	0.3250
B=3, P=20	0.2783	0.2863	0.2886	0.2878	0.2893
B=4, P=20	0.2789	0.3019	0.3144	0.3191	0.3220

mAP for a sample of different parameters in the Saavedra's dataset.

Experimental Evaluation

	K=50	K=100	K=150	K=200	K=300
B=3, P=10	0.2246	0.2407	0.2450	0.2431	0.2381
B=4, P=10	0.2208	0.2370	0.2351	0.2272	0.2104
B=3, P=15	0.2124	0.2348	0.2437	0.2452	0.2472
B=4, P=15	0.2056	0.2330	0.2390	0.2375	0.2300
B=3, P=15	0.2058	0.2276	0.2387	0.2446	0.2497
B=4, P=15	0.1964	0.2255	0.2361	0.2402	0.2387

mAP for a sample of different parameters in the Flickr15k dataset.

Experimental Evaluation

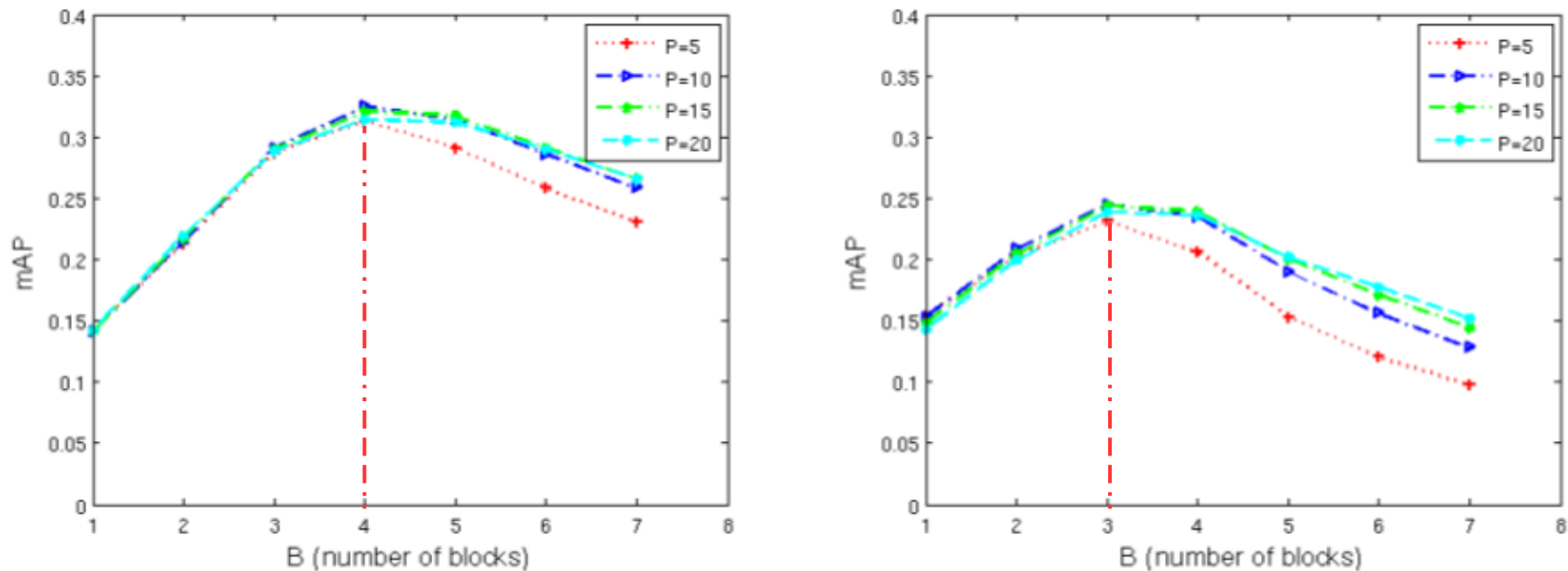


Figure 6: Performance of LKS varying the number of blocks for spatial division and the number of P for voting when $K = 150$. On the left, we see the performance on the Saavedra's dataset. On the right, we show the performance on the Flick15k dataset

Experimental Evaluation

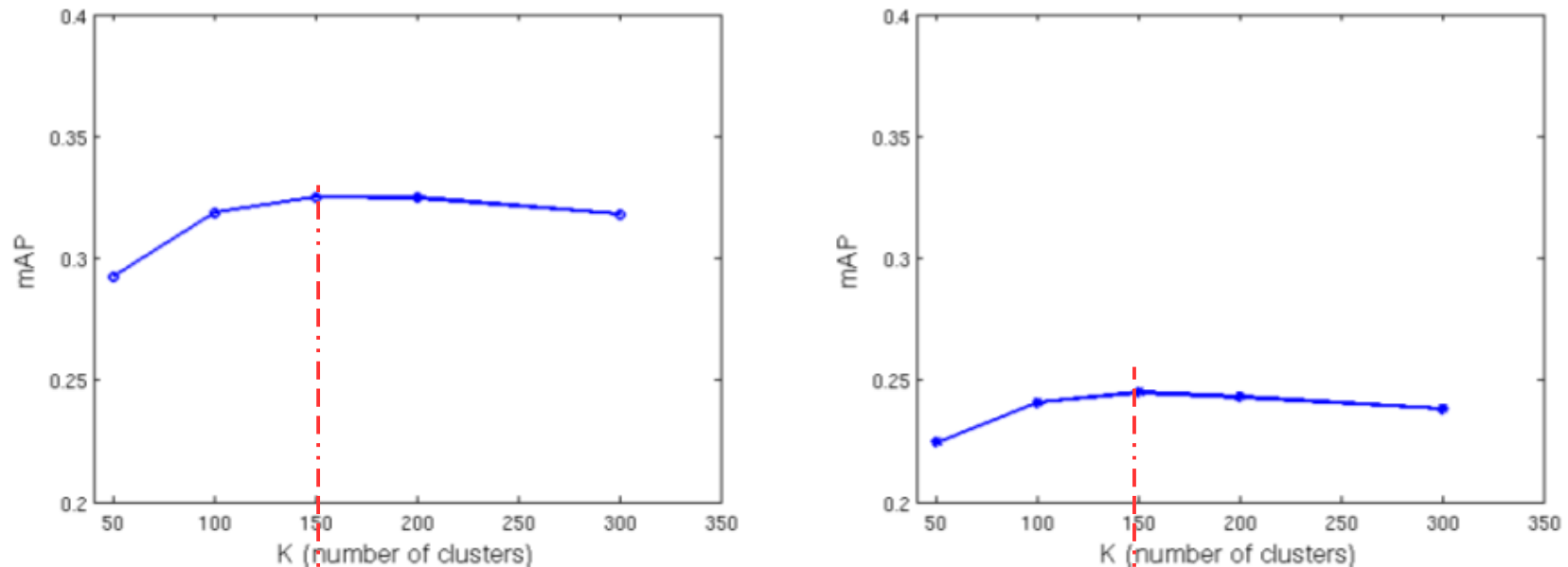


Figure 7: Performance of LKS varying the number of clusters on the Saavedra's dataset (on the left), and Flickr15k (on the right).

Experimental Evaluation

More efficiency?

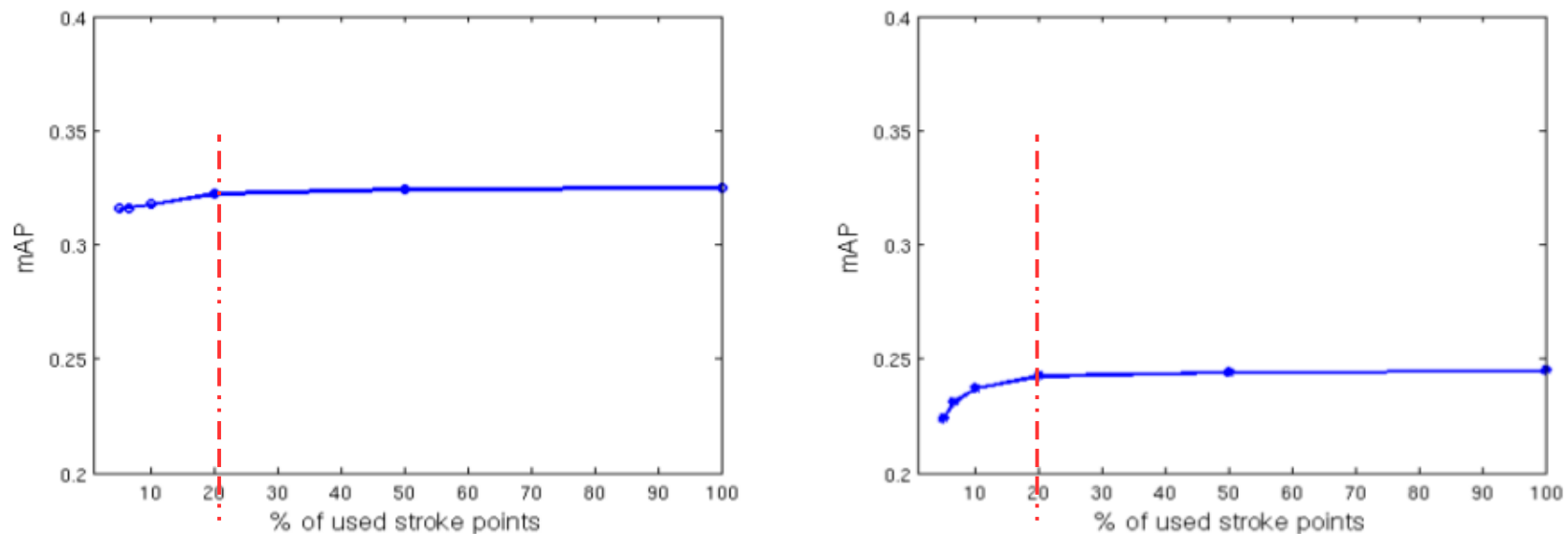
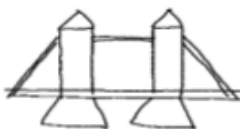
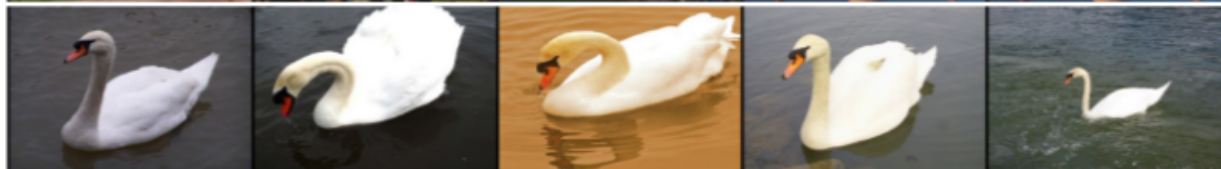


Figure 8: Impact of reducing the number of patches for computing the LKS histogram. On the left, the performance on the Saavedra's dataset. On the right, the performance on Flickr15k.

Results (own dataset)



Results (Flickr15K)



Thanks!!!