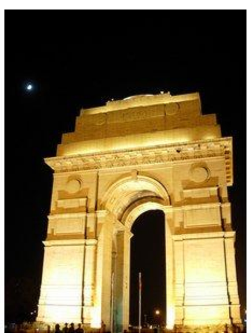
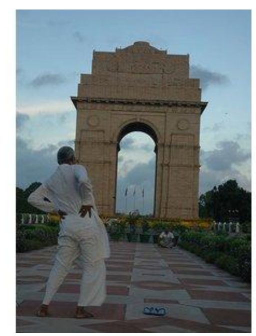
Three things everyone should know to improve object retrieval

Relja Arandjelović and Andrew Zisserman (CVPR 2012)

Large scale object retrieval

- Find all instances of an object in a large dataset
  - Do it instantly
  - Be robust to scale, viewpoint, lighting, partial occlusion

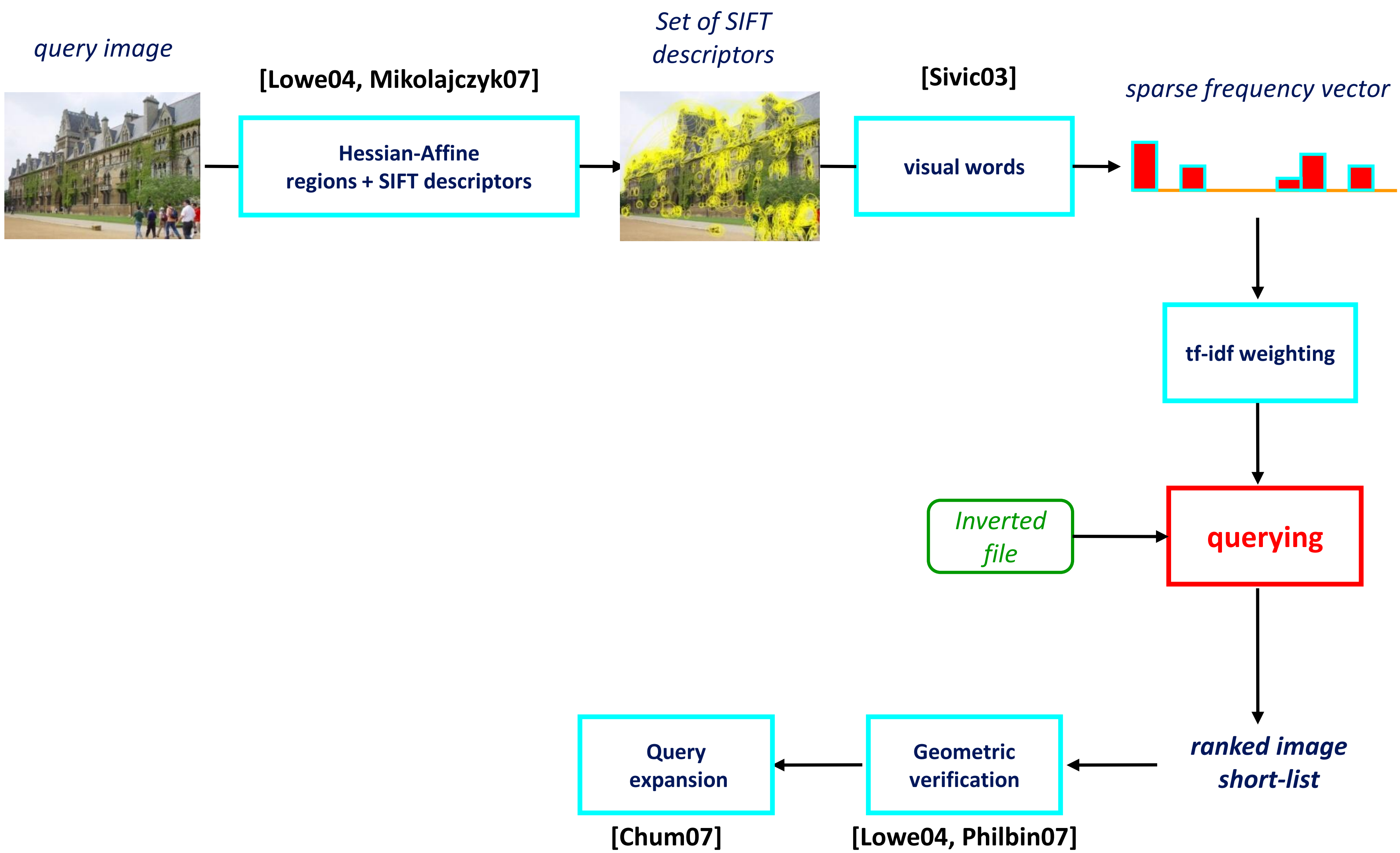


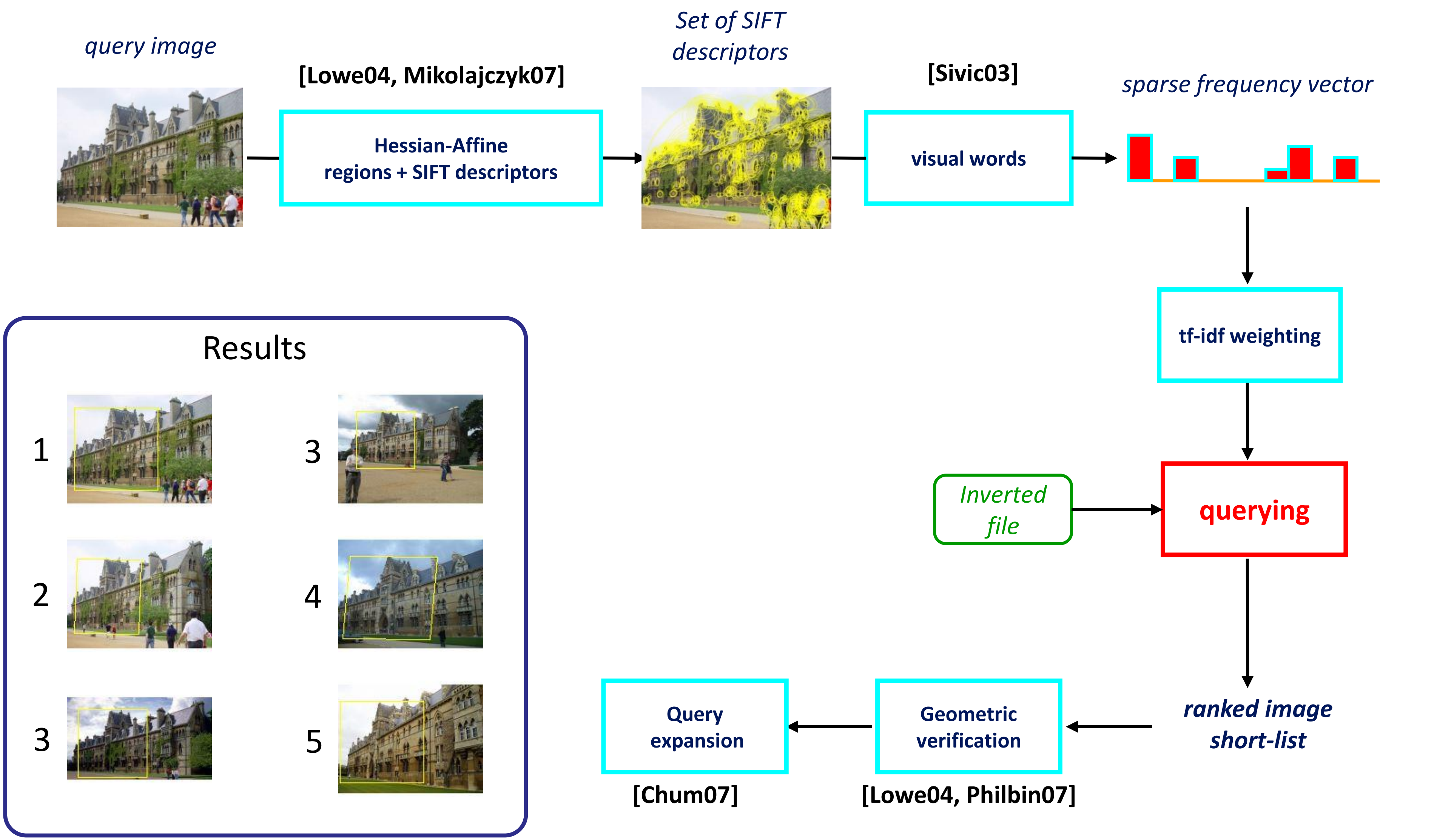
Three things everyone should know

1. RootSIFT
2. Discriminative query expansion
3. Database-side feature augmentation

Bag of visual words particular object retrieval



Bag of visual words particular object retrieval



First thing everyone should know

1. RootSIFT
   - Not only specific to retrieval
   - Everyone using SIFT is affected
2. Discriminative query expansion
3. Database-side feature augmentation

Improving SIFT

- Hellinger or χ^2 measures outperform Euclidean distance when comparing histograms, examples in image categorization, object and texture classification etc.
- These can be implemented efficiently using approximate feature maps in the case of additive kernels
- SIFT is a histogram: can performance be boosted using a better distance measure?

Improving SIFT

- Hellinger or χ^2 measures outperform Euclidean distance when comparing histograms, examples in image categorization, object and texture classification etc.

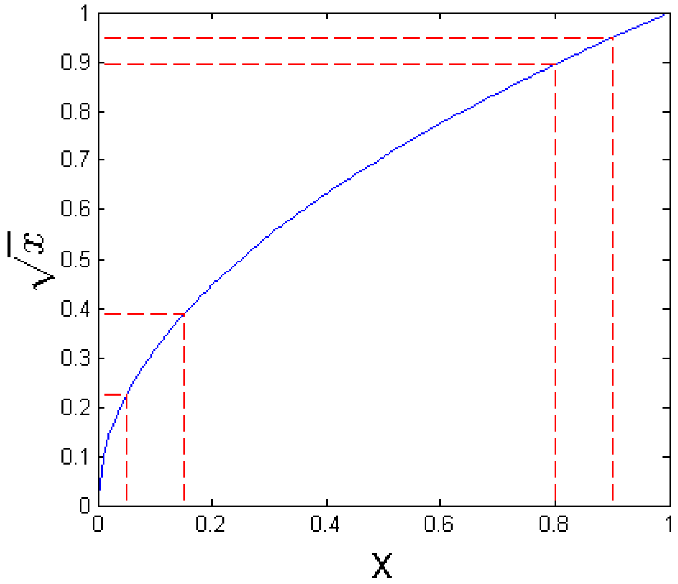
- These can be implemented efficiently using approximate feature maps in the case of additive kernels

- SIFT is a histogram: can performance be boosted using a better distance measure?

Yes!

Hellinger distance

- Hellinger kernel (Bhattacharyya's coefficient) for L1 normalized histograms x and y: $$H(x,y)=\sum_{i=1}^{n}\sqrt{x_i y_i}$$
- Intuition: Euclidean distance can be dominated by large bin values, using Hellinger distance is more sensitive to smaller bin values



Hellinger distance (cont’d)

- Hellinger kernel (Bhattacharyya’s coefficient) for L1 normalized histograms x and y:

$$H(x, y) = \sum_{i=1}^{n} \sqrt{x_i y_i}$$

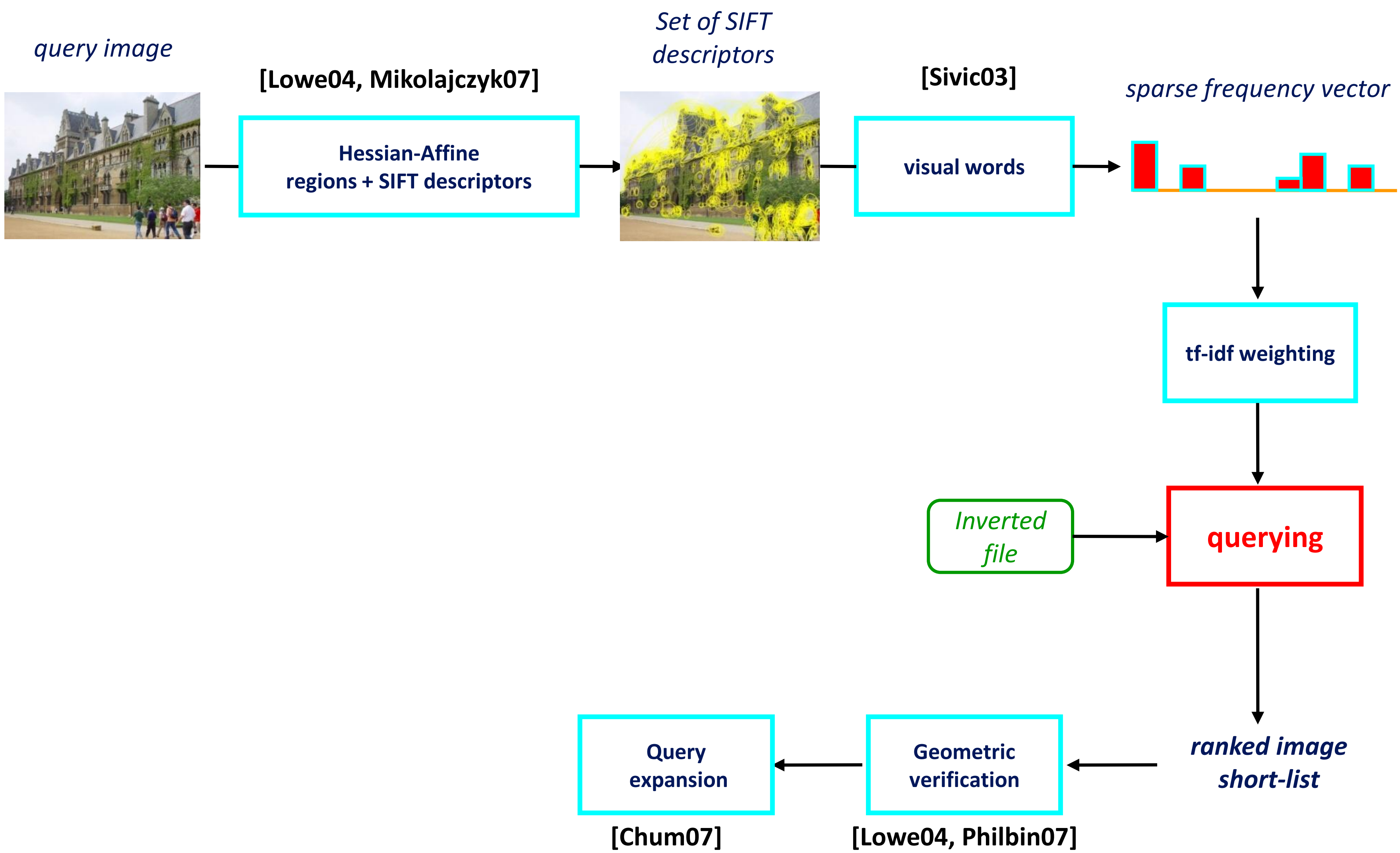
- Explicit feature map of x into x’ :
  - L1 normalize x
  - element-wise square root x to give x’
  - then x’ is L2 normalized

RootSIFT

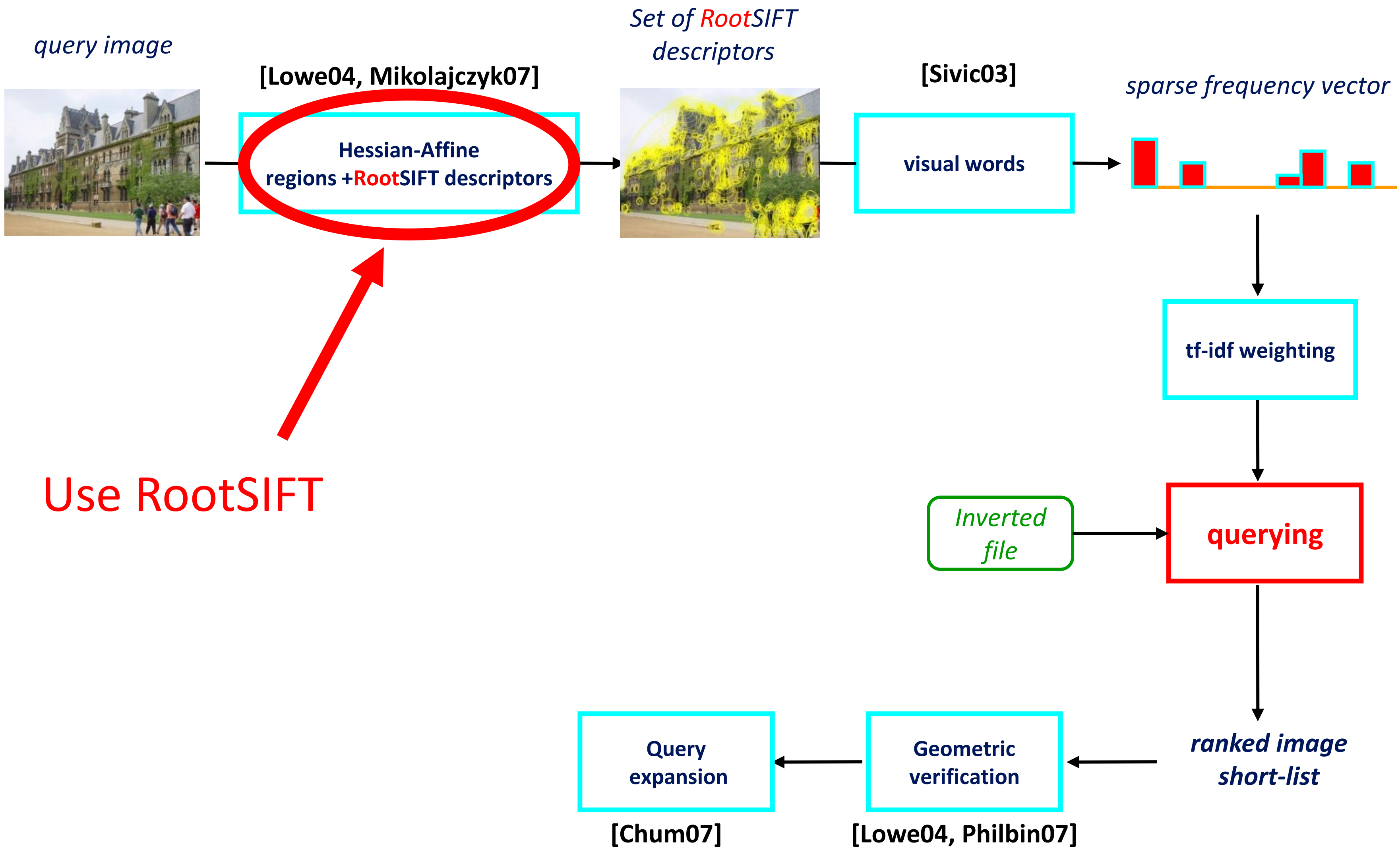
- Computing Euclidean distance in the feature map space is equivalent to Hellinger distance in the original space, since:

$$x'^T y' = H(x, y)$$

Bag of visual words particular object retrieval



Bag of visual words particular object retrieval



Oxford buildings dataset

- Landmarks plus queries used for evaluation

All Souls

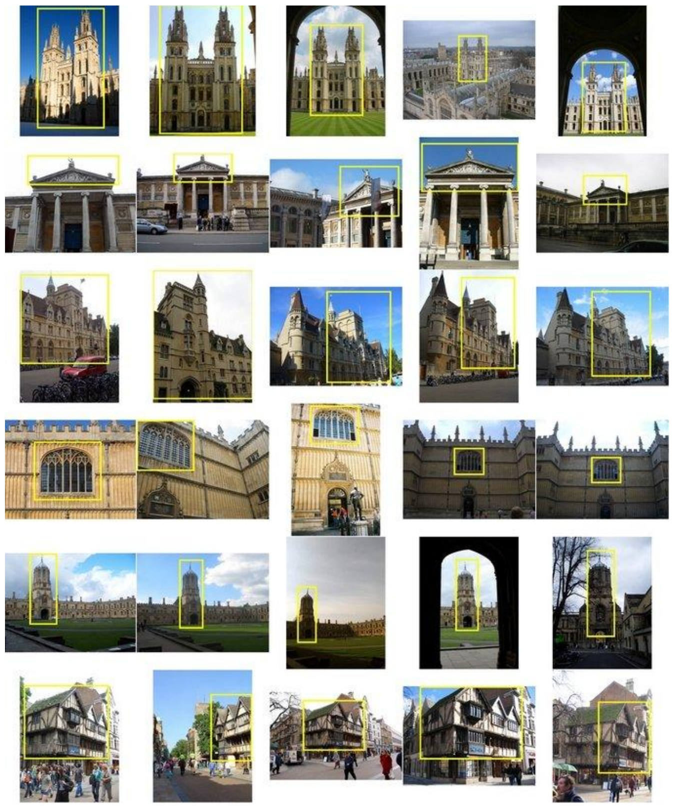
Ashmolean

Balliol

Bodleian

Christ Church

Cornmarket



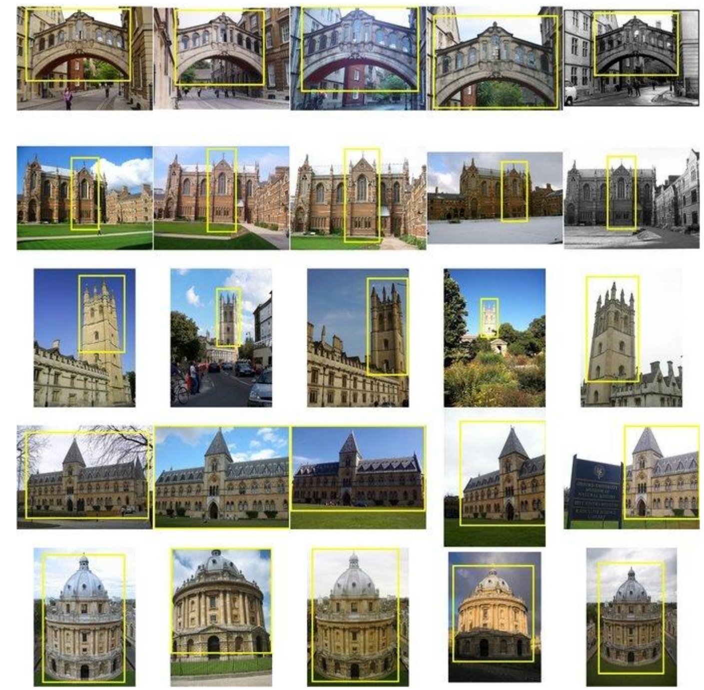
Hertford

Keble

Magdalen

Pit Rivers

Radcliffe Camera



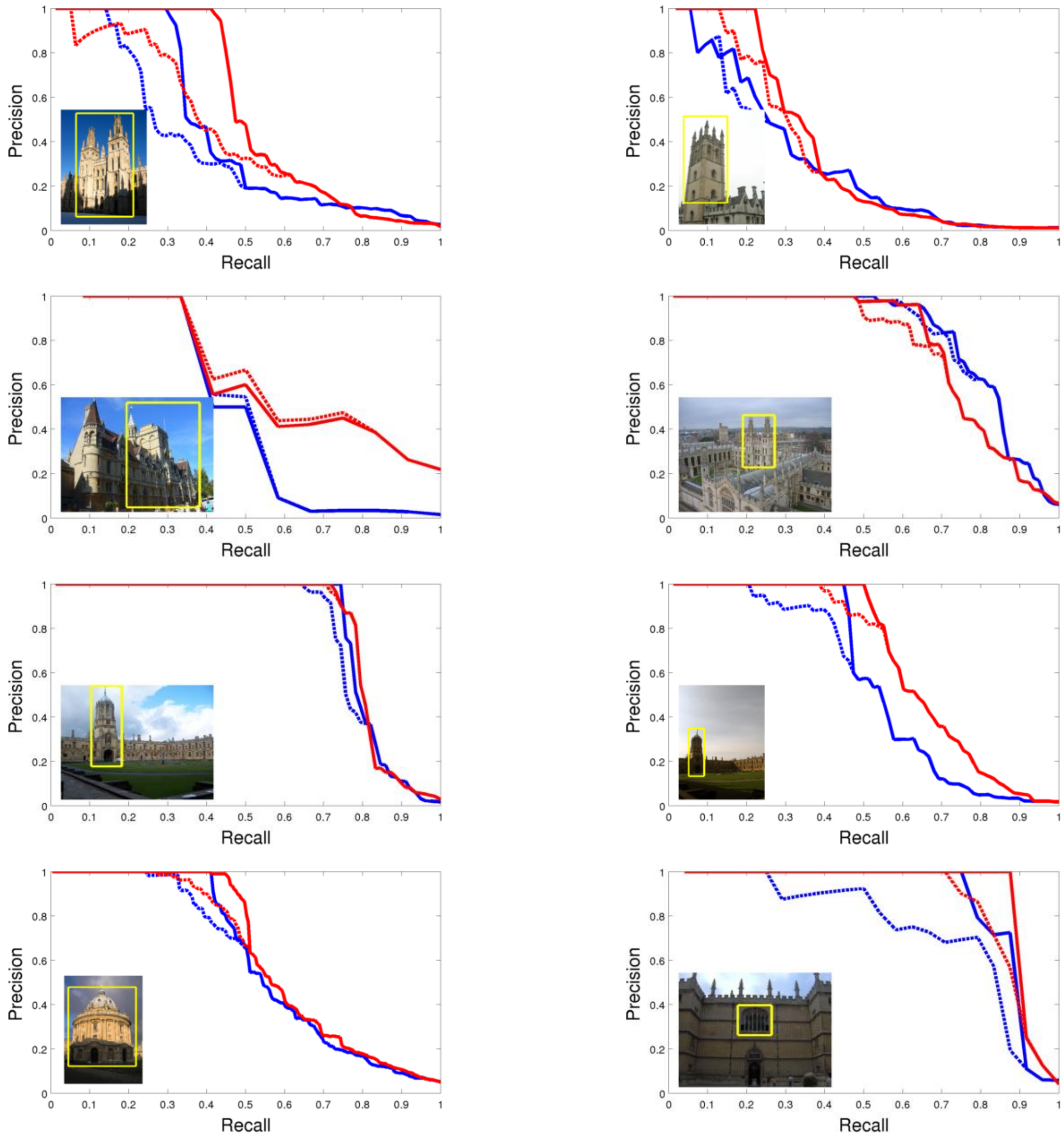
- Ground truth obtained for 11 landmarks over 5062 images
- Evaluate performance by Precision - Recall curves

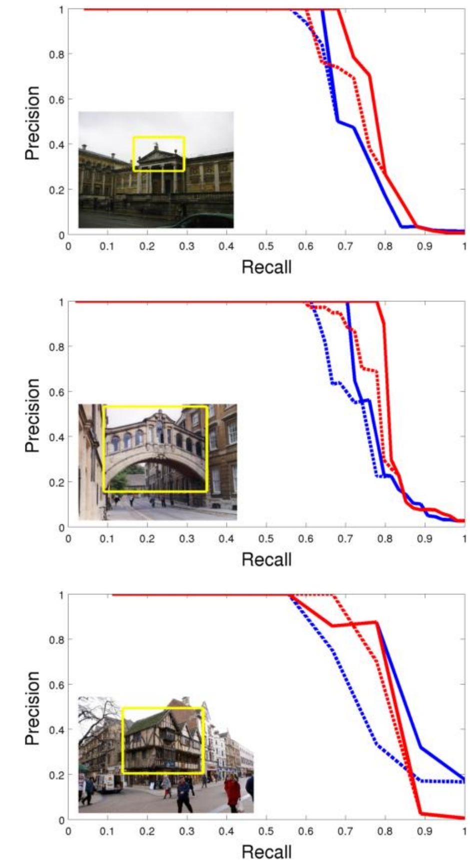
RootSIFT: results

- Philbin et.al. 2007: bag of visual words with:
  - tf-idf ranking
  - or tf-idf ranking with spatial reranking

Retrieval method	Oxford 5k	Oxford 105k	Paris 6k
SIFT: tf-idf ranking	0.636	0.515	0.647
SIFT: tf-idf with spatial reranking	0.672	0.581	0.657
RootSIFT: tf-idf ranking	0.683	0.581	0.681
RootSIFT: tf-idf with spatial reranking	**0.720**	**0.642**	**0.689**

RootSIFT: results, Oxford 5k





Legend:

tfidf:	dashed --
spatial rerank:	solid –
RootSIFT:	red
SIFT:	blue

RootSIFT: results

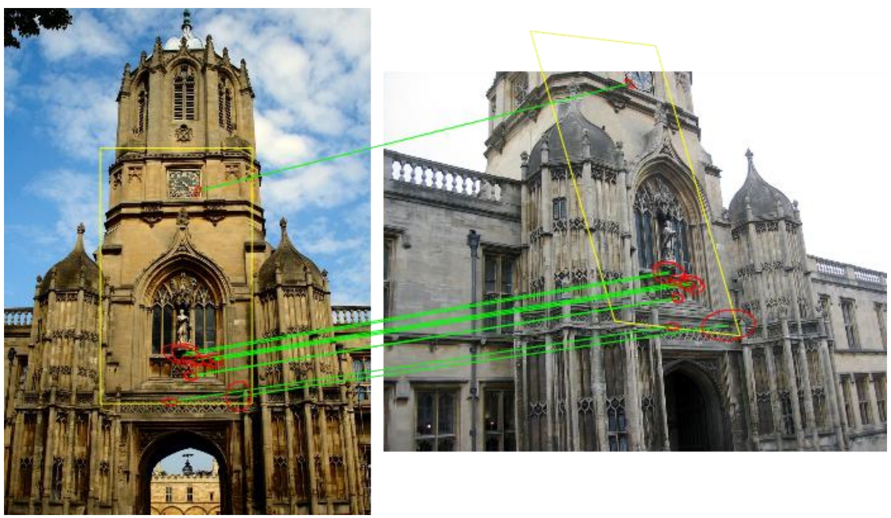
- "Descriptor Learning for Efficient Retrieval", Philbin *et al.,* ECCV'10
  - Discriminative large margin metric learning approach
  - Learn a non-linear mapping function of the DBN form
  - 3M training pairs (positive and negative matches)

Retrieval method	Oxford 5k	Oxford 105k	Paris 6k
SIFT: tf-idf ranking	0.636	0.515	0.647
SIFT: tf-idf with spatial reranking	0.672	0.581	0.657
DBN SIFT: tf-idf with spatial reranking	0.707	0.615	**0.689**
RootSIFT: tf-idf ranking	0.683	0.581	0.681
RootSIFT: tf-idf with spatial reranking	**0.720**	**0.642**	**0.689**

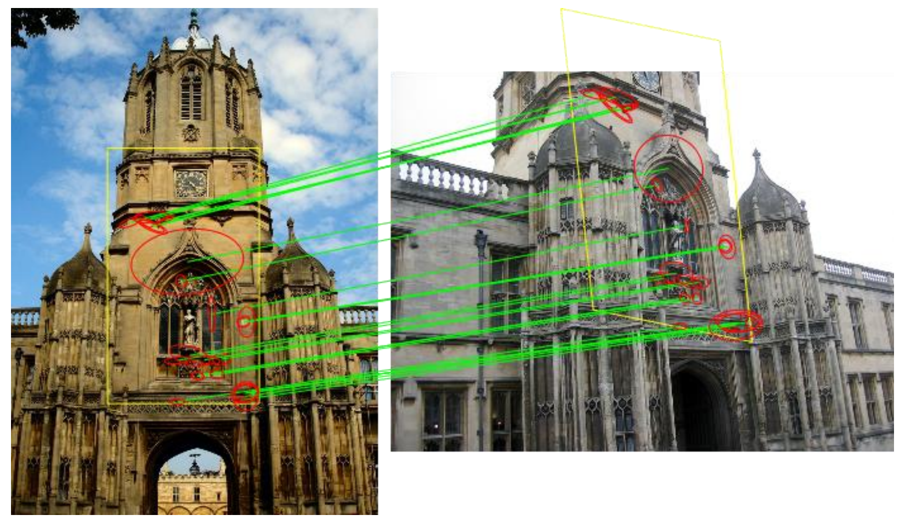
Other applications of RootSIFT

- Superior to SIFT in every single setting
  - Image classification (dense SIFT used as feature vector, PHOW)
  - Repeatability under affine transformations (original use case)

SIFT: 10 matches



RootSIFT: 26 matches



RootSIFT: PASCAL VOC image classification

- Using the evaluation package of [Chatfield11]
- Mean average precision over 20 classes:
  - Hard assignment into visual words
    - SIFT: 0.5530
    - RootSIFT: 0.5614
  - Soft assignment using Locality Constrained Linear encoding
    - SIFT: 0.5726
    - RootSIFT: 0.5915

RootSIFT: properties

- Extremely simple to implement and use
  - One line of Matlab code to convert SIFT to RootSIFT:

```
rootsift= sqrt( sift / sum(sift) );
```

- Conversion from SIFT to RootSIFT can be done on-the-fly
  - No need to modify your favourite SIFT implementation, no need to have SIFT source code, just use the same binaries
  - No need to re-compute stored SIFT descriptors for large image datasets
  - No added storage requirements
  - Applications throughout computer vision

    k-means, approximate nearest neighbour methods, soft-assignment to visual words, Fisher vector coding, PCA, descriptor learning, hashing methods, product quantization etc.

RootSIFT: conclusions

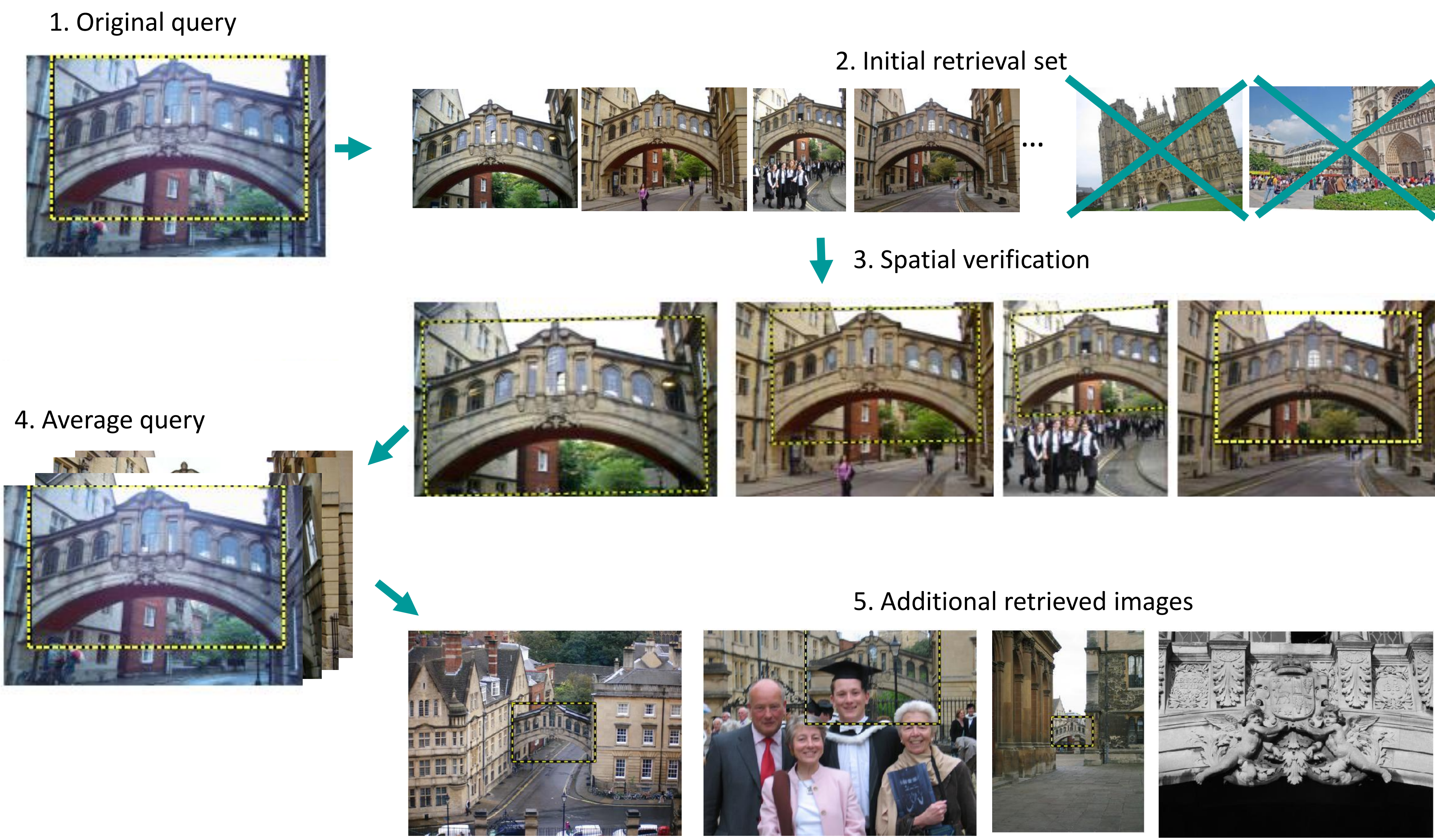
- Superior to SIFT in every single setting
- Every system which uses SIFT is ready to use RootSIFT
- No added computational or storage costs
- Extremely simple to implement and use

We strongly encourage everyone to try it!

Second thing everyone should know

1. RootSIFT
2. Discriminative query expansion
3. Database-side feature augmentation

Query expansion



Chum *et al.*, ICCV 2007

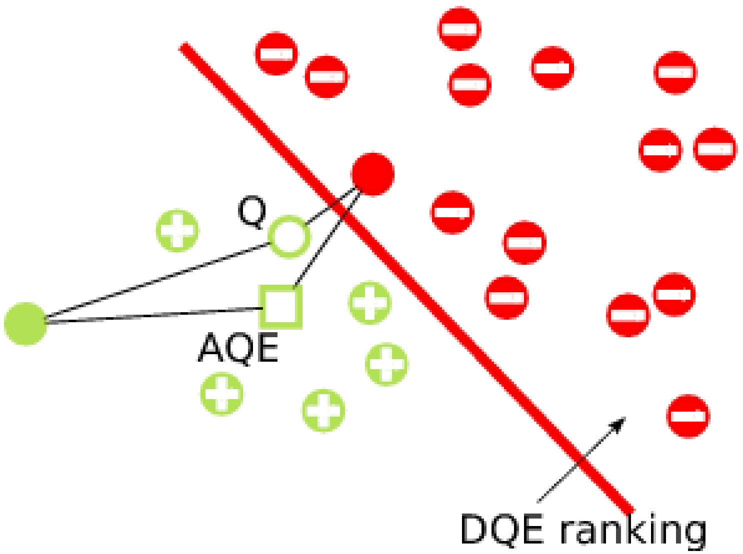
Average Query Expansion (AQE)

- BoW vectors from spatially verified regions are used to build a richer model for the query
- Average query expansion (AQE) [Chum07]:
  - Use the mean of the BoW vectors to re-query
  - Other methods exist (e.g. transitive closure, multiple image resolution) but the performance is similar to AQE while they are slower as several queries are issued
  - Average QE is the de facto standard
  - mAP on Oxford 105k:

Retrieval method	SIFT	RootSIFT
Philbin et.al. 2007: tf-idf with spatial reranking	0.581	0.642
Chum et.al. 2007: Average Query expansion (AQE)	0.726	0.756

Discriminative Query Expansion (DQE)

- Train a linear SVM classifier
  - Use query expanded BoW vectors as positive training data
  - Use low ranked images as negative training data
  - Rank images on their signed distance from the decision boundary

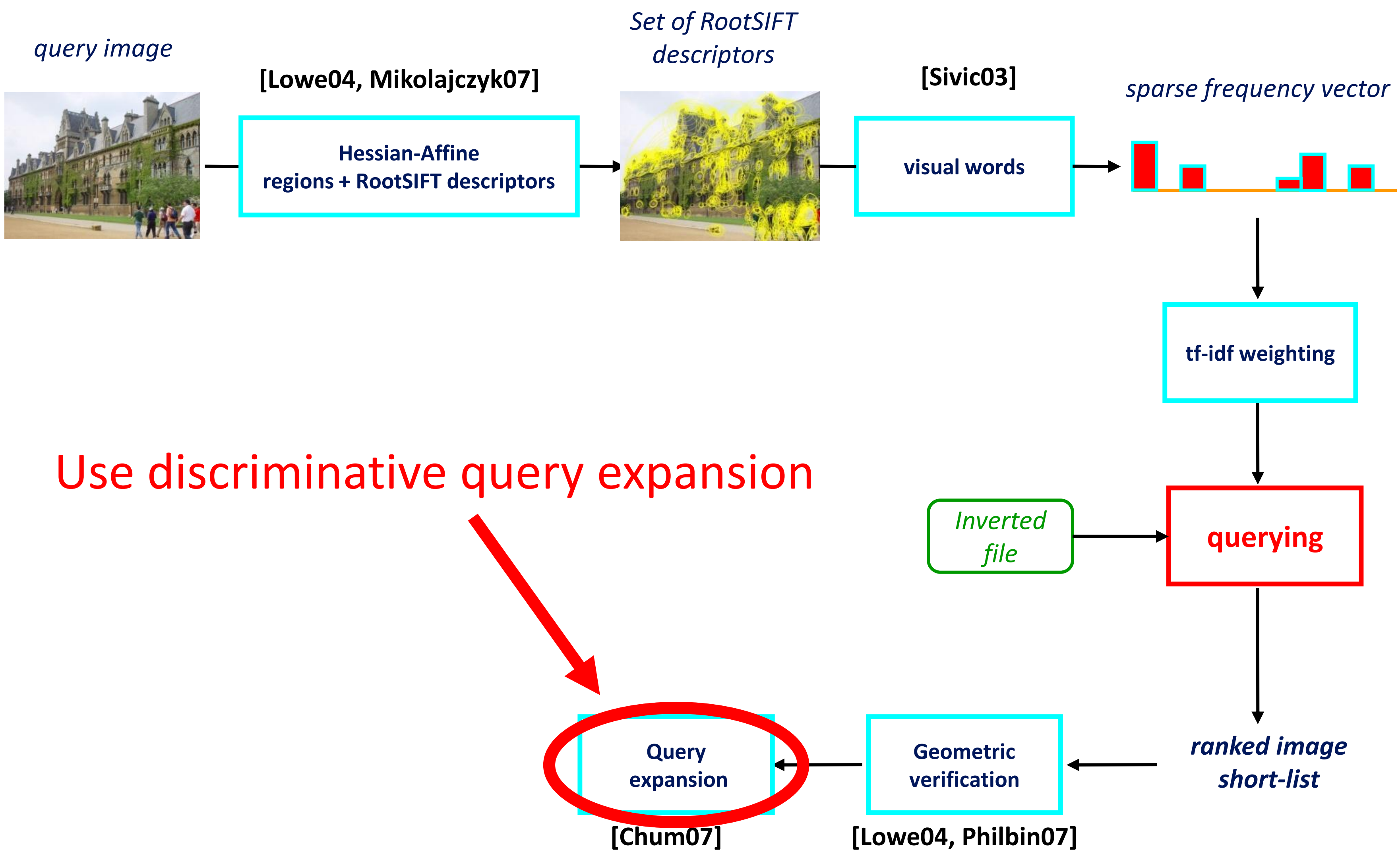


Discriminative Query Expansion: efficiency

- Ranking images using inverted index (as in average QE case)

- Both operations are just scalar products between a vector and x
  - For average QE the vector is the average query idf-weighted BoW vector
  - For discriminative QE the vector is the learnt weight vector w
  - Training the linear SVM on the fly takes negligible amount of time (30ms on average)

Query expansion



Discriminative Query Expansion: results

- Significant boost in performance, at no added cost

- mAP on Oxford 105k:

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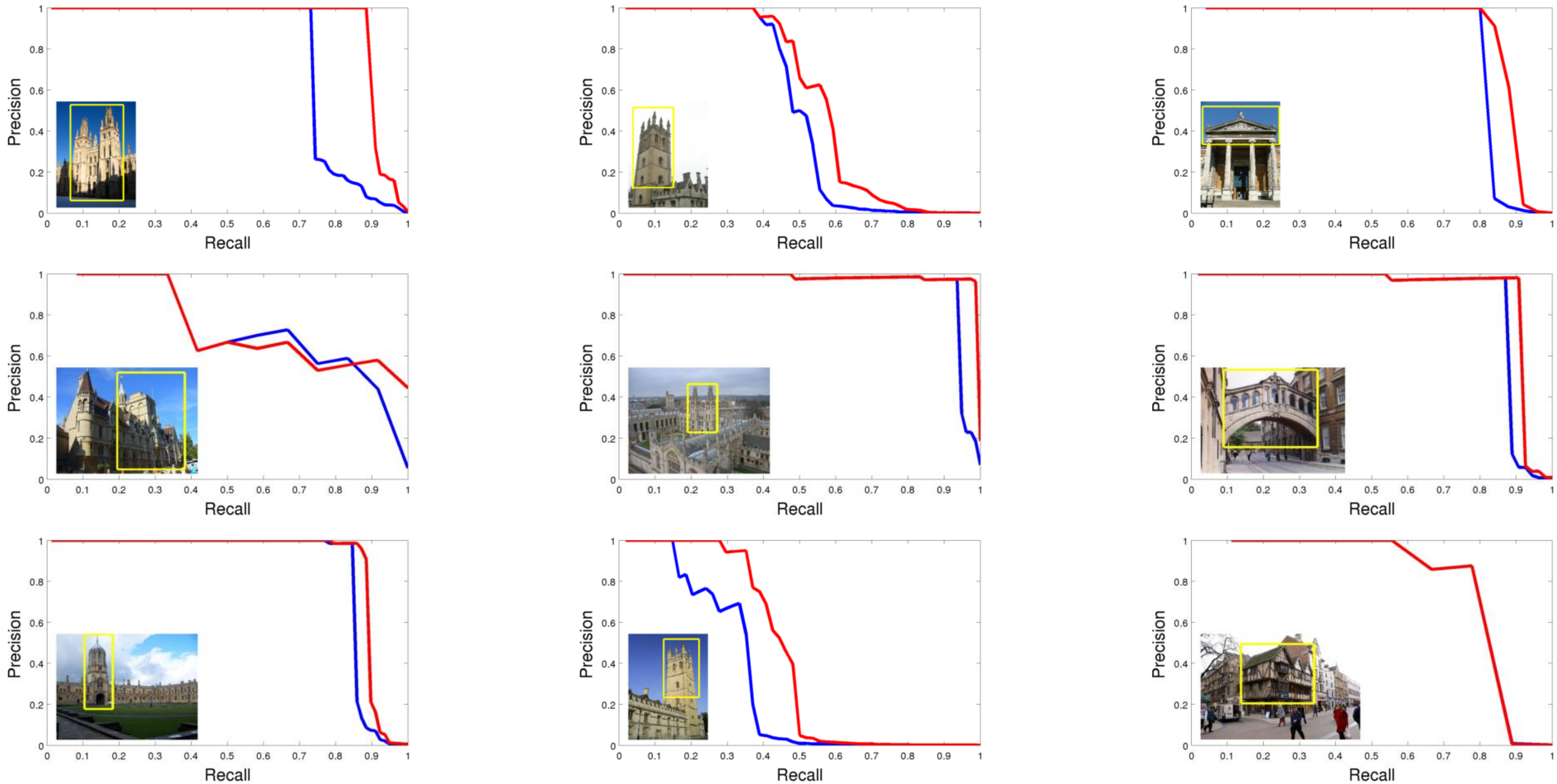
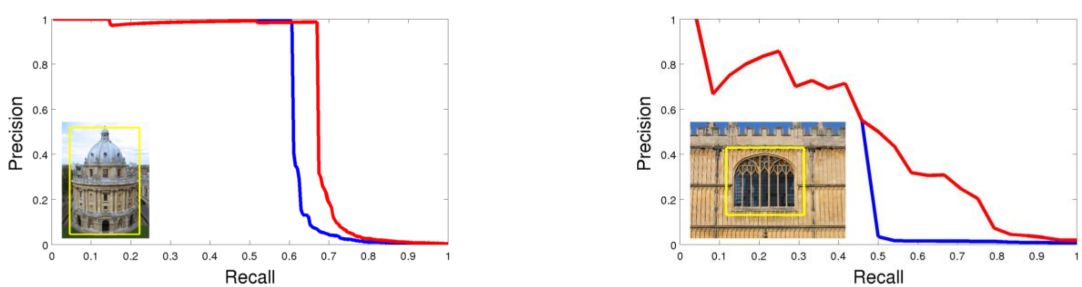
Chum et.al. 2007: Average Query expansion (AQE)	0.726	0.756
Discriminative Query Expansion (DQE)	**0.752**	**0.781**

DQE: results, Oxford 105k (RootSIFT)





Legend:

Discriminative QE: red

Average QE: blue

Third thing everyone should know

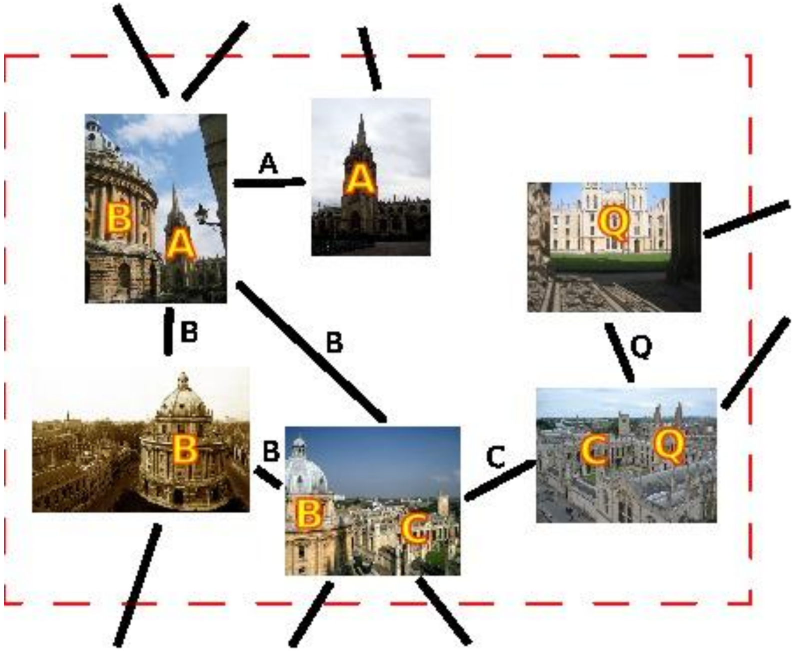
1. RootSIFT
2. Discriminative query expansion
3. Database-side feature augmentation

Database-side feature augmentation

- Query expansion improves retrieval performance by obtaining a better model for the *query*
- Natural complement: obtain a better model for the *database* images [Turcot09]
  - Augment database images with features from other images of the same object

Image graph

- Construct an image graph [Philbin08]
  - Nodes: images
  - Edges connect images containing the same object
  - Compute the graph offline by using the standard retrieval system to query each database image in turn and record spatially verified images



Database-side feature augmentation (AUG)

- Turcot and Lowe 2009:
  - Obtain a better model for database images
  - Each image is augmented with all visual words from neighbouring images

Uses RootSIFT

Retrieval method	Oxford 5k	Oxford 105k
tf-idf ranking	0.683	0.581
tf-idf with spatial reranking	0.720	0.642
AUG: tf-idf ranking	0.785	0.720
AUG: tf-idf with spatial reranking	0.827	0.759

Note: idf weights are re-computed for the augmented dataset which improves performance, also our contribution

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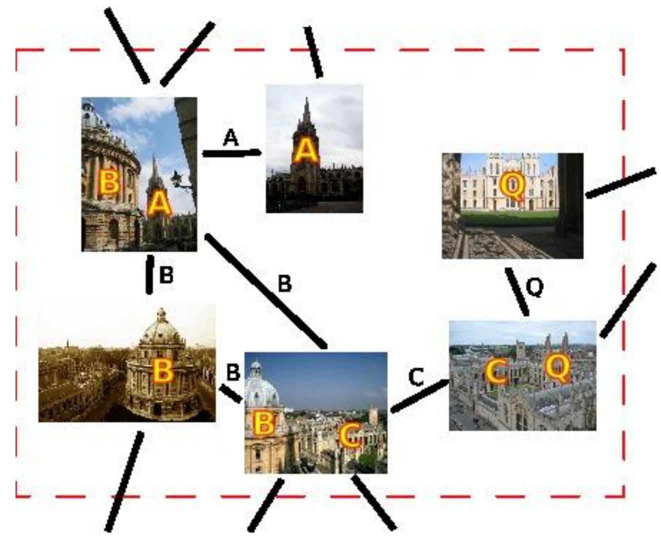
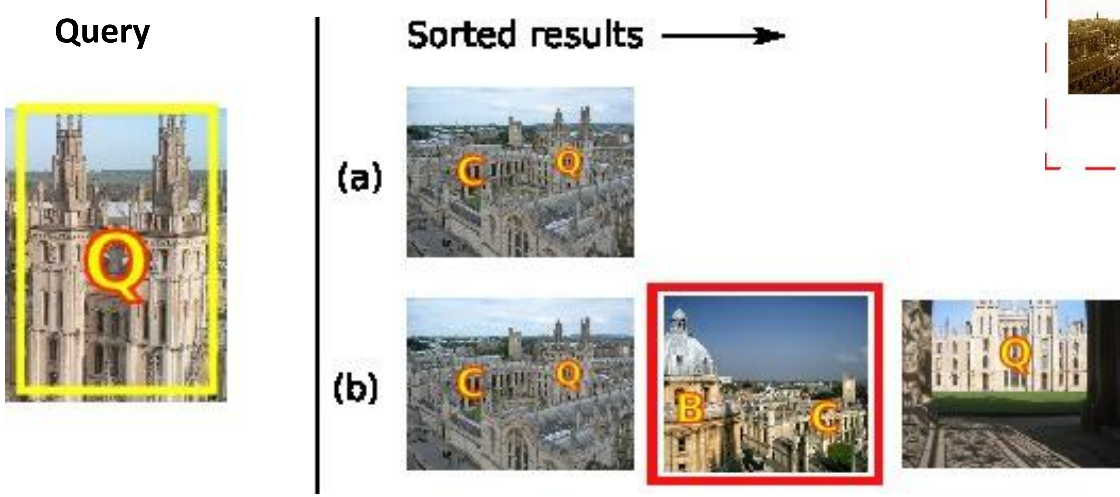
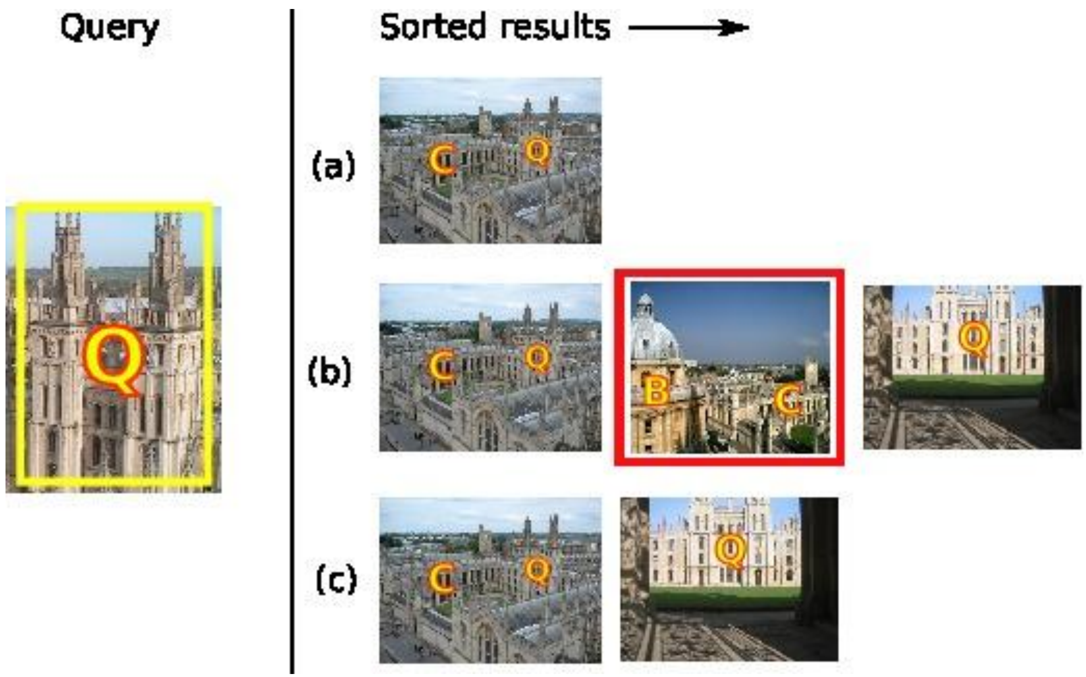
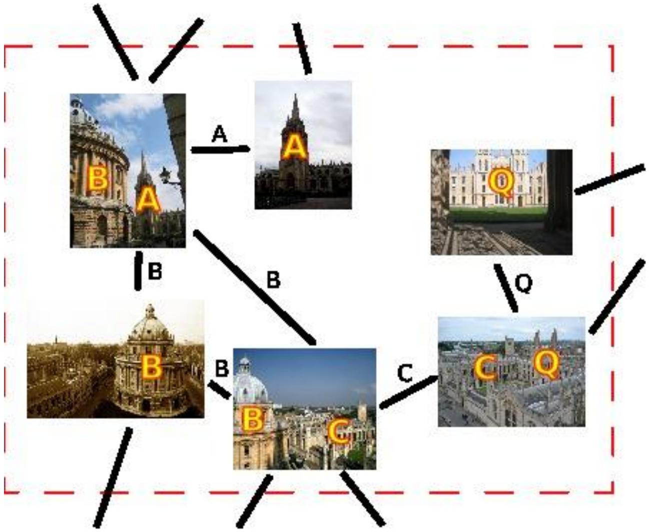




Spatial database-side feature aug. (SPAUG)

- AUG: Augment with *all* visual words from neighbouring images
- Spatial AUG: Only augment with *visible* visual words





Spatial db-side feature aug. (SPAUG): results

- 28% less features are augmented than in the original method
  - The original approach introduces a large number of irrelevant and detrimental visual words

Uses RootSIFT

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tf-idf with spatial reranking	0.720	0.642
AUG: tf-idf ranking	0.785	0.720
AUG: tf-idf with spatial reranking	0.827	0.759
Spatial AUG: tf-idf ranking	0.820	0.746
Spatial AUG: tf-idf with spatial reranking	**0.838**	**0.767**

Spatial AUG vs AUG

- Negative:
  - The original method does not need to explicitly augment images, it is equivalent to sum tf-idf scores of neighbouring images at runtime
  - Spatial database-side feature augmentation has to explicitly augment images, thus storage requirements are increased significantly
- Positive:
  - While achieving high recall of the original method, precision is improved

Final retrieval system

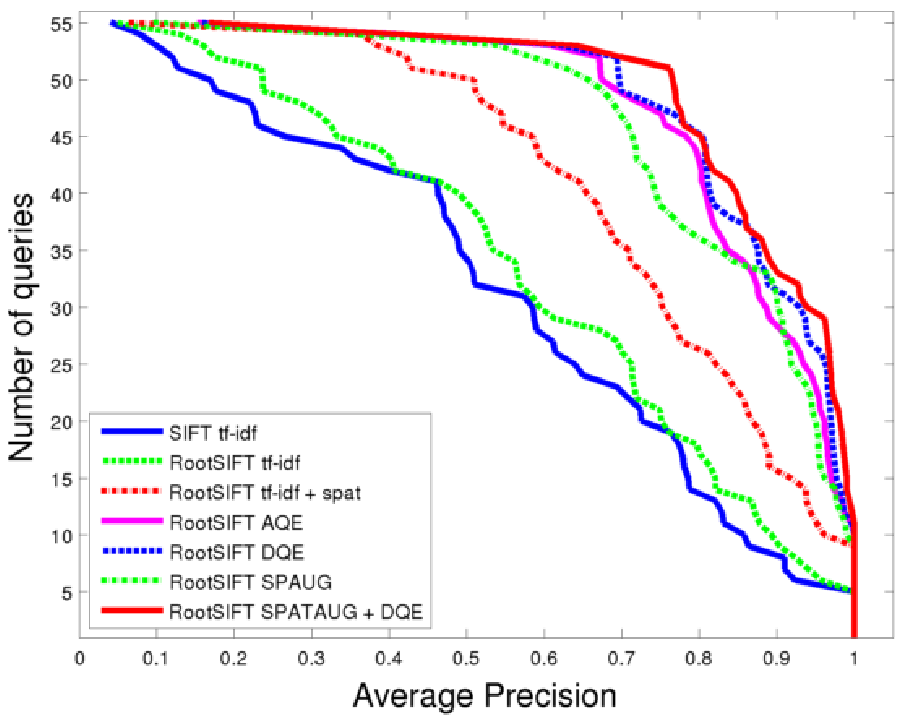
- Combine all the improvements into one system
  - RootSIFT
  - Discriminative query expansion
  - Spatial database-side feature augmentation

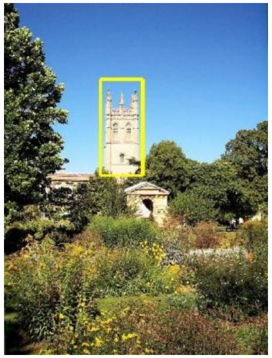
Final results

- New state of the art on all three datasets (without soft assignment!):

Oxford 5k	Oxford 105k	Paris 6k
0.929	0.891	0.910

- Quite close to total recall on Oxford 105k:





Summary

1. RootSIFT:
   - Improves performance in every single experiment **(not just retrieval)**
   - Every system which uses SIFT is ready to use RootSIFT
   - Easy to implement, no added computational or storage cost
2. Discriminative query expansion:
   - Consistently outperforms average query expansion
   - At least as efficient as average QE
   - No arguments against it except for slightly increased implementation complexity
3. Database-size feature augmentation:
   - Useful for increasing recall
   - Our extension improves precision but increases storage requirements; this trade-off should be considered when deciding whether to use it or not