
CS588: Deep learning Image Search

Re-Ranking and Inverted Index

Sung-Eui Yoon
(윤성익)

Course URL:
<http://sgvr.kaist.ac.kr/~sungeui/IR>

Class Objectives

- **Discuss re-ranking (i.e., post-processing) for achieving higher accuracy**
 - **Spatial verification**
 - **Query expansion**
- **Understand approximate nearest neighbor search**
 - **Inverted index and inverted multi-index**
- **At the last class:**
 - **CNN based image descriptors**
 - **Training losses, and data**
 - **Benchmarks**

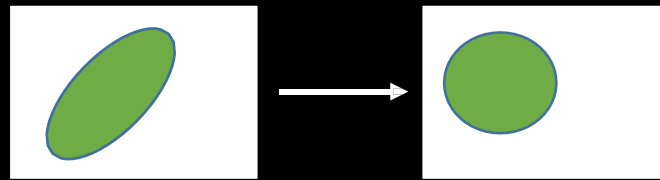
Descriptor processing with PCA

$$\hat{\mathbf{x}} = P^{\top} (\mathbf{x} - \mu)$$

$$P \in \mathbb{R}^{d \times d} \quad \text{eigen-vectors as columns}$$

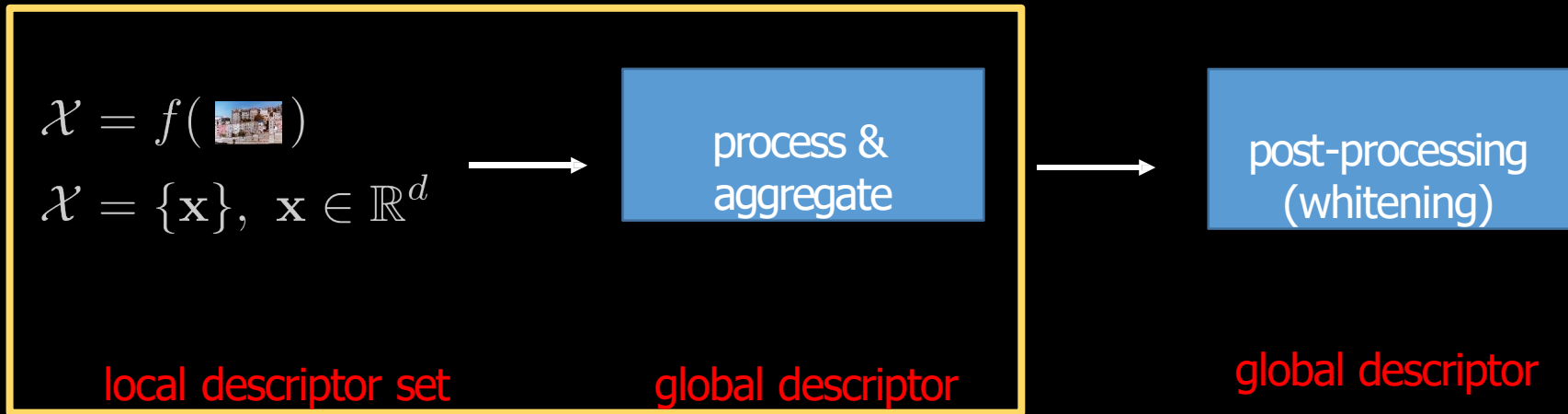
$$\mu \in \mathbb{R}^d \quad \text{mean vector}$$

$$\mathbf{x} \in \mathbb{R}^d \quad \text{global descriptor}$$



[Jegou & Chum, ECCV'12]

Post-processing with whitening



learned end-to-end

Post-processing with whitening

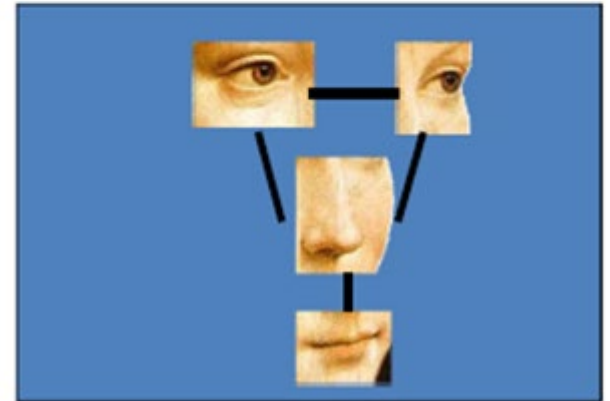
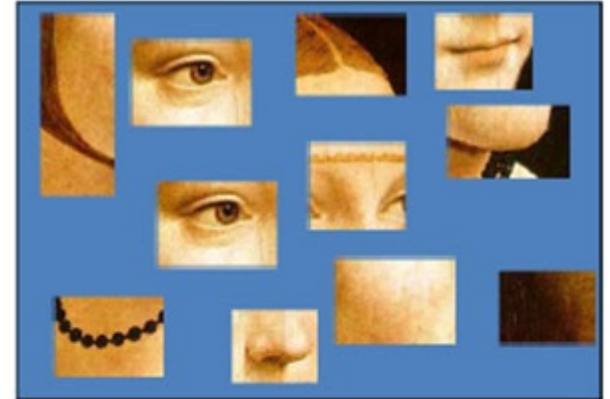


learned end-to-end

<https://github.com/filipradenovic/cnnimageretrieval-pytorch>

Problems of BoW or Global Descriptors

- **No spatial relationship between words**
- **How can we do better?**



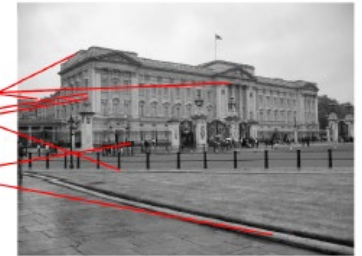
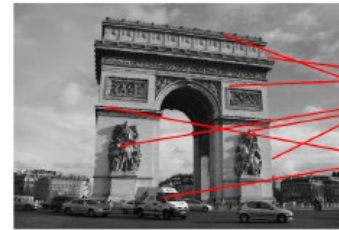
Ack.: Fei-Fei Li

Post-Processing or Reranking



Post-Processing

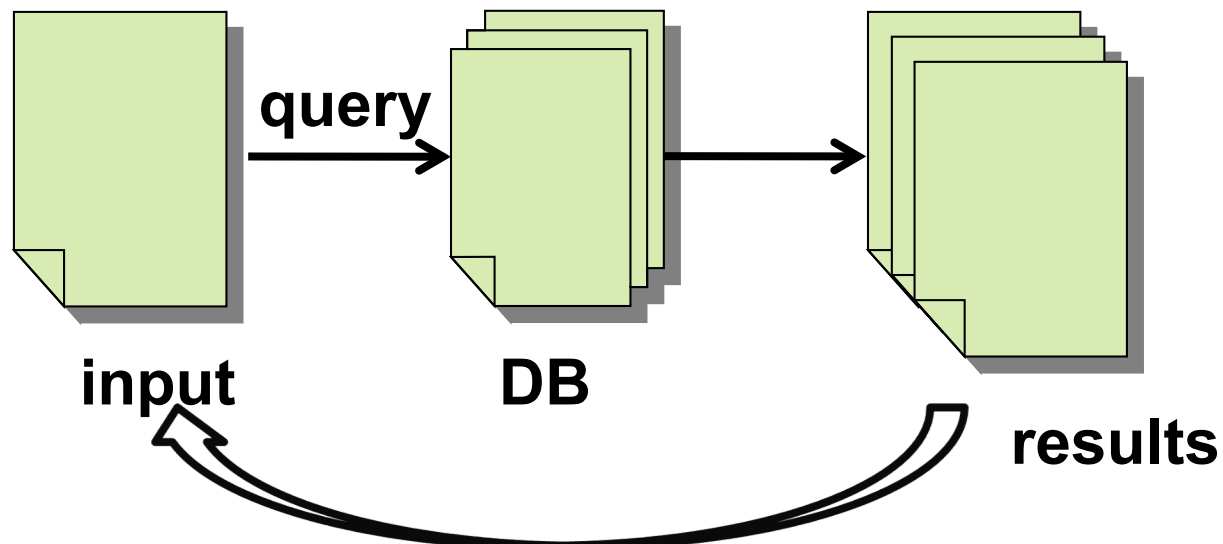
- Geometric verification
 - RANSAC



Matching w/o spatial matching

(Ack: Edward Johns et al.)

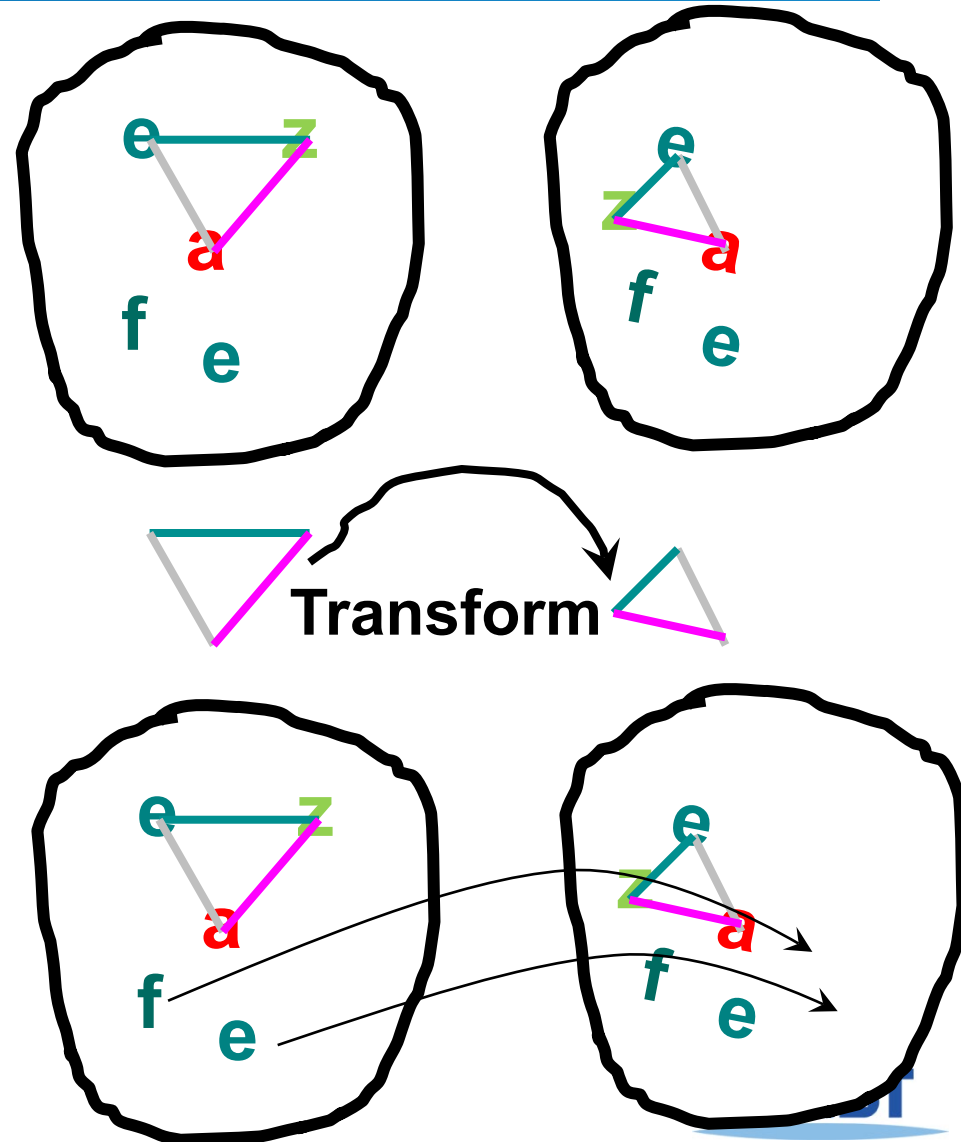
- Query expansion



Geometric Verification using RANSAC

Repeat N times:

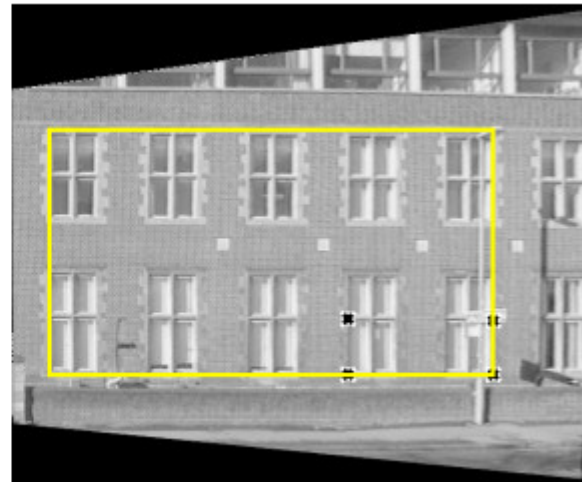
- Randomly choose 4 matching pairs
- Estimate transformation
 - Assume a particular transformation (Homography)
- Predict remaining points and count “inliers”



Homography

- Transformation, H , between two planes
 - 8 DoF due to normalization to 1

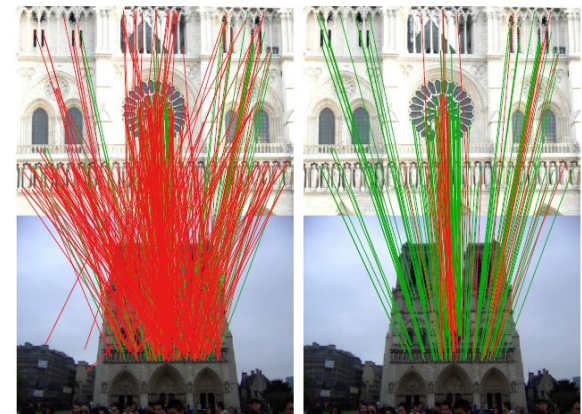
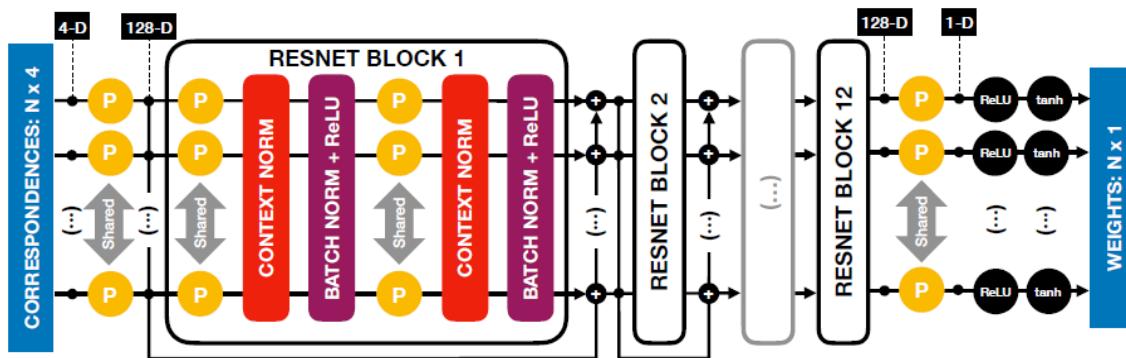
$$s \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = H \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$



from Hartley & Zisserman

Learning to Find Good Correspondences, CVPR 18

- Given two sets of input features (e.g., SIFTs), return a prob. of being inliers for each feature
 - Adopt the classification approach being inlier or not
 - Consider the relative motion between two images for the loss function



(a) RANSAC

(b) Our approach

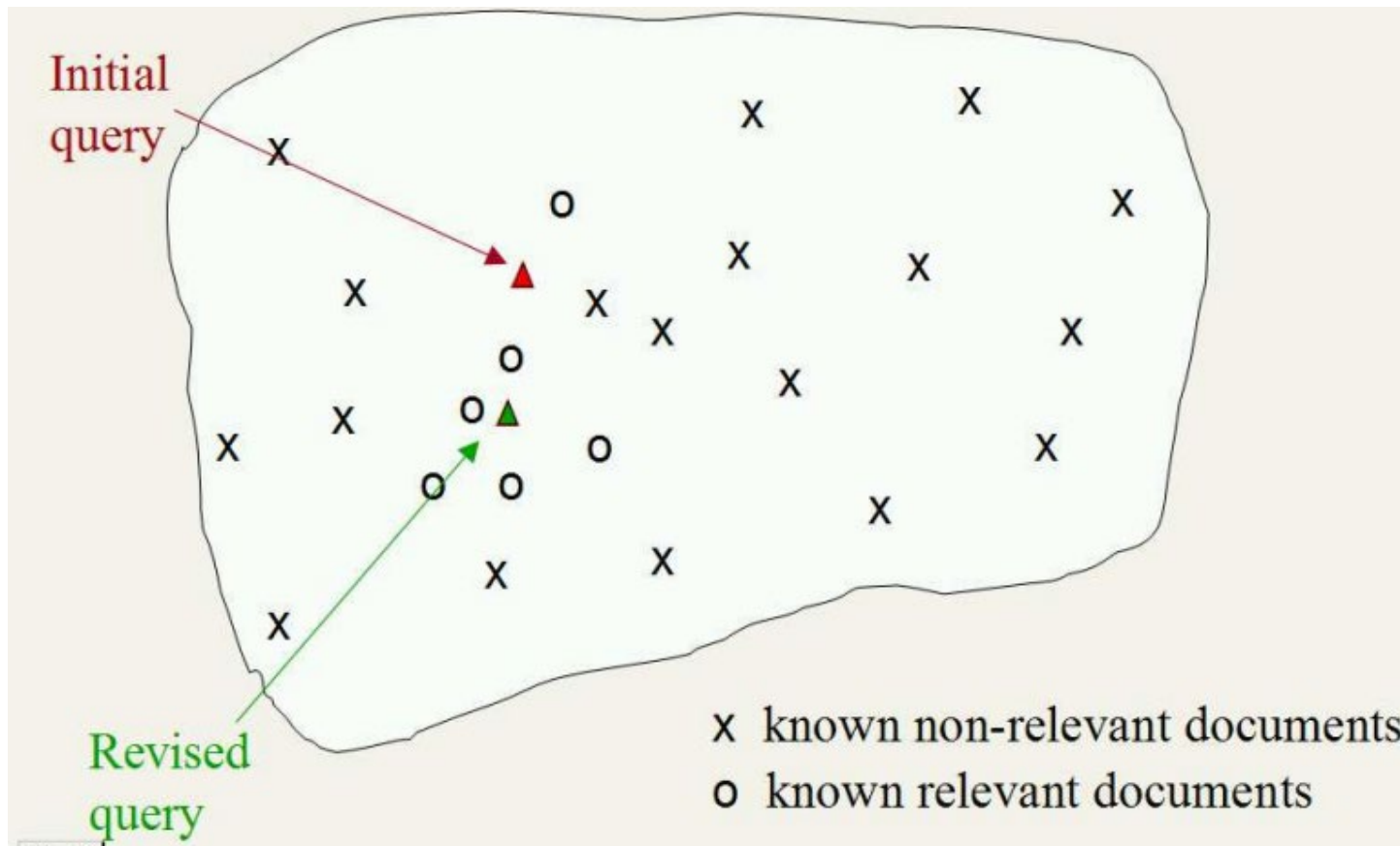
Pattern matching

- Drones surveying city
 - Identify a particular car
- Related to tracking



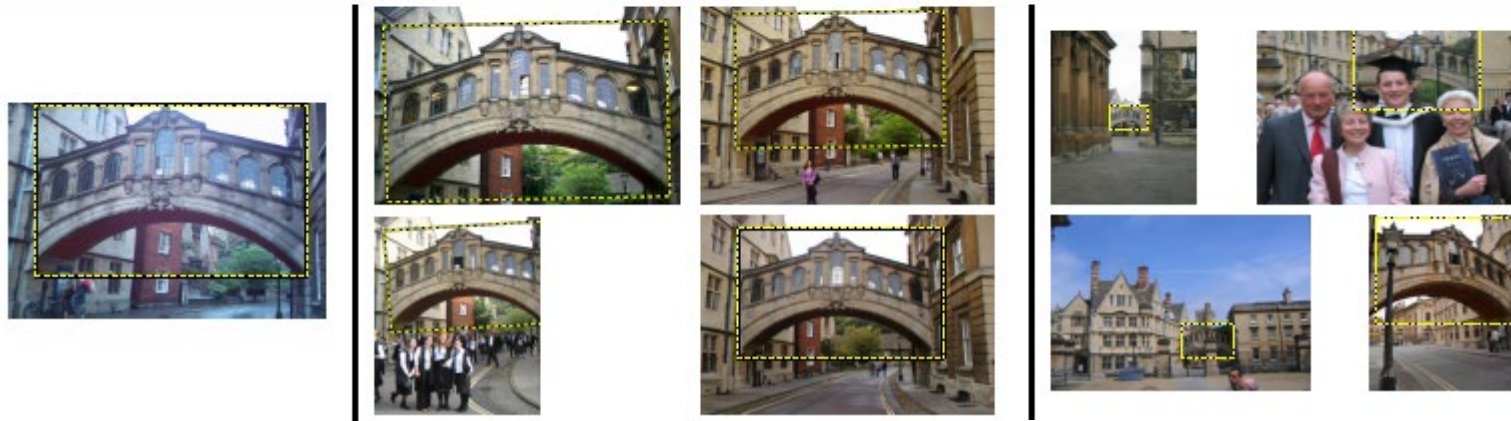
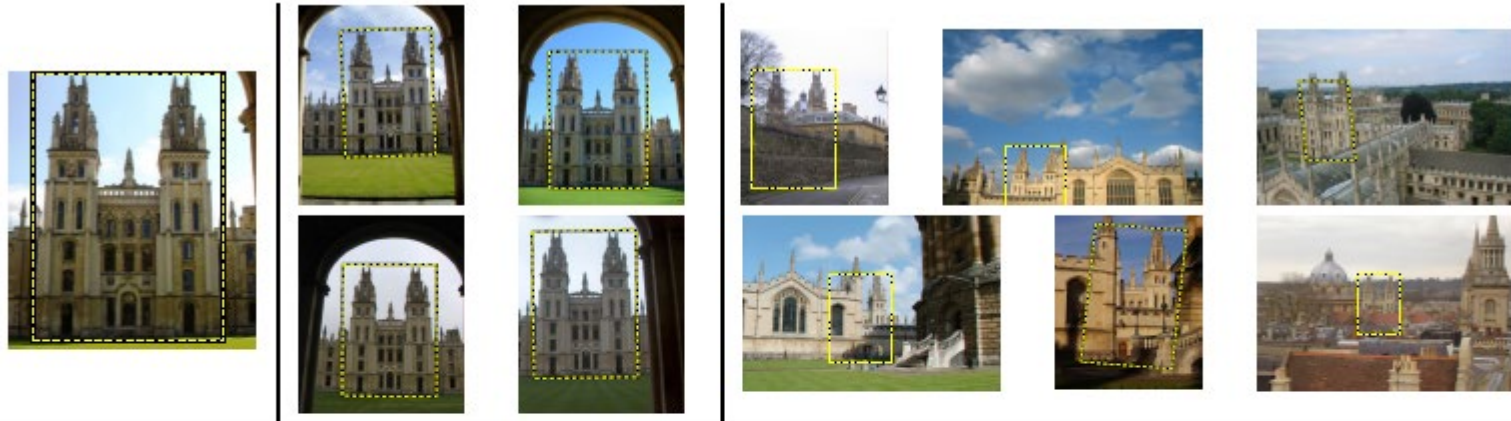
Query Expansion

- Use NN information to get more confident query



[Chum et al.
ICCV'07]

Query Expansion



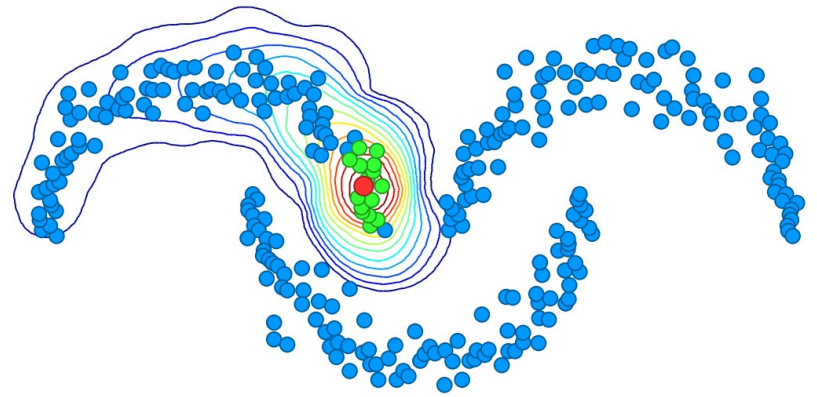
Original query

Top 4 images

Expanded results that were not identified by the original query

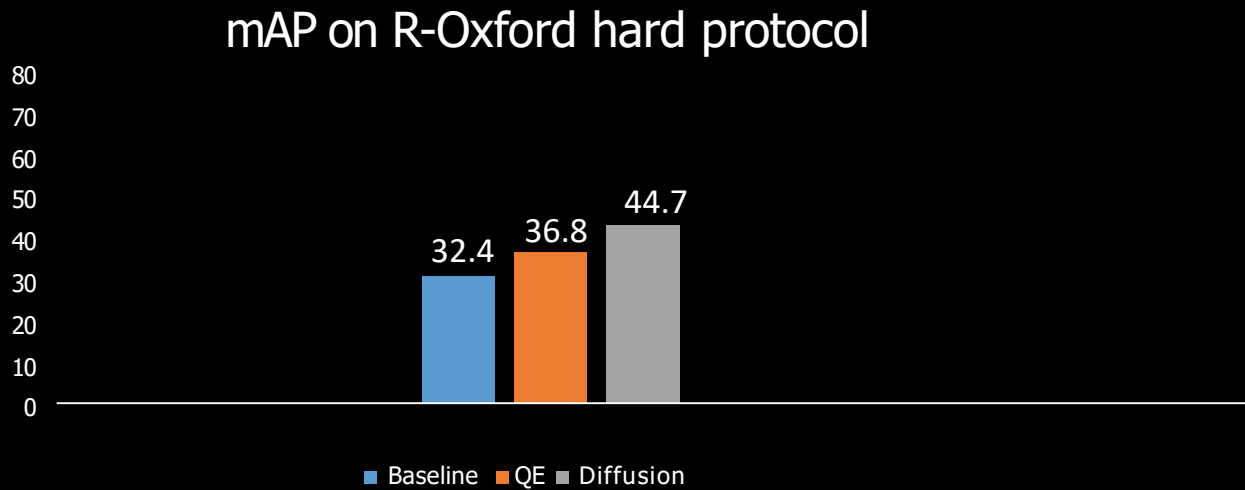
Diffusion (random walk) on Feature Space

- High dimensional feature is likely to have a manifold shape
- Identify related images by the diffusion process, i.e., random walks
 - Perform random walks based on the similarity between a pair of images
- Utilize k-Nearest Neighbor (NNs) of the query images



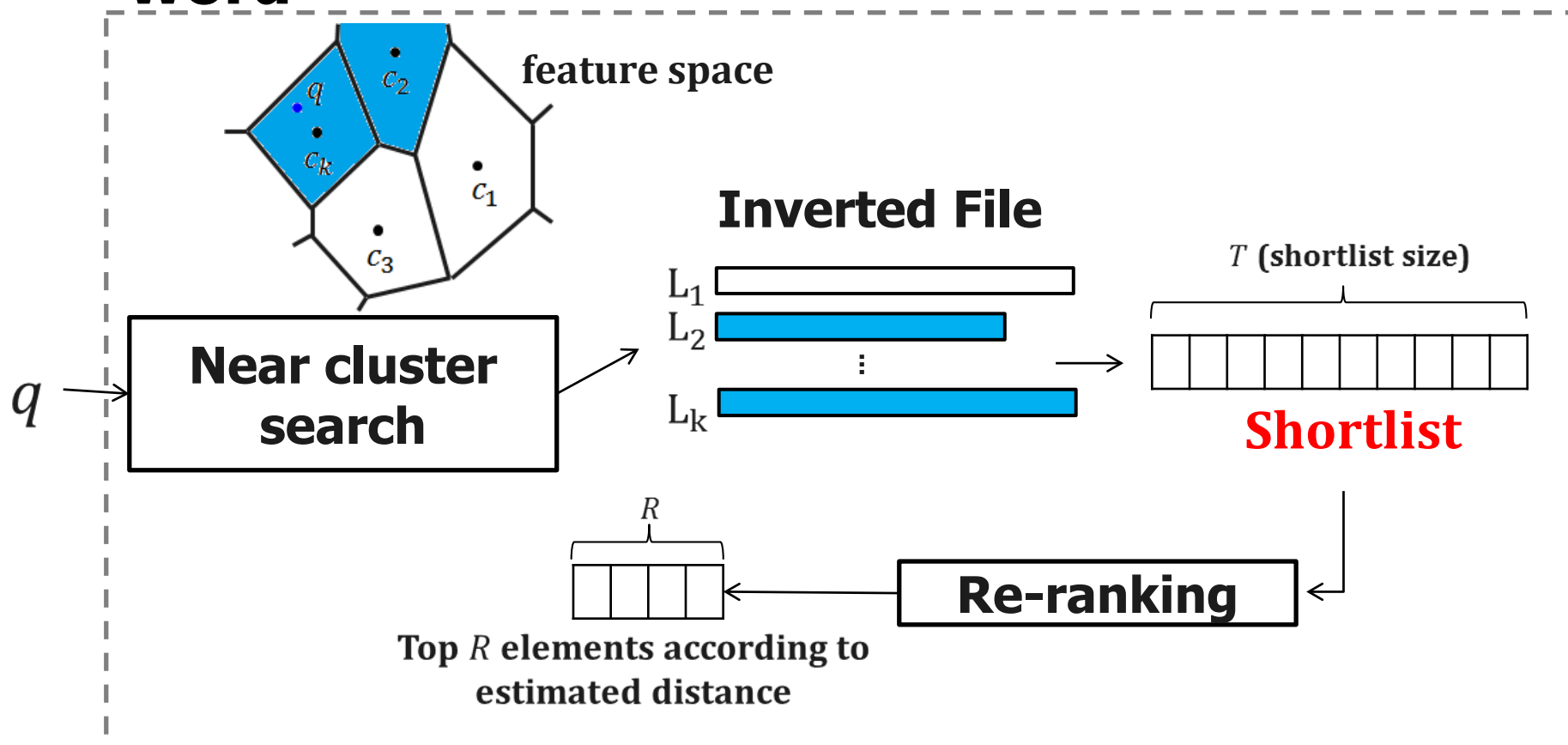
[Ischen et al. CVPR'19]

Performance comparison



Inverted File or Index for Efficient Search

- For each word, list images containing the word



Inverted Index

Construction time:

- Generate a codebook by quantization
 - e.g. k-means clustering

- Build an inverted index
 - Quantize each descriptor into the closest word
 - Organize desc. IDs in terms of words

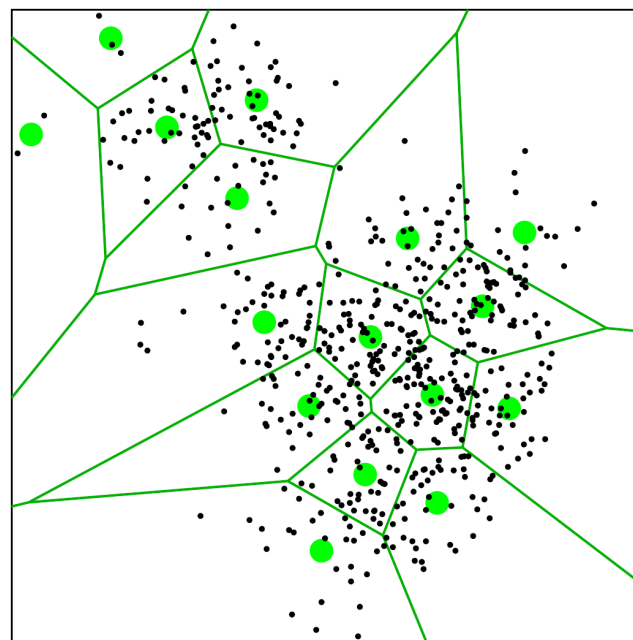
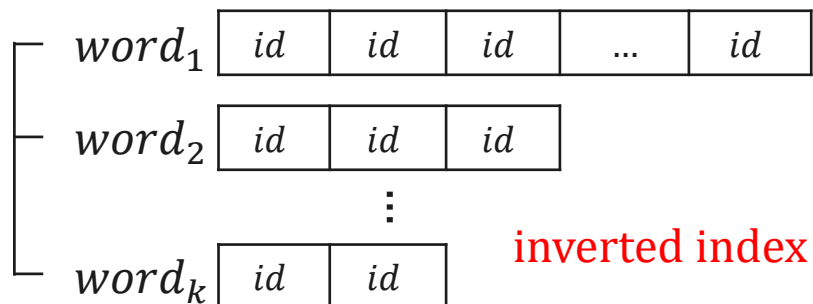


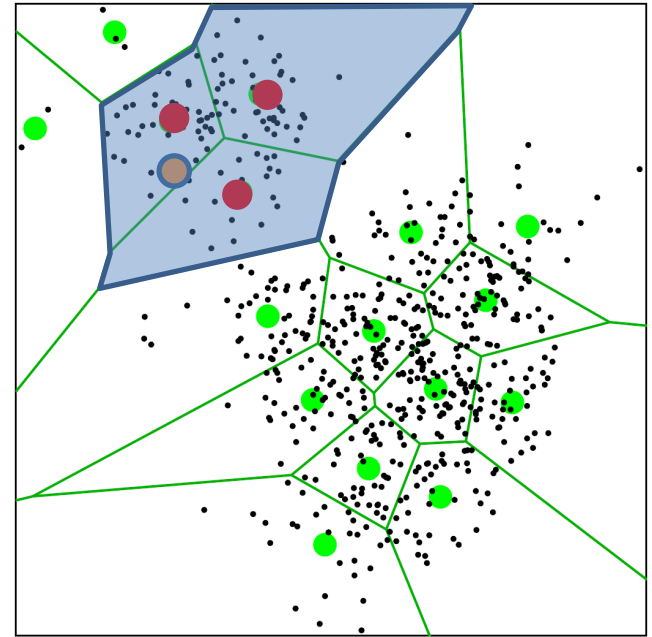
Figure from Lempitsky's slides



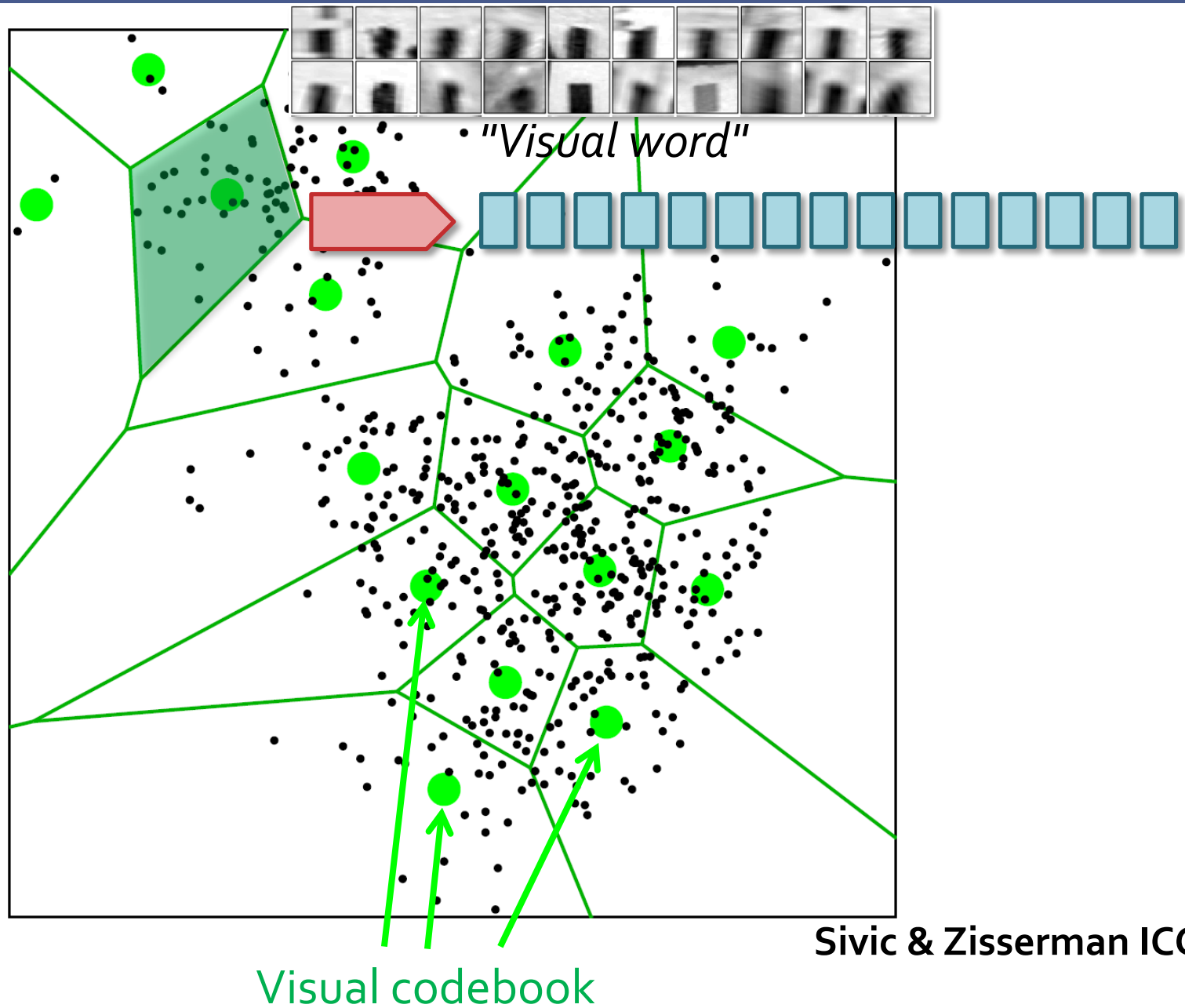
Inverted Index

Query time:

- Given a query,
 - Find its K closest **words**
 - Retrieve all the data in the K lists corresponding to the words
- Large K
 - Low quantization distortion
 - Expensive to find kNN words



The inverted index



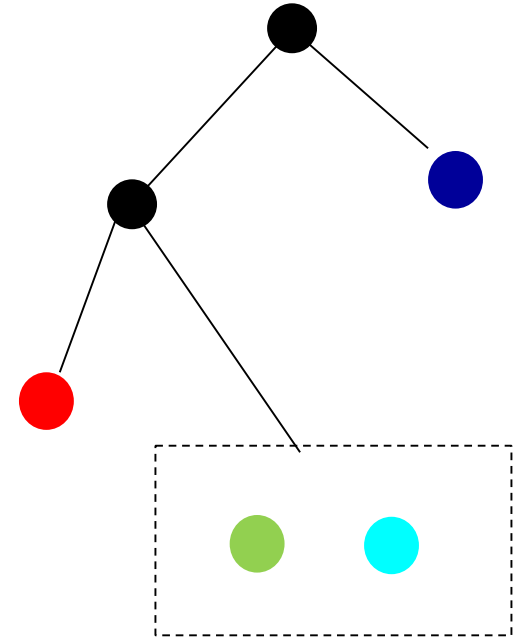
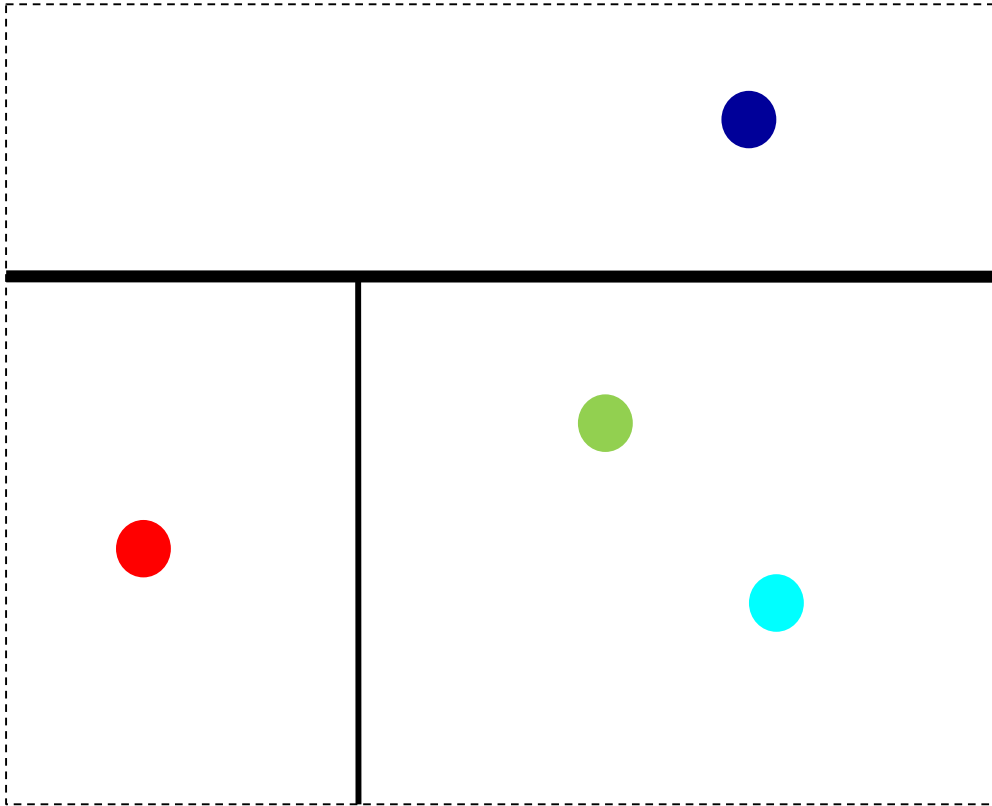
Sivic & Zisserman ICCV 2003

Visual codebook

Approximate Nearest Neighbor (ANN) Search

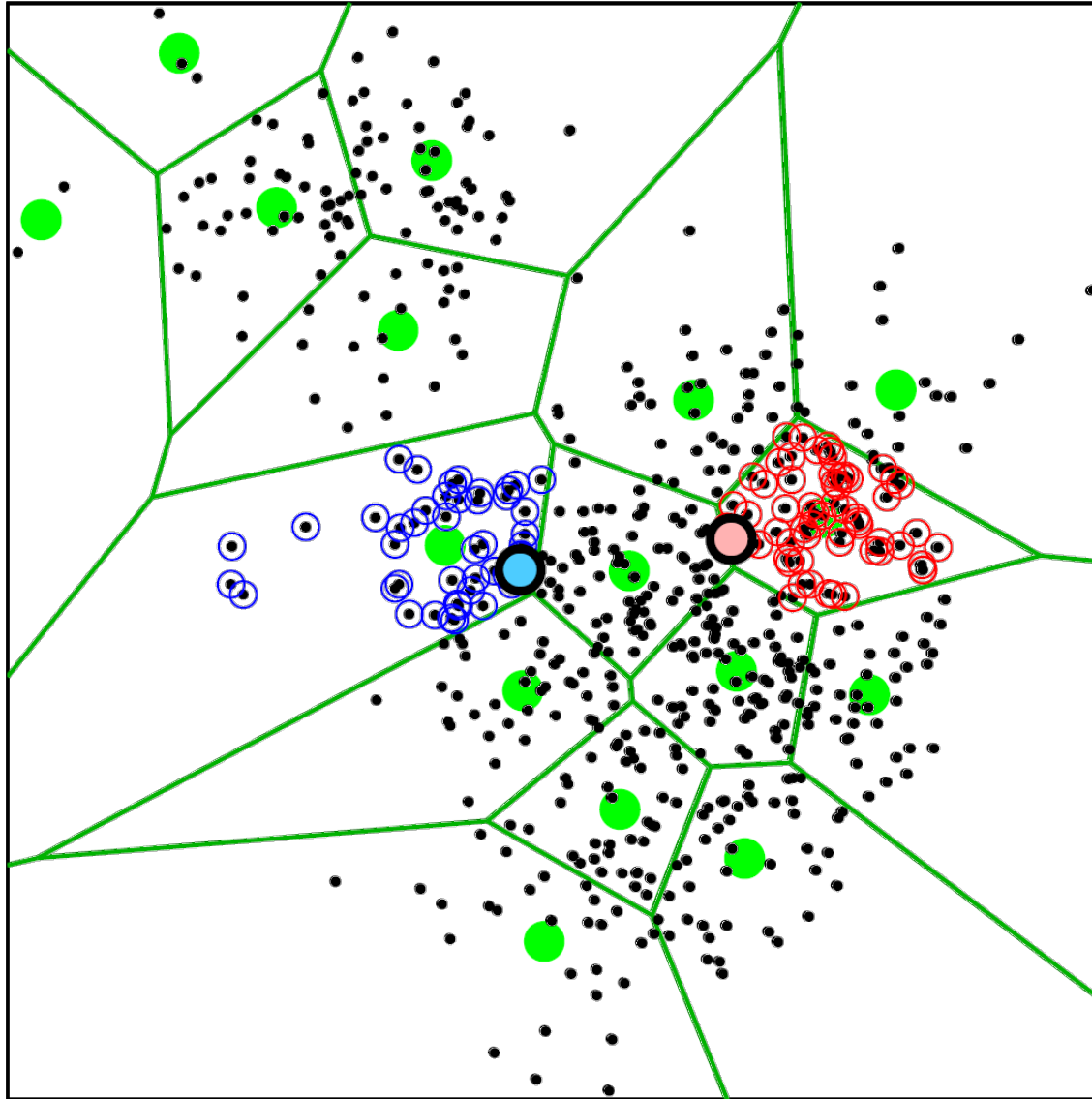
- **For large K**
 - Takes time to find clusters given the query
 - Use those ANN techniques for efficiently finding near clusters
- **ANN search techniques**
 - **kd-trees: hierarchical approaches for low-dimensional problems**
 - **Hashing for high dimensional problems; will be discussed later with binary code embedding**
 - **Quantization (k-means cluster and product quantization)**

kd-tree Example

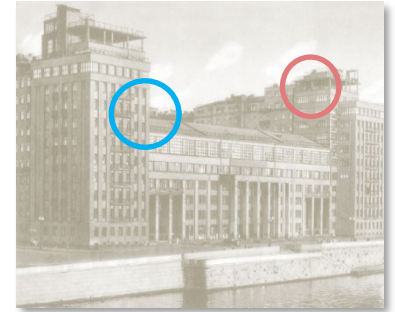


- Many good implementations (e.g., vl-feat)

Querying the inverted index



Query:



- Have to consider several words for best accuracy
- Want to use as big codebook as possible

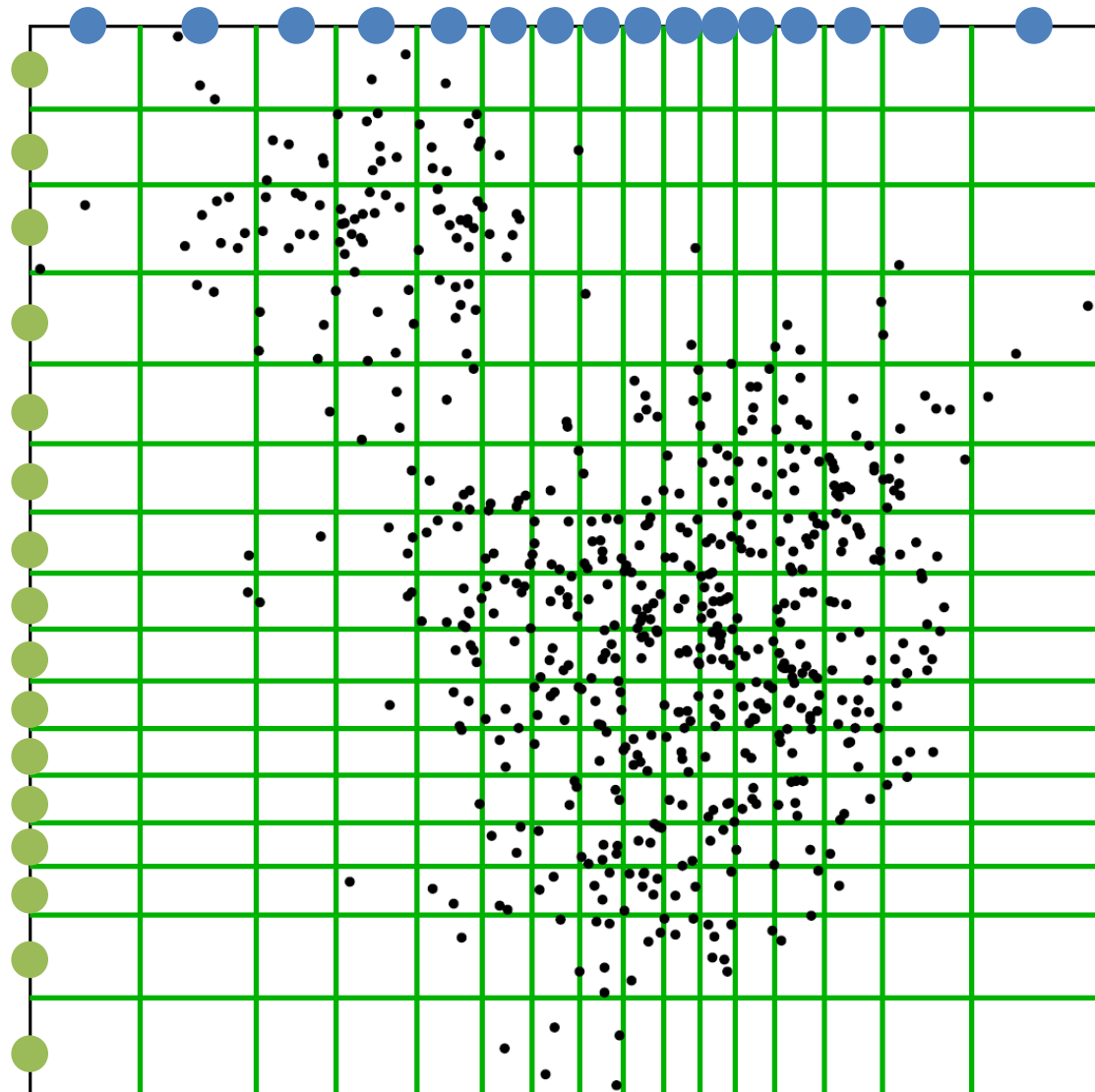


- Want to spend as little time as possible for matching to codebooks

Ack.: Lempitsky

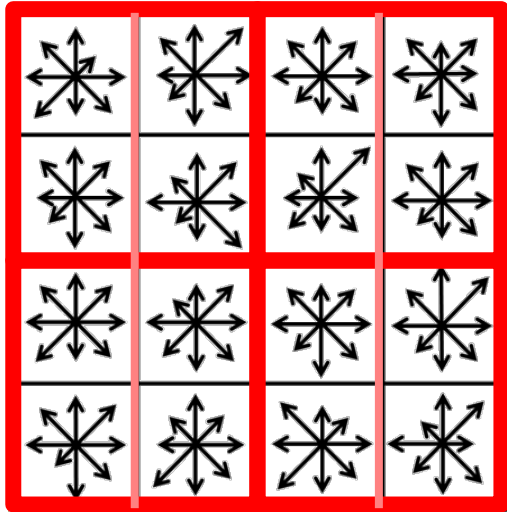
Inverted Multi-Index [Babenko and Lempitsky, CVPR 2012]

- **Product quantization for indexing**
- **Main advantage:**
 - For the same K , much finer subdivision
 - Very efficient in finding k NN codewords



Ack.: Lempitsky

Product quantization

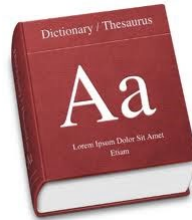


1. Split vector into correlated subvectors
2. use separate small codebook for each chunk

Quantization vs. Product quantization:

For a budget of 4 bytes per descriptor:

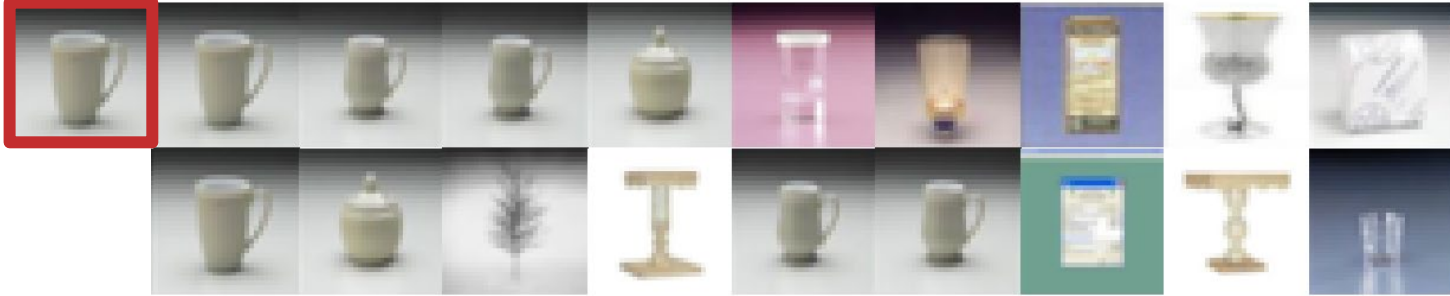
1. Use a single codebook with 1 billion codewords or
2. Use 4 different codebooks with 256 codewords each



many minutes **128GB**

< 1 millisecond **32KB**

Retrieval examples



Exact NN
Uncompressed GIST
Multi-D-ADC
16 bytes



Exact NN
Uncompressed GIST
Multi-D-ADC
16 bytes



Exact NN
Uncompressed GIST
Multi-D-ADC
16 bytes



Exact NN
Uncompressed GIST
Multi-D-ADC
16 bytes

Scalability

- **Issues with billions of images?**
 - **Searching speed → inverted index**
 - **Accuracy → larger codebooks, spatial verification, expansion, features**
 - **Memory → compact representations**
 - **Easy to use?**
 - **Applications?**
 - **A new aspect?**

Class Objectives were:

- **Discuss re-ranking (i.e., post-processing) for achieving higher accuracy**
 - **Spatial verification**
 - **Query expansion**
- **Understand approximate nearest neighbor search**
 - **Inverted index and inverted multi-index**

Next Time...

- **Hashing techniques**

Homework for Every Class

- **Go over the next lecture slides**
- **Come up with one question on what we have discussed today**
 - **1 for typical questions (that were answered in the class)**
 - **2 for questions with thoughts or that surprised me**
- **Write questions 3 times**