lecture 10: image retrieval and manifold learning

deep learning for vision

Yannis Avrithis

Inria Rennes-Bretagne Atlantique

Rennes, Nov. 2017 – Jan. 2018

outline

background
indexing
pooling
manifold learning
fine-tuning
graph-based methods

background

image classification challenges

- scale
- viewpoint
- occlusion
- clutter
- lighting
- number of instances
- texture/color
- pose
- deformability
- intra-class variability

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main difference to classification:

- no intra-class variability

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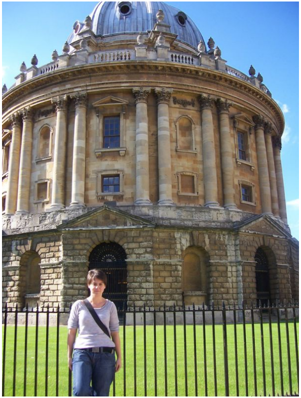
vector quantization → visual words



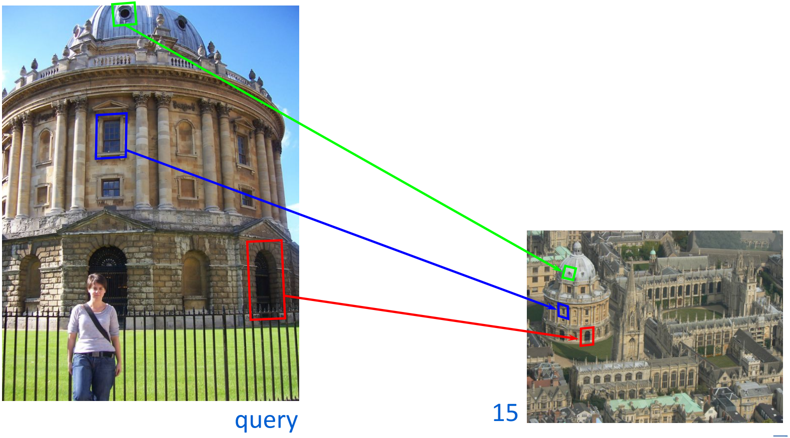
query

15

- query *vs.* dataset image

Sivic and Zisserman. ICCV 2003. Video Google: A Text Retrieval Approach to Object Matching in videos.

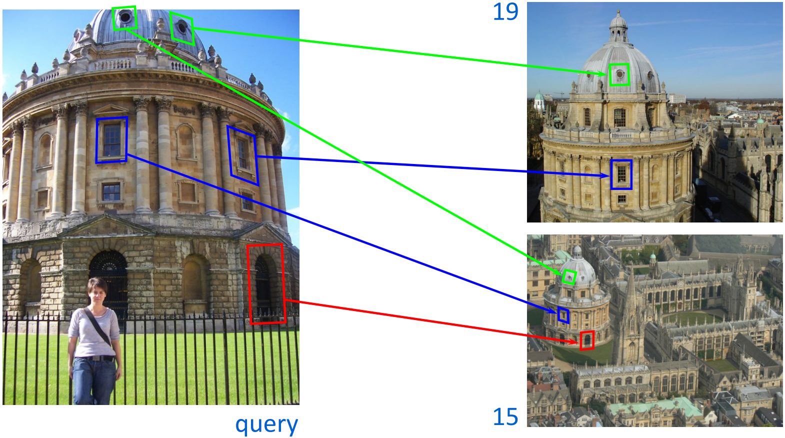
vector quantization → visual words



- pairwise descriptor matching

Sivic and Zisserman. ICCV 2003. Video Google: A Text Retrieval Approach to Object Matching in videos.

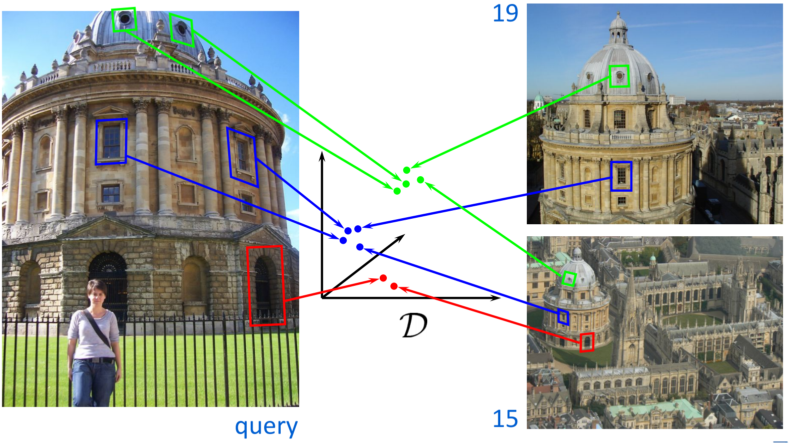
vector quantization → visual words



- pairwise descriptor matching for every dataset image

Sivic and Zisserman. ICCV 2003. Video Google: A Text Retrieval Approach to Object Matching in videos.

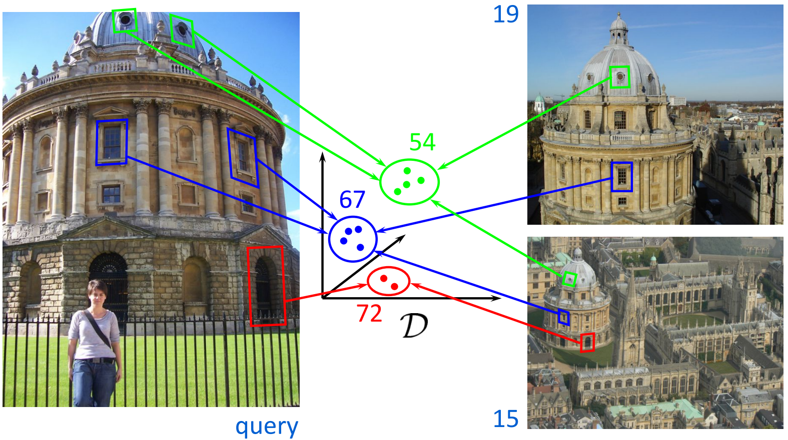
vector quantization → visual words



- similar descriptors should all be nearby in the descriptor space

Sivic and Zisserman. ICCV 2003. Video Google: A Text Retrieval Approach to Object Matching in videos.

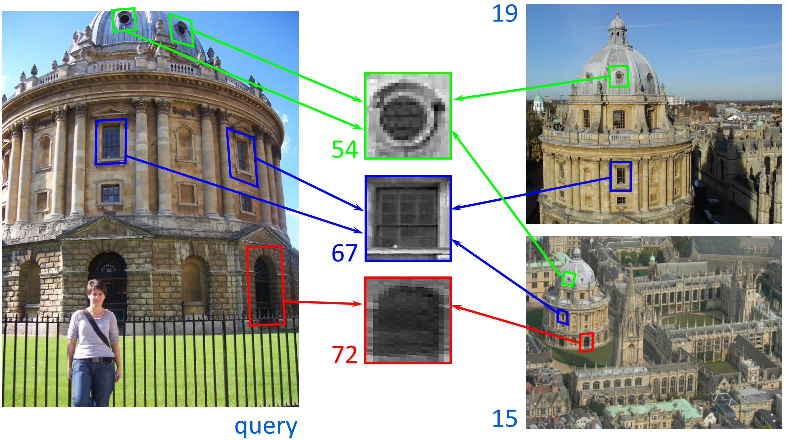
vector quantization → visual words



- let's quantize them into visual words

Sivic and Zisserman. ICCV 2003. Video Google: A Text Retrieval Approach to Object Matching in videos.

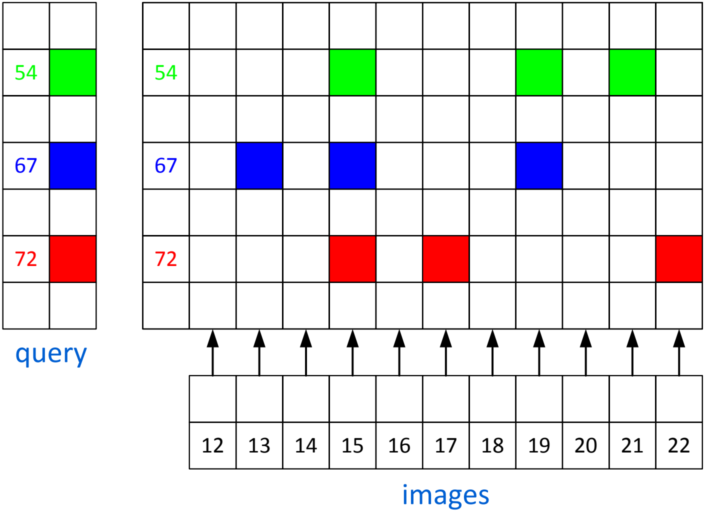
vector quantization → visual words



- now visual words act as a proxy; no pairwise matching needed

Sivic and Zisserman. ICCV 2003. Video Google: A Text Retrieval Approach to Object Matching in videos.

inverted file indexing



Sivic and Zisserman. ICCV 2003. Video Google: A Text Retrieval Approach to Object Matching in videos.

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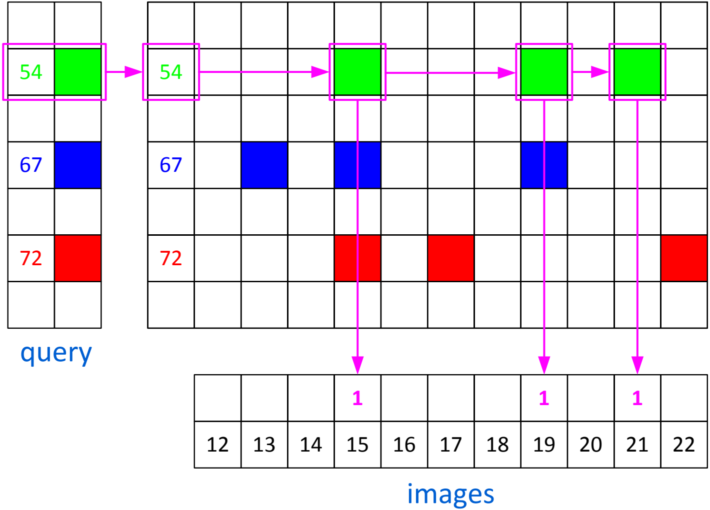

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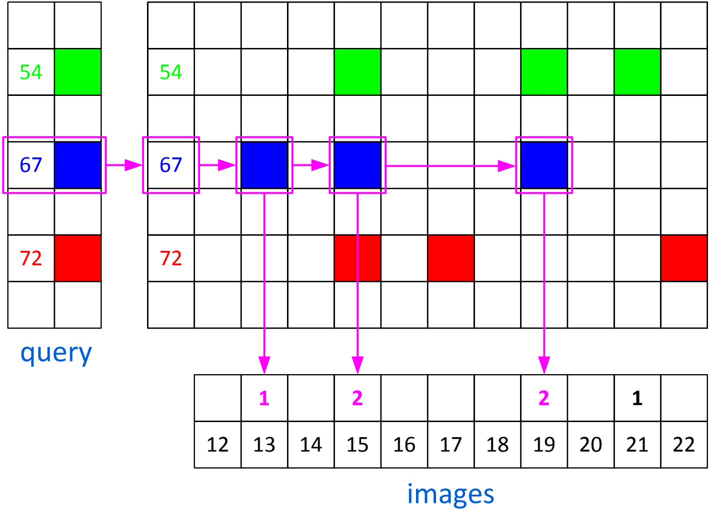

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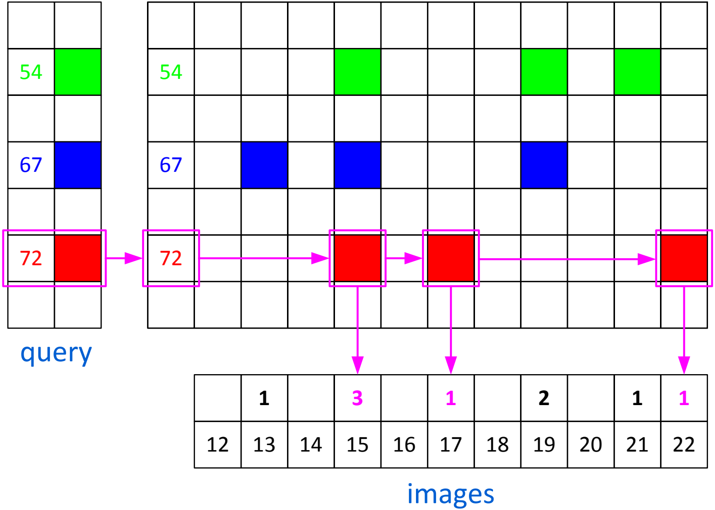

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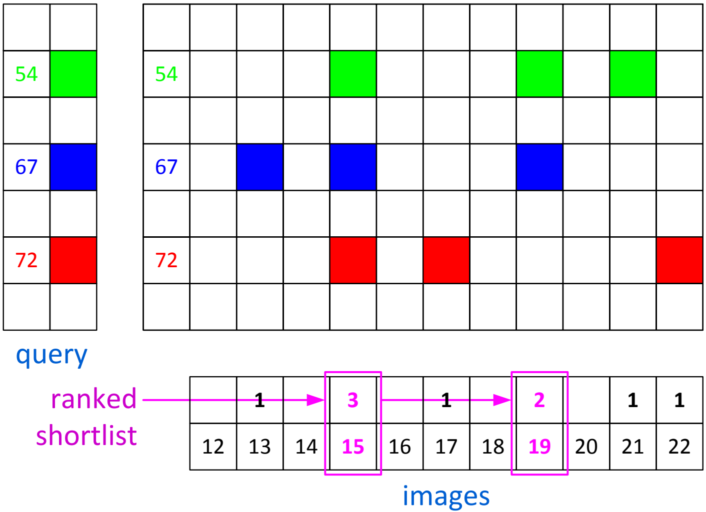
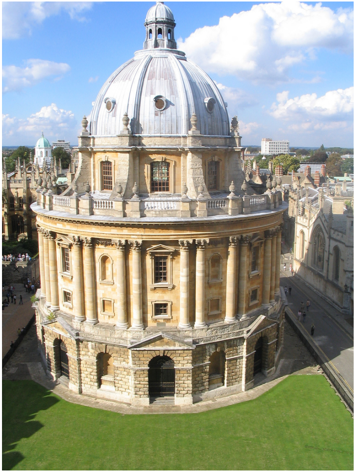


Sivic and Zisserman. ICCV 2003. Video Google: A Text Retrieval Approach to Object Matching in videos.

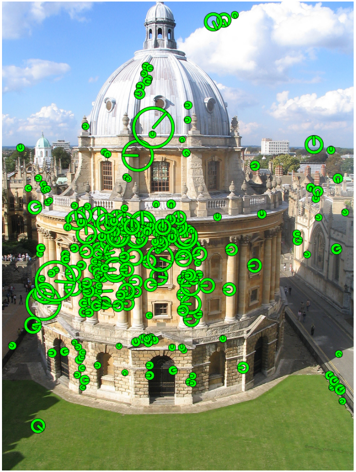
back to geometry: re-ranking



original images

Fischler and Bolles. CACM 1981. Random Sample Consensus: A Paradigm for Model Fitting With Applications to Image Analysis and Automated Cartography.

back to geometry: re-ranking



local features

Fischler and Bolles. CACM 1981. Random Sample Consensus: A Paradigm for Model Fitting With Applications to Image Analysis and Automated Cartography.

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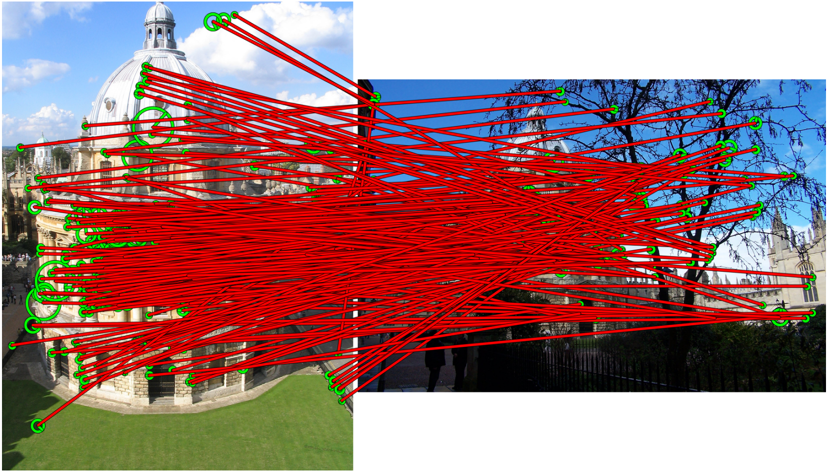
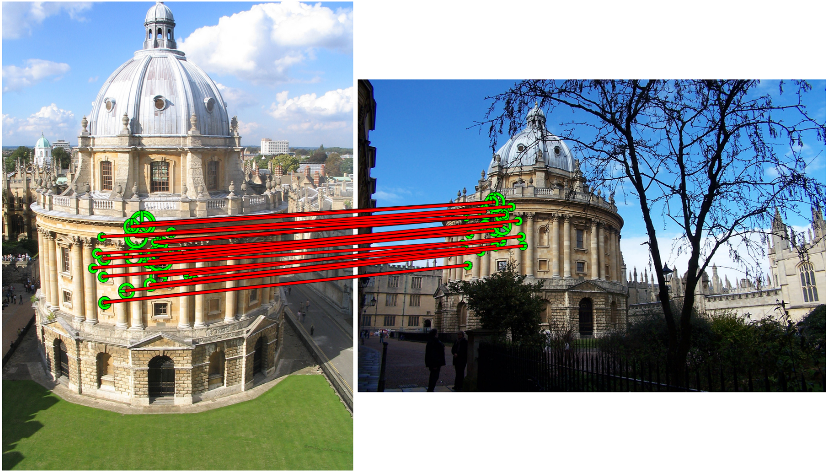


tentative correspondences: too many

Fischler and Bolles. CACM 1981. Random Sample Consensus: A Paradigm for Model Fitting With Applications to Image Analysis and Automated Cartography.

back to geometry: re-ranking



inliers: now more expensive to find

Fischler and Bolles. CACM 1981. Random Sample Consensus: A Paradigm for Model Fitting With Applications to Image Analysis and Automated Cartography.

application: location and landmark recognition

Estimated Location, Similar Image, Incorrectly geo-tagged, Unavailable

Suggested tags: Buxton Memorial Fountain, Victoria Tower Gardens, London
Frequent user tags: Victoria Tower Gardens, Buxton Memorial Fountain, Winchester Palace, Architecture, Victorian gothic

Similar Images

Similarity: 0.619
Details Original

Similarity: 0.491
Details Original

Similarity: 0.397
Details Original

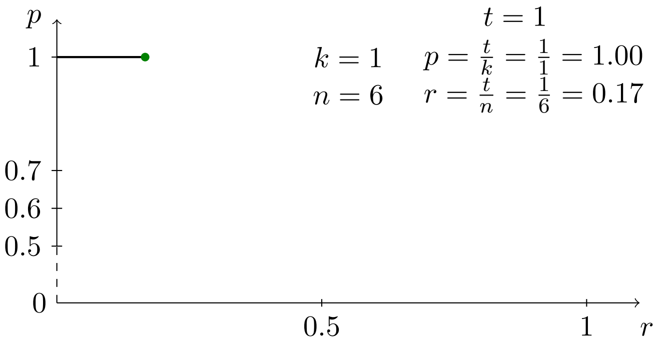
Similarity: 0.385
Details Original

http://viral.image.ntua.gr

average precision (AP)

- ranked list of items with true/false labels

1	2	3	4	5	6	7	8	9	10	11	12
T	T	F	T	F	F	T	F	T	T	F	F



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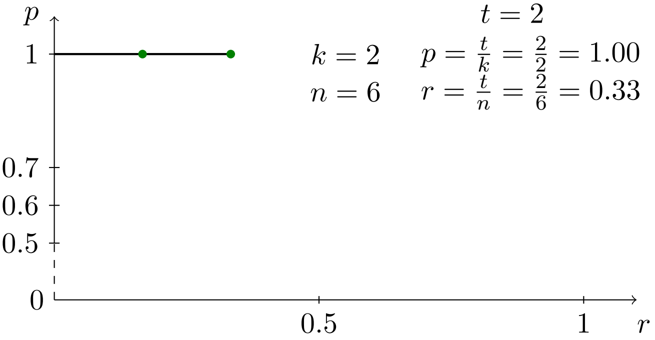

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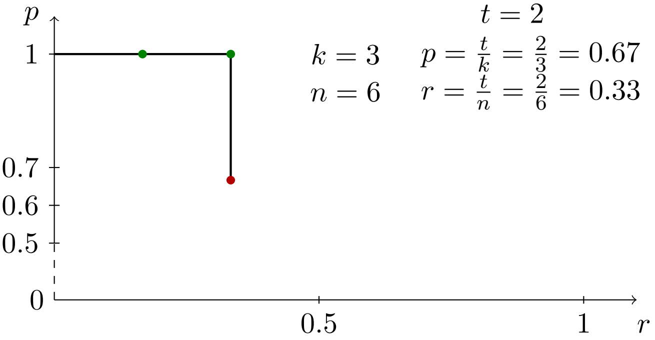

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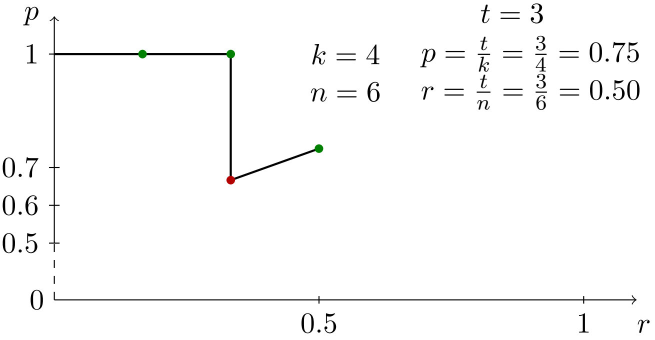

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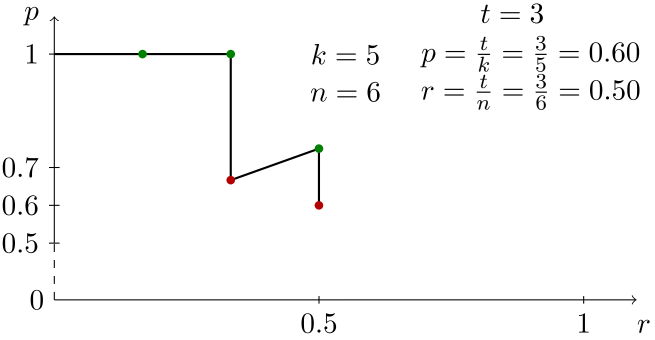

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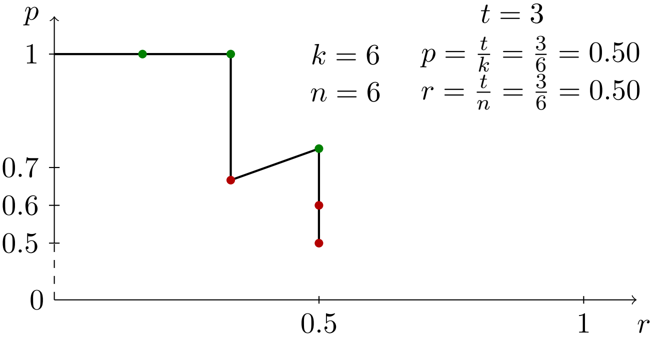

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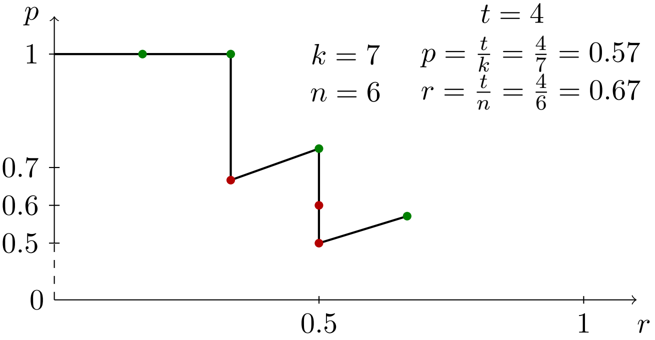

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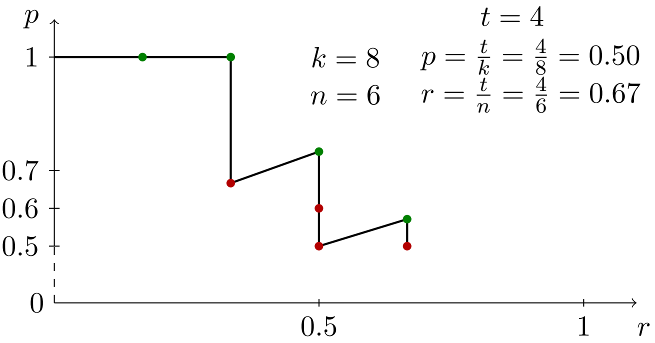

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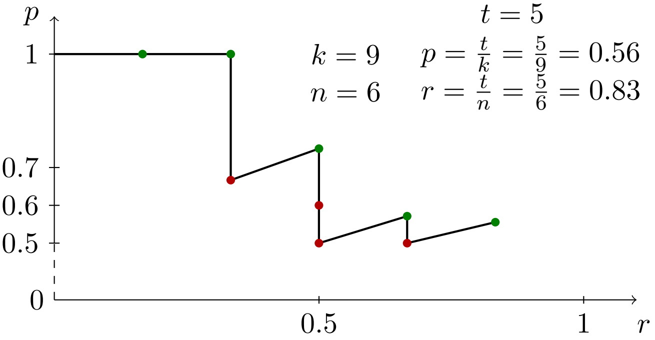

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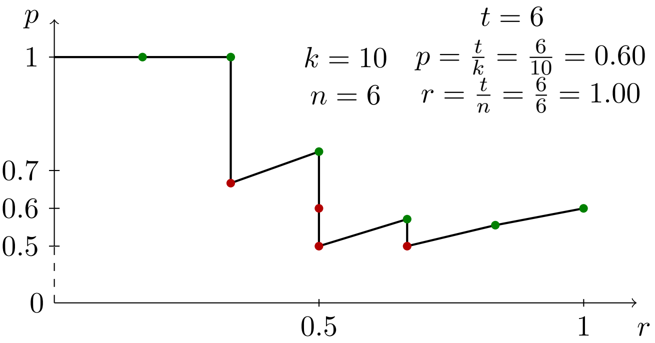

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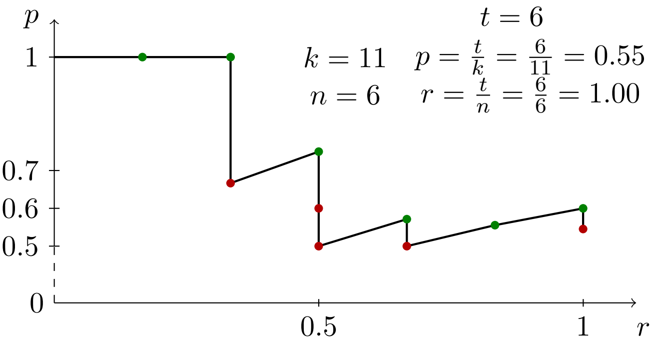

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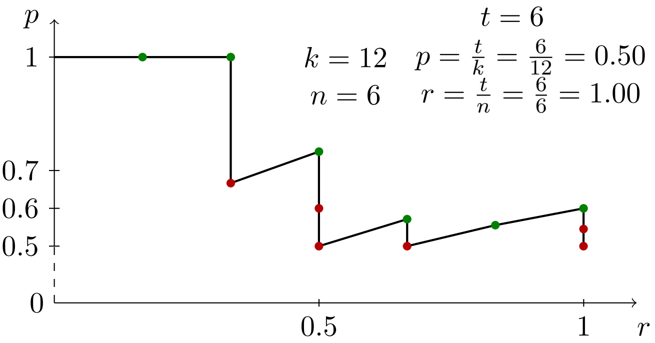

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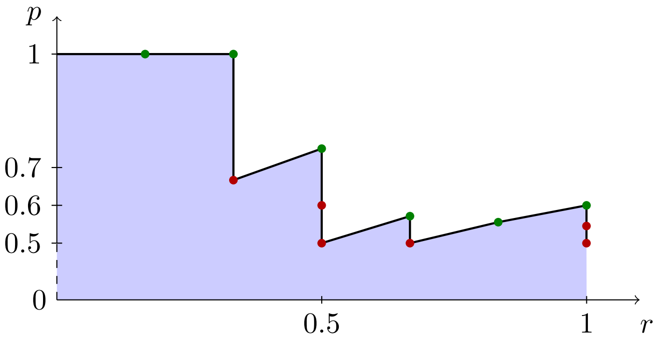

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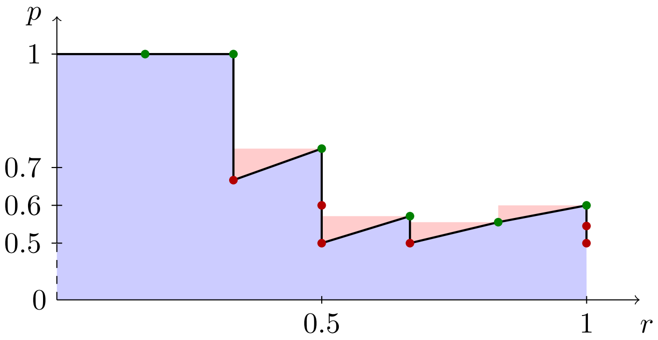


- average precision = area under curve (filled-in curve)
- the mean average precision (mAP) is the mean over queries

Oxford buildings dataset

[Philbin et al. 2007]


All Souls


Ashmolean


Balliol


Bodleian


Christ Church


Cornmarket


Hertford


Keble


Magdalen


Pitt Rivers

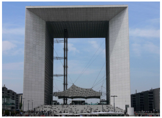

Radcliffe Camera

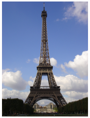
- Oxford5k: 5k images, 11 landmarks, $5 \times 11 = 55$ queries, $10 \sim 200$ positives/query
- Oxford105k: 100k additional distractor images

Philbin, Chum, Isard, Sivic and Zisserman. CVPR 2007. Object Retrieval With Large Vocabularies and Fast Spatial Matching.

Paris dataset

[Philbin et al. 2008]


Defense


Eiffel


Invalides


Louvre

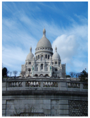

Moulin Rouge


Musée d'Orsay


Notre Dame


Pantheon


Pompidou


Sacré-Cœur

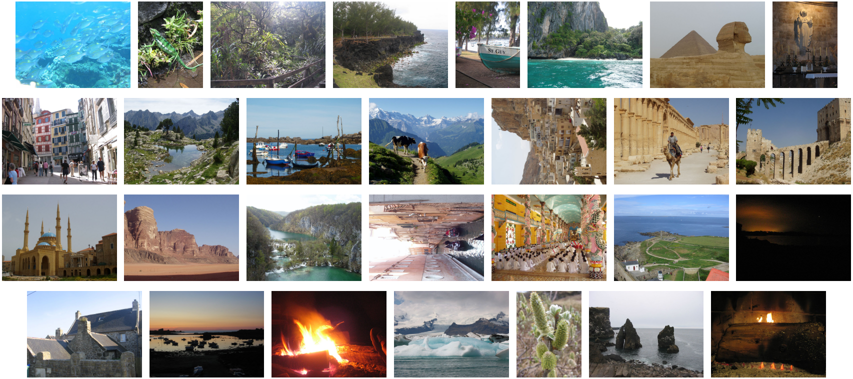

Triomphe

- Paris6k: 6k images, 11 landmarks, $5 \times 11 = 55$ queries, $50 \sim 300$ positives/query
- Paris106k: same 100k distractor images as Oxford

Philbin, Chum, Isard, Sivic and Zisserman. CVPR 2008. Lost in Quantization: Improving Particular Object Retrieval in Large Scale Image Databases.

Holidays dataset

[Jégou et al. 2008]



- personal holiday photos, natural and man-made scenes
- 1.5k images, 500 groups, 1 query/group, 1000 positives, $1 \sim 12$ positives/query

Jégou, Douze and Schmid. ECCV 2008. Hamming Embedding and Weak Geometric Consistency for Large Scale Image Search.

aggregated selective match kernel (ASMK)

[Tolias et al. 2013]

- residual pooling within cells

$$V(X_c) := \sum_{x \in X_c} r(x) = \sum_{x \in X_c} x - q(x)$$

- nonlinear selectivity between cells

$$K(X,Y) := \gamma(X)\gamma(Y) \sum_{c \in C} w_c \sigma_\alpha \left(\hat{V}(X_c)^\top \hat{V}(Y_c) \right)$$

where $\hat{x} := x/\|x\|$ and σ_α a nonlinear function

Tolias, Avrithis and Jegou. ICCV 2013. To Aggregate or not to Aggregate: Selective Match Kernels for Image Search.

triangulation embedding (T-embedding)

[Jégou and Zisserman 2014]

- normalized residuals, concatenated over cells, pooling over dataset

$$R(X) := \sum_{x \in X} (\hat{r}_1(x), \dots, \hat{r}_k(x)) = \sum_{x \in X} \left(\frac{x - c_1}{\|x - c_1\|}, \dots, \frac{x - c_k}{\|x - c_k\|} \right)$$

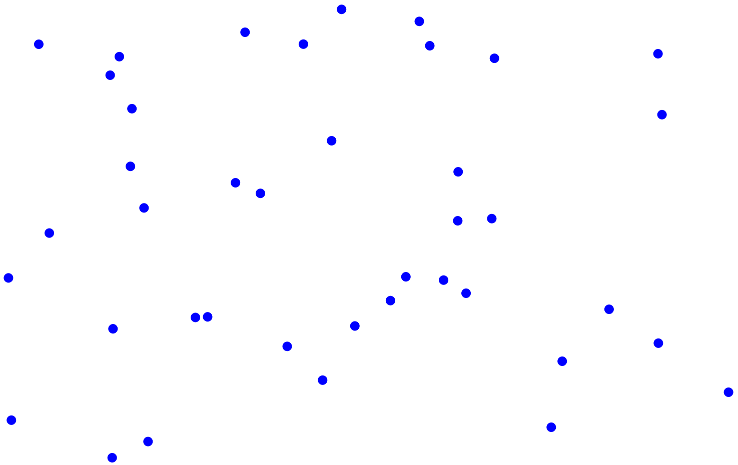
  where $r_j(x) := x - c_j$ and $\hat{x} := x/\|x\|$

- linear kernel, written as inner product

$$K(X, Y) := (\gamma(X)R(X))^\top (\gamma(Y)R(Y))$$

Jégou and Zisserman. CVPR 2014. Triangulation Embedding and Democratic Aggregation for Image Search.

triangulation embedding geometry



- input vectors – codebook – residuals – normalized residuals

Jégou and Zisserman. CVPR 2014. Triangulation Embedding and Democratic Aggregation for Image Search.

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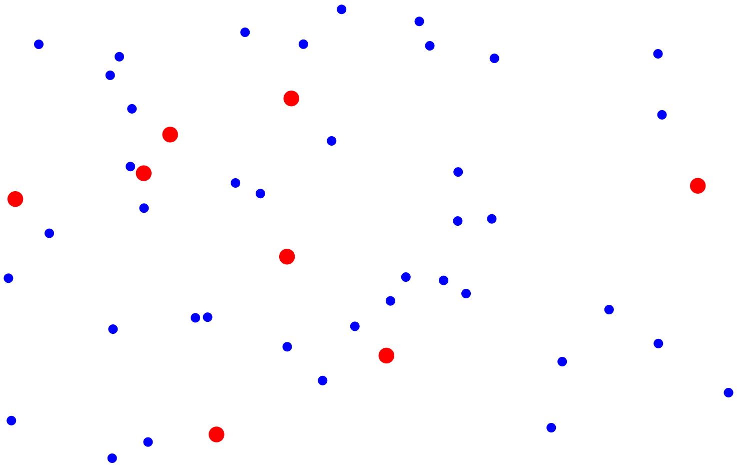

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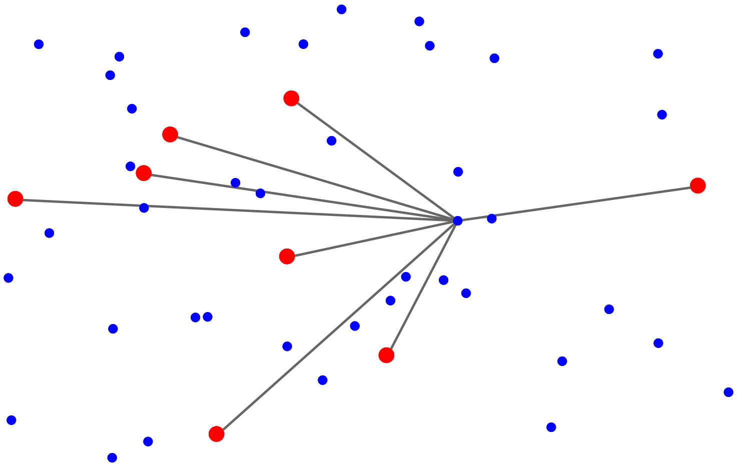

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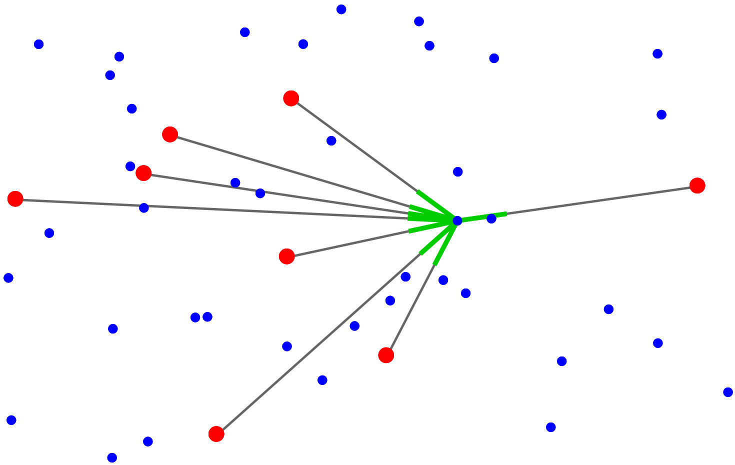

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performance

- aggregated selective match kernel
  - mAP 81.7 (83.8) mAP on Oxford5k, 78.2 (80.5) on Paris6k, 82.2 (86.5) on Holidays
  - ~ 2.2k (3.8k) descriptors/image $\times$ 128 dimensions
- triangulation embedding
  - mAP 57.1 (67.6) on Oxford5k, 72.3 (77.1) on Holidays
  - global descriptor, 1920 (8064) dimensions
- no spatial verification or other post-processing

state of the art before deep learning

- bag of words and inverted index is only a crude form of approximate nearest neighbor search for each local descriptor, followed by a kernel function
- for good performance, storing descriptors is necessary, even compressed
- very good performance achieved with thousands descriptors/image
- a global descriptor/image allows nearest neighbor search directly on images, but is inferior

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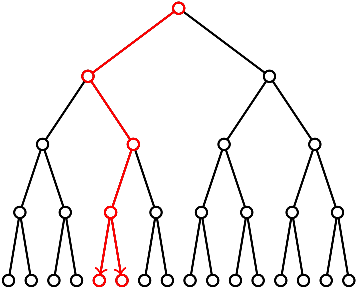
indexing

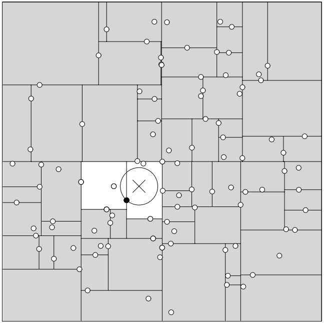
nearest neighbor search

- given query point y, find its nearest neighbor with respect to Euclidean distance within data set X in a d-dimensional space
- image retrieval: same problem; one or multiple queries depending on global or local representation
- image classification: nearest neighbor or naïve Bayes nearest neighbor classifier, again depending on representation

k-d tree

[Bentley 1975]



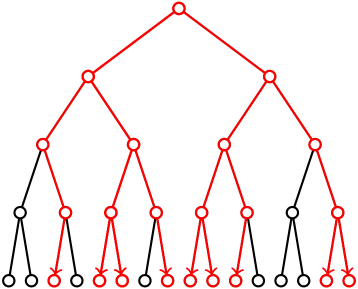


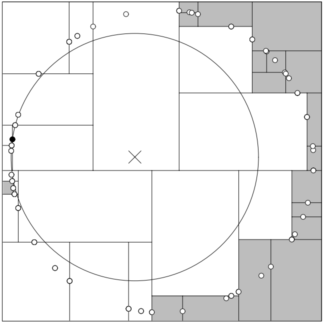
- index: recursively split at medoid on some dimension, make balanced binary tree
- search: descend recursively from root, choosing child according to splitting dimension and value
- backtracking becomes exhaustive at high dimensions

Bentley. CACM 1975. Multidimensional Binary Search Trees Used for Associative Searching.

k-d tree

[Bentley 1975]





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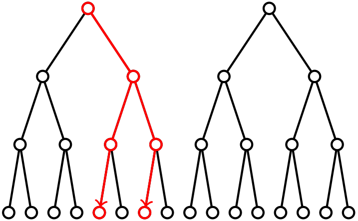
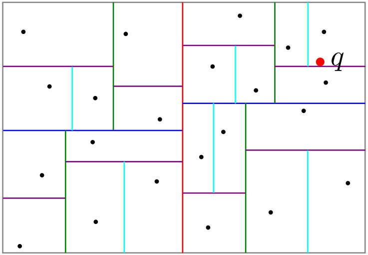
randomized k-d trees

[Silpa-Anan and Hartley 1975]





- index: same as before, but now multiple randomized trees
- search: descend trees in parallel according to shared priority queue
- still, points are stored, distances are exact

Silpa-Anan and Hartley CVPR 2008. Optimized KD-trees for fast image descriptor matching.

randomized k-d trees

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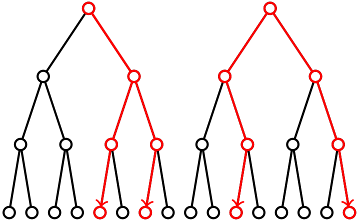

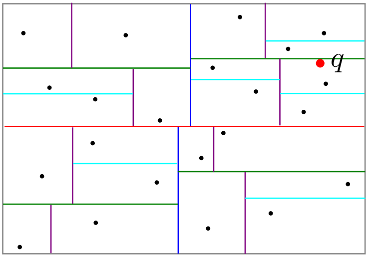

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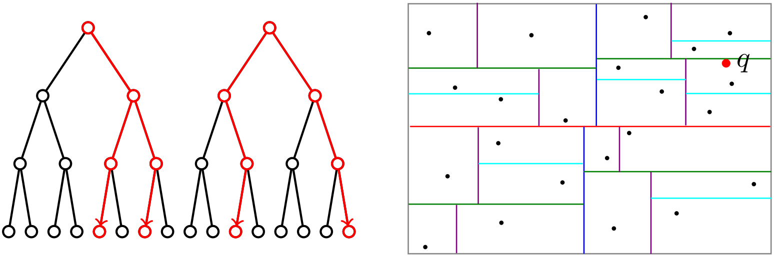

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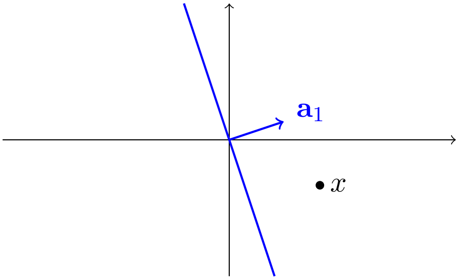
locality sensitive hashing (LSH)

[Charikar 2002]



- index: choose $\mathbf{a}_i \sim \mathcal{N}(0,1)$; encode each data point $x \in X$ by binary code $h(x) := (h_{\mathbf{a}_1}(x), \dots, h_{\mathbf{a}_k}(x)) \in \{-1,1\}^d$ with hash function

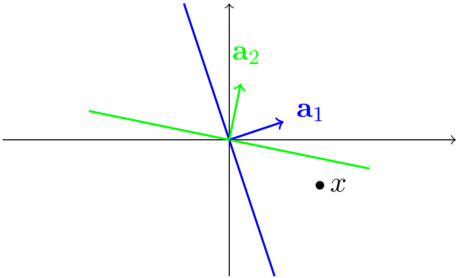
$$h_{\mathbf{a}}(x) = \operatorname{sgn}(\mathbf{a}^\top x)$$

- search: encode query y as $h(y)$ and search by Hamming distance
- not adapted to data distribution

Charikar. STOC 2002. Similarity Estimation Techniques From Rounding Algorithms.

locality sensitive hashing (LSH)

[Charikar 2002]



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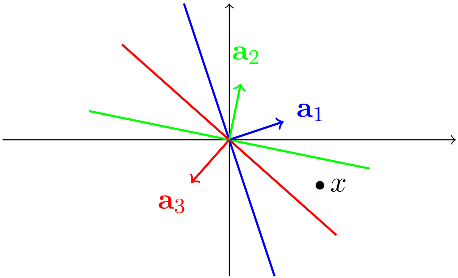

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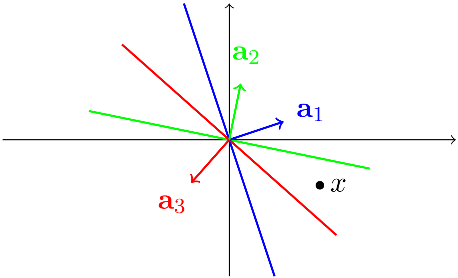

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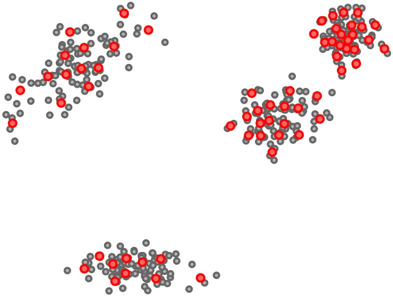
vector quantization (VQ)

[Gray 1984]

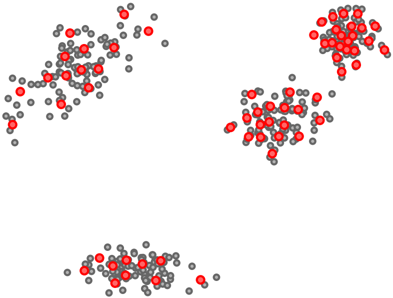


- index: cluster X into codebook $C = \{c_1, \dots, c_k\}$; quantize each $x \in X$ to $q(x) = \min_{c \in C} \|x - c\|^2$ and encode it by $\log k$ bits
- search: pre-compute distances $\|y - c\|^2$ for $c \in C$ and approximate distances $\|y - x\|^2$ by $\|y - q(x)\|^2$ where $q(x) \in C$
- small distortion $\to$ large k, too large to store, too slow to search

Gray. SPM 1984. Vector quantization.

vector quantization (VQ)

[Gray 1984]



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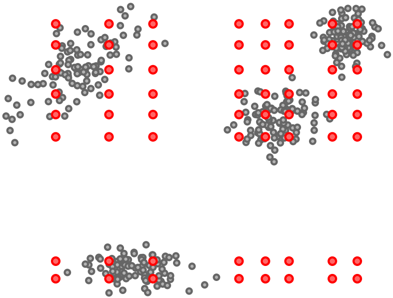
product quantization (PQ)

[Jégou et al. 2011]



- index: decompose vectors as $x = (x^1, \dots, x^m)$, cluster X into codebook $C = C^1 \times \cdots \times C^m$ with k cells each and $|C| = k^m$
- search: pre-compute distances $\|y^j - c\|^2$ for $c \in C^j$ and approximate $\|y - x\|^2$ by $\|y - q(x)\|^2 = \sum_{j=1}^{m} \|y^j - q^j(x^j)\|^2$ where $q^j(x^j) \in C^j$
- a lot of centroids do not represent data and are unused

Jegou, Douze and Schmid. PAMI 2011. Product Quantization for Nearest Neighbor Search.

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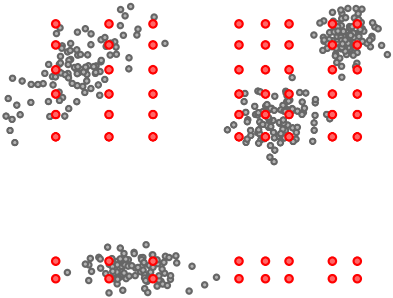

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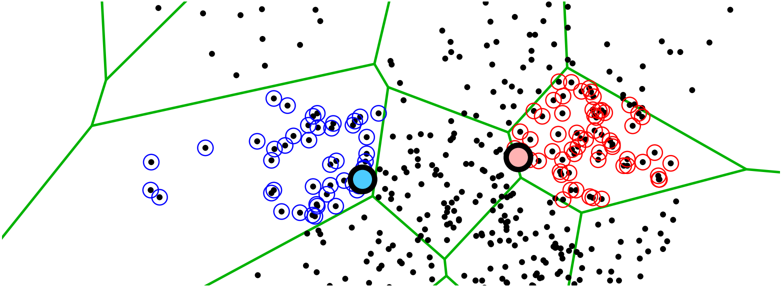
Jegou, Douze and Schmid. PAMI 2011. Product Quantization for Nearest Neighbor Search.

inverted index

[Jégou et al. 2011]



- index: train a coarse quantizer Q of k cells; quantize each $x \in X$ to $Q(x)$, compute residual $r(x) = x - Q(x)$ and encode residuals by a product quantizer q
- search: quantize query y to a fixed number of nearest cells; exhaustively search by PQ only within those cells
- a lot of points in the coarse cells are too far away from query

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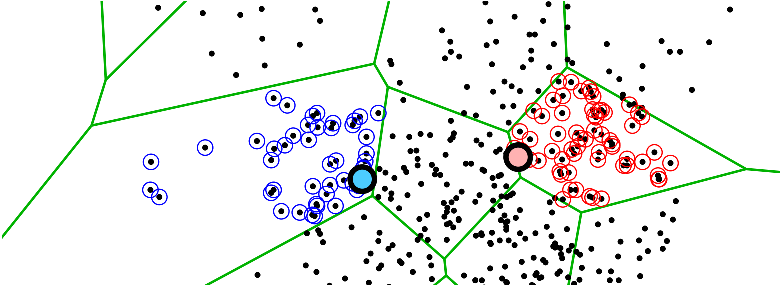

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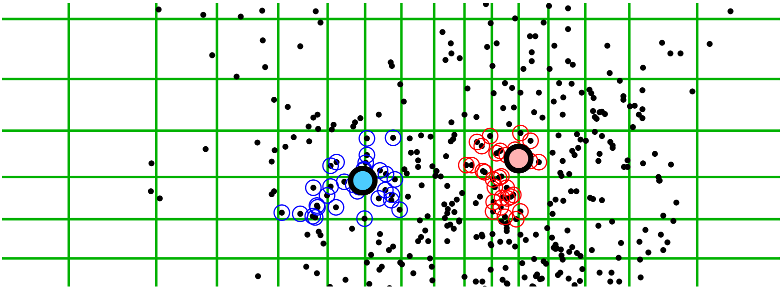
Jegou, Douze and Schmid. PAMI 2011. Product Quantization for Nearest Neighbor Search.

inverted multi-index

[Babenko and Lempitsky 2012]

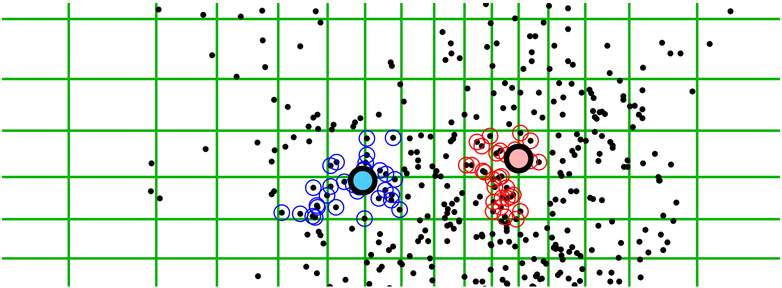


- index: decompose vectors as $x = (x^1, x^2)$; train two coarse quantizers Q^1, Q^2 of k cells each, quantize each $x \in X$ to $Q^1(x^1), Q^2(x^2)$ and encode residuals by product quantizers q^1, q^2
- search: visit cells $(c^1, c^2) \in C^1 \times C^2$ in ascending order of distance to y by multi-sequence algorithm
- two coarse quantizers induce a finer partition than one

Babenko and Lempitsky. CVPR 2012. The Inverted Multi-Index.

inverted multi-index

[Babenko and Lempitsky 2012]



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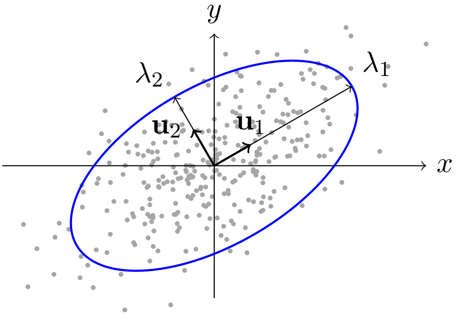
principal component analysis (PCA)



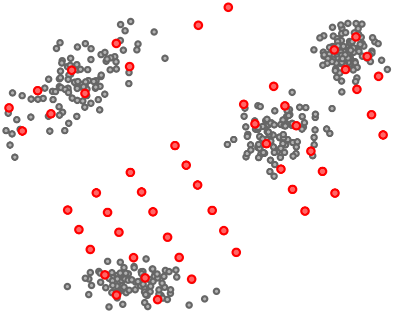
- given data $\{\mathbf{x}_1, \dots, \mathbf{x}_n\}$, compute empirical mean $\bar{\mathbf{x}} := \frac{1}{n}\sum_{i=1}^n \mathbf{x}_i$ and covariance matrix

$$S := \frac{1}{n}\sum_{i=1}^n (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^\top$$

- then diagonalize S by $S = U\Lambda U^\top$ where $U = (\mathbf{u}_1 \ \mathbf{u}_2)$ and $\Lambda = \mathrm{diag}(\lambda_1, \lambda_2)$

optimized product quantization (OPQ)

[Ge et al. 2013]

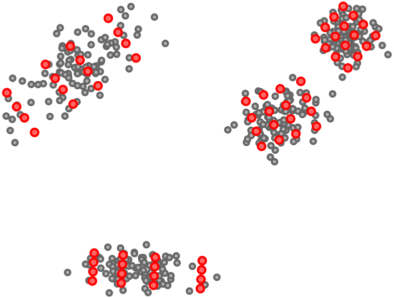


- no correlation: PCA-align by diagonalizing $\mathrm{cov}(X)$ as $U\Lambda U^\top$
- balanced variance: shuffle eigenvalues Λ by permutation π such that the product $\prod_i \lambda_i$ is constant in each subspace
- find codebook $\hat{C}$ by PQ on rotated data $\hat{X} := RX$ where $R := UP_\pi^\top$ and P_π is the permutation matrix of π

Ge, He, Ke and Sun. CVPR 2013. Optimized Product Quantization for Approximate Nearest Neighbor Search.

locally optimized product quantization (LOPQ)

[Kalantidis and Avrithis 2014]



- same as PQ with inverted index (or multi-index), but residuals are encoded by OPQ
- better on multimodal data: residual distributions closer to Gaussian assumption

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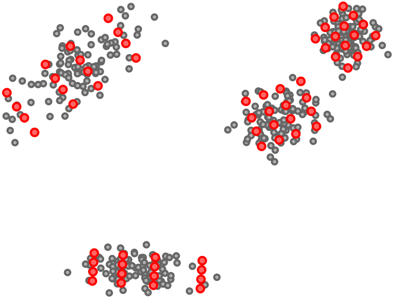

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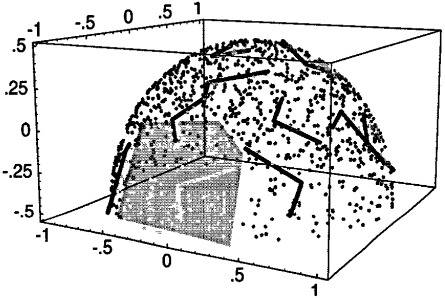
local principal component analysis

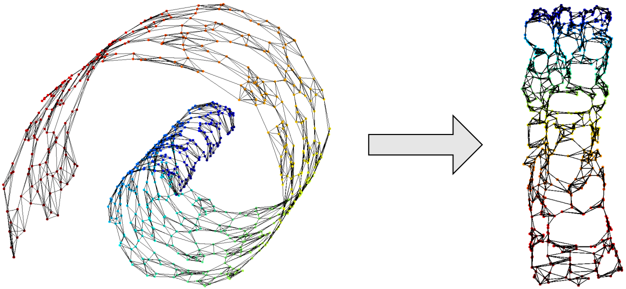
[Kambhatla & Leen 1997]



- cluster data, then apply PCA per cell
- captures the support of data distribution
  - multimodal (*e.g.* mixture) distributions
  - distributions on nonlinear manifolds

Kambhatla and Leen. NC 1997. Dimension Reduction By Local Principal Component Analysis.

manifold learning

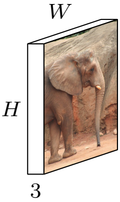


- *e.g.* Isomap: apply PCA to the geodesic (graph) distance matrix
- *e.g.* kernel PCA: apply PCA to the Gram matrix of a nonlinear kernel
- other topology-preserving methods are only focusing on distances to nearest neighbors
- many classic methods use eigenvalue decomposition and most do not learn and explicit mapping from the input to the embedding space

pooling

image ranking by CNN features

[Krizhevsky et al. 2012]



- 3-channel RGB input, 224×224
- AlexNet pre-trained on ImageNet for classification
- last fully connected layer (fc_6): global descriptor of dimension $k = 4096$

Krizhevsky, Sutskever, Hinton. NIPS 2012. Imagenet Classification with Deep Convolutional Neural Networks.

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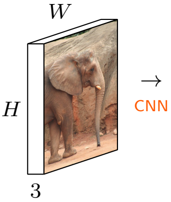

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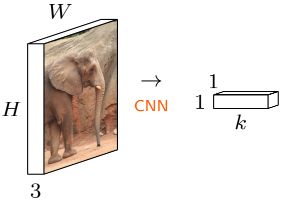

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image ranking by CNN features

- query images
- nearest neighbors in ImageNet according to Euclidean distance

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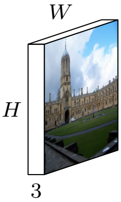
neural codes for image retrieval

[Babenko et al. 2014]



- 3-channel RGB input, 224×224
- AlexNet last pooling layer, global descriptor of dimension $w \times h \times k = 6 \times 6 \times 256 = 9216$
- alternatively: fully connected layers $\mathrm{fc}_6, \mathrm{fc}_7$, global descriptors of dimension $k' = 4096$ (best is fc_6)
- in each case: PCA-whitening, ℓ_2 normalization

Babenko, Slesarev, Chigorin, Lempitsky. ECCV 2014. Neural Codes for Image Retrieval.

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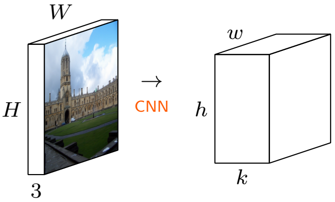

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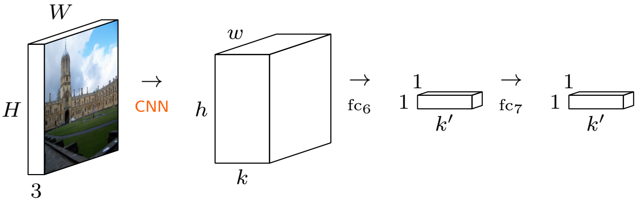

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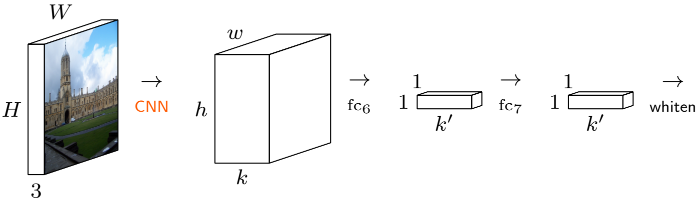

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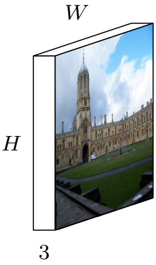
neural codes for image retrieval

- fine-tuning by softmax on 672 classes of 200k landmark photos
- outperforms VLAD and Fisher vectors on standard retrieval benchmarks, but still inferior to SIFT local descriptors

Babenko, Slesarev, Chigorin, Lempitsky. ECCV 2014. Neural Codes for Image Retrieval.

regional CNN features

[Razavian et al. 2015]

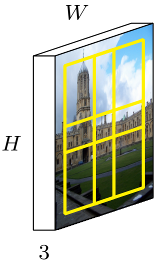


- 3-channel RGB input, largest square region extracted
- fixed multiscale overlapping regions, warped into $w \times h = 227 \times 227$
- each region yields a $w' \times h' \times k = 36 \times 36 \times 256$ dimensional feature at the last convolutional layer of AlexNet
- global spatial max-pooling
- ℓ_2-normalization, PCA-whitening of each descriptor

Razavian, Sullivan, Maki and Carlsson 2015. Visual Instance Retrieval with Deep Convolutional Networks.

regional CNN features

[Razavian et al. 2015]



- 3-channel RGB input, largest square region extracted
- fixed multiscale overlapping regions, warped into $w \times h = 227 \times 227$
- each region yields a $w' \times h' \times k = 36 \times 36 \times 256$ dimensional feature at the last convolutional layer of AlexNet
- global spatial max-pooling
- ℓ_2-normalization, PCA-whitening of each descriptor

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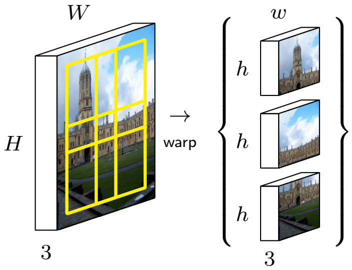
regional CNN features

[Razavian et al. 2015]



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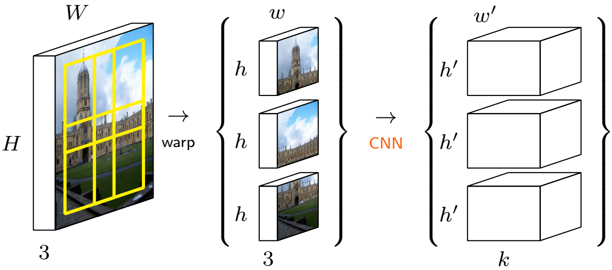

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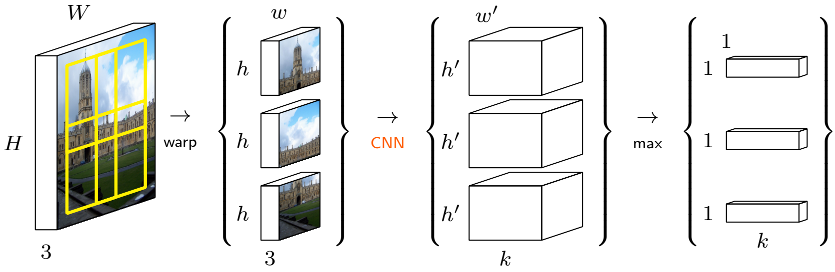

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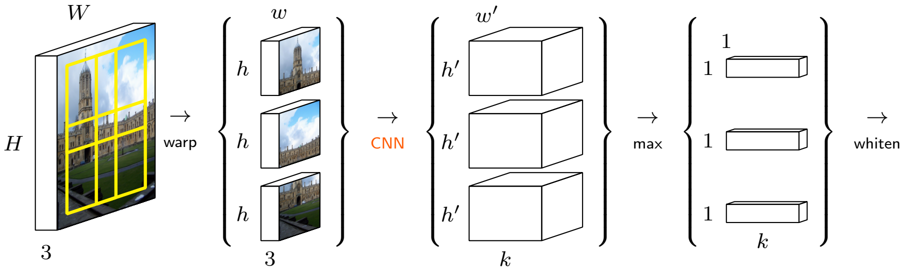

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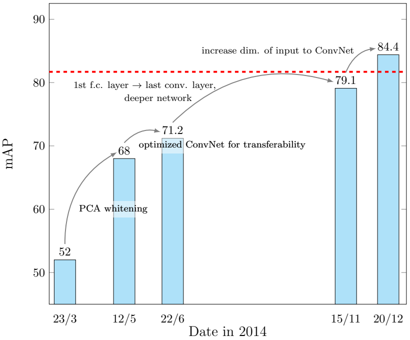

- CNN visual representation jumps by more than 30% mAP to outperform standard SIFT pipeline in a few months
- however, this is based on multiple regional descriptors per image and exhaustive pairwise matching of all descriptors of query and all dataset images, which is not practical

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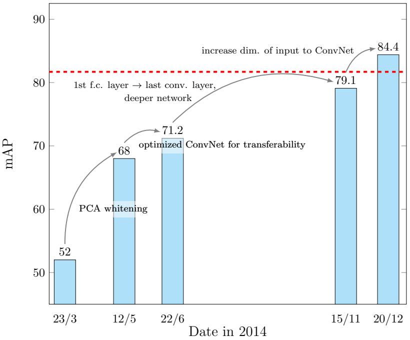

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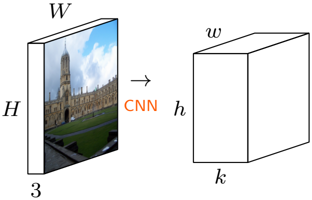
regional max-pooling (R-MAC)

[Tolias et al. 2016]



- VGG-16 last convolutional layer, $k = 512$
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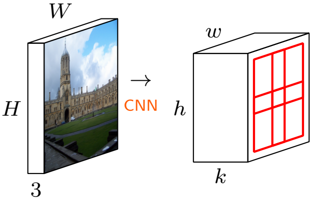

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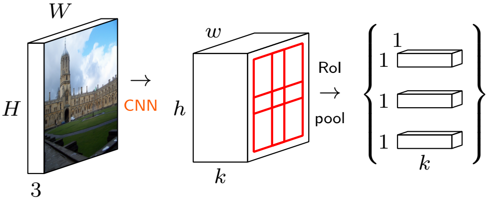

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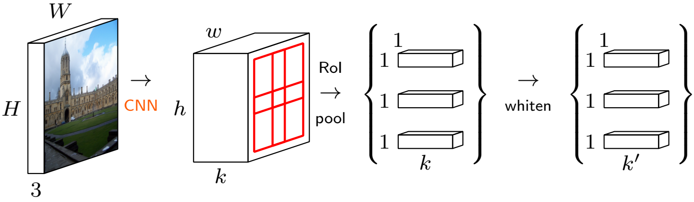

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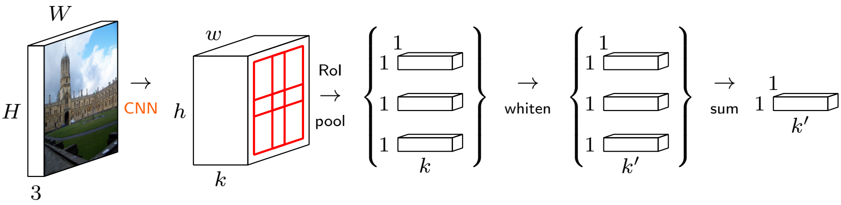

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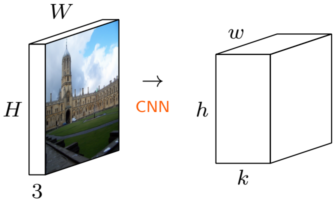
global max-pooling (MAC)



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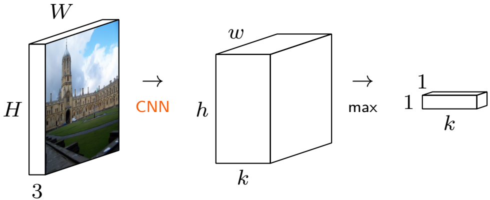

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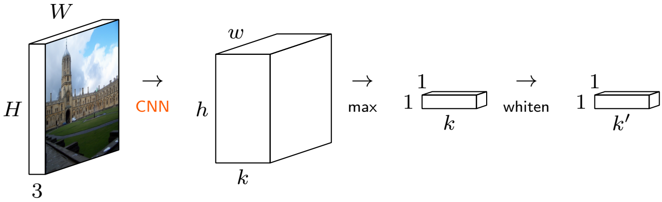

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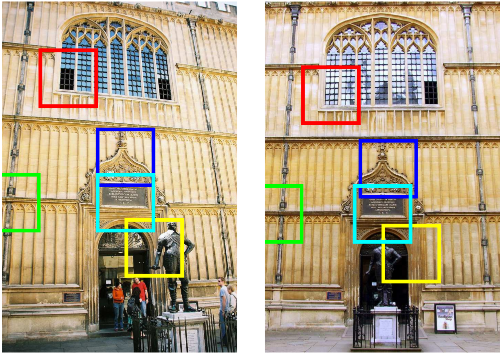
global max-pooling: matching



- receptive fields of 5 components of MAC vectors that contribute most to image similarity

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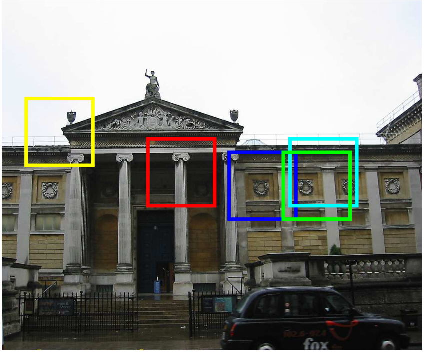
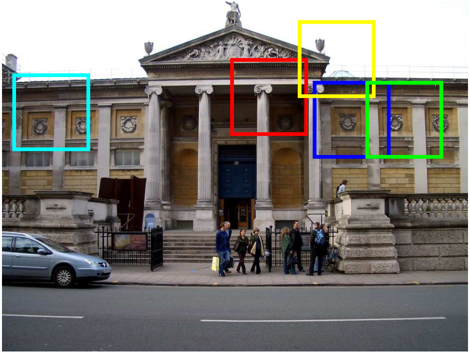
global max-pooling: matching

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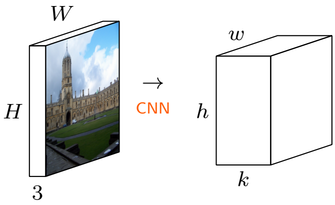
global sum-pooling (SPoC)

[Babenko and Lempitsky 2015]



- VGG-19 last convolutional layer, $k = 512$
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- ℓ_2-normalization, PCA-whitening, ℓ_2-normalization
- SPoC: sum-pooled convolutional features

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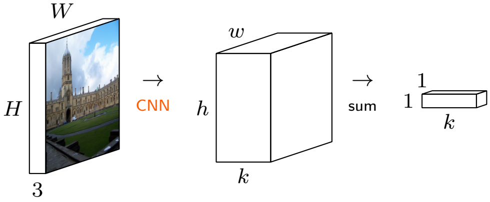

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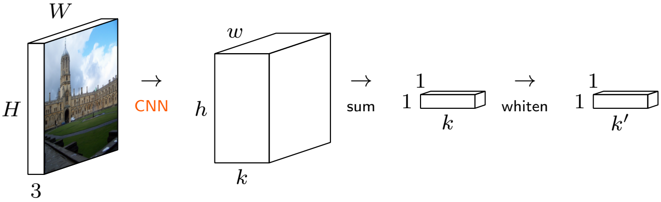

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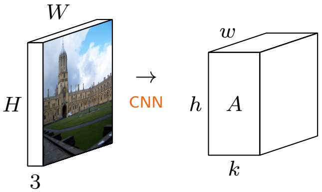
cross-dimensional weighting (CroW)

[Kalantidis et al. 2016]



- VGG-16 feature map A, last pooling layer, $k = 512$
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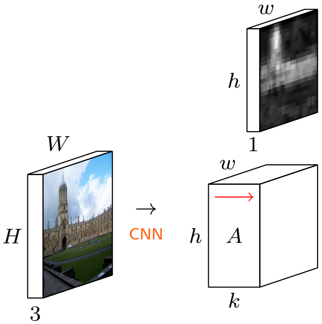

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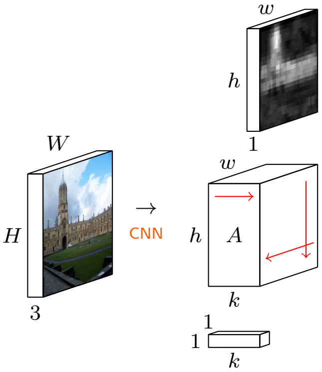

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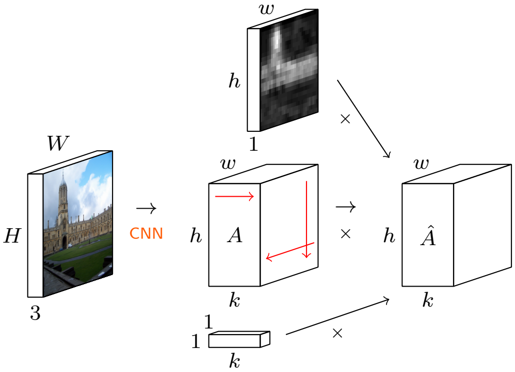

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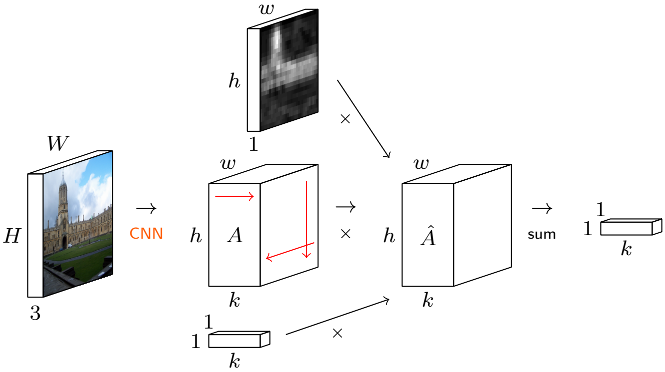

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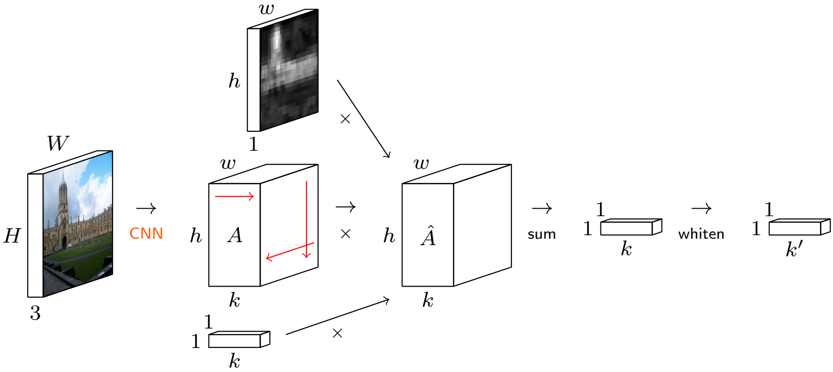

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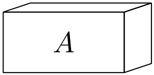

- spatial weights (visual saliency)

$$F(x,y) = \sum_k A_k(x,y)$$

- channel weights (sparsity sensitive)

$$w_j = -\log\left(\epsilon + \sum_{x,y} \mathbb{1}[A_j(x,y)]\right)$$

- weighted feature map

$$\hat{A} = A \times F \times \mathbf{w}$$

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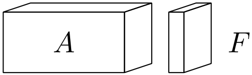
cross-dimensional weighting (CroW)



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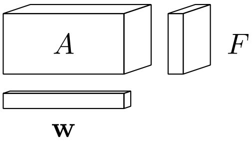

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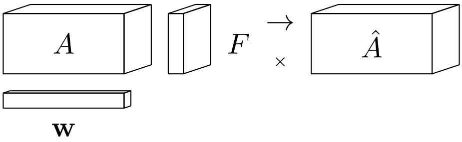

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cross-dimensional weighting (CroW)




- input image

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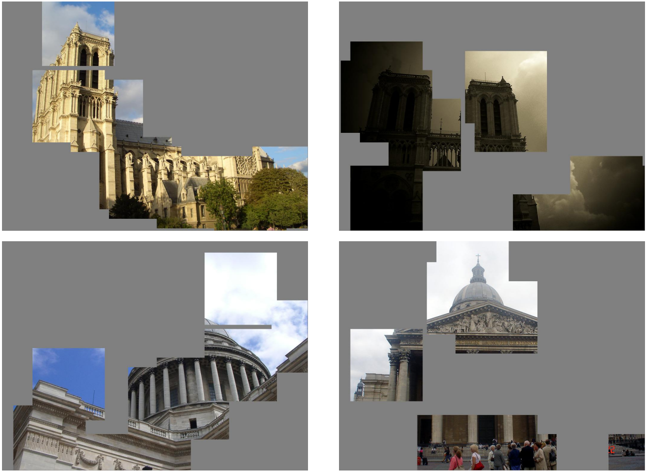

- receptive fields of nonzero elements of the 10 channels with the highest sparsity-sensitive weights

manifold learning

siamese architecture

[Chopra et al. 2005]

$\mathbf{x}_i$ $\mathbf{x}_j$

- an input sample is a pair $(\mathbf{x}_i, \mathbf{x}_j)$
- both $\mathbf{x}_i, \mathbf{x}_j$ go through the same function f with shared parameters θ
- loss ℓ_{ij} is measured on output pair $(\mathbf{y}_i, \mathbf{y}_j)$ and target t_{ij}

Chopra, Hadsell, Lecun, CVPR 2005. Learning a Similarity Metric Discriminatively, with Application to Face Verification.

siamese architecture

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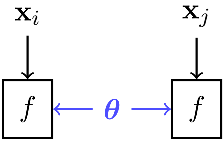

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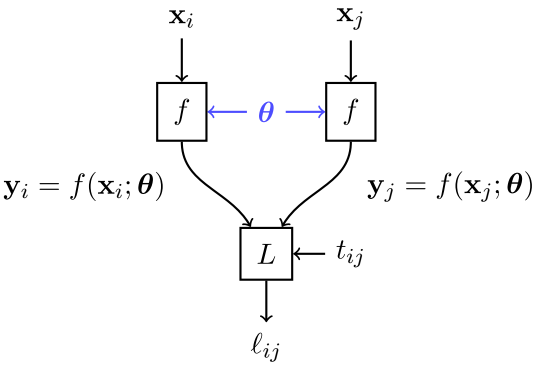

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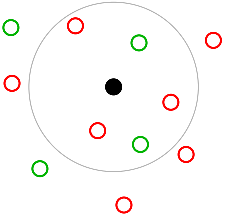
contrastive loss

[Hadsel et al. 2006]



- input samples $\mathbf{x}_i$, output vectors $\mathbf{y}_i = f(\mathbf{x}_i; \boldsymbol{\theta})$
- target variables $t_{ij} = \mathbb{1}[\mathrm{sim}(\mathbf{x}_i, \mathbf{x}_j)]$
- contrastive loss is a function of distance $\|\mathbf{y}_i - \mathbf{y}_j\|$ only

$$\ell_{ij} = L((\mathbf{y}_i, \mathbf{y}_j), t_{ij}) = \ell(\|\mathbf{y}_i - \mathbf{y}_j\|, t_{ij})$$

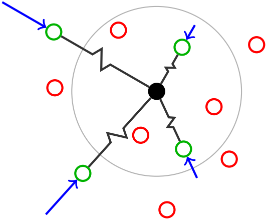
- similar samples are attracted

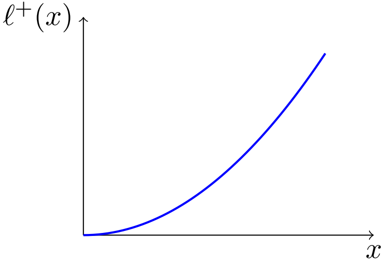
$$\ell(x, t) = t\ell^+(x) + (1-t)\ell^-(x) = tx^2 + (1-t)[m-x]_+^2$$

Hadsell, Chopra, Lecun. CVPR 2006. Dimensionality Reduction By Learning an Invariant Mapping.

contrastive loss

[Hadsel et al. 2006]





- input samples $\mathbf{x}_i$, output vectors $\mathbf{y}_i = f(\mathbf{x}_i; \boldsymbol{\theta})$
- target variables $t_{ij} = \mathbb{1}[\mathrm{sim}(\mathbf{x}_i, \mathbf{x}_j)]$
- contrastive loss is a function of distance $\|\mathbf{y}_i - \mathbf{y}_j\|$ only

$$\ell_{ij} = L((\mathbf{y}_i, \mathbf{y}_j), t_{ij}) = \ell(\|\mathbf{y}_i - \mathbf{y}_j\|, t_{ij})$$

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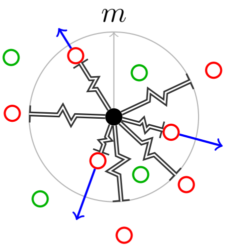

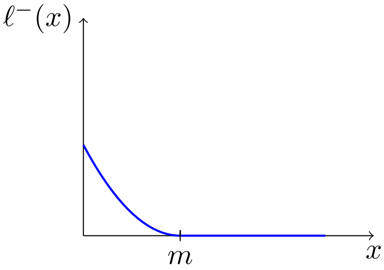

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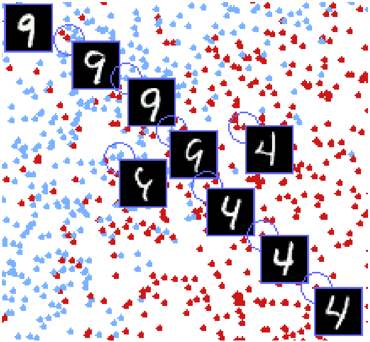
- dissimilar samples are repelled if closer than margin m

$$\ell(x, t) = t\ell^+(x) + (1-t)\boxed{\ell^-(x)} = tx^2 + (1-t)\boxed{[m-x]_+^2}$$

Hadsell, Chopra, Lecun. CVPR 2006. Dimensionality Reduction By Learning an Invariant Mapping.

manifold learning: MNIST



- 3k samples of each of digits $4, 9$
- each sample similar to its 5 Euclidean nearest neighbors, and dissimilar to all other points
- 30k similar pairs, 18M dissimilar pairs

Hadsell, Chopra, Lecun. CVPR 2006. Dimensionality Reduction By Learning an Invariant Mapping.

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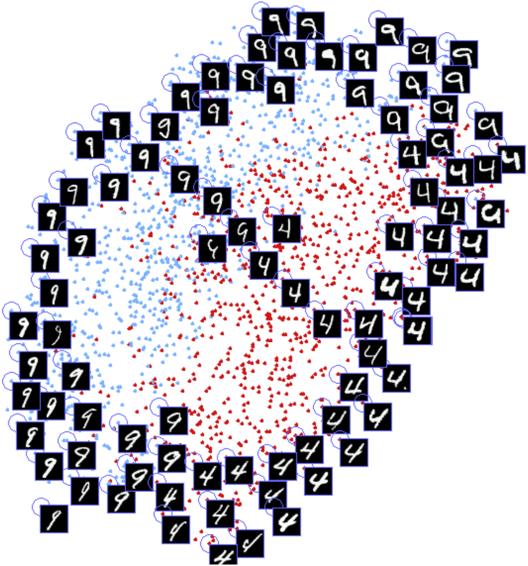

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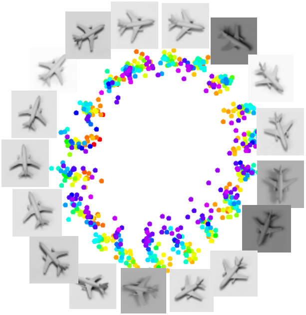
manifold learning: NORB



- 972 images of airplane class: 18 azimuths (every 20°), 9 elevations (in $[30^\circ, 70^\circ]$, every 5°), 6 lighting conditions
- samples similar if taken from contiguous azimuth or elevation, regardless of lighting
- 11k similar pairs, 206M dissimilar pairs
- cylindrer in 3d: azimuth on circumference, elevation on height

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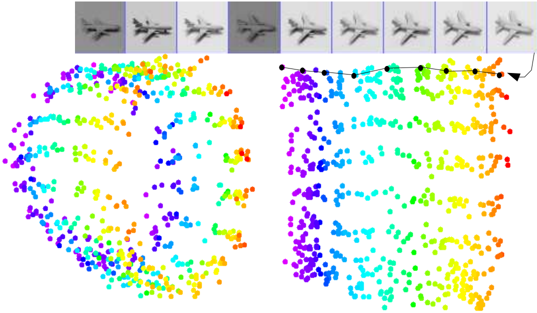

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triplet architecture

[Wang et al. 2014]

$$\mathbf{x}_i \qquad \mathbf{x}_i^+ \qquad \mathbf{x}_i^-$$

- an input sample is a triplet $(\mathbf{x}_i, \mathbf{x}_i^+, \mathbf{x}_i^-)$
- $\mathbf{x}_i, \mathbf{x}_i^+, \mathbf{x}_i^-$ go through the same function f with shared parameters $\boldsymbol{\theta}$
- loss ℓ_i measured on output triplet $(\mathbf{y}_i, \mathbf{y}_i^+, \mathbf{y}_i^-)$

Wang, Song, Leung, Rosenberg, Wang, Philbin, Chen, Wu. CVPR 2014. Learning Fine-Grained Image Similarity with Deep Ranking.

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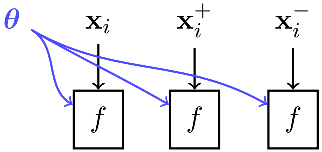

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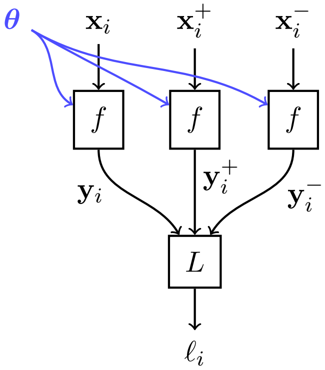

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triplet loss

- input "anchor" $\mathbf{x}_i$, output vector $\mathbf{y}_i = f(\mathbf{x}_i; \boldsymbol{\theta})$
- positive $\mathbf{y}_i^+ = f(\mathbf{x}_i^+; \boldsymbol{\theta})$, negative $\mathbf{y}_i^- = f(\mathbf{x}_i^-; \boldsymbol{\theta})$
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$$\ell_i = L(\mathbf{y}_i, \mathbf{y}_i^+, \mathbf{y}_i^-) = \ell(\|\mathbf{y}_i - \mathbf{y}_i^+\|, \|\mathbf{y}_i - \mathbf{y}_i^-\|)$$

$$\ell(x^+, x^-) = \left[m + (x^+)^2 - (x^-)^2\right]_+$$

so distance $\|\mathbf{y}_i - \mathbf{y}_i^+\|$ should be less than $\|\mathbf{y}_i - \mathbf{y}_i^-\|$ by margin m

- by taking two pairs $(\mathbf{x}_i, \mathbf{x}_i^+)$ and $(\mathbf{x}_i, \mathbf{x}_i^-)$ at a time with targets $1, 0$ respectively, the contrastive loss can be written similarly

$$\ell(x^+, x^-) = (x^+)^2 + \left[m - x^-\right]_+^2$$

so distance $\|\mathbf{y}_i - \mathbf{y}_i^+\|$ should small and $\|\mathbf{y}_i - \mathbf{y}_i^-\|$ larger than m

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unsupervised learning by context prediction

[Doersch et al. 2015]

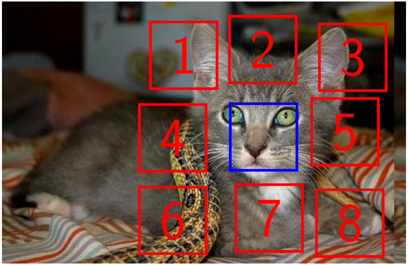
- sample random pairs of patches in one of eight spatial configurations
- patches are randomly jittered and do not overlap
- like solving a puzzle, learn to predict the relative position

$$f\left(\quad , \quad \right) = 3$$

Doersch, Gupta, Efros. ICCV 2015. Unsupervised Visual Representation Learning By Context Prediction.

unsupervised learning by context prediction

[Doersch et al. 2015]



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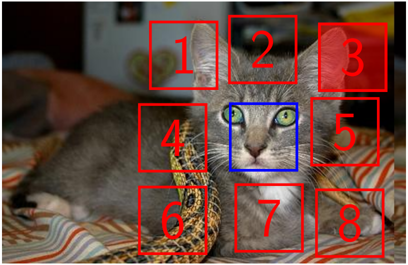

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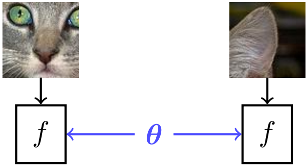
context prediction: architecture



- network f learned by siamese architecture
- representations are concatenated and followed by softmax classifier, where each spatial configuration is a class

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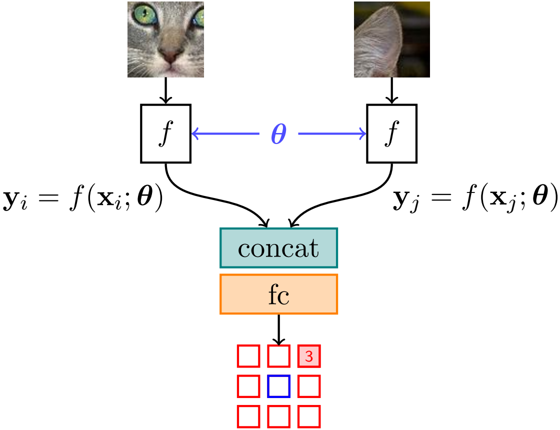

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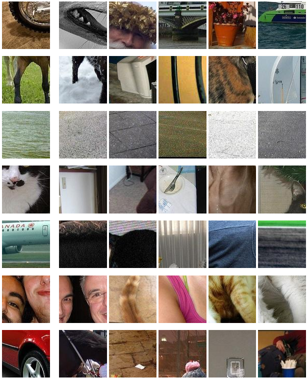
context prediction: examples

- input image
- nearest neighbors with randomly initialized network
- trained by supervised classification on ImageNet
- unsupervised training from scratch on the context prediction task

Doersch, Gupta, Efros. ICCV 2015. Unsupervised Visual Representation Learning By Context Prediction.

context prediction: examples



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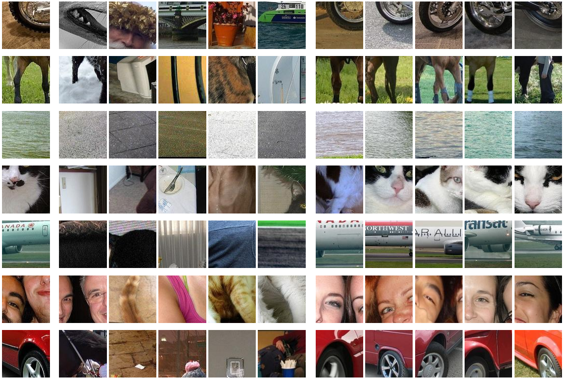

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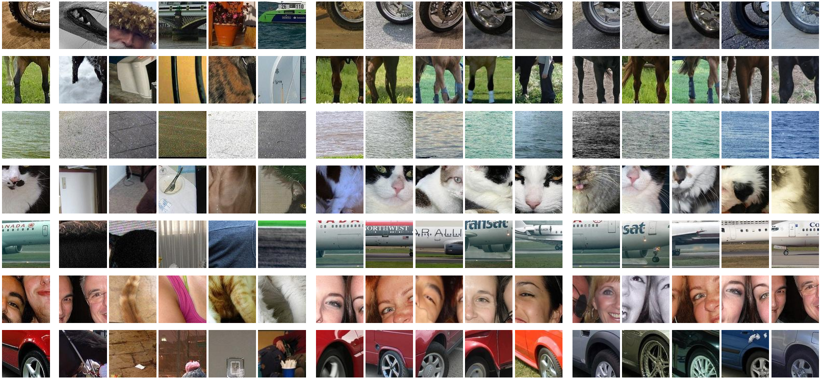

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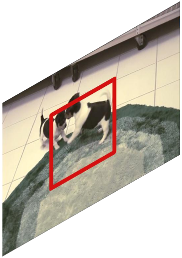
Doersch, Gupta, Efros. ICCV 2015. Unsupervised Visual Representation Learning By Context Prediction.

unsupervised learning on video: tracking

[Wang et al. 2015]

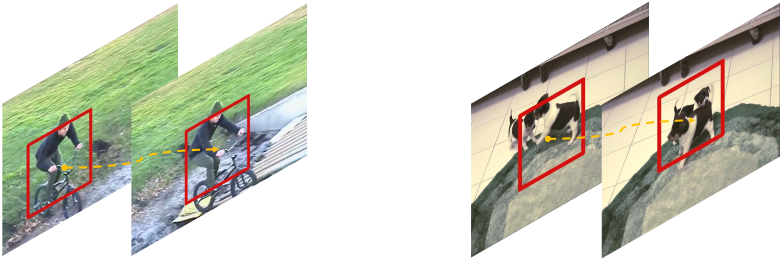


- estimate motion and find the region that contains most motion
- track this region for a number of frames
- generate a pair of matching patches on the first and last frames

Wang and Gupta. ICCV 2015. Unsupervised Learning of Visual Representations Using Videos.

unsupervised learning on video: tracking

[Wang et al. 2015]



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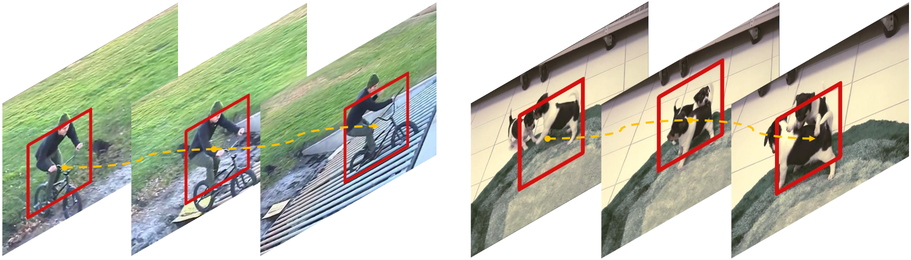

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unsupervised learning on video: architecture

- input query $\mathbf{x}_i$ (first frame), tracked $\mathbf{x}_i^+$ (last frame), random $\mathbf{x}_i^-$
- $\mathbf{x}_i, \mathbf{x}_i^+, \mathbf{x}_i^-$ go through the same function f with shared parameters $\boldsymbol{\theta}$
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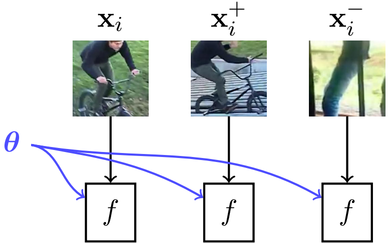

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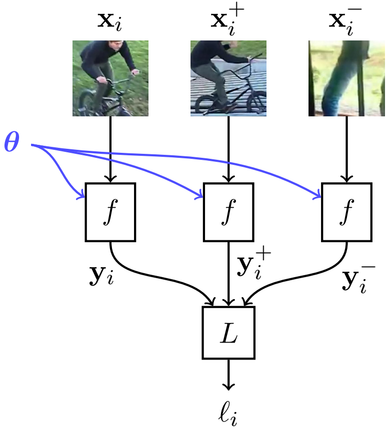

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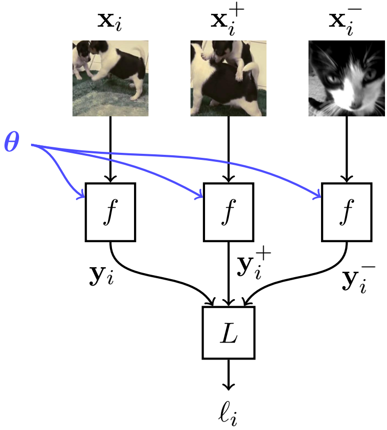

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Wang and Gupta. ICCV 2015. Unsupervised Learning of Visual Representations Using Videos.

unsupervised learning on video: objective

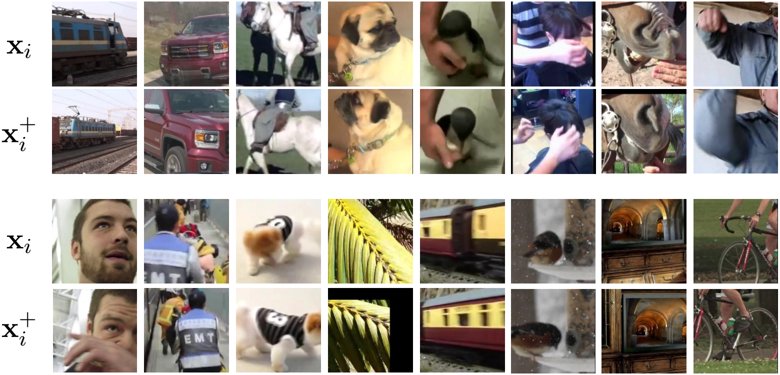
$\Big\| f\Big($  $\Big) - f\Big($  $\Big)\Big\|^2 < \Big\| f\Big($  $\Big) - f\Big($  $\Big)\Big\|^2 - m$

$\Big\| f\Big($  $\Big) - f\Big($  $\Big)\Big\|^2 < \Big\| f\Big($  $\Big) - f\Big($  $\Big)\Big\|^2 - m$

- so, the objective is that squared distance $\|\mathbf{y}_i - \mathbf{y}_i^+\|^2$ is less than $\|\mathbf{y}_i - \mathbf{y}_i^-\|^2$ by margin m

Wang and Gupta. ICCV 2015. Unsupervised Learning of Visual Representations Using Videos.

unsupervised learning on video: more examples



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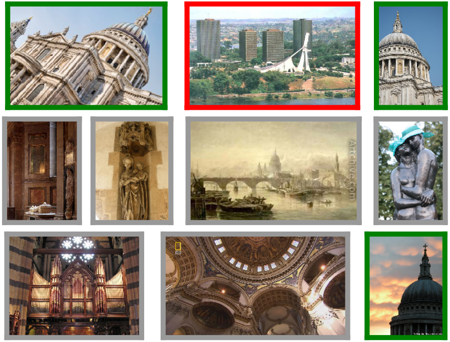
fine-tuning

deep image retrieval: dataset cleaning

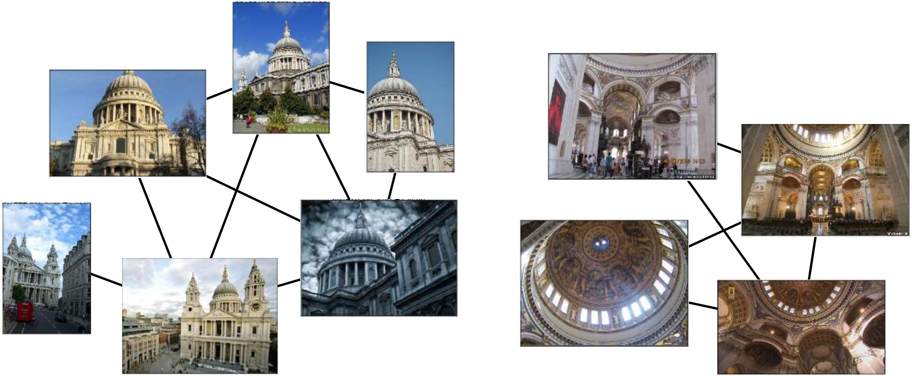
[Gordo et al. 2016]



- start from landmark dataset (192k images) and clean it (49k images)
- use it to fine-tune a network pre-trained on ImageNet for classification
- prototypical, non-prototypical and incorrect images per class
- only prototypical are kept to reduce intra-class variability

Gordo, Almazan, Revaud, Larlus. ECCV 2016. Deep Image Retrieval: Learning Global Representations for Image Search.

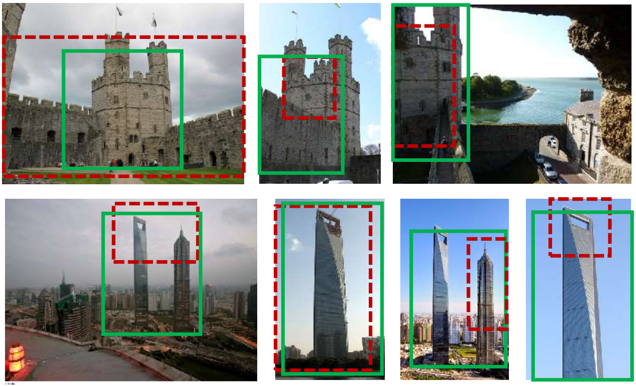
deep image retrieval: prototypical views



- pairwise match images per class by SIFT descriptors and fast spatial matching
- connect images into a graph and compute the connected components
- keep only the largest component

Gordo, Almazan, Revaud, Larlus. ECCV 2016. Deep Image Retrieval: Learning Global Representations for Image Search.

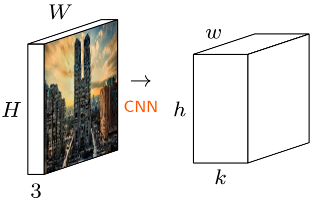
deep image retrieval: bounding boxes



- automatically find object bounding boxes
  - initialize with inlier features per image
  - update such that boxes are consistent over all matching pairs
- use bounding boxes to train a region proposal network

Gordo, Almazan, Revaud, Larlus. ECCV 2016. Deep Image Retrieval: Learning Global Representations for Image Search.

deep image retrieval: network, regions, pooling



- VGG-16 or ResNet-101 feature maps
- proposals detected on feature maps by RPN and max-pooled
- ℓ_2-normalization, PCA-whitening (FC layer), ℓ_2-normalization
- sum-pooling, ℓ_2-normalization (as in R-MAC)

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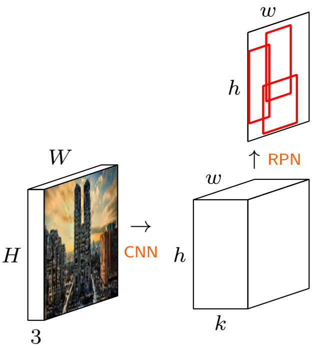
deep image retrieval: network, regions, pooling



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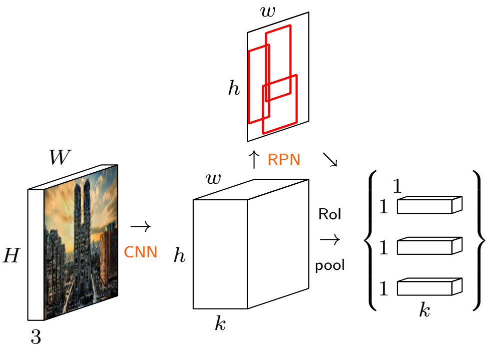

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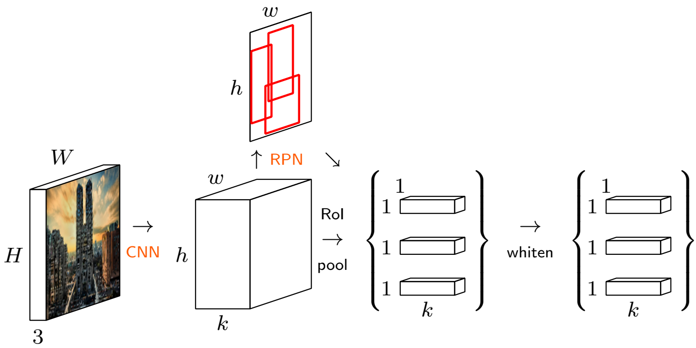

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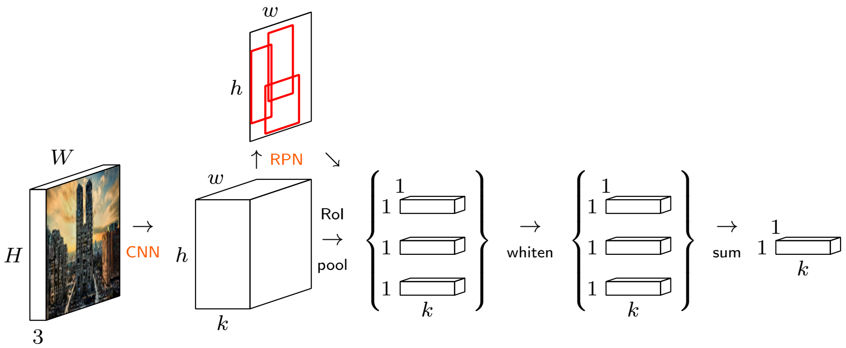
Gordo, Almazan, Revaud, Larlus. ECCV 2016. Deep Image Retrieval: Learning Global Representations for Image Search.

deep image retrieval: network, regions, pooling



- VGG-16 or ResNet-101 feature maps
- proposals detected on feature maps by RPN and max-pooled
- ℓ_2-normalization, PCA-whitening (FC layer), ℓ_2-normalization
- sum-pooling, ℓ_2-normalization (as in R-MAC)

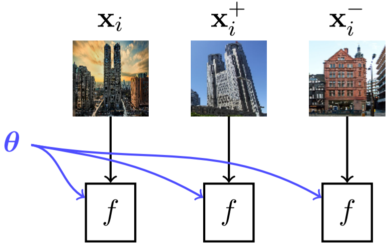
Gordo, Almazan, Revaud, Larlus. ECCV 2016. Deep Image Retrieval: Learning Global Representations for Image Search.

deep image retrieval: architecture

$\mathbf{x}_i$ $\mathbf{x}_i^+$ $\mathbf{x}_i^-$

- query $\mathbf{x}_i$, relevant $\mathbf{x}_i^+$ (same building), irrelevant $\mathbf{x}_i^-$ (other building)
- $\mathbf{x}_i, \mathbf{x}_i^+, \mathbf{x}_i^-$ go through function f including features, RPN, pooling
- triplet loss ℓ_i measured on output $(\mathbf{y}_i, \mathbf{y}_i^+, \mathbf{y}_i^-)$

deep image retrieval: architecture



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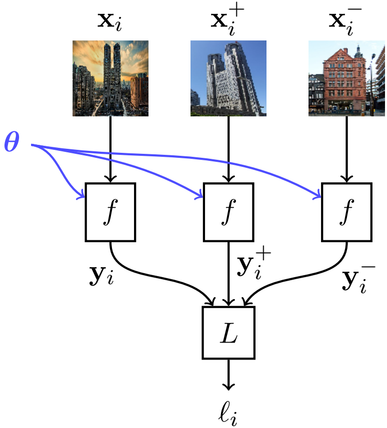

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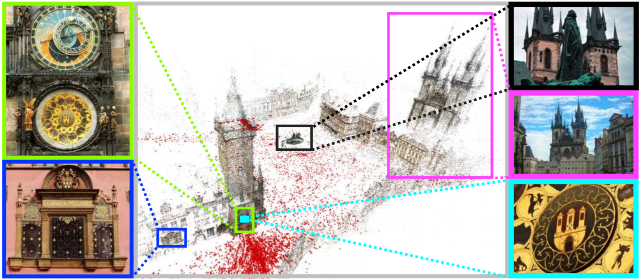
Gordo, Almazan, Revaud, Larlus. ECCV 2016. Deep Image Retrieval: Learning Global Representations for Image Search.

learning from bag-of-words: 3d reconstruction

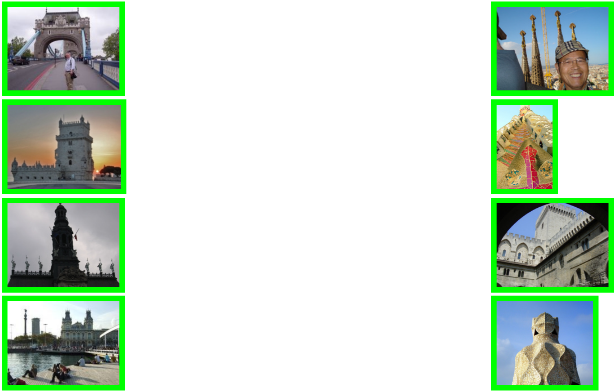
[Radenovic et al. 2016]



- start from an independent dataset of 7.4M images, no class labels
- clustering, pairwise matching and reconstruction of 713 3d models containing 165k unique images
- 3d models playing the same role as classes in deep image retrieval
- again, fine-tune a network pre-trained on ImageNet for classification

Radenovic, Tolias, Chum. ECCV 2016. CNN Image Retrieval Learns From BoW: Unsupervised Fine-Tuning with Hard Examples.
Schönberger, Radenovic, Chum and Frahm. CVPR 2015. From Single Image Query to Detailed 3D Reconstruction.

learning from bag-of-words: positive pairs



- input query
- positive images found in same model by minimum MAC distance, maximum inliers, or drawn at random from images having at least a given number of inliers (more challenging)

Radenovic, Tolias, Chum. ECCV 2016. CNN Image Retrieval Learns From BoW: Unsupervised Fine-Tuning with Hard Examples.

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learning from bag-of-words: negative pairs

- input query
- negative images found in different models
- hard negatives are most similar to query, *i.e.* with minimum MAC distance
- hardest negative, nearest neighbors from all other models, or nearest neighbors, one per model (higher variability)

Radenovic, Tolias, Chum. ECCV 2016. CNN Image Retrieval Learns From BoW: Unsupervised Fine-Tuning with Hard Examples.

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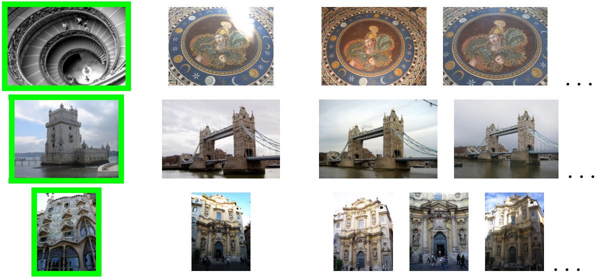

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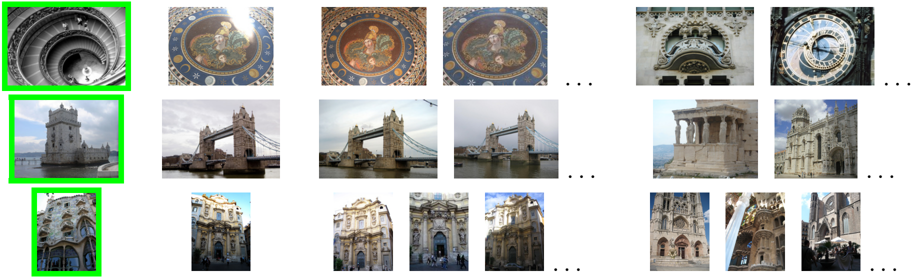

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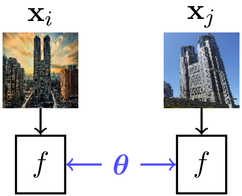
learning from bag-of-words: architecture

$\mathbf{x}_i$ $\mathbf{x}_j$

- input $(\mathbf{x}_i, \mathbf{x}_j)$ of relevant or irrelevant images
- both $\mathbf{x}_i, \mathbf{x}_j$ go through function f including features and MAC pooling
- contrastive loss ℓ_{ij} measured on output $(\mathbf{y}_i, \mathbf{y}_j)$ and target t_{ij}

learning from bag-of-words: architecture



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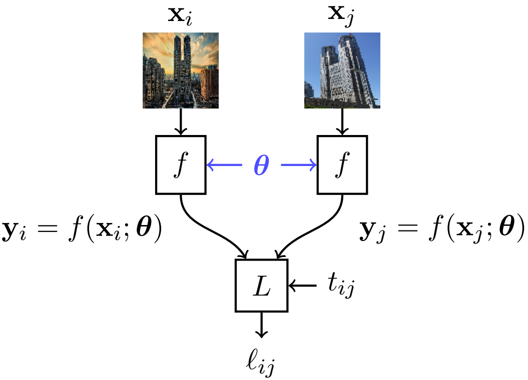

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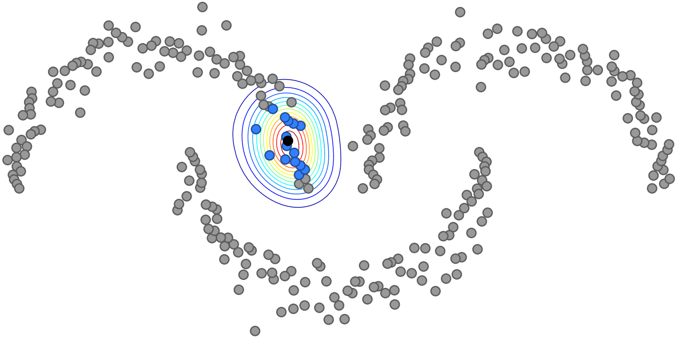
Radenovic, Tolias, Chum. ECCV 2016. CNN Image Retrieval Learns From BoW: Unsupervised Fine-Tuning with Hard Examples.

graph-based methods

ranking on manifolds: single query

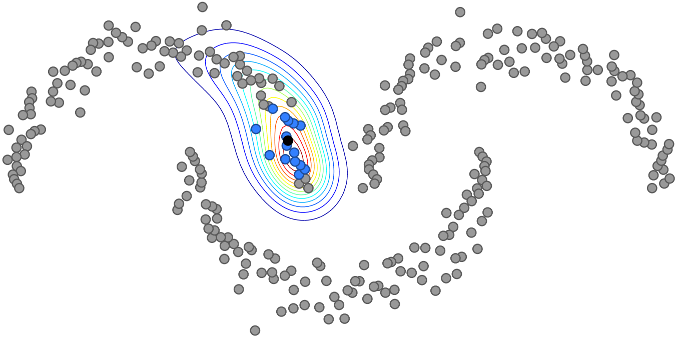
- data points (•), query point (•), nearest neighbors (•)
- iteration $\times 30$

ranking on manifolds: single query



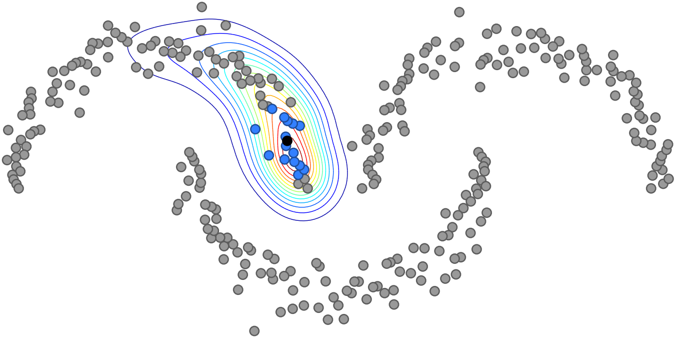
- data points (∘), query point (•), nearest neighbors (•)
- iteration 0×30

ranking on manifolds: single query



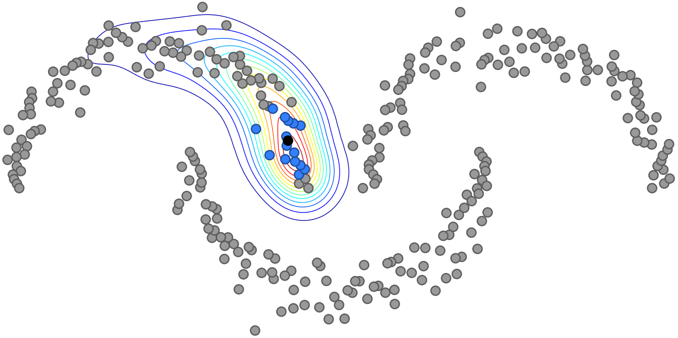
- data points (∘), query point (•), nearest neighbors (∘)
- iteration 1×30

ranking on manifolds: single query



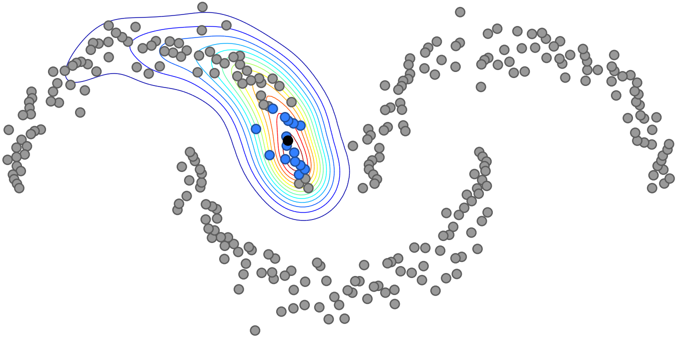
- data points (∘), query point (•), nearest neighbors (∘)
- iteration 2×30

ranking on manifolds: single query



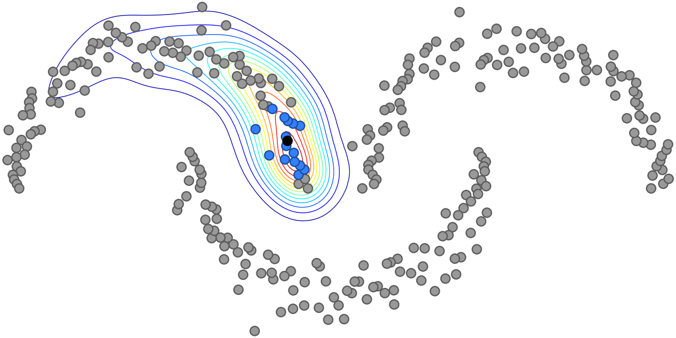
- data points (∘), query point (•), nearest neighbors (∘)
- iteration 3×30

ranking on manifolds: single query



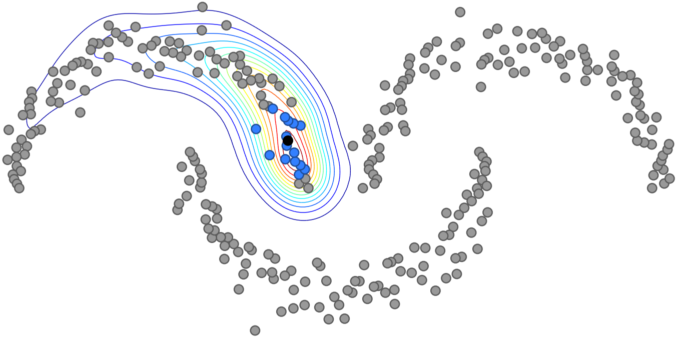
- data points (∘), query point (•), nearest neighbors (∘)
- iteration 4×30

ranking on manifolds: single query



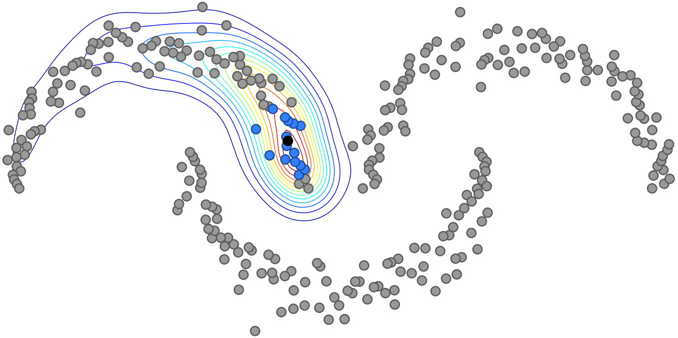
- data points (∘), query point (•), nearest neighbors (∘)
- iteration 5×30

ranking on manifolds: single query



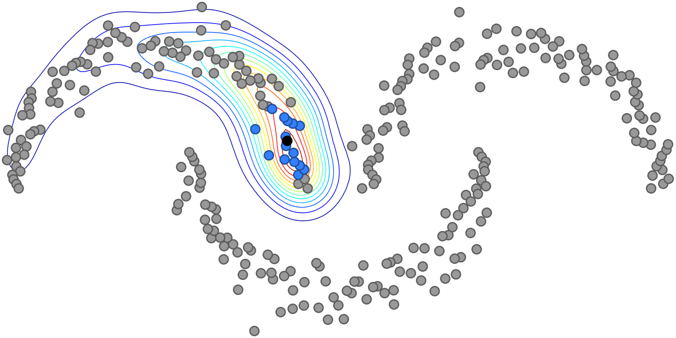
- data points (∘), query point (•), nearest neighbors (∘)
- iteration 6×30

ranking on manifolds: single query



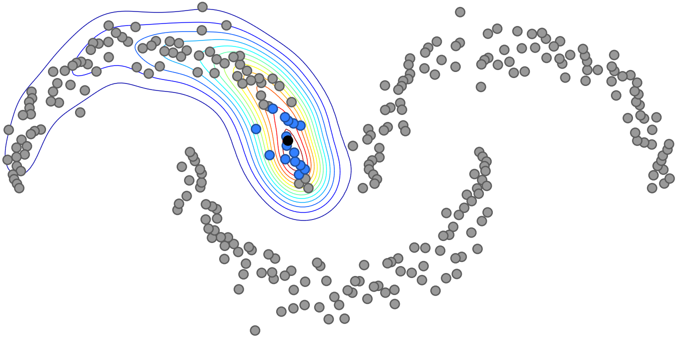
- data points (∘), query point (•), nearest neighbors (∘)
- iteration 7×30

ranking on manifolds: single query



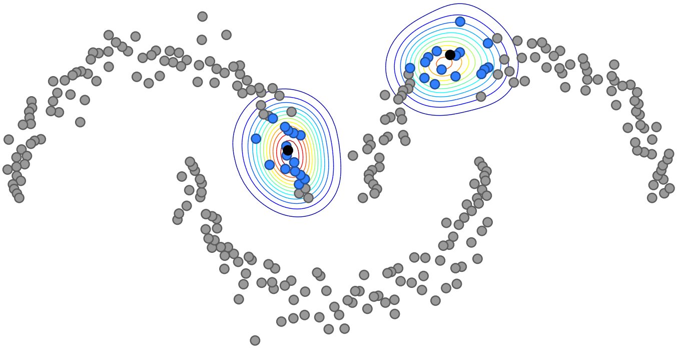
- data points (∘), query point (•), nearest neighbors (∘)
- iteration 8×30

ranking on manifolds: single query



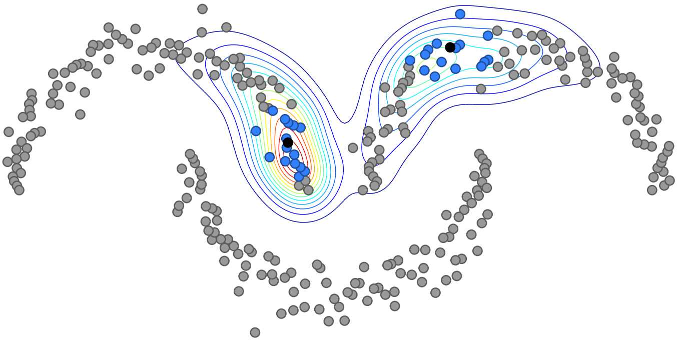
- data points (∘), query point (•), nearest neighbors (∘)
- iteration 9×30

ranking on manifolds: multiple queries



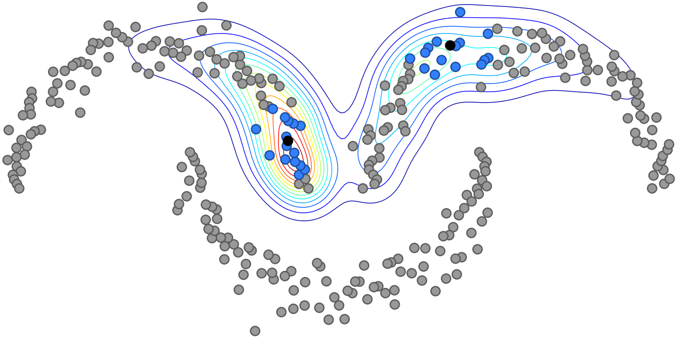
- data points (∘), query points (•), nearest neighbors (∘)
- iteration 0×30

ranking on manifolds: multiple queries



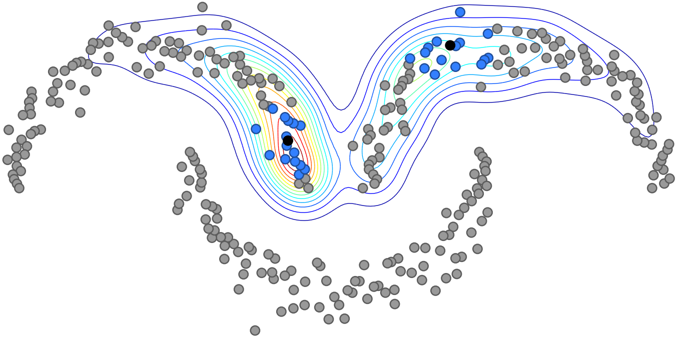
- data points (∘), query points (•), nearest neighbors (∘)
- iteration 1×30

ranking on manifolds: multiple queries



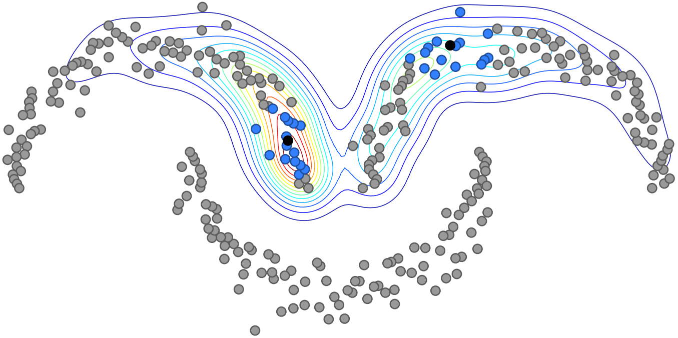
- data points (∘), query points (•), nearest neighbors (∘)
- iteration 2×30

ranking on manifolds: multiple queries



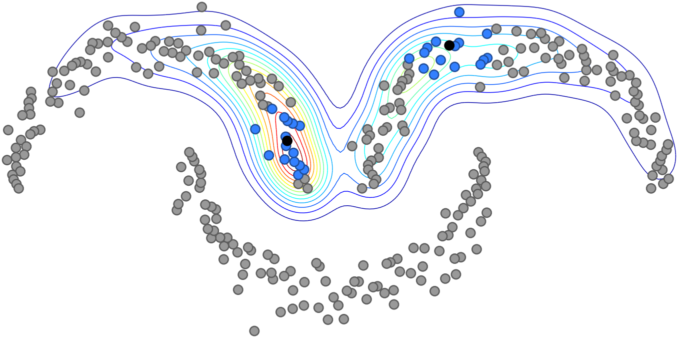
- data points (∘), query points (•), nearest neighbors (∘)
- iteration 3×30

ranking on manifolds: multiple queries



- data points (∘), query points (•), nearest neighbors (∘)
- iteration 4×30

ranking on manifolds: multiple queries



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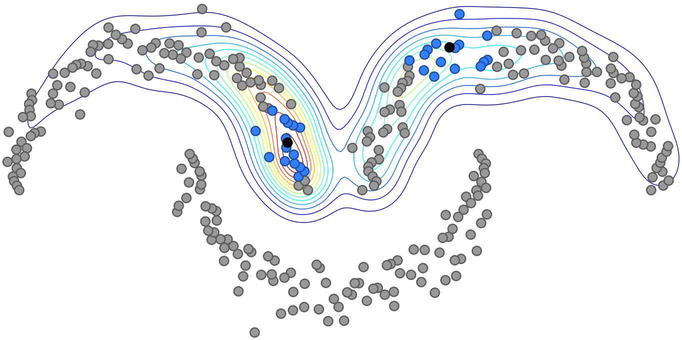
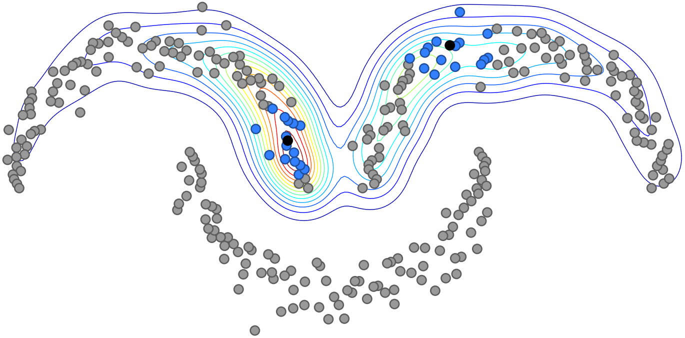
ranking on manifolds: multiple queries



- data points (∘), query points (•), nearest neighbors (∘)
- iteration 6×30

ranking on manifolds: multiple queries



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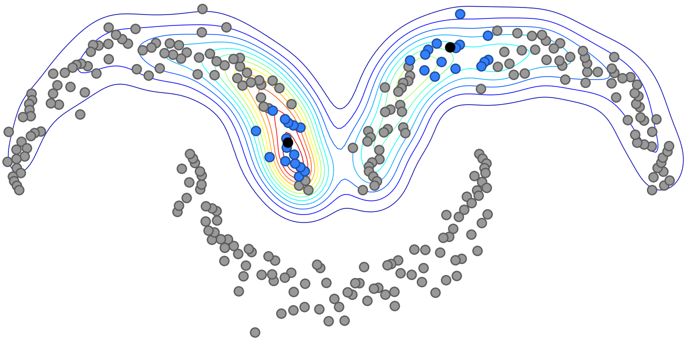
ranking on manifolds: multiple queries



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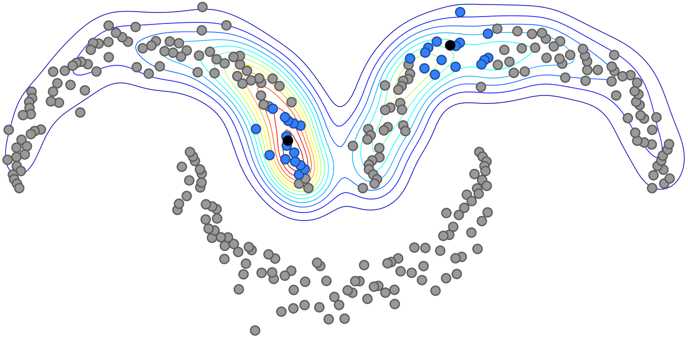
ranking on manifolds: multiple queries



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ranking on manifolds: random walk

[Zhou et al. 2003]

- reciprocal nearest neighbor graph on n data points
- non-negative, symmetric, sparse adjacency matrix $W \in \mathbb{R}^{n \times n}$, with zero diagonal (no self-loops)
- symmetrically normalized adjacency matrix

$$\mathcal{W} := D^{-1/2} W D^{-1/2}$$

  where $D = \mathrm{diag}(W\mathbf{1})$ is the degree matrix
- query: vector $\mathbf{y} \in \mathbb{R}^n$ with $y_i = \mathbb{1}[i \text{ is query}]$
- random walk: starting with any $\mathbf{f}^{(0)} \in \mathbb{R}^n$, iterate

$$\mathbf{f}^{(\tau)} = \alpha \mathcal{W} \mathbf{f}^{(\tau-1)} + (1-\alpha)\mathbf{y}$$

  where $\alpha \in [0,1)$ (typically close to 1)
- rank data points by descending order of $\mathbf{f}$

Zhou, Weston, Gretton, Bousquet and Schölkopf. NIPS 2003. Ranking on Data Manifolds.

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ranking as solving a linear system

[Iscen et al. 2017]

- query: sparse vector $\mathbf{y} \in \mathbb{R}^n$ with nearest neighbor similarities

$$y_i = \sum_{\mathbf{q} \in Q} s(\mathbf{q}, \mathbf{x}_i) \times \mathbb{1}[\mathbf{x}_i \in \mathrm{NN}_X^k(\mathbf{q})]$$

where $Q, X \subset \mathbb{R}^d$ query/data points, $\mathbf{x}_i \in X$, s similarity function

- regularized Laplacian

$$\mathcal{L}_\alpha = \frac{I - \alpha \mathcal{W}}{1 - \alpha}$$

- solve linear system

$$\mathcal{L}_\alpha \mathbf{f} = \mathbf{y}$$

by conjugate gradient method

Iscen, Tolias, Avrithis, Furon and Chum. CVPR 2017. Efficient Diffusion on Region Manifolds: Recovering Small Objects With Compact CNN Representations.

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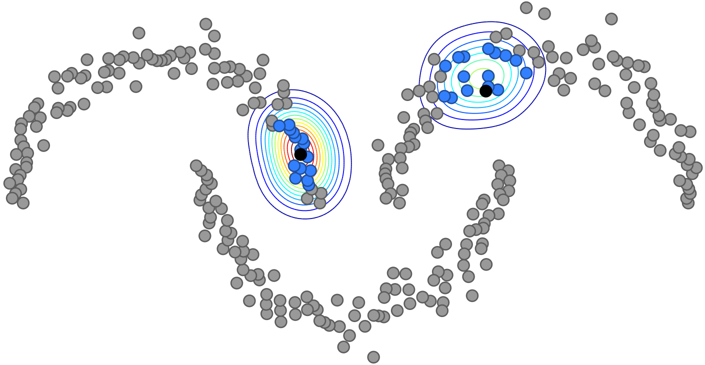
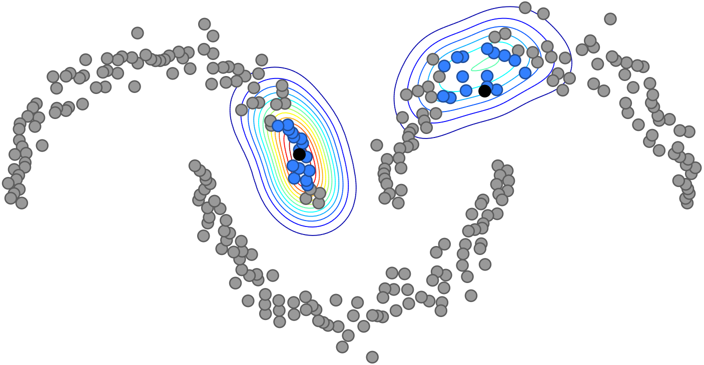
ranking by conjugate gradient



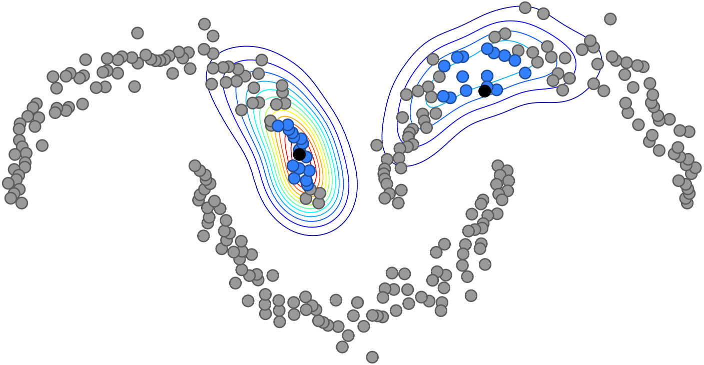
- data points (∘), query points (•), nearest neighbors (•)
- iteration 0×2

ranking by conjugate gradient



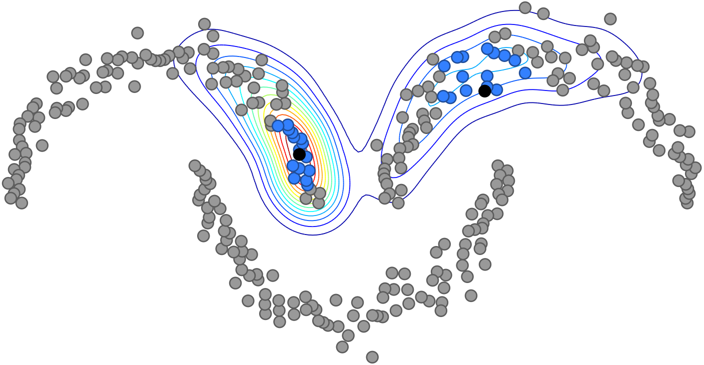
- data points (•), query points (•), nearest neighbors (•)
- iteration 1×2

ranking by conjugate gradient



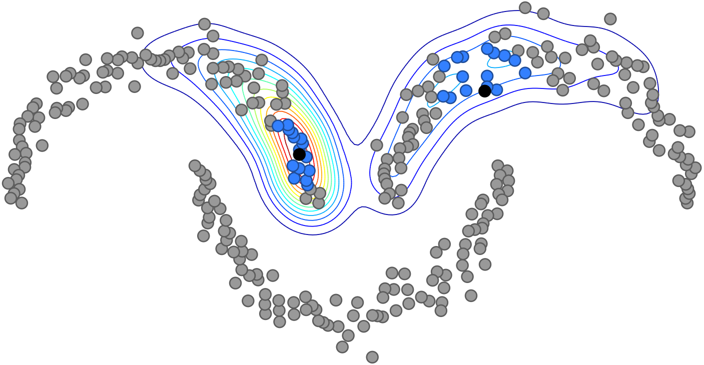
- data points (∘), query points (•), nearest neighbors (•)
- iteration 2×2

ranking by conjugate gradient



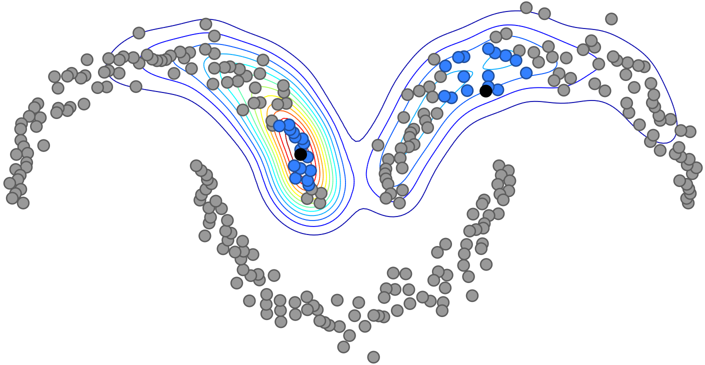
- data points (∘), query points (•), nearest neighbors (∘)
- iteration 3×2

ranking by conjugate gradient



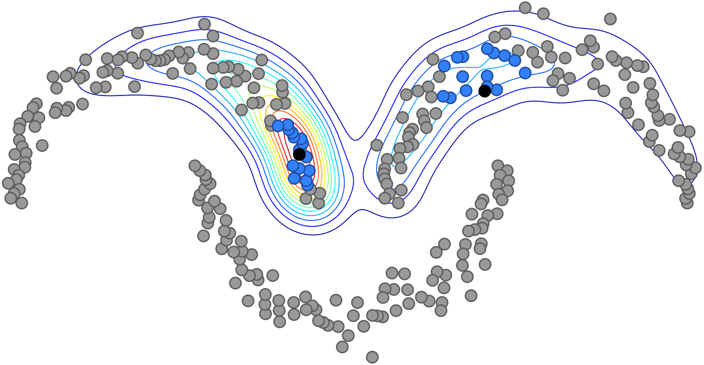
- data points (∘), query points (•), nearest neighbors (•)
- iteration 4×2

ranking by conjugate gradient



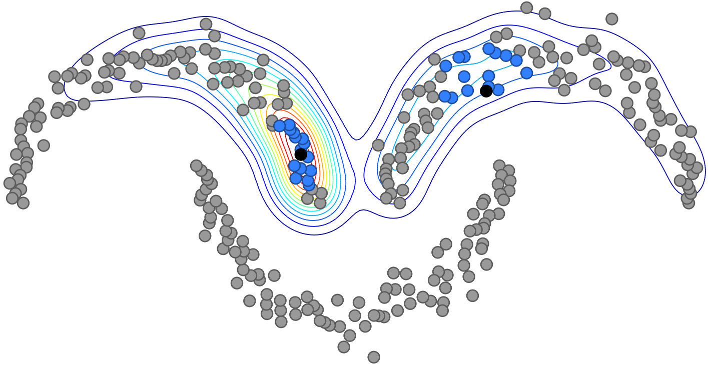
- data points (∘), query points (•), nearest neighbors (∘)
- iteration 5×2

ranking by conjugate gradient



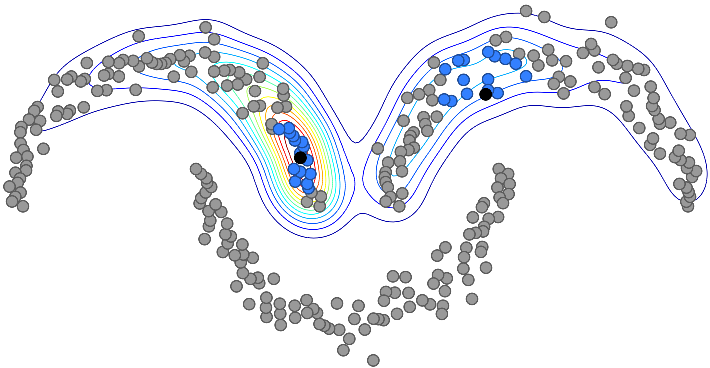
- data points (∘), query points (•), nearest neighbors (∘)
- iteration 6×2

ranking by conjugate gradient



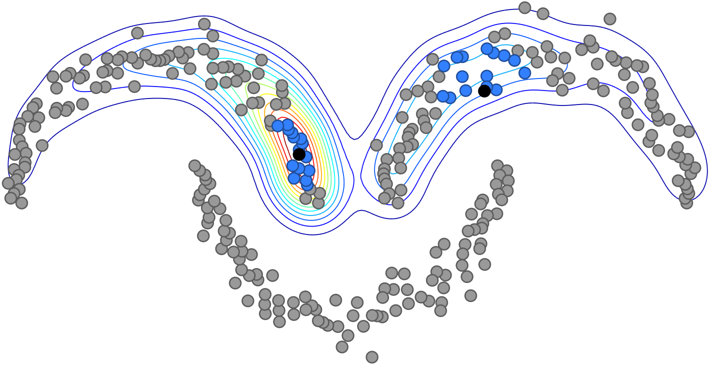
- data points (∘), query points (•), nearest neighbors (•)
- iteration 7×2

ranking by conjugate gradient



- data points (∘), query points (•), nearest neighbors (∘)
- iteration 8×2

ranking by conjugate gradient



- data points (∘), query points (•), nearest neighbors (•)
- iteration 9×2

ranking as solving a linear system

- represent image by global descriptor or multiple regional descriptors
- perform initial query based on Euclidean nearest neighbors
- re-rank by solving linear system
- ResNet-101 fine-tuned by BoW + R-MAC + re-ranking:
    - mAP 87.1 (95.8) on Oxford5k, 96.5 (96.9) on Paris6k
    - 1 (21) descriptors/image $\times$ 2048 dimensions

Iscen, Tolias, Avrithis, Furon and Chum. CVPR 2017. Efficient Diffusion on Region Manifolds: Recovering Small Objects With Compact CNN Representations.

mining on manifolds

[Iscen et al. 2018]

- data points (∘), query point $\mathbf{x}$ (•)

Iscen, Tolias, Avrithis and Chum. 2018 (unpublished). Mining on Manifolds: Metric Learning without Labels.

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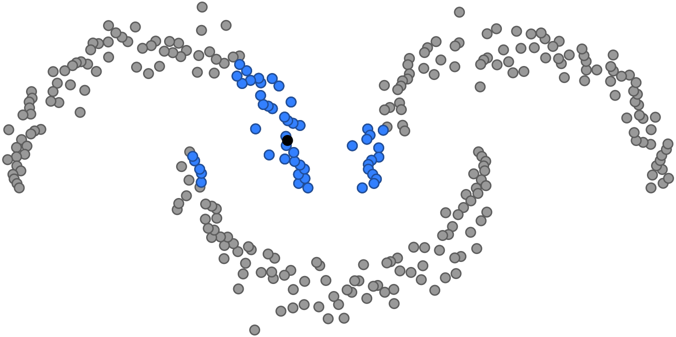

- data points (∘), query point $\mathbf{x}$ (•)
- Euclidean nearest neighbors $E(\mathbf{x})$ (∘)

Iscen, Tolias, Avrithis and Chum. 2018 (unpublished). Mining on Manifolds: Metric Learning without Labels.

mining on manifolds

[Iscen et al. 2018]

- data points ($\circ$), query point $\mathbf{x}$ ($\bullet$)
- manifold nearest neighbors $M(\mathbf{x})$ ($\circ$)

Iscen, Tolias, Avrithis and Chum. 2018 (unpublished). Mining on Manifolds: Metric Learning without Labels.

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[Iscen et al. 2018]

- data points (∘), query point $\mathbf{x}$ (•)
- hard positives $S^+ = M(\mathbf{x}) \setminus E(\mathbf{x})$ (∘)

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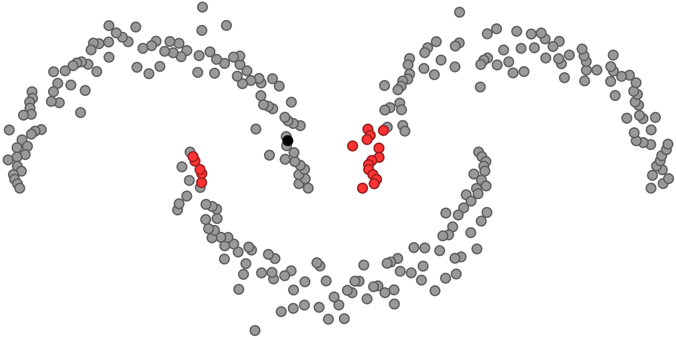
[Iscen et al. 2018]



- data points (∘), query point $\mathbf{x}$ (•)
- hard negatives $S^- = E(\mathbf{x}) \setminus M(\mathbf{x})$ (•)

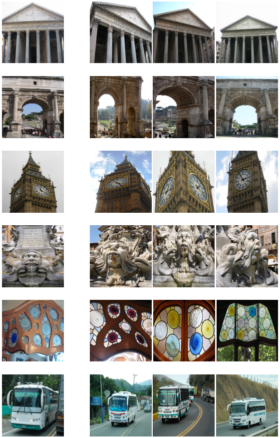
Iscen, Tolias, Avrithis and Chum. 2018 (unpublished). Mining on Manifolds: Metric Learning without Labels.

mining on manifolds

- query (anchor) $(\mathbf{x})$
- positives $S^{+}(\mathbf{x})$ *vs.* Euclidean neighbors $E(\mathbf{x})$
- negatives $S^{-}(\mathbf{x})$ *vs.* Euclidean non-neighbors $X \setminus E(\mathbf{x})$

Iscen, Tolias, Avrithis and Chum. 2018 (unpublished). Mining on Manifolds: Metric Learning without Labels.

mining on manifolds



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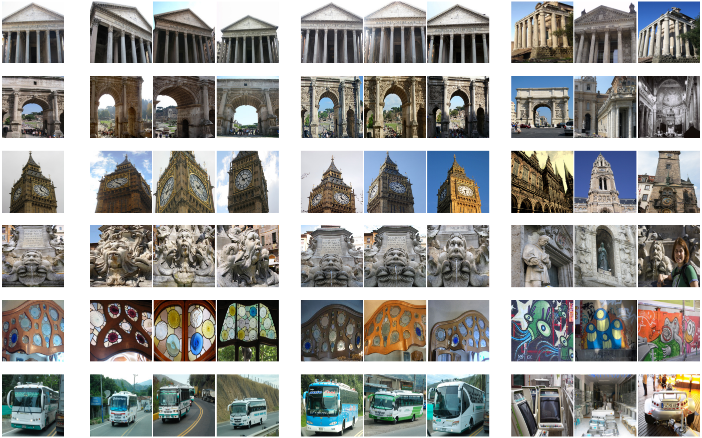

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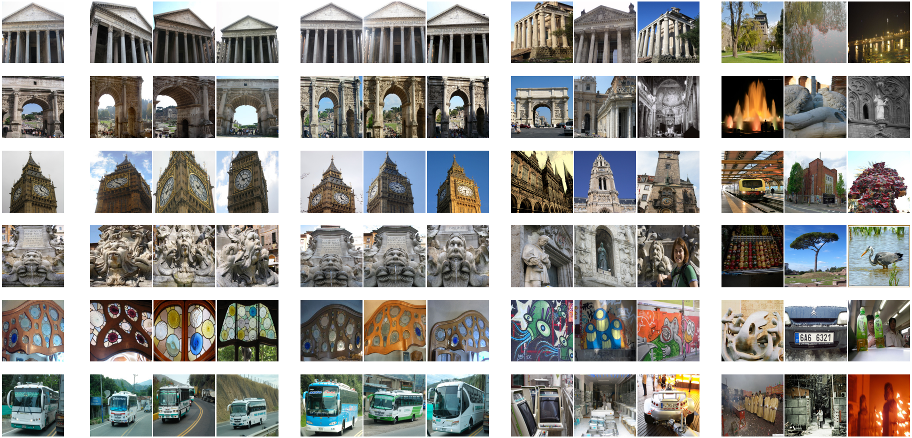

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mining on manifolds

- pre-train network
- extract descriptors on unlabeled dataset
- construct nearest neighbor graph
- sample anchors, measure Euclidean and manifold distances
- sample positives and negatives
- fine-tune using contrastive or triplet loss
- VGG-16 + R-MAC, mAP on Oxford5k (Paris6k):
  - pre-trained on ImageNet: 68.0 (76.6)
  - fine-tuning with SIFT + 3d reconstruction pipeline: 77.8 (84.1)
  - unsupervised fine-tuning: 78.2 (85.1)

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summary

- bag-of-words and inverted index is only a crude form of approximate nearest neighbor search
- global descriptors are compact and fast, but do not perform as well as local descriptors
- compressed representation for nearest neighbor search are effective if manifold is captured correctly
- pooling CNN representations is best at last convolutional layers: MAC, R-MAC, SPoC, CroW
- fine-tuning with constrastive or triplet loss allows transferring to a new domain and learning to rank as opposed to classify
- now that images are represented by a global descriptor or just a few regional descriptors, graph methods are more applicable than ever
- modeling the manifold explicitly allows unsupervised fine-tuning without labels, auxiliary systems (*e.g.* SIFT pipeline), or other information (*e.g.* temporal neighborhood in video)

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