



DEEP LEARNING WORKSHOP

Dublin City University
28-29 April 2017



Day 2 Lecture 6

Content-based Image Retrieval



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Overview

- What is content based image retrieval?
- The classic SIFT retrieval pipeline
- Using off the shelf CNN features for retrieval
- Learning representations for retrieval

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The problem: query by example

Given:

- An example query image that illustrates the user's information need
- A very large dataset of images

Task:

- Rank all images in the dataset according to how likely they are to fulfil the user's information need



Classification

Query: This chair



Results from dataset classified as “chair”

Retrieval

Query: This chair

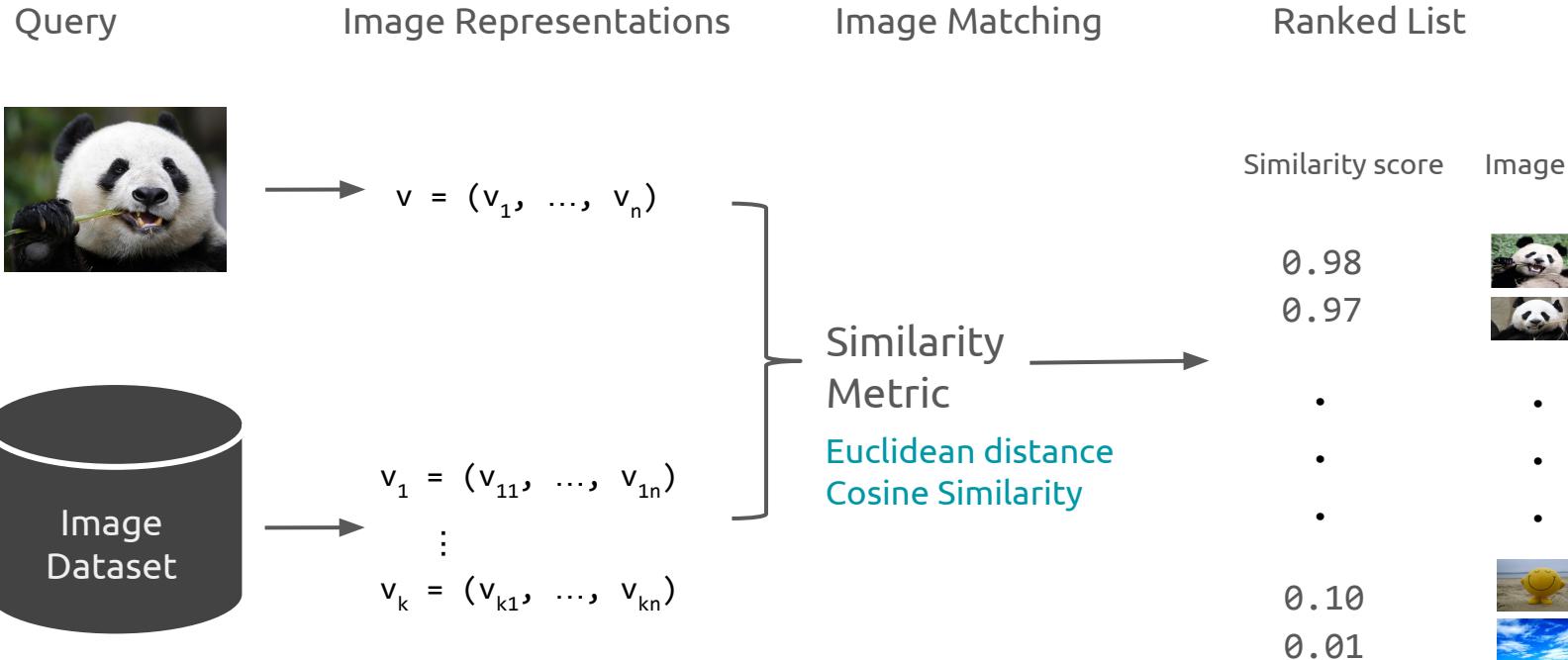


Results from dataset ranked by similarity to the query

Overview

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- The classic SIFT retrieval pipeline
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- Learning representations for retrieval

The retrieval pipeline

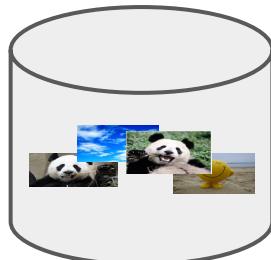


The classic SIFT retrieval pipeline

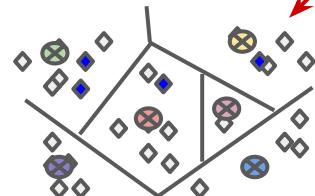


variable number of
feature vectors per image

$$\begin{aligned} v_1 &= (v_{11}, \dots, v_{1n}) \\ &\vdots \\ v_k &= (v_{k1}, \dots, v_{kn}) \end{aligned}$$



N-Dimensional
feature space



Bag of Visual
Words

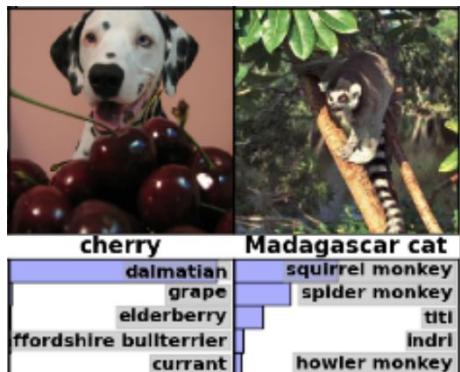
M visual words
(M clusters)

INVERTED FILE	
word	Image ID
1	1, 12,
2	1, 30, 102
3	10, 12
4	2,3
6	10

Large vocabularies (50k-1M)
Very fast!
Typically used with SIFT features

Convolutional neural networks and retrieval

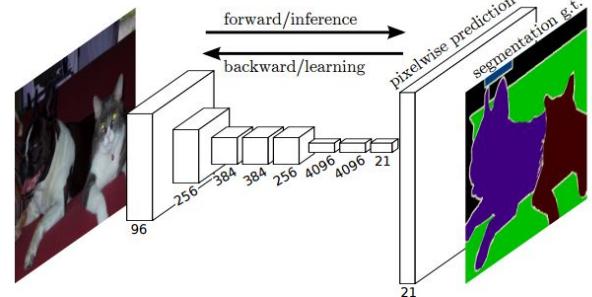
Classification



Object Detection



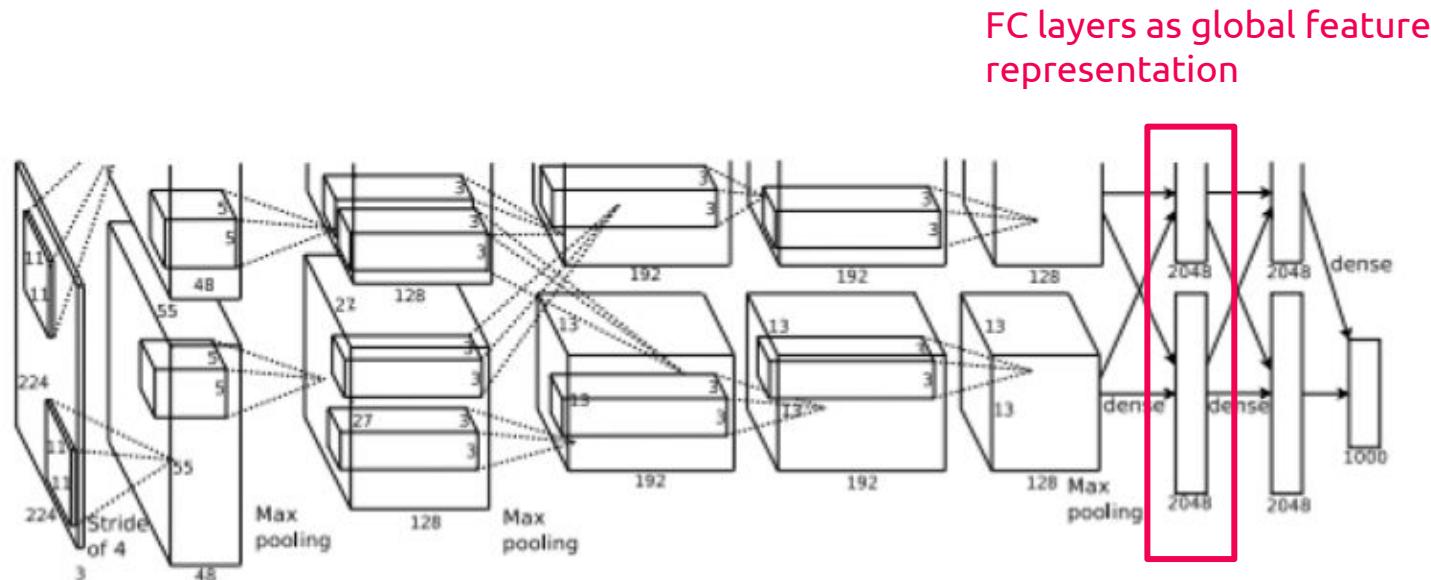
Segmentation



Overview

- What is content based image retrieval?
- The classic SIFT retrieval pipeline
- **Using off-the-shelf CNN features for retrieval**
- Learning representations for retrieval

Off-the-shelf CNN representations



Off-the-shelf CNN representations

Neural codes for retrieval [1]

- FC7 layer (4096D)
- L^2 norm + PCA whitening + L^2 norm
- Euclidean distance
- Only better than traditional SIFT approach after fine tuning on similar domain image dataset.

CNN features off-the-shelf: an astounding baseline for recognition [2]

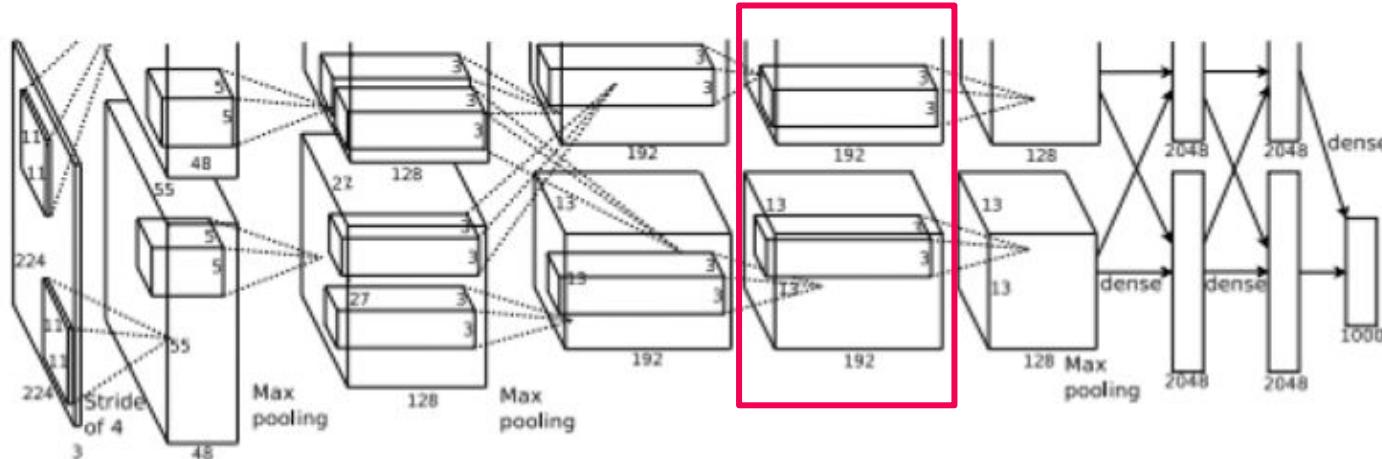
- Extending Babenko's approach with spatial search
- Several features extracted by image (sliding window approach)
- Really good results but too computationally expensive for practical situations

[1] Babenko et al, [Neural codes for image retrieval](#) CVPR 2014

[2] Razavian et al, [CNN features off-the-shelf: an astounding baseline for recognition](#), CVPR 2014

Off-the-shelf CNN representations

sum/max pool conv features across filters



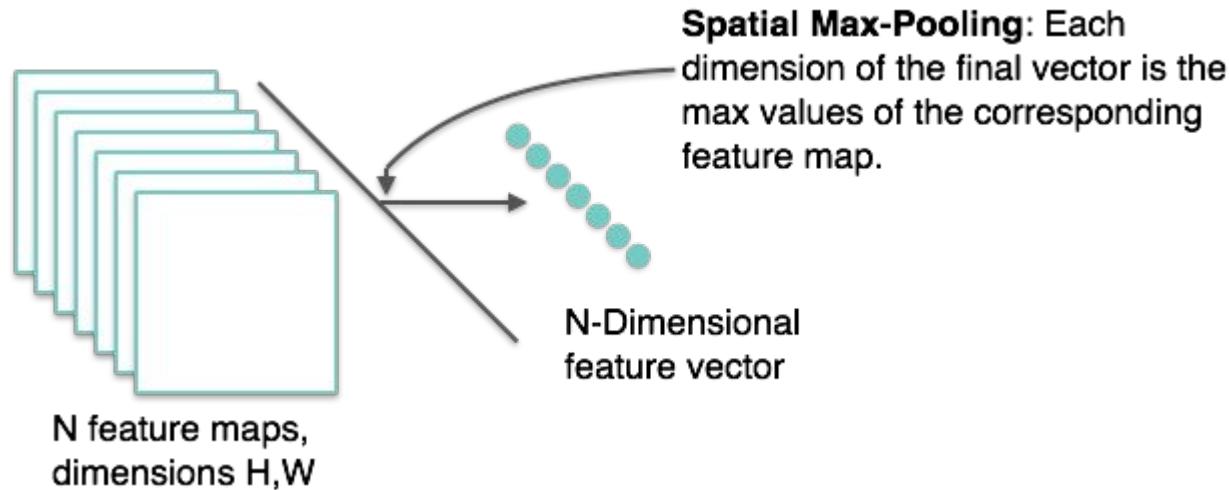
Babenko and Lempitsky, [Aggregating local deep features for image retrieval](#). ICCV 2015

Tolias et al. [Particular object retrieval with integral max-pooling of CNN activations](#). arXiv:1511.05879.

Kalantidis et al. Cross-dimensional Weighting for Aggregated Deep Convolutional Features. arXiv:1512.04065.

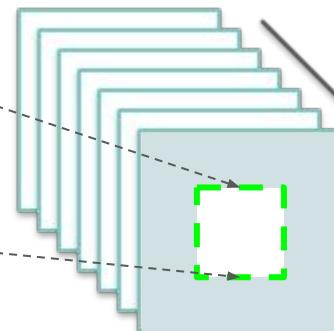
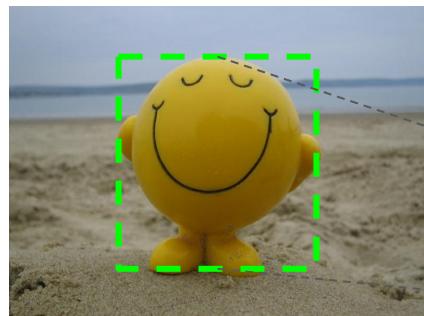
Off-the-shelf CNN representations

Descriptors from convolutional layers



Off-the-shelf CNN representations

Pooling features on conv layers allow to describe specific parts of an image



N feature maps,
dimensions H, W

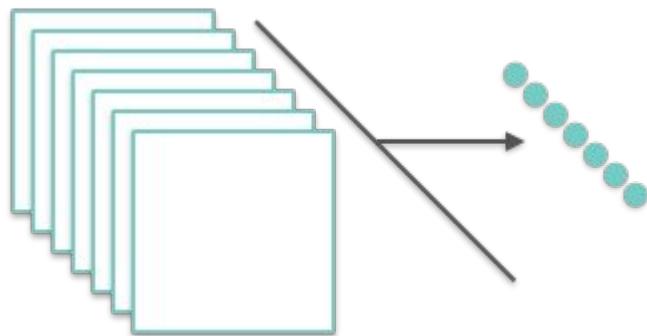
Spatial Max-Pooling: Each dimension of the final vector is the max values of the corresponding feature map.



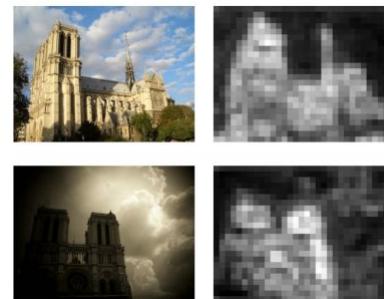
N -Dimensional
feature vector

Off-the-shelf CNN representations

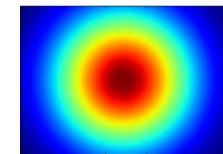
Sum/max pooling operation of a conv layer



Apply spatial weighting on the features before pooling them



[1] weighting based on 'strength' of the local features



[2] weighting based on the distance to the center of the image

[2] Babenko and Lempitsky, [Aggregating local deep features for image retrieval](#). ICCV 2015

[1] Kalantidis et al. [Cross-dimensional Weighting for Aggregated Deep Convolutional Features](#). ECCV 2016

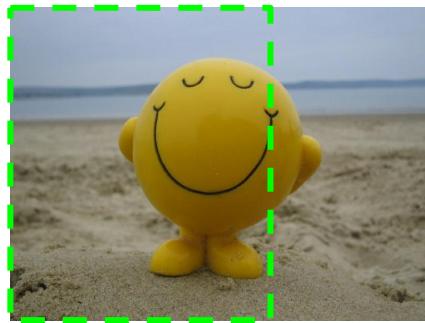
R-MAC

Regional Maximum Activation of Convolution.

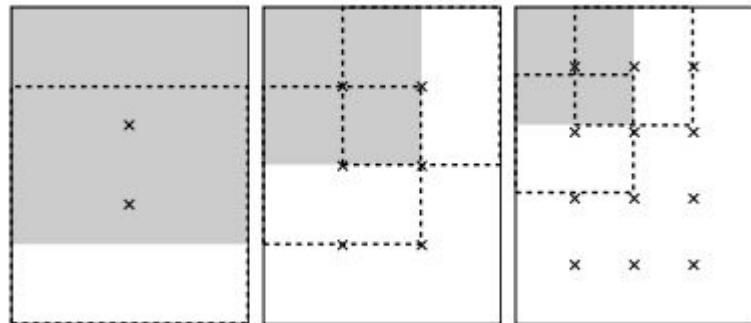
Settings

- Fully convolutional off-the-shelf VGG16
- Pool5
- Spatial Max pooling
- High Resolution images
- Global descriptor based on aggregating region vectors
- Sliding window approach

R-MAC



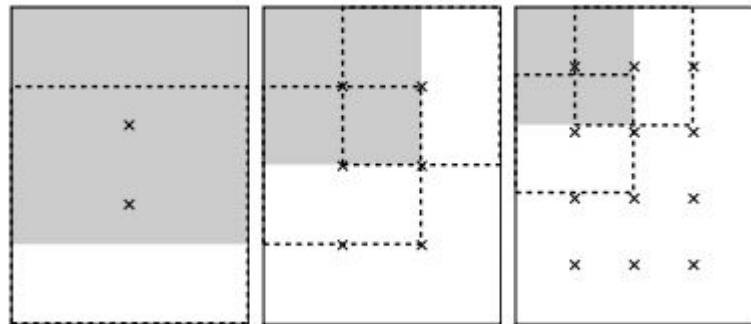
Region1



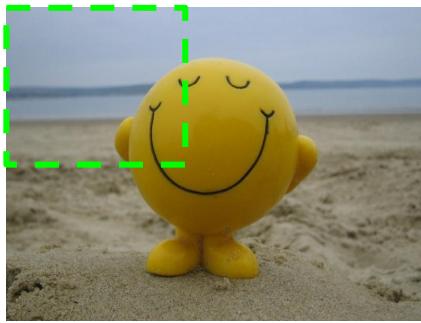
R-MAC



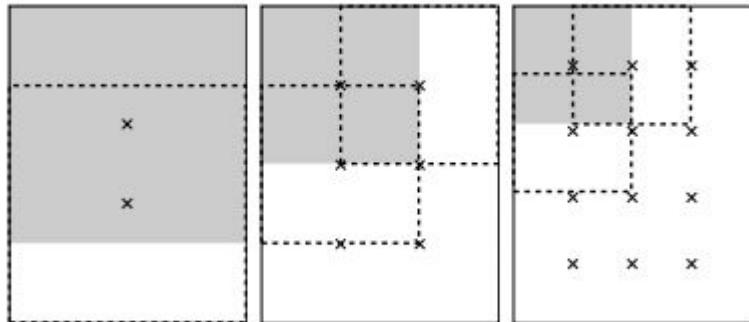
Region1
Region2



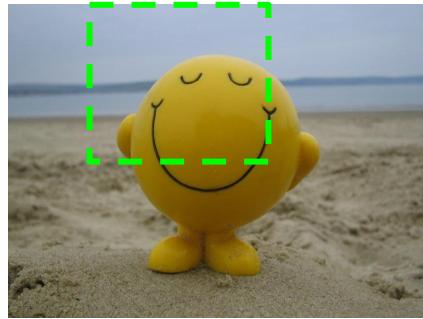
R-MAC



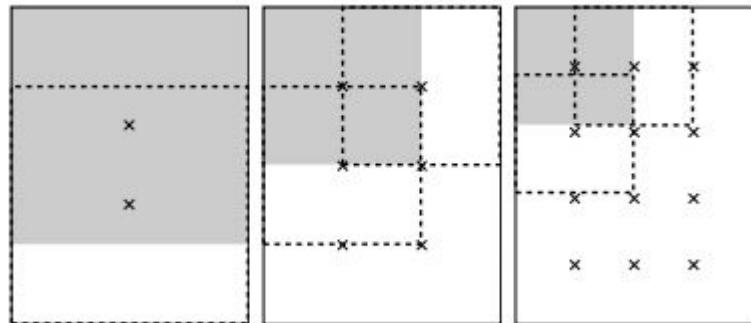
Region1
Region2
Region3



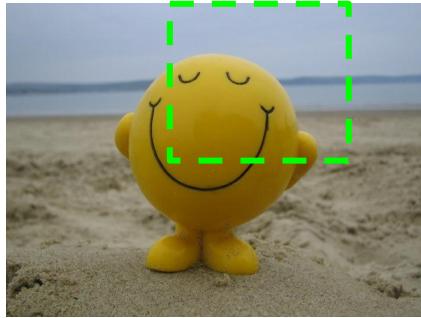
R-MAC



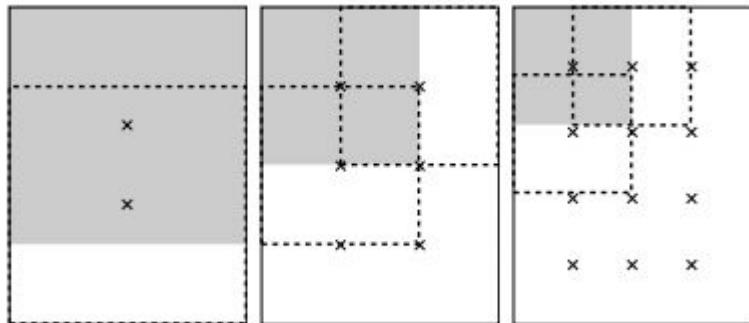
Region1
Region2
Region3
Region4



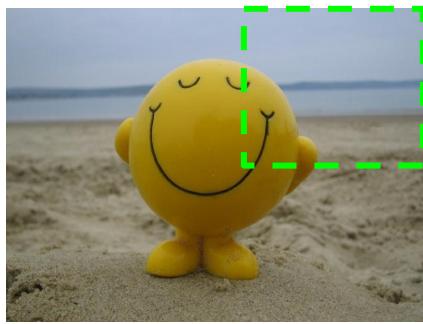
R-MAC



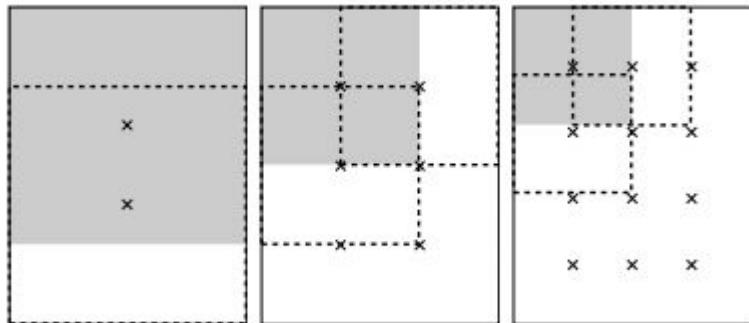
Region1
Region2
Region3
Region4
...



R-MAC



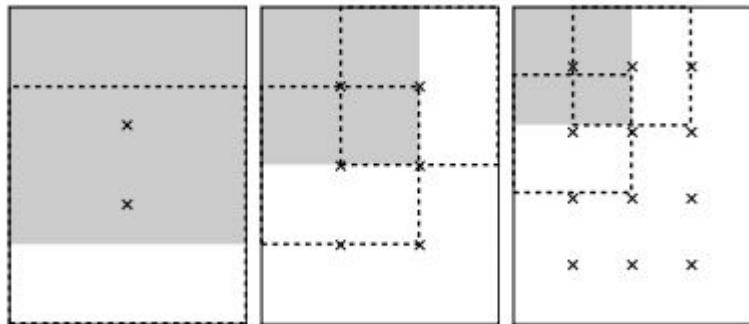
Region1
Region2
Region3
Region4
...



R-MAC



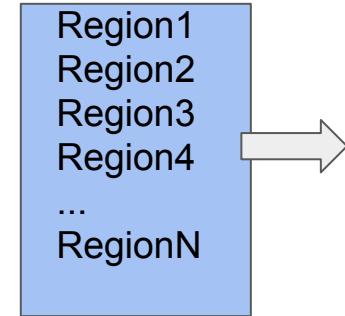
Region1
Region2
Region3
Region4
...
RegionN



R-MAC

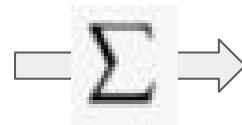


Region vectors
512D

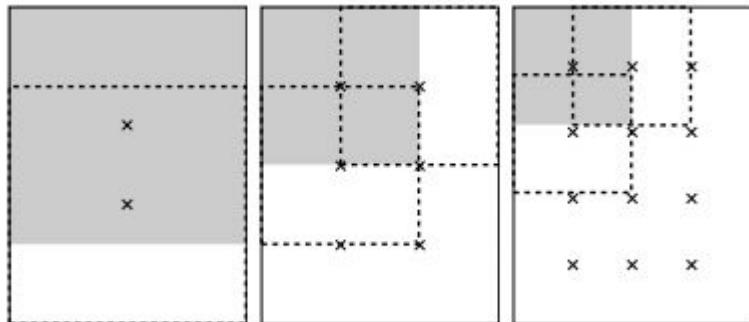


I2-PCAw-I2

Region1
Region2
Region3
Region4
...
RegionN

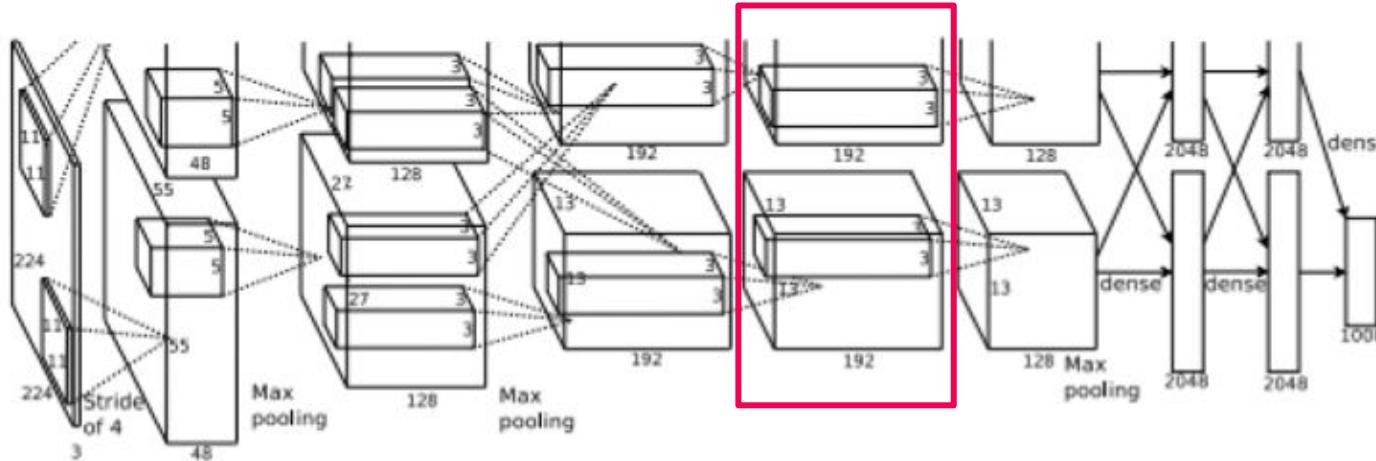


Global
vector
512D



Off-the-shelf CNN representations

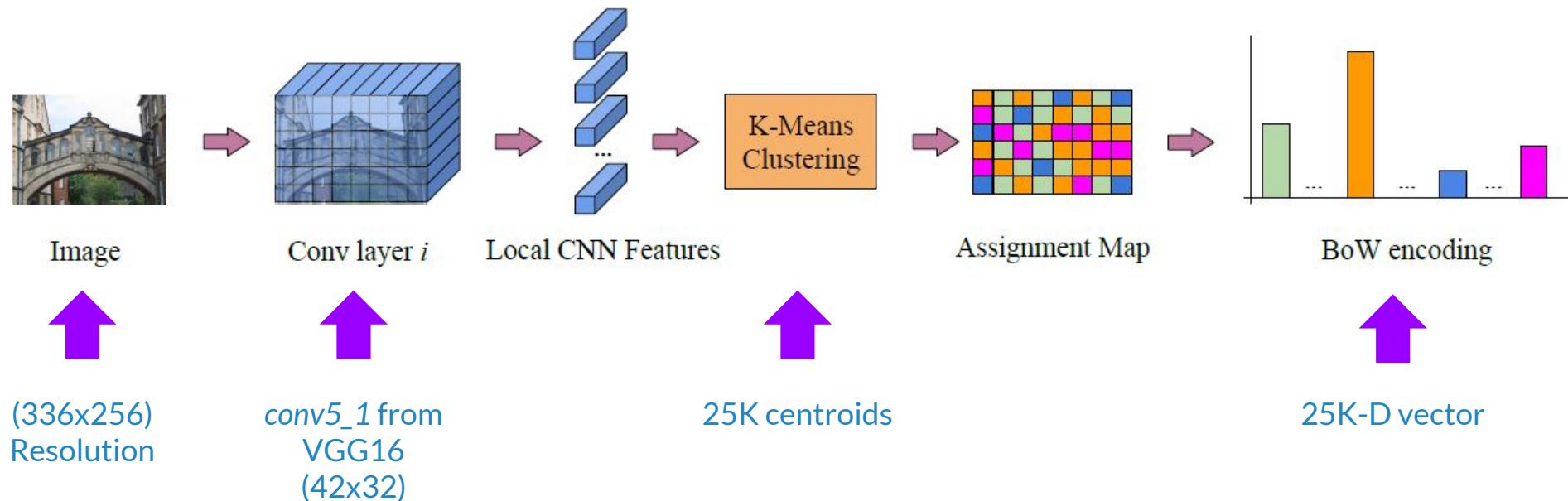
BoW, VLAD encoding of conv features



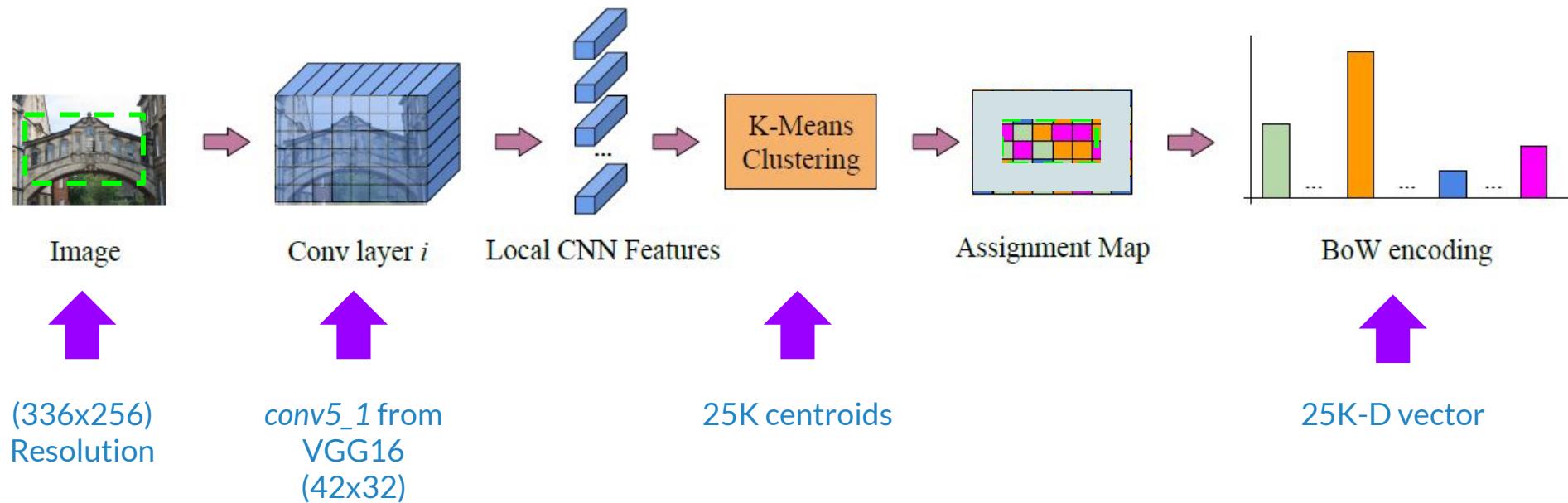
Ng et al. [Exploiting local features from deep networks for image retrieval](#). CVPR Workshops 2015
Mohedano et al. [Bags of Local Convolutional Features for Scalable Instance Search](#). ICMR 2016

Off-the-shelf CNN representations

Descriptors from convolutional layers

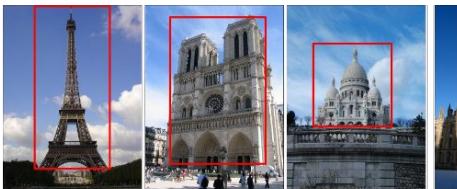


Off-the-shelf CNN representations



Off-the-shelf CNN representations

Paris Buildings 6k



Oxford Buildings 5k



TRECVID Instance Search 2013
(subset of 23k frames)

		Oxford 5k	Paris 6k	INS 23k
BoW	GS	0.650	0.698	0.323
	LS	0.739	0.819	0.295
Sum pooling (as ours)	GS	0.606	0.712	0.156
	LS	0.583	0.742	0.097
Sum pooling (as in [7])	GS	0.672	0.774	0.139
	LS	0.683	0.763	0.120

[7] Kalantidis et al. [Cross-dimensional Weighting for Aggregated Deep Convolutional Features](#). arXiv:1512.04065.

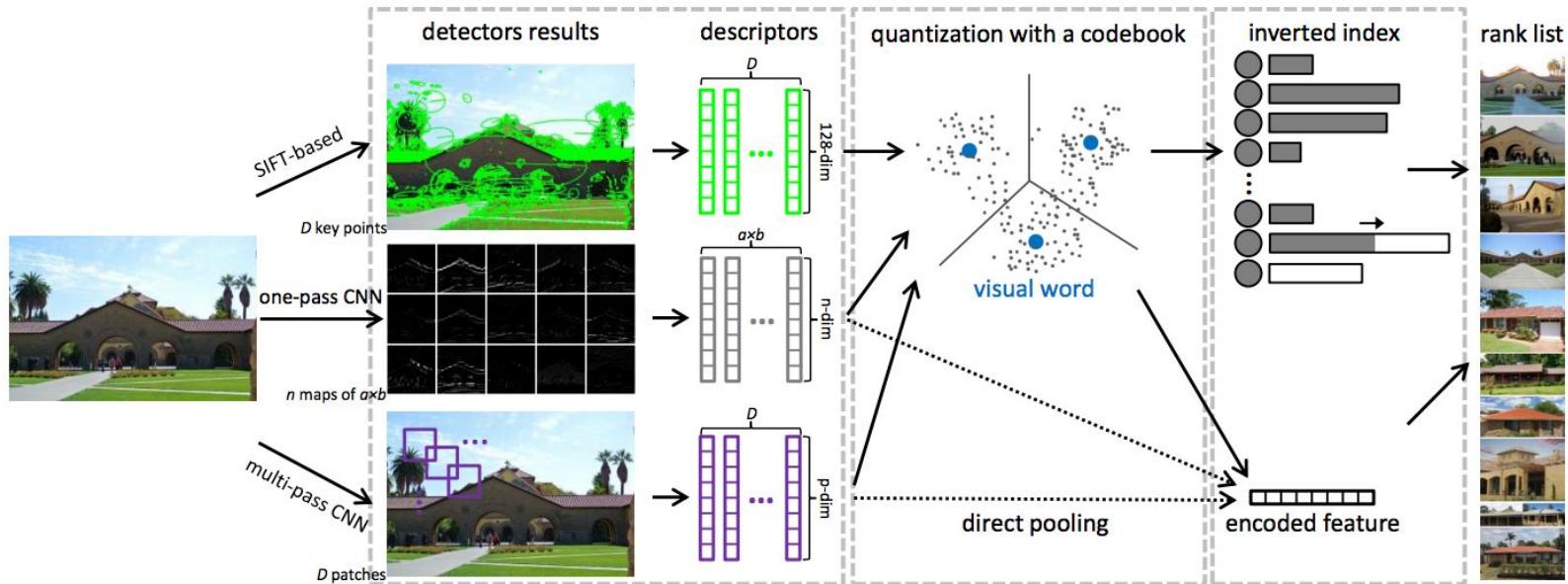
Mohedano et al. [Bags of Local Convolutional Features for Scalable Instance Search](#). ICMR 2016

Off-the-shelf CNN representations

CNN representations

- L^2 Normalization + PCA whitening + L^2 Normalization
- Cosine similarity
- Convolutional features better than fully connected features
- Convolutional features keep spatial information → retrieval + object location
- Convolutional layers allows custom input size.
- If data labels available, fine tuning the network to the image domain improves CNN representations.

CNN as a feature extractor



source : Zheng, [SIFT Meets CNN: A Decade Survey of Instance Retrieval](#), 2016

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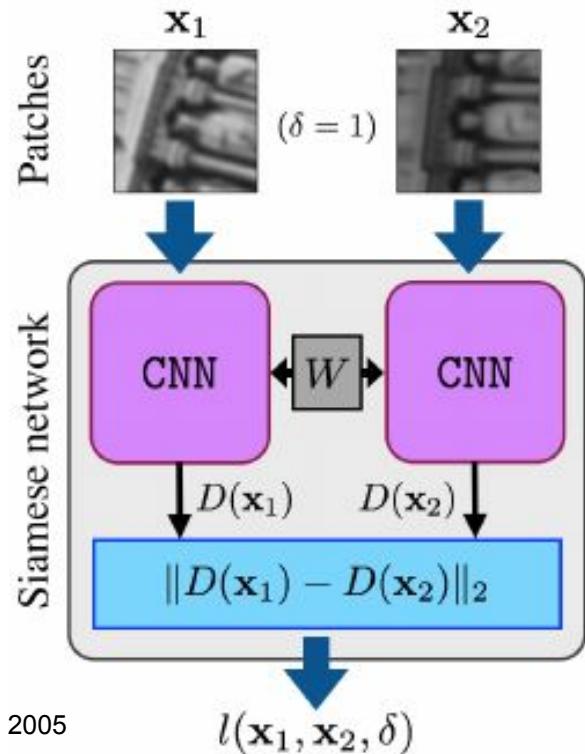
What loss function should we use?

Learning representations for retrieval

Siamese network: network to learn a function that maps input patterns into a target space such that L^2 norm in the target space approximates the semantic distance in the input space.

Applied in:

- Dimensionality reduction [1]
- Face verification [2]
- Learning local image representations [3]



[1] Song et al.: [Deep metric learning via lifted structured feature embedding](#). CVPR 2015

[2] Chopra et al. [Learning a similarity metric discriminatively, with application to face verification](#) CVPR' 2005

[3] Simo-Serra et al. [Fracking deep convolutional image descriptors](#). CoRR, abs/1412.6537, 2014

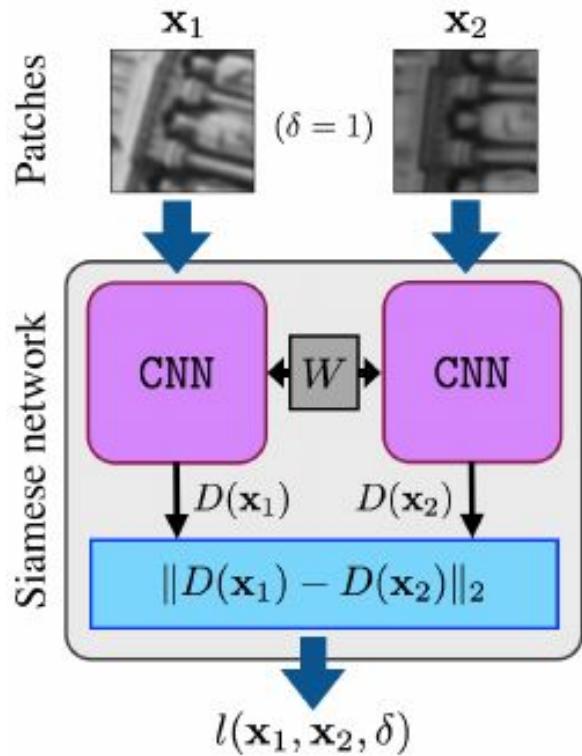
Learning representations for retrieval

Siamese network: network to learn a function that maps input patterns into a target space such that L^2 norm in the target space approximates the semantic distance in the input space.

$$l(\mathbf{x}_1, \mathbf{x}_2, \delta) = \boxed{\delta \cdot l_P(d_D(\mathbf{x}_1, \mathbf{x}_2))} + \boxed{(1 - \delta) \cdot l_N(d_D(\mathbf{x}_1, \mathbf{x}_2))}$$

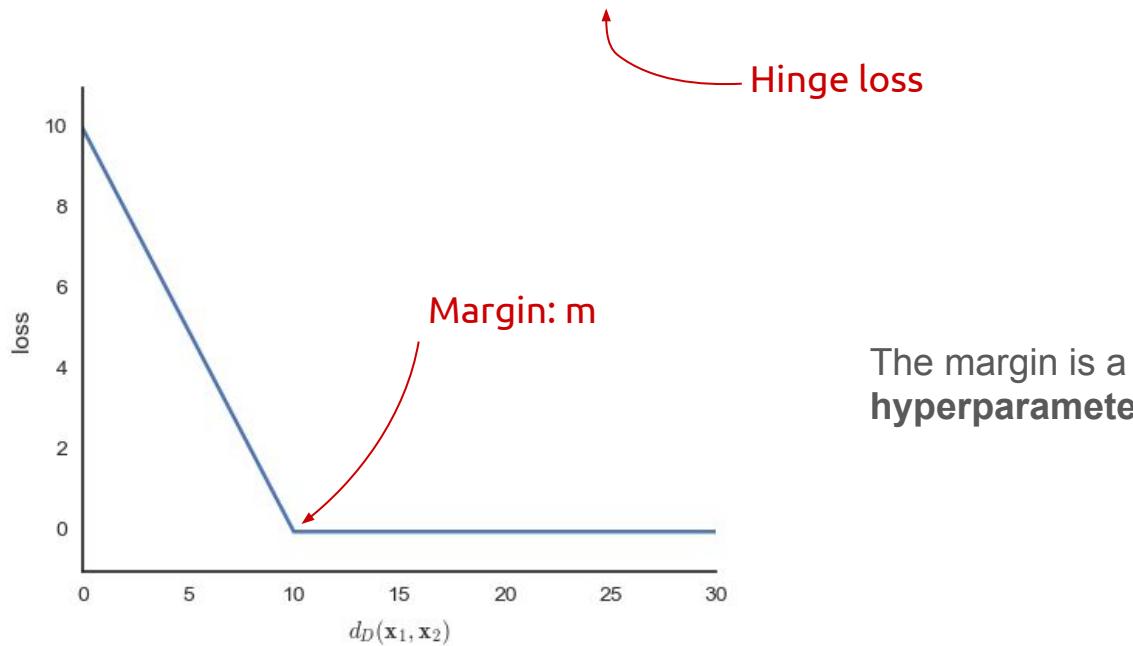
$$l_P(d_D(\mathbf{x}_1, \mathbf{x}_2)) = d_D(\mathbf{x}_1, \mathbf{x}_2)$$

$$l_N(d_D(\mathbf{x}_1, \mathbf{x}_2)) = \max(0, m - d_D(\mathbf{x}_1, \mathbf{x}_2))$$



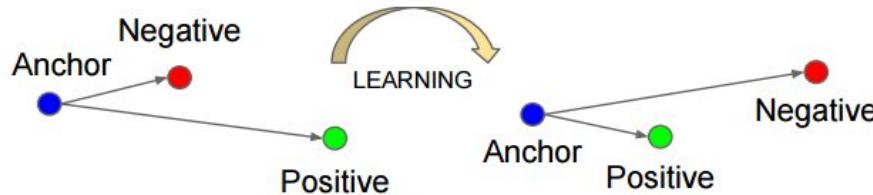
$$l_N(d_D(\mathbf{x}_1, \mathbf{x}_2)) = \max(0, m - d_D(\mathbf{x}_1, \mathbf{x}_2))$$

Negative pairs: if nearer than the margin, pay a linear penalty

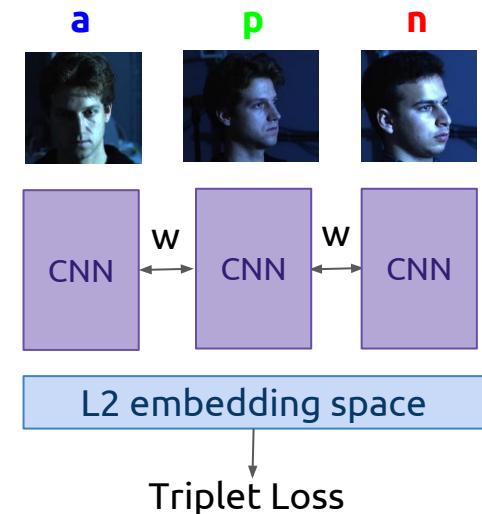


Learning representations for retrieval

Siamese network with triplet loss: loss function minimizes distance between query and positive and maximizes distance between query and negative

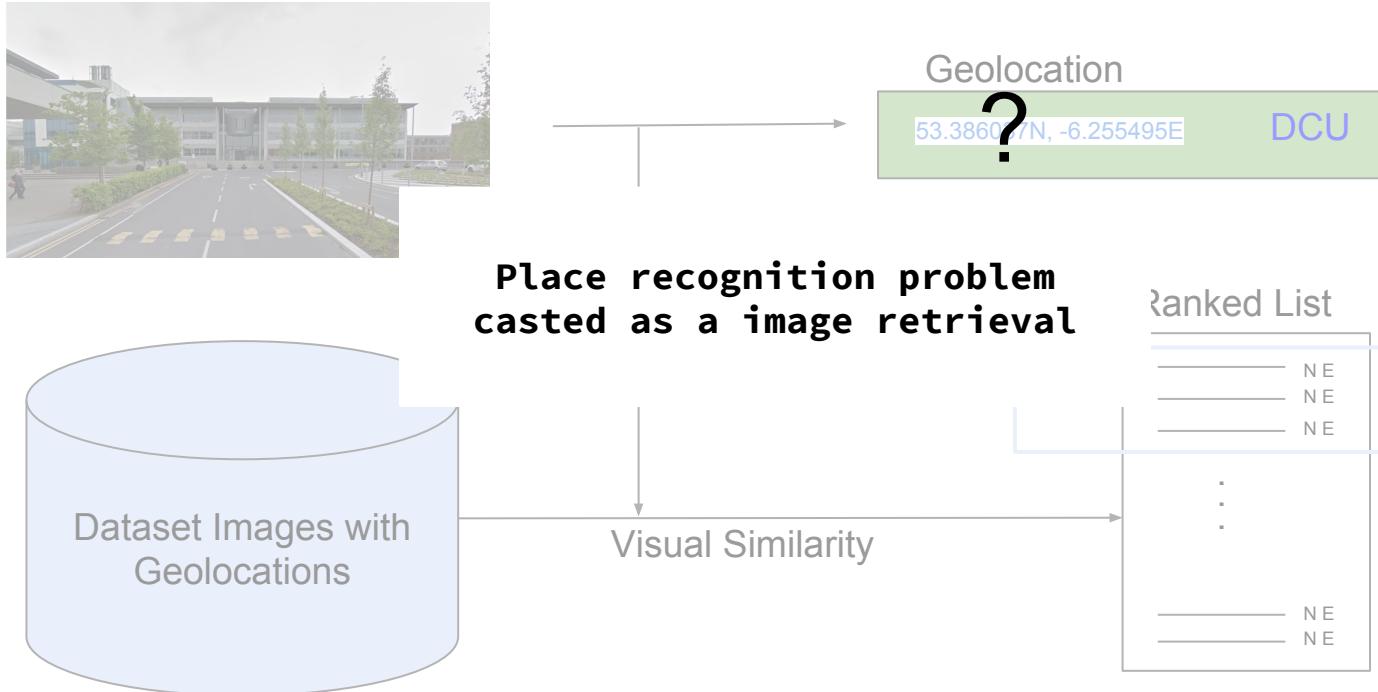


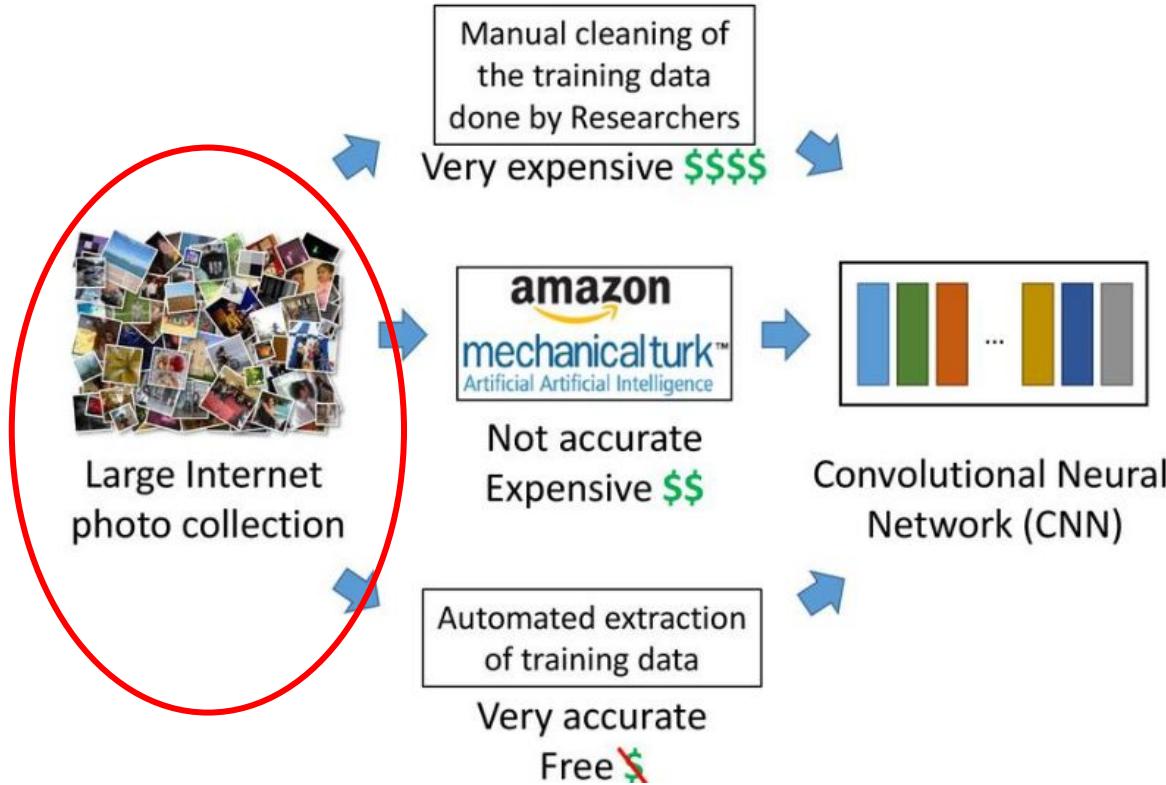
$$\|f(x_i^a) - f(x_i^p)\|_2^2 + \alpha < \|f(x_i^a) - f(x_i^n)\|_2^2$$



**How do we get the training
data?**

Exploring Image datasets with GPS coordinates (Google Time Machine Data)





Automatic data cleaning

Strong baseline (SIFT) + geometric verification + 3D camera estimation[1]

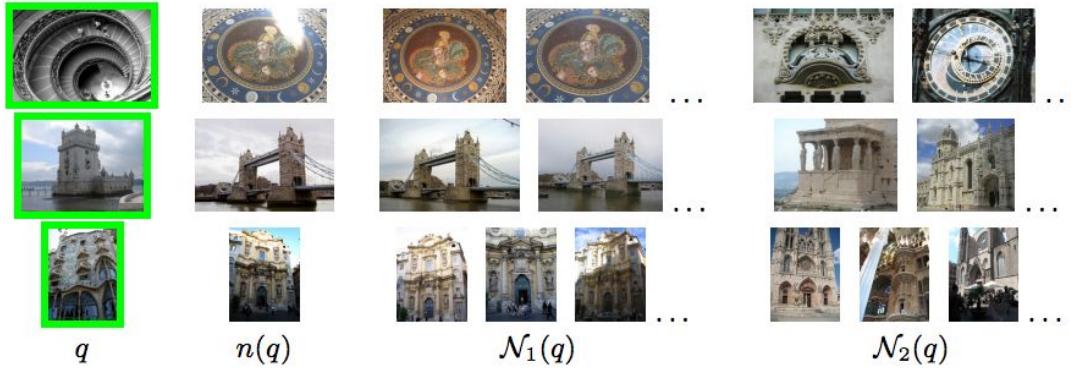
Further manual inspection

Further manual inspection

Radenović, [CNN Image Retrieval Learns from BoW: Unsupervised Fine-Tuning with Hard Examples](#), CVPR 2016
Gordo, [Deep Image Retrieval: Learning global representations for image search](#), CVPR 2016

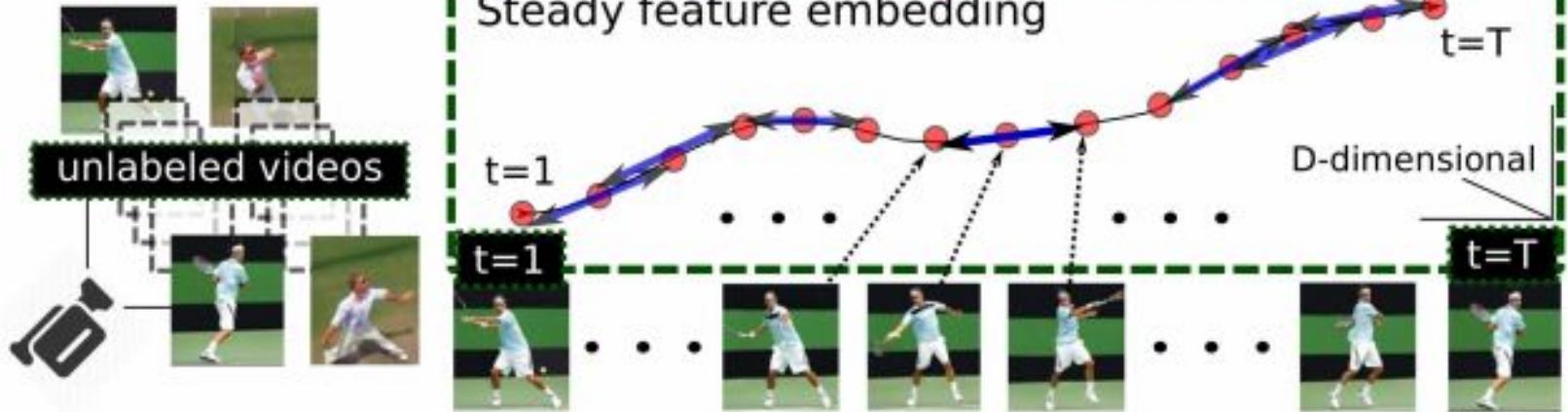
[1] Schonberger [From single image query to detailed 3D reconstruction](#)

Generating training pairs



Select the hardest negative

Select triplet which generates larger loss



Jayaraman and Grauman, [Slow and steady feature analysis: higher order temporal coherence in video](#), ECCV 2016

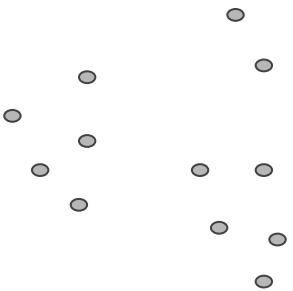
NetVLAD

Relja Arandjelović et al, [NetVLAD: CNN architecture for weakly supervised place recognition](#), CVPR 2016

VLAD

$\{\mathbf{x}_i\}$ Local features
Vectors dimension D

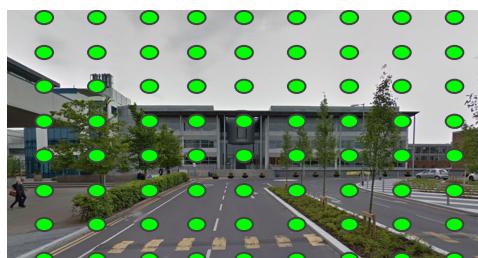
Feature Space D-dim



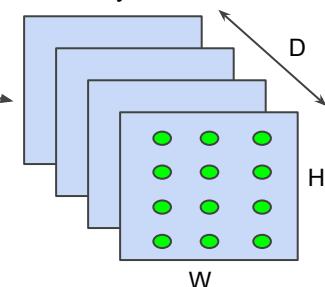
Sparse local feature extraction



Dense Local Feature extraction



Conv layer i



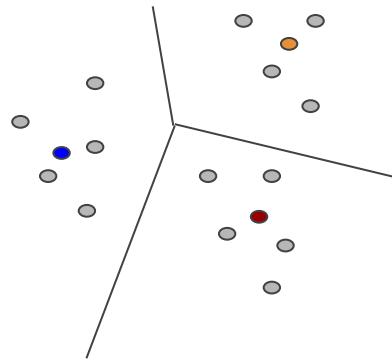
$N = H \times W$ local descriptors of dimension D

VLAD

$\{\mathbf{x}_i\}$ Local features
Vectors dimension D

$\{\mathbf{c}_k\}$ K cluster centers
Visual Vocabulary
(K vectors with dimension D)
Learnt from data with K-means

Feature Space D-dim



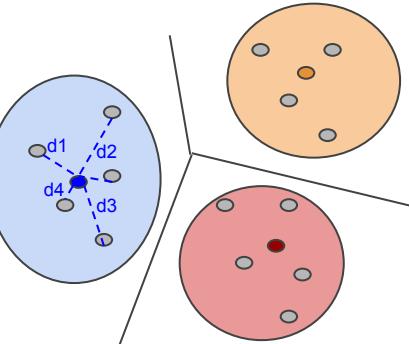
VLAD

$\{\mathbf{x}_i\}$ Local features
Vectors dimension D

$\{\mathbf{c}_k\}$ K cluster centers
Visual Vocabulary
(K vectors with dimension D)
Learnt from data with K-means

Feature Space D-dim

Sum of all residuals of the assignments to the cluster 1



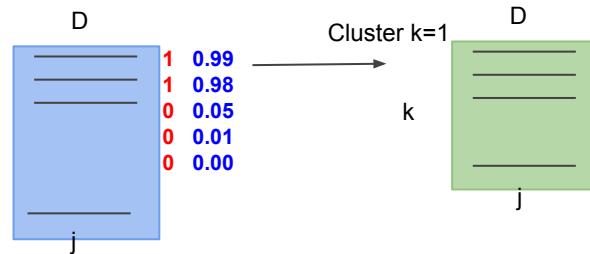
VLAD vector



Dim $K \times D$

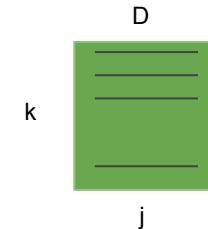
VLAD

N Local features $\{\mathbf{x}_i\}$



K Clusters features $\{\mathbf{c}_k\}$

V Matrix VLAD (residuals)



$$V(j, k) = \sum_{i=1}^N a_k(\mathbf{x}_i) (x_i(j) - c_k(j)),$$

Hard Assignment

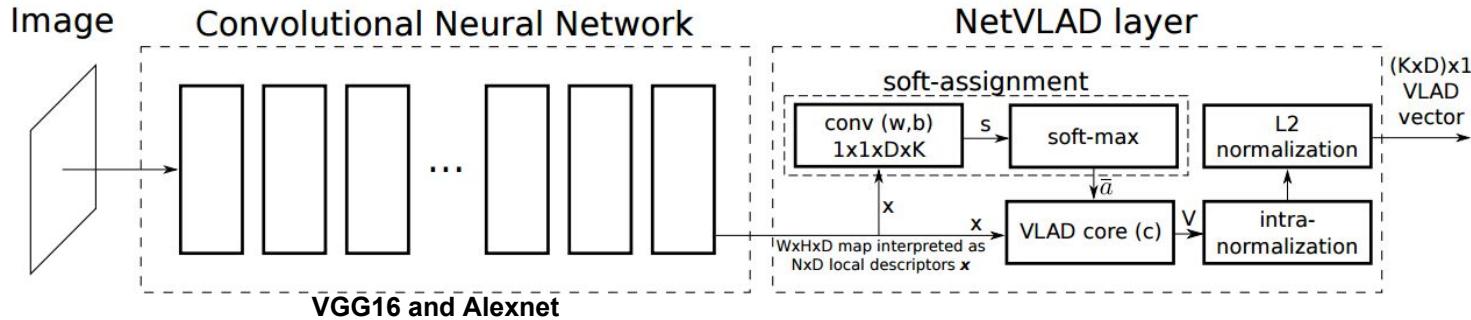
Not differentiable !

Soft Assignment

$$\bar{a}_k(\mathbf{x}_i) = \frac{e^{-\alpha \|\mathbf{x}_i - \mathbf{c}_k\|^2}}{\sum_{k'} e^{-\alpha \|\mathbf{x}_i - \mathbf{c}_{k'}\|^2}},$$

↓ Softmax function :

$$\bar{a}_k(\mathbf{x}_i) = \frac{e^{\mathbf{w}_k^T \mathbf{x}_i + b_k}}{\sum_{k'} e^{\mathbf{w}_{k'}^T \mathbf{x}_i + b_{k'}}},$$



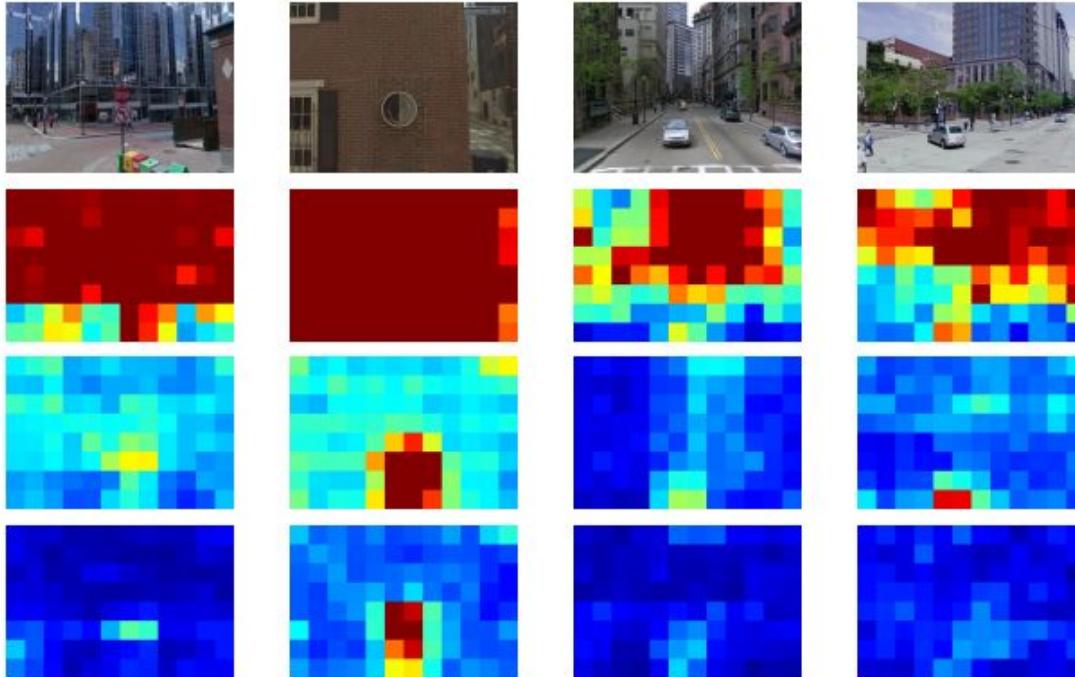
$$L_\theta = \sum_j l \left(\min_i d_\theta^2(q, p_i^q) + \underbrace{m - d_\theta^2(q, n_j^q)}_{\text{Consider all negative candidates}} \right)$$

With distance inferior to a certain margin

Consider the positive example closer to the query

l(x) = max(x, 0),

Places205 AlexNet off-shelf AlexNet ours Input image



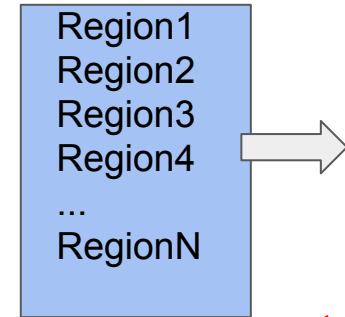
Method	Oxford 5k (full)	Oxford 5k (crop)	Paris 6k (full)	Paris 6k (crop)	Holidays (orig)	Holidays (rot)
Jégou and Zisserman [32]	–	47.2	–	–	65.7	65.7
Gordo <i>et al.</i> [23]	–	–	–	–	78.3	–
Razavian <i>et al.</i> [62]	53.3 [†]	–	67.0 [†]	–	74.2	–
Babenko and Lempitsky [7]	58.9	53.1	–	–	–	80.2
a. Ours: NetVLAD off-the-shelf	53.4	55.5	64.3	67.7	82.1	86.0
b. Ours: NetVLAD trained	62.5	63.5	72.0	73.5	79.9	84.3

Fine-tuned R-MAC

R-MAC

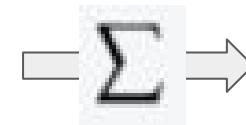


Region vectors
512D

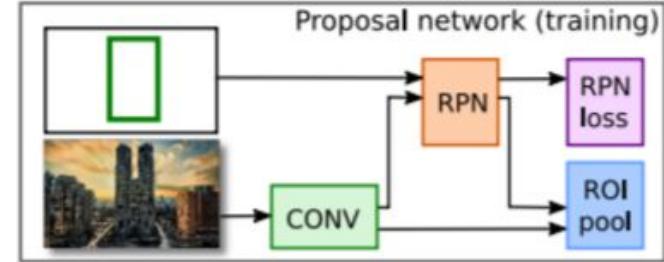
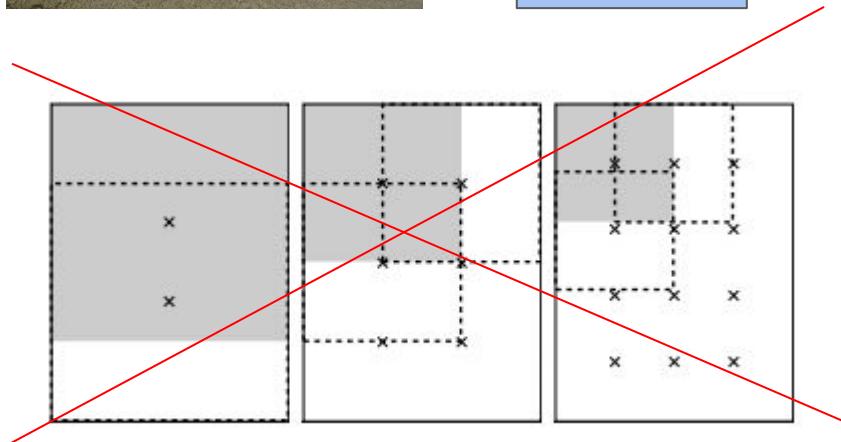


I2-PCAw-I2

Region1
Region2
Region3
Region4
...
RegionN



Global
vector
512D

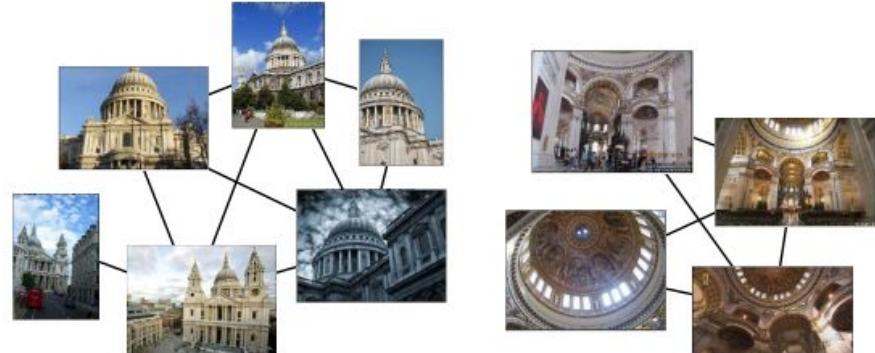


Learning representations for retrieval

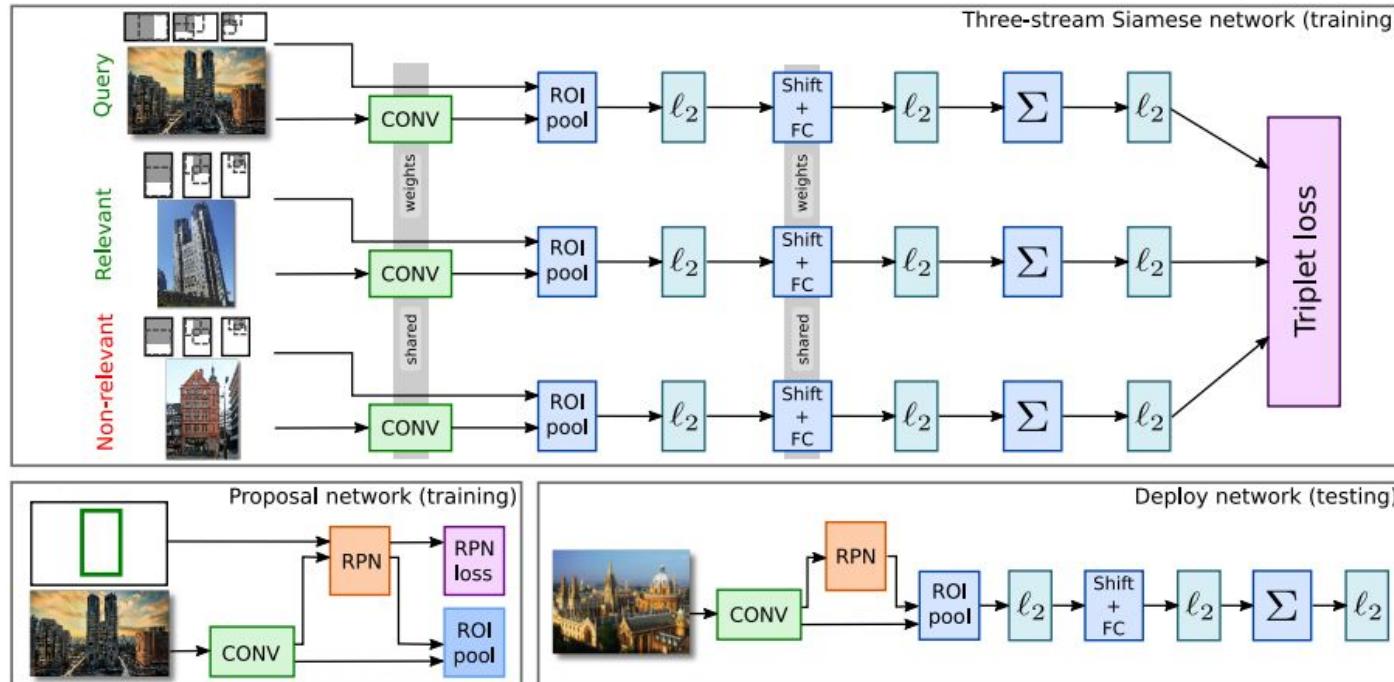
Generated dataset to create the training triplets

Dataset: Landmarks dataset:

- 214K images of 672 famous landmark site.
- Dataset processing based on a matching baseline: SIFT + Hessian-Affine keypoint detector.
- Important to select the “useful” triplets.



Learning representations for retrieval



Learning representations for retrieval

Comparison between R-MAC from off-the-shelf network and R-MAC retrained for retrieval

Dataset	PCA	R-MAC		Learned R-MAC		
		[14]	Reimp.	C-Full	C-Clean	R-Clean
Oxford 5k	PCA Paris	66.9	66.1	-	-	-
	PCA Landmarks	-	64.7	75.3	75.9	78.6
Paris 6k	PCA Oxford	83.0	82.5	-	-	-
	PCA Landmarks	-	81.6	82.2	83.7	84.5

Summary

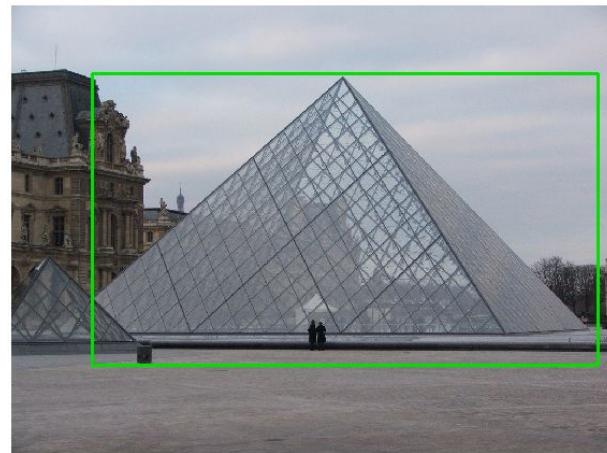
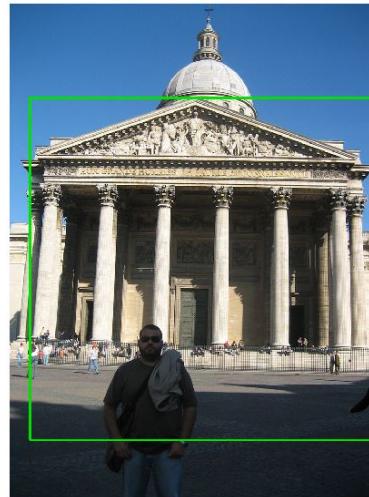
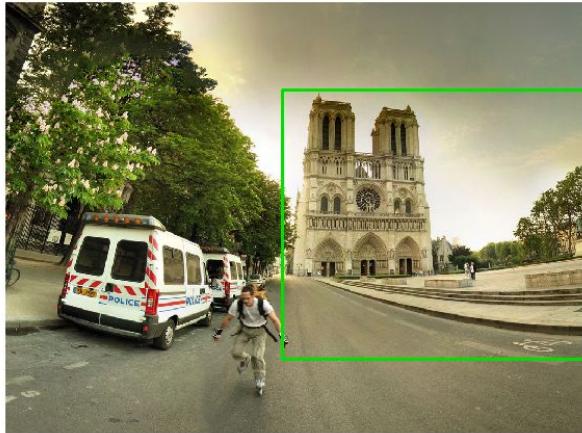
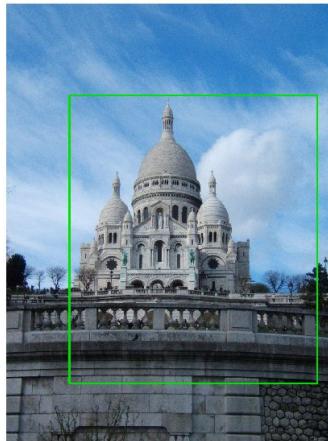
- Pre-trained CNN are useful to generate image descriptors for retrieval
- Convolutional layers allow us to encode local information
- Knowing how to rank similarity is the primary task in retrieval
- Designing CNN architectures to learn how to rank

Questions?

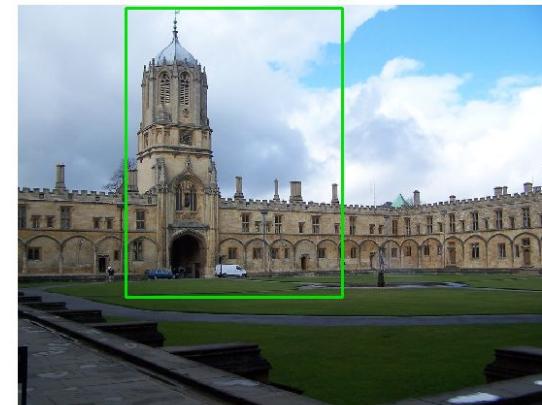
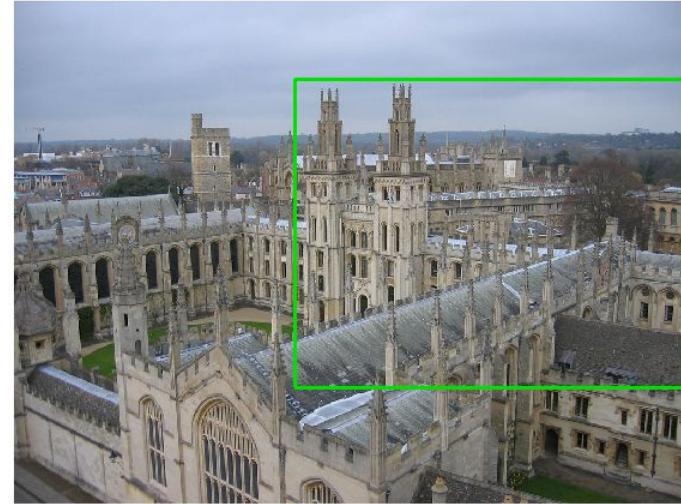
Summary state-of-the-art

		Layer	Method	Dim	Oxford 5k	Paris 6k
Off-the-shelf CNN representations	Global representation	fc	Neural Codes	128	0.433	-
		conv	SPoC	256	0.657	-
			CroW	256	0.684	0.765
			R-MAC	256	0.561	0.729
		conv	NetVLAD	256	0.555	0.643
			BoCF	25k(*)	0.739	0.82
	Multiple representations	fc	CNN-astounding	4-15k	0.68	0.795
		conv	CNN-astounding2	32k	0.843	0.879
Learning representations for retrieval	Global representation	conv	MAC	512	0.774	0.824
			regionProposal+MAC	512	0.813	0.855
			NetVLAD	512	0.676	0.749

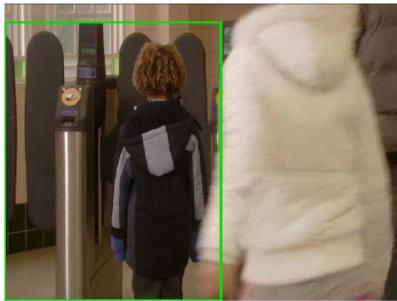
PARIS dataset



Oxford dataset



TRECVID dataset



INSTRE dataset

