Computer Vision

DATA.ML.300, 5 study credits

Esa Rahtu
Laboratory of Signal Processing, Tampere University

What is content based image retrieval

What we would like to be able to do?

- Query by example
- Given:
  - An example **query image** illustrating the users needs
  - A very large dataset of image
- Task:
  - **Rank** all images in the dataset according to relevance to the query

Difference to classification

Query: This chair

Results from dataset classified as “chair”

Classification

Difference to classification

Query: This chair

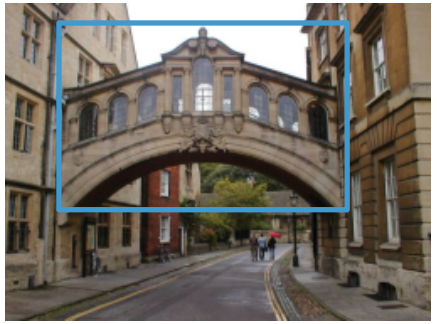
Results from dataset ranked by similarity to the query

Retrieval

Instance level retrieval

Query

Retrieved results



The retrieval pipeline

The retrieval pipeline

Query

The retrieval pipeline

Query

Image representation

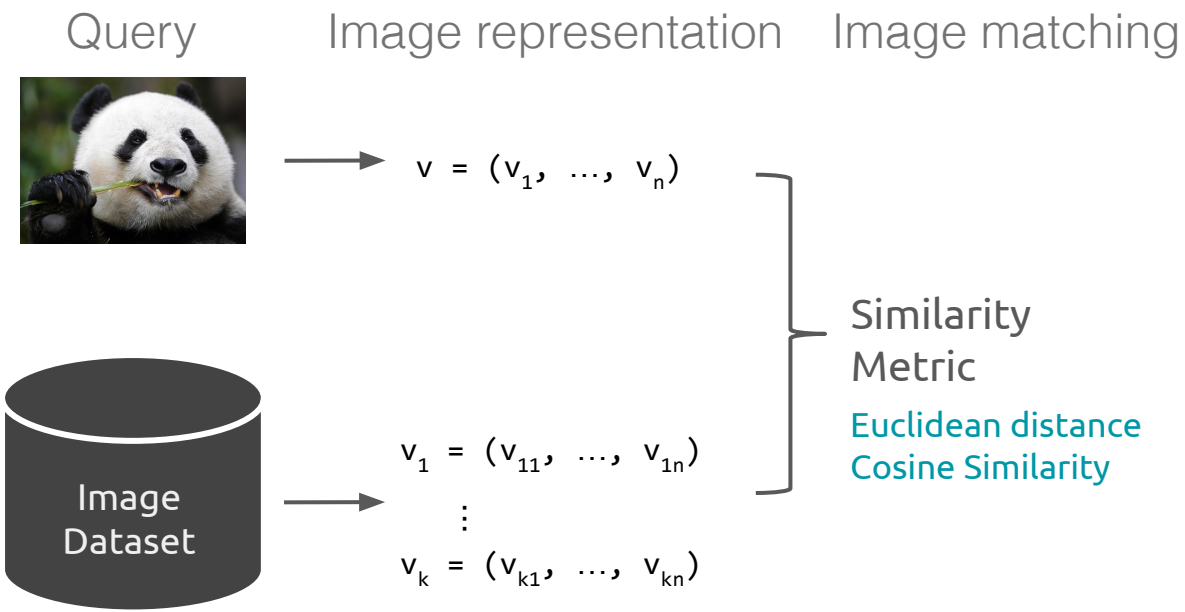
$$v = (v_1, \ldots, v_n)$$

$$v_1 = (v_{11}, \ldots, v_{1n})$$

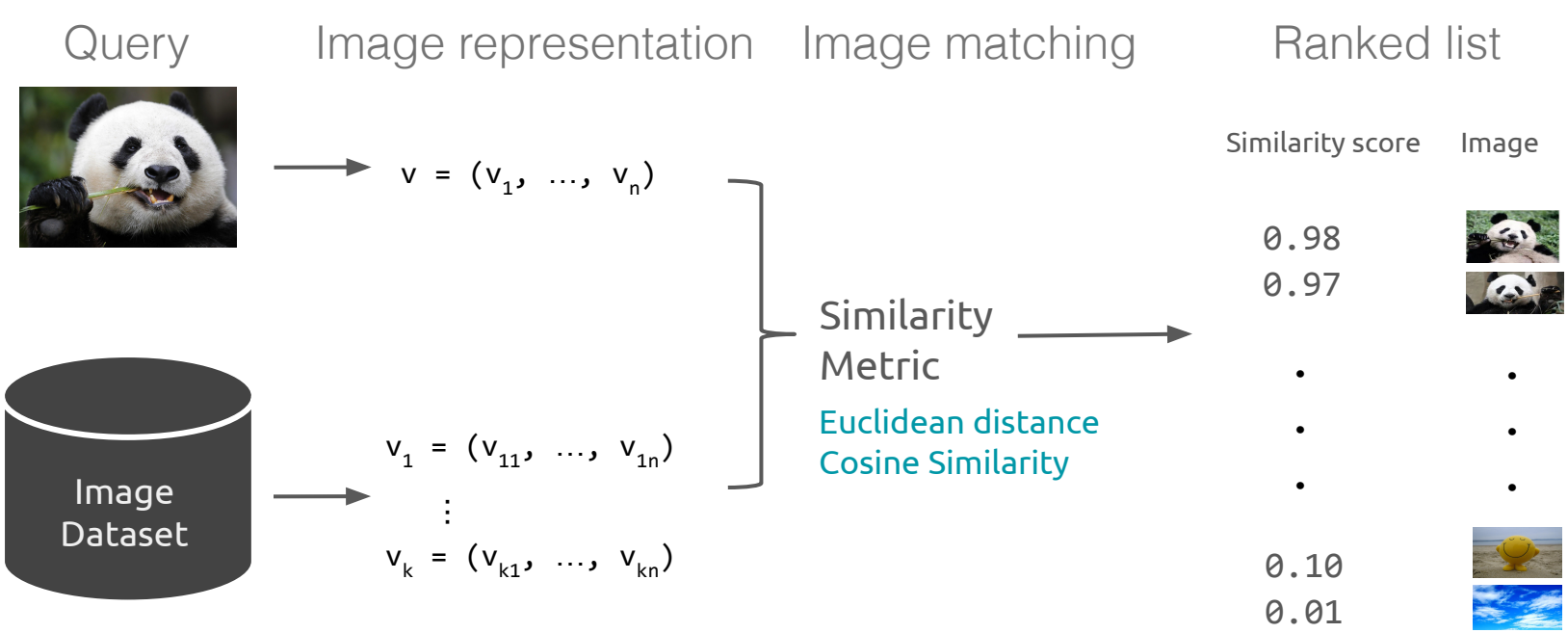
$$\vdots$$

$$v_k = (v_{k1}, \ldots, v_{kn})$$

The retrieval pipeline

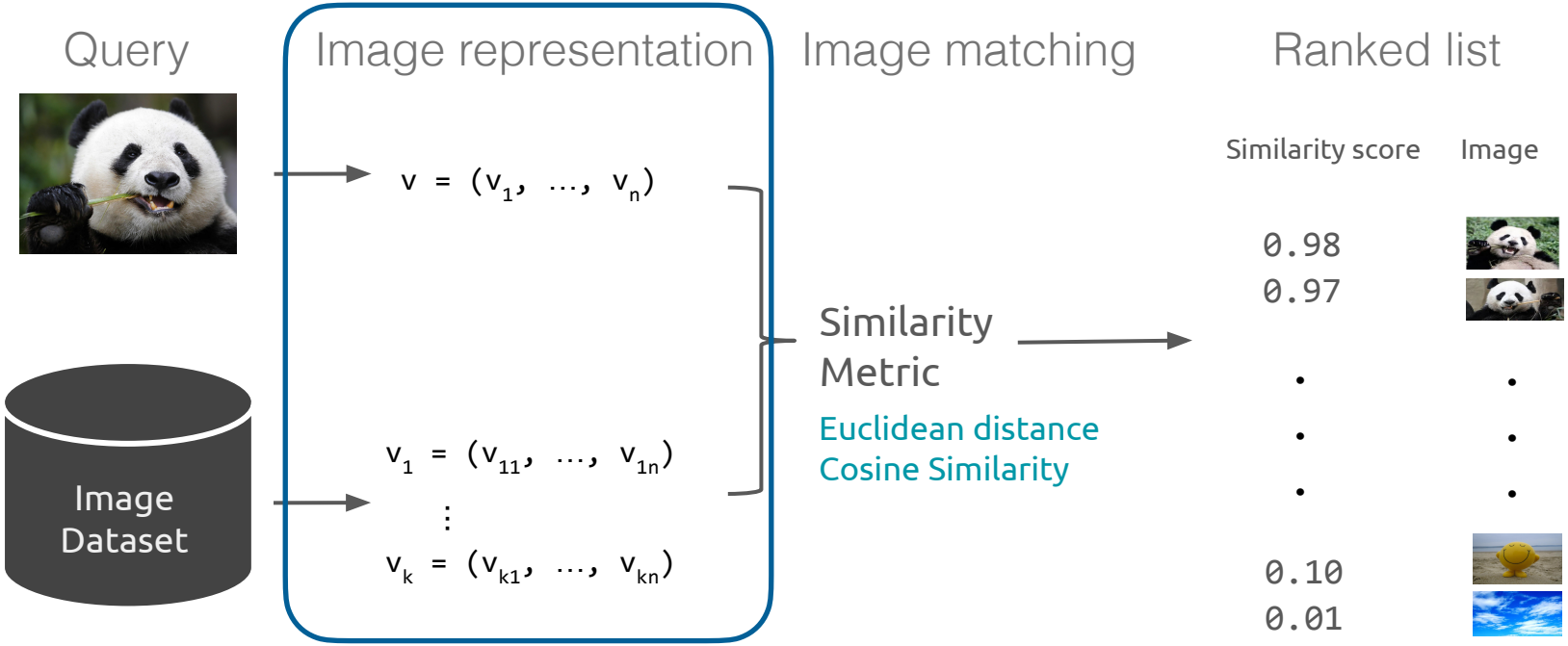


The retrieval pipeline



The image representation

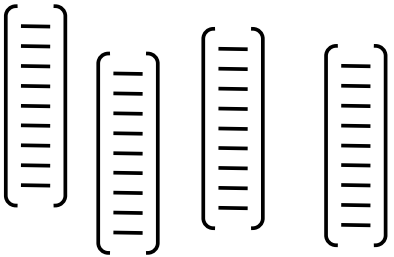
The retrieval pipeline



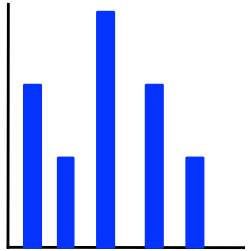
Classical approach

Detect variable number of local features (e.g. SIFT)

Compute descriptor (e.g. SIFT)

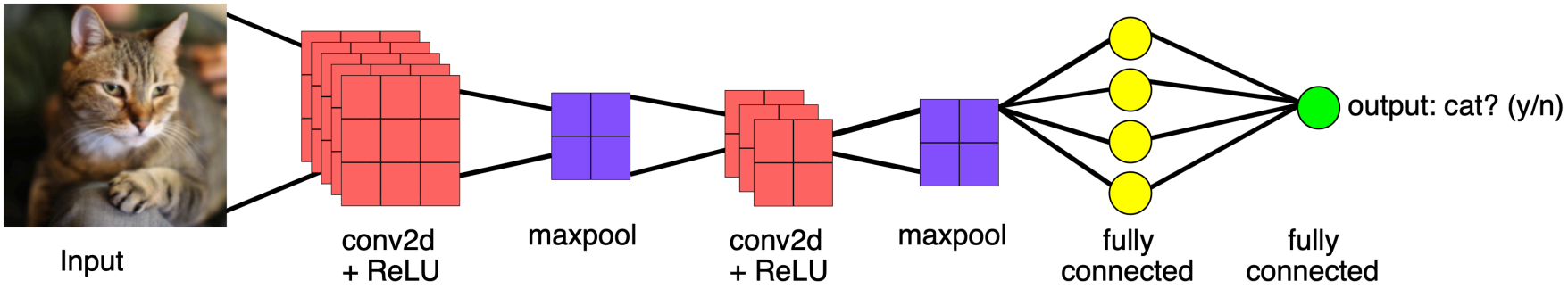


Quantise to form an image level descriptor



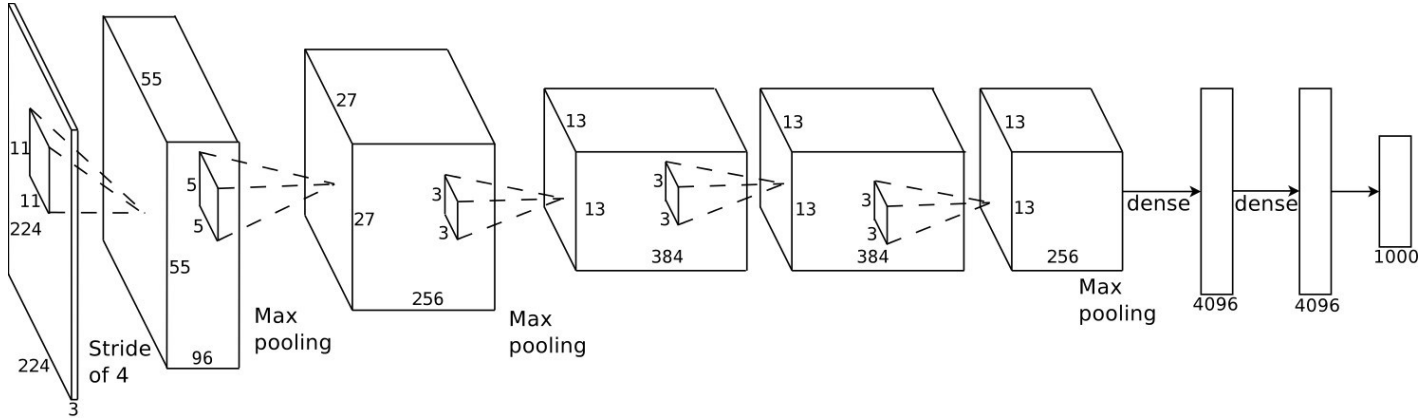
CNNs and retrieval

- CNNs are state-of-the-art in classification
- Could they be used for retrieval?



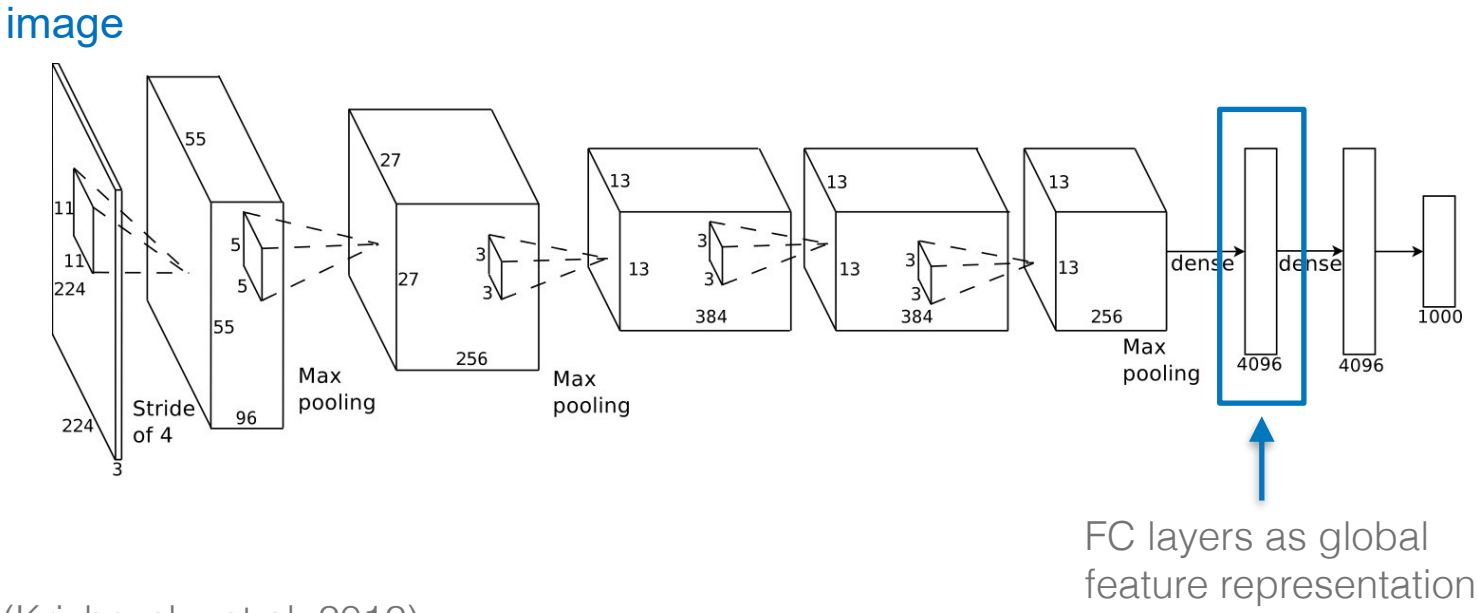
Using off-the-self CNN representations

image



AlexNet (Krizhevsky et al. 2012)

Using off-the-self CNN representations



AlexNet (Krizhevsky et al. 2012)

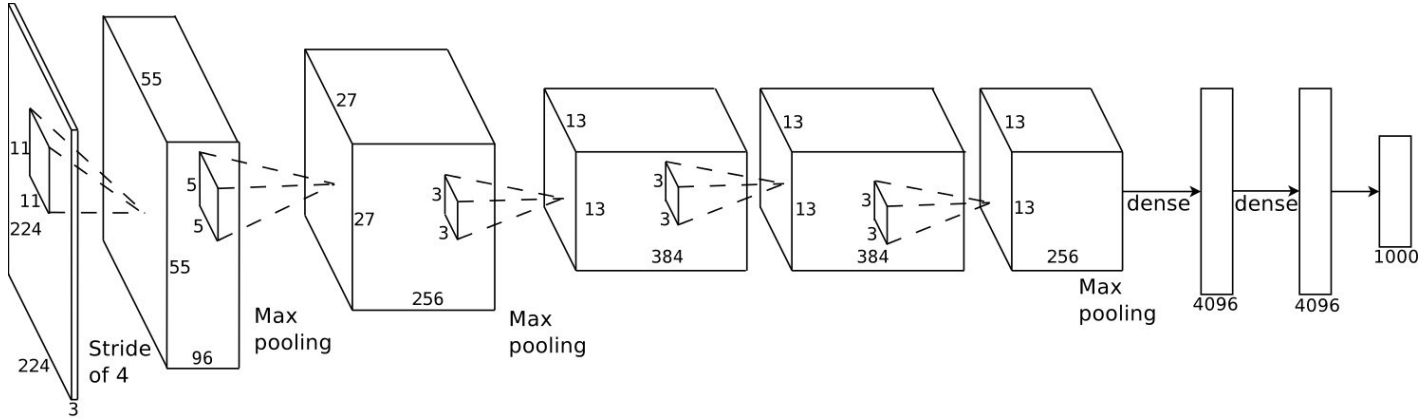
Using off-the-self CNN representations

- Babenko et al. [1]
  - FC7 layer features (4096D)
  - Euclidean distance
  - Slightly outperform traditional SIFT baseline after fine-tuning
- Razavian et al. [2]
  - Extracts features from several sub windows (sliding window)
  - Excellent results, but computationally impractically heavy

[1] Babenko et al, Neural codes for image retrieval, 2014, CVPR
[2] Razavian et al., CNN features off-the-shelf: an astounding baseline for recognition, 2014, CVPR

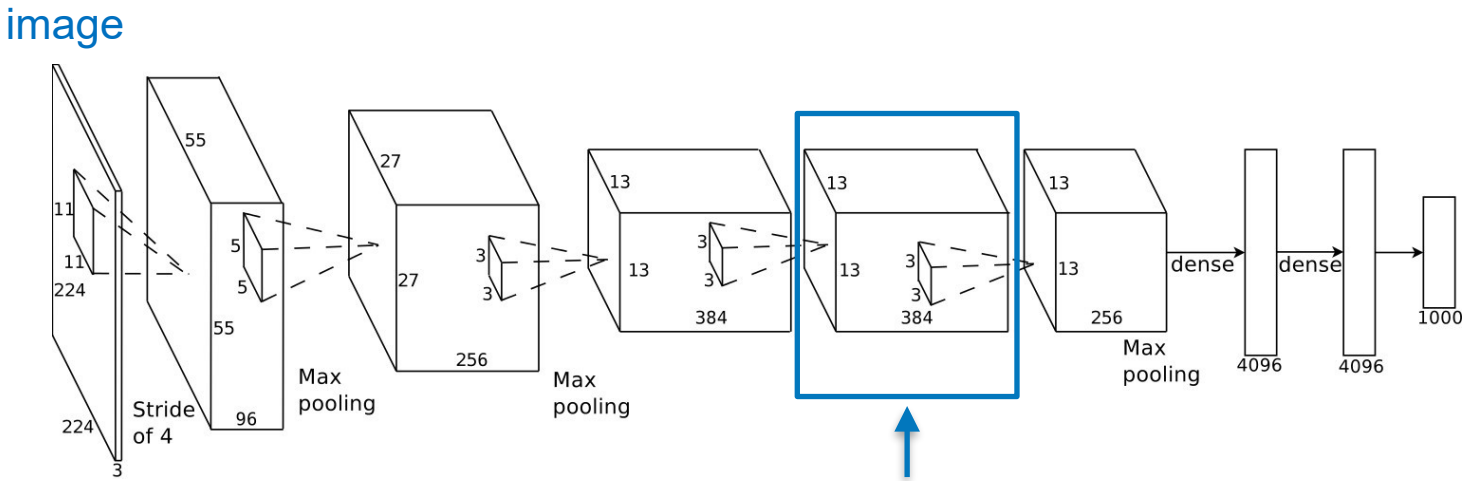
Using off-the-self CNN representations

image



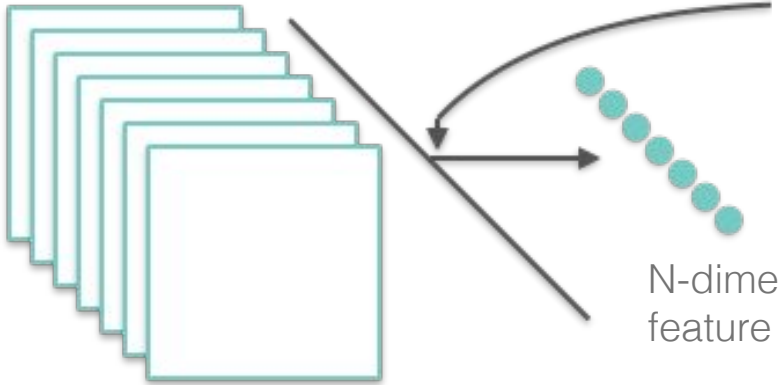
Could we obtain spatial information without explicit sliding window?

Using off-the-self CNN representations



Babenko et al, Aggregating local deep features for image retrieval, 2015, ICCV

Obtaining descriptors from conv layers



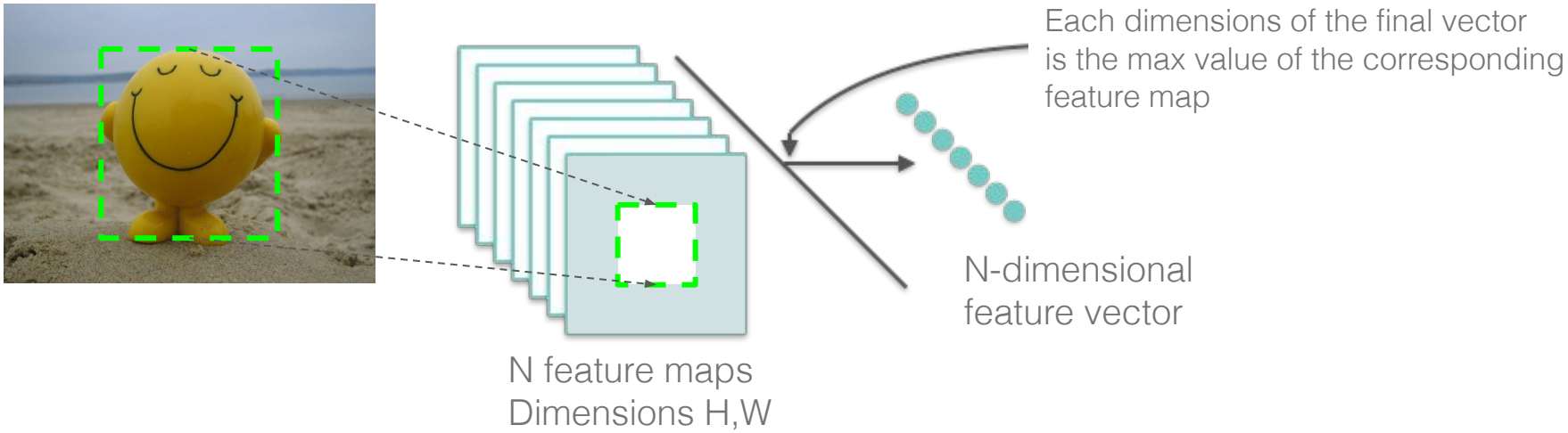
N feature maps
dimensions H,W

N-dimensional
feature vector

Spatial max-pooling:
Each dimensions of the final vector
is the max value of the corresponding
feature map

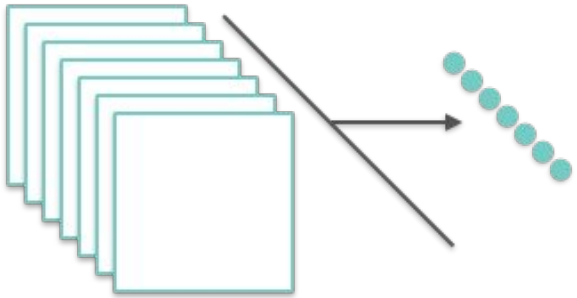
Obtaining descriptors from conv layers

- Pooling features allow to describe specific parts of an image

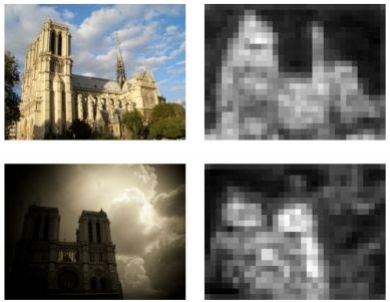


Obtaining descriptors from conv layers

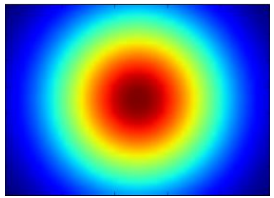
Sum/max pooling of a conv layer



Apply spatial weighting on the features before pooling them



Weighting based on feature ‘strength’ [2]

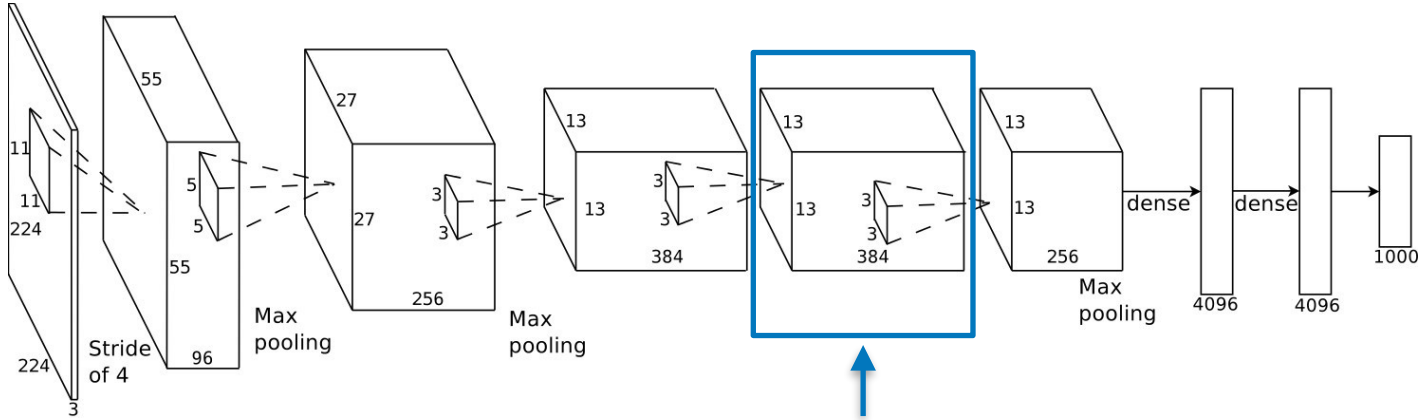


Weighting based on distance to center [1]

[1] Babenko et al, Aggregating local deep features for image retrieval, 2015, ICCV
[2] Kalantidis et al., Cross-dimensional weighting for aggregated deep convolutional features, 2016, ECCV

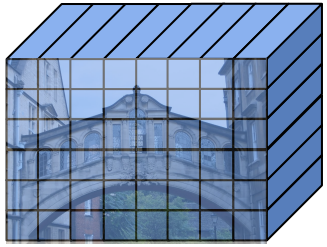
Obtaining descriptors from conv layers

image

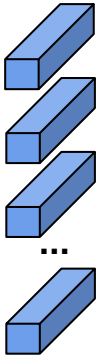


Obtaining descriptors from conv layers

Input image



Conv Layer:
N feature maps of
dimension HxW

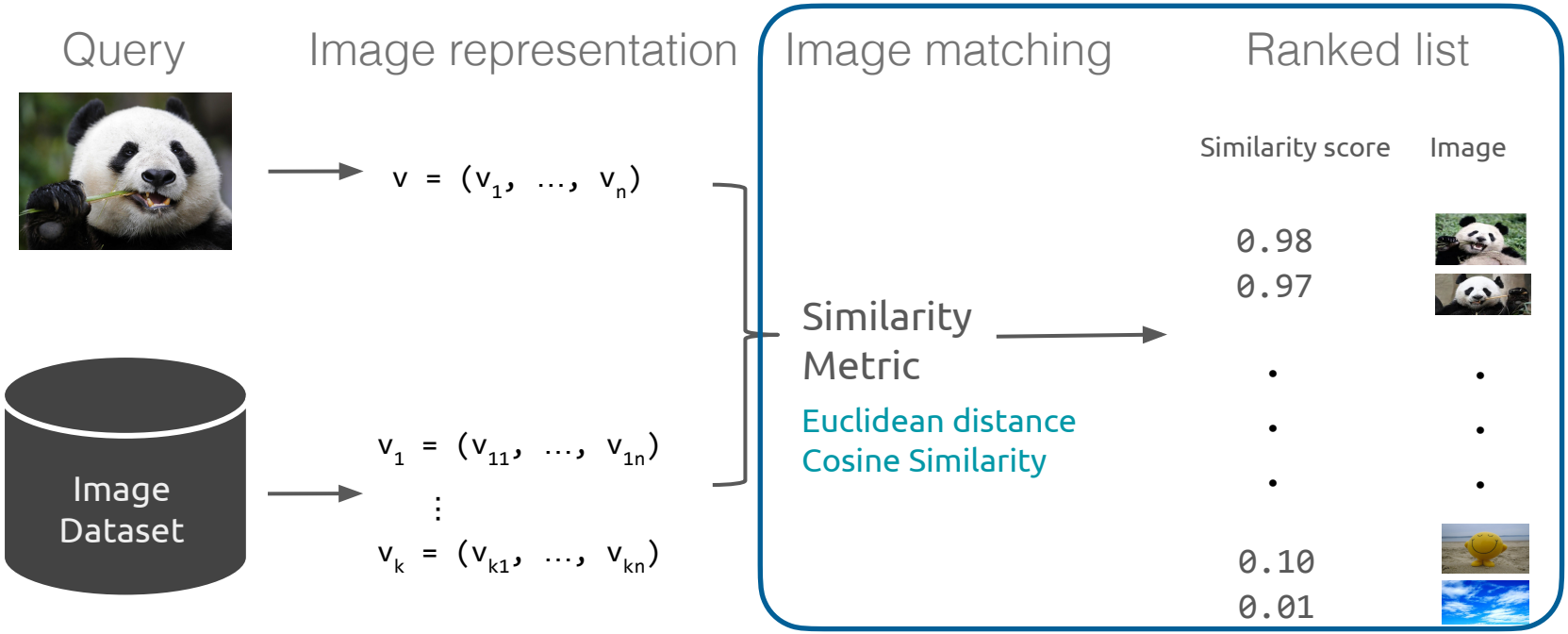


Local CNN features
HxW descriptors
of dimension N

Mohedano et al., Bags of local convolutional features for scalable instance search, ICMR 2016

Obtaining similarity and ranking

The retrieval pipeline



Calculating similarities

- Euclidean distance or cosine similarity between feature vectors

$$d_{L2}(x, a) = \sqrt{\sum_{i=1}^{n}(x_i - a_i)^2}$$

$$similarity(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

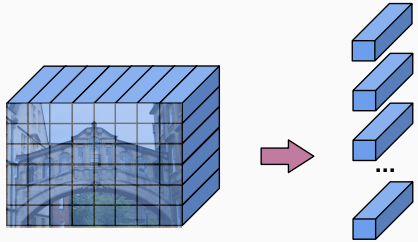
Calculating similarities

- Euclidean distance or cosine similarity between feature vectors

$$d_{L2}(x, a) = \sqrt{\sum_{i=1}^{n} (x_i - a_i)^2}$$

$$similarity(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

- Exhaustive evaluation unfeasible for large datasets
- What if we have multiple descriptors per image?



Idea: Inverted file index

- For text documents, an efficient way to find all **pages** that contain a specific **word** is to use an index
- We want to find all **images** in which a **feature** occurs
- To apply the idea in practice, we need to map the features to "**visual words**"

Index

A

Abel, Micah 18
Adkins, Melinda 40, 55
Adndrick, Kayla 20
Akers, William 8, 51
Algebra, Advanced 34
Allen, Shyla 8
Allshouse, Damon 32
Anderson, Cassie 38, 59
Andrick, Kayla 20
Asterino, Thomas 66
Audia, Sidney 16

B

Baker, Catherine 36
Baker, Savannah 44, 69
Bartimus, Jerad 40
Basketball, Junior Varsity Boys' 50, 51
Basketball, Junior Varsity Girls' 50
Basketball, Varsity Boys' 48, 49, 52, 53
Basketball, Varsity Girls' 52
Baylor, Nicholas 14
Bell, Charles 22, 23
Benedum, Anastasia 16, 56
Bennett, Brittany 34, 50, 57
Bennett, Coach Greg 50
Bennett, Dylan 6
Brooks, Orry 34, 51
Brooks, Susan 46
Brown, Benjamin 14
Brown, Delante 6
Brown, Nikki 42
Brumage, Brett 30
Brumage, Brittiany 28
Brummage, Lindsey 18
Burks, Dylan 10
Burns, Tameka 10
Burton, Cherise 40, 52, 58, 67
Burton, Coach Ed 52
Burton, Julia 57
Burton, Linda 60
Burton, Lucille 18, 46
Butcher, Jack 34, 35
Butler, Alexis 14
Byrne, Devin 24

C

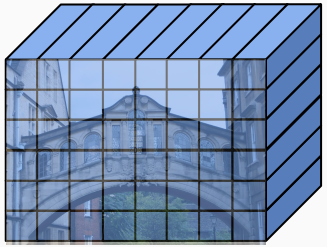
Canfield, Marisa 32
Carnes, Sara 14, 55
Carpenter, Phoenix 8
Centeno, Ashley 26
Cheerleaders, Junior Varsity 54, 55
Cheerleaders, Varsity 55
Clay, Jamie 6
Clevenger, Clayton 30
Club, Girls' 56, 57
Clutter, Jacob 20, 21
Cogar, Tyler 38
Cole, Anthony 10
Cole, Marcus 12
Denoon, Christian 30
Dent, Ashton 44
Dent, Bailee 12
des Mond, Adrian 68
Devalt, Jack 36, 37, 51
di Rosa, Rene 68
Dick, Jacob 8
Dick, Victoria 16
Dixon, Bethany 26
Donini, Jasmine 28, 29
Du Toit, Kim 68
Duckworth, Caleb 6
Duckworth, Mariah 10
Duckworth, Melyssa 36
Duckworth, Trenton 6
Dukich, Mikayla 32, 48
Duskey, David 26

E

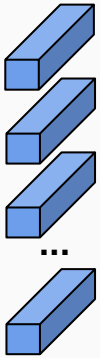
Echols, LC 34, 51
Eckles, Carson 30
Eddy, Brady 14
Efaw, Adrianna 26
Efaw, Breanna 36, 50, 54
Efaw, Coach Susie 54
Efaw, Danielle 14
Efaw, Hannah 42, 55, 57, 69
Elliott, Thomas 12
Eubank, Jacob 14, 15
Evan, Izaiha 28, 48, 49
Evans, Mason 32
Evanson, Jamie 42, 69
Evanson, Jenna 3, 5, 55, 69
Evanson, Jennifer 41

Obtaining visual words

Input image



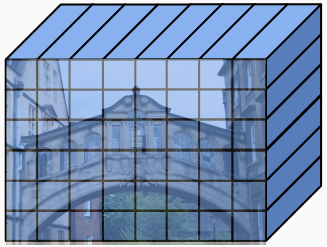
Conv Layer



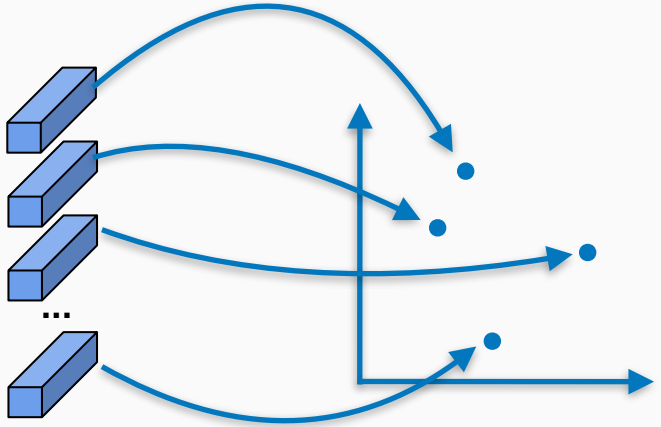
Local CNN descriptors of dimension N

Obtaining visual words

Input image



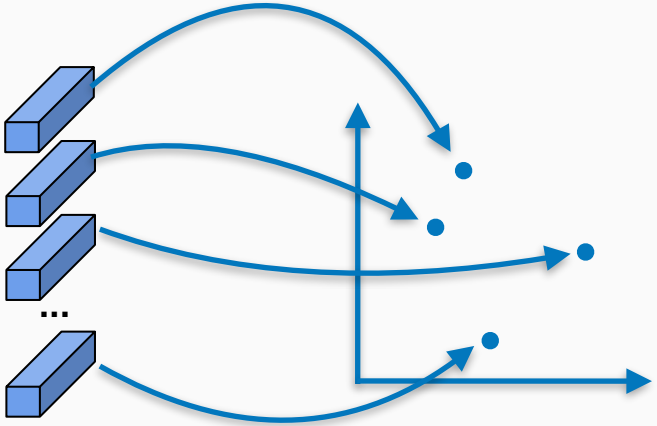
Conv Layer



Local CNN descriptors of dimension N

Represent as points in N dimensional feature space

Obtaining visual words

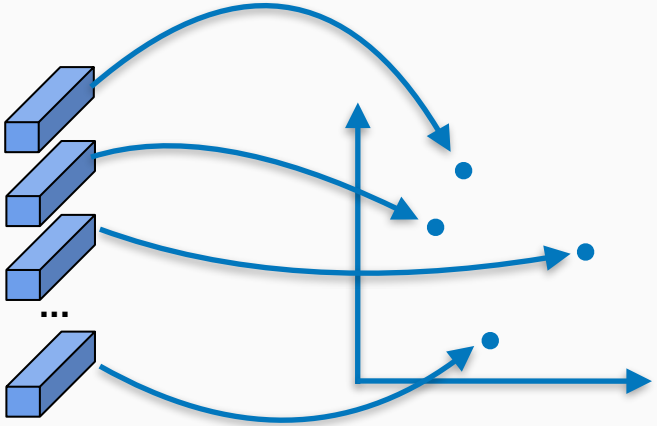


Local CNN descriptors of dimension N

Represent as points in N dimensional feature space

Training dataset

Obtaining visual words



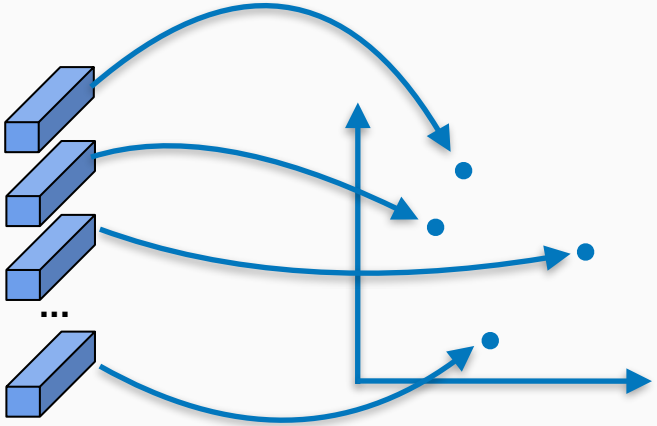
Local CNN descriptors of dimension N

Represent as points in N dimensional feature space

Collect descriptor from the entire training set

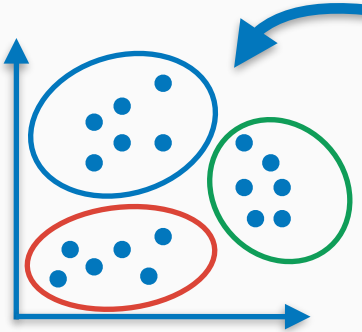
Training dataset

Obtaining visual words



Local CNN descriptors of dimension N

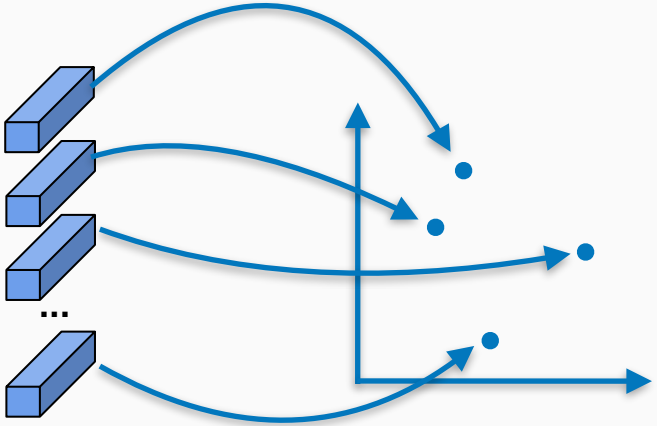
Represent as points in N dimensional feature space



Quantise the feature space (clustering)

Training dataset

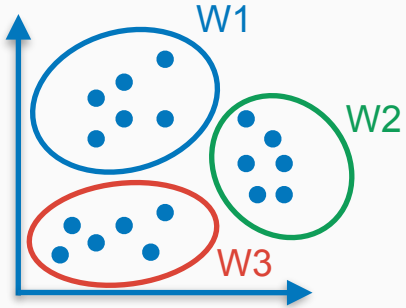
Obtaining visual words



Local CNN descriptors of dimension N

Represent as points in N dimensional feature space

Each cluster represents a “visual word” = **vocabulary**



Quantise the feature space (clustering)

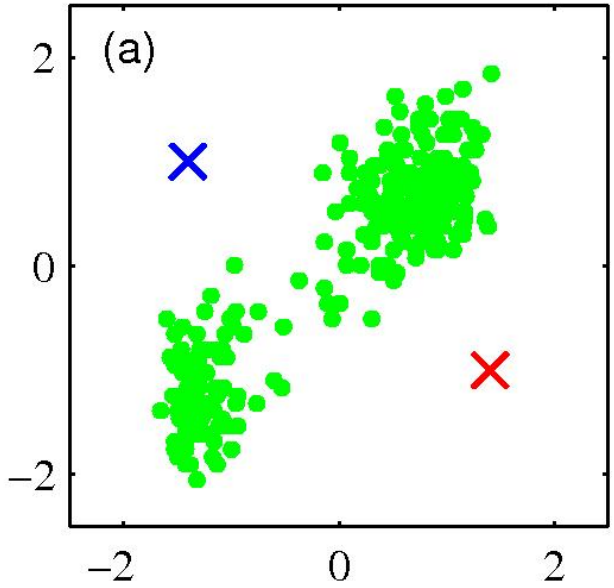
K-mean clustering

- Idea is to minimise sum of Euclidean distances between points x_i and their nearest cluster centres m_k

$$D(X,M) = \sum_{\text{cluster } k} \sum_{\substack{\text{point } i \text{ in} \\ \text{cluster } k}} (\mathbf{x}_i - \mathbf{m}_k)^2$$

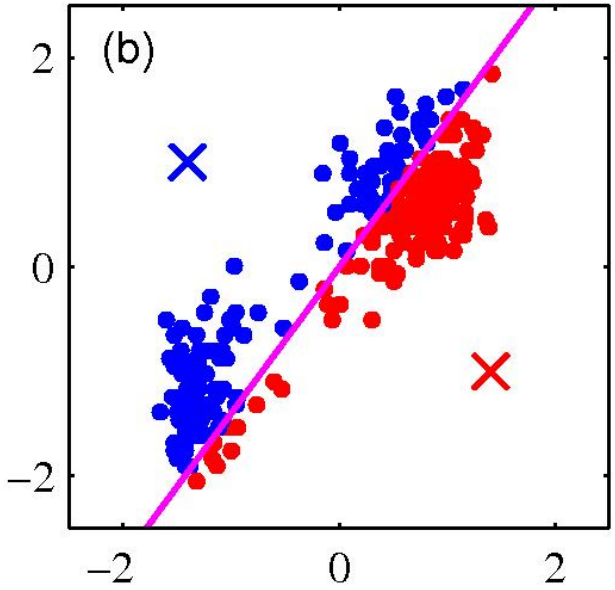
- Algorithm:
  1. Randomly initialise K cluster centres
  2. Assign all points to nearest cluster center
  3. Recompute cluster centres as the mean of all points assigned to it
  4. Return to 2 until convergence

K-means clustering: example



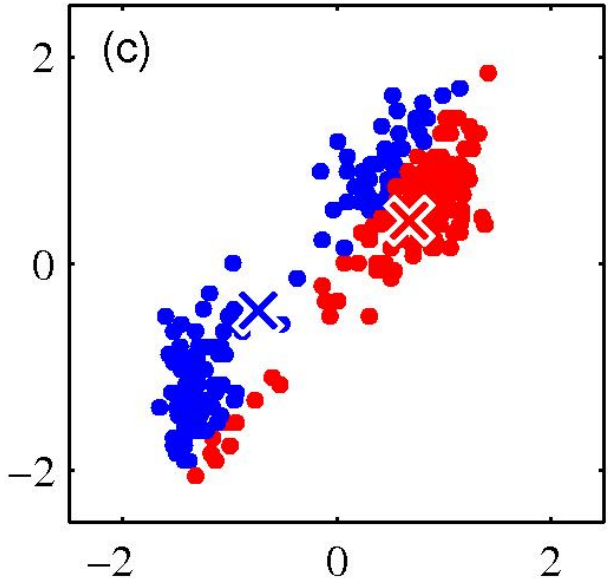
Initial state
2-dimensional space
K = 2

K-means clustering: example



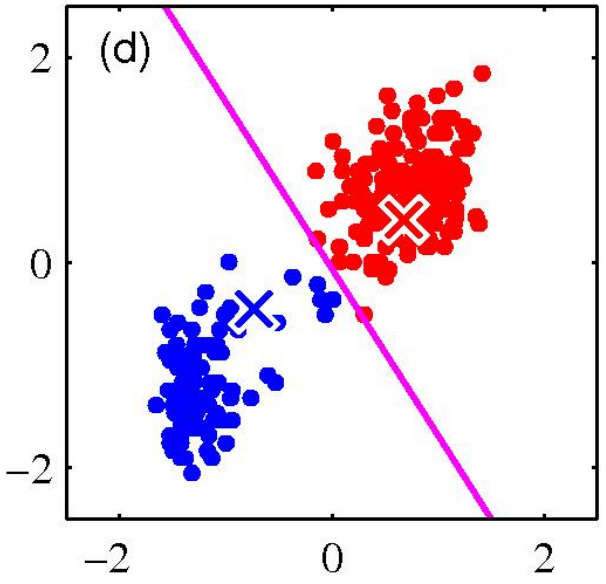
Result after step 3.
(assign data points to nearest cluster centre)

K-means clustering: example



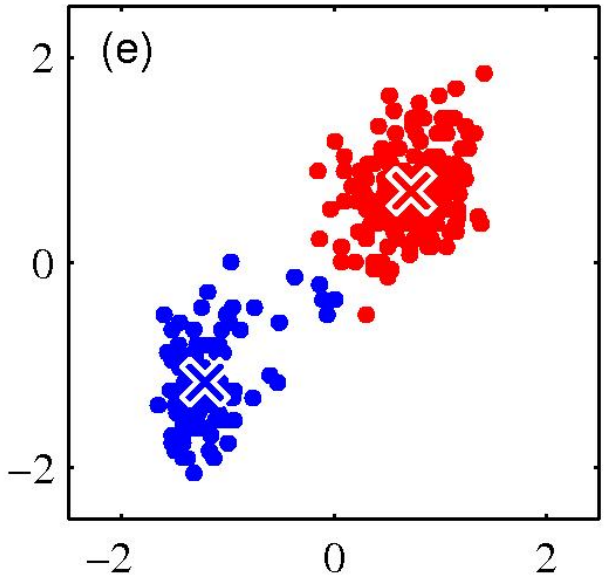
Result after step 4.
(move cluster centres
to the means of data points)

K-means clustering: example



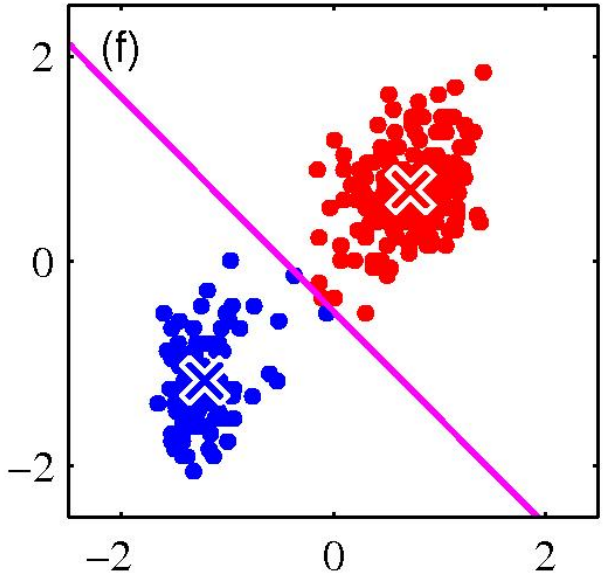
2nd iteration
result after step 3.

K-means clustering: example



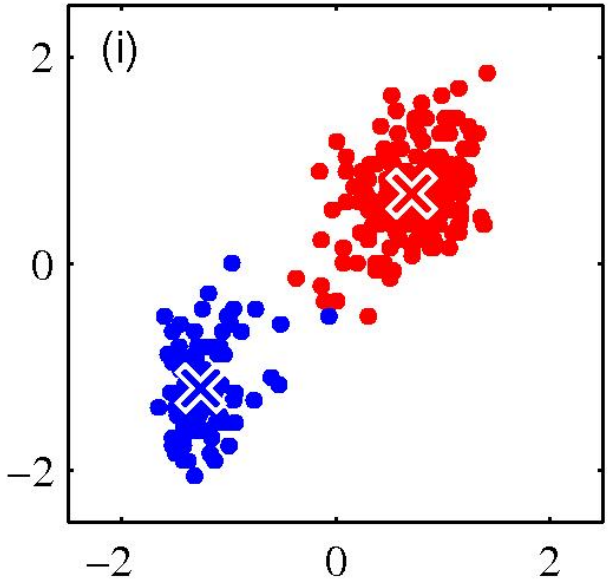
2nd iteration
result after step 4.

K-means clustering: example



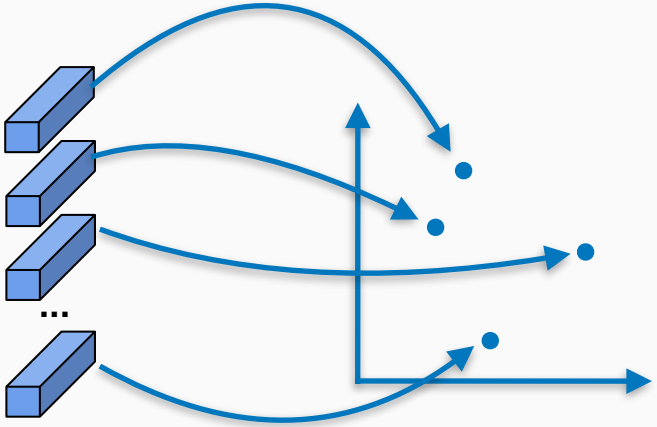
3rd iteration
result after step 3.

K-means clustering: example



Final clustering

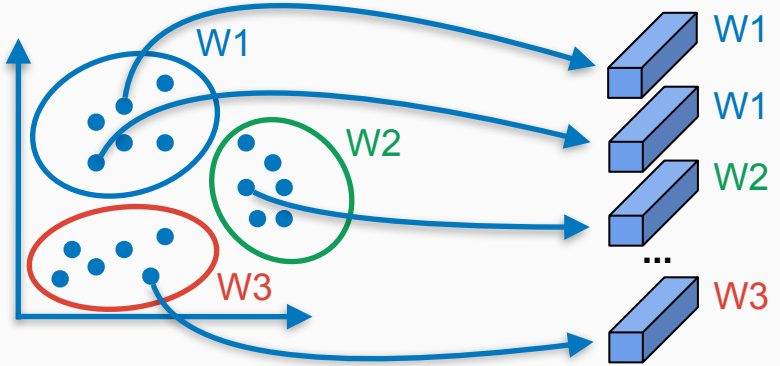
Obtaining visual words



Local CNN descriptors of dimension N

Represent as points in N dimensional feature space

Each cluster represents a “visual word” = **vocabulary**

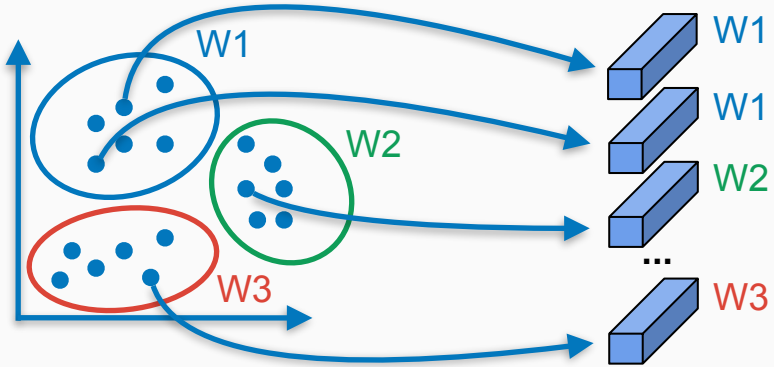


Quantise the feature space (clustering)

Assign the words to corresponding local descriptor

Forming inverted index

Each cluster represents
a “visual word” = **vocabulary**



Quantise the feature space (clustering)

Assign the words to corresponding local descriptor

Inverted index file

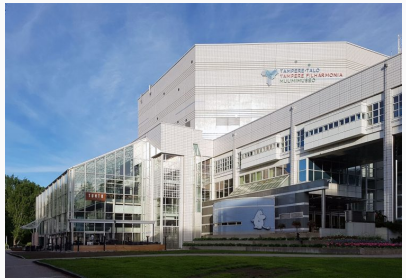
Word #	Image #
1	1,2
2	2
3	1
4	
5	2,3
6	
7	3
8	
…	…

Visual words in retrieval (pipeline)

- Training phase
  - Compute local (CNN) descriptors from the **training** images
  - Form a **vocabulary** by clustering the local descriptors from the training set
  - Assign visual words to each **database image** using vocabulary and form an index
- Query phase
  - At query time, obtain the local descriptors and visual words for the **query image**
  - **Search** matching images from the index

Example

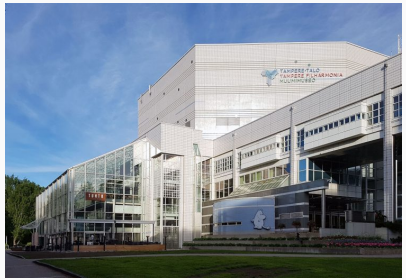
Database images



...

Example

Database images



W1 W1 W3 …

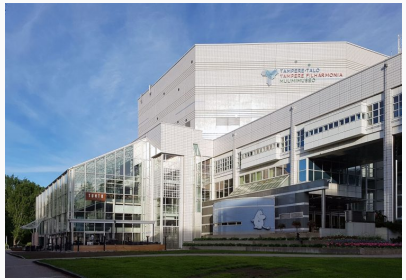
W2 W5 W1 …

W7 W5 W5 …

…

Example

Database images



…

W1 W1 W3 …

W2 W5 W1 …

W7 W5 W5 …

Inverted index file

Word #	Image #
1	1,2
2	2
3	1
4	
5	2,3
6	
7	3
8	
…	…

Example

New query image

W5 …

Inverted index file

Word #	Image #
1	1,2
2	2
3	1
4	
5	2,3
6	
7	3
8	
…	…

Example

New query image

W5 …

Inverted index file

Word #	Image #
1	1,2
2	2
3	1
4	
5	2,3
6	
7	3
8	
…	…

Example

New query image

W5 …

Inverted index file

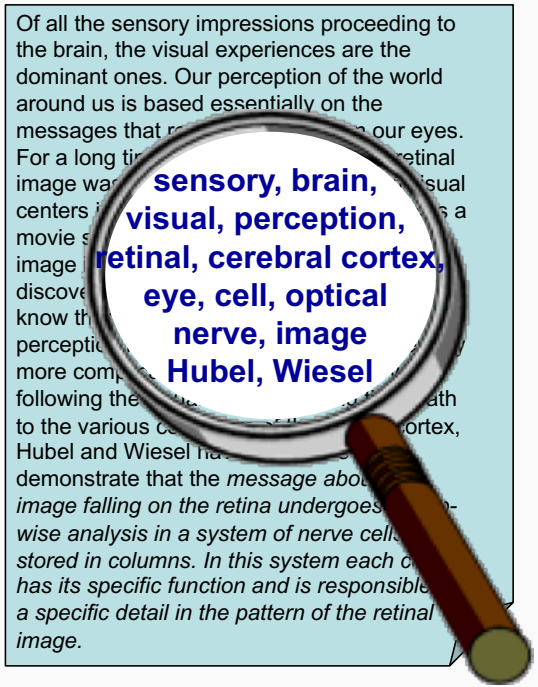
Word #	Image #
1	1,2
2	2
3	1
4	
5	2,3
6	
7	3
8	
…	…

Inverted file index

- Inverted file index is efficient only if it is **sparse**
- If most pages/images contain most words, then indexing gives no advantage over exhaustive comparison to each dataset image
- Problem solved?
- But how to summarise and compare the content of an entire image?

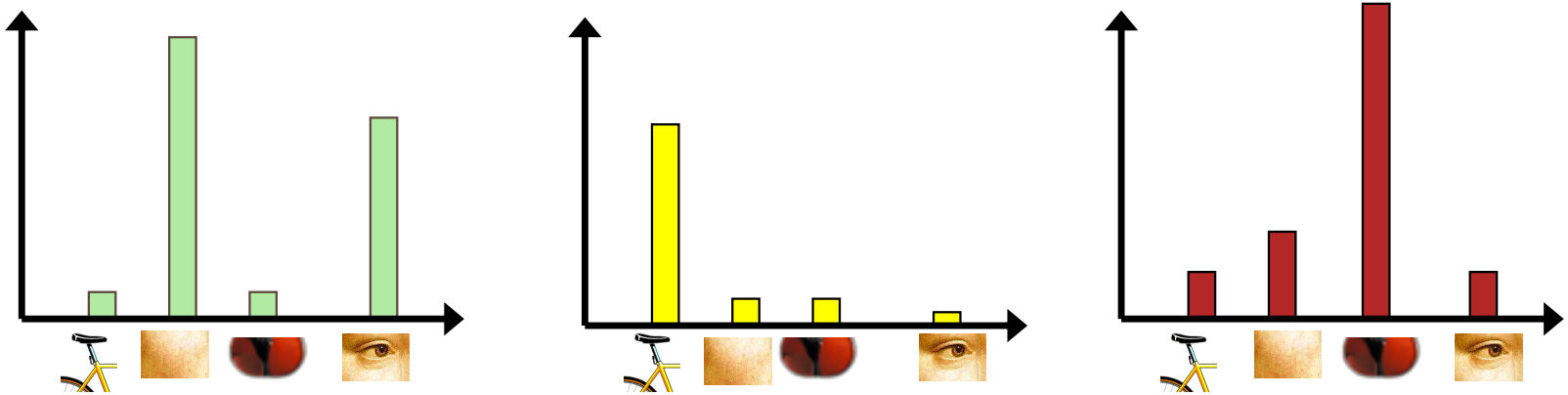
Comparing entire images with visual words

Analogy to documents



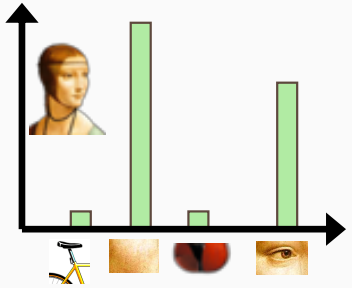
Credit: Fei-Fei Li

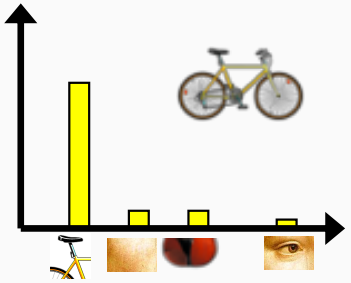
Bags of visual words



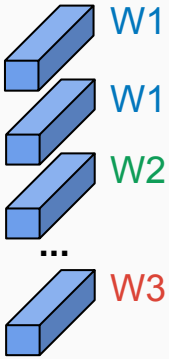
Bags of visual words

- Summarise the image using the histogram of word occurrences
- Analogous to bag of words representation used for documents





Bags of visual words



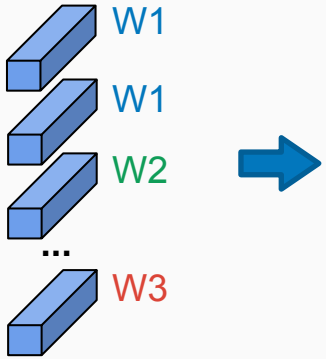
Quantised local
(CNN) descriptors

Bags of visual words

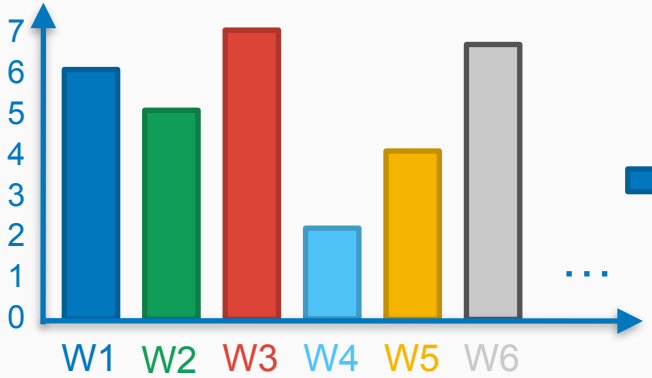
Quantised local (CNN) descriptors

Count the occurrences of each word in the image

Bags of visual words



Quantised local (CNN) descriptors

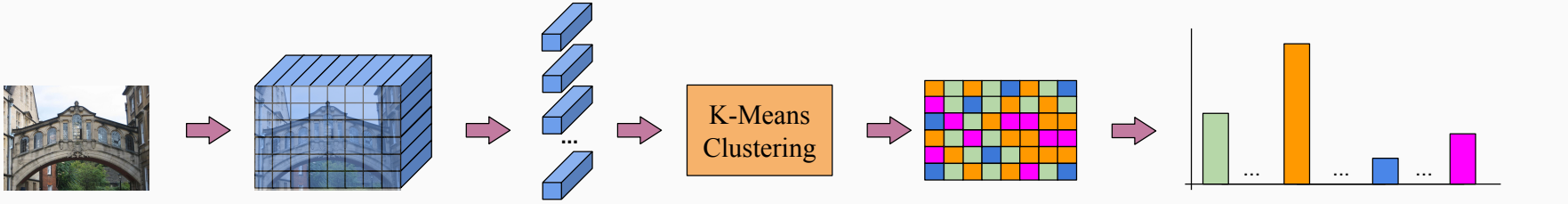


Count the occurrences of each word in the image

[6, 5, 7, 2, 4, 6, …]

Quantised descriptor for the entire image content

Bags of local convolutional features pipeline



Mohedano et al., Bags of local convolutional features for scalable instance search, ICMR 2016

Comparing bags of words

- Measure similarity using normalised scalar product between the bags of words descriptor vectors
- Rank dataset images based on similarity to the query image

$$sim(d_j, q) = \frac{\langle d_j, q \rangle}{\|d_j\| \|q\|}$$

Inverted file index and bags of words similarity

1. Extract words from the query image

Query image

W5,W9,…

Inverted index file

Word #	Image #
1	1,2
2	2
3	1
4	8
5	2,3
6	
7	3
8	
9	8,3
…	…

Inverted file index and bags of words similarity

1. Extract words from the query image
2. Find relevant database images from inverted file index

Query image

W5,W9,…

Inverted index file

Word #	Image #
1	1,2
2	2
3	1
4	8
5	2,3
6	
7	3
8	
9	8,3
…	…

Inverted file index and bags of words similarity

1. Extract words from the query image
2. Find relevant database images from inverted file index
3. Compare word counts

[0, 0, 0, 0, 9, 0, …]

Query image

W5,W9,…

Inverted index file

Word #	Image #
1	1,2
2	2
3	1
4	8
5	2,3
6	
7	3
8	
9	8,3
…	…

[1, 2, 0, 0, 9, 0, …]

[0, 0, 0, 0, 1, 0, …]

[0, 0, 0, 7, 0, 0, …]

How to evaluate retrieval results?

How to evaluate retrieval quality?

Query

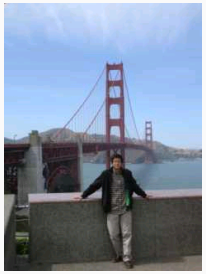
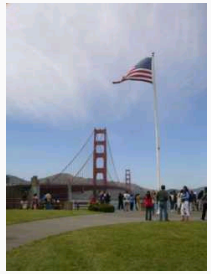
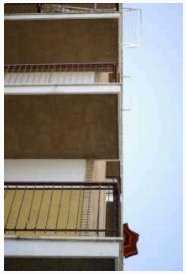
Dataset size: 10 images
Relevant (total): 5 images

Credit: O. Chum

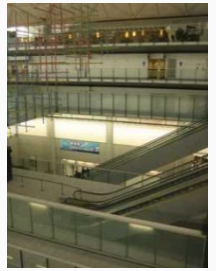
How to evaluate retrieval quality?

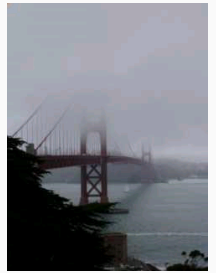
Query

Dataset size: 10 images
Relevant (total): 5 images





Results (ordered)

Credit: O. Chum

How to evaluate retrieval quality?

Query

Dataset size: 10 images
Relevant (total): 5 images

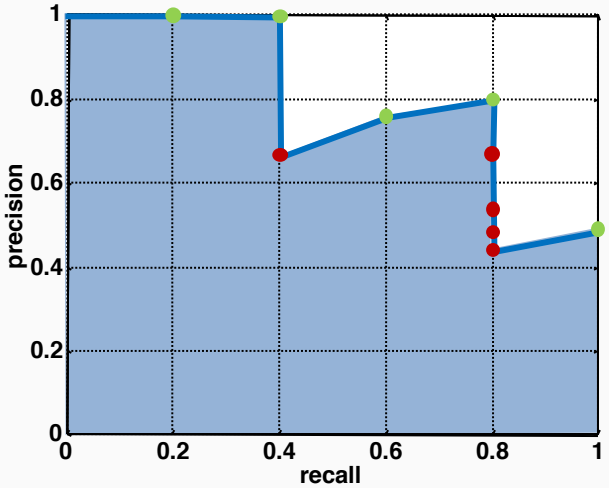
Results (ordered)

Credit: O. Chum

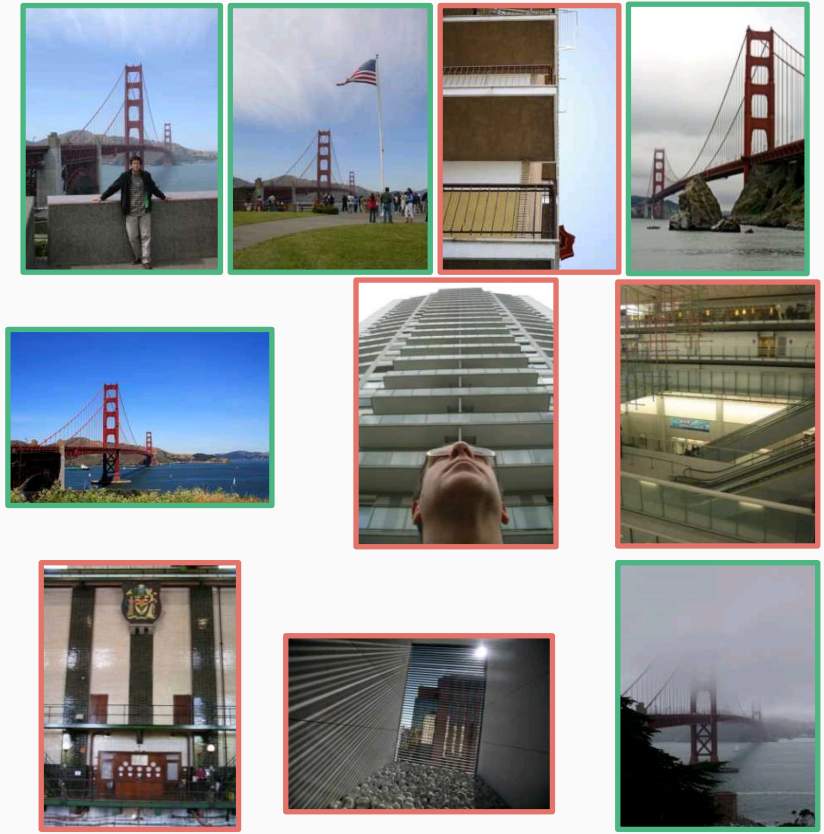
How to evaluate retrieval quality?

Query

Dataset size: 10 images
Relevant (total): 5 images



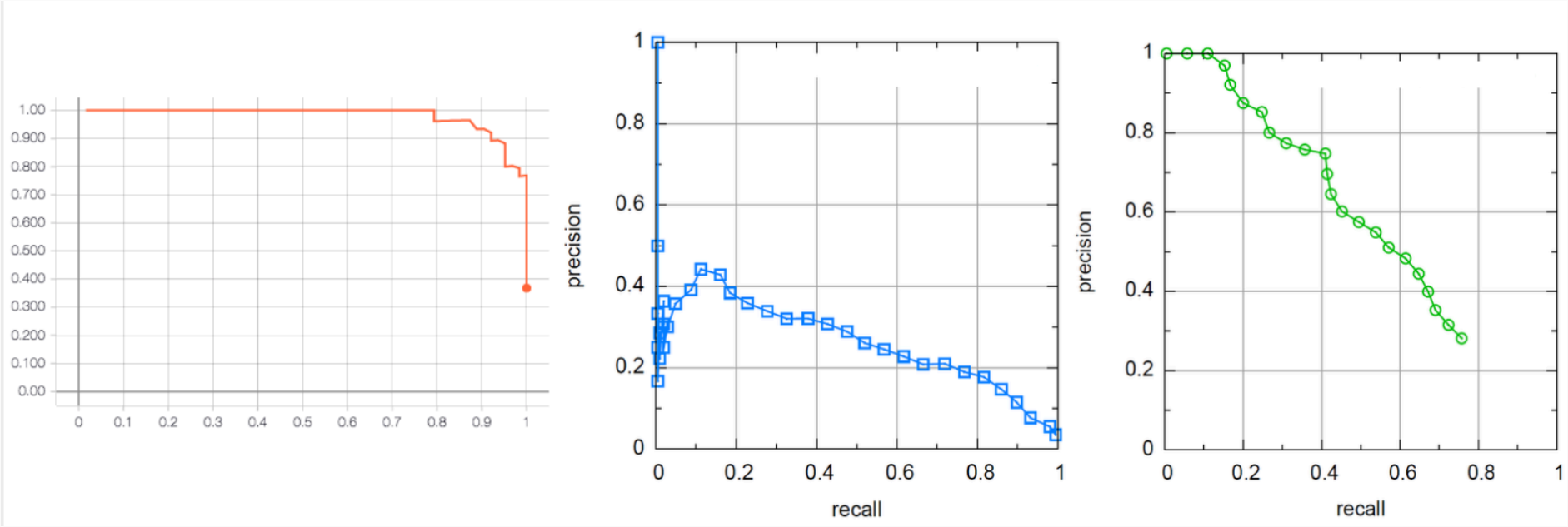
Precision = #relevant / #returned
Recall = #relevant / #total relevant



Results (ordered)

Credit: O. Chum

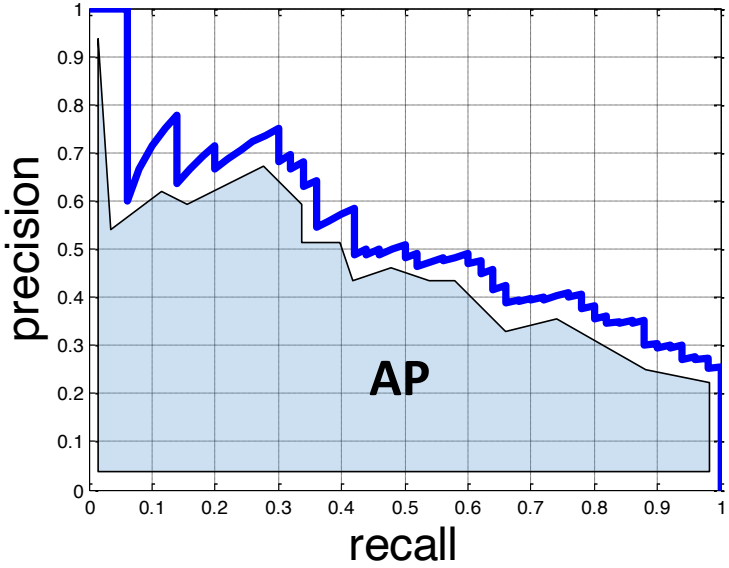
A pot-pourri of PR curves

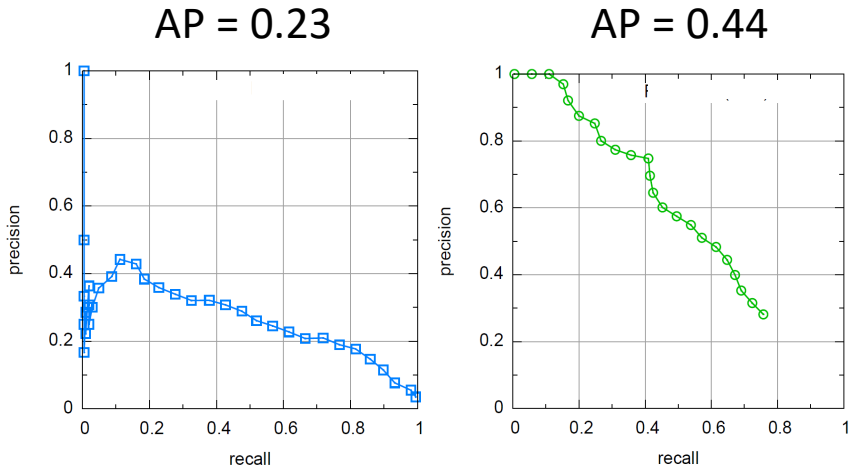


Credit: A. Zisserman

Average precision

- Area under Precision-Recall curve
- Single score to assess performance





A good score requires both high recall and high precision

Credit: A. Zisserman

Things to remember

- Two phases of image retrieval:
  - Obtain image descriptors for database and query image
  - Calculate similarity metrics and rank the database images according to similarity with query
- (Pre-trained) CNNs can form powerful image descriptors for retrieval
- Descriptors can be quantised to “visual words” for efficient search
  - Learn a vocabulary from a training set by clustering
  - Summarise image by distribution of words (bag of words)
- Precompute index to enable fast search at query time (inverted index)
- Retrieval quality can be evaluated using precision vs recall plot

That’s it folks!