Recognition

Topics that we will try to cover:

- Indexing for fast retrieval (we still owe this one)
- History of recognition techniques
- Object classification
  - Bag-of-words
  - Spatial pyramids
  - Neural Networks
- Object class detection
  - Hough-voting techniques
  - Support Vector Machines (SVM) detector on HOG features
  - Deformable part-based model (DPM)
  - R-CNN (detector with Neural Networks)
- Object (class) segmentation
  - Unsupervised segmentation ("bottom-up" techniques)
  - Supervised segmentation ("top-down" techniques)

Recognition:

Indexing for Fast Retrieval

Recognizing or Retrieving Specific Objects

- Example: Visual search in feature films

Visually defined query

“Groundhog Day” [Rammis, 1993]

“Find this clock”

“Find this place”

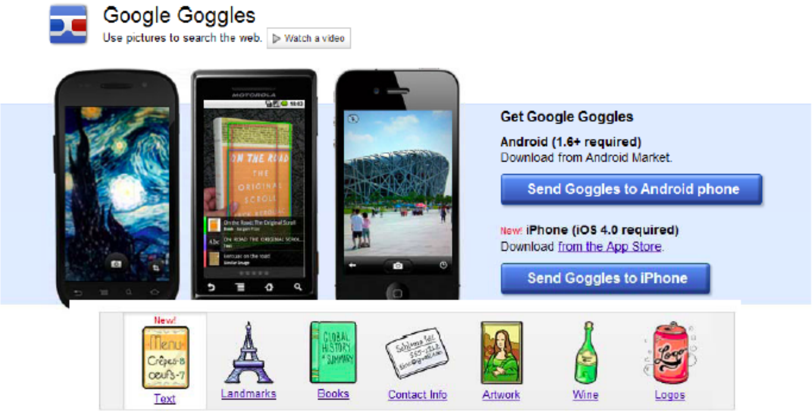
[Source: J. Sivic, slide credit: R. Urtasun]

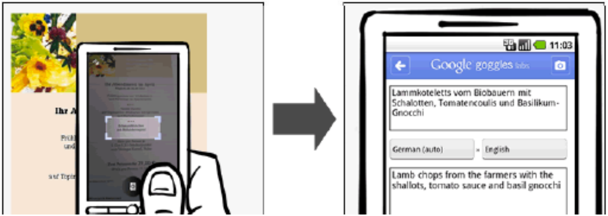
Recognizing or Retrieving Specific Objects

- Example: Search photos on the web for particular places

Find these landmarks ...in these images and 1M more

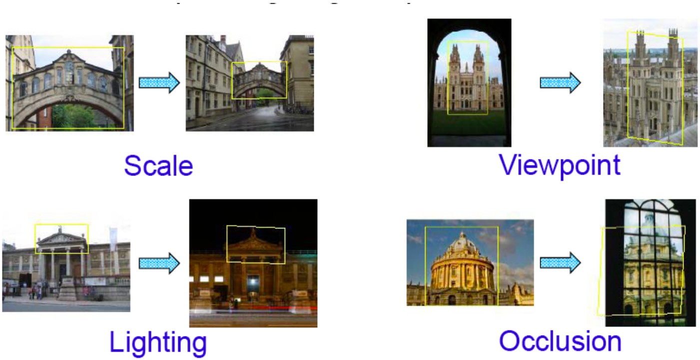
[Source: J. Sivic, slide credit: R. Urtasun]


Google Goggles
Use pictures to search the web.
Watch a video
Get Google Goggles
Android (1.6+ required)
Download from Android Market.
Send Goggles to Android phone
New! iPhone (iOS 4.0 required)
Download from the App Store.
Send Goggles to iPhone
New!
Text
Landmarks
Books
Contact Info
Artwork
Wine
Logos


11:03
Google goggles labs
Lammkoteletts vom Biobauern mit Schalotten, Tomatencoulis und Basilikum-Gnocchi
German (auto)
English
Lamb chops from the farmers with the shallots, tomato sauce and basil gnocchi

Why is it Difficult?

- Objects can have possibly large changes in scale, viewpoint, lighting and partial occlusion.



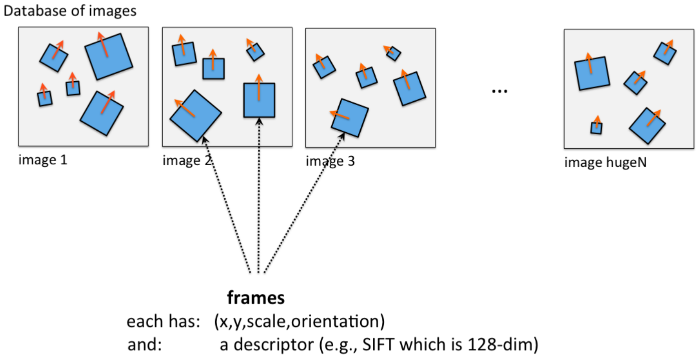
[Source: J. Sivic, slide credit: R. Urtasun]

Why is it Difficult?

- There is tones of data.

Our Case: Matching with Local Features

- For each image in our database we extracted local descriptors (e.g., SIFT)



Our Case: Matching with Local Features

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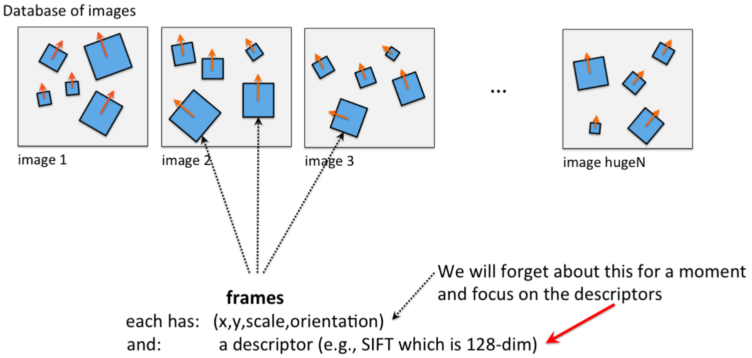

Our Case: Matching with Local Features

- Let's focus on descriptors only (vectors of e.g. 128 dim for SIFT)

Database of images

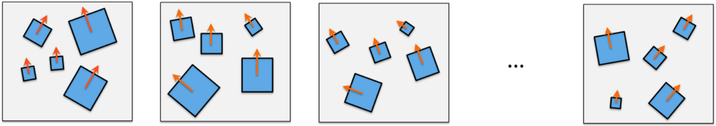

image 1 | image 2 | image 3 | ... | image hugeN

$f_1^1 = [0.1, 0.2, \ldots, 0.15]^T$
$f_2^1 = [0.23, 0.12, \ldots, 0.1]^T$
$f_3^1 = [0.12, 0.15, \ldots, 0.05]^T$
$\vdots$
$f_n^1 = [0.05, 0.18, \ldots, 0.09]^T$

$f_1^2 = [0.05, 0.11, \ldots, 0.2]^T$
$f_2^2 = [0.09, 0.01, \ldots, 0.18]^T$
$f_3^2 = [0.0, 0.08, \ldots, 0.1]^T$
$f_m^2 = [0.1, 0.15, \ldots, 0.14]^T$

$f_1^{hugeN} = [0.12, 0.15, \ldots, 0.19]^T$
$f_2^{hugeN} = [0.1, 0.2, \ldots, 0.2]^T$
$f_3^{hugeN} = [0.12, 0.22, \ldots, 0.18]^T$
$f_k^{hugeN} = [0.15, 0.02, \ldots, 0.08]^T$

descriptors (vectors)

Our Case: Matching with Local Features

Database of images

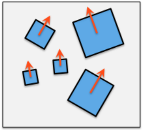

image 1

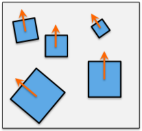

image 2

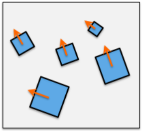

image 3

...

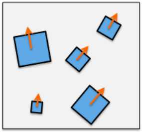

image hugeN

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$f_3^1 = [0.12, 0.15, \dots, 0.05]^T$
$\vdots$
$f_n^1 = [0.05, 0.18, \dots, 0.09]^T$

$f_1^2 = [0.05, 0.11, \dots, 0.2]^T$
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$f_3^2 = [0.0, 0.08, \dots, 0.1]^T$
$\vdots$
$f_m^2 = [0.1, 0.15, \dots, 0.14]^T$

descriptors (vectors)

$f_1^{hugeN} = [0.12, 0.15, \dots, 0.19]^T$
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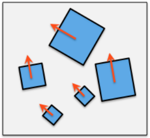
$f_3^{hugeN} = [0.12, 0.22, \dots, 0.18]^T$
$\vdots$
$f_k^{hugeN} = [0.15, 0.02, \dots, 0.08]^T$

Now I get a reference (query) image of an object. I want to retrieve all images from the database that contain the object. **How?**

$f_1^{ref} = [0.1, 0.2, \dots, 0.16]^T$
$f_2^{ref} = [0.15, 0.02, \dots, 0.06]^T$
$f_3^{ref} = [0.14, 0.22, \dots, 0.09]^T$
$\vdots$
$f_p^{ref} = [0.17, 0.18, \dots, 0.2]^T$



reference (query) image

Our Case: Matching with Local Features

Database of images

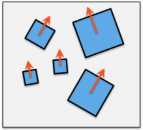


image 1

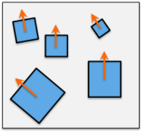


image 2

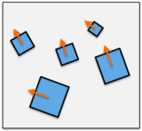


image 3

...

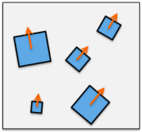


image hugeN

$$f_1^1 = [0.1, 0.2, \ldots, 0.15]^T$$
$$f_2^1 = [0.23, 0.12, \ldots, 0.1]^T$$
$$f_3^1 = [0.12, 0.15, \ldots, 0.05]^T$$
$$\vdots$$
$$f_n^1 = [0.05, 0.18, \ldots, 0.09]^T$$

$$f_1^2 = [0.05, 0.11, \ldots, 0.2]^T$$
$$f_2^2 = [0.09, 0.01, \ldots, 0.18]^T$$
$$f_3^2 = [0.0, 0.08, \ldots, 0.1]^T$$
$$\vdots$$
$$f_m^2 = [0.1, 0.15, \ldots, 0.14]^T$$

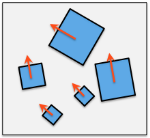
descriptors (vectors)

$$f_1^{hugeN} = [0.12, 0.15, \ldots, 0.19]^T$$
$$f_2^{hugeN} = [0.1, 0.2, \ldots, 0.2]^T$$
$$f_3^{hugeN} = [0.12, 0.22, \ldots, 0.18]^T$$
$$\vdots$$
$$f_k^{hugeN} = [0.15, 0.02, \ldots, 0.08]^T$$

SLOW

Before (Assignment 3) we were matching **all** reference descriptors to **all** descriptors in **each** database image. Not very efficient.

$$f_1^{ref} = [0.1, 0.2, \ldots, 0.16]^T$$
$$f_2^{ref} = [0.15, 0.02, \ldots, 0.06]^T$$
$$f_3^{ref} = [0.14, 0.22, \ldots, 0.09]^T$$
$$\vdots$$
$$f_p^{ref} = [0.17, 0.18, \ldots, 0.2]^T$$



reference (query) image

Our Case: Matching with Local Features

Database of images

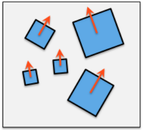


image 1

$f_1^1 = [0.1, 0.2, \ldots, 0.15]^T$
$f_2^1 = [0.23, 0.12, \ldots, 0.1]^T$
$f_3^1 = [0.12, 0.15, \ldots, 0.05]^T$
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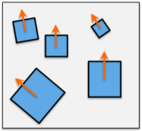

image 2

$f_1^2 = [0.05, 0.11, \ldots, 0.2]^T$
$f_2^2 = [0.09, 0.01, \ldots, 0.18]^T$
$f_3^2 = [0.0, 0.08, \ldots, 0.1]^T$
$\vdots$
$f_m^2 = [0.1, 0.15, \ldots, 0.14]^T$

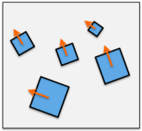

image 3

...

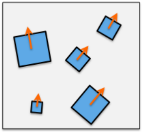

image hugeN

$f_1^{hugeN} = [0.12, 0.15, \ldots, 0.19]^T$
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$\vdots$
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descriptors (vectors)

What can we do to speed-up?

Before (Assignment 3) we were matching **all** reference descriptors to **all** descriptors in **each** database image. Not very efficient.

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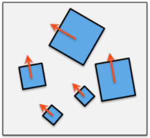
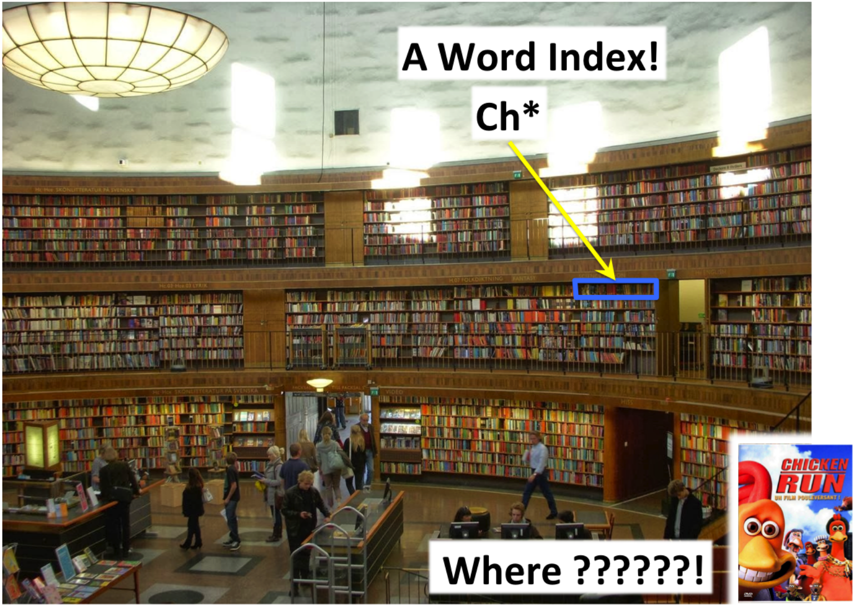
$f_3^{ref} = [0.14, 0.22, \ldots, 0.09]^T$
$\vdots$
$f_p^{ref} = [0.17, 0.18, \ldots, 0.2]^T$



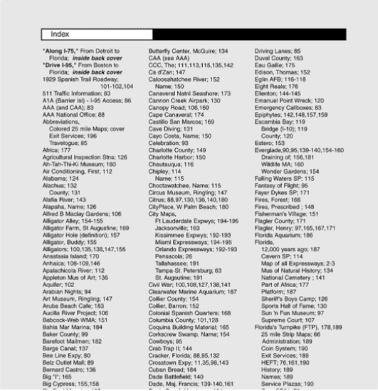
reference (query) image

Indexing!



Indexing Local Features: Inverted File Index

- For text documents, an efficient way to find all pages on which a word occurs is to use an index.
- We want to find all images in which a feature occurs.
- To use this idea, well need to map our features to "visual words".
- Why?



Index

[Source: K. Grauman, slide credit: R. Urtasun]

What Are Our Visual "Words"?

Database of images

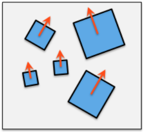


image 1

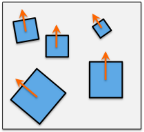


image 2

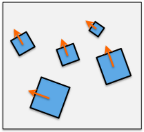


image 3

...

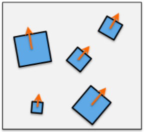


image hugeN

$f_1^1 = [0.1, 0.2, \ldots, 0.15]^T$
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$f_3^1 = [0.12, 0.15, \ldots, 0.05]^T$
$\vdots$
$f_n^1 = [0.05, 0.18, \ldots, 0.09]^T$

$f_1^2 = [0.05, 0.11, \ldots, 0.2]^T$
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$\vdots$
$f_m^2 = [0.1, 0.15, \ldots, 0.14]^T$

descriptors (vectors)

$f_1^{hugeN} = [0.12, 0.15, \ldots, 0.19]^T$
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$f_k^{hugeN} = [0.15, 0.02, \ldots, 0.08]^T$

What are our visual ``words''?

$f_1^{ref} = [0.1, 0.2, \ldots, 0.16]^T$
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$\vdots$
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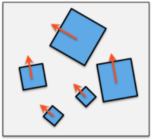

reference (query) image

What Are Our Visual “Words”?

Database of images

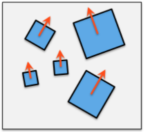

image 1

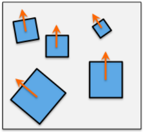

image 2

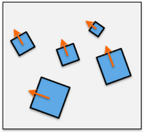

image 3

...

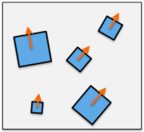

image hugeN

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$\vdots$
$f_n^1 = [0.05, 0.18, \ldots, 0.09]^T$

$f_1^2 = [0.05, 0.11, \ldots, 0.2]^T$
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descriptors (vectors)

$f_1^{hugeN} = [0.12, 0.15, \ldots, 0.19]^T$
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$f_3^{hugeN} = [0.12, 0.22, \ldots, 0.18]^T$
$\vdots$
$f_k^{hugeN} = [0.15, 0.02, \ldots, 0.08]^T$

The quest for visual words

We could do something like:

If all coordinates of vector smaller than 0.1, then call this vector word 1
If first n-1 coordinates < 0.1, but last coordinate is > 0.1, call this vector word 2
If first n-2 and last coordinate < 0.1, but n-1 coordinate > 0.1, call this vector word 3
...

Why is this not a very good choice? How can we do this better?

What Are Our Visual "Words"?

Database of images

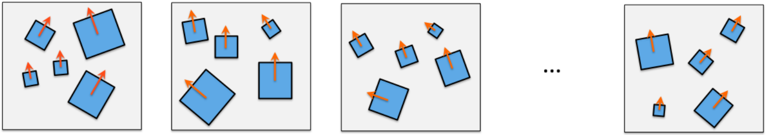

image 1 image 2 image 3 ... image hugeN

$f_1^1 = [0.1, 0.2, \ldots, 0.15]^T$
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$f_1^{hugeN} = [0.12, 0.15, \ldots, 0.19]^T$
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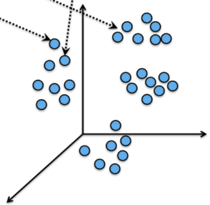
descriptors (vectors)

The quest for visual words



You can imagine each descriptor vector as a point in a high-dimensional space (128-dim for SIFT).

Disclaimer: This is only for the purpose of easier visualization of the solution.

What Are Our Visual "Words"?

Database of images

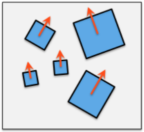


image 1

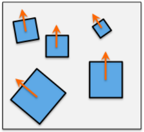


image 2

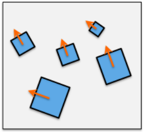


image 3

...

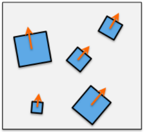


image hugeN

$f_1^1 = [0.1, 0.2, \ldots, 0.15]^T$
$f_2^1 = [0.23, 0.12, \ldots, 0.1]^T$
$f_3^1 = [0.12, 0.15, \ldots, 0.05]^T$
$\vdots$
$f_n^1 = [0.05, 0.18, \ldots, 0.09]^T$

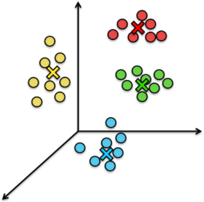
$f_1^2 = [0.05, 0.11, \ldots, 0.2]^T$
$f_2^2 = [0.09, 0.01, \ldots, 0.18]^T$
$f_3^2 = [0.0, 0.08, \ldots, 0.1]^T$
$\vdots$
$f_m^2 = [0.1, 0.15, \ldots, 0.14]^T$

descriptors (vectors)

$f_1^{hugeN} = [0.12, 0.15, \ldots, 0.19]^T$
$f_2^{hugeN} = [0.1, 0.2, \ldots, 0.2]^T$
$f_3^{hugeN} = [0.12, 0.22, \ldots, 0.18]^T$
$\vdots$
$f_k^{hugeN} = [0.15, 0.02, \ldots, 0.08]^T$

The quest for visual words

- We can choose our visual words as ``representative" vectors in this space
- We can perform **clustering** (for example **k-means**)



What Are Our Visual "Words"?

Database of images

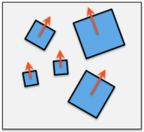


image 1

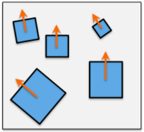


image 2

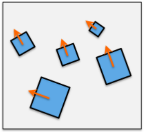


image 3

...

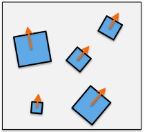


image hugeN

$f_1^1 = [0.1, 0.2, \ldots, 0.15]^T$
$f_2^1 = [0.23, 0.12, \ldots, 0.1]^T$
$f_3^1 = [0.12, 0.15, \ldots, 0.05]^T$
$\vdots$
$f_n^1 = [0.05, 0.18, \ldots, 0.09]^T$

$f_1^2 = [0.05, 0.11, \ldots, 0.2]^T$
$f_2^2 = [0.09, 0.01, \ldots, 0.18]^T$
$f_3^2 = [0.0, 0.08, \ldots, 0.1]^T$
$\vdots$
$f_m^2 = [0.1, 0.15, \ldots, 0.14]^T$

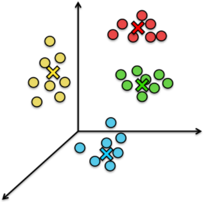
descriptors (vectors)

$f_1^{hugeN} = [0.12, 0.15, \ldots, 0.19]^T$
$f_2^{hugeN} = [0.1, 0.2, \ldots, 0.2]^T$
$f_3^{hugeN} = [0.12, 0.22, \ldots, 0.18]^T$
$\vdots$
$f_k^{hugeN} = [0.15, 0.02, \ldots, 0.08]^T$

Visual words

- ✖ $W1 = [0.1, 0.15, \ldots, 0.8]^T$
- ✖ $W2 = [0.15, 0.01, \ldots, 0.09]^T$
- ✖ $W3 = [0.01, 0.09, \ldots, 0.1]^T$
- ✖ $W4 = [0.2, 0.02, \ldots, 0.14]^T$

$\vdots$



What Are Our Visual "Words"?

Database of images

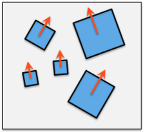


image 1

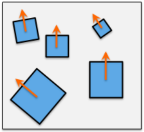


image 2

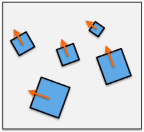


image 3

...

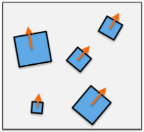


image hugeN

$\boxed{f_1^1 = [0.1, 0.2, \ldots, 0.15]^T}$
$f_2^1 = [0.23, 0.12, \ldots, 0.1]^T$
$f_3^1 = [0.12, 0.15, \ldots, 0.05]^T$
$\vdots$
$f_n^1 = [0.05, 0.18, \ldots, 0.09]^T$

$f_1^2 = [0.05, 0.11, \ldots, 0.2]^T$
$f_2^2 = [0.09, 0.01, \ldots, 0.18]^T$
$f_3^2 = [0.0, 0.08, \ldots, 0.1]^T$
$\vdots$
$f_m^2 = [0.1, 0.15, \ldots, 0.14]^T$

descriptors (vectors)

$f_1^{hugeN} = [0.12, 0.15, \ldots, 0.19]^T$
$f_2^{hugeN} = [0.1, 0.2, \ldots, 0.2]^T$
$f_3^{hugeN} = [0.12, 0.22, \ldots, 0.18]^T$
$\vdots$
$f_k^{hugeN} = [0.15, 0.02, \ldots, 0.08]^T$

Visual words

How do we map this vector to a visual word?

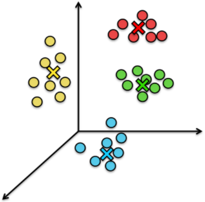
$W1 = [0.1, 0.15, \ldots, 0.8]^T$

$W2 = [0.15, 0.01, \ldots, 0.09]^T$

$W3 = [0.01, 0.09, \ldots, 0.1]^T$

$W4 = [0.2, 0.02, \ldots, 0.14]^T$

$\vdots$



What Are Our Visual "Words"?

Database of images

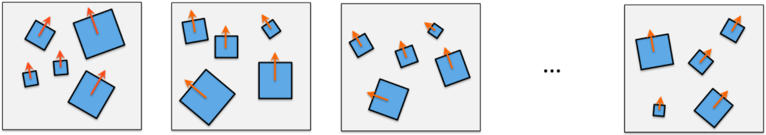


image 1 image 2 image 3 ... image hugeN

$\boxed{W1}$

$f_2^1 = [0.23, 0.12, \ldots, 0.1]^T$

$f_3^1 = [0.12, 0.15, \ldots, 0.05]^T$

$\vdots$

$f_n^1 = [0.05, 0.18, \ldots, 0.09]^T$

$f_1^2 = [0.05, 0.11, \ldots, 0.2]^T$

$f_2^2 = [0.09, 0.01, \ldots, 0.18]^T$

$f_3^2 = [0.0, 0.08, \ldots, 0.1]^T$

$\vdots$

$f_m^2 = [0.1, 0.15, \ldots, 0.14]^T$

descriptors (vectors)

$f_1^{hugeN} = [0.12, 0.15, \ldots, 0.19]^T$

$f_2^{hugeN} = [0.1, 0.2, \ldots, 0.2]^T$

$f_3^{hugeN} = [0.12, 0.22, \ldots, 0.18]^T$

$\vdots$

$f_k^{hugeN} = [0.15, 0.02, \ldots, 0.08]^T$

Visual words

✖ $W1 = [0.1, 0.15, \ldots, 0.8]^T$

✖ $W2 = [0.15, 0.01, \ldots, 0.09]^T$

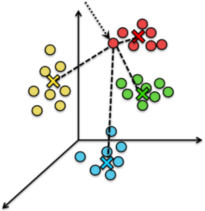
✖ $W3 = [0.01, 0.09, \ldots, 0.1]^T$

✖ $W4 = [0.2, 0.02, \ldots, 0.14]^T$

$\vdots$

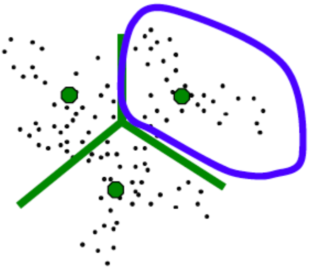
We find the closest visual word (Euclidean distance)

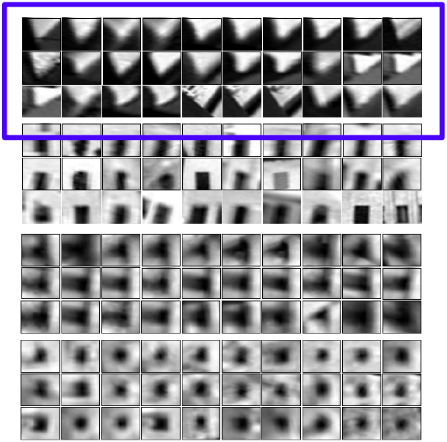
$$\arg\min_i ||f - Wi||$$



Visual Words

- All example patches on the right belong to the same visual word.





[Source: R. Urtasun]

What Are Our Visual "Words"?

Database of images

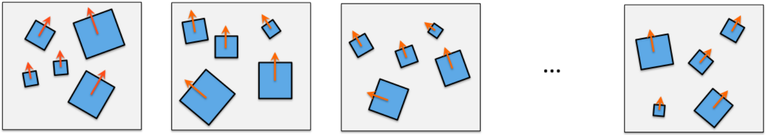


image 1	image 2	image 3		image hugeN
$W1$	$W2$	$W7$		$W6$
$W5$	$W3$	$W9$		$W2$
$W4$	$W6$	$W1$	**words**	$W7$
$\vdots$	$\vdots$	$\vdots$		$\vdots$
$W1$	$W7$	$W9$		$W8$

Then we can assign each descriptor vector to a word

Now what?

What Are Our Visual "Words"?

Database of images

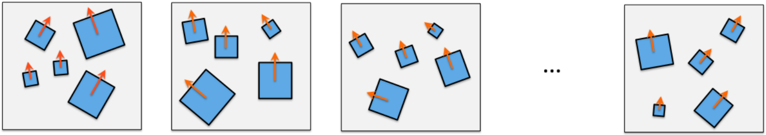


image 1 | image 2 | image 3 | ... | image hugeN

image 1	image 2	image 3		image hugeN
$W1$	$W2$	$W7$		$W6$
$W5$	$W3$	$W9$		$W2$
$W4$	$W6$	$W1$	**words**	$W7$
$\vdots$	$\vdots$	$\vdots$		$\vdots$
$W1$	$W7$	$W9$		$W8$

Visual word	Image
1	1,3
2	2,hugeN
3	2
4	1
5	1
6	2,hugeN
7	2,3,hugeN
...	

We can now build an **inverted file index**

This is like an Index of a book

What Are Our Visual "Words"?

Database of images

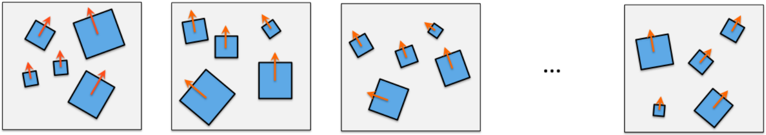


image 1 | image 2 | image 3 | … | image hugeN

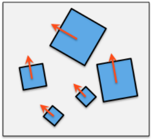
image 1	image 2	image 3	image hugeN
$W1$	$W2$	$W7$	$W6$
$W5$	$W3$	$W9$	$W2$
$W4$	$W6$	$W1$	$W7$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
$W1$	$W7$	$W9$	$W8$

words

Visual word	Image
1	1,3
2	2,hugeN
3	2
4	1
5	1
6	2,hugeN
7	2,3,hugeN
…	

We can also assign the descriptors in the reference image to the visual words

$W5$
$W1$
$W4$
$\vdots$
$W1$



reference (query) image

What Are Our Visual "Words"?

Database of images

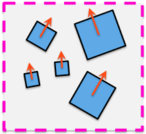


image 1

$W1$, $W5$, $W4$, $\vdots$, $W2$

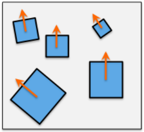


image 2

$W2$, $W3$, $W6$, $\vdots$, $W7$

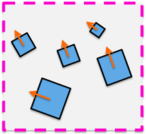


image 3

$W7$, $W1$, $W9$, $\vdots$, $W91$

...

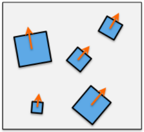


image hugeN

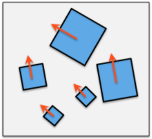
$W6$, $W2$, $W7$, $\vdots$, $W8$

words

Visual word	Image
1	1,3
2	2,hugeN
3	2
4	1
5	1
6	2,hugeN
7	2,3,hugeN
...	

And for each word in the reference image, we lookup our inverted file and check which images contain it. **We only need to match our reference image to the retrieved set of images.**

$W5$, $W1$, $W4$, $\vdots$, $W1$



reference (query) image

Inverted File Index

- Now we found all images in the database that have at least one visual word in common with the query image
- But this can still give us lots of images... What can we do?

New query image

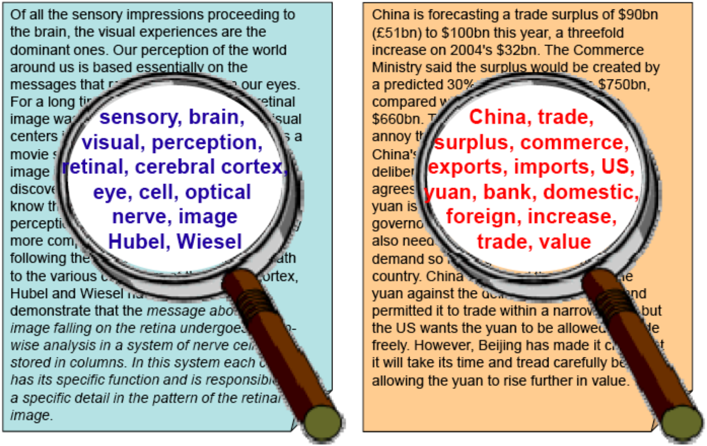
Word #	Image #
1	3
2	
...	
7	1, 2
8	3
9	
10	
...	
91	2

...

Inverted File Index

- Now we found all images in the database that have at least one visual word in common with the query image
- But this can still give us lots of images... What can we do?
- Idea: Compute similarity between query image and retrieved images. How can we do this fast?

Relation to Documents

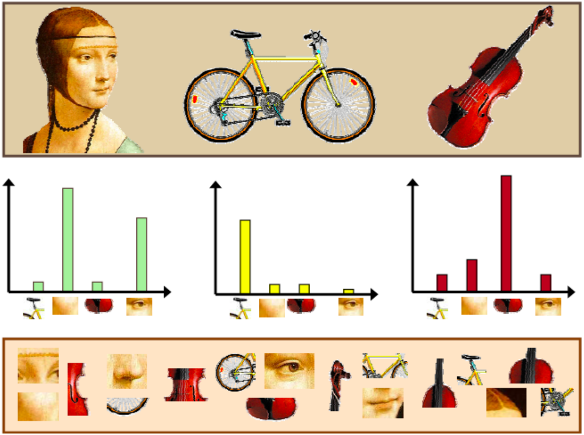


[Slide credit: R. Urtasun]

Bags of Visual Words

[Slide credit: R. Urtasun]

- Summarize entire image based on its distribution (histogram) of word occurrences.
- Analogous to bag of words representation commonly used for documents.



Compute a Bag-of-Words Description

Database of images

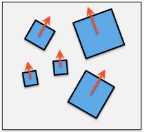


image 1

$W1$
$W5$
$W4$
⋮
$W1$

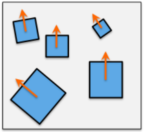


image 2

$W2$
$W3$
$W6$
⋮
$W7$

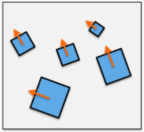


image 3

$W7$
$W9$
$W1$
⋮
$W9$

...

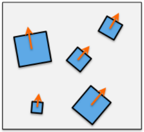


image hugeN

$W6$
$W2$
$W7$
⋮
$W8$

words

How many times a word repeats in image (frequency)

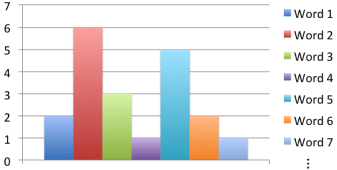


image 1 representation

$$\begin{bmatrix} 2 & 6 & 3 & 1 & 5 & 2 & 1 & \ldots \end{bmatrix}$$

Compute a Bag-of-Words Description

Database of images

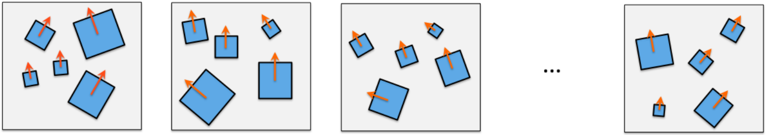


image 1 | image 2 | image 3 | ... | image hugeN

image 1	image 2	image 3		image hugeN
$W1$	$W2$	$W7$		$W6$
$W5$	$W3$	$W9$		$W2$
$W4$	$W6$	$W1$	**words**	$W7$
$\vdots$	$\vdots$	$\vdots$		$\vdots$
$W1$	$W7$	$W9$		$W8$

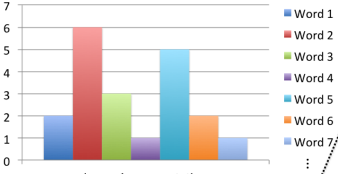


image 1 representation

$$[\ 2\ \ 6\ \ 3\ \ 1\ \ 5\ \ 2\ \ 1\ \ ...\ ]$$

Better to re-weigh these values with **tf-idf:**

$$[t_1, t_2, t_3, \ldots]^T$$

$$t_i = \frac{n_{id}}{n_d} \log \frac{N}{n_i}$$

Compute a Bag-of-Words Description

- Instead of a histogram, for retrieval it's better to re-weight the image description vector $T = [t_1, t_2, \ldots, t_i, \ldots]$ with **term frequency-inverse document frequency** (tf-idf), a standard trick in document retrieval:

$$t_i = \frac{n_{id}}{n_d} \log \frac{N}{n_i}$$

where:

n_{id} ... is the number of occurrences of word i in image d
n_d ... is the total number of words in image d
n_i ... is the number of occurrences of word i in the whole database
N ... is the number of documents in the whole database

Compute a Bag-of-Words Description

- Instead of a histogram, for retrieval it's better to re-weight the image description vector $T = [t_1, t_2, \ldots, t_i, \ldots]$ with **term frequency-inverse document frequency** (tf-idf), a standard trick in document retrieval:

$$t_i = \frac{n_{id}}{n_d} \log \frac{N}{n_i}$$

  where:

  n_{id} ... is the number of occurrences of word i in image d
  n_d ... is the total number of words in image d
  n_i ... is the number of occurrences of word i in the whole database
  N ... is the number of documents in the whole database

- The weighting is a product of two terms: the word frequency $\frac{n_{id}}{n_d}$, and the inverse document frequency $\log \frac{N}{n_i}$

Compute a Bag-of-Words Description

- Instead of a histogram, for retrieval it's better to re-weight the image description vector $\mathbf{t} = [t_1, t_2, \ldots, t_i, \ldots]$ with **term frequency-inverse document frequency** (tf-idf), a standard trick in document retrieval:

$$t_i = \frac{n_{id}}{n_d} \log \frac{N}{n_i}$$

where:

n_{id}	$\ldots$	is the number of occurrences of word i in image d
n_d	$\ldots$	is the total number of words in image d
n_i	$\ldots$	is the number of occurrences of word i in the whole database
N	$\ldots$	is the number of documents in the whole database

- The weighting is a product of two terms: the word frequency $\frac{n_{id}}{n_d}$, and the inverse document frequency $\log \frac{N}{n_i}$
- Intuition behind this: word frequency weights words occurring often in a particular document, and thus describe it well, while the inverse document frequency downweights the words that occur often in the full dataset

Compute a Bag-of-Words Description

Database of images

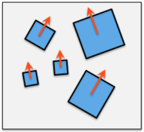


image 1

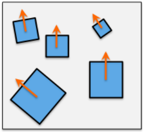


image 2

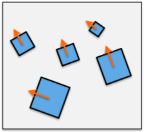


image 3

...

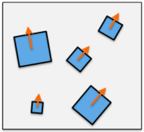


image hugeN

image 1	image 2	image 3		image hugeN
$W1$	$W2$	$W7$		$W6$
$W5$	$W3$	$W9$		$W2$
$W4$	$W6$	$W1$	**words**	$W7$
$\vdots$	$\vdots$	$\vdots$		$\vdots$
$W1$	$W7$	$W9$		$W8$

We can do the same for the reference image

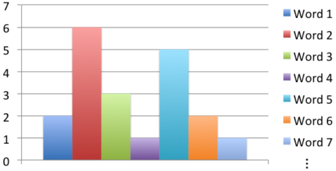
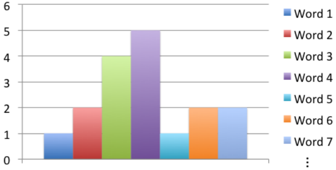


image 1 representation

$$[\ 2\ \ 6\ \ 3\ \ 1\ \ 5\ \ 2\ \ 1\ \ \ldots\ ]$$



reference image representation

$$[\ 1\ \ 2\ \ 4\ \ 5\ \ 1\ \ 2\ \ 2\ \ \ldots\ ]$$

Compute a Bag-of-Words Description

Database of images

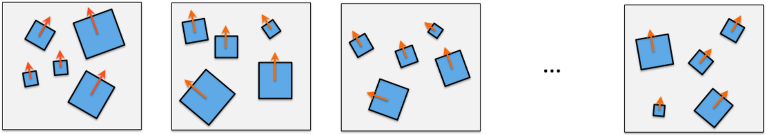


image 1 image 2 image 3 image hugeN

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words

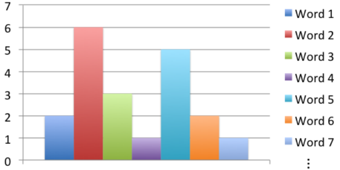
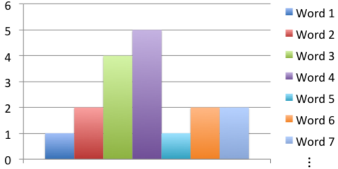


image 1 representation



reference image representation

How do we compare?

$[\ 2\ \ 6\ \ 3\ \ 1\ \ 5\ \ 2\ \ 1\ \ \dots\ ]$ $[\ 1\ \ 2\ \ 4\ \ 5\ \ 1\ \ 2\ \ 2\ \ \dots\ ]$

Comparing Images

- Compute the similarity by normalized dot product between their (tf-idf weighted) occurrence counts

$$\text{sim}(\mathbf{t_j}, \mathbf{q}) = \frac{< \mathbf{t_j}, \mathbf{q} >}{||\mathbf{t_j}|| \cdot ||\mathbf{q}||}$$

- Rank images in database based on the similarity score (the higher the better)
- Are we done?

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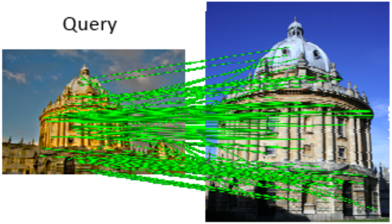
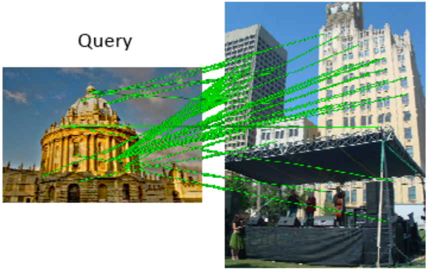
Spatial Verification

- Both image pairs have many visual words in common
- Only some of the matches are mutually consistent



DB image with high BoW similarity



DB image with high BoW similarity

[Source: O. Chum]

Summary – Stuff You Need To Know

Fast image retrieval:

- Compute features in all images from database, and query image.
- Cluster the descriptors from the images in the database (e.g., k-means) to get k clusters. These clusters are vectors that live in the same dimensional space as the descriptors. We call them **visual words**.
- Assign each descriptor in database and query image to the closest cluster.
- Build an inverted file index
- For a query image, lookup all the visual words in the inverted file index to get a list of images that share at least one visual word with the query
- Compute a bag-of-words (BoW) vector for each retrieved image and query. This vector just counts the number of occurrences of each word. It has as many dimensions as there are visual words. Weight the vector with tf-idf.
- Compute similarity between query BoW vector and all retrieved image BoW vectors. Sort (highest to lowest). Take top K most similar images (e.g, 100)
- Do spatial verification on all top K retrieved images (RANSAC + affine or homography + remove images with too few inliers)

Summary – Stuff You Need To Know

Matlab function:

- [IDX, W] = KMEANS(X, K); where rows of X are descriptors, rows of W are visual words vectors, and IDX are assignments of rows of X to visual words
- Once you have W, you can quickly compute IDX via the DIST2 function (Assignment 2):

  D = DIST2(X', W'); [~,IDX] = MIN(D, [], 2);
- A much faster way of computing the closest cluster (IDX) is via the FLANN library: `http://www.cs.ubc.ca/research/flann/`

- Since X is typically super large, KMEANS will run for days... A solution is to randomly sample a few descriptors from X and cluster those. Another great possibility is to use this: `http://www.robots.ox.ac.uk/~vgg/software/fastanncluster/`

Even Faster?

- Can we make the retrieval process even more efficient?

Vocabulary Trees

- Hierarchical clustering for large vocabularies, [Nister et al., 06].
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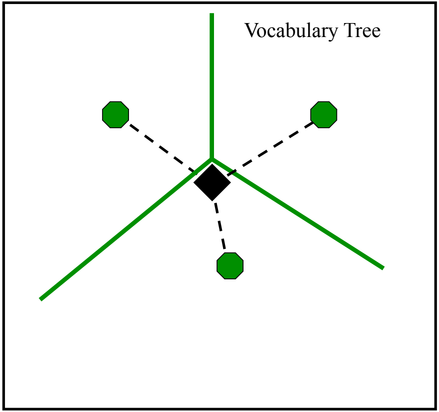
Constructing the tree

- Offline phase: hierarchical clustering.



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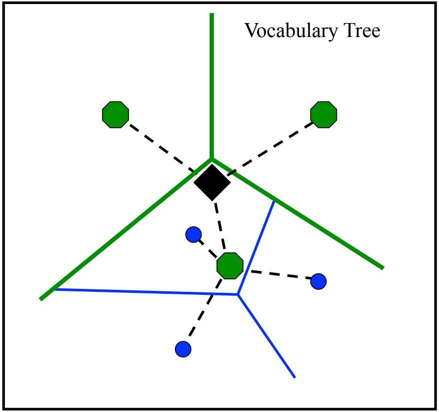

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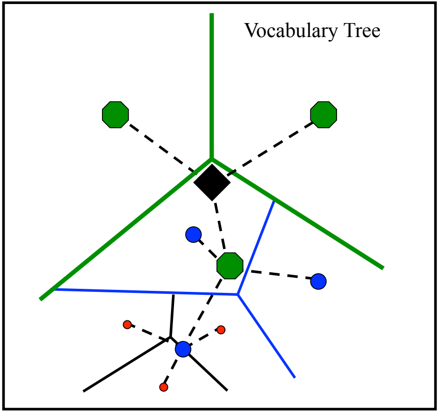

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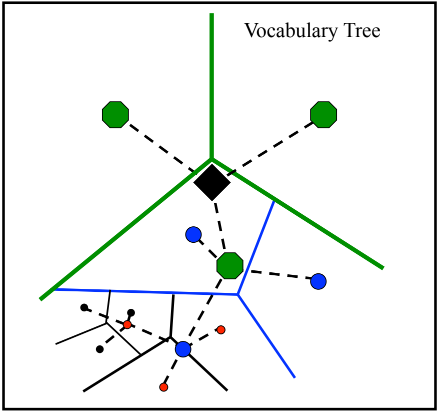
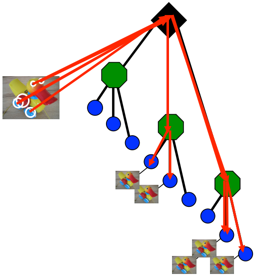
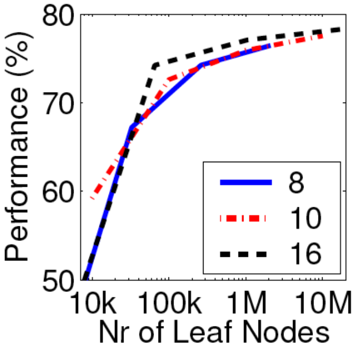


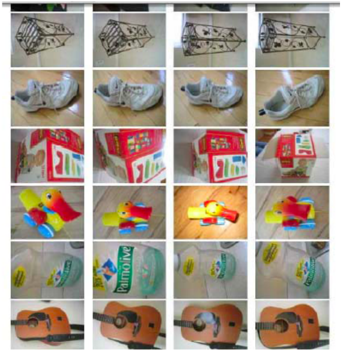
Parsing the tree

- Online phase: each descriptor vector is propagated down the tree by at each level comparing the descriptor vector to the k candidate cluster centers (represented by k children in the tree) and choosing the closest one.
- The tree directly defines the visual vocabulary and an efficient search procedure in an integrated manner.
- Every node in the vocabulary tree is associated with an inverted file.
- The inverted files of inner nodes are the concatenation of the inverted files of the leaf nodes (virtual).



- Complexity: branching factor and number of levels
- Most important for the retrieval quality is to have a large vocabulary





Visual words/bags of words

Good

- flexible to geometry / deformations / viewpoint
- compact summary of image content
- provides vector representation for sets
- very good results in practice

Bad

- background and foreground mixed when bag covers whole image
- optimal vocabulary formation remains unclear
- basic model ignores geometry must verify afterwards, or encode via features

Next Time

Recognition Techniques in 20 min