# CS4670 / 5670: Computer Vision

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## Bag-of-words models

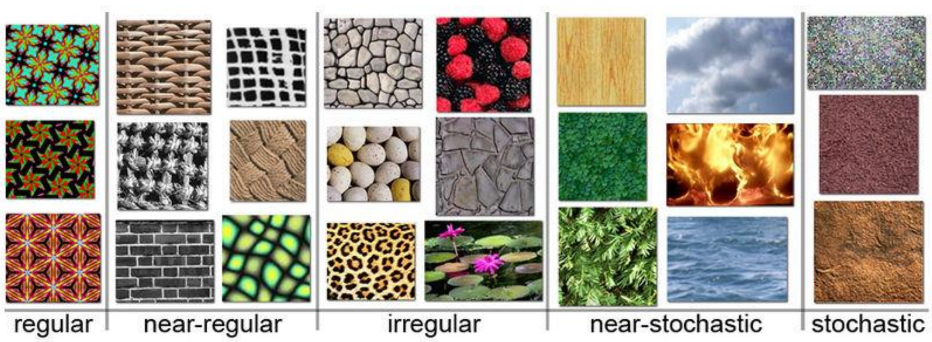
Object → Bag of 'words'

# Bag of Words Models

Adapted from slides by Rob Fergus and Svetlana Lazebnik

**Object** → **Bag of 'words'**

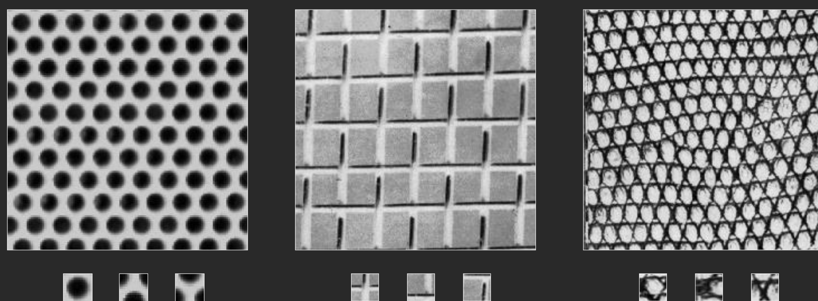
# Origin 1: Texture Recognition




Example textures (from Wikipedia)

## Origin 1: Texture recognition

- Texture is characterized by the repetition of basic elements or *textons*
- For stochastic textures, it is the identity of the textons, not their spatial arrangement, that matters



Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

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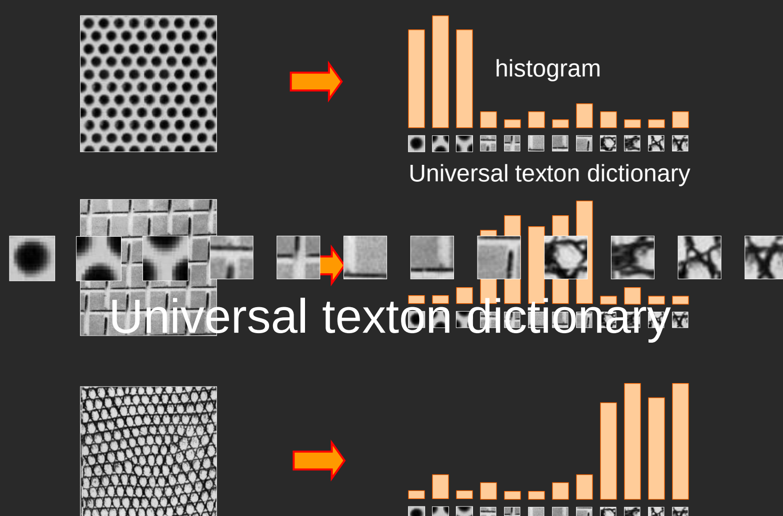


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# Origin 2: Bag-of-words models

- Orderless document representation: frequencies of words from a dictionary   Salton & McGill (1983)

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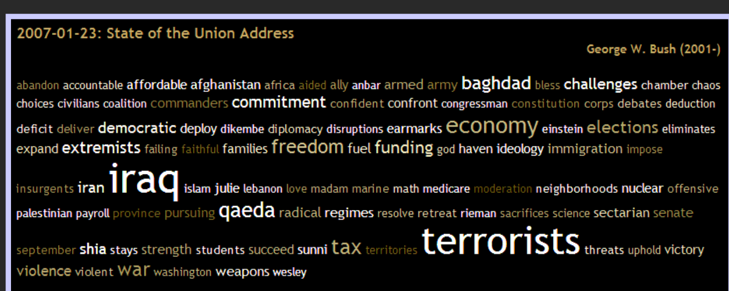


US Presidential Speeches Tag Cloud
`http://chir.ag/phernalia/preztags/`

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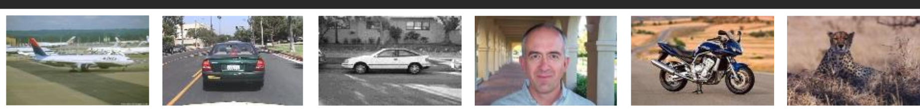
# Bags of features for object recognition


- Works pretty well for image-level classification and for recognizing object *instances*

Csurka et al. (2004), Willamowski et al. (2005), Grauman & Darrell (2005), Sivic et al. (2003, 2005)

# Bags of features for object recognition

Caltech6 dataset



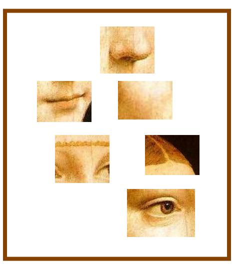
| class | bag of features<br>Zhang et al. (2005) | bag of features<br>Willamowski et al. (2004) | Parts-and-shape model<br>Fergus et al. (2003) |
|---|---|---|---|
| airplanes | **98.8** | 97.1 | 90.2 |
| cars (rear) | 98.3 | **98.6** | 90.3 |
| cars (side) | **95.0** | 87.3 | 88.5 |
| faces | **100** | 99.3 | 96.4 |
| motorbikes | **98.5** | 98.0 | 92.5 |
| spotted cats | **97.0** | — | 90.0 |

## Bag of features

- First, take a bunch of images, extract features, and build up a “dictionary” or “visual vocabulary” – a list of common features
- Given a new image, extract features and build a histogram – for each feature, find the closest visual word in the dictionary

## Bag of features: outline

1. Extract features



## Bag of features: outline

1. Extract features
2. Learn “visual vocabulary”

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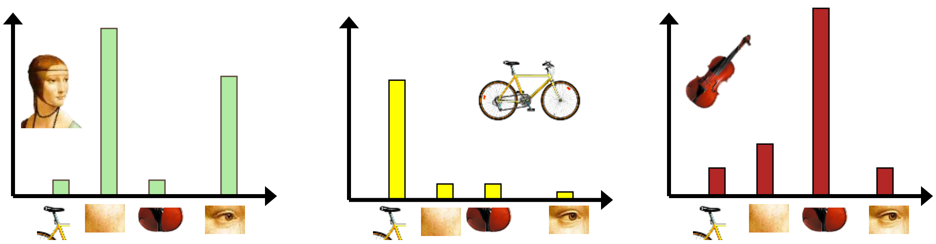
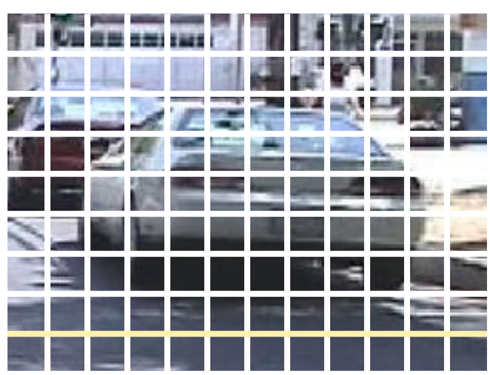
1. Extract features
2. Learn “visual vocabulary”
3. Quantize features using visual vocabulary
4. Represent images by frequencies of “visual words”



## 1. Feature extraction

Regular grid

- Vogel & Schiele, 2003
- Fei-Fei & Perona, 2005



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Interest point detector
- Csurka et al. 2004
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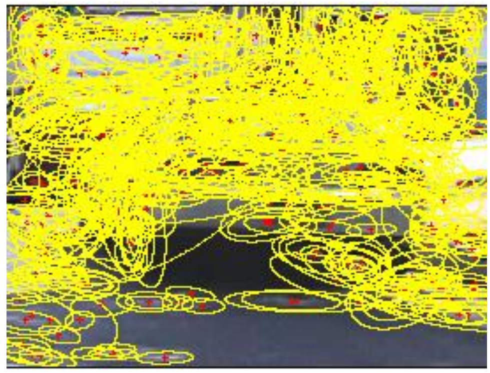
- Sivic et al. 2005



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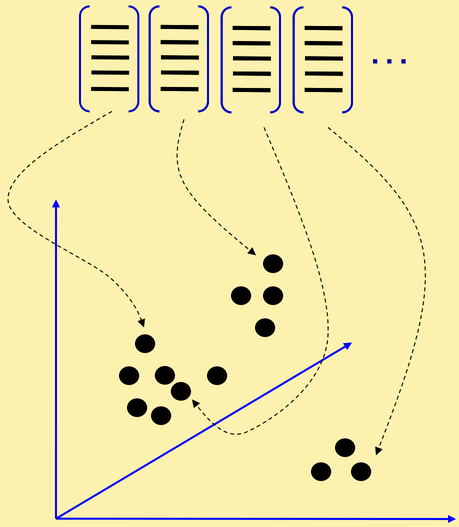
Other methods
- Random sampling (Vidal-Naquet & Ullman, 2002)
- Segmentation-based patches (Barnard et al. 2003)

## 2. Learning the visual vocabulary

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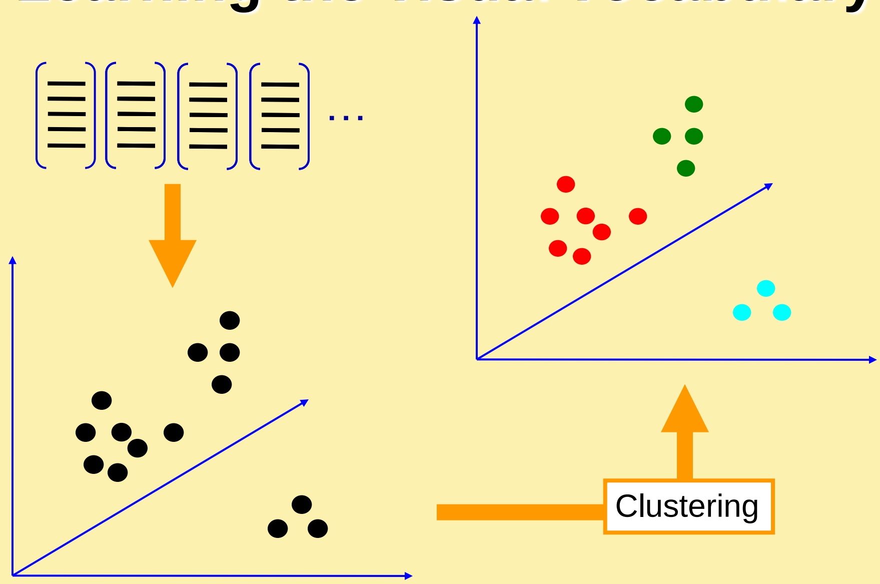


Slide credit: Josef Sivic

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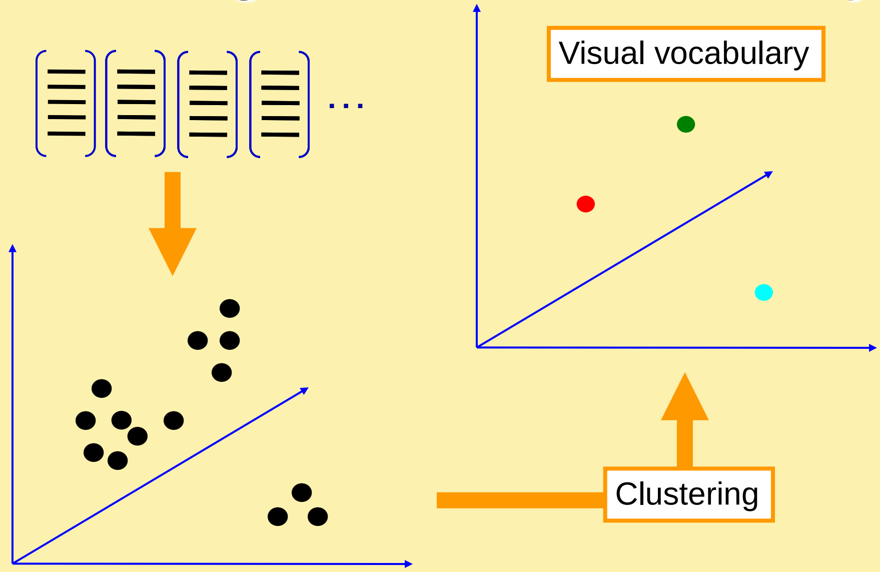



Slide credit: Josef Sivic

## K-means clustering

- Want to minimize sum of squared Euclidean distances between points $x_i$ and their nearest cluster centers $m_k$

$$D(X,M)=\sum_{\text{cluster } k}\ \sum_{\substack{\text{point } i \text{ in} \\ \text{cluster } k}} (x_i - m_k)^2$$

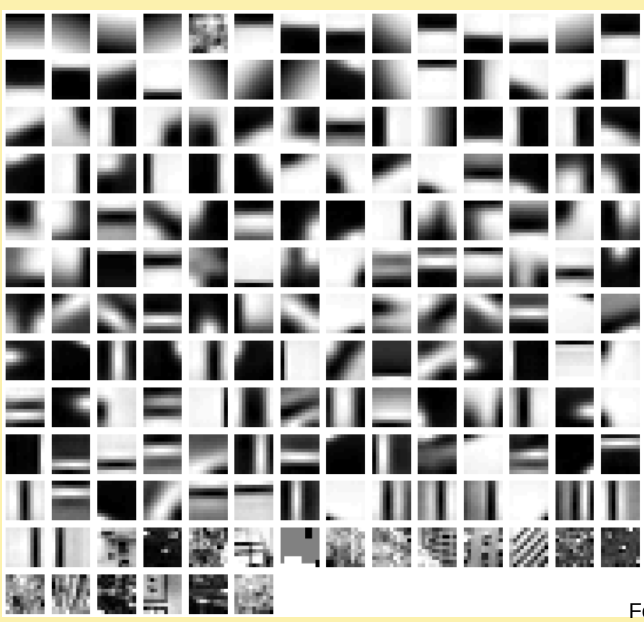
Algorithm:

- Randomly initialize K cluster centers
- Iterate until convergence:
  - Assign each data point to the nearest center
  - Recompute each cluster center as the mean of all points assigned to it

## From clustering to vector quantization

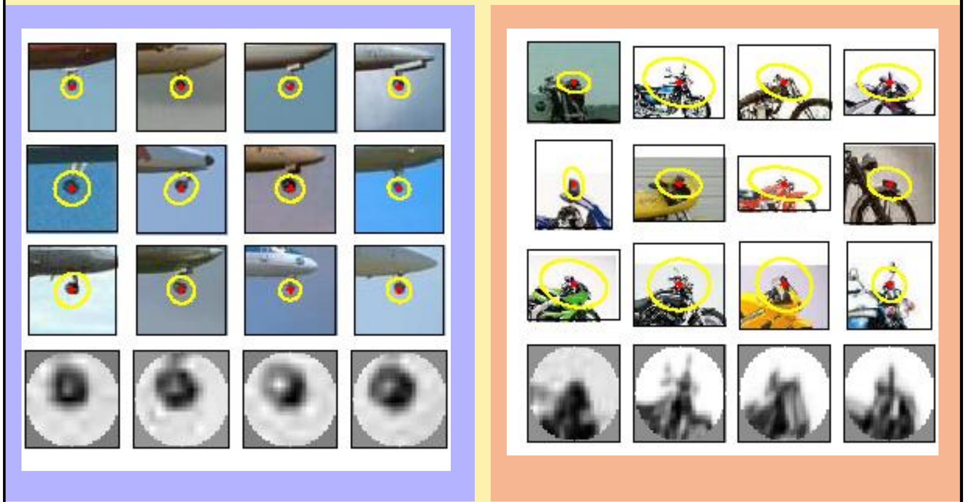
- Clustering is a common method for learning a visual vocabulary or codebook
  - Unsupervised learning process
  - Each cluster center produced by k-means becomes a codevector
  - Codebook can be learned on separate training set
  - Provided the training set is sufficiently representative, the codebook will be "universal"
- The codebook is used for quantizing features
  - A *vector quantizer* takes a feature vector and maps it to the index of the nearest codevector in a codebook
  - Codebook = visual vocabulary
  - Codevector = visual word

## Example visual vocabulary



Fei-Fei et al. 2005

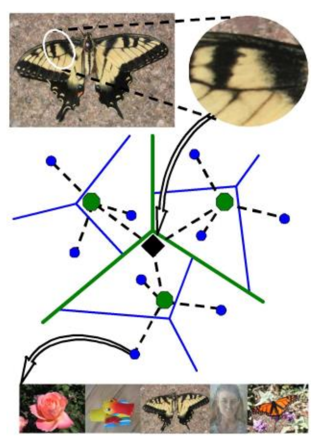
## Image patch examples of visual words



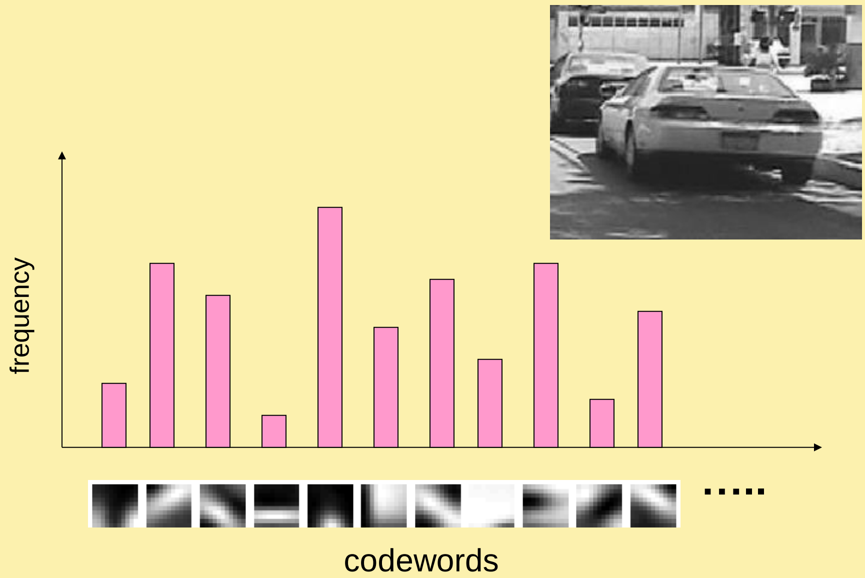
Sivic et al. 2005

## Visual vocabularies: Issues

- How to choose vocabulary size?
  - Too small: visual words not representative of all patches
  - Too large: quantization artifacts, overfitting
- Computational efficiency
  - Vocabulary trees
    (Nister & Stewenius, 2006)

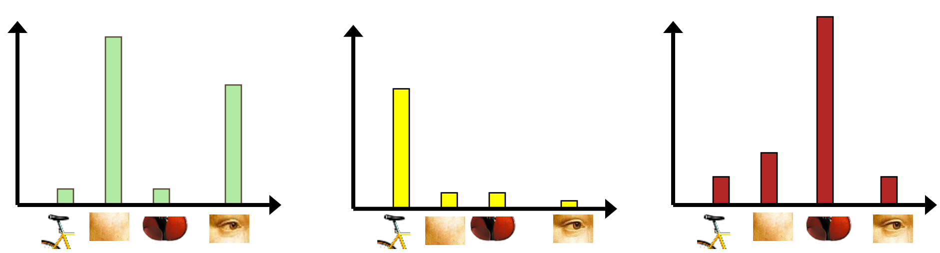


# 3. Image representation




## Image classification

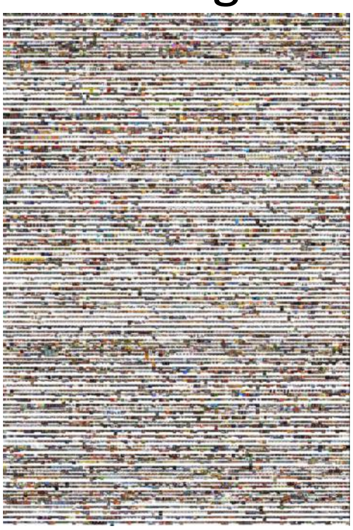
- Given the bag-of-features representations of images from different classes, how do we learn a model for distinguishing them?



## Uses of BoW representation

- Treat as feature vector for standard classifier
  - e.g k-nearest neighbors, support vector machine
- Cluster BoW vectors over image collection
  - Discover visual themes

## Large-scale image matching

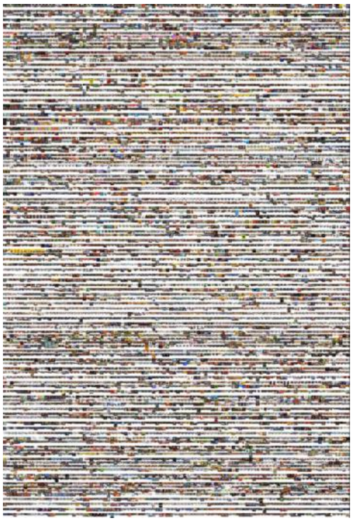


11,400 images of game covers (Caltech games dataset)

- Bag-of-words models have been useful in matching an image to a large database of object *instances*


how do I find this image in the database?

# Large-scale image search



- Build the database:
  - Extract features from the database images
  - Learn a vocabulary using k-means (typical k: 100,000)
  - Compute *weights* for each word
  - Create an inverted file mapping words → images

# Weighting the words

- Just as with text, some visual words are more discriminative than others

***the, and, or*** vs. ***cow, AT&T, Cher***

- the bigger fraction of the documents a word appears in, the less useful it is for matching
  - e.g., a word that appears in *all* documents is not helping us

# TF-IDF weighting

- Instead of computing a regular histogram distance, we'll weight each word by it's *inverse document frequency*

- inverse document frequency (IDF) of word *j* =

$$\log \frac{\text{number of documents}}{\text{number of documents in which } j \text{ appears}}$$

# TF-IDF weighting

- To compute the value of bin *j* in image *I*:

*term frequency* of *j* in *I* **x** *inverse document frequency* of *j*

# Inverted file

- Each image has ~1,000 features
- We have ~100,000 visual words

  →each histogram is extremely sparse (mostly zeros)

- Inverted file
  – mapping from words to documents

```
"a":      {2}
"banana": {2}
"is":     {0, 1, 2}
"it":     {0, 1, 2}
"what":   {0, 1}
```

# Inverted file

- Can quickly use the inverted file to compute similarity between a new image and all the images in the database
  – Only consider database images whose bins overlap the query image

# Large-scale image search

query image top 6 results

- Cons:
  - not as accurate as per-image-pair feature matching
  - performance degrades as the database grows

# Large-scale image search

- Pros:
  - Works well for CD covers, movie posters
  - Real-time performance possible

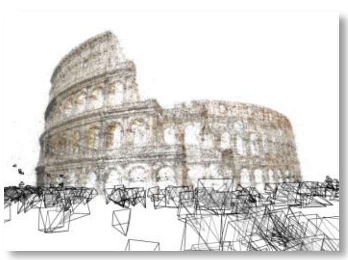
real-time retrieval from a database of 40,000 CD covers
Nister & Stewenius, **Scalable Recognition with a Vocabulary Tree**

# Large-scale image matching

Turn 1,000,000 images of Rome…

# …into 3D models

St. Peter’s Basilica



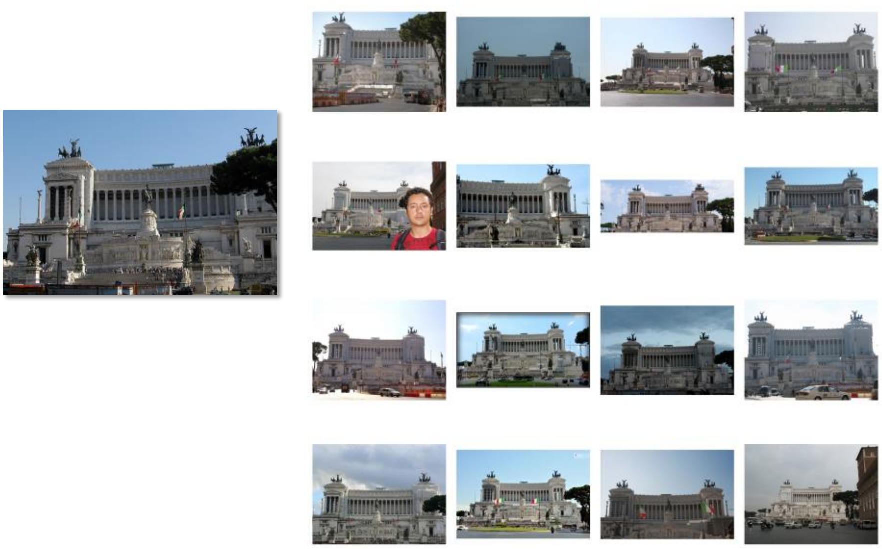
Colosseum

Trevi Fountain

# Large-scale image matching

- How can we match 1,000,000 images to each other?
- Brute force approach: 500,000,000,000 pairs
  - won't scale
- Better approach: use bag-of-words technique to find *likely* matches
- For each image, find the top M scoring other images, do detailed SIFT matching with those

# Example bag-of-words matches



## Example bag-of-words matches

## Matching Statistics

| Dataset | Size | Matches possible | Matches Tried | Matches Found | Time |
|---|---|---|---|---|---|
| Dubrovnik | 58K | 1.6 Billion | 2.6M | 0.5M | 5 hrs |
| Rome | 150K | 11.2 Billion | 8.8M | 2.7M | 13 hrs |
| Venice | 250K | 31.2 Billion | 35.5M | 6.2M | 27 hrs |

## What about spatial info?