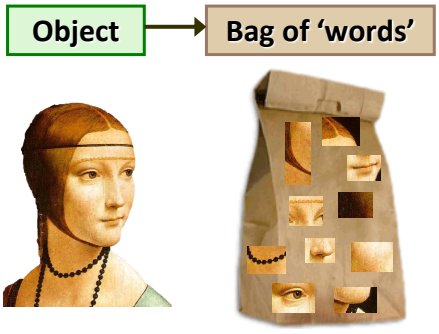
CS4670 / 5670: Computer Vision

Noah Snavely

Lecture 28: Bag-of-words models



Announcements

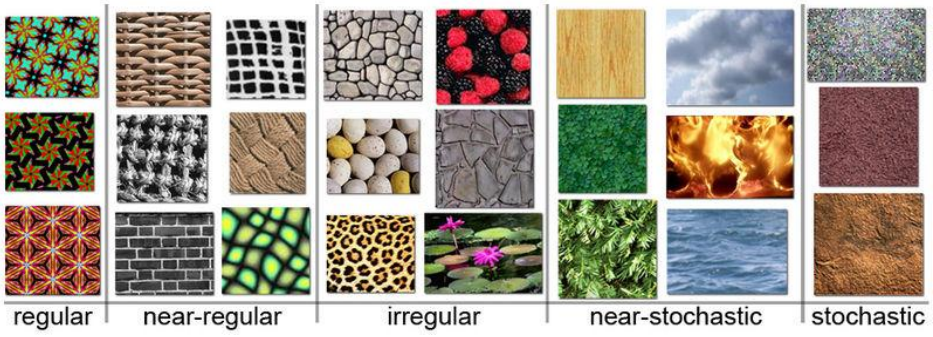
- Quiz on Friday
- Assignment 4 due next Friday

Bag of Words Models

Adapted from slides by Rob Fergus and Svetlana Lazebnik

Object → **Bag of 'words'**

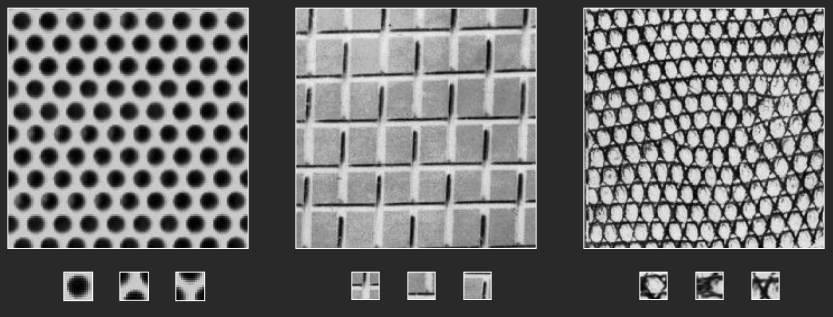
Origin 1: Texture Recognition



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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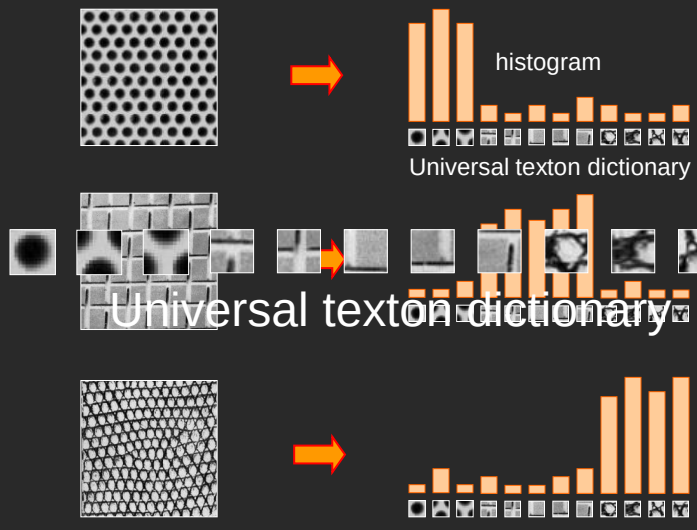

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Origin 2: Bag-of-words models

- 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

face, flowers, building

- 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





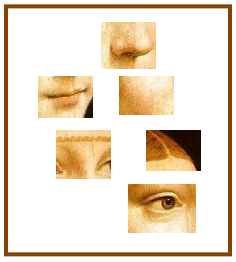

class	bag of features Zhang et al. (2005)	bag of features Willamowski et al. (2004)	Parts-and-shape model Fergus et al. (2003)
airplanes	**98.8**	97.1	90.2
cars (rear)	98.3	**98.6**	90.3
cars (side)	**95.0**	87.3	88.5
faces	**100**	99.3	96.4
motorbikes	**98.5**	98.0	92.5
spotted cats	**97.0**	—	90.0

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

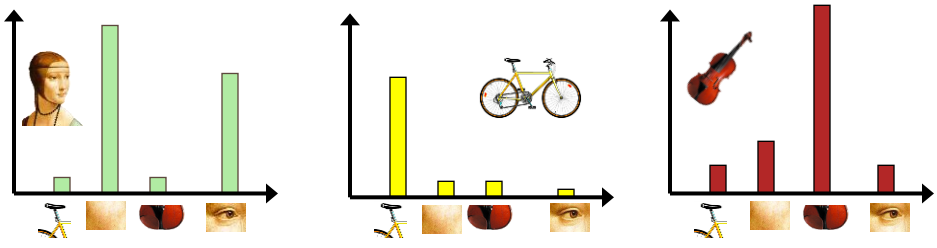
1. Extract features
2. Learn “visual vocabulary”

Bag of features: outline

1. Extract features
2. Learn “visual vocabulary”
3. Quantize features using visual vocabulary

Bag of features: outline

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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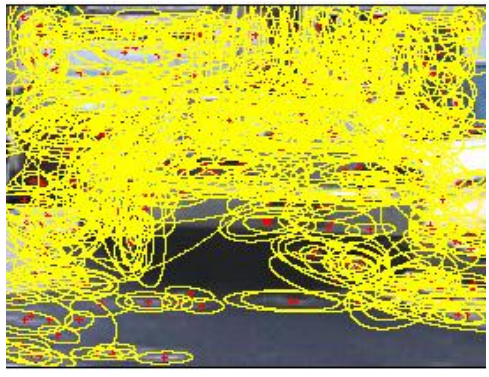
Interest point detector

- Csurka et al. 2004
- Fei-Fei & Perona, 2005
- Sivic et al. 2005



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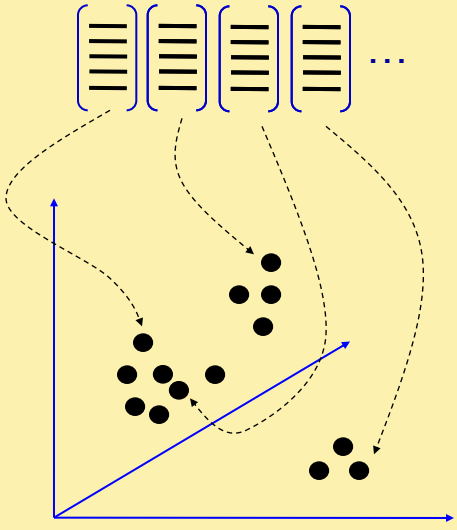
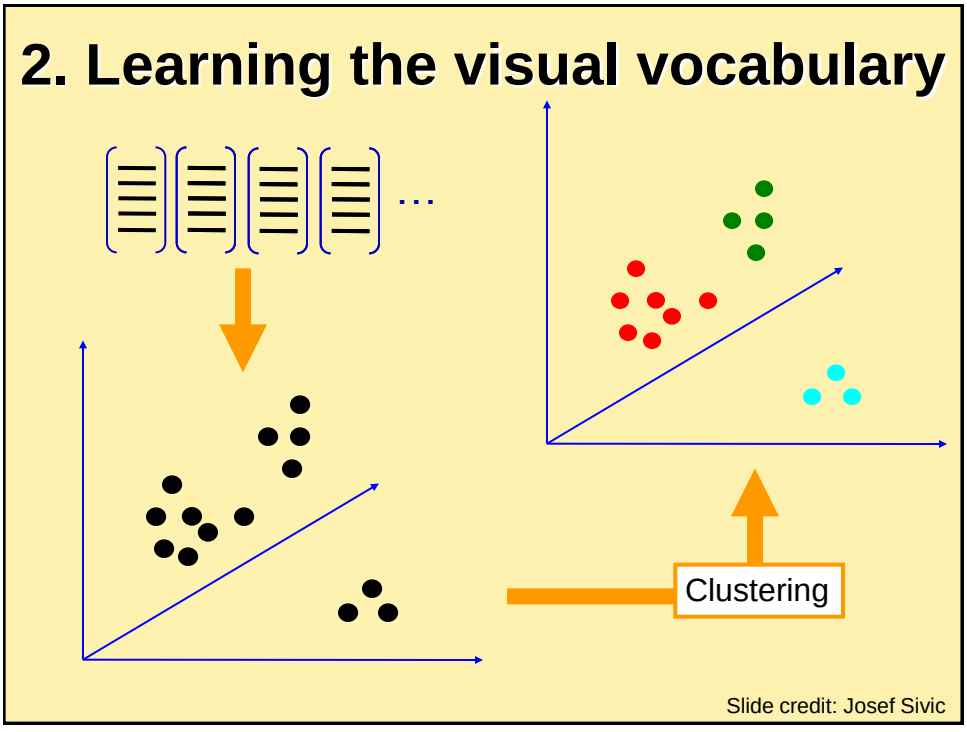
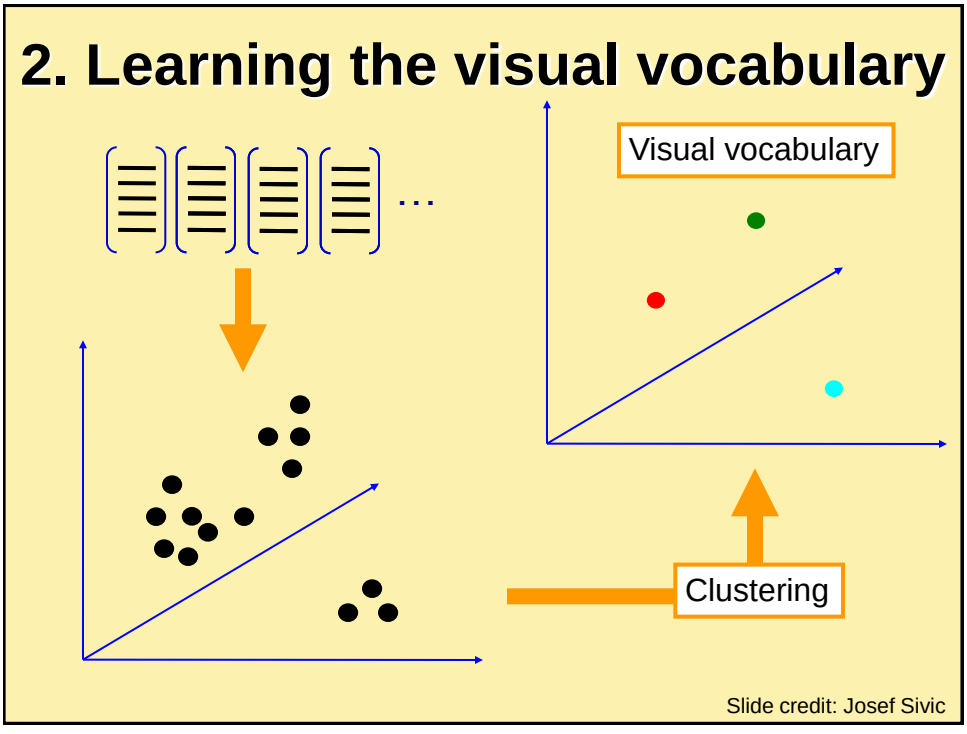
Other methods

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

2. Learning the visual vocabulary




2. Learning the visual vocabulary
Clustering
Slide credit: Josef Sivic


2. Learning the visual vocabulary
Visual vocabulary
Clustering
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

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

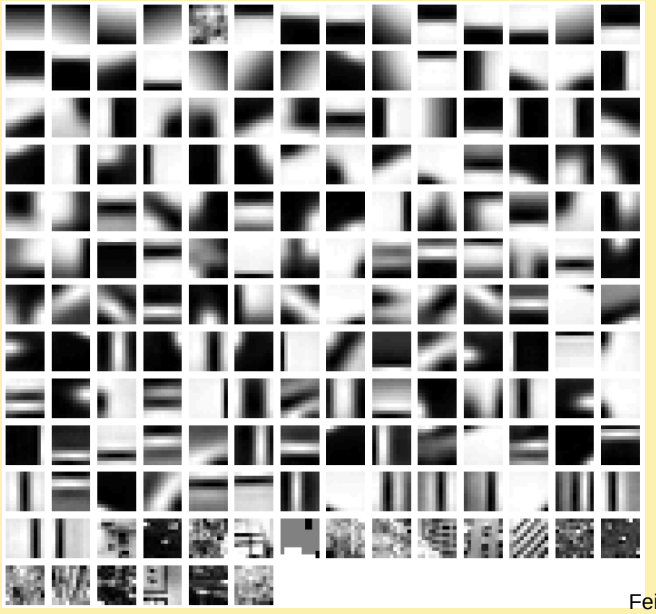
Algorithm:

- 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

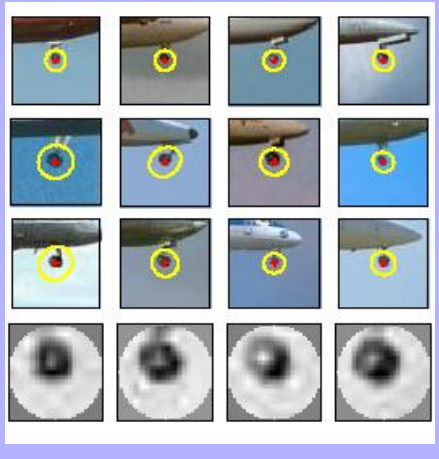
- Clustering is a common method for learning a visual vocabulary or codebook
  - Unsupervised learning process
  - Each cluster center produced by k-means becomes a codevector
  - Codebook can be learned on separate training set
  - Provided the training set is sufficiently representative, the codebook 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

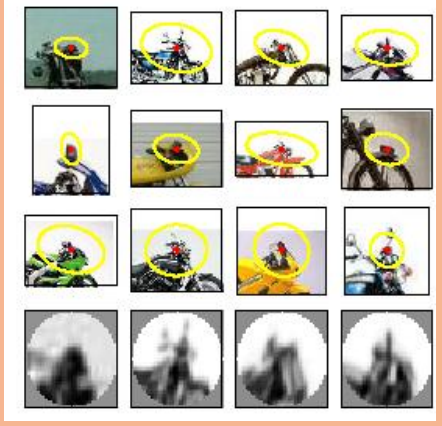
Example visual vocabulary



Fei-Fei et al. 2005

Image patch examples of visual words

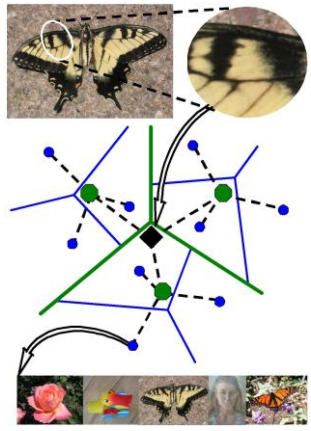




Sivic et al. 2005

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

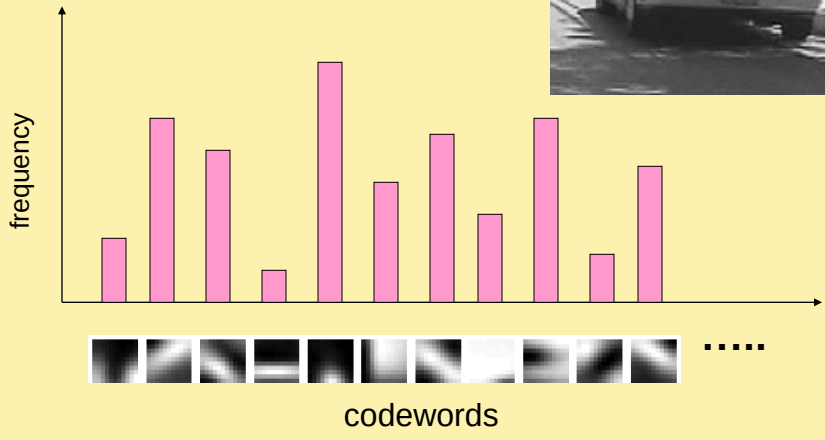
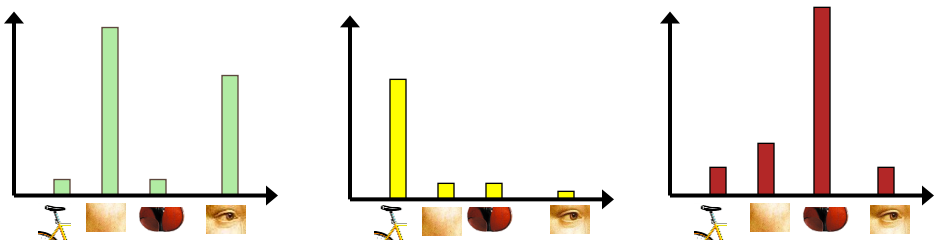


Image classification

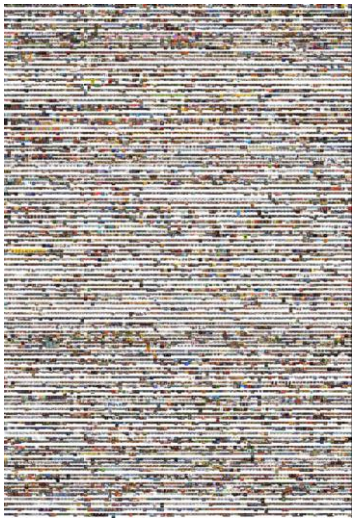
- Given the bag-of-features representations of images from different classes, how do we learn a model for distinguishing them?



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

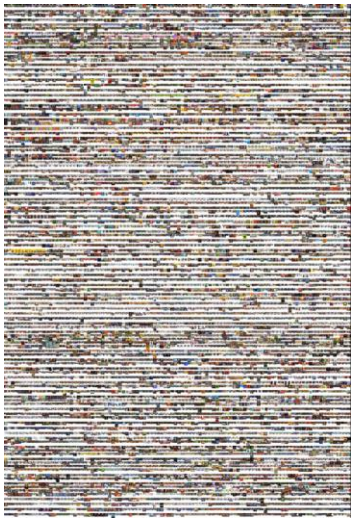


11,400 images of game covers
(Caltech games dataset)

- 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**