Computer Vision
and Geometry Lab

Computer Vision

Exercise Session 10 – Image Categorization

Object Categorization

- Task Description
  - "Given a small number of training images of a category, recognize a-priori unknown instances of that category and assign the correct category label."
- How to recognize ANY car

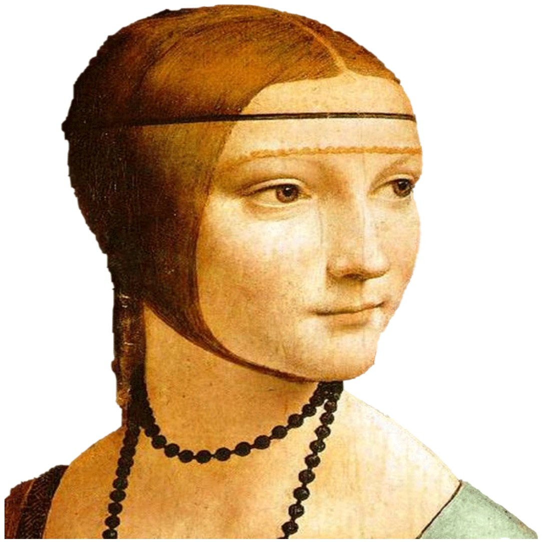
Object Categorization

- Two main tasks:
  - Classification
  - Detection

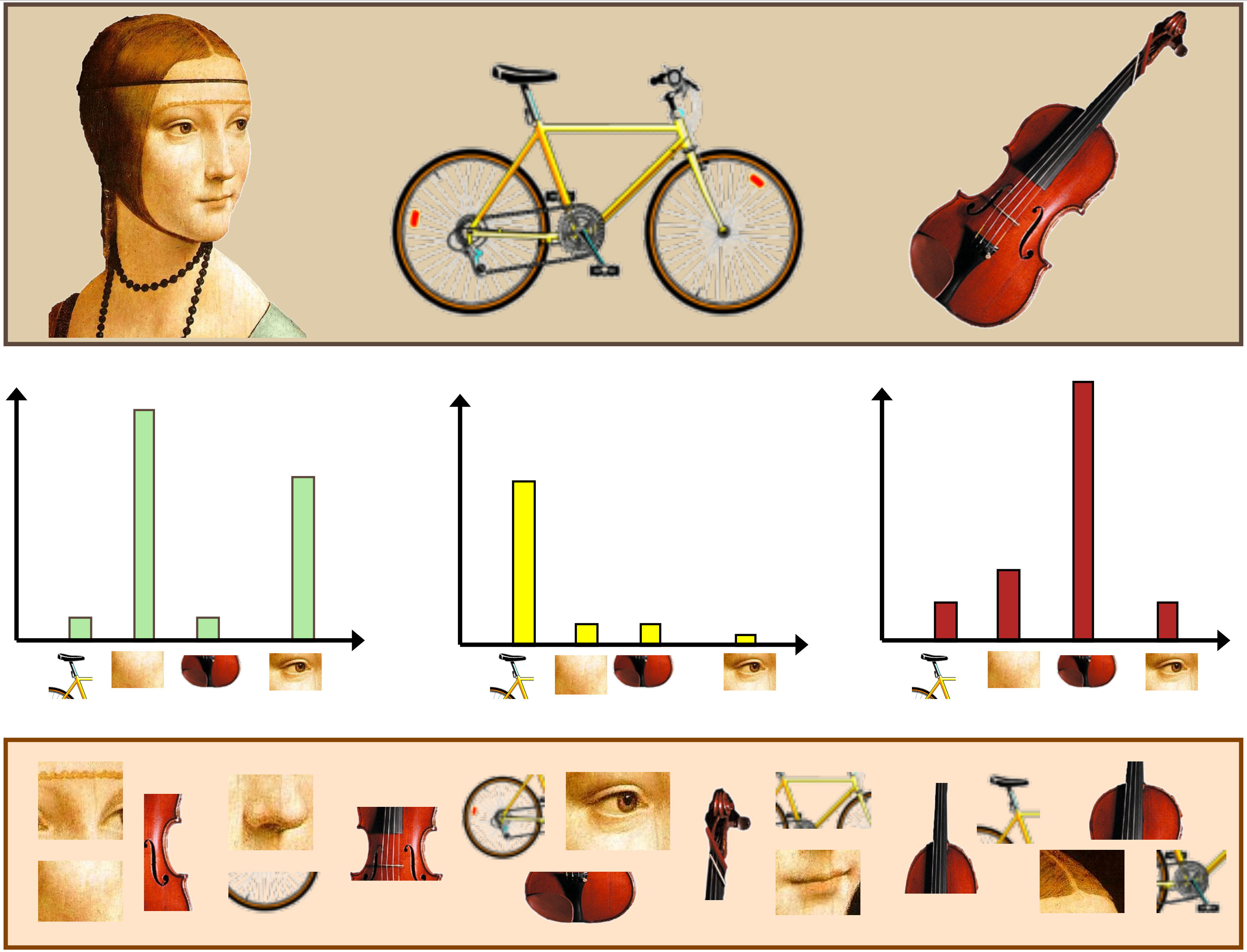
- Classification
  - *Is there* a car in the image?
  - Binary answer is enough
- Detection
  - *Where* is the car?
  - Need localization e.g. a bounding box

Bag of Visual Words

Object → Bag of 'words'



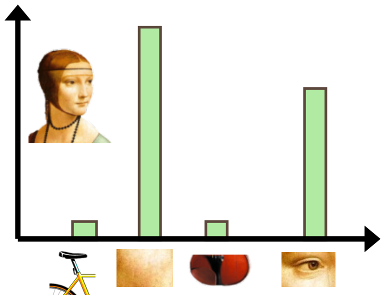
Bag of Visual Words

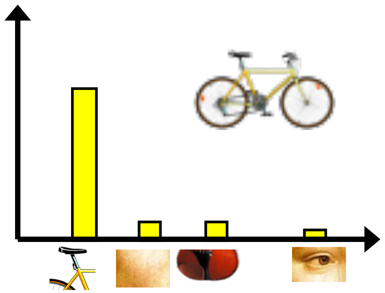


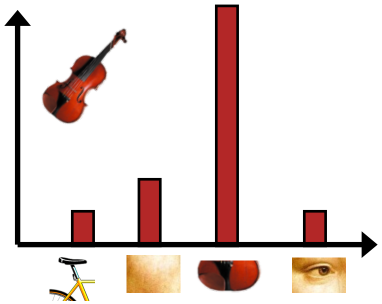
Bag of Visual Words

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

- Image representation







BoW for Image Classification

{face, flowers, building}

- Works pretty well for whole-image classification

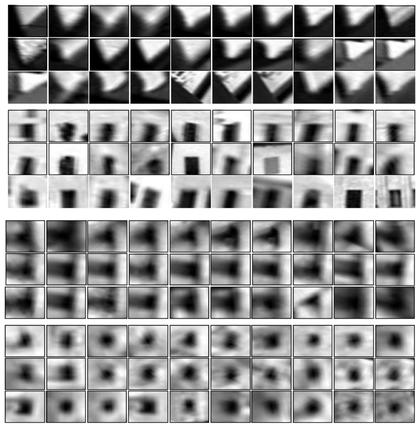
BoW for Image Classification

1. **Codebook construction**
2. **Training**
3. **Testing**

positive negative

Images → Feature detection and description

Feature detection and description → Codebook construction → Codebook (visual words)



Feature detection and description → Bag of words image representation

Codebook (visual words) → Bag of words image representation

Bag of words image representation → Train image classifier → Classifier

Bag of words image representation → Image classification

Classifier → Image classification

Image classification → Binary classification

Your Task

- Implement a BoW image classifier :
  - Feature detection
  - Feature description
  - Codebook construction
  - BoW image representation
  - BoW image classification

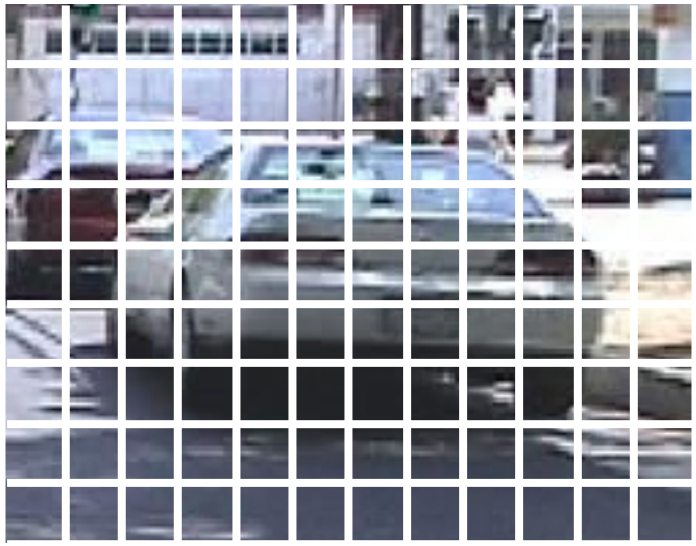
Dataset

- Training set
  - 50 images CAR - back view
  - 50 images NO CAR

- Testing set
  - 49 images CAR - back view
  - 50 images NO CAR

Feature Extraction

- Feature detection
  - For object classification, dense sampling offers better coverage.
  - Extract interest points on a grid



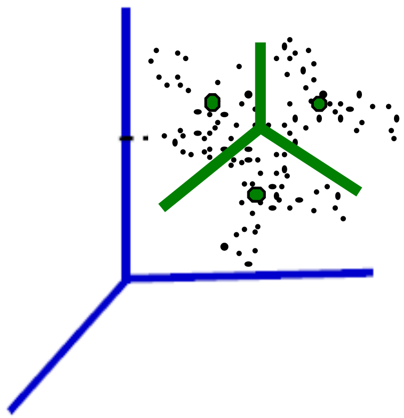
- Feature description
  - Histogram of oriented gradients (HOG) descriptor

Codebook Construction

- Map high-dimensional descriptors to words by quantizing the feature space

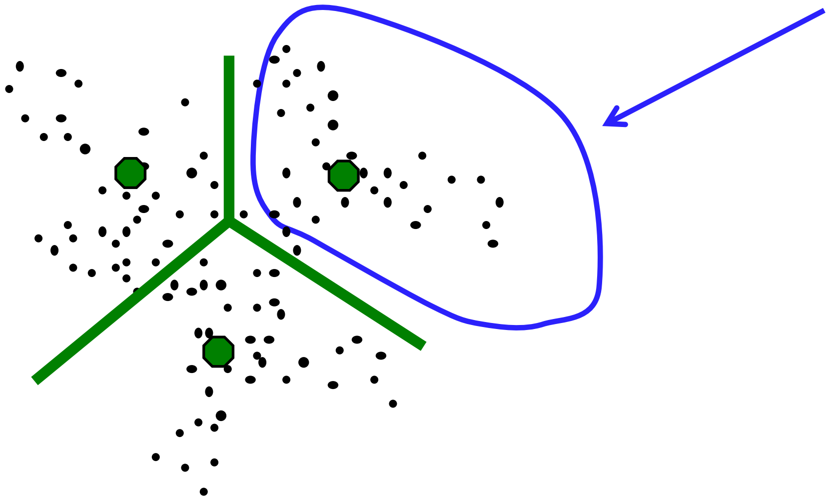
- Quantize via clustering   K-means

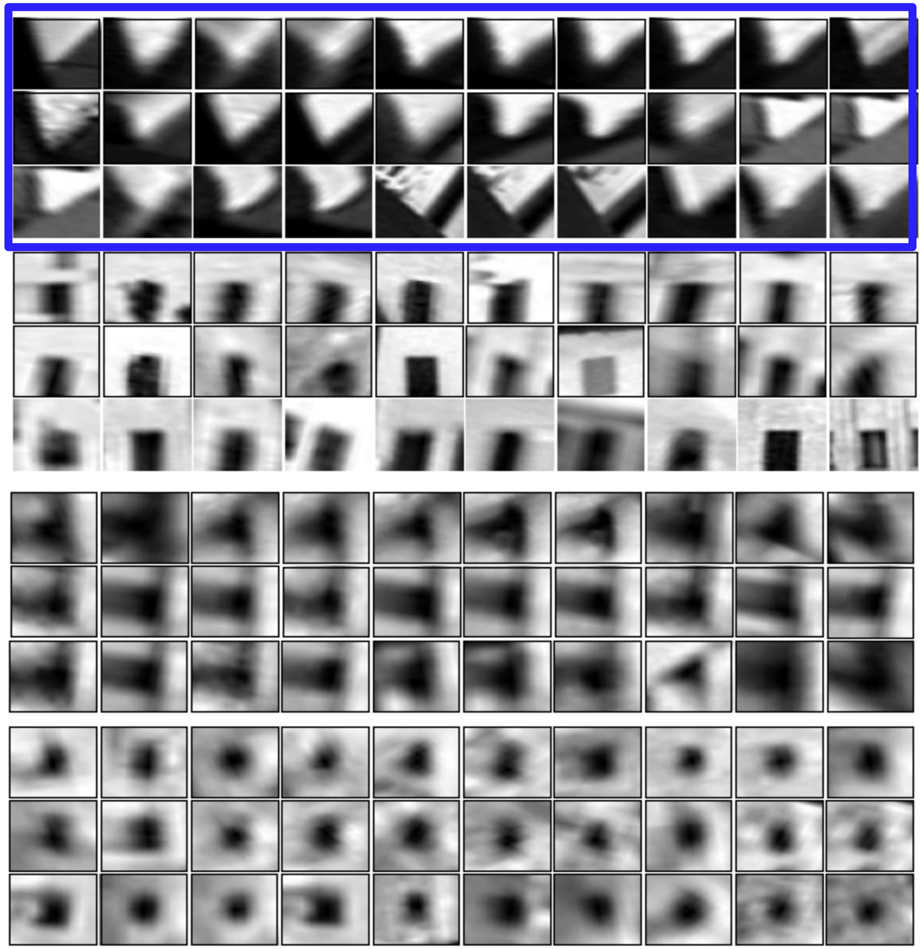
- Let cluster centers be the prototype "visual words"



Codebook Construction

- Example: each group of patches belongs to the same visual word





- Ideally: an object part = a visual word

Codebook Construction

- K-means

  1. Initialize K clusters centers randomly

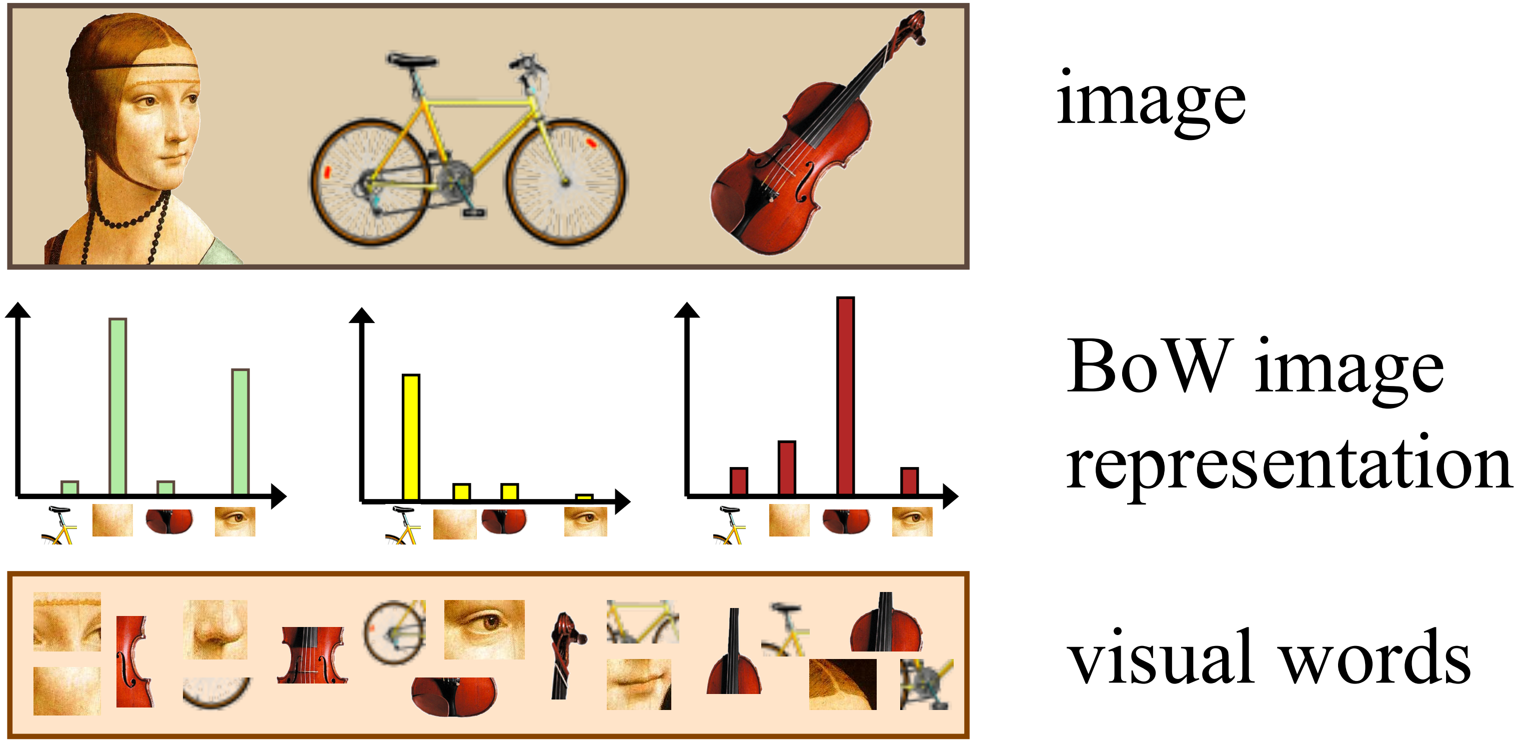
  2. Repeat for a number of iterations:

     a. Assign each point to the closest cluster center

     b. Update the position of each cluster center to the mean of its assigned points

BoW Image Representation

- Histogram of visual words



BoW Image Classification

- Nearest Neighbor Classification
- Bayesian Classification

Nearest Neighbor Classifier

Training:

- Training images i -> BoW image representation $\mathbf{y}_i$ with binary label c_i

Testing:

- Test image -> BoW image representation $\mathbf{x}$
- Find training image j with $\mathbf{y}_j$ closest to $\mathbf{x}$
- Classifier test image with binary label c_j

Bayesian Classifier

- Probabilistic classification scheme based on Bayes' theorem

- Classify a test image based on the posterior probabilities

Bayesian Classifier

- Test image -> BoW image representation

- Compute the posterior probabilities

$$P(Car|hist) = \frac{P(hist|Car) \cdot P(Car)}{P(hist)}$$

$$P(!Car|hist) = \frac{P(hist|!Car) \cdot P(!Car)}{P(hist)}$$

- Classification rule

$$P(Car|hist) > P(!Car|hist) => Car$$

$$P(Car|hist) <= P(!Car|hist) => !Car$$

Bayesian Classifier

- In this assignment consider equal priors

$$P(Car) = P(!Car) = 0.5$$

- Notice that the posterior probabilities have the same denominator – normalization factor $P(hist)$

- Classification rule

$$P(hist|Car) > P(hist|!Car) => Car$$

$$P(hist|Car) <= P(hist|!Car) => !Car$$

Bayesian Classifier

- **How to compute the likelihoods?**

$$P(hist|Car), P(hist|!Car)$$

- Each BoW image representation is a K-dimensional vector

$$\text{hist} = [2 \quad \underset{\substack{\uparrow \\ \text{Number of counts for the } 2^{nd} \text{ visual word in the codebook}}}{3} \quad 0 \quad 0 \quad 0 \ldots \underset{\substack{\uparrow \\ \text{Number of counts for the K-th visual word in the codebook}}}{1} \quad 0]$$

Bayesian Classifier

- Consider the number of counts for each visual word a random variable with normal distribution

$$counts(i) \rightsquigarrow \mathcal{N}(\mu(i), \sigma(i))$$

Warning: this is a very non-principled approximation as *counts(i)* is discrete and non-negative!

  - For positive training images estimate:

$$\mathcal{N}(\mu_p(i), \sigma_p(i))$$

  - For negative training images estimate:

$$\mathcal{N}(\mu_n(i), \sigma_n(i))$$

Bayesian Classifier

- BoW test image representation= $[U_1\ U_2\ \dots\ U_K]$
- Probability of observing U_i counts for the ith visual word
  - in a car image
    $$P(U_i|\mathcal{N}(\mu_p(i), \sigma_p(i)))$$
  - In a !car image
    $$P(U_i|\mathcal{N}(\mu_n(i), \sigma_n(i)))$$

Bayesian Classifier

- Using independence assumption:

$$P(hist|Car) = \prod_{i=1}^{K} P(U_i|\mathcal{N}(\mu_p(i), \sigma_p(i)))$$

$$P(hist|!Car) = \prod_{i=1}^{K} P(U_i|\mathcal{N}(\mu_n(i), \sigma_n(i)))$$

- Numerical stability – use logarithm

- $$log(\prod_{i=1}^{K} p_i) = \sum_{i=1}^{K} log(p_i)$$

- **Now we have the likelihoods**

Hand-in

- Report should include:
  - Your classification performance
    - Nearest neighbor classifier
    - Bayesian classifier
  - Variation of classification performance with K
  - Your description of the method and discussion of your results
- Source code
- Try on your own dataset (for bonus marks!)

Hand-in

By **1pm** on **Thursday 19th November 2015**

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