HA NOI UNIVERSITY OF SCIENCE AND TECHNOLOGY
SCHOOL OF INFORMATION AND COMMUNICATION TECHNOLOGY

Computer Vision

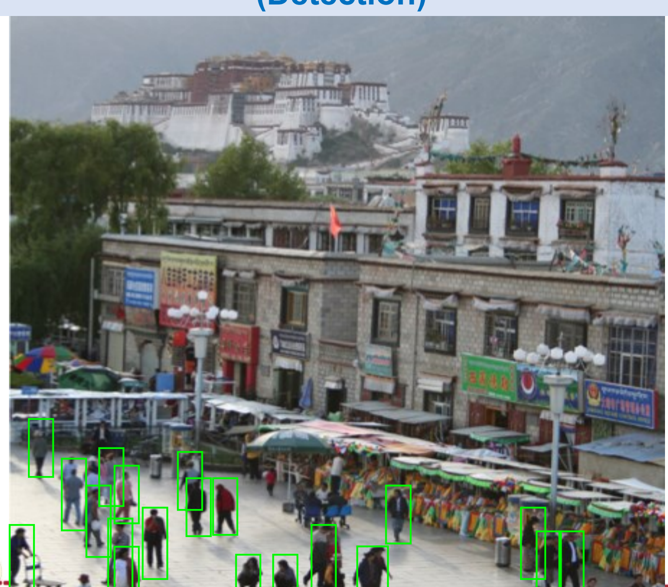
Chapter 7 (part 1): Object recognition

Contents

- Overview of ‘semantic vision’?
- Image classification/ recognition
- Bag-of-words
  - Recall
  - Vocabulary tree
- Classification
  - K nearest neighbors
  - Naïve Bayes
  - [Support vector machine]

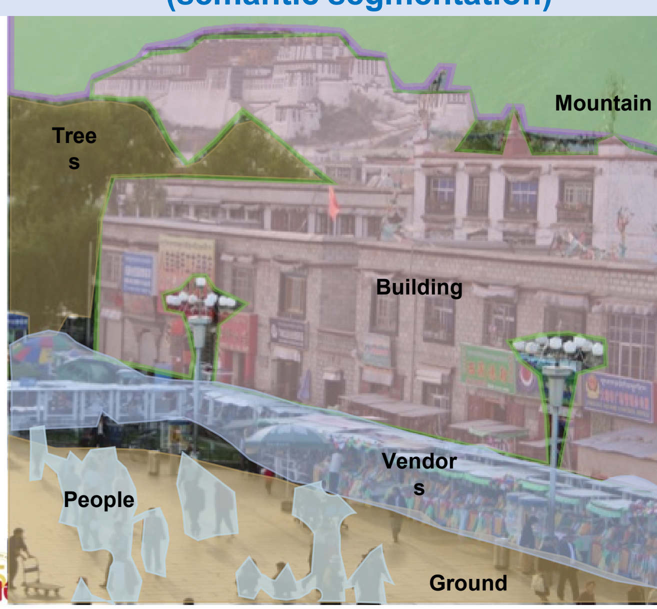
Is this a street light?
(Recognition / classification)

Where are the people?
(Detection)

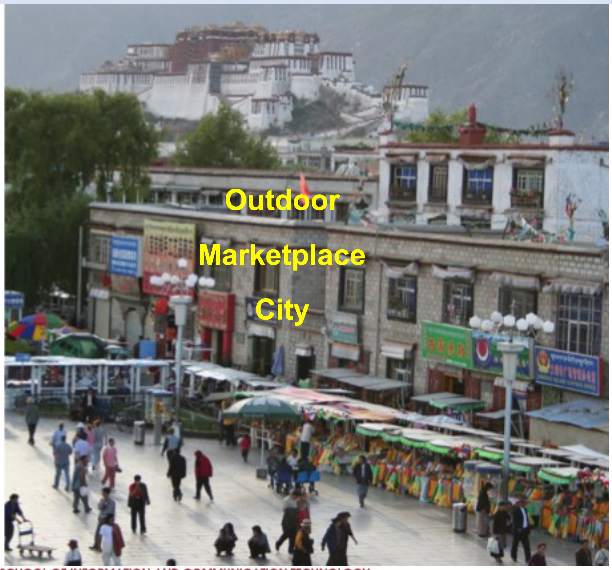


Is that Potala palace?
(Identification)

What's in the scene?
(semantic segmentation)



What type of scene is it?
(Scene categorization)



How many object categories are there?

Challenge: variable viewpoint

Michelangelo 1475-1564

Challenge: variable illumination

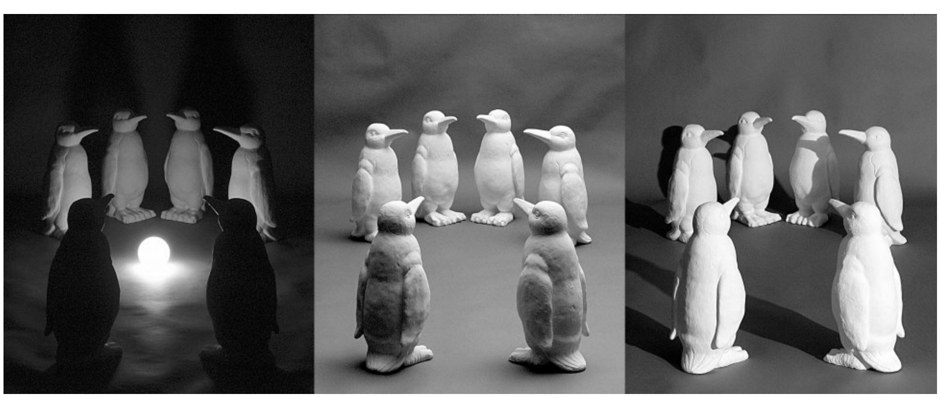


image credit: J. Koenderink

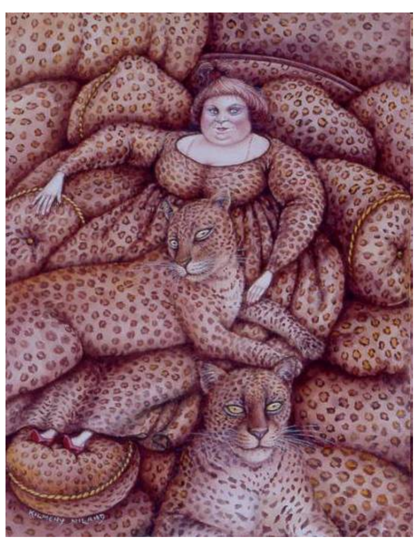
Challenge: scale

Challenge: deformation

Challenge: Occlusion

Magritte, 1957

Challenge: background clutter



Kilmeny Niland. 1995

Challenge: Background clutter

Challenge: intra-class variations

Svetlana Lazebnik

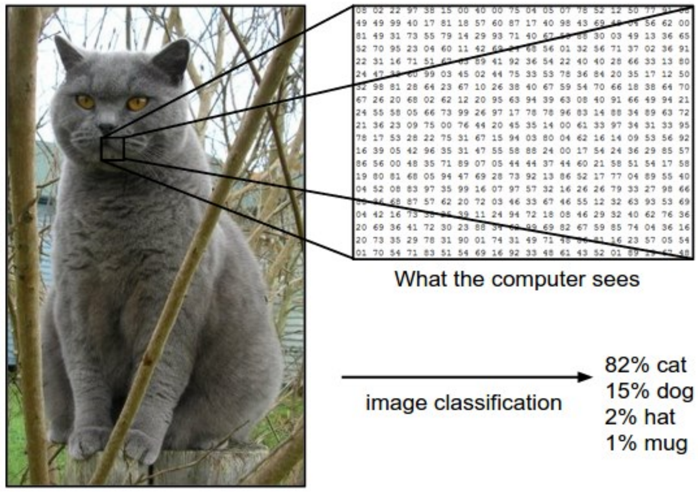
Image Classification/ Recognition

Image Classification/ Recognition

(assume given set of discrete labels)
{dog, cat, truck, plane, ...}

→ cat

Image Classification: Problem



Data-driven approach

- Collect a database of images with labels
- Use ML to train an image classifier
- Evaluate the classifier on test images

Example training set

A simple pipeline - Training

Training
Images

Image
Features

A simple pipeline - Training

Training
Labels

Training
Images

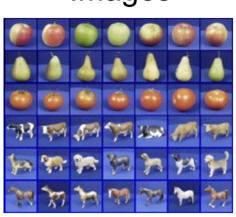
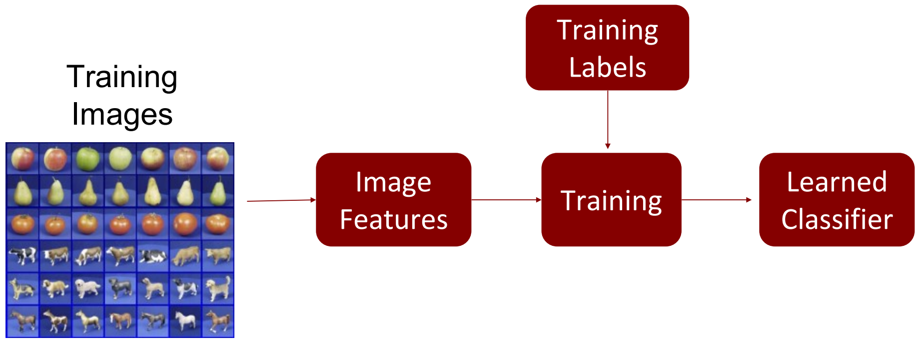


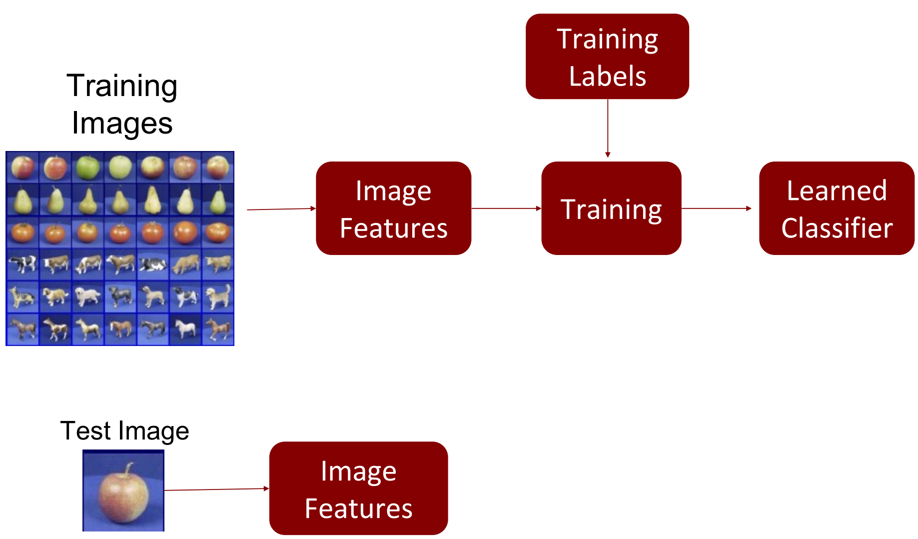
Image
Features

Training

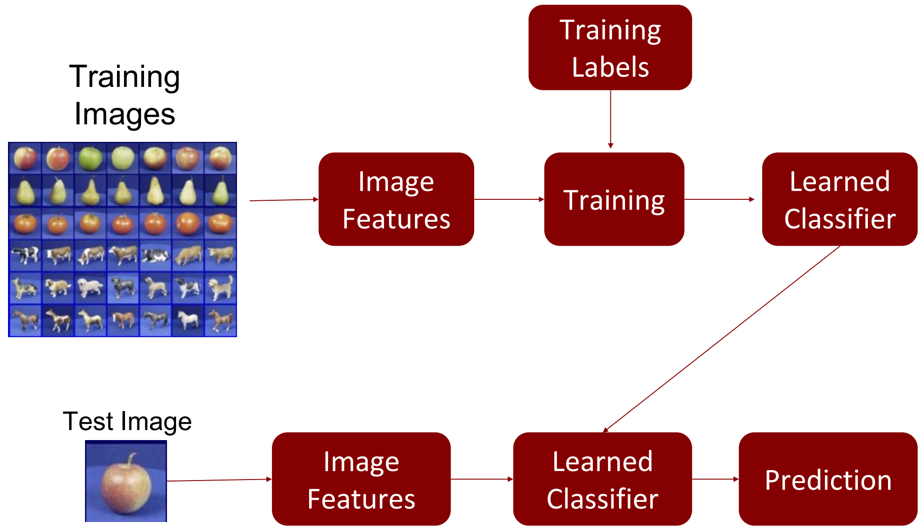
A simple pipeline - Training



A simple pipeline - Training



A simple pipeline - Training



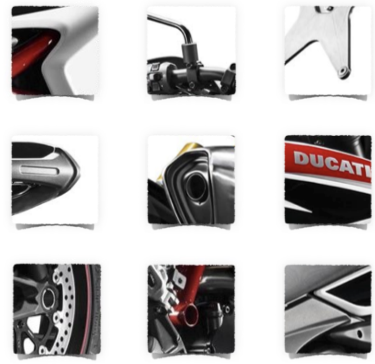
Bag of words

Basic model

Vocabulary tree

Some local feature are very informative

An object as



a collection of local features

(bag-of-features)

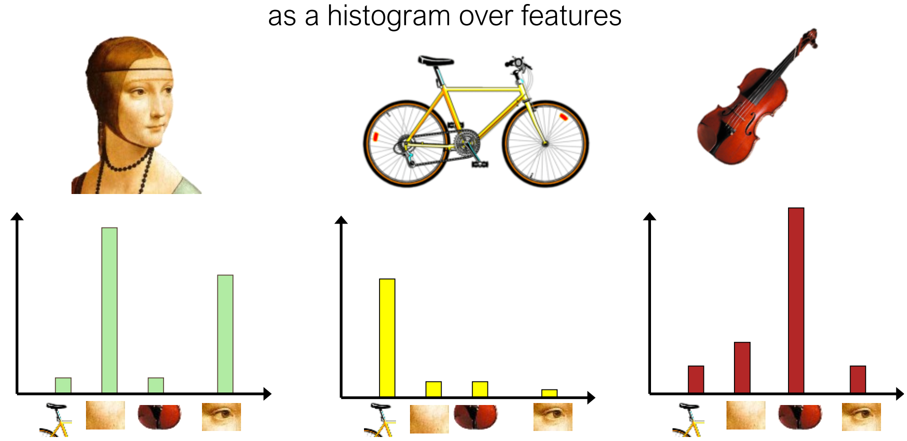
- deals well with occlusion
- scale invariant
- rotation invariant

Bag-of-words

- Local feature ~~ a word
- An image ~~ a document
- Apply a technique for textual document representation: vector model

Bag-of-words

represent a data item (document, texture, image)
as a histogram over features



Standard BOW pipeline

(for image classification)

Dictionary Learning:
Learn Visual Words using clustering

Encode:
build Bags-of-Words (BOW) vectors
for each image

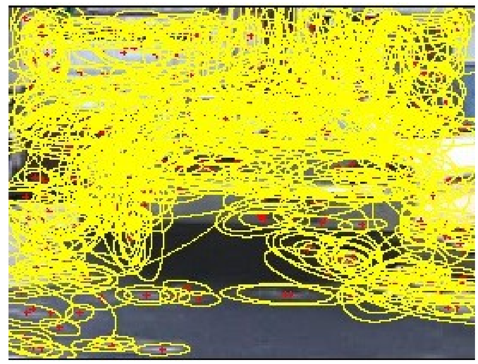
Classify:
Train and test data using BOWs

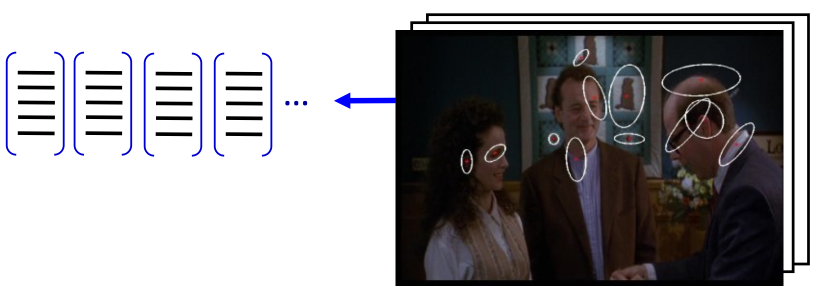
Dictionary Learning:
Learn Visual Words using clustering

1. **extract features** (e.g., SIFT) from images

What kinds of features can we extract?

- Regular grid
  - Vogel & Schiele, 2003
  - Fei-Fei & Perona, 2005
- Interest point detector
  - Csurka et al. 2004
  - Fei-Fei & Perona, 2005
  - Sivic et al. 2005
- Other methods
  - Random sampling (Vidal-Naquet & Ullman, 2002)
  - Segmentation-based patches (Barnard et al. 2003)

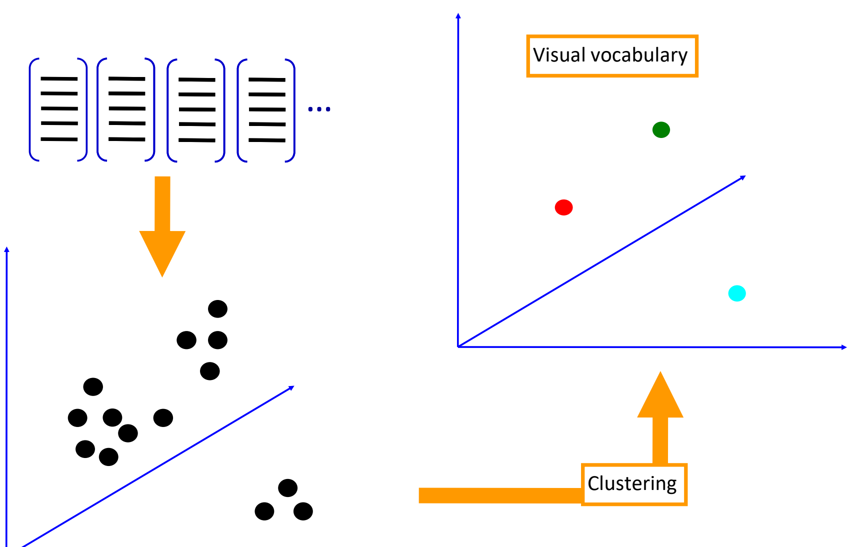




Dictionary Learning:
Learn Visual Words using clustering

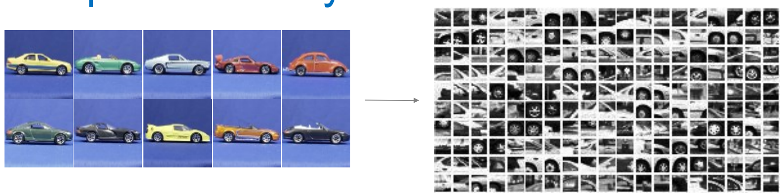
2. **Learn visual dictionary** (e.g., K-means clustering)

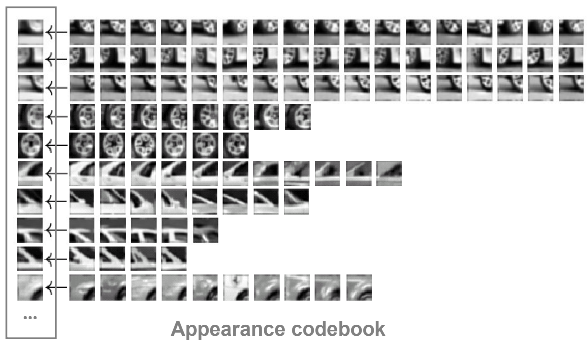
How do we learn the dictionary?



K-means clustering

Example dictionary





Appearance codebook

Source: B. Leibe

Dictionary Learning:
Learn Visual Words using clustering

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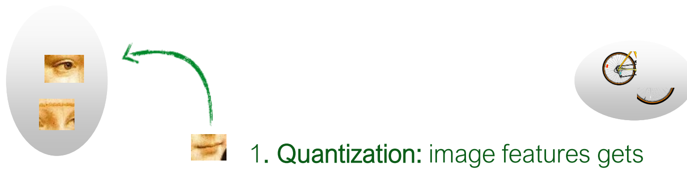
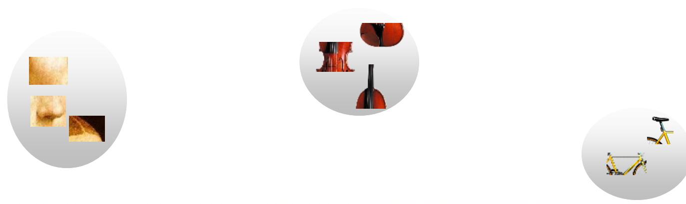


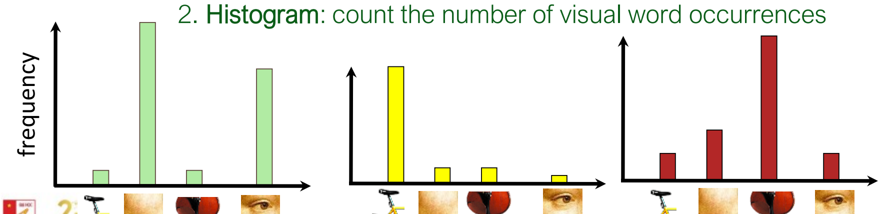
1. **Quantization:** image features gets associated to a visual word (nearest cluster center)

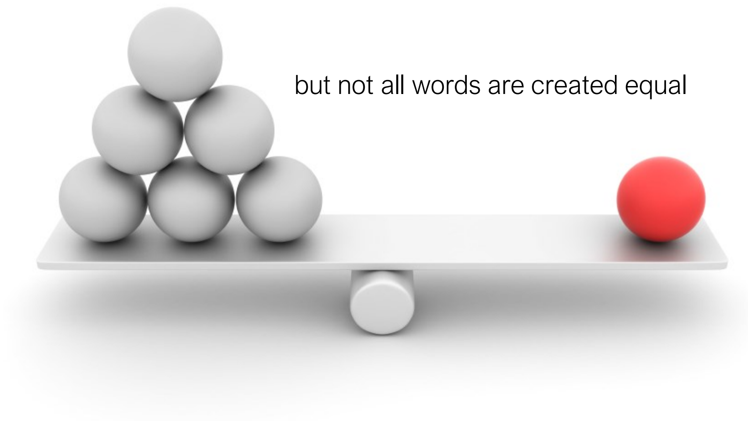
Encode:
build Bags-of-Words (BOW) vectors
for each image



Encode:
build Bags-of-Words (BOW) vectors
for each image

2. **Histogram**: count the number of visual word occurrences





TF-IDF

Term **F**requency **I**nverse **D**ocument **F**requency

$$\boldsymbol{v}_d = [n(w_{1,d}) \quad n(w_{2,d}) \quad \cdots \quad n(w_{T,d})]$$

weight each word by a heuristic

$$\boldsymbol{v}_d = [n(w_{1,d})\alpha_1 \quad n(w_{2,d})\alpha_2 \quad \cdots \quad n(w_{T,d})\alpha_T]$$

$$n(w_{i,d})\alpha_i = \underbrace{n(w_{i,d})}_{\text{term frequency}} \underbrace{\log\left\{\frac{D}{\sum_{d'} \mathbf{1}[w_i \in d']}\right\}}_{\text{inverse document frequency}}$$

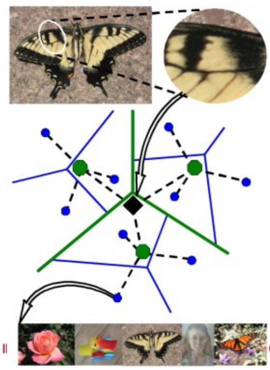
Scalability: Alignment to large databases

- What if we need to align a test image with thousands or millions of images in a model database?
  - Efficient putative match generation
    - Fast nearest neighbor search, inverted indexes

Test image

Vocabulary tree with inverted index

Database

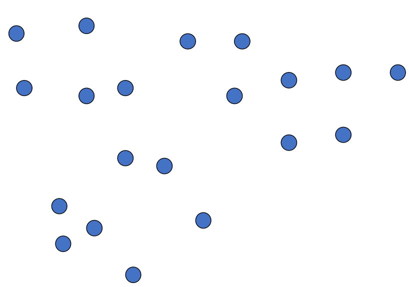


D. Nistér and H. Stewénius, Scalable Recognition with a Vocabulary Tree, CVPR 2006

slide: S. Lazebnik

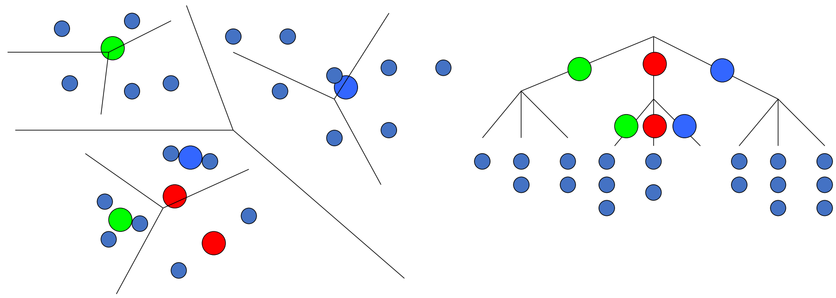
What is a Vocabulary Tree?

Nister and Stewenius CVPR 2006

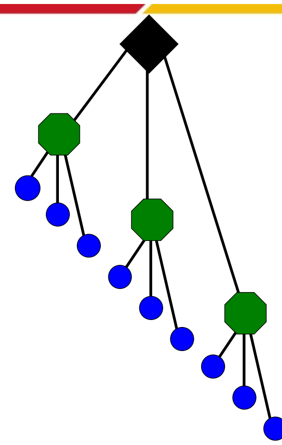


What is a Vocabulary Tree?

Nister and Stewenius CVPR 2006



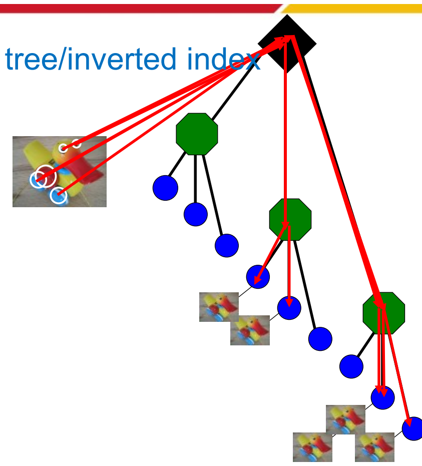
- Multiple rounds of K-Means to compute decision tree (offline)
- Fill and query tree online



Slide credit: D. Nister

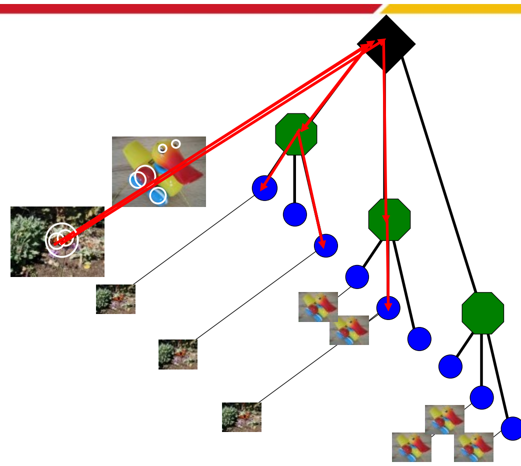
Populating the vocabulary tree/inverted index

Model images



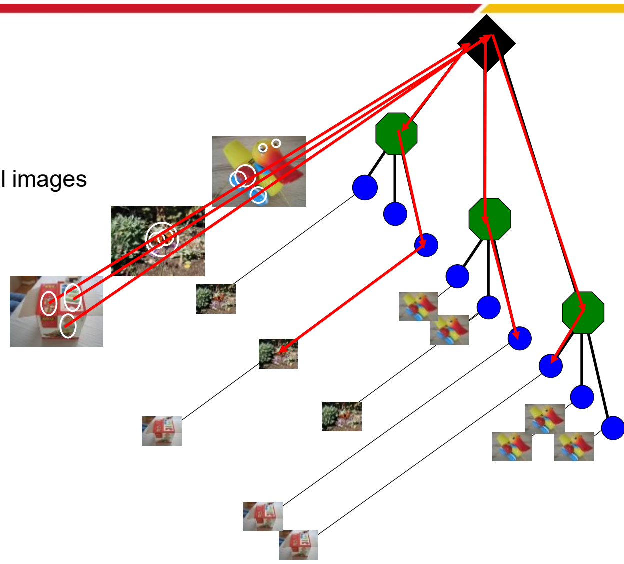
Slide credit: D. Nister

Model images



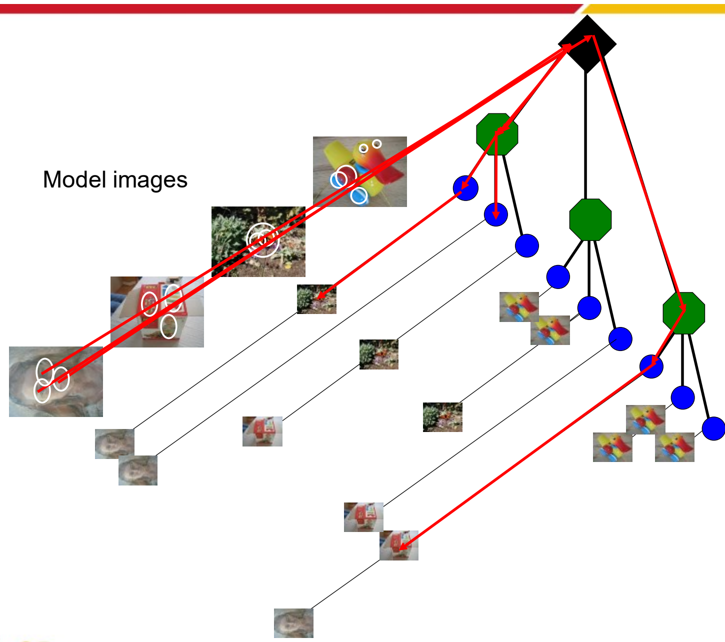
Slide credit: D. Nister

Model images

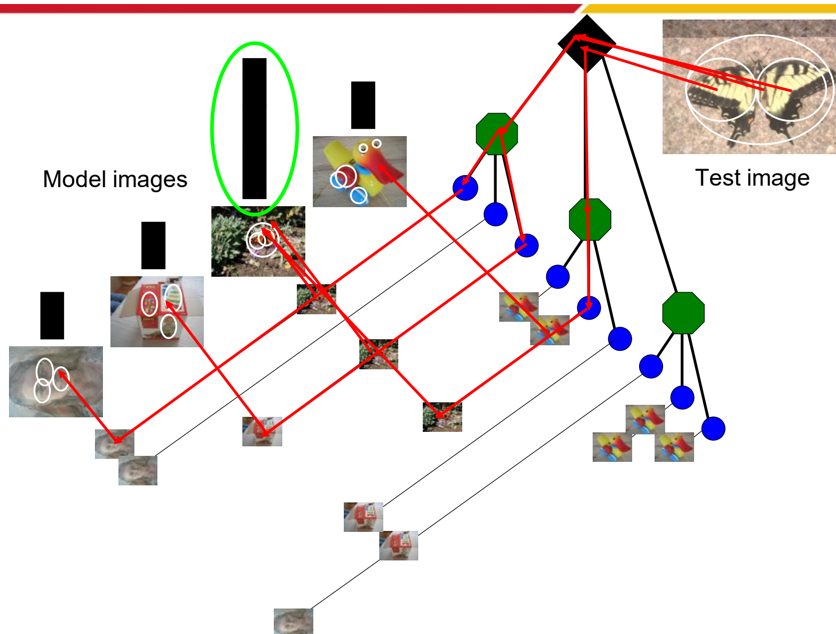


Slide credit: D. Nister

Model images



Slide credit: D. Nister



Looking up a test image

Slide credit: D. Nister

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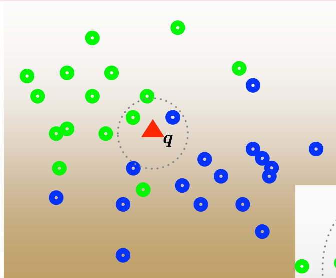
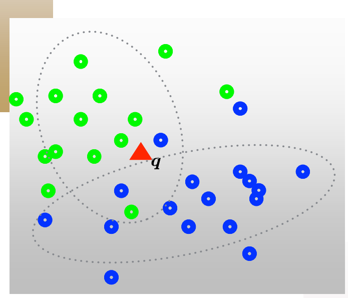
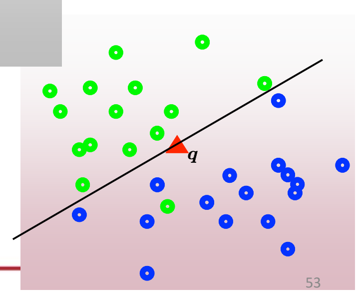


K nearest neighbors



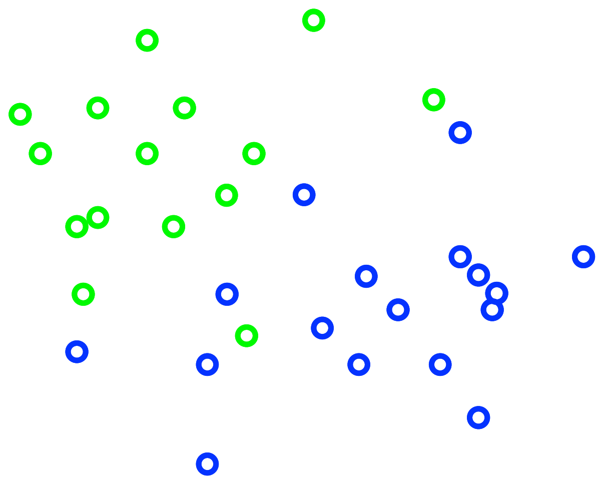
Naïve Bayes

Support Vector Machine

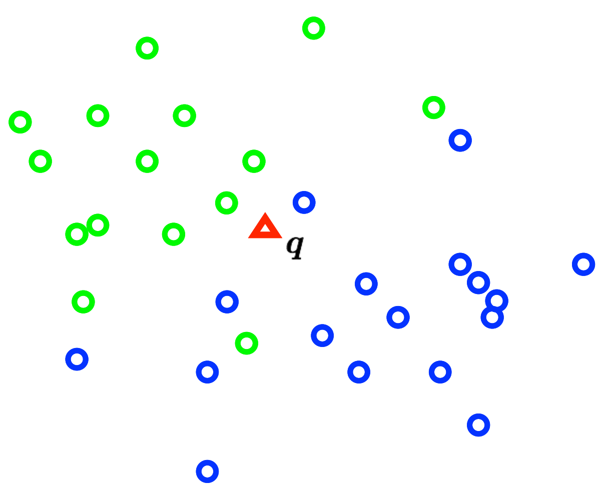


K nearest neighbors

Distribution of data from two classes

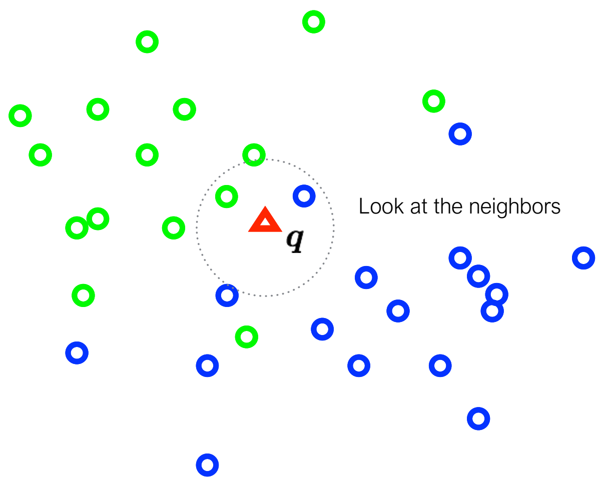


Distribution of data from two classes

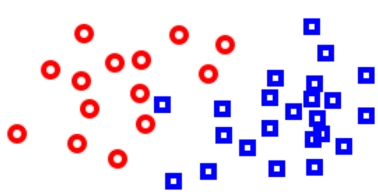


Which class does q belong too?

Distribution of data from two classes



K-Nearest Neighbor (KNN) Classifier

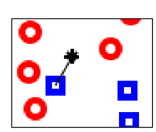


Non-parametric pattern classification approach

Consider a two class problem where each sample consists of two measurements (x,y).

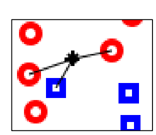
For a given query point q, assign the class of **the nearest neighbor**

k = 1



Compute the **k nearest neighbors** and assign the class by majority vote.

k = 3



Nearest Neighbor is competitive

MNIST Digit Recognition
- Handwritten digits
- 28x28 pixel images: d = 784
- 60,000 training samples
- 10,000 test samples

Yann LeCunn

	Test Error Rate (%)
Linear classifier (1-layer NN)	12.0
K-nearest-neighbors, Euclidean	5.0
K-nearest-neighbors, Euclidean, deskewed	2.4
K-NN, Tangent Distance, 16x16	1.1
K-NN, shape context matching	0.67
1000 RBF + linear classifier	3.6
SVM deg 4 polynomial	1.1
2-layer NN, 300 hidden units	4.7
2-layer NN, 300 HU, [deskewing]	1.6
LeNet-5, [distortions]	0.8
Boosted LeNet-4, [distortions]	0.7

What is the best distance metric between data points?

- Typically Euclidean distance
- Locality sensitive distance metrics
- Important to normalize.
  Dimensions have different scales

How many K?

- Typically k=1 is good
- Cross-validation (try different k!)

Distance metrics

$$D(\boldsymbol{x},\boldsymbol{y}) = \sqrt{(x_1-y_1)^2+\cdots+(x_N-y_N)^2}$$ Euclidean

$$D(\boldsymbol{x},\boldsymbol{y}) = \frac{\boldsymbol{x}\cdot\boldsymbol{y}}{\|\boldsymbol{x}\|\|\boldsymbol{y}\|} = \frac{x_1y_1+\cdots+x_Ny_N}{\sqrt{\sum_n x_n^2}\sqrt{\sum_n y_n^2}}$$ Cosine

$$D(\boldsymbol{x},\boldsymbol{y}) = \frac{1}{2}\sum_n \frac{(x_n-y_n)^2}{(x_n+y_n)}$$ Chi-squared

Distance metrics

L1 (Manhattan) distance

$$d_1(I_1,I_2) = \sum_p |I_1^p - I_2^p|$$

L2 (Euclidean) distance

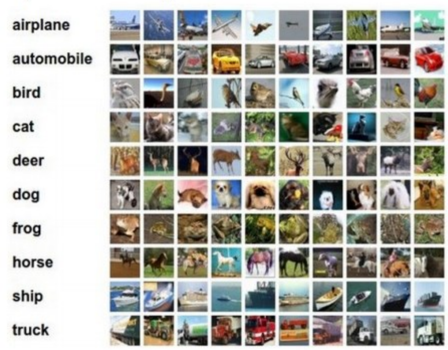
$$d_2(I_1,I_2) = \sqrt{\sum_p \left(I_1^p - I_2^p\right)^2}$$

- Two most commonly used special cases of p-norm

$$\|x\|_p = \left(|x_1|^p + \cdots + |x_n|^p\right)^{\frac{1}{p}} \qquad p \geq 1, x \in \mathbb{R}^n$$

CIFAR-10 and NN results

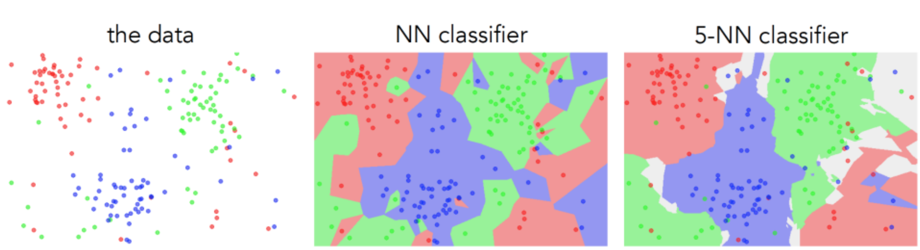
Example dataset: **CIFAR-10**
10 labels
50,000 training images
10,000 test images.



For every test image (first column), examples of nearest neighbors in rows

k-nearest neighbor

- Find the k closest points from training data
- Labels of the ***k points "vote"*** to classify



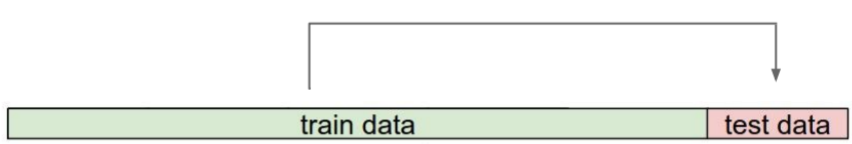
Hyperparameters

- What is the best distance to use?
- What is the best value of k to use?

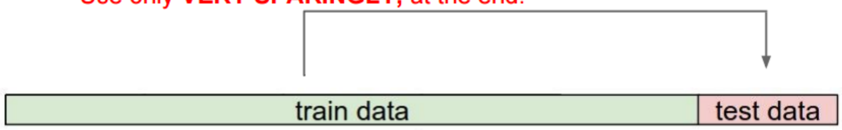
- i.e., how do we set the hyperparameters?

- Very problem-dependent
- Must try them all and see what works best

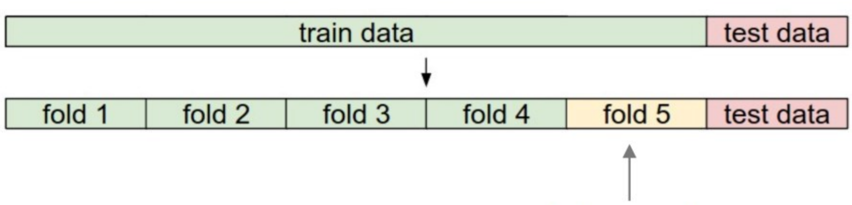
Try out what hyperparameters work best on test set.



Trying out what hyperparameters work best on test set:
Very bad idea. The test set is a proxy for the generalization performance!
Use only **VERY SPARINGLY,** at the end.

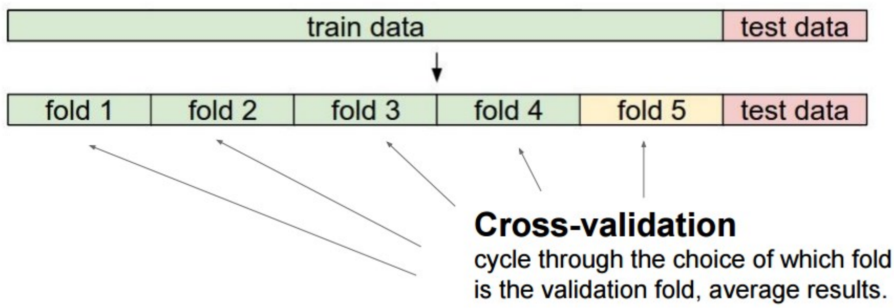


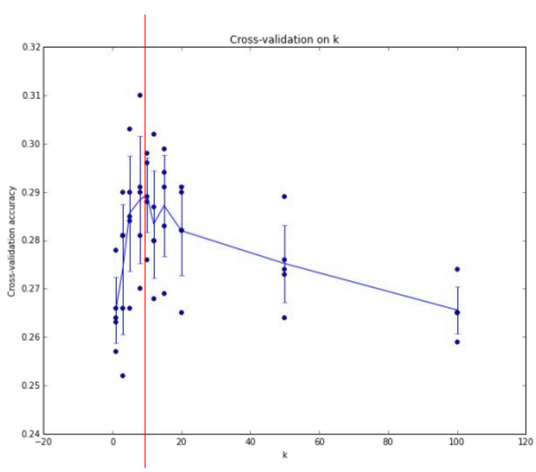
Validation



Validation data
use to tune hyperparameters
evaluate on test set ONCE at the end

Cross-validation





Example of
5-fold cross-validation
for the value of **k.**

Each point: single
outcome.

The line goes
through the mean, bars
indicated standard
deviation

(Seems that k ~= 7 works best
for this data)

How to pick hyperparameters?

- Methodology
  - Train and test
  - Train, validate, test

- Train for original model
- Validate to find hyperparameters
- Test to understand generalizability

kNN

Pros

- simple yet effective

Cons

- search is expensive (can be speed-up)
- storage requirements
- difficulties with high-dimensional data

kNN -- Complexity and Storage

- N training images, M test images
- Training: O(1)
- Testing: O(MN)
- Hmm…
  - Normally need the opposite
  - Slow training (ok), fast testing (necessary)

Other classifiers

- Naïve Bayes
- SVM
- Random Forest
- Neural Network
- …

References

Most of these slides were adapted from:

1. Ioannis Yannis, Gkioulekas (16-385 Computer Vision, Spring 2020, CMU)
2. Kristen Grauman (CS 376: Computer Vision, Spring 2018, The University of Texas at Austin)
3. Noah Snavely (Cornell University)
4. Fei-Fei Li (Stanford University)

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