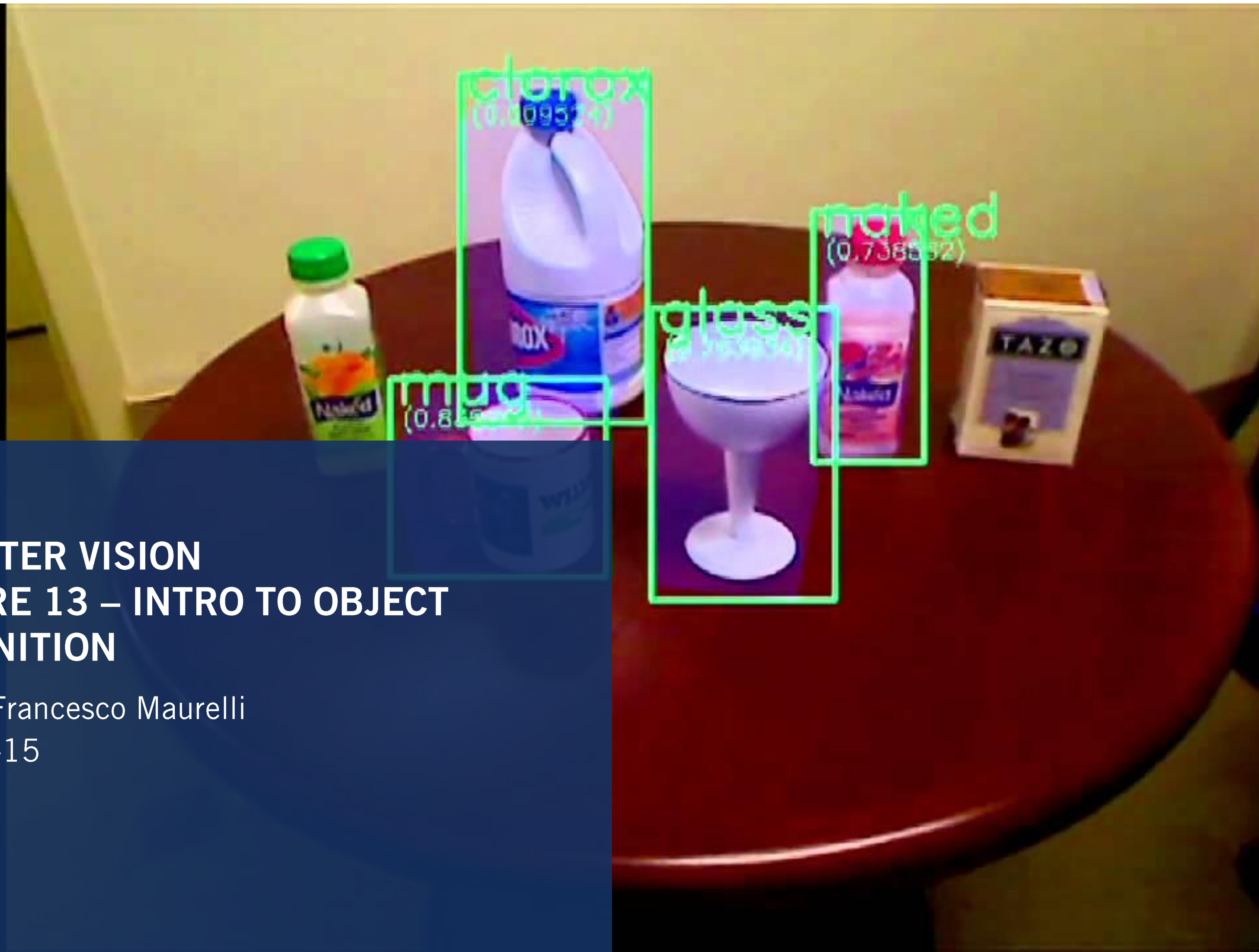


COMPUTER VISION
LECTURE 13 – INTRO TO OBJECT RECOGNITION

Prof. Dr. Francesco Maurelli

2019-10-15

What we will learn today?

- Introduction to object recognition
- K-nearest neighbor algorithm
- A simple Object Recognition pipeline

What are the different visual recognition tasks?

Classification:

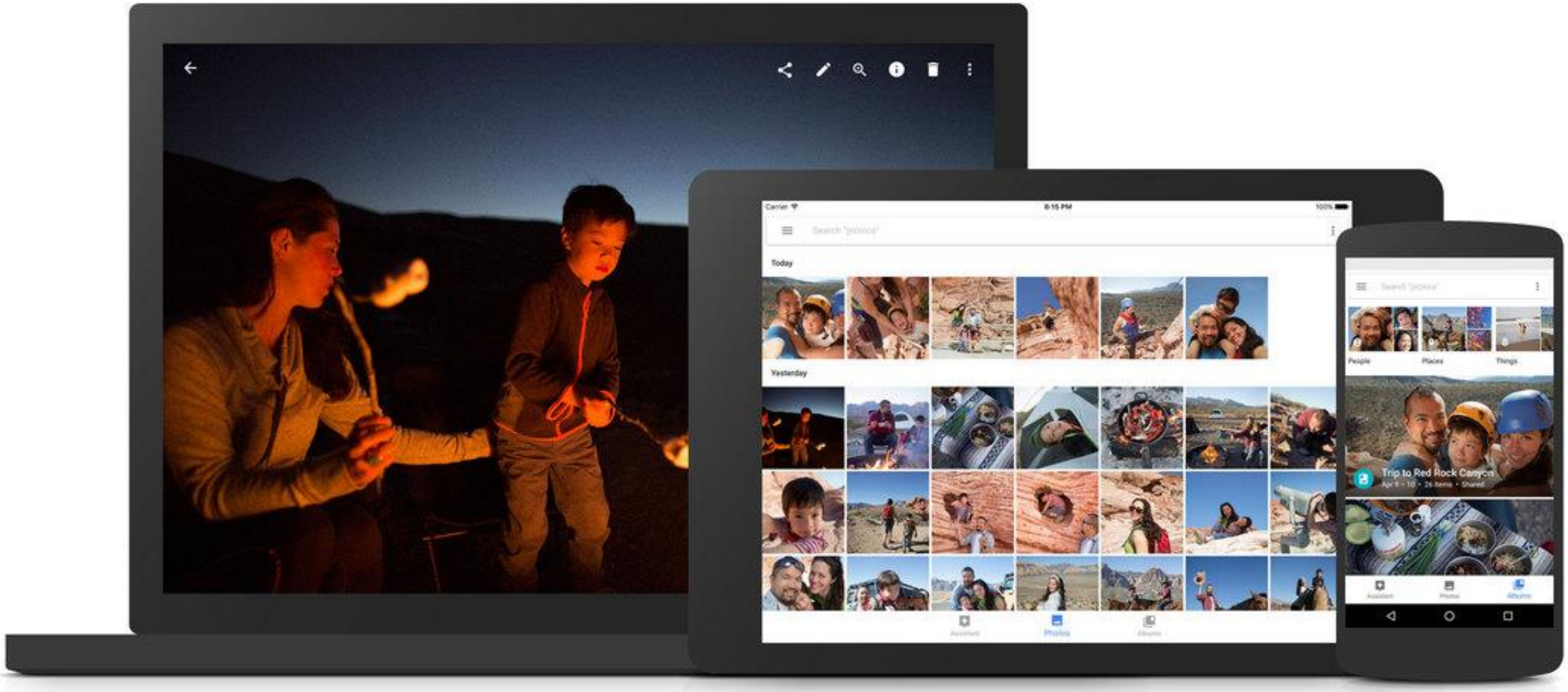
Does this image contain a building? [yes/no]

Classification:

Is this a beach?

Image Search

Organizing photo collections

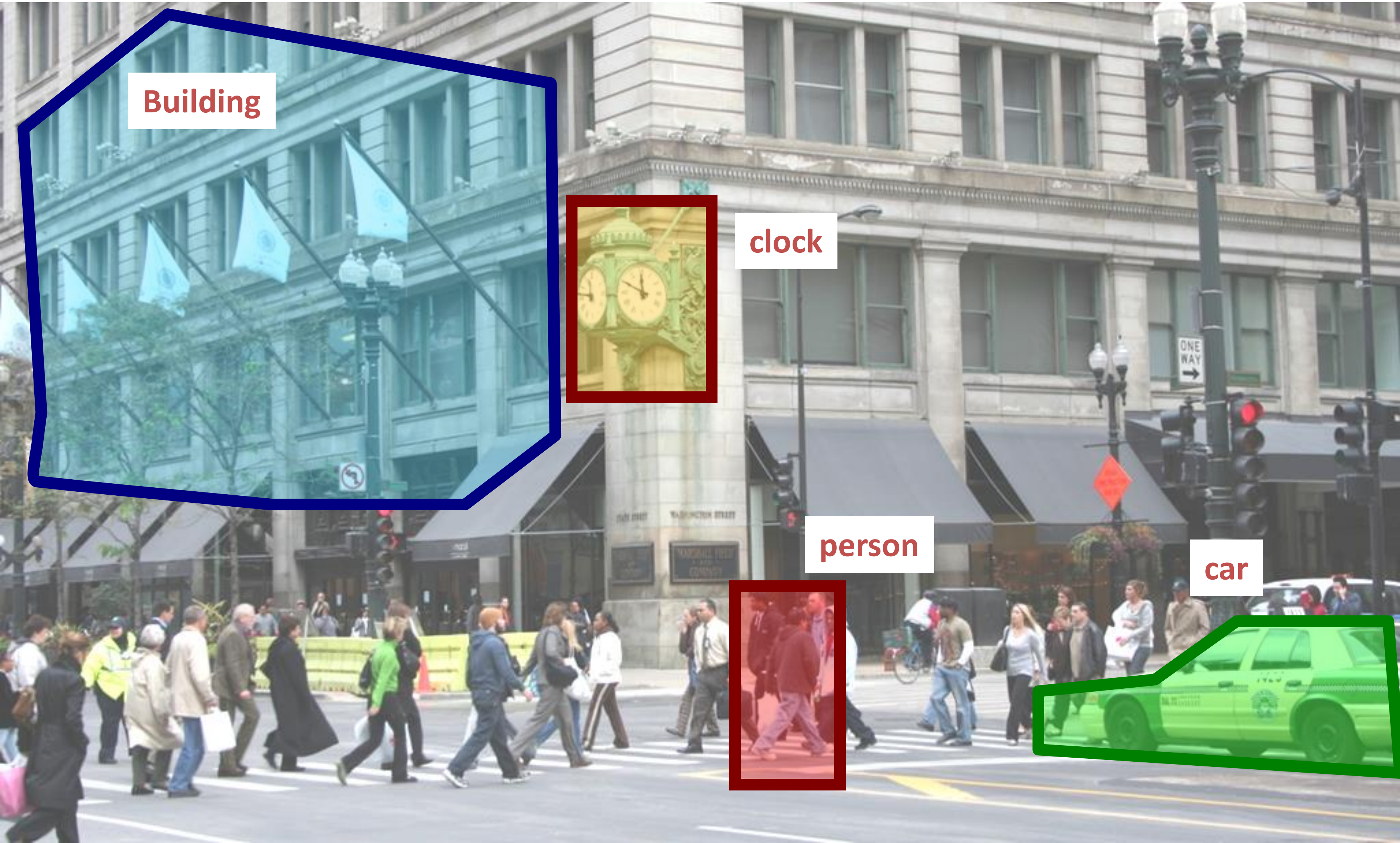


Detection:

Does this image contain a car? [where?]

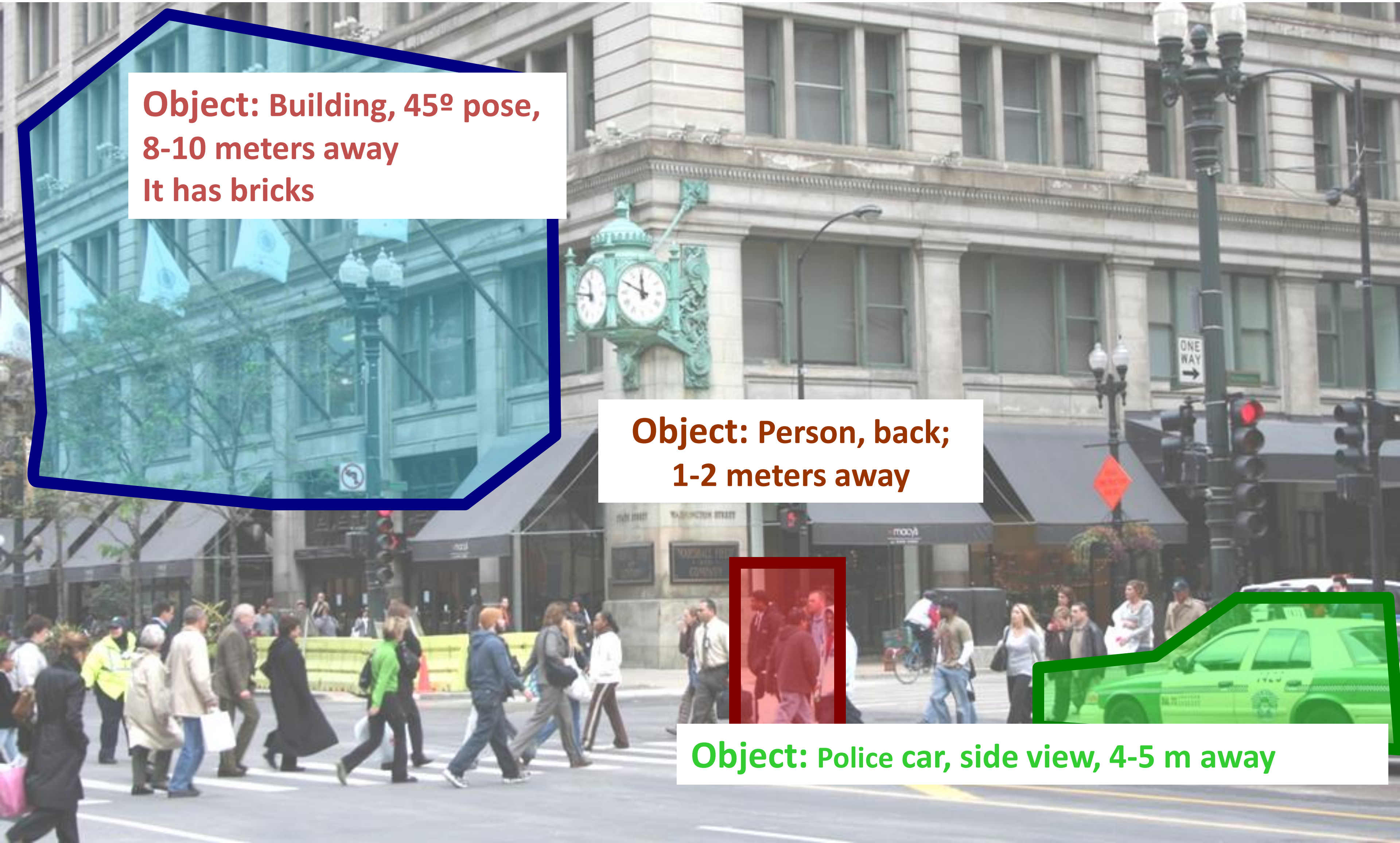
Detection:

Which object does this image contain? [where?]



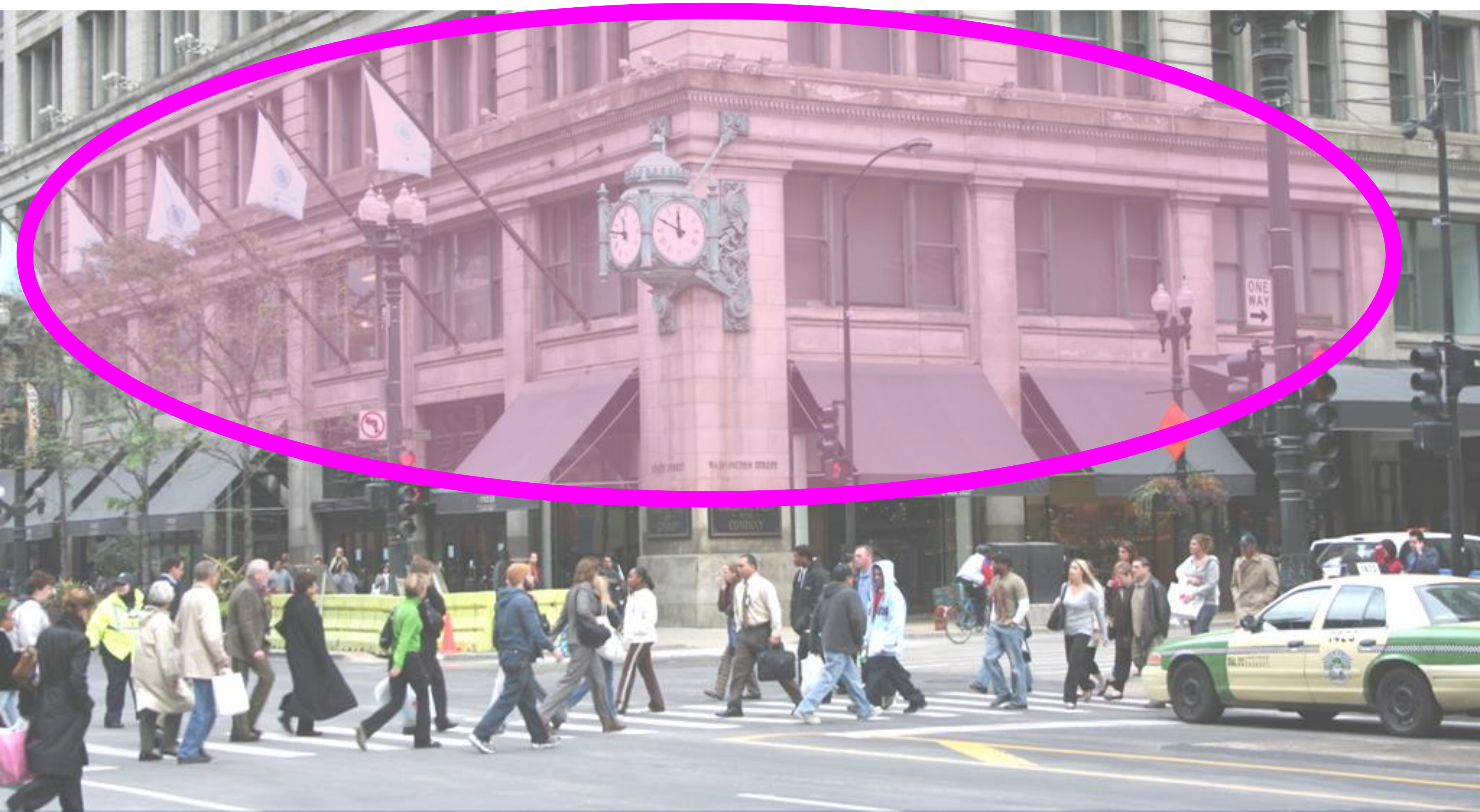
Detection:
Accurate localization (segmentation)

Detection: Estimating object semantic & geometric attributes



Categorization vs Single instance recognition

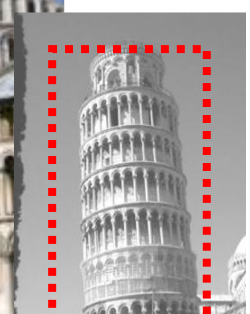
Does this image contain the Chicago Macy's building?



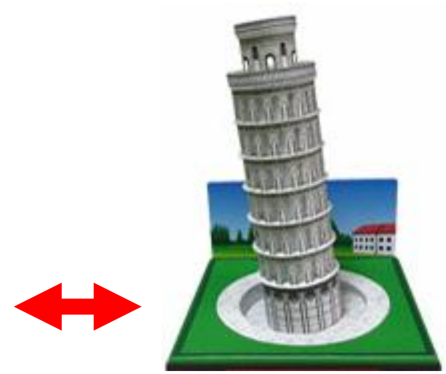
Categorization vs Single instance recognition

Where is the crunchy nut?

Applications of computer vision



- Recognizing landmarks in mobile platforms



+ GPS

Activity or Event recognition
What are these people doing?

Visual Recognition

- Design algorithms that have the capability to:
  - Classify images or videos
  - Detect and localize objects
  - Estimate semantic and geometrical attributes
  - Classify human activities and events

Why is this challenging?

How many object categories are there?

~10,000 to 30,000

Challenges: viewpoint variation

Michelangelo 1475-1564

Challenges: illumination

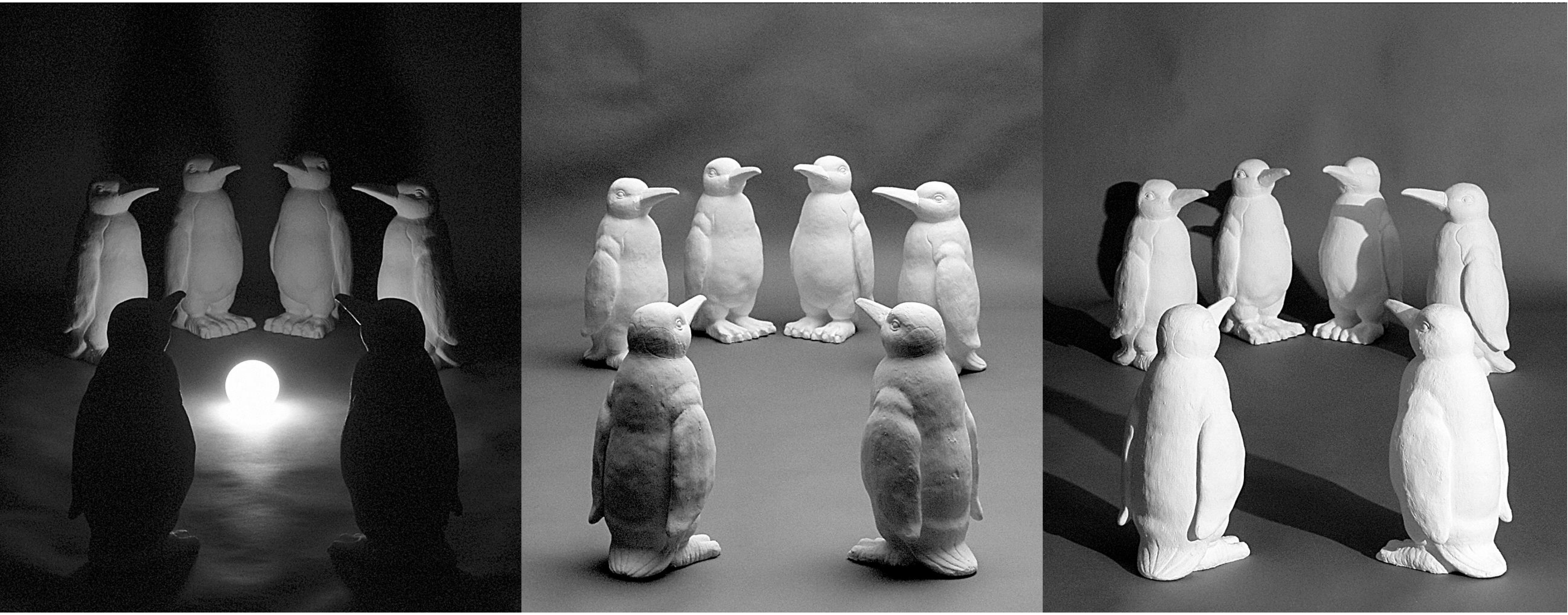
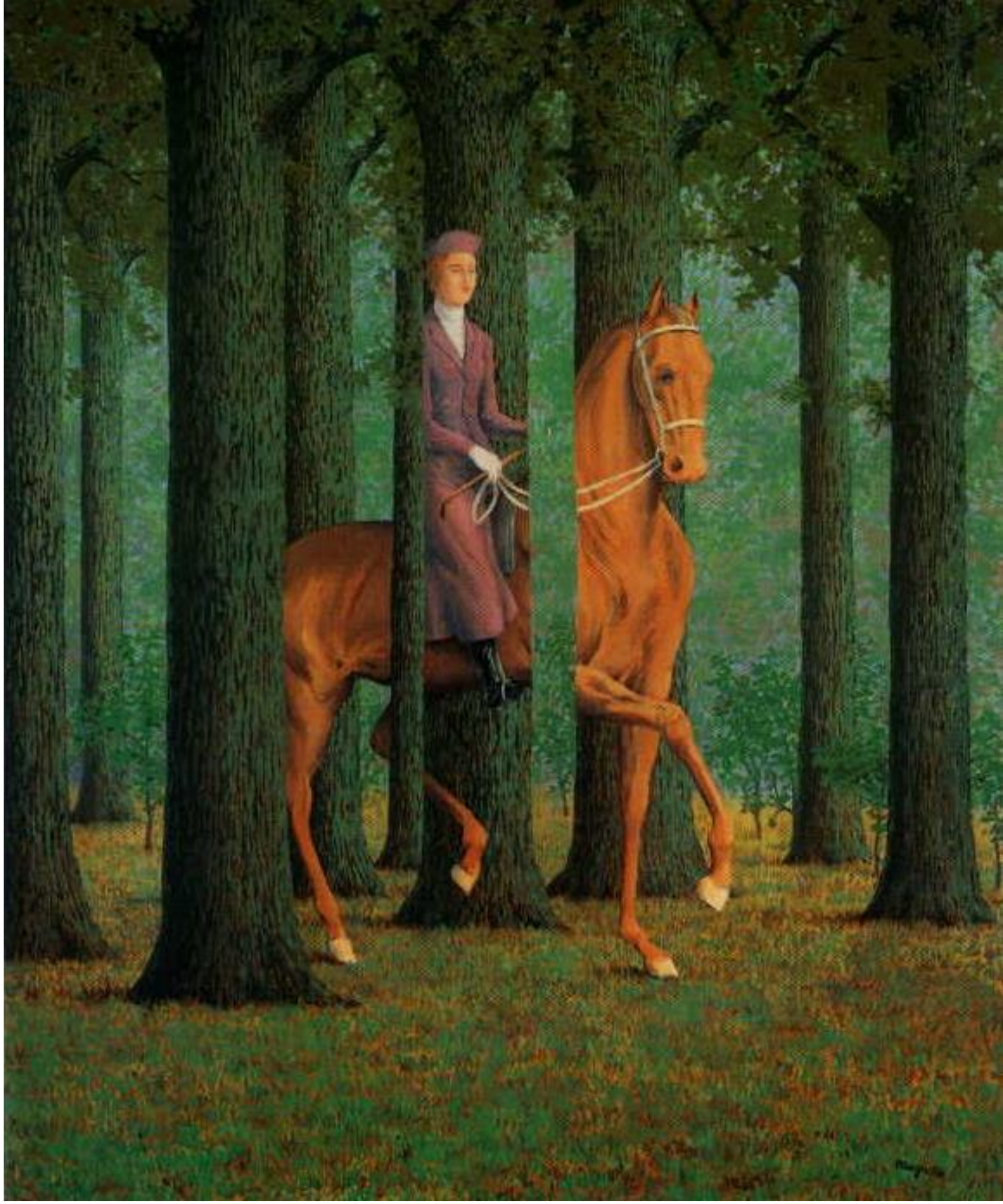


image credit: J. Koenderink

Challenges: scale

Challenges: deformation

Challenges: occlusion



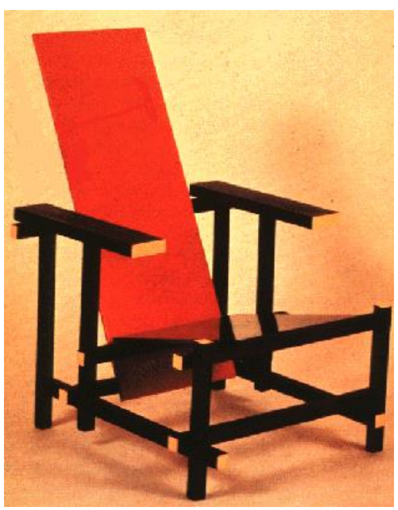
Magritte, 1957

Challenges: background clutter

Kilmeny Niland. 1995

Challenges: intra-class variation



What we will learn today?

- Introduction
- K-nearest neighbor algorithm
- A simple Object Recognition pipeline

The machine learning framework

$$y = f(\mathbf{x})$$

output

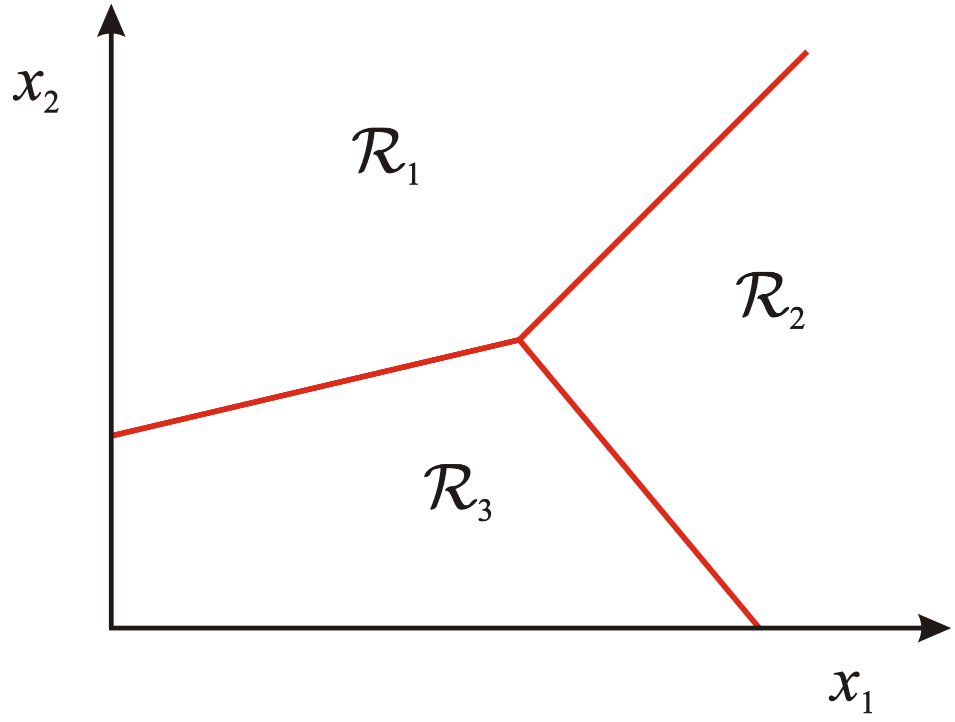
prediction function

Image feature

- **Training:** given a *training set* of labeled examples $\{(\mathbf{x}_1,y_1), \ldots, (\mathbf{x}_N,y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set
- **Testing:** apply f to a never before seen *test example* $\mathbf{x}$ and output the predicted value $y = f(\mathbf{x})$

Classification

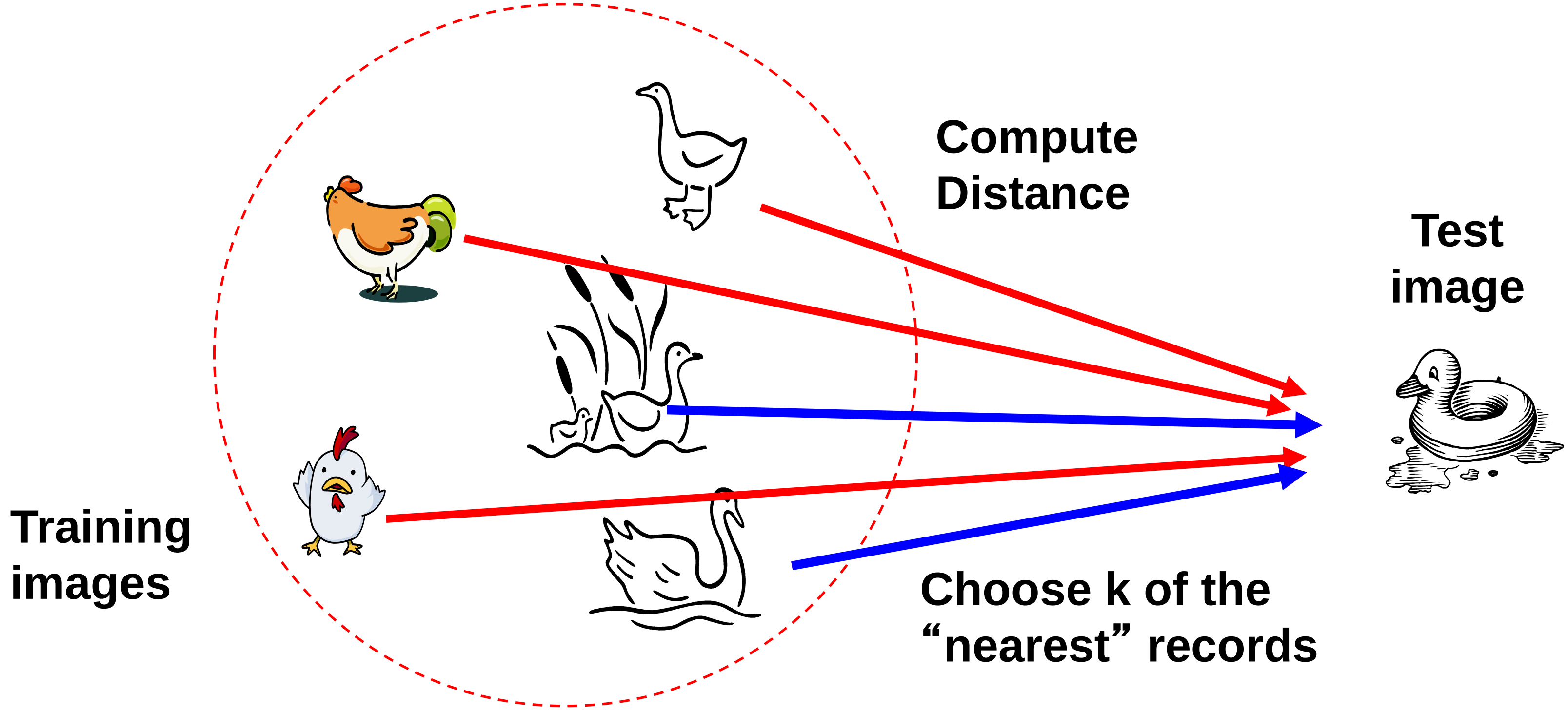
- Assign input vector to one of two or more classes
- Any decision rule divides input space into *decision regions* separated by *decision boundaries*



Slide credit: L. Lazebnik

Nearest Neighbor Classifier

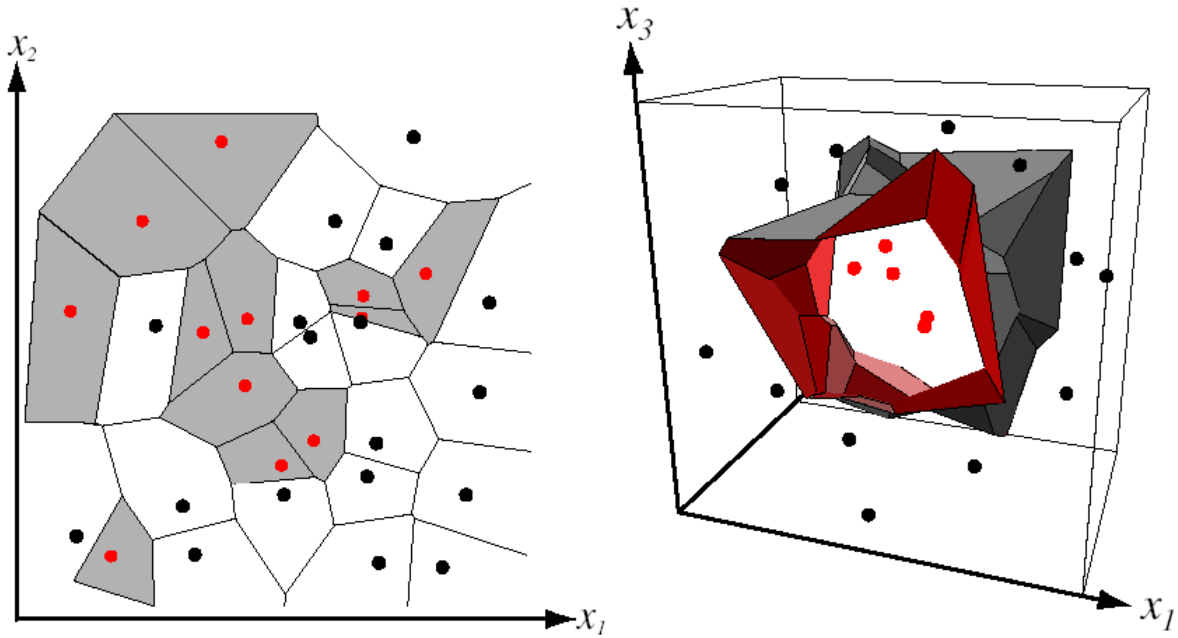
- Assign label of nearest training data point to each test data point



Source: N. Goyal

Nearest Neighbor Classifier

- Assign label of nearest training data point to each test data point



from Duda *et al.*

partitioning of feature space
for two-category 2D and 3D data

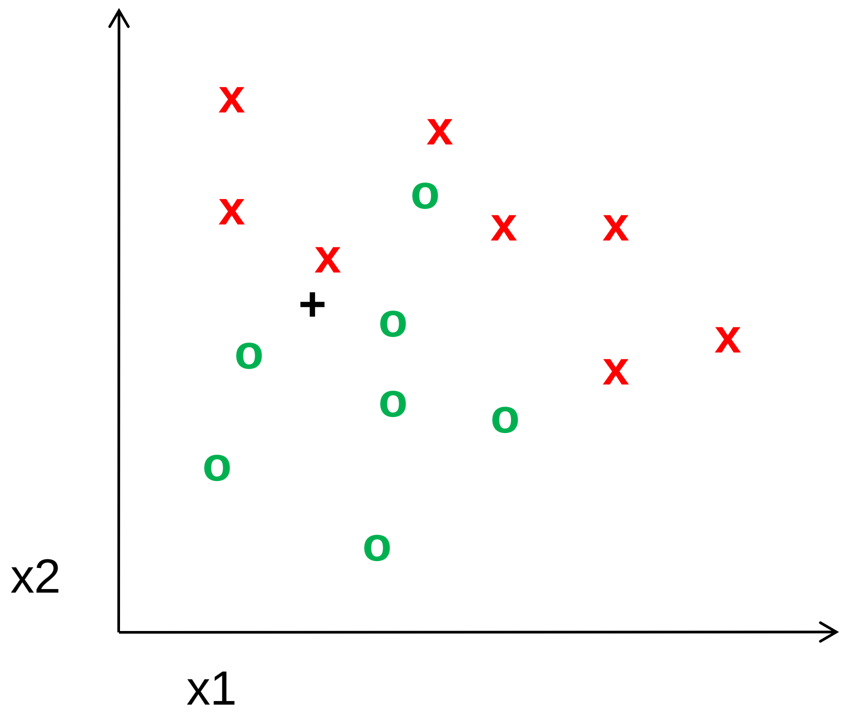
Source: D. Lowe

K-nearest neighbor

Distance measure - Euclidean

$$Dist(X^n, X^m) = \sqrt{\sum_{i=1}^{D} (X_i^n - X_i^m)^2}$$

Where X^n and X^m are the n-th and m-th data points

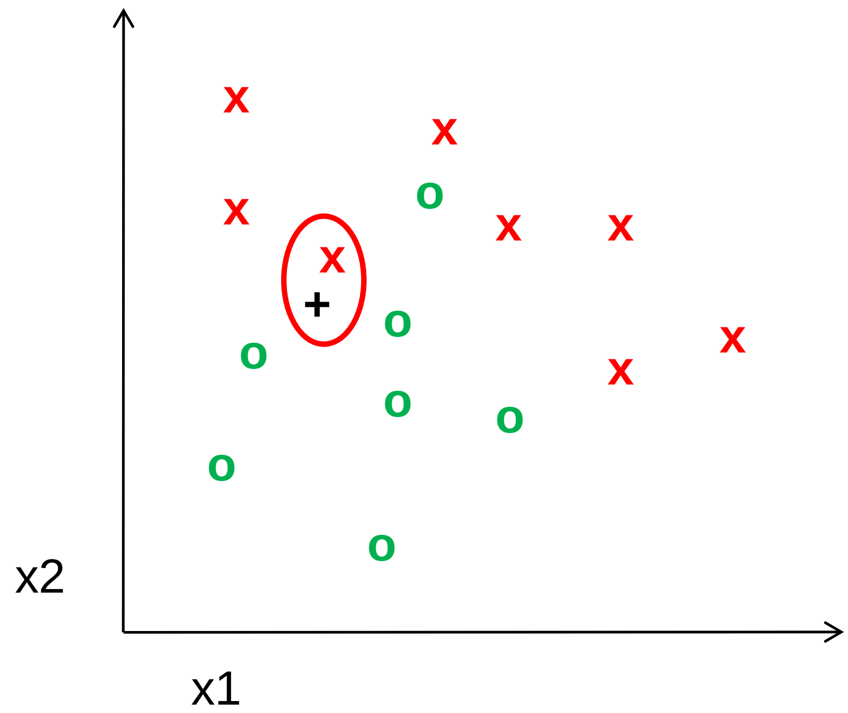


1-nearest neighbor

Distance measure - Euclidean

$$Dist(X^n, X^m) = \sqrt{\sum_{i=1}^{D} (X_i^n - X_i^m)^2}$$

Where X^n and X^m are the n-th and m-th data points

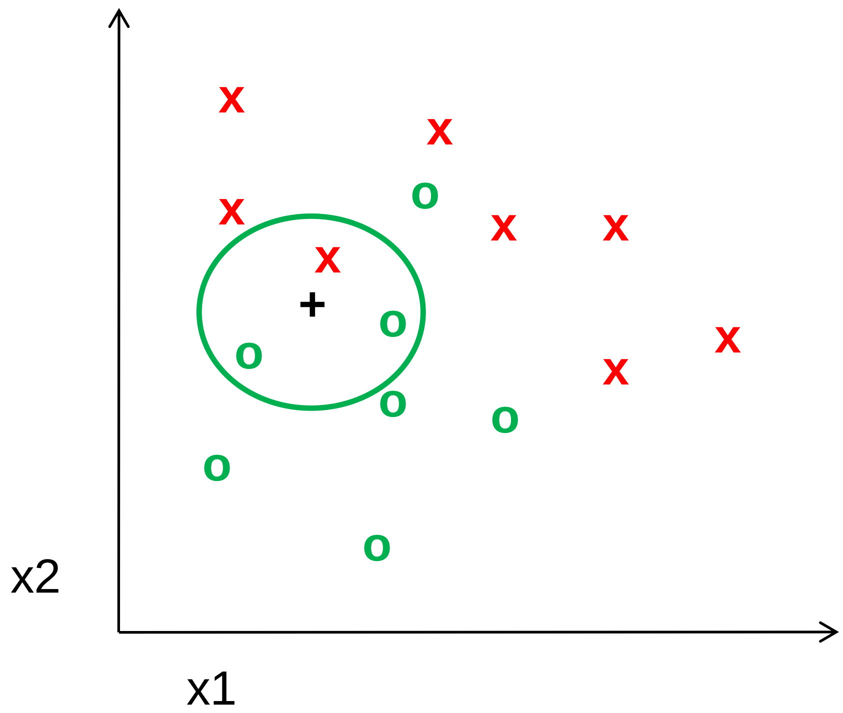


3-nearest neighbor

Distance measure - Euclidean

$$Dist(X^n, X^m) = \sqrt{\sum_{i=1}^{D} (X_i^n - X_i^m)^2}$$

Where X^n and X^m are the n-th and m-th data points

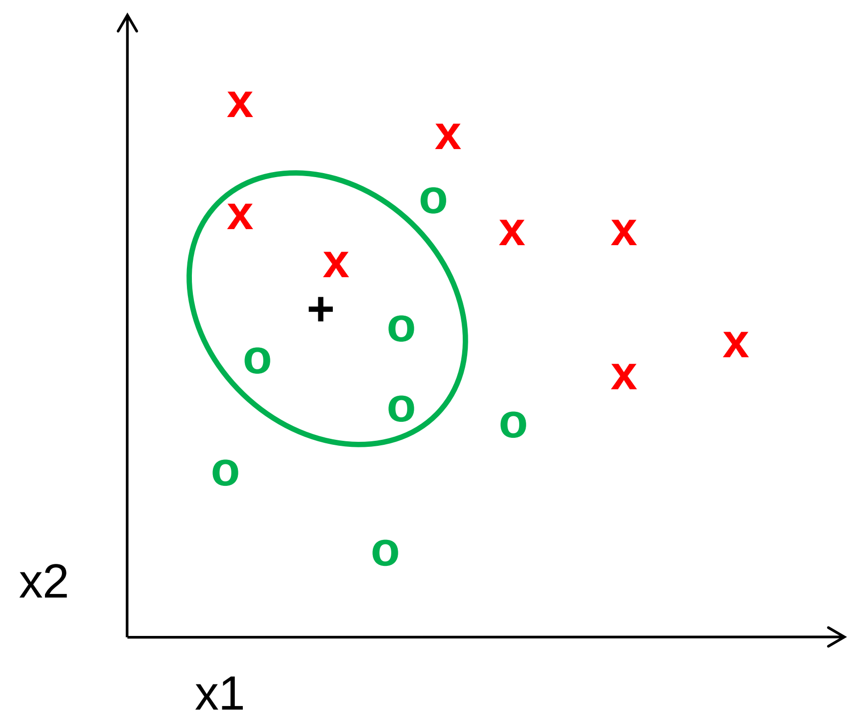


5-nearest neighbor

Distance measure - Euclidean

$$Dist(X^n, X^m) = \sqrt{\sum_{i=1}^{D} (X_i^n - X_i^m)^2}$$

Where X^n and X^m are the n-th and m-th data points

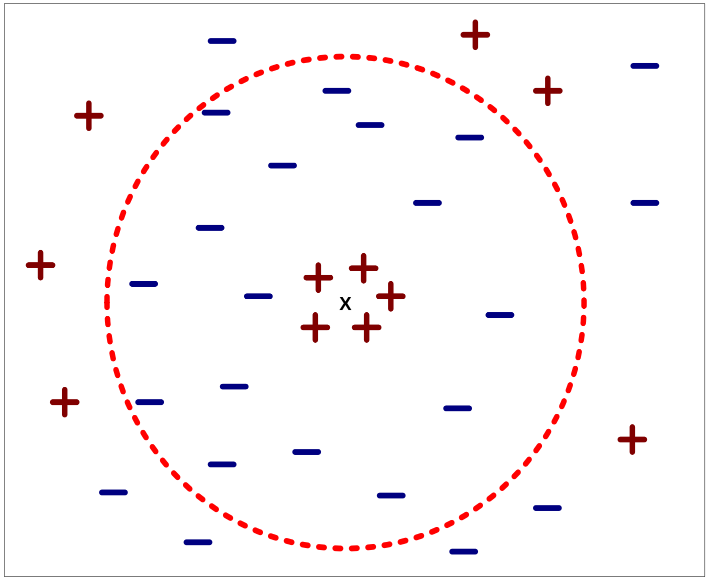


K-NN: a very useful algorithm

- Simple, a good one to try first
- Very flexible decision boundaries

K-NN: issues to keep in mind

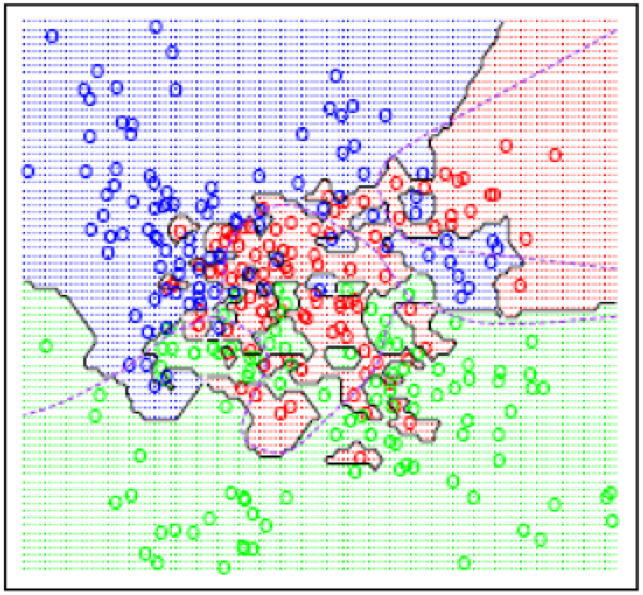
- Choosing the value of k:
  - If too small, sensitive to noise points
  - If too large, neighborhood may include points from other classes



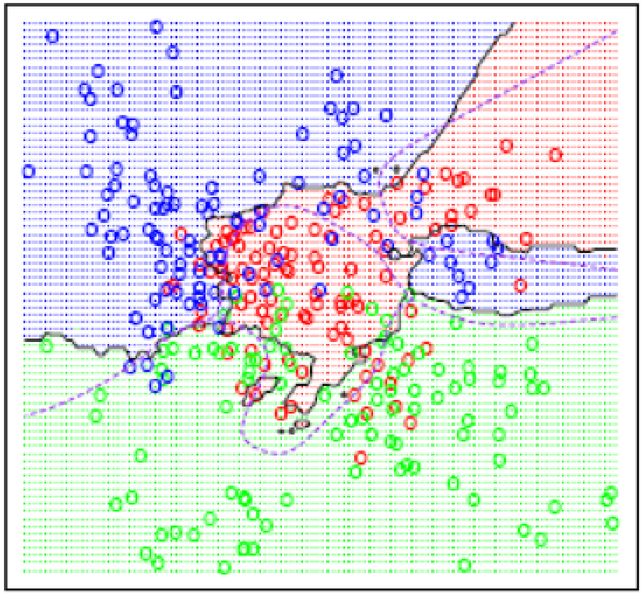
K-NN: issues to keep in mind

- Choosing the value of k:
  - If too small, sensitive to noise points
  - If too large, neighborhood may include points from other classes

K=1

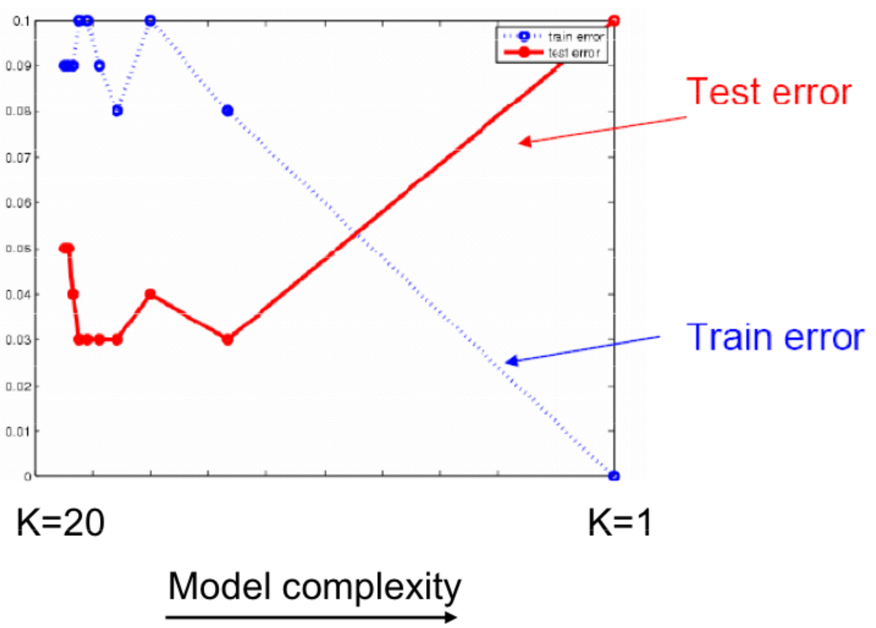


K=15

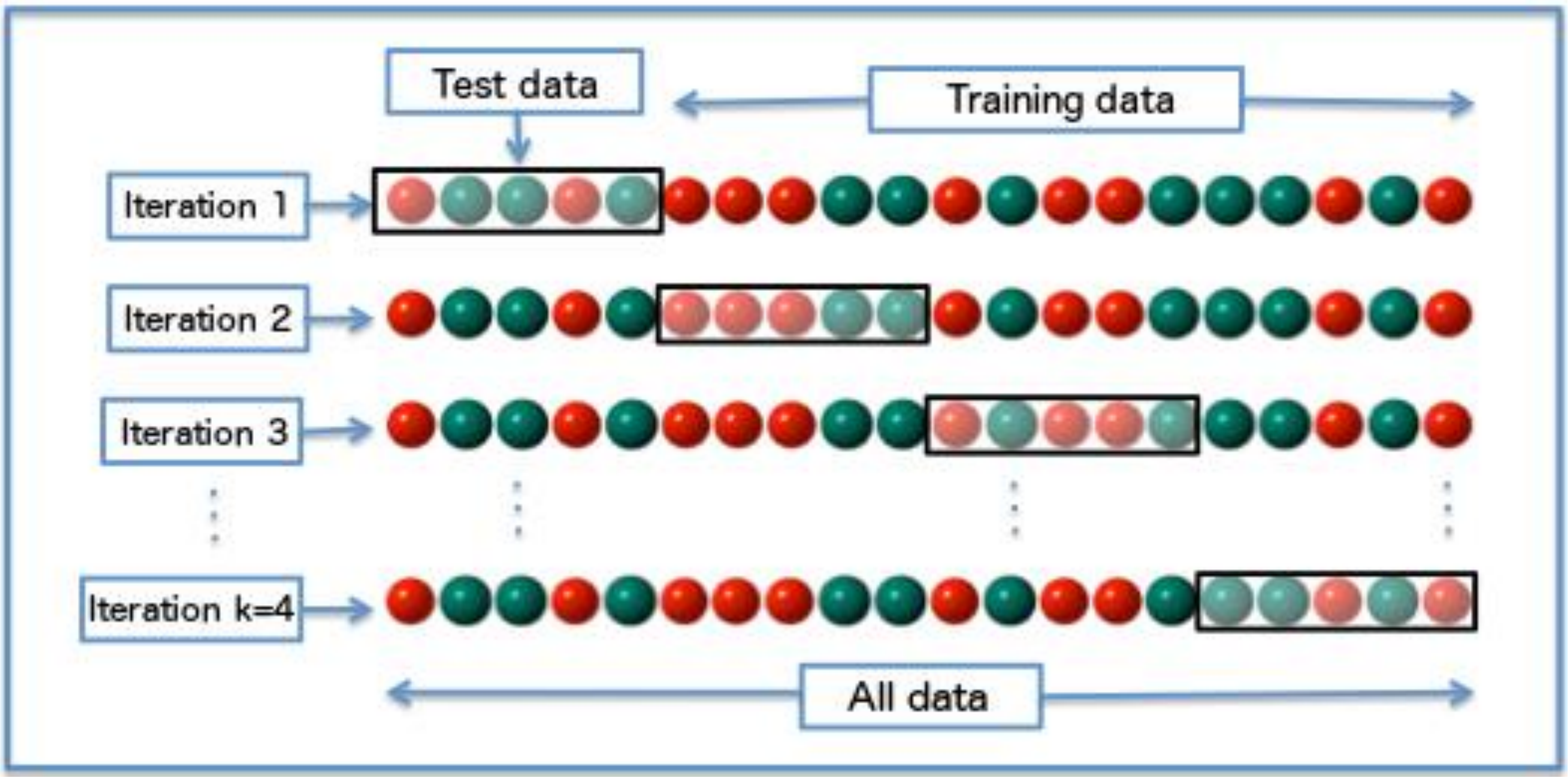


K-NN: issues to keep in mind

- Choosing the value of k:
  - If too small, sensitive to noise points
  - If too large, neighborhood may include points from other classes
  - Solution: cross validate!



Cross validation



K-NN: issues to keep in mind

- Choosing the value of k:
  - If too small, sensitive to noise points
  - If too large, neighborhood may include points from other classes
  - Solution: cross validate!
- Can produce counter-intuitive results (using Euclidean measure)

Euclidean measure

1 1 1 1 1 1 1 1 1 1 1 0
0 1 1 1 1 1 1 1 1 1 1 1

d = 1.4142

vs

1 0 0 0 0 0 0 0 0 0 0 0
0 0 0 0 0 0 0 0 0 0 0 1

d = 1.4142

K-NN: issues to keep in mind

- Choosing the value of k:
  - If too small, sensitive to noise points
  - If too large, neighborhood may include points from other classes
  - Solution: cross validate!
- Can produce counter-intuitive results (using Euclidean measure)
  - Solution: normalize the vectors to unit length

Many classifiers to choose from

- **K-nearest neighbor**
- SVM
- Neural networks
- Naïve Bayes
- Bayesian network
- Logistic regression
- Randomized Forests
- Boosted Decision Trees
- RBMs
- Etc.

Which is the best one?

Slide credit: D. Hoiem

Generalization

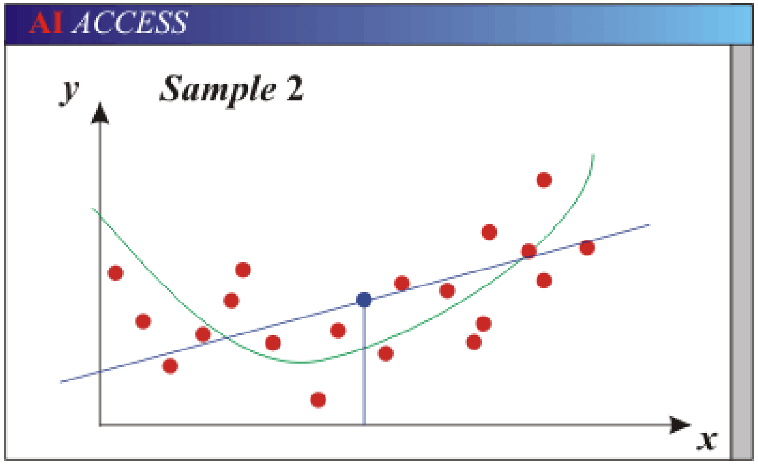
Training set (labels known)

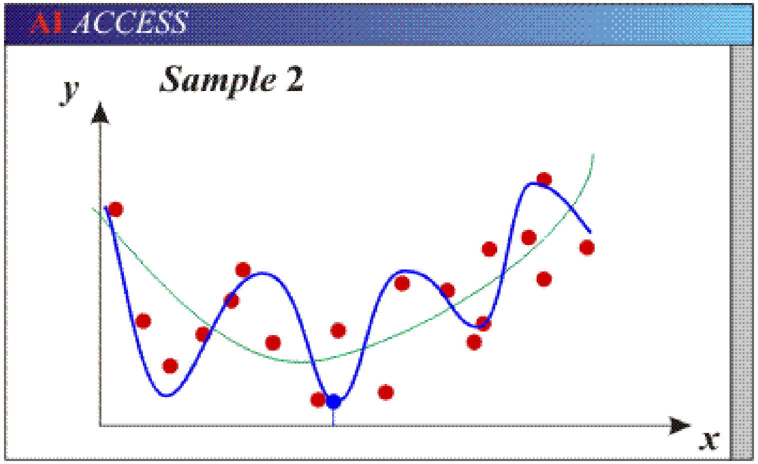
Test set (labels unknown)

- How well does a learned model generalize from the data it was trained on to a new test set?

Slide credit: L. Lazebnik

Bias-Variance Trade-off





- Models with too few parameters are inaccurate because of a large bias (not enough flexibility).
- Models with too many parameters are inaccurate because of a large variance (too much sensitivity to the sample).

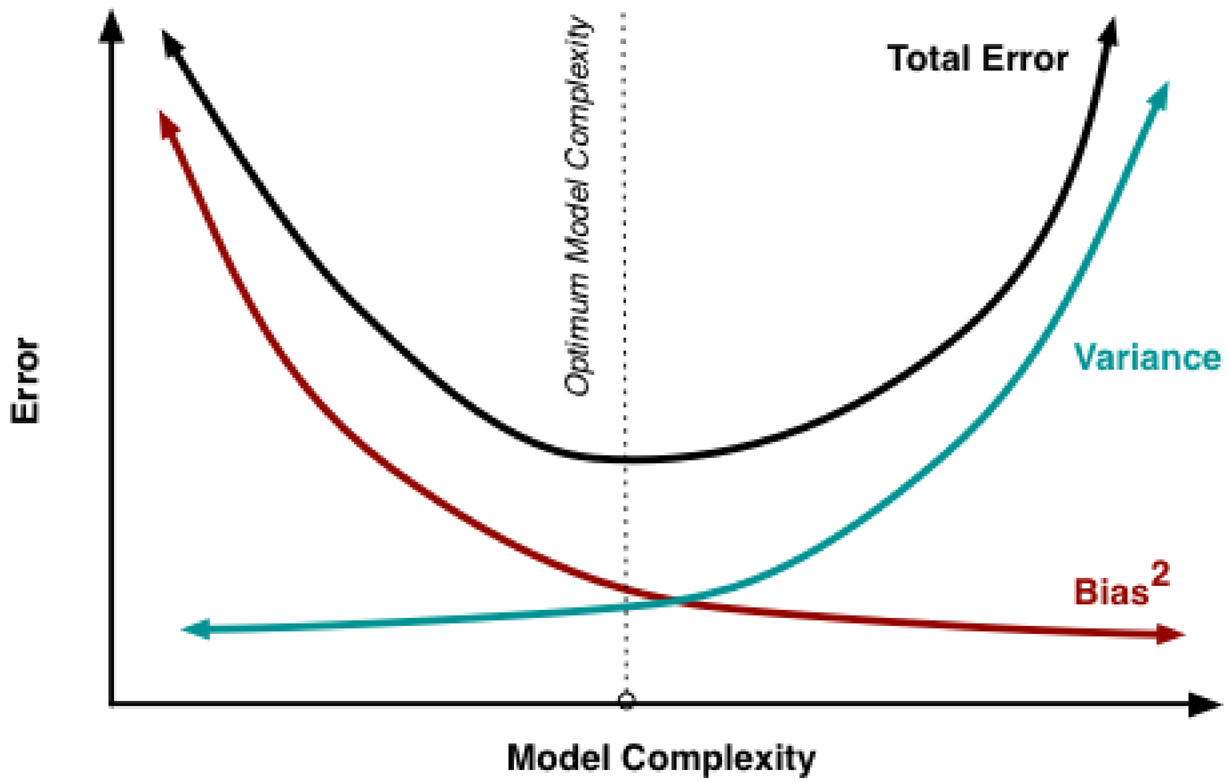
Slide credit: D. Hoiem

Bias versus variance

- Components of generalization error
  - **Bias:** how much the average model over all training sets differ from the true model?
    - Error due to inaccurate assumptions/simplifications made by the model
  - **Variance:** how much models estimated from different training sets differ from each other
- **Underfitting:** model is too "simple" to represent all the relevant class characteristics
  - High bias and low variance
  - High training error and high test error
- **Overfitting:** model is too "complex" and fits irrelevant characteristics (noise) in the data
  - Low bias and high variance
  - Low training error and high test error

Slide credit: L. Lazebnik

Bias versus variance trade off



No Free Lunch Theorem

In a supervised learning setting, we can't tell which classifier will have best generalization

Slide credit: D. Hoiem

Remember…

- No classifier is inherently better than any other: you need to make assumptions to generalize
- Three kinds of error
  – Inherent: unavoidable
  – Bias: due to over-simplifications
  – Variance: due to inability to perfectly estimate parameters from limited data

Slide credit: D. Hoiem

How to reduce variance?

- Choose a simpler classifier
- Regularize the parameters
- Get more training data

Slide credit: D. Hoiem

Last remarks about applying machine learning methods to object recognition

- There are machine learning algorithms to choose from
- Know your data:
  - How much supervision do you have?
  - How many training examples can you afford?
  - How noisy?
- Know your goal (i.e. task):
  - Affects your choices of representation
  - Affects your choices of learning algorithms
  - Affects your choices of evaluation metrics
- Understand the math behind each machine learning algorithm under consideration!

What we will learn today?

- Introduction
- K-nearest neighbor algorithm
- A simple Object Recognition pipeline

Object recognition: a classification framework

- Apply a prediction function to a feature representation of the image to get the desired output:

f() = “apple”

f() = “tomato”

f() = “cow”

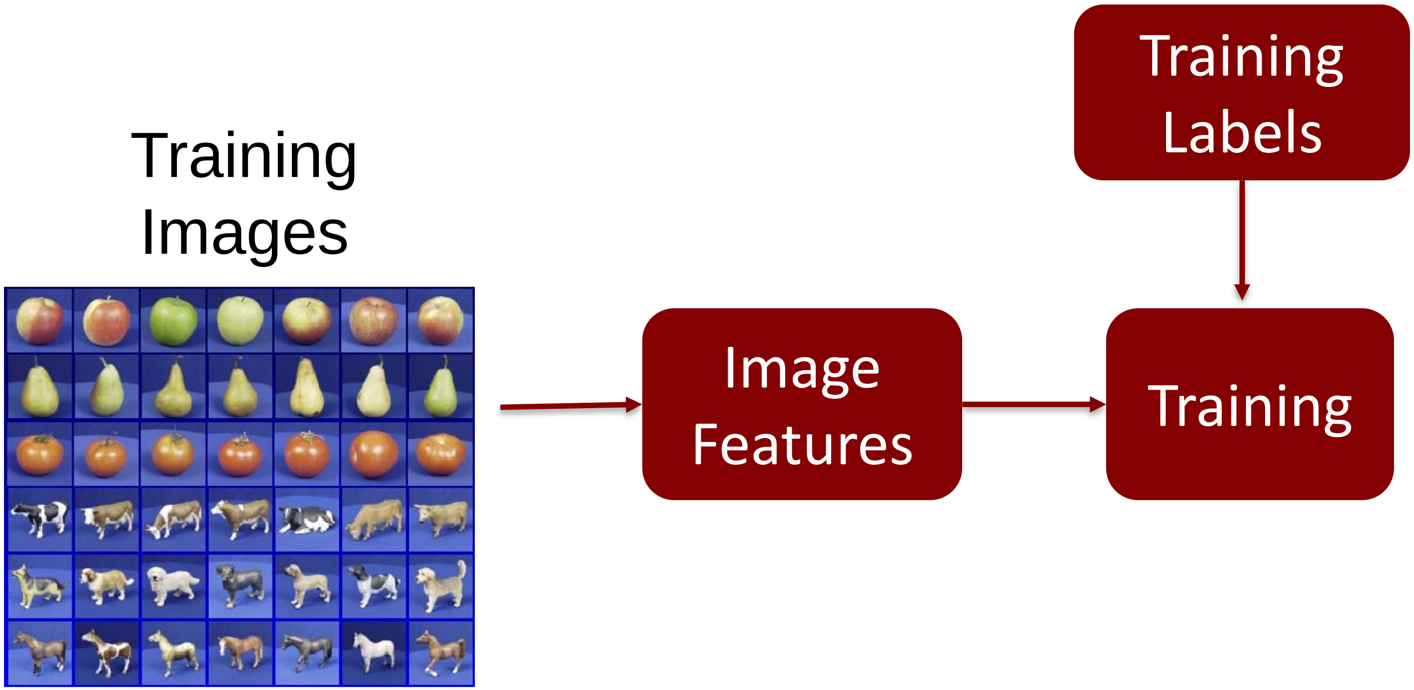
Dataset: ETH-80, by B. Leibe Slide credit: L. Lazebnik

A simple pipeline - Training

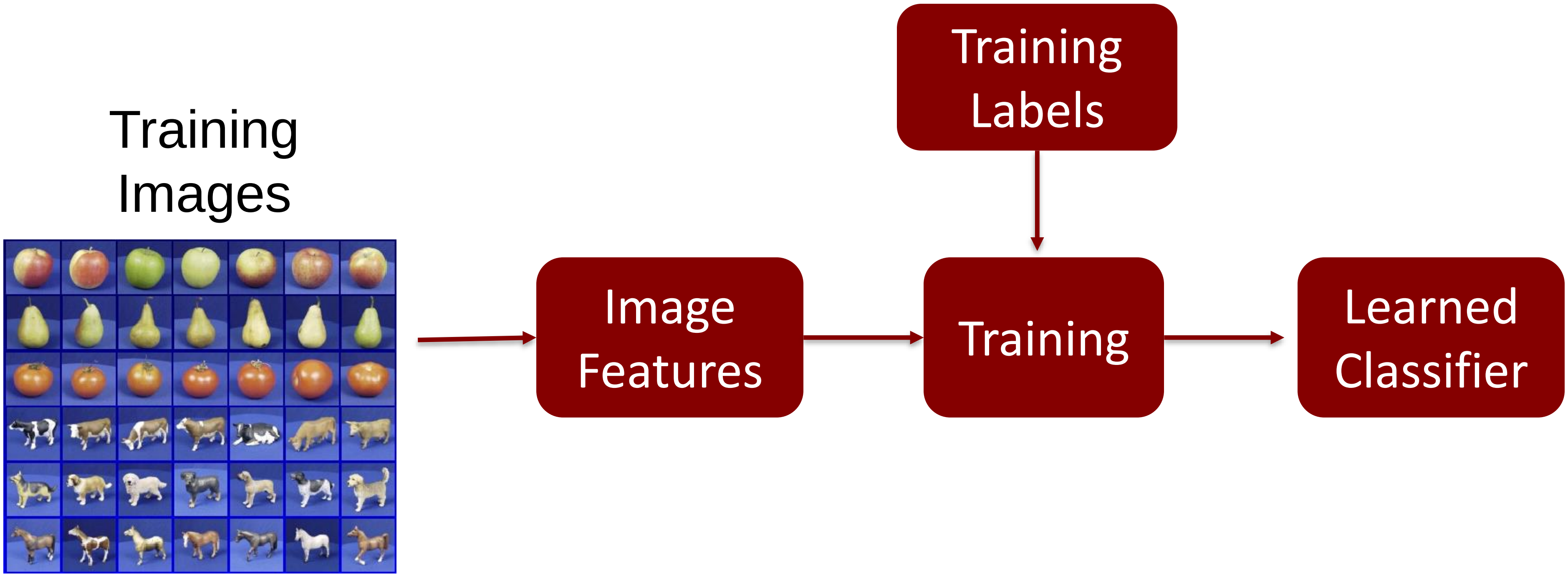
Training
Images

Image
Features

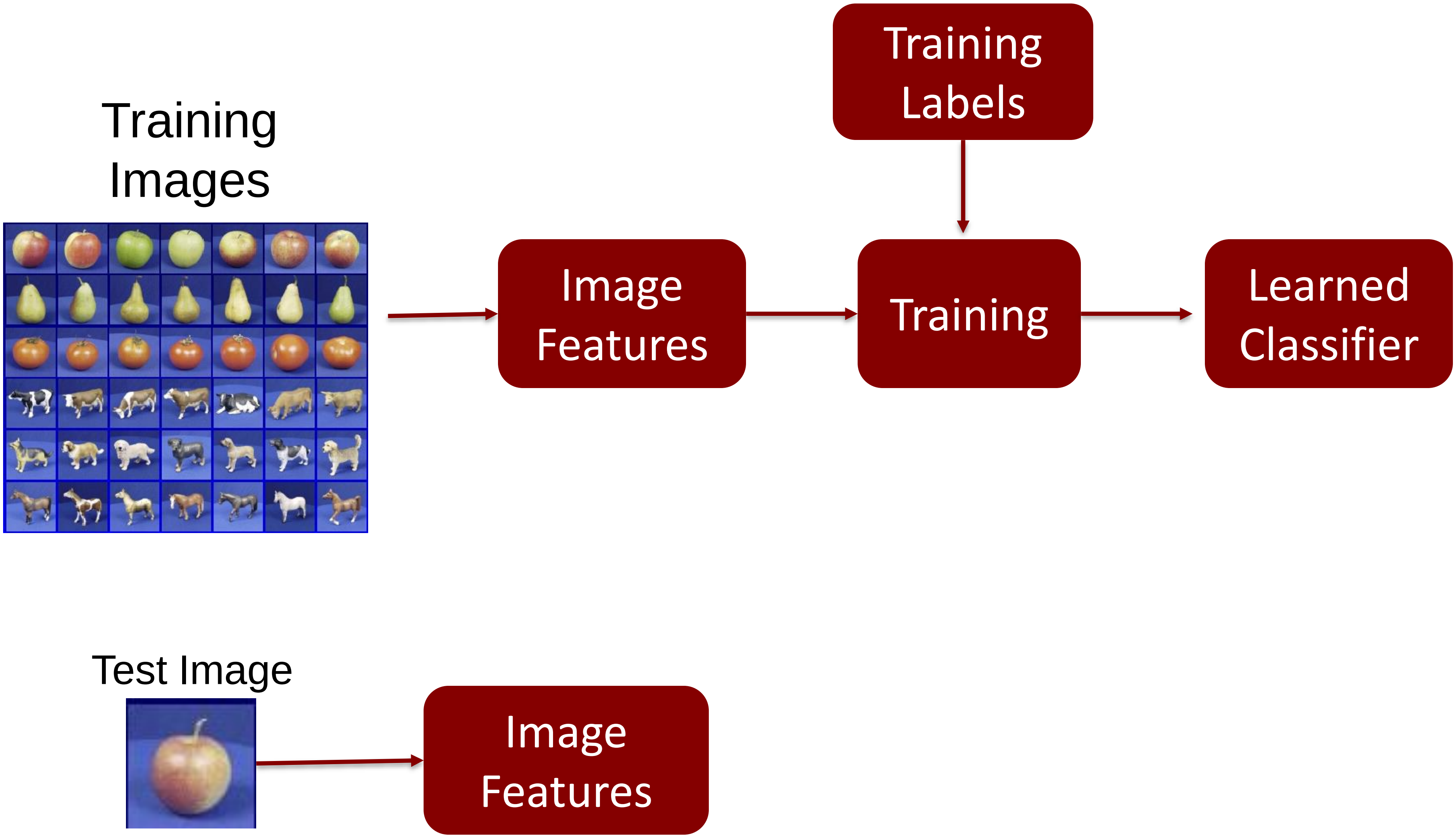
A simple pipeline - Training



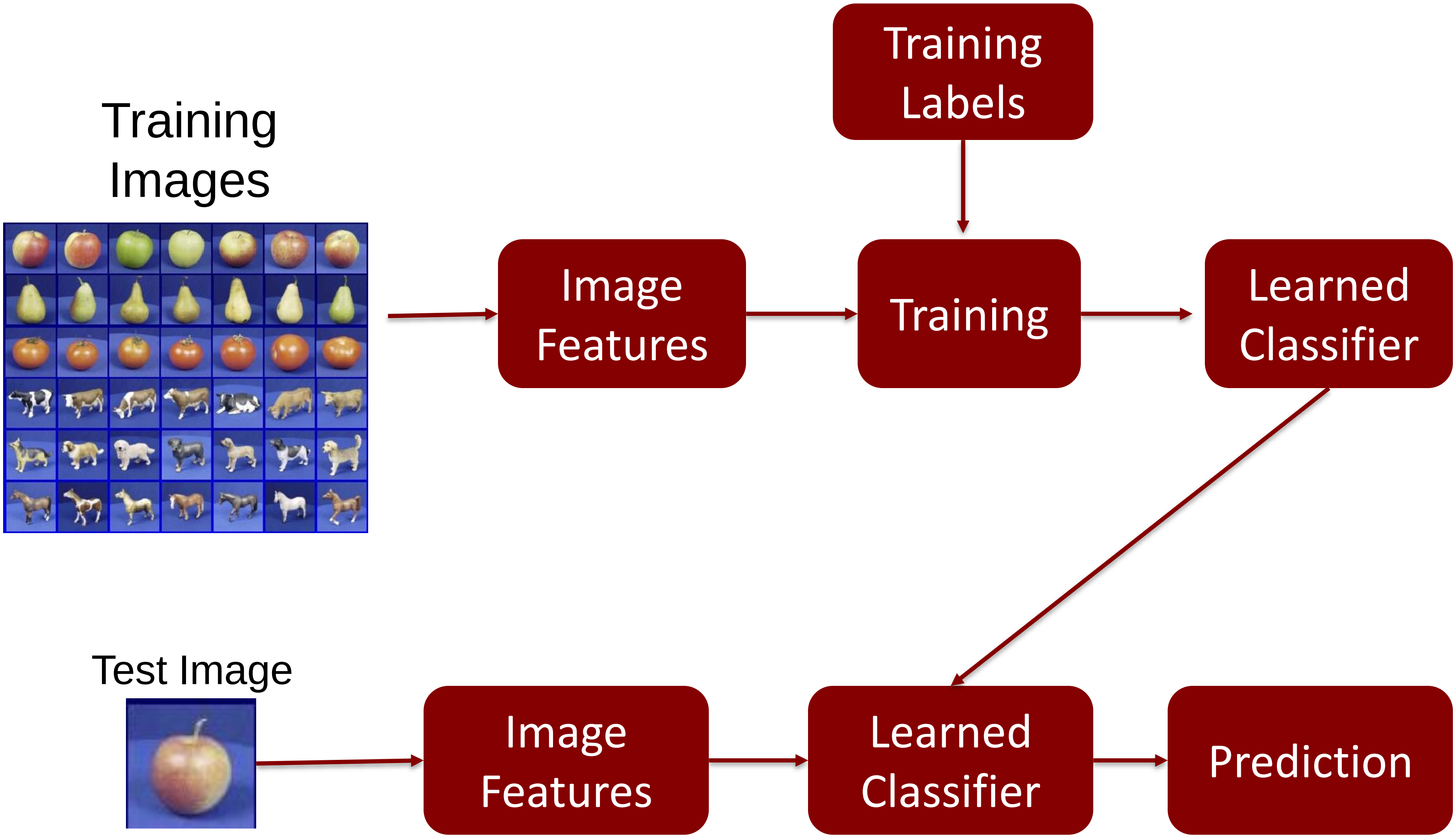
A simple pipeline - Training



A simple pipeline - Training



A simple pipeline - Training



A simple pipeline - Training

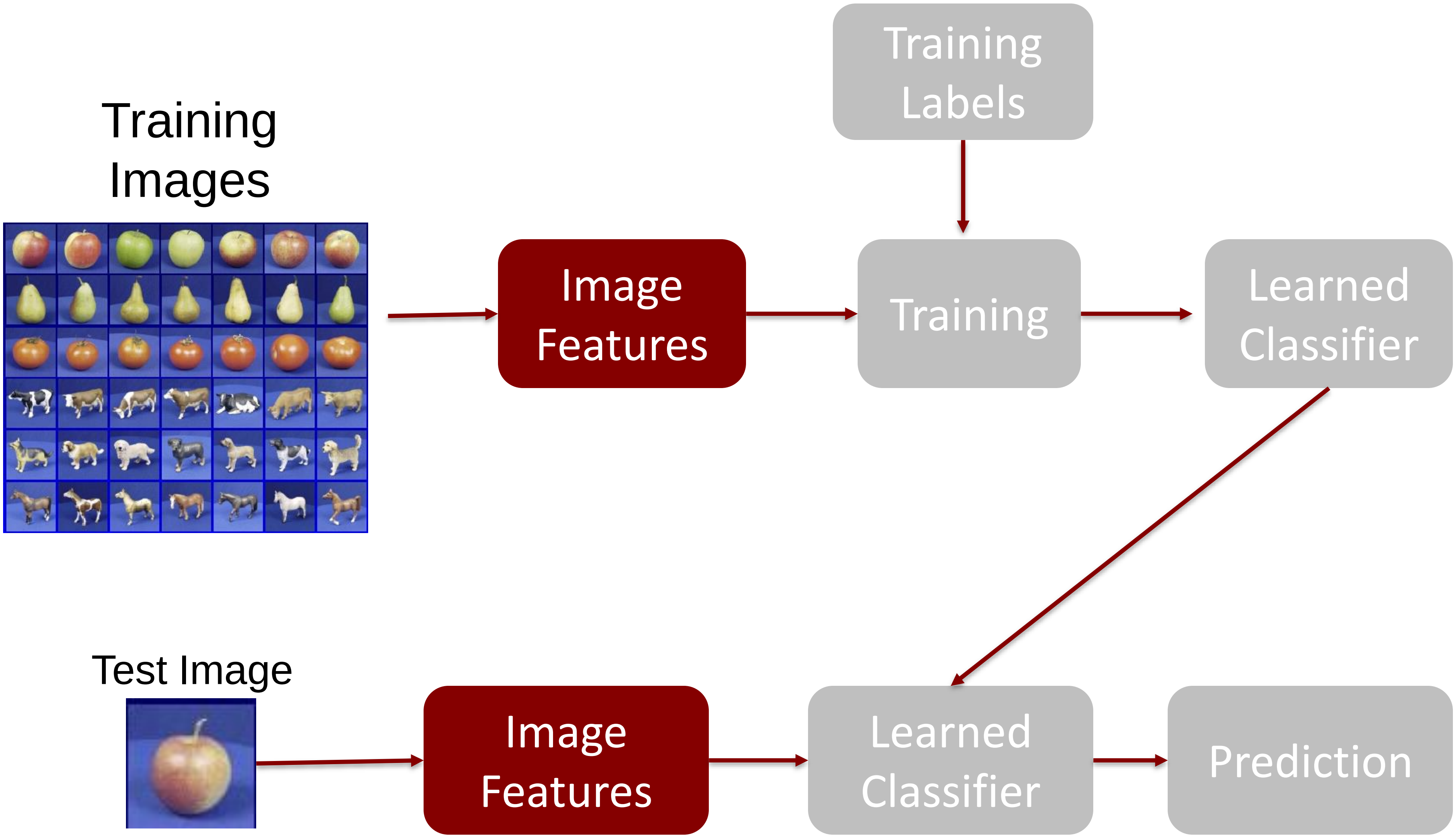
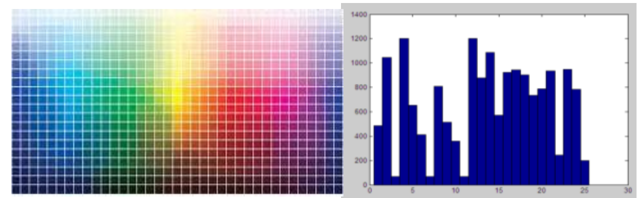


Image features

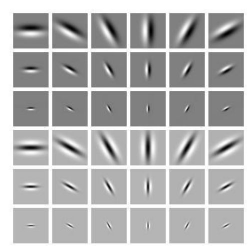
Input image

Color: Quantize RGB values

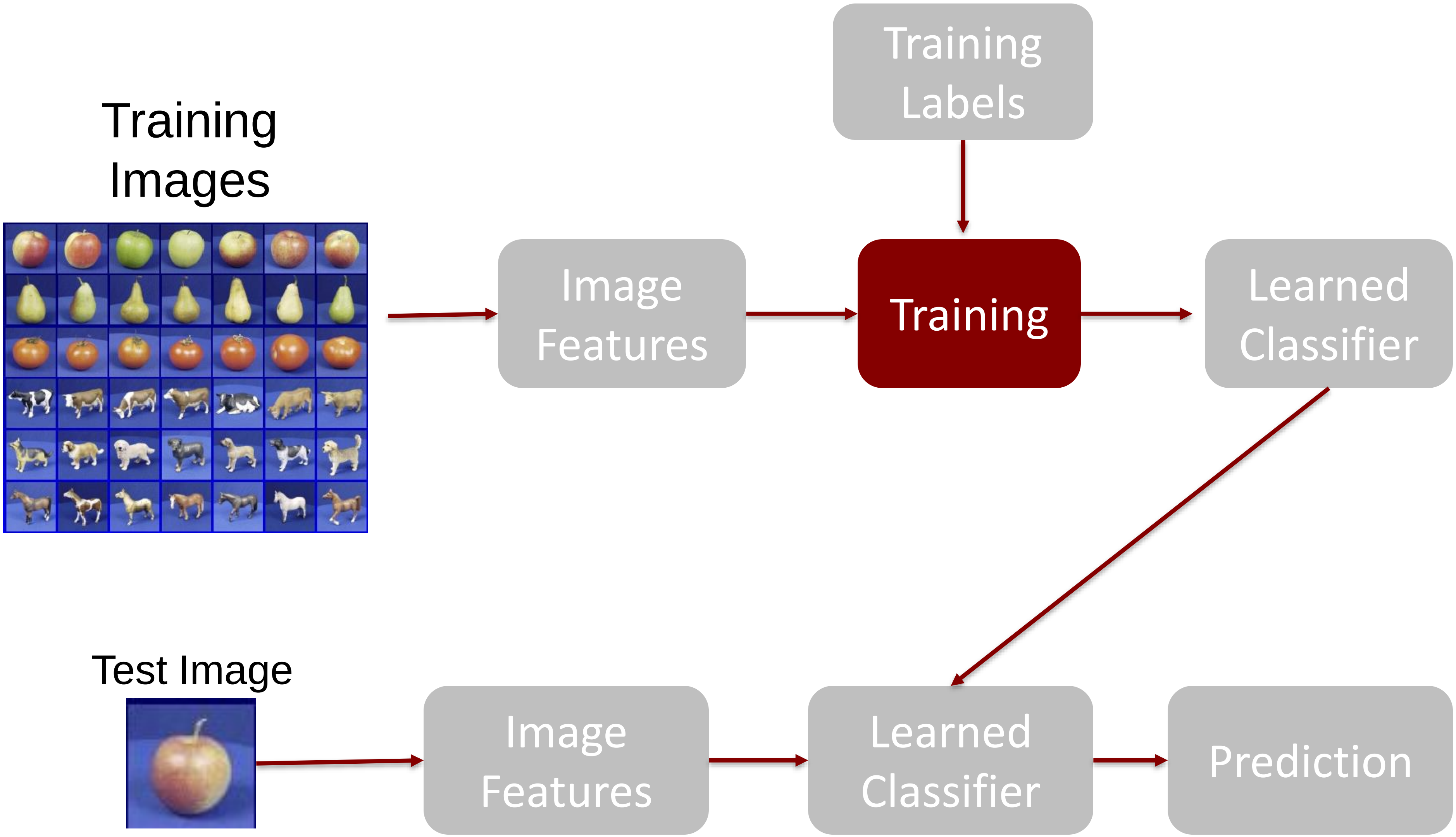


Global shape: PCA

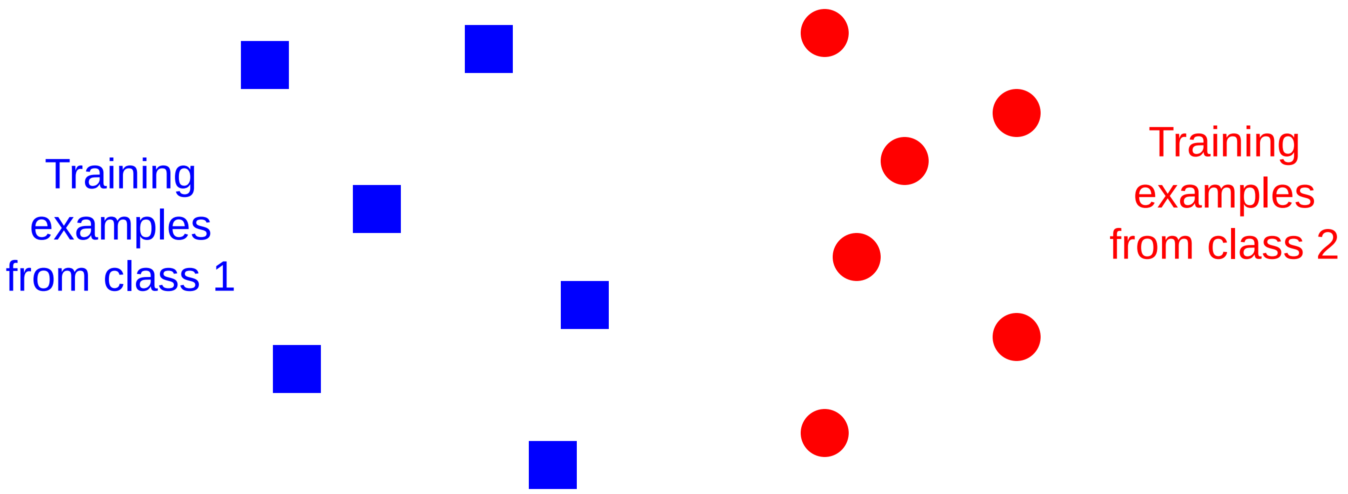
Texture: Filter banks



A simple pipeline - Training



Classifiers: Nearest neighbor



Slide credit: L. Lazebnik

A simple pipeline - Training

Training Images

Image Features

Training Labels

Training

Learned Classifier

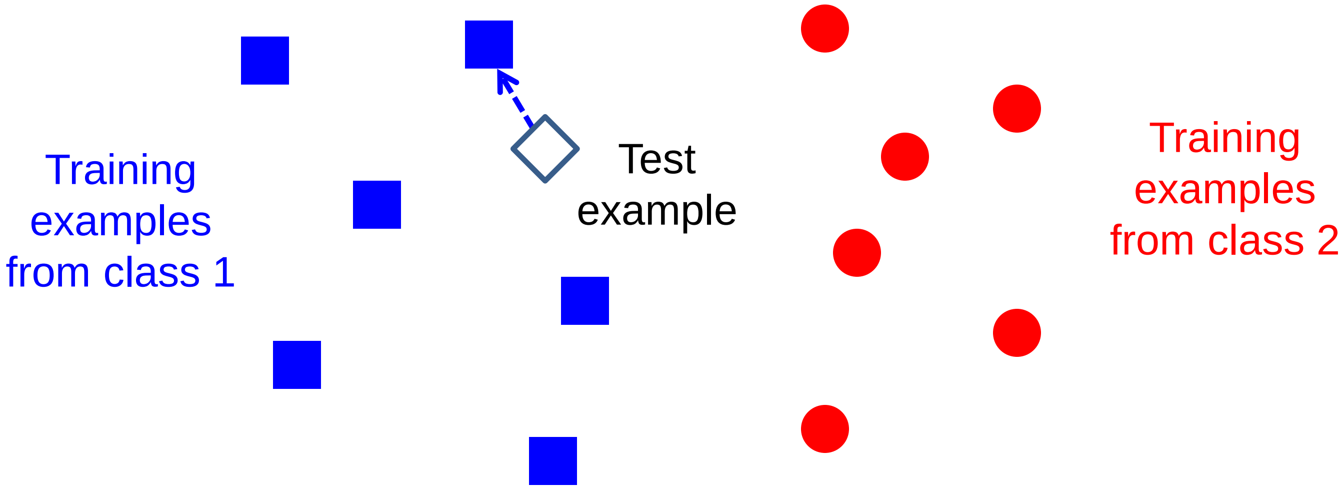
Test Image

Image Features

Learned Classifier

Prediction

Classifiers: Nearest neighbor



Slide credit: L. Lazebnik

Results

	Color	$D_x D_y$	Mag-Lap	PCA Masks	PCA Gray	Cont. Greedy	Cont. DynProg	Avg.
apple	57.56%	**85.37%**	80.24%	78.78%	**88.29%**	77.07%	76.34%	77.66%
pear	66.10%	90.00%	85.37%	**99.51%**	**99.76%**	90.73%	91.71%	89.03%
tomato	**98.54%**	94.63%	**97.07%**	67.80%	76.59%	70.73%	70.24%	82.23%
cow	86.59%	82.68%	**94.39%**	75.12%	62.44%	86.83%	86.34%	82.06%
dog	34.63%	62.44%	74.39%	72.20%	66.34%	**81.95%**	**82.93%**	67.84%
horse	32.68%	58.78%	70.98%	77.80%	77.32%	**84.63%**	**84.63%**	69.55%
cup	79.76%	66.10%	77.80%	**96.10%**	**96.10%**	**99.76%**	**99.02%**	87.81%
car	62.93%	**98.29%**	77.56%	**100.0%**	**97.07%**	**99.51%**	**100.0%**	90.77%
total	64.85%	79.79%	82.23%	83.41%	82.99%	86.40%	86.40%	80.87%

Dataset: ETH-80, by B. Leibe, 2003

What we have learned today?

- Introduction
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- A simple Object Recognition pipeline