Lecture: Object Recognition

Juan Carlos Niebles and Ranjay Krishna
Stanford Vision and Learning Lab

CS 131 Roadmap

Pixels	Segments	Images	Videos	Web
Convolutions Edges Descriptors	Resizing Segmentation Clustering	Recognition Detection Machine learning	Motion Tracking	Neural networks Convolutional neural networks

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 an beach?

Image search

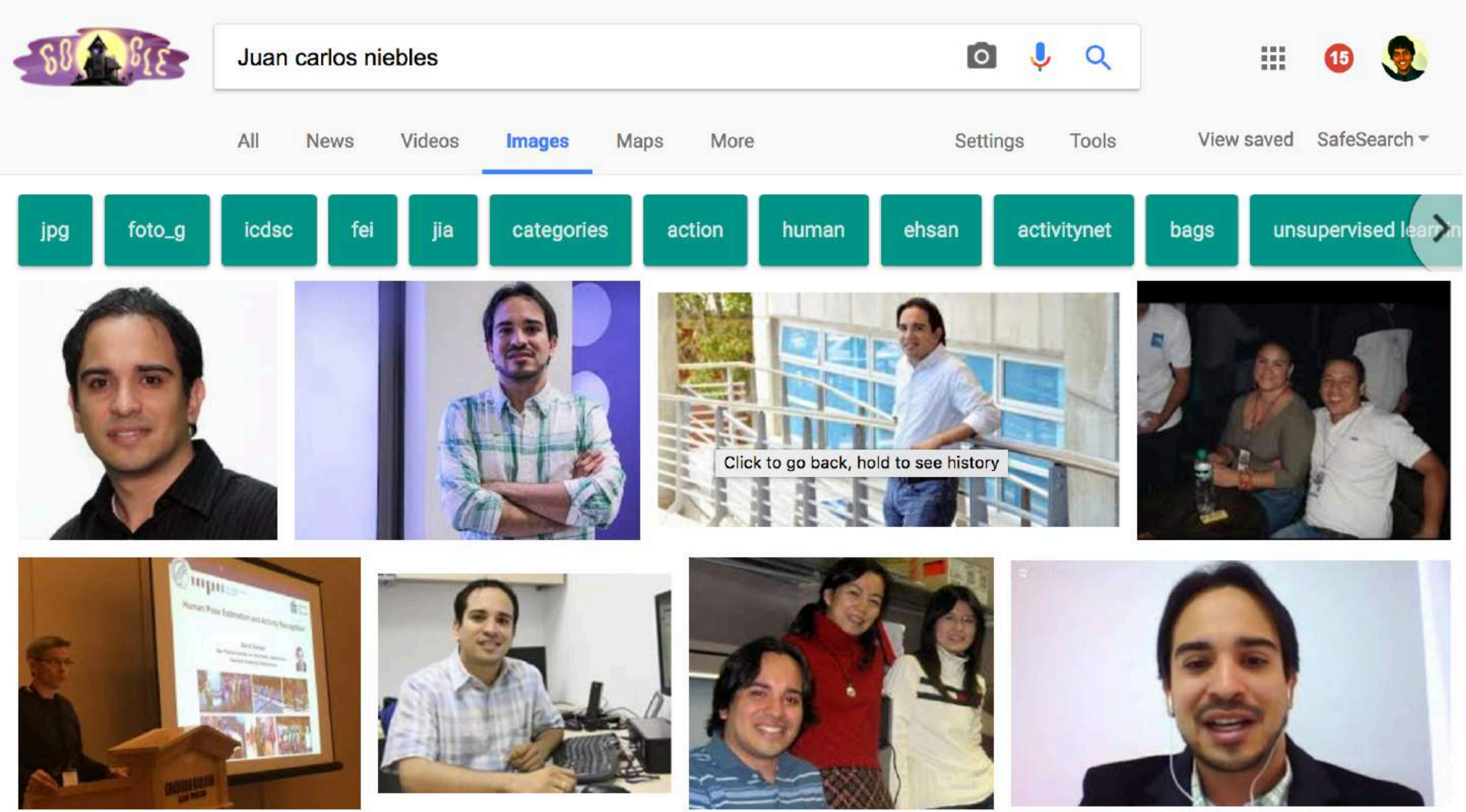
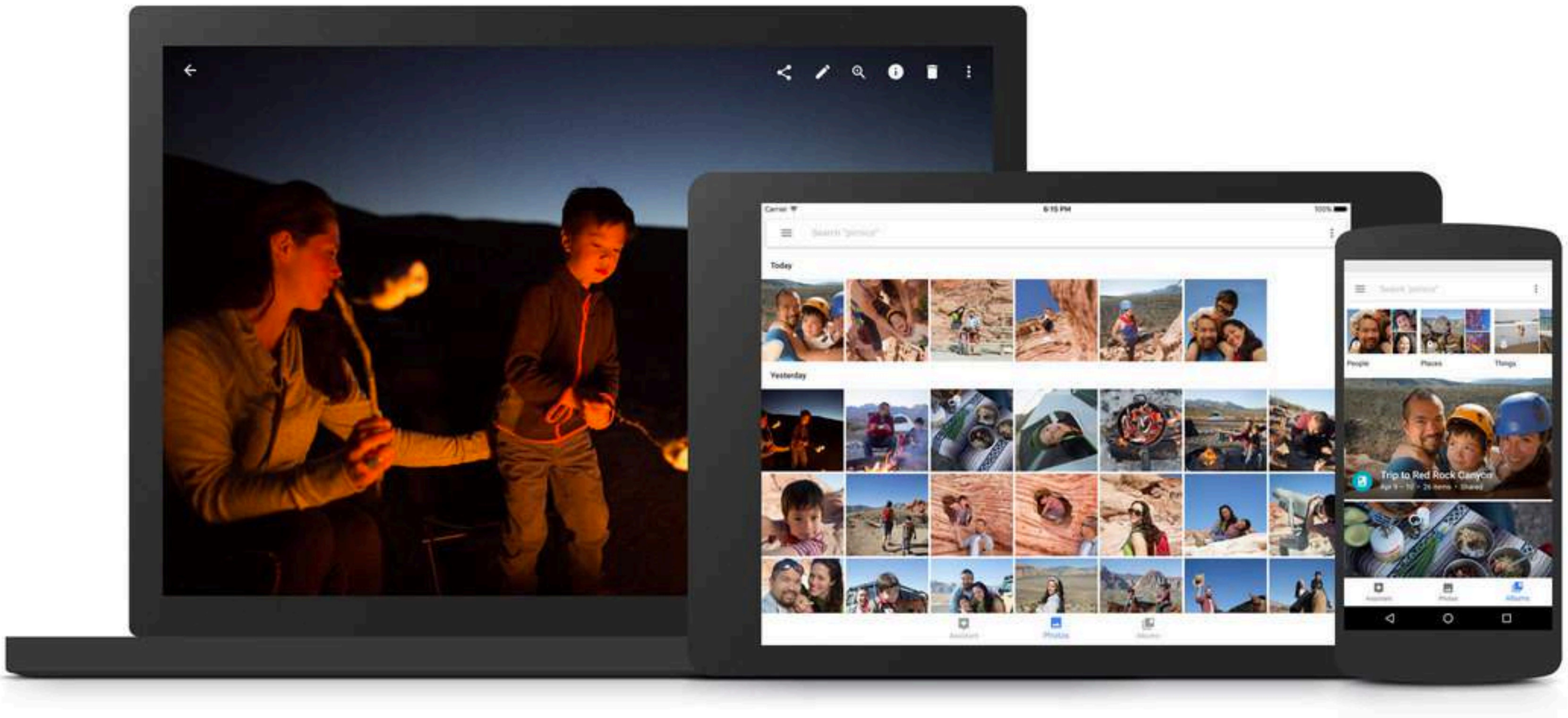


Image Search

Organizing photo collections

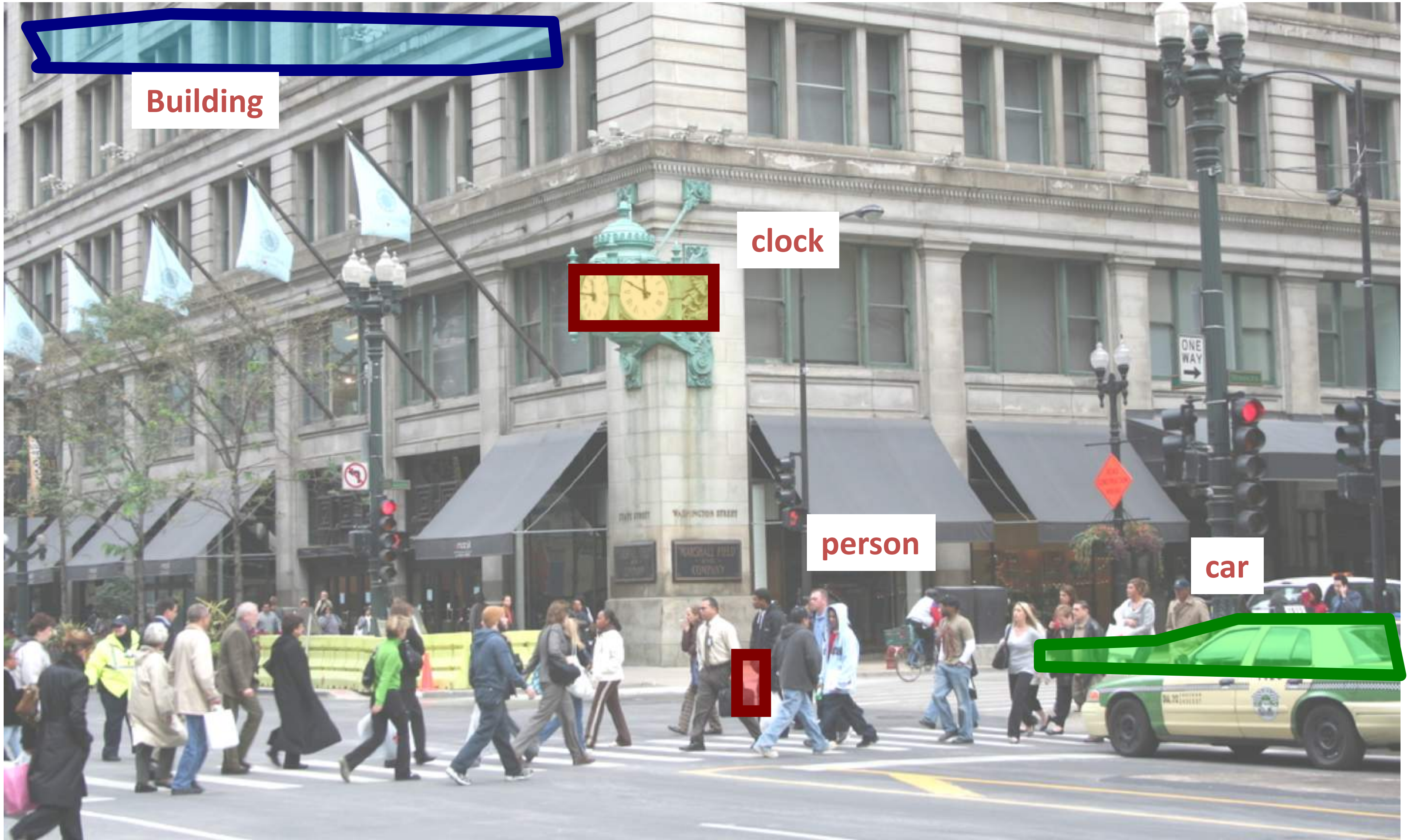


Detection:

Does this image contain a car? [where?]

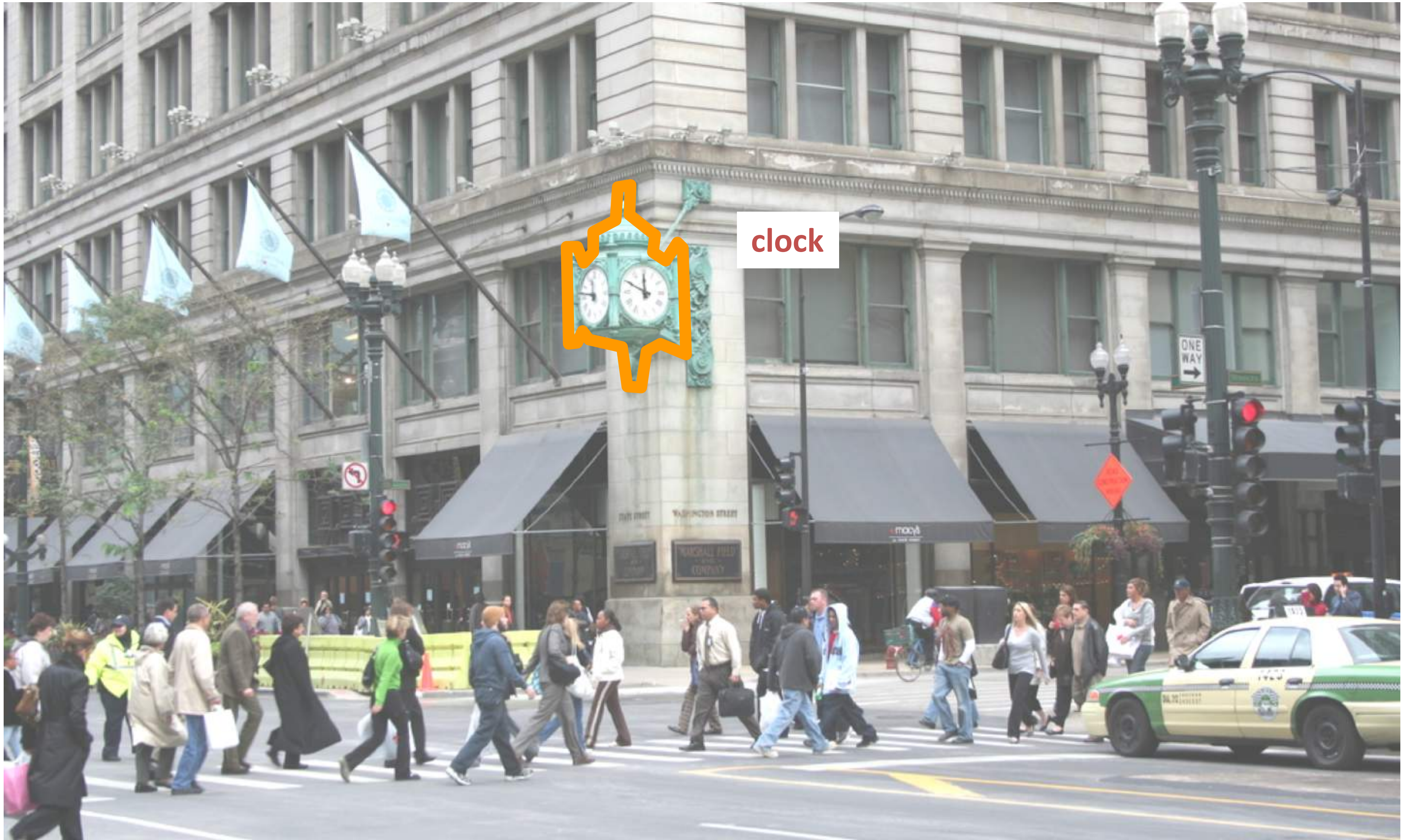
Detection:

Which object does this image contain? [where?]

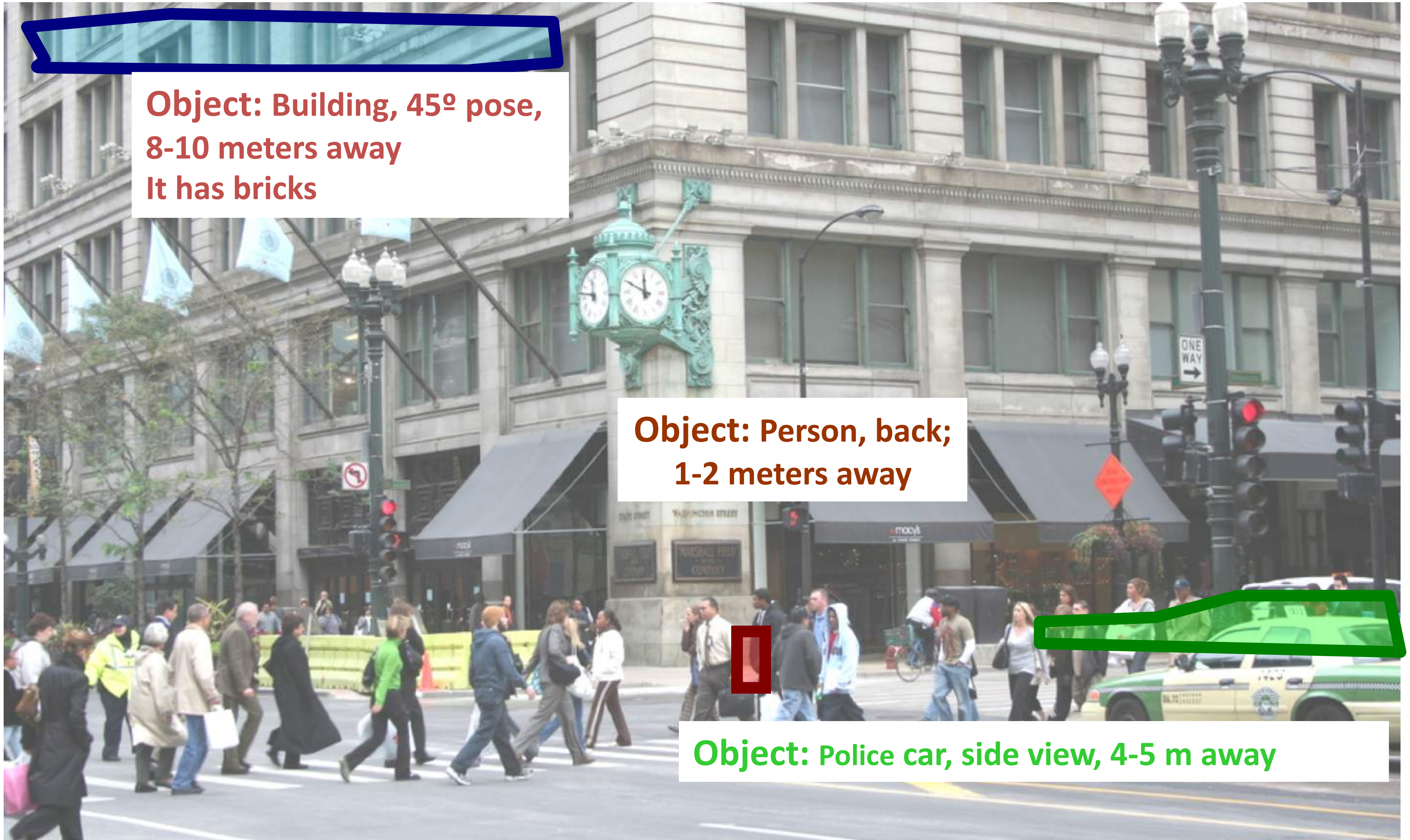


Detection:

Accurate localization (segmentation)

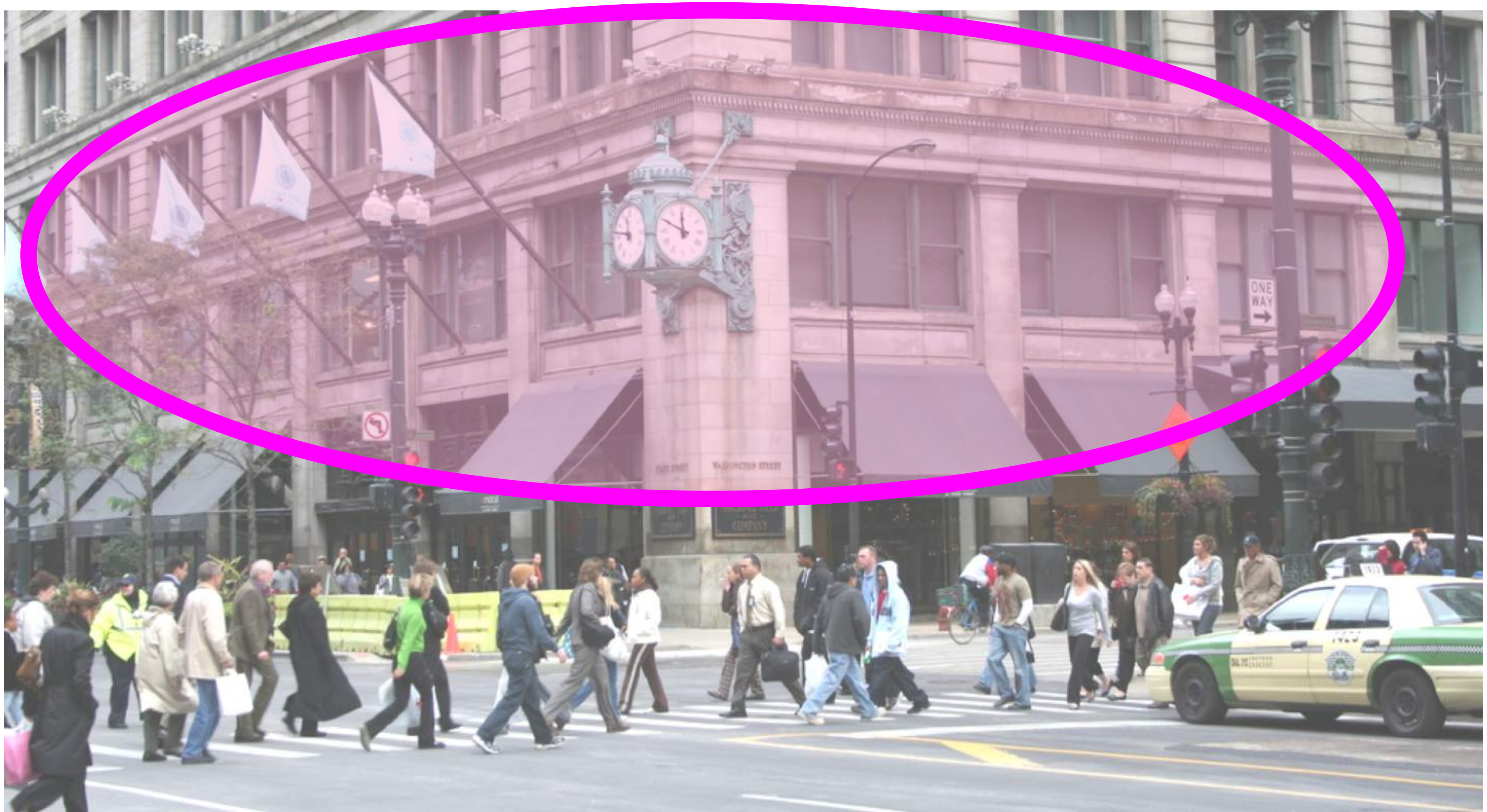


Detection: Estimating object semantic & geometric attributes



Categorization vs Single instance recognition

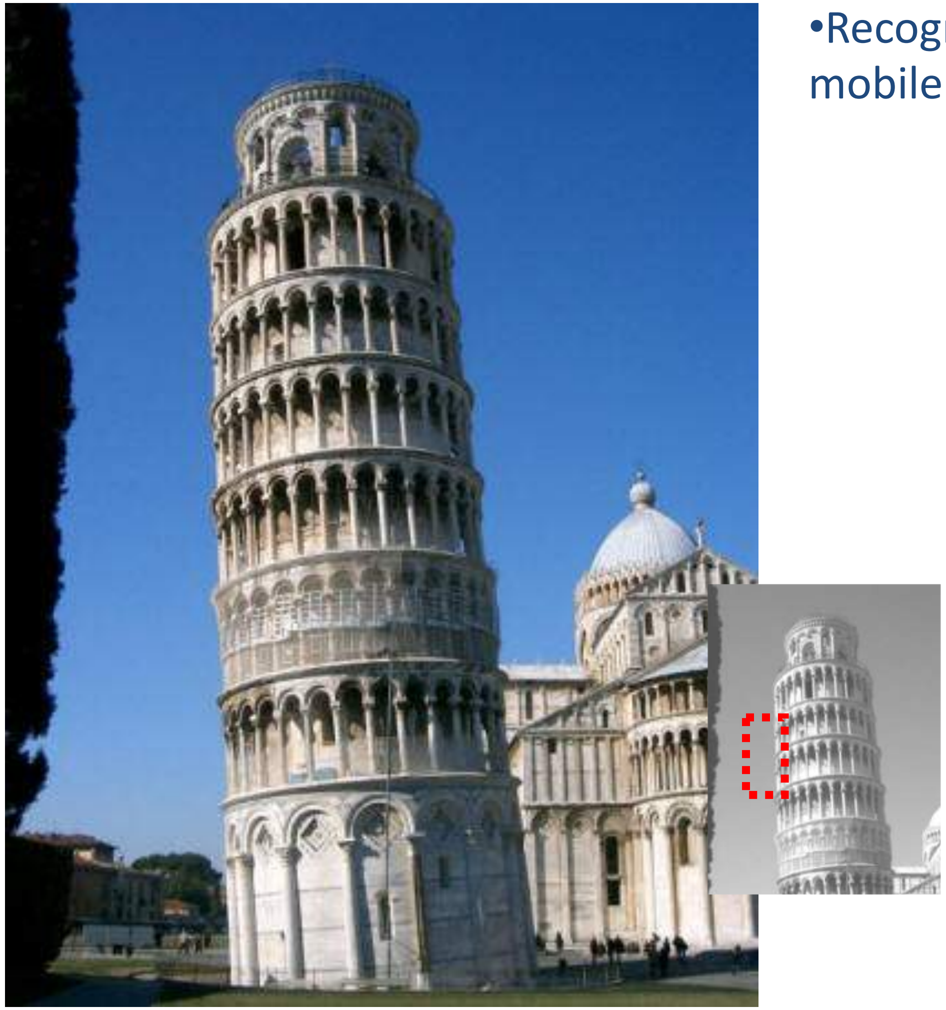
Does this image contain the Chicago Macy's building?



Categorization vs Single instance recognition

Where is the crunchy nut?

Applications of computer vision

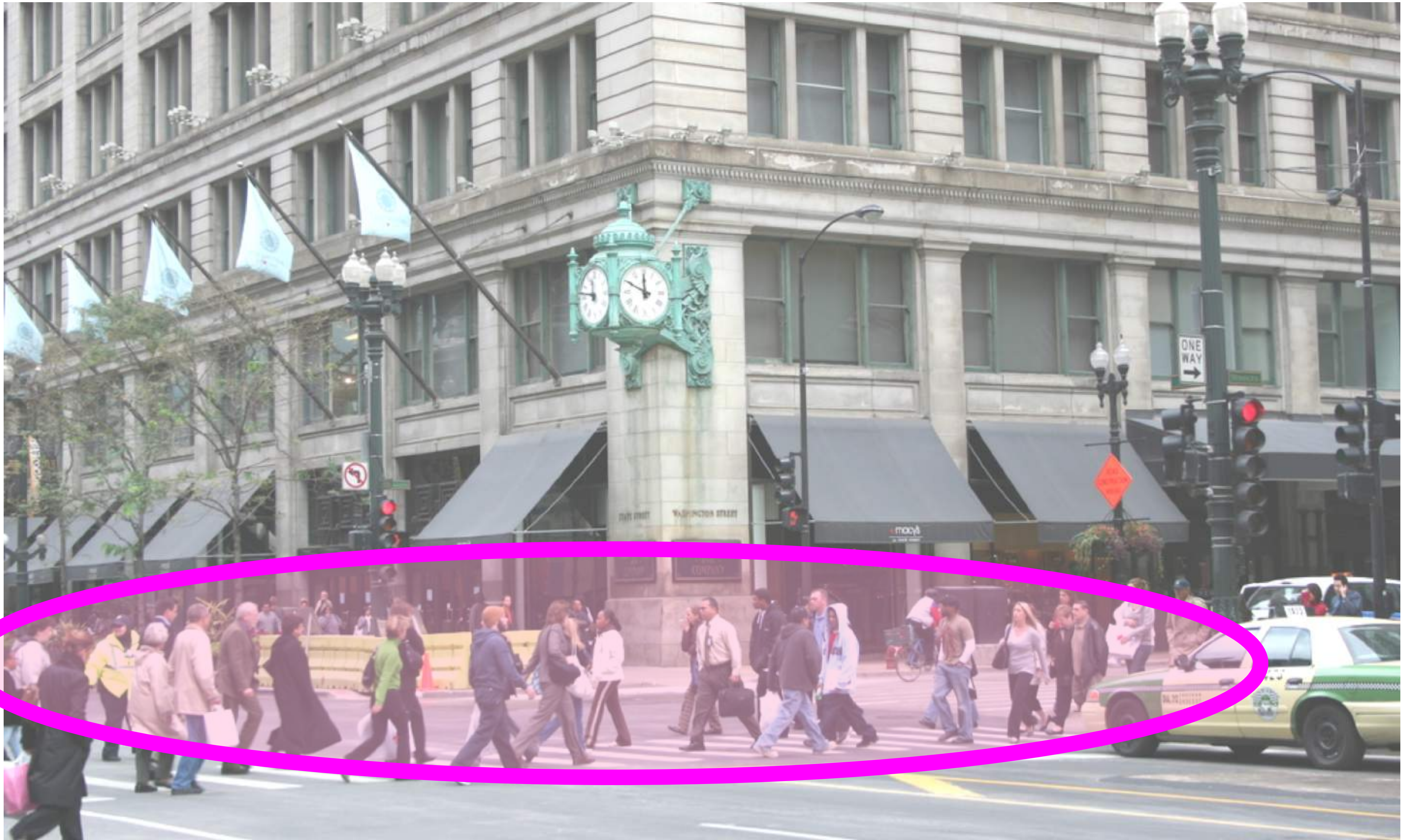


- Recognizing landmarks in mobile platforms

+ GPS

Activity or Event recognition

What are these people doing?



Visual Recognition

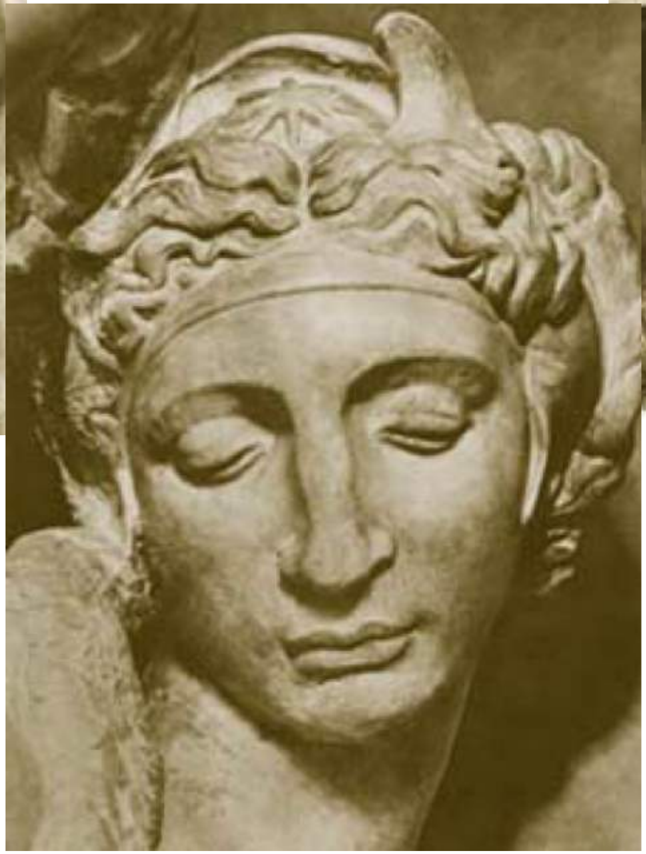
- Design algorithms that have the capability to:
  - Classify images or videos
  - Detect and localize objects
  - Estimate semantic and geometrical attributes
  - Classify human activities and events

Why is this challenging?

How many object categories are there?

~10,000 to 30,000

Challenges: viewpoint variation



Michelangelo 1475-1564

Challenges: illumination

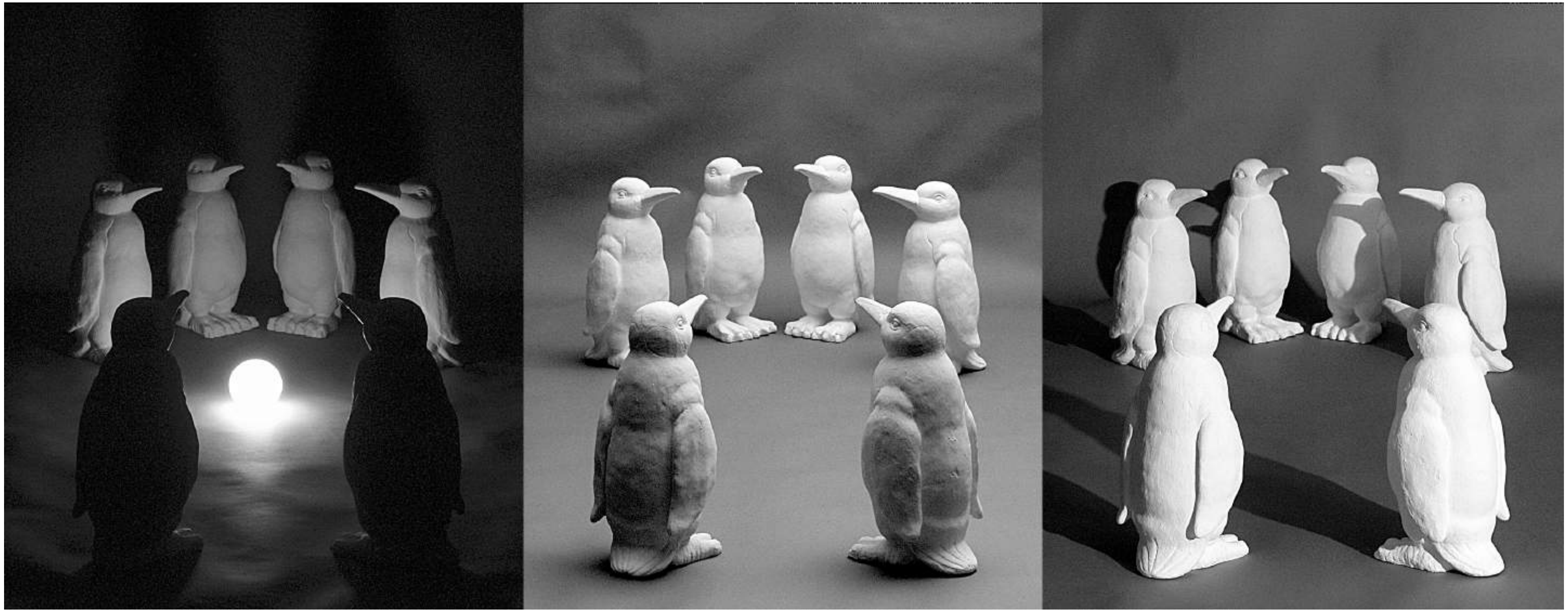
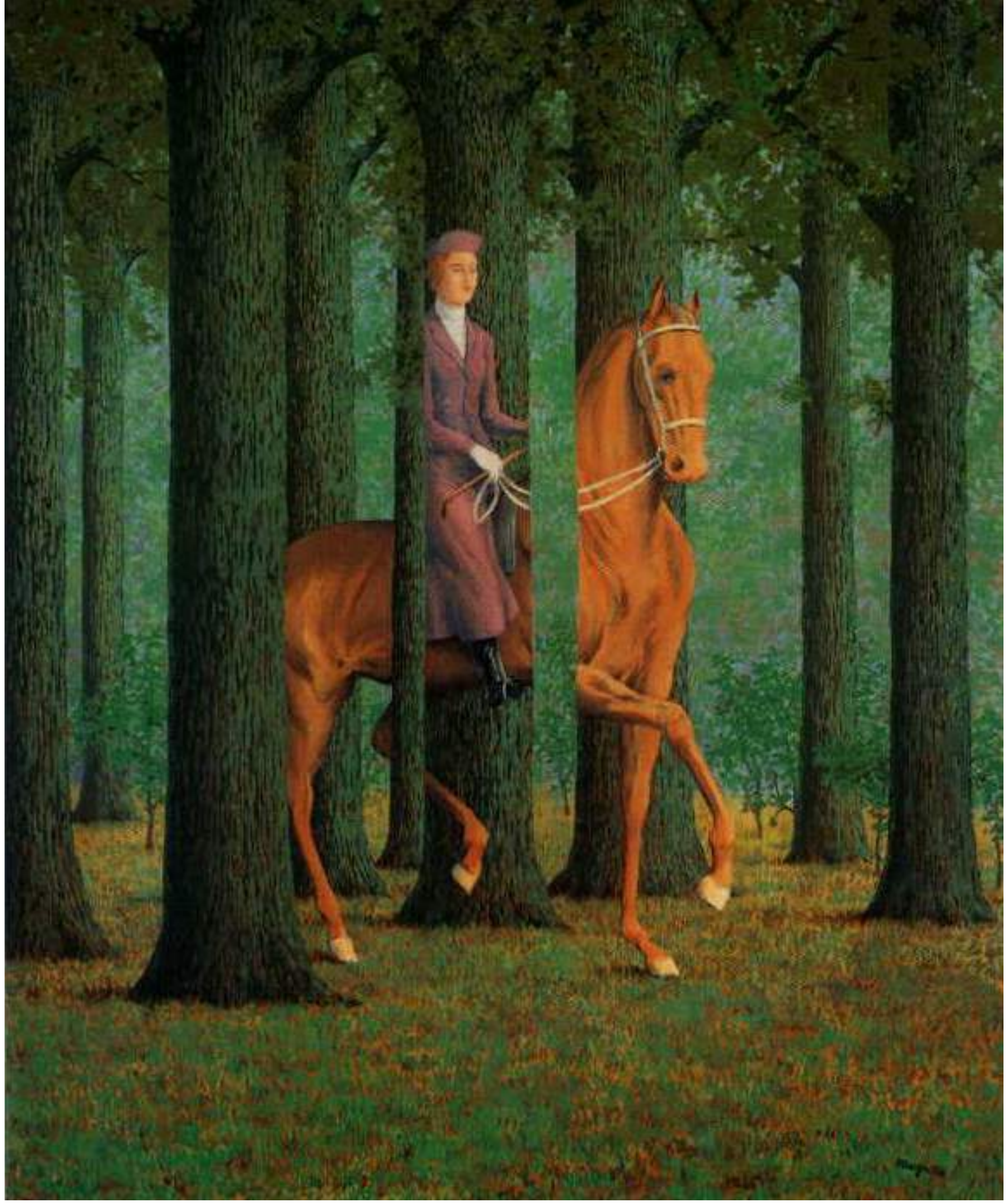


image credit: J. Koenderink

Challenges: scale

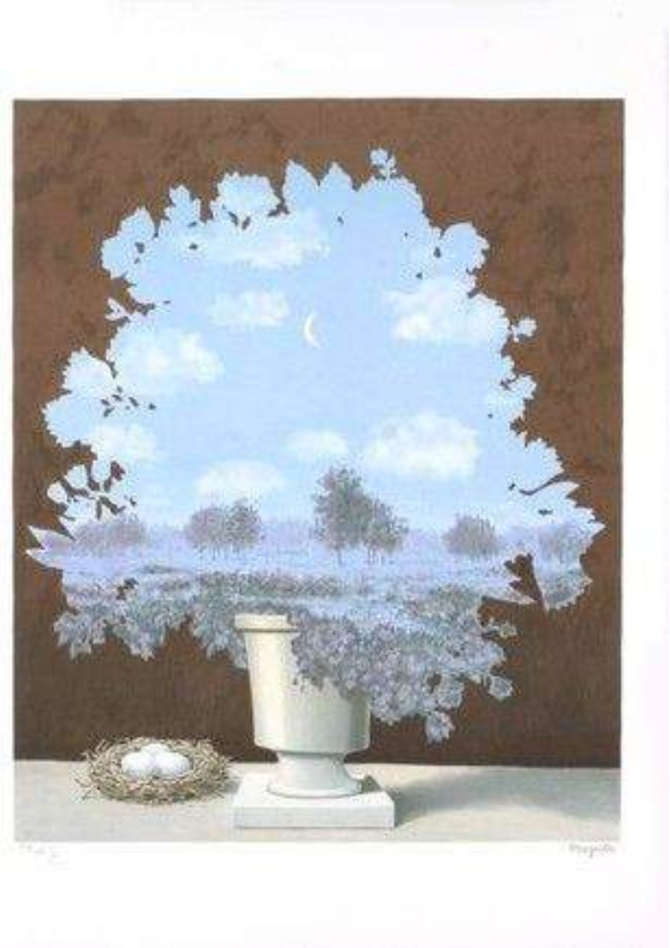
Challenges: deformation

Challenges: occlusion



Magritte, 1957

Art Segway - Magritte



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

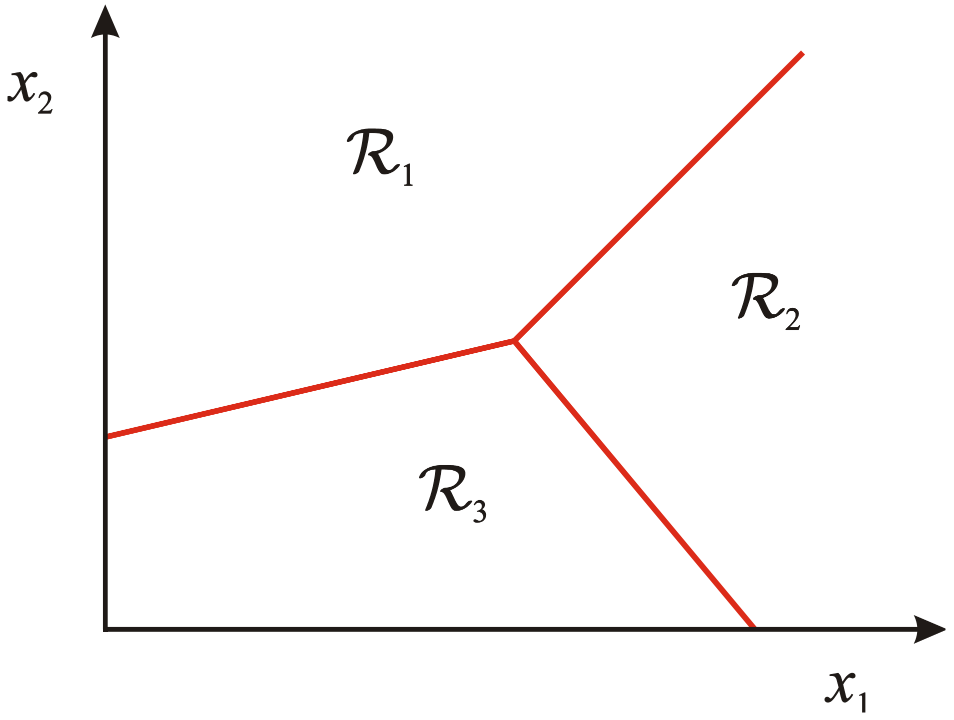
Image feature

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

Slide credit: L. Lazebnik

Classification

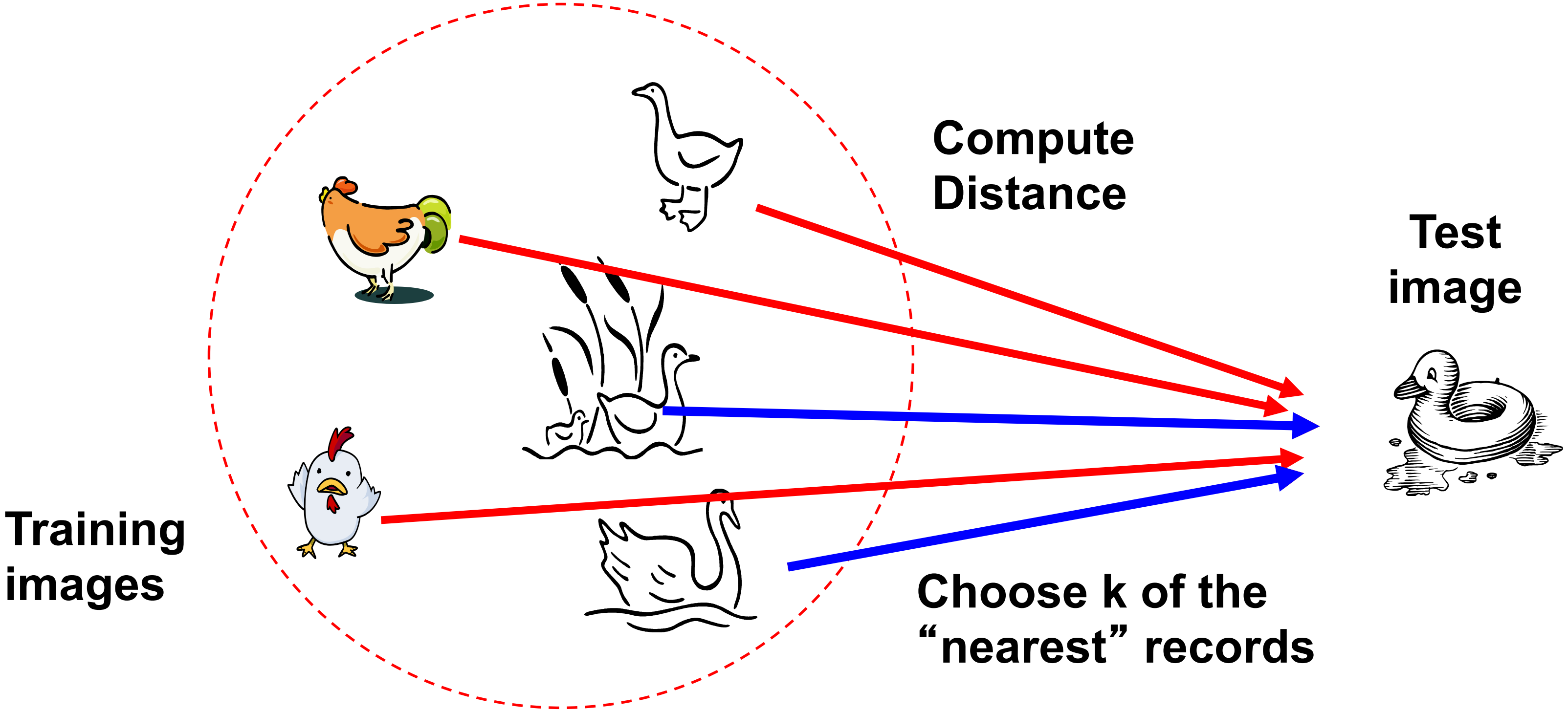
- Assign input vector to one of two or more classes
- Any decision rule divides input space into *decision regions* separated by *decision boundaries*



Slide credit: L. Lazebnik

Nearest Neighbor Classifier

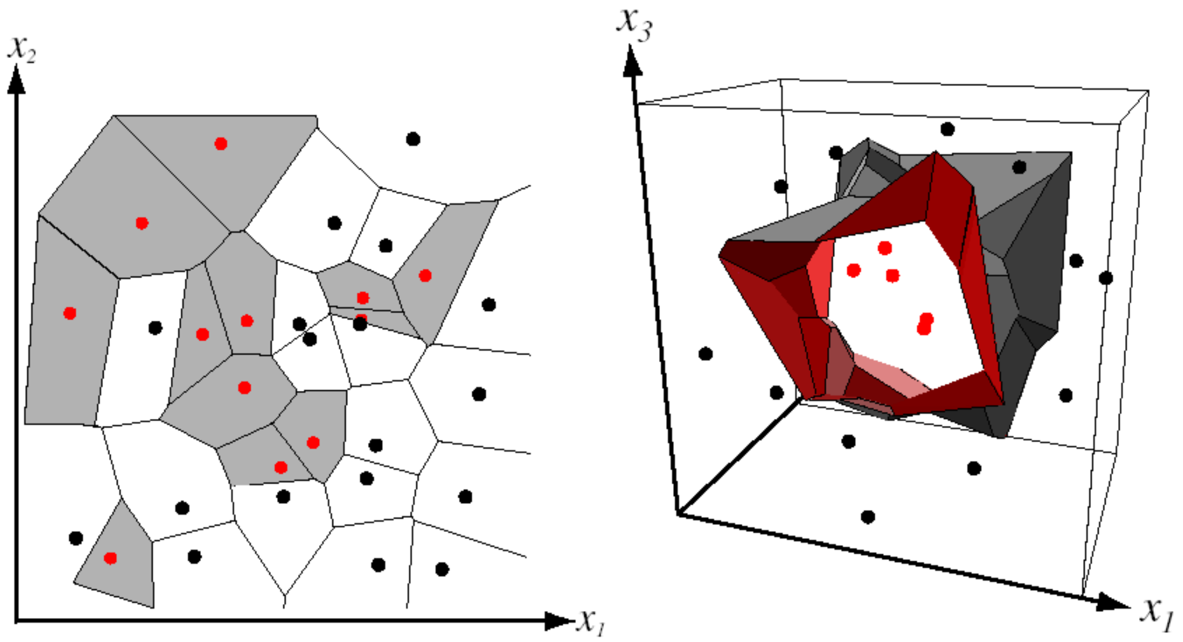
- Assign label of nearest training data point to each test data point



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

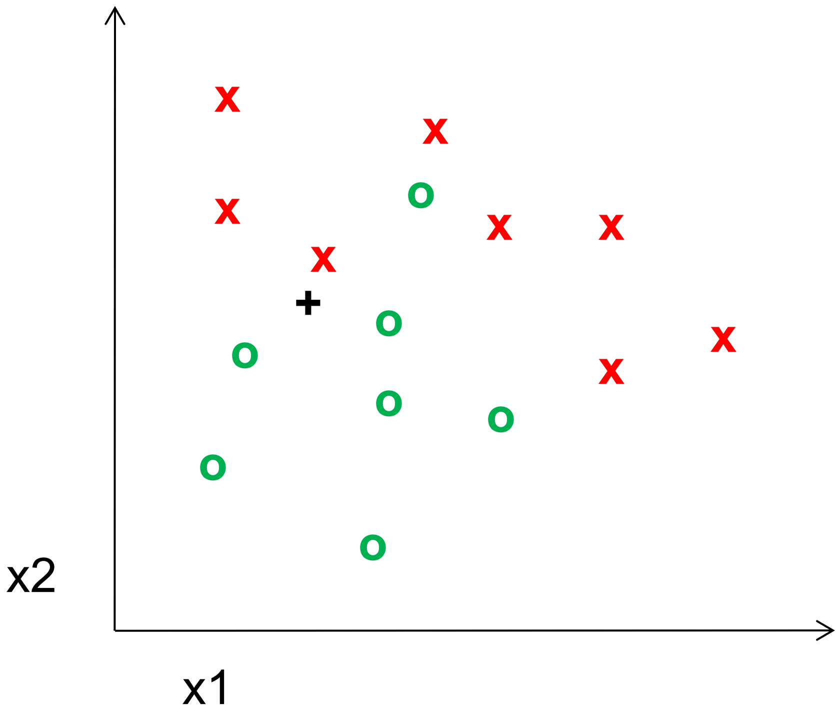
Source: D. Lowe

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

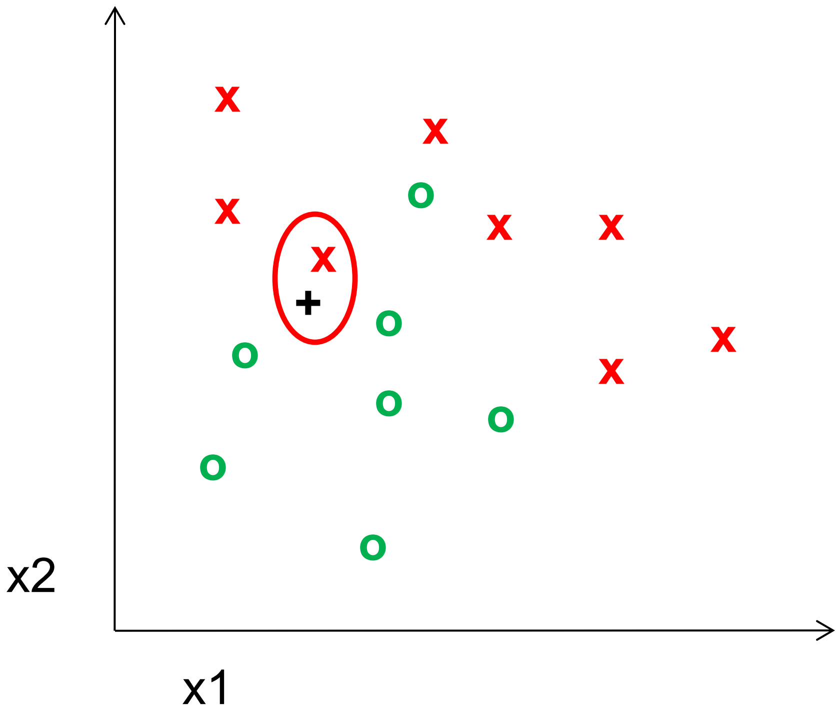


1-nearest neighbor

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

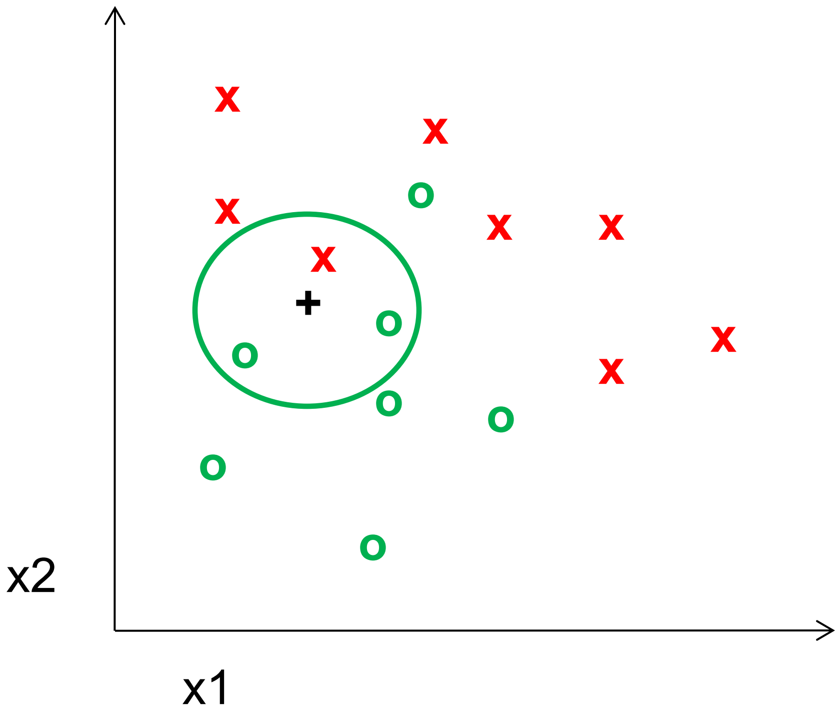


3-nearest neighbor

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

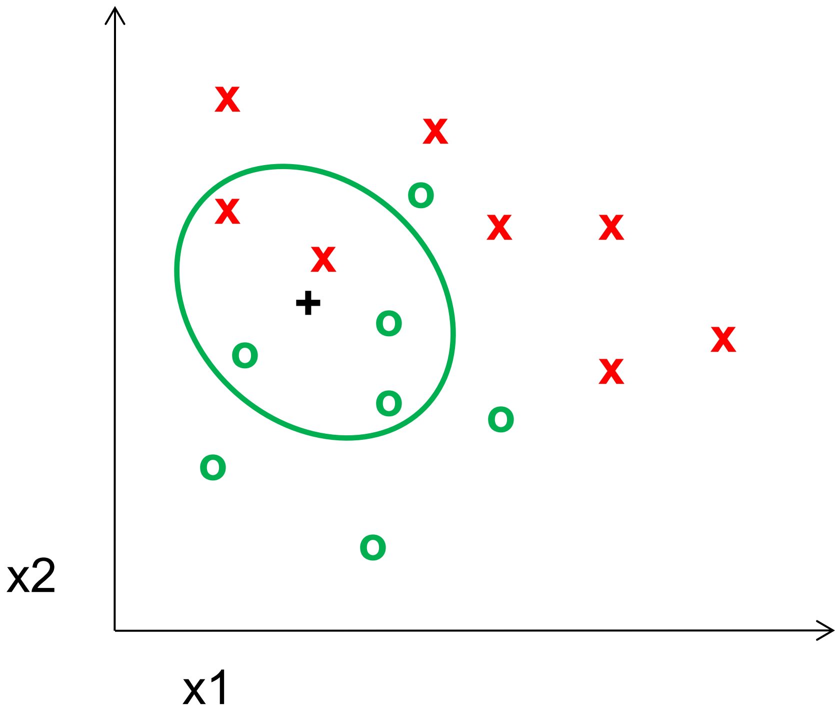


5-nearest neighbor

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

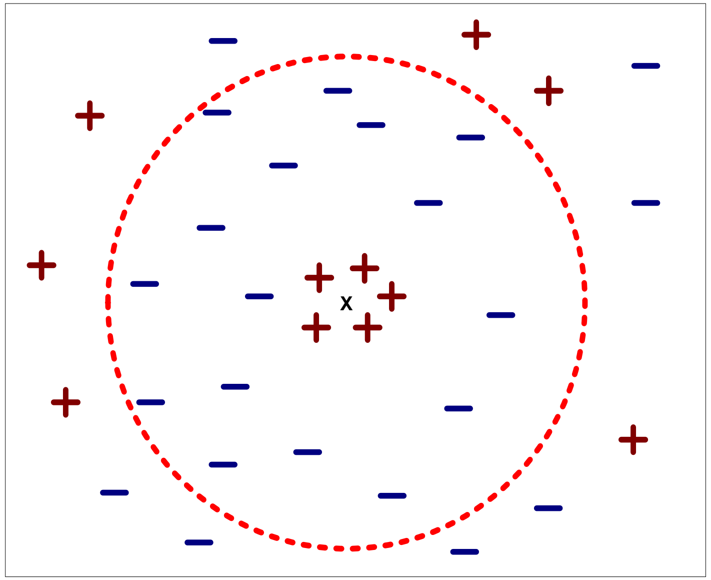


K-NN: a very useful algorithm

- Simple, a good one to try first
- Very flexible decision boundaries
- With infinite examples, 1-NN provably has error that is at most twice Bayes optimal error (out of scope for this class).

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

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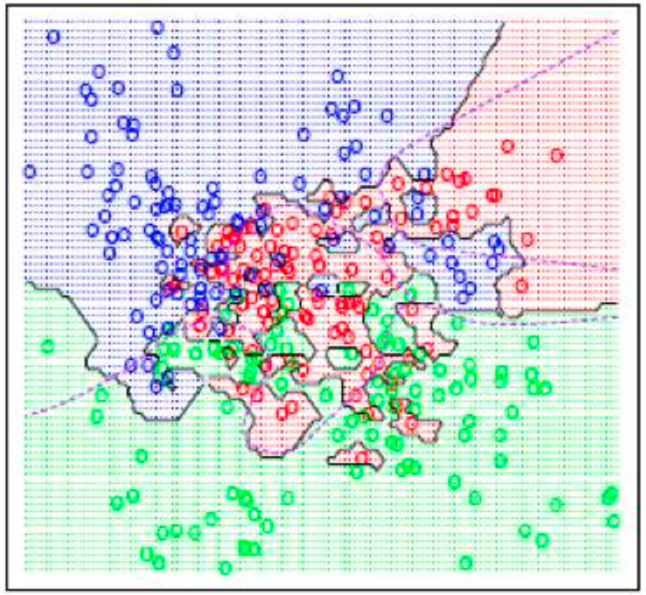
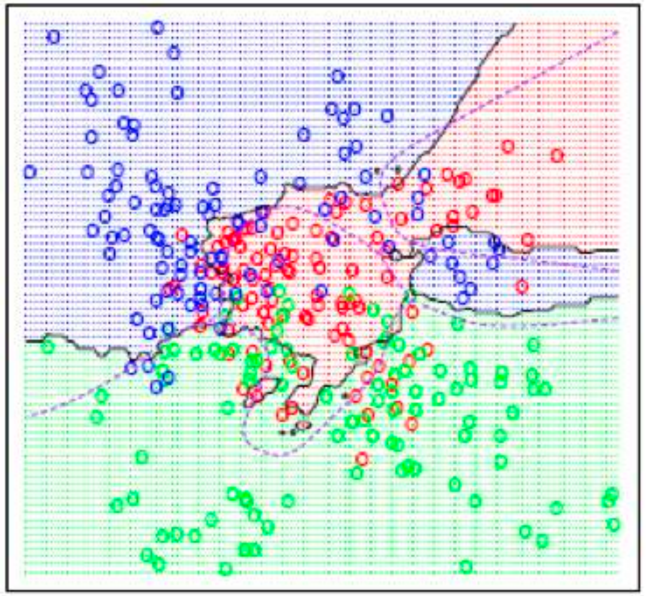
K=1

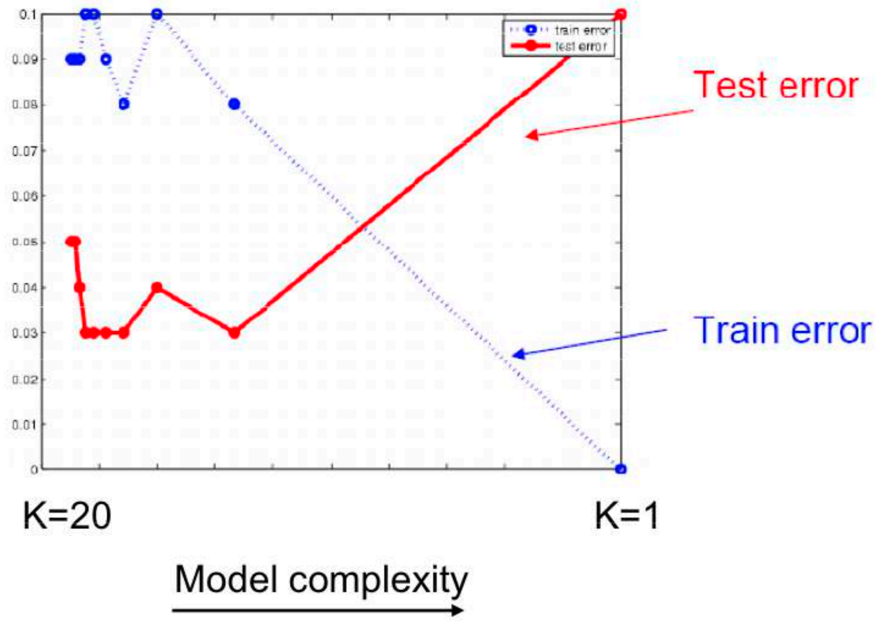


K=15

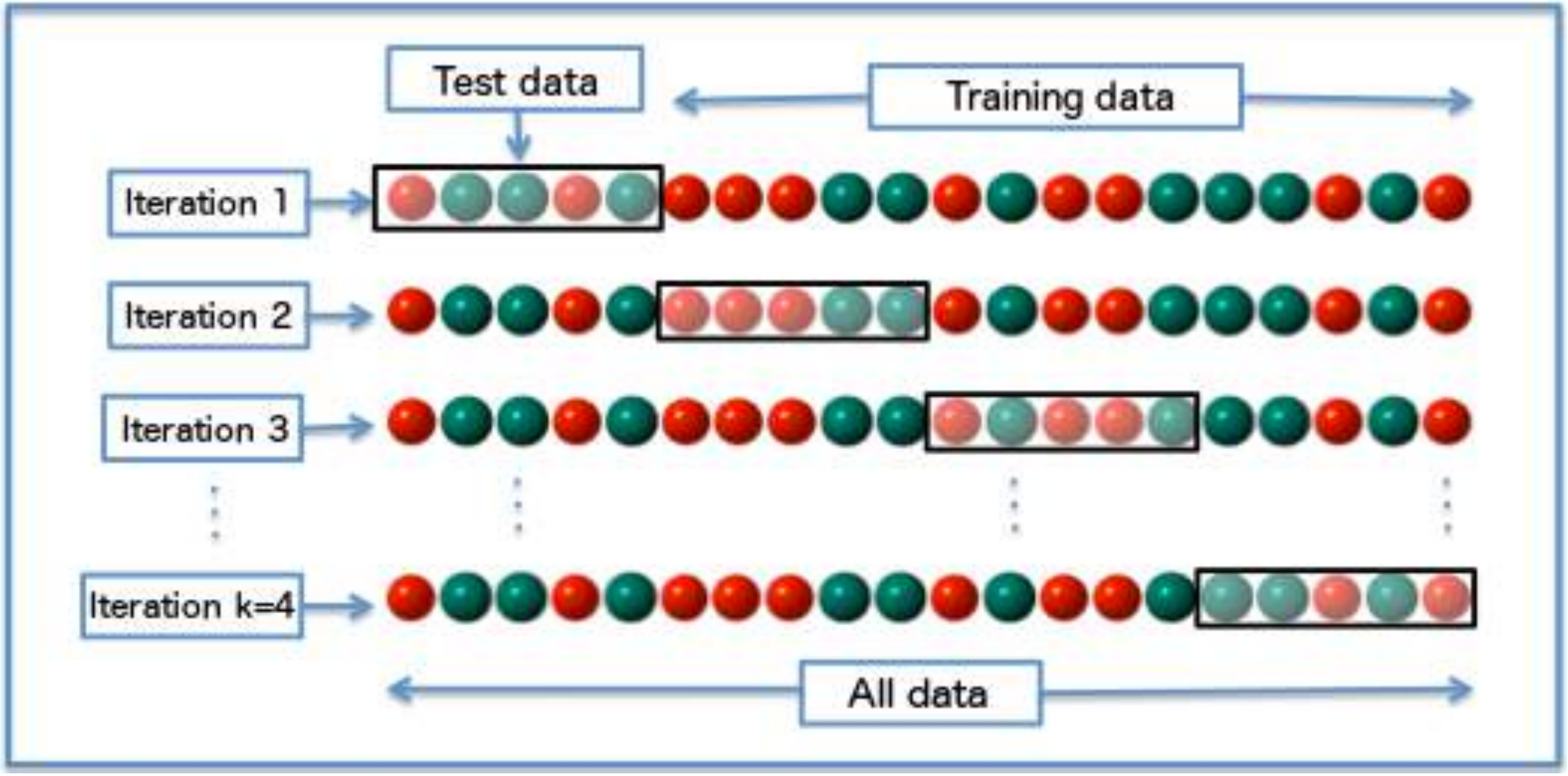


K-NN: issues to keep in mind

- 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
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  - 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

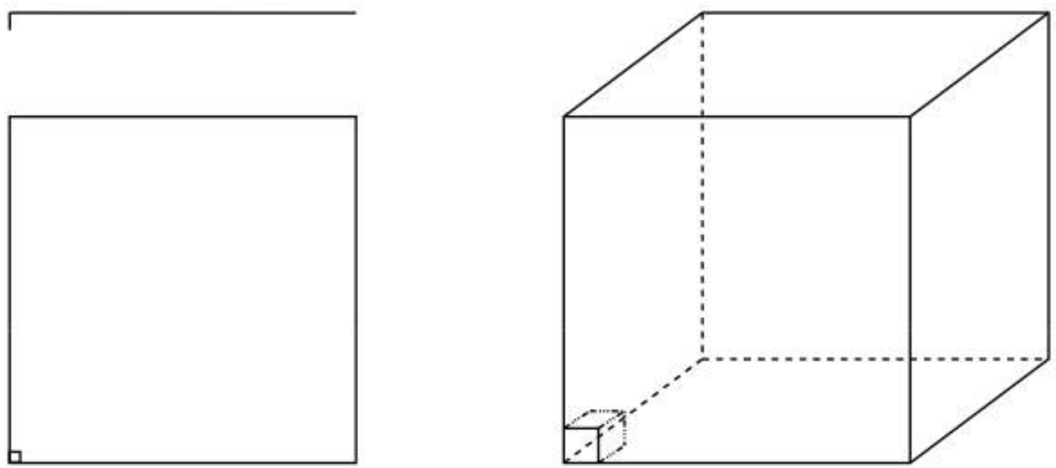
- Choosing the value of k:
  - If too small, sensitive to noise points
  - If too large, neighborhood may include points from other classes
  - Solution: cross validate!
- Can produce counter-intuitive results (using Euclidean measure)
  - Solution: normalize the vectors to unit length

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
- Curse of Dimensionality

Curse of dimensionality

- Assume 5000 points uniformly distributed in the unit hypercube and we want to apply 5-NN. Suppose our query point is at the origin.
  - In 1-dimension, we must go a distance of 5/5000=0.001 on the average to capture 5 nearest neighbors.
  - In 2 dimensions, we must go $\sqrt{0.001}$ to get a square that contains 0.001 of the volume.
  - In d dimensions, we must go $(0.001)^{1/d}$



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
- Curse of Dimensionality
  - Solution: no good one

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

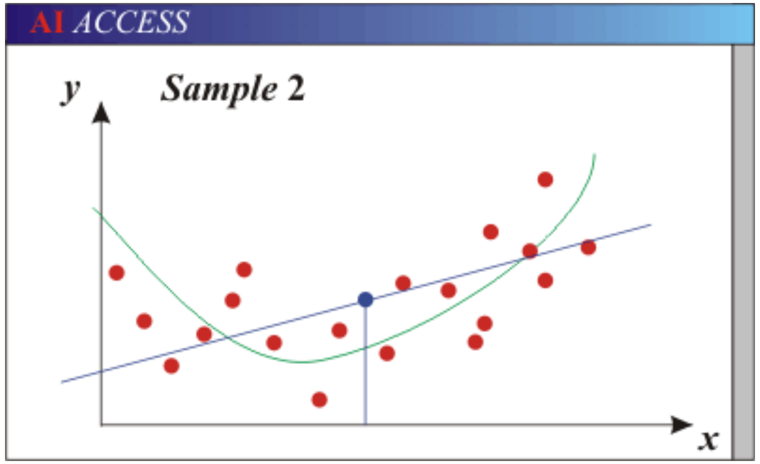
Training set (labels known)

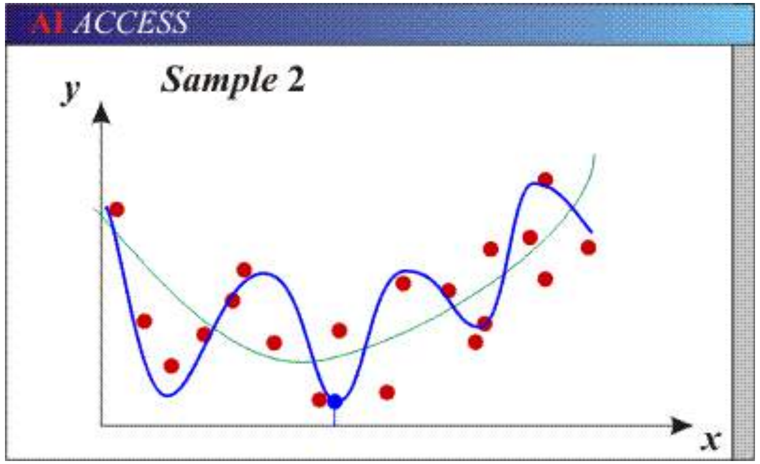
Test set (labels unknown)

- 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).

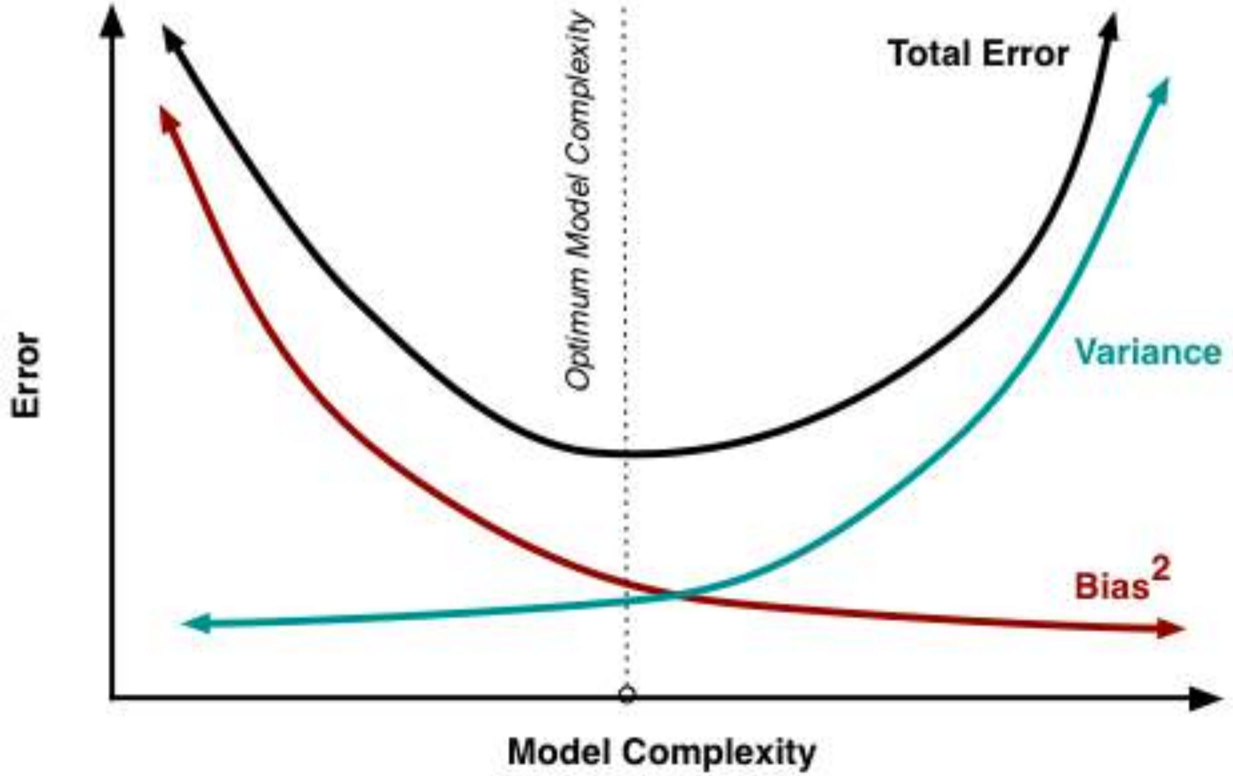
Slide credit: D. Hoiem

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

How do you reduce bias?

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?

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- 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

Training Images

Image Features

Training Labels

Training

A simple pipeline - Training

Training Images

Image Features → Training → Learned Classifier

Training Labels → Training

A simple pipeline - Training

Training Images

Image Features

Training Labels

Training

Learned Classifier

Test Image

Image Features

A simple pipeline - Training

Training Images

Image Features → Training → Learned Classifier

Training Labels → Training

Test Image

Image Features → Learned Classifier → Prediction

A simple pipeline - Training

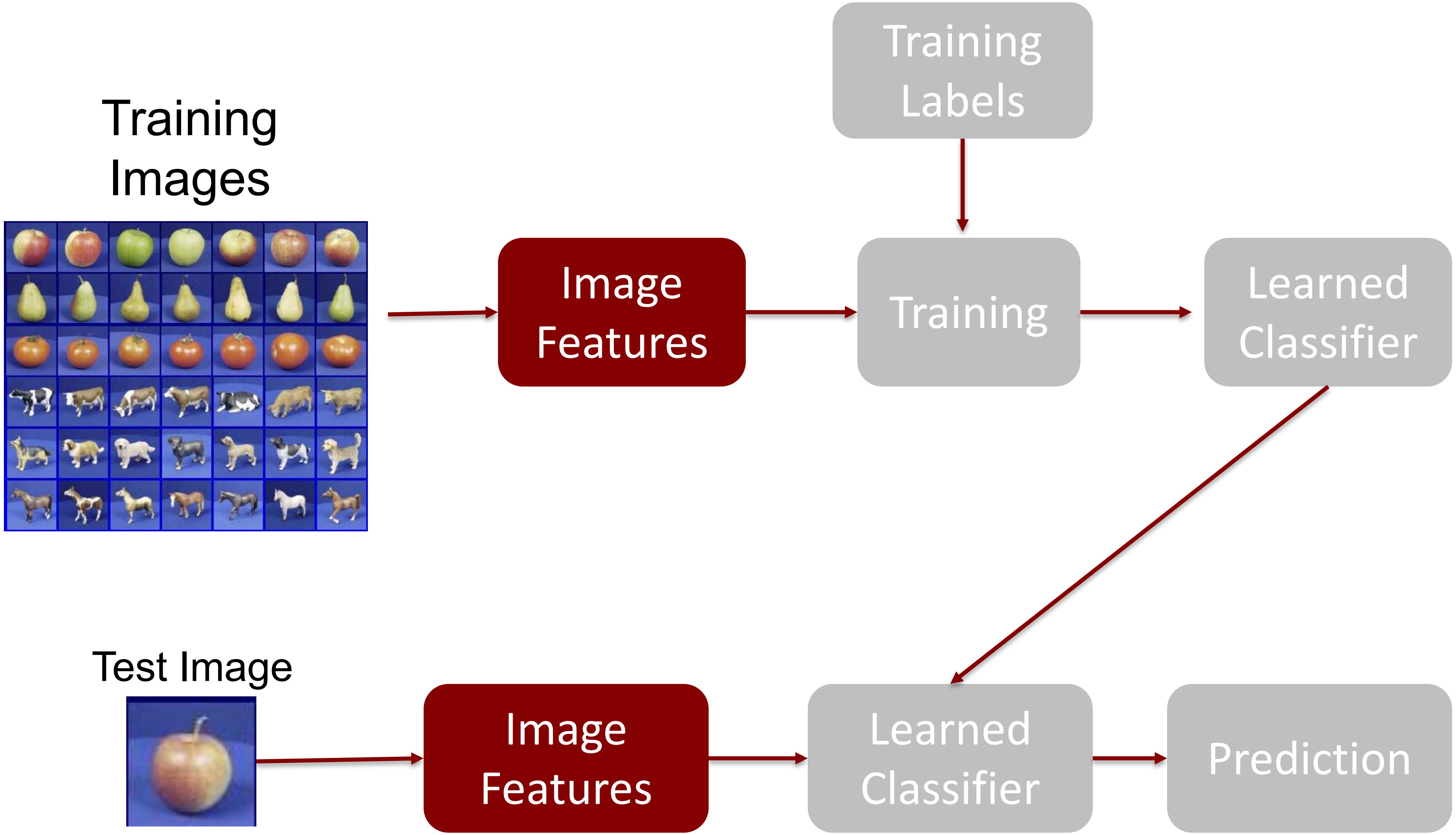
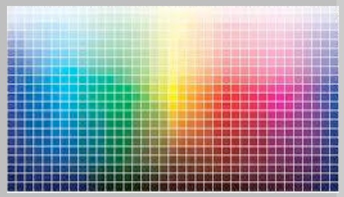
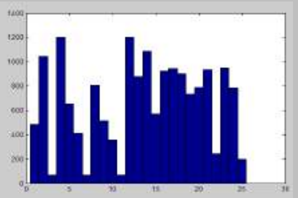


Image features

Input image

Color: Quantize RGB values





Invariance?

? Translation

? Scale

? Rotation

? Occlusion

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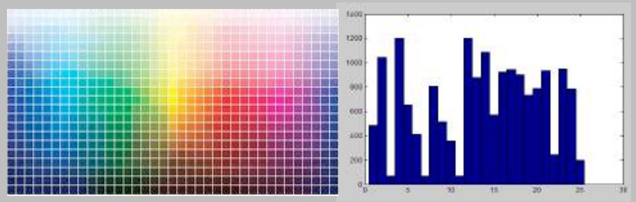

Invariance?

- 🙂 Translation
- ? Scale
- 🙂 Rotation (in-planar)
- 🙁 Occlusion

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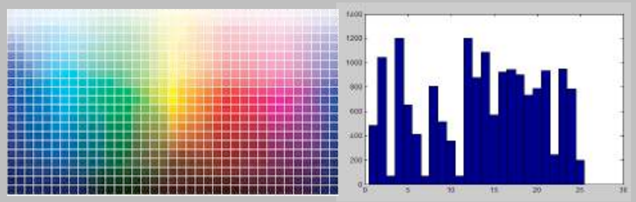

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Global shape: PCA space

Invariance?

? Translation

? Scale

? Rotation (in-planar)

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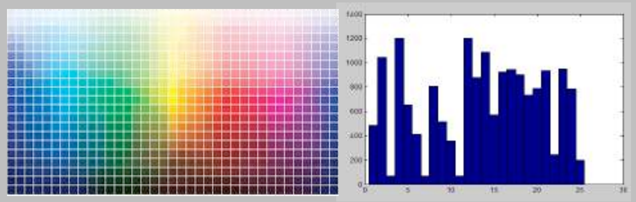

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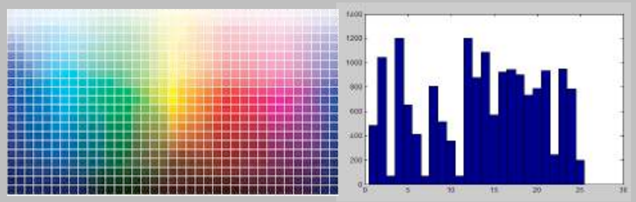

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Global shape: PCA space

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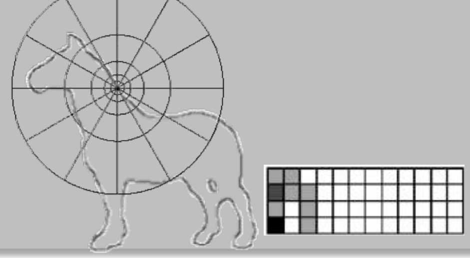
Local shape: shape context



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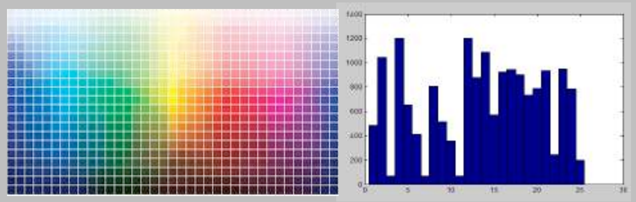

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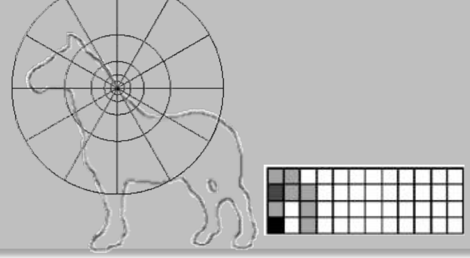

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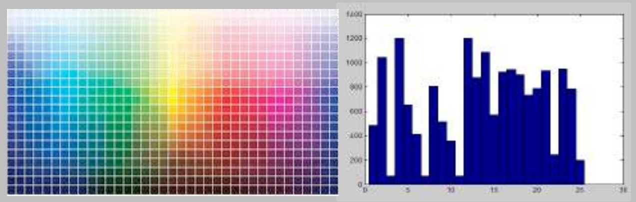

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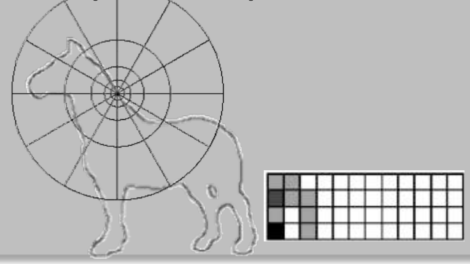

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Texture: Filter banks

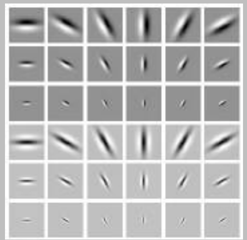

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Image features

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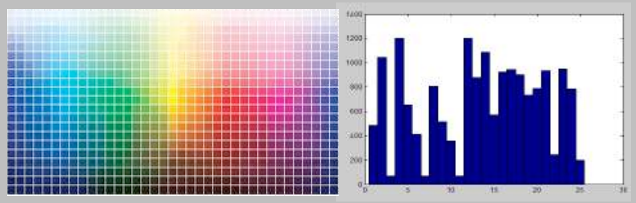

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Global shape: PCA space

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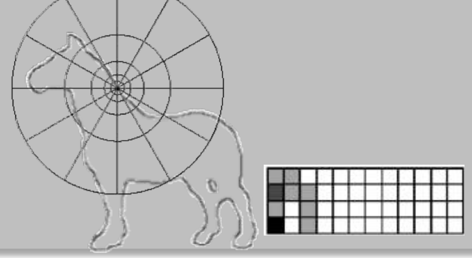
Local shape: shape context



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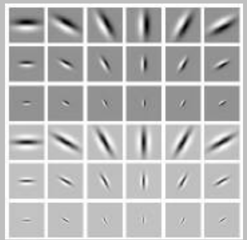
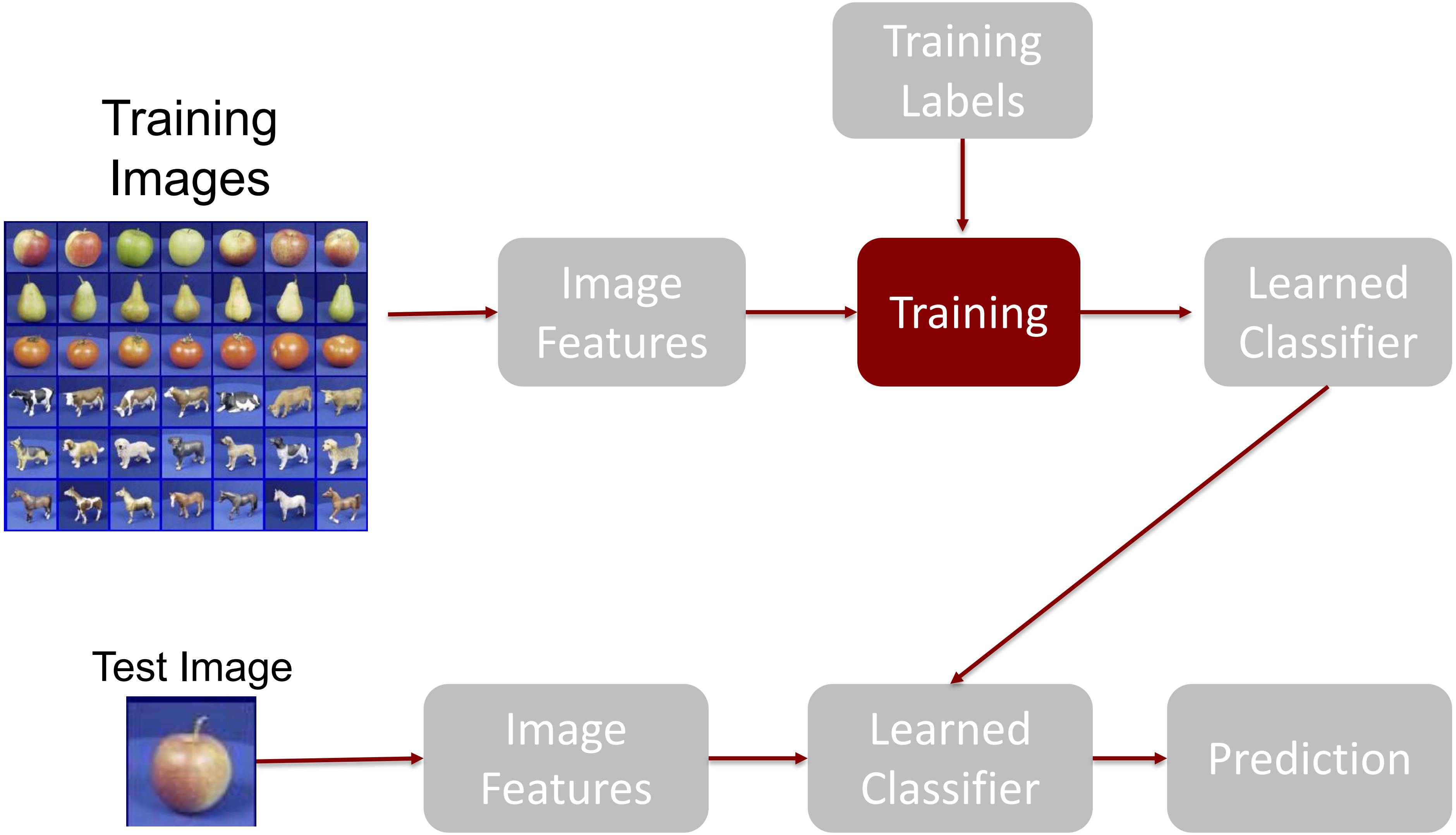
Texture: Filter banks

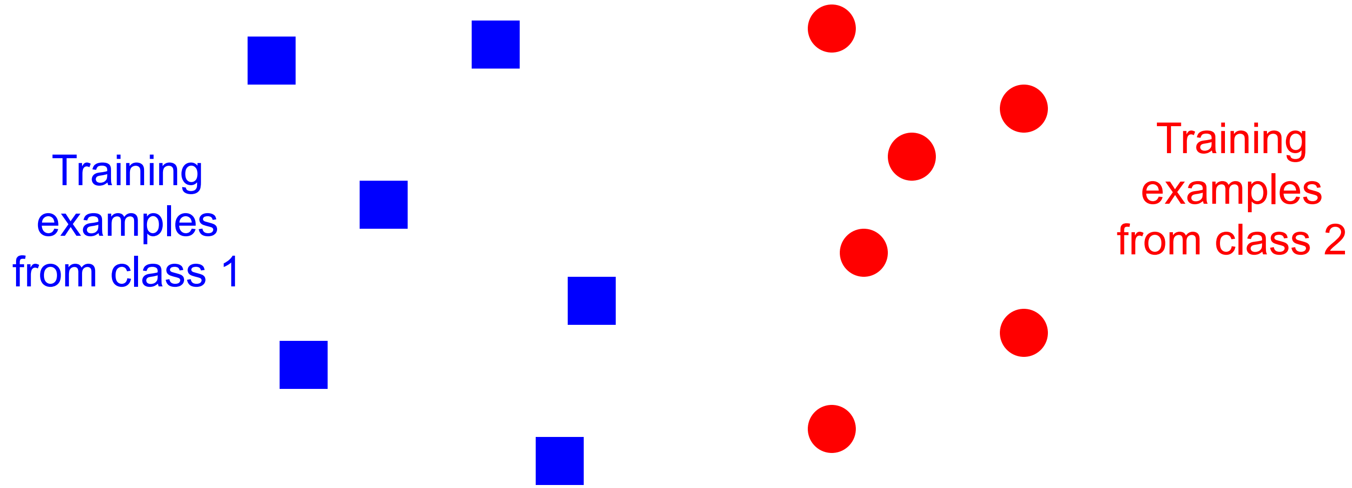


Invariance?
- Translation
- ? Scale
- ? Rotation (in-planar)
- Occlusion

A simple pipeline - Training

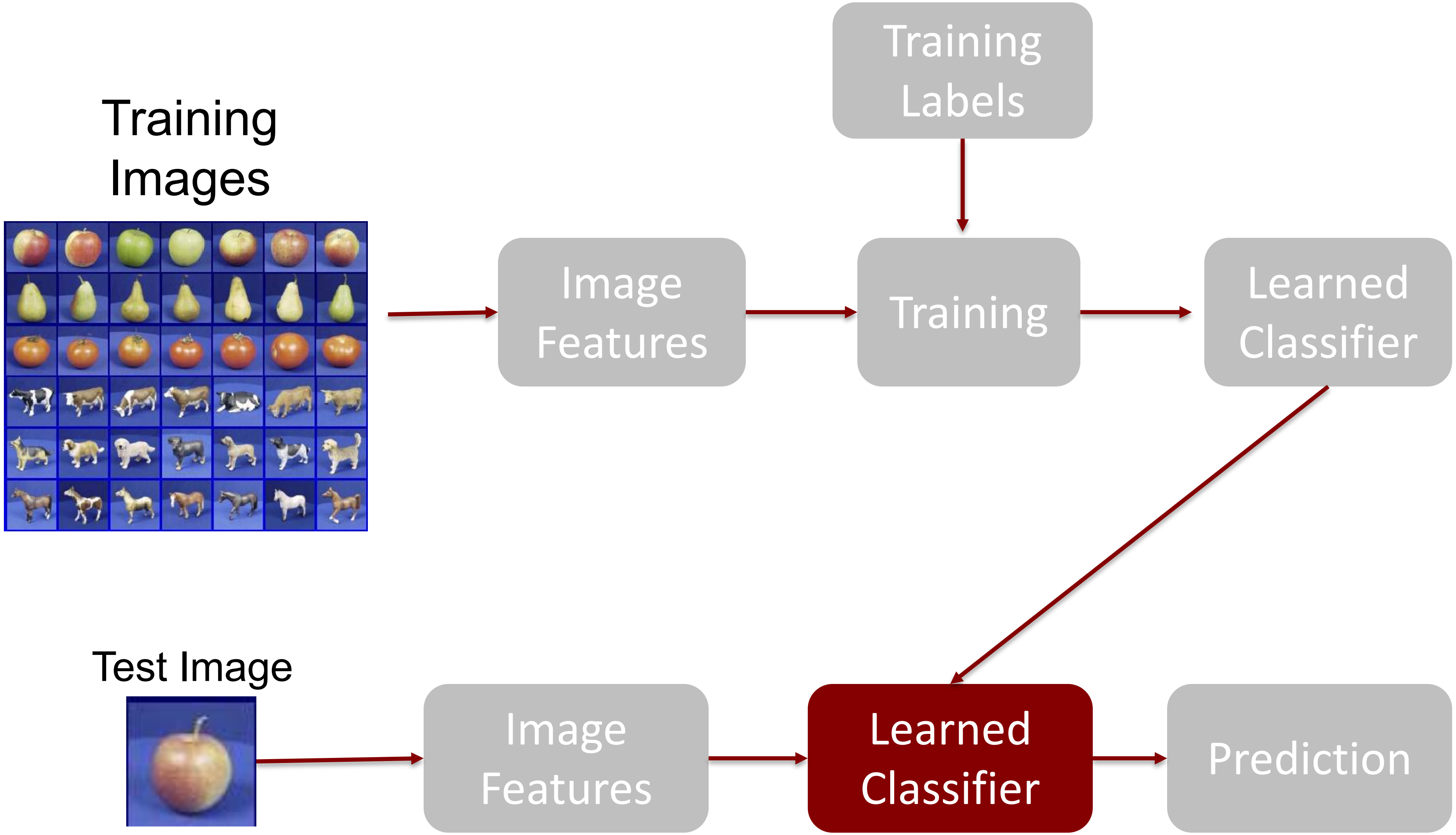


Classifiers: Nearest neighbor

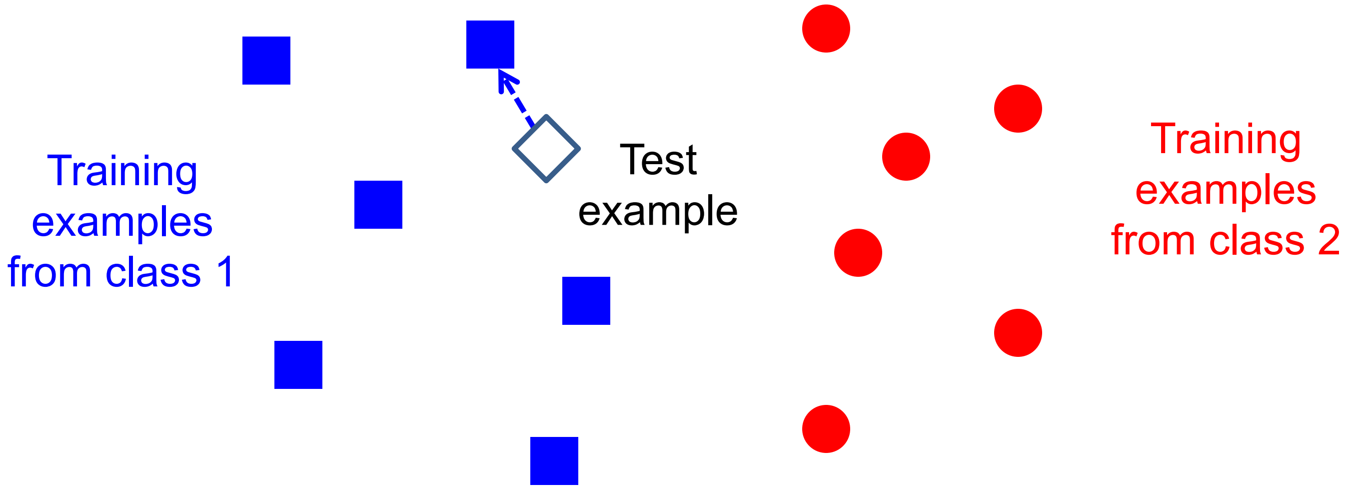


Slide credit: L. Lazebnik

A simple pipeline - Training



Classifiers: Nearest neighbor



Slide credit: L. Lazebnik

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