Computer Vision & Image Processing
CSE 473 / 573

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Lecture 21

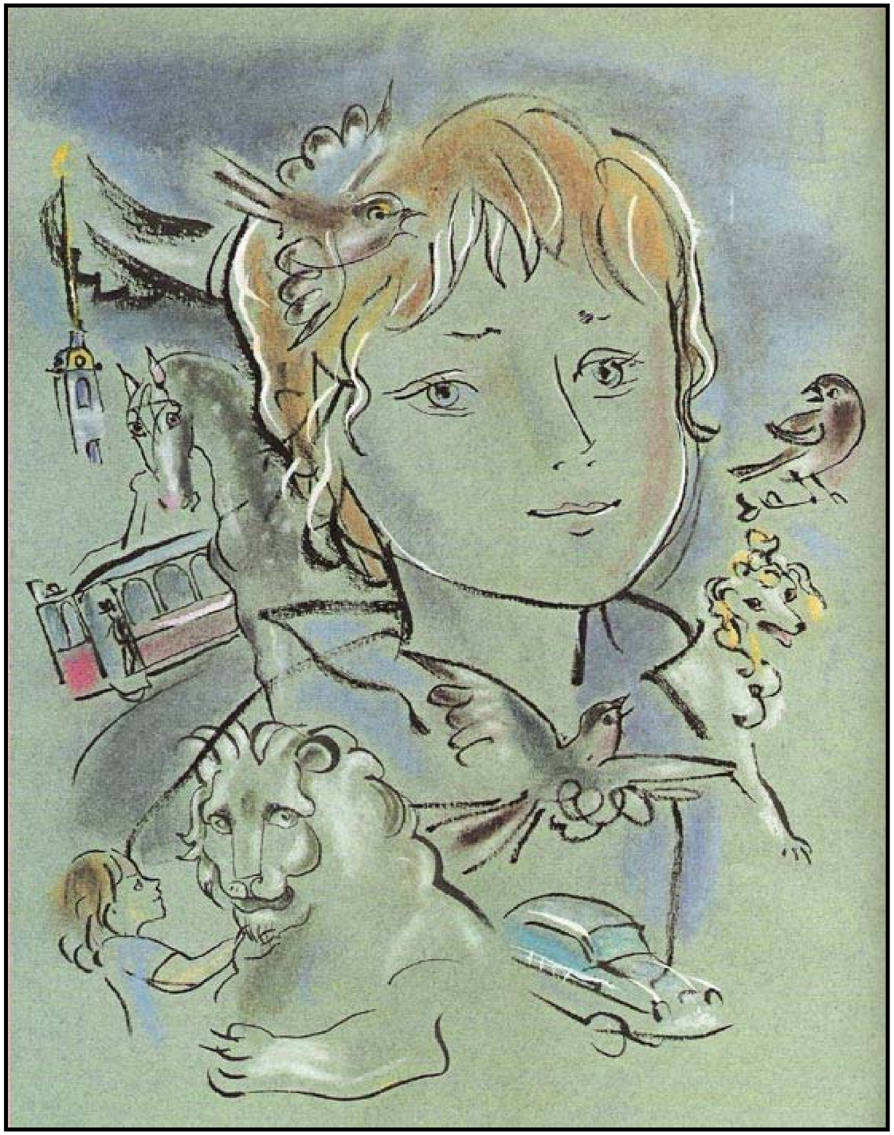
October 18, 2017

Introduction to Recognition

Slide credits

Svetlana Lazebnik

Introduction to object recognition



Slides adapted from Fei-Fei Li, Rob Fergus, Antonio Torralba, and others

Overview

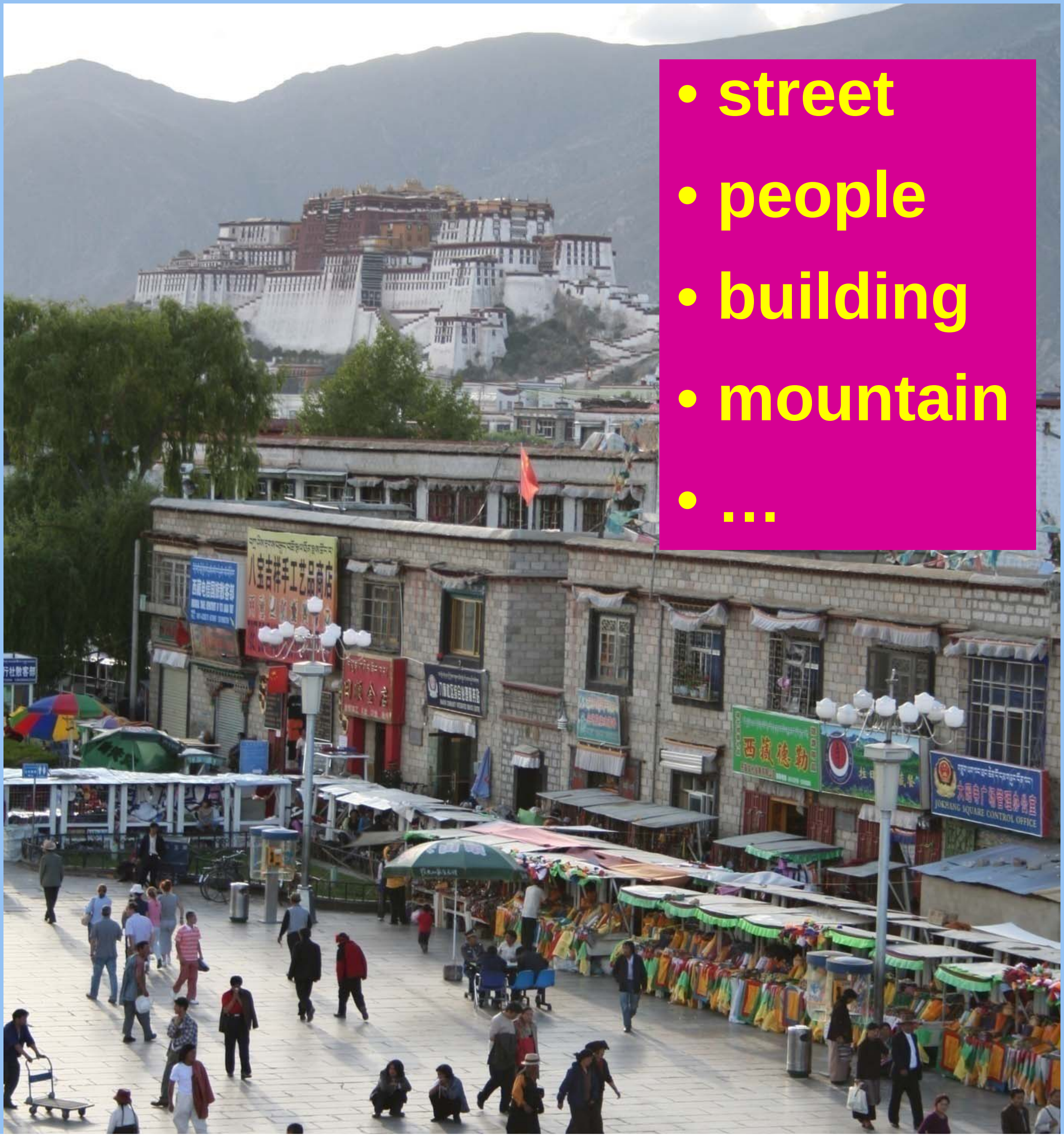
- Basic recognition tasks
- A statistical learning approach
- Traditional or “shallow” recognition pipeline
  - Bags of features
  - Classifiers
- Next time: neural networks and “deep” recognition pipeline

Common recognition tasks

Image classification

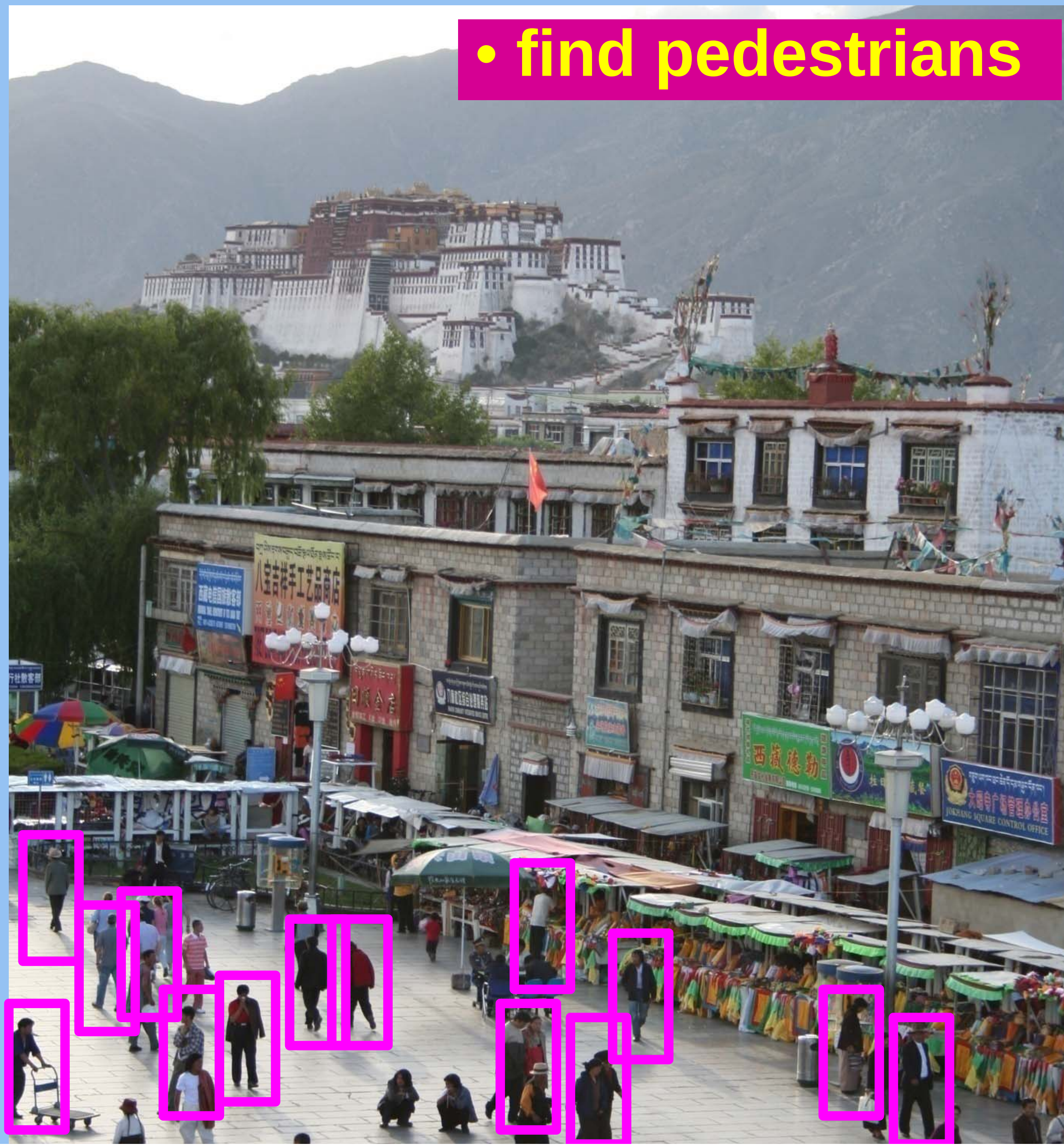
- **outdoor/indoor**
- **city/forest/factory/etc.**

Image tagging



- **street**
- **people**
- **building**
- **mountain**
- **…**

Object detection



Activity recognition

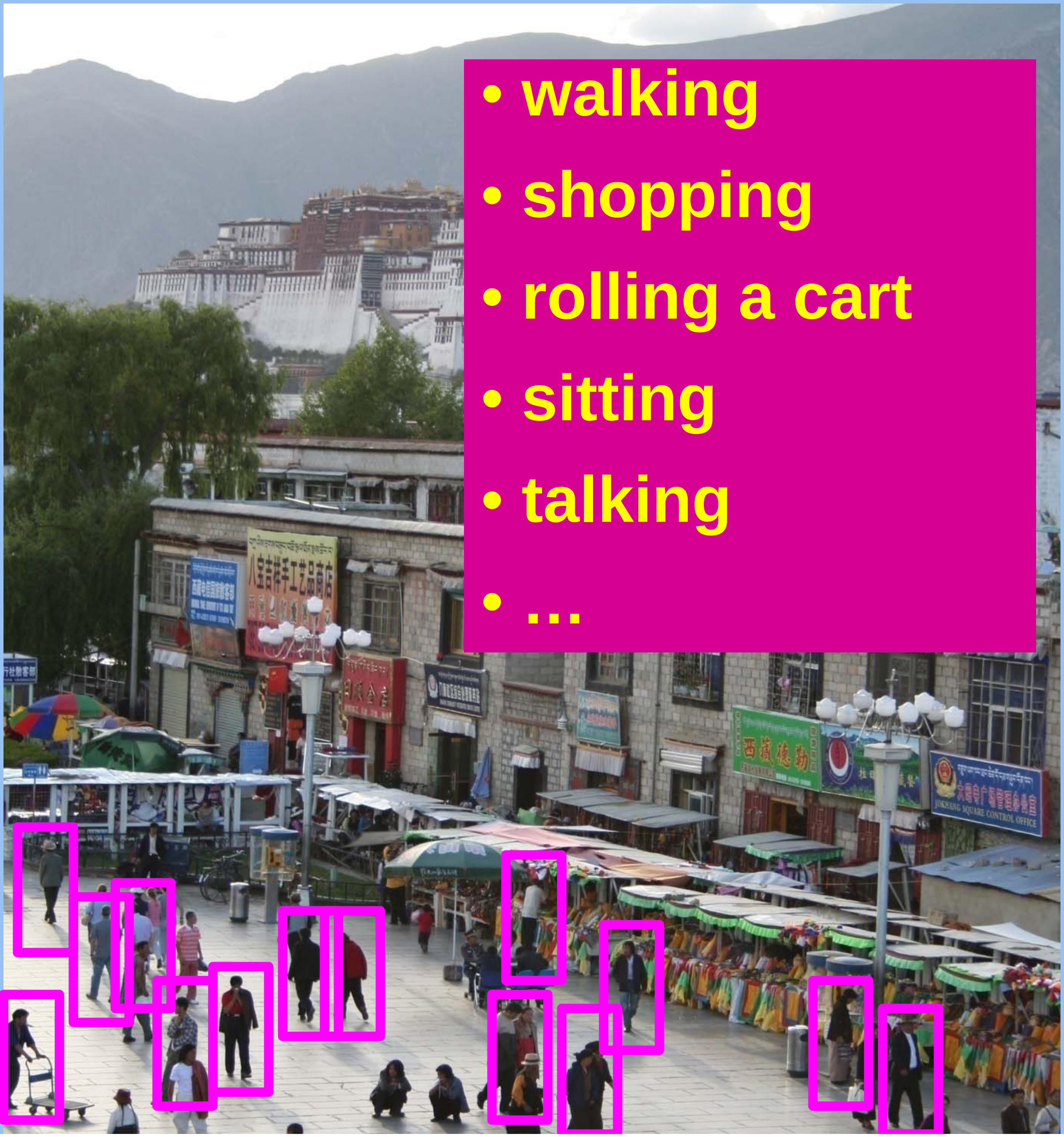
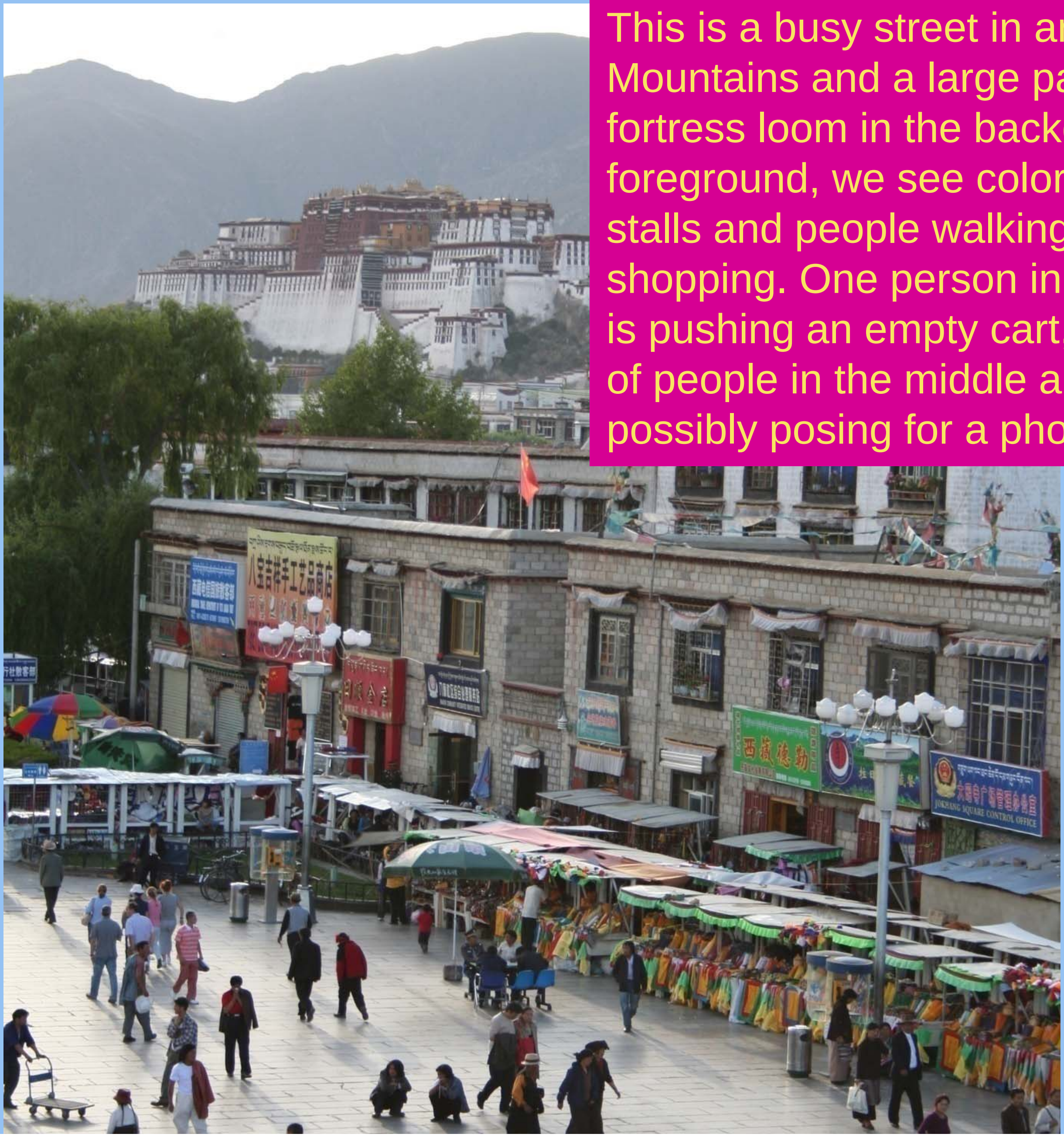


Image parsing

Image description



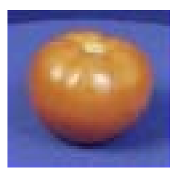
This is a busy street in an Asian city. Mountains and a large palace or fortress loom in the background. In the foreground, we see colorful souvenir stalls and people walking around and shopping. One person in the lower left is pushing an empty cart, and a couple of people in the middle are sitting, possibly posing for a photograph.

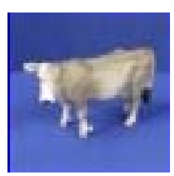
Image classification

The statistical learning framework

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

f() = “apple”

f() = “tomato”

f() = “cow”

The statistical learning framework

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

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

Steps

Training

Training Images

Image Features

Training Labels

Training

Learned model

Testing

Test Image

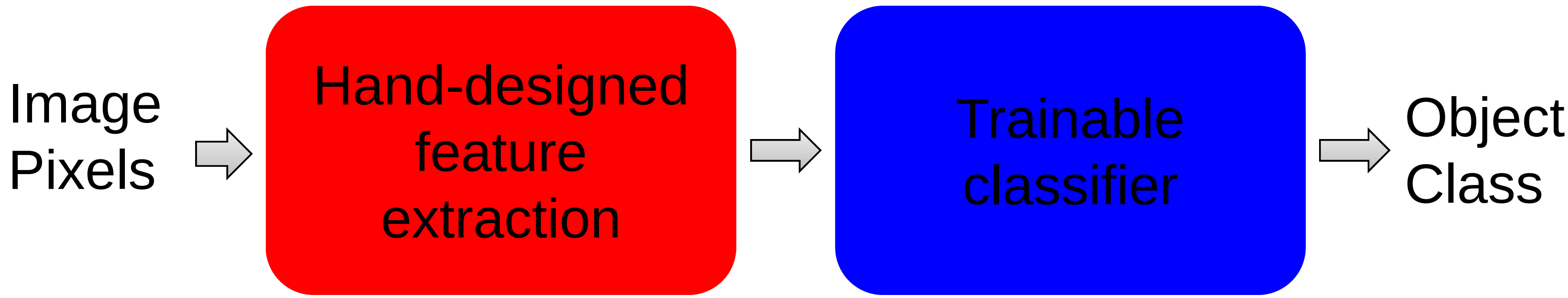
Image Features

Learned model

Prediction

Slide credit: D. Hoiem

Traditional recognition pipeline

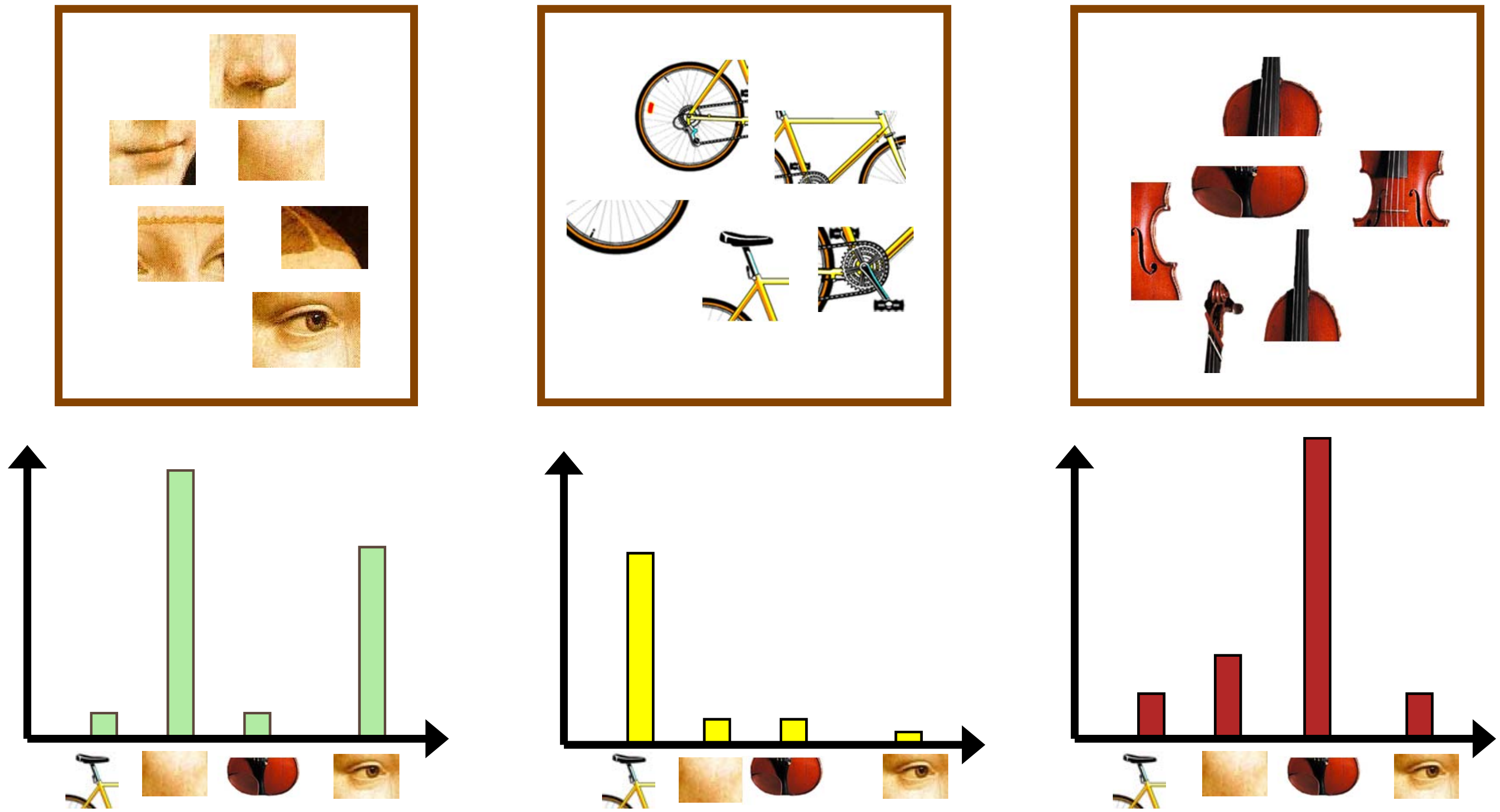


- Features are not learned
- Trainable classifier is often generic (e.g. SVM)

Bags of features

Traditional features: Bags-of-features

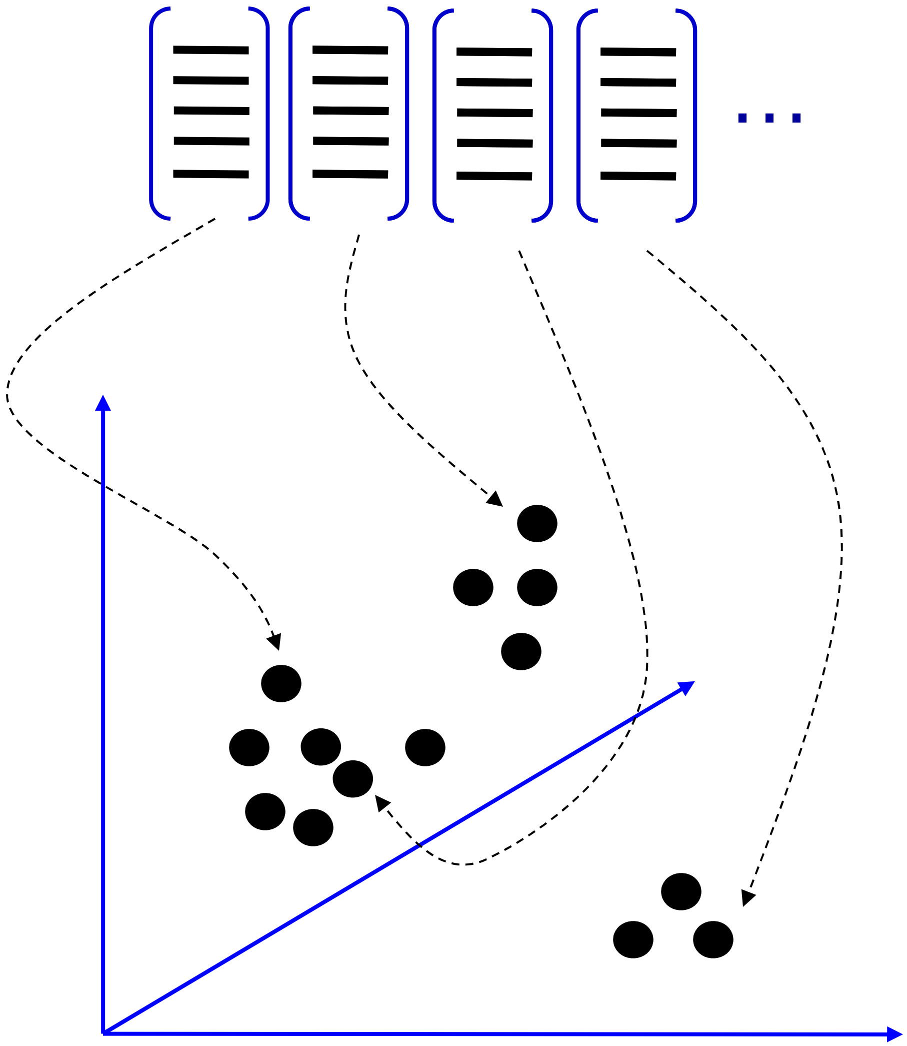
1. Extract local features
2. Learn "visual vocabulary"
3. Quantize local features using visual vocabulary
4. Represent images by frequencies of "visual words"



1. Local feature extraction

- Sample patches and extract descriptors

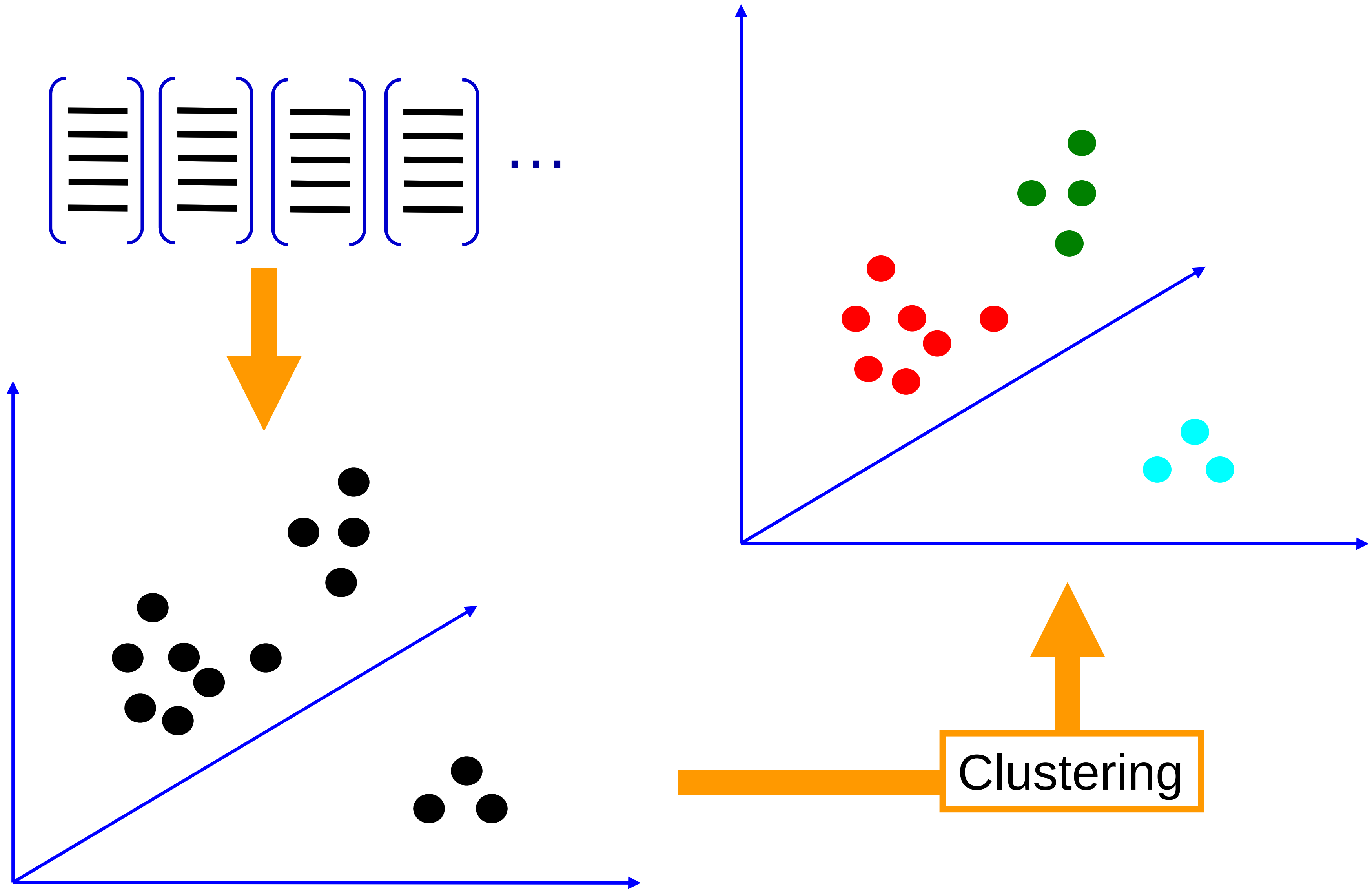
2. Learning the visual vocabulary



Extracted descriptors from the training set

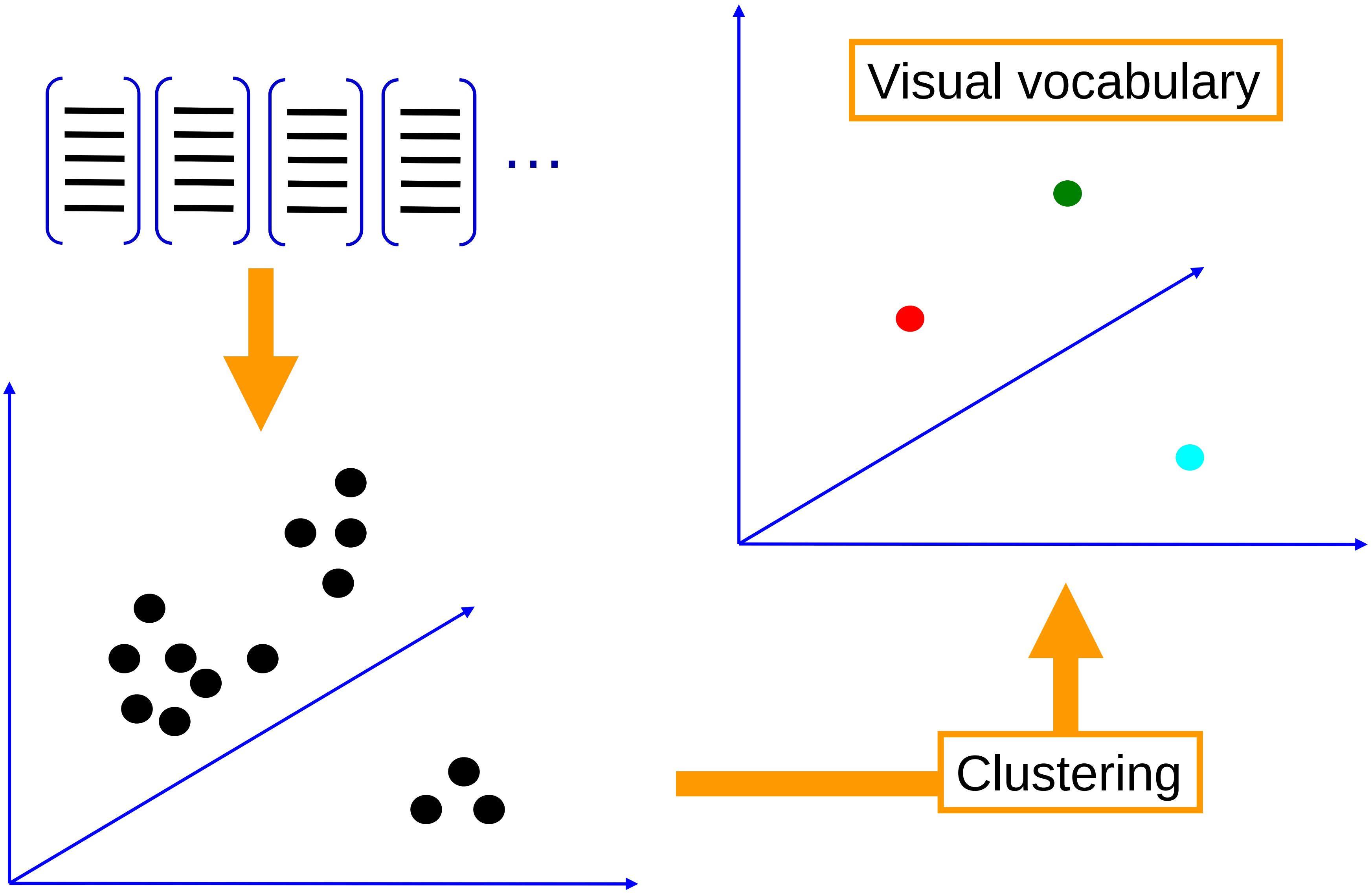
Slide credit: Josef Sivic

2. Learning the visual vocabulary



Slide credit: Josef Sivic

2. Learning the visual vocabulary



Slide credit: Josef Sivic

Review: K-means clustering

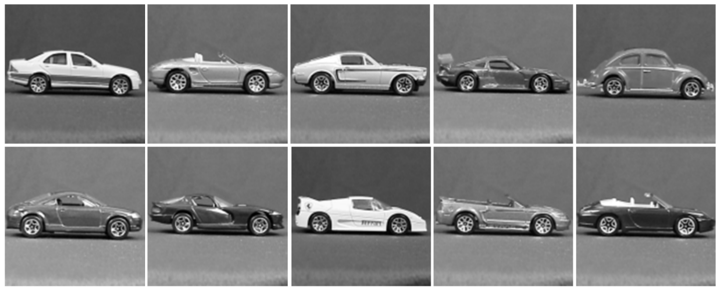
- Want to minimize sum of squared Euclidean distances between features $\mathbf{x}_i$ and their nearest cluster centers $\mathbf{m}_k$

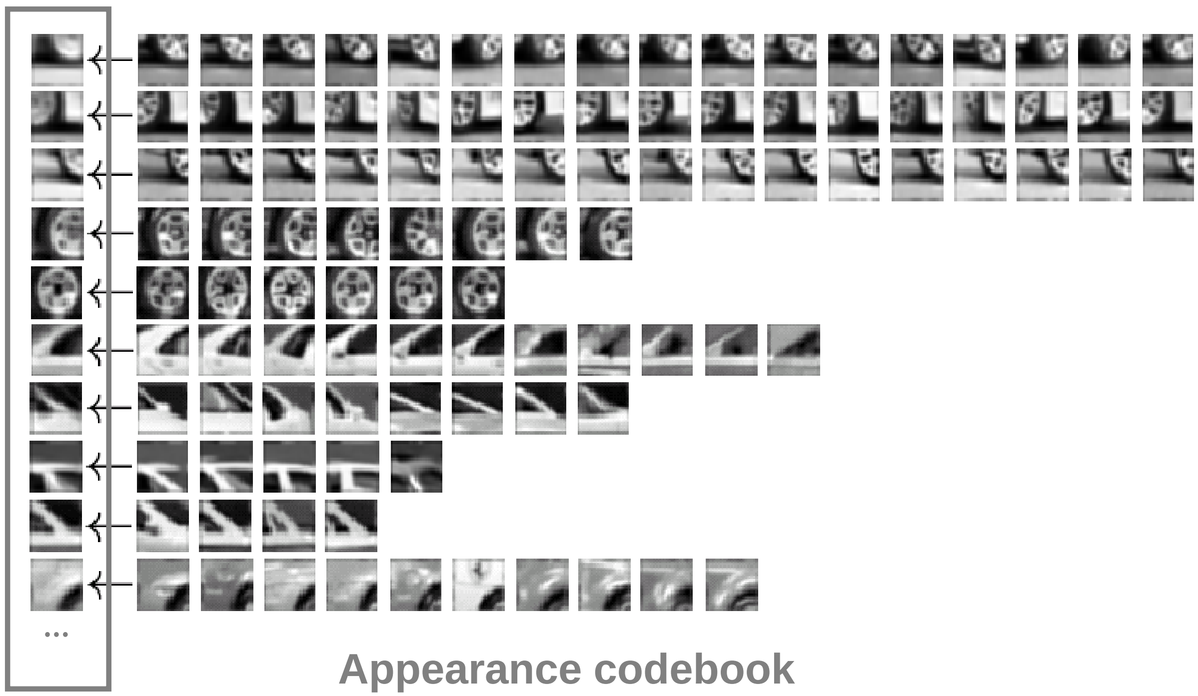
$$D(X, M) = \sum_{\text{cluster } k} \sum_{\substack{\text{point } i \text{ in} \\ \text{cluster } k}} (\mathbf{x}_i - \mathbf{m}_k)^2$$

Algorithm:

- Randomly initialize K cluster centers
- Iterate until convergence:
  - Assign each feature to the nearest center
  - Recompute each cluster center as the mean of all features assigned to it

Example visual vocabulary



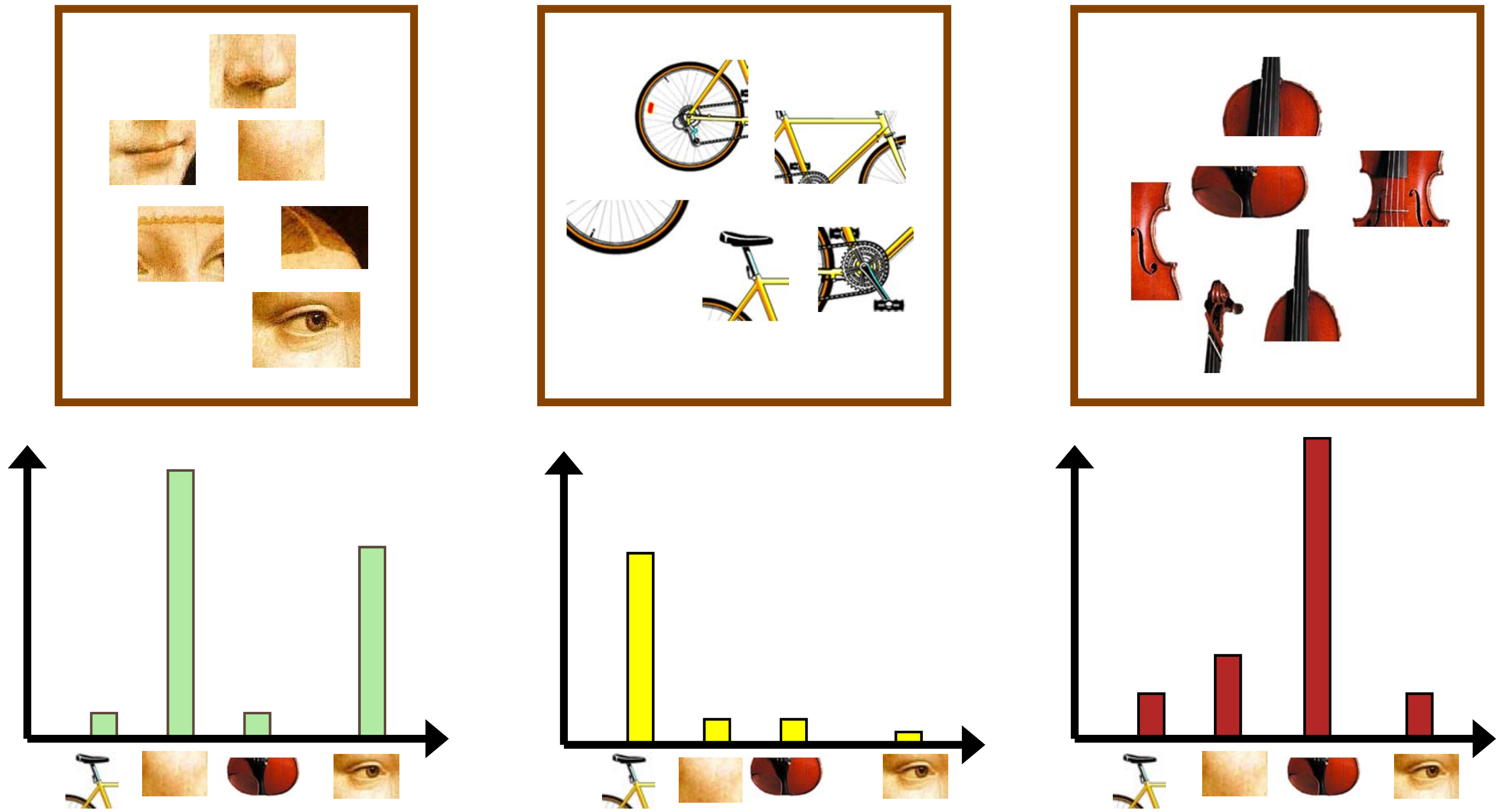


Appearance codebook

Source: B. Leibe

Bag-of-features steps

1. Extract local features
2. Learn "visual vocabulary"
3. **Quantize local features using visual vocabulary**
4. **Represent images by frequencies of "visual words"**



Bags of features: Motivation

- Orderless document representation: frequencies of words from a dictionary Salton & McGill (1983)

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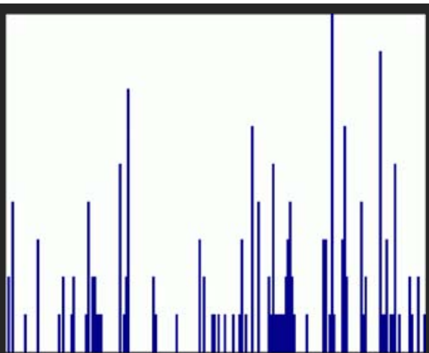
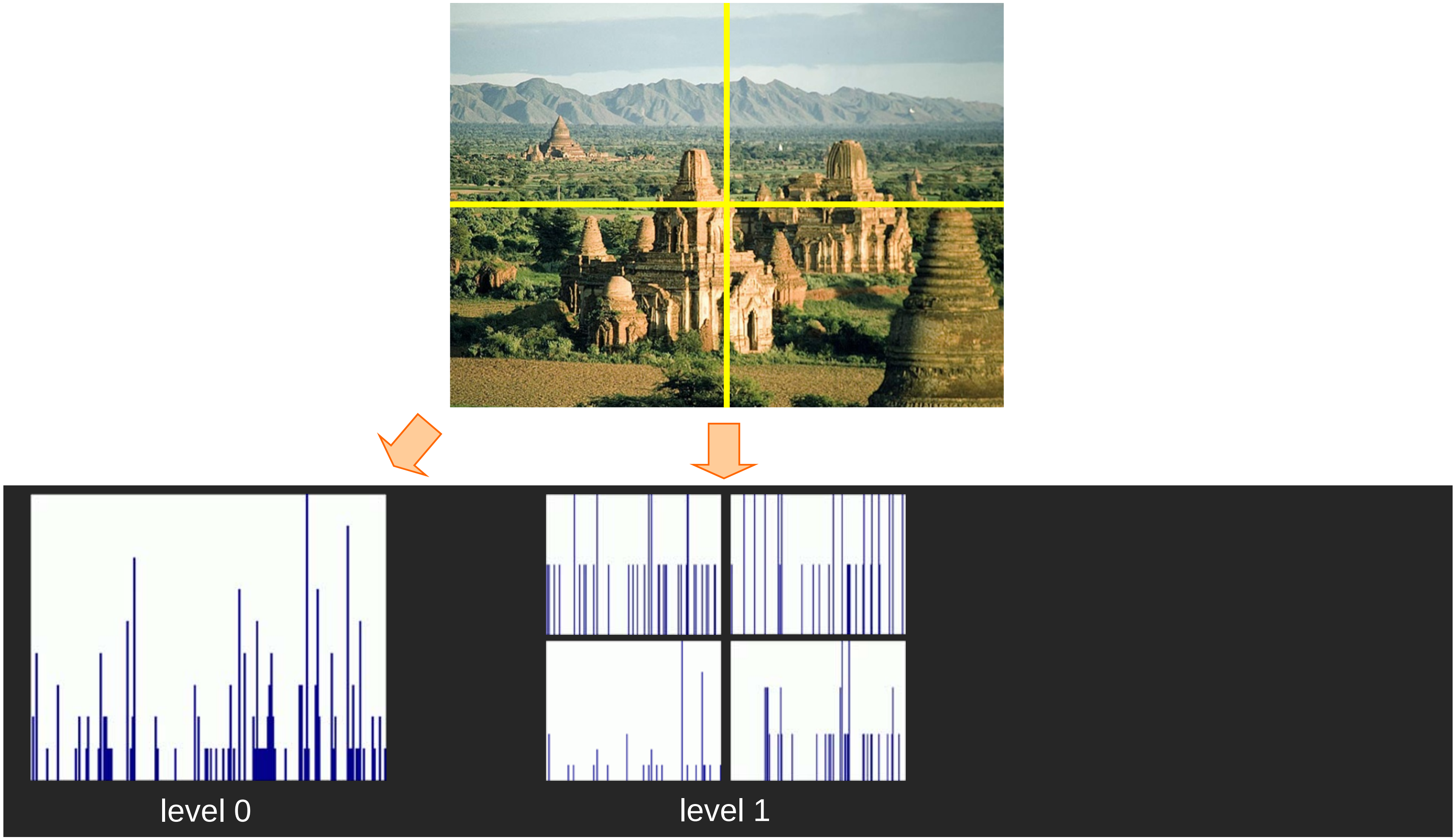
Spatial pyramids



level 0

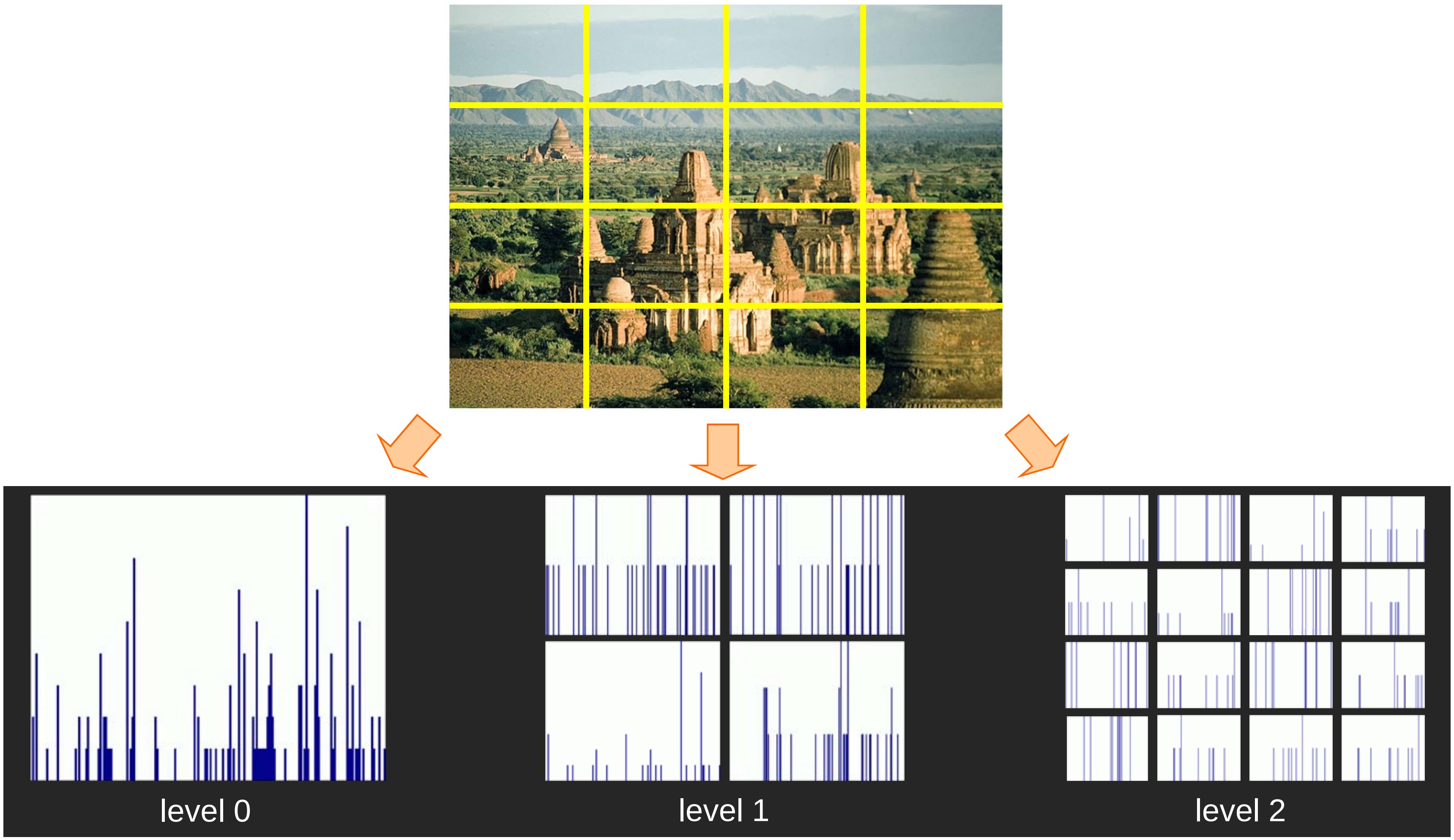
Lazebnik, Schmid & Ponce (CVPR 2006)

Spatial pyramids



Lazebnik, Schmid & Ponce (CVPR 2006)

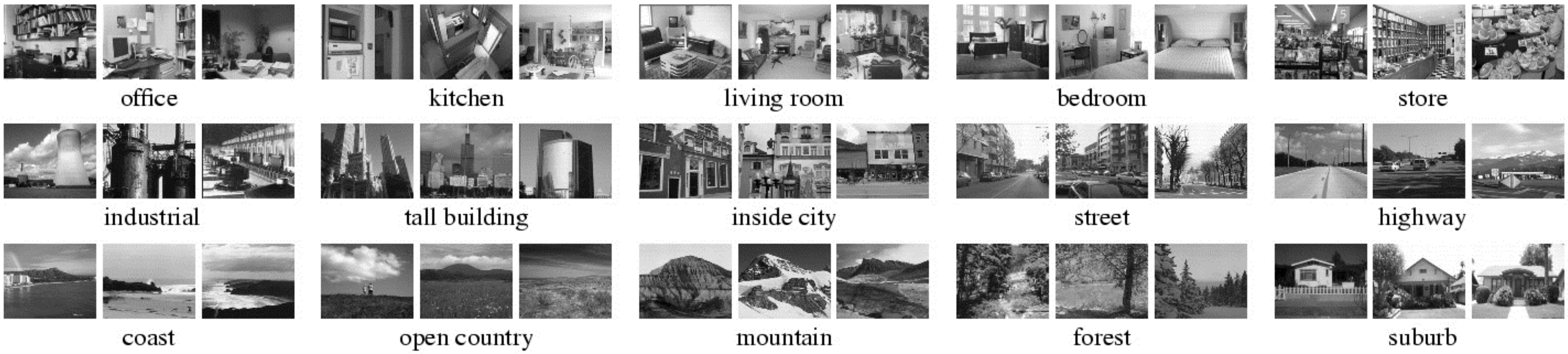
Spatial pyramids



Lazebnik, Schmid & Ponce (CVPR 2006)

Spatial pyramids

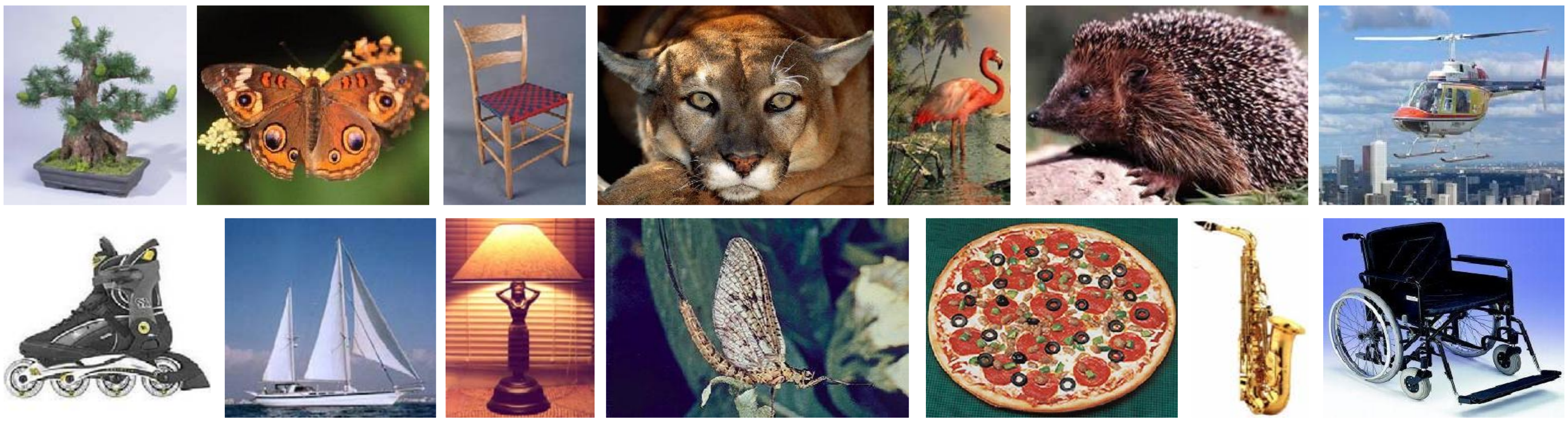
- Scene classification results



	Weak features (vocabulary size: 16)		Strong features (vocabulary size: 200)	
Level	Single-level	Pyramid	Single-level	Pyramid
0 (1×1)	45.3 ±0.5		72.2 ±0.6	
1 (2×2)	53.6 ±0.3	56.2 ±0.6	77.9 ±0.6	79.0 ±0.5
2 (4×4)	61.7 ±0.6	64.7 ±0.7	79.4 ±0.3	**81.1** ±0.3
3 (8×8)	63.3 ±0.8	**66.8** ±0.6	77.2 ±0.4	80.7 ±0.3

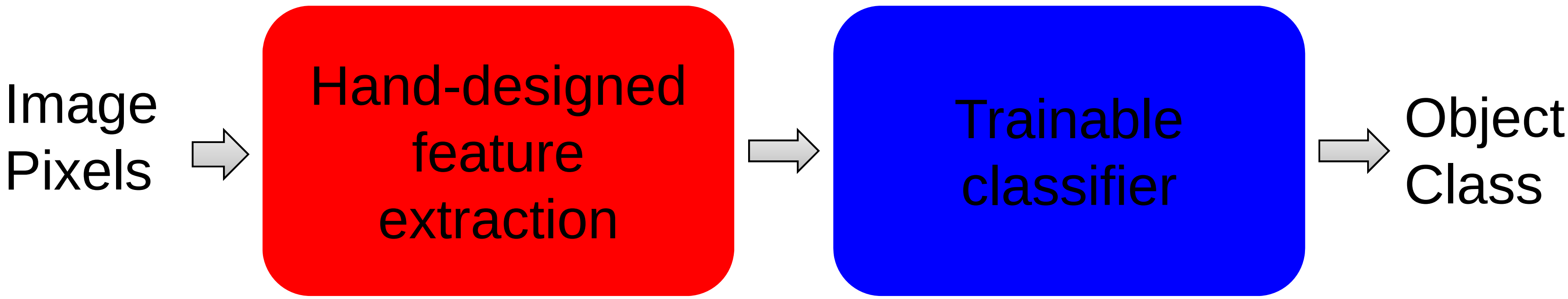
Spatial pyramids

- Caltech101 classification results

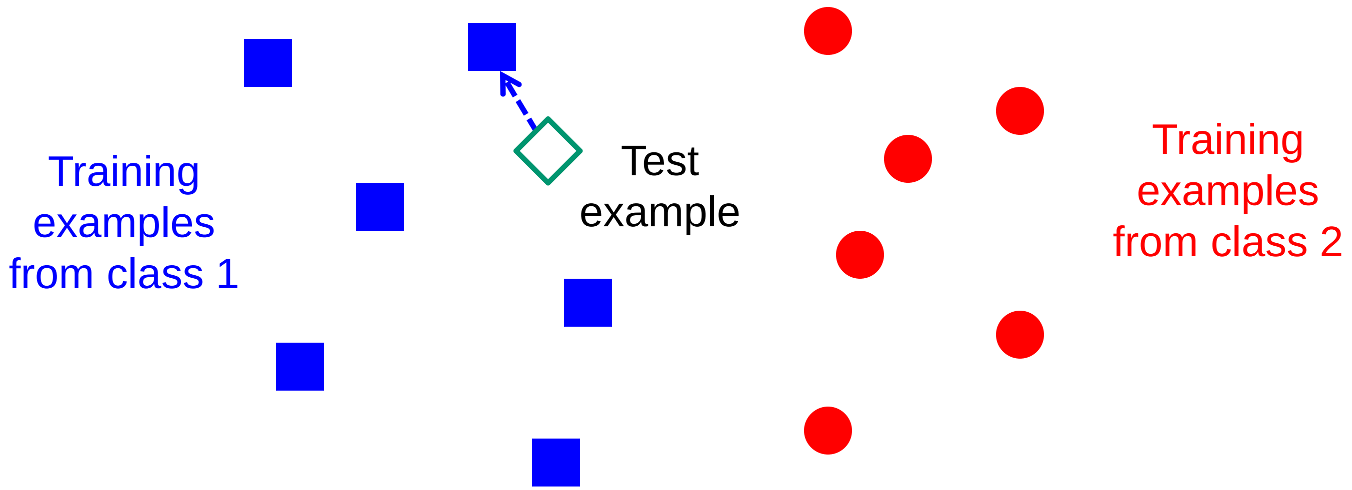


	Weak features (16)		Strong features (200)	
Level	Single-level	Pyramid	Single-level	Pyramid
0	15.5 $\pm$0.9		41.2 $\pm$1.2	
1	31.4 $\pm$1.2	32.8 $\pm$1.3	55.9 $\pm$0.9	57.0 $\pm$0.8
2	47.2 $\pm$1.1	49.3 $\pm$1.4	63.6 $\pm$0.9	**64.6** $\pm$0.8
3	52.2 $\pm$0.8	**54.0** $\pm$1.1	60.3 $\pm$0.9	64.6 $\pm$0.7

Traditional recognition pipeline



Classifiers: Nearest neighbor



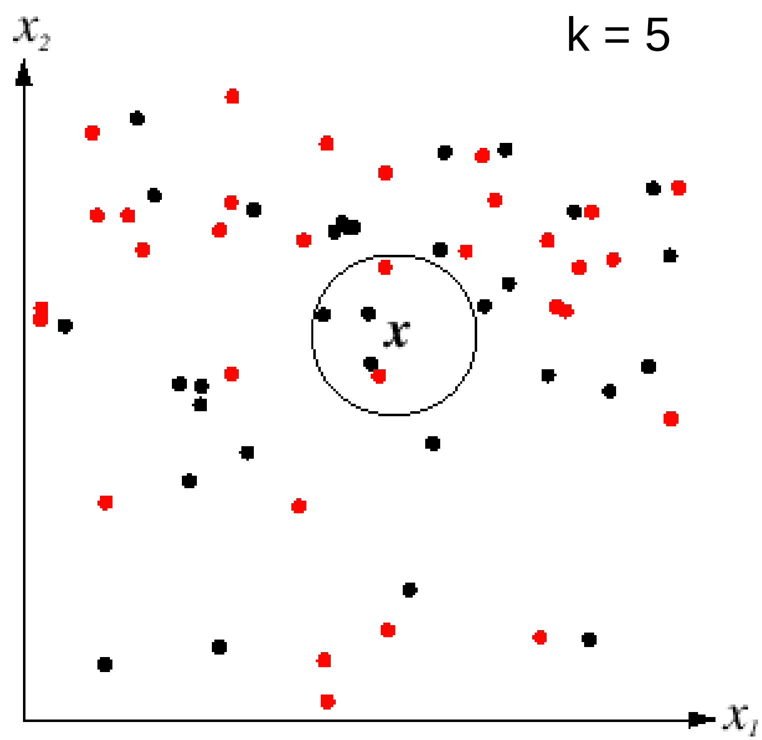
f(**x**) = label of the training example nearest to **x**

All we need is a distance function for our inputs

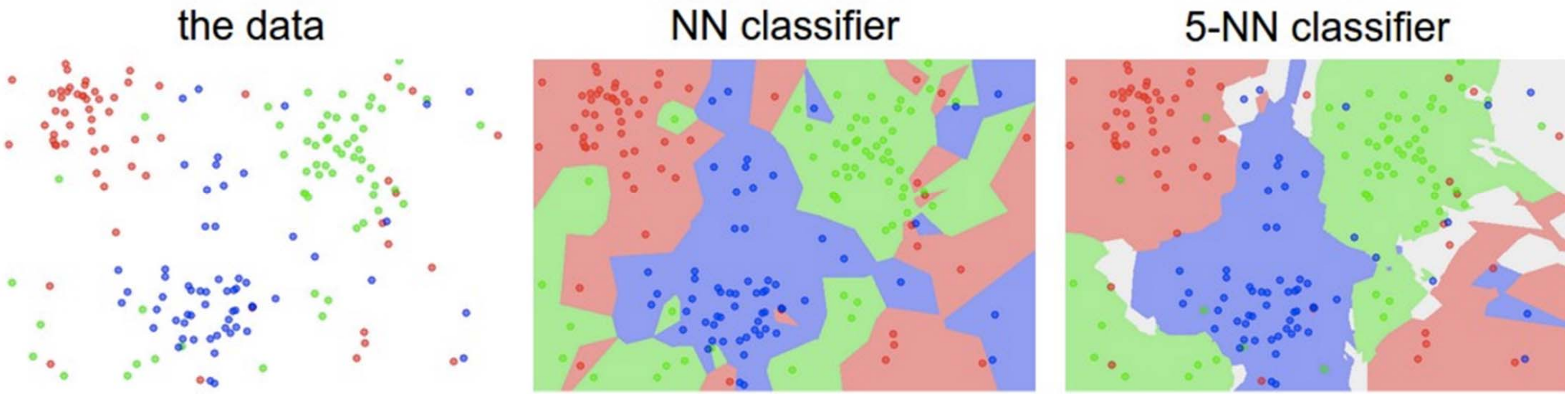
No training required!

K-nearest neighbor classifier

- For a new point, find the k closest points from training data
- Vote for class label with labels of the k points



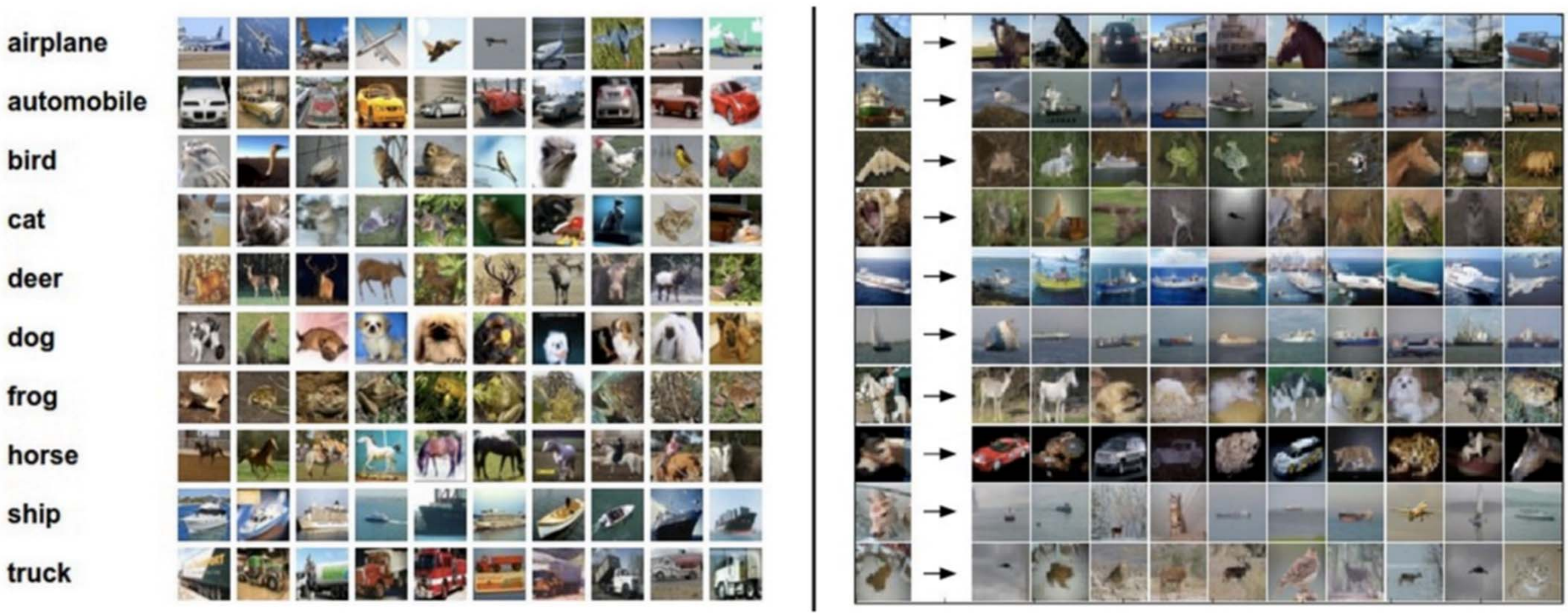
K-nearest neighbor classifier



Which classifier is more robust to *outliers*?

Credit: Andrej Karpathy, http://cs231n.github.io/classification/

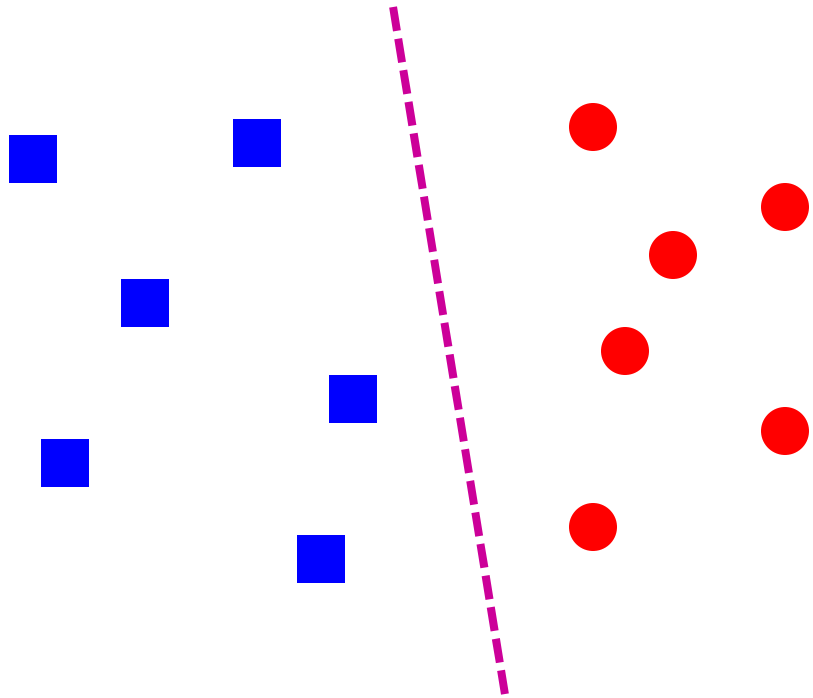
K-nearest neighbor classifier



Left: Example images from the CIFAR-10 dataset. Right: first column shows a few test images and next to each we show the top 10 nearest neighbors in the training set according to pixel-wise difference.

Credit: Andrej Karpathy, http://cs231n.github.io/classification/

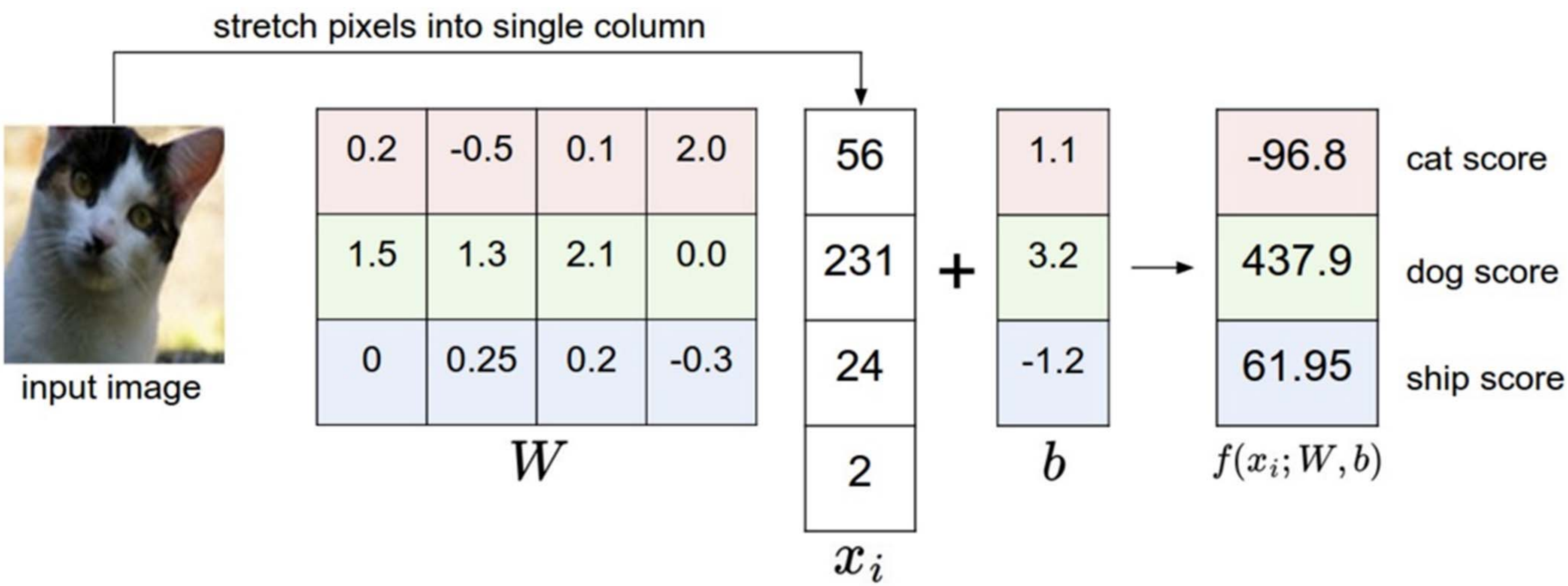
Linear classifiers



Find a *linear function* to separate the classes:

$$f(\mathbf{x}) = \mathrm{sgn}(\mathbf{w} \cdot \mathbf{x} + b)$$

Visualizing linear classifiers



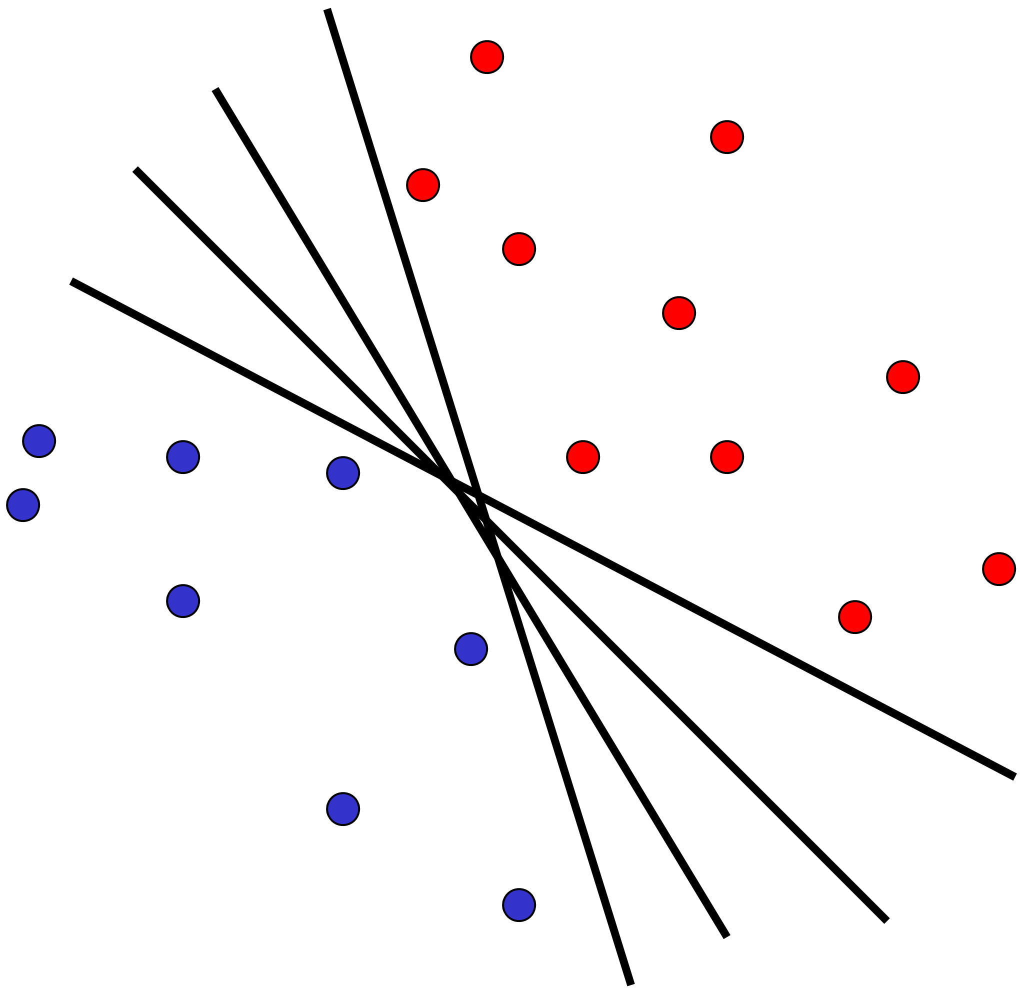
Source: Andrej Karpathy, http://cs231n.github.io/linear-classify/

Nearest neighbor vs. linear classifiers

- NN pros:
  - Simple to implement
  - Decision boundaries not necessarily linear
  - Works for any number of classes
  - *Nonparametric* method
- NN cons:
  - Need good distance function
  - Slow at test time
- Linear pros:
  - Low-dimensional *parametric* representation
  - Very fast at test time
- Linear cons:
  - Works for two classes
  - How to train the linear function?
  - What if data is not linearly separable?

Support vector machines

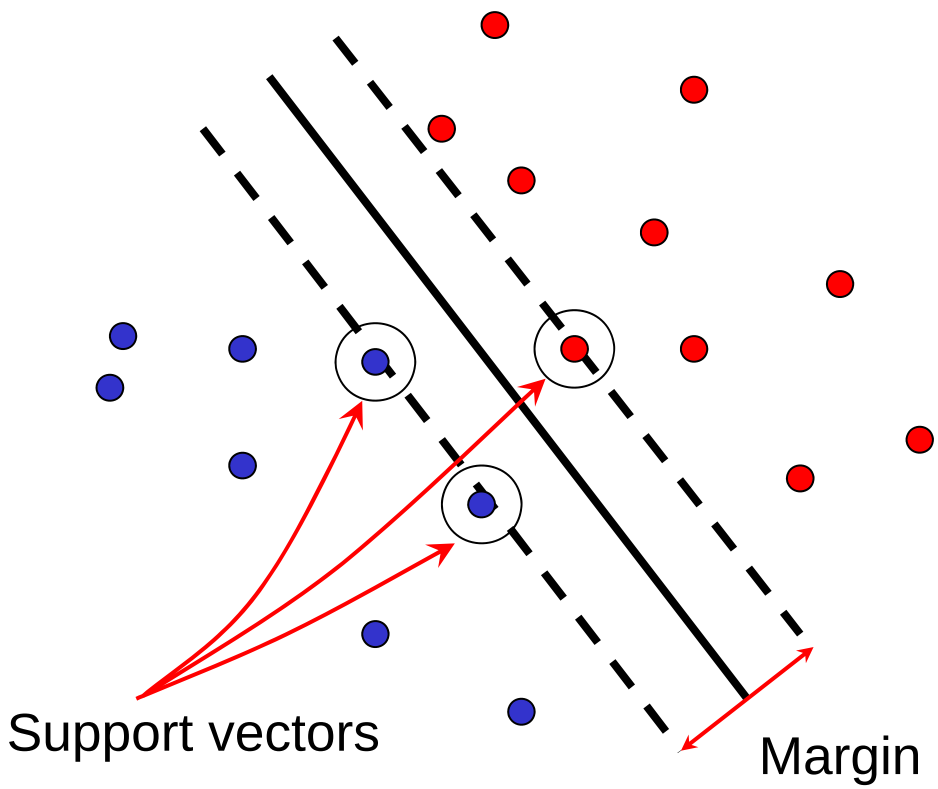
- When the data is linearly separable, there may be more than one separator (hyperplane)



Which separator is best?

Support vector machines

- Find hyperplane that maximizes the *margin* between the positive and negative examples



$\mathbf{x}_i$ positive $(y_i = 1)$: $\quad \mathbf{x}_i \cdot \mathbf{w} + b \geq 1$

$\mathbf{x}_i$ negative $(y_i = -1)$: $\quad \mathbf{x}_i \cdot \mathbf{w} + b \leq -1$

For support vectors, $\quad \mathbf{x}_i \cdot \mathbf{w} + b = \pm 1$

Distance between point and hyperplane: $\quad \dfrac{|\mathbf{x}_i \cdot \mathbf{w} + b|}{\|\mathbf{w}\|}$

Therefore, the margin is $2 / \|\mathbf{w}\|$

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

Finding the maximum margin hyperplane

1. Maximize margin $2 / \|\mathbf{w}\|$
2. Correctly classify all training data:

$$\mathbf{x}_i \text{ positive } (y_i = 1): \qquad \mathbf{x}_i \cdot \mathbf{w} + b \geq 1$$

$$\mathbf{x}_i \text{ negative } (y_i = -1): \qquad \mathbf{x}_i \cdot \mathbf{w} + b \leq -1$$

Quadratic optimization problem:

$$\boxed{\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 \quad \text{subject to} \quad y_i(\mathbf{w} \cdot \mathbf{x}_i + b) \geq 1}$$

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

SVM parameter learning

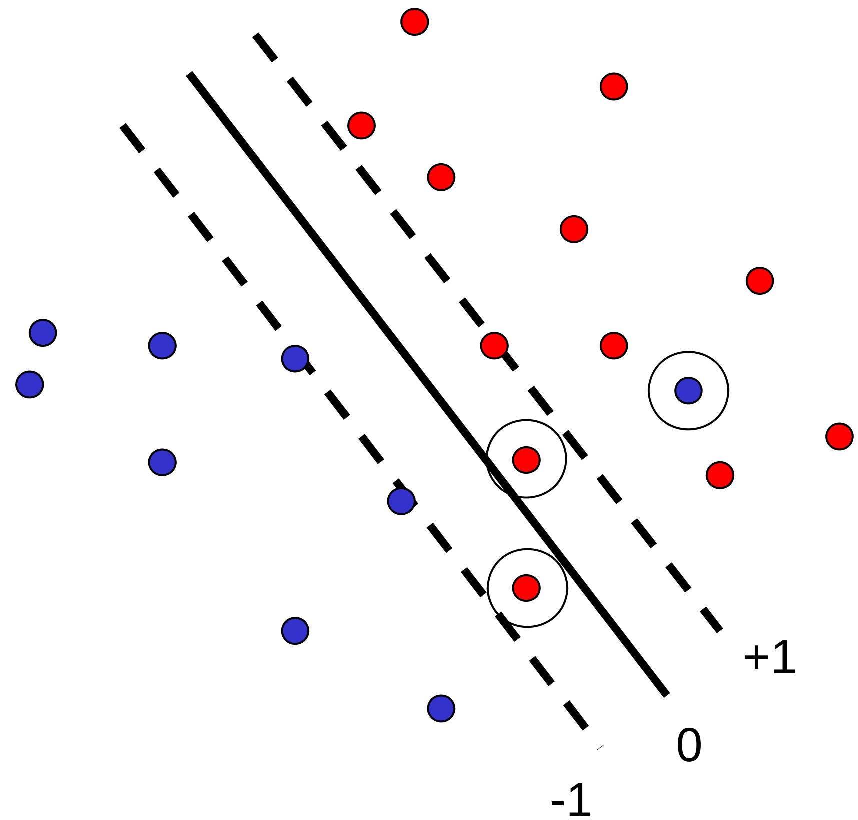
- Separable data: $$\underbrace{\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2}_{\text{Maximize margin}} \quad \underbrace{\text{subject to} \quad y_i(\mathbf{w}\cdot\mathbf{x}_i + b) \geq 1}_{\text{Classify training data correctly}}$$

- Non-separable data:

$$\min_{\mathbf{w},b} \quad \underbrace{\frac{1}{2}\|\mathbf{w}\|^2}_{\text{Maximize margin}} + \underbrace{C\sum_{i=1}^{n}\max\left(0, 1 - y_i(\mathbf{w}\cdot\mathbf{x}_i + b)\right)}_{\text{Minimize classification mistakes}}$$

SVM parameter learning

$$\min_{\mathbf{w},b} \quad \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\max\left(0, 1 - y_i(\mathbf{w}\cdot\mathbf{x}_i + b)\right)$$



Demo: http://cs.stanford.edu/people/karpathy/svmjs/demo

Nonlinear SVMs

- General idea: the original input space can always be mapped to some higher-dimensional feature space where the training set is separable

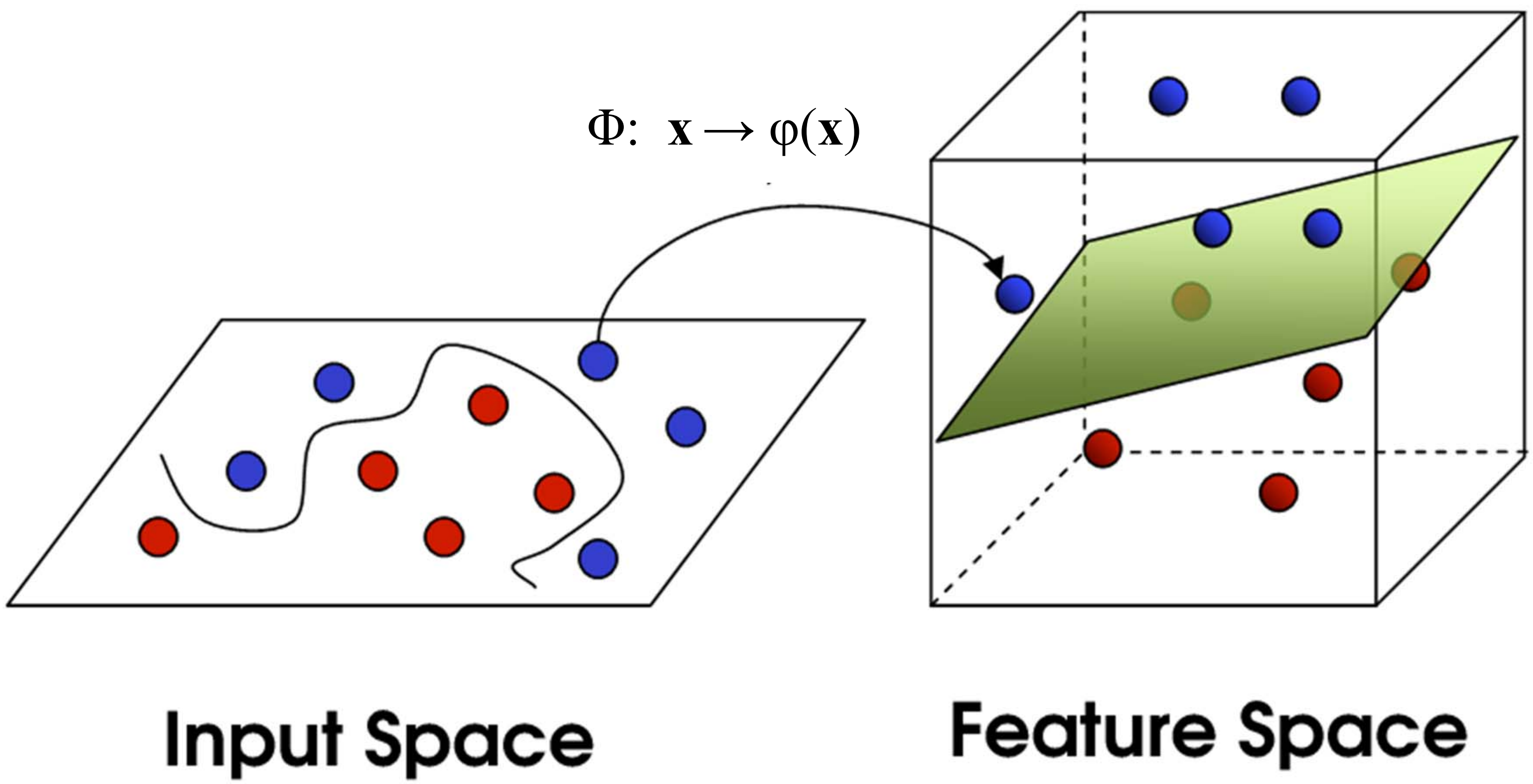
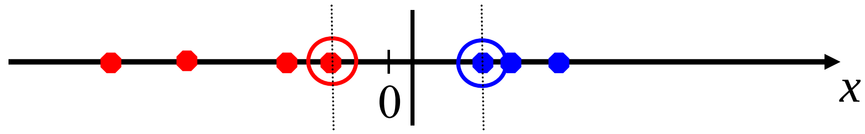


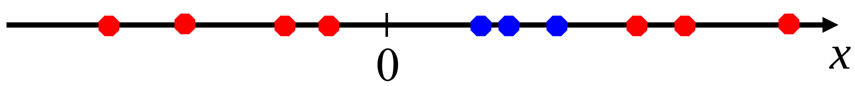
Image source

Nonlinear SVMs

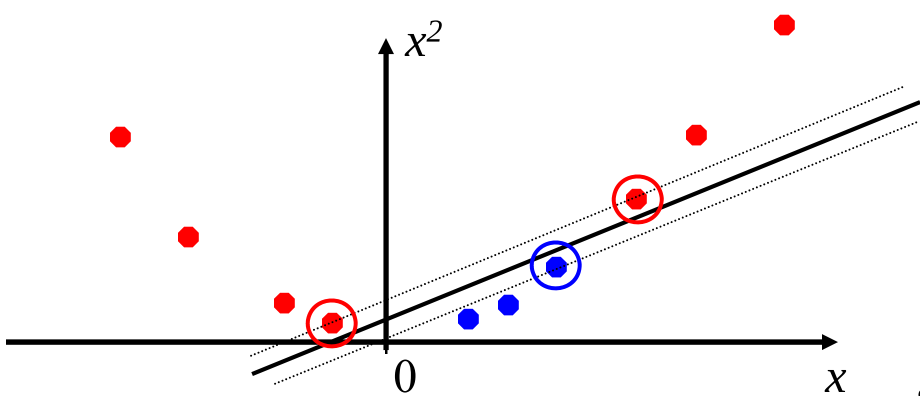
- Linearly separable dataset in 1D:



- Non-separable dataset in 1D:



- We can map the data to a *higher-dimensional space*:



Slide credit: Andrew Moore

The kernel trick

- General idea: the original input space can always be mapped to some higher-dimensional feature space where the training set is separable

- **The kernel trick:** instead of explicitly computing the lifting transformation $\boldsymbol{\varphi}(\mathbf{x})$, define a kernel function K such that

$$K(\mathbf{x}, \mathbf{y}) = \boldsymbol{\varphi}(\mathbf{x}) \cdot \boldsymbol{\varphi}(\mathbf{y})$$

(to be valid, the kernel function must satisfy *Mercer's condition*)

The kernel trick

- Linear SVM decision function:

$$\mathbf{w} \cdot \mathbf{x} + b = \sum_i \alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} + b$$

learned weight

Support vector

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

The kernel trick

- Linear SVM decision function:

$$\mathbf{w}\cdot\mathbf{x}+b=\sum\nolimits_i \alpha_i y_i \mathbf{x}_i \cdot \mathbf{x} \ +b$$

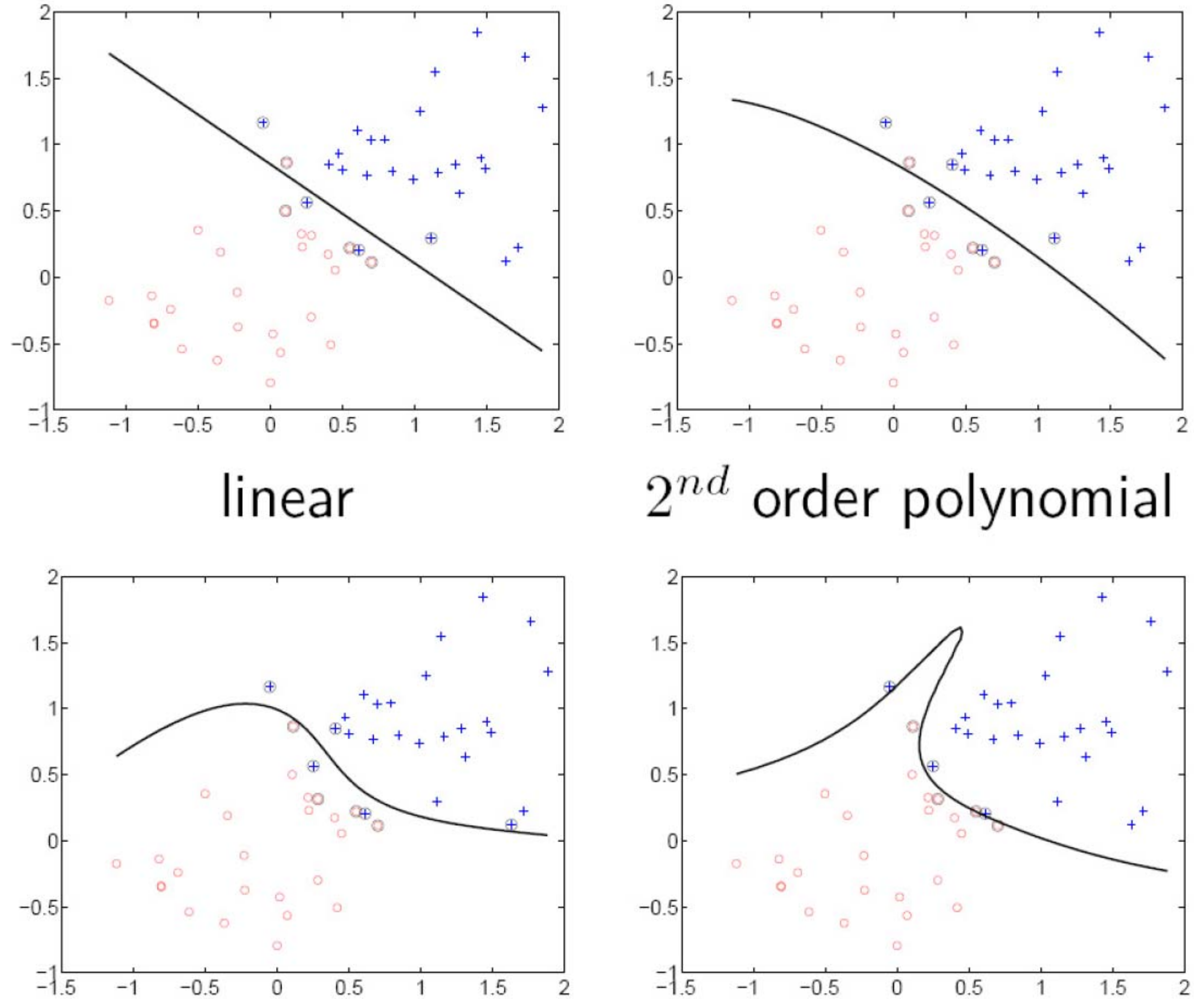
- Kernel SVM decision function:

$$\sum_i \alpha_i y_i \varphi(\mathbf{x}_i)\cdot\varphi(\mathbf{x}) \ +b=\sum_i \alpha_i y_i K(\mathbf{x}_i,\mathbf{x}) \ +b$$

- This gives a nonlinear decision boundary in the original feature space

C. Burges, A Tutorial on Support Vector Machines for Pattern Recognition, Data Mining and Knowledge Discovery, 1998

Polynomial kernel: $K(\mathbf{x},\mathbf{y}) = (c + \mathbf{x}\cdot\mathbf{y})^d$



linear

2^{nd} order polynomial

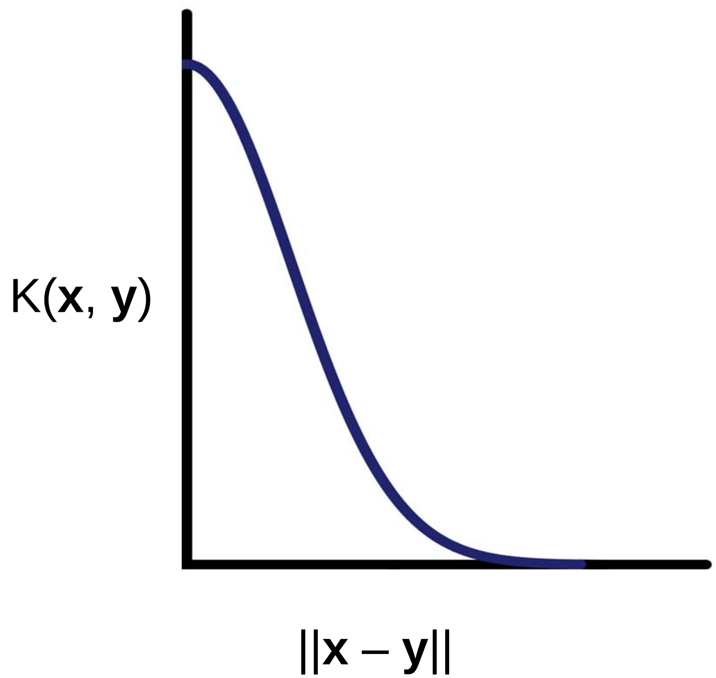
4^{th} order polynomial

8^{th} order polynomial

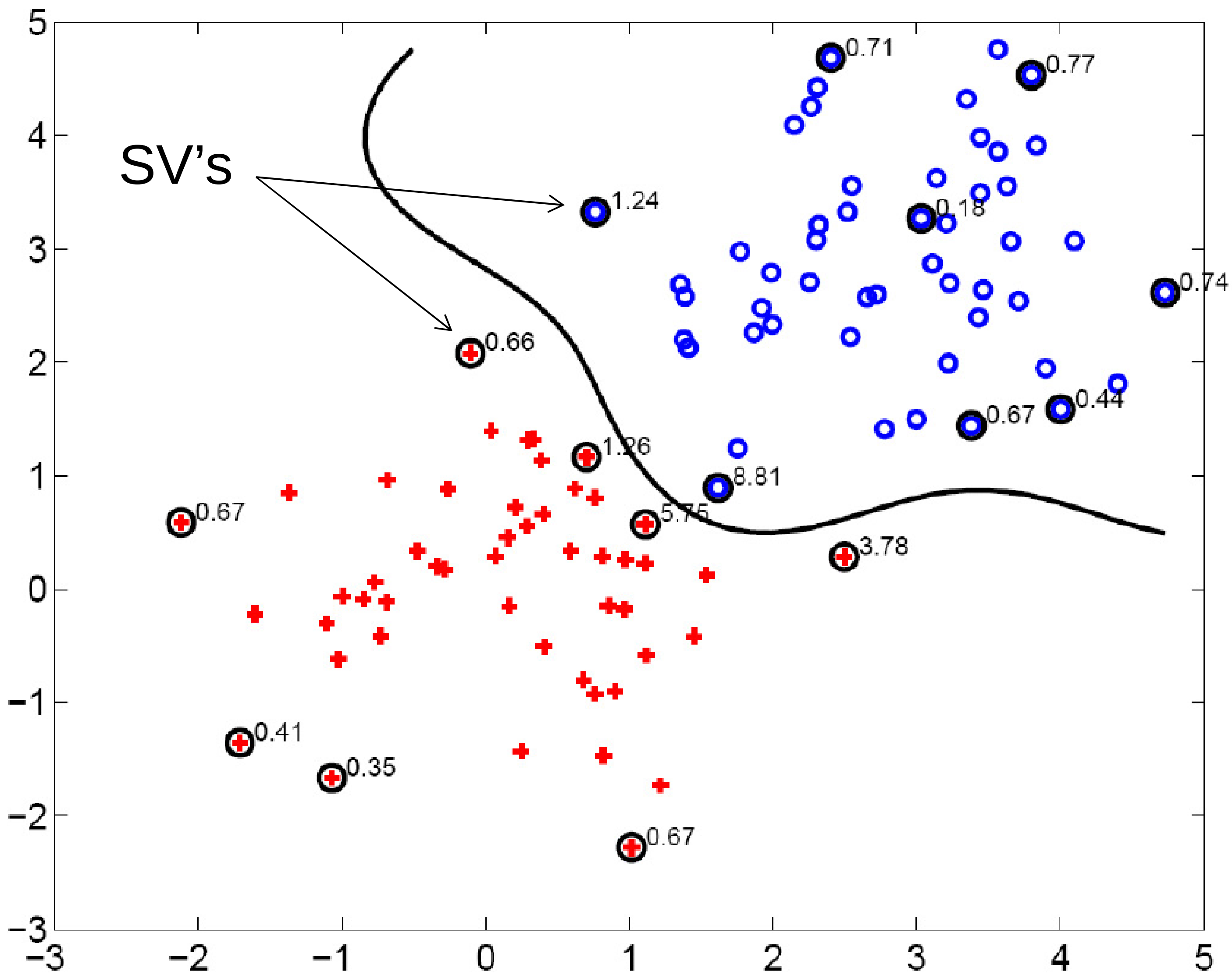
Gaussian kernel

- Also known as the radial basis function (RBF) kernel:

$$K(\mathbf{x},\mathbf{y}) = \exp\left(-\frac{1}{\sigma^2}\|\mathbf{x}-\mathbf{y}\|^2\right)$$



Gaussian kernel



Kernels for histograms

- Histogram intersection:

$$K(h_1, h_2) = \sum_{i=1}^{N} \min(h_1(i), h_2(i))$$

- Square root (Bhattacharyya kernel):

$$K(h_1, h_2) = \sum_{i=1}^{N} \sqrt{h_1(i) h_2(i)}$$

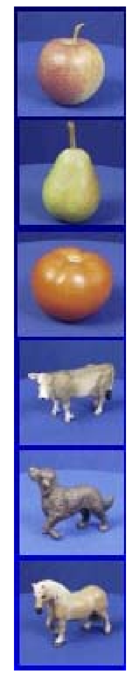
SVMs: Pros and cons

- Pros
  - Kernel-based framework is very powerful, flexible
  - Training is convex optimization, globally optimal solution can be found
  - Amenable to theoretical analysis
  - SVMs work very well in practice, even with very small training sample sizes
- Cons
  - No “direct” multi-class SVM, must combine two-class SVMs (e.g., with one-vs-others)
  - Computation, memory (esp. for nonlinear SVMs)

Generalization

- Generalization refers to the ability to correctly classify never before seen examples
- Can be controlled by turning "knobs" that affect the complexity of the model

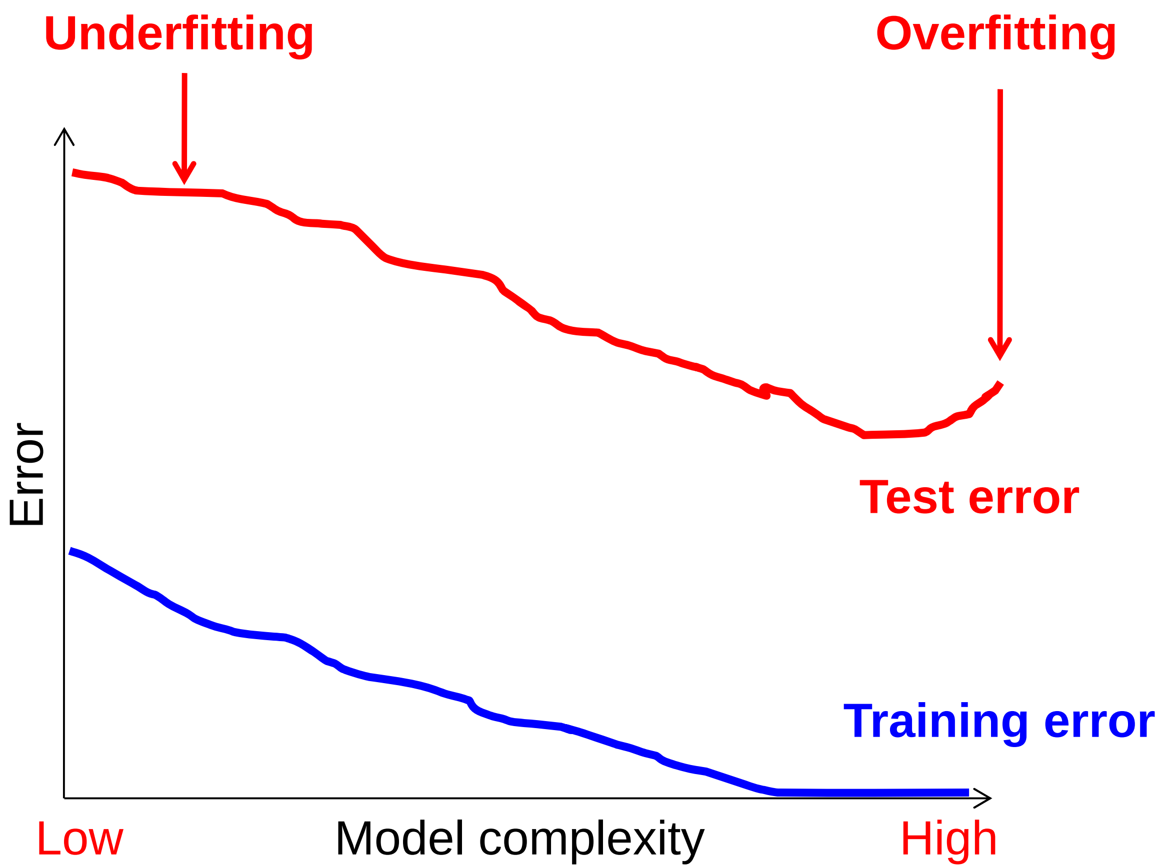
Training set (labels known)



Test set (labels unknown)

Diagnosing generalization ability

- **Training error:** how does the model perform on the data on which it was trained?
- **Test error:** how does it perform on never before seen data?



Source: D. Hoiem

Underfitting and overfitting

- **Underfitting:** training and test error are both *high*
  - Model does an equally poor job on the training and the test set
  - Either the training procedure is ineffective or the model is too “simple” to represent the data
- **Overfitting:** Training error is *low* but test error is *high*
  - Model fits irrelevant characteristics (noise) in the training data
  - Model is too complex or amount of training data is insufficient

Underfitting | Good generalization | Overfitting

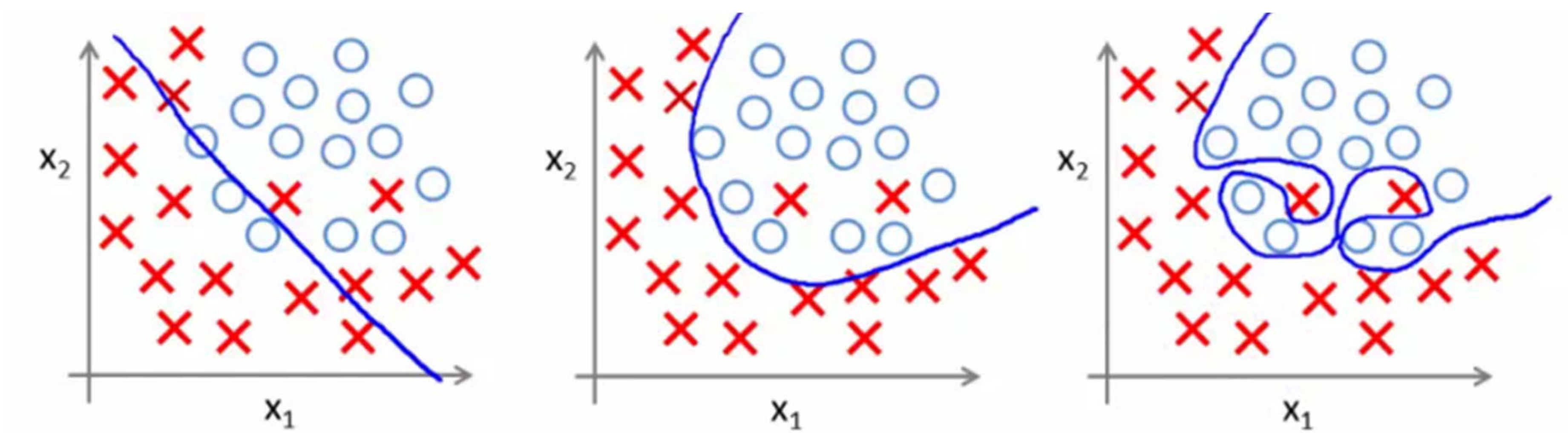
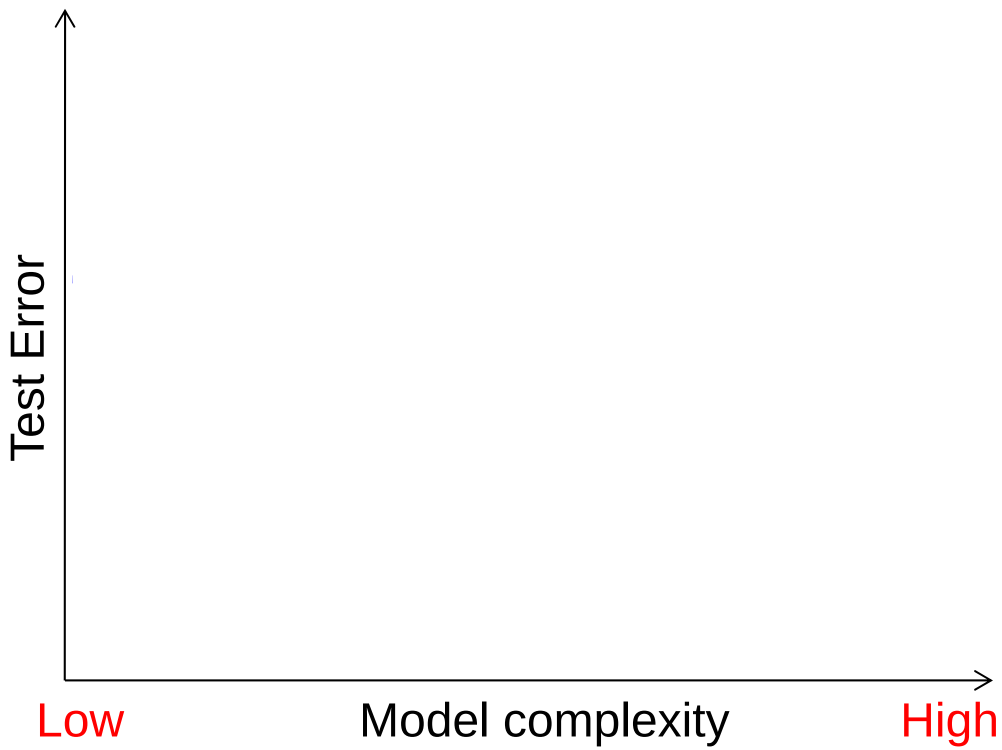


Figure source

Effect of training set size



Source: D. Hoiem

Validation

- Split the data into **training**, **validation**, and **test** subsets
- Use training set to **optimize model parameters**
- Use validation test to **choose the best model**
- Use test set only to **evaluate performance**