# EBU7240

# Computer Vision

## - Machine learning basics and recognition -

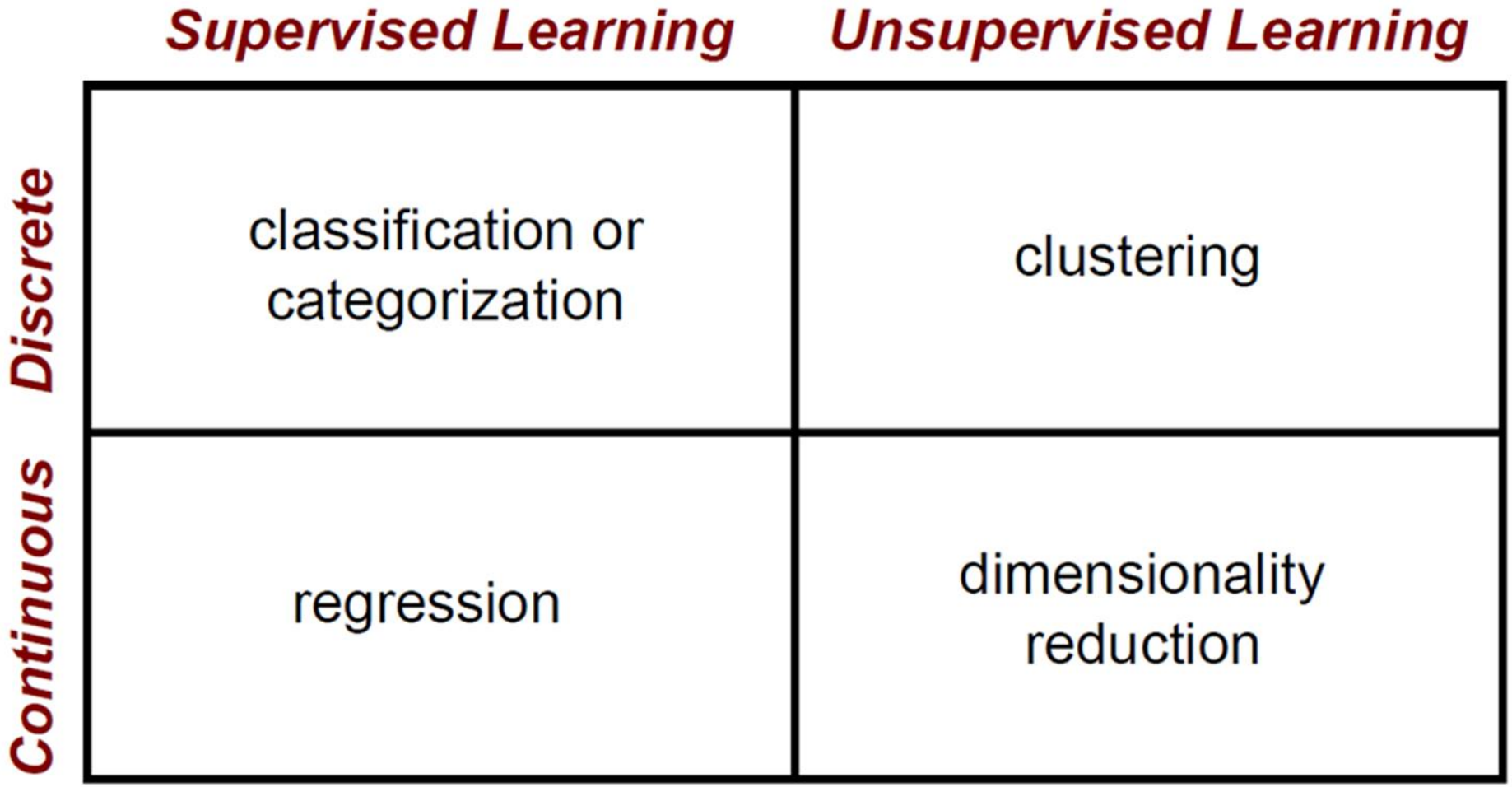
*Semester 1, 2021*

**Changjae Oh**

# Objectives

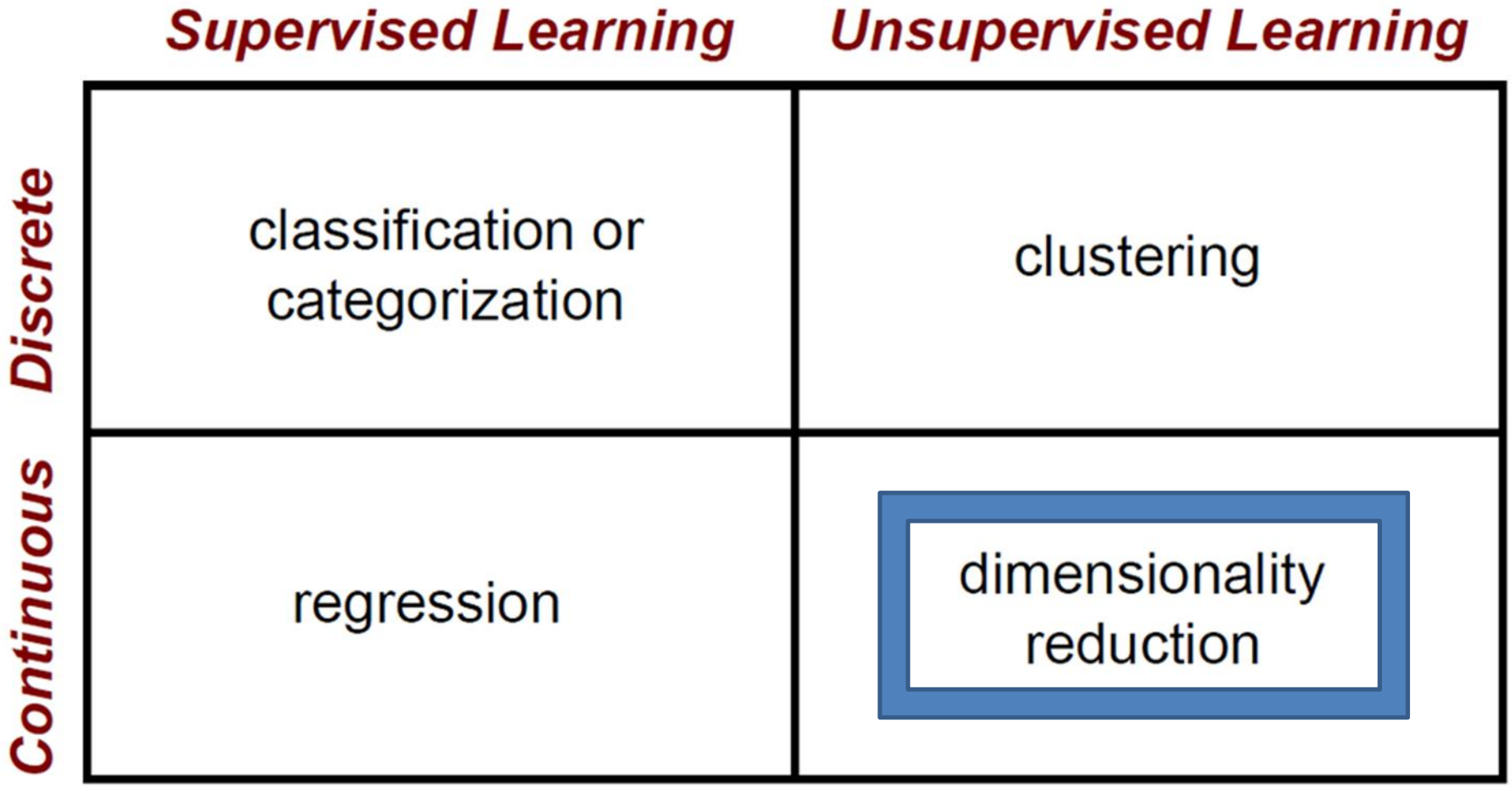
- To understand machine learning basics for high-level vision problems

# Machine learning problems




Slide credit: J. Hays

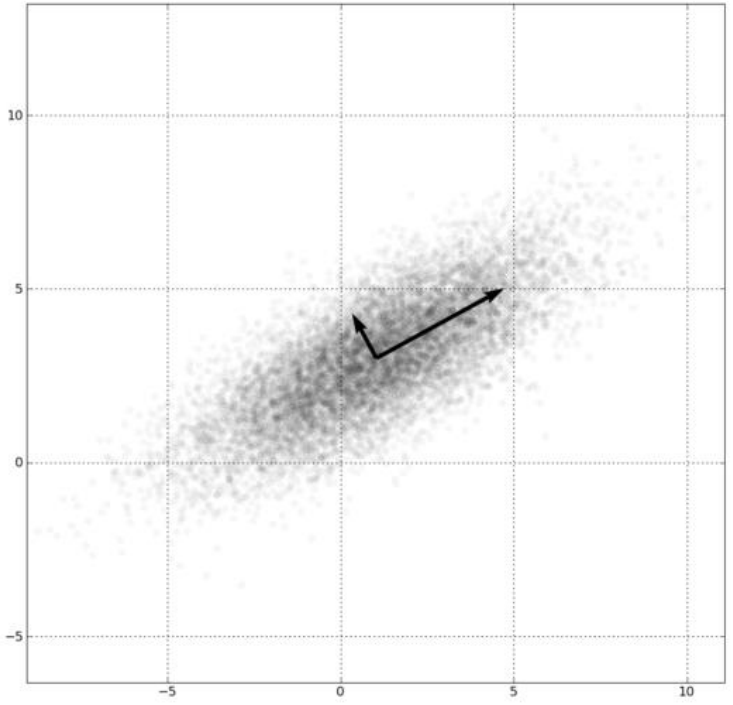
# Machine learning problems




Slide credit: J. Hays

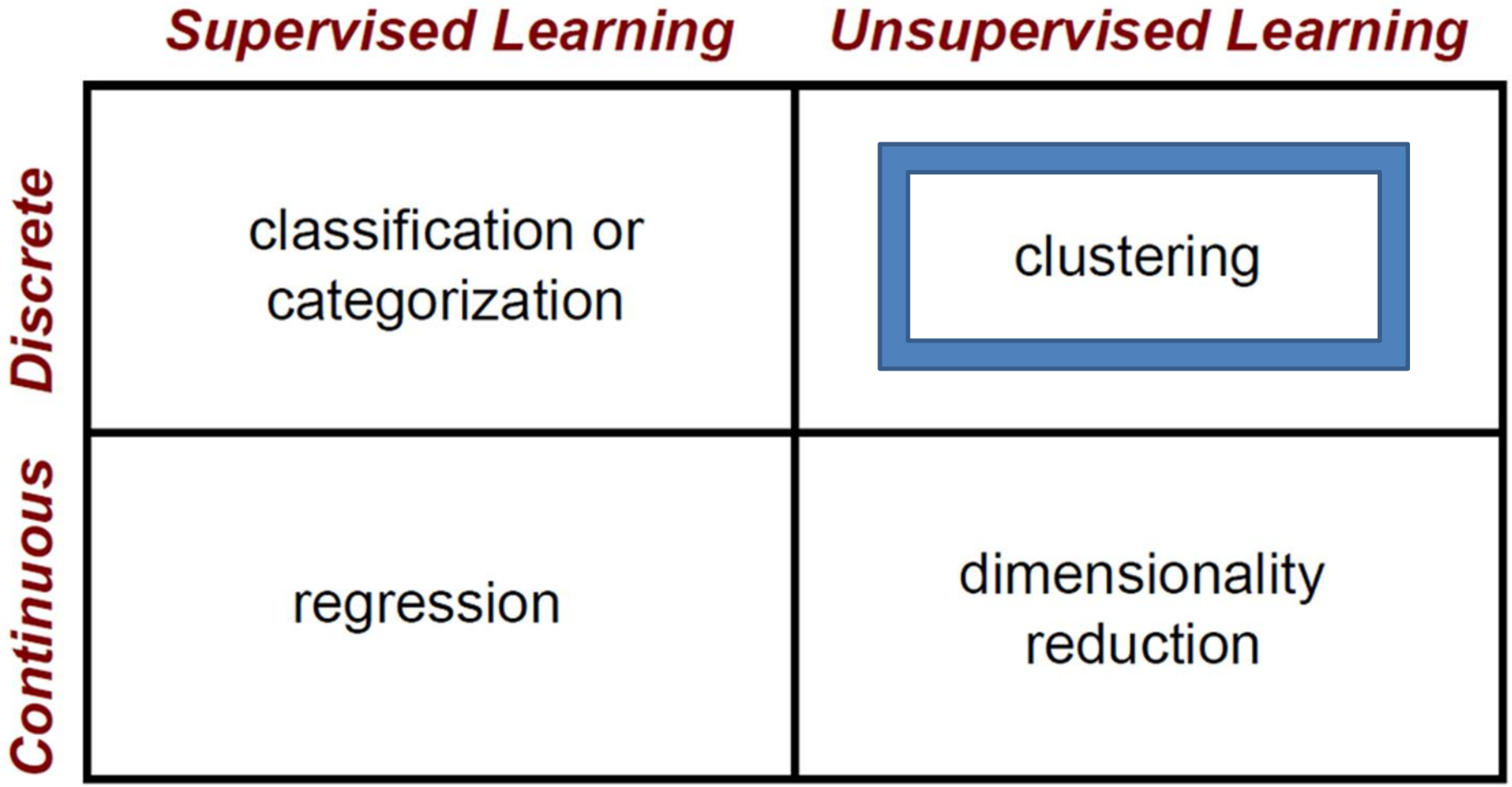
# Dimensionality Reduction

- **Principal component analysis (PCA),**
  - PCA takes advantage of correlations in data dimensions t o produce the best possible lower dimensional representa tion based on linear projections (minimizes reconstruction error).
  - PCA should be used for dimensionality reduction, not for discovering patterns or making predictions. Don't try to as sign semantic meaning to the bases.




- **Locally Linear Embedding, Isomap, Autoencoder, etc.**

# Machine learning problems



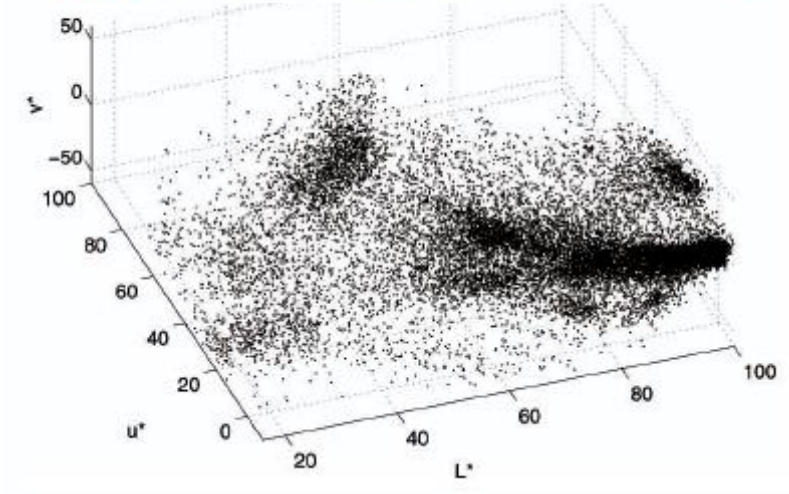
# K-means clustering

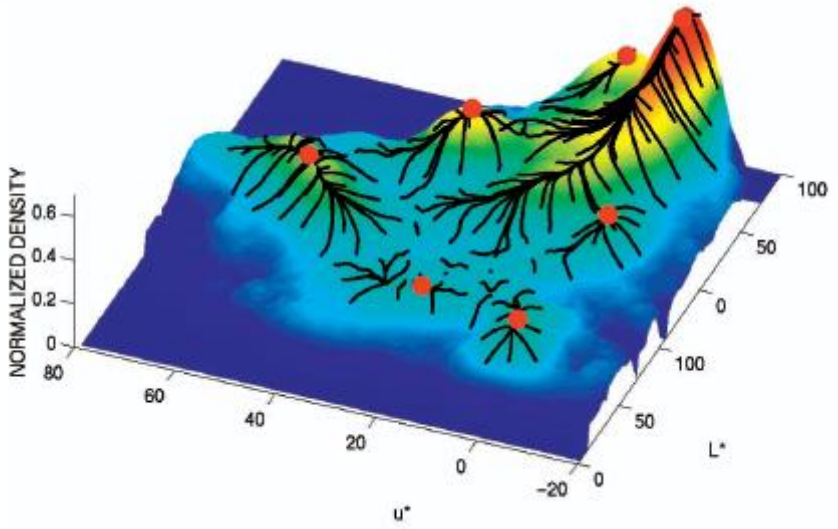
Image

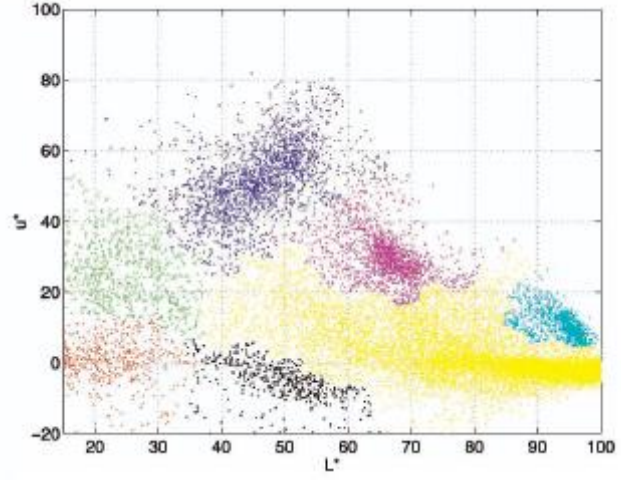
Clusters on intensity

Clusters on color

# Mean shift algorithm

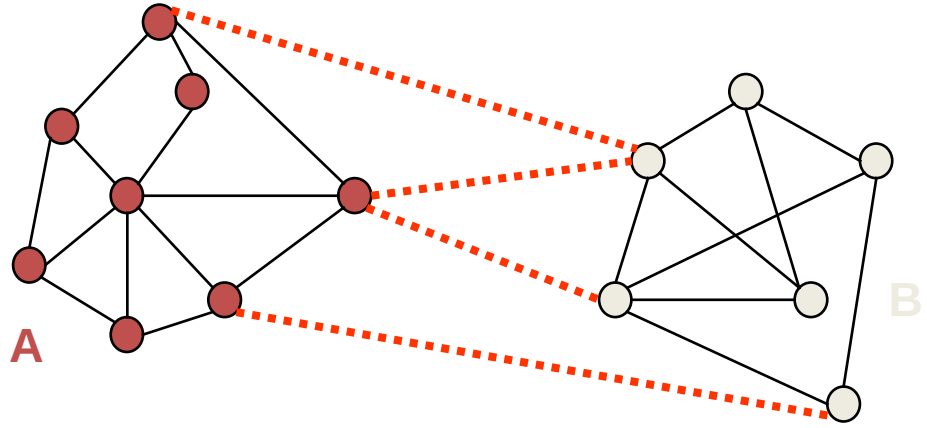


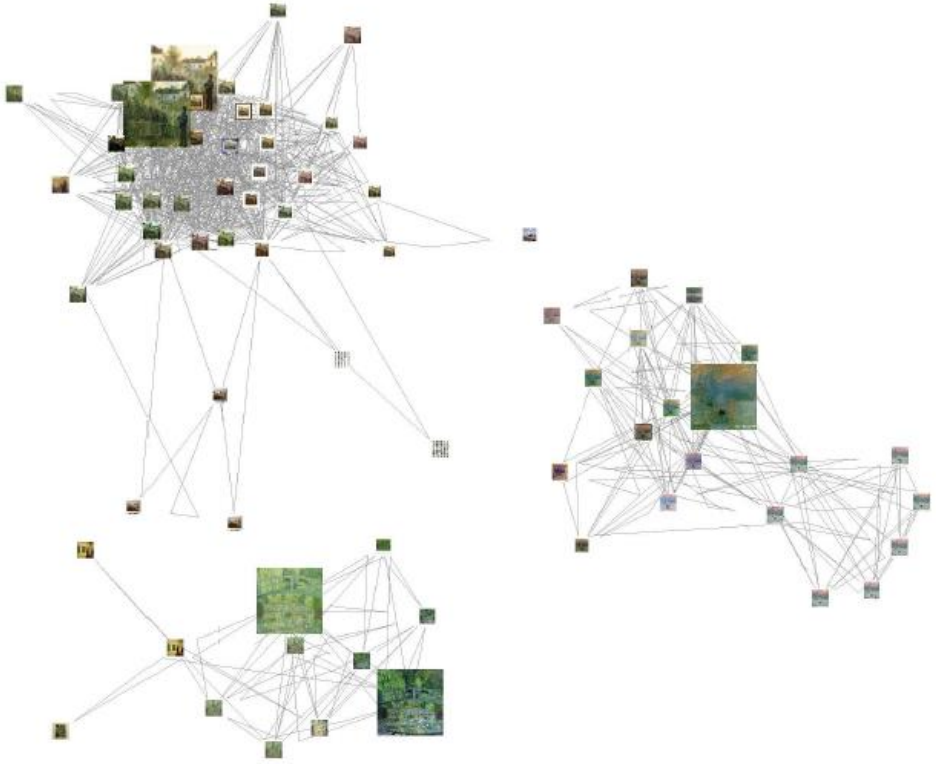



# Spectral clustering

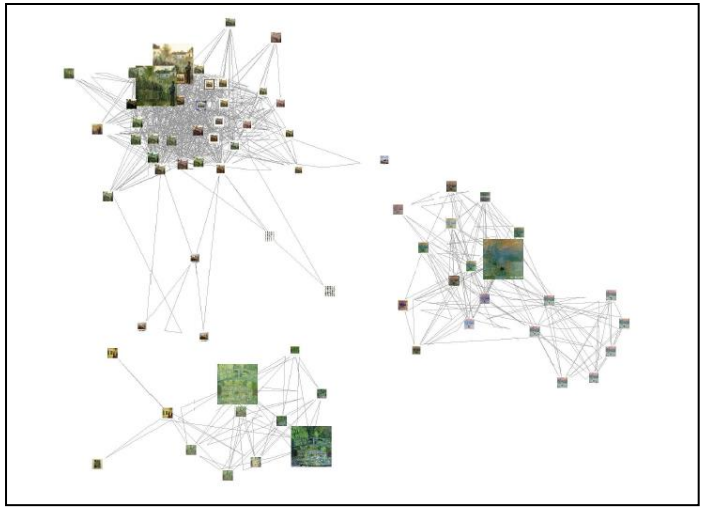
## Group points based on links in a graph

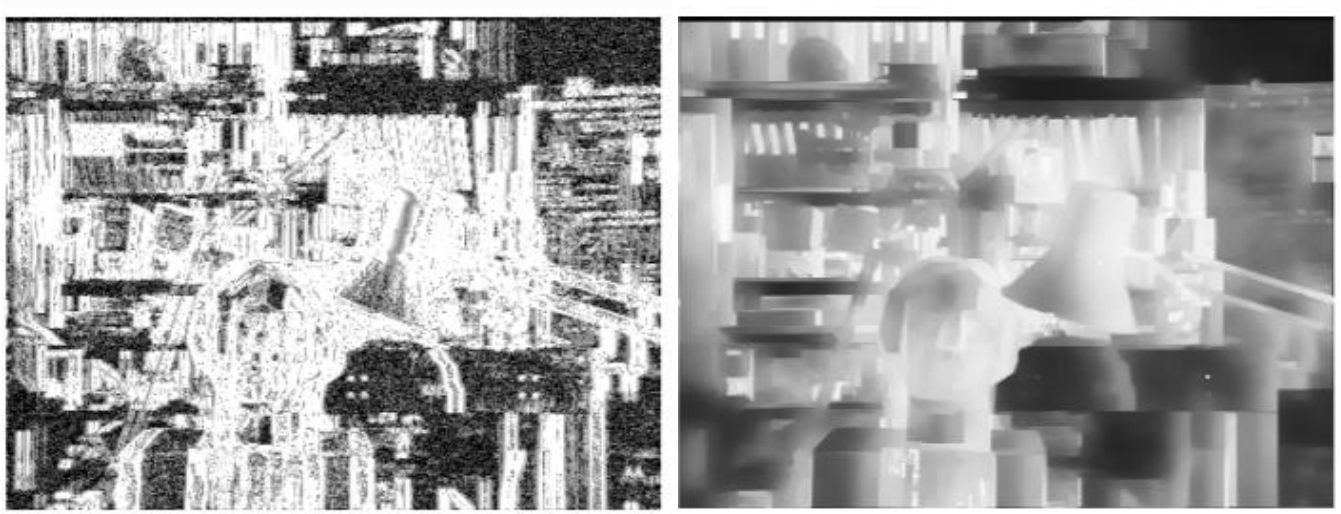


# Visual PageRank

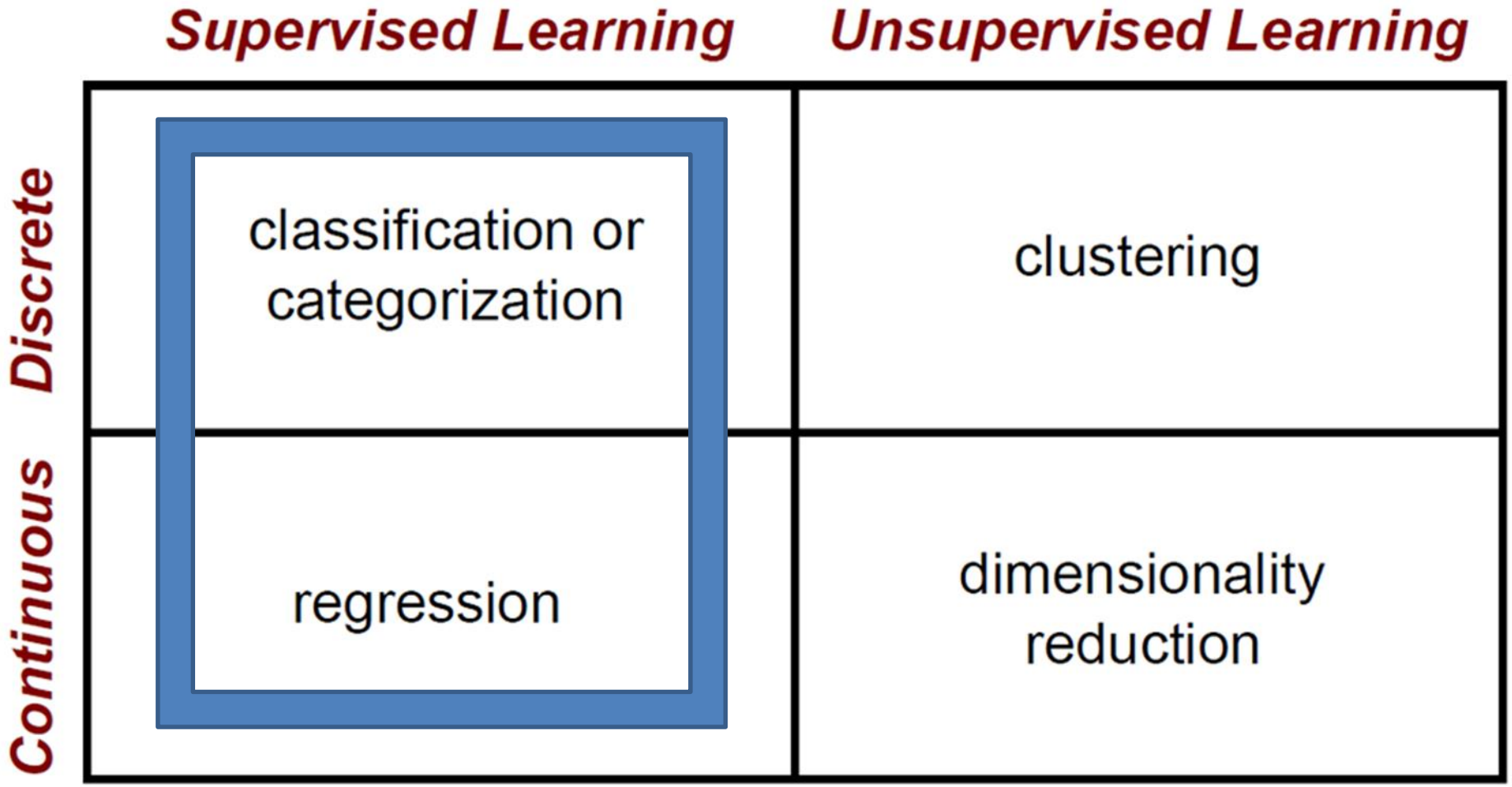
- **Determining importance by random walk**
  - What's the probability that you will randomly walk to a given node?
    - Create adjacency matrix based on visual similarity
    - Edge weights determine probability of transition





C. Oh et al., Probabilistic Correspondence Matching using Random Walk with Restart, BMVC 2012

# Machine learning problems



# The machine learning framework

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

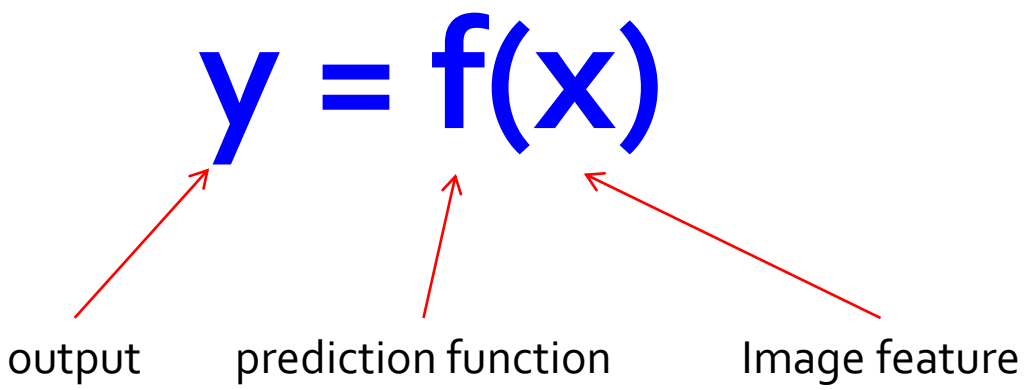
f(  ) = "apple"

f(  ) = "tomato"

f(  ) = "cow"

Slide credit: L. Lazebnik

# Machine learning framework




- **Training:** given a *training set* of labeled examples $\{(x_1,y_1), \ldots, (x_N,y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set
- **Testing:** apply f to a never before seen *test example* x and output the predicted value y = f(x)

# Machine learning framework


*Training*

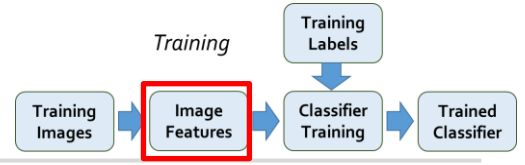
Training Labels

Training Images → Image Features → Classifier Training → Trained Classifier

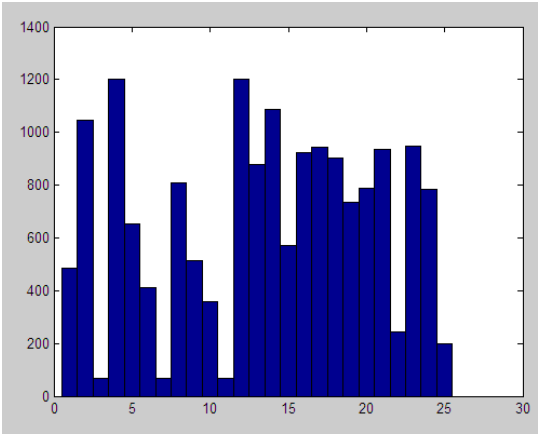
Test Image → Image Features → Trained Classifier → Prediction "Cat"

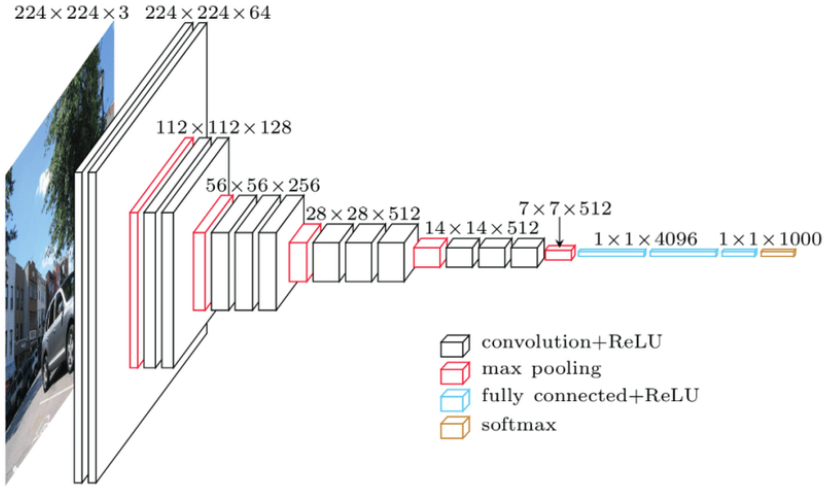
*Testing*

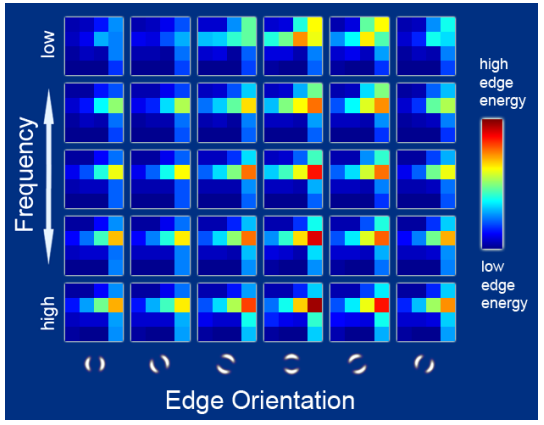
# Features



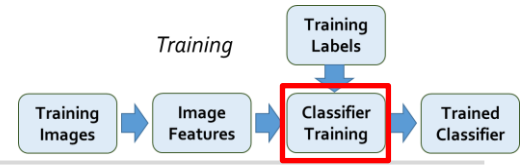

- Raw pixels
- Histograms
- GIST descriptors
- CNNs
- …



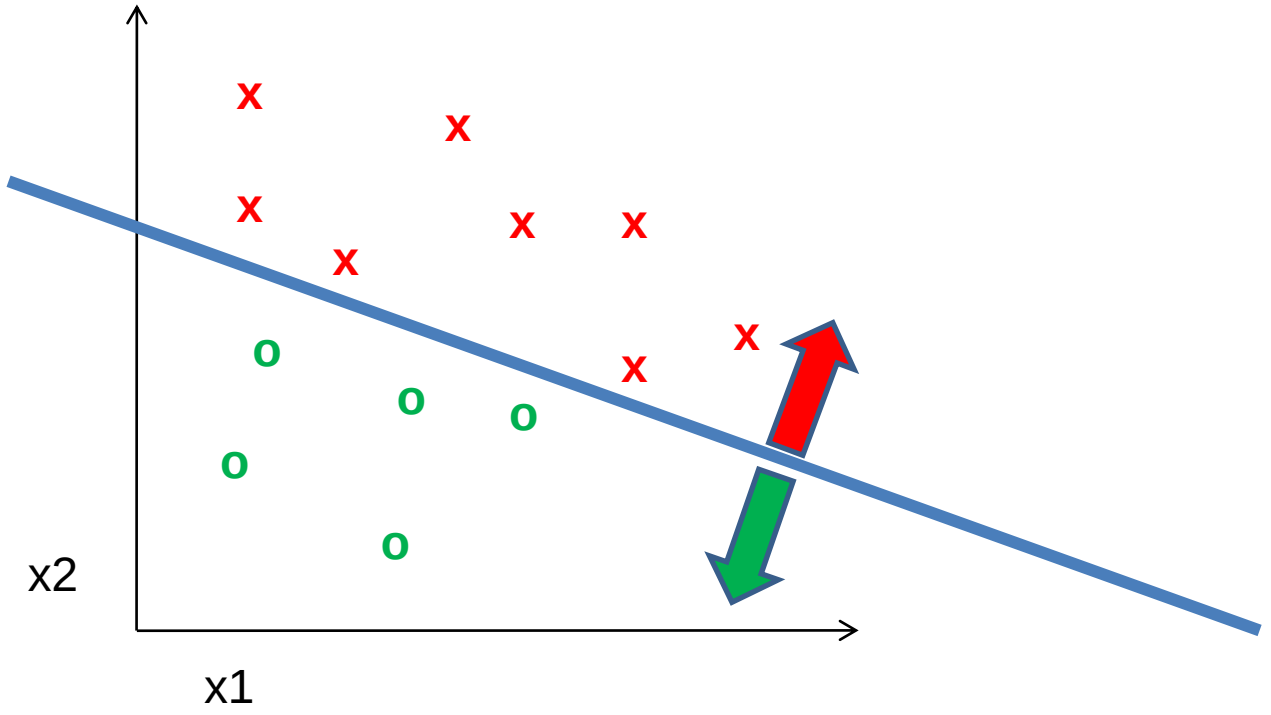



# Learning a classifier



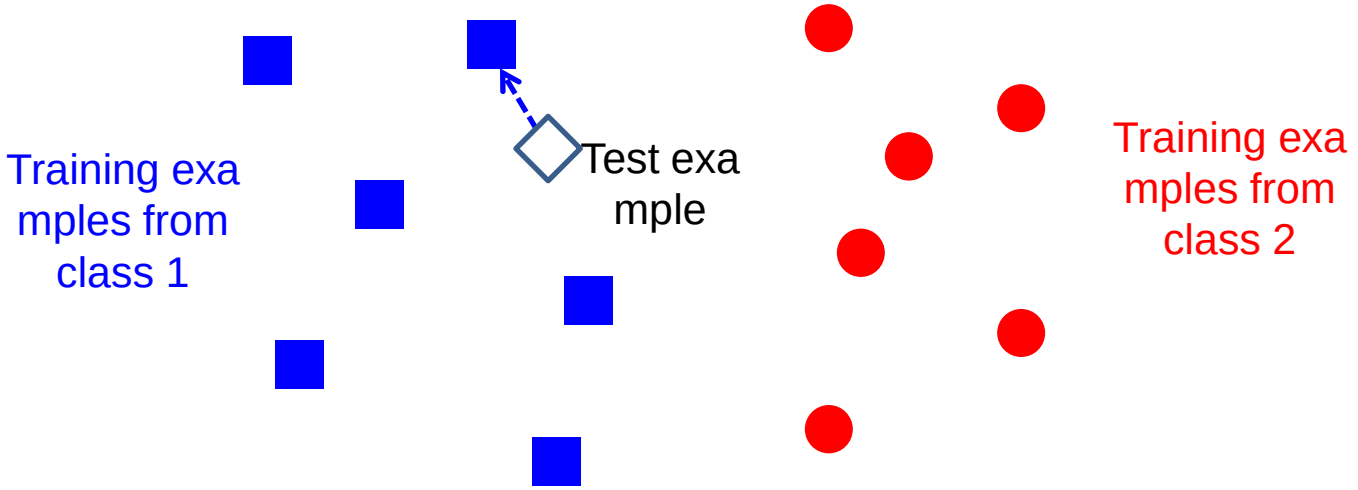

- Given some set of features with corresponding labels, learn **a function to p redict the labels from the features**



# Many classifiers to choose from

- SVM
- Neural networks
- Naïve Bayes
- K-nearest neighbour
- Bayesian network
- Logistic regression
- Randomized Forests
- Boosted Decision Trees
- RBMs
- Deep Convolutional Network
- Etc.

# Classifiers: Nearest neighbor

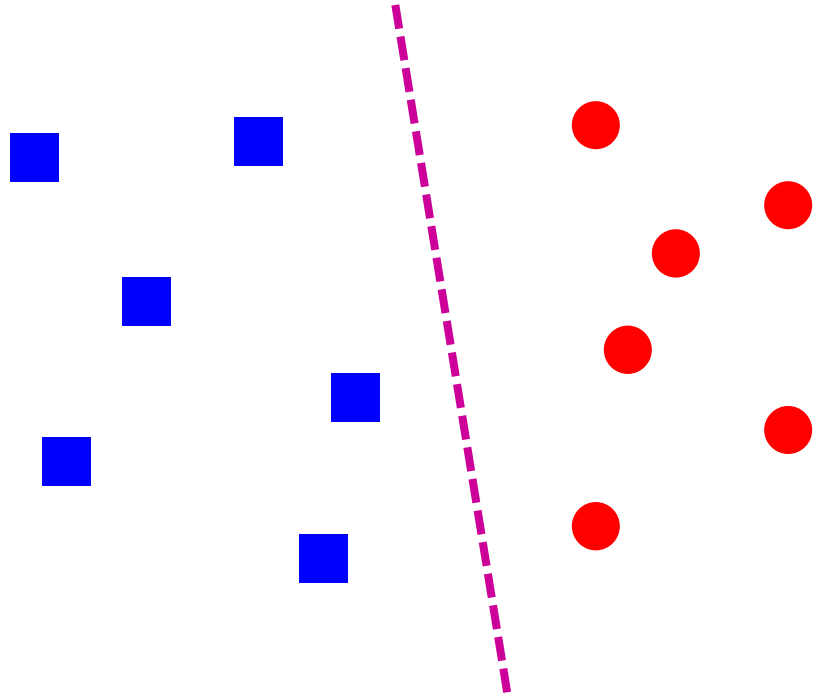



**f(x) = label of the training example nearest to x**

- **All we need is a distance function for our inputs**
- **No training required!**

Slide credit: S. Lazebnik

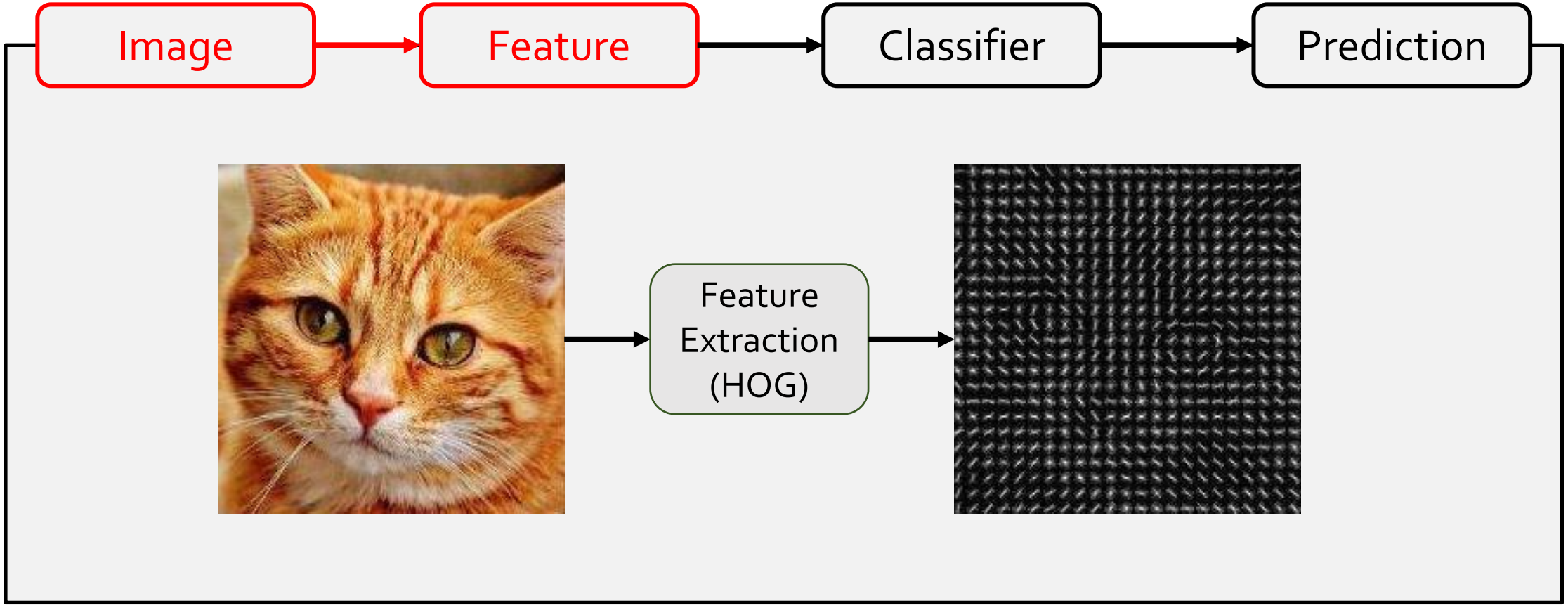
# Classifiers: Linear



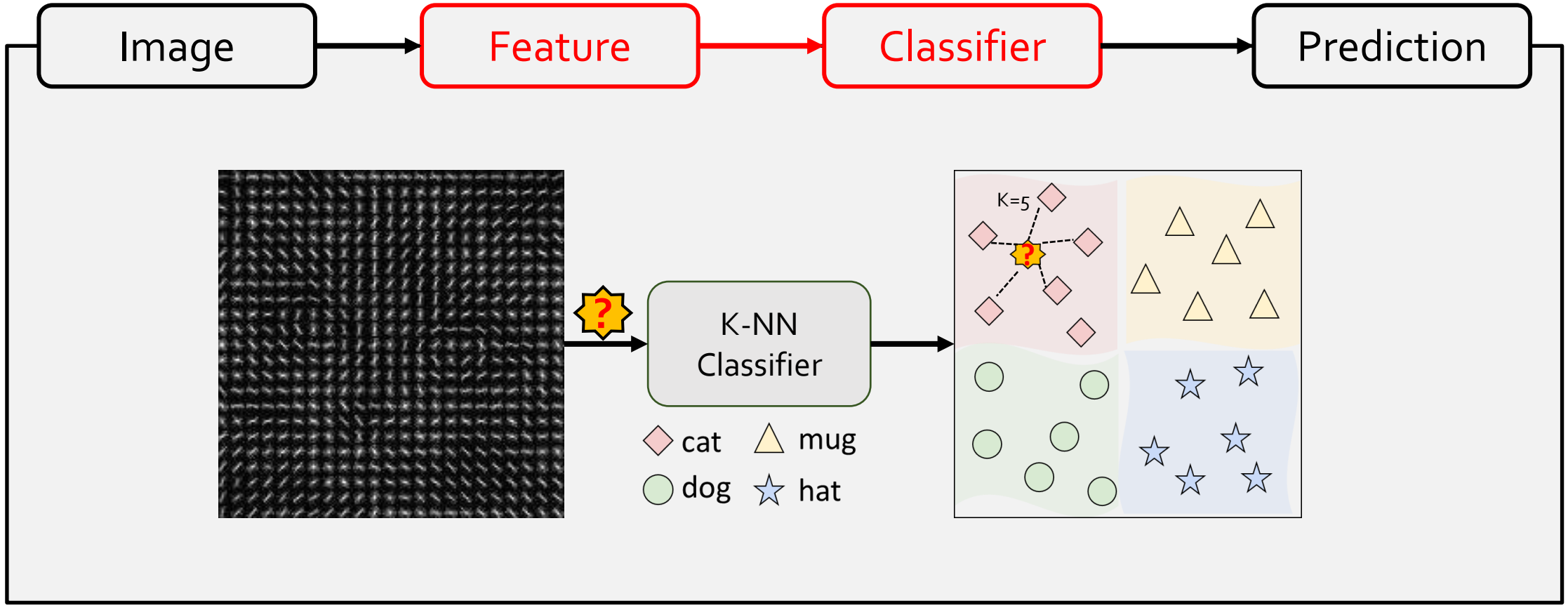
- Find a *linear function* to separate the classes:

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

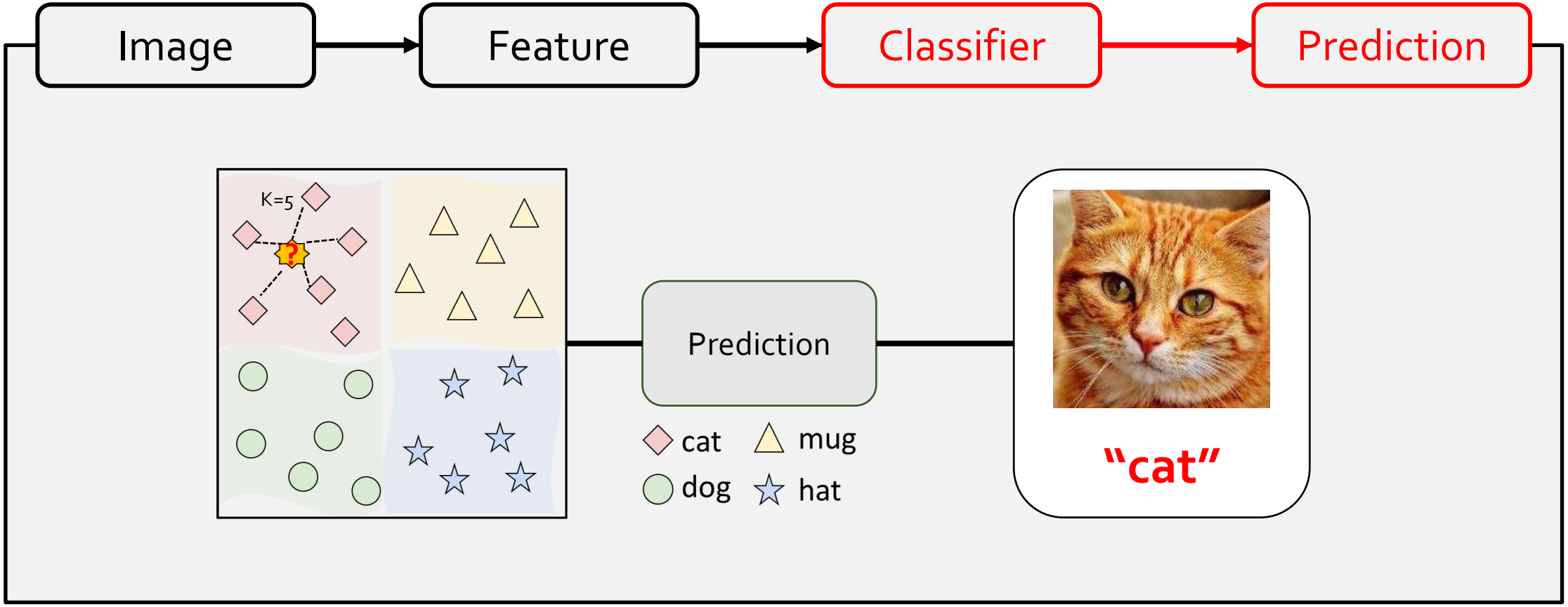
# Example: Image Classification by K-NN



# Example: Image Classification by K-NN



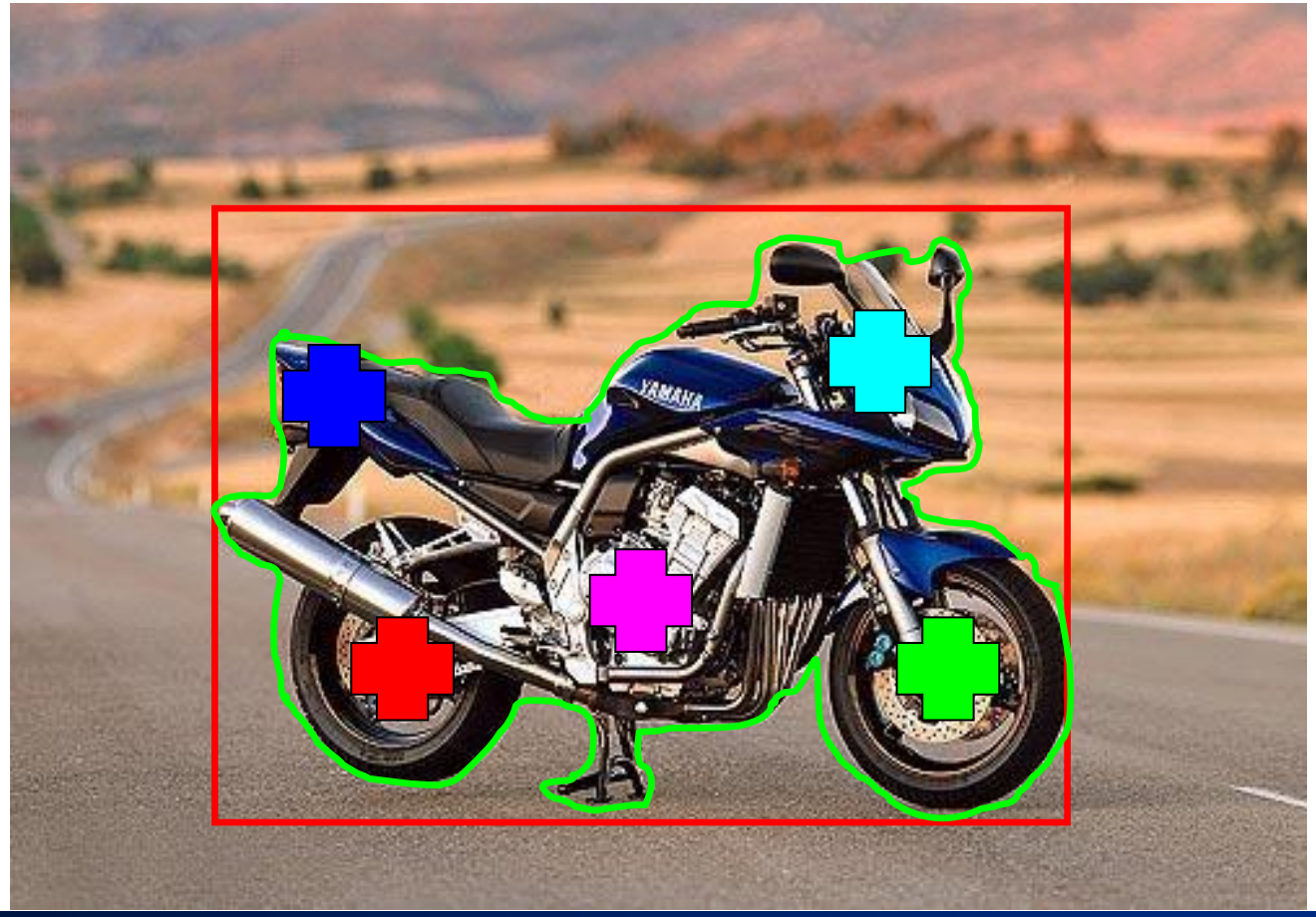
# Example: Image Classification by K-NN



# Recognition task and supervision

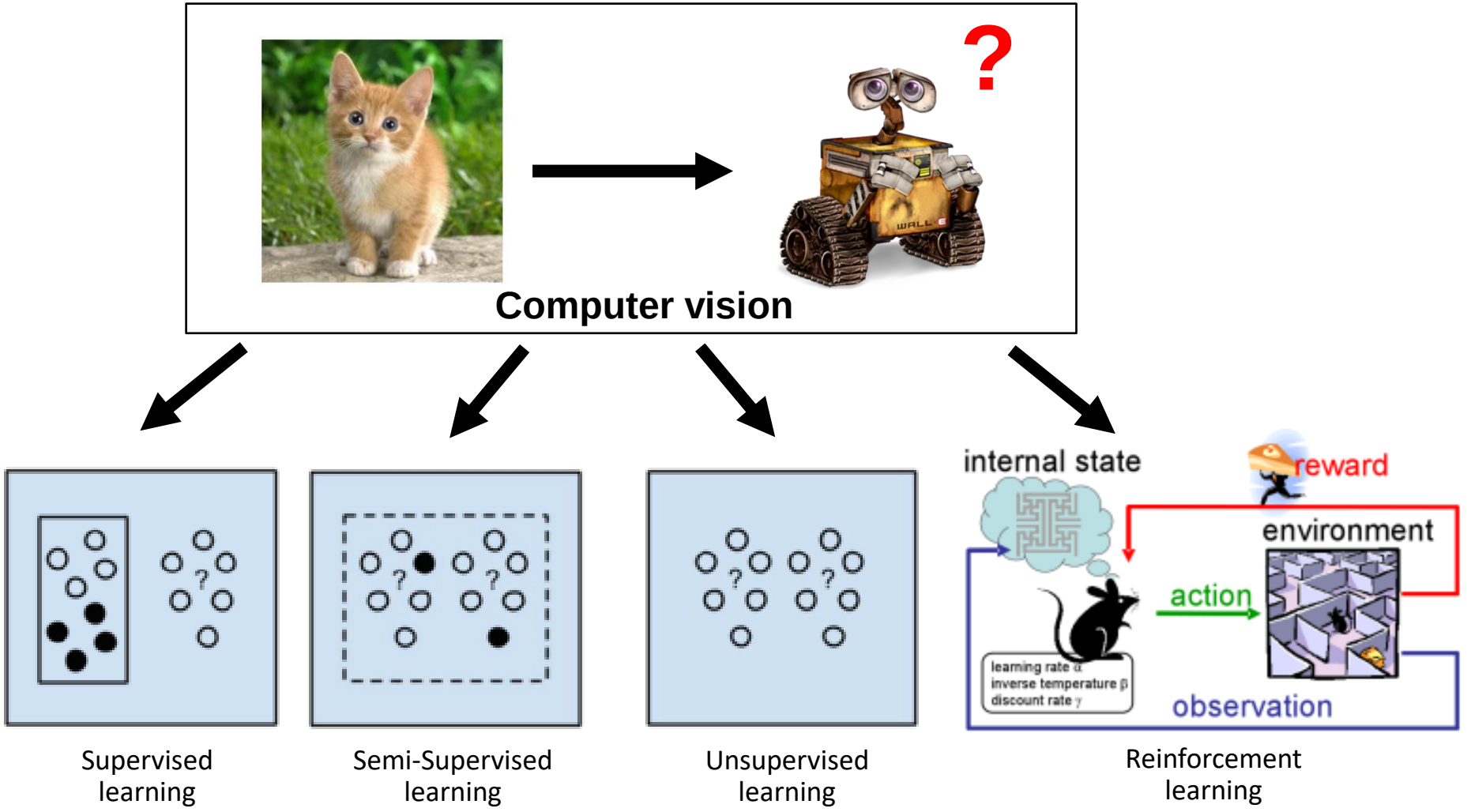
- Images in the training set must be annotated with the "**correct answer**" that the model is expected to produce

Contains a motorbike

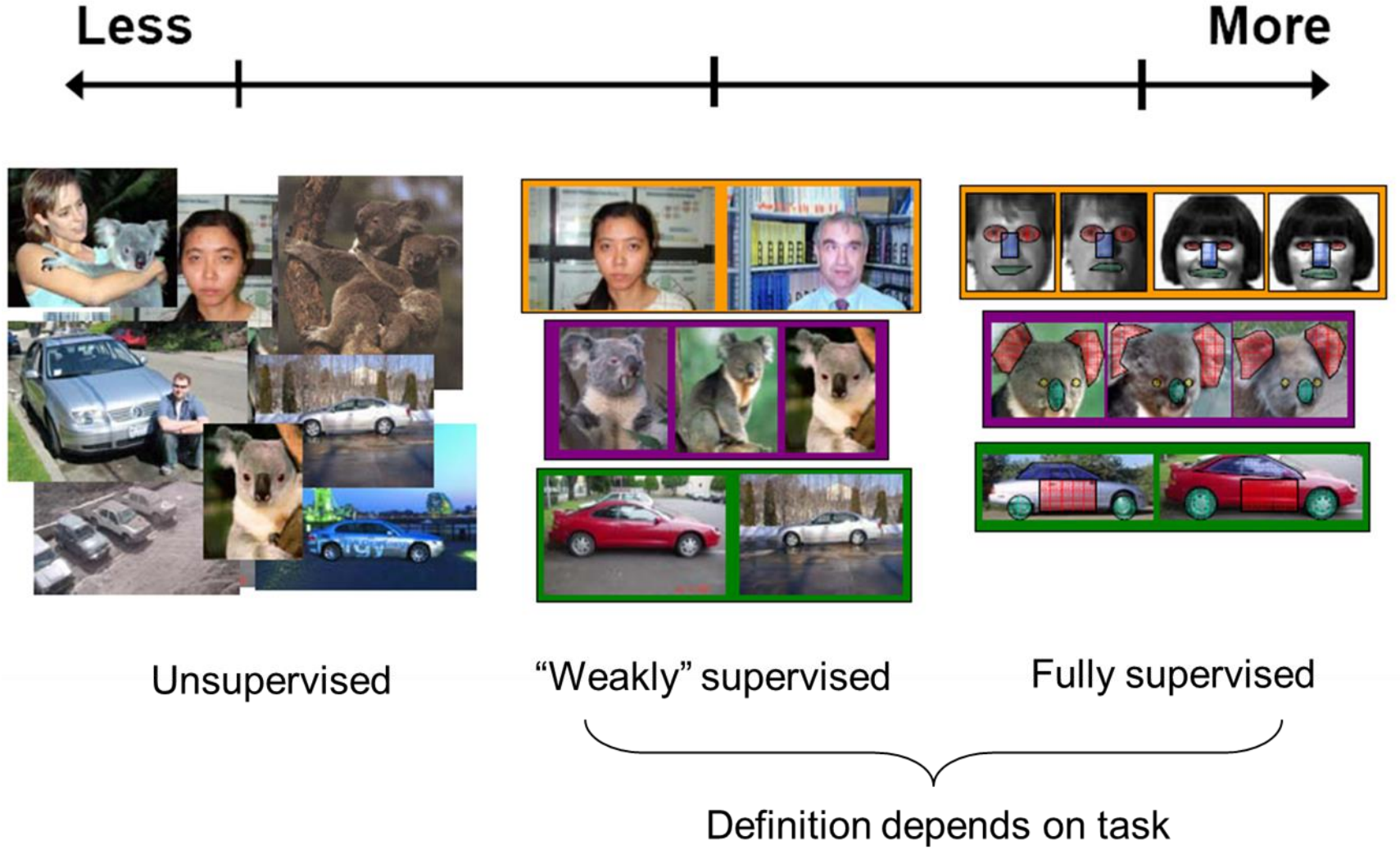



Slide credit: S. Lazebnik

# Spectrum of supervision



# Spectrum of supervision




Slide credit: S. Lazebnik

# Generalisation

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

Training set (labels known)

Test set (labels unknown)

# Generalisation

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

# EBU7240

# Computer Vision

## - Classification -

*Semester 1, 2021*

**Changjae Oh**

# Outline

- **Overview of recognition tasks**
- **A statistical learning approach**
- **"Classic" or "shallow" classification pipeline**
  - "Bag of features" representation
  - Classifiers: nearest neighbor, linear, SVM

# Verification/Classification


Adapted from Fei-fei -Li

# Detection


Adapted from Fei-fei -Li

# Identification


Adapted from Fei-fei -Li

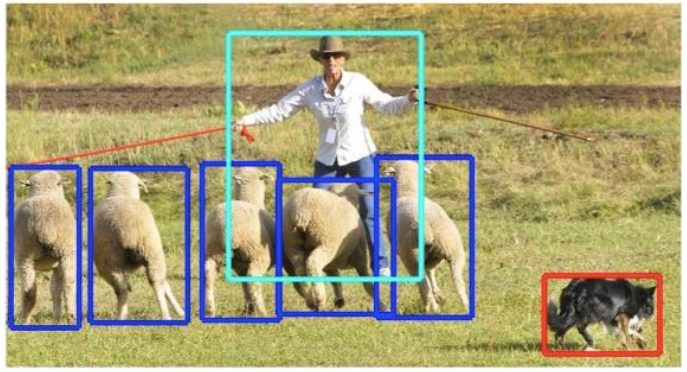
# Semantic Segmentation


Adapted from Fei-fei -Li

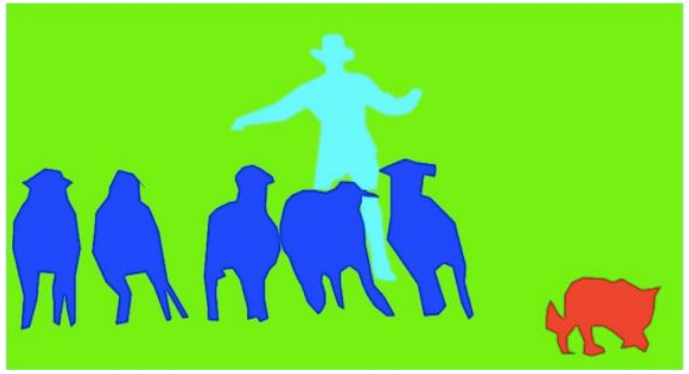
# Object recognition

- A collection of related tasks for identifying objects in digital photographs.
- Consists of recognizing, identifying, and locating objects within a picture with a given de gree of confidence.

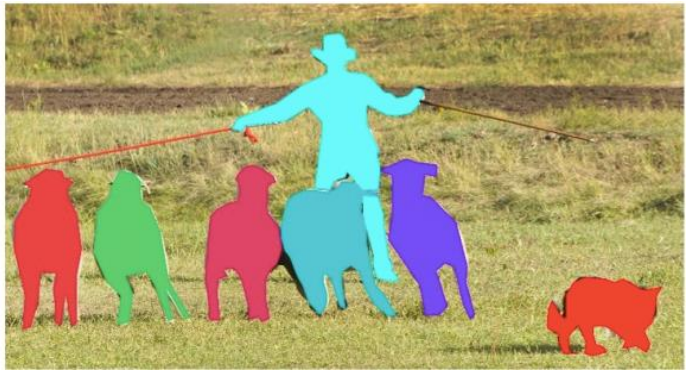

image classification



object detection



semantic segmentation



instance segmentation

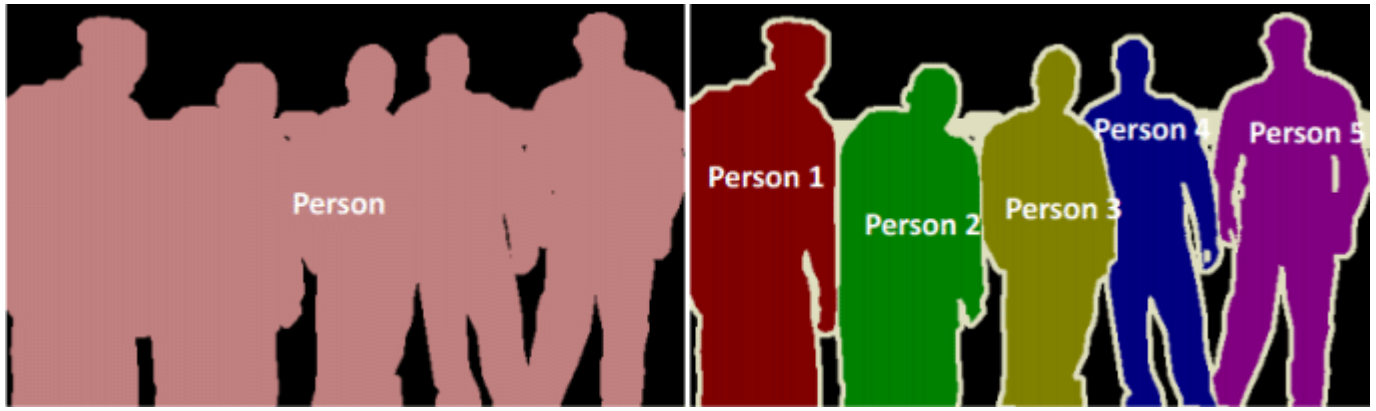
Image source

# Image classification vs Object detection

- **Image classification**
  - Identifying what is in the image and the associated level of confidence.
  - can be binary label or multi-label classification
- **Object detection**
  - Localising and classifying one or more objects in an image
  - Object localisation and image classification

# Semantic segmentation vs Instance segmentation

- **Semantic segmentation**
  - Assigning a label to every pixel in the image.
  - Treating multiple objects of the same class as a single entity
- **Instance segmentation**
  - Similar process as semantic segmentation, but identifies , for each pixel, the object in stance it belongs to.
  - Treating multiple objects of the same class as distinct individual objects (or instances)
  - typically, instance segmentation is harder than semantic segmentation



# Image classification

# The machine learning framework

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

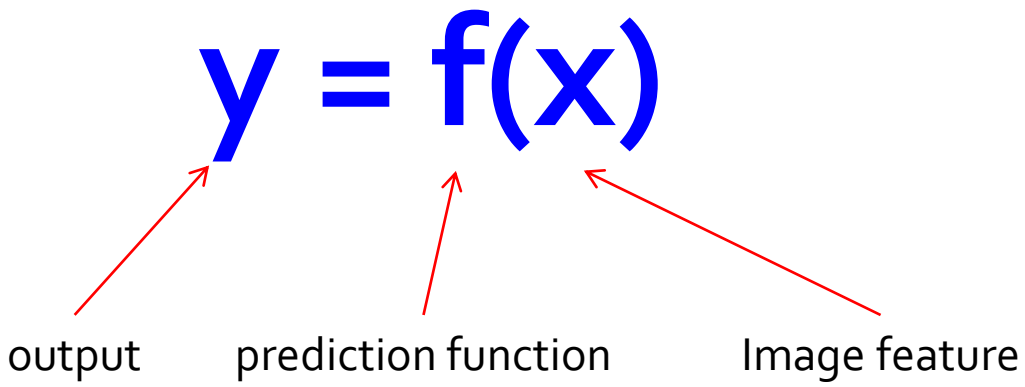
f(  ) = "apple"

f(  ) = "tomato"

f(  ) = "cow"

Slide credit: L. Lazebnik

# Machine learning framework




- **Training:** given a *training set* of labeled examples $\{(x_1,y_1), \ldots, (x_N,y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set
- **Testing:** apply f to a never before seen *test example* x and output the predicted value y = f(x)

Slide credit: S. Lazebnik

# Machine learning framework


*Training*

Training Labels

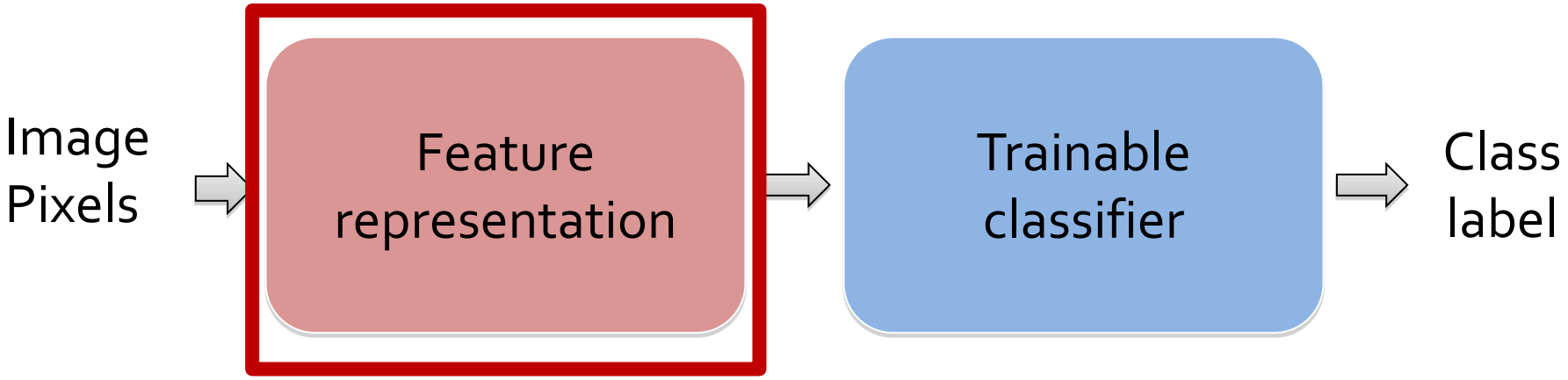
Training Images → Image Features → Classifier Training → Trained Classifier

Test Image → Image Features → Trained Classifier → Prediction "Cat"

*Testing*

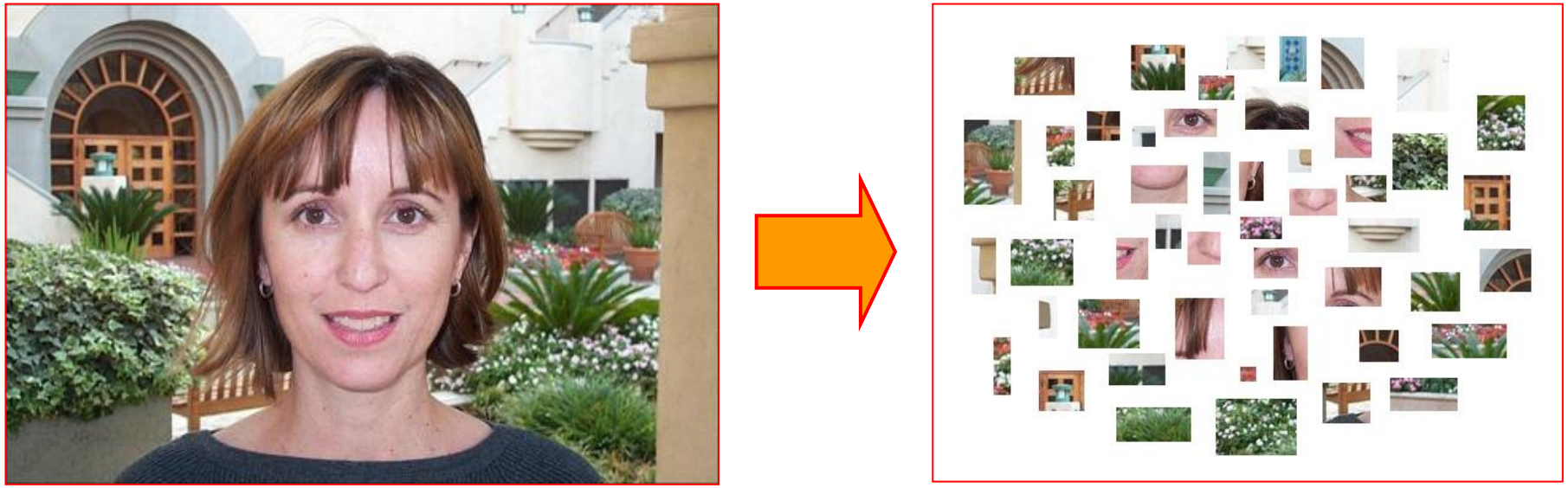
# “Classic” recognition pipeline

- **Hand-crafted feature representation**
- **Off-the-shelf trainable classifier**



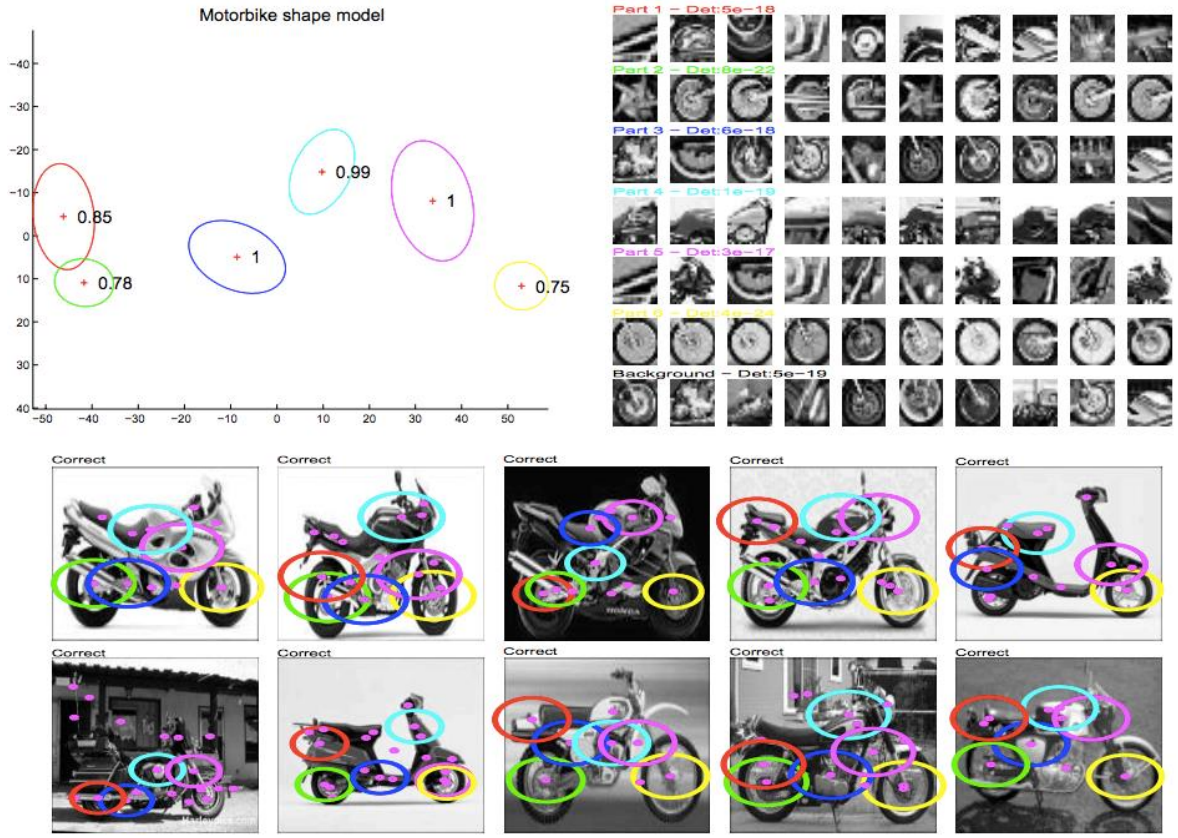
# “Classic” representation: Bag of features

- Representing images as orderless collections of local features



# Motivation 1: Part-based models

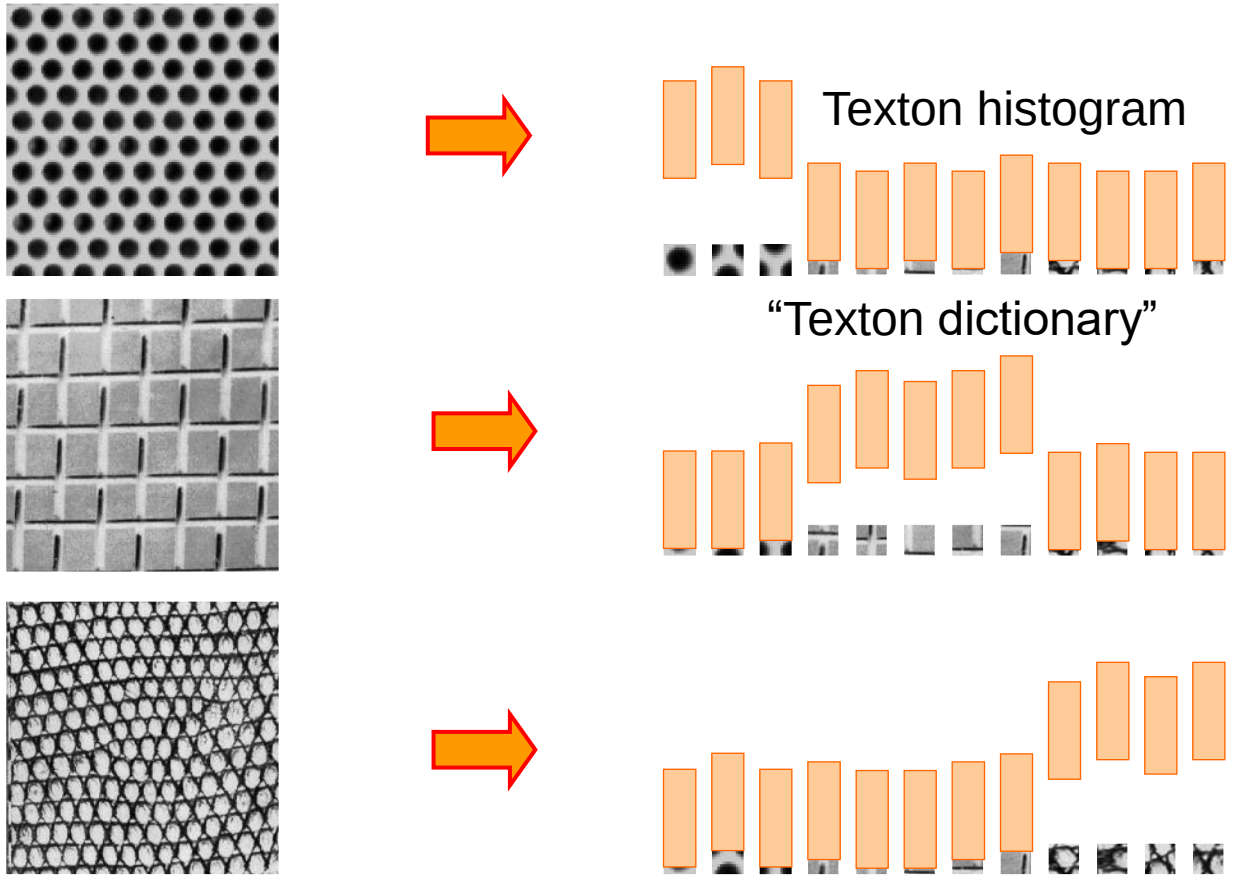
- Various parts of the image are used separately to determine if and wher e an object of interest exists




Weber, Welling & Perona (2000), Fergus, Perona & Zisserman (2003)

# Motivation 2: Texture models

- **Texture is characterised by the repetition of basic elements or textons**




Julesz, 1981; Cula & Dana, 2001; Leung & Malik 2001; Mori, Belongie & Malik, 2001; Schmid 2001; Varma & Zisserman, 2002, 2003; Lazebnik, Schmid & Ponce, 2003

# Motivation 3: Bags of words

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

# Motivation 3: Bags of words

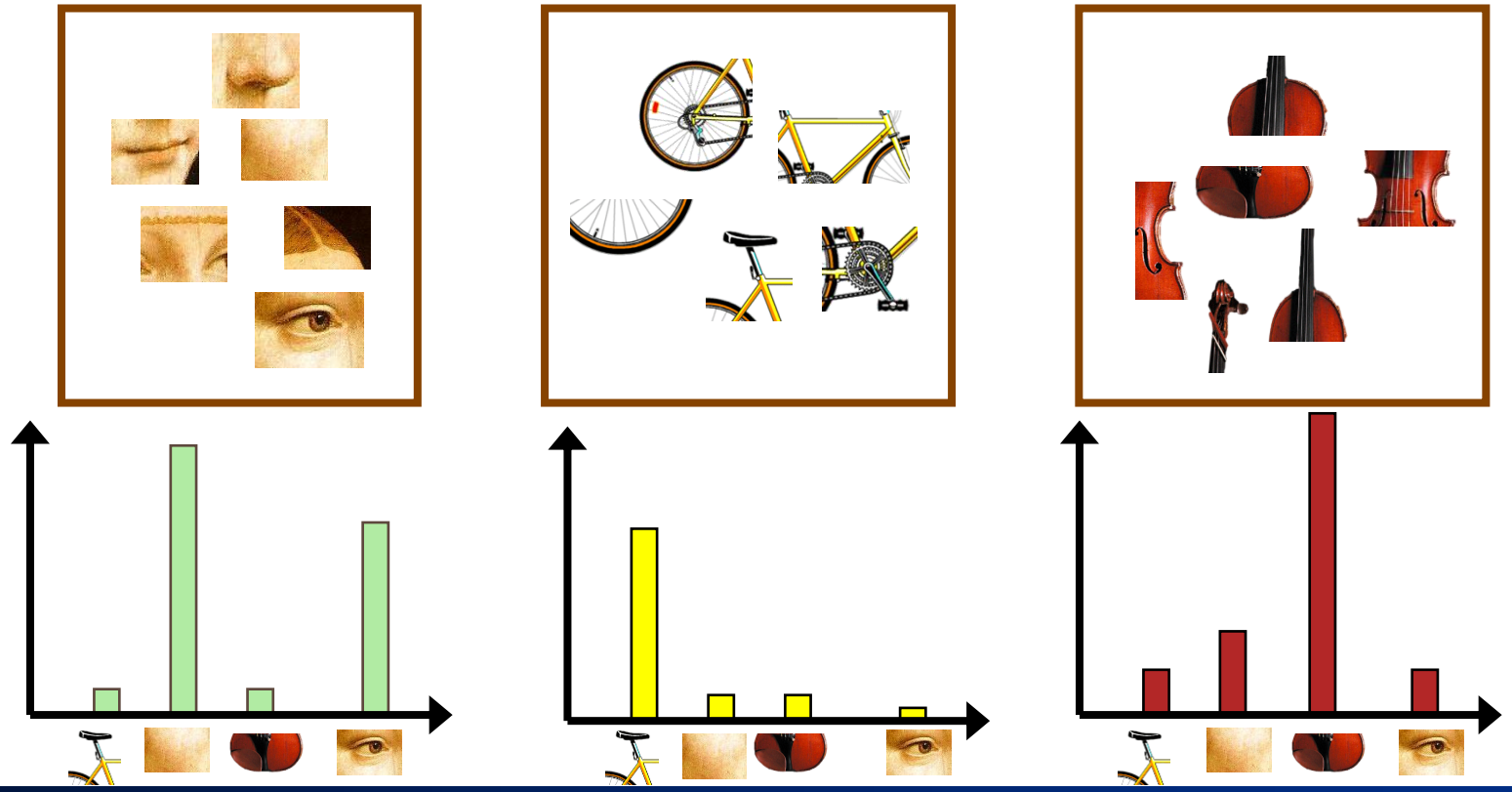
- **Orderless document representation:**
  - Frequencies of words from a dictionary  Salton & McGill (1983)

# Motivation 3: Bags of words

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

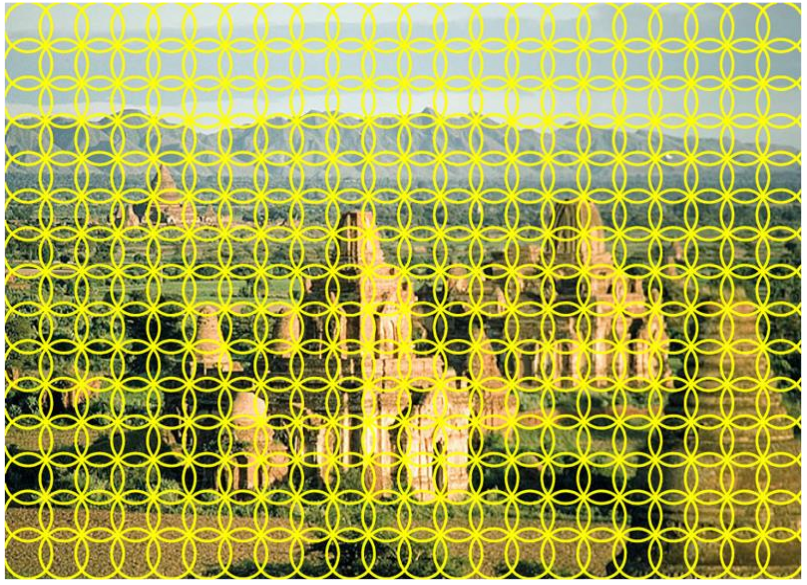
# Bag of features: Outline

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

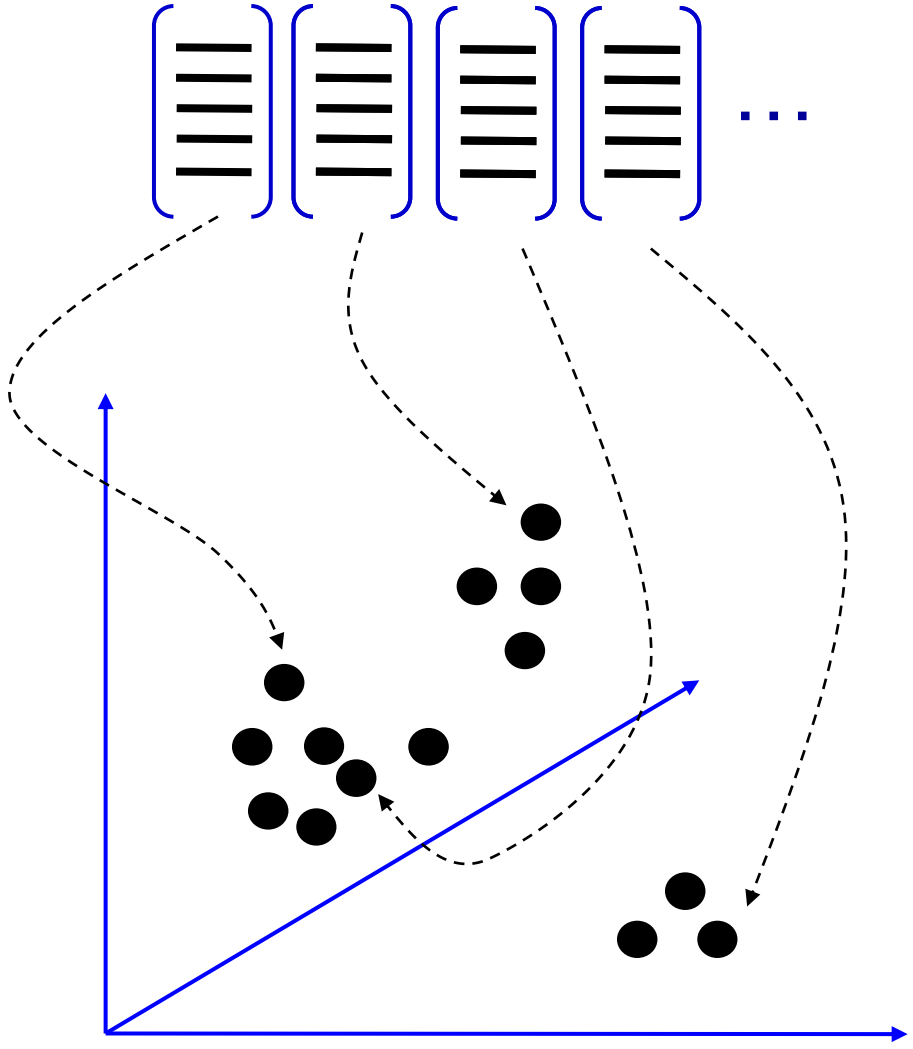


# 1. Local feature extraction

- Sample patches and extract descriptors



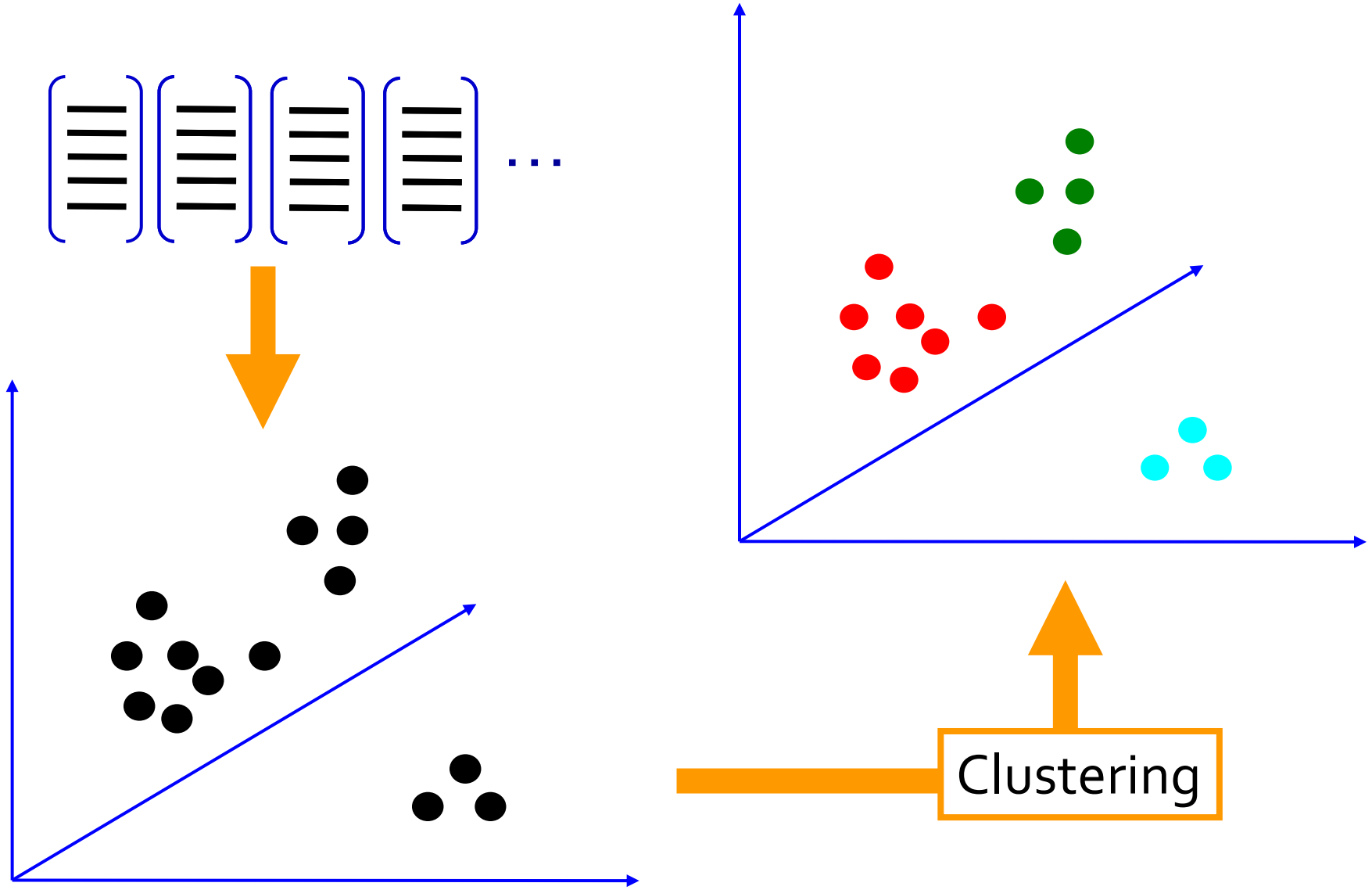
# 2. Learning the visual vocabulary



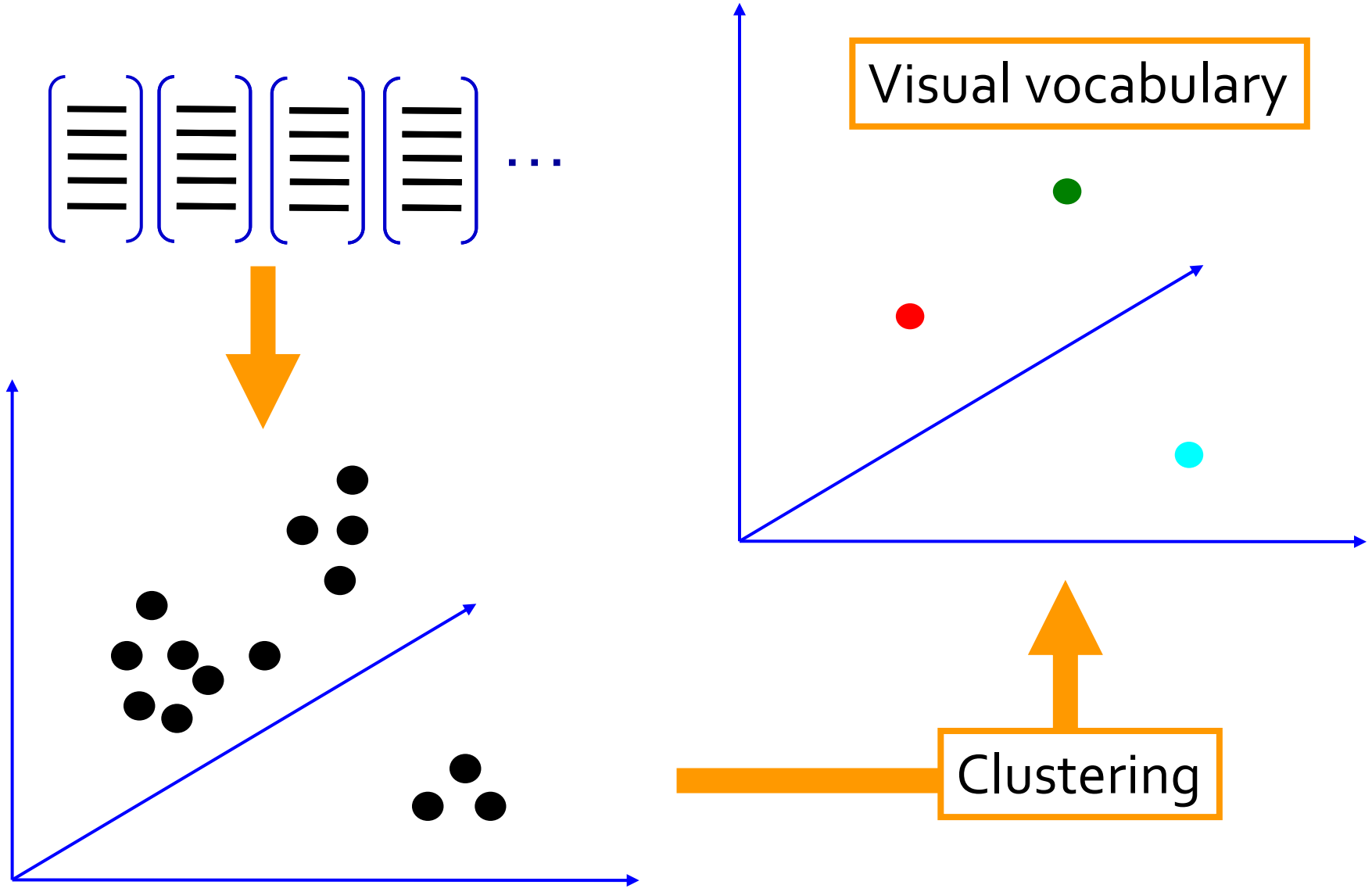
Extracted descriptors from the training set

Slide credit: Josef Sivic

# 2. Learning the visual vocabulary



# 2. Learning the visual vocabulary



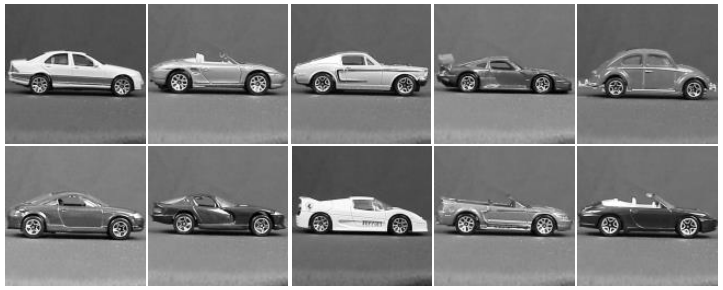
# Recall: K-means clustering

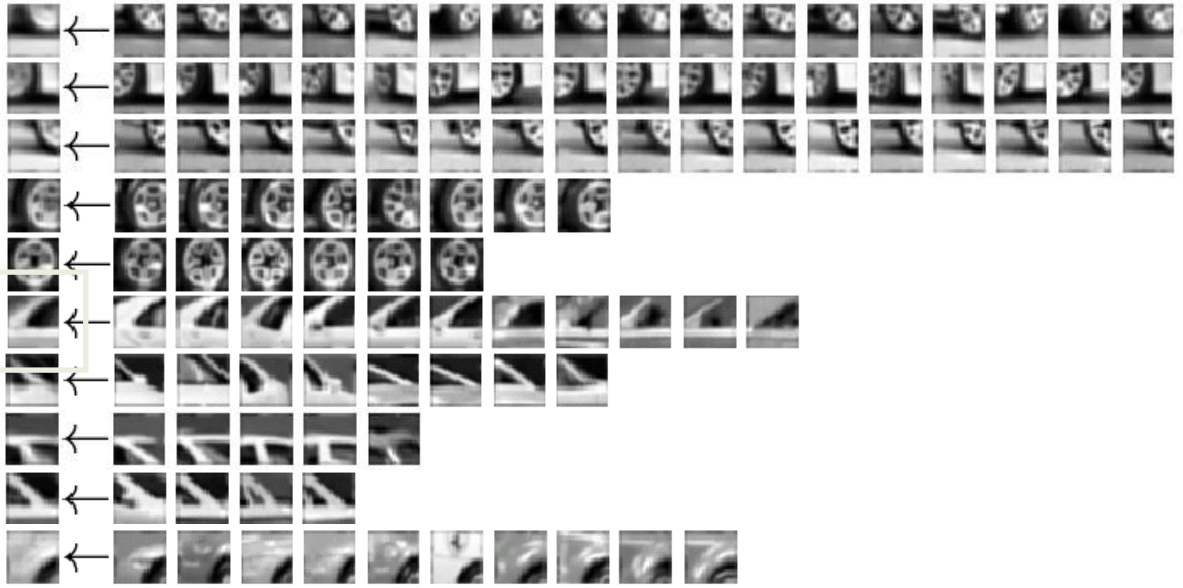
- **Want to minimize sum of squared Euclidean distances between features $x_i$ and their nearest cluster centers $m_k$**

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

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

# Visual vocabularies



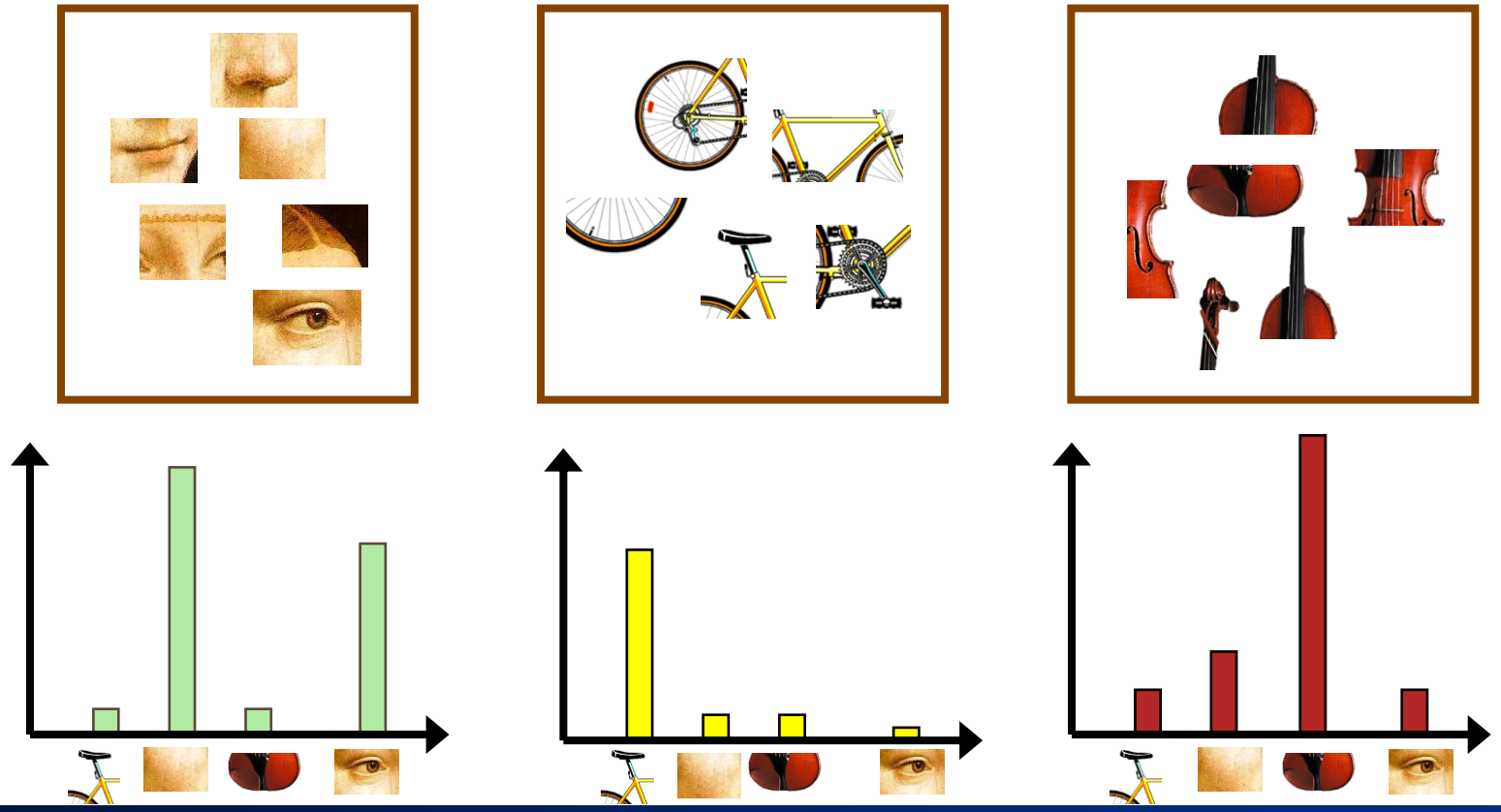


Appearance codebook

Source: B. Leibe

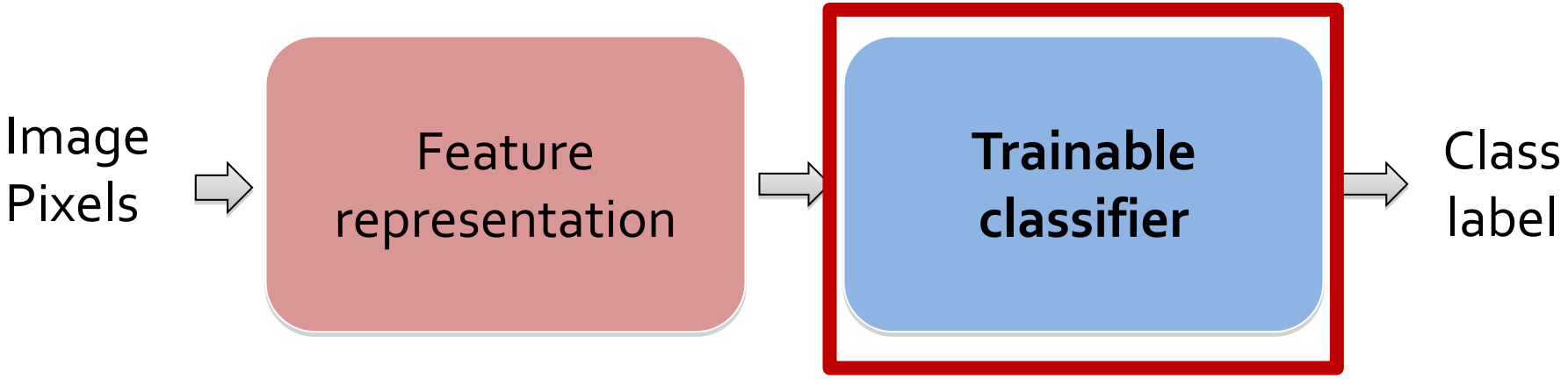
# Bag of features: Outline

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

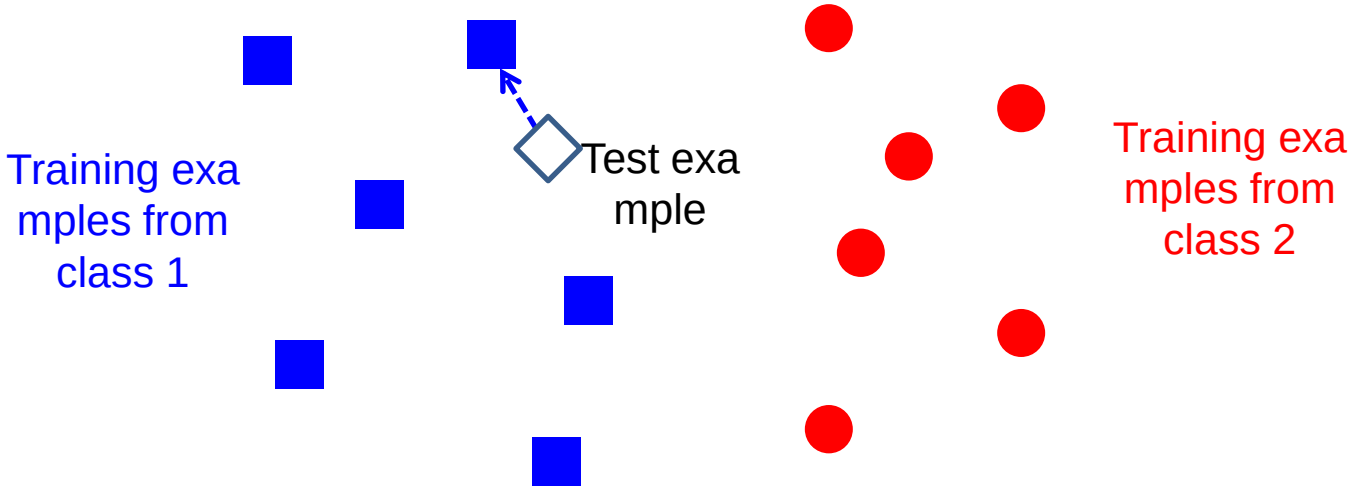


# "Classic" recognition pipeline

- **Hand-crafted feature representation**
- **Trainable classifier**
  - Nearest Neighbor classifiers
  - Support Vector machines



# Classifiers: Nearest neighbor




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

- **All we need is a distance or similarity function for our inputs**
- **No training required!**

# Functions for comparing histograms

- **L1 distance:** $D(h_1, h_2) = \sum_{i=1}^{N} | h_1(i) - h_2(i) |$
- **$\chi^2$ distance:** $D(h_1, h_2) = \sum_{i=1}^{N} \frac{(h_1(i) - h_2(i))^2}{h_1(i) + h_2(i)}$
- **Quadratic distance (*cross-bin distance*):**

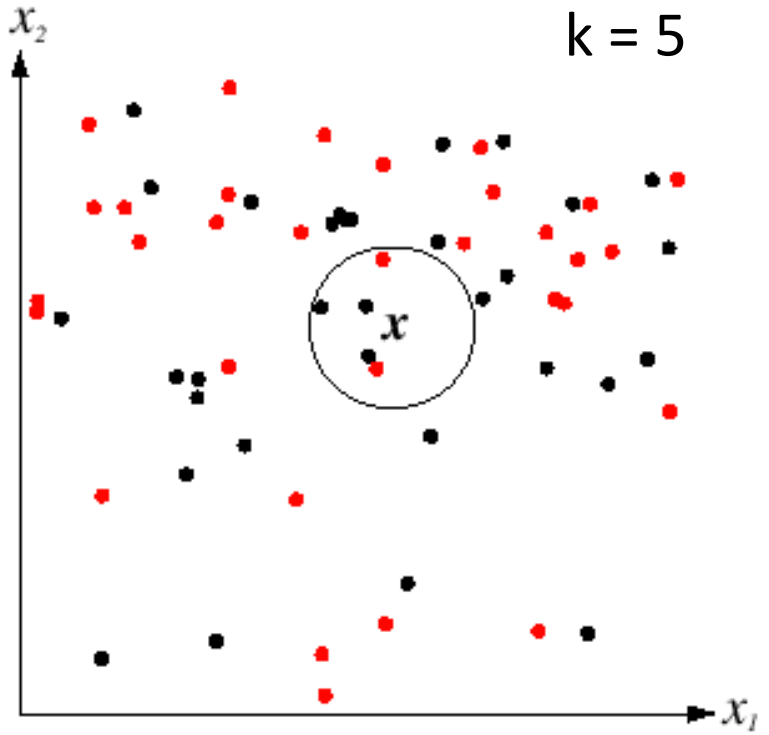
$$D(h_1, h_2) = \sum_{i,j} A_{ij} (h_1(i) - h_2(j))^2$$

- **Histogram intersection (similarity function):**

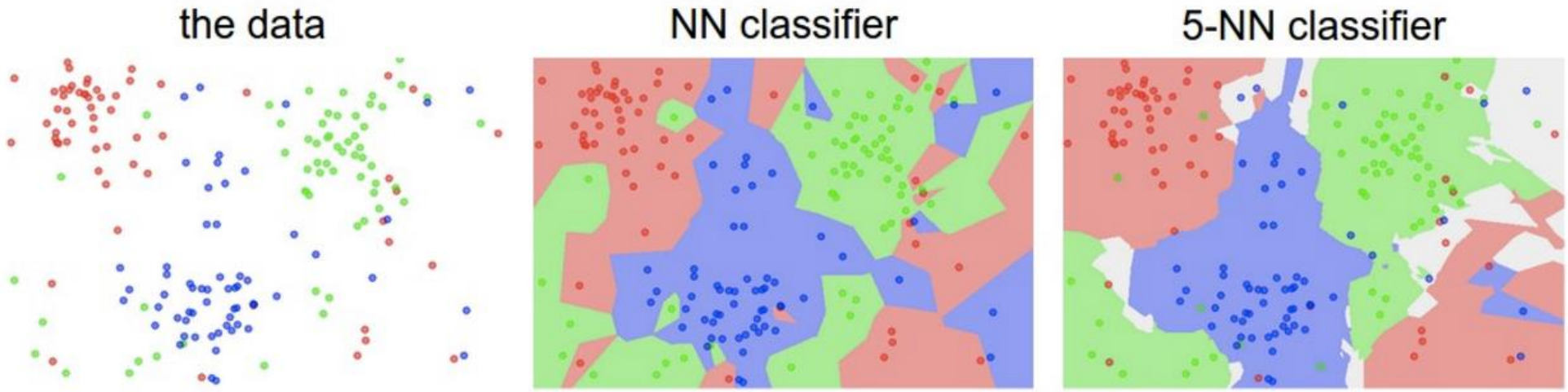
$$I(h_1, h_2) = \sum_{i=1}^{N} \min(h_1(i), h_2(i))$$

# 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



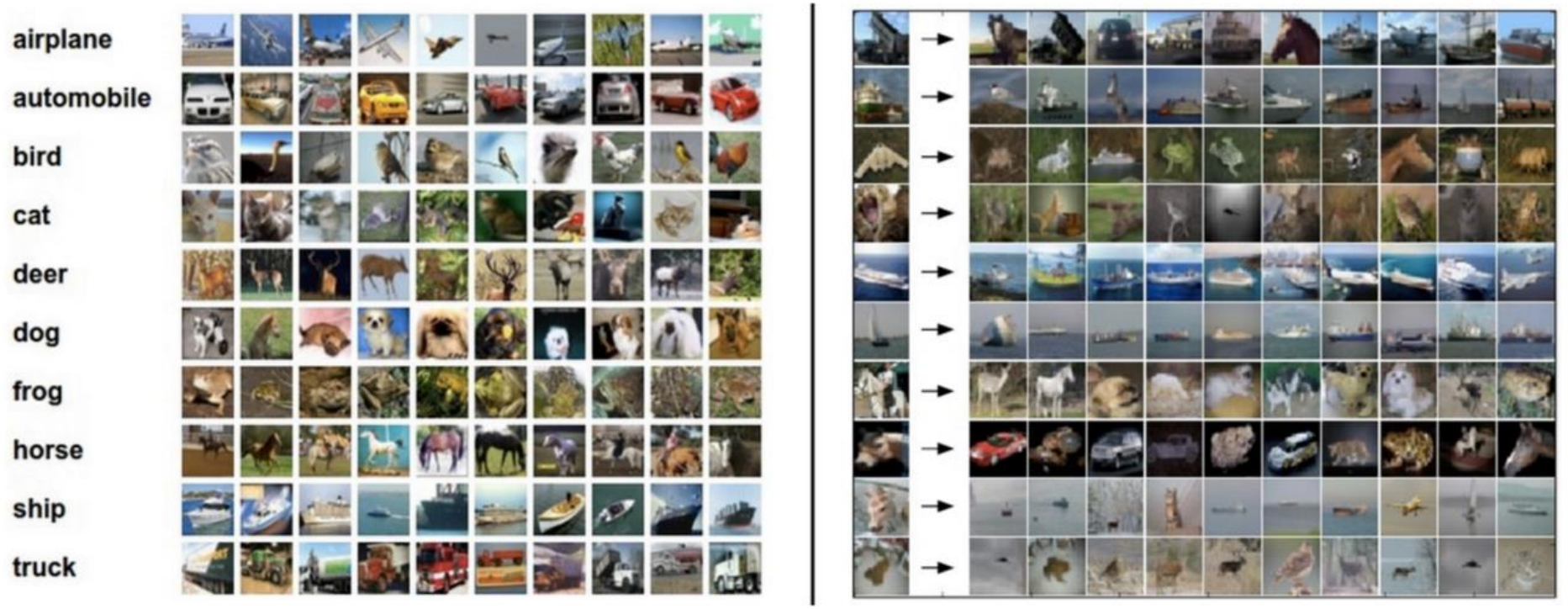
# K-nearest neighbor classifier




- **Which classifier is more robust to *outliers*?**

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

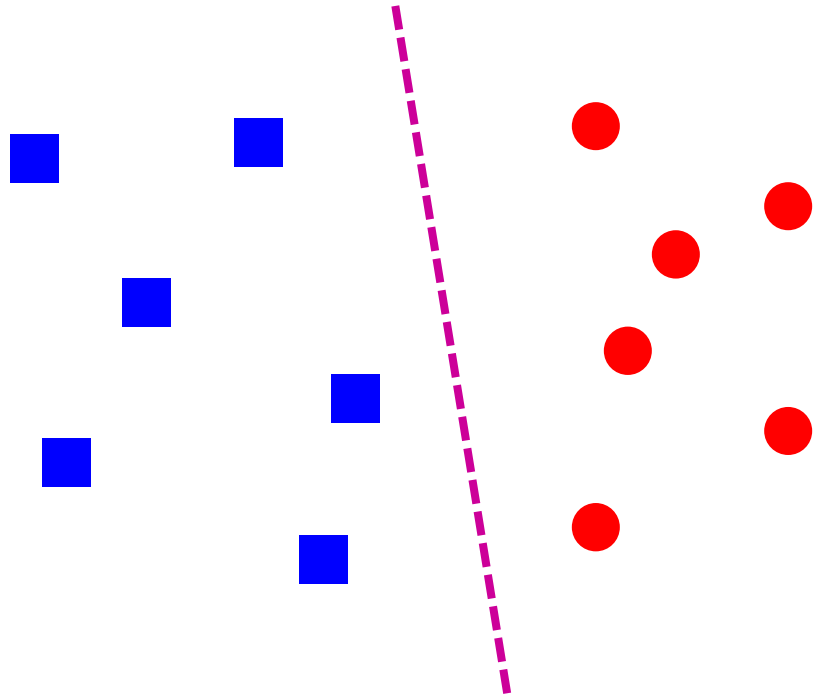
# K-nearest neighbor classifier




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/

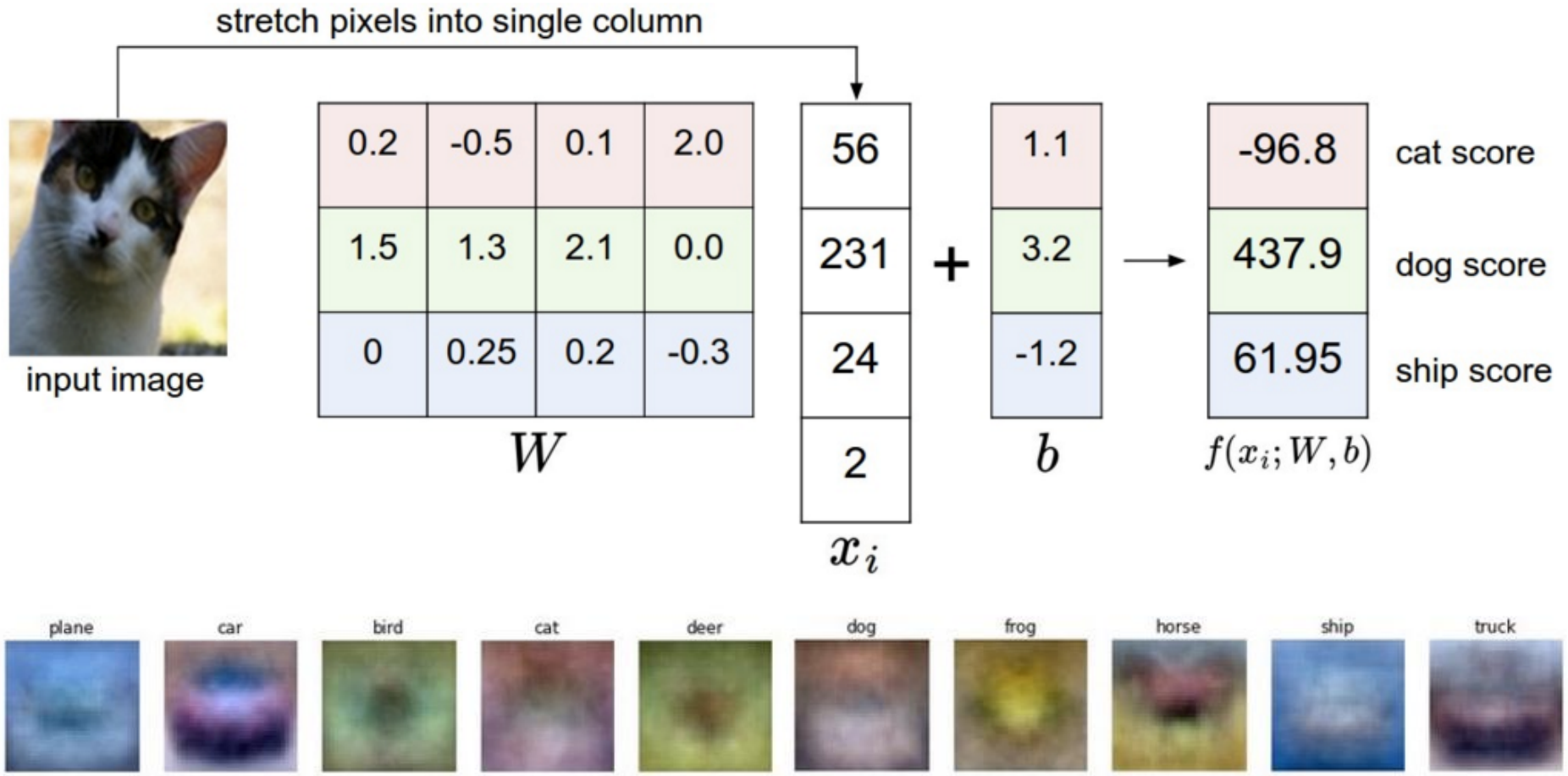
# Linear classifiers



- Find a *linear function* to separate the classes:

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

# Visualizing linear classifiers




Example learned weights at the end of learning for CIFAR-10.

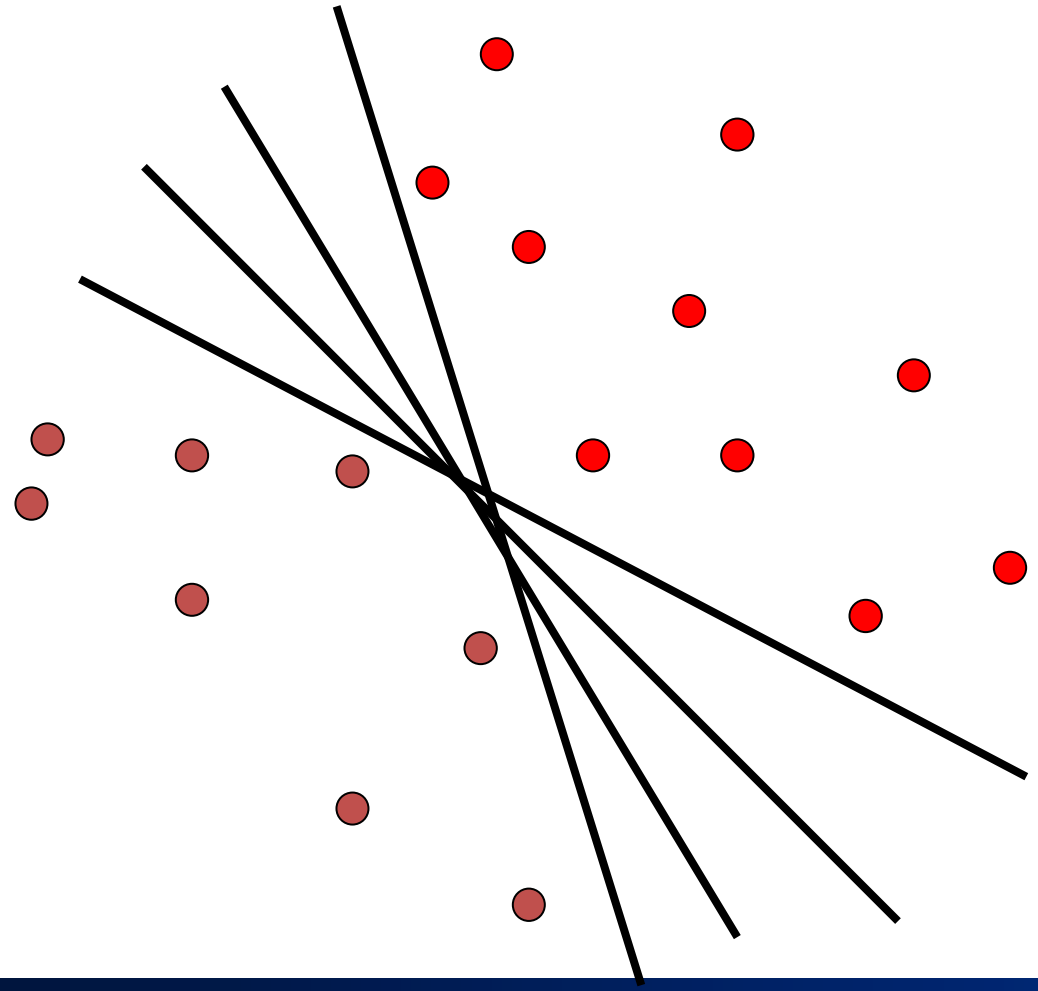
Credit: Andrej Karpathy, http://cs231n.github.io/classification/

# 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?

# Linear classifiers

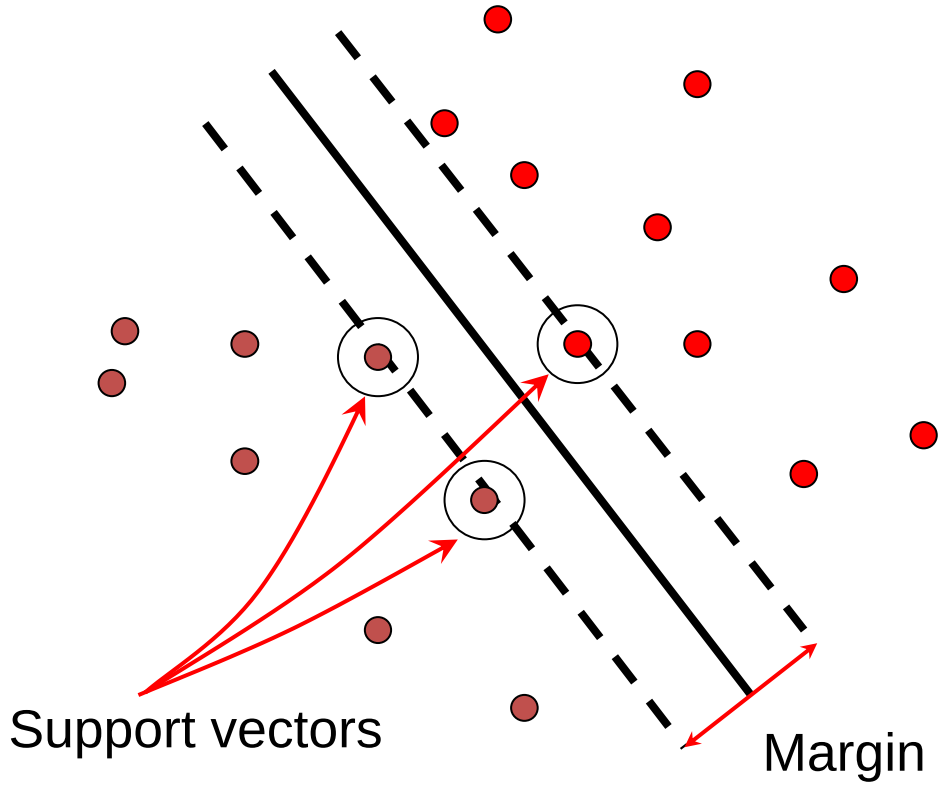
- When the data is linearly separable, there may be more than one separa tor (hyperplane)



Which separator is the best?

# Support vector machines

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




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

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

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

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

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 / ||w||**
2. **Correctly classify all training data:**

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

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

- ***Quadratic optimization problem*:**

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

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

# SVM parameter learning

- **Separable data:**

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

Maximize margin

Classify training data correctly

- **Non-separable data:**

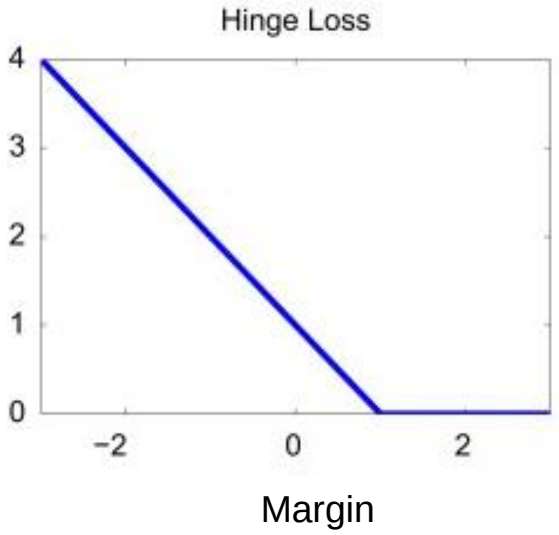
$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n} \max\left(0, 1 - y_i(\mathbf{w}\cdot\mathbf{x}_i + b)\right)$$

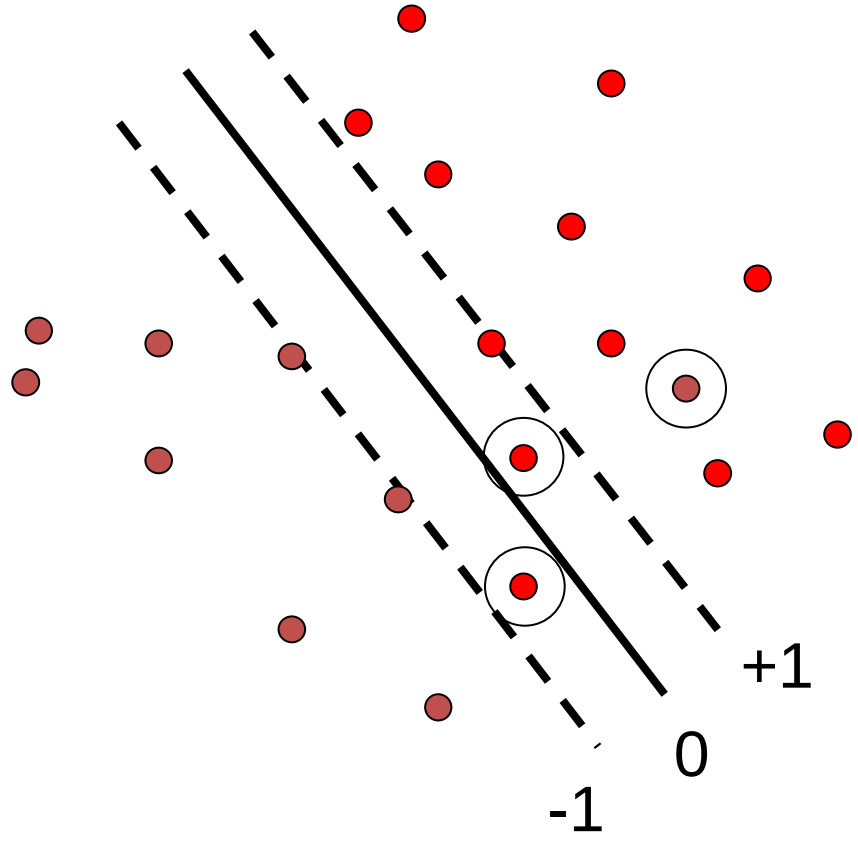
Maximize margin

Minimize classification mistakes

# SVM parameter learning

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

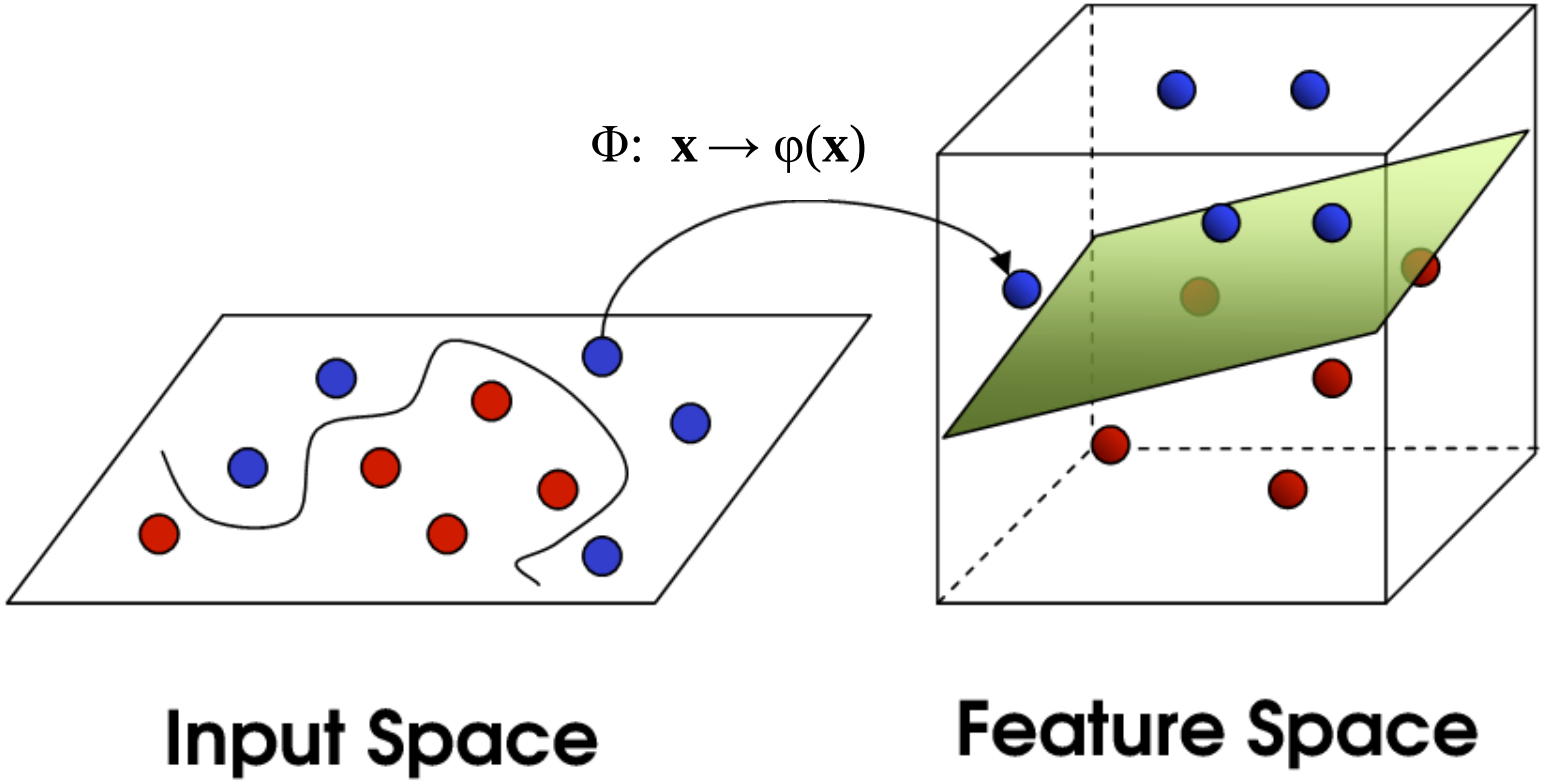



Demo: http://cs.stanford.edu/people/karpathy/svmjs/demo

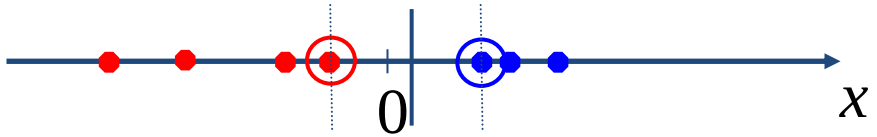
# Nonlinear SVMs

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

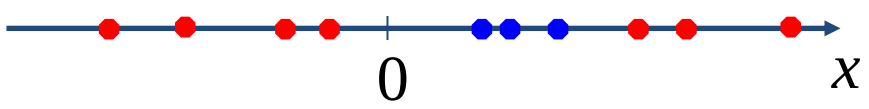


# Nonlinear SVMs

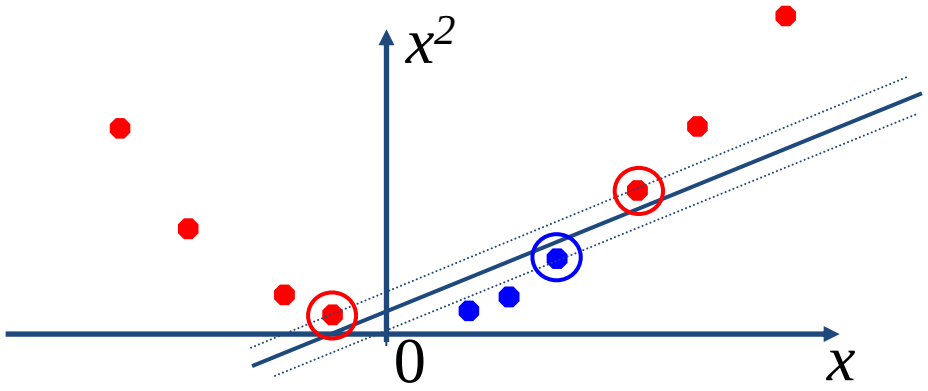
- Linearly separable dataset in 1D:




- Non-separable dataset in 1D:




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



# SVMs: Pros and cons

- **Pros**
  - Non-linear SVM framework is very powerful, flexible
  - Training is convex optimization, globally optimal solution can be found
  - 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)