Object Recognition Model

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Object Recognition in Images

Problem Statement

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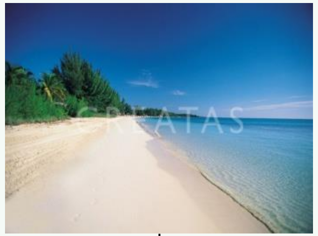
Given: Some images and their corresponding descriptions

{trees, grass, cherry trees}

{cheetah, trunk}

{mountains, sky}



{beach, sky, trees, water}

●●●

To solve: What object classes are present in new images

?

?

?

?

●●●

Image Features for Object Recognition

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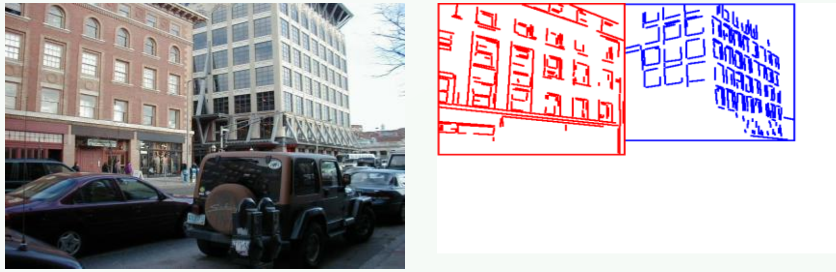
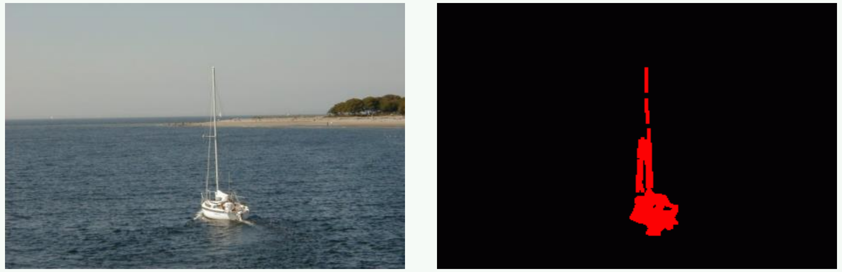
- Color

- Texture

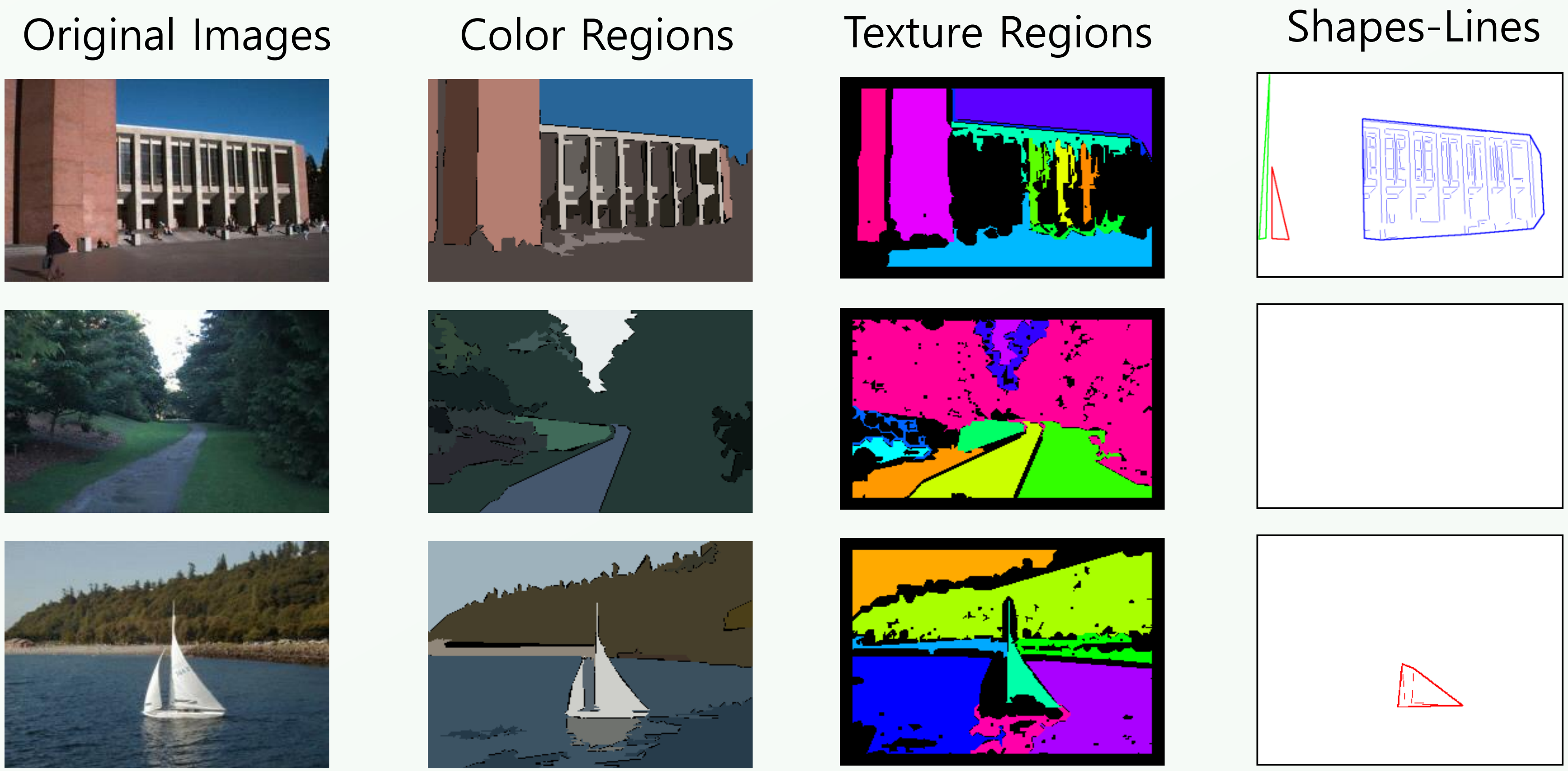
- Shapes



- Context



Abstract Regions



Object Model Learning (Ideal)

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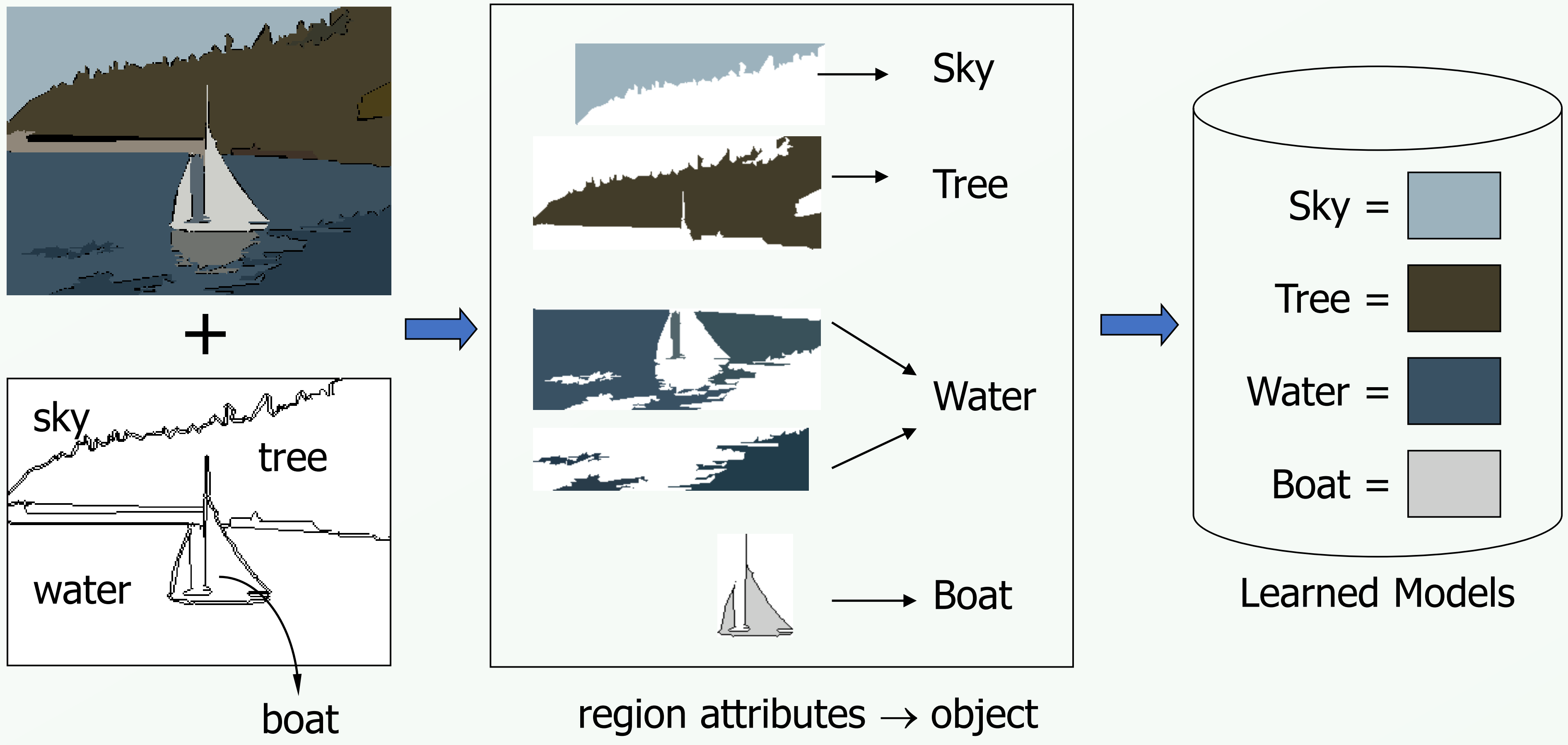


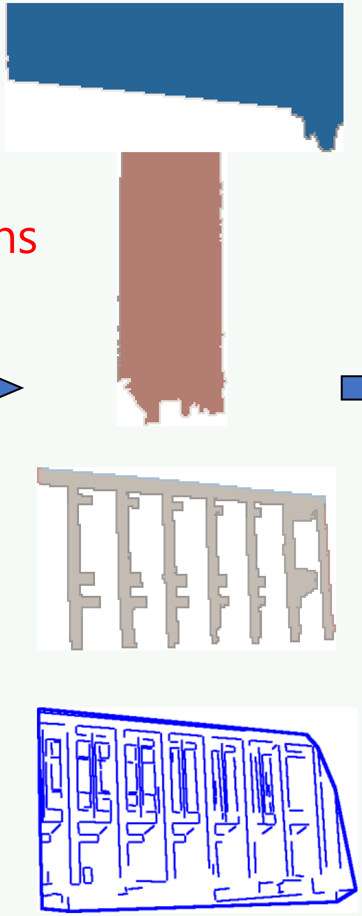
Object Model Learning (practical)

image

labels

{sky, building}

segmentations



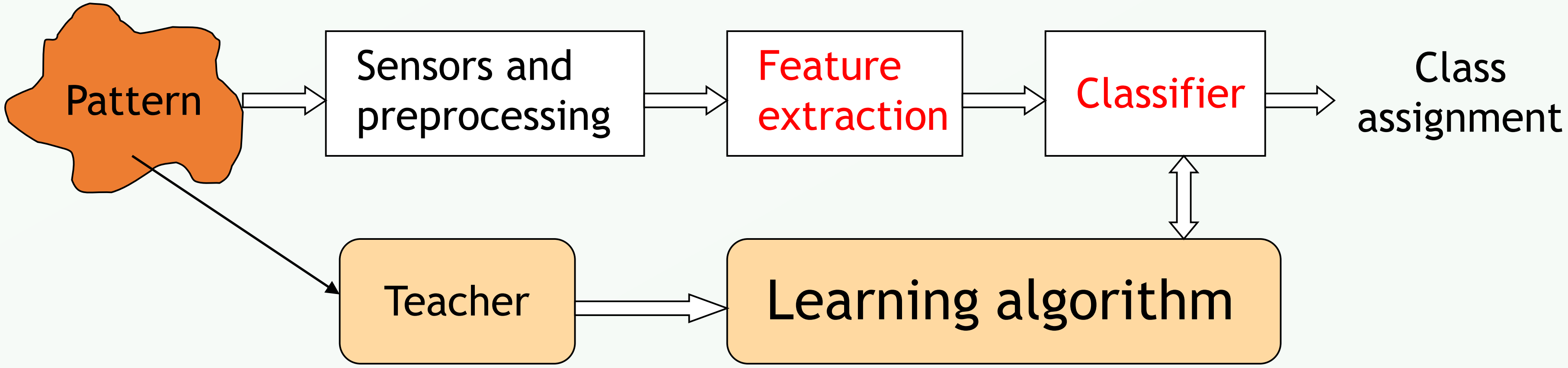
region attributes from several different types of regions

Classifier

Short Overview of Pattern Recognition

Components of PR System

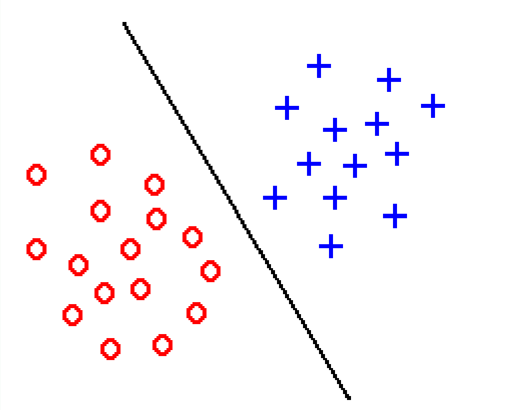
- Hand designed features – manually extracted features
- Deep features – automatic generated features



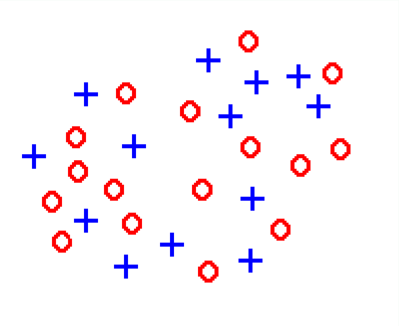
- Supervised learning
- Unsupervised learning

Feature extraction

- Task: to extract features which are good for classification.
- Good features:
  - For a given group of patterns coming from the same class, feature values should all be similar
  - For patterns coming from different classes, the features values should be different



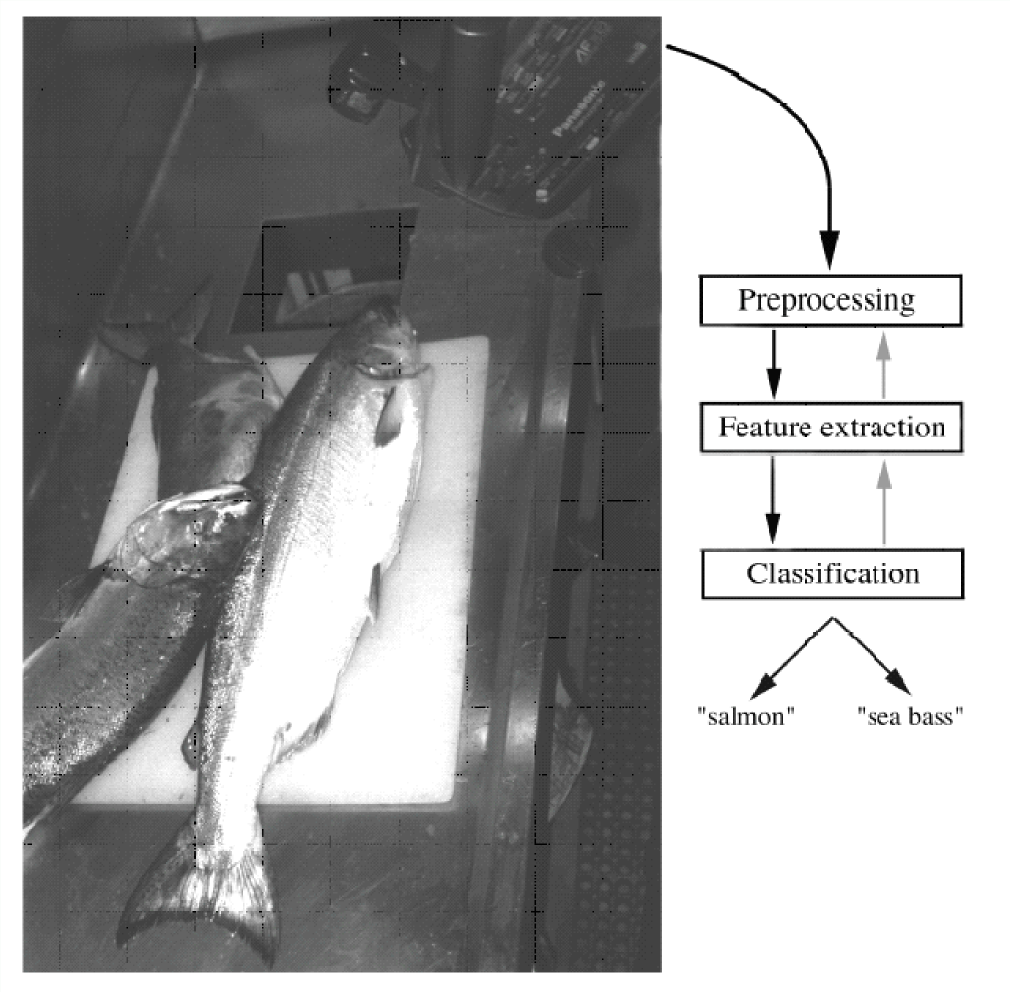
"Good" features



"Bad" features

Example : Salmon or Sea Bass

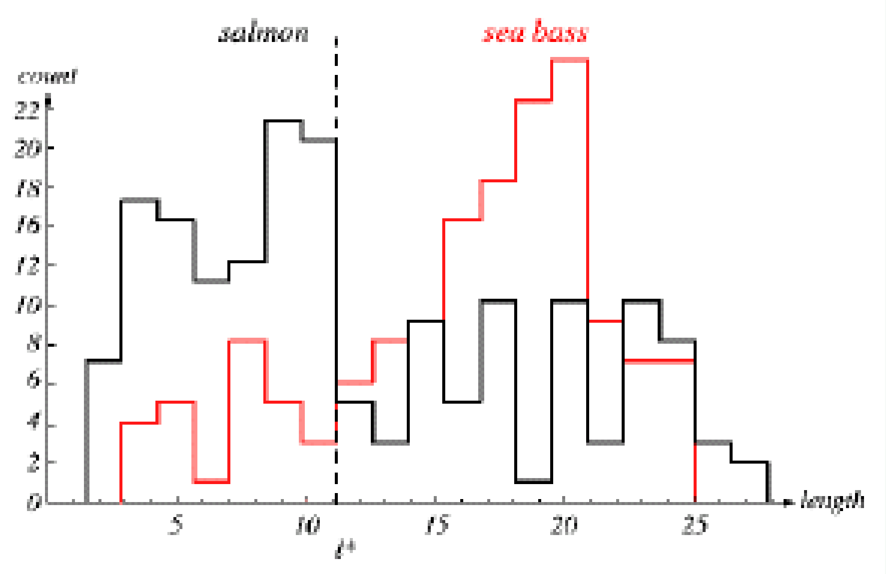
- Sort incoming fish on a belt according to two classes:
  - Salmon or
  - Sea Bass



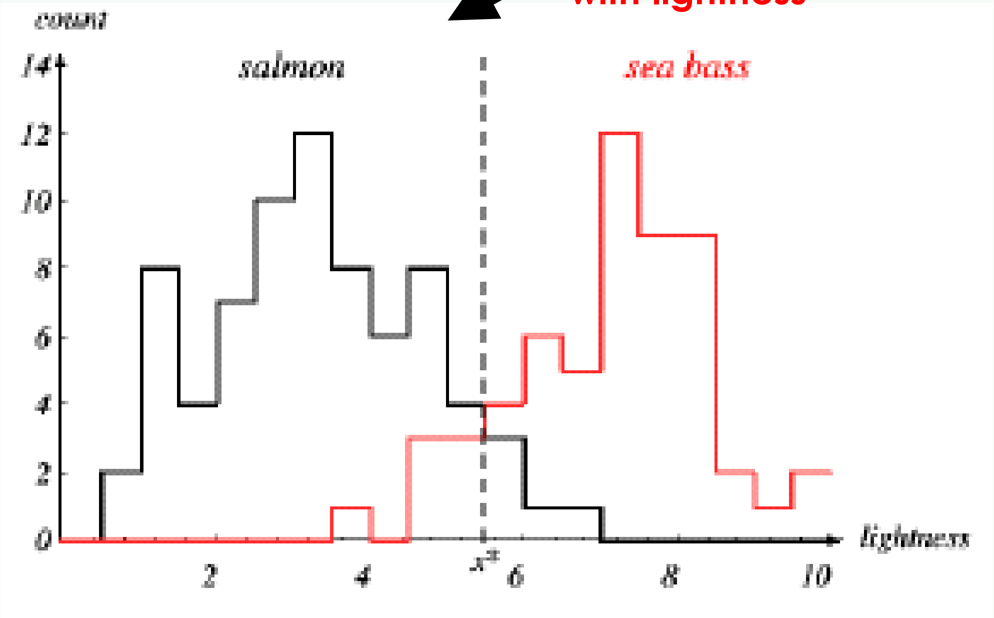
Sea bass vs Salmon Discrimination

- Possible features to be used:
  - Length
  - Lightness
  - Width
  - Number and shape of fins
  - Position of the mouth
  - Etc …

Feature extraction



Best Decision Strategy
with lightness



- Length or lightness, which one is better feature?
- If you were to make the decision based on the value of a single feature, which one would you choose?
  - And then, what would the decision value be?
- No value of either feature will "classify" all fish correctly. What to do?

How Many Features and Which?

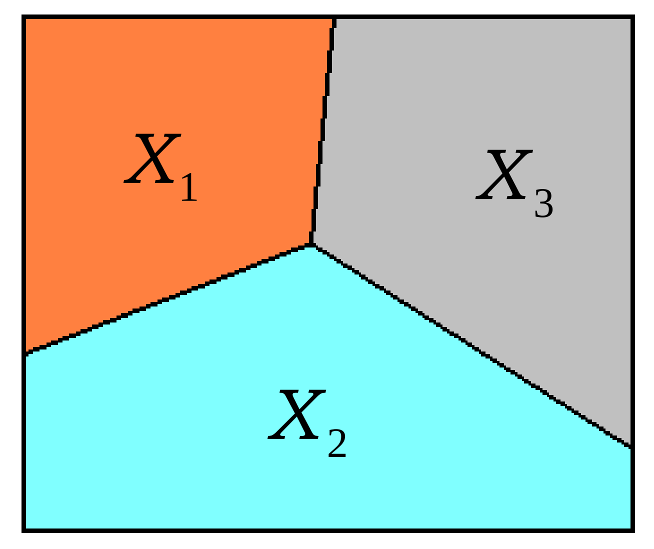
- Choice of features determines success or failure of classification task

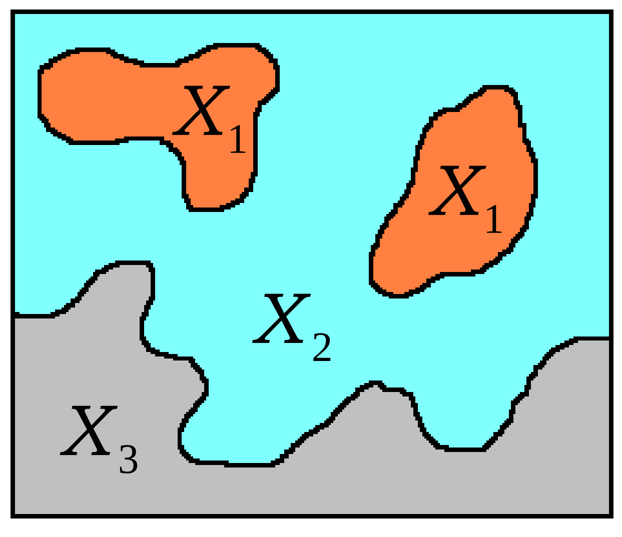
- Issues with feature extraction:
  - The number of features
    - Too few will make it impossible to separate the samples
    - Too many cause generalization problems and increase computational complexity
  - Feature selection
    - It might be difficult to extract certain features.
    - Correlated features do not improve performance.

Classifier

A classifier partitions feature space X into class-labeled regions such that

$$X = X_1 \cup X_2 \cup \ldots \cup X_{|Y|} \quad \text{and} \quad X_1 \cap X_2 \cap \ldots \cap X_{|Y|} = \{0\}$$





Borders between decision regions are called as decision boundaries

Classifier

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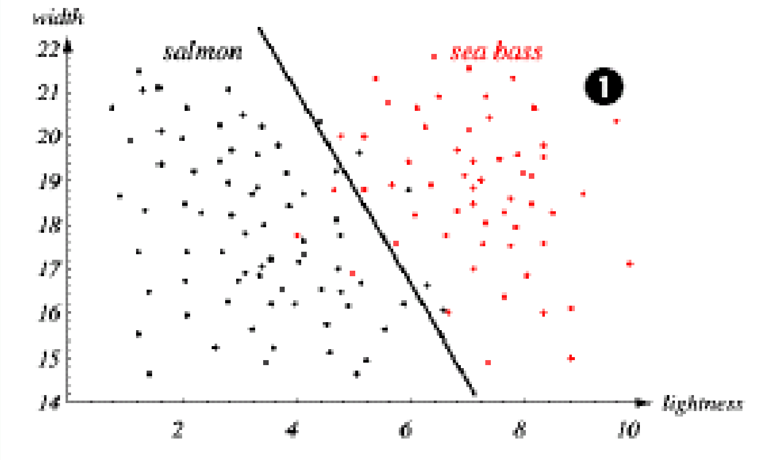
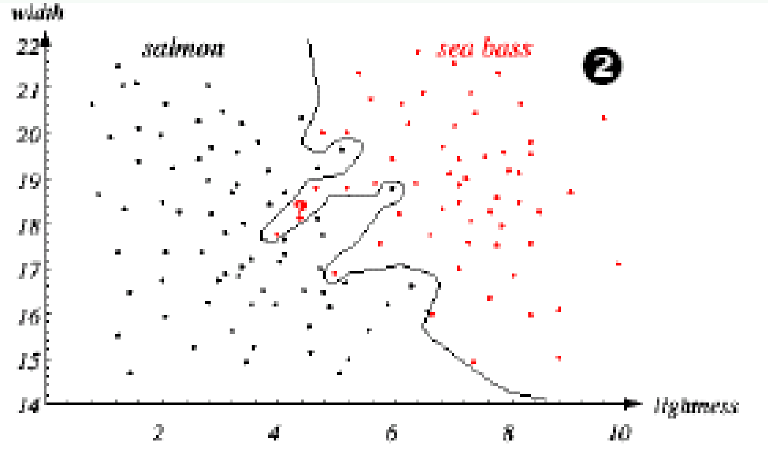
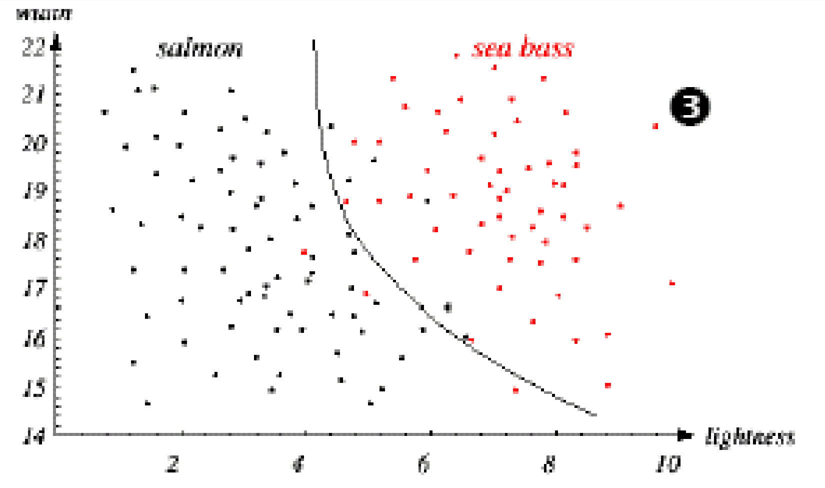






- Which of the boundaries would you choose?

❶ **Simple linear boundary – training error > 0**

❷ **Nonlinear complex boundary – tr. error = 0**

❸ **Simpler nonlinear boundary – tr. error > 0**

Cost of Misclassification

- A classifier, intuitively, is designed to minimize classification error, the total number of instances (fish) classified incorrectly.
- Is this the best objective function to minimize?
- What kinds of error can be made?
  (1) Sea bass misclassified as salmon
  (2) Salmon misclassified as sea bass
- Are they all equally bad? Which error is more costly?
  (1Pleasant surprise for the consumer, tastier fish/ merchant lose money for selling expensive fish for the cost of inexpensive fish
  (2) Customer upset, paid too much for inferior fish
- The objective is to look for the decision of minimum Risk
  - Risk = Expected Loss

	Salmon	Sea Bass
Salmon	0	-10
Sea bass	-20	0

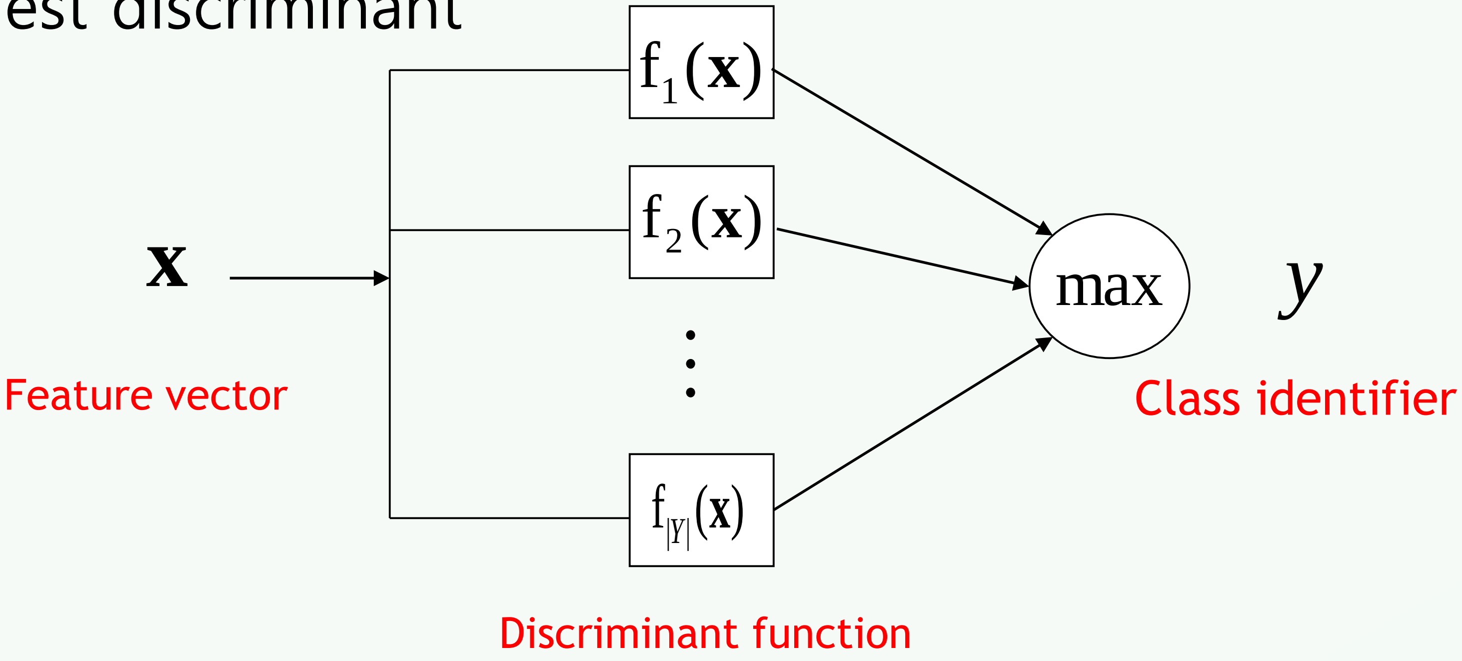
Loss Function

Representation of classifier

- A classifier is typically represented as a set of discriminant functions

$$f_i(\mathbf{x}) : X \rightarrow \Re, i = 1, \ldots, |Y|$$

- We computes Y discriminants and selects the category corresponding to the largest discriminant



Types of Classifier

- What algorithms can be used for recognition (or analysis)?

- Decision tree- Ensemble Learning
- Nearest mean – Clustering
- Nearest neighbors – KNNs
- Discriminant functions - Bayesian
- Artificial neural networks

Simple Classification

- Decision Tree Classifier
- Nearest Class Mean
- Nearest Neighbor

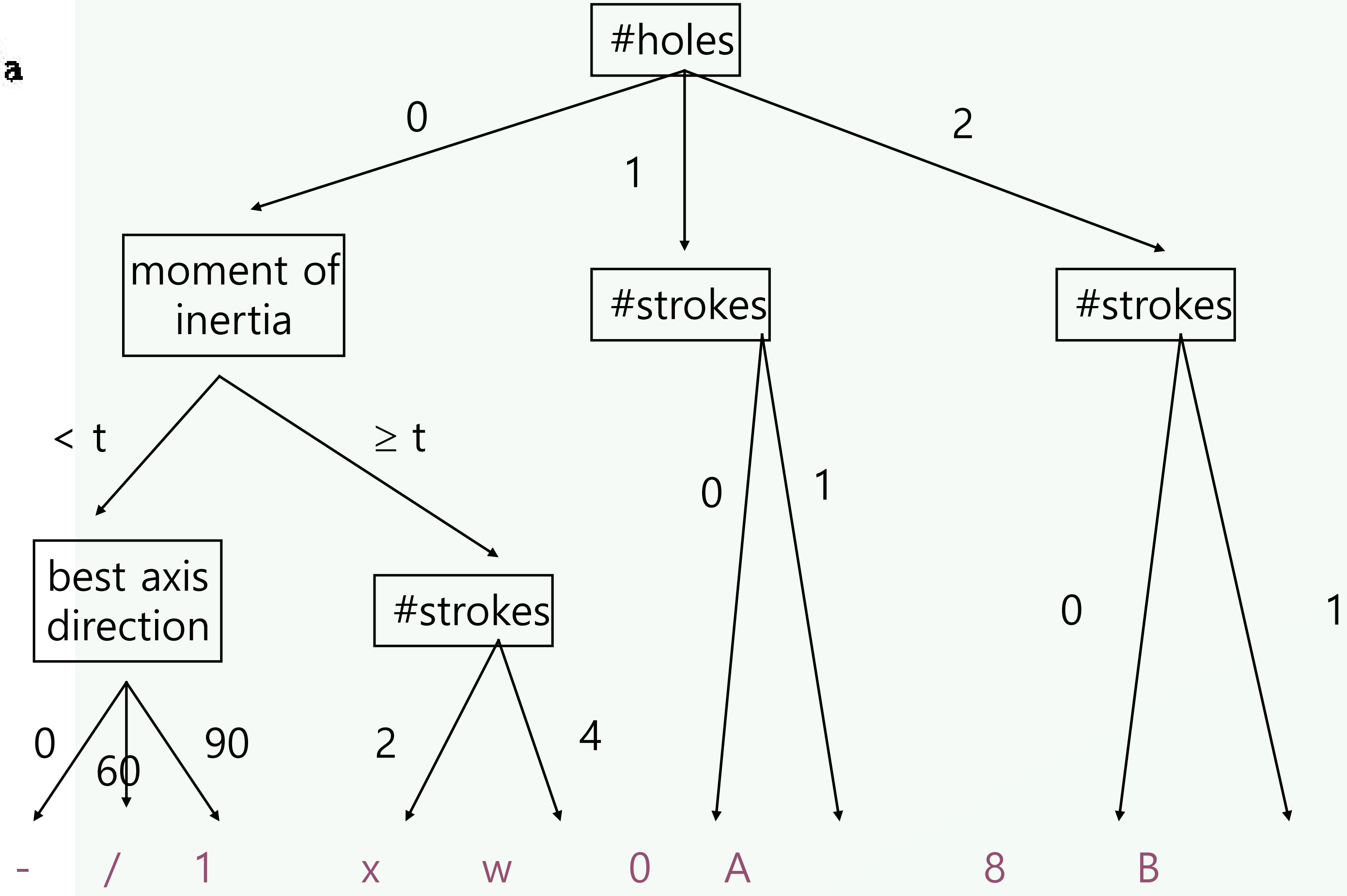
Decision-Tree Classifier

- Uses subsets of features in seq.
- Feature extraction may be interleaved with classification decisions
- Can be easy to design and efficient in execution

Decision-Tree Classifier


```
case of #holes
   0: character is 1, W, X, *, -, or /
        case of moment about axis of least inertia
           low: character is  1, -, or /
                  case of best axis direction
                     0: character is  -
                    60: character is  /
                    90: character is  1

         large: character is W or X
                  case of #strokes
                     2: character is X
                     4: character is W
   1: character is A or O
        case of #strokes
           0: character is o
           1: character is A
```

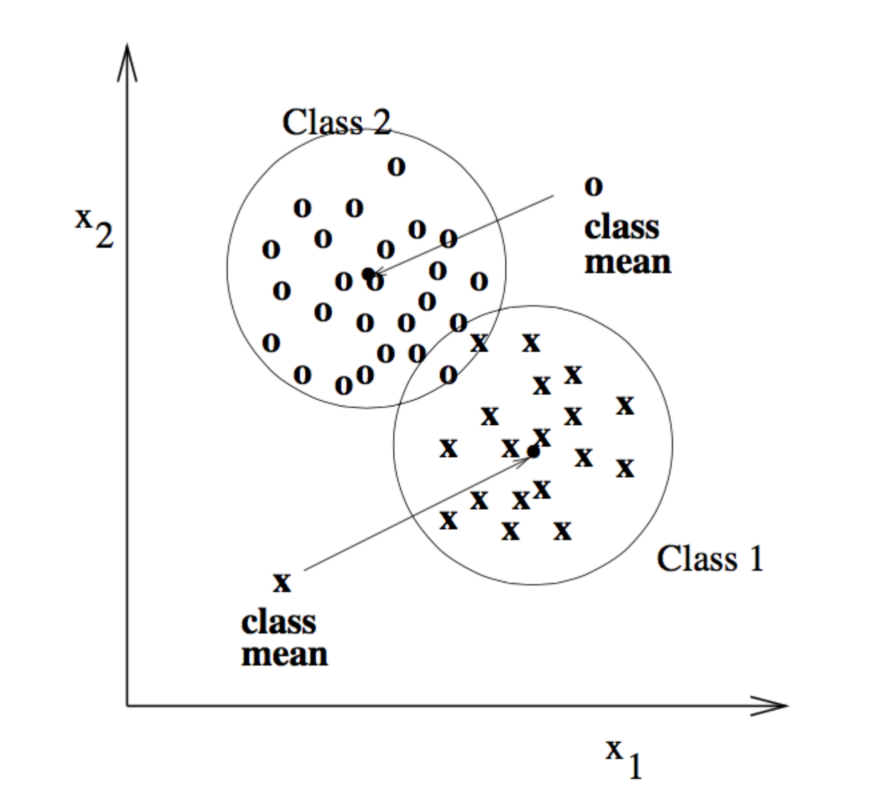


Classification using nearest mean

- Compute the Euclidean distance between feature vector X and the mean of each class.
  - The Euclidean distance between two d-dimensional feature vectors x1 and x2 is

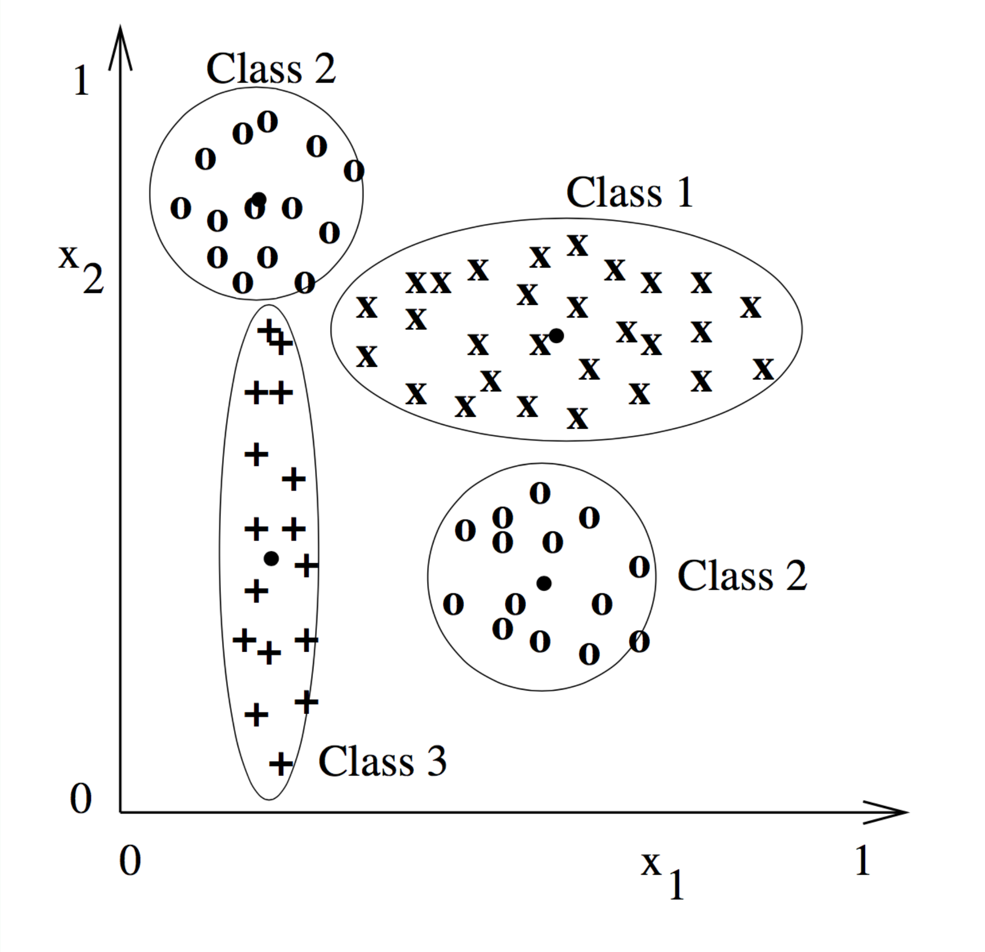
$$\left\| x_1 - x_2 \right\| = \sqrt{\sum_{i=1,d} (x_1[i] - x_2[i])^2}$$

- Choose closest class, if close enough (reject otherwise)



Classification using nearest mean

- Nearest mean might yield poor results with complex structure
- In a example,
  - Class 2 has two modes
    - But if modes are detected, two subclass mean vectors can be used
  - Different distribution on each classes



Scaled Euclidean Distance

- We can computer a modified distance from feature vector x to class mean vector xc by scaling by the spread, or standard deviation σc of class c along each dimension i.

$$\|x - x_c\| = \sqrt{\sum_{i=1,d} ((x[i] - x_c[i]) / \sigma_i)^2}$$

K-nearest neighbor (K-NN)

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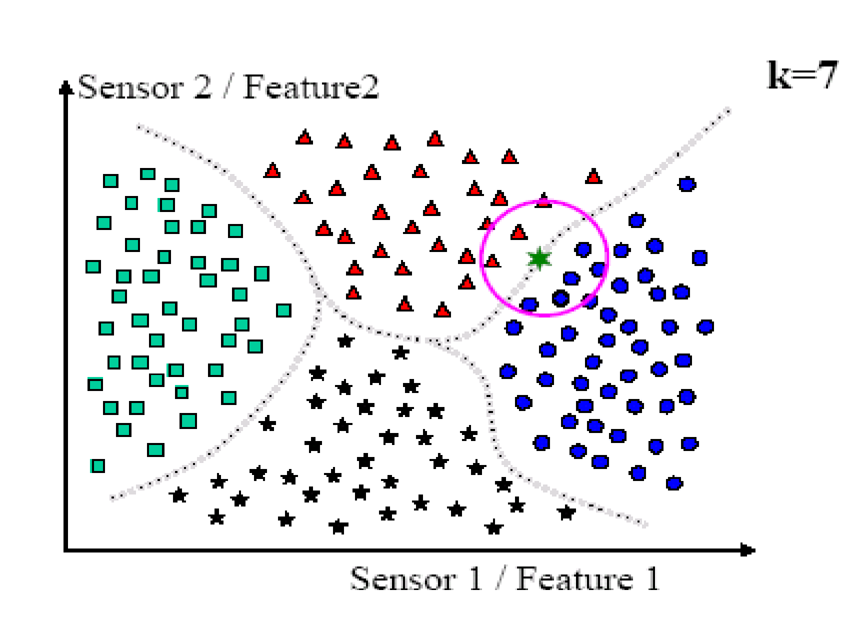
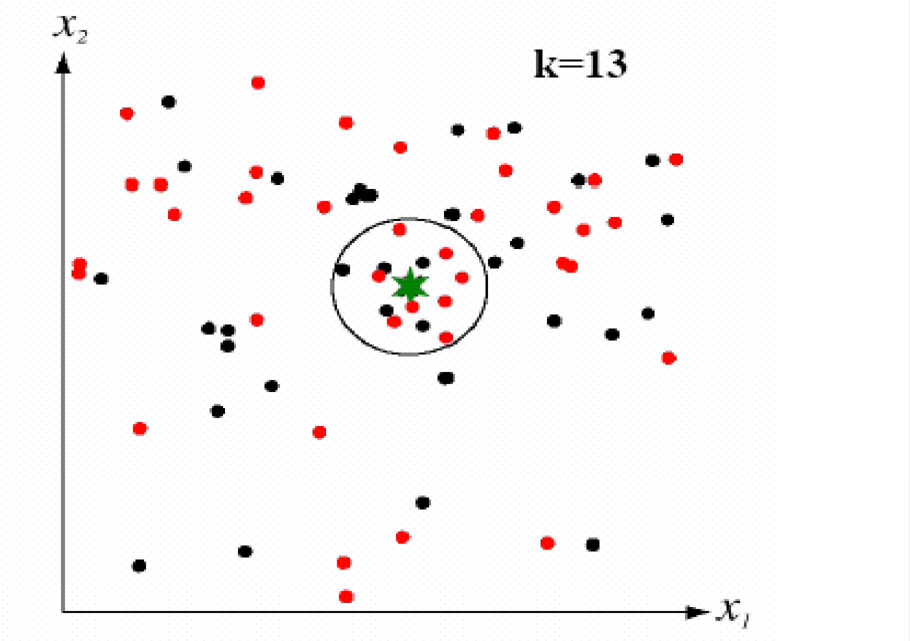
- An object is classified by a majority vote of its neighbors, that is, the object being assigned to the class most common among its k nearest neighbor.





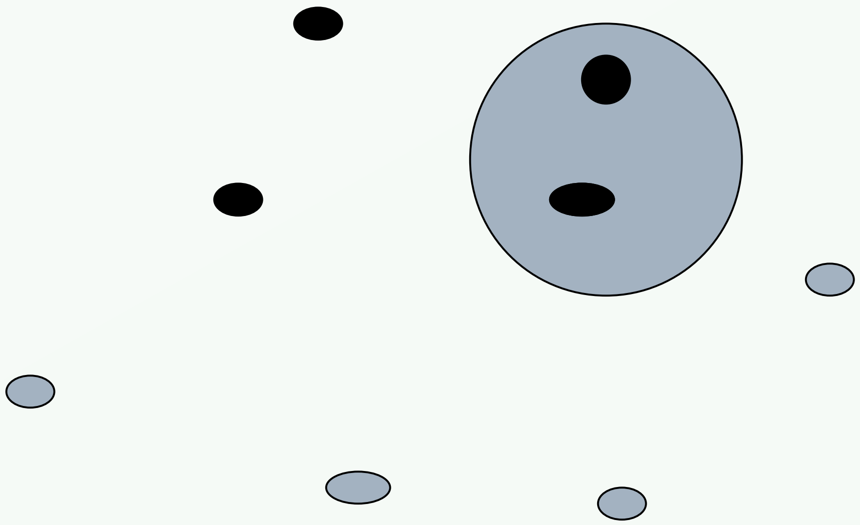
Nearest-neighbor Classification

S is a set of n labeled class samples s_i where $s_i.\mathbf{x}$ is a feature vector and $s_i.c$ is its integer class label.
x is the unknown input feature vector to be classified.
A is an array capable of holding up to k samples in sorted order by distance d.
The value returned is a class label in the range $[\mathbf{1}, \mathbf{m}]$

procedure K_Nearest_Neighbors($\mathbf{x}, \mathbf{S}$)
{
make **A** empty;
for all samples s_i in S
{
    $d =$ Euclidean distance between s_i and $\mathbf{x}$;
    if A has less than k elements **then** insert (d, s_i) into **A**;
    else **if** d is less than max **A**
        then {
            remove the max from **A**;
            insert (d, s_i) in **A**;
        }
} ;
assert **A** has k samples from **S** closest to **x**;
if a majority of the labels $s_i.c$ from **A** are class c_0
    then classify **x** into class c_o;
    else classify **x** into the reject class;
return(class_of_x);
}

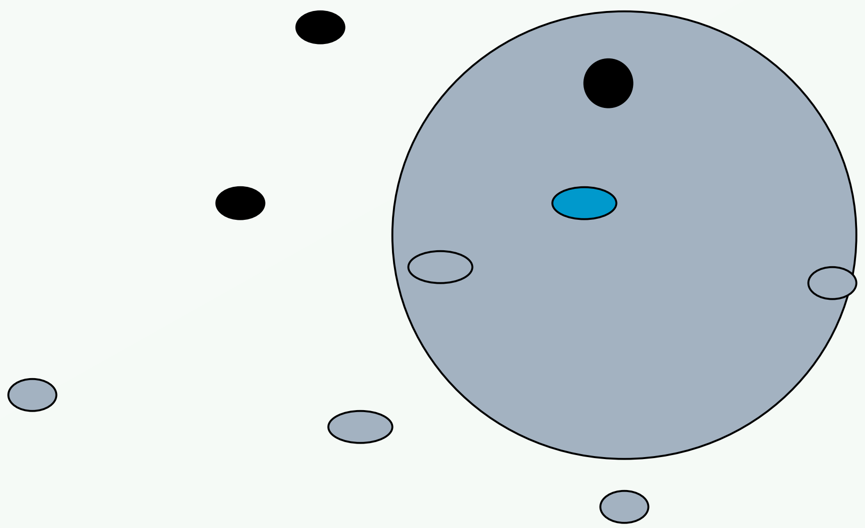
1-Nearest neighbor classification

- An object is classified by a majority vote of its neighbors, that is, the object being assigned to the class most common among its k nearest neighbor.



3-Nearest neighbor classification

- An object is classified by a majority vote of its neighbors, that is, the object being assigned to the class most common among its k nearest neighbor.



Nearest neighbor classification

- It is called memory(instance) based learning
  - It simply compares the unknown data instance to those that are in the training data, for which it must have access to the entire database
- It is a lazy learning algorithm
  - It have little or no computational cost of training, but more computational cost during the actual testing, compared to eager learners.
- It provides usually quite good results
  - If the training data is well and it is large enough
- However, it also has disadvantages
  - it is computationally intensive and requires large memory.

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