Introduction to Pattern Recognition

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Human Perception

- Humans have developed highly sophisticated skills for sensing their environment and taking actions according to what they observe, e.g.,
  - Recognizing a face.
  - Understanding spoken words.
  - Reading handwriting.
  - Distinguishing fresh food from its smell.
  - ...

Human and Machine Perception

- We are often influenced by the knowledge of how patterns are modeled and recognized in nature when we develop pattern recognition algorithms.

- Research on machine perception also helps us gain deeper understanding and appreciation for pattern recognition systems in nature.

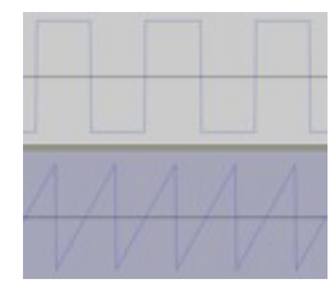
- Yet, we also apply many techniques that are purely numerical and do not have any correspondence in natural systems.

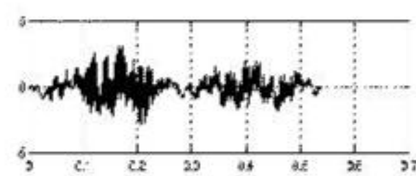
Pattern Recognition (PR)

- Pattern Recognition is the study of how machines can:
  - observe the environment,
  - learn to distinguish patterns of interest,
  - make sound and reasonable decisions about the categories of the patterns.

Pattern Recognition (PR)

- **What is a Pattern?**
  - is an abstraction, represented by a set of measurements describing a "physical" object
- Many types of patterns exist:
  - visual, temporal, sonic, logical, ...

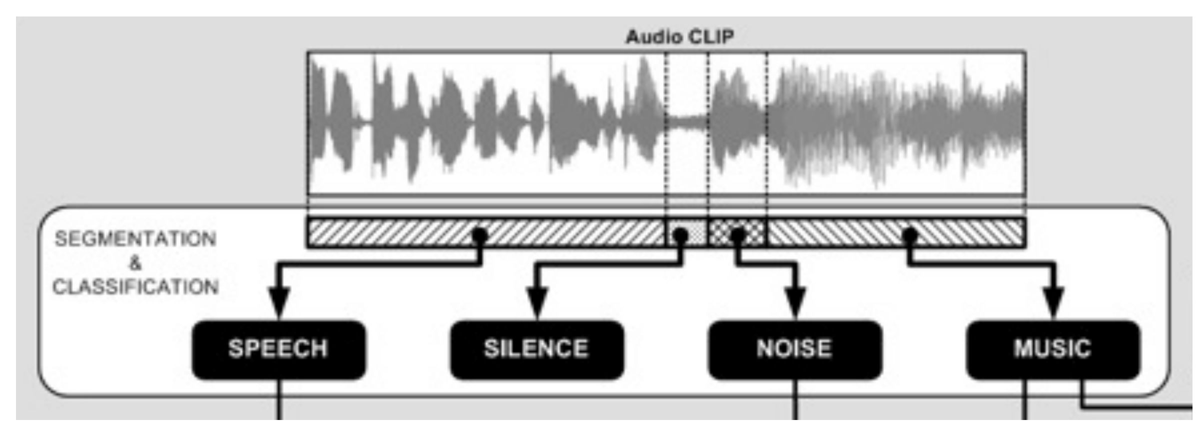





Pattern Recognition (PR)

- **What is a Pattern Class** (or category)?
  - is a set of patterns sharing common attributes
  - a collection of "similar", not necessarily identical, objects
  - During recognition, given objects are assigned to a prescribed class



Pattern Recognition (PR)

- No single theory of Pattern Recognition can possibly cope with such a broad range of problems...
- However, there are several standard models, including:
  - **Statistical** or fuzzy pattern recognition (see Fukunaga)
  - Syntactic or structural pattern recognition (see Schalkoff)
  - Knowledge-based pattern recognition (see Stefik)

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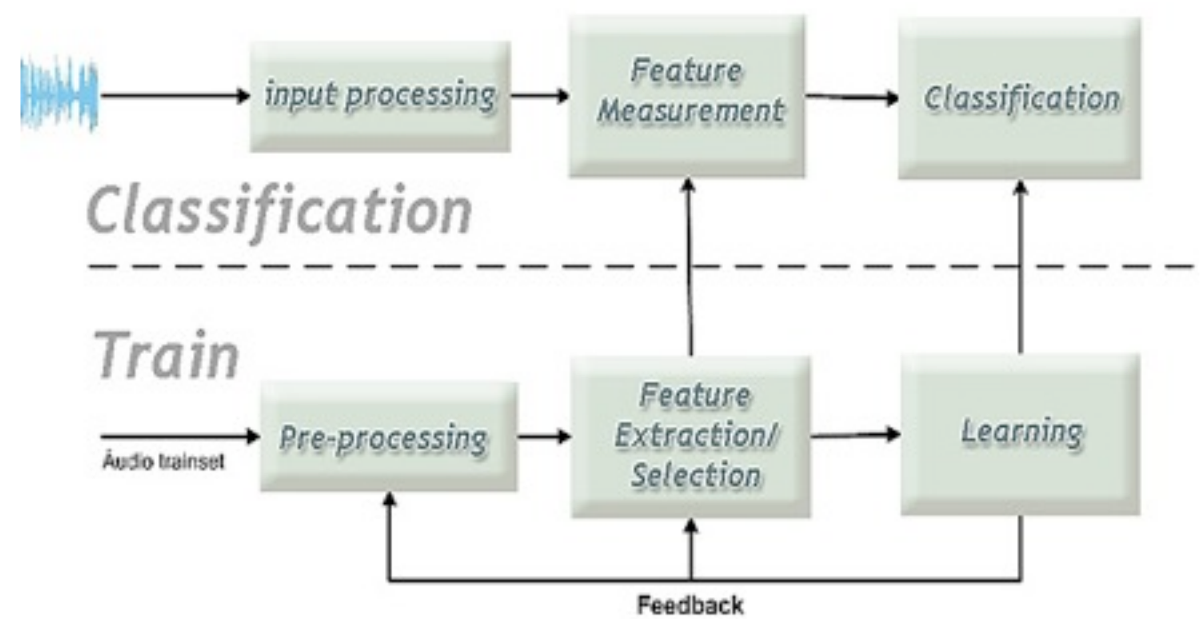
Pattern Recognition

- Two phase Process
  1. Training/Learning
     - Learning is hard and time consuming
     - System must be exposed to several examples of each class
     - Creates a "model" for each class
     - Once learned, it becomes natural
  2. Detecting/Classifying

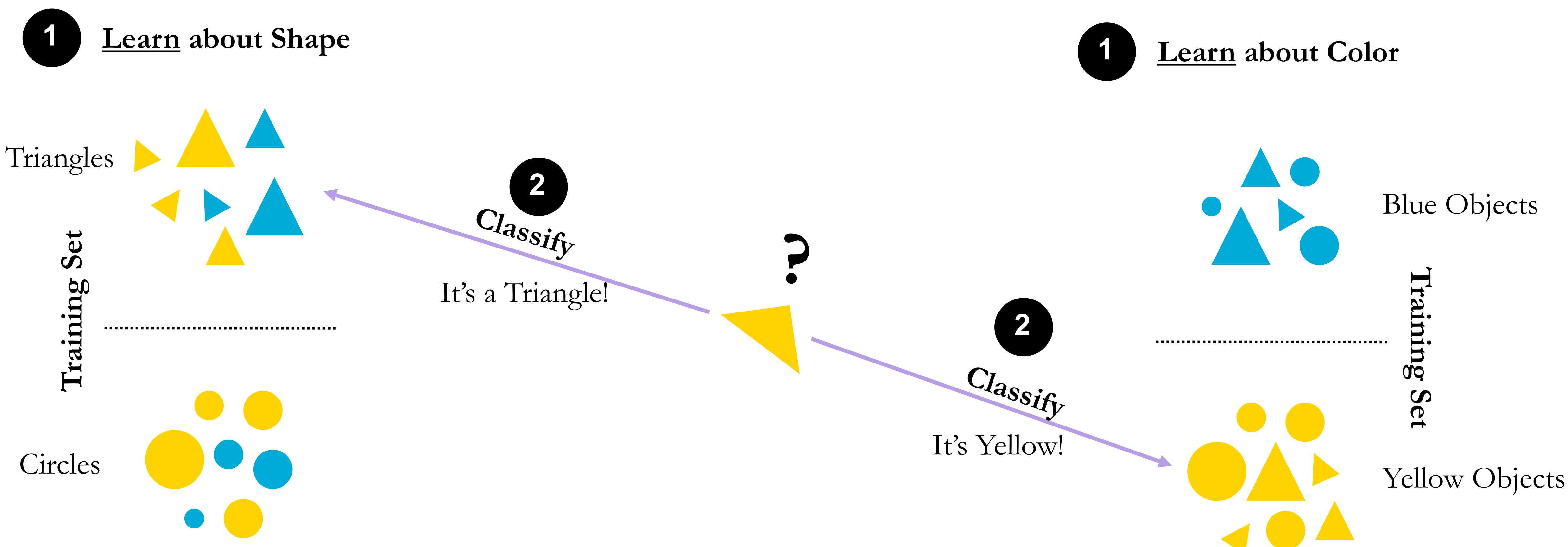


Pattern Recognition

- How can a machine learn the rule from data?
  - **Supervised learning:** a teacher provides a category label or cost for each pattern in the training set.
    - ➡*Classification*
  - **Unsupervised learning:** the system forms clusters or natural groupings of the input patterns (based on some similarity criteria).
    - ➡*Clustering*
  - **Reinforcement learning:** no desired category is given but the teacher provides feedback to the system such as the decision is right or wrong.

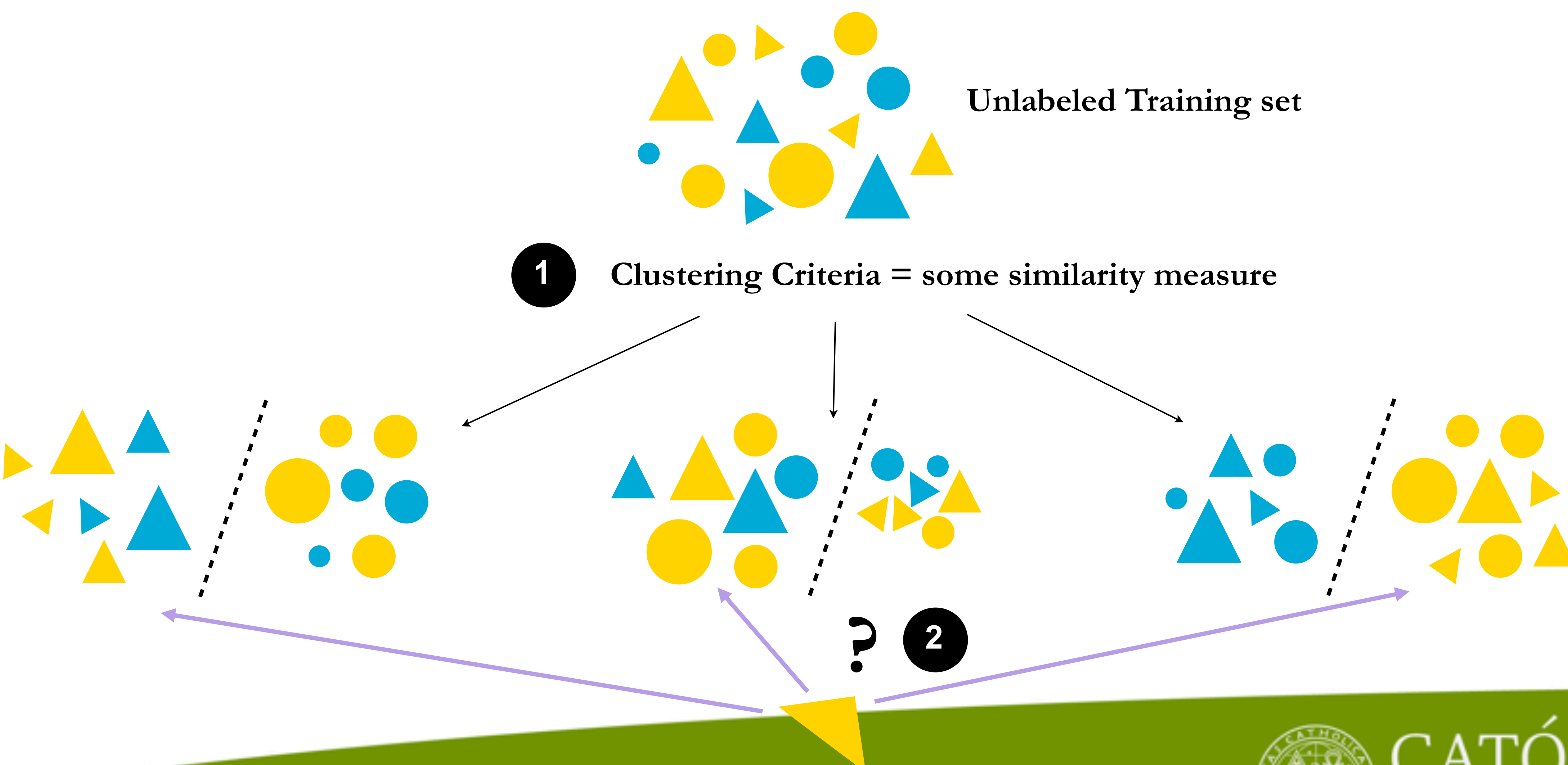
Pattern Recognition

- **Supervised Training/Learning**
  - a "teacher" provides labeled training sets, used to train a classifier



Pattern Recognition

- **Unsupervised Training/Learning**
  - No labeled training sets are provided
  - System applies a specified clustering/grouping criteria to unlabeled dataset
  - Clusters/groups together "most similar" objects (according to given criteria)



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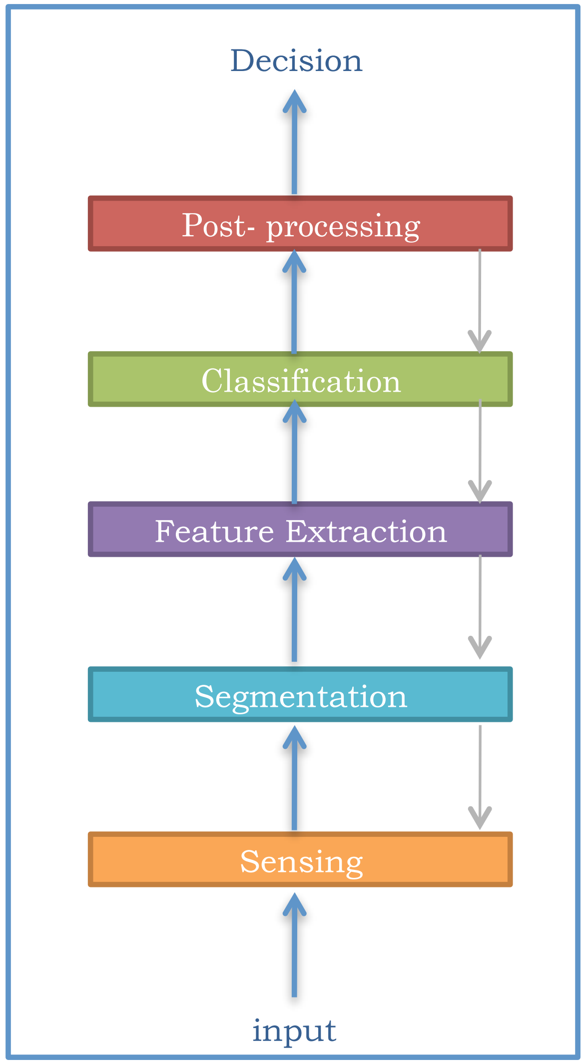
Pattern Recognition Process

- **Data acquisition and sensing:**
  - Measurements of physical variables.
  - Important issues: bandwidth, resolution , etc.
- **Pre-processing:**
  - Removal of noise in data.
  - Isolation of patterns of interest from the background.
- **Feature extraction:**
  - Finding a new representation in terms of features.
- **Classification**
  - Using features and learned models to assign a pattern to a category.
- **Post-processing**
  - Evaluation of confidence in decisions.

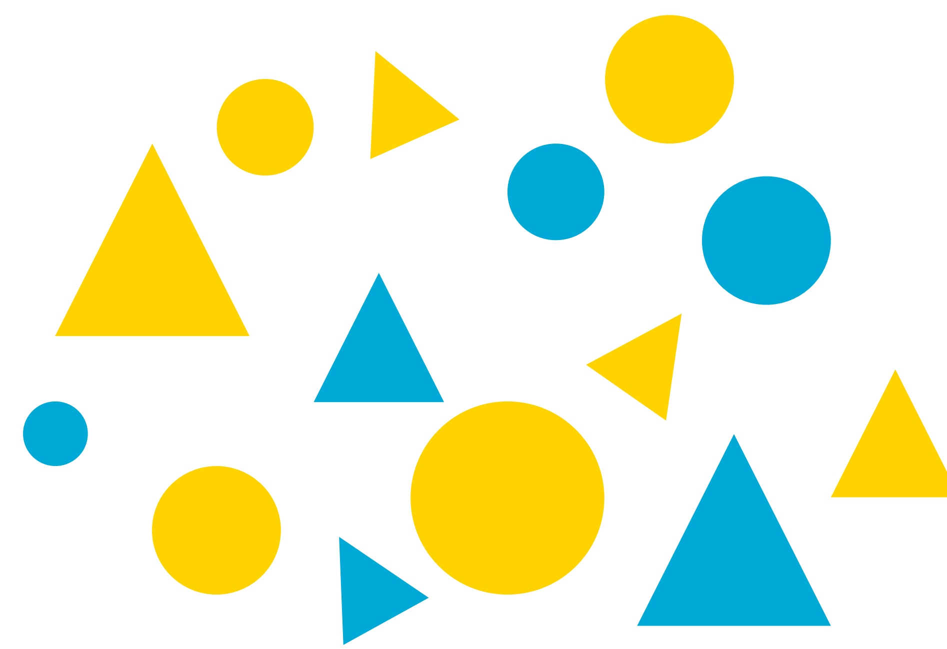


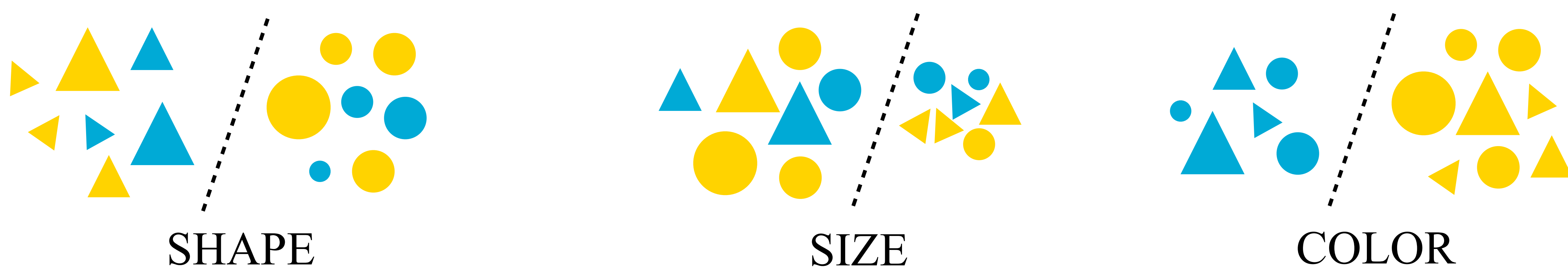
Features

- Features are properties of an object:
  - Ideally representative of a specific type (i.e. class) of objects
  - Compact (memory efficient)
  - Computationally simple (CPU efficient)
  - Perceptual relevant (if trying to implement a human inspired classifier)
- **=> Should pave the way to a good discrimination of different classes of objects!**

Features

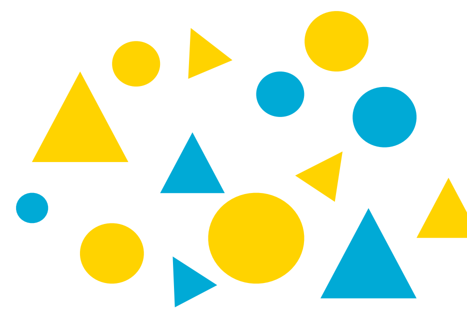
- Take a group of graphical objects
  - Possible features:
    - Shape
    - Color
    - Size
    - ...
  - Allows to group them into different classes:





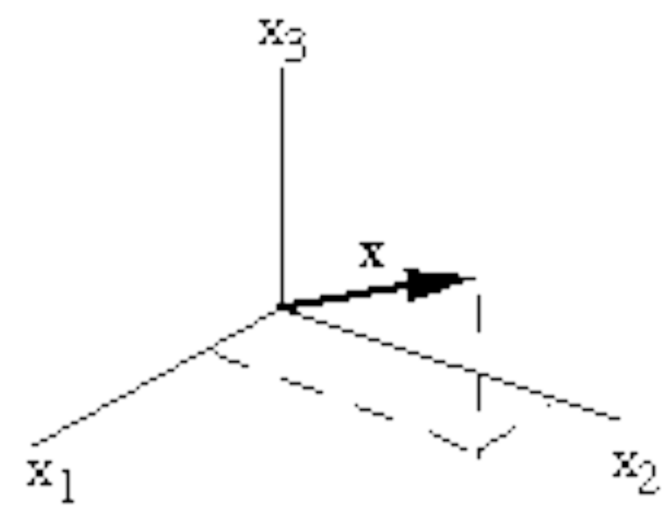
Feature Vectors

- Usually a single object can be represented using several features, e.g.
  - **x1** = shape (e.g. nr of sides)
  - **x2** = size (e.g. some numeric value)
  - **x3** = color (e.g. rgb values)
  - ...
  - **xd** = some other (numeric) feature.



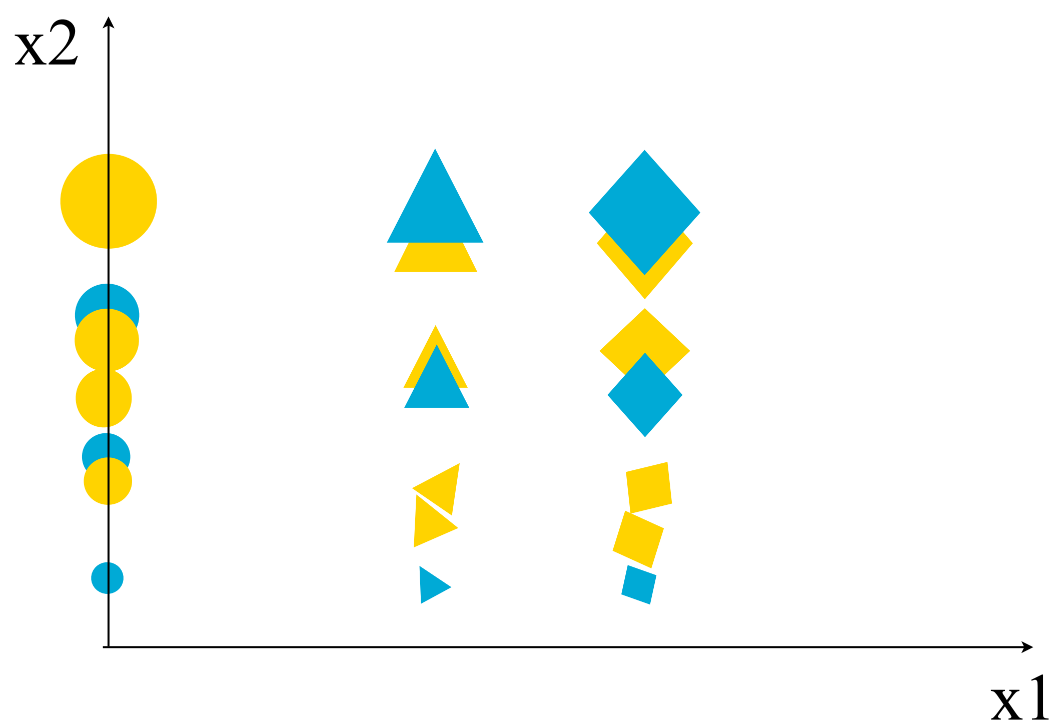
- **X** becomes a feature vector
  - x is a point in a d-dimensional **feature space.**

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ \cdot \\ x_d \end{bmatrix}$$



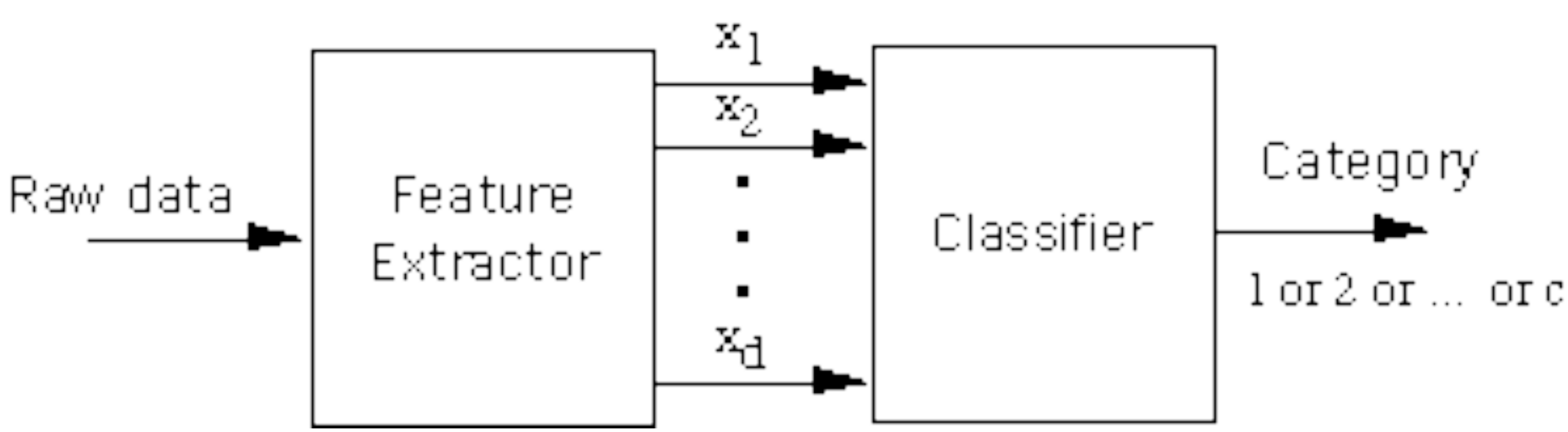
Feature Vectors

- Example of a 2D Feature Space
  - **x1** = shape (e.g. nr of sides)
  - **x2** = size (e.g. some numeric value)



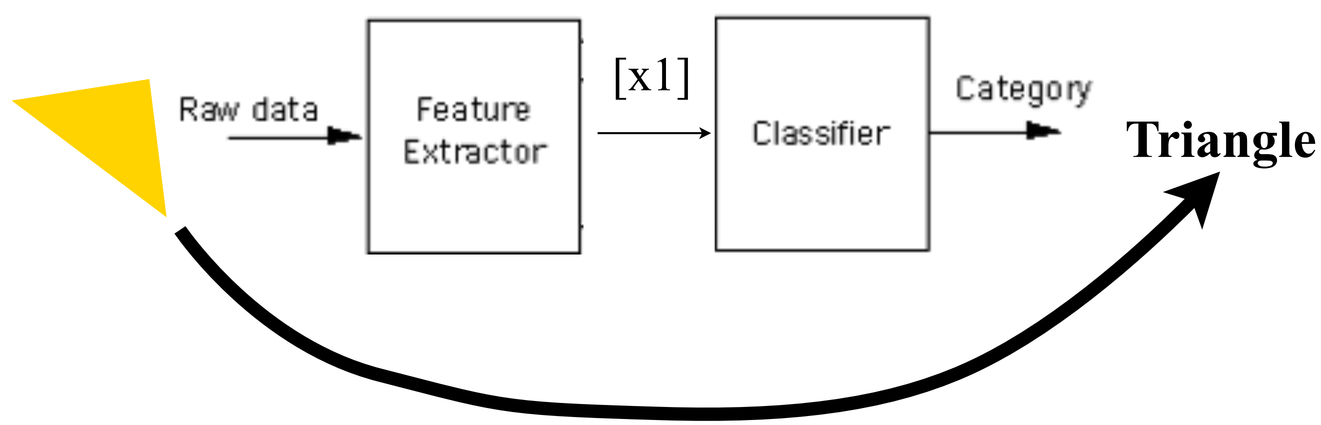
The Classical Model for PR

1. A **Feature Extractor** extracts features from raw data (e.g. audio, image, weather data, etc)
2. A **Classifier** receives X and assigns it to one of c categories, Class 1, Class 2, ..., Class c (i.e. labels the raw data).



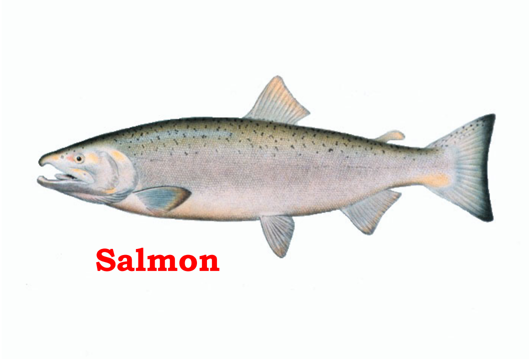
The Classical Model for PR

- Example: classify graphic objects according to their shape
  - Feature extracted:
    - nr. of sides (x1)
  - Classifier:
    - 0 sides => circle
    - 3 sides => triangle
    - (4 sides => rectangle)
  - How does the classifier know that a circle has no sides and that a triangle has 3 sides?!



A Case Study: Fish Classification

- Problem:
  - sort incoming fish on a conveyor belt according to species
  - Assume only two classes exist:
    - Sea Bass and Salmon



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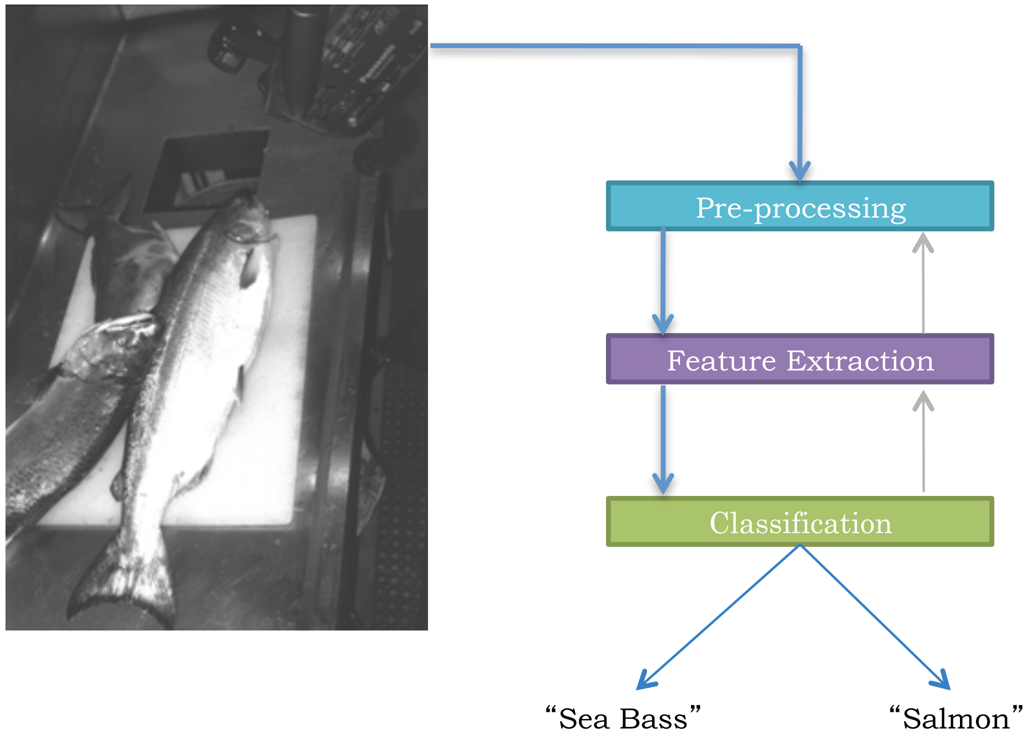
A Case Study: Fish Classification

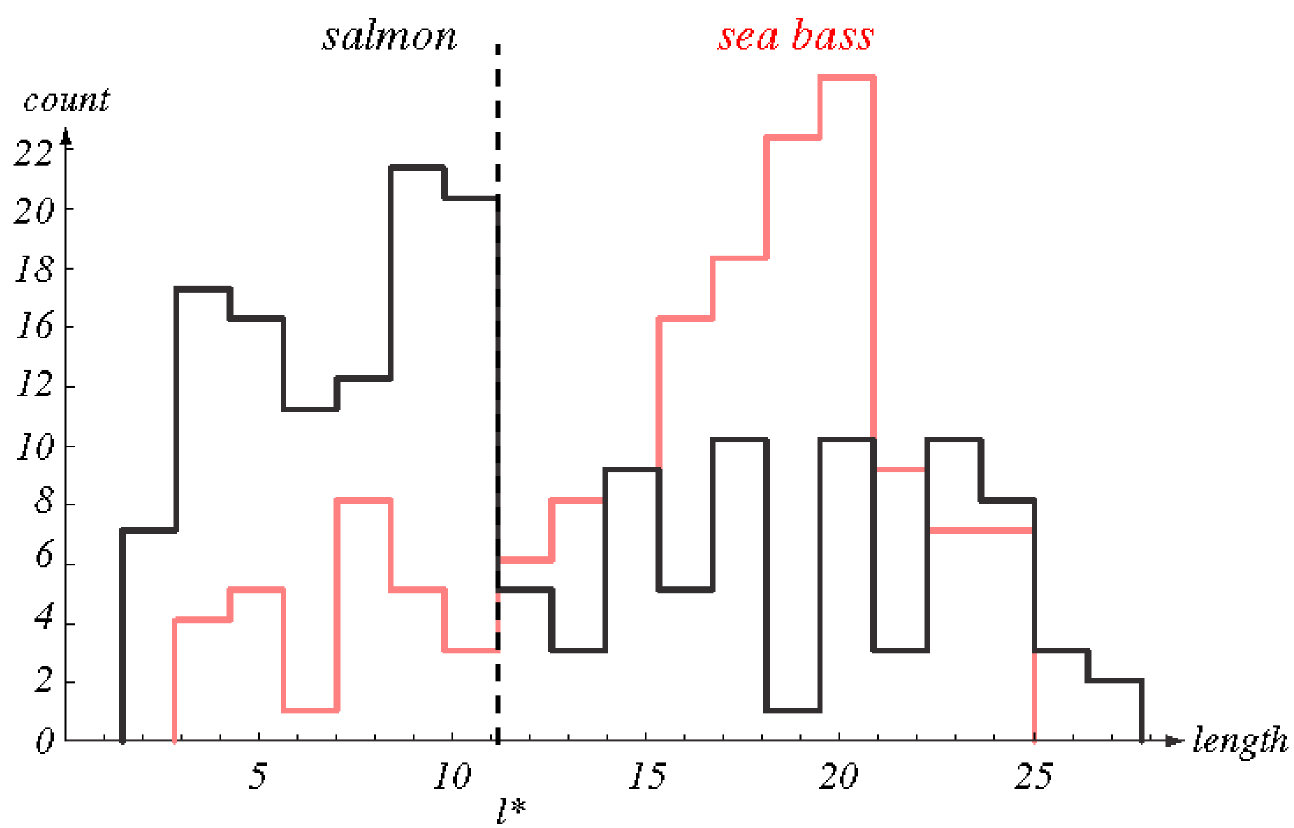
- What kind of information can distinguish one species from the other?
  - length, width, weight, number and shape of fins, tail shape, etc.
- What can cause problems during sensing?
  - lighting conditions, position of fish on the conveyor belt, camera noise, etc.
- What are the steps in the process?
  1. Capture image.
  2. Isolate fish
  3. Take measurements
  4. Make decision



A Case Study: Fish Classification

- Selecting Features
  - Assume a fisherman told us that a sea bass is generally longer than a salmon.
  - We can use length as a feature and decide between sea bass and salmon according to a threshold on length.
  - How can we choose this threshold?

Histograms of the length feature for two types of fish in training samples. How can we choose the threshold l* to make a reliable decision?



Even though "sea bass" is longer than "salmon" on the average, **there are many examples of fish where this observation does not hold...**

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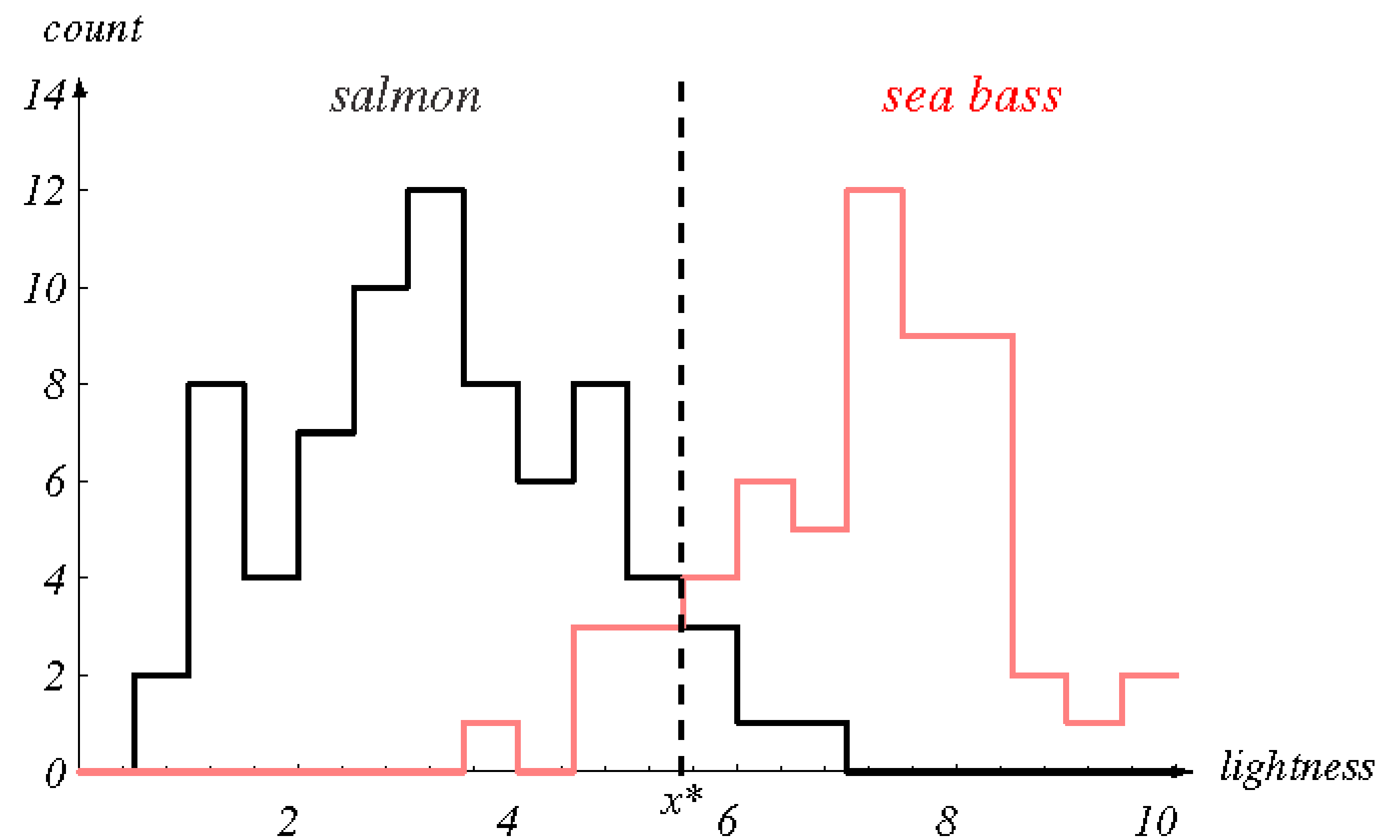
A Case Study: Fish Classification

- Selecting Features
  - Let's try another feature and see if we get better discrimination
    - ➡Average Lightness of the fish scales

Histograms of the lightness feature for two types of fish in training samples.



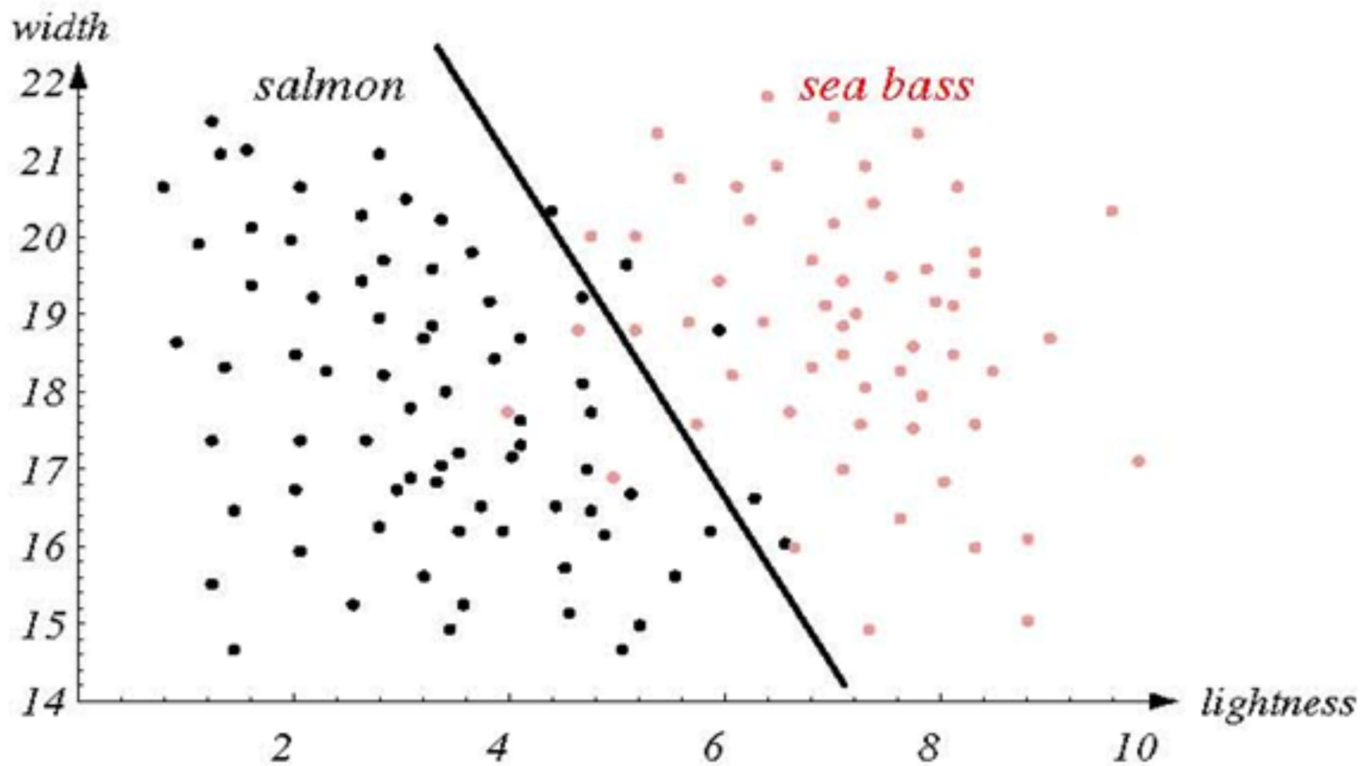
It looks easier to choose the threshold x$*$ but we still cannot make a perfect decision.

A Case Study: Fish Classification

- Multiple Features
  - Single features might not yield the best performance.
  - To improve recognition, we might have to use more than one feature at a time.
  - Combinations of features might yield better performance.
  - Assume we also observed that sea bass are typically wider than salmon.

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad \begin{matrix} x_1 : lightness \\ x_2 : width \end{matrix}$$

Each fish image is now represented by a point in this 2D feature space



Scatter plot of lightness and width features for training samples. **We can draw a decision boundary to divide the feature space into two regions. Does it look better than using only lightness?**

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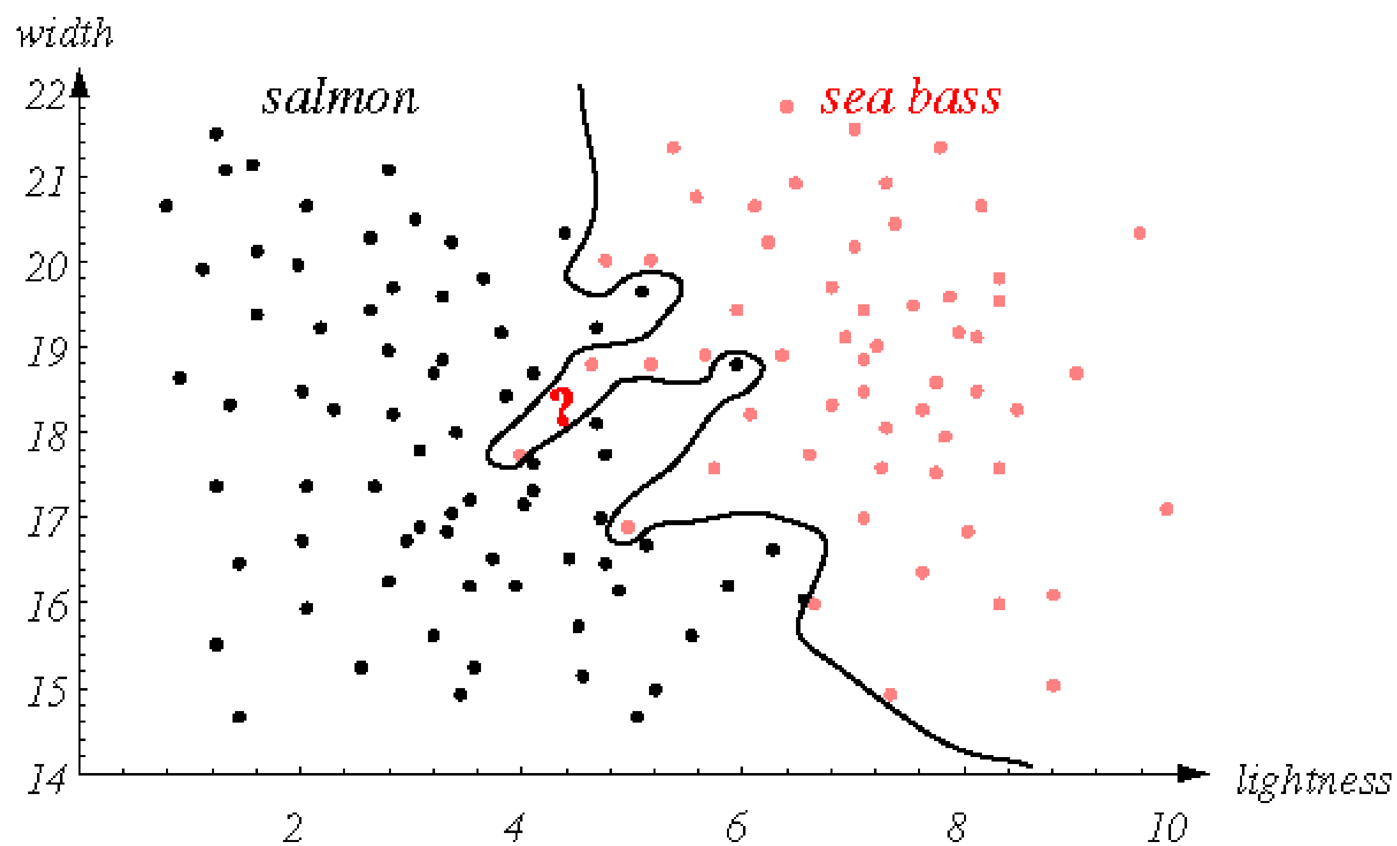
A Case Study: Fish Classification

- Designing a **Classifier**
  - Can we do better with another decision rule?
  - More complex models result in more complex boundaries.

We may distinguish training samples perfectly but **how can we predict how well we can generalize to unknown samples?**



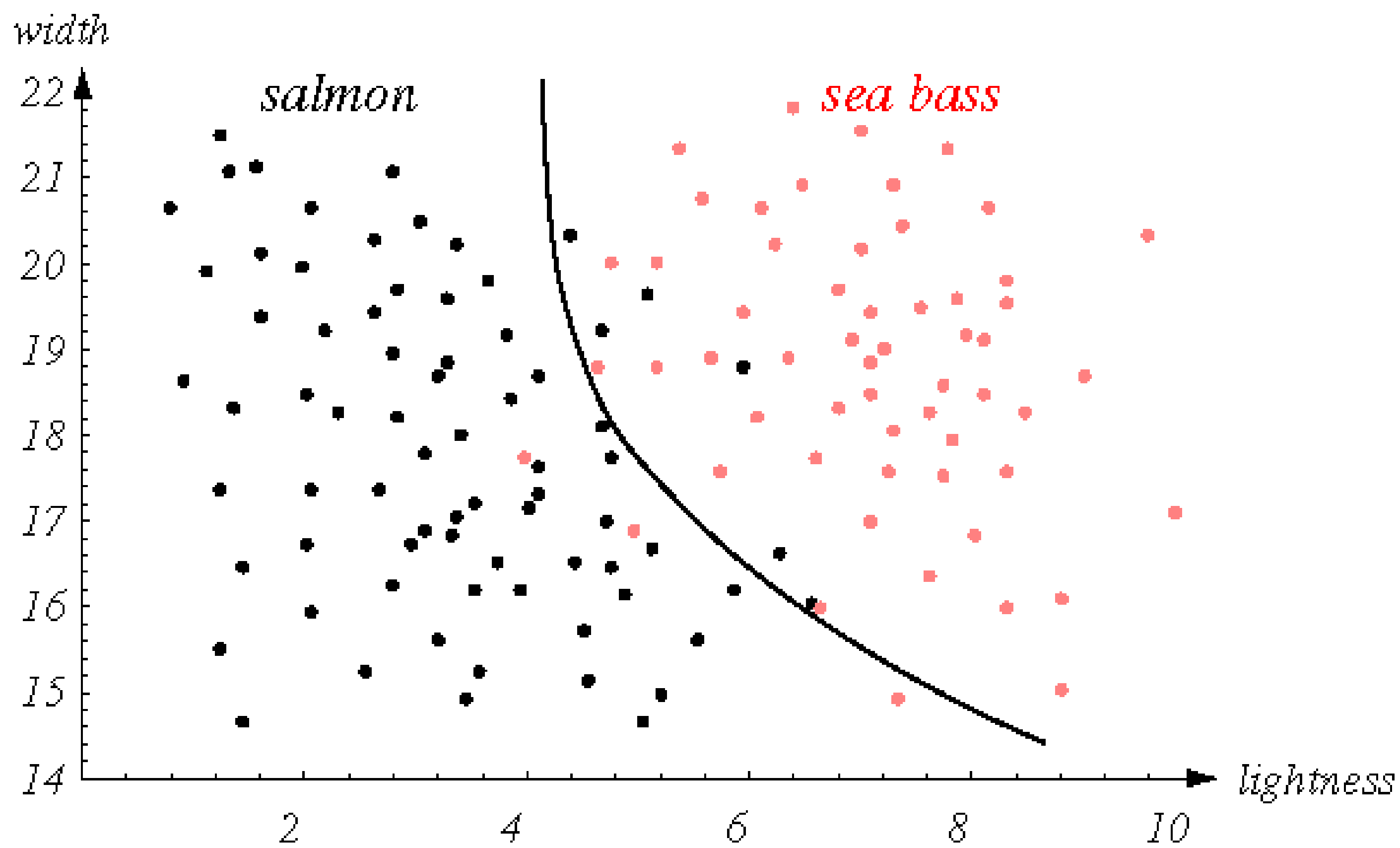
DANGER OF **OVER FITTING!!**

CLASSIFIER WILL FAIL TO GENERALIZE TO NEW DATA...

A Case Study: Fish Classification

- Designing a **Classifier**
  - How can we manage the tradeoff between complexity of decision rules and their performance to unknown samples?

Different criteria lead to different decision boundaries



Feature Extraction

- Designing a **Feature Extractor**
  - Its design is **problem specific** (e.g. features to extract from graphic objects may be quite different from sound events...)
  - The ideal feature extractor would produce the same feature vector X for all patterns in the same class, and different feature vectors for patterns in different classes.
  - In practice, different inputs to the feature extractor will always produce different feature vectors, but we hope that the **within-class variability** is small relative to the **between-class variability**.
- **Designing a good set of features is sometimes "more of an art than a science"...**

Feature Extraction

- Multiple Features
  - Does adding more features always improve the results?
    - No!! So we must:
      - Avoid unreliable features.
      - Be careful about correlations with existing features.
      - Be careful about measurement costs.
      - Be careful about noise in the measurements.
  - **Is there some curse for working in very high dimensions?**
    - YES THERE IS! ==> **CURSE OF DIMENSIONALITY**
      - ➡**thumb rule: n >= d(d-1)/2** n = nr of examples in training dataset
        d = nr of features

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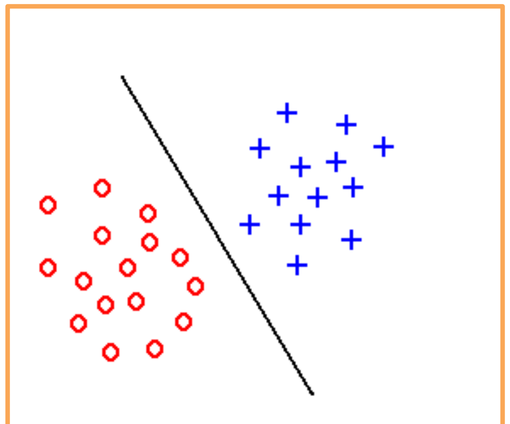
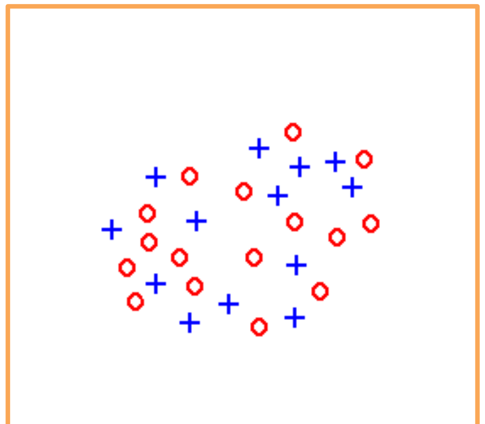
Feature Extraction

- Problem: Inadequate Features
  - features simply do not contain the information needed to separate the classes, it doesn't matter how much effort you put into designing the classifier.
  - **Solution**: go back and design better features.



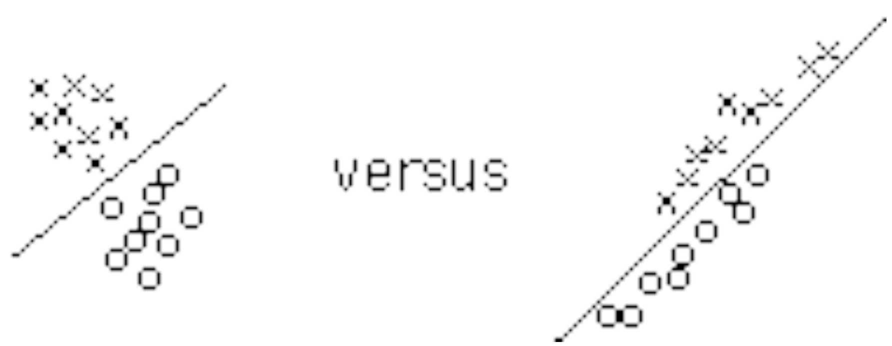
"Good" features



"Bad" features

Feature Extraction

- Problem: Correlated Features
  - Often happens that two features that were meant to measure different characteristics are influenced by some common mechanism and tend to vary together.
    - E.g. the perimeter and the maximum width of a figure will both vary with scale; larger figures will have both larger perimeters and larger maximum widths.
  - This degrades the performance of a classifier based on Euclidean distance to a template.
    - A pattern at the extreme of one class can be closer to the template for another class than to its own template. A similar problem occurs if features are badly scaled, for example, by measuring one feature in microns and another in kilometers.
  - **Solution**: (Use other metrics, e.g. Mahalanobis...) or extract features known to be uncorrelated!



Designing a Classifier

- Model selection:
  - Domain dependence and prior information.
  - Definition of design criteria.
  - Parametric vs. non-parametric models.
  - Handling of missing features.
  - Computational complexity.
  - Types of models: templates, decision-theoretic or statistical, syntactic or structural, neural, and hybrid.
  - How can we know how close we are to the true model underlying the patterns?

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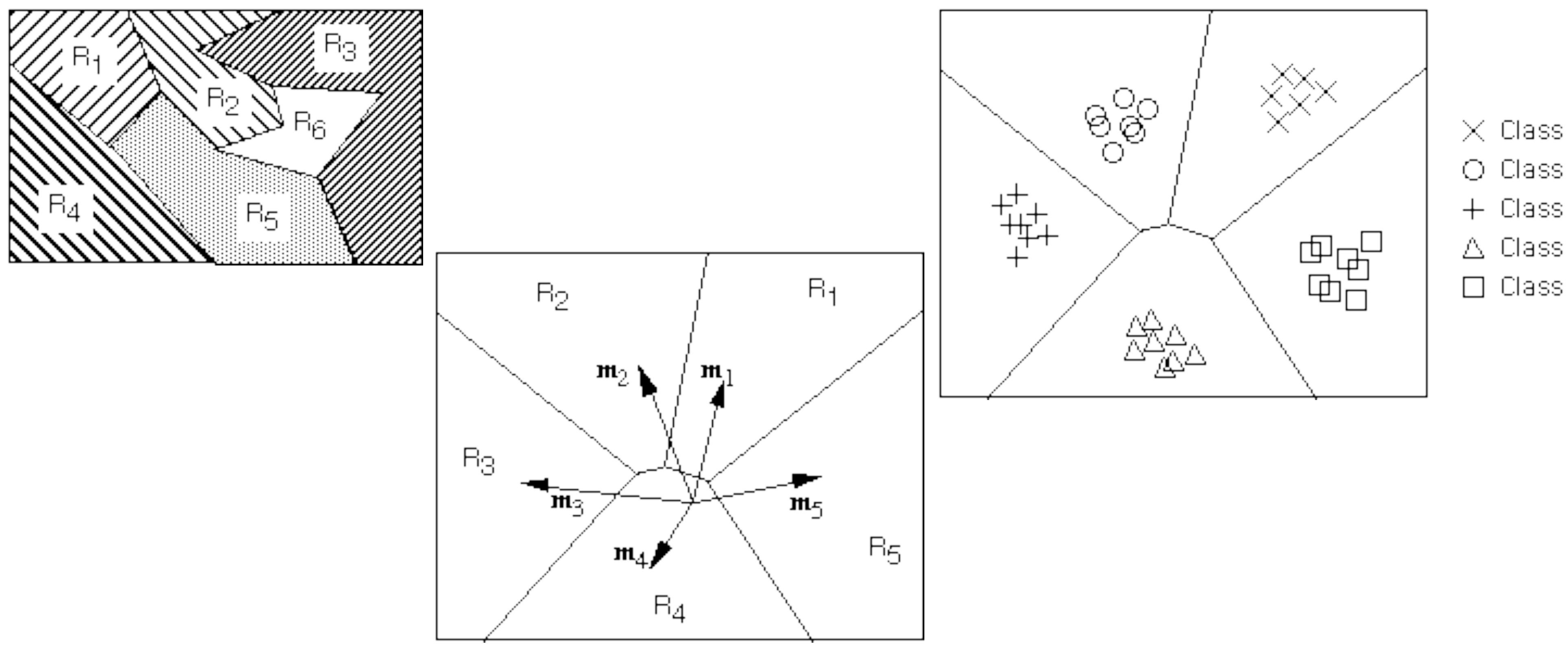
Designing a Classifier

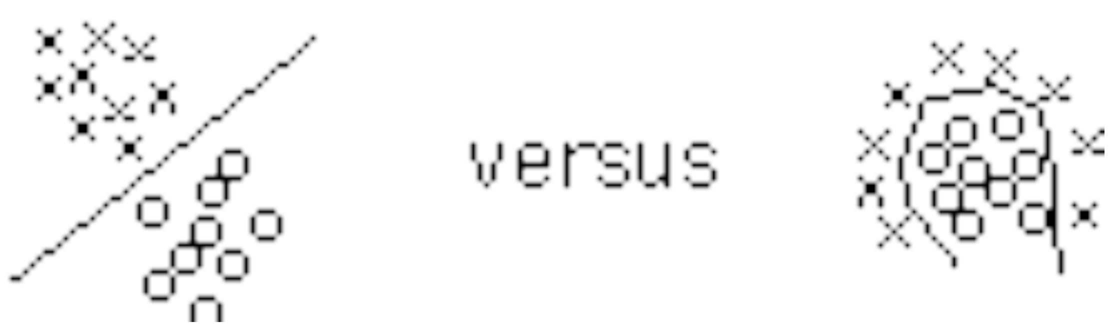
- Designing a **Classifier**
  - How can we manage the tradeoff between complexity of decision rules and their performance to unknown samples?

Different criteria lead to different decision boundaries



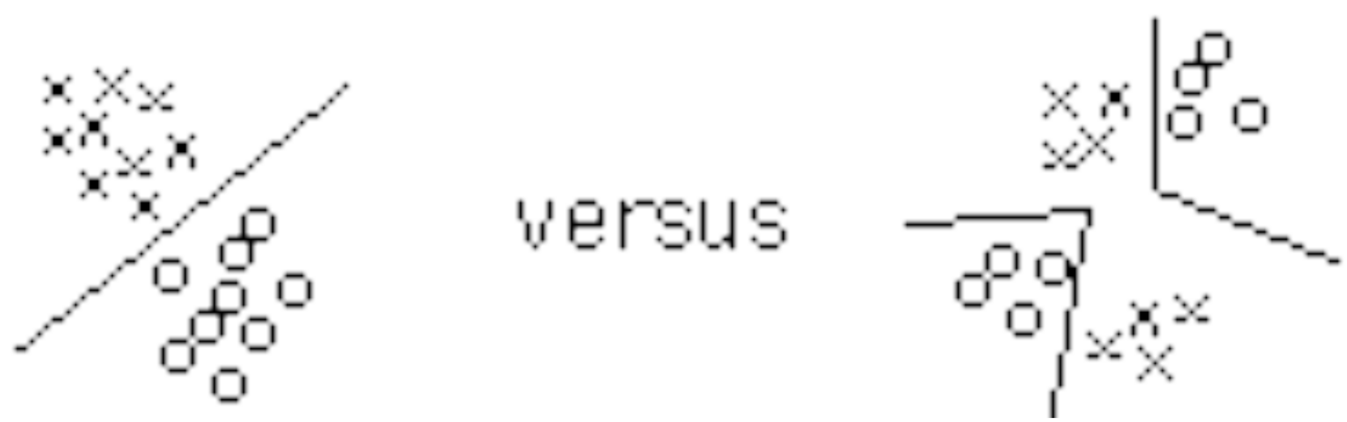
Designing a Classifier

- Problem: Curved Boundaries
  - linear boundaries produced by a minimum-Euclidean-distance classifier may not be flexible enough.
    - For example, if x1 is the perimeter and x2 is the area of a figure, x1 will grow linearly with scale, while x2 will grow quadratically. This will "warp" the feature space and prevent a linear discriminant function from performing well.
  - **Solutions:**
    - Redesign the feature set (e.g., let x2 be the square root of the area)
    - *Try using Mahalanobis distance, which can produce quadratic decision boundaries*
    - *Try using a neural network (beyond the scope of these notes; see Haykin)*



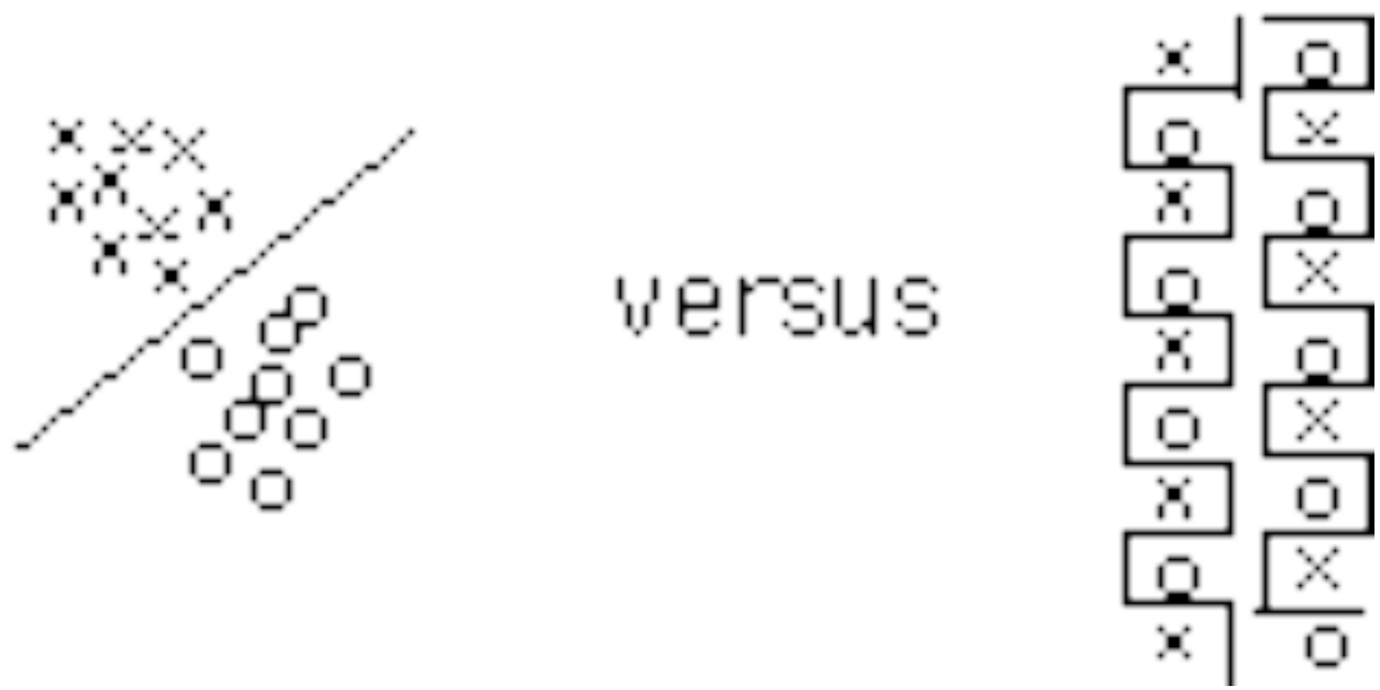
Designing a Classifier

- Problem: Subclasses in the dataset
  - frequently happens that the classes defined by the end user are not the "natural" classes...
  - **Solution**: use CLUSTERING.



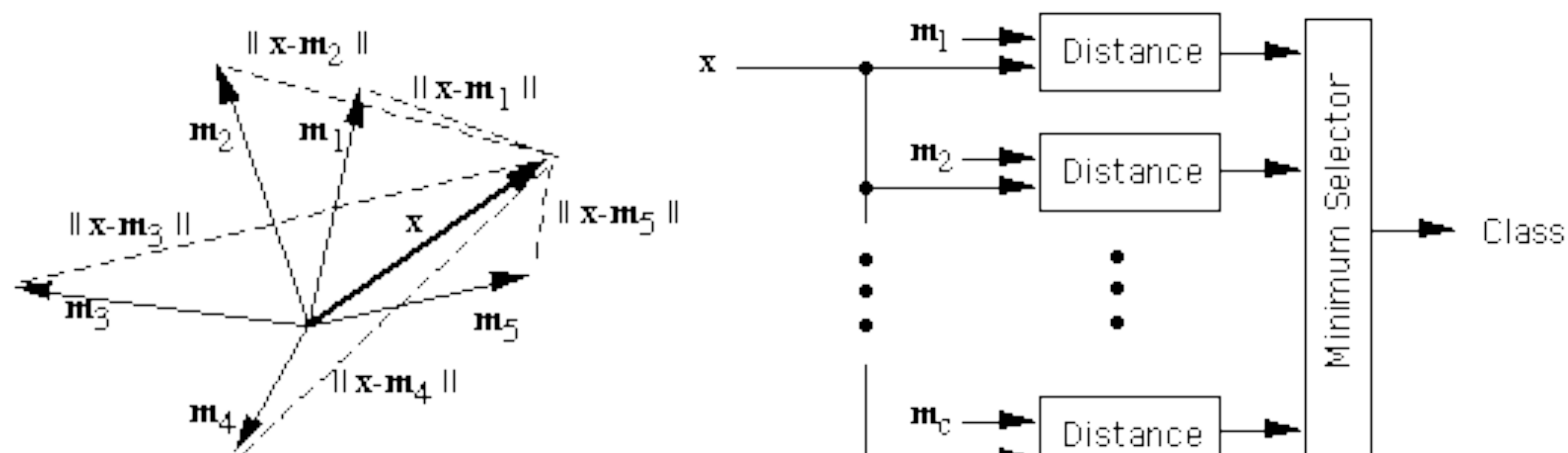
Designing a Classifier

- Problem: Complex Feature Space
  - **Solution**: use different type of Classifier...



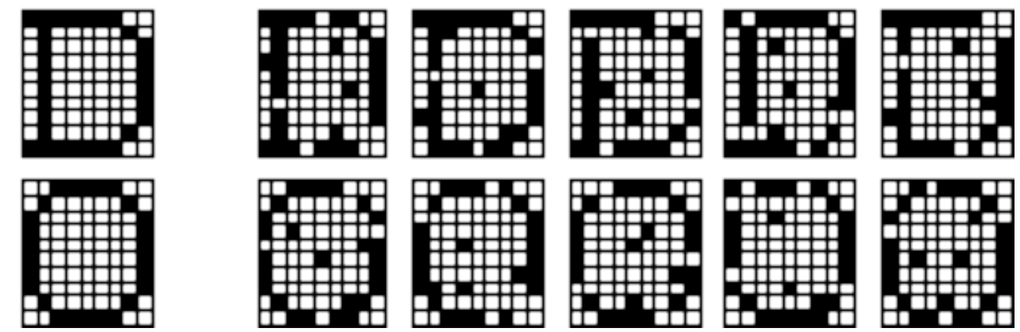
Simple Classifiers

- Minimum-distance Classifiers
  - based on some specified **“metric” ||x-m||**
  - e.g. Template Matching



Simple Classifiers

- Template Matching



TEMPLATES NOISY EXAMPLES

  – To classify one of the noisy examples, simply compare it to the two templates. This can be done in a couple of equivalent ways:

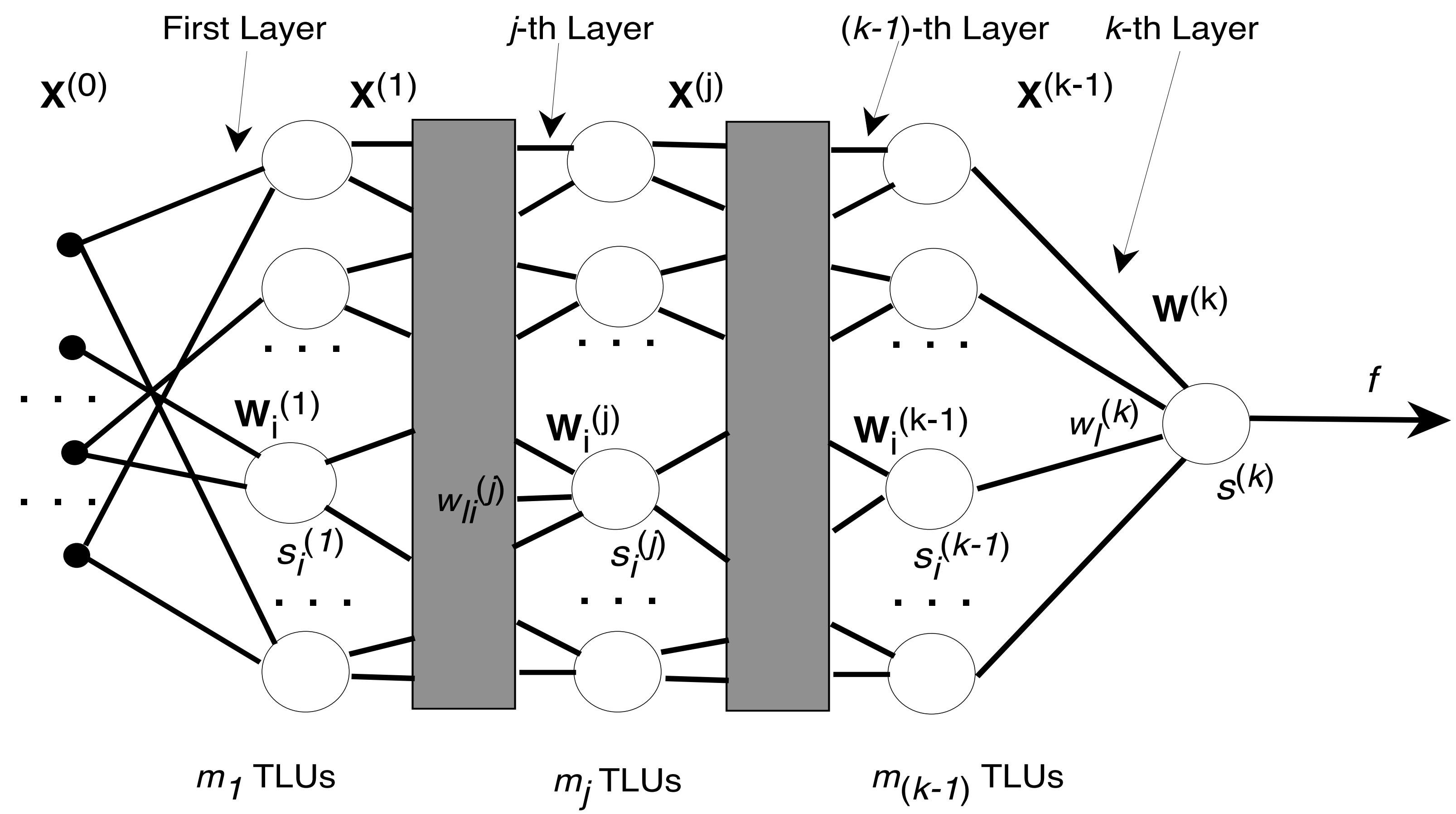
    1. Count the number of agreements. Pick the class that has the maximum number of agreements. **This is a maximum correlation approach**.
    2. Count the number of disagreements. Pick the class with the minimum number of disagreements. **This is a minimum error approach.**

- Works well when the variations within a class are due to "additive noise", and there are no other distortions of the characters -- translation, rotation, shearing, warping, expansion, contraction or occlusion.

Simple Classifiers

- Metrics
  - different ways of measuring distance:
    - **Euclidean metric:**
      - $|| u || = sqrt(u12 + u22 + ... + ud2)$
    - **Manhattan (or taxicab) metric:**
      - $|| u || = |u1| + |u2| + ... + |ud|$
    - Contours of constant...
      - ... Euclidean distance are circles (or spheres)
      - ... Manhattan distance are squares (or boxes)
      - ... Mahalanobis distance are ellipses (or ellipsoids)

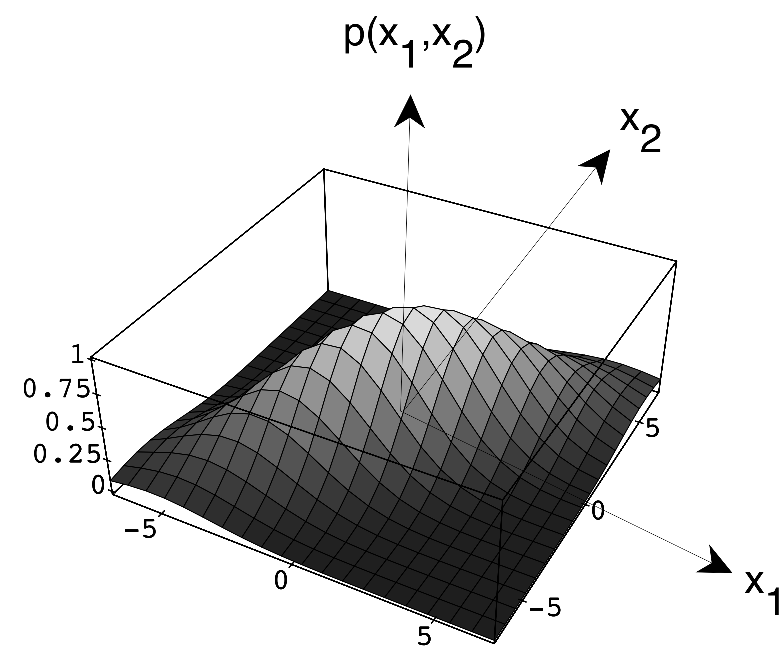
Classifiers: Neural Networks

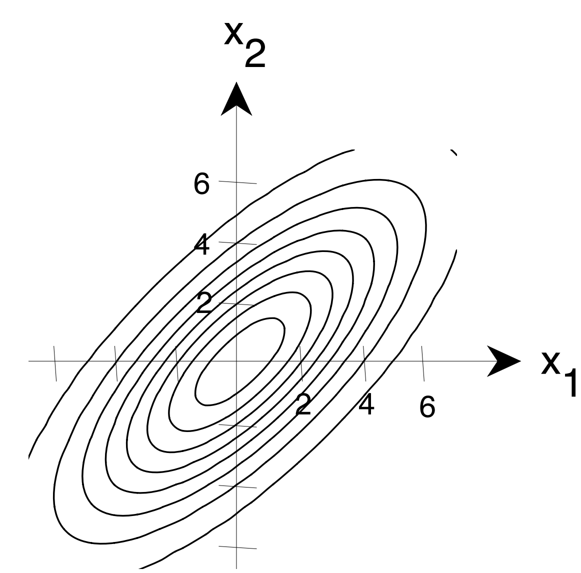


http://robotics.stanford.edu/people/nilsson/MLBOOK.pdf

Gaussian Modeling

$$N(\mu,\Sigma) = \frac{1}{\sqrt{(2\pi)^n.\left|\Sigma\right|}} e^{-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)}, n = 2$$





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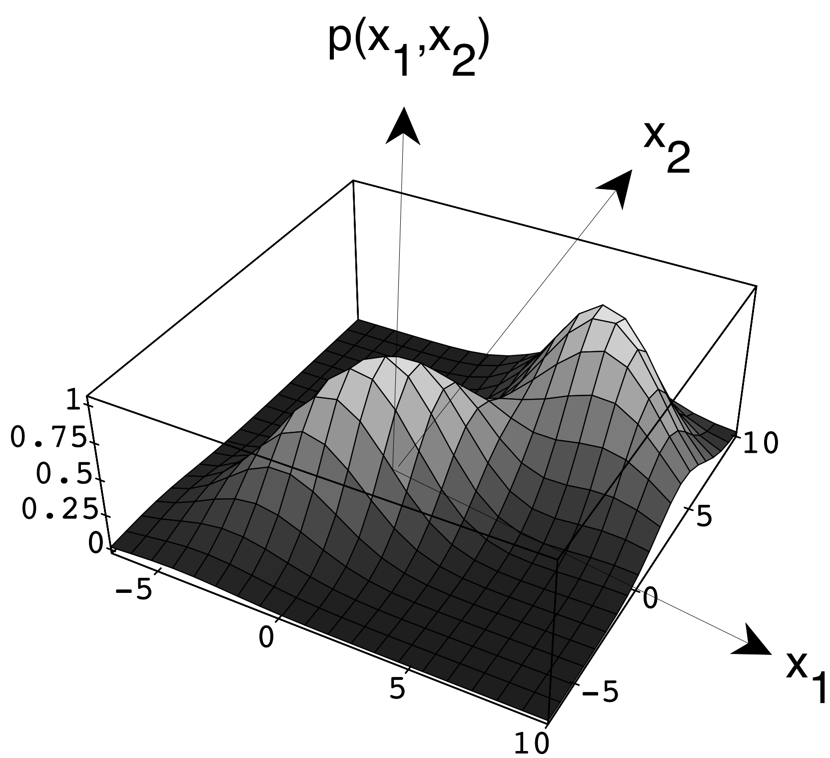
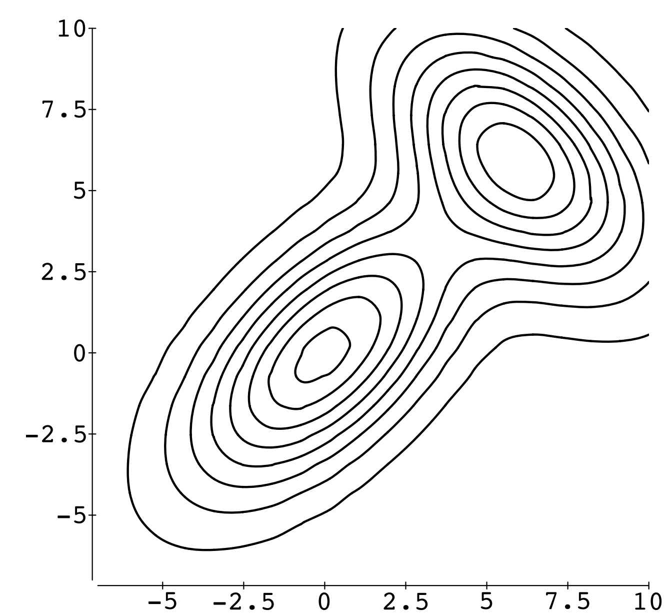
Gaussian Mixture Models

- Use multiple Gaussians to model the data





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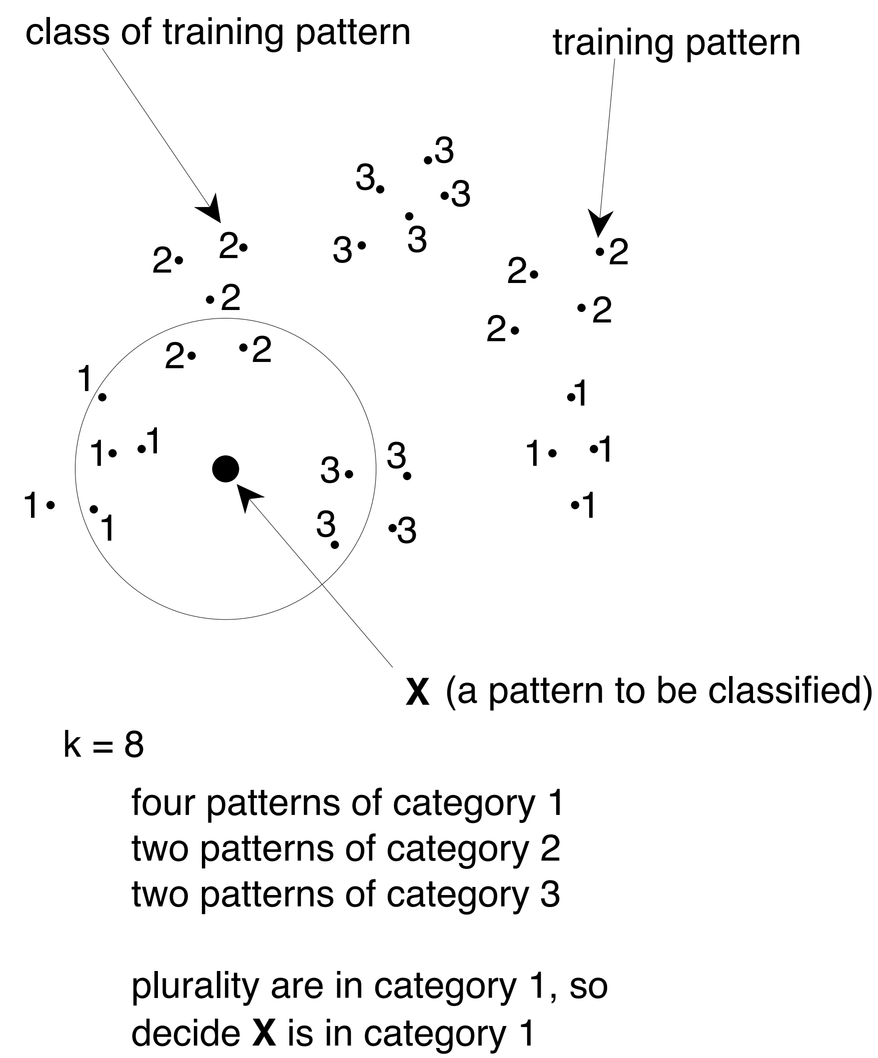
Classifiers: kNN

- k-Nearest Neighbours Classifier
  - Lazy Classifier
    - no training is actually performed (hence, lazy ;-))
  - An example of Instance Based Learning



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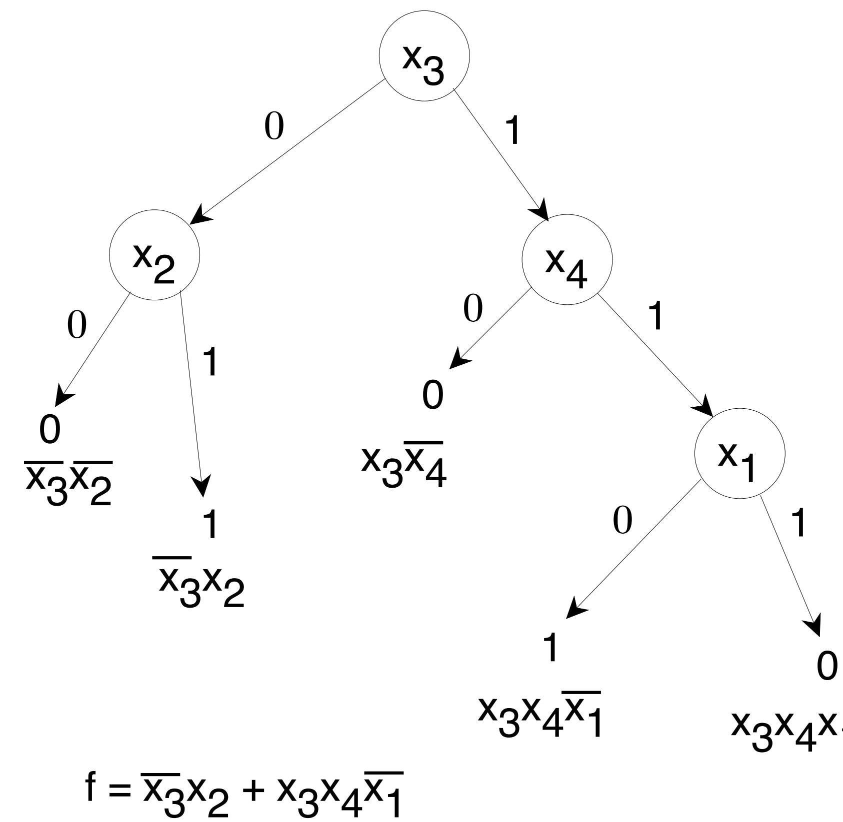
Decision Trees

- Learn rules from data
- Apply each rule at each node
- classification is at the leafs of the tree



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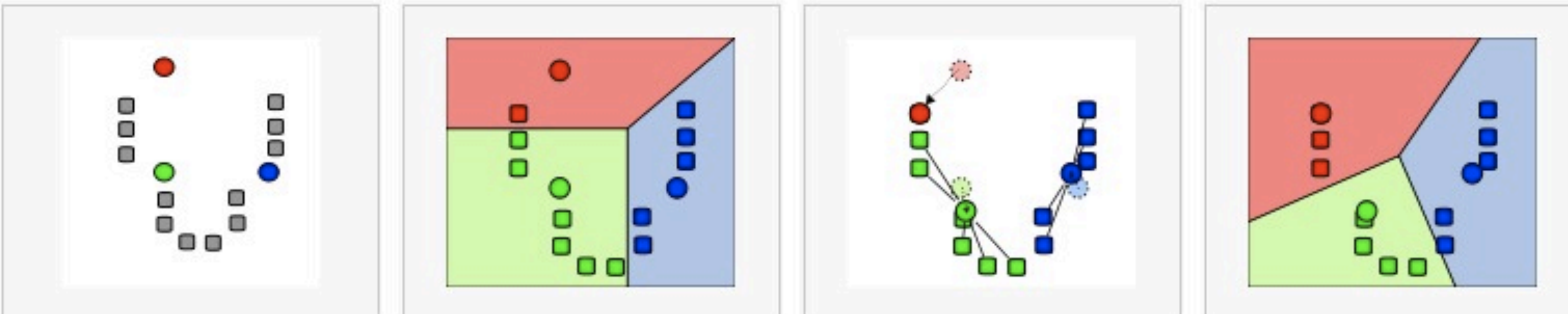
Clustering: k-means



1) *k* initial "means" (in this case *k*=3) are randomly selected from the data set (shown in color).

2) *k* clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means.

3) The centroid of each of the *k* clusters becomes the new means.

4) Steps 2 and 3 are repeated until convergence has been reached.

http://en.wikipedia.org/wiki/K-means_clustering

Evaluating a Classifier

- **Training Set**
  - used for training the classifier
- **Testing Set**
  - examples not used for training
  - avoids overfitting to the data
  - tests generalization abilities of the trained classifiers
- Data sets are usually hard to obtain...
  - Labeling examples is time and effort consuming
  - Large labeled datasets usually not widely available
  - Requirement of separate training and testing datasets imposes higher difficulties...
  - Use **Cross-Validation** techniques!

Evaluating a Classifier

- **Confusion Matrix**

Example confusion matrix

		Predicted		
		Cat	Dog	Rabbit
Actual	Cat	5	3	0
	Dog	2	3	1
	Rabbit	0	2	11

		prediction outcome		
		p	*n*	total
actual value	*p'*	True Positive	False Negative	P'
	n'	False Positive	True Negative	N'
	total	P	N	

http://en.wikipedia.org/wiki/Confusion_matrix

Evaluating a Classifier

- **Costs of Error**
  - We should also consider costs of different errors we make in our decisions. For example, if the fish packing company knows that:
    - Customers who buy salmon will object vigorously if they see sea bass in their cans.
    - Customers who buy sea bass will not be unhappy if they occasionally see some expensive salmon in their cans.
- **How does this knowledge affect our decision?**

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