LECTURE 1: Course introduction

- **Introduction**
  - Course organization
  - Grading policy
  - Outline
- **What is Pattern Recognition?**
  - Definitions from the literature
  - Related fields and applications
- **Components of a Pattern Recognition system**
  - Pattern Recognition problems
  - Features and Patterns
  - The Pattern Recognition design cycle
- **Pattern Recognition approaches**
  - Statistical
  - Neural
  - Structural

Course organization

- **Instructor**
  - Ricardo Gutierrez-Osuna
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  - Tel: (979) 845-2942
  - E-mail: rgutier@cs.tamu.edu
  - URL: http://faculty.cs.tamu.edu/rgutier/
- **Grading**
  - **Homework**
    - 3 assignments, every 3 weeks
  - **Tests**
    - 1 midterm, 1 final (comprehensive)
  - **Term project**
    - Open-ended
    - Public presentation

	Weight (%)
Homework	30
Project	40
Midterm	15
Final Exam	15

Course outline

- **Introduction (3 lectures)**
  - Pattern Recognition
  - Probability and Statistics
  - MATLAB® and Linear Algebra
- **Statistical Pattern Recognition (7 lectures)**
  - Bayesian Decision Theory
  - Quadratic Classifiers
  - Parameter and Density Estimation
  - Nearest Neighbors
  - Linear Discriminants
  - Validation
- **Dimensionality Reduction (4 lectures)**
  - Principal Components Analysis
  - Fisher's Discriminants Analysis
  - Feature Subset Selection
- **Clustering (3 lectures)**
  - Mixture models
  - Hierarchical Clustering
  - On-line Clustering
  - Self-Organizing Maps
- **Neural network approaches (4 lectures)**
  - Multilayer Perceptrons
  - Radial Basis Functions
  - Associative Memories
- **Advanced topics (5 lectures)**
  - Support Vector Machines
  - Hidden Markov Models
  - Ensemble Learning

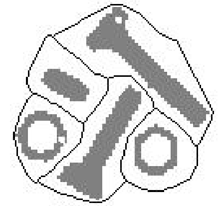
What is pattern recognition?

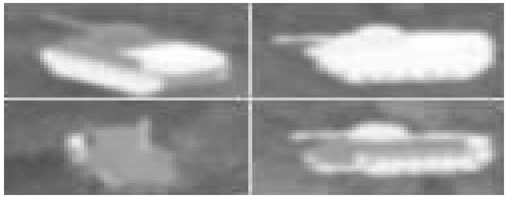
Definitions from the literature

- "The assignment of a physical object or event to one of several pre-specified categories" *–Duda and Hart*
- "A problem of estimating density functions in a high-dimensional space and dividing the space into the regions of categories or classes" *– Fukunaga*
- "Given some examples of complex signals and the correct decisions for them, make decisions automatically for a stream of future examples" *–Ripley*
- "The science that concerns the description or classification (recognition) of measurements" *–Schalkoff*
- "The process of giving names ω to observations **x**", *–Schürmann*
- Pattern Recognition is concerned with answering the question "***What is this?***" *–Morse*

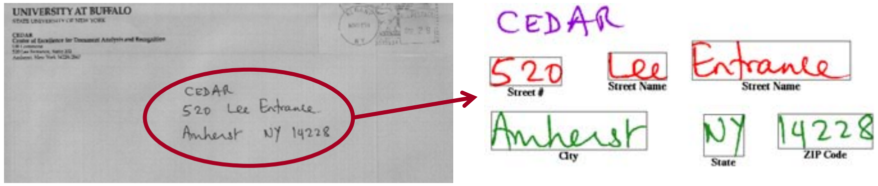
Examples of pattern recognition problems

- **Machine vision**
  - Visual inspection, ATR
  - Imaging device detects ground target
  - Classification into “friend” or “foe”

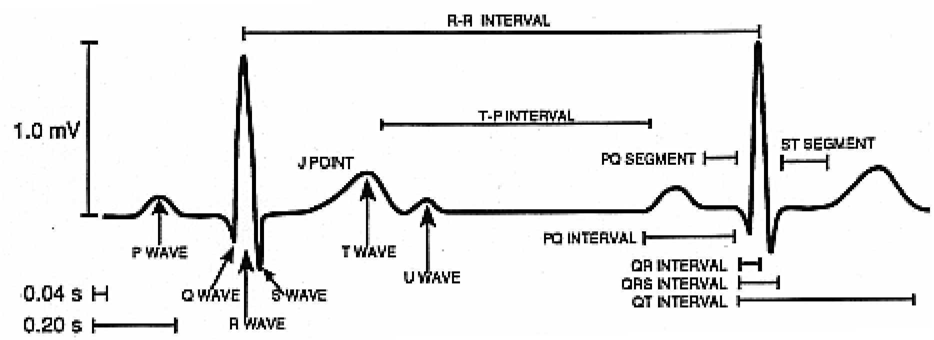




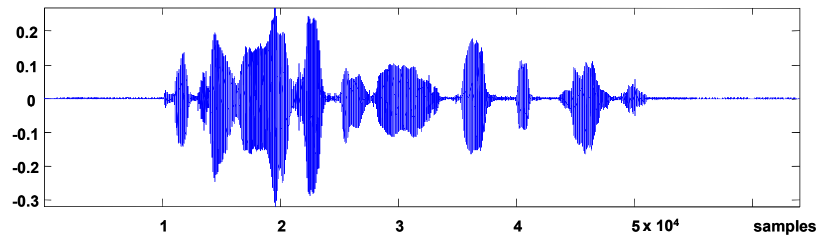
- **Character recognition**
  - Automated mail sorting, processing bank checks
  - Scanner captures an image of the text
  - Image is converted into constituent characters



- **Computer aided diagnosis**
  - Medical imaging, EEG, ECG signal analysis
  - Designed to assist (not replace) physicians
  - Example: X-ray mammography
    - 10-30% false negatives in x-ray mammograms
    - 2/3 of these could be prevented with proper analysis



- **Speech recognition**
  - Human Computer Interaction, Universal Access
  - Microphone records acoustic signal
  - Speech signal is classified into phonemes and/or words



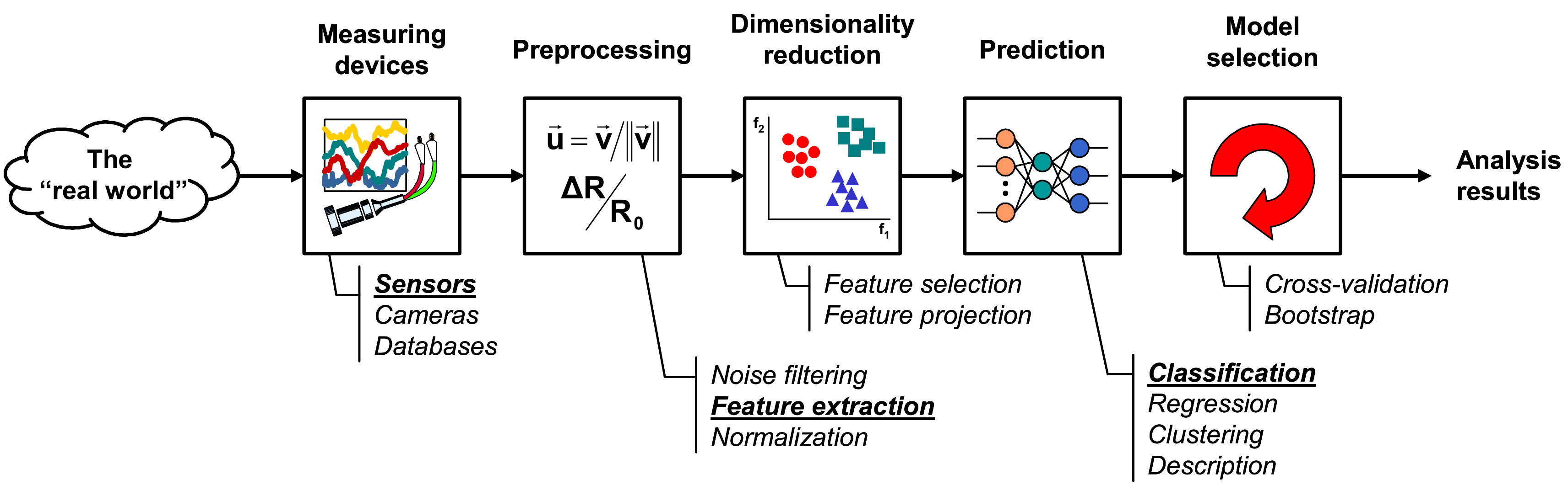
Related fields and application areas for PR

- **Related fields**
  - Adaptive Signal Processing
  - Machine Learning
  - Artificial Neural Networks
  - Robotics and Vision
  - Cognitive Sciences
  - Mathematical Statistics
  - Nonlinear Optimization
  - Exploratory Data Analysis
  - Fuzzy and Genetic systems
  - Detection and Estimation Theory
  - Formal Languages
  - Structural Modeling
  - Biological Cybernetics
  - Computational Neuroscience

- **Applications**
  - Image Preprocessing / Segmentation
  - Computer Vision
  - Speech Recognition
  - Automated Target Recognition
  - Optical Character Recognition
  - Seismic Analysis
  - Man and Machine Diagnostics
  - Fingerprint Identification
  - Industrial Inspection
  - Financial Forecast
  - Medical Diagnosis
  - ECG Signal Analysis

Components of a pattern recognition system

- **A basic pattern classification system contains**
  - A sensor
  - A preprocessing mechanism
  - A feature extraction mechanism (manual or automated)
  - A classification algorithm
  - A set of examples (training set) already classified or described



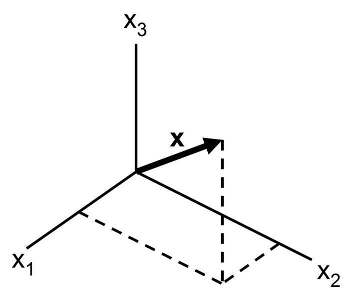
Types of prediction problems

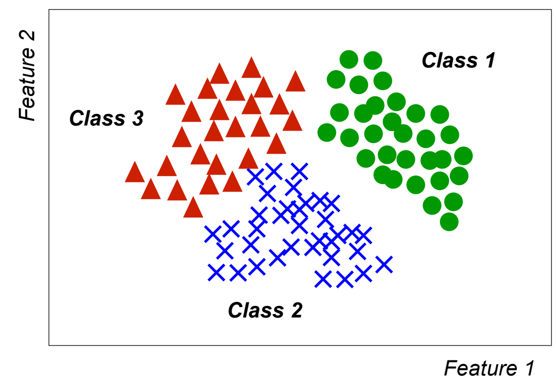
- **Classification**
  - The PR problem of assigning an object to a class
  - The output of the PR system is an integer label
    - e.g. classifying a product as “good” or “bad” in a quality control test
- **Regression**
  - A generalization of a classification task
  - The output of the PR system is a real-valued number
    - e.g. predicting the share value of a firm based on past performance and stock market indicators
- **Clustering**
  - The problem of organizing objects into meaningful groups
  - The system returns a (sometimes hierarchical) grouping of objects
    - e.g. organizing life forms into a taxonomy of species
- **Description**
  - The problem of representing an object in terms of a series of primitives
  - The PR system produces a structural or linguistic description
    - e.g. labeling an ECG signal in terms of P, QRS and T complexes

Features and patterns (1)

- **Feature**
  - Feature is any <u>distinctive</u> aspect, quality or characteristic
    - Features may be symbolic (i.e., color) or numeric (i.e., height)
  - Definitions
    - The combination of d features is represented as a d-dimensional column vector called a **feature vector**
    - The d-dimensional space defined by the feature vector is called the **feature space**
    - Objects are represented as points in feature space. This representation is called a **scatter plot**

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



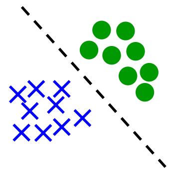


Feature vector | **Feature space (3D)** | **Scatter plot (2D)**

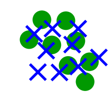
- **Pattern**
  - Pattern is a <u>composite</u> of traits or features <u>characteristic of an individual</u>
  - In classification tasks, a pattern is a <u>pair</u> of variables $\{x, \omega\}$ where
    - $\boldsymbol{x}$ is a collection of observations or features (feature vector)
    - ω is the concept behind the observation (label)

Features and patterns (2)

- **What makes a "good" feature vector?**
  - The quality of a feature vector is related to its ability to discriminate examples from different classes
    - Examples from the same class should have similar feature values
    - Examples from different classes have different feature values

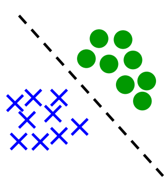


"Good" features

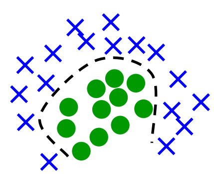


"Bad" features

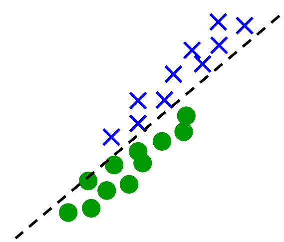
- **More feature properties**



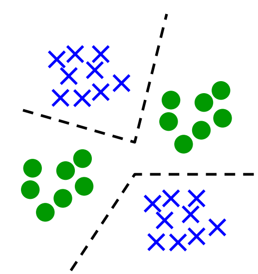
Linear separability



Non-linear separability



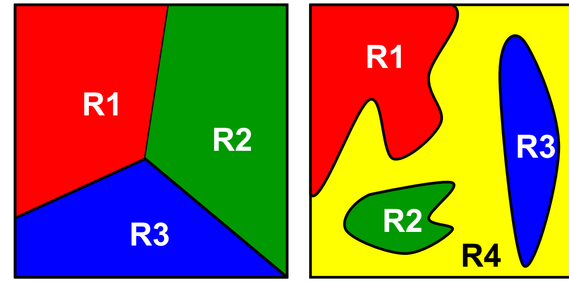
Highly correlated features



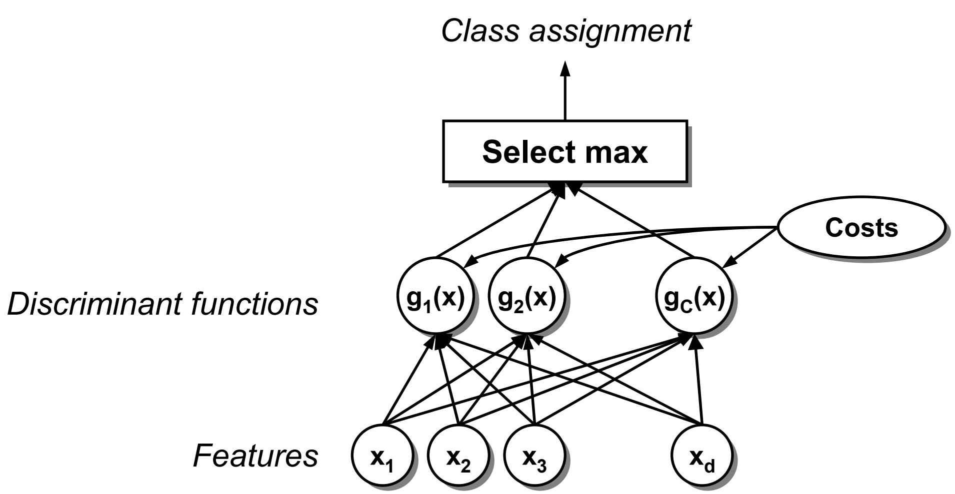
Multi-modal

Classifiers

- **The task of a classifier is to partition feature space into class-labeled decision regions**
  - Borders between decision regions are called **decision boundaries**
  - The classification of feature vector ***x*** consists of determining which decision region it belongs to, and assign ***x*** to this class



- **A classifier can be represented as a set of discriminant functions**
  - The classifier assigns a feature vector ***x*** to class ω_i if $g_i(\boldsymbol{x}) > g_j(\boldsymbol{x}) \quad \forall j \neq i$

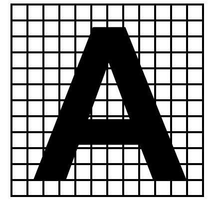


Pattern recognition approaches

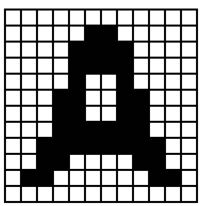
- **Statistical (StatPR)**
  - Patterns classified based on an underlying statistical model of the features
    - The statistical model is defined by a family of **class-conditional probability** density functions $Pr(x|c_i)$ (Probability of feature vector $\boldsymbol{x}$ given class $\boldsymbol{c_i}$)
- **Neural (NeurPR)**
  - Classification is based on the response of a network of processing units (neurons) to an input stimuli (pattern)
    - "Knowledge" is stored in the **connectivity and strength of the synaptic weights**
  - NeurPR is a trainable, non-algorithmic, black-box strategy
  - NeurPR is very attractive since
    - it requires minimum a priori knowledge
    - with enough layers and neurons, an ANN can create **any** complex decision region
- **Syntactic (SyntPR)**
  - Patterns classified based on measures of structural similarity
    - "Knowledge" is represented by means of **formal grammars or relational descriptions** (graphs)
  - SyntPR is used not only for classification, but also for description
    - Typically, SyntPR approaches formulate hierarchical descriptions of complex patterns built up from simpler sub patterns

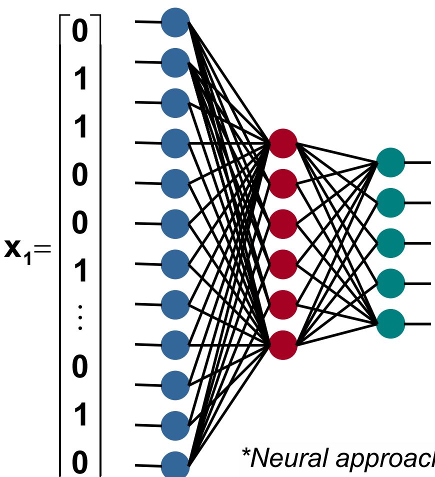
Example: neural, statistical and structural OCR

From [Schalkoff, 1992]



Neural* **Statistical** **Structural**

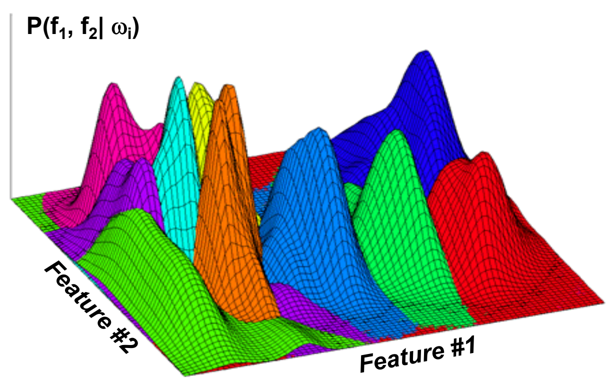


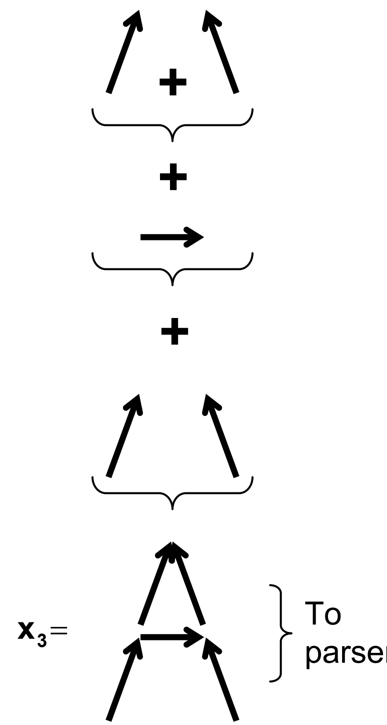


*Neural approaches may also employ feature extraction

Feature extraction:
- # intersections
- # right oblique lines
- # left oblique lines
- # horizontal lines
- # “holes”

$$x_2 = [3 \quad 2 \quad 1 \quad 2 \quad 1]^T \xrightarrow{\text{Probabilistic model}} p(x_2 \,|\, \text{"A"})$$

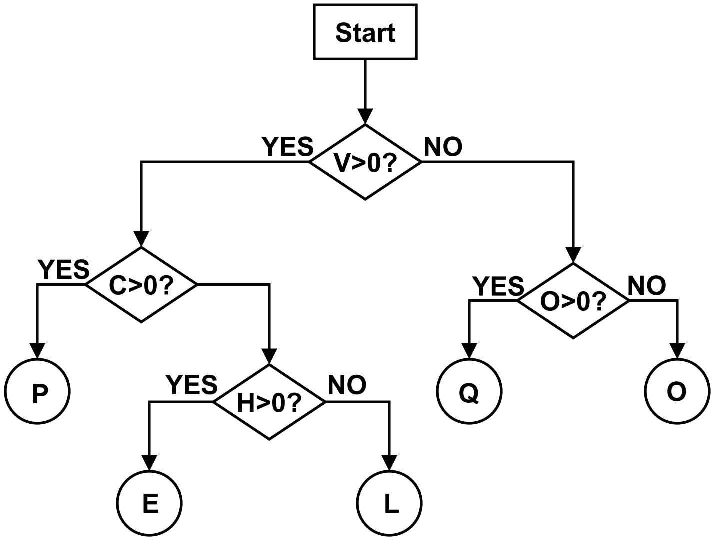




A simple pattern recognition problem

- **Consider the problem of recognizing the letters L,P,O,E,Q**
  - Determine a sufficient set of features
  - Design a tree-structured classifier

Character	Features			
	Vertical straight lines	*Horizontal straight lines*	*Oblique straight lines*	*Curved lines*
L	*1*	*1*	*0*	*0*
P	*1*	*0*	*0*	*1*
O	*0*	*0*	*0*	*1*
E	*1*	*3*	*0*	*0*
Q	*0*	*0*	*1*	*1*

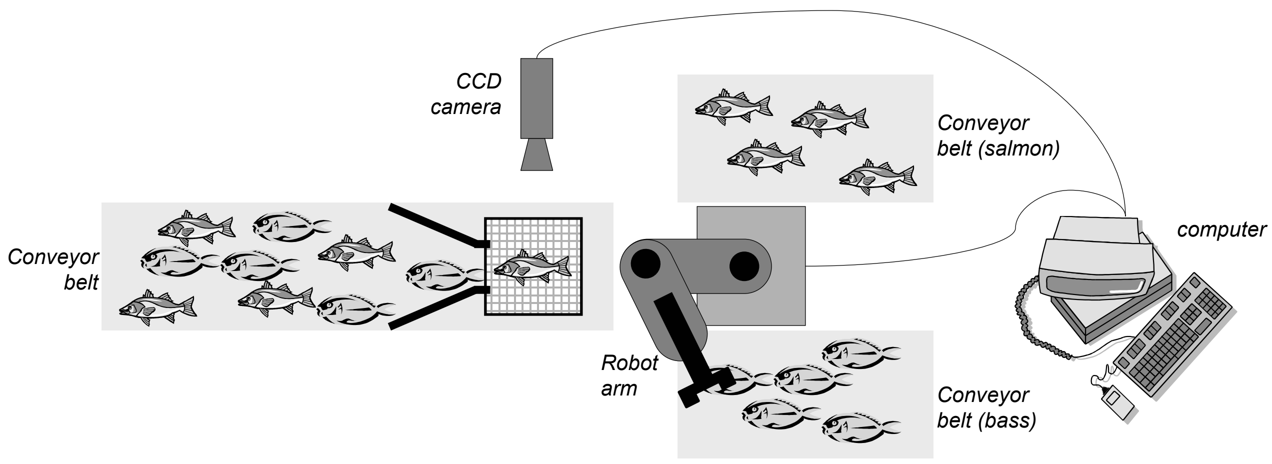


The pattern recognition design cycle (1)

- **Data collection**
  - Probably the most time-intensive component of a PR project
  - How many examples are enough?
- **Feature choice**
  - Critical to the success of the PR problem
    - "Garbage in, garbage out"
  - Requires basic prior knowledge
- **Model choice**
  - Statistical, neural and structural approaches
  - Parameter settings
- **Training**
  - Given a feature set and a "blank" model, adapt the model to explain the data
  - Supervised, unsupervised and reinforcement learning
- **Evaluation**
  - How well does the trained model do?
  - Overfitting vs. generalization

The pattern recognition design cycle (2)

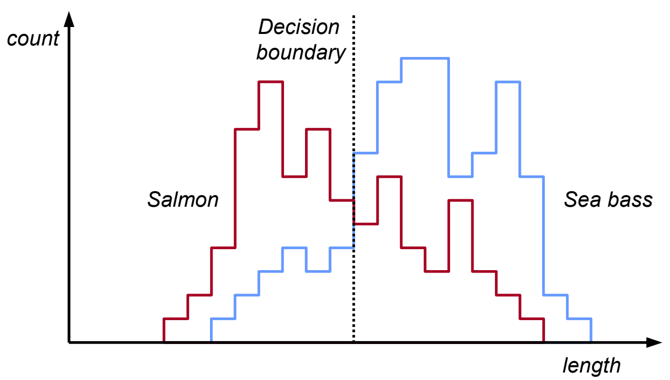
- **Consider the following scenario**
  - A fish processing plan wants to automate the process of sorting incoming fish according to species (salmon or sea bass)
  - The automation system consists of
    - a conveyor belt for incoming products
    - two conveyor belts for sorted products
    - a pick-and-place robotic arm
    - a vision system with an overhead CCD camera
    - a computer to analyze images and control the robot arm



From [Duda, Hart and Stork, 2001]

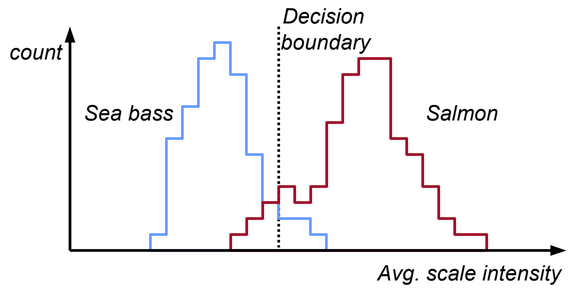
The pattern recognition design cycle (3)

- **Sensor**
  - The vision system captures an image as a new fish enters the sorting area
- **Preprocessing**
  - Image processing algorithms
    - adjustments for average intensity levels
    - segmentation to separate fish from background
- **Feature Extraction**
  - Suppose we know that, on the average, sea bass is larger than salmon
    - From the segmented image we estimate the length of the fish
- **Classification**
  - Collect a set of examples from both species
  - Compute the distribution of lengths for both classes
  - Determine a decision boundary (threshold) that minimizes the classification error
  - We estimate the classifier’s probability of error and obtain a discouraging result of 40%
  - **What do we do now?**

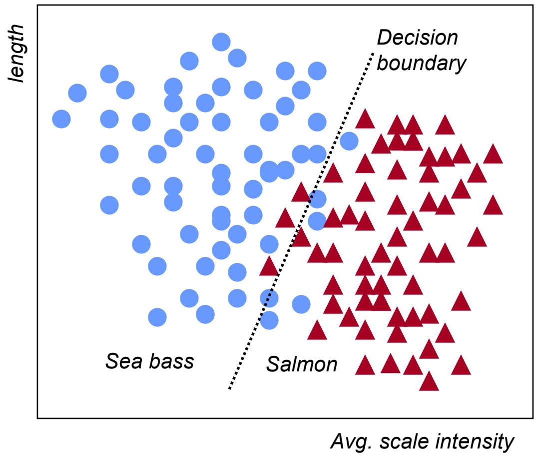


The pattern recognition design cycle (4)

- **Improving the performance of our PR system**
  - Determined to achieve a recognition rate of 95%, we try a number of features
    - Width, Area, Position of the eyes w.r.t. mouth...
    - only to find out that these features contain no discriminatory information
  - Finally we find a “good” feature: average intensity of the scales

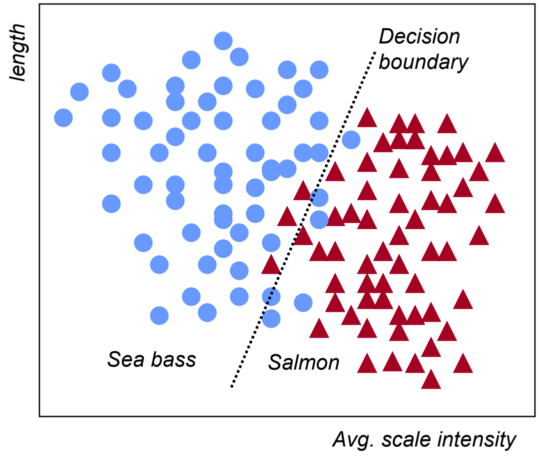


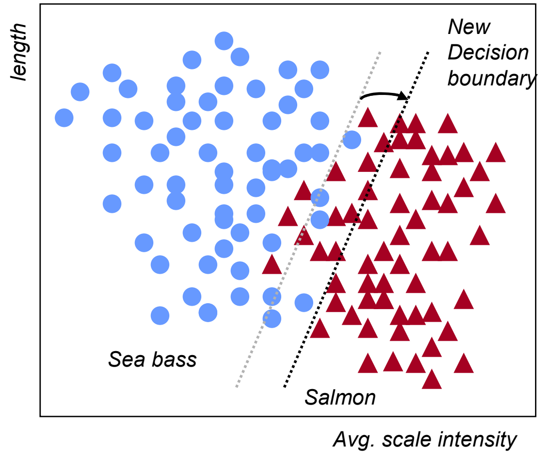
- We combine “*length*” and “*average intensity of the scales*” to improve class separability
- We compute a linear discriminant function to separate the two classes, and obtain a classification rate of 95.7%



The pattern recognition design cycle (5)

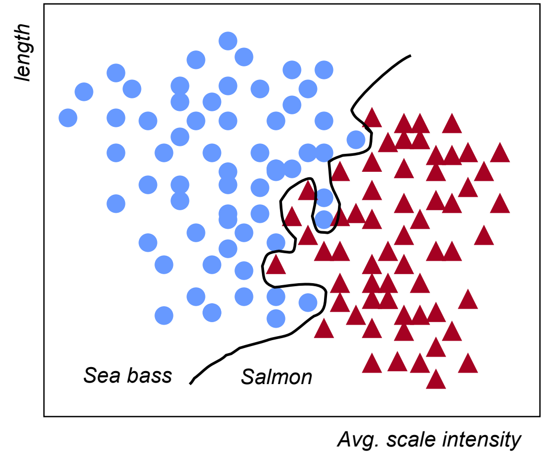
- **Cost Versus Classification rate**
  - Our linear classifier was designed to minimize the overall misclassification rate
  - Is this the best objective function for our fish processing plant?
    - The **cost** of misclassifying salmon as sea bass is that the end customer will occasionally find a tasty piece of salmon when he purchases sea bass
    - The **cost** of misclassifying sea bass as salmon is an end customer upset when he finds a piece of sea bass purchased at the price of salmon
  - Intuitively, we could adjust the decision boundary to minimize this cost function





The pattern recognition design cycle (6)

- **The issue of generalization**
  - The recognition rate of our linear classifier (95.7%) met the design specs, but we still think we can improve the performance of the system
    - We then design an artificial neural network with five hidden layers, a combination of logistic and hyperbolic tangent activation functions, train it with the Levenberg-Marquardt algorithm and obtain an impressive classification rate of 99.9975% with the following decision boundary



  - Satisfied with our classifier, we integrate the system and deploy it to the fish processing plant
    - After a few days, the plant manager calls to complain that the system is misclassifying an average of 25% of the fish
    - What went wrong?