Pattern Recognition

Pattern Recognition

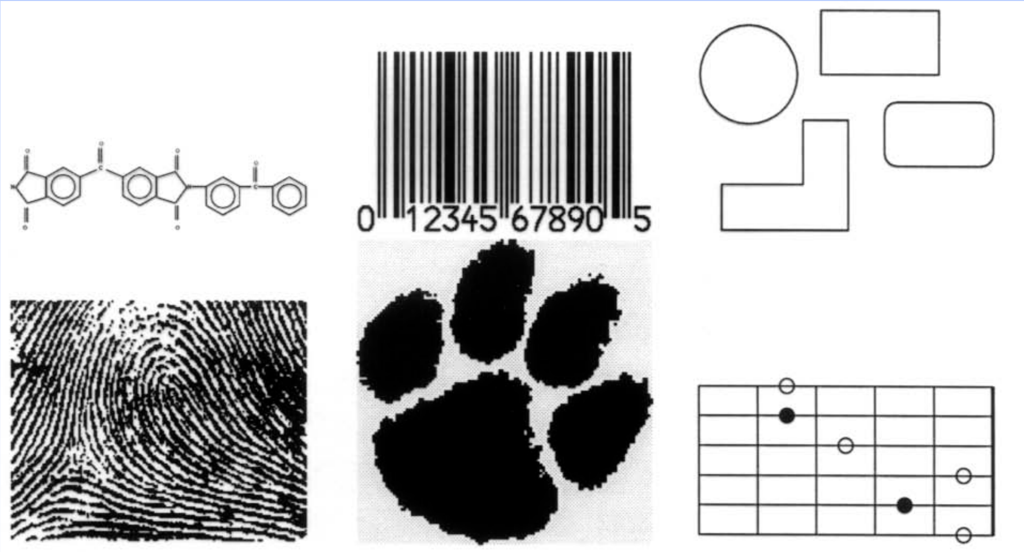
"The real power of human thinking is based on recognizing patterns. The better computers get at pattern recognition, the more humanlike they will become."

Ray Kurzweil, NY Times, Nov 24, 2003

"The problem of searching for patterns in data is a fundamental one and has a long and successful history." Bishop

What is a Pattern?

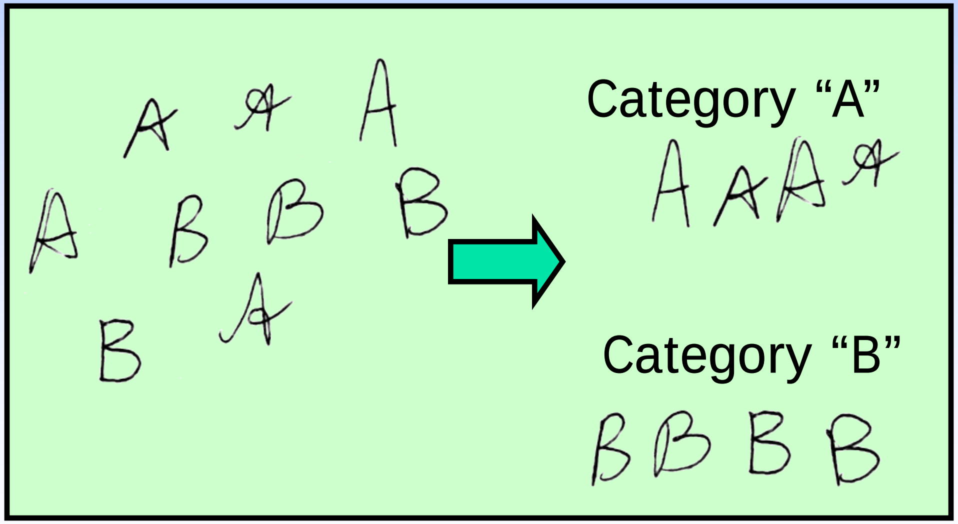
"A pattern is the opposite of a chaos; it is an entity vaguely defined, that could be given a name." (Watanabe)



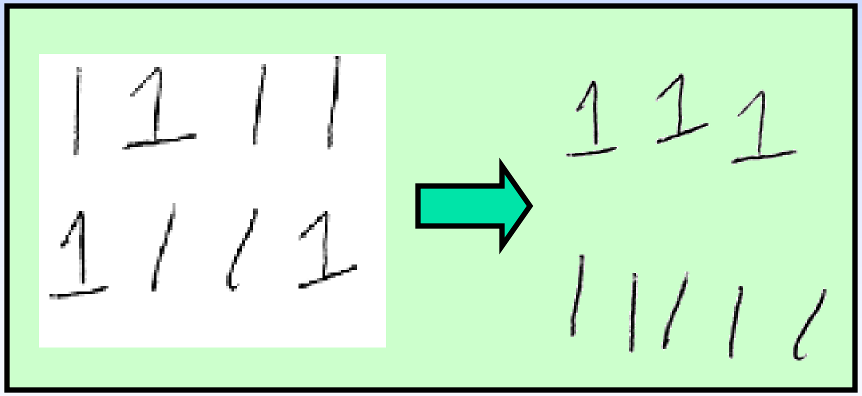
Recognition

Identification of a pattern as a member of a category we already know, or we are familiar with

- Classification (known categories)
- Clustering (learning categories)



Classification



Clustering

Supervised Classification

Training samples are labeled

Unsupervised Classification

Training samples are unlabeled

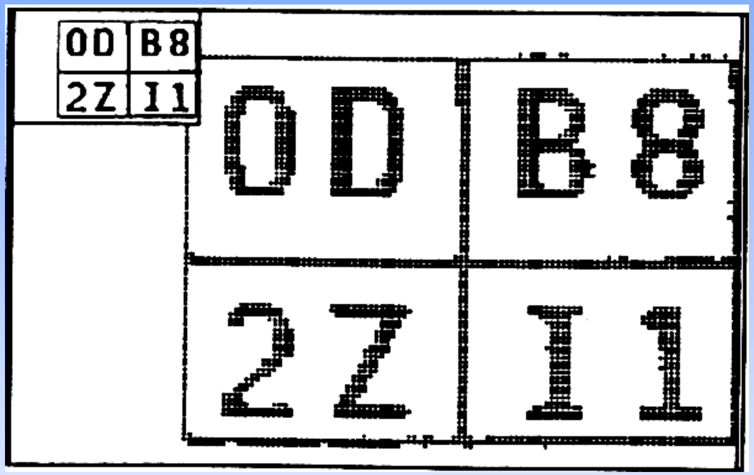
Intra-class Variability

The letter “T” in different typefaces

Same face under different expression, pose, illumination

Inter-class Similarity

Identical twins



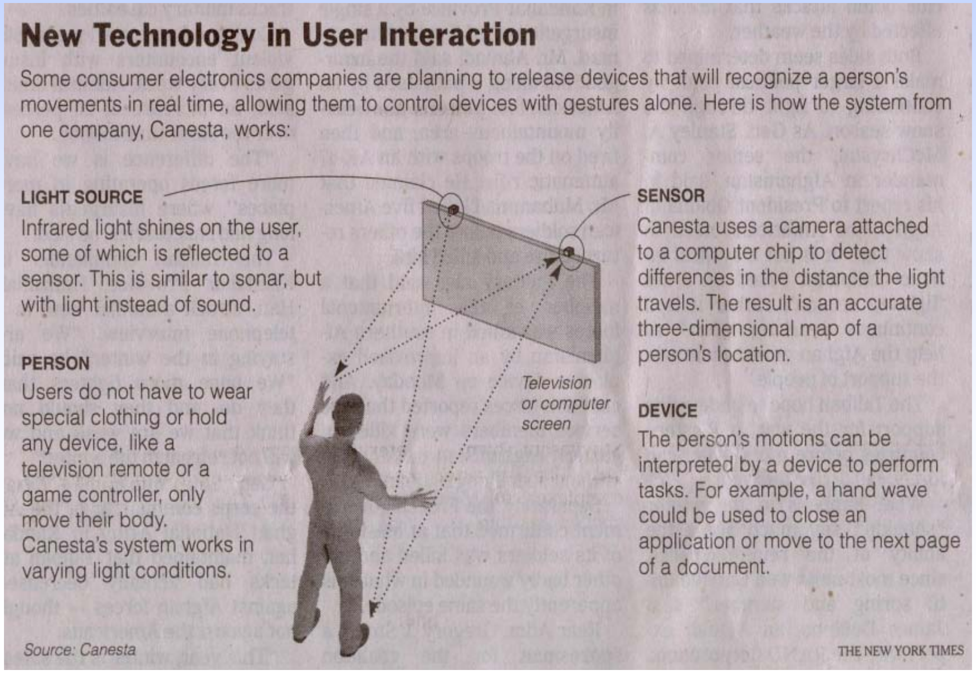
Characters that look similar

Pattern Recognition in Practice

FIGURE 2. Single-camera solutions, such as this cookie packing system from Bosch Packaging Technology, use a geometric pattern-matching algorithm to determine the shape and location of cookies and then stack them in the appropriate section of the tray.

FIGURE 3. To automate the process of orange picking, Vision Robotics has proposed the development of a stereo camera-based system that will use multiple cameras placed at the end of multiaxis arms to create a virtual 3-D image of the entire orange tree.

Vision System Design, Nov 2009



New Technology in User Interaction

Some consumer electronics companies are planning to release devices that will recognize a person's movements in real time, allowing them to control devices with gestures alone. Here is how the system from one company, Canesta, works:

LIGHT SOURCE
Infrared light shines on the user, some of which is reflected to a sensor. This is similar to sonar, but with light instead of sound.

PERSON
Users do not have to wear special clothing or hold any device, like a television remote or a game controller, only move their body. Canesta's system works in varying light conditions.

SENSOR
Canesta uses a camera attached to a computer chip to detect differences in the distance the light travels. The result is an accurate three-dimensional map of a person's location.

Television or computer screen

DEVICE
The person's motions can be interpreted by a device to perform tasks. For example, a hand wave could be used to close an application or move to the next page of a document.

Source: Canesta

THE NEW YORK TIMES

NY Times, Jan 12, 2010

Pattern Recognition System

- Domain-specific knowledge
  - Acquisition, representation
- Data acquisition
  - camera, ultrasound, MRI,....
- Preprocessing
  - Image enhancement, segmentation
- Representation
  - Features: color, shape, texture,...
- Decision making
  - Statistical (geometric) pattern recognition
  - Syntactic (structural) pattern recognition
  - Artificial neural networks
- Post-processing; use of context

System Performance

- Error rate (Prob. of misclassification)
- Speed (throughput)
- Cost
- Robustness
- Reject option
- Return on investment

Pattern Recognition Applications

Problem	Input	Output
Speech recognition	Speech waveforms	Spoken words, speaker identity
Non-destructive testing	Ultrasound, eddy current, acoustic emission waveforms	Presence/absence of flaw, type of flaw
Detection and diagnosis of disease	EKG, EEG waveforms	Types of cardiac conditions, classes of brain conditions
Natural resource identification	Multispectral images	Terrain forms, vegetation cover
Aerial reconnaissance	Visual, infrared, radar images	Tanks, airfields
Character recognition (page readers, zip code, license plate)	scanned image	Alphanumeric characters

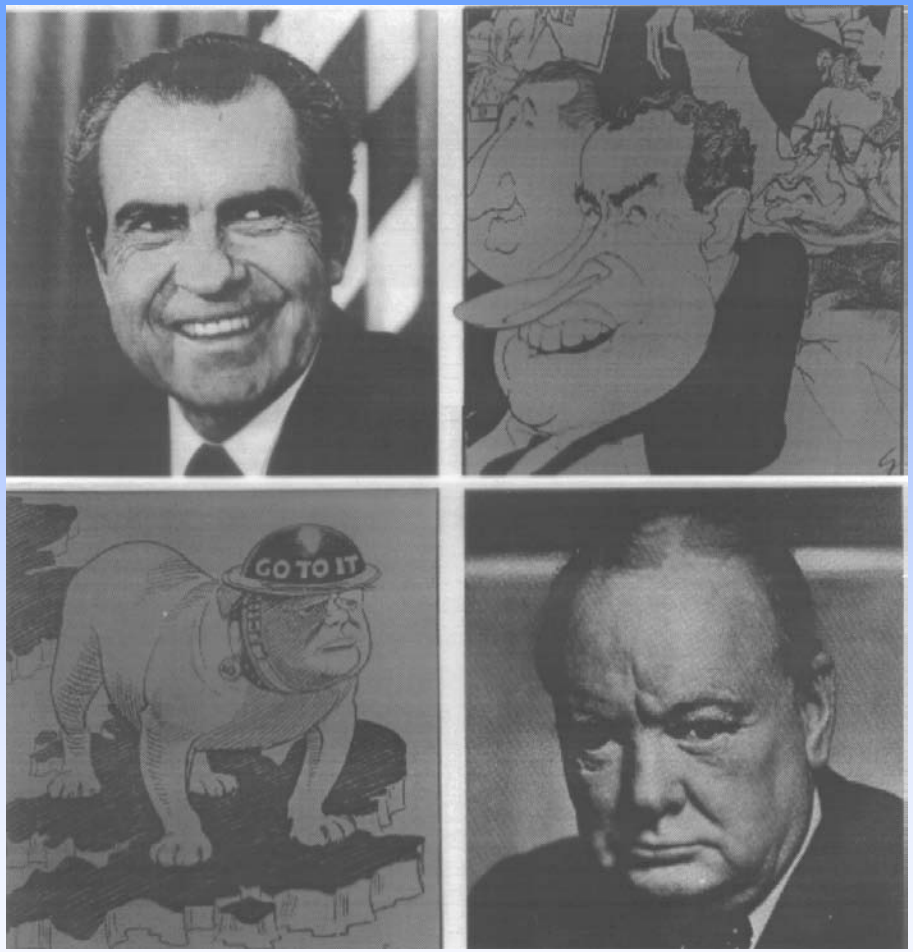
Pattern Recognition Applications

Problem	Input	Output
Identification and counting of cells	Slides of blood samples, micro-sections of tissues	Type of cells
Inspection (PC boards, IC masks, textiles)	Scanned image (visible, infrared)	Acceptable/unacceptable
Manufacturing	3-D images (structured light, laser, stereo)	Identify objects, pose, assembly
Web search	Key words specified by a user	Text relevant to the user
Fingerprint identification	Input image from fingerprint sensors	Owner of the fingerprint, fingerprint classes
Online handwriting retrieval	Query word written by a user	Occurrence of the word in the database

Pattern Recognition System

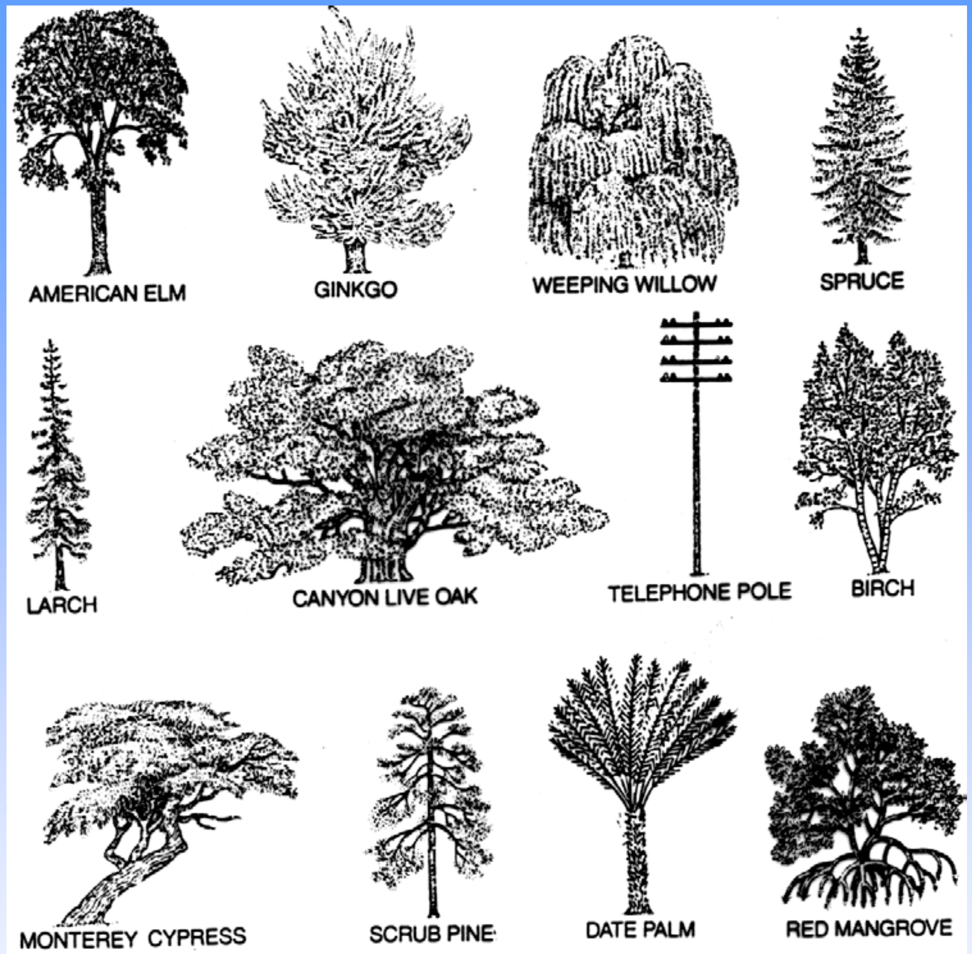
- Challenges
  - Representation
  - Matching
- A pattern recognition system involves
  - Training/design/learning
  - Testing

Difficulties of Representation



How should we model a face to account for the large intra-class variability?

John P. Frisby, *Seeing. Illusion, Brian and Mind*, Oxford University Press, 1980



ARE ALL THESE OBJECTS TREES? Even a young child can answer correctly; a conventional computer, however, has enormous difficulty in doing so. Although there is a fair amount of regularity among the trees shown (each has a trunk and branches, for example), there is also a major component of arboreal irregularity among them. A generalized definition of a tree based on the underlying regularity could lead to erroneous identifications (such as mistaking a telephone pole, which has a "trunk" and "branches," for a tree). Hence any effective program designed to recognize trees would essentially have to be a list of all types of trees, which cannot be done in a few lines of computer code.

Good Representation

- Should have some invariant properties (e.g., w.r.t. rotation, translation, scale...)
- Account for intra-class variations
- Ability to discriminate pattern classes of interest
- Robustness to noise, occlusion,..
- Lead to simple decision making strategies (e.g., linear decision boundary)
- Low measurement cost; real-time

Fish Classification: Salmon v. Sea Bass

Preprocessing involves image enhancement and segmentation; (i) separate touching or occluding fishes and (ii) extract fish contour

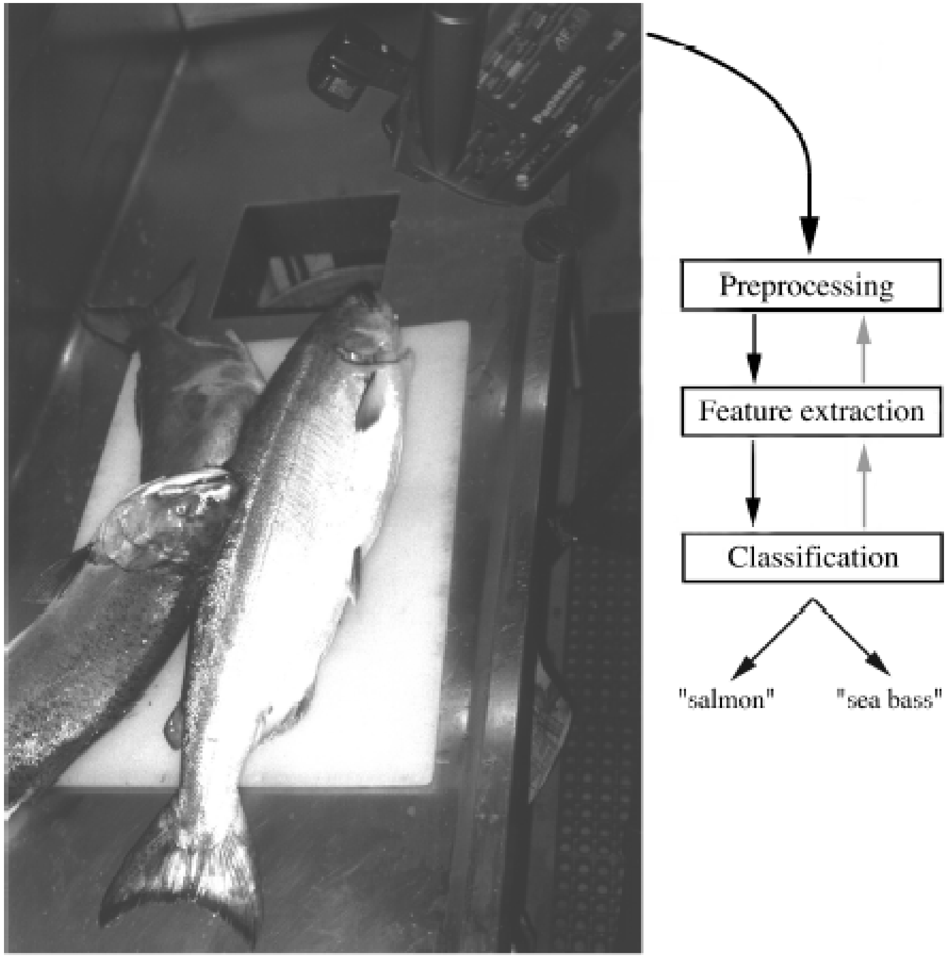


FIGURE 1.1. The objects to be classified are first sensed by a transducer (camera), whose signals are preprocessed. Next the features are extracted and finally the classification is emitted, here either "salmon" or "sea bass." Although the information flow is often chosen to be from the source to the classifier, some systems employ information flow in which earlier levels of processing can be altered based on the tentative or preliminary response in later levels (gray arrows). Yet others combine two or more stages into a unified step, such as simultaneous segmentation and feature extraction. From: Richard O. Duda, Peter E. Hart, and David G. Stork, *Pattern Classification*. Copyright © 2001 by John Wiley & Sons, Inc.

Representation: Fish Length As Feature

Training (design or learning) Samples

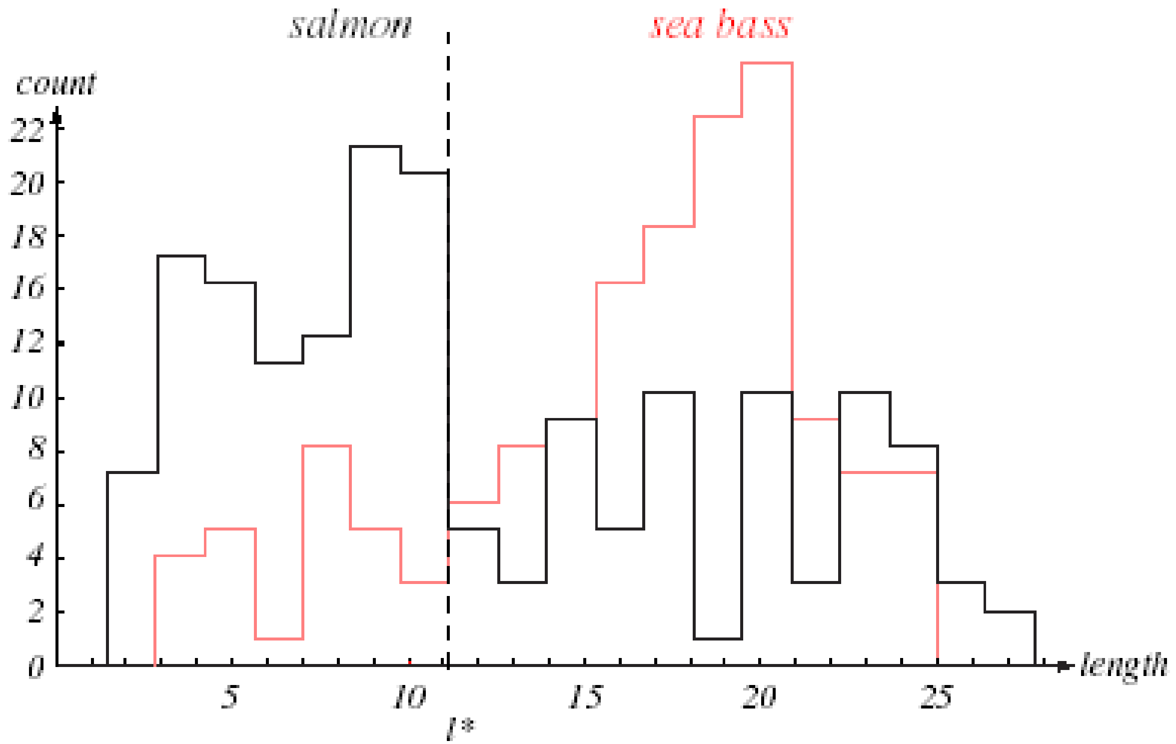


FIGURE 1.2. Histograms for the length feature for the two categories. No single threshold value of the length will serve to unambiguously discriminate between the two categories; using length alone, we will have some errors. The value marked l^* will lead to the smallest number of errors, on average. From: Richard O. Duda, Peter E. Hart, and David G. Stork, *Pattern Classification*. Copyright © 2001 by John Wiley & Sons, Inc.

Fish Lightness As Feature

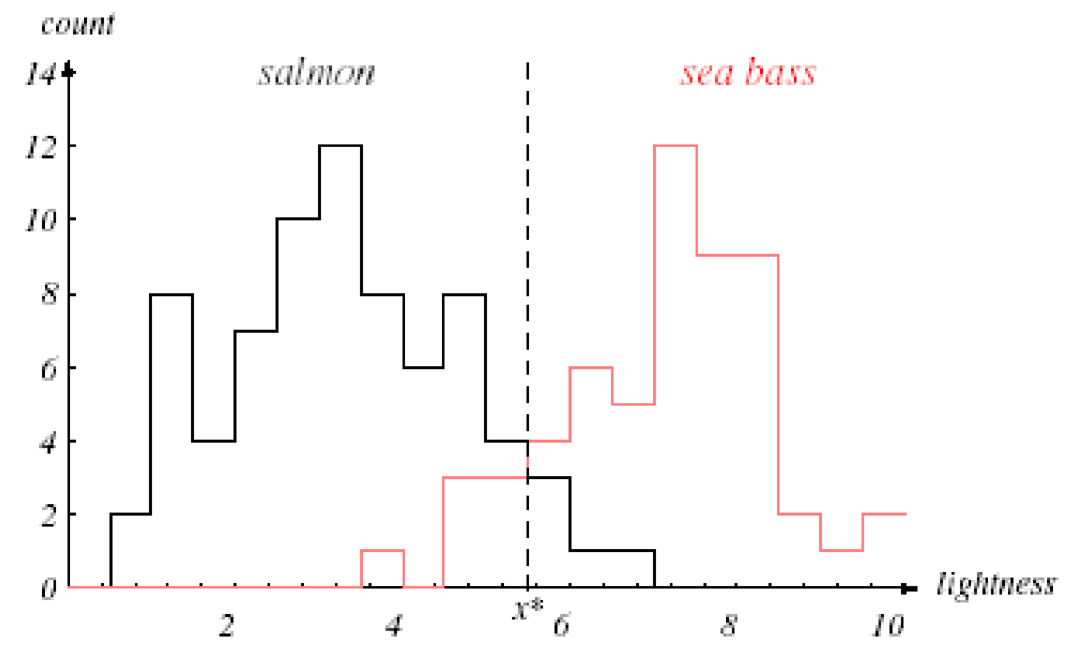


FIGURE 1.3. Histograms for the lightness feature for the two categories. No single threshold value x^* (decision boundary) will serve to unambiguously discriminate between the two categories; using lightness alone, we will have some errors. The value x^* marked will lead to the smallest number of errors, on average. From: Richard O. Duda, Peter E. Hart, and David G. Stork, *Pattern Classification*. Copyright © 2001 by John Wiley & Sons, Inc.

Overlap of these histograms is small compared to length feature

Two-dimensional Feature Space

Linear (simple) decision boundary; Cost of misclassification?

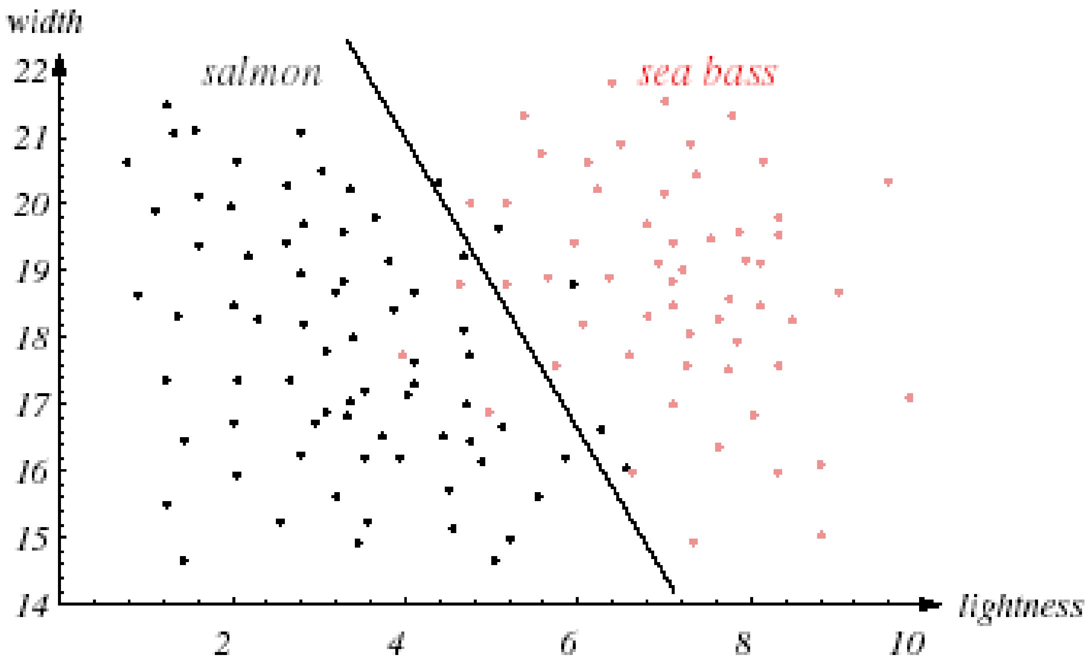


FIGURE 1.4. The two features of lightness and width for sea bass and salmon. The dark line could serve as a decision boundary of our classifier. Overall classification error on the data shown is lower than if we use only one feature as in Fig. 1.3, but there will still be some errors. From: Richard O. Duda, Peter E. Hart, and David G. Stork, *Pattern Classification*. Copyright © 2001 by John Wiley & Sons, Inc.

Two features together are better than individual features

Complex Decision Boundary

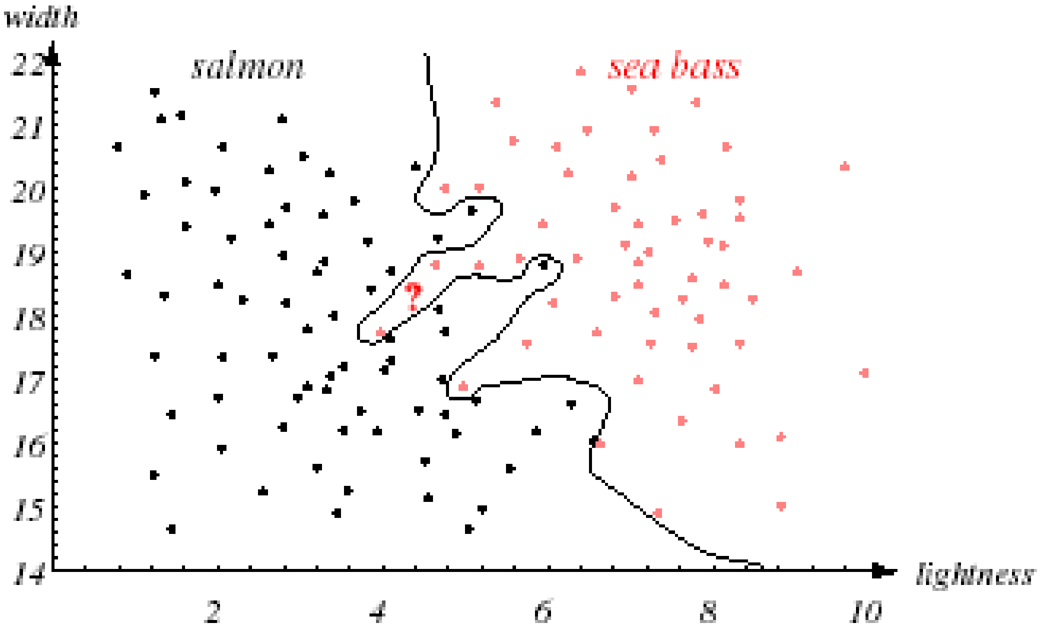


FIGURE 1.5. Overly complex models for the fish will lead to decision boundaries that are complicated. While such a decision may lead to perfect classification of our training samples, it would lead to poor performance on future patterns. The novel test point marked ? is evidently most likely a salmon, whereas the complex decision boundary shown leads it to be classified as a sea bass. From: Richard O. Duda, Peter E. Hart, and David G. Stork, *Pattern Classification*. Copyright © 2001 by John Wiley & Sons, Inc.

Generalization ability of the learned boundary

Boundary With Good Generalization

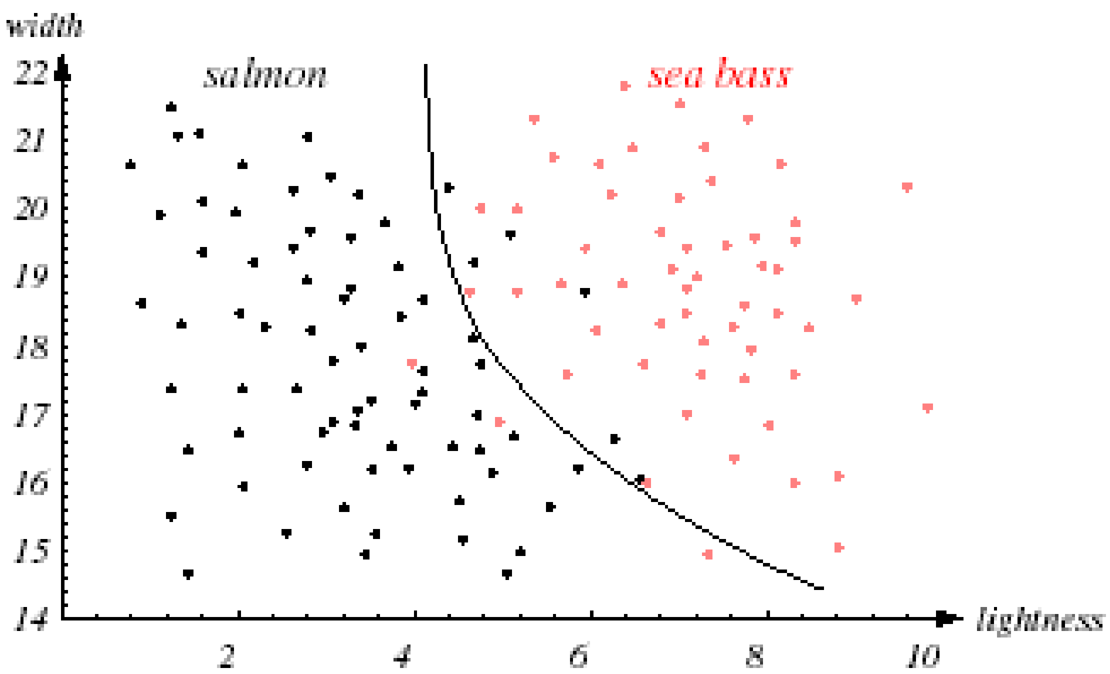


FIGURE 1.6. The decision boundary shown might represent the optimal tradeoff between performance on the training set and simplicity of classifier, thereby giving the highest accuracy on new patterns. From: Richard O. Duda, Peter E. Hart, and David G. Stork, *Pattern Classification*. Copyright © 2001 by John Wiley & Sons, Inc.

Simple decision boundaries are preferred

Feature Selection & Extraction

- How many and which subset of features to use in constructing the decision boundary?
- Some features may be redundant
- Curse of dimensionality—Error rate may in fact increase with too many features in the case of small number of training samples

Utilizing Context

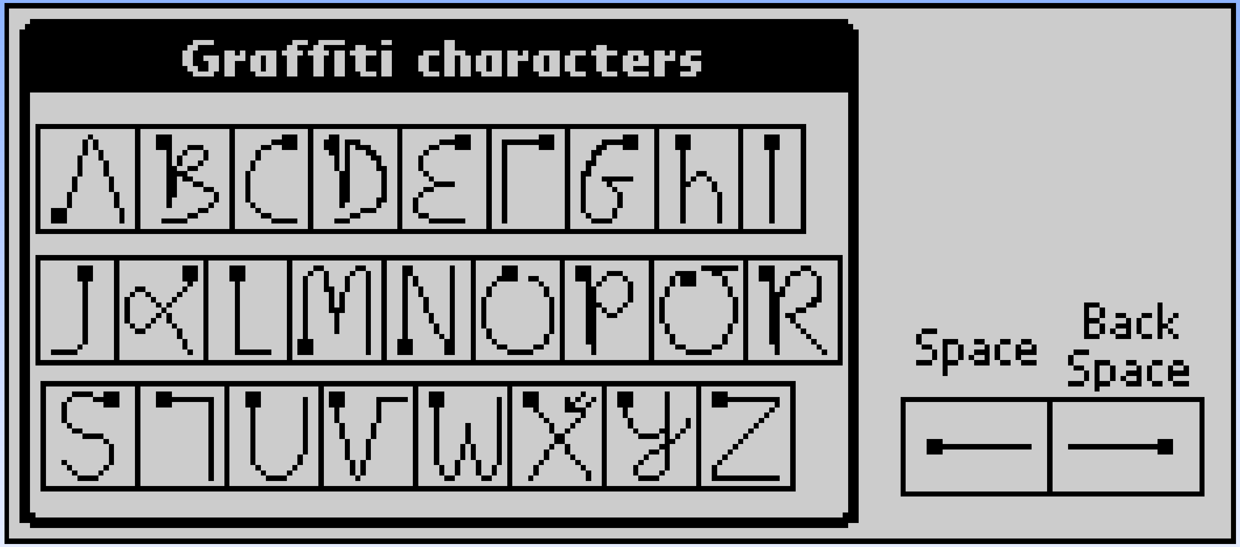
How m ch info mation are y u mi sing

Qvest

Context

Constraining the Recognition Problem

- Graffiti alphabet



GRAFFITI'S MODIFIED alphabet is largely based on single pen strokes, starting at the dots. As soon as the pen is lifted from the screen, the letter is immediately translated into normal text. The letter "X" is the exception

Super Classifier

Pool the evidence from component recognizers; also known as classifier combination, mixture of experts, evidence accumulation

Summary

- Pattern recognition is needed for
  - Automatic decision making
  - Assisting human decision makers
- General-purpose pattern recognition is a very difficult problem
- Successful systems available in well-constrained domains
- No single recognition approach has been found to be optimal for all pattern recognition problems
- Use of object models, constraints and context is necessary for identifying complex patterns
- Careful sensor design and feature extraction often lead to simple classifiers