MCSE 666:Pattern and Speech Recognition

Introduction to Pattern Recognition

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What Is Pattern Recognition?

Pattern recognition (PR) is a process by which some input is measured, analyzed, and then classified as belonging to one of a set of classes

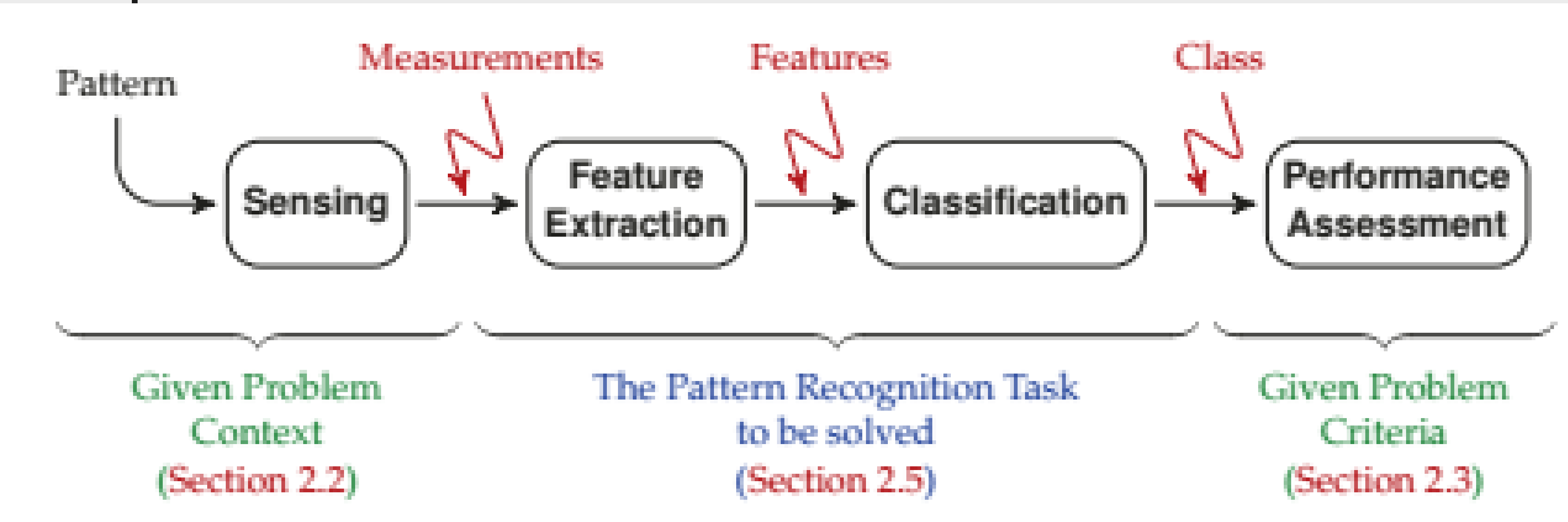
Process of PR and classification is a continual, never ending aspect of every-day human existence:

Pattern recognition task	Possible classes
What is in front of you as you walk?	Door vs. Window Sidewalk vs. Road
What music are you listening to?	Familiar or Unfamiliar Genre (Rock, Classical, ...) Name of Composer or Group
Is the traffic intersection safe to cross?	Green vs. Red light Pedestrian Walk vs. Stop Car Present vs. Not Present
Reading a page in a textbook	Letters of the Alphabet Text vs. Graphics Languages
You smell something in your	Cookies finished baking? (Yes/No) Is something burning? (Yes/No)

What Is Pattern Recognition? Cont.

- PR as a human experience refers to a perceptual process: some form of sensory input is sensed, analyzed, and recognized (classified), either subconsciously (by instinct) or consciously (based on previous experience).
- Patterns may be presented in any sensory modality: vision, hearing, touch, taste, or smell.
- PR as a technical discipline: a process in which an input object is measured, analyzed, and classified by a machine as being more or less similar to some class in a set of classes.

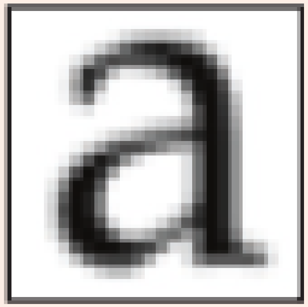
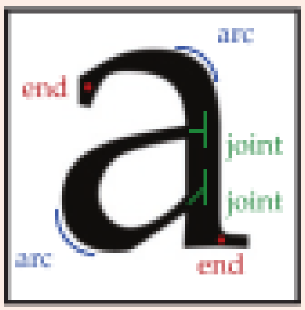
Pattern Recognition Framework



The goal of PR is to provide a machine with a kind of perceptual capability to automatically extract useful information from measured data.

PR Illustration with Example

Pattern Recognition of Text

Pattern	Attributes to Measure	Measurements	Strengths and Weaknesses
"a" →		Vector of pixel values	Fast, easy, explicit Sensitive to changes in font style, size, and rotation
"a" →		Vector of shape properties	Robust to changes in size and rotation Complicated features to extract
"a" →	Complex Nonlinear Algorithm	Vector of values, but with no intuition	Possibly very flexible May be very hard to learn Difficult to analyze

PR Illustration with Example

Pattern Recognition of the Mind

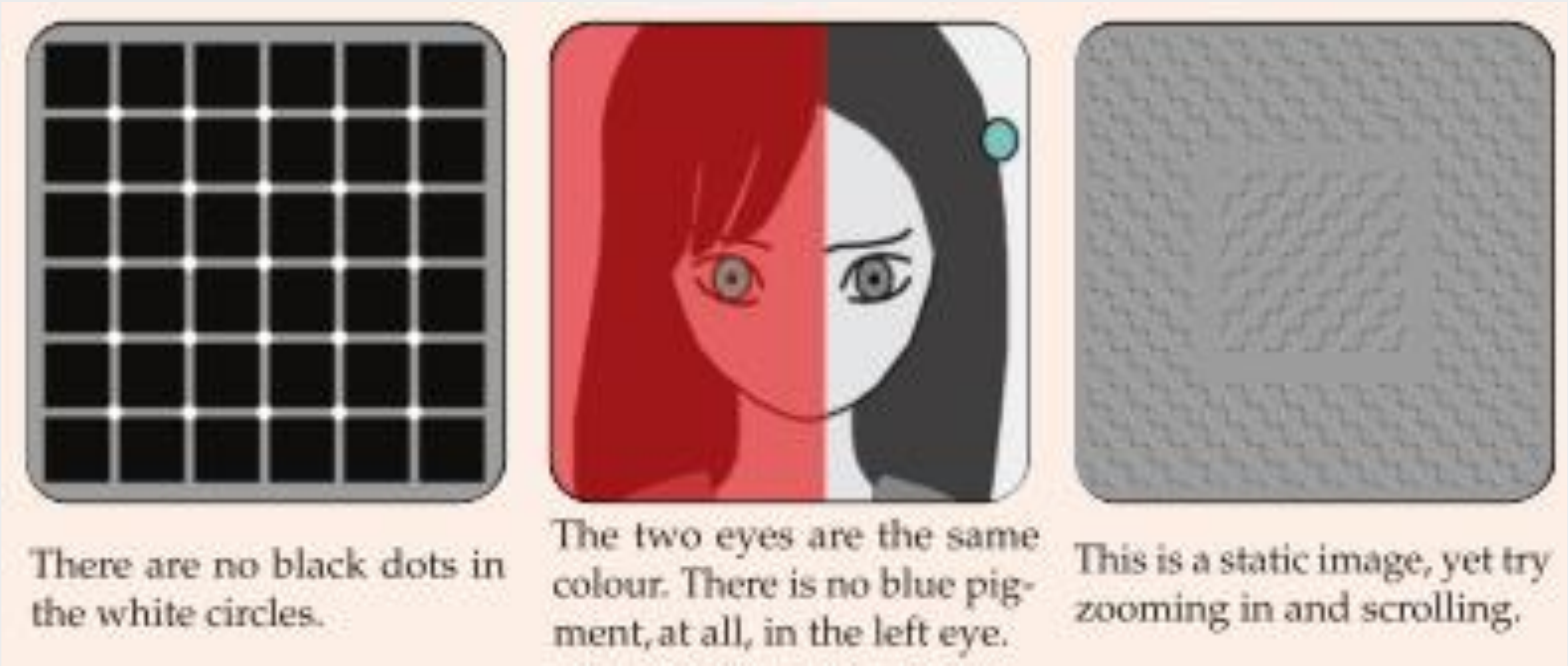
The typesetting may be weird, but for the human brain this is very easy to read.

It deons’t mettar in waht oerdr the lrttees in a wrod are, as lnog as the frist and lsat ltteres rmeain in the rgiht pacle.

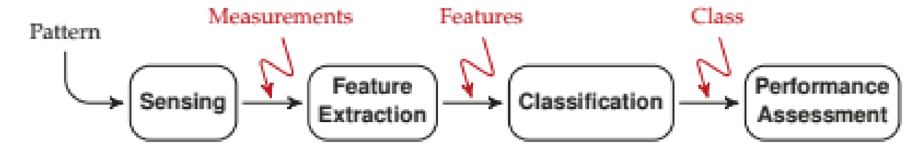
- The retina in the eye is densely packed with light-sensitive cells, so that it may be tempting to think
- Our brain effectively sees and perceives the world as a great many pixels.
- There are many simple mind tricks or optical illusions

PR Illustration with Example

Pattern Recognition of the Mind



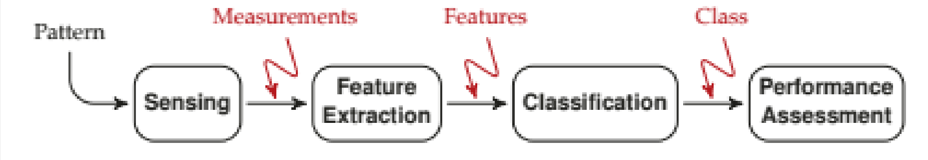
- The eye is not just sending pixellated images to the brain.
- There is a great deal of feature extraction taking place, much already in the retina
- It is very helpful in running through a forest, but perhaps not so useful in staring at deliberately manipulated images on a page.



Features from Patterns

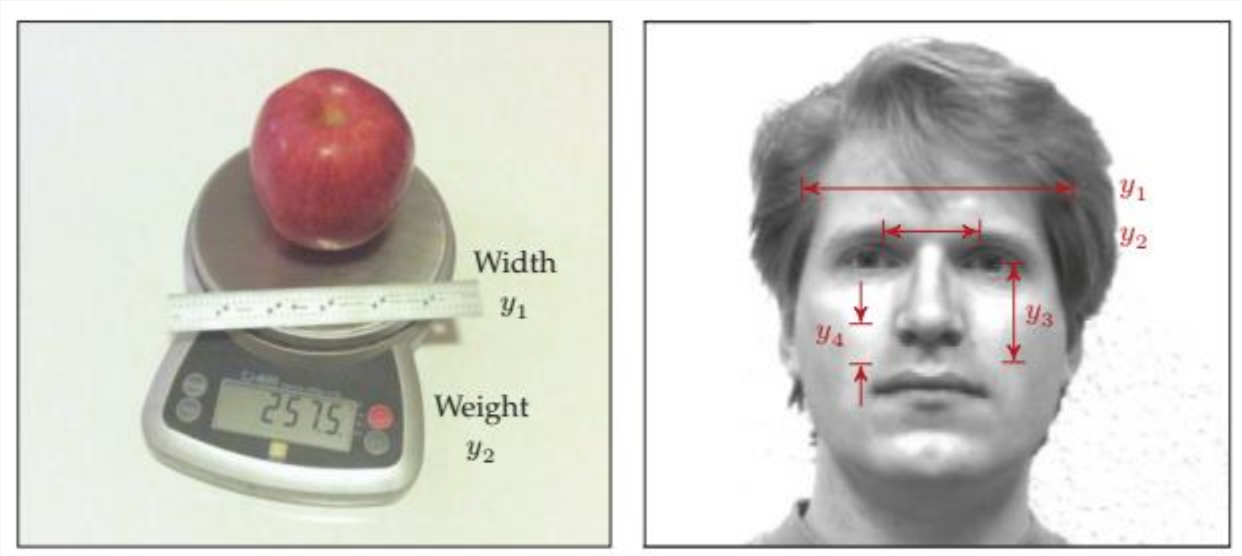
- The word "pattern" may bring to mind texture, fabric, or shape.
- In the context of *pattern recognition*, the notion of pattern is far more broad, and can apply to any *thing* that can be distinguished from another *thing*.
- Identity view point: infer the unknown *identity* of an object
- Type of wildflower, type of songbird, or the name of the person facing a camera — each of these has a certain identity to determine from measurements.

A pattern is assumed to have certain *properties* or *attributes* which distinguishes it from other patterns.



Features from Patterns (Cont.)

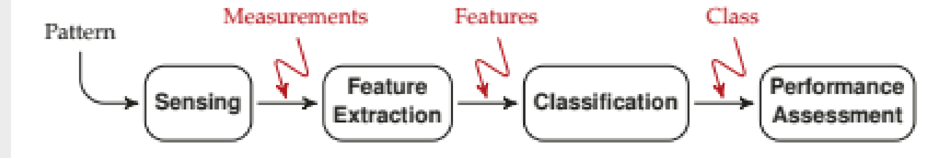
One or more measurements are taken of a pattern



Size / weight of a piece

Various dimensions from face

Does all measurements from patterns important to distinguish?

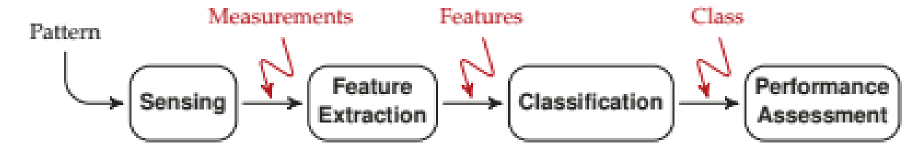


Features from Patterns (Cont.)

- The selection of appropriate measurements is an essential
- Measurements may cost money and/or time, and
- Poor measurements lead to poor performance of the resulting classifier.

The process of transforming measurements into features facilitate classification, normally in one or both of the following ways:
1. By reducing the dimensionality of the problem: n < m
2. By creating features in which patterns are more clearly distinguished.

$$\text{Measurements } \underline{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix} \xrightarrow{\underline{x} = f(\underline{y})} \text{Features } \underline{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

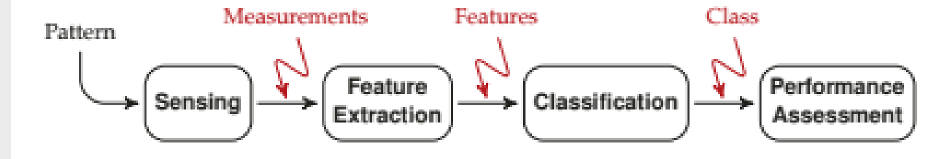


Features from Patterns (Cont.)

$$\text{Measurements} \quad \underline{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix} \xrightarrow{\underline{x} = f(\underline{y})} \text{Features} \quad \underline{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}$$

- The feature extraction function *f()* can focus the information from x, or it can remove irrelevant information from x, but *f()* never adds information.
- Data Processing Theorem: *x can never have more information than was present in y.*

- An effective feature extraction function *f*() can make the PR problem *easier,*
- However, in principle, the best possible classifier based on the measurements *y* should perform at least as well as the best possible classifier based on the features *x*.



Features from Patterns (Cont.)

Features may be intuitive or they may be quite abstract. Consider, the measurements of an electric motor:

$$\text{Measurements} \quad \underline{y} = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \\ y_4 \\ y_5 \end{bmatrix} = \begin{bmatrix} \text{Motor voltage (Volts)} \\ \text{Motor current (Amperes)} \\ \text{Motor speed (RPM)} \\ \text{Motor winding temperature (°C)} \\ \text{Surrounding air temperature (°C)} \end{bmatrix}$$

$$x = f(\underline{y}) = y_1 \cdot y_2$$

Power as Feature: Understandable

$$x = f(\underline{y}) = \sqrt{y_1 - y_2} - \frac{y_3}{y_4}$$

- Uninterpretable feature do not make any physical sense,
- But perhaps be effective as a feature for classification.

Classes and Classification

- The whole purpose of PR or classification consists of assigning an object to a class.
- A class is a particular pattern, or possibly a group of patterns which are similar or equivalent in some sense.

In a given problem, the set of classes *C* is defined as

$$C = \{C_1; C_2; -; -; -; -; C_K\};$$

Have to choose one class from *K* different classes.

Members of a class share some common properties or attributes

In PR problems the class set *C* is predefined and has been specified as part of the problem to be solved.

Classes and Classification

So, for example, in a face recognition problem each person is their own class, so the set of classes would be defined as

$$\mathcal{C} = \{\text{“Paul Fieguth”}, \text{“Bob”}, \text{“Jane”}, \text{“Ali”}, \ldots\}$$

so that I would be a member of the “Paul Fieguth” class:

$\in$ “Paul Fieguth”

At a university we might define a different set of classes

$$\mathcal{C} = \{\text{“Professors”}, \text{“Staff”}, \text{“Undergraduate Students”}, \text{“Graduate Students”}\}$$

such that

$$\text{“Paul Fieguth”} \in \text{“Professor”}$$

One *could* use pattern recognition to estimate age, in which case one might have classes like

$$\mathcal{C} = \{\text{“0–10 years”}, \text{“10–20 years”}, \text{“20–30 years”}, \ldots\}$$

such that now I appear in a class as

$$\text{“Paul Fieguth”} \in \text{“50–60 years”}$$

Classes and Classification

Way of Describing Classes

Via Prototype Idealized representation or notion of the "essence" of the class. Pros: each class is unambiguously defined, Cons: no scope for variability.

Via Parameterized Shape: A generalization of the prototype; the class has a known shape (e.g., rectangular or elliptical), the shape is described in some number of parameters (e.g., ellipse centre, rotation, and axis lengths). Pros. more flexible than that of a single prototype, Cons: still requires the type of shape to be assumed or known.

Via Statistical Distribution: Some description of the likelihood or probability of a class member having a particular set of measurements or features. Pros.: very comprehensive, Cons: There will be circumstances when the statistics are not known and may be difficult to infer.

Via Samples: A set of given samples (many apples, or tigers, or bicycles) directly characterizes the class. Pros: Highly convenient, since nothing further needs to be done to describe the class Cons: Storage and computational challenges, since all of the data need to be saved.

Classes and Classification

Variability in a Class

Patterns do not need to be identical to belong to the same class: not all pictures of a person the same, or of tigers, or of apples.

There are at least two sources of variability present in the measurements associated with a single class:

1. The inherent variability within a class: Every class will consist of members which differ in some way. The degree and nature of the inherent variability will depend greatly on the class definition.

"Fruit" class contains all manners of variability in colour, size, and shape; "Apple" class is much more specific, but apples do come in different colours and patterning; the "Granny Smith Apple" class is even more specific, but still will have apples of different sizes or with more or fewer blemishes.

2. Noise or random variations in measurement: Every measurement involves some sort of physical process which will be subject to error, such as thermal noise in electronics, or quantization noise in converting an analogue signal to a digital representation.

Classifier and Classification

In PR tasks the class set C is predefined and has been specified as part of the problem to be solved.

A *classifier* is some function *g*(), possibly analytical (i.e., an equation) or a computer algorithm, which assigns a class label to a given feature:

$$g(x) \in C = \{C_1; C_2; : : : ; C_K\}$$

There is a strong relationship between feature extraction and classification, such that

- Good features allow for simpler classifiers, whereas
- Complex classifiers can compensate for weaker features, which are unable to fully separate the pattern classes.

Classifier and Classification

Two Fundamental Steps Associated With Classification:

I. Classifier Learning and II. Classifier Testing or Validation

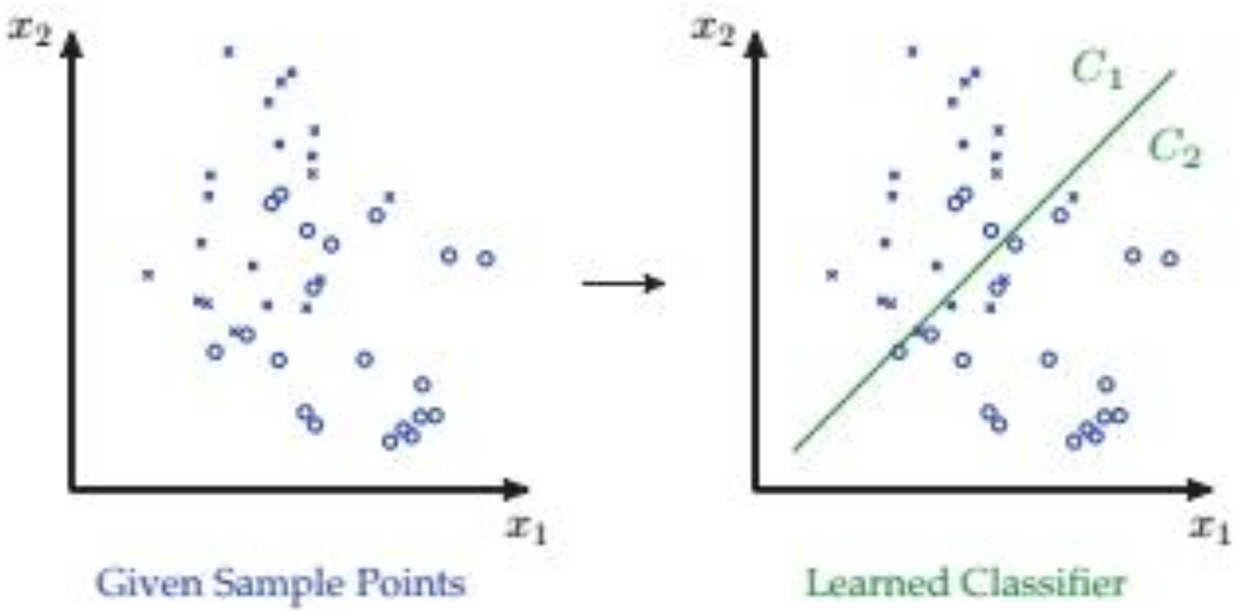


Fig. 2.3. PATTERN RECOGNITION I — CLASSIFIER LEARNING: A classifier, here a straight line (right) dividing a feature space into classifications C_1 and C_2, can be *learned* from a given set of sample points (left).

Classifier and Classification

II. Classifier Testing or Validation

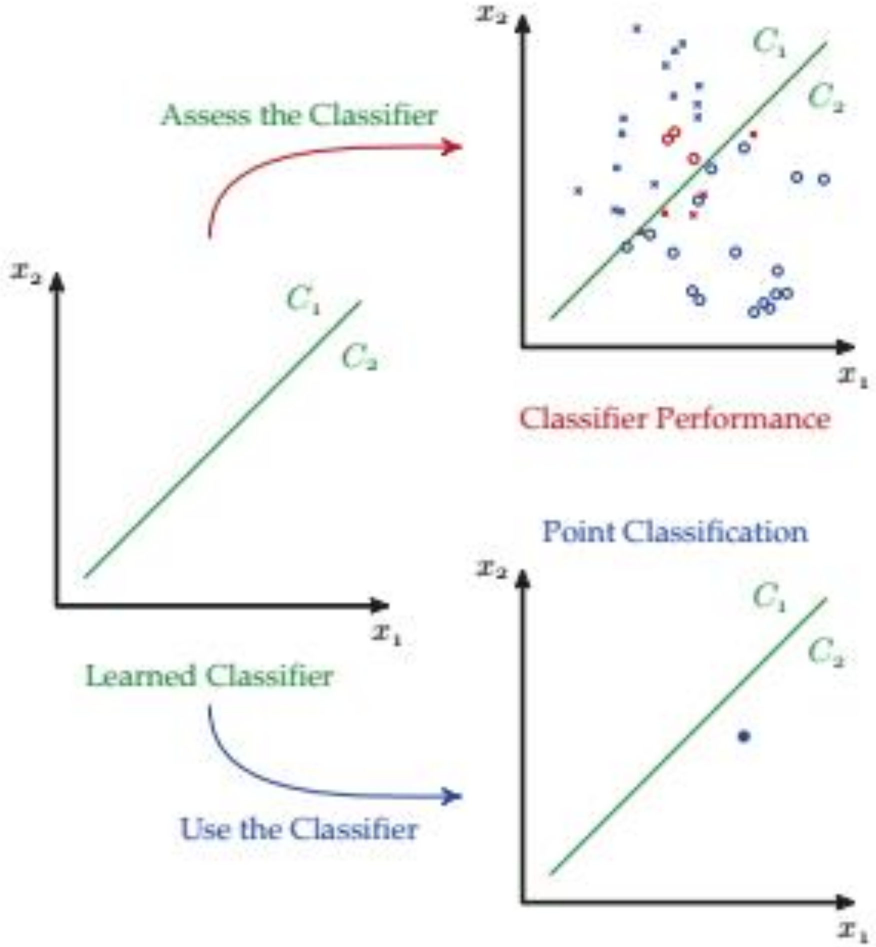


Fig. 2.4. PATTERN RECOGNITION II — CLASSIFIER TESTING: What can we do with the learned classifier, left, from Figure 2.3? We could assess its performance (top), for example by counting how many sample points are classified correctly (blue) and incorrectly (red). Or we could apply the classifier (bottom) to a new, unknown point and then classify it.

Classifier and Classification

Illustrative Examples of Classification

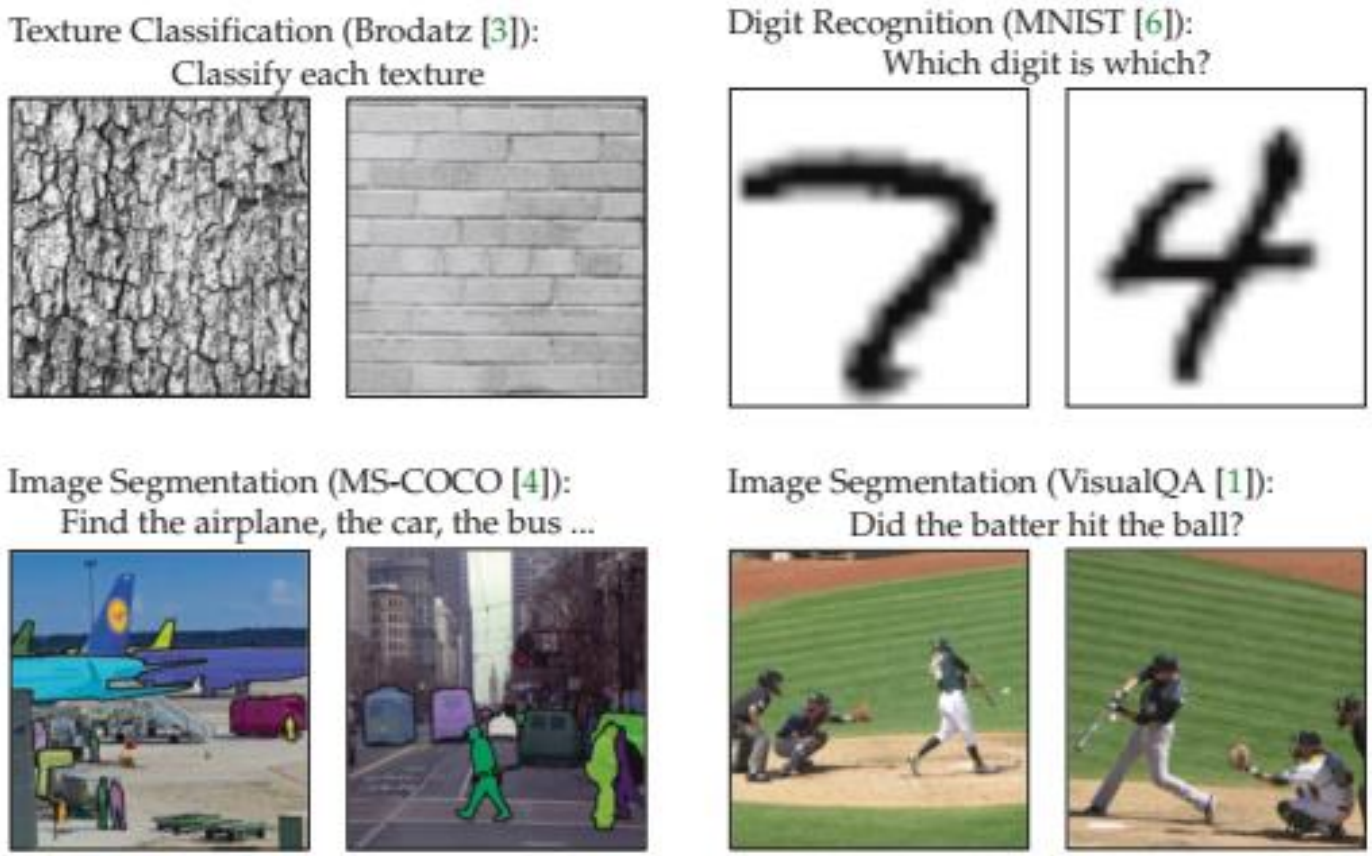


Fig. 2.5. PATTERN RECOGNITION ON IMAGES: Since the human visual system is so dominant in human perception, a great deal of pattern recognition focuses on image-related problems. Here four examples are shown, from comparatively straightforward (top), the classification or recognition of whole images, to rather advanced (bottom), such as recognizing the objects within an image or being able to answer complex high-level questions.

Classifier and Classification

Pattern Recognition Problems

Four Fundament Types PR Problems:

1. Model-Based
2. Supervised
3. Semi-Supervised
4. Unsupervised

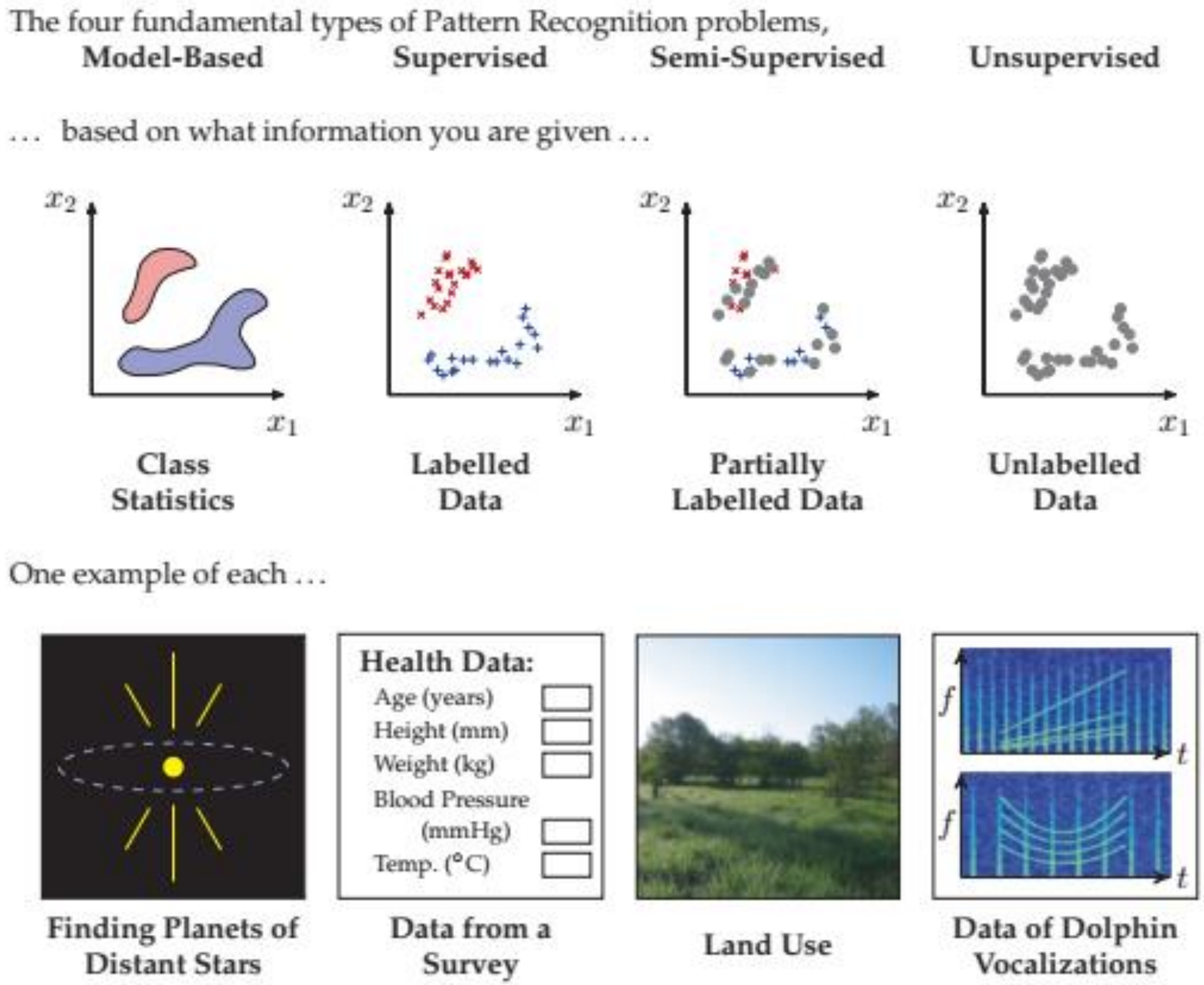


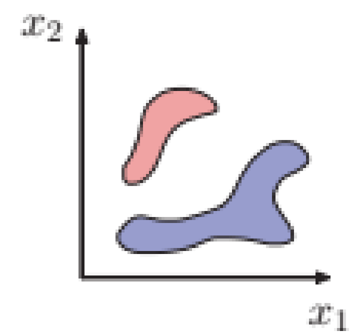
Fig. 2.6. THE FUNDAMENTAL PROBLEMS: There are four fundamental pattern recognition problems, ordered from the most detailed problem description (left) to the most ambiguous (right).

Classifier and Classification

Pattern Recognition Problem: Model-Based

Scenario 1 (Model-Based): Model is known or given

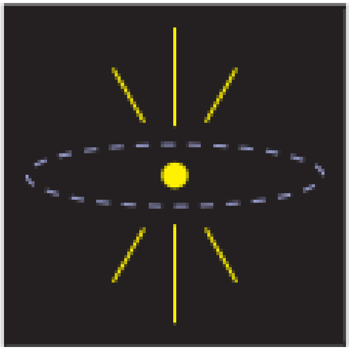
- Hope to have most information regarding a PR problem the behaviour of the measurements for each of the pattern classes.
- Normally characterized in a statistical fashion, such as *p*(*y*|*C*) = The distribution of measurement vector *y* given class *C*



Class Statistics

One example of each . . .

- Such detailed information will be available only in those contexts where the physical process is known by which a given pattern class gives rise to measurements.
- Very convenient to have detailed information, since statistical decision theory allow to explicitly define the optimal classifier, in the sense of minimizing the probability of classification error



Finding Planets of Distant Stars

Classifier and Classification

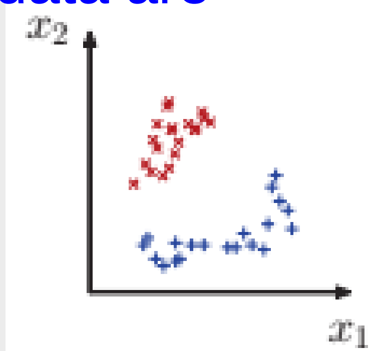
Pattern Recognition Problem: Supervised

Scenario 2 (Supervised): Model is not known, labelled data are available

- Do not have an exact description of the problem, as in Scenario 1
- Given labelled data, meaning data pairs of the form

$\{y_i; C_k\}$ -> The ith measurement vector y_i is in class C_k

- Labelled data do not just *magically* appear; labelled or tagged by a human observer, so refer scenario as *supervised*
- Exceptionally expensive or labour-intensive with larger datasets.
- May derive a classifier directly from the given labelled or learn an empirical probability model as of Scenario 1



Labelled Data

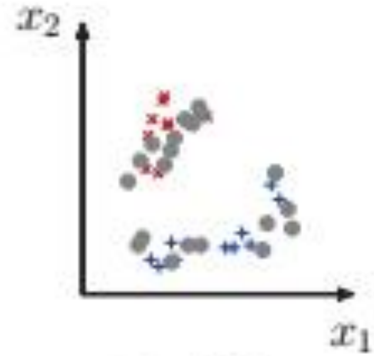
Data from a Survey

Classifier and Classification

Pattern Recognition Problem: Semi-Supervised

Scenario 3 (Semi-Supervised): Model is not known, some are labelled data, some are not

- Labelled data can be expensive, requiring manual labelling. A huge data be unlabeled and Scenario 2 ignores all unlabeled data.
- Problem refers to as semi-supervised when some degree of human input is required
- In semi-supervised case, a small set of samples have been manually labelled for classification (e.g., face images tagged by a human observer), but then also to leverage a very large set of unlabeled data



Partially Labelled Data

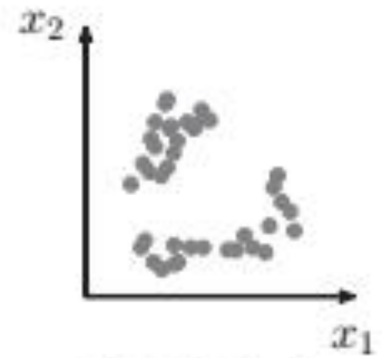
Land Use

Classifier and Classification

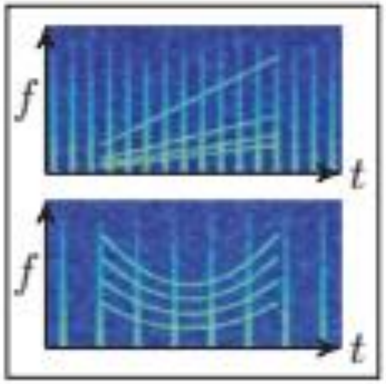
Pattern Recognition Problem: Unsupervised

Scenario 4 (Unsupervised): Model is not known, no labelled data available

- Pattern measurements are available, however the points have no associated class information; this is known as an unsupervised problem.
- The range of problems here is still very broad, depending on whether we are told the number of classes, or their typical size or separation, or perhaps nothing at all.
- Clustering problems are in Unsupervised category



Unlabelled Data



Data of Dolphin Vocalizations

PR Case Study: Biometric Recognition

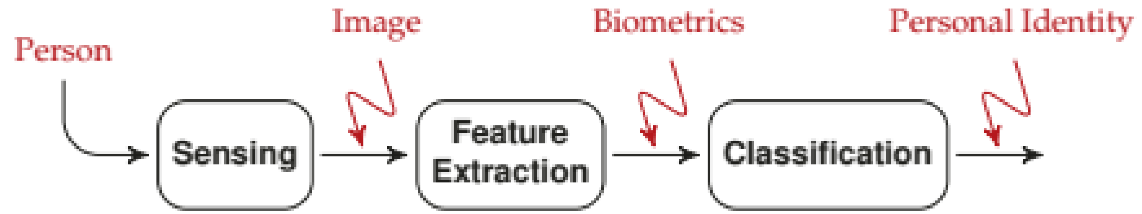


Fig. 2.7. BIOMETRIC RECOGNITION: In order to recognize a specific person on the basis of remotely-sensed biometrics, we need to acquire (sense) an image of some part of the body which has a unique signature (fingerprint, retina etc), extract biometric features from this image, and then develop a classifier that reliably recognizes the individual.

Biometrics

- Face
- Fingerprint
- Iris (the colored region in your eye around the pupil)
- Retina (the pattern of arteries in the back of your eye)
- Veins (vein structure in hand or arm)
- DNA

Basic Components of Biometric Recognition:

1. Image Acquisition
2. Feature Extraction
3. Classification

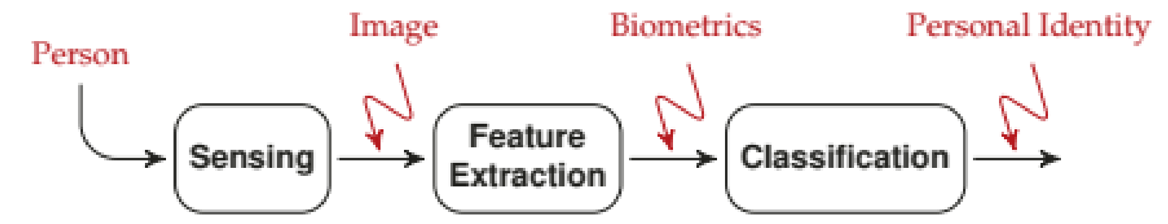
The classifier returns one member of the class set

$$C = \{NoMatch; Person_1; Person_2; : : : ; Person_K\}$$

Classifying *x* as *NoMatch* where *Person*1 is correct: Frustration

Classifying *x* as *Person*2 where *Person*1 is correct: Security Breach

PR Case Study: Biometric Recognition



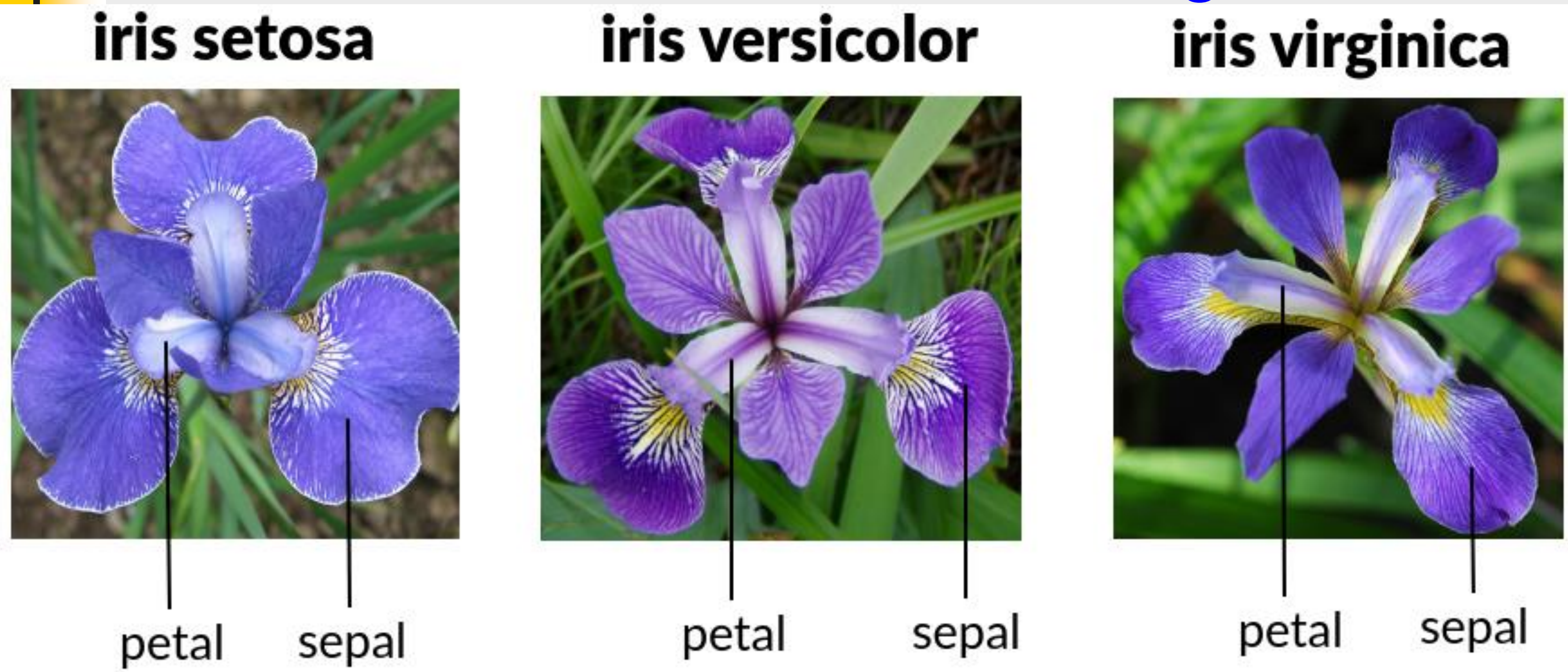
Classifying *x* as *NoMatch* where *Person*1 is correct: Frustration
Classifying *x* as *Person*2 where *Person*1 is correct: Security Breach

Avoiding frustration and security breaches, a successful biometric strategy must also satisfy

- Universality: Every person should be measurable, regardless of age and health
- Uniqueness: The feature vectors extracted for a given person should be robustly unique
- Consistency: For a given person the feature vector should be highly repeatable from one try to the next, and should be slowly (or not at all) varying over time.

Other criteria: non-invasiveness, social acceptability, or how easily the system would be to defeat via nefarious means and so on

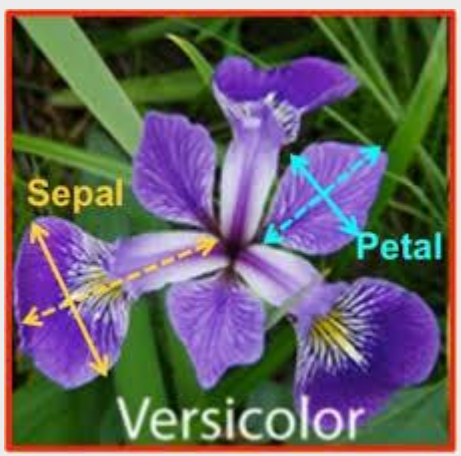
PR Hands-on: Iris Flower Recognition



$C = \{C_1; C_2; C_3\}$ = {"Iris Setosa", "Iris Versicolor", "Iris Virginica"}

Each plant four measurements were taken:

$$y = \begin{pmatrix} \text{Sepal Length} \\ \text{Sepal Width} \\ \text{Petal Length} \\ \text{Petal Width} \end{pmatrix}$$



Open Discussion