Introduction to Pattern Recognition

Selim Aksoy

Department of Computer Engineering
Bilkent University
saksoy@cs.bilkent.edu.tr

CS 551, Spring 2019

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.
- We would like to give similar capabilities to machines.

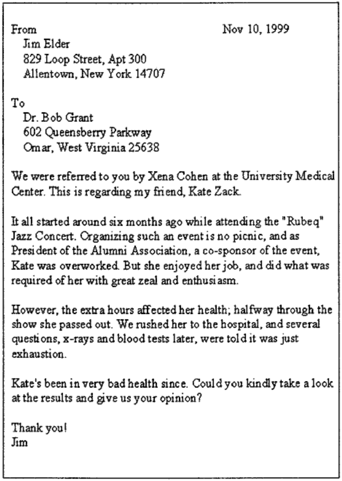
What is Pattern Recognition?

- A *pattern* is an entity, vaguely defined, that could be given a name, e.g.,
  - fingerprint image,
  - handwritten word,
  - human face,
  - speech signal,
  - DNA sequence,
  - ...
- *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.

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 Applications



From Nov 10, 1999
Jim Elder
829 Loop Street, Apt 300
Allentown, New York 14707

To
Dr. Bob Grant
602 Queensberry Parkway
Omar, West Virginia 25638

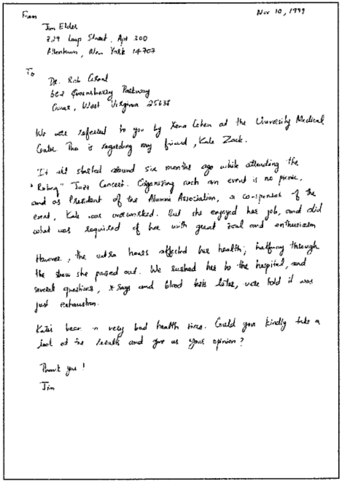
We were referred to you by Xena Cohen at the University Medical Center. This is regarding my friend, Kate Zack.

It all started around six months ago while attending the "Rubeq" Jazz Concert. Organizing such an event is no picnic, and as President of the Alumni Association, a co-sponsor of the event, Kate was overworked. But she enjoyed her job, and did what was required of her with great zeal and enthusiasm.

However, the extra hours affected her health; halfway through the show she passed out. We rushed her to the hospital, and several questions, x-rays and blood tests later, were told it was just exhaustion.

Kate's been in very bad health since. Could you kindly take a look at the results and give us your opinion?

Thank you!
Jim



From Nov 10, 1999
Jim Elder
829 Loop Street, Apt 300
Allentown, New York 14707

To
Dr. Bob Grant
602 Queensberry Parkway
Omar, West Virginia 25638

We were referred to you by Xena Cohen at the University Medical Center. This is regarding my friend, Kate Zack.

It all started around six months ago while attending the "Rubeq" Jazz Concert. Organizing such an event is no picnic, and as President of the Alumni Association, a co-sponsor of the event, Kate was overworked. But she enjoyed her job, and did what was required of her with great zeal and enthusiasm.

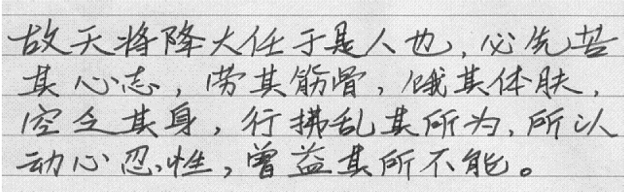
However, the extra hours affected her health; halfway through the show she passed out. We rushed her to the hospital, and several questions, x-rays and blood tests later, were told it was just exhaustion.

Kate's been in very bad health since. Could you kindly take a look at the results and give us your opinion?

Thank you!
Jim

Figure 1: English handwriting recognition.

Pattern Recognition Applications



(a) Handwriting

故天将降大任于是人也，必先苦
其心志，劳其筋骨，饿其体肤，
空乏其身，行拂乱其所为，所以
动心忍性，曾益其所不能。

(b) Corresponding Machine Print

Figure 2: Chinese handwriting recognition.

Pattern Recognition Applications

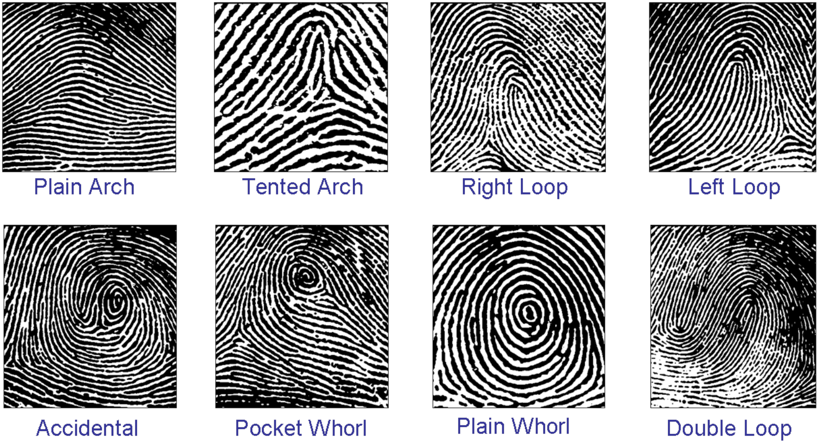


Figure 3: Fingerprint recognition.

Pattern Recognition Applications

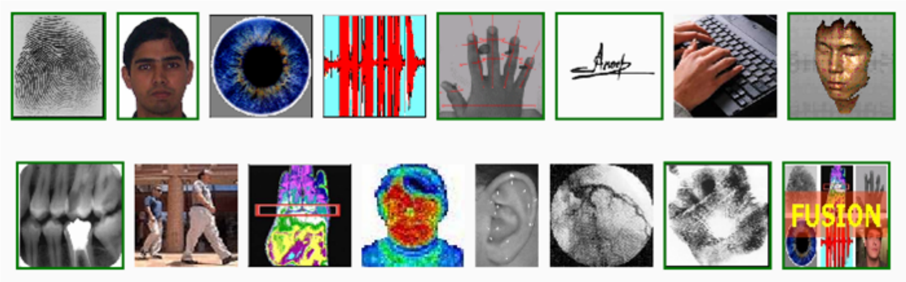


Figure 4: Biometric recognition.

Pattern Recognition Applications

Figure 5: Autonomous navigation.

Pattern Recognition Applications

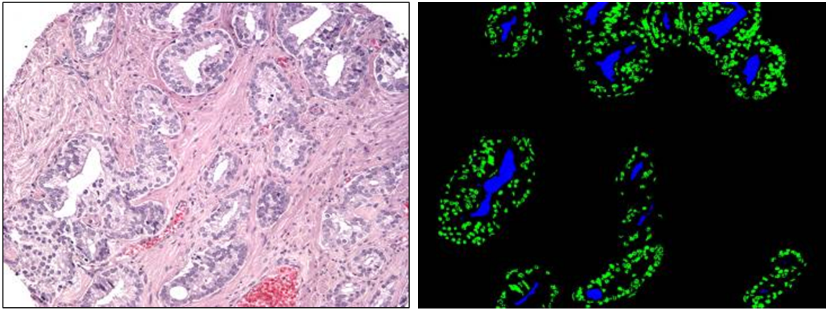
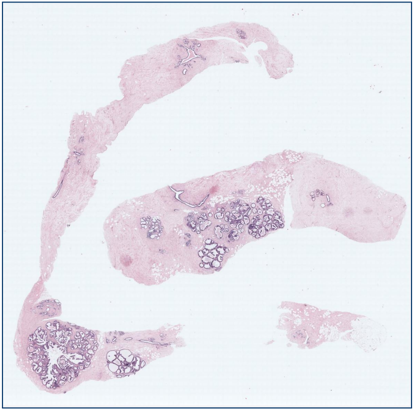


Figure 6: Cancer detection and grading using microscopic tissue data.

Pattern Recognition Applications



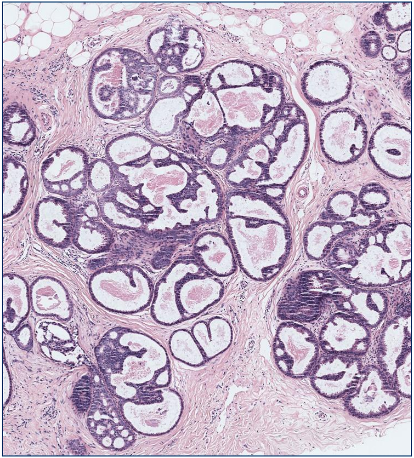


Figure 7: Cancer detection and grading using microscopic tissue data. (left) A whole slide image with 75568×74896 pixels. (right) A region of interest with 7440×8260 pixels.

Pattern Recognition Applications

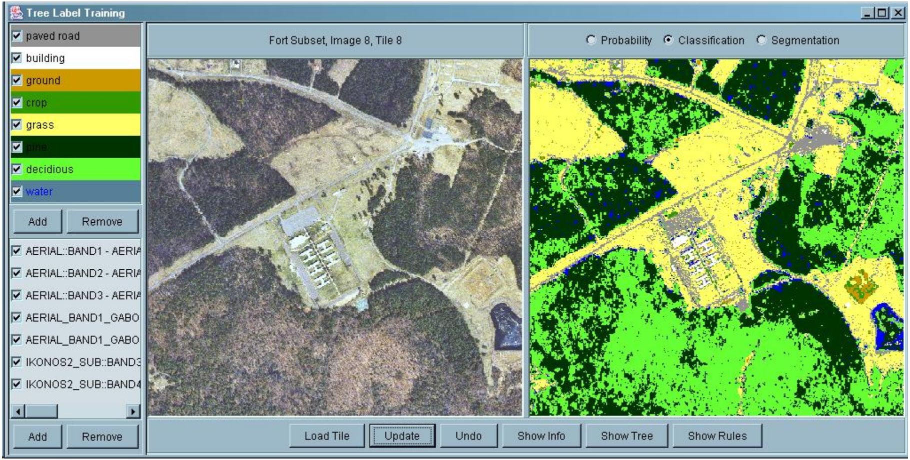


Figure 8: Land cover classification using satellite data.

Pattern Recognition Applications

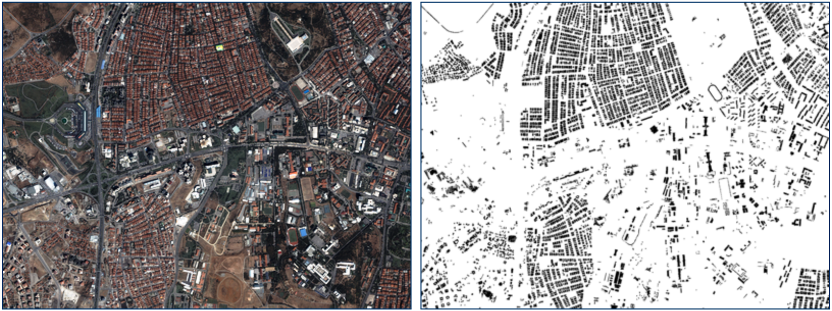


Figure 9: Building and building group recognition using satellite data.

Pattern Recognition Applications

Figure 10: License plate recognition: US license plates.

Pattern Recognition Applications

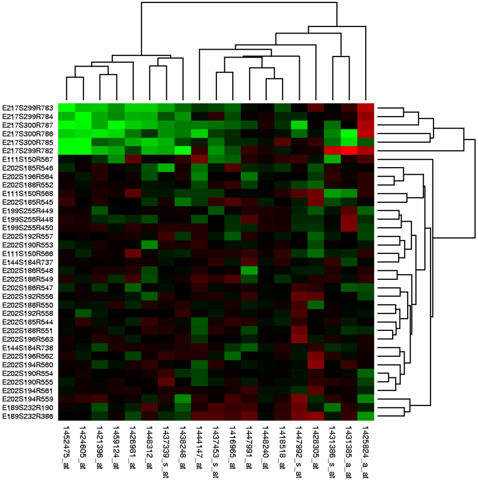


Figure 11: Clustering of microarray data.

An Example

- Problem: Sorting incoming fish on a conveyor belt according to species.
- Assume that we have only two kinds of fish:
  - sea bass,
  - salmon.

Figure 12: Picture taken from a camera.

An Example: Decision Process

- 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?
  - capture image $\rightarrow$ isolate fish $\rightarrow$ take measurements $\rightarrow$ make decision

An Example: 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?

An Example: Selecting Features

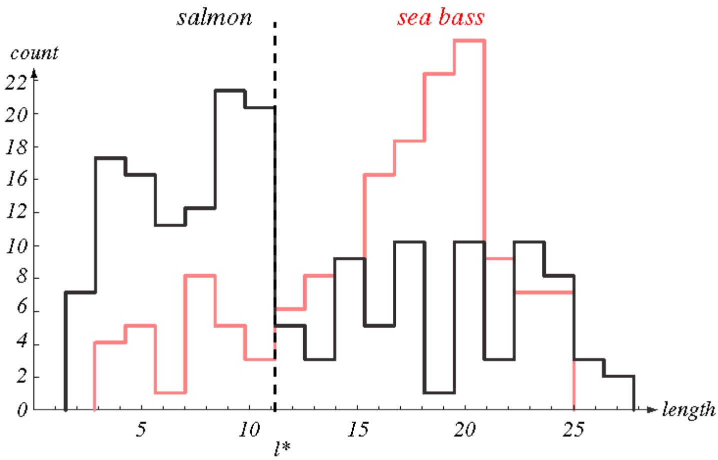


Figure 13: *Histograms* of the length feature for two types of fish in *training samples*. How can we choose the threshold l^* to make a reliable decision?

An Example: Selecting Features

- Even though sea bass is longer than salmon on the average, there are many examples of fish where this observation does not hold.
- Try another feature: average lightness of the fish scales.

An Example: Selecting Features

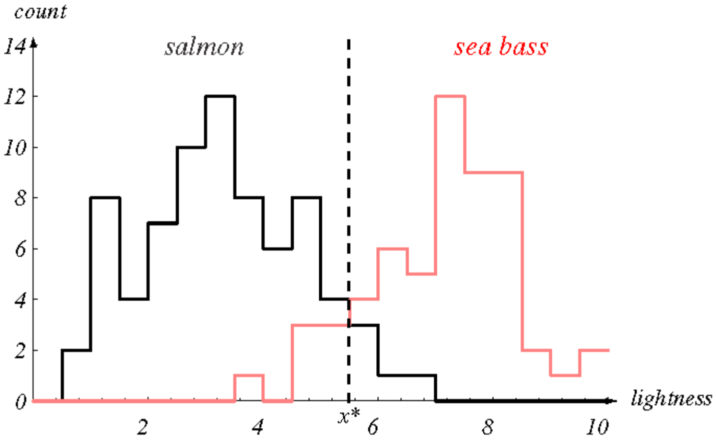


Figure 14: Histograms of the lightness feature for two types of fish in training samples. It looks easier to choose the threshold x^* but we still cannot make a perfect decision.

An Example: Cost 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?

An Example: Multiple Features

- Assume we also observed that sea bass are typically wider than salmon.
- We can use two features in our decision:
  - lightness: x_1
  - width: x_2
- Each fish image is now represented as a point (*feature vector*)

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

in a two-dimensional *feature space*.

An Example: Multiple Features

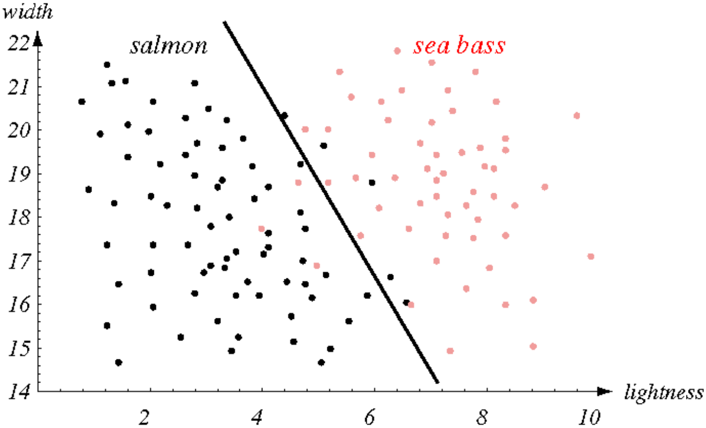


Figure 15: *Scatter plot* of lightness and width features for training samples. We can draw a *decision boundary* to divide the feature space into two regions. Does it look better than using only lightness?

An Example: Multiple Features

- Does adding more features always improve the results?
  - 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?

An Example: Decision Boundaries

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

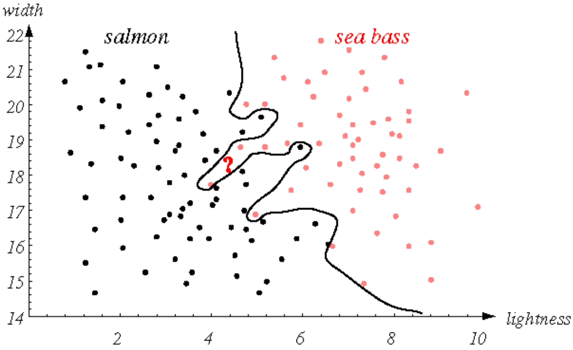


Figure 16: We may distinguish training samples perfectly but how can we predict how well we can *generalize* to unknown samples?

An Example: Decision Boundaries

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

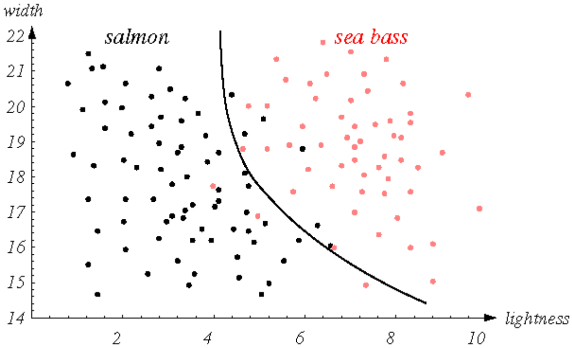


Figure 17: Different criteria lead to different decision boundaries.

More on Complexity

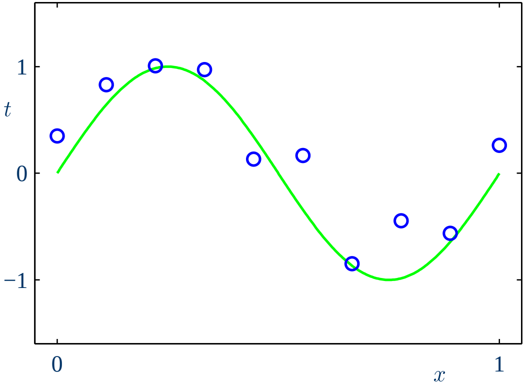
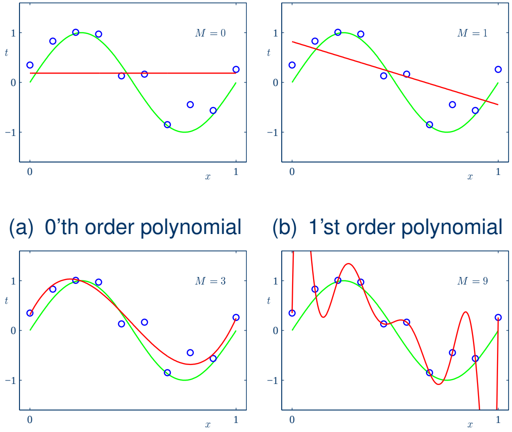


Figure 18: Regression example: plot of 10 sample points for the input variable x along with the corresponding target variable t. Green curve is the true function that generated the data.

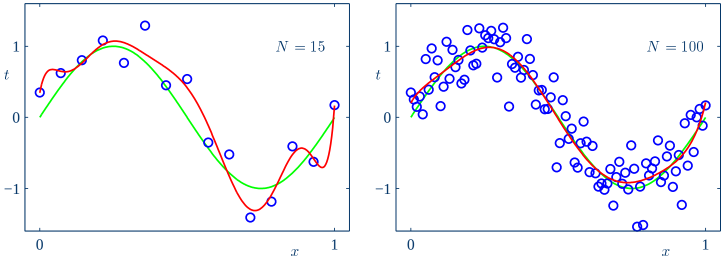


(a) 0'th order polynomial (b) 1'st order polynomial

(c) 3'rd order polynomial (d) 9'th order polynomial

Figure 19: Polynomial curve fitting: plots of polynomials having various orders, shown as red curves, fitted to the set of 10 sample points.

More on Complexity



(a) 15 sample points (b) 100 sample points

Figure 20: Polynomial curve fitting: plots of 9'th order polynomials fitted to 15 and 100 sample points.

Pattern Recognition Systems

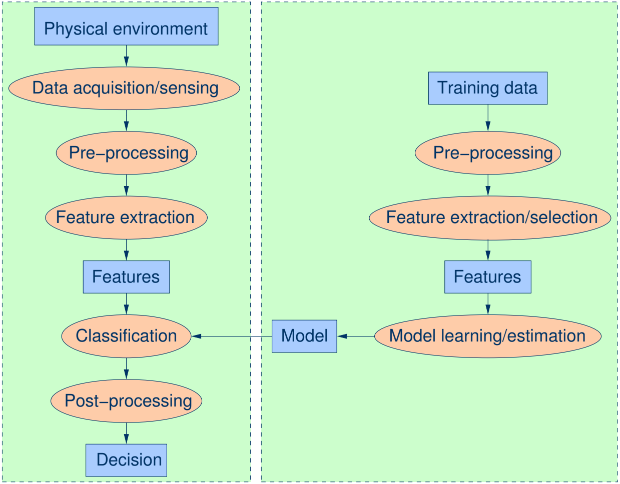


Figure 21: Object/process diagram of a pattern recognition system.

Pattern Recognition Systems

- Data acquisition and sensing:
  - Measurements of physical variables.
  - Important issues: bandwidth, resolution, sensitivity, distortion, SNR, latency, 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.

Pattern Recognition Systems

- Model learning and estimation:
  - Learning a mapping between features and pattern groups and categories.
- Classification:
  - Using features and learned models to assign a pattern to a category.
- Post-processing:
  - Evaluation of confidence in decisions.
  - Exploitation of context to improve performance.
  - Combination of experts.

The Design Cycle

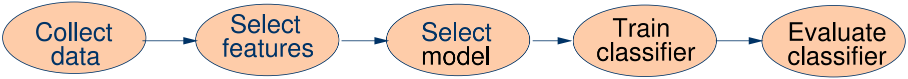


Figure 22: The design cycle.

- Data collection:
  - Collecting training and testing data.
  - How can we know when we have adequately large and representative set of samples?

The Design Cycle

- Feature selection:
  - Domain dependence and prior information.
  - Computational cost and feasibility.
  - Discriminative features.
    - Similar values for similar patterns.
    - Different values for different patterns.
  - Invariant features with respect to translation, rotation and scale.
  - Robust features with respect to occlusion, distortion, deformation, and variations in environment.

The Design Cycle

- 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?

The Design Cycle

- Training:
  - How can we learn the rule from data?
  - Supervised learning: a teacher provides a category label or cost for each pattern in the training set.
  - Unsupervised learning: the system forms clusters or natural groupings of the input patterns.
  - Reinforcement learning: no desired category is given but the teacher provides feedback to the system such as the decision is right or wrong.

The Design Cycle

- Evaluation:
  - How can we estimate the performance with training samples?
  - How can we predict the performance with future data?
  - Problems of overfitting and generalization.

Summary

- Pattern recognition techniques find applications in many areas: machine learning, statistics, mathematics, computer science, biology, etc.
- There are many sub-problems in the design process.
- Many of these problems can indeed be solved.
- More complex learning, searching and optimization algorithms are developed with advances in computer technology.
- There remain many fascinating unsolved problems.