Statistical Pattern Recognition & Learning

An Introduction

Dr Muhammad Sarim

Contents

Contents

Course Objectives

- Provide Basic to Intermediate level understanding of Pattern Recognition.

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- Provide Basic to Intermediate level understanding of Pattern Recognition.
- Make you think solution(s) of a problem rather than providing it.

Contents

Course Material & Grading

- **Books**
  - “Pattern Classification”, R. O. Duda, P. E. Hart, D. G. Stork, John Wiley & Sons, Second Edition.
  - “Pattern Recognition and Machine Learning”, Christopher M. Bishop,Springer, 2006.
- **Marks Breakup**

Assignments / Quizzes: 30%	Class Participation: 10%
Mid Term(s): 20%	Final: 40%

Course Material & Grading

- **Assignments**
  will be submitted through www.turnitin.com
  - Class ID:13319365
    Passwd: pr123
  - Small coding assignments in the class
- **Tools**
  - MATLAB (Image processing toolbox)
    - Implement different techniques rather than just going through theory
    - Learn simple operations during implementation of complex algorithms

Contents

Course Sketch

Pattern Recognition

Course Sketch

Human & Machine perception

Complexity Pattern Recognition System

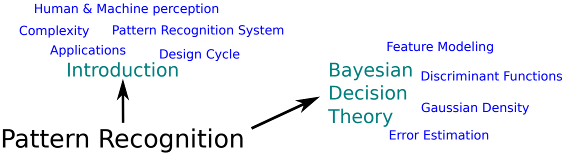
Applications Design Cycle

Introduction

↑

Pattern Recognition

Course Sketch



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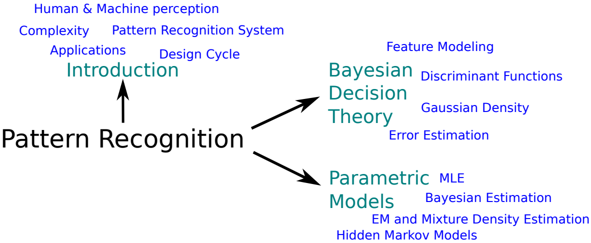

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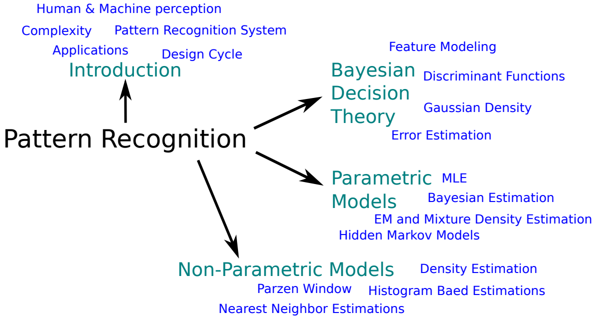

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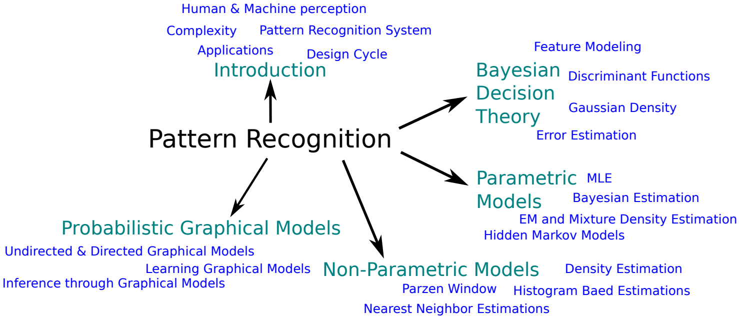

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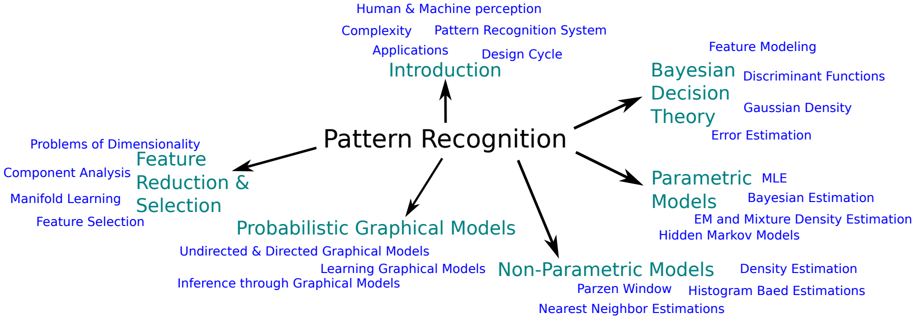

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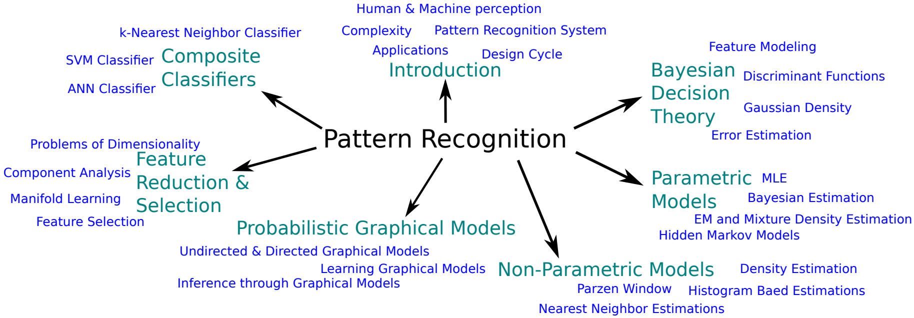

Contents

How Humans perceive?

- Humans have developed highly sophisticated skills for sensing their environment and taking actions according to what they observe, e.g.

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So What We Want from Machines!

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So What We Want from Machines!

We would like to give similar capabilities to machines.

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Pattern recognition is the study of how machines can

- observe the environment,
- learn to distinguish patterns of interest,
- make reasonable decisions about the categories of the patterns.

Contents

Machine Perception

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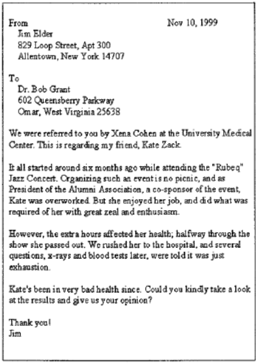
- Research on machine perception also helps us gain deeper understanding and appreciation for pattern recognition systems in nature.
- Yet, we also apply many techniques that are purely numerical and do not have any correspondence in natural systems.

Contents

Pattern Recognition Applications

Problem Domain	**Application**	**Input Pattern**	**Pattern Classes**
Document image analysis	Optical character recognition	Document image	Characters, words
Document classification	Internet search	Text document	Semantic categories
Document classification	Junk mail filtering	Email	Junk/non-junk
Multimedia database retrieval	Internet search	Video clip	Video genres
Speech recognition	Telephone directory assistance	Speech waveform	Spoken words
Natural language processing	Information extraction	Sentences	Parts of speech
Biometric recognition	Personal identification	Face, iris, fingerprint	Authorized users for access control
Medical	Computer aided diagnosis	Microscopic image	Cancerous/healthy cell
Military	Automatic target recognition	Optical or infrared image	Target type
Industrial automation	Printed circuit board inspection	Intensity or range image	Defective/non-defective product
Industrial automation	Fruit sorting	Images taken on a conveyor belt	Grade of quality
Remote sensing	Forecasting crop yield	Multispectral image	Land use categories
Bioinformatics	Sequence analysis	DNA sequence	Known types of genes
Data mining	Searching for meaningful patterns	Points in multidimensional space	Compact and well-separated clusters

Pattern Recognition Applications



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

Nov 10, 1999

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

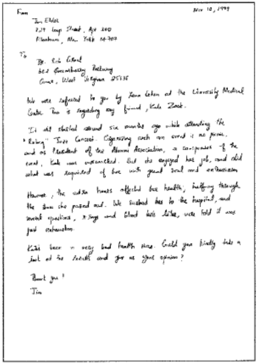
We were referred to you by Xena Cohen at the University Medical Center. This is regarding my friend, Kate Zack.

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.

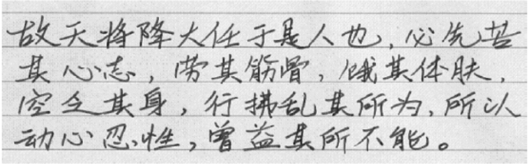
Kate's been in very bad health since. Could you kindly take a look at the results and give us your opinion?

Thank you!
Jim



English Handwriting Recognition

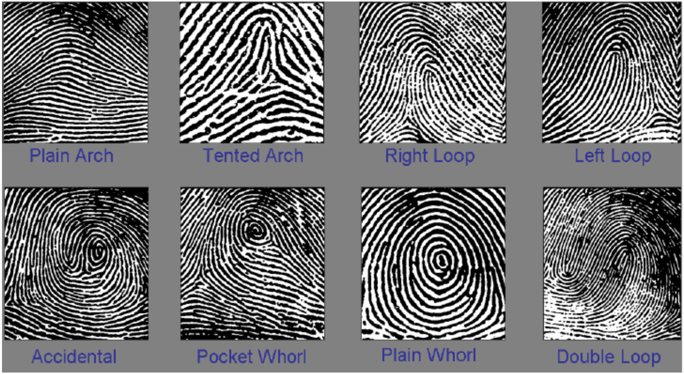
Pattern Recognition Applications



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。

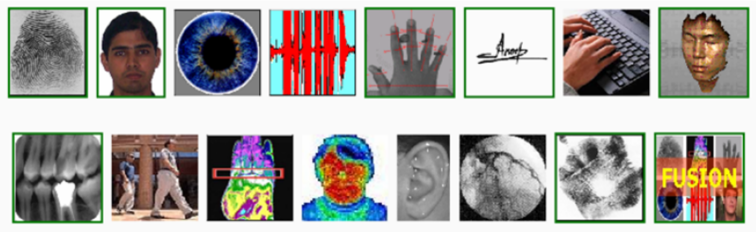
Chinese Handwriting Recognition

Pattern Recognition Applications



Finger Print Recognition

Pattern Recognition Applications

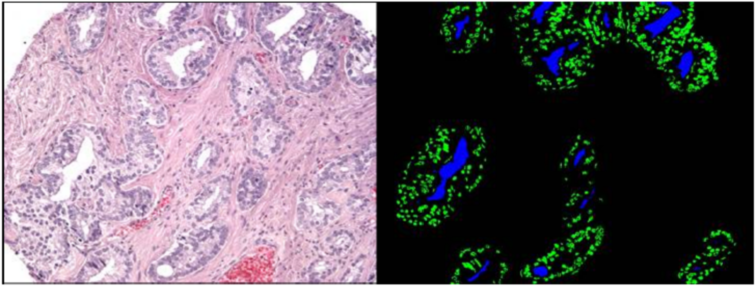


Biometric Recognition

Pattern Recognition Applications

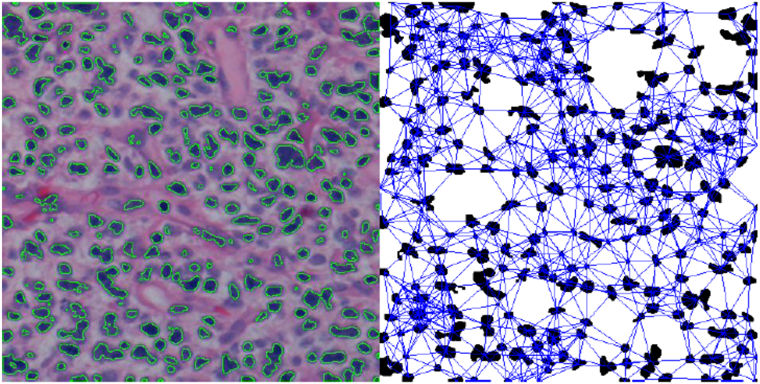
Autonomous Navigation

Pattern Recognition Applications



Cancer Detection using Microscopic tissue data

Pattern Recognition Applications



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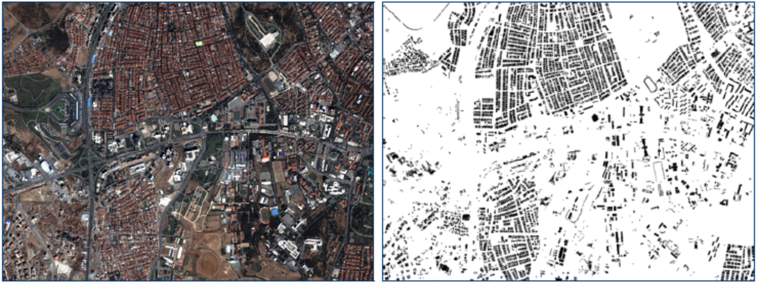
Pattern Recognition Applications

Land Cover Classification on Satellite Images

Pattern Recognition Applications

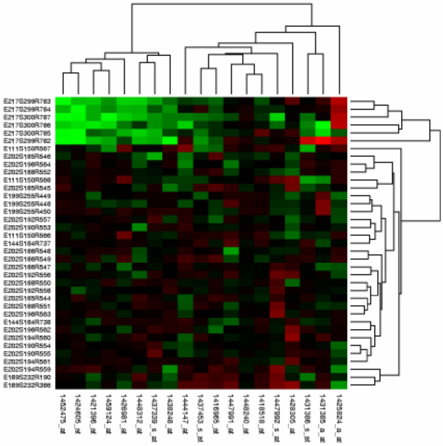


Building Group Recognition using Satellite Images

Pattern Recognition Applications

License Plate Recognition

Pattern Recognition Applications



Clustering of Micro-array data

Contents

An Example

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An Example: Decision Process

- What kind of information can distinguish one species from the other?

An Example: Decision Process

- What kind of information can distinguish one species from the other?
  - length

An Example: Decision Process

- What kind of information can distinguish one species from the other?
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- What are the steps in the process?
  - capture image → isolate fish → take measurements → make decision

An Example: Feature Selection

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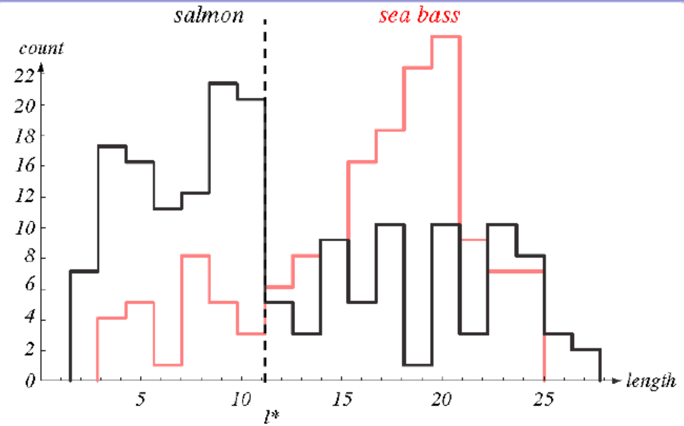
- We can use length as a feature and decide between sea bass and salmon according to a threshold on length.
- How can we choose this threshold?

An Example: Feature Selection



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?

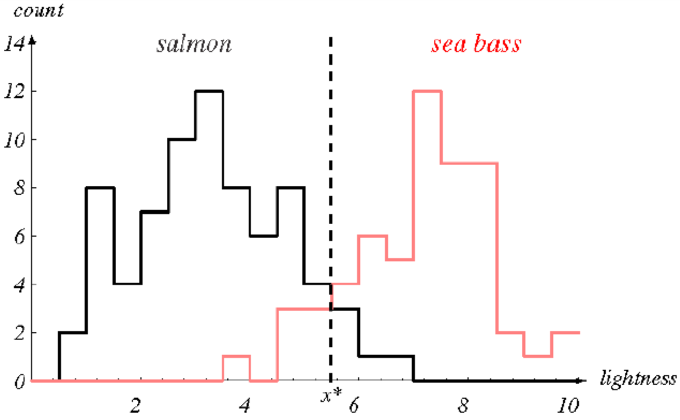
An Example: Feature Selection

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

An Example: Feature Selection

- 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: Feature Selection



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

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- For example, if the fish packing company knows that:
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- How does this knowledge affect our decision?

An Example: Multiple Features

- Assume we also observed that sea bass are typically wider than salmon.

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$$\begin{pmatrix} x1 \\ x2 \end{pmatrix}$$

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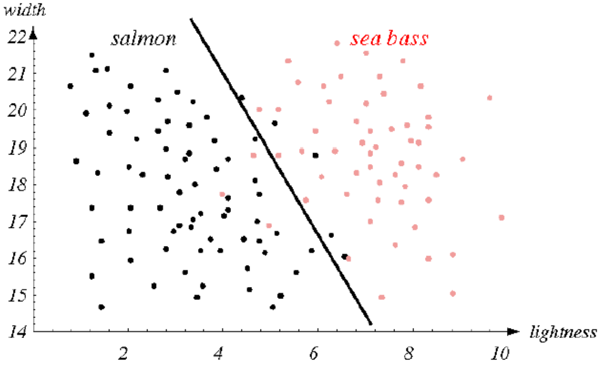

Scatter plot of lightness and width features for training samples. We can draw a decision boundary to divide the feature space into two regions. Does it look better than using only lightness?

An Example: Multiple Features

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  - Be careful about noise in the measurements.
- Is there some curse for working in very high dimensions?

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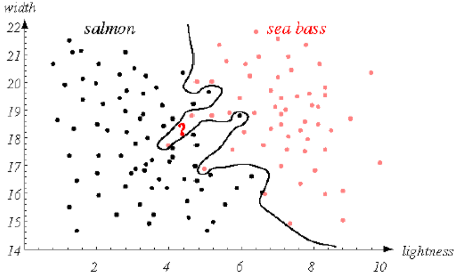

We may distinguish training samples perfectly but how can we predict how well we can generalize to unknown samples?

An Example: Decision Boundaries

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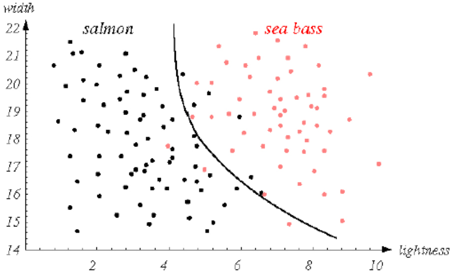
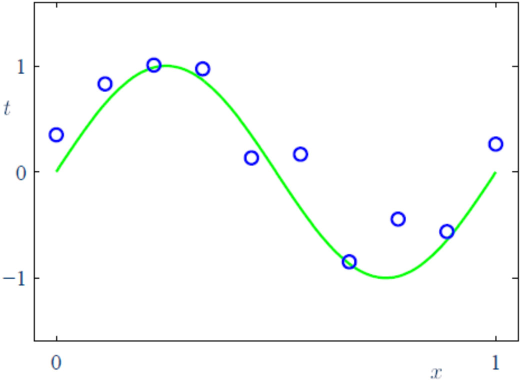


Different criteria lead to different decision boundaries.

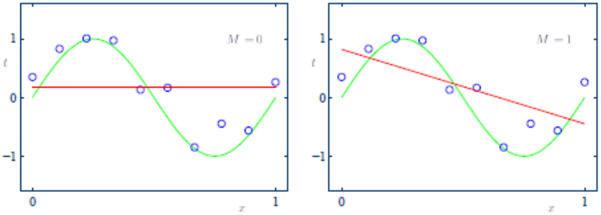
Contents

More on Complexity



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.

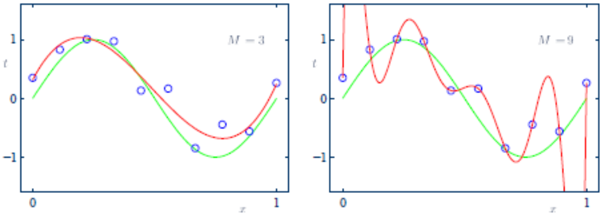
More on Complexity



(a) 0^{th} order polynomial (b) 1^{st} order polynomial

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

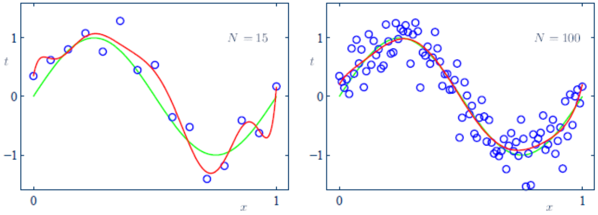
More on Complexity



(c) 3^{rd} order polynomial (d) 9^{th} order polynomial

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

More on Complexity

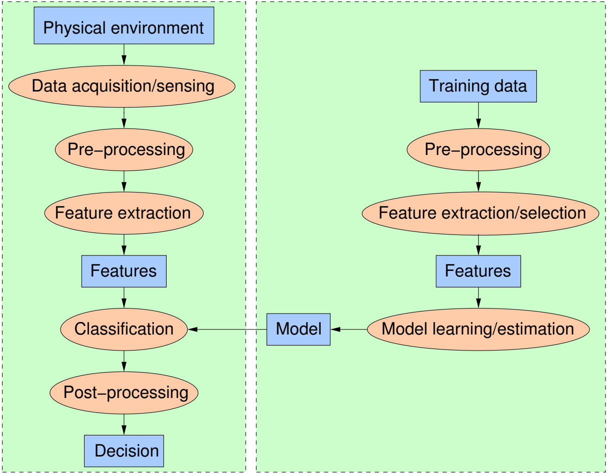


(a) 15 sample points (b) 100 sample points

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

Contents

Pattern recognition system



Object/process diagram of a pattern recognition system.

Pattern recognition system

- Data acquisition and sensing:

Pattern recognition system

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  - Isolation of patterns of interest from the background.

Pattern recognition system

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- Feature extraction:

Pattern recognition system

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  - 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 system

- Model learning and estimation:

Pattern recognition system

- Model learning and estimation:
  - Learning a mapping between features and pattern groups and categories.

Pattern recognition system

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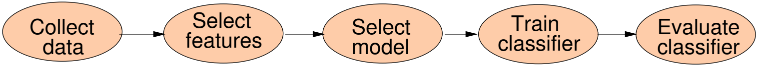
  - Exploitation of context to improve performance.
  - Combination of experts.

Contents

Design cycle



The design cycle

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

Design cycle

- Feature selection:

Design cycle

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  - Domain dependence and prior information.

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  - Robust features with respect to occlusion, distortion, deformation, and variations in environment.

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  - 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?

Design cycle

- Training:

Design cycle

- Training:
  - How can we learn the rule from data?

Design cycle

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  - Supervised learning: a teacher provides a category label or cost for each pattern in the training set.

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  - Reinforcement learning: no desired category is given but the teacher provides feedback to the system such as the decision is right or wrong.

Design cycle

- Evaluation:

Design cycle

- Evaluation:
  - How can we estimate the performance with training samples?

Design cycle

- Evaluation:
  - How can we estimate the performance with training samples?
  - How can we predict the performance with future data?

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.

Contents

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.