

Pattern Recognition

An Introduction

Dr Muhammad Sarim

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1 About the Course

- Objectives
- Course Material & Grading
- Course Sketch

2 How Humans perceive?

3 What is Pattern Recognition?

4 Machine Perception

5 Pattern Recognition Applications

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6 Complexity

7 PR system

- Design cycle

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Objectives

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Course Objectives

- Provide Basic to Intermediate level understanding of Pattern Recognition.

Objectives

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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.

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 - Design cycle
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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

Course Material & Grading

• **Assignments**

will be submitted through www.turnitin.com

- Class ID:10439310
- 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

Course Sketch

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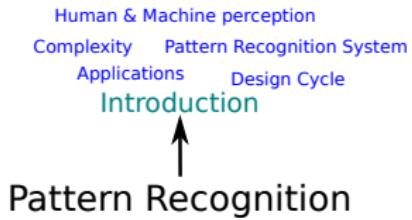
Course Sketch

Course Sketch

Pattern Recognition

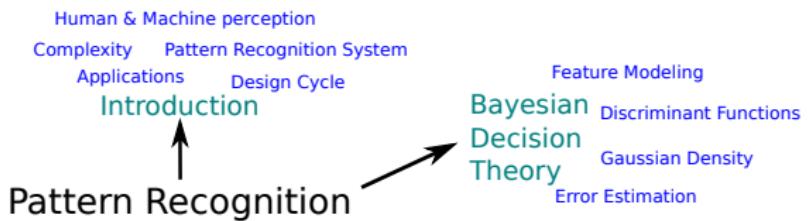
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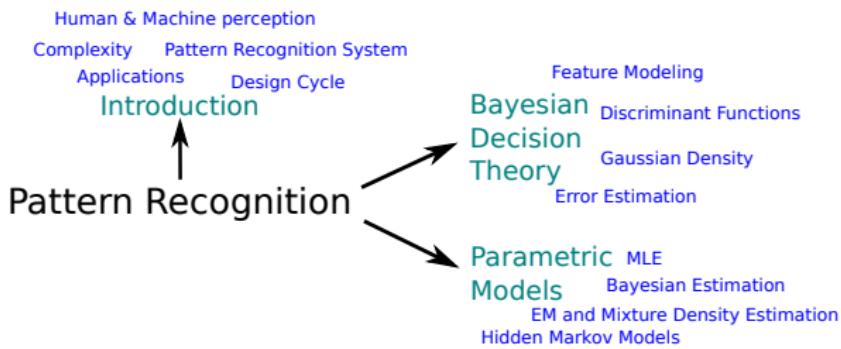


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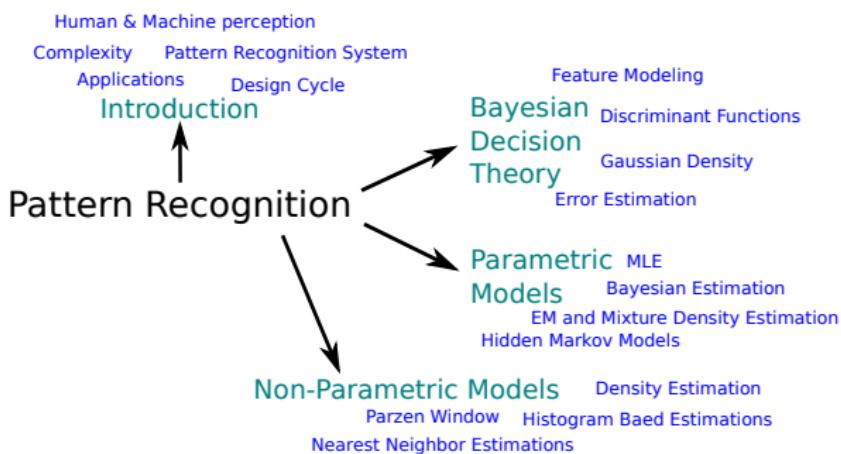
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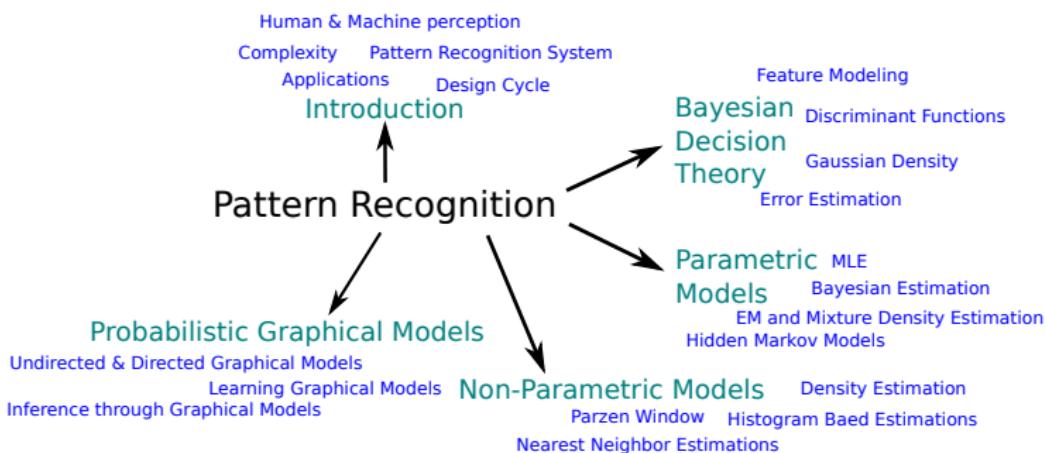
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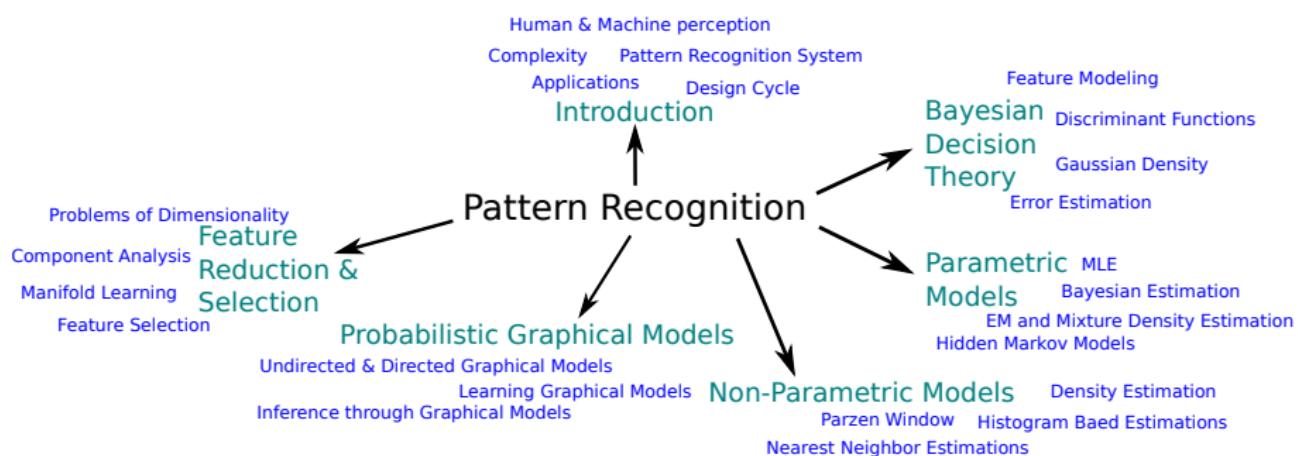
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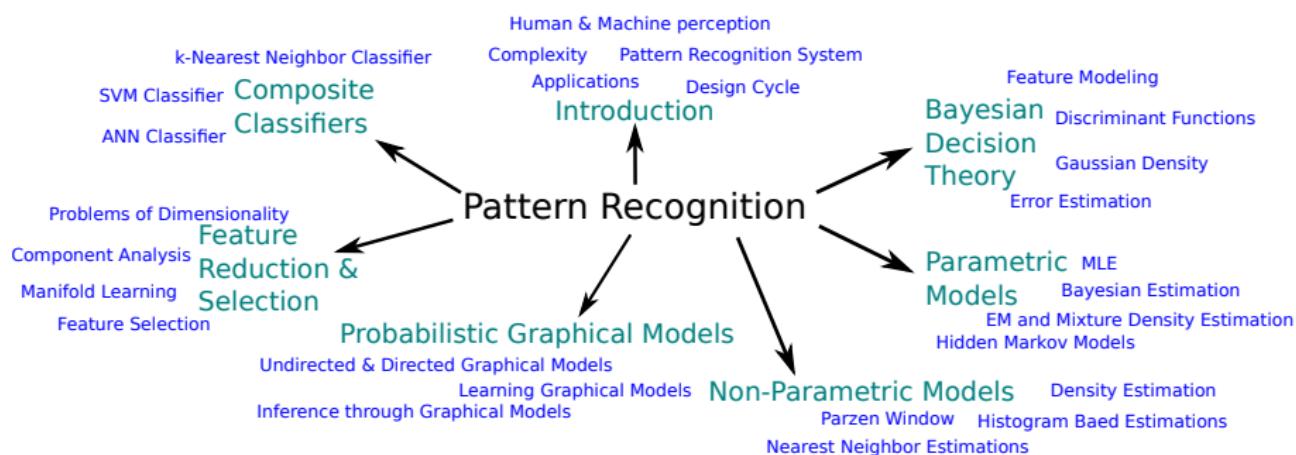


Course Sketch



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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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 - distinguishing food from its smell.

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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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- crystal structure, etc.

Pattern recognition is the study of how machines can

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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.

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Machine Perception

- We are often influenced by the knowledge of how patterns are modeled and recognized in nature when we develop pattern recognition algorithms.

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- Research on machine perception also helps us gain deeper understanding and appreciation for pattern recognition systems in nature.

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- 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.

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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

<p>From Jim Elder Nov 10, 1999</p> <p>829 Loop Street, Apt 300 Allentown, New York 14707</p> <p>To Dr. Bob Grant 602 Queenberry Parkway Omar, West Virginia 25638</p> <p>We were referred to you by Xena Cohen at the University Medical Center. This is regarding my friend, Kate Zack.</p> <p>It all started around six months ago while attending the "Bubeq" 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.</p> <p>However, the extra hours affected her health; halfway through the show she passed out. We rushed her to the hospital, and several questionnaires, x-rays and blood tests later, were told it was just exhaustion.</p> <p>Kate's been in very bad health since. Could you kindly take a look at the results and give us your opinion?</p> <p>Thank you! Jim</p>	<p>From Jim Elder Nov 10, 1999 829 Loop Street, Apt 300 Allentown, New York 14707</p> <p>To Dr. Ed Gant 602 Queenberry Parkway Omar, West Virginia 25638</p> <p>He was referred to you by Xena Cohen at the University Medical Center. This is regarding my friend, Kate Zack.</p> <p>It all started around six months ago while attending the "Bubeq" 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.</p> <p>However, the extra hours affected her health; halfway through the show she passed out. We rushed her to the hospital, and several questionnaires, x-rays and blood tests later, were told it was just exhaustion.</p> <p>Kate's been in very bad health since. Could you kindly take a look at the results and give us your opinion?</p> <p>Thank you! Tim</p>
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English Handwriting Recognition

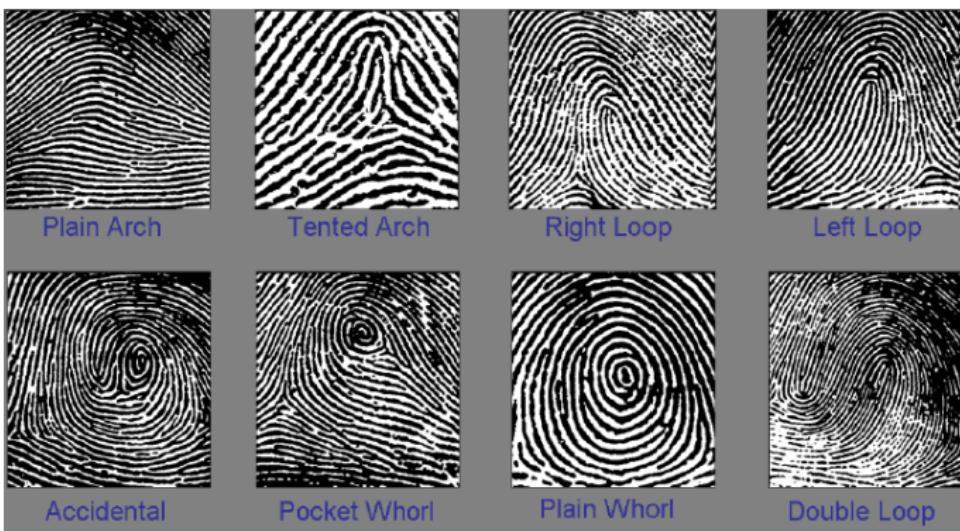
Pattern Recognition Applications

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。

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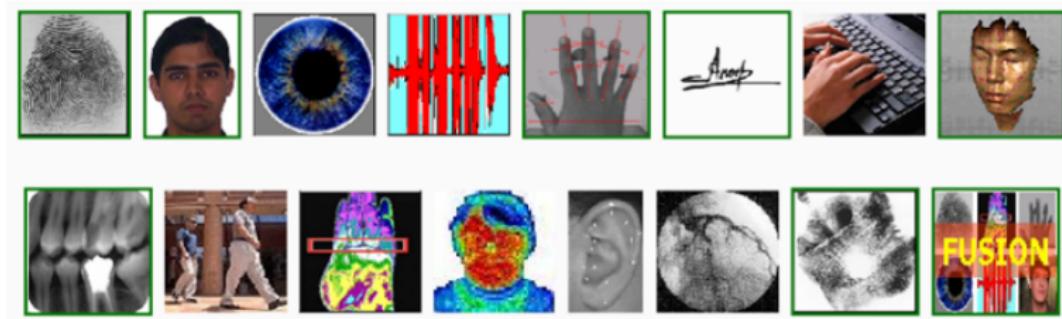
Chinese Handwriting Recognition

Pattern Recognition Applications



Finger Print Recognition

Pattern Recognition Applications



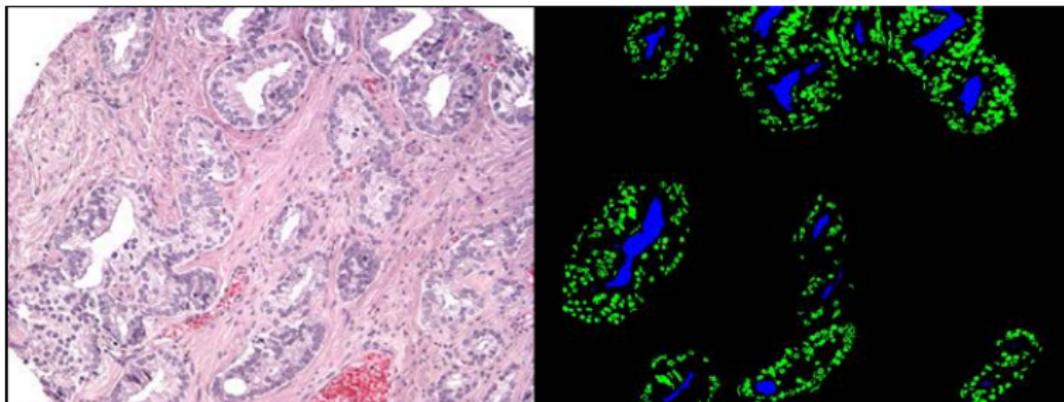
Biometric Recognition

Pattern Recognition Applications



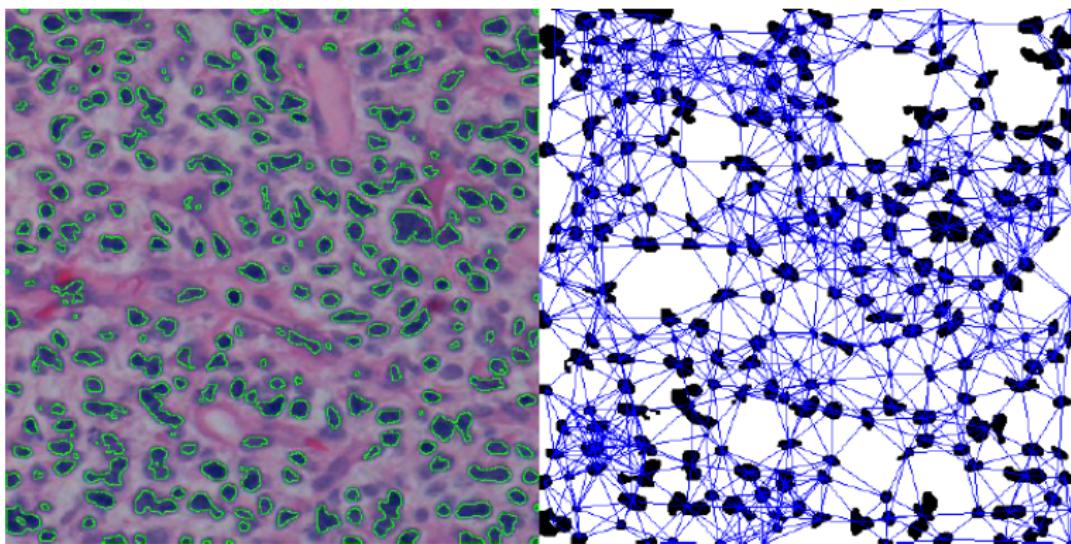
Autonomous Navigation

Pattern Recognition Applications



Cancer Detection using Microscopic tissue data

Pattern Recognition Applications



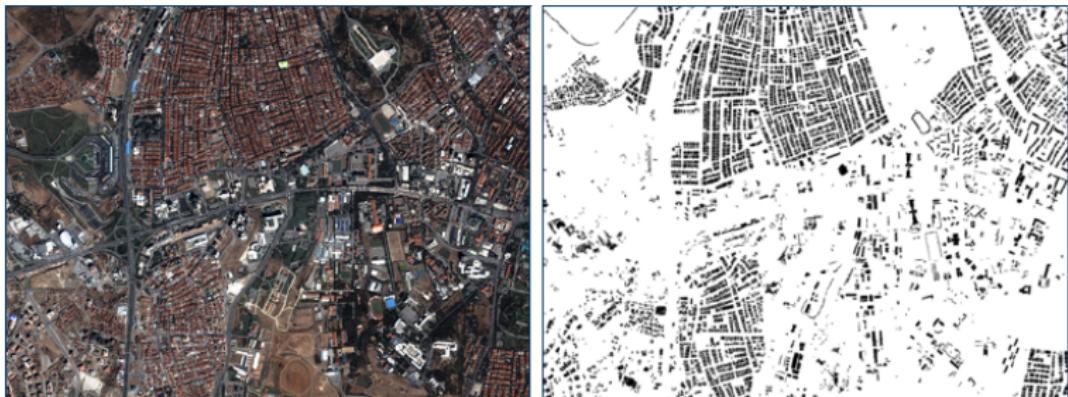
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Pattern Recognition Applications



Land Cover Classification on Satellite Images

Pattern Recognition Applications



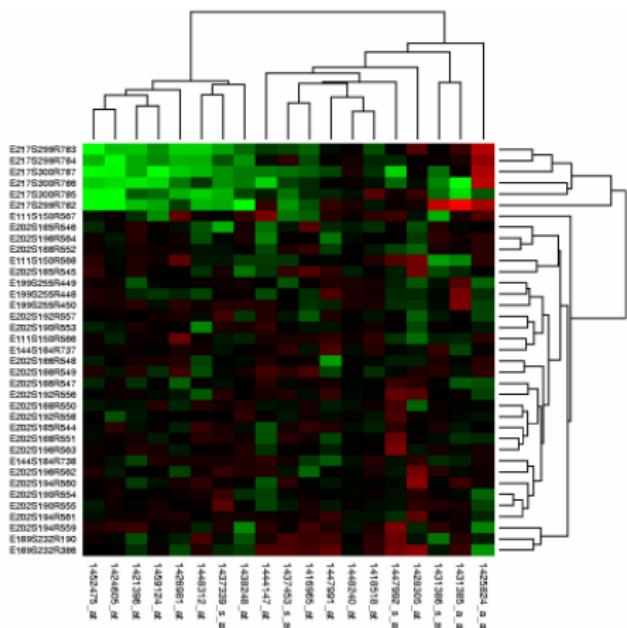
Building Group Recognition using Satellite Images

Pattern Recognition Applications



License Plate Recognition

Pattern Recognition Applications



Clustering of Micro-array data

An Example

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An Example

An Example

- Problem: Sorting incoming fish on a conveyor belt according to species.



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An Example

An Example: Decision Process

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

An Example

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

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

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

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- What kind of information can distinguish one species from the other?
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- What are the steps in the process?

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- 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 → isolate fish → take measurements → make decision

An Example

An Example: Feature Selection

- Assume a fisherman told us that a sea bass is generally longer than a salmon.

An Example

An Example: Feature Selection

- 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.

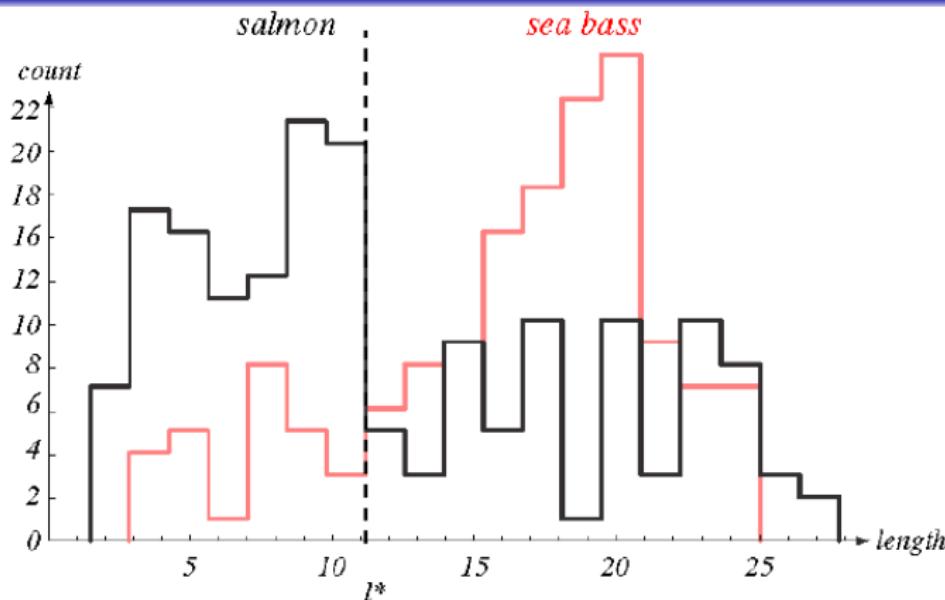
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- Assume a fisherman told us that a sea bass is generally longer than a salmon.
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- How can we choose this threshold?

An Example

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

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.

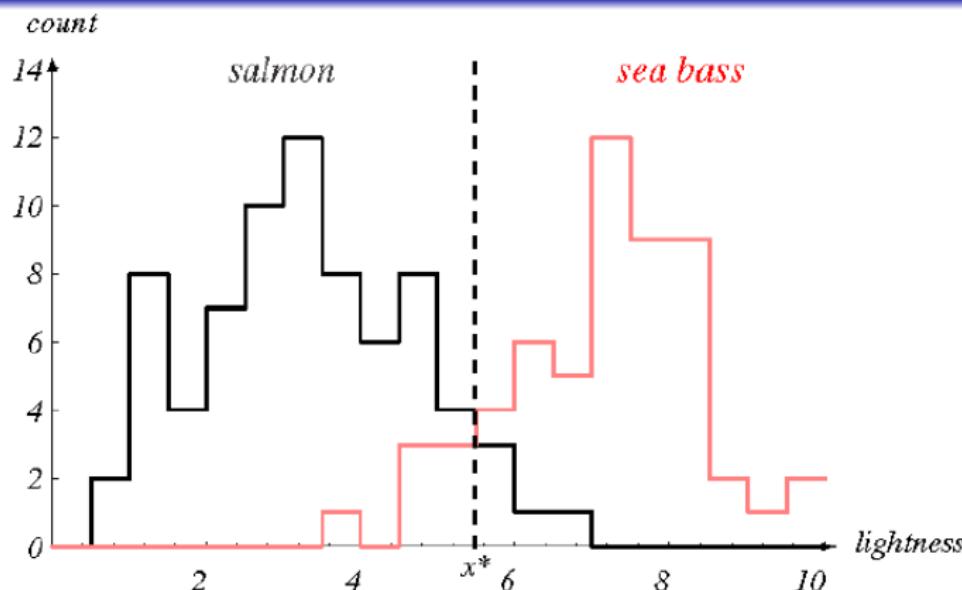
An Example

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

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

An Example: Cost of Error

- We should also consider **cost of different errors** we make in our decisions.

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- We should also consider **cost 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

An Example: Multiple Features

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

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- Assume we also observed that sea bass are typically wider than salmon.
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- Each fish image is now represented as a point (**feature vector**) in a two-dimensional **feature space**.

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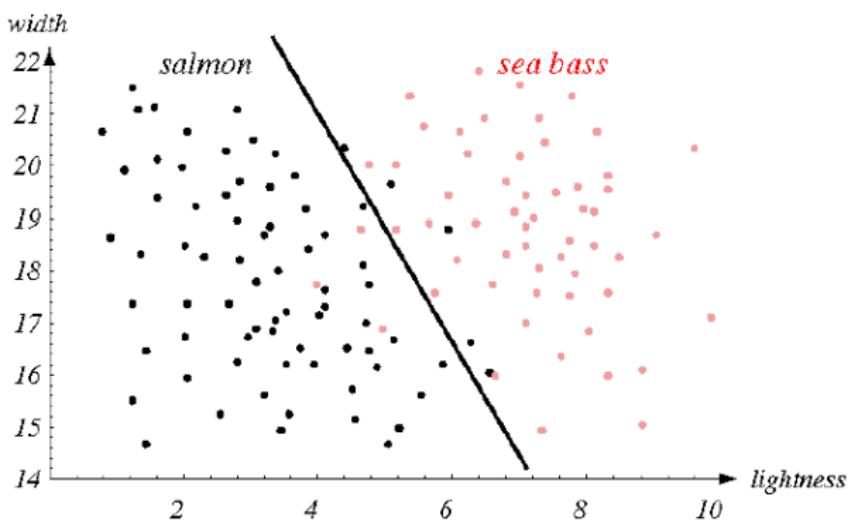
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$$\begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

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An Example: Multiple Features



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?

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An Example: Multiple Features

- Does adding more features always improve the results?

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- Does adding more features always improve the results?
 - Avoid unreliable features.

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- Does adding more features always improve the results?
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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

An Example: Decision Boundaries

- Can we do better with another decision rule?

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

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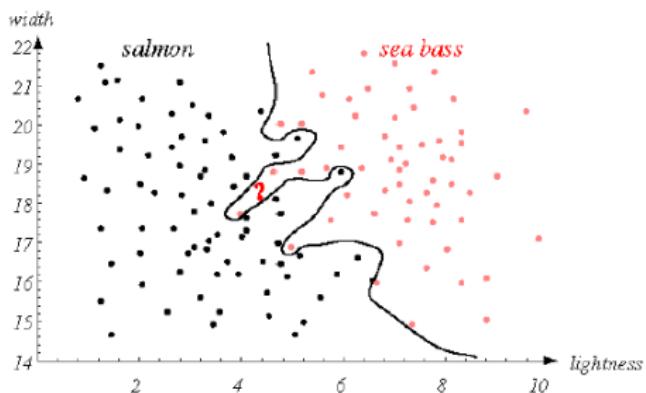
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We may distinguish training samples perfectly but how can we predict how well we can **generalize** to unknown samples?

An Example

An Example: Decision Boundaries

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

An Example

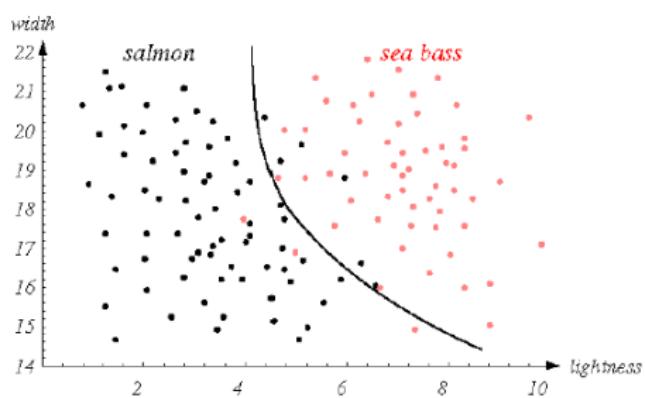
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Different criteria lead to different decision boundaries.

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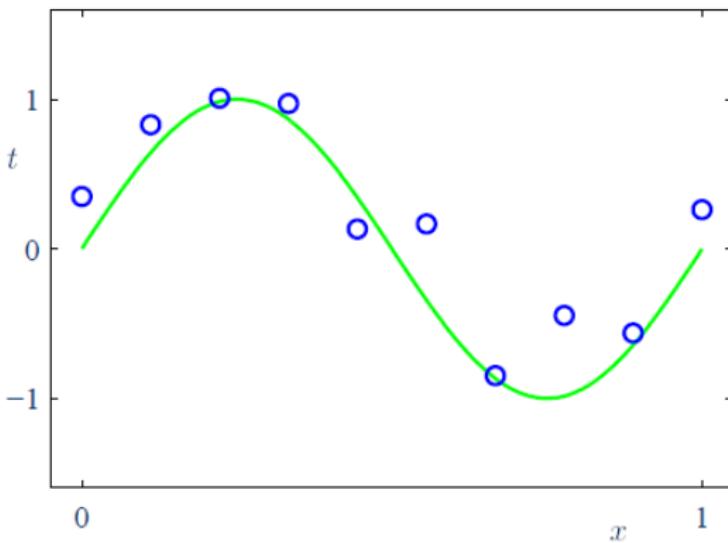
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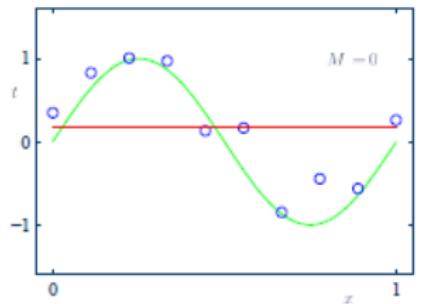
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More on Complexity



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



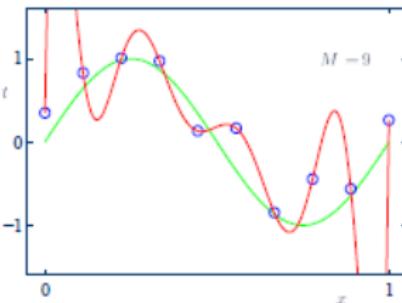
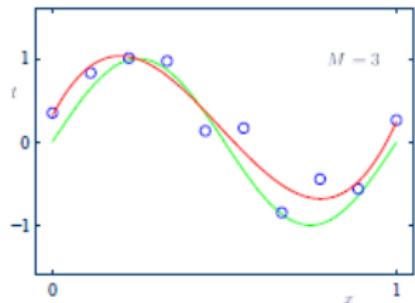
(a) 0th order polynomial



(b) 1st order polynomial

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

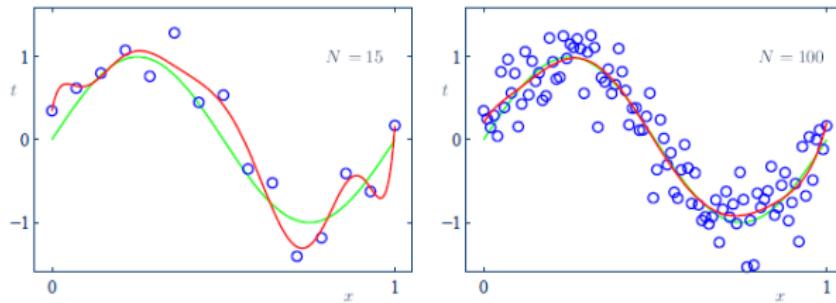
More on Complexity



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

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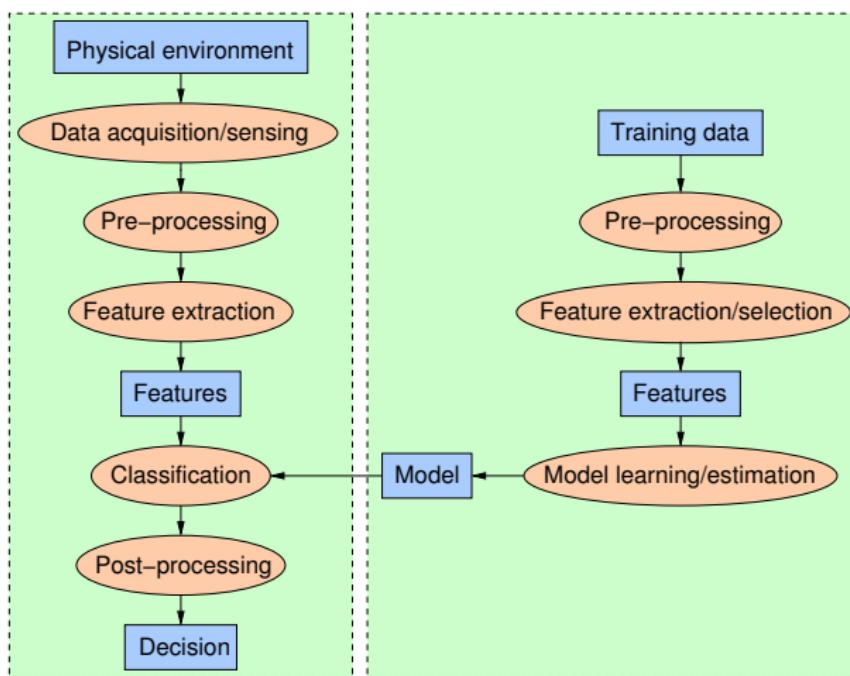
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Pattern recognition system



Object/process diagram of a pattern recognition system.

Pattern recognition system

- Data acquisition and sensing:

Pattern recognition system

- Data acquisition and sensing:
 - Measurements of physical variables.

Pattern recognition system

- Data acquisition and sensing:
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 - Important issues: bandwidth, resolution, sensitivity, distortion, SNR, latency, etc.

Pattern recognition system

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 - Removal of noise in data.

Pattern recognition system

- Data acquisition and sensing:
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 - Removal of noise in data.
 - Isolation of patterns of interest from the background.

Pattern recognition system

- Data acquisition and sensing:
 - Measurements of physical variables.
 - Important issues: bandwidth, resolution, sensitivity, distortion, SNR, latency, etc.
- Pre-processing:
 - Removal of noise in data.
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- Feature extraction:

Pattern recognition system

- 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 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

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

Pattern recognition system

- 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.

Pattern recognition system

- Model learning and estimation:
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- Post-processing:

Pattern recognition system

- Model learning and estimation:
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- Post-processing:
 - Evaluation of confidence in decisions.

Pattern recognition system

- 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.

Pattern recognition system

- 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.

Design cycle

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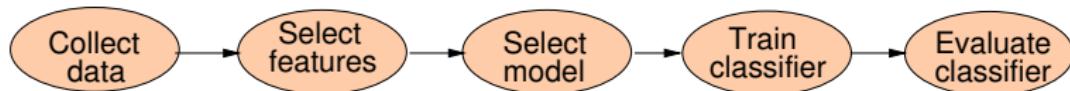
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Design cycle

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

Design cycle

- Feature selection:

Design cycle

Design cycle

- Feature selection:
 - Domain dependence and prior information.

Design cycle

Design cycle

- Feature selection:
 - Domain dependence and prior information.
 - Computational cost and feasibility.

Design cycle

Design cycle

- Feature selection:
 - Domain dependence and prior information.
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 - Discriminative features.

Design cycle

Design cycle

- Feature selection:
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 - Similar values for similar patterns.

Design cycle

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.

Design cycle

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.

Design cycle

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.

Design cycle

Design cycle

- Model selection:

Design cycle

Design cycle

- Model selection:
 - Domain dependence and prior information.

Design cycle

Design cycle

- Model selection:
 - Domain dependence and prior information.
 - Definition of design criteria.

Design cycle

Design cycle

- Model selection:
 - Domain dependence and prior information.
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 - Parametric vs. non-parametric models.

Design cycle

Design cycle

- Model selection:
 - Domain dependence and prior information.
 - Definition of design criteria.
 - Parametric vs. non-parametric models.
 - Handling of missing features.

Design cycle

Design cycle

- Model selection:
 - Domain dependence and prior information.
 - Definition of design criteria.
 - Parametric vs. non-parametric models.
 - Handling of missing features.
 - Computational complexity.

Design cycle

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.

Design cycle

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?

Design cycle

Design cycle

- Training:

Design cycle

Design cycle

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

Design cycle

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.

Design cycle

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.

Design cycle

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.

Design cycle

Design cycle

- Evaluation:

Design cycle

Design cycle

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

Design cycle

Design cycle

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

Design cycle

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.

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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.