## Probabistic Models and Machine Learning





No. 1

## Introduction

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### **Course Info (tentative)**

Instructor:

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Course web site:

https://www.eecs.yorku.ca/course/6327/

- Course Format:
  - Lectures (40 hours):
    - Covers basic probabilistic models, pattern classification theory, machine learning algorithms;
    - Self-study on some advanced machine learning topics.
- Evaluation:
  - Class Participation (10%)
  - Two assignments (30%)
  - Two lab projects (40%)
  - In-class presentation (20%)

#### **Course Outline**

- Part I: Introduction (6 hours)
  - Machine Learning: basic concepts
  - Math foundation: review
- Part II: Basic theory of pattern classification and machine learning (24 hours)
  - Bayesian decision rule; Model Estimation
  - Generative models: Gaussian, GMM, Markov Chain, HMM, Graphical models
  - Discriminative models: SVM, Neural networks (NN) and beyond
- Part III: Advanced Topics (6 hours)
  - Self-select and self-study
  - Presentation

### **Reference Materials**

- Lecture notes
- Assigned reading materials through the course
- Reference books:
  - [1] Pattern Recognition and Machine Learning by C. M. Bishop. (Springer, ISBN 0-387-31073-8)
  - [2] Pattern Classification (2<sup>nd</sup> Edition) by R. O. Duda, P. Hart and D. Stork. (John Wiley & Sons, Inc., ISBN 0-471-05669-3)
  - [3] Machine Learning: A Probabilistic Perspectives by K. P. Murphy. (The MIT Press, ISBN 978-0-262-01802-9)
- Prerequisite:
  - □ Probability and statistics
  - ☐ Linear algebra and/or matrix theory
  - □ C/C++/Java; matlab; perl/python/shell (plus)

#### Relevant Al Research Topics

- Theory
  - ✓ Knowledge Representation and Inference
  - ✓ Machine Learning
  - ✓ Pattern Recognition
  - ✓ Statistical Signal Processing
- Applications
  - ✓ Speech Processing
  - ✓ Natural Language Processing
  - ✓ Computer Vision
  - ✓ Data Mining
  - **√** ...

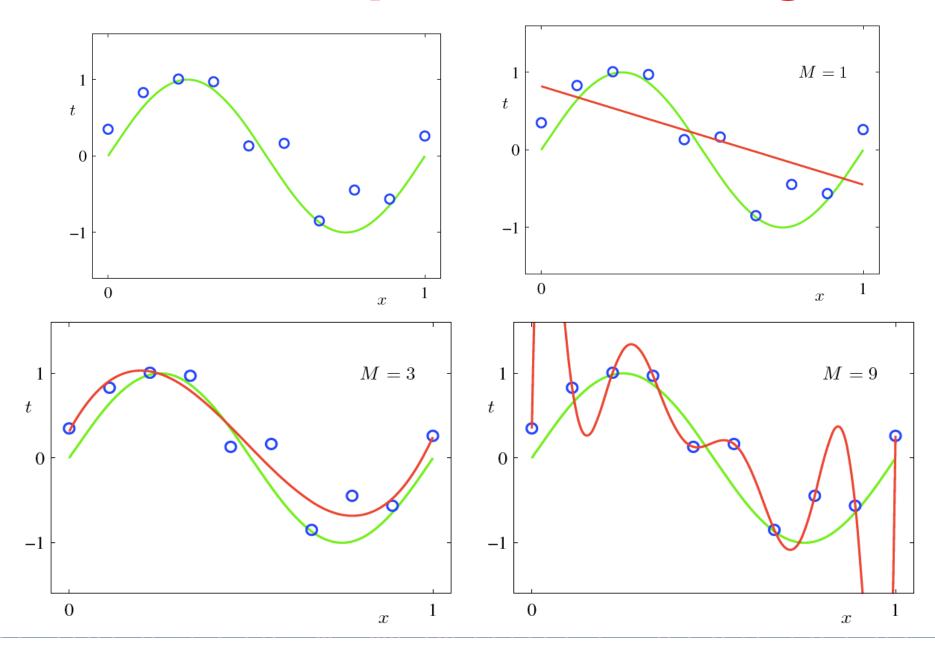
# Artificial Intelligence (AI): Paradigm Shift

- Knowledge based → KR
  - Reply on expert(s); Small data samples
  - Simple toy problems
- Data-Driven → ML
  - Large data samples
  - Statistical models; machine learning algorithms
- Big Data Era
  - Massive real-world data samples → powerful models
  - Data intensive computing → computation power
  - Parallel/distributed platform: e.g. GPU, map-reduce

#### **Some Machine Learning Concepts**

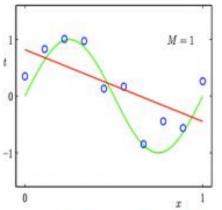
- Classification vs. Regression
- Supervised vs. Unsupervised (Clustering)
- Parametric vs. Non-parametric
- Linear vs. Nonlinear
- Underfitting vs. Overfitting (Regularization)
- Frequentist vs. Bayesian
- Probabilistic models vs. Rule-based (Al vs. ML)

## **An Example: Curve fitting**

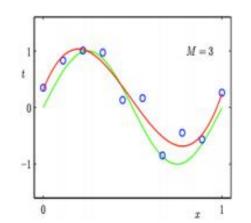


## **Under-fitting vs. Overfillting** (Regularization)

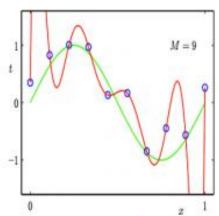
Regression:



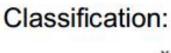
predictor too inflexible:

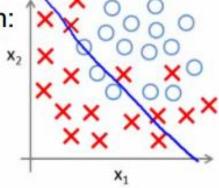


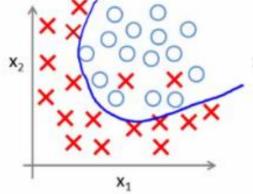
cannot capture pattern

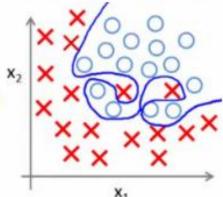


predictor too flexible: fits noise in the data

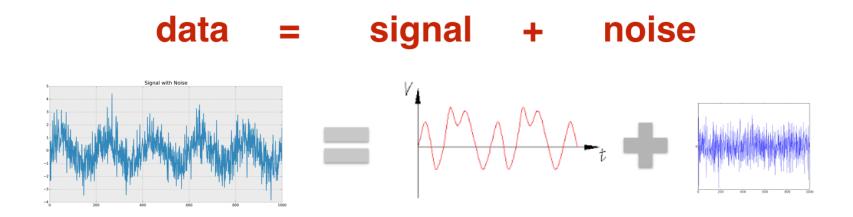








## Under-fitting vs. Overfillting (Regularization)



- Too strong models → over-fitting (why?)

## **Machine Learning Procedure**

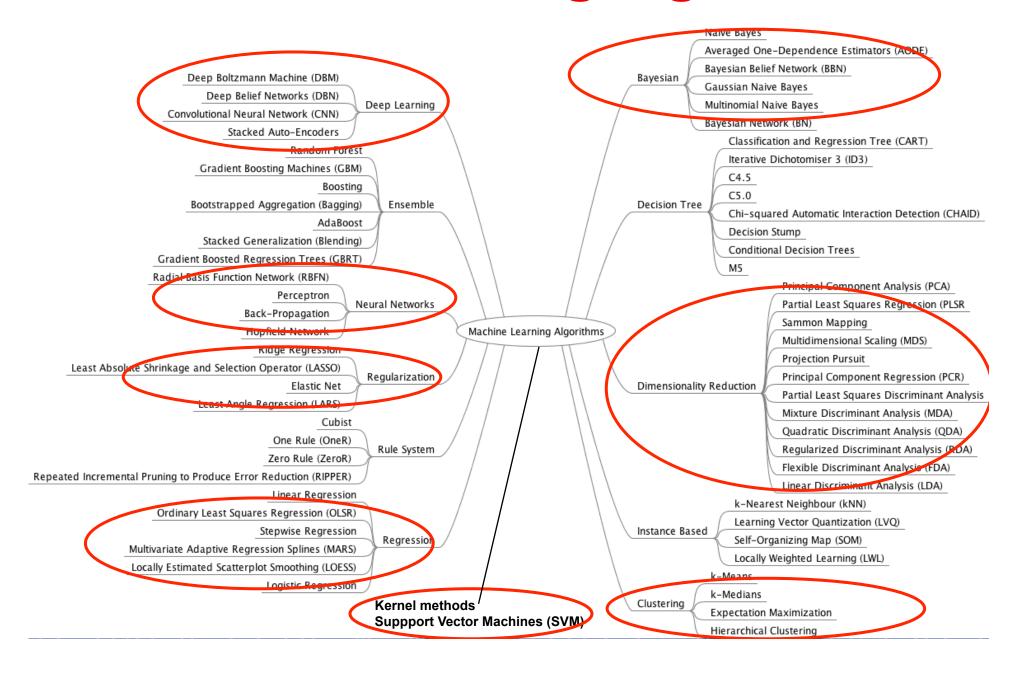
- Feature extraction (feature engineering):
  - Need to know objects to extract good features
  - Varies a lot among different applications (speech, audio, text, image, video, gestures, biological sequences, etc)
  - May need reduce dimensionality
- Statistical model training/learning
- Inference, matching, decision

The basic theories common to various applications

#### **Machine Learning Algorithms**



#### **Machine Learning Algorithms**



## **Advanced ML Topics**

- Learnability
- On-line Learning
- Reinforcement Learning
- Transfer Learning / Adaptation / One-shot Learning
- Active Learning
- Ensemble Learning
- Imitation Learning
- Gaussian Processes
- Causal Learning