CS 2750 Machine Learning

Lecture 1

Machine Learning

Milos Hauskrecht
milos@cs.pitt.edu
5329 Sennott Square, x4-8845

people.cs.pitt.edu/~milos/courses/cs2750-Spring2020/

Administration

Instructor:

Prof. Milos Hauskrecht
milos@cs.pitt.edu
5329 Sennott Square, x4-8845

TA: TBA

Office hours: TBA

Who am I?

- **Milos Hauskrecht –Professor of Computer Science**
- **Secondary affiliations:**
  - Intelligent Systems Program (ISP),
  - Department of Biomedical Informatics (DBMI)

- **Research work:**
  - Machine learning, Data mining, Outlier detection, Probabilistic modeling, Time-series models and analysis

  Applications to healthcare:
  - EHR data analysis, Patient monitoring and alerting, Patient safety

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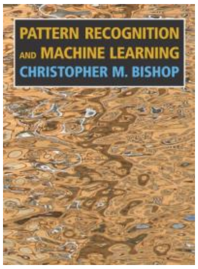
Study material

- **Handouts, your notes and course readings**
- **Primary textbook:**



  - Chris. Bishop. Pattern Recognition and Machine Learning. Springer, 2006.

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Study material

- **Other books:**
  - K. Murphy. Machine Learning: A probabilistic perspective, MIT Press, 2012.
  - J. Han, M. Kamber. Data Mining. Morgan Kauffman, 2011.
  - Friedman, Hastie, Tibshirani. Elements of statistical learning. Springer, 2nd edition, 2011.
  - Koller, Friedman. Probabilistic graphical models. MIT Press, 2009.
  - Duda, Hart, Stork. Pattern classification. 2nd edition. J Wiley and Sons, 2000.
  - T. Mitchell. Machine Learning. McGraw Hill, 1997.

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- **Homework assignments: weekly**
  - **Programming tool**: Matlab (free license, CSSD machines and labs)
  - **Matlab Tutorial:** next week
- **Exams:**
  - **Midterm + Final**
  - **Midterm** – before Spring break
- **Term project**
- **Lectures:**
  - **Attendance and Activity**

Tentative topics

- **Introduction**
- **Density estimation**
  - Parametric (maximum likelihood, Bayesian)
  - Nonparametric
- **Supervised Learning**
  - Linear models for regression and classification.
  - Generative models for classification
  - Multi-layer neural networks.
  - Support vector machines. Kernel methods.
  - Decision trees

Tentative topics (cont)

- **Unsupervised Learning**
  - Bayesian belief networks
  - Learning Bayesian networks
  - Expectation maximization.
  - Clustering
- **Ensemble methods**
  - Mixture models
  - Bagging and boosting
- **Dimensionality reduction**
  - Feature selection
  - Principal component analysis (PCA)
- **Reinforcement learning**

Machine Learning

- The field of **machine learning** studies the design of computer programs (agents) capable of learning from past experience or adapting to changes in the environment

- The need for building agents capable of learning is everywhere.

  Examples:

  - text, web page classification
  - web search
  - speech recognition

Machine Learning

- **Examples:**
  - Image/video classification, annotation and retrieval
  - adaptive interfaces
  - commercial software
  - Game playing

Car
Race car

nature
At last — a computer program that can beat a champion Go player
ALL SYSTEMS GO

Learning process

Model of data

Learner (a computer program) processes data ***D*** representing past experiences and tries to build a **model** that either:

- Generates appropriate response to future data, or
- Describes in some meaningful way the data seen

Example:

Learner sees a set of patient cases (patient records) with corresponding diagnoses. It can either try:

- to predict the occurrence of a disease for future patients
- describe the dependencies between diseases, symptoms

Types of learning problems

- **Supervised learning**
  - Takes data that consists of pairs (**x,y**)
  - Learns mapping ***f:*** **x** (input) → **y** (output, response)
- **Unsupervised learning**
  - Takes data that consist of vectors **x**
    - Learns relations **x** among vector components
    - Groups/clusters data into the groups
- **Reinforcement learning**
  - Learns mapping ***f:*** **x** (input) → **y** (desired output)
  - From (**x,y,**r) triplets where **x** is an input, **y** is a response chosen by the user/system, and r is a reinforcement signal
  - **Online:** see x, choose y and observe r
- **Other types of learning: Active learning, Transfer learning, Deep learning**

Supervised learning

Data: $D = \{d_1, d_2, .., d_n\}$ **a set of *n* examples**

$d_i = < \mathbf{x}_i, y_i >$

$\mathbf{x}_i$ is input vector, and y is desired output (given by a teacher)

Objective: learn the mapping $f : X \rightarrow Y$

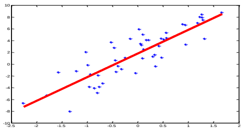
s.t. $y_i \approx f(x_i)$ for all $i = 1, .., n$

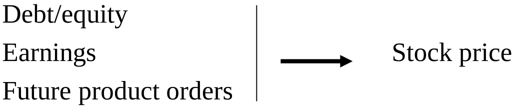
Two types of problems:

- **Regression:** X discrete or continuous →
  Y is **continuous**
- **Classification:** X discrete or continuous →
  Y is **discrete**

Supervised learning examples

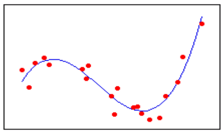
- **Regression:** Y is **continuous**





Debt/equity
Earnings
Future product orders

Stock price



Data:

Debt/equity	Earnings	Future prod orders	Stock price
20	115	20	123.45
18	120	31	140.56
….			

Supervised learning examples

- **Classification:** Y is **discrete**

```
# ######
      ##
     ##
  ######
      ###
#      ##
# ##   ##
  #######
```

Label “3”

Handwritten digit (array of 0,1s)

Data:

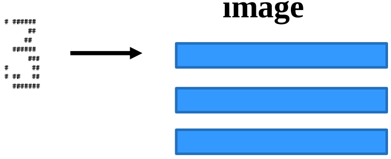


image	digit
	3
	7
	5

….

Unsupervised learning

- **Data:** $D = \{d_1, d_2, .., d_n\}$

  $d_i = \mathbf{x}_i$ vector of values

  No target value (output) y

- **Objective:**
  - learn relations between samples, components of samples

Types of problems:

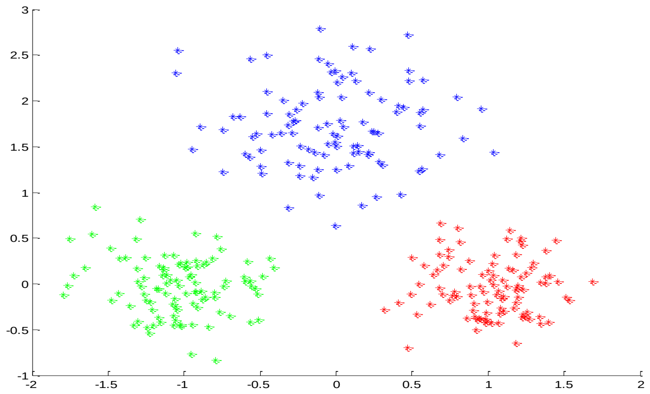
- **Clustering**

  Group together “similar” examples, e.g. patient cases

- **Density estimation**
  - Model probabilistically the population of samples

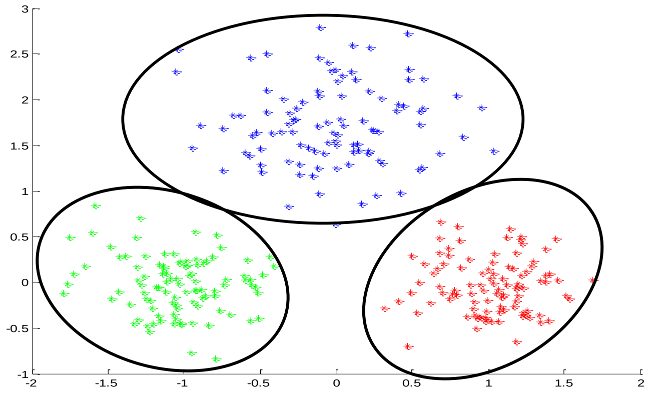
Unsupervised learning example

- **Clustering.** Group together similar examples $d_i = \mathbf{x}_i$



Unsupervised learning example

- **Clustering.** Group together similar examples $d_i = \mathbf{x}_i$

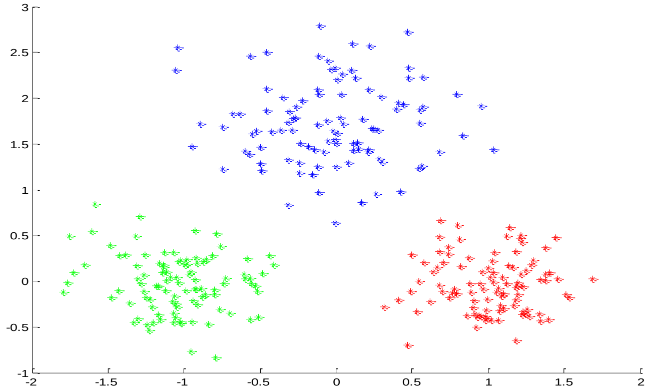


Unsupervised learning example

- **Clustering.** Group together similar examples

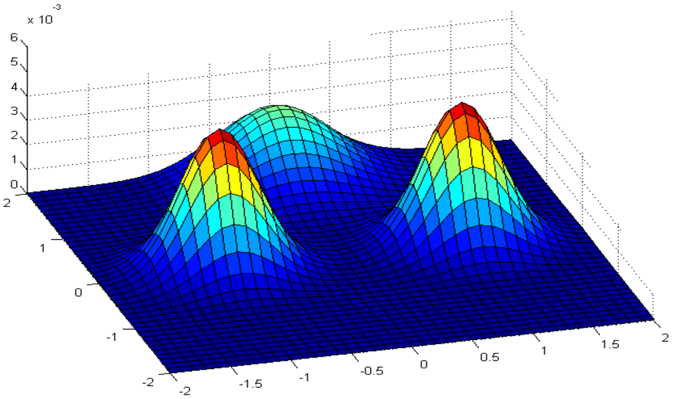
Unsupervised learning example

- **Density estimation.** We want to build a probability model P(**x**) of a population from which we drew examples $d_i = \mathbf{x}_i$



Unsupervised learning. Density estimation

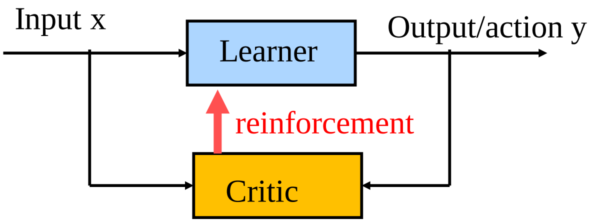
- A probability density of a point in the two dimensional space
  - Model used here: **Mixture of Gaussians**



Reinforcement learning

We want to learn: $f : X \to Y$

- We see examples of inputs **x** but not *y*
- We select y for observed x from available choices
- We get a feedback (reinforcement) from a **critic** about how good our choice of y was



Input x

Learner

Output/action y

reinforcement

Critic

- The goal is to select outputs that lead to the best reinforcement