

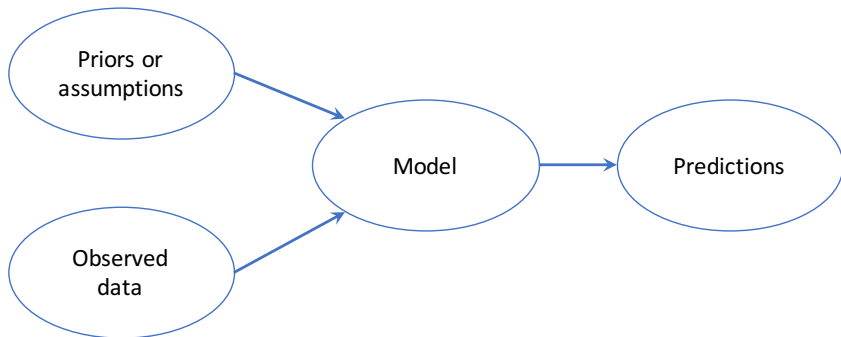
Lecture 0

Course Overview

Prof. Dahua Lin
dhlin@ie.cuhk.edu.hk

What is **Machine Learning**?

Machine Learning is to **make predictions** by **learning** from the past.



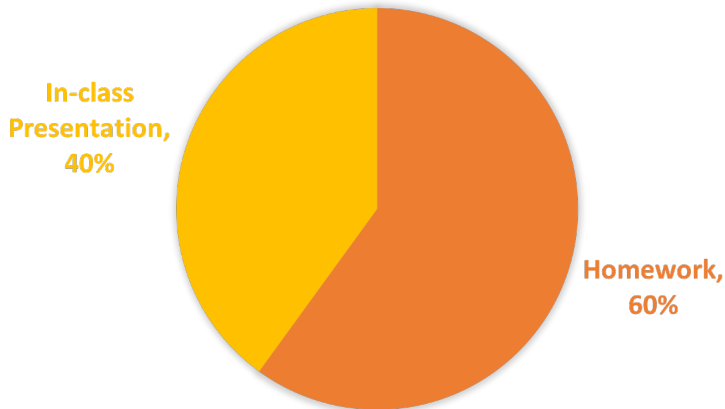
Logistics

- Time
 - Tue, 1:30pm - 2:15pm
 - Fri, 3:30pm - 5:15pm
- Venue
 - ERB 1009
- Piazza
 - URL:
<https://piazza.com/cuhk.edu.hk/fall2018/ierg5130/home>

Course Structure

- Topic-driven
 - Composed of several topics
- Each topic
 - Takes 3 - 4 weeks
 - Three phases
 - Teaching
 - Assignment (exercises & paper reading)
 - In class presentation & discussion

Assessment

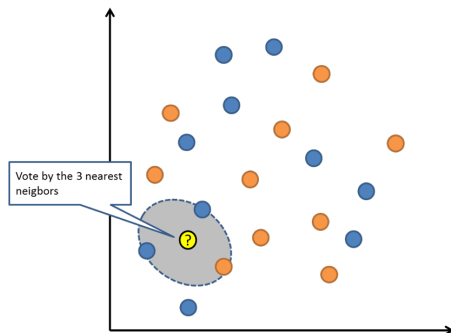


Approaches to Machine Learning

- Exemplar-based approach
- Functional approach
- Probabilistic approach

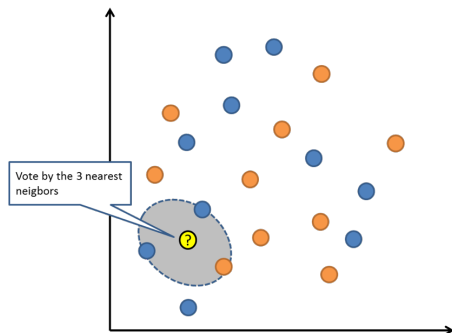
Exemplar-based Approach

K Nearest Neighbor (KNN)



Exemplar-based Approach

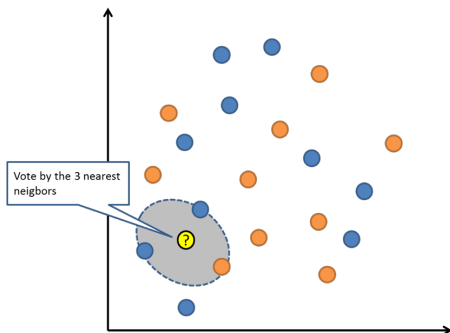
K Nearest Neighbor (KNN)



- Are there any assumptions?

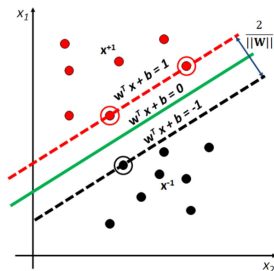
Exemplar-based Approach

K Nearest Neighbor (KNN)



- Are there any assumptions?
- Are there any issues/limitations?

Functional Approach



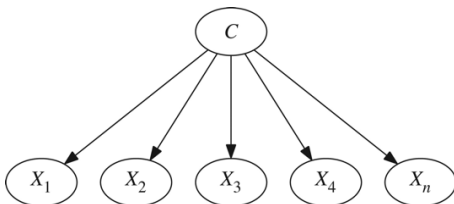
$$f(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b$$

Learning Objective:

$$L(\mathbf{w}, b) = \sum_{i=1}^n \text{loss}(f(\mathbf{x}_i; \mathbf{w}, b), y_i) + \frac{\lambda}{2} \|\mathbf{w}\|^2.$$

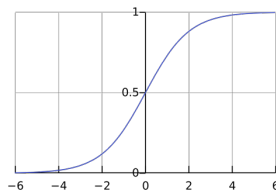
Probabilistic Approach

Generative: Naive Bayes



$$\mathbf{x} = (x^{(1)}, \dots, x^{(m)})$$
$$x^{(j)} \mid c \sim \mathcal{N}(\mu_c^{(j)}, \sigma_c^{(j)})$$

Discriminative: Logistic Model



$$p(c|\mathbf{x}) = \sigma(c \cdot (\mathbf{w}^T \mathbf{x} + b))$$
$$c \in \{-1, 1\}$$

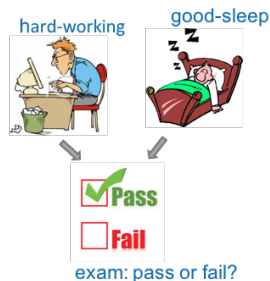
Functional vs. Probabilistic

Functional	Loss + Regularization
Probabilistic	Likelihood + Prior

Generally, there are no clear boundaries between them.

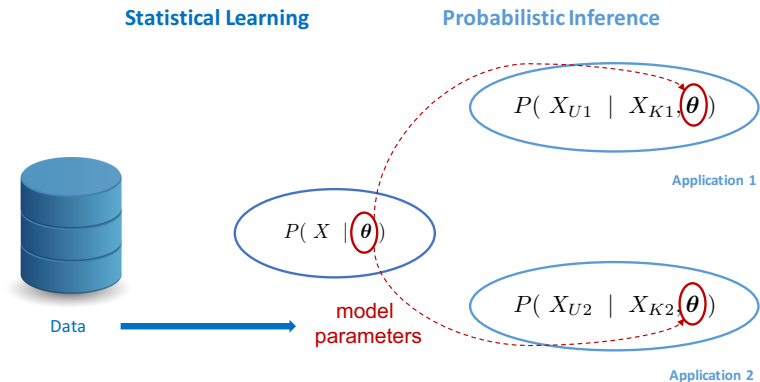
Probabilistic Modeling

- Elements formalized as **random variables**.
- **Joint distributions** capture **relations**, while allowing **uncertainties**.



Hard-working	Good-sleep	Pass ($P=1$)	Fail ($P=0$)
0	0	0.05	0.15
0	1	0.30	0.10
1	0	0.15	0.15
1	1	0.10	0.00

Probabilistic Learning



Models

- Basic concepts
- Conditional independence
- Exponential families & conjugacy
- Model formulation in practice

Inference

- Sum-product & belief propagation
- Mean field methods
- Gibbs sampling & MCMC

Estimation

- Variational Bayes
- Contrastive divergence
- Discriminative training

Advanced

- Graphical models with deep learning
- Gaussian processes
- Bayesian nonparametrics (brief)

Thank You!