# Week 1
# Introduction to Machine Learning

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EECS 6327 Probabilistic Models and Machine Learning

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# Outline

# Machine Learning

- **artificial intelligence** (AI):
  - AI refer to building computers to mimic human intelligence
  - a long history of AI since 1950s
  - traditional AI uses the rule-based symbolic approaches
  - traditional AI relies on manual construction of knowledge bases
- paradigm shift: knowledge-based $\rightarrow$ data-driven
- **machine learning** (ML): data-driven statistical methods
- ML vs. AI
  - ML is a sub-field in AI
  - ML: automatic learning from training data
- machine learning pipeline:

# Basic Concepts in Machine Learning

- classification vs. regression
- supervised vs. unsupervised learning
- simple vs. complex models
- parametric vs. non-parametric models
- over-fitting vs. under-fitting
  - bias-variance tradeoff

# Machine Learning: classification vs. regression

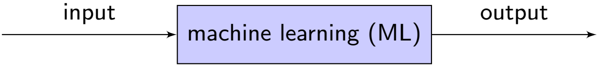



Figure: A system view of any machine learning problem

- **classification** problems: outputs are discrete and finite
- **regression** problems: outputs are continuous
- **structured prediction**: outputs are structured objects

# Machine Learning: supervised vs. unsupervised learning

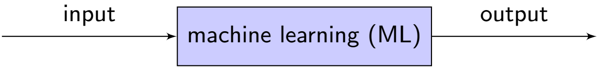



Figure: A system view of any machine learning problem

- supervised learning
- unsupervised learning
- semi-supervised learning
- weakly-supervised learning
  - self-supervised learning

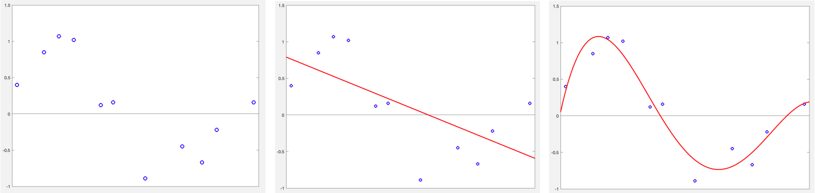
# Simple vs. Complex Models

- crucial to choose a **right** model in machine learning
- simple vs. complex models
- model complexity depends on the function form and the number of free parameters.
- simple models: linear models
  - less training data; less computing resources
  - mediocre performance in practice
- complex models: nonlinear models (e.g. *neural networks*, *decision trees*)
  - superior performance when sufficient training data are available
  - more training data require more computing resources
  - difficult to analyze and interpret

# Simple vs. Complex Models

**Example**: curve fitting

- a regression problem: $x \mapsto y$
- a simple model: a linear model $y = a_0 + a_1\, x$
- a complex model: a 4th-order polynomial
  $y = a_0 + a_1\, x + a_2\, x^2 + a_3\, x^3 + a_4\, x^4$



(a) training data (b) simple model (c) complex model

# Parametric vs. Non-parametric Models

- parametric models: *a.k.a.* finite-dimensional models
  - the function form is given
  - the model is fully determined by a *fixed number of parameters*
- non-parametric models: *a.k.a.* distribution-free models
  - the function form is not specified
  - the model complexity depends on the available data

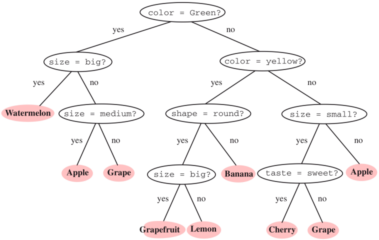
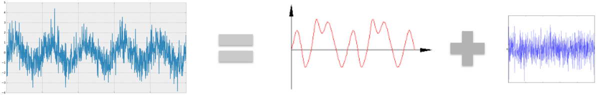



Figure: Decision trees: a non-parametric model

# Over-fitting vs. Under-fitting

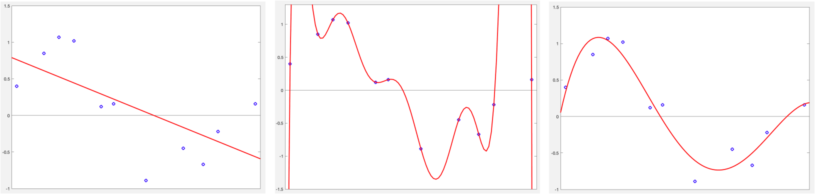


data signal noise

$$\text{data} = \text{signal} + \text{noise}$$

- simple models $\implies$ under-fitting
  - too weak to capture the regularities in data
  - increase model complexity
- complex models $\implies$ over-fitting
  - perfectly fit random noises
  - totally useless to fit noises as they vastly change each time
  - decrease model complexity; add more data; *regularization*

# Over-fitting vs. Under-fitting



(a) under-fitting (b) over-fitting (c) good-fitting

Figure: under-fitting vs. over-fitting in regression

# Over-fitting vs. Under-fitting

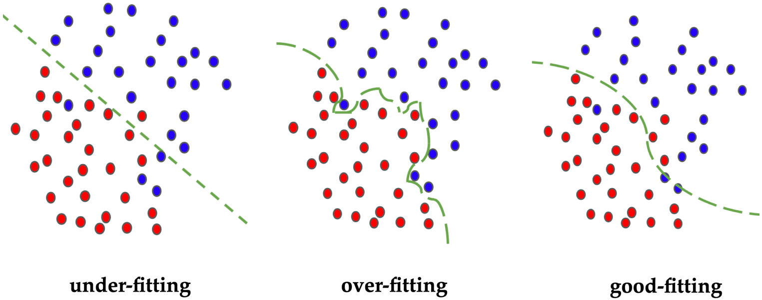
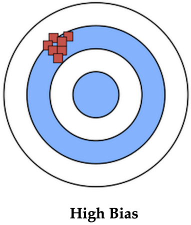



Figure: under-fitting vs. over-fitting in classification

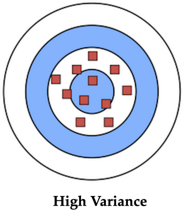
# Bias-Variance Tradeoff

- simple models $\Longrightarrow$ under-fitting $\Longrightarrow$ high biases
- complex models $\Longrightarrow$ over-fitting $\Longrightarrow$ high variances
- bias and variance decomposition:

$$\text{average learning error} = \text{bias}^2 + \text{variance}$$




(a) high learning bias




(b) high learning variance

# Bias-Variance Tradeoff

- cannot simultaneously reduce both bias and variance when learning from a fixed amount of data
- tradeoff between bias and variance for the lowest total error

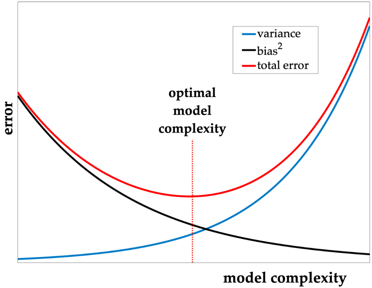



Figure: bias-variance tradeoff as a function of model complexity

# General Principles in Machine Learning

- Occam's Razor
- No Free Lunch Theorem
- Law of the Smooth World
- Curse of Dimensionality
- Blessing of Non-uniformity

# Occam's Razor

- a general principle in philosophy
  - *the simplest solution is most likely the right one*
- a preference for simplicity in model selection
- it suggests the **minimum description length** (MDL) principle
  - an important learning criterion in machine learning
  - the best model to describe the regularities in data is the one that can compress the data most.

# No Free Lunch Theorem

- no learning method is universally superior to other methods for all possible learning problems
- no machine learning algorithm can learn anything useful **merely** from the training data
- a successful machine learning algorithm must have explicitly or implicitly used some knowledge beyond the training data

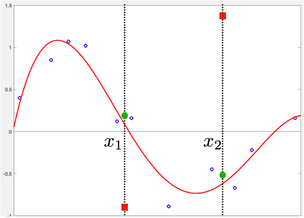



Figure: An illustration of No Free Lunch Theorem

# Law of the Smooth World

- physical processes are smooth due to energy/power constraints
- real-world data are smooth, e.g. audio/speech/images/video
- the smoothness of the ground-truth is mathematically quantified by *Lipschitz continuity* or *bandlimitedness*

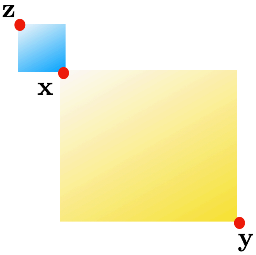
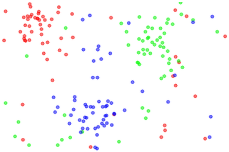


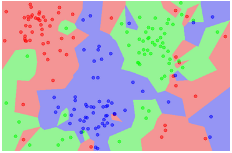

Figure: How the law of the smooth world helps in machine learning

# $k$-nearest neighbors ($k$-NN)

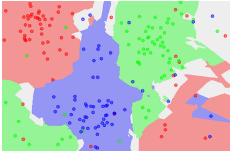
- the law of the smooth world suggests the $k$-nearest neighbors ($k$-NN) method:
  - an unknown object is classified based on its $k$ nearest neighbors in the training set
- $k$-NN is simple and intuitive
- how to measure distance? e.g. *metric learning*
- whether training data are enough to cover the whole space?



(a) training data



(b) $k$-NN ($k = 1$)



(c) $k$-NN ($k = 5$)

## Curse of Dimensionality

- **curse of dimensionality**: the dilemma of learning in high-dimensional spaces
  - as the dimensionality grows, it requires the exponentially increasing amount of training data and computing resources to ensure the effectiveness of learning
- e.g. the $k$-NN method requires $N$ training samples to ensure classification error $\epsilon$ $(0 < \epsilon < 1)$ in a $d$-dimensional space:

$$N \propto \left(\frac{\sqrt{d}}{\epsilon}\right)^{d+1}$$

Assume $\epsilon = 0.01$, if it requires $N = 100$ when $d = 3$. When $d = 10$, it needs $N = 2 \times 10^8$, and it requires $N = 7 \times 10^{123}$ when $d = 100$.

# Blessing of Non-uniformity

- the worst-case scenarios predicted by the curse of dimensionality normally occur when the data are uniformly distributed in high-dimensional spaces
- **blessing of non-uniformility**: real-world data never spreads evenly throughout the high-dimensional spaces but rather congregates on
  - linear subspaces
  - lower-dimensional nonlinear subspaces, called *manifolds*.
- it makes machine learning in high-dimensional spaces feasible
- it suggests **dimensionality reduction**:
  - linear dimensionality reduction
  - manifold learning

# Advanced Topics in Machine Learning

- reinforcement learning
- meta-learning (*a.k.a.* learning to learn)
- causal inference
- transfer learning (*a.k.a.* domain adaptation)
- online learning
- active learning
- imitation learning