CS 480 – Introduction to Artificial Intelligence

Topic: Learning – Intro

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LEARNING

- What's learning?

- Intro to Chapter 19: *"In which we describe agents that can improve their behavior through diligent study of past experiences and predictions about the future."*

- We do not make any philosophical statements about whether the agent is *truly* learning

- *"An agent is learning if it improves its performance after making observations about the world."*

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WHY LEARN AND NOT PROGRAM DIRECTLY?

- We cannot anticipate all possible situations that the agent might find itself in

- Time/location/context changes knowledge and rules

- We might not know the solution crisp enough to program it

- We might not have time to encode all the knowledge

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WHAT TO LEARN?

- Which action to take in a state (state $\rightarrow$ action)

- Outcomes of our actions (action $\rightarrow$ state)

- Mapping percepts to world states (percept $\rightarrow$ state)

- Utility of the states (state $\rightarrow$ utility)

- and more…

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FEEDBACK

1. Unsupervised learning

   - No feedback; the agent discovers patterns in the data
   - E.g., clustering, dimensionality reduction, outlier detection

2. Supervised learning

   - Feedback: input-output pairs
   - E.g., classification, regression, ranking

3. Reinforcement learning

   - Feedback: rewards

EPISODIC VS SEQUENTIAL

- Supervised and unsupervised learning are often episodic
  - E.g., speech recognition, medical diagnosis, credit score prediction, …
- Reinforcement learning is often sequential
  - E.g., game playing

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1. UNSUPERVISED LEARNING

- Given a set of objects: X

- Density estimation, P(X)
  - E.g., Bayesian networks

- Clustering
  - E.g., K-Means, Expectation Maximization (EM), Latent Dirichlet allocation (LDA), DBScan, …

- Dimensionality reduction
 - Principal component analysis (PCA), independent component analysis (ICA), …

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2. Supervised learning

- Given objects with their labels, <X,Y>

- Learn a function f that maps objects, X, to labels, Y

- We want f to perform well on unseen objects

- Several applications

  - Face recognition, speech recognition, medical diagnosis, fraud detection, credit scoring, home value prediction, temperature prediction, …

- If Y is

  - Discrete, the task is called classification

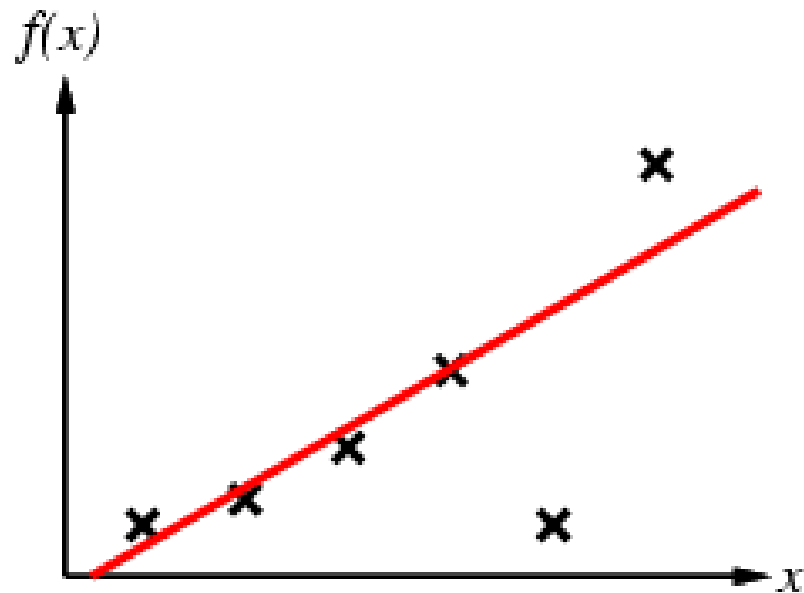 - Continuous, the task is called regression

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FUNCTION FITTING?

- Isn't classification/regression simply "function fitting?"
  - Yes and No
- The purpose is to generalize and perform well on unseen data
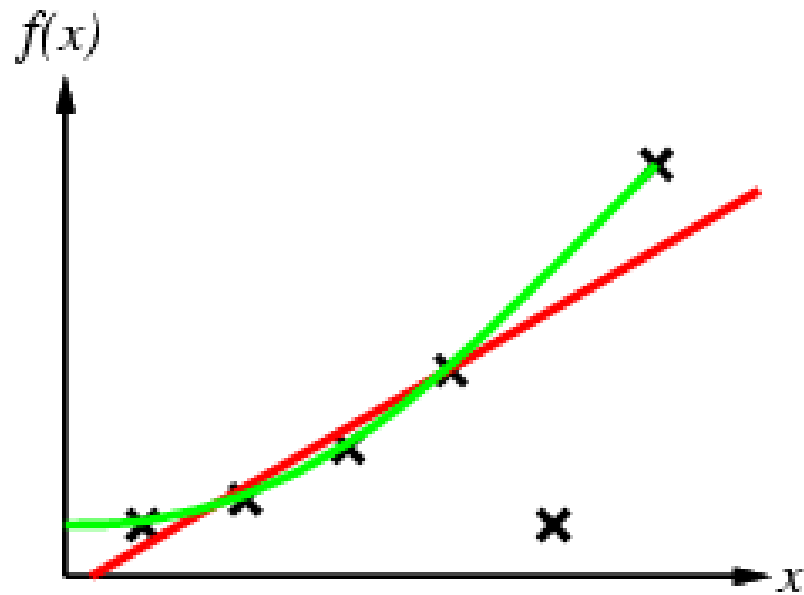- We don't want to **underfit** or **overfit** to the training data
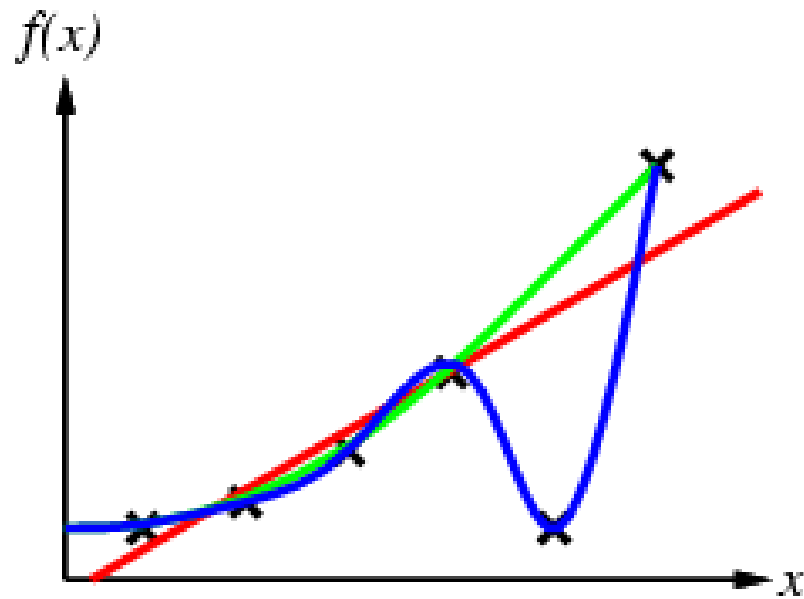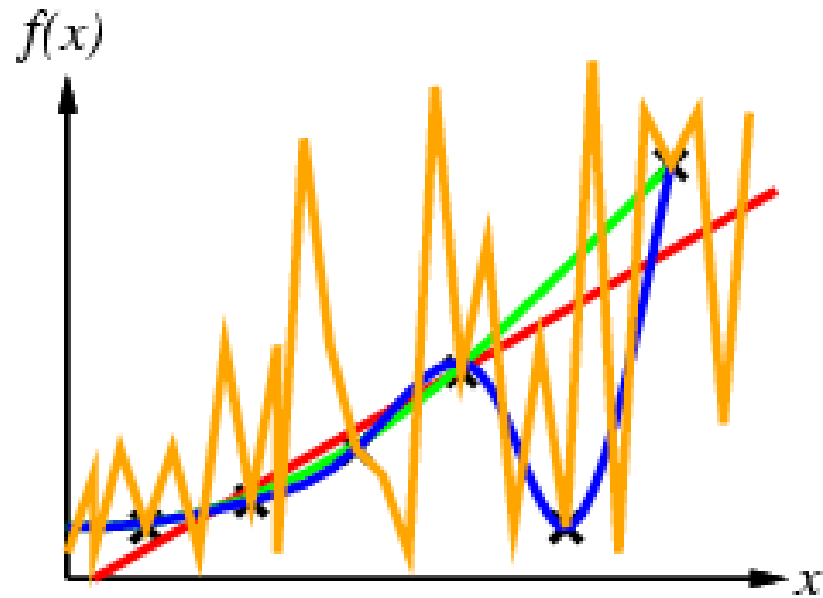
CURVE FITTING
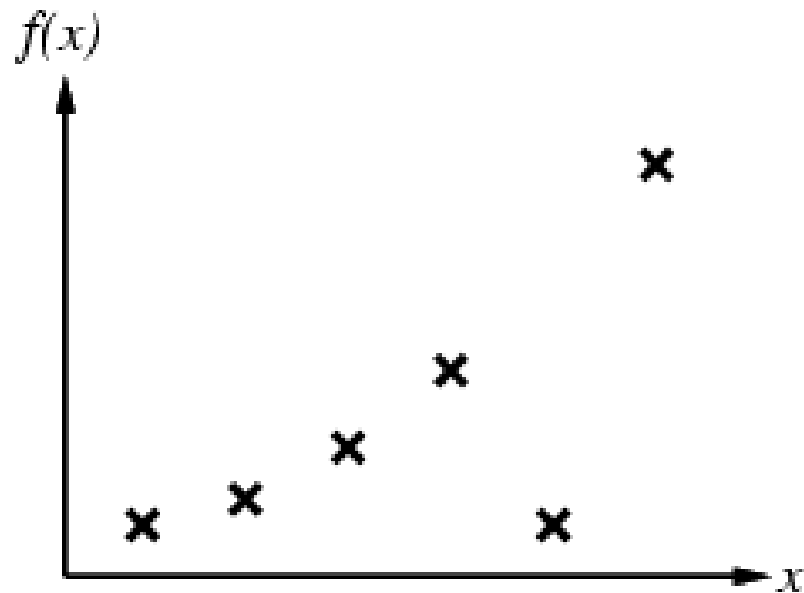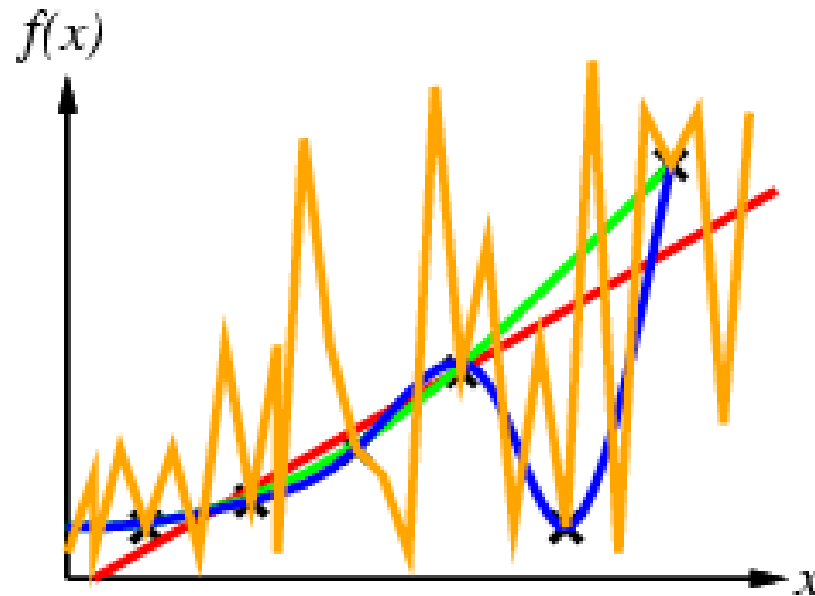
Curve Fitting

CURVE FITTING

CURVE FITTING

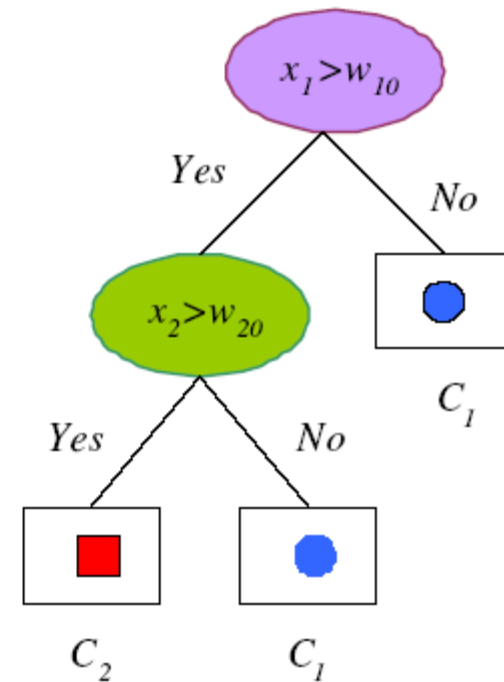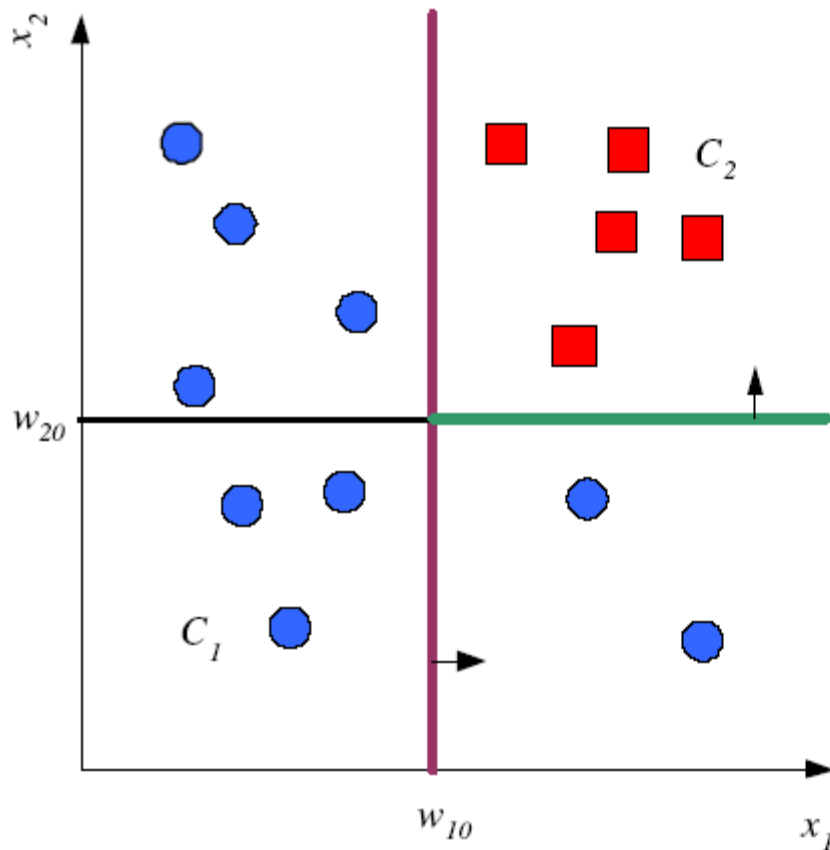# CURVE FITTING

Curve Fitting

So, which function is the "right" one?

CLASSIFICATION

- Decision trees

- Nearest neighbors

- Naïve Bayes

- Logistic regression
    - Note: it's called regression, but it is a classification model

- Support vector machines

- Neural networks

DECISION TREES

Learning: how do you learn a small tree that generalizes to unseen data? **17**

Naïve Bayes

- Given $X_1, X_2, \ldots, X_n$, and class Y
- Assume $X_i \perp X_j \mid Y$

$$P(Y|X_1, X_2, \ldots, X_n) = \frac{P(X_1, X_2, \ldots, X_n|Y)P(Y)}{P(X_1, X_2, \ldots, X_n)} = \frac{P(Y)\prod_{i=1}^{n}P(X_i|Y)}{P(X_1, X_2, \ldots, X_n)}$$

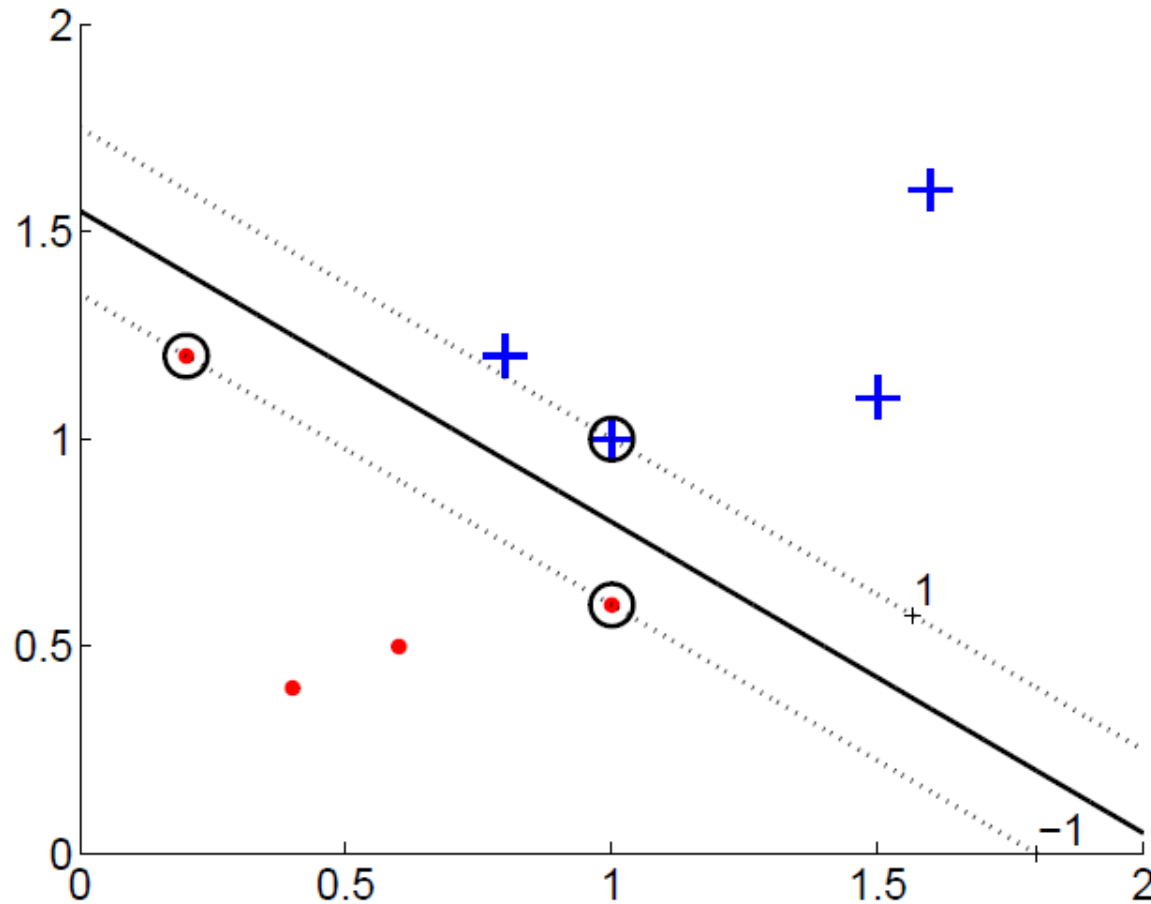We need to estimate $P(Y)$ and $P(X_i \mid Y)$

LOGISTIC REGRESSION

- Learns $P(Y|\boldsymbol{X})$ directly, without going through $P(\boldsymbol{X}|Y)$ and $P(Y)$

- Assumes $P(Y|\boldsymbol{X})$ follows the logistic function

$$P(Y = false \mid X_1, X_2, \cdots, X_n) \quad = \quad \frac{1}{1 + e^{w_0 + \sum_{i=1}^{n} w_i X_i}}$$

$$P(Y = true \mid X_1, X_2, \cdots, X_n) \quad = \quad \frac{e^{w_0 + \sum_{i=1}^{n} w_i X_i}}{1 + e^{w_0 + \sum_{i=1}^{n} w_i X_i}}$$

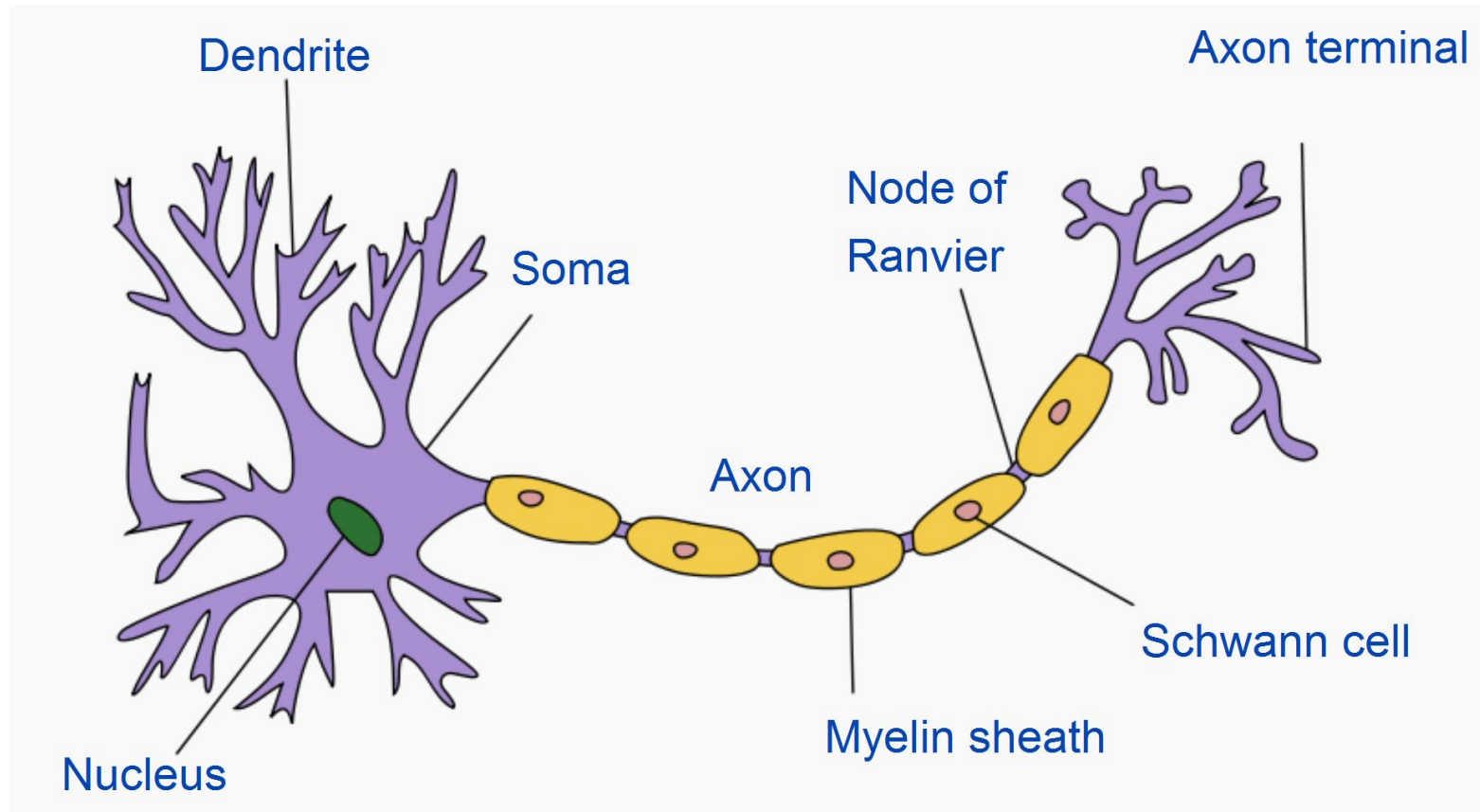- Learning: estimate the weights $w_0, w_1, \ldots, w_n$

SUPPORT VECTOR MACHINES

$$\min \frac{1}{2} w^T w \text{ subject to } y^{(d)}\left(w^T x^{(d)} + b\right) \geq +1$$

Image credit: Ethem Alpaydin. Introduction to Machine Learning. 3rd Edition. http://www.cmpe.boun.edu.tr/~ethem/i2ml3e

NEURON

By Quasar Jarosz at English Wikipedia, CC BY-SA 3.0,
https://commons.wikimedia.org/w/index.php?curid=7616130

WHAT AN ARTIFICIAL NEURON DOES

- Takes a weighted sum of its inputs
  - $w_0 + \sum_{i=1}^{k} w_i x_i$
  - Assume that there is always a constant input 1, that is, $x_0 = 1$. Then,
  - $\sum_{i=0}^{k} w_i x_i$
- Passes this sum through its activation function
  - $f\left(\sum_{i=0}^{k} w_i x_i\right)$

MULTILAYER NEURAL NETWORKS

- An input layer

- One or more hidden layers

- An output layer

- Learning: estimate the weights

REGRESSION

- Linear regression

- Ridge

- Lasso

- Support vector machines

- Decision trees

- Nearest neighbors

- Gaussian processes

3. REINFORCEMENT LEARNING

- Agent interacts with the environment and receives rewards
  - E.g., play a game and receives a reward (which could be negative) after the game is over
- Goal: learn to maximize future rewards
- Might not receive a reward for each action
  - E.g., in the game of chess, the agent does not receive feedback for each move
  - Providing a reward at the end is easier to specify than providing feedback on each move
- Might need to learn the transition model (from one state to another) and/or the reward function
- Has to balance between exploration and exploitation

WE'LL COVER

- Unsupervised learning
  - Maximum likelihood estimation for density estimation in Bayesian networks
- Supervised learning
  - Naïve Bayes
- How related courses touch on ML
  - CS 584 – Machine Learning
    - All three types of ML; focuses on unsupervised and supervised learning
  - CS 577 – Deep learning
  - CS 422/522 – Data mining
    - Decision trees, random forests, support vector machines with a focus on data
  - CS 581 – Advanced AI
    - Reinforcement learning (and of course other advanced AI topics)

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SCIKIT-LEARN

- An open-source Python package for primarily unsupervised and supervised learning

- https://scikit-learn.org/stable/
  - Preprocessing
  - Classification
  - Regression
  - Clustering
  - Dimensionality reduction