COMPSCI 589
Lecture 1: Course Overview - Supervised and Unsupervised Learning

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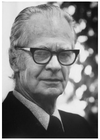
Outline

1. Introduction
2. About the Course
3. Review and Notation

Introduction

What is Learning?

Definitions of Learning



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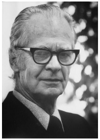

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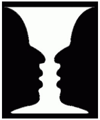

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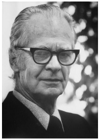

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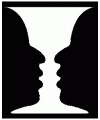

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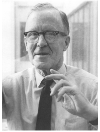

Connectionism (Hebb, 1949): Learning is a physical process in which neurons join by developing the synapses between them.

Introduction

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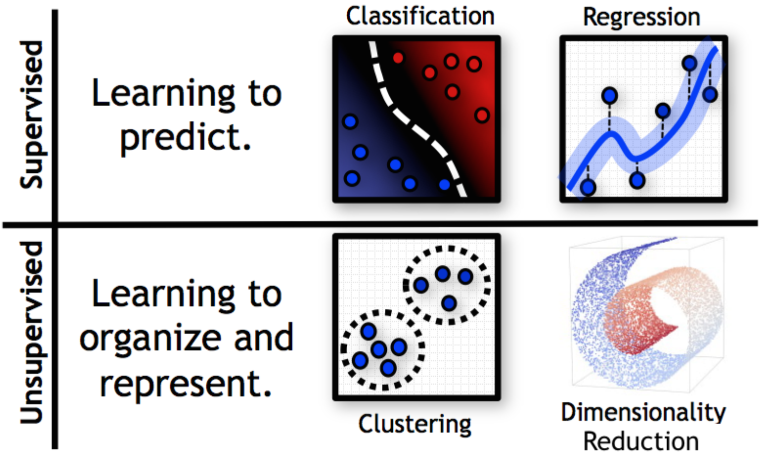
Mitchell (1997): "A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E."

Substitute "training data D" for "experience E."

Machine Learning Tasks



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$$f_\theta(\mathbf{x}) = \sum_{d=1}^{D} \theta_d x_d$$

Machine Learning Applications

Machine Learning in Industry

xerox
amazon.com
AdRoll
Baidu Research
Google
Symantec
QUALCOMM
facebook
TOYOTA
BOSCH
Microsoft Research
TWO SIGMA
Booking.com
YAHOO! LABS
D E Shaw & Co
NVIDIA
twitter
IBM Research
Disney Research

Relationship to Other Fields

- Machine Learning and Artificial Intelligence

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- Machine Learning and Data Science
- Machine Learning and Big Data

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The aim of this course is to develop the knowledge and skills necessary to effectively apply existing machine learning models and algorithms to solve real-world problems. The course will cover:

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This course **will not** teach you how to design new machine learning models and algorithms.

Prerequisites

The course has formal prerequisites as listed below. All students are expected to be familiar with this material or have the ability to make up any gaps in their backgrounds on their own.

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The course requires the use of Python for programming. Students are expected to learn Python as we go.

Text Books

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Readings are intended to be completed before class.

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- Access to cloud computing resources is required to complete course components using Apache Spark.

Outline

Linear Algebra

Definition: Vector Space

The real vector space $\mathbb{R}^n$ is a set with elements $\mathbf{x} = [x_1, ..., x_n]$ where each $x_i \in \mathbb{R}$. The elements $\mathbf{x}$ are called vectors, and they satisfy the following properties:

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- **Addition:** If $\mathbf{x} \in \mathbb{R}^n$ and $\mathbf{y} \in \mathbb{R}^n$, then $\mathbf{x} + \mathbf{y} = [x_1 + y_1, ..., x_n + y_n] \in \mathbb{R}^n$.

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- **Inner Product:** If $\mathbf{x} \in \mathbb{R}^n$ and $\mathbf{y} \in \mathbb{R}^n$, then $\mathbf{x} \cdot \mathbf{y} = \sum_{i=1}^n x_i y_i$.

Linear Algebra

Definition: Matrix

A matrix $\mathbf{X} \in \mathbb{R}^{n \times m}$ is rectangular array of elements $x_{ij} \in \mathbb{R}$, $1 \leq i \leq n$, $1 \leq j \leq m$:

$$\mathbf{X} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{pmatrix}$$

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Yous should be familiar with basic matrix types (square, diagonal, identity), basic matrix operations (transpose, inverse, trace, determinant, etc.), and matrix concepts (eigenvalues, eigenvectors, orthogonality, etc.).

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- Non-negativity: $P(\alpha) \geq 0$ for all $\alpha \subseteq \Omega$
- Normalization: $P(\Omega) = 1$
- Additivity: For all $\alpha, \beta \subseteq \Omega$ that are disjoint sets, $P(\alpha \bigcup \beta) = P(\alpha) + P(\beta)$

Random Variables

Definition: Random Variable

A random variable X is defined by a function f_X that maps each element ω of the sample space Ω to a value $f_X(\omega)$ in a set $\mathcal{X}$ called the *range* of the random variable.

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For each $x \in \mathcal{X}$ the probability $P(X = x) = P(\{\omega | \omega \in \Omega, f_X(\omega) = x\})$.

Probability and Random Variables

We can also specify a probability distribution for a random variable X with range $\mathcal{X}$ directly instead of via an underlying sample space Ω. The following conditions must hold:

- **Discrete PMF:** $P(X = x) \geq 0 \;\; \forall x \in \mathcal{X}$ and $\sum_{x \in \mathcal{X}} P(X = x) = 1$.

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- **Continuous PDF:** $p(X = x) \geq 0 \ \ \forall x \in \mathcal{X}$ and $\int_{\mathcal{X}} p(X = x) dx = 1$.

Random Variables and Data Sets

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Example: Heart Disease Dataset

Gender	Blood Pressure	Cholesterol	Heart Disease
Male	Med	Low	No
Male	Hi	Hi	Yes
Male	Med	Med	Yes
Male	Med	Hi	No
Female	Med	Low	No
Male	Low	Med	No

Joint Probability Distributions

- A *joint probability distribution* is a probability distribution defined over a collection of random variables $(X_1, ..., X_m)$ with ranges $\mathcal{X}_1, ..., \mathcal{X}_m$: $P(X_1 = x_1, ..., X_m = x_m)$.

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- A joint distribution defined over random variables $X_1, ..., X_m$ must satisfy normalization and non-negativity with respect to the Cartesian product of their ranges $\mathcal{X} = \mathcal{X}_1 \times \cdots \times \mathcal{X}_m$.
- Alternatively, a joint distribution can be viewed as a probability distribution over a single vector-valued random variable $\mathbf{X} = [X_1, ..., X_m]$ whose range is $\mathcal{X} = \mathcal{X}_1 \times \cdots \times \mathcal{X}_m$.

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Gender	BloodPressure	Cholesterol	HeartDisease	P
F	L	L	N	0.0127
F	L	L	Y	0.0007
F	L	M	N	0.0098
F	L	M	Y	0.0009
F	L	H	N	0.0087
F	L	H	Y	0.0010
⋮	⋮	⋮	⋮	⋮

Important Probability Concepts

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- Marginalization
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- Bayes Rules
- Expectations
- Classical Distributions (Bernoulli, Binomial, Multinomial, Gaussian)