# CPE 486/586: Machine Learning for Engineers

01 Introduction

Fall 2025

**Rahul Bhadani**

# Outline

# About Me

**Rahul Bhadani**
Assistant Professor
Electrical and Computer Engineering
The University of Alabama in Huntsville
Office: 217-H
Email: rahul.bhadani@uah.edu
Web: `https://rahulbhadani.github.io/`

**Research Interests**

Cyber-physical Systems, Intelligent Transportation, Connected-and-Autonomous Driving, Applied machine learning, Quantum Information Science

# Course Logistics

**Lecture:**
M/W 4:20 PM - 5:40 PM

**Location:**
TBD

**Office Hours:**

- TBD

**Instructor Email:** rahul.bhadani@uah.edu

# Textbooks

# Grading

| **CPE 486** | |
|---|---|
| **Homework:** | 30% |
| **Quizzes:** | 5% |
| **Attendance/In-Class Participation:** | 5% |
| **Mid-term Exam 1:** | 15% |
| **Mid-term Exam 2:** | 15% |
| **Final Exam:** | 30% |

| **CPE 586** | |
|---|---|
| **Homework:** | 25% |
| **Quizzes:** | 5% |
| **Attendance/In-Class Participation:** | 5% |
| **Mid-term Exam 1:** | 15% |
| **Mid-term Exam 2:** | 15% |
| **Final Exam:** | 30% |
| **Project Report:** | 5% |

| **Grading Scale** | |
|---|---|
| **Percentage** | **Grade** |
| 90% - 100% | A |
| 75% - 89% | B |
| 60% - 74% | C |
| 45% - 59% | D |
| 0% - 44% | F |

# Homework Policy

- Each late submission will be penalized by 10% per day for up to 5 days maximum, thereafter, if later, one will receive 0 credit.
- Solution to homework will be posted 5 days after the due date.

# Classwork

- Each lecture will be followed by in-class problem-solving that students will turn in the next lecture day. If you miss the lecture day (either the day it is handed to you, or the day you need to turn in), you will not receive any credit.
- There will be intermediate small tests to assess your skills based on lectures and the classwork. This portion will count towards your classwork credits.

# Attendance Policy

- Must attend all lectures.
- Two unexcused absences permitted.
- No option to make up for classwork.

# Exam Schedule

| Exam Dates | | |
|---|---|---|
| **Exam** | **Date** | **Time** |
| Mid-Term 1 | Wednesday, September 24, 2025 | 4:20 PM to 5:40 PM |
| Mid-Term 2 | Wednesday, November 5, 2025 | 4:20 PM to 5:40 PM |
| Final Exam | Friday, December 12, 2025 | 3:00 PM to 5:30 PM |

# Tentatative Topics

- Course Introduction, Mathematical Preliminaries: Linear Algebra, Probability and Statistics
- Tools for Machine Learning: Installing Python, Unix Terminal, SSH, Git, Jupyter Notebook, Markdown, Latex, Package Manager,
- Scientific Python Numpy, Scikit-learn, IPython & Jupyter Notebook, Matplotlib, Pandas, Matrix Algebra with Python, Root-finding using Newton Raphson Method, Probability and Statistics with Python, PyTorch for Linear Algebra
- Optimization and Gradient Descent Continuous Optimization, Optimization Using Gradient Descent, Univariate Optimization, Multivariate Optimization, Constrained Optimization and Lagrange Multipliers, Convex Optimization, Methods of Least Square, Implementation in Pandas, Scipy and Pytorch
- Supervised Learning – Regression Simple Linear Regression, Variance Estimation, Goodness of Fit, Confidence-band, Matrix approach to Regression, Multiple Linear Regression, Polynomial Regression, Locally Weighted Regression, Kernel Methods for Regression, Implementation in Scipy and PyTorch
- Supervised Learning – Logistics Regression Classification Problem, Logistics Function, Model Assessment
- Overfitting and Regularization Overfitting, Underfitting, Bias-Variance Tradeoff, Regularization, Ridge-Regression, LASSO, Elastic-Net
- Dimensionality Reduction and Feature Selections Maximum Variance Perspective, Projection Perspective, Eigenvector Computation and Low-Rank Approximations, Principal Component Analysis, Latent Variable Perspective, Feature Selection, Data Transforms, Implementation using Scikit-learn, Pandas, and Pytorch
- Supervised Learning – Support Vector Machine (SVM) Linear Classifier, Concept of Hyperplane, Hard Margin SVM, Soft-Margin SVM, Kernel-based SVM, Implementation using Scipy
- Unsupervised Learning – Classification Clustering techniques, K-means, Hierarchical Clustering, Agglomerative Clustering, DBSCAN, Graph-based Clustering, Expectation Maximization Algorithms, Gaussian Mixture Model, Evaluating Cluster Qualities, Implementation using Scipy
- Introducing Deep Learning – Neural Networks Perceptron, Multi-layer Perceptron, Nonlinear Activation Functions, Backpropagation Algorithms, Vectorization and Batch Techniques, Neural Network Layers, Training Neural Networks, Learning Rates and Optimization Techniques in Neural Network, Implementation using PyTorch

# Getting ML Specific Help with Python

Where can I get resources to help with Python programming?

- Python for Everybody by Dr. Charles Severance (https://www.youtube.com/watch?v=PKrC027wIUU&list=PLAtoCfxWRIErTozMKGdHmUieMuQDGEoEJ) is a great place to refresh your Python
- Sklearn has some extremely helpful documentation pages (https://scikit-learn.org/stable/index.html)
- Matplotlib: the most used visualization tool in Python: (https://matplotlib.org/stable/tutorials/index.html)
- Polars for Data Analysis: https://docs.pola.rs/user-guide/getting-started/
- Learning PyTorch with Examples: (https://pytorch.org/tutorials/beginner/pytorch_with_examples.html)

# How to get help for this course?

- Ask questions in the class without hesitation. No question is silly.
- Utilize office hours to the maximum extent.
- Start your homework as soon as it is posted. The more you delay, the chance of your success will diminish.
- Do additional self-reading related to topics covered in the class.

> Remember, you are here to learn the material in this course, and not just pass it.

# In-Class Activity

**Introduce Yourself**

- Why do you want to take this course?
- What are your research intersts? How are you planning to utilize Machine Learning in your research/career?

# Introduction to the Course

# Contributors to ML

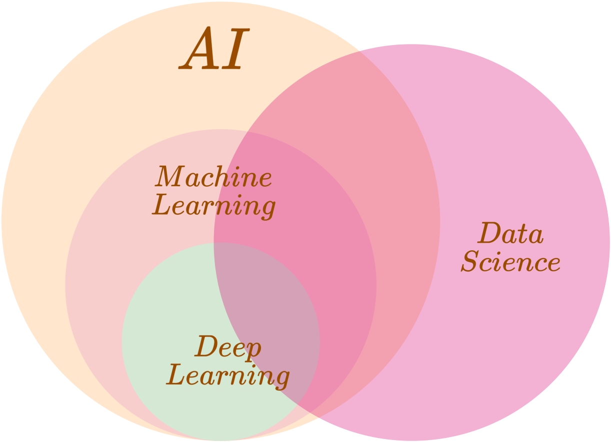
## Machine Learning

| Computer Science | Statistics | Engineering & Optimization | Neuroscience |
|---|---|---|---|
| Artificial Intelligence | Statistical Learning Theory | Computational Intelligence | Computational Neuroscience |
| Learning Theory | Statistical Pattern Recognition | Pattern Recognition | Learning & Memory Models |

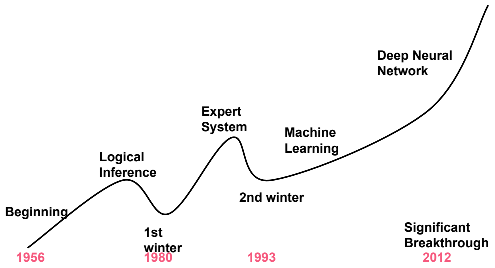
# Is AI Machine Learning?

# Is Data Science Machine Learning?

# Machine Learning, Data Science, Artificial Intelligence



# Milestones in AI




First AI winter: AI cannot solve ‘combinatorial explosion’ problems
Second AI winter: expert system failed to scale
Reasons for AI winter: mismatch of expectations and technology gap

# What's Different Now?

### More Data

1. Cheap storage
2. A lot more crowdsourced data: social media, android apps, data brokers

### Better Algorithms

1. Decades of research
2. Key breakthrough: deep learning, attention-mechanism, transformers

### Better Computing Stack

1. GPU computation
2. Cloud computing

### Investment and Mindset

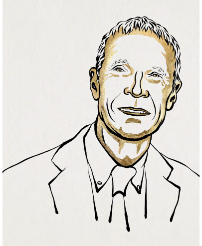
1. More investment and funding
2. Larger pool of talents

THE NOBEL PRIZE

# The 2024 physics laureates

*"for foundational discoveries and inventions that enable machine learning with artificial neural networks"*

The laureates built computer systems that lay the foundation that made it possible to train computers to do things like chatting or driving a car.



John Hopfield
Born: 1933, USA

Geoffrey Hinton
Born: 1947, United Kingdom

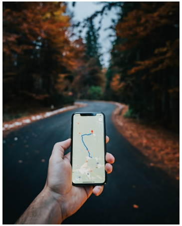


Source:

https://www.nobelprize.org/uploads/2024/12/Slideshow_All_NobelPrizes_2024_NobelPrizeLessons.pdf

# What is possible with Machine Learning, Data Science and AI?

# Big Data is Fueling AI



Source:
https://unsplash.com/photos/person-holding-white-iphone-5-c-rEn-AdBr3Ig

**Previously**

Best route by shortest path: no data-driven solution, no learning

**Now**

Best route by current traffic: some form of data-driven solution

**Trending**

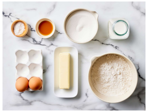
Best route by predicted travel time: data-driven, learning-based solution

# Machine Learning Connecting Big Data and AI

Big Data → ML → Artificial Intelligence

Tools/Methods

Ingredients



Cake

# Example of Prediction using Students' Records


- Data: Students' records on quizzes
- AI: Predict if a student can answer correctly to another quiz question

## A Possible Solution using Machine Learning

1. Give an ML model 10 million records from 5000 students
2. ML determines strength and difficulty of each students automatically, and make prediction about students' performance

# Broader Steps in Machine Learning

- **Explore:**
  - Summarize
  - Visualize
- **Predict:**
  - On Continuous Data
  - On Categorical Data
- **Simplify:**
  - Group together based on common characteristics
  - Model reduction

# Text Prediction

Given a word $\mathbf{w}(t)$ and some history $\mathbf{h}(t)$, what is the next word (i.e., $\mathbf{w}(t+1)$)? What is the probability distribution over the next word (i.e., $\mathbb{P}(\mathbf{w}(t+1)|\mathbf{w}(t), \mathbf{h}(t))$)?

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```
I love --?
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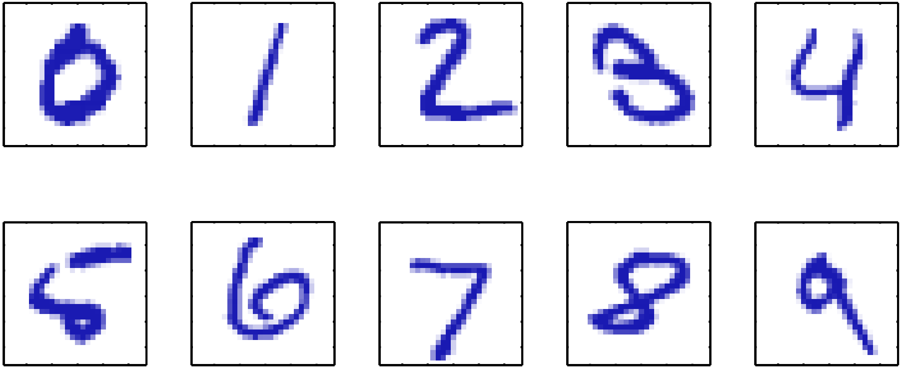
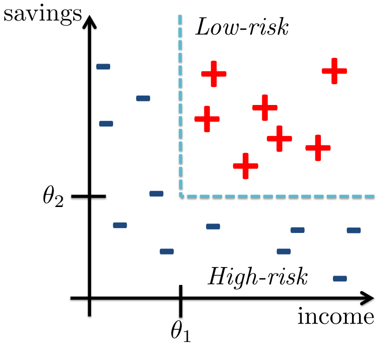
```
I love --?
Can you pick up milk at the --?
```

# Optical Character Recognition

## Bishop (2006)

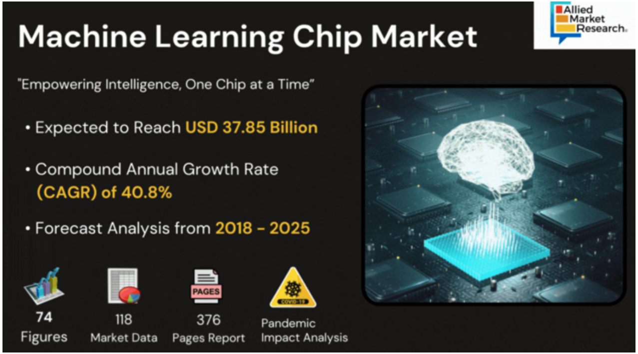


# Prediction of Low/High Risk Loans




$\texttt{if}$ (income $> \theta_1$ AND savings $> \theta_2$) $\texttt{then}$ {low-risk} $\texttt{else}$ {high-risk}

# Semiconductor




https://www.linkedin.com/pulse/revolutionizing-tomorrow-unstoppable-rise-machine-learning-white-cyvef/

# Drug Discovery and Medicine

THE NOBEL PRIZE

The 2024 chemistry laureates

David Baker is awarded *" for computational protein design"* and
Demis Hassabis and John Jumper are awarded *"for protein structure prediction"*

The laureates' discoveries are about the form, or three-dimensional structure, of proteins.

David Baker
Born: 1962, USA

Demis Hassabis
Born: 1976, United Kingdom

John Jumper
Born: 1985, USA

https://www.nobelprize.org/uploads/2024/12/Slideshow_All_NobelPrizes_2024_NobelPrizeLessons.pdf

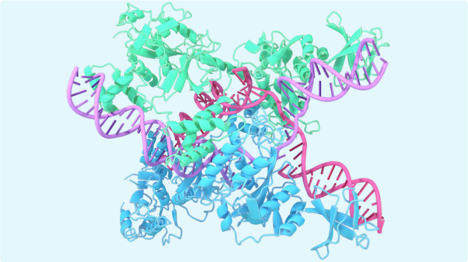
RESEARCH

A glimpse of the next generation of AlphaFold

31 OCTOBER 2023

Google DeepMind AlphaFold team and Isomorphic Labs team

Share



Protein structure understanding and discovery: https://deepmind.google/discover/blog/a-glimpse-of-the-next-generation-of-alphafold/

# Intelligent Transportation


https://news.vanderbilt.edu/2022/11/23/ai-powered-cruise-control-system-may-pave-the-way-to-fuel-efficiency-and-traffic-relief/

# What is Machine Learning

## An Informal Definition

Automated analysis of – typically large volumes of – data in search of hidden structures / patterns / information

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Automated analysis of – typically large volumes of – data in search of hidden structures / patterns / information

- **Pattern recognition**: Classification of objects into (predefined) categories or classes
  - Given data, assign labels (categories) that identify the correct class
  - Identify the input/output relationship (mapping) of an unknown system (system identification)

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Automated analysis of – typically large volumes of – data in search of hidden structures / patterns / information

- **Pattern recognition**: Classification of objects into (predefined) categories or classes
  - Given data, assign labels (categories) that identify the correct class
  - Identify the input/output relationship (mapping) of an unknown system (system identification)
- **Mathematically**: $f : \mathcal{X} \mapsto \mathcal{Y}$. How are we going to find $f(\mathbf{x})$?

# What is Data Mining

**Precursor to Machine Learning**

Process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data

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- Extract previously unknown, comprehensible, and actionable information from large databases and use it to make crucial business decisions

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- Discover advantageous patterns in data

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- Extract previously unknown, comprehensible, and actionable information from large databases and use it to make crucial business decisions
- A set of methods used in the knowledge discovery process
- Discover advantageous patterns in data
- A decision support process where we look in large databases for unknown and unexpected patterns of information

# Machine Learning in Era of Large Language Models

# How to Machine Learning with LLMs!

LLMs are as good as you can think![1]

[1] With Some Caution!

# Learning to Learn

## How to learn is even more important now!

1. What to ask!
2. Ask better questions
3. How do I know if the response from LLMs are correct?
4. Can I stop learning to code? Then why am I learning Machine Learning?

# Types of Learning

## Learning Modalities

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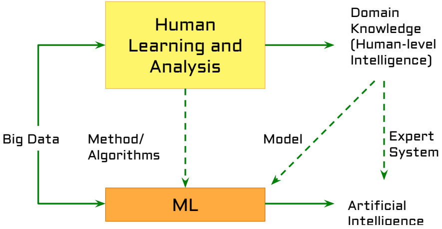
- **Unsupervised learning**: Given unlabeled data obtained from an unknown number of categories, learn how to group such data into meaningful clusters based on some measure of similarity
- **Reinforcement learning**: Given a sequence of outputs, learn a policy to obtain the desired output game-playing problems.

# Machine Learning for Modern AI




## Human Learning

1. Subjective
2. Domain knowledge generation
3. Fast basic solution

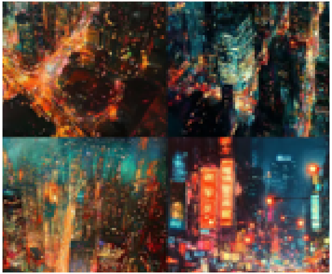
## Machine Learning

1. Objective
2. Harness computing power
3. Incremental improvement

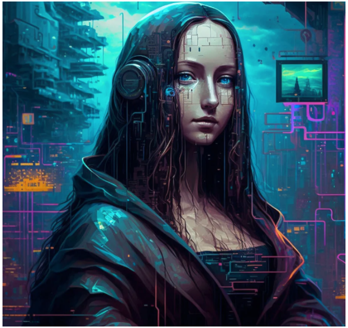
# Generative Artificial Intelligence /Generative ML

1. Pattern Recognition
   - Listen/Read/Watch
2. Generative ML
   - Speak/Write/Draw

Variations:

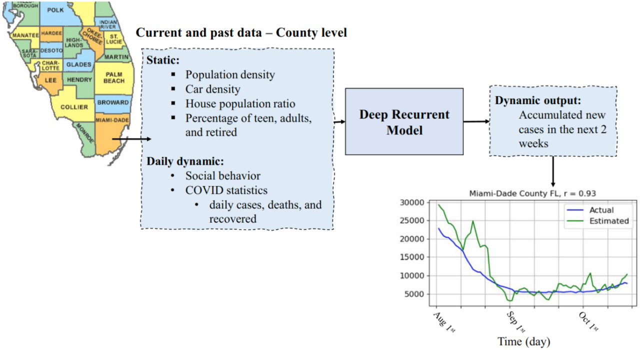


Style change:



# Example of Learning Problems

- Forecast the spread of disease (Regression): Using health records, demographic data, and travel patterns, predict the spread of a disease like COVID-19.




From paper: **The forecast of COVID-19 spread risk at the county level**

# Example of Learning Problems

- Identify fraudulent credit card transactions (Classification): Based on transaction details, customer behavior, and historical fraud patterns, build a model to predict whether a new transaction is likely to be fraudulent.

# Example of Learning Problems

- Predict the impact of climate change on crop yields (Regression): Using climate models, historical weather data, and crop yield records, predict how climate change will affect crop yields in different regions.

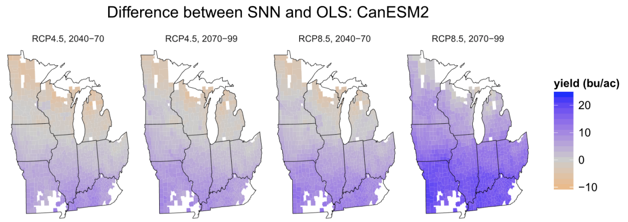



**Figure 5.** Spatial distribution of difference in yield projections between the semiparametric neural network, and the parametric model for a single member of our climate model ensemble (CanESM2). The OLS regression tends to be more optimistic than the SNN in the northern sections of the study region, and more pessimistic in the southern regions. See supplementary figures for output from other GCMs.

From paper: **Machine learning methods for crop yield prediction and climate change impact assessment in agriculture**

# Example of Learning Problems

- Predict the failure of a mechanical component (Classification): Based on operational data and component characteristics, predict whether a mechanical component will fail in the next cycle.

# Example of Learning Problems

- Predict the efficiency of a power plant (Regression): Based on operational data and environmental conditions, predict the efficiency of a power plant.

# Example of Learning Problems

- Optimize the operation of a supply chain (Optimization): Using historical data and predictive models, optimize the operation of a supply chain to minimize cost and maximize efficiency.

# Example of Learning Problems

- Predict the traffic flow in a city (Regression): Using historical traffic data, weather data, and event information, predict the traffic flow in a city.

# Example of Learning Problems

- Predict the load on a power grid (Regression): Based on weather data, time of day, and historical load data, predict the load on a power grid.

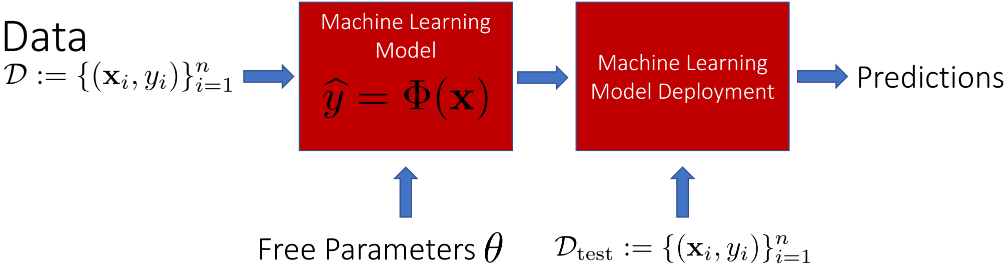
# Example of Learning Problems

- Traffic signal timing (Reinforcement Learning): Optimize the timing of traffic signals in a city to minimize traffic congestion and improve traffic flow.

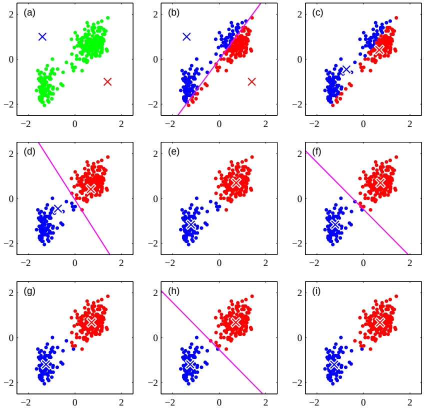
# Example of Learning Problems

- Optimal bidding in energy markets (Reinforcement Learning): Determine the optimal bidding strategy in energy markets to maximize profit.

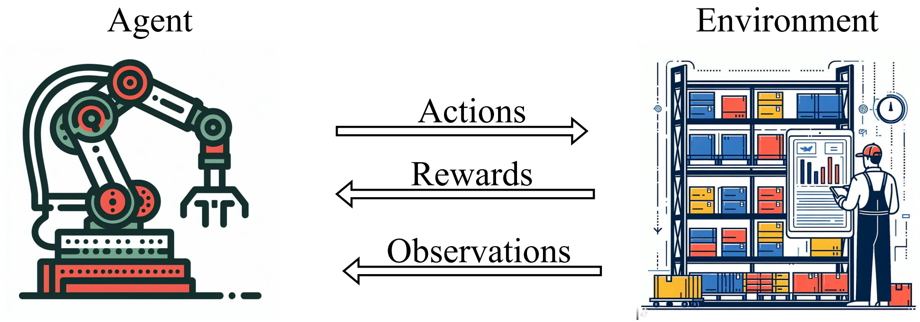
# Supervised Learning



# Unsupervised Learning



# Reinforcement Learning



# Terminology

- **Feature**: a variable, $x$, believed to carry information about the task. *example*, cholesterol level.

# Terminology

- Feature vector: collection of variables, or features, $\mathbf{x} = [x_1, \ldots, x_D]^\mathsf{T}$. *example*, collection of medical tests for a patient.

# Terminology

- Feature space: $D$-dimensional vector space where the vectors $\mathbf{x}$ lie. *example*, $\mathbf{x} \in \mathbb{R}_{+}^{D}$

# Terminology

- Class: a category/value assigned to a feature vector. in general we can refer to this as the target variable ($t$). *example*, $t = \text{cancer}$ or $t = 10.2\,^{\circ}\text{C}$.

# Terminology

- Pattern: a collection of features of an object under consideration, along with the correct class information of that object defined by, $\{\mathbf{x}_n, t_n\}$.

# Terminology

- Training data: data used during training of a classifier for which the correct labels are *a priori* known.

# Terminology

- Testing/Validation Data: data not used during training, but rather set aside to estimate the true (generalization) performance of a classifier, for which correct labels are also a priori known.

# Terminology

- Cost Function: a quantitative measure that represents the cost of making an error. a model is produced to minimize this function. Is zero error always a good thing?

# Terminology

- Classifier: a parametric or nonparametric model which adjusts its parameters or weights to find the mapping from the feature space to the outcome (class) space. $f : \mathcal{X} \mapsto \mathcal{T}$.
  - $y(\mathbf{x}) = \mathbf{w}^\mathsf{T}\mathbf{x} + b$
  - $\mathbf{y}(\mathbf{x}) = \sigma(\mathbf{W}^\mathsf{T}\mathbf{x} + \mathbf{b})$ where $\sigma$ is a soft-max
  - $\mathbf{y}(\mathbf{x}) = \sigma(\mathbf{Q}^\mathsf{T}\nu(\mathbf{W}^\mathsf{T}\mathbf{x} + \mathbf{b}) + \mathbf{q})$ where $\sigma$ is a soft-max and $\nu$ is a sigmoid
  - We need to optimize parameters $\mathbf{Q}$, $\mathbf{W}$, $\mathbf{w}$, $\mathbf{b}$, $\mathbf{q}$ and/or $b$ to minimize a cost

# Terminology

- Model: a simplified mathematical/statistical construct that mimics (acts like) the underlying physical phenomenon that generated the original data.

# Machine Learning for AI in Reality

# Frequently Asked Questions on ML for AI

- Finding AI Projects $\approx$ Find a research topic
  - Motivation: what are you interested in?
    - Something to publish?
    - Something than can improve performance of xyz?
    - Something that may lead to deeper study and novel insights?
  - Feasibility: what can or cannot be done?
    - Modeling
    - Computation
    - Budget
    - Timeline

# Frequently Asked Questions on ML for AI

- What is the best machine learning model for the given data and AI?

**Answer**

We don't know, I don't know, requires exploration, but perhaps start with simpler models.

# Frequently Asked Questions on ML for AI

- Myth: AI works best with the sophisticated models

**Response**

Sophisticated models:

- time-consuming to train and predict
- difficult to tune or modify
- hard to “simplify” nor “analyze”

A simpler models should be the first choice.

# Frequently Asked Questions on ML for AI

- Simpler model first

**Keep it simple and safe**

- Easy to train and predict
- Easy to tune parameters and modify
- Easy to analyze
- Smaller risk

# Planning your Machine Learning Project

**Data**

- Data collection
- Data cleaning
- Data storing
- ⋮

**Methods**

- Modeling
- Computation
- Applying other non-ML techniques

**End-use**

- Evaluation
- Deployment
- User-interface
- Scalability

A necessary first step: set up an evaluation criteria

# What do you need to be successful in this course?

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- **Calculus**: A little bit of calculus is needed to understand how optimization problem works!
- **Probability and Statistics**: We need a way to capture uncertainty in our data and models. Probability theory provides us a way to capture and harness uncertainty.
- **Coding/Software**: Not only are you going to be talk the talk in machine learning, but with software you're going to be able to walk the walk.

# Setting Up Development Environment

# Clound-based Solution

Google Colab

`https://colab.research.google.com/`

- No local setup needed.
- Packages can be installed as needed.
- GPU can be bought if needed.

# Setting Python Virtual Environment using Anaconda

Download: `https://www.anaconda.com/download/success`

# Creating Virtual Environment in Python using Anaconda

```
conda create --name pythonenv python=3.11
conda activate pythonenv
```

# Installing Jupyter Kernel in Your Anaconda Environment

The following code snippet install python kernel for use with Jupyter Notebook within your Anaconda virtual environment.

```
conda install ipykernel
ipython kernel install --user --name=pythonenv
conda install jupyter
jupyter notebook
```

# Setting up Package Manager using UV

UV is a package management written in Rust and for any local development and coding, we will use that.

**Installation**

```
curl -LsSf https://astral.sh/uv/install.sh | sh
```

Documentation for UV: `https://docs.astral.sh/uv/`

**Installing Python**

```
uv python install 3.12
```

Note: When Python is installed by uv, it will not be available globally (i.e. via the `python` command).

# Creating Python Virtual Environment

The following will create a new virtual environment and download a managed Python version if Python is not found:

```
uv venv
```

# Running Python Scripts

Running scripts without dependencies

example.py

```python
print("Hello world")
```

```
uv run example.py
```

# Running Python Scripts

Running scripts with dependencies

example.py

```python
import time
from rich.progress import track
for i in track(range(20), description="For example:"):
    time.sleep(0.05)
```

```
uv run --with rich example.py
```

# The End