

CPE 486/586: Machine Learning for Engineers

01 Introduction

Fall 2025

Rahul Bhadani

Outline

1. Course Logistics

2. Introduction to the Course

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

3. Machine Learning in Era of Large Language Models

3.1 Machine Learning for AI in Reality

4. Setting Up

Development Environment

About Me

Rahul Bhadani

Assistant Professor

Electrical and Computer Engineering

The University of Alabama in Huntsville

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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

Tentative 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=PLAtocfxWRIErTozMKGdHmUiemQDGEoEJ>) 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 interests? How are you planning to utilize Machine Learning in your research/career?



Introduction to the Course

Machine Learning

Computer Science

Statistics

Engineering & Optimization

Neuroscience

Artificial Intelligence

Statistical Learning Theory

Computational Intelligence

Computational Neuroscience

Learning Theory

Statistical Pattern Recognition

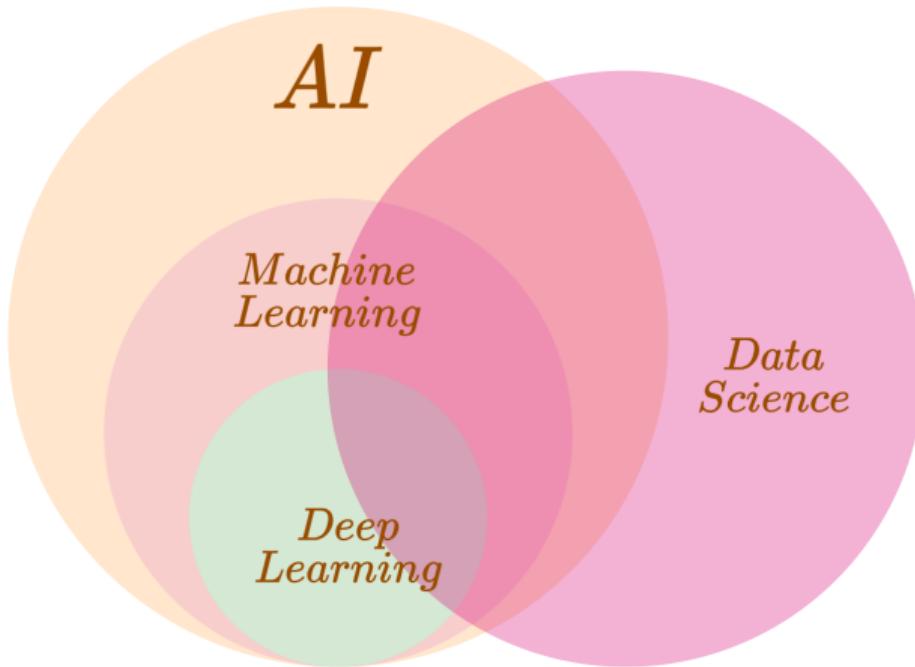
Pattern Recognition

Learning & Memory Models

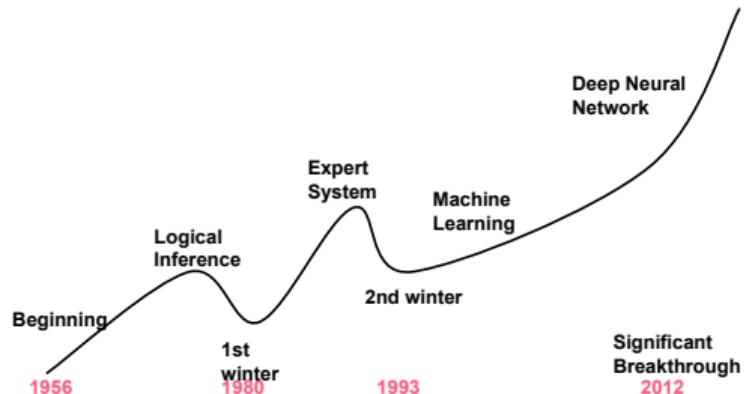
Is AI Machine Learning?

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 Computing Stack

- ① GPU computation
- ② Cloud computing

Better Algorithms

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

Investment and Mindset

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

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

HOPFIELD AND HINTON © 2024 THE NOBEL FOUNDATION

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



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 --?

Text Prediction

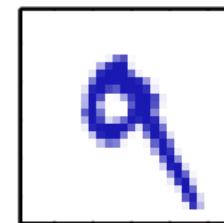
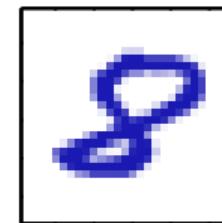
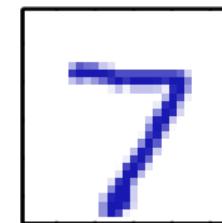
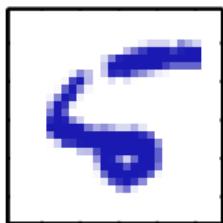
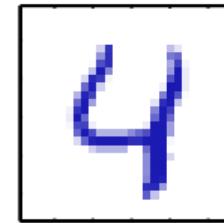
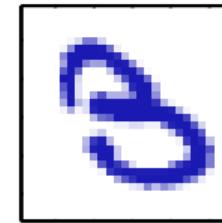
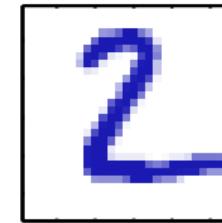
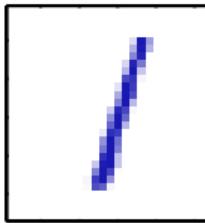
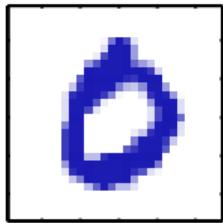
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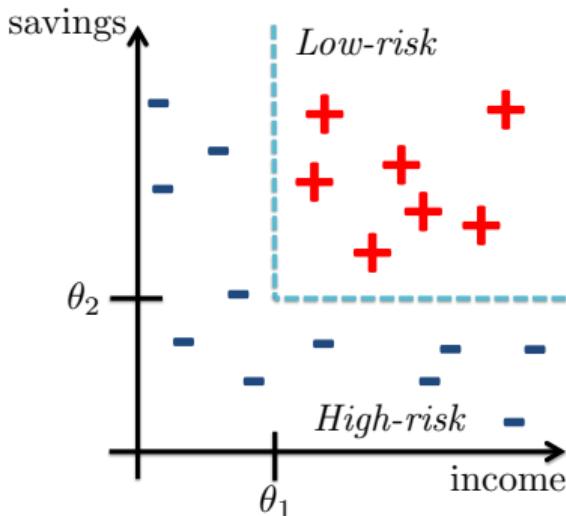
Can you pick up milk at the --?

Optical Character Recognition

Bishop (2006)



Prediction of Low/High Risk Loans



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

Machine Learning Chip Market

"Empowering Intelligence, One Chip at a Time"

- Expected to Reach **USD 37.85 Billion**
- Compound Annual Growth Rate (**CAGR**) of **40.8%**
- Forecast Analysis from **2018 – 2025**

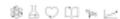


74 Figures 118 Market Data 376 Pages Report Pandemic Impact Analysis

<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 Isomeric Labs team

◀ Share

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

Intelligent Transportation



AI-powered cruise control system may pave the way to fuel efficiency and traffic relief

<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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⚡ **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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What is Data Mining

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- ⚡ A set of methods used in the knowledge discovery process
- ⚡ Discover advantageous patterns in data

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

- ⚡ 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

1 1 1 1 0 0 1 0 1 1 1 1 1 1 1 0 1 0 0 1 1
1 1 0 1 0 0 1 0 1 1 0 0 0 1 0 0 0 0 0 0
0 0 0 0 0 0 1 0 1 1 1 0 0 1 0 0 1 1 1 1

How to Machine Learning with LLMs!

LLMs are as good as you can think!¹

¹With Some Caution!

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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⚡ **Supervised learning:** Given training data with previously labeled classes, learn the mapping between the data and their correct classes.

Types of Learning

Learning Modalities

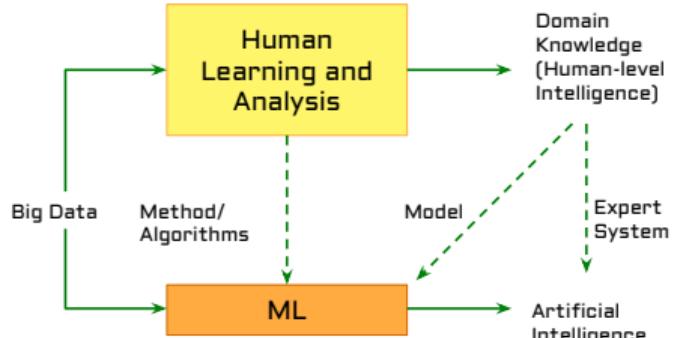
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- ⚡ **Reinforcement learning:** Given a sequence of outputs, learn a policy to obtain the desired output game-playing problems.

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:

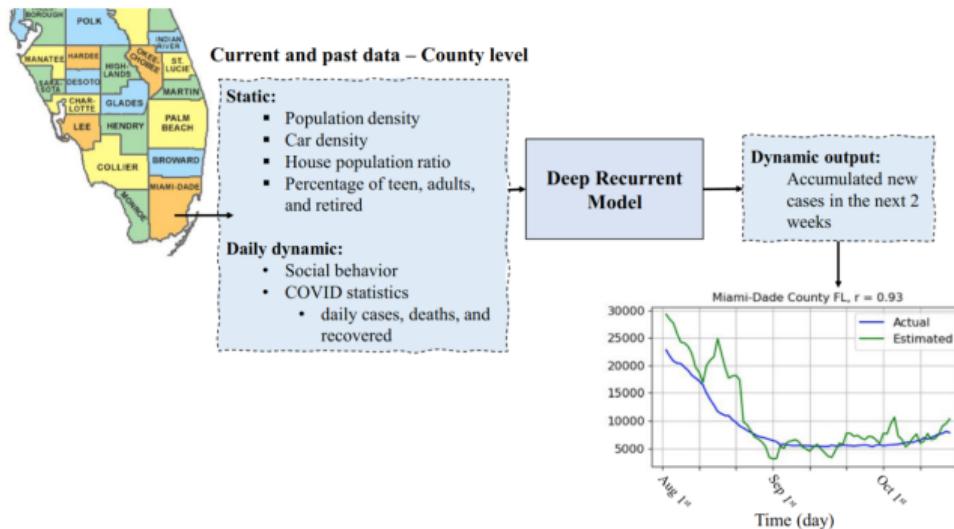


Style change:



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.



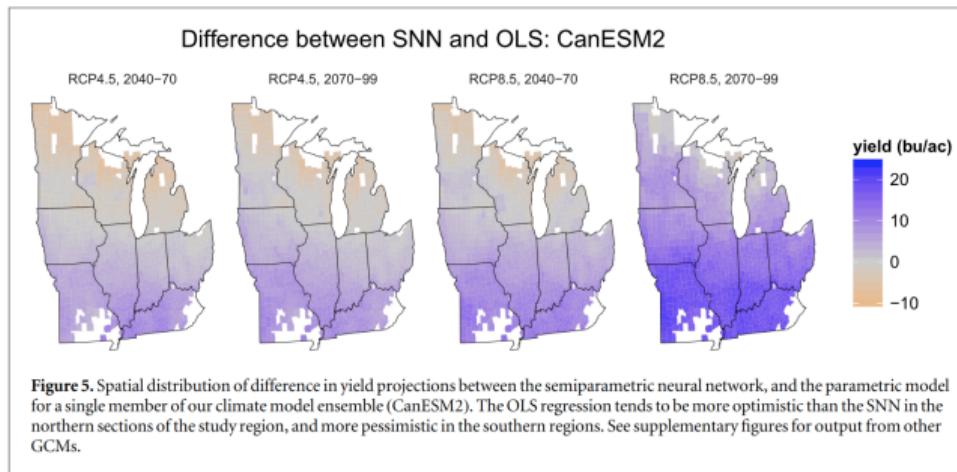
From paper: **The forecast of COVID-19 spread risk at the county level**

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.



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.

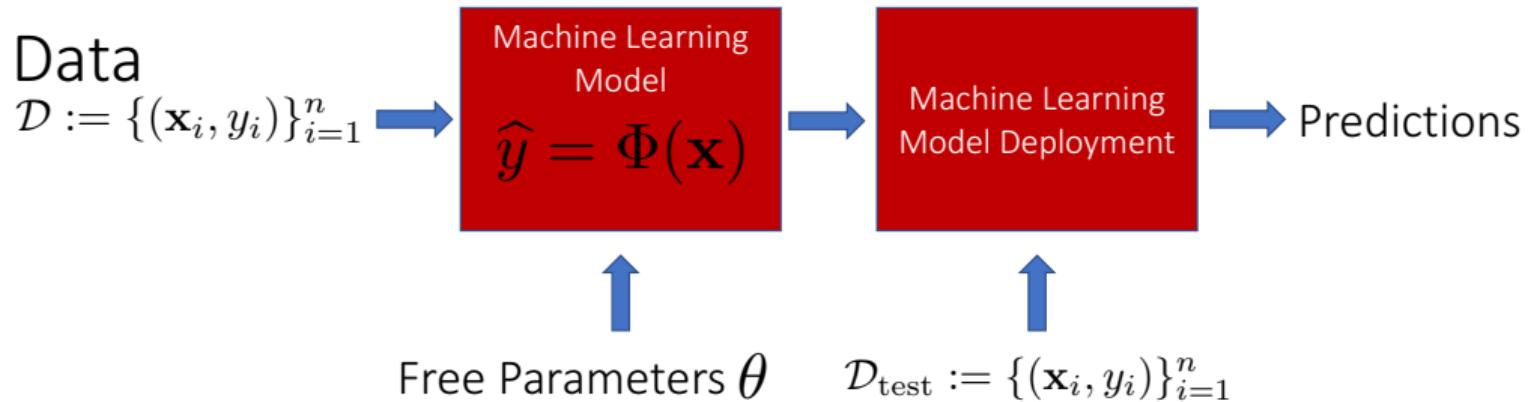
Example of Learning Problems

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

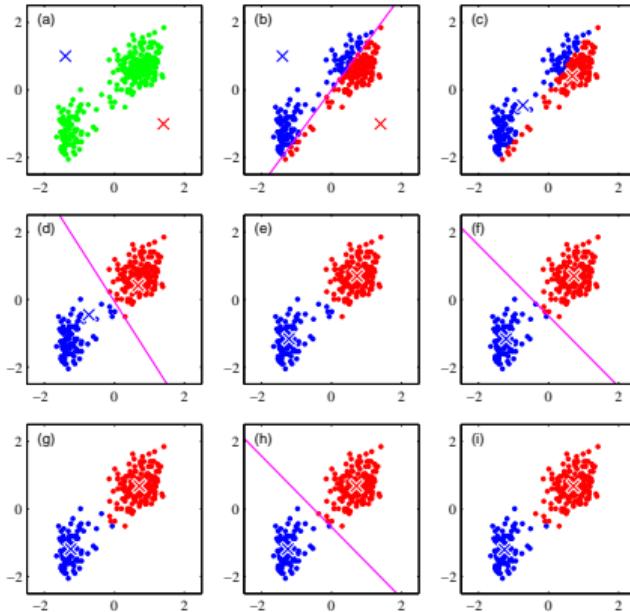
Example of Learning Problems

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

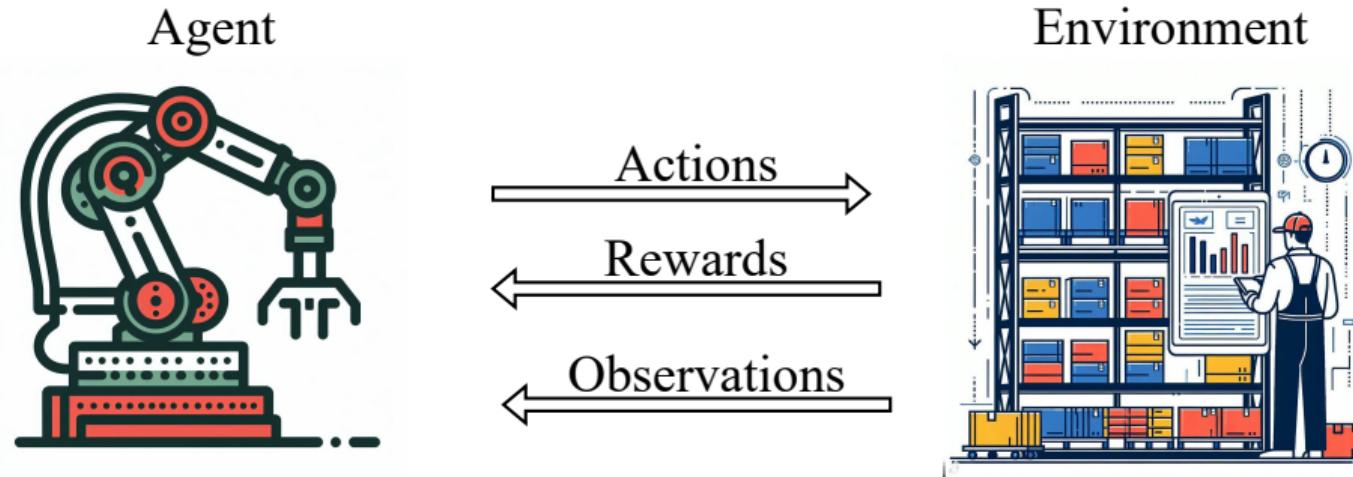
Supervised Learning



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, $\mathbf{x} = [x_1, \dots, x_D]^T$. *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.
 $f : \mathcal{X} \mapsto \mathcal{T}$.

- $y(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b$
- $\mathbf{y}(\mathbf{x}) = \sigma(\mathbf{W}^T \mathbf{x} + \mathbf{b})$ where σ is a soft-max
- $\mathbf{y}(\mathbf{x}) = \sigma(\mathbf{Q}^T \nu(\mathbf{W}^T \mathbf{x} + \mathbf{b}) + \mathbf{q})$ where σ is a soft-max and ν 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 ≈ 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

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- ⚡ **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

Cloud-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



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

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

```
uv run example.py
```

Running Python Scripts

Running scripts with dependencies

example.py

```
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