

# Machine Learning

## Introduction to Machine Learning

Slides adapted from material created by E. Alpaydin  
Prof. Mordohai, Prof. Greenstadt, Pattern Classification (2<sup>nd</sup> Ed.),  
Pattern Recognition and Machine Learning  
Matt Burlick, Drexel University

# Objectives

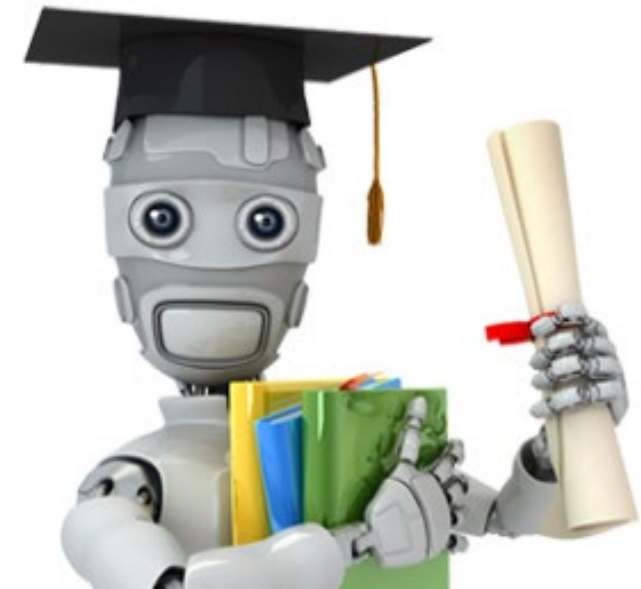
- Understand common machine learning problems
- Understand basic ML terminology

# What is Machine Learning?

- Definition: “The study of computer algorithms that improve automatically through experience”
- Formally:
  - Improve at task  $T$
  - With respect to performance measure  $P$
  - Based on experience  $E$
- Example: Recognize a Person
  - $T$ : recognize a person
  - $P$ : number of time we recognized a person correctly
  - $E$ : a database of labeled faces

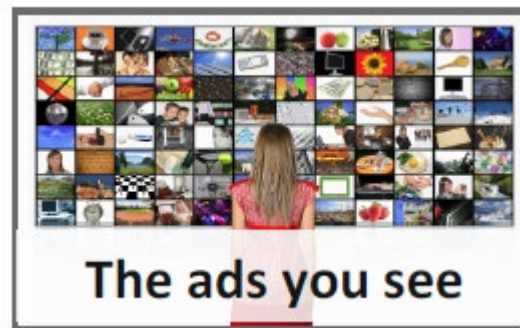
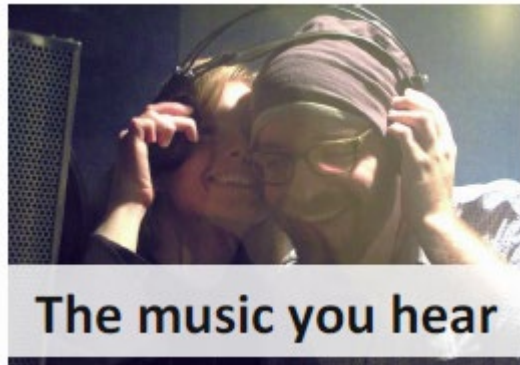
# ML vs AI

- How is this different than AI?
  - ML can be thought of as a sub-topic within AI
- AI deals with any “intelligent” task performed by a non-human agent
  - Often “path finding algorithms”
- ML specifically deals with making decisions based on acquired data
  - Both past and current

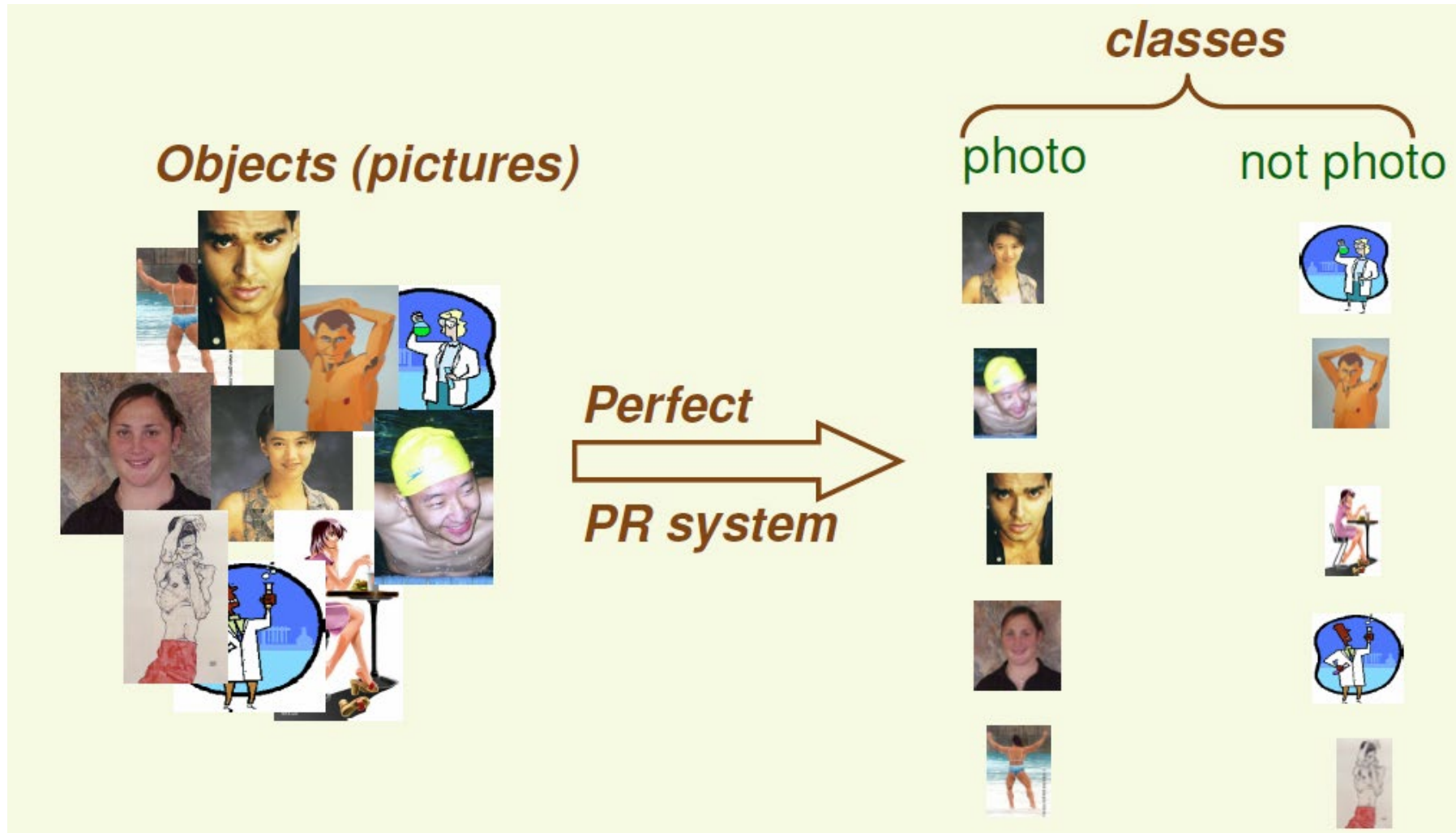


# Why do we care?

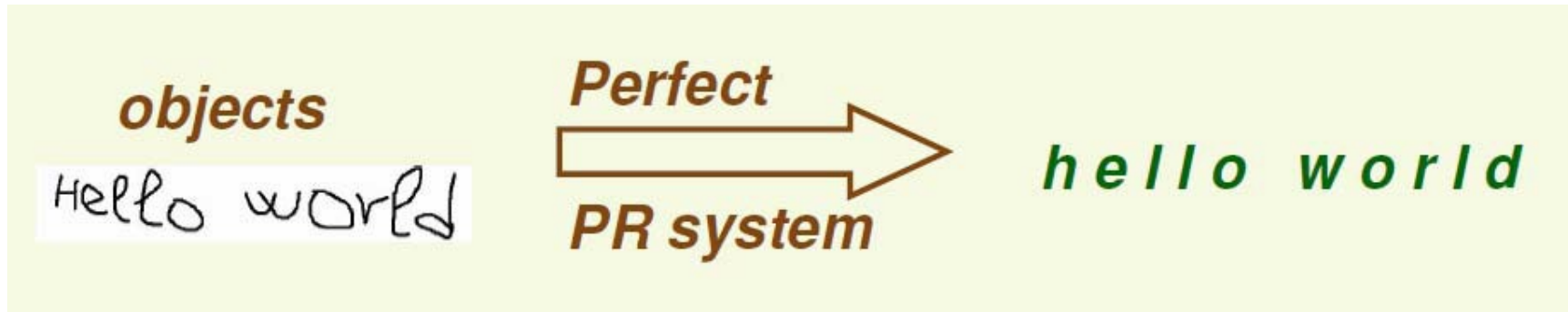
- It's everywhere!!!



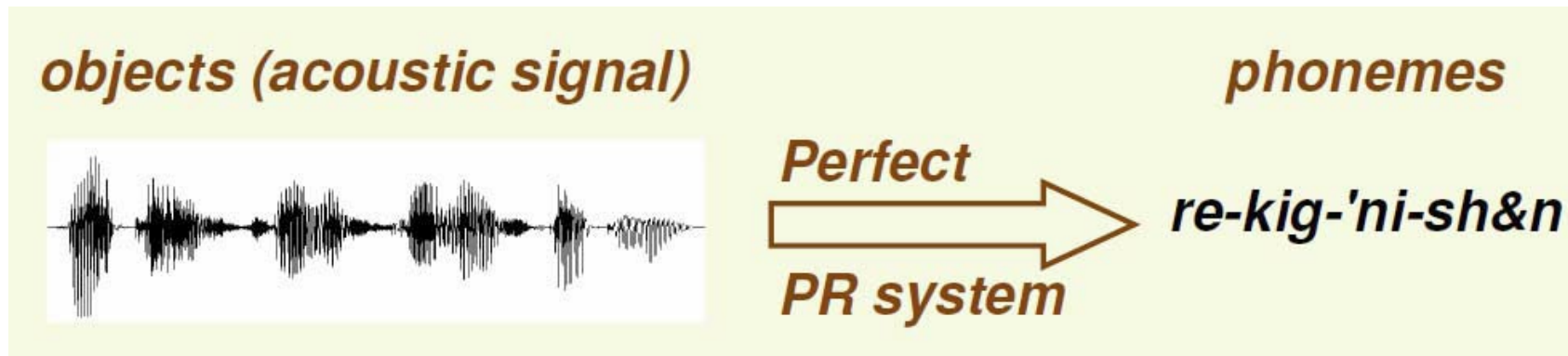
# Example: Photograph or Not?



# Example: Character Recognition



# Example: Speech Understanding



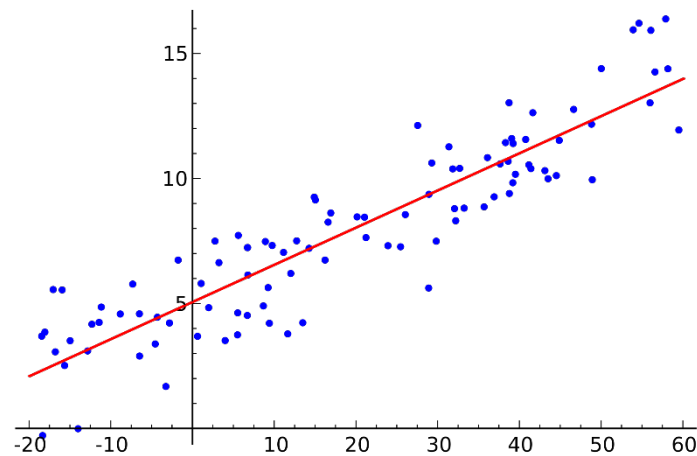


# How Do We Do It?

- We need to think about
  1. What needs to be learned?
    - What's our task/goal?
  2. What feedback can we get and in what form?
    - Supervised learning (correct answers for each example)
    - Unsupervised learning (correct answers not given. **Not covered in this class**)
  3. What representation should we use (features)?

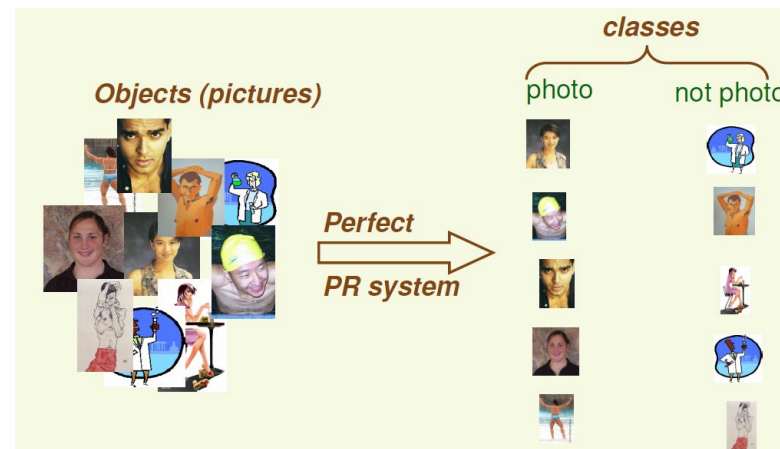
# Problems in ML

- There are two types of machine learning problems that we'll tackle in the course
- Regression
  - Given some data, can we predict an outcome value?
  - Example: We have a car's brand, year, mpgs and want to figure out its worth
  - This is an example of *supervised* learning
    - To build our prediction system, we have data with labels.



# Problems in ML

- Classification
  - Given data, can we predict which category something belongs to.
  - Typically involves *learning* some rules.
  - This is also an example of *supervised* learning
    - To build our prediction system, we have data with labels.



# Course Objectives

- Foundations of Machine Learning
  - Regression
  - Classification
- Applications of Machine Learning algorithms
- Implementation and use of Machine Learning algorithms
- Note: This course should probably be called something like “Foundations of Traditional Machine Learning”

# CCI AI Course Offerings

## Computer Science

- CS 380/510 – Artificial Intelligence
- **CS 383/613 – Machine Learning**
- CS 387/611 – Game AI Development
- CS 481/610 – Advanced Artificial Intelligence
- CS 482/589 – Robust Machine Learning
- CS 486/770 – Topics in Artificial Intelligence
- CS 614 – Applications of Machine Learning
- CS 615 – Deep Learning
- CS 616 – Robust Deep Learning
- CS 617 – Reinforcement Learning

## Information Science/Data Science

- DSCI 471 – Applied Deep Learning
- DSCI 631 - Applied Machine Learning for Data Science
- DSCI 691 – Natural Language Processing with Deep Learning
- INFO 629 – Applied Artificial Intelligence
- INFO 692 – Explainable Artificial Intelligence
- INFO 693 – Human-Artificial Intelligence Interaction

# Administrative Stuff...

# Contacts

## Instructor

- Professor Matt Burlick:
  - Email: [mjburlick@drexel.edu](mailto:mjburlick@drexel.edu)
  - Office:
    - 3675 Market St., Room 925
  - Office Hours:
    - Mondays 01:00pm – 03:00pm (Hybrid)
    - Thursdays 01:00pm – 03:00pm (Hybrid)



## Teacher Assistants

- None ☹️

# Contacts

- Questions are to be asked during class or office hours.
  - Time is allocated for questions at both the beginning and end of class time.
- Outside of logistical questions, questions will not be answered over email or discord.
- Discord will be used for student-led discussions (although monitored by faculty) and for announcements.



# Pre-Requisites

- CS 260 [Min Grade: C] – Data Structures and Algorithms
- MATH 201 [Min Grade: C] or ENGR 231 [Min Grade: D] – Linear Algebra
- MATH 221 [Min Grade: C] or MATH 222 [Min Grade: C] – Discrete Math
- MATH 311 [Min Grade: C] or MATH 410 [Min Grade: C] or ECE 361 [Min Grade: D] – Prob and Stats
- The idea is that you should be a proficient programmer such that you can pick up a new language “on the fly” and use it as a tool.
- You should also be comfortable with linear algebra, probability, statistics, and calculus.

# Course Resources

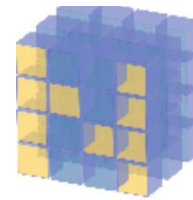
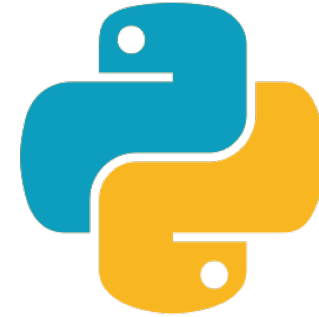
- Official Textbook:
  - None
- Recommended Textbooks:
  - Basic: An Introduction to Statistical Learning (free PDF), Gareth James, et. al.
  - Medium: Introduction to Machine Learning (Alpaydin)
  - Advanced: Machine Learning (Murphy)
- Blackboard for lecture material, labs and assignments
- Discord Channel

## *CS383-Sp25*

- Use this as your first place to pose questions
  - Hopefully not just I can help
- But don't post code.

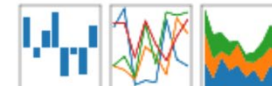
# Course Software

- Programming Environment: Python 3.x w/
  - NumPy
  - Matplotlib
  - Opencv-python
  - Pandas
  - Pillow



NumPy

pandas  
data science | tools | python

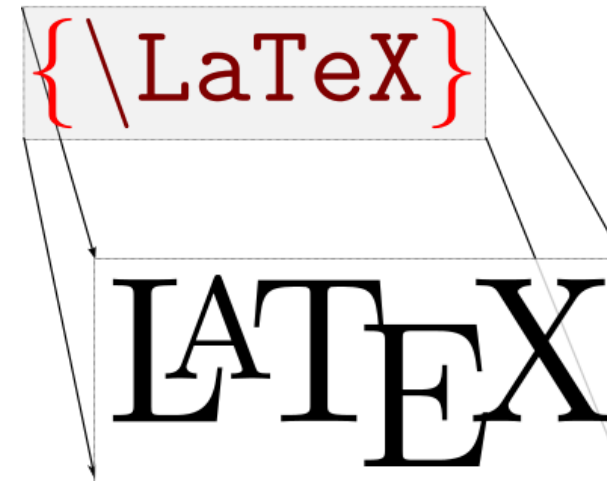


**SciPy**

matplotlib

# Course Software

- Typesetting Environment:
  - LaTeX, MS Word w/ Equation Editor (or similar)
  - If you opt to do LaTeX, unless you already have a LaTeX environment set up, I recommend using an online LaTeX typesetter, ala [www.overleaf.com](https://www.overleaf.com)



# Grade Breakdown

- Labs 30%
- Homework Assignments 20%
- Exams 50%

Points	Grade	Points	Grade	Points	Grade
[97-100]	A+	[83-98)	B	[70-73)	C-
[93-97)	A	[80-83)	B-	[67-70)	D+
[90-93)	A-	[77-80)	C+	[60-67)	D
[87-90)	B+	[73-77)	C	[0-60)	F

# Labs

- Most weeks there will be a **lab** conducted during the second lecture.
- Lab attendance is **required**
  - But you can miss up to two without penalty.
  - Subsequent will result in zeros.
- You may work with another student if you like.
- Your lowest lab grade will be dropped.
- No late labs will be accepted.

# Assignments

- Most weeks there will be a **homework assignment**.
  - These focus on the theory and math.
  - These are to be typeset via LaTeX or Microsoft Equation Editor (or similar) and converted to PDF.
- Your lowest assignment grade will be dropped.
- No late assignments will be accepted.

# Exams

- There will be a midterm and final exam.
- These will be similar in style to the questions in the assignments.



# Use of AI Tools

- Artificial intelligence tools such as large language models (e.g., ChatGPT) are permitted to be used as a reference in studying and understanding labs and assignments.
- HOWEVER, you may not use AI tools to generate solutions (code and/or computations) for your work.

# Additional Course Policies

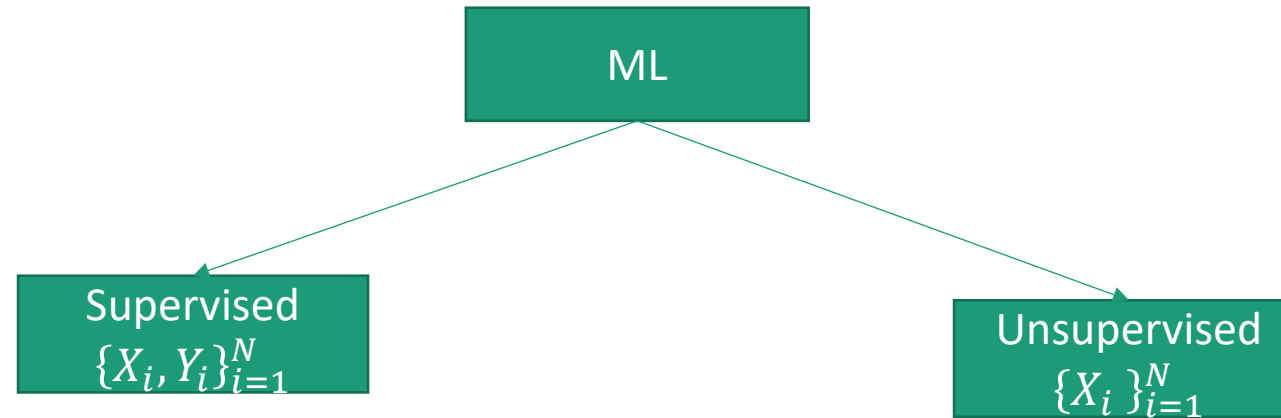
- Assignments and Exams are to be done individually unless otherwise noted
- While you are encouraged to use a versioning system like github or bitbucket, please make your work for this course **private**.
- Any dispute about an assignment grade must be formally made (email) and resolved within 5 days of receiving your grade. After this period your grade cannot be adjusted.

# Notation/Mathematics/Matlab

- I have placed on Blackboard a number of resources:
  - Course Notation – There will be a lot of symbols used in this course. This document tries to give you an overview of them.
  - Similarity and Distance Functions – Often we will need to compute the distance and/or similarity between observations. This document includes several commonly used ones.
  - Python Functions – Here's a list of most of the Python functions I used in developing this course.
  - Math Review – A quick review of the most critical math needed for this course. Including..
    - Calculus
    - Linear Algebra
    - Probability and Statistics
  - Math Reference Sheet – This is a quick reference sheet that we'll use often when doing derivations and whatnot.

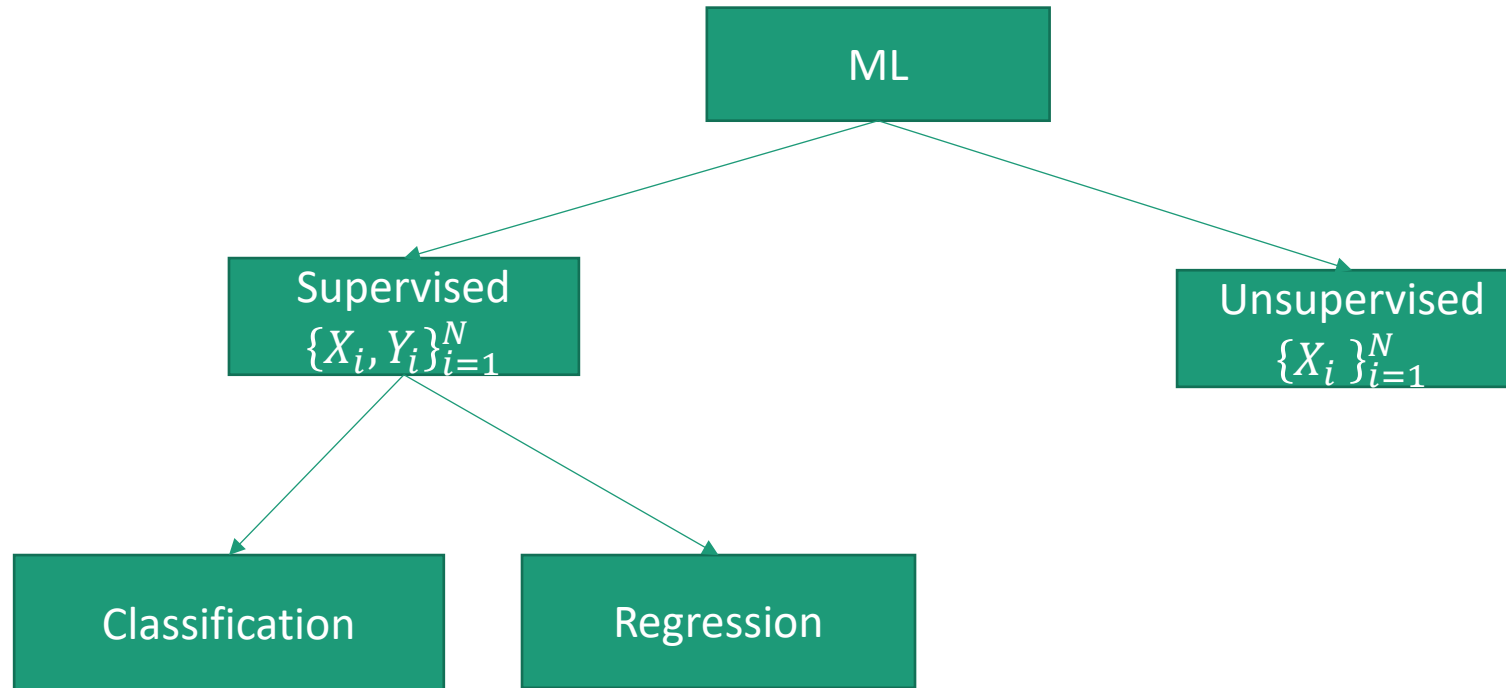
# Fundamental ML Concepts

# ML Overview

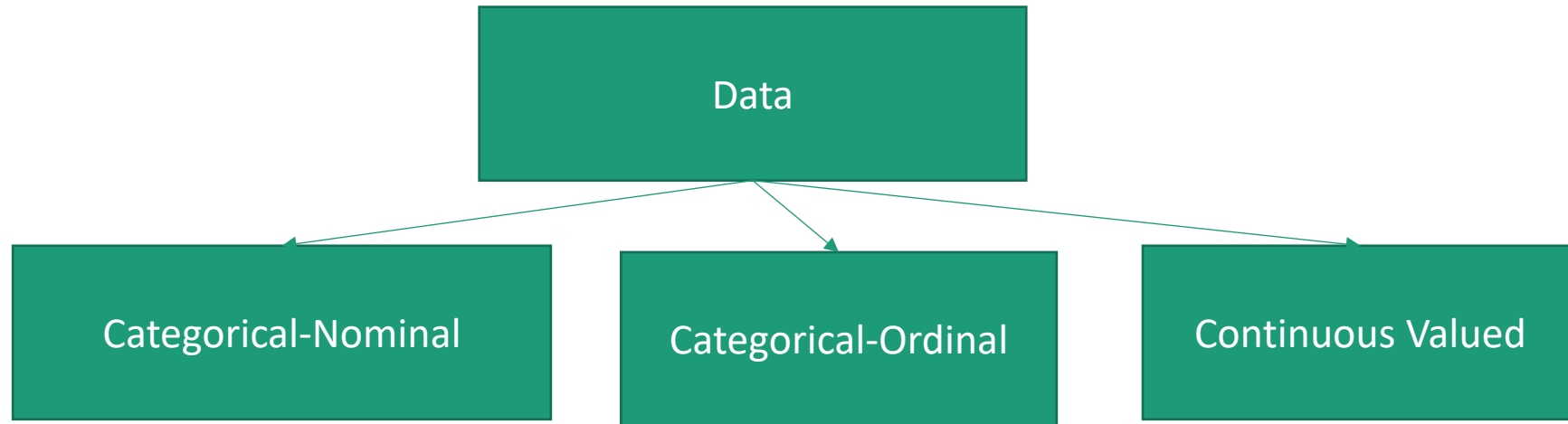


- We can basically break machine learning tasks into two categories
  1. Supervised Learning
  2. Unsupervised Learning
- *Supervised learning*
  - Data  $X_i$  and correct answer (label)  $Y_i$  given for each example  $i \in \{1, \dots, N\}$
- *Unsupervised learning*
  - Only data given for each example,  $X_i$
- Again, we'll be just focusing on *supervised learning*.

# Types of Problems



# Types of Data



- Each piece of information pertaining to an observation can fall into one of three categories:
  - *Continuous Valued*
    - Examples: Blood Pressure, Height
  - *Categorical-Nominal (unordered)*
    - Examples: Car Model, School
  - *Categorical-Ordinal (can be ordered)*
    - Examples: Colors, small < medium < large

# No Free Lunch Theorem

- Unfortunately, there's no single machine learning algorithm to rule them all 😞
- Hopefully, the nature of the problem and data will guide us towards some subset of the options.
- We then try them out and select the best.



# ML Algorithms

- Here's a list of algorithms we'll look at in the class and what types they are

1. Principal Component Analysis (PCA)

2. Linear Regression

3. Classification

- a. Binary

- a. Logistic Regression

- b. Support Vector Machines (SVMs)

- b. Multi-Class

- a. Decision Trees (DTs)

- b. Nearest Neighbors (KNN)

- c. Statistical Classification

- d. Markov Models