Welcome to ECE 421 – Introduction to ML

- Course Instructors:
  - Prof. Brendan Frey (OH: Mon 4-5 PM, BA 4136).
  - Erfan Meskar (OH: Thursday 10-noon, Pratt Building 371).
  - You will be interacting with both of us.
- See the course syllabus for lecture/tutorials time and location
- We will be using Quercus for our course page to post annoncements, assignments, notes, etc.
- Piazza for questions.
- For personal matters only use e.meskar@utoronto.ca include "ece421" in the email subject.

- This semester, we intend to have multiple guest lectures. Stay tuned for that.
- Marking Scheme:
    - Assignments: 4 assignments, each worth 10%
        - programming assignments to be done in Python.
        - PA3 need pytorch.
        - 5% penalty per day of lateness. No submission will be accepted after 72 hours.
        - Can be done in group of two
    - Term test: on Monday, oct. 21. Time and location: TBA worth 25%
    - Final Exam: 35%, Date, time, and location: TBA

- Textbooks:
  - See the Quercus page for a comprehensive list
  - The posted readings are mainly from LFD and AIMA.
    - LFD (Learning From Data), by Abu_Mostafa, et. al., 2012
    - AIMA (Artificial Intelligence: A Modern Approach, 4th US ed.)
- Tentative Course Schedule and weekly readings
  - See the Quercus page

Introduction to Machine Learning (ML)

- ML, or more accurately speaking AI, is having real-world Impact:
  - Public Imagination
  - Economy
  - Science
  - politics
  - Law
  - labor
  - Education
  - Health

vibrant portrait painting of Salvador Dalí with a robotic half face
a shiba inu wearing a beret and black turtleneck
a close up of a handpalm with leaves growing from it
an espresso machine that makes coffee from human souls, artstation
panda mad scientist mixing sparkling chemicals, artstation
a corgi's head depicted as an explosion of a nebula

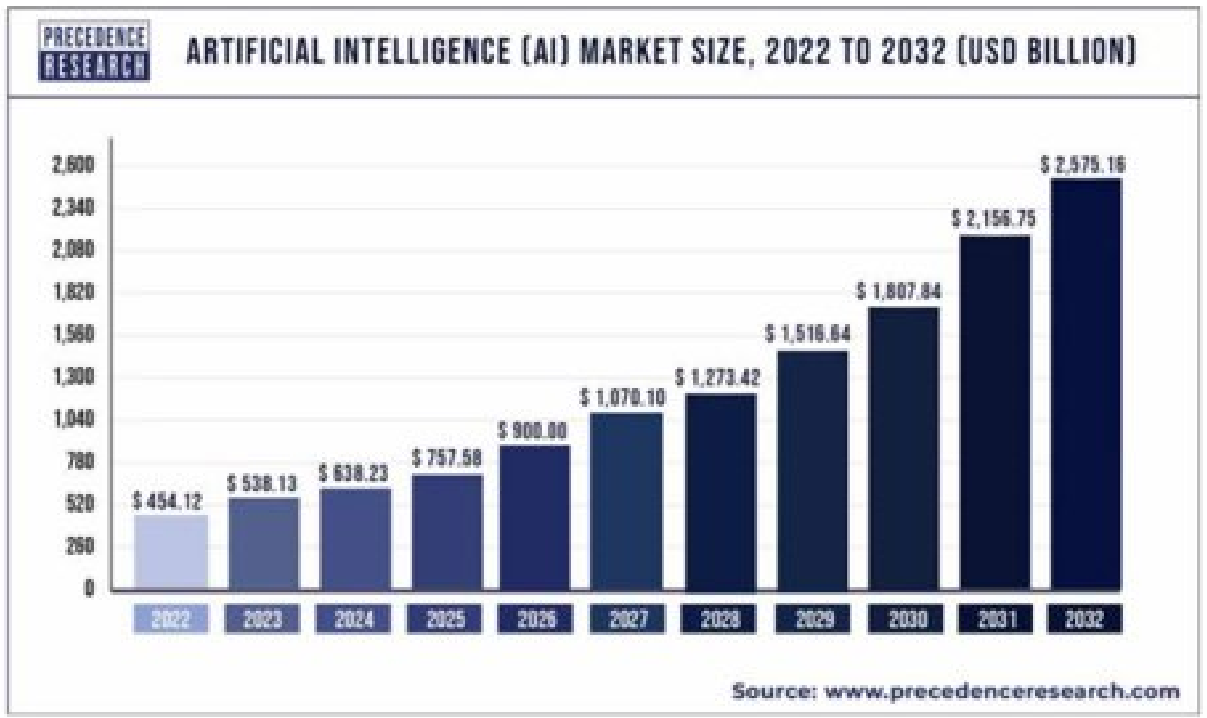
Aug. 18, 2023, 12:18 PM; Updated: Aug. 18, 2023, 12:48 PM

AI-Generated Art Lacks Copyright Protection, D.C. Court Says (1)

Riddhi Setty
Reporter

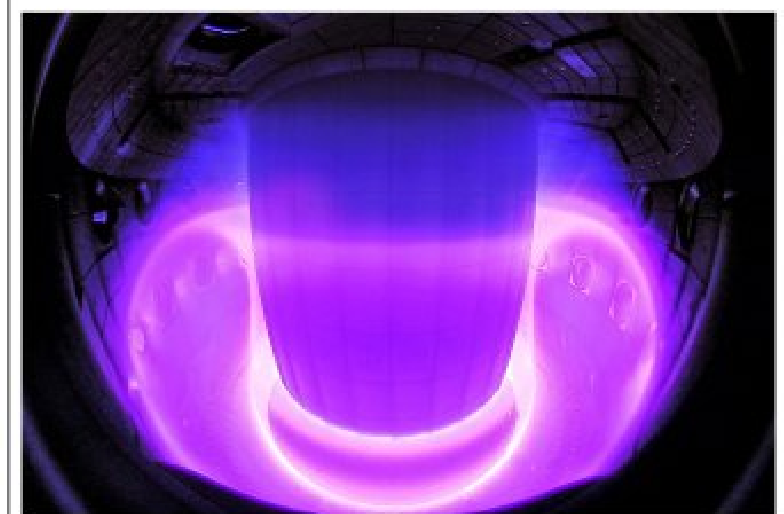
Isaiah Poritz
Legal Reporter

Bloomberg Law, 2023



DeepMind Has Trained an AI to Control Nuclear Fusion

The Google-backed firm taught a reinforcement learning algorithm to control the fiery plasma inside a tokamak nuclear fusion reactor.



The Optimist's Guide to Artificial Intelligence and Work

The focus of much discussion is on how it will replace jobs, but nothing is inevitable.

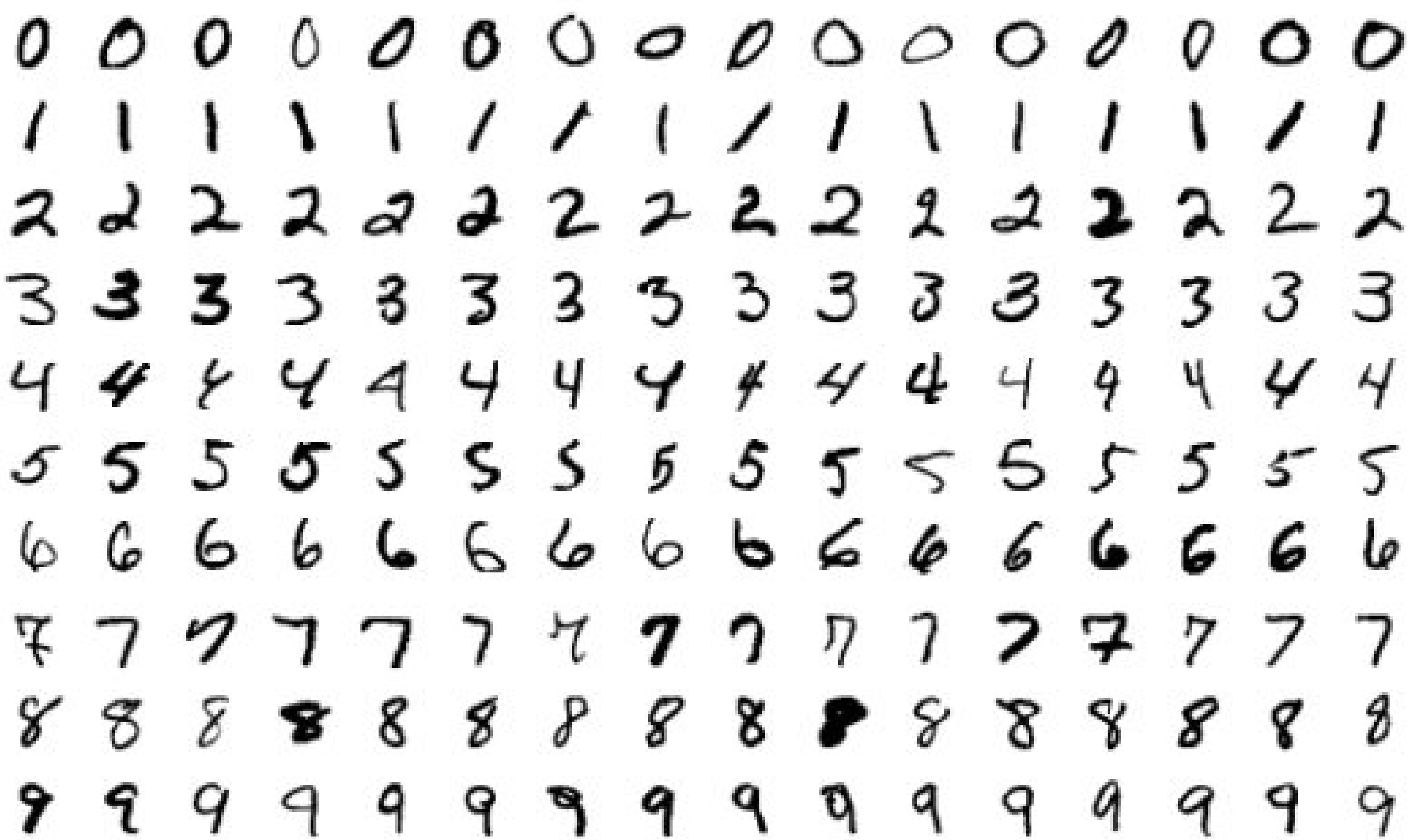
New York Times, 2023

But what is ML?

- ML is the Science of developing Computational systems to adaptively improve their performance with experience accumulated from the observed data.
- Broadly speaking, there are three different types of Learning
  - Supervised Learning
  - Unsupervised Learning
  - Reinforcement Learning

Supervised learning

- Given known/labeled data samples,
- Train machines to recognize new/unlabeled data samples

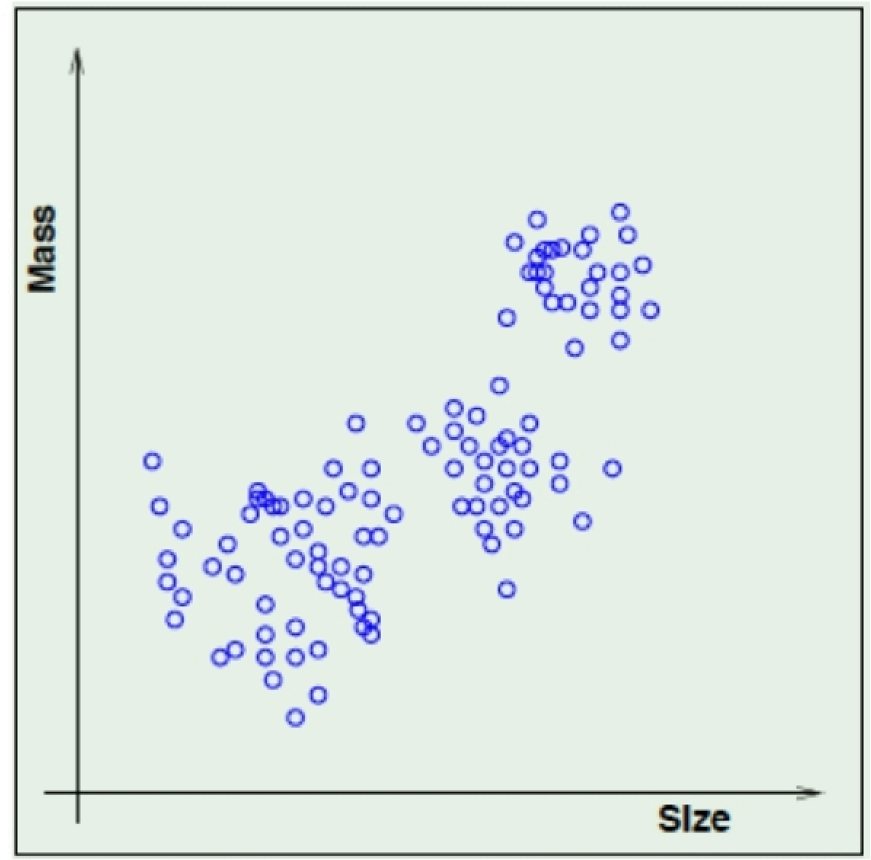


MNIST handwritten digits

Unsupervised Learning

- Given unlabeled data samples
- Train machines to find the pattern behind these data samples

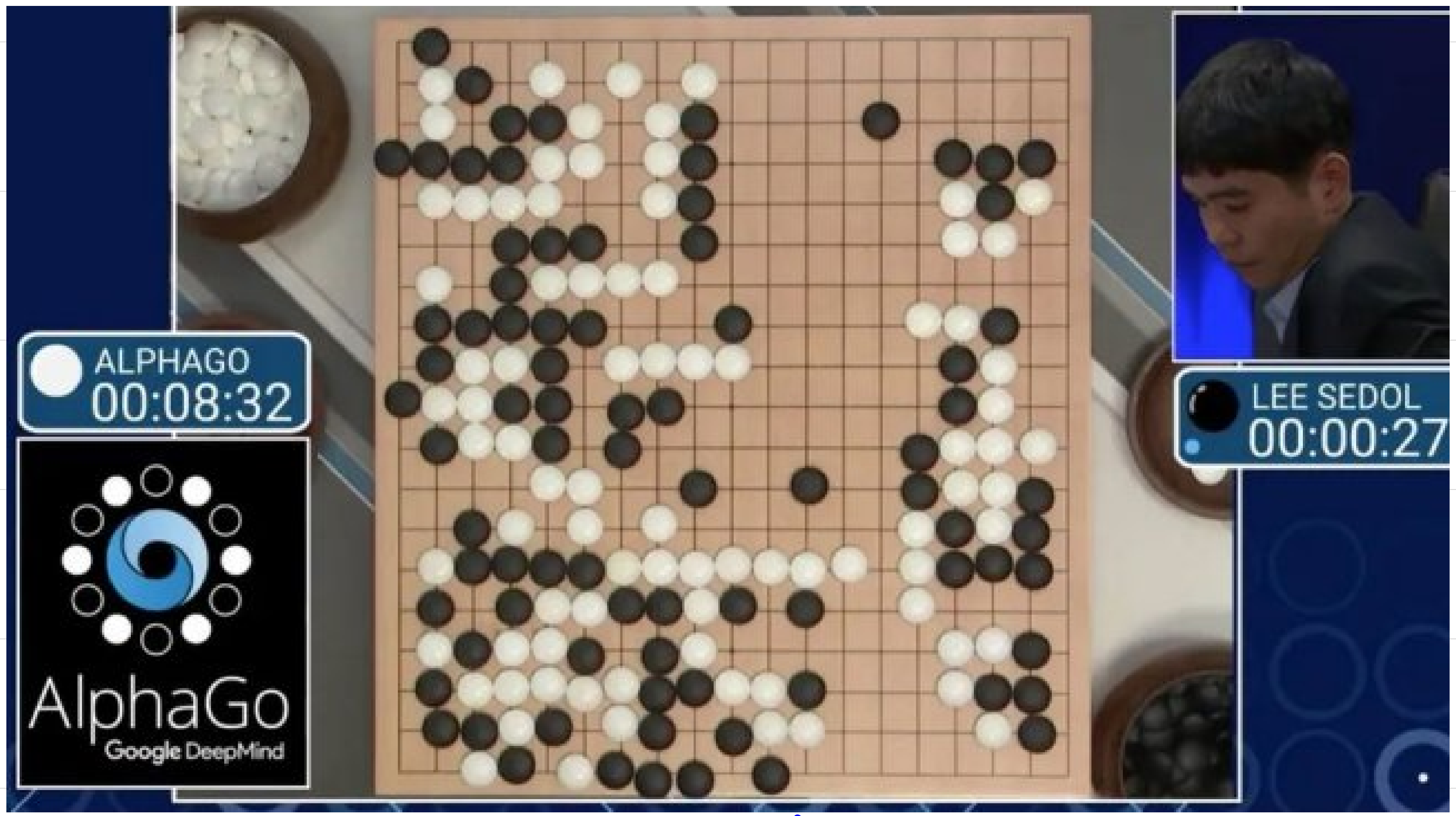
From Deep Learning: Foundations and Concepts.



clustering

Reinforcement learning

- Give machine guidence signals ("rewards") for its action
- Train machine to explore the environment and find optimal actions.



AlphaGo VS. World champion, 2016

ECE421 Course Overview

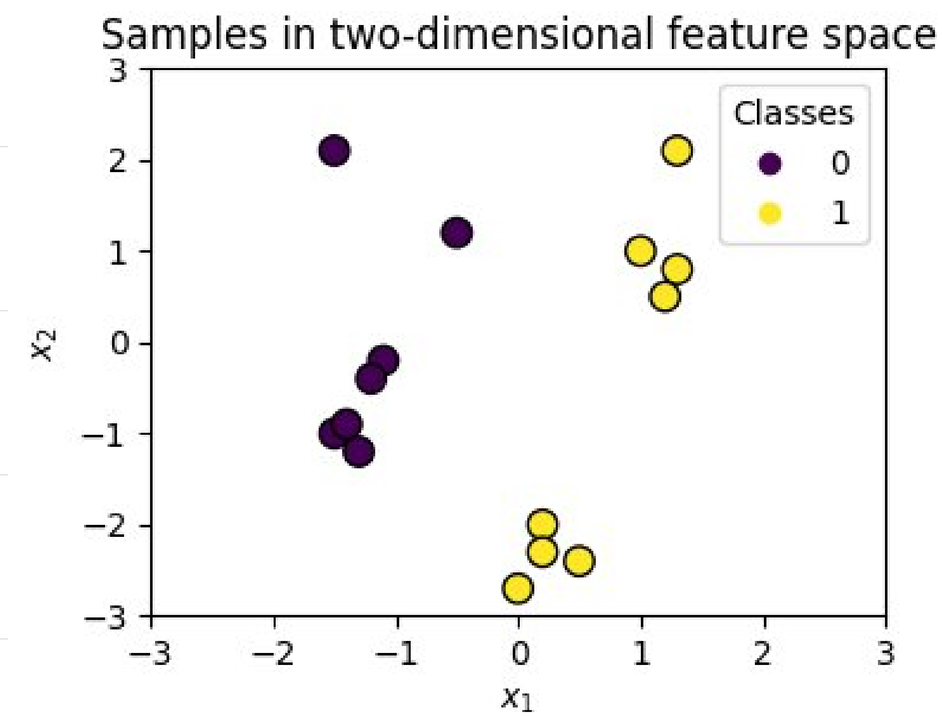
- Learning Methods
  - Supervised learning
    - Linear Models, and Neural Networks (NN)
  - unsupervised learning
    - clustering, Density estimation, Expectation Maximization Algorithm,
  - Reinforcement learning
    - TD and Q-Learning

- Deep learning Arcitecture
  - Convolutional NN
  - Language Models
    - Recurrent NN
    - Attention
    - LSTM

- Learning Techniques:
  - Regularization
  - Validation

Learning Methods - Supervised Learning

Linear Classification:



- Given N training Samples:

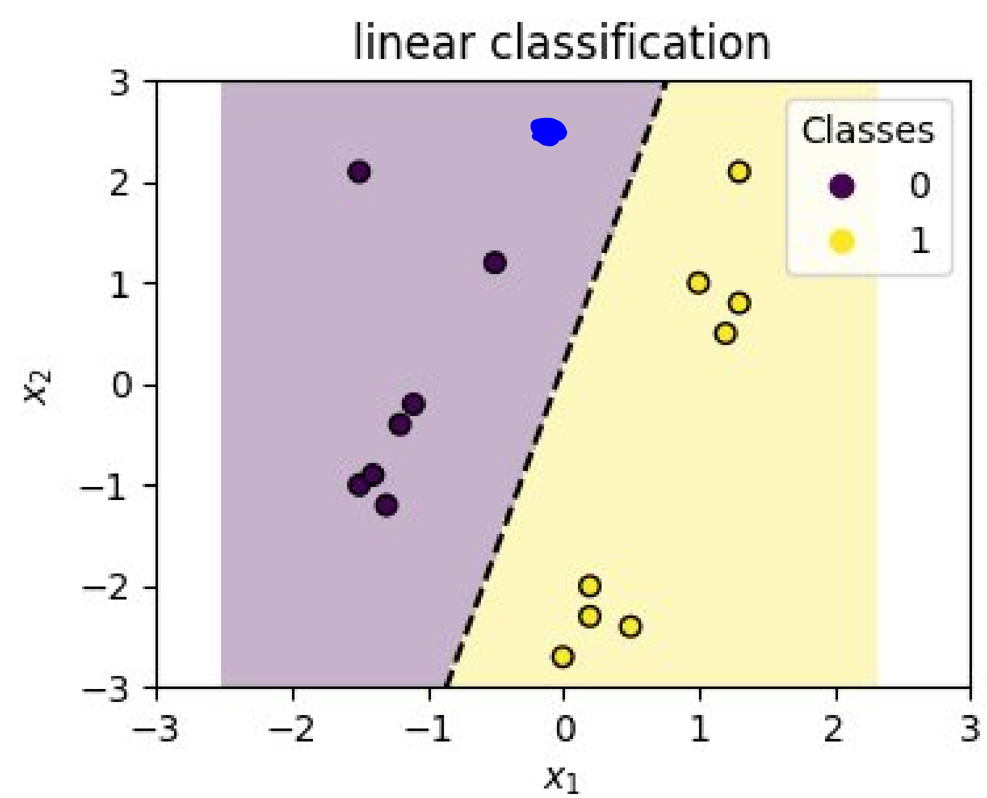
  $(\underline{x}_1, y_1), (\underline{x}_2, y_2), \dots, (\underline{x}_N, y_N)$,

  where $\underline{x}_i \in \mathbb{R}^d$, $y_i \in \{+1, -1\}$.

- Determine a classification rule

  $$y = \text{Sign}\left(\sum_{j=0}^{d} w_j x_j\right)$$

  to minimize classification error



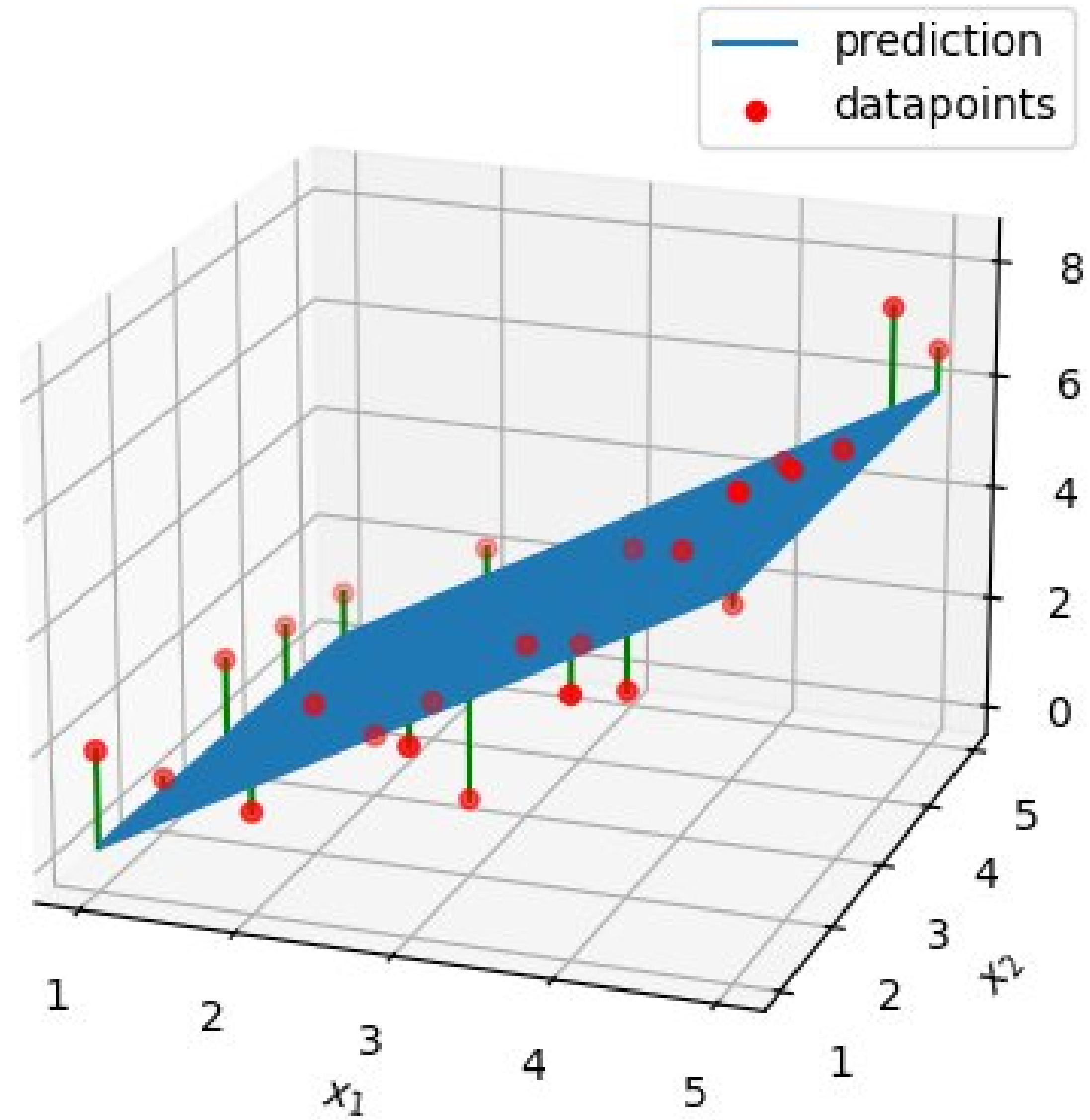
We will See Perceptron Learning algorithm, logistic regression and Gradient descent

Linear Regression:

- Given N training samples:

  $(\underline{x}_1, y_1), (\underline{x}_2, y_2), \ldots, (\underline{x}_N, y_N)$,

  where $\underline{x}_i \in \mathbb{R}^d$, $y_i \in \mathbb{R}$



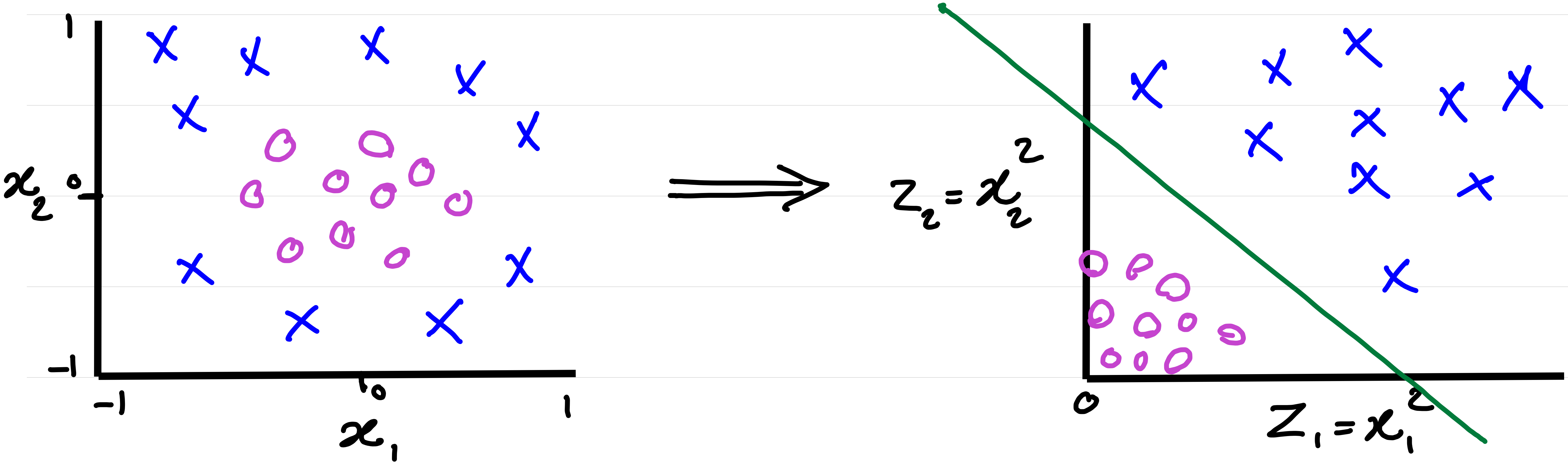
- Determine a "regression rule"

  $$\hat{y} = \sum_{i=0}^{d} w_i x_i$$

  to minimize the prediction error: $\sum_{i=1}^{N} (y_i - \hat{y}_i)^2$

We will see least squares and its variations

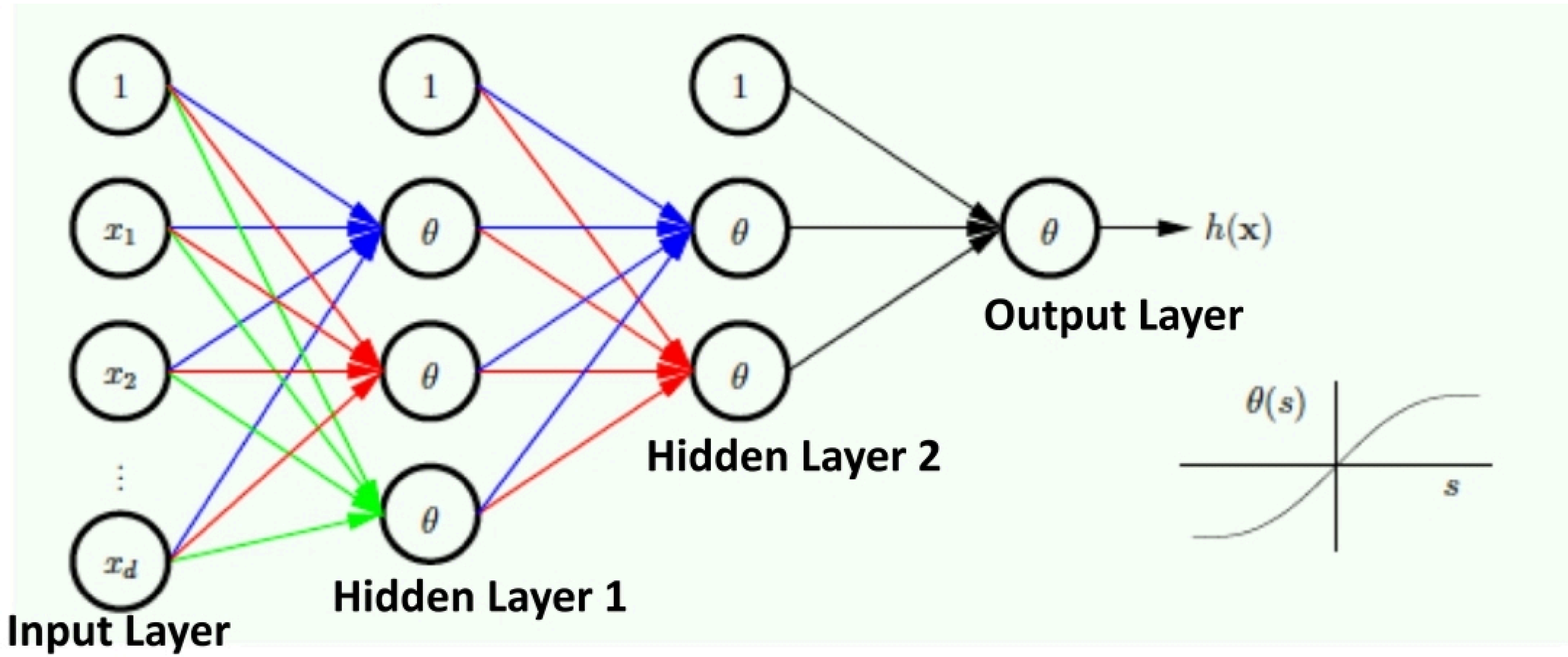
Non-Linear Transformation of Data



$$\underline{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \longrightarrow \underline{z} = \begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \qquad \hat{y} = \text{Sign}\left(\underline{w}^T \underline{z}\right)$$

We will see non-linear transforms, ...

Neural Networks



$$h_i^{(1)} = \theta\left(\sum_{j=0}^{d} w_{ji}^{(1)} \cdot x_j\right) \qquad h_i^{(2)} = \theta\left(\sum_{j=0}^{d} w_{ji}^{(2)} \cdot h_j^{(1)}\right) \qquad y = sign\left(\sum_{j=0}^{d} w_{ji}^{(3)} \cdot h_j^{(2)}\right)$$

Output `i' (Hidden Layer 1)

Weights:Layer 1

Inputs

Output `i' (Hidden Layer 2)

Weights: Layer 2

Output

Neural Networks – Learning

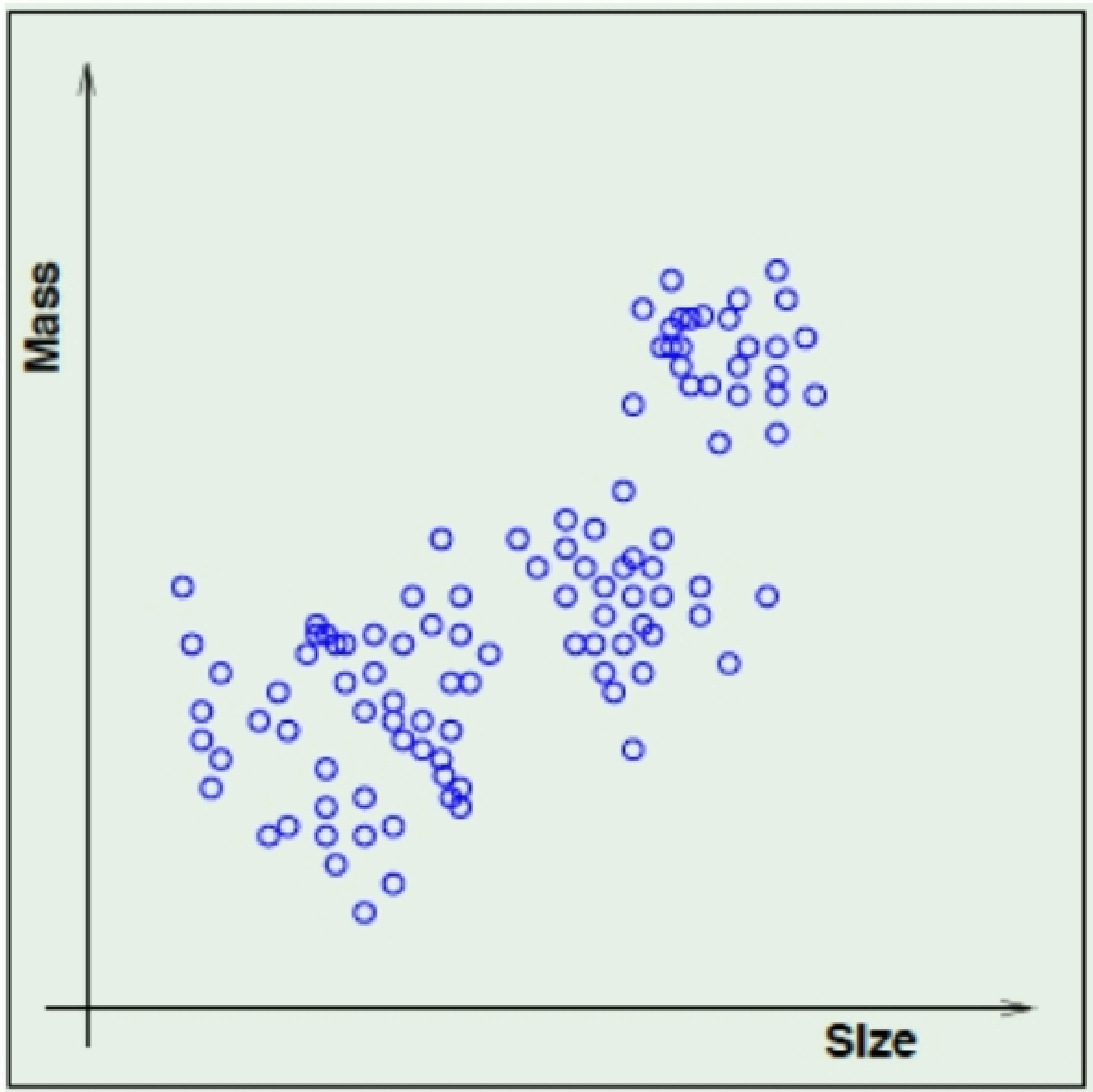
- Given N training samples $(\underline{x}_1, y_1), (\underline{x}_2, y_2), \dots, (\underline{x}_N, y_N)$
- Fix:
  - Number of Hidden units per layer
  - Activation Function θ
- Learn weights w_{ij}^{k} by minimizing the loss function

$$E(W) = \sum_{i=1}^{\ell} l_W(y_i, \hat{y}_i)$$

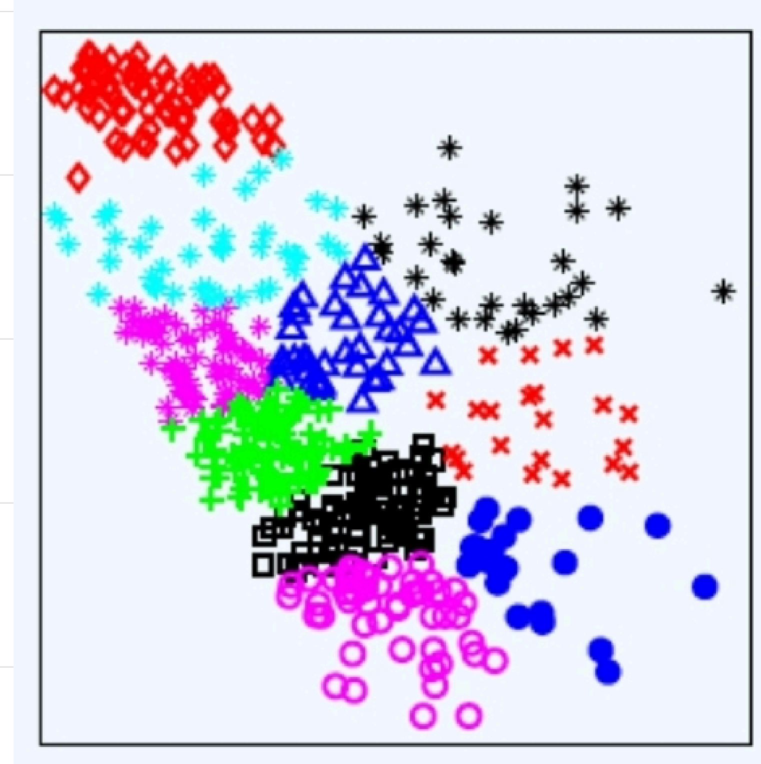
We will see stocastic gradient descent, backpropagation, early stopping rule, dropout and regularization

Learning Methods - Unsupervised Learning

- Given N training data points $\underline{x}_1, \dots, \underline{x}_N$
  Learn the pattern behind the dataset.



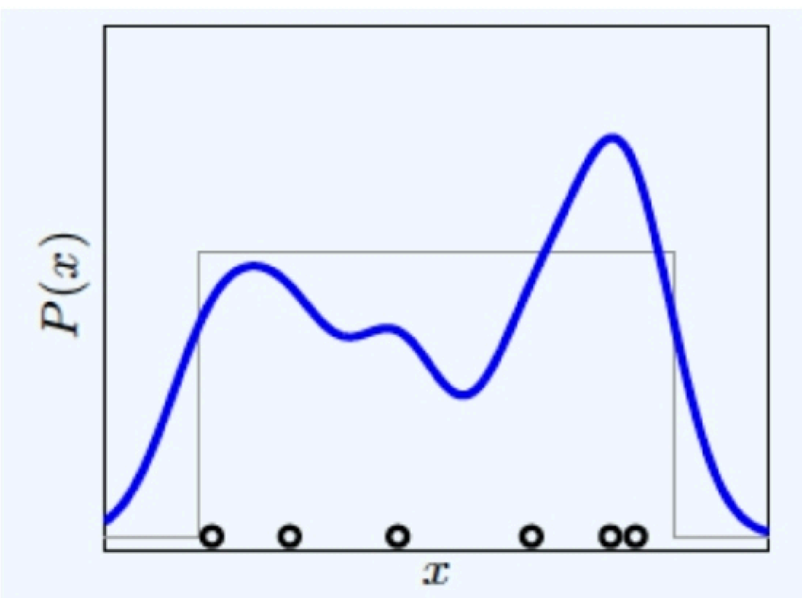
K-Means Clustering



- Cluster Centers: $\underline{\mu}_1, \underline{\mu}_2, \dots, \underline{\mu}_K$
- Partitions: $S_1, S_2, \dots, S_K$
- Minimize: $\sum_{j=1}^{N} \|\underline{x}_j - \mu(\underline{x}_j)\|^2$

We will see Lloyd's Algorithm

Density Estimation - Gaussian Mixture Models

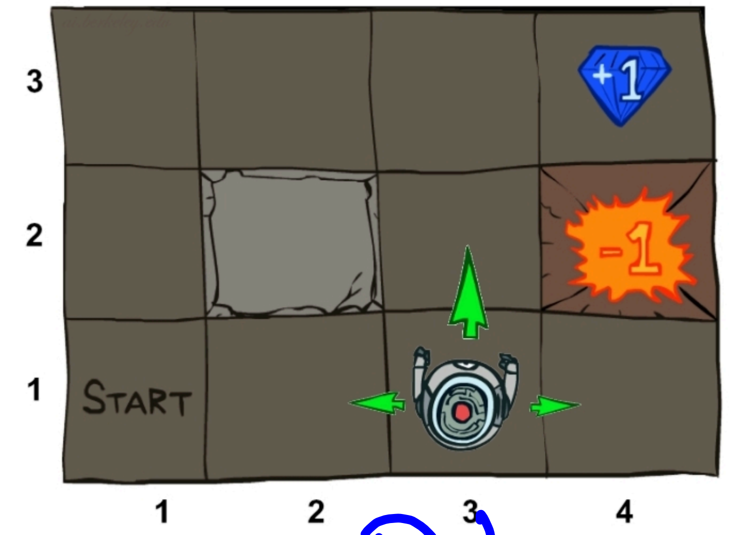


$$f(\mathbf{x}) = \sum_{j=1}^{k} w_j \cdot \mathcal{N}(\mathbf{x}; \mu_j, \Sigma_j)$$

<demo: cocktail party effect>

Learning Methods – Reinforcement Learning

Markov Decision Processes (MDP)



- This is a formalism for modeling how the world works.
- An MDP is a five-tuple $(S, A, P_{sa}, \gamma, R)$
  - S : the set of states
  - A : the set of actions
  - P_{sa} : state transition probabilities $\left(\sum_{s' \in S} P_{sa}(s') = 1\right)$
  - γ : discount factor $(\gamma \in [0,1))$
  - R : reward function
  - Total payoff : $R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + \cdots$
- Goal: Choose actions over time to maximize $\mathbb{E}[R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + \cdots]$

- What if the MDP is initially unknown?
  How can we find a policy?
- Reinforcement Learning
  - We learn the MDP model
  - OR the parts with which we can find the optimal policy (e.g., value functions or Q-functions)
  - Learning from what?
    from samples of the process

Deep Learning Architectures

- Convolutional Neural Networks
- Language Models: RNN, Attention, LSTM