NYU

Introduction to Machine Learning

NYU K12 STEM Education: Machine Learning

Department of Electrical and Computer Engineering,
NYU Tandon School of Engineering
Brooklyn, New York

Course Details

- Course Website
- Instructors:

Rugved Mhatre
rugved.mhatre@nyu.edu

Akshath Mahajan
akshathmahajan@nyu.edu

NYU

Outline

1. Review
2. Limitations of Linear Classifiers
3. Neural Networks
4. Stochastic Gradient Descent
5. Overparameterized Models

Outline

1. Review
2. Limitations of Linear Classifiers
3. Neural Networks
4. Stochastic Gradient Descent
5. Overparameterized Models

The XOR Problem

- What is XOR?

The XOR Problem

- What is XOR?
  The logical operation eXclusive-OR outptus 1 when inputs differ, and 0 otherwise.

Input A	Input B	Output
0	0	0
0	1	1
1	0	1
1	1	0

Table 1: XOR Truth Table

The XOR Problem

- What is XOR?
  The logical operation eXclusive-OR outptus 1 when inputs differ, and 0 otherwise.

Input A	Input B	Output
0	0	0
0	1	1
1	0	1
1	1	0

Table 1: XOR Truth Table

- Why is this a problem?

The XOR Problem

- Let's see the decision boundary for AND and OR gates graphically

The XOR Problem

- Let's see the decision boundary for AND and OR gates graphically

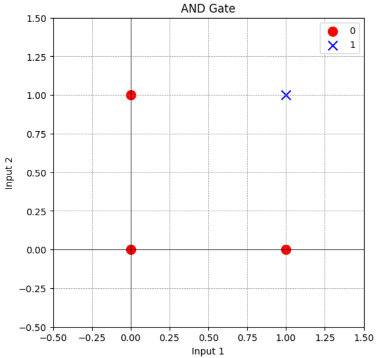


Figure 1: AND Gate

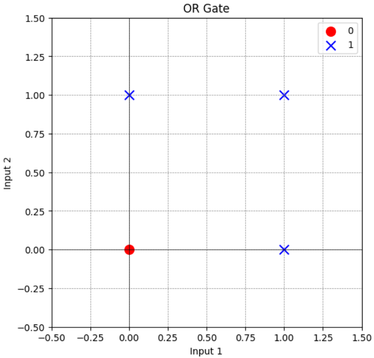


Figure 2: OR Gate

The XOR Problem

- Let's see the decision boundary for AND and OR gates graphically

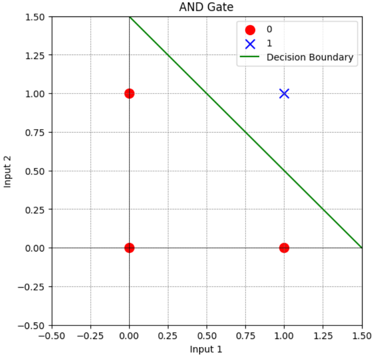


Figure 1: AND Gate

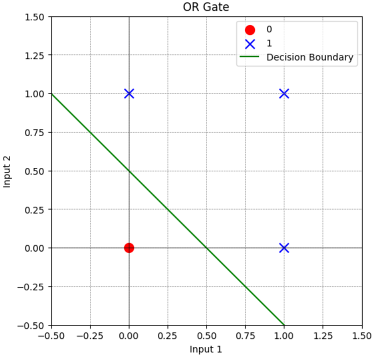


Figure 2: OR Gate

The XOR Problem

- Let's see the decision boundary for AND and OR gates graphically

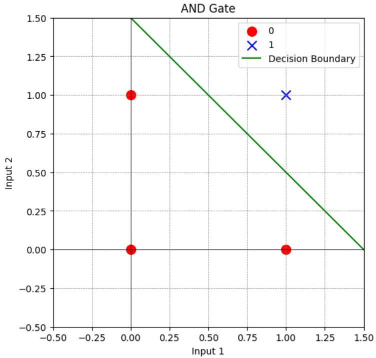


Figure 1: AND Gate

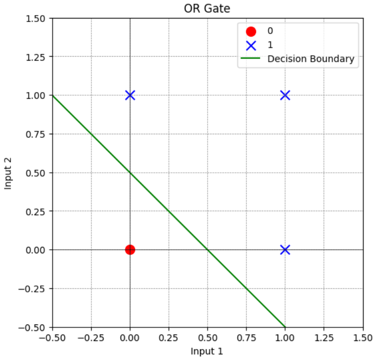


Figure 2: OR Gate

- What about the XOR gate?

The XOR Problem

- What about the XOR gate?

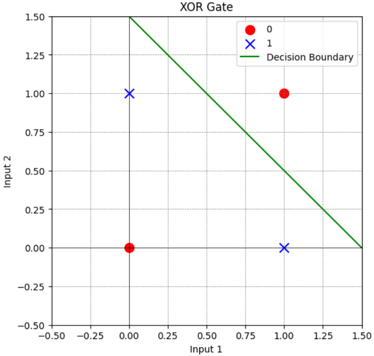


Figure 3: XOR Gate

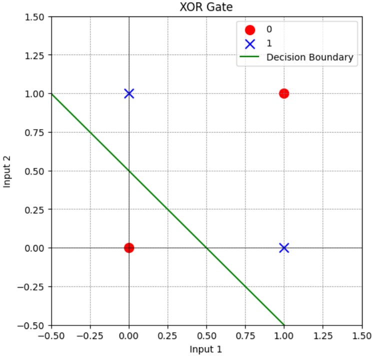


Figure 4: XOR Gate

Describing the General Limitation

- What about other distribution shapes?

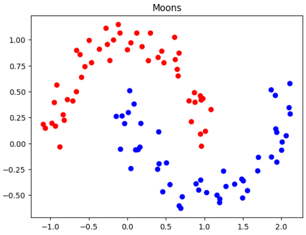


Figure 5: Moons

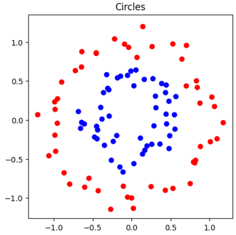


Figure 6: Cirles

Describing the General Limitation

- What about other distribution shapes?

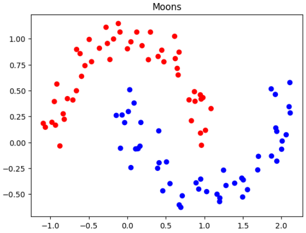


Figure 5: Moons

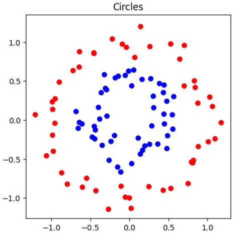


Figure 6: Cirles

- Can you suggest other shapes?

Describing the General Limitation

- What about other distribution shapes?

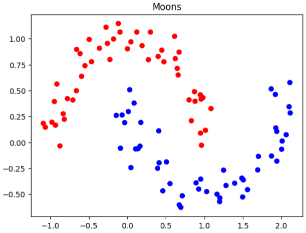


Figure 5: Moons

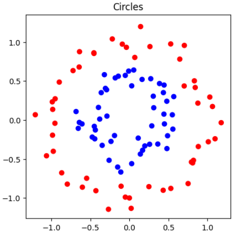


Figure 6: Cirles

- Can you suggest other shapes?
- What can we do about this?

Describing the General Limitation

- What about other distribution shapes?

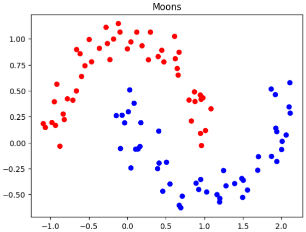


Figure 5: Moons

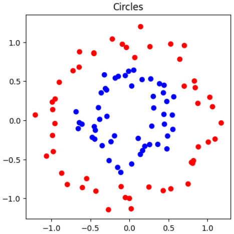


Figure 6: Cirles

- Can you suggest other shapes?
- What can we do about this?
  - Non-Linear classifiers?

Describing the General Limitation

- What about other distribution shapes?

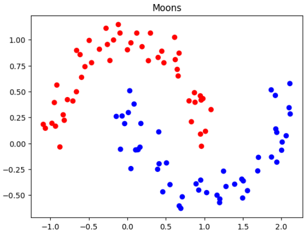


Figure 5: Moons

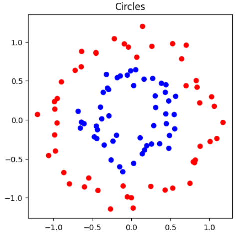


Figure 6: Cirles

- Can you suggest other shapes?
- What can we do about this?
  - Non-Linear classifiers?
  - Enter Neural Networks

Outline

Neurons

- What is a Neuron?

Neurons

- What is a Neuron?
- There are 2 definitions

Neurons

- What is a Neuron?
- There are 2 definitions
  - Biological Neuron

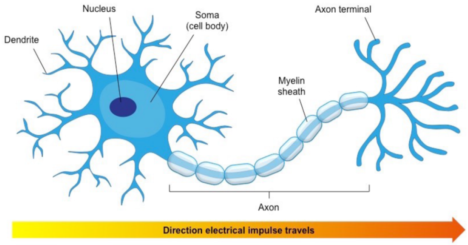


Figure 7: Biological Neuron
Source: Arizona State University

Neurons

- What is a Neuron?
- There are 2 definitions
  - Biological Neuron
  - Mathematical Neuron (Perceptron)

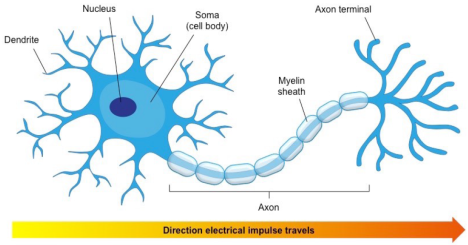


Figure 7: Biological Neuron
Source: Arizona State University

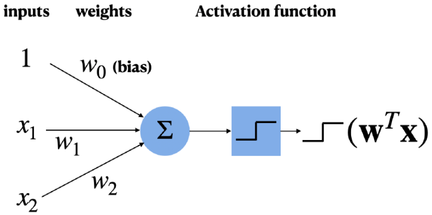
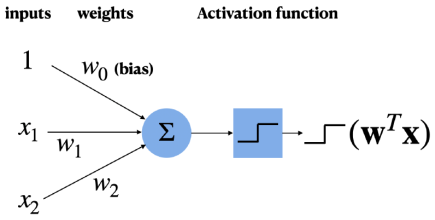
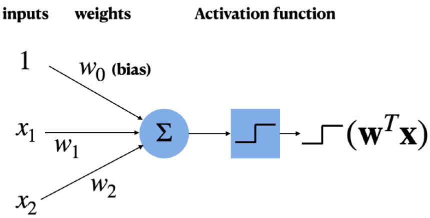


Figure 8: Mathematical Neuron

The Perceptron



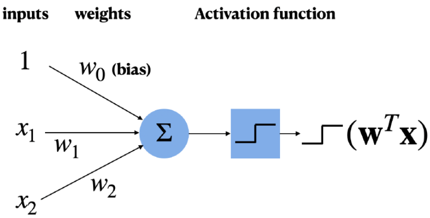
The Perceptron



$$y = \varphi(\mathbf{W}^T \cdot \mathbf{X})$$

- Looks similar to Linear Classification!

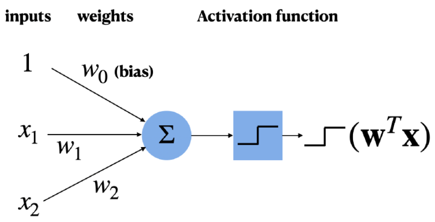
The Perceptron



$$y = \varphi(\mathbf{W}^T \cdot \mathbf{X})$$

- Looks similar to Linear Classification!
- How is this supposed to revolutionize Machine Learning?

The Perceptron



$$y = \varphi(\mathbf{W}^T \cdot \mathbf{X})$$

- Looks similar to Linear Classification!
- How is this supposed to revolutionize Machine Learning?
- HINT: How many neurons are in your brain?
  Does the Activation need to be Logistic/Sigmoid?

Neural Networks

- Solution 1: Connect many neurons together!
- This is the basic concept of a neural network
- Let's see a Multi-Layer Perceptron/Fully Connected Feed-Forward Network

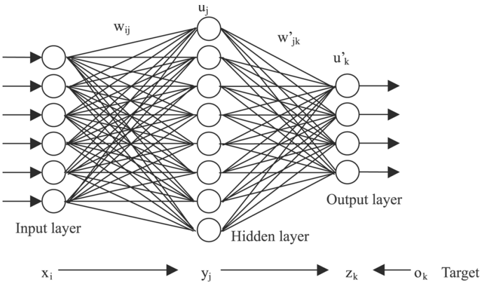


Figure 9: Neural Network

Activation Functions

- Solution 2: Use different Activation Functions

Activation Functions

- Solution 2: Use different Activation Functions
- These have a significant impact on the behavior of a Neuron

Activation Functions

- Solution 2: Use different Activation Functions
- These have a significant impact on the behavior of a Neuron

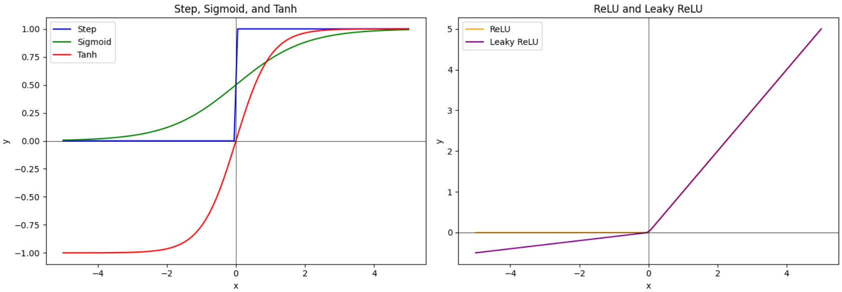


Figure 10: Different Activation Functions

Activation Functions

- Solution 2: Use different Activation Functions
- These have a significant impact on the behavior of a Neuron
- Softmax activation is particularly important!

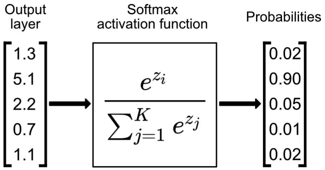


Figure 10: Softmax Activation
Source: Towards Data Science

MLP Example - 1

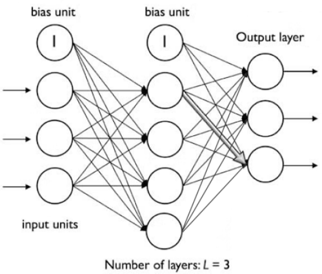


Figure 11: MLP Example 1

- What is the shape of input and output?

MLP Example - 1

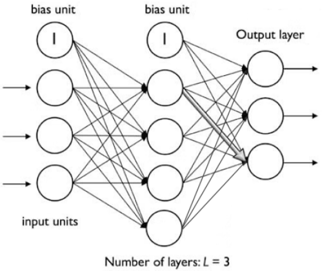


Figure 11: MLP Example 1

- What is the shape of input and output?

MLP Example - 1

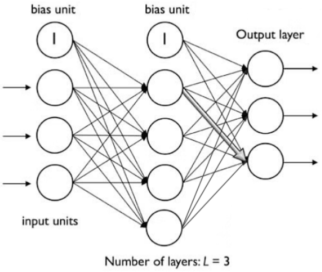


Figure 11: MLP Example 1

- What is the shape of input and output? (3, 3)
- How many parameters does the model have?

MLP Example - 1

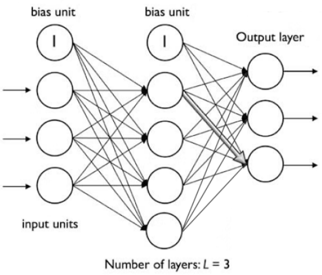


Figure 11: MLP Example 1

- What is the shape of input and output? (3, 3)
- How many parameters does the model have? 31
- What activation functions would you use for output layer?

MLP Example - 1

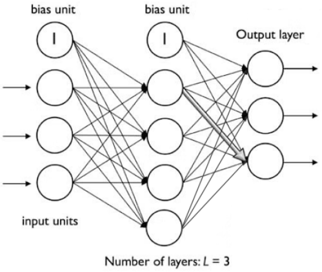


Figure 11: MLP Example 1

- What is the shape of input and output? (3, 3)
- How many parameters does the model have? 31
- What activation functions would you use for output layer? Sigmoid

MLP Example - 2

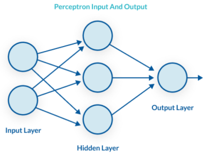


Figure 12: MLP Example 2

- What is the shape of input and output?
- How many parameters does the model have?
- What activation functions would you use for output layer?

MLP Example - 2

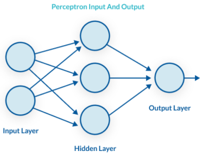


Figure 12: MLP Example 2

- What is the shape of input and output? (2, 1)
- How many parameters does the model have? 13
- What activation functions would you use for output layer? Depends on the task

Deep Neural Networks

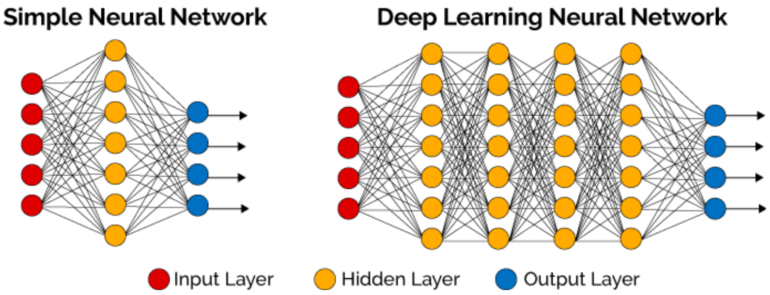


Figure 13: Simple vs Deep Networks

- There are many choices for the number of hidden layers and number of neurons per layer

Deep Neural Networks

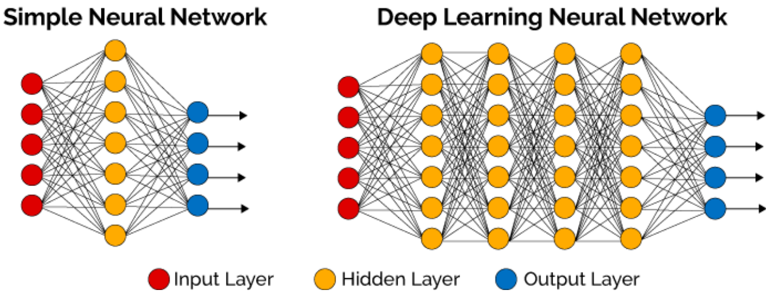


Figure 13: Simple vs Deep Networks

- There are many choices for the number of hidden layers and number of neurons per layer
- MLPs can approximate almost any continuous function

Deep Learning

- What does deep learning mean?
  - Deep: Neural network architectures with many hidden layers
  - Learning: Optimizing model parameters given a dataset

Deep Learning

- What does deep learning mean?
  - Deep: Neural network architectures with many hidden layers
  - Learning: Optimizing model parameters given a dataset
- Generally, deeper models have more parameters and require larger datasets to learn

Deep Learning

- What does deep learning mean?
  - Deep: Neural network architectures with many hidden layers
  - Learning: Optimizing model parameters given a dataset
- Generally, deeper models have more parameters and require larger datasets to learn
- What problems can we expect?

Deep Learning

- What does deep learning mean?
  - Deep: Neural network architectures with many hidden layers
  - Learning: Optimizing model parameters given a dataset
- Generally, deeper models have more parameters and require larger datasets to learn
- What problems can we expect?
  - Overfitting

Deep Learning

- What does deep learning mean?
  - Deep: Neural network architectures with many hidden layers
  - Learning: Optimizing model parameters given a dataset
- Generally, deeper models have more parameters and require larger datasets to learn
- What problems can we expect?
  - Overfitting
  - Computational Limitations

Outline

Computational Limitations

- For deep learning systems to perform well, we need large datasets -
  - COCO - 330K images (25 GB)
  - ImageNet - 14 million images (300 GB)

Computational Limitations

- For deep learning systems to perform well, we need large datasets -
  - COCO - 330K images (25 GB)
  - ImageNet - 14 million images (300 GB)
- Computational Challenges

Computational Limitations

- For deep learning systems to perform well, we need large datasets -
  - COCO - 330K images (25 GB)
  - ImageNet - 14 million images (300 GB)
- Computational Challenges
  - Memory Limitation - GeForce RTX 2080 Ti has 11 GB memory, while ImageNet is about 300 GB.

Computational Limitations

- For deep learning systems to perform well, we need large datasets -
  - COCO - 330K images (25 GB)
  - ImageNet - 14 million images (300 GB)
- Computational Challenges
  - Memory Limitation - GeForce RTX 2080 Ti has 11 GB memory, while ImageNet is about 300 GB.
  - Computation - Calculating gradients for the whole dataset is slow and done several times.

Stochastic Gradient Descent

- We don’t really need to calculate gradients from the whole data

Stochastic Gradient Descent

- We don't really need to calculate gradients from the whole data
- Calculate gradients from subsets of the whole dataset, one at a time

Stochastic Gradient Descent

- We don't really need to calculate gradients from the whole data
- Calculate gradients from subsets of the whole dataset, one at a time
  - The subset can fit in memory
  - The gradient of subset is calculated fast

Stochastic Gradient Descent

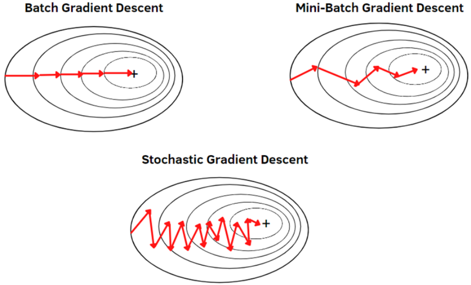
- We don’t really need to calculate gradients from the whole data
- Calculate gradients from subsets of the whole dataset, one at a time
  - The subset can fit in memory
  - The gradient of subset is calculated fast
- But there is a tradeoff:

Stochastic Gradient Descent

- We don't really need to calculate gradients from the whole data
- Calculate gradients from subsets of the whole dataset, one at a time
  - The subset can fit in memory
  - The gradient of subset is calculated fast
- But there is a tradeoff:
  - Each gradient is a bit noisy
  - More number of gradients need to be calculated

Stochastic Gradient Descent

- The descent ends up looking like this -



Stochastic Gradient Descent

- Consider a subset of the original dataset having size B
- The loss is then calculated as -

$$L(W) = \frac{1}{B}\sum_{i=1}^{B}(y_i - \hat{y}_i)^2$$

- The weight update rule then becomes -

$$W_{new} = W - \alpha \nabla L(W)$$

Stochastic Gradient Descent

- For different sizes of B, we have -
  - SGD: $B = 1$, and results in very noisy gradients
  - Mini-batch GD: B is small (typically 32, 64, 128 for images), and gradients have some noise
  - GD: $B = N$, and gradients have no noise

Stochastic Gradient Descent

- For different sizes of B, we have -
  - SGD: $B = 1$, and results in very noisy gradients
  - Mini-batch GD: B is small (typically 32, 64, 128 for images), and gradients have some noise
  - GD: $B = N$, and gradients have no noise
- Even if feasible, GD is not a good idea. Noisy gradients can help
  - escape from local minima
  - escape from saddle points
  - improve generalization

Outline

Overparameterized Models

- Modern deep learning models are heavily overparameterized

Overparameterized Models

- Modern deep learning models are heavily overparameterized
  - GPT-3: State-of-the-art language model, 175 billion parameters
  - ResNet: State-of-the-art vision model, 10-60 million parameters

Overparameterized Models

- Modern deep learning models are heavily overparameterized
  - GPT-3: State-of-the-art language model, 175 billion parameters
  - ResNet: State-of-the-art vision model, 10-60 million parameters
- Conventional wisdom: Such models overfit.

Overparameterized Models

- Modern deep learning models are heavily overparameterized
  - GPT-3: State-of-the-art language model, 175 billion parameters
  - ResNet: State-of-the-art vision model, 10-60 million parameters
- Conventional wisdom: Such models overfit.
- It is not the case in practice!