

# Week 8 Discussion

# Agenda

- Introduction to Deep Learning
- PyTorch

# Machine Learning vs. Deep Learning

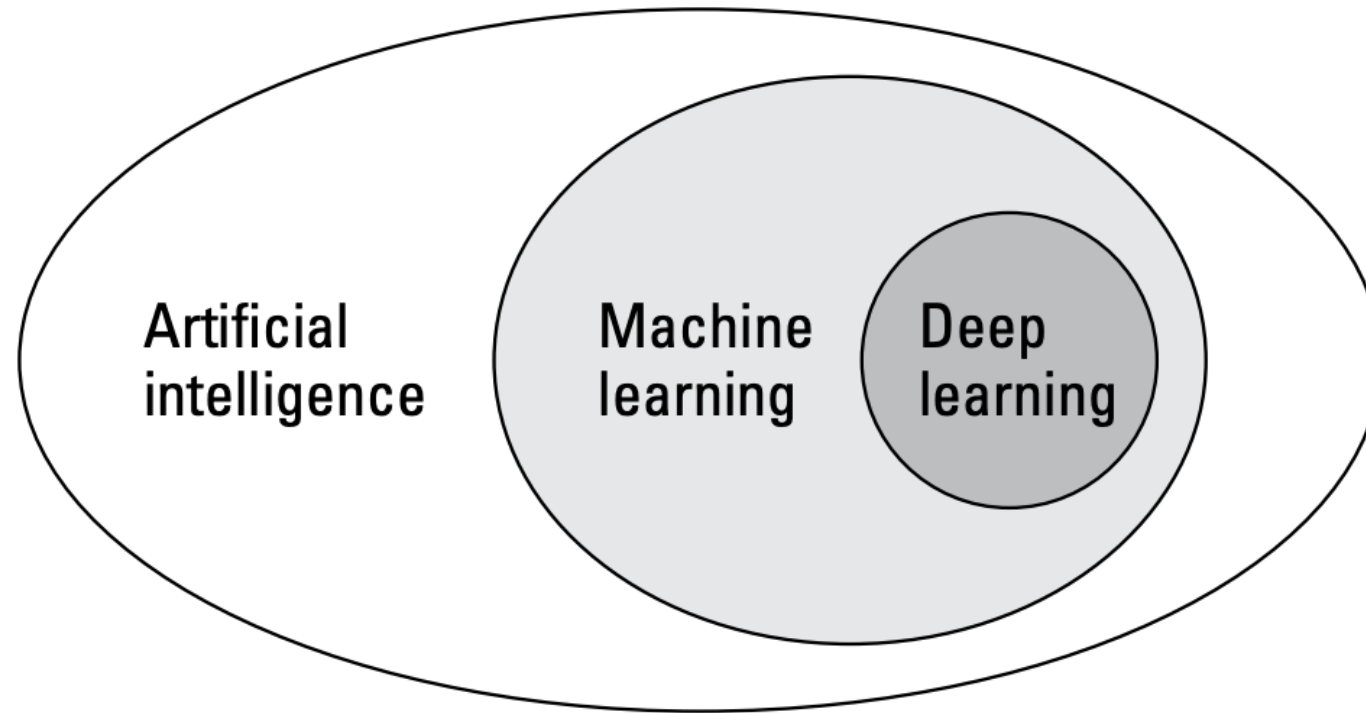
## Machine Learning

- Algorithms that can learn from data and generalize to unseen data
- In ML, the programmer does not explicitly define the rules

## Deep Learning

- Subset of machine learning that utilizes artificial neural networks
- “Deep” refers to the many layers that a neural network can have

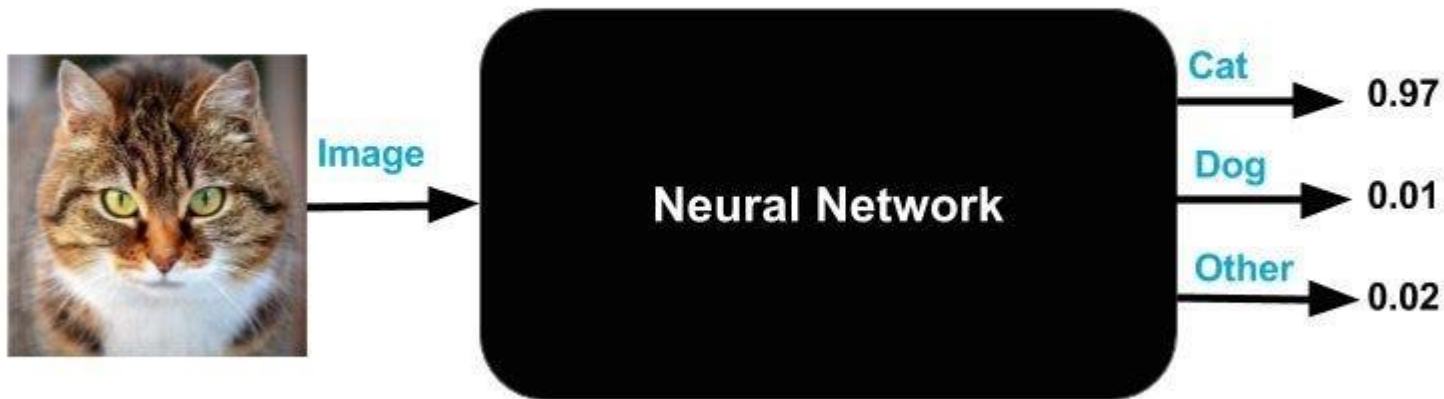
# Field of Artificial Intelligence



**FIGURE 1-1:** Deep learning, a subset of a subset of AI.

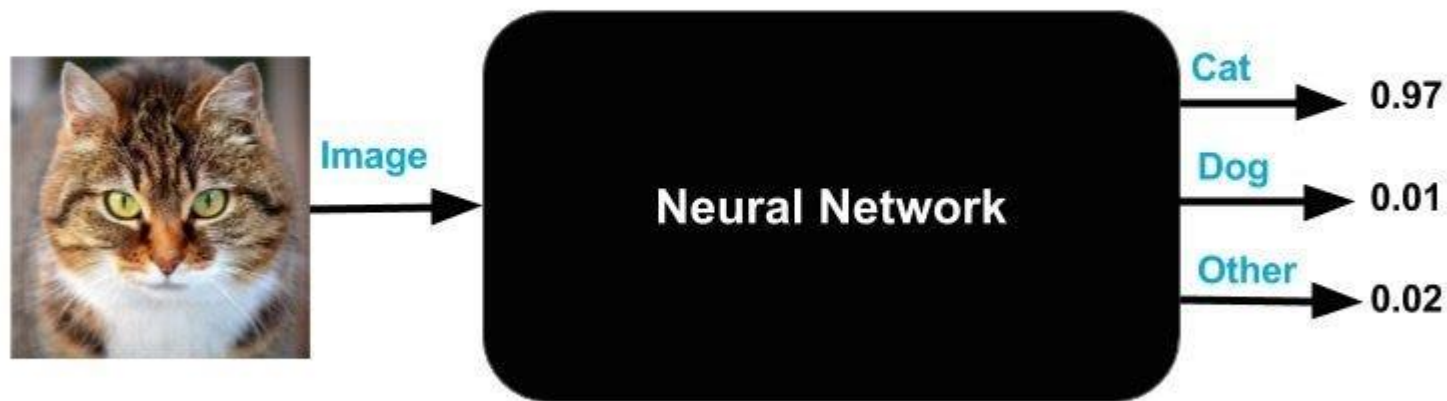
# Neural Networks

- At first, let's imagine neural networks as a black box
- Here, we are trying to solve a classification problem
  - Given an image, can we predict the class label? (cat, dog, other)



# Neural Networks

- You can first imagine that a neural network is just a (differentiable) function  $f(x)$ 
  - $x$  is the input data, and the function  $f$  is the network. What comes out is the prediction of the problem we want to solve



# Neural Networks

- Neural networks are made up of connected neurons
- The network takes in some data and outputs a prediction

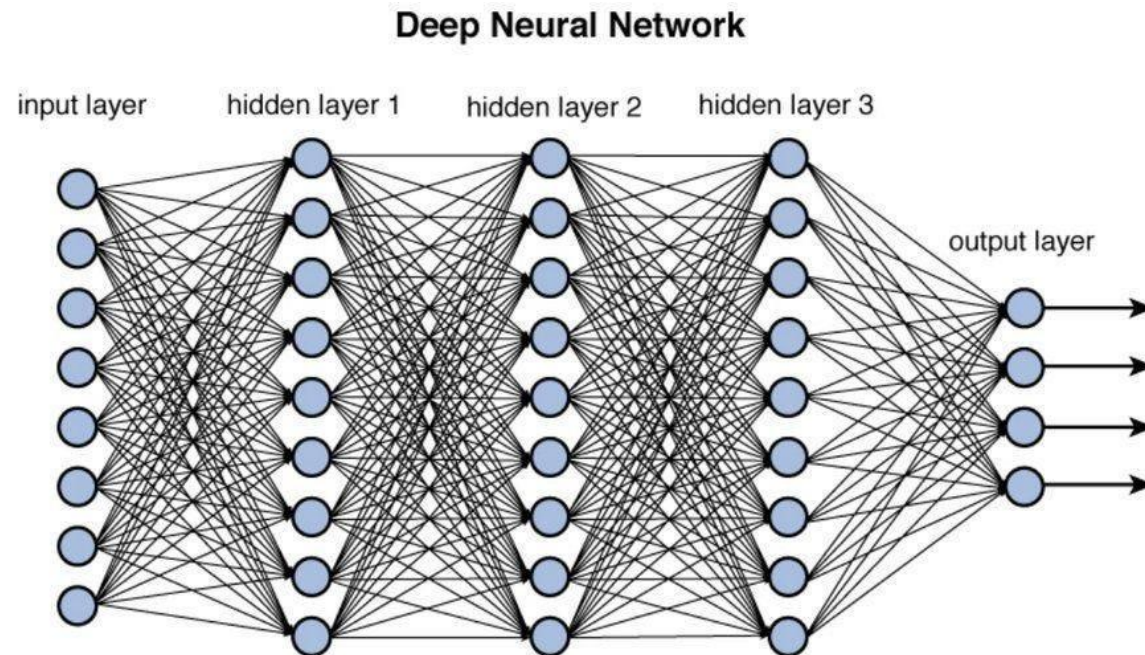


Figure 12.2 Deep network architecture with multiple layers.

# Neural Networks

- The neurons are computational units that have one or more weighted inputs
  - They take in some data, perform a mathematical operation, and produce some output

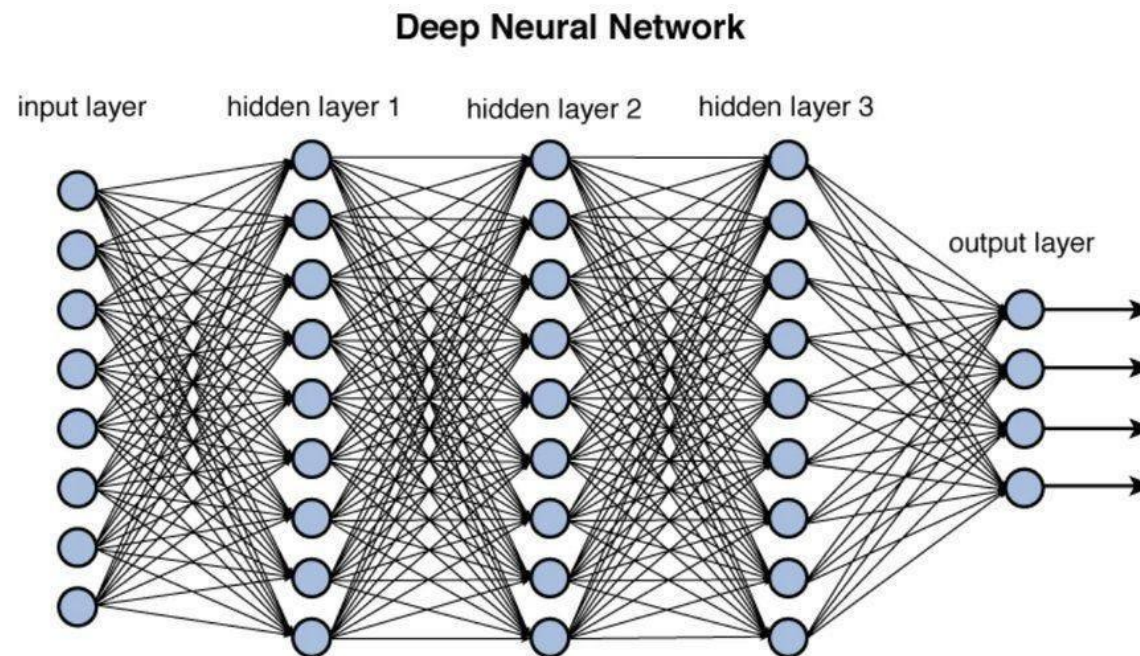


Figure 12.2 Deep network architecture with multiple layers.



# Neural Networks

- The neurons are organized into the layers of the network
- The hidden layers are “hidden” because their inputs and outputs are not directly understandable from outside of the neural network

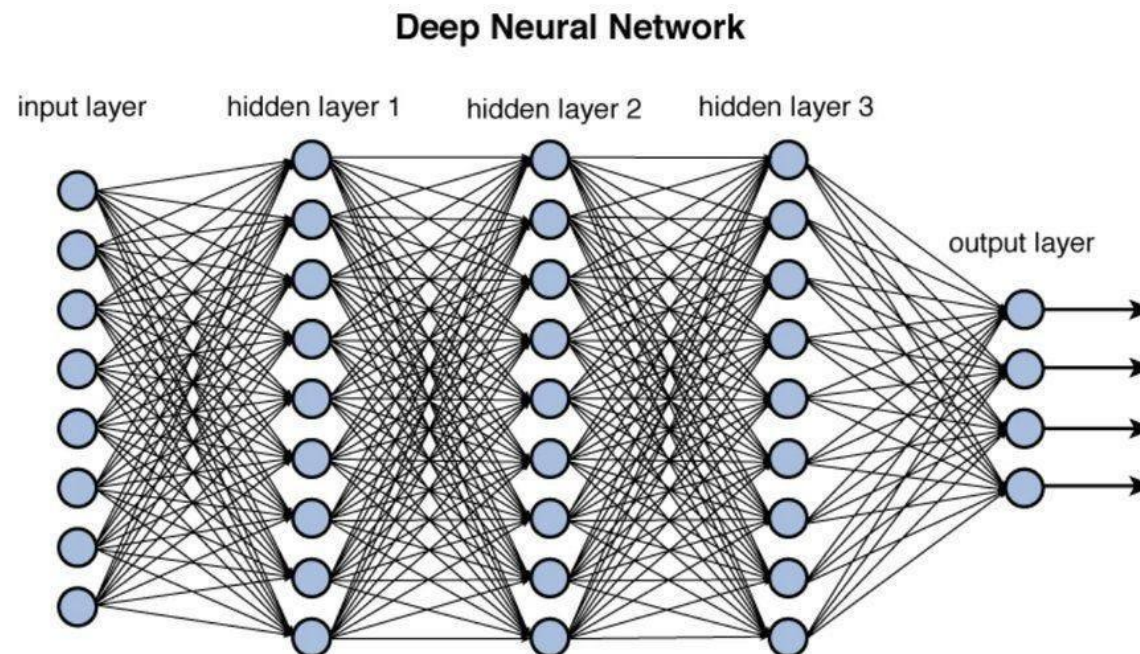
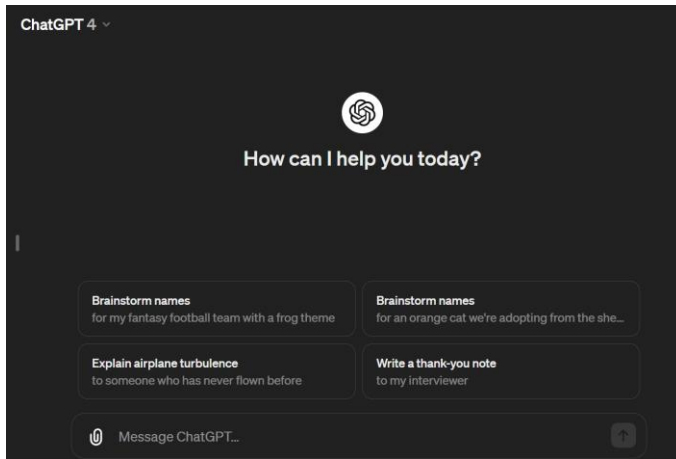


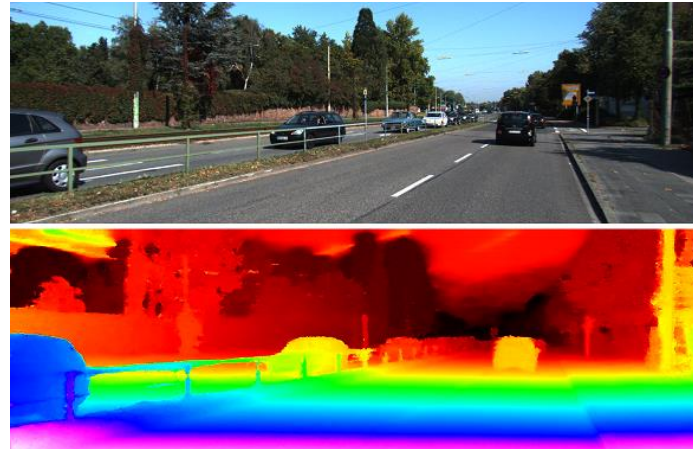
Figure 12.2 Deep network architecture with multiple layers.

# Neural Networks

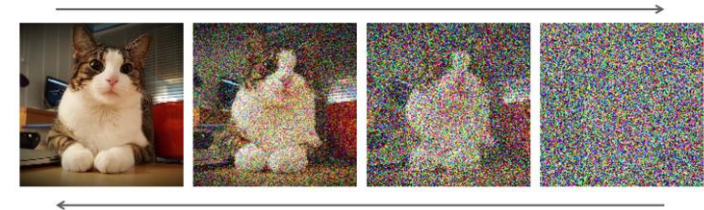
- Neural networks have enabled many applications



<https://chat.openai.com/>



[https://research.nvidia.com/publication/2018-04\\_importance-stereo-accurate-depth-estimation-efficient-semi-supervised-deep](https://research.nvidia.com/publication/2018-04_importance-stereo-accurate-depth-estimation-efficient-semi-supervised-deep)



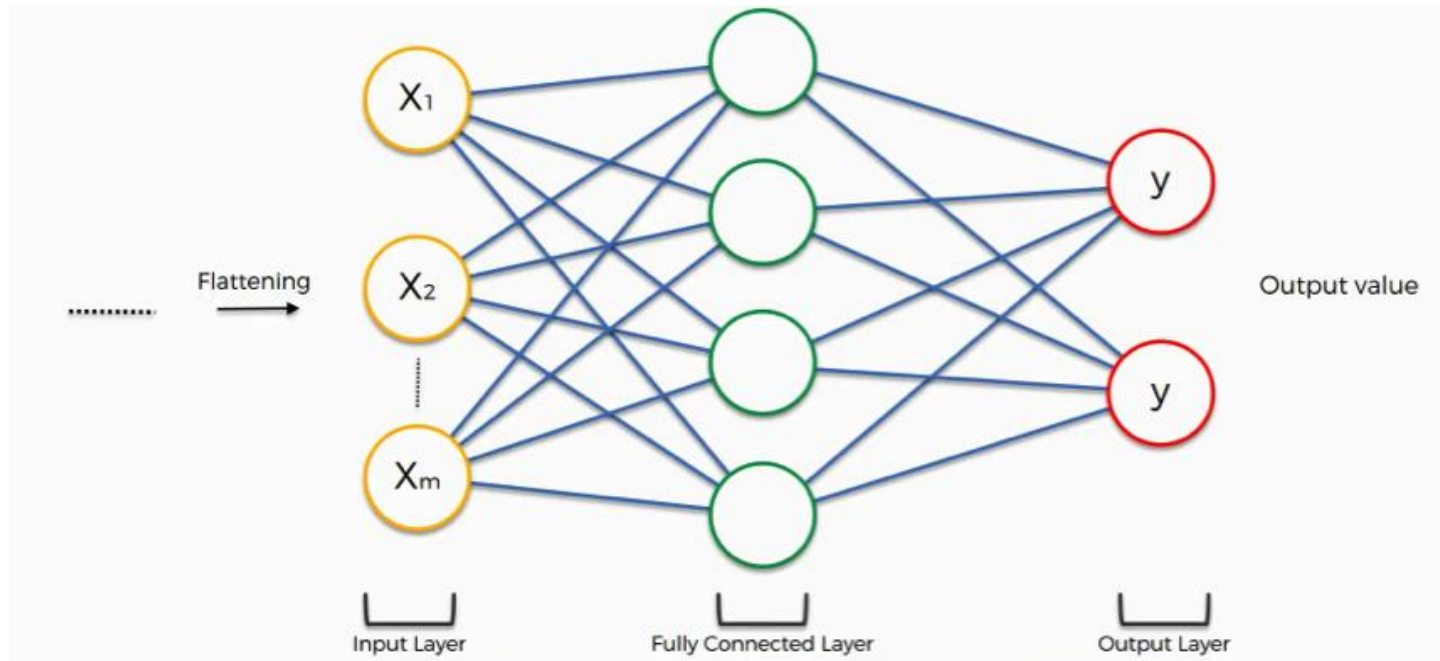
<https://developer.nvidia.com/blog/improving-diffusion-models-as-an-alternative-to-gans-part-2/>

# Inside the Layers of a Neural Network

- There are a few examples of layers inside of a neural network
- Fully-connected layer
  - Performs a matrix-vector product  $Ax=b$
  - Called *Linear* layers in PyTorch
- Convolutional Layers
  - Performs a convolution operation

# Fully-Connected Layer

- Matrix-vector multiplication  $Ax=b$ 
  - $A$  is a matrix of parameters/weights that needs to be optimized
  - $x$  is the input data from the previous layer



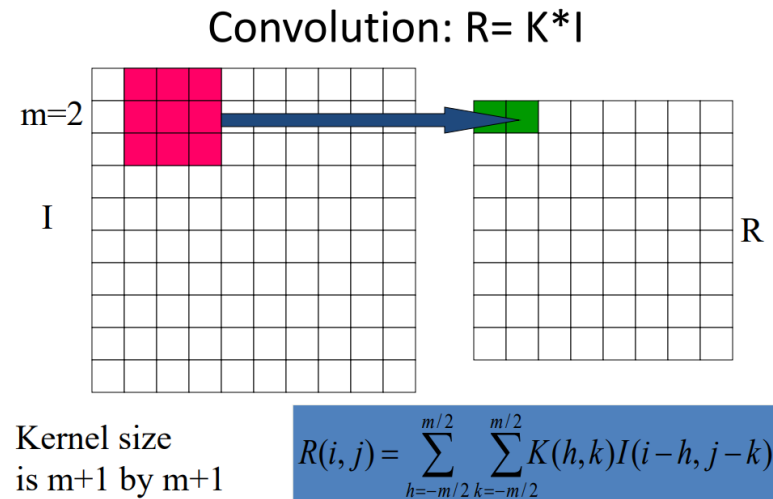
# Parameters or Weights of a Network

- The parameters or weights of the network are the things inside the network that we want to optimize
  - This is what is “learned” from our data
- For a fully-connected layer, we want to find the values in our matrix  $A$  that gives our network the best performance
  - We can first initialize them randomly and optimize them through training

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix} \quad \text{and} \quad \mathbf{b} = \begin{bmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{bmatrix}.$$

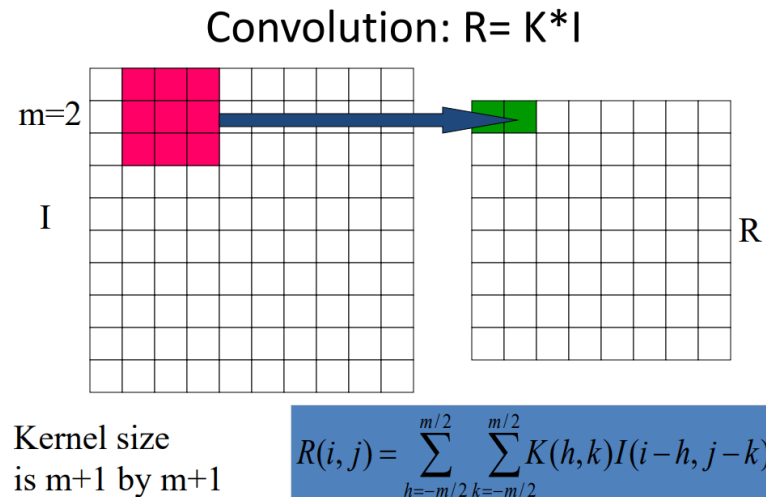
# Convolutional Layers

- In CV, we often work with images or 2D/3D tensors. Convolutions can take advantage of the structure of image data
- A network that utilizes convolutional layers are convolutional neural networks or CNNs
  - They have quickly become state-of-the-art in many problems



# Convolutional Layers

- We've seen convolutions many times in the course so far, but we used them with a specific goal
  - We needed to specify the kernel for a specific calculation
  - Calculating derivatives of an image, smoothing
- In a CNN, the weights in the kernel are optimized by the network



# Network Architecture Design

## **Question:**

OK, We have defined the layers of a network. How do you know how to design one specifically?

There is no single correct answer to this. It will depend on a variety of factors such as:

- The problem you want to solve and the data you have
- Problem complexity/difficulty
- Hardware limitations

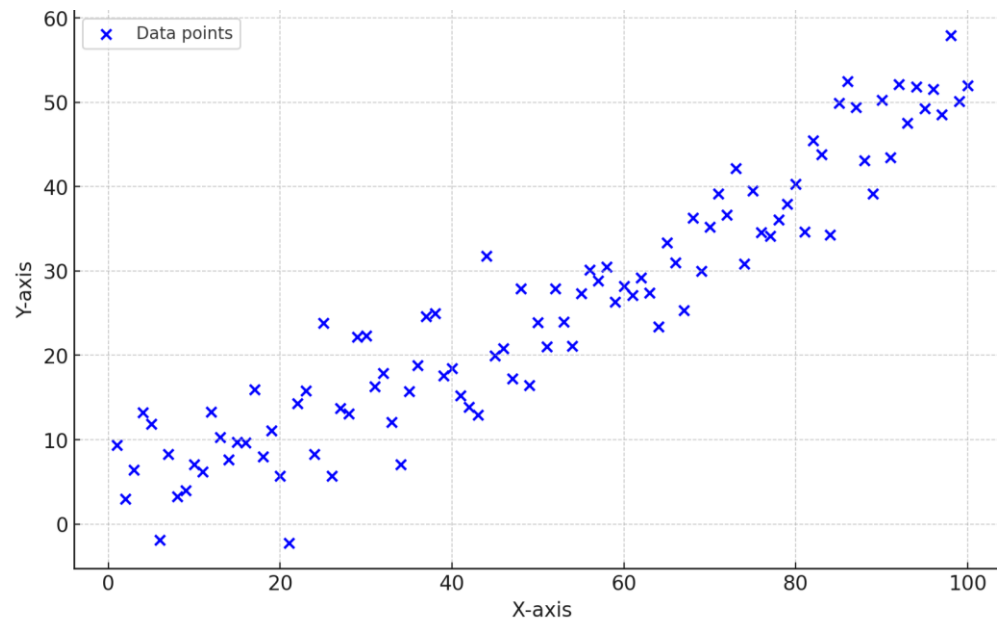
You could often just start with a well-known architecture and tweak it for your needs.

In the homework, it will be provided to you.



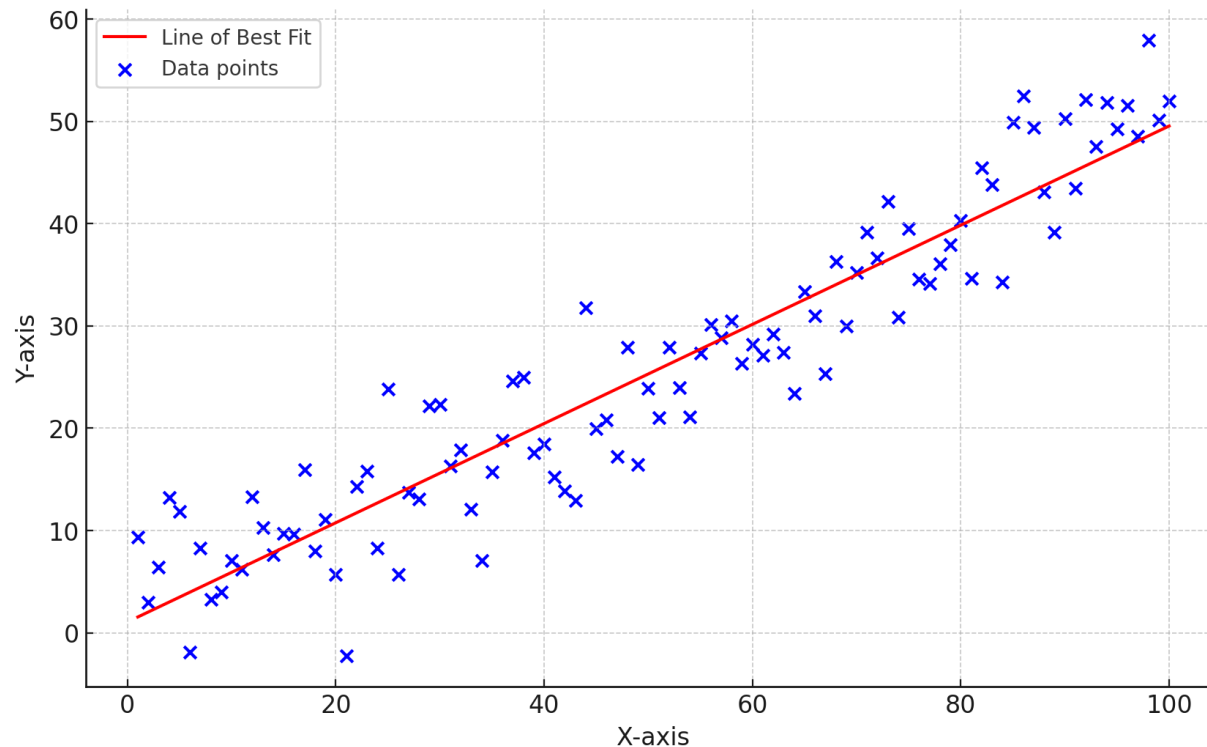
# Taking a step back

- We've discussed the main components of a deep neural network and general applications, but what exactly do they do?
  - Simply put, they are functions that model the underlying patterns in our data
- Taking a step backwards, let's look at some data



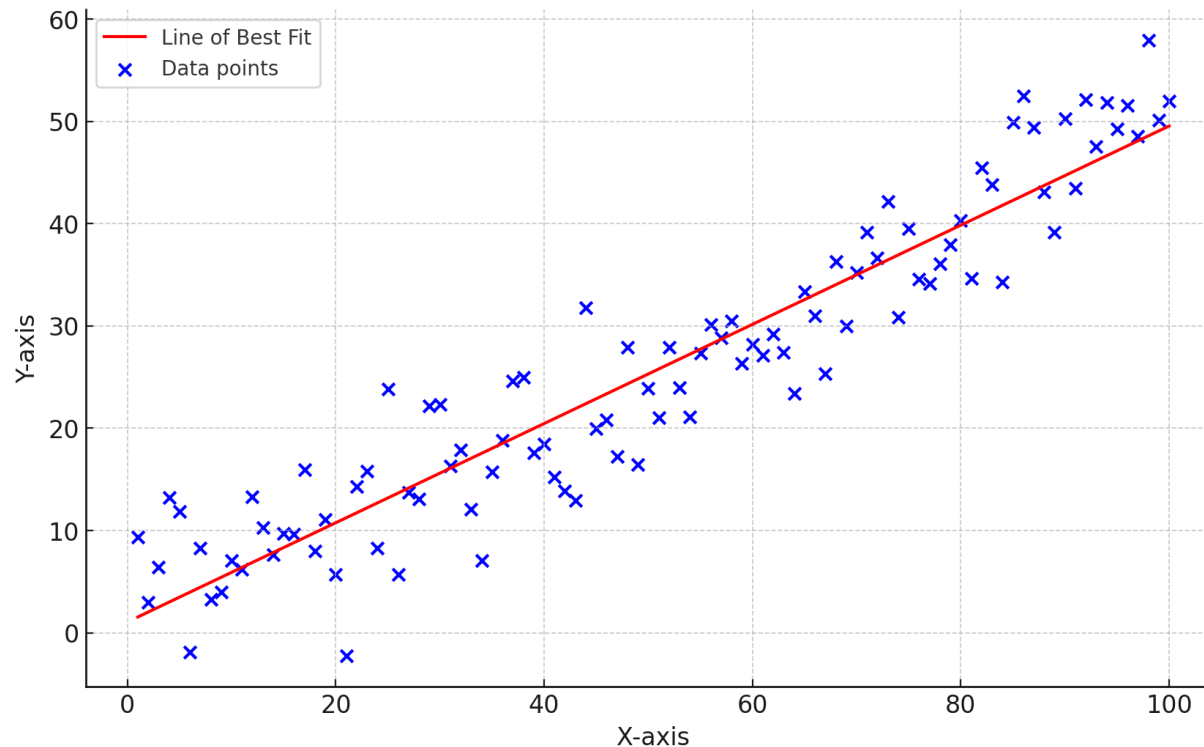
# Taking a step back

- What kind of model fits this data best?
  - Probably a line!  $f(x)=mx+b$
  - $m$  and  $b$  would be the weights that we want to optimize!



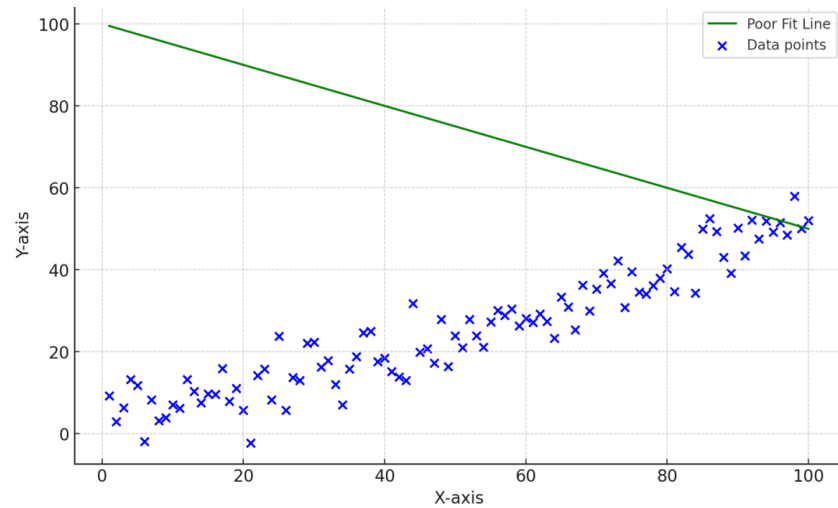
# Taking a step back

- Looking at the function  $f(x)=mx+b$ , we can describe this line with a neural network.
- This network would have a single fully-connected layer!
  - $f(x)=Ax$



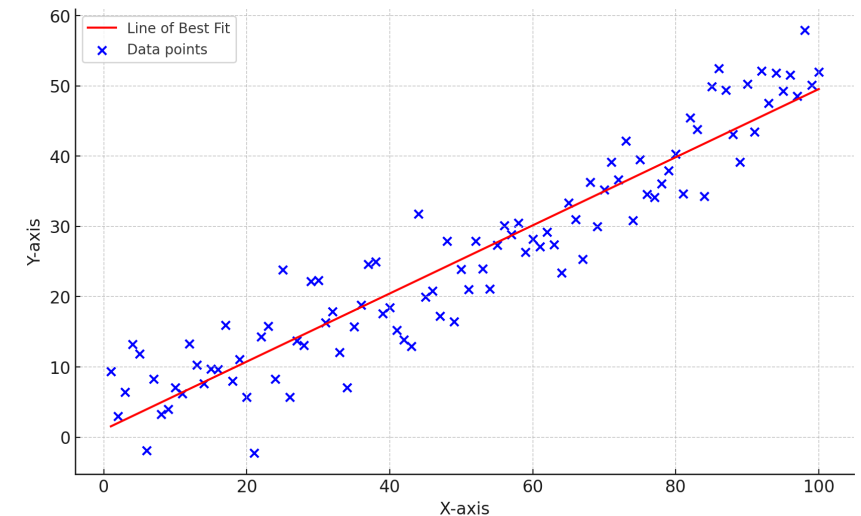
# So, we have a network. How do we train it?

- At this point, we have our model, and we have our data
  - Say we initialize the weights randomly
- So, how do we optimize or train it?



Random weights produce a line with a poor fit

$f(x)=mx+b$   
Training



After training, we obtain a line with a much better fit

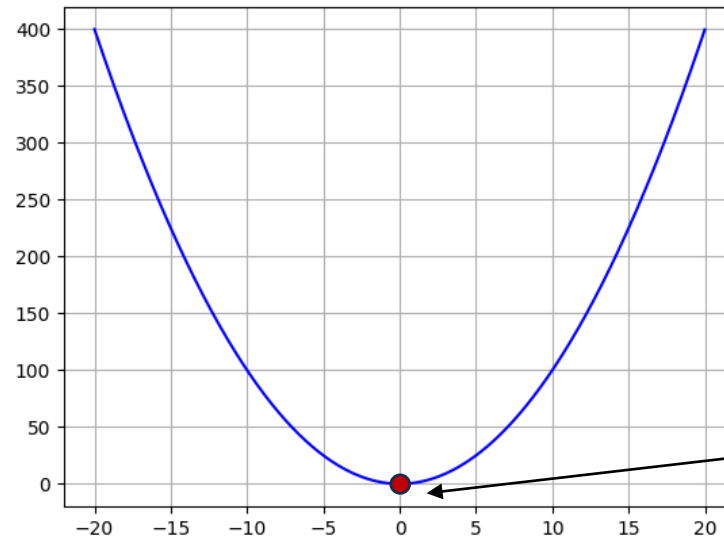
# So, we have a network. How do we train it?

- First, we need to define a loss function
  - For a regression problem, we can use something like mean squared error (MSE)
- Loss functions are a quantitative evaluation of how well your model is performing
- By minimizing the loss on the training data, we are modifying the parameters in the network that gives us the best performance

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$$

Diagram illustrating the components of the MSE formula:

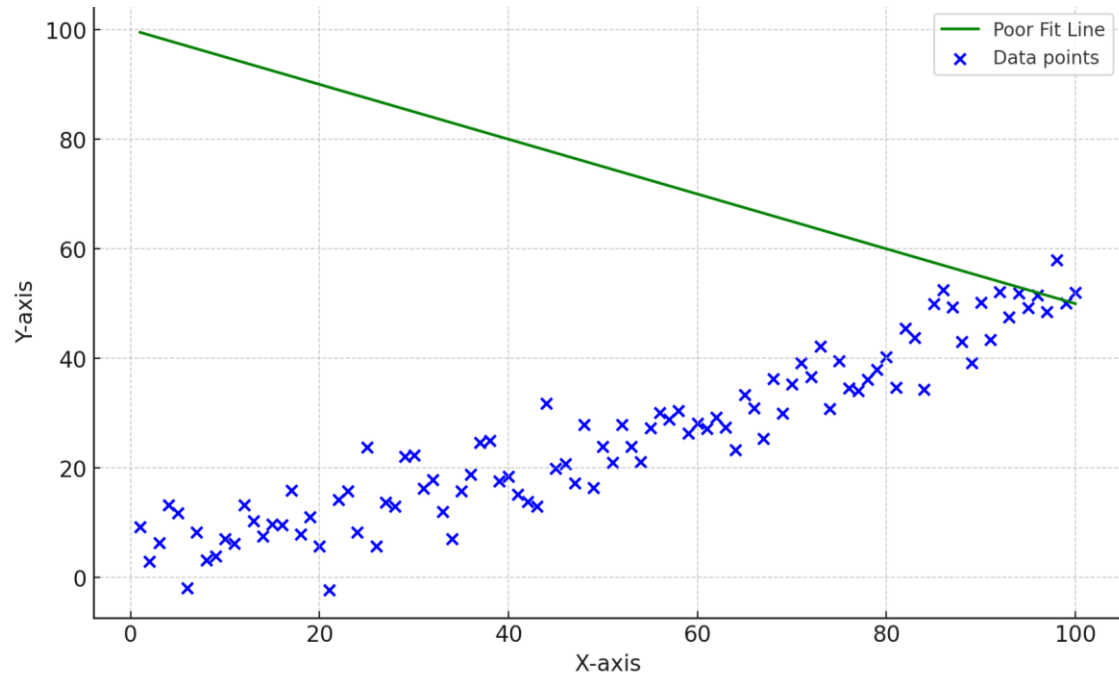
- Mean**: Indicated by a blue box around the  $\frac{1}{n}$  term.
- Squared**: Indicated by a blue box around the  $^2$  term.
- Error**: Indicated by a blue box around the  $(Y_i - \hat{Y}_i)$  term.
- Ground-truth label**: Points to  $Y_i$ .
- prediction**: Points to  $\hat{Y}_i$ , which is also labeled as  $f(x)=mx+b$ .



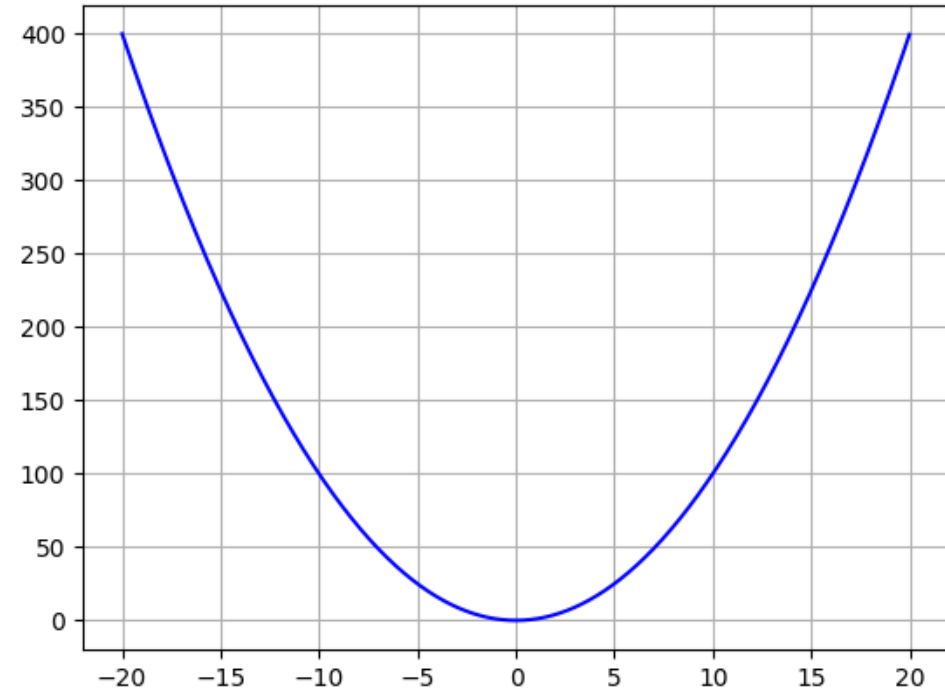
MSE plot might look something like this

A model with a perfect fit would produce 0 error on the training data

# So, we have a network. How do we train it?



Plot of data x versus label y



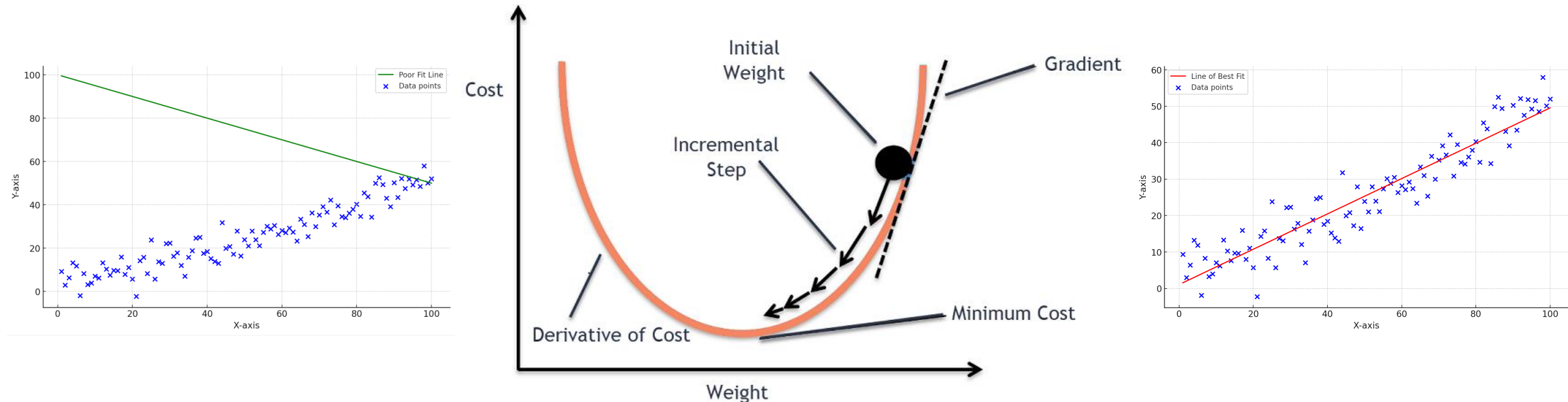
Plot of weights versus MSE

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n \text{Error}^2$$

The equation is annotated with 'Mean' above the fraction  $\frac{1}{n}$ , 'Error' above the term  $(Y_i - \hat{Y}_i)$ , and 'Squared' above the exponent  $^2$ .

# So, we have a network. How do we train it?

- We will train the network through some flavor of gradient descent
- We want move towards the minima of our loss function by adjusting the parameters of the network iteratively
- This is done by calculating the gradient of the loss function w.r.t. each parameter that you want to optimize



PyTorch



# PyTorch

- PyTorch is a machine learning framework primarily used in deep learning applications and research
- Has a well-supported Python interface and provides the ability to utilize hardware (GPU) acceleration
- Has a very similar syntax and feel as NumPy
- Can go back and forth between PyTorch and NumPy easily!