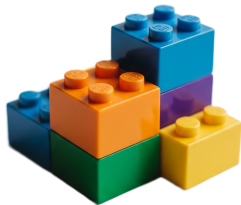


# Neural Network Building Blocks

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Maleeha Hassan  
Helmholtz AI

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# AI vs ML vs DL

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## Artificial Intelligent

- Creation of machines that can mimic human intelligence

## Machine Learning

- Allows machines to learn from data without explicitly being programmed

## Deep Learning

- Uses artificial NNs to train models on big data



## THE FASTEST THINGS ON EARTH



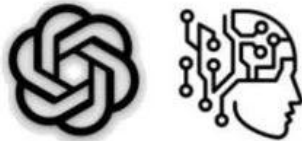
CHEETAH



AIRPLANE



SPEED OF LIGHT



PEOPLE BECOMING  
EXPERTS IN AI

**Difference between machine  
learning and AI:**  
If it is written in Python,  
it's probably machine learning  
If it is written in PowerPoint,  
it's probably AI

Curt Simon Harlinghausen // PUBLICIS.SAPIENT | 48FRWD AI ML

# Goal

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- Creating an algorithm to achieve a certain task for example image recognition
- Historically one had to invent algorithms
- Nowadays one trains a generalized algorithm that is already invented and implemented



# Some examples of AI

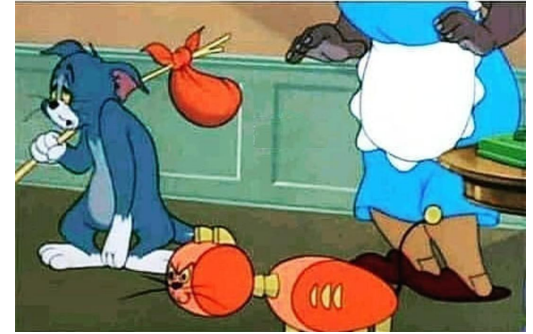
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## AlphaFold

Accelerating breakthroughs in biology with AI

The first victim of  
**Artificial Intelligence**



SCIENCE

GraphCast: AI model for faster and more accurate global weather forecasting

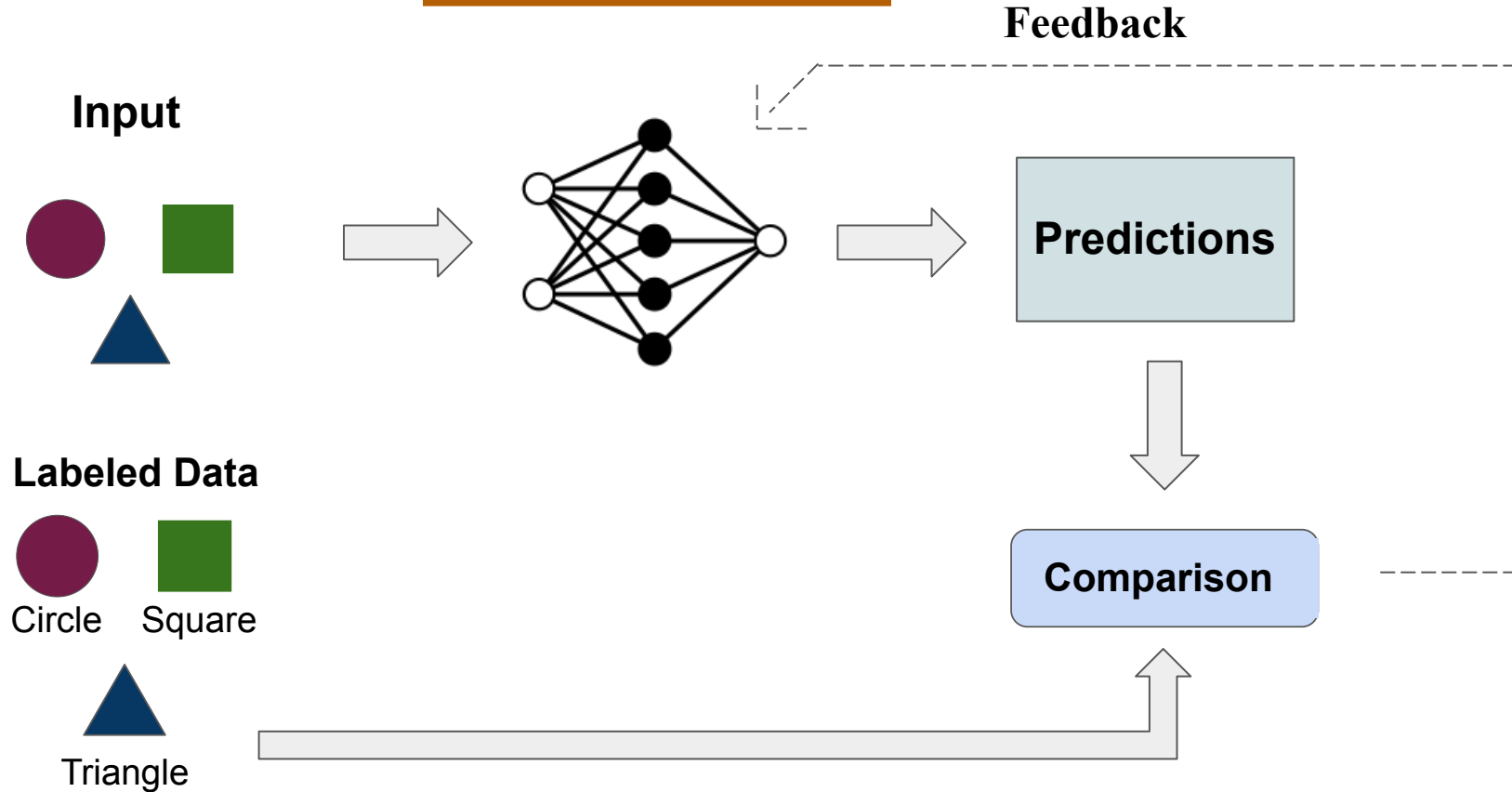
DINOv3:  
Revolutionary Self-Supervised Vision Model

# Machine Learning Vocabulary

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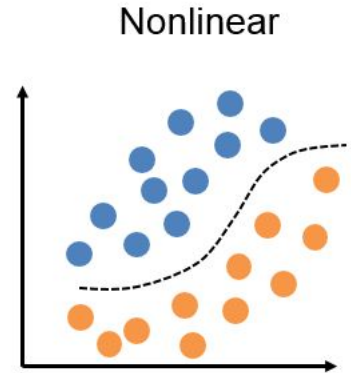
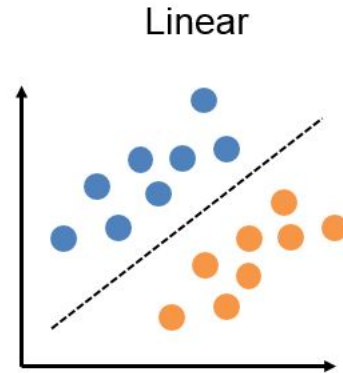
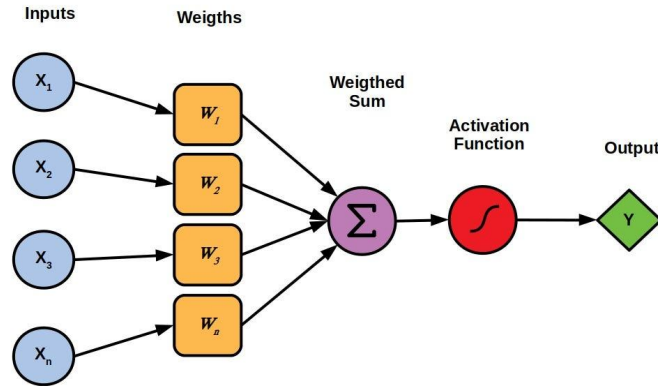
Supervised Learning	Unsupervised Learning	Reinforcement Learning
Learns a mapping from labeled inputs to target outputs.	Discovers structure in unlabeled data.	Learns decisions by interacting with an environment to maximize reward.
Classification, regression.	Clustering, dimensionality reduction.	Control, game playing, robotics.
Labeled examples (X,y).	Unlabeled examples (X).	No fixed dataset; experiences of states, actions, rewards.
Generalizes from labels to predict outputs on new data.	Groups, compresses, or reveals latent structure.	Learns a policy via trial-and-error.

# Supervised learning



# The Perceptron by Rosenblatt

A Perceptron is the simplest type of artificial neuron, introduced by Frank Rosenblatt in 1958.



credits: starship-knowledge.com

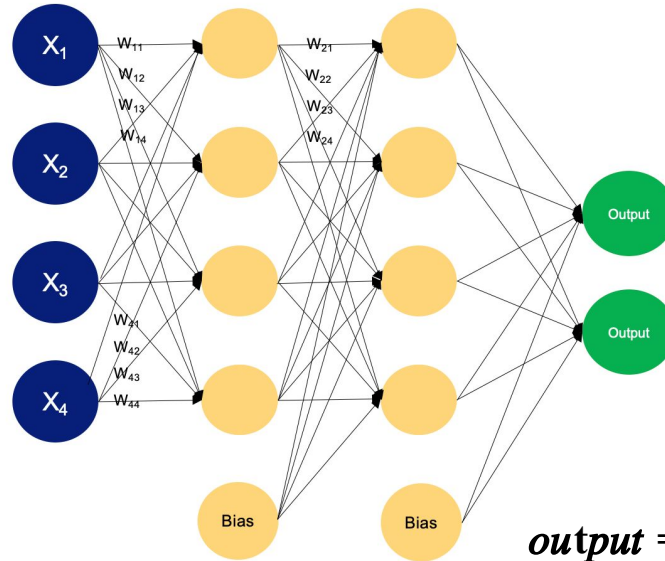
<https://github.com/jtsulliv/ML-from-scratch/blob/master/Neural-Networks/perceptron.ipynb>



# MultiLayer Perceptron

A multilayer perceptron (MLP) has multiple layers, including one or more hidden layers, allowing it to learn and represent more complex.

Inner layer | Hidden layers | Outer layer



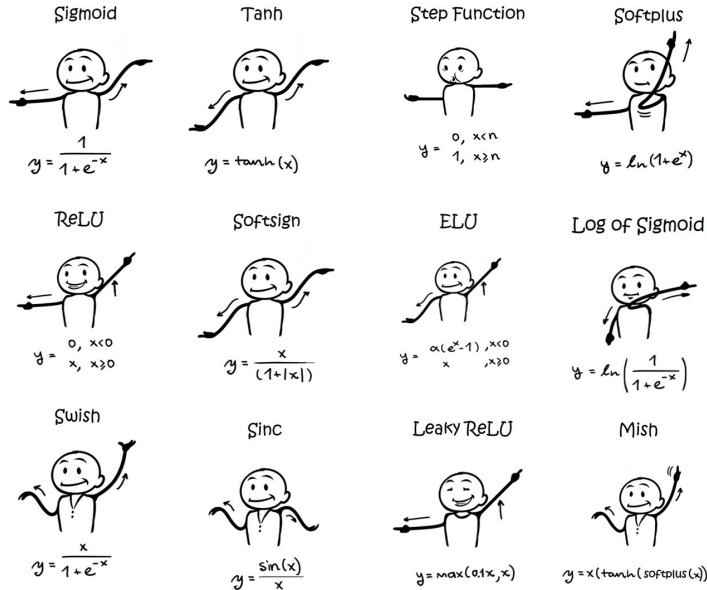
$$output = Activation (\sum (xi*wi)+bias)$$

# Activation Functions



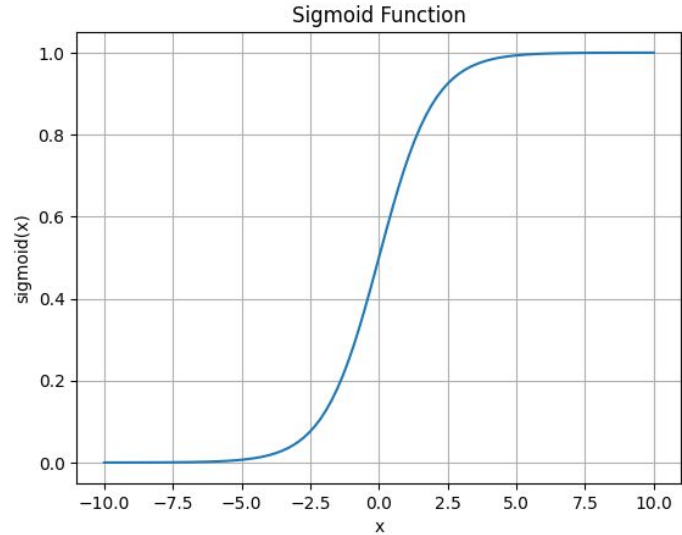
# Activation Functions

- Activation function decides whether a neuron should be activated by calculating the weighted sum of inputs and adding a bias term.
- Activation functions introduce non-linearity to neural networks.



# Sigmoid Activation Function

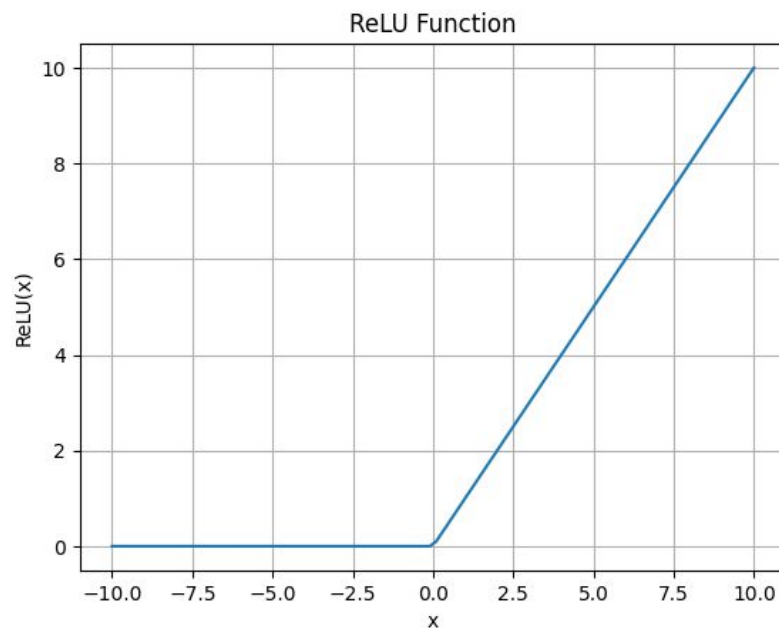
- values are between 0 and 1.
- Example: Output = 0.85  $\rightarrow$  85% chance this is a cat.
- The derivative of sigmoid is  $\sigma'(x) = \sigma(x) \cdot (1 - \sigma(x))$ .
- Mainly used in binary classification.
- Has vanishing gradient problem (network stops learning when inputs are large or too small).



$$\sigma(x) = 1 / (1 + e^{-x})$$

# Rectified Linear Units (ReLU)

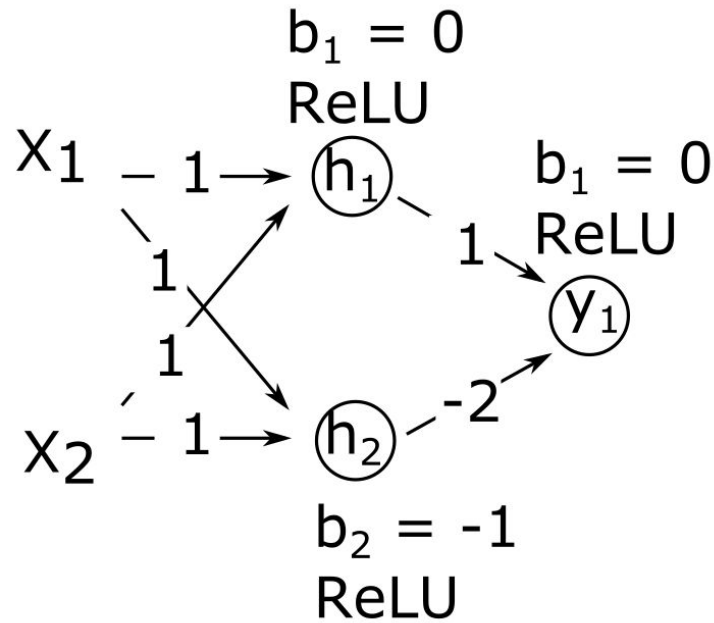
- If the function receives any negative input, it returns 0; however, if the function receives any positive value  $x$ , it returns that value.
- Doesn't saturate for positive values which avoids vanishing gradient problem.
- Fast to compute (no exponentials).
- Dying ReLU problem → if a neuron always gets negative inputs, it outputs 0 forever and becomes dead.
- Leaky ReLU fixes the problem by allowing a small curve when  $x < 0$ .



$$f(x) = \max(0, x)$$

# NEURAL NETWORK CALCULATIONS

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<b>x1</b>	<b>x2</b>	<b>y</b>
0	0	..
0	1	..
1	0	..
1	1	..

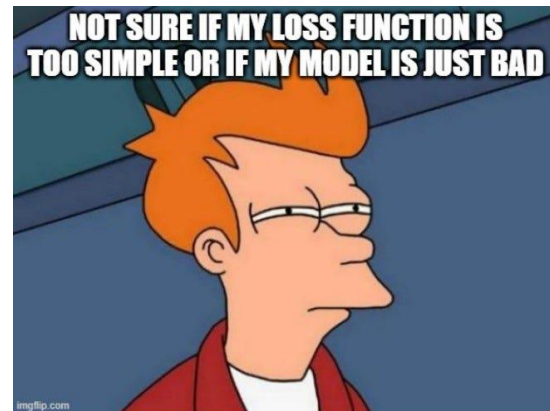
?

Now that we've seen how activation functions turn numbers into meaningful predictions — *How do we measure whether those predictions are correct?*

# Loss Function

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- A loss function (also called a cost function or error function) measures how wrong the model's prediction is compared to the true answer.
- Input is prediction + true label and output is a single number (loss).
- Provides the *learning signal* (error) for backpropagation.
- The goal of training is to minimize loss.
- The choice of loss function depends on the task at hand.





# Loss Function

- **Regression losses**

- Mean Absolute Error (L1)

- $MAE = (1/n) * \sum |actual - predicted|$

- Mean Squared Error (L2)

- $MSE = (1/n) * \sum |actual - predicted|^2$

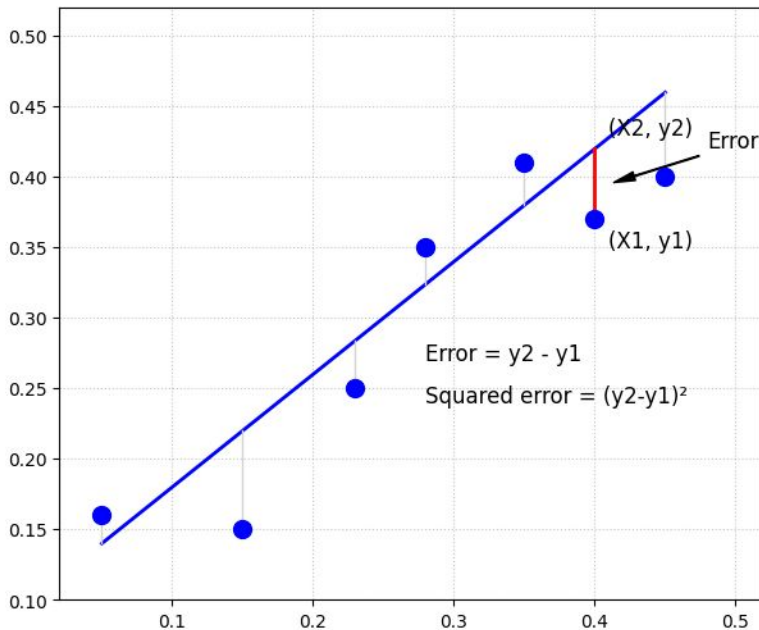
- **Classification losses**

- Binary Cross Entropy (BCE)

- $Loss = - ( y * \log(p) + (1 - y) * \log(1 - p) )$

- $-(1/N) * \sum [ y_i * \log(p_i) + (1 - y_i) * \log(1 - p_i) ]$

- Categorical Class Entropy (CCE)



# Helping Materials

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- Youtube Channels
  - 3blue1brown
  - StatQuest
  - Digital Sreeni
- Websites and Blogs
  - [Introduction to Deep Learning](#)
  - [Understanding Deep Learning](#)
  - [https://gombru.github.io/2018/05/23/cross\\_entropy\\_loss/](https://gombru.github.io/2018/05/23/cross_entropy_loss/)
  - [Neural Networks, Manifolds, and Topology -- colah's blog](#)
  - [ConvNetJS demo: Classify toy 2D data](#)
  - [Neural networks: Activation functions | Machine Learning | Google for Developers](#)

# Hands On

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<https://github.com/maleehahassan/NNBuildingBlocksTeachingPt1>