Introduction to Machine Learning

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How to design machine learning tools for Optics

Workshop

May 6th 2024

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SCIENCES SORBONNE UNIVERSITÉ

ENS Département de Physique École normale supérieure

cnrs

Reference and good ressource

- 3blue1brown on Neural Networks:
- https://youtube.com/playlist?list=PLZHQObOWTQDNU6R1_67000Dx_ZCJB-3pi&si=xvbZnuQsteonsFpn

Outline

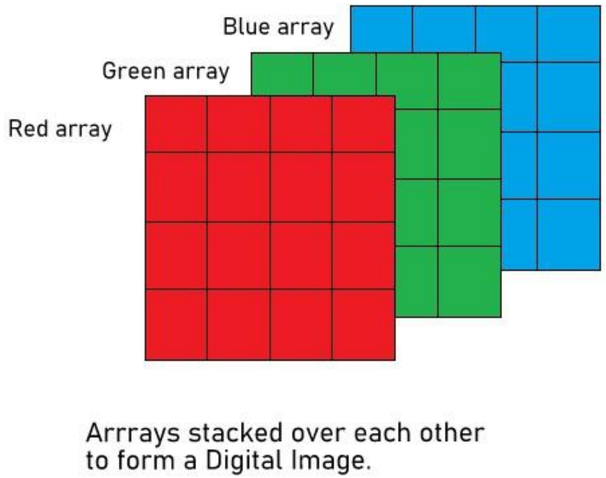
- Introduction
- Machine learning mechanics
  - Back-propagation of Error and Gradient Descent
  - Activation function
  - Loss function
    - Cross entropy loss and Classification
    - Mean Squared Error and Regression
  - Convolutional Neural Networks

Introduction

- Data
- Model
- Loss function

Introduction
-
Data

Image [1]



Pig

Dog

Cat

Sound [2]

Classification

[1] - https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.geeksforgeeks.org%2Fmatlab-rgb-image-representation%2F&psig=AOvVaw3nGrGp2TvHzoNbSHI8GIK8&ust=1714476975492000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCNDEicqq54UDFQAAAAAdAAAAABAE

[2] - https://www.google.com/url?sa=i&url=https%3A%2F%2Fpngtree.com%2Fso%2Fblack-and-white-sound-waves&psig=AOvVaw3ZKMWpx1T6W2Yw4UVqrS33&ust=1714476738077000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCID-oNmp54UDFQAAAAAdAAAAABAK

Introduction
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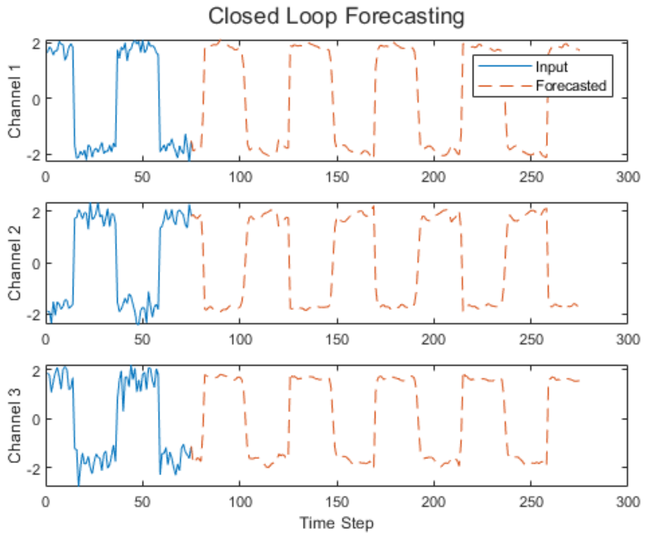
Data

Image [1]

Sound [2]



Forecasting

[1] - https://www.google.com/url?sa=i&url=https%3A%2F%2Fstock.adobe.com%2Ffr%2Fsearch%2Fimages%3Fk%3Dsequence&psig=AOvVaw3FXo8WKCjXAvoFTo8OsmGb&ust=1714477066240000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCMDZ4fWq54UDFQAAAAAdAAAAABAE

[2] - https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.mathworks.com%2Fhelp%2Fdeeplearning%2Fug%2Ftime-series-forecasting-using-deep-learning.html&psig=AOvVaw35v6rvPsQNiSFWjHxQY4-i&ust=1714477261772000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCNCR9tKr54UDFQAAAAAdAAAAABAJ

Introduction
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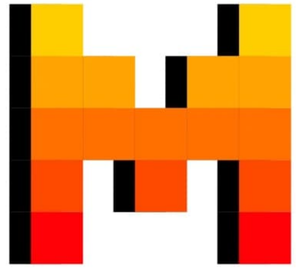
Data

Text



Text prediction

[1] - https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.iemoji.com%2Fview%2Femoji%2F1068%2Fproposed%2Fpages&psig=AOvVaw2xFcqlKl-W9YG-DS6hZKb5&ust=1714479822672000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCKiygZi154UDFQAAAAAdAAAAABAE

[2] - https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.geeky-gadgets.com%2Fchat-gpt-login%2F&psig=AOvVaw0zJUSVrrfJX2mgnomf1Yvv&ust=1714479965542000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCPDb5aS254UDFQAAAAAdAAAAABAE
https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.jaimelesstartups.fr%2Fmistral-ai-ia-generative-llm%2F&psig=AOvVaw3HoeZ6G6buYd5ZIUq6MDgK&ust=1714479988170000&source=images&cd=vfe&opi=89978449&ved=0CBIQjRxqFwoTCNCNzqO254UDFQAAAAAdAAAAABAK
https://plugins.jetbrains.com/plugin/17718-github-copilot
https://www.google.com/url?sa=i&url=https%3A%2F%2Fca.linkedin.com%2Fcompany%2Fblackboxtech&psig=AOvVaw363p8kpYRiUvRuvnxwoGb9&ust=1714480207899000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCNiZoM-254UDFQAAAAAdAAAAABAE

Important

- Generalization
- Data formatting
- **Model**

Introduction
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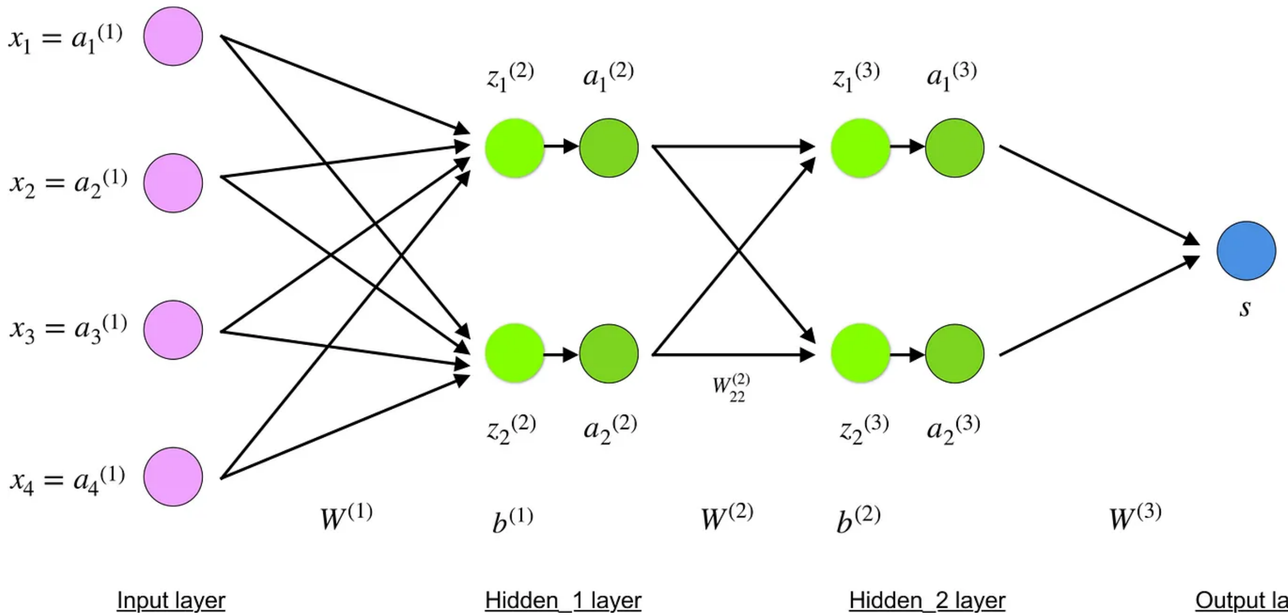
Model

Fully connected layer [1]



[1] -https://www.google.com/url?sa=i&url=https%3A%2F%2Fmedium.com%2F%40mayankverma05032001%2Fbinary-classification-using-convolution-neural-network-cnn-model-6e35cdf5bdbb&psig=AOvVaw2y5GRO7aT-W01WYOiBYh3j&ust=1714480373134000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCJCdup6354UDFQAAAAAdAAAAABAE

Introduction
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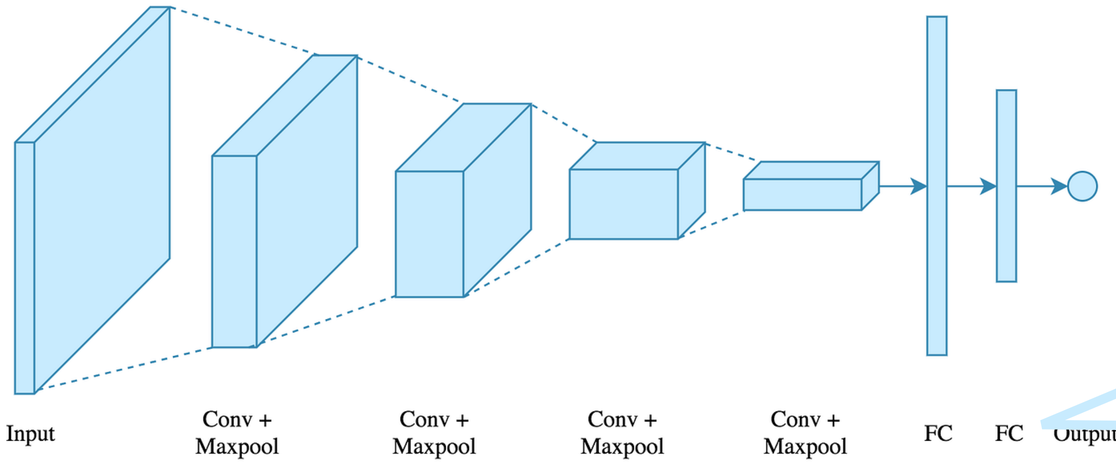
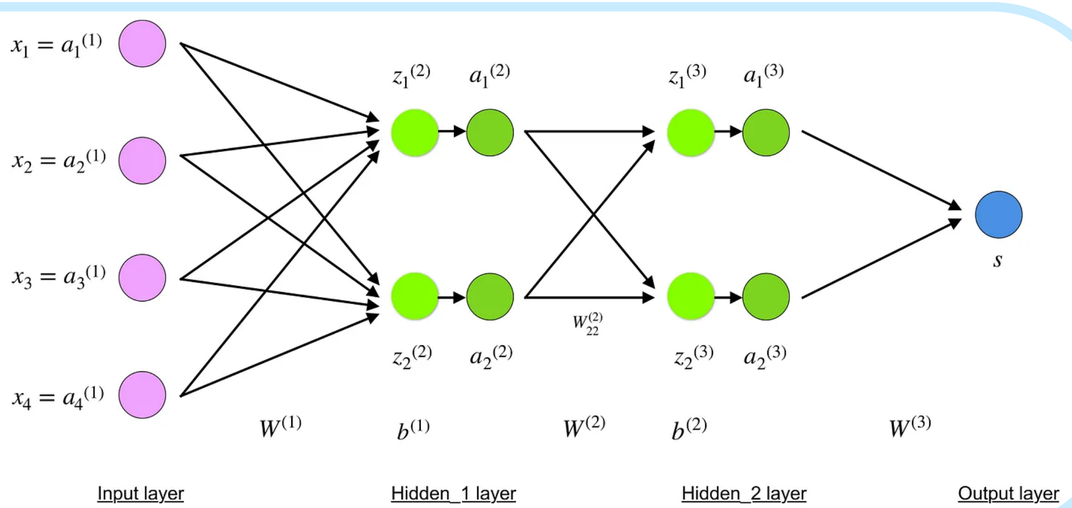
Model

Convolutional Neural Network [1]



Fully connected layer [2]



[1] -https://www.google.com/url?sa=i&url=https%3A%2F%2Fmedium.com%2F%40mayankverma05032001%2Fbinary-classification-using-convolution-neural-network-cnn-model-6e35cdf5bdbb&psig=AOvVaw2y5GRO7aT-Wo1WYOiBYh3j&ust=1714480373134000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCJCdup6354UDFQAAAAAdAAAAABAE

[2] - https://towardsdatascience.com/understanding-backpropagation-algorithm-7bb3aa2f95fd

Important

- The proper model for data
- Mindful of the memory and computing power
- **Loss function**

Introduction
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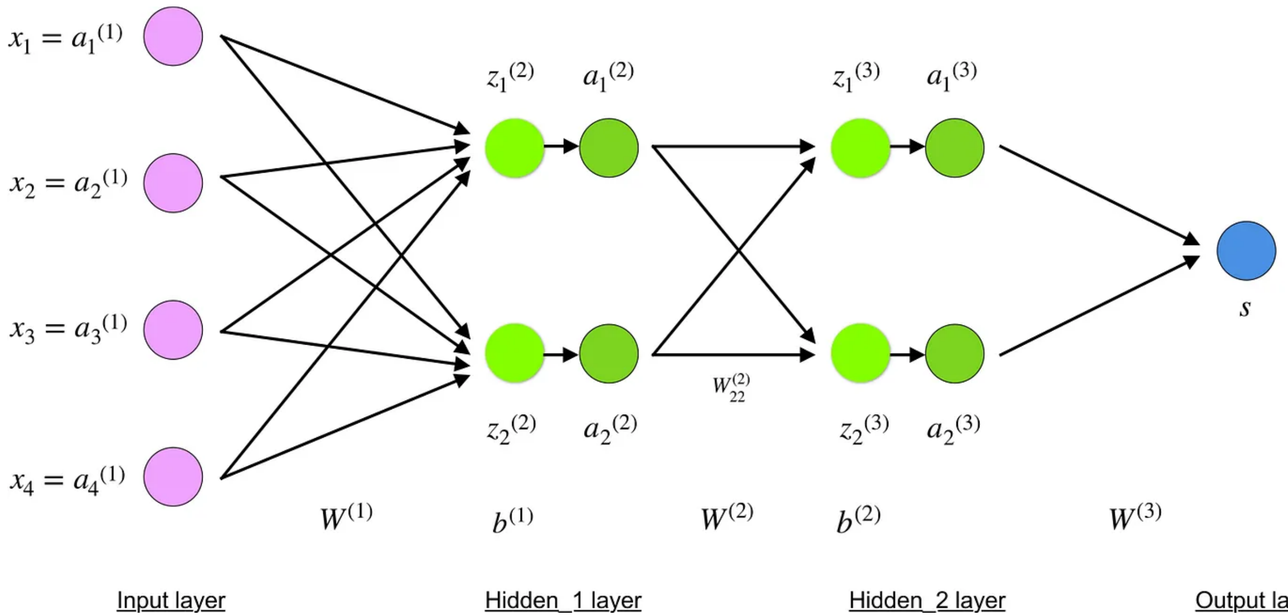
Model

Fully connected layer [1]



[1] -https://www.google.com/url?sa=i&url=https%3A%2F%2Fmedium.com%2F%40mayankverma05032001%2Fbinary-classification-using-convolution-neural-network-cnn-model-6e35cdf5bdbb&psig=AOvVaw2y5GRO7aT-W01WYOiBYh3j&ust=1714480373134000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCJCdup6354UDFQAAAAAdAAAAABAE

Introduction
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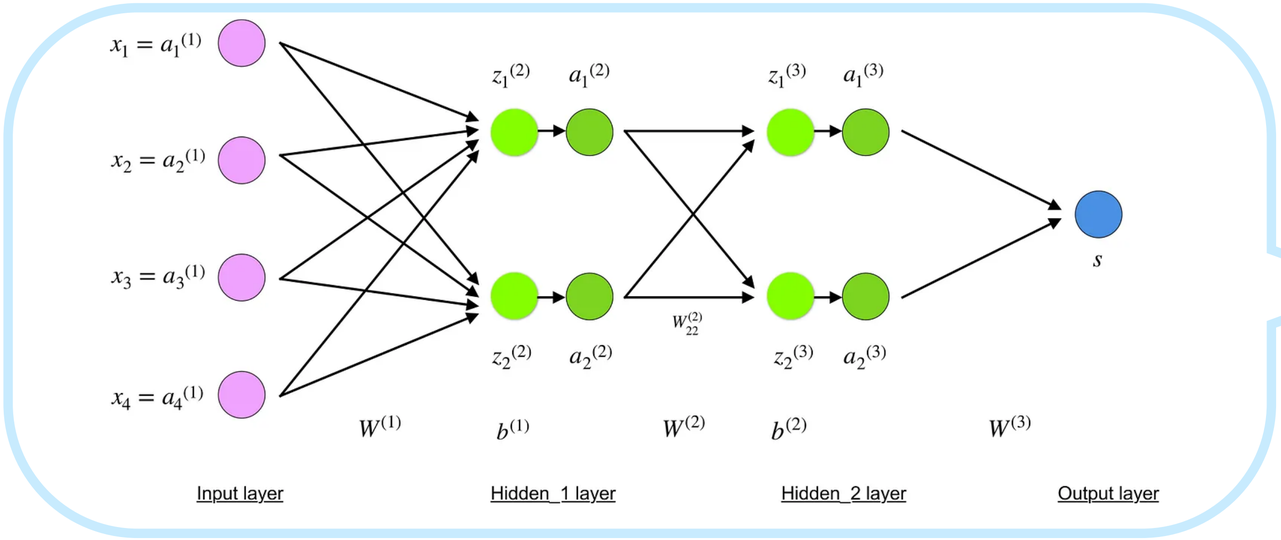
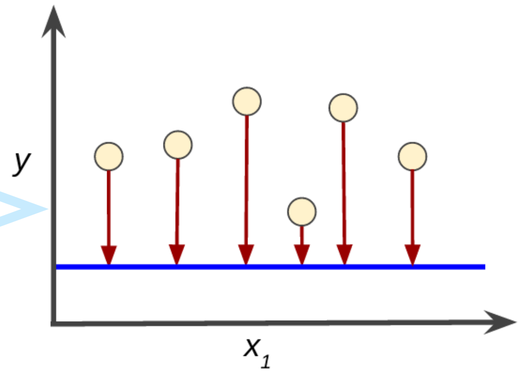
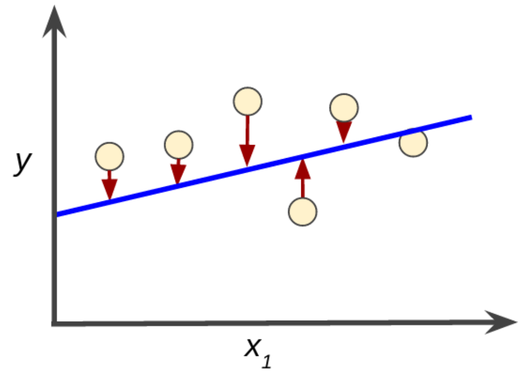
Loss function

Fully connected layer [1]



Loss Function [1]





[1] -https://www.google.com/url?sa=i&url=https%3A%2F%2Fmedium.com%2F%40omayankverma05032001%2Fbinary-classification-using-convolution-neural-network-cnn-model-6e35cdf5bdbb&psig=AOvVaw2y5GRO7aT-W01WYOiBYh3j&ust=1714480373134000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCJCdup6354UDFQAAAAAdAAAAABAE

[2] - https://developers.google.com/machine-learning/crash-course/descending-into-ml/training-and-loss

Machine learning mechanics

- Back-propagation of Error and Gradient Descent
- Activation function
- Convolutional Neural Networks
- Loss function

Machine learning mechanics
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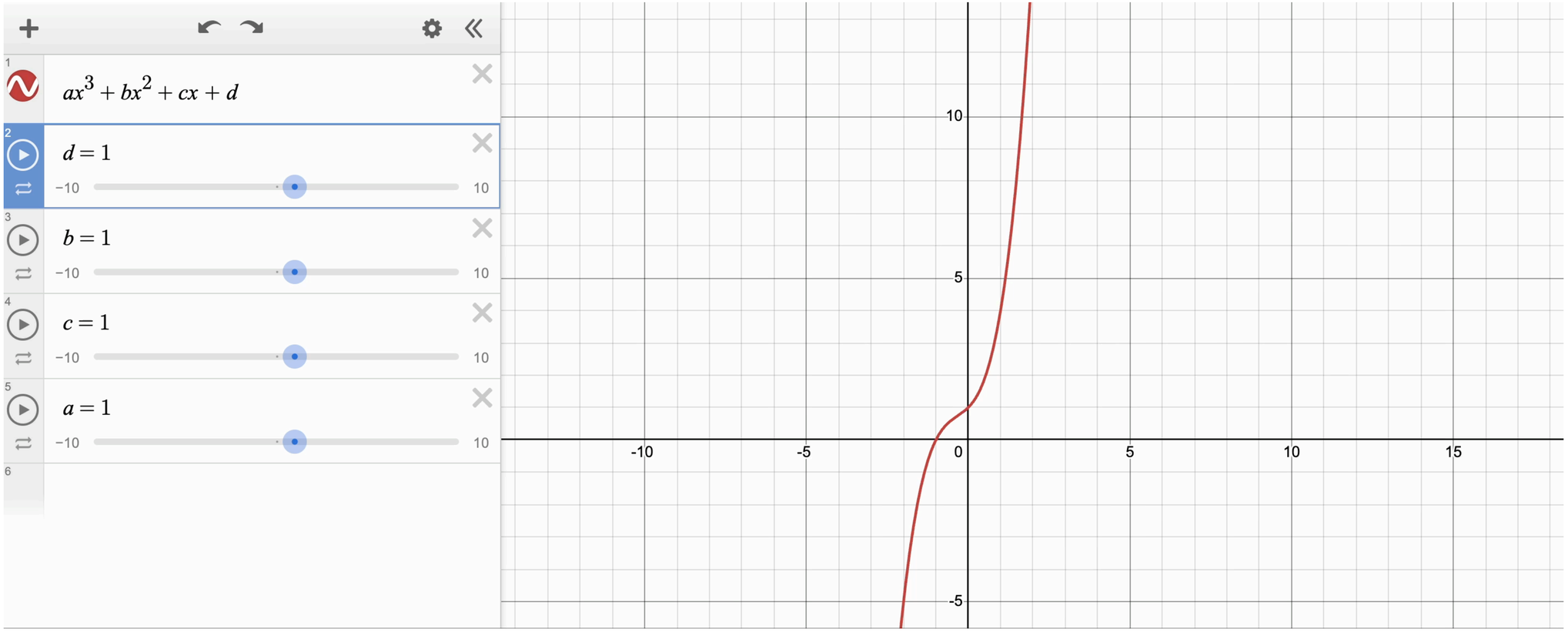
Back-propagation of Error and Gradient Descent



Machine learning mechanics
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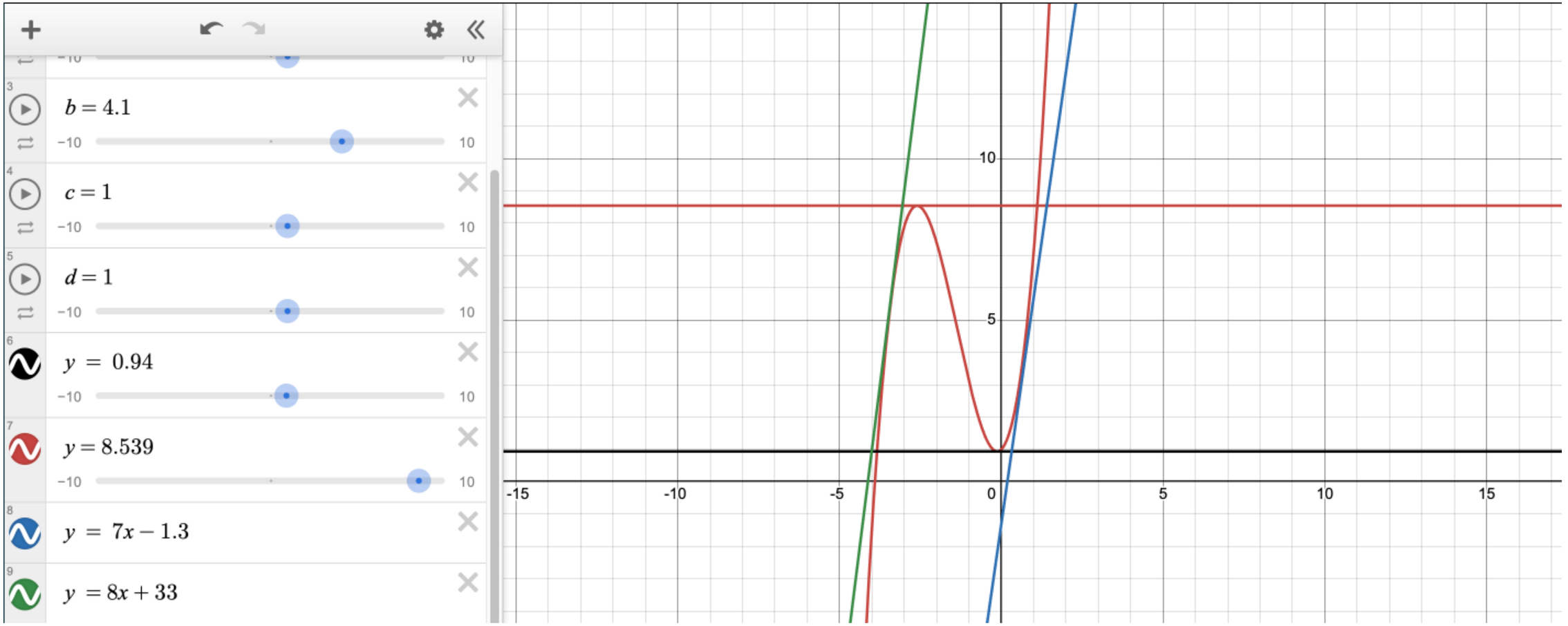
Back-propagation of Error and Gradient Descent



Machine learning mechanics
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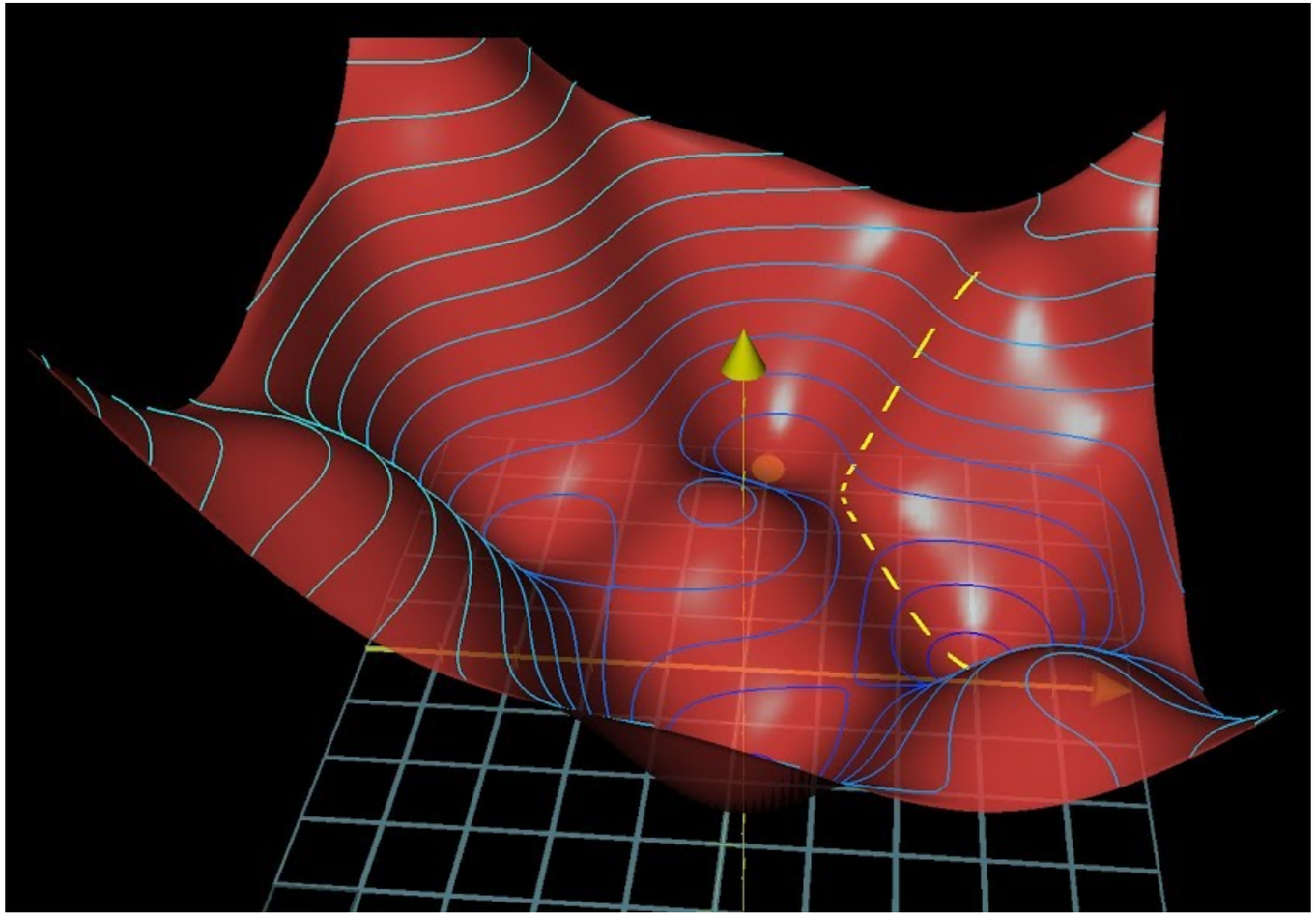
Gradient Descent



https://www.google.com/url?sa=i&url=https%3A%2F%2Fm.youtube.com%2Fwatch%3Fv%3DIHZwWFHWa-w&psig=AOvVaw0Cn41Px9Jc3_dY_qNyZEfg&ust=1714573793103000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCND01qCT60UDFQAAAAAdAAAAABAE

Machine learning mechanics
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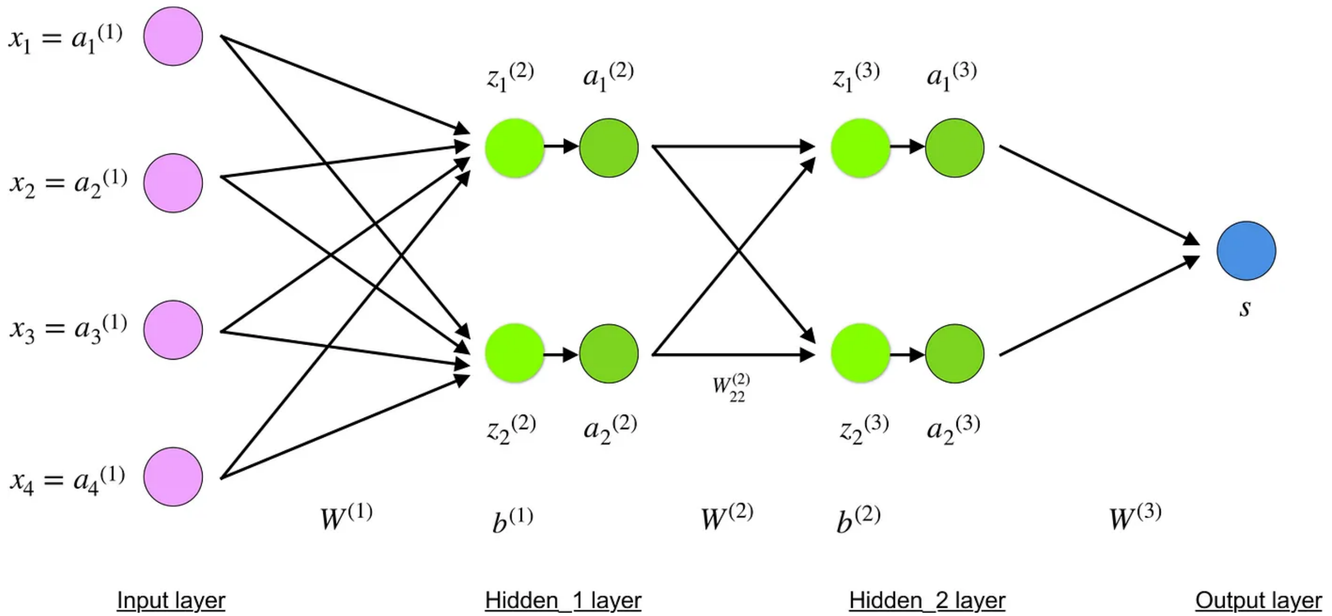
Back-propagation of Error and Gradient Descent

Fully connected layer [1]



[1] -https://www.google.com/url?sa=i&url=https%3A%2F%2Fwww.researchgate.net%2Ffigure%2FMulti-Layer-Perceptron-MLP-diagram-with-four-hidden-layers-and-a-collection-of-single_fig1_334609713&psig=AOvVaw29hcG3fO4ZfJHPdcwvvhqg&ust=1714481773623000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCLiQqLq854UDFQAAAAAdAAAAABAE

Machine learning mechanics
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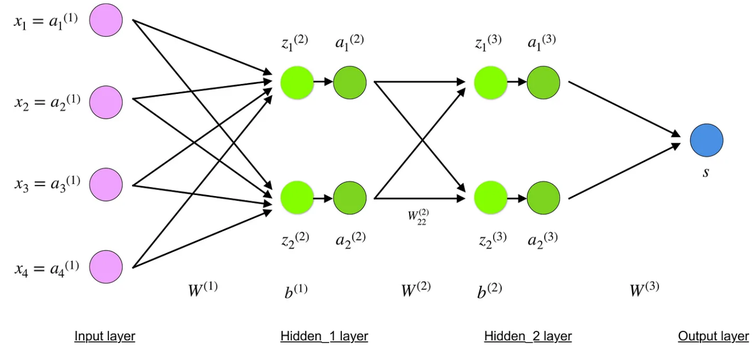
Back-propagation of Error and Gradient Descent



$$W^{(1)} = \begin{bmatrix} W_{11}^{(1)} & W_{12}^{(1)} & W_{13}^{(1)} & W_{14}^{(1)} \\ W_{21}^{(1)} & W_{22}^{(1)} & W_{23}^{(1)} & W_{24}^{(1)} \end{bmatrix} \qquad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} \qquad b^{(1)} = \begin{bmatrix} b_1^{(1)} \\ b_2^{(1)} \end{bmatrix}$$

$$z^{(2)} = \begin{bmatrix} W_{11}^{(1)}x_1 + W_{12}^{(1)}x_2 + W_{13}^{(1)}x_3 + W_{14}^{(1)}x_4 \\ W_{21}^{(1)}x_1 + W_{22}^{(1)}x_2 + W_{23}^{(1)}x_3 + W_{24}^{(1)}x_4 \end{bmatrix} + \begin{bmatrix} b_1^{(1)} \\ b_2^{(1)} \end{bmatrix}$$

[1] -https://www.google.com/url?sa=i&url=https%3A%2F%2Fmedium.com%2F%40mayankverma05032001%2Fbinary-classification-using-convolution-neural-network-cnn-model-6e35cdf5bdbb&psig=AOvVaw2y5GRO7aT-W01WYOiBYh3j&ust=1714480373134000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCJCdup6354UDFQAAAAAdAAAAABAE

Machine learning mechanics
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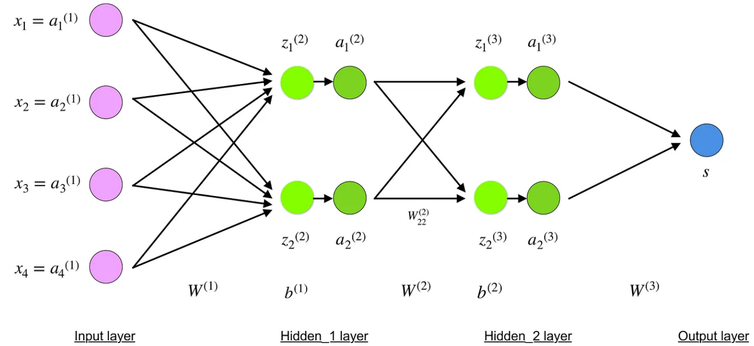
Forward Propagation



$$x = a^{(1)} \qquad Input\ layer$$

$$z^{(2)} = W^{(1)}x + b^{(1)} \qquad neuron\ value\ at\ Hidden_1\ layer$$

$$a^{(2)} = f(z^{(2)}) \qquad activation\ value\ at\ Hidden_1\ layer$$

$$z^{(3)} = W^{(2)}a^{(2)} + b^{(2)} \qquad neuron\ value\ at\ Hidden_2\ layer$$

$$a^{(3)} = f(z^{(3)}) \qquad activation\ value\ at\ Hidden_2\ layer$$

$$s = W^{(3)}a^{(3)} \qquad Output\ layer \qquad ==> \qquad C = cost(s, y)$$

[1] -https://www.google.com/url?sa=i&url=https%3A%2F%2Fmedium.com%2F%40mayankverma05032001%2Fbinary-classification-using-convolution-neural-network-cnn-model-6e35cdf5bdbb&psig=AOvVaw2y5GRO7aT-W01WYOiBYh3j&ust=1714480373134000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCJCdup6354UDFQAAAAAdAAAAABAE

Machine learning mechanics
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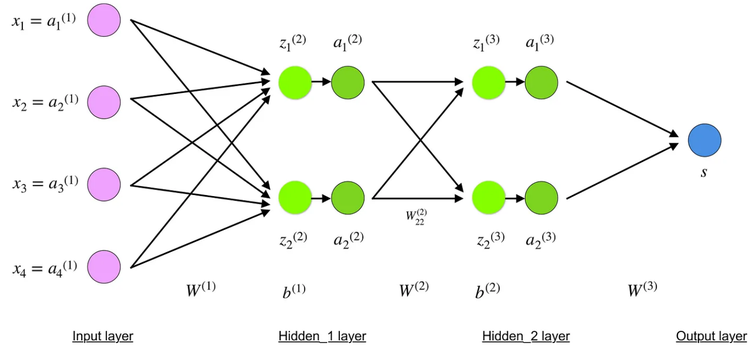
Back Propagation



$$z_j^l = \sum_{k=1}^{m} w_{jk}^l a_k^{l-1} + b_j^l \qquad by\ definition$$

$$m\ -\ number\ of\ neurons\ in\ l-1\ layer$$

$$\frac{\partial C}{\partial w_{jk}^l} = \frac{\partial C}{\partial z_j^l}\frac{\partial z_j^l}{\partial w_{jk}^l} \qquad chain\ rule \qquad \frac{\partial z_j^l}{\partial w_{jk}^l} = a_k^{l-1} \qquad by\ differentiation\ (calculating\ derivative)$$

$$\frac{\partial C}{\partial w_{jk}^l} = \frac{\partial C}{\partial z_j^l} a_k^{l-1} \qquad final\ value$$

[1] -https://www.google.com/url?sa=i&url=https%3A%2F%2Fmedium.com%2F%40mayankverma05032001%2Fbinary-classification-using-convolution-neural-network-cnn-model-6e35cdf5bdbb&psig=AOvVaw2y5GRO7aT-W01WYOiBYh3j&ust=1714480373134000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCJCdup6354UDFQAAAAAdAAAAABAE

Machine learning mechanics
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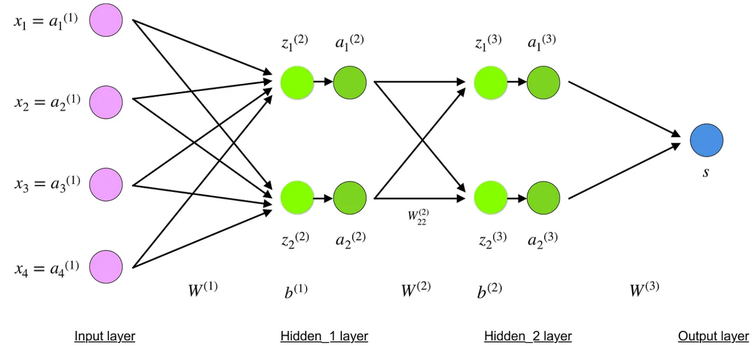
Back Propagation



$$z_j^l = \sum_{k=1}^{m} w_{jk}^l a_k^{l-1} + b_j^l \qquad by\ definition$$

$$m\ -\ number\ of\ neurons\ in\ l-1\ layer$$

$$\frac{\partial C}{\partial b_j^l} = \frac{\partial C}{\partial z_j^l}\frac{\partial z_j^l}{\partial b_j^l} \qquad chain\ rule \qquad \frac{\partial z_j^l}{\partial b_j^l} = 1 \qquad by\ differentiation\ (calculating\ derivative)$$

$$\frac{\partial C}{\partial b_j^l} = \frac{\partial C}{\partial z_j^l}1 \qquad final\ value$$

[1] -https://www.google.com/url?sa=i&url=https%3A%2F%2Fmedium.com%2F%40mayankverma05032001%2Fbinary-classification-using-convolution-neural-network-cnn-model-6e35cdf5bdbb&psig=AOvVaw2y5GRO7aT-W01WYOiBYh3j&ust=1714480373134000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCJCdup6354UDFQAAAAAdAAAAABAE

Machine learning mechanics
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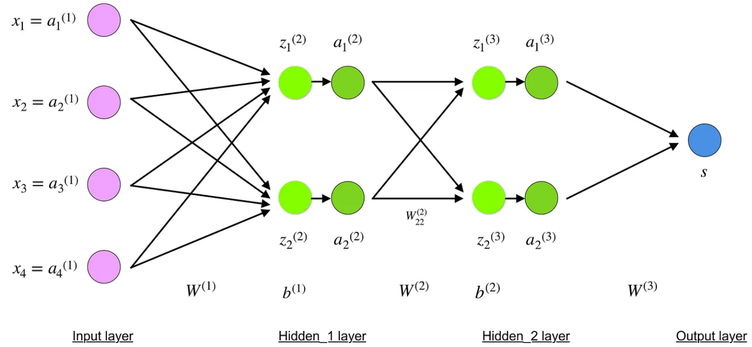
Back Propagation



$$while\ (termination\ condition\ not\ met)$$

$$w := w - \epsilon \frac{\partial C}{\partial w}$$

$$b := b - \epsilon \frac{\partial C}{\partial b}$$

$$end$$

Learning rate ϵ

[1] -https://www.google.com/url?sa=i&url=https%3A%2F%2Fmedium.com%2F%40mayankverma05032001%2Fbinary-classification-using-convolution-neural-network-cnn-model-6e35cdf5bdbb&psig=AOvVaw2y5GRO7aT-W01WYOiBYh3j&ust=1714480373134000&source=images&cd=vfe&opi=89978449&ved=0CBQQjhxqFwoTCJCdup6354UDFQAAAAAdAAAAABAE

Machine learning mechanics
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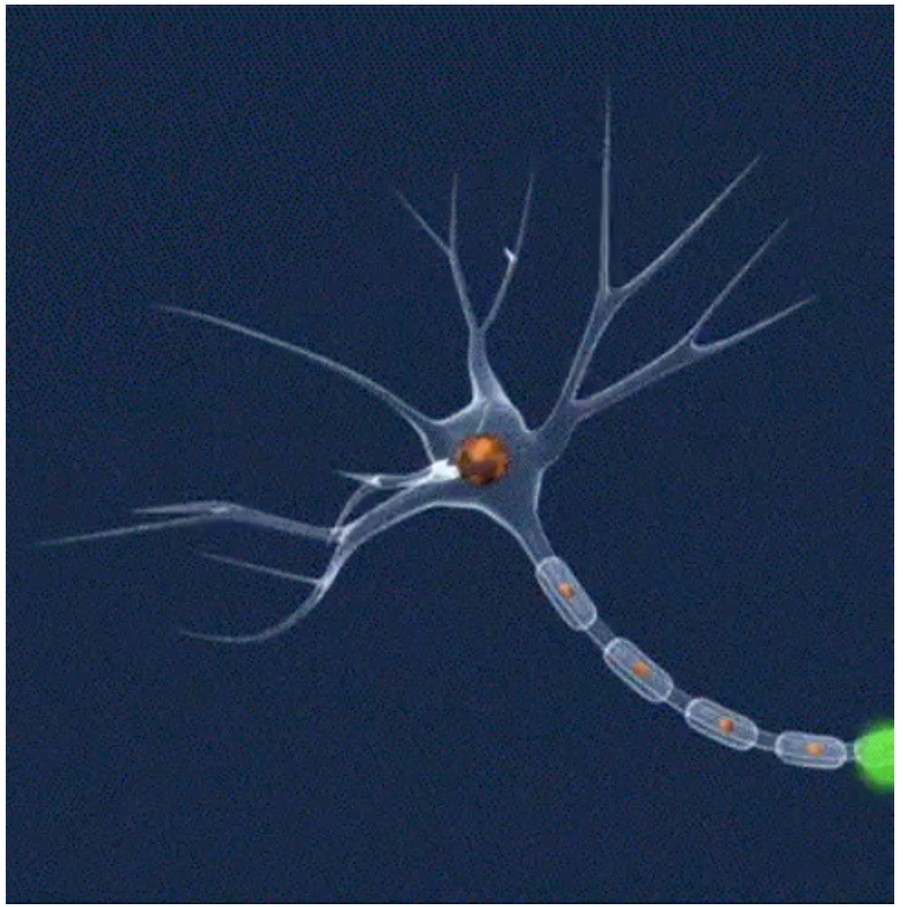
Activation Functions



https://medium.com/the-theory-of-everything/understanding-activation-functions-in-neural-networks-9491262884e0

https://www.nichd.nih.gov/newsroom/releases/031813-backwards-neurons

Machine learning mechanics

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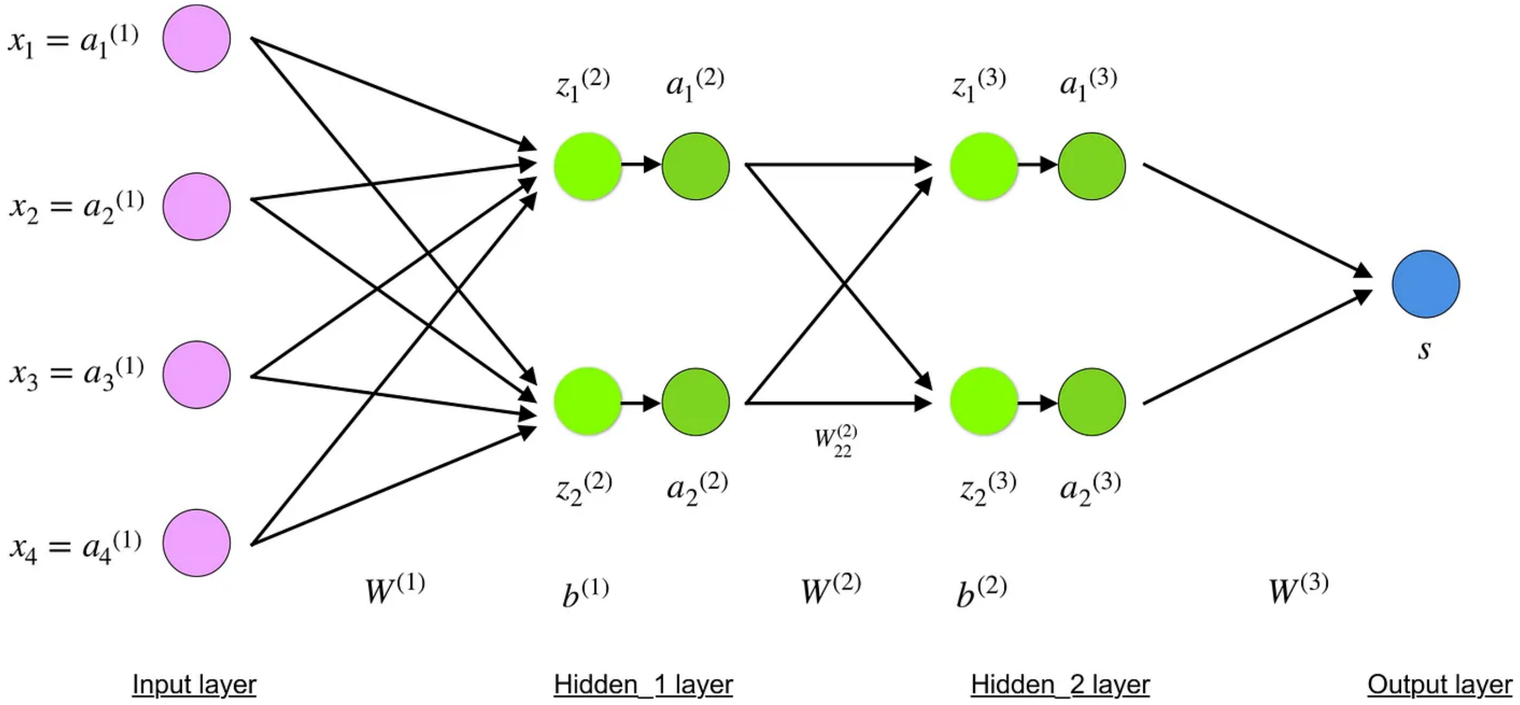
Activation Functions



$$Y = \sum (weight * input) + bias$$

https://medium.com/the-theory-of-everything/understanding-activation-functions-in-neural-networks-9491262884e0

Machine learning mechanics
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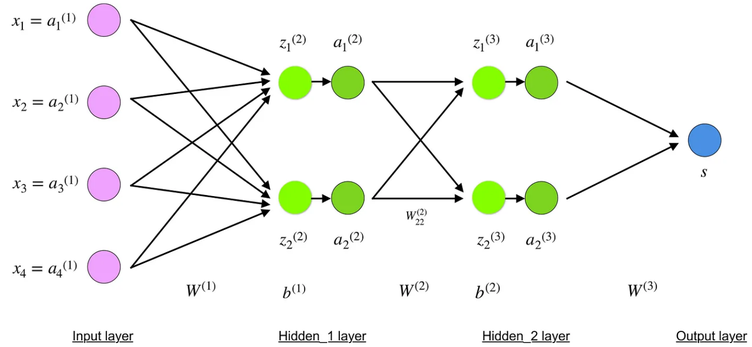
Activation Functions



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Machine learning mechanics
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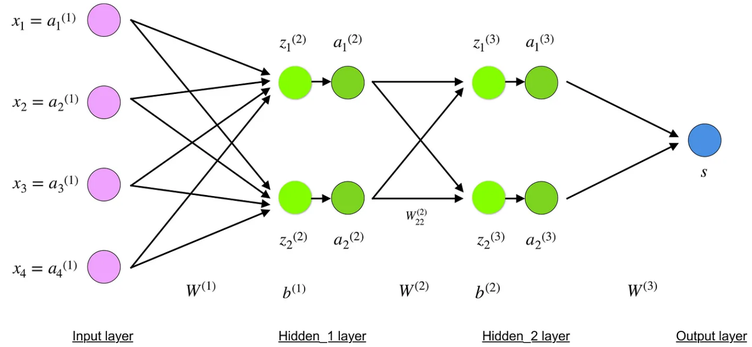
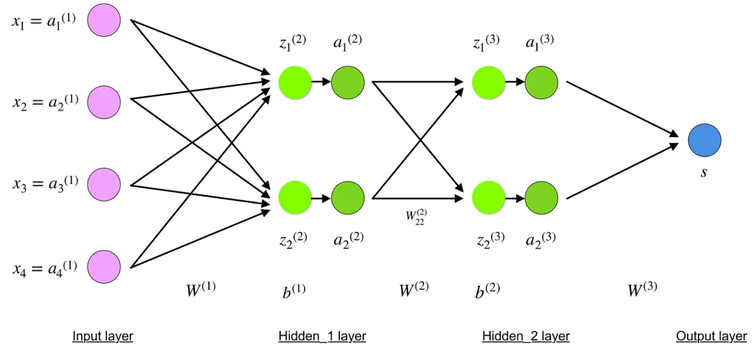
Activation Functions



$$Y \quad \in [-\infty; \infty]$$

https://medium.com/the-theory-of-everything/understanding-activation-functions-in-neural-networks-9491262884e0

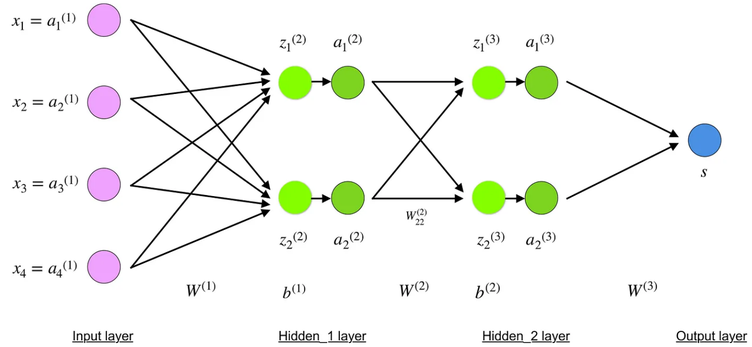
Machine learning mechanics
-
Activation Functions

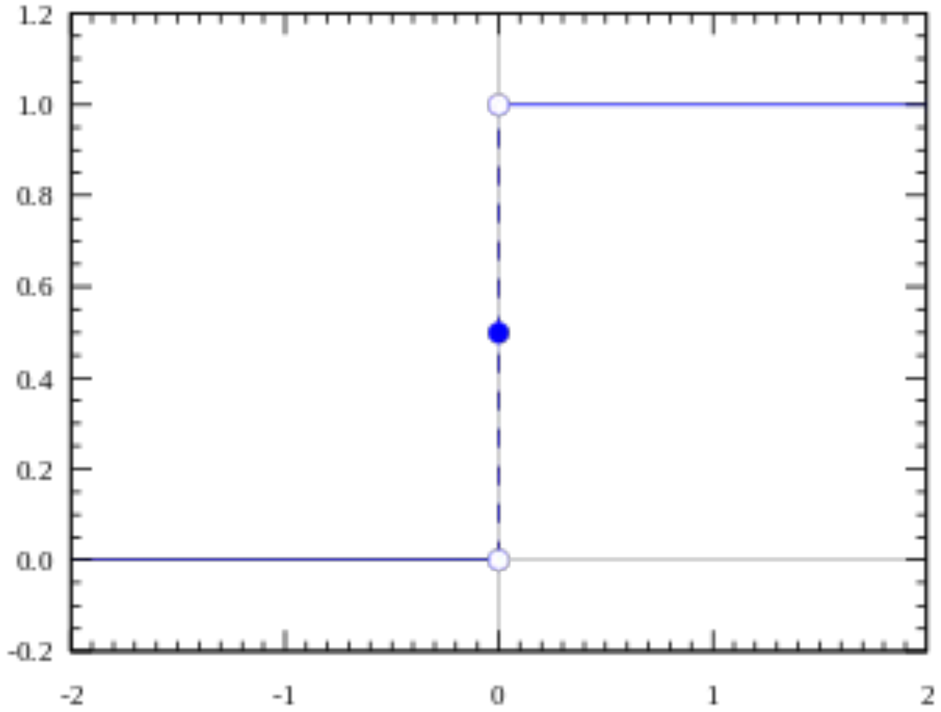


$$f(Y) \quad \in [\text{min} ; \text{max}]$$

https://medium.com/the-theory-of-everything/understanding-activation-functions-in-neural-networks-9491262884e0

Machine learning mechanics
-
Activation Functions
-
Step function





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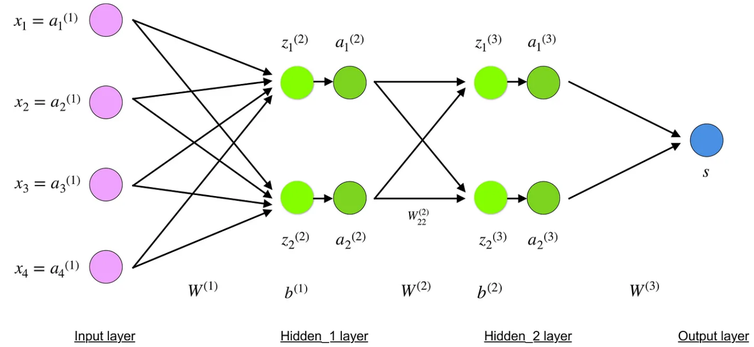
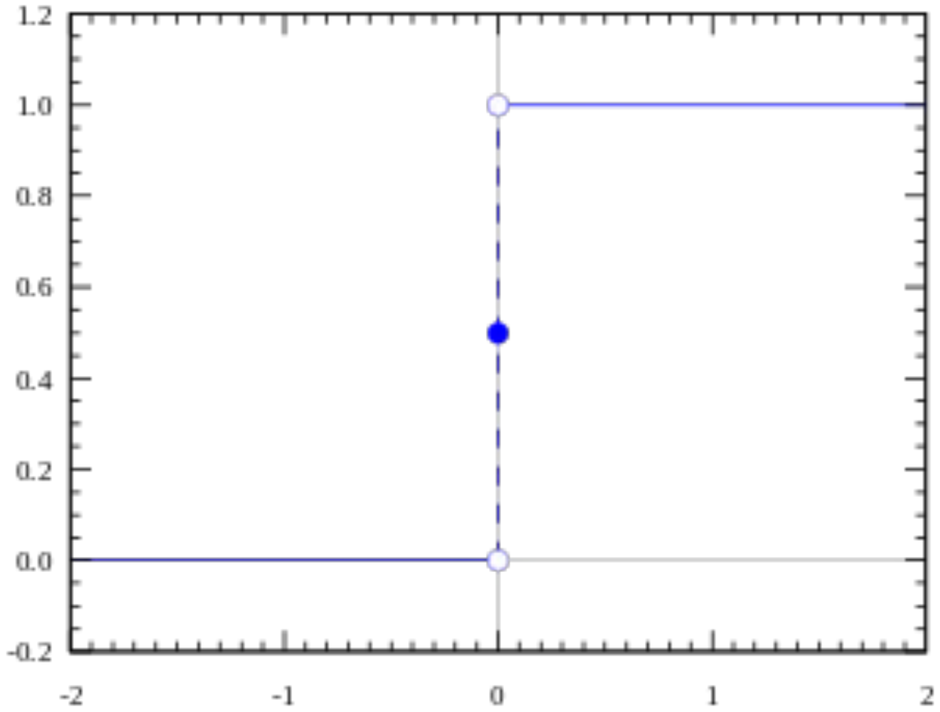
Machine learning mechanics
-
Activation Functions
-
Step function

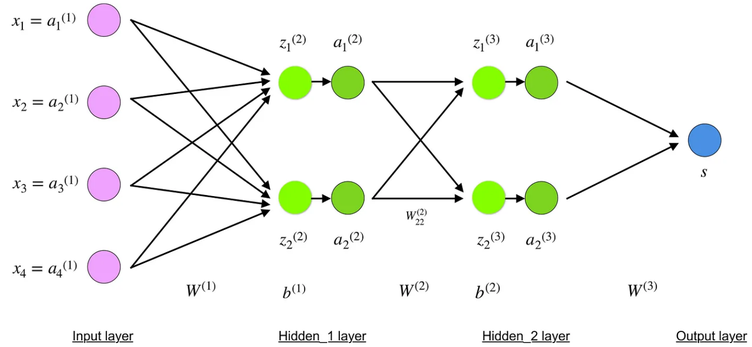




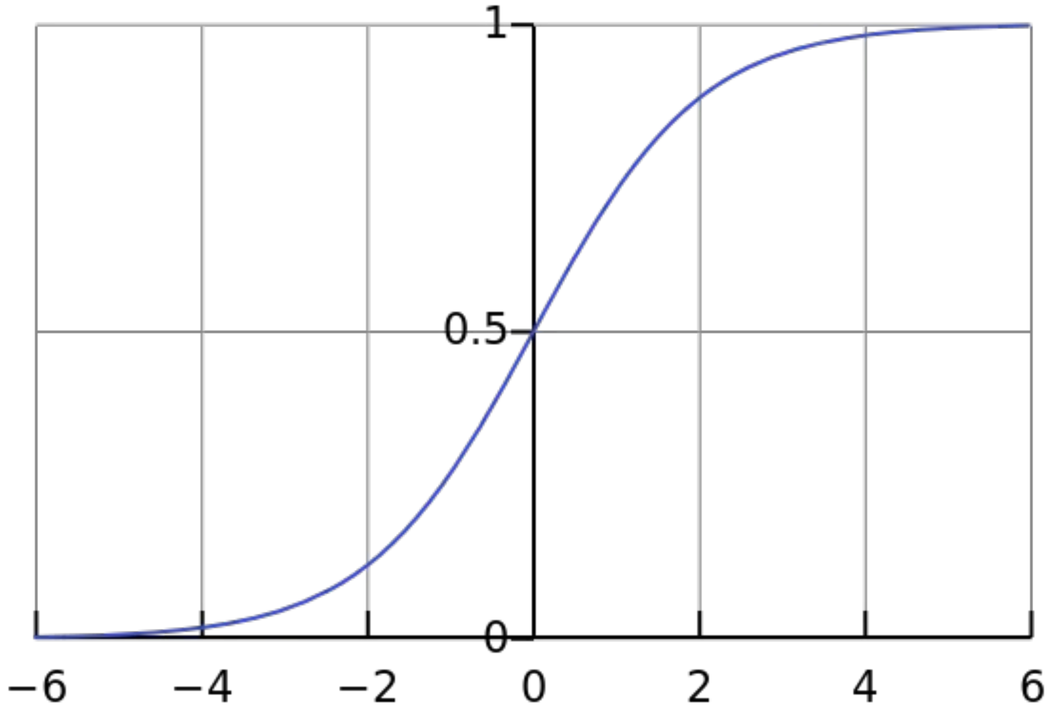
- Pros:
  - Mimics the neuron
  - $Y \in [0; 1]$
- Cons:
  - No smooth gradient
  - Binary

https://medium.com/the-theory-of-everything/understanding-activation-functions-in-neural-networks-9491262884e0

Machine learning mechanics
-
Activation Functions
-
Sigmoid function



$$A = \frac{1}{1+e^{-x}}$$



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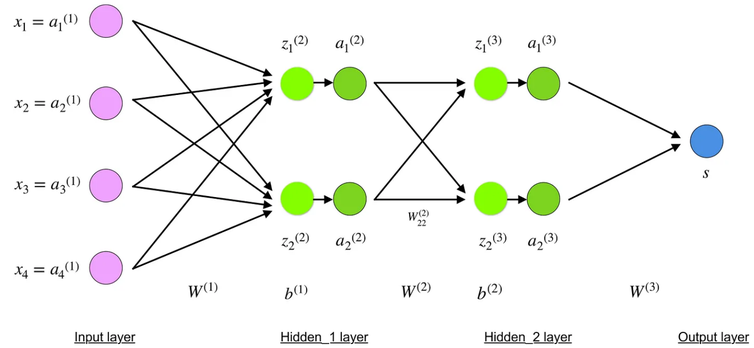
Machine learning mechanics
-
Activation Functions
-
Sigmoid function



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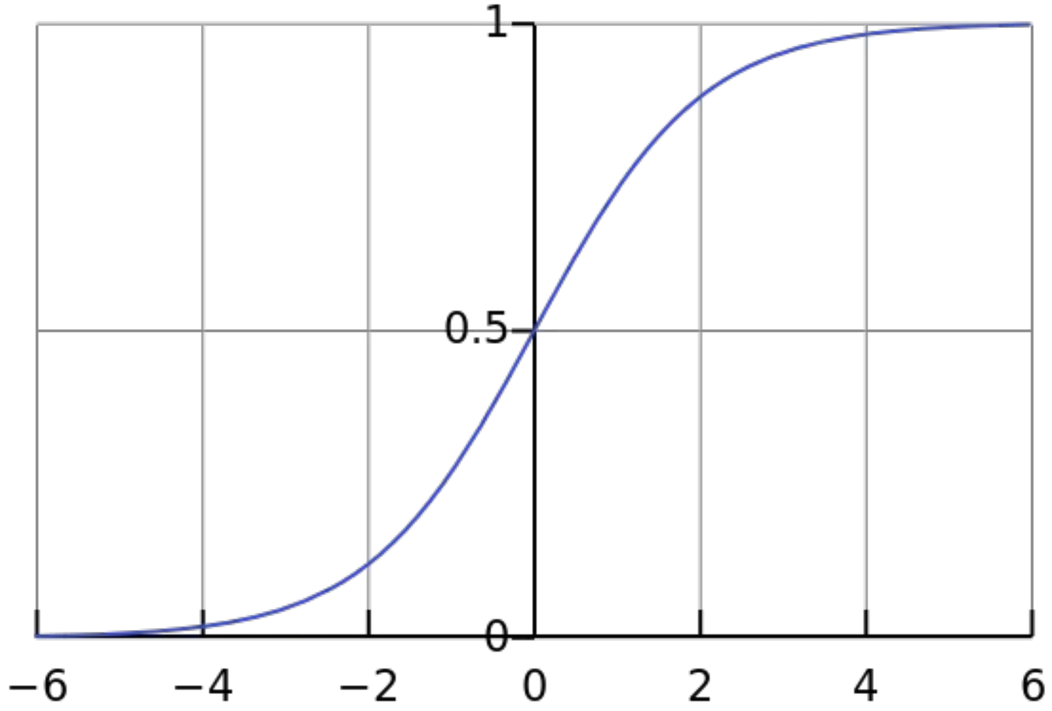

- Pros:
  - Smooth step
  - Smooth gradient
  - Not Binary
  - $Y \in [0; 1]$
- Cons:
  - Small gradient at the top and bottom
  - Computationally intensive

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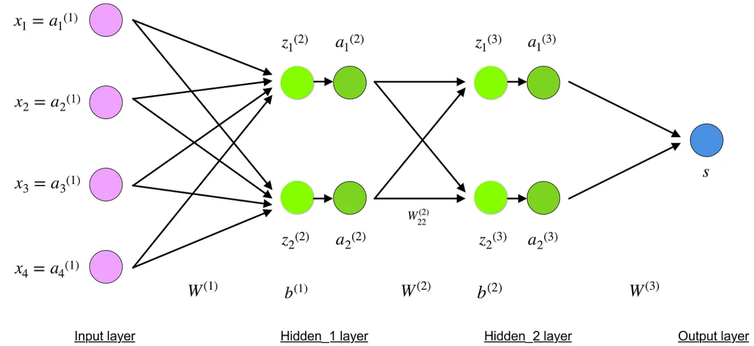
Machine learning mechanics
-
Activation Functions
-
Sigmoid function



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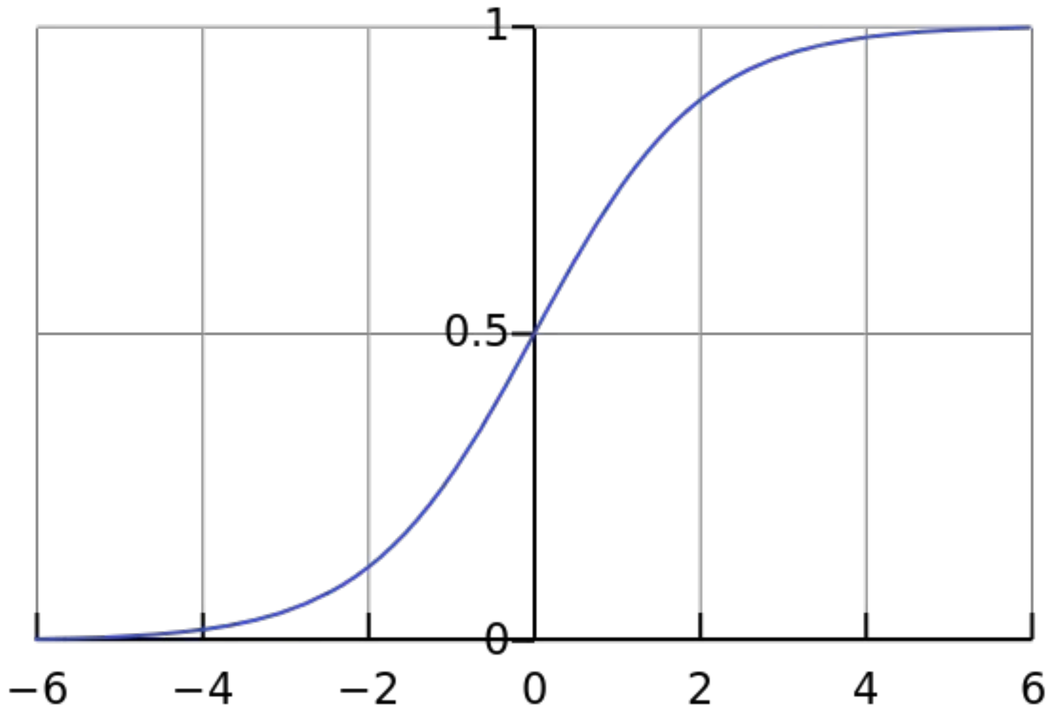

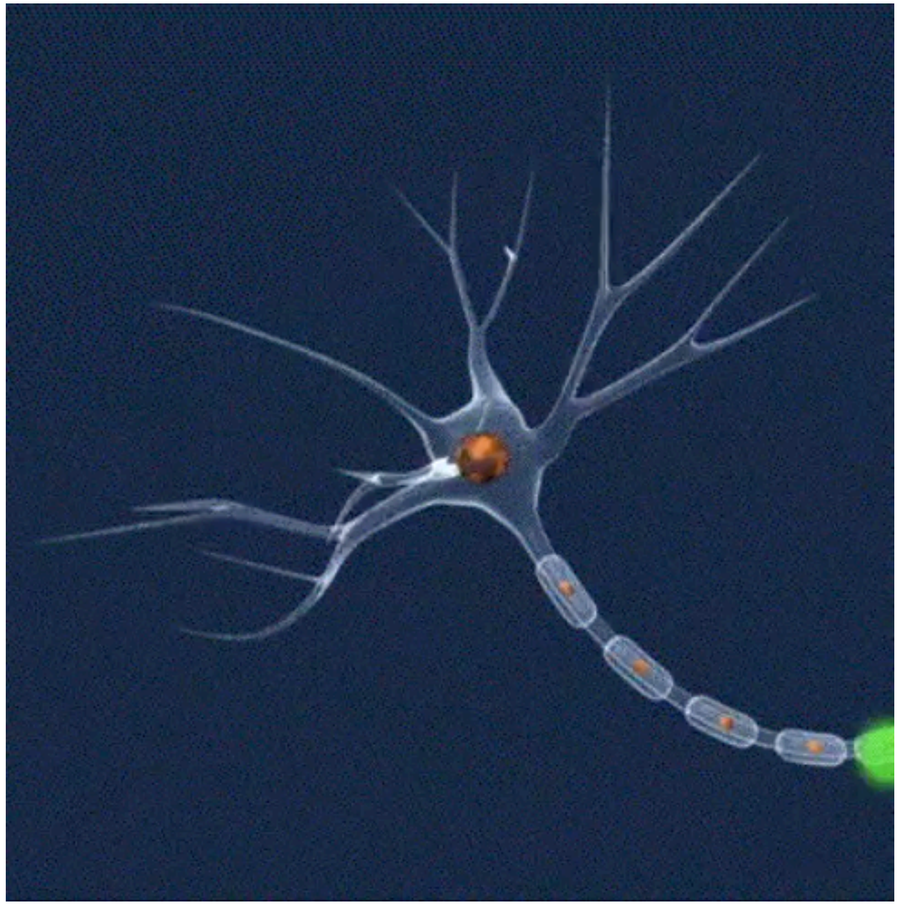

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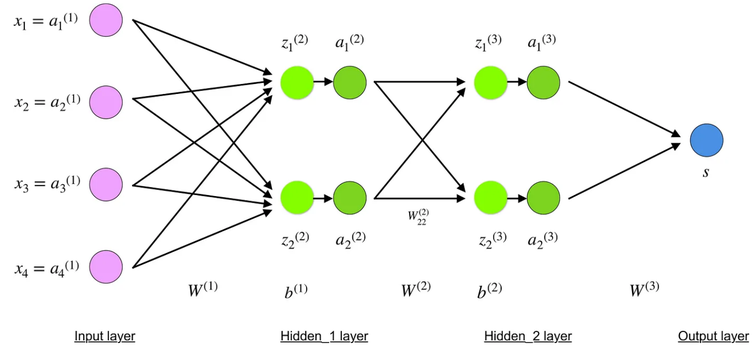
Machine learning mechanics
-
Activation Functions
-
Sigmoid function



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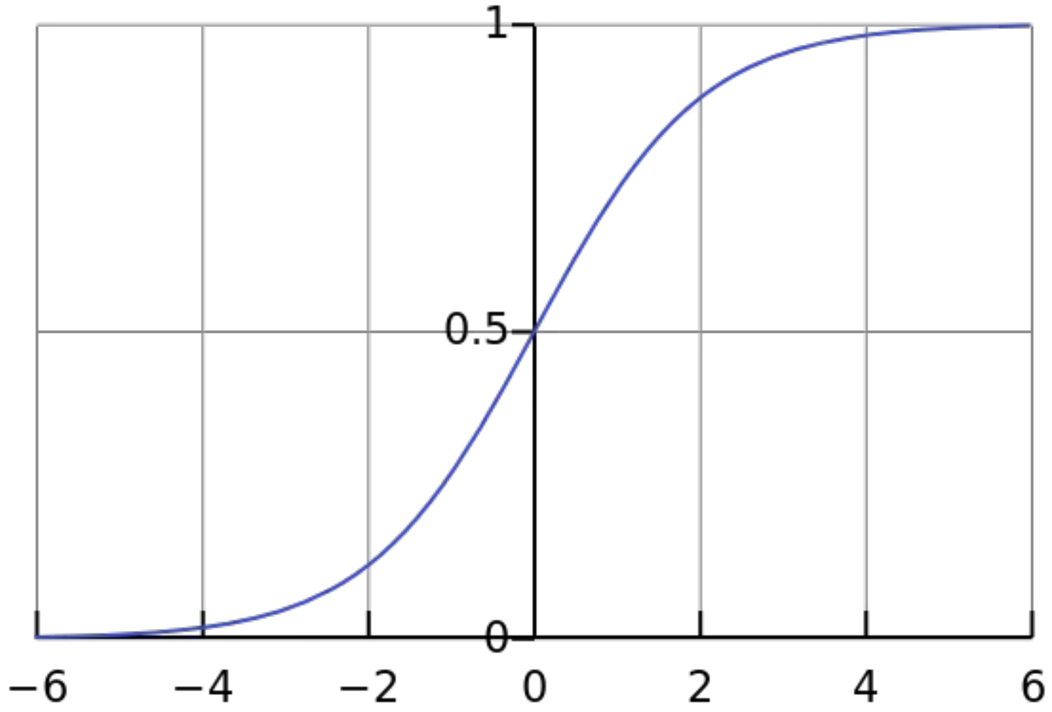

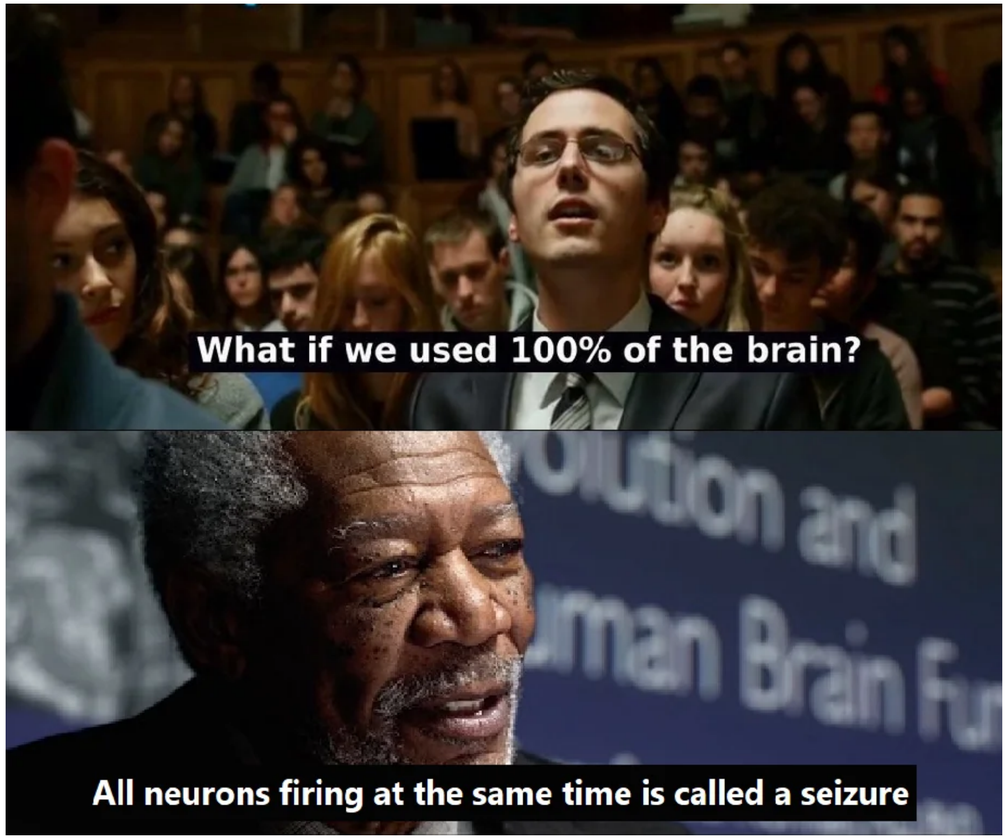

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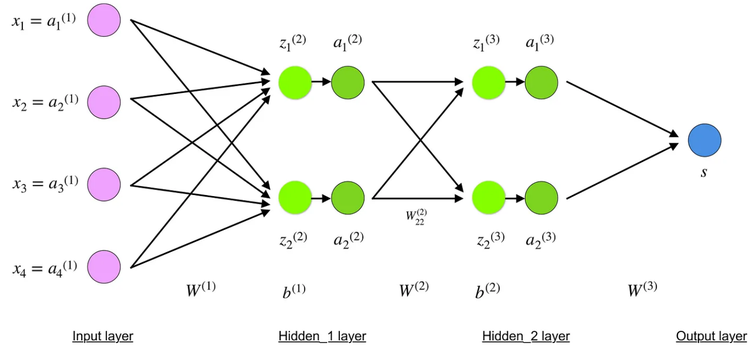
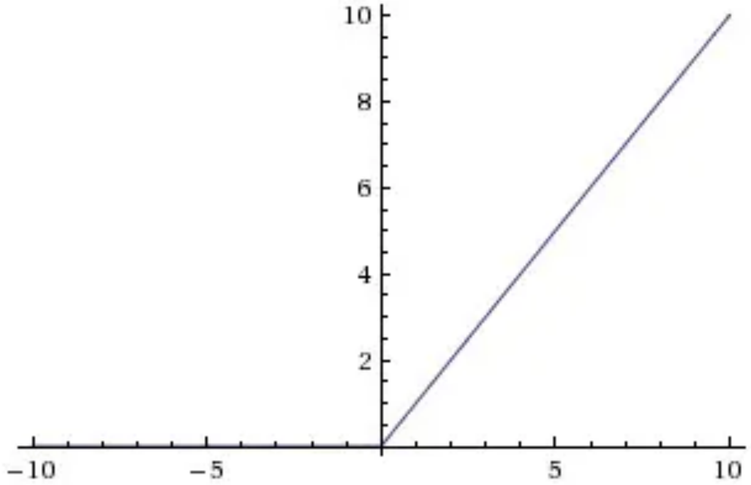
So people with epilepsy are actually geniuses : r/memes

Machine learning mechanics
-
Activation Functions
-
ReLu function



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



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Machine learning mechanics

-

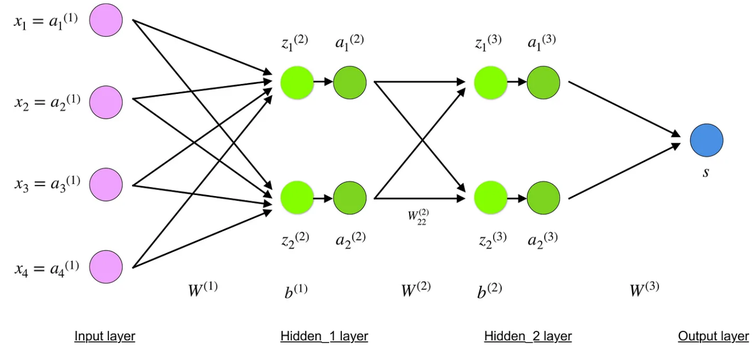
Activation Functions

-

Rectified Linear Unit (ReLU)

-

Sparsity of the activation



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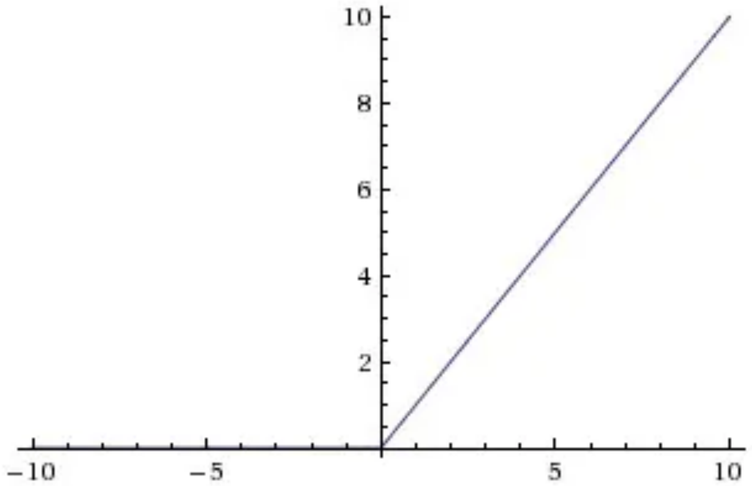
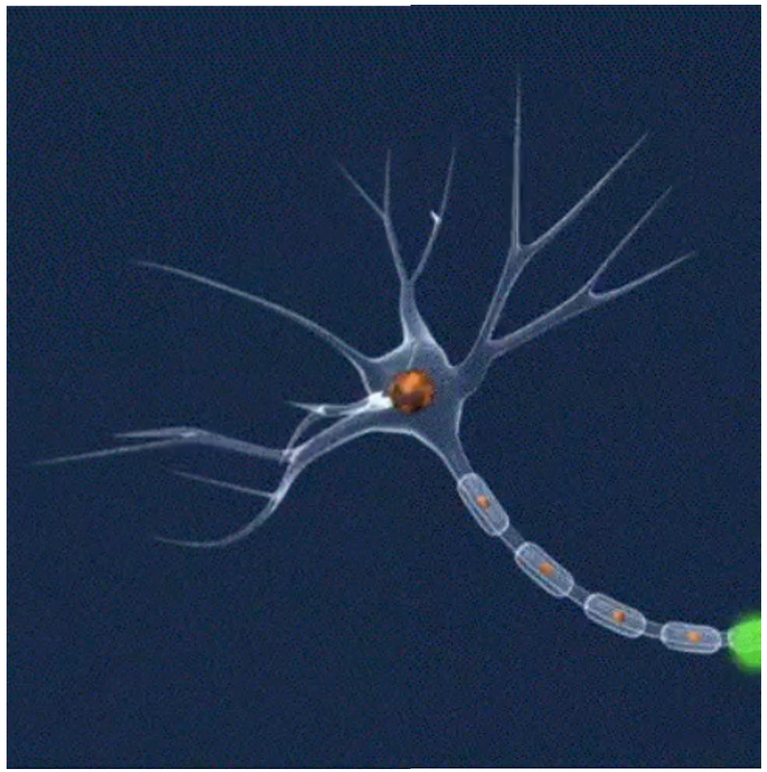


$$Y \in [0; \infty]$$



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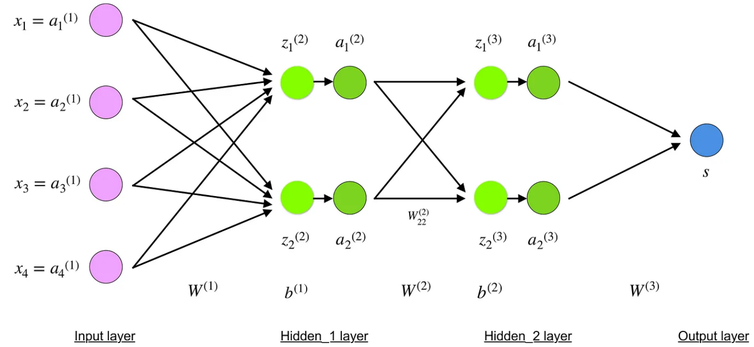
https://www.nichd.nih.gov/newsroom/releases/031813-backwards-neurons

Machine learning mechanics
-
Activation Functions
-
Rectified Linear Unit (ReLU)



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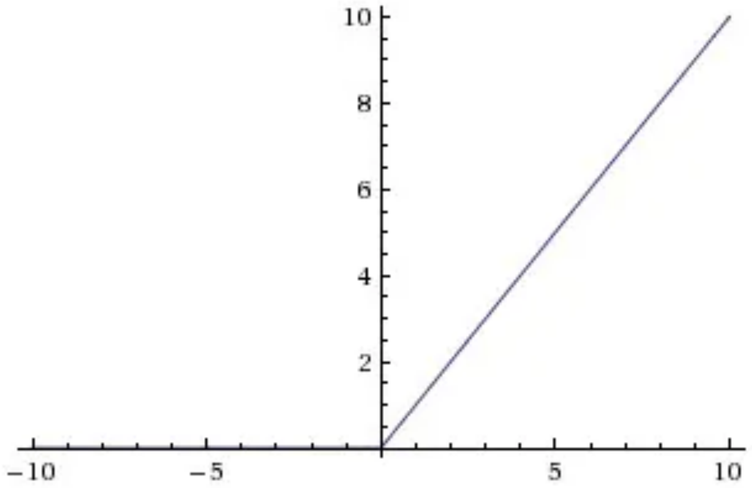

$$Y \in [0; \infty]$$

- Pros:
  - Less computationally intensive
  - Not Binary
  - Constant gradient
- Cons:
  - Dying ReLU
  - Can Blow up

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Machine learning mechanics

-

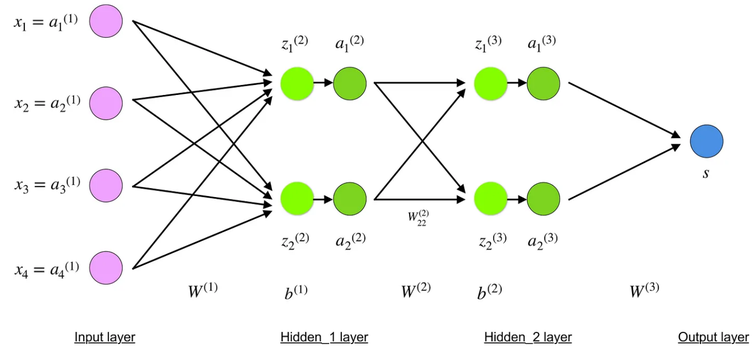
Activation Functions

-

Rectified Linear Unit (ReLU)

-

Dying ReLu Problem



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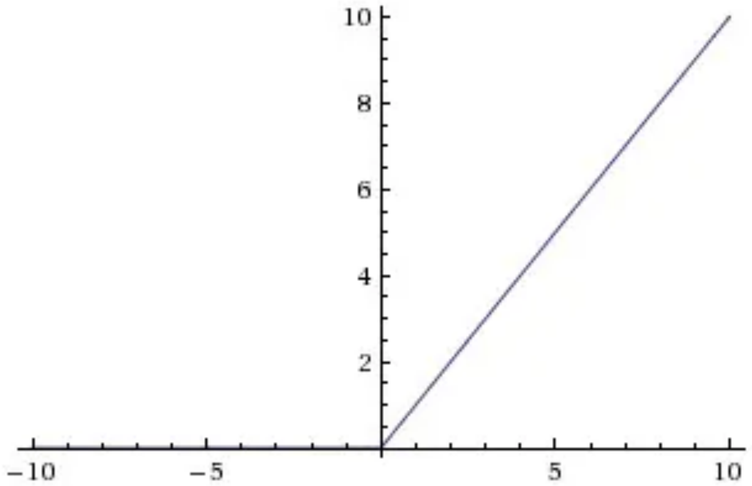
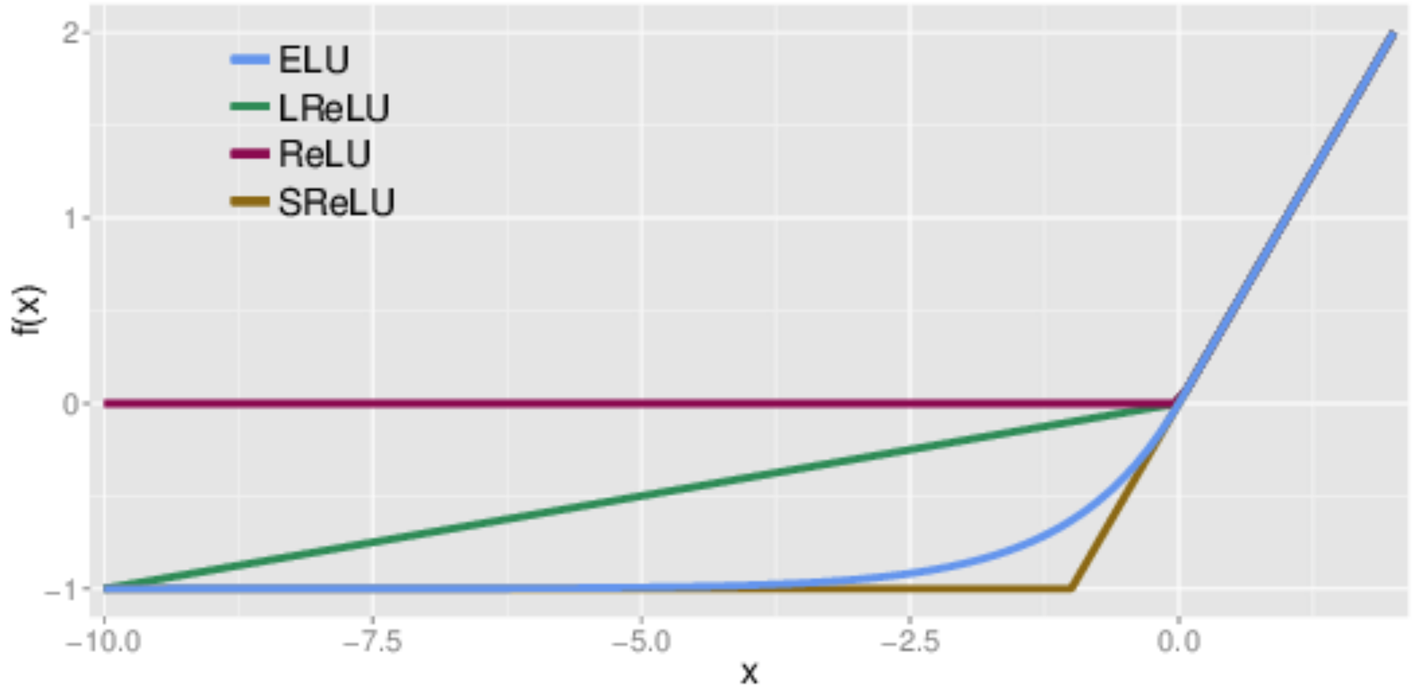


$$Y \in [0; \infty]$$



https://medium.com/the-theory-....ng/understanding-activation-functions-in-neural-networks-9491262884e0

https://www.nichd.nih.gov/newsroom/releases/031813-backwards-neurons

Which one to choose ?

- Depends on the size of the model
- A good and balanced combination of both 😯

Machine learning mechanics
-
Loss Functions

- Metric to characterize how far the model is from the label
  - Classification Losses:
    - Discrete (Ex: Character recognition, Animals, (n_2, I_{sat}))
  - Regression Losses:
    - Continuous (Ex: Someone's age, (n_2, I_{sat}))

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Machine learning mechanics

-

Loss Functions

-

Classification Losses

Mean Square Error: $\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$ (better gradients, penalizes off values)

Mean Absolute Error: $\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid Y_i - \hat{Y}_i \mid$ (less penalizes off values)

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Machine learning mechanics

-

Loss Functions

-

Regression Losses

Mean Square Error: $\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2$ (better gradients, penalizes off values)

Mean Absolute Error: $\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid Y_i - \hat{Y}_i \mid$ (less penalizes off values)

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Machine learning mechanics

-

Loss Functions

-

Classification Losses

$$CrossEntropyLoss = -(y_i log(\hat{y}_i) + (1 - y_i) log(1 - \hat{y}_i))$$

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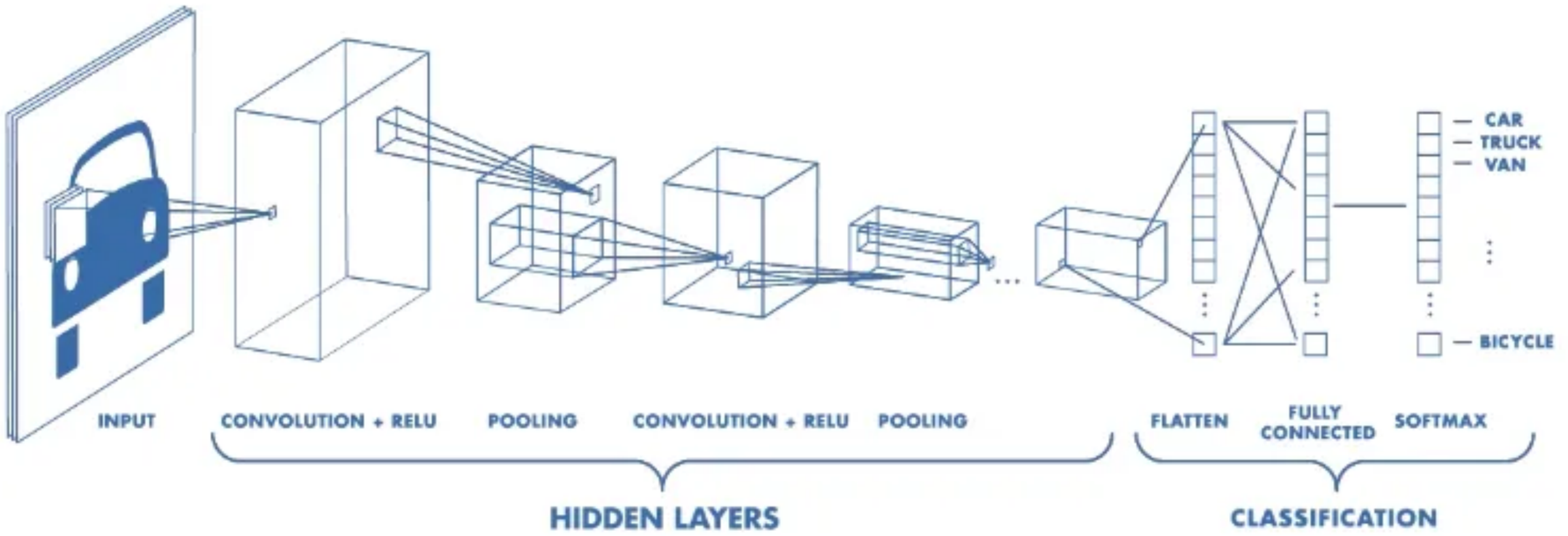
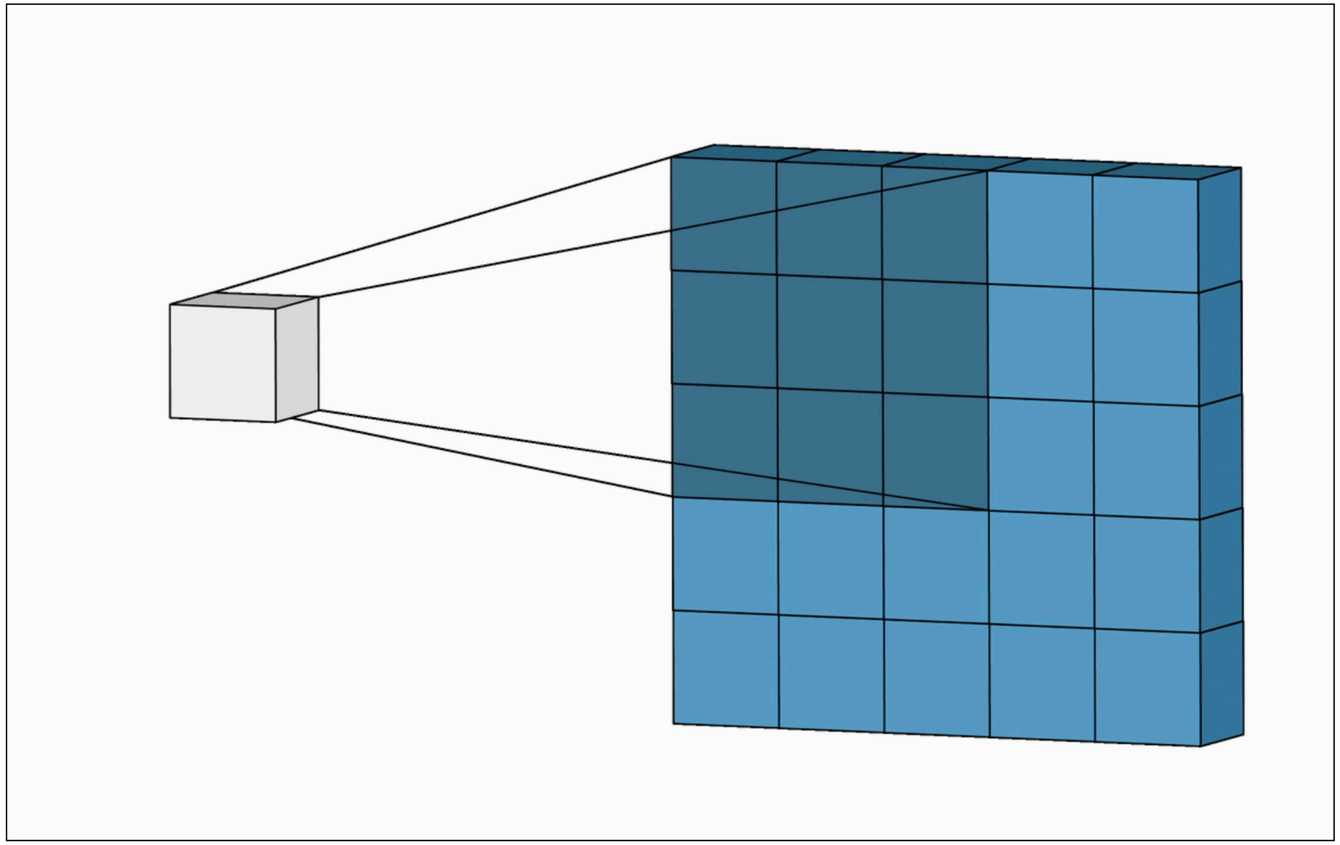
https://www.nichd.nih.gov/newsroom/releases/031813-backwards-neurons

Machine learning mechanics
-
Convolutional Neural Networks



https://towardsdatascience.com/convolutional-neural-networks-explained-9cc5188c4939

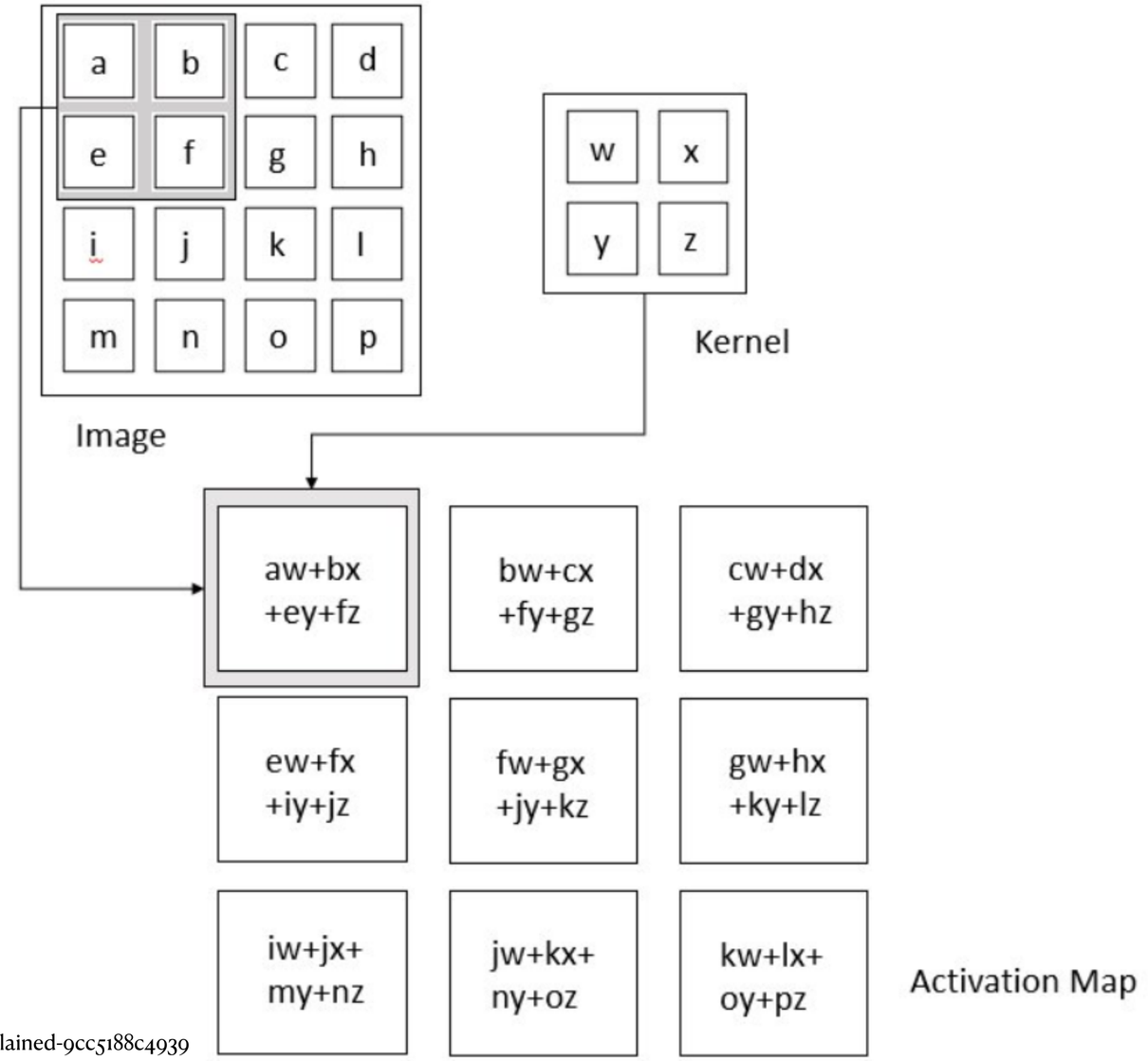
Machine learning mechanics
-
Convolution



https://towardsdatascience.com/convolutional-neural-networks-explained-9cc5188c4939

Machine learning mechanics
-
Convolution

$$W_{out} = \frac{W - F + 2P}{S} + 1$$



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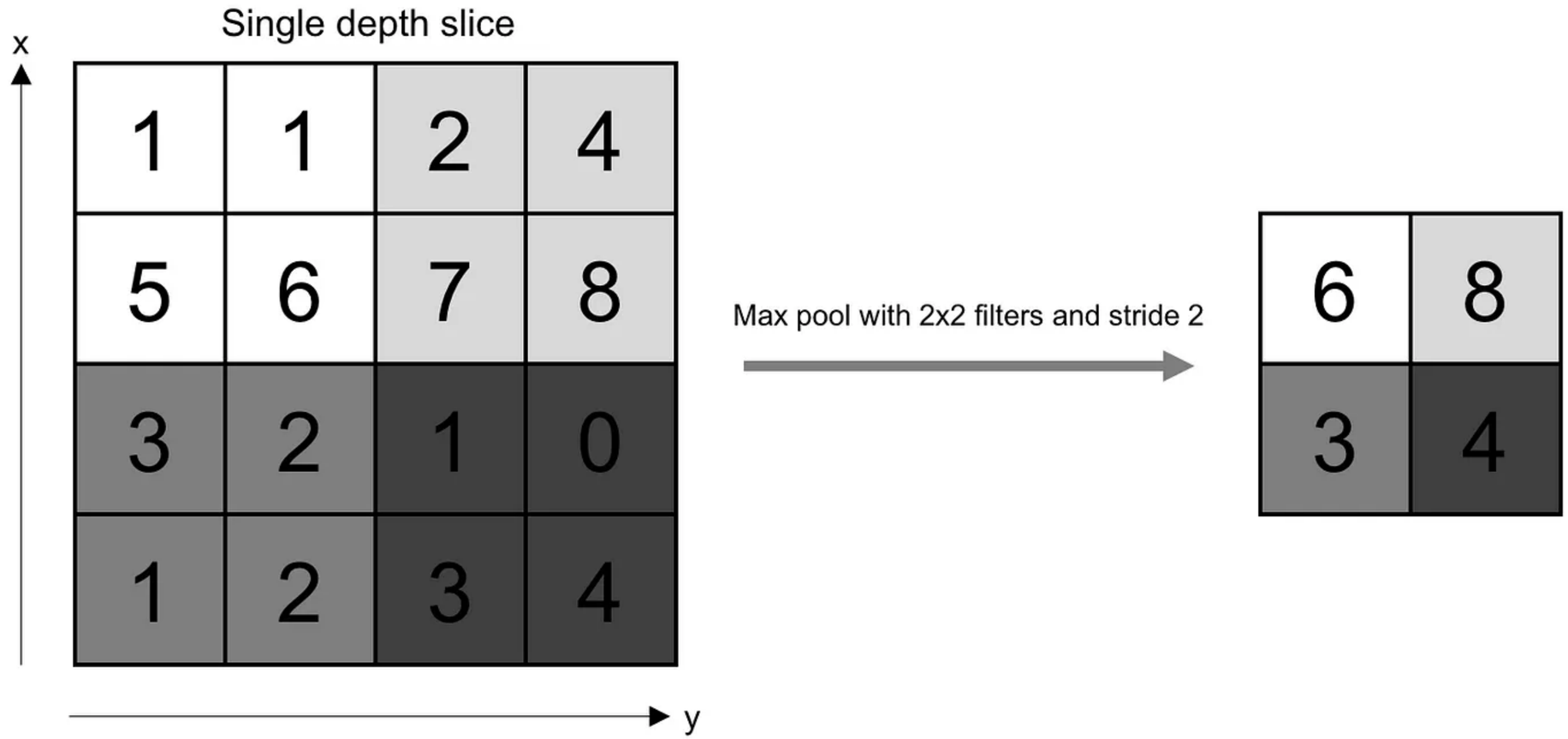
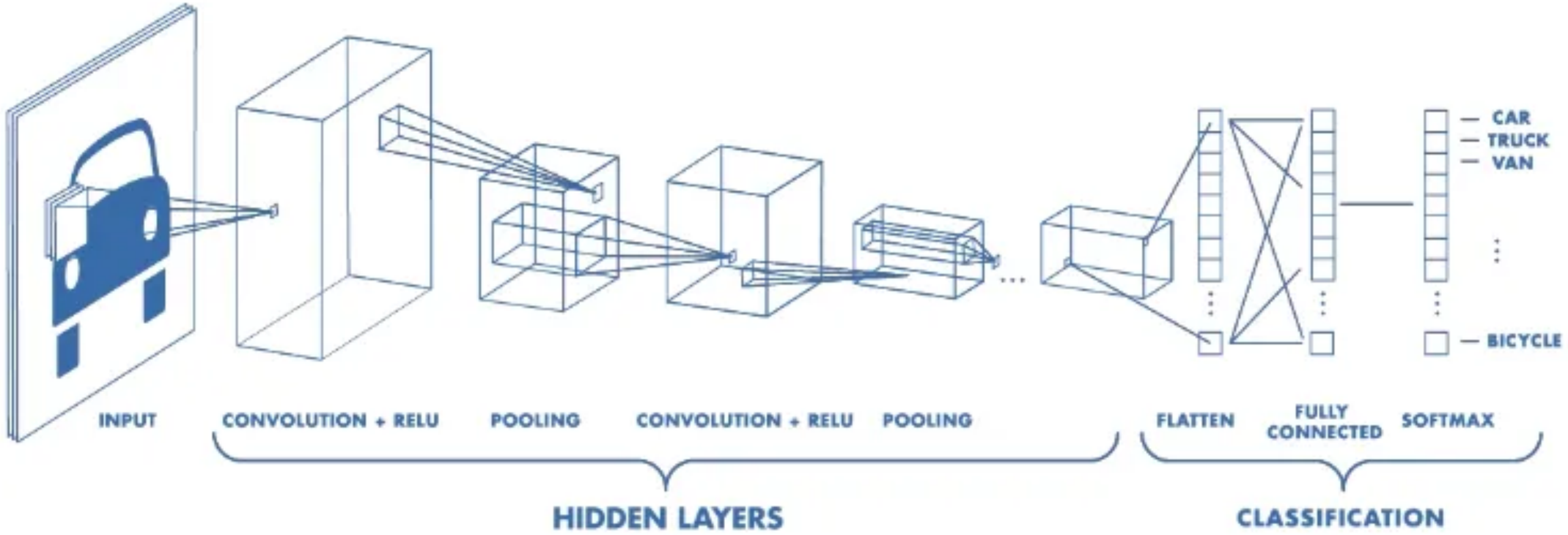
Machine learning mechanics

-

Pooling Layer



Machine learning mechanics
-
Convolutional Neural Networks



https://towardsdatascience.com/convolutional-neural-networks-explained-9cc5188c4939

Why CNN ?

- Deals with signals and images as a whole
- Parameter sharing
- Better generalization

Thank You