

Fundamentals of Machine Learning

Multi Layer Perceptrons

Workshop Lead: Tugce Gurbuz

Jul 24th, 2024





<u>Mission statement:</u> deliver quality workshops designed to help biomedical researchers develop the skills they need to succeed.



Location: 550 Sherbrooke Street, Montreal, Quebec



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McGill initiative in Computational Medicine

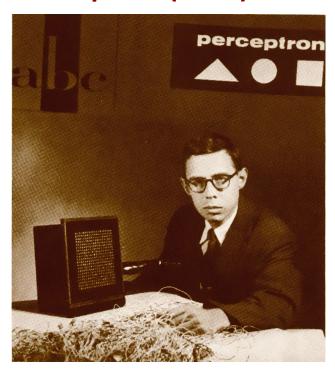


Summer 2024 Workshop Series

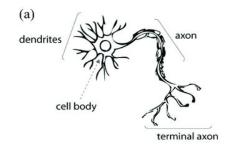
Workshop	Date	Lead/Facilitator	Location	Registration
How to think in Code	July 3 10AM-1PM	Thomas Zheng	Education Room 133	<u>Open</u>
Intro to UNIX and HPC	July 11 9AM-1pm	Georgi Mehri	Education Room 133	<u>Open</u>
Intro to Git & GitHub	July 12 1PM-5PM	Adrien Osakwe	Education Room 133	<u>Open</u>
Intro to Python (Part 1)	July 16 9AM-1PM	Benjamin Rudski	Education Room 133	<u>Open</u>
Intermediate Python (Part 2)	July 18 9AM-1PM	Benjamin Rudski	Education Room 133	<u>Open</u>
Fundamentals of Machine Learning	July 24 9AM-1PM	Tugce Gurbuz	Education Room 133	<u>Open</u>
Intro to Matlab	August 7 9AM-1PM	Meghana Munipalle	Education Room 133	TBA
Intro to R (Part 1)	August 12 9AM-1PM	TBA	Education Room 133	TBA
Intermediate R (Part 2)	August 14 1PM-5PM	Gerardo Martinez	Education Room 133	TBA
Intro to Bayesian Inference in R	August 16 1PM-5PM	Adrien Osakwe	Education Room 133	TBA
Proteogenomics	August 19 1PM-5PM	Thomas Zheng	Education Room 133	TBA



Perceptron (1958)



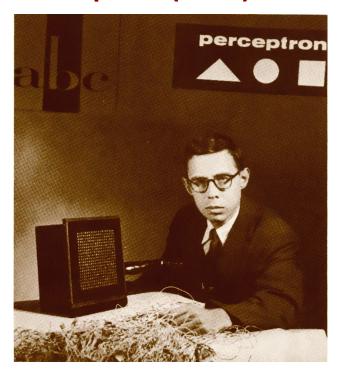
Source



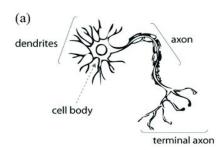
1: fire 0: not fire



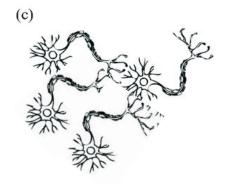
Perceptron (1958)



Source



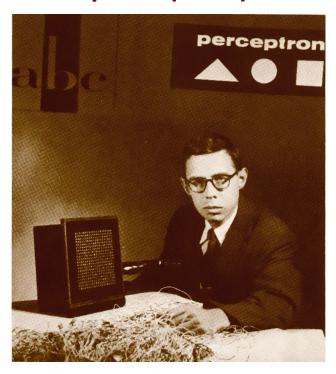
1: fire 0: not fire



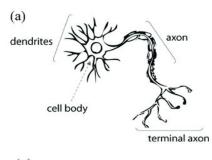
Excitatory and inhibitory connections



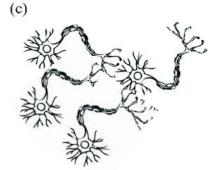
Perceptron (1958)



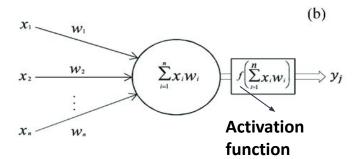
Source



1: fire 0: not fire

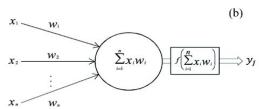


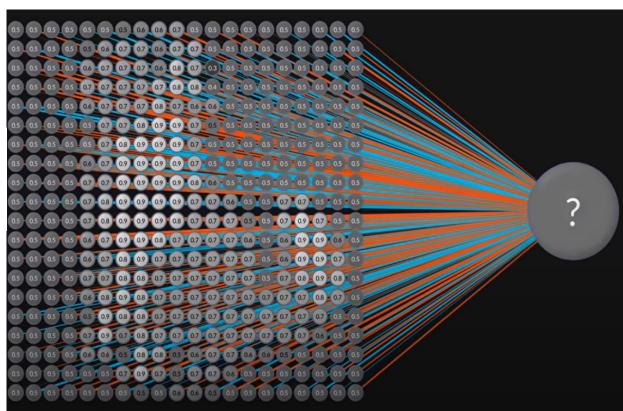
Excitatory and inhibitory connections



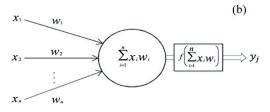


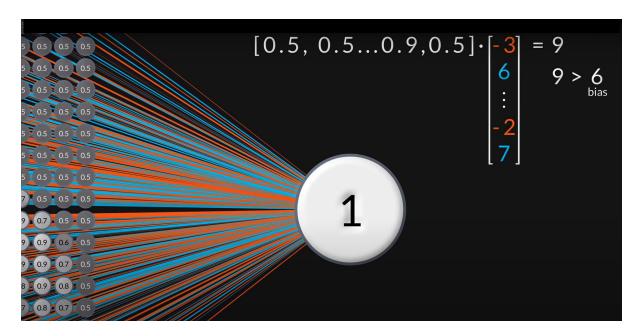




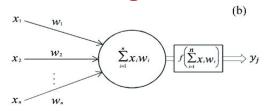


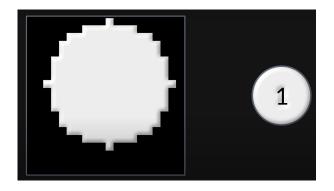


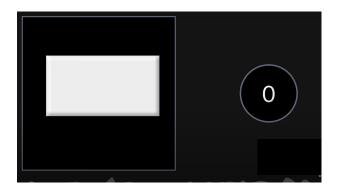




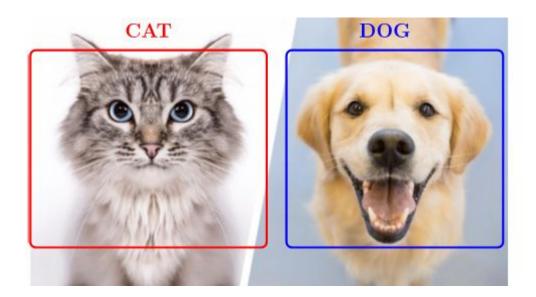






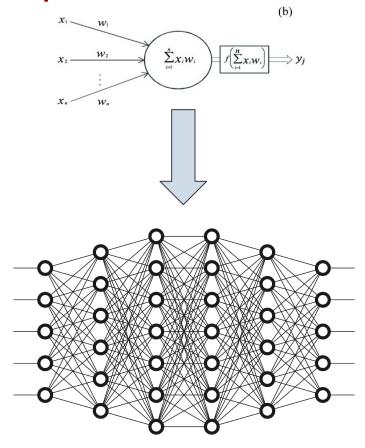






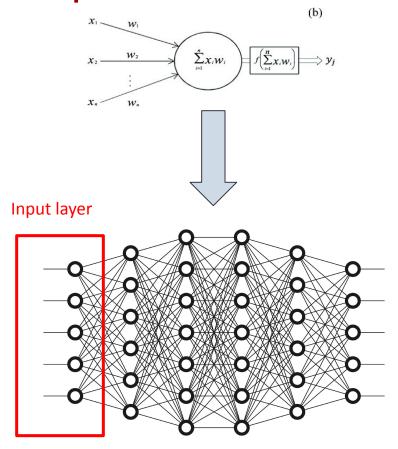




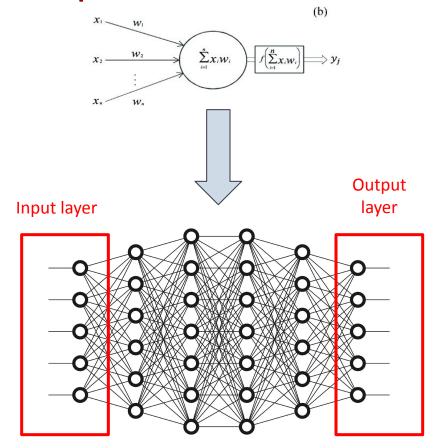




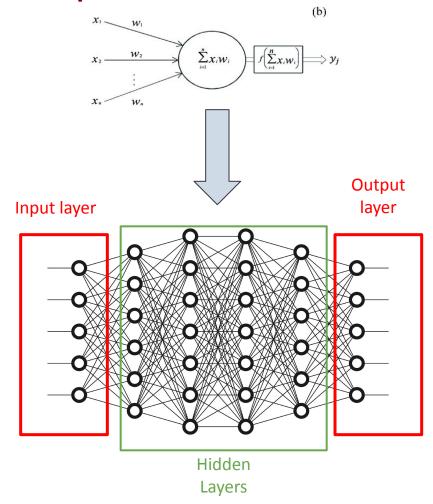






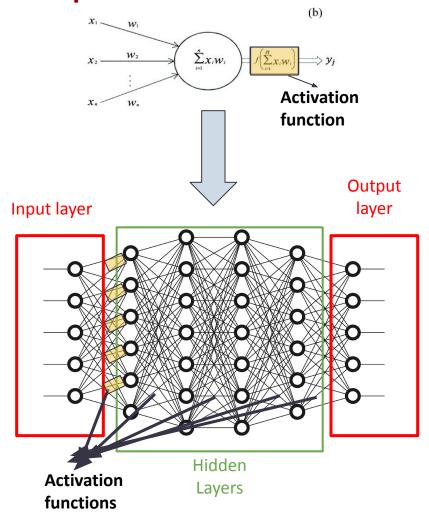












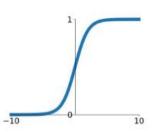




Activation Functions

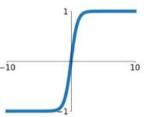
Sigmoid

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



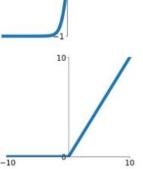
tanh

tanh(x)



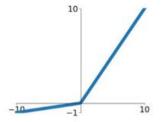
ReLU

 $\max(0,x)$



Leaky ReLU

 $\max(0.1x, x)$

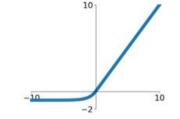


Maxout

 $\max(w_1^T x + b_1, w_2^T x + b_2)$

ELU

$$\begin{cases} x & x \ge 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$

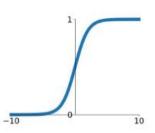




Activation Functions

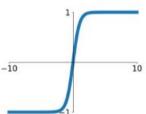
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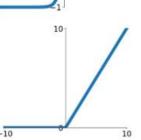
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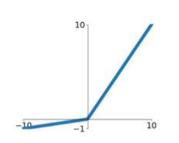
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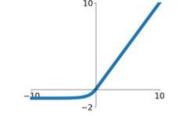


Maxout

 $\max(w_1^T x + b_1, w_2^T x + b_2)$

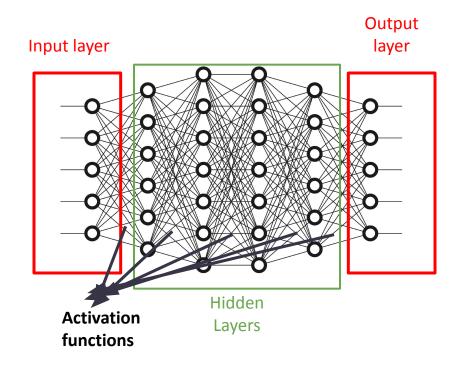
ELU

$$\begin{cases} x & x \ge 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$





Let's implement our first ML model!



Let's go to our first tutorial and implement our first ML model!!

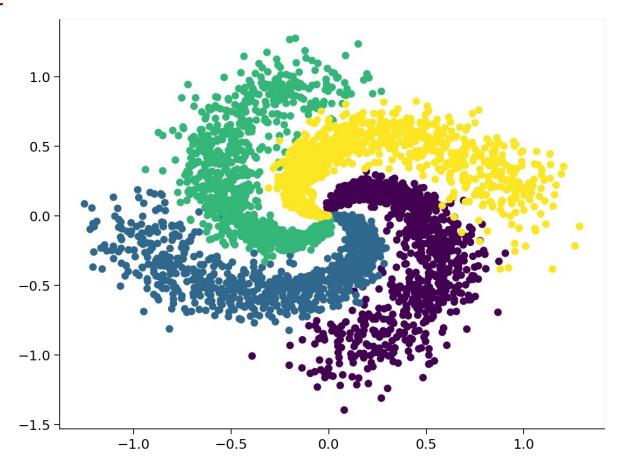






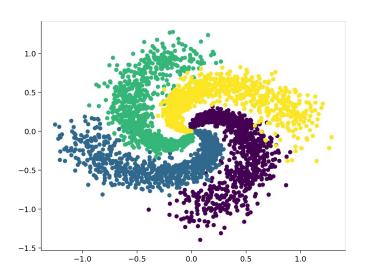


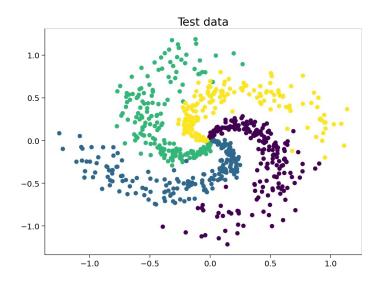
Dataset





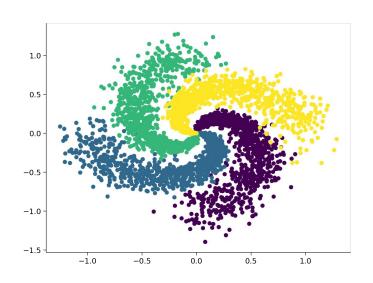


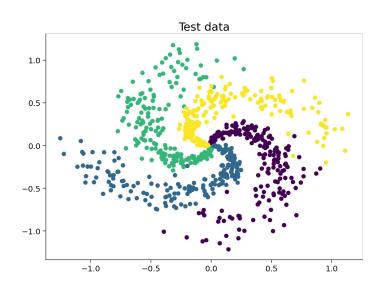






Dataset

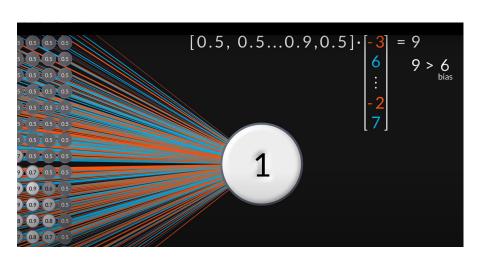


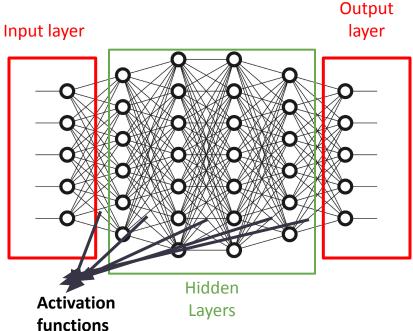


Let's prepare data for our model!





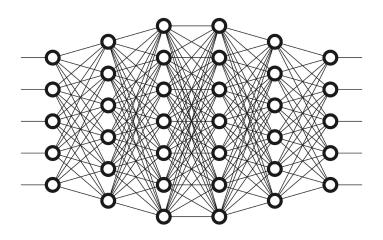








Learning good weights



Learning Recipe:

1-Initialize weights

2-Run a forward pass and make a prediction

3-Calculate loss to evaluate how good/bad your prediction was

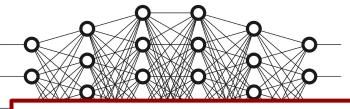
4-Adjust your weights in a way so that loss will be minimized

Popular weight initialization methods: <u>Xavier/Glorot Initialization</u>, Normalized Xavier/Glorot Initialization, <u>He Weight Initialization</u>, <u>Random Weight Initialization</u>





Learning good weights

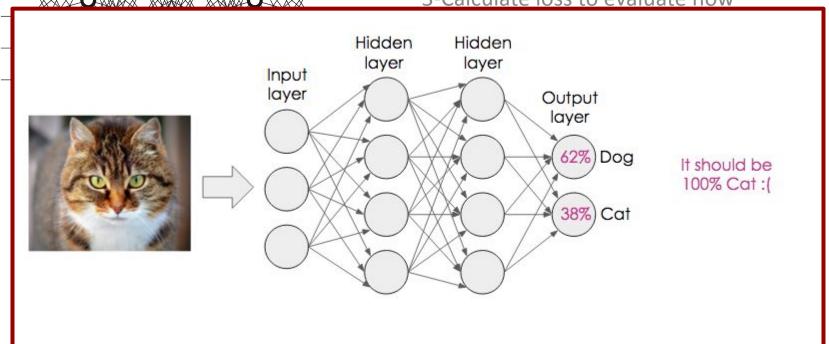


Learning Recipe:

1-Initialize weights

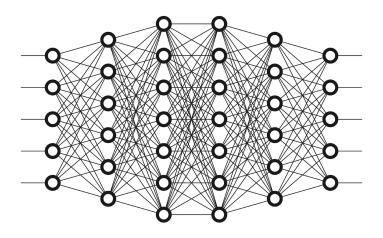
2-Run a forward pass and make a prediction

3-Calculate loss to evaluate how





Learning good weights



Learning Recipe:

1-Initialize weights

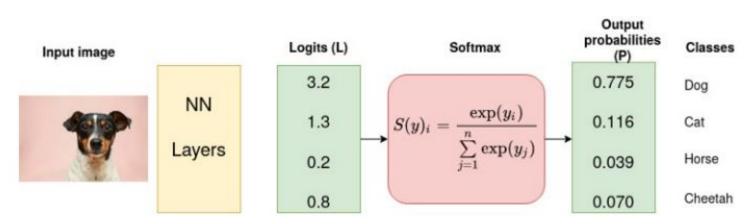
2-Run a forward pass and make a prediction

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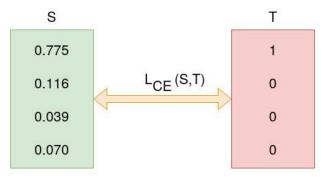
4-Adjust your weights in a way so that loss will be minimized

Classifying categorical variables -> Cross-entropy Loss Function

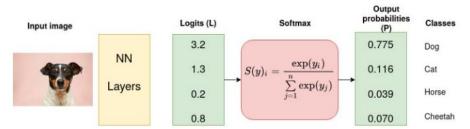




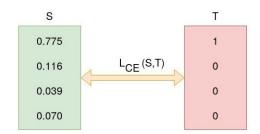
Input image source: Photo by Victor Grabarczyk on Unsplash. Diagram by author.



Cross Entropy (L) (Source: Author).



Input image source: Photo by Victor Grabarczyk on Unsplash. Diagram by author.



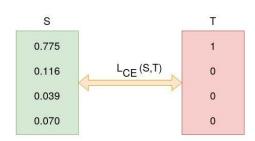
Cross Entropy (L) (Source: Author).

$$L_{\text{CE}} = -\sum_{i=1}^{n} t_i \log(p_i)$$
, for n classes,

where t_i is the truth label and p_i is the Softmax probability for the i^{th} class.

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Cross Entropy (L) (Source: Author).

$$L_{CE} = -\sum_{i=1}^{\infty} T_i \log(S_i)$$

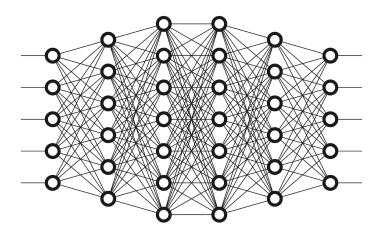
$$= -\left[1 \log_2(0.775) + 0 \log_2(0.126) + 0 \log_2(0.039) + 0 \log_2(0.070)\right]$$

$$= -\log_2(0.775)$$

$$= 0.3677$$



Learning good weights



Learning Recipe:

1-Initialize weights

2-Run a forward pass and make a prediction

3-Calculate loss to evaluate how good/bad your prediction was

4-Adjust your weights in a way so that loss will be minimized

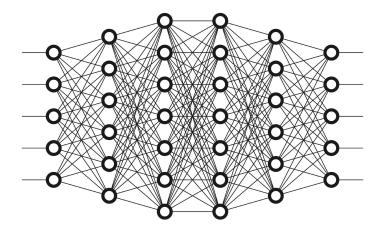
Optimization! -> More details in the next lecture

We will use Adam Optimizer for this tutorial





Learning good weights



Learning Recipe:

1-Initialize weights

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Let's train our MLP model!!

