

Workshop on Neural Networks

Machine Learning and Optimization Seminar

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Start Downloading!

Setup

Information on setting up a Python environment and package management can be found in the [first workshop](#).

In Terminal:

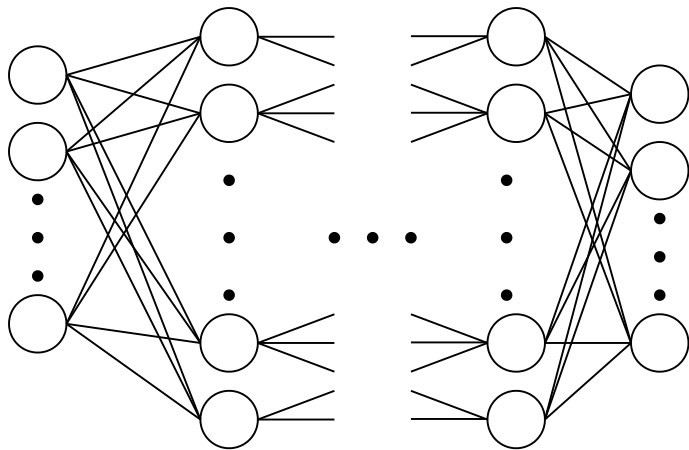
```
mamba activate workshop
mamba install numpy py-pde tensorflow matplotlib
```

You can use [Google colab](#) if unable to run local Jupyter Notebooks.

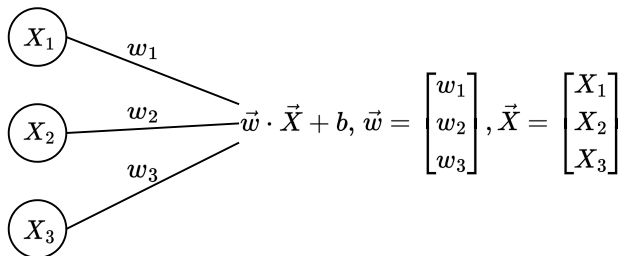
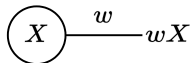
In cell:

```
!pip install numpy py-pde tensorflow matplotlib
```

What is a Neural Network?



Components



Affine Mapping

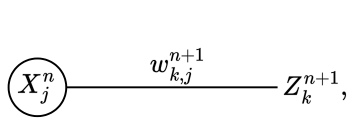


Diagram showing a single neuron with input X_j^n and weight $w_{k,j}^{n+1}$ leading to output Z_k^{n+1} .

$$\vec{w}_k^{n+1} = \begin{bmatrix} w_{k,1}^{n+1} \\ w_{k,2}^{n+1} \\ w_{k,3}^{n+1} \end{bmatrix}, \vec{Z}^{n+1} = \begin{bmatrix} z_1^{n+1} \\ z_2^{n+1} \\ z_3^{n+1} \\ z_4^{n+1} \end{bmatrix}$$

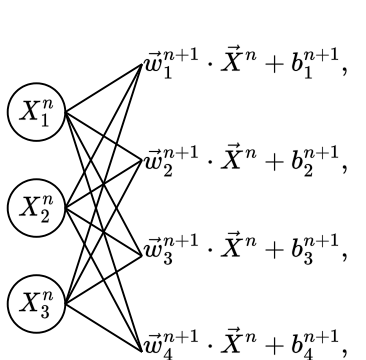


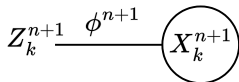
Diagram showing a fully connected layer with three input nodes X_1^n , X_2^n , and X_3^n and four output nodes.

$$\vec{b}^{n+1} = \begin{bmatrix} b_1^{n+1} \\ b_2^{n+1} \\ b_3^{n+1} \\ b_4^{n+1} \end{bmatrix}$$

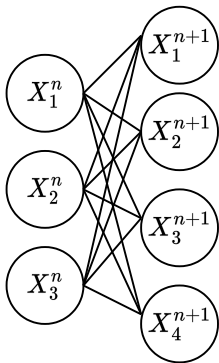
$$\underline{W}^{n+1} = \begin{bmatrix} | & | & | & | \\ \vec{w}_1^{n+1} & \vec{w}_2^{n+1} & \vec{w}_3^{n+1} & \vec{w}_4^{n+1} \\ | & | & | & | \end{bmatrix}^T$$

$$\underline{W}^{n+1} \vec{X}^n + \vec{b}^{n+1} = \vec{Z}^{n+1}$$

Nonlinear Mapping



$$X_k^{n+1} := \phi^{n+1}(Z_k^{n+1})$$



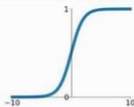
$$\vec{X}^{n+1} := \phi^{n+1}(\vec{Z}^{n+1}) = \begin{bmatrix} \phi^{n+1}(Z_1^{n+1}) \\ \phi^{n+1}(Z_2^{n+1}) \\ \phi^{n+1}(Z_3^{n+1}) \\ \phi^{n+1}(Z_4^{n+1}) \end{bmatrix}$$

$$\vec{X}^{n+1} = \phi^{n+1}(\underline{W}^{n+1} \vec{X}^n + \vec{b}^{n+1})$$

Activation Functions

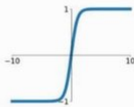
Sigmoid

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



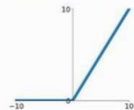
tanh

$$\tanh(x)$$



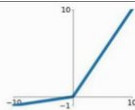
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

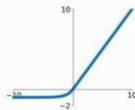


Maxout

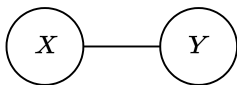
$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

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

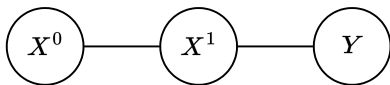


Example 1



$$Y = wX + b$$

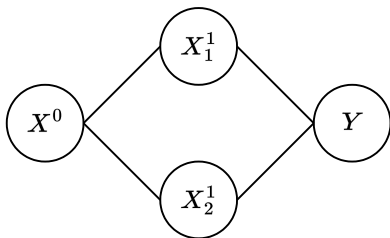
Example 2



$$Z^1 = w^1 X^0 + b^1, \quad X^1 = \phi(Z^1), \quad Y = w^2 X^1 + b^2$$

$$Y = w^2 \phi(w^1 X^0 + b^1) + b^2$$

Example 3



$$\vec{Z}^1 = \vec{w}^1 X^0 + \vec{b}^1, \quad \vec{X}^1 = \phi(\vec{Z}^1), \quad Y = \vec{w}^2 \cdot \vec{X}^1 + b^2$$

$$\begin{aligned} Y &= \vec{w}^2 \cdot \phi(\vec{w}^1 X^0 + \vec{b}^1) + b^2 \\ &= w_1^2 \phi(w_1^1 X^0 + b_1^1) + w_2^2 \phi(w_2^1 X^0 + b_2^1) + b^2 \end{aligned}$$

Remarks

- Can have arbitrary number of hidden layers
- Hidden layers can have arbitrary depth, independent of each other
- Each hidden layer can have it's own activation function
- Activation function on output layer \vec{Y} is optional, depends on context
- In general, a NN with L hidden layers can be represented as

$$\begin{aligned} Y &= \underline{W}^{L+1} \vec{X}^L + \vec{b}^{L+1} \\ &= \underline{W}^{L+1} \phi^L(\underline{W}^L \vec{X}^{L-1} + \vec{b}^L) + \vec{b}^{L+1} \\ &\vdots \\ &= \underline{W}^{L+1} \phi^L(\underline{W}^L \phi^{L-1}(\dots \phi^1(\underline{W}^1 \vec{X}^0 + \vec{b}^1)\dots) + \vec{b}^{L-1}) + \vec{b}^L + \vec{b}^{L+1} \end{aligned}$$

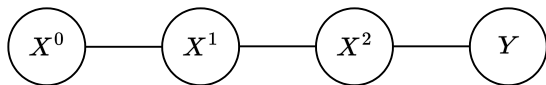
Training

$$\bar{X} = \{X_1, \dots, X_N\}, \bar{Y} = \{\hat{Y}_1, \dots, \hat{Y}_N\}$$

$$(X_i, \hat{Y}_i) \Rightarrow E_i(\beta) = (Y_i - \hat{Y}_i)^2 \Rightarrow E(\beta) = \sum_{i=1}^N E_i(\beta)$$

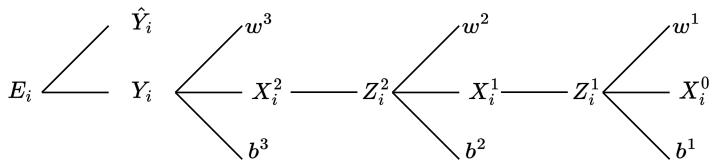
$$\begin{aligned}\beta_{n+1} &= \beta_n - \gamma_n \nabla E(\beta_n) \\ &= \beta_n - \gamma_n \sum_{i=1}^N \nabla E_i(\beta_n)\end{aligned}$$

Propagation



$$\begin{aligned} E_i &= (Y_i - \hat{Y}_i)^2, & \frac{\partial E_i}{\partial Y_i} &= 2(Y_i - \hat{Y}_i) \\ Y_i &= w^3 X_i^2 + b^3, & \frac{\partial Y_i}{\partial w^3} &= X_i^2, \quad \frac{\partial Y_i}{\partial b^3} = 1 \\ X_i^2 &= \phi^2(Z_i^2), & \frac{\partial X_i^2}{\partial Z_i^2} &= \dot{\phi}^2(Z_i^2), \\ Z_i^2 &= w^2 X_i^1 + b^2, & \frac{\partial Z_i^2}{\partial w^2} &= X_i^1, \quad \frac{\partial Z_i^2}{\partial b^2} = 1, \\ X_i^1 &= \phi^1(Z_i^1), & \frac{\partial X_i^1}{\partial Z_i^1} &= \dot{\phi}^1(Z_i^1), \\ Z_i^1 &= w^1 X_i^0 + b^1, & \frac{\partial Z_i^1}{\partial w^1} &= X_i^0, \quad \frac{\partial Z_i^1}{\partial b^1} = 1 \end{aligned}$$

Chain Rule



$$\frac{\partial E_i}{\partial w^3} = \frac{\partial E_i}{\partial Y_i} \frac{\partial Y_i}{\partial w^3}$$

$$\frac{\partial E_i}{\partial b^3} = \frac{\partial E_i}{\partial Y_i} \frac{\partial Y_i}{\partial b^3}$$

$$\frac{\partial E_i}{\partial w^2} = \frac{\partial E_i}{\partial Y_i} \frac{\partial Y_i}{\partial X_i^2} \frac{\partial X_i^2}{\partial Z_i^2} \frac{\partial Z_i^2}{\partial w^2}$$

$$\frac{\partial E_i}{\partial b^2} = \frac{\partial E_i}{\partial Y_i} \frac{\partial Y_i}{\partial X_i^2} \frac{\partial X_i^2}{\partial Z_i^2} \frac{\partial Z_i^2}{\partial b^2}$$

$$\frac{\partial E_i}{\partial w^1} = \frac{\partial E_i}{\partial Y_i} \frac{\partial Y_i}{\partial X_i^2} \frac{\partial X_i^2}{\partial Z_i^2} \frac{\partial Z_i^2}{\partial X_i^1} \frac{\partial X_i^1}{\partial Z_i^1} \frac{\partial Z_i^1}{\partial w^1}$$

$$\frac{\partial E_i}{\partial b^1} = \frac{\partial E_i}{\partial Y_i} \frac{\partial Y_i}{\partial X_i^2} \frac{\partial X_i^2}{\partial Z_i^2} \frac{\partial Z_i^2}{\partial X_i^1} \frac{\partial X_i^1}{\partial Z_i^1} \frac{\partial Z_i^1}{\partial b^1}$$