Deep Learning - Theory and Practice

IE 643
Lecture 5

August 19, 2022.

Recap: Convergence of Perceptron Training

Perceptron Convergence - Separability Assumption

Linear Separability Assumption

Let $D = \{(x^t, y^t)\}_{t=1}^{\infty}$ denote the training data where $x^t \in \mathbb{R}^d$, $y^t \in \{+1, -1\}$, $\forall t = 1, 2, \ldots$. Then there exist $\mathbb{R}^d \ni w^* \neq 0, \ \gamma > 0$, such that:

$$\langle w^*, x^t \rangle > \gamma \text{ where } y^t = 1,$$
$$\langle w^*, x^t \rangle < -\gamma \text{ where } y^t = -1.$$

Perceptron Convergence - Separability Assumption

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$$y^t \langle w^*, x^t \rangle > \gamma.$$

Perceptron Convergence - Mistake Bound

- We will try to derive useful bounds on the number of mistakes that a perceptron can commit during its training.
- **Assumption on data:** Linear Separability
- Assume that the T rounds of training have been completed in perceptron training. Assume T to be some large number.
- Assume that M mistakes are made by the perceptron in these T rounds. (Obviously, $M \leq T$.)
- We ask if the number of mistakes M can be bounded by some suitable quantity.

Perceptron Convergence - Mistake Bound

Recall: We wanted to handle the inner product term:

$$\langle w^*, w^{T+1} \rangle > M\gamma$$

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$$M\gamma < \langle w^*, w^{T+1} \rangle \leq \|w^*\|_2 \|w^{T+1}\|_2$$

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$$\begin{aligned} M\gamma < \langle w^*, w^{T+1} \rangle &\leq \|w^*\|_2 \|w^{T+1}\|_2 \\ \implies M^2\gamma^2 &< \|w^*\|_2^2 \|w^{T+1}\|_2^2 \end{aligned}$$

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Using the bound $\|w^{T+1}\|_2^2 \leq MR^2$ we obtain:

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Thus, assuming that $\|w^*\|_2$ and R can be controlled, the number of mistakes M is inversely proportional to γ, which determines the closeness of the data points to the separating hyperplane.

Perceptron - Caveat

- Not suitable when **linear separability assumption** fails
- Example: Classical XOR problem

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Heavily criticized by M. Minsky and S. Papert in their book: **Perceptrons**, *MIT Press*, 1969.

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- Not suitable when **linear separability assumption** fails
- Example: Classical XOR problem

x_1	x_2	$y = x_1 \oplus x_2$
0	0	-1
0	1	1
1	0	1
1	1	-1

Perceptron - Caveat

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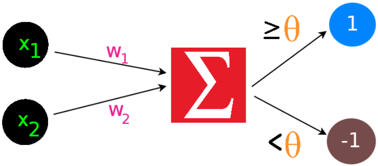
- Example: Classical XOR problem



x_1	x_2	$y = x_1 \oplus x_2$	$\hat{y} = \text{sign}(w_1x_1 + w_2x_2 - \theta)$
0	0	-1	$\text{sign}(-\theta)$
0	1	1	$\text{sign}(w_2 - \theta)$
1	0	1	$\text{sign}(w_1 - \theta)$
1	1	-1	$\text{sign}(w_1 + w_2 - \theta)$

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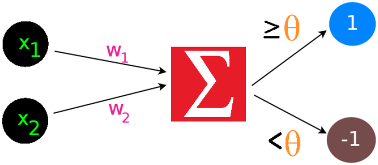
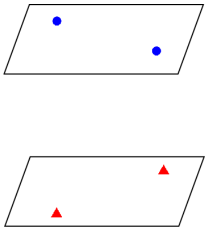


$$\text{sign}(-\theta) = -1 \implies \theta > 0$$
$$\text{sign}(w_2 - \theta) = 1 \implies w_2 - \theta \geq 0$$
$$\text{sign}(w_1 - \theta) = 1 \implies w_1 - \theta \geq 0$$
$$\text{sign}(w_1 + w_2 - \theta) = -1 \implies -w_1 - w_2 + \theta > 0$$

Note: This system is inconsistent. (Homework!)

Moving away from perceptron - Dealing with XOR problem



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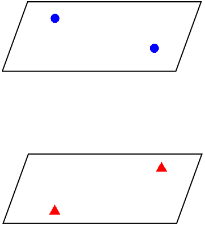

- Assume that the sample features $x \in \mathbb{R}^d$.

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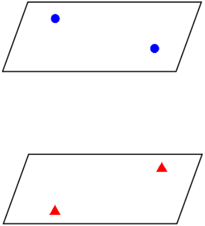

- Assume that the sample features $x \in \mathbb{R}^d$.
- **Idea:** Use a transformation $\psi : \mathbb{R}^d \to \mathbb{R}^q$, where $q \gg d$, to lift the data samples $x \in \mathbb{R}^d$ into $\psi(x) \in \mathbb{R}^q$ hoping to see a separating hyperplane in the transformed space.

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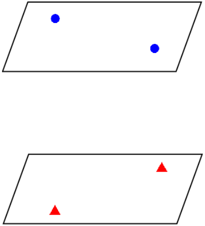

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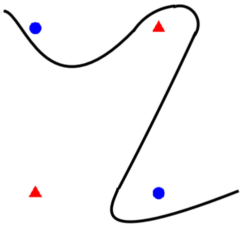
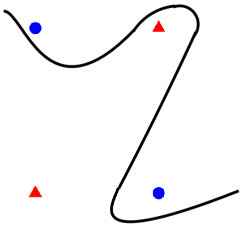
- Forms the core idea behind kernel methods. (Will not be pursued in this course!)

Moving away from perceptron - Dealing with XOR problem

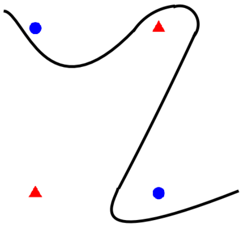


Moving away from perceptron - Dealing with XOR problem



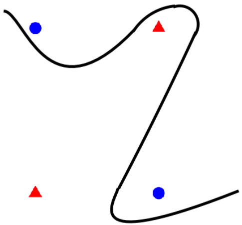
- **Idea:** The separating surface need not be linear and can be assumed to take some non-linear form.

Moving away from perceptron - Dealing with XOR problem



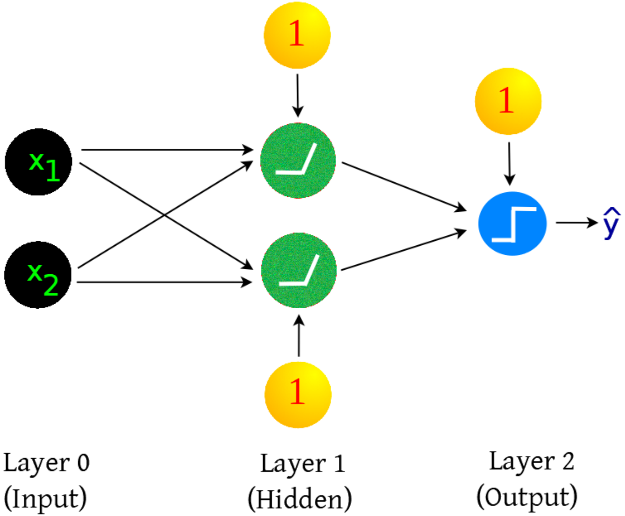
- **Idea:** The separating surface need not be linear and can be assumed to take some non-linear form.
- Hence for an input space $\mathcal{X}$ and output space $\mathcal{Y}$, the learned map $h : \mathcal{X} \to \mathcal{Y}$ can take some non-linear form.

Moving away from perceptron - Dealing with XOR problem



- **Idea:** The separating surface need not be linear and can be assumed to take some non-linear form.
- Hence for an input space $\mathcal{X}$ and output space $\mathcal{Y}$, the learned map $h : \mathcal{X} \to \mathcal{Y}$ can take some non-linear form.
- Forms the idea behind multi-layer perceptrons!

Moving away from perceptron - Dealing with XOR problem



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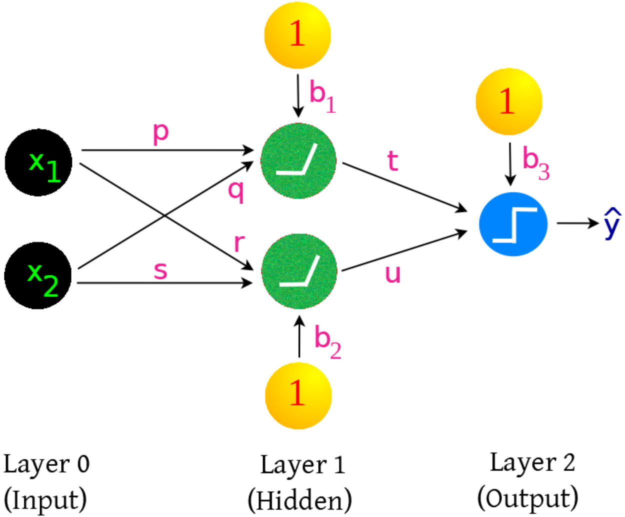

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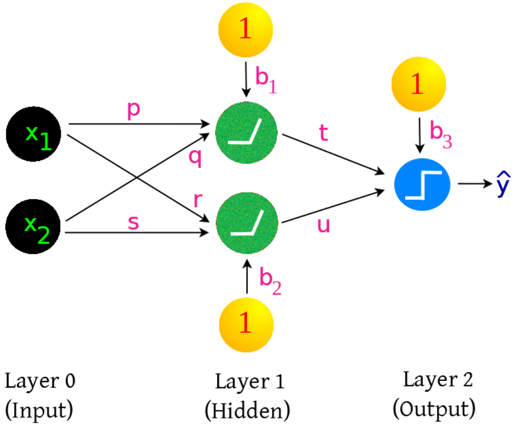
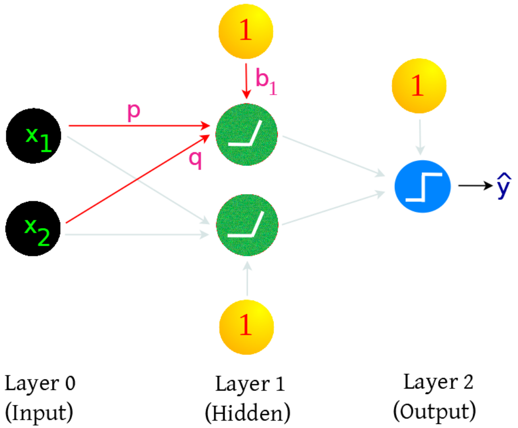


Some notations

- n_k^ℓ denotes k-th neuron at layer ℓ.
- a_k^ℓ denotes the activation of the neuron n_k^ℓ.

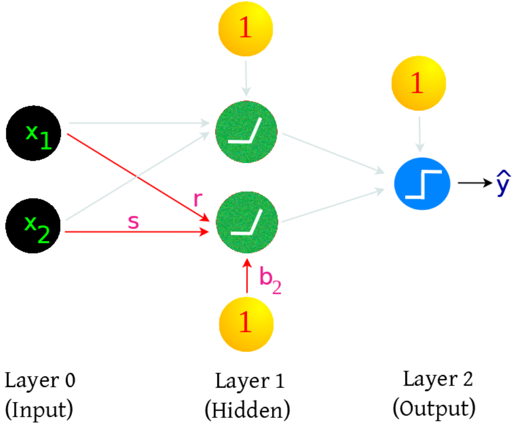
Moving away from perceptron - Dealing with XOR problem



- Activation at neuron n_1^1:

$$a_1^1 = \max\{px_1 + qx_2 + b_1, 0\}.$$

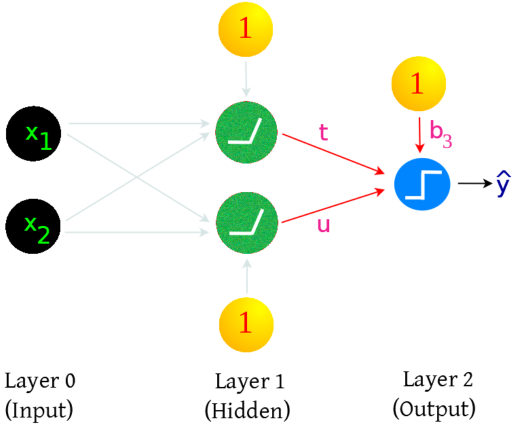
Moving away from perceptron - Dealing with XOR problem



- Activation at neuron n_2^1:

$$a_2^1 = \max\{rx_1 + sx_2 + b_2, 0\}.$$

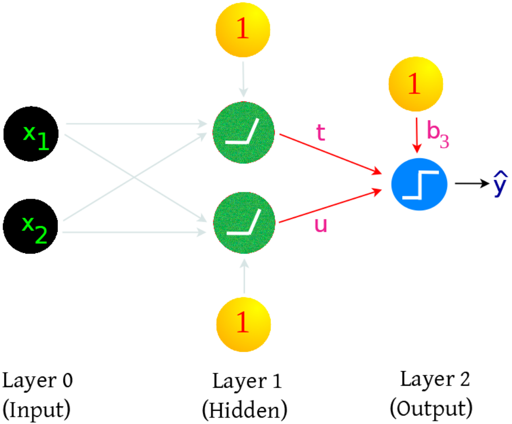
Moving away from perceptron - Dealing with XOR problem



- Activation at neuron n_1^2:

$$a_1^2 = \text{sign}(ta_1^1 + ua_2^1 + b_3).$$

Moving away from perceptron - Dealing with XOR problem



- Activation at neuron n_1^2:

$$a_1^2 = \text{sign}(ta_1^1 + ua_2^1 + b_3).$$

- **Note:** The activation a_1^2 is the output of the network denoted by $\hat{y}$.

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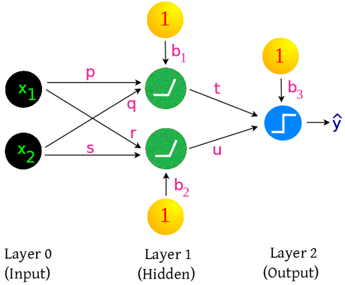
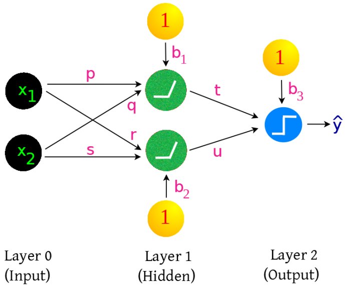


x_1	x_2	a_1^1	a_2^1	$\hat{y}$	y
0	0	$\max\{b_1, 0\}$	$\max\{b_2, 0\}$	$\text{sign}(ta_1^1 + ua_2^1 + b_3)$	-1
0	1	$\max\{q + b_1, 0\}$	$\max\{s + b_2, 0\}$	$\text{sign}(ta_1^1 + ua_2^1 + b_3)$	+1
1	0	$\max\{p + b_1, 0\}$	$\max\{r + b_2, 0\}$	$\text{sign}(ta_1^1 + ua_2^1 + b_3)$	+1
1	1	$\max\{p + q + b_1, 0\}$	$\max\{r + s + b_2, 0\}$	$\text{sign}(ta_1^1 + ua_2^1 + b_3)$	-1

Moving away from perceptron - Dealing with XOR problem



x_1	x_2	a_1^1	a_2^1	$\hat{y}$	y
0	0	$\max\{b_1, 0\}$	$\max\{b_2, 0\}$	$\text{sign}(ta_1^1 + ua_2^1 + b_3)$	-1
0	1	$\max\{q + b_1, 0\}$	$\max\{s + b_2, 0\}$	$\text{sign}(ta_1^1 + ua_2^1 + b_3)$	$+1$
1	0	$\max\{p + b_1, 0\}$	$\max\{r + b_2, 0\}$	$\text{sign}(ta_1^1 + ua_2^1 + b_3)$	$+1$
1	1	$\max\{p + q + b_1, 0\}$	$\max\{r + s + b_2, 0\}$	$\text{sign}(ta_1^1 + ua_2^1 + b_3)$	-1

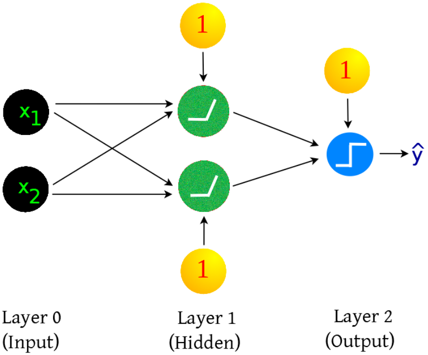
Homework: Find weights $p, q, r, s, t, u, b_1, b_2, b_3$ such that the MLP solves the XOR problem.

Moving away from perceptron - Dealing with XOR problem

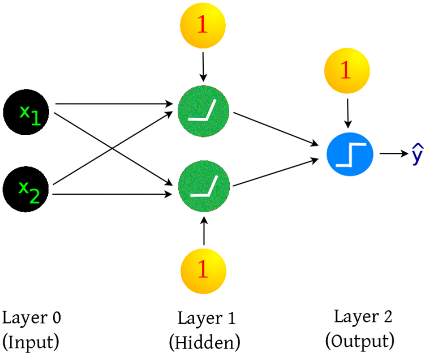
A different Multi Layer Perceptron (MLP) architecture is given for XOR problem in:

- David. E. Rumelhart, Geoffrey E. Hinton and Ronald J. Williams. **Learning Internal Representations by Error Propagation**, Technical Report, UCSD, 1985.

Multi Layer Perceptron

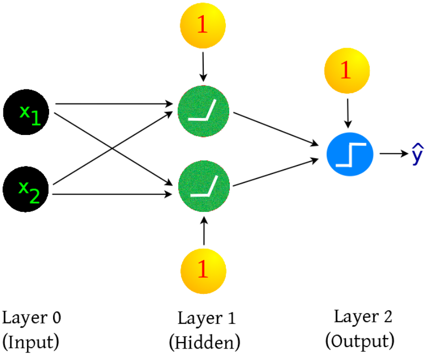


Multi Layer Perceptron



Notable features:

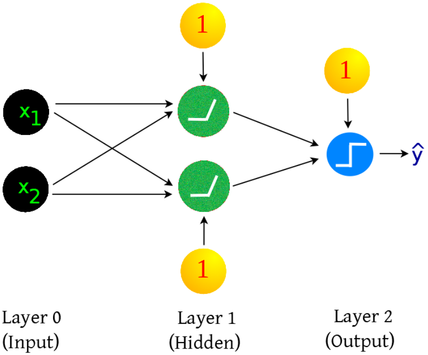
Multi Layer Perceptron



Notable features:

- Multiple layers stacked together.

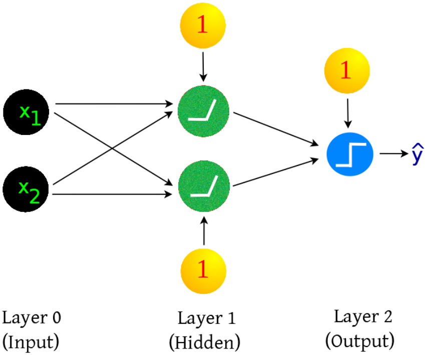
Multi Layer Perceptron



Notable features:

- Multiple layers stacked together.
- Zero-th layer usually called input layer.

Multi Layer Perceptron



Notable features:

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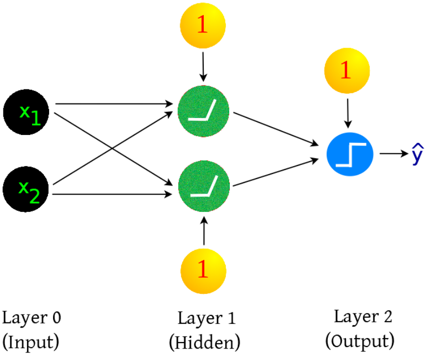
- Zero-th layer usually called input layer.
- Final layer usually called output layer.

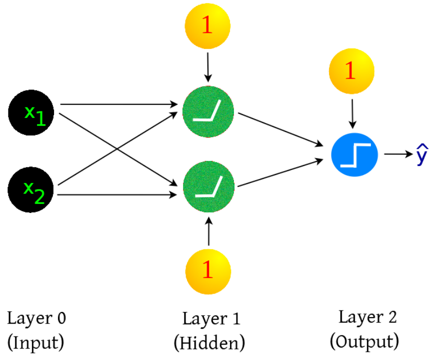
Multi Layer Perceptron



Notable features:

- Multiple layers stacked together.
- Zero-th layer usually called input layer.
- Final layer usually called output layer.
- Intermediate layers are called hidden layers.

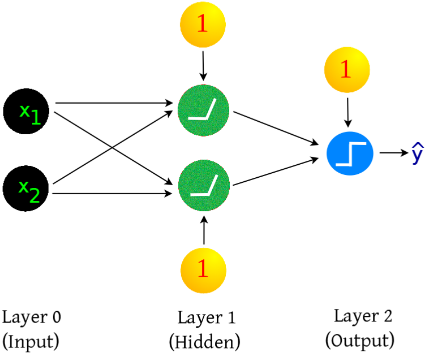
Multi Layer Perceptron



Notable features:

- Each neuron in the hidden and output layer is like a perceptron.

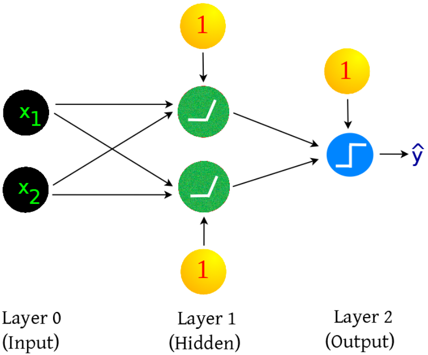
Multi Layer Perceptron



Notable features:

- Each neuron in the hidden and output layer is like a perceptron.
- However, unlike perceptron, different activation functions are used.

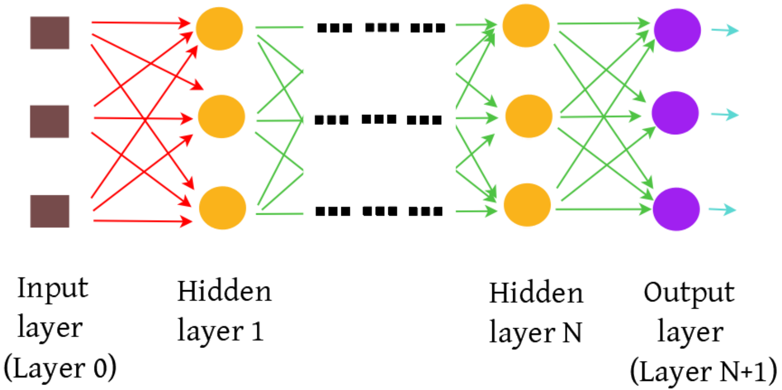
Multi Layer Perceptron



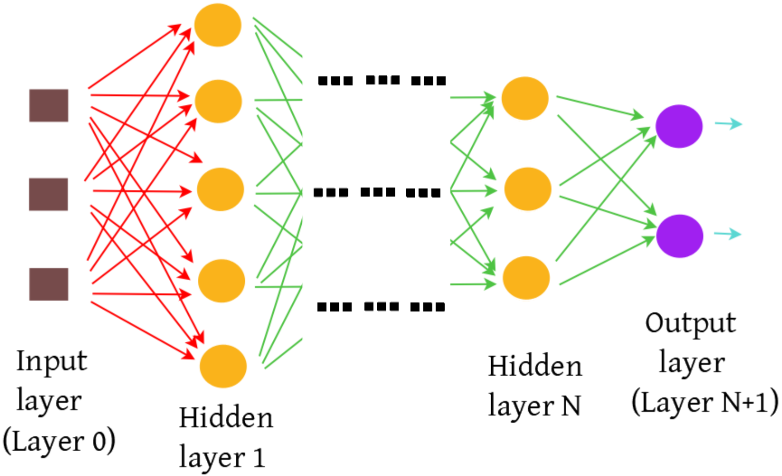
Notable features:

- Each neuron in the hidden and output layer is like a perceptron.
- However, unlike perceptron, different activation functions are used.
- $\max\{x, 0\}$ has a special name called **ReLU** (**R**ectified **L**inear **U**nit).

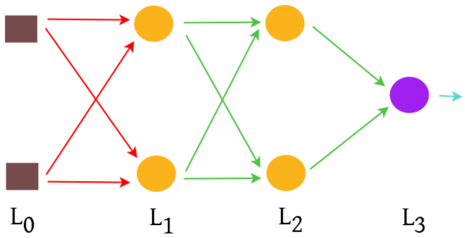
Multi Layer Perceptron



Multi Layer Perceptron



Multi Layer Perceptron - More notations



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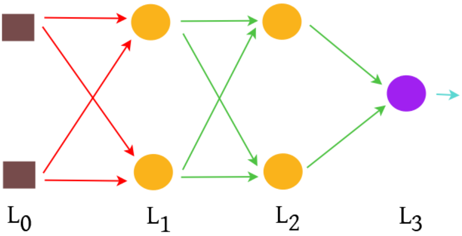
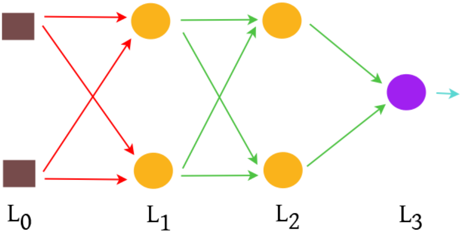


- This MLP contains an input layer L_0, 2 hidden layers denoted by L_1, L_2, and output layer L_3.

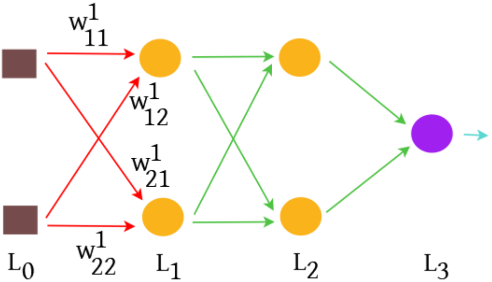
Multi Layer Perceptron - More notations



Recall:

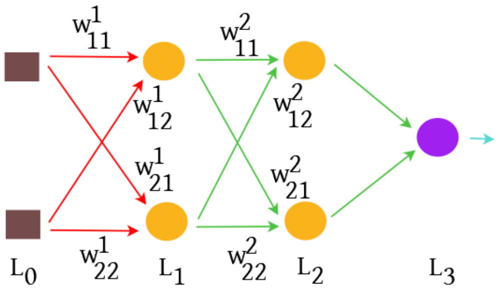
- n_k^ℓ denotes k-th neuron at ℓ-th layer.
- a_k^ℓ denotes activation of neuron n_k^ℓ.

Multi Layer Perceptron - More notations



- w^{ℓ}_{ij} denotes weight of connection connecting n^{ℓ}_i from $n^{\ell-1}_j$.

Multi Layer Perceptron - More notations



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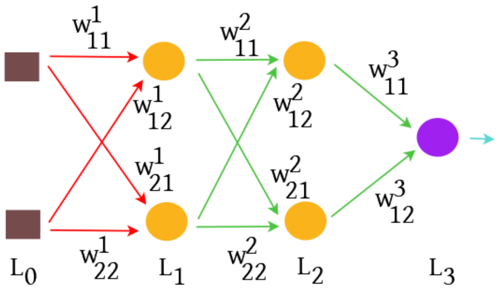

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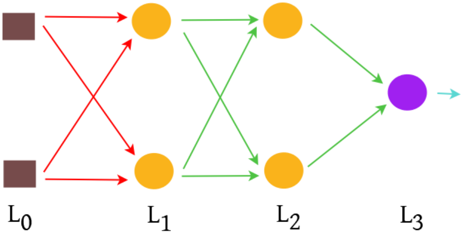
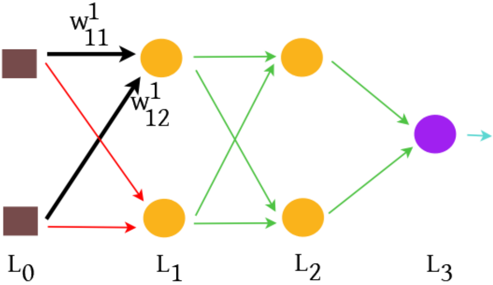


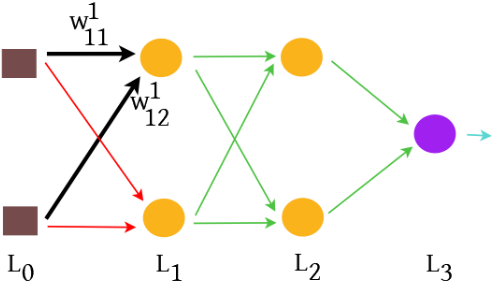
- In this particular case, the inputs are x_1 and x_2 at input layer L_0.

Multi Layer Perceptron - More notations



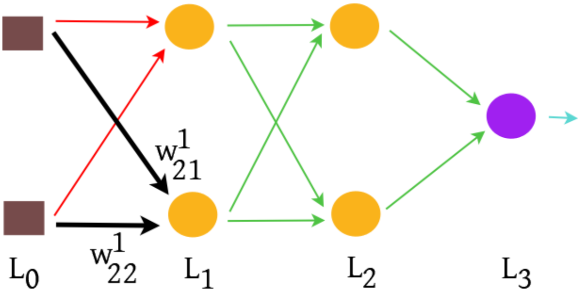
- At layer L_1:
  - At neuron n^1_1:
    - ★ $a^1_1 = \phi(w^1_{11}x_1 + w^1_{12}x_2)$.

Multi Layer Perceptron - More notations



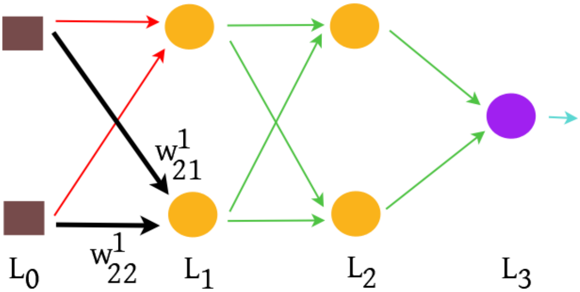
- At layer L_1:
  - At neuron n^1_1:
    - ★ $a^1_1 = \phi(w^1_{11}x_1 + w^1_{12}x_2) =: \phi(z^1_1)$.

Multi Layer Perceptron - More notations



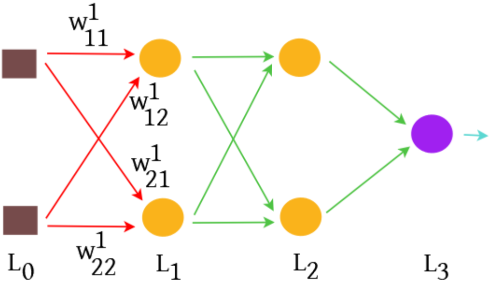
- At layer L_1:
  - At neuron n^1_2:
    - ★ $a^1_2 = \phi(w^1_{21}x_1 + w^1_{22}x_2)$.

Multi Layer Perceptron - More notations



- At layer L_1:
  - At neuron n^1_2:
    - $a^1_2 = \phi(w^1_{21}x_1 + w^1_{22}x_2) =: \phi(z^1_2)$.

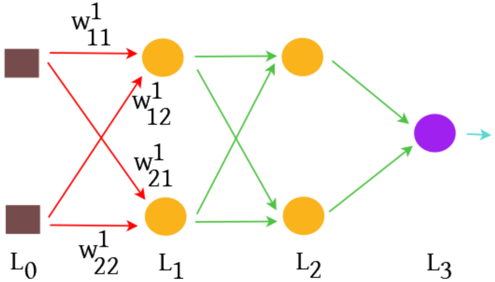
Multi Layer Perceptron - More notations



- At layer L_1:

$$\begin{bmatrix} a^1_1 \\ a^1_2 \end{bmatrix} = \begin{bmatrix} \phi(z^1_1) \\ \phi(z^1_2) \end{bmatrix} = \begin{bmatrix} \phi(w^1_{11}x_1 + w^1_{12}x_2) \\ \phi(w^1_{21}x_1 + w^1_{22}x_2) \end{bmatrix}$$

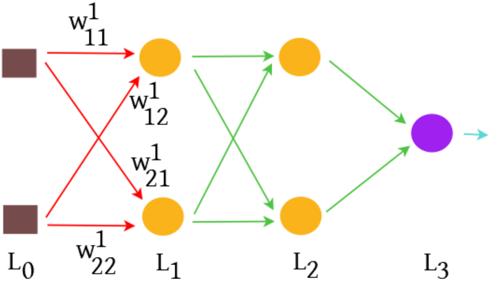
Multi Layer Perceptron - More notations



- Letting $W^1 = \begin{bmatrix} w^1_{11} & w^1_{12} \\ w^1_{21} & w^1_{22} \end{bmatrix}$ and $x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$, we have at layer L_1:

$$\begin{bmatrix} a^1_1 \\ a^1_2 \end{bmatrix} = \phi\left(\begin{bmatrix} z^1_1 \\ z^1_2 \end{bmatrix}\right) = \phi\left(\begin{bmatrix} w^1_{11}x_1 + w^1_{12}x_2 \\ w^1_{21}x_1 + w^1_{22}x_2 \end{bmatrix}\right) = \phi(W^1 x)$$

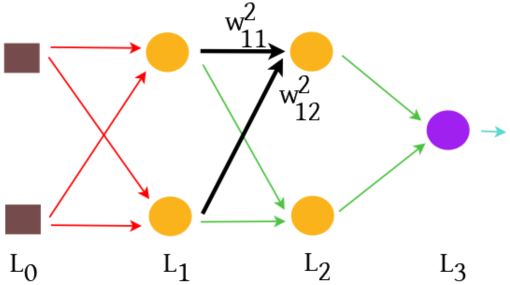
Multi Layer Perceptron - More notations



- Letting $a^1 = \begin{bmatrix} a_1^1 \\ a_2^1 \end{bmatrix}$, we have at layer L_1:

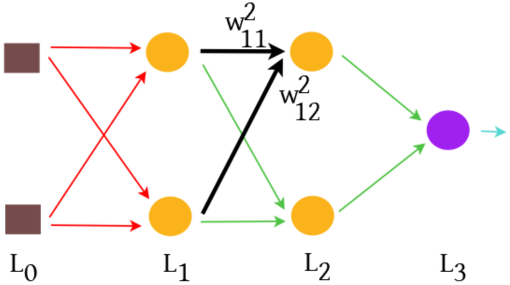
$$a^1 = \begin{bmatrix} a_1^1 \\ a_2^1 \end{bmatrix} = \phi(W^1 x)$$

Multi Layer Perceptron - More notations



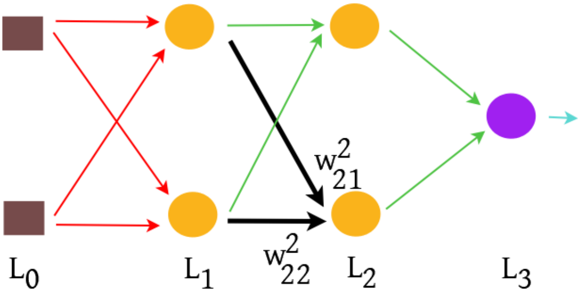
- At layer L_2:
  - At neuron n^2_1:
    - ★ $a^2_1 = \phi(w^2_{11} a^1_1 + w^2_{12} a^1_2)$.

Multi Layer Perceptron - More notations



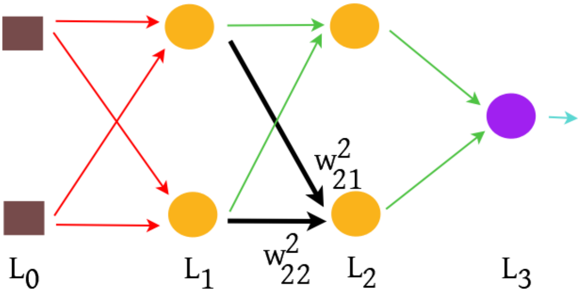
- At layer L_2:
  - At neuron n_1^2:
    - ★ $a_1^2 = \phi(w_{11}^2 a_1^1 + w_{12}^2 a_2^1) =: \phi(z_1^2)$.

Multi Layer Perceptron - More notations



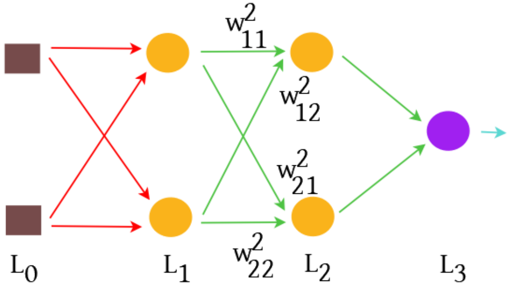
- At layer L_2:
  - At neuron n_2^2:
    - ★ $a_2^2 = \phi(w_{21}^2 a_1^1 + w_{22}^2 a_2^1)$.

Multi Layer Perceptron - More notations



- At layer L_2:
  - At neuron n_2^2:
    - ★ $a_2^2 = \phi(w_{21}^2 a_1^1 + w_{22}^2 a_2^1) =: \phi(z_2^2)$.

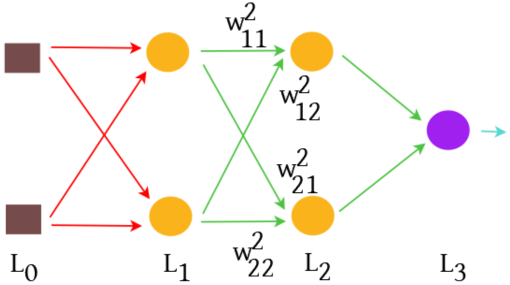
Multi Layer Perceptron - More notations



- At layer L_2:

$$a^2 = \begin{bmatrix} a_1^2 \\ a_2^2 \end{bmatrix} = \begin{bmatrix} \phi(z_1^2) \\ \phi(z_2^2) \end{bmatrix} = \begin{bmatrix} \phi(w_{11}^2 a_1^1 + w_{12}^2 a_2^1) \\ \phi(w_{21}^2 a_1^1 + w_{22}^2 a_2^1) \end{bmatrix}$$

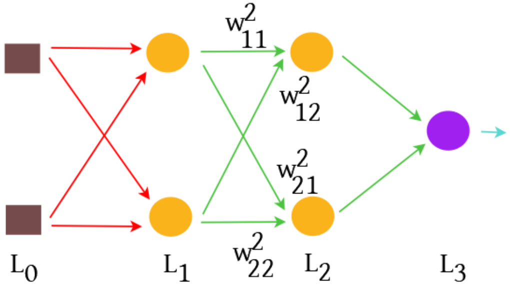
Multi Layer Perceptron - More notations



- Letting $W^2 = \begin{bmatrix} w^2_{11} & w^2_{12} \\ w^2_{21} & w^2_{22} \end{bmatrix}$, we have at layer L_2:

$$a^2 = \begin{bmatrix} a^2_1 \\ a^2_2 \end{bmatrix} = \phi\left(\begin{bmatrix} z^2_1 \\ z^2_2 \end{bmatrix}\right) = \phi\left(\begin{bmatrix} w^2_{11}a^1_1 + w^2_{12}a^1_2 \\ w^2_{21}a^1_1 + w^2_{22}a^1_2 \end{bmatrix}\right) = \phi\left(W^2 \begin{bmatrix} a^1_1 \\ a^1_2 \end{bmatrix}\right)$$

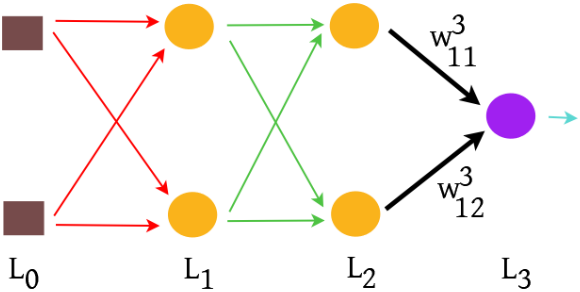
Multi Layer Perceptron - More notations



- We have at layer L_2:

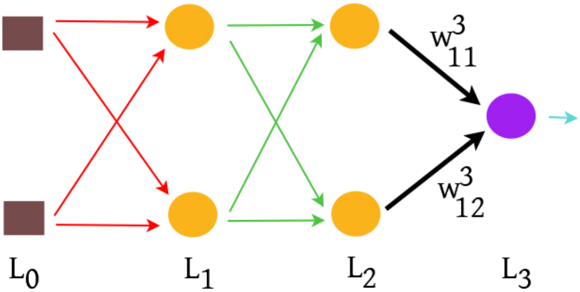
$$a^2 = \begin{bmatrix} a_1^2 \\ a_2^2 \end{bmatrix} = \phi\left(\begin{bmatrix} z_1^2 \\ z_2^2 \end{bmatrix}\right) = \phi\left(W^2 \begin{bmatrix} a_1^1 \\ a_2^1 \end{bmatrix}\right) = \phi(W^2 a^1)$$

Multi Layer Perceptron - More notations



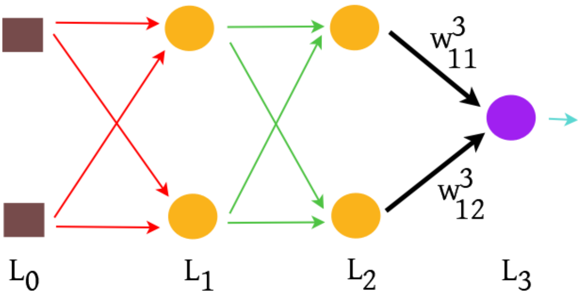
- At layer L_3:
  - At neuron n_1^3:
    - ★ $a_1^3 = \phi(w_{11}^3 a_1^2 + w_{12}^3 a_2^2)$.

Multi Layer Perceptron - More notations



- At layer L_3:
  - At neuron n^3_1:
    - ★ $a^3_1 = \phi(w^3_{11}a^2_1 + w^3_{12}a^2_2) =: \phi(z^3_1)$.

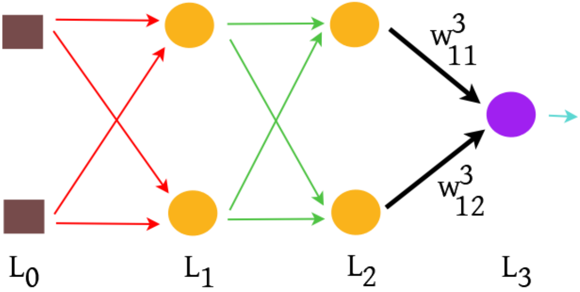
Multi Layer Perceptron - More notations



- At layer L_3:

$$a^3 = [a_1^3] = [\phi(z_1^3)] = [\phi(w_{11}^3 a_1^2 + w_{12}^3 a_2^2)]$$

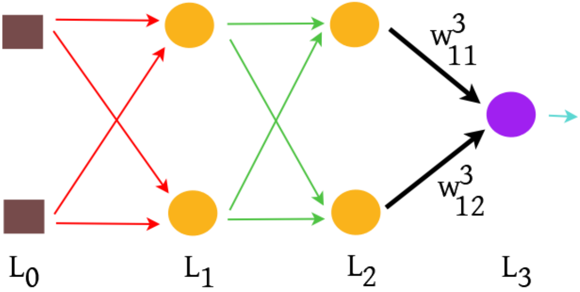
Multi Layer Perceptron - More notations



- Letting $W^3 = \begin{bmatrix} w_{11}^3 & w_{12}^3 \end{bmatrix}$, we have at layer L_3:

$$a^3 = \begin{bmatrix} a_1^3 \end{bmatrix} = \phi\left(\begin{bmatrix} z_1^3 \end{bmatrix}\right) = \phi\left(\begin{bmatrix} w_{11}^3 a_1^2 + w_{12}^3 a_2^2 \end{bmatrix}\right) = \phi\left(W^3 \begin{bmatrix} a_1^2 \\ a_2^2 \end{bmatrix}\right)$$

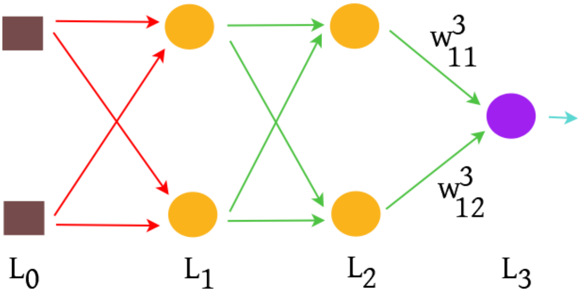
Multi Layer Perceptron - More notations



- Letting $W^3 = \begin{bmatrix} w_{11}^3 & w_{12}^3 \end{bmatrix}$, we have at layer L_3:

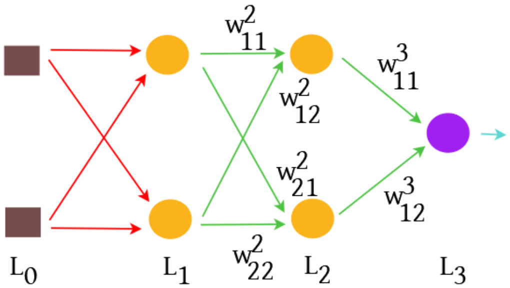
$$a^3 = \begin{bmatrix} a_1^3 \end{bmatrix} = \phi\left(\begin{bmatrix} z_1^3 \end{bmatrix}\right) = \phi\left(W^3 \begin{bmatrix} a_1^2 \\ a_2^2 \end{bmatrix}\right) = \phi(W^3 a^2)$$

Multi Layer Perceptron - More notations



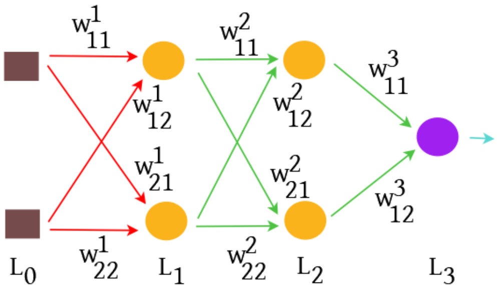
$$a^3 = \phi(W^3 a^2)$$

Multi Layer Perceptron - More notations



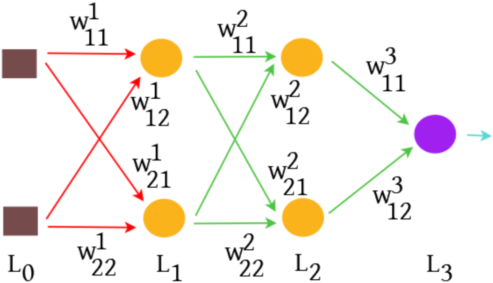
$$a^3 = \phi(W^3 a^2) = \phi(W^3 \phi(W^2 a^1))$$

Multi Layer Perceptron - More notations



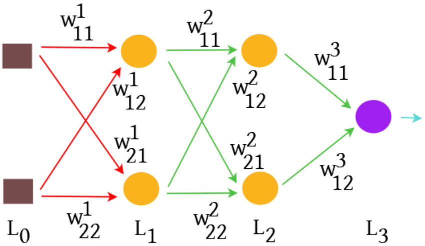
$$a^3 = \phi(W^3 a^2) = \phi(W^3 \phi(W^2 a^1)) = \phi(W^3 \phi(W^2 \phi(W^1 x)))$$

Multi Layer Perceptron - More notations



$$\hat{y} = a^3 = \phi(W^3 a^2) = \phi(W^3 \phi(W^2 a^1)) = \phi(W^3 \phi(W^2 \phi(W^1 x)))$$

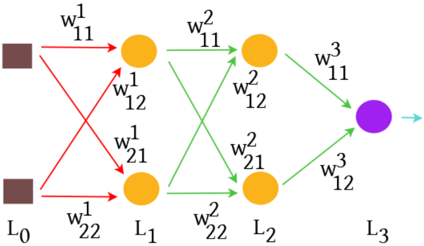
Multi Layer Perceptron - Data Perspective



Given data (x, y), multi layer perceptron predicts:

$$\hat{y} = \phi(W^3\phi(W^2\phi(W^1x)))$$

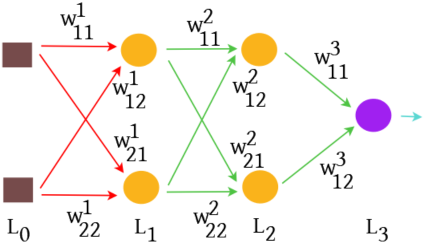
Multi Layer Perceptron - Data Perspective



Given data (x, y), multi layer perceptron predicts:

$$\hat{y} = \phi(W^3\phi(W^2\phi(W^1x))) =: \mathrm{MLP}(x)$$

Multi Layer Perceptron - Data Perspective



Given data (x, y), multi layer perceptron predicts:

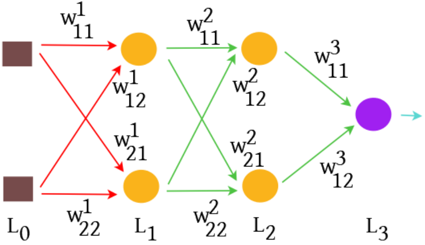
$$\hat{y} = \phi(W^3\phi(W^2\phi(W^1 x))) =: \mathrm{MLP}(x)$$

Note: The same activation function ϕ was assumed for simplicity. Typically different activations functions are used for different layers. Then we can write:

$$\hat{y} = \phi_3(W^3\phi_2(W^2\phi_1(W^1 x))) =: \mathrm{MLP}(x)$$

where ϕ_1, ϕ_2 and ϕ_3 are activation functions for layers L_1, L_2 and L_3 respectively.

Multi Layer Perceptron - Data Perspective

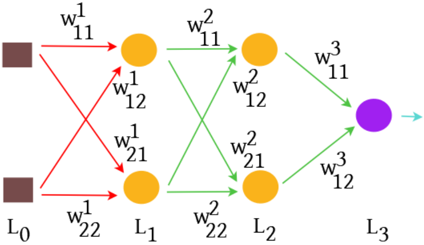


Given data (x, y), multi layer perceptron predicts:

$$\hat{y} = \phi(W^3\phi(W^2\phi(W^1x))) =: \text{MLP}(x)$$

Similar to perceptron, if $y \neq \hat{y}$ an error $E(y, \hat{y})$ is incurred.

Multi Layer Perceptron - Data Perspective

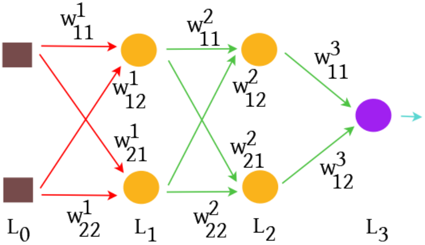


Given data (x, y), multi layer perceptron predicts:

$$\hat{y} = \phi(W^3\phi(W^2\phi(W^1x))) =: \mathrm{MLP}(x)$$

Similar to perceptron, if $y \neq \hat{y}$ an error $E(y, \hat{y})$ is incurred.
Aim: To change the weights W^1, W^2, W^3, such that the error $E(y, \hat{y})$ is minimized.

Multi Layer Perceptron - Data Perspective



Given data (x, y), multi layer perceptron predicts:

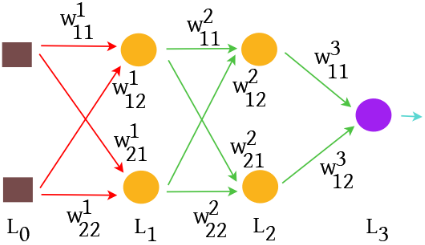
$$\hat{y} = \phi(W^3\phi(W^2\phi(W^1x))) =: \mathrm{MLP}(x)$$

Similar to perceptron, if $y \neq \hat{y}$ an error $E(y, \hat{y})$ is incurred.

Aim: To change the weights W^1, W^2, W^3, such that the error $E(y, \hat{y})$ is minimized.

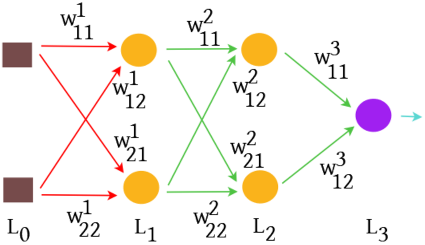
Leads to an error minimization problem.

Multi Layer Perceptron - Data Perspective



- **Input:** Training Data $D = \{(x^s, y^s)\}_{s=1}^{S}$.
- For each sample x^s the prediction $\hat{y}^s = \mathrm{MLP}(x^s)$.
- **Error:** $e^s = E(y^s, \hat{y}^s)$.
- **Aim:** To minimize $\sum_{s=1}^{S} e^s$.

Multi Layer Perceptron - Data Perspective

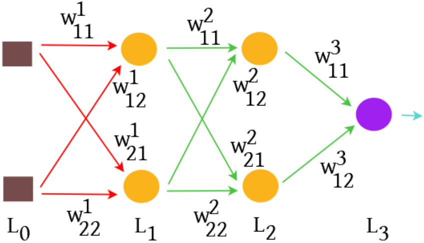


Optimization perspective

- Given training data $D = \{(x^s, y^s)\}_{s=1}^{S}$,

$$\min \sum_{s=1}^{S} e^s$$

Multi Layer Perceptron - Data Perspective

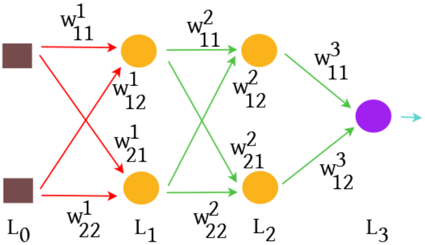


Optimization perspective

- Given training data $D = \{(x^s, y^s)\}_{s=1}^{S}$,

$$\min \sum_{s=1}^{S} e^s = \sum_{s=1}^{S} E(y^s, \hat{y}^s)$$

Multi Layer Perceptron - Data Perspective

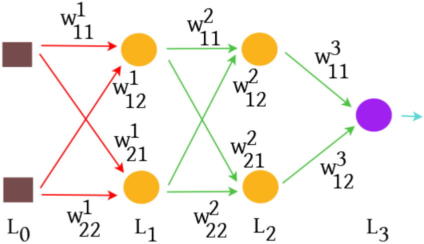


Optimization perspective

- Given training data $D = \{(x^s, y^s)\}_{s=1}^{S}$,

$$\min \sum_{s=1}^{S} e^s = \sum_{s=1}^{S} E(y^s, \hat{y}^s) = \sum_{s=1}^{S} E(y^s, \mathrm{MLP}(x^s))$$

Multi Layer Perceptron - Data Perspective



Optimization perspective

- Given training data $D = \{(x^s, y^s)\}_{s=1}^{S}$,

$$\min \sum_{s=1}^{S} e^s = \sum_{s=1}^{S} E(y^s, \hat{y}^s) = \sum_{s=1}^{S} E(y^s, \mathrm{MLP}(x^s))$$

- Note: The minimization is over the weights of the MLP $W^1, \ldots, W^L$, where L denotes number of layers in MLP.