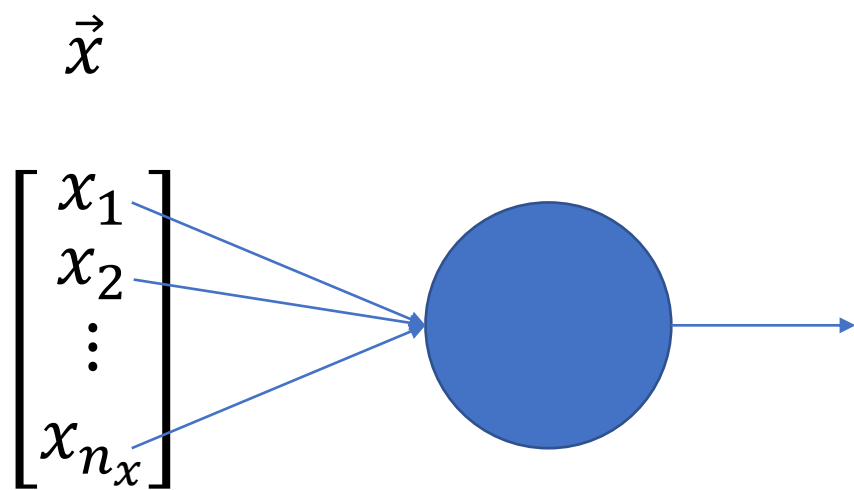
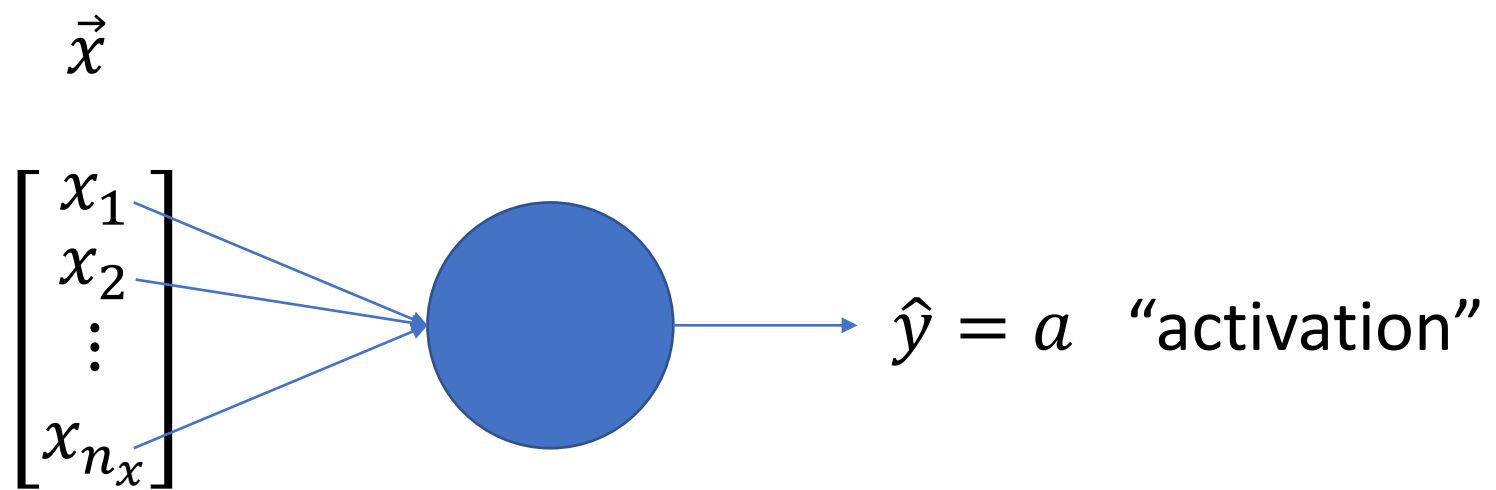


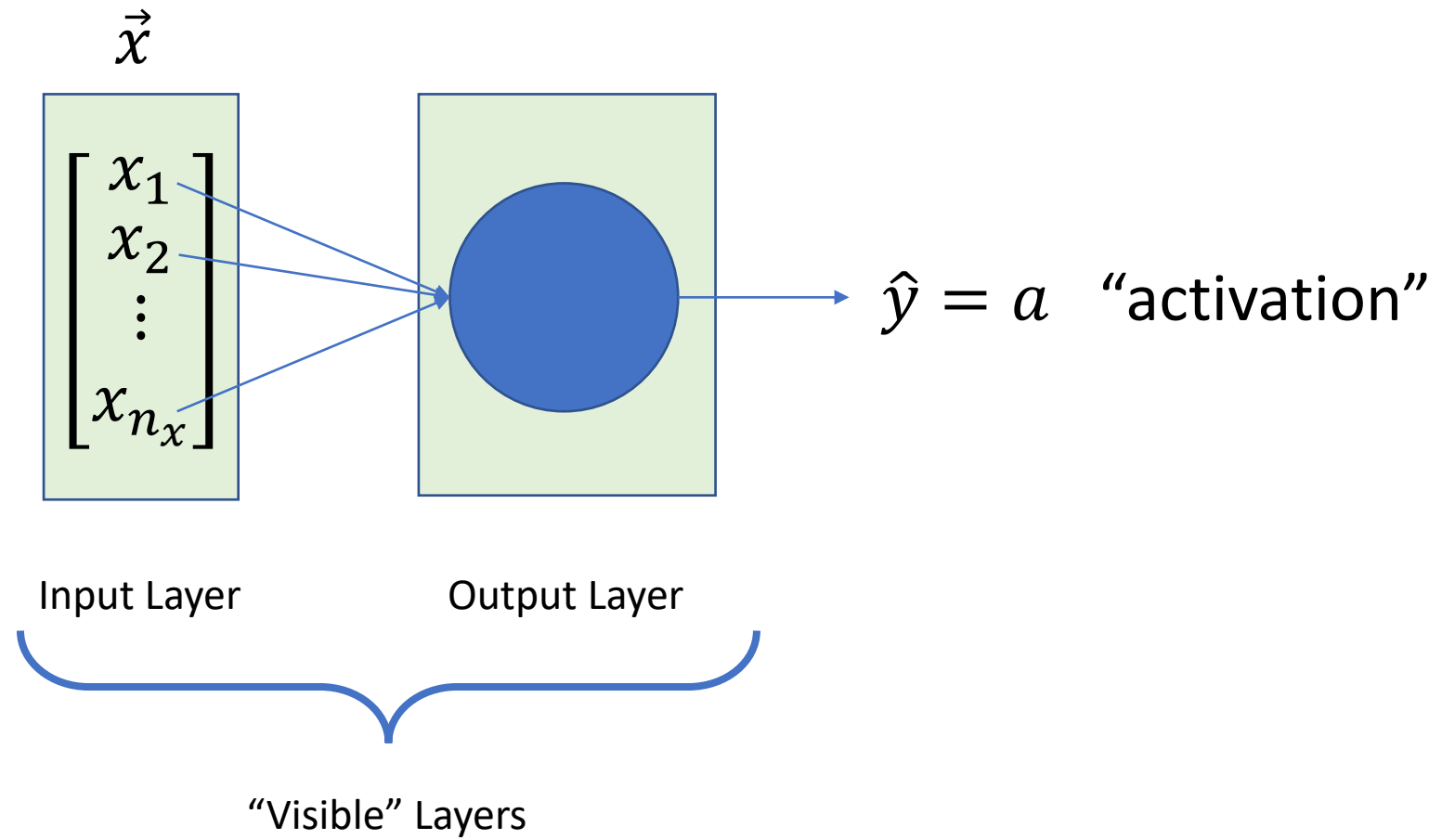
Neural Networks

$$\vec{x}$$

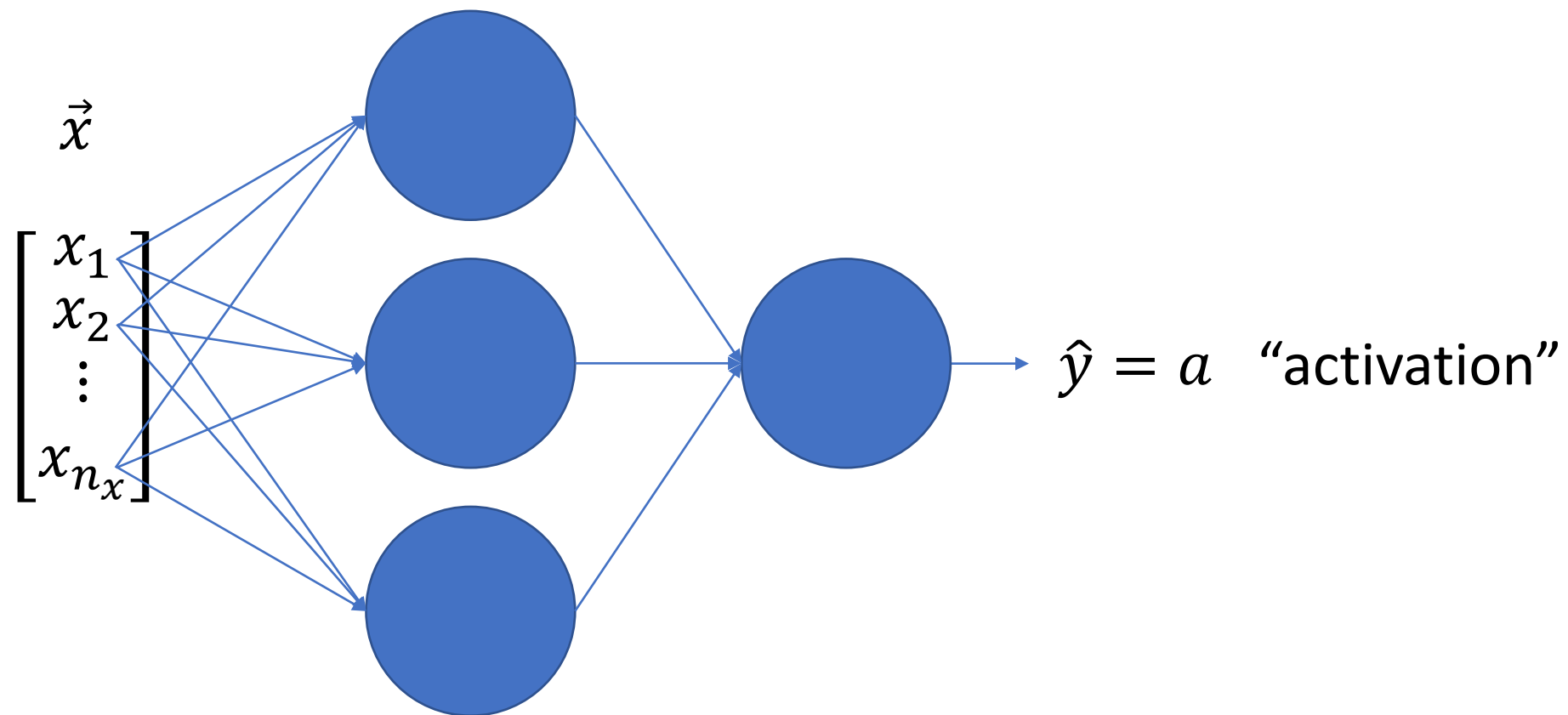
$$\begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{n_x} \end{bmatrix}$$

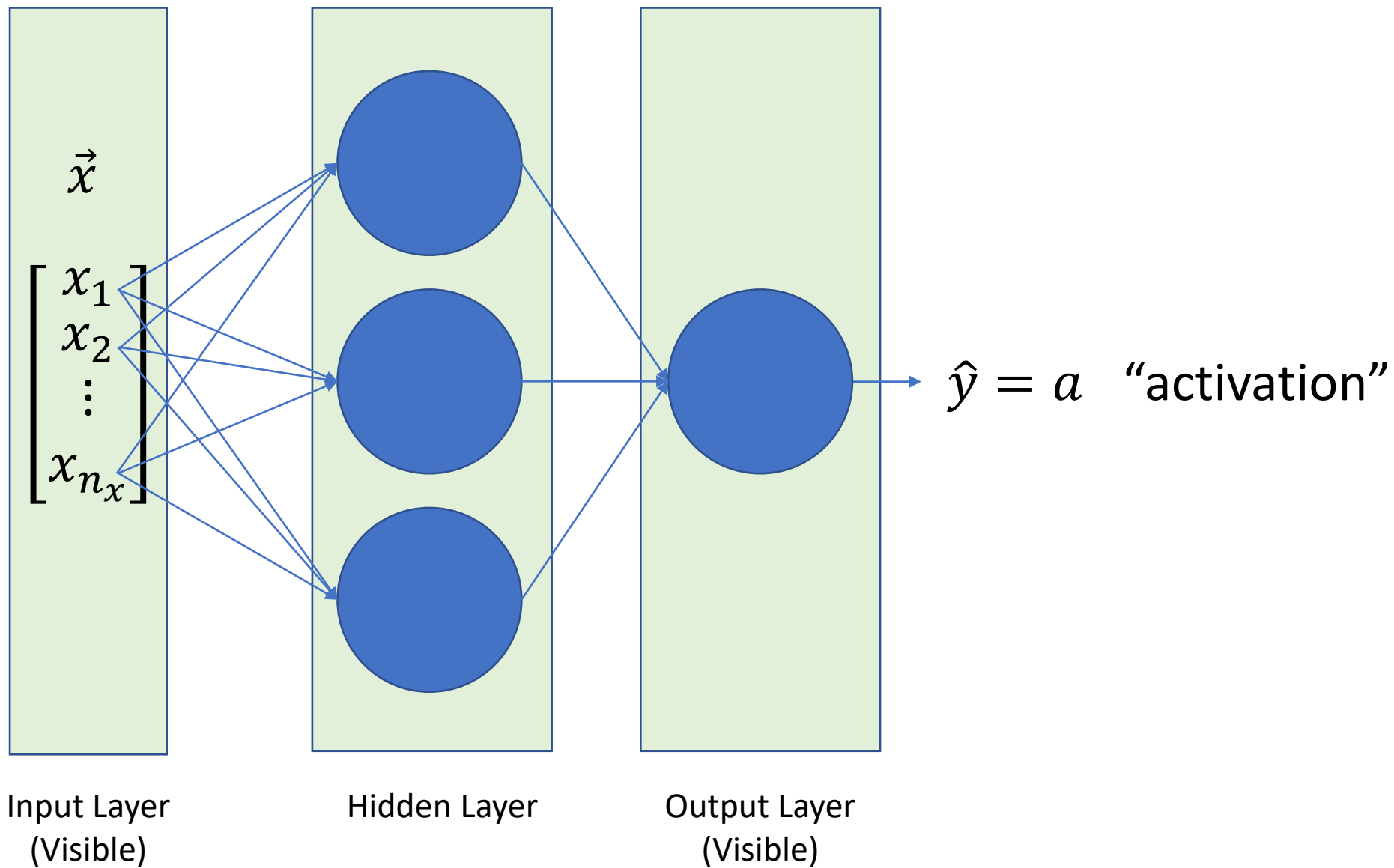


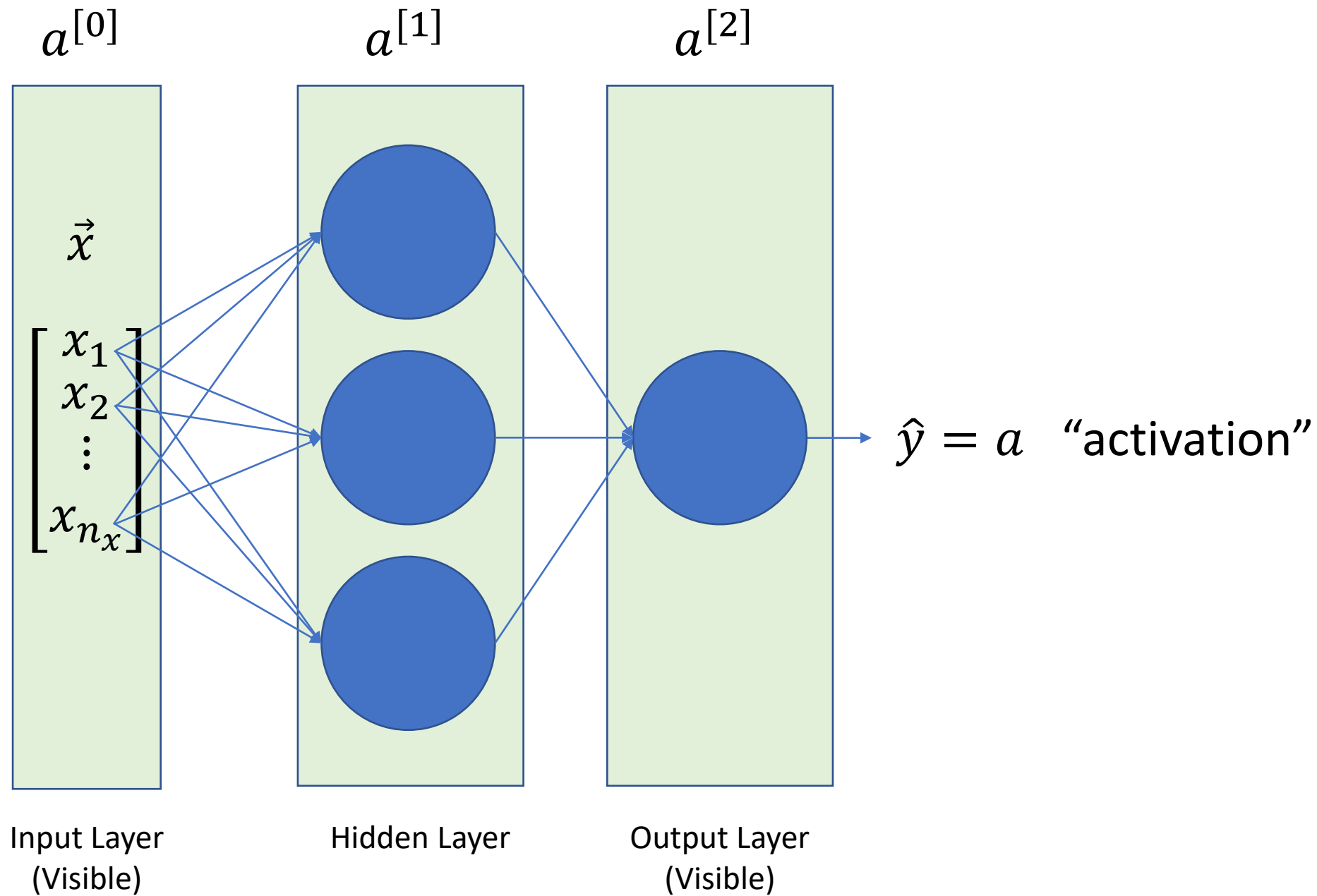


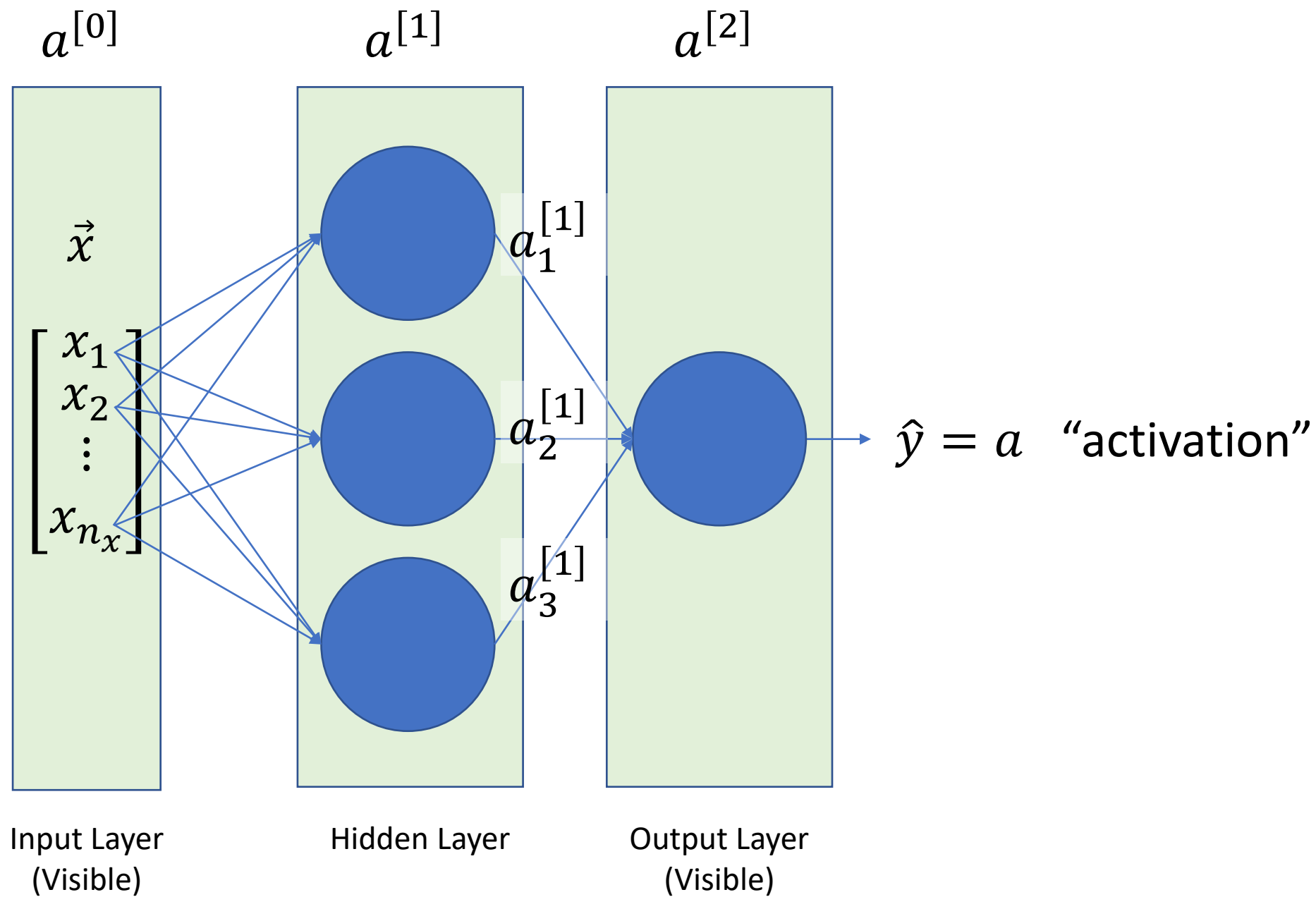


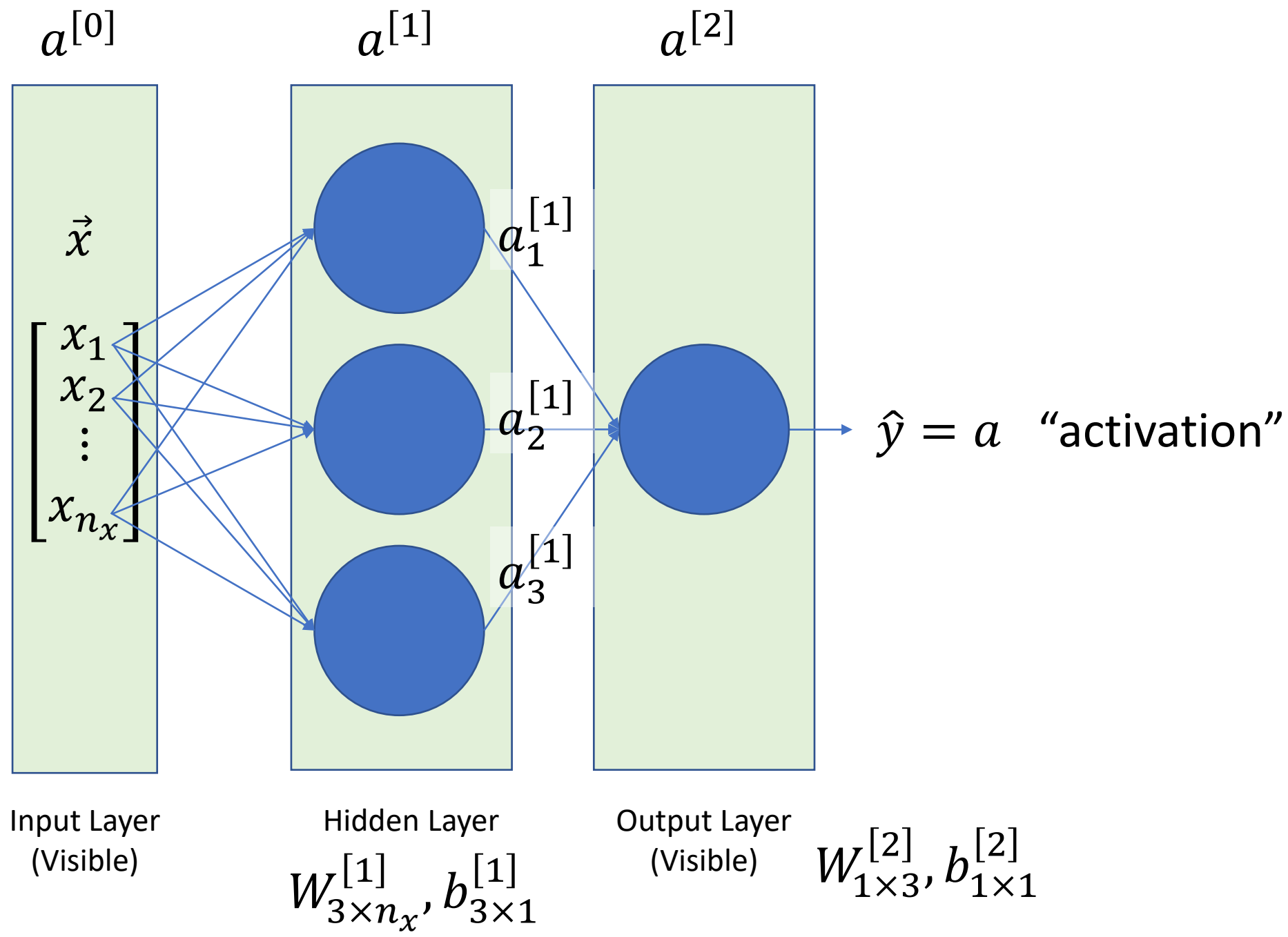
One hidden layer



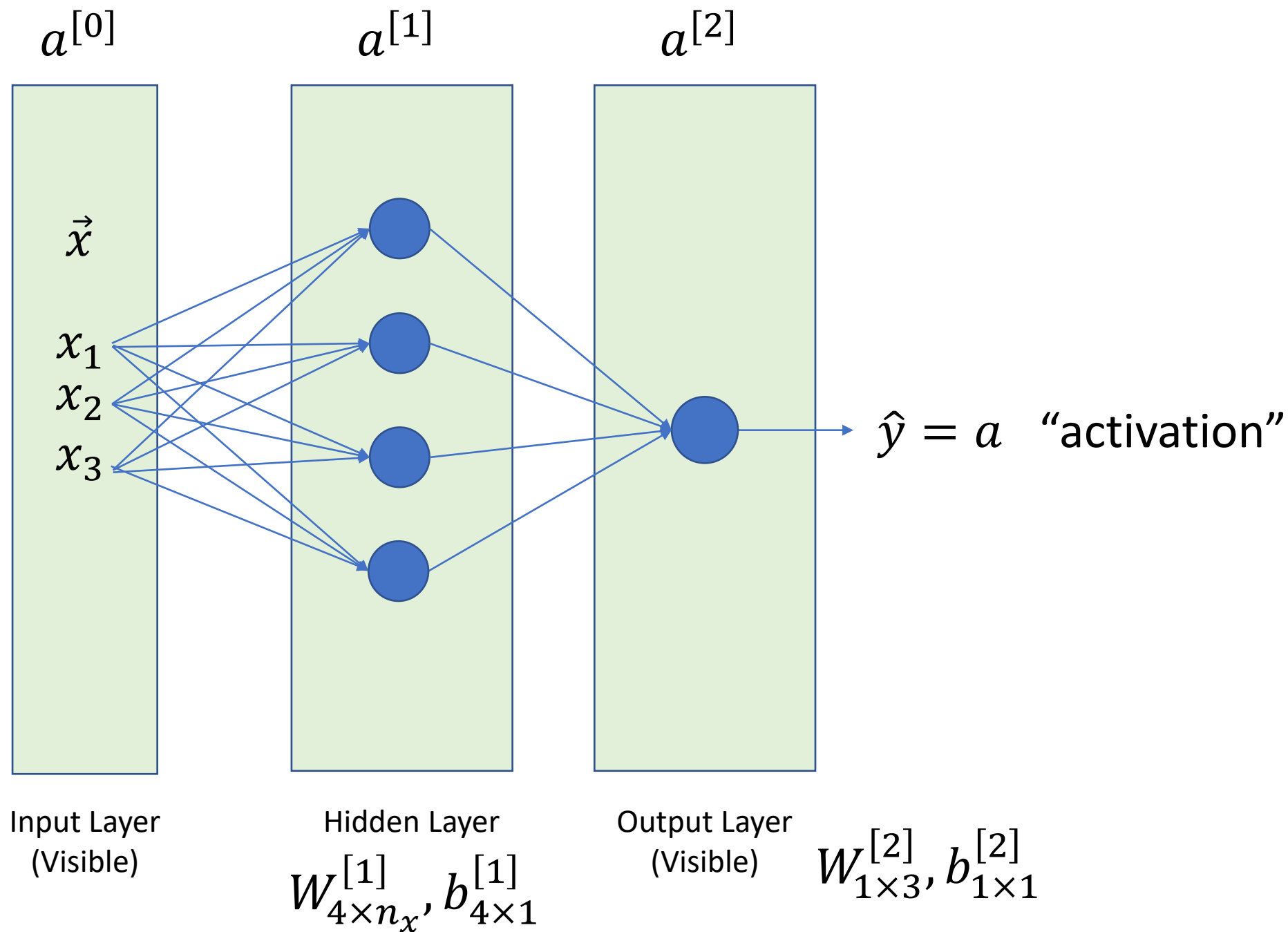


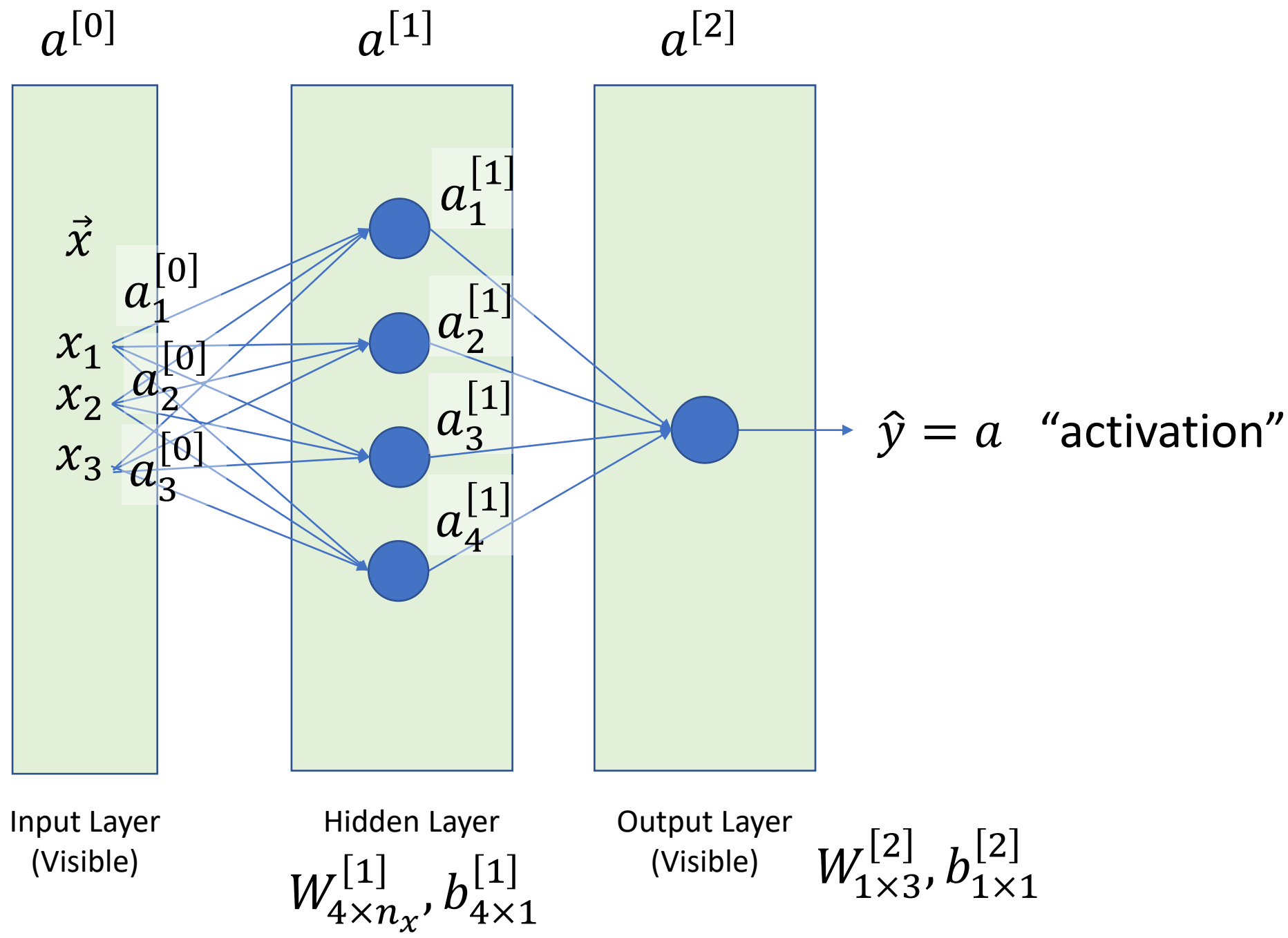




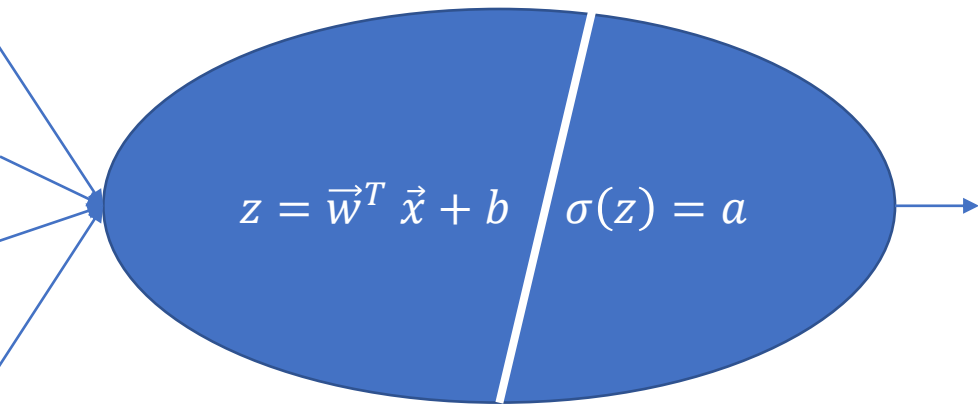


Computing an NN's output

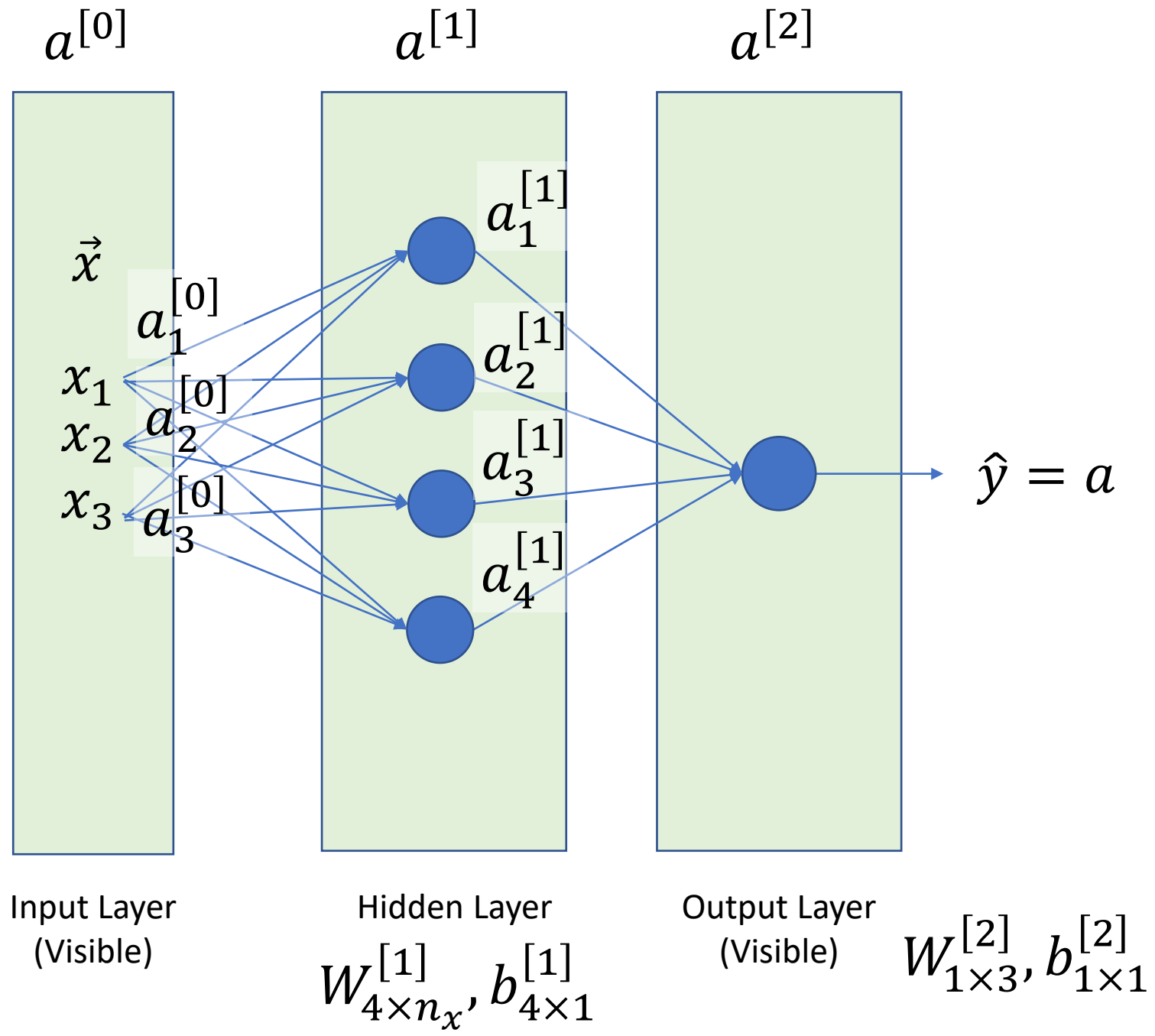




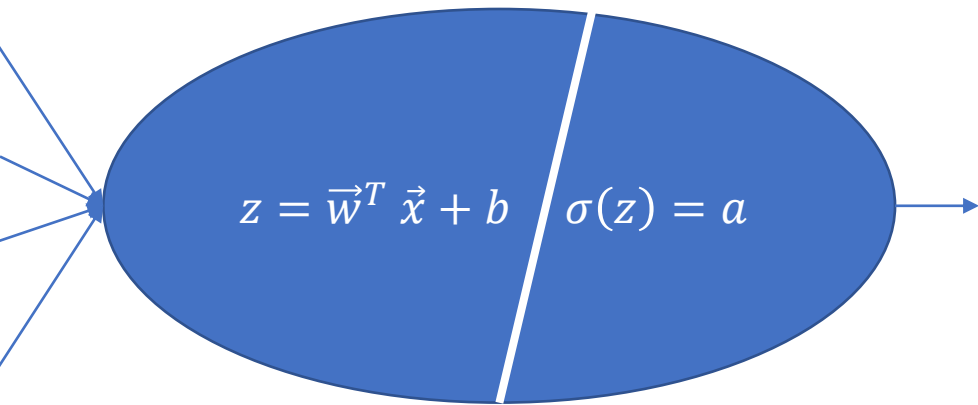
Each Neuron:



$$\begin{aligned} z_1^{[1]} &= \vec{w}_1^{[1]T} \vec{x} + b_1^{[1]}; & a_1^{[1]} &= \sigma(z_1^{[1]}) + b_1^{[1]} \\ z_2^{[1]} &= \vec{w}_2^{[1]T} \vec{x} + b_2^{[1]}; & a_2^{[1]} &= \sigma(z_2^{[1]}) + b_2^{[1]} \\ z_3^{[1]} &= \vec{w}_3^{[1]T} \vec{x} + b_3^{[1]}; & a_3^{[1]} &= \sigma(z_3^{[1]}) + b_3^{[1]} \\ z_4^{[1]} &= \vec{w}_4^{[1]T} \vec{x} + b_4^{[1]}; & a_4^{[1]} &= \sigma(z_4^{[1]}) + b_4^{[1]} \end{aligned}$$



Each Neuron:



$$z_1^{[1]} = \vec{w}_1^{[1]T} \vec{x} + b_1^{[1]}; \quad a_1^{[1]} = \sigma(z_1^{[1]}) + b_1^{[1]}$$

$$z_2^{[1]} = \vec{w}_2^{[1]T} \vec{x} + b_2^{[1]}; \quad a_2^{[1]} = \sigma(z_2^{[1]}) + b_2^{[1]}$$

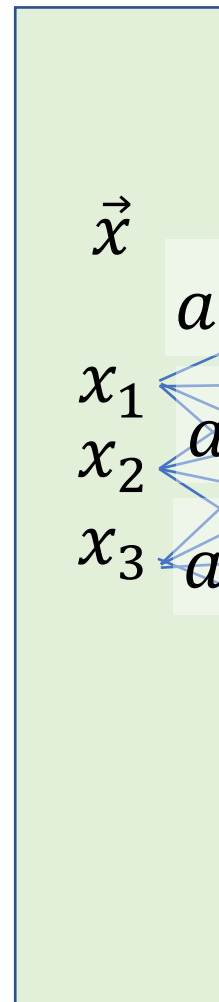
$$z_3^{[1]} = \vec{w}_3^{[1]T} \vec{x} + b_3^{[1]}; \quad a_3^{[1]} = \sigma(z_3^{[1]}) + b_3^{[1]}$$

$$z_4^{[1]} = \vec{w}_4^{[1]T} \vec{x} + b_4^{[1]}; \quad a_4^{[1]} = \sigma(z_4^{[1]}) + b_4^{[1]}$$

$$\begin{bmatrix} z_1^{[1]} \\ z_2^{[1]} \\ z_3^{[1]} \\ z_4^{[1]} \end{bmatrix} = \begin{bmatrix} -\vec{w}_1^{[1]T} & - \\ -\vec{w}_2^{[1]T} & - \\ -\vec{w}_3^{[1]T} & - \\ -\vec{w}_4^{[1]T} & - \end{bmatrix}_{4 \times 3} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1^{[1]} \\ b_2^{[1]} \\ b_3^{[1]} \\ b_4^{[1]} \end{bmatrix}$$

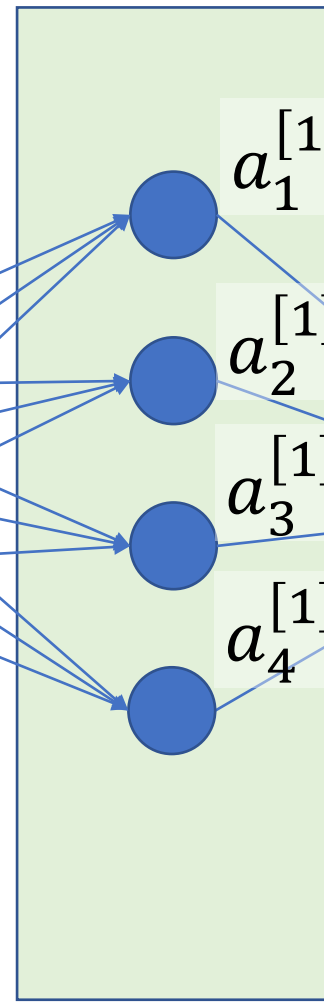
$$A_{4 \times 1}^{[1]} = \sigma(Z_{4 \times 1}^{[1]})$$

$a^{[0]}$



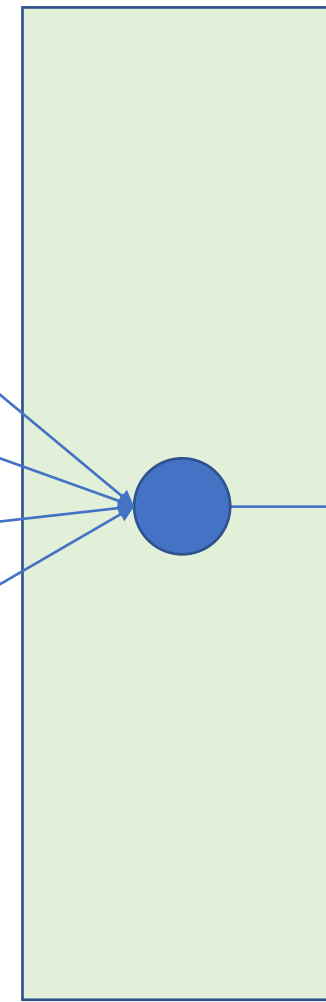
Input Layer
(Visible)

$a^{[1]}$



Hidden Layer
 $W_{4 \times n_x}^{[1]}, b_{4 \times 1}^{[1]}$

$a^{[2]}$

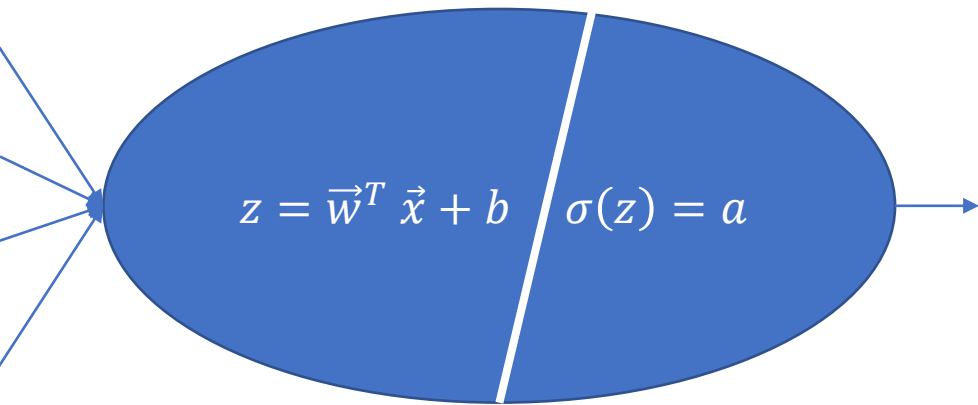


Output Layer
(Visible)

$W_{1 \times 3}^{[2]}, b_{1 \times 1}^{[2]}$

$\hat{y} = a$

Each Neuron:



$$z_1^{[1]} = \vec{w}_1^{[1]T} \vec{x} + b_1^{[1]}; \quad a_1^{[1]} = \sigma(z_1^{[1]}) + b_1^{[1]}$$

$$z_2^{[1]} = \vec{w}_2^{[1]T} \vec{x} + b_2^{[1]}; \quad a_2^{[1]} = \sigma(z_2^{[1]}) + b_2^{[1]}$$

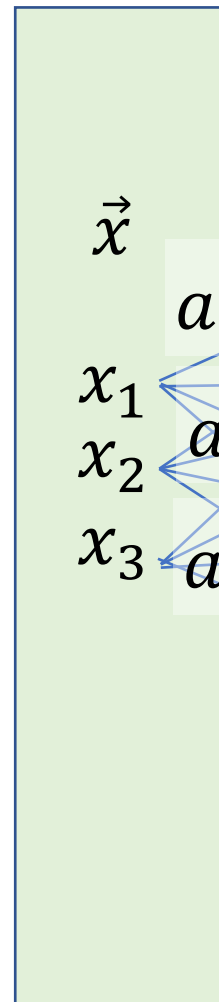
$$z_3^{[1]} = \vec{w}_3^{[1]T} \vec{x} + b_3^{[1]}; \quad a_3^{[1]} = \sigma(z_3^{[1]}) + b_3^{[1]}$$

$$z_4^{[1]} = \vec{w}_4^{[1]T} \vec{x} + b_4^{[1]}; \quad a_4^{[1]} = \sigma(z_4^{[1]}) + b_4^{[1]}$$

$$\begin{bmatrix} z_1^{[1]} \\ z_2^{[1]} \\ z_3^{[1]} \\ z_4^{[1]} \end{bmatrix} = \begin{bmatrix} -\vec{w}_1^{[1]T} & - \\ -\vec{w}_2^{[1]T} & - \\ -\vec{w}_3^{[1]T} & - \\ -\vec{w}_4^{[1]T} & - \end{bmatrix}_{4 \times 3} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1^{[1]} \\ b_2^{[1]} \\ b_3^{[1]} \\ b_4^{[1]} \end{bmatrix}$$

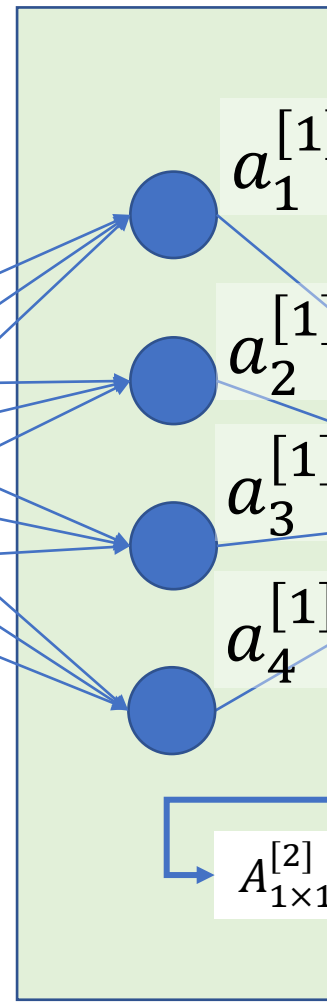
$$A_{4 \times 1}^{[1]} = \sigma(Z_{4 \times 1}^{[1]}) = \sigma(W_{4 \times 3}^{[1]} A_{3 \times 1}^{[0]} + b_{4 \times 1}^{[1]})$$

$a^{[0]}$



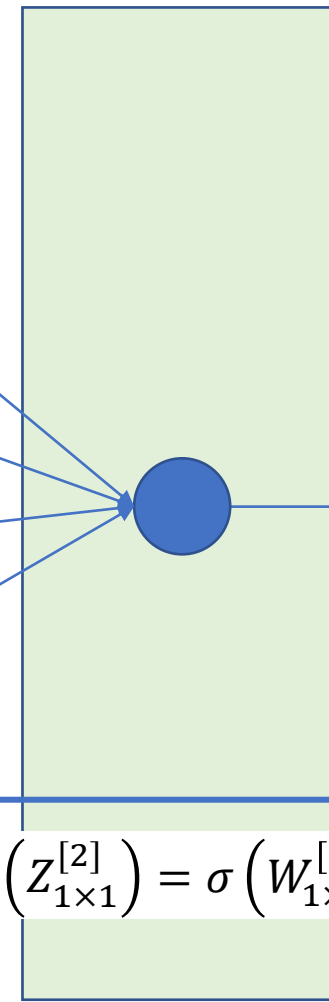
Input Layer
(Visible)

$a^{[1]}$



Hidden Layer
 $W_{4 \times n_x}^{[1]}, b_{4 \times 1}^{[1]}$

$a^{[2]}$



Output Layer
(Visible)

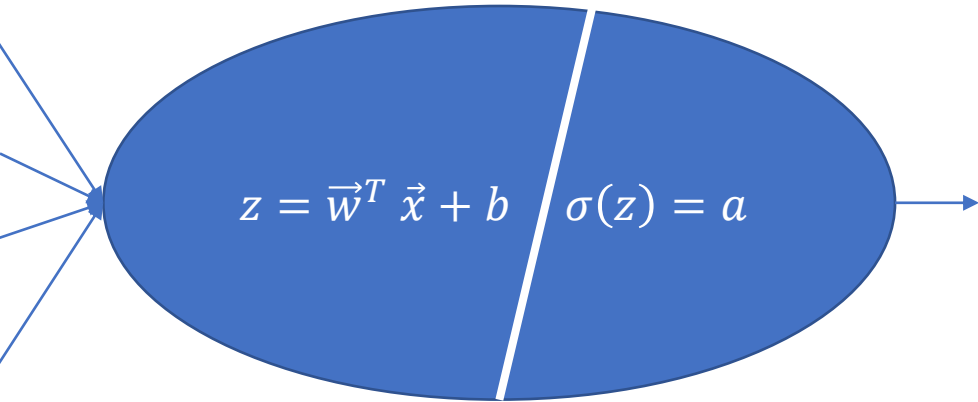
$$W_{1 \times 3}^{[2]}, b_{1 \times 1}^{[2]}$$

$$A_{1 \times 1}^{[2]} = \sigma(Z_{1 \times 1}^{[2]}) = \sigma(W_{1 \times 4}^{[2]} A_{4 \times 1}^{[1]} + b_{1 \times 1}^{[2]})$$

$$\hat{y} = a$$

Gradient descent for NNs
(one hidden layer)

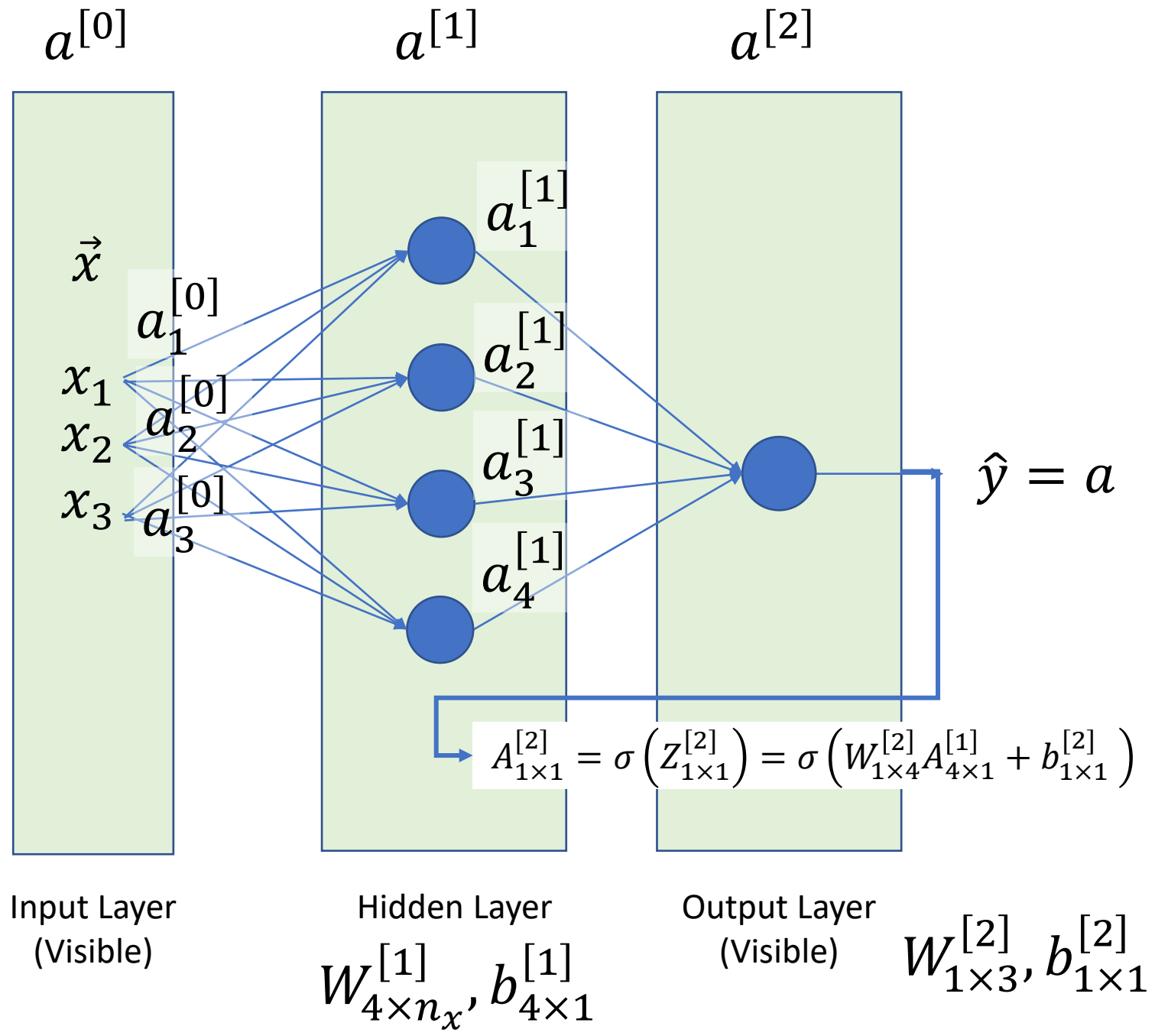
Each Neuron:



$$\begin{bmatrix} -\vec{w}_1^{[1]T} & - \\ -\vec{w}_2^{[1]T} & - \\ -\vec{w}_3^{[1]T} & - \\ -\vec{w}_4^{[1]T} & - \end{bmatrix}_{4 \times 3} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + \begin{bmatrix} b_1^{[1]} \\ b_2^{[1]} \\ b_3^{[1]} \\ b_4^{[1]} \end{bmatrix}$$

Parameters:

- $W_{n^{[1]} \times n^{[0]}}, \vec{b}_{n^{[1]},1}^{[1]}, W_{n^{[2]} \times n^{[1]}}, \vec{b}_{n^{[2]},1}^{[2]}$
- $n^{[0]} = n_x$: Number of input features.
- $n^{[1]}$: Number of hidden units.
- $n^{[2]} = 1$: Number of output units.



Cost Function:

$$J(W^{[1]}, \vec{b}^{[1]}, W^{[2]}, \vec{b}^{[2]}) = \frac{1}{m} \sum_{i=1}^m \mathcal{L}(\hat{y}, y)$$

Gradient descent (to “learn” the parameters):

repeat {

1. Compute predictions ($\hat{y}^{(i)}, i = 1, \dots, m$);

2. Compute derivatives

- $dw^{[1]} = \frac{\partial J}{\partial w^{[1]}}$,

- $db^{[1]} = \frac{\partial J}{\partial b^{[1]}}$,

- $dw^{[2]} = \frac{\partial J}{\partial w^{[2]}}$,

- $db^{[2]} = \frac{\partial J}{\partial b^{[2]}}$.

3. Update parameters:

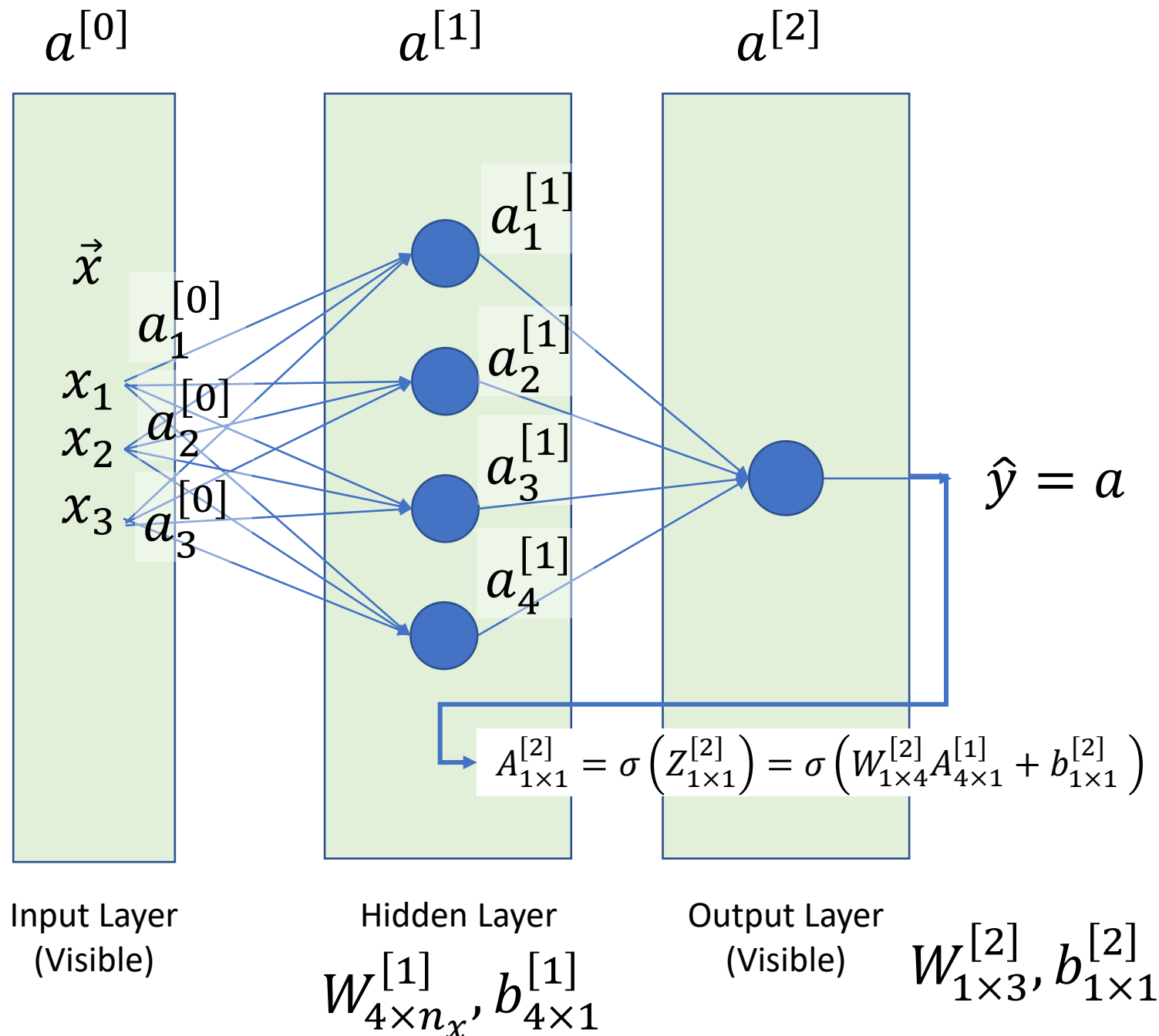
- $w^{[1]} \leftarrow w^{[1]} - \alpha dw^{[1]}$

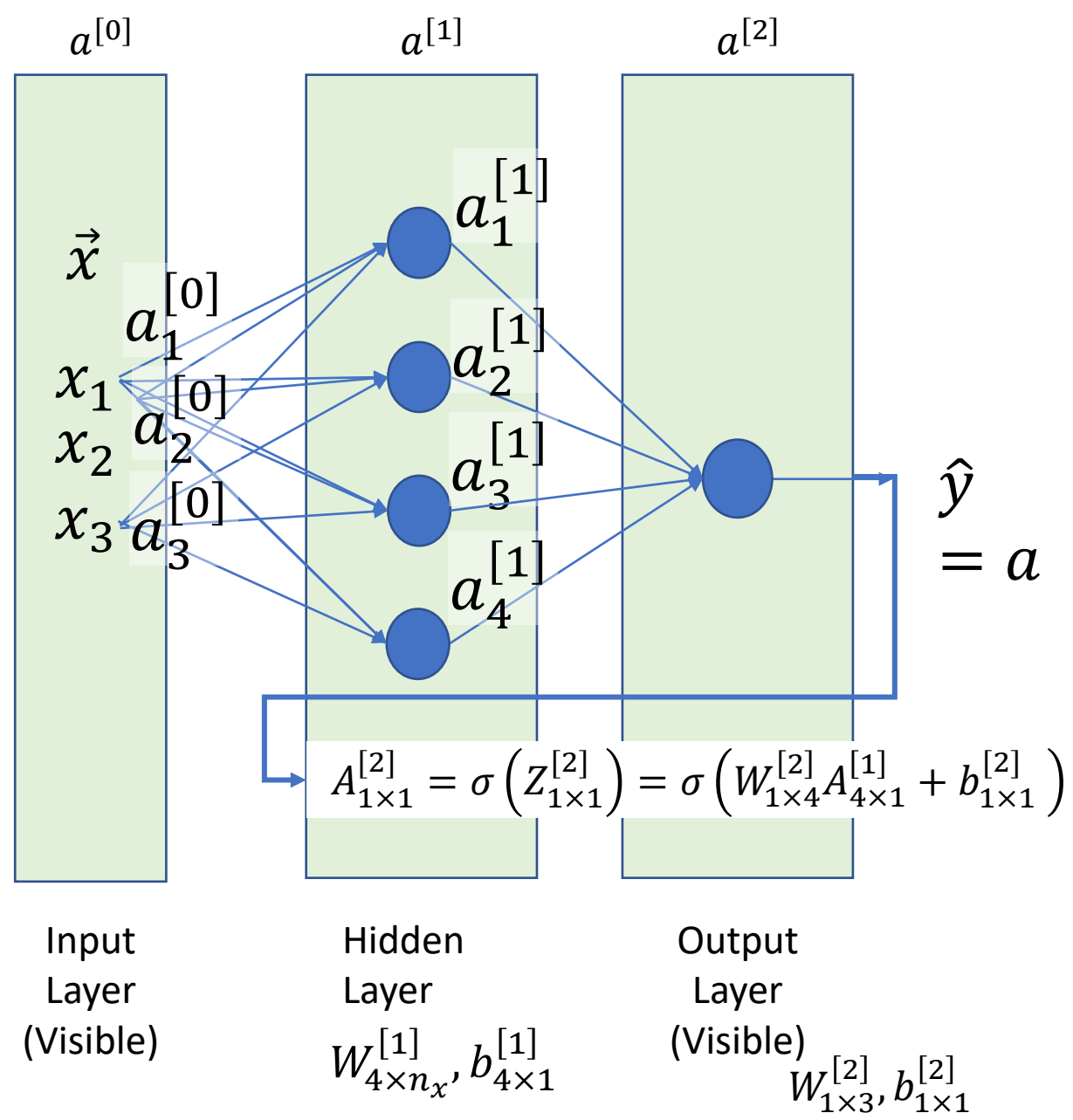
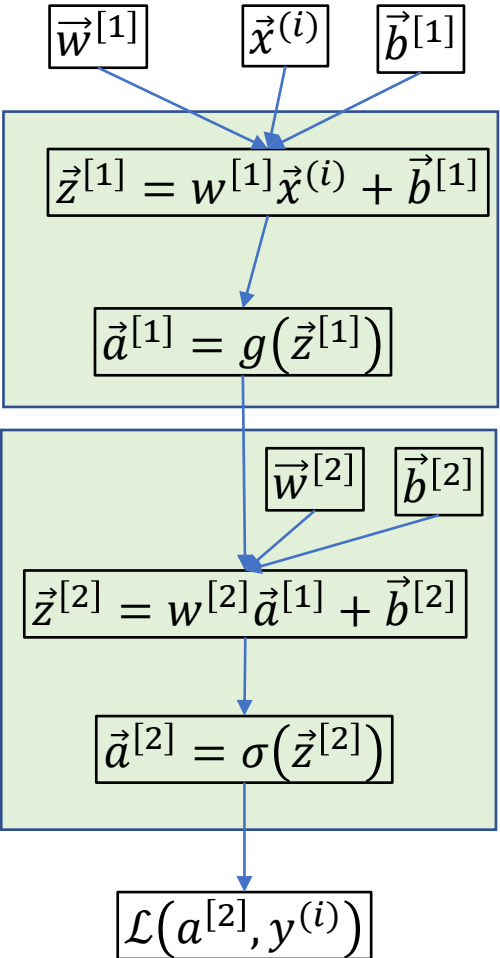
- $b^{[1]} \leftarrow b^{[1]} + \alpha db^{[1]}$

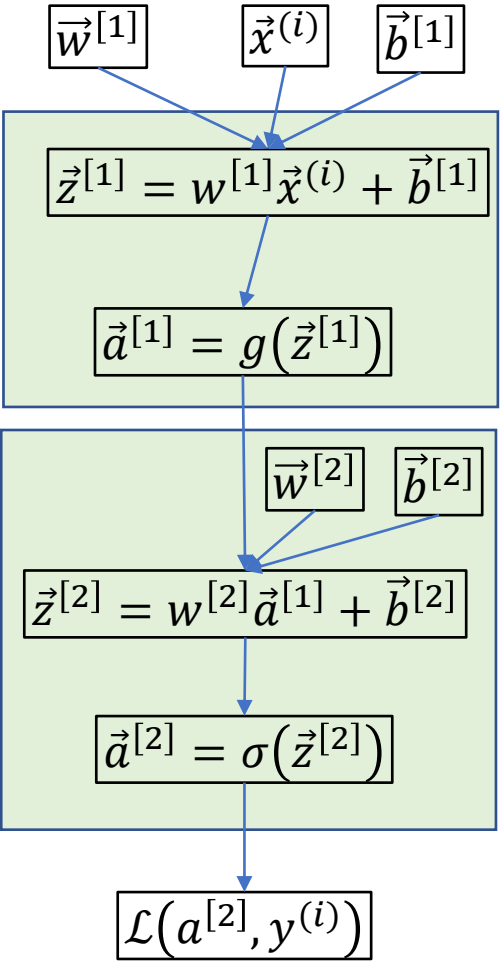
- $w^{[2]} \leftarrow w^{[2]} - \alpha dw^{[2]}$

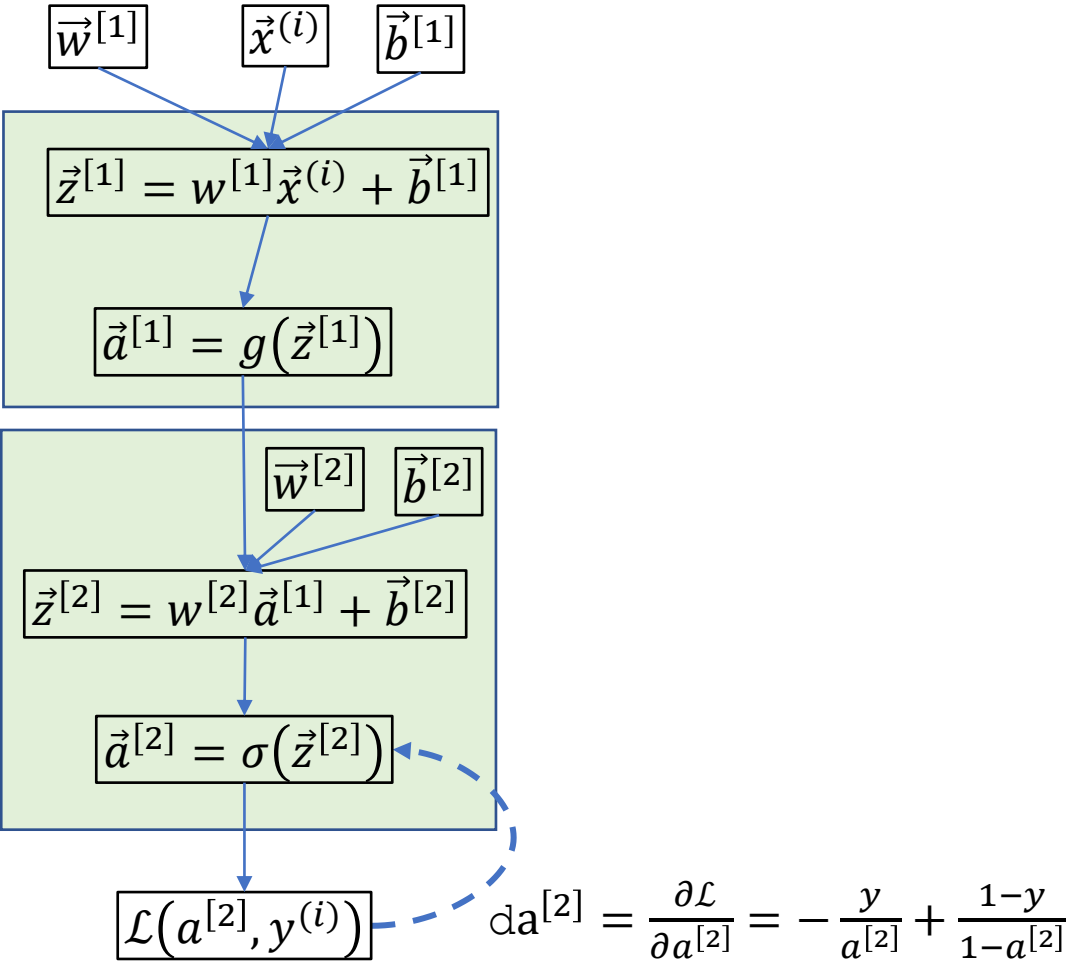
- $b^{[2]} \leftarrow b^{[2]} + \alpha db^{[2]}$

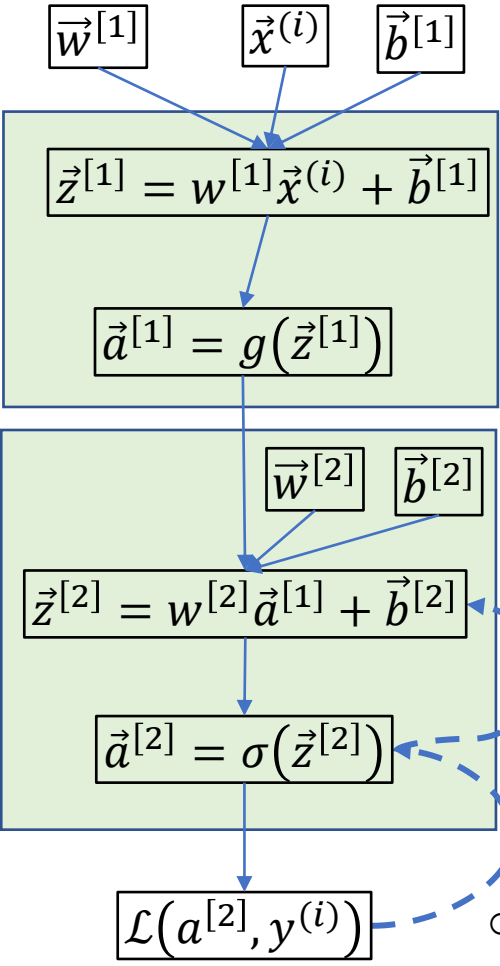
}





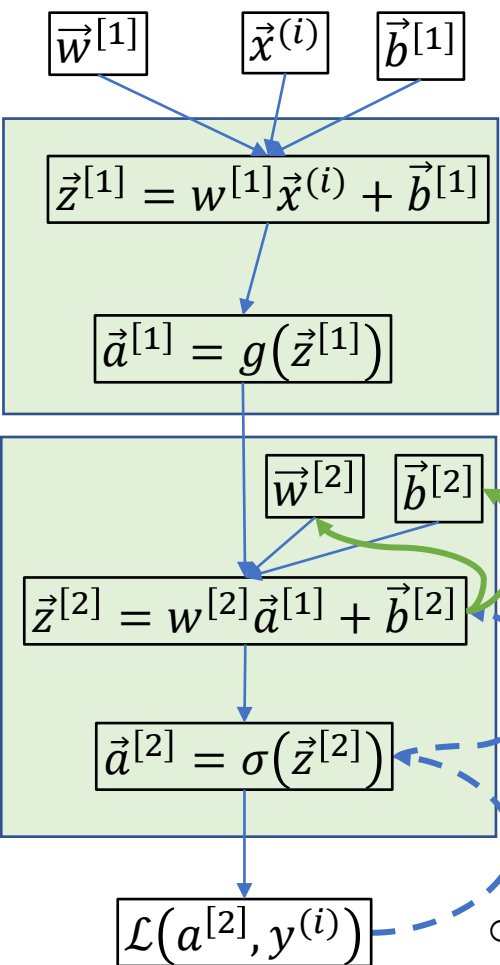






$$dz^{[2]} = \frac{\partial \mathcal{L}}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} = \left[-\frac{y}{a^{[2]}} + \frac{1-y}{1-a^{[2]}} \right] [a^{[2]}(1-a^{[2]})] = [a^{[2]} - y]$$

$$da^{[2]} = \frac{\partial \mathcal{L}}{\partial a^{[2]}} = -\frac{y}{a^{[2]}} + \frac{1-y}{1-a^{[2]}}$$



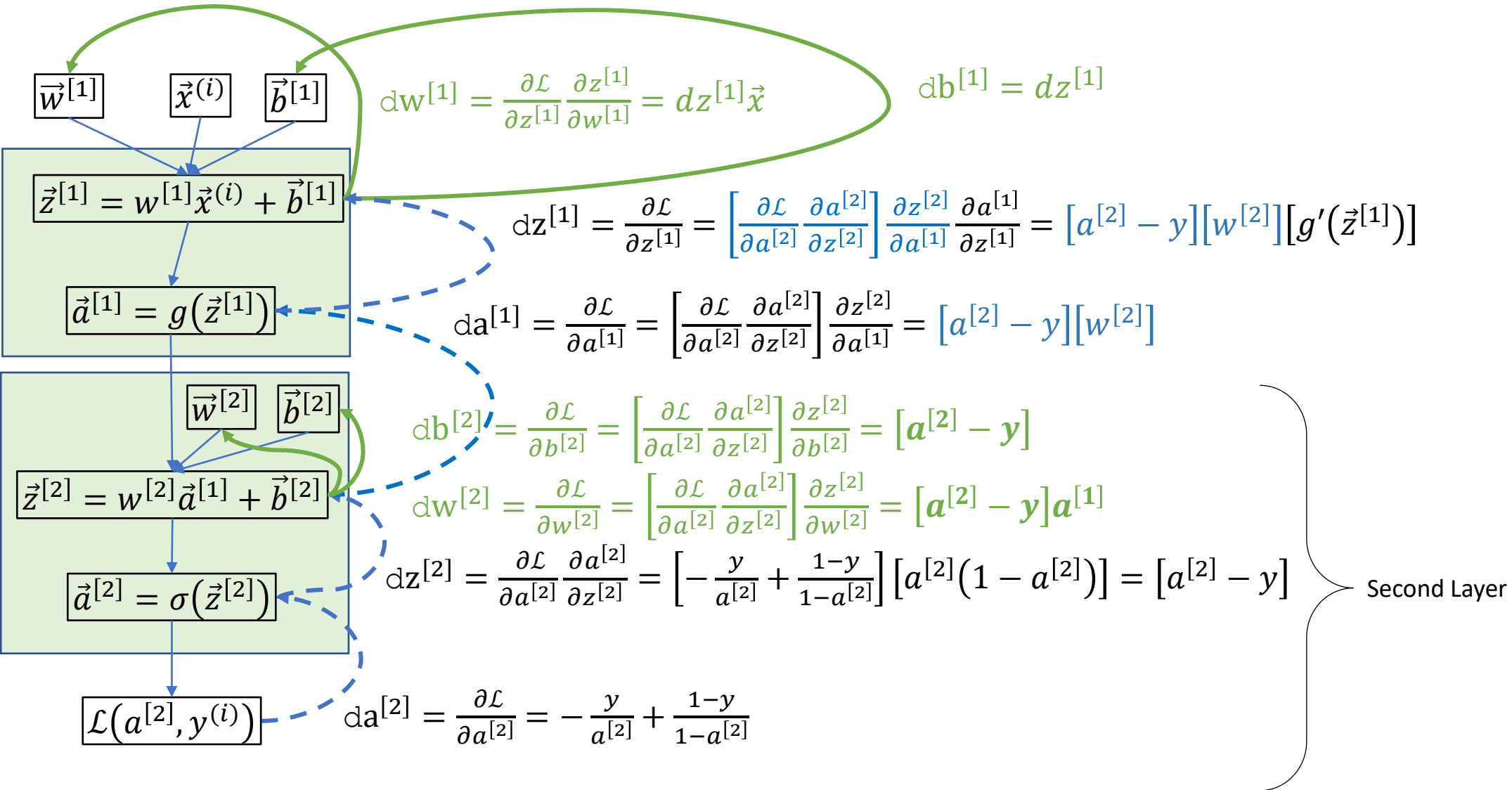
$$db^{[2]} = \frac{\partial \mathcal{L}}{\partial b^{[2]}} = \left[\frac{\partial \mathcal{L}}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} \right] \frac{\partial z^{[2]}}{\partial b^{[2]}} = [a^{[2]} - y]$$

$$dw^{[2]} = \frac{\partial \mathcal{L}}{\partial w^{[2]}} = \left[\frac{\partial \mathcal{L}}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} \right] \frac{\partial z^{[2]}}{\partial w^{[2]}} = [a^{[2]} - y] a^{[1]}$$

$$dz^{[2]} = \frac{\partial \mathcal{L}}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} = \left[-\frac{y}{a^{[2]}} + \frac{1-y}{1-a^{[2]}} \right] [a^{[2]}(1-a^{[2]})] = [a^{[2]} - y]$$

$$da^{[2]} = \frac{\partial \mathcal{L}}{\partial a^{[2]}} = -\frac{y}{a^{[2]}} + \frac{1-y}{1-a^{[2]}}$$

Second Layer



Six key equations

$$1. \quad dz^{[2]} = \frac{\partial \mathcal{L}}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} = \left[-\frac{y}{a^{[2]}} + \frac{1-y}{1-a^{[2]}} \right] [a^{[2]}(1-a^{[2]})] = [\mathbf{a}^{[2]} - \mathbf{y}]$$

$$2. \quad dw^{[2]} = \frac{\partial \mathcal{L}}{\partial w^{[2]}} = \left[\frac{\partial \mathcal{L}}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} \right] \frac{\partial z^{[2]}}{\partial w^{[2]}} = [\mathbf{a}^{[2]} - \mathbf{y}] \mathbf{a}^{[1]}$$

$$3. \quad db^{[2]} = \frac{\partial \mathcal{L}}{\partial b^{[2]}} = \left[\frac{\partial \mathcal{L}}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} \right] \frac{\partial z^{[2]}}{\partial b^{[2]}} = [\mathbf{a}^{[2]} - \mathbf{y}]$$

$$4. \quad dz^{[1]} = \frac{\partial \mathcal{L}}{\partial z^{[1]}} = \left[\frac{\partial \mathcal{L}}{\partial a^{[2]}} \frac{\partial a^{[2]}}{\partial z^{[2]}} \right] \frac{\partial z^{[2]}}{\partial a^{[1]}} \frac{\partial a^{[1]}}{\partial z^{[1]}} = [\mathbf{a}^{[2]} - \mathbf{y}] [\mathbf{w}^{[2]}] [\mathbf{g}'(\vec{\mathbf{z}}^{[1]})]$$

$$5. \quad dw^{[1]} = \frac{\partial \mathcal{L}}{\partial z^{[1]}} \frac{\partial z^{[1]}}{\partial w^{[1]}} = dz^{[1]} \vec{x} = [\mathbf{a}^{[2]} - \mathbf{y}] [\mathbf{w}^{[2]}] [\mathbf{g}'(\vec{\mathbf{z}}^{[1]})] \vec{x}$$

$$6. \quad db^{[1]} = dz^{[1]} = [\mathbf{a}^{[2]} - \mathbf{y}] [\mathbf{w}^{[2]}] [\mathbf{g}'(\vec{\mathbf{z}}^{[1]})]$$

For m samples

$$\begin{bmatrix} \begin{array}{c} | \\ \vec{Z}^{[l](1)} \\ | \end{array} & \begin{array}{c} | \\ \vec{Z}^{[l](2)} \\ | \end{array} & \dots & \begin{array}{c} | \\ \vec{Z}^{[l](m)} \\ | \end{array} \end{bmatrix}_{n^{[l]} \times m} = \begin{bmatrix} - & \vec{W}_1^{[l]T} & - \\ - & \vec{W}_2^{[l]T} & - \\ & \vdots & \\ - & \vec{W}_{n^{[l]}}^{[l]T} & - \end{bmatrix}_{n^{[l]} \times n^{[l]-1}} \begin{bmatrix} \begin{array}{c} | \\ \vec{a}^{[l-1](1)} \\ | \end{array} & \begin{array}{c} | \\ \vec{a}^{[l-1](2)} \\ | \end{array} & \dots & \begin{array}{c} | \\ \vec{a}^{[l-1](m)} \\ | \end{array} \end{bmatrix}_{n^{[l-1]} \times m} + \begin{bmatrix} b_1^{[l]} \\ b_2^{[l]} \\ \vdots \\ b_{n^{[l]}}^{[l]} \end{bmatrix}_{n^{[l]} \times m}$$

$$Z^{[l]} = W^{[l]T} X + B$$

$$A^{[l]} = g^{[l]}(Z) = g^{[l]}(W^{[l]T} X + B)$$

Deep Neural Networks

DL Building Blocks

Forward:

Input:

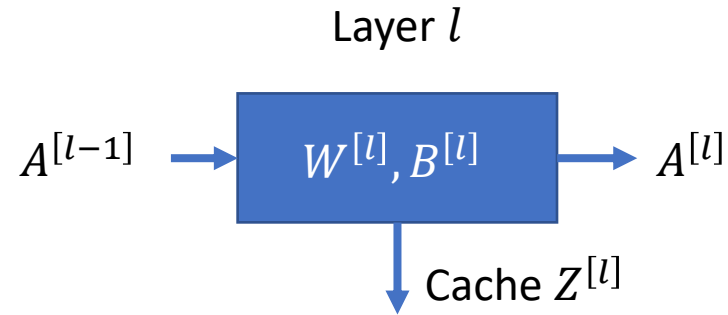
- $A^{[l-1]}$.

Compute:

- $Z^{[l]} = W^{[l]}A^{[l-1]} + B^{[l]}$.
- $A^{[l]} = g^{[l]}(Z^{[l]})$.

Output:

- $A^{[l]}$.
- Cache $Z^{[l]}$.



DL Building Blocks

Forward:

Input:

- $A^{[l-1]}$.

Compute:

- $Z^{[l]} = W^{[l]}A^{[l-1]} + B^{[l]}$.
- $A^{[l]} = g^{[l]}(Z^{[l]})$.

Output:

- $A^{[l]}$.
- Cache $Z^{[l]}$.

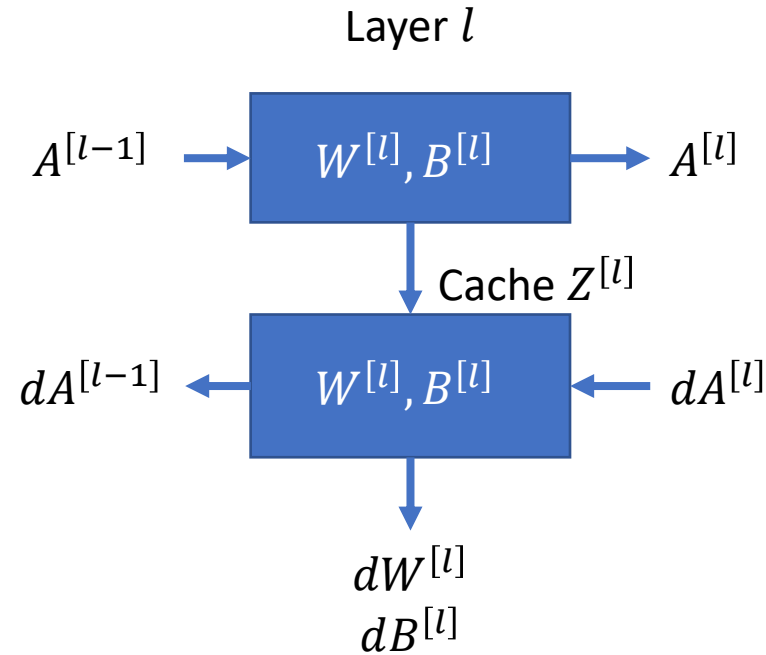
Backward:

Input:

- $dA^{[l]}$.
- Cache $Z^{[l]}$.

Output:

- $dA^{[l-1]}$.
- $dW^{[l]}$.
- $dB^{[l]}$.



DL Building Blocks

Forward:

Input:

- $A^{[l-1]}$.

Compute:

- $Z^{[l]} = W^{[l]}A^{[l-1]} + B^{[l]}$.
- $A^{[l]} = g^{[l]}(Z^{[l]})$.

Output:

- $A^{[l]}$.
- Cache $Z^{[l]}$.

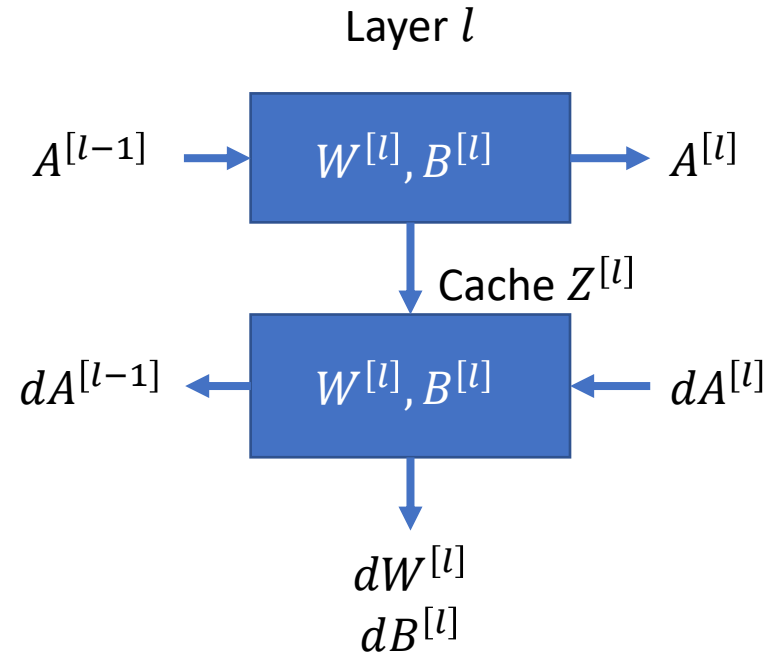
Backward:

Input:

- $dA^{[l]}$.
- Cache $Z^{[l]}$.

Output:

- $dA^{[l-1]}$.
- $dW^{[l]}$.
- $dB^{[l]}$.



$$\begin{aligned} W^{[l]} &\leftarrow W^{[l]} - \alpha dW^{[l]} \\ B^{[l]} &\leftarrow B^{[l]} - \alpha dB^{[l]} \end{aligned}$$

Training adjustment

- Parameters:
 - $W^{[l]}, B^{[l]}$.
- Hyperparameters:
 - Learning rate α .
 - Number of iterations.
 - Number of hidden units $n^{[1]}, n^{[2]}, \dots$.
 - Choice of activation function.

Thank you