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BAYESIANS AGAINST DISCRIMINATION
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BAN GENETIC ALGORITHMS

Google software can see your heart attack risk in your eyes

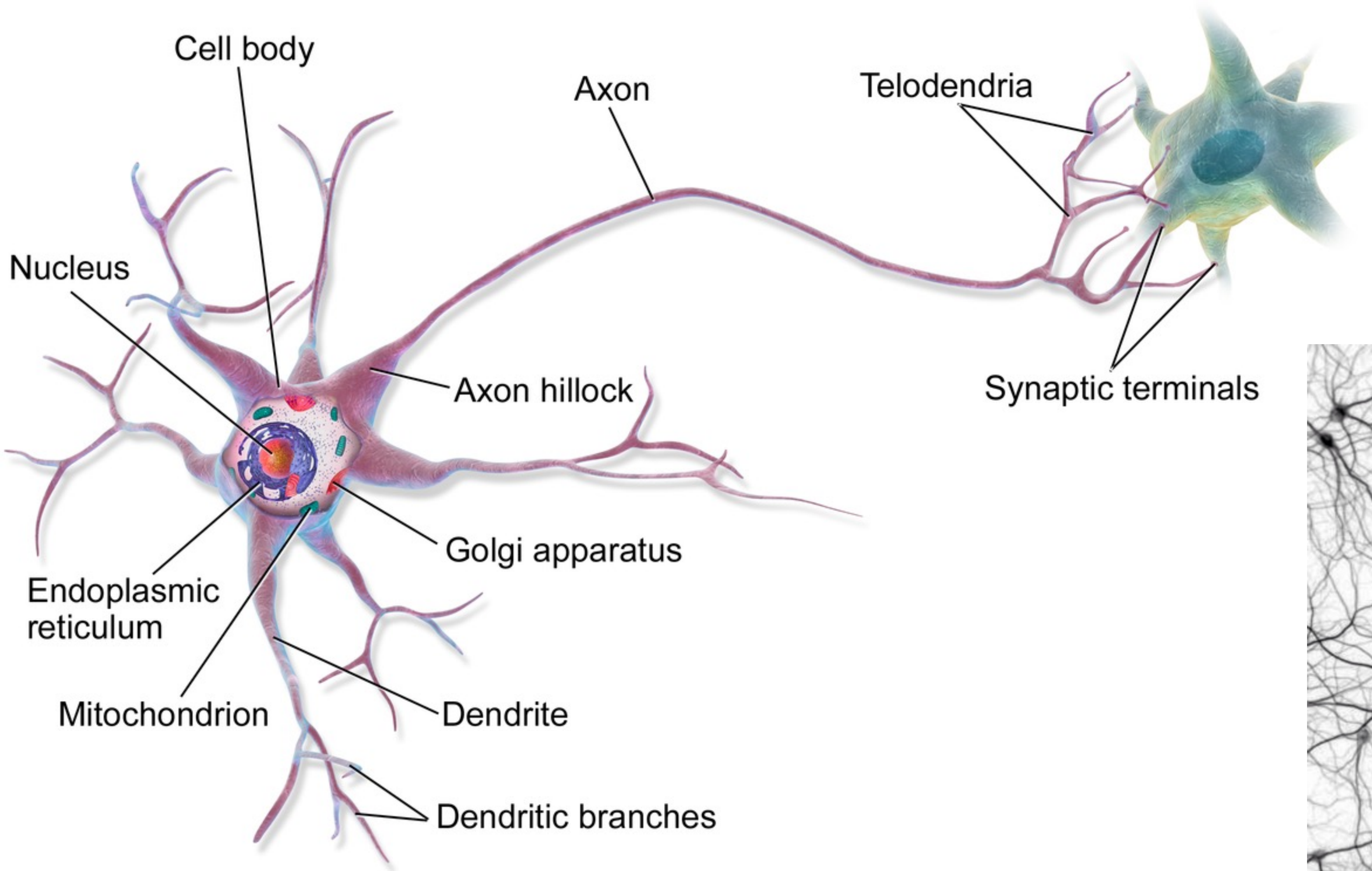
THE WASHINGTON POST | Monday, Feb. 19, 2018, 12:18 p.m.

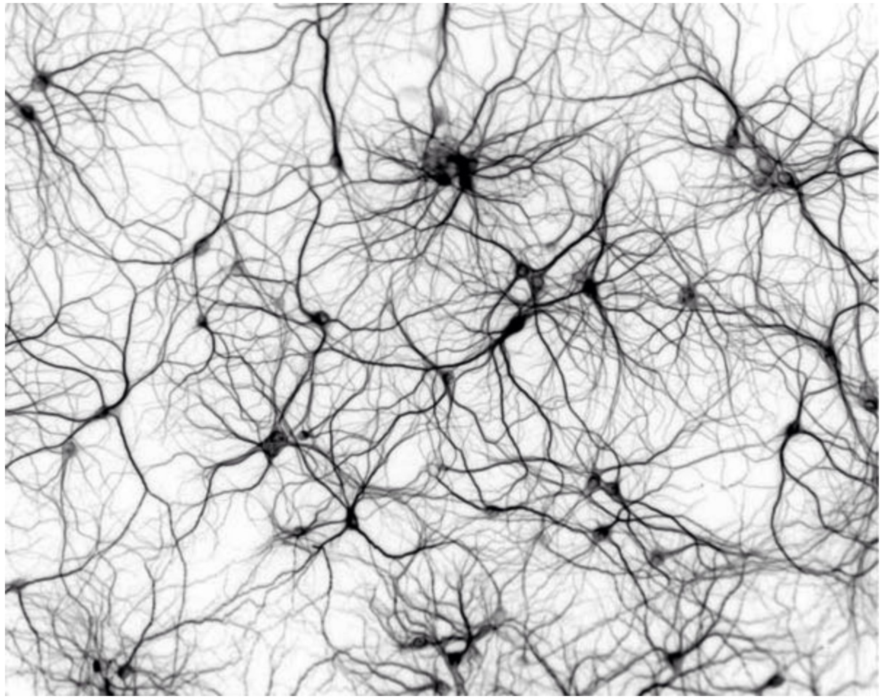
PIXABAY

Neural Networks

Nature Inspires Engineering

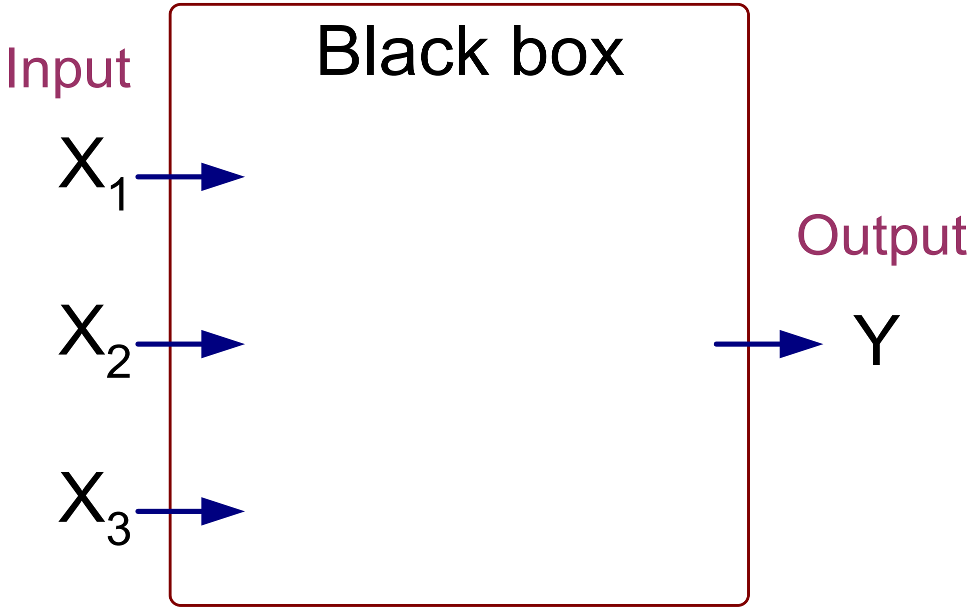
Neurons


Cell body
Axon
Telodendria
Nucleus
Axon hillock
Synaptic terminals
Golgi apparatus
Endoplasmic reticulum
Mitochondrion
Dendrite
Dendritic branches



Artificial Neural Networks (ANN)

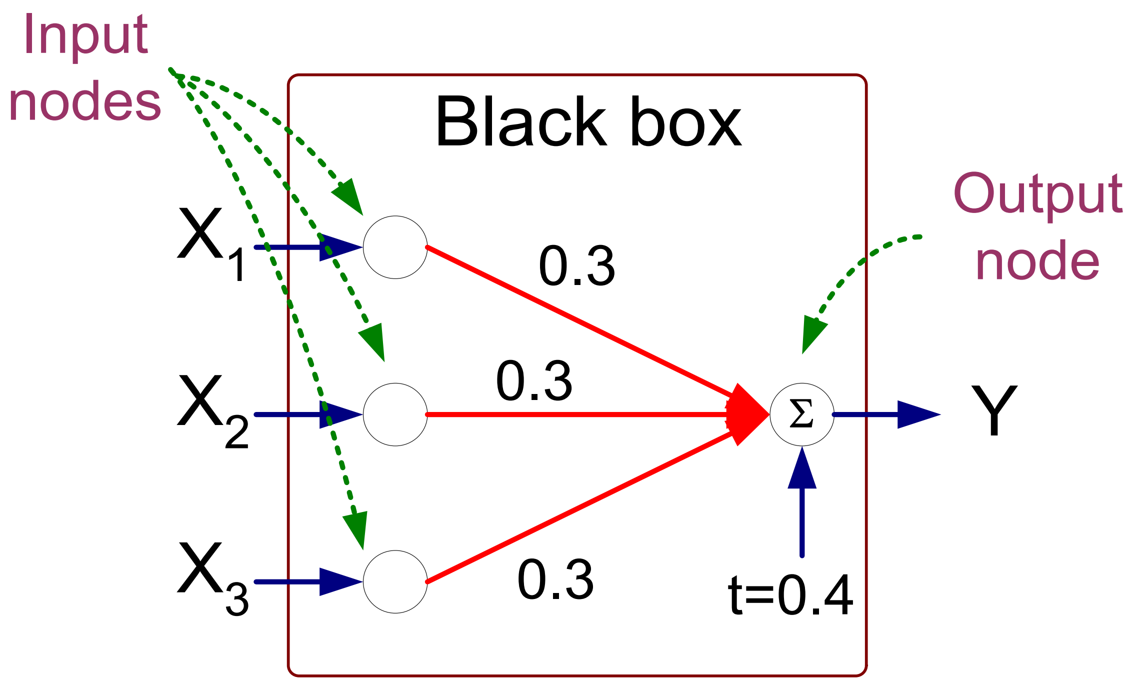
X_1	X_2	X_3	Y
1	0	0	-1
1	0	1	1
1	1	0	1
1	1	1	1
0	0	1	-1
0	1	0	-1
0	1	1	1
0	0	0	-1



Output Y is 1 if at least two of the three inputs are equal to 1.

Artificial Neural Networks (ANN)

X_1	X_2	X_3	Y
1	0	0	-1
1	0	1	1
1	1	0	1
1	1	1	1
0	0	1	-1
0	1	0	-1
0	1	1	1
0	0	0	-1

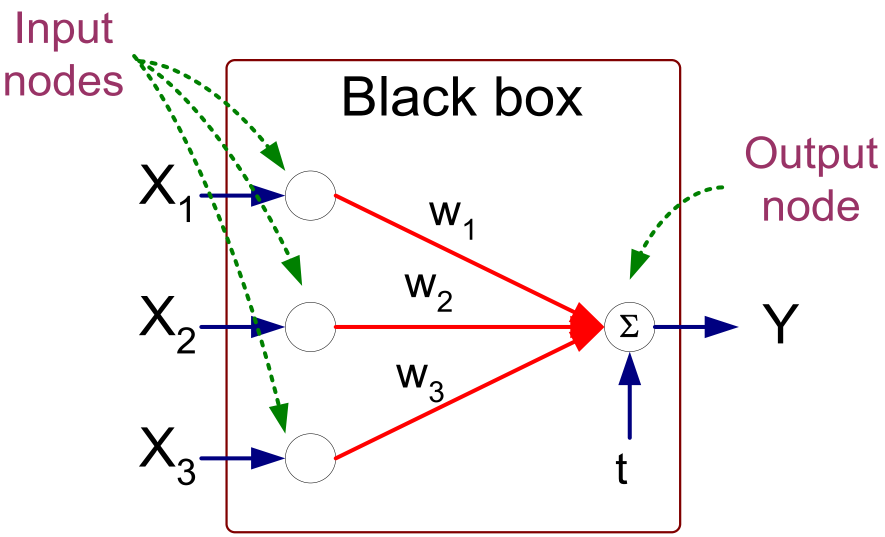


$$Y = sign(0.3X_1 + 0.3X_2 + 0.3X_3 - 0.4)$$

$$\text{where } sign(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ -1 & \text{if } x < 0 \end{cases}$$

Artificial Neural Networks (ANN)

- Model is an assembly of inter-connected nodes and weighted links
- Output node sums up each of its input value according to the weights of its links
- Compare output node against some threshold t



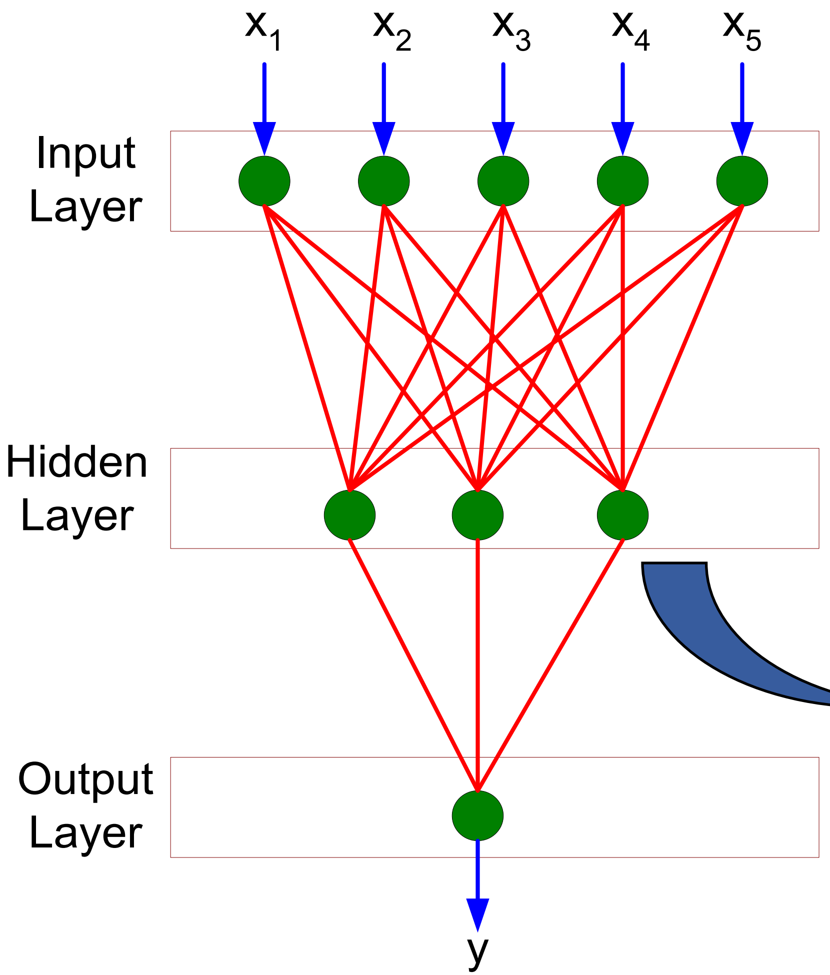
Perceptron Model

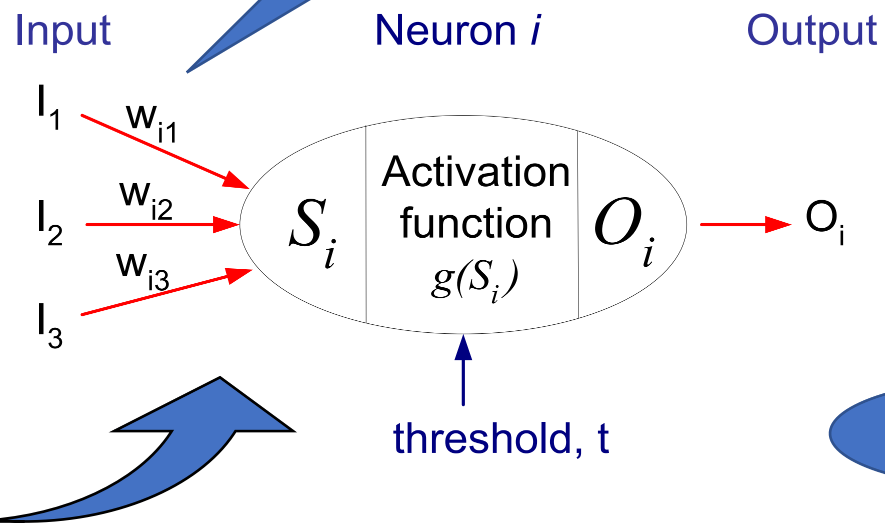
$$Y = sign(\sum_{i=1}^{d} w_i X_i - t)$$

$$= sign(\sum_{i=0}^{d} w_i X_i)$$

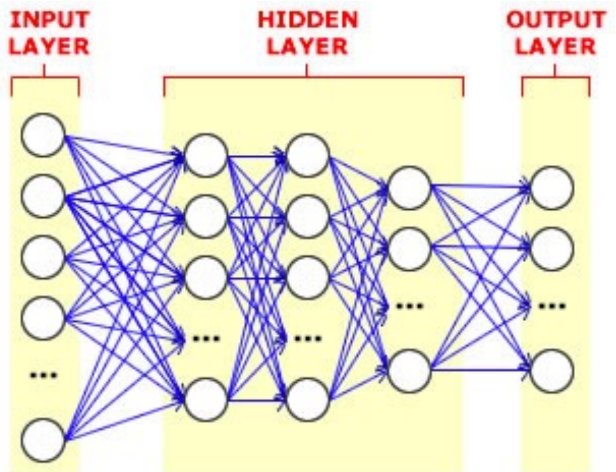
General Structure of ANN

Training ANN means learning the weights of the neurons





Can have more than one output node

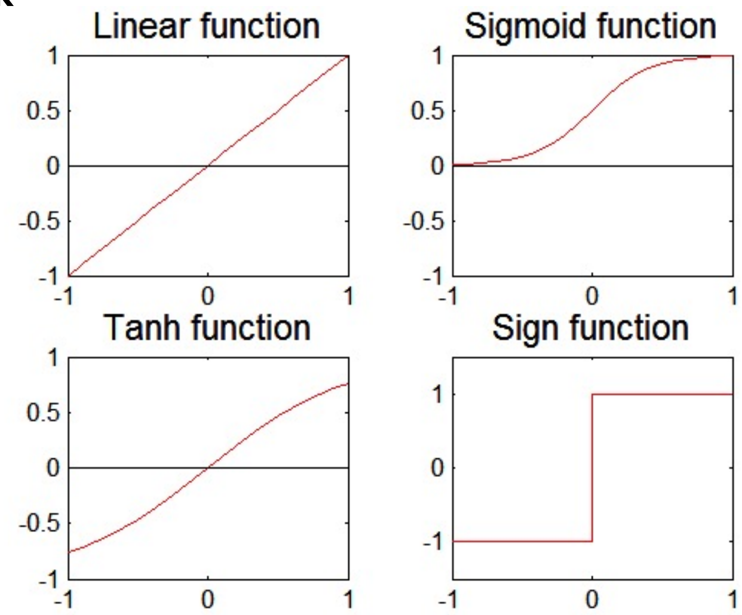


Artificial Neural Networks (ANN)

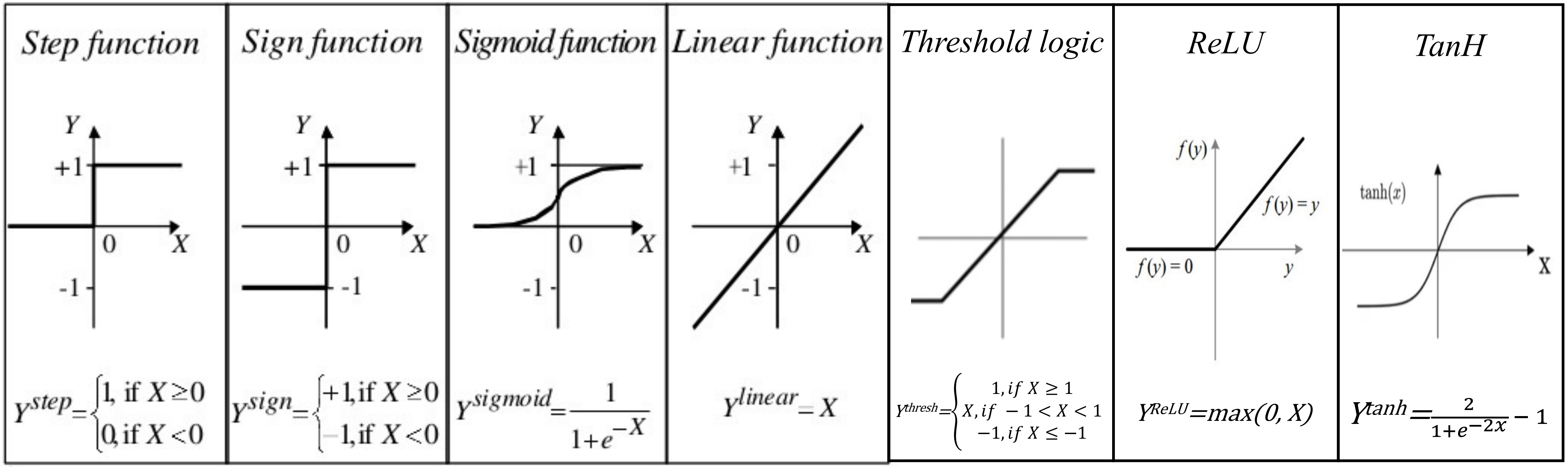
- Various types of neural network topology
  - single-layered network (perceptron) versus multi-layered network
  - Feed-forward versus recurrent network

- Various types of activation functions (f)

$$Y = f(\sum_i w_i X_i)$$



Activation Functions



The bias value will shift the activation function left or right.
https://stackoverflow.com/questions/2480650/role-of-bias-in-neural-networks

Perceptron

- Single layer network
  - Contains only input and output nodes
- Activation function: f = sign(w•x)
- Applying model is straightforward

$$Y = sign(0.3X_1 + 0.3X_2 + 0.3X_3 - 0.4)$$

$$\text{where } sign(x) = \begin{cases} 1 & \text{if } x \geq 0 \\ -1 & \text{if } x < 0 \end{cases}$$

  - $X_1 = 1$, $X_2 = 0$, $X_3 = 1$ => y = sign(0.2) = 1

Perceptron Learning Rule

- Initialize the weights (w_0, w_1, …, w_d)
- Repeat
  - For each training example (x_i, y_i)
    - Compute f(w, x_i)
    - Update the weights:

$$w^{(k+1)} = w^{(k)} + \lambda\left[y_i - f(w^{(k)}, x_i)\right]x_i$$

- Until stopping condition is met

Perceptron Learning Rule

- Weight update formula:

$$w^{(k+1)} = w^{(k)} + \lambda\big[y_i - f(w^{(k)}, x_i)\big]x_i \;\;;\;\; \lambda\text{: learning rate}$$

$$e = \left[y_i - f(w^{(k)}, x_i)\right]$$

- Intuition:
  - Update weight based on error:
  - If y=f(x,w), e=0: no update needed
  - If y>f(x,w), e=2: weight must be increased so that f(x,w) will increase
  - If y<f(x,w), e=-2: weight must be decreased so that f(x,w) will decrease

Example of Perceptron Learning

$$w^{(k+1)} = w^{(k)} + \lambda\left[y_i - f(w^{(k)}, x_i)\right]x_i$$

$$Y = sign(\sum_{i=0}^{d} w_i X_i)$$

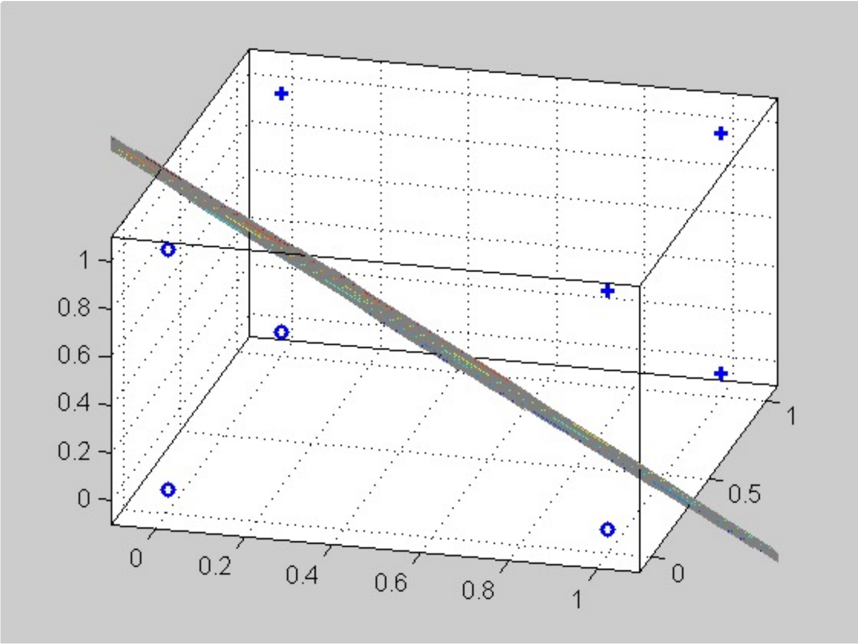
$$\lambda = 0.1$$

X_1	X_2	X_3	Y
1	0	0	-1
1	0	1	1
1	1	0	1
1	1	1	1
0	0	1	-1
0	1	0	-1
0	1	1	1
0	0	0	-1

	w_0	w_1	w_2	w_3
0	0	0	0	0
1	-0.2	-0.2	0	0
2	0	0	0	0.2
3	0	0	0	0.2
4	0	0	0	0.2
5	-0.2	0	0	0
6	-0.2	0	0	0
7	0	0	0.2	0.2
8	-0.2	0	0.2	0.2

Epoch	w_0	w_1	w_2	w_3
0	0	0	0	0
1	-0.2	0	0.2	0.2
2	-0.2	0	0.4	0.2
3	-0.4	0	0.4	0.2
4	-0.4	0.2	0.4	0.4
5	-0.6	0.2	0.4	0.2
6	-0.6	0.4	0.4	0.2

Perceptron Learning Rule



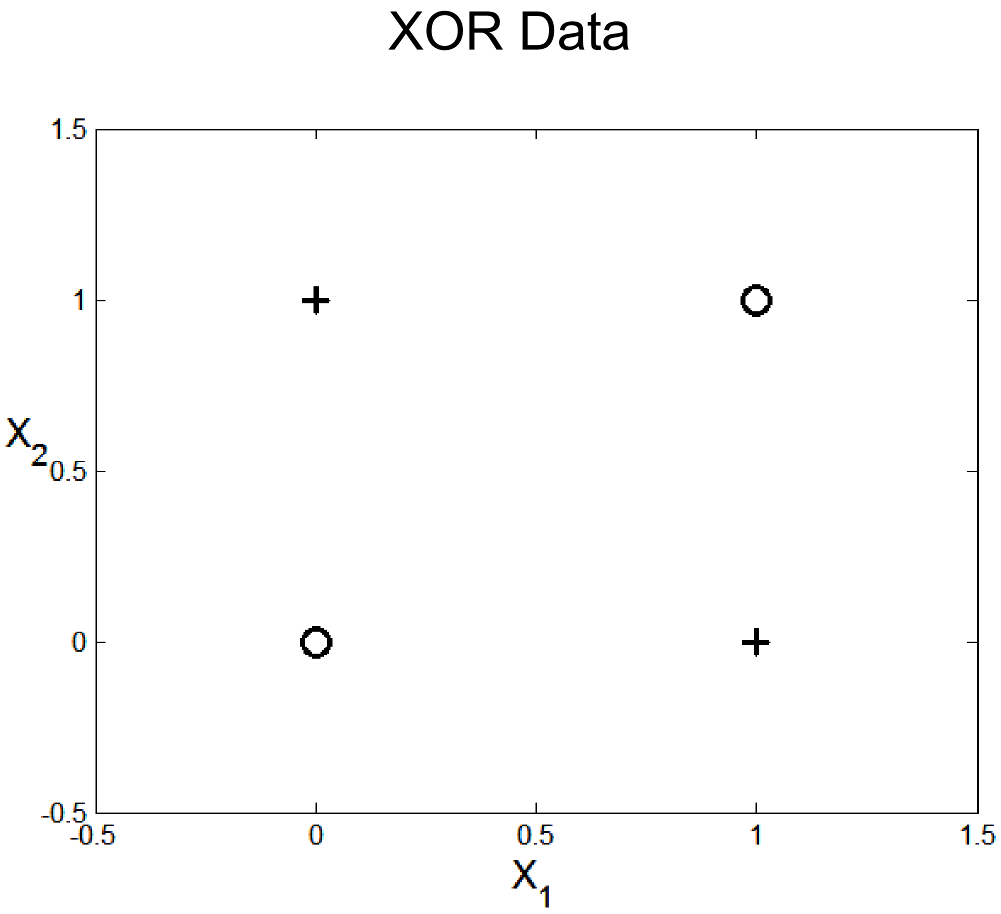
- Since f(w,x) is a linear combination of input variables, decision boundary is linear

- For nonlinearly separable problems, perceptron learning algorithm will fail because no linear hyperplane can separate the data perfectly

Nonlinearly Separable Data

$$y = x_1 \oplus x_2$$

x_1	x_2	y
0	0	-1
1	0	1
0	1	1
1	1	-1



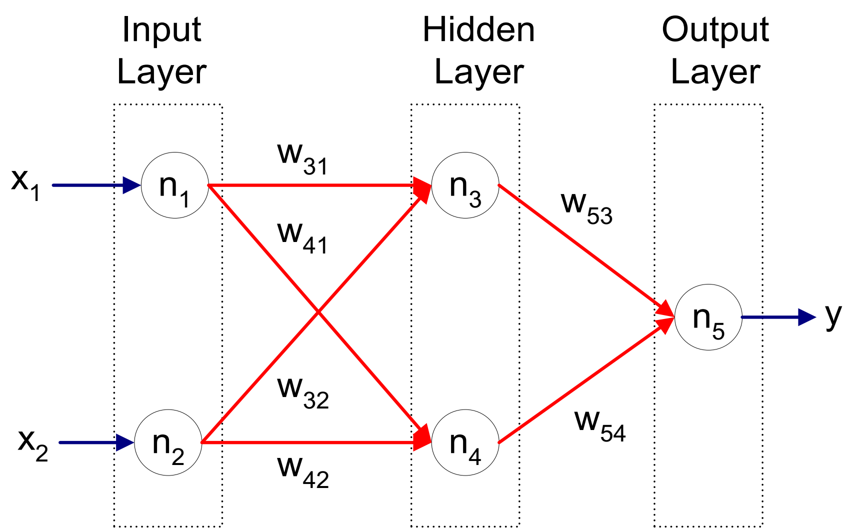
Multilayer Neural Network

- Hidden layers
  - intermediary layers between input & output layers

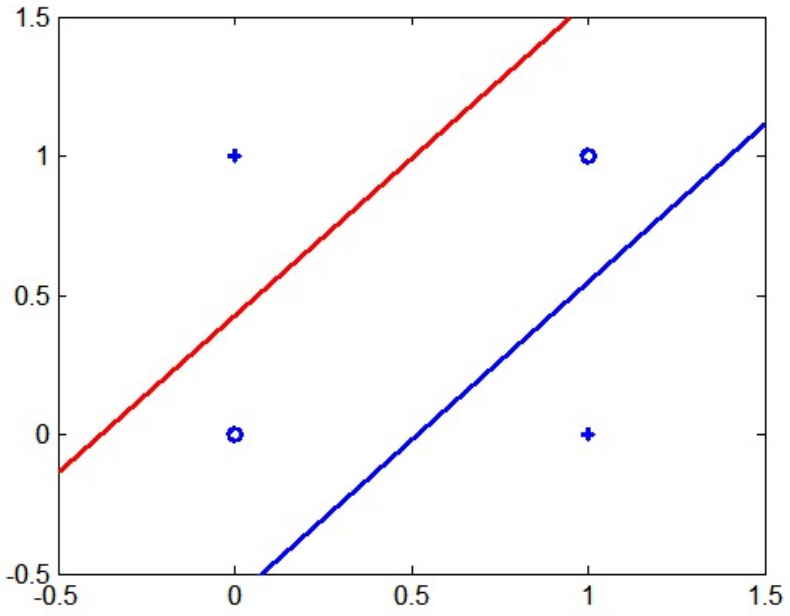
- More general activation functions (sigmoid, linear, etc)

Multi-layer Neural Network

- Multi-layer neural network can solve any type of classification task involving nonlinear decision surfaces



XOR Data

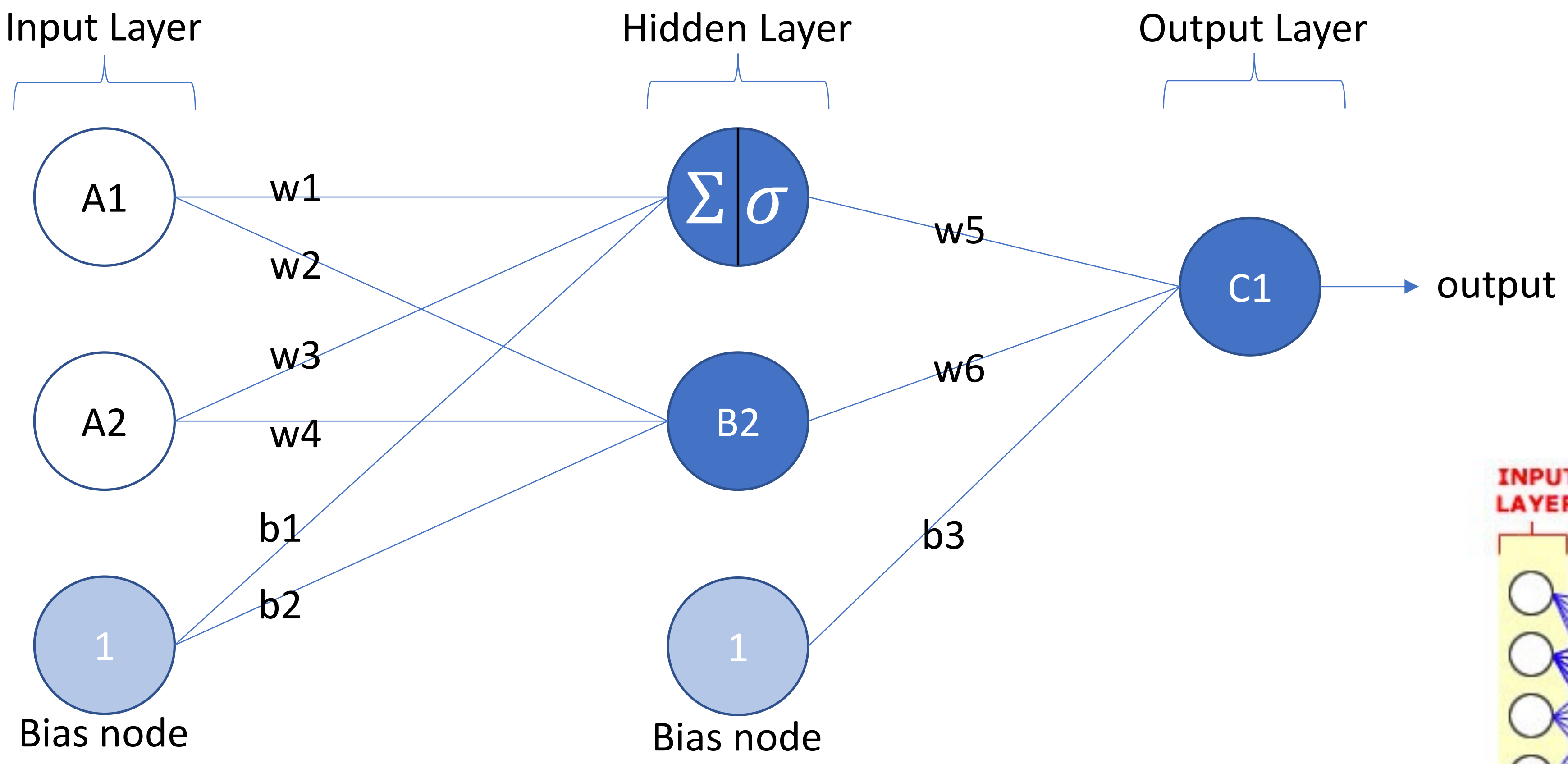


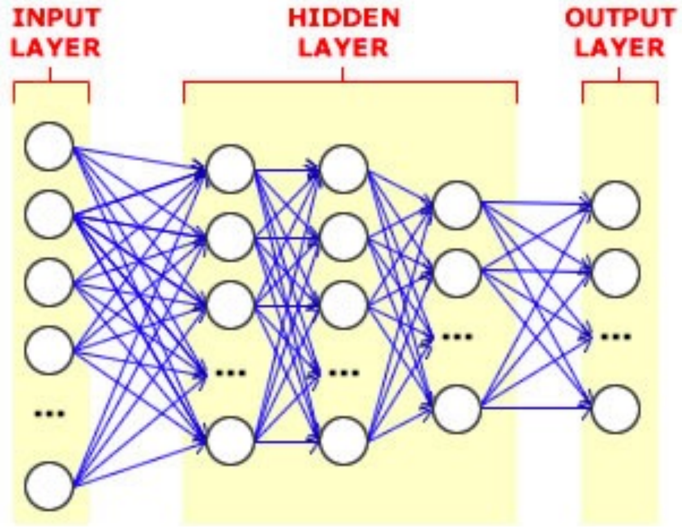
Training an Artificial Neural Network: Rinse and Repeat

- Step 1: Forward Propagation
  - Summation Operator
  - Activation Function
- Step 2: Calculate Total Error
  - Cost Function
- Step 3: Calculate Gradients
  - Partial Derivative
  - Chain Rule
- Step 4: Update Weights
  - Weight Update Formula

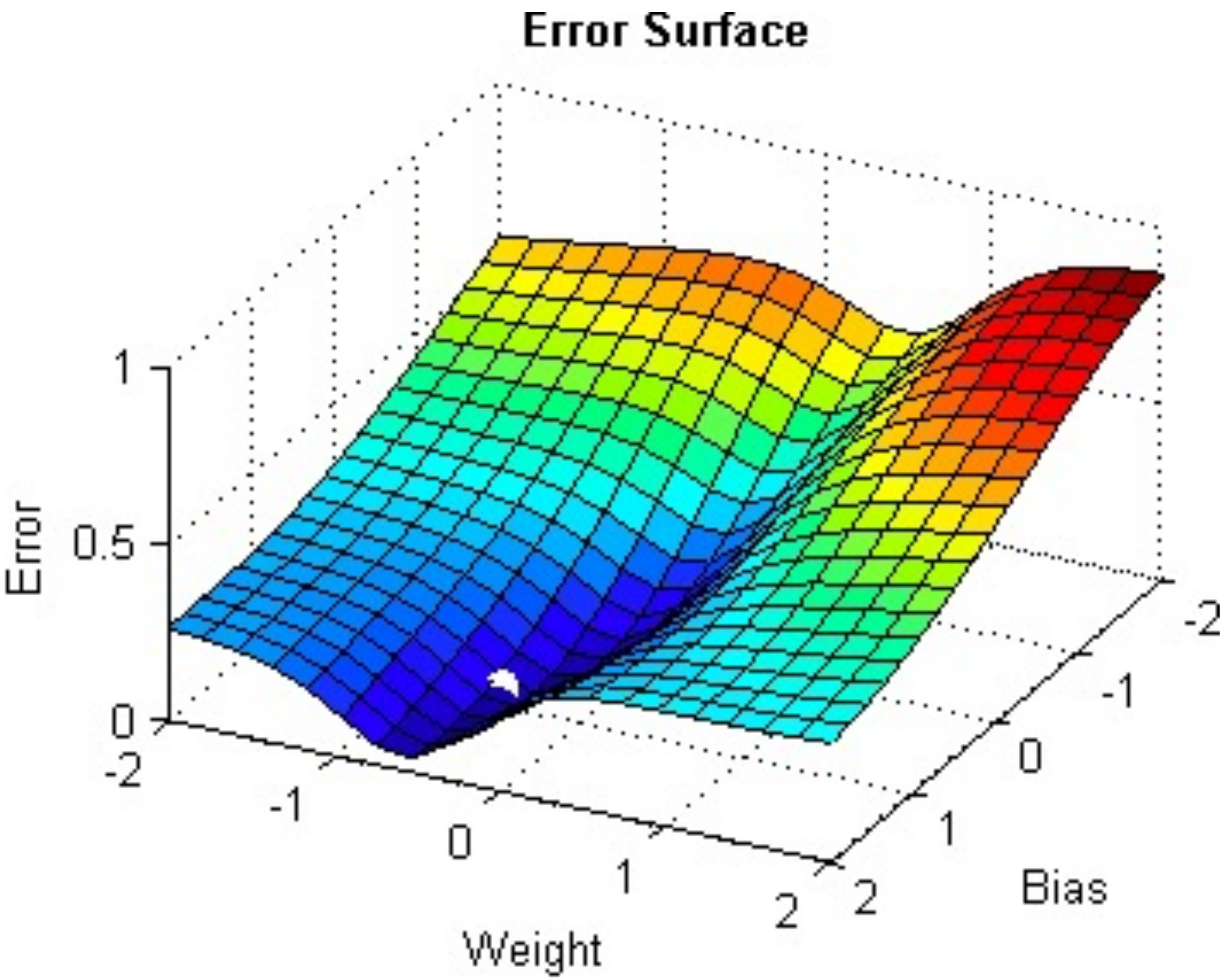
Backpropagation

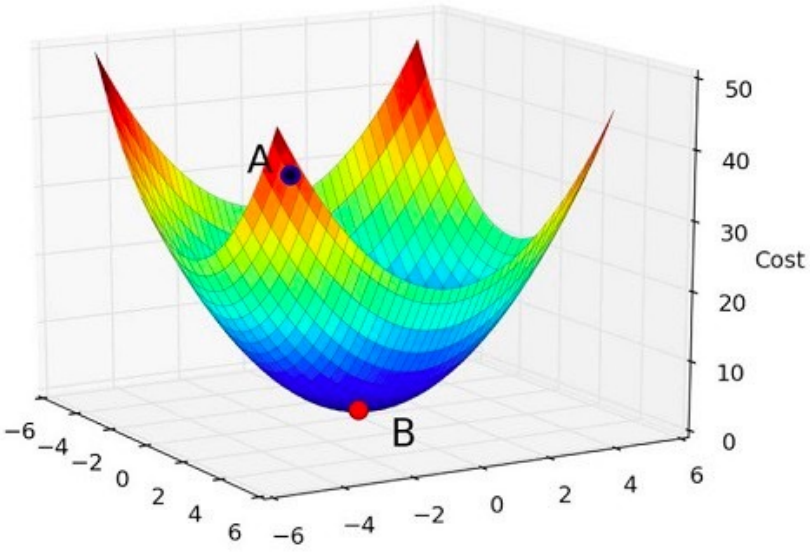
Forward Propagation Example

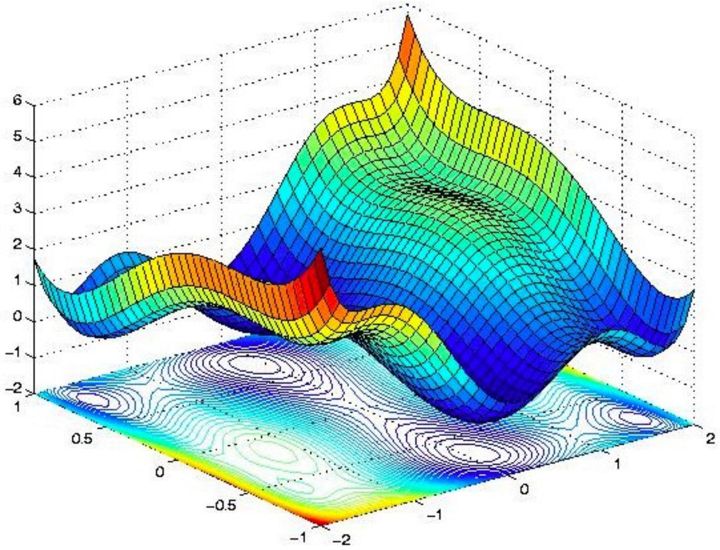




Gradient Descent

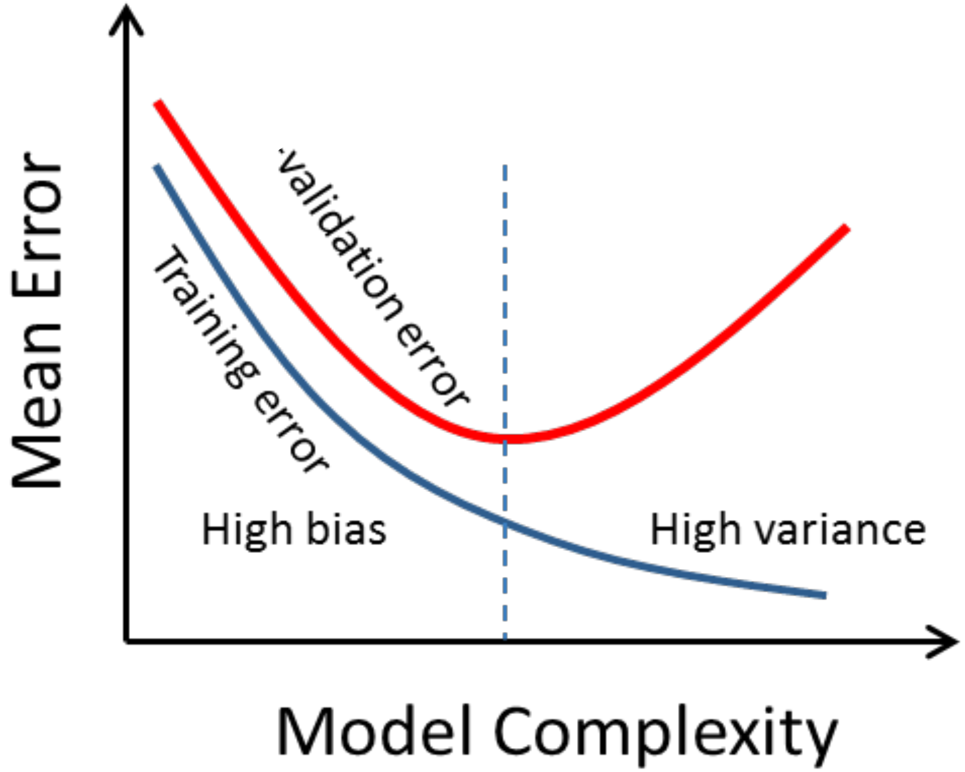






Stopping Conditions

- Error reaches some threshold
- Weights and bias terms converge
- Number of epochs reached
- Overfitting begins



Characteristics of Neural Networks

- Multi-layer neural networks with at least one hidden layer can learn complex and diverse decision boundaries
- Susceptible to overfitting
- Can handle irrelevant attributes by using zero weights; can handle redundant attributes by using similar weights
- Can get stuck at a local minima (a non-optimal solution)
- Training is time consuming and requires a lot of data
- Difficult to interpret the results
- Difficult to handle missing attributes


DEEP LEARNING,
SO HOT RIGHT NOW
imgflip.com

Deep Neural Networks

- Involve a large number of hidden layers
- Can represent features at multiple levels of abstraction
- Often require fewer nodes per layer to achieve generalization performance similar to shallow networks
- Deep networks have become the technique of choice for complex problems such as vision and language processing

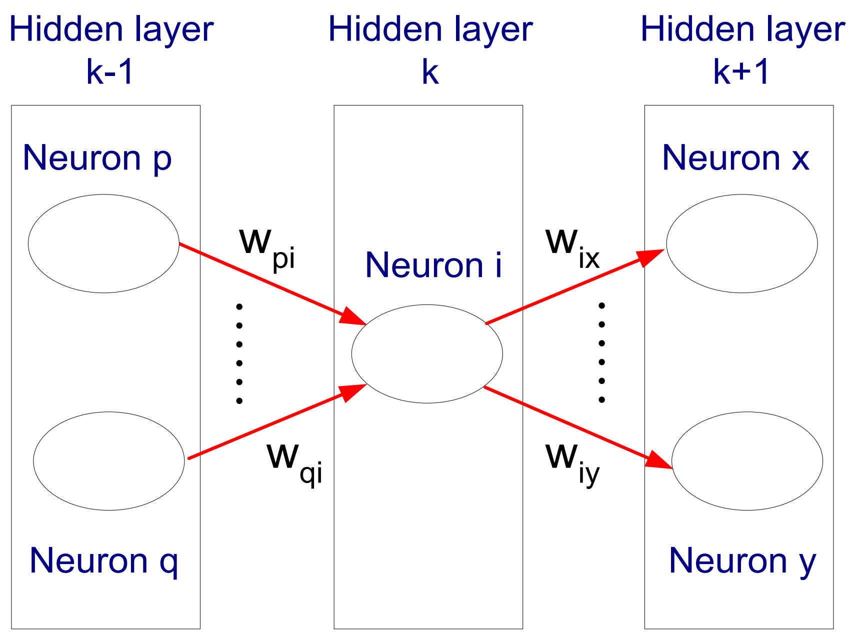
Expanded Explanation

(optional back up material)

Gradient Descent for MultiLayer NN

- For output neurons, weight update formula is the same as before (gradient descent for perceptron)

- For hidden neurons:



$$w_{pi}^{(k+1)} = w_{pi}^{(k)} + \lambda o_i (1 - o_i) \sum_{j \in \Phi_i} \delta_j w_{ij} x_{pi}$$

$$\text{Output neurons}: \delta_j = o_j (1 - o_j)(t_j - o_j)$$

$$\text{Hidden neurons}: \delta_j = o_j (1 - o_j) \sum_{k \in \Phi_j} \delta_k w_{jk}$$

Learning Multi-layer Neural Network

- Can we apply the perceptron learning rule to each node, including hidden nodes?
  - Perceptron learning rule computes error term e = y-f(w,x) and updates weights accordingly
    - Problem: how to determine the true value of y for hidden nodes?
  - Approximate error in hidden nodes by error in the output nodes
    - Problem:
      - Not clear how adjustment in the hidden nodes affect overall error
      - No guarantee of convergence to optimal solution

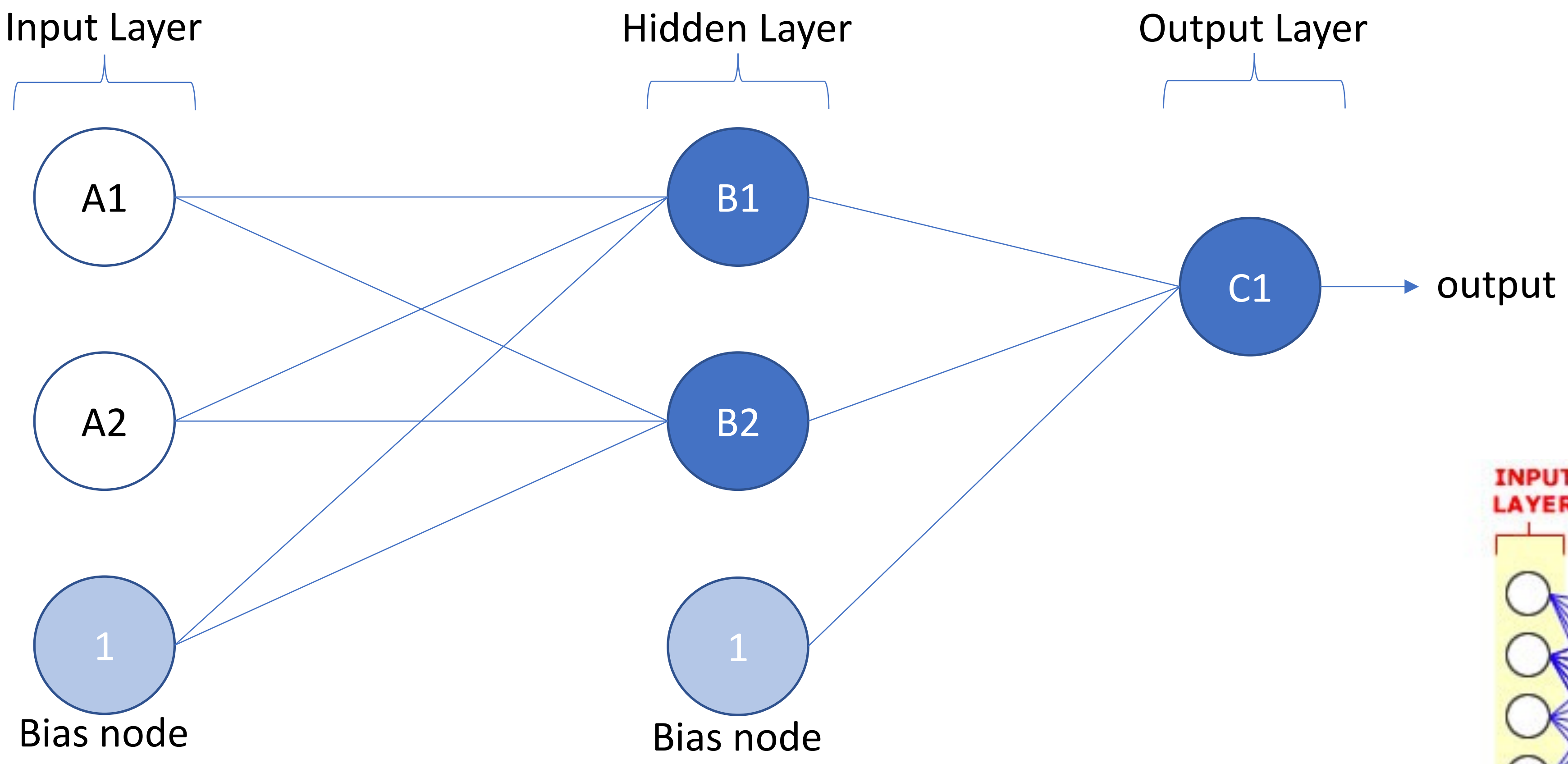
Gradient Descent for Multilayer NN

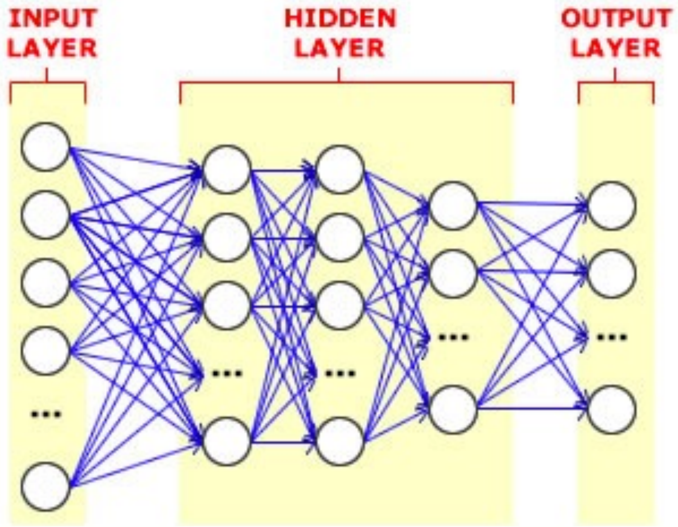
- Weight update: $$w_j^{(k+1)} = w_j^{(k)} - \lambda \frac{\partial E}{\partial w_j}$$
- Loss/Error function: $$E = \frac{1}{2}\sum_{i=1}^{N}\left(t_i - f\left(\sum_j w_j x_{ij}\right)\right)^2$$
- Activation function f must be differentiable
- For sigmoid function:

$$w_j^{(k+1)} = w_j^{(k)} + \lambda \sum_i \overbrace{(t_i - o_i)}^{\text{From loss}} \underbrace{o_i(1-o_i)}_{\text{From activation (sigmoid)}} x_{ij}$$

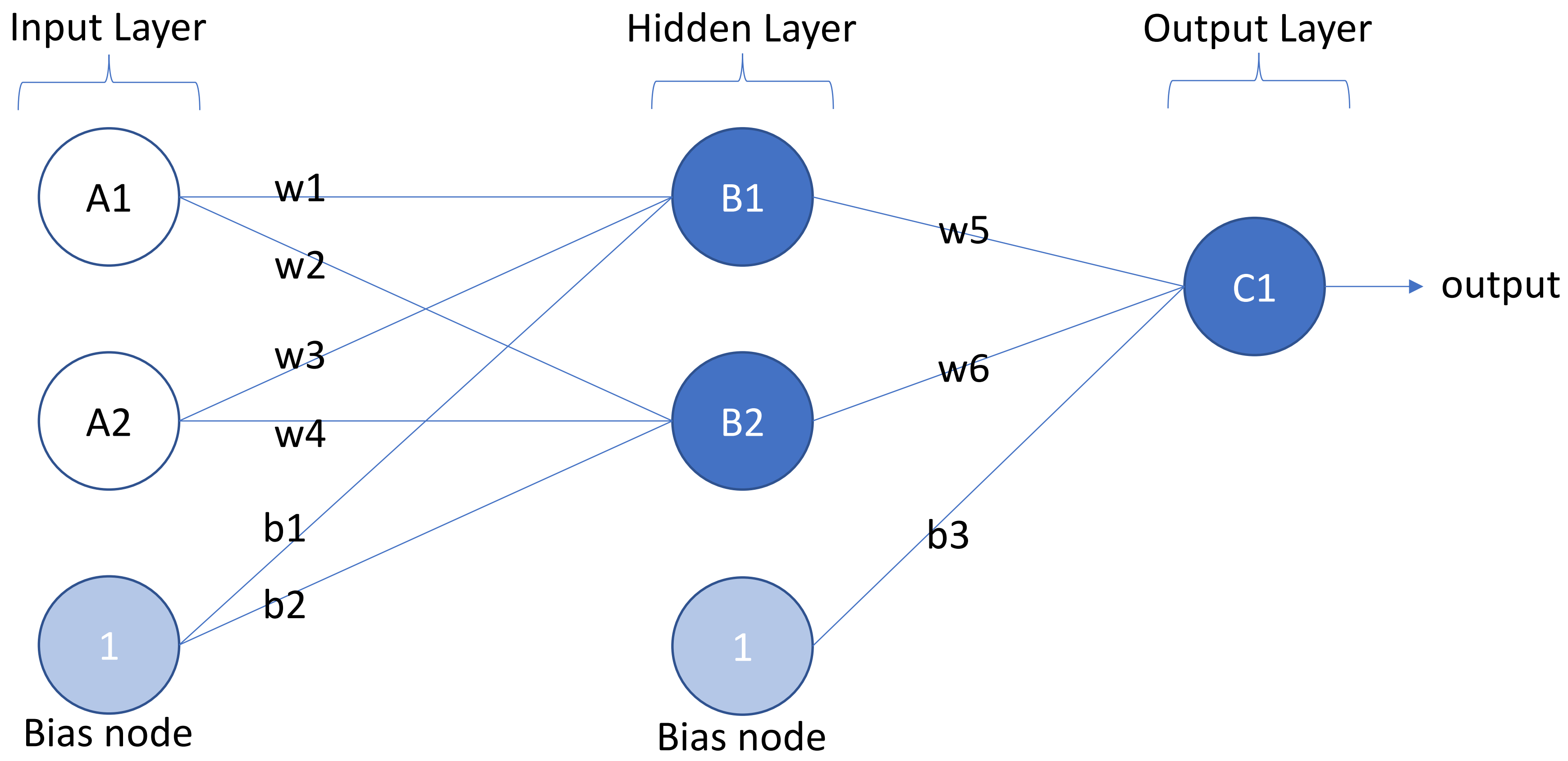
- Stochastic gradient descent (update the weight immediately)

Artificial Neural Network A-Z Example





Weights A-Z Example



Artificial Neural Nets A-Z Example

- **Step 1: Forward Propagation**
  - **Summation Operator**
  - **Activation Function**
- Step 2: Calculate Total Error
  - Cost Function
- Step 3: Calculate Gradients
  - Partial Derivative
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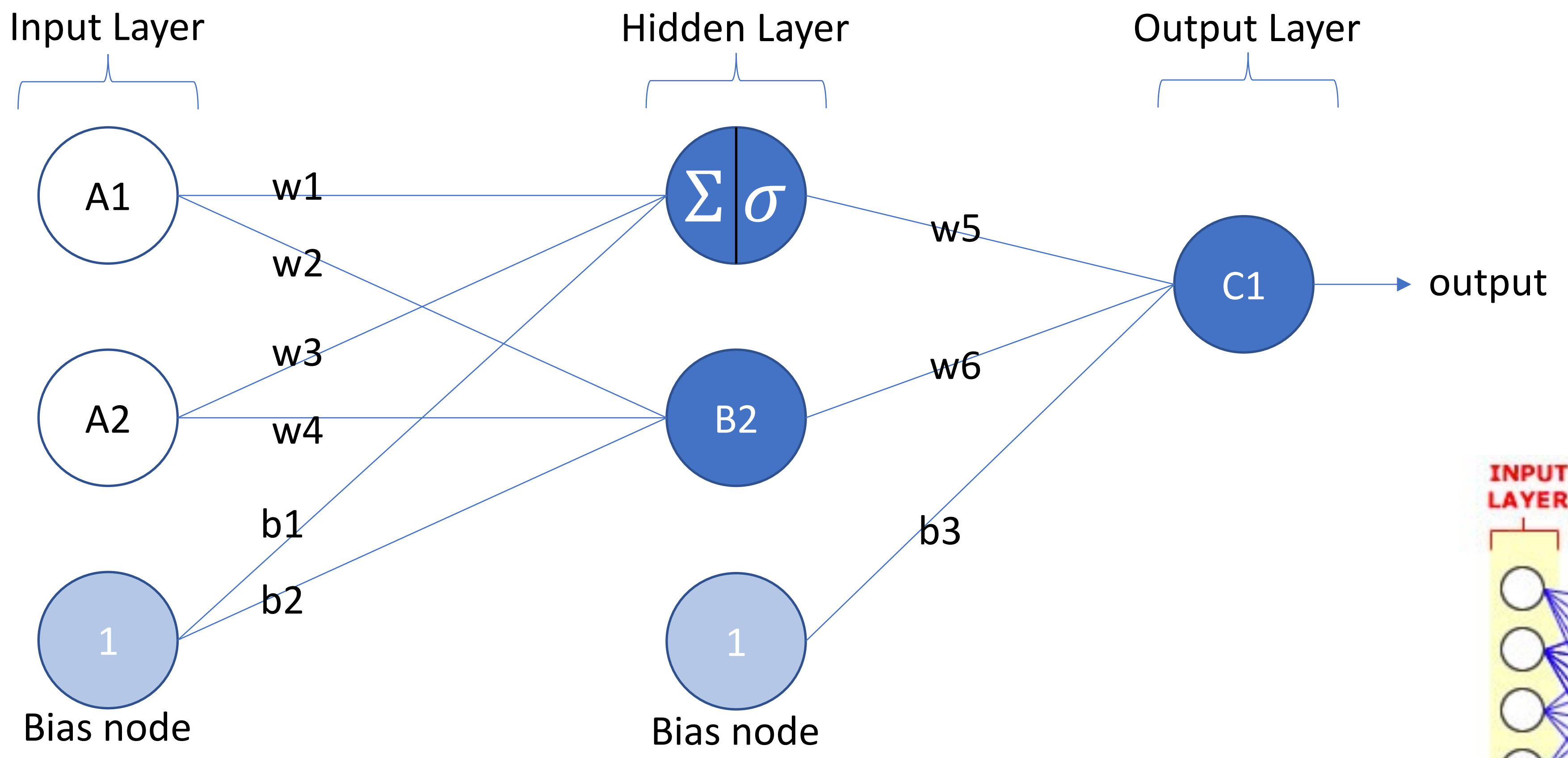
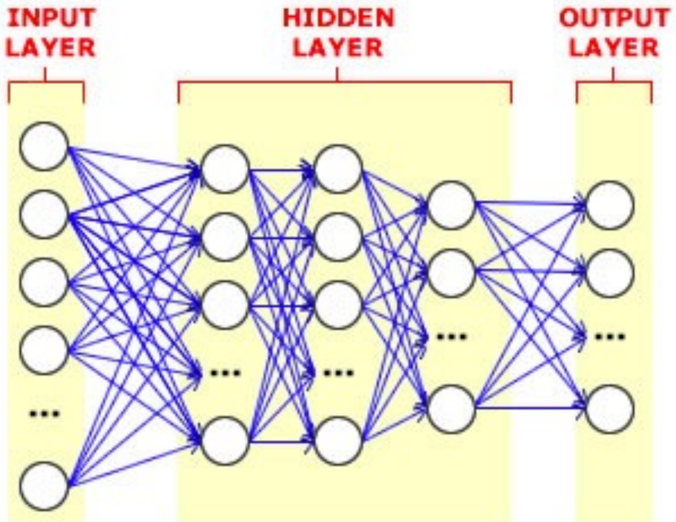
  - Weight Update Formula

Backpropagation

Forward Propagation A-Z Example

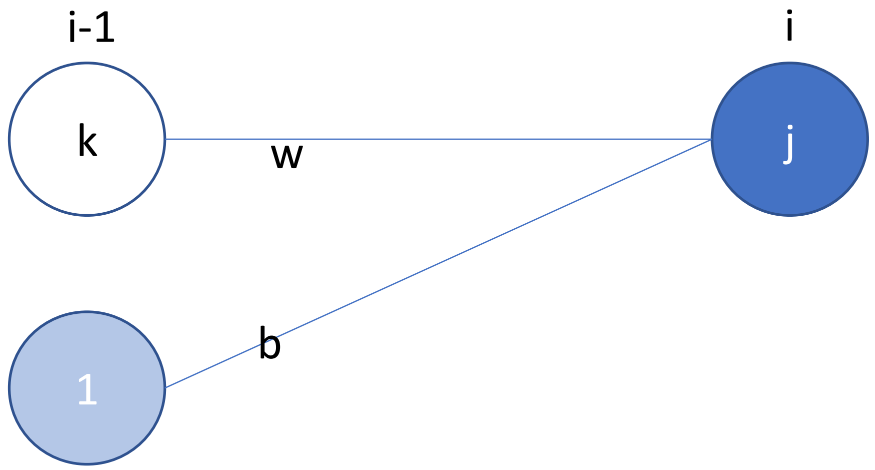




Summation Operator A-Z Example

- Call w^i_{jk} the weight of the connection to the j^{th} node in the i^{th} layer from the k^{th} node in the previous layer
- Call a^i_k the output (activation) of the k^{th} node in the i^{th} layer
- Call b^i_j the bias of the j^{th} node in the i^{th} layer

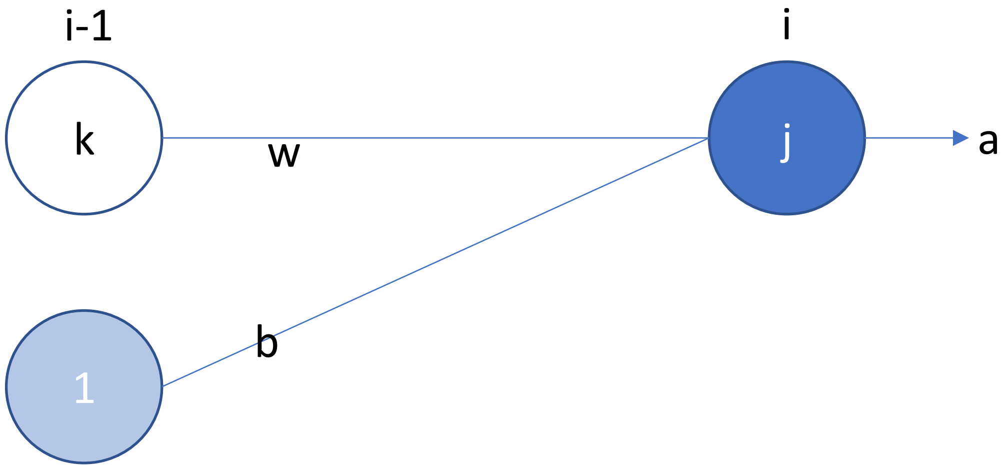
$$net_j = \left(\sum_k (w^i_{jk} \cdot a^{i-1}_k) + b^i_j\right)$$



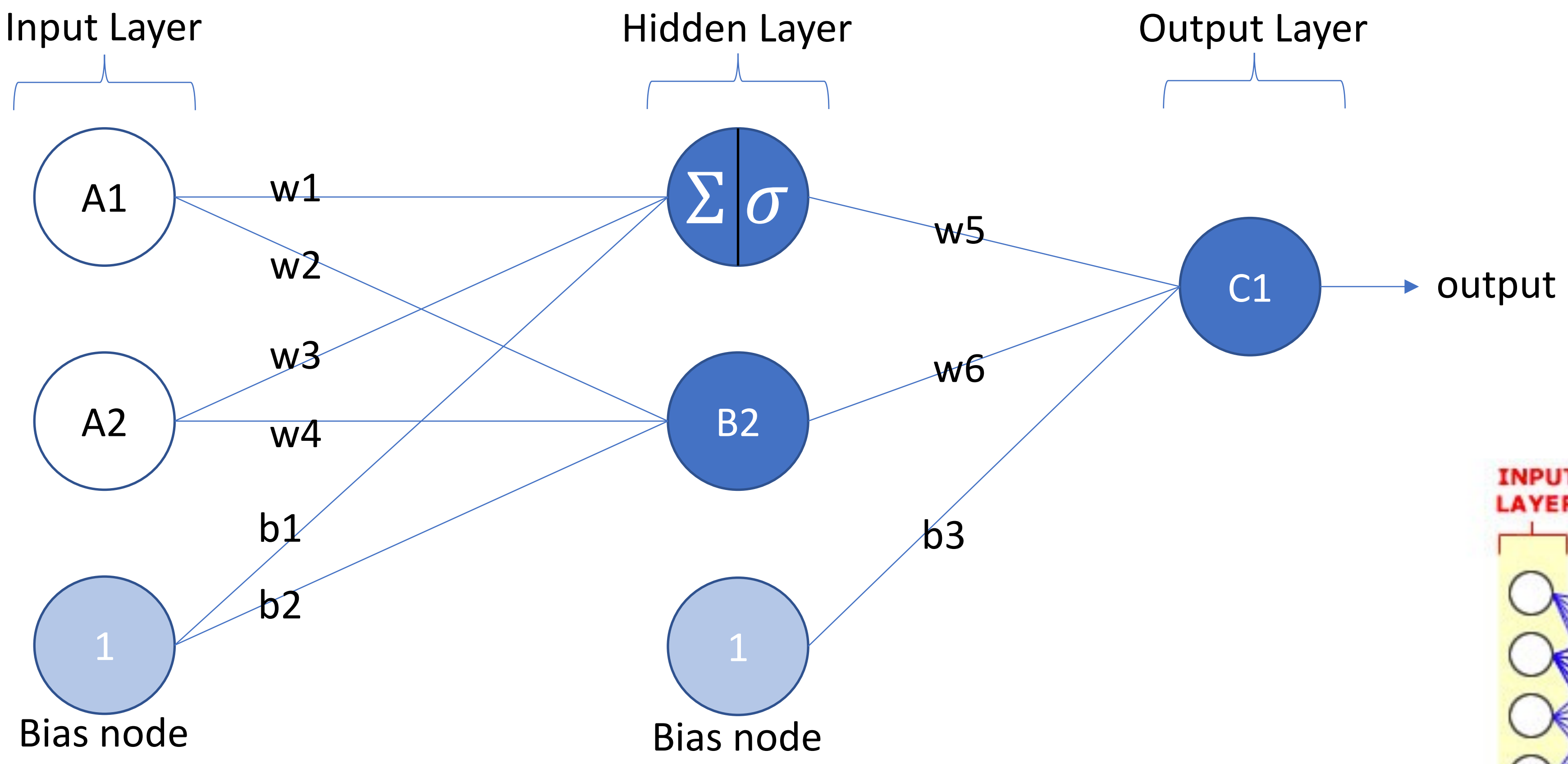
Activation A-Z Example

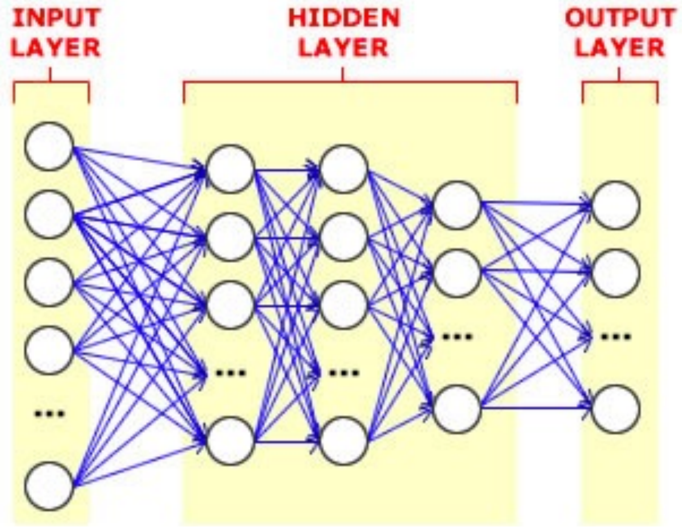
- Call a^i_j the output (activation) of the j^{th} neuron in the i^{th} layer
- Sigma is the activation function

$$a^i_j = \sigma\Big(\sum_k (w^i_{jk} \cdot a^{i-1}_k) + b^i_j\Big)$$



Forward Propagation A-Z Example





Artificial Neural Nets A-Z Example

- Step 1: Forward Propagation
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Backpropagation

Cost Function (or Loss Function) A-Z Example

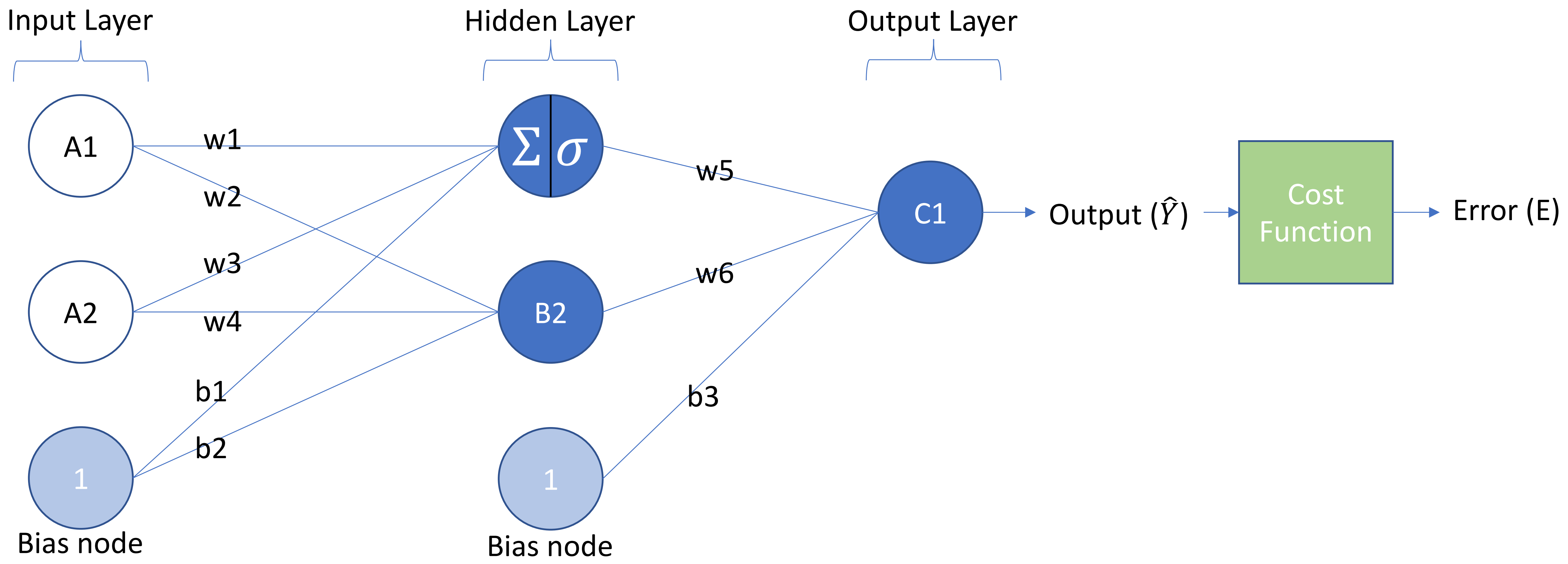
- Mean Squared Error

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(\hat{Y}_i - Y_i)^2$$

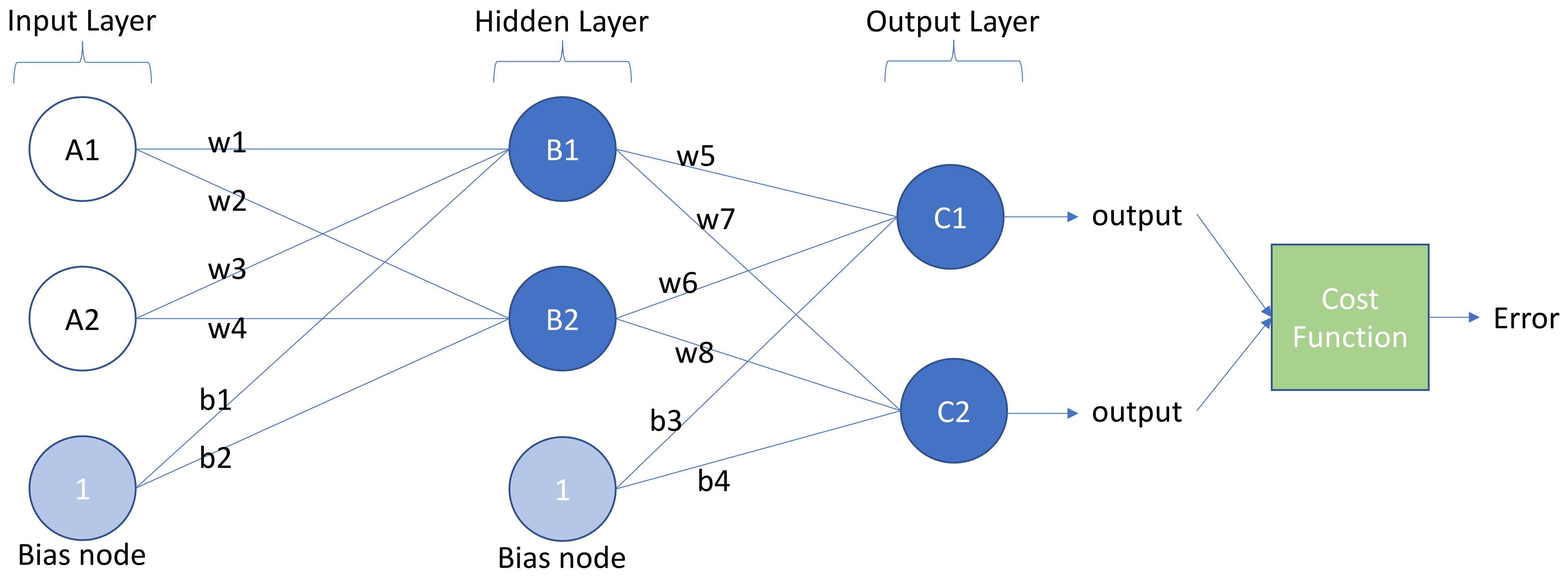
n = number of training examples
$\hat{Y}_i$ = predicted output for example i
Y_i = actual output for example i

[A list of cost functions used in neural networks]

Calculating Error A-Z Example



Calculating Error with multiple outputs A-Z Example



Artificial Neural Nets A-Z Example

- Step 1: Forward Propagation
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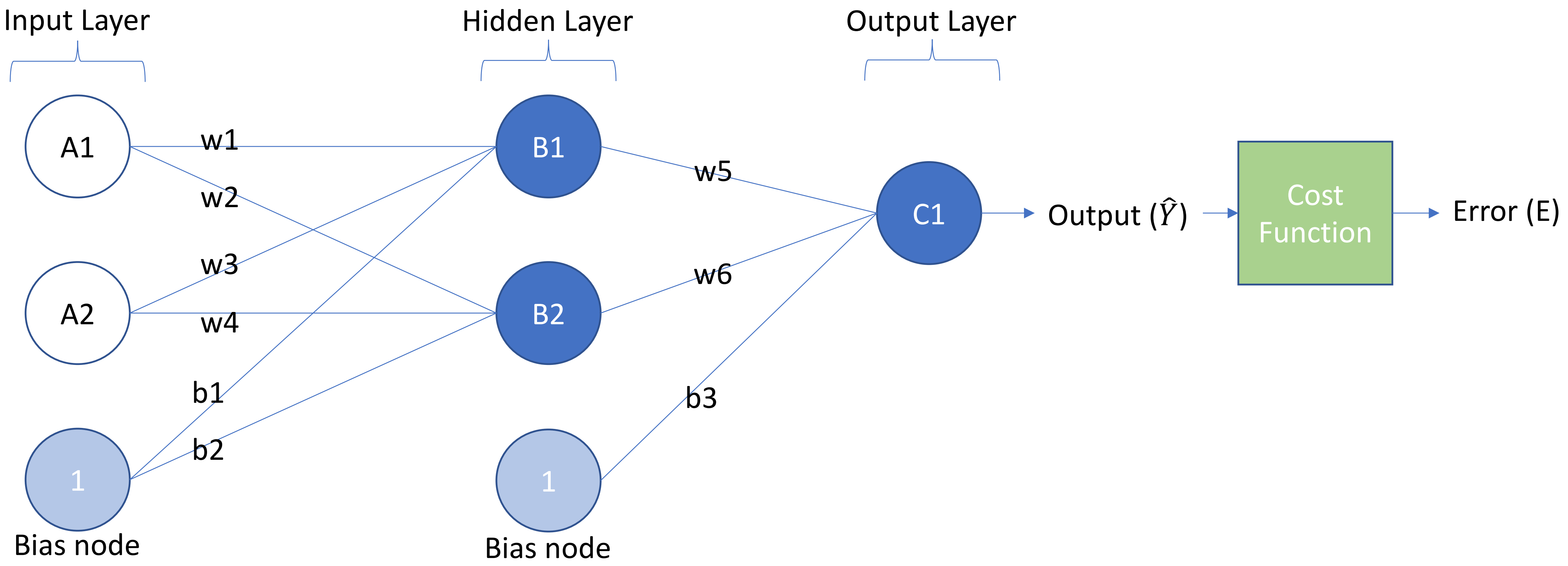
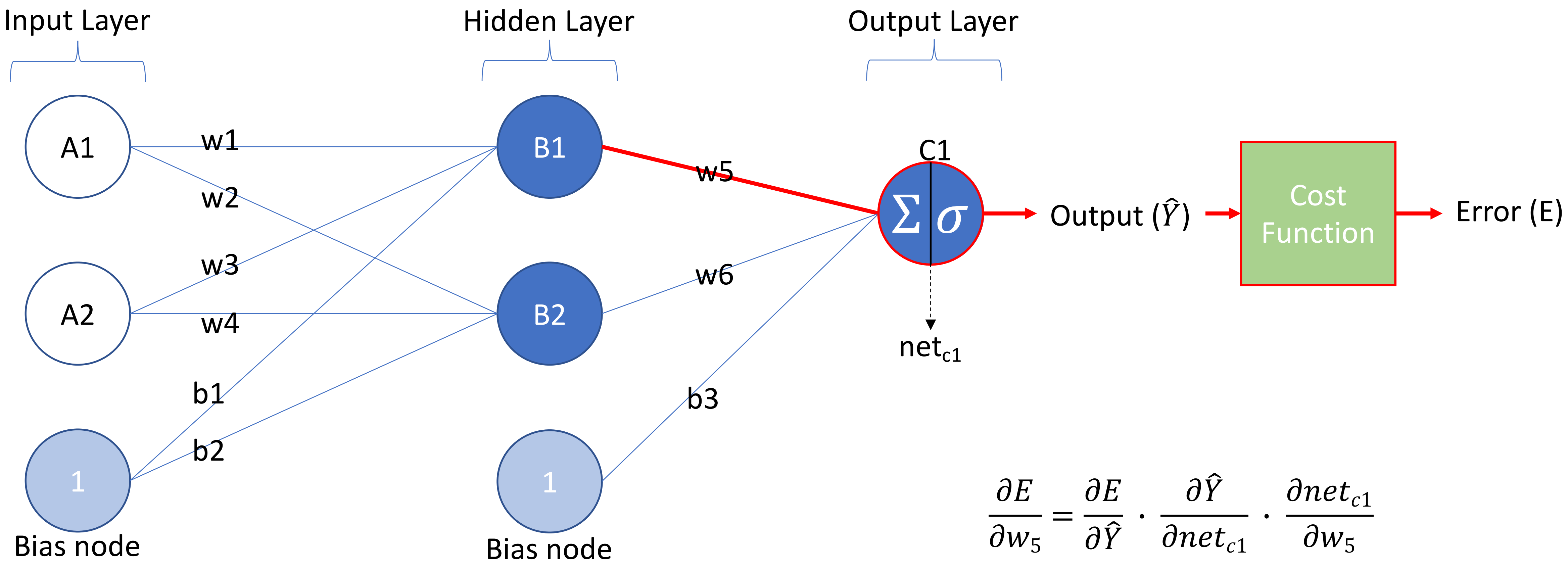
Backpropagation

Calculating Gradients A-Z Example



Calculating Gradients A-Z Example



$$\frac{\partial E}{\partial w_5} = \frac{\partial E}{\partial \hat{Y}} \cdot \frac{\partial \hat{Y}}{\partial net_{c1}} \cdot \frac{\partial net_{c1}}{\partial w_5}$$

Calculating Gradients A-Z Example

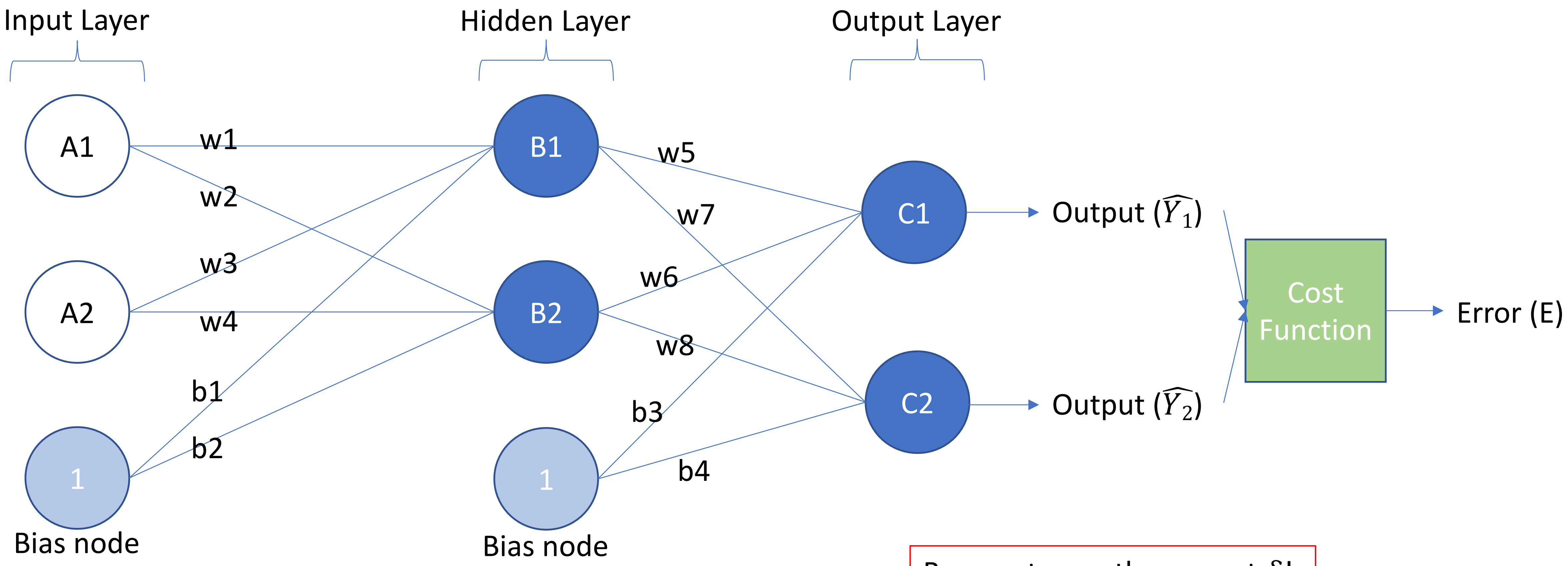
$$\frac{\partial E}{\partial w_5} = \frac{\partial E}{\partial \hat{Y}} \cdot \frac{\partial \hat{Y}}{\partial net_{C1}} \cdot \frac{\partial net_{C1}}{\partial w_5}$$

$$\frac{\partial E}{\partial w_5} = (\hat{Y} - Y) \cdot \hat{Y}\left(1 - \hat{Y}\right) \cdot B1_{out}$$

$$\frac{\partial E}{\partial w_5} = \delta_{c1} \, . \, B1_{out}$$

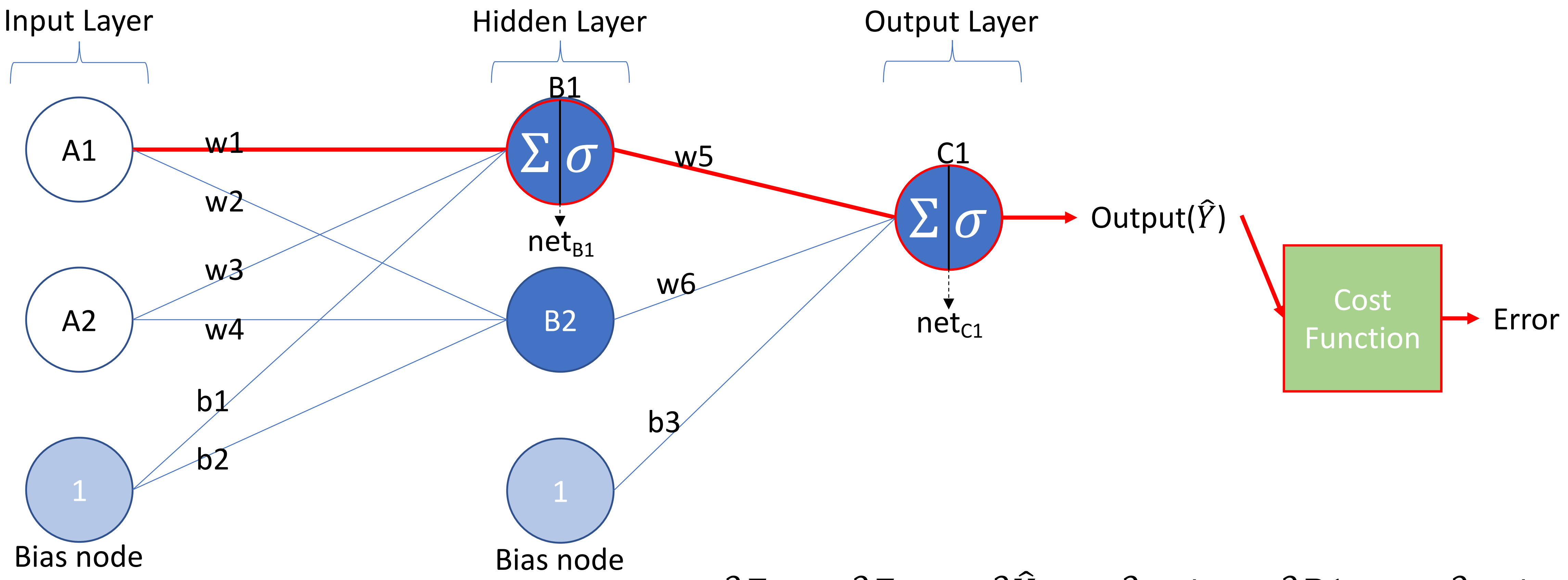
Where $\delta = \underbrace{(\hat{Y} - Y)}_{\text{Derivative of the cost function}} \cdot \underbrace{\hat{Y}\left(1 - \hat{Y}\right)}_{\text{Derivative of the activation function}}$

Calculating Gradients with multiple outputs A-Z Example



Be sure to use the correct δ!
w5, w6, b3 will use C1's delta
w7, w8, b4 will use C2's delta

Calculating Gradients for inner layers A-Z Example



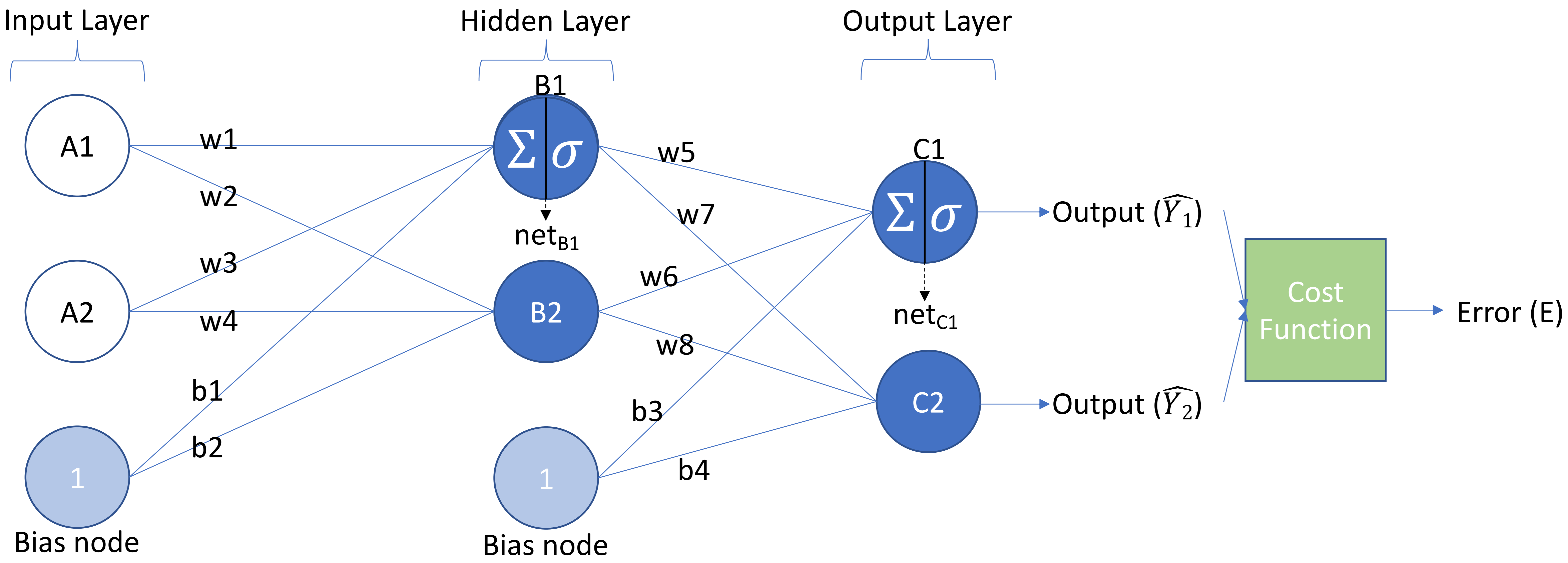
$$\frac{\partial E}{\partial W_1} = \frac{\partial E}{\partial \hat{Y}} \cdot \frac{\partial \hat{Y}}{\partial net_{C1}} \cdot \frac{\partial net_{C1}}{\partial B1_{out}} \cdot \frac{\partial B1_{out}}{\partial net_{B1}} \cdot \frac{\partial net_{B1}}{\partial W_1}$$

Calculating Gradients A-Z Example

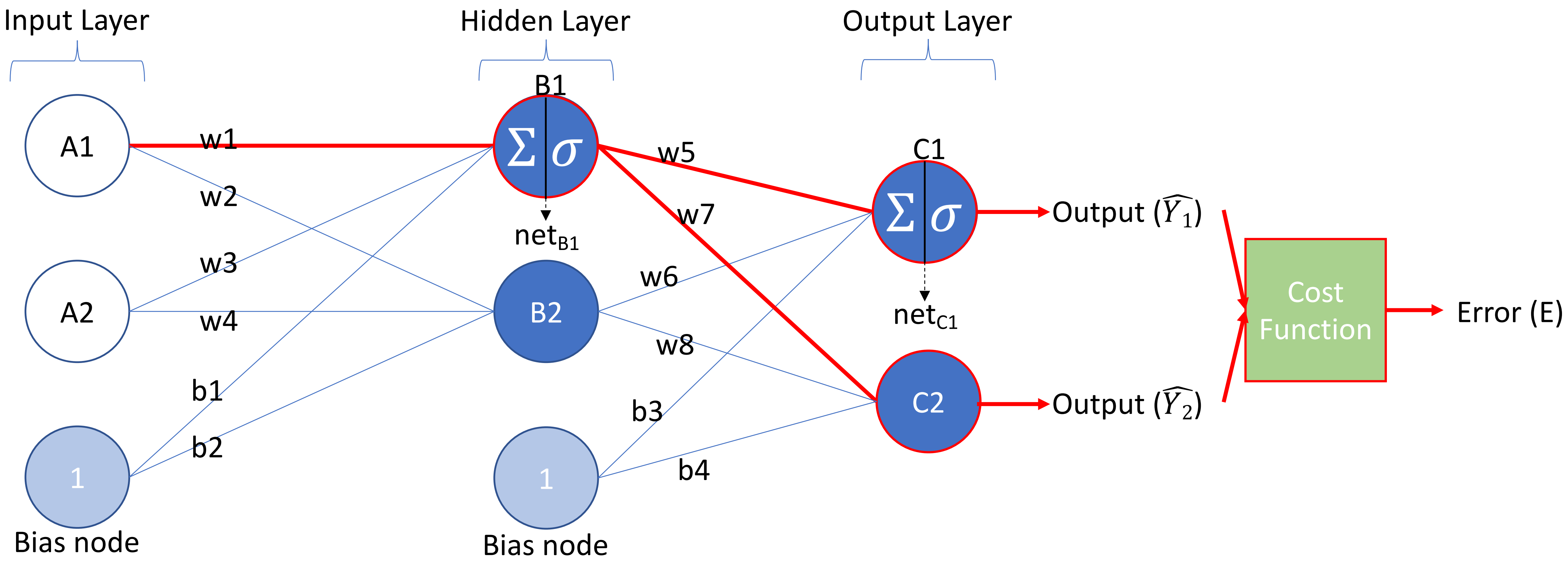
$$\frac{\partial E}{\partial W_1} = \frac{\partial E}{\partial \hat{Y}} \cdot \frac{\partial \hat{Y}}{\partial net_{C1}} \cdot \frac{\partial net_{C1}}{\partial B1_{out}} \cdot \frac{\partial B1_{out}}{\partial net_{B1}} \cdot \frac{\partial net_{B1}}{\partial W_1}$$

$$\frac{\partial E}{\partial w_1} = (\hat{Y} - Y) \cdot \hat{Y}\left(1 - \hat{Y}\right) \cdot w_5 \cdot B1_{out}(1 - B1_{out}) \cdot A1_{out}$$

Calculating Gradients for inner layers A-Z Example



Calculating Gradients for inner layers A-Z Example



$$\frac{\partial E}{\partial W_1} = \Sigma\left(\frac{\partial E}{\partial \hat{Y}_i} \cdot \frac{\partial \hat{Y}_i}{\partial net_{Ci}} \cdot \frac{\partial net_{Ci}}{\partial B1_{out}}\right) \cdot \frac{\partial B1_{out}}{\partial net_{B1}} \cdot \frac{\partial net_{B1}}{\partial W_1}$$

Calculating Gradients A-Z Example

$$\frac{\partial E}{\partial w_1} = \Sigma(\frac{\partial E}{\partial \hat{Y}} \cdot \frac{\partial \hat{Y}}{\partial net_{Ci}} \cdot \frac{\partial net_{Ci}}{\partial out_{B1}}) \cdot \frac{\partial out_{B1}}{\partial net_{B1}} \cdot \frac{\partial net_{B1}}{\partial w_1}$$

$$\frac{\partial E}{\partial w_1} = \Sigma\left(\left(\widehat{Y}_i - Y_i\right) \cdot \hat{Y}_i\left(1 - \hat{Y}_i\right) w_j\right) \cdot B1_{out(}1 - B1_{out)} \cdot A1_{out}$$

$$\frac{\partial E}{\partial w_1} = \Sigma(\delta_{ci}\, w_j) \cdot B1_{out(}1 - B1_{out)} \cdot A1_{out}$$

Where $\delta_{ci} = (\widehat{Y}_i - Y_i) \cdot \widehat{Y}_i\left(1 - \widehat{Y}_i\right)$

$$\frac{\partial E}{\partial w_1} = \delta_{B1} \,.\, A1_{out}$$

Where $\delta_{Bi} = \Sigma(\delta_c\, w_j) \cdot Bi_{out}(1 - Biout)$

Artificial Neural Nets A-Z Example

- Step 1: Forward Propagation
  - Summation Operator
  - Activation Function
- Step 2: Calculate Total Error
  - Cost Function
- Step 3: Calculate Gradients
  - Partial Derivative
  - Chain Rule
- **Step 4: Update Weights**
  - **Weight Update Formula**

Backpropagation

Updating Weights A-Z Example

$$w_{new} = w - \alpha \frac{\partial E}{\partial w}$$

Where α is the learning rate

Design Issues in ANN

- Number of nodes in input layer
  - One input node per binary/continuous attribute
  - k or $\log_2$ k nodes for each categorical attribute with k values
- Number of nodes in output layer
  - One output for binary class problem
  - k or $\log_2$ k nodes for k-class problem
- Number of nodes in hidden layer
- Initial weights and biases

Characteristics of Neural Networks

- Multi-layer neural networks with at least one hidden layer can learn complex and diverse decision boundaries
- Susceptible to overfitting
- Can handle irrelevant attributes by using zero weights; can handle redundant attributes by using similar weights
- Can get stuck at a local minima (a non-optimal solution)
- Training is time consuming and requires a lot of data
- Difficult to interpret the results
- Difficult to handle missing attributes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Recent Noteworthy Developments in ANN

- Use in deep learning and unsupervised feature learning
  - Seek to automatically learn a good representation of the input from unlabeled data
- Google Brain project
  - Learned the concept of a ‘cat’ by looking at unlabeled pictures from YouTube
  - One billion connection network

Deep Neural Networks

- Involve a large number of hidden layers
- Can represent features at multiple levels of abstraction
- Often require fewer nodes per layer to achieve generalization performance similar to shallow networks
- Deep networks have become the technique of choice for complex problems such as vision and language processing

Deep Nets: Challenges and Solutions

- Challenges
  - Slow convergence
  - Sensitivity to initial values of model parameters
  - The larger number of nodes makes deep networks susceptible to overfitting

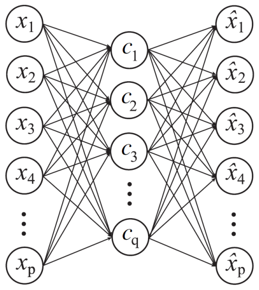
- Solutions
  - Large training data sets
  - Advances in computational power, e.g., GPUs
  - Algorithmic advances
    - New architectures and activation units
    - Better parameter and hyper-parameter selection
    - Regularization

Deep Learning Characteristics

- Pre-training allow deep learning models to reuse previous learning.
  - The learned parameters of the original task are used as initial parameter choices for the target task
  - Particularly useful when the target application has a smaller number of labeled training instances than the one used for pre-training

- Deep learning techniques for regularization help in reducing the model complexity
  - Lower model complexity promotes good generalization performance
  - The dropout method is one regularization approach
  - Regularization is especially important when we have
    - high-dimensional data
    - a small number of training labels
    - the classification problem is inherently difficult.

Deep Learning Characteristics …



Single-layer Autoencoder

- Using an autoencoder for pretraining can
  - Help eliminate irrelevant attributes
  - Reduce the impact of redundant attributes.
- ANN models, especially deep models, can find inferior and locally optimal solutions,
  - Deep learning techniques have been proposed to ensure adequate learning of an ANN
  - Example: Skip connections
- Specialized ANN architectures have been designed to handle various data sets.
  - Convolutional Neural Networks} (CNN) handle two-dimensional gridded data and are used for image processing
  - Recurrent Neural Network handles sequences and are used to process speech and language