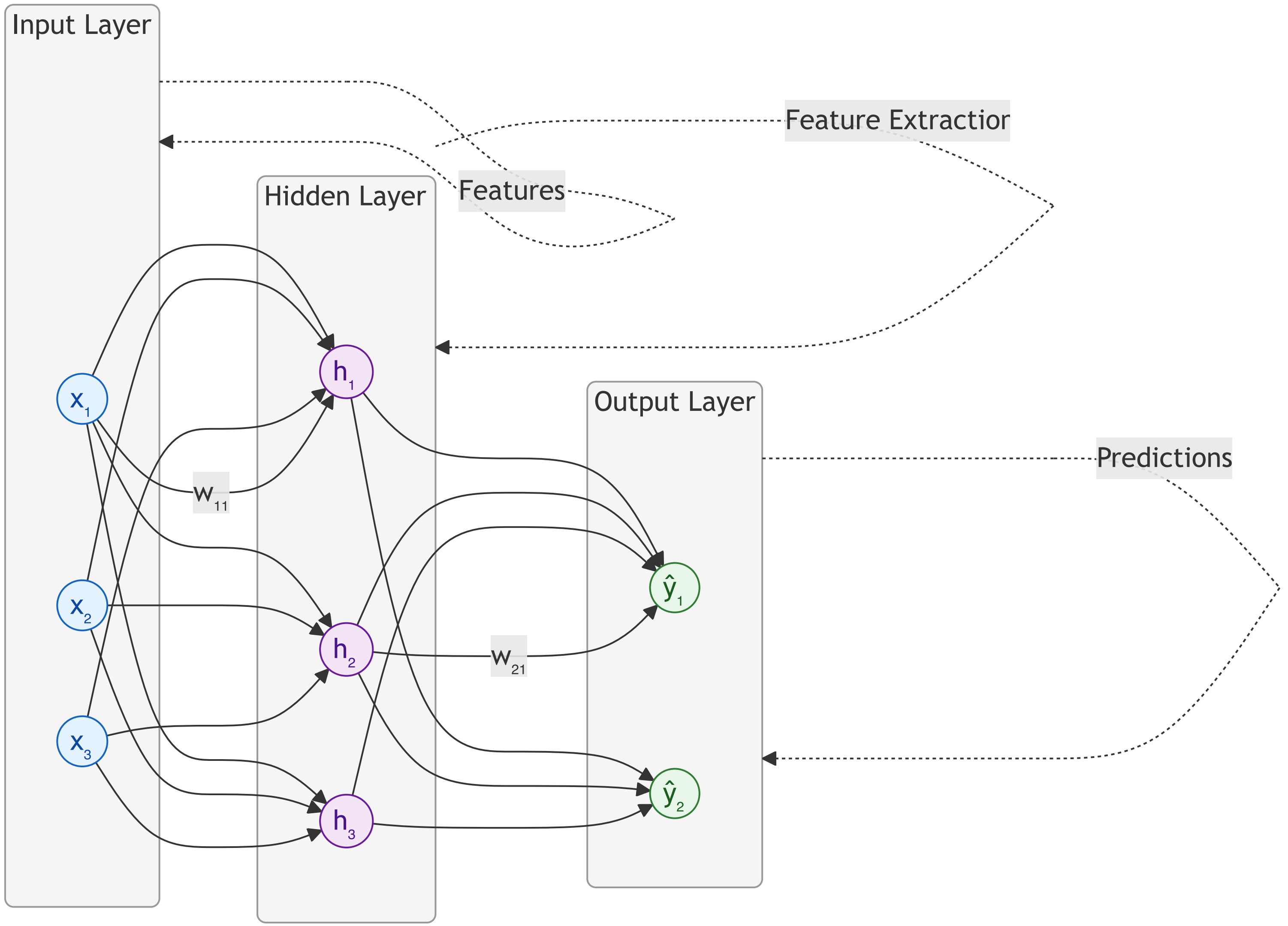
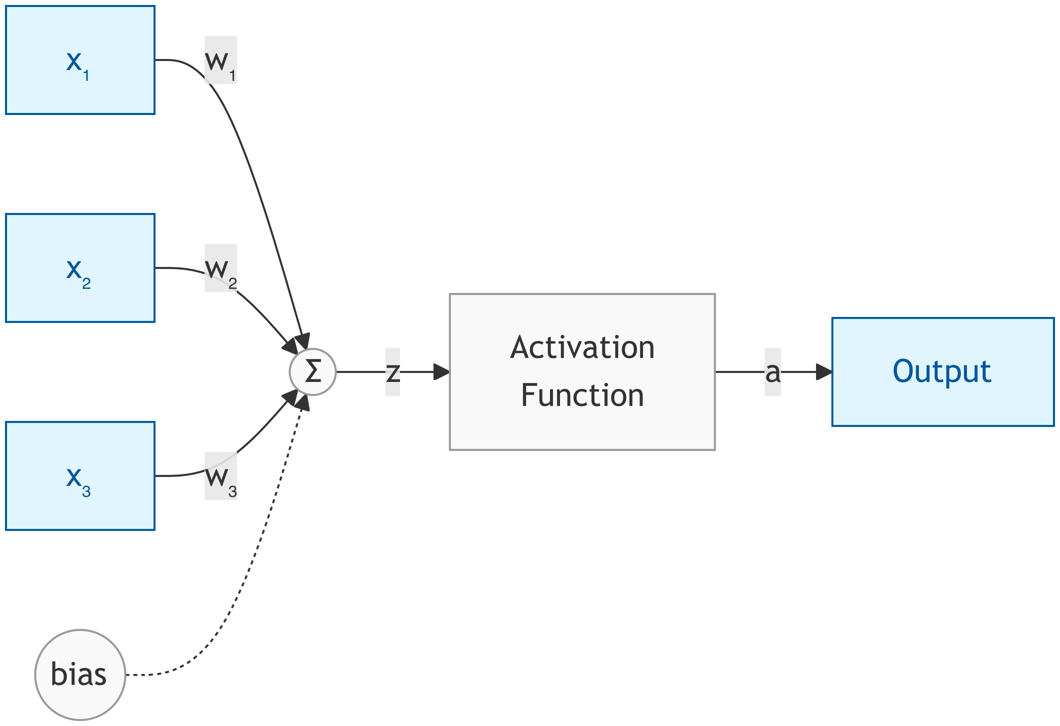
The Building Blocks of Deep Learning



The Building Blocks of Deep Learning

- Foundation of modern neural networks
- Versatile architecture for diverse problems
- Combines simplicity with powerful learning capabilities

From Neurons to Networks



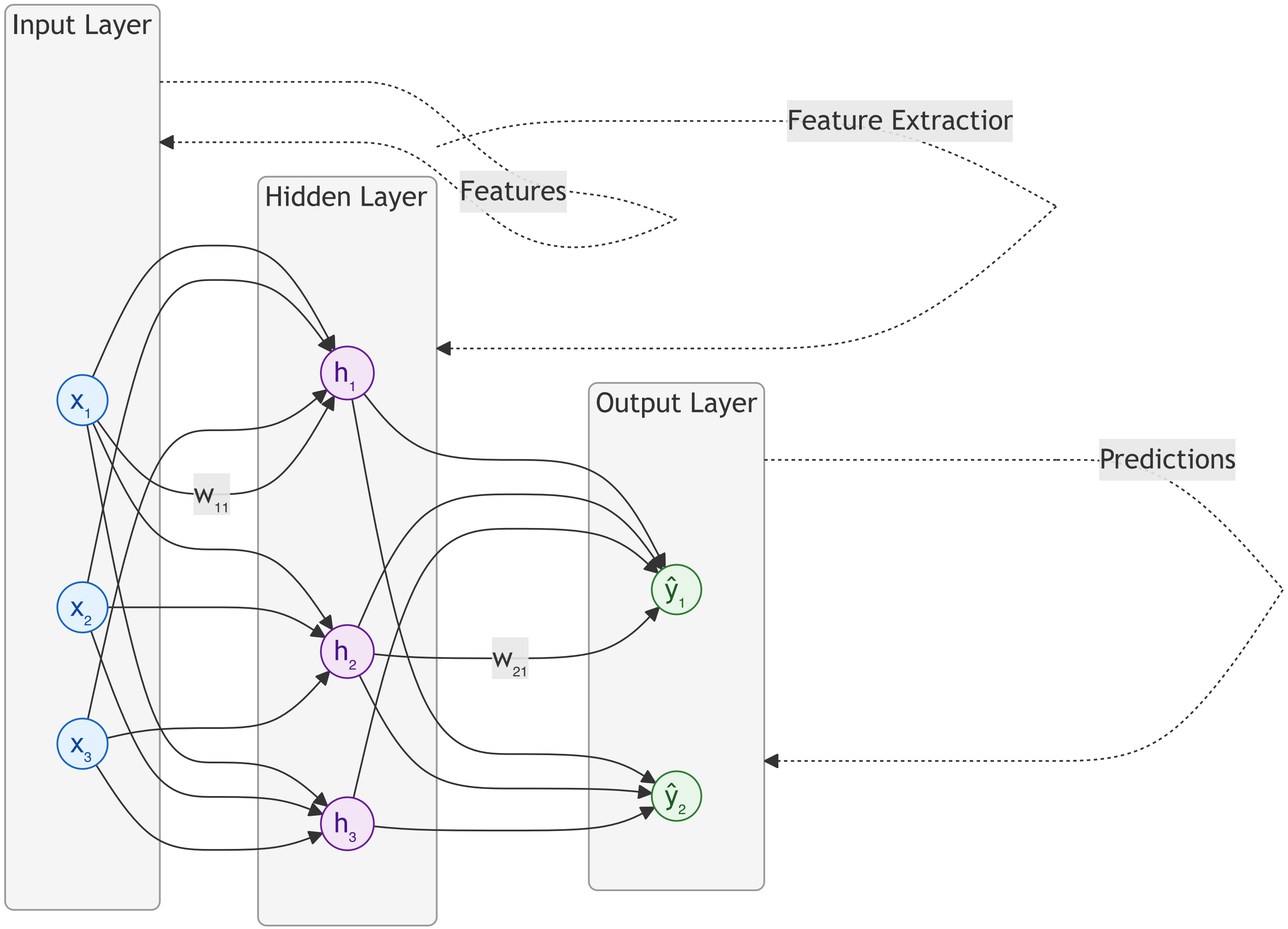
From Neurons to Networks

- **Biological inspiration**: Mimics brain's neural structure
  - Neurons receive, process, and transmit information
- **Artificial neuron**: Weighted sum + activation function
  - Processes inputs through mathematical operations
- **Network topology**: Input layer → Hidden layers → Output layer
  - Organized structure for information processing
- **Information flow**: Forward propagation for predictions
  - Data travels from input to output through the network

The Perceptron Journey

- **1958**: Rosenblatt's single-layer perceptron
  - First implementation of a neural learning algorithm
- **1969**: Minsky & Papert expose limitations (XOR problem)
  - Demonstrated that single-layer networks couldn't solve nonlinear problems
- **1986**: Rumelhart, Hinton & Williams introduce backpropagation
  - Breakthrough algorithm enabling training of multi-layer networks
- **Today**: Foundation for advanced architectures (CNNs, RNNs, Transformers)
  - Core concepts extended to specialized network designs

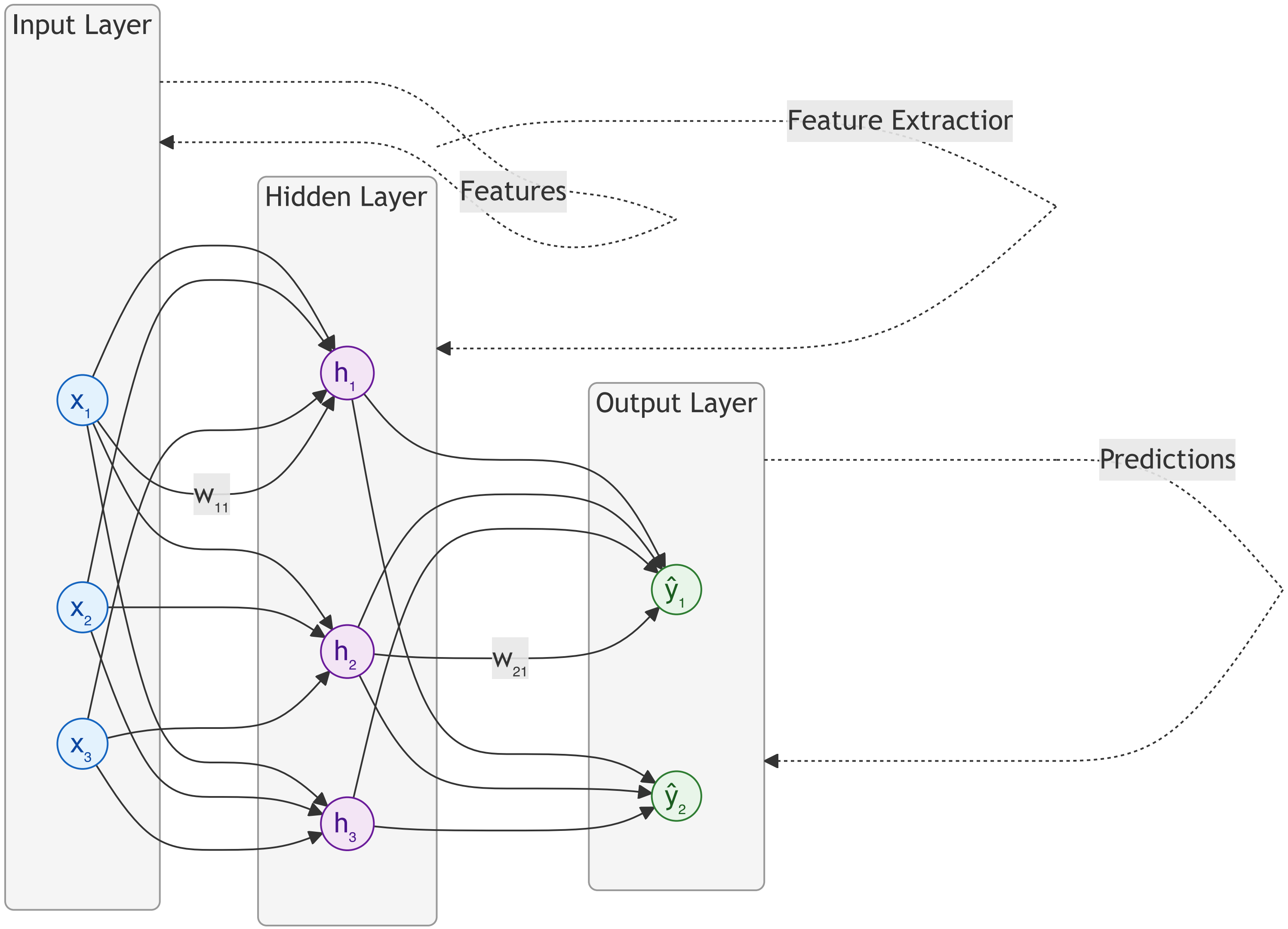
MLP Architecture



Key Components

- **Input layer**: Raw data reception
  - Receives and standardizes input features
- **Hidden layers**: Feature extraction and transformation
  - Learns hierarchical representations of data
- **Output layer**: Final prediction/classification
  - Produces the network's answer to the given problem

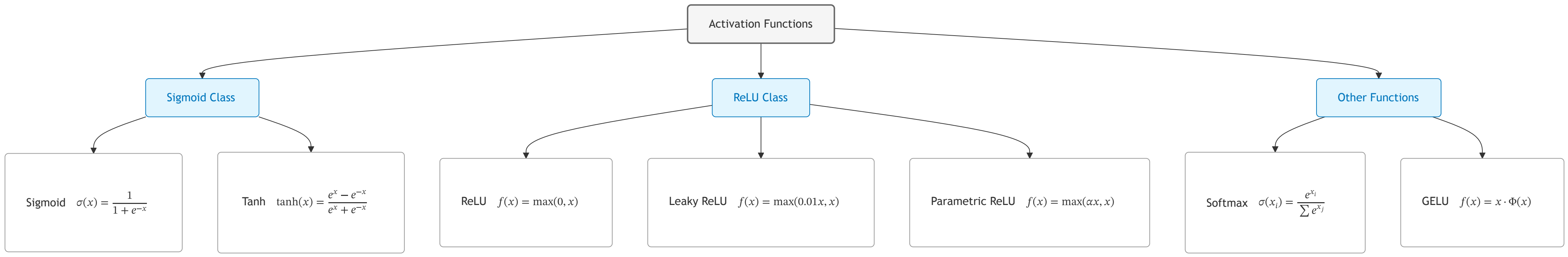
MLP Architecture



Key Components

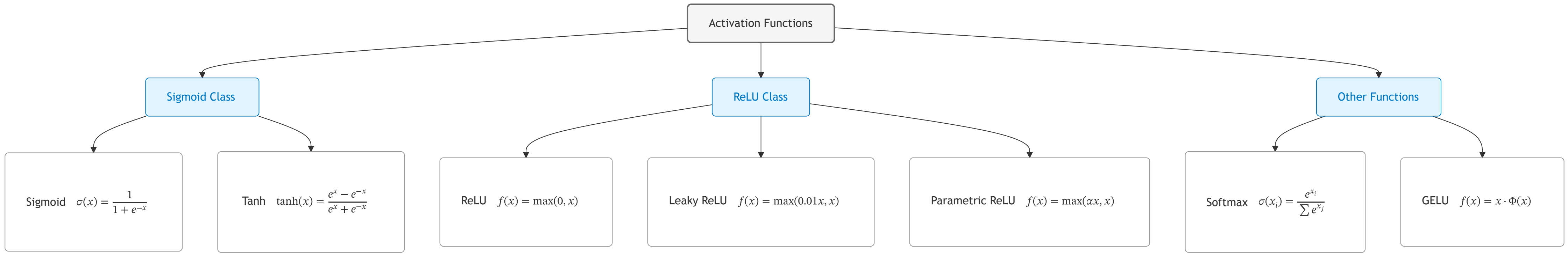
- **Weights & biases**: Learnable parameters
  - Adjusted during training to minimize error
- **Activation functions**: Introduce non-linearity
  - Enable the network to learn complex patterns

Activation Functions



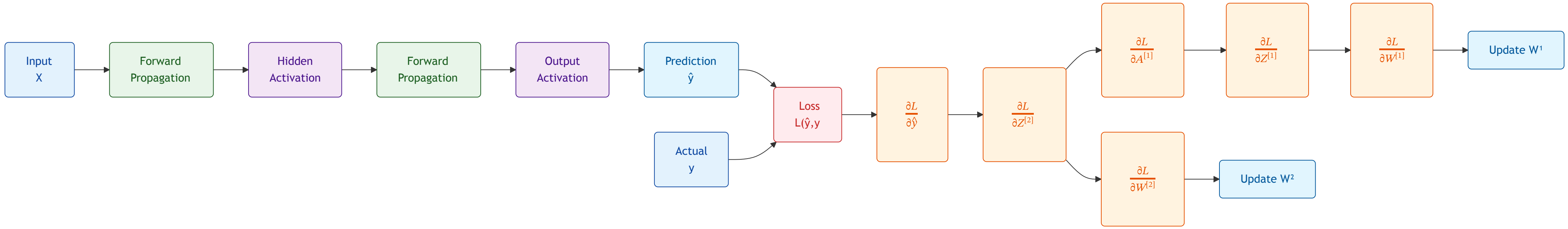
Function	Formula	Characteristics
Sigmoid	$\sigma(x) = \frac{1}{1+e^{-x}}$	Output range [0,1], vanishing gradient
Tanh	$\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$	Output range [-1,1], zero-centered

Activation Functions



Function	Formula	Characteristics
ReLU	$f(x) = \max(0, x)$	Computationally efficient, sparse activation
Leaky ReLU	$f(x) = \max(0.01x, x)$	Prevents dying ReLU problem

Forward Propagation



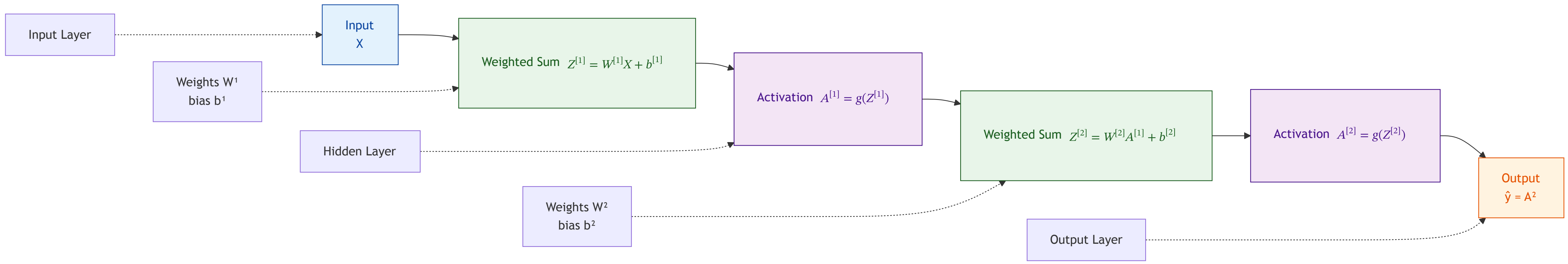
For each layer l:

$$Z^{[l]} = W^{[l]} \cdot A^{[l-1]} + b^{[l]}$$
$$A^{[l]} = g^{[l]}(Z^{[l]})$$

Where:

- $W^{[l]}$ = weights matrix
- $b^{[l]}$ = bias vector

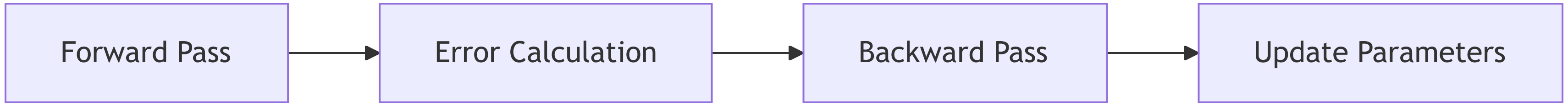
Forward Propagation



Where:

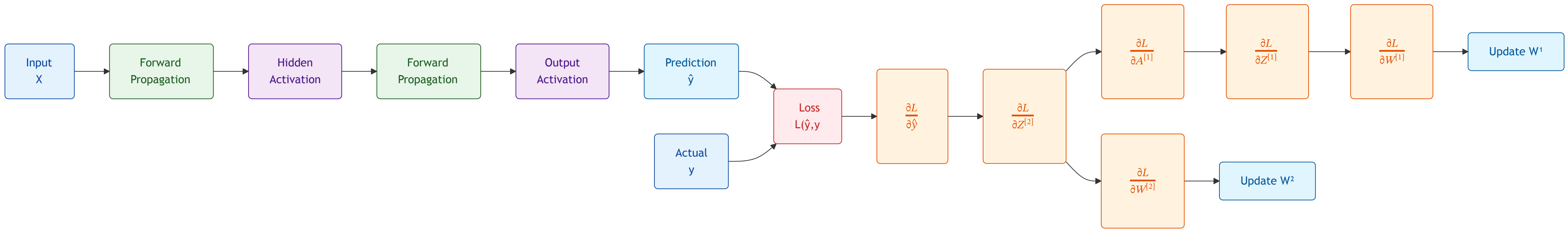
- $g^{[l]}$ = activation function
- $A^{[l]}$ = activation output

Backpropagation: Learning Process



1. **Forward pass**: Compute predictions
    - Process inputs through the network
2. **Error calculation**: Compare with ground truth

Backpropagation: Learning Process



3. **Backward pass**: Compute gradients
4. **Parameter update**: Adjust weights and biases

$$W^{[l]} = W^{[l]} - \alpha \frac{\partial J}{\partial W^{[l]}}$$

$$b^{[l]} = b^{[l]} - \alpha \frac{\partial J}{\partial b^{[l]}}$$

Loss Functions

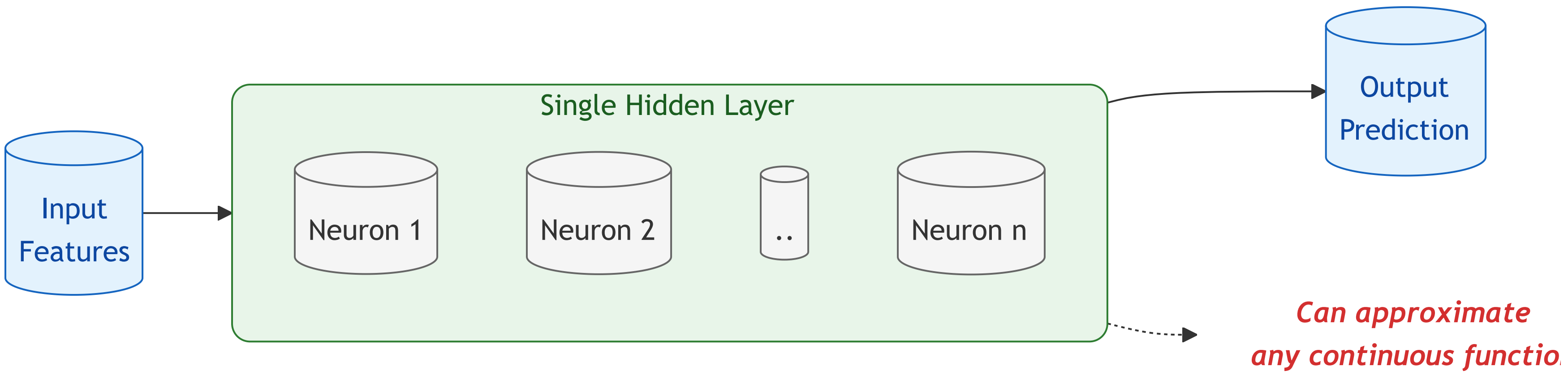
Task	Loss Function	Formula
Regression	Mean Squared Error	$\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
Binary Classification	Binary Cross-Entropy	$-\frac{1}{n}\sum_{i=1}^{n}[y_i \log(\hat{y}_i) + (1 - y_i)\log(1 - \hat{y}_i)]$

Loss Functions

Task	Loss Function	Formula
Multi-class Classification	Categorical Cross-Entropy	$-\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{m} y_{ij}\log(\hat{y}_{ij})$

- Loss guides the learning process
- Different tasks use specialized error measurements
- Optimization aims to minimize loss

Universal Approximation Theorem

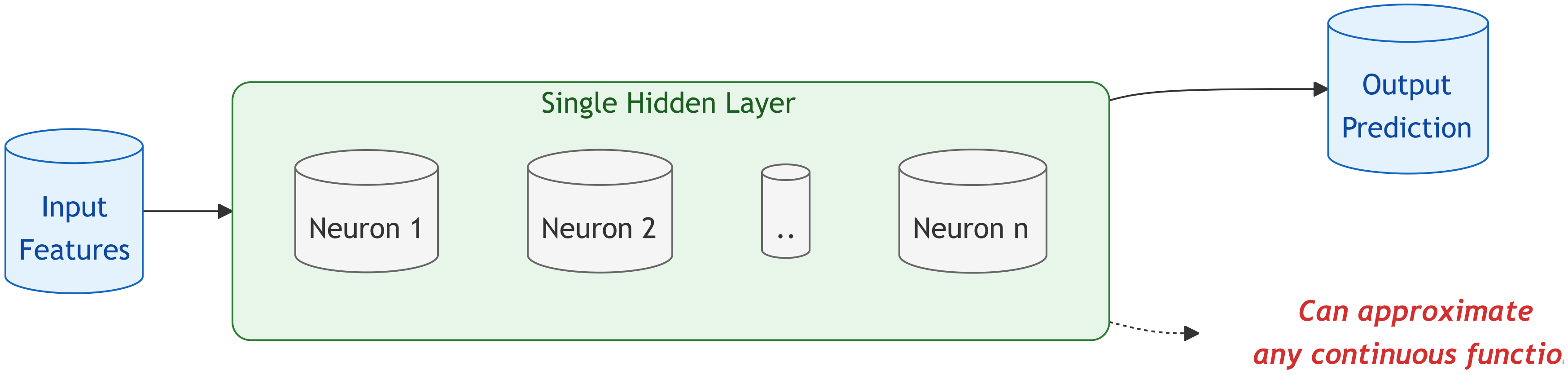


Universal Approximation Theorem

> "A feedforward network with a single hidden layer containing a finite number of neurons can approximate any continuous function, under mild assumptions on the activation function."

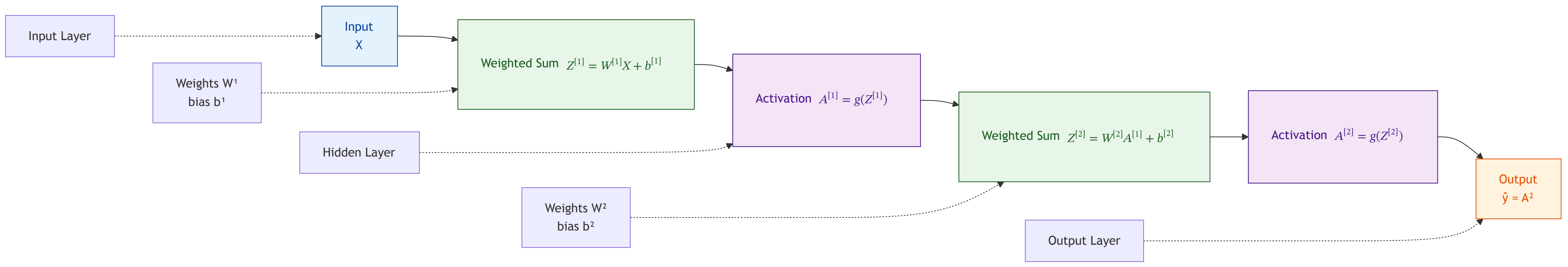
- The theoretical foundation for MLP capabilities

Universal Approximation Theorem



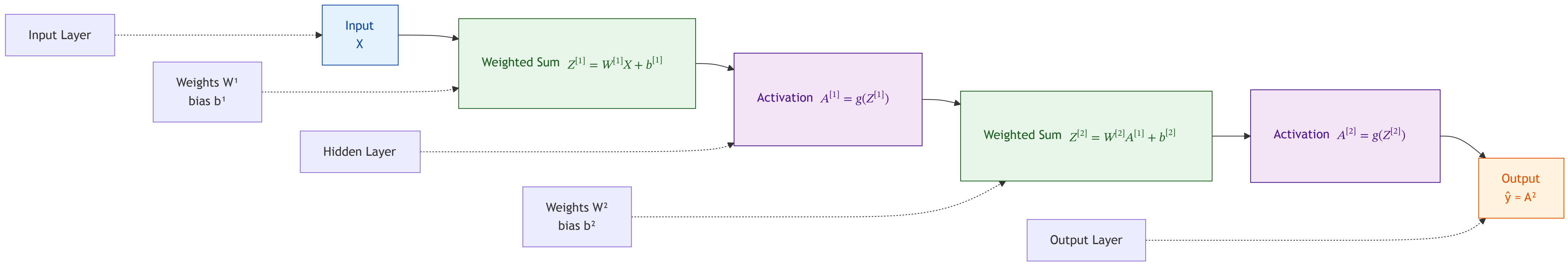
- More complex functions may require more neurons
- Practical implementations must balance capacity and training challenges

Visualizing Decision Boundaries



- **Linear boundaries**: Single-layer perceptrons
  - Separate data with straight lines
- **Non-linear boundaries**: MLPs with hidden layers
  - Can form complex separation surfaces

Visualizing Decision Boundaries



- **Complexity increases** with deeper architectures
- Explore an interactive demo at perceptron.marcr.xyz

Quick Quiz: Test Your Knowledge

Which of these problems can a single-layer perceptron solve?

A) XOR problem

B) Linear classification

C) Image recognition

D) All of the above

Use the poll feature to submit your answer!

Practical Implementation Challenges

What's your biggest challenge with neural networks?

- Understanding the math
- Choosing the right architecture
- Overfitting/underfitting
- Computational resources
- Interpreting results

Share your thoughts!

Thank You

Contact Information

- Email: hi@marcr.xyz

Resources

- Interactive Demo: perceptron.marcr.xyz
- Slides: github.com/mabreyes/dlsu-lecture-slides