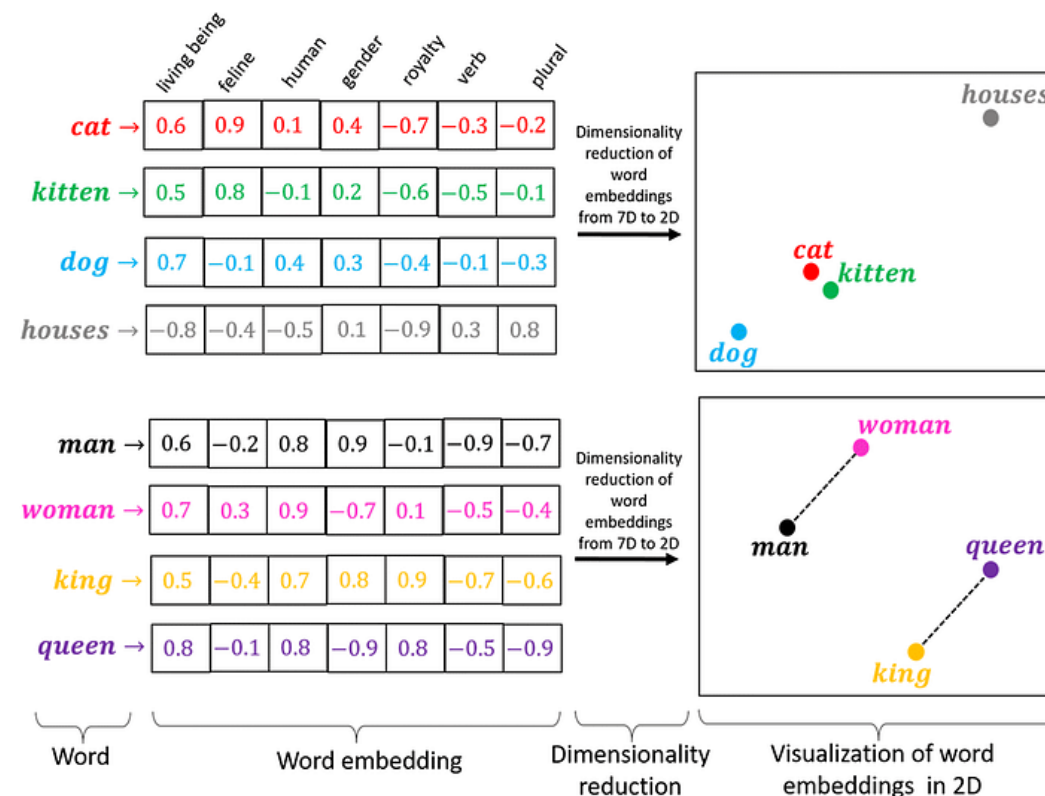


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## Part 2 – Introduction to Neural Networks and Word Embeddings

# Preface

- In the previous section, we used Bow and TDIDF to convert documents and words into numerical representations.
- These representations were simple, they had no semantics for words, just on/off switches for existing and non-existing words in a document.
- In this part of the course, we want to convert words into meaningful list of numbers.
- These numbers are called **Word Embeddings**.
- We will use Neural Networks to create these Word Embeddings.



# Outcomes

- Fundamentals of neural networks
- Evolution from single Perceptrons to MLPs
- Detailed MLP architecture (input, hidden, and output layers)
- Mathematical representations
- Various activation functions (Sigmoid, ReLU, etc.)
- Backpropagation and training methodologies
- Loss functions and optimization techniques
- Architecture design considerations
- Real-world applications
- Advantages and limitations
- Modern MLP variants and implementations

# History of Neural Networks

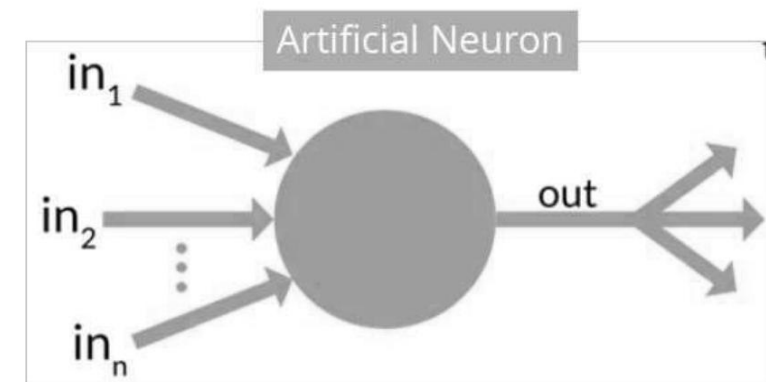
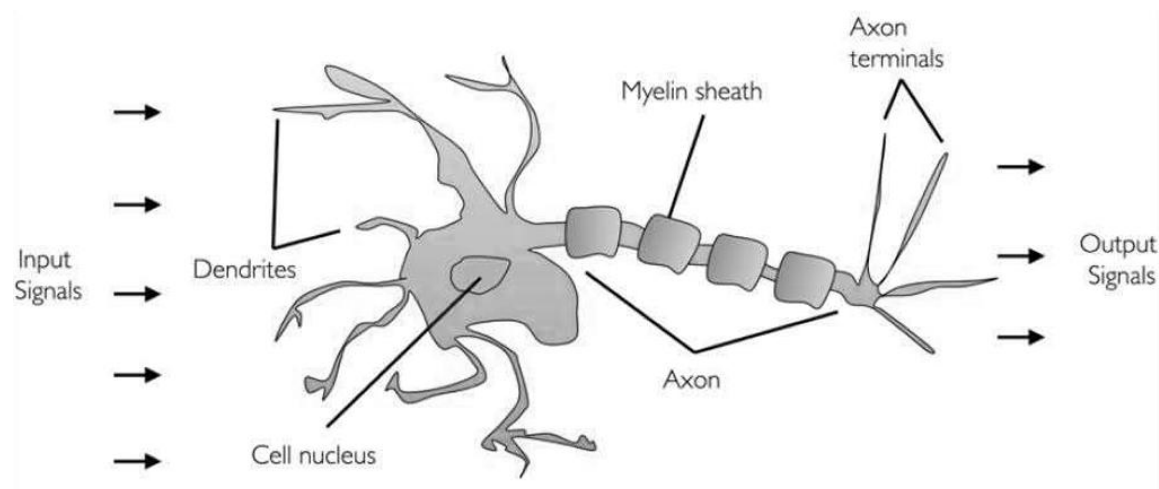
- In 1943, researchers Warren McCulloch and published their first concept of simplified brain cell.
- This was called McCulloch-Pitts (MCP) neuron.
- They described such a nerve cell as a simple logic gate with binary outputs.
- Multiple signals arrive at the dendrites and are then integrated into the cell body, and, if the accumulated signal exceeds a certain threshold, an output signal is generated that will be passed on by the axon.



Warren Sturgis McCulloch  
(1898 – 1969)

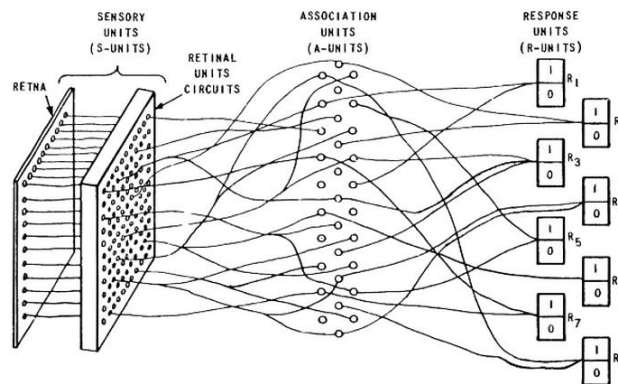


Walter Harry Pitts, Jr.  
(1923 – 1969)

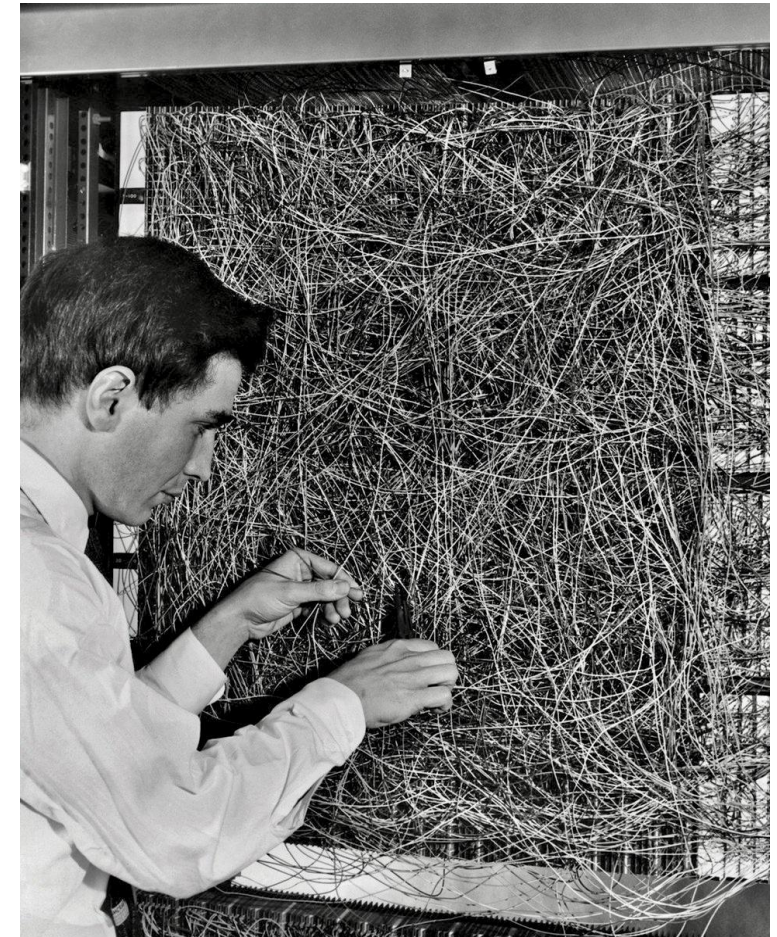


# The Perceptron: Building Block of Neural Networks

- In 1953, inspired by McCulloch work, Frank Rosenblatt invented the Perceptron.
- The Perceptron is the simplest form of a neural network
- Binary classifier: separates data into two categories
- Models a single neuron with multiple inputs and one output

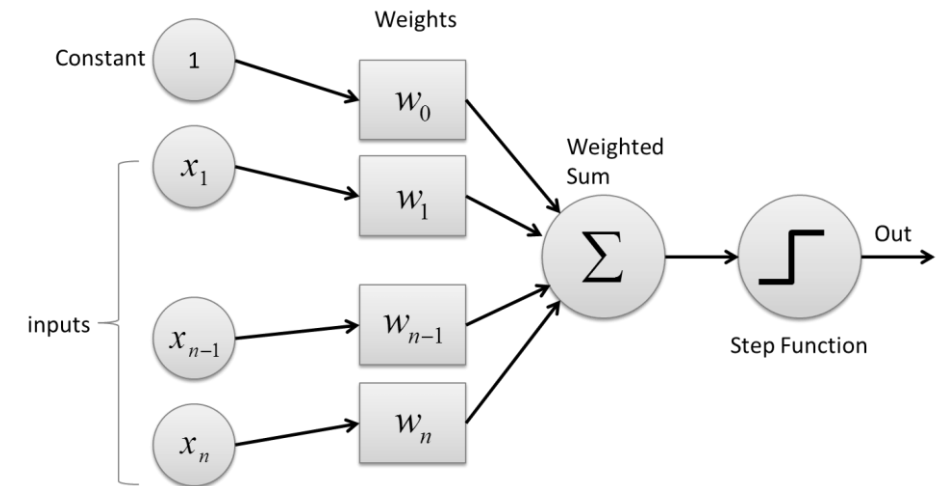


F. Rosenblatt



# The Perceptron

- Inputs:  $x_1, x_2, \dots, x_n$
- Weights:  $w_1, w_2, \dots, w_n$
- Bias:  $b$
- Activation function: Step function
- Output: 1 if weighted sum  $>$  threshold, 0 otherwise



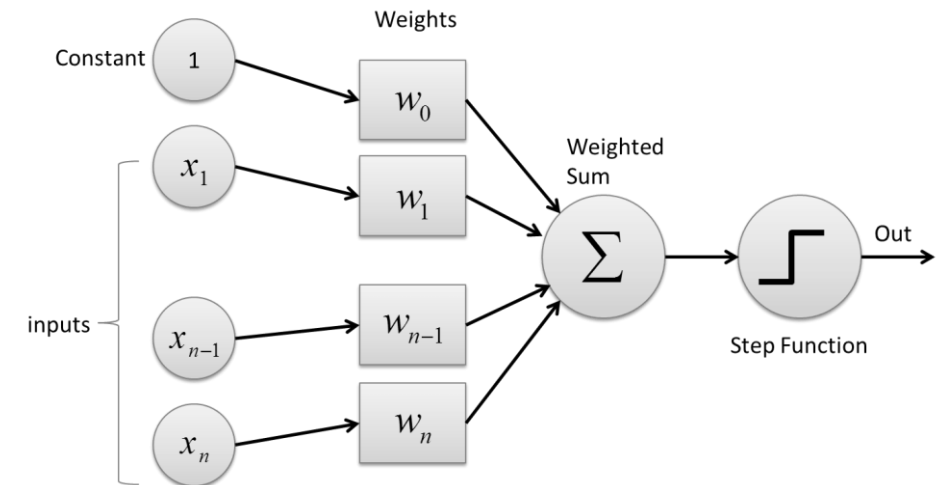


# How a Perceptron Works

1. Multiply each input by its corresponding weight
2. Sum all weighted inputs
3. Add the bias term
4. Apply the activation function
5. Output the result

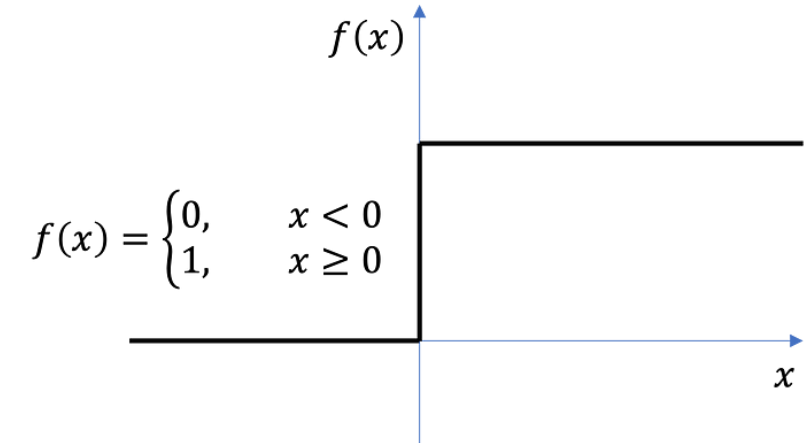
Mathematically:

- $z = w_1x_1 + w_2x_2 + \dots + w_nx_n + b$
- $\text{output} = \text{activation}(z)$



# Perceptron Activation Function

- **Step Function:**
  - Output: 1 if  $z \geq 0$ , 0 if  $z < 0$
  - Used in original perceptrons
  - Not differentiable at 0

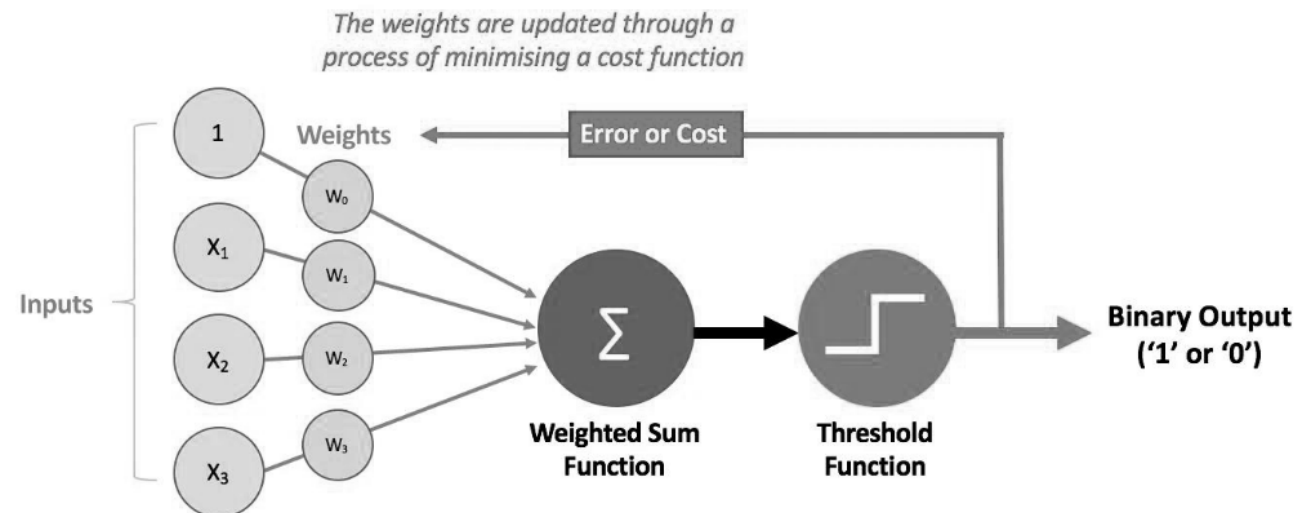




# How Perceptron Learn (The Cost Function)

For each training example:

1. Calculate predicted output  $y_{\text{pred}}$
2. Calculate error:  $\text{error} = y_{\text{true}} - y_{\text{pred}}$
3. Update weights:  $w_{\text{new}} = w_{\text{old}} + \text{learning\_rate} * \text{error} * x$
4. Update bias:  $b_{\text{new}} = b_{\text{old}} + \text{learning\_rate} * \text{error}$



# Step-by-Step Hand Calculation for AND Gate

Let's work through the perceptron learning algorithm by hand for the AND gate:

- Training data:  $X = [[0,0], [0,1], [1,0], [1,1]]$ ,  $y = [0, 0, 0, 1]$
- Learning rate ( $\eta$ ) = 0.1
- Initial weights (randomly assigned):  $w_1 = 0.3$ ,  $w_2 = -0.1$
- Initial bias:  $b = 0.2$

## First Iteration:

### Example 1: (0,0) → 0

- Inputs:  $x_1 = 0$ ,  $x_2 = 0$
- Weighted sum:  $z = w_1x_1 + w_2x_2 + b = 0.3(0) + (-0.1)(0) + 0.2 = 0.2$
- Activation: output = 1 (since  $z > 0$ )
- True output:  $y = 0$
- Error: error =  $y - \text{output} = 0 - 1 = -1$
- Weight updates:
  - $w_1 = w_1 + \eta * \text{error} * x_1 = 0.3 + 0.1 * (-1) * 0 = 0.3$
  - $w_2 = w_2 + \eta * \text{error} * x_2 = -0.1 + 0.1 * (-1) * 0 = -0.1$
  - $b = b + \eta * \text{error} = 0.2 + 0.1 * (-1) = 0.1$

# Step-by-Step Hand Calculation for AND Gate

## Example 2: (0,1) → 0

- Inputs:  $x_1 = 0$ ,  $x_2 = 1$
- Weighted sum:  $z = w_1x_1 + w_2x_2 + b = 0.3(0) + (-0.1)(1) + 0.1 = 0$
- Activation: output = 1 (since  $z \geq 0$ )
- True output:  $y = 0$
- Error: error =  $y - \text{output} = 0 - 1 = -1$
- Weight updates:
  - $w_1 = w_1 + \eta * \text{error} * x_1 = 0.3 + 0.1 * (-1) * 0 = 0.3$
  - $w_2 = w_2 + \eta * \text{error} * x_2 = -0.1 + 0.1 * (-1) * 1 = -0.2$
  - $b = b + \eta * \text{error} = 0.1 + 0.1 * (-1) = 0$

## Example 3: (1,0) → 0

- Inputs:  $x_1 = 1$ ,  $x_2 = 0$
- Weighted sum:  $z = w_1x_1 + w_2x_2 + b = 0.3(1) + (-0.2)(0) + 0 = 0.3$
- Activation: output = 1 (since  $z > 0$ )
- True output:  $y = 0$
- Error: error =  $y - \text{output} = 0 - 1 = -1$
- Weight updates:
  - $w_1 = w_1 + \eta * \text{error} * x_1 = 0.3 + 0.1 * (-1) * 1 = 0.2$
  - $w_2 = w_2 + \eta * \text{error} * x_2 = -0.2 + 0.1 * (-1) * 0 = -0.2$
  - $b = b + \eta * \text{error} = 0 + 0.1 * (-1) = -0.1$

# Step-by-Step Hand Calculation for AND Gate

## Example 4: (1,1) → 1

- Inputs:  $x_1 = 1, x_2 = 1$
- Weighted sum:  $z = w_1x_1 + w_2x_2 + b = 0.2(1) + (-0.2)(1) + (-0.1) = -0.1$
- Activation: output = 0 (since  $z < 0$ )
- True output:  $y = 1$
- Error: error =  $y - \text{output} = 1 - 0 = 1$
- Weight updates:
  - $w_1 = w_1 + \eta * \text{error} * x_1 = 0.2 + 0.1 * 1 * 1 = 0.3$
  - $w_2 = w_2 + \eta * \text{error} * x_2 = -0.2 + 0.1 * 1 * 1 = -0.1$
  - $b = b + \eta * \text{error} = -0.1 + 0.1 * 1 = 0$

## End of Iteration 1:

- Updated weights:  $w_1 = 0.3, w_2 = -0.1$
- Updated bias:  $b = 0$

# Second Iteration

## Example 1: (0,0) → 0

- Inputs:  $x_1 = 0, x_2 = 0$
- Weighted sum:  $z = w_1x_1 + w_2x_2 + b = 0.3(0) + (-0.1)(0) + 0 = 0$
- Activation: output = 1 (since  $z \geq 0$ )
- True output:  $y = 0$
- Error: error =  $y - \text{output} = 0 - 1 = -1$
- Weight updates:
  - $w_1 = w_1 + \eta * \text{error} * x_1 = 0.3 + 0.1 * (-1) * 0 = 0.3$
  - $w_2 = w_2 + \eta * \text{error} * x_2 = -0.1 + 0.1 * (-1) * 0 = -0.1$
  - $b = b + \eta * \text{error} = 0 + 0.1 * (-1) = -0.1$

## Example 2: (0,1) → 0

- Inputs:  $x_1 = 0, x_2 = 1$
- Weighted sum:  $z = w_1x_1 + w_2x_2 + b = 0.3(0) + (-0.1)(1) + (-0.1) = -0.2$
- Activation: output = 0 (since  $z < 0$ )
- True output:  $y = 0$
- Error: error =  $y - \text{output} = 0 - 0 = 0$
- Weight updates (no change as error = 0):
  - $w_1 = 0.3$
  - $w_2 = -0.1$
  - $b = -0.1$
- **After several iterations**, the perceptron will converge to weights that correctly classify all AND gate examples.

# Python Implementation Perceptron from Scratch

```
from sklearn.linear_model import Perceptron
import numpy as np

# Training data for AND gate
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
y = np.array([0, 0, 0, 1])

# Initialize and train Perceptron
model = Perceptron(max_iter=100, eta0=0.1, random_state=42)
model.fit(X, y)

# Results
print("Weights:", model.coef_)
print("Bias:", model.intercept_)
print("Predictions:", model.predict(X))

Weights: [[0.2 0.2]]
Bias: [-0.2]
Predictions: [0 0 0 1]
```

The code shows a scikit-learn Perceptron implementation for the AND gate problem.

The code:

- 1.Imports NumPy, scikit-learn's Perceptron, and matplotlib
- 2.Sets up the training data for the AND gate
- 3.Initializes a Perceptron with 100 max iterations and a random seed of 42
- 4.Trains the perceptron on the AND gate data
- 5.Prints the learned weights, bias, and predictions

The output shows:

- **Weights: [[0.2 0.2]]** - The perceptron learned to assign a weight of 0.2 to both inputs
- **Bias: [-0.2]** - The bias is -0.2
- **Predictions: [0 0 0 1]** - The perceptron correctly classified all four examples of the AND gate

With these weights and bias, the decision function is:  $0.2 \times (\text{input1}) + 0.2 \times (\text{input2}) - 0.2$

For the four input combinations:

- [0,0]:  $0.2 \times 0 + 0.2 \times 0 - 0.2 = -0.2 < 0 \rightarrow \text{output } 0$
- [0,1]:  $0.2 \times 0 + 0.2 \times 1 - 0.2 = 0 \rightarrow \text{output } 0$
- [1,0]:  $0.2 \times 1 + 0.2 \times 0 - 0.2 = 0 \rightarrow \text{output } 0$
- [1,1]:  $0.2 \times 1 + 0.2 \times 1 - 0.2 = 0.2 > 0 \rightarrow \text{output } 1$

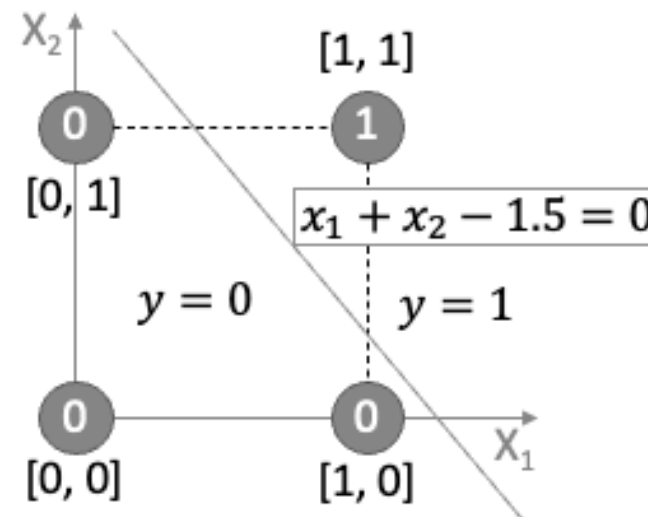
This perceptron implements the AND gate logic.

The decision boundary is the line  $2x_1 + 2x_2 - 0.2 = 0$ , which separates the point (1,1) from the other three points.

# Decision Boundary

- The perceptron learns a decision boundary:  $w_1x_1 + w_2x_2 + b = 0$
- Points above the line are classified as 1
- Points below the line are classified as 0
- For AND gate, only the point (1,1) should be above the line

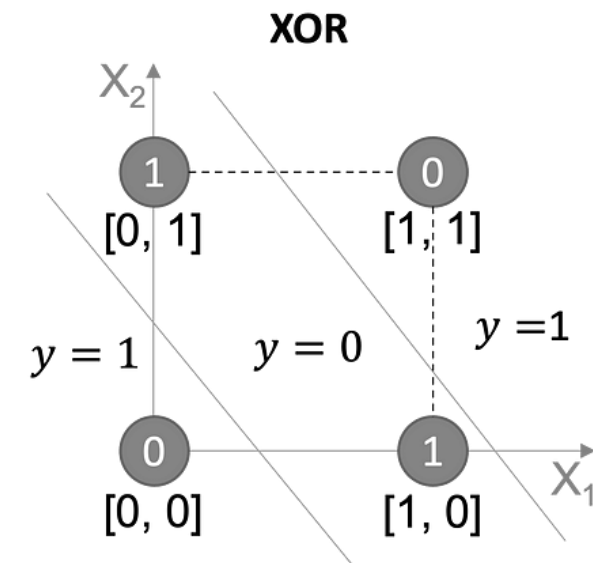
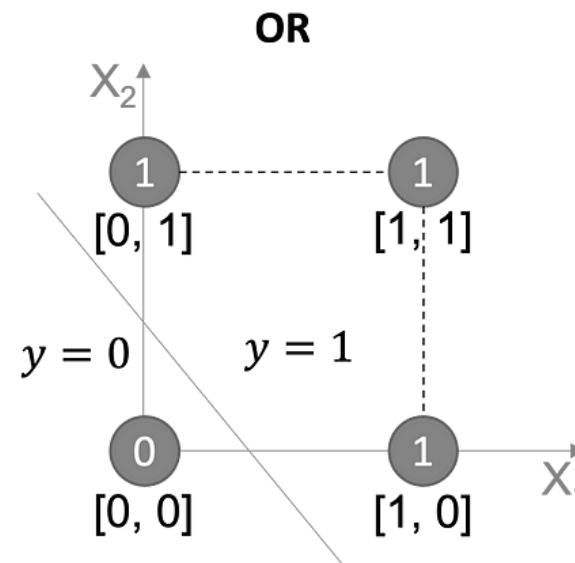
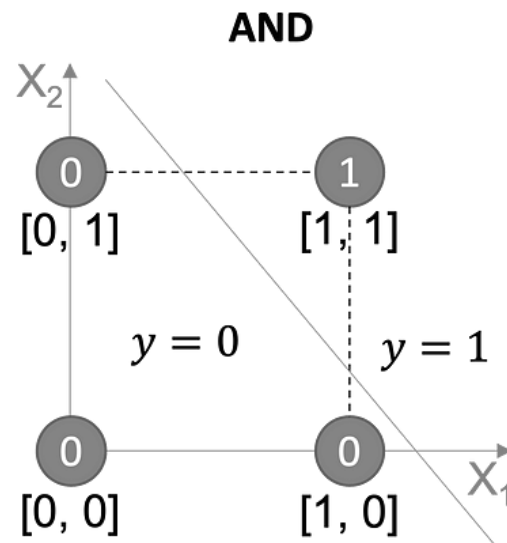
$x_1$	$x_2$	$y$
0	0	0
0	1	0
1	0	0
1	1	1





# Limitations of Simple Perceptron

- Can only learn linearly separable patterns
- Cannot solve XOR problem (need multiple layers)
- No probabilistic output
- Simple update rule isn't suitable for complex problems



# Introduction to Neural Networks

## Multi-Layer Neural Networks

# The Multi-Layer Perceptron (MLP)

## Limitations of the Perceptron

While useful for linearly separable problems, the single perceptron cannot solve complex problems like XOR classification, as demonstrated by Minsky and Papert in their 1969 book "Perceptrons."

## The Multi-Layer Perceptron

The Multi-Layer Perceptron addresses the limitations of the single perceptron by introducing:

- Multiple layers of neurons
- Non-linear activation functions
- More sophisticated learning algorithms



# Structure of an MLP

**Definition:** An MLP is a class of feedforward artificial neural network that consists of at least three layers of nodes: **input**, **hidden**, and **output** layers.

**Key Feature:** Each neuron in one layer is connected to every neuron in the next layer (fully connected).

## 1. Input Layer

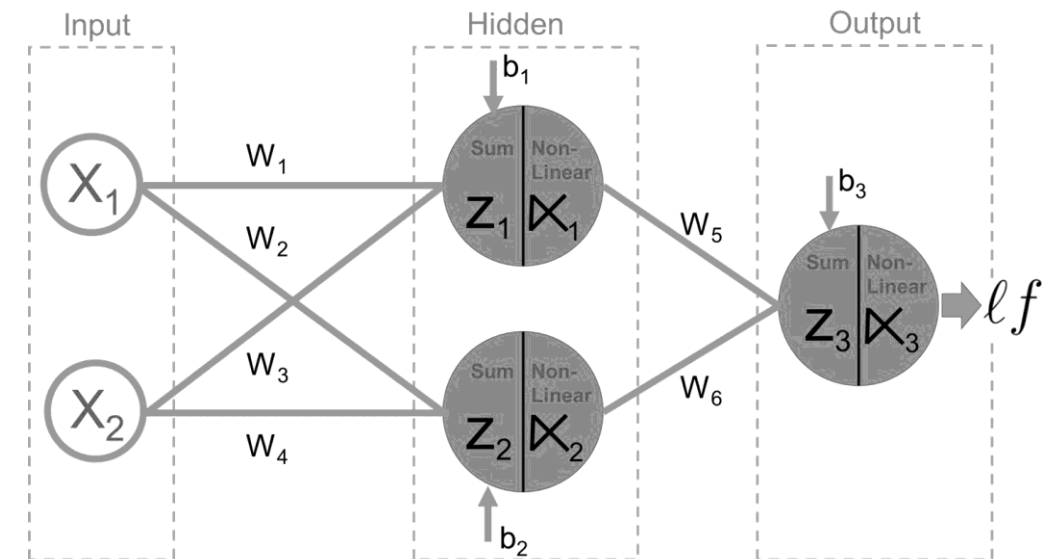
- Receives the raw input features
- One neuron per input feature
- No computation occurs here; inputs are simply passed forward

## 2. Hidden Layer(s)

- One or more layers between input and output
- Each neuron in a hidden layer:
  - Receives inputs from all neurons in the previous layer
  - Computes a weighted sum
  - Applies a non-linear activation function
  - Passes the result to the next layer

## 3. Output Layer

- Produces the final prediction or classification
- Structure depends on the task:
  - Regression: Often a single neuron with linear activation
  - Binary classification: One neuron with sigmoid activation
  - Multi-class classification: Multiple neurons (one per class) with softmax activation



# Structure of an MLP

## 3. Neurons and Connections

- Each neuron computes a weighted sum of inputs and applies an activation function
- Fully connected between layers (dense connections)

## 4. Activation Functions

- Introduce non-linearity
- Examples: ReLU, Sigmoid, Tanh, Softmax

## 5. Loss Function

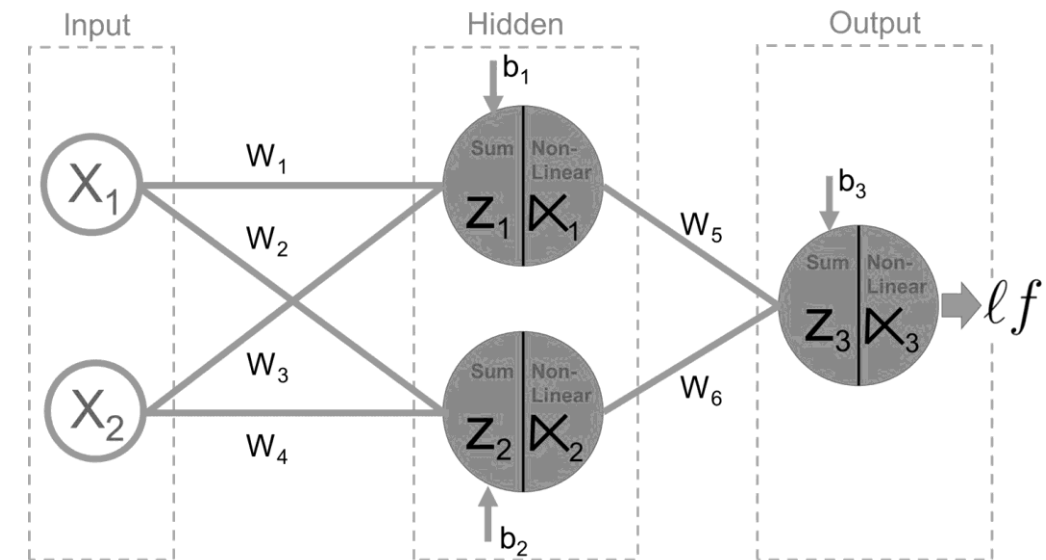
- Measures the error between predicted and true outputs
- Examples: Mean Squared Error, Cross-Entropy

## 6. Optimizer

- Updates weights to minimize loss
- Examples: SGD, Adam

## 7. Training Data

- Labeled data used to train the network
- Split into training, validation, and test sets



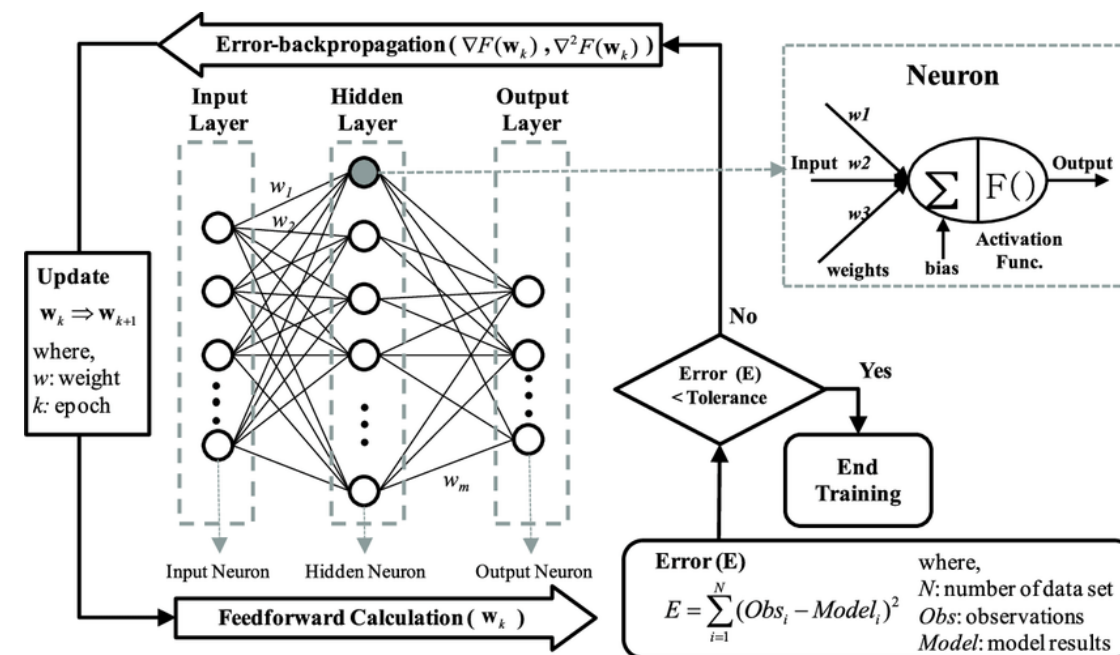
# How an MLP Learn – Step by Step

## Forward Propagation

- Input features pass through the network layer by layer.
- Each neuron computes a weighted sum of inputs and applies an activation function.
- The final layer produces a prediction.

## Loss Computation

- A loss function measures the difference between predicted and actual outputs.
- Common loss functions:
  - Mean Squared Error (regression)
  - Cross-Entropy Loss (classification)



# How an MLP Learn – Training Process

## Backpropagation

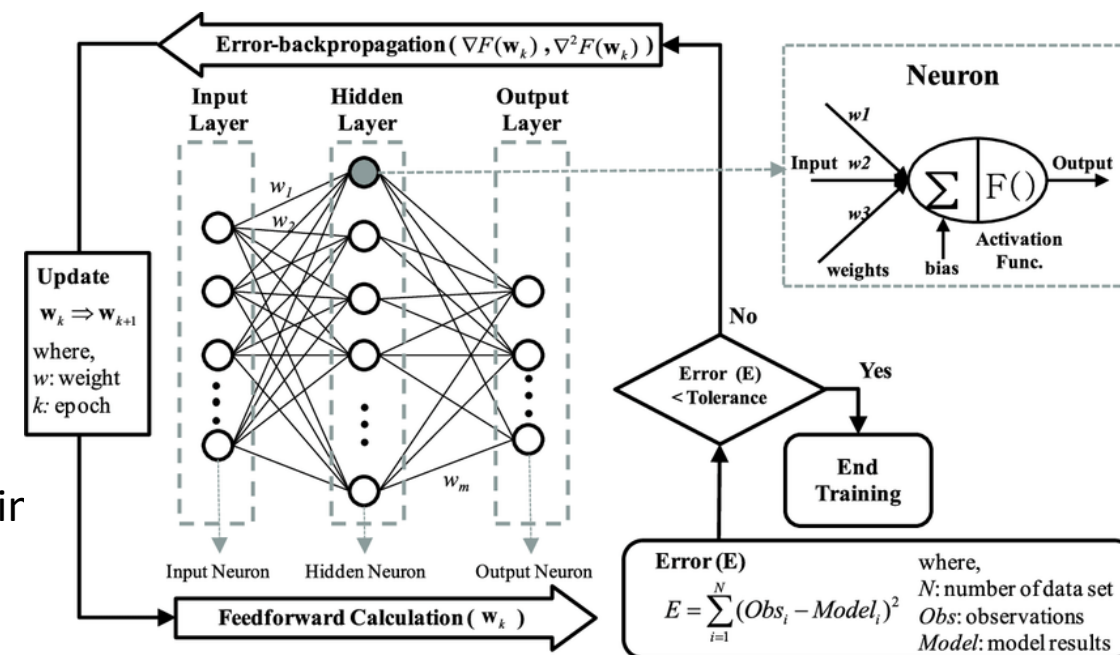
- Gradients of the loss are calculated with respect to each weight using the chain rule.
- This identifies how each weight contributed to the error.

## Weight Update

- An optimizer (e.g., SGD) adjusts weights to reduce loss:
  - $w := w - \text{learning\_rate} \times \text{gradient}$
- This process repeats over multiple iterations (epochs) using training data.

## Goal

- Gradually minimize the loss and improve prediction accuracy.
- Loss Function:** MSE for regression, Cross-Entropy for classification.
- Optimization:** Backpropagation + Gradient Descent (or Adam).



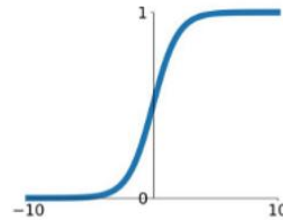


# Activation Functions other than Step Function

- Neural Networks use activation functions other than the simple step function in the Perceptron.
- Activation Function helps the neural network use important information while suppressing irrelevant data points (i.e., allows local “gating” of information).

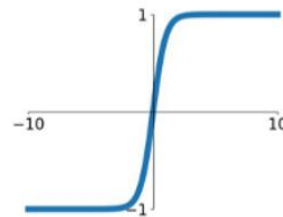
## Sigmoid

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



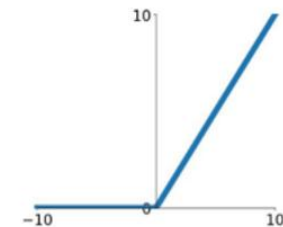
## tanh

$$\tanh(x)$$



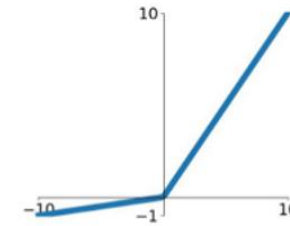
## ReLU

$$\max(0, x)$$



## Leaky ReLU

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

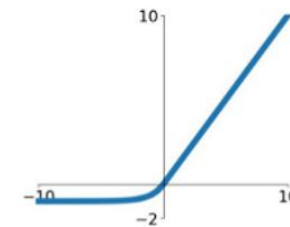


## Maxout

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

## ELU

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



# Representing Weights as Matrices

## Matrix Representations for Weights

### 1. Weight Matrices:

$W^{(1)}$ : Weights from Input to Hidden Layer  
(shape: input\_size  $\times$  hidden\_size):

$$\begin{bmatrix} w_{1,1}^{(1)} & w_{1,2}^{(1)} \\ w_{2,1}^{(1)} & w_{2,2}^{(1)} \end{bmatrix}$$

Hidden Layer Bias ( $b_1$ ):  
 $[b_{11} \ b_{12}]$

$W^{(2)}$ : Weights from Hidden to Output Layer  
(shape: hidden\_size  $\times$  output\_size):

$$\begin{bmatrix} w_{1,1}^{(2)} \\ w_{2,1}^{(2)} \end{bmatrix}$$

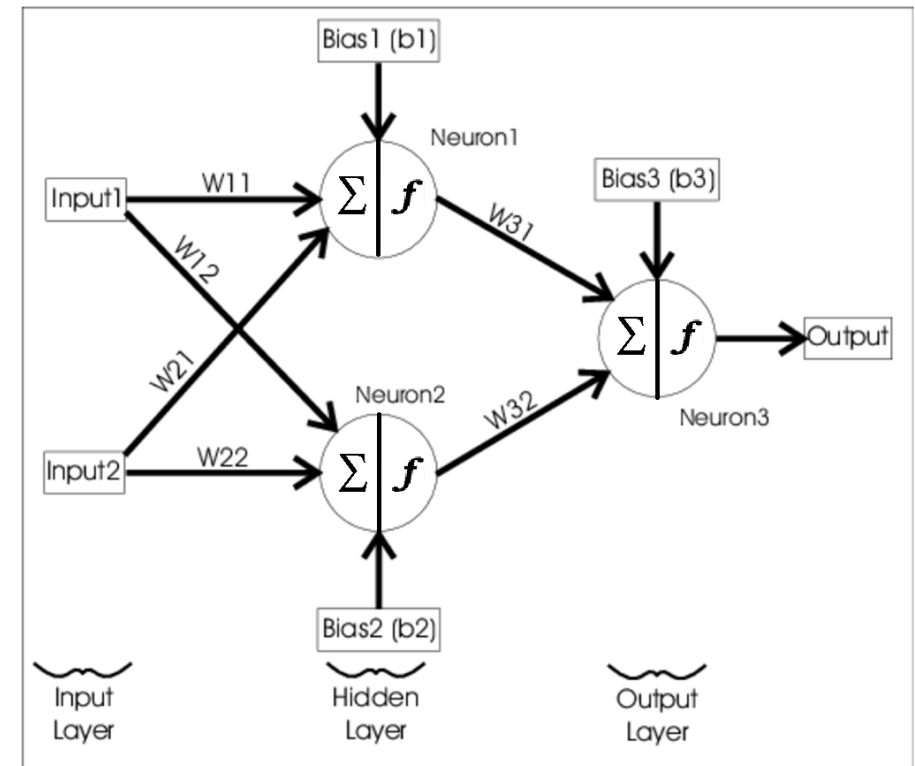
Output Layer Bias ( $b_2$ ):  
 $[b_{21}]$

### 2. Forward Pass Matrix Operations:

- Input to hidden layer:  $Z_1 = X \cdot W_1 + b_1$
- Hidden to output layer:  $Z_2 = A_1 \cdot W_2 + b_2$

### 3. Backpropagation Matrix Operations:

- Weight updates use matrix multiplication between layer activations and error gradients
- $W_2$  update:  $W_2 += A_1^T \cdot \delta_2 \times \text{learning\_rate}$
- $W_1$  update:  $W_1 += X^T \cdot \delta_1 \times \text{learning\_rate}$



The Neural Network Model to solve the XOR Logic (from: <https://stopsmokingaids.me/>)



# Multi-Layer Perceptron in Python

```
from sklearn.neural_network import MLPClassifier
import numpy as np

# XOR input and output
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
y = np.array([0, 1, 1, 0])

# Define MLP with 1 hidden layer of 2 neurons (minimal config for XOR)
mlp = MLPClassifier(hidden_layer_sizes=(2,), activation='tanh', solver='adam', learning_rate_init=0.01,
                    max_iter=10000, random_state=42)

# Train the model
mlp.fit(X, y)

# Make predictions
predictions = mlp.predict(X)

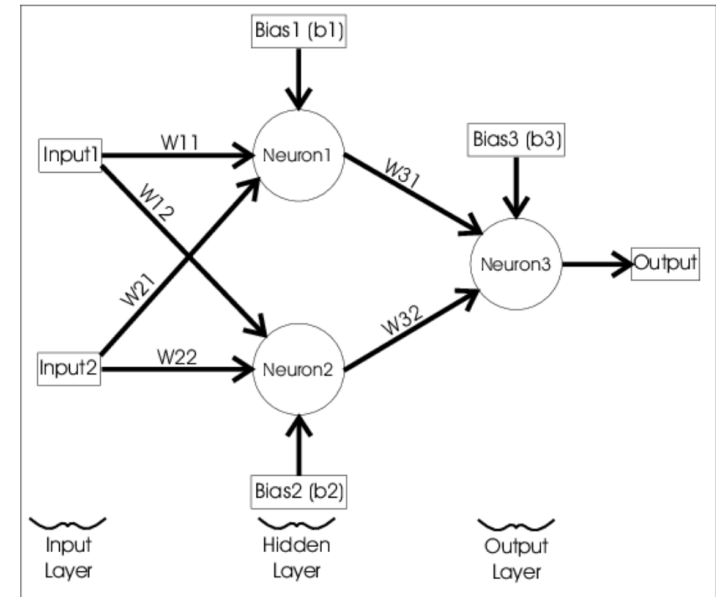
print("Predictions:\n", predictions)

print("\nWeights (input to hidden):\n", mlp.coefs_[0])
print("\nBias hidden:\n", mlp.intercepts_[0])

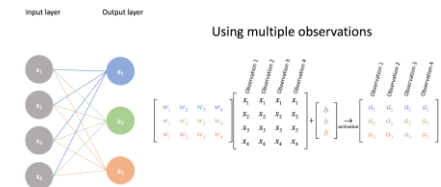
print("\nWeights (hidden to output):\n", mlp.coefs_[1])
print("\nBias output:\n", mlp.intercepts_[1])
```

```
Weights (input to hidden):          Weights (hidden to output):
[[ 2.7144501  3.27401218]          [[-4.37775211]
 [-2.73418453 -3.17014048]]        [ 4.46553876]]
```

```
Bias hidden:                        Bias output:
[ 1.21994174 -1.63451199]          [3.61855675]
```

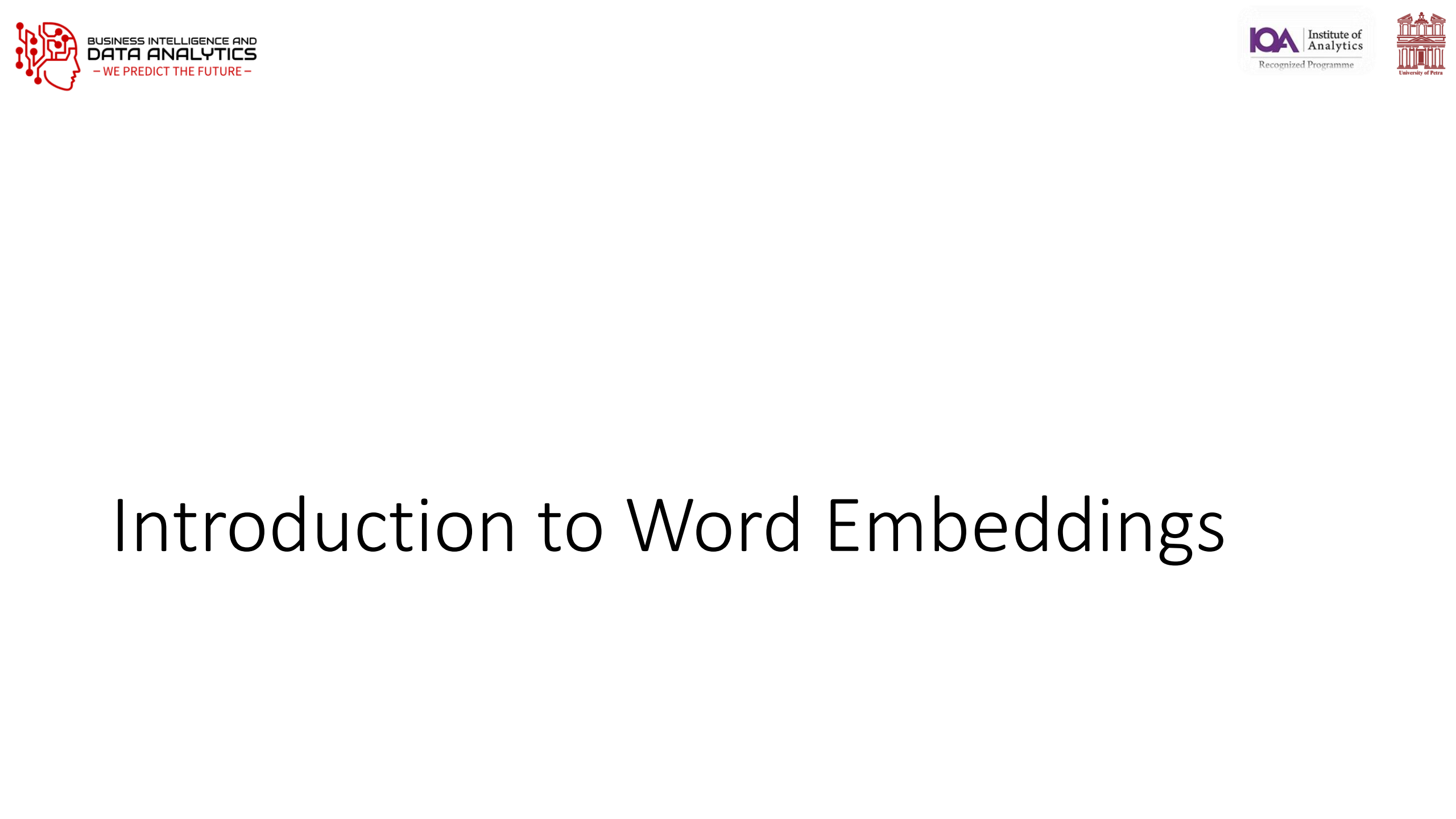


The Neural Network Model to solve the XOR Logic (from: <https://stopsmokingaids.me/>)



# The Difference Between a Perceptron and an MLP?

Feature	Perceptron	Multilayer Perceptron (MLP)
Layers	Only 1 layer (no hidden layers)	2+ layers (has hidden layers)
Activation Function	Step function (hard threshold)	Nonlinear (e.g., ReLU, sigmoid, tanh)
Learning Rule	Simple rule: update on error	Gradient descent + backpropagation
Tasks It Can Solve	Only linearly separable problems	Nonlinear, complex problems



# Introduction to Word Embeddings

## How Did We Represent Words Pre-2013

- Traditional models like Bag-of-Words (BoW) or TF-IDF, treat words as independent, ignoring semantic similarity.
- **One-hot encoding:** Sparse, binary vectors (dimension = vocabulary size)
- Example: "king" and "queen" are as unrelated as "king" and "banana" in BoW.

Word	Dimension 1 (cat)	Dimension 2 (dog)	Dimension 3 (fish)	Dimension 4 (bird)
cat	1	0	0	0
dog	0	1	0	0
fish	0	0	1	0
bird	0	0	0	1



# The Evolution of Word Representations

- **Problem:** How do we represent meaning mathematically?
- **Solution:** Distributional hypothesis - "You shall know a word by the company it keeps" (J.R. Firth, 1957)
- J.R. Firth **did not** provide a detailed technical implementation like an algorithm or computational method. His statement was more of a **linguistic philosophy** or a **theoretical principle**, not a specific engineering method.
- And much later, it inspired the **distributional hypothesis** in computational linguistics, especially by scholars like Zellig Harris and later computational models (Word2Vec, etc.)



...government debt problems turning into **banking** crises as happened in 2009...  
...saying that Europe needs unified **banking** regulation to replace the hodgepodge...  
...India has just given its **banking** system a shot in the arm...

These **context words** will represent **banking**

# Word2Vec (Tomas Mikolov et al., 2013)

- Developed by Tomas Mikolov and team at Google.

## Key Innovation

- Transformed NLP by creating dense vector representations through prediction-based models

## Two Architectures

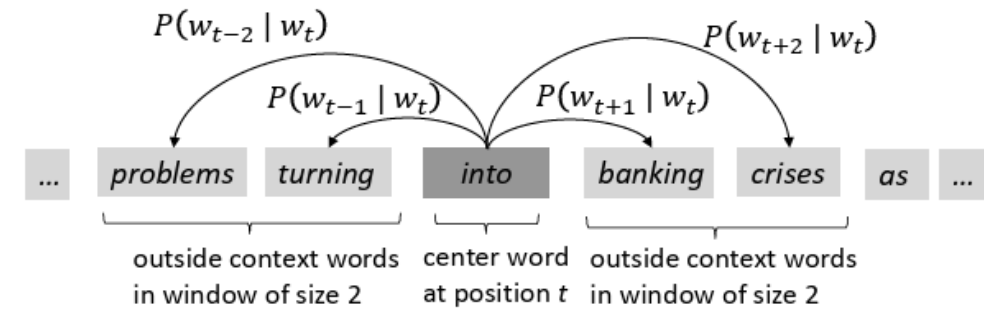
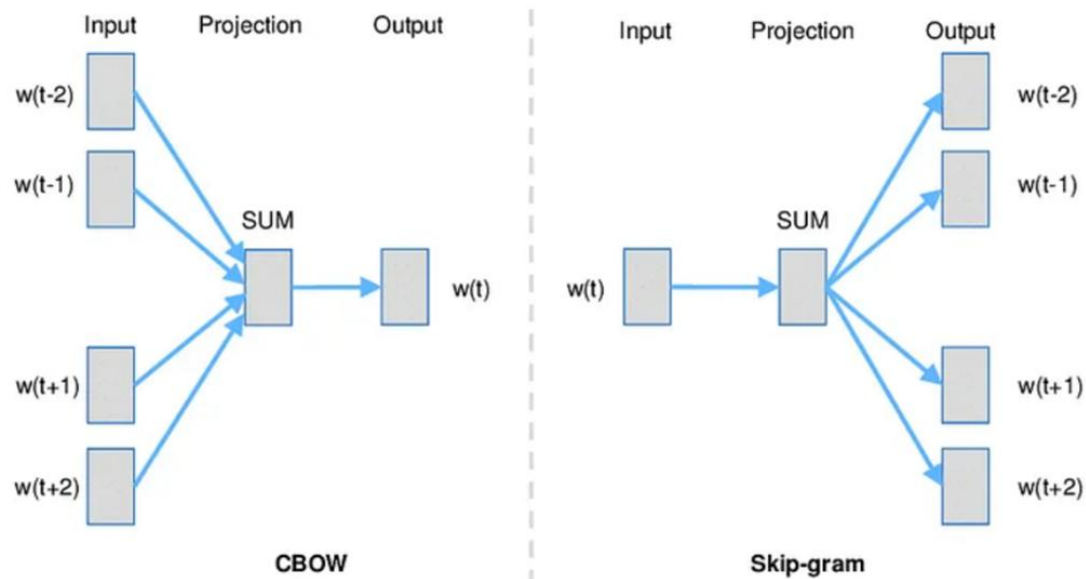
- **Continuous Bag of Words (CBOW):**
  - Predicts target word from context words
  - Faster training, better for frequent words
- **Skip-gram:**
  - Predicts context words from target word
  - Better for rare words, captures more semantic information

## Characteristics

- Uses **shallow neural networks** and trains on local context windows.
- Typically, 100-300 dimensions (vs. vocabulary size)
- Linear relationships: king - man + woman  $\approx$  queen
- Efficient training through negative sampling
- **Limitations: Fixed vectors, one vector per word regardless of context**



# CBow and Skip-Gram Models

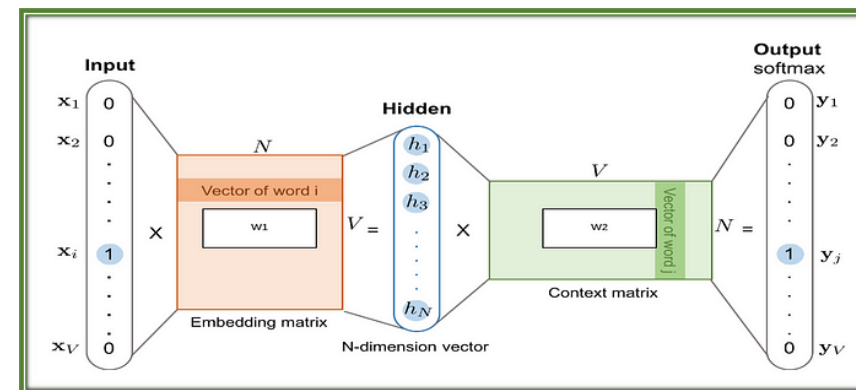


For each position  $t=1, \dots, T$ , predict context words within a window of fixed size  $m$ , given center word  $w_t$ .

# Skip-gram Architecture (Word2Vec)

This diagram illustrates how Word2Vec's **Skip-gram model** works:

- **Input:** A one-hot encoded vector for the center word (word  $i$ ).
- **Embedding Matrix:** Multiplies the input vector to produce a **dense embedding** ( $N$ -dimensional vector) — this becomes the **vector representation of the input word**.
- **Context Matrix:** The dense vector is then multiplied with another matrix to predict surrounding context words via softmax output.
- **Output:** A probability distribution over the vocabulary, aiming to maximize the likelihood of actual context words.
- This training process helps learn **meaningful word vectors** based on how words appear in context.



<https://python.plainenglish.io/understanding-word-embeddings-tf-idf-word2vec-glove-fasttext-996a59c1a8d3>

## The Result of the Training Process - Similar Words -> Similar Vectors

- Visual example of how embedding changes before and after training. `sports` and `exercise` have similar embedding value post training because they are closely related

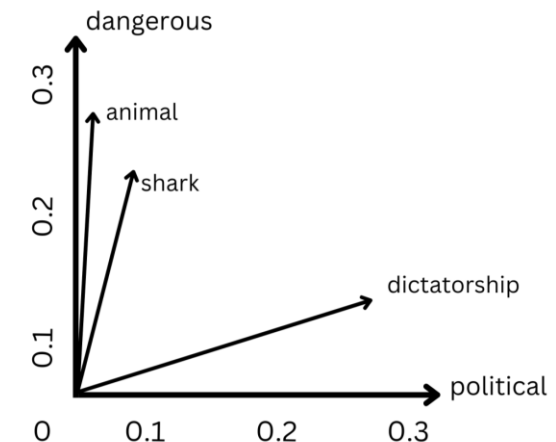


# Vector Spaces and Word Embeddings

## What is a Vector Space?

- A mathematical space where each word is represented as a point (or vector) in multi-dimensional space.
- Words are encoded as dense numerical vectors instead of one-hot or sparse representations (**Word Embeddings**) e.g., "king"  $\rightarrow$  [0.21, 0.72, ..., ..., 0.35]
- Word Embeddings captures **semantic** and **syntactic** relationships about/between words.
- Each dimension potentially captures semantic meaning.
- These vectors are learned from text by models like Word2Vec or GloVe.

Word	Dimension 1 (political)	Dimension 2 (dangerous)
shark	0.05	0.22
animal	0.03	0.25
dangerous	0.07	0.32
political	0.31	0.04
dictatorship	0.28	0.15



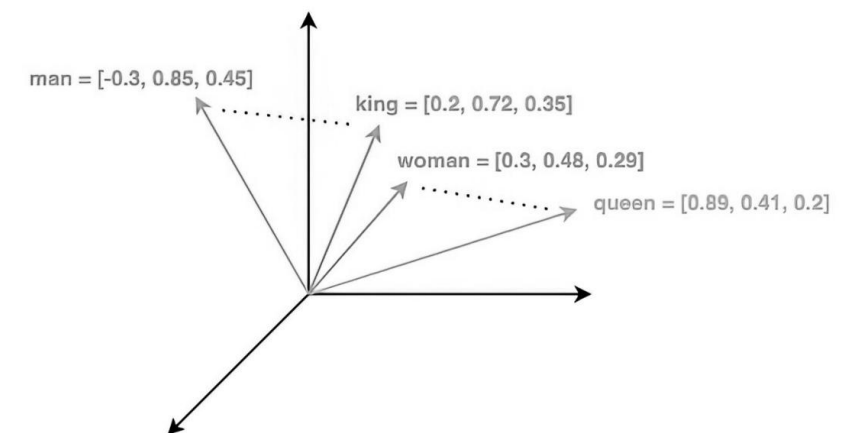
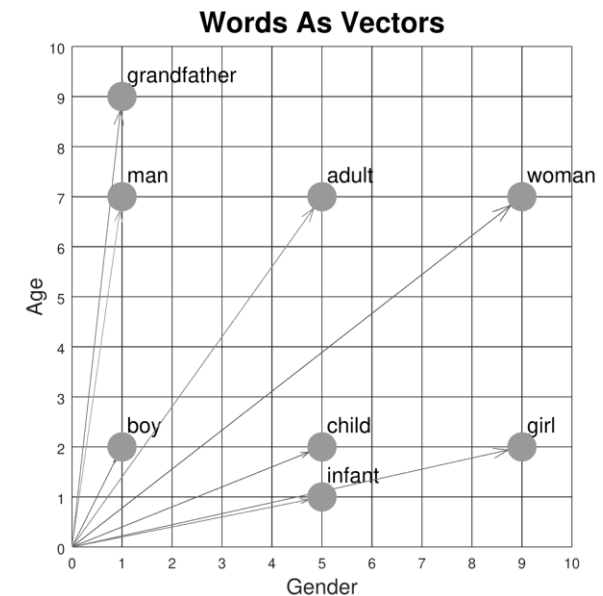
# Vector Spaces and Word Embeddings

## Why Use a Vector Space?

- Makes it possible to compare, visualize, and manipulate meanings of words using math.
- Enables operations like:
  - **Similarity:** "king" is close to "queen"
  - **Analogy:** "king" - "man" + "woman"  $\approx$  "queen"

## Properties of Vector Space

- Semantic relationships are preserved (e.g., "shark" is closer to "dangerous" than "political").
- Similar meanings  $\rightarrow$  closer vectors.
- Dissimilar meanings  $\rightarrow$  vectors farther apart.





# Glove (Pennington, Socher, Manning 2014)

- Developed by Stanford NLP Group (Pennington, Socher, Manning)

- Key Innovation**

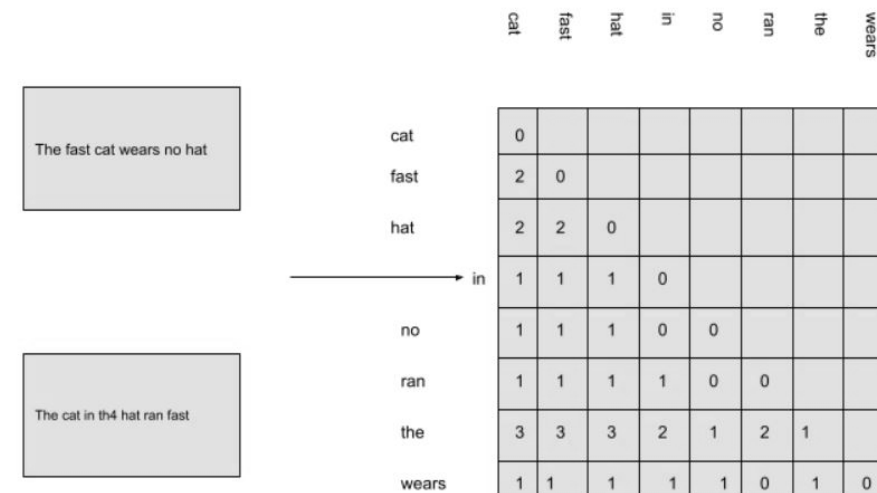
Bridges the gap between count-based methods and prediction-based methods by using global co-occurrence statistics to learn word vectors

- Approach**

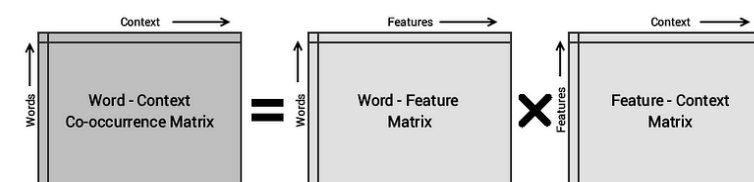
- Builds a word-word co-occurrence matrix over a large corpus
- Learns embeddings by factorizing the matrix using a weighted least squares objective

## Characteristics

- Captures global statistical information while maintaining useful properties of local context
- Produces dense word vectors (typically 100–300 dimensions)
- Linear relationships in vector space are preserved: king - man + woman  $\approx$  queen
- Trained on massive corpora (Wikipedia, Common Crawl)
- Limitations: Ignores context variability—still one vector per word regardless of usage**



	cat	fast	hat	in	no	ran	the	wears
cat	0							
fast	2	0						
hat	2	2	0					
in	1	1	1	0				
no	1	1	1	0	0			
ran	1	1	1	1	0	0		
the	3	3	3	2	1	2	1	
wears	1	1	1	1	1	0	1	0



# Measuring Similarity Between Word Vectors

## Why Compare Word Vectors?

- Word embeddings map words into a vector space.
- **Words with similar meanings** are placed **close together** in that space.
- To quantify this "closeness," we use **vector similarity**.

### Cosine Similarity

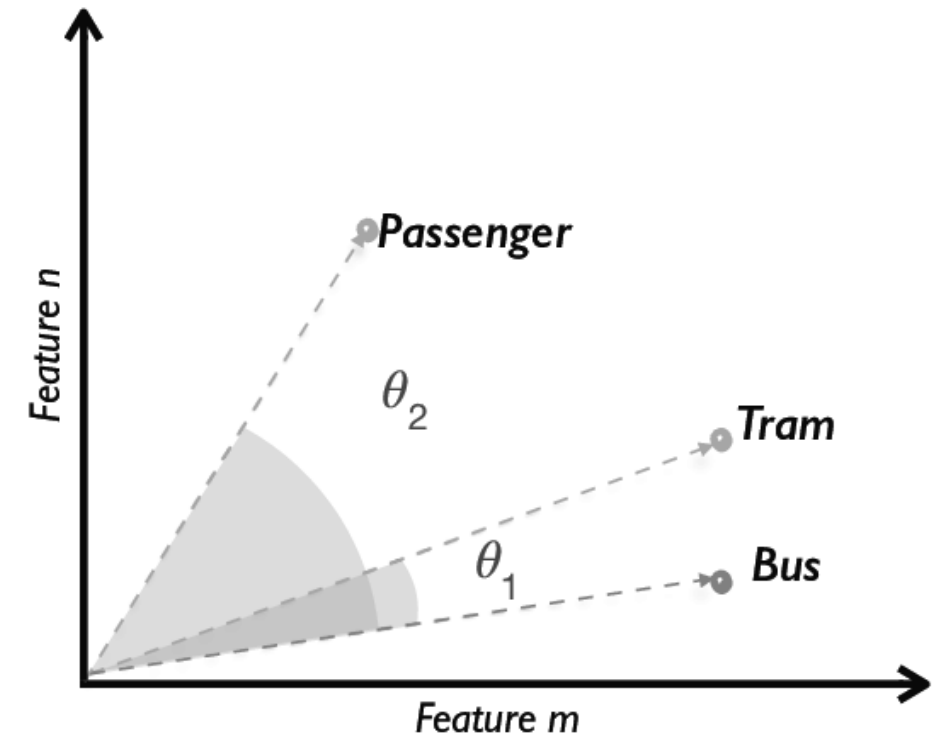
Most common metric used to compare word vectors:

$$\text{cosine\_similarity}(\vec{A}, \vec{B}) = \frac{\vec{A} \cdot \vec{B}}{\|\vec{A}\| \|\vec{B}\|}$$

- Measures the **angle** between two vectors (not their magnitude).
- Ranges from **-1 to 1**:
  - 1 → Same direction (very similar)
  - 0 → Orthogonal (unrelated)
  - -1 → Opposite directions (very different)

### Intuition

- Vectors for "king" and "queen" will have high cosine similarity.
- Vectors for "apple" and "keyboard" will have low similarity.



# Experimenting with Fake Embeddings

```
import numpy as np

from sklearn.metrics.pairwise import cosine_similarity

# Fake word vectors (3D for simplicity)
word_vectors = {
    "king": np.array([0.8, 0.65, 0.1]),
    "queen": np.array([0.78, 0.66, 0.12]),
    "man": np.array([0.9, 0.1, 0.1]),
    "woman": np.array([0.88, 0.12, 0.12]),
    "apple": np.array([0.1, 0.8, 0.9]),
}

def similarity(w1, w2):
    return cosine_similarity([word_vectors[w1]], [word_vectors[w2]])[0][0]

print("Similarity(king, queen):", similarity("king", "queen"))
print("Similarity(man, woman):", similarity("man", "woman"))
print("Similarity(king, apple):", similarity("king", "apple"))
```

# Learn Embeddings From Scratch

```
from gensim.models import Word2Vec

# Sample corpus
sentences = [['data', 'science', 'is', 'fun'],
              ['machine', 'learning', 'is', 'powerful'],
              ['data', 'and', 'learning', 'are', 'related']]

# Train the model
model = Word2Vec(sentences, vector_size=50, window=2, min_count=1, workers=2)

# Access the embedding for a word
print("Vector for 'data':\n", model.wv['data'])

# Find similar words
print("Words similar to 'data':", model.wv.most_similar('data'))
```

Vector for 'data':

```
[-0.01723938  0.00733148  0.01037977  0.01148388  0.01493384 -0.01233535
 0.00221123  0.01209456 -0.0056801  -0.01234705 -0.00082045 -0.0167379
-0.01120002  0.01420908  0.00670508  0.01445134  0.01360049  0.01506148
-0.00757831 -0.00112361  0.00469675 -0.00903806  0.01677746 -0.01971633
 0.01352928  0.00582883 -0.00986566  0.00879638 -0.00347915  0.01342277
 0.0199297  -0.00872489 -0.00119868 -0.01139127  0.00770164  0.00557325
 0.01378215  0.01220219  0.01907699  0.01854683  0.01579614 -0.01397901
-0.01831173 -0.00071151 -0.00619968  0.01578863  0.01187715 -0.00309133
 0.00302193  0.00358008]
```

Words similar to 'data': [('are', 0.16563551127910614), ('fun', 0.13940520584583282), ('learning', 0.1267007291316986), ('powerful', 0.08872982114553452), ('is', 0.011071977205574512), ('and', -0.027849990874528885),

# Use Pre-Trained Embeddings

## Gensim

- Gensim is a powerful open-source Python library designed specifically for unsupervised topic modeling and natural language processing tasks, with a strong focus on working with large corpora.
- It excels in handling word embeddings and semantic similarity, offering efficient implementations of models like Word2Vec, FastText, and Doc2Vec.
- Gensim is known for its memory-efficient, streaming-based approach, which allows it to process text data without loading everything into memory.
- This makes it especially useful for working with real-world, large-scale text data.

```
import gensim.downloader as api
from gensim.models import Word2Vec

# Load pre-trained Word2Vec model
word2vec_model = api.load("word2vec-google-news-300")

# Find similar words
similar_words = word2vec_model.most_similar('computer', topn=5)
print("Words similar to 'computer':", similar_words)

# Word analogies
result = word2vec_model.most_similar(positive=['woman', 'king'],
                                     negative=['man'], topn=1)
print("king - man + woman =", result)

# Train your own Word2Vec model
sentences = [["cat", "say", "meow"], ["dog", "say", "woof"]]
model = Word2Vec(sentences, vector_size=100, window=5, min_count=1,
                 workers=4)

# Get vector for a word
cat_vector = model.wv['cat']
print("Vector for 'cat':", cat_vector[:5]) # Show first 5 dimensions
```

# Word Embeddings Example using Spacy Library

## spaCy

- spaCy is a fast and robust natural language processing library for Python that provides industrial-strength tools for text preprocessing and linguistic analysis.
  - It comes with pre-trained models for multiple languages and supports features like tokenization, part-of-speech tagging, named entity recognition, dependency parsing, and sentence segmentation.
  - spaCy is designed for performance and ease of use in production environments and integrates well with deep learning libraries.
  - While it's not primarily focused on word embeddings, it includes pre-trained word vectors and supports similarity comparisons out of the box.
- `pip install spacy`
  - `python -m spacy download en_core_web_md`

```
import spacy
nlp = spacy.load("en_core_web_md")

word1 = nlp("king")
word2 = nlp("queen")
print("Similarity:", word1.similarity(word2))
```

# Applications of Word Embeddings in NLP

## 1. Semantic Similarity

Measure how similar two words, phrases, or documents are by comparing their vector representations.  
Example: Identifying that "doctor" and "physician" are closely related.

## 2. Text Classification

Used as input features for tasks like spam detection, sentiment analysis, and topic classification.  
Embeddings provide rich, dense input for machine learning models.

## 3. Named Entity Recognition (NER)

Help identify proper nouns and classify them into categories like person, location, or organization.  
Embedding-based models improve contextual understanding of named entities.

## 4. Machine Translation

Map words from one language to another by aligning embeddings in multilingual space.  
Improves translation accuracy by leveraging semantic proximity.

## 5. Question Answering & Chatbots

Used to understand queries and match them with appropriate answers or responses.  
Enable bots to interpret intent and context more accurately.

- **6. Information Retrieval**

Enhance search engines by retrieving results based on semantic meaning, not just keyword matches.  
Example: Searching for "heart attack" returns documents containing "cardiac arrest."