

# Backpropagation

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COMP 4630 | Winter 2025

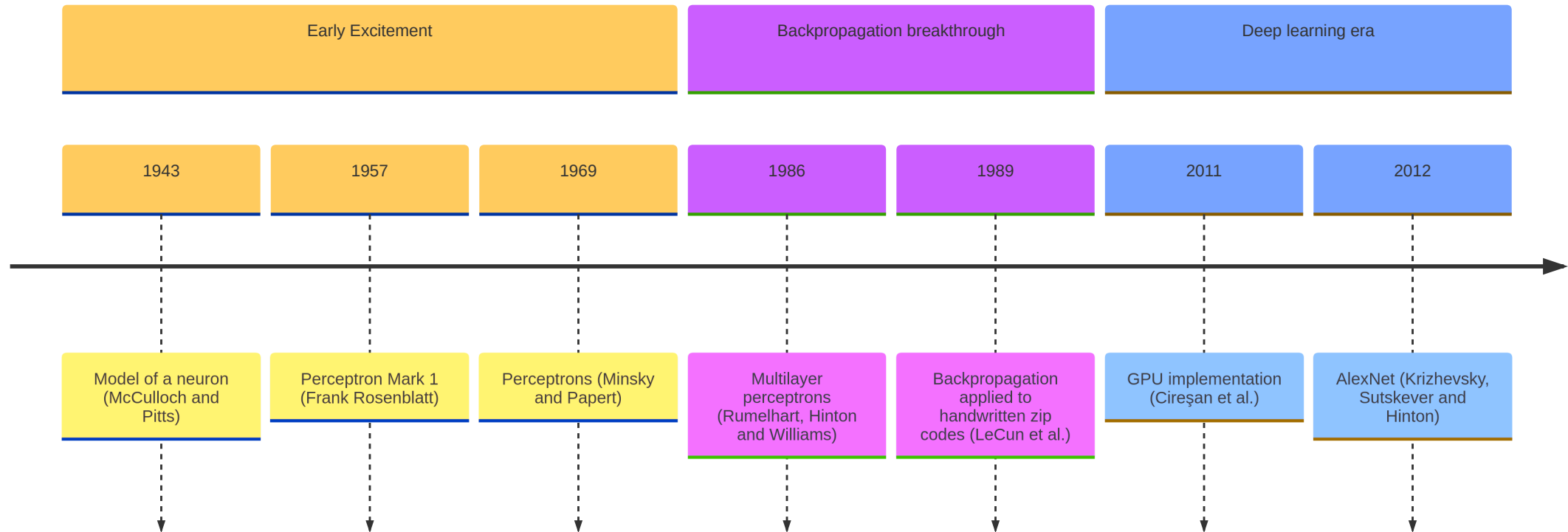
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# Overview

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- A brief review of the history of neural networks
- Neurons, perceptrons, and multilayer perceptrons
- Backpropagation
- References and suggested reading:
  - [Scikit-learn book](#): Chapter 10, introduction to artificial neural networks
  - [Deep Learning Book](#): Chapter 6, deep feedforward networks

# The rise and fall of neural networks



In between each era of excitement and advancement there was an "AI winter"

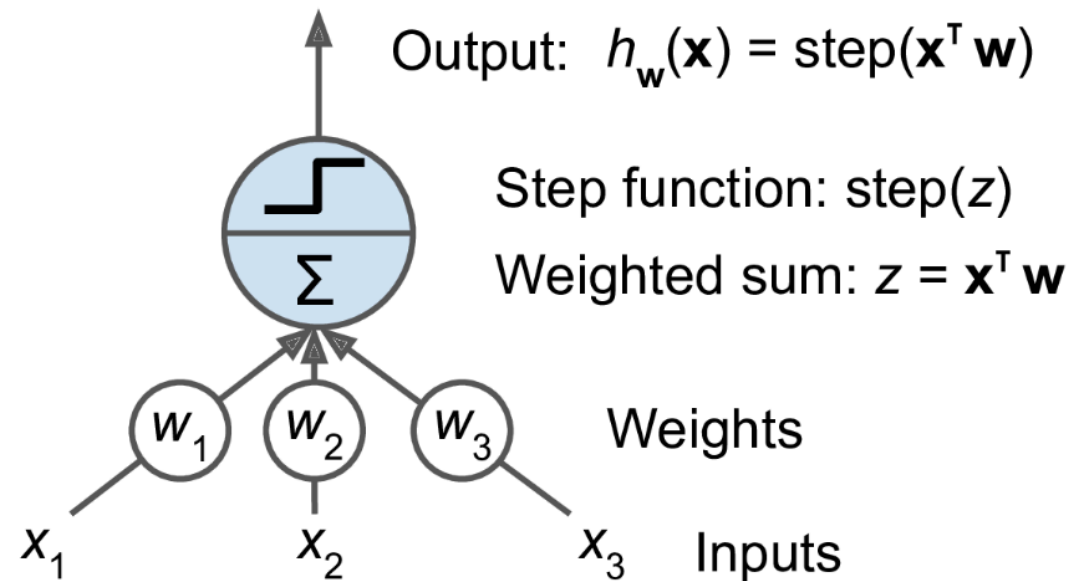
# Model of a neuron



- McCulloch and Pitts (1943)
- Neuron as a logic gate with time delay
- "Activates" when the sum of inputs exceeds a threshold
- Non-invertible (forward propagation only)

# Threshold Linear Units (TLUs)

- Linear I/O instead of binary
- Rosenblatt (1957) combined multiple TLUs in a single layer
- Physical machine: the [Mark I Perceptron](#), designed for image recognition
- Criticized by Minsky and Papert (1969) for its inability to solve the XOR problem - first AI winter



A single threshold logic unit (TLU)

Image source: Scikit-learn book

# Training a perceptron

- Hebb's rule: "neurons that fire together, wire together"

$$w_{ij}^{(updated)} = w_{ij} + \eta(y_j - \hat{y}_j)x_i$$

where  $i$  = input,  $j$  = output

- Fed one instance at a time,
- Guaranteed to converge if inputs are **linearly separable**
-  Simple example: AND gate



A perceptron with two inputs and three outputs

Image source: Scikit-learn book

# Multilayer perceptrons (MLPs)

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- If a perceptron can't even solve XOR, how can it do higher order logic?
- Consider that XOR can be rewritten as:

$$A \text{ xor } B = (A \text{ and } !B) \text{ or } (!A \text{ and } B)$$

- A perceptron can solve `and` and `or` and `not` ... so what if the input to the `or` perceptron is the output of two `and` perceptrons?

# A solution to XOR



Figure 10-6. XOR classification problem and an MLP that solves it



# Backpropagation

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- I just gave you the weights to solve XOR, but how do we actually find them?
- Applying the perceptron learning rule no longer works, need to know how much to adjust each weight relative to the **overall output error**
- Solution presented in 1986 by Rumelhart, Hinton, and Williams
- Key insight: Good old chain rule! Plus some recursive efficiencies

# Training MLPs with backpropagation

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1. Initialize the weights, through some random-ish strategy
2. Perform a **forward pass** to compute the output of each neuron
3. Compute the **loss** of the output layer (e.g. MSE)
4. Calculate the **gradient of the loss** with respect to each weight
5. Update the weights using gradient descent (minibatch, stochastic, etc)
6. Repeat steps 2-5 until stopping criteria met

*Step 4 is the "backpropagation" part*

# Example: forward pass

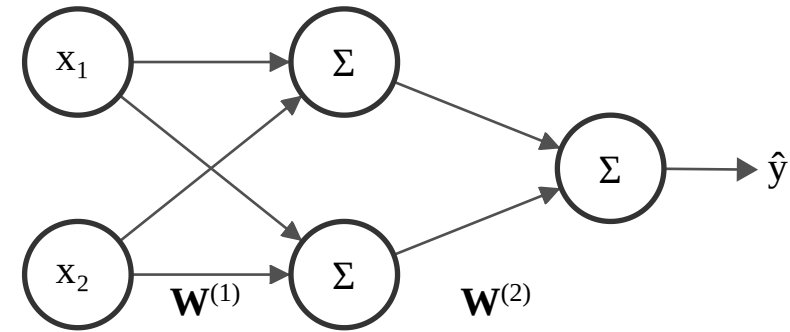
- With a linear activation function:

$$\hat{\mathbf{y}} = \mathbf{X}\mathbf{W}^{(1)}\mathbf{W}^{(2)}$$

- In summation notation for a single sample:

$$\hat{y} = \sum_{j=1}^2 w_j^{(2)} \sum_{i=1}^2 x_i w_{ij}^{(1)}$$

- In this case,  $\hat{y} = 2.162$



$$\mathbf{x} = \begin{bmatrix} 2 & 3 \end{bmatrix}, \quad y = 1$$

and

$$\mathbf{W}^{(1)} = \begin{bmatrix} -0.78 & 0.13 \\ 0.85 & 0.23 \end{bmatrix}, \quad \mathbf{W}^{(2)} = \begin{bmatrix} 1.8 \\ 0.40 \end{bmatrix}$$

# Example: calculate error and gradient

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- We never picked a loss function! Let's assume we're using MSE
- For a single sample:

$$\mathcal{L}(\mathbf{w}^{(1)}, \mathbf{w}^{(2)}) = \frac{1}{2}(\hat{y} - y)^2 = \frac{1}{2} \left( \sum_{j=1}^2 w_j^{(2)} \sum_{i=1}^2 x_i w_{ij}^{(1)} - y \right)^2$$

with the  $1/2$  added for convenience

- The goal is to update each weight by a small amount to minimize the loss
- Fortunately, we know how to find a small change in a function with respect to one of the variables: the partial derivative!

# Recursively applying the chain rule

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- Weights in the second layer (connecting hidden and output):

$$\frac{\partial \mathcal{L}}{\partial w_j^{(2)}} = \frac{\partial \mathcal{L}}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial w_j^{(2)}} = (\hat{y} - y) \frac{\partial \hat{y}}{\partial w_j^{(2)}} = (\hat{y} - y) \sum_i x_i w_{ij}^{(1)}$$

- For the first layer (connecting inputs to hidden):

$$\frac{\partial \mathcal{L}}{\partial w_{ij}^{(1)}} = \frac{\partial \mathcal{L}}{\partial \hat{y}} \frac{\partial \hat{y}}{h_j} \frac{\partial h_j}{\partial w_{ij}^{(1)}} = (\hat{y} - y) w_j^{(2)} x_i$$

where  $h_j = x_i w_{ij}^{(1)}$  is the output of the hidden layer

# Bias terms

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- The toy example did not include bias terms, but these are very important (as seen in the perceptron examples)
- With a single layer we can add a column of 1s to  $\mathbf{X}$ , but with multiple layers we need to add bias at **every layer**
- The forward pass becomes:

$$\hat{\mathbf{y}} = (\mathbf{X}\mathbf{W}^{(1)} + \mathbf{b}^{(1)})\mathbf{W}^{(2)} + \mathbf{b}^{(2)}$$

- Or in summation form:

$$\hat{y} = \sum_{j=1}^2 w_j^{(2)} \left( \sum_{i=1}^2 x_i w_{ij}^{(1)} + b^{(1)} \right) + b^{(2)}$$

# Gradient with respect to the bias terms

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- For layer 2 (the output layer):

$$\frac{\partial \mathcal{L}}{\partial b_j^{(2)}} = \frac{\partial \mathcal{L}}{\partial \hat{y}} \frac{\partial \hat{y}}{\partial b^{(2)}} = (\hat{y} - y)(1)$$

- For layer 1:

$$\frac{\partial \mathcal{L}}{\partial b^{(1)}} = \frac{\partial \mathcal{L}}{\partial \hat{y}} \frac{\partial \hat{y}}{h} \frac{\partial h}{\partial b^{(1)}} = (\hat{y} - y) \sum_i w_{ij}^{(2)}$$

where  $h = \sum_i x_i w_{ij}^{(1)} + b^{(1)}$  is the input to the hidden layer

# Summary in matrix form

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| Parameter          | Gradient  |
|--------------------|---|
| Weights of layer 2 | $\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(2)}} = (\hat{y} - y)(\mathbf{X}\mathbf{W}^{(1)} + \mathbf{b}^{(1)})$ |
| Bias of layer 2    | $\frac{\partial \mathcal{L}}{\partial \mathbf{b}^{(2)}} = (\hat{y} - y)$  |
| Weights of layer 1 | $\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(1)}} = (\hat{y} - y)\mathbf{W}^{(2)}\mathbf{X}$                      |
| Bias of layer 1    | $\frac{\partial \mathcal{L}}{\partial \mathbf{b}^{(1)}} = (\hat{y} - y)\mathbf{W}^{(2)}$                                |



# Computational considerations

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- Many of the terms computed in the **forward pass** are reused in the **backward pass** (such as the inputs to each layer)
- Similarly, gradients computed in layer  $l + 1$  are reused in layer  $l$
- Typically each intermediate value is stored, but modern networks are **big**

| Model          | Parameters  |
|----------------|-------------|
| Our example    | 6           |
| AlexNet (2012) | 60 million  |
| GPT-3 (2020)   | 175 billion |

# Choices in neural network design

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# Activation functions

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- The simple example used a **linear activation function** (identity)
- To include other activation functions, the forward pass becomes:

$$\hat{y} = \mathbf{f}_2(\mathbf{f}_1(\mathbf{X}\mathbf{W}^{(1)} + \mathbf{b}^{(1)})\mathbf{W}^{(2)} + \mathbf{b}^{(2)})$$

- The gradient in the output layer becomes:

$$\frac{\partial \mathcal{L}}{\partial \mathbf{W}^{(2)}} = \frac{\partial \mathcal{L}}{\partial \mathbf{f}_2} \frac{\partial \mathbf{f}_2}{\partial \mathbf{z}^{(2)}} \frac{\partial \mathbf{z}^{(2)}}{\partial \mathbf{W}^{(2)}}$$

where  $\mathbf{z}^{(2)} = \mathbf{f}_1(\mathbf{X}\mathbf{W}^{(1)} + \mathbf{b}^{(1)})\mathbf{W}^{(2)} + \mathbf{b}^{(2)}$ , or the summation the second layer before applying the activation function

- Problem! That step function in the original perceptron is not differentiable

# Activation functions

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- A common early choice was the sigmoid function:

$$\sigma(z) = \frac{1}{1 + e^{-z}}, \quad \frac{d\sigma}{dz} = \sigma(z)(1 - \sigma(z))$$

- A more computationally efficient choice common today is the "ReLU" (Rectified Linear Unit) function:

$$\text{ReLU}(z) = \max(0, z), \quad \frac{d\text{ReLU}}{dz} = \begin{cases} 0 & z < 0 \\ 1 & z > 0 \end{cases}$$

- What about  $z = 0$ ? Most implementations just set it to 0

# Activation functions in hidden layers

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*The design of hidden units is an extremely active area of research and does not yet have many definitive guiding theoretical principles.*

*-- Deep Learning Book, Section 6.3*

- Activation functions in hidden layers serve to **introduce nonlinearity**
- Common for multiple hidden layers to use the same activation function
- Sigmoid, ReLU, and tanh (hyperbolic tangent) are common choices
- Also "leaky" ReLU, Parameterized ReLU, absolute value, etc
- Can be considered a **hyperparameter** of the network

# Loss functions

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- The choice of loss function is very important!
- Depends on the task at hand, e.g.:
  - Regression: MSE, MAE, etc
  - Classification: Usually some kind of cross-entropy (log likelihood)
- May or may not include regularization terms
- Must be differentiable, just like the activation functions

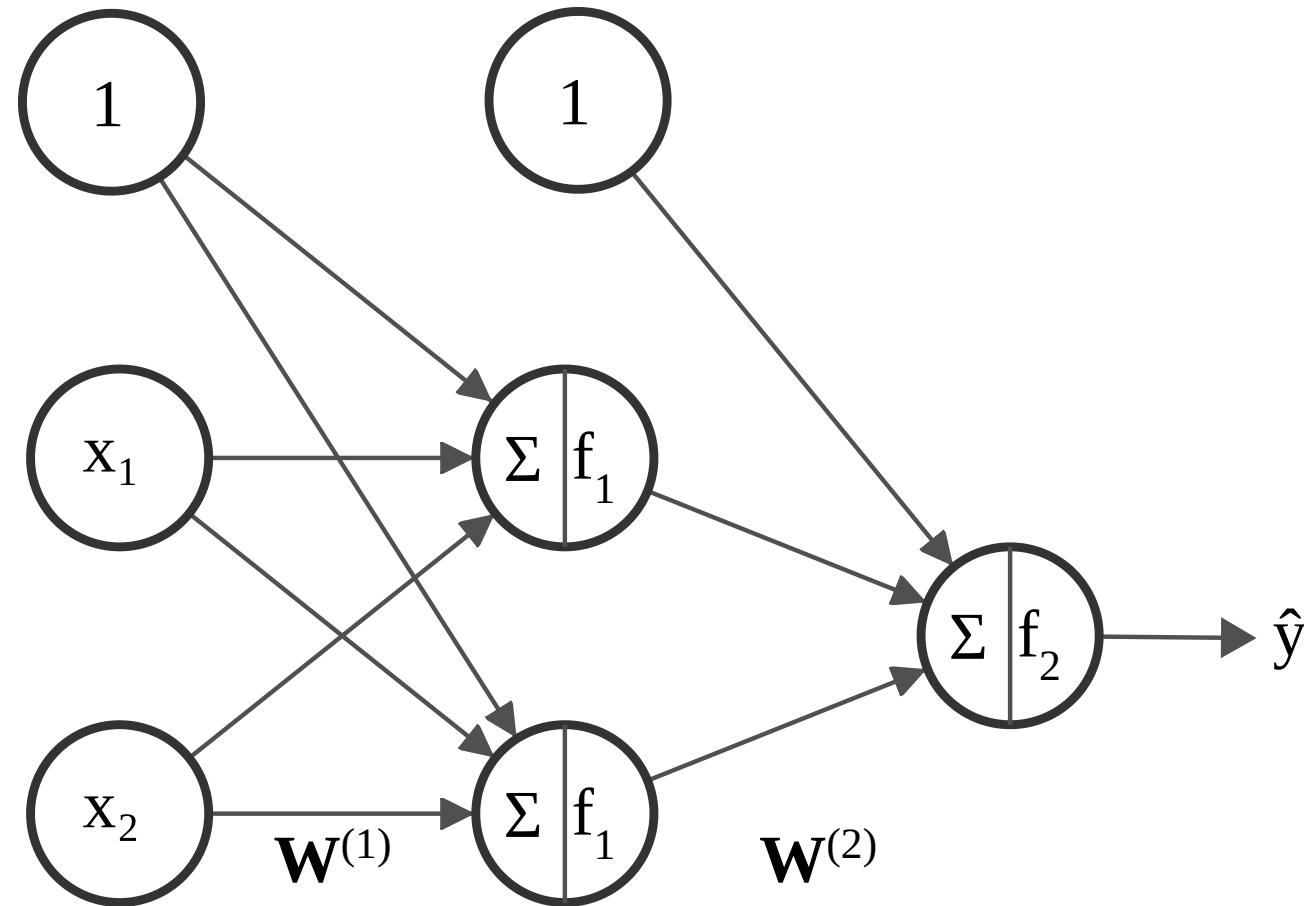
# Activation functions in the output layer

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- Activation functions in the **output** layer should be chosen based on the loss function (and thus the task)
  - Regression: linear
  - Binary classification: sigmoid
  - Multiclass classification: softmax (generalization of sigmoid)
- Again, must be differentiable

# A complete fully connected network

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**Next up: Classification loss functions and metrics**

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