

History and Biological Inspiration

Neural Networks for Finance

Neural Networks for Finance

BSc Lecture Series

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How Does a Committee Make Decisions?

Imagine an investment committee evaluating a stock:

- **Analyst A:** “Strong earnings growth” (+1 vote)
- **Analyst B:** “High debt levels” (-1 vote)
- **Analyst C:** “Good momentum” (+1 vote)
- **Senior Partner:** “Market risk is elevated” (-2 votes)

The Decision Process:

1. Gather evidence from each analyst
2. Weight opinions by seniority/expertise
3. Sum the weighted votes
4. If total > threshold: **Buy**

Weighted Voting

Analyst	Vote	Weight
Analyst A	+1	1.0
Analyst B	-1	1.0
Analyst C	+1	1.0
Senior Partner	-1	2.0
Weighted Sum		-1.0

Decision: Don't Buy

Finance Hook: This is exactly how a perceptron works!

What If Machines Could Decide?

The Central Question

In 1943, scientists asked:

“Can we build a machine that learns to make decisions like a brain?”

Why This Matters for Finance:

- Humans are slow and biased
- Markets process millions of data points
- Pattern recognition at scale
- Consistent, emotionless decisions

The Promise

If we could capture how neurons compute:

- Automatic stock screening
- Risk assessment at scale
- Pattern detection in market data
- Learning from historical decisions

The Challenge

How do we translate biological processes into mathematical operations?

This module tells the story of how scientists attempted this translation.

The fundamental question that started neural network research

The Complete Journey (4 Modules)

1. The Perceptron (Today)

- Single neuron foundations
- 1943-1969 history

2. Multi-Layer Perceptrons

- Stacking layers, activation functions

3. Training Neural Networks

- Backpropagation, optimization

4. Applications in Finance

- Stock prediction case study

Today's Module Structure

1. Historical Context (1943-1969)

- McCulloch-Pitts, Hebb, Rosenblatt

2. Biological Inspiration

- From neurons to mathematics

3. The Perceptron

- Intuition, then math

4. Learning Algorithm

- How it adjusts weights

5. Limitations

- XOR problem, AI Winter

Your journey through neural network fundamentals

By the end of this module, you will be able to:

1. Understand biological inspiration

- How real neurons inspired artificial ones
- What we kept and what we simplified

2. Master the perceptron model

- Inputs, weights, sum, activation
- The decision-making unit

3. Interpret decision boundaries

- Geometric meaning of weights
- Linear separability concept

4. Apply the learning algorithm

- Weight update rule
- Convergence conditions

5. Recognize limitations

- XOR problem
- Why single layers are not enough

Finance Connection: Throughout, we'll use stock classification as our running example.

By the end of this module, you will be able to...

1943: The Mathematical Neuron

Warren McCulloch & Walter Pitts

In 1943, a neurophysiologist and a logician asked:

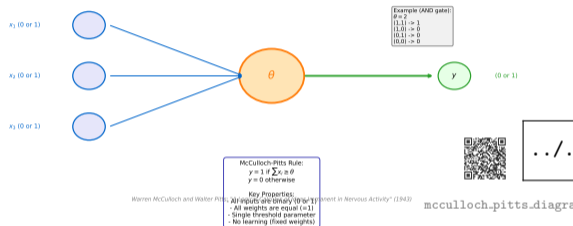
"Can we describe what neurons do using mathematics?"

Their paper: "A Logical Calculus of Ideas Immanent in Nervous Activity"

Key Insight:

- Neurons have binary states (fire or not)
- This is like TRUE/FALSE in logic
- Networks of neurons can compute any logical function

McCulloch-Pitts Neuron (1943): Binary Threshold Logic



Warren McCulloch and Walter Pitts: "A Logical Calculus of Ideas Immanent in Nervous Activity"

What McCulloch & Pitts Proposed

The brain performs computation through:

1. Binary Signals

- Neurons either fire (1) or don't (0)
- Like bits in a computer

2. Threshold Logic

- Sum of inputs exceeds threshold \rightarrow fire
- Otherwise \rightarrow stay quiet

3. Network Composition

- Complex behaviors from simple units
- AND, OR, NOT gates from neurons

Logical Operations with Neurons

AND Gate (threshold = 2):

- Both inputs = 1 \rightarrow output = 1
- Otherwise \rightarrow output = 0

OR Gate (threshold = 1):

- Any input = 1 \rightarrow output = 1
- All inputs = 0 \rightarrow output = 0

Implication: If neurons compute logic, and computers compute logic, then we can build artificial brains!

If neurons compute, can we build artificial ones?

Donald Hebb's Insight

McCulloch-Pitts neurons were fixed. But how does the brain *learn*?

Hebb's Rule (1949):

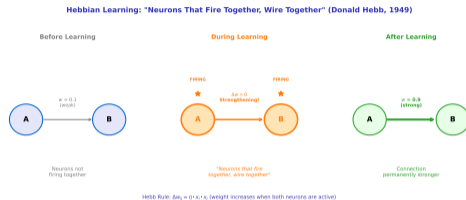
"Neurons that fire together, wire together."

In Plain Terms:

- If neuron A consistently activates neuron B
- The connection $A \rightarrow B$ grows stronger
- Repeated patterns reinforce pathways

Finance Analogy:

An analyst who repeatedly identifies winning stocks gains more influence in the committee.



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hebb_learning_visualization

Donald Hebb: "Neurons that fire together, wire together"

1958: The Perceptron is Born

Frank Rosenblatt at Cornell

Combined McCulloch-Pitts neurons with Hebbian learning into a machine that could *learn from examples*.

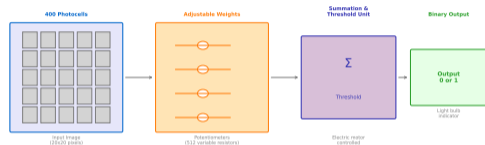
The Perceptron:

- A single artificial neuron
- Adjustable connection weights
- Learns to classify patterns
- Implemented in hardware (Mark I)

Key Innovation:

Not just fixed logic gates, but a system that **learns** the right weights from training data.

Mark I Perceptron (1958): First Neural Network Hardware



Specifications (1958):
- Weights: 2 bits
- Scale: Motor-adjusted
- 512 motor-driven potentiometers (weights)
- Could recognize simple shapes
- Training: Electric motor adjusted weights

Frank Rosenblatt, Cornell University, funded by U.S. Navy



The Mark I Perceptron used 400 photocells connected to a single layer of neurons with adjustable weights.

Frank Rosenblatt creates a machine that can learn

July 8, 1958 - The New York Times

"New Navy Device Learns By Doing; Psychologist Shows Embryo of Computer Designed to Read and Grow Wiser"

The Promises Made:

- Machines that recognize faces
- Automatic translation of languages
- Systems that "perceive" like humans
- The Navy predicted: walking, talking, self-reproducing machines

The Reality:

The perceptron could classify simple patterns, but the gap between promise and capability was vast.

Lessons for Today

Sound Familiar?

- "AI will replace all jobs"
- "Machines will be smarter than humans by 20XX"
- "This changes everything"

Pattern:

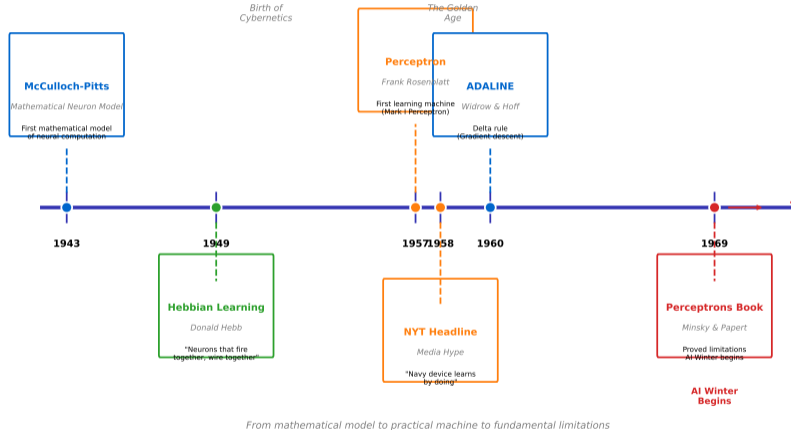
1. Genuine breakthrough
2. Media amplification
3. Overpromising
4. Disappointment
5. "AI Winter"

History repeats...

"New Navy Device Learns By Doing" - The hype cycle begins

Timeline: The Early Years

Neural Networks: The Early Years (1943-1969)



timeline_1943_1969

From theory to hardware in 15 years

“The perceptron was funded by the US Navy for military applications. How does funding source shape research direction? Are there parallels in modern AI development?”

Consider:

- Military vs. commercial vs. academic funding
- What problems get prioritized?
- Open vs. closed research
- Today: Tech giants fund most AI research
- Government initiatives (CHIPS Act, etc.)
- Startup ecosystem influence

Think-Pair-Share: 3 minutes

Anatomy of a Real Neuron

1. **Dendrites (Input)**
 - Tree-like branches
 - Receive signals from other neurons
 - Thousands of connections
2. **Cell Body (Soma) (Processing)**
 - Integrates incoming signals
 - Contains the nucleus
 - Determines if neuron fires
3. **Axon (Output)**
 - Long fiber carrying output signal
 - Connects to other neurons
 - All-or-nothing signal

How It Works

1. Signals arrive at dendrites
2. Soma sums the inputs
3. If sum exceeds threshold: neuron **fires**
4. Action potential travels down axon
5. Signal reaches next neurons

Key Numbers:

- Human brain: ~86 billion neurons
- Each neuron: ~7,000 connections
- Total synapses: ~100 trillion

Dendrites receive, soma processes, axon transmits

Mathematical Abstraction

1. **Inputs** (x_1, x_2, \dots, x_n)
 - Numerical values (features)
 - Replace dendrites
2. **Weights** (w_1, w_2, \dots, w_n)
 - Importance of each input
 - Replace synapse strength
3. **Weighted Sum**
 - $z = \sum_{i=1}^n w_i x_i + b$
 - Replace soma integration
4. **Activation Function**
 - $y = f(z)$
 - Replace firing decision

The Complete Model

$$y = f \left(\sum_{i=1}^n w_i x_i + b \right)$$

Components:

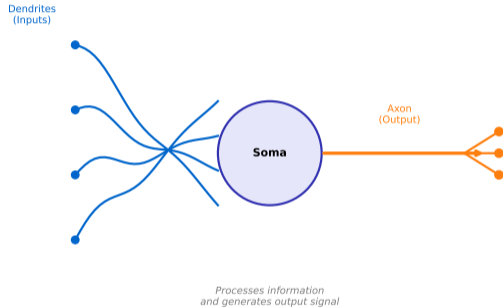
- x_i : Input features
- w_i : Learnable weights
- b : Bias (threshold adjustment)
- f : Activation function
- y : Output (prediction)

Key Point: The weights are what the network *learns*.

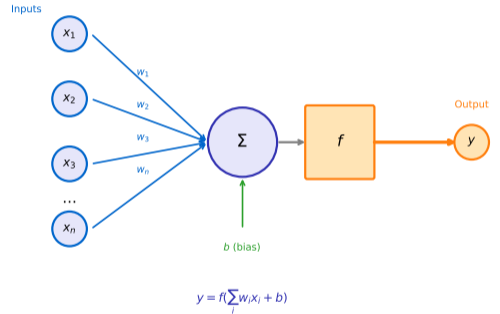
From biology to mathematics: the abstraction trade-off

Biological vs. Artificial: Side by Side

Biological Neuron



Artificial Neuron



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biological_vs_artificial_neuro

What did we keep? What did we simplify?

A Financial Analyst as a Neuron

Biology	Finance
Dendrites	Market data feeds
Synapses	Data reliability weights
Soma	Analyst's judgment
Threshold	Conviction level
Axon	"Buy" recommendation

The Process:

1. Receive multiple data points
2. Weight by source quality
3. Aggregate into overall view
4. If conviction $>$ threshold: recommend

Example: Stock Screening

Inputs (Data):

- x_1 : P/E ratio = 15
- x_2 : Revenue growth = 20%
- x_3 : Debt/Equity = 0.5

Weights (Importance):

- $w_1 = 0.3$ (value focus)
- $w_2 = 0.5$ (growth priority)
- $w_3 = -0.2$ (debt penalty)

Decision:

$$z = 0.3(15) + 0.5(20) - 0.2(0.5) = 14.4$$

If $z > 10$: **Buy**

Inputs (data) - \rightarrow Weights (importance) - \rightarrow Decision (output)

Benefits of Simplification

1. Mathematical Tractability

- We can write equations
- Analyze behavior formally
- Prove theorems

2. Computability

- Easy to implement in code
- Fast computation
- Scales to millions of units

3. Trainability

- Can adjust weights systematically
- Gradient-based optimization
- Learn from data

What We Can Now Do

- Define learning algorithms
- Compute exact outputs
- Train on historical data
- Make predictions on new data
- Analyze decision boundaries

Scale Comparison:

	Brain	GPU
Operations/sec	10^{16}	10^{15}
Power	20W	300W
Training time	Years	Hours

Different trade-offs, different capabilities.

Simplification enables computation

Biological Complexity We Ignored

1. Temporal Dynamics

- Real neurons have timing
- Spike patterns carry information
- We use static activations

2. Structural Complexity

- Dendrites have local computation
- Different neuron types
- We use uniform units

3. Neurochemistry

- Neurotransmitters vary
- Modulatory systems
- We use simple multiplication

Implications

What ANNs Cannot Do (Well):

- Energy efficiency of brain
- One-shot learning
- Continuous adaptation
- Common sense reasoning

The Trade-off:



Artificial neurons are inspired by biology, not copies of it.

The brain does far more than our models capture