Introduction to Neural Networks

From Brain to Business: How Machines Learn to Predict

Neural Networks for Business Applications

November 24, 2025

Learning Objectives

- **Explain** how biological neurons inspire artificial neural networks
- **Calculate** the output of an artificial neuron given inputs and weights
- **Design** a simple multilayer network architecture
- **Trace** information flow through forward propagation
- **Describe** how networks learn by minimizing prediction errors
- **Evaluate** when neural networks are appropriate for business

The Prediction Challenge: Can We Predict Markets?

The Business Question

Can we predict if a stock price will rise or fall tomorrow?

- Traditional: Statistical analysis, expert intuition
- Challenge: Markets are complex, non-linear
- Many factors: price, volume, sentiment, volatility

The Limitation

Rule-based systems cannot capture all interactions

Why This Matters

- Better investment decisions
- Risk management
- Portfolio optimization
- Automated trading strategies

What We Need

A system that learns patterns from data, not explicit rules

Our journey begins with understanding how nature solved similar prediction problems

Why Simple Rules Fail: Market Data Complexity

Observe: Can you draw a single line that separates green (up) from red (down) in any panel?

What We Need: A Learning System

System Requirements

1. Process multiple inputs simultaneously
2. Learn patterns from historical data
3. Handle **non-linear** relationships
4. Improve predictions over time
5. Generalize to new conditions

Key Insight

We need a system that learns, not one we program

Inspiration from Nature

The human brain solves complex pattern recognition every day

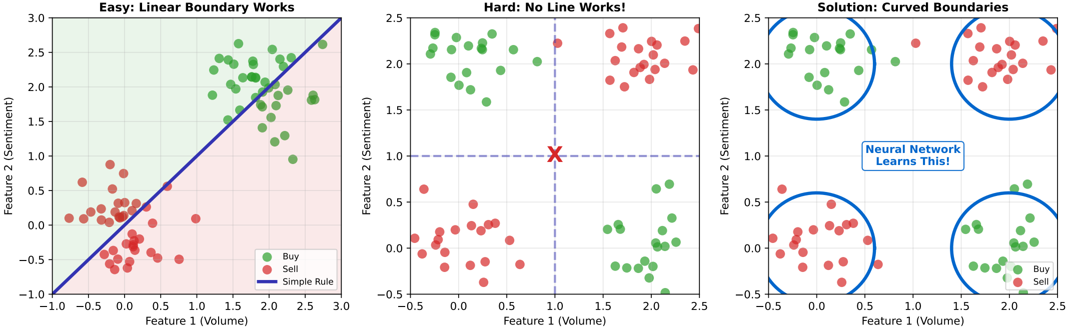
Brain Capabilities

- Processes millions of inputs
- Learns from experience
- Handles ambiguity
- Generalizes to new situations

Can we mimic this for business predictions?

Next: Understanding biological neurons as the foundation

The Goal: Learn Complex Decision Boundaries



Observe: The rightmost panel shows what neural networks can learn - curved boundaries that adapt to data

Part 1: Foundations

From biological neurons to artificial intelligence

Let's begin with the inspiration from nature

[1] – [2] – [3] – [4] – [5]

Nature's Computer: How Your Brain Makes Predictions

Biological Neuron Structure

- **Dendrites:** Receive signals
- **Soma:** Integrates weighted signals
- **Axon:** Transmits output
- **Synapses:** Variable connection strengths

Key Principle

Fire when weighted sum exceeds threshold

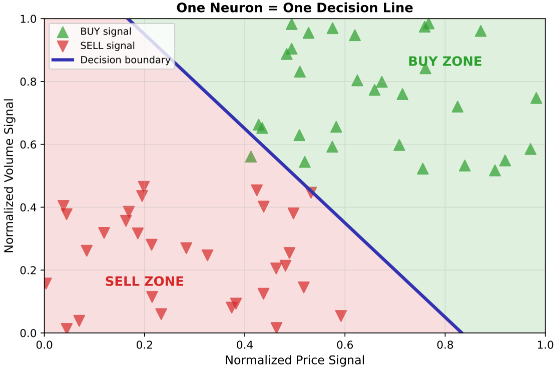
Business AI Insights

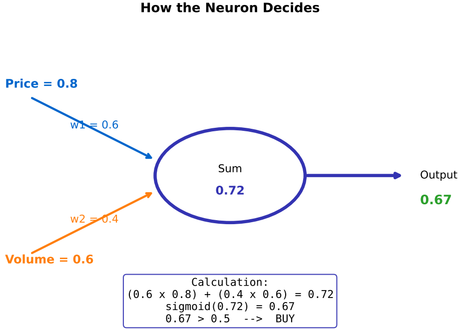
1. Multiple inputs combined
2. Weighted connections (importance)
3. Non-linear activation (thresholds)
4. Layered processing (abstraction)

Mathematical models can learn the same way!

Next: See the visual comparison of biological vs artificial neurons

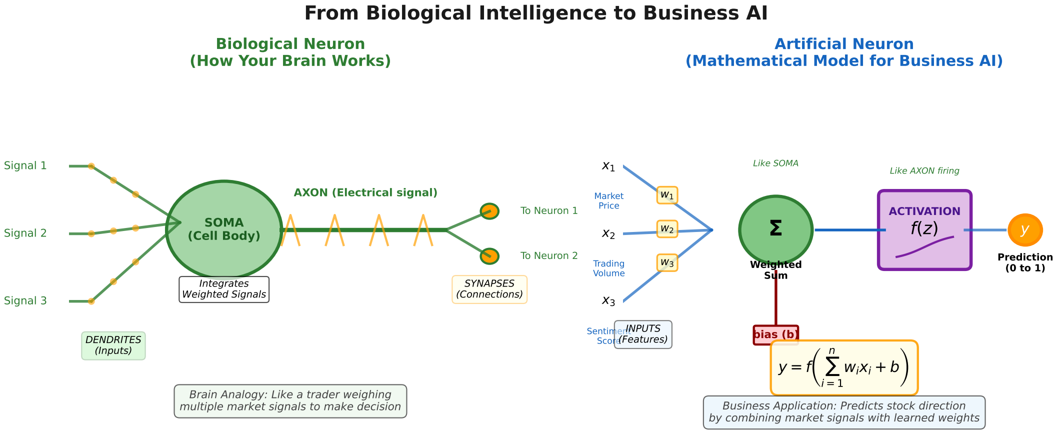
From Concept to Computation: Neuron as Decision Maker





Observe: The decision boundary (purple line) divides the space into BUY and SELL zones based on weighted inputs

From Biology to Artificial Intelligence



Observe: Which biological components map directly to mathematical operations?

The Artificial Neuron: Mathematical Model

Step 1: Weighted Sum

$$z = \sum_{i=1}^{n} w_i x_i + b$$

- x_i: Inputs (market data)
- w_i: Weights (learned)
- b: Bias (baseline)

Step 2: Activation

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

- Adds non-linearity
- Output: probability (0 to 1)
- Mimics neuron firing

Complete: $y = \sigma\left(\sum w_i x_i + b\right)$

Next: See a concrete example with real market numbers

Practice: Calculate a Neuron's Output

Given Values

- Inputs: $x_1 = 1.2$, $x_2 = 0.8$
- Weights: $w_1 = 0.3$, $w_2 = 0.5$
- Bias: $b = -0.2$

Step 1: Weighted Sum

$z = w_1 x_1 + w_2 x_2 + b$
$z = (0.3)(1.2) + (0.5)(0.8) + (-0.2)$
$z = 0.36 + 0.40 - 0.20 = \mathbf{0.56}$

Step 2: Apply Sigmoid

$$\sigma(z) = \frac{1}{1 + e^{-z}} = \frac{1}{1 + e^{-0.56}}$$

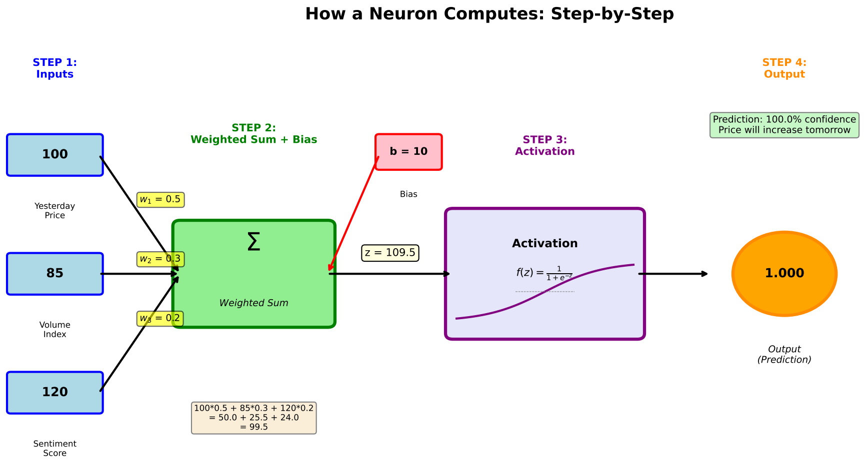
$\sigma(0.56) = \frac{1}{1+0.571} = \frac{1}{1.571} = \mathbf{0.636}$

Interpretation

63.6% confidence: price will rise

Your Turn: What if $w_1 = 0.6$?

Work through this calculation – it's the foundation of all neural network predictions



Observe: How would changing the weights affect the final output probability?

Think – Pair – Share

What other business processes might benefit from 'learning from data' instead of following explicit rules?

1. Think (1 min)
Reflect individually on the question

2. Pair (2 min)
Discuss with a neighbor

3. Share (2 min)
Share insights with class

Part 2: Building Blocks

Activation functions and their role in learning

Now that we understand neurons, let's explore what makes them powerful

[1] – **[2]** – [3] – [4] – [5]

Activation Functions: Why Non-Linearity Matters

The Problem

Without activation functions:

- Networks = linear regression
- Cannot learn complex patterns

Three Common Functions

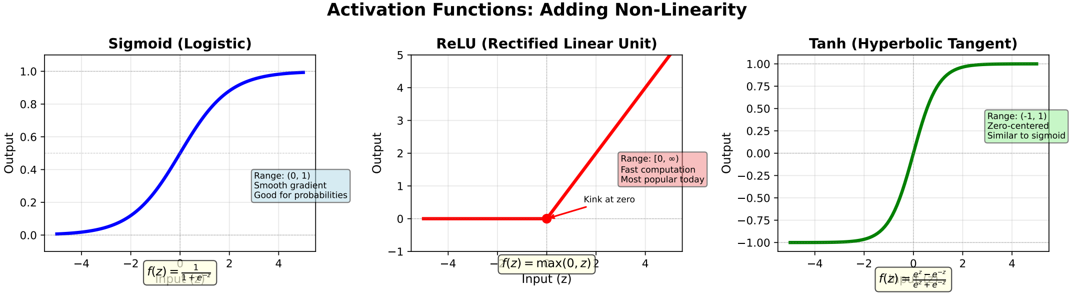
- **Sigmoid:** (0,1) for probabilities
- **ReLU:** Fast, efficient
- **Tanh:** Zero-centered (-1,1)

Business Non-Linearity

1. Diminishing returns
2. Threshold effects
3. Saturation points
4. Network effects

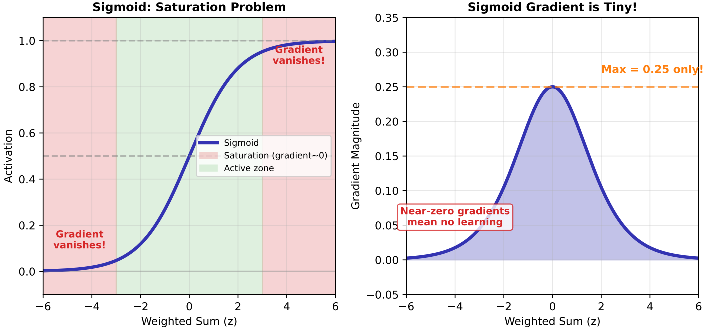
Activation functions capture these patterns!

Next: Visual comparison of these three activation functions



Observe: Where does each function's output change most rapidly? Why does this matter?

Advanced: The Vanishing Gradient Problem



Advanced insight: Sigmoid's tiny gradients in saturation zones slow learning – ReLU solves this in deep networks

The Limitation: Why One Neuron Is Not Enough

What One Neuron Can Do

- Single straight decision boundary
- Separate linearly separable patterns
- Simple rules only

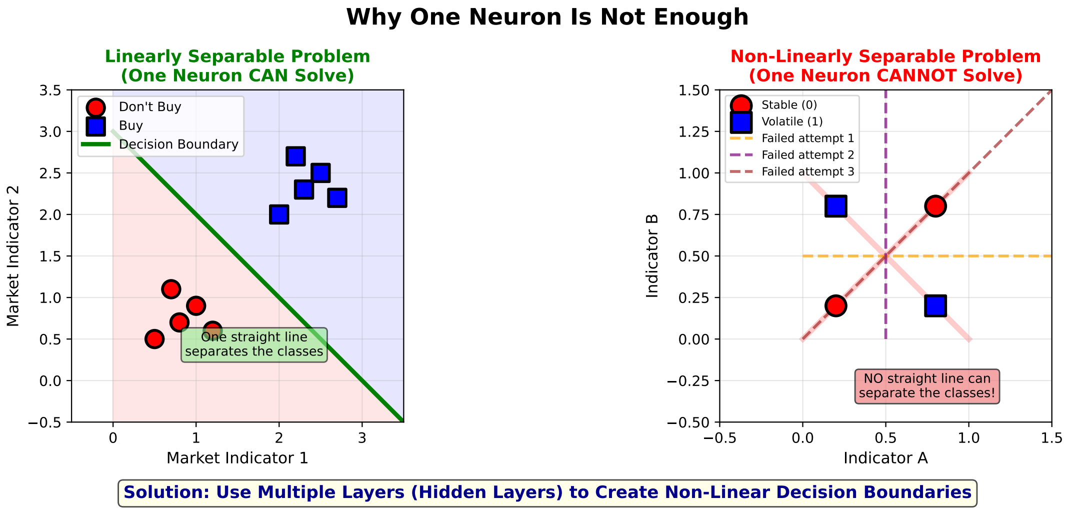
Analogy: One rule for decisions

What One Neuron Cannot Do

- Complex, curved boundaries
- XOR-like patterns
- Real-world market interactions

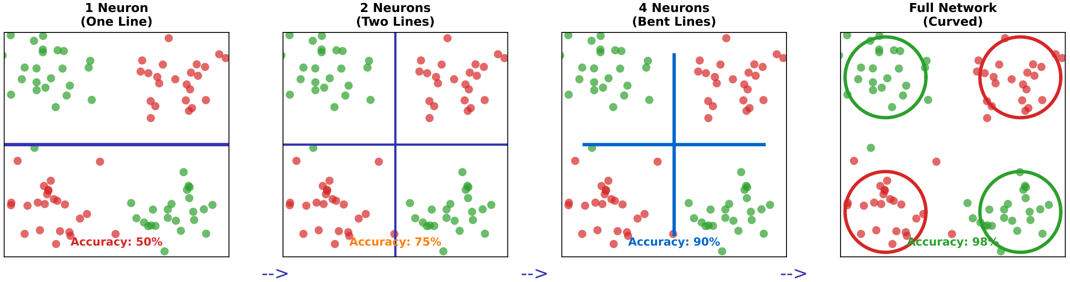
Solution: Multiple Layers!

Next: See the XOR problem that proves one neuron's limitation



Observe: Why is it impossible to draw a single straight line separating orange from blue?

Solution: How Adding Neurons Creates Curved Boundaries



Key insight: More neurons = more flexibility. Each neuron adds a decision line; combined, they form complex shapes

Think – Pair – Share

Can you think of a business metric that shows diminishing returns or threshold effects?

1. Think (1 min)
Reflect individually on the question

2. Pair (2 min)
Discuss with a neighbor

3. Share (2 min)
Share insights with class

Part 3: Network Architecture

Building layers of intelligence

With building blocks ready, let's construct full networks

[1] – [2] – **[3]** – [4] – [5]

Building the Network: Layers of Intelligence

Multi-Layer Architecture

- **Input:** Raw features (no computation)
- **Hidden:** Pattern detection
- **Output:** Final prediction

Result: Buy/Sell decision

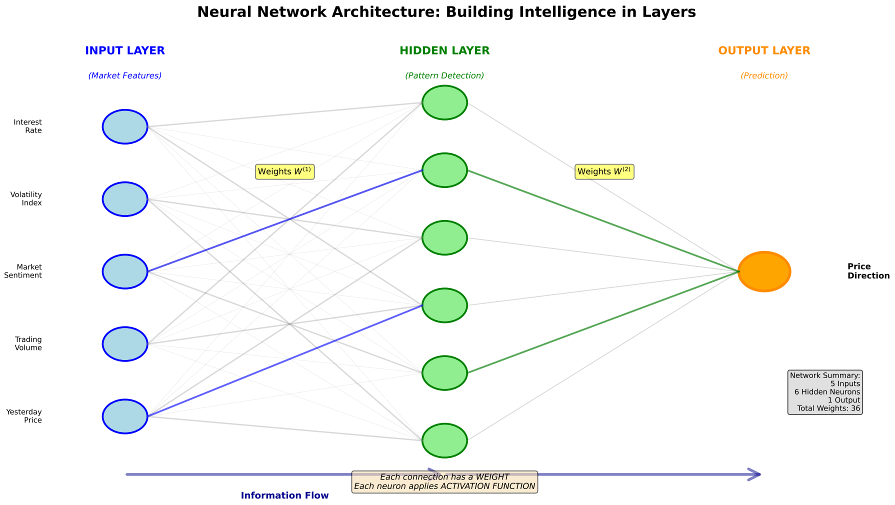
Hierarchical Learning

- Layer 1: Simple patterns
- Layer 2: Complex patterns
- Layer 3: Strategic decisions

Each layer builds on previous abstractions

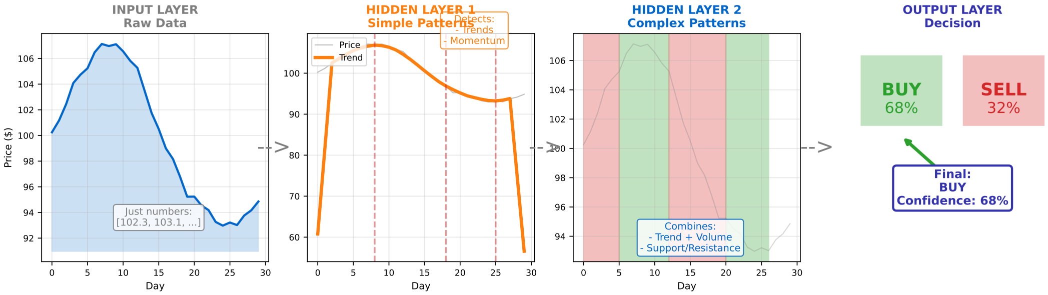
Next: See the full network architecture with all connections

Neural Network Architecture Diagram



Observe: Count the connections. Why are there 36 weights total?

What Each Layer “Sees”: Feature Hierarchy



Observe: Raw data transforms through layers into increasingly abstract representations until a decision emerges

Forward Propagation: How Networks Make Predictions

The Forward Pass

1. **Input:** Feed market features
2. **Hidden:** $a = \sigma(Wx + b)$
3. **Output:** $y = \sigma(Wa + b)$

All neurons compute in parallel!

Example

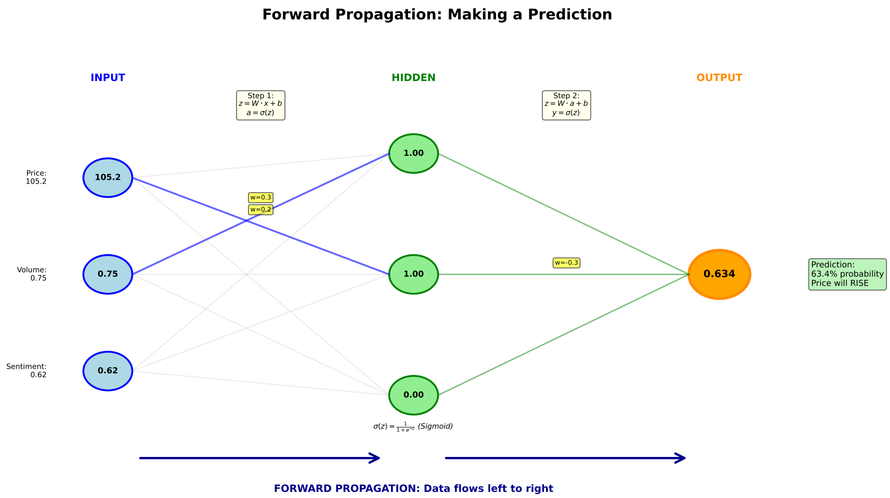
Input: price=105.2, volume=0.75
Output: $y = 0.742$

Interpretation:

- 74.2% confidence price rises
- $y > 0.5$: **BUY**
- $y < 0.5$: **SELL**

Next: See forward propagation with actual numbers and calculations

Forward Propagation: Detailed Example



Observe: How do the hidden layer values combine to produce the final 0.742 output?

Discussion: Part 3 Reflection

Think – Pair – Share

For your industry, what would be the 'inputs' and 'outputs' of a useful neural network?

1. Think (1 min)
Reflect individually on the question

2. Pair (2 min)
Discuss with a neighbor

3. Share (2 min)
Share insights with class

Part 4: Learning Process

How networks learn from mistakes

We can make predictions – now let's learn how to improve them

[1] – [2] – [3] – **[4]** – [5]

Learning from Mistakes: The Training Process

Learning Steps

1. **Predict** with random weights
2. **Measure error:**

$$L = \frac{1}{n}\sum(y - \hat{y})^2$$

3. **Adjust weights:**

$$w_{new} = w_{old} - \eta\nabla L$$

4. **Repeat** until convergence

Example

Predicted: 55% rise, Actual: fell
Error: $(0 - 0.55)^2 = 0.30$

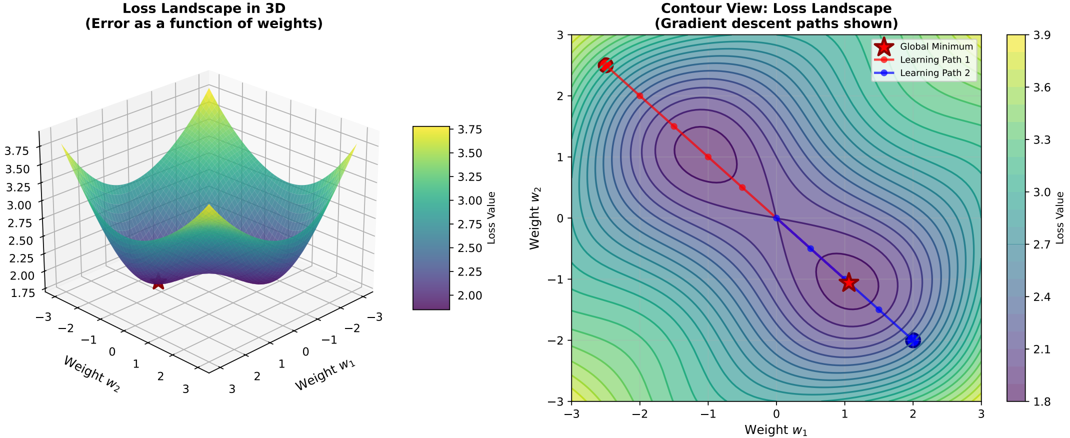
Learning:

- Calculate gradient direction
- Move weights to reduce error

Like a trader learning from mistakes

Next: Visualize the loss landscape that we're trying to navigate

Loss Landscape: The Error Surface



Goal: Find the weights that minimize the loss
(The red star shows the optimal solution)

Observe: What happens if we start from different random initial weights?

Gradient Descent: Learning by Stepping Downhill

Algorithm

1. Calculate gradient (slope)
2. Step opposite direction
3. Repeat until convergence

Learning Rate Trade-offs

- Too small: Slow
- Too large: Unstable
- Just right: Steady

Business Analogy

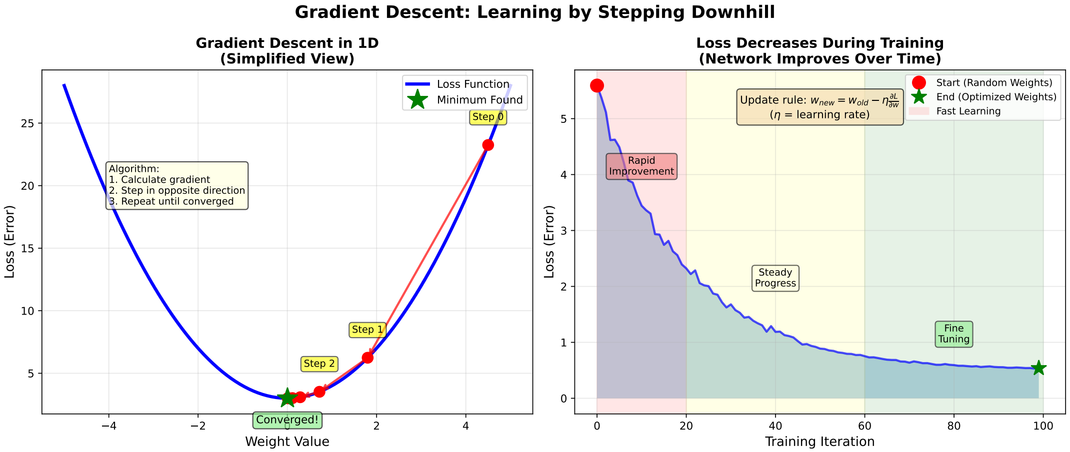
Like a trader learning:

- Fast learning from obvious patterns
- Steady fine-tuning
- Convergence to optimal rules

Gradient shows fastest error reduction

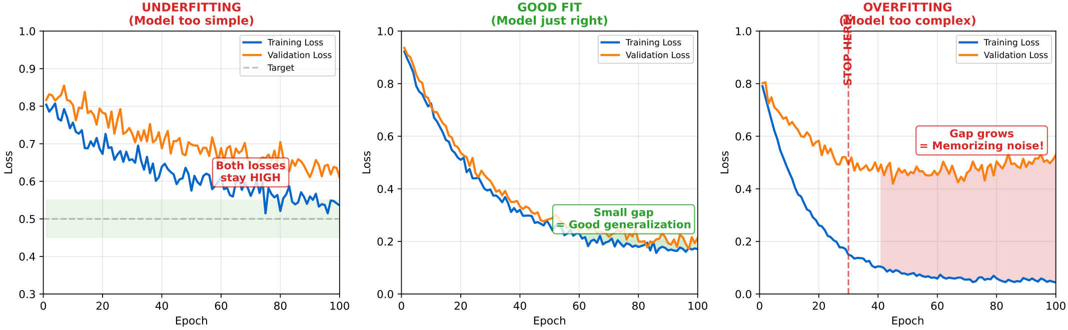
Next: See how loss decreases over training iterations

Gradient Descent: Optimization in Action



Observe: How does the step size (learning rate) affect how quickly we reach the minimum?

Critical Concept: Overfitting vs Underfitting



Key practical skill: Watch for diverging training/validation loss – that's when to stop training!

Think – Pair – Share

How is gradient descent similar to how businesses optimize through trial and error?

1. Think (1 min)
Reflect individually on the question

2. Pair (2 min)
Discuss with a neighbor

3. Share (2 min)
Share insights with class

Part 5: Application

Putting it all together with market prediction

Theory complete – let's apply everything to a real case

[1] – [2] – [3] – [4] – **[5]**

Putting It Together: Market Prediction Case Study

Business Application

- **Goal:** Predict price direction
- **Data:** 60 days market data

Input Features

1. Stock Price
2. Trading Volume
3. Market Sentiment
4. Volatility Index

Target Variable

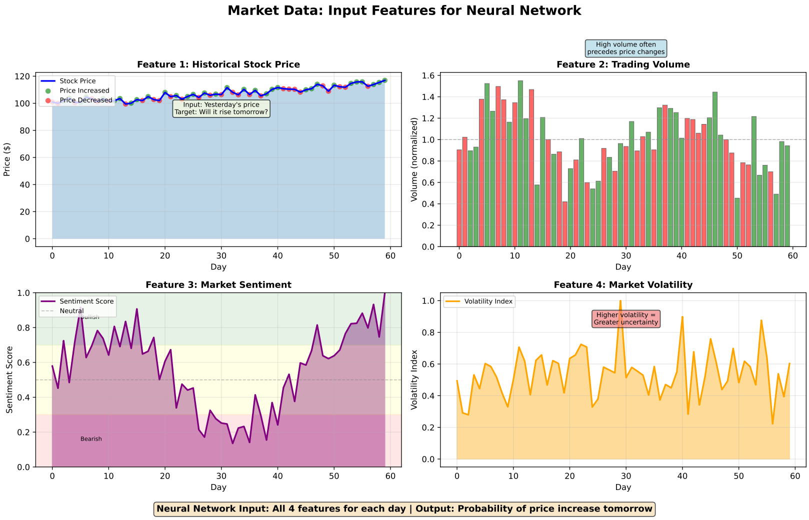
Binary: $1 = \text{up}$, $0 = \text{down}$
Network outputs: $p(\text{rise})$

Setup

- Train: 45 days
- Test: 15 days
- Network: 4-6-1

Next: See the actual market data used for training

Market Data: Input Features for Neural Network



Observe: Which features seem most correlated with the price direction markers?

Training Results: Before vs After

The Experiment

- Before: Random weights (coin flip)
- After: Learned weights
- Test: 30 days unseen data

Results

- Before: 50% accuracy
- After: 70% accuracy
- **Gain:** +20 points

What Network Learned

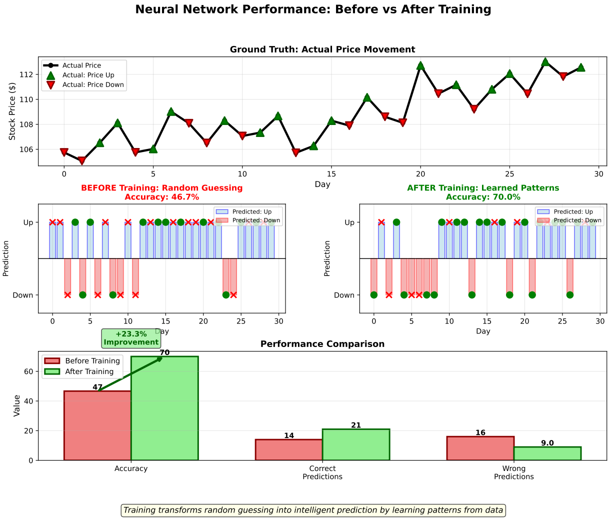
- Volume + price + sentiment patterns
- Volatility indicates uncertainty
- Sentiment confirms trends

Discovered from data alone!

70% is good for markets (100% impossible)

Next: See detailed before/after comparison with prediction accuracy

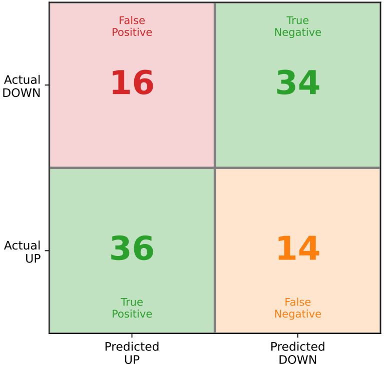
Prediction Results: Before vs After Training



Observe: Where does the trained model still make errors? What might explain these?

Understanding Model Performance: Confusion Matrix

Trading Confusion Matrix (100 test days)



Performance Metrics Explained

ACCURACY	PRECISION
70%	69%
RECALL	**F1 SCORE**
72%	0.71

Accuracy:	Overall correct predictions	70/100
Precision:	When we say BUY, how often right?	36/52
Recall:	Of all UP days, how many caught?	36/50
F1 Score:	Balance of precision & recall	harmonic mean

Trading Insight: 69% precision means ~1/3 of BUY signals are wrong!

Business insight: 70% accuracy means different things for trading – precision determines false BUY rate

Discussion: Part 5 Reflection

Think – Pair – Share

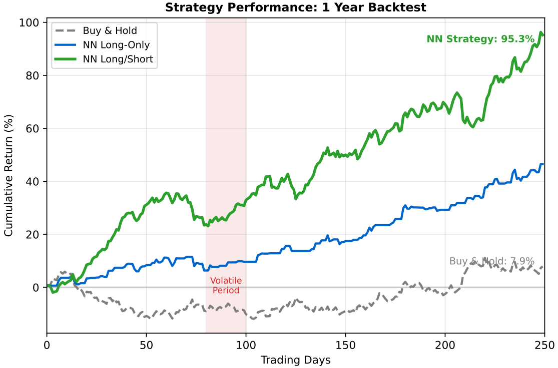
What data would you need to predict customer behavior in your domain?

1. Think (1 min)
Reflect individually on the question

2. Pair (2 min)
Discuss with a neighbor

3. Share (2 min)
Share insights with class

The Business Case: Strategy Backtest Results



PERFORMANCE COMPARISON

Metric	Buy & Hold	NN Strategy
Total Return	7.9%	**95.3%**
Sharpe Ratio	0.40	**3.76**
Max Drawdown	-16.8%	**-9.2%**
Win Rate	52%	**66%**

Key Insight: 70% accuracy translates to significant alpha!

(Backtest only - past performance does not guarantee future results)

Bottom line: 70% accuracy translates to meaningful outperformance – this is why neural networks matter for business

Summary: Three Key Insights

1. Neurons Compute Weighted Sums

Each artificial neuron multiplies inputs by learned weights, adds a bias, and applies a non-linear activation function. This simple operation, repeated across layers, enables complex pattern recognition.

2. Networks Learn from Errors

Training uses gradient descent to minimize prediction errors. The network adjusts weights in the direction that reduces loss – like a trader learning from past mistakes.

3. Patterns Emerge from Data

Neural networks discover relationships we never explicitly programmed. They find what matters in the data, enabling predictions for complex, non-linear business problems.

These three principles underpin all deep learning – master them and you understand neural networks

Quick Check: Test Your Understanding

Q1: What does the activation function do?

(a) Stores the input data
(b) **Adds non-linearity to enable complex patterns**
(c) Calculates the learning rate

Q2: Why do we need multiple layers?

(a) To make training faster
(b) To use more data
(c) **To learn hierarchical, complex patterns**

Q3: What does gradient descent minimize?

(a) The number of neurons
(b) **The prediction error (loss function)**
(c) The training time

Check Your Answers

Answer Key

- Q1: (b) Non-linearity
- Q2: (c) Hierarchical patterns
- Q3: (b) Loss/error

Scoring

- 3/3: Excellent grasp!
- 2/3: Review that topic
- 1/3: Revisit core concepts

If any answer surprised you, go back and review that section

When to Use Neural Networks

Use Neural Networks When

- Large dataset (thousands+ examples)
- Complex patterns
- Difficult to specify rules
- Pattern recognition tasks
- Black-box acceptable

Applications
Churn, fraud, recommendations, images, NLP

Do NOT Use When

- Small dataset
- Simple relationships
- Need interpretability
- Rules are known
- Real-time constraints

Alternatives
Regression, decision trees, expert systems

Choose the right tool - neural networks are powerful but not always appropriate

Important Limitations & Ethical Responsibilities

Technical Limitations

- Data hungry
- Black box decisions
- Overfitting risk
- No guarantees
- Computational cost

Ethical Concerns

- **Fairness:** Biased data leads to biased predictions
- **Transparency:** GDPR requires explanations
- **Accountability:** Who is responsible?
- **Impact:** Job displacement, market stability

With great predictive power comes great responsibility!

Always consider ethical implications before deploying AI systems

Appendix: Mathematical Details (Backpropagation)

Output Layer Gradient

$$\frac{\partial L}{\partial w^{(2)}} = (\hat{y} - y) \cdot \sigma'(z) \cdot a$$

Hidden Layer Gradient

$$\frac{\partial L}{\partial w^{(1)}} = \delta^{(2)} \cdot w^{(2)} \cdot \sigma'(z^{(1)}) \cdot x$$

Loss Functions
MSE (Regression):

$$L = \frac{1}{n} \sum (y - \hat{y})^2$$

Cross-Entropy (Classification):

$$L = -\sum [y \log \hat{y} + (1 - y) \log(1 - \hat{y})]$$

Backpropagation efficiently computes how each weight contributed to the error

Appendix: Practical Tips & Resources

Practical Tips

- Start simple (baseline first)
- Feature engineering matters
- Avoid overfitting (validation, dropout)
- Tune hyperparameters
- Monitor training curves

Books
Goodfellow (Deep Learning), Nielsen, Geron

Courses

- Andrew Ng (Coursera)
- Fast.ai
- MIT 6.S191

Tools
PyTorch, TensorFlow, scikit-learn

Practice
Kaggle, Yahoo Finance, UCI Repository

Best way to learn: Build real projects with real data!

Appendix: Practice Problem for Business Students

Design Challenge
You are a data scientist at a retail company.
Problem: Predict customer churn
Data Available:

- Demographics
- Purchase history
- Service interactions
- Website engagement

Your Tasks

1. Design network architecture
2. Select input features
3. Choose activation functions
4. Select loss function
5. Define evaluation metrics
6. Identify ethical concerns
7. Plan stakeholder explanation

Discuss in groups - there's no single right answer!