# Introduction to Neural Networks

## From Brain to Business: How Machines Learn to Predict

Neural Networks for Business Applications

November 26, 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

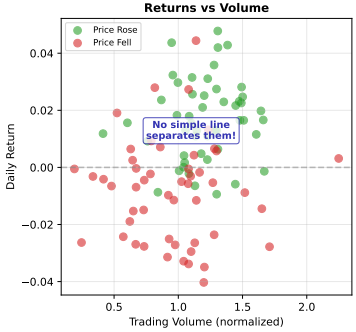
**Why This Matters**

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

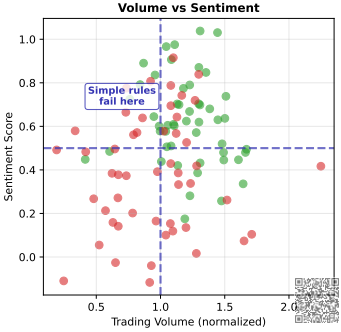
**What We Need**
A system that learns patterns from data, not explicit rules

**Our journey begins with understanding how nature solved similar prediction problems**

# Why Simple Rules Fail: Market Data Complexity








11_problem_visualizatio

**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

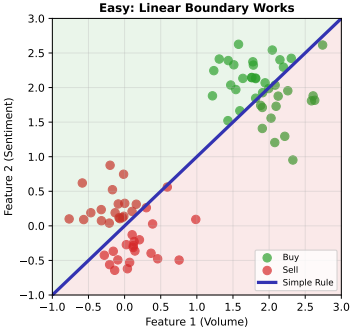
**Brain Capabilities**

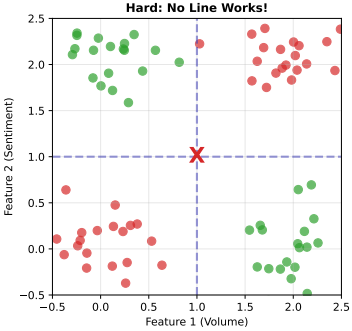
- Processes millions of inputs
- Learns from experience
- Handles ambiguity
- Generalizes to new situations

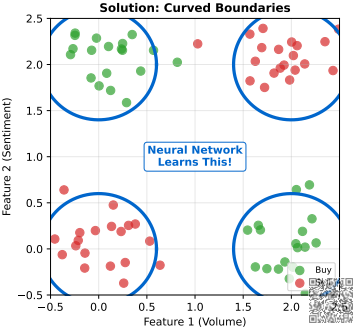
*Can we mimic this for business predictions?*

**Next: Understanding biological neurons as the foundation**

# The Goal: Learn Complex Decision Boundaries




12_decision_boundary_concep

**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!*

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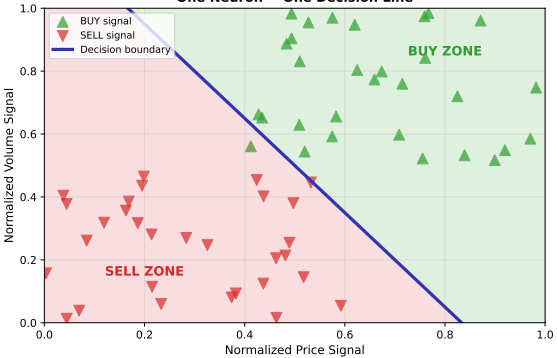
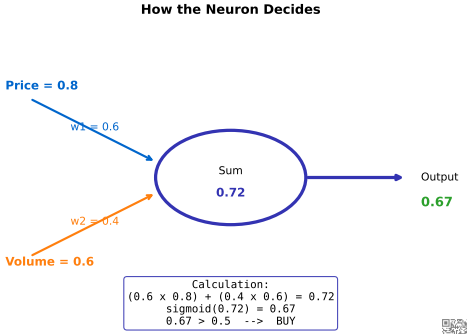
**Next: See the visual comparison of biological vs artificial neurons**

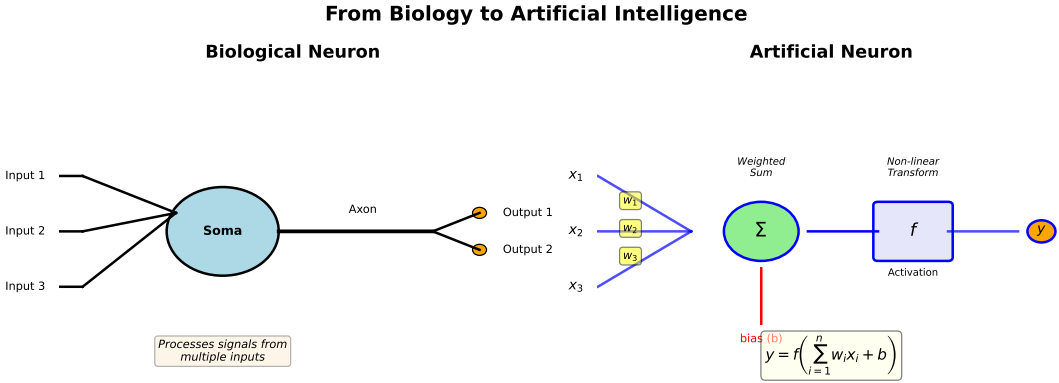
# From Concept to Computation: Neuron as Decision Maker




13_neuron_decision_make

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




01_biological_neuro

**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**

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

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

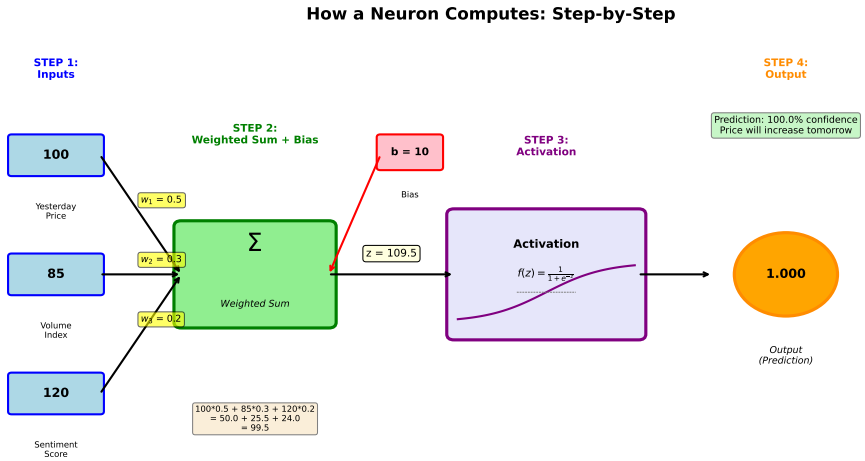
**Interpretation**

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**

# Single Neuron Computation: Step-by-Step Example



**Think – Pair – Share**

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

| 1. Think (1 min) | 2. Pair (2 min) | 3. Share (2 min) |
|---|---|---|
| Reflect individually on the question | Discuss with a neighbor | 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)

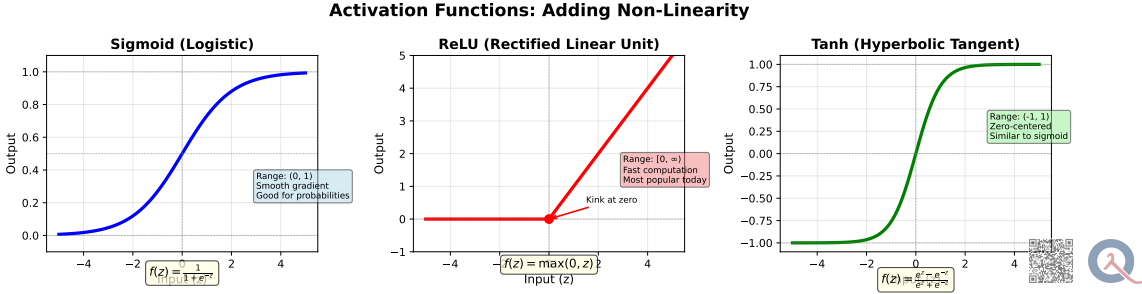
**Business Non-Linearity**

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

*Activation functions capture these patterns!*

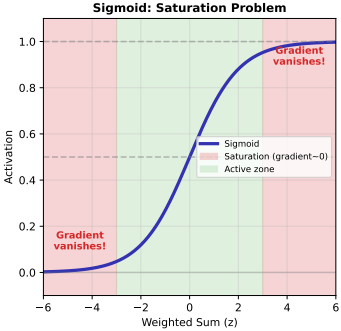
**Next: Visual comparison of these three activation functions**

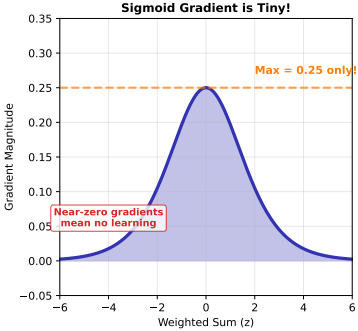
# Activation Functions: Visual Comparison

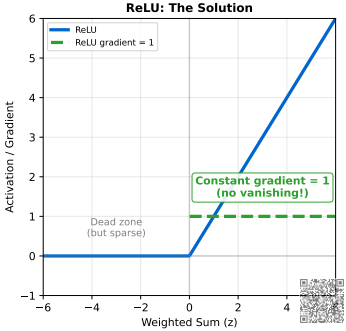



**Observe: Where does each function's output change most rapidly? Why does this matter?**

# Advanced: The Vanishing Gradient Problem




14_sigmoid_saturatio

**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

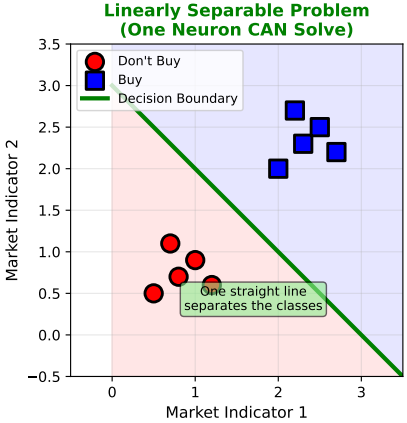
**What One Neuron Cannot Do**

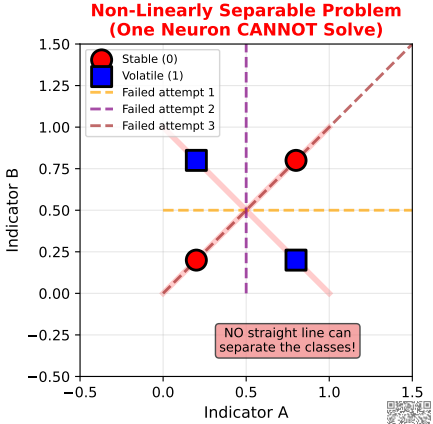
- Complex, curved boundaries
- XOR-like patterns
- Real-world market interactions

**Solution: Multiple Layers!**

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

## Why One Neuron Is Not Enough

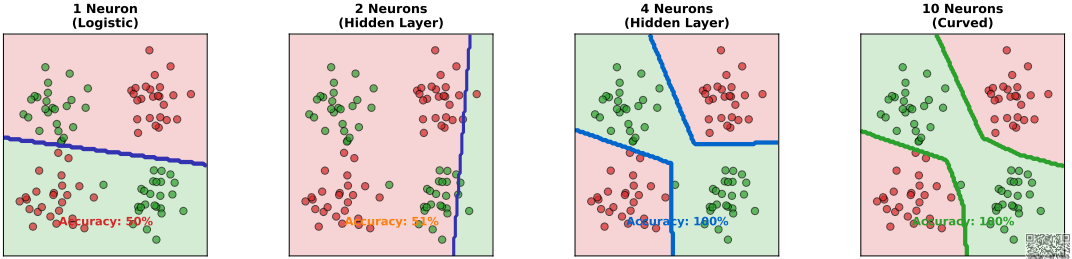



**Solution: Use Multiple Layers (Hidden Layers) to Create Non-Linear Decision Boundaries**

04_linear_limitatio

# Solution: How Adding Neurons Creates Curved Boundaries




15_boundary_evolutio

**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) | 2. Pair (2 min) | 3. Share (2 min) |
| --- | --- | --- |
| Reflect individually on the question | Discuss with a neighbor | 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

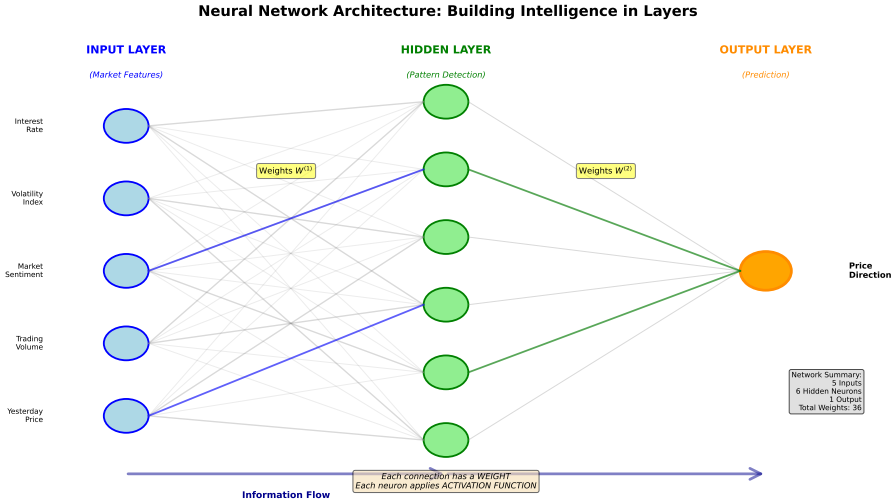
**Hierarchical Learning**

- 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




05_network_architectur

# Feature Hierarchy (Part 1): From Raw Data to Patterns

**Input Layer: Raw Numbers**
The network receives:

- Stock prices: [102.3, 103.1, ...]
- Trading volume: [1.2M, 0.9M, ...]
- Sentiment scores: [0.6, 0.5, ...]

Just numbers – no meaning yet!

**Hidden Layer 1: Simple Patterns**
The first layer detects:

- Upward trends
- Downward trends
- Momentum shifts
- Volume spikes

Finds basic features in the noise

**First transformation: Raw numbers become recognizable patterns**

# Feature Hierarchy (Part 2): From Patterns to Decisions

**Hidden Layer 2: Complex Patterns**
Combines simple patterns:

- Trend + High volume = Bullish
- Trend + Low volume = Bearish
- Support/resistance levels
- Multi-day patterns

Strategic insights emerge!

**Output Layer: Trading Decision**
Final decision:

- **BUY**: 68% confidence
- SELL: 32% confidence

Since 68% > 50% threshold:

**ACTION: BUY**

**Final transformation: Patterns become actionable trading signals**

# 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**

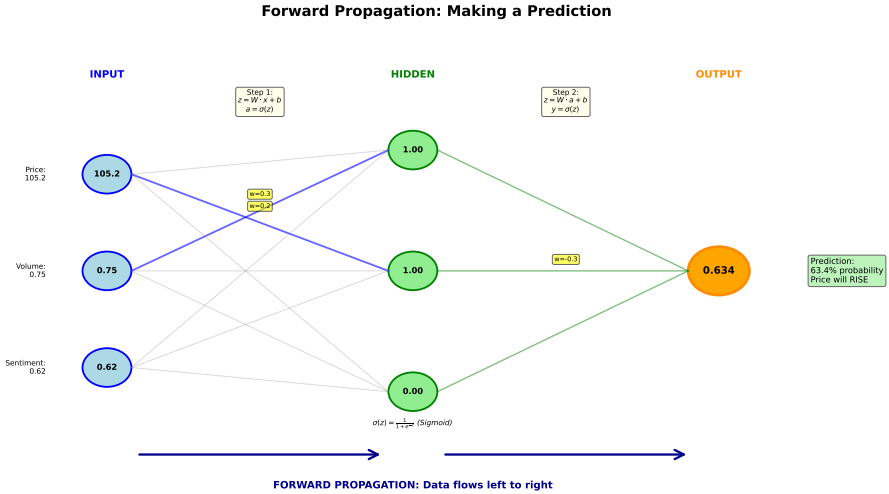
Input: price=105.2, volume=0.75
Output: $y = 0.742$

**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




06_forward_propagatio

**Think – Pair – Share**

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

| 1. Think (1 min) | 2. Pair (2 min) | 3. Share (2 min) |
| --- | --- | --- |
| Reflect individually on the question | Discuss with a neighbor | 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: $(0 - 0.55)^2 = 0.30$

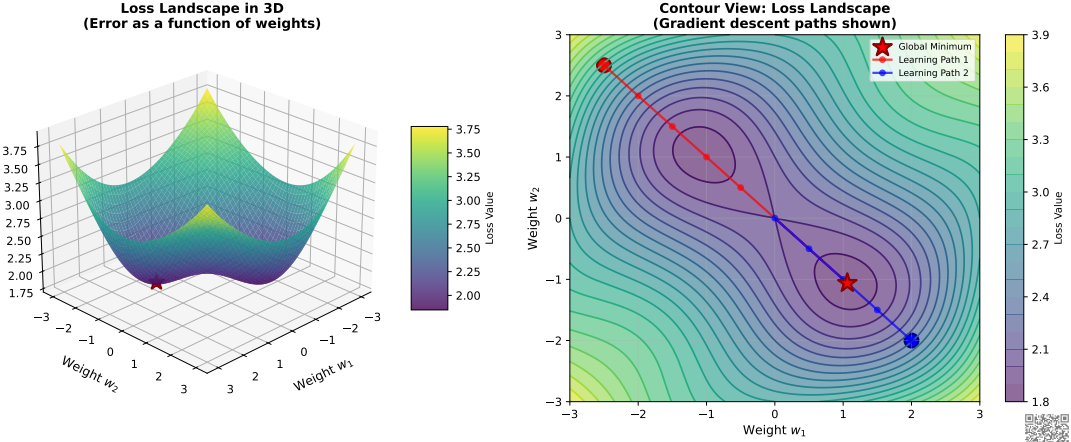
**Learning:**

- 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




07_loss_landscap

**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**

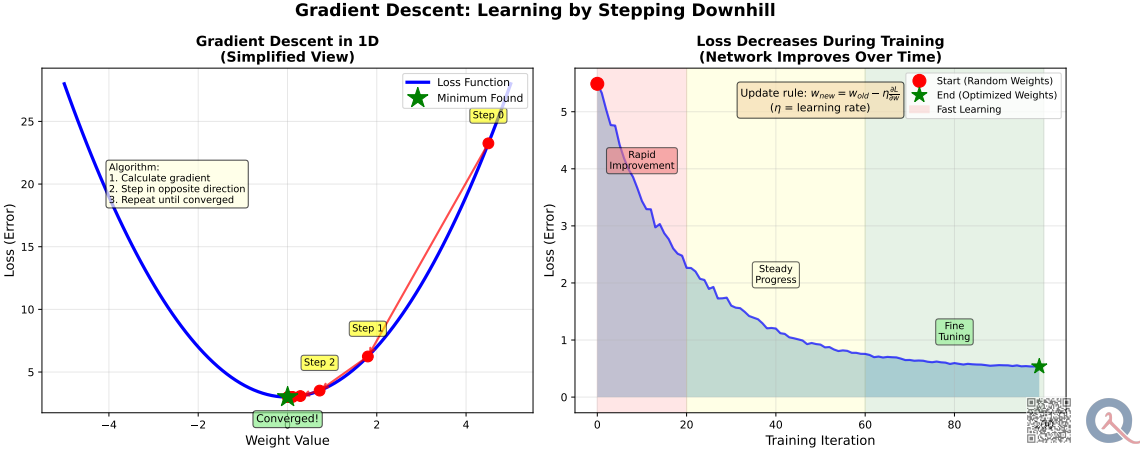
Like a trader learning:

- 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**

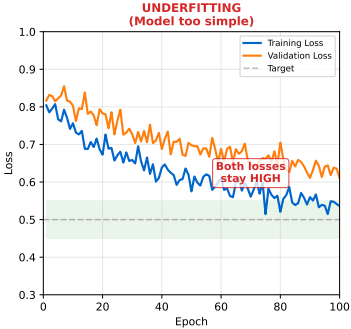
# Gradient Descent: Optimization in Action

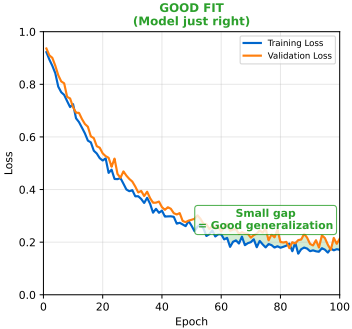


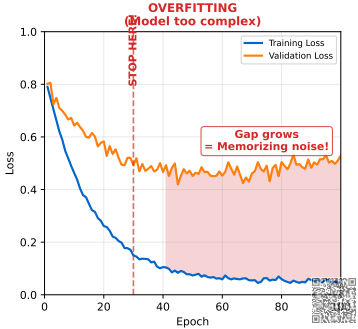

08_gradient_descen

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

# Critical Concept: Overfitting vs Underfitting




17_overfitting_underfittin

**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) | 2. Pair (2 min) | 3. Share (2 min) |
| --- | --- | --- |
| Reflect individually on the question | Discuss with a neighbor | 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**

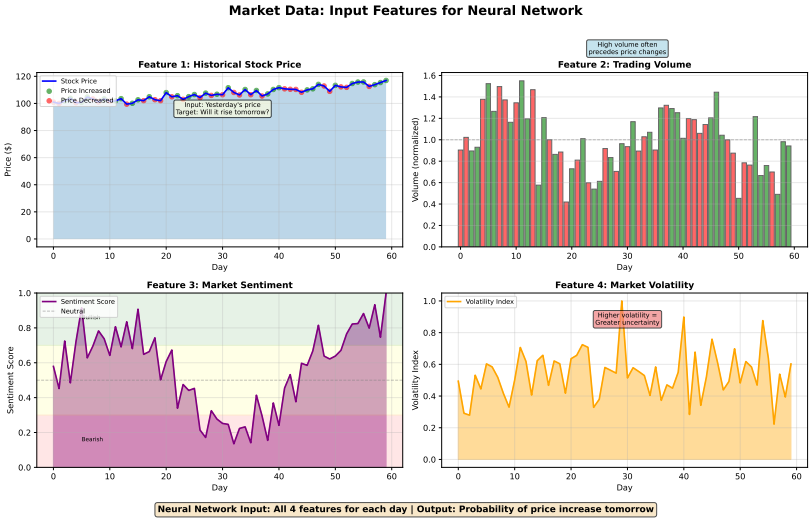
Binary: 1 = up, 0 = down
Network outputs: $p(\text{rise})$

**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




09_market_prediction_dat

# 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**

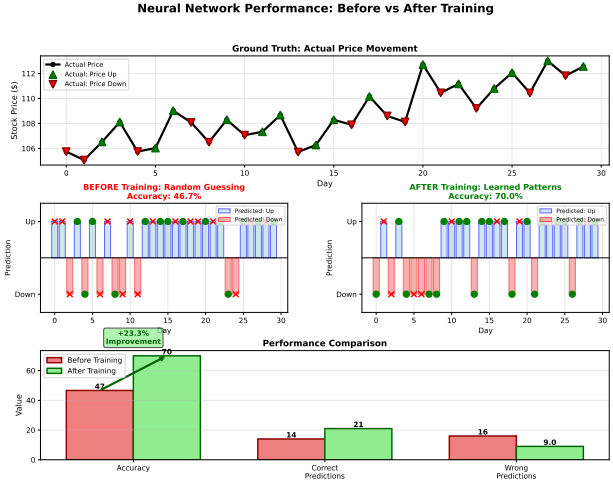
- Volume + price + sentiment patterns
- Volatility indicates uncertainty
- Sentiment confirms trends

*Discovered from data alone!*

70% is good for markets (100% impossible)

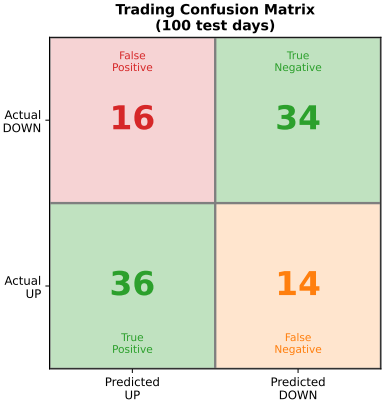
**Next: See detailed before/after comparison with prediction accuracy**

# Prediction Results: Before vs After Training




10_prediction_result

# Understanding Model Performance: Confusion Matrix




**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!**

19_confusion_matri

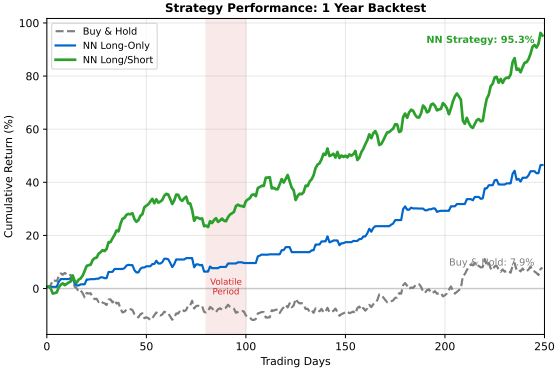
**Business insight: 70% accuracy means different things for trading – precision determines false BUY rate**

**Think – Pair – Share**

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

| 1. Think (1 min) | 2. Pair (2 min) | 3. Share (2 min) |
|---|---|---|
| Reflect individually on the question | Discuss with a neighbor | 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)*

20_trading_backtes

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

# Summary: Three Key Insights

**Definition**

**1. Neurons Compute Weighted Sums**

Each neuron:

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

- Weighted inputs
- Non-linear activation
- Parallel processing

**2. Networks Learn from Errors**

Gradient descent:

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

- Measure prediction error
- Adjust weights
- Minimize loss function

**3. Patterns Emerge from Data**

- No explicit rules
- Discovers relationships

**Business Example**

*Market Prediction*

Input: Price (0.8), Volume (0.6)
Computation:

- $(0.6 \times 0.8) + (0.4 \times 0.6) = 0.72$
- $\sigma(0.72) = 0.67$
- $0.67 > 0.5 \rightarrow$ **BUY**

*Learning Process*

- Predicted: 55% rise, Actual: fell
- Error: $(0 - 0.55)^2 = 0.30$
- Adjust: Reduce weights on price
- Next time: Better prediction

*Discovered Patterns*

- Volume + sentiment $\rightarrow$ direction
- 70% accuracy (no manual rules!)
- Outperforms buy-and-hold

# 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!**