December 6, 2025

Learning Goal

Compare network performance before and after training to understand the impact of learning.

This slide establishes the learning objective for this topic

Key Concept (1/2)

Before training, a neural network with random weights is essentially guessing. For binary classification (up/down), random guessing yields about **50% accuracy** - no better than flipping a coin.
After training on historical data, the network learns patterns that improve predictions. A well-trained network might achieve **70% accuracy** on unseen test data - significantly better than chance.
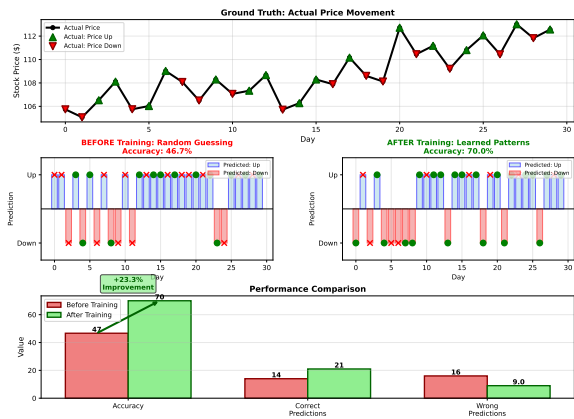
Understanding this concept is crucial for neural network fundamentals

The improvement from 50% to 70% represents real predictive power extracted from the data. However, it's crucial to evaluate on **held-out test data** that wasn't used during training. Performance on training data is often inflated (the network may have memorized specifics rather than learning generalizable patterns).

Even modest accuracy improvements can be valuable in finance, where small edges compound over many trades.

Understanding this concept is crucial for neural network fundamentals

Neural Network Performance: Before vs After Training

Visual representations help solidify abstract concepts

Key Formula

Accuracy:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Predictions}} \times 100\%$$

Improvement over baseline:

$$\text{Improvement} = \text{Trained Accuracy} - \text{Random Baseline}$$

For binary classification:

$$\text{Random Baseline} = 50\%$$

Mathematical formalization provides precision

Intuitive Explanation

Imagine two weather forecasters: - **Forecaster A** (random): Flips a coin to predict rain or shine - **Forecaster B** (trained): Studies historical weather patterns

Over 100 days: - Forecaster A: 50 correct (coin flip) - Forecaster B: 70 correct (learned patterns)

Forecaster B adds real value by capturing patterns that random guessing misses. Similarly, a trained neural network extracts predictive information from data that raw chance cannot access.

Intuitive explanations bridge theory and practice

Practice Problem 1

Problem 1
A trained network makes 140 correct predictions out of 200 test samples. Calculate: (a) accuracy, (b) improvement over random baseline.

Solution

(a) Accuracy:

$$\text{Accuracy} = \frac{140}{200} \times 100\% = 70\%$$

(b) Improvement over baseline:

$$\text{Improvement} = 70\% - 50\% = 20\%$$

The network predicts **20 percentage points** better than random guessing - a substantial improvement that could translate to profitable trading.

Practice problems reinforce understanding

Practice Problem 2

Problem 2
Network A achieves 95% accuracy on training data but 52% on test data. Network B achieves 72% on training data and 68% on test data. Which network is better?

Solution

Network B is better, despite lower training accuracy.
Analysis:
Network A: - Training: 95%, Test: 52% - Gap: 43 percentage points - Severe **overfitting** - memorized training data - Test accuracy barely better than chance (52% vs 50%)
Network B: - Training: 72%, Test: 68% - Gap: 4 percentage points - Good **generalization** - learned transferable patterns - Test accuracy significantly better than chance
Network B's 68% test accuracy represents real predictive power. Network A's 95% training accuracy is misleading - it fails on new data.

Practice problems reinforce understanding

Key Takeaways

- Random guessing yields 50% accuracy on binary classification
- Training extracts patterns that improve beyond baseline
- Always evaluate on held-out test data, not training data
- Even modest improvements (55-70%) can be valuable in finance
- Gap between training and test accuracy indicates overfitting

These key points summarize the essential learnings