December 6, 2025

Learning Goal

Understand how to prepare financial features for neural network input.

This slide establishes the learning objective for this topic

Key Concept (1/3)

Before training a neural network, we must convert raw market data into numerical features the network can process. This **feature engineering** step is crucial - the network can only learn patterns present in the features we provide.

Understanding this concept is crucial for neural network fundamentals

Key Concept (2/3)

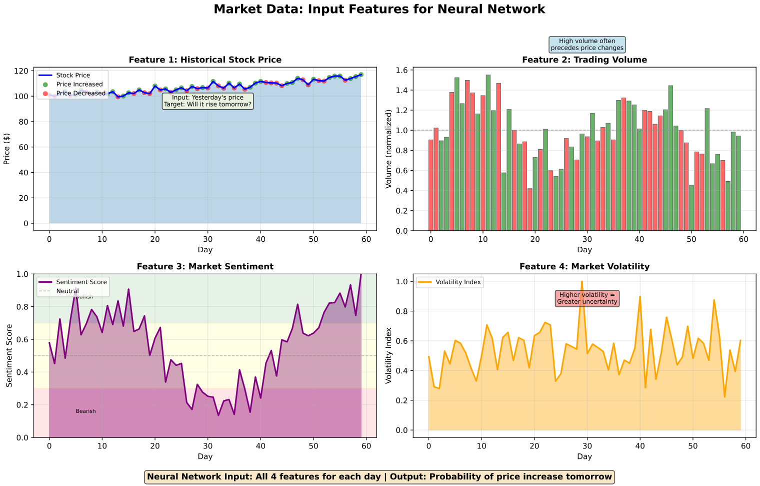
For stock prediction, common features include: - **Price data**: Returns, moving averages, momentum - **Volume**: Trading activity, normalized by average - **Sentiment**: News sentiment scores, social media signals - **Volatility**: Price variability, option-implied volatility

Each feature should be **normalized** (scaled to similar ranges) so no single feature dominates due to scale differences. For example, stock prices might be hundreds of dollars while sentiment scores are between 0 and 1.

Understanding this concept is crucial for neural network fundamentals

The **target variable** is what we're predicting - in binary classification, this might be 1 (price went up) or 0 (price went down).

Understanding this concept is crucial for neural network fundamentals



Visual representations help solidify abstract concepts

Normalization (Min-Max Scaling):

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

Normalization (Z-score):

$$x_{norm} = \frac{x - \mu}{\sigma}$$

Where: - **x** = original value - $\mathbf{x_m in}, \mathbf{x_m ax}$ = minimum and maximum in dataset - **mu** = mean - **sigma** = standard deviation

Mathematical formalization provides precision

Intuitive Explanation

Think of feature engineering as translation. Raw market data speaks in different "languages" (dollars, shares, percentages). The neural network needs all inputs in the same "language" (normalized numbers near 0).
Without normalization: - Price: 150.00 - Volume: 1,500,000 - Sentiment: 0.65
The network would focus on volume (biggest numbers) while ignoring sentiment (smallest). After normalization, all features are equally important to start.

Intuitive explanations bridge theory and practice

Practice Problem 1

Problem 1
A stock's price history shows minimum $= 95$, maximum $= 105$. Today's price is 102. Calculate the min-max normalized value.

Solution

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} = \frac{102 - 95}{105 - 95} = \frac{7}{10} = 0.70$$

The normalized price is **0.70**, indicating it's 70% of the way from minimum to maximum.

Practice problems reinforce understanding

Practice Problem 2

Problem 2
Volume data has mean = 1,000,000 and standard deviation = 250,000. Today's volume is 1,500,000. Calculate the z-score.

Solution

$$x_{norm} = \frac{x - \mu}{\sigma} = \frac{1,500,000 - 1,000,000}{250,000} = \frac{500,000}{250,000} = 2.0$$

The z-score is **2.0**, meaning today's volume is 2 standard deviations above average - unusually high trading activity.

Practice problems reinforce understanding

Key Takeaways

- Feature engineering converts raw data to network-friendly format
- Normalization ensures all features are on similar scales
- Common features: price, volume, sentiment, volatility
- Avoid data leakage - only use information available at prediction time
- Target variable for classification: 1 (up) or 0 (down)

These key points summarize the essential learnings