December 6, 2025

Learning Goal

Understand how different layers learn increasingly abstract representations.

This slide establishes the learning objective for this topic

Key Concept (1/2)

Neural networks learn **hierarchical representations**. Each layer transforms the data into a more abstract form:
- **Input layer**: Raw features (price, volume, sentiment) - **Hidden layer 1**: Simple patterns (uptrend, high volume, positive sentiment) - **Hidden layer 2**: Combinations (momentum + volume spike = strong signal) - **Output layer**: Final decision (BUY/SELL with confidence)

Understanding this concept is crucial for neural network fundamentals

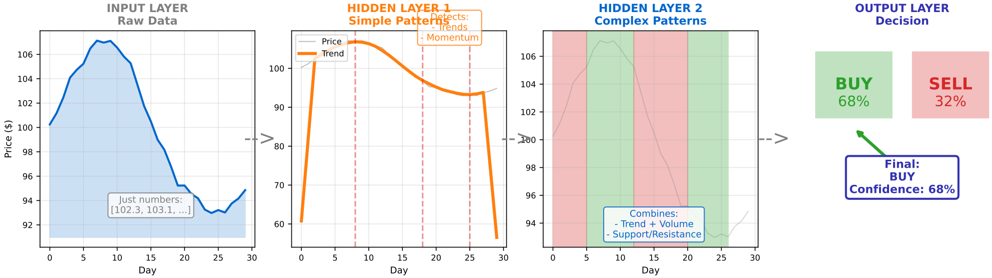
Key Concept (2/2)

This hierarchy emerges automatically through training. The network learns what intermediate representations are useful for the final task. Early layers detect simple patterns; later layers combine these into complex concepts.

In image recognition, this is visible: early layers detect edges, middle layers detect shapes, late layers detect objects. For financial data, the learned features are less visually interpretable but follow the same principle.

Understanding this concept is crucial for neural network fundamentals

Visualization



Visual representations help solidify abstract concepts

Layer-by-layer transformation:

$$h^{[1]} = f(W^{[1]}x + b^{[1]}) \quad \text{(simple patterns)}$$

$$h^{[2]} = f(W^{[2]}h^{[1]} + b^{[2]}) \quad \text{(complex patterns)}$$

$$\hat{y} = \sigma(W^{[3]}h^{[2]} + b^{[3]}) \quad \text{(decision)}$$

Each layer builds on the representations from the previous layer.

Mathematical formalization provides precision

Intuitive Explanation

Think of a corporate decision-making process:
1. **Analysts (Input)**: Collect raw data - stock prices, trading volumes 2. **Junior managers (Hidden 1)**: Identify simple patterns - "prices rising," "unusual volume" 3. **Senior managers (Hidden 2)**: Combine patterns - "rising prices + high volume = momentum" 4. **Executive (Output)**: Make final call - "Confidence: 68% BUY"
Each level adds interpretation and abstraction. The executive doesn't need raw numbers - they need the synthesized judgment of their team.

Intuitive explanations bridge theory and practice

Practice Problem 1

Problem 1
A network for fraud detection has 3 hidden layers. What might each layer learn?

Solution

Layer 1 - **Simple anomalies:** - Transaction amount unusually high - Time of transaction (late night) - Location different from usual - Transaction frequency spike
Layer 2 - **Pattern combinations:** - High amount + unusual time = suspicious - New location + high frequency = potential card theft - Normal amount + normal patterns = likely legitimate
Layer 3 - **Complex fraud signatures:** - Combination of multiple suspicious patterns - Sequential transaction patterns (testing then big purchase) - Network of related suspicious accounts
Output - **Fraud score:** - Probability of fraud (0-100%) - Decision threshold (e.g., flag if ¿ 80%)
Each layer abstracts further from raw data toward the final fraud determination.

Practice problems reinforce understanding

Problem 2
Why can't we interpret what middle layer neurons have learned as easily as input features?

Solution

Reasons for difficulty:
1. **Distributed representations**: Information is spread across many neurons, not localized in one
2. **Non-linear transformations**: Multiple activation functions make the relationship to inputs complex and non-obvious
3. **Abstract representations**: Middle layers don't correspond to concepts humans naturally think about - they optimize for the task, not human understanding
4. **Lack of semantic meaning**: Unlike "price" or "volume," a hidden neuron might activate for a combination that has no simple label
5. **Entangled features**: Multiple concepts are mixed together in the same neuron activations

Contrast with input features: - Input features have clear meaning: "closing price = \$150" - Hidden features are abstract: "neuron 7 in layer 2 = 0.83" - what does that mean?
This is why neural networks are often called "black boxes" - they work well but are hard to interpret.

Practice problems reinforce understanding

Key Takeaways

- Networks learn hierarchical representations automatically
- Early layers: simple patterns; Later layers: complex combinations
- Deeper networks can represent more abstract concepts
- Hidden representations are often not human-interpretable
- More layers isn't always better - match complexity to problem

These key points summarize the essential learnings