10. Forward Propagation

Neural Networks - From Brain to Business

Learning Goal

Trace how input data flows through a neural network to produce a prediction.

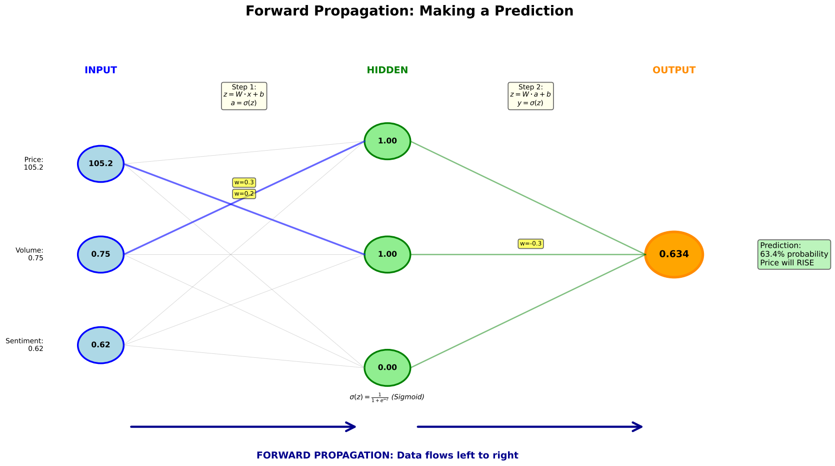
Key Concept (1/2)

Forward propagation is the process of computing a network's output given an input. Data flows forward from input layer through hidden layers to the output layer - hence the name.
At each layer, we perform two operations: 1. **Linear transformation**: Multiply inputs by weights and add bias (z = Wx + b) 2. **Non-linear activation**: Apply activation function (a = f(z))

Key Concept (2/2)

The output of one layer becomes the input to the next. When data reaches the output layer, we have our prediction.
During training, we compare this prediction to the true value to calculate error.
For a trading application, forward propagation answers: "Given today's market data, what does the network predict about tomorrow's price?"

Visualization


Forward Propagation: Making a Prediction
INPUT
HIDDEN
OUTPUT
Step 1: $z = W \cdot x + b$ $a = \sigma(z)$
Step 2: $z = W \cdot a + b$ $y = \sigma(z)$
Price: 105.2
105.2
Volume: 0.75
0.75
Sentiment: 0.62
0.62
w=0.3
w=0.2
1.00
1.00
0.00
w=-0.3
0.634
Prediction: 63.4% probability Price will RISE
$\sigma(z) = \frac{1}{1+e^{-z}}$ (Sigmoid)
FORWARD PROPAGATION: Data flows left to right

Key Formula

Hidden layer computation:

$$z^{[1]} = W^{[1]}x + b^{[1]}$$
$$a^{[1]} = \sigma(z^{[1]})$$

Output layer computation:

$$z^{[2]} = W^{[2]}a^{[1]} + b^{[2]}$$
$$\hat{y} = \sigma(z^{[2]})$$

Where: - **x** = input features - **W**$^{[}$**l**] = weight matrix for layer l - **b**$^{[}$**l**] = bias vector for layer l - **z**$^{[}$**l**] = pre-activation values - **a**$^{[}$**l**] = activation values (layer output) - **y-hat** = predicted output

Intuitive Explanation

Imagine a relay race where each runner transforms the baton before passing it:
1. **Start**: Raw market data (price = 105.2, volume = 0.75, sentiment = 0.62) 2. **Hidden layer**: Each neuron "weighs" this data, adds its perspective, and outputs a transformed signal 3. **Output layer**: The final neuron combines all hidden signals into a single prediction 4. **Finish**: Probability of price increase (e.g., 74.2%)
The weights determine how much each neuron "listens" to each input. Training adjusts these weights to improve predictions.

Practice Problem 1

Problem 1
A network has 2 inputs, 2 hidden neurons, and 1 output. Given: - Input: x = [1.0, 0.5] - Hidden weights: W1 = [[0.2, 0.4], [0.6, 0.3]] - Hidden bias: b1 = [0.1, -0.1]
Calculate z1 (pre-activation for hidden layer).

Solution

For hidden neuron 1:

$$z_1^{[1]} = 0.2(1.0) + 0.4(0.5) + 0.1 = 0.2 + 0.2 + 0.1 = 0.5$$

For hidden neuron 2:

$$z_2^{[1]} = 0.6(1.0) + 0.3(0.5) + (-0.1) = 0.6 + 0.15 - 0.1 = 0.65$$

z1 = [0.5, 0.65]

Practice Problem 2

Problem 2
Continuing from Problem 1, apply sigmoid activation to get a1 (hidden layer output).

Solution

$$a_1^{[1]} = \sigma(0.5) = \frac{1}{1+e^{-0.5}} = \frac{1}{1+0.607} = 0.622$$

$$a_2^{[1]} = \sigma(0.65) = \frac{1}{1+e^{-0.65}} = \frac{1}{1+0.522} = 0.657$$

a1 = [0.622, 0.657]

Key Takeaways

- Forward propagation computes output from input layer to output layer
- Each layer: linear transformation ($Wx + b$) then activation (f)
- All neurons in a layer compute in parallel
- The final output is the network's prediction
- No learning happens during forward propagation - just computation