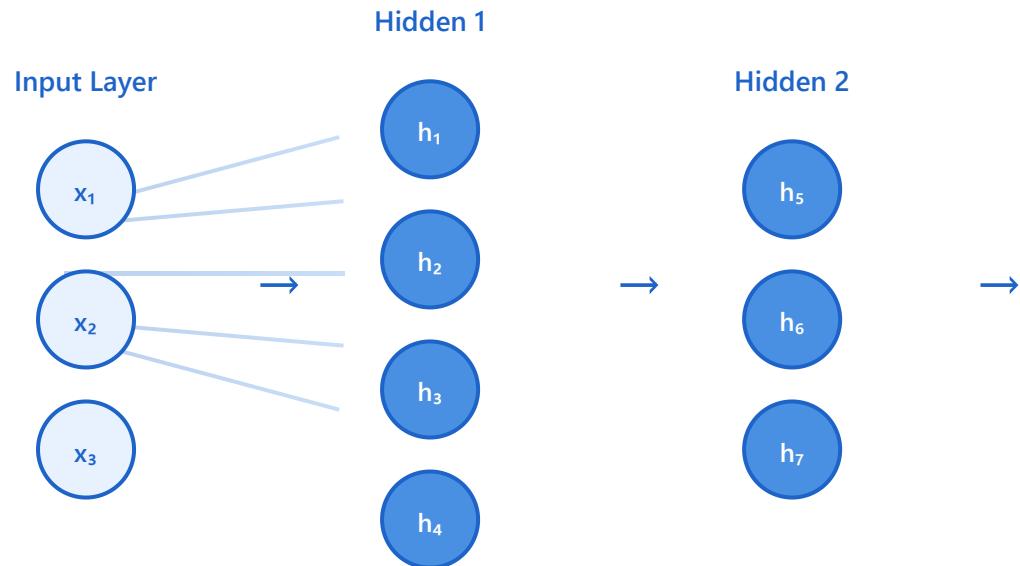


# DeepSHAP: DeepLIFT + SHAP for Neural Networks

Backpropagation of reference activation differences

## Neural Network Computation Flow



## DeepSHAP Computation Steps

- Compute reference activations (average)
- Forward pass: input → output
- Backward pass: propagate differences



### Key Features

- Combines DeepLIFT with Shapley value sampling
- Layer-wise decomposition
  - Handles nonlinear activations
  - Reference-based differences



### Output Activations

- Supports various activation functions
- ReLU
  - Sigmoid
  - Tanh



### Reference Value

Typically uses average of training data as baseline



### Implementation

→ Assign contributions to each input

```
import shap  
  
# Create explainer  
explainer = shap.DeepExplainer(  
    model,  
    X_train[:100]  
)  
  
# Compute SHAP values  
shap_values = explainer.shap_values(X_test)
```

## DeepSHAP Computation Principle

### Core Formulas

$$\varphi_i = \Delta\text{output} \times (\Delta x_i / \sum \Delta x_j)$$

$\varphi_i$ : Feature i's SHAP value

$\Delta\text{output}$ : Output difference from reference

$\Delta x_i$ : Input i difference from reference

$\sum \Delta x_j$ : Sum of all input differences

### Layer-wise propagation:

$$C_{ij} = m_{ij} \times \Delta x_j \Delta h_i$$

$C_{ij}$ : Contribution from neuron j to i

$m_{ij}$ : Multiplier (weight effect)

$\Delta x_j$ : Input activation difference

$\Delta h_i$ : Hidden activation difference

### Numerical Example

#### Step 1: Set Reference

Reference (baseline):  $x_0 = [0, 0, 0]$

Input (actual):  $x = [1, 2, 1]$

Differences:  $\Delta x = [1, 2, 1]$

#### Step 2: Forward Pass

Hidden layer:  $h = \text{ReLU}(W \cdot x + b)$

Reference:  $h_0 = \text{ReLU}(W \cdot x_0 + b) = [0, 0]$

Actual:  $h = [2, 3]$

Differences:  $\Delta h = [2, 3]$

#### Step 3: Output Difference

Reference output:  $y_0 = 0.3$

Actual output:  $y = 0.8$

Output difference:  $\Delta y = 0.5$

#### Step 4: Backward Propagation

Calculate each input's contribution via backpropagation:

$$\varphi_1 = 0.5 \times (1/4) = 0.125$$

$$\varphi_2 = 0.5 \times (2/4) = 0.250$$

$$\varphi_3 = 0.5 \times (1/4) = 0.125$$

### Final Result Interpretation

- Feature  $x_2$  has the largest impact ( $\varphi_2 = 0.250$ )
- Sum of all SHAP values =  $0.5 = \Delta y$  ✓
- Features  $x_1, x_3$  have equal contributions (0.125)