

```

# Import necessary libraries
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.optimizers import Adam
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

# Define input data for the AND gate
X = np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
y = np.array([0, 0, 0, 1])

# Build the model
model = Sequential()
model.add(Dense(4, input_dim=2, activation='relu'))
model.add(Dense(1, activation='sigmoid'))

C:\Users\jayaraman\anaconda3\Lib\site-packages\keras\src\layers\core\dense.py:87: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(activity_regularizer=activity_regularizer,
**kwargs)

# Compile the model
model.compile(loss='binary_crossentropy', optimizer='adam',
metrics=['accuracy'])

# Train the model
history = model.fit(X, y, epochs=100, batch_size=4, verbose=1)

Epoch 1/100
1/1 _____ 2s 2s/step - accuracy: 0.5000 - loss: 0.7780
Epoch 2/100
1/1 _____ 0s 144ms/step - accuracy: 0.5000 - loss:
0.7764
Epoch 3/100
1/1 _____ 0s 45ms/step - accuracy: 0.5000 - loss:
0.7749
Epoch 4/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7735
Epoch 5/100
1/1 _____ 0s 54ms/step - accuracy: 0.5000 - loss:
0.7720
Epoch 6/100
1/1 _____ 0s 88ms/step - accuracy: 0.5000 - loss:
0.7706
Epoch 7/100
1/1 _____ 0s 64ms/step - accuracy: 0.5000 - loss:

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0.7692
Epoch 8/100
1/1 _____ 0s 67ms/step - accuracy: 0.5000 - loss:
0.7677
Epoch 9/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.7663
Epoch 10/100
1/1 _____ 0s 68ms/step - accuracy: 0.5000 - loss:
0.7649
Epoch 11/100
1/1 _____ 0s 62ms/step - accuracy: 0.5000 - loss:
0.7634
Epoch 12/100
1/1 _____ 0s 55ms/step - accuracy: 0.5000 - loss:
0.7620
Epoch 13/100
1/1 _____ 0s 52ms/step - accuracy: 0.5000 - loss:
0.7606
Epoch 14/100
1/1 _____ 0s 57ms/step - accuracy: 0.5000 - loss:
0.7592
Epoch 15/100
1/1 _____ 0s 53ms/step - accuracy: 0.5000 - loss:
0.7578
Epoch 16/100
1/1 _____ 0s 57ms/step - accuracy: 0.5000 - loss:
0.7564
Epoch 17/100
1/1 _____ 0s 73ms/step - accuracy: 0.5000 - loss:
0.7550
Epoch 18/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.7536
Epoch 19/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7522
Epoch 20/100
1/1 _____ 0s 53ms/step - accuracy: 0.5000 - loss:
0.7508
Epoch 21/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7494
Epoch 22/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7480
Epoch 23/100
1/1 _____ 0s 50ms/step - accuracy: 0.5000 - loss:
0.7467
```

Epoch 24/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7453

Epoch 25/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7439

Epoch 26/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7426

Epoch 27/100
1/1 _____ 0s 64ms/step - accuracy: 0.5000 - loss:
0.7412

Epoch 28/100
1/1 _____ 0s 72ms/step - accuracy: 0.5000 - loss:
0.7399

Epoch 29/100
1/1 _____ 0s 72ms/step - accuracy: 0.5000 - loss:
0.7386

Epoch 30/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7372

Epoch 31/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7359

Epoch 32/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7346

Epoch 33/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.7333

Epoch 34/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.7320

Epoch 35/100
1/1 _____ 0s 57ms/step - accuracy: 0.5000 - loss:
0.7307

Epoch 36/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.7294

Epoch 37/100
1/1 _____ 0s 88ms/step - accuracy: 0.5000 - loss:
0.7281

Epoch 38/100
1/1 _____ 0s 50ms/step - accuracy: 0.5000 - loss:
0.7268

Epoch 39/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7255

Epoch 40/100

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1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.7242
Epoch 41/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.7230
Epoch 42/100
1/1 _____ 0s 43ms/step - accuracy: 0.5000 - loss:
0.7217
Epoch 43/100
1/1 _____ 0s 50ms/step - accuracy: 0.5000 - loss:
0.7204
Epoch 44/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.7192
Epoch 45/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.7179
Epoch 46/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.7167
Epoch 47/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.7155
Epoch 48/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.7142
Epoch 49/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7130
Epoch 50/100
1/1 _____ 0s 53ms/step - accuracy: 0.5000 - loss:
0.7118
Epoch 51/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.7106
Epoch 52/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.7094
Epoch 53/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.7082
Epoch 54/100
1/1 _____ 0s 41ms/step - accuracy: 0.5000 - loss:
0.7070
Epoch 55/100
1/1 _____ 0s 58ms/step - accuracy: 0.5000 - loss:
0.7058
Epoch 56/100
1/1 _____ 0s 57ms/step - accuracy: 0.5000 - loss:
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0.7046
Epoch 57/100
1/1 _____ 0s 96ms/step - accuracy: 0.5000 - loss:
0.7034
Epoch 58/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7022
Epoch 59/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.7010
Epoch 60/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6999
Epoch 61/100
1/1 _____ 0s 72ms/step - accuracy: 0.5000 - loss:
0.6987
Epoch 62/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6976
Epoch 63/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.6964
Epoch 64/100
1/1 _____ 0s 45ms/step - accuracy: 0.5000 - loss:
0.6953
Epoch 65/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.6941
Epoch 66/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.6930
Epoch 67/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.6918
Epoch 68/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.6907
Epoch 69/100
1/1 _____ 0s 50ms/step - accuracy: 0.5000 - loss:
0.6896
Epoch 70/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.6885
Epoch 71/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.6874
Epoch 72/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.6862
```

Epoch 73/100
1/1 _____ 0s 50ms/step - accuracy: 0.5000 - loss:
0.6851

Epoch 74/100
1/1 _____ 0s 55ms/step - accuracy: 0.5000 - loss:
0.6840

Epoch 75/100
1/1 _____ 0s 40ms/step - accuracy: 0.5000 - loss:
0.6829

Epoch 76/100
1/1 _____ 0s 72ms/step - accuracy: 0.5000 - loss:
0.6819

Epoch 77/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.6808

Epoch 78/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6797

Epoch 79/100
1/1 _____ 0s 80ms/step - accuracy: 0.5000 - loss:
0.6786

Epoch 80/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6775

Epoch 81/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6765

Epoch 82/100
1/1 _____ 0s 72ms/step - accuracy: 0.5000 - loss:
0.6754

Epoch 83/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6744

Epoch 84/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6733

Epoch 85/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6722

Epoch 86/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6712

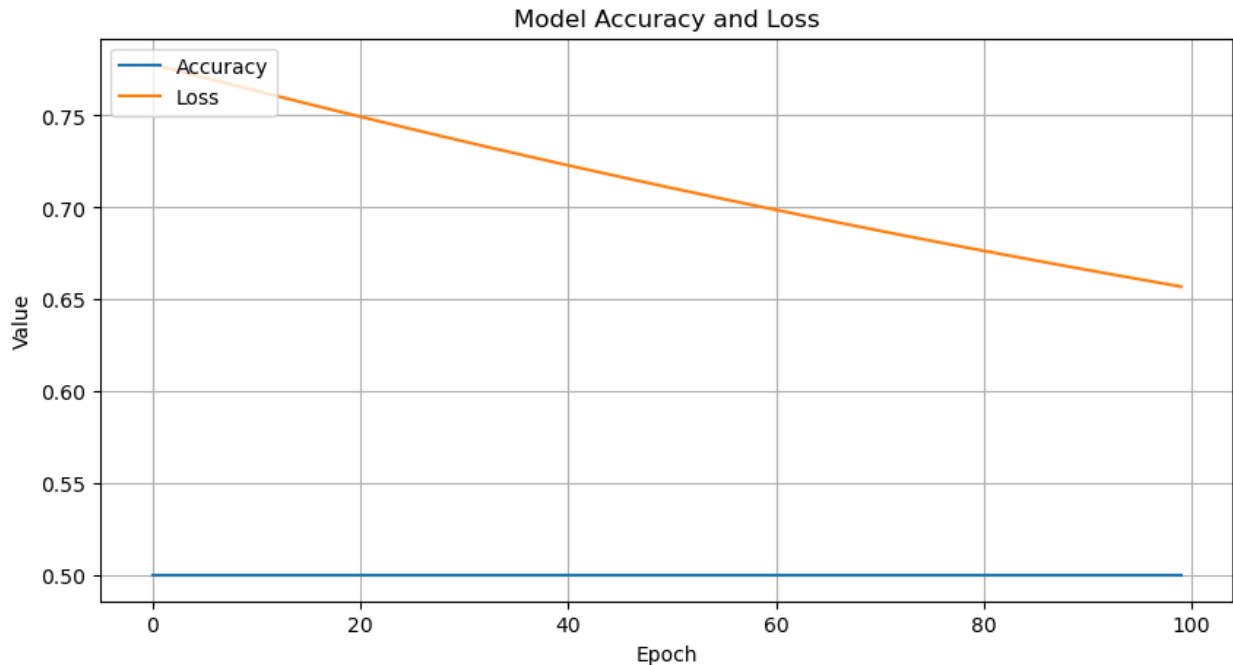
Epoch 87/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6702

Epoch 88/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6691

Epoch 89/100

```
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6681
Epoch 90/100
1/1 _____ 0s 57ms/step - accuracy: 0.5000 - loss:
0.6671
Epoch 91/100
1/1 _____ 0s 62ms/step - accuracy: 0.5000 - loss:
0.6660
Epoch 92/100
1/1 _____ 0s 64ms/step - accuracy: 0.5000 - loss:
0.6650
Epoch 93/100
1/1 _____ 0s 74ms/step - accuracy: 0.5000 - loss:
0.6640
Epoch 94/100
1/1 _____ 0s 64ms/step - accuracy: 0.5000 - loss:
0.6630
Epoch 95/100
1/1 _____ 0s 56ms/step - accuracy: 0.5000 - loss:
0.6620
Epoch 96/100
1/1 _____ 0s 57ms/step - accuracy: 0.5000 - loss:
0.6610
Epoch 97/100
1/1 _____ 0s 57ms/step - accuracy: 0.5000 - loss:
0.6600
Epoch 98/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6590
Epoch 99/100
1/1 _____ 0s 49ms/step - accuracy: 0.5000 - loss:
0.6580
Epoch 100/100
1/1 _____ 0s 48ms/step - accuracy: 0.5000 - loss:
0.6570
```

```
# Plot the training history
plt.figure(figsize=(10, 5))
plt.plot(history.history['accuracy'], label='Accuracy')
plt.plot(history.history['loss'], label='Loss')
plt.title('Model Accuracy and Loss')
plt.xlabel('Epoch')
plt.ylabel('Value')
plt.legend(['Accuracy', 'Loss'], loc='upper left')
plt.grid(True)
plt.show()
```



```
# Evaluate the model
loss, accuracy = model.evaluate(X, y, verbose=0)
print(f'Loss: {loss:.4f}, Accuracy: {accuracy:.4f}')

Loss: 0.6560, Accuracy: 0.5000

predictions = model.predict(X)
print("Predictions on training data:")
print(predictions)

1/1 _____ 0s 100ms/step
Predictions on training data:
[[0.45468077]
 [0.5600624 ]
 [0.5748106 ]
 [0.7108084 ]]

# Convert predictions to binary (0 or 1)
binary_predictions = (predictions > 0.5).astype(int)
print("Binary Predictions on training data:")
print(binary_predictions)

Binary Predictions on training data:
[[0]
 [1]
 [1]
 [1]]

# Make a prediction for a specific input [0, 1]
single_prediction = model.predict(np.array([[0, 1]]))
```



```
binary_single_prediction = int(single_prediction > 0.5)
print(f"Prediction for input [0, 1]: {single_prediction[0][0]:.4f},  
Binary Output: {binary_single_prediction}")
```

```
1/1 ————— 0s 96ms/step  
Prediction for input [0, 1]: 0.5601, Binary Output: 1
```

```
C:\Users\jayaraman\AppData\Local\Temp\ipykernel_9860\2550651135.py:3:  
DeprecationWarning: Conversion of an array with ndim > 0 to a scalar  
is deprecated, and will error in future. Ensure you extract a single  
element from your array before performing this operation. (Deprecated  
NumPy 1.25.)
```

```
    binary_single_prediction = int(single_prediction > 0.5)
```

```
# Plotting the decision boundary
```

```
# Generate a grid of points to evaluate the model's predictions
```

```
xx, yy = np.meshgrid(np.arange(0, 1.1, 0.01), np.arange(0, 1.1, 0.01))  
grid = np.c_[xx.ravel(), yy.ravel()]
```

```
# Predict the model's output for the grid points
```

```
pred_grid = model.predict(grid).reshape(xx.shape)
```

```
# Scatter plot of original data points
```

```
plt.figure(figsize=(10, 6))  
plt.scatter(X[:, 0], X[:, 1], c=y, cmap='viridis', s=100,  
edgecolor='k', label='Data Points')  
plt.title('AND Gate Decision Boundary')  
plt.xlabel('Input 1')  
plt.ylabel('Input 2')
```

```
# Contour plot for decision boundary
```

```
plt.contourf(xx, yy, pred_grid, levels=[0, 0.5, 1], alpha=0.3,  
cmap='viridis')  
plt.colorbar(label='Model Output Probability')  
plt.legend(loc='upper left')  
plt.show()
```

```
379/379 ————— 1s 2ms/step
```

