Task 1

Implement the OR Boolean logic gate using perceptron Neural Network. Inputs = x1, x2 and bias, weights should be fed into the perceptron with single Output = y. Display final weights and bias of each perceptron.

In [80]:
```
import numpy as np
import tensorflow as tf
```

In [51]:
```
X = np.array([
    [0, 0],
    [0, 1],
    [1, 0],
    [1, 1]
])
y = np.array([0, 1, 1, 1])
w1 = 1
w2 = 1
b = 0
```

In [52]:
```
def step(z):
    return 1 if z>=1 else 0
```

In [53]:
```
for i in range(X.shape[0]):
    z = w1*X[i][0] + w2*X[i][1] + b
    print(f"Input: {X[i]} → Output:", step(z))
```

```
Input: [0 0] → Output: 0
Input: [0 1] → Output: 1
Input: [1 0] → Output: 1
Input: [1 1] → Output: 1
```

Using the updating weights and bias approach:

In [54]:
```
w = np.random.rand(2)
b = np.random.rand(1)

epochs = 5
learning_rate = 0.1

for epoch in range(epochs):
    for i in range(X.shape[0]):
        z = np.dot(w, X[i]) + b
        y_pred = step(z)
        error = y[i] - y_pred
        w += learning_rate * error * X[i]
        b += learning_rate * error

print("Trained weights:", w)
print("Trained bias:", b)
```

```
Trained weights: [0.46398638 0.64831232]
Trained bias: [0.56438044]
```

In [55]:
```
print("\nPredictions:")
for i in range(len(X)):
    z = np.dot(w, X[i]) + b
    print(f"Input: {X[i]} → Output:", step(z))
```

```
Predictions:
Input: [0 0] → Output: 0
Input: [0 1] → Output: 1
Input: [1 0] → Output: 1
Input: [1 1] → Output: 1
```

Task 2

- Use the iris dataset Encode the input and show the new representation
- Decode the lossy representation for the output
- Map the input to reconstruction and visualize

In [56]:
```
from sklearn.datasets import load_iris
```

In [57]:
```
iris =load_iris()
```

In [58]:
```
data = iris.data
```

In [59]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
data = scaler.fit_transform(data)
```

In [60]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Input
```

In [61]:
```
autoencoder = Sequential([
    Input(shape = (4,)),
    Dense(2, activation='relu'),
    Dense(4, activation='sigmoid')
])
```

In [62]:
```
autoencoder.compile(optimizer='adam', loss='mse')
```

In [63]:
```
autoencoder.summary()
```

Model: "sequential_4"

Layer (type)	Output Shape	Param #
dense_4 (Dense)	(None, 2)	10
dense_5 (Dense)	(None, 4)	12

Total params: 22 (88.00 B)

Trainable params: 22 (88.00 B)

Non-trainable params: 0 (0.00 B)

In [64]:

```
autoencoder.fit(data, data, epochs=50, batch_size=8, shuffle=True)
```

```
Epoch 1/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9844
Epoch 2/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9777
Epoch 3/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9709
Epoch 4/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9649
Epoch 5/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9589
Epoch 6/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9533
Epoch 7/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9480
Epoch 8/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9428
Epoch 9/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9379
Epoch 10/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9328
Epoch 11/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9281
Epoch 12/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9233
Epoch 13/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9185
Epoch 14/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9135
Epoch 15/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9086
Epoch 16/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.9035
Epoch 17/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8981
Epoch 18/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8929
Epoch 19/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8872
Epoch 20/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8816
Epoch 21/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8758
Epoch 22/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8701
Epoch 23/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8641
Epoch 24/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8582
Epoch 25/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 975us/step - loss:
0.8522
Epoch 26/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8460
Epoch 27/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8399
Epoch 28/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8338
Epoch 29/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8275
Epoch 30/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8213
Epoch 31/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8150
Epoch 32/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8089
Epoch 33/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.8027
```

```
Epoch 34/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7966
Epoch 35/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7907
Epoch 36/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7853
Epoch 37/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7797
Epoch 38/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7746
Epoch 39/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7699
Epoch 40/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7654
Epoch 41/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7614
Epoch 42/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7574
Epoch 43/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7537
Epoch 44/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7503
Epoch 45/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7470
Epoch 46/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7441
Epoch 47/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 992us/step - loss:
0.7414
Epoch 48/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7385
Epoch 49/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7361
Epoch 50/50
[1m19/19[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 1ms/step - loss: 0.7337
```

Out[64]:
```
<keras.src.callbacks.history.History at 0x2f4c7be51f0>
```

In [66]:
```python
encoder = Sequential([
    autoencoder.layers[0]
])

encoded_data = encoder.predict(data)

print("Encoded (Lossy) Representation - First 5 Samples:\n")
print(encoded_data[:5])
```

```
[1m5/5[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 5ms/step
Encoded (Lossy) Representation - First 5 Samples:

[[5.126318  0.       ]
 [5.3782887 0.       ]
 [5.74848   0.       ]
 [5.7439027 0.       ]
 [5.2762113 0.       ]]
```

In [67]:
```python
decoded_data = autoencoder.predict(data)

# Convert back to original scale
decoded_original = scaler.inverse_transform(decoded_data)
```

```
[1m5/5[0m [32m━━━━━━━━━━━━━━━━━━━━[0m[37m[0m [1m0s[0m 6ms/step
```

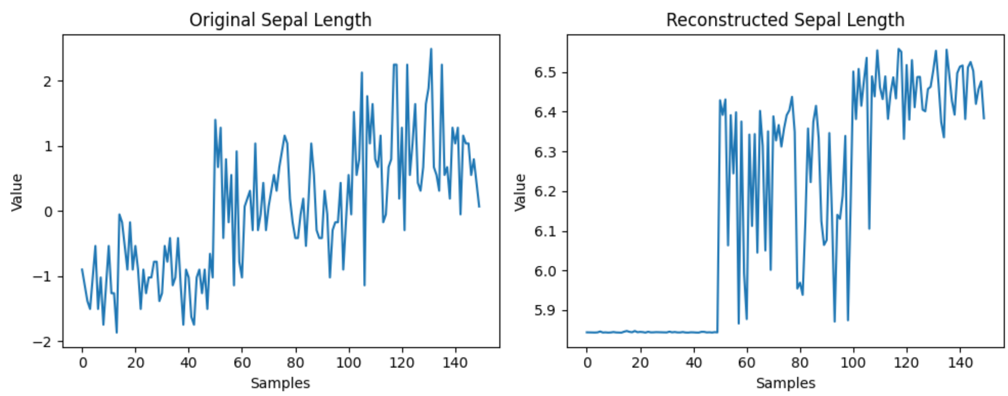
In [69]:

```
import matplotlib.pyplot as plt
plt.figure(figsize=(10,4))

# Original Sepal Length
plt.subplot(1,2,1)
plt.title("Original Sepal Length")
plt.plot(data[:, 0])
plt.xlabel("Samples")
plt.ylabel("Value")

# Reconstructed Sepal Length
plt.subplot(1,2,2)
plt.title("Reconstructed Sepal Length")
plt.plot(decoded_original[:, 0])
plt.xlabel("Samples")
plt.ylabel("Value")

plt.tight_layout()
plt.show()
```



In [76]:

```
import numpy as np

def mean_squared_error(original, reconstructed):
    return np.mean((original - reconstructed) ** 2)
```

In [77]:

```
for i in range(data.shape[1]):
    mse = mean_squared_error(data[:, i], decoded_data[:, i])
    print(f"MSE for feature {i+1}: {mse}")
```

```
MSE for feature 1: 0.6729832965435186
MSE for feature 2: 0.9959780458365102
MSE for feature 3: 0.6365716894583316
MSE for feature 4: 0.6239168277227577
```