```
import numpy as np
import matplotlib.pyplot as plt
```

```
def logistic_function(x):
  """
  Computes the logistic function applied to any value of x.
  Arguments:
  x: scalar or numpy array of any size.
  Returns:
  y: logistic function applied to x.
  """
  import numpy as np
  y = 1 / (1 + np.exp(-x))
  return y
```

```
import numpy as np
def test_logistic_function():
  """
  Test cases for the logistic_function.
  """
  # Test with scalar input
  x_scalar = 0
  expected_output_scalar = round(1 / (1 + np.exp(0)), 3) # Expected output: 0.5
  assert round(logistic_function(x_scalar), 3) == expected_output_scalar, "Test 
  # Test with positive scalar input
  x_pos = 2
  expected_output_pos = round(1 / (1 + np.exp(-2)), 3) # Expected output: ~0.881
  assert round(logistic_function(x_pos), 3) == expected_output_pos, "Test failed
  # Test with negative scalar input
  x_neg = -3
  expected_output_neg = round(1 / (1 + np.exp(3)), 3) # Expected output: ~0.047
  assert round(logistic_function(x_neg), 3) == expected_output_neg, "Test failed
  # Test with numpy array input
  x_array = np.array([0, 2, -3])
  expected_output_array = np.array([0.5, 0.881, 0.047]) # Adjusted expected valu
  # Use np.round to round the array element-wise and compare
  assert np.all(np.round(logistic_function(x_array), 3) == expected_output_array
  print("All tests passed!")
  # Run the test case
test_logistic_function()
```

```
All tests passed!
```

```
def log_loss(y_true, y_pred):
  """
  Computes log loss for true target value y ={0 or 1} and predicted target valu
  Arguments:
```

```
    y_true (scalar): true target value {0 or 1}.
    y_pred (scalar): predicted taget value {0-1}.
    Returns:
    loss (float): loss/error value
    """
    import numpy as np

    # Ensure y_pred is clipped to avoid log(0)
    y_pred = np.clip(y_pred, 1e-10, 1 - 1e-10)
    loss = -(y_true * np.log(y_pred) + (1 - y_true) * np.log(1 - y_pred))
    return loss
```

```
y_true, y_pred = 0, 0.1
print(f'log loss({y_true}, {y_pred}) ==> {log_loss(y_true, y_pred)}')
print("++++++++++++--------------------------------------------++++++++++++++++++++++++")
y_true, y_pred = 1, 0.9
print(f'log loss({y_true}, {y_pred}) ==> {log_loss(y_true, y_pred)}')
```

```
log loss(0, 0.1) ==> 0.10536051565782628
++++++++++++--------------------------------------------++++++++++++++++++++++++
log loss(1, 0.9) ==> 0.10536051565782628
```

```
def test_log_loss():
  """
  Test cases for the log_loss function.
  """
  import numpy as np
  # Test case 1: Perfect prediction (y_true = 1, y_pred = 1)
  y_true = 1
  y_pred = 1
  expected_loss = 0.0 # Log loss is 0 for perfect prediction
  assert np.isclose(log_loss(y_true, y_pred), expected_loss), "Test failed for
  # Test case 2: Perfect prediction (y_true = 0, y_pred = 0)
  y_true = 0
  y_pred = 0
  expected_loss = 0.0 # Log loss is 0 for perfect prediction
  assert np.isclose(log_loss(y_true, y_pred), expected_loss), "Test failed for
  # Test case 3: Incorrect prediction (y_true = 1, y_pred = 0)
  y_true = 1
  y_pred = 0
  try:
    log_loss(y_true, y_pred) # This should raise an error due to log(0)
  except ValueError:
    pass # Test passed if ValueError is raised for log(0)
  # Test case 4: Incorrect prediction (y_true = 0, y_pred = 1)
  y_true = 0
  y_pred = 1
  try:
    log_loss(y_true, y_pred) # This should raise an error due to log(0)
  except ValueError:
```

```
      pass # Test passed if ValueError is raised for log(0)
    # Test case 5: Partially correct prediction
    y_true = 1
    y_pred = 0.8
    expected_loss = -(1 * np.log(0.8)) - (0 * np.log(0.2)) # ~0.2231
    assert np.isclose(log_loss(y_true, y_pred), expected_loss, atol=1e-6), "Test
    y_true = 0
    y_pred = 0.2
    expected_loss = -(0 * np.log(0.2)) - (1 * np.log(0.8)) # ~0.2231
    assert np.isclose(log_loss(y_true, y_pred), expected_loss, atol=1e-6), "Test
    print("All tests passed!")
  # Run the test case
  test_log_loss()
```

```
All tests passed!
```

```
def cost_function(y_true, y_pred):
  """
  Computes log loss for inputs true value (0 or 1) and predicted value (betweer
  Args:
  y_true (array_like, shape (n,)): array of true values (0 or 1)
  y_pred (array_like, shape (n,)): array of predicted values (probability of y_
  Returns:
  cost (float): nonnegative cost corresponding to y_true and y_pred
  """
  assert len(y_true) == len(y_pred), "Length of true values and length of predi
  n = len(y_true)

  loss_vec = -(y_true * np.log(y_pred) + (1 - y_true) * np.log(1 - y_pred))
  cost =  np.mean(loss_vec)
  return cost
```

```
import numpy as np
def test_cost_function():
  # Test case 1: Simple example with known expected cost
  y_true = np.array([1, 0, 1])
  y_pred = np.array([0.9, 0.1, 0.8])
  # Expected output: Manually calculate cost for these values
  # log_loss(y_true, y_pred) for each example
  expected_cost = (-(1 * np.log(0.9)) - (1 - 1) * np.log(1 - 0.9) +
  -(0 * np.log(0.1)) - (1 - 0) * np.log(1 - 0.1) +
  -(1 * np.log(0.8)) - (1 - 1) * np.log(1 - 0.8)) / 3

  # Call the cost_function to get the result
  result = cost_function(y_true, y_pred)
  # Assert that the result is close to the expected cost with a tolerance of 1e
  assert np.isclose(result, expected_cost, atol=1e-6), f"Test failed: {result}
  print("Test passed for simple case!")
```

```
# Run the test case
test_cost_function()
```

```
Test passed for simple case!
```

```
# Function to compute cost function in terms of model parameters - using vector
def costfunction_logreg(X, y, w, b):
  """
  Computes the cost function, given data and model parameters.
  Args:
  X (ndarray, shape (m,n)): data on features, m observations with n features.
  y (array_like, shape (m,)): array of true values of target (0 or 1).
  w (array_like, shape (n,)): weight parameters of the model.
  b (float): bias parameter of the model.
  Returns:
  cost (float): nonnegative cost corresponding to y and y_pred.
  """
  n, d = X.shape
  assert len(y) == n, "Number of feature observations and number of target obse
  assert len(w) == d, "Number of features and number of weight parameters do nc
  # Compute z using np.dot
  z = np.dot(X, w) + b # Matrix-vector multiplication and adding bias
  # Compute predictions using logistic function (sigmoid)
  y_pred = 1 / (1 + np.exp(-z))
  # Compute the cost using the cost function
  cost = cost_function(y, y_pred)
  return cost
```

```
# Testing the Function:
X, y, w, b = np.array([[10, 20], [-10, 10]]), np.array([1, 0]), np.array([0.5,
print(f"cost for logistic regression(X = {X}, y = {y}, w = {w}, b = {b}) = {cos
```

```
cost for logistic regression(X = [[ 10  20]
 [-10  10]], y = [1 0], w = [0.5 1.5], b = 1) = 5.500008350784906
```

```
def compute_gradient(X, y, w, b):
  """
  Computes gradients of the cost function with respect to model parameters.
  Args:
  X (ndarray, shape (n,d)): Input data, n observations with d features
  y (array_like, shape (n,)): True labels (0 or 1)
  w (array_like, shape (d,)): Weight parameters of the model
  b (float): Bias parameter of the model
  Returns:
  grad_w (array_like, shape (d,)): Gradients of the cost function with respect
  parameters
  grad_b (float): Gradient of the cost function with respect to the bias parame
  """
  n, d = X.shape # X has shape (n, d)
  assert len(y) == n, f"Expected y to have {n} elements, but got {len(y)}"
```

```
  assert len(w) == d, f"Expected w to have {d} elements, but got {len(w)}"
  # Compute predictions using logistic function (sigmoid)
  z = np.dot(X, w) + b  # Compute z = X * w + b
  y_pred = 1 / (1 + np.exp(-z))
  # Compute gradients
  error = y_pred - y
  grad_w = (1/n) * np.dot(X.T, error)  # Gradient w.r.t weights, shape (d,)
  grad_b = (1/n) * np.sum(error) # Gradient w.r.t bias, scalar
  return grad_w, grad_b
```

```
# Simple test case
X = np.array([[10, 20], [-10, 10]]) # shape (2, 2)
y = np.array([1, 0]) # shape (2,)
w = np.array([0.5, 1.5]) # shape (2,)
b = 1 # scalar
# Assertion tests
try:
  grad_w, grad_b = compute_gradient(X, y, w, b)
  print("Gradients computed successfully.")
  print(f"grad_w: {grad_w}")
  print(f"grad_b: {grad_b}")
except AssertionError as e:
  print(f"Assertion error: {e}")
```

```
Gradients computed successfully.
grad_w: [-4.99991649  4.99991649]
grad_b: 0.4999916492890759
```

```
def gradient_descent(X, y, w, b, alpha, n_iter, show_cost=False, show_params=Tru
  """
  Implements batch gradient descent to optimize logistic regression parameters.
  Args:
  X (ndarray, shape (n,d)): Data on features, n observations with d features
  y (array_like, shape (n,)): True values of target (0 or 1)
  w (array_like, shape (d,)): Initial weight parameters
  b (float): Initial bias parameter
  alpha (float): Learning rate
  n_iter (int): Number of iterations
  show_cost (bool): If True, displays cost every 100 iterations
  show_params (bool): If True, displays parameters every 100 iterations
  Returns:
  w (array_like, shape (d,)): Optimized weight parameters
  b (float): Optimized bias parameter
  cost_history (list): List of cost values over iterations
  params_history (list): List of parameters (w, b) over iterations
  """
  n, d = X.shape
  assert len(y) == n, "Number of observations in X and y do not match"
  assert len(w) == d, "Number of features in X and w do not match"
  cost_history = []
  params_history = []
```

```
  for i in range(n_iter):
    # Compute gradients
    grad_w, grad_b = compute_gradient(X, y, w, b)
    # Update weights and bias
    w -= alpha * grad_w
    b -= alpha * grad_b
    # Compute cost
    cost = costfunction_logreg(X, y, w, b)
    # Store cost and parameters
    cost_history.append(cost)
    params_history.append((w.copy(), b))
  # Optionally print cost and parameters
  if show_cost and (i % 100 == 0 or i == n_iter - 1):
    print(f"Iteration {i}: Cost = {cost:.6f}")
  if show_params and (i % 100 == 0 or i == n_iter - 1):
    print(f"Iteration {i}: w = {w}, b = {b:.6f}")

  return w, b, cost_history, params_history
```

```
# Test the gradient_descent function with sample data
X = np.array([[0.1, 0.2], [-0.1, 0.1]]) # Shape (2, 2)
y = np.array([1, 0]) # Shape (2,)
w = np.zeros(X.shape[1]) # Shape (2,) - same as number of features
b = 0.0 # Scalar
alpha = 0.1 # Learning rate
n_iter = 100000 # Number of iterations
# Perform gradient descent
w_out, b_out, cost_history, params_history = gradient_descent(X, y, w, b, alpha,
show_params=False)
# Print final parameters and cost
print("\nFinal parameters:")
print(f"w: {w_out}, b: {b_out}")
print(f"Final cost: {cost_history[-1]:.6f}")
```

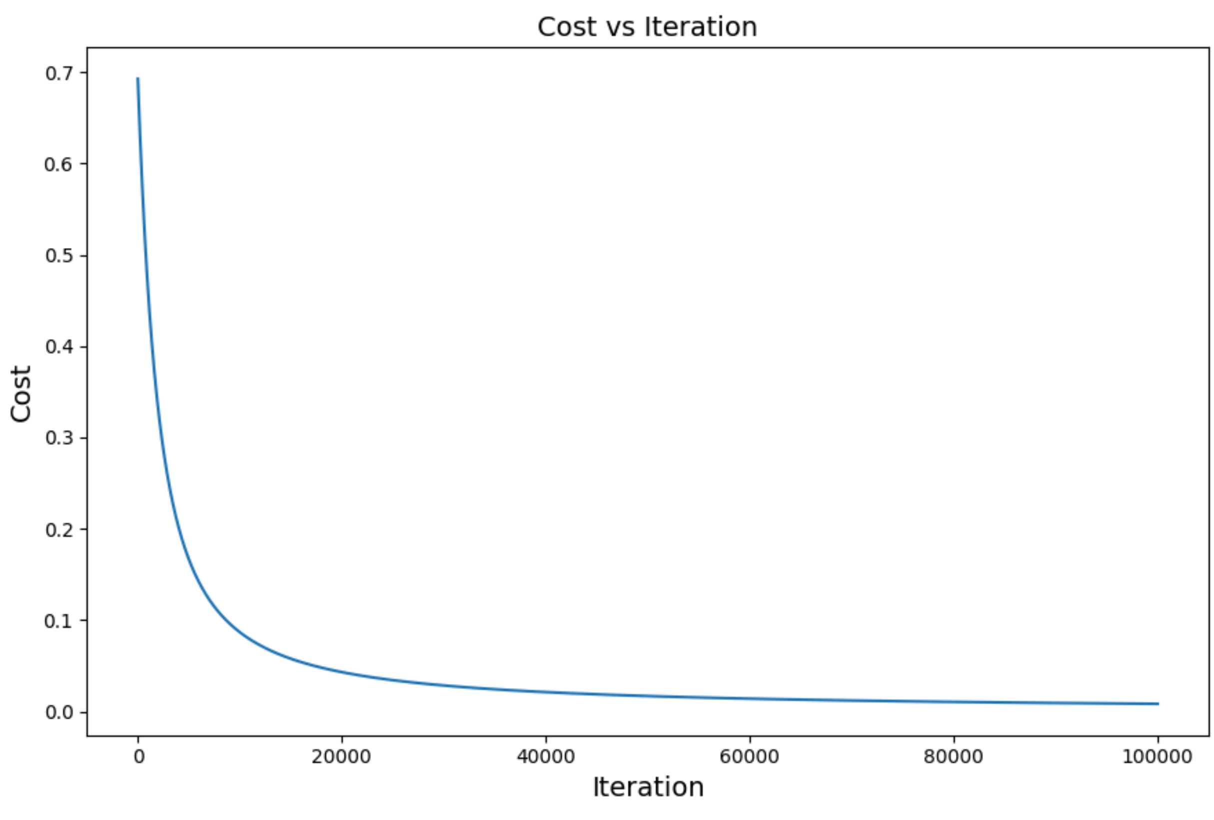
```
Iteration 99999: Cost = 0.008254

Final parameters:
w: [38.51304248 18.83386869], b: -2.8176836626325836
Final cost: 0.008254
```

```
# Simple assertion test for gradient_descent
def test_gradient_descent():
  X = np.array([[0.1, 0.2], [-0.1, 0.1]]) # Shape (2, 2)
  y = np.array([1, 0]) # Shape (2,)
  w = np.zeros(X.shape[1]) # Shape (2,)
  b = 0.0 # Scalar
  alpha = 0.1 # Learning rate
  n_iter = 100 # Number of iterations
  # Run gradient descent
  w_out, b_out, cost_history, _ = gradient_descent(X, y, w, b, alpha, n_iter, s
```

```
    show_params=False)
    # Assertions
    assert len(cost_history) == n_iter, "Cost history length does not match the r
    assert w_out.shape == w.shape, "Shape of output weights does not match the ir
    assert isinstance(b_out, float), "Bias output is not a float"
    assert cost_history[-1] < cost_history[0], "Cost did not decrease over iterat
    print("All tests passed!")
# Run the test
test_gradient_descent()
```

```
All tests passed!
```

```
# Plotting cost over iteration
plt.figure(figsize = (9, 6))
plt.plot(cost_history)
plt.xlabel("Iteration", fontsize = 14)
plt.ylabel("Cost", fontsize = 14)
plt.title("Cost vs Iteration", fontsize = 14)
plt.tight_layout()
plt.show()
```




```
import numpy as np
def prediction(X, w, b, threshold=0.5):
    """
    Predicts binary outcomes for given input features based on logistic regressic
    Arguments:
```

```
    X (ndarray, shape (n,d)): Array of test independent variables (features) with
    features.
    w (ndarray, shape (d,)): Array of weights learned via gradient descent.
    b (float): Bias learned via gradient descent.
    threshold (float, optional): Classification threshold for predicting class la
    Returns:
    y_pred (ndarray, shape (n,)): Array of predicted dependent variable (binary c
    """
    # Compute the predicted probabilities using the logistic function
    # z = wx + b
    z = np.dot(X, w) + b
    y_test_prob = 1 / (1 + np.exp(-z))
    # Classify based on the threshold
    y_pred = (y_test_prob >= threshold).astype(int)
    return y_pred
```

```
def test_prediction():
    X_test = np.array([[0.5, 1.0], [1.5, -0.5], [-0.5, -1.0]]) # Shape (3, 2)
    w_test = np.array([1.0, -1.0]) # Shape (2,)
    b_test = 0.0 # Scalar bias
    threshold = 0.5 # Default threshold
    # Updated expected output
    expected_output = np.array([0, 1, 1])
    # Call the prediction function
    y_pred = prediction(X_test, w_test, b_test, threshold)
    # Assert that the output matches the expected output
    assert np.array_equal(y_pred, expected_output), f"Expected {expected_output},
    print("Test passed!")
test_prediction()
```

```
Test passed!
```

```
def evaluate_classification(y_true, y_pred):
    """
    Computes the confusion matrix, precision, recall, and F1-score for binary cla
    Arguments:
    y_true (ndarray, shape (n,)): Ground truth binary labels (0 or 1).
    y_pred (ndarray, shape (n,)): Predicted binary labels (0 or 1).
    Returns:
    metrics (dict): A dictionary containing confusion matrix, precision, recall,
    """
    # Initialize confusion matrix components
    TP = np.sum((y_true == 1) & (y_pred == 1)) # True Positives
    TN = np.sum((y_true == 0) & (y_pred == 0))  # True Negatives
    FP = np.sum((y_true == 0) & (y_pred == 1))  # False Positives
    FN = np.sum((y_true == 1) & (y_pred == 0))  # False Negatives
    # Confusion matrix
    confusion_matrix = np.array([[TN, FP],
    [FN, TP]])
    # Precision, recall, and F1-score
```

```
    precision = TP / (TP + FP) if (TP + FP) > 0.0 else 0.0
    recall =  TP / (TP + FN) if (TP + FN) > 0.0 else 0.0
    f1_score = 2 * (precision * recall) / (precision + recall)
    # Metrics dictionary
    metrics = {
    "confusion_matrix": confusion_matrix,
    "precision": precision,
    "recall": recall,
    "f1_score": f1_score
    }
    return metrics
```

```
# Load dataset
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt

url = "https://raw.githubusercontent.com/jbrownlee/Datasets/master/pima-indians
columns = ['Pregnancies', 'Glucose', 'BloodPressure', 'SkinThickness', 'Insulir
           'BMI', 'DiabetesPedigreeFunction', 'Age', 'Outcome']

data_pima_diabetes = pd.read_csv(url, names=columns)
```

```
# Data cleaning
columns_to_clean = ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BM
data_pima_diabetes[columns_to_clean] = data_pima_diabetes[columns_to_clean].rep
data_pima_diabetes.fillna(data_pima_diabetes.median(), inplace=True)
data_pima_diabetes.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    float64
 2   BloodPressure             768 non-null    float64
 3   SkinThickness             768 non-null    float64
 4   Insulin                   768 non-null    float64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(6), int64(3)
memory usage: 54.1 KB
```

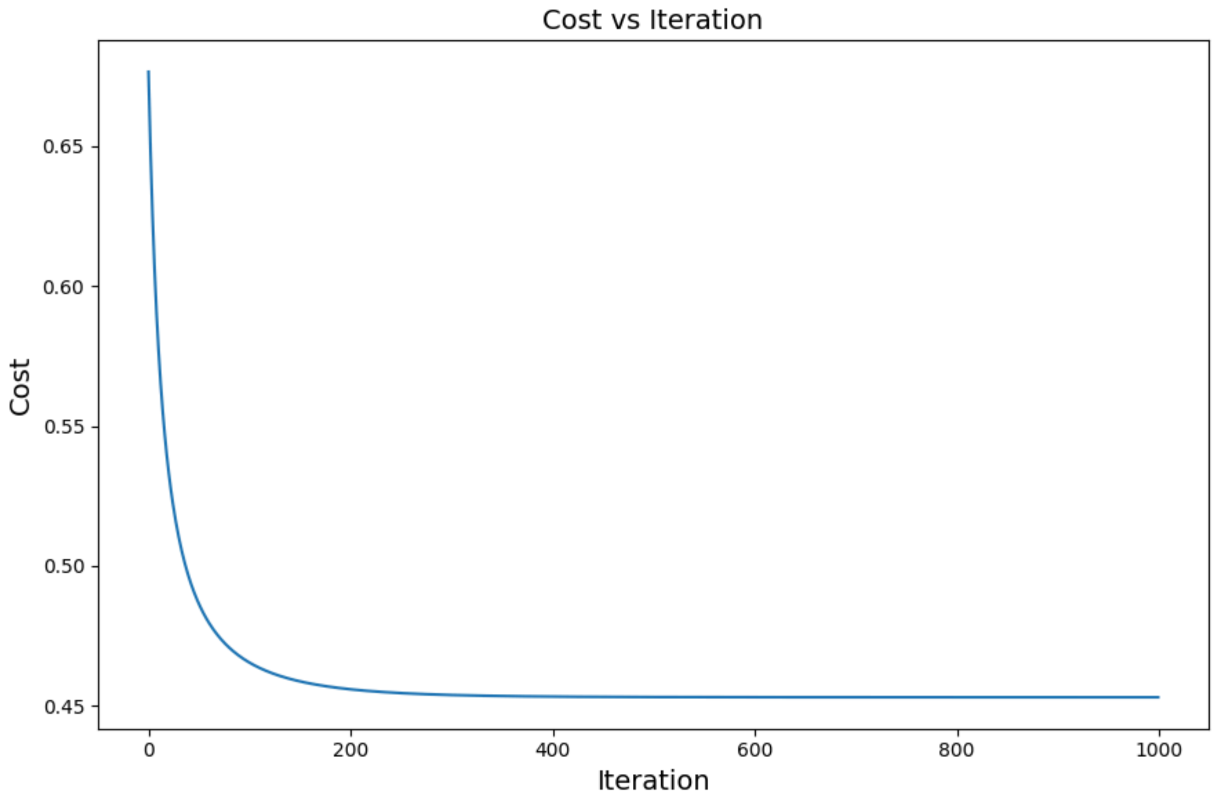
```
data_pima_diabetes.describe()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000
mean	3.845052	121.656250	72.386719	29.108073	140.671875	32.455
std	3.369578	30.438286	12.096642	8.791221	86.383060	6.875
min	0.000000	44.000000	24.000000	7.000000	14.000000	18.200
25%	1.000000	99.750000	64.000000	25.000000	121.500000	27.500
50%	3.000000	117.000000	72.000000	29.000000	125.000000	32.300
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600
max	17.000000	199.000000	122.000000	99.000000	846.000000	67.100

```
# Train-test split
X = data_pima_diabetes.drop(columns=['Outcome']).values
y = data_pima_diabetes['Outcome'].values
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random
# Standardize features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
# Initialize parameters
w = np.zeros(X_train_scaled.shape[1])
b = 0.0
alpha = 0.1
n_iter = 1000
# Train model
print("\nTraining Logistic Regression Model:")
w, b, cost_history,params_history = gradient_descent(X_train_scaled, y_train, w
show_cost=True, show_params=False)
# Plot cost history
plt.figure(figsize=(9, 6))
plt.plot(cost_history)
plt.xlabel("Iteration", fontsize=14)
plt.ylabel("Cost", fontsize=14)
plt.title("Cost vs Iteration", fontsize=14)
plt.tight_layout()
```

```
Training Logistic Regression Model:
Iteration 999: Cost = 0.453071
```




```
# Test model
y_train_pred = prediction(X_train_scaled, w, b)
y_test_pred = prediction(X_test_scaled, w, b)
# Evaluate train and test performance
train_cost = costfunction_logreg(X_train_scaled, y_train, w, b)
test_cost = costfunction_logreg(X_test_scaled, y_test, w, b)
print(f"\nTrain Loss (Cost): {train_cost:.4f}")
print(f"Test Loss (Cost): {test_cost:.4f}")
```

```
Train Loss (Cost): 0.4531
Test Loss (Cost): 0.5146
```

```
# Accuracy on test data
test_accuracy = np.mean(y_test_pred == y_test) * 100
print(f"\nTest Accuracy: {test_accuracy:.2f}%")

# Evaluation
metrics = evaluate_classification(y_test, y_test_pred)
confusion_matrix = metrics["confusion_matrix"]
precision = metrics["precision"]
recall = metrics["recall"]
f1_score = metrics["f1_score"]
```

```
print(f"\nConfusion Matrix:\n{confusion_matrix}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1_score:.4f}")

# Optional - Visualizing the Confusion Matrix
import matplotlib.pyplot as plt

fig, ax = plt.subplots(figsize=(6, 6))
ax.imshow(confusion_matrix, cmap='Blues')
ax.grid(False)
ax.xaxis.set(ticks=(0, 1), ticklabels=('Predicted 0s', 'Predicted 1s'))
ax.yaxis.set(ticks=(0, 1), ticklabels=('Actual 0s', 'Actual 1s'))
ax.set_ylim(1.5, -0.5)

# Add text annotations
for i in range(2):
    for j in range(2):
        value = confusion_matrix[i, j]
        # Choose text color based on cell value (dark or light background)
        text_color = 'white' if value > confusion_matrix.max()/2 else 'black'
        ax.text(j, i, f'{value}\n({value/len(y_test)*100:.1f}%)',
                ha='center', va='center', color=text_color, fontsize=12, fontwei

# Add title
ax.set_title('Confusion Matrix', fontsize=14, fontweight='bold', pad=20)

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

```
Test Accuracy: 70.78%

Confusion Matrix:
[[82 18]
 [27 27]]
Precision: 0.6000
Recall: 0.5000
F1-Score: 0.5455
```