1 Notebook Information

- **Name:** Azzaleah Faith G. Oxina
- **Y&S:** BSCS 3A IS
- **Course:** CSST 102 | Basic Machine Learning
- **Topic:** Topic 2: Supervised Learning Techniques
- **Due date:** N/A

2 Laboratory Exercise #2: Exercises for K-Nearest Neighbors (KNN) and Logistic Regression on Breast Cancer Diagnosis Dataset

3 Exercise 1: Data Exploration and Preprocessing

[ ]:
```
# Load necessary libraries
import pandas as pd

# Load the dataset, ensure flexibility in file path handling
df = pd.read_csv('Breast Cancer Diagnosis Dataset with Tumor Characteristics.
↪csv')

# Check column names for consistency
print("Column Names:", df.columns)

# Display the first 10 rows
print("First 10 Rows:")
print(df.head(10))

# Check for missing values
print("Missing Values per Column:")
print(df.isnull().sum())

# Descriptive statistics
print("Descriptive Statistics:")
print(df.describe())
```

```
Column Names: Index(['id', 'diagnosis', 'radius_mean', 'texture_mean',
'perimeter_mean',
       'area_mean', 'smoothness_mean', 'compactness_mean', 'concavity_mean',
       'concave points_mean', 'symmetry_mean', 'fractal_dimension_mean',
       'radius_se', 'texture_se', 'perimeter_se', 'area_se', 'smoothness_se',
       'compactness_se', 'concavity_se', 'concave points_se', 'symmetry_se',
       'fractal_dimension_se', 'radius_worst', 'texture_worst',
       'perimeter_worst', 'area_worst', 'smoothness_worst',
       'compactness_worst', 'concavity_worst', 'concave points_worst',
       'symmetry_worst', 'fractal_dimension_worst', 'Unnamed: 32'],
      dtype='object')
```

```
First 10 Rows:
         id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0    842302         M        17.99         10.38          122.80     1001.0
1    842517         M        20.57         17.77          132.90     1326.0
2  84300903         M        19.69         21.25          130.00     1203.0
3  84348301         M        11.42         20.38           77.58      386.1
4  84358402         M        20.29         14.34          135.10     1297.0
5    843786         M        12.45         15.70           82.57      477.1
6    844359         M        18.25         19.98          119.60     1040.0
7  84458202         M        13.71         20.83           90.20      577.9
8    844981         M        13.00         21.82           87.50      519.8
9  84501001         M        12.46         24.04           83.97      475.9

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0          0.11840           0.27760         0.30010              0.14710
1          0.08474           0.07864         0.08690              0.07017
2          0.10960           0.15990         0.19740              0.12790
3          0.14250           0.28390         0.24140              0.10520
4          0.10030           0.13280         0.19800              0.10430
5          0.12780           0.17000         0.15780              0.08089
6          0.09463           0.10900         0.11270              0.07400
7          0.11890           0.16450         0.09366              0.05985
8          0.12730           0.19320         0.18590              0.09353
9          0.11860           0.23960         0.22730              0.08543

   ...  texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0  ...          17.33           184.60      2019.0            0.1622
1  ...          23.41           158.80      1956.0            0.1238
2  ...          25.53           152.50      1709.0            0.1444
3  ...          26.50            98.87       567.7            0.2098
4  ...          16.67           152.20      1575.0            0.1374
5  ...          23.75           103.40       741.6            0.1791
6  ...          27.66           153.20      1606.0            0.1442
7  ...          28.14           110.60       897.0            0.1654
8  ...          30.73           106.20       739.3            0.1703
9  ...          40.68            97.65       711.4            0.1853

   compactness_worst  concavity_worst  concave points_worst  symmetry_worst  \
0             0.6656           0.7119                0.2654          0.4601
1             0.1866           0.2416                0.1860          0.2750
2             0.4245           0.4504                0.2430          0.3613
3             0.8663           0.6869                0.2575          0.6638
4             0.2050           0.4000                0.1625          0.2364
5             0.5249           0.5355                0.1741          0.3985
6             0.2576           0.3784                0.1932          0.3063
7             0.3682           0.2678                0.1556          0.3196
8             0.5401           0.5390                0.2060          0.4378
9             1.0580           1.1050                0.2210          0.4366
```

```
   fractal_dimension_worst  Unnamed: 32
0                  0.11890          NaN
1                  0.08902          NaN
2                  0.08758          NaN
3                  0.17300          NaN
4                  0.07678          NaN
5                  0.12440          NaN
6                  0.08368          NaN
7                  0.11510          NaN
8                  0.10720          NaN
9                  0.20750          NaN

[10 rows x 33 columns]
Missing Values per Column:
id                           0
diagnosis                    0
radius_mean                  0
texture_mean                 0
perimeter_mean               0
area_mean                    0
smoothness_mean              0
compactness_mean             0
concavity_mean               0
concave points_mean          0
symmetry_mean                0
fractal_dimension_mean       0
radius_se                    0
texture_se                   0
perimeter_se                 0
area_se                      0
smoothness_se                0
compactness_se               0
concavity_se                 0
concave points_se            0
symmetry_se                  0
fractal_dimension_se         0
radius_worst                 0
texture_worst                0
perimeter_worst              0
area_worst                   0
smoothness_worst             0
compactness_worst            0
concavity_worst              0
concave points_worst         0
symmetry_worst               0
fractal_dimension_worst      0
Unnamed: 32                569
```

```
dtype: int64
Descriptive Statistics:
                 id  radius_mean  texture_mean  perimeter_mean    area_mean  \
count  5.690000e+02   569.000000    569.000000      569.000000   569.000000
mean   3.037183e+07    14.127292     19.289649       91.969033   654.889104
std    1.250206e+08     3.524049      4.301036       24.298981   351.914129
min    8.670000e+03     6.981000      9.710000       43.790000   143.500000
25%    8.692180e+05    11.700000     16.170000       75.170000   420.300000
50%    9.060240e+05    13.370000     18.840000       86.240000   551.100000
75%    8.813129e+06    15.780000     21.800000      104.100000   782.700000
max    9.113205e+08    28.110000     39.280000      188.500000  2501.000000

       smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
count       569.000000        569.000000      569.000000           569.000000
mean          0.096360          0.104341        0.088799             0.048919
std           0.014064          0.052813        0.079720             0.038803
min           0.052630          0.019380        0.000000             0.000000
25%           0.086370          0.064920        0.029560             0.020310
50%           0.095870          0.092630        0.061540             0.033500
75%           0.105300          0.130400        0.130700             0.074000
max           0.163400          0.345400        0.426800             0.201200

       symmetry_mean  ...  texture_worst  perimeter_worst   area_worst  \
count     569.000000  ...     569.000000       569.000000   569.000000
mean        0.181162  ...      25.677223       107.261213   880.583128
std         0.027414  ...       6.146258        33.602542   569.356993
min         0.106000  ...      12.020000        50.410000   185.200000
25%         0.161900  ...      21.080000        84.110000   515.300000
50%         0.179200  ...      25.410000        97.660000   686.500000
75%         0.195700  ...      29.720000       125.400000  1084.000000
max         0.304000  ...      49.540000       251.200000  4254.000000

       smoothness_worst  compactness_worst  concavity_worst  \
count        569.000000         569.000000       569.000000
mean           0.132369           0.254265         0.272188
std            0.022832           0.157336         0.208624
min            0.071170           0.027290         0.000000
25%            0.116600           0.147200         0.114500
50%            0.131300           0.211900         0.226700
75%            0.146000           0.339100         0.382900
max            0.222600           1.058000         1.252000

       concave points_worst  symmetry_worst  fractal_dimension_worst  \
count            569.000000      569.000000               569.000000
mean               0.114606        0.290076                 0.083946
std                0.065732        0.061867                 0.018061
min                0.000000        0.156500                 0.055040
25%                0.064930        0.250400                 0.071460
```

```
50%                 0.099930        0.282200                  0.080040
75%                 0.161400        0.317900                  0.092080
max                 0.291000        0.663800                  0.207500

       Unnamed: 32
count          0.0
mean           NaN
std            NaN
min            NaN
25%            NaN
50%            NaN
75%            NaN
max            NaN

[8 rows x 32 columns]
```

[ ]:
```python
#@title ## **Task: Summarize the Dataset:**

# Number of instances and features
print(f'Number of Instances: {df.shape[0]}')
print(f'Number of Features: {df.shape[1]}')

# Breakdown of target variable (diagnosis)
print("Diagnosis Breakdown (M = Malignant, B = Benign):")
print(df['diagnosis'].value_counts())

# Display missing values for further action
missing_values = df.isnull().sum()
print("Missing Values:")
print(missing_values[missing_values > 0])
```

```
Number of Instances: 569
Number of Features: 33
Diagnosis Breakdown (M = Malignant, B = Benign):
diagnosis
B    357
M    212
Name: count, dtype: int64
Missing Values:
Unnamed: 32    569
dtype: int64
```

[ ]:
```python
#@title ## **3. Preprocessing:**

from sklearn.preprocessing import StandardScaler

# Drop irrelevant columns
if 'id' in df.columns:
```

```
    df = df.drop(columns=['id'])
if 'Unnamed: 32' in df.columns:
    df = df.drop(columns=['Unnamed: 32'])

# Convert Diagnosis column to binary (M -> 1, B -> 0)
df['diagnosis'] = df['diagnosis'].map({'M': 1, 'B': 0})

# Check for any missing values before scaling
missing_values = df.isnull().sum()
if missing_values.any():
    print("There are still missing values. Consider handling them before scaling.
 ↪")
else:
    # Normalize features
    scaler = StandardScaler()
    features = df.drop(columns=['diagnosis'])
    scaled_features = scaler.fit_transform(features)
```

[ ]:
```
#@title ## **4. Train-Test Split:**

from sklearn.model_selection import train_test_split

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(
    scaled_features, df['diagnosis'],
    test_size=0.2, random_state=42, stratify=df['diagnosis'])

# Print the sizes of training and testing sets
print(f'Training Set Size: {X_train.shape[0]} samples')
print(f'Testing Set Size: {X_test.shape[0]} samples')
```

```
Training Set Size: 455 samples
Testing Set Size: 114 samples
```

4 Exercise 2: Implementing K-Nearest Neighbors (KNN) Model

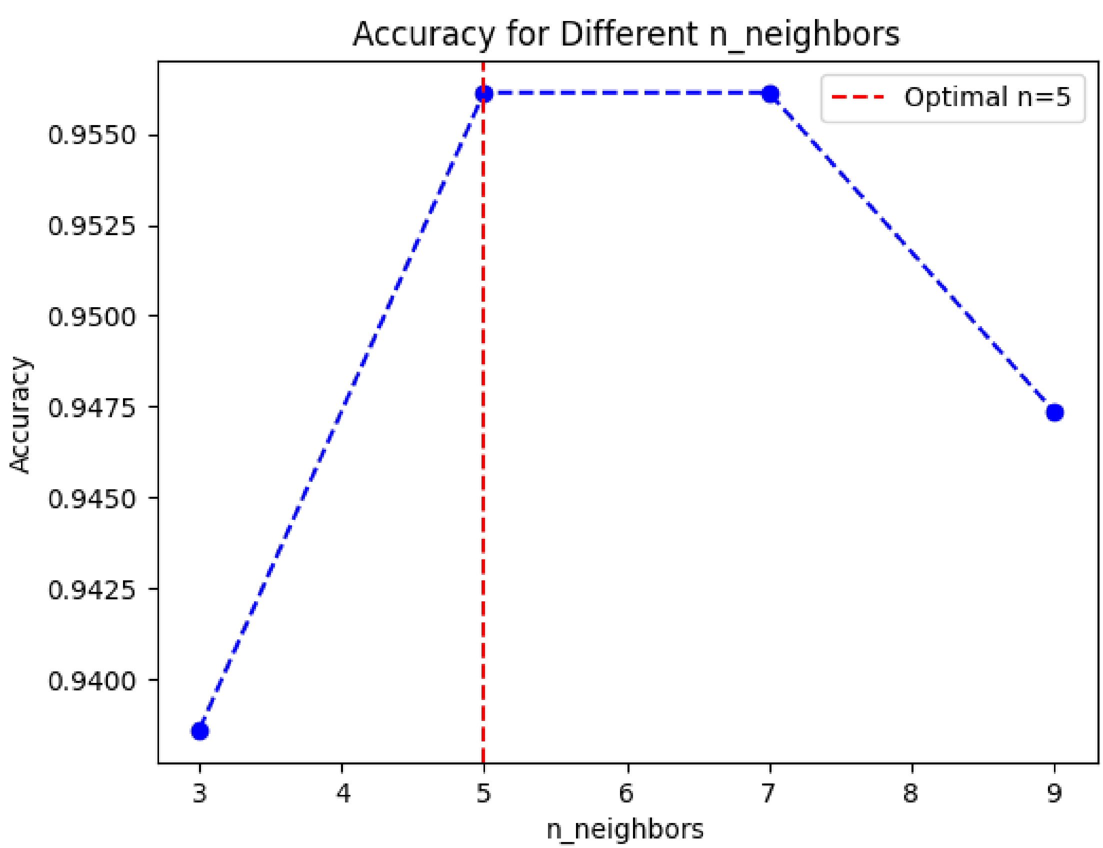
[ ]:
```
#@title ## **1. Train the KNN Classifier:**

from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report

# Initialize and train the KNN classifier
knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)

# Predict the test set
```

```python
y_pred = knn.predict(X_test)

# Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy * 100:.2f}%')

# Confusion matrix
conf_matrix = confusion_matrix(y_test, y_pred)
print('Confusion Matrix:')
print(conf_matrix)

# Classification report
print('Classification Report:')
print(classification_report(y_test, y_pred, target_names=['Benign',␣
 ↪'Malignant']))
```

```
Accuracy: 95.61%
Confusion Matrix:
[[71  1]
 [ 4 38]]
Classification Report:
              precision    recall  f1-score   support

      Benign       0.95      0.99      0.97        72
   Malignant       0.97      0.90      0.94        42

    accuracy                           0.96       114
   macro avg       0.96      0.95      0.95       114
weighted avg       0.96      0.96      0.96       114
```

[ ]:
```python
#@title ## **2. Experiment with Different n_neighbors:**

import matplotlib.pyplot as plt
from sklearn.metrics import accuracy_score

# Define a list of different neighbor values to experiment with
neighbors = [3, 5, 7, 9]
accuracies = []

# Iterate over different n_neighbors values
for n in neighbors:
    knn = KNeighborsClassifier(n_neighbors=n)
    knn.fit(X_train, y_train)
    y_pred = knn.predict(X_test)

    # Calculate accuracy for each model
```

```
    accuracy = accuracy_score(y_test, y_pred)
    accuracies.append(accuracy)

# Plot accuracy vs n_neighbors
plt.plot(neighbors, accuracies, marker='o', color='blue', linestyle='--')
plt.xlabel('n_neighbors')
plt.ylabel('Accuracy')
plt.title('Accuracy for Different n_neighbors')

# Highlight the optimal n_neighbors
optimal_n = neighbors[accuracies.index(max(accuracies))]
optimal_acc = max(accuracies)

plt.axvline(x=optimal_n, color='red', linestyle='--', label=f'Optimal␣
↪n={optimal_n}')
plt.legend()
plt.show()

# Print the best n_neighbors
print(f'The optimal n_neighbors is {optimal_n} with an accuracy of {optimal_acc␣
↪* 100:.2f}%.')
```



The optimal n_neighbors is 5 with an accuracy of 95.61%.

5 Exercise 3: Implementing Logistic Regression

[ ]:
```
#@title ## **1. Train Logistic Regression:**

from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score,␣
↪confusion_matrix

# Logistic Regression
logreg = LogisticRegression(max_iter=10000)
logreg.fit(X_train, y_train)

# Predict the test set
y_pred_lr = logreg.predict(X_test)

# Accuracy and classification report
accuracy_lr = accuracy_score(y_test, y_pred_lr)
print(f'Logistic Regression Accuracy: {accuracy_lr * 100:.2f}%')

# Confusion matrix
conf_matrix_lr = confusion_matrix(y_test, y_pred_lr)
print('Confusion Matrix (Logistic Regression):')
print(conf_matrix_lr)

# Classification report
print('Classification Report (Logistic Regression):')
print(classification_report(y_test, y_pred_lr, target_names=['Benign',␣
↪'Malignant']))
```

```
Logistic Regression Accuracy: 97.37%
Confusion Matrix (Logistic Regression):
[[71  1]
 [ 2 40]]
Classification Report (Logistic Regression):
              precision    recall  f1-score   support

      Benign       0.97      0.99      0.98        72
   Malignant       0.98      0.95      0.96        42

    accuracy                           0.97       114
   macro avg       0.97      0.97      0.97       114
weighted avg       0.97      0.97      0.97       114
```

[ ]:
```python
#@title ## **2. Comparison of KNN and Logistic Regression:**

import pandas as pd

# Accuracy for KNN and Logistic Regression
accuracy_knn = accuracy_score(y_test, y_pred)
accuracy_lr = accuracy_score(y_test, y_pred_lr)

# Precision, Recall, F1-Score for both models
report_knn = classification_report(y_test, y_pred, target_names=['Benign',␣
↪'Malignant'], output_dict=True)
report_lr = classification_report(y_test, y_pred_lr, target_names=['Benign',␣
↪'Malignant'], output_dict=True)

# Create a comparison DataFrame
comparison_df = pd.DataFrame({
    'Model': ['KNN', 'Logistic Regression'],
    'Accuracy': [accuracy_knn * 100, accuracy_lr * 100],
    'Precision (Benign)': [report_knn['Benign']['precision'],␣
↪report_lr['Benign']['precision']],
    'Recall (Benign)': [report_knn['Benign']['recall'],␣
↪report_lr['Benign']['recall']],
    'F1-Score (Benign)': [report_knn['Benign']['f1-score'],␣
↪report_lr['Benign']['f1-score']],
    'Precision (Malignant)': [report_knn['Malignant']['precision'],␣
↪report_lr['Malignant']['precision']],
    'Recall (Malignant)': [report_knn['Malignant']['recall'],␣
↪report_lr['Malignant']['recall']],
    'F1-Score (Malignant)': [report_knn['Malignant']['f1-score'],␣
↪report_lr['Malignant']['f1-score']]
})

# Display the comparison
print(comparison_df)

# Determine which model performs better
if accuracy_knn > accuracy_lr:
    print("KNN performs better in terms of accuracy.")
elif accuracy_knn < accuracy_lr:
    print("Logistic Regression performs better in terms of accuracy.")
else:
    print("Both models have the same accuracy.")
```

```
                 Model   Accuracy  Precision (Benign)  Recall (Benign)  \
0                  KNN  94.736842            0.934211         0.986111
1  Logistic Regression  97.368421            0.972603         0.986111
```

```
   F1-Score (Benign)  Precision (Malignant)  Recall (Malignant)  \
0           0.959459               0.973684            0.880952
1           0.979310               0.975610            0.952381

   F1-Score (Malignant)
0              0.925000
1              0.963855
Logistic Regression performs better in terms of accuracy.
```

6 Exercise 4: Hyperparameter Tuning and Cross-Validation

[ ]:
```
#@title ## **1. GridSearchCV for KNN:**

from sklearn.model_selection import GridSearchCV

# Defining the parameter grid for KNN
param_grid = {'n_neighbors': [3, 5, 7, 9], 'weights': ['uniform', 'distance'],␣
↪'p': [1, 2]}

# Perform Grid Search with 5-fold cross-validation
grid_search = GridSearchCV(KNeighborsClassifier(), param_grid, cv=5)
grid_search.fit(X_train, y_train)

# Output the best parameters and corresponding accuracy
best_params = grid_search.best_params_
best_score = grid_search.best_score_

print(f'Best Parameters: {best_params}')
print(f'Best Cross-Validation Accuracy: {best_score * 100:.2f}%')
```

```
Best Parameters: {'n_neighbors': 3, 'p': 2, 'weights': 'uniform'}
Best Cross-Validation Accuracy: 96.92%
```

[ ]:
```
#@title ## **2. Cross-Validation for Logistic Regression:**

from sklearn.model_selection import cross_val_score

# Perform 5-fold cross-validation for Logistic Regression
cv_scores = cross_val_score(logreg, scaled_features, df['diagnosis'], cv=5)

# Output the mean cross-validated accuracy
mean_cv_accuracy = cv_scores.mean()

print(f'Cross-Validated Accuracy (Logistic Regression): {mean_cv_accuracy * 100:.
↪2f}%')
```

```
Cross-Validated Accuracy (Logistic Regression): 98.07%
```

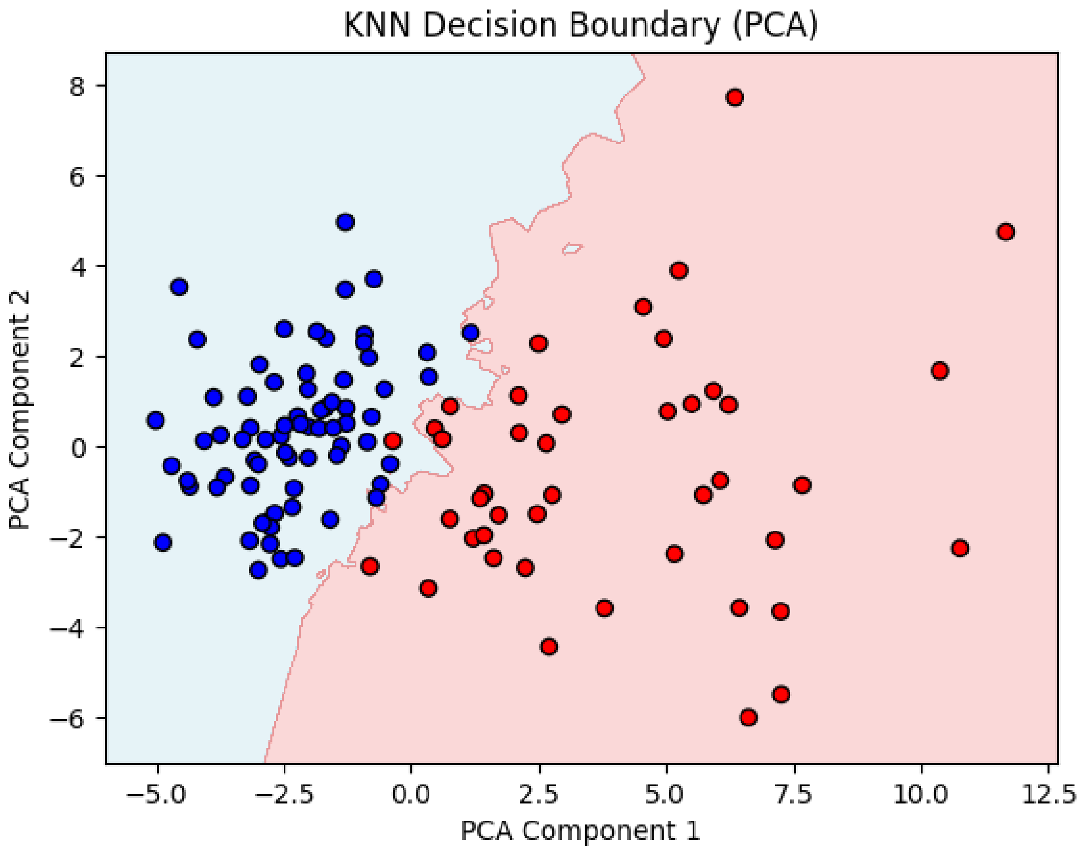
7 Exercise 5: Decision Boundary Visualization

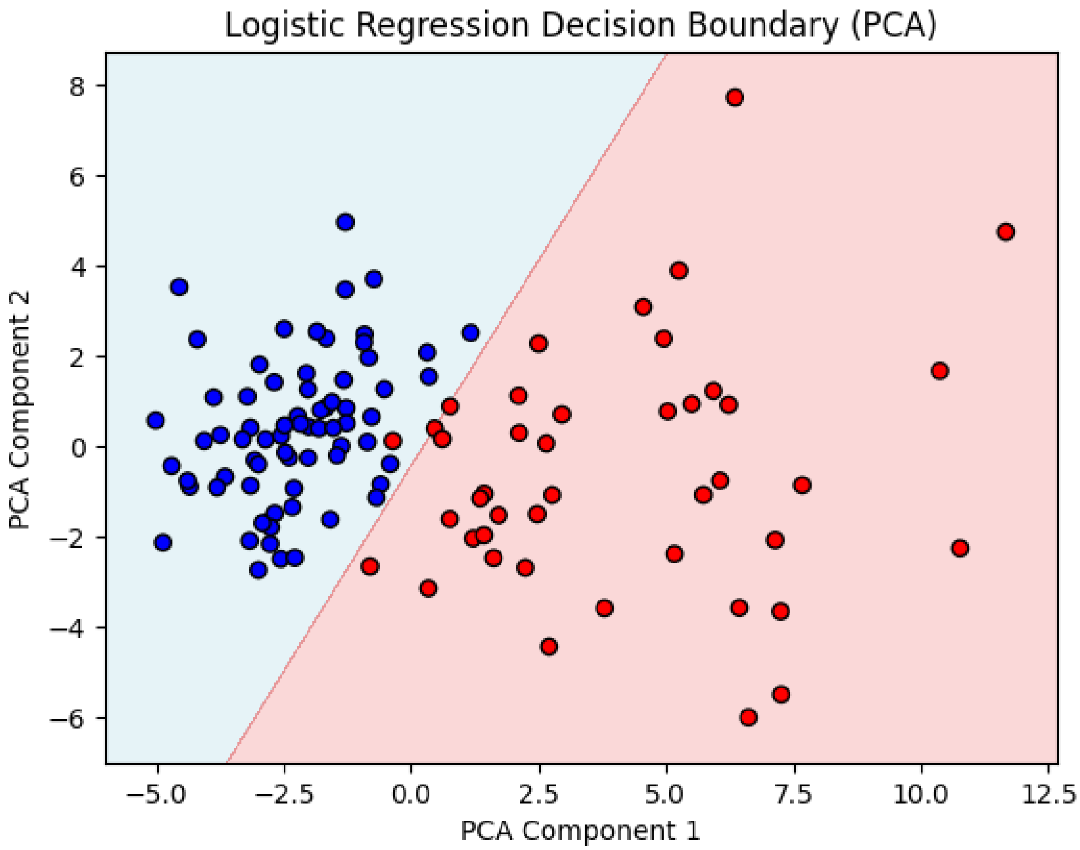
[ ]:
```
#@title ## **1. Use PCA for Dimensionality Reduction:**

from sklearn.decomposition import PCA

# Apply PCA to reduce dimensionality to 2 components
pca = PCA(n_components=2)
X_pca = pca.fit_transform(scaled_features)

# Train-test split after PCA
X_pca_train, X_pca_test, y_train_pca, y_test_pca = train_test_split(X_pca,␣
↪df['diagnosis'], test_size=0.2, random_state=42)

# KNN with PCA data
knn_pca = KNeighborsClassifier(n_neighbors=5)
knn_pca.fit(X_pca_train, y_train_pca)

# Logistic Regression with PCA data
logreg_pca = LogisticRegression(max_iter=10000)
logreg_pca.fit(X_pca_train, y_train_pca)
```

[ ]:
```
LogisticRegression(max_iter=10000)
```

[ ]:
```
#@title ## **Task: Plot the Decision Boundary:**

import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap

def plot_decision_boundary(model, X, y, title):
    x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, 0.01),
                         np.arange(y_min, y_max, 0.01))

    # Predict on the mesh grid
    Z = model.predict(np.c_[xx.ravel(), yy.ravel()])
    Z = Z.reshape(xx.shape)

    # Plot decision boundary
    plt.contourf(xx, yy, Z, alpha=0.3, cmap=ListedColormap(('lightblue',␣
↪'lightcoral')))
    plt.scatter(X[:, 0], X[:, 1], c=y, edgecolor='k',␣
↪cmap=ListedColormap(('blue', 'red')))
    plt.title(title)
    plt.xlabel('PCA Component 1')
```

```
    plt.ylabel('PCA Component 2')
    plt.show()

# Plot decision boundaries for KNN and Logistic Regression
plot_decision_boundary(knn_pca, X_pca_test, y_test_pca, title='KNN Decision␣
↪Boundary (PCA)')
plot_decision_boundary(logreg_pca, X_pca_test, y_test_pca, title='Logistic␣
↪Regression Decision Boundary (PCA)')
```




Logistic Regression Decision Boundary (PCA)
PCA Component 2
PCA Component 1
8
6
4
2
0
−2
−4
−6
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
12.5