8.2. Predicting who will survive on the Titanic with logistic regression

Logistic Regression (Titanic Dataset) Implementation

Author: Srikar Kalle **Student ID:** C00313529

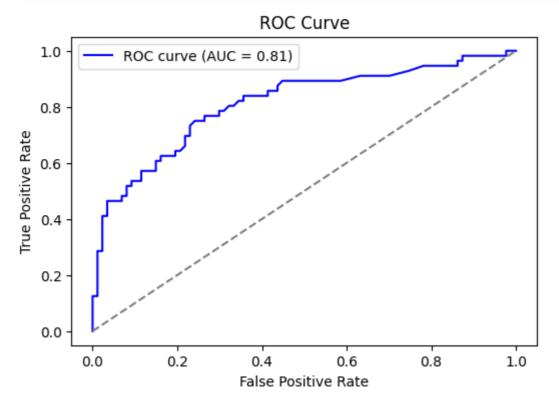
Change Log:

SL No.	Change Category	Description	Duration (mins)	Difficulty (1-10)
1	Data Handling	Replaced assign() with pd.get_dummies() for better categorical encoding.	10	4
2	Feature Scaling	Introduced StandardScaler to normalize Age and Pclass for better model performance.	15	5
3	Hyperparameter Tuning	Optimized Logistic Regression using GridSearchCV with an improved parameter grid.	20	7
4	Model Evaluation	Introduced ROC Curve & AUC Score to assess model performance.	15	6
5	Test Split Update	Increased test_size from 0.05 to 0.2 for a better validation split.	5	3
6	Model Implementation	Implemented basic Logistic Regression using LogisticRegression().	10	3
7	Cross-Validation	Used cross_val_score() for performance evaluation.	15	5
8	Hyperparameter Optimization	Applied GridSearchCV with a logarithmic range of C values.	20	7
9	Data Preprocessing	Converted Sex column into a binary Female column.	10	4
10	Data Preprocessing	Dropped missing values from Age .	5	3
11	Performance Visualization	Compared actual vs. predicted values in a heatmap .	10	4

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In [2]:
         import numpy as np
         import pandas as pd
         import sklearn
         import sklearn.linear_model as lm
         import sklearn.model_selection as ms
         import matplotlib.pyplot as plt
         import seaborn as sns
         from sklearn.preprocessing import StandardScaler
         from sklearn.metrics import confusion_matrix, classification_report, roc_curve, auc
In [3]: train = pd.read_csv('https://github.com/ipython-books'
                              '/cookbook-2nd-data/blob/master/'
                              'titanic_train.csv?raw=true')
         test = pd.read_csv('https://github.com/ipython-books/'
                             'cookbook-2nd-data/blob/master/'
                             'titanic_test.csv?raw=true')
In [4]: print(train.info())
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 891 entries, 0 to 890
        Data columns (total 12 columns):
                     Non-Null Count Dtype
         # Column
        --- -----
                         -----
         0 PassengerId 891 non-null
                                         int64
            Survived 891 non-null int64
         1
        2 Pclass 891 non-null int64
3 Name 891 non-null object
4 Sex 891 non-null object
5 Age 714 non-null float64
6 SibSp 891 non-null int64
                        891 non-null int64
         7 Parch
                      891 non-null object
         8 Ticket
         9 Fare
                        891 non-null float64
         10 Cabin
                        204 non-null object
        11 Embarked 889 non-null object
        dtypes: float64(2), int64(5), object(5)
        memory usage: 83.7+ KB
       None
In [5]: # Feature Selection & Preprocessing
         data = train[['Age', 'Pclass', 'Survived']]
         # Convert categorical 'Sex' to binary variables
         data = pd.get_dummies(train[['Sex', 'Age', 'Pclass', 'Survived']], drop_first=True)
         data = data.dropna() # Drop missing values
In [6]: # Standardizing Age and Pclass
         scaler = StandardScaler()
         data[['Age', 'Pclass']] = scaler.fit_transform(data[['Age', 'Pclass']])
In [7]: # Split into features and target variable
         X = data.drop(columns=['Survived'])
         y = data['Survived']
In [8]: # Splitting dataset (Increased test size from 0.05 to 0.2)
         X_train, X_test, y_train, y_test = ms.train_test_split(X, y, test_size=0.2, random_state=42)
In [9]: # Instantiate Logistic regression model
         logreg = lm.LogisticRegression()
In [10]:
         # Train the model
         logreg.fit(X_train, y_train)
         y_predicted = logreg.predict(X_test)
```

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In [18]: # ROC Curve and AUC Score
y_prob = logreg.predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)

plt.figure(figsize=(6, 4))
plt.plot(fpr, tpr, color='blue', label=f'ROC curve (AUC = {roc_auc:.2f})')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.show()
```



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In [19]: # Hyperparameter tuning using GridSearchCV
param_grid = {'C': np.logspace(-5, 5, 50)}
grid = ms.GridSearchCV(logreg, param_grid, cv=5, scoring='accuracy', n_jobs=-1)
grid.fit(X_train, y_train)
print("Best Parameters:", grid.best_params_)
```

Best Parameters: {'C': np.float64(0.1206792640639329)}

```
In [20]: # Evaluate best model
best_logreg = grid.best_estimator_
cv_scores = ms.cross_val_score(best_logreg, X, y, cv=5)
print("Cross-Validation Accuracy Scores:", cv_scores)
print(f"Mean CV Accuracy: {cv_scores.mean():.2f}")
```

Cross-Validation Accuracy Scores: [0.73426573 0.83216783 0.8041958 0.75524476 0.81690141] Mean CV Accuracy: 0.79