# ML project ridge regression

March 3, 2024

Ridge regression

This Ridge Regression project is based on the previous simple model of logistic regression.

necessary imports

[ ]:
```
#!pip install pandas
```

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import Ridge, LogisticRegression
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score,␣
↪precision_score, recall_score, f1_score, roc_auc_score
import numpy as np
```

Import and display df

[ ]:
```
import tkinter as tk
from tkinter import filedialog

# No full GUI, keep the root window from appearing
root = tk.Tk()
root.withdraw()

# Open file dialog to choose the dataset file
file_path = filedialog.askopenfilename()
if not file_path:
    print("No file selected. Exiting...")
    exit()

# Data Loading
print("Loading data from file...")
df = pd.read_csv(file_path)


# Check if a file was selected
if file_path:  # If a file was selected
```

```
    print(f"Loading data from {file_path}")
    df = pd.read_csv(file_path)  # Load the selected CSV into a pandas DataFrame
    print(df.head())  # Display the first few rows of the DataFrame
else:
    print("No file selected.")
```

```
Loading data from file…
Loading data from C:/Users/wjbea/Downloads/20240213 ML project credit card
defaults/archive/UCI_Credit_Card.csv
   ID  LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
0   1    20000.0    2          2         1   24      2      2     -1     -1
1   2   120000.0    2          2         2   26     -1      2      0      0
2   3    90000.0    2          2         2   34      0      0      0      0
3   4    50000.0    2          2         1   37      0      0      0      0
4   5    50000.0    1          2         1   57     -1      0     -1      0

   …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  \
0  …        0.0        0.0        0.0       0.0     689.0       0.0
1  …     3272.0     3455.0     3261.0       0.0    1000.0    1000.0
2  …    14331.0    14948.0    15549.0    1518.0    1500.0    1000.0
3  …    28314.0    28959.0    29547.0    2000.0    2019.0    1200.0
4  …    20940.0    19146.0    19131.0    2000.0   36681.0   10000.0

   PAY_AMT4  PAY_AMT5  PAY_AMT6  default.payment.next.month
0       0.0       0.0       0.0                           1
1    1000.0       0.0    2000.0                           1
2    1000.0    1000.0    5000.0                           0
3    1100.0    1069.0    1000.0                           0
4    9000.0     689.0     679.0                           0

[5 rows x 25 columns]
```

data preparation and partitioning

[ ]:
```
# Splitting data into features and target
X = df.drop(columns=['default.payment.next.month'])  # Features
y = df['default.payment.next.month']  # Target variable

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.3,␣
↪random_state=42)
```

Training on simple ridge model

```
[ ]: # Initialize the Ridge Regression model
ridge_model = Ridge(alpha=1.0)

# Fit the Ridge model on the training data
ridge_model.fit(X_train, y_train)

# Predict on the test data using Ridge Regression
y_pred_ridge = ridge_model.predict(X_test)

# Convert predicted values to binary predictions for Ridge Regression
y_pred_ridge_binary = np.where(y_pred_ridge >= 0.5, 1, 0)

# Calculate classification metrics for Ridge Regression
mse_ridge = mean_squared_error(y_test, y_pred_ridge_binary)
r2_ridge = r2_score(y_test, y_pred_ridge_binary)
accuracy_ridge = accuracy_score(y_test, y_pred_ridge_binary)
precision_ridge = precision_score(y_test, y_pred_ridge_binary)
recall_ridge = recall_score(y_test, y_pred_ridge_binary)
f1_ridge = f1_score(y_test, y_pred_ridge_binary)
roc_auc_ridge = roc_auc_score(y_test, y_pred_ridge)
```

Training on logistic ridge model

```
[ ]: # Initialize the Logistic Regression model with ridge regularization
logistic_ridge_model = LogisticRegression(penalty='l2', C=1.0)

# Fit the Logistic Ridge model on the training data
logistic_ridge_model.fit(X_train, y_train)

# Predict on the test data using Logistic Ridge Regression
y_pred_logistic_ridge = logistic_ridge_model.predict(X_test)

# Calculate classification metrics for Logistic Ridge Regression
mse_logistic_ridge = mean_squared_error(y_test, y_pred_logistic_ridge)
r2_logistic_ridge = r2_score(y_test, y_pred_logistic_ridge)
accuracy_logistic_ridge = accuracy_score(y_test, y_pred_logistic_ridge)
precision_logistic_ridge = precision_score(y_test, y_pred_logistic_ridge)
recall_logistic_ridge = recall_score(y_test, y_pred_logistic_ridge)
f1_logistic_ridge = f1_score(y_test, y_pred_logistic_ridge)
roc_auc_logistic_ridge = roc_auc_score(y_test, logistic_ridge_model.
 ↪predict_proba(X_test)[:, 1])
```

comparison of the two models

```
[ ]: # Print metrics for both models
print("Ridge Regression Metrics:")
print(f'Mean Squared Error: {mse_ridge}')
print(f'R^2 Score: {r2_ridge}')
```

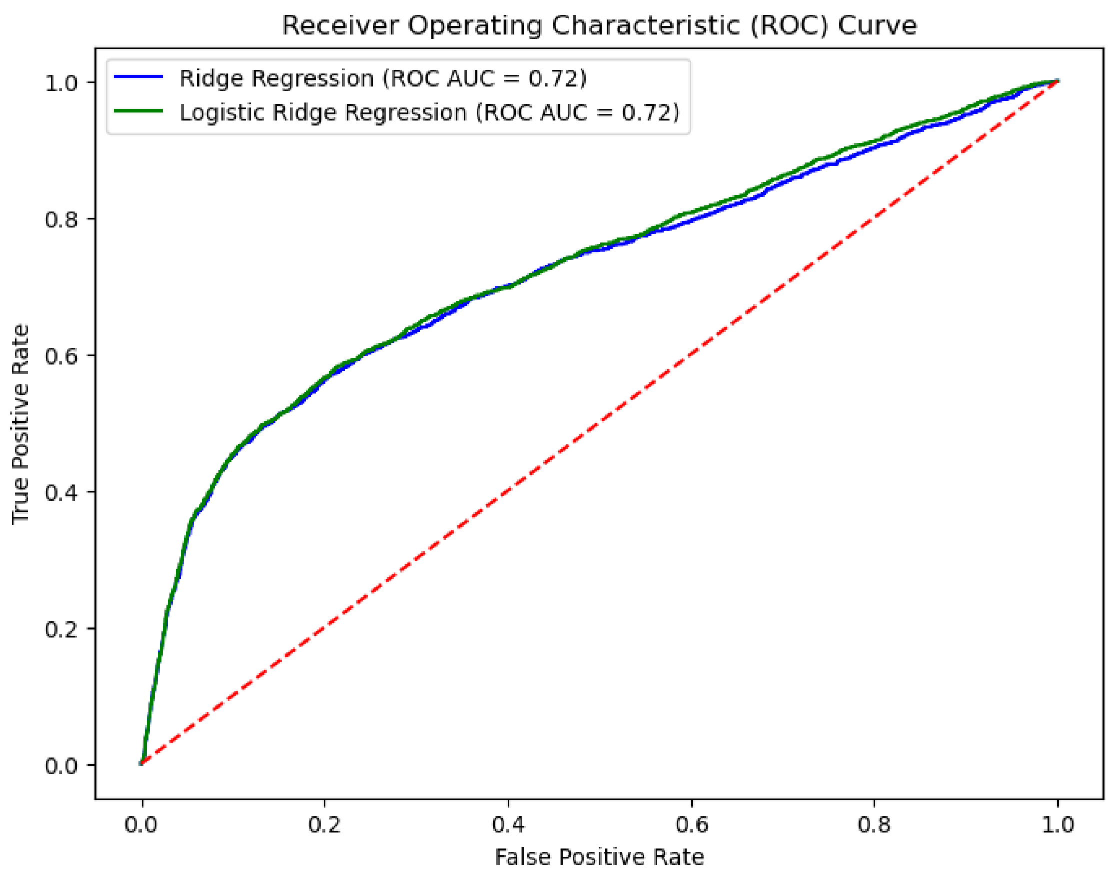
```python
print(f'Accuracy: {accuracy_ridge}')
print(f'Precision: {precision_ridge}')
print(f'Recall: {recall_ridge}')
print(f'F1 Score: {f1_ridge}')
print(f'ROC AUC: {roc_auc_ridge}')
print("\n")

print("Logistic Ridge Regression Metrics:")
print(f'Mean Squared Error: {mse_logistic_ridge}')
print(f'R^2 Score: {r2_logistic_ridge}')
print(f'Accuracy: {accuracy_logistic_ridge}')
print(f'Precision: {precision_logistic_ridge}')
print(f'Recall: {recall_logistic_ridge}')
print(f'F1 Score: {f1_logistic_ridge}')
print(f'ROC AUC: {roc_auc_logistic_ridge}')
```

```
Ridge Regression Metrics:
Mean Squared Error: 0.20044444444444445
R^2 Score: -0.17665816326530615
Accuracy: 0.7995555555555556
Precision: 0.6893203883495146
Recall: 0.14489795918367346
F1 Score: 0.23946037099494097
ROC AUC: 0.7170384247448979


Logistic Ridge Regression Metrics:
Mean Squared Error: 0.191
R^2 Score: -0.12121695269016697
Accuracy: 0.809
Precision: 0.680119581464873
Recall: 0.23214285714285715
F1 Score: 0.3461392164321035
ROC AUC: 0.7230513682745825
```

Visual comaprison

[ ]:
```python
from sklearn.metrics import roc_curve

# Compute ROC curve for Ridge Regression
fpr_ridge, tpr_ridge, _ = roc_curve(y_test, y_pred_ridge)

# Compute ROC curve for Logistic Ridge Regression
fpr_logistic_ridge, tpr_logistic_ridge, _ = roc_curve(y_test,␣
 ↪logistic_ridge_model.predict_proba(X_test)[:, 1])

# Plot ROC curves
plt.figure(figsize=(8, 6))
```

```
plt.plot(fpr_ridge, tpr_ridge, color='blue', label='Ridge Regression (ROC AUC =␣
↪{:.2f})'.format(roc_auc_ridge))
plt.plot(fpr_logistic_ridge, tpr_logistic_ridge, color='green', label='Logistic␣
↪Ridge Regression (ROC AUC = {:.2f})'.format(roc_auc_logistic_ridge))
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```




for each model, sample train and test data each 5 times, 50 cases, calculate and compare accuracy results.

[ ]:
```
from sklearn.model_selection import StratifiedKFold

# Initialize lists to store accuracy results
ridge_accuracies = []
logistic_ridge_accuracies = []
```

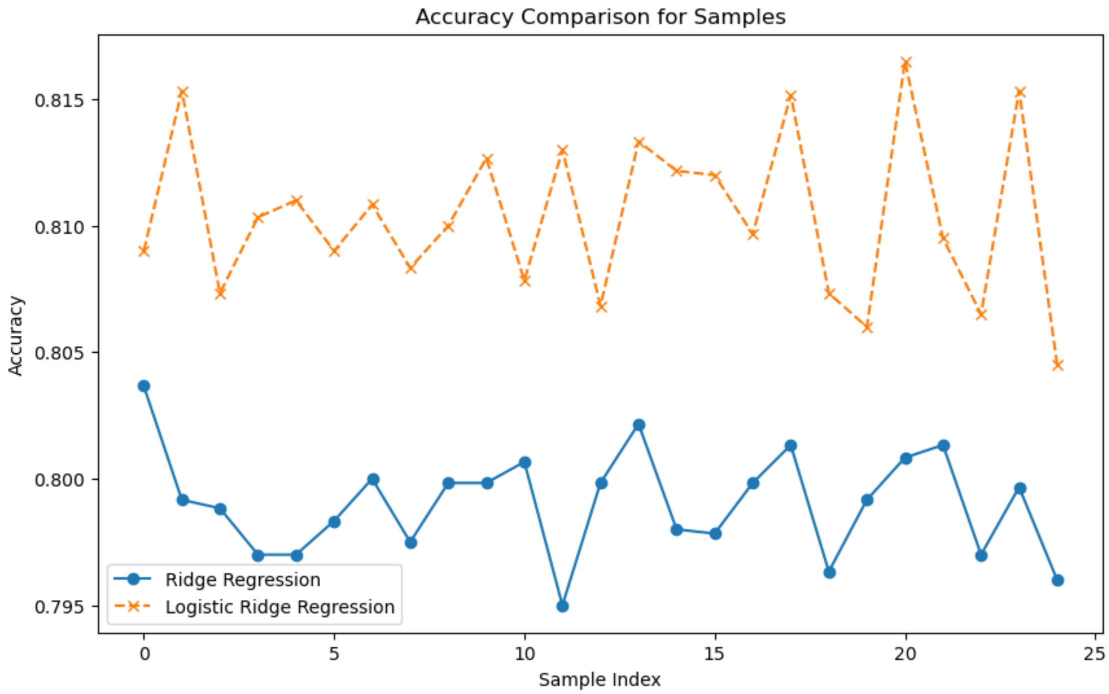
```python
# Repeatedly sample train and test data and calculate accuracy for Ridge␣
↪Regression
for _ in range(5):  # Repeat 5 times
    # Split the data into train and test sets using stratified k-fold
    skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=None)
    for train_index, test_index in skf.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        # Standardize the features
        scaler = StandardScaler()
        X_train_scaled = scaler.fit_transform(X_train)
        X_test_scaled = scaler.transform(X_test)

        # Initialize the Ridge Regression model
        ridge_model = Ridge(alpha=1.0)

        # Fit the Ridge model on the training data
        ridge_model.fit(X_train_scaled, y_train)

        # Predict on the test data using Ridge Regression
        y_pred_ridge = ridge_model.predict(X_test_scaled)

        # Calculate accuracy for Ridge Regression
        accuracy_ridge = accuracy_score(y_test, np.round(y_pred_ridge))
        ridge_accuracies.append(accuracy_ridge)

# Repeatedly sample train and test data and calculate accuracy for Logistic␣
↪Ridge Regression
for _ in range(5):  # Repeat 5 times
    # Split the data into train and test sets using stratified k-fold
    skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=None)
    for train_index, test_index in skf.split(X, y):
        X_train, X_test = X.iloc[train_index], X.iloc[test_index]
        y_train, y_test = y.iloc[train_index], y.iloc[test_index]

        # Standardize the features
        scaler = StandardScaler()
        X_train_scaled = scaler.fit_transform(X_train)
        X_test_scaled = scaler.transform(X_test)

        # Initialize the Logistic Ridge Regression model
        logistic_ridge_model = LogisticRegression(penalty='l2', C=1.0)

        # Fit the Logistic Ridge model on the training data
        logistic_ridge_model.fit(X_train_scaled, y_train)
```

```
        # Predict on the test data using Logistic Ridge Regression
        y_pred_logistic_ridge = logistic_ridge_model.predict(X_test_scaled)

        # Calculate accuracy for Logistic Ridge Regression
        accuracy_logistic_ridge = accuracy_score(y_test, y_pred_logistic_ridge)
        logistic_ridge_accuracies.append(accuracy_logistic_ridge)

# Print average accuracy results
print("Ridge Regression Average Accuracy:", sum(ridge_accuracies) /␣
 ↪len(ridge_accuracies))
print("Logistic Ridge Regression Average Accuracy:",␣
 ↪sum(logistic_ridge_accuracies) / len(logistic_ridge_accuracies))
```

```
Ridge Regression Average Accuracy: 0.7990466666666667
Logistic Ridge Regression Average Accuracy: 0.8103800000000001
```

Plot accuracy comparison for each sample

[ ]:
```
# Plot accuracy comparison for each sample
plt.figure(figsize=(10, 6))
plt.plot(range(len(ridge_accuracies)), ridge_accuracies, label='Ridge␣
 ↪Regression', marker='o', linestyle='-')
plt.plot(range(len(logistic_ridge_accuracies)), logistic_ridge_accuracies,␣
 ↪label='Logistic Ridge Regression', marker='x', linestyle='--')
plt.xlabel('Sample Index')
plt.ylabel('Accuracy')
plt.title('Accuracy Comparison for Samples')
plt.legend()
plt.show()

# Clear lists for next iteration
ridge_accuracies.clear()
logistic_ridge_accuracies.clear()
```




Model Summaries

[ ]:
```python
import statsmodels.api as sm

# Fit Ridge Regression model
ridge_model = sm.OLS(y_train, X_train).fit()

# Print summary
print("Ridge Regression Model Summary:")
print(ridge_model.summary())

# Fit Logistic Ridge Regression model
logistic_ridge_model = sm.Logit(y_train, X_train).fit()

# Print summary
print("\nLogistic Ridge Regression Model Summary:")
print(logistic_ridge_model.summary())
```

```
Ridge Regression Model Summary:
                                     OLS Regression Results
================================================================================
===============
Dep. Variable:     default.payment.next.month   R-squared (uncentered):
0.316
Model:                                     OLS   Adj. R-squared (uncentered):
```

```
0.315
Method:                 Least Squares   F-statistic:
460.5
Date:                Sun, 03 Mar 2024   Prob (F-statistic):
0.00
Time:                        23:35:14   Log-Likelihood:
-11402.
No. Observations:               24000   AIC:
2.285e+04
Df Residuals:                   23976   BIC:
2.305e+04
Df Model:                          24
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
ID          8.988e-07   2.87e-07      3.134      0.002    3.37e-07    1.46e-06
LIMIT_BAL  -1.901e-08   2.39e-08     -0.796      0.426   -6.58e-08    2.78e-08
SEX            0.0208      0.005      4.563      0.000       0.012       0.030
EDUCATION     -0.0015      0.003     -0.475      0.634      -0.008       0.005
MARRIAGE       0.0319      0.004      8.211      0.000       0.024       0.040
AGE            0.0048      0.000     20.909      0.000       0.004       0.005
PAY_0          0.0949      0.003     30.728      0.000       0.089       0.101
PAY_2          0.0242      0.004      6.490      0.000       0.017       0.031
PAY_3          0.0129      0.004      3.239      0.001       0.005       0.021
PAY_4          0.0006      0.004      0.132      0.895      -0.008       0.009
PAY_5          0.0088      0.005      1.830      0.067      -0.001       0.018
PAY_6          0.0001      0.004      0.036      0.971      -0.008       0.008
BILL_AMT1  -6.467e-07   1.26e-07     -5.115      0.000   -8.95e-07   -3.99e-07
BILL_AMT2   5.492e-08   1.79e-07      0.307      0.759   -2.96e-07    4.06e-07
BILL_AMT3   1.194e-07   1.72e-07      0.693      0.488   -2.18e-07    4.57e-07
BILL_AMT4  -1.197e-07   1.75e-07     -0.683      0.495   -4.63e-07    2.24e-07
BILL_AMT5   6.354e-08   2.07e-07      0.307      0.758   -3.42e-07    4.69e-07
BILL_AMT6   1.086e-07   1.65e-07      0.660      0.510   -2.14e-07    4.31e-07
PAY_AMT1   -7.898e-07   2.01e-07     -3.929      0.000   -1.18e-06   -3.96e-07
PAY_AMT2     -3.2e-07   1.68e-07     -1.903      0.057    -6.5e-07    9.54e-09
PAY_AMT3    -1.77e-07   1.85e-07     -0.959      0.337   -5.39e-07    1.85e-07
PAY_AMT4    -4.86e-07   2.08e-07     -2.340      0.019   -8.93e-07   -7.89e-08
PAY_AMT5   -2.654e-07   2.15e-07     -1.235      0.217   -6.86e-07    1.56e-07
PAY_AMT6    -1.47e-07   1.52e-07     -0.969      0.333   -4.44e-07     1.5e-07
==============================================================================
Omnibus:                     3680.258   Durbin-Watson:                   2.007
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             5678.303
Skew:                           1.188   Prob(JB):                         0.00
Kurtosis:                       3.194   Cond. No.                     6.12e+05
==============================================================================

Notes:
```

```
[1] R² is computed without centering (uncentered) since the model does not
contain a constant.
[2] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[3] The condition number is large, 6.12e+05. This might indicate that there are
strong multicollinearity or other numerical problems.
Optimization terminated successfully.
         Current function value: 0.462521
         Iterations 7

Logistic Ridge Regression Model Summary:
                               Logit Regression Results
================================================================================
======
Dep. Variable:     default.payment.next.month   No. Observations:
24000
Model:                                  Logit   Df Residuals:
23976
Method:                                   MLE   Df Model:
23
Date:                        Sun, 03 Mar 2024   Pseudo R-squ.:
0.1247
Time:                                23:35:14   Log-Likelihood:
-11101.
converged:                               True   LL-Null:
-12682.
Covariance Type:                    nonrobust   LLR p-value:
0.000
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ID         -2.789e-06   1.92e-06     -1.453      0.146   -6.55e-06    9.73e-07
LIMIT_BAL  -8.233e-07   1.74e-07     -4.742      0.000   -1.16e-06   -4.83e-07
SEX           -0.2088      0.030     -6.954      0.000      -0.268      -0.150
EDUCATION     -0.1399      0.023     -6.164      0.000      -0.184      -0.095
MARRIAGE      -0.2766      0.026    -10.711      0.000      -0.327      -0.226
AGE            0.0024      0.002      1.592      0.111      -0.001       0.005
PAY_0          0.5611      0.020     28.426      0.000       0.522       0.600
PAY_2          0.1021      0.022      4.545      0.000       0.058       0.146
PAY_3          0.0746      0.025      2.973      0.003       0.025       0.124
PAY_4          0.0123      0.028      0.439      0.661      -0.043       0.067
PAY_5          0.0470      0.030      1.574      0.115      -0.012       0.106
PAY_6          0.0106      0.025      0.429      0.668      -0.038       0.059
BILL_AMT1  -5.511e-06   1.28e-06     -4.296      0.000   -8.03e-06      -3e-06
BILL_AMT2   1.203e-06   1.75e-06      0.688      0.491   -2.22e-06    4.63e-06
BILL_AMT3   1.862e-06   1.58e-06      1.181      0.238   -1.23e-06    4.95e-06
BILL_AMT4   1.363e-07   1.56e-06      0.087      0.931   -2.93e-06     3.2e-06
BILL_AMT5   7.997e-07   1.73e-06      0.461      0.645    -2.6e-06     4.2e-06
```

```
BILL_AMT6     5.29e-07    1.38e-06      0.384      0.701    -2.17e-06    3.23e-06
PAY_AMT1    -1.442e-05     2.7e-06     -5.346      0.000    -1.97e-05   -9.14e-06
PAY_AMT2    -1.016e-05    2.35e-06     -4.319      0.000    -1.48e-05   -5.55e-06
PAY_AMT3    -4.604e-06    2.08e-06     -2.211      0.027    -8.69e-06   -5.23e-07
PAY_AMT4    -6.596e-06    2.23e-06     -2.962      0.003     -1.1e-05   -2.23e-06
PAY_AMT5    -3.086e-06    1.99e-06     -1.554      0.120    -6.98e-06    8.06e-07
PAY_AMT6    -2.713e-06    1.47e-06     -1.842      0.065     -5.6e-06    1.74e-07
==============================================================================
```

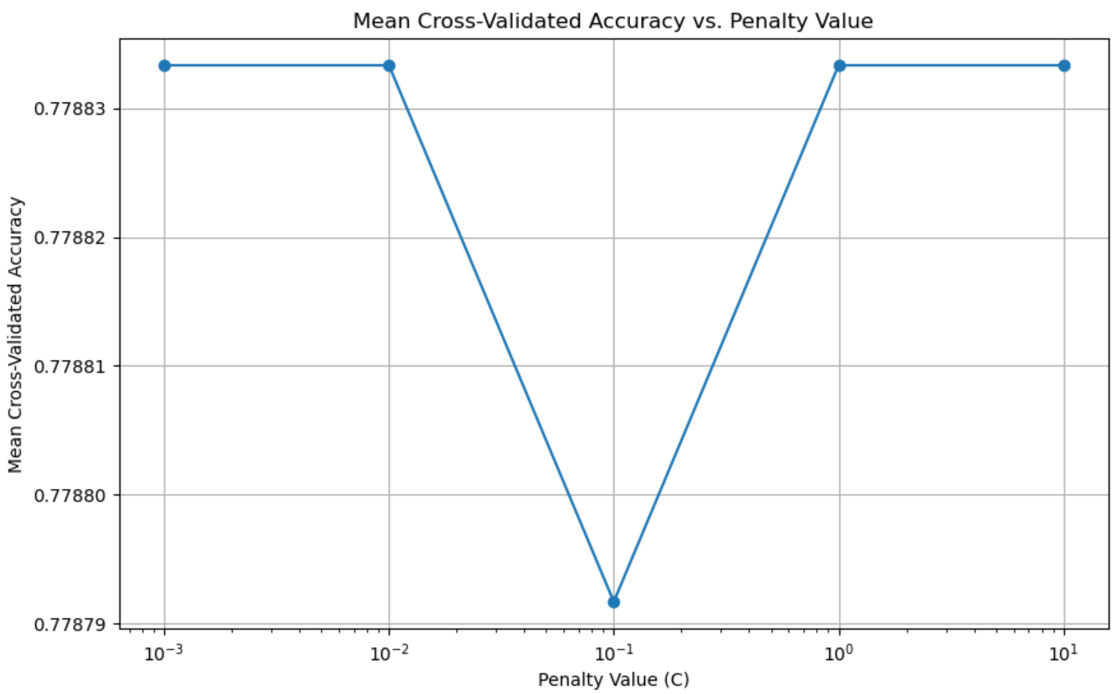
Improve on finding best model

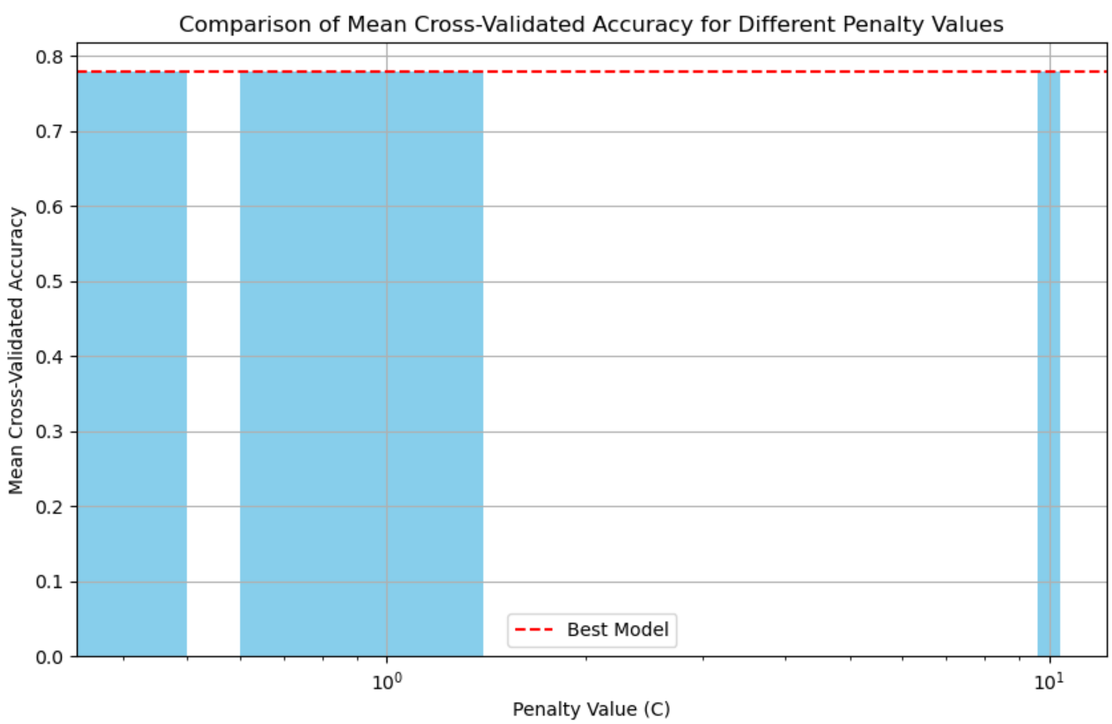
[ ]:
```python
from sklearn.model_selection import GridSearchCV

# Define a range of penalty values
penalty_values = [0.001, 0.01, 0.1, 1, 10]  # Trial values

# Define parameter grid
param_grid = {'C': penalty_values}  # C is the inverse of regularization␣
 ↪strength

# Initialize Logistic Regression model
logistic_regression = LogisticRegression(penalty='l2', solver='liblinear')

# Initialize GridSearchCV
grid_search = GridSearchCV(logistic_regression, param_grid, cv=5,␣
 ↪scoring='accuracy')

# Perform grid search
grid_search.fit(X_train, y_train)

# Get best parameter
best_penalty = grid_search.best_params_['C']

# Get best model
best_model = grid_search.best_estimator_

# Print best penalty value
print("Best Penalty Value:", best_penalty)

# Print best model
print("\nBest Model:")
print(best_model)
```

```
Best Penalty Value: 0.001

Best Model:
LogisticRegression(C=0.001, solver='liblinear')
```

cross-validated accuracy plot

```
[ ]: import numpy as np
import matplotlib.pyplot as plt

# Get mean cross-validated accuracy for each penalty value
mean_scores = grid_search.cv_results_['mean_test_score']

# Plot mean cross-validated accuracy for each penalty value
plt.figure(figsize=(10, 6))
plt.plot(penalty_values, mean_scores, marker='o')
plt.xlabel('Penalty Value (C)')
plt.ylabel('Mean Cross-Validated Accuracy')
plt.title('Mean Cross-Validated Accuracy vs. Penalty Value')
plt.xscale('log')  # Use logarithmic scale for penalty values
plt.grid(True)
plt.show()

# Compare the performance of the best model with other models
model_comparison = {'Penalty Value': penalty_values, 'Mean Accuracy':␣
 ↪mean_scores}
model_comparison_df = pd.DataFrame(model_comparison)

plt.figure(figsize=(10, 6))
plt.bar(model_comparison_df['Penalty Value'], model_comparison_df['Mean␣
 ↪Accuracy'], color='skyblue')
plt.axhline(y=model_comparison_df['Mean Accuracy'].max(), color='red',␣
 ↪linestyle='--', label='Best Model')
plt.xlabel('Penalty Value (C)')
plt.ylabel('Mean Cross-Validated Accuracy')
plt.title('Comparison of Mean Cross-Validated Accuracy for Different Penalty␣
 ↪Values')
plt.xscale('log')  # Use logarithmic scale for penalty values
plt.legend()
plt.grid(True)
plt.show()
```




Model metrics

[ ]:
```python
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score, roc_auc_score

# Initialize lists to store metric values for each model
accuracy_values = []
precision_values = []
recall_values = []
f1_values = []
roc_auc_values = []

# Calculate metrics for each model
for penalty in penalty_values:
    # Initialize Logistic Regression model with current penalty value
    logistic_regression = LogisticRegression(penalty='l2', C=penalty,␣
↪solver='liblinear')

    # Fit the model on the training data
    logistic_regression.fit(X_train, y_train)

    # Predict on the test data
    y_pred = logistic_regression.predict(X_test)

    # Calculate metrics
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    roc_auc = roc_auc_score(y_test, y_pred)

    # Append metric values to lists
    accuracy_values.append(accuracy)
    precision_values.append(precision)
    recall_values.append(recall)
    f1_values.append(f1)
    roc_auc_values.append(roc_auc)

# Print metric values for each model
print("Penalty Value\tAccuracy\tPrecision\tRecall\t\tF1 Score\tROC AUC")
for i, penalty in enumerate(penalty_values):
    print(f"{penalty}\t\t{accuracy_values[i]:.4f}\t\t{precision_values[i]:.
↪4f}\t\t{recall_values[i]:.4f}\t\t{f1_values[i]:.4f}\t\t{roc_auc_values[i]:.
↪4f}")
```

```
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
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c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

```
Penalty Value   Accuracy        Precision       Recall          F1 Score
ROC AUC
0.001           0.7788          0.0000          0.0000          0.0000
0.5000
0.01            0.7788          0.0000          0.0000          0.0000
0.5000
0.1             0.7788          0.0000          0.0000          0.0000
0.5000
1               0.7788          0.0000          0.0000          0.0000
0.5000
10              0.7788          0.0000          0.0000          0.0000
0.5000
```

Resampling to check if there is error

[ ]:
```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, precision_score, recall_score,
 ↪f1_score, roc_auc_score

# Function to perform penalty test and calculate metric values
def perform_penalty_test(X_train, y_train, X_test, y_test, penalty_values):
    # Initialize lists to store metric values for each model
    accuracy_values = []
    precision_values = []
```

```
    recall_values = []
    f1_values = []
    roc_auc_values = []

    # Calculate metrics for each model
    for penalty in penalty_values:
        # Initialize Logistic Regression model with current penalty value
        logistic_regression = LogisticRegression(penalty='l2', C=penalty,␣
↪solver='liblinear')

        # Fit the model on the training data
        logistic_regression.fit(X_train, y_train)

        # Predict on the test data
        y_pred = logistic_regression.predict(X_test)

        # Calculate metrics
        accuracy = accuracy_score(y_test, y_pred)
        precision = precision_score(y_test, y_pred)
        recall = recall_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred)
        roc_auc = roc_auc_score(y_test, y_pred)

        # Append metric values to lists
        accuracy_values.append(accuracy)
        precision_values.append(precision)
        recall_values.append(recall)
        f1_values.append(f1)
        roc_auc_values.append(roc_auc)

    return accuracy_values, precision_values, recall_values, f1_values,␣
↪roc_auc_values

# Function to visualize the performance of different models
def visualize_performance(penalty_values, metric_values, metric_name):
    plt.figure(figsize=(10, 6))
    for i, penalty in enumerate(penalty_values):
        plt.plot(penalty_values, metric_values[i], label=f'Penalty {penalty}')
    plt.xlabel('Penalty Value (C)')
    plt.ylabel(metric_name)
    plt.title(f'{metric_name} vs. Penalty Value')
    plt.xscale('log')
    plt.legend()
    plt.show()

# Resample the original dataset into five samples
num_samples = 5
```

```
sample_size = int(0.2 * len(X))  # 20% of original size
samples = [X.sample(sample_size, replace=False) for _ in range(num_samples)]

# Initialize lists to store metric values for each sample
accuracy_values_samples = []
precision_values_samples = []
recall_values_samples = []
f1_values_samples = []
roc_auc_values_samples = []

# Define penalty values
penalty_values = [0.001, 0.01, 0.1, 1, 10, 100, 1000, 10000]

# Perform penalty test for each sample
for sample in samples:
    X_train, X_test, y_train, y_test = train_test_split(sample, y[sample.
 ↪index], test_size=0.2, random_state=42)
    accuracy_values, precision_values, recall_values, f1_values, roc_auc_values␣
 ↪= perform_penalty_test(X_train, y_train, X_test, y_test, penalty_values)
    accuracy_values_samples.append(accuracy_values)
    precision_values_samples.append(precision_values)
    recall_values_samples.append(recall_values)
    f1_values_samples.append(f1_values)
    roc_auc_values_samples.append(roc_auc_values)

# Print metric values for each sample
for i, (accuracy_values, precision_values, recall_values, f1_values,␣
 ↪roc_auc_values) in enumerate(zip(accuracy_values_samples,␣
 ↪precision_values_samples, recall_values_samples, f1_values_samples,␣
 ↪roc_auc_values_samples)):
    print(f"\nSample {i+1} Metrics:")
    print("Penalty Value\tAccuracy\tPrecision\tRecall\t\tF1 Score\tROC AUC")
    for j, penalty in enumerate(penalty_values):
        print(f"{penalty}\t\t{accuracy_values[j]:.4f}\t\t{precision_values[j]:.
 ↪4f}\t\t{recall_values[j]:.4f}\t\t{f1_values[j]:.4f}\t\t{roc_auc_values[j]:.
 ↪4f}")

# Visualize the performance of different models
visualize_performance(penalty_values, accuracy_values_samples, 'Accuracy')
visualize_performance(penalty_values, precision_values_samples, 'Precision')
visualize_performance(penalty_values, recall_values_samples, 'Recall')
visualize_performance(penalty_values, f1_values_samples, 'F1 Score')
visualize_performance(penalty_values, roc_auc_values_samples, 'ROC AUC')
```

```
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
```

```
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
```

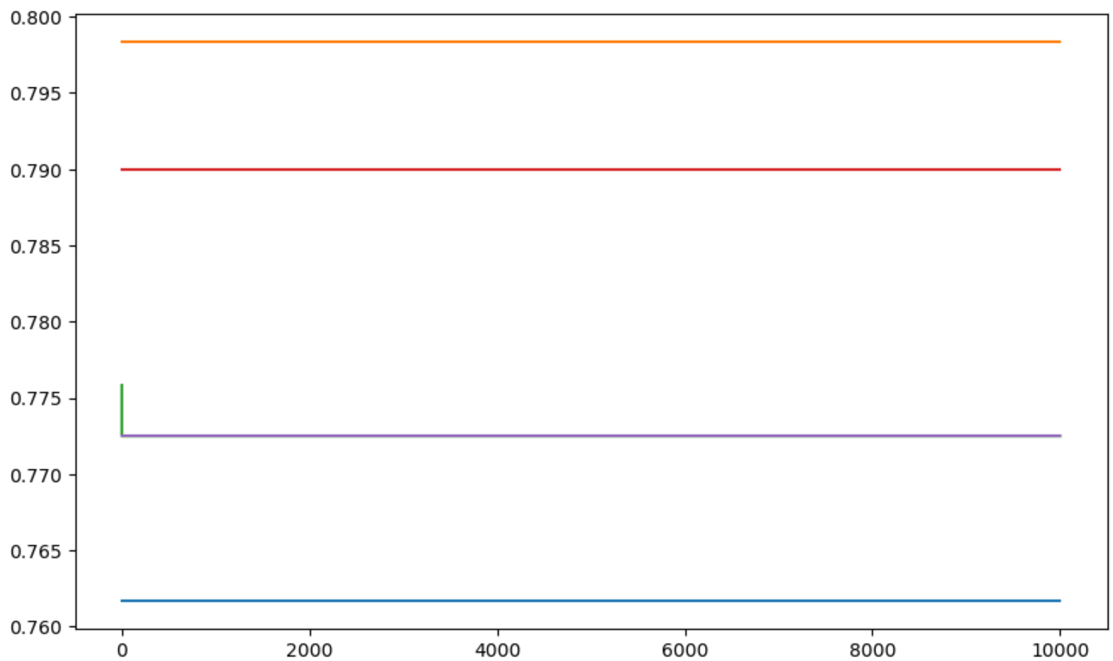
```
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
c:\ProgramData\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 due to no predicted samples. Use
`zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))


Sample 1 Metrics:
Penalty Value   Accuracy        Precision       Recall          F1 Score
ROC AUC
0.001           0.7617          0.0000          0.0000          0.0000
0.4989
0.01            0.7617          0.0000          0.0000          0.0000
0.4989
0.1             0.7617          0.0000          0.0000          0.0000
0.4989
1               0.7617          0.0000          0.0000          0.0000
0.4989
10              0.7617          0.0000          0.0000          0.0000
0.4989
100             0.7617          0.0000          0.0000          0.0000
0.4989
1000            0.7617          0.0000          0.0000          0.0000
0.4989
10000           0.7617          0.0000          0.0000          0.0000
0.4989

Sample 2 Metrics:
Penalty Value   Accuracy        Precision       Recall          F1 Score
```

```
ROC AUC
0.001          0.7983         0.0000         0.0000         0.0000
0.5000
0.01           0.7983         0.0000         0.0000         0.0000
0.5000
0.1            0.7983         0.0000         0.0000         0.0000
0.5000
1              0.7983         0.0000         0.0000         0.0000
0.5000
10             0.7983         0.0000         0.0000         0.0000
0.5000
100            0.7983         0.0000         0.0000         0.0000
0.5000
1000           0.7983         0.0000         0.0000         0.0000
0.5000
10000          0.7983         0.0000         0.0000         0.0000
0.5000

Sample 3 Metrics:
Penalty Value  Accuracy       Precision      Recall         F1 Score
ROC AUC
0.001          0.7758         1.0000         0.0147         0.0289
0.5073
0.01           0.7725         0.0000         0.0000         0.0000
0.5000
0.1            0.7725         0.0000         0.0000         0.0000
0.5000
1              0.7725         0.0000         0.0000         0.0000
0.5000
10             0.7725         0.0000         0.0000         0.0000
0.5000
100            0.7725         0.0000         0.0000         0.0000
0.5000
1000           0.7725         0.0000         0.0000         0.0000
0.5000
10000          0.7725         0.0000         0.0000         0.0000
0.5000

Sample 4 Metrics:
Penalty Value  Accuracy       Precision      Recall         F1 Score
ROC AUC
0.001          0.7900         1.0000         0.0040         0.0079
0.5020
0.01           0.7900         1.0000         0.0040         0.0079
0.5020
0.1            0.7900         1.0000         0.0040         0.0079
0.5020
1              0.7900         1.0000         0.0040         0.0079
```

```
0.5020
10              0.7900          1.0000          0.0040          0.0079
0.5020
100             0.7900          1.0000          0.0040          0.0079
0.5020
1000            0.7900          1.0000          0.0040          0.0079
0.5020
10000           0.7900          1.0000          0.0040          0.0079
0.5020

Sample 5 Metrics:
Penalty Value   Accuracy        Precision       Recall          F1 Score
ROC AUC
0.001           0.7725          0.7500          0.0109          0.0215
0.5049
0.01            0.7725          0.7500          0.0109          0.0215
0.5049
0.1             0.7725          0.7500          0.0109          0.0215
0.5049
1               0.7725          0.7500          0.0109          0.0215
0.5049
10              0.7725          0.7500          0.0109          0.0215
0.5049
100             0.7725          0.7500          0.0109          0.0215
0.5049
1000            0.7725          0.7500          0.0109          0.0215
0.5049
10000           0.7725          0.7500          0.0109          0.0215
0.5049
```

```
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
Cell In[26], line 88
     85         print(f"{penalty}\t\t{accuracy_values[j]:.
 ↪4f}\t\t{precision_values[j]:.4f}\t\t{recall_values[j]:.4f}\t\t{f1_values[j]:.
 ↪4f}\t\t{roc_auc_values[j]:.4f}")
     87 # Visualize the performance of different models
---> 88␣
 ↪visualize_performance(penalty_values, accuracy_values_samples, 'Accuracy')
     89 visualize_performance(penalty_values, precision_values_samples,␣
 ↪'Precision')
     90 visualize_performance(penalty_values, recall_values_samples, 'Recall')

Cell In[26], line 47, in visualize_performance(penalty_values, metric_values,␣
 ↪metric_name)
     45 plt.figure(figsize=(10, 6))
     46 for i, penalty in enumerate(penalty_values):
```

```
---> 47     plt.plot(penalty_values, metric_values[i], label=f'Penalty␣
↪{penalty}')
     48 plt.xlabel('Penalty Value (C)')
     49 plt.ylabel(metric_name)

IndexError: list index out of range
```



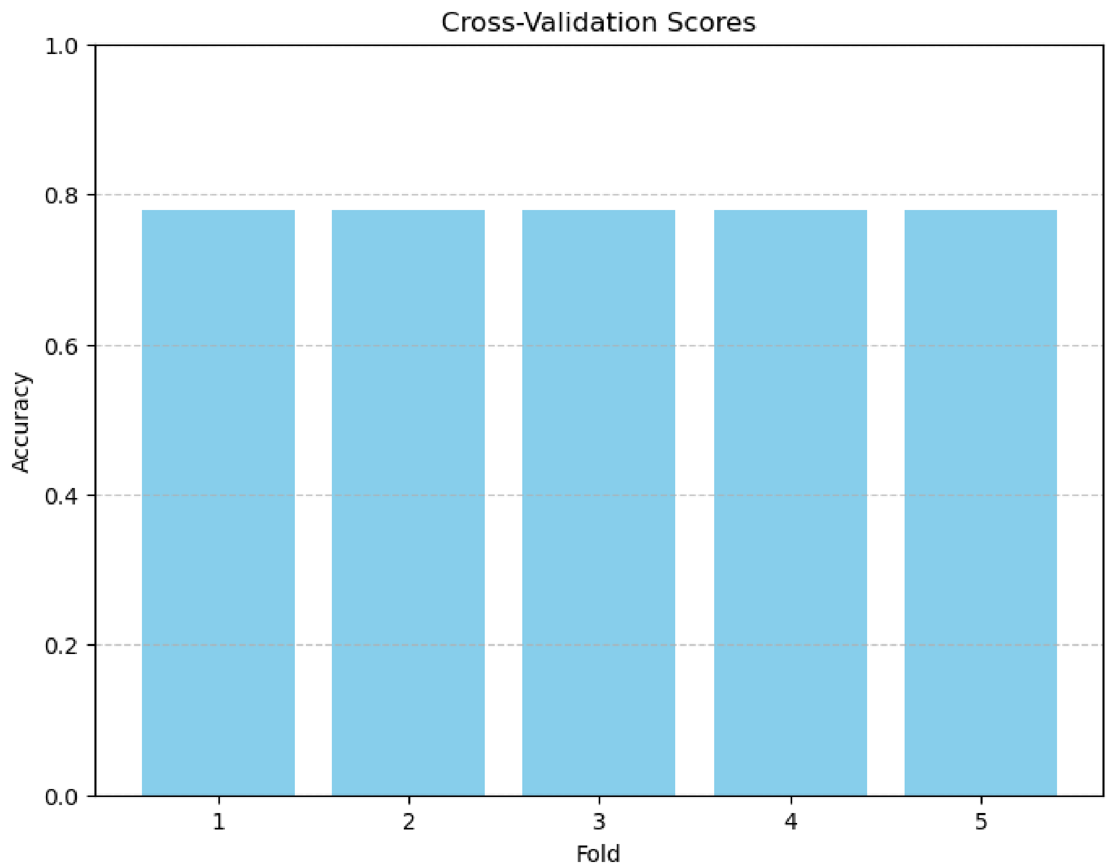

Cross validation check

```
[ ]: from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression

# Initialize logistic regression model
logistic_regression = LogisticRegression(penalty='l2', C=1.0,␣
↪solver='liblinear')

# Perform cross-validation
cv_scores = cross_val_score(logistic_regression, X, y, cv=5, scoring='accuracy')

# Print cross-validation scores
print("Cross-Validation Scores:", cv_scores)
print("Mean CV Score:", np.mean(cv_scores))
```

```
Cross-Validation Scores: [0.779      0.77883333 0.77883333 0.77883333
0.77883333]
Mean CV Score: 0.7788666666666668
```

visualize cross validation

[ ]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression

# Initialize logistic regression model
logistic_regression = LogisticRegression(penalty='l2', C=1.0,␣
 ↪solver='liblinear')

# Perform cross-validation
cv_scores = cross_val_score(logistic_regression, X, y, cv=5, scoring='accuracy')

# Plot cross-validation scores
plt.figure(figsize=(8, 6))
plt.bar(np.arange(len(cv_scores)), cv_scores, color='skyblue')
plt.xlabel('Fold')
plt.ylabel('Accuracy')
plt.title('Cross-Validation Scores')
plt.ylim(0, 1)  # Set y-axis limit from 0 to 1 for accuracy
plt.xticks(np.arange(len(cv_scores)), np.arange(1, len(cv_scores) + 1))
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()

# Print mean cross-validation score
print("Mean CV Score:", np.mean(cv_scores))
```




```
Mean CV Score: 0.7788666666666668
```