```
from google.colab import files
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving loan_borrower_data.csv to loan_borrower_data.csv
```

Case Study – Banking & Loans in Ghana

Focus: Reducing Non-Performing Loans (NPLs)

Welcome to the assignment on reducing Non-Performing Loans (NPLs) at GhanaLoanConnect. In this project, you will build a supervised learning model to predict whether a borrower is likely to default on a loan. Use this notebook as a guide to complete your work.

Business Challenge

GhanaLoanConnect is a peer-to-peer lending platform that connects borrowers with lenders. Your task is to develop a machine learning model that predicts loan default. The main objectives are:

- **Minimize the risk of non-performing loans (NPLs).**
- **Enable informed decision-making in the loan approval process.**

Dataset Overview

The dataset `loan_borrower_data.csv` contains approximately 9,578 records with the following key attributes:

- **credit.policy:** 1 if the borrower meets the credit approval standards, 0 otherwise.
- **purpose:** The intended use of the loan (e.g., `credit_card`, `debt_consolidation`, etc.).
- **int.rate:** The interest rate of the loan (e.g., 0.11 for 11%).
- **installment:** The monthly repayment amount.
- **log.annual.inc:** The natural logarithm of the borrower's annual income.

Make sure to load this dataset into your notebook.

```
# Import necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
import seaborn as sns

from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, roc_auc_score, confusion_matrix,
                             classification_report)

# Load the dataset
data = pd.read_csv('loan_borrower_data.csv')
print(data.head())
```

```
   credit.policy             purpose  int.rate  installment  log.annual.inc  \
0              1  debt_consolidation    0.1189       829.10       11.350407
1              1         credit_card    0.1071       228.22       11.082143
2              1  debt_consolidation    0.1357       366.86       10.373491
3              1  debt_consolidation    0.1008       162.34       11.350407
4              1         credit_card    0.1426       102.92       11.299732

     dti  fico  days.with.cr.line  revol.bal  revol.util  inq.last.6mths  \
0  19.48   737        5639.958333      28854        52.1               0
1  14.29   707        2760.000000      33623        76.7               0
2  11.63   682        4710.000000       3511        25.6               1
3   8.10   712        2699.958333      33667        73.2               1
4  14.97   667        4066.000000       4740        39.5               0

   delinq.2yrs  pub.rec  not.fully.paid
0            0        0               0
1            0        0               0
2            0        0               0
3            0        0               0
4            1        0               0
```

1. Data Exploration

Explore the dataset by checking its structure, missing values, and basic statistics. Answer the following questions:

- What are the data types of each column?
- Are there any missing or anomalous values?
- What is the distribution of the target variable?

```
# TODO: Perform data exploration
print(data.info())
print(data.describe())

# Check for missing values
print(data.isnull().sum())
```

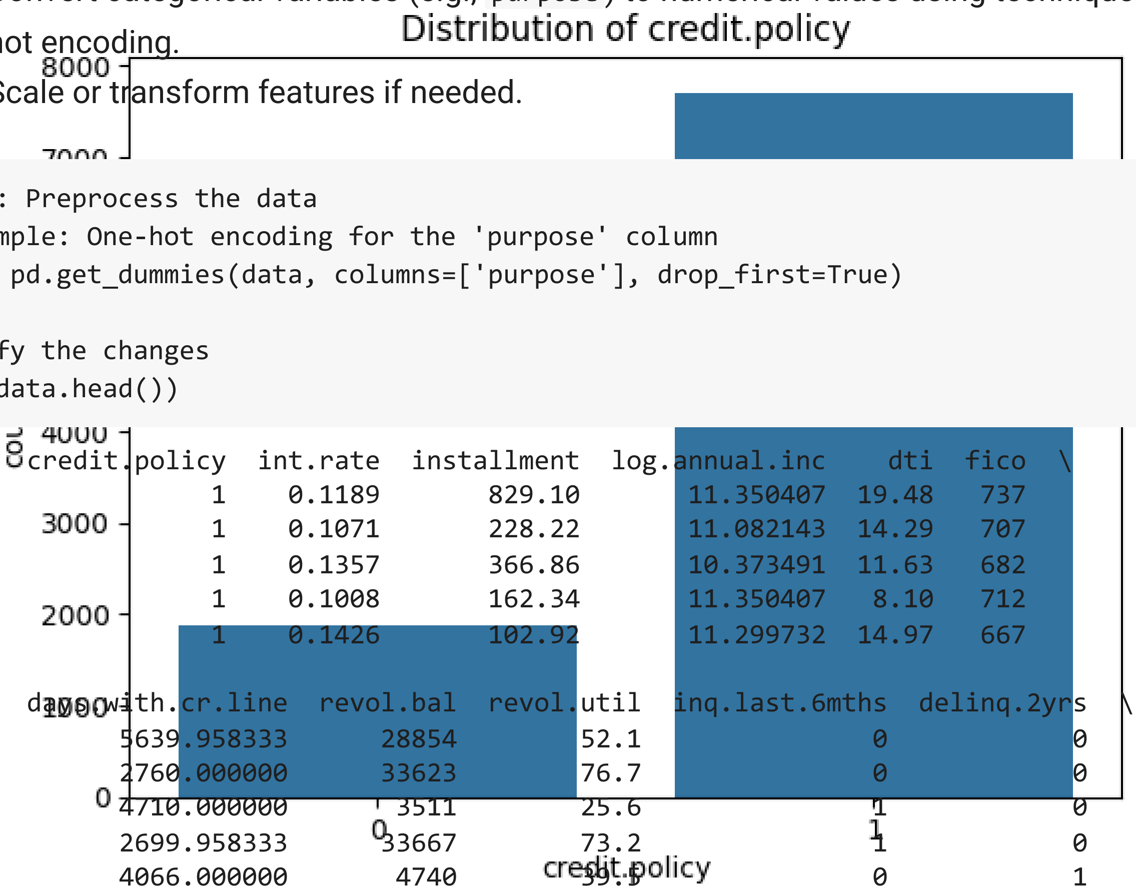
```
# Visualize the distribution of the target variable (credit.policy)
sns.countplot(x='credit.policy', data=data)
plt.title('Distribution of credit.policy')
plt.show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   credit.policy      9578 non-null   int64  
 1   purpose            9578 non-null   object 
 2   int.rate           9578 non-null   float64
 3   installment        9578 non-null   float64
 4   log.annual.inc     9578 non-null   float64
 5   dti                9578 non-null   float64
 6   fico               9578 non-null   int64  
 7   days.with.cr.line  9578 non-null   float64
 8   revol.bal          9578 non-null   int64  
 9   revol.util         9578 non-null   float64
 10  inq.last.6mths     9578 non-null   int64  
 11  delinq.2yrs        9578 non-null   int64  
 12  pub.rec            9578 non-null   int64  
 13  not.fully.paid     9578 non-null   int64  
dtypes: float64(6), int64(7), object(1)
memory usage: 1.0+ MB
None
       credit.policy     int.rate  installment  log.annual.inc          dti  \
count    9578.000000  9578.000000  9578.000000     9578.000000  9578.000000   
mean        0.804970     0.122640   319.089413       10.932117    12.606679   
std         0.396245     0.026847   207.071301        0.614813     6.883970   
min         0.000000     0.060000    15.670000        7.547502     0.000000   
25%         1.000000     0.103900   163.770000       10.558414     7.212500   
50%         1.000000     0.122100   268.950000       10.928884    12.665000   
75%         1.000000     0.140700   432.762500       11.291293    17.950000   
max         1.000000     0.216400   940.140000       14.528354    29.960000   

              fico  days.with.cr.line     revol.bal   revol.util  \
count  9578.000000        9578.000000  9.578000e+03  9578.000000   
mean    710.846314        4560.767197  1.691396e+04    46.799236   
std      37.970537        2496.930377  3.375619e+04    29.014417   
min     612.000000         178.958333  0.000000e+00     0.000000   
25%     682.000000        2820.000000  3.187000e+03    22.600000   
50%     707.000000        4139.958333  8.596000e+03    46.300000   
75%     737.000000        5730.000000  1.824950e+04    70.900000   
max     827.000000       17639.958330  1.207359e+06   119.000000   

       inq.last.6mths  delinq.2yrs      pub.rec  not.fully.paid  
count     9578.000000  9578.000000  9578.000000     9578.000000  
mean         1.577469     0.163708     0.062122        0.160054  
std          2.200245     0.546215     0.262126        0.366676  
min          0.000000     0.000000     0.000000        0.000000  
25%          0.000000     0.000000     0.000000        0.000000  
50%          1.000000     0.000000     0.000000        0.000000  
75%          2.000000     0.000000     0.000000        0.000000  
max         33.000000    13.000000     5.000000        1.000000  
credit.policy        0
purpose              0
int.rate             0
installment          0
log.annual.inc       0
```

```
dti                  0
fico                 0
days.with.cr.line    0
revol.bal            0
revol.util           0
inq.last.6mths       0
delinq.2yrs          0
pub.rec              0
not.fully.paid       0
dtype: int64
```



2. Data Preprocessing

Prepare the data for modeling:

- Handle missing values if there are any.
- Convert categorical variables (e.g., `purpose`) to numerical values using techniques like one-hot encoding.
- Scale or transform features if needed.

```
# TODO: Preprocess the data
## Example: One-hot encoding for the 'purpose' column
data = pd.get_dummies(data, columns=['purpose'], drop_first=True)

# Verify the changes
print(data.head())
```

```
   credit.policy  int.rate  installment  log.annual.inc    dti  fico  \
0              1    0.1189       829.10       11.350407  19.48   737
1              1    0.1071       228.22       11.082143  14.29   707
2              1    0.1357       366.86       10.373491  11.63   682
3              1    0.1008       162.34       11.350407   8.10   712
4              1    0.1426       102.92       11.299732  14.97   667

   days.with.cr.line  revol.bal  revol.util  inq.last.6mths  delinq.2yrs  \
0        5639.958333      28854        52.1               0            0
1        2760.000000      33623        76.7               0            0
2        4710.000000       3511        25.6               1            0
3        2699.958333      33667        73.2               1            0
4        4066.000000       4740        39.5               0            1

   pub.rec  not.fully.paid  purpose_credit_card  purpose_debt_consolidation  \
0        0               0                False                        True
1        0               0                 True                       False
2        0               0                False                        True
3        0               0                False                        True
4        0               0                 True                       False

   purpose_educational  purpose_home_improvement  purpose_major_purchase  \
0                False                     False                   False
1                False                     False                   False
2                False                     False                   False
3                False                     False                   False
4                False                     False                   False

   purpose_small_business
0                   False
1                   False
2                   False
3                   False
```

```
4                    False
```

3. Feature Engineering

Enhance the dataset by creating or transforming features that could help improve model performance. Consider:

- Interactions between features
- Derived features based on domain knowledge
- Any other transformation that might help the model

Document your feature engineering steps and rationale.

```
# TODO: Perform feature engineering

# Example: Create a new feature (if applicable)
 #data['new_feature'] = data['installment'] / data['log.annual.inc']
data['not_fully_paid'] = (data['days.with.cr.line'] > 5000).astype(int)



# Check the new features
print(data.head())
```

```
   credit.policy  int.rate  installment  log.annual.inc    dti  fico  \
0              1    0.1189       829.10       11.350407  19.48   737   
1              1    0.1071       228.22       11.082143  14.29   707   
2              1    0.1357       366.86       10.373491  11.63   682   
3              1    0.1008       162.34       11.350407   8.10   712   
4              1    0.1426       102.92       11.299732  14.97   667   

   days.with.cr.line  revol.bal  revol.util  inq.last.6mths  delinq.2yrs  \
0        5639.958333      28854        52.1               0            0   
1        2760.000000      33623        76.7               0            0   
2        4710.000000       3511        25.6               1            0   
3        2699.958333      33667        73.2               1            0   
4        4066.000000       4740        39.5               0            1   

   pub.rec  not.fully.paid  purpose_credit_card  purpose_debt_consolidation  \
0        0               0                False                        True   
1        0               0                 True                       False   
2        0               0                False                        True   
3        0               0                False                        True   
4        0               0                 True                       False   

   purpose_educational  purpose_home_improvement  purpose_major_purchase  \
0                False                     False                   False   
1                False                     False                   False   
2                False                     False                   False   
3                False                     False                   False   
4                False                     False                   False   
```

```
   purpose_small_business  not_fully_paid
0                   False               1
1                   False               0
2                   False               0
3                   False               0
4                   False               0
```

4. Model Selection and Training

Split the data into training and testing sets, and train your model(s). Consider using multiple models such as Logistic Regression, Random Forest, or other suitable algorithms. Use cross-validation to assess model robustness.

```
# Split the data into features and target
X = data.drop('credit.policy', axis=1)
y = data['credit.policy']

# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

# TODO: Train your models
## Example with Logistic Regression
logreg = LogisticRegression(max_iter=1000)
logreg.fit(X_train, y_train)

# Evaluate the model on the testing set
y_pred = logreg.predict(X_test)
print('Accuracy:', accuracy_score(y_test, y_pred))
print('Precision:', precision_score(y_test, y_pred))
print('Recall:', recall_score(y_test, y_pred))
print('F1 Score:', f1_score(y_test, y_pred))

# TODO: Try additional models (e.g., Random Forest, Gradient Boosting) and compare performar
```

```
Accuracy: 0.8987473903966597
Precision: 0.9064632677639503
Recall: 0.9749568221070811
F1 Score: 0.9394632827127106
/usr/local/lib/python3.11/dist-packages/sklearn/linear_model/_logistic.py:465: Converger
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  n_iter_i = _check_optimize_result(
```

```
from sklearn.ensemble import GradientBoostingClassifier

# TODO: Try additional models (e.g., Random Forest, Gradient Boosting) and compare performar

## Add Gradient Boosting Model
gb = GradientBoostingClassifier(random_state=42)
gb.fit(X_train, y_train)

# Evaluate the Gradient Boosting model on the testing set
y_pred_gb = gb.predict(X_test)

print('Gradient Boosting Accuracy:', accuracy_score(y_test, y_pred_gb))
print('Gradient Boosting Precision:', precision_score(y_test, y_pred_gb))
print('Gradient Boosting Recall:', recall_score(y_test, y_pred_gb))
print('Gradient Boosting F1 Score:', f1_score(y_test, y_pred_gb))
print('Gradient Boosting ROC AUC:', roc_auc_score(y_test, gb.predict_proba(X_test)[:, 1]))
```

```
Gradient Boosting Accuracy: 0.9895615866388309
Gradient Boosting Precision: 0.9901372212692967
Gradient Boosting Recall: 0.9969775474956822
Gradient Boosting F1 Score: 0.9935456110154905
Gradient Boosting ROC AUC: 0.995736376523607
```

5. Model Evaluation and Testing

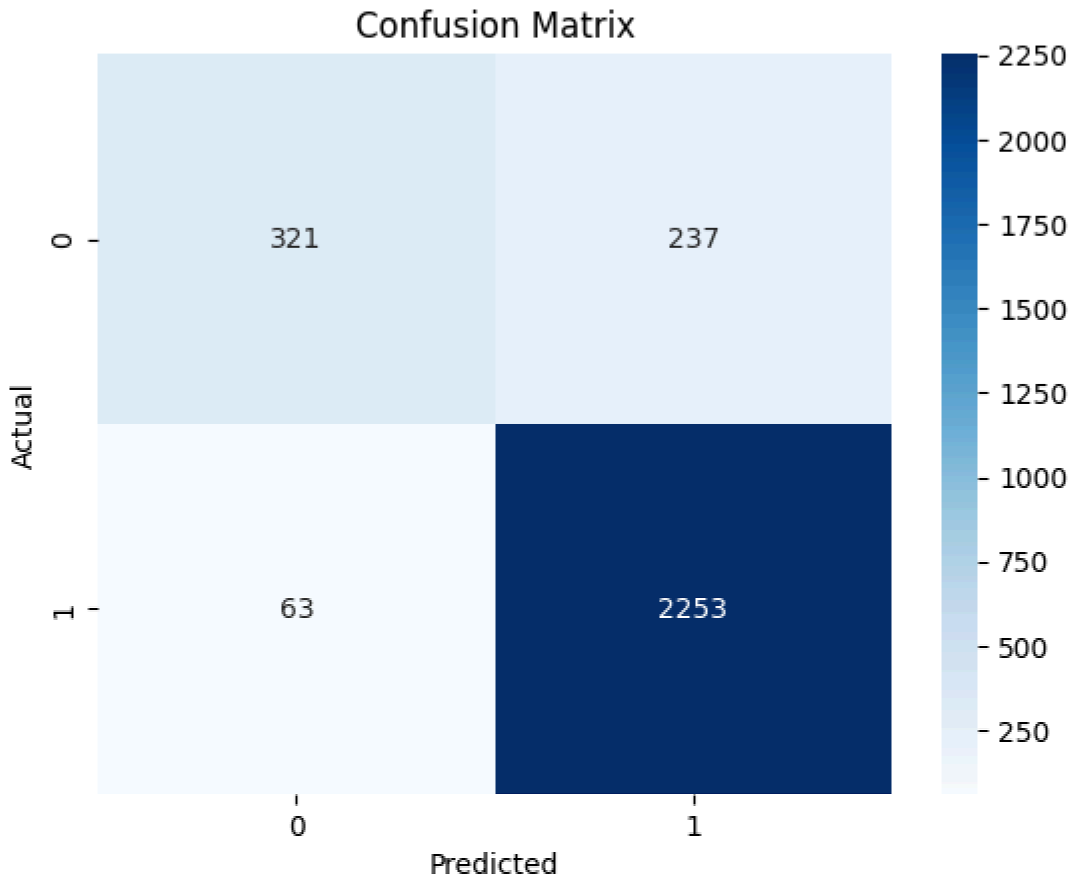
Assess your model using various metrics such as:

- Accuracy
- Precision
- Recall
- F1 Score
- ROC-AUC

Plot confusion matrices and ROC curves as needed.

```
# TODO: Evaluate your model further
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# Classification Report
print(classification_report(y_test, y_pred))
```




```
              precision    recall  f1-score   support

           0       0.84      0.58      0.68       558
           1       0.90      0.97      0.94      2316

    accuracy                           0.90      2874
   macro avg       0.87      0.77      0.81      2874
weighted avg       0.89      0.90      0.89      2874
```

6. Model Interpretation and Insights

Discuss the following:

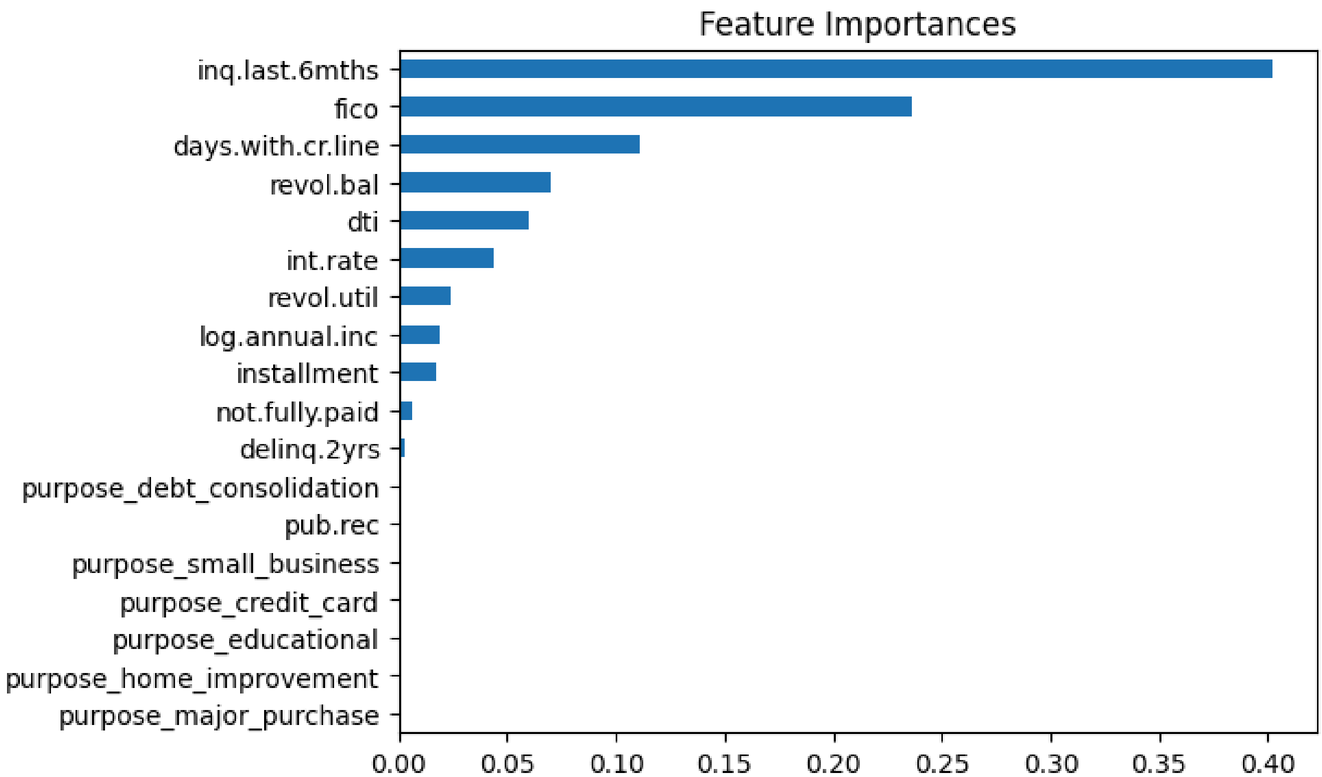
- Which features are most important in predicting loan default?
- What business insights can be drawn from your model?

Provide clear interpretations and, if possible, visualize feature importance.

```
# TODO: Interpret model results

# Example for a tree-based model (if used):
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier()
model.fit(X_train, y_train)
```

```
feature_importances = pd.Series(model.feature_importances_, index=X_train.columns)
feature_importances.sort_values().plot(kind='barh')
plt.title('Feature Importances')
plt.show()
```



Start coding or generate with AI.

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_auc_score, precision_score, recall_score, f1_score, accuracy
# Import SMOTE for oversampling
from imblearn.over_sampling import SMOTE

# Set up the model and hyperparameters
rf = RandomForestClassifier(random_state=42)
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [4, 6, 8],
    'min_samples_split': [2, 5],
    'min_samples_leaf': [1, 2],
}

# Run GridSearch on original training data

def run_gridsearch(X_train, y_train, param_grid):
    rf = RandomForestClassifier(random_state=42)
```

```
    grid_search = GridSearchCV(estimator=rf, param_grid=param_grid,
                               scoring='roc_auc', cv=3, verbose=1, n_jobs=-1)
    grid_search.fit(X_train, y_train)
    return grid_search

    # For original training data
grid_original = run_gridsearch(X_train, y_train, param_grid)

# For SMOTE-resampled training data

from imblearn.over_sampling import SMOTE

sm = SMOTE(random_state=42)
X_resampled, y_resampled = sm.fit_resample(X_train, y_train)

grid_resampled = run_gridsearch(X_resampled, y_resampled, param_grid)

# Best models
best_rf_original = grid_original.best_estimator_
best_rf_resampled = grid_resampled.best_estimator_


# Fit GridSearch to resampled data
# NOTE: It is generally better to perform resampling within the cross-validation loop
# to avoid data leakage. However, to match the user's apparent intent of fitting
# after resampling, we will fit the GridSearchCV object on the resampled data here.
# For a more robust approach, consider using Pipeline with resampling and GridSearchCV.
grid_search_resampled = GridSearchCV(estimator=rf, param_grid=param_grid,
                           scoring='roc_auc', cv=3, verbose=1, n_jobs=-1)

grid_search_resampled.fit(X_resampled, y_resampled)

# Best model from resampling
best_rf = grid_search_resampled.best_estimator_

# Evaluate the best model from resampling
# Predict probabilities on the original, untouched test set
y_pred_proba_resampled = best_rf.predict_proba(X_test)[:, 1]
auc_score_resampled = roc_auc_score(y_test, y_pred_proba_resampled)
print("Best AUC Score after GridSearch on Resampled Data:", auc_score_resampled)
print(" Best Parameters after Resampling:", grid_search_resampled.best_params_)

# Optionally, evaluate the best model from the initial grid search on original data as well
best_rf_original = grid_original.best_estimator_
y_pred_proba_original = best_rf_original.predict_proba(X_test)[:, 1]
auc_score_original = roc_auc_score(y_test, y_pred_proba_original)
print("Best AUC Score after GridSearch on Original Data:", auc_score_original)
print(" Best Parameters on Original Data:", grid_original.best_params_)
```

```
Fitting 3 folds for each of 24 candidates, totalling 72 fits
Fitting 3 folds for each of 24 candidates, totalling 72 fits
```

```
Fitting 3 folds for each of 24 candidates, totalling 72 fits
Best AUC Score after GridSearch on Resampled Data: 0.9864299156251354
 Best Parameters after Resampling: {'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_
Best AUC Score after GridSearch on Original Data: 0.9914944193734099
 Best Parameters on Original Data: {'max_depth': 8, 'min_samples_leaf': 1, 'min_samples_
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import roc_auc_score, precision_score, recall_score, f1_score, accurac
import matplotlib.pyplot as plt

# Assuming 'best_rf' is the trained Random Forest model from the previous cell
# that you want to use for the ROC curve.
# If you want to use a different trained model, replace 'best_rf' with the correct variable
rf_probs = best_rf.predict_proba(X_test)[:,1]
fpr, tpr, thresholds = roc_curve(y_test, rf_probs)

plt.plot(fpr, tpr, label='Random Forest')
plt.plot([0,1],[0,1],'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.legend()
plt.show()
```