Restaurant-Customer-Satisfaction-Prediction

July 31, 2025

[1]:
```
### Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import chi2_contingency
from sklearn.dummy import DummyClassifier
from sklearn.model_selection import␣
↪(train_test_split,StratifiedKFold,cross_val_score,GridSearchCV)
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import␣
↪(classification_report,roc_auc_score,confusion_matrix,accuracy_score,precision_score,recall_
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from imblearn.over_sampling import SMOTE
```

[2]:
```
##load Data
data_path = "restaurant_customer_satisfaction.csv"
df = pd.read_csv(data_path)
```

[3]:
```
#overlook data
df.describe()
```

[3]:
```
         CustomerID          Age         Income  AverageSpend    GroupSize  \
count  1500.000000  1500.000000    1500.000000   1500.000000  1500.000000
mean   1403.500000    43.832000   85921.890000    105.659004     5.035333
std     433.157015    14.967157   38183.051749     52.381849     2.558864
min     654.000000    18.000000   20012.000000     10.306127     1.000000
25%    1028.750000    31.750000   52444.000000     62.287907     3.000000
50%    1403.500000    44.000000   85811.000000    104.626408     5.000000
75%    1778.250000    57.000000  119159.250000    148.649330     7.000000
max    2153.000000    69.000000  149875.000000    199.973526     9.000000

       OnlineReservation  DeliveryOrder  LoyaltyProgramMember     WaitTime  \
count        1500.000000    1500.000000           1500.000000  1500.000000
mean            0.296667       0.405333              0.480000    30.163550
std             0.456941       0.491120              0.499766    17.214184
min             0.000000       0.000000              0.000000     0.001380
```

```
25%            0.000000       0.000000                0.000000     15.235423
50%            0.000000       0.000000                0.000000     30.044055
75%            1.000000       1.000000                1.000000     45.285649
max            1.000000       1.000000                1.000000     59.970762

       ServiceRating   FoodRating  AmbianceRating  HighSatisfaction
count    1500.000000  1500.000000     1500.000000       1500.000000
mean        3.044000     2.997333        2.987333          0.134000
std         1.423405     1.418920        1.450716          0.340766
min         1.000000     1.000000        1.000000          0.000000
25%         2.000000     2.000000        2.000000          0.000000
50%         3.000000     3.000000        3.000000          0.000000
75%         4.000000     4.000000        4.000000          0.000000
max         5.000000     5.000000        5.000000          1.000000
```

[4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1500 entries, 0 to 1499
Data columns (total 19 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   CustomerID            1500 non-null   int64
 1   Age                   1500 non-null   int64
 2   Gender                1500 non-null   object
 3   Income                1500 non-null   int64
 4   VisitFrequency        1500 non-null   object
 5   AverageSpend          1500 non-null   float64
 6   PreferredCuisine      1500 non-null   object
 7   TimeOfVisit           1500 non-null   object
 8   GroupSize             1500 non-null   int64
 9   DiningOccasion        1500 non-null   object
 10  MealType              1500 non-null   object
 11  OnlineReservation     1500 non-null   int64
 12  DeliveryOrder         1500 non-null   int64
 13  LoyaltyProgramMember  1500 non-null   int64
 14  WaitTime              1500 non-null   float64
 15  ServiceRating         1500 non-null   int64
 16  FoodRating            1500 non-null   int64
 17  AmbianceRating        1500 non-null   int64
 18  HighSatisfaction      1500 non-null   int64
dtypes: float64(2), int64(11), object(6)
memory usage: 222.8+ KB
```

[5]:
```
df.head(5)
```

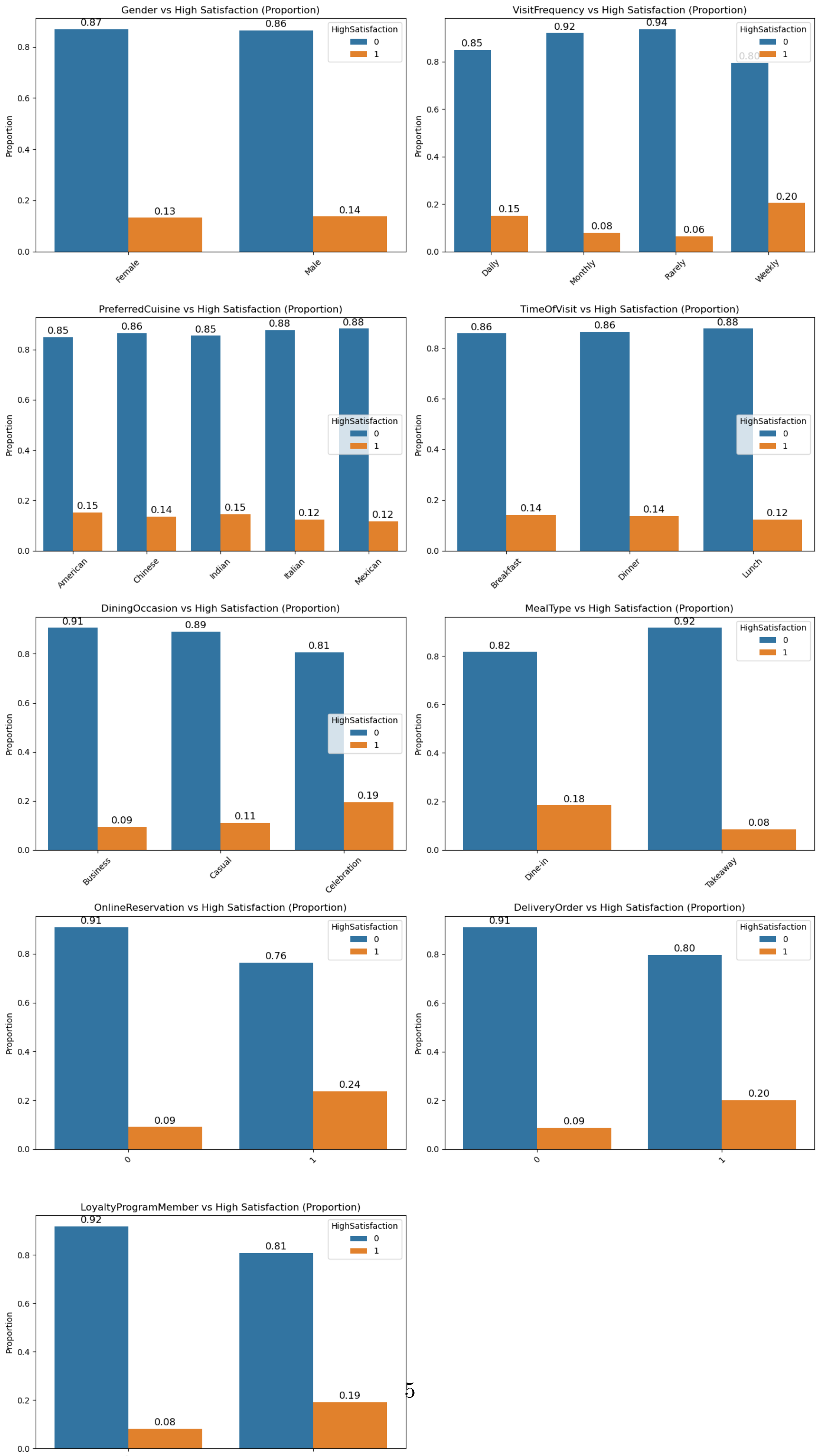
[5]:
```
   CustomerID  Age  Gender  Income VisitFrequency  AverageSpend  \
0         654   35    Male   83380         Weekly     27.829142
1         655   19    Male   43623         Rarely    115.408622
2         656   41  Female   83737         Weekly    106.693771
3         657   43    Male   96768         Rarely     43.508508
4         658   55  Female   67937        Monthly    148.084627

  PreferredCuisine TimeOfVisit  GroupSize DiningOccasion  MealType  \
0          Chinese   Breakfast          3       Business  Takeaway
1         American      Dinner          1         Casual   Dine-in
2         American      Dinner          6    Celebration   Dine-in
3           Indian       Lunch          1    Celebration   Dine-in
4          Chinese   Breakfast          1       Business  Takeaway

   OnlineReservation  DeliveryOrder  LoyaltyProgramMember   WaitTime  \
0                  0              1                     1  43.523929
1                  0              0                     0  57.524294
2                  0              1                     0  48.682623
3                  0              0                     0   7.552993
4                  0              0                     1  37.789041

   ServiceRating  FoodRating  AmbianceRating  HighSatisfaction
0              2           5               4                 0
1              5           5               3                 0
2              3           4               5                 0
3              4           5               1                 0
4              2           3               5                 0
```

[6]:
```python
df.drop(["CustomerID"], axis=1, inplace=True)
```

[7]:
```python
col_numerical = ["Age","Income","AverageSpend","WaitTime"]
col_categorical =␣
↪["Gender","VisitFrequency","PreferredCuisine","TimeOfVisit","DiningOccasion","MealType","On
col_ordinal= ["GroupSize","ServiceRating","FoodRating","AmbianceRating"]
```

[8]:
```python
### Categorical plot VS HighSatisfaction
df_prop = df.copy()
proportion_data = []

for col in col_categorical:
    temp = df_prop.groupby([col, 'HighSatisfaction']).size().
↪reset_index(name='count')
    total = temp.groupby(col)['count'].transform('sum')
    temp['proportion'] = temp['count'] / total
    temp['feature'] = col
    temp.rename(columns={col: 'category'}, inplace=True)
    proportion_data.append(temp)
```

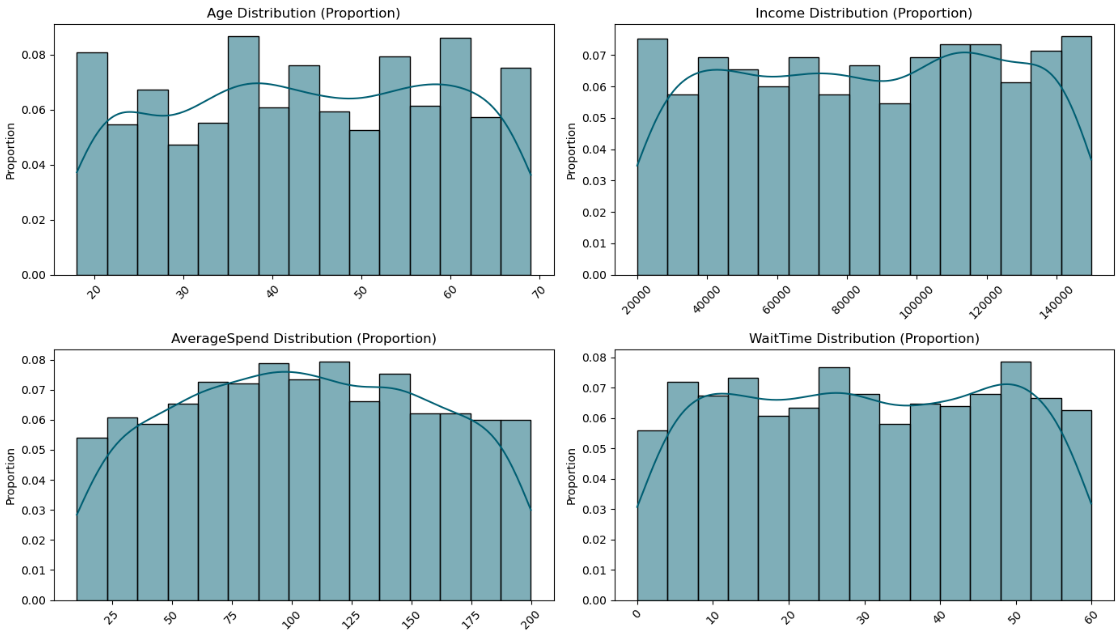
```python
prop_df = pd.concat(proportion_data)

#labels
num_cols = col_categorical
n_cols = 2
n_rows = (len(num_cols) + 1) // n_cols
fig, axes = plt.subplots(n_rows, n_cols, figsize=(14, 5 * n_rows))

axes = axes.flatten()

for i, col in enumerate(col_categorical):
    subset = prop_df[prop_df['feature'] == col]
    ax = axes[i]
    bars = sns.barplot(data=subset, x='category', y='proportion',␣
 ↪hue='HighSatisfaction', ax=ax)
    ax.set_title(f'{col} vs High Satisfaction (Proportion)')
    ax.set_ylabel('Proportion')
    ax.set_xlabel('')
    ax.tick_params(axis='x', rotation=45)

    # labels to bars
    for container in ax.containers:
        ax.bar_label(container, fmt='%.2f', label_type='edge', fontsize=12,␣
 ↪padding=2)

# Remove subplots
if len(col_categorical) < len(axes):
    for j in range(len(col_categorical), len(axes)):
        fig.delaxes(axes[j])

plt.tight_layout()
#plt.savefig("C:/Users/MAAP/Pictures/Proportionlplot.png")
plt.show()
plt.clf()
```


Gender vs High Satisfaction (Proportion)
HighSatisfaction
0
1
0.87
0.86
0.13
0.14
Proportion
Female
Male
VisitFrequency vs High Satisfaction (Proportion)
0.85
0.92
0.94
0.80
0.15
0.08
0.06
0.20
Daily
Monthly
Rarely
Weekly
PreferredCuisine vs High Satisfaction (Proportion)
0.85
0.86
0.85
0.88
0.88
0.15
0.14
0.15
0.12
0.12
American
Chinese
Indian
Italian
Mexican
TimeOfVisit vs High Satisfaction (Proportion)
0.86
0.86
0.88
0.14
0.14
0.12
Breakfast
Dinner
Lunch
DiningOccasion vs High Satisfaction (Proportion)
0.91
0.89
0.81
0.09
0.11
0.19
Business
Casual
Celebration
MealType vs High Satisfaction (Proportion)
0.82
0.92
0.18
0.08
Dine-in
Takeaway
OnlineReservation vs High Satisfaction (Proportion)
0.91
0.76
0.09
0.24
DeliveryOrder vs High Satisfaction (Proportion)
0.91
0.80
0.09
0.20
LoyaltyProgramMember vs High Satisfaction (Proportion)
0.92
0.81
0.08
0.19

```
<Figure size 640x480 with 0 Axes>
```

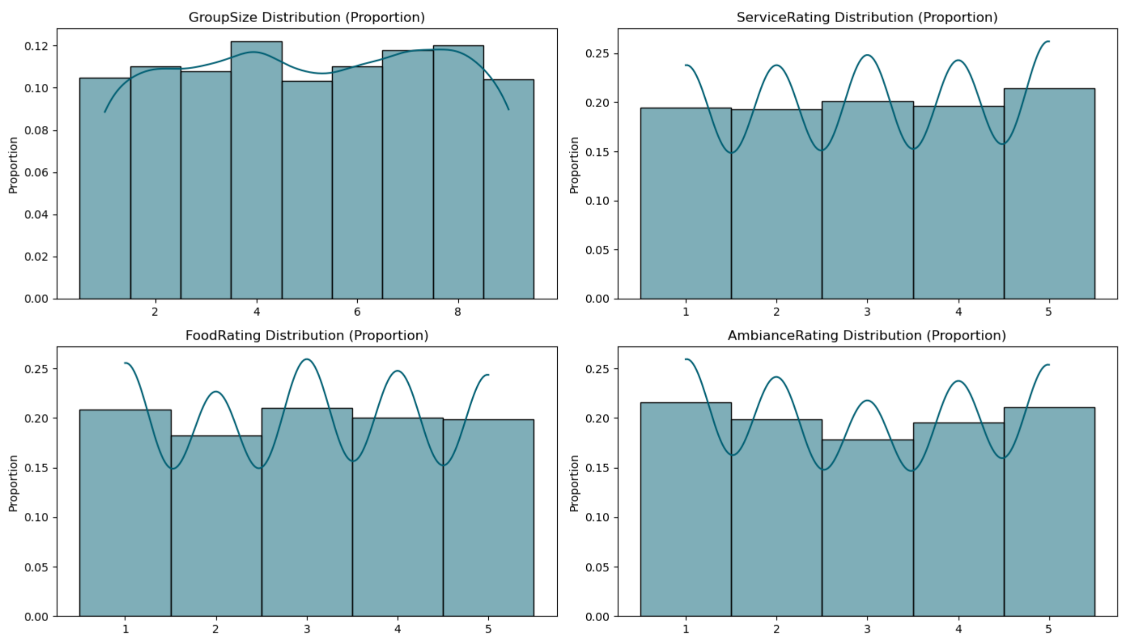
[9]:

```python
# plot numerical features

num_cols = col_numerical

n_cols = 2
n_rows = (len(num_cols) + 1) // n_cols
fig, axes = plt.subplots(n_rows, n_cols, figsize=(14, 4 * n_rows))
axes = axes.flatten()

for i, col in enumerate(num_cols):
    sns.histplot(data=df, x=col, kde=True, bins=15, ax=axes[i],␣
 ↪color="#005f73", stat='probability')
    axes[i].set_title(f'{col} Distribution (Proportion)', fontsize=12)
    axes[i].set_ylabel('Proportion')
    axes[i].set_xlabel('')
    axes[i].tick_params(axis='x', rotation=45)

# Remove unused axes
if len(num_cols) < len(axes):
    for j in range(len(num_cols), len(axes)):
        fig.delaxes(axes[j])

plt.tight_layout()
#plt.savefig("C:/Users/MAAP/Pictures/Continueslplot.png")
plt.show()
```



[10]:
```
# plot ordinal

num_cols = col_ordinal

n_cols = 2
n_rows = (len(num_cols) + 1) // n_cols
fig, axes = plt.subplots(n_rows, n_cols, figsize=(14, 4 * n_rows))
axes = axes.flatten()

for i, col in enumerate(num_cols):
    sns.histplot(
        data=df,
        x=col,
        kde=True,
        bins=5,
        ax=axes[i],
        color="#005f73",
        discrete=True,
        stat='probability'  # show proportion instead of count
    )
    axes[i].set_title(f'{col} Distribution (Proportion)', fontsize=12)
    axes[i].set_ylabel('Proportion')
    axes[i].set_xlabel('')

    axes[i].tick_params(axis='x', rotation=0)
```

```
# Remove unused axes
if len(num_cols) < len(axes):
    for j in range(len(num_cols), len(axes)):
        fig.delaxes(axes[j])

plt.tight_layout()
#plt.savefig("C:/Users/MAAP/Pictures/Discreteplot.png")
plt.show()
```



[11]:
```
##chi-2test - https://www.geeksforgeeks.org/python-pearsons-chi-square-test/
 ↪#performing-chisquare-test-in-python
chi_results = []

for feature in col_categorical:
    contingency_table = pd.crosstab(df[feature], df['HighSatisfaction'])
    chi2, p, dof, expected = chi2_contingency(contingency_table)
    chi_results.append({
        'Feature': feature,
        'Chi² Value': round(chi2, 2),
        'Degrees of Freedom': dof,
        'p-value': round(p, 5),
        'significant':  'significant' if p < 0.05 else 'insignificant'
    })

# Convert to DataFrame for display
chi_results_df = pd.DataFrame(chi_results)
```

```python
chi_results_df = chi_results_df.sort_values(by='p-value')

# Print the results
print(chi_results_df)
```

```
                Feature  Chi² Value  Degrees of Freedom  p-value  \
1        VisitFrequency       50.63                   3  0.00000
4        DiningOccasion       25.67                   2  0.00000
5              MealType       31.23                   1  0.00000
6     OnlineReservation       55.43                   1  0.00000
7         DeliveryOrder       40.12                   1  0.00000
8   LoyaltyProgramMember      38.73                   1  0.00000
3           TimeOfVisit        0.80                   2  0.67154
2      PreferredCuisine        2.15                   4  0.70907
0                Gender        0.03                   1  0.85493

     significant
1    significant
4    significant
5    significant
6    significant
7    significant
8    significant
3  insignificant
2  insignificant
0  insignificant
```

[12]:
```python
##prepare data for ML
encoded_df = pd.get_dummies(df, columns=col_categorical, drop_first=True)
#separate the data
X = encoded_df.drop("HighSatisfaction", axis=1)
y = encoded_df["HighSatisfaction"] #target satisfy = 0 no-satisfy = 1
scalert =  StandardScaler()
X[col_numerical] =  scalert.fit_transform(X[col_numerical])

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)
```

[13]:
```python
"""
Naive Classifier
This is to know what the accuracy is for always choosen No == 0
"""
```

[13]:
```
'\nNaive Classifier\nThis is to know what the accuracy is for always choosen No
== 0\n'
```

[14]:
```
dummy_clf = DummyClassifier(strategy="most_frequent", random_state=42)
dummy_clf.fit(X_train, y_train)
y_dummy_pred = dummy_clf.predict(X_test)

# Evaluate its performance
print("=== Naive Classifier (Most Frequent) ===")
print(classification_report(y_test, y_dummy_pred))
```

```
=== Naive Classifier (Most Frequent) ===
              precision    recall  f1-score   support

           0       0.87      1.00      0.93       260
           1       0.00      0.00      0.00        40

    accuracy                           0.87       300
   macro avg       0.43      0.50      0.46       300
weighted avg       0.75      0.87      0.80       300


C:\Users\MAAP\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\MAAP\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
C:\Users\MAAP\anaconda3\Lib\site-
packages\sklearn\metrics\_classification.py:1531: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

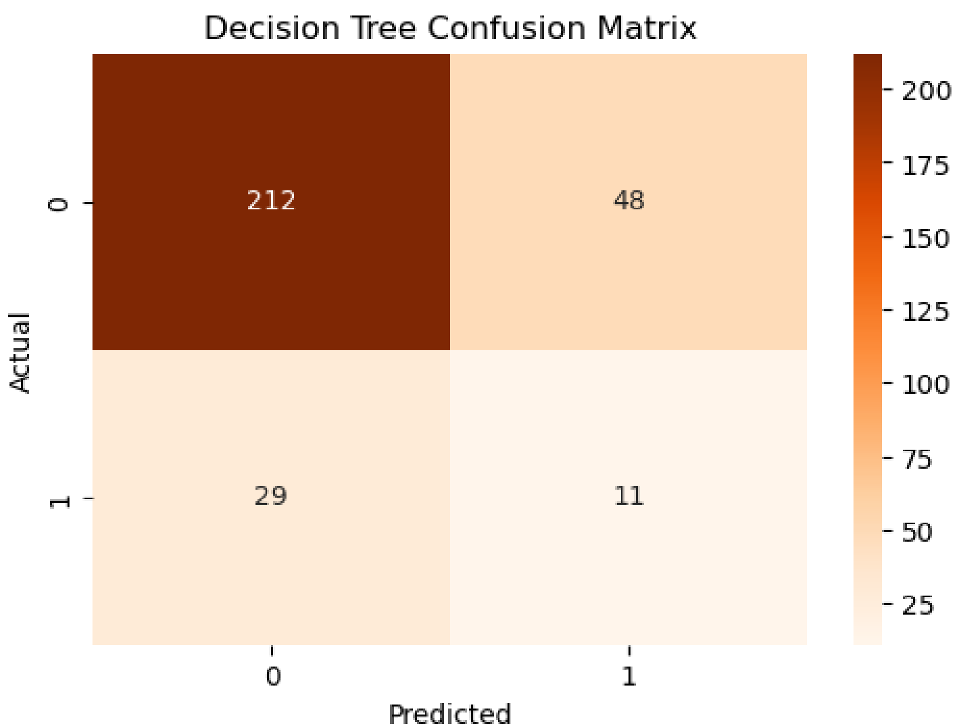
[15]:
```
#Model without SMOTE
```

[16]:
```
##https://www.kaggle.com/

#prepared Models, remember that 42 is just a number
dt_model = DecisionTreeClassifier(random_state=42)
rf_model = RandomForestClassifier(random_state=42)

# k-Fold CV scores
dt_scores = cross_val_score(dt_model, X, y, cv=StratifiedKFold(n_splits=5),␣
 ↪scoring='roc_auc')
rf_scores = cross_val_score(rf_model, X, y, cv=StratifiedKFold(n_splits=5),␣
 ↪scoring='roc_auc')
```

```python
dt_model.fit(X_train, y_train)
y_pred_dt = dt_model.predict(X_test)
y_proba_dt = dt_model.predict_proba(X_test)[:, 1]

rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)
y_proba_rf = rf_model.predict_proba(X_test)[:, 1]

# Decision Tree Evaluation
print("=== Decision Tree Evaluation ===")
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_dt))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_dt))
print("ROC AUC Score:", roc_auc_score(y_test, dt_model.predict_proba(X_test)[:,␣
↪1]))

# Confusion matrix for Decision Tree
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred_dt), annot=True, fmt='d',␣
↪cmap='Oranges')
plt.title('Decision Tree Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# Random Forest Evaluation
print("\n=== Random Forest Evaluation ===")
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_rf))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_rf))
print("ROC AUC Score:", roc_auc_score(y_test, rf_model.predict_proba(X_test)[:,␣
↪1]))


# Confusion matrix for Random Forest
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred_rf), annot=True, fmt='d',␣
↪cmap='Blues')
plt.title('Random Forest Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

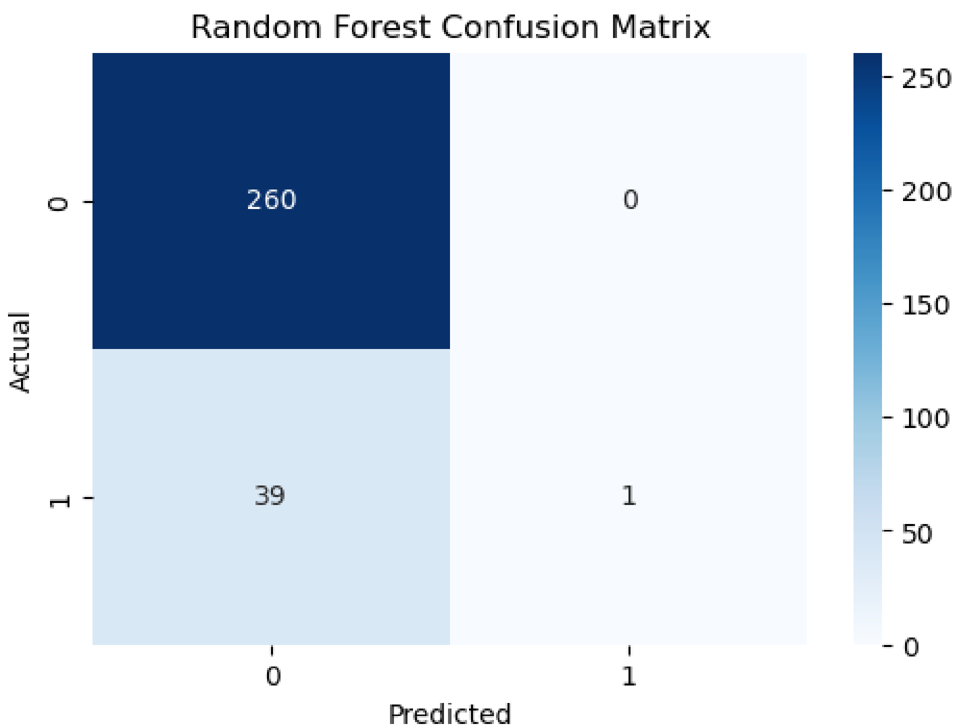
```
=== Decision Tree Evaluation ===
```

```
Confusion Matrix:
[[212  48]
 [ 29  11]]

Classification Report:
              precision    recall  f1-score   support

           0       0.88      0.82      0.85       260
           1       0.19      0.28      0.22        40

    accuracy                           0.74       300
   macro avg       0.53      0.55      0.53       300
weighted avg       0.79      0.74      0.76       300

ROC AUC Score: 0.5451923076923076
```




```
=== Random Forest Evaluation ===
Confusion Matrix:
[[260   0]
 [ 39   1]]

Classification Report:
              precision    recall  f1-score   support
```

```
           0       0.87      1.00      0.93       260
           1       1.00      0.03      0.05        40

    accuracy                           0.87       300
   macro avg       0.93      0.51      0.49       300
weighted avg       0.89      0.87      0.81       300

ROC AUC Score: 0.7449038461538462
```



[17]:
```
#With SMOTE
```

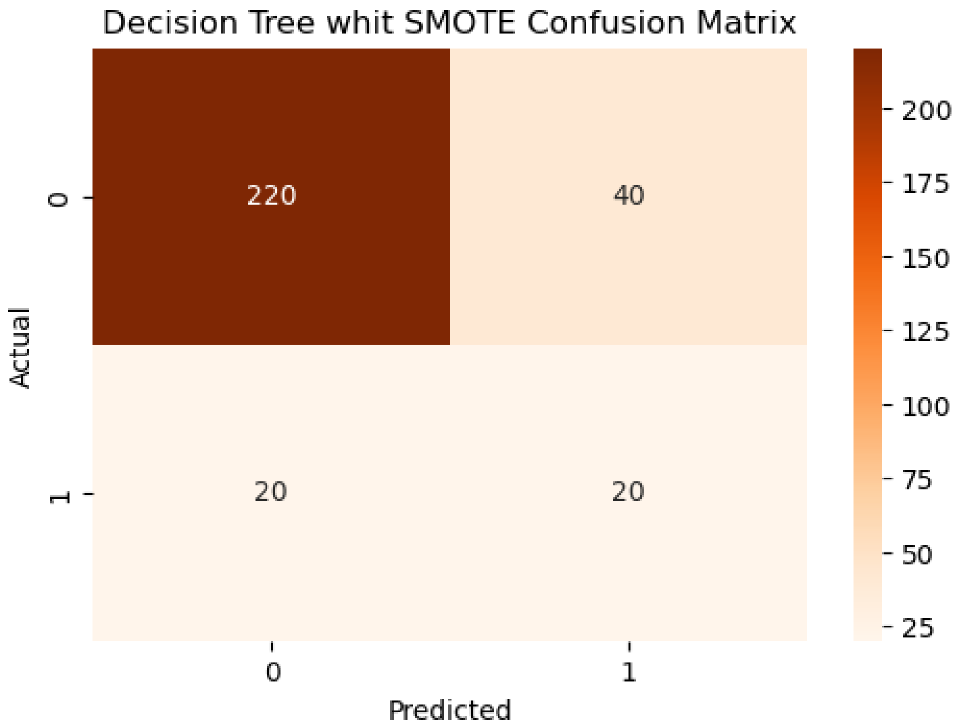
[18]:
```
sm = SMOTE(random_state=12)
X_train, y_train = sm.fit_resample(X_train, y_train)
```

[19]:
```
#prepared Models, remember that 42 is just a number
dt_model = DecisionTreeClassifier(criterion='entropy', max_depth= 15,␣
 ↪min_samples_split = 10,random_state=42)
rf_model = RandomForestClassifier(criterion='entropy', max_depth= 15,␣
 ↪min_samples_split = 2,random_state=42)

# k-Fold CV scores
```

```python
dt_scores = cross_val_score(dt_model, X, y, cv=StratifiedKFold(n_splits=5),␣
 ↪scoring='roc_auc')
rf_scores = cross_val_score(rf_model, X, y, cv=StratifiedKFold(n_splits=5),␣
 ↪scoring='roc_auc')

dt_model.fit(X_train, y_train)
y_pred_dt = dt_model.predict(X_test)
y_proba_dt = dt_model.predict_proba(X_test)[:, 1]

rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)
y_proba_rf = rf_model.predict_proba(X_test)[:, 1]

# Decision Tree Evaluation
print("=== Decision Tree whit SMOTE Evaluation ===")
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_dt))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_dt))
print("ROC AUC Score:", roc_auc_score(y_test, dt_model.predict_proba(X_test)[:,␣
 ↪1]))

# Confusion matrix for Decision Tree
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred_dt), annot=True, fmt='d',␣
 ↪cmap='Oranges')
plt.title('Decision Tree whit SMOTE Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# Random Forest Evaluation
print("\n=== Random Forest with SMOTE Evaluation ===")
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_rf))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_rf))
print("ROC AUC Score:", roc_auc_score(y_test, rf_model.predict_proba(X_test)[:,␣
 ↪1]))


# Confusion matrix for Random Forest
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred_rf), annot=True, fmt='d',␣
 ↪cmap='Blues')
plt.title('Random Forest with SMOTE Confusion Matrix')
```

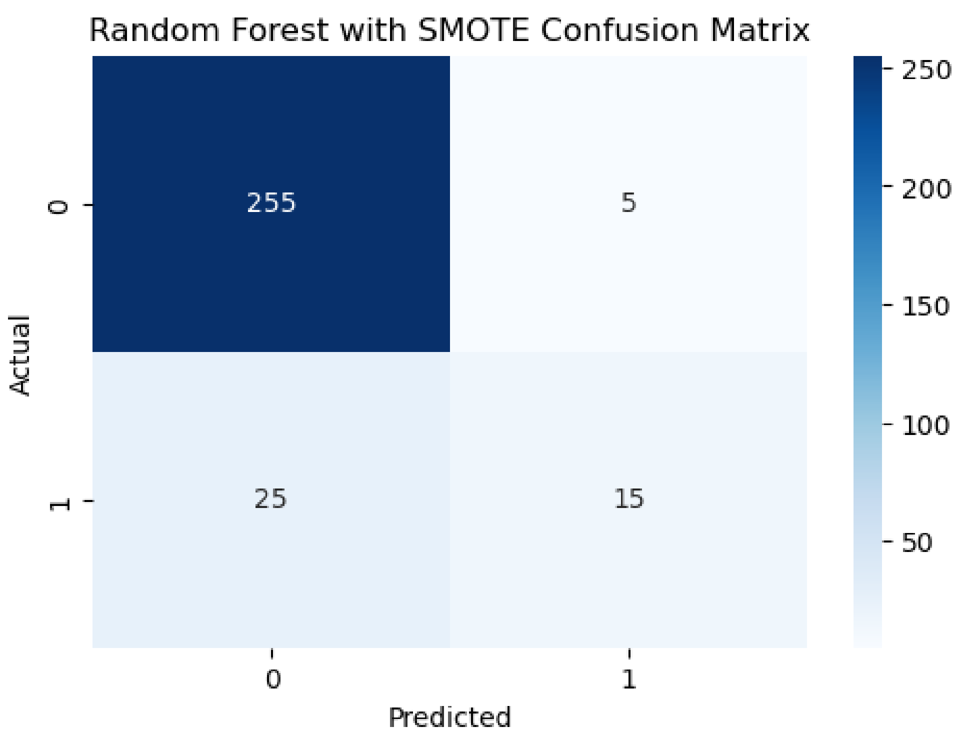
```
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
=== Decision Tree whit SMOTE Evaluation ===
Confusion Matrix:
[[220  40]
 [ 20  20]]

Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.85      0.88       260
           1       0.33      0.50      0.40        40

    accuracy                           0.80       300
   macro avg       0.62      0.67      0.64       300
weighted avg       0.84      0.80      0.82       300

ROC AUC Score: 0.6724038461538462
```




```
=== Random Forest with SMOTE Evaluation ===
Confusion Matrix:
```

```
[[255   5]
 [ 25  15]]

Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.98      0.94       260
           1       0.75      0.38      0.50        40

    accuracy                           0.90       300
   macro avg       0.83      0.68      0.72       300
weighted avg       0.89      0.90      0.89       300

ROC AUC Score: 0.7543269230769232
```



[20]:
```
"""Find the best criteria for the desicion Tree with GridSearchCV"""
```

[20]: 'Find the best criteria for the desicion Tree with GridSearchCV'

[21]:
```
#Set up hyperparameter grid
param_grid_dt = {
    'max_depth': [3, 5, 10, 15],
    'min_samples_split': [2, 5, 10],
```

```
    'criterion': ['gini', 'entropy']
}

#Grid Search
grid_search_dt = GridSearchCV(
    DecisionTreeClassifier(random_state=42),
    #RandomForestClassifier(random_state=42),
    param_grid=param_grid_dt,
    scoring='f1',
    cv=StratifiedKFold(n_splits=5, shuffle=True, random_state=42),
    n_jobs=-1
)

# Fit model on SMOTE-balanced training data
grid_search_dt.fit(X_train, y_train)

# Use best model to predict
best_dt = grid_search_dt.best_estimator_
y_pred_dt = best_dt.predict(X_test)

# Print evaluation metrics
print("Best Parameters:", grid_search_dt.best_params_)
print("Accuracy:", accuracy_score(y_test, y_pred_dt))
print("Precision:", precision_score(y_test, y_pred_dt))
print("Recall:", recall_score(y_test, y_pred_dt))
print("F1 Score:", f1_score(y_test, y_pred_dt))
print("ROC-AUC:", roc_auc_score(y_test, y_pred_dt))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred_dt))
```

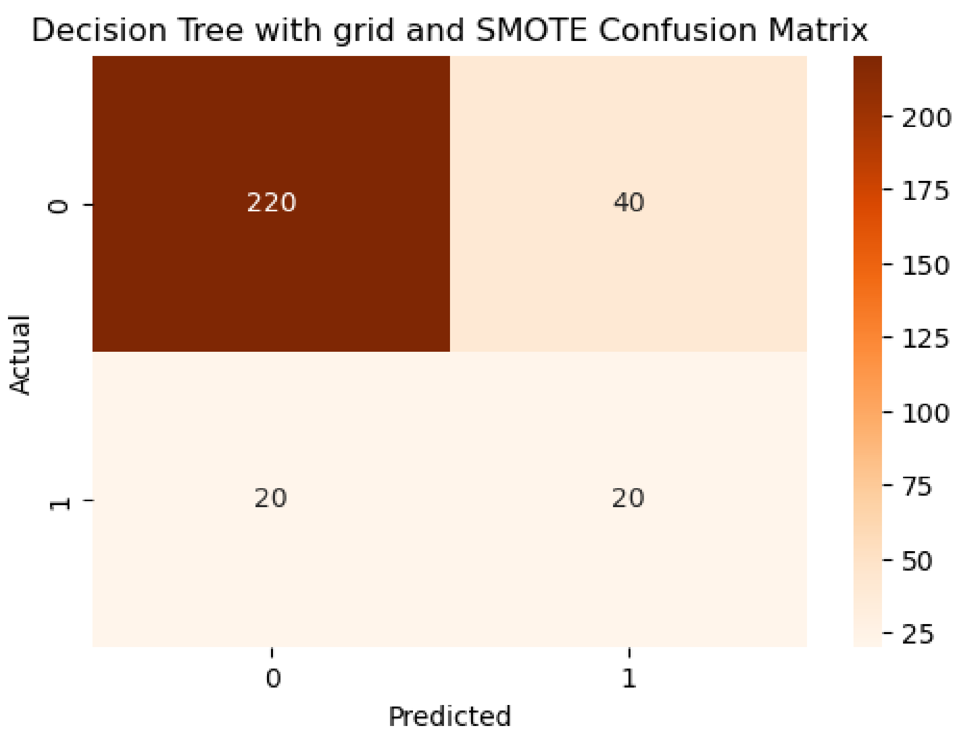
```
Best Parameters: {'criterion': 'entropy', 'max_depth': 15, 'min_samples_split':
10}
Accuracy: 0.8
Precision: 0.3333333333333333
Recall: 0.5
F1 Score: 0.4
ROC-AUC: 0.673076923076923
Confusion Matrix:
 [[220  40]
 [ 20  20]]
```

[22]:
```
#prepared Models, remember that 42 is just a number
dt_model =␣
 ↪DecisionTreeClassifier(criterion='entropy',max_depth=15,min_samples_split=10,random_state=4
 ↪the criterial for best performance of  GridSearchCV
rf_model = RandomForestClassifier(criterion='entropy', max_depth= 15,␣
 ↪min_samples_split=2,random_state=42)##use the criterial for best performance␣
 ↪of  GridSearchCV
```

```python
# k-Fold CV scores
dt_scores = cross_val_score(dt_model, X, y, cv=StratifiedKFold(n_splits=5),␣
↪scoring='roc_auc')
rf_scores = cross_val_score(rf_model, X, y, cv=StratifiedKFold(n_splits=5),␣
↪scoring='roc_auc')

dt_model.fit(X_train, y_train)
y_pred_dt = dt_model.predict(X_test)
y_proba_dt = dt_model.predict_proba(X_test)[:, 1]

rf_model.fit(X_train, y_train)
y_pred_rf = rf_model.predict(X_test)
y_proba_rf = rf_model.predict_proba(X_test)[:, 1]

# Decision Tree Evaluation
print("=== Decision Tree with Gred and SMOTE Evaluation ===")
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_dt))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_dt))
print("ROC AUC Score:", roc_auc_score(y_test, dt_model.predict_proba(X_test)[:,␣
↪1]))

# Confusion matrix for Decision Tree
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred_dt), annot=True, fmt='d',␣
↪cmap='Oranges')
plt.title('Decision Tree with grid and SMOTE Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# Random Forest Evaluation
print("\n=== Random Forest with Gred and SMOTE Evaluation ===")
print("Confusion Matrix:")
print(confusion_matrix(y_test, y_pred_rf))
print("\nClassification Report:")
print(classification_report(y_test, y_pred_rf))
print("ROC AUC Score:", roc_auc_score(y_test, rf_model.predict_proba(X_test)[:,␣
↪1]))


# Confusion matrix for Random Forest
plt.figure(figsize=(6, 4))
sns.heatmap(confusion_matrix(y_test, y_pred_rf), annot=True, fmt='d',␣
↪cmap='Blues')
```

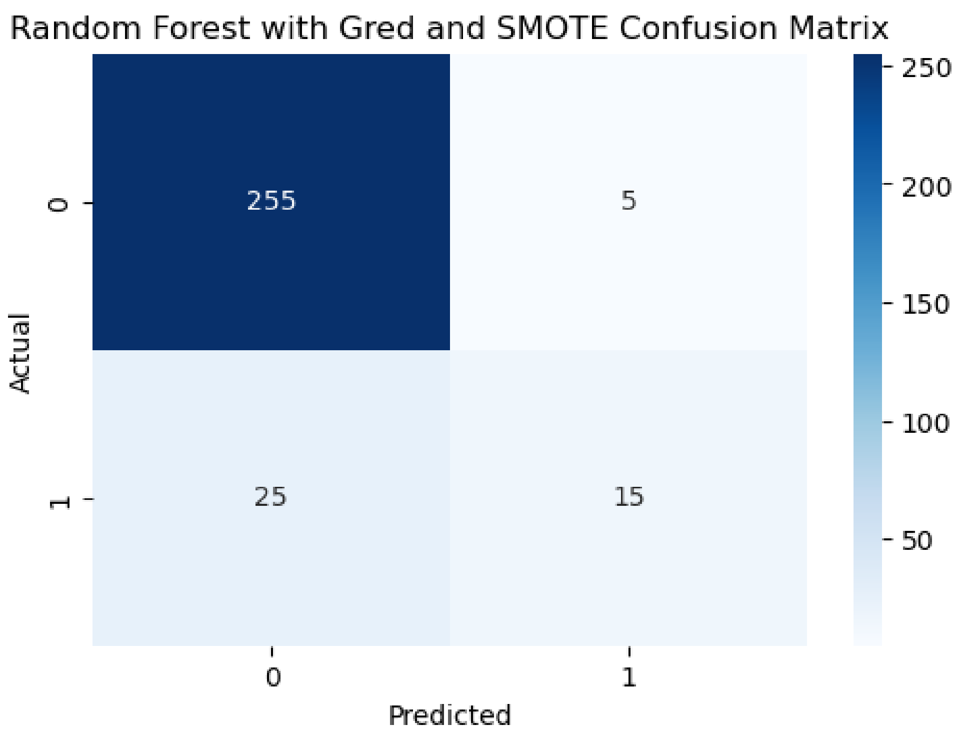
```python
plt.title('Random Forest with Gred and SMOTE Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()
```

```
=== Decision Tree with Gred and SMOTE Evaluation ===
Confusion Matrix:
[[220  40]
 [ 20  20]]

Classification Report:
              precision    recall  f1-score   support

           0       0.92      0.85      0.88       260
           1       0.33      0.50      0.40        40

    accuracy                           0.80       300
   macro avg       0.62      0.67      0.64       300
weighted avg       0.84      0.80      0.82       300

ROC AUC Score: 0.6724038461538462
```




```
=== Random Forest with Gred and SMOTE Evaluation ===
```

```
Confusion Matrix:
[[255   5]
 [ 25  15]]

Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.98      0.94       260
           1       0.75      0.38      0.50        40

    accuracy                           0.90       300
   macro avg       0.83      0.68      0.72       300
weighted avg       0.89      0.90      0.89       300

ROC AUC Score: 0.7543269230769232
```



[ ]:

```
[25]: import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
```

```python
from sklearn.metrics import classification_report, confusion_matrix, roc_auc_score



# Define selected features based on statistical tests
selected_features = [
    'VisitFrequency', 'DiningOccasion', 'MealType', 'OnlineReservation',
    'DeliveryOrder', 'LoyaltyProgramMember', 'ServiceRating', 'FoodRating',
    'AmbianceRating', 'GroupSize', 'WaitTime'
]

# Filter relevant columns
df_selected = df[selected_features + ['HighSatisfaction']]

# One-hot encode categorical features
categorical_features = ['VisitFrequency', 'DiningOccasion', 'MealType',
                        'OnlineReservation', 'DeliveryOrder', 'LoyaltyProgramMember']
df_encoded = pd.get_dummies(df_selected, columns=categorical_features, drop_first=True)

# Define X and y
X = df_encoded.drop(columns='HighSatisfaction')
y = df_encoded['HighSatisfaction']

# Scale numeric features
numeric_features = ['ServiceRating', 'FoodRating', 'AmbianceRating', 'GroupSize', 'WaitTime']
X[numeric_features] = StandardScaler().fit_transform(X[numeric_features])

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, random_state=42)
sm = SMOTE(random_state=12)
X_train, y_train = sm.fit_resample(X_train, y_train)

# Train models
dt_model = DecisionTreeClassifier(criterion='entropy',max_depth=15,min_samples_split=10,random_state=4
the criterial for best performance of  GridSearchCV
rf_model = RandomForestClassifier(criterion='entropy', max_depth= 15, min_samples_split=2,random_state=42)##use the criterial for best performance of  GridSearchCV

dt_model.fit(X_train, y_train)
```

```python
rf_model.fit(X_train, y_train)

# Evaluate
y_pred_dt = dt_model.predict(X_test)
y_pred_rf = rf_model.predict(X_test)

print("=== Decision Tree ===")
print(confusion_matrix(y_test, y_pred_dt))
print(classification_report(y_test, y_pred_dt))
print("ROC AUC:", roc_auc_score(y_test, y_pred_dt))

print("\n=== Random Forest ===")
print(confusion_matrix(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
print("ROC AUC:", roc_auc_score(y_test, y_pred_rf))
```

```
=== Decision Tree ===
[[225  35]
 [ 23  17]]
              precision    recall  f1-score   support

           0       0.91      0.87      0.89       260
           1       0.33      0.42      0.37        40

    accuracy                           0.81       300
   macro avg       0.62      0.65      0.63       300
weighted avg       0.83      0.81      0.82       300

ROC AUC: 0.6451923076923077

=== Random Forest ===
[[247  13]
 [ 23  17]]
              precision    recall  f1-score   support

           0       0.91      0.95      0.93       260
           1       0.57      0.42      0.49        40

    accuracy                           0.88       300
   macro avg       0.74      0.69      0.71       300
weighted avg       0.87      0.88      0.87       300

ROC AUC: 0.6875
```

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