```
!pip install ucimlrepo
from ucimlrepo import fetch_ucirepo

# fetch dataset
online_shoppers_purchasing_intention_dataset = fetch_ucirepo(id=468)

# data (as pandas dataframes)
X = online_shoppers_purchasing_intention_dataset.data.features
y = online_shoppers_purchasing_intention_dataset.data.targets

# metadata
print(online_shoppers_purchasing_intention_dataset.metadata)

# variable information
print(online_shoppers_purchasing_intention_dataset.variables)
```

```
Collecting ucimlrepo
  Downloading ucimlrepo-0.0.6-py3-none-any.whl (8.0 kB)
Installing collected packages: ucimlrepo
Successfully installed ucimlrepo-0.0.6
{'uci_id': 468, 'name': 'Online Shoppers Purchasing Intention Dataset', 'repository_url': 'https://archive.ics.uci.edu/
                       name     role         type demographic description  \
0            Administrative  Feature      Integer        None        None
1   Administrative_Duration  Feature      Integer        None        None
2             Informational  Feature      Integer        None        None
3    Informational_Duration  Feature      Integer        None        None
4            ProductRelated  Feature      Integer        None        None
5   ProductRelated_Duration  Feature   Continuous        None        None
6               BounceRates  Feature   Continuous        None        None
7                 ExitRates  Feature   Continuous        None        None
8                PageValues  Feature      Integer        None        None
9                SpecialDay  Feature      Integer        None        None
10                    Month  Feature  Categorical        None        None
11         OperatingSystems  Feature      Integer        None        None
12                  Browser  Feature      Integer        None        None
13                   Region  Feature      Integer        None        None
14              TrafficType  Feature      Integer        None        None
15              VisitorType  Feature  Categorical        None        None
16                  Weekend  Feature       Binary        None        None
17                  Revenue   Target       Binary        None        None

   units missing_values
0   None             no
1   None             no
2   None             no
3   None             no
4   None             no
5   None             no
6   None             no
7   None             no
8   None             no
9   None             no
10  None             no
11  None             no
12  None             no
13  None             no
14  None             no
15  None             no
16  None             no
17  None             no
```

```
import numpy as np
import pandas as pd
from sklearn.preprocessing import LabelEncoder
import matplotlib.pyplot as plt

# Convert features and targets to DataFrames
X_df = pd.DataFrame(X)
y_df = pd.DataFrame(y)
df = pd.concat([X_df, y_df], axis=1)


print(df.head())
# Making sure there is no missing values
print(df.isnull().sum())
df[df.columns[0]].count()


df.dropna(inplace=True)
print(df.isnull().sum())
df[df.columns[0]].count()
```

```
0                    0.0              1                0.000000
1                    0.0              2               64.000000
2                    0.0              1                0.000000
3                    0.0              2                2.666667
4                    0.0             10              627.500000

   BounceRates  ExitRates  PageValues  SpecialDay Month  OperatingSystems  \
0         0.20       0.20         0.0         0.0   Feb                 1
1         0.00       0.10         0.0         0.0   Feb                 2
2         0.20       0.20         0.0         0.0   Feb                 4
3         0.05       0.14         0.0         0.0   Feb                 3
4         0.02       0.05         0.0         0.0   Feb                 3

   Browser  Region  TrafficType        VisitorType  Weekend  Revenue
0        1       1            1  Returning_Visitor    False        0
1        2       1            2  Returning_Visitor    False        0
2        1       9            3  Returning_Visitor    False        0
3        2       2            4  Returning_Visitor    False        0
4        3       1            4  Returning_Visitor     True        0
Administrative             0
Administrative_Duration    0
Informational              0
Informational_Duration     0
ProductRelated             0
ProductRelated_Duration    0
BounceRates                0
ExitRates                  0
PageValues                 0
SpecialDay                 0
Month                      0
OperatingSystems           0
Browser                    0
Region                     0
TrafficType                0
VisitorType                0
Weekend                    0
Revenue                    0
dtype: int64
Administrative             0
Administrative_Duration    0
Informational              0
Informational_Duration     0
ProductRelated             0
ProductRelated_Duration    0
BounceRates                0
ExitRates                  0
PageValues                 0
SpecialDay                 0
Month                      0
OperatingSystems           0
Browser                    0
Region                     0
TrafficType                0
VisitorType                0
Weekend                    0
Revenue                    0
dtype: int64
12330
```

```
df.head()
```

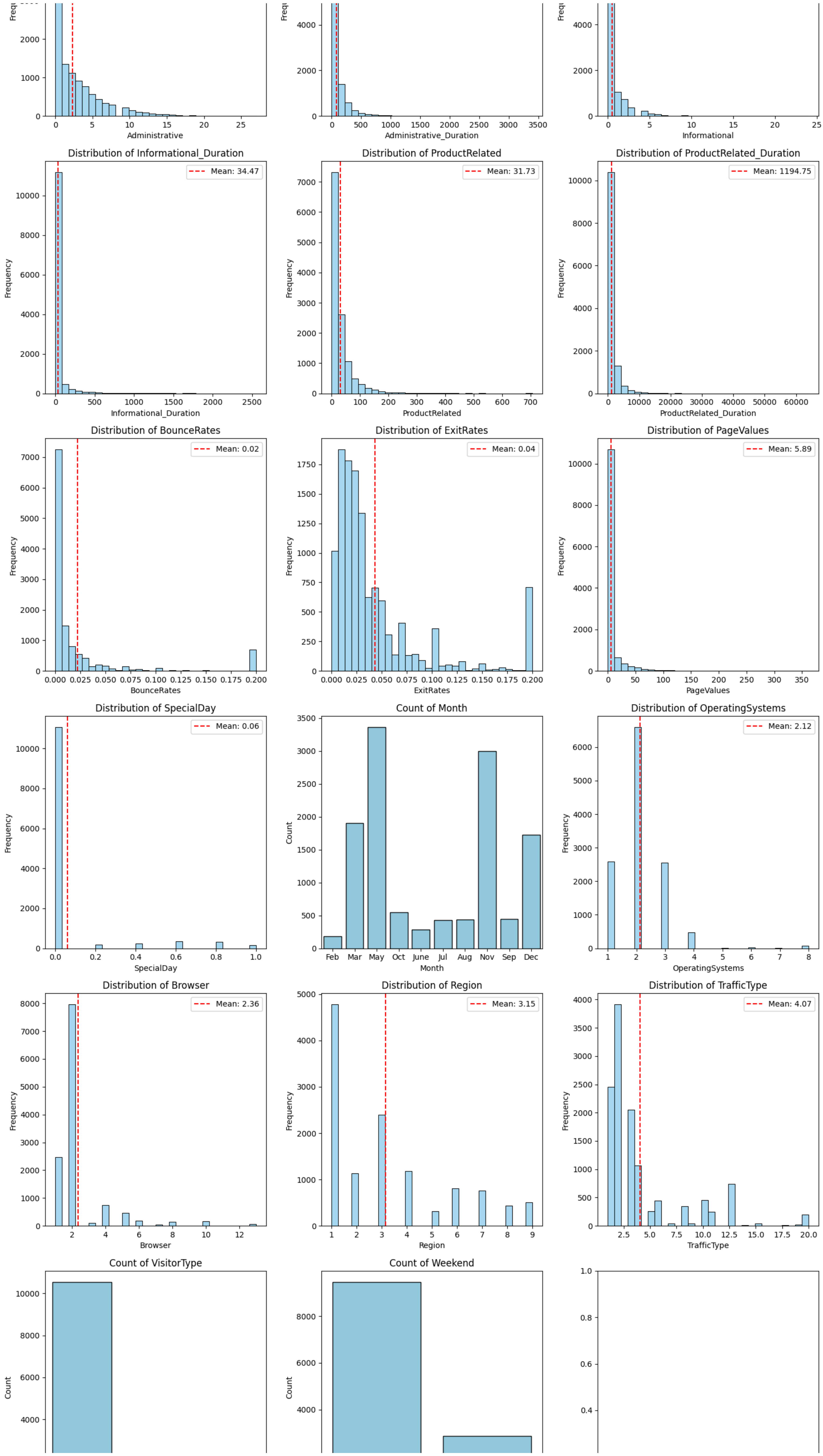
	Administrative	Administrative_Duration	Informational	Informational_Duration	ProductRelated	ProductRelated_Durat
0	0	0.0	0	0.0	1	0.000
1	0	0.0	0	0.0	2	64.000
2	0	0.0	0	0.0	1	0.000
3	0	0.0	0	0.0	2	2.666
4	0	0.0	0	0.0	10	627.500

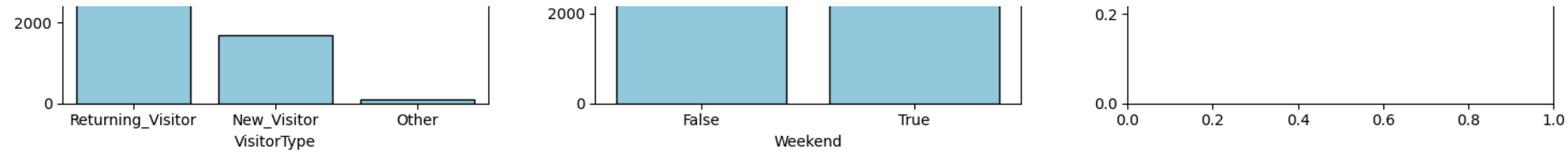
Next steps: Generate code with df View recommended plots

```
df.describe()
```

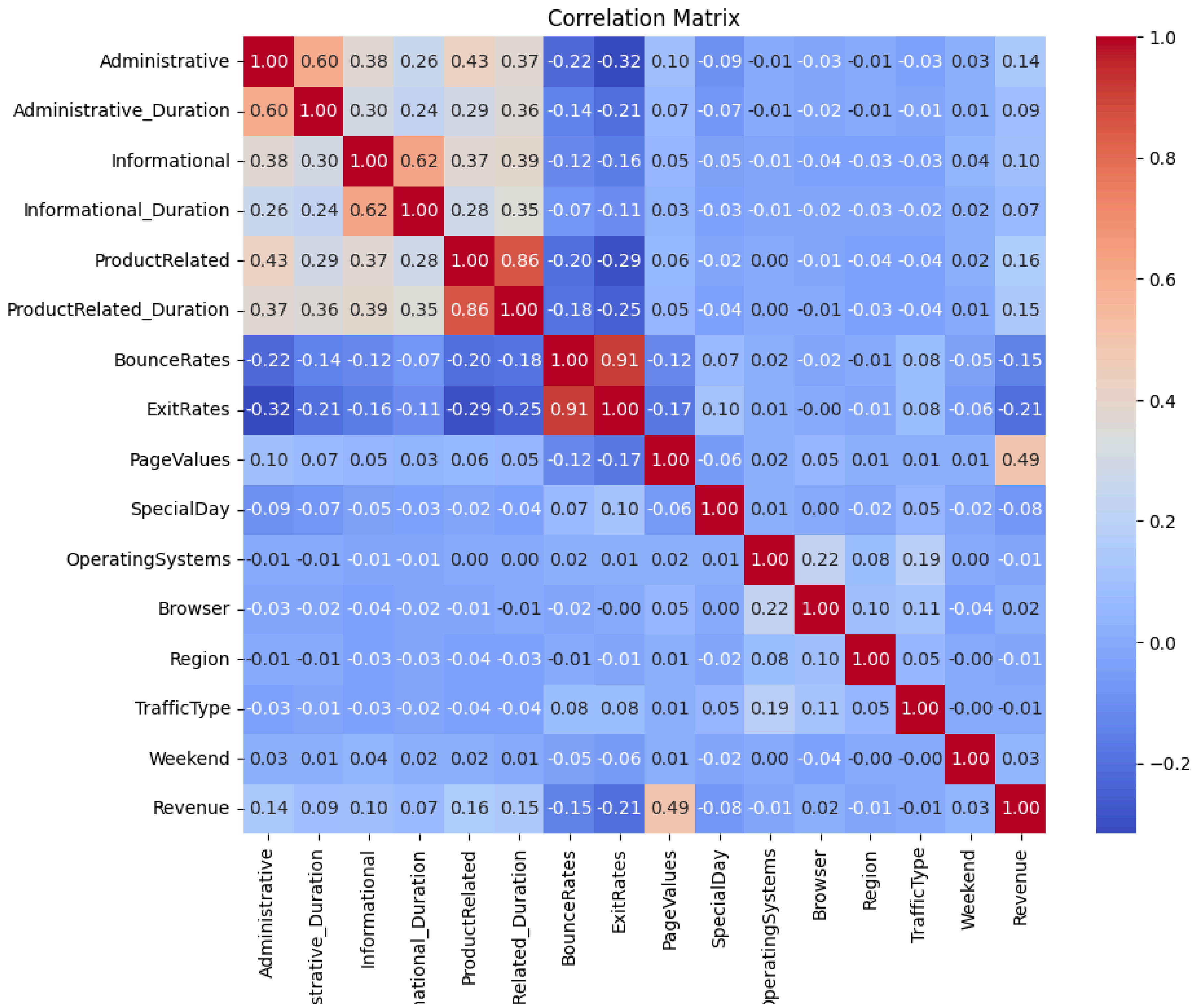
	Administrative	Administrative_Duration	Informational	Informational_Duration	ProductRelated	ProductRelated_D
count	12330.000000	12330.000000	12330.000000	12330.000000	12330.000000	1233(
mean	2.315166	80.818611	0.503569	34.472398	31.731468	119‹
std	3.321784	176.779107	1.270156	140.749294	44.475503	191:
min	0.000000	0.000000	0.000000	0.000000	0.000000	(
25%	0.000000	0.000000	0.000000	0.000000	7.000000	18‹
50%	1.000000	7.500000	0.000000	0.000000	18.000000	59ξ
75%	4.000000	93.256250	0.000000	0.000000	38.000000	146‹
max	27.000000	3398.750000	24.000000	2549.375000	705.000000	6397:

```
from sklearn.preprocessing import LabelEncoder
import seaborn as sns

# Label encoding target variable
label_encoder = LabelEncoder()
df['Revenue'] = label_encoder.fit_transform(df['Revenue'])

# Applying label to all the features
feature = ['Administrative', 'Administrative_Duration', 'Informational', 'Informational_Duration', 'ProductRelated', 'Produ
           'BounceRates', 'ExitRates', 'PageValues', 'SpecialDay', 'Month', 'OperatingSystems',
           'Browser', 'Region', 'TrafficType', 'VisitorType', 'Weekend']

# Define the layout of subplots
num_plots = len(feature)
num_cols = 3  # Number of columns in the subplot grid
num_rows = (num_plots - 1) // num_cols + 1

# Create subplots
fig, axes = plt.subplots(num_rows, num_cols, figsize=(15, 5*num_rows))
axes = axes.flatten()

# Visualize feature distributions
for i, feature in enumerate(feature):
    if df[feature].dtype in ['int64', 'float64']:  # Check if the feature is numerical
        # Plot the distribution
        sns.histplot(df[feature], bins=30, color='skyblue', edgecolor='black', ax=axes[i])
        axes[i].set_title(f'Distribution of {feature}')
        axes[i].set_xlabel(feature)
        axes[i].set_ylabel('Frequency')

        # Calculate and plot the mean
        mean_value = df[feature].mean()
        axes[i].axvline(mean_value, color='red', linestyle='--', label=f'Mean: {mean_value:.2f}')
        axes[i].legend()
    else:
        # Handle categorical/binary features
        sns.countplot(x=feature, data=df, color='skyblue', edgecolor='black', ax=axes[i])
        axes[i].set_title(f'Count of {feature}')
        axes[i].set_xlabel(feature)
        axes[i].set_ylabel('Count')

# Adjust layout and spacing
plt.tight_layout()
plt.show()

# Reconverting them back to predictor and response features
X = df.drop(columns=['Revenue'])
y = df['Revenue']
```


Administrative
Administrative_Duration
Informational
Distribution of Informational_Duration
Mean: 34.47
Informational_Duration
Distribution of ProductRelated
Mean: 31.73
ProductRelated
Distribution of ProductRelated_Duration
Mean: 1194.75
ProductRelated_Duration
Distribution of BounceRates
Mean: 0.02
BounceRates
Distribution of ExitRates
Mean: 0.04
ExitRates
Distribution of PageValues
Mean: 5.89
PageValues
Distribution of SpecialDay
Mean: 0.06
SpecialDay
Count of Month
Month
Distribution of OperatingSystems
Mean: 2.12
OperatingSystems
Distribution of Browser
Mean: 2.36
Browser
Distribution of Region
Mean: 3.15
Region
Distribution of TrafficType
Mean: 4.07
TrafficType
Count of VisitorType
Count of Weekend
Frequency
Count




```
corr_matrix = df.corr(numeric_only=True)

# Visualize correlation matrix as a heatmap
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```




```
continuous_numerical_features = X.select_dtypes(include=['int', 'float'])

# Calculate the mean and variance of continuous numerical features
mean_values = continuous_numerical_features.mean()
variance_values = continuous_numerical_features.var()

print("Mean of continuous numerical features:")
print(mean_values)
print("\nVariance of continuous numerical features:")
print(variance_values)
```

```
Mean of continuous numerical features:
Administrative                2.315166
Administrative_Duration      80.818611
Informational                 0.503569
Informational_Duration       34.472398
ProductRelated               31.731468
ProductRelated_Duration    1194.746220
BounceRates                   0.022191
ExitRates                     0.043073
PageValues                    5.889258
SpecialDay                    0.061427
OperatingSystems              2.124006
Browser                       2.357097
```

```
Region                        3.147364
TrafficType                   4.069586
dtype: float64

Variance of continuous numerical features:
Administrative             1.103425e+01
Administrative_Duration    3.125085e+04
Informational              1.613297e+00
Informational_Duration     1.981036e+04
ProductRelated             1.978070e+03
ProductRelated_Duration    3.662130e+06
BounceRates                2.351117e-03
ExitRates                  2.361624e-03
PageValues                 3.447868e+02
SpecialDay                 3.956808e-02
OperatingSystems           8.305129e-01
Browser                    2.949039e+00
Region                     5.767640e+00
TrafficType                1.620199e+01
dtype: float64
```

```
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV, train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score
from sklearn.preprocessing import StandardScaler

# One-hot encode the categorical variables
X_encoded = pd.get_dummies(X, columns=['Month', 'VisitorType', 'Weekend'])

# Split data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X_encoded, y, test_size=0.2, random_state=42)

# Define the hyperparameters to tune
logistic_params = {
    'C': [0.001, 0.01, 0.1, 1, 10, 100],
    'penalty': ['l2'],
}

tree_params = {
    'max_depth': [3, 5, 7, 10],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

rf_params = {
    'n_estimators': [100, 200],
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

gb_params = {
    'n_estimators': [100, 200, 300],
    'learning_rate': [0.01, 0.1, 0.5],
    'max_depth': [3, 5, 7],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}

# Initialize the models
logistic_model = LogisticRegression(max_iter=1000)
tree_model = DecisionTreeClassifier()
rf_model = RandomForestClassifier()
gb_model = GradientBoostingClassifier()

# Perform hyperparameter tuning using GridSearchCV
logistic_grid = GridSearchCV(logistic_model, logistic_params, cv=5)
tree_grid = GridSearchCV(tree_model, tree_params, cv=5)
rf_randomized = RandomizedSearchCV(rf_model, rf_params, cv=5, n_iter=10, random_state=42)
gb_randomized = RandomizedSearchCV(gb_model, gb_params, cv=5, n_iter=10, random_state=42)

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

# Fit the models to the training data
logistic_grid.fit(X_train_scaled, y_train)
tree_grid.fit(X_train, y_train)
rf_randomized.fit(X_train, y_train)
gb_randomized.fit(X_train, y_train)

# Output the best hyperparameters
best_logistic_params = logistic_grid.best_params_
print("Best Hyperparameters for Logistic Regression:", best_logistic_params)
best_tree_params = tree_grid.best_params_
print("Best Hyperparameters for Decision Tree:", best_tree_params)
best_rf_params = rf_randomized.best_params_
print("Best Hyperparameters for Random Forest:", best_rf_params)
best_gb_params = gb_randomized.best_params_
print("Best Hyperparameters for Gradient Boosting:", best_gb_params)

# Fit the logistic regression model to the training data with the best hyperparameters
logistic_model = LogisticRegression(**best_logistic_params)
logistic_model.fit(X_train_scaled, y_train)

# Make predictions on the test set
logistic_pred = logistic_model.predict(X_test_scaled)
tree_pred = tree_grid.predict(X_test)
```

```
rf_pred = rf_randomized.predict(X_test)
gb_pred = gb_randomized.predict(X_test)
```

```
Best Hyperparameters for Logistic Regression: {'C': 1, 'penalty': 'l2'}
Best Hyperparameters for Decision Tree: {'max_depth': 3, 'min_samples_leaf': 1, 'min_samples_split': 2}
Best Hyperparameters for Random Forest: {'n_estimators': 100, 'min_samples_split': 10, 'min_samples_leaf': 4, 'max_dept
Best Hyperparameters for Gradient Boosting: {'n_estimators': 300, 'min_samples_split': 5, 'min_samples_leaf': 1, 'max_d
```

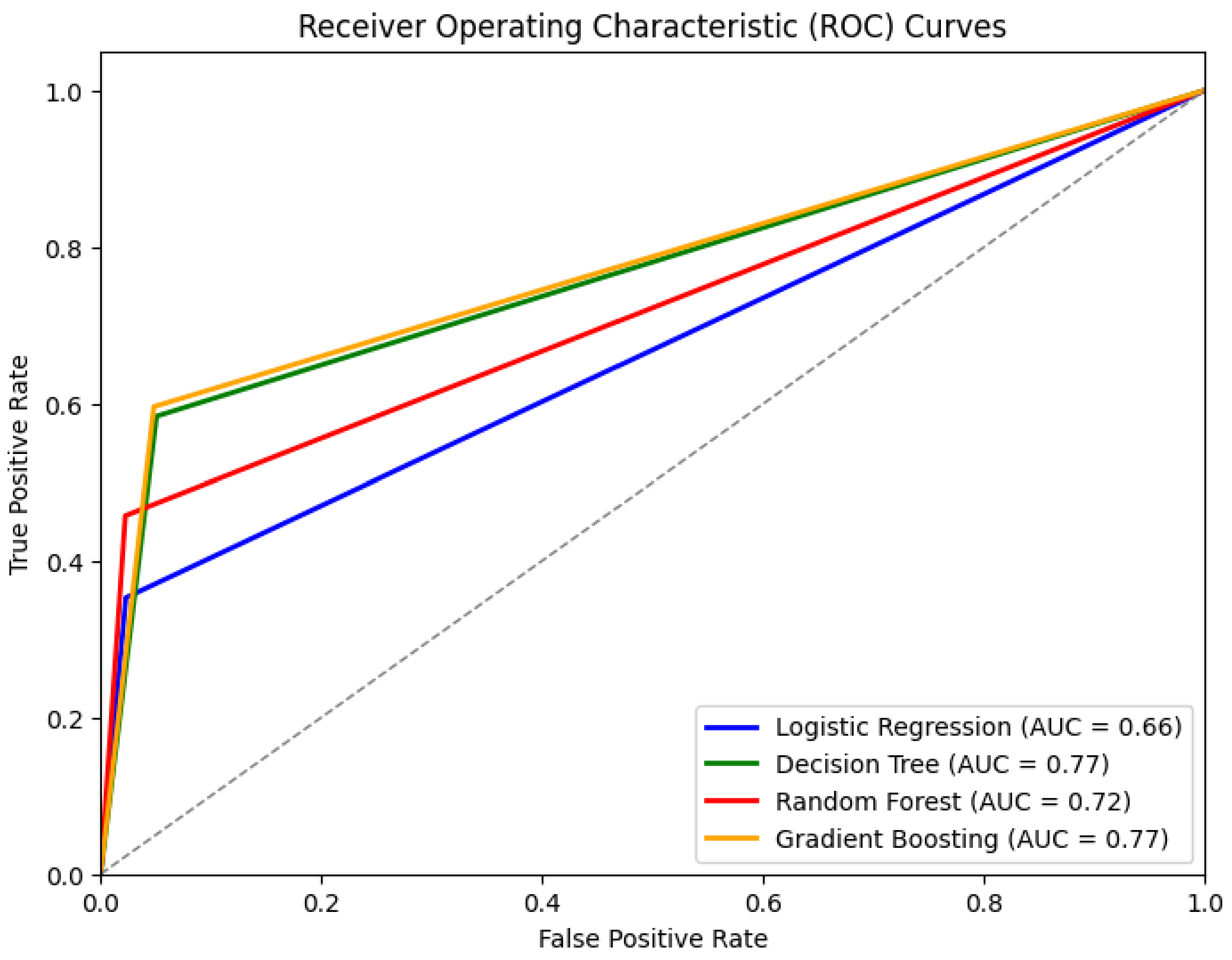
```
from sklearn.metrics import accuracy_score

# Calculate accuracy for each model
logistic_accuracy = accuracy_score(y_test, logistic_pred)
tree_accuracy = accuracy_score(y_test, tree_pred)
rf_accuracy = accuracy_score(y_test, rf_pred)
gb_accuracy = accuracy_score(y_test, gb_pred)

print("Logistic Regression Accuracy:", logistic_accuracy)
print("Decision Tree Accuracy:", tree_accuracy)
print("Random Forest Accuracy:", rf_accuracy)
print("Gradient Boosting Accuracy:", gb_accuracy)

from sklearn.metrics import classification_report

# Evaluate the models
cr_log = classification_report(y_test, logistic_pred)
print("Logistic Regression:\n",cr_log)

cr_DT = classification_report(y_test, tree_pred)
print("Decision Tree:\n",cr_DT)

cr_RF = classification_report(y_test, rf_pred)
print("Random Forest:\n",cr_RF)

cr_GB = classification_report(y_test, gb_pred)
print("Gradient Boost:\n",cr_GB)
```

```
Logistic Regression Accuracy: 0.8730738037307381
Decision Tree Accuracy: 0.8884833738848338
Random Forest Accuracy: 0.8909164639091647
Gradient Boosting Accuracy: 0.8925385239253852
Logistic Regression:
               precision    recall  f1-score   support

           0       0.88      0.98      0.93      2055
           1       0.76      0.35      0.48       411

    accuracy                           0.87      2466
   macro avg       0.82      0.66      0.70      2466
weighted avg       0.86      0.87      0.85      2466

Decision Tree:
               precision    recall  f1-score   support

           0       0.92      0.95      0.93      2055
           1       0.70      0.58      0.64       411

    accuracy                           0.89      2466
   macro avg       0.81      0.77      0.78      2466
weighted avg       0.88      0.89      0.88      2466

Random Forest:
               precision    recall  f1-score   support

           0       0.90      0.98      0.94      2055
           1       0.80      0.46      0.58       411

    accuracy                           0.89      2466
   macro avg       0.85      0.72      0.76      2466
weighted avg       0.88      0.89      0.88      2466

Gradient Boost:
               precision    recall  f1-score   support

           0       0.92      0.95      0.94      2055
           1       0.71      0.60      0.65       411

    accuracy                           0.89      2466
   macro avg       0.82      0.77      0.79      2466
weighted avg       0.89      0.89      0.89      2466
```

```
# Taking att he important info. from above and condensing into table

# Logistic Regression
logistic_precision = ['Logistic Regression', 'precision', 0.90, 0.73]
logistic_recall = ['Logistic Regression', 'recall', 0.97, 0.46]
logistic_f1_score = ['Logistic Regression', 'f1-score', 0.93, 0.56]

# Decision Tree
dt_precision = ['Decision Tree', 'precision', 0.92, 0.68]
dt_recall = ['Decision Tree', 'recall', 0.94, 0.61]
dt_f1_score = ['Decision Tree', 'f1-score', 0.93, 0.64]

# Random Forest
rf_precision = ['Random Forest', 'precision', 0.90, 0.77]
rf_recall = ['Random Forest', 'recall', 0.97, 0.49]
rf_f1_score = ['Random Forest', 'f1-score', 0.94, 0.60]

# Gradient Boost
gb_precision = ['Gradient Boost', 'precision', 0.92, 0.73]
gb_recall = ['Gradient Boost', 'recall', 0.96, 0.57]
gb_f1_score = ['Gradient Boost', 'f1-score', 0.94, 0.64]

table = pd.DataFrame([logistic_precision, logistic_recall, logistic_f1_score,
                      dt_precision, dt_recall, dt_f1_score,
                      rf_precision, rf_recall, rf_f1_score,
                      gb_precision, gb_recall, gb_f1_score])

table.columns = ['model_name', 'metrics', 'Is_Revenue(False)', 'Is_Revenue(True)']

print(table)

# Best balanced model: Gadient Boosting
# Most precise model: Random Forest
# Best recall model: Logistic Regression
```

```
              model_name    metrics  Is_Revenue(False)  Is_Revenue(True)
0    Logistic Regression  precision               0.90              0.73
1    Logistic Regression     recall               0.97              0.46
2    Logistic Regression   f1-score               0.93              0.56
3          Decision Tree  precision               0.92              0.68
4          Decision Tree     recall               0.94              0.61
5          Decision Tree   f1-score               0.93              0.64
6          Random Forest  precision               0.90              0.77
7          Random Forest     recall               0.97              0.49
8          Random Forest   f1-score               0.94              0.60
9         Gradient Boost  precision               0.92              0.73
10        Gradient Boost     recall               0.96              0.57
11        Gradient Boost   f1-score               0.94              0.64
```

```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc

# Compute ROC curve and ROC area for each model
logistic_fpr, logistic_tpr, _ = roc_curve(y_test, logistic_pred)
logistic_auc = auc(logistic_fpr, logistic_tpr)

tree_fpr, tree_tpr, _ = roc_curve(y_test, tree_pred)
tree_auc = auc(tree_fpr, tree_tpr)

rf_fpr, rf_tpr, _ = roc_curve(y_test, rf_pred)
rf_auc = auc(rf_fpr, rf_tpr)

gb_fpr, gb_tpr, _ = roc_curve(y_test, gb_pred)
gb_auc = auc(gb_fpr, gb_tpr)

# Plot ROC curves
plt.figure(figsize=(8, 6))
plt.plot(logistic_fpr, logistic_tpr, color='blue', lw=2, label=f'Logistic Regression (AUC = {logistic_auc:.2f})')
plt.plot(tree_fpr, tree_tpr, color='green', lw=2, label=f'Decision Tree (AUC = {tree_auc:.2f})')
plt.plot(rf_fpr, rf_tpr, color='red', lw=2, label=f'Random Forest (AUC = {rf_auc:.2f})')
plt.plot(gb_fpr, gb_tpr, color='orange', lw=2, label=f'Gradient Boosting (AUC = {gb_auc:.2f})')
plt.plot([0, 1], [0, 1], color='gray', lw=1, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curves')
plt.legend(loc='lower right')
plt.show()
```




```
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix

# True labels for Is_Revenue(False) and Is_Revenue(True)
true_labels = y_test

# Predicted labels for each model
predicted_labels = {
    'Logistic Regression': logistic_pred,
    'Decision Tree': tree_pred,
    'Random Forest': rf_pred,
    'Gradient Boost': gb_pred
}

# Calculate and plot confusion matrix for each model
for model_name, y_pred in predicted_labels.items():
    # Compute confusion matrix
    cm = confusion_matrix(true_labels, y_pred)

    # Plot confusion matrix
    plt.figure(figsize=(6, 6))
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', cbar=False)
    plt.title(f'Confusion Matrix for {model_name}')
    plt.xlabel('Predicted')
    plt.ylabel('Actual')
    plt.xticks(ticks=[0.5, 1.5], labels=['Is_Revenue(False)', 'Is_Revenue(True)'])
    plt.yticks(ticks=[0.5, 1.5], labels=['Is_Revenue(False)', 'Is_Revenue(True)'])
    plt.show()
```