Predictive Modelling

September 24, 2024

[3]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[4]:
```
df = pd.read_csv("C:/Users/bendh/Desktop/data science/JN/
 ↪filtered_customer_booking.csv", encoding="ISO-8859-1")
df = df.drop(columns=['Unnamed: 0'])
df.head()
```

[4]:

	num_passengers	sales_channel	trip_type	purchase_lead	length_of_stay	flight_hour	flight_day	route	booking_origin	wants_extra_baggage	wants_preferred_seat	wants_in_flight_meals	flight_duration	booking_complete
0	2	Internet	RoundTrip	262	19	7	6	AKLDEL	New Zealand	1	0	0	5.52	0
1	1	Internet	RoundTrip	112	20	3	6	AKLDEL	New Zealand	0	0	0	5.52	0
2	2	Internet	RoundTrip	243	22	17	3	AKLDEL	India	1	1	0	5.52	0
3	1	Internet	RoundTrip	96	31	4	6	AKLDEL	New Zealand	0	0	1	5.52	0
4	2	Internet	RoundTrip	68	22	15	3	AKLDEL	India	1	0	1	5.52	0

0.0.1 One Hot Encode

[5]:
```
#one hot encode categorical values
from sklearn.preprocessing import OneHotEncoder

df2 = df

#create instanc"e of one hot encoder
encoder = OneHotEncoder(handle_unknown='ignore')

#one hot encode Sales Channel
encoder_df = pd.DataFrame(encoder.fit_transform(df[["sales_channel"]]).
 ↪toarray())
encoder_df = encoder_df.rename(columns={0:'Internet', 1:'Phone'})
df2 = df2.join(encoder_df)

#one hot encode trip type
encoder_df = pd.DataFrame(encoder.fit_transform(df[["trip_type"]]).toarray())
encoder_df = encoder_df.rename(columns={0:'RoundTrip', 1:'OneWayTrip',2:
 ↪'CircleTrip'})
df2 = df2.join(encoder_df)
```

[6]:
```
#drop categorical columns now
df2.drop(['sales_channel', 'trip_type', 'booking_origin', 'route'], axis=1,␣
 ↪inplace = True)
```

[7]:
```
#store the label for supervised learning
label = df["booking_complete"]
```

[8]:
```
df2 = df2.drop("booking_complete", axis=1)
```

[9]:
```
df2
```

[9]:

	num_passengers	purchase_lead	length_of_stay	flight_hour	flight_day	\
0	2	262	19	7	6	
1	1	112	20	3	6	
2	2	243	22	17	3	
3	1	96	31	4	6	
4	2	68	22	15	3	
…	…	…	…	…	…	
49977	2	27	6	9	6	
49978	1	111	6	4	7	
49979	1	24	6	22	6	
49980	1	15	6	11	1	
49981	1	19	6	10	4	

	wants_extra_baggage	wants_preferred_seat	wants_in_flight_meals	\
0	1	0	0	

```
1                        0                    0                        0
2                        1                    1                        0
3                        0                    0                        1
4                        1                    0                        1
…                      …                      …                      …
49977                    1                    0                        1
49978                    0                    0                        0
49979                    0                    0                        1
49980                    1                    0                        1
49981                    0                    1                        0

       flight_duration  Internet  Phone  RoundTrip  OneWayTrip  CircleTrip
0                 5.52       1.0    0.0        0.0         0.0         1.0
1                 5.52       1.0    0.0        0.0         0.0         1.0
2                 5.52       1.0    0.0        0.0         0.0         1.0
3                 5.52       1.0    0.0        0.0         0.0         1.0
4                 5.52       1.0    0.0        0.0         0.0         1.0
…                    …       …      …          …           …           …
49977             5.62       1.0    0.0        0.0         0.0         1.0
49978             5.62       1.0    0.0        0.0         0.0         1.0
49979             5.62       1.0    0.0        0.0         0.0         1.0
49980             5.62       1.0    0.0        0.0         0.0         1.0
49981             5.62       1.0    0.0        0.0         0.0         1.0

[49982 rows x 14 columns]
```

0.1 Normalizing values

[10]:
```
from sklearn.preprocessing import StandardScaler

#create a standard scaler object
scaler = StandardScaler()

#fit and transform the data
scaled_df = scaler.fit_transform(df2)
```

[11]:
```
#create a dataframe of scaled data
scaled_df = pd.DataFrame(scaled_df, columns = df2.columns)
```

[12]:
```
#add the labels back to the dataframe
scaled_df['label'] = label
```

[13]:
```
scaled_df
```

[13]:
```
       num_passengers  purchase_lead  length_of_stay  flight_hour  flight_day  \
0            0.400769       1.971093       -0.119401    -0.381588    1.096876
1           -0.579424       0.302987       -0.089895    -1.120618    1.096876
```

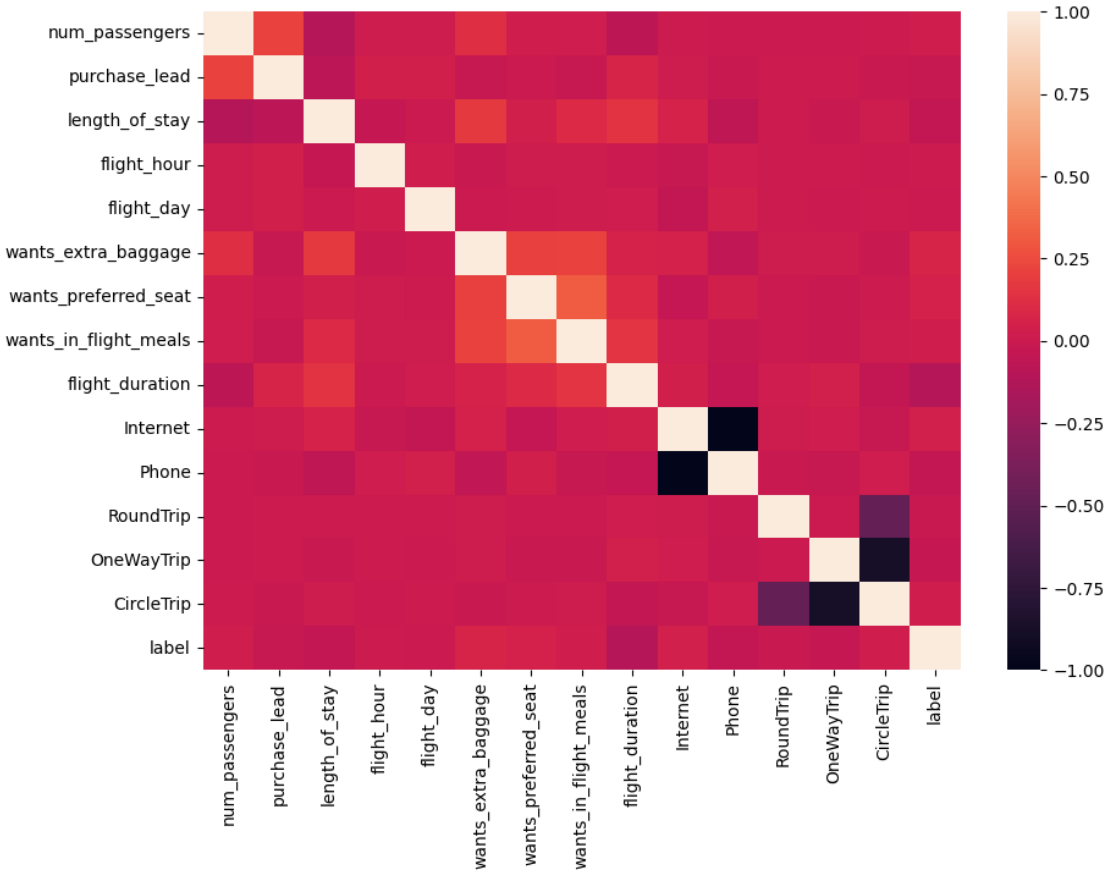
```
2           0.400769       1.759799       -0.030885     1.465988   -0.408618
3          -0.579424       0.125056        0.234662    -0.935861    1.096876
4           0.400769      -0.186323       -0.030885     1.096473   -0.408618
…                …              …               …            …          …
49977       0.400769      -0.642272       -0.502969    -0.012073    1.096876
49978      -0.579424       0.291867       -0.502969    -0.935861    1.598707
49979      -0.579424      -0.675634       -0.502969     2.389776    1.096876
49980      -0.579424      -0.775721       -0.502969     0.357443   -1.412280
49981      -0.579424      -0.731238       -0.502969     0.172685    0.093214

       wants_extra_baggage  wants_preferred_seat  wants_in_flight_meals  \
0                 0.703587             -0.650054              -0.863557
1                -1.421288             -0.650054              -0.863557
2                 0.703587              1.538334              -0.863557
3                -1.421288             -0.650054               1.158002
4                 0.703587             -0.650054               1.158002
…                    …                     …                      …
49977             0.703587             -0.650054               1.158002
49978            -1.421288             -0.650054              -0.863557
49979            -1.421288             -0.650054               1.158002
49980             0.703587             -0.650054               1.158002
49981            -1.421288              1.538334              -0.863557

       flight_duration  Internet     Phone  RoundTrip  OneWayTrip  CircleTrip  \
0            -1.174049  0.355786 -0.355786  -0.048231   -0.088336    0.100826
1            -1.174049  0.355786 -0.355786  -0.048231   -0.088336    0.100826
2            -1.174049  0.355786 -0.355786  -0.048231   -0.088336    0.100826
3            -1.174049  0.355786 -0.355786  -0.048231   -0.088336    0.100826
4            -1.174049  0.355786 -0.355786  -0.048231   -0.088336    0.100826
…                …         …       …         …          …          …
49977        -1.107240  0.355786 -0.355786  -0.048231   -0.088336    0.100826
49978        -1.107240  0.355786 -0.355786  -0.048231   -0.088336    0.100826
49979        -1.107240  0.355786 -0.355786  -0.048231   -0.088336    0.100826
49980        -1.107240  0.355786 -0.355786  -0.048231   -0.088336    0.100826
49981        -1.107240  0.355786 -0.355786  -0.048231   -0.088336    0.100826

       label
0          0
1          0
2          0
3          0
4          0
…      …
49977      0
49978      0
49979      0
49980      0
```

```
49981      0

[49982 rows x 15 columns]
```

0.2 Correlation matrix

[14]:
```
corr = scaled_df.corr()

plt.figure(figsize=(10,7))

#plot the heatmap
sns.heatmap(corr)
```

[14]:
```
<Axes: >
```



0.2.1 Splitting Train and Test Data

[15]:
```
from sklearn.model_selection import train_test_split

X = scaled_df.iloc[:,:-1]
y = scaled_df['label']

X_train, X_test, y_train, y_test = train_test_split(X.to_numpy(), y.to_numpy(),␣
 ↪test_size=0.20, random_state = 42)
```

[16]:
```
!pip install yellowbrick

from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.inspection import permutation_importance

from yellowbrick.classifier import ConfusionMatrix
from sklearn.model_selection import GridSearchCV, RepeatedStratifiedKFold
```

```
Requirement already satisfied: yellowbrick in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (1.5)
Requirement already satisfied: matplotlib!=3.0.0,>=2.0.2 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
yellowbrick) (3.9.1.post1)
Requirement already satisfied: scipy>=1.0.0 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
yellowbrick) (1.13.1)
Requirement already satisfied: scikit-learn>=1.0.0 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
yellowbrick) (1.5.1)
Requirement already satisfied: numpy>=1.16.0 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
yellowbrick) (1.26.4)
Requirement already satisfied: cycler>=0.10.0 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
yellowbrick) (0.12.1)
Requirement already satisfied: contourpy>=1.0.1 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.2.1)
Requirement already satisfied: fonttools>=4.22.0 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (4.53.1)
Requirement already satisfied: kiwisolver>=1.3.1 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
```

```
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.4.5)
Requirement already satisfied: packaging>=20.0 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (24.1)
Requirement already satisfied: pillow>=8 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (10.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (3.1.2)
Requirement already satisfied: python-dateutil>=2.7 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (2.9.0.post0)
Requirement already satisfied: importlib-resources>=3.2.0 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
matplotlib!=3.0.0,>=2.0.2->yellowbrick) (6.4.0)
Requirement already satisfied: joblib>=1.2.0 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
scikit-learn>=1.0.0->yellowbrick) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
scikit-learn>=1.0.0->yellowbrick) (3.5.0)
Requirement already satisfied: zipp>=3.1.0 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
importlib-resources>=3.2.0->matplotlib!=3.0.0,>=2.0.2->yellowbrick) (3.19.2)
Requirement already satisfied: six>=1.5 in
c:\users\bendh\appdata\local\programs\python\python39\lib\site-packages (from
python-dateutil>=2.7->matplotlib!=3.0.0,>=2.0.2->yellowbrick) (1.16.0)
```

[17]:
```python
#create functions to fit and predict the values of wether customer would␣
 ↪complete the booking or not
#create functions with metrics to evaluate the model prediction

#check how well the model is performing on known data
def model_fit_predict(model, X, y, X_predict):
    model.fit(X,y)
    return model.predict(X_predict)

def acc_score(y_true, y_pred):
    return accuracy_score(y_true, y_pred)

def pre_score(y_true, y_pred):
    return precision_score(y_true, y_pred)

def f_score(y_true, y_pred):
    return f1_score(y_true, y_pred)
```

1 Random Forest Classifier

[18]:
```
#create an isntance of the classifier and fit the training data
clf_rf = RandomForestClassifier(max_depth = 50, min_samples_split= 5,␣
 ↪random_state= 0)
```

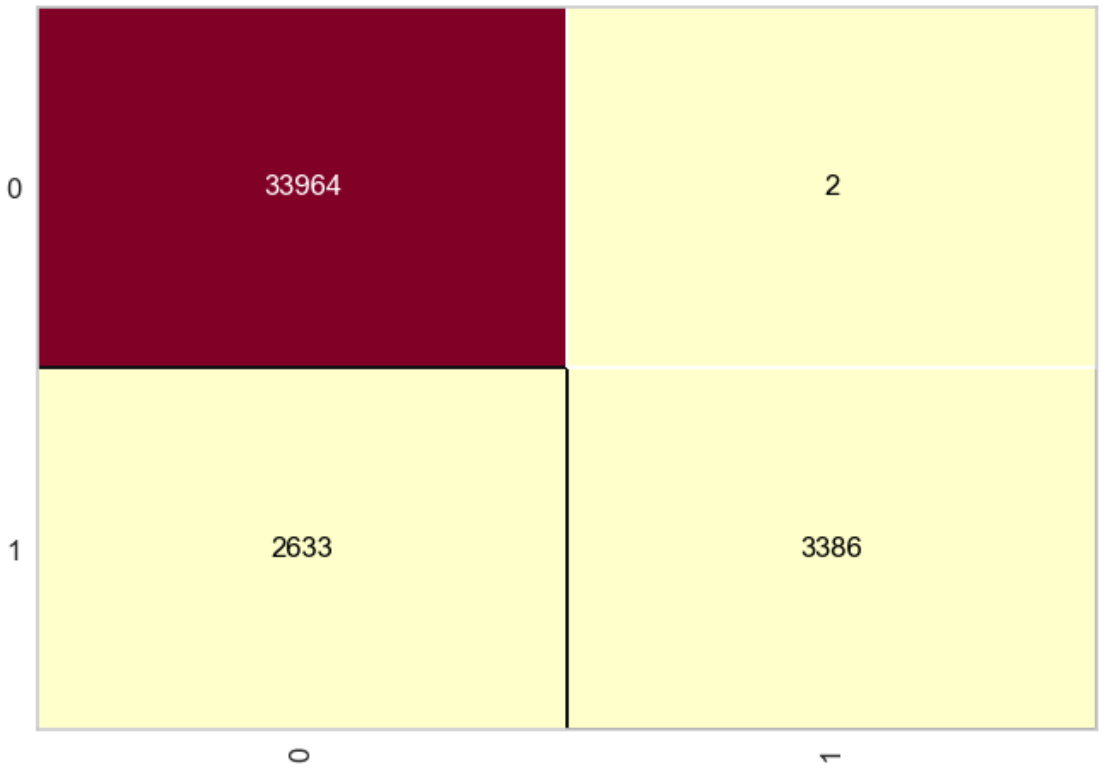
1.0.1 Checking Training Accuracy

[19]:
```
y_pred_train = model_fit_predict(clf_rf, X_train, y_train, X_train)
set(y_pred_train)

#f1 score for training data : It balances both false positives and false␣
 ↪negatives
f1 = round(f1_score(y_train, y_pred_train),2)

#accuracy score for training data : the ratio of correctly predicted instances␣
 ↪to total instances.
acc = round(accuracy_score(y_train, y_pred_train),2)

#precision score for training data : how many of the predicted positive cases␣
 ↪were actually correct.
pre = round(precision_score(y_train, y_pred_train),2)

print(f"Accuracy, precision and f1-score for training data are {acc}, {pre} and␣
 ↪{f1} respectively")
```

```
Accuracy, precision and f1-score for training data are 0.93, 1.0 and 0.72
respectively
```

[20]:
```
# confusion matrix shows the number of correct and incorrect predictions for␣
 ↪each class.
cm = ConfusionMatrix(clf_rf, classes=[0,1])
cm.fit(X_train, y_train)

cm.score(X_train, y_train)
```

[20]:
```
0.9341002876078529
```



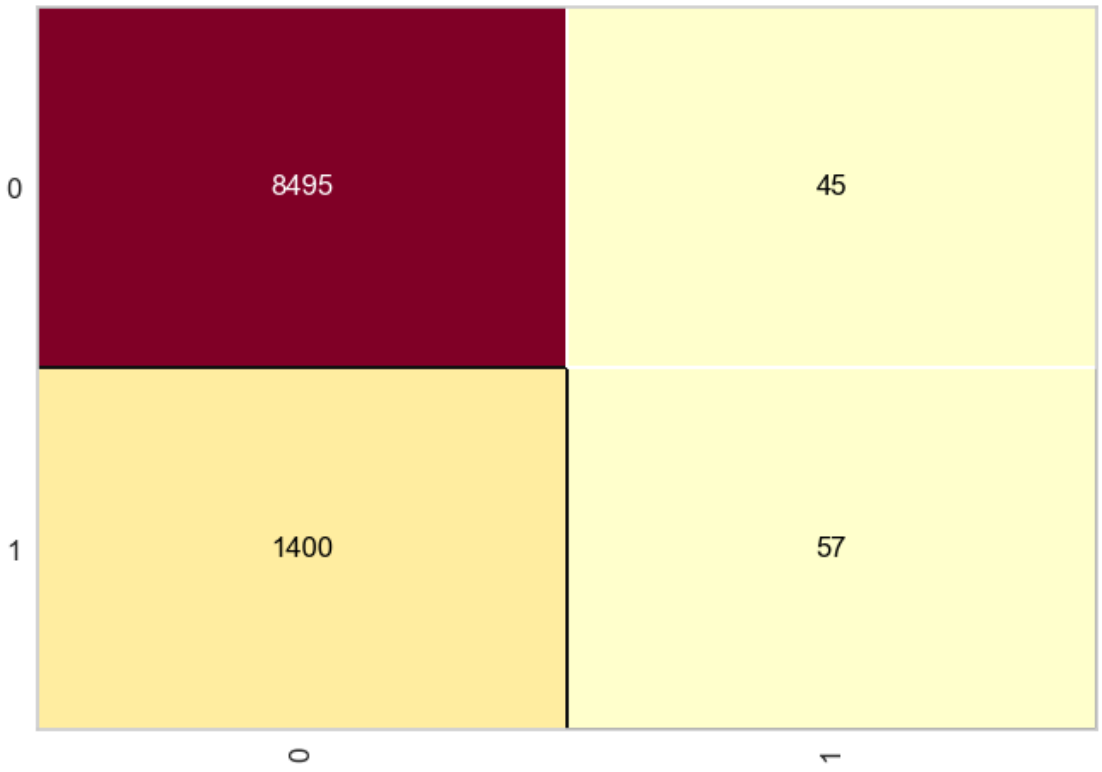
1.0.2 Checking Testing accuracy

[21]:
```
#create an instance of the classifier and fit the training data
clf_rf = RandomForestClassifier(max_depth =50 ,␣
 ↪min_samples_split=5,random_state=0)

y_pred_test = model_fit_predict(clf_rf, X_train, y_train, X_test)

#f1 score for training data
f1 = round(f1_score(y_test, y_pred_test),2)

#accuracy score for training data
acc = round(accuracy_score(y_test, y_pred_test),2)

#precision score for training data
pre = round(precision_score(y_test, y_pred_test),2)

print(f"Accuracy, precision and f1-score for training data are {acc}, {pre} and␣
 ↪{f1} respectively")
```

```
Accuracy, precision and f1-score for training data are 0.86, 0.56 and 0.07
respectively
```

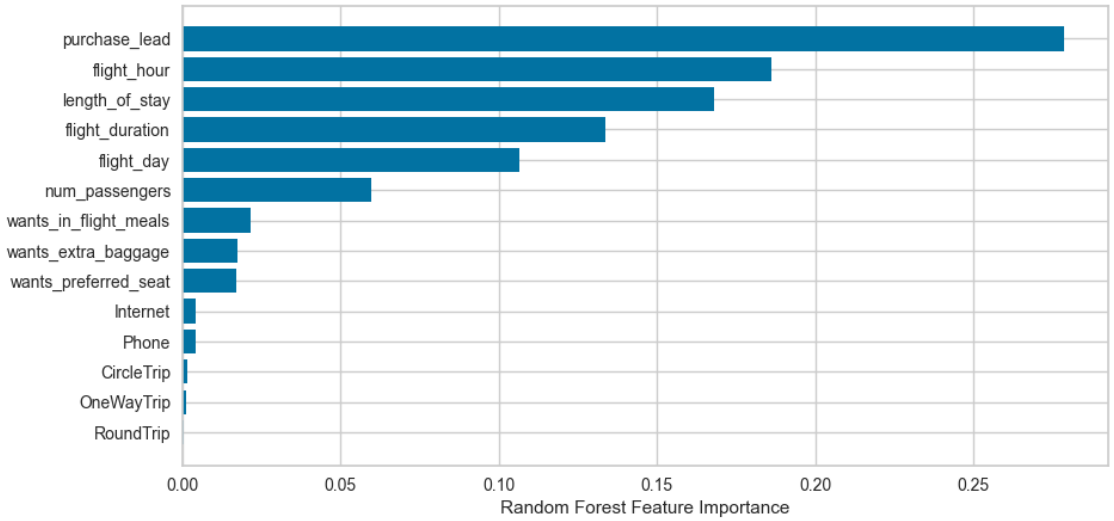
[22]:
```
cm = ConfusionMatrix(clf_rf, classes=[0,1])
cm.fit(X_train, y_train)

cm.score(X_test, y_test)
```

[22]:
```
0.8554566369910973
```



[23]:
```
plt.figure(figsize=(10,5))
sorted_idx = clf_rf.feature_importances_.argsort()
plt.barh(scaled_df.iloc[:,:-1].columns[sorted_idx], clf_rf.
  ↪feature_importances_[sorted_idx])
plt.xlabel("Random Forest Feature Importance")
```

[23]:
```
Text(0.5, 0, 'Random Forest Feature Importance')
```



[24]:
```
# One major problem behind getting low F1 score is imbalanced dataset. We have higher entries that are classified 0 than 1.
#We could reduce the number of entries that are classified 0 to be equal around the number of entries that are classified as 1.
```

1.0.3 Balancing the dataset

[25]:
```
scaled_df.label.value_counts()
```

[25]:
```
label
0    42506
1     7476
Name: count, dtype: int64
```

[26]:
```
#create a dataframe having all labels 0 with 10000 samples
scaled_df_0 = scaled_df[scaled_df.label ==0].sample(n=8000)
```

[27]:
```
#concatenate the two dataframee, one havng all labels 0 and other having all labels as 1
scaled_df_new = pd.concat([scaled_df[scaled_df.label==1], scaled_df_0], ignore_index=True)
```

[28]:
```
#shuffle the dataframe rows
scaled_df_new = scaled_df_new.sample(frac = 1).reset_index(drop=True)
```

[29]:
```
scaled_df_new
```

[29]:

	num_passengers	purchase_lead	length_of_stay	flight_hour	flight_day	\
0	2.361155	-0.030634	-0.030885	0.726958	0.595045	

```
1            0.400769       1.092557       -0.502969    -0.566346    0.595045
2            0.400769       2.971956        0.175652    -0.935861   -0.408618
3           -0.579424      -0.909169        0.028126    -0.012073    1.096876
4            0.400769       0.013849       -0.119401    -0.935861    0.595045
…                 …              …               …            …           …
15471       -0.579424      -0.486582        1.119820     0.357443   -1.412280
15472       -0.579424      -0.920290       -0.650495    -0.935861    0.595045
15473        0.400769      -0.764600       -0.532474     1.281231    0.595045
15474        0.400769      -0.030634       -0.591484    -0.935861    0.595045
15475        1.380962       0.369712       -0.532474    -0.566346    0.093214

       wants_extra_baggage  wants_preferred_seat  wants_in_flight_meals  \
0                 0.703587              1.538334               1.158002
1                 0.703587             -0.650054              -0.863557
2                 0.703587              1.538334               1.158002
3                 0.703587             -0.650054              -0.863557
4                 0.703587              1.538334               1.158002
…                    …                     …                      …
15471             0.703587             -0.650054               1.158002
15472            -1.421288             -0.650054              -0.863557
15473             0.703587              1.538334               1.158002
15474            -1.421288             -0.650054              -0.863557
15475             0.703587             -0.650054               1.158002

       flight_duration  Internet     Phone  RoundTrip  OneWayTrip  CircleTrip  \
0            -1.107240 -2.810681  2.810681  -0.048231   -0.088336    0.100826
1            -0.185282  0.355786 -0.355786  -0.048231   -0.088336    0.100826
2             1.037314  0.355786 -0.355786  -0.048231   -0.088336    0.100826
3            -1.708517  0.355786 -0.355786  -0.048231   -0.088336    0.100826
4            -1.107240  0.355786 -0.355786  -0.048231   -0.088336    0.100826
…                  …         …         …          …           …           …
15471        -0.439155  0.355786 -0.355786  -0.048231   -0.088336    0.100826
15472        -1.741921  0.355786 -0.355786  -0.048231   -0.088336    0.100826
15473        -0.439155  0.355786 -0.355786  -0.048231   -0.088336    0.100826
15474        -0.439155  0.355786 -0.355786  -0.048231   -0.088336    0.100826
15475        -0.185282  0.355786 -0.355786  -0.048231   -0.088336    0.100826

       label
0          1
1          0
2          1
3          1
4          0
…        …
15471      0
15472      1
15473      1
```

```
15474      0
15475      1

[15476 rows x 15 columns]
```

[30]:
```
X = scaled_df_new.iloc[:,:-1]
y = scaled_df_new['label']

X_train, X_test, y_train, y_test = train_test_split(X.to_numpy(), y.to_numpy(),␣
 ↪test_size=0.20, random_state=42)
```

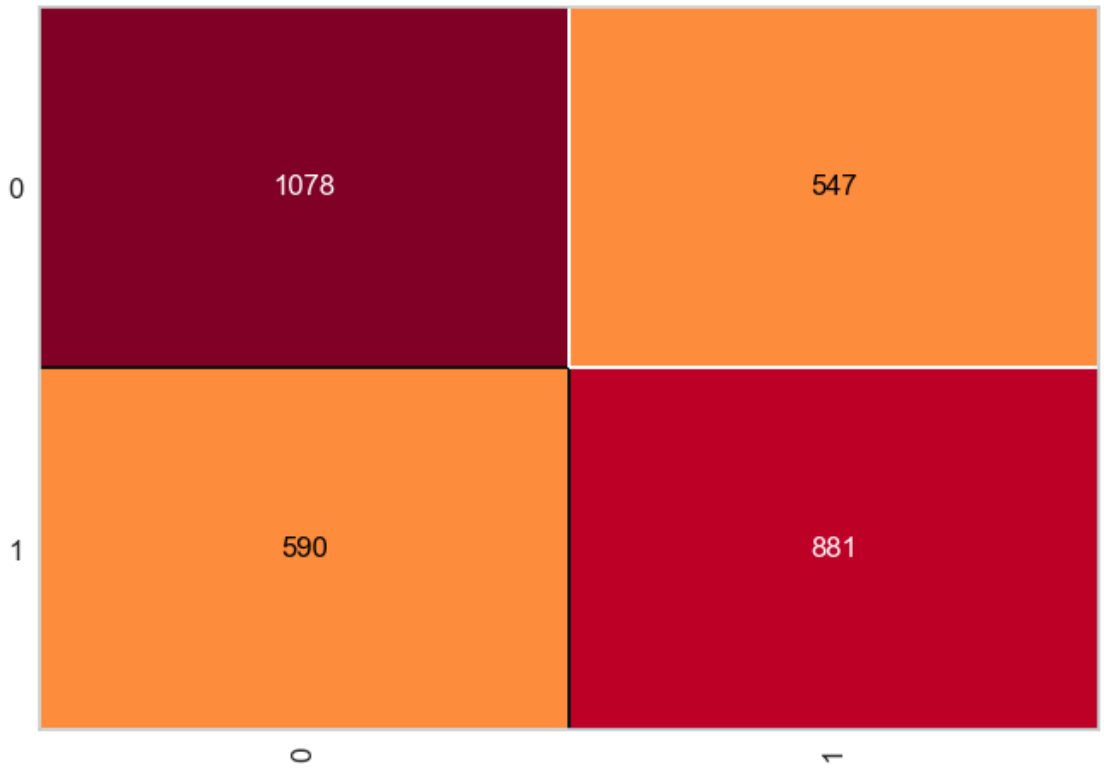
[31]:
```
#create an instance of the classifier and fit the training data
clf_rf = RandomForestClassifier(n_estimators=50,max_depth =50 ,␣
 ↪min_samples_split=5,random_state=0)
```

[32]:
```
y_pred_test = model_fit_predict(clf_rf, X_train, y_train, X_test)

#f1 score for training data
f1 = round(f1_score(y_test, y_pred_test),2)

#accuracy score for training data
acc = round(accuracy_score(y_test, y_pred_test),2)

#precision score for training data
pre = round(precision_score(y_test, y_pred_test),2)

#Measures how well the model identifies all the true positives (completed␣
 ↪bookings).
recall = round(recall_score(y_test, y_pred_test),2)

#Measures how well the model identifies the true negatives (non-completed␣
 ↪bookings).
specificity = round(recall_score(y_test, y_pred_test, pos_label=0),2)

print(f"Accuracy, precision, recall and f1-score for training data are {acc},␣
 ↪{pre}, {recall}, {specificity} and {f1} respectively")
```

```
Accuracy, precision, recall and f1-score for training data are 0.63, 0.62, 0.6,
0.66 and 0.61 respectively
```

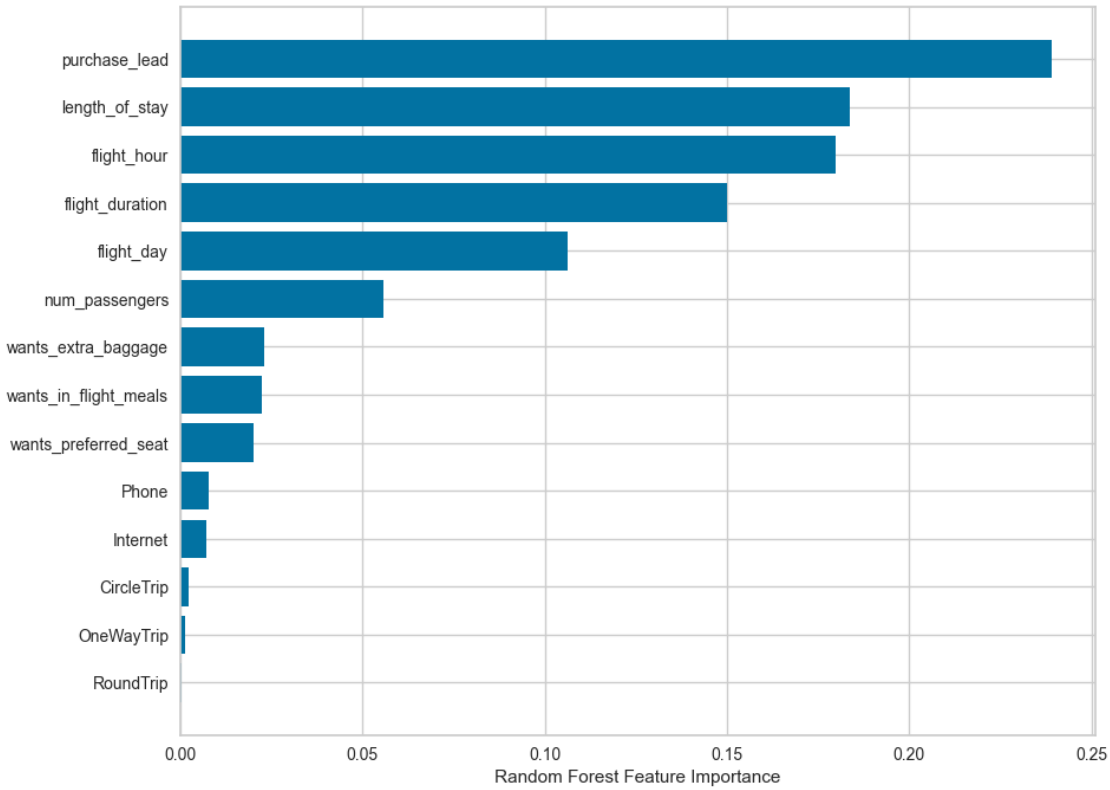
[33]:
```
cm = ConfusionMatrix(clf_rf, classes=[0,1])
cm.fit(X_train, y_train)

cm.score(X_test, y_test)
```

[33]:
```
0.6327519379844961
```



[34]:
```
plt.figure(figsize=(10,8))
sorted_idx = clf_rf.feature_importances_.argsort()
plt.barh(scaled_df.iloc[:,:-1].columns[sorted_idx], clf_rf.
  ↪feature_importances_[sorted_idx])
plt.xlabel("Random Forest Feature Importance")
```

[34]:
```
Text(0.5, 0, 'Random Forest Feature Importance')
```



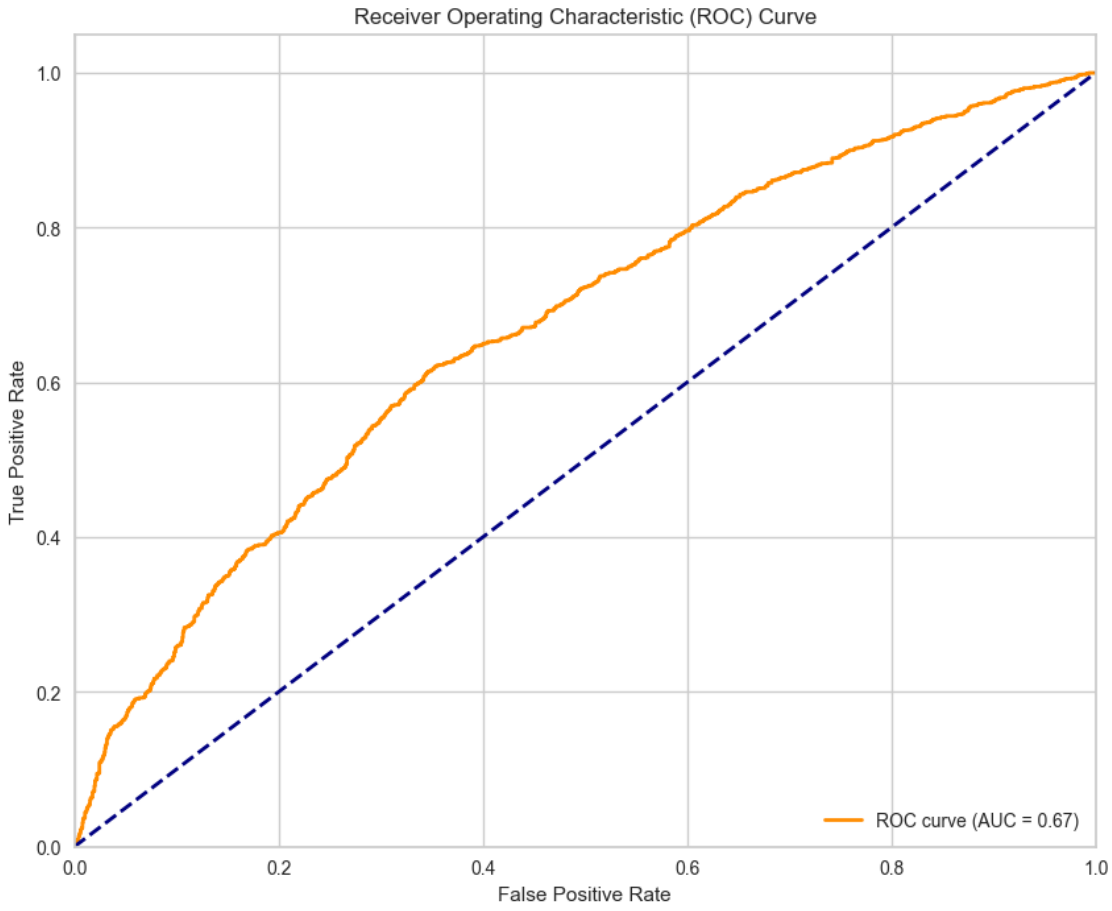
[35]:
```
from sklearn.metrics import roc_curve, auc
```

[36]:
```
y_pred_proba = clf_rf.predict_proba(X_test)[:, 1]
```

[37]:
```
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
```

[38]:
```
roc_auc = auc(fpr, tpr)
```

[39]:
```
plt.figure(figsize=(10, 8))
plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC = {roc_auc:.
↪2f})')
plt.plot([0, 1], [0, 1], color='navy', lw=2, 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) Curve')
plt.legend(loc="lower right")
plt.show()
```


Receiver Operating Characteristic (ROC) Curve
True Positive Rate
False Positive Rate
0.0
0.2
0.4
0.6
0.8
1.0
ROC curve (AUC = 0.67)

[ ]: