

April 22, 2024

## 1 Prodigy InfoTech Internship: Task 3

Build a decision tree classifier to predict whether a customer will purchase a product or service based on their demographic and behavioral data. Use a dataset such as the Bank Marketing dataset from the UCI Machine Learning Repository.

Sample Dataset: [Bank Marketing](#)

```
[1]: import warnings
warnings.filterwarnings("ignore")

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_theme(context="notebook", style="whitegrid", palette="muted")
```

### 1.1 Understand the shape of the data

```
[2]: df = pd.read_csv("data/Bank.csv", sep=";")
```

```
[3]: df
```

```
[3]:
```

	age	job	marital	education	default	balance	housing	loan	\
0	58	management	married	tertiary	no	2143	yes	no	
1	44	technician	single	secondary	no	29	yes	no	
2	33	entrepreneur	married	secondary	no	2	yes	yes	
3	47	blue-collar	married	unknown	no	1506	yes	no	
4	33	unknown	single	unknown	no	1	no	no	
...	...	...	...	...	...	...	...	...	
45206	51	technician	married	tertiary	no	825	no	no	
45207	71	retired	divorced	primary	no	1729	no	no	
45208	72	retired	married	secondary	no	5715	no	no	
45209	57	blue-collar	married	secondary	no	668	no	no	
45210	37	entrepreneur	married	secondary	no	2971	no	no	
	contact	day	month	duration	campaign	pdays	previous	poutcome	y

0	unknown	5	may	261	1	-1	0	unknown	no
1	unknown	5	may	151	1	-1	0	unknown	no
2	unknown	5	may	76	1	-1	0	unknown	no
3	unknown	5	may	92	1	-1	0	unknown	no
4	unknown	5	may	198	1	-1	0	unknown	no
...	...	...	...	...	...	...	...	...	...
45206	cellular	17	nov	977	3	-1	0	unknown	yes
45207	cellular	17	nov	456	2	-1	0	unknown	yes
45208	cellular	17	nov	1127	5	184	3	success	yes
45209	telephone	17	nov	508	4	-1	0	unknown	no
45210	cellular	17	nov	361	2	188	11	other	no

[45211 rows x 17 columns]

[4]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45211 entries, 0 to 45210
Data columns (total 17 columns):
#   Column      Non-Null Count  Dtype
---  -
0   age         45211 non-null  int64
1   job         45211 non-null  object
2   marital     45211 non-null  object
3   education   45211 non-null  object
4   default     45211 non-null  object
5   balance     45211 non-null  int64
6   housing     45211 non-null  object
7   loan        45211 non-null  object
8   contact     45211 non-null  object
9   day         45211 non-null  int64
10  month       45211 non-null  object
11  duration    45211 non-null  int64
12  campaign    45211 non-null  int64
13  pdays      45211 non-null  int64
14  previous    45211 non-null  int64
15  poutcome    45211 non-null  object
16  y           45211 non-null  object
dtypes: int64(7), object(10)
memory usage: 5.9+ MB
```

[5]: df.describe()

	age	balance	day	duration	campaign \
count	45211.000000	45211.000000	45211.000000	45211.000000	45211.000000
mean	40.936210	1362.272058	15.806419	258.163080	2.763841
std	10.618762	3044.765829	8.322476	257.527812	3.098021
min	18.000000	-8019.000000	1.000000	0.000000	1.000000

25%	33.000000	72.000000	8.000000	103.000000	1.000000
50%	39.000000	448.000000	16.000000	180.000000	2.000000
75%	48.000000	1428.000000	21.000000	319.000000	3.000000
max	95.000000	102127.000000	31.000000	4918.000000	63.000000

	pdays	previous
count	45211.000000	45211.000000
mean	40.197828	0.580323
std	100.128746	2.303441
min	-1.000000	0.000000
25%	-1.000000	0.000000
50%	-1.000000	0.000000
75%	-1.000000	0.000000
max	871.000000	275.000000

```
[6]: df.describe(include='object')
```

```
[6]:
```

	job	marital	education	default	housing	loan	contact \
count	45211	45211	45211	45211	45211	45211	45211
unique	12	3	4	2	2	2	3
top	blue-collar	married	secondary	no	yes	no	cellular
freq	9732	27214	23202	44396	25130	37967	29285

	month	poutcome	y
count	45211	45211	45211
unique	12	4	2
top	may	unknown	no
freq	13766	36959	39922

```
[7]: df.duplicated().sum()
```

```
[7]: 0
```

## 1.2 Data Cleaning

```
[8]: df = df.rename(columns={'y': 'subscribed'})
df['subscribed'] = df['subscribed'].map({'yes': 'Subscribed', 'no': 'Not_
↳ Subscribed'})
```

```
[9]: categorical_cols = ['job', 'marital', 'education', 'contact', 'month', '
↳ poutcome']
df[categorical_cols] = (df[categorical_cols].apply(lambda x: x.str.title())
↳ .astype('category'))

binary_cols = ['default', 'housing', 'loan']
df[binary_cols] = df[binary_cols] == 'yes'
```

```
[10]: cols_with_outliers = ["age", "balance", "duration", "campaign"]
```

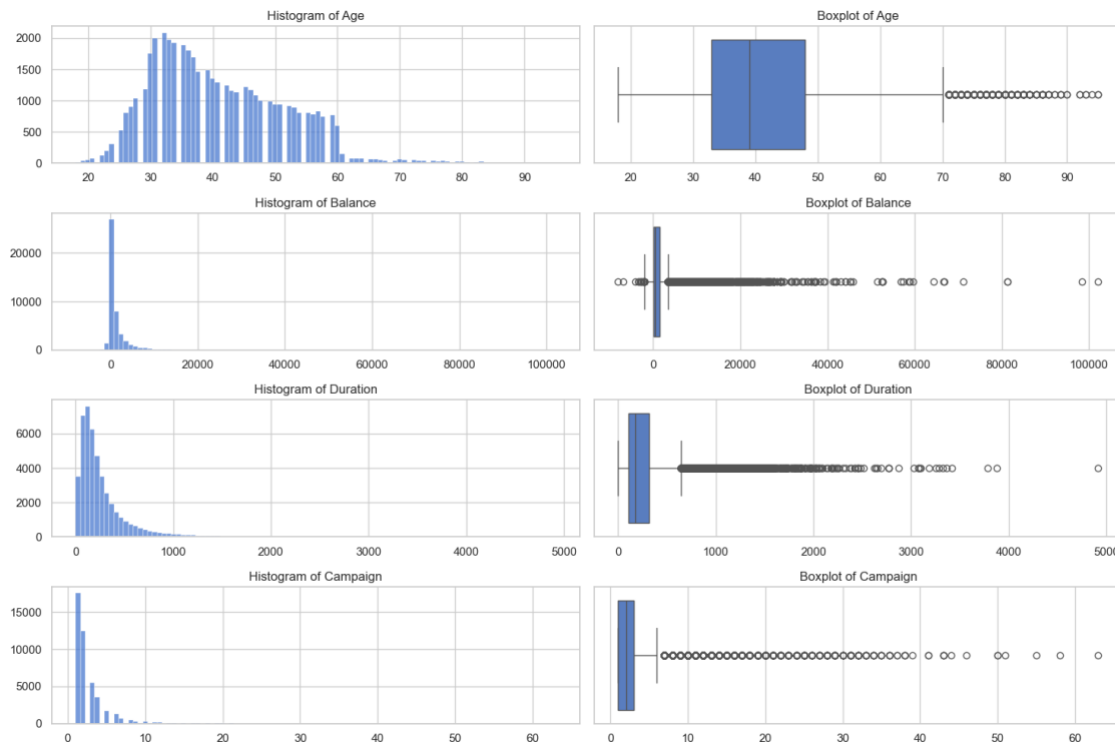
```
[11]: fig, axes = plt.subplots(4, 2, figsize=(15, 10))

for i, col in enumerate(cols_with_outliers):
    hist_ax, box_ax = axes[i, :]

    sns.histplot(data=df, x=col, bins=100, ax=hist_ax)
    hist_ax.set_title(f'Histogram of {col.title()}')
    hist_ax.set_xlabel("")
    hist_ax.set_ylabel("")

    sns.boxplot(data=df, x=col, ax=box_ax)
    box_ax.set_title(f'Boxplot of {col.title()}')
    box_ax.set_xlabel("")
    box_ax.set_ylabel("")

plt.tight_layout()
plt.show();
```



```
[12]: def remove_outliers(df, columns):
    df_outliers_removed = df.copy()
```

```

for col in columns:
    Q1 = df_outliers_removed[col].quantile(0.25)
    Q3 = df_outliers_removed[col].quantile(0.75)

    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    df_outliers_removed = df_outliers_removed[
        (df_outliers_removed[col] >= lower_bound) &
        (df_outliers_removed[col] <= upper_bound)
    ]

return df_outliers_removed

```

```
df = remove_outliers(df, cols_with_outliers)
```

```
[13]: fig, axes = plt.subplots(4, 2, figsize=(15, 10))
```

```

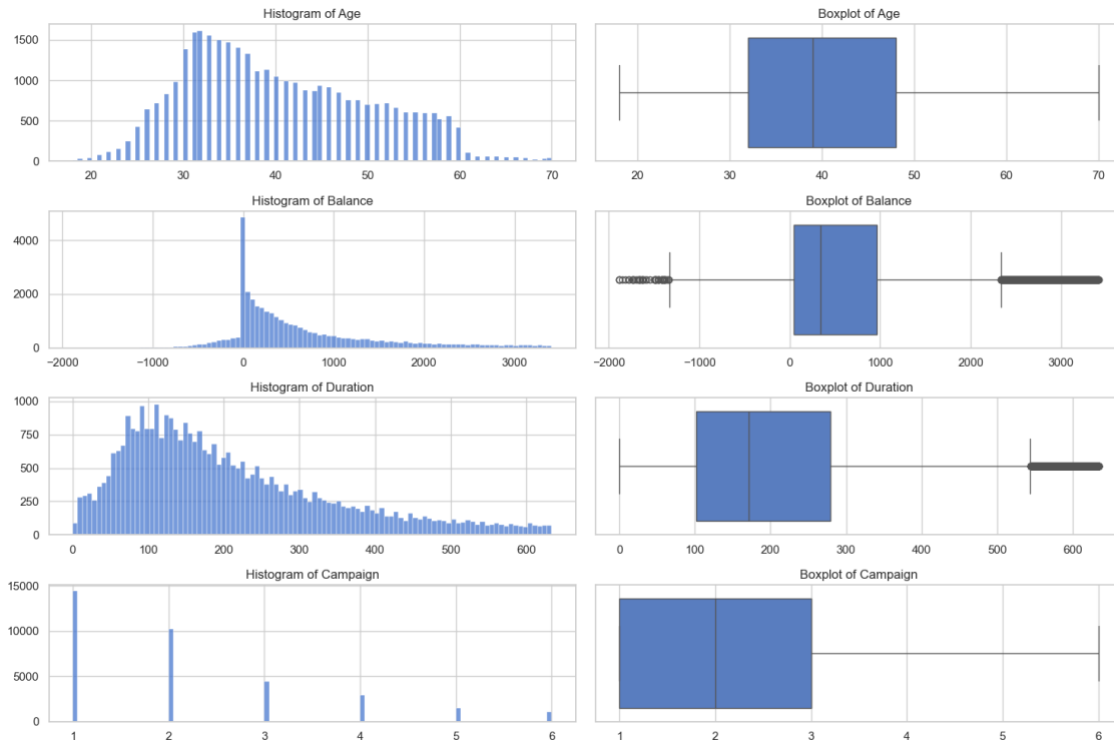
for i, col in enumerate(cols_with_outliers):
    hist_ax, box_ax = axes[i, :]

    sns.histplot(data=df, x=col, bins=100, ax=hist_ax)
    hist_ax.set_title(f'Histogram of {col.title()}')
    hist_ax.set_xlabel('')
    hist_ax.set_ylabel('')

    sns.boxplot(data=df, x=col, ax=box_ax)
    box_ax.set_title(f'Boxplot of {col.title()}')
    box_ax.set_xlabel('')
    box_ax.set_ylabel('')

plt.tight_layout()
plt.show();

```



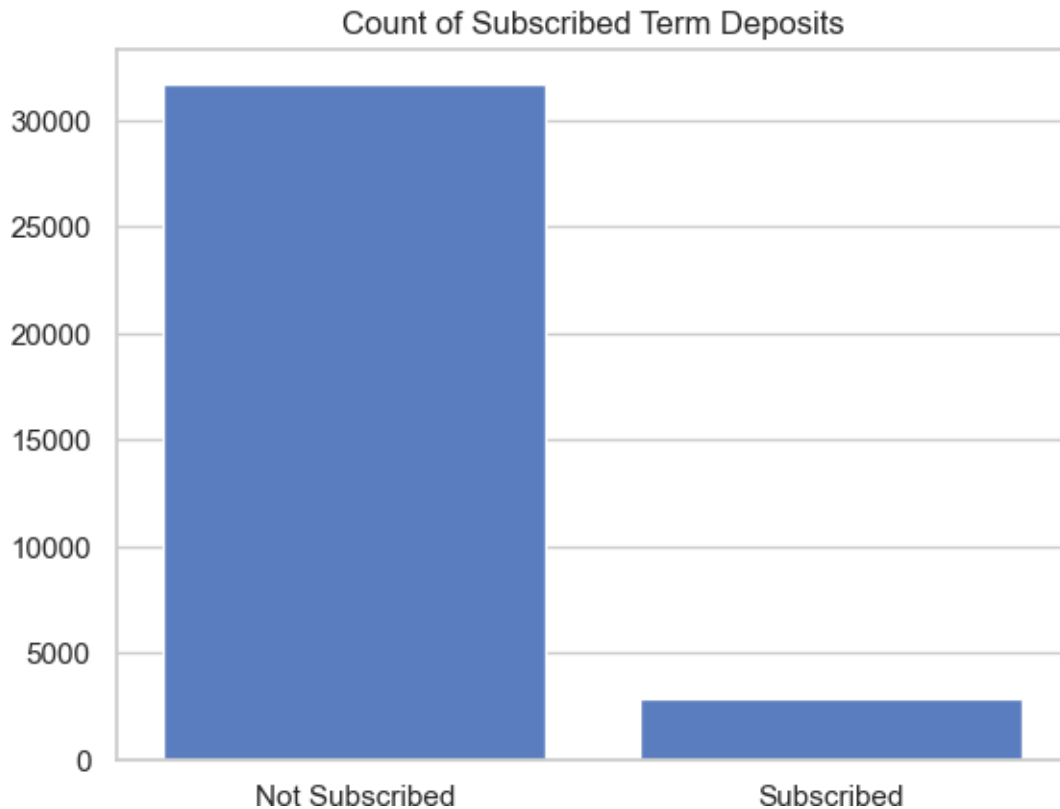
### 1.3 Data Exploration

```
[14]: num_cols = df.select_dtypes('number').columns.tolist()
      bool_cols = df.select_dtypes('bool').columns.tolist()
      cat_cols = df.select_dtypes('category').columns.tolist()
```

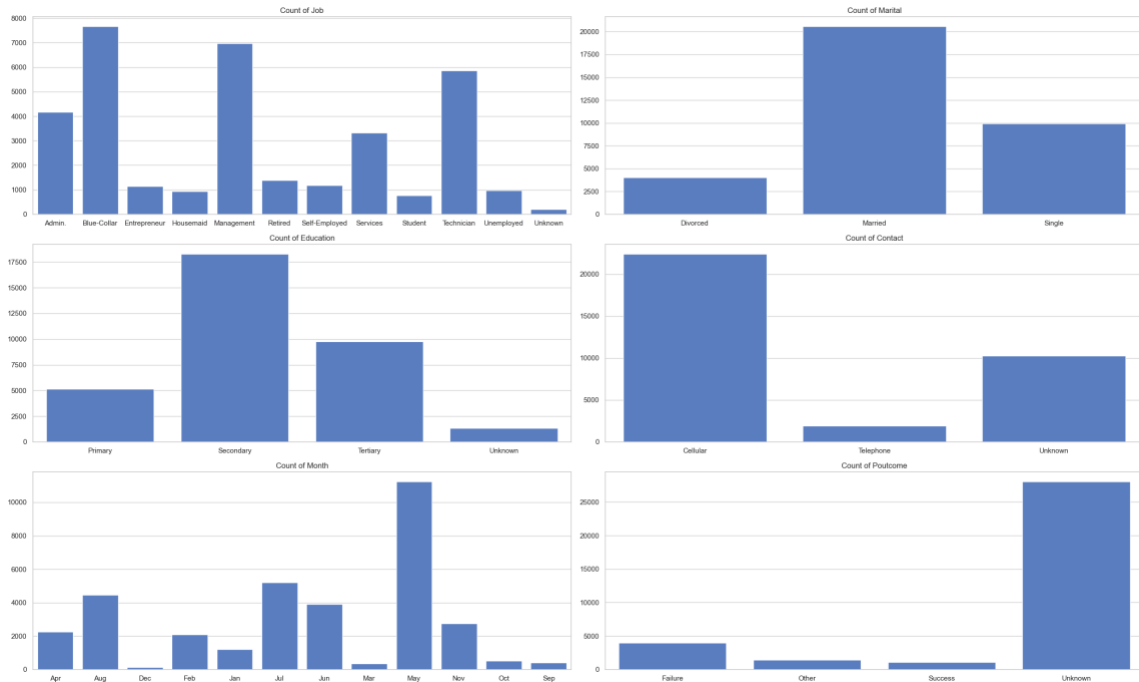
```
[15]: sns.countplot(data=df, x='subscribed');

plt.title('Count of Subscribed Term Deposits')
plt.xlabel('')
plt.ylabel('')

plt.show();
```



```
[16]: fig, axes = plt.subplots(3, 2, figsize=(25, 15))  
  
for feature, ax in zip(cat_cols, axes.flatten()):  
    sns.countplot(data=df, x=feature, ax=ax)  
  
    ax.set_title(f'Count of {feature.title()}')  
    ax.set_xlabel('')  
    ax.set_ylabel('')  
  
plt.tight_layout()  
plt.show();
```



## 1.4 Data Preprocessing for Model

```
[17]: from sklearn.model_selection import train_test_split
      from sklearn.preprocessing import OneHotEncoder, StandardScaler
      from sklearn.compose import ColumnTransformer

      from imblearn.over_sampling import RandomOverSampler
```

```
[18]: X = df.drop(columns='subscribed')
      y = df['subscribed']

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

```
[19]: num_vars = df.select_dtypes('number').columns.tolist()
      cat_vars = df.select_dtypes('category').columns.tolist()
```

```
[20]: preprocessing_pipeline = ColumnTransformer([
      ('numerical', StandardScaler(), num_vars),
      ('categorical', OneHotEncoder(), cat_vars),
      ])
```



```
X_train = preprocessing_pipeline.fit_transform(X_train)
X_test = preprocessing_pipeline.transform(X_test)
```

```
[21]: sampler = RandomOverSampler(random_state=42)

X_train, y_train = sampler.fit_resample(X_train, y_train)
```

## 1.5 Basic Model Building

```
[22]: from sklearn.tree import DecisionTreeClassifier
      from sklearn.metrics import classification_report
```

```
[23]: %%time

      model = DecisionTreeClassifier(random_state=42)
      model.fit(X_train, y_train)
```

CPU times: user 1.06 s, sys: 3.91 ms, total: 1.06 s  
Wall time: 1.06 s

```
[23]: DecisionTreeClassifier(random_state=42)
```

```
[24]: y_pred = model.predict(X_test)

      accuracy = model.score(X_test, y_test)
      report = classification_report(y_test, y_pred)

      print(f'Accuracy: {accuracy:.2%}')
      print(f'Classification Report:\n{report}')
```

Accuracy: 90.09%

Classification Report:

	precision	recall	f1-score	support
Not Subscribed	0.95	0.95	0.95	6343
Subscribed	0.40	0.41	0.40	570
accuracy			0.90	6913
macro avg	0.67	0.68	0.67	6913
weighted avg	0.90	0.90	0.90	6913

## 1.6 Model Tuning

```
[25]: from sklearn.model_selection import GridSearchCV
      from sklearn.metrics import make_scorer, f1_score
```

```
[26]: param_grid = {  
        'max_depth': [None, 10, 20],  
        'min_samples_split': [2, 5, 10],  
        'min_samples_leaf': [1, 2, 4],  
    }
```

```
[27]: scorer = make_scorer(f1_score, pos_label="Subscribed")
```

```
[28]: base_model = DecisionTreeClassifier(random_state=42)  
grid_search = GridSearchCV(estimator=base_model,  
                           param_grid=param_grid,  
                           cv=5,  
                           scoring=scorer,  
                           verbose=1,  
                           n_jobs=-1)
```

```
[29]: %%time  
  
grid_search.fit(X_train, y_train)
```

Fitting 5 folds for each of 27 candidates, totalling 135 fits

CPU times: user 1.8 s, sys: 196 ms, total: 2 s

Wall time: 24.6 s

```
[29]: GridSearchCV(cv=5, estimator=DecisionTreeClassifier(random_state=42), n_jobs=-1,  
                  param_grid={'max_depth': [None, 10, 20],  
                              'min_samples_leaf': [1, 2, 4],  
                              'min_samples_split': [2, 5, 10]},  
                  scoring=make_scorer(f1_score, response_method='predict',  
                                      pos_label=Subscribed),  
                  verbose=1)
```

```
[30]: best_params = grid_search.best_params_  
best_model = grid_search.best_estimator_  
accuracy = best_model.score(X_test, y_test)  
  
print(f"Best Accuracy: {accuracy:.2%}")  
print(f"Best Parameters:\n{best_params}")
```

Best Accuracy: 90.11%

Best Parameters:

{'max\_depth': None, 'min\_samples\_leaf': 1, 'min\_samples\_split': 5}

```
[31]: y_pred = best_model.predict(X_test)  
report = classification_report(y_test, y_pred)  
  
print(f"Classification Report:\n{report}")
```

Classification Report:

	precision	recall	f1-score	support
Not Subscribed	0.95	0.95	0.95	6343
Subscribed	0.40	0.41	0.41	570
accuracy			0.90	6913
macro avg	0.67	0.68	0.68	6913
weighted avg	0.90	0.90	0.90	6913

## 1.7 Results

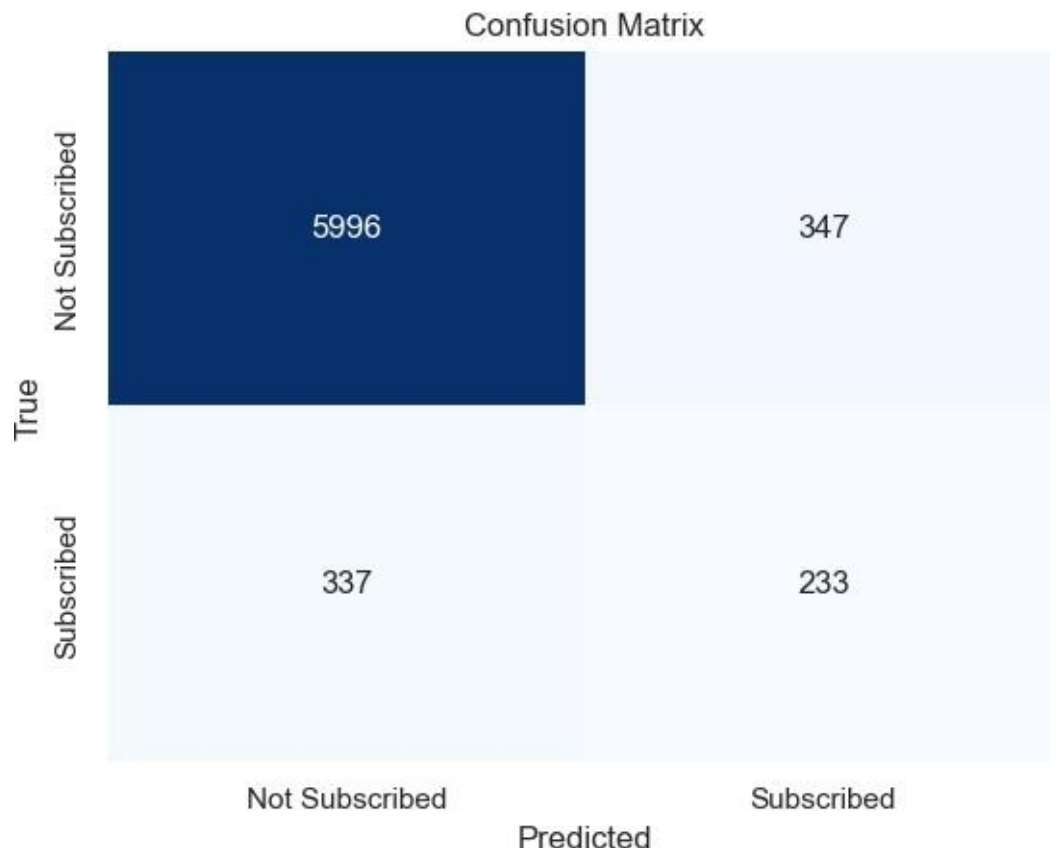
```
[32]: from sklearn.metrics import confusion_matrix
```

```
[33]: conf_matrix = confusion_matrix(y_test, y_pred)
labels = best_model.classes_
```

```
sns.heatmap(conf_matrix,
             annot=True,
             fmt='d',
             cmap='Blues',
             cbar=False,
             xticklabels=labels,
             yticklabels=labels)
```

```
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('True')
```

```
plt.show();
```



Thank you