Practical Application III: Comparing Classifiers

Overview: In this practical application, your goal is to compare the performance of the classifiers we encountered in this section, namely K Nearest Neighbor, Logistic Regression, Decision Trees, and Support Vector Machines. We will utilize a dataset related to marketing bank products over the telephone.

Getting Started

Our dataset comes from the UCI Machine Learning repository [link (https://archive.ics.uci.edu/ml/datasets/bank+marketing)](https://archive.ics.uci.edu/ml/datasets/bank+marketing). The data is from a Portugese banking institution and is a collection of the results of multiple marketing campaigns. We will make use of the article accompanying the dataset [here (CRISP-DM-BANK.pdf)](CRISP-DM-BANK.pdf) for more information on the data and features.

Problem 1: Understanding the Data

To gain a better understanding of the data, please read the information provided in the UCI link above, and examine the **Materials and Methods** section of the paper. How many marketing campaigns does this data represent?

In total 17 campaigns were carried out between May 2008 and November 2010, corresponding to a total of 79354 contacts. During these phone campaigns, an attractive long-term deposit application, with good interest rates, was offered.

Problem 2: Read in the Data

Use pandas to read in the dataset `bank-additional-full.csv` and assign to a meaningful variable name.

In [84]:
```python
import pandas as pd
import numpy as np
import plotly.express as px
import plotly.graph_objects as go
from collections import defaultdict
import plotly.graph_objects as go
import matplotlib.pyplot as plt
from sklearn import svm
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split,cross_val_score
import seaborn as sns
import plotly.subplots as sp
from calendar import month_abbr
from sklearn.neighbors import KNeighborsRegressor,KNeighborsClassifier
from sklearn.impute import KNNImputer
from imblearn.over_sampling import SMOTE
# preprocessing
from sklearn.preprocessing import MinMaxScaler
# calculate the MSE score
from sklearn.metrics import mean_squared_error,confusion_matrix
from sklearn.metrics import roc_auc_score,precision_score,recall_score,accuracy_score,f1_score,balanced_accuracy_score
# cross validation
from sklearn.model_selection import GridSearchCV,StratifiedKFold,RandomizedSearchCV
# modeling
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression,RidgeClassifier
# model evaluation
from sklearn.metrics import classification_report, plot_roc_curve
from sklearn.metrics import classification_report,plot_confusion_matrix, ConfusionMatrixDisplay
from sklearn.dummy import DummyClassifier
from sklearn.inspection import permutation_importance
import random
import warnings
import time

warnings.filterwarnings("ignore")
```

In [2]:
```python
df = pd.read_csv('data/bank-additional-full.csv', sep = ';')
```

In [3]:
```python
df.head()
```

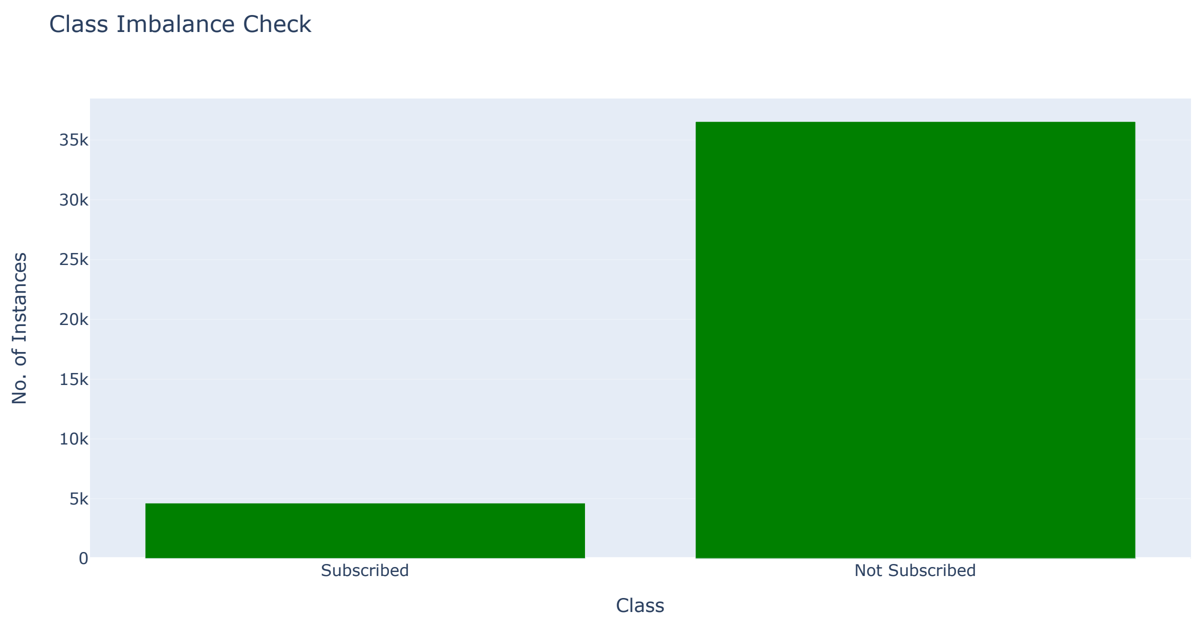
Out[3]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	...	campaign	pdays	previous	poutcome	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed	y
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
2	37	services	married	high.school	no	yes	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	...	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no
4	56	services	married	high.school	no	no	yes	telephone	may	mon	...	1	999	0	nonexistent	1.1	93.994	-36.4	4.857	5191.0	no

5 rows × 21 columns

Given our data is imbalanced with the majority not subscribing a term deposit, we might want to do re-sampling to adjust the proportion while training.

In [4]:
```python
y = list(df['y'])
instances_per_class = {'yes' : y.count('yes'), 'no' : y.count('no')}

fig = go.Figure(data=[go.Bar(x=list(instances_per_class.keys()), y=list(instances_per_class.values()),
                      marker=dict(color='green'))])
fig.update_layout(title='Class Imbalance Check', xaxis_title='Class', yaxis_title='No. of Instances',
                  xaxis=dict(tickmode='array', tickvals=[0,1], ticktext=['Subscribed', 'Not Subscribed']))
fig.show()

print(f"Class Labels : {list(instances_per_class.keys())}\nNo. of Inst. : {list(instances_per_class.values())}\n\nTotal number of features : {len(df.columns)-1}")
```




```
Class Labels : ['yes', 'no']
No. of Inst. : [4640, 36548]

Total number of features : 20
```

Problem 3: Understanding the Features

Examine the data description below, and determine if any of the features are missing values or need to be coerced to a different data type.

```
Input variables:
# bank client data:
1 - age (numeric)
2 - job : type of job (categorical: 'admin.','blue-collar','entrepreneur','housemaid','management','retired','self-employed','services','student','technician','unemplo
yed','unknown')
3 - marital : marital status (categorical: 'divorced','married','single','unknown'; note: 'divorced' means divorced or widowed)
4 - education (categorical: 'basic.4y','basic.6y','basic.9y','high.school','illiterate','professional.course','university.degree','unknown')
5 - default: has credit in default? (categorical: 'no','yes','unknown')
6 - housing: has housing loan? (categorical: 'no','yes','unknown')
7 - loan: has personal loan? (categorical: 'no','yes','unknown')
# related with the last contact of the current campaign:
8 - contact: contact communication type (categorical: 'cellular','telephone')
9 - month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')
10 - day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')
11 - duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the
duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes
and should be discarded if the intention is to have a realistic predictive model.
# other attributes:
12 - campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
13 - pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
14 - previous: number of contacts performed before this campaign and for this client (numeric)
15 - poutcome: outcome of the previous marketing campaign (categorical: 'failure','nonexistent','success')
# social and economic context attributes
16 - emp.var.rate: employment variation rate - quarterly indicator (numeric)
17 - cons.price.idx: consumer price index - monthly indicator (numeric)
18 - cons.conf.idx: consumer confidence index - monthly indicator (numeric)
19 - euribor3m: euribor 3 month rate - daily indicator (numeric)
20 - nr.employed: number of employees - quarterly indicator (numeric)

Output variable (desired target):
21 - y - has the client subscribed a term deposit? (binary: 'yes','no')
```

3.1) Describe Data

The describe() function in a pandas DataFrame is used to generate descriptive statistics of the data. It returns a summary of the central tendency, dispersion, and shape of the distribution, excluding missing values.

In [5]:
```
df.describe()
```

Out[5]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000
mean	40.02406	258.285010	2.567593	962.475454	0.172963	0.081886	93.575664	-40.502600	3.621291	5167.035911
std	10.42125	259.279249	2.770014	186.910907	0.494901	1.570960	0.578840	4.628198	1.734447	72.251528
min	17.00000	0.000000	1.000000	0.000000	0.000000	-3.400000	92.201000	-50.800000	0.634000	4963.600000
25%	32.00000	102.000000	1.000000	999.000000	0.000000	-1.800000	93.075000	-42.700000	1.344000	5099.100000
50%	38.00000	180.000000	2.000000	999.000000	0.000000	1.100000	93.749000	-41.800000	4.857000	5191.000000
75%	47.00000	319.000000	3.000000	999.000000	0.000000	1.400000	93.994000	-36.400000	4.961000	5228.100000
max	98.00000	4918.000000	56.000000	999.000000	7.000000	1.400000	94.767000	-26.900000	5.045000	5228.100000

3.2) Data Types

The dtypes attribute in a pandas DataFrame returns the data types of each column in the DataFrame. The attribute returns a Series object where the index is the column name and the value is the data type.

In [85]:
```
df.dtypes
```

Out[85]:
```
age               int64
job              object
marital          object
education        object
default          object
housing          object
loan             object
contact          object
month            object
day_of_week      object
duration          int64
campaign          int64
pdays             int64
previous          int64
poutcome         object
y                 int64
dtype: object
```

3.3) Data Dimensions

The shape attribute in a pandas DataFrame returns the number of rows and columns in the DataFrame. The attribute returns a tuple, where the first element is the number of rows and the second element is the number of columns.

In [7]:
```
df.shape
```

Out[7]:
```
(41188, 21)
```

3.4) Data Collection - Check NA

There are several ways to check for missing values (also known as "null" values) in a pandas DataFrame.

One way is to use the isnull() function, which returns a DataFrame of the same shape as the original, but with True for missing values and False for non-missing values. We will then use the sum() function to count the number of missing values in each column:

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
age               0
job               0
marital           0
education         0
default           0
housing           0
loan              0
contact           0
month             0
day_of_week       0
duration          0
campaign          0
pdays             0
previous          0
poutcome          0
emp.var.rate      0
cons.price.idx    0
cons.conf.idx     0
euribor3m         0
nr.employed       0
y                 0
dtype: int64
```

3.5) Numerical and Categorical Attributes

The select_dtypes() method is used to select columns in a DataFrame based on their data types. It takes as input the data types to be selected, and returns a new DataFrame containing only the columns that match the specified data types. We will use this to look at the list of numerical and categorical attributes.

In [9]:
```
num_attributes = df.select_dtypes(include=['int64', 'float64'] )
cat_attributes = df.select_dtypes(exclude=['int64', 'float64','datetime64[ns]'] )
num_attributes.sample()
```

Out[9]:

	age	duration	campaign	pdays	previous	emp.var.rate	cons.price.idx	cons.conf.idx	euribor3m	nr.employed
35663	37	442	1	999	0	-1.8	92.893	-46.2	1.244	5099.1

In [10]:
```
cat_attributes.sample()
```

Out[10]:

	job	marital	education	default	housing	loan	contact	month	day_of_week	poutcome	y
27792	student	single	high.school	no	yes	yes	cellular	mar	tue	nonexistent	no

3.6) Clean Dataset by dropping columns

In [11]:
```
mapping_yn = {'no': 0, 'yes': 1}
df['y'] = df['y'].map(mapping_yn)
df = df.drop(['emp.var.rate','cons.price.idx', 'cons.conf.idx', 'euribor3m', 'nr.employed'], axis = 1)
```

In [12]:
```
df_raw = df.copy()
```

In [13]:
```
X = df_raw.drop('y', axis=1)
y = df_raw['y']

unique_val_count = {}

cat = list(X.columns)
cat.remove('age')
cat.remove('duration')
cat.remove('pdays')
cat.remove('campaign')
cat.remove('previous')


for col in X.columns:
    if col not in cat:
        continue
    unique_values = np.unique(X[col])
    temp = defaultdict(int)
    for val in X[col]:
        temp[val] += 1
    unique_val_count[col] = temp

print(f"Number of Categorical columns : {len(unique_val_count.keys())}")

for col, attr in unique_val_count.items():
    map_val = {}
    count = 0
    for key in attr.keys():
        map_val[key] = count
        count += 1
    X[col] = X[col].map(map_val)

X.head(10)
```

```
Number of Categorical columns : 10
```

Out[13]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome
0	56	0	0	0	0	0	0	0	0	0	261	1	999	0	0
1	57	1	0	1	1	0	0	0	0	0	149	1	999	0	0
2	37	1	0	1	0	1	0	0	0	0	226	1	999	0	0
3	40	2	0	2	0	0	0	0	0	0	151	1	999	0	0
4	56	1	0	1	0	0	1	0	0	0	307	1	999	0	0
5	45	1	0	3	1	0	0	0	0	0	198	1	999	0	0
6	59	2	0	4	0	0	0	0	0	0	139	1	999	0	0
7	41	3	0	5	1	0	0	0	0	0	217	1	999	0	0
8	24	4	1	4	0	1	0	0	0	0	380	1	999	0	0
9	25	1	1	1	0	1	0	0	0	0	50	1	999	0	0

3.7) Exploratory Data Analysis

Exploratory Data Analysis (EDA) is a critical step in the machine learning process that involves analyzing and understanding the data before building a model. The goal of EDA is to uncover patterns, relationships, and insights in the data that can inform the model building process.

EDA is an iterative process and it's essential to keep in mind the business objective and the problem statement.

In [14]:
```
cross_tables = []
for i in unique_val_count.keys():
    cross_tables.append(pd.crosstab(X[i], y))
```

In [15]:
```
mapping_yn = {0:'no',1:'yes'}
for df1 in cross_tables:
    df1.rename(columns=mapping_yn, inplace=True)
```

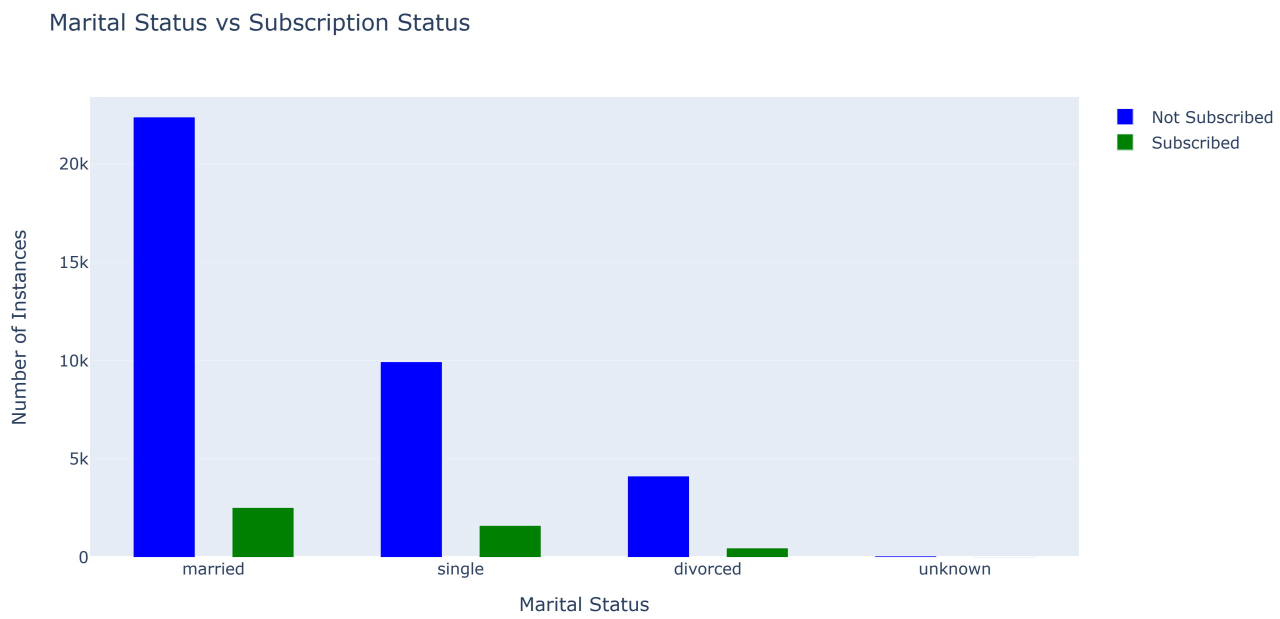
In [16]:
```
unique_val_count
```

Out[16]:
```
{'job': defaultdict(int,
             {'housemaid': 1060,
              'services': 3969,
              'admin.': 10422,
              'blue-collar': 9254,
              'technician': 6743,
              'retired': 1720,
              'management': 2924,
              'unemployed': 1014,
              'self-employed': 1421,
              'unknown': 330,
              'entrepreneur': 1456,
              'student': 875}),
 'marital': defaultdict(int,
             {'married': 24928,
              'single': 11568,
              'divorced': 4612,
              'unknown': 80}),
 'education': defaultdict(int,
             {'basic.4y': 4176,
              'high.school': 9515,
              'basic.6y': 2292,
              'basic.9y': 6045,
              'professional.course': 5243,
              'unknown': 1731,
              'university.degree': 12168,
              'illiterate': 18}),
 'default': defaultdict(int, {'no': 32588, 'unknown': 8597, 'yes': 3}),
 'housing': defaultdict(int, {'no': 18622, 'yes': 21576, 'unknown': 990}),
 'loan': defaultdict(int, {'no': 33950, 'yes': 6248, 'unknown': 990}),
 'contact': defaultdict(int, {'telephone': 15044, 'cellular': 26144}),
 'month': defaultdict(int,
             {'may': 13769,
              'jun': 5318,
              'jul': 7174,
              'aug': 6178,
              'oct': 718,
              'nov': 4101,
              'dec': 182,
              'mar': 546,
              'apr': 2632,
              'sep': 570}),
 'day_of_week': defaultdict(int,
             {'mon': 8514,
              'tue': 8090,
              'wed': 8134,
              'thu': 8623,
              'fri': 7827}),
 'poutcome': defaultdict(int,
             {'nonexistent': 35563, 'failure': 4252, 'success': 1373})}
```

1) There're some binary variables such as 'default', 'housing', 'loan'. We might want to transform it for better predicting.
2) Although no NULL is detected, there are many 'unknown' values, which we should deal with when preprocessing.
3) There are a large percentage of unknown previous outcomes, which is not surprising because many customers don't have previous contacts (previous=0).

3.7.1) Comparing Marital Status with Subscription Status

In [17]:
```
width = 0.25
fig = go.Figure()
fig.add_trace(go.Bar(x=list(unique_val_count['marital'].keys()), y=cross_tables[1]['no'],marker=dict(color='blue'), width=width, name='Not Subscribed'))
fig.add_trace(go.Bar(x=list(unique_val_count['marital'].keys()), y=cross_tables[1]['yes'],marker=dict(color='green'), width=width, name='Subscribed'))
fig.update_layout(title='Marital Status vs Subscription Status', xaxis_title='Marital Status', yaxis_title='Number of Instances',
                  yaxis=dict(range=[0, max((list(cross_tables[1]['no'])) + list(cross_tables[1]['yes']))+1000]))
fig.show()
```

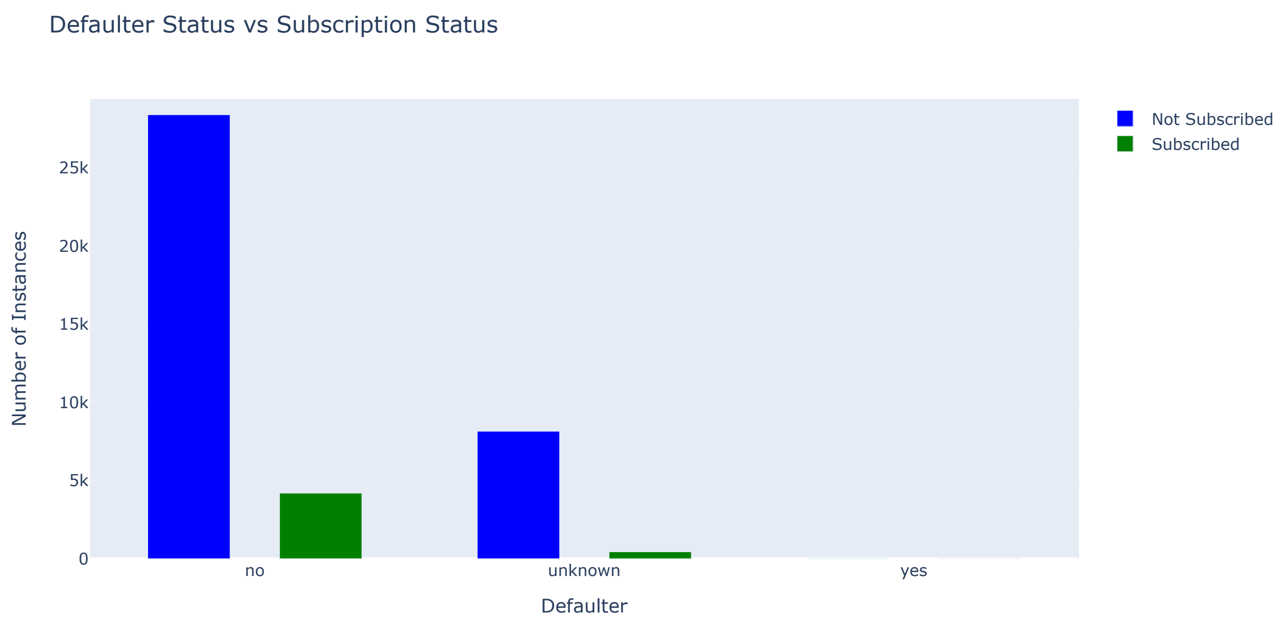


Contacts who are married are subscribed more compared to those that are single and divorced. The total number of those unsubscribed far exceeds those that are subscribed.

3.7.2) Comparing Defaulter with Subscription Status

In [18]:

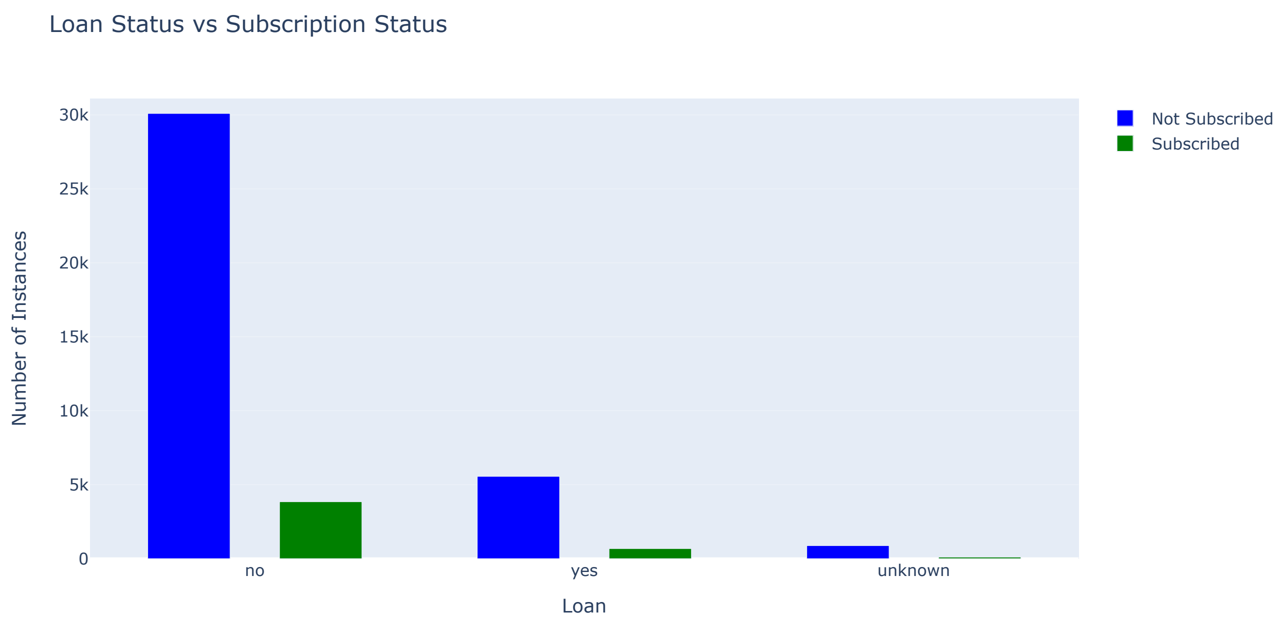
```
width = 0.25
fig = go.Figure()
fig.add_trace(go.Bar(x=list(unique_val_count['default'].keys()), y=cross_tables[3]['no'],
                     marker=dict(color='blue'), width=width, name='Not Subscribed'))
fig.add_trace(go.Bar(x=list(unique_val_count['default'].keys()), y=cross_tables[3]['yes'],
                     marker=dict(color='green'), width=width, name='Subscribed'))
fig.update_layout(title='Defaulter Status vs Subscription Status', xaxis_title='Defaulter', yaxis_title='Number of Instances',
                  yaxis=dict(range=[0, max((list(cross_tables[3]['no'])) + list(cross_tables[3]['yes']))+1000]))
fig.show()
```



From the above, we see The number of defaulters is almost none compared to those unknown or with value yes. Those who have not defaulted, have subscribed more compared to those who have defaulted or to those who have no information.

3.7.3) Comparing Loan status with Subscription Status

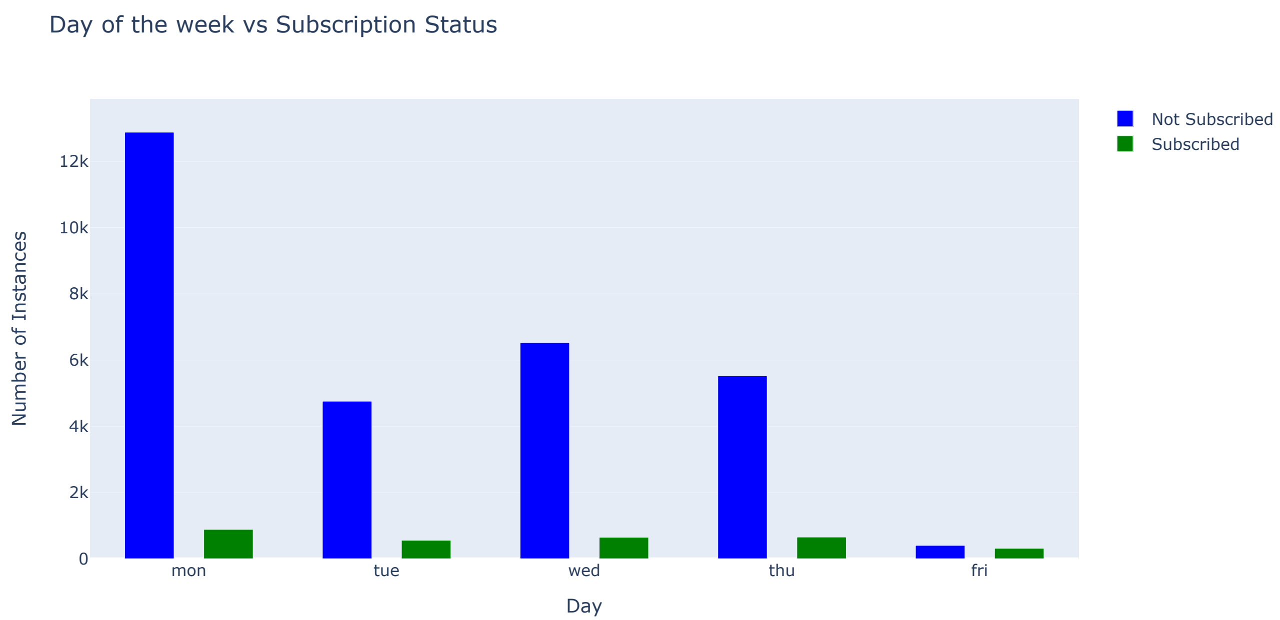
In [19]:
```
width = 0.25
fig = go.Figure()
fig.add_trace(go.Bar(x=list(unique_val_count['loan'].keys()), y=cross_tables[5]['no'],
                    marker=dict(color='blue'), width=width, name='Not Subscribed'))
fig.add_trace(go.Bar(x=list(unique_val_count['loan'].keys()), y=cross_tables[5]['yes'],
                    marker=dict(color='green'), width=width, name='Subscribed'))
fig.update_layout(title='Loan Status vs Subscription Status', xaxis_title='Loan', yaxis_title='Number of Instances',
                  yaxis=dict(range=[0, max((list(cross_tables[5]['no'])) + list(cross_tables[5]['yes']))+1000]))
fig.show()
```



From the above, we see that those without any loans are subscribed more compared to those who have loans.

3.7.4) Comparing Day of the week with Subscription Status

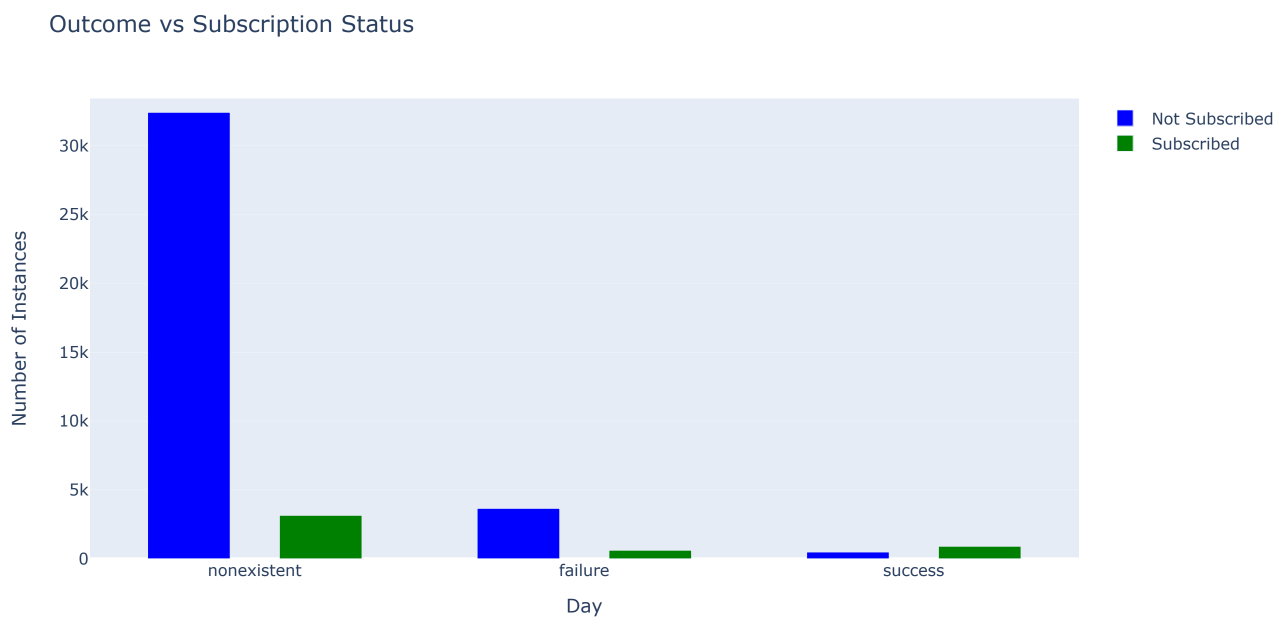
In [20]:
```
width = 0.25
fig = go.Figure()
fig.add_trace(go.Bar(x=list(unique_val_count['day_of_week'].keys()), y=cross_tables[7]['no'],
                     marker=dict(color='blue'), width=width, name='Not Subscribed'))
fig.add_trace(go.Bar(x=list(unique_val_count['day_of_week'].keys()), y=cross_tables[7]['yes'],
                     marker=dict(color='green'), width=width, name='Subscribed'))
fig.update_layout(title='Day of the week vs Subscription Status', xaxis_title='Day', yaxis_title='Number of Instances',
                  yaxis=dict(range=[0, max((list(cross_tables[7]['no'])) + list(cross_tables[7]['yes']))+1000]))
fig.show()
```



Monday is the day where most people subscribed and unsubscribed compared to the other days of the week.

3.7.5) Comparing Previous Campaign with Subscription Status

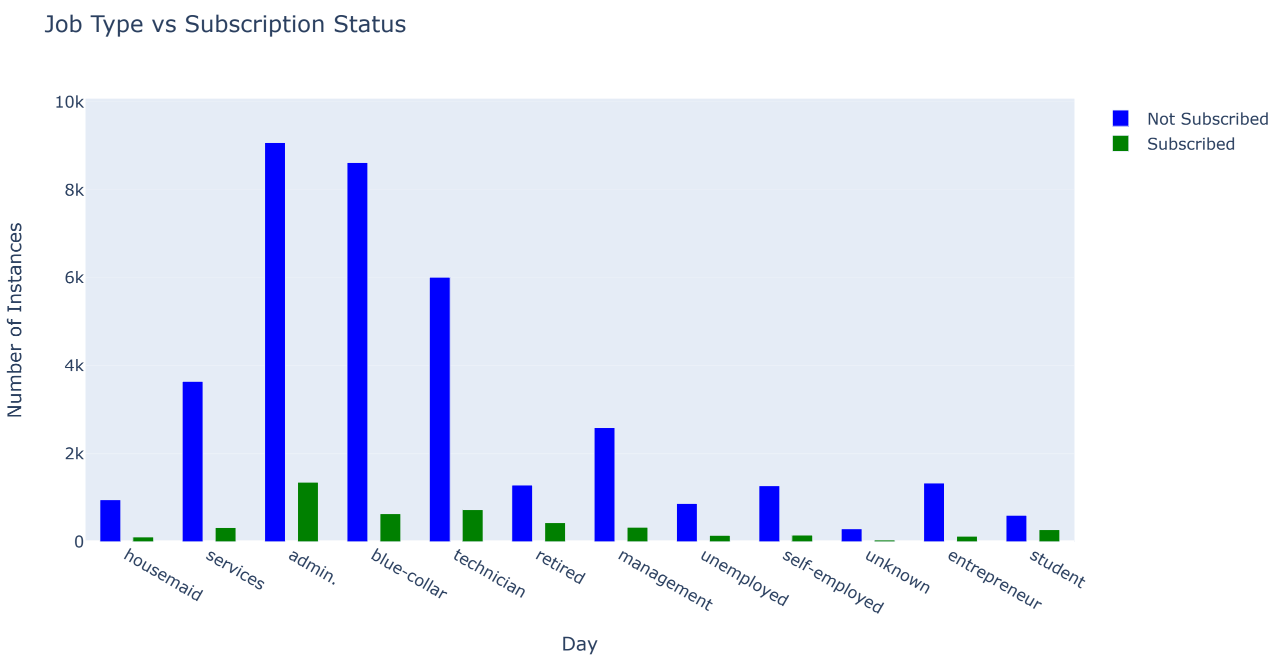
In [21]:
```
width = 0.25
fig = go.Figure()
fig.add_trace(go.Bar(x=list(unique_val_count['poutcome'].keys()), y=cross_tables[9]['no'],
                     marker=dict(color='blue'), width=width, name='Not Subscribed'))
fig.add_trace(go.Bar(x=list(unique_val_count['poutcome'].keys()), y=cross_tables[9]['yes'],
                     marker=dict(color='green'), width=width, name='Subscribed'))
fig.update_layout(title='Outcome vs Subscription Status', xaxis_title='Day', yaxis_title='Number of Instances',
                  yaxis=dict(range=[0, max((list(cross_tables[9]['no'])) + list(cross_tables[9]['yes']))+1000]))
fig.show()
```



From the above, we can see that those with non-existent outcomes have more subscriptions compared to those that are failure or success.

3.7.6) Comparing Job type with Subscription Status

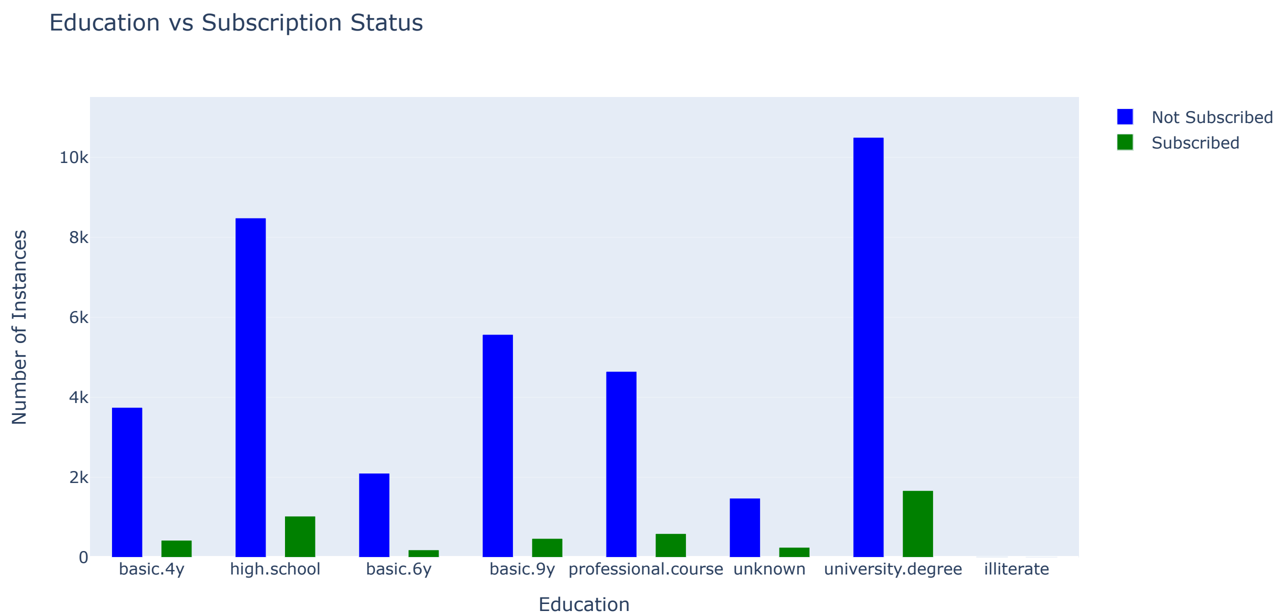
In [22]:
```python
width = 0.25
fig = go.Figure()
fig.add_trace(go.Bar(x=list(unique_val_count['job'].keys()), y=cross_tables[0]['no'],
                    marker=dict(color='blue'), width=width, name='Not Subscribed'))
fig.add_trace(go.Bar(x=list(unique_val_count['job'].keys()), y=cross_tables[0]['yes'],
                    marker=dict(color='green'), width=width, name='Subscribed'))
fig.update_layout(title='Job Type vs Subscription Status', xaxis_title='Day', yaxis_title='Number of Instances',
                  yaxis=dict(range=[0, max((list(cross_tables[0]['no'])) + list(cross_tables[0]['yes']))+1000]))
fig.show()
```



Those with admin, blue-collar and technician job types subscribe more compared to other job types.

3.7.7) Comparing Education with Subscription Status

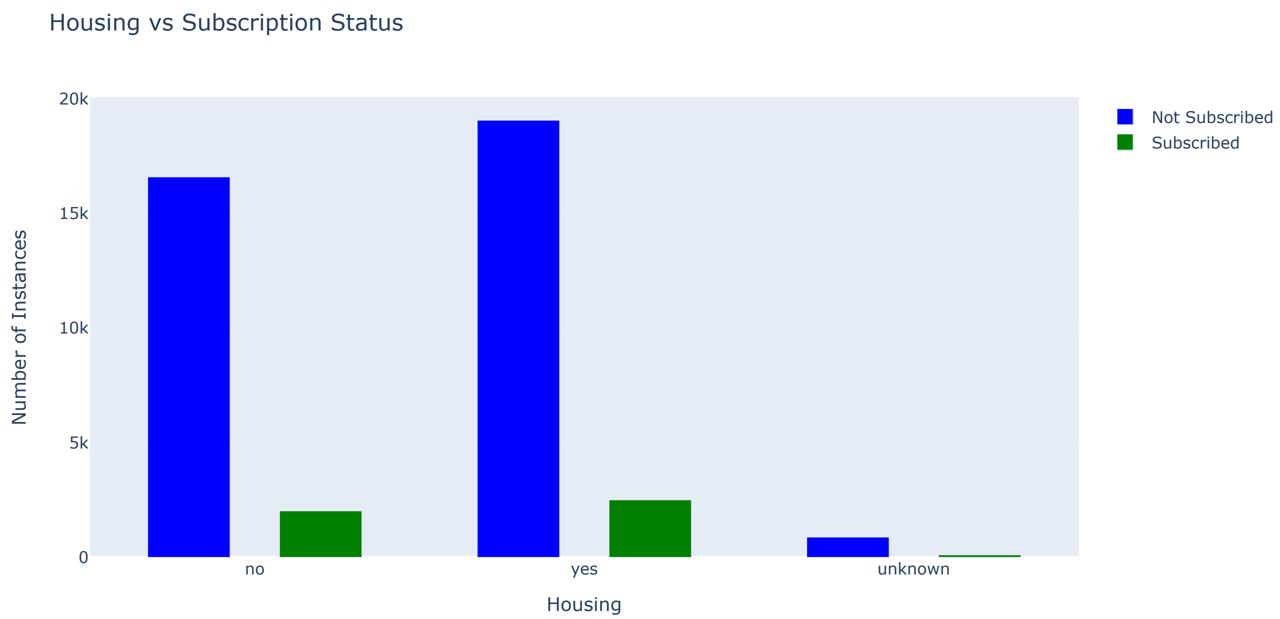
In [23]:
```
width = 0.25
fig = go.Figure()
fig.add_trace(go.Bar(x=list(unique_val_count['education'].keys()), y=cross_tables[2]['no'],marker=dict(color='blue'), width=width, name='Not Subscribed'))
fig.add_trace(go.Bar(x=list(unique_val_count['education'].keys()), y=cross_tables[2]['yes'],marker=dict(color='green'), width=width, name='Subscribed'))
fig.update_layout(title='Education vs Subscription Status', xaxis_title='Education', yaxis_title='Number of Instances',
                  yaxis=dict(range=[0, max((list(cross_tables[2]['no'])) + list(cross_tables[2]['yes']))+1000]))
fig.show()
```



From the above, we can see that contacts with high school and university degree subscribe more compared to other education levels.

3.7.8) Comparing Housing Status with Subscription Status

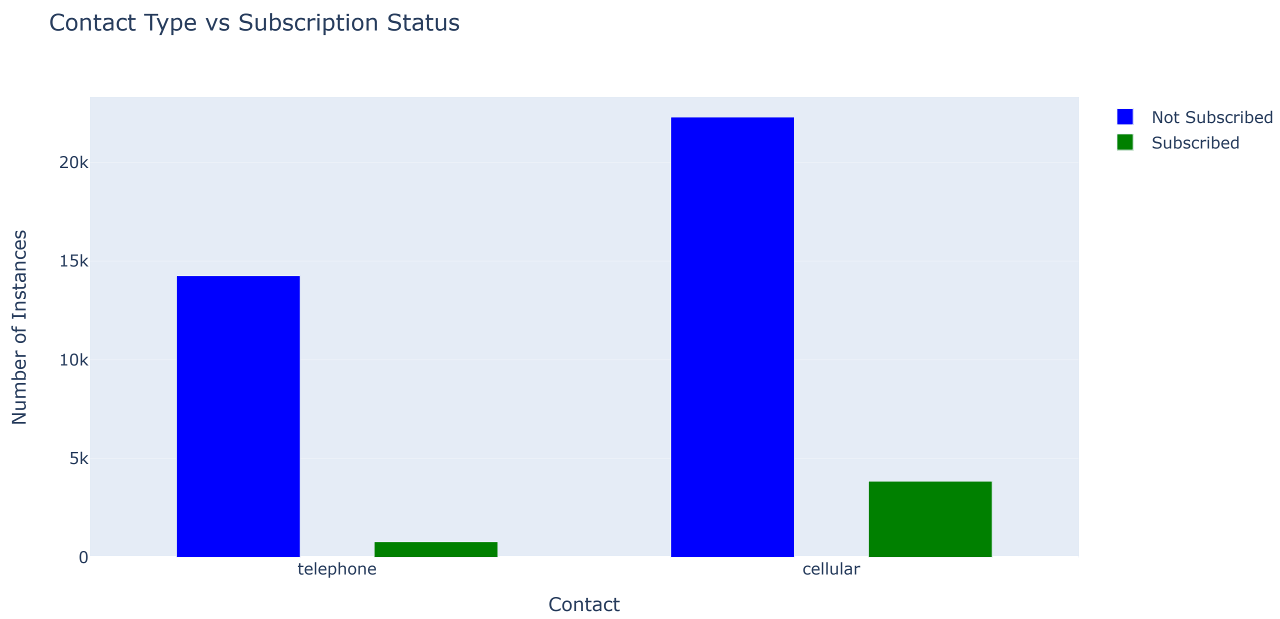
In [24]:
```python
width = 0.25
fig = go.Figure()
fig.add_trace(go.Bar(x=list(unique_val_count['housing'].keys()), y=cross_tables[4]['no'],marker=dict(color='blue'), width=width, name='Not Subscribed'))
fig.add_trace(go.Bar(x=list(unique_val_count['housing'].keys()), y=cross_tables[4]['yes'],marker=dict(color='green'), width=width, name='Subscribed'))
fig.update_layout(title='Housing vs Subscription Status', xaxis_title='Housing', yaxis_title='Number of Instances',
                  yaxis=dict(range=[0, max((list(cross_tables[4]['no'])) + list(cross_tables[4]['yes']))+1000]))
fig.show()
```



As you can see from the above, we can see that there is not much difference between those with housing and those without housing. However, those with housing seem to have subscribed more compared to those without housing.

3.7.9) Comparing Contact Type with Subscription Status

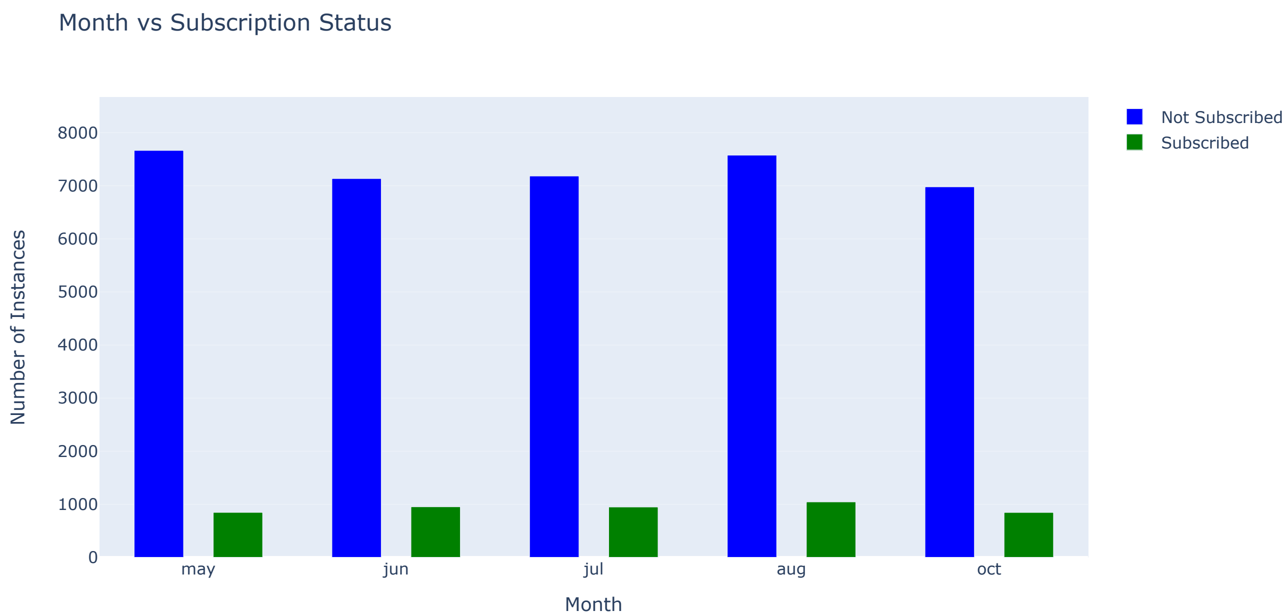
In [25]:
```
width = 0.25
fig = go.Figure()
fig.add_trace(go.Bar(x=list(unique_val_count['contact'].keys()), y=cross_tables[6]['no'],marker=dict(color='blue'), width=width, name='Not Subscribed'))
fig.add_trace(go.Bar(x=list(unique_val_count['contact'].keys()), y=cross_tables[6]['yes'],marker=dict(color='green'), width=width, name='Subscribed'))
fig.update_layout(title='Contact Type vs Subscription Status', xaxis_title='Contact', yaxis_title='Number of Instances',
                  yaxis=dict(range=[0, max((list(cross_tables[6]['no'])) + list(cross_tables[6]['yes']))+1000]))
fig.show()
```



From the above, we see that those with cellular contact type subscribe more compared to those with telephone contact type.

3.7.10) Comparing Month with Subscription Status

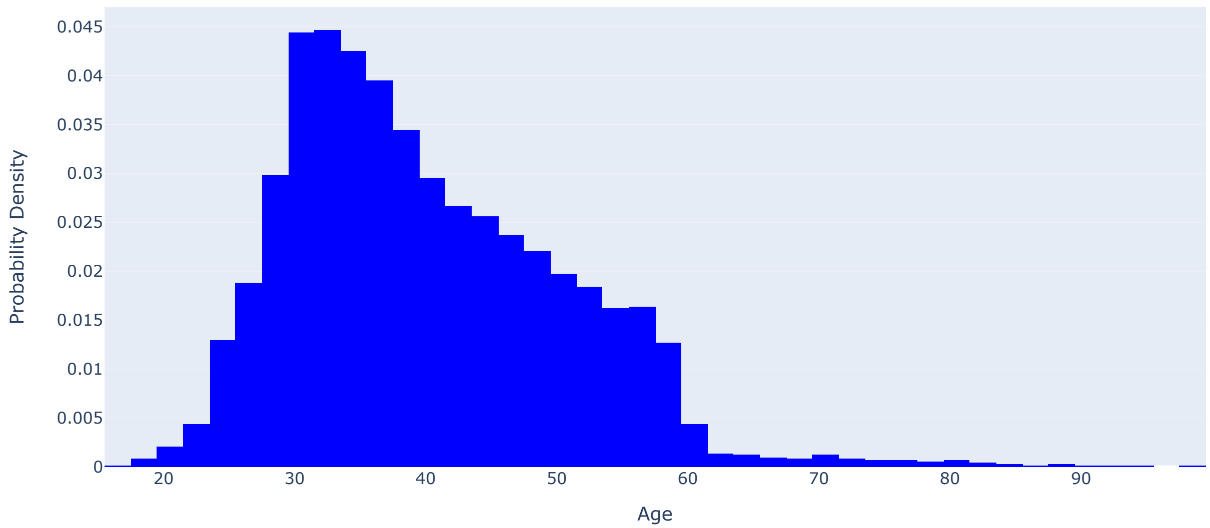
In [26]:
```
width = 0.25
fig = go.Figure()
fig.add_trace(go.Bar(x=list(unique_val_count['month'].keys()), y=cross_tables[8]['no'],marker=dict(color='blue'), width=width, name='Not Subscribed'))
fig.add_trace(go.Bar(x=list(unique_val_count['month'].keys()), y=cross_tables[8]['yes'],marker=dict(color='green'), width=width, name='Subscribed'))
fig.update_layout(title='Month vs Subscription Status', xaxis_title='Month', yaxis_title='Number of Instances',
                  yaxis=dict(range=[0, max((list(cross_tables[8]['no'])) + list(cross_tables[8]['yes']))+1000]))
fig.show()
```



From the above, we can see that August month had more number of subscriptions compared to other months.

3.7.11) Subscriptions by Age

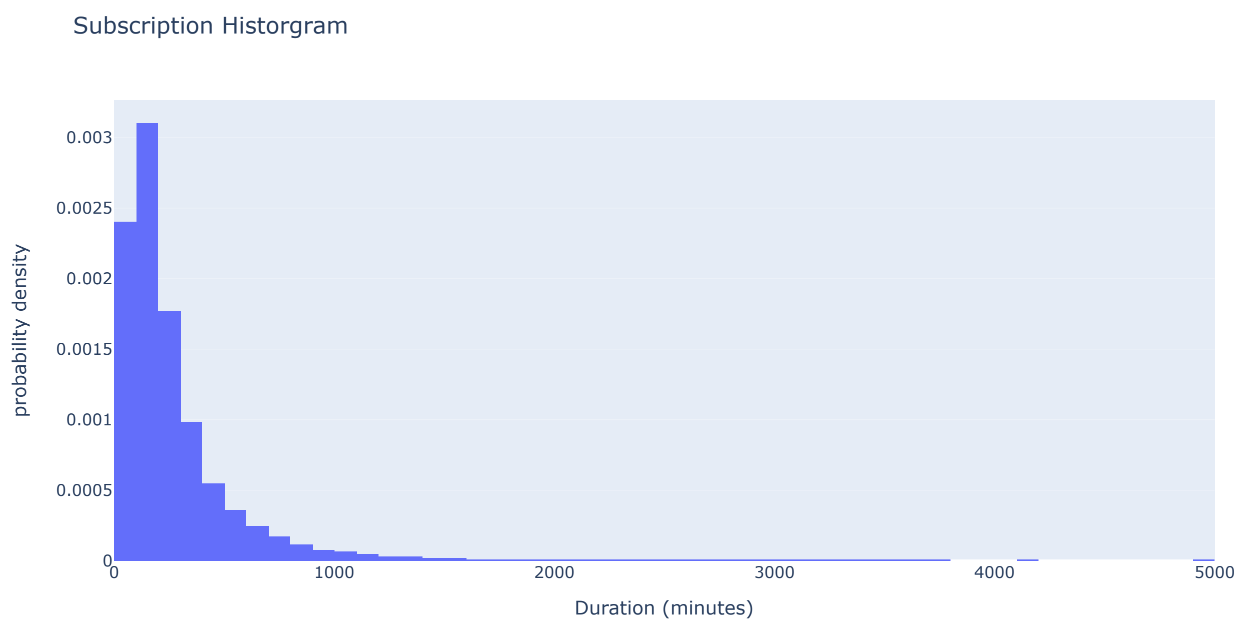
In [27]:
```python
fig = go.Figure()
fig.add_trace(go.Histogram(x=df['age'],
                           nbinsx=len(df['age'].unique()),
                           histnorm='probability density',
                           name='Age Distribution',
                           marker_color='blue'))

fig.update_layout(xaxis_title='Age',
                  yaxis_title='Probability Density')
```



From the above, we can see that majority of contacts are <= 60 years. Among those with age <= 60, the younger the clients are most likely to subscribe.

3.7.12) Subscriptions by Duration

In [86]:
```
px.histogram(df, x='duration', nbins=50, title='Subscription Historgram',
             labels={'duration':'Duration (minutes)'},
             histnorm='probability density',
             )
```

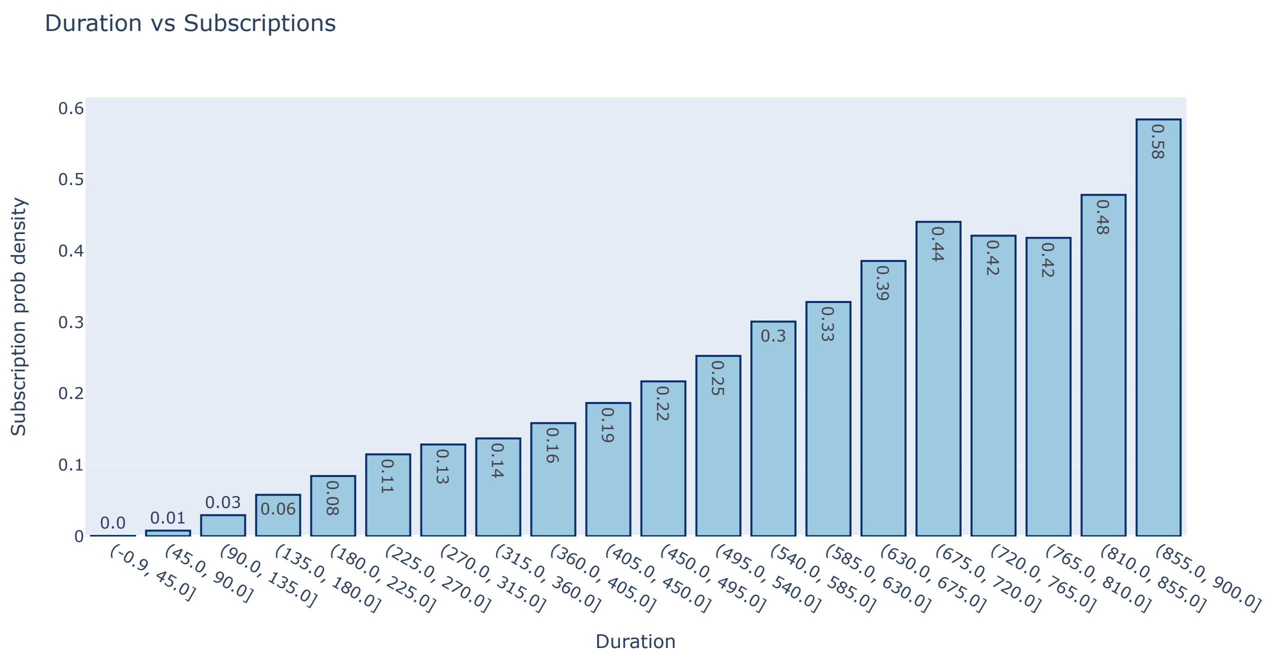


As we can see from the above plot, the graph contains many outliers. We will try to zoom into those with less than 1200.

In [29]:
```
df_duration_ranged = df[df['duration'] /60 <= 15]
```

In [30]:

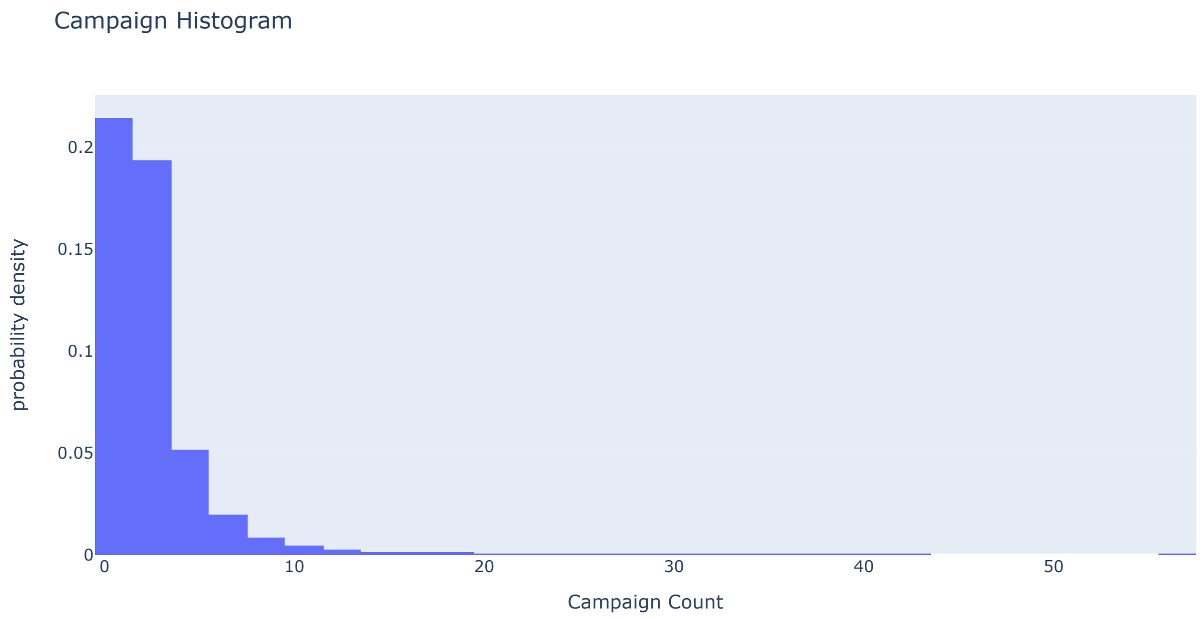
```
data = [go.Bar(
    x=df_duration_ranged.groupby(pd.cut(df_duration_ranged['duration'], bins=20)).mean().index.astype(str),
    y=df_duration_ranged.groupby(pd.cut(df_duration_ranged['duration'], bins=20)).mean()['y'],
    text=df_duration_ranged.groupby(pd.cut(df_duration_ranged['duration'], bins=20)).mean()['y'].round(2).astype(str),
    textposition='auto',
    marker=dict(color='rgb(158,202,225)', line=dict(color='rgb(8,48,107)',width=1.5))
)]

layout = go.Layout(
    title='Duration vs Subscriptions',
    xaxis=dict(title='Duration'),
    yaxis=dict(title='Subscription prob density')
)

fig = go.Figure(data=data, layout=layout)
fig.show()
```



From the above, Based on campaigns, clients being contacted more are less likely to subscribe.

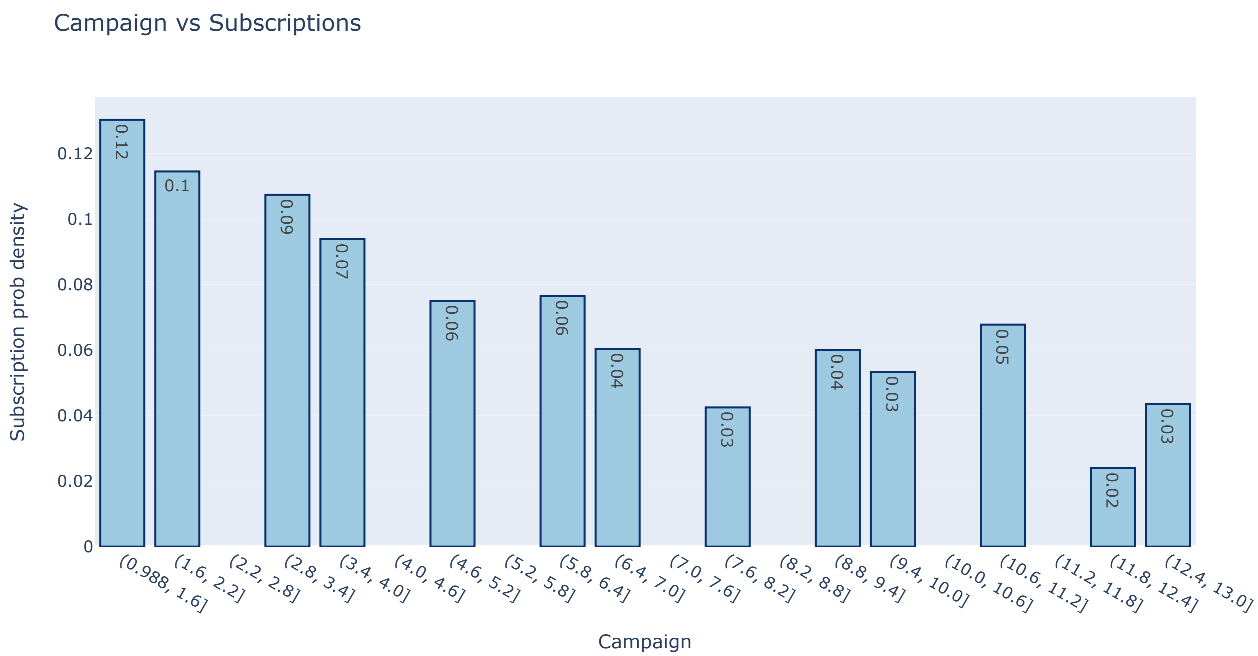
3.7.13) Subscriptions by Campaign

In [31]:
```
px.histogram(df, x='campaign', nbins=50, title='Campaign Histogram',
             labels={'campaign':'Campaign Count'},
             histnorm='probability density',
            )
```



As 'campaign' > 13 don't have enough samples, we just take those <= 13 for deep diving

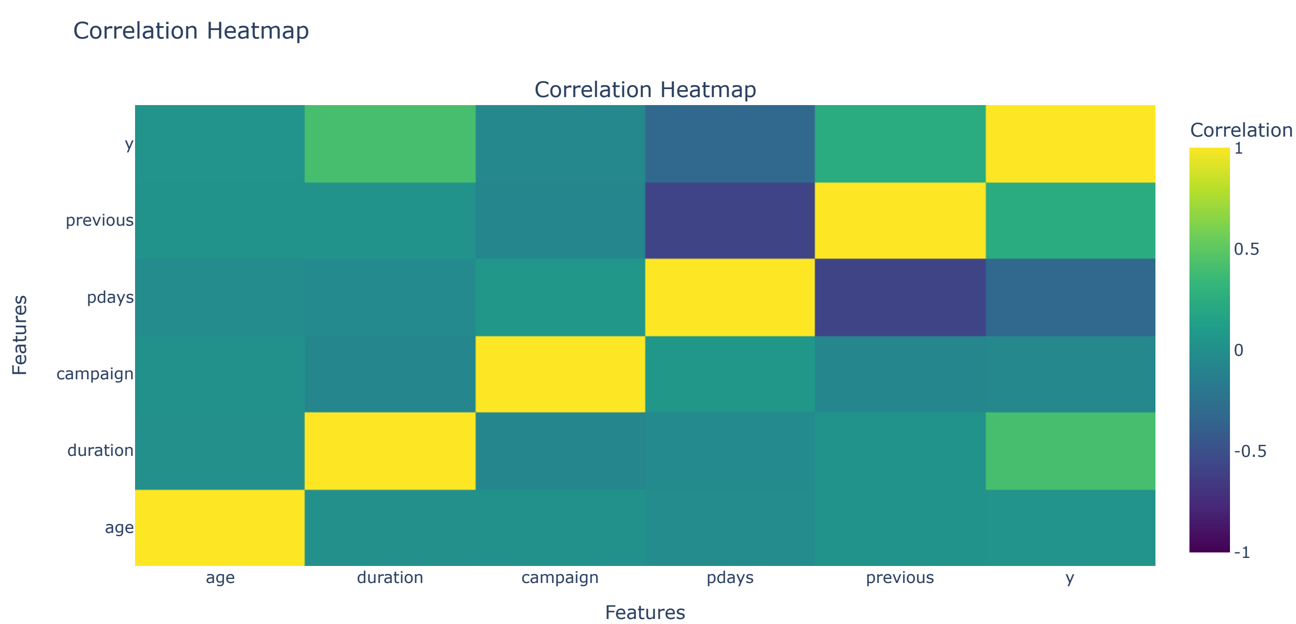
In [32]:
```python
df_campaign = df[df['campaign'] <= 13]
data = [go.Bar(
    x=df_campaign.groupby(pd.cut(df_campaign['campaign'], bins=20)).mean().index.astype(str),
    y=df_campaign.groupby(pd.cut(df_campaign['campaign'], bins=20)).mean()['y'],
    text=df_duration_ranged.groupby(pd.cut(df_campaign['campaign'], bins=20)).mean()['y'].round(2).astype(str),
    textposition='auto',
    marker=dict(color='rgb(158,202,225)', line=dict(color='rgb(8,48,107)',width=1.5))
)]

layout = go.Layout(
    title='Campaign vs Subscriptions',
    xaxis=dict(title='Campaign'),
    yaxis=dict(title='Subscription prob density')
)

fig = go.Figure(data=data, layout=layout)
fig.show()
```



From the above, we can see that the clients being contacted more are less likely to subscribe.

3.7.14) Correlation

In [33]:
```python
# Create a subplot with 1 row and 1 column
fig = sp.make_subplots(rows=1, cols=1, specs=[[{}]],
                      subplot_titles=('Correlation Heatmap',))

# Compute the correlation matrix
corr = df.dropna().corr()
mask = np.triu(df.corr())

# Add heatmap trace
fig.add_trace(go.Heatmap(z=corr, x=corr.columns, y=corr.columns,
                         colorscale='Viridis', showscale=True,
                         colorbar=dict(title='Correlation', titleside='top', tickmode='array',
                                       tickvals=[-1, -0.5, 0, 0.5, 1], ticktext=['-1', '-0.5', '0', '0.5', '1']),
                         zmin=-1, zmax=1,
                         hoverongaps=False
                         ))

# Update layout
fig.update_layout(title='Correlation Heatmap',
                  xaxis=dict(title='Features'),
                  yaxis=dict(title='Features'))

fig.show()
```



From the above, we see that pdays & previous are correlated, while the rest are not considered correlated with each other.

Problem 4: Understanding the Task

After examining the description and data, your goal now is to clearly state the *Business Objective* of the task. State the objective below.

In [34]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 16 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   age          41188 non-null  int64 
 1   job          41188 non-null  object
 2   marital      41188 non-null  object
 3   education    41188 non-null  object
 4   default      41188 non-null  object
 5   housing      41188 non-null  object
 6   loan         41188 non-null  object
 7   contact      41188 non-null  object
 8   month        41188 non-null  object
 9   day_of_week  41188 non-null  object
 10  duration     41188 non-null  int64 
 11  campaign     41188 non-null  int64 
 12  pdays        41188 non-null  int64 
 13  previous     41188 non-null  int64 
 14  poutcome     41188 non-null  object
 15  y            41188 non-null  int64 
dtypes: int64(6), object(10)
memory usage: 5.0+ MB
```

Business Objective

The goal was to increase efficiency of directed campaigns for long-term deposit subscriptions by reducing the number of contacts to do.For this, we need to develop a predictive model using real-world data from a Portuguese marketing campaign for bank deposit subscriptions to increase campaign efficiency by identifying key factors that influence success and optimize resource allocation and target customer selection.

Problem 5: Engineering Features

Now that you understand your business objective, we will build a basic model to get started. Before we can do this, we must work to encode the data. Using just the bank information features (columns 1 - 7), prepare the features and target column for modeling with appropriate encoding and transformations.

5.1) Encoding

In [35]:
```
df_engg = df.copy()
```

In [37]:
```python
df_engg
```

Out[37]:

	age	job	marital	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome	y
0	56	housemaid	married	basic.4y	no	no	no	telephone	may	mon	261	1	999	0	nonexistent	0
1	57	services	married	high.school	unknown	no	no	telephone	may	mon	149	1	999	0	nonexistent	0
2	37	services	married	high.school	no	yes	no	telephone	may	mon	226	1	999	0	nonexistent	0
3	40	admin.	married	basic.6y	no	no	no	telephone	may	mon	151	1	999	0	nonexistent	0
4	56	services	married	high.school	no	no	yes	telephone	may	mon	307	1	999	0	nonexistent	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
41183	73	retired	married	professional.course	no	yes	no	cellular	nov	fri	334	1	999	0	nonexistent	1
41184	46	blue-collar	married	professional.course	no	no	no	cellular	nov	fri	383	1	999	0	nonexistent	0
41185	56	retired	married	university.degree	no	yes	no	cellular	nov	fri	189	2	999	0	nonexistent	0
41186	44	technician	married	professional.course	no	no	no	cellular	nov	fri	442	1	999	0	nonexistent	1
41187	74	retired	married	professional.course	no	yes	no	cellular	nov	fri	239	3	999	1	failure	0

41188 rows × 16 columns

In [38]:
```python
cols_dumm = ['job', 'marital']
df_engg = pd.get_dummies(df_engg, columns=cols_dumm)
```

In [39]:
```python
# Remove the columns corresponding to unknown value
cols_onehot_unknown = [col for col in df_engg.columns if 'unknown' in col]
df_engg = df_engg.drop(cols_onehot_unknown, axis=1)
```

In [87]:
```python
# Check current data set
pd.set_option('display.max_columns', None)
df_engg.head(10)
```

Out[87]:

	age	education	default	housing	loan	contact	month	day_of_week	duration	campaign	pdays	previous	poutcome	y	job_admin.	job_blue-collar	job_entrepreneur	job_housemaid	job_management	job_retired	job_self-employed	job_services
0	56	1.0	1.0	1.0	1.0	1	5	0	261	1	999	0	2	0	0	0	0	1	0	0	0	0
1	57	4.0	1.0	1.0	1.0	1	5	0	149	1	999	0	2	0	0	0	0	0	0	0	0	1
2	37	4.0	1.0	1.0	1.0	1	5	0	226	1	999	0	2	0	0	0	0	0	0	0	0	1
3	40	2.0	1.0	1.0	1.0	1	5	0	151	1	999	0	2	0	1	0	0	0	0	0	0	0
4	56	4.0	1.0	1.0	1.0	1	5	0	307	1	999	0	2	0	0	0	0	0	0	0	0	1
5	45	3.0	1.0	1.0	1.0	1	5	0	198	1	999	0	2	0	0	0	0	0	0	0	0	1
6	59	6.0	1.0	1.0	1.0	1	5	0	139	1	999	0	2	0	1	0	0	0	0	0	0	0
7	41	2.5	1.0	1.0	1.0	1	5	0	217	1	999	0	2	0	0	1	0	0	0	0	0	0
8	24	6.0	1.0	1.0	1.0	1	5	0	380	1	999	0	2	0	0	0	0	0	0	0	0	0
9	25	4.0	1.0	1.0	1.0	1	5	0	50	1	999	0	2	0	0	0	0	0	0	0	0	1

5.2) Preprocessing

In [41]:
```
mapping_month = dict((month.lower(), number) for number, month in enumerate(month_abbr))
df_engg['month'] = df_engg['month'].map(mapping_month)
```

In [42]:
```
edu_map = {'unknown':0, 'basic.4y':1, 'basic.6y':2, 'basic.9y':3, 'high.school': 4, 'illiterate':5,'professional.course':6, 'university.degree':7}
df_engg['education'] = df_engg.education.map(edu_map).astype('int')
```

In [43]:
```
boolean_map = {'unknown':0, 'no':1, 'yes': 1}
df_engg['default'] = df_engg.default.map(boolean_map).astype('int')
df_engg['housing'] = df_engg.housing.map(boolean_map).astype('int')
df_engg['loan'] = df_engg.loan.map(boolean_map).astype('int')
```

In [44]:
```
day_map = {'mon': 0, 'tue': 1, 'wed':2, 'thu':3, 'fri':4}
df_engg['day_of_week'] = df_engg.day_of_week.map(day_map).astype('int')
```

In [45]:
```
contact_map = {'cellular': 0, 'telephone': 1}
df_engg['contact'] = df_engg.contact.map(contact_map).astype(int)
```

In [46]:
```
poutcome_map = {'failure': 0, 'success': 1, 'nonexistent':2}
df_engg['poutcome'] = df_engg.poutcome.map(poutcome_map).astype(int)
```

Problem 6: Train/Test Split

With your data prepared, split it into a train and test set.

6.1) Imputing Education using KNN

In [47]:
```
# Train KNN imputer using data with known education
knn_imputer = KNNImputer(n_neighbors=2,missing_values=0)

# fit the imputer on the dataset
knn_imputer.fit(df_engg[['education','default', 'housing','loan']])

# use the imputer to fill in missing values
imputed_df = knn_imputer.transform(df_engg[['education','default', 'housing','loan']])
```

In [48]:
```
# calculate the MSE score
mse = mean_squared_error(df_engg[['education','default', 'housing','loan']], imputed_df)
print("MSE score:", mse)
```

```
MSE score: 0.13149990522961696
```

In [49]:
```
# Transform the training set
imputed_data = knn_imputer.transform(df_engg[['education','default', 'housing','loan']])
```

In [50]:
```
df_engg[['education','default', 'housing','loan']] = imputed_data
```

In [51]:
```
df_encoded = df_engg.drop(['contact','month','day_of_week','duration','campaign','pdays','previous','poutcome'], axis=1)
```

In [52]:
```
X = df_encoded.drop('y', axis = 1)
y = df_encoded['y']
```

In [53]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,random_state = 52)
```

In [54]:
```
print(f"Train size : {len(X_train)}\tValidation size : {len(X_test)}")
```

```
Train size : 32950      Validation size : 8238
```

6.2) Standardization

In [55]:
```
scaler = MinMaxScaler()
# Standarding (for algorithms that can apply balanced class weights)
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

6.3) Oversampling

In [56]:
```
sm = SMOTE(random_state=52)
# Only oversampling (for decision-tree-based algorithms and cannot apply balanced class weights)
X_train_sm, y_train_sm = sm.fit_resample(X_train, y_train)
# Stardardized + Oversampling (for algorithms cannot apply balanced class weights)
X_train_scaled_sm, y_train_scaled_sm = sm.fit_resample(X_train_scaled, y_train)
```

Problem 7: A Baseline Model

Before we build our first model, we want to establish a baseline. What is the baseline performance that our classifier should aim to beat?

Before we begin lets define some helper functions that we will use to output the scores. We will be using this to determine the best model.

Helper Functions

In [57]:
```python
r_seed = 52
def GenerateOutput(model_name,y_train,y_train_pred,x_test,y_test, y_pred,model):
    # Accuracy - Precision - Recall - F1 Score - Kappa Metrics - Confusion Matrix
    print(classification_report( y_test, y_pred, digits=2) )
    #confusion matrix display
    lr_matrix = ConfusionMatrixDisplay.from_predictions(y_test,y_pred, display_labels=['yes', 'no'])

    # =========== Balanced Dataframe Metrics =============
    #train Accuracy
    lr_train_acc = accuracy_score(y_train,y_train_pred)
    # Accuracy
    lr_acc = accuracy_score( y_test, y_pred)
    print( 'Accuracy: {}'.format(lr_acc))


    # =========== Unbalanced Dataframe Metrics =============
    # Weighted F1-Score
    f1score = f1_score( y_test, y_pred, average='weighted' )
    print( 'Weighted F1-Score: {}'.format( f1score ) )

    # Balanced Accuracy Score
    balanced_acc = balanced_accuracy_score( y_test, y_pred )
    print( 'Balanced Accuracy Score: {}'.format( balanced_acc))

    if(model_name == "Baseline model"):
        model = DummyClassifier(random_state=r_seed)
    start_time = time.time()
    model.fit(X_train, y_train)
    fit_time = time.time() - start_time

    y_pred_proba = model.predict_proba(x_test)[:, 1]
    # Calculate the AUC-ROC score
    auc = roc_auc_score(y_test, y_pred_proba)
    print("AUC-ROC:", auc)

    df_score = CalculateScores(model_name,lr_train_acc,lr_acc,f1score,balanced_acc,auc, fit_time)
    return df_score

def CalculateScores(model_name, train_accuracy,accuracy, f1_score, balanced_accuracy, roc_auc,fit_time):
    return pd.DataFrame( { 'Model Name': model_name,
                           'Train Time': fit_time,
                           'Train Accuracy': train_accuracy,
                           'Test accuracy': accuracy,
                           'f1_score': f1_score,
                           'balanced_accuracy': balanced_accuracy,
                           'roc_auc score': roc_auc }, index=[0] )

def CrossVal_model(modelName, x_train, y_train):
    #As discussed above, we will be using stratifiedKfold to deal with imbalanced data.
    fold = 5
    kfold = StratifiedKFold(n_splits=fold, shuffle=True,random_state=r_seed)

    trainacc_list = []
    accuracy_list = []
    balanced_acc_list = []
    weighted_f1_score_list = []
    auc_score_list = []
    iter = 1
    for train_index, test_index in kfold.split(x_train, y_train):
        X_train_f, X_test_f = x_train.iloc[train_index], x_train.iloc[test_index]
        y_train_f, y_test_f = y_train.iloc[train_index], y_train.iloc[test_index]

        if(modelName == "Logistic Regression"):
            #define a Logistic Regression model
            model = LogisticRegression(random_state=r_seed)
        if(modelName == "SVM"):
            model = svm.SVC(random_state=r_seed, probability=True)
        if(modelName == "DecisionTree"):
            model = DecisionTreeClassifier(random_state=r_seed)
        if(modelName == "KNN"):
            model = KNeighborsClassifier(random_state=r_seed)
```

```python
        #fit the model
        start_time = time.time()
        model.fit(X_train_f, y_train_f)
        fit_time = time.time() - start_time
        #prediction
        y_f_pred = model.predict(X_test_f)
        y_t_pred = model.predict(X_train_f)
        #Train Accuracy,
        train_acc = accuracy_score(y_train_f, y_t_pred)
        trainacc_list.append(train_acc)
        #Accuracy
        acc = accuracy_score(y_test_f, y_f_pred)
        accuracy_list.append(acc)
        # Balanced Accuracy
        balanced_acc = balanced_accuracy_score( y_test_f, y_f_pred )
        balanced_acc_list.append( balanced_acc )
        # Weighted F1-Score
        weighted_f1_score = f1_score( y_test_f, y_f_pred, average='weighted')
        weighted_f1_score_list.append( weighted_f1_score )

        #auc score
        y_pred_proba = model.predict_proba(X_test_f)[:, 1]
        # Calculate the AUC-ROC score
        auc = roc_auc_score(y_test_f, y_pred_proba)
        auc_score_list.append(auc)
        iter += 1

    print( 'Avg Balanced Accuracy: {}'.format( np.mean( balanced_acc_list ) ) )
    print( 'Avg Weighted F1-Score: {}'.format( np.mean( weighted_f1_score_list ) ) )
    print( 'Avg AUC-ROC Score: {}'.format( np.mean( auc_score_list ) ) )

    modelName = modelName + " - Cross Validation"

    return CalculateScores(modelName,np.mean(trainacc_list),np.mean(accuracy_list),
                        np.mean( balanced_acc_list ),np.mean( weighted_f1_score_list),np.mean( auc_score_list), fit_time)
```

Baseline Model

In [58]:

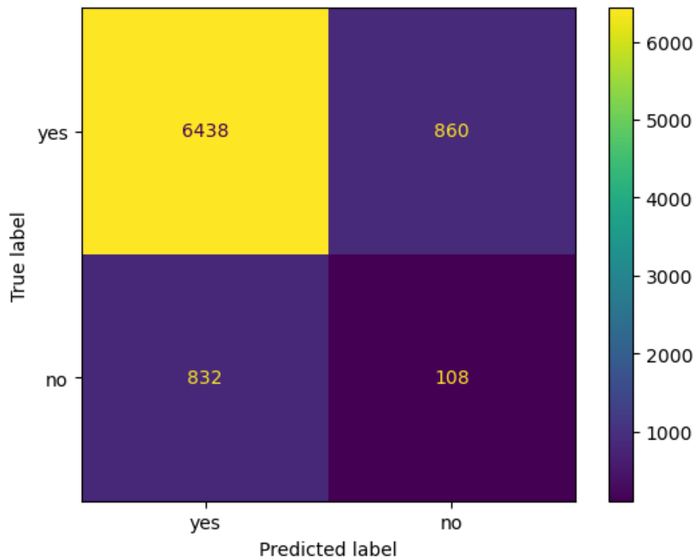
```python
train_list = y_train.drop_duplicates().sort_values().tolist()

target_list = y_test.drop_duplicates().sort_values().tolist()
target_weights = df_engg['y'].value_counts( normalize=True ).sort_index().tolist()
# prediction
y_train_pred = random.choices(train_list, k=X_train_scaled.shape[0],
                              weights=target_weights )
y_pred= random.choices(target_list, k=X_test_scaled.shape[0],
                              weights=target_weights )
```

In [59]:
```
df_score_base = GenerateOutput("Baseline model",y_train,y_train_pred,X_test_scaled,y_test, y_pred, DummyClassifier())
df_score_base
```

```
              precision    recall  f1-score   support

           0       0.89      0.88      0.88      7298
           1       0.11      0.11      0.11       940

    accuracy                           0.79      8238
   macro avg       0.50      0.50      0.50      8238
weighted avg       0.80      0.79      0.80      8238

Accuracy: 0.7946103423160962
Weighted F1-Score: 0.7959200127076458
Balanced Accuracy Score: 0.4985265563867688
AUC-ROC: 0.5
```

Out[59]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	Baseline model	0.000641	0.802428	0.79461	0.79592	0.498527	0.5



Problem 8: A Simple Model

Use Logistic Regression to build a basic model on your data.

Logistic Regression is a statistical method that we use to fit a regression model when the response variable is binary. It is a type of generalized linear model (GLM) that uses a logistic function to model a binary dependent variable.

In logistic regression, the goal is to find the best fitting model to describe the relationship between the independent variables (predictors) and the dependent binary variable.Logistic Regression is a simple yet powerful method for modeling binary data and is widely used in various fields, including medical research, economics, and social sciences. It has several advantages such as it's simple to implement, efficient to train and easy to interpret. However, it also has some limitations, such as it's assumption of linearity between the independent variables and the log-odds of the response, and it's inability to model complex non-linear relationships.

In [60]:
```
#model definition
mlm_lr = LogisticRegression(random_state=r_seed)
#fit the model
mlm_lr.fit(X_train_scaled, y_train)
```

Out[60]: LogisticRegression(random_state=52)

Problem 9: Score the Model

What is the accuracy of your model?

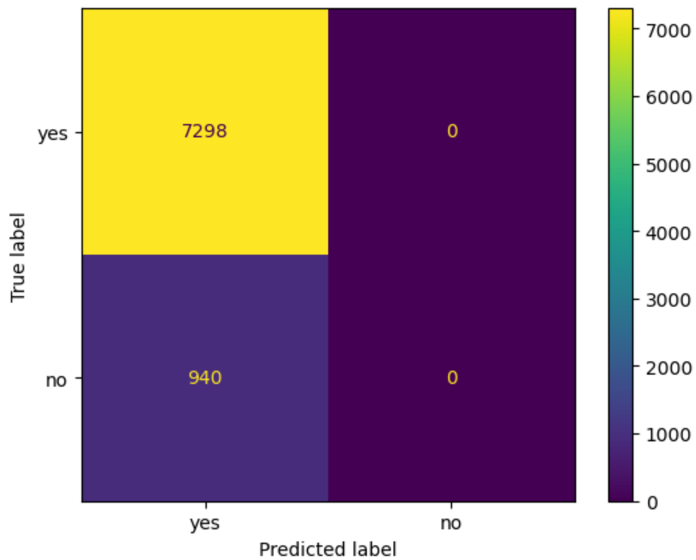
In [61]:
```
y_pred = mlm_lr.predict(X_test_scaled)
y_train_pred = mlm_lr.predict(X_train_scaled)
```

In [62]:
```
df_score = GenerateOutput("Logistic Regression",y_train,y_train_pred,X_test_scaled,y_test, y_pred, mlm_lr)
df_score
```

```
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      7298
           1       0.00      0.00      0.00       940

    accuracy                           0.89      8238
   macro avg       0.44      0.50      0.47      8238
weighted avg       0.78      0.89      0.83      8238

Accuracy: 0.8858946346200534
Weighted F1-Score: 0.8322939036376351
Balanced Accuracy Score: 0.5
AUC-ROC: 0.6173354110423724
```

Out[62]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	Logistic Regression	0.263456	0.887709	0.885895	0.832294	0.5	0.617335



Problem 10: Model Comparisons

Now, we aim to compare the performance of the Logistic Regression model to our KNN algorithm, Decision Tree, and SVM models. Using the default settings for each of the models, fit and score each. Also, be sure to compare the fit time of each of the models. Present your findings in a `DataFrame` similar to that below:

Model	Train Time	Train Accuracy	Test Accuracy
		.	.

10.1) KNN

K-Nearest Neighbors (KNN) is a simple and popular machine learning algorithm that can be used for both classification and regression.

In the case of KNN classification, the algorithm works by finding the K nearest neighbors of a given data point and using their class labels to predict the class label of the data point. For example, if the K nearest neighbors of a data point are all labeled as "positive," the data point is predicted to be positive as well.

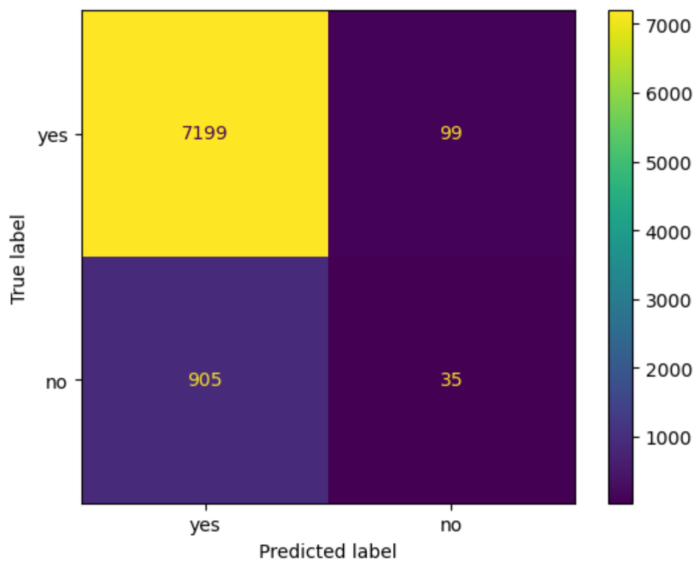
On the other hand, KNN regression works by finding the K nearest neighbors of a given data point and using their values to predict the value of the data point. For example, if the K nearest neighbors of a data point have values of 1, 2, and 3, the predicted value for the data point might be 2 (the average of the values of the nearest neighbors).

In [63]:
```
# model definition
model_knn = KNeighborsClassifier(n_neighbors=2)
# train model
model_knn.fit(X_train_scaled,y_train)
y_pred = model_knn.predict(X_test_scaled)
y_train_pred = model_knn.predict(X_train_scaled)
df_score1 = GenerateOutput('KNN',y_train,y_train_pred,X_test_scaled,y_test, y_pred, model_knn)
df_score1
```

```
              precision    recall  f1-score   support

           0       0.89      0.99      0.93      7298
           1       0.26      0.04      0.07       940

    accuracy                           0.88      8238
   macro avg       0.57      0.51      0.50      8238
weighted avg       0.82      0.88      0.84      8238

Accuracy: 0.8781257586792911
Weighted F1-Score: 0.8355834412503123
Balanced Accuracy Score: 0.5118343410902433
AUC-ROC: 0.5
```

Out[63]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	KNN	0.002873	0.889014	0.878126	0.835583	0.511834	0.5



10.2) Support Vector Machines

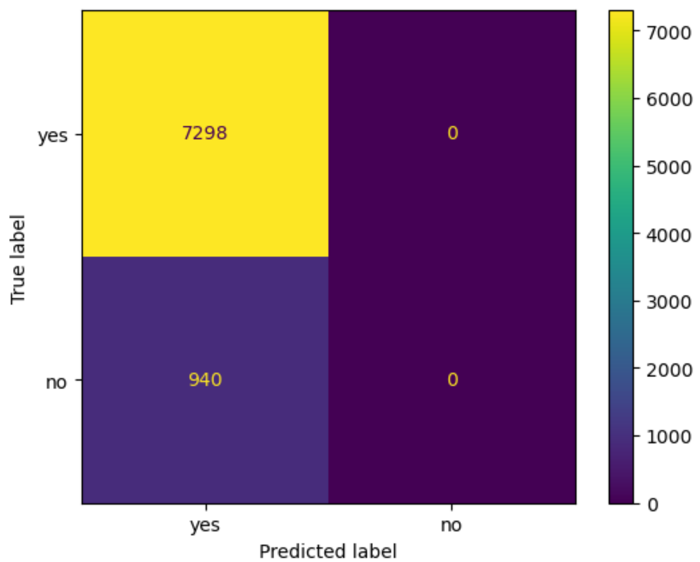
The main idea behind SVMs is to find the line (or hyperplane) that maximally separates the data points of different classes. This line is called the "maximum margin hyperplane." The points that lie closest to this line are called "support vectors." Once the support vectors are found, the algorithm uses them to construct the maximum margin hyperplane. However, SVMs can be sensitive to the choice of hyperparameters and can be computationally expensive to train, especially for large datasets. They also do not work well with noisy or highly imbalanced data, and they may not be suitable for tasks that require probability estimates.

In [64]:
```
# model definition
model_svm = svm.SVC(random_state=r_seed,probability=True)
# model training
model_svm.fit( X_train_scaled, y_train )
y_pred = model_svm.predict(X_test_scaled)
y_train_pred = model_svm.predict(X_train_scaled)
df_score2 = GenerateOutput('SVM',y_train,y_train_pred,X_test_scaled,y_test, y_pred, model_svm)
df_score2
```

```
              precision    recall  f1-score   support

           0       0.89      1.00      0.94      7298
           1       0.00      0.00      0.00       940

    accuracy                           0.89      8238
   macro avg       0.44      0.50      0.47      8238
weighted avg       0.78      0.89      0.83      8238

Accuracy: 0.8858946346200534
Weighted F1-Score: 0.8322939036376351
Balanced Accuracy Score: 0.5
AUC-ROC: 0.470892928986665
```

Out[64]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	SVM	113.990209	0.887709	0.885895	0.832294	0.5	0.470893



10.3) Decision Trees

A decision tree works by recursively partitioning the input data into subsets, called branches, based on the values of the input features. Each internal node in the tree represents a feature, and each branch represents a possible value of that feature. The leaves of the tree represent the predicted class or output value.

The process of building a decision tree begins with selecting the feature that best splits the data into subsets that are as pure as possible. This feature is chosen by evaluating a metric such as information gain, Gini index or gain ratio. Once a feature is selected, the data is split according to the values of that feature, and the process is repeated for each subset of the data. This continues until the tree reaches a stopping criterion, such as a maximum depth or a minimum number of samples per leaf.

In [65]:
```python
# model definition
model_clf = DecisionTreeClassifier()
# model training
model_clf.fit( X_train_scaled, y_train )
```

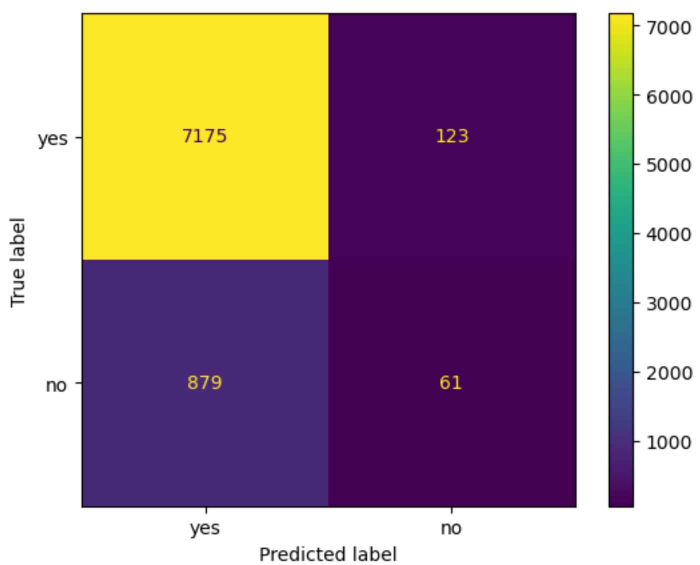
Out[65]:
```
DecisionTreeClassifier()
```

In [66]:
```python
#prediction
y_pred = model_clf.predict(X_test_scaled)
y_train_pred = model_clf.predict(X_train_scaled)
df_score3 = GenerateOutput('SVM',y_train, y_train_pred, X_test_scaled, y_test, y_pred, model_clf)
df_score3
```

```
              precision    recall  f1-score   support

           0       0.89      0.98      0.93      7298
           1       0.33      0.06      0.11       940

    accuracy                           0.88      8238
   macro avg       0.61      0.52      0.52      8238
weighted avg       0.83      0.88      0.84      8238

Accuracy: 0.8783685360524399
Weighted F1-Score: 0.8404588387000516
Balanced Accuracy Score: 0.5240198422185034
AUC-ROC: 0.545889284735544
```

Out[66]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	SVM	0.040731	0.898877	0.878369	0.840459	0.52402	0.545889



Problem 11: Improving the Model

Now that we have some basic models on the board, we want to try to improve these. Below, we list a few things to explore in this pursuit.

- More feature engineering and exploration. For example, should we keep the gender feature? Why or why not?
- Hyperparameter tuning and grid search. All of our models have additional hyperparameters to tune and explore. For example the number of neighbors in KNN or the maximum depth of a Decision Tree.
- Adjust your performance metric

11.1) Feature Importance

Permutation importance is a technique used to determine the importance of individual features in a machine learning model. It works by randomly shuffling the values of a single feature and evaluating the effect on the model's performance. The idea is that if a feature is important, then shuffling its values should result in a significant decrease in model performance.

In [67]:
```
#Let us perform permutation importance in order to determine the features.
X = df_engg.drop('y', axis = 1)
y = df_engg['y']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,random_state = 52)

print(f"Train size : {len(X_train)}\tValidation size : {len(X_test)}")

# Create a list of feature names
feature_names = ['Feature ' + str(i) for i in range(X.shape[1])]

# train a model
# model definition
model = DecisionTreeClassifier()
# model training
model.fit( X_train, y_train )

# calculate the permutation importance of each feature
result = permutation_importance(model, X_test, y_test, n_repeats=10, random_state=0)

# extract the importance scores
importance_scores = result.importances_mean

# create a dictionary mapping feature names to importance scores
feature_importance = dict(zip(X_test.columns, importance_scores))

# sort the features by importance
sorted_features = sorted(feature_importance.items(), key=lambda x: x[1], reverse=True)
```

```
Train size : 32950      Validation size : 8238
```

In [68]:
```
sorted_features
```

Out[68]:
```
[('duration', 0.04304442825928623),
 ('month', 0.04294731731002669),
 ('contact', 0.021376547705753823),
 ('pdays', 0.014955086185967447),
 ('age', 0.006360767176499161),
 ('poutcome', 0.005948045642146127),
 ('previous', 0.004236465161446967),
 ('education', 0.0035809662539451393),
 ('job_student', 0.0011774702597717624),
 ('job_blue-collar', 0.0011410536537994399),
 ('day_of_week', 0.0007161932507890323),
 ('job_housemaid', 0.0006676377761592467),
 ('job_unemployed', 0.0004976936149550748),
 ('marital_married', 0.0003277494537509029),
 ('job_retired', 0.00027919397912113953),
 ('campaign', 0.00023063850449138722),
 ('job_services', 0.00010924981791696765),
 ('job_entrepreneur', 4.8555474629763394e-05),
 ('marital_divorced', 1.2138868657440849e-05),
 ('default', 0.0),
 ('housing', 0.0),
 ('loan', 0.0),
 ('job_admin.', -0.00013352755523186045),
 ('job_technician', -0.00026705511046369866),
 ('job_self-employed', -0.0003034717164360212),
 ('job_management', -0.0007768875940762143),
 ('marital_single', -0.0011167759164845581)]
```

Based on the feature importance, we see that the month and duration are two features that have a higher feature importance compared to other features. We will add these two features to the dataframe.

In [69]:
```
df_perm_imp = df_engg.drop(['contact','day_of_week','campaign','pdays','previous','poutcome'], axis=1)
```

In [70]:
```
X = df_perm_imp.drop('y', axis = 1)
y = df_perm_imp['y']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,random_state = 52)
```

11.1) Logistic Regression - Cross Validation

StratifiedKFold is a type of cross-validation technique used to evaluate the performance of machine learning models. It is a variant of KFold, which divides the data into a specified number of folds (or "splits") and iteratively trains and evaluates the model on each fold. The key difference between StratifiedKFold and KFold is that StratifiedKFold ensures that the proportion of samples belonging to each class is approximately the same across all the folds. This is particularly useful when the data is imbalanced, meaning that one class is significantly more prevalent than the others.

In [71]:
```
df_score4 = CrossVal_model("Logistic Regression", X_train, y_train)
df_score4
```

```
Avg Balanced Accuracy: 0.5836696696696697
Avg Weighted F1-Score: 0.8682089274899699
Avg AUC-ROC Score: 0.8429837144837145
```

Out[71]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	Logistic Regression - Cross Validation	0.296021	0.89409	0.893748	0.58367	0.868209	0.842984

11.2) K-neighbors fine tuning

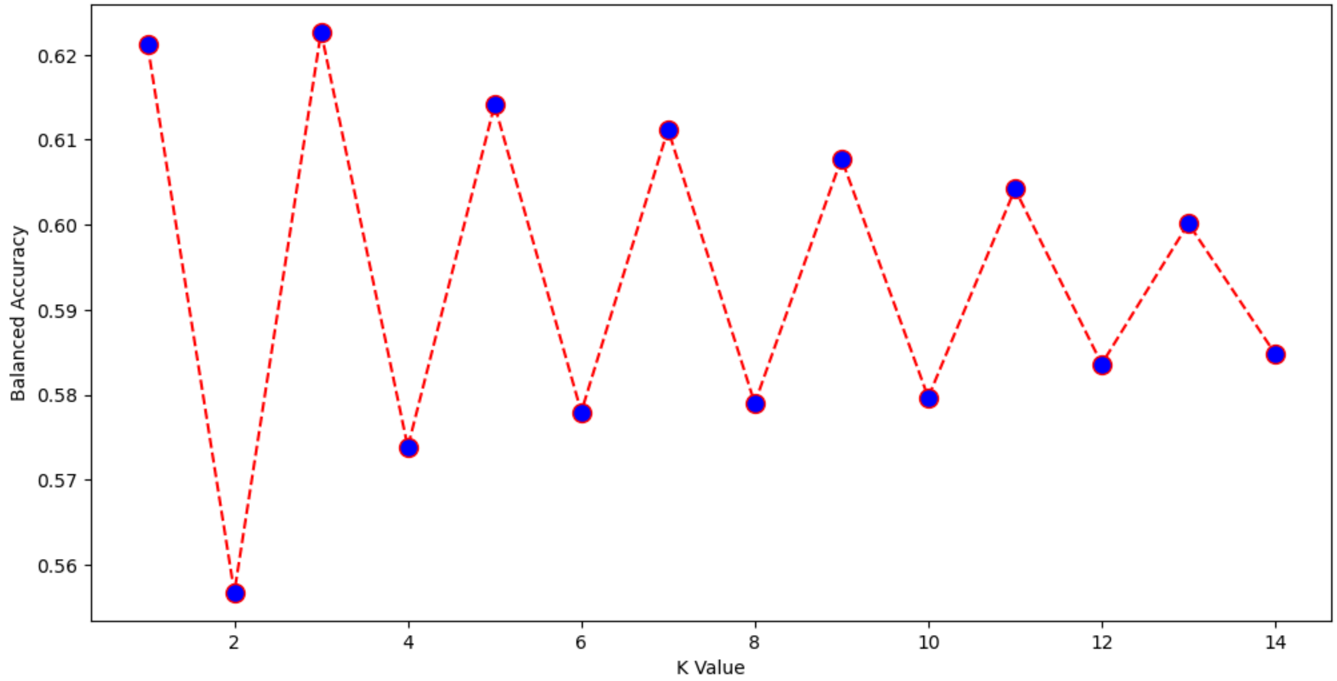
Fine-tuning a KNN model involves adjusting the parameters of the algorithm to optimize its performance. The main parameter that can be adjusted in KNN is the value of "K", which determines the number of nearest neighbors to consider when making predictions. A smaller value of K will make the model more sensitive to individual data points, while a larger value of K will make the model more robust to outliers.

In order to fine-tune a KNN model, you can use a technique called cross-validation. This involves dividing the data into a training set and a validation set, training the model on the training set, and evaluating its performance on the validation set. This process can be repeated multiple times, using different combinations of the parameters, and the model with the best performance on the validation set can be chosen as the final model.

In [72]:
```
balanced_acc_list = []
for i in range( 1, 15 ):
    # model definition
    model_knn = KNeighborsClassifier(n_neighbors=i, n_jobs=-1 )
    # train model
    model_knn.fit(X_train, y_train )
    # prediction
    y_pred = model_knn.predict( X_test )
    # Balanced Accuracy Score
    balanced_acc_list.append( balanced_accuracy_score( y_test, y_pred))
```

In [73]:
```
plt.figure( figsize=(12, 6) )
plt.plot( range( 1, 15 ), balanced_acc_list, color='red', linestyle='dashed', marker='o',
                                             markerfacecolor='blue', markersize=10 )
plt.xlabel('K Value' )
plt.ylabel('Balanced Accuracy')
```

Out[73]: `Text(0, 0.5, 'Balanced Accuracy')`



From the above, it is clear that balanced accuracy is greater for K values 1 and 3. We will be using K-Value of 1 for fine tuning the results

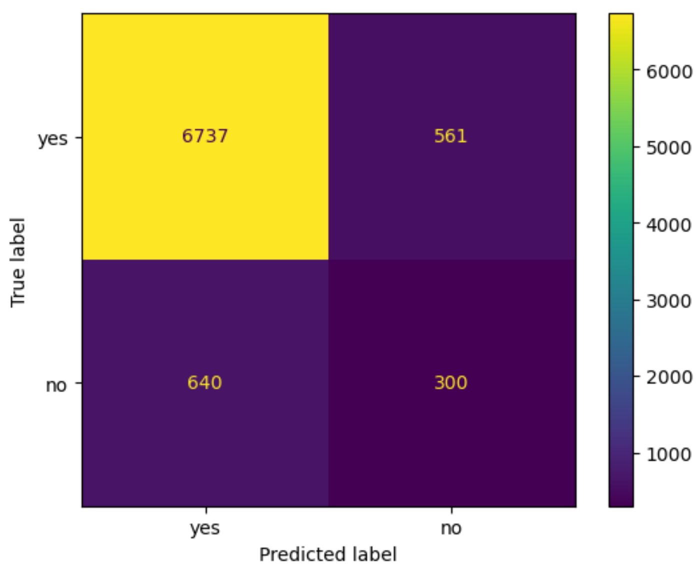
In [74]:

```
# model definition
model_knn = KNeighborsClassifier(n_neighbors=1, n_jobs=-1 )
# train model
model_knn.fit( X_train, y_train)
# prediction
y_train_pred = model_knn.predict(X_train)
y_pred = model_knn.predict( X_test )
#score calculation
df_score5 = GenerateOutput('KNN',y_train,y_train_pred,X_test,y_test, y_pred, model_knn)
df_score5
```

```
              precision    recall  f1-score   support

           0       0.91      0.92      0.92      7298
           1       0.35      0.32      0.33       940

    accuracy                           0.85      8238
   macro avg       0.63      0.62      0.63      8238
weighted avg       0.85      0.85      0.85      8238

Accuracy: 0.8542121874241321
Weighted F1-Score: 0.8514071413607764
Balanced Accuracy Score: 0.6211392803624427
AUC-ROC: 0.6211392803624426
```

Out[74]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	KNN	0.001981	0.999575	0.854212	0.851407	0.621139	0.621139



11.3) SVM - Cross Validation

Cross-validation is a technique that can be used to evaluate the performance of a SVM model and fine-tune its parameters. It involves dividing the data into multiple subsets, called "folds", and training the model on different combinations of the folds. The most commonly used techniques for cross-validation for SVM are k-fold cross-validation and Leave-One-Out cross-validation (LOOCV).

In [75]:
```python
df_score6 = CrossVal_model("SVM", X_train, y_train)
df_score6
```

```
Avg Balanced Accuracy: 0.5825592515592515
Avg Weighted F1-Score: 0.8680776556426398
Avg AUC-ROC Score: 0.6973198198198197
```

Out[75]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	SVM - Cross Validation	101.120975	0.894105	0.894082	0.582559	0.868078	0.69732

11.4) DecisionTreeClassifier - Cross Validation

The main parameters that can be adjusted in decision tree are the maximum depth of the tree, the minimum number of samples required to split an internal node, the minimum number of samples in a leaf node and the criterion used to split the nodes.

For decision trees, cross-validation is important because it allows to evaluate the performance of the model and select the best combination of parameters that minimize the overfitting problem. Overfitting occurs when a decision tree is too complex and is able to fit the noise in the data. This can be mitigated by techniques such as pruning or using ensembles of decision trees.

In [76]:
```python
df_score7 = CrossVal_model("DecisionTree", X_train, y_train)
df_score7
```

```
Avg Balanced Accuracy: 0.6576417186417186
Avg Weighted F1-Score: 0.8610096934307316
Avg AUC-ROC Score: 0.6577968583968585
```

Out[76]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	DecisionTree - Cross Validation	0.066258	0.999643	0.859727	0.657642	0.86101	0.657797

Hyperparameter Tuning

11.5) Logistic Regression - GridSearchCV

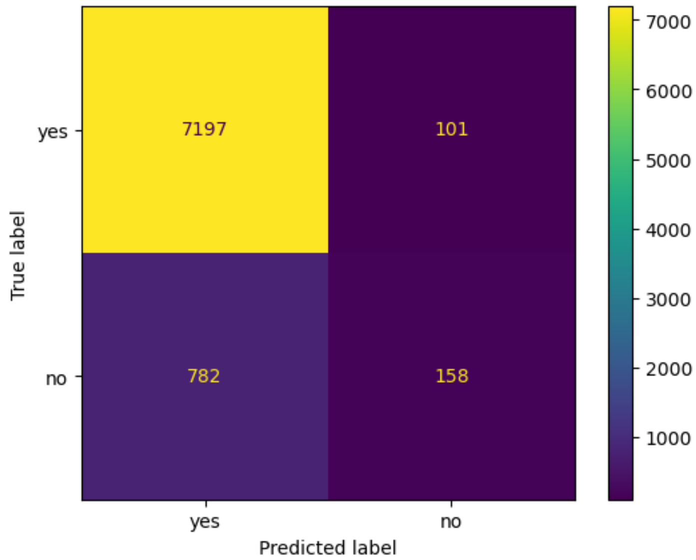
In logistic regression, the main parameters that can be fine-tuned are the regularization parameter (C) and the solver. The regularization parameter (C) controls the trade-off between maximizing the margin and minimizing the classification error. The solver determines the algorithm used to optimize the parameters.

In [77]:
```python
# Define the logistic regression model
logreg = LogisticRegression()

# Define the parameter grid
param_grid = {
    'C': [0.1, 1, 10, 100],
    'penalty': ['l1', 'l2']
}

# Create the GridSearchCV object
grid_search = GridSearchCV(estimator=logreg, param_grid=param_grid, cv=5, scoring='accuracy')

# Fit the model
grid_search.fit(X_train, y_train)

#prediction
y_pred = grid_search.predict(X_test)

#Print the best params
best_params = grid_search.best_params_
best_score = grid_search.best_score_
print(best_params)
print(best_score)

# Use the best hyperparameters to fit the final model
logreg_best = LogisticRegression(**best_params)
logreg_best.fit(X_train, y_train)

# Make predictions on the test set
predictions = logreg_best.predict(X_test)
y_train_pred = logreg_best.predict(X_train)
df_score8 = GenerateOutput('LogisticRegression-GridSearchCV', y_train, y_train_pred,X_test,y_test, predictions, logreg_best)
df_score8
```

```
{'C': 100, 'penalty': 'l2'}
0.8938088012139606
              precision    recall  f1-score   support

           0       0.90      0.99      0.94      7298
           1       0.61      0.17      0.26       940

    accuracy                           0.89      8238
   macro avg       0.76      0.58      0.60      8238
weighted avg       0.87      0.89      0.86      8238

Accuracy: 0.8928137897547949
Weighted F1-Score: 0.8647633463092386
Balanced Accuracy Score: 0.5771228491629884
AUC-ROC: 0.8348812411444697
```

Out[77]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	LogisticRegression-GridSearchCV	0.489536	0.894021	0.892814	0.864763	0.577123	0.834881



11.6) KNN - RandomSearchCV

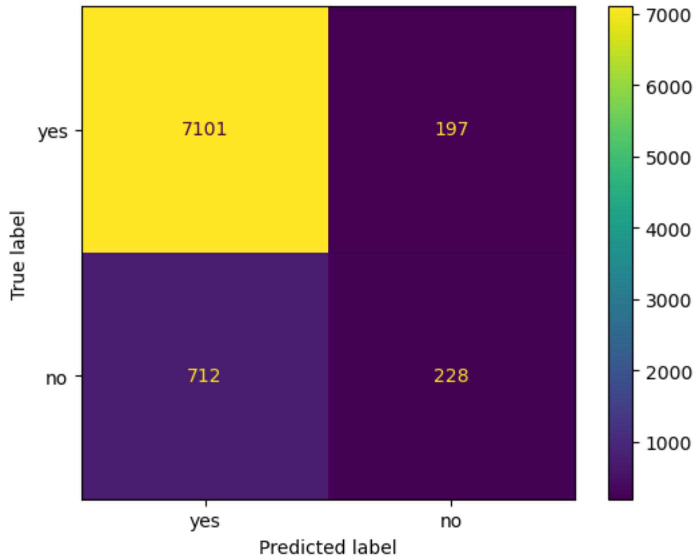
The param_dist dictionary specifies the hyperparameters to search over and the possible values for each. The n_iter parameter specifies the number of random combinations to try. The cv parameter specifies the number of folds to use in cross-validatio

In [78]:
```python
# Set up the parameter distribution for the KNN hyperparameters
param_dist = {'n_neighbors': [1, 3, 5, 7, 9],
              'weights': ['uniform', 'distance'],
              'metric': ['euclidean', 'manhattan']}

# Initialize the KNN model
knn = KNeighborsClassifier()

# Initialize the randomized search
random_search = RandomizedSearchCV(estimator=knn, param_distributions=param_dist, cv=5, n_iter=10)

# Fit the randomized search to the data
random_search.fit(X_train, y_train)

# Print the best hyperparameters
print(random_search.best_params_)

# Print the best cross-validation score
print(random_search.best_score_)
# Predict on the test set
y_pred = random_search.predict(X_test)
y_train_pred = random_search.predict(X_train)
#performance
df_score9 = GenerateOutput('KNN-RandomSearchCV',y_train,y_train_pred,X_test,y_test, y_pred, random_search)
df_score9
```

```
{'weights': 'uniform', 'n_neighbors': 9, 'metric': 'euclidean'}
0.891350531107739
              precision    recall  f1-score   support

           0       0.91      0.97      0.94      7298
           1       0.54      0.24      0.33       940

    accuracy                           0.89      8238
   macro avg       0.72      0.61      0.64      8238
weighted avg       0.87      0.89      0.87      8238

Accuracy: 0.8896576839038601
Weighted F1-Score: 0.8707224876119846
Balanced Accuracy Score: 0.6077797472930503
AUC-ROC: 0.7942707270426758
```

Out[78]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	KNN-RandomSearchCV	132.429425	0.904036	0.889658	0.870722	0.60778	0.794271



11.7) DecisionTrees - RandomizedSearchCV

In decision trees, the main parameters that can be fine-tuned are the maximum depth of the tree, the minimum number of samples required to split an internal node, the minimum number of samples in a leaf node, the criterion used to split the nodes and the maximum number of features to consider when looking for the best split.

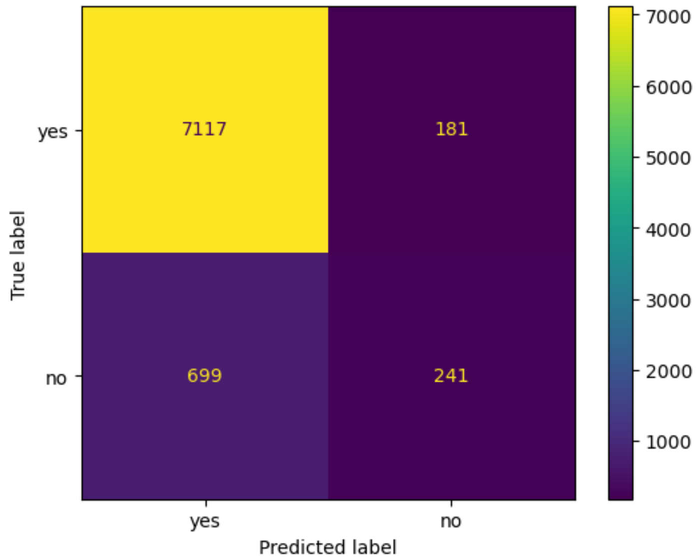
Random search can be more computationally efficient than grid search, especially when the number of hyperparameters and their possible values is large, but it doesn't guarantee to always find the best combination of parameters.

In [81]:
```
# Set up the parameter distribution for the decision tree hyperparameters
param_dist = {'max_depth': [1,3,5,7,9],
              'min_samples_split': [2,4,6,8,10,12,14,16],
              'min_samples_leaf': [1,3,5,7,9,13,15,17]}

# Initialize the decision tree model
tree = DecisionTreeClassifier()

# Initialize the randomized search
random_search = RandomizedSearchCV(estimator=tree, param_distributions=param_dist, cv=5, n_iter=10)

# Fit the randomized search to the data
random_search.fit(X_train, y_train)

# Print the best hyperparameters
print(random_search.best_params_)

# Print the best cross-validation score
print(random_search.best_score_)

# Predict on the test set
y_pred = random_search.predict(X_test)
y_train_pred = random_search.predict(X_train)

#performance
df_score10 = GenerateOutput('DecisonTree-RandomSearchCV',y_train, y_train_pred,X_test,y_test, y_pred,random_search)
df_score10
```

```
{'min_samples_split': 8, 'min_samples_leaf': 5, 'max_depth': 5}
0.8971775417298937
              precision    recall  f1-score   support

           0       0.91      0.98      0.94      7298
           1       0.57      0.26      0.35       940

    accuracy                           0.89      8238
   macro avg       0.74      0.62      0.65      8238
weighted avg       0.87      0.89      0.87      8238

Accuracy: 0.8931779558145181
Weighted F1-Score: 0.874695061218517
Balanced Accuracy Score: 0.6157908316472598
AUC-ROC: 0.8416102050692988
```

Out[81]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	DecisonTree-RandomSearchCV	1.255225	0.90088	0.893178	0.874695	0.615791	0.84161



12) Evaluation

With some modeling accomplished, we aim to reflect on what we identify as a high quality model and what we are able to learn from this. We should review our business objective and explore how well we can provide meaningful insight on drivers of used car prices. Your goal now is to distill your findings and determine whether the earlier phases need revisitation and adjustment or if you have information of value to bring back to your client.

12.1) Metric Evaluation

12.1.1) Identification of Evaluation Metric

The following are evaulation metrics used for this particular binary classification.

Accuracy: This is the percentage of correct predictions made by the classifier. It is calculated as (true positives + true negatives) / total samples.

Precision: This is the percentage of positive predictions that were correct. It is calculated as true positives / (true positives + false positives).

F1 score: This is a weighted average of precision and recall, with a higher score indicating better performance. It is calculated as 2 * (precision * recall) / (precision + recall).

AUC (Area Under the Curve): This is a metric used to evaluate the performance of a binary classifier using an ROC (Receiver Operating Characteristic) curve. The ROC curve plots the true positive rate against the false positive rate at different classification thresholds, and the AUC is the area under this curve. AUC provides a single measure of the classifier's performance.

Balanced accuracy: This is a metric used to evaluate the performance of a classifier when the classes are imbalanced. It is defined as the average of the class-specific accuracies, where the class-specific accuracy for a class is the number of true positives for that class divided by the sum of the true positives and false negatives for that class.

In [88]:
```
modelling_result = pd.concat( [df_score_base,
                               df_score,
                               df_score2,
                               df_score3,
                               df_score4,
                               df_score5,
                               df_score6,
                               df_score7,
                               df_score8,
                               df_score9,
                               df_score10
                              ] )
modelling_result.sort_values( 'roc_auc score' )
```

Out[88]:

	Model Name	Train Time	Train Accuracy	Test accuracy	f1_score	balanced_accuracy	roc_auc score
0	SVM	113.990209	0.887709	0.885895	0.832294	0.500000	0.470893
0	Baseline model	0.000641	0.802428	0.794610	0.795920	0.498527	0.500000
0	SVM	0.040731	0.898877	0.878369	0.840459	0.524020	0.545889
0	Logistic Regression	0.263456	0.887709	0.885895	0.832294	0.500000	0.617335
0	KNN	0.001981	0.999575	0.854212	0.851407	0.621139	0.621139
0	DecisionTree - Cross Validation	0.066258	0.999643	0.859727	0.657642	0.861010	0.657797
0	SVM - Cross Validation	101.120975	0.894105	0.894082	0.582559	0.868078	0.697320
0	KNN-RandomSearchCV	132.429425	0.904036	0.889658	0.870722	0.607780	0.794271
0	LogisticRegression-GridSearchCV	0.489536	0.894021	0.892814	0.864763	0.577123	0.834881
0	DecisonTree-RandomSearchCV	1.255225	0.900880	0.893178	0.874695	0.615791	0.841610
0	Logistic Regression - Cross Validation	0.296021	0.894090	0.893748	0.583670	0.868209	0.842984

From the above, it is prety clear that Logistic Regression with Cross Validation performed much better compared to other models.

13) Findings

Details findings are located [here (https://github.com/spalakollu/Bank_Products_Marketing/blob/main/BankMarketingFindings.pdf)](https://github.com/spalakollu/Bank_Products_Marketing/blob/main/BankMarketingFindings.pdf)

14) Next Steps and Recommendations

Further classification can be performed in a variety of ways. For example, a bank can use a customer's past transaction history, demographics, and other data to make personalized product recommendations, such as credit cards or loans, that are likely to be of interest to the customer. These recommendations can be made through email campaigns, in-app notifications, or through the bank's website or mobile app. Additionally, AI/ML can also be used to predict which customers are most likely to churn, so the bank can proactively reach out to those customers to try to retain them.

In [ ]: