

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import streamlit as st
import seaborn as sns
import statsmodels.api as sm
from sklearn.impute import SimpleImputer
from statsmodels.formula.api import ols
from IPython.display import Image
from sklearn.metrics import classification_report
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.svm import LinearSVC
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.neighbors import KNeighborsClassifier
from xgboost import XGBClassifier
from sklearn.linear_model import SGDClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, log_loss
import warnings
warnings.filterwarnings("ignore", category=UserWarning)
warnings.filterwarnings("ignore", category=RuntimeWarning)
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

use case

perform data cleaning

perform EDA to analyse data with diagrams

perform pre processing like scaling

split data into x and Y variables

build model(use different classifier) and tuning (using random search)

conclusion

In [3]:

```
# Use the absolute path to the xls file
file_path = '/Users/saheedadeitan/Downloads/BusyQA_bootcamp//default of credit card clients.xls'
# Read the xls file into a DataFrame, function sheet_name and header to work on the selected header
df = pd.read_excel(file_path, sheet_name= "Data", header = 1)

# Display the first few rows of the DataFrame to verify the import
df.describe()

# always check for sheet name to confirm you are on the right file .
# i remove the first the row
```

Out [3]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	
count	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	30000.000000	3
mean	15000.500000	167484.322667	1.603733	1.853133	1.551867	35.485500	-0.016700	-0.133767	
std	8660.398374	129747.661567	0.489129	0.790349	0.521970	9.217904	1.123802	1.197186	
min	1.000000	10000.000000	1.000000	0.000000	0.000000	21.000000	-2.000000	-2.000000	
25%	7500.750000	50000.000000	1.000000	1.000000	1.000000	28.000000	-1.000000	-1.000000	
50%	15000.500000	140000.000000	2.000000	2.000000	2.000000	34.000000	0.000000	0.000000	
75%	22500.250000	240000.000000	2.000000	2.000000	2.000000	41.000000	0.000000	0.000000	
max	30000.000000	1000000.000000	2.000000	6.000000	3.000000	79.000000	8.000000	8.000000	

8 rows x 25 columns

In [8]:

```
# list of head columns
df.head()
```

Out [8]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_AMT6
0	1	20000	2	2	1	24	2	2	-1	-1	...	0	0	
1	2	120000	2	2	2	26	-1	2	0	0	...	3272	3455	32
2	3	90000	2	2	2	34	0	0	0	0	...	14331	14948	155
3	4	50000	2	2	1	37	0	0	0	0	...	28314	28959	295
4	5	50000	1	2	1	57	-1	0	-1	0	...	20940	19146	191

5 rows x 25 columns

In [9]:

```
# dataset itself
df
```

Out [9]:

	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_AMT6
0	1	20000	2	2	1	24	2	2	-1	-1	...	0	0	
1	2	120000	2	2	2	26	-1	2	0	0	...	3272	3455	
2	3	90000	2	2	2	34	0	0	0	0	...	14331	14948	
3	4	50000	2	2	1	37	0	0	0	0	...	28314	28959	
4	5	50000	1	2	1	57	-1	0	-1	0	...	20940	19146	
...	
29995	29996	220000	1	3	1	39	0	0	0	0	...	88004	31237	
29996	29997	150000	1	3	2	43	-1	-1	-1	-1	...	8979	5190	

29997	29998	30000	1	2	2	37	4	3	2	-1	...	20878	20582
	ID	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	...	BILL_AMT4	BILL_AMT5
29998	29999	80000	1	3	1	41	-1	-1	0	0	...	52774	11855
29999	30000	50000	1	2	1	46	0	0	0	0	...	36535	32428

30000 rows x 25 columns



In [10]:

```
# checking for value types
dict(df.dtypes)
```

Out[10]:

```
{'ID': dtype('int64'),
 'LIMIT_BAL': dtype('int64'),
 'SEX': dtype('int64'),
 'EDUCATION': dtype('int64'),
 'MARRIAGE': dtype('int64'),
 'AGE': dtype('int64'),
 'PAY_0': dtype('int64'),
 'PAY_2': dtype('int64'),
 'PAY_3': dtype('int64'),
 'PAY_4': dtype('int64'),
 'PAY_5': dtype('int64'),
 'PAY_6': dtype('int64'),
 'BILL_AMT1': dtype('int64'),
 'BILL_AMT2': dtype('int64'),
 'BILL_AMT3': dtype('int64'),
 'BILL_AMT4': dtype('int64'),
 'BILL_AMT5': dtype('int64'),
 'BILL_AMT6': dtype('int64'),
 'PAY_AMT1': dtype('int64'),
 'PAY_AMT2': dtype('int64'),
 'PAY_AMT3': dtype('int64'),
 'PAY_AMT4': dtype('int64'),
 'PAY_AMT5': dtype('int64'),
 'PAY_AMT6': dtype('int64'),
 'default payment next month': dtype('int64')}
```

In [11]:

```
# checking for no of columns and cloumns in dataset
print('Number of columns: ' + str(len(df.columns)))
print('Columns in df: ' + str(df.columns))
```

Number of columns: 25

```
Columns in df: Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6',
 'default payment next month'],
 dtype='object')
```

In [12]:

```
# list of columns without Y
df.drop('default payment next month', axis=1).columns
```

Out[12]:

```
Index(['ID', 'LIMIT_BAL', 'SEX', 'EDUCATION', 'MARRIAGE', 'AGE', 'PAY_0',
 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'BILL_AMT1', 'BILL_AMT2',
 'BILL_AMT3', 'BILL_AMT4', 'BILL_AMT5', 'BILL_AMT6', 'PAY_AMT1',
 'PAY_AMT2', 'PAY_AMT3', 'PAY_AMT4', 'PAY_AMT5', 'PAY_AMT6'],
 dtype='object')
```

In [13]:

```
# no of rows
```

```
print('Number of rows: ' + str(df.shape[0]))
```

Number of rows: 30000

In [14]:

```
# information about the given dataset, like the range, no of columns, the type of value  
# the memory usage  
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 30000 entries, 0 to 29999
```

```
Data columns (total 25 columns):
```

#	Column	Non-Null Count	Dtype
0	ID	30000 non-null	int64
1	LIMIT_BAL	30000 non-null	int64
2	SEX	30000 non-null	int64
3	EDUCATION	30000 non-null	int64
4	MARRIAGE	30000 non-null	int64
5	AGE	30000 non-null	int64
6	PAY_0	30000 non-null	int64
7	PAY_2	30000 non-null	int64
8	PAY_3	30000 non-null	int64
9	PAY_4	30000 non-null	int64
10	PAY_5	30000 non-null	int64
11	PAY_6	30000 non-null	int64
12	BILL_AMT1	30000 non-null	int64
13	BILL_AMT2	30000 non-null	int64
14	BILL_AMT3	30000 non-null	int64
15	BILL_AMT4	30000 non-null	int64
16	BILL_AMT5	30000 non-null	int64
17	BILL_AMT6	30000 non-null	int64
18	PAY_AMT1	30000 non-null	int64
19	PAY_AMT2	30000 non-null	int64
20	PAY_AMT3	30000 non-null	int64
21	PAY_AMT4	30000 non-null	int64
22	PAY_AMT5	30000 non-null	int64
23	PAY_AMT6	30000 non-null	int64
24	default payment next month	30000 non-null	int64

```
dtypes: int64(25)
```

```
memory usage: 5.7 MB
```

In [15]:

```
# checking array for column ('Y : default payment next month')  
df['default payment next month'].unique()
```

Out[15]:

```
array([1, 0])
```

In [16]:

```
# checking correlation in the dataset  
df.corr
```

Out[16]:

```
<bound method DataFrame.corr of  
AY_0  PAY_2  PAY_3  \  
0      1      20000  2      2      1  24      2      2      -1  
1      2      120000  2      2      2  26     -1      2      0  
2      3      90000  2      2      2  34      0      0      0  
3      4      50000  2      2      1  37      0      0      0  
4      5      50000  1      2      1  57     -1      0     -1  
...    ...    ...    ...    ...    ...    ...    ...    ...  
29995  29996  220000  1      3      1  39      0      0      0  
29996  29997  150000  1      3      2  43     -1     -1     -1  
29997  29998   30000  1      2      2  37      4      3      2  
29998  29999   80000  1      3      1  41      1     -1      0  
29999  30000   50000  1      2      1  46      0      0      0
```

	PAY_4	...	BILL_AMT4	BILL_AMT5	BILL_AMT6	PAY_AMT1	PAY_AMT2	\
0	-1	...	0	0	0	0	689	
1	0	...	3272	3455	3261	0	1000	
2	0	...	14331	14948	15549	1518	1500	
3	0	...	28314	28959	29547	2000	2019	
4	0	...	20940	19146	19131	2000	36681	
...	
29995	0	...	88004	31237	15980	8500	20000	
29996	-1	...	8979	5190	0	1837	3526	
29997	-1	...	20878	20582	19357	0	0	
29998	0	...	52774	11855	48944	85900	3409	
29999	0	...	36535	32428	15313	2078	1800	

	PAY_AMT3	PAY_AMT4	PAY_AMT5	PAY_AMT6	default payment next month
0	0	0	0	0	1
1	1000	1000	0	2000	1
2	1000	1000	1000	5000	0
3	1200	1100	1069	1000	0
4	10000	9000	689	679	0
...
29995	5003	3047	5000	1000	0
29996	8998	129	0	0	0
29997	22000	4200	2000	3100	1
29998	1178	1926	52964	1804	1
29999	1430	1000	1000	1000	1

[30000 rows x 25 columns]>

In [17]:

```
# data cleaning
# checking for missing values, no missing value seen, no ? or nan
dict(df.isnull().sum())
```

Out[17]:

```
{'ID': 0,
 'LIMIT_BAL': 0,
 'SEX': 0,
 'EDUCATION': 0,
 'MARRIAGE': 0,
 'AGE': 0,
 'PAY_0': 0,
 'PAY_2': 0,
 'PAY_3': 0,
 'PAY_4': 0,
 'PAY_5': 0,
 'PAY_6': 0,
 'BILL_AMT1': 0,
 'BILL_AMT2': 0,
 'BILL_AMT3': 0,
 'BILL_AMT4': 0,
 'BILL_AMT5': 0,
 'BILL_AMT6': 0,
 'PAY_AMT1': 0,
 'PAY_AMT2': 0,
 'PAY_AMT3': 0,
 'PAY_AMT4': 0,
 'PAY_AMT5': 0,
 'PAY_AMT6': 0,
 'default payment next month': 0}
```

In []:

```
#EDA
```

Pearson’s correlation coefficient measures the statistical relationship, or association, between two continuous variables.

It gives information about the magnitude of the association, or correlation, as well as the direction of the relationship.

from the diagram below, it shows numerical value not categorical association of the values. i should not be using pearson correlation

Age and marriage (age on Y axis and marriage on x axis) and (marriage on y axis and age on x axis) both have the same value

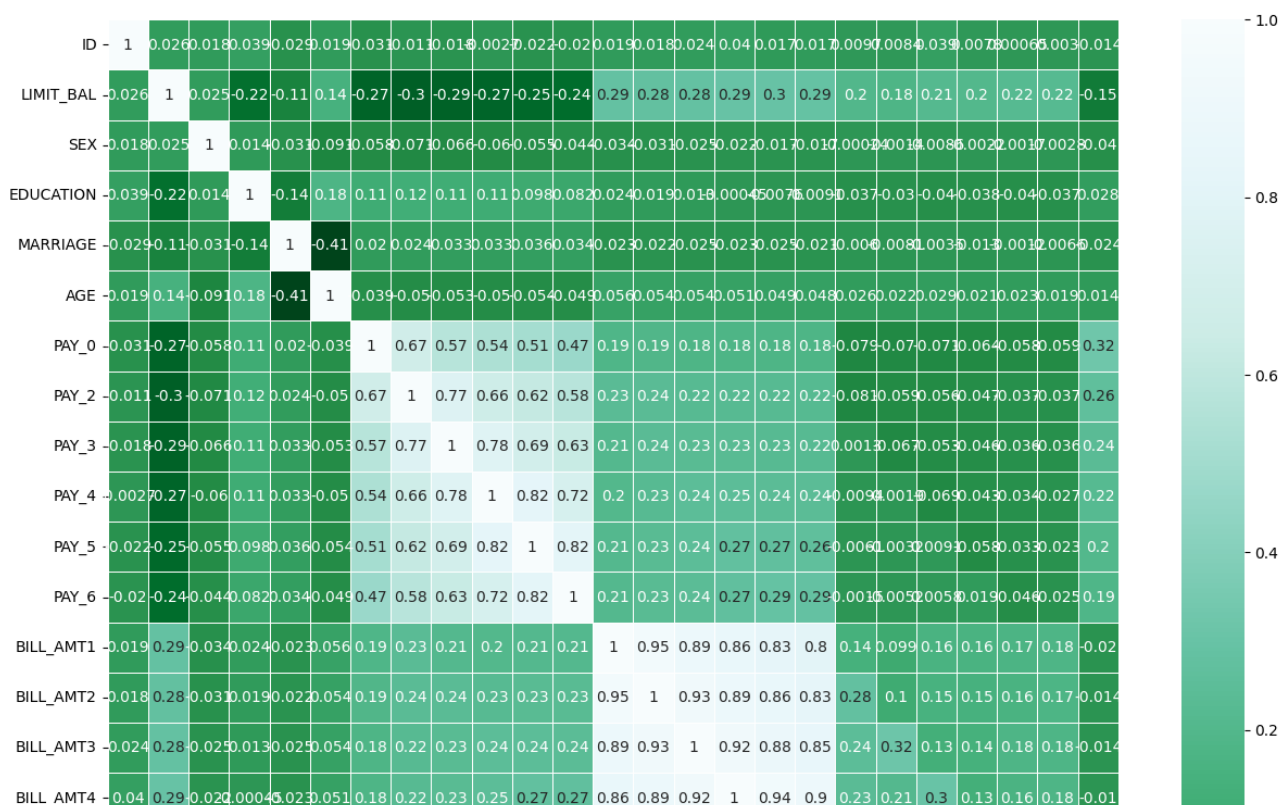
PAY_0 and PAY_2 (0.32, 0.26) have close association with our target variable 'default payment next month', which might affect our models.

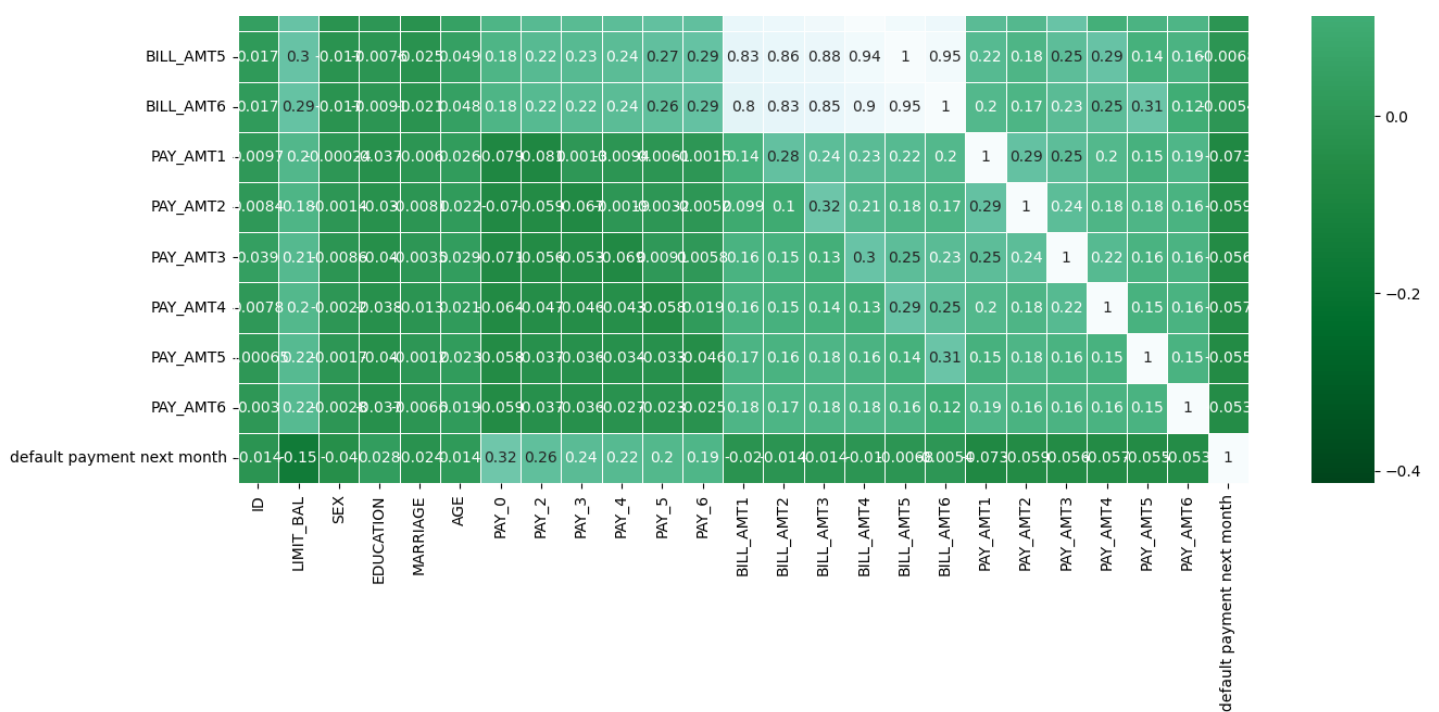
same with LIMIT_BAL on x axis and BILL_AMT1, BILL_AMT2, BILL_AMT3, BILL_AMT4, BILL_AMT5, BILL_AMT6 on Y-axis (0.29, 0.28, 0.28, 0.29, 0.3, 0.29)

BILL_AMT6 on y axis and BIL_AMT1 gives 0.8, BIL_AMT2 gives 0.83, BIL_AMT3 0.85. since the values looks similar, we can remove one of the values as zero

In [18]:

```
# Pearson's correlation coefficient
a = df.corr()
plt.rcParams['figure.figsize']=(15,15)
ax = sns.heatmap(a, linewidth=0.5, cmap= 'BuGn_r', annot = True)
# plot the heatmap
plt.show()
```





or using heatmap

age and marriage have the same value (age on Y axis and marriage on x axis) and (marriage on y axis and age on x axis)

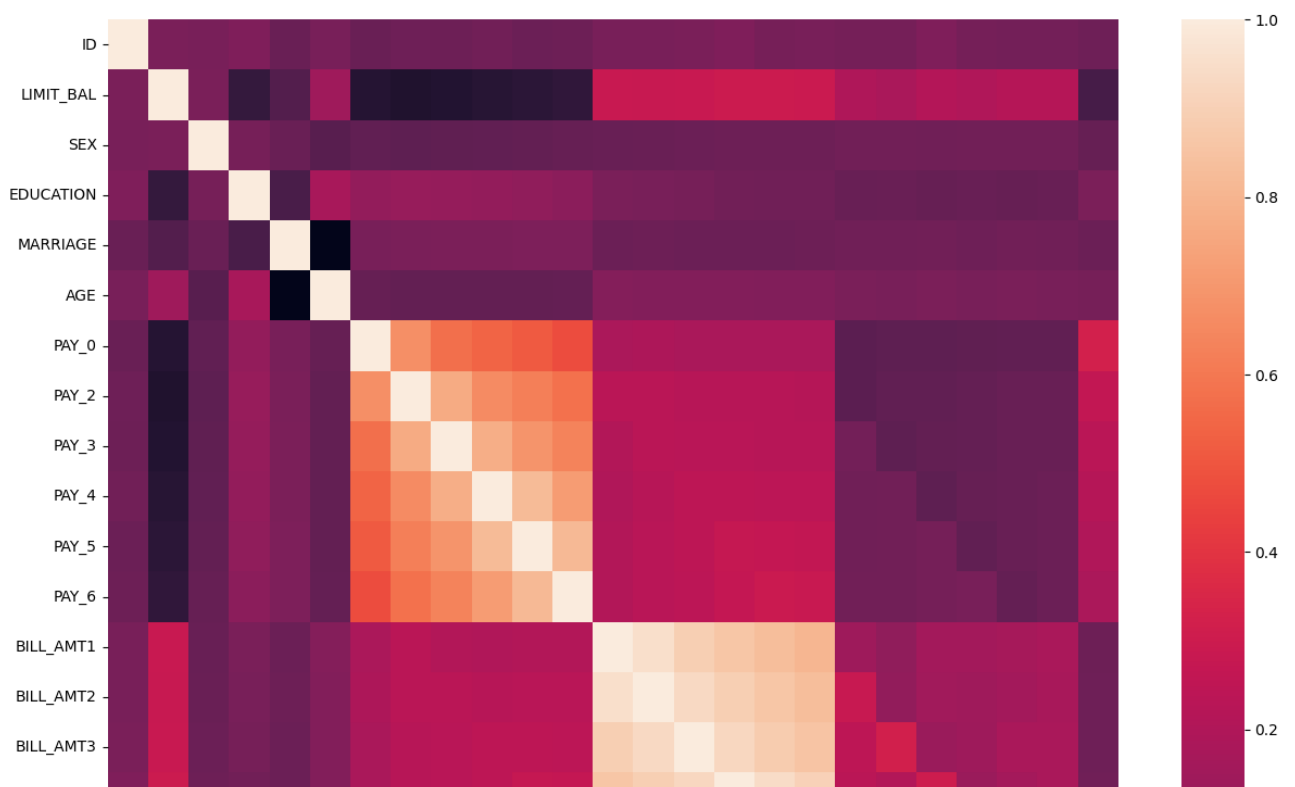
In [20]:

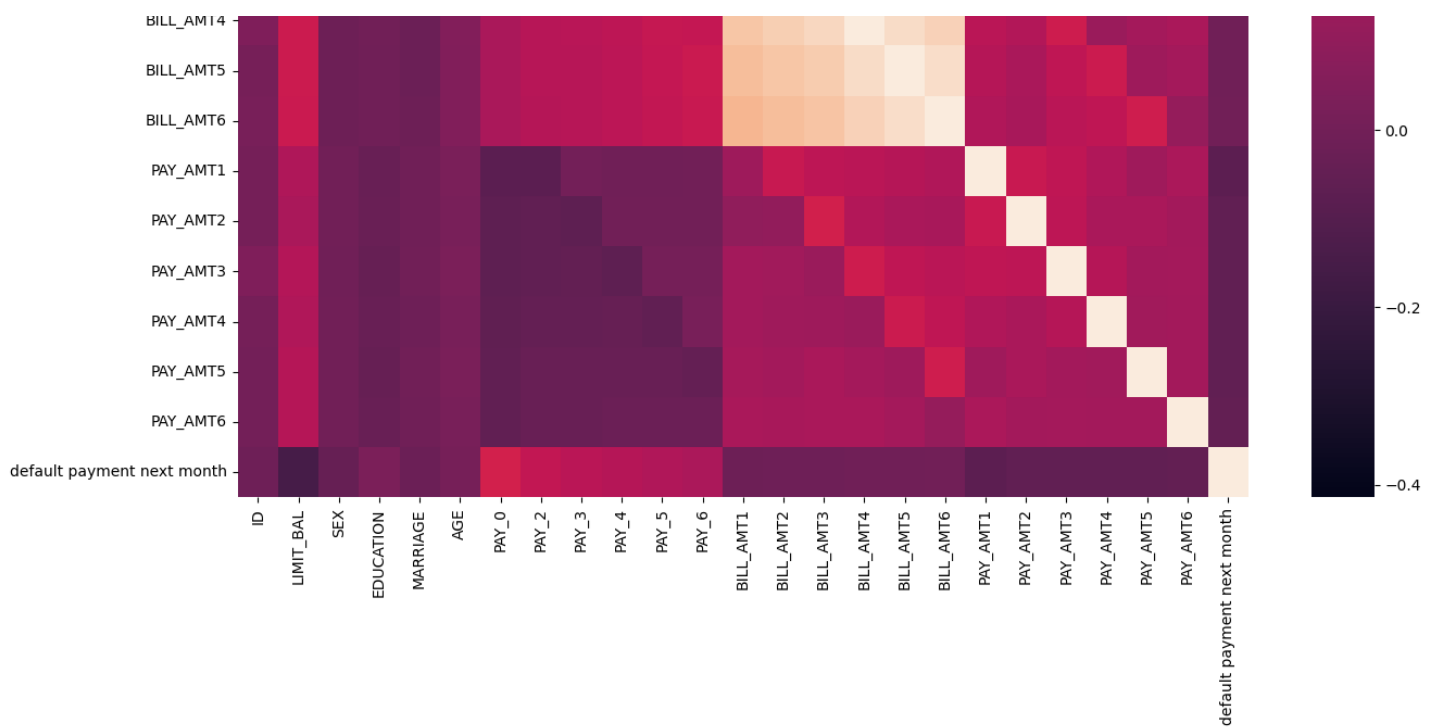
```
# Heatmap
# calculate the correlation matrix on the numeric columns
corr = df.select_dtypes('number').corr()

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

Out[20]:

<Axes: >





In [69]:

```
import sweetviz as sv
# understanding dataset with bar chat and Association dataframe (showing uncertainty coefficient)
# using sweetviz to view target values corr df_c #EDA
# to view sweetviz kindly click on file:///Users/saheedadeitan/Downloads/BusyQA_bootcamp/SWEETVIZ_REPORT.html
my_report = sv.analyze(df)
my_report.show_notebook( w=None,
                        h=None,
                        scale=None,
                        layout='widescreen',
                        filepath=None,
                        file_layout=None,
                        file_scale=None)
```


Outliers

more than 30% dont remove outliers but less than 30% you remove outliers -->

checking for outliers , only for values

function for removing outlier based on IQR

It is effective for datasets that may not follow a normal distribution.

it should only be used for continuous variable

Reason for not using outliers

Not all outliers are errors; some may represent legitimate data points with unique characteristics.

the method of outlier detection and removal should be carefully chosen to avoid biasing the dataset or losing valuable information.

i decided not to remove outlier because when i did, 'default payment next month' column had few values. Like most of it were removed and it affected my data

In [14]:

In [26]:

```
# removing ID column before splitting
df_d = df.drop(columns=['ID'])
# confirming if ID has been removed
df_d
```

Out [26]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_AMT4	BILL_AMT5
0	20000	2	2	1	24	2	2	-1	-1	-2	...	0	0
1	120000	2	2	2	26	-1	2	0	0	0	...	3272	3455
2	90000	2	2	2	34	0	0	0	0	0	...	14331	14948
3	50000	2	2	1	37	0	0	0	0	0	...	28314	28959
4	50000	1	2	1	57	-1	0	-1	0	0	...	20940	19146
...
29995	220000	1	3	1	39	0	0	0	0	0	...	88004	31237
29996	150000	1	3	2	43	-1	-1	-1	-1	0	...	8979	5190
29997	30000	1	2	2	37	4	3	2	-1	0	...	20878	20582
29998	80000	1	3	1	41	1	-1	0	0	0	...	52774	11855
29999	50000	1	2	1	46	0	0	0	0	0	...	36535	32428

30000 rows × 24 columns



NB to myself.

the general syntax for iloc is `df.iloc[:, :-1]`: This selects all rows (:) and all columns up to the last one (:-1)

It effectively excludes the last column from the selection, resulting in a DataFrame containing only the feature columns (independent variables).

`df.iloc[:, -1]`: This selects all rows (:) and only the last column (-1). It effectively selects only the last column of the DataFrame, which typically represents the target variable (dependent variable).

splitting X and y variables

In [28]:

```
#splitting X and y variables,  
# we remove ID and focused from LIMIT_BAL to PAY_AMT6  
X = df_d.iloc[:, :23]  
y = df['default payment next month']
```

In [29]:

```
X.head()
```

Out [29]:

	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_AMT3	BILL_AMT4	BILL
0	20000	2	2	1	24	2	2	-1	-1	-2	...	689		0

1	LIMIT_BAL	SEX	EDUCATION	MARRIAGE	AGE	PAY_0	PAY_2	PAY_3	PAY_4	PAY_5	...	BILL_AMT3	BILL_AMT4	BILL
2	90000	2	2	2	34	0	0	0	0	0	...	13559	14331	
3	50000	2	2	1	37	0	0	0	0	0	...	49291	28314	
4	50000	1	2	1	57	-1	0	-1	0	0	...	35835	20940	

5 rows x 23 columns



In [30]:

```
y.head()
```

Out[30]:

```
0    1
1    1
2    0
3    0
4    0
Name: default payment next month, dtype: int64
```

Scaling data

In [31]:

```
# scaling data
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
df_s = sc.fit_transform(X)
```

In [32]:

```
print(df_s)
```

```
[[-1.13672015  0.81016074  0.18582826 ... -0.30806256 -0.31413612
 -0.29338206]
 [-0.3659805   0.81016074  0.18582826 ... -0.24422965 -0.31413612
 -0.18087821]
 [-0.59720239  0.81016074  0.18582826 ... -0.24422965 -0.24868274
 -0.01212243]
 ...
 [-1.05964618 -1.23432296  0.18582826 ... -0.03996431 -0.18322937
 -0.11900109]
 [-0.67427636 -1.23432296  1.45111372 ... -0.18512036  3.15253642
 -0.19190359]
 [-0.90549825 -1.23432296  0.18582826 ... -0.24422965 -0.24868274
 -0.23713013]]
```

In [33]:

```
df_s
```

Out[33]:

```
array([[ -1.13672015,  0.81016074,  0.18582826, ..., -0.30806256,
        -0.31413612, -0.29338206],
       [-0.3659805 ,  0.81016074,  0.18582826, ..., -0.24422965,
        -0.31413612, -0.18087821],
       [-0.59720239,  0.81016074,  0.18582826, ..., -0.24422965,
        -0.24868274, -0.01212243],
       ...,
       [-1.05964618, -1.23432296,  0.18582826, ..., -0.03996431,
        -0.18322937, -0.11900109],
       [-0.67427636, -1.23432296,  1.45111372, ..., -0.18512036,
         3.15253642, -0.19190359],
       [-0.90549825, -1.23432296,  0.18582826, ..., -0.24422965,
        -0.24868274, -0.23713013]])
```

In [35]:

```
#train_test_split- train our model
import pandas as pd
from sklearn.model_selection import train_test_split
# Assuming 'X' is your feature matrix and 'y' is your target variable
X_train, X_test, y_train, y_test = train_test_split(df_s, y, test_size=0.25, random_state=0)

print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(22500, 23)
(22500,)
(7500, 23)
(7500,)
```

In [36]:

```
# X_test.head() or
print(X_test[:5])
```

```
[[-1.13672015 -1.23432296 -1.0794572  0.85855728 -0.2696428  0.90471219
  1.78234817  1.8099213  1.89943574  1.99987907  1.99231551 -0.45158548
 -0.44652132 -0.40312715 -0.38565616 -0.33812015 -0.32884527 -0.34194162
 -0.15890131 -0.29680127 -0.2059299 -0.31413612 -0.25715582]
 [-1.13672015  0.81016074  0.18582826  0.85855728 -0.05267012  0.01486052
  0.1117361  1.8099213  0.18874609  0.23491652  0.25313738 -0.47118223
 -0.41915123 -0.40971708 -0.37715337 -0.3505387 -0.31688956 -0.13666485
 -0.25698952 -0.24000461 -0.30806256 -0.24868274 -0.29338206]
 [ 0.48183311  0.81016074 -1.0794572 -1.05729503  0.92370693  0.90471219
 -0.72356993 -0.69666346 -0.66659873 -0.64756476 -1.48604076 -0.64289491
 -0.67764964 -0.63662986 -0.65799433 -0.66305853 -0.65272422 -0.28464525
 -0.13229597 -0.24380999 -0.30806256 -0.31413612 -0.29338206]
 [-0.52012843 -1.23432296  0.18582826 -1.05729503  0.70673426  0.01486052
  0.1117361  0.1388648  0.18874609  0.23491652  0.25313738  0.64109329
  0.7140239 -0.44521906 -0.39645953 -0.35425604 -0.31232221 -0.04006402
 -0.1701858 -0.18320795 -0.18039673 -0.18322937 -0.18087821]
 [-0.13475861 -1.23432296 -1.0794572  0.85855728 -0.70358815 -1.76484282
 -1.55887596 -1.53219171 -1.52194355 -1.53004603 -1.48604076 -0.63340209
 -0.59379713 -0.66594567 -0.57194044 -0.57854659 -0.52158078  0.08002289
 -0.22083577  0.07169548  0.02086846  0.19856017  0.10769417]]
```

In [37]:

```
y_test.head()
```

Out[37]:

```
8225    0
10794    0
9163     0
26591    0
6631     0
Name: default payment next month, dtype: int64
```

In [38]:

```
y_train.value_counts()
```

Out[38]:

```
default payment next month
0    17496
1     5004
Name: count, dtype: int64
```

In [39]:

```
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import precision_score
```

In [42]:

```
#LogisticRegression Model

# I decided to use Logistic regression because it is straightforward, and can handle large dataset efficiently.
# metrics to evaluate the performance of classification algorithms: F1, Accuracy, Recall, Precision
# F1 Score considers both precision and recall metric

LR = LogisticRegression()
#fitting the model
LR.fit(X_train, y_train)

#prediction
y_pred = LR.predict(X_test)

#Accuracy
accuracy = LR.score(X_test, y_test)
print("Accuracy ", LR.score(X_test, y_test)*100)

# recall
recall = recall_score(y_test, y_pred)
print("recall ", recall_score(y_test, y_pred))

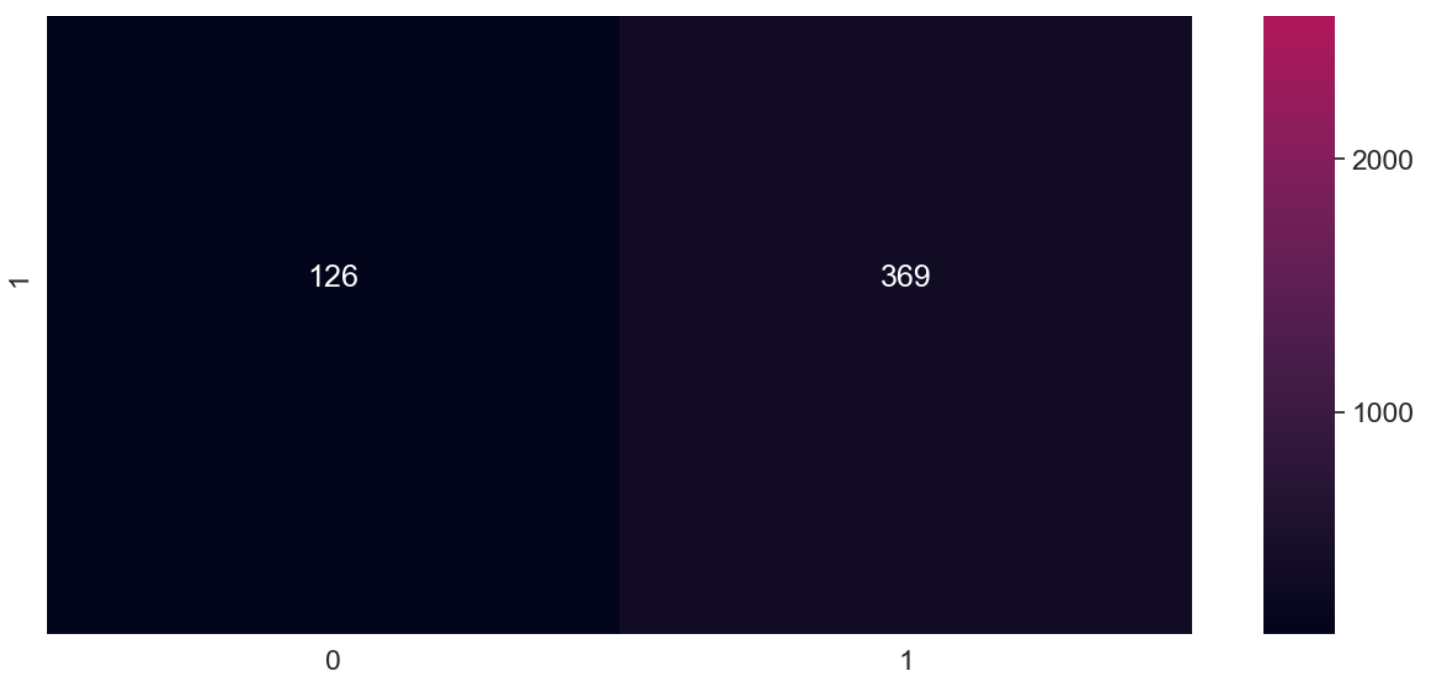
# F1
f1 = f1_score(y_test, y_pred)
print("f1 ",f1_score(y_test, y_pred) )

# Precision
precision = precision_score(y_test, y_pred)
print("precision ",precision_score(y_test, y_pred))

#Plot the confusion matrix
sns.set(font_scale=1.5)
cm = confusion_matrix(y_pred, y_test)
sns.heatmap(cm, annot=True, fmt='g')
plt.show()
```

```
Accuracy  81.47999999999999
recall    0.2261029411764706
f1        0.3469675599435825
precision 0.7454545454545455
```





In [51]:

```
#XGBoost Model
# We should use this algorithm when we require fast and accurate predictions after the model is deployed.

XGB = XGBClassifier(loss = 'deviance',
                    learning_rate = 0.01,
                    n_estimators = 10,
                    max_depth = 5,
                    verbosity=0,
                    random_state=0)

#fiting the model
XGB.fit(X_train, y_train)

#prediction
y_pred = XGB.predict(X_test)

#Accuracy
accuracy = XGB.score(X_test, y_test)
print("Accuracy ", XGB.score(X_test, y_test)*100)

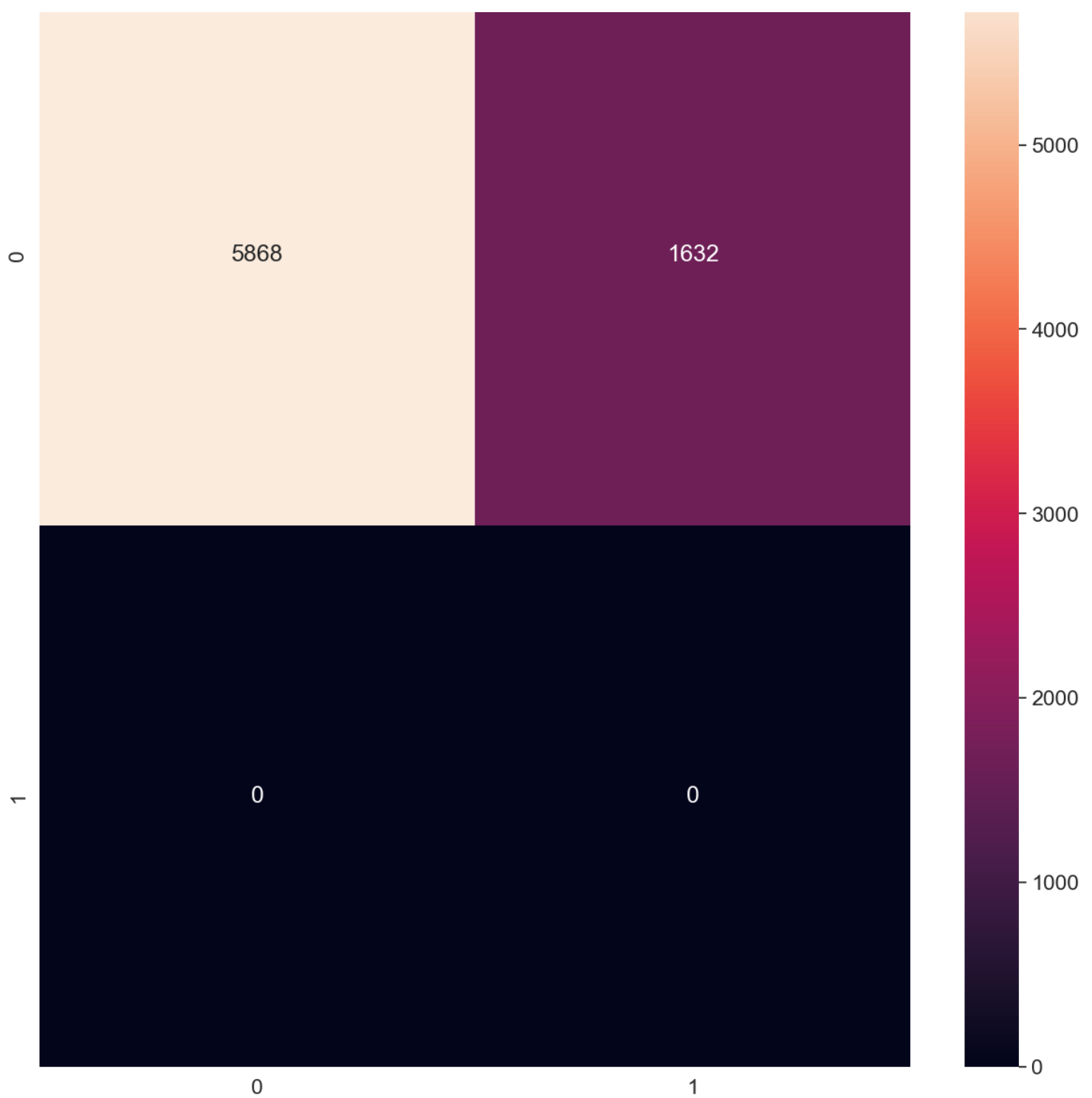
# recall
recall = recall_score(y_test, y_pred)
print("recall ", recall_score(y_test, y_pred))

# F1
f1 = f1_score(y_test, y_pred)
print("f1 ",f1_score(y_test, y_pred) )

# Precision
precision = precision_score(y_test, y_pred)
print("precision ",precision_score(y_test, y_pred))

#Plot the confusion matrix
sns.set(font_scale=1.5)
cm = confusion_matrix(y_pred, y_test)
sns.heatmap(cm, annot=True, fmt='g')
plt.show()
```

```
Accuracy  78.24
recall    0.0
f1         0.0
precision  0.0
```



In [45]:

```
# Decision Tree Model

# Decision Trees for both classification and regression tasks.
# It can handle both numerical and categorical features without requiring preprocessing like normalization or encoding.

DT = DecisionTreeClassifier(criterion= 'entropy',
                             max_depth = 10,
                             splitter='best',
                             random_state=0)

#fitting the model
DT.fit(X_train, y_train)

#prediction
y_pred = DT.predict(X_test)

#Accuracy
accuracy = DT.score(X_test, y_test)
```

```

print("Accuracy ", DT.score(X_test, y_test)*100)

# recall
recall = recall_score(y_test, y_pred)
print("recall ", recall_score(y_test, y_pred))

# F1
f1 = f1_score(y_test, y_pred)
print("f1 ",f1_score(y_test, y_pred) )

# Precision
precision = precision_score(y_test, y_pred)
print("precision ",precision_score(y_test, y_pred))

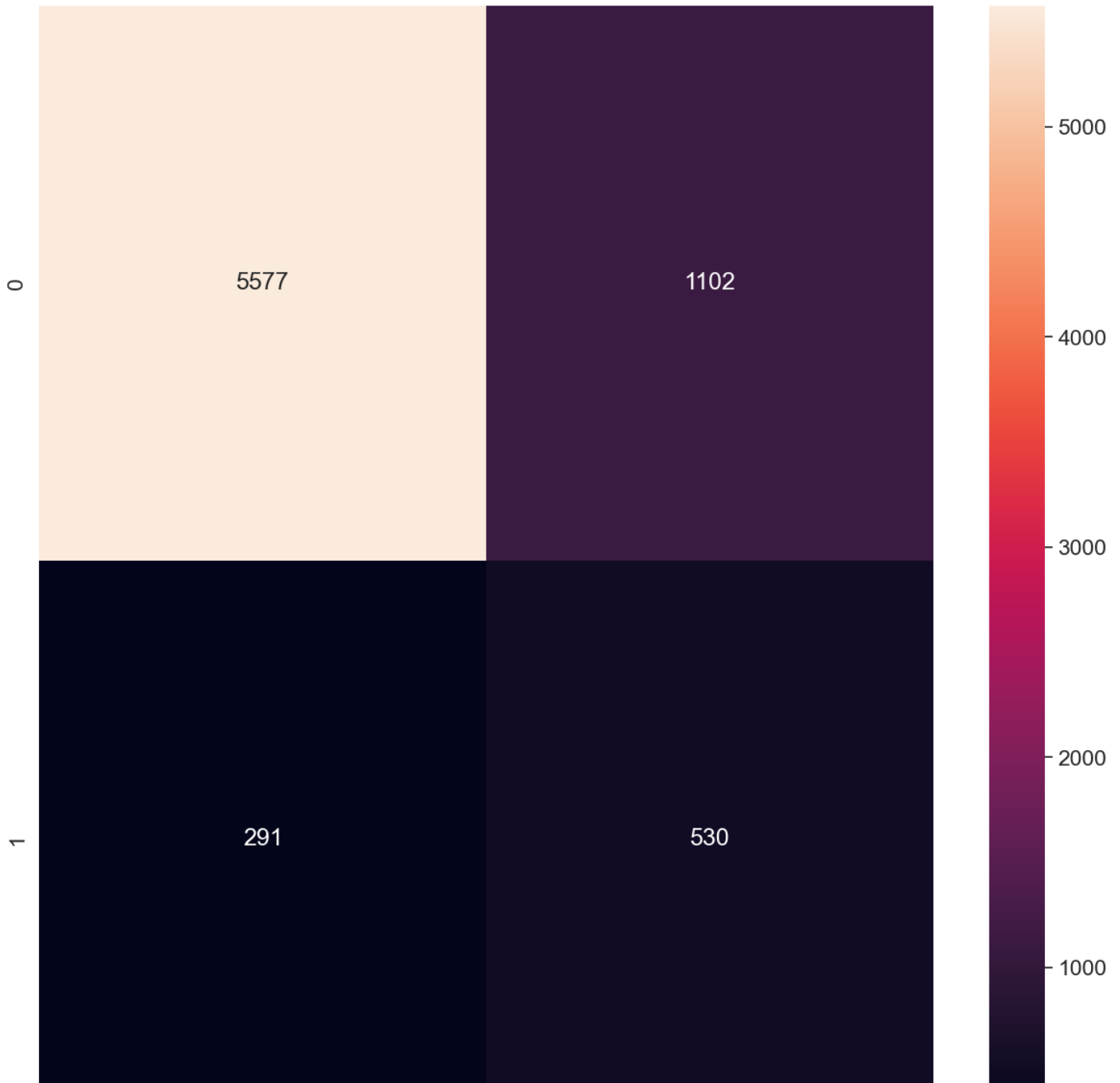
#Plot the confusion matrix
sns.set(font_scale=1.5)
cm = confusion_matrix(y_pred, y_test)
sns.heatmap(cm, annot=True, fmt='g')
plt.show()

```

```

Accuracy  81.42666666666668
recall    0.3247549019607843
f1        0.4321239298817774
precision  0.6455542021924482

```



0

1

In [47]:

```

#Model RandomForest
# It is a versatile and powerful algorithm with high accuracy, robustness, and ability to
handle complex datasets

RF = RandomForestClassifier()

#fiting the model
RF.fit(X_train, y_train)

#prediction
prediction = y_pred
y_pred = RF.predict(X_test)

#Accuracy
accuracy = RF.score(X_test, y_test)
print("Accuracy ", RF.score(X_test, y_test)*100)

# recall
recall = recall_score(y_test, y_pred)
print("recall ", recall_score(y_test, y_pred))

# F1
f1 = f1_score(y_test, y_pred)
print("f1 ",f1_score(y_test, y_pred))

# Precision
precision = precision_score(y_test, y_pred)
print("precision ",precision_score(y_test, y_pred))

#Plot the confusion matrix
sns.set(font_scale=1.5)
cm = confusion_matrix(y_pred, y_test)
sns.heatmap(cm, annot=True, fmt='g')
plt.show()

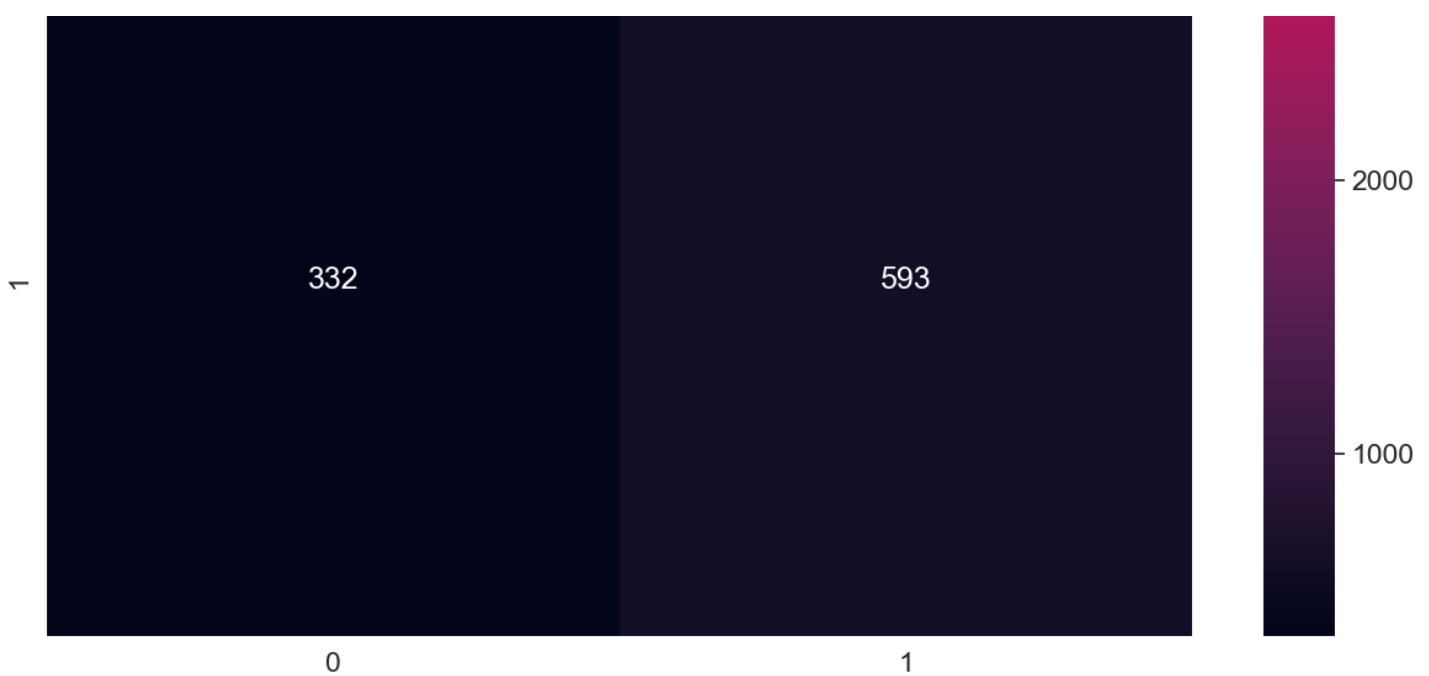
```

```

Accuracy 81.72
recall 0.3633578431372549
f1 0.4638247946812671
precision 0.6410810810810811

```





Classifier report

In [52]:

```
classifiers = [ LogisticRegression(),
                  # MultinomialNB(),
                  # GradientBoostingClassifier(loss = 'deviance', n_estimators = 10,max_de
pth = 5,random_state=0),
                  XGBClassifier(loss = 'deviance', n_estimators = 10,max_depth = 5,random_
state=2020,verbosity=0),
                  DecisionTreeClassifier(criterion= 'entropy',max_depth = 10,splitter='bes
t', random_state=0),
                  RandomForestClassifier(),
                  # KNeighborsClassifier(n_neighbors = 10,weights = 'distance',algorithm =
'brute')
                ]

# Logging for Visual Comparison
log_cols=["Classifier", "Accuracy", "Log Loss"]
log = pd.DataFrame(columns=log_cols)

log_entries = []

for clf in classifiers:
    model = clf.fit(X_train, y_train)
    name = clf.__class__.__name__

    # Accuracy
    train_predictions = clf.predict(X_test)
    acc = accuracy_score(y_test, train_predictions)

    # Log Loss
    train_predictions_proba = clf.predict_proba(X_test)
    ll = log_loss(y_test, train_predictions_proba)

    log_entries.append([name, acc * 100, ll])
    log_entry = pd.DataFrame([[name, acc*100, ll]], columns=log_cols)

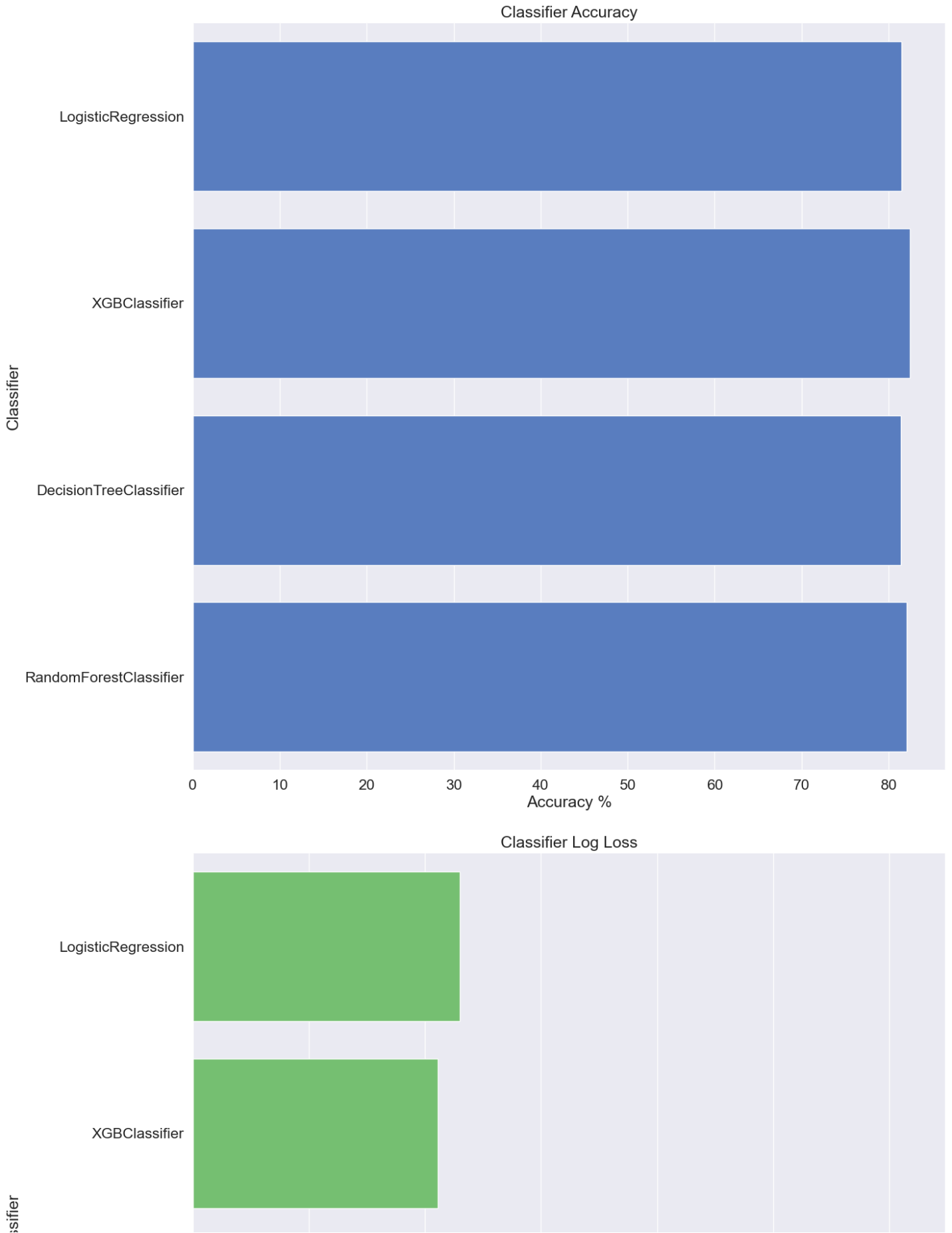
# Convert list of entries to DataFrame
log = pd.DataFrame(log_entries, columns=log_cols)

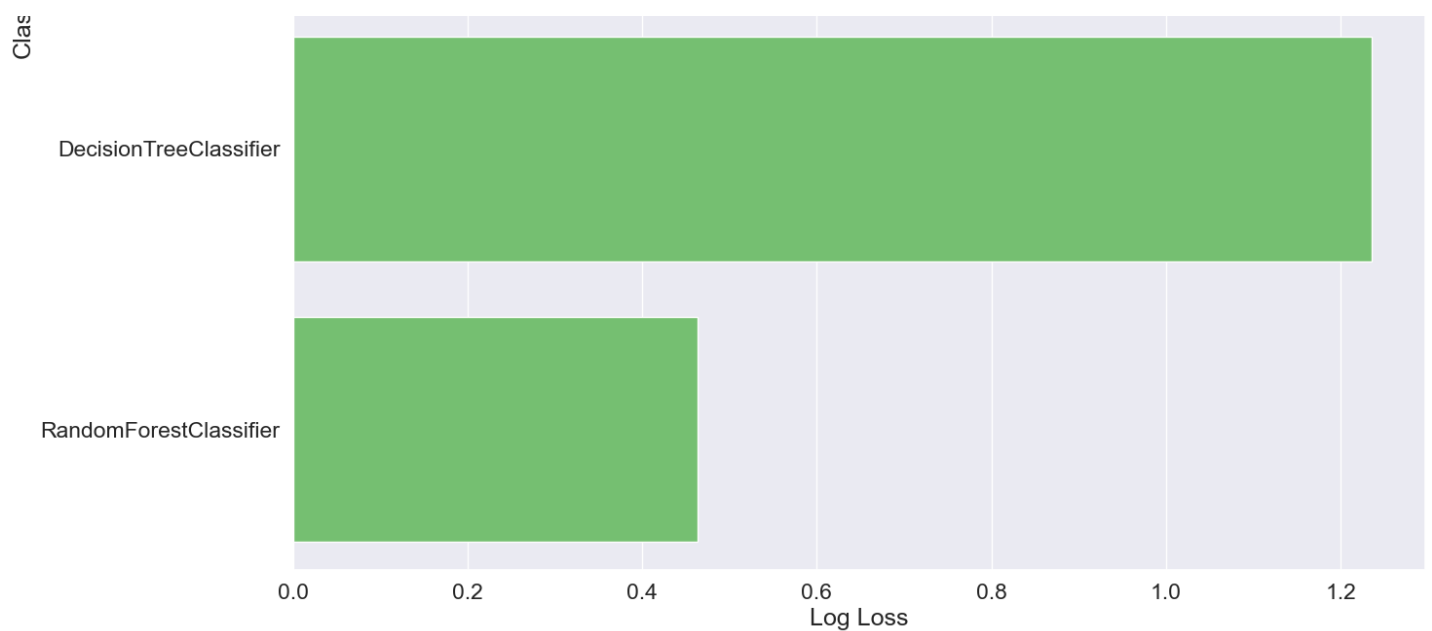
#Visualization
sns.set_color_codes("muted")
sns.barplot(x='Accuracy', y='Classifier', data=log, color="b")
```

```
plt.xlabel('Accuracy %')
plt.title('Classifier Accuracy')
plt.show()

sns.set_color_codes("muted")
sns.barplot(x='Log Loss', y='Classifier', data=log, color="g")

plt.xlabel('Log Loss')
plt.title('Classifier Log Loss')
plt.show()
```





From above report, in terms of accuracy they all are above 80%(81.71 for RF, 81.4 for DT and 81.4 for LR) except for XGB 78.2 and for Log Loss , XGB has the lowest and decision tree has the highest

Hyperparameter tuning

In [55]:

```
rf = RandomForestClassifier()
model = rf.fit(X_train, y_train)
prediction = model.predict(X_test)
```

In [62]:

```
#RandomSearch
from sklearn.model_selection import RandomizedSearchCV
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 10, stop = 50, num = 3)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(3, 6, num = 3)]
max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4]
# Method of selecting samples for training each tree
bootstrap = [True, False]
# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}

print(random_grid)

{'n_estimators': [10, 30, 50], 'max_features': ['auto', 'sqrt'], 'max_depth': [3, 4, 6, N
one], 'min_samples_split': [2, 5, 10], 'min_samples_leaf': [1, 2, 4], 'bootstrap': [True,
False]}
```

In [63]:

```
# Use the random grid to search for best hyperparameters. this can be done on both large
and small data.
# especially if you want a quick result.
```

```
# First create the base model to tune
rf = RandomForestClassifier()

# Random search of parameters, using 3 fold cross validation,
# search across 10 different combinations(n_iter), and use all available cores
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_iter
= 100, cv = 3, verbose=2, random_state=42, n_jobs = -1)

# Fit the random search model
rf_random.fit(X_train, y_train)
```

Fitting 3 folds for each of 100 candidates, totalling 300 fits

```
[CV] END bootstrap=True, max_depth=4, max_features=auto, min_samples_leaf=4, min_samples_
split=5, n_estimators=10; total time= 0.0s
[CV] END bootstrap=True, max_depth=4, max_features=auto, min_samples_leaf=4, min_samples_
split=5, n_estimators=10; total time= 0.0s
[CV] END bootstrap=True, max_depth=4, max_features=auto, min_samples_leaf=4, min_samples_
split=5, n_estimators=10; total time= 0.0s
[CV] END bootstrap=True, max_depth=None, max_features=auto, min_samples_leaf=4, min_sampl
es_split=2, n_estimators=10; total time= 0.0s
[CV] END bootstrap=True, max_depth=None, max_features=auto, min_samples_leaf=4, min_sampl
es_split=2, n_estimators=10; total time= 0.0s
[CV] END bootstrap=True, max_depth=None, max_features=auto, min_samples_leaf=4, min_sampl
es_split=2, n_estimators=10; total time= 0.1s
[CV] END bootstrap=True, max_depth=3, max_features=sqrt, min_samples_leaf=1, min_samples_
split=5, n_estimators=10; total time= 0.2s
[CV] END bootstrap=True, max_depth=3, max_features=sqrt, min_samples_leaf=1, min_samples_
split=5, n_estimators=10; total time= 0.2s
[CV] END bootstrap=True, max_depth=3, max_features=sqrt, min_samples_leaf=1, min_samples_
split=5, n_estimators=10; total time= 0.3s
[CV] END bootstrap=False, max_depth=None, max_features=auto, min_samples_leaf=2, min_samp
les_split=5, n_estimators=50; total time= 0.0s
[CV] END bootstrap=False, max_depth=None, max_features=auto, min_samples_leaf=2, min_samp
les_split=5, n_estimators=50; total time= 0.0s
[CV] END bootstrap=False, max_depth=None, max_features=auto, min_samples_leaf=2, min_samp
les_split=5, n_estimators=50; total time= 0.0s
[CV] END bootstrap=False, max_depth=4, max_features=auto, min_samples_leaf=1, min_samples_
_split=5, n_estimators=50; total time= 0.0s
[CV] END bootstrap=False, max_depth=4, max_features=auto, min_samples_leaf=1, min_samples_
_split=5, n_estimators=50; total time= 0.0s
[CV] END bootstrap=False, max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=2, n_estimators=10; total time= 1.1s
[CV] END bootstrap=False, max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=2, n_estimators=10; total time= 2.5s
[CV] END bootstrap=False, max_depth=None, max_features=sqrt, min_samples_leaf=4, min_samp
les_split=2, n_estimators=30; total time= 4.7s
[CV] END bootstrap=False, max_depth=None, max_features=sqrt, min_samples_leaf=4, min_samp
les_split=2, n_estimators=30; total time= 4.8s
[CV] END bootstrap=False, max_depth=None, max_features=sqrt, min_samples_leaf=4, min_samp
les_split=2, n_estimators=30; total time= 4.7s
[CV] END bootstrap=True, max_depth=None, max_features=sqrt, min_samples_leaf=1, min_sampl
es_split=10, n_estimators=10; total time= 0.7s
[CV] END bootstrap=True, max_depth=None, max_features=sqrt, min_samples_leaf=1, min_sampl
es_split=10, n_estimators=10; total time= 0.8s
[CV] END bootstrap=True, max_depth=6, max_features=sqrt, min_samples_leaf=4, min_samples_
split=2, n_estimators=30; total time= 0.9s
[CV] END bootstrap=False, max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samp
les_split=2, n_estimators=10; total time= 1.2s
[CV] END bootstrap=True, max_depth=None, max_features=sqrt, min_samples_leaf=1, min_sampl
es_split=10, n_estimators=10; total time= 1.1s
[CV] END bootstrap=True, max_depth=6, max_features=sqrt, min_samples_leaf=4, min_samples_
split=2, n_estimators=30; total time= 1.2s
[CV] END bootstrap=True, max_depth=6, max_features=sqrt, min_samples_leaf=2, min_samples_
split=5, n_estimators=30; total time= 1.3s
[CV] END bootstrap=True, max_depth=6, max_features=sqrt, min_samples_leaf=4, min_samples_
split=2, n_estimators=30; total time= 1.1s
[CV] END bootstrap=True, max_depth=4, max_features=auto, min_samples_leaf=2, min_samples_
split=10, n_estimators=30; total time= 0.0s
```

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

[illegible]

```
[CV] END bootstrap=True, max_depth=3, max_features=sqrt, min_samples_leaf=1, min_samples_split=5, n_estimators=30; total time= 0.5s
[CV] END bootstrap=True, max_depth=None, max_features=sqrt, min_samples_leaf=4, min_samples_split=5, n_estimators=10; total time= 0.7s
[CV] END bootstrap=False, max_depth=3, max_features=sqrt, min_samples_leaf=4, min_samples_split=2, n_estimators=10; total time= 0.2s
[CV] END bootstrap=False, max_depth=3, max_features=sqrt, min_samples_leaf=4, min_samples_split=2, n_estimators=10; total time= 0.2s
[CV] END bootstrap=True, max_depth=3, max_features=auto, min_samples_leaf=1, min_samples_split=5, n_estimators=50; total time= 0.0s
[CV] END bootstrap=True, max_depth=3, max_features=auto, min_samples_leaf=1, min_samples_split=5, n_estimators=50; total time= 0.0s
[CV] END bootstrap=True, max_depth=3, max_features=auto, min_samples_leaf=1, min_samples_split=5, n_estimators=50; total time= 0.0s
[CV] END bootstrap=True, max_depth=None, max_features=sqrt, min_samples_leaf=4, min_samples_split=5, n_estimators=10; total time= 0.6s
[CV] END bootstrap=True, max_depth=3, max_features=sqrt, min_samples_leaf=4, min_samples_split=2, n_estimators=10; total time= 0.2s
[CV] END bootstrap=True, max_depth=3, max_features=sqrt, min_samples_leaf=4, min_samples_split=2, n_estimators=10; total time= 0.2s
[CV] END bootstrap=True, max_depth=3, max_features=sqrt, min_samples_leaf=4, min_samples_split=2, n_estimators=10; total time= 0.2s
[CV] END bootstrap=True, max_depth=None, max_features=sqrt, min_samples_leaf=4, min_samples_split=5, n_estimators=10; total time= 0.7s
[CV] END bootstrap=False, max_depth=3, max_features=sqrt, min_samples_leaf=4, min_samples_split=2, n_estimators=10; total time= 0.2s
[CV] END bootstrap=False, max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samples_split=5, n_estimators=30; total time= 2.7s
[CV] END bootstrap=False, max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samples_split=5, n_estimators=30; total time= 2.8s
[CV] END bootstrap=False, max_depth=None, max_features=auto, min_samples_leaf=1, min_samples_split=2, n_estimators=10; total time= 0.0s
[CV] END bootstrap=False, max_depth=None, max_features=auto, min_samples_leaf=1, min_samples_split=2, n_estimators=10; total time= 0.0s
[CV] END bootstrap=False, max_depth=None, max_features=auto, min_samples_leaf=1, min_samples_split=2, n_estimators=10; total time= 0.0s
[CV] END bootstrap=False, max_depth=None, max_features=sqrt, min_samples_leaf=2, min_samples_split=5, n_estimators=30; total time= 2.9s
```

Out[63]:

```
► RandomizedSearchCV i ?
► estimator: RandomForestClassifier
► RandomForestClassifier ?
```

In [65]:

```
rf_random.best_params_
```

Out[65]:

```
{'n_estimators': 30,
 'min_samples_split': 5,
 'min_samples_leaf': 2,
 'max_features': 'sqrt',
 'max_depth': 6,
 'bootstrap': True}
```

In [67]:

```
LR = LogisticRegression()
#fitting the model
LR.fit(X_train, y_train)

#prediction
y_pred = LR.predict(X_test)

#Accuracy
accuracy = LR.score(X_test, y_test)
```

```

print("Accuracy ", LR.score(X_test, y_test)*100)

# recall
recall = recall_score(y_test, y_pred)
print("recall ", recall_score(y_test, y_pred))

# F1
f1 = f1_score(y_test, y_pred)
print("f1 ",f1_score(y_test, y_pred) )

# Precision
precision = precision_score(y_test, y_pred)
print("precision ",precision_score(y_test, y_pred))

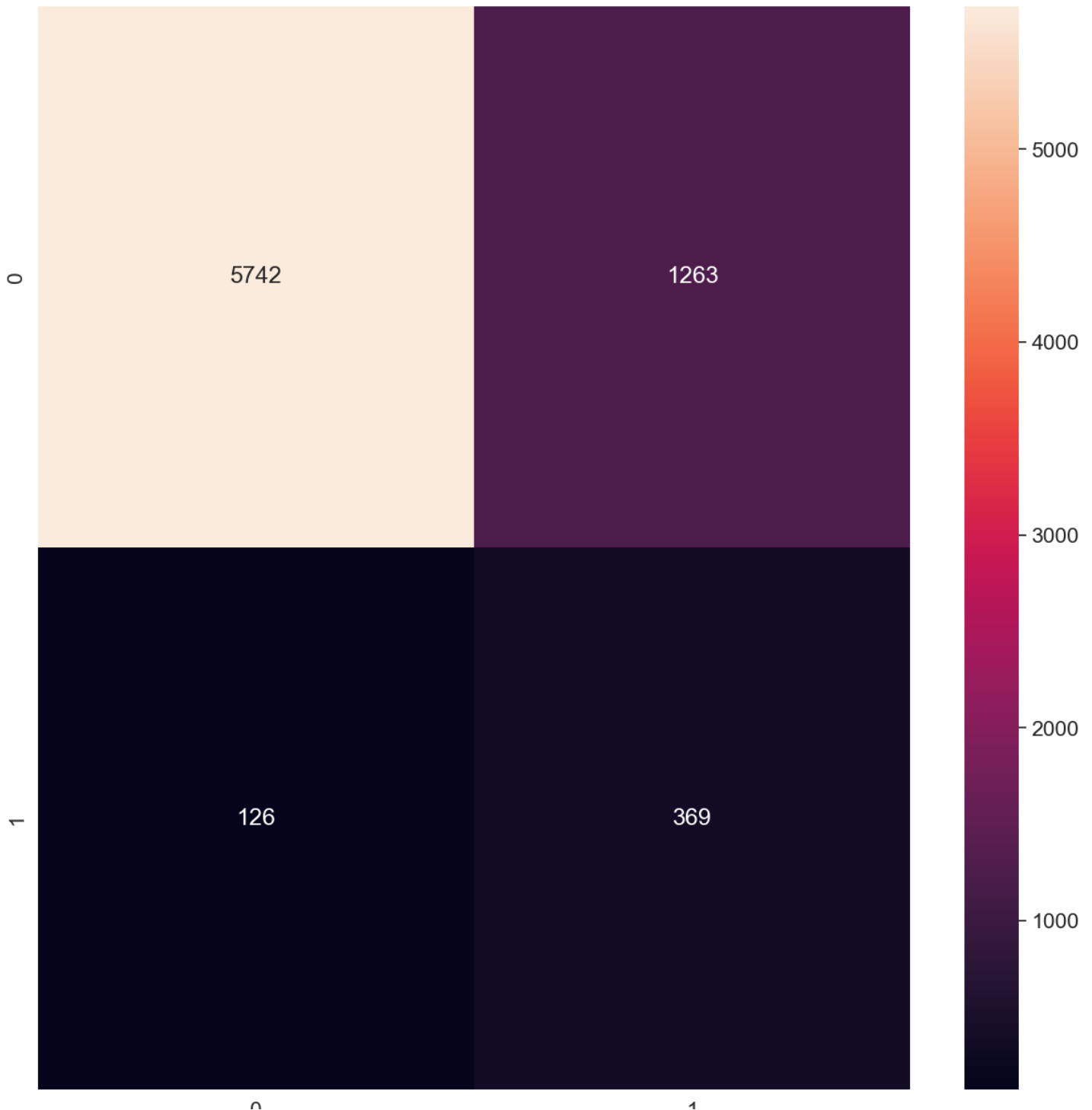
#Plot the confusion matrix
sns.set(font_scale=1.5)
cm = confusion_matrix(y_pred, y_test)
sns.heatmap(cm, annot=True, fmt='g')
plt.show()

```

```

Accuracy  81.47999999999999
recall    0.2261029411764706
f1         0.3469675599435825
precision  0.7454545454545455

```



in conclusion, LR Accuracy 81.47999999999999 recall 0.2261029411764706 f1 0.3469675599435825 precision 0.7454545454545455

XGB Accuracy 78.24 recall 0.0 f1 0.0 precision 0.0

Decision tree Accuracy 81.42666666666668 recall 0.3247549019607843 f1 0.4321239298817774 precision 0.6455542021924482

Random forest Accuracy 81.72 recall 0.3633578431372549 f1 0.4638247946812671 precision 0.6410810810810811

using F1 score, the best model is Random forest followed by Decision tree and both precision, recall and accuracy are almost in the same range