BT2103_Group_3_Jupyter_Notebook

April 13, 2023

1 Introduction

This dataset is taken from https://www.kaggle.com/datasets/uciml/default-of-credit-card-clients-dataset and it contains information on 30,000 credit card holders from a bank in Taiwan. Each credit card holder is described by 23 feature attributes as outlined below.

1.1 Data Modelling Problem

We aim to predict whether a credit card holder will be defauting his payment in the next month.

1.2 Feature Descriptions

Client info

- ID: ID of each client
- LIMIT_BAL: Amount of given credit in NT dollars (includes individual and family/supplementary credit)
- SEX: Gender (1=male, 2=female)
- EDUCATION: (1=graduate school, 2=university, 3=high school, 4=others, 5=unknown, 6=unknown)
- MARRIAGE: Marital status (1=married, 2=single, 3=others)
- AGE: Age in years

Payment *(-2 = No consumption; -1 = Paid in full; 0 = The use of revolving credit (Customer paid amount due, but not all); 1 = payment delay for one month; 2 = payment delay for two months;…; 8 = payment delay for eight months; 9 = payment delay for nine months and above.)* https://www.kaggle.com/datasets/uciml/default-of-credit-card-clients-dataset/discussion/34608

- PAY_0: Repayment status in September, 2005
- PAY_2: Repayment status in August, 2005 (scale same as above)
- PAY_3: Repayment status in July, 2005 (scale same as above)
- PAY_4: Repayment status in June, 2005 (scale same as above)
- PAY_5: Repayment status in May, 2005 (scale same as above)
- PAY_6: Repayment status in April, 2005 (scale same as above)

Bill Statement *(Possible to have negative values –> Overpayment)*

- BILL_AMT1: Amount of bill statement in September, 2005 (NT dollar)
- BILL_AMT2: Amount of bill statement in August, 2005 (NT dollar)
- BILL_AMT3: Amount of bill statement in July, 2005 (NT dollar)
- BILL_AMT4: Amount of bill statement in June, 2005 (NT dollar)

- BILL_AMT5: Amount of bill statement in May, 2005 (NT dollar)
- BILL_AMT6: Amount of bill statement in April, 2005 (NT dollar)

Previous Payment

- PAY_AMT1: Amount of previous payment in September, 2005 (NT dollar)
- PAY_AMT2: Amount of previous payment in August, 2005 (NT dollar)
- PAY_AMT3: Amount of previous payment in July, 2005 (NT dollar)
- PAY_AMT4: Amount of previous payment in June, 2005 (NT dollar)
- PAY_AMT5: Amount of previous payment in May, 2005 (NT dollar)
- PAY_AMT6: Amount of previous payment in April, 2005 (NT dollar)

Target Variable

- default.payment.next.month: Default payment (1=yes, 0=no)

2 Importing Libraries

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

import seaborn as sns

from sklearn.linear_model import LogisticRegression, LinearRegression
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score,␣
↪recall_score, roc_auc_score, classification_report, roc_curve
from sklearn.model_selection import GridSearchCV, train_test_split
from sklearn.preprocessing import StandardScaler, MinMaxScaler
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.feature_selection import chi2, SelectKBest
from mlxtend.feature_selection import SequentialFeatureSelector as sfs

import tensorflow as tf
from scikeras.wrappers import KerasClassifier

from xgboost import XGBClassifier

from imblearn.over_sampling import SMOTE
```

3 Exploratory Data Analysis

[2]:
```
data = pd.read_csv("./card.csv", index_col=0, header=1)

data.head()
```

[2]:
```
    LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_0  PAY_2  PAY_3  PAY_4  \
ID
1       20000    2          2         1   24      2      2     -1     -1
2      120000    2          2         2   26     -1      2      0      0
3       90000    2          2         2   34      0      0      0      0
4       50000    2          2         1   37      0      0      0      0
5       50000    1          2         1   57     -1      0     -1      0

    PAY_5  …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  \
ID         …
1      -2  …          0          0          0         0       689         0
2       0  …       3272       3455       3261         0      1000      1000
3       0  …      14331      14948      15549      1518      1500      1000
4       0  …      28314      28959      29547      2000      2019      1200
5       0  …      20940      19146      19131      2000     36681     10000

    PAY_AMT4  PAY_AMT5  PAY_AMT6  default payment next month
ID
1          0         0         0                           1
2       1000         0      2000                           1
3       1000      1000      5000                           0
4       1100      1069      1000                           0
5       9000       689       679                           0

[5 rows x 24 columns]
```

[3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 30000 entries, 1 to 30000
Data columns (total 24 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   LIMIT_BAL                   30000 non-null  int64
 1   SEX                         30000 non-null  int64
 2   EDUCATION                   30000 non-null  int64
 3   MARRIAGE                    30000 non-null  int64
 4   AGE                         30000 non-null  int64
 5   PAY_0                       30000 non-null  int64
 6   PAY_2                       30000 non-null  int64
 7   PAY_3                       30000 non-null  int64
 8   PAY_4                       30000 non-null  int64
 9   PAY_5                       30000 non-null  int64
 10  PAY_6                       30000 non-null  int64
 11  BILL_AMT1                   30000 non-null  int64
 12  BILL_AMT2                   30000 non-null  int64
 13  BILL_AMT3                   30000 non-null  int64
 14  BILL_AMT4                   30000 non-null  int64
```

```
 15  BILL_AMT5                   30000 non-null  int64
 16  BILL_AMT6                   30000 non-null  int64
 17  PAY_AMT1                    30000 non-null  int64
 18  PAY_AMT2                    30000 non-null  int64
 19  PAY_AMT3                    30000 non-null  int64
 20  PAY_AMT4                    30000 non-null  int64
 21  PAY_AMT5                    30000 non-null  int64
 22  PAY_AMT6                    30000 non-null  int64
 23  default payment next month  30000 non-null  int64
dtypes: int64(24)
memory usage: 5.7 MB
```

[4]:

```
data.describe()
```

[4]:

```
             LIMIT_BAL           SEX     EDUCATION      MARRIAGE           AGE  \
count     30000.000000  30000.000000  30000.000000  30000.000000  30000.000000
mean     167484.322667      1.603733      1.853133      1.551867     35.485500
std      129747.661567      0.489129      0.790349      0.521970      9.217904
min       10000.000000      1.000000      0.000000      0.000000     21.000000
25%       50000.000000      1.000000      1.000000      1.000000     28.000000
50%      140000.000000      2.000000      2.000000      2.000000     34.000000
75%      240000.000000      2.000000      2.000000      2.000000     41.000000
max     1000000.000000      2.000000      6.000000      3.000000     79.000000

              PAY_0         PAY_2         PAY_3         PAY_4         PAY_5  \
count  30000.000000  30000.000000  30000.000000  30000.000000  30000.000000
mean      -0.016700     -0.133767     -0.166200     -0.220667     -0.266200
std        1.123802      1.197186      1.196868      1.169139      1.133187
min       -2.000000     -2.000000     -2.000000     -2.000000     -2.000000
25%       -1.000000     -1.000000     -1.000000     -1.000000     -1.000000
50%        0.000000      0.000000      0.000000      0.000000      0.000000
75%        0.000000      0.000000      0.000000      0.000000      0.000000
max        8.000000      8.000000      8.000000      8.000000      8.000000

       …      BILL_AMT4      BILL_AMT5      BILL_AMT6       PAY_AMT1  \
count  …   30000.000000   30000.000000   30000.000000   30000.000000
mean   …   43262.948967   40311.400967   38871.760400    5663.580500
std    …   64332.856134   60797.155770   59554.107537   16563.280354
min    … -170000.000000  -81334.000000 -339603.000000       0.000000
25%    …    2326.750000    1763.000000    1256.000000    1000.000000
50%    …   19052.000000   18104.500000   17071.000000    2100.000000
75%    …   54506.000000   50190.500000   49198.250000    5006.000000
max    …  891586.000000  927171.000000  961664.000000  873552.000000

           PAY_AMT2     PAY_AMT3       PAY_AMT4       PAY_AMT5  \
count  3.000000e+04  30000.00000   30000.000000   30000.000000
mean   5.921163e+03   5225.68150    4826.076867    4799.387633
```

```
std     2.304087e+04   17606.96147   15666.159744   15278.305679
min     0.000000e+00       0.00000       0.000000       0.000000
25%     8.330000e+02     390.00000     296.000000     252.500000
50%     2.009000e+03    1800.00000    1500.000000    1500.000000
75%     5.000000e+03    4505.00000    4013.250000    4031.500000
max     1.684259e+06  896040.00000  621000.000000  426529.000000

             PAY_AMT6  default payment next month
count    30000.000000                30000.000000
mean      5215.502567                    0.221200
std      17777.465775                    0.415062
min          0.000000                    0.000000
25%        117.750000                    0.000000
50%       1500.000000                    0.000000
75%       4000.000000                    0.000000
max     528666.000000                    1.000000

[8 rows x 24 columns]
```

From the output above, we observe that there are no missing data entries in the dataset, however, there are potential outliers that will have to be cleaned later on.

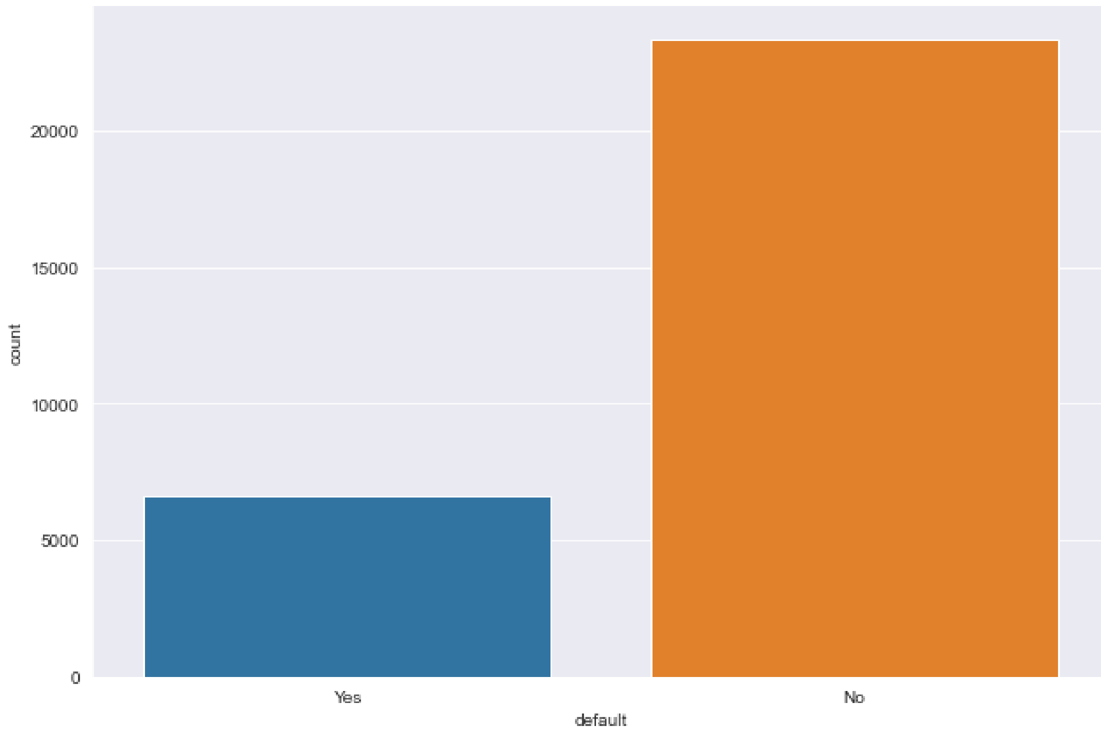
[5]:
```python
## Renaming Target Variable Column
data.rename(columns={"default payment next month": "default"}, inplace=True)
```

[6]:
```python
## Renaming "PAY_0" to "PAY_1" for consistency
data.rename(columns={"PAY_0" : "PAY_1"}, inplace=True)
```

3.1 Analysis of the Target Variable (Default)

[7]:
```python
default = data[["default"]]
default = default.replace({1:"Yes", 0:"No"})
sns.catplot(data=default, x="default", height=6, aspect=1.5, kind="count")
```

[7]:
```
<seaborn.axisgrid.FacetGrid at 0x298abda30>
```

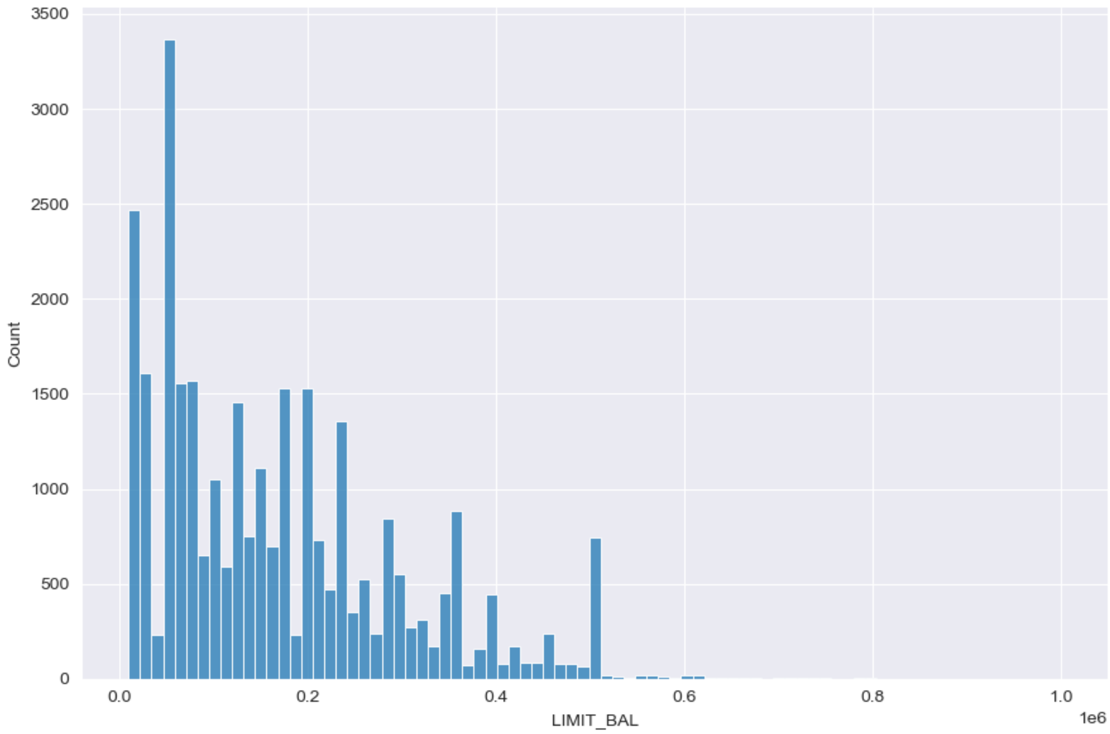


We observe that the number of defaulters is significantly lesser than the amount of non defaulters in the given dataset

3.2 Analysis of amount of given credit (LIMIT_BAL)

[8]:
```
sns.displot(data=data, x="LIMIT_BAL", height=6, aspect=1.5)
```

[8]:
```
<seaborn.axisgrid.FacetGrid at 0x298f9b520>
```



The amount of credit given to card-holders is not normally distributed. It is right skewed.

3.3 Analysis on SEX

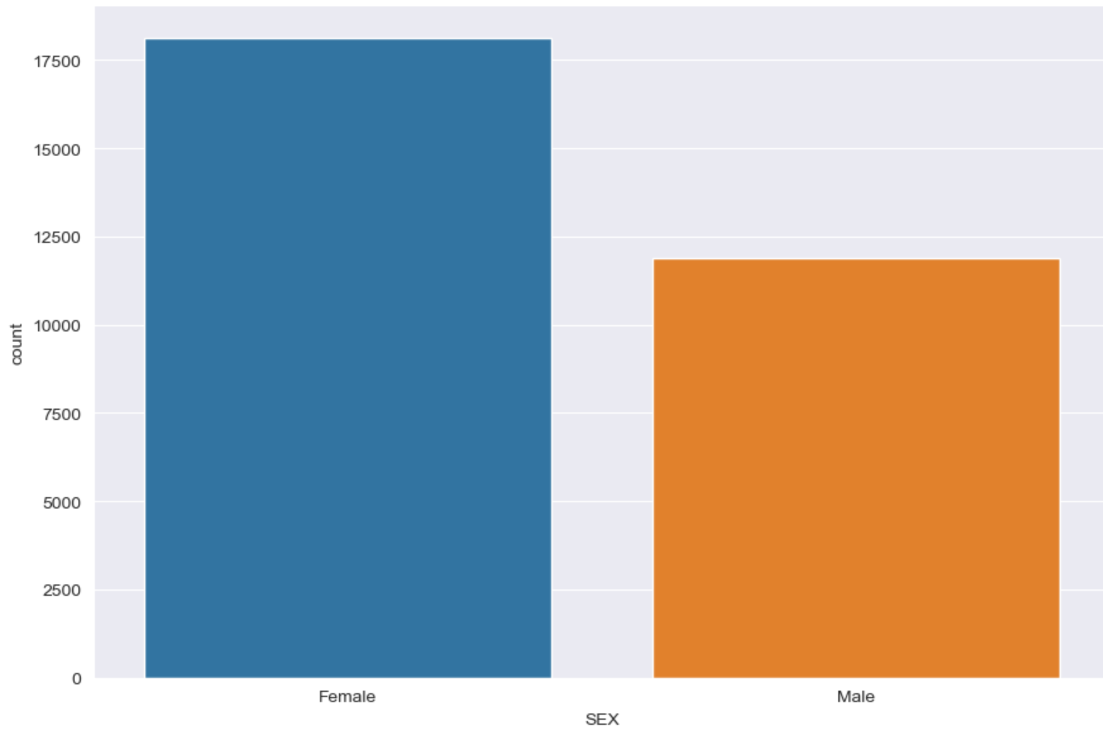
[9]:
```
sex = data["SEX"].replace({1:"Male", 2:"Female"})
sex.value_counts()
```

[9]:
```
Female    18112
Male      11888
Name: SEX, dtype: int64
```

[10]:
```
sex = sex.reset_index()
```

[11]:
```
sns.catplot(data=sex, x="SEX", kind="count", height=6, aspect=1.5)
```

[11]:
```
<seaborn.axisgrid.FacetGrid at 0x298eda850>
```



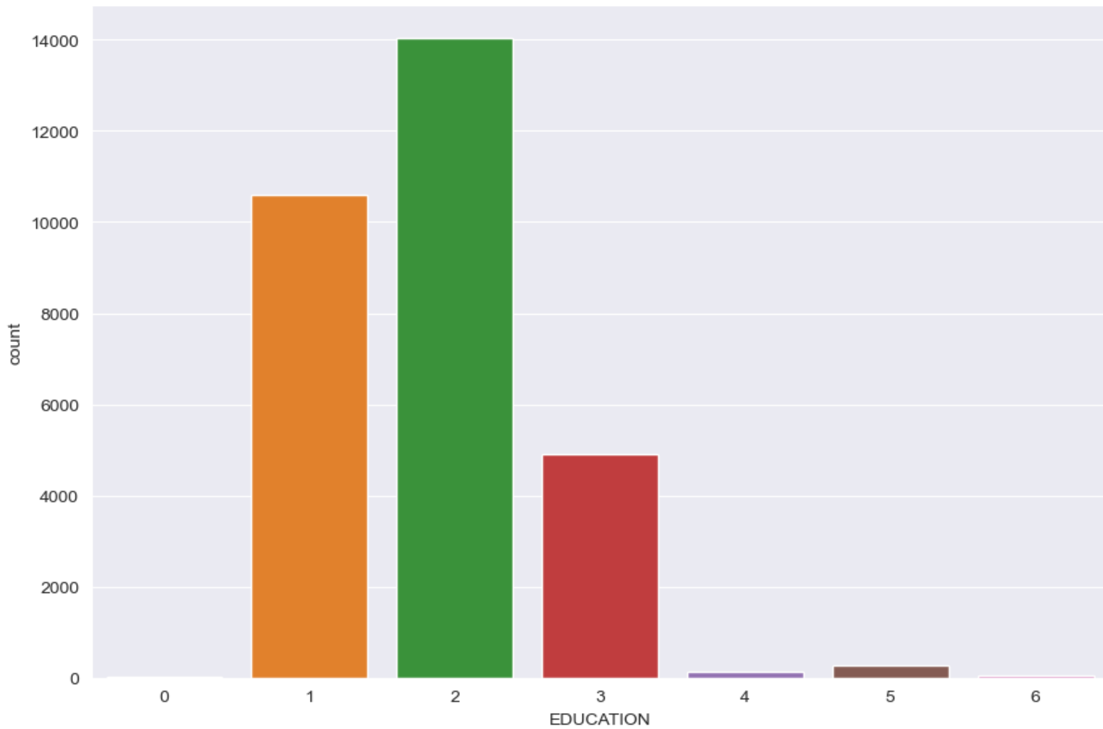
[12]:
```
# convert the "SEX" column to map 0=male, 1=female instead of 1=male, 2=female
data["SEX"] = data["SEX"] - 1
data["SEX"].value_counts()
```

[12]:
```
1    18112
0    11888
Name: SEX, dtype: int64
```

3.4 Analysis on Education

[13]:
```
sns.catplot(data=data, kind="count", x="EDUCATION", height=6, aspect=1.5)
```

[13]:
```
<seaborn.axisgrid.FacetGrid at 0x299190e50>
```

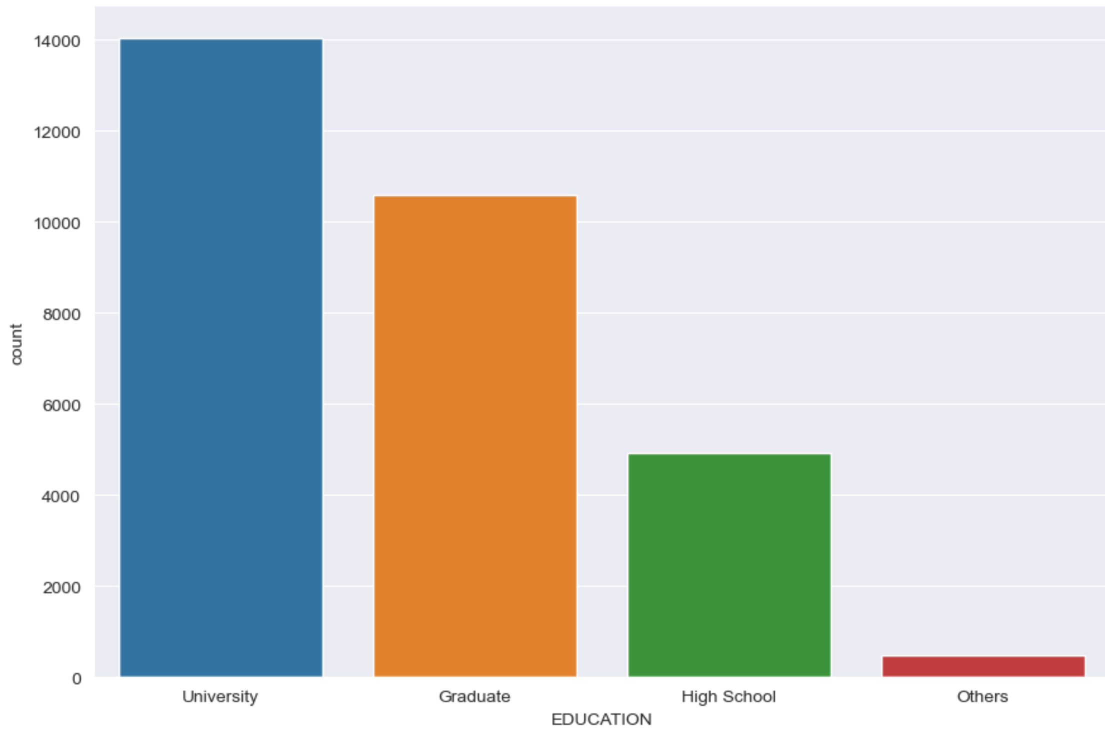


[14]:
```
# We observe additional EDUCATION categories (0, 5, 6)
# We will convert them to others (4)
data["EDUCATION"] = data["EDUCATION"].replace({0:4, 5:4, 6:4})
data['EDUCATION'].value_counts()
```

[14]:
```
2    14030
1    10585
3     4917
4      468
Name: EDUCATION, dtype: int64
```

[15]:
```
education = data[["EDUCATION"]].replace({1:"Graduate", 2:"University", 3:"High␣
↪School", 4:"Others"})
sns.catplot(data=education, kind="count", x="EDUCATION", height=6, aspect=1.5)
```

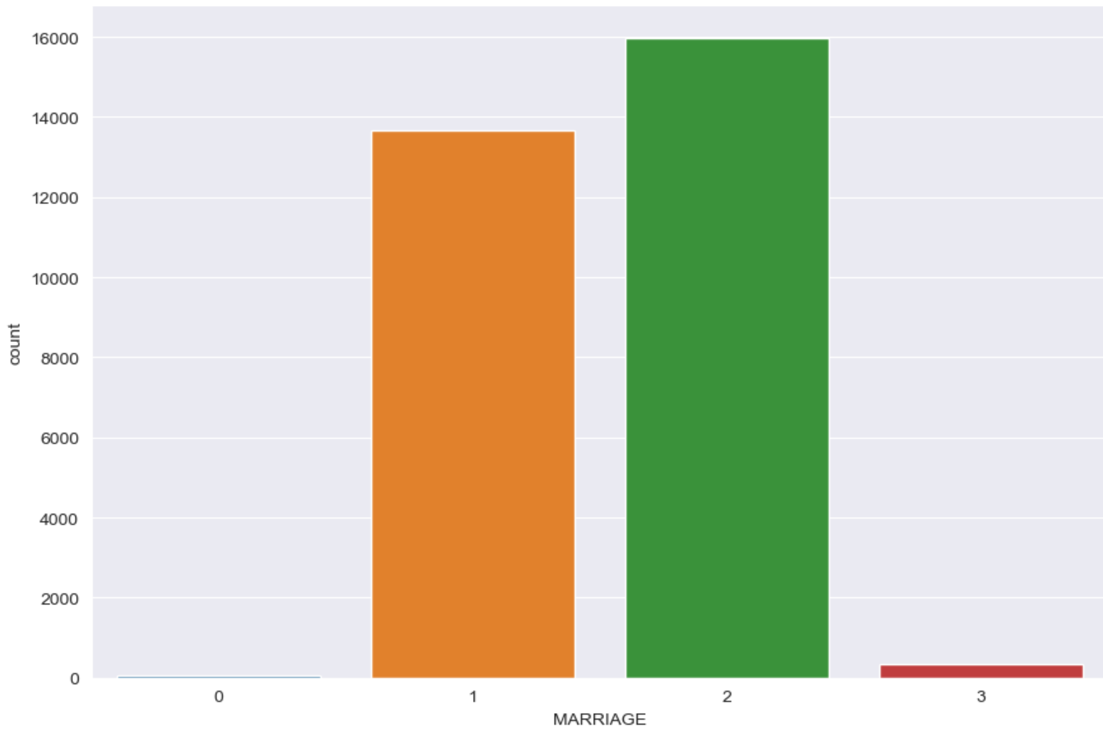
[15]:
```
<seaborn.axisgrid.FacetGrid at 0x2991bad30>
```



3.5 Analysis of Marriage

[16]:
```
sns.catplot(data=data, kind="count", x="MARRIAGE", height=6, aspect=1.5)
```

[16]: <seaborn.axisgrid.FacetGrid at 0x2992b15b0>

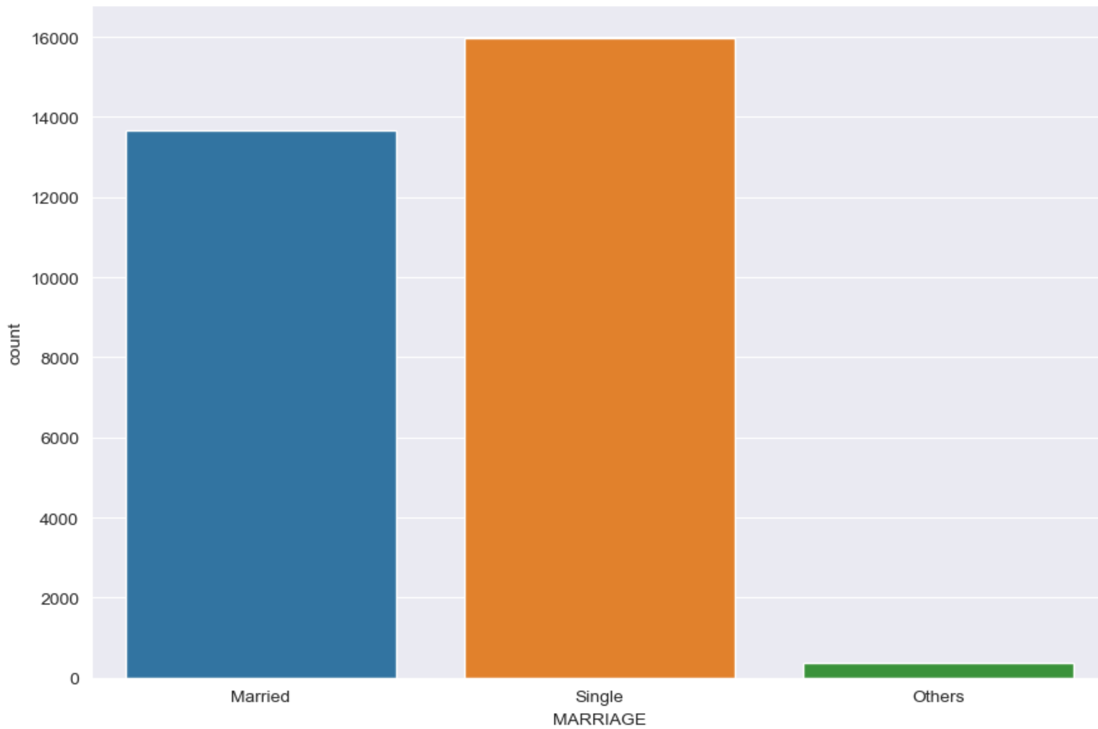


[17]:
```
# 0 value for marriage will be converted to 3 (others)
data["MARRIAGE"] = data["MARRIAGE"].replace({0:3})
data['MARRIAGE'].value_counts()
```

[17]:
```
2    15964
1    13659
3      377
Name: MARRIAGE, dtype: int64
```

[18]:
```
marriage = data[["MARRIAGE"]].replace({1:"Married", 2:"Single", 3:"Others"})
sns.catplot(data=marriage, kind="count", x="MARRIAGE", height=6, aspect=1.5)
```

[18]:
```
<seaborn.axisgrid.FacetGrid at 0x299258790>
```



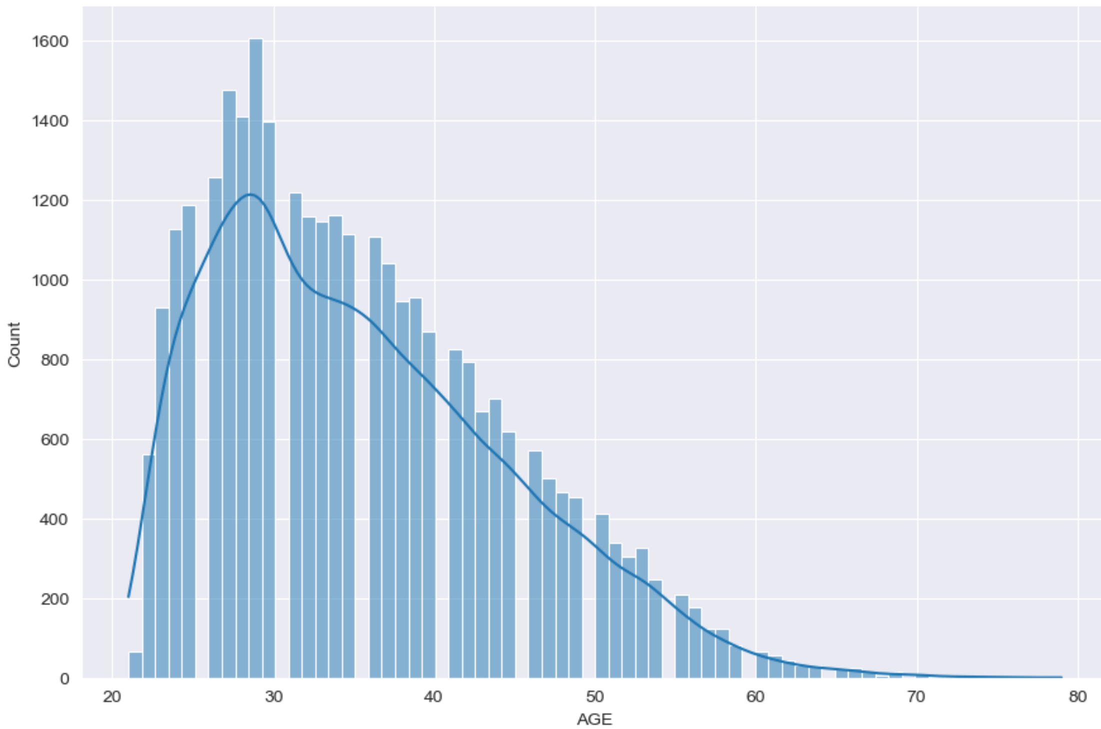
3.6 Analysis of Age

[19]:
```
data["AGE"].describe()
```

[19]:
```
count    30000.000000
mean        35.485500
std          9.217904
min         21.000000
25%         28.000000
50%         34.000000
75%         41.000000
max         79.000000
Name: AGE, dtype: float64
```

[20]:
```
# Age distribution looks approximately normally distributed
sns.displot(data = data, x = "AGE", height=6, aspect=1.5, kde=True)
```

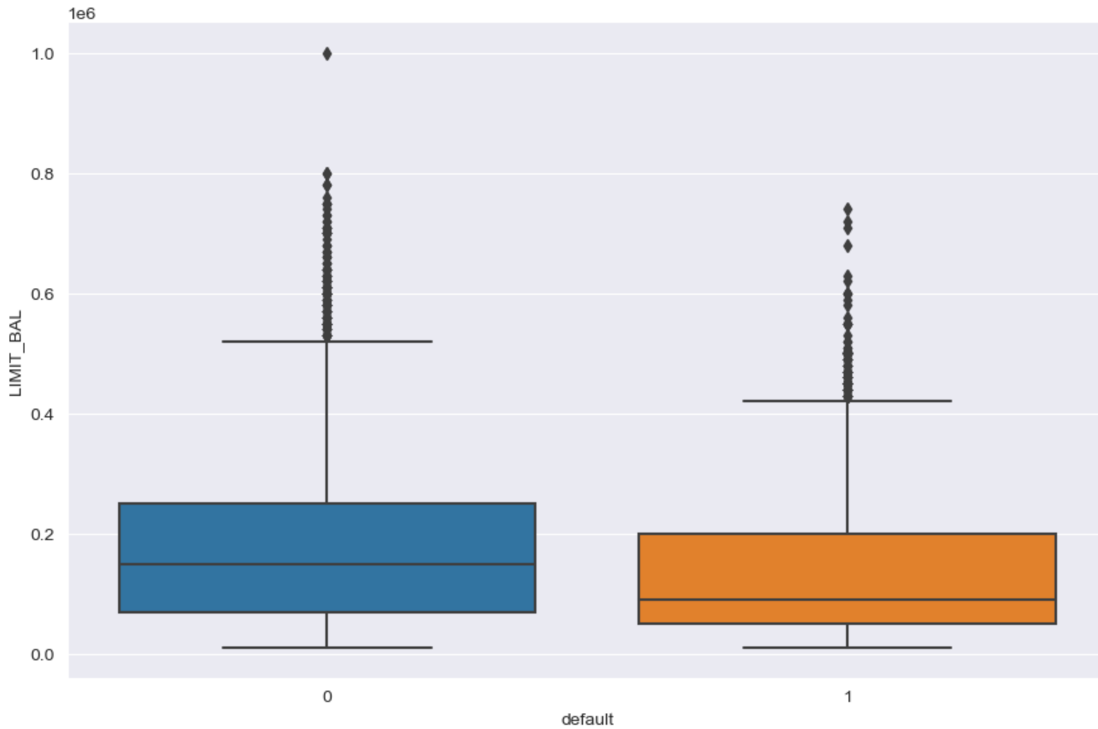
[20]:
```
<seaborn.axisgrid.FacetGrid at 0x2992c6850>
```



3.7 Investigating relationship between Limit Balance and Default

[21]:
```
sns.catplot(data=data, x="default", y="LIMIT_BAL", kind="box", height=6,␣
↪aspect=1.5)
```

[21]:
```
<seaborn.axisgrid.FacetGrid at 0x154180e20>
```

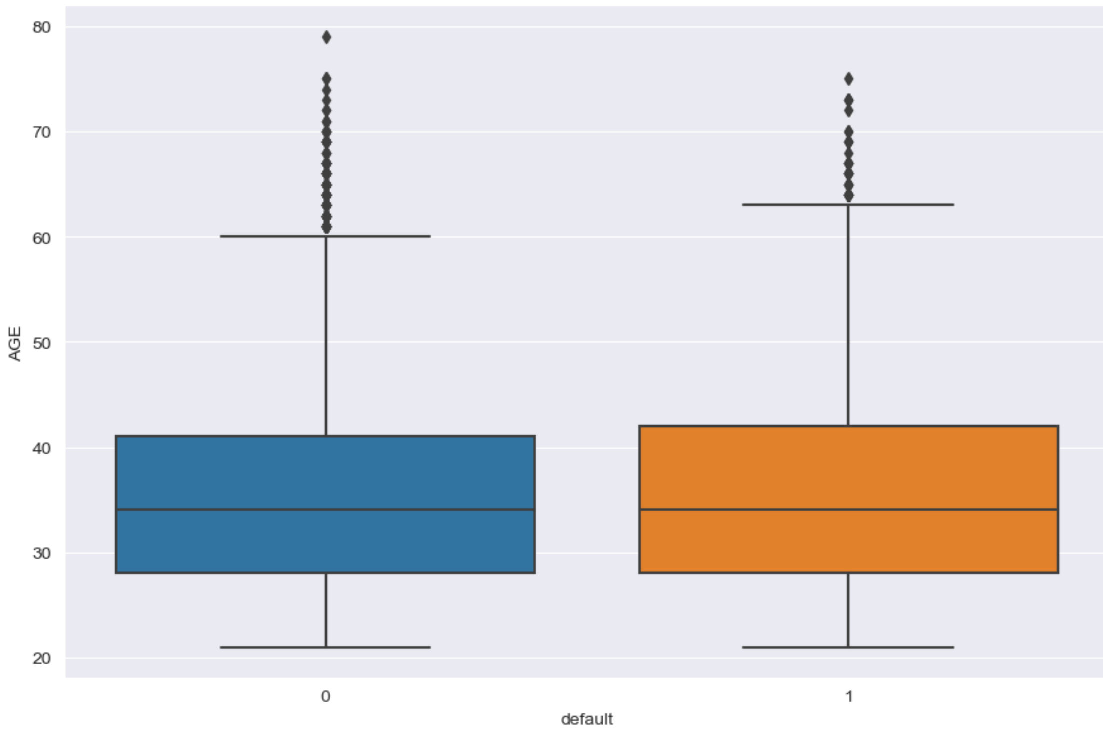


We had expected defaulters to have been given a higher credit, but the boxplot does not seem to show such a relationship

3.8 Investigating relationship between AGE and Default

[22]:
```
sns.catplot(data=data, y="AGE", x="default", kind="box", height=6, aspect=1.5)
```

[22]:
```
<seaborn.axisgrid.FacetGrid at 0x299224cd0>
```

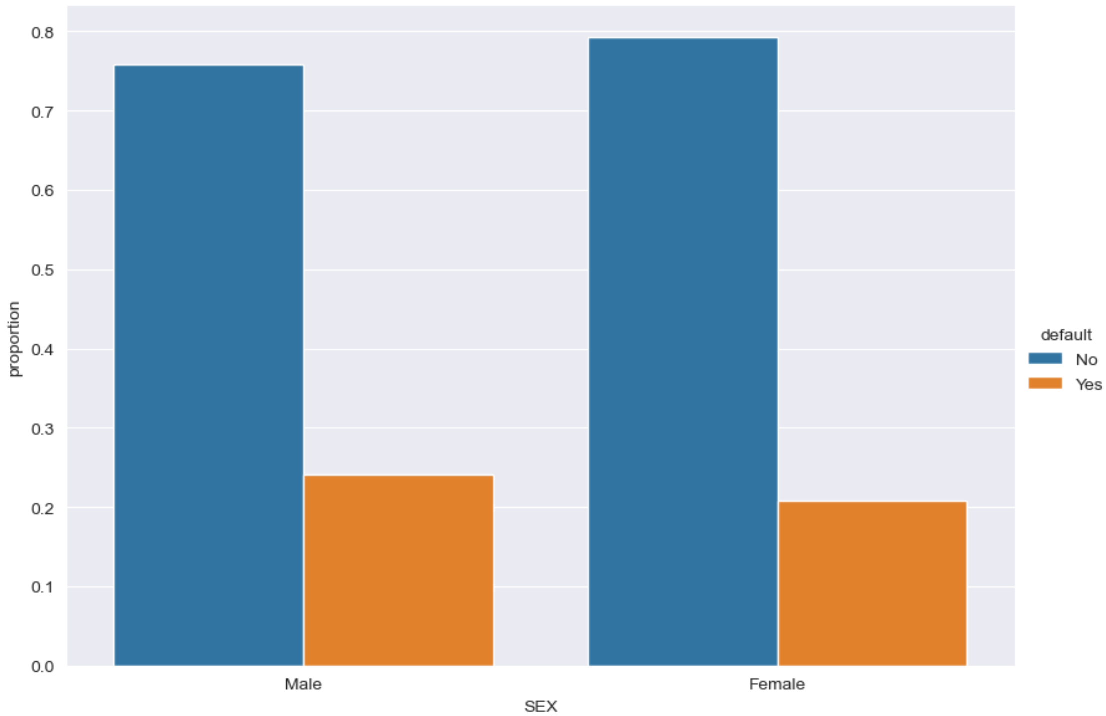


Whether a person defaults on his payment or not does not seem to be influenced by a person's age

3.9 Investigating relationship between Sex and Defaults

[23]:
```
# creating proportions
sex_default = data["default"].groupby(data["SEX"]).value_counts(normalize=True).
↪rename("proportion").reset_index()

# renaming
sex_default["SEX"] = sex_default[["SEX"]].replace({0:"Male", 1:"Female"})
sex_default["default"] = sex_default[["default"]].replace({0:"No", 1:"Yes"})

# plotting
sns.catplot(data=sex_default, x="SEX", y="proportion", kind="bar",␣
↪hue="default", height=6, aspect = 1.4)

## Stacked
# sex_default.pivot(index="SEX", columns = ["default"], values="proportion").
↪plot(kind='bar', stacked=True, color=['steelblue', 'red'])
```

[23]:
```
<seaborn.axisgrid.FacetGrid at 0x299190d00>
```

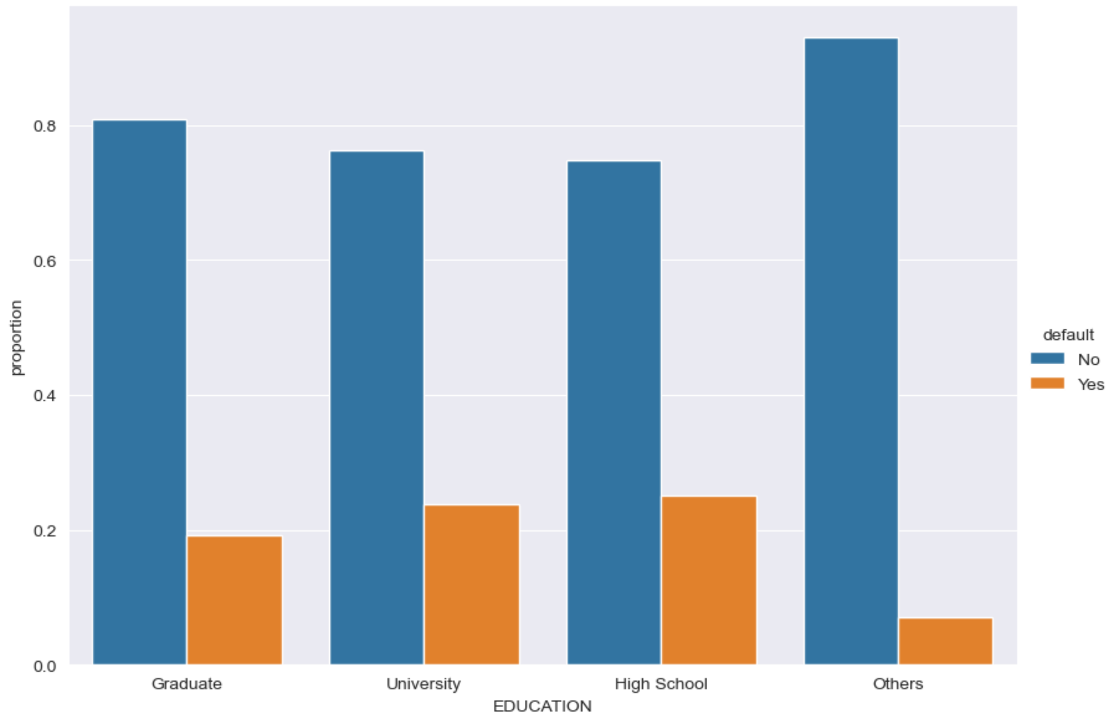


It would appear from the barplot, that a larger proportion of males (1) default as compared to females (2).

3.10 Investigating relationship between Education and Default

[24]:
```
# creating proportions
edu_default = data["default"].groupby(data["EDUCATION"]).
    ↪value_counts(normalize=True).rename("proportion").reset_index()

# renaming
edu_default["EDUCATION"] = edu_default[["EDUCATION"]].replace({1:"Graduate", 2:
    ↪"University", 3:"High School", 4:"Others"})
edu_default["default"] = edu_default[["default"]].replace({0:"No", 1:"Yes"})

# plotting
sns.catplot(data=edu_default, x="EDUCATION", y="proportion", kind="bar",␣
    ↪hue="default", height=6, aspect = 1.4)
```

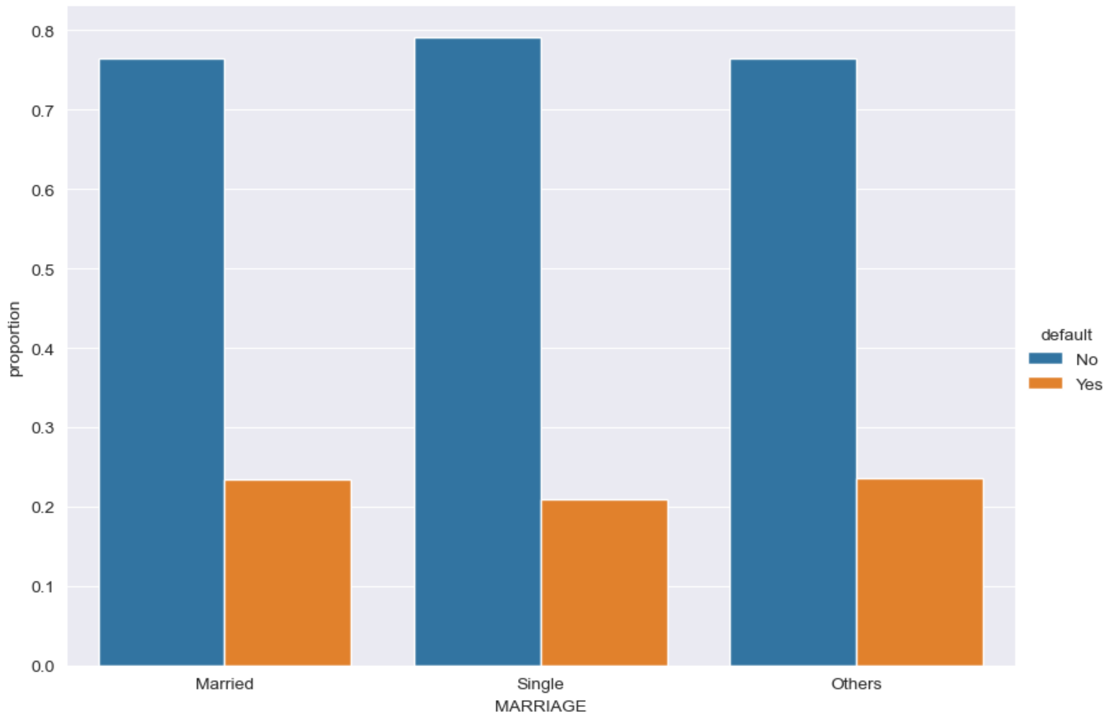
[24]: <seaborn.axisgrid.FacetGrid at 0x29cdf7340>



From the proportion barplot as shown above, there is a higher proportion of people who are defaulting if their education levels is 2 (university), 3 (high school), compared to those who have education levels of 1 (graduate school) or 4 (others).

3.11 Investigating relationship between Marital Status and Default

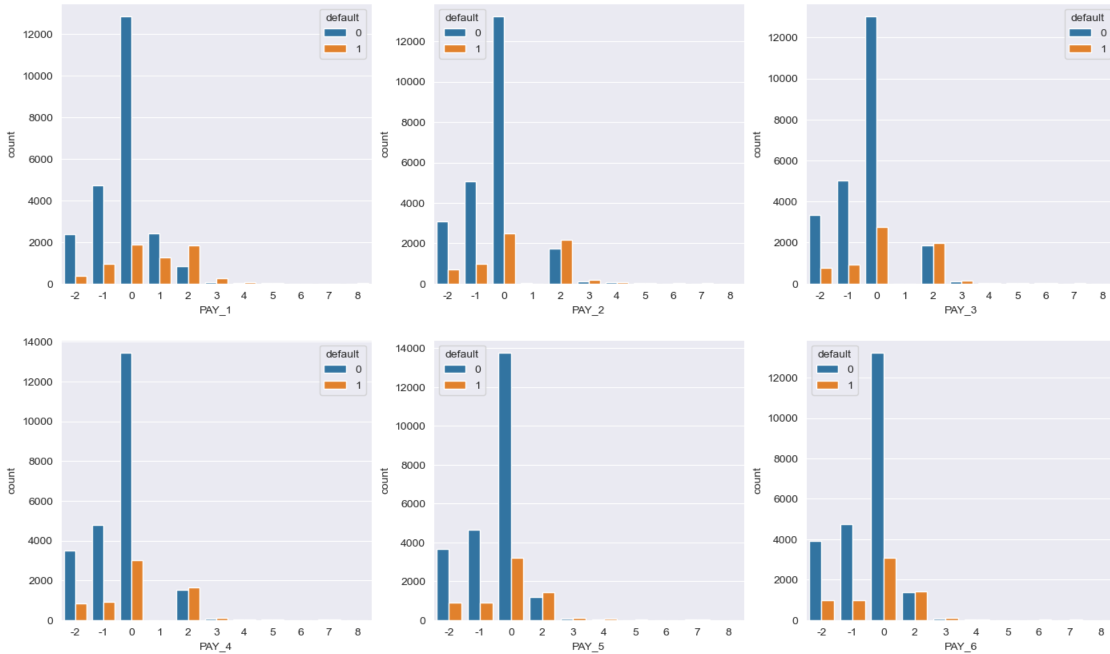
[25]:
```
# creating proportions
marriage_default = data["default"].groupby(data["MARRIAGE"]).
    ↪value_counts(normalize=True).rename("proportion").reset_index()

# renaming
marriage_default["MARRIAGE"] = marriage_default["MARRIAGE"].replace({3:␣
    ↪"Others", 2:"Single", 1:"Married"})
marriage_default["default"] = marriage_default["default"].replace({1: "Yes", 0:␣
    ↪"No"})

# plotting
sns.catplot(data=marriage_default, x="MARRIAGE", y="proportion", kind="bar",␣
    ↪hue="default", height=6, aspect = 1.4);
```



From the proportion barplots as shown above, it would seem that people who are married (1) are more likely to default on their payments as compared to those who are single.

3.12 Analysis on Repayment Status for 6 months, from April - September 2005

[26]:
```
fig, ax = plt.subplots(nrows = 2, ncols = 3, figsize = (17, 10))
sns.countplot(x = "PAY_1", hue = "default", data = data, ax = ax[0, 0])
sns.countplot(x = "PAY_2", hue = "default", data = data, ax = ax[0, 1])
sns.countplot(x = "PAY_3", hue = "default", data = data, ax = ax[0, 2])
sns.countplot(x = "PAY_4", hue = "default", data = data, ax = ax[1, 0])
sns.countplot(x = "PAY_5", hue = "default", data = data, ax = ax[1, 1])
sns.countplot(x = "PAY_6", hue = "default", data = data, ax = ax[1, 2])
plt.show()
```



Majority of non-defaulters pay on time indicated by the 0 value. However, we can observe that those who pay late are more likely to be defaulters (orange bar is larger than blue bar). As such, we will merge payments that are 1, 2 … 8 as late, indicated by 1, and payments that are on time , -2, -1, 0, as on time, indicated by 0.

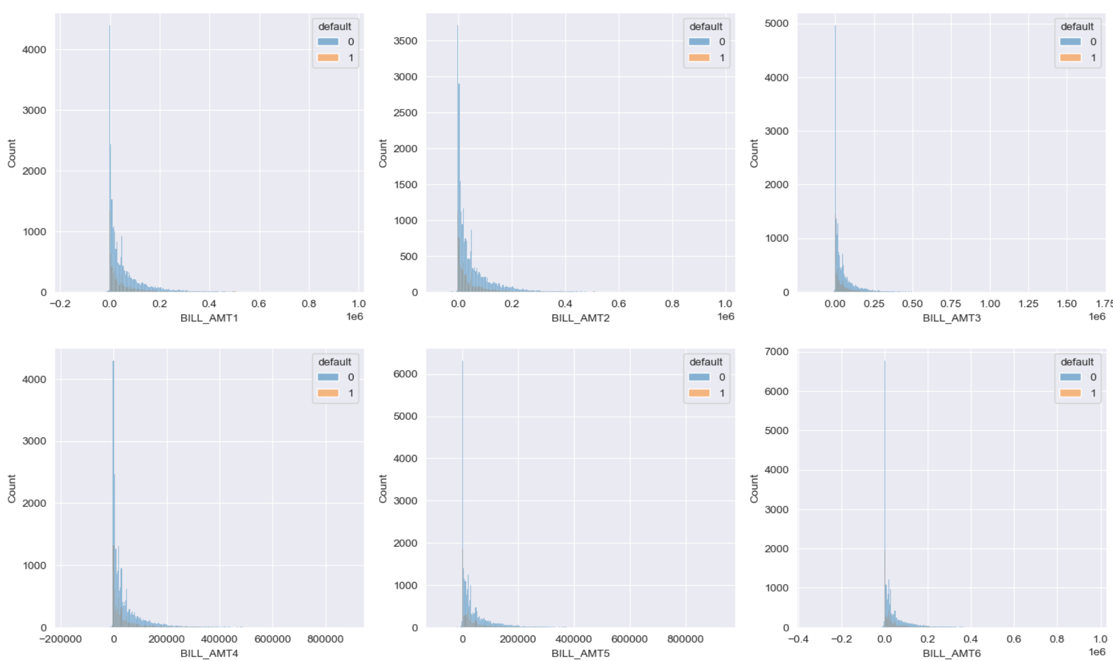
[27]:
```
columns = ["PAY_1","PAY_2","PAY_3","PAY_4","PAY_5","PAY_6"]

for column in columns:
    data[column] = data[column].apply(lambda x: 0 if x <= 0 else 1)

data.head()
```

[27]:
```
    LIMIT_BAL  SEX  EDUCATION  MARRIAGE  AGE  PAY_1  PAY_2  PAY_3  PAY_4  \
ID
1       20000    1          2         1   24      1      1      0      0
2      120000    1          2         2   26      0      1      0      0
3       90000    1          2         2   34      0      0      0      0
4       50000    1          2         1   37      0      0      0      0
5       50000    0          2         1   57      0      0      0      0

    PAY_5  …  BILL_AMT4  BILL_AMT5  BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  \
ID         …
1       0  …          0          0          0         0       689         0
2       0  …       3272       3455       3261         0      1000      1000
3       0  …      14331      14948      15549      1518      1500      1000
4       0  …      28314      28959      29547      2000      2019      1200
```

```
5         0  …        20940        19146        19131        2000        36681        10000

    PAY_AMT4  PAY_AMT5  PAY_AMT6  default
ID
1          0         0         0        1
2       1000         0      2000        1
3       1000      1000      5000        0
4       1100      1069      1000        0
5       9000       689       679        0

[5 rows x 24 columns]
```

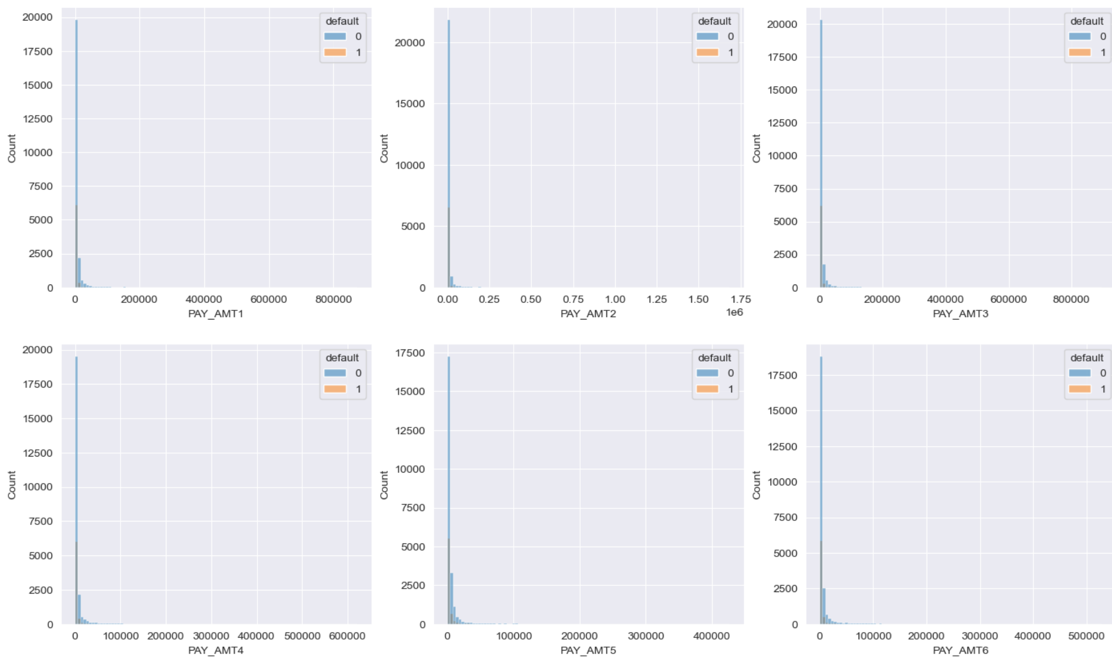
3.13 Comparing Distributions of Amounts of Bill Statements for 6 months, from April - September 2005, between defaulters and non-defaulters

[28]:
```python
fig, ax = plt.subplots(nrows = 2, ncols = 3, figsize = (17, 10))
sns.histplot(x = "BILL_AMT1", hue = "default", data = data, ax = ax[0, 0])
sns.histplot(x = "BILL_AMT2", hue = "default", data = data, ax = ax[0, 1])
sns.histplot(x = "BILL_AMT3", hue = "default", data = data, ax = ax[0, 2])
sns.histplot(x = "BILL_AMT4", hue = "default", data = data, ax = ax[1, 0])
sns.histplot(x = "BILL_AMT5", hue = "default", data = data, ax = ax[1, 1])
sns.histplot(x = "BILL_AMT6", hue = "default", data = data, ax = ax[1, 2])
plt.show()
```



3.14 Comparing Amount of Previous Payments for 6 months, from April - September 2005, between defaulters and non-defaulters

[29]:
```
fig, ax = plt.subplots(nrows = 2, ncols = 3, figsize = (17, 10))
sns.histplot(x = "PAY_AMT1", hue = "default", data = data, ax = ax[0, 0],␣
 ↪bins=100)
sns.histplot(x = "PAY_AMT2", hue = "default", data = data, ax = ax[0, 1],␣
 ↪bins=100)
sns.histplot(x = "PAY_AMT3", hue = "default", data = data, ax = ax[0, 2],␣
 ↪bins=100)
sns.histplot(x = "PAY_AMT4", hue = "default", data = data, ax = ax[1, 0],␣
 ↪bins=100)
sns.histplot(x = "PAY_AMT5", hue = "default", data = data, ax = ax[1, 1],␣
 ↪bins=100)
sns.histplot(x = "PAY_AMT6", hue = "default", data = data, ax = ax[1, 2],␣
 ↪bins=100)
plt.show()
```



4 Data Pre-Processing

4.1 One Hot Encoding

[30]:
```
# Get dummy variables for Education and Marriage (since they have more than 2␣
↪categories)
data = pd.get_dummies(data, columns = ["EDUCATION", "MARRIAGE"])
data.head()
```

[30]:
```
    LIMIT_BAL  SEX  AGE  PAY_1  PAY_2  PAY_3  PAY_4  PAY_5  PAY_6  BILL_AMT1  \
ID
1       20000    1   24      1      1      0      0      0      0       3913
2      120000    1   26      0      1      0      0      0      1       2682
3       90000    1   34      0      0      0      0      0      0      29239
4       50000    1   37      0      0      0      0      0      0      46990
5       50000    0   57      0      0      0      0      0      0       8617

    …  PAY_AMT5  PAY_AMT6  default  EDUCATION_1  EDUCATION_2  EDUCATION_3  \
ID  …
1   …         0         0        1            0            1            0
2   …         0      2000        1            0            1            0
3   …      1000      5000        0            0            1            0
4   …      1069      1000        0            0            1            0
5   …       689       679        0            0            1            0

    EDUCATION_4  MARRIAGE_1  MARRIAGE_2  MARRIAGE_3
ID
1             0           1           0           0
2             0           0           1           0
3             0           0           1           0
4             0           1           0           0
5             0           1           0           0

[5 rows x 29 columns]
```

4.2 Feature scaling

[31]:
```
# Scale dataset to be between [0, 1] as range of each variable varies a lot.␣
↪Min-max scaler being used.
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(data)
col_names = data.columns.tolist()
data = pd.DataFrame(scaled_data, columns = col_names)
data.head()
```

[31]:
```
   LIMIT_BAL  SEX       AGE  PAY_1  PAY_2  PAY_3  PAY_4  PAY_5  PAY_6  \
0   0.010101  1.0  0.051724    1.0    1.0    0.0    0.0    0.0    0.0
```

```
1   0.111111  1.0  0.086207    0.0    1.0    0.0    0.0    0.0    1.0
2   0.080808  1.0  0.224138    0.0    0.0    0.0    0.0    0.0    0.0
3   0.040404  1.0  0.275862    0.0    0.0    0.0    0.0    0.0    0.0
4   0.040404  0.0  0.620690    0.0    0.0    0.0    0.0    0.0    0.0

   BILL_AMT1  …  PAY_AMT5  PAY_AMT6  default  EDUCATION_1  EDUCATION_2  \
0   0.149982  …  0.000000  0.000000      1.0          0.0          1.0
1   0.148892  …  0.000000  0.003783      1.0          0.0          1.0
2   0.172392  …  0.002345  0.009458      0.0          0.0          1.0
3   0.188100  …  0.002506  0.001892      0.0          0.0          1.0
4   0.154144  …  0.001615  0.001284      0.0          0.0          1.0

   EDUCATION_3  EDUCATION_4  MARRIAGE_1  MARRIAGE_2  MARRIAGE_3
0          0.0          0.0         1.0         0.0         0.0
1          0.0          0.0         0.0         1.0         0.0
2          0.0          0.0         0.0         1.0         0.0
3          0.0          0.0         1.0         0.0         0.0
4          0.0          0.0         1.0         0.0         0.0

[5 rows x 29 columns]
```

[32]:
```
y_data = data["default"]
X_data = data.drop(["default"], axis = 1)
```

5 Initial Model Building

We will run our desired models on all features first before doing features selection to justify that feature selection is indeed helpful in our predictive modelling

The models we are interested in building are 1. Logistic Regression 2. Support Vector Machine 3. Random Forest 4. XGBoost 5. Neural Network

5.1 Creating Training and Testing data set

we will use a train/test size of 80/20

[34]:
```
# creating training and testing data to be used for model selection
X_train, X_test, y_train, y_test = train_test_split(X_data, y_data, test_size =
 ↪0.20, random_state = 0)
```

5.2 Logistic Regression

5.2.1 Model Fitting for Logistic Regression

[171]:
```
logistic_regression_model = LogisticRegression(max_iter = 1000, random_state =
 ↪0)
logistic_regression_model.fit(X_train, y_train)
```

```python
logistic_regression_model_y_pred = logistic_regression_model.predict(X_test)
```

5.2.2 Evaluation Metrics for Logistic Regression

[172]:
```python
print(classification_report(y_test, logistic_regression_model_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.82995   0.95577   0.88843      4703
         1.0    0.64384   0.28990   0.39979      1297

    accuracy                        0.81183      6000
   macro avg    0.73689   0.62284   0.64411      6000
weighted avg    0.78972   0.81183   0.78280      6000
```

[173]:
```python
print("AUC: " + str(roc_auc_score(y_test, logistic_regression_model_y_pred)))
```

```
AUC: 0.6228363398024621
```

[174]:
```python
pd.DataFrame(confusion_matrix(y_test, logistic_regression_model_y_pred),
 ↪columns = ["Predicted 0", "Predicted 1"], index = ["True 0", "True 1"])
```

[174]:

	Predicted 0	Predicted 1
True 0	4495	208
True 1	921	376

5.3 Support Vector Machine

5.3.1 Model Fitting for SVM

[175]:
```python
svm_model = SVC(random_state = 0)
svm_model.fit(X_train, y_train)
svm_model_y_pred = svm_model.predict(X_test)
```

Evaluation Metrics for SVM

[176]:
```python
print(classification_report(y_test, svm_model_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.83049   0.95322   0.88763      4703
         1.0    0.63455   0.29453   0.40232      1297

    accuracy                        0.81083      6000
   macro avg    0.73252   0.62387   0.64498      6000
weighted avg    0.78814   0.81083   0.78273      6000
```

[177]:
```python
print("AUC: " + str(roc_auc_score(y_test, svm_model_y_pred)))
```

```
AUC: 0.6238735884557356
```

[178]:
```python
pd.DataFrame(confusion_matrix(y_test, svm_model_y_pred), columns = ["Predicted␣
↪0", "Predicted 1"], index = ["True 0", "True 1"])
```

[178]:

	Predicted 0	Predicted 1
True 0	4483	220
True 1	915	382

5.4 Random Forest

5.4.1 Model fitting for Random Forest

[179]:
```python
random_forest_model = RandomForestClassifier(random_state = 0)
random_forest_model.fit(X_train, y_train)

random_forest_model_y_pred = random_forest_model.predict(X_test)
```

Evaluation Metrics for Random Forest

[180]:
```python
print(classification_report(y_test, random_forest_model_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.84300   0.93961   0.88869      4703
         1.0    0.62533   0.36546   0.46131      1297

    accuracy                        0.81550      6000
   macro avg    0.73416   0.65254   0.67500      6000
weighted avg    0.79595   0.81550   0.79630      6000
```

[181]:
```python
print("AUC: " + str(roc_auc_score(y_test, random_forest_model_y_pred)))
```

```
AUC: 0.6525358819671035
```

[182]:
```python
pd.DataFrame(confusion_matrix(y_test, random_forest_model_y_pred), columns =␣
↪["Predicted 0", "Predicted 1"], index = ["True 0", "True 1"])
```

[182]:

	Predicted 0	Predicted 1
True 0	4419	284
True 1	823	474

5.5 XGBoost

5.5.1 Model fitting for XGBoost

[183]:
```
xgboost_model = XGBClassifier(random_state = 0)
xgboost_model.fit(X_train, y_train)

xgboost_model_y_pred = xgboost_model.predict(X_test)
```

5.5.2 Evaluation metrics for XGBoost

[184]:
```
print(classification_report(y_test, xgboost_model_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.84132   0.93685   0.88652      4703
         1.0    0.61075   0.35929   0.45243      1297

    accuracy                        0.81200      6000
   macro avg    0.72603   0.64807   0.66947      6000
weighted avg    0.79148   0.81200   0.79268      6000
```

[185]:
```
print("AUC: " + str(roc_auc_score(y_test, xgboost_model_y_pred)))
```

```
AUC: 0.6480697453404551
```

[186]:
```
pd.DataFrame(confusion_matrix(y_test, xgboost_model_y_pred), columns =␣
 ↪["Predicted 0", "Predicted 1"], index = ["True 0", "True 1"])
```

[186]:

	Predicted 0	Predicted 1
True 0	4406	297
True 1	831	466

5.6 Neural Network

5.6.1 Building Neural Network

We will be building a dense neural network with 2 hidden layers

[187]:
```
tf.random.set_seed(0)
```

[188]:
```
nn_model = tf.keras.Sequential([
    tf.keras.layers.Dense(16, activation = "relu"), #Hidden 1
    tf.keras.layers.Dense(8, activation = "relu"), #Hidden 2
    tf.keras.layers.Dense(1, activation = "sigmoid") #Output
])
```

[189]:
```
# Hyperparameters
learning_rate = 0.01
loss_function = tf.keras.losses.binary_crossentropy
optimiser_function = tf.keras.optimizers.Adam(learning_rate=learning_rate)
```

[190]:
```
nn_model.compile(
    loss = loss_function,
    optimizer = optimiser_function,
    metrics=[
        tf.keras.metrics.BinaryAccuracy(name='accuracy'),
        tf.keras.metrics.Recall(name='recall'),
        tf.keras.metrics.Precision(name='precision')
    ]
)
```

[191]:
```
nn_model.fit(X_train, y_train, epochs=50)
```

```
Epoch 1/50

2023-04-08 14:58:59.596691: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

750/750 [==============================] - 7s 9ms/step - loss: 0.4537 -
accuracy: 0.8041 - recall: 0.3094 - precision: 0.6197
Epoch 2/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4496 -
accuracy: 0.8066 - recall: 0.3120 - precision: 0.6325
Epoch 3/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4483 -
accuracy: 0.8070 - recall: 0.3182 - precision: 0.6311
Epoch 4/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4479 -
accuracy: 0.8078 - recall: 0.3263 - precision: 0.6318
Epoch 5/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4462 -
accuracy: 0.8090 - recall: 0.3216 - precision: 0.6407
Epoch 6/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4455 -
accuracy: 0.8087 - recall: 0.3255 - precision: 0.6369
Epoch 7/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4451 -
accuracy: 0.8083 - recall: 0.3340 - precision: 0.6307
Epoch 8/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4448 -
accuracy: 0.8100 - recall: 0.3315 - precision: 0.6411
Epoch 9/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4448 -
accuracy: 0.8100 - recall: 0.3385 - precision: 0.6374
Epoch 10/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4439 -
accuracy: 0.8112 - recall: 0.3454 - precision: 0.6405
Epoch 11/50
750/750 [==============================] - 7s 10ms/step - loss: 0.4436 -
```

```
accuracy: 0.8097 - recall: 0.3319 - precision: 0.6390
Epoch 12/50
750/750 [==============================] - 8s 10ms/step - loss: 0.4439 -
accuracy: 0.8088 - recall: 0.3394 - precision: 0.6305
Epoch 13/50
750/750 [==============================] - 8s 10ms/step - loss: 0.4427 -
accuracy: 0.8101 - recall: 0.3452 - precision: 0.6344
Epoch 14/50
750/750 [==============================] - 8s 10ms/step - loss: 0.4433 -
accuracy: 0.8097 - recall: 0.3499 - precision: 0.6302
Epoch 15/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4422 -
accuracy: 0.8118 - recall: 0.3444 - precision: 0.6441
Epoch 16/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4419 -
accuracy: 0.8120 - recall: 0.3497 - precision: 0.6420
Epoch 17/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4415 -
accuracy: 0.8126 - recall: 0.3553 - precision: 0.6424
Epoch 18/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4418 -
accuracy: 0.8125 - recall: 0.3429 - precision: 0.6488
Epoch 19/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4420 -
accuracy: 0.8114 - recall: 0.3508 - precision: 0.6384
Epoch 20/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4415 -
accuracy: 0.8124 - recall: 0.3521 - precision: 0.6432
Epoch 21/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4409 -
accuracy: 0.8130 - recall: 0.3609 - precision: 0.6417
Epoch 22/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4410 -
accuracy: 0.8122 - recall: 0.3504 - precision: 0.6427
Epoch 23/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4409 -
accuracy: 0.8135 - recall: 0.3594 - precision: 0.6448
Epoch 24/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4409 -
accuracy: 0.8128 - recall: 0.3516 - precision: 0.6455
Epoch 25/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4408 -
accuracy: 0.8127 - recall: 0.3557 - precision: 0.6431
Epoch 26/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4398 -
accuracy: 0.8122 - recall: 0.3559 - precision: 0.6399
Epoch 27/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4402 -
```

```
accuracy: 0.8121 - recall: 0.3634 - precision: 0.6361
Epoch 28/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4398 -
accuracy: 0.8138 - recall: 0.3572 - precision: 0.6475
Epoch 29/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4400 -
accuracy: 0.8129 - recall: 0.3654 - precision: 0.6388
Epoch 30/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4396 -
accuracy: 0.8130 - recall: 0.3602 - precision: 0.6419
Epoch 31/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4399 -
accuracy: 0.8126 - recall: 0.3564 - precision: 0.6420
Epoch 32/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4395 -
accuracy: 0.8125 - recall: 0.3576 - precision: 0.6406
Epoch 33/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4399 -
accuracy: 0.8120 - recall: 0.3617 - precision: 0.6365
Epoch 34/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4389 -
accuracy: 0.8132 - recall: 0.3628 - precision: 0.6416
Epoch 35/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4386 -
accuracy: 0.8137 - recall: 0.3664 - precision: 0.6426
Epoch 36/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4387 -
accuracy: 0.8128 - recall: 0.3636 - precision: 0.6393
Epoch 37/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4387 -
accuracy: 0.8131 - recall: 0.3544 - precision: 0.6457
Epoch 38/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4393 -
accuracy: 0.8131 - recall: 0.3572 - precision: 0.6440
Epoch 39/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4394 -
accuracy: 0.8134 - recall: 0.3581 - precision: 0.6451
Epoch 40/50
750/750 [==============================] - 7s 9ms/step - loss: 0.4387 -
accuracy: 0.8146 - recall: 0.3555 - precision: 0.6529
Epoch 41/50
750/750 [==============================] - 8s 10ms/step - loss: 0.4390 -
accuracy: 0.8138 - recall: 0.3660 - precision: 0.6434
Epoch 42/50
750/750 [==============================] - 8s 10ms/step - loss: 0.4381 -
accuracy: 0.8138 - recall: 0.3542 - precision: 0.6492
Epoch 43/50
750/750 [==============================] - 8s 10ms/step - loss: 0.4382 -
```

```
accuracy: 0.8131 - recall: 0.3555 - precision: 0.6449
Epoch 44/50
750/750 [==============================] - 7s 10ms/step - loss: 0.4378 -
accuracy: 0.8139 - recall: 0.3592 - precision: 0.6473
Epoch 45/50
750/750 [==============================] - 7s 10ms/step - loss: 0.4383 -
accuracy: 0.8138 - recall: 0.3619 - precision: 0.6455
Epoch 46/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4380 -
accuracy: 0.8137 - recall: 0.3641 - precision: 0.6437
Epoch 47/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4377 -
accuracy: 0.8138 - recall: 0.3641 - precision: 0.6439
Epoch 48/50
750/750 [==============================] - 6s 9ms/step - loss: 0.4380 -
accuracy: 0.8139 - recall: 0.3634 - precision: 0.6452
Epoch 49/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4369 -
accuracy: 0.8151 - recall: 0.3667 - precision: 0.6494
Epoch 50/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4368 -
accuracy: 0.8138 - recall: 0.3630 - precision: 0.6449
```

[191]: <keras.callbacks.History at 0x30c8e3100>

[192]:
```
# Make predictions
nn_pred_raw = nn_model.predict(X_test)

nn_pred = [1 if p > 0.5 else 0 for p in np.ravel(nn_pred_raw)]
```

```
 90/188 [============>…] - ETA: 0s

2023-04-08 15:04:32.810346: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

188/188 [==============================] - 0s 2ms/step
```

5.6.2 Evaluation metrics for Neural Network

[193]:
```
print(classification_report(y_test, nn_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.84267   0.93727   0.88746      4703
         1.0    0.61638   0.36546   0.45886      1297

    accuracy                        0.81367      6000
   macro avg    0.72953   0.65137   0.67316      6000
```

```
weighted avg     0.79375    0.81367    0.79481       6000
```

[194]:
```python
print("AUC: " + str(roc_auc_score(y_test, nn_pred)))
```

```
AUC: 0.6513664156689959
```

[195]:
```python
pd.DataFrame(confusion_matrix(y_test, nn_pred), columns = ["Predicted 0",
 ↪"Predicted 1"], index = ["True 0", "True 1"])
```

[195]:

	Predicted 0	Predicted 1
True 0	4408	295
True 1	823	474

6 Feature selection

6.0.1 Filter Method - Chi2

H0: There is no relationship between "default" and other categorical independent variables.

H1: There is a relationship between "default" and other categorical independent variables.

Testing this hypothesis at 5% level of significance, with (r-1)(c-1) degrees of freedom

[35]:
```python
# extracting categorical columns
x = X_train[["SEX", "PAY_1", "PAY_2", "PAY_3", "PAY_4", "PAY_5", "PAY_6",
 ↪"EDUCATION_1", "EDUCATION_2", "EDUCATION_3", "EDUCATION_4", "MARRIAGE_1",
 ↪"MARRIAGE_2", "MARRIAGE_3"]]
y = y_train

# chi2
statistics = chi2(x, y)

# # creating the chi2 statistics
# chi_sq= SelectKBest(chi2, k = 8)
# chi_sq.fit(x, y)

# observing the chi2 scores
chi_scores = pd.DataFrame(list(zip(x.columns, *statistics)), columns
 ↪=["feature", "score", "pvalue"])
chi_scores
```

[35]:

	feature	score	pvalue
0	SEX	19.328592	1.100461e-05
1	PAY_1	2504.407508	0.000000e+00
2	PAY_2	2336.386495	0.000000e+00
3	PAY_3	1783.040210	0.000000e+00
4	PAY_4	1596.935908	0.000000e+00
5	PAY_5	1567.964929	0.000000e+00

```
6          PAY_6  1352.401621  4.632186e-296
7    EDUCATION_1    39.102150   4.022009e-10
8    EDUCATION_2    20.157046   7.133698e-06
9    EDUCATION_3    14.052988   1.777313e-04
10   EDUCATION_4    49.763611   1.734309e-12
11    MARRIAGE_1    18.253826   1.933372e-05
12    MARRIAGE_2    16.289254   5.437141e-05
13    MARRIAGE_3     0.415601   5.191403e-01
```

[36]:
```
# selecting the features that reject the null hypothesis (5%)
significant_features = chi_scores[chi_scores["pvalue"] < 0.05]["feature"]
significant_features.tolist()
```

[36]:
```
['SEX',
 'PAY_1',
 'PAY_2',
 'PAY_3',
 'PAY_4',
 'PAY_5',
 'PAY_6',
 'EDUCATION_1',
 'EDUCATION_2',
 'EDUCATION_3',
 'EDUCATION_4',
 'MARRIAGE_1',
 'MARRIAGE_2']
```

Features that have p-value less than 0.05 are

'SEX', 'PAY_1', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'EDUCATION_1', 'EDUCATION_2', 'EDUCATION_3', 'EDUCATION_4', 'MARRIAGE_1', 'MARRIAGE_2'

6.0.2 Wrapper Method - Forward Selection

We use Linear Regression as our test for variables to keep

[60]:
```
# Forward Selection
lreg = LinearRegression()
fws = sfs(lreg, k_features=10, forward=True, scoring='r2', cv = 5) # keep␣
 ↪approximately half of the total number of features
fws.fit(X_train, y_train)
table = pd.DataFrame(fws.subsets_).T
table
```

[60]:
```
                          feature_idx  \
1                                (3,)
2                              (3, 7)
3                           (3, 5, 7)
4                        (0, 3, 5, 7)
```

```
5                    (0, 3, 5, 7, 8)
6                (0, 3, 5, 7, 8, 26)
7             (0, 3, 4, 5, 7, 8, 26)
8         (0, 3, 4, 5, 7, 8, 24, 26)
9      (0, 1, 3, 4, 5, 7, 8, 24, 26)
10  (0, 1, 3, 4, 5, 7, 8, 15, 24, 26)

                                              cv_scores avg_score  \
1   [0.1493453338652141, 0.15603158985458587, 0.10…  0.134645
2   [0.16689715979474085, 0.18346492163381334, 0.1…  0.157067
3   [0.1776180954004405, 0.1919190131535382, 0.143…  0.166702
4   [0.1816902129537168, 0.195047685075718, 0.1462…  0.170809
5   [0.18244146637156478, 0.19761495156268338, 0.1…  0.172928
6   [0.18471736060559452, 0.19664098349476122, 0.1…  0.174311
7   [0.18419494977466977, 0.19493017522635647, 0.1…  0.175213
8   [0.18395368107918797, 0.19614342955272046, 0.1…  0.175969
9   [0.18523891652939084, 0.19726953839960093, 0.1…  0.176697
10  [0.18600923529533686, 0.19801381812057617, 0.1…  0.177418

                                      feature_names
1                                          (PAY_1,)
2                                    (PAY_1, PAY_5)
3                             (PAY_1, PAY_3, PAY_5)
4                  (LIMIT_BAL, PAY_1, PAY_3, PAY_5)
5           (LIMIT_BAL, PAY_1, PAY_3, PAY_5, PAY_6)
6   (LIMIT_BAL, PAY_1, PAY_3, PAY_5, PAY_6, MARRIA…
7   (LIMIT_BAL, PAY_1, PAY_2, PAY_3, PAY_5, PAY_6,…
8   (LIMIT_BAL, PAY_1, PAY_2, PAY_3, PAY_5, PAY_6,…
9   (LIMIT_BAL, SEX, PAY_1, PAY_2, PAY_3, PAY_5, P…
10  (LIMIT_BAL, SEX, PAY_1, PAY_2, PAY_3, PAY_5, P…
```

The top 10 features to select will be LIMIT_BAL, SEX, PAY_1, PAY_2, PAY_3, PAY_5, PAY_6, PAY_AMT1, EDUCATION_4, MARRIAGE_2

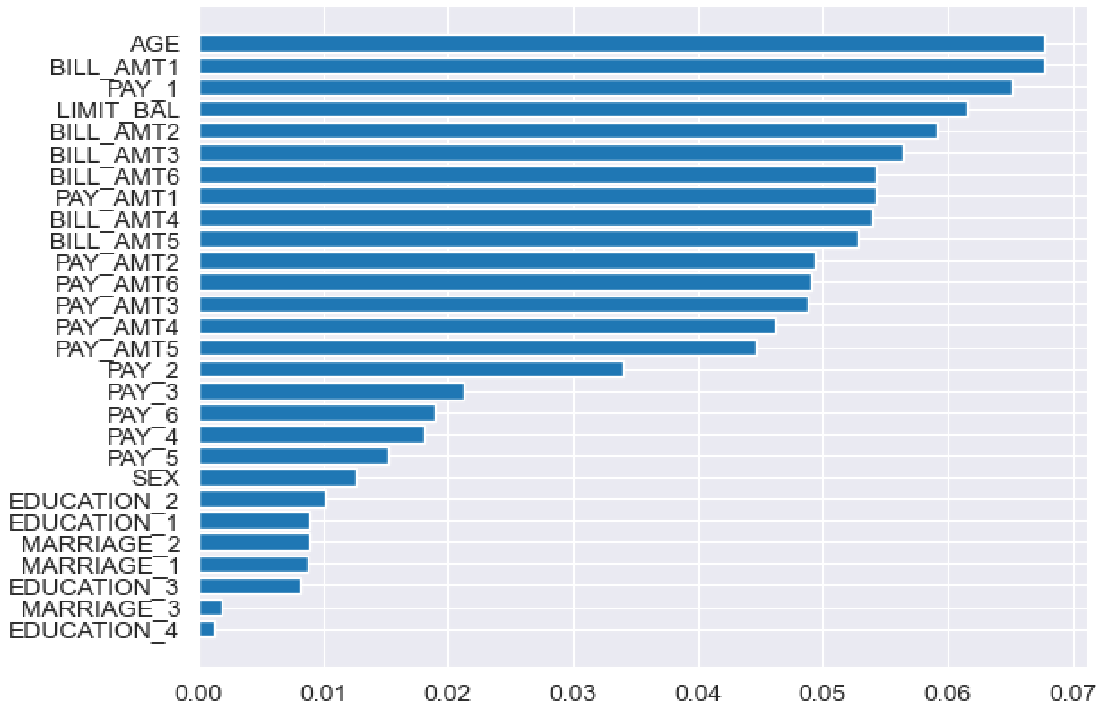
6.0.3 Embedded Method - Random Forest

[61]:
```
rf = RandomForestClassifier(random_state=0)
rf.fit(X_train, y_train)
rf.feature_importances_
```

[61]:
```
array([0.06164632, 0.01267104, 0.06781958, 0.06520381, 0.03397051,
       0.0212019 , 0.01812225, 0.01525486, 0.01892131, 0.0678045 ,
       0.05917926, 0.05643935, 0.05404311, 0.05282601, 0.05430341,
       0.05421721, 0.04942933, 0.0488772 , 0.0463043 , 0.04461673,
       0.04904686, 0.0089207 , 0.01012574, 0.00821934, 0.00127353,
       0.00875422, 0.00887152, 0.00193611])
```

[62]:
```
# Plot RF scores
sorted_idx = rf.feature_importances_.argsort()
plt.barh(rf.feature_names_in_[sorted_idx], rf.feature_importances_[sorted_idx])
```

[62]: <BarContainer object of 28 artists>



The most important feature is "AGE" and the least important feature is "EDUCATION_4"

From the 3 feature selection methods as shown above, we derive these conclusions 1. From chi2 test, 'SEX', 'PAY_1', 'PAY_2', 'PAY_3', 'PAY_4', 'PAY_5', 'PAY_6', 'EDUCATION_1', 'EDUCATION_2', 'EDUCATION_3', 'EDUCATION_4', 'MARRIAGE_1', 'MARRIAGE_2' are features whose p-value are less than 0.05 2. From forward selection, 'LIMIT_BAL', 'SEX', 'PAY_1', 'PAY_2', 'PAY_3', 'PAY_5', 'PAY_6', 'PAY_AMT1', 'EDUCATION_4', 'MARRIAGE_2' are the 10 most important features 3. From Embedded method, 'AGE', 'BILL_AMT1', 'PAY_1', 'LIMIT_BAL', 'BILL_AMT2', 'BILL_AMT3', 'BILL_AMT6', 'BILL_AMT4', 'PAY_AMT1', 'BILL_AMT5' are the 10 most important features

For categorical variables, we will select features that appear in both (1) and (2) These features are 'SEX', 'PAY_1', 'PAY_2', 'PAY_3', 'PAY_5', 'PAY_6', 'MARRIAGE_2', 'EDUCATION_4'

For continuous variables, we will select features that appear in both (2) and (3) These features are 'LIMIT_BAL', 'PAY_AMT1'

As such, our final set of selected features are 'SEX', 'PAY_1', 'PAY_2', 'PAY_3', 'PAY_5', 'PAY_6', 'MARRIAGE_2', 'EDUCATION_4', 'LIMIT_BAL', 'PAY_AMT1'

[34]:
```
features_selected = [
    'SEX',
    'PAY_1',
    'PAY_2',
    'PAY_3',
    'PAY_5',
    'PAY_6',
    'MARRIAGE_2',
    'EDUCATION_4',
    'LIMIT_BAL',
    'PAY_AMT1'
]
```

6.1 Refactoring dataset

[35]:
```
X_train = X_train[features_selected]
X_train.head()
```

[35]:
```
       SEX  PAY_1  PAY_2  PAY_3  PAY_5  PAY_6  MARRIAGE_2  EDUCATION_4  \
3225   1.0    0.0    0.0    1.0    0.0    0.0         0.0          0.0
11815  1.0    0.0    0.0    0.0    0.0    0.0         1.0          0.0
7338   0.0    1.0    0.0    0.0    0.0    0.0         0.0          0.0
14980  0.0    1.0    1.0    1.0    1.0    1.0         0.0          0.0
27167  0.0    0.0    0.0    0.0    0.0    0.0         0.0          0.0

       LIMIT_BAL  PAY_AMT1
3225    0.010101  0.003434
11815   0.252525  0.000189
7338    0.010101  0.001717
14980   0.020202  0.002061
27167   0.000000  0.003205
```

[36]:
```
X_test = X_test[features_selected]
X_test.head()
```

[36]:
```
       SEX  PAY_1  PAY_2  PAY_3  PAY_5  PAY_6  MARRIAGE_2  EDUCATION_4  \
8225   0.0    1.0    1.0    1.0    1.0    1.0         1.0          0.0
10794  1.0    0.0    0.0    1.0    0.0    0.0         1.0          0.0
9163   1.0    1.0    0.0    0.0    0.0    0.0         0.0          0.0
26591  0.0    0.0    0.0    0.0    0.0    0.0         0.0          0.0
6631   0.0    0.0    0.0    0.0    0.0    0.0         1.0          0.0

       LIMIT_BAL  PAY_AMT1
8225    0.010101  0.000000
10794   0.010101  0.003892
9163    0.222222  0.001086
26591   0.090909  0.005724
```

```
6631    0.141414  0.008001
```

7 Creating a balanced dataset using SMOTE

[37]:
```
sm = SMOTE(random_state=0, sampling_strategy= 1.0)
X_SMOTE, y_SMOTE = sm.fit_resample(X_train, y_train)
```

[38]:
```
y_SMOTE.value_counts()
```

[38]:
```
0.0    18661
1.0    18661
Name: default, dtype: int64
```

8 Model Selection

We will now run the 5 models on the dataset that has undergone feature selection, followed by using the balanced dataset from SMOTE and finally tune the hyparameters of each model. 1. Logistic Regression 2. Support Vector Machine 3. Random Forest 4. XGBoost 5. Neural Network

8.1 Logistic Regression

8.1.1 Model Fitting for Logistic Regression after Feature Selection

[202]:
```
logistic_regression_model = LogisticRegression(max_iter = 1000, random_state =␣
↪0)
logistic_regression_model.fit(X_train, y_train)

logistic_regression_model_y_pred = logistic_regression_model.predict(X_test)
```

[203]:
```
print(classification_report(y_test, logistic_regression_model_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.83019   0.95322   0.88746      4703
         1.0    0.63333   0.29298   0.40063      1297

    accuracy                        0.81050      6000
   macro avg    0.73176   0.62310   0.64405      6000
weighted avg    0.78763   0.81050   0.78222      6000
```

[204]:
```
print("AUC: " + str(roc_auc_score(y_test, logistic_regression_model_y_pred)))
```

```
AUC: 0.6231025784326053
```

[205]:
```
pd.DataFrame(confusion_matrix(y_test, logistic_regression_model_y_pred),␣
↪columns = ["Predicted 0", "Predicted 1"], index = ["True 0", "True 1"])
```

[205]:

	Predicted 0	Predicted 1
True 0	4483	220
True 1	917	380

8.1.2 Model Fitting for Logistic Regression on Balanced Dataset after SMOTE

[326]:
```
smote_lr = LogisticRegression(max_iter = 1000, random_state = 0)
smote_lr.fit(X_SMOTE, y_SMOTE)

smote_lr_y_pred = smote_lr.predict(X_test)
```

[327]:
```
print(classification_report(y_test, smote_lr_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.87679   0.82160   0.84830      4703
         1.0    0.47332   0.58134   0.52180      1297

    accuracy                        0.76967      6000
   macro avg    0.67505   0.70147   0.68505      6000
weighted avg    0.78957   0.76967   0.77772      6000
```

[328]:
```
print("AUC: " + str(roc_auc_score(y_test, smote_lr_y_pred)))
```

```
AUC: 0.7014723947099172
```

[329]:
```
pd.DataFrame(confusion_matrix(y_test, smote_lr_y_pred), columns = ["Predicted␣
↪0", "Predicted 1"], index = ["True 0", "True 1"])
```

[329]:

	Predicted 0	Predicted 1
True 0	3864	839
True 1	543	754

8.1.3 Tuning Logistic Regression

[330]:
```
# create the grid
lr_param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],
    'penalty' : ['l2'],
    'solver' : ['newton-cg', 'lbfgs']
}
```

[331]:
```
# perform grid search and then fit
lr_grid = GridSearchCV(LogisticRegression(max_iter = 1000, random_state = 0),␣
↪lr_param_grid, scoring = 'accuracy')
lr_grid.fit(X_SMOTE, y_SMOTE)
print(lr_grid.best_params_)
```

```
{'C': 10, 'penalty': 'l2', 'solver': 'newton-cg'}
```

[39]:
```
optimised_lr = LogisticRegression(C = 10, penalty='l2', solver='newton-cg',␣
↪max_iter = 1000, random_state = 0)
optimised_lr.fit(X_SMOTE, y_SMOTE)

lr_grid_y_predict = optimised_lr.predict(X_test)
```

[40]:
```
print(classification_report(y_test, lr_grid_y_predict, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.87750   0.81948   0.84750      4703
         1.0    0.47201   0.58520   0.52255      1297

    accuracy                        0.76883      6000
   macro avg    0.67476   0.70234   0.68502      6000
weighted avg    0.78985   0.76883   0.77725      6000
```

[41]:
```
print("AUC: " + str(roc_auc_score(y_test, lr_grid_y_predict)))
```

```
AUC: 0.702336768587645
```

[42]:
```
pd.DataFrame(confusion_matrix(y_test, lr_grid_y_predict), columns = ["Predicted␣
↪0", "Predicted 1"], index = ["True 0", "True 1"])
```

[42]:

	Predicted 0	Predicted 1
True 0	3854	849
True 1	538	759

8.2 Support Vector Machine

8.2.1 Model Fitting for SVM after Feature Selection

[216]:
```
svm_model = SVC(random_state = 0)
svm_model.fit(X_train, y_train)
svm_model_y_pred = svm_model.predict(X_test)
```

[217]:
```
print(classification_report(y_test, svm_model_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.83027   0.95173   0.88686      4703
         1.0    0.62726   0.29453   0.40084      1297

    accuracy                        0.80967      6000
   macro avg    0.72877   0.62313   0.64385      6000
weighted avg    0.78639   0.80967   0.78180      6000
```

[218]:
```python
print("AUC: " + str(roc_auc_score(y_test, svm_model_y_pred)))
```

```
AUC: 0.6231293826296671
```

[219]:
```python
pd.DataFrame(confusion_matrix(y_test, svm_model_y_pred), columns = ["Predicted␣
↪0", "Predicted 1"], index = ["True 0", "True 1"])
```

[219]:

	Predicted 0	Predicted 1
True 0	4476	227
True 1	915	382

8.2.2 Model Fitting for SVM on Balanced Dataset after SMOTE

[220]:
```python
smote_svm = SVC(random_state = 0)
smote_svm.fit(X_SMOTE, y_SMOTE)
smote_svm_y_pred = smote_svm.predict(X_test)
```

[221]:
```python
print(classification_report(y_test, smote_svm_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.88213   0.79247   0.83490      4703
         1.0    0.45014   0.61604   0.52018      1297

    accuracy                        0.75433      6000
   macro avg    0.66614   0.70425   0.67754      6000
weighted avg    0.78875   0.75433   0.76687      6000
```

[222]:
```python
print("AUC: " + str(roc_auc_score(y_test, smote_svm_y_pred)))
```

```
AUC: 0.7042549490630089
```

[223]:
```python
pd.DataFrame(confusion_matrix(y_test, smote_svm_y_pred), columns = ["Predicted␣
↪0", "Predicted 1"], index = ["True 0", "True 1"])
```

[223]:

	Predicted 0	Predicted 1
True 0	3727	976
True 1	498	799

8.2.3 Tuning SVM

[90]:
```python
# create the grid
svm_param_grid = {
    'C': [0.01, 0.1, 1, 10, 100],
    'kernel': ['rbf']
}
```

[91]:
```
# perform grid search and then fit
svm_grid = GridSearchCV(SVC(random_state = 0), svm_param_grid, scoring =
  ↪'accuracy')
svm_grid.fit(X_SMOTE, y_SMOTE)
print(svm_grid.best_params_)
```

```
{'C': 100, 'kernel': 'rbf'}
```

[43]:
```
optimised_svm = SVC(random_state = 0, kernel = 'rbf', C = 100, probability=True)
optimised_svm.fit(X_SMOTE, y_SMOTE)

svm_grid_y_pred = optimised_svm.predict(X_test)
```

[44]:
```
print(classification_report(y_test, svm_grid_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.88024   0.79545   0.83570      4703
         1.0    0.45029   0.60756   0.51723      1297

    accuracy                        0.75483      6000
   macro avg    0.66526   0.70150   0.67646      6000
weighted avg    0.78729   0.75483   0.76686      6000
```

[45]:
```
print("AUC: " + str(roc_auc_score(y_test, svm_grid_y_pred)))
```

```
AUC: 0.7015028055879291
```

[46]:
```
pd.DataFrame(confusion_matrix(y_test, svm_grid_y_pred), columns = ["Predicted
  ↪0", "Predicted 1"], index = ["True 0", "True 1"])
```

[46]:

	Predicted 0	Predicted 1
True 0	3741	962
True 1	509	788

8.3 Random Forest

8.3.1 Model Fitting for Random Forest after Feature Selection

[228]:
```
random_forest_model = RandomForestClassifier(random_state = 0)
random_forest_model.fit(X_train, y_train)

random_forest_model_y_pred = random_forest_model.predict(X_test)
```

[229]:
```
print(classification_report(y_test, random_forest_model_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.82991   0.88497   0.85655      4703
```

```
         1.0    0.45076   0.34233   0.38913      1297

    accuracy                        0.76767      6000
   macro avg    0.64034   0.61365   0.62284      6000
weighted avg    0.74795   0.76767   0.75551      6000
```

[230]:
```
print("AUC: " + str(roc_auc_score(y_test, random_forest_model_y_pred)))
```

```
AUC: 0.6136477462916352
```

[231]:
```
pd.DataFrame(confusion_matrix(y_test, random_forest_model_y_pred), columns =␣
 ↪["Predicted 0", "Predicted 1"], index = ["True 0", "True 1"])
```

[231]:

	Predicted 0	Predicted 1
True 0	4162	541
True 1	853	444

8.3.2 Model Fitting for Random Forest on Balanced Dataset after SMOTE

[232]:
```
smote_rf = RandomForestClassifier(random_state = 0)
smote_rf.fit(X_SMOTE, y_SMOTE)

smote_rf_y_pred = smote_rf.predict(X_test)
```

[233]:
```
print(classification_report(y_test, smote_rf_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.84835   0.73272   0.78631      4703
         1.0    0.35139   0.52506   0.42102      1297

    accuracy                        0.68783      6000
   macro avg    0.59987   0.62889   0.60366      6000
weighted avg    0.74092   0.68783   0.70735      6000
```

[234]:
```
print("AUC: " + str(roc_auc_score(y_test, smote_rf_y_pred)))
```

```
AUC: 0.6288908095375727
```

[235]:
```
pd.DataFrame(confusion_matrix(y_test, smote_rf_y_pred), columns = ["Predicted␣
 ↪0", "Predicted 1"], index = ["True 0", "True 1"])
```

[235]:

	Predicted 0	Predicted 1
True 0	3446	1257
True 1	616	681

8.3.3 Tuning Random Forest

[236]:
```
# create the grid
rf_params_grid = {
    'n_estimators': [10, 50, 100, 250, 500],
    'max_depth': [2, 3, 4, 5]
}
```

[237]:
```
# perform grid search and then fit
rf_grid = GridSearchCV(RandomForestClassifier(random_state = 0),␣
 ↪rf_params_grid, scoring = 'accuracy')
rf_grid.fit(X_SMOTE, y_SMOTE)
print(rf_grid.best_params_)
```

```
{'max_depth': 5, 'n_estimators': 500}
```

[47]:
```
optimised_rf = RandomForestClassifier(random_state = 0, max_depth = 5,␣
 ↪n_estimators = 500)
optimised_rf.fit(X_SMOTE, y_SMOTE)

rf_grid_y_pred = optimised_rf.predict(X_test)
```

[48]:
```
print(classification_report(y_test, rf_grid_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.87853   0.81352   0.84478      4703
         1.0    0.46687   0.59214   0.52209      1297

    accuracy                        0.76567      6000
   macro avg    0.67270   0.70283   0.68344      6000
weighted avg    0.78954   0.76567   0.77502      6000
```

[49]:
```
print("AUC: " + str(roc_auc_score(y_test, rf_grid_y_pred)))
```

```
AUC: 0.7028294903874575
```

[50]:
```
pd.DataFrame(confusion_matrix(y_test, rf_grid_y_pred), columns = ["Predicted␣
 ↪0", "Predicted 1"], index = ["True 0", "True 1"])
```

[50]:

	Predicted 0	Predicted 1
True 0	3826	877
True 1	529	768

8.4 XGBoost

8.4.1 Model Fitting for XGBoost after Feature Selection

[242]:
```
xgboost_model = XGBClassifier(random_state = 0)
xgboost_model.fit(X_train, y_train)

xgboost_model_y_pred = xgboost_model.predict(X_test)
```

[243]:
```
print(classification_report(y_test, xgboost_model_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.83434   0.94238   0.88507      4703
         1.0    0.60610   0.32151   0.42015      1297

    accuracy                        0.80817      6000
   macro avg    0.72022   0.63194   0.65261      6000
weighted avg    0.78500   0.80817   0.78457      6000
```

[244]:
```
print("AUC: " + str(roc_auc_score(y_test, xgboost_model_y_pred)))
```

```
AUC: 0.6319441928420171
```

[245]:
```
pd.DataFrame(confusion_matrix(y_test, xgboost_model_y_pred), columns =␣
↪["Predicted 0", "Predicted 1"], index = ["True 0", "True 1"])
```

[245]:

	Predicted 0	Predicted 1
True 0	4432	271
True 1	880	417

8.4.2 Model Fitting for XGBoost on Balanced Dataset after SMOTE

[246]:
```
smote_xgboost = XGBClassifier(random_state = 0)
smote_xgboost.fit(X_SMOTE, y_SMOTE)

smote_xgboost_y_pred = smote_xgboost.predict(X_test)
```

[247]:
```
print(classification_report(y_test, smote_xgboost_y_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.86759   0.79970   0.83226      4703
         1.0    0.43423   0.55744   0.48818      1297

    accuracy                        0.74733      6000
   macro avg    0.65091   0.67857   0.66022      6000
weighted avg    0.77391   0.74733   0.75789      6000
```

```
[248]: print("AUC: " + str(roc_auc_score(y_test, smote_xgboost_y_pred)))
```

```
AUC: 0.6785712821963898
```

```
[249]: pd.DataFrame(confusion_matrix(y_test, smote_xgboost_y_pred), columns =␣
        ↪["Predicted 0", "Predicted 1"], index = ["True 0", "True 1"])
```

[249]:

	Predicted 0	Predicted 1
True 0	3761	942
True 1	574	723

8.4.3 Tuning XGBoost

```
[250]: # create the grid
xgboost_params_grid = {
    'n_estimators': [10, 50, 100, 250, 500],
    'max_depth': [2, 3, 4, 5]
}
```

```
[251]: # perform grid search and then fit
xgboost_grid = GridSearchCV(XGBClassifier(random_state = 0),␣
 ↪xgboost_params_grid, scoring = 'accuracy')
xgboost_grid.fit(X_SMOTE, y_SMOTE)
print(xgboost_grid.best_params_)
```

```
{'max_depth': 5, 'n_estimators': 500}
```

```
[64]: optimised_xgboost = XGBClassifier(random_state = 0, max_depth = 5, n_estimators␣
 ↪= 500)
optimised_xgboost.fit(X_SMOTE, y_SMOTE)

xgboost_grid_y_predict = optimised_xgboost.predict(X_test)
```

```
[65]: print(classification_report(y_test, xgboost_grid_y_predict, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.86080   0.79417   0.82614      4703
         1.0    0.41722   0.53431   0.46856      1297

    accuracy                        0.73800      6000
   macro avg    0.63901   0.66424   0.64735      6000
weighted avg    0.76491   0.73800   0.74885      6000
```

```
[66]: print("AUC: " + str(roc_auc_score(y_test, xgboost_grid_y_predict)))
```

```
AUC: 0.6642419387811812
```

[67]:
```
pd.DataFrame(confusion_matrix(y_test, xgboost_grid_y_predict), columns =␣
↪["Predicted 0", "Predicted 1"], index = ["True 0", "True 1"])
```

[67]:

	Predicted 0	Predicted 1
True 0	3735	968
True 1	604	693

8.5 Neural Network

8.5.1 Helper Functions

[58]:
```
# this function will help us to visualise the training graphs for the neural␣
↪network
def plot_graphs(history, metric):
    plt.plot(history.history[metric])
    plt.xlabel("Epochs")
    plt.ylabel(metric)
```

8.5.2 Model Fitting for Neural Network after Feature Selection

[125]:
```
tf.random.set_seed(0)
```

[126]:
```
nn_fs_model = tf.keras.Sequential([
    tf.keras.layers.Dense(16, activation = "relu"), #Hidden 1
    tf.keras.layers.Dense(8, activation = "sigmoid"), #Hidden 2
    tf.keras.layers.Dense(1, activation = "sigmoid") #Output
])

#Hyperparameters
learning_rate = 0.01
loss_function = tf.keras.losses.binary_crossentropy
optimiser_function = tf.keras.optimizers.Adam(learning_rate=learning_rate)

nn_fs_model.compile(
    loss = loss_function,
    optimizer = optimiser_function,
    metrics=[
        tf.keras.metrics.BinaryAccuracy(name='accuracy'),
        tf.keras.metrics.Recall(name='recall'),
        tf.keras.metrics.Precision(name='precision')
    ]
)
```

[127]:
```
history_nn_fs = nn_fs_model.fit(X_train, y_train, epochs=50)
```

```
Epoch 1/50
  1/750 […] - ETA: 5:27 - loss: 0.6599 - accuracy:
0.6875 - recall: 0.0000e+00 - precision: 0.0000e+00
```

```
2023-04-08 05:32:15.731019: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

750/750 [==============================] - 6s 8ms/step - loss: 0.4547 -
accuracy: 0.8028 - recall: 0.3023 - precision: 0.6158
Epoch 2/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4500 -
accuracy: 0.8059 - recall: 0.3169 - precision: 0.6257
Epoch 3/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4491 -
accuracy: 0.8059 - recall: 0.3235 - precision: 0.6228
Epoch 4/50
750/750 [==============================] - 919s 1s/step - loss: 0.4500 -
accuracy: 0.8074 - recall: 0.3199 - precision: 0.6328
Epoch 5/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4489 -
accuracy: 0.8058 - recall: 0.3171 - precision: 0.6250
Epoch 6/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4484 -
accuracy: 0.8068 - recall: 0.3272 - precision: 0.6257
Epoch 7/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4484 -
accuracy: 0.8074 - recall: 0.3267 - precision: 0.6294
Epoch 8/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4482 -
accuracy: 0.8073 - recall: 0.3255 - precision: 0.6295
Epoch 9/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4485 -
accuracy: 0.8065 - recall: 0.3276 - precision: 0.6240
Epoch 10/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4478 -
accuracy: 0.8065 - recall: 0.3207 - precision: 0.6271
Epoch 11/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4476 -
accuracy: 0.8063 - recall: 0.3208 - precision: 0.6263
Epoch 12/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4479 -
accuracy: 0.8071 - recall: 0.3302 - precision: 0.6258
Epoch 13/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4473 -
accuracy: 0.8065 - recall: 0.3261 - precision: 0.6249
Epoch 14/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4475 -
accuracy: 0.8066 - recall: 0.3229 - precision: 0.6267
Epoch 15/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4473 -
accuracy: 0.8077 - recall: 0.3298 - precision: 0.6292
```

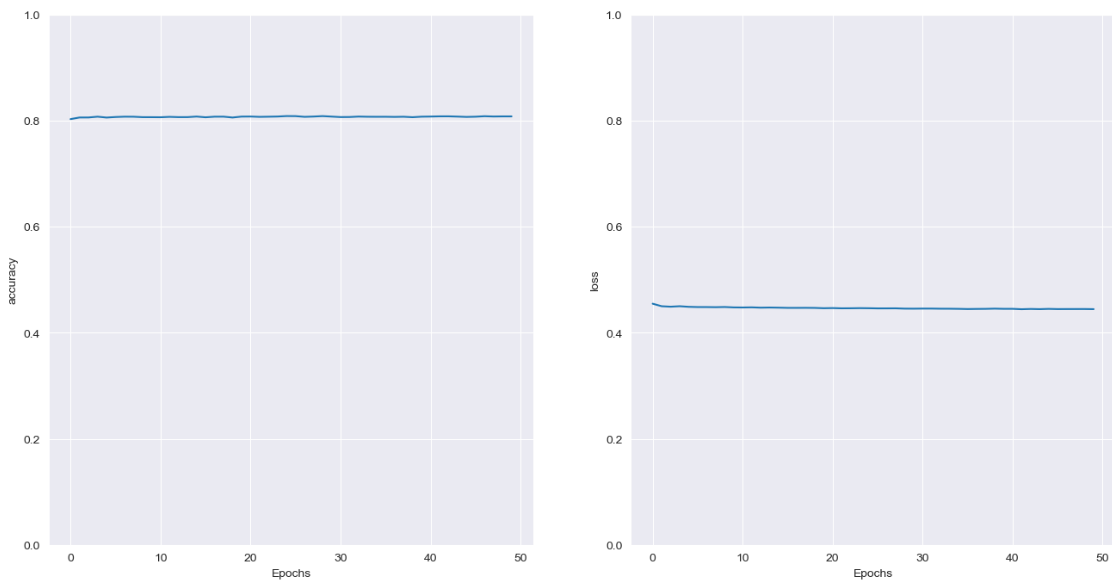
```
Epoch 16/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4469 -
accuracy: 0.8062 - recall: 0.3257 - precision: 0.6235
Epoch 17/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4469 -
accuracy: 0.8074 - recall: 0.3334 - precision: 0.6261
Epoch 18/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4470 -
accuracy: 0.8075 - recall: 0.3244 - precision: 0.6307
Epoch 19/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4468 -
accuracy: 0.8058 - recall: 0.3195 - precision: 0.6242
Epoch 20/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4462 -
accuracy: 0.8076 - recall: 0.3306 - precision: 0.6283
Epoch 21/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4465 -
accuracy: 0.8077 - recall: 0.3280 - precision: 0.6303
Epoch 22/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4460 -
accuracy: 0.8071 - recall: 0.3197 - precision: 0.6311
Epoch 23/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4461 -
accuracy: 0.8074 - recall: 0.3250 - precision: 0.6300
Epoch 24/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4464 -
accuracy: 0.8077 - recall: 0.3291 - precision: 0.6297
Epoch 25/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4462 -
accuracy: 0.8086 - recall: 0.3235 - precision: 0.6375
Epoch 26/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4459 -
accuracy: 0.8085 - recall: 0.3306 - precision: 0.6331
Epoch 27/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4459 -
accuracy: 0.8071 - recall: 0.3313 - precision: 0.6255
Epoch 28/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4460 -
accuracy: 0.8077 - recall: 0.3296 - precision: 0.6292
Epoch 29/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4454 -
accuracy: 0.8085 - recall: 0.3263 - precision: 0.6355
Epoch 30/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4453 -
accuracy: 0.8076 - recall: 0.3302 - precision: 0.6285
Epoch 31/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4455 -
accuracy: 0.8067 - recall: 0.3154 - precision: 0.6309
```

```
Epoch 32/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4455 -
accuracy: 0.8068 - recall: 0.3175 - precision: 0.6306
Epoch 33/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4453 -
accuracy: 0.8076 - recall: 0.3268 - precision: 0.6304
Epoch 34/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4452 -
accuracy: 0.8073 - recall: 0.3218 - precision: 0.6312
Epoch 35/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4450 -
accuracy: 0.8072 - recall: 0.3253 - precision: 0.6289
Epoch 36/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4446 -
accuracy: 0.8073 - recall: 0.3216 - precision: 0.6310
Epoch 37/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4449 -
accuracy: 0.8070 - recall: 0.3092 - precision: 0.6362
Epoch 38/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4450 -
accuracy: 0.8073 - recall: 0.3321 - precision: 0.6261
Epoch 39/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4454 -
accuracy: 0.8064 - recall: 0.3190 - precision: 0.6277
Epoch 40/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4450 -
accuracy: 0.8074 - recall: 0.3162 - precision: 0.6348
Epoch 41/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4450 -
accuracy: 0.8077 - recall: 0.3137 - precision: 0.6376
Epoch 42/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4443 -
accuracy: 0.8080 - recall: 0.3248 - precision: 0.6338
Epoch 43/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4448 -
accuracy: 0.8081 - recall: 0.3267 - precision: 0.6330
Epoch 44/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4445 -
accuracy: 0.8076 - recall: 0.3233 - precision: 0.6320
Epoch 45/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4449 -
accuracy: 0.8070 - recall: 0.3188 - precision: 0.6308
Epoch 46/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4446 -
accuracy: 0.8074 - recall: 0.3149 - precision: 0.6353
Epoch 47/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4446 -
accuracy: 0.8083 - recall: 0.3231 - precision: 0.6361
```

```
Epoch 48/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4446 -
accuracy: 0.8077 - recall: 0.3214 - precision: 0.6339
Epoch 49/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4447 -
accuracy: 0.8080 - recall: 0.3282 - precision: 0.6316
Epoch 50/50
750/750 [==============================] - 6s 8ms/step - loss: 0.4444 -
accuracy: 0.8080 - recall: 0.3126 - precision: 0.6400
```

[128]:
```
# Visualising the learning curves
plt.figure(figsize=(16, 8))
plt.subplot(1, 2, 1)
plot_graphs(history_nn_fs, 'accuracy')
plt.ylim(0, 1)
plt.subplot(1, 2, 2)
plot_graphs(history_nn_fs, 'loss')
plt.ylim(0, 1)
```

[128]:
```
(0.0, 1.0)
```



[166]:
```
#Make predictions
nn_fs_pred_raw = nn_fs_model.predict(X_test)
nn_fs_pred = [1 if p > 0.5 else 0 for p in np.ravel(nn_fs_pred_raw)]

print(classification_report(y_test, nn_fs_pred, digits=5))
```

```
188/188 [==============================] - 0s 2ms/step
              precision    recall  f1-score   support
```

```
         0.0     0.83399   0.94642   0.88665      4703
         1.0     0.61991   0.31689   0.41939      1297

    accuracy                         0.81033      6000
   macro avg     0.72695   0.63165   0.65302      6000
weighted avg     0.78771   0.81033   0.78565      6000
```

[130]:
```
print("AUC: " + str(roc_auc_score(y_test, nn_fs_pred)))
```

```
AUC: 0.631651150014812
```

[131]:
```
pd.DataFrame(confusion_matrix(y_test, nn_fs_pred), columns = ["Predicted 0",␣
↪"Predicted 1"], index = ["True 0", "True 1"])
```

[131]:

	Predicted 0	Predicted 1
True 0	4451	252
True 1	886	411

8.5.3 Model Fitting for Neural Network on Balanced Dataset after SMOTE

[263]:
```
nn_smote_model = tf.keras.Sequential([
    tf.keras.layers.Dense(16, activation = "relu"), #Hidden 1
    tf.keras.layers.Dense(8, activation = "sigmoid"), #Hidden 2
    tf.keras.layers.Dense(1, activation = "sigmoid") #Output
])

#Hyperparameters
learning_rate = 0.01
loss_function = tf.keras.losses.binary_crossentropy
optimiser_function = tf.keras.optimizers.Adam(learning_rate=learning_rate)

nn_smote_model.compile(
    loss = loss_function,
    optimizer = optimiser_function,
    metrics=[
        tf.keras.metrics.BinaryAccuracy(name='accuracy'),
        tf.keras.metrics.Recall(name='recall'),
        tf.keras.metrics.Precision(name='precision')
    ]
)
```

[264]:
```
history_nn_model_smote = nn_smote_model.fit(X_SMOTE, y_SMOTE, epochs=50,␣
↪batch_size=50)
```

```
Epoch 1/50

2023-04-08 15:18:40.111880: I
```

```
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.

747/747 [==============================] - 8s 10ms/step - loss: 0.5897 -
accuracy: 0.6990 - recall: 0.6026 - precision: 0.7465
Epoch 2/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5828 -
accuracy: 0.7045 - recall: 0.6132 - precision: 0.7502
Epoch 3/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5808 -
accuracy: 0.7049 - recall: 0.6107 - precision: 0.7524
Epoch 4/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5801 -
accuracy: 0.7055 - recall: 0.6181 - precision: 0.7491
Epoch 5/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5795 -
accuracy: 0.7050 - recall: 0.6232 - precision: 0.7451
Epoch 6/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5787 -
accuracy: 0.7054 - recall: 0.6192 - precision: 0.7482
Epoch 7/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5777 -
accuracy: 0.7058 - recall: 0.6275 - precision: 0.7440
Epoch 8/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5776 -
accuracy: 0.7061 - recall: 0.6235 - precision: 0.7469
Epoch 9/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5768 -
accuracy: 0.7054 - recall: 0.6240 - precision: 0.7453
Epoch 10/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5766 -
accuracy: 0.7067 - recall: 0.6225 - precision: 0.7486
Epoch 11/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5766 -
accuracy: 0.7073 - recall: 0.6239 - precision: 0.7489
Epoch 12/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5761 -
accuracy: 0.7077 - recall: 0.6202 - precision: 0.7517
Epoch 13/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5760 -
accuracy: 0.7075 - recall: 0.6189 - precision: 0.7521
Epoch 14/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5757 -
accuracy: 0.7079 - recall: 0.6220 - precision: 0.7510
Epoch 15/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5756 -
accuracy: 0.7080 - recall: 0.6214 - precision: 0.7515
Epoch 16/50
```

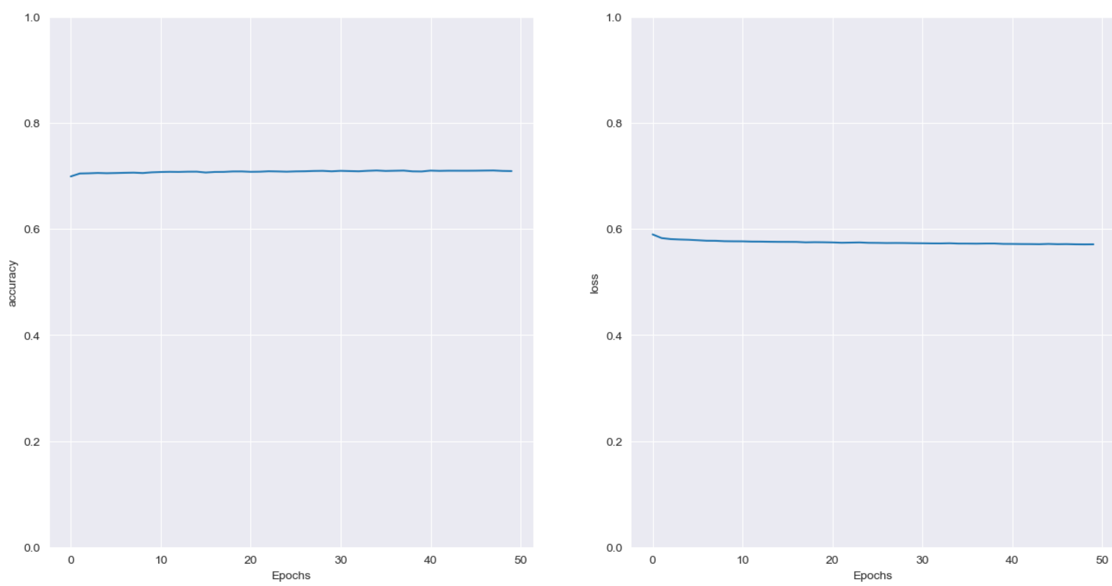
```
747/747 [==============================] - 7s 9ms/step - loss: 0.5755 -
accuracy: 0.7064 - recall: 0.6153 - precision: 0.7523
Epoch 17/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5755 -
accuracy: 0.7074 - recall: 0.6223 - precision: 0.7500
Epoch 18/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5747 -
accuracy: 0.7075 - recall: 0.6172 - precision: 0.7533
Epoch 19/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5750 -
accuracy: 0.7084 - recall: 0.6186 - precision: 0.7540
Epoch 20/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5748 -
accuracy: 0.7084 - recall: 0.6208 - precision: 0.7527
Epoch 21/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5745 -
accuracy: 0.7077 - recall: 0.6163 - precision: 0.7541
Epoch 22/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5739 -
accuracy: 0.7079 - recall: 0.6188 - precision: 0.7530
Epoch 23/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5742 -
accuracy: 0.7087 - recall: 0.6194 - precision: 0.7541
Epoch 24/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5745 -
accuracy: 0.7084 - recall: 0.6174 - precision: 0.7548
Epoch 25/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5738 -
accuracy: 0.7079 - recall: 0.6193 - precision: 0.7527
Epoch 26/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5737 -
accuracy: 0.7085 - recall: 0.6211 - precision: 0.7527
Epoch 27/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5734 -
accuracy: 0.7087 - recall: 0.6227 - precision: 0.7521
Epoch 28/50
747/747 [==============================] - 8s 10ms/step - loss: 0.5735 -
accuracy: 0.7093 - recall: 0.6183 - precision: 0.7558
Epoch 29/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5734 -
accuracy: 0.7095 - recall: 0.6193 - precision: 0.7556
Epoch 30/50
747/747 [==============================] - 8s 10ms/step - loss: 0.5731 -
accuracy: 0.7086 - recall: 0.6209 - precision: 0.7530
Epoch 31/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5729 -
accuracy: 0.7095 - recall: 0.6263 - precision: 0.7513
Epoch 32/50
```

```
747/747 [==============================] - 7s 10ms/step - loss: 0.5727 -
accuracy: 0.7091 - recall: 0.6210 - precision: 0.7538
Epoch 33/50
747/747 [==============================] - 8s 10ms/step - loss: 0.5726 -
accuracy: 0.7087 - recall: 0.6177 - precision: 0.7551
Epoch 34/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5730 -
accuracy: 0.7096 - recall: 0.6225 - precision: 0.7538
Epoch 35/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5724 -
accuracy: 0.7102 - recall: 0.6259 - precision: 0.7528
Epoch 36/50
747/747 [==============================] - 8s 10ms/step - loss: 0.5724 -
accuracy: 0.7093 - recall: 0.6203 - precision: 0.7547
Epoch 37/50
747/747 [==============================] - 8s 10ms/step - loss: 0.5722 -
accuracy: 0.7097 - recall: 0.6213 - precision: 0.7547
Epoch 38/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5725 -
accuracy: 0.7100 - recall: 0.6238 - precision: 0.7538
Epoch 39/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5725 -
accuracy: 0.7085 - recall: 0.6216 - precision: 0.7524
Epoch 40/50
747/747 [==============================] - 8s 10ms/step - loss: 0.5718 -
accuracy: 0.7083 - recall: 0.6226 - precision: 0.7514
Epoch 41/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5717 -
accuracy: 0.7100 - recall: 0.6257 - precision: 0.7525
Epoch 42/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5715 -
accuracy: 0.7095 - recall: 0.6245 - precision: 0.7524
Epoch 43/50
747/747 [==============================] - 8s 10ms/step - loss: 0.5714 -
accuracy: 0.7098 - recall: 0.6215 - precision: 0.7547
Epoch 44/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5712 -
accuracy: 0.7097 - recall: 0.6267 - precision: 0.7515
Epoch 45/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5717 -
accuracy: 0.7097 - recall: 0.6200 - precision: 0.7556
Epoch 46/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5712 -
accuracy: 0.7098 - recall: 0.6267 - precision: 0.7517
Epoch 47/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5714 -
accuracy: 0.7101 - recall: 0.6231 - precision: 0.7543
Epoch 48/50
```

```
747/747 [==============================] - 7s 9ms/step - loss: 0.5710 -
accuracy: 0.7102 - recall: 0.6242 - precision: 0.7539
Epoch 49/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5709 -
accuracy: 0.7094 - recall: 0.6258 - precision: 0.7514
Epoch 50/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5710 -
accuracy: 0.7091 - recall: 0.6235 - precision: 0.7522
```

[265]:
```python
# Visualising the learning curves
plt.figure(figsize=(16, 8))
plt.subplot(1, 2, 1)
plot_graphs(history_nn_model_smote, 'accuracy')
plt.ylim(0, 1)
plt.subplot(1, 2, 2)
plot_graphs(history_nn_model_smote, 'loss')
plt.ylim(0, 1)
```

[265]: (0.0, 1.0)



[266]:
```python
# making predictions on test set
nn_smote_pred_raw = nn_smote_model.predict(X_test)

nn_smote_pred = [1 if p > 0.5 else 0 for p in np.ravel(nn_smote_pred_raw)]

print(classification_report(y_test, nn_smote_pred, digits=5))
```

```
92/188 [=============>…] - ETA: 0s
```

```
2023-04-08 15:24:41.627117: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
```

```
188/188 [==============================] - 0s 2ms/step
              precision    recall  f1-score   support

         0.0    0.87929   0.79609   0.83562      4703
         1.0    0.44948   0.60370   0.51530      1297

    accuracy                        0.75450      6000
   macro avg    0.66438   0.69989   0.67546      6000
weighted avg    0.78638   0.75450   0.76638      6000
```

[267]:
```python
print("AUC: " + str(roc_auc_score(y_test, nn_smote_pred)))
```

```
AUC: 0.6998942258841326
```

[268]:
```python
pd.DataFrame(confusion_matrix(y_test, nn_smote_pred), columns = ["Predicted 0",␣
 ↪"Predicted 1"], index = ["True 0", "True 1"])
```

[268]:

	Predicted 0	Predicted 1
True 0	3744	959
True 1	514	783

8.5.4 Neural Network Tuning

[138]:
```python
def define_model(learning_rate = 0.001, neurons_1 = 8, neurons_2 = 4):
    model = tf.keras.Sequential([
        tf.keras.layers.Dense(neurons_1, activation = "relu", input_shape=(10,␣
 ↪)),
        tf.keras.layers.Dense(neurons_2, activation = "sigmoid"),
        tf.keras.layers.Dense(1, activation = "sigmoid")
    ])

    optimizer = tf.keras.optimizers.Adam(learning_rate = learning_rate)

    model.compile(
        loss=tf.keras.losses.binary_crossentropy,
        optimizer = optimizer,
        metrics = ['acc']
    )
    return model

learning_rate = [0.001, 0.01, 0.1]
neurons_1 = [8, 16]
neurons_2 = [4, 8]
```

```
param_grid = dict(learning_rate = learning_rate, neurons_1 = neurons_1,␣
↪neurons_2 = neurons_2)
```

[139]:
```
nn_model_temp = KerasClassifier(model = define_model, epochs=50, batch_size =␣
↪50,
                                learning_rate=0.001, neurons_1=8, neurons_2=4,␣
↪verbose=0)
nn_grid_model = GridSearchCV(estimator = nn_model_temp, param_grid =␣
↪param_grid, scoring = "accuracy", cv = 3, verbose = 0)
```

[140]:
```
nn_grid_model.fit(X_SMOTE, y_SMOTE)
print(nn_grid_model.best_params_)
```

```
2023-04-08 06:33:53.693735: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 06:35:51.294481: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 06:35:51.864794: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 06:37:49.100805: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 06:37:49.662360: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 07:00:59.427460: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 07:01:00.004853: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 07:33:33.112069: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 07:33:33.678112: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 07:52:21.924525: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 07:52:22.477506: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 08:09:59.150052: I
```

```
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 08:09:59.794674: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 08:11:56.856607: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 08:11:57.421311: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 08:46:31.354975: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 08:46:31.919385: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 09:21:10.189272: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 09:21:10.750783: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 10:09:41.909988: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 10:09:42.467727: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 10:11:41.253550: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 10:11:41.817866: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 10:45:08.791129: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 10:45:09.366404: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:03:38.532051: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:03:39.096888: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:05:37.972301: I
```

```
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:05:38.539991: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:07:37.334446: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:07:37.894833: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:09:37.286243: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:09:37.923098: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:12:13.020215: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:12:14.305142: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:17:03.396704: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:17:04.850747: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:48:47.176956: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:48:48.196213: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:50:52.781287: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:50:53.366962: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:52:57.348449: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:52:57.964482: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:55:02.351613: I
```

```
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:55:02.947552: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:57:08.193507: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:57:08.786068: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:59:12.597589: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 11:59:13.191180: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:01:17.118341: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:01:17.715229: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:03:21.407998: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:03:22.000616: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:05:25.102859: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:05:25.757317: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:07:30.107472: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:07:30.717262: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:09:35.045776: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:09:35.641994: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:11:40.739902: I
```

```
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:11:41.378237: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:13:45.520290: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:13:46.114949: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:15:49.601896: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:15:50.240346: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:17:54.235077: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:17:54.844210: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:20:00.574210: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:20:01.185509: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:22:07.048759: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:22:07.645391: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:24:12.856743: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
2023-04-08 12:24:13.495964: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
```

```
{'learning_rate': 0.01, 'neurons_1': 8, 'neurons_2': 8}
```

8.5.5 Creating the Optimised Neural Network from the Tuned Hyperparameters

[55]:
```
optimised_nn = tf.keras.Sequential([
    tf.keras.layers.Dense(8, activation = "relu", input_shape=(10, )),
    tf.keras.layers.Dense(8, activation = "sigmoid"),
    tf.keras.layers.Dense(1, activation = "sigmoid")
])

optimizer = tf.keras.optimizers.Adam(learning_rate = 0.01)

optimised_nn.compile(
    loss=tf.keras.losses.binary_crossentropy,
    optimizer = optimizer,
    metrics=[
        tf.keras.metrics.BinaryAccuracy(name='accuracy'),
        tf.keras.metrics.Recall(name='recall'),
        tf.keras.metrics.Precision(name='precision')
    ]
)
```

```
Metal device set to: Apple M1 Pro
```

```
2023-04-09 13:30:23.189610: I
tensorflow/core/common_runtime/pluggable_device/pluggable_device_factory.cc:305]
Could not identify NUMA node of platform GPU ID 0, defaulting to 0. Your kernel
may not have been built with NUMA support.
2023-04-09 13:30:23.189904: I
tensorflow/core/common_runtime/pluggable_device/pluggable_device_factory.cc:271]
Created TensorFlow device (/job:localhost/replica:0/task:0/device:GPU:0 with 0
MB memory) -> physical PluggableDevice (device: 0, name: METAL, pci bus id:
<undefined>)
```

[56]:
```
optimised_nn_history = optimised_nn.fit(X_SMOTE, y_SMOTE, batch_size=50,␣
↪epochs=50)
```

```
Epoch 1/50
```

```
2023-04-09 13:30:23.526673: W
tensorflow/core/platform/profile_utils/cpu_utils.cc:128] Failed to get CPU
frequency: 0 Hz
2023-04-09 13:30:23.865839: I
tensorflow/core/grappler/optimizers/custom_graph_optimizer_registry.cc:113]
Plugin optimizer for device_type GPU is enabled.
```

```
747/747 [==============================] - 7s 9ms/step - loss: 0.5882 -
accuracy: 0.7016 - recall: 0.6052 - precision: 0.7497
Epoch 2/50
747/747 [==============================] - 6s 9ms/step - loss: 0.5839 -
accuracy: 0.7038 - recall: 0.6047 - precision: 0.7542
Epoch 3/50
```

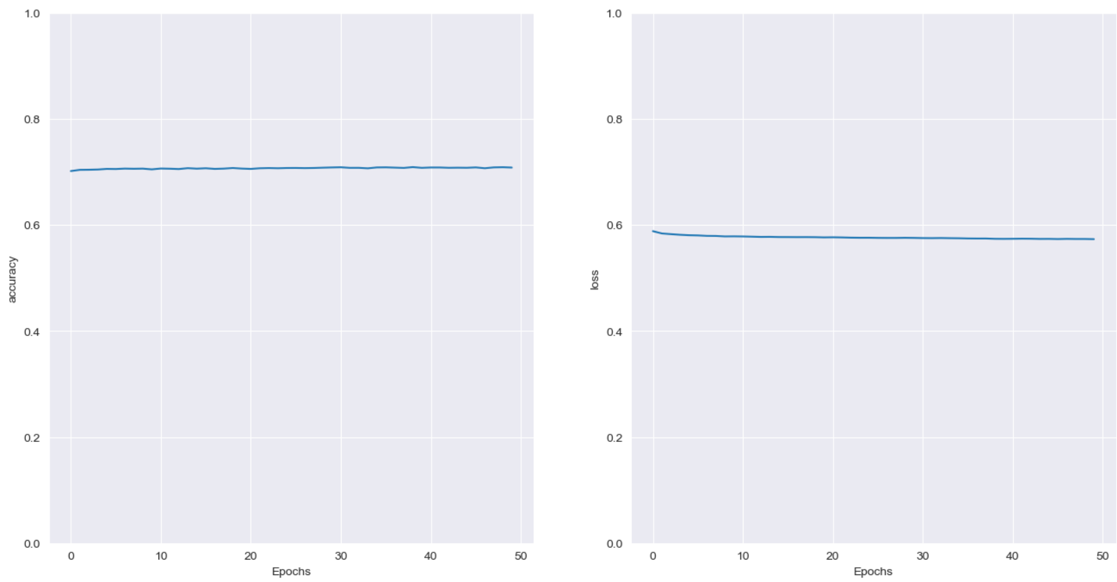
```
747/747 [==============================] - 7s 9ms/step - loss: 0.5826 -
accuracy: 0.7040 - recall: 0.6089 - precision: 0.7520
Epoch 4/50
747/747 [==============================] - 6s 9ms/step - loss: 0.5814 -
accuracy: 0.7045 - recall: 0.6133 - precision: 0.7501
Epoch 5/50
747/747 [==============================] - 6s 8ms/step - loss: 0.5806 -
accuracy: 0.7056 - recall: 0.6162 - precision: 0.7504
Epoch 6/50
747/747 [==============================] - 6s 8ms/step - loss: 0.5802 -
accuracy: 0.7054 - recall: 0.6165 - precision: 0.7499
Epoch 7/50
747/747 [==============================] - 6s 9ms/step - loss: 0.5793 -
accuracy: 0.7062 - recall: 0.6178 - precision: 0.7505
Epoch 8/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5792 -
accuracy: 0.7059 - recall: 0.6178 - precision: 0.7499
Epoch 9/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5783 -
accuracy: 0.7062 - recall: 0.6205 - precision: 0.7487
Epoch 10/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5785 -
accuracy: 0.7048 - recall: 0.6202 - precision: 0.7465
Epoch 11/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5783 -
accuracy: 0.7063 - recall: 0.6197 - precision: 0.7496
Epoch 12/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5778 -
accuracy: 0.7060 - recall: 0.6219 - precision: 0.7476
Epoch 13/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5774 -
accuracy: 0.7054 - recall: 0.6189 - precision: 0.7483
Epoch 14/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5775 -
accuracy: 0.7070 - recall: 0.6235 - precision: 0.7485
Epoch 15/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5771 -
accuracy: 0.7061 - recall: 0.6219 - precision: 0.7478
Epoch 16/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5771 -
accuracy: 0.7068 - recall: 0.6247 - precision: 0.7475
Epoch 17/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5770 -
accuracy: 0.7056 - recall: 0.6165 - precision: 0.7503
Epoch 18/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5770 -
accuracy: 0.7062 - recall: 0.6189 - precision: 0.7498
Epoch 19/50
```

```
747/747 [==============================] - 7s 9ms/step - loss: 0.5769 -
accuracy: 0.7073 - recall: 0.6188 - precision: 0.7520
Epoch 20/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5765 -
accuracy: 0.7062 - recall: 0.6208 - precision: 0.7488
Epoch 21/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5767 -
accuracy: 0.7056 - recall: 0.6205 - precision: 0.7478
Epoch 22/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5764 -
accuracy: 0.7068 - recall: 0.6258 - precision: 0.7469
Epoch 23/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5760 -
accuracy: 0.7073 - recall: 0.6261 - precision: 0.7474
Epoch 24/50
747/747 [==============================] - 7s 9ms/step - loss: 0.5758 -
accuracy: 0.7069 - recall: 0.6254 - precision: 0.7472
Epoch 25/50
747/747 [==============================] - 7s 10ms/step - loss: 0.5758 -
accuracy: 0.7073 - recall: 0.6245 - precision: 0.7485
Epoch 26/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5755 -
accuracy: 0.7074 - recall: 0.6222 - precision: 0.7500
Epoch 27/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5754 -
accuracy: 0.7071 - recall: 0.6249 - precision: 0.7479
Epoch 28/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5754 -
accuracy: 0.7074 - recall: 0.6230 - precision: 0.7495
Epoch 29/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5757 -
accuracy: 0.7079 - recall: 0.6226 - precision: 0.7507
Epoch 30/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5755 -
accuracy: 0.7084 - recall: 0.6179 - precision: 0.7544
Epoch 31/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5752 -
accuracy: 0.7087 - recall: 0.6239 - precision: 0.7514
Epoch 32/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5751 -
accuracy: 0.7076 - recall: 0.6198 - precision: 0.7519
Epoch 33/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5753 -
accuracy: 0.7077 - recall: 0.6195 - precision: 0.7521
Epoch 34/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5750 -
accuracy: 0.7067 - recall: 0.6205 - precision: 0.7498
Epoch 35/50
```

```
747/747 [==============================] - 8s 11ms/step - loss: 0.5748 -
accuracy: 0.7084 - recall: 0.6222 - precision: 0.7518
Epoch 36/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5745 -
accuracy: 0.7086 - recall: 0.6235 - precision: 0.7513
Epoch 37/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5743 -
accuracy: 0.7081 - recall: 0.6219 - precision: 0.7514
Epoch 38/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5744 -
accuracy: 0.7075 - recall: 0.6190 - precision: 0.7521
Epoch 39/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5738 -
accuracy: 0.7090 - recall: 0.6219 - precision: 0.7531
Epoch 40/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5737 -
accuracy: 0.7077 - recall: 0.6221 - precision: 0.7505
Epoch 41/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5738 -
accuracy: 0.7083 - recall: 0.6225 - precision: 0.7514
Epoch 42/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5741 -
accuracy: 0.7083 - recall: 0.6241 - precision: 0.7505
Epoch 43/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5739 -
accuracy: 0.7077 - recall: 0.6188 - precision: 0.7527
Epoch 44/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5736 -
accuracy: 0.7079 - recall: 0.6187 - precision: 0.7531
Epoch 45/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5737 -
accuracy: 0.7078 - recall: 0.6198 - precision: 0.7521
Epoch 46/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5734 -
accuracy: 0.7085 - recall: 0.6239 - precision: 0.7509
Epoch 47/50
747/747 [==============================] - 8s 10ms/step - loss: 0.5737 -
accuracy: 0.7069 - recall: 0.6189 - precision: 0.7511
Epoch 48/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5735 -
accuracy: 0.7085 - recall: 0.6188 - precision: 0.7541
Epoch 49/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5735 -
accuracy: 0.7088 - recall: 0.6207 - precision: 0.7535
Epoch 50/50
747/747 [==============================] - 8s 11ms/step - loss: 0.5732 -
accuracy: 0.7082 - recall: 0.6216 - precision: 0.7518
```

[59]:
```
# Visualising the learning curves
plt.figure(figsize=(16, 8))
plt.subplot(1, 2, 1)
plot_graphs(optimised_nn_history, 'accuracy')
plt.ylim(0, 1)
plt.subplot(1, 2, 2)
plot_graphs(optimised_nn_history, 'loss')
plt.ylim(0, 1)
```

[59]: (0.0, 1.0)



[68]:
```
# Make predictions
nn_grid_pred_raw = optimised_nn.predict(X_test)

nn_grid_pred = [1 if p > 0.5 else 0 for p in np.ravel(nn_grid_pred_raw)]
```

```
188/188 [==============================] - 0s 2ms/step
```

[69]:
```
print(classification_report(y_test, nn_grid_pred, digits=5))
```

```
              precision    recall  f1-score   support

         0.0    0.87457   0.81246   0.84237      4703
         1.0    0.45923   0.57749   0.51161      1297

    accuracy                        0.76167      6000
   macro avg    0.66690   0.69497   0.67699      6000
weighted avg    0.78479   0.76167   0.77087      6000
```

[70]:
```
print("AUC: " + str(roc_auc_score(y_test, nn_grid_pred)))
```

```
AUC: 0.6949733195776706
```

[71]:
```
pd.DataFrame(confusion_matrix(y_test, nn_grid_pred), columns = ["Predicted 0",␣
↪"Predicted 1"], index = ["True 0", "True 1"])
```

[71]:

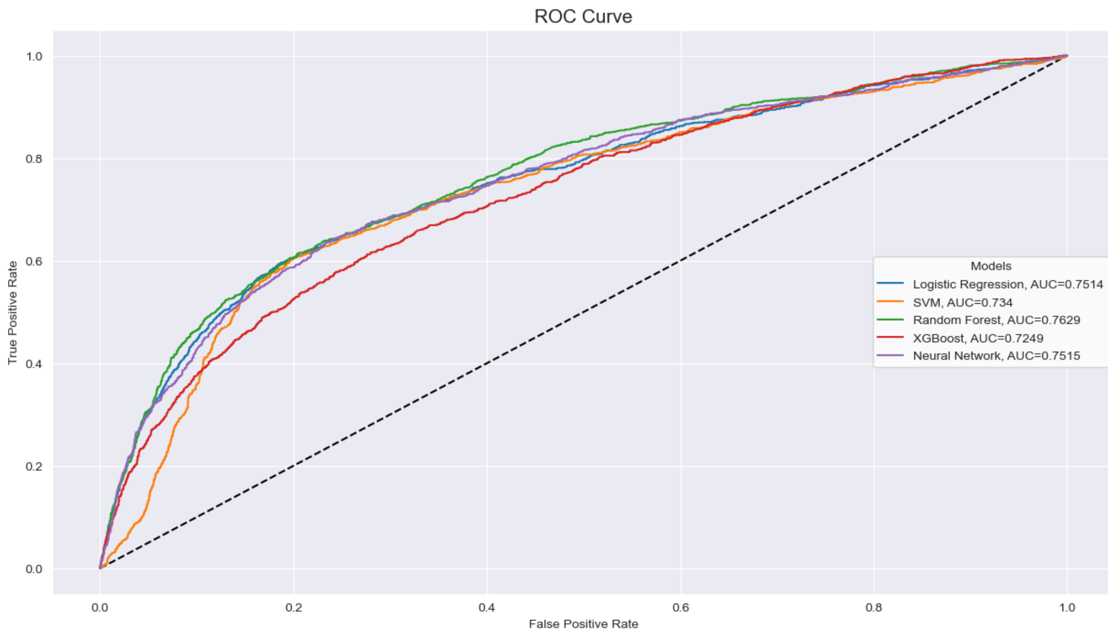
	Predicted 0	Predicted 1
True 0	3821	882
True 1	548	749

8.6 ROC Curve for all models

[72]:
```
# Logistic Regression
lr_y_pred_proba = optimised_lr.predict_proba(X_test)[::,-1]
lr_fpr, lr_tpr, _ = roc_curve(y_test, lr_y_pred_proba)
lr_auc = roc_auc_score(y_test, lr_y_pred_proba)

# SVM
svm_y_pred_proba = optimised_svm.predict_proba(X_test)[::,1]
svm_fpr, svm_tpr, _ = roc_curve(y_test, svm_y_pred_proba)
svm_auc = roc_auc_score(y_test, svm_y_pred_proba)

# Random Forest
rf_y_pred_proba = optimised_rf.predict_proba(X_test)[::,1]
rf_fpr, rf_tpr, _ = roc_curve(y_test, rf_y_pred_proba)
rf_auc = roc_auc_score(y_test, rf_y_pred_proba)

# XGBoost
xgb_y_pred_proba = optimised_xgboost.predict_proba(X_test)[::,1]
xgb_fpr, xgb_tpr, _ = roc_curve(y_test, xgb_y_pred_proba)
xgb_auc = roc_auc_score(y_test, xgb_y_pred_proba)

# Neural Network
nn_y_pred_proba = optimised_nn.predict(X_test)[::,-1]
nn_fpr, nn_tpr, _ = roc_curve(y_test, nn_y_pred_proba)
nn_auc = roc_auc_score(y_test, nn_y_pred_proba)

# Plotting
plt.figure(figsize = (15, 8))
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(lr_fpr, lr_tpr, label=f"Logistic Regression, AUC={round(lr_auc, 4)}")
plt.plot(svm_fpr, svm_tpr, label=f"SVM, AUC={round(svm_auc, 4)}")
plt.plot(rf_fpr, rf_tpr, label=f"Random Forest, AUC={round(rf_auc, 4)}")
plt.plot(xgb_fpr, xgb_tpr, label=f"XGBoost, AUC={round(xgb_auc, 4)}")
plt.plot(nn_fpr, nn_tpr, label=f"Neural Network, AUC={round(nn_auc, 4)}")
plt.legend(loc=5, title='Models', facecolor='white')
plt.ylabel('True Positive Rate')
```

```
plt.xlabel('False Positive Rate')
plt.title('ROC Curve', size=15)
plt.show()
```

```
188/188 [==============================] - 0s 2ms/step
```



[145]:

```

```