Import all the libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import scipy.stats as stats
from sklearn.preprocessing import LabelEncoder,StandardScaler
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score
import plotly.express as px
from mpl_toolkits import mplot3d
import yellowbrick
from yellowbrick.cluster import SilhouetteVisualizer
from sklearn.model_selection import train_test_split,GridSearchCV,cross_val_score,KFold,cros
from sklearn.preprocessing import MinMaxScaler
from collections import Counter
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix,accuracy_score,classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.feature_selection import RFE
from sklearn import tree
from sklearn.ensemble import RandomForestClassifier
import tensorflow as tf
from keras.models import Sequential
from keras.layers import Dense,Dropout
import warnings
warnings.filterwarnings('ignore')

```

Load the dataset:

In [2]:
```
application = pd.read_csv("application_record.csv")
application.head()
```

Out[2]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
0	5008804	M	Y	Y	0	427500.0	Working
1	5008805	M	Y	Y	0	427500.0	Working
2	5008806	M	Y	Y	0	112500.0	Working
3	5008808	F	N	Y	0	270000.0	Commercial associate
4	5008809	F	N	Y	0	270000.0	Commercial associate

In [3]:
```
print("Number of rows", application.shape[0])
print("Number of columns", application.shape[1])
```

```
Number of rows 438557
Number of columns 18
```

In [4]:
```
print("Duplicated data:",{application.ID.duplicated().any()})

```

```
Duplicated data: {True}
```

In [5]:
```
application.drop_duplicates('ID',keep = 'first', inplace = True )
```

In [6]:
```
application.head()
```

Out[6]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
0	5008804	M	Y	Y	0	427500.0	Working
1	5008805	M	Y	Y	0	427500.0	Working
2	5008806	M	Y	Y	0	112500.0	Working
3	5008808	F	N	Y	0	270000.0	Commercial associate
4	5008809	F	N	Y	0	270000.0	Commercial associate

In [7]:
```
application = application.reset_index(drop=True)
application.head()
```

Out[7]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
0	5008804	M	Y	Y	0	427500.0	Working
1	5008805	M	Y	Y	0	427500.0	Working
2	5008806	M	Y	Y	0	112500.0	Working
3	5008808	F	N	Y	0	270000.0	Commercial associate
4	5008809	F	N	Y	0	270000.0	Commercial associate

In [8]:
```
print("Number of rows after removing duplicates", application.shape[0])
print("Number of columns after removing duplicates", application.shape[1])
```

```
Number of rows after removing duplicates 438510
Number of columns after removing duplicates 18
```

In [9]:
```
credit_df = pd.read_csv("credit_record.csv")
credit_df.head()
```

Out[9]:

	ID	MONTHS_BALANCE	STATUS
0	5001711	0	X
1	5001711	-1	0
2	5001711	-2	0
3	5001711	-3	0
4	5001712	0	C

In [10]:
```
LE = LabelEncoder()
```

In [11]:
```
credit_df['STATUS']= LE.fit_transform(credit_df['STATUS'].astype(str))
credit_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1048575 entries, 0 to 1048574
Data columns (total 3 columns):
 #   Column          Non-Null Count    Dtype
---  ------          --------------    -----
 0   ID              1048575 non-null  int64
 1   MONTHS_BALANCE  1048575 non-null  int64
 2   STATUS          1048575 non-null  int64
dtypes: int64(3)
memory usage: 24.0 MB
```

In [12]:
```
#credit_df.drop('MONTHS_BALANCE', axis = 1, inplace = True)
```

In [13]:
```
credit_df['STATUS'].replace(['C', 'X'],0, inplace=True)
```

In [14]:
```
print("Duplicated data:",{credit_df.ID.duplicated().any()})
```

```
Duplicated data: {True}
```

In [15]:
```
print("Number of rows", credit_df.shape[0])
print("Number of columns", credit_df.shape[1])
```

```
Number of rows 1048575
Number of columns 3
```

In [16]:
```
credit = credit_df.groupby('ID').agg(max).reset_index()
credit.head()
```

Out[16]:

	ID	MONTHS_BALANCE	STATUS
0	5001711	0	7
1	5001712	0	6
2	5001713	0	7
3	5001714	0	7
4	5001715	0	7

In [17]:
```
print("Number of rows after removing duplicates", credit.shape[0])
print("Number of columns after removing duplicates",credit.shape[1])
```

```
Number of rows after removing duplicates 45985
Number of columns after removing duplicates 3
```

Merging Two dataset:

In [18]:
```
mydata = application.merge(credit,on= 'ID')
mydata.head()
```

Out[18]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
0	5008804	M	Y	Y	0	427500.0	Working
1	5008805	M	Y	Y	0	427500.0	Working
2	5008806	M	Y	Y	0	112500.0	Working
3	5008808	F	N	Y	0	270000.0	Commercial associate
4	5008809	F	N	Y	0	270000.0	Commercial associate

In [19]:
```
print("Number of rows", mydata.shape[0])
print("Number of columns", mydata.shape[1])
```

```
Number of rows 36457
Number of columns 20
```

In [20]:
```
#print("Duplicated data:" ,{mydata.index.duplicated().any()})

#mydata = list(mydata.index)
```

Check Datatypes:

Numeric Features:

In [21]:
```
mydata.columns[(mydata.dtypes !='object').values].tolist()
```

Out[21]:
```
['ID',
 'CNT_CHILDREN',
 'AMT_INCOME_TOTAL',
 'DAYS_BIRTH',
 'DAYS_EMPLOYED',
 'FLAG_MOBIL',
 'FLAG_WORK_PHONE',
 'FLAG_PHONE',
 'FLAG_EMAIL',
 'CNT_FAM_MEMBERS',
 'MONTHS_BALANCE',
 'STATUS']
```

Categorical Features:

In [22]:
```
for i in mydata.columns[(mydata.dtypes =='object').values].tolist():
    print(i,'\n')
    print(mydata[i].value_counts())
    print('-----------------------------------------------')

```

```
CODE_GENDER

F    24430
M    12027
Name: CODE_GENDER, dtype: int64
-----------------------------------------------
FLAG_OWN_CAR

N    22614
Y    13843
Name: FLAG_OWN_CAR, dtype: int64
```

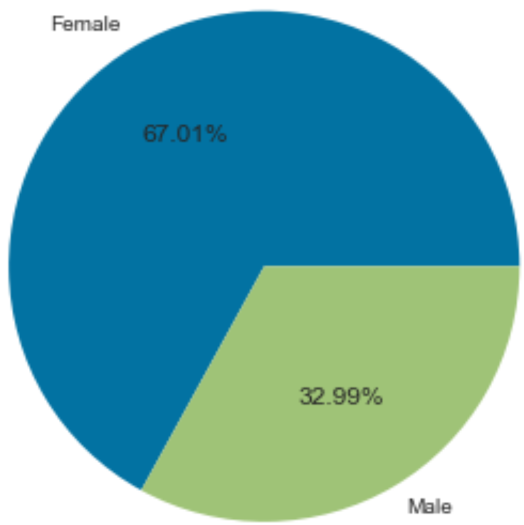
```
----------------------------------------------
FLAG_OWN_REALTY

Y    24506
N    11951
Name: FLAG_OWN_REALTY, dtype: int64
----------------------------------------------
NAME_INCOME_TYPE

Working                 18819
Commercial associate     8490
Pensioner                6152
State servant            2985
Student                    11
Name: NAME_INCOME_TYPE, dtype: int64
----------------------------------------------
NAME_EDUCATION_TYPE

Secondary / secondary special    24777
Higher education                  9864
Incomplete higher                 1410
Lower secondary                    374
Academic degree                     32
Name: NAME_EDUCATION_TYPE, dtype: int64
----------------------------------------------
NAME_FAMILY_STATUS

Married                 25048
Single / not married     4829
Civil marriage           2945
Separated                2103
Widow                    1532
Name: NAME_FAMILY_STATUS, dtype: int64
----------------------------------------------
NAME_HOUSING_TYPE

House / apartment      32548
```

```
With parents            1776
Municipal apartment     1128
Rented apartment         575
Office apartment         262
Co-op apartment          168
Name: NAME_HOUSING_TYPE, dtype: int64
----------------------------------------------
OCCUPATION_TYPE

Laborers                 6211
Core staff               3591
Sales staff              3485
Managers                 3012
Drivers                  2138
High skill tech staff    1383
Accountants              1241
Medicine staff           1207
Cooking staff             655
Security staff            592
Cleaning staff            551
Private service staff     344
Low-skill Laborers        175
Waiters/barmen staff      174
Secretaries               151
HR staff                   85
Realty agents              79
IT staff                   60
Name: OCCUPATION_TYPE, dtype: int64
----------------------------------------------
```

Visualizing Categorical variable total count:

CODE_GENDER Count:

In [23]:
```
plt.pie(mydata['CODE_GENDER'].value_counts(), labels=['Female', 'Male'], autopct='%1.2f%%')
```

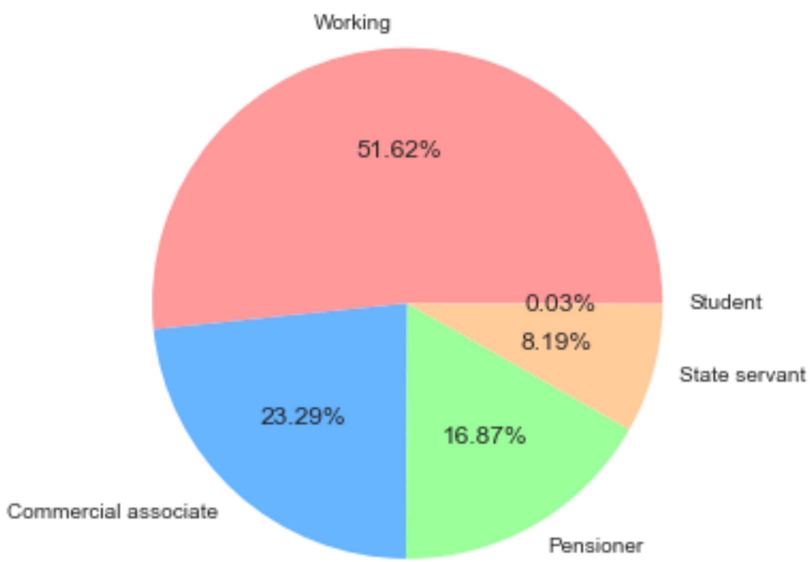


NAME_INCOME_TYPE Count:

In [24]:
```
plt.pie(mydata['NAME_INCOME_TYPE'].value_counts(), labels=['Working', 'Commercial associate',
```

Out[24]:
```
([<matplotlib.patches.Wedge at 0x7ffbe3e06430>,
  <matplotlib.patches.Wedge at 0x7ffbe3e068e0>,
  <matplotlib.patches.Wedge at 0x7ffbe3e06f70>,
  <matplotlib.patches.Wedge at 0x7ffbe3e33640>,
  <matplotlib.patches.Wedge at 0x7ffbe3e06370>],
 [Text(-0.05594916302333328, 1.0985762109007224, 'Working'),
  Text(-0.7396198522188606, -0.8142250758873439, 'Commercial associate'),
  Text(0.5506838377905776, -0.9522328028356516, 'Pensioner'),
  Text(1.063277145409221, -0.2818540616177429, 'State servant'),
```

```
 Text(1.099999505715993, -0.0010427965147598564, 'Student')],
[Text(-0.030517725285454513, 0.5992233877640304, '51.62%'),
 Text(-0.40342901030119666, -0.4441227686658239, '23.29%'),
 Text(0.3003730024312241, -0.519399710637628, '16.87%'),
 Text(0.5799693520413932, -0.15373857906422336, '8.19%'),
 Text(0.5999997303905417, -0.0005687980989599216, '0.03%')])
```

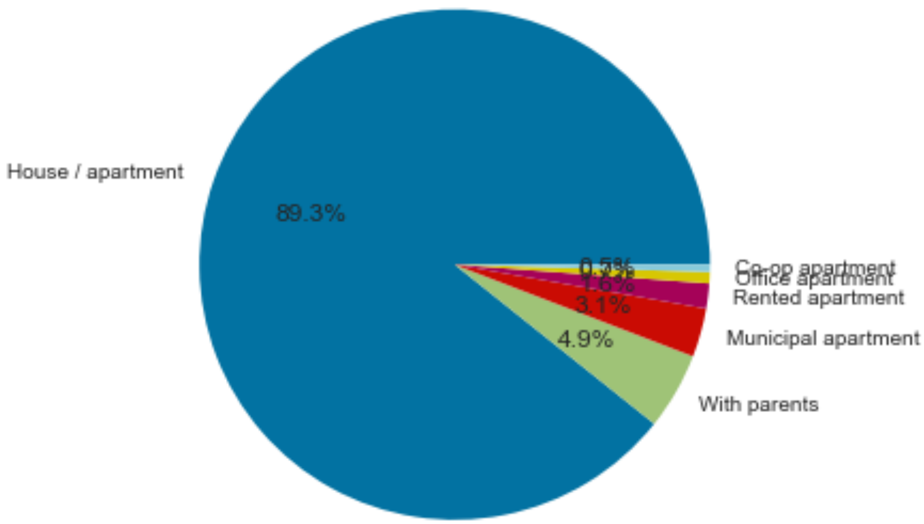


NAME_HOUSING_TYPE

In [25]:
```
plt.pie(mydata['NAME_HOUSING_TYPE'].value_counts(), labels=['House / apartment ', 'With parer
```

Out[25]:
```
([<matplotlib.patches.Wedge at 0x7ffbe3f04370>,
  <matplotlib.patches.Wedge at 0x7ffbe3f04850>,
  <matplotlib.patches.Wedge at 0x7ffbe3f04ee0>,
  <matplotlib.patches.Wedge at 0x7ffbe3f115e0>,
  <matplotlib.patches.Wedge at 0x7ffbe3f11c70>,
```

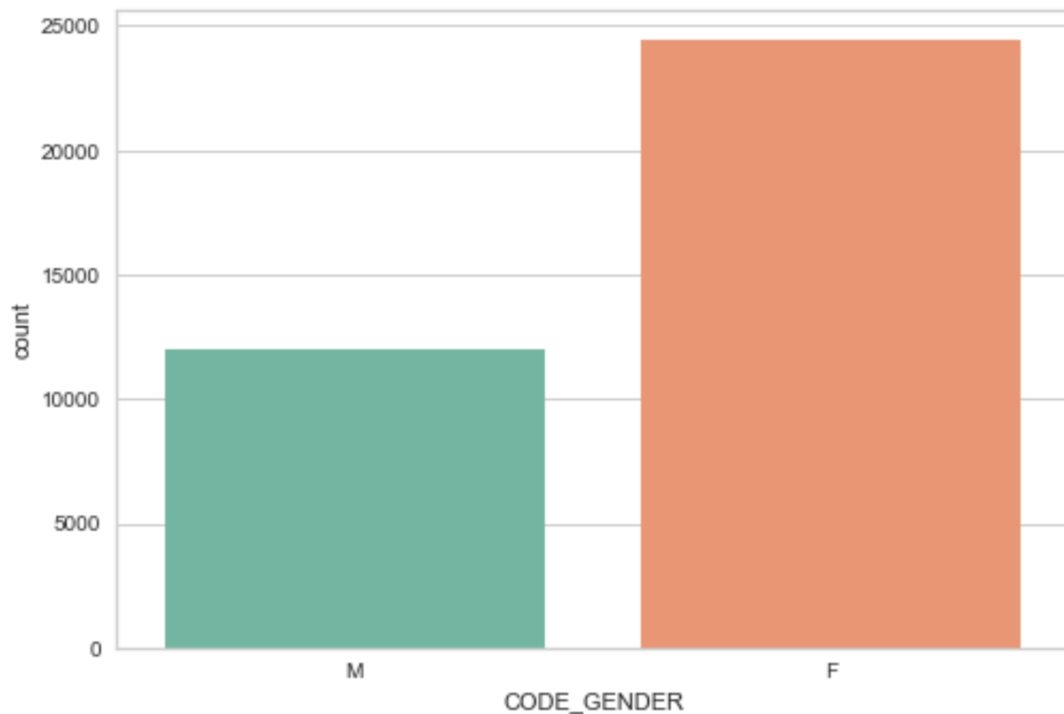
```
 <matplotlib.patches.Wedge at 0x7ffbe3f1e340>],
[Text(-1.0381810727628487, 0.36356575767937904, 'House / apartment '),
 Text(0.9542431649728385, -0.5471928198566026, 'With parents'),
 Text(1.0600277738995736, -0.2938385927027192, 'Municipal apartment'),
 Text(1.0916005560473383, -0.1356769178495078, 'Rented apartment'),
 Text(1.098539821456324, -0.05665916231914935, 'Office apartment'),
 Text(1.0998847320855107, -0.01592407376221483, 'Co-op apartment')],
[Text(-0.5662805851433719, 0.1983085950978431, '89.3%'),
 Text(0.5204962718033664, -0.2984688108308741, '4.9%'),
 Text(0.5781969675815856, -0.160275596019665, '3.1%'),
 Text(0.5954184851167299, -0.07400559155427698, '1.6%'),
 Text(0.5992035389761767, -0.030904997628626914, '0.7%'),
 Text(0.5999371265920967, -0.008685858415753542, '0.5%')])
```



In [26]:
```
#sns_plot = sns.distplot(application["NAME_EDUCATION_TYPE"]) univariate numberical
```

In [27]:
```
sns.countplot(mydata['CODE_GENDER'],palette="Set2")
```

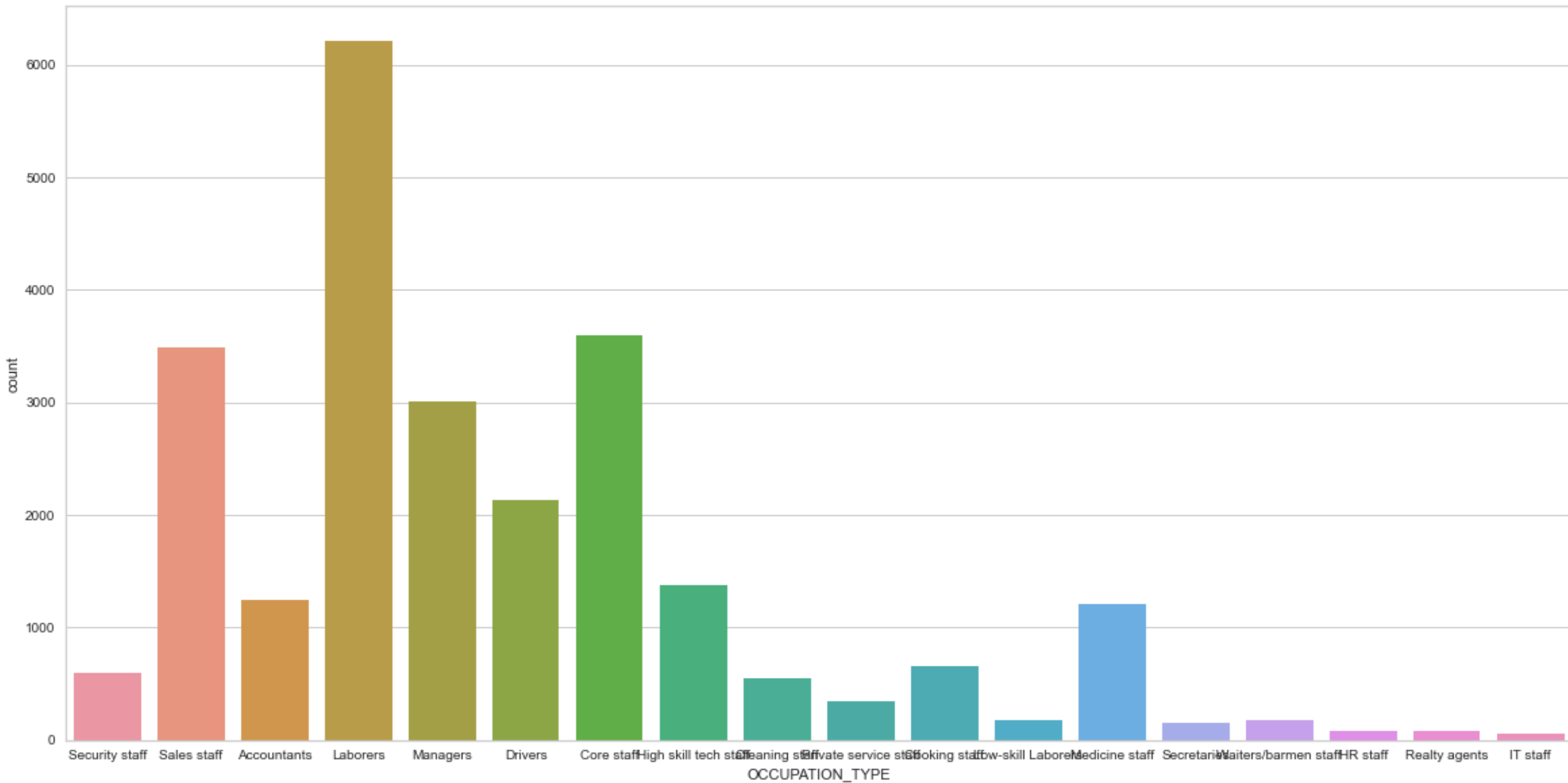
Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffbe3f348b0>



OCCUPATION_TYPE

In [28]:
```
plt.figure(figsize = (20,10))
sns.countplot(mydata['OCCUPATION_TYPE'])
```

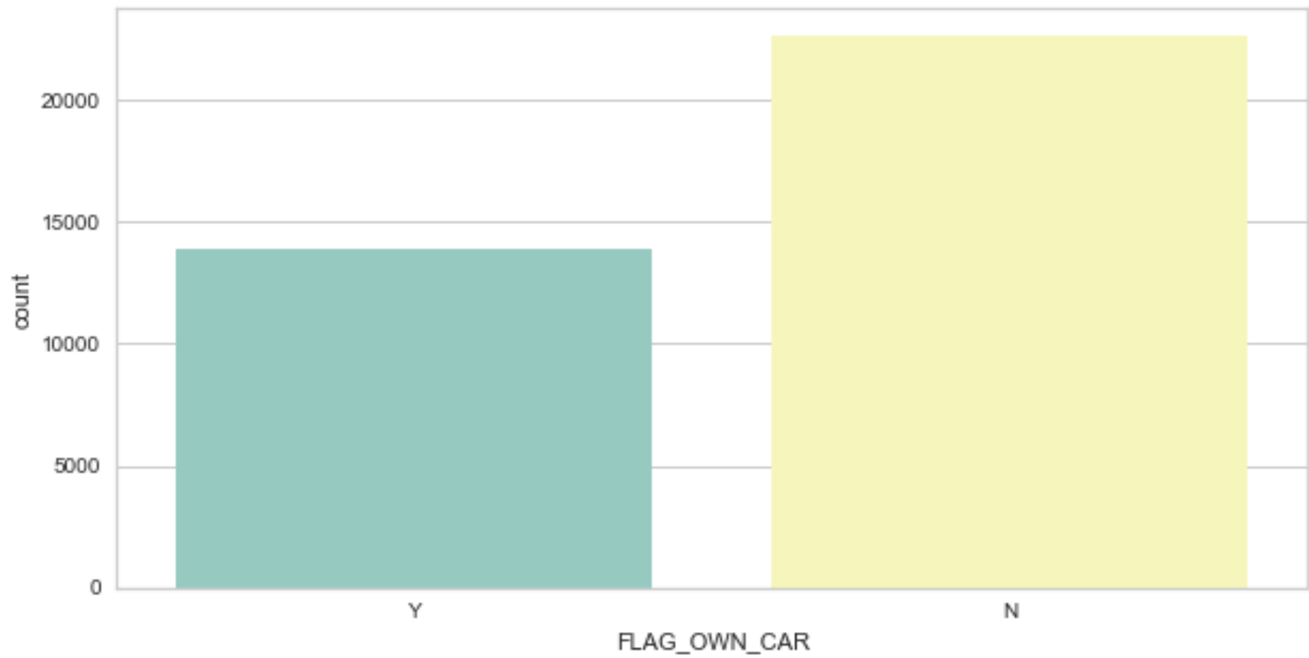
Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffbe4233d30>



FLAG_OWN_CAR

In [29]:
```
plt.figure(figsize = (10,5))
sns.countplot(mydata['FLAG_OWN_CAR'],palette="Set3")
```

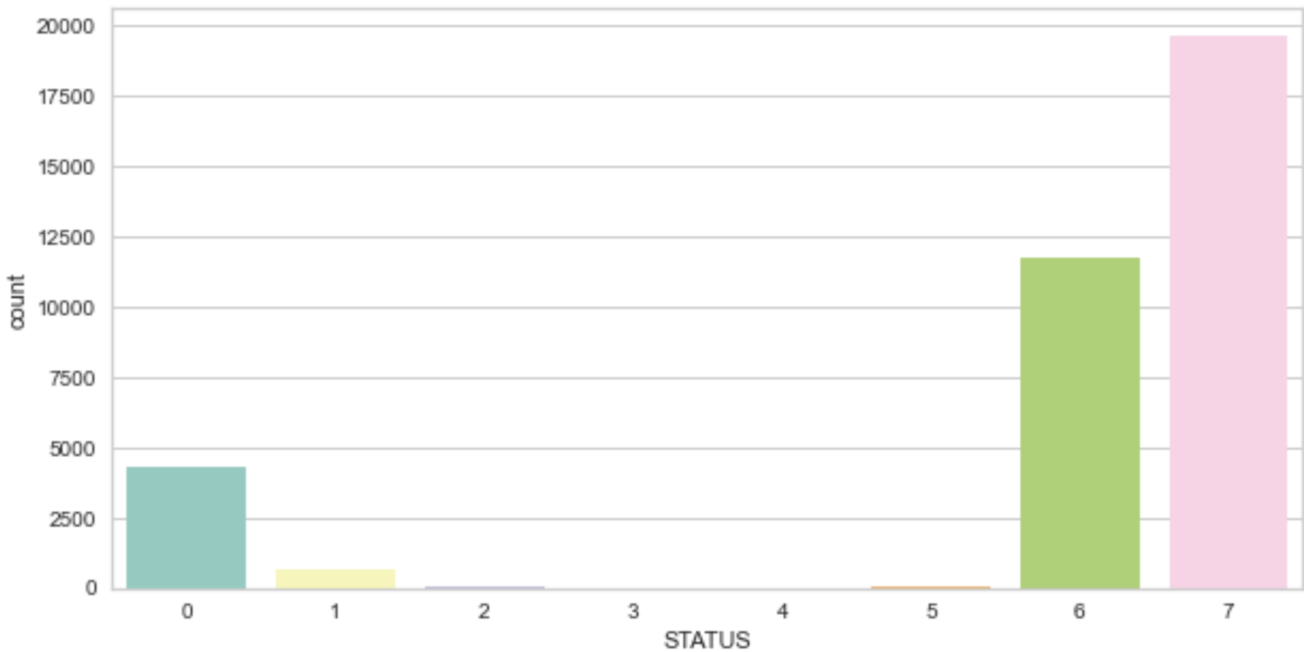
Out[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffbe4233ca0>



STATUS

In [30]:
```
plt.figure(figsize = (10,5))
sns.countplot(mydata['STATUS'],palette="Set3")
```

Out[30]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffbe3f34070>

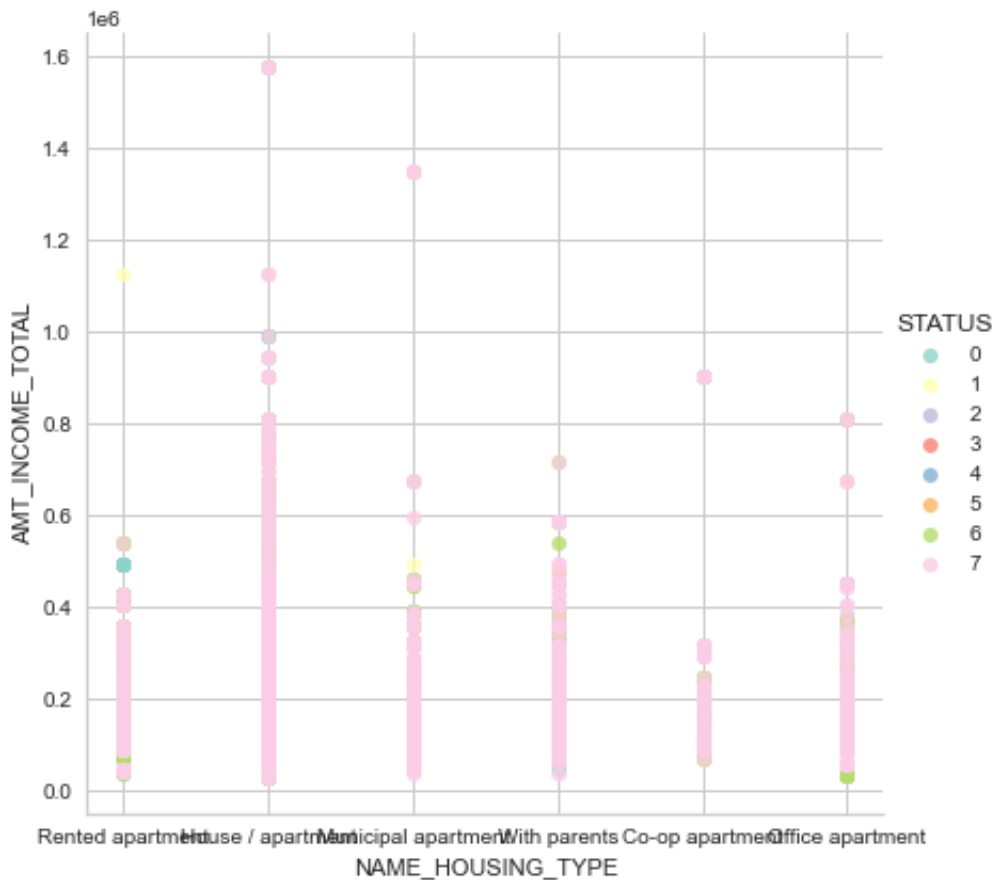


In [31]:

```
plt.figure(figsize = (30,20))
sns.lmplot(x='NAME_HOUSING_TYPE', y='AMT_INCOME_TOTAL', data=mydata,
          fit_reg=False,
          hue='STATUS',
          legend=True,
          palette="Set3",height=6)
```

Out[31]:

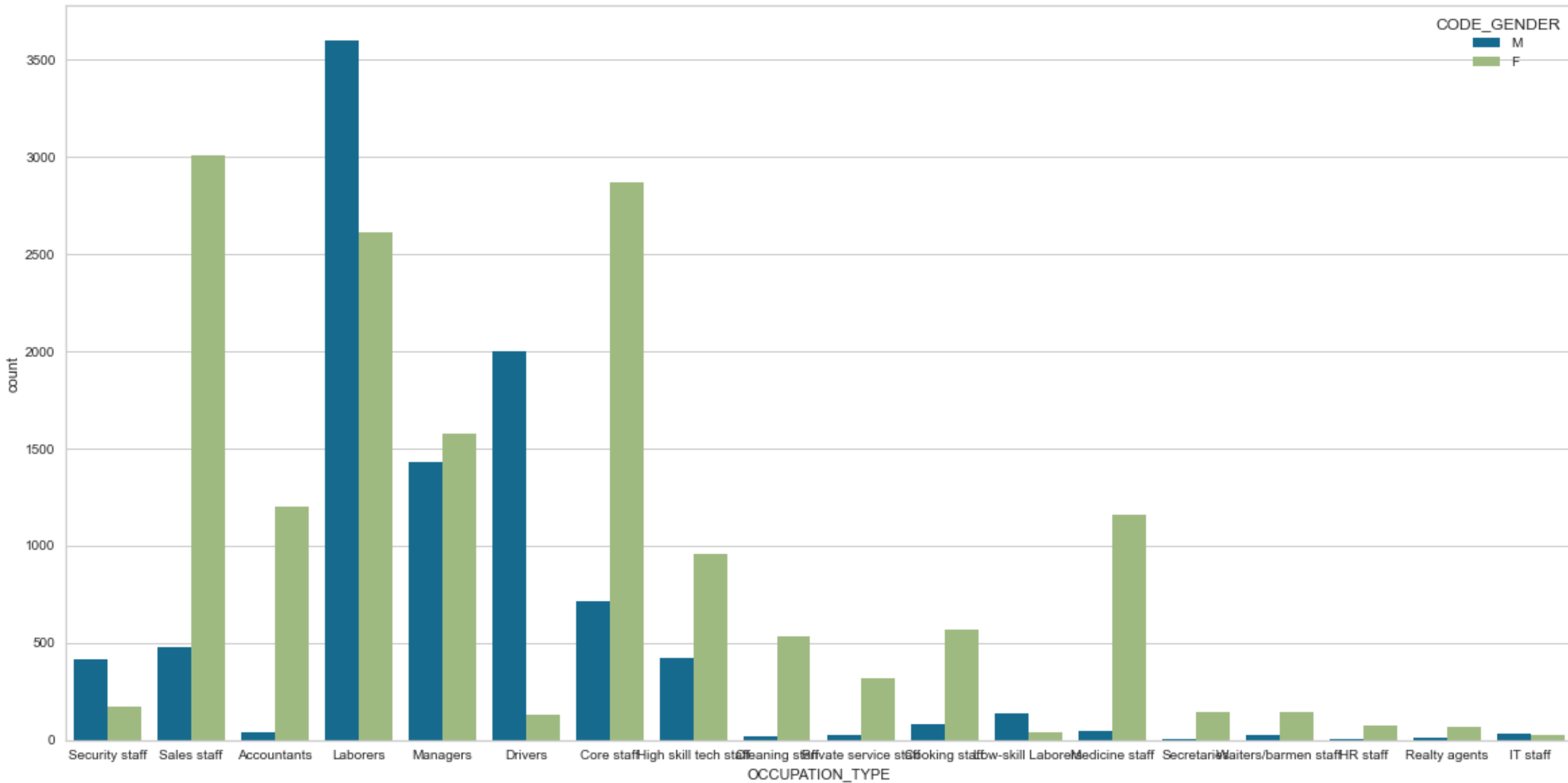
```
<seaborn.axisgrid.FacetGrid at 0x7ffbdbd272b0>

<Figure size 2160x1440 with 0 Axes>
```



Plotting Occupation type based on gender:

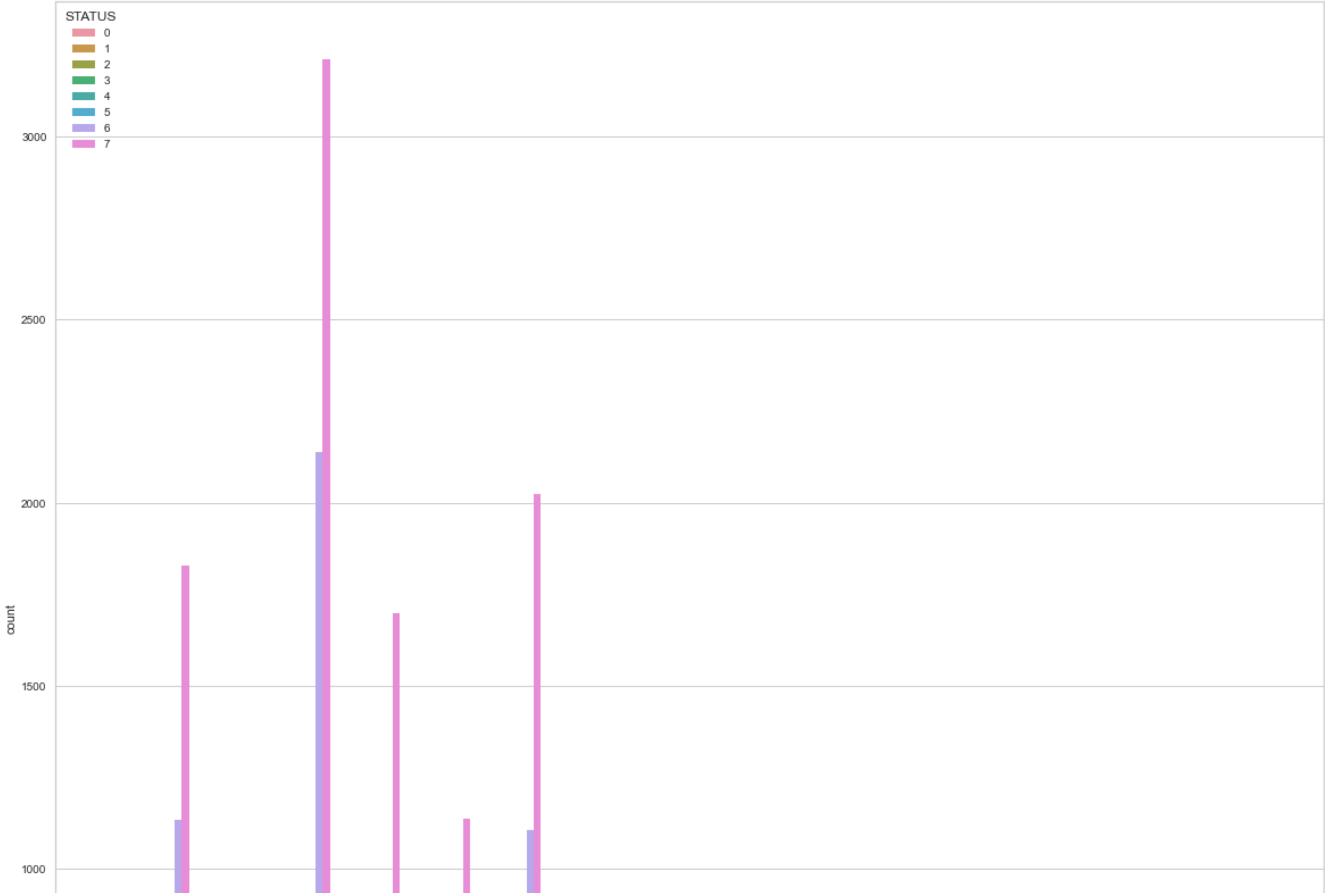
In [32]:

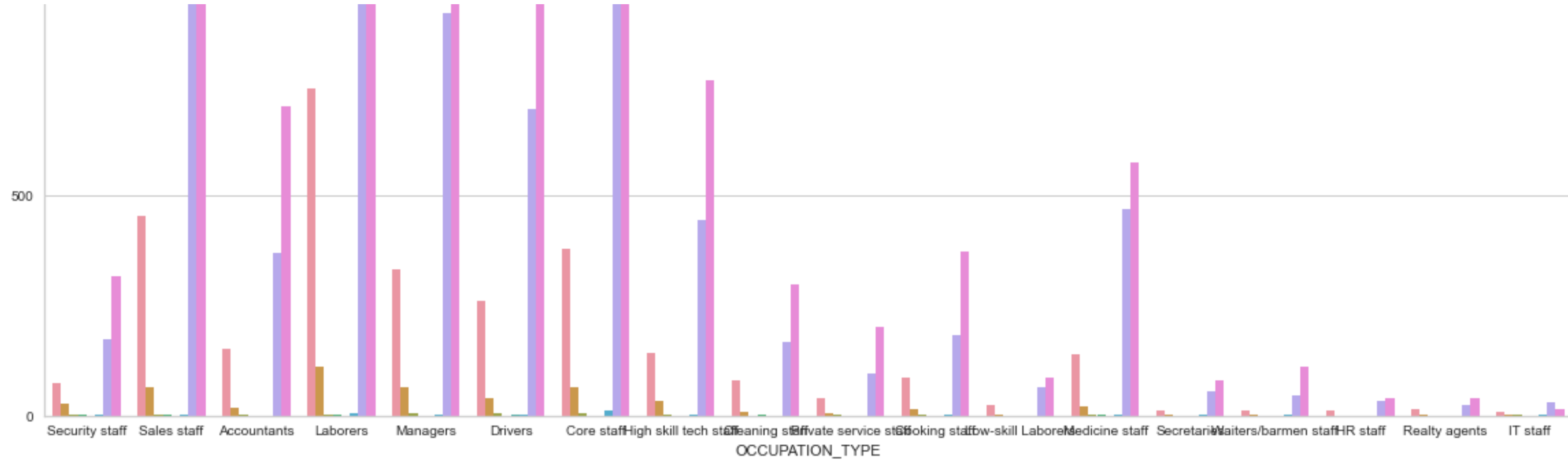
```
plt.figure(figsize=(20,10))
sns.countplot(x='OCCUPATION_TYPE', data=mydata,
              hue="CODE_GENDER")
plt.show()
```



Plotting Occupation type based on status:

In [33]:
```
plt.figure(figsize=(20,20))
sns.countplot(x='OCCUPATION_TYPE', data=mydata,
              hue="STATUS")
plt.show()
```

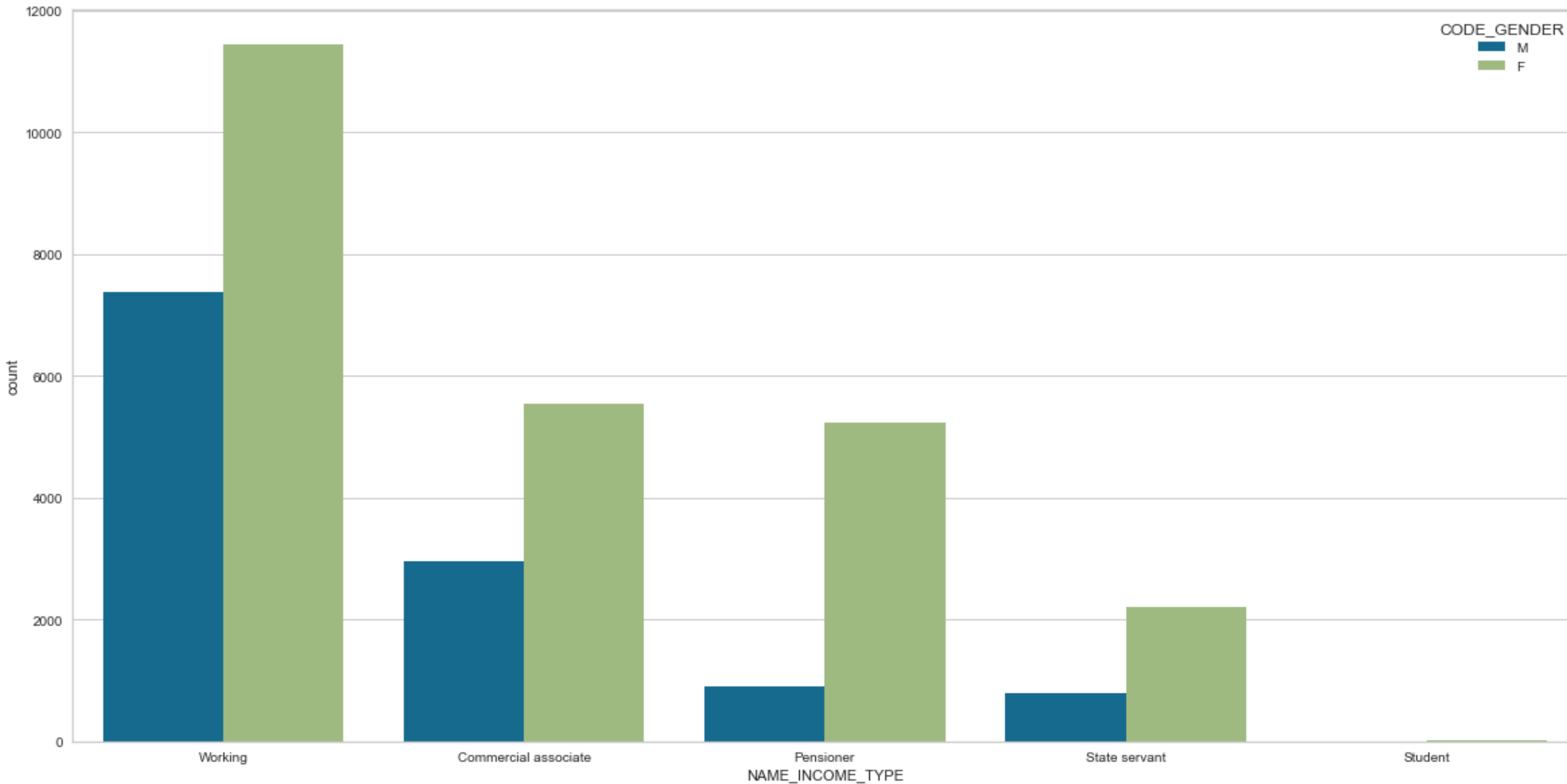




Plotting name_income_type based on code gender:

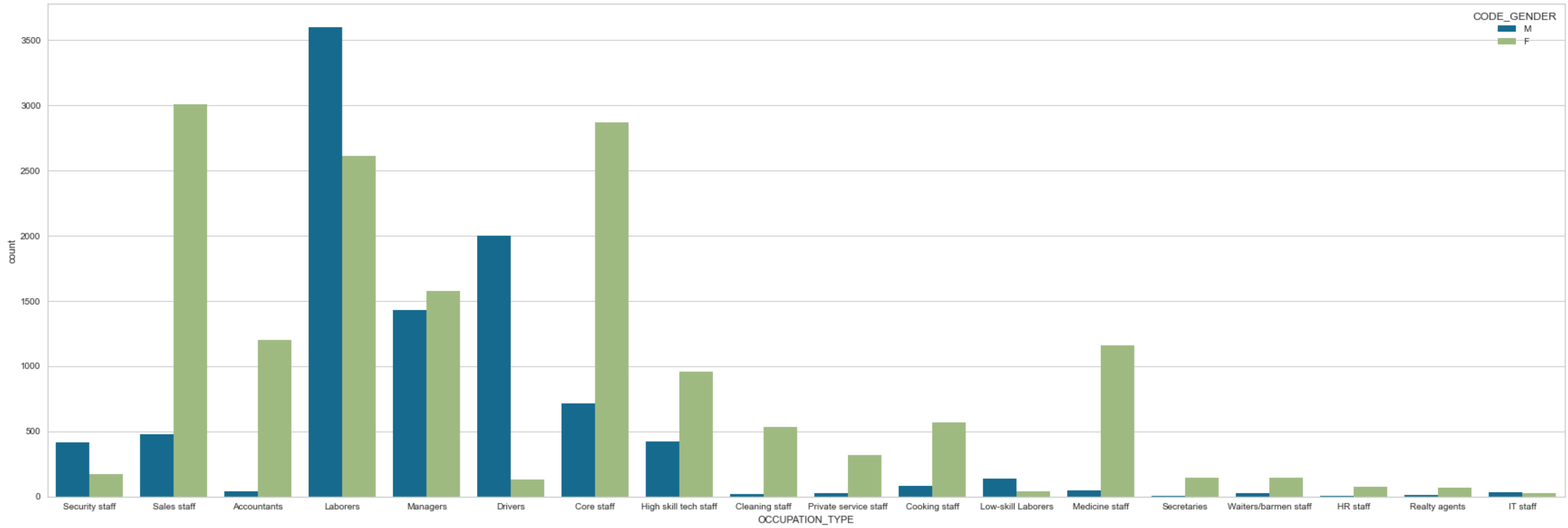
In [34]:

```
plt.figure(figsize=(20,10))
sns.countplot(x='NAME_INCOME_TYPE', data=mydata,
              hue="CODE_GENDER")
plt.show()
```



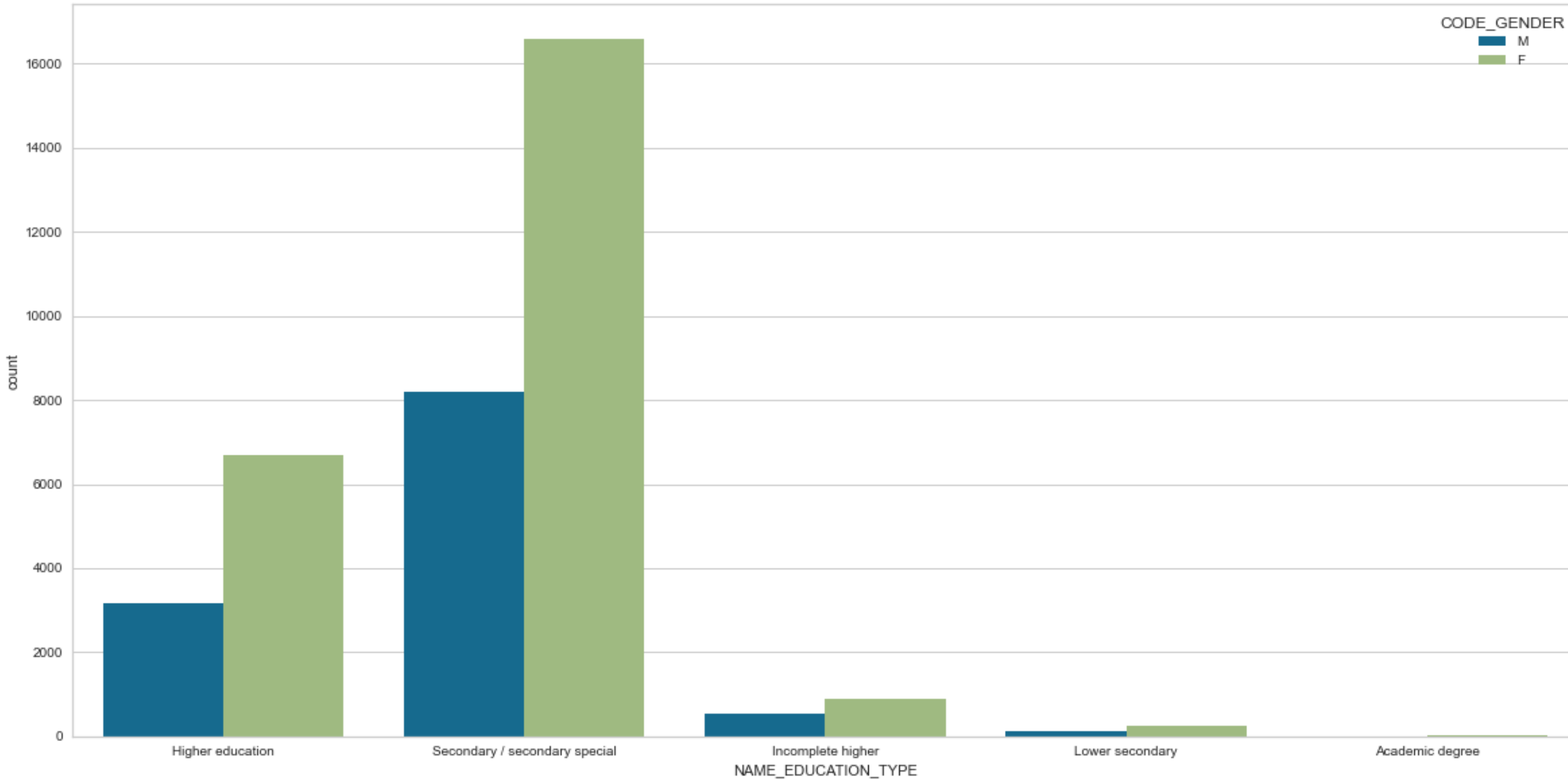
Plotting occupation_type based on code gender:

In [35]:
```
plt.figure(figsize=(30,10))
sns.countplot(x='OCCUPATION_TYPE', data=mydata,
              hue="CODE_GENDER")
plt.show()
```



Plotting Name_education_type based on code gender

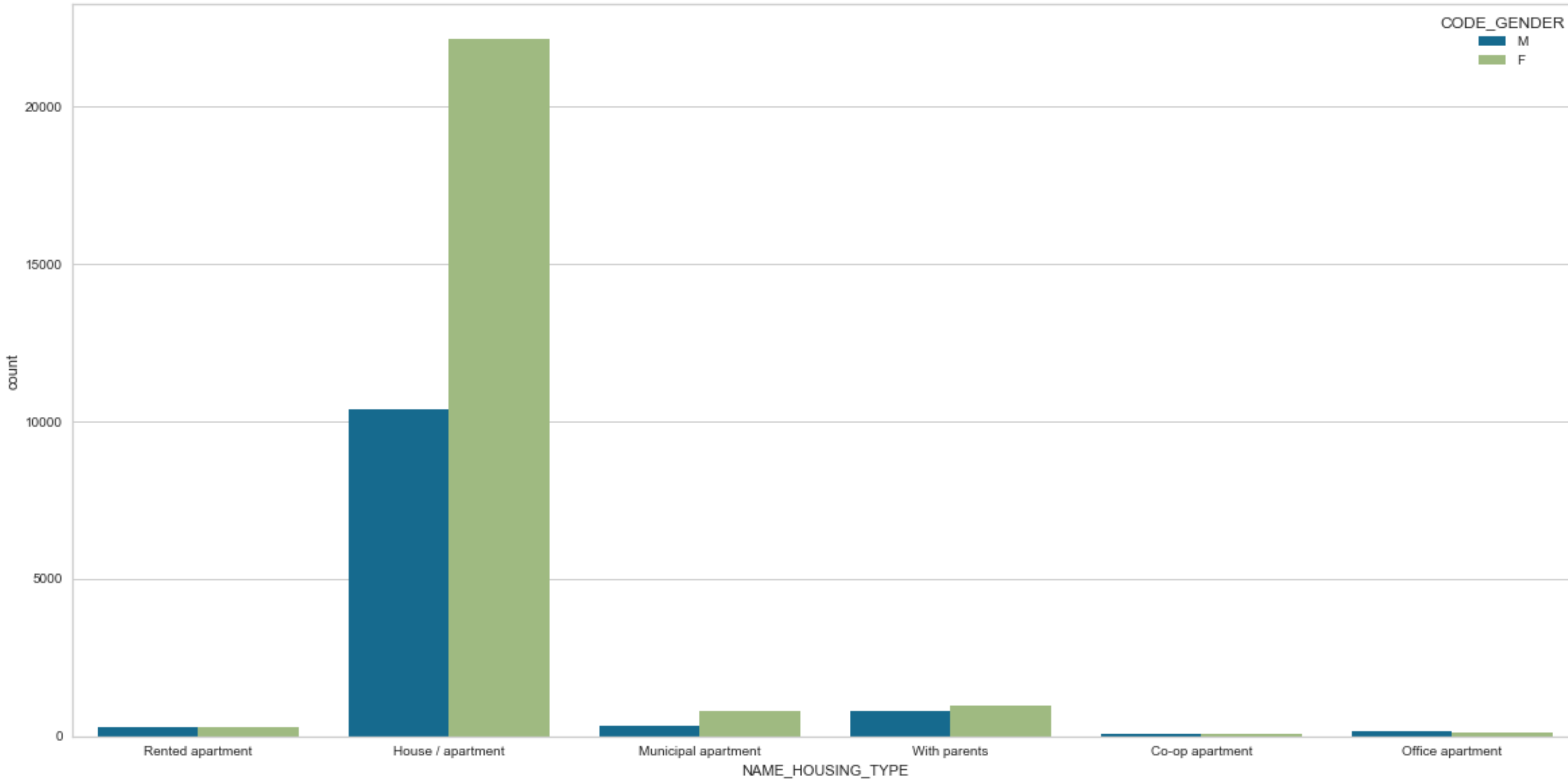
In [36]:
```
plt.figure(figsize=(20,10))
sns.countplot(x='NAME_EDUCATION_TYPE', data=mydata,
              hue="CODE_GENDER")
plt.show()
```



Plotting Name_housing_type based on code gender

In [37]:

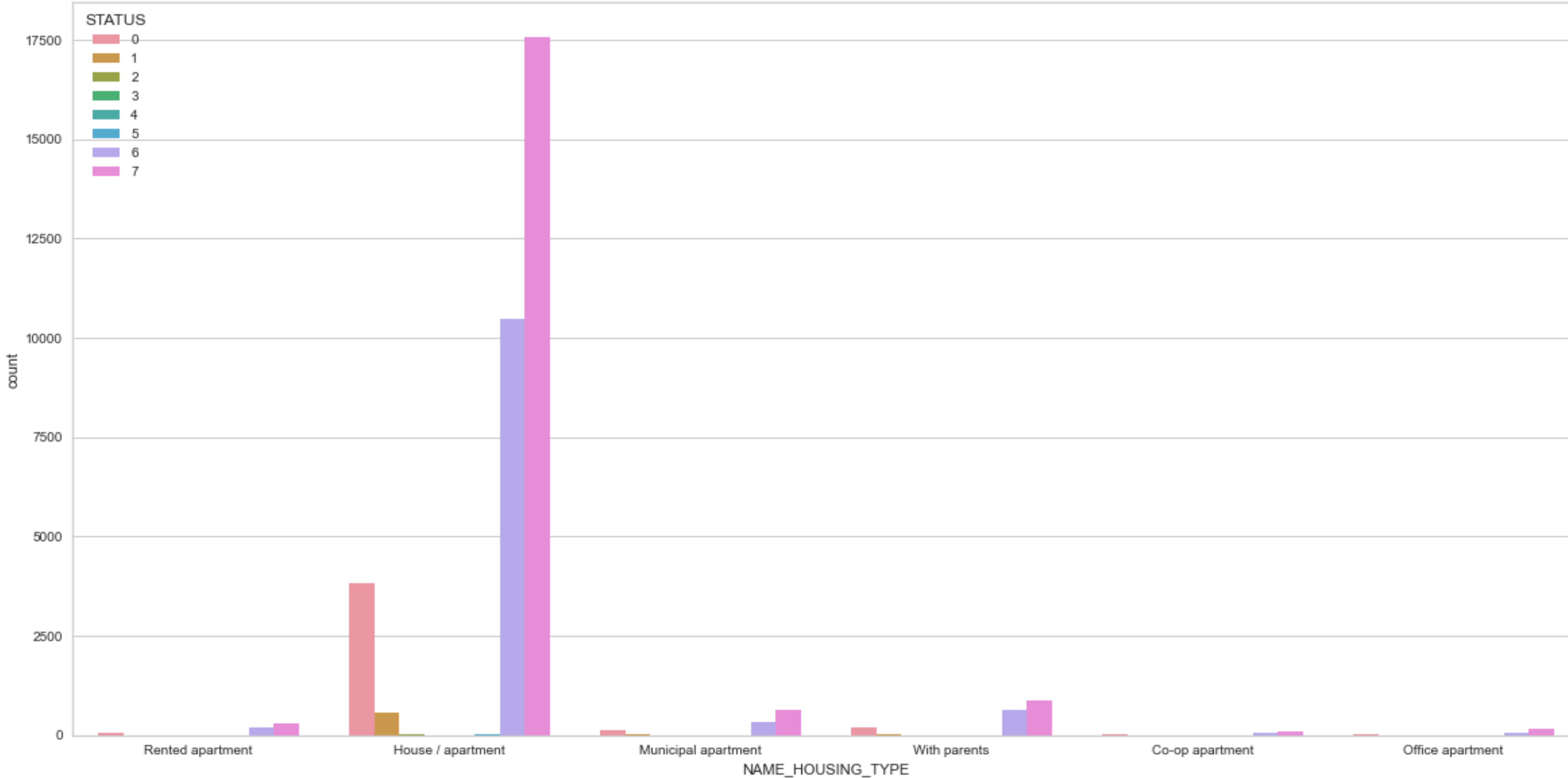
```
plt.figure(figsize=(20,10))
sns.countplot(x='NAME_HOUSING_TYPE', data=mydata,
              hue="CODE_GENDER")
plt.show()
```



Plotting Name_housing_type based on status

In [38]:

```
plt.figure(figsize=(20,10))
sns.countplot(x='NAME_HOUSING_TYPE', data=mydata,
              hue="STATUS")
plt.show()
```



Categroical variables: Object Datatype variable in dataset:

In [39]:
```
objList = mydata.select_dtypes(include = "object").columns # only columns with object datatyp
print (objList)
```

```
Index(['CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'NAME_INCOME_TYPE',
       'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE',
       'OCCUPATION_TYPE'],
      dtype='object')
```

Label Encoder: Convert categorical into numerical values:

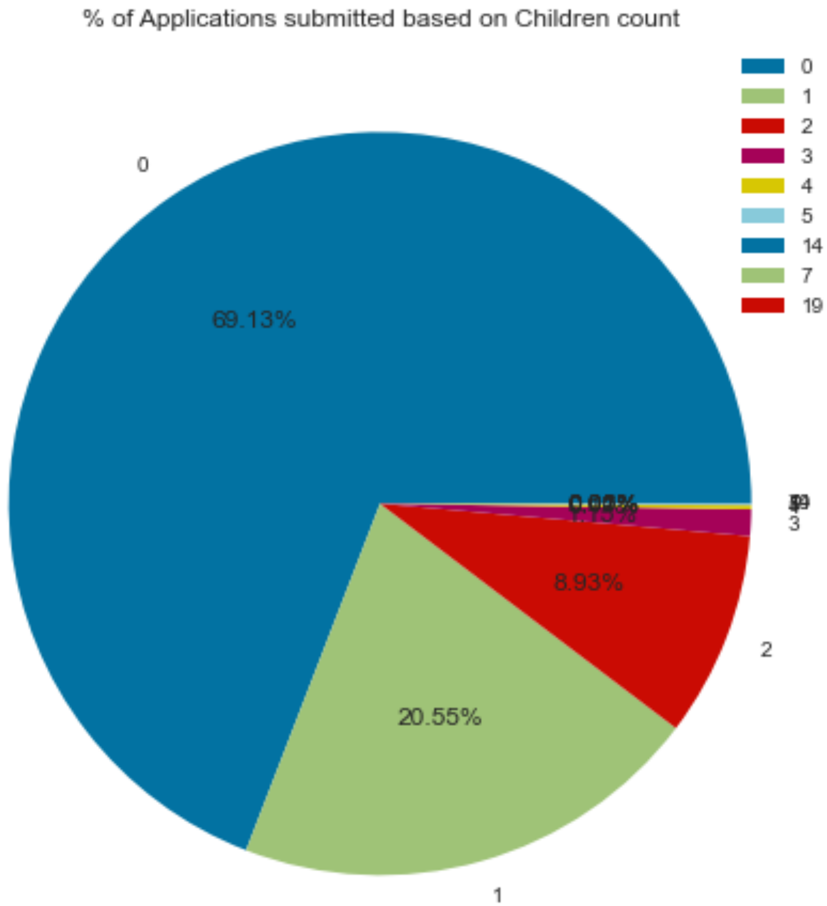
In [40]:
```
from sklearn.preprocessing import LabelEncoder
LE = LabelEncoder()

for i in objList:
    mydata[i] = LE.fit_transform(mydata[i].astype(str))
mydata.head()
```

Out[40]:

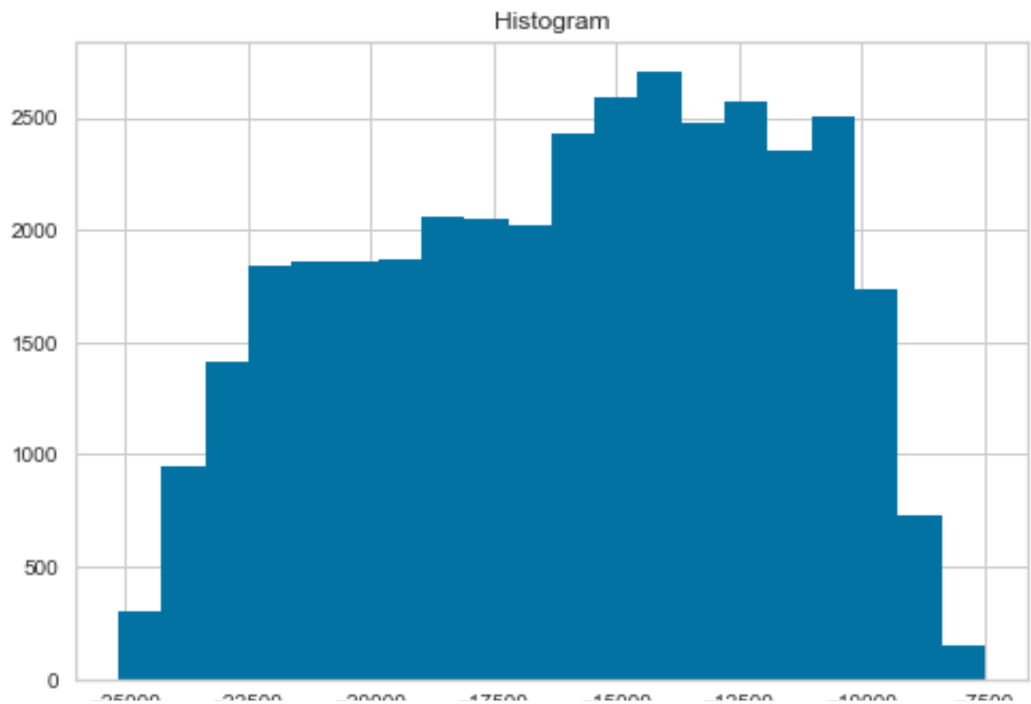
	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
0	5008804	1	1	1	0	427500.0	4
1	5008805	1	1	1	0	427500.0	4
2	5008806	1	1	1	0	112500.0	4
3	5008808	0	0	1	0	270000.0	0
4	5008809	0	0	1	0	270000.0	0

% of Applications submitted based on Children count'

In [41]:
```
plt.figure(figsize = (8,8))
plt.pie(mydata ['CNT_CHILDREN'].value_counts(), labels=mydata['CNT_CHILDREN'].value_counts()
plt.title('% of Applications submitted based on Children count')
plt.legend()
plt.show()
```



In [42]:
```
plt.hist(mydata['DAYS_BIRTH'], bins=20)
plt.xlabel('Age')
plt.title('Histogram')
plt.show()
```



Null Value:

In [43]:
```
application.isnull().sum()
```

Out[43]:
```
ID                          0
CODE_GENDER                 0
FLAG_OWN_CAR                0
FLAG_OWN_REALTY             0
CNT_CHILDREN                0
AMT_INCOME_TOTAL            0
NAME_INCOME_TYPE            0
NAME_EDUCATION_TYPE         0
NAME_FAMILY_STATUS          0
NAME_HOUSING_TYPE           0
DAYS_BIRTH                  0
DAYS_EMPLOYED               0
FLAG_MOBIL                  0
FLAG_WORK_PHONE             0
FLAG_PHONE                  0
FLAG_EMAIL                  0
OCCUPATION_TYPE        134193
CNT_FAM_MEMBERS             0
dtype: int64
```

Statistical Summary:

In [44]:
```
mydata.describe()
```

Out[44]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOM
count	3.645700e+04	36457.000000	36457.000000	36457.000000	36457.000000	3.645700e+04	36457
mean	5.078227e+06	0.329895	0.379708	0.672189	0.430315	1.866857e+05	2
std	4.187524e+04	0.470181	0.485321	0.469422	0.742367	1.017892e+05	1
min	5.008804e+06	0.000000	0.000000	0.000000	0.000000	2.700000e+04	0
25%	5.042028e+06	0.000000	0.000000	0.000000	0.000000	1.215000e+05	1
50%	5.074614e+06	0.000000	0.000000	1.000000	0.000000	1.575000e+05	4
75%	5.115396e+06	1.000000	1.000000	1.000000	1.000000	2.250000e+05	4
max	5.150487e+06	1.000000	1.000000	1.000000	19.000000	1.575000e+06	4

Check Datatypes:

In [45]:
```
mydata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 36457 entries, 0 to 36456
Data columns (total 20 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   ID                   36457 non-null  int64  
 1   CODE_GENDER          36457 non-null  int64  
 2   FLAG_OWN_CAR         36457 non-null  int64  
 3   FLAG_OWN_REALTY      36457 non-null  int64  
 4   CNT_CHILDREN         36457 non-null  int64  
 5   AMT_INCOME_TOTAL     36457 non-null  float64
 6   NAME_INCOME_TYPE     36457 non-null  int64  
 7   NAME_EDUCATION_TYPE  36457 non-null  int64  
 8   NAME_FAMILY_STATUS   36457 non-null  int64  
 9   NAME_HOUSING_TYPE    36457 non-null  int64  
 10  DAYS_BIRTH           36457 non-null  int64  
 11  DAYS_EMPLOYED        36457 non-null  int64  
 12  FLAG_MOBIL           36457 non-null  int64  
 13  FLAG_WORK_PHONE      36457 non-null  int64  
 14  FLAG_PHONE           36457 non-null  int64  
 15  FLAG_EMAIL           36457 non-null  int64  
 16  OCCUPATION_TYPE      36457 non-null  int64  
 17  CNT_FAM_MEMBERS      36457 non-null  float64
 18  MONTHS_BALANCE       36457 non-null  int64  
 19  STATUS               36457 non-null  int64  
dtypes: float64(2), int64(18)
memory usage: 6.8 MB
```

Convert status datatype:

In [46]:

```
mydata['STATUS']= LE.fit_transform(mydata['STATUS'].astype(str))
mydata.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 36457 entries, 0 to 36456
Data columns (total 20 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   ID                   36457 non-null  int64  
 1   CODE_GENDER          36457 non-null  int64  
 2   FLAG_OWN_CAR         36457 non-null  int64  
 3   FLAG_OWN_REALTY      36457 non-null  int64  
 4   CNT_CHILDREN         36457 non-null  int64  
 5   AMT_INCOME_TOTAL     36457 non-null  float64
 6   NAME_INCOME_TYPE     36457 non-null  int64  
 7   NAME_EDUCATION_TYPE  36457 non-null  int64  
 8   NAME_FAMILY_STATUS   36457 non-null  int64  
 9   NAME_HOUSING_TYPE    36457 non-null  int64  
 10  DAYS_BIRTH           36457 non-null  int64  
 11  DAYS_EMPLOYED        36457 non-null  int64  
 12  FLAG_MOBIL           36457 non-null  int64  
 13  FLAG_WORK_PHONE      36457 non-null  int64  
 14  FLAG_PHONE           36457 non-null  int64  
 15  FLAG_EMAIL           36457 non-null  int64  
 16  OCCUPATION_TYPE      36457 non-null  int64  
 17  CNT_FAM_MEMBERS      36457 non-null  float64
 18  MONTHS_BALANCE       36457 non-null  int64  
 19  STATUS               36457 non-null  int64  
dtypes: float64(2), int64(18)
memory usage: 6.8 MB
```

In [47]:
```
mydata.head()
```

Out[47]:

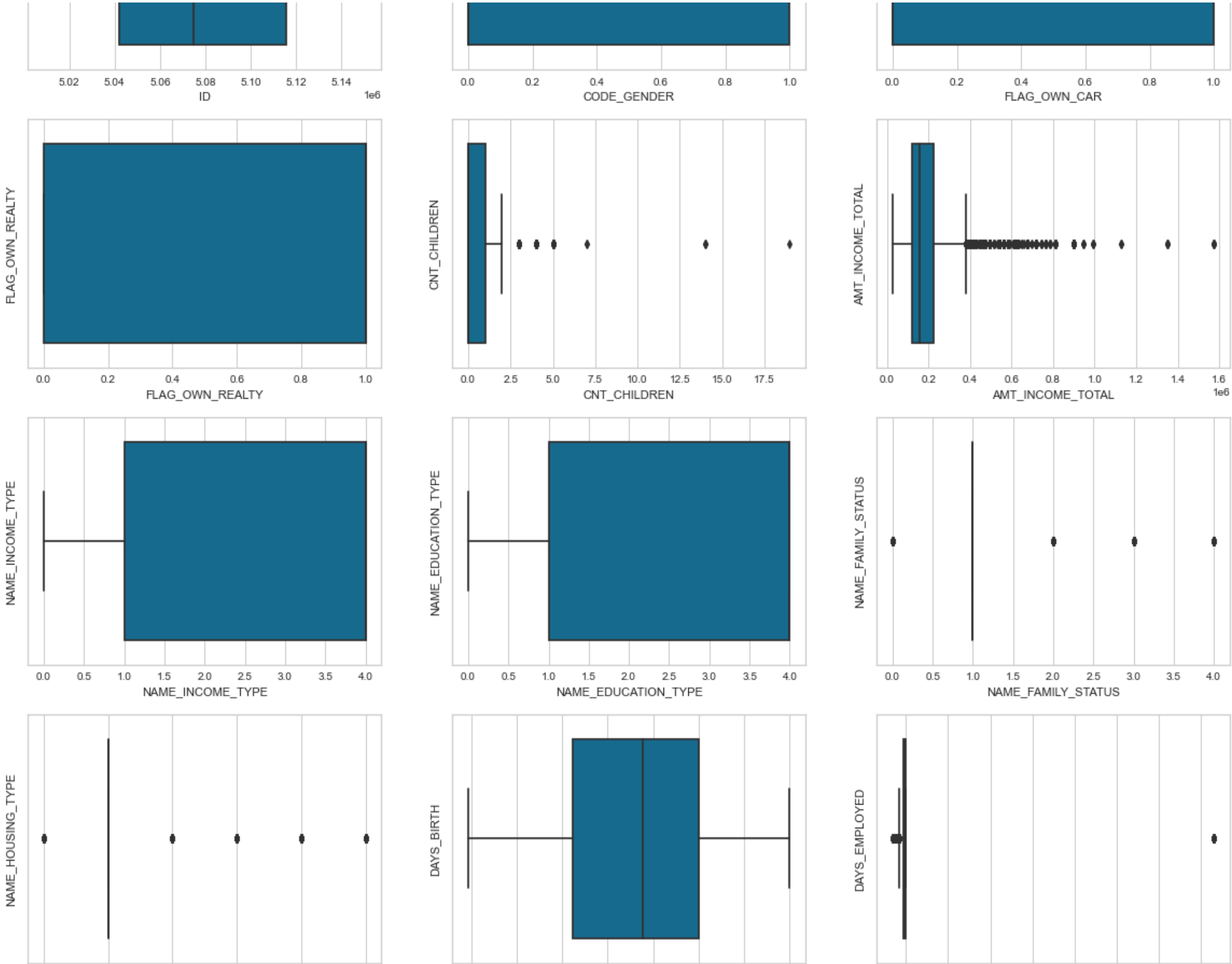
	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
0	5008804	1	1	1	0	427500.0	4
1	5008805	1	1	1	0	427500.0	4
2	5008806	1	1	1	0	112500.0	4
3	5008808	0	0	1	0	270000.0	0
4	5008809	0	0	1	0	270000.0	0

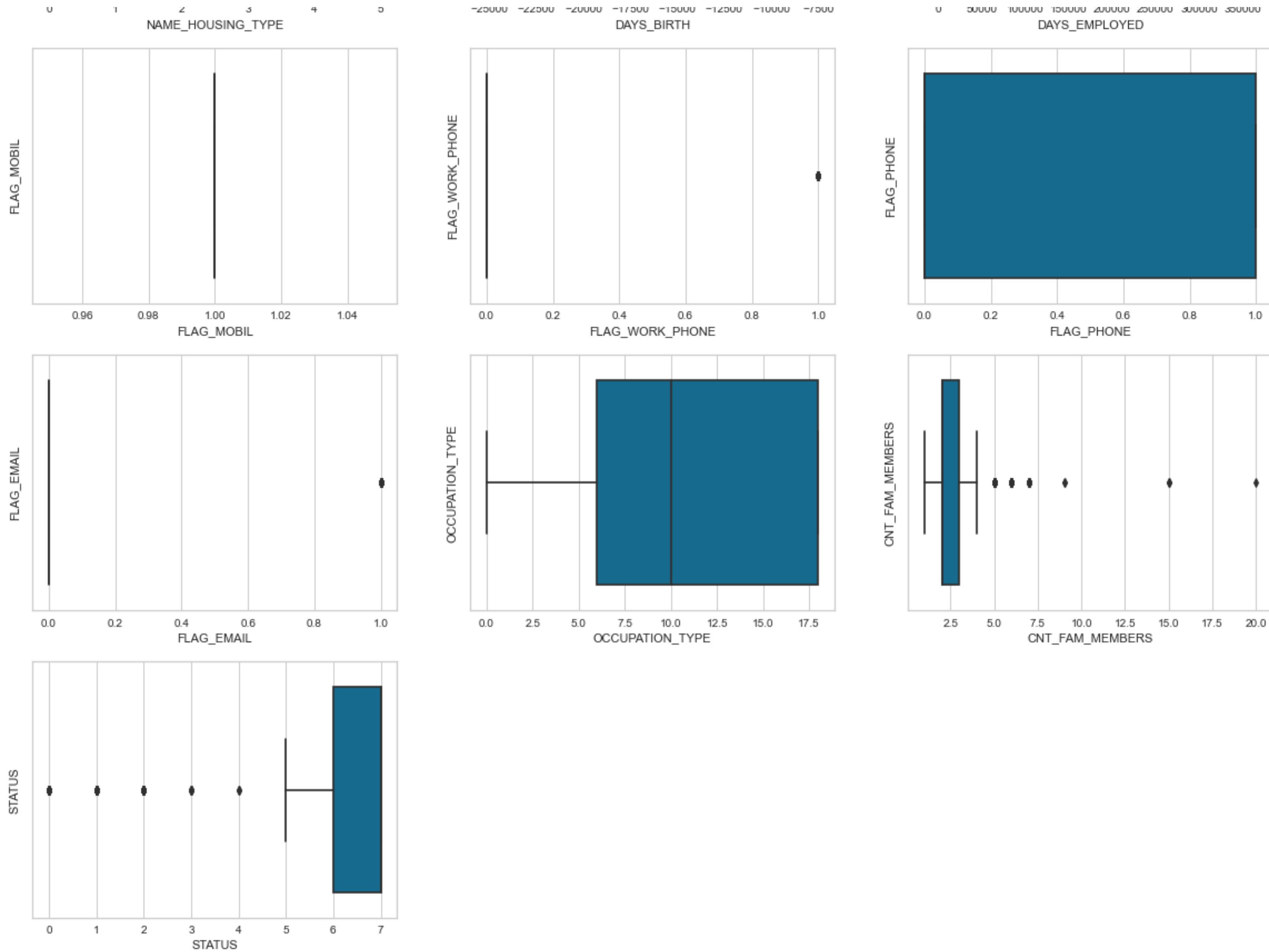
Drop Month_Balance:

In [48]:
```
mydata.drop('MONTHS_BALANCE',axis = 1,inplace = True)
```

Boxplot:To detect outlier:

In [49]:
```
plt.figure(figsize=(20,50))
for i,col in enumerate(mydata,1):
    plt.subplot(10,3,i)
    sns.boxplot(mydata[col])
    plt.ylabel(col)
plt.show()
```


ID
CODE_GENDER
FLAG_OWN_CAR
FLAG_OWN_REALTY
CNT_CHILDREN
AMT_INCOME_TOTAL
NAME_INCOME_TYPE
NAME_EDUCATION_TYPE
NAME_FAMILY_STATUS
NAME_HOUSING_TYPE
DAYS_BIRTH
DAYS_EMPLOYED


NAME_HOUSING_TYPE
DAYS_BIRTH
DAYS_EMPLOYED
FLAG_MOBIL
FLAG_WORK_PHONE
FLAG_PHONE
FLAG_EMAIL
OCCUPATION_TYPE
CNT_FAM_MEMBERS
STATUS

InterQuantile Range:

In [50]:
```
iqr_high = mydata['CNT_CHILDREN'].quantile(0.999)
iqr_low = mydata['CNT_CHILDREN'].quantile(0.001)
mydata = mydata[(mydata['CNT_CHILDREN']>iqr_low) & (mydata['CNT_CHILDREN']<iqr_high)]
```

In [51]:
```
income_high = mydata['AMT_INCOME_TOTAL'].quantile(0.999)
income_low = mydata['AMT_INCOME_TOTAL'].quantile(0.001)
mydata = mydata[(mydata['AMT_INCOME_TOTAL']>income_low) & (mydata['AMT_INCOME_TOTAL']<income_
```

In [52]:
```
#FOR CNT_FAM_MEMBERS COLUMN
fam_high = mydata['CNT_FAM_MEMBERS'].quantile(0.999)
fam_low = mydata['CNT_FAM_MEMBERS'].quantile(0.001)
mydata= mydata[(mydata['CNT_FAM_MEMBERS']>fam_low) & (mydata['CNT_FAM_MEMBERS']<fam_high)]
```

Datatset after removing outlier:

In [53]:
```
mydata.head()
```

Out[53]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
27	5008838	1	0	1	1	405000.0	0
28	5008839	1	0	1	1	405000.0	0
29	5008840	1	0	1	1	405000.0	0
30	5008841	1	0	1	1	405000.0	0
31	5008842	1	0	1	1	405000.0	0

In [54]:
```
mydata = mydata.reset_index(drop=True)
mydata.head()
```

Out[54]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
0	5008838	1	0	1	1	405000.0	0
1	5008839	1	0	1	1	405000.0	0
2	5008840	1	0	1	1	405000.0	0
3	5008841	1	0	1	1	405000.0	0
4	5008842	1	0	1	1	405000.0	0

K means Clustering:

In [55]:
```
from sklearn.cluster import KMeans
Km_cluster=KMeans(2)
Km_cluster
```

Out[55]: KMeans(n_clusters=2)

In [56]:
```
Km_cluster.fit(mydata)
```

Out[56]: KMeans(n_clusters=2)

In [57]:
```
my_Cluster=mydata.copy()
my_Cluster['cluster']=Km_cluster.predict(my_Cluster)
my_Cluster.head()
```

Out[57]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
0	5008838	1	0	1	1	405000.0	0
1	5008839	1	0	1	1	405000.0	0
2	5008840	1	0	1	1	405000.0	0
3	5008841	1	0	1	1	405000.0	0
4	5008842	1	0	1	1	405000.0	0

In [58]:
```
my_Cluster['cluster'].value_counts(normalize=True)
```

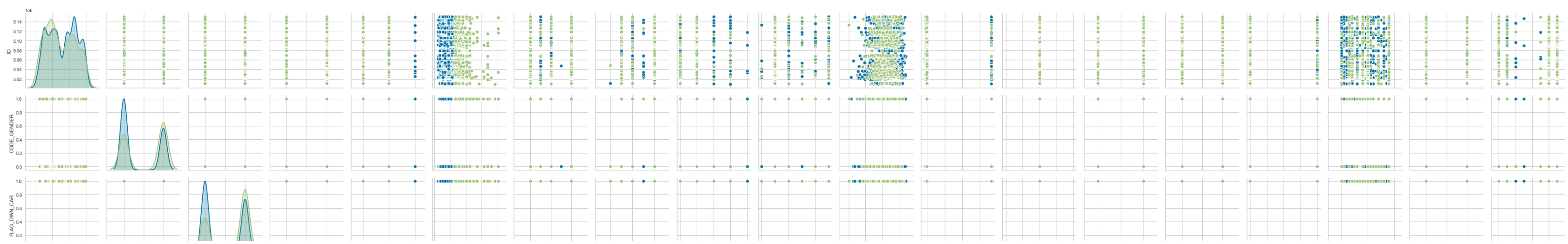
Out[58]:
```
0    0.803917
1    0.196083
Name: cluster, dtype: float64
```

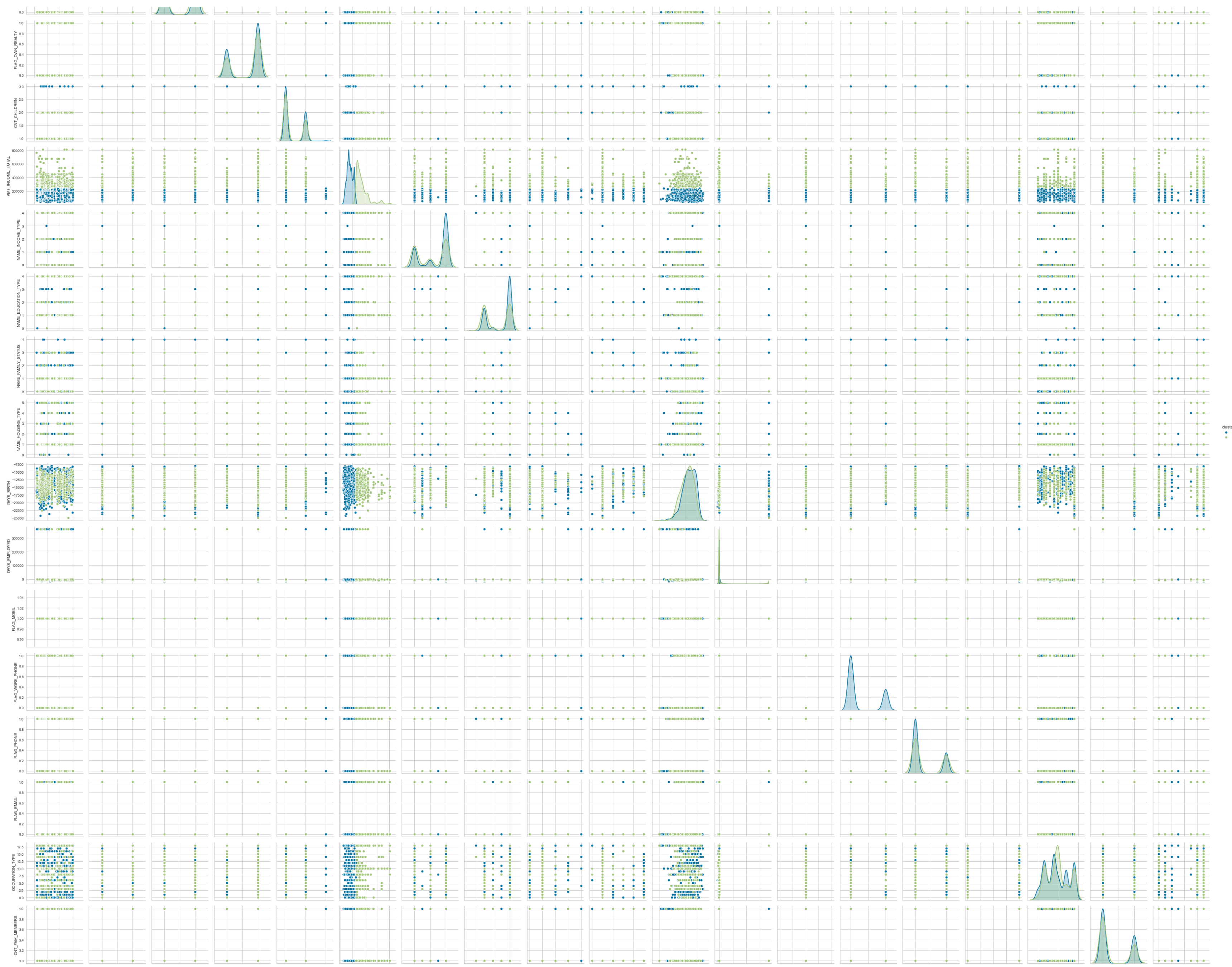
In [59]:
```
my_Cluster.shape
```

Out[59]:
```
(9496, 20)
```

In [60]:
```
sns.pairplot(data=my_Cluster,hue='cluster')
```

Out[60]:
```
<seaborn.axisgrid.PairGrid at 0x7ffbe85716d0>
```

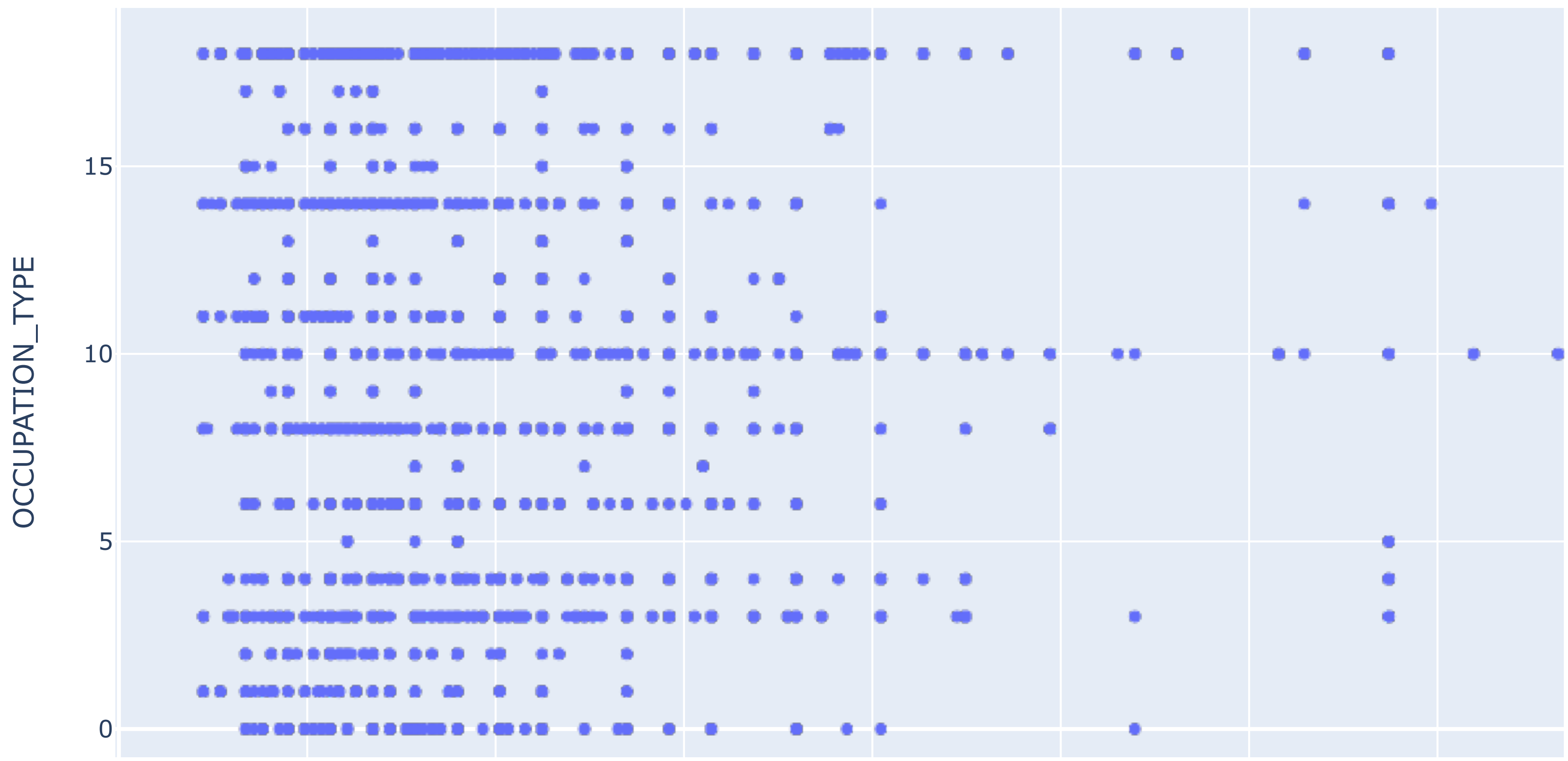



FLAG_OWN_REALTY
CNT_CHILDREN
AMT_INCOME_TOTAL
NAME_INCOME_TYPE
NAME_EDUCATION_TYPE
NAME_FAMILY_STATUS
NAME_HOUSING_TYPE
DAYS_BIRTH
DAYS_EMPLOYED
FLAG_MOBIL
FLAG_WORK_PHONE
FLAG_PHONE
FLAG_EMAIL
OCCUPATION_TYPE
CNT_FAM_MEMBERS
cluster

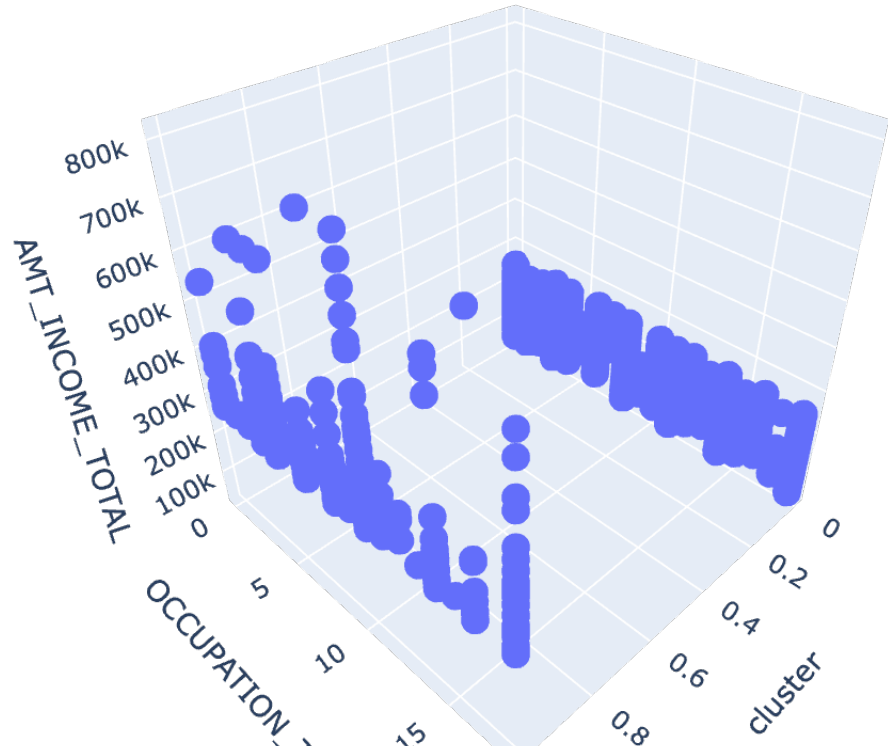
3D Visualization:

In [61]:
```
import plotly.express as px
```

In [62]:
```
fig = px.scatter(my_Cluster, x = 'AMT_INCOME_TOTAL', y='OCCUPATION_TYPE')
fig.show()
```



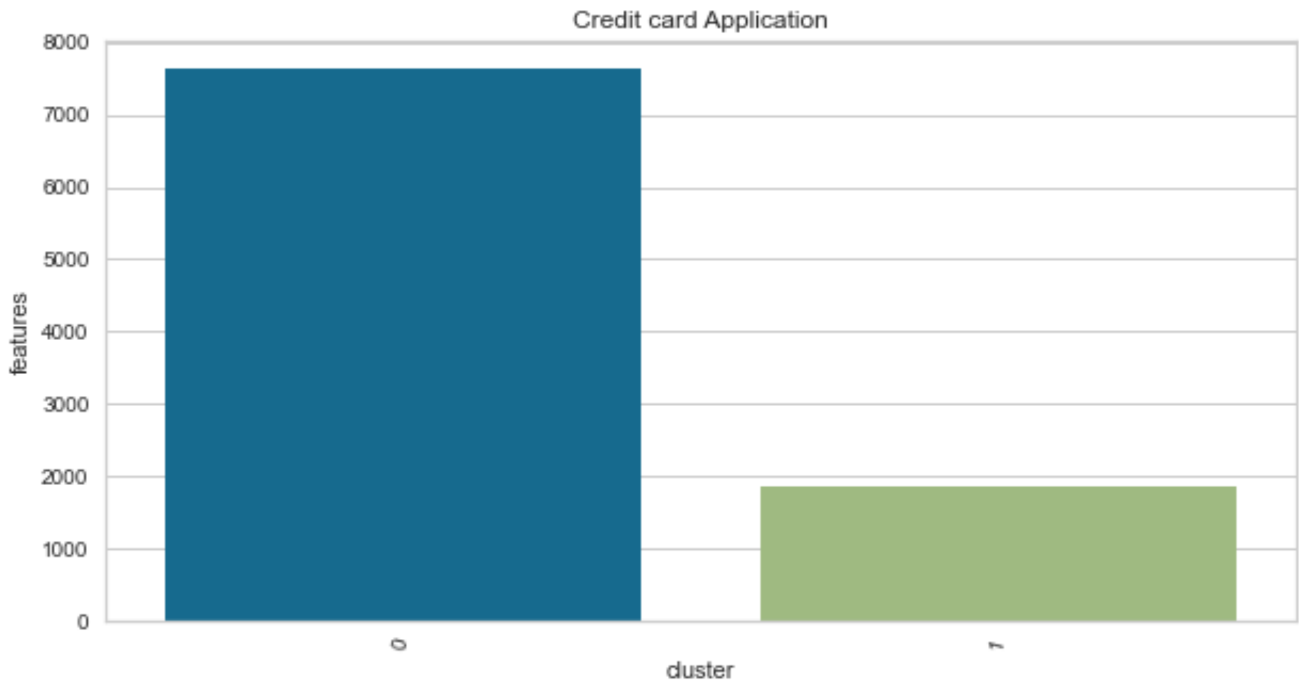
In [63]:
```
1 px.scatter_3d(data_frame = my_Cluster , x ='cluster',y = 'OCCUPATION_TYPE',z= 'AMT_INCOME_TO
```



To visualize the how much Features on each cluster:

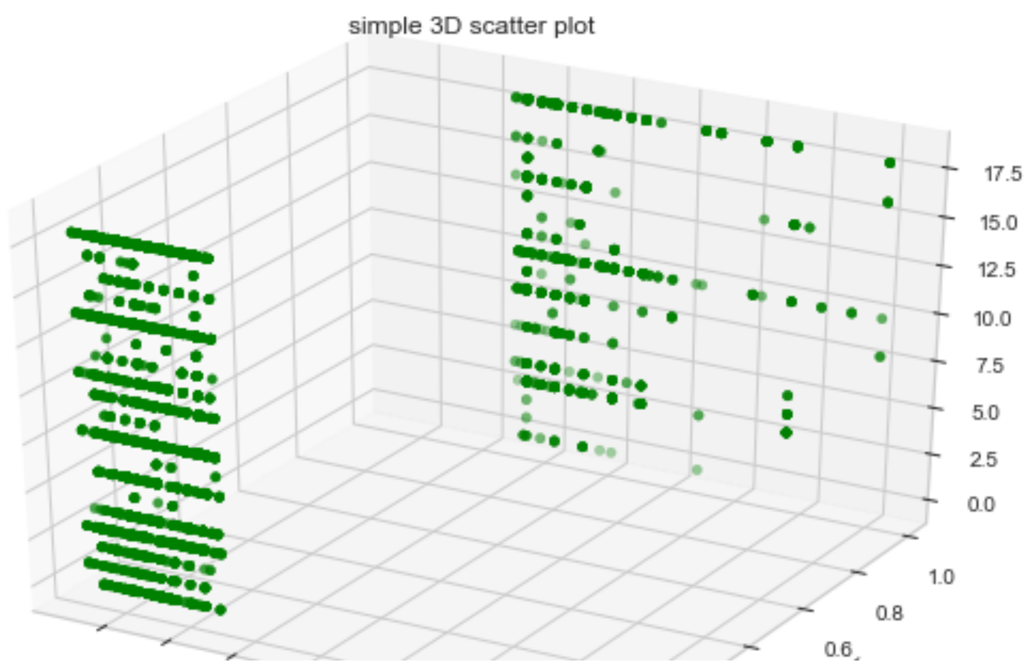
In [64]:
```
plt.figure(figsize=(10,5))
labels = my_Cluster['cluster'].value_counts().index
sns.countplot(data=my_Cluster, x='cluster')
plt.xticks(rotation=75)
plt.title('Credit card Application')
plt.xlabel('cluster')
plt.ylabel('features')
```

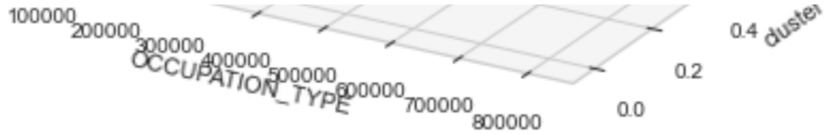
Out[64]: Text(0, 0.5, 'features')



In [65]:
```
from mpl_toolkits import mplot3d
import numpy as np
import matplotlib.pyplot as plt
```

```python

z = my_Cluster['OCCUPATION_TYPE']
x = my_Cluster['AMT_INCOME_TOTAL']
y = my_Cluster['cluster']

 # Creating figure
fig = plt.figure(figsize = (10, 7))
ax = plt.axes(projection ="3d")

# Creating plot
ax.scatter3D(x, y, z, color = "green")
plt.title("simple 3D scatter plot")
plt.xlabel('AMT_INCOME_TOTA')
plt.ylabel('cluster')
plt.xlabel('OCCUPATION_TYPE')
# show plot
plt.show()
```

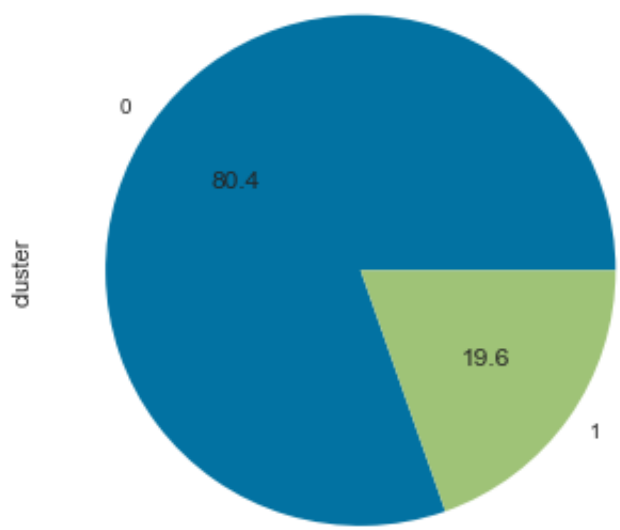




PIE CHART:

In [66]:
```
my_Cluster['cluster'].value_counts(normalize=True).plot(kind='pie', autopct="%.1f")
```

Out[66]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffbbc0e3d90>



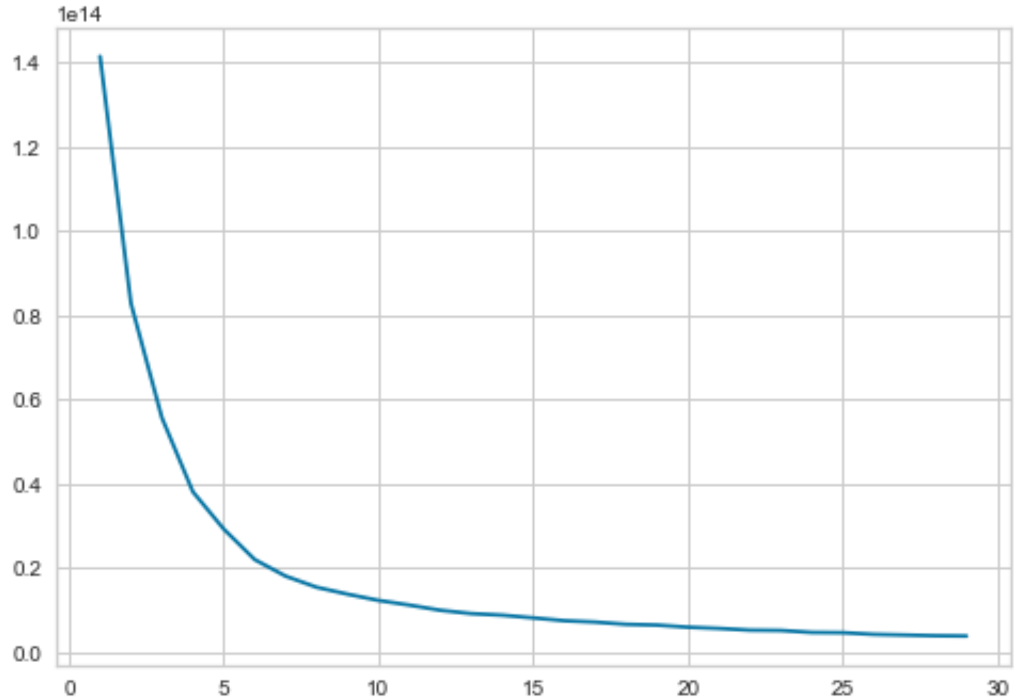
In [67]:

```
from sklearn.cluster import KMeans

# function returns WSS score for k values from 1 to kmax
def calculate_WSS(points, kmax):
    sse = []
    for k in range(1, kmax+1):
        kmeans = KMeans(n_clusters = k).fit(points)
        centroids = kmeans.cluster_centers_
        pred_clusters = kmeans.predict(points)
        curr_sse = 0

    # calculate square of Euclidean distance of each point from its cluster center and add to
    for i in range(len(points)):
        curr_center = centroids[pred_clusters[i]]
        curr_sse += (points[i, 0] - curr_center[0]) ** 2 + (points[i, 1] - curr_center[1]) **

    sse.append(curr_sse)
    return sse
```

Elbow method:

In [68]:
```
a=[]
for i in range(1,30): #max :20
    kmeans_em=KMeans(i)
    kmeans_em.fit(mydata)
    a.append(kmeans_em.inertia_) #
plt.plot(range(1,30),a)
```

Out[68]:
```
[<matplotlib.lines.Line2D at 0x7ffbbc064610>]
```



Silhouette_score

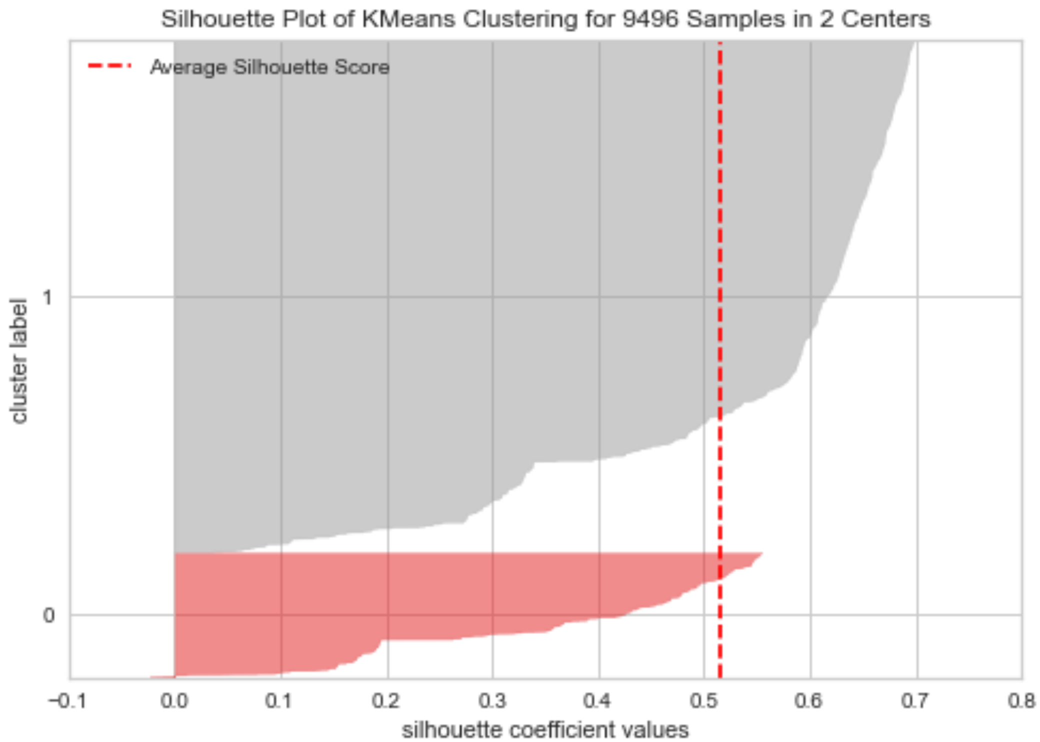
In [69]:

```
from sklearn.metrics import silhouette_score
for i in range(2,5):
    kmeans = KMeans(n_clusters = i, max_iter = 30)
    kmeans.fit(mydata)
    cluster_labels = kmeans.labels_
    silhouette_avg = silhouette_score(mydata,cluster_labels)
    print ("For _clusters={0},the silhouette score is {1}]". format(i, silhouette_avg))
```

```
For _clusters=2,the silhouette score is 0.5152288877893476]
For _clusters=3,the silhouette score is 0.5493212360977041]
For _clusters=4,the silhouette score is 0.44027184447742845]
```

In [70]:

```python
import yellowbrick
from yellowbrick.cluster import SilhouetteVisualizer

model =  KMeans(2)
visualizer = SilhouetteVisualizer(model, color = 'yellowbrick')
visualizer.fit(mydata)
visualizer.show()
```



Out[70]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffbbc090160>

In [71]:
```
df = my_Cluster.copy()
df.head()
```

Out[71]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
0	5008838	1	0	1	1	405000.0	0
1	5008839	1	0	1	1	405000.0	0
2	5008840	1	0	1	1	405000.0	0
3	5008841	1	0	1	1	405000.0	0
4	5008842	1	0	1	1	405000.0	0

In [72]:
```
df.shape
```

Out[72]: (9496, 20)

In [73]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9496 entries, 0 to 9495
Data columns (total 20 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   ID                   9496 non-null   int64  
 1   CODE_GENDER          9496 non-null   int64  
 2   FLAG_OWN_CAR         9496 non-null   int64  
 3   FLAG_OWN_REALTY      9496 non-null   int64  
 4   CNT_CHILDREN         9496 non-null   int64  
 5   AMT_INCOME_TOTAL     9496 non-null   float64
 6   NAME_INCOME_TYPE     9496 non-null   int64  
 7   NAME_EDUCATION_TYPE  9496 non-null   int64  
 8   NAME_FAMILY_STATUS   9496 non-null   int64  
 9   NAME_HOUSING_TYPE    9496 non-null   int64  
 10  DAYS_BIRTH           9496 non-null   int64  
 11  DAYS_EMPLOYED        9496 non-null   int64  
 12  FLAG_MOBIL           9496 non-null   int64  
 13  FLAG_WORK_PHONE      9496 non-null   int64  
 14  FLAG_PHONE           9496 non-null   int64  
 15  FLAG_EMAIL           9496 non-null   int64  
 16  OCCUPATION_TYPE      9496 non-null   int64  
 17  CNT_FAM_MEMBERS      9496 non-null   float64
 18  STATUS               9496 non-null   int64  
 19  cluster              9496 non-null   int32  
dtypes: float64(2), int32(1), int64(17)
memory usage: 1.4 MB
```

In [74]:
```
df.isnull().sum()
```

Out[74]:
```
ID                    0
CODE_GENDER           0
FLAG_OWN_CAR          0
FLAG_OWN_REALTY       0
CNT_CHILDREN          0
AMT_INCOME_TOTAL      0
NAME_INCOME_TYPE      0
NAME_EDUCATION_TYPE   0
NAME_FAMILY_STATUS    0
NAME_HOUSING_TYPE     0
DAYS_BIRTH            0
DAYS_EMPLOYED         0
FLAG_MOBIL            0
FLAG_WORK_PHONE       0
FLAG_PHONE            0
FLAG_EMAIL            0
OCCUPATION_TYPE       0
CNT_FAM_MEMBERS       0
STATUS                0
cluster               0
dtype: int64
```

In [75]:
```
#df['OCCUPATION_TYPE'] = df['OCCUPATION_TYPE'].fillna(0)
```

In [76]:
```
df.drop('FLAG_MOBIL',axis = 1,inplace = True)
```

In [77]:
```
df.shape
```

Out[77]:
```
(9496, 19)
```

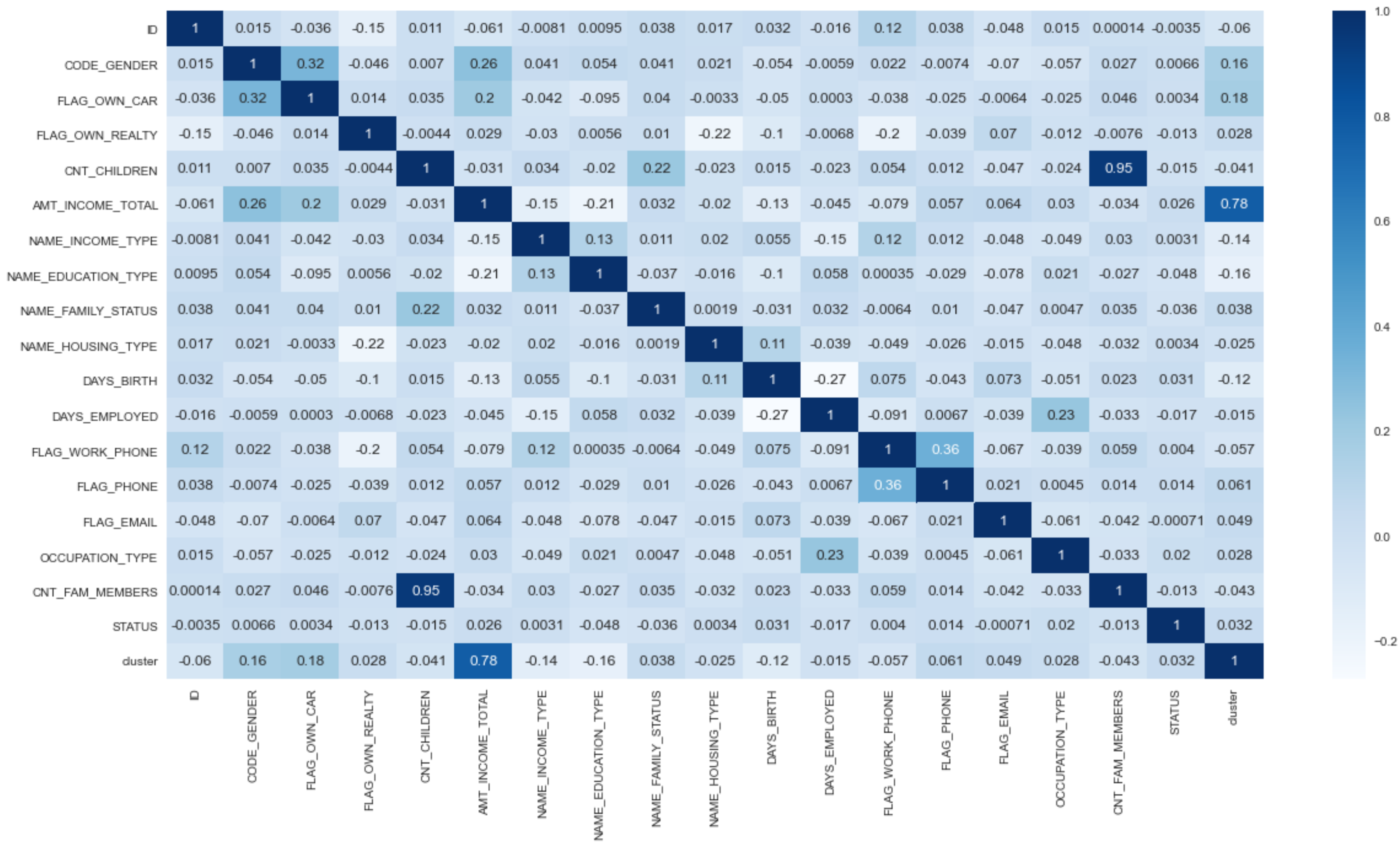
In [78]:
```
df_corr = df.corr()
df_corr
```

Out[78]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL
ID	1.000000	0.015163	-0.035838	-0.153897	0.011231	-0.061171
CODE_GENDER	0.015163	1.000000	0.321284	-0.045768	0.006981	0.257917
FLAG_OWN_CAR	-0.035838	0.321284	1.000000	0.014120	0.035072	0.201429
FLAG_OWN_REALTY	-0.153897	-0.045768	0.014120	1.000000	-0.004354	0.028598
CNT_CHILDREN	0.011231	0.006981	0.035072	-0.004354	1.000000	-0.031060
AMT_INCOME_TOTAL	-0.061171	0.257917	0.201429	0.028598	-0.031060	1.000000
NAME_INCOME_TYPE	-0.008064	0.041423	-0.041542	-0.030321	0.033510	-0.150192
NAME_EDUCATION_TYPE	0.009533	0.053862	-0.094515	0.005615	-0.020341	-0.210327
NAME_FAMILY_STATUS	0.037691	0.040947	0.039716	0.010398	0.215785	0.032122
NAME_HOUSING_TYPE	0.016703	0.021469	-0.003269	-0.220412	-0.023037	-0.020242
DAYS_BIRTH	0.032189	-0.053889	-0.049873	-0.102026	0.014791	-0.132882
DAYS_EMPLOYED	-0.015908	-0.005878	0.000299	-0.006783	-0.022605	-0.044852
FLAG_WORK_PHONE	0.117498	0.022488	-0.038051	-0.195077	0.054277	-0.078722
FLAG_PHONE	0.037808	-0.007447	-0.024979	-0.038960	0.011824	0.056545
FLAG_EMAIL	-0.047885	-0.070093	-0.006363	0.070195	-0.047300	0.064418
OCCUPATION_TYPE	0.014912	-0.056975	-0.024722	-0.011775	-0.023940	0.029623
CNT_FAM_MEMBERS	0.000139	0.027465	0.045547	-0.007585	0.953941	-0.034290
STATUS	-0.003470	0.006601	0.003374	-0.013343	-0.015491	0.025616
cluster	-0.060265	0.162293	0.176160	0.027800	-0.041048	0.779185

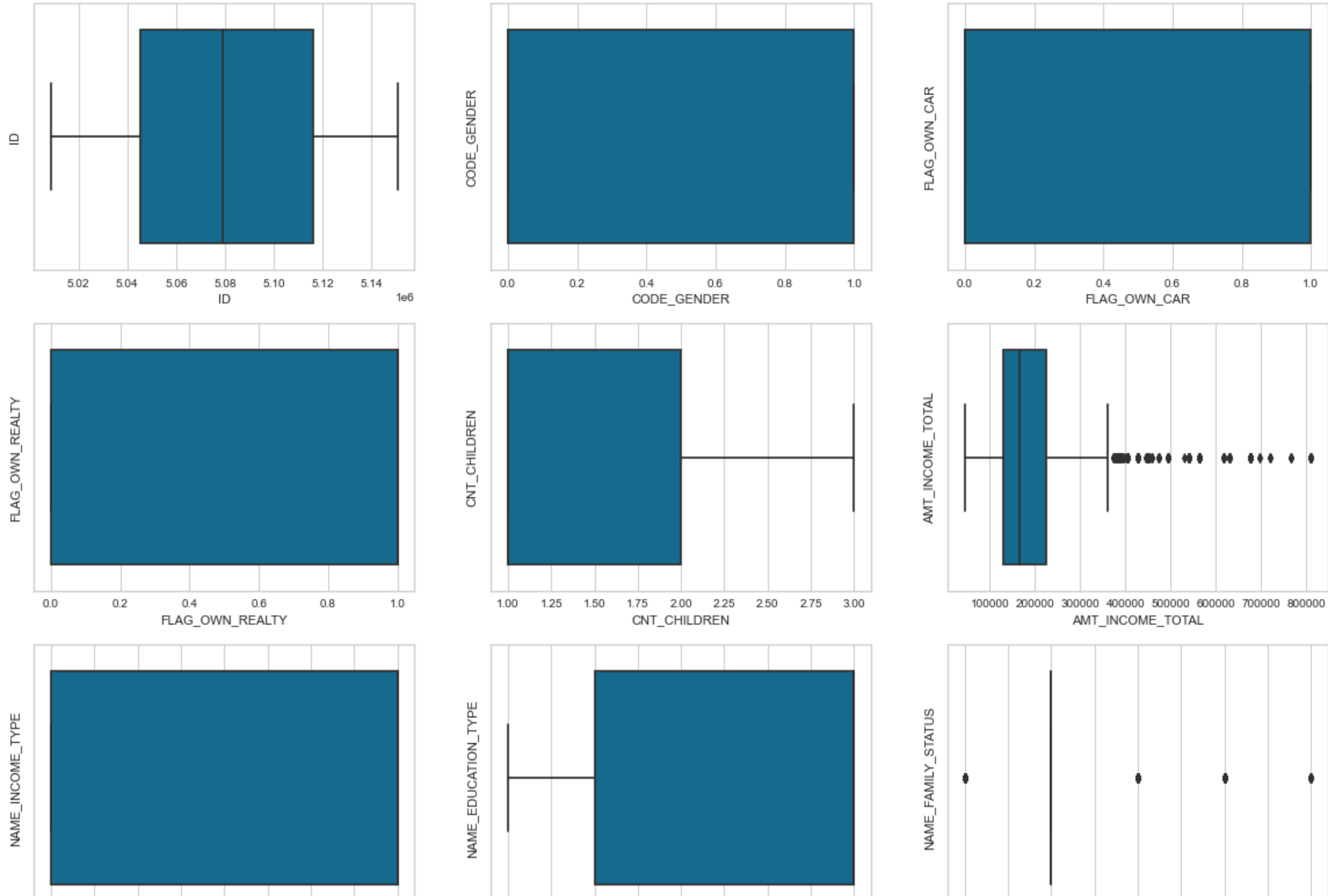
In [79]:
```python
plt.figure(figsize = (20,10))
sns.heatmap(df_corr,annot = True,cmap = 'Blues')
```

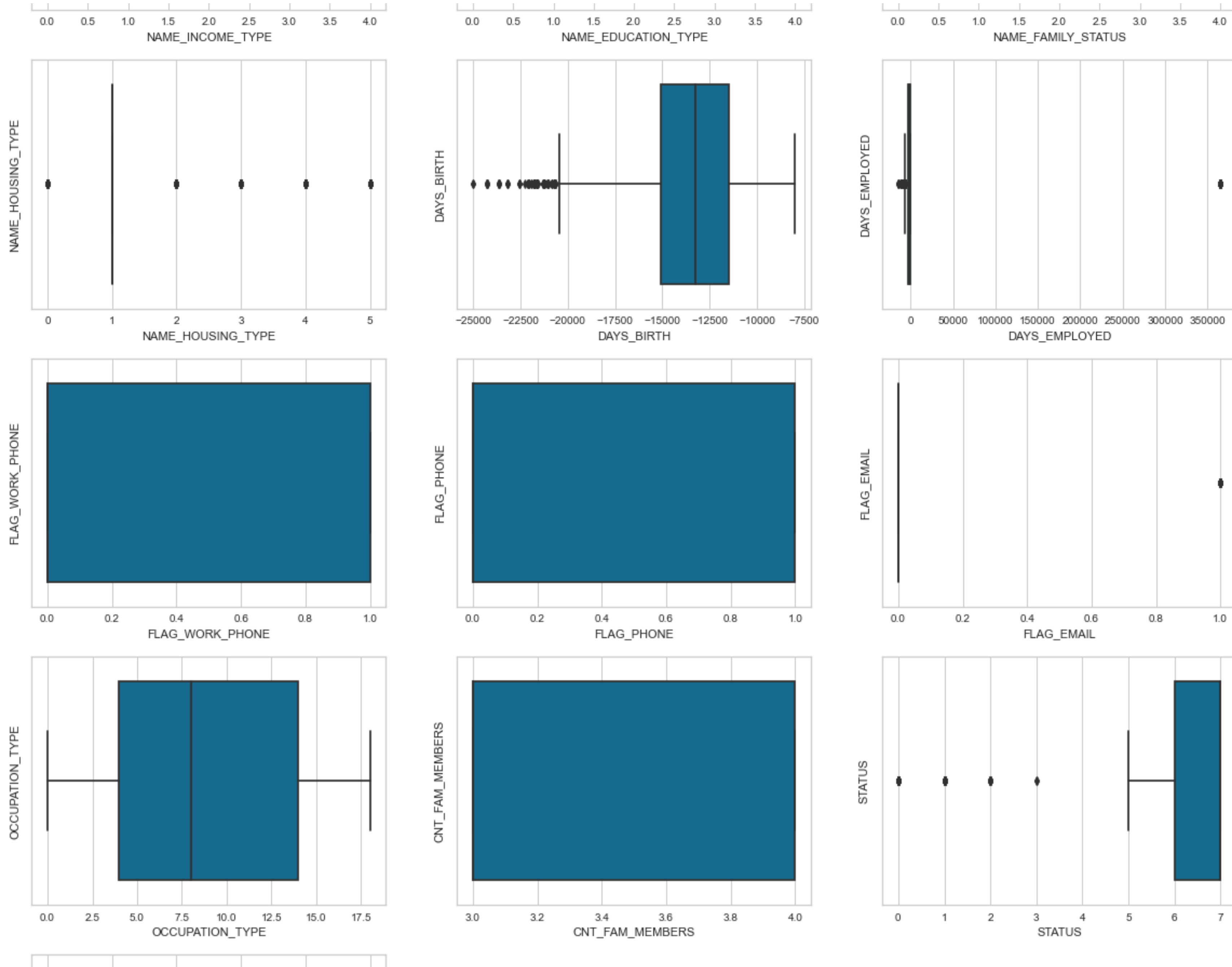
Out[79]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffbe88d99d0>

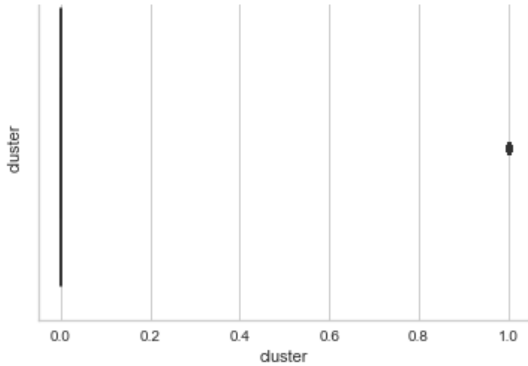


In [80]:
```python
plt.figure(figsize=(20,50))
for i,col in enumerate(df,1):
```

```
    plt.subplot(10,3,i)
    sns.boxplot(df[col])
    plt.ylabel(col)
plt.show()
```




NAME_INCOME_TYPE
NAME_EDUCATION_TYPE
NAME_FAMILY_STATUS
NAME_HOUSING_TYPE
DAYS_BIRTH
DAYS_EMPLOYED
FLAG_WORK_PHONE
FLAG_PHONE
FLAG_EMAIL
OCCUPATION_TYPE
CNT_FAM_MEMBERS
STATUS



In [81]:
```
df1 = df[pd.notnull(df['ID'])]
df1
```

Out[81]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYP
0	5008838	1	0	1	1	405000.0	
1	5008839	1	0	1	1	405000.0	
2	5008840	1	0	1	1	405000.0	
3	5008841	1	0	1	1	405000.0	
4	5008842	1	0	1	1	405000.0	
...	...	...	...	...	...	...	
9491	5142964	1	0	0	1	180000.0	
9492	5142972	1	0	0	1	180000.0	
9493	5143342	1	0	0	1	216000.0	
9494	5145846	0	0	1	1	256500.0	
9495	5149190	1	1	0	1	450000.0	

9496 rows × 19 columns

In [82]:
```
df1.shape
```

Out[82]:
```
(9496, 19)
```

In [83]:
```
cat_mydata= (['CODE_GENDER', 'FLAG_OWN_REALTY', 'NAME_INCOME_TYPE',
       'NAME_EDUCATION_TYPE', 'NAME_FAMILY_STATUS', 'NAME_HOUSING_TYPE',
       'OCCUPATION_TYPE'])
categorical = df1[cat_mydata]
categorical
```

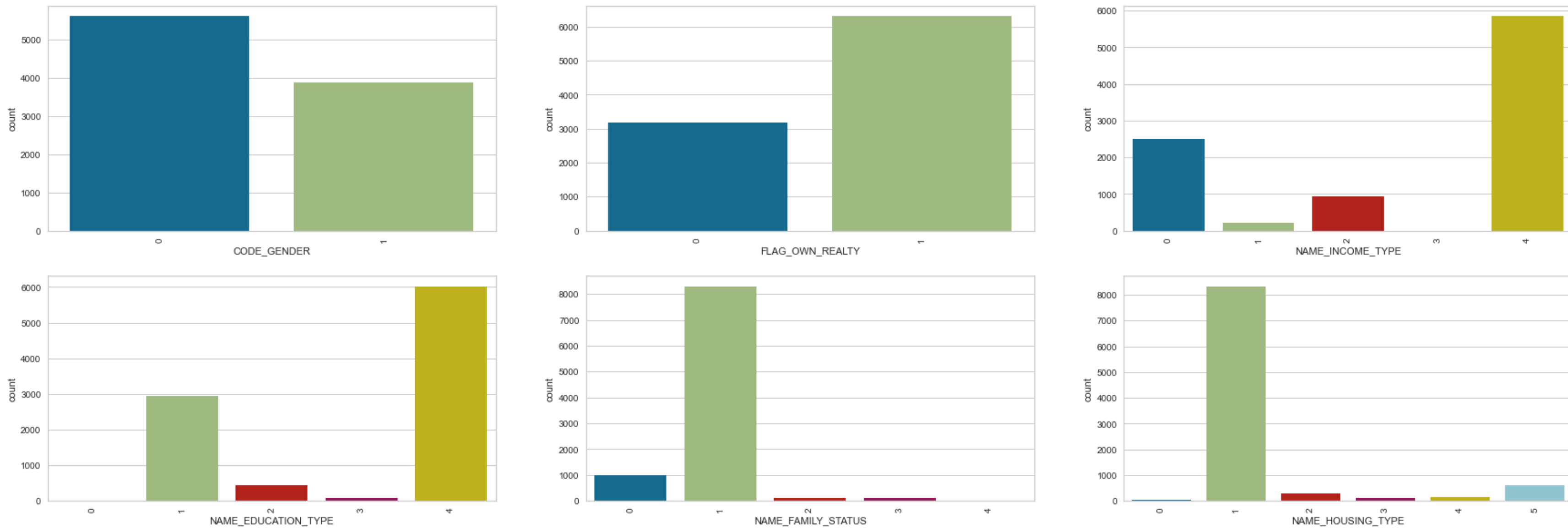
Out[83]:

	CODE_GENDER	FLAG_OWN_REALTY	NAME_INCOME_TYPE	NAME_EDUCATION_TYPE	NAME_FAMILY_STATUS	NAME_HOUSII
0	1	1	0	1	1	
1	1	1	0	1	1	
2	1	1	0	1	1	
3	1	1	0	1	1	
4	1	1	0	1	1	
...	...	...	...	...	...	
9491	1	0	4	4	1	
9492	1	0	4	4	3	
9493	1	0	4	4	1	
9494	0	1	2	1	1	
9495	1	0	4	1	1	

9496 rows × 7 columns

In [84]:

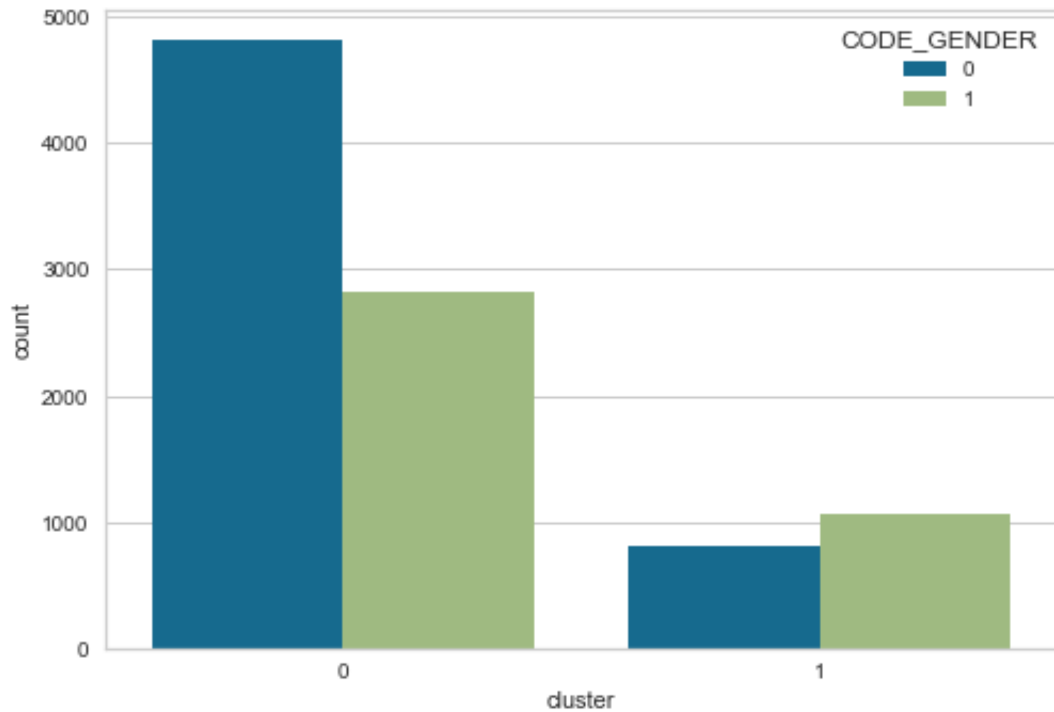
```
ig, ax = plt.subplots(2, 3, figsize=(30, 10))
for variable, subplot in zip(categorical, ax.flatten()):
    sns.countplot(mydata[variable], ax=subplot)
    for label in subplot.get_xticklabels():
        label.set_rotation(90)
```



In [85]:
```
histograms = df1.hist(figsize=(30,15))
```

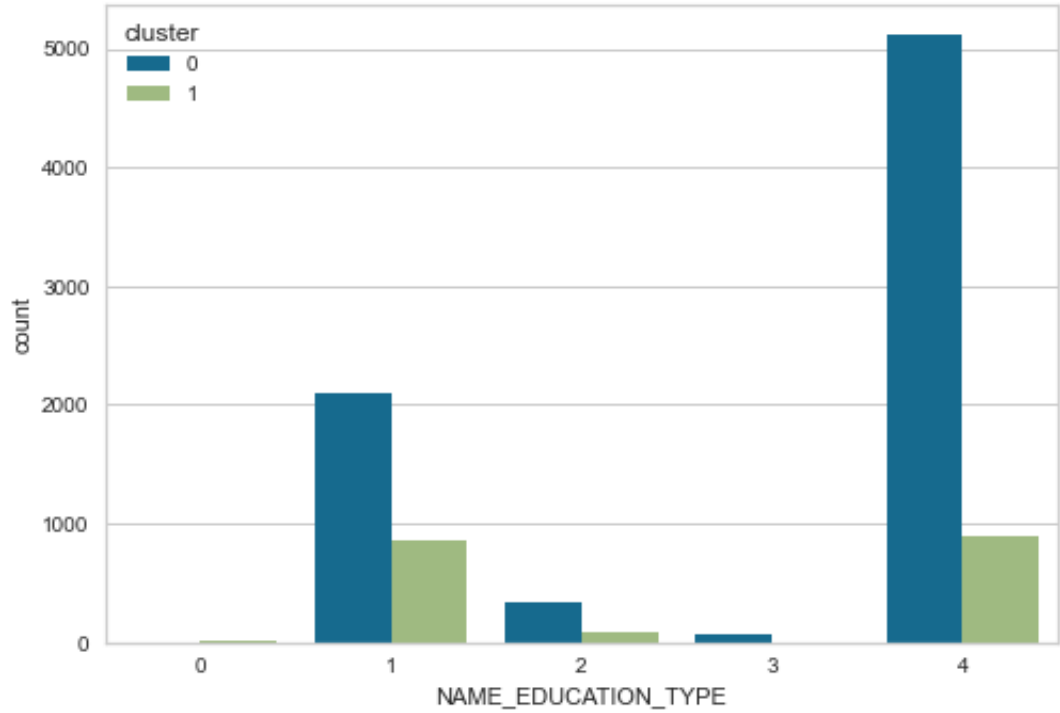
In [86]:
```
sns.countplot(x="cluster",data=df1,hue="CODE_GENDER")
```

Out[86]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb8e637ac0>



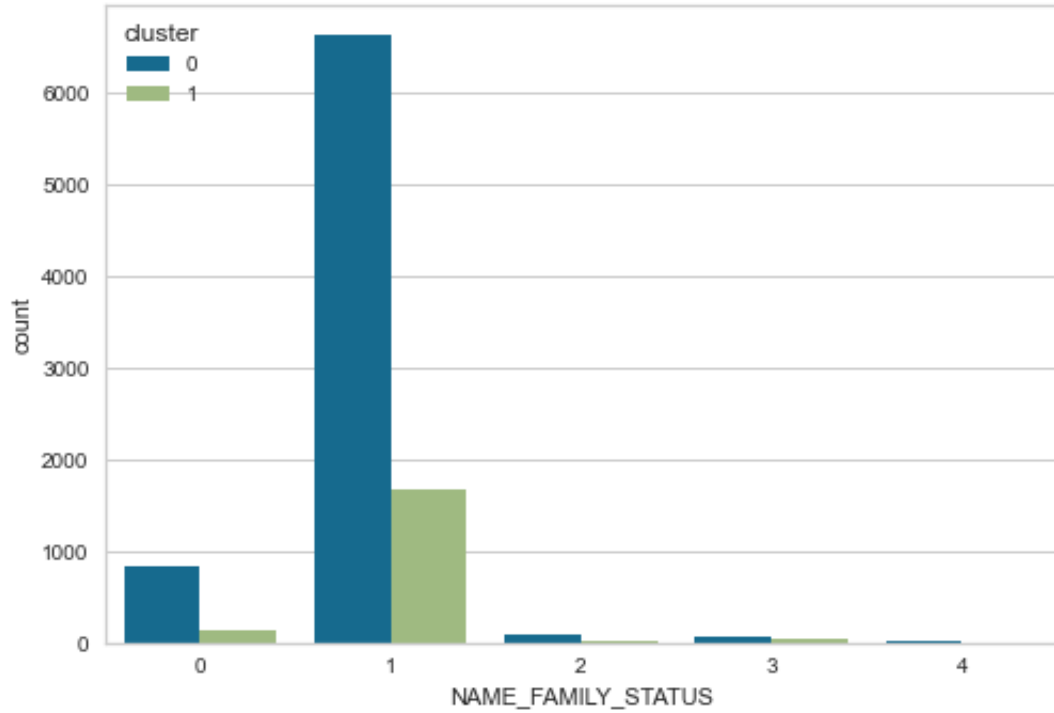
In [87]:
```
sns.countplot(x='NAME_EDUCATION_TYPE',hue='cluster',data=df1)
```

Out[87]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb8d890940>



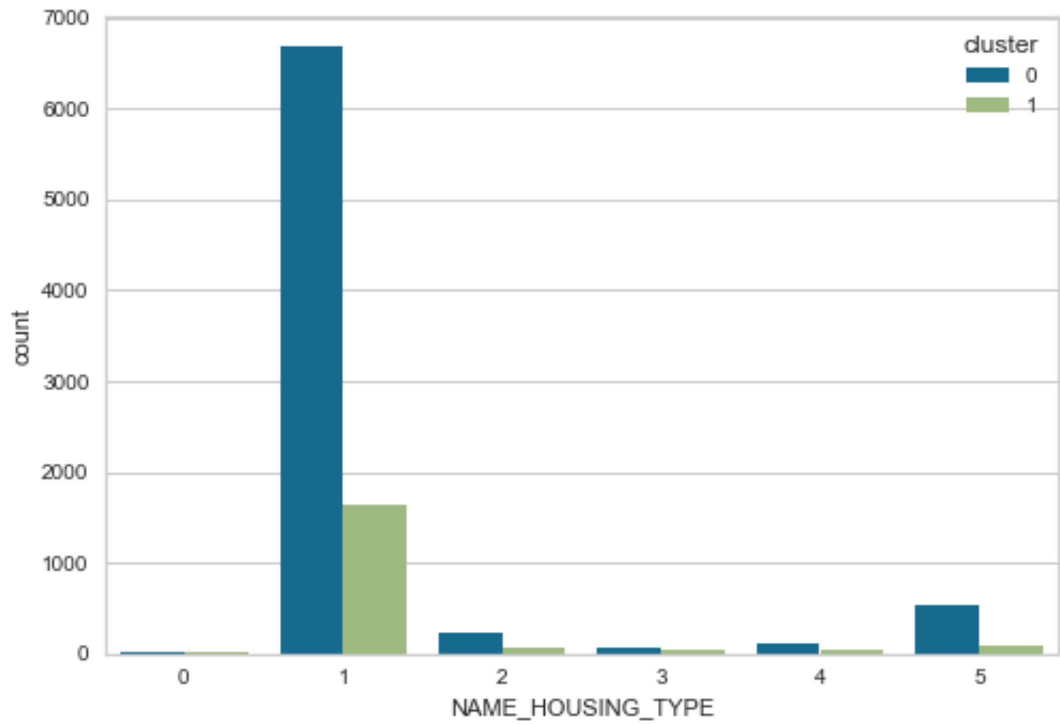
In [88]:
```
sns.countplot(x='NAME_FAMILY_STATUS',hue='cluster',data=df1)
```

Out[88]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ffb8e6dad90>
```

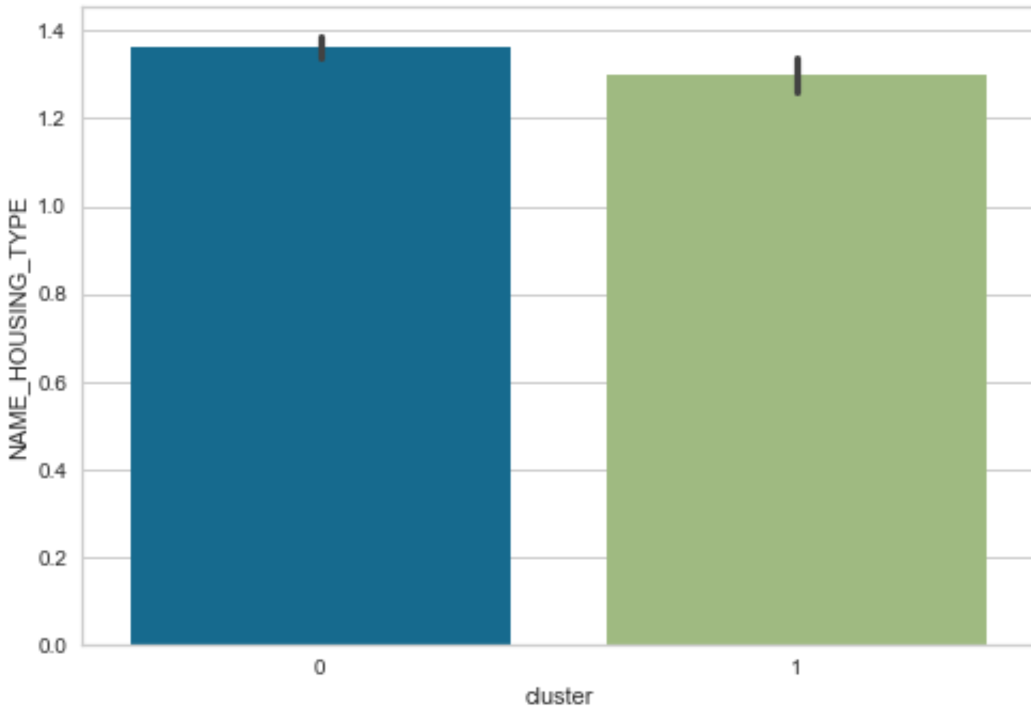


In [89]:
```
sns.countplot(x='NAME_HOUSING_TYPE',hue='cluster',data=df1)
```

Out[89]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb8ee60220>



In [90]:
```
sns.barplot(x="cluster",y='NAME_HOUSING_TYPE',data=df1);
```



In [91]:
```
df1.shape
```

Out[91]: (9496, 19)

In [92]:
```
df1.drop('DAYS_EMPLOYED',axis = 1,inplace = True)
```

In [93]:
```
x_ind = df1.iloc[:,:-1]
x_ind.shape
```

Out[93]: (9496, 17)

In [94]:
```
y_dep = df1.iloc[:,-1]

```

In [95]:
```
#x_ind.equals(y_dep)
```

Train and Test split:

In [96]:
```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x_ind,y_dep,test_size=0.2,random_state=2)
```

Scaling : MinMaxScaler

In [97]:
```
from sklearn.preprocessing import MinMaxScaler
scale = MinMaxScaler()
x_scaled = pd.DataFrame(scale.fit_transform(x_train), columns=x_train.columns)
x_test_scaled = pd.DataFrame(scale.fit_transform(x_test), columns=x_test.columns)
```

Distribution of observation in each cluster

Python counter: Python Counter is a container that will hold the count of each of the elements present in the container. The counter is a sub-class available inside the dictionary class. The counter is a sub-class available inside the dictionary class. Using the Python Counter tool, you can count the key-value pairs in an object, also called a hash table object

In [98]:
```
from collections import Counter
Counter(y_train)
```

Out[98]:
```
Counter({0: 6101, 1: 1495})
```

Oversampling:

In [99]:
```
from imblearn.over_sampling import SMOTE
oversample = SMOTE()
x_balanced, y_balanced = oversample.fit_resample(x_scaled, y_train)
x_test_balanced, y_test_balanced = oversample.fit_resample(x_test_scaled, y_test)

```

In [100]:
```
x_balanced.shape
```

Out[100]: (12202, 17)

In [101]:
```
y_balanced.shape
```

Out[101]: (12202,)

In [102]:
```
x_test_balanced.shape
```

Out[102]: (3066, 17)

In [103]:
```
x_test.shape
```

Out[103]: (1900, 17)

Model Building :

Logistic Regression:

In [104]:
```
from sklearn.linear_model import LogisticRegression

model1=LogisticRegression()
```

In [105]:
```
model1.fit(x_balanced,y_balanced)
```

Out[105]:
```
LogisticRegression()
```

In [106]:
```
y_pred1=model1.predict(x_test_balanced)
y_pred1
```

Out[106]:
```
array([0, 1, 0, ..., 1, 1, 1], dtype=int32)
```

In [107]:
```
from sklearn.metrics import f1_score,accuracy_score,classification_report,confusion_matrix,p
```

In [108]:
```
#Confusion matrix:
print(confusion_matrix(y_test_balanced,y_pred1))  # using predicted and test values
```

```
[[1450   83]
 [   0 1533]]
```

In [109]:
```
acc_LR =accuracy_score(y_test_balanced,y_pred1)
acc_LR
```

Out[109]:
```
0.9729288975864319
```

In [110]:
```
roc_auc_score_LR = roc_auc_score(y_test_balanced,y_pred1)
roc_auc_score_LR
```

Out[110]:
```
0.9729288975864319
```

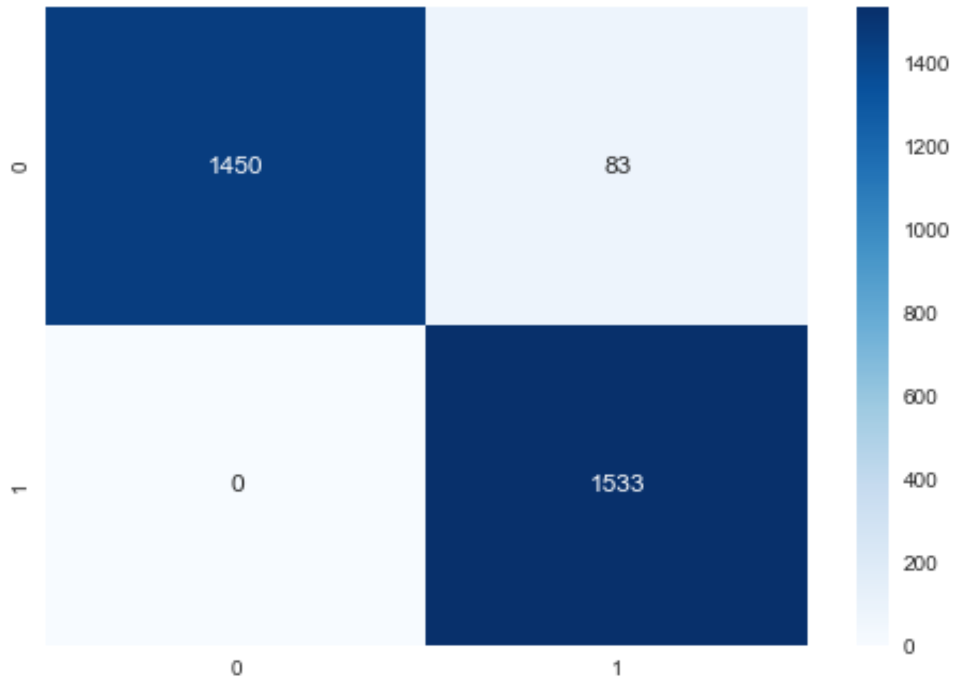
In [111]:
```
F1score_LR =  f1_score(y_test_balanced,y_pred1)
recall_LR = recall_score(y_test_balanced,y_pred1)
```

In [112]:
```
from sklearn.metrics import classification_report
c_report = classification_report(y_test_balanced,y_pred1)
print(c_report)
```

```
              precision    recall  f1-score   support

           0       1.00      0.95      0.97      1533
           1       0.95      1.00      0.97      1533

    accuracy                           0.97      3066
   macro avg       0.97      0.97      0.97      3066
weighted avg       0.97      0.97      0.97      3066
```

In [113]:
```
sns.heatmap(confusion_matrix(y_test_balanced,y_pred1), annot = True ,cmap = "Blues",fmt = 'd
```

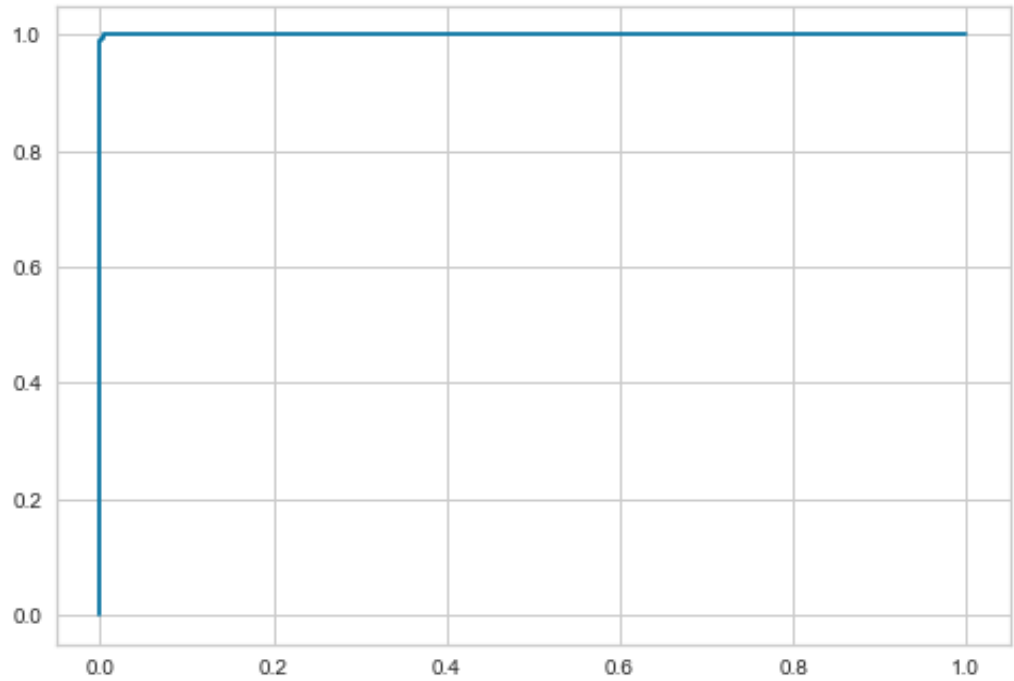
Out[113]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb8f1efdf0>



In [114]:
```
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
```

In [115]:
```
logis_roc_curve= roc_auc_score(y_test_balanced,y_pred1)

fpr,tpr,thresholds = roc_curve(y_test_balanced,model1.predict_proba(x_test_balanced)[:,1])
plt.plot(fpr,tpr,logis_roc_curve)
```

Out[115]:
```
[<matplotlib.lines.Line2D at 0x7ffb8f9736d0>,
 <matplotlib.lines.Line2D at 0x7ffb8f973700>]
```



In [116]:
```
roc_t = LogisticRegression(class_weight = "Balanced")
roc_t.fit(x_balanced,y_balanced)
THRESHOLD = 0.9
```

In [117]:
```
y_pred_roc = np.where(roc_t.predict_proba(x_test_balanced)[:,1]>THRESHOLD,1,0)
```

In [118]:
```
accuracy_score(y_test_balanced,y_pred_roc)
```

Out[118]:
```
0.9292237442922374
```

In [119]:
```
from sklearn.metrics import classification_report
c_report = classification_report(y_test_balanced,y_pred_roc)
print(c_report)
```

```
              precision    recall  f1-score   support

           0       0.88      1.00      0.93      1533
           1       1.00      0.86      0.92      1533

    accuracy                           0.93      3066
   macro avg       0.94      0.93      0.93      3066
weighted avg       0.94      0.93      0.93      3066
```

In [120]:
```
df_comp=pd.DataFrame({'Actual':y_test_balanced, 'Predicted':y_pred1})
df_comp
```

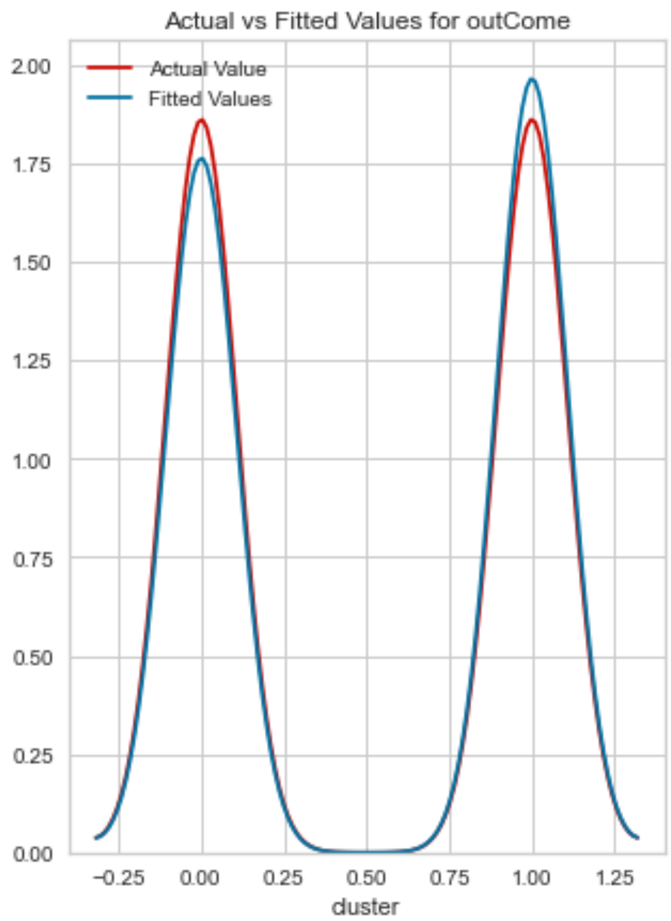
Out[120]:

	Actual	Predicted
0	0	0
1	1	1
2	0	0
3	0	0
4	0	0
...	...	...
3061	1	1
3062	1	1
3063	1	1
3064	1	1
3065	1	1

3066 rows × 2 columns

In [121]:
```

plt.figure(figsize=(5, 7))


ax = sns.distplot(y_test_balanced, hist=False, color="r", label="Actual Value")
sns.distplot(y_pred1, hist=False, color="b", label="Fitted Values" , ax=ax)


plt.title('Actual vs Fitted Values for outCome')

```

```
plt.show()
plt.close()
```



KNN - K nearest neighbors:

In [122]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [123]:
```
df1.shape
```
Out[123]:
```
(9496, 18)
```

In [124]:
```
np.sqrt(9496)
```
Out[124]:
```
97.44742172063866
```

In [125]:
```
KNN=KNeighborsClassifier(n_neighbors=95,p=2,metric='euclidean')

```

In [126]:
```
y_dep.value_counts()
```
Out[126]:
```
0    7634
1    1862
Name: cluster, dtype: int64
```

In [127]:
```
model2=KNN.fit(x_balanced,y_balanced)
```

In [128]:
```
y_pred2=KNN.predict(x_test_balanced)
y_pred2
```
Out[128]:
```
array([0, 1, 0, ..., 1, 1, 1], dtype=int32)
```

In [129]:
```
confusion_matrix(y_test_balanced,y_pred2)
```
Out[129]:
```
array([[1064,  469],
       [ 232, 1301]])
```

In [130]:
```
accuracy_score(y_test_balanced,y_pred2)
```
Out[130]:
```
0.7713633398564905
```

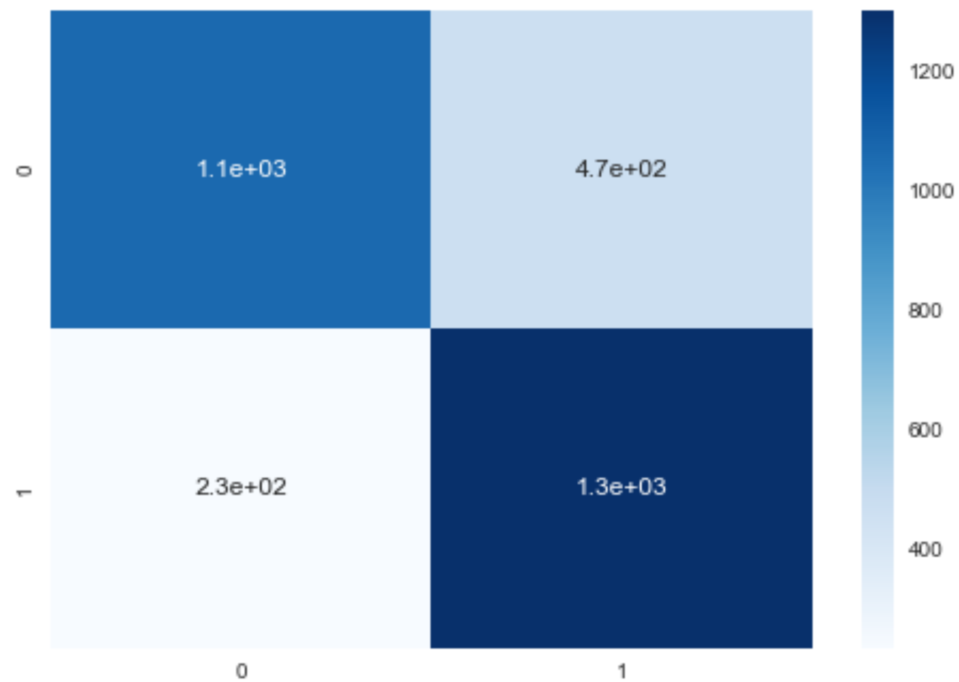
In [131]:
```
F1score_KNN =  f1_score(y_test_balanced,y_pred2)
recall_KNN= recall_score(y_test_balanced,y_pred2)
```

In [132]:
```
roc_auc_score_KNN = roc_auc_score(y_test_balanced,y_pred2)
roc_auc_score_KNN
```

Out[132]: 0.7713633398564905

In [133]:
```
sns.heatmap(confusion_matrix(y_test_balanced,y_pred2), annot = True ,cmap = "Blues")
```

Out[133]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb8fbee400>



In [134]:
```
c_report = classification_report(y_test_balanced,y_pred2)
print(c_report)
```

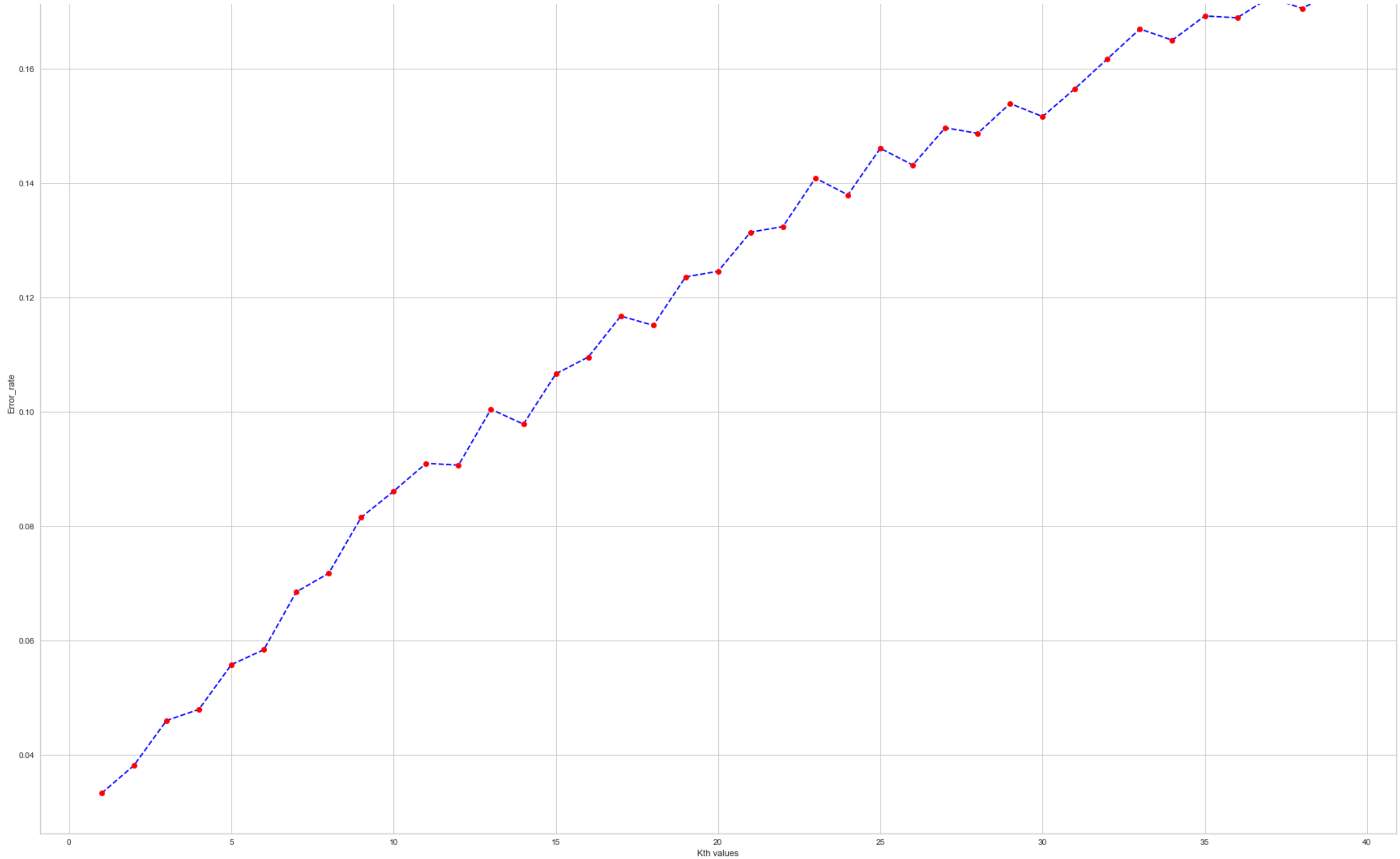
```
              precision    recall  f1-score   support

           0       0.82      0.69      0.75      1533
           1       0.74      0.85      0.79      1533

    accuracy                           0.77      3066
   macro avg       0.78      0.77      0.77      3066
weighted avg       0.78      0.77      0.77      3066
```

Error rate method:

In [135]:
```
error_rate=[]

for i in range(1,40):
    knn_new=KNeighborsClassifier(n_neighbors=i)
    knn_new.fit(x_balanced,y_balanced)
    y_pred_er=knn_new.predict(x_test_balanced)
    error_rate.append(np.mean(y_pred_er !=y_test_balanced))
```

In [136]:
```
plt.figure(figsize=(30,20))
plt.plot(range(1,40),error_rate,color='blue',linestyle='dashed',
        marker='o',markerfacecolor='red')
plt.title("Error rate method")
plt.xlabel("Kth values")
plt.ylabel("Error_rate")
```

Out[136]: Text(0, 0.5, 'Error_rate')



In [137]:
```
KNN1=KNeighborsClassifier(n_neighbors=2,p=2,metric='euclidean')
```

In [138]:
```
KNN1=KNN1.fit(x_balanced,y_balanced)
```

In [139]:
```
y_pred3 = KNN1.predict(x_test_balanced)
accuracy_score(y_test_balanced, y_pred3)
```

Out[139]: 0.961839530332681

In [140]:
```
y_train_pred3 = KNN1.predict(x_balanced)
acc_KNN = accuracy_score(y_balanced, y_train_pred3)
acc_KNN
```

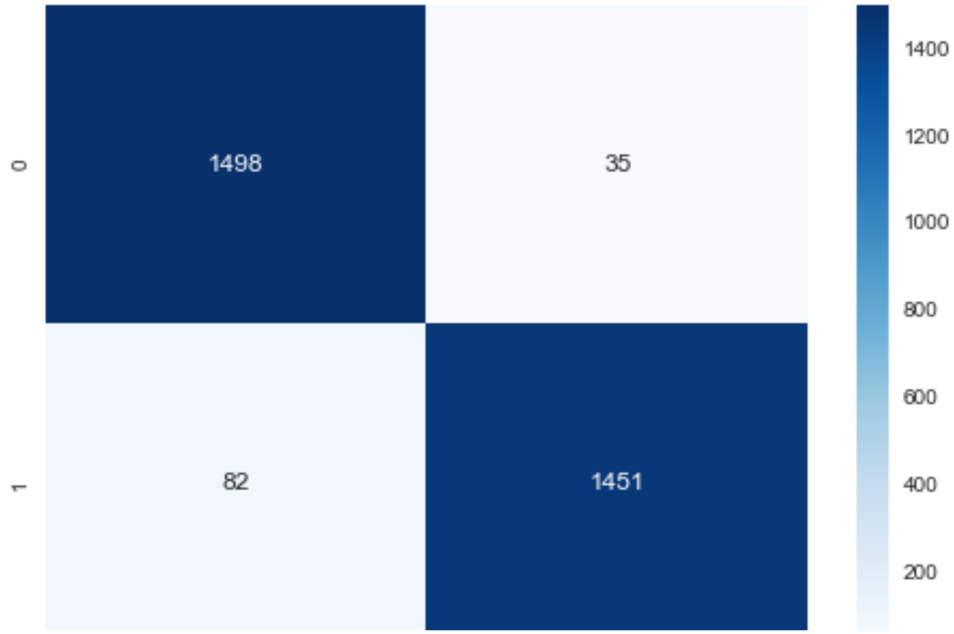
Out[140]: 0.9986067857728241

In [141]:
```
confusion_matrix(y_test_balanced,y_pred3),
```

Out[141]:
```
(array([[1498,   35],
        [  82, 1451]]),)
```

In [142]:
```
sns.heatmap(confusion_matrix(y_test_balanced,y_pred3), annot = True ,cmap = "Blues",fmt = 'd
```

Out[142]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb8f7debe0>



In [143]:
```
from sklearn.model_selection import GridSearchCV
```

In [144]:
```
K_values= range (2,40)
param_grid = {"n_neighbors": K_values,"p": [2],"weights": ['uniform','distance']}
```

In [145]:
```
KNN_grid = KNeighborsClassifier()
KNN_grid_model = GridSearchCV(KNN_grid, param_grid, cv=5, scoring='accuracy')
KNN_grid_model.fit(x_balanced,y_balanced)
```

Out[145]:
```
GridSearchCV(cv=5, estimator=KNeighborsClassifier(),
             param_grid={'n_neighbors': range(2, 40), 'p': [2],
                         'weights': ['uniform', 'distance']},
             scoring='accuracy')
```

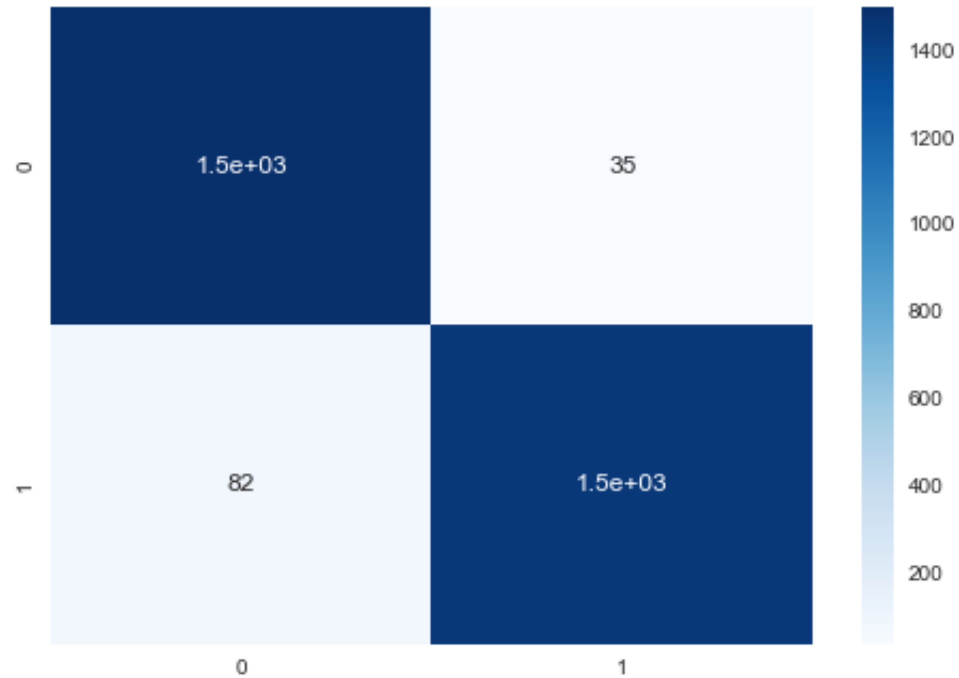
In [146]:
```
print('Best parameters of GridsearchCV for KNN :', KNN_grid_model.best_params_)
print("------------------------------------------------------------------------------------------
print('Best estimators of GridsearchCV for KNN :', KNN_grid_model.best_estimator_)
```

```
Best parameters of GridsearchCV for KNN : {'n_neighbors': 2, 'p': 2, 'weights': 'distance'}
-----------------------------------------------------------------------------------------------
-----
Best estimators of GridsearchCV for KNN : KNeighborsClassifier(n_neighbors=2, weights='distance
')
```

In [147]:
```
#Build a model with n= 2
KNN2=KNeighborsClassifier(n_neighbors=2,p=2,metric='euclidean')
KNN2=KNN2.fit(x_balanced,y_balanced)
y_pred4 = KNN2.predict(x_test_balanced)
print("accuracy_score:",accuracy_score(y_test_balanced, y_pred4))
print("------------------------------------------------------------------------------------------
print(confusion_matrix(y_test_balanced,y_pred4),":confusion_matrix")
print("------------------------------------------------------------------------------------------
print(f1_score(y_test_balanced,y_pred4),":Fiscore")
print("------------------------------------------------------------------------------------------
sns.heatmap(confusion_matrix(y_test_balanced,y_pred4), annot = True ,cmap = "Blues")
c_report = classification_report(y_test_balanced,y_pred4)
print(c_report)
```

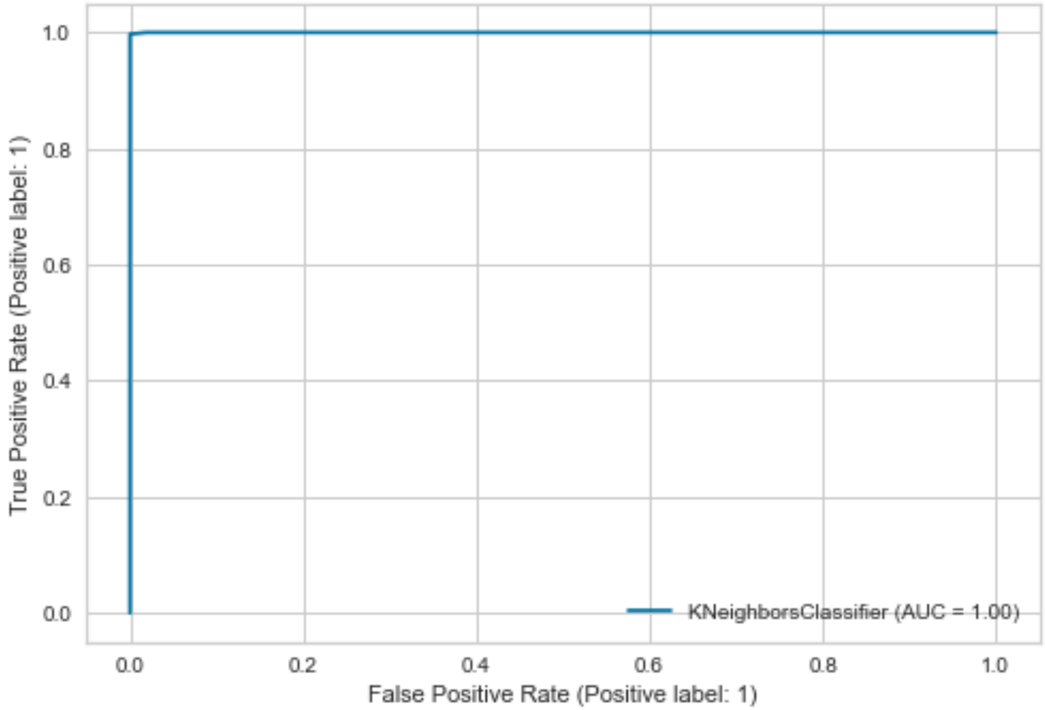
```
accuracy_score: 0.961839530332681
-----------------------------------------------------------------------------------------------
-----
```

```
[[1498   35]
 [  82 1451]] :confusion_matrix
----------------------------------------------------------------------------------------------------
-----
0.9612454455117588 :Fiscore
----------------------------------------------------------------------------------------------------
-------
              precision    recall  f1-score   support

           0       0.95      0.98      0.96      1533
           1       0.98      0.95      0.96      1533

    accuracy                           0.96      3066
   macro avg       0.96      0.96      0.96      3066
weighted avg       0.96      0.96      0.96      3066
```

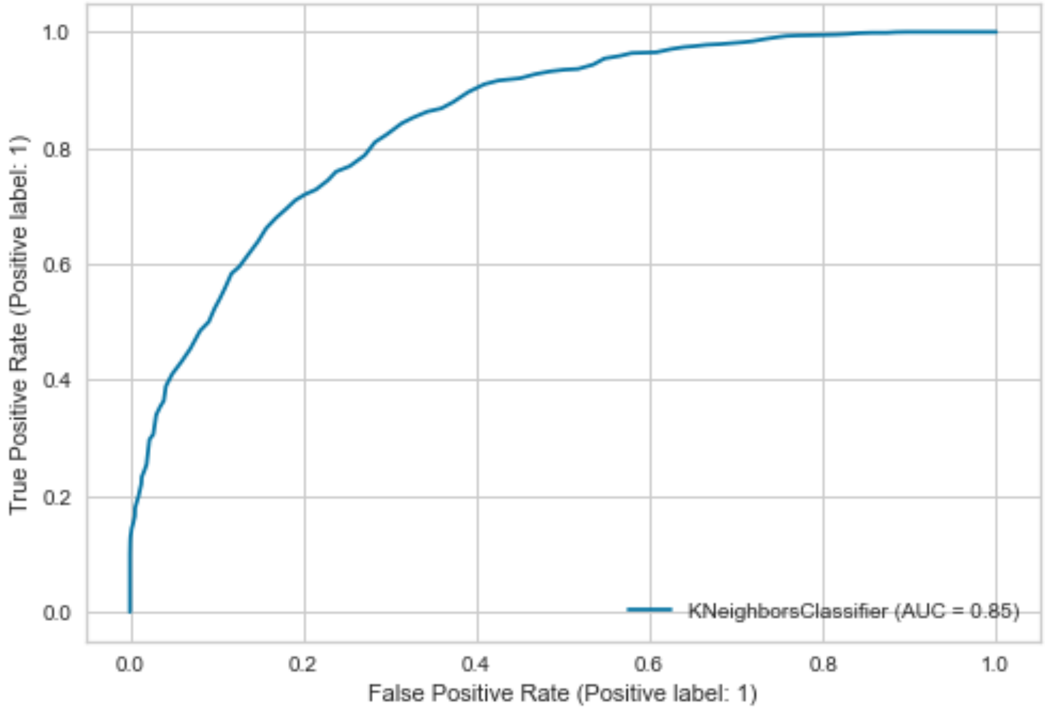


In [148]:
```
from sklearn.metrics import plot_roc_curve,plot_precision_recall_curve
```

In [149]:
```
plot_roc_curve(KNN2,x_balanced,y_balanced);
```



In [150]:
```
plot_roc_curve(model2,x_balanced,y_balanced);
```



SVM:

In [151]:
```
from sklearn.svm import SVC
```

In [152]:
```
model=SVC(kernel='linear')
SVM_model=model.fit(x_balanced,y_balanced)
```

In [153]:
```
y_pred5=SVM_model.predict(x_test_balanced)
confusion_mat = confusion_matrix(y_test_balanced,y_pred5)
confusion_mat
```

Out[153]:
```
array([[1490,   43],
       [   0, 1533]])
```

In [154]:
```
acc_SVM = accuracy_score(y_test_balanced, y_pred5)
acc_SVM
```

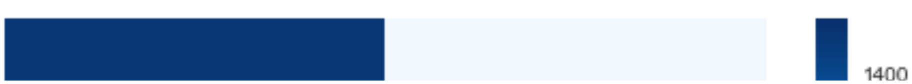
Out[154]:
```
0.9859752120026093
```

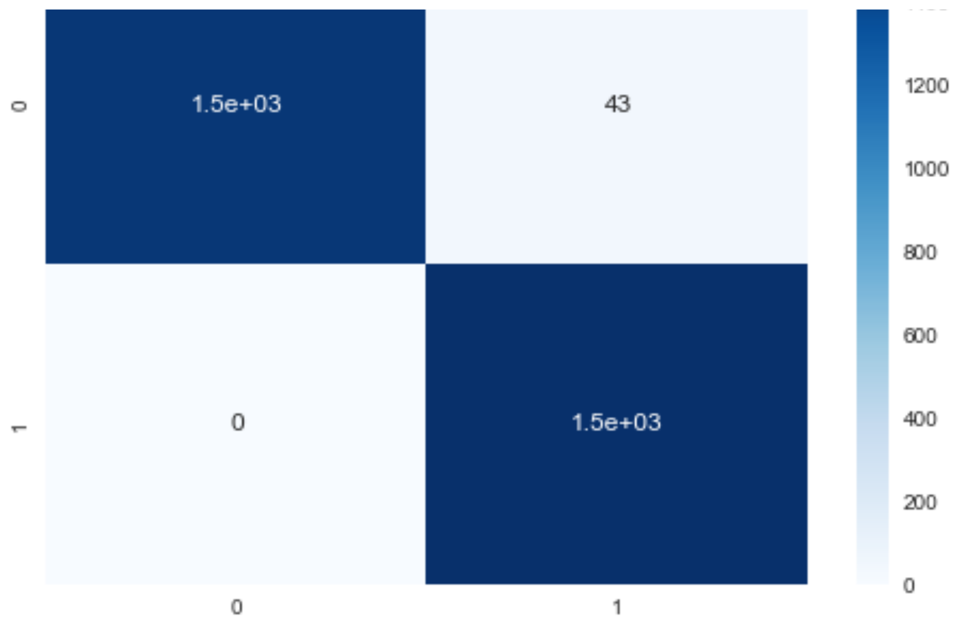
In [155]:
```
roc_auc_score_SVM = roc_auc_score(y_test_balanced,y_pred5)
roc_auc_score_SVM
```

Out[155]:
```
0.9859752120026093
```

In [156]:
```
F1score_SVM =  f1_score(y_test_balanced,y_pred5)
recall_SVM= recall_score(y_test_balanced,y_pred5)

sns.heatmap(confusion_mat, annot = True ,cmap = "Blues")
c_report = classification_report(y_test_balanced,y_pred5)
print(c_report)
```

```
              precision    recall  f1-score   support

           0       1.00      0.97      0.99      1533
           1       0.97      1.00      0.99      1533

    accuracy                           0.99      3066
   macro avg       0.99      0.99      0.99      3066
weighted avg       0.99      0.99      0.99      3066
```




1.5e+03
43
0
1.5e+03
0
1
0
1
1200
1000
800
600
400
200
0

In [157]:
```
from sklearn.model_selection import GridSearchCV

# defining parameter range
param_grid1 = {'C': [0.1, 1, 10, 100, 1000],'gamma': [1, 0.1, 0.01, 0.001, 0.0001],'kernel':

grid1 = GridSearchCV(SVC(), param_grid1, refit = True, verbose = 3)

# fitting the model for grid search
grid1.fit(x_balanced, y_balanced)
```

```
Fitting 5 folds for each of 25 candidates, totalling 125 fits
[CV 1/5] END ........C=0.1, gamma=1, kernel=rbf;, score=0.935 total time=   4.8s
[CV 2/5] END ........C=0.1, gamma=1, kernel=rbf;, score=0.940 total time=   4.8s
[CV 3/5] END ........C=0.1, gamma=1, kernel=rbf;, score=0.950 total time=   5.1s
[CV 4/5] END ........C=0.1, gamma=1, kernel=rbf;, score=0.941 total time=   4.8s
[CV 5/5] END ........C=0.1, gamma=1, kernel=rbf;, score=0.953 total time=   5.1s
[CV 1/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.930 total time=   4.9s
[CV 2/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.933 total time=   4.8s
[CV 3/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.936 total time=   4.8s
[CV 4/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.938 total time=   5.0s
[CV 5/5] END ......C=0.1, gamma=0.1, kernel=rbf;, score=0.945 total time=   4.9s
[CV 1/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.750 total time=   6.4s
[CV 2/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.743 total time=   6.5s
[CV 3/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.749 total time=   6.4s
[CV 4/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.737 total time=   6.5s
[CV 5/5] END .....C=0.1, gamma=0.01, kernel=rbf;, score=0.752 total time=   6.5s
[CV 1/5] END ....C=0.1, gamma=0.001, kernel=rbf;, score=0.513 total time=   7.2s
[CV 2/5] END ....C=0.1, gamma=0.001, kernel=rbf;, score=0.516 total time=   7.3s
[CV 3/5] END ....C=0.1, gamma=0.001, kernel=rbf;, score=0.684 total time=   7.3s
```

In [158]:
```
print('Best parameters of GridsearchCV for SVM :',grid1.best_params_)
print("-------------------------------------------------------------------------------------------
print('Best estimators of GridsearchCV for SVM :', grid1.best_estimator_)
```

```
Best parameters of GridsearchCV for SVM : {'C': 1000, 'gamma': 0.1, 'kernel': 'rbf'}
----------------------------------------------------------------------------------------------
-----
Best estimators of GridsearchCV for SVM : SVC(C=1000, gamma=0.1)
```

In [159]:
```
y_pred6=grid1.predict(x_test_balanced)
confusion_mat = confusion_matrix(y_test_balanced,y_pred6)
confusion_mat
```

Out[159]:
```
array([[1520,   13],
       [   0, 1533]])
```

In [160]:
```
F1score_SVMCV =  f1_score(y_test_balanced,y_pred6)
recall_SVMCV = recall_score(y_test_balanced,y_pred6)
```

In [161]:
```
print("accuracy_score:",accuracy_score(y_test_balanced, y_pred6))
print("-------------------------------------------------------------------")
sns.heatmap(confusion_matrix(y_test_balanced,y_pred6), annot = True ,cmap = "Blues",fmt = 'd
c_report = classification_report(y_test_balanced,y_pred6)
print(c_report)
```

```
accuracy_score: 0.9957599478147423
-------------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      0.99      1.00      1533
           1       0.99      1.00      1.00      1533

    accuracy                           1.00      3066
   macro avg       1.00      1.00      1.00      3066
weighted avg       1.00      1.00      1.00      3066
```

Naive Bayes theorem:

Naive Bayes is a statistical classification technique based on Bayes Theorem. It is one of the simplest supervised learning algorithms. Naive Bayes classifier is the fast, accurate and reliable algorithm. Naive Bayes classifiers have high accuracy and speed on large datasets.

In [162]:
```
#Import GuassianNB model
from sklearn.naive_bayes import GaussianNB
#Create a Gaussian Classifier
NB_model=GaussianNB()
# Train the model using the training sets
NB_model.fit(x_balanced,y_balanced)
```

Out[162]:
```
GaussianNB()
```

In [163]:
```
#Predict Output
y_pred7=NB_model.predict(x_test_balanced)
y_pred7
```

Out[163]:
```
array([0, 1, 0, ..., 1, 1, 1], dtype=int32)
```

In [164]:
```
#Confusion matrix
confusion_mat = confusion_matrix(y_test_balanced,y_pred7)
confusion_mat
```

Out[164]:
```
array([[1317,  216],
       [   4, 1529]])
```

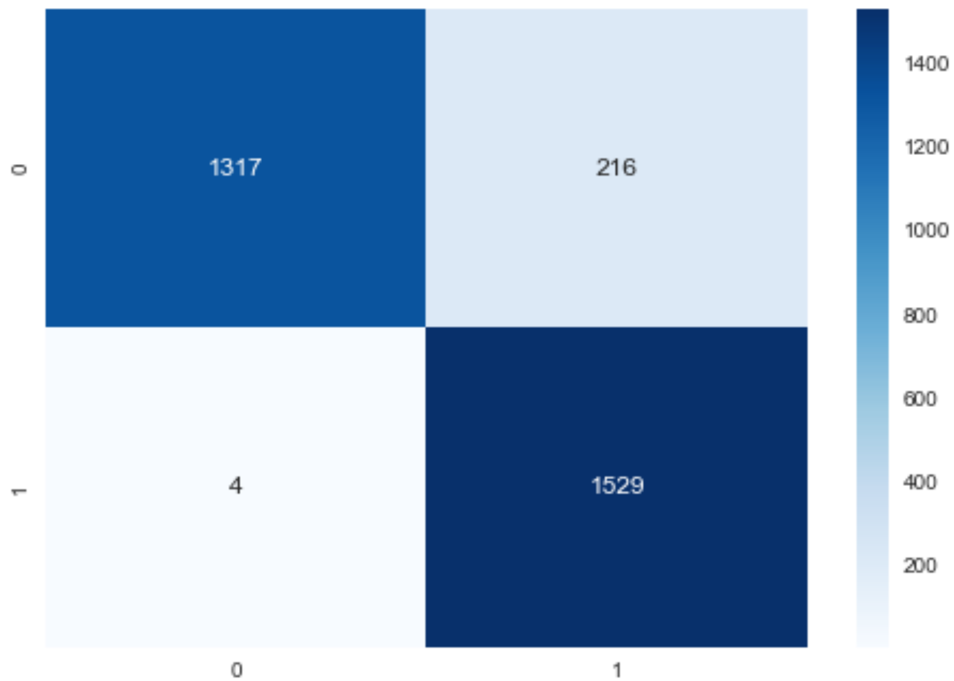
In [165]:
```
#Accuracy
acc_NB = accuracy_score(y_test_balanced, y_pred7)
acc_NB
```

Out[165]:
```
0.9282452707110241
```

In [166]:
```

print("accuracy_score:",accuracy_score(y_test_balanced, y_pred7))
print("------------------------------------------------------------------")
sns.heatmap(confusion_matrix(y_test_balanced,y_pred7), annot = True ,cmap = "Blues",fmt = 'd
c_report = classification_report(y_test_balanced,y_pred7)
print(c_report)
```

```
accuracy_score: 0.9282452707110241
```

```
accuracy_score: 0.9282452707110241
------------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      0.86      0.92      1533
           1       0.88      1.00      0.93      1533

    accuracy                           0.93      3066
   macro avg       0.94      0.93      0.93      3066
weighted avg       0.94      0.93      0.93      3066
```



In [167]:
```
#Roc_auc_score
roc_auc_score_NB = roc_auc_score(y_test_balanced,y_pred7)
roc_auc_score_NB
```

Out[167]: 0.9282452707110241

In [168]:
```
#F1score
F1score_NB =  f1_score(y_test_balanced,y_pred7)
#Recall
recall_NB = recall_score(y_test_balanced,y_pred7)
```

Adaboost:

In [169]:
```
#Adaboostclassifer model
from sklearn.ensemble import AdaBoostClassifier
#create Adaboost classifier
model_ada=AdaBoostClassifier(random_state=123)
#Train the model using the training sets
model_ada.fit(x_balanced,y_balanced)
#Output predict
y_pred_ada=model_ada.predict(x_test_balanced)
y_pred_ada
```

Out[169]:
```
array([0, 1, 0, ..., 1, 1, 1], dtype=int32)
```

In [170]:
```
#confusion matrix
confusion_mat = confusion_matrix(y_test_balanced,y_pred_ada)
confusion_mat
```

Out[170]:
```
array([[1491,   42],
       [   0, 1533]])
```

In [171]:

```
#Accuracy
acc_ADA = accuracy_score(y_test_balanced, y_pred_ada)
acc_ADA
```

Out[171]: 0.9863013698630136

In [172]:

```
#Roc_auc_score
roc_auc_score_ADA = roc_auc_score(y_test_balanced,y_pred_ada)
roc_auc_score_ADA
```

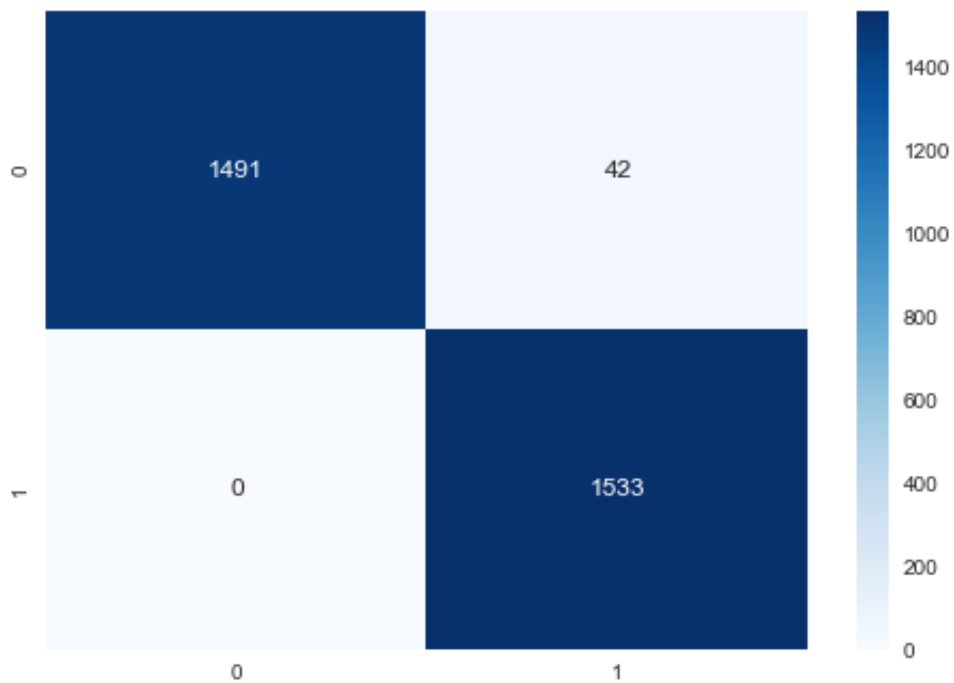
Out[172]: 0.9863013698630136

In [173]:

```
#F1score
F1score_Ada =  f1_score(y_test_balanced,y_pred_ada)
#Recall
recall_Ada = recall_score(y_test_balanced,y_pred_ada)
```

In [174]:
```python

sns.heatmap(confusion_mat, annot = True ,cmap = "Blues",fmt = 'd')
c_report = classification_report(y_test_balanced,y_pred_ada)
print(c_report)
```

```
              precision    recall  f1-score   support

           0       1.00      0.97      0.99      1533
           1       0.97      1.00      0.99      1533

    accuracy                           0.99      3066
   macro avg       0.99      0.99      0.99      3066
weighted avg       0.99      0.99      0.99      3066
```



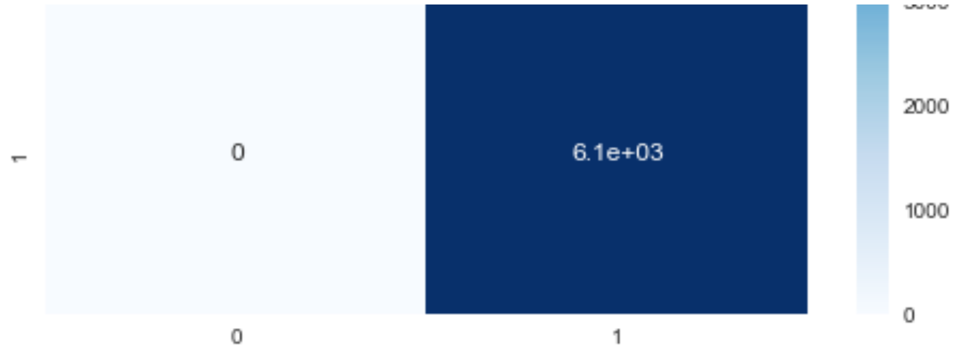
In [ ]:

```

```

In [175]:

```
# Train prediction:
y_train_pred =model_ada.predict(x_balanced)
print(confusion_matrix(y_balanced,y_train_pred))
print("---------------------------------------------------------------------------")
print("accuracy_score:",accuracy_score(y_balanced, y_train_pred))
print("-------------------------------------------------------------------")
sns.heatmap(confusion_matrix(y_balanced,y_train_pred), annot = True ,cmap = "Blues")
c_report = classification_report(y_balanced,y_train_pred)
print(c_report)
```

```
[[6101    0]
 [   0 6101]]
---------------------------------------------------------------------------
accuracy_score: 1.0
-------------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      1.00      1.00      6101
           1       1.00      1.00      1.00      6101

    accuracy                           1.00     12202
   macro avg       1.00      1.00      1.00     12202
weighted avg       1.00      1.00      1.00     12202
```



Hyperparameter Tuning: GridSearchCV

In [176]:
```
from sklearn.ensemble import AdaBoostClassifier
from sklearn import tree
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
```

In [177]:
```
#Cross validation:
crossvalidation=KFold(n_splits=10,shuffle=True,random_state=1)
for depth in range (1,10):
    tree_classifier=tree.DecisionTreeClassifier(max_depth=depth,random_state=1)
    if tree_classifier.fit(x_balanced,y_balanced).tree_.max_depth<depth:
        break
    score=np.mean(cross_val_score(tree_classifier,x_balanced,y_balanced,scoring='accuracy', 
    print(depth, "score", score)
```

```
1 score 0.9993443294262967
2 score 0.9993443294262967
3 score 1.0
```

In [178]:

```
#create ada boost classifier
ada=AdaBoostClassifier()
search_grid={'n_estimators':[200,500,600],'learning_rate':[.001,0.01,.1]}
search=GridSearchCV(estimator=ada,param_grid=search_grid,scoring='accuracy',n_jobs=1,cv=cros
```

In [179]:

```
#Train the model using train sets usig hyper parameter
search.fit(x_balanced,y_balanced)
search.best_params_
search.best_score_
```

Out[179]:

```
1.0
```

In [180]:

```
from sklearn.model_selection import cross_validate
```

In [181]:

```
ad_validation = AdaBoostClassifier(n_estimators = 50,random_state =2)

ad_validation_scores = cross_validate(ad_validation,x_balanced,y_balanced,scoring = ['accura
ad_validation_scores
```

Out[181]:

```
{'fit_time': array([0.33301806, 0.3242383 , 0.32173395, 0.31959915, 0.35555792,
        0.32681894, 0.31701088, 0.31183624, 0.31888604, 0.32576013]),
 'score_time': array([0.01483607, 0.01362395, 0.01420403, 0.0132947 , 0.01743627,
        0.01466322, 0.01326704, 0.01333189, 0.01321602, 0.01335692]),
 'test_accuracy': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
 'test_precision': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.]),
 'test_recall': array([1., 1., 1., 1., 1., 1., 1., 1., 1., 1.])}
```

In [182]:
```
ad_validation_scores = pd.DataFrame(ad_validation_scores )
ad_validation_scores
```

Out[182]:

	fit_time	score_time	test_accuracy	test_precision	test_recall
0	0.333018	0.014836	1.0	1.0	1.0
1	0.324238	0.013624	1.0	1.0	1.0
2	0.321734	0.014204	1.0	1.0	1.0
3	0.319599	0.013295	1.0	1.0	1.0
4	0.355558	0.017436	1.0	1.0	1.0
5	0.326819	0.014663	1.0	1.0	1.0
6	0.317011	0.013267	1.0	1.0	1.0
7	0.311836	0.013332	1.0	1.0	1.0
8	0.318886	0.013216	1.0	1.0	1.0
9	0.325760	0.013357	1.0	1.0	1.0

In [183]:
```
ad_validation_scores.mean()
```

Out[183]:
```
fit_time          0.325446
score_time        0.014123
test_accuracy     1.000000
test_precision    1.000000
test_recall       1.000000
dtype: float64
```

Gradient Boosting

In [184]:
```
#Gradient Boosting CLassifier modle
from sklearn.ensemble import GradientBoostingClassifier
```

In [185]:
```
#Create GradientBoosting classifier
model_GB=GradientBoostingClassifier(random_state=2)
model_GB.fit(x_balanced,y_balanced)
```

Out[185]:
```
GradientBoostingClassifier(random_state=2)
```

In [186]:
```
#Train the model
y_pred_GB=model_GB.predict(x_test_balanced)
```

In [187]:
```
#Confusion matrix
confusion_mat = confusion_matrix(y_test_balanced,y_pred_GB)
confusion_mat
```

Out[187]:
```
array([[1491,   42],
       [   0, 1533]])
```

In [188]:
```
#Accuracy:
acc_GB = accuracy_score(y_test_balanced, y_pred_GB)
acc_GB
```

Out[188]:
```
0.9863013698630136
```

In [189]:
```
y_balanced.shape
```

Out[189]:
```
(12202,)
```

In [190]:
```
#F1Score
F1score_GB =  f1_score(y_test_balanced,y_pred_GB)
#Recall
recall_GB = recall_score(y_test_balanced,y_pred_GB)
```

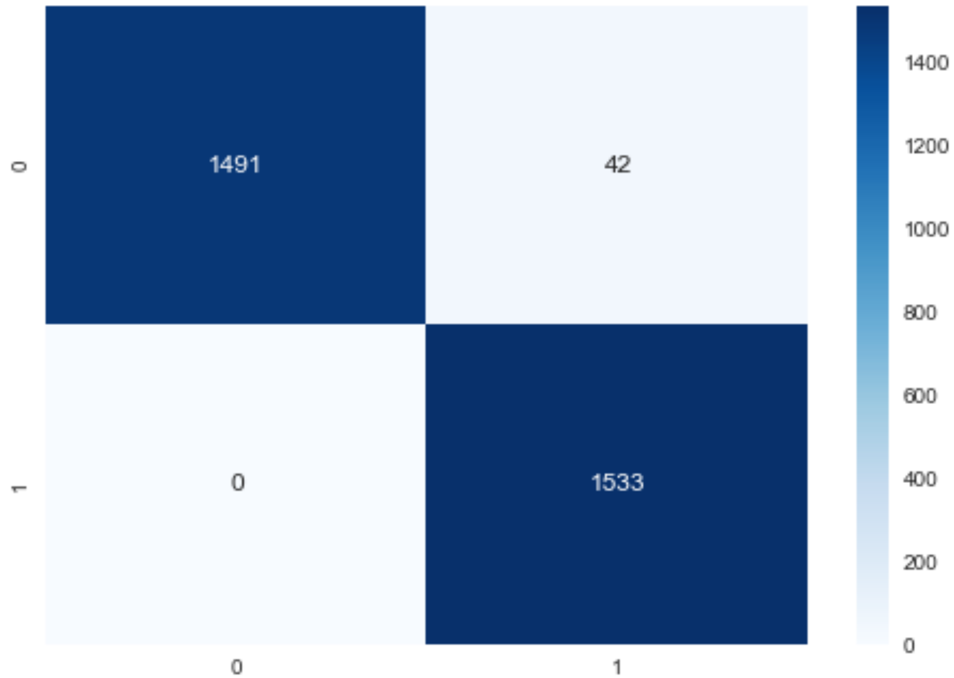
In [191]:
```
#Roc_auc_score
roc_auc_score_GB = roc_auc_score(y_test_balanced,y_pred_GB)
roc_auc_score_GB
```

Out[191]:
```
0.9863013698630136
```

In [192]:

```
sns.heatmap(confusion_mat, annot = True ,cmap = "Blues",fmt = 'd')
c_report = classification_report(y_test_balanced,y_pred_GB)
print(c_report)
```

```
              precision    recall  f1-score   support

           0       1.00      0.97      0.99      1533
           1       0.97      1.00      0.99      1533

    accuracy                           0.99      3066
   macro avg       0.99      0.99      0.99      3066
weighted avg       0.99      0.99      0.99      3066
```



Feature Selection using Recursive Feature Elimination:

In [193]:
```
from sklearn.feature_selection import RFE
```

In [194]:
```
#Create RFE model
FS_Recursive = RFE(model_GB)
fit = FS_Recursive.fit(x_balanced,y_balanced)
```

In [195]:
```
fit.support_
```

Out[195]:
```
array([ True, False, False, False, False,  True,  True, False, False,
       False,  True, False,  True, False,  True,  True,  True])
```

In [196]:
```
#Rank the Feature
fit.ranking_
```

Out[196]:
```
array([ 1, 10,  9,  6,  8,  1,  1,  3,  2,  5,  1,  7,  1,  4,  1,  1,  1])
```

In [197]:
```
#Dataframe
scores1 = pd.DataFrame(fit.ranking_,columns = ['Score'])
dfcolumns = pd.DataFrame(x_balanced.columns)

```

In [198]:
```
feature_rank1 = pd.concat([dfcolumns,scores1],axis = 1)
```

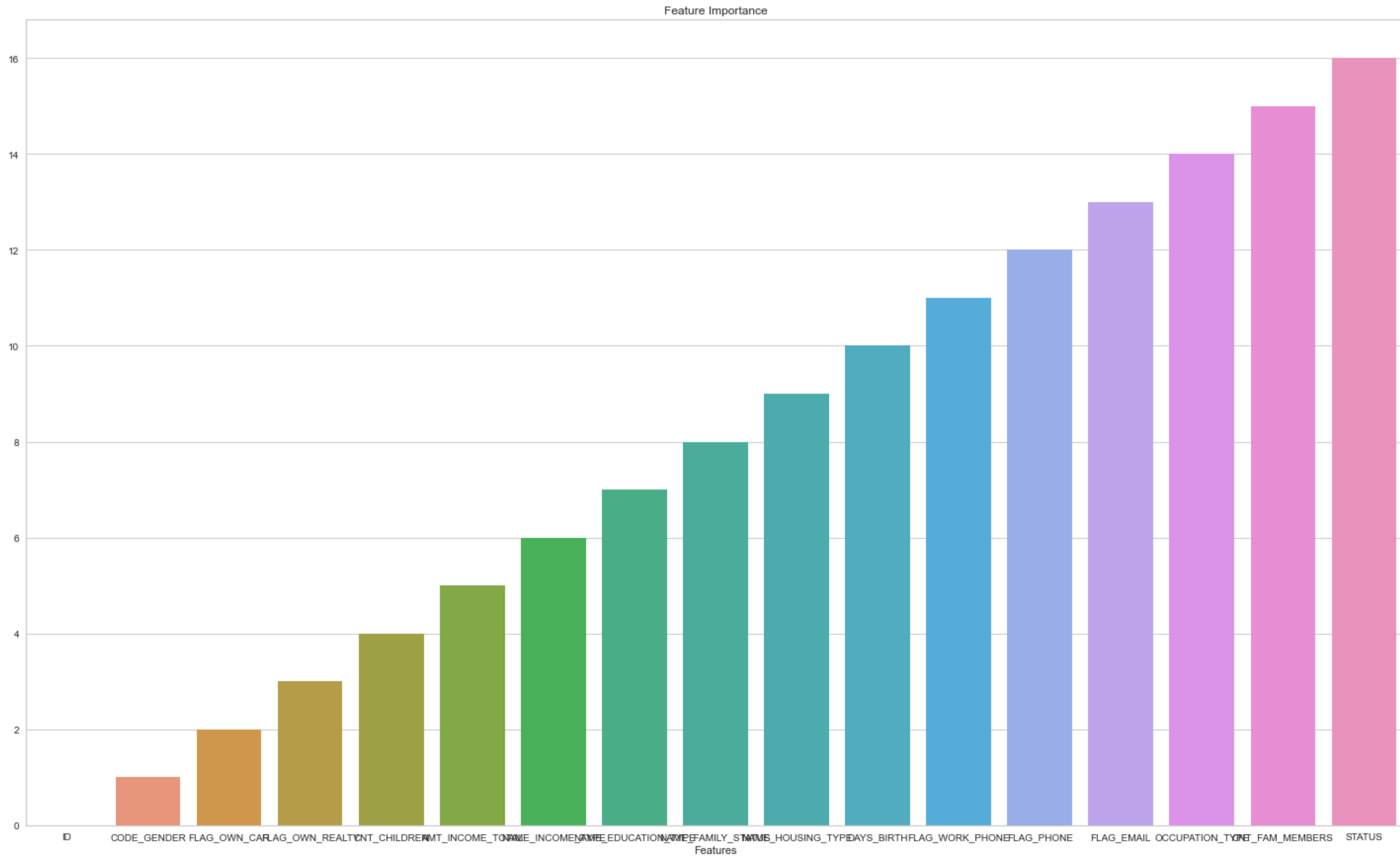
In [199]:
```
feature_rank1.columns = ['Features','Score']
feature_rank1
```

Out[199]:

	Features	Score
0	ID	1
1	CODE_GENDER	10
2	FLAG_OWN_CAR	9
3	FLAG_OWN_REALTY	6
4	CNT_CHILDREN	8
5	AMT_INCOME_TOTAL	1
6	NAME_INCOME_TYPE	1
7	NAME_EDUCATION_TYPE	3
8	NAME_FAMILY_STATUS	2
9	NAME_HOUSING_TYPE	5
10	DAYS_BIRTH	1
11	FLAG_WORK_PHONE	7
12	FLAG_PHONE	1
13	FLAG_EMAIL	4
14	OCCUPATION_TYPE	1
15	CNT_FAM_MEMBERS	1
16	STATUS	1

In [200]:

```
#Barplot
plt.figure(figsize= (25,15))
sns.barplot(x=feature_rank1["Features"], y=feature_rank1.index)
plt.title("Feature Importance")
plt.show()
```



In [201]:
```
# Feature with rank 1:
col_to_use = ['ID','AMT_INCOME_TOTAL','NAME_INCOME_TYPE', 'NAME_EDUCATION_TYPE','DAYS_BIRTH',
```

In [202]:
```
#Combine the RFE feature to dataset:
mydata_rfe =df1[col_to_use]
mydata_rfe.head()
```

Out[202]:

	ID	AMT_INCOME_TOTAL	NAME_INCOME_TYPE	NAME_EDUCATION_TYPE	DAYS_BIRTH	OCCUPATION_TYPE	CNT_FAM_M
0	5008838	405000.0	0	1	-11842	10	
1	5008839	405000.0	0	1	-11842	10	
2	5008840	405000.0	0	1	-11842	10	
3	5008841	405000.0	0	1	-11842	10	
4	5008842	405000.0	0	1	-11842	10	

In [203]:
```
#Number of rows and column after feature elimination
print("Number of rows and column after feature elimination :",mydata_rfe.shape)
```

```
Number of rows and column after feature elimination : (9496, 8)
```

In [204]:
```
x = mydata_rfe.iloc[:,:8]
```

In [205]:
```
y = df1['cluster']
```

In [206]:
```
# Train and Test split
from sklearn.model_selection import train_test_split
x_train_rfe,x_test_rfe,y_train_rfe,y_test_rfe=train_test_split(x,y,test_size=0.2,random_state
```

In [207]:
```
x_train_rfe.shape
```
Out[207]: (7596, 8)

In [208]:
```
x_test_rfe.shape
```
Out[208]: (1900, 8)

In [209]:
```
#Standardization: MinMaxScale
from sklearn.preprocessing import MinMaxScaler
scale = MinMaxScaler()
x_scaled_rfe = pd.DataFrame(scale.fit_transform(x_train_rfe), columns=x_train_rfe.columns)
x_test_scaled_rfe= pd.DataFrame(scale.fit_transform(x_test_rfe), columns=x_test_rfe.columns)
```

In [210]:
```
#Oversampling: SMOTE
from imblearn.over_sampling import SMOTE
oversample_rfe = SMOTE()
x_balanced_rfe, y_balanced_rfe = oversample_rfe.fit_resample(x_scaled_rfe, y_train_rfe)
x_test_balanced_rfe, y_test_balanced_rfe = oversample_rfe.fit_resample(x_test_scaled_rfe, y_
```

In [211]:
```
#Create gradientBoosting classifier
model_GB_rfe=GradientBoostingClassifier(random_state=2)
model_GB_rfe.fit(x_balanced_rfe,y_balanced_rfe)
```
Out[211]: GradientBoostingClassifier(random_state=2)

In [212]:
```
#Predict output
y_pred_GB_rfe=model_GB_rfe.predict(x_test_balanced_rfe)
```

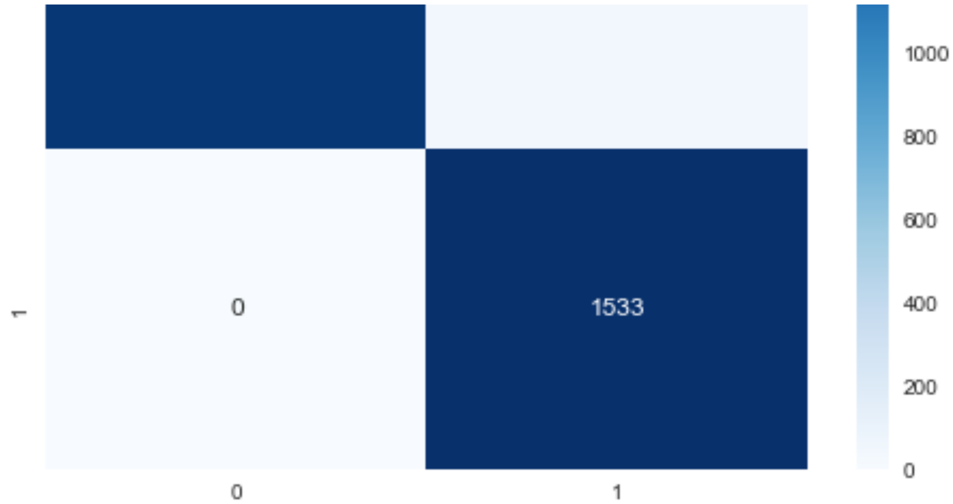
In [213]:
```
#Confusion matrix
confusion_mat = confusion_matrix(y_test_balanced_rfe,y_pred_GB_rfe)
confusion_mat
```

Out[213]:
```
array([[1490,   43],
       [   0, 1533]])
```

In [214]:
```
#F1 score
F1score_GB_rfe =  f1_score(y_test_balanced,y_pred_GB_rfe)
#Recall
recall_GB_rfe = recall_score(y_test_balanced,y_pred_GB_rfe)
```

In [215]:
```
#Accuracy and classification report
print("accuracy_score:",accuracy_score(y_test_balanced_rfe, y_pred_GB_rfe))
print("-----------------------------------------------------------------")
sns.heatmap(confusion_matrix(y_test_balanced_rfe,y_pred_GB_rfe), annot = True ,cmap = "Blues'
c_report = classification_report(y_test_balanced_rfe,y_pred_GB_rfe)
print(c_report)
```

```
accuracy_score: 0.9859752120026093
-------------------------------------------------------------------
              precision    recall  f1-score   support

           0       1.00      0.97      0.99      1533
           1       0.97      1.00      0.99      1533

    accuracy                           0.99      3066
   macro avg       0.99      0.99      0.99      3066
weighted avg       0.99      0.99      0.99      3066
```



Decision Tree:

In [216]:
```
df.head()
```

Out[216]:

	ID	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	NAME_INCOME_TYPE
0	5008838	1	0	1	1	405000.0	0
1	5008839	1	0	1	1	405000.0	0
2	5008840	1	0	1	1	405000.0	0
3	5008841	1	0	1	1	405000.0	0
4	5008842	1	0	1	1	405000.0	0

In [217]:
```
x_ind = df.iloc[:,:19]
y_dep = df['cluster']
```

In [218]:
```

from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x_ind,y_dep,train_size = 0.8, random_state =
```

In [219]:
```
#Decision Tree model:
from sklearn import tree
#Create Decision Tree Classifier:
model_DT = tree.DecisionTreeClassifier()
```

In [220]:
```
#Train the model
model_DT.fit(x_balanced,y_balanced)
```

Out[220]:
```
DecisionTreeClassifier()
```

In [221]:
```
#predict output:
y_pred_DT = model_DT.predict(x_test_balanced)
y_pred_DT
```

Out[221]:
```
array([0, 1, 0, ..., 1, 1, 1], dtype=int32)
```

In [222]:
```
from sklearn.metrics import accuracy_score,confusion_matrix
```

In [223]:
```
#Confusion matrix:
confusion_matrix(y_test_balanced,y_pred_DT)
```

Out[223]:
```
array([[1490,   43],
       [   0, 1533]])
```

In [224]:
```
#F1score_DT:
F1score_DT =  f1_score(y_test_balanced,y_pred_DT)
#Recall

recall_DT = recall_score(y_test_balanced,y_pred_DT)
```

In [225]:
```
#Roc_Auc_curve
roc_auc_score_DT= roc_auc_score(y_test_balanced,y_pred_DT)
roc_auc_score_DT
```

Out[225]: 0.9859752120026093

In [226]:
```
#Accuracy
acc_DT = accuracy_score(y_test_balanced,y_pred_DT)
acc_DT
```

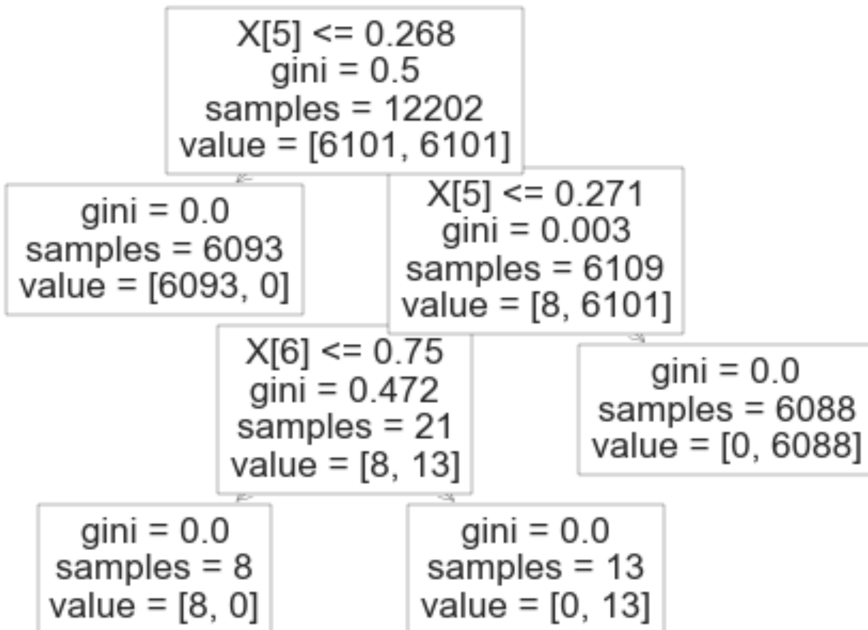
Out[226]: 0.9859752120026093

In [227]:

```
tree.plot_tree(model_DT,max_depth=4)
```

Out[227]:

```
[Text(178.56, 261.6075, 'X[5] <= 0.268\ngini = 0.5\nsamples = 12202\nvalue = [6101, 6101]'),
 Text(89.28, 186.8625, 'gini = 0.0\nsamples = 6093\nvalue = [6093, 0]'),
 Text(267.84000000000003, 186.8625, 'X[5] <= 0.271\ngini = 0.003\nsamples = 6109\nvalue = [8, 6
101]'),
 Text(178.56, 112.1175, 'X[6] <= 0.75\ngini = 0.472\nsamples = 21\nvalue = [8, 13]'),
 Text(89.28, 37.3725, 'gini = 0.0\nsamples = 8\nvalue = [8, 0]'),
 Text(267.84000000000003, 37.3725, 'gini = 0.0\nsamples = 13\nvalue = [0, 13]'),
 Text(357.12, 112.1175, 'gini = 0.0\nsamples = 6088\nvalue = [0, 6088]')]
```



Hyperparameter Tuning : RandiomizedSearchCV

In [228]:

```
from sklearn.model_selection import RandomizedSearchCV
#parameter:
parameters={"max_depth":(10,20,30,40,50,60,70,100),'criterion':('gini','entropy'),
            'max_features':('log2','auto','sqrt'),'min_samples_split':(2,4,6)}
DT_hp=RandomizedSearchCV(tree.DecisionTreeClassifier(),param_distributions=parameters,cv=5)
DT_hp.fit(x_balanced,y_balanced)
```

Out[228]:

```
RandomizedSearchCV(cv=5, estimator=DecisionTreeClassifier(),
                   param_distributions={'criterion': ('gini', 'entropy'),
                                        'max_depth': (10, 20, 30, 40, 50, 60,
                                                      70, 100),
                                        'max_features': ('log2', 'auto',
                                                         'sqrt'),
                                        'min_samples_split': (2, 4, 6)})
```

In [229]:

```
DT_hp.best_estimator_
```

Out[229]:

```
DecisionTreeClassifier(criterion='entropy', max_depth=10, max_features='sqrt',
                       min_samples_split=4)
```

In [230]:

```
#model Building after randomized CV
model_after_HT=tree.DecisionTreeClassifier(criterion='entropy', max_depth=20, max_features='
```

In [231]:

```
model_after_HT=model_after_HT.fit(x_balanced,y_balanced)
```

In [232]:

```
y_pred_after_hT=model_after_HT.predict(x_test_balanced)
confusion_matrix(y_test_balanced,y_pred_after_hT)
```

Out[232]:

```
array([[1497,   36],
       [  29, 1504]])
```

In [233]:
```
roc_auc_score_DT= roc_auc_score(y_test_balanced,y_pred_DT)
roc_auc_score_DT
```

Out[233]: 0.9859752120026093

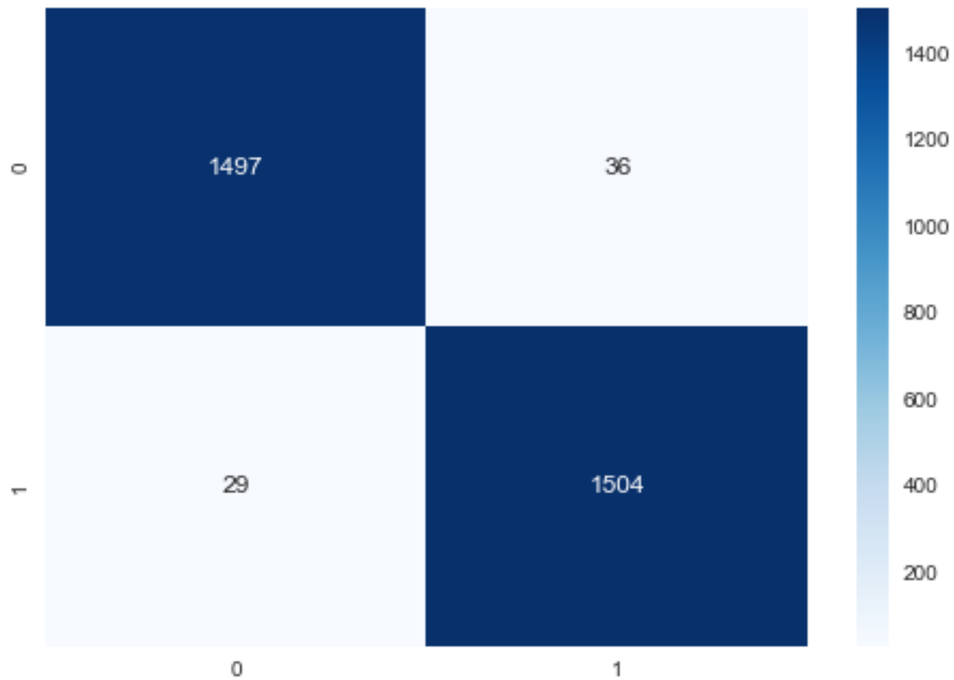
In [234]:
```
accuracy_score(y_test_balanced,y_pred_after_hT)
```

Out[234]: 0.9787997390737116

In [235]:

```
sns.heatmap(confusion_matrix(y_test_balanced,y_pred_after_hT), annot = True ,cmap = "Blues",
c_report = classification_report(y_test_balanced,y_pred_after_hT)
print(c_report)
```

```
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1533
           1       0.98      0.98      0.98      1533

    accuracy                           0.98      3066
   macro avg       0.98      0.98      0.98      3066
weighted avg       0.98      0.98      0.98      3066
```



Random Forest:

In [236]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [237]:
```
#RandomForest model
model_rf = RandomForestClassifier(random_state = 2)
#create Random Forest classifier
model_rf = model_rf.fit(x_balanced,y_balanced)
```

In [238]:
```
#predict output
y_pred_RF = model_rf.predict(x_test_balanced)
y_pred_RF
```

Out[238]:
```
array([0, 1, 0, ..., 1, 1, 1], dtype=int32)
```

In [239]:
```
#Confusion matrix
from sklearn.metrics import confusion_matrix,accuracy_score
confusion_matrix_RF = confusion_matrix(y_test_balanced,y_pred_RF)
confusion_matrix_RF
```

Out[239]:
```
array([[1493,   40],
       [   0, 1533]])
```

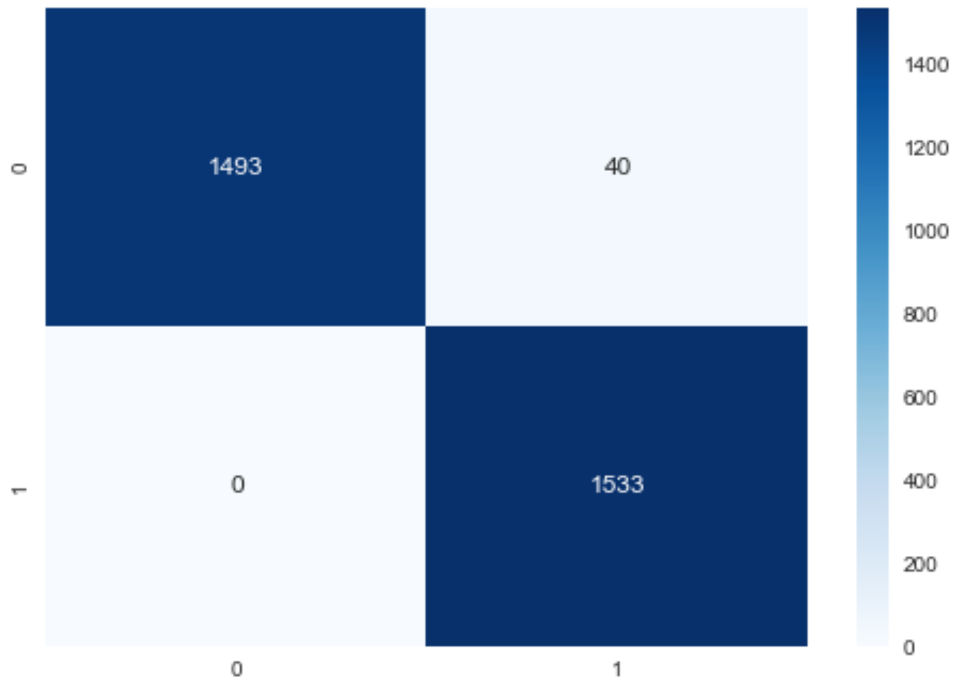
In [240]:
```
#F1score
F1score_RF =  f1_score(y_test_balanced,y_pred_RF)
#Recall
recall_RF = recall_score(y_test_balanced,y_pred_RF)
```

In [241]:
```
#Accuracy
acc_RF = accuracy_score(y_test_balanced,y_pred_RF)
acc_RF
```

Out[241]: 0.9869536855838226

In [243]:
```
sns.heatmap(confusion_matrix_RF, annot = True ,cmap = "Blues",fmt = 'd')
c_report = classification_report(y_test_balanced,y_pred_RF)
print(c_report)
```

```
              precision    recall  f1-score   support

           0       1.00      0.97      0.99      1533
           1       0.97      1.00      0.99      1533

    accuracy                           0.99      3066
   macro avg       0.99      0.99      0.99      3066
weighted avg       0.99      0.99      0.99      3066
```



In [244]:
```
model_c = RandomForestClassifier(criterion = 'entropy',random_state = 2)
```

In [245]:
```
model_c = model_c.fit(x_balanced,y_balanced)
```

In [246]:
```
y_pred_c = model_c.predict(x_test_balanced)
y_pred_c
```

Out[246]:
```
array([0, 1, 0, ..., 1, 1, 1], dtype=int32)
```

In [247]:
```
from sklearn.metrics import confusion_matrix,accuracy_score
confusion_matrix_c = confusion_matrix(y_test_balanced,y_pred_c)
confusion_matrix_c
```

Out[247]:
```
array([[1493,   40],
       [   0, 1533]])
```

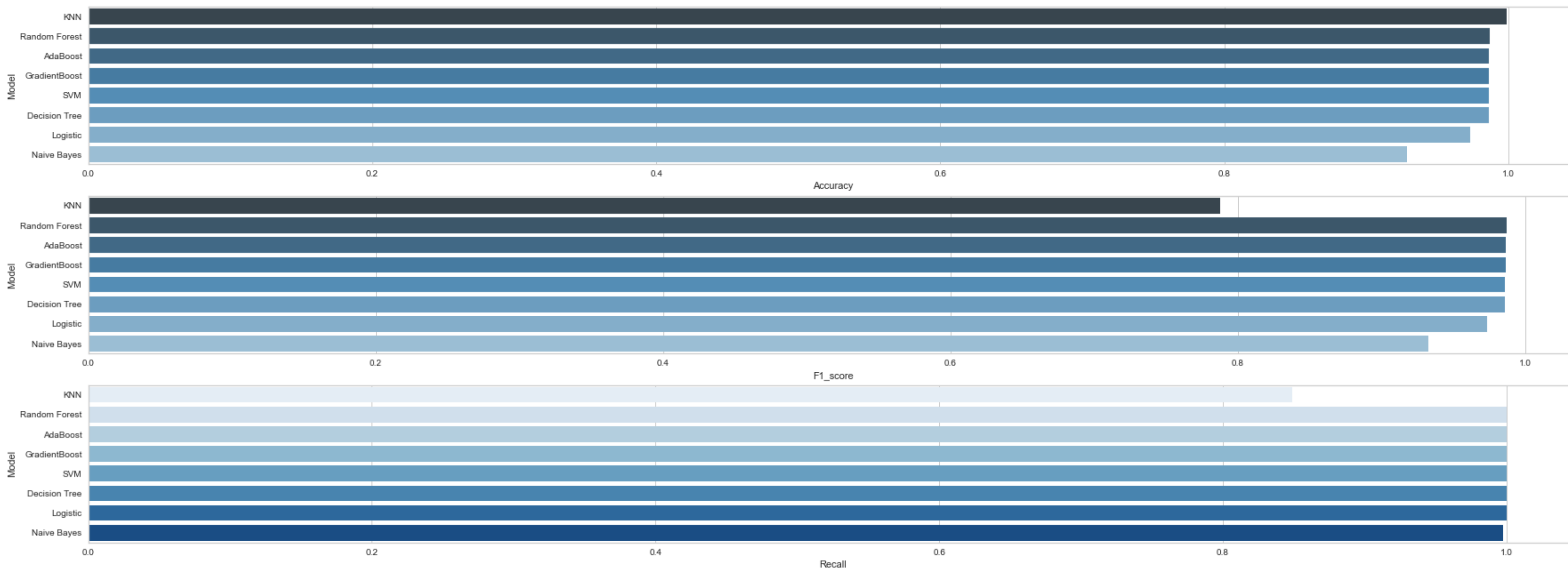
In [248]:
```
accuracy_score(y_test_balanced,y_pred_c)
```

Out[248]:
```
0.9869536855838226
```

Model Performance:

In [249]:
```
compare_acc = pd.DataFrame({"Model": [ "Logistic","SVM", "KNN","Naive Bayes", "Decision Tree"
                             "Accuracy": [ acc_LR,acc_SVM, acc_KNN,acc_NB,acc_DT, acc_RF, acc_
                            "F1_score" : [F1score_LR,F1score_SVM,F1score_KNN,F1score_NB,F1scor
                            "Recall" : [recall_LR,recall_SVM,recall_KNN,recall_NB,recall_DT,re
                            })
def lables(ax):
    for p in ax.patches:
        width = p.get_width()                       # get bar length
        ax.text(width,                              # set the text at 1 unit right of the ba
        p.get_y() + p.get_height() / 2,      # get Y coordinate + X coordinate / 2
        '{:1.3f}'.format(width),             # set variable to display, 2 decimals
        ha = 'left',                         # horizontal alignment
        va = 'center')

```

```
plt.figure(figsize =(30,15))
plt.subplot(411)
compare_acc = compare_acc.sort_values(by="Accuracy", ascending=False)
ax=sns.barplot(x="Accuracy", y="Model", data=compare_acc, palette="Blues_d")



#plt.figure(figsize =(20,10))
plt.subplot(412)
compare_f1 = compare_acc.sort_values(by="F1_score", ascending=False)
ax=sns.barplot(x="F1_score", y="Model", data=compare_acc, palette="Blues_d")

#plt.figure(figsize =(20,10))
plt.subplot(413)
compare_recall = compare_acc.sort_values(by="Recall", ascending=False)
ax=sns.barplot(x="Recall", y="Model", data=compare_acc, palette="Blues")
```



In [250]:
```
Model_accuracy = compare_acc.reset_index()
Model_accuracy
```

Out[250]:

	index	Model	Accuracy	F1_score	Recall
0	2	KNN	0.998607	0.787769	0.848663
1	5	Random Forest	0.986954	0.987122	1.000000
2	6	AdaBoost	0.986301	0.986486	1.000000
3	7	GradientBoost	0.986301	0.986486	1.000000
4	1	SVM	0.985975	0.986169	1.000000
5	4	Decision Tree	0.985975	0.986169	1.000000
6	0	Logistic	0.972929	0.973642	1.000000
7	3	Naive Bayes	0.928245	0.932886	0.997391

Deep learninng:

Aritfical Neural Network - ANN

In [251]:
```
import tensorflow as tf
```

In [252]:
```
from keras.models import Sequential
from keras.layers import Dense,Dropout
```

In [253]:
```
model_ANN=Sequential()
```

In [254]:
```
#first hidden layer
model_ANN.add(Dense(units=100,kernel_initializer='he_uniform',activation='relu',input_dim=17)
#second hidden layer
model_ANN.add(Dense(units=50,kernel_initializer='he_uniform',activation='relu'))
# last layer or output layer
model_ANN.add(Dense(units=1,kernel_initializer='glorot_uniform',activation='sigmoid'))
```

In [255]:
```
model_ANN.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 100)               1800
_________________________________________________________________
dense_1 (Dense)              (None, 50)                5050
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 51
=================================================================
Total params: 6,901
Trainable params: 6,901
Non-trainable params: 0
_________________________________________________________________
```

In [256]:
```
model_ANN.compile(optimizer='adam',loss='binary_crossentropy',metrics=['accuracy'])
```

In [257]:
```
model1_ANN= model_ANN.fit(x_balanced,y_balanced,batch_size=100,epochs=100)
```

```
Epoch 91/100
123/123 [==============================] - 0s 838us/step - loss: 7.3585e-05 - accuracy: 1.0000
Epoch 92/100
123/123 [==============================] - 0s 784us/step - loss: 6.6072e-05 - accuracy: 1.0000
Epoch 93/100
123/123 [==============================] - 0s 841us/step - loss: 6.7743e-05 - accuracy: 1.0000
Epoch 94/100
123/123 [==============================] - 0s 819us/step - loss: 0.0064 - accuracy: 0.9973
Epoch 95/100
123/123 [==============================] - 0s 833us/step - loss: 0.0050 - accuracy: 0.9980
Epoch 96/100
123/123 [==============================] - 0s 797us/step - loss: 0.0022 - accuracy: 0.9992
Epoch 97/100
123/123 [==============================] - 0s 846us/step - loss: 0.0027 - accuracy: 0.9992
Epoch 98/100
123/123 [==============================] - 0s 836us/step - loss: 1.2663e-04 - accuracy: 1.0000
Epoch 99/100
123/123 [==============================] - 0s 831us/step - loss: 8.0144e-05 - accuracy: 1.0000
Epoch 100/100
123/123 [==============================] - 0s 817us/step - loss: 7.2157e-05 - accuracy: 1.0000
```

In [258]:
```
y_pred_ANN=model.predict(x_test_balanced)
y_pred_ANN
```

Out[258]:
```
array([0, 1, 0, ..., 1, 1, 1], dtype=int32)
```

In [259]:
```
y_pred_ANN=(y_pred_ANN>0.5)
```

In [260]:
```
from sklearn.metrics import confusion_matrix,accuracy_score
```

In [261]:
```
accuracy_score(y_pred_ANN,y_test_balanced)
```

Out[261]:
```
0.9859752120026093
```

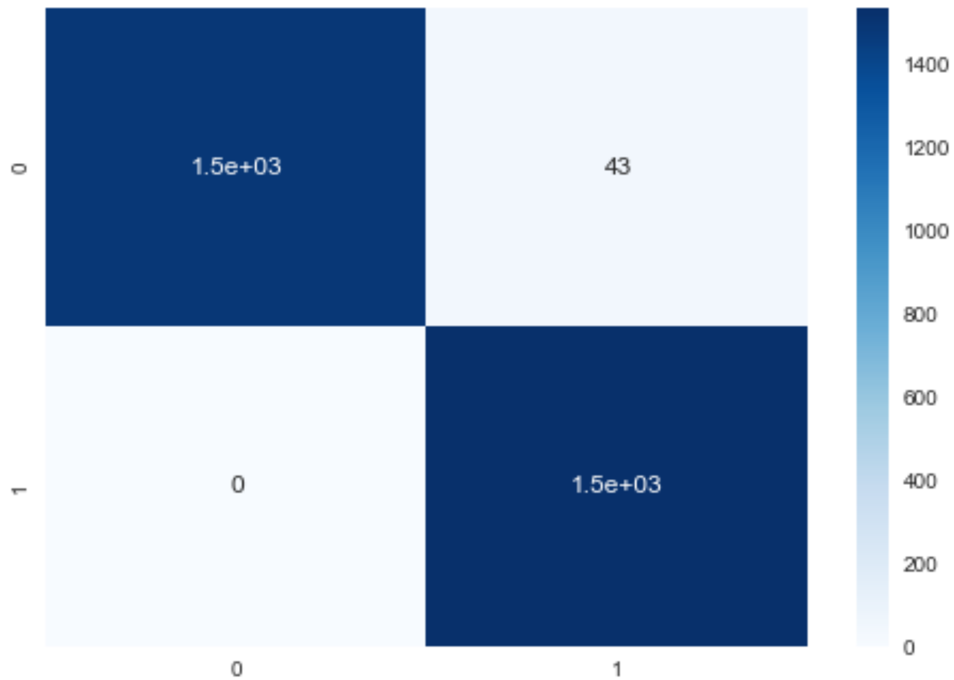
In [262]:
```
confusion_matrix(y_pred_ANN,y_test_balanced)
```

Out[262]:
```
array([[1490,    0],
       [  43, 1533]])
```

In [263]:

```
sns.heatmap(confusion_matrix(y_test_balanced,y_pred_ANN), annot = True ,cmap = "Blues")
c_report = classification_report(y_test_balanced,y_pred_ANN)
print(c_report)
```

```
              precision    recall  f1-score   support

           0       1.00      0.97      0.99      1533
           1       0.97      1.00      0.99      1533

    accuracy                           0.99      3066
   macro avg       0.99      0.99      0.99      3066
weighted avg       0.99      0.99      0.99      3066
```



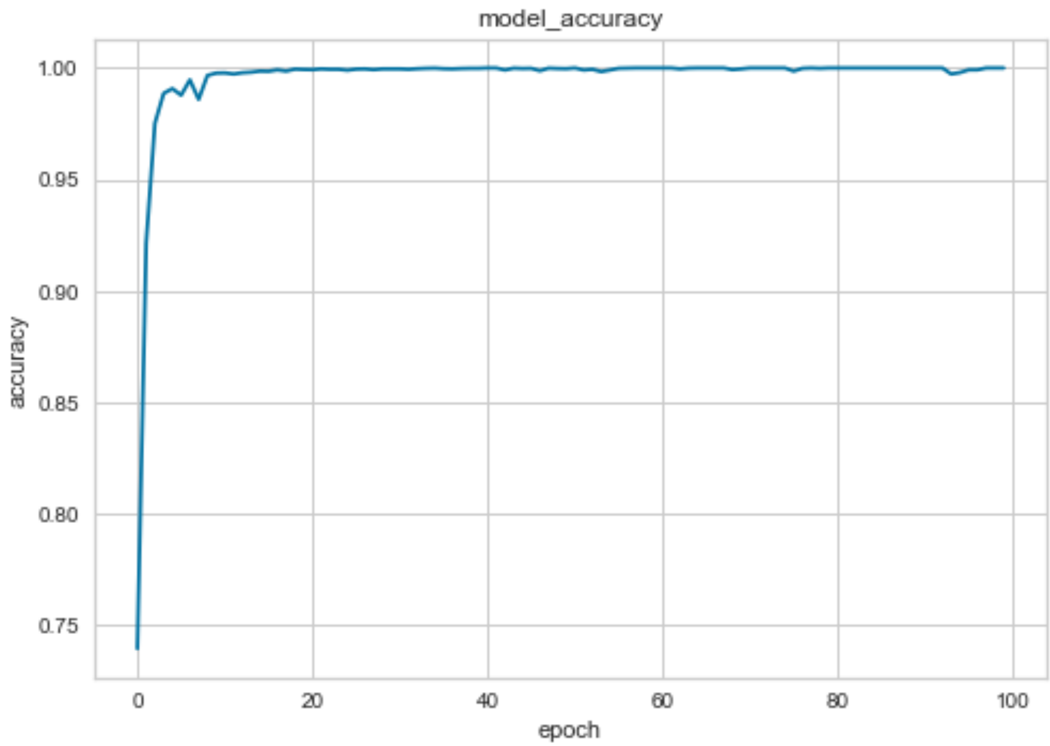
In [264]:

```
print(model1_ANN.history.keys())
```

```
dict_keys(['loss', 'accuracy'])
```

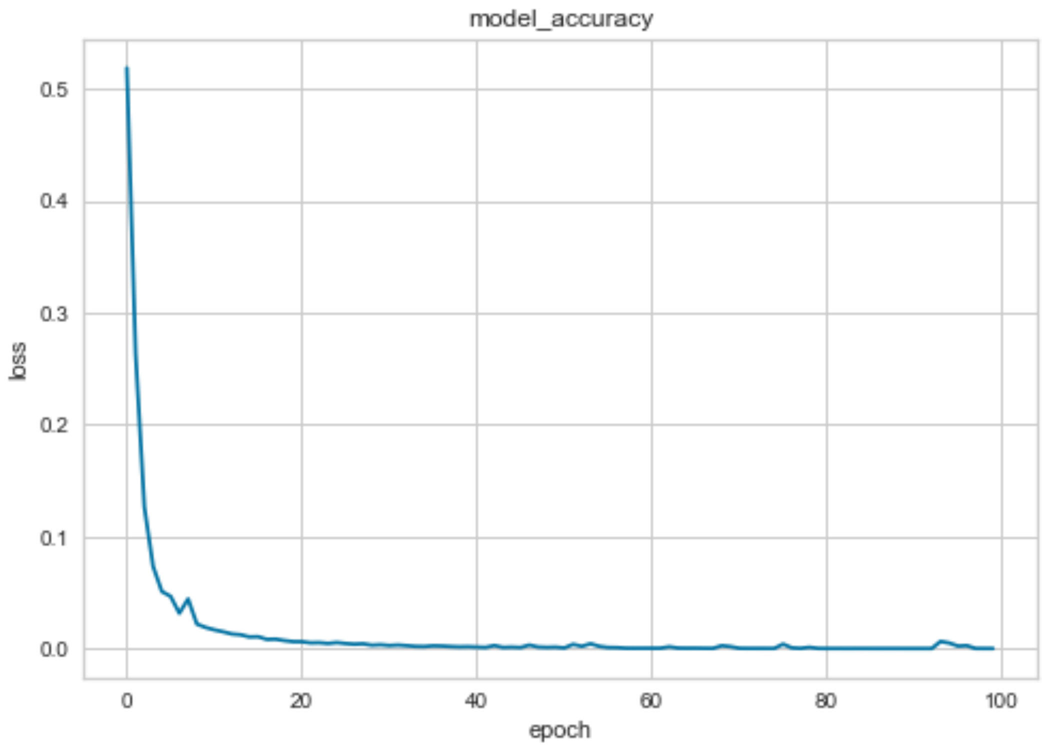
In [265]:

```
plt.plot(model1_ANN.history['accuracy'])
plt.title("model_accuracy")
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.show()
```



In [266]:

```
plt.plot(model1_ANN.history['loss'])
plt.title("model_accuracy")
plt.ylabel('loss')
plt.xlabel('epoch')
plt.show()
```



Conclusion:

The objective of this paper is to train multiple supervised learning algorithms to predict customers behavior on paying off credit card balance. We first investigated the data by using the exploratory data analysis techniques including cleaning missing or invalid values and exploring the relationship between different features. The bar chart helps to visualize the relationships between features and important features. We started with the logistic regression algorithm, then built a KNN which has a better performance than the former model. Next, we experimented with an AdaBoosting model and compared it with the Gradient Boosting model. The prediction accuracy rate of AdaBoosting model is higher than the Gradient Boosting model. At the end, we also tried to build a neural network with two hidden layers and hidden layer. By using the ROC curve andconfusion matrix to evaluate the model performance, we conclude that the AdaBoostingmodel and neural network are the two most effective models to predict the output.According to the bar chart of feature importance score, the feature “STATUS” is the most significant one and its represents at first position bar graph. This feature not only indicates that the customers payment behavior in September, it also indicates the overall behavior. Therefore, when the financial institution considers issuing the client a credit card, it is very important for the institutionto check the payment history of that person because the decision on whether pay on duly or owe the bill on a specific month usually relates to the previous payment history. For instance, if a person owes numerous bills already, he or she is likely to delay the payment of current month unless the total arrears can be paid off .Besides the payment history, it is also very important to look at the applicants’ imit of their current credit cards. Although the financial institution often collects clients’ personal information such as age,educational level and marital status when people apply for the credit cards, this information rarely affects the default behavior. In the other word, Banks should equally consider their potential clients who are men or women, obtain bachelor degrees or masterdegrees, single or married when decide whether approve their credit card/loan applications. Even though I tried my best to make a thorough analysis, there are still a few possible improvements that may require longer-term action. For the boosting models, I only trainedAdaBoost and Gradient Boosting models this time but I can try XGBoosting to see whether it will generate a better result as it is one of the most robust and popular boosting algorithms. Moreover, I can also improve my data collection and entry in the future.Thus, I am confident to say that my model is accurate in predicting whether a person will default or not, as I will have more inputs

References:

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3. https://medium.datadriveninvestor.com/predicting-credit-card-approvals-using-mltechniques- (https://medium.datadriveninvestor.com/predicting-credit-card-approvals-using-mltechniques-) 9cd8eaeb5b8c
4. https://www.researchgate.net/publication/348755769_Application_of_Deep_Learning (https://www.researchgate.net/publication/348755769_Application_of_Deep_Learning) _for_Credit_Card_Approval_A_Comparison_with_Two_Machine_Learning_Techniq ues

In [ ]: