importing libraries / modules

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import sklearn
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier

import xgboost
from xgboost import XGBClassifier
from sklearn.svm import SVC
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV , RandomizedSearchCV
from sklearn.metrics import confusion_matrix, accuracy_score , classification_report

import warnings
warnings.filterwarnings('ignore')
```

loading data

In [3]:
```
df=pd.read_csv('loan_detection.csv')
```

basic eda and data cleaning

In [4]:
```
df.head(10)
```

Out[4]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job_blue-collar	job_entreprene
0	56	1	999	0	1	0	0	0	
1	57	1	999	0	1	0	0	0	
2	37	1	999	0	1	0	0	0	
3	40	1	999	0	1	0	1	0	
4	56	1	999	0	1	0	0	0	
5	45	1	999	0	1	0	0	0	
6	59	1	999	0	1	0	1	0	
7	41	1	999	0	1	0	0	1	
8	24	1	999	0	1	0	0	0	
9	25	1	999	0	1	0	0	0	

10 rows × 60 columns

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

Out[5]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job_blue-collar	job_entrep
41183	73	1	999	0	1	1	0	0	
41184	46	1	999	0	1	0	0	1	
41185	56	2	999	0	1	1	0	0	
41186	44	1	999	0	1	0	0	0	
41187	74	3	999	1	1	1	0	0	

5 rows × 60 columns

In [6]:
```
df.columns
```

Out[6]:
```
Index(['age', 'campaign', 'pdays', 'previous', 'no_previous_contact',
       'not_working', 'job_admin.', 'job_blue-collar', 'job_entrepreneur',
       'job_housemaid', 'job_management', 'job_retired', 'job_self-employed',
       'job_services', 'job_student', 'job_technician', 'job_unemployed',
       'job_unknown', 'marital_divorced', 'marital_married', 'marital_single',
       'marital_unknown', 'education_basic.4y', 'education_basic.6y',
       'education_basic.9y', 'education_high.school', 'education_illiterate',
       'education_professional.course', 'education_university.degree',
       'education_unknown', 'default_no', 'default_unknown', 'default_yes',
       'housing_no', 'housing_unknown', 'housing_yes', 'loan_no',
       'loan_unknown', 'loan_yes', 'contact_cellular', 'contact_telephone',
       'month_apr', 'month_aug', 'month_dec', 'month_jul', 'month_jun',
       'month_mar', 'month_may', 'month_nov', 'month_oct', 'month_sep',
       'day_of_week_fri', 'day_of_week_mon', 'day_of_week_thu',
       'day_of_week_tue', 'day_of_week_wed', 'poutcome_failure',
       'poutcome_nonexistent', 'poutcome_success', 'Loan_Status_label'],
      dtype='object')
```

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

Out[7]:
```
(41188, 60)
```

In [8]:
```
df.describe()
```

Out[8]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_adm
count	41188.00000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000000	41188.000
mean	40.02406	2.567593	962.475454	0.172963	0.963217	0.087623	0.253
std	10.42125	2.770014	186.910907	0.494901	0.188230	0.282749	0.434
min	17.00000	1.000000	0.000000	0.000000	0.000000	0.000000	0.000
25%	32.00000	1.000000	999.000000	0.000000	1.000000	0.000000	0.000
50%	38.00000	2.000000	999.000000	0.000000	1.000000	0.000000	0.000
75%	47.00000	3.000000	999.000000	0.000000	1.000000	0.000000	1.000
max	98.00000	56.000000	999.000000	7.000000	1.000000	1.000000	1.000

8 rows × 60 columns

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
age                              0
campaign                         0
pdays                            0
previous                         0
no_previous_contact              0
not_working                      0
job_admin.                       0
job_blue-collar                  0
job_entrepreneur                 0
job_housemaid                    0
job_management                   0
job_retired                      0
job_self-employed                0
job_services                     0
job_student                      0
job_technician                   0
job_unemployed                   0
job_unknown                      0
marital_divorced                 0
marital_married                  0
marital_single                   0
marital_unknown                  0
education_basic.4y               0
education_basic.6y               0
education_basic.9y               0
education_high.school            0
education_illiterate             0
education_professional.course    0
education_university.degree      0
education_unknown                0
default_no                       0
default_unknown                  0
default_yes                      0
housing_no                       0
housing_unknown                  0
housing_yes                      0
loan_no                          0
loan_unknown                     0
loan_yes                         0
contact_cellular                 0
contact_telephone                0
month_apr                        0
month_aug                        0
month_dec                        0
month_jul                        0
month_jun                        0
month_mar                        0
month_may                        0
month_nov                        0
month_oct                        0
month_sep                        0
day_of_week_fri                  0
day_of_week_mon                  0
day_of_week_thu                  0
day_of_week_tue                  0
day_of_week_wed                  0
poutcome_failure                 0
poutcome_nonexistent             0
poutcome_success                 0
```

```
Loan_Status_label              0
dtype: int64
```

In [10]:
```
df.isnull()
```

Out[10]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job_blue-collar	job_entr
0	False	False	False	False	False	False	False	False	
1	False	False	False	False	False	False	False	False	
2	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	
41183	False	False	False	False	False	False	False	False	
41184	False	False	False	False	False	False	False	False	
41185	False	False	False	False	False	False	False	False	
41186	False	False	False	False	False	False	False	False	
41187	False	False	False	False	False	False	False	False	

41188 rows × 60 columns

In [11]:
```
''' since no null values are found, no need to handle missing data '''
```

Out[11]: ' since no null values are found, no need to handle missing data '

In [12]:
```
df.duplicated().sum()
```

Out[12]: 2417

In [13]:
```
''' but since the data is encoded to 0 and 1 , no need for removing duplicates'''
```

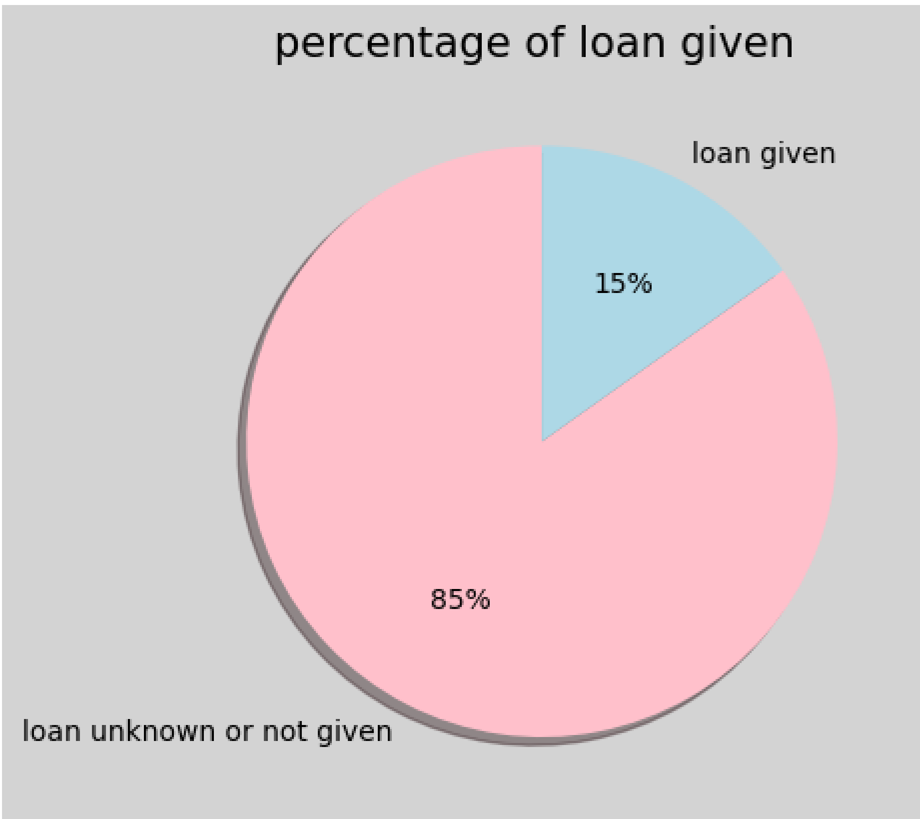
Out[13]: ' but since the data is encoded to 0 and 1 , no need for removing duplicates'

In [14]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 41188 entries, 0 to 41187
Data columns (total 60 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   age                            41188 non-null  int64
 1   campaign                       41188 non-null  int64
 2   pdays                          41188 non-null  int64
 3   previous                       41188 non-null  int64
 4   no_previous_contact            41188 non-null  int64
 5   not_working                    41188 non-null  int64
 6   job_admin.                     41188 non-null  int64
 7   job_blue-collar                41188 non-null  int64
 8   job_entrepreneur               41188 non-null  int64
 9   job_housemaid                  41188 non-null  int64
 10  job_management                 41188 non-null  int64
 11  job_retired                    41188 non-null  int64
 12  job_self-employed              41188 non-null  int64
 13  job_services                   41188 non-null  int64
 14  job_student                    41188 non-null  int64
 15  job_technician                 41188 non-null  int64
 16  job_unemployed                 41188 non-null  int64
 17  job_unknown                    41188 non-null  int64
 18  marital_divorced               41188 non-null  int64
 19  marital_married                41188 non-null  int64
 20  marital_single                 41188 non-null  int64
 21  marital_unknown                41188 non-null  int64
 22  education_basic.4y             41188 non-null  int64
 23  education_basic.6y             41188 non-null  int64
 24  education_basic.9y             41188 non-null  int64
 25  education_high.school          41188 non-null  int64
 26  education_illiterate           41188 non-null  int64
 27  education_professional.course  41188 non-null  int64
 28  education_university.degree    41188 non-null  int64
 29  education_unknown              41188 non-null  int64
 30  default_no                     41188 non-null  int64
 31  default_unknown                41188 non-null  int64
 32  default_yes                    41188 non-null  int64
 33  housing_no                     41188 non-null  int64
 34  housing_unknown                41188 non-null  int64
 35  housing_yes                    41188 non-null  int64
 36  loan_no                        41188 non-null  int64
 37  loan_unknown                   41188 non-null  int64
 38  loan_yes                       41188 non-null  int64
 39  contact_cellular               41188 non-null  int64
 40  contact_telephone              41188 non-null  int64
 41  month_apr                      41188 non-null  int64
 42  month_aug                      41188 non-null  int64
 43  month_dec                      41188 non-null  int64
 44  month_jul                      41188 non-null  int64
 45  month_jun                      41188 non-null  int64
 46  month_mar                      41188 non-null  int64
 47  month_may                      41188 non-null  int64
 48  month_nov                      41188 non-null  int64
 49  month_oct                      41188 non-null  int64
 50  month_sep                      41188 non-null  int64
 51  day_of_week_fri                41188 non-null  int64
 52  day_of_week_mon                41188 non-null  int64
 53  day_of_week_thu                41188 non-null  int64
```

```
 54  day_of_week_tue                 41188 non-null  int64
 55  day_of_week_wed                 41188 non-null  int64
 56  poutcome_failure                41188 non-null  int64
 57  poutcome_nonexistent            41188 non-null  int64
 58  poutcome_success                41188 non-null  int64
 59  Loan_Status_label               41188 non-null  int64
dtypes: int64(60)
memory usage: 18.9 MB
```

In [15]:
```
plt.figure(facecolor='lightgrey')
count1=df['loan_yes'].value_counts()
cols1=['pink','lightblue']
label1=['loan unknown or not given','loan given ']
plt.pie(count1,colors=cols1,autopct='%1.0f%%',shadow=True,startangle=90,labels=label1
plt.title('percentage of loan given ', fontsize=15)
plt.show()
```



In [16]:
```
loan_yes=df['loan_yes'].sum()
loan_not_unknown=len(df)-df['loan_yes'].sum()
total=len(df)
print (f'loan not given to {round((loan_not_unknown*100)/total)}% applicants ')
print (f'loan given to {round((loan_yes*100)/total)}% applicants ')
```

```
loan not given to 85% applicants
loan given to 15% applicants
```

feature selection through correlation

In [17]:

```
df.corr()['Loan_Status_label']
```

```
Out[17]: age                              0.030399
         campaign                        -0.066357
         pdays                           -0.324914
         previous                         0.230181
         no_previous_contact             -0.324877
         not_working                      0.121246
         job_admin.                       0.031426
         job_blue-collar                 -0.074423
         job_entrepreneur                -0.016644
         job_housemaid                   -0.006505
         job_management                  -0.000419
         job_retired                      0.092221
         job_self-employed               -0.004663
         job_services                    -0.032301
         job_student                      0.093955
         job_technician                  -0.006149
         job_unemployed                   0.014752
         job_unknown                     -0.000151
         marital_divorced                -0.010608
         marital_married                 -0.043398
         marital_single                   0.054133
         marital_unknown                  0.005211
         education_basic.4y              -0.010798
         education_basic.6y              -0.023517
         education_basic.9y              -0.045135
         education_high.school           -0.007452
         education_illiterate             0.007246
         education_professional.course    0.001003
         education_university.degree      0.050364
         education_unknown                0.021430
         default_no                       0.099344
         default_unknown                 -0.099293
         default_yes                     -0.003041
         housing_no                      -0.011085
         housing_unknown                 -0.002270
         housing_yes                      0.011743
         loan_no                          0.005123
         loan_unknown                    -0.002270
         loan_yes                        -0.004466
         contact_cellular                 0.144773
         contact_telephone               -0.144773
         month_apr                        0.076136
         month_aug                       -0.008813
         month_dec                        0.079303
         month_jul                       -0.032230
         month_jun                       -0.009182
         month_mar                        0.144014
         month_may                       -0.108271
         month_nov                       -0.011796
         month_oct                        0.137366
         month_sep                        0.126067
         day_of_week_fri                 -0.006996
         day_of_week_mon                 -0.021265
         day_of_week_thu                  0.013888
         day_of_week_tue                  0.008046
         day_of_week_wed                  0.006302
         poutcome_failure                 0.031799
         poutcome_nonexistent            -0.193507
         poutcome_success                 0.316269
```

```
Loan_Status_label                1.000000
Name: Loan_Status_label, dtype: float64
```

In [18]:
```
df.corr()['poutcome_success']
```

Out[18]:

```
age                              0.035626
campaign                        -0.050893
pdays                           -0.950700
previous                         0.524045
no_previous_contact             -0.950283
not_working                      0.104134
job_admin.                       0.025069
job_blue-collar                 -0.061403
job_entrepreneur                -0.017238
job_housemaid                    0.002276
job_management                  -0.001302
job_retired                      0.068061
job_self-employed               -0.012871
job_services                    -0.028558
job_student                      0.083321
job_technician                  -0.005036
job_unemployed                   0.024612
job_unknown                      0.012136
marital_divorced                -0.010612
marital_married                 -0.029876
marital_single                   0.039238
marital_unknown                  0.007167
education_basic.4y              -0.005918
education_basic.6y              -0.021478
education_basic.9y              -0.034593
education_high.school           -0.007439
education_illiterate             0.002588
education_professional.course    0.003338
education_university.degree      0.037762
education_unknown                0.018400
default_no                       0.075763
default_unknown                 -0.075740
default_yes                     -0.001585
housing_no                      -0.011349
housing_unknown                 -0.004417
housing_yes                      0.012664
loan_no                          0.002231
loan_unknown                    -0.004417
loan_yes                        -0.000481
contact_cellular                 0.111934
contact_telephone               -0.111934
month_apr                        0.012864
month_aug                       -0.000357
month_dec                        0.079391
month_jul                       -0.046769
month_jun                       -0.013421
month_mar                        0.074265
month_may                       -0.065652
month_nov                        0.012780
month_oct                        0.115812
month_sep                        0.149349
day_of_week_fri                 -0.013760
day_of_week_mon                 -0.002276
day_of_week_thu                  0.008827
day_of_week_tue                  0.007258
day_of_week_wed                 -0.000390
poutcome_failure                -0.063006
poutcome_nonexistent            -0.466928
poutcome_success                 1.000000
```

```
Loan_Status_label                0.316269
Name: poutcome_success, dtype: float64
```

splitting data

In [19]:
```
X=df.iloc[:,:-1]
y=df['Loan_Status_label']
```

In [20]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y, test_size=0.2,random_state=42)
```

In [21]:
```
X
```

Out[21]:

	age	campaign	pdays	previous	no_previous_contact	not_working	job_admin.	job_blue-collar	job_entrep
0	56	1	999	0	1	0	0	0	
1	57	1	999	0	1	0	0	0	
2	37	1	999	0	1	0	0	0	
3	40	1	999	0	1	0	1	0	
4	56	1	999	0	1	0	0	0	
...	...	...	...	...	...	...	...	...	
41183	73	1	999	0	1	1	0	0	
41184	46	1	999	0	1	0	0	1	
41185	56	2	999	0	1	1	0	0	
41186	44	1	999	0	1	0	0	0	
41187	74	3	999	1	1	1	0	0	

41188 rows × 59 columns

In [22]:
```
y
```

Out[22]:
```
0        0
1        0
2        0
3        0
4        0
        ..
41183    1
41184    0
41185    0
41186    1
41187    0
Name: Loan_Status_label, Length: 41188, dtype: int64
```

In [23]:
```
print(X_train.shape,"  ", X_test.shape)
print(y_train.shape,"  ", y_test.shape)
```

```
(32950, 59)    (8238, 59)
(32950,)    (8238,)
```

model selection

In [24]:
```
sc=StandardScaler()
X_train_sc=sc.fit_transform(X_train)
X_test_sc=sc.transform(X_train)
```

In [25]:
```
X_train_sc
```

Out[25]:
```
array([[-1.66930454e-03, -2.06241614e-01,  1.94660673e-01, ...,
        -3.40481710e-01,  3.98373809e-01, -1.84965343e-01],
       [-8.64094846e-01,  5.13675879e-01,  1.94660673e-01, ...,
        -3.40481710e-01,  3.98373809e-01, -1.84965343e-01],
       [ 1.81900684e+00,  1.23359337e+00,  1.94660673e-01, ...,
         2.93701532e+00, -2.51020518e+00, -1.84965343e-01],
       ...,
       [-4.80794606e-01, -5.66200360e-01, -5.14775262e+00, ...,
        -3.40481710e-01, -2.51020518e+00,  5.40641820e+00],
       [-1.66930454e-03, -2.06241614e-01,  1.94660673e-01, ...,
        -3.40481710e-01,  3.98373809e-01, -1.84965343e-01],
       [-1.05574497e+00, -2.06241614e-01,  1.94660673e-01, ...,
        -3.40481710e-01,  3.98373809e-01, -1.84965343e-01]])
```

In [26]:
```
X_test_sc
```

Out[26]:
```
array([[-1.66930454e-03, -2.06241614e-01,  1.94660673e-01, ...,
        -3.40481710e-01,  3.98373809e-01, -1.84965343e-01],
       [-8.64094846e-01,  5.13675879e-01,  1.94660673e-01, ...,
        -3.40481710e-01,  3.98373809e-01, -1.84965343e-01],
       [ 1.81900684e+00,  1.23359337e+00,  1.94660673e-01, ...,
         2.93701532e+00, -2.51020518e+00, -1.84965343e-01],
       ...,
       [-4.80794606e-01, -5.66200360e-01, -5.14775262e+00, ...,
        -3.40481710e-01, -2.51020518e+00,  5.40641820e+00],
       [-1.66930454e-03, -2.06241614e-01,  1.94660673e-01, ...,
        -3.40481710e-01,  3.98373809e-01, -1.84965343e-01],
       [-1.05574497e+00, -2.06241614e-01,  1.94660673e-01, ...,
        -3.40481710e-01,  3.98373809e-01, -1.84965343e-01]])
```

In [27]:
```
lr=LogisticRegression()
lr.fit(X_train,y_train)
```

Out[27]:
```
LogisticRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [28]:
```
print(f'training accuracy : { round(lr.score(X_train,y_train)*100)}%')
print(f'test accuracy : { round(lr.score(X_test,y_test)*100)}%')
```

```
training accuracy : 90%
test accuracy : 90%
```

In [29]:
```
lrc=LogisticRegression()
lrc.fit(X_train_sc,y_train)
```

Out[29]:
```
LogisticRegression()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [30]:
```
dt=DecisionTreeClassifier(max_depth=5)
dt.fit(X_train,y_train)
```

Out[30]:
```
DecisionTreeClassifier(max_depth=5)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [31]:
```
print(f'training accuracy : { round(dt.score(X_train,y_train)*100)}%')
print(f'test accuracy : { round(dt.score(X_test,y_test)*100)}%')
```

```
training accuracy : 90%
test accuracy : 89%
```

In [32]:
```
xgb=XGBClassifier(gamma=0.7,reg_alpha=0.5,reg_lambda=0.2)
xgb.fit(X_train,y_train)
```

Out[32]:
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0.7, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [33]:
```
print(f'training accuracy : { round(xgb.score(X_train,y_train)*100)}%')
print(f'test accuracy : { round(xgb.score(X_test,y_test)*100)}%')
```

```
training accuracy : 91%
test accuracy : 89%
```

model training

In [34]:
```
y_train_pred_lr=lr.predict(X_train)
y_test_pred_lr=lr.predict(X_test)
y_train_pred_xgb=xgb.predict(X_train)
y_test_pred_xgb=xgb.predict(X_test)
```

In [35]:
```
y_train[:3]
```

Out[35]:
```
12556    0
35451    0
30592    0
Name: Loan_Status_label, dtype: int64
```

In [36]:
```
y_train_pred_lr[:3]
```

Out[36]:
```
array([0, 0, 0], dtype=int64)
```

In [37]:
```
y_train_pred_xgb[:3]
```

Out[37]:
```
array([0, 0, 0])
```

In [38]:
```
y_test[:3]
```

Out[38]:
```
32884    0
3169     0
32206    0
Name: Loan_Status_label, dtype: int64
```

In [39]:
```
y_test_pred_lr[:3]
```

Out[39]:
```
array([0, 0, 0], dtype=int64)
```

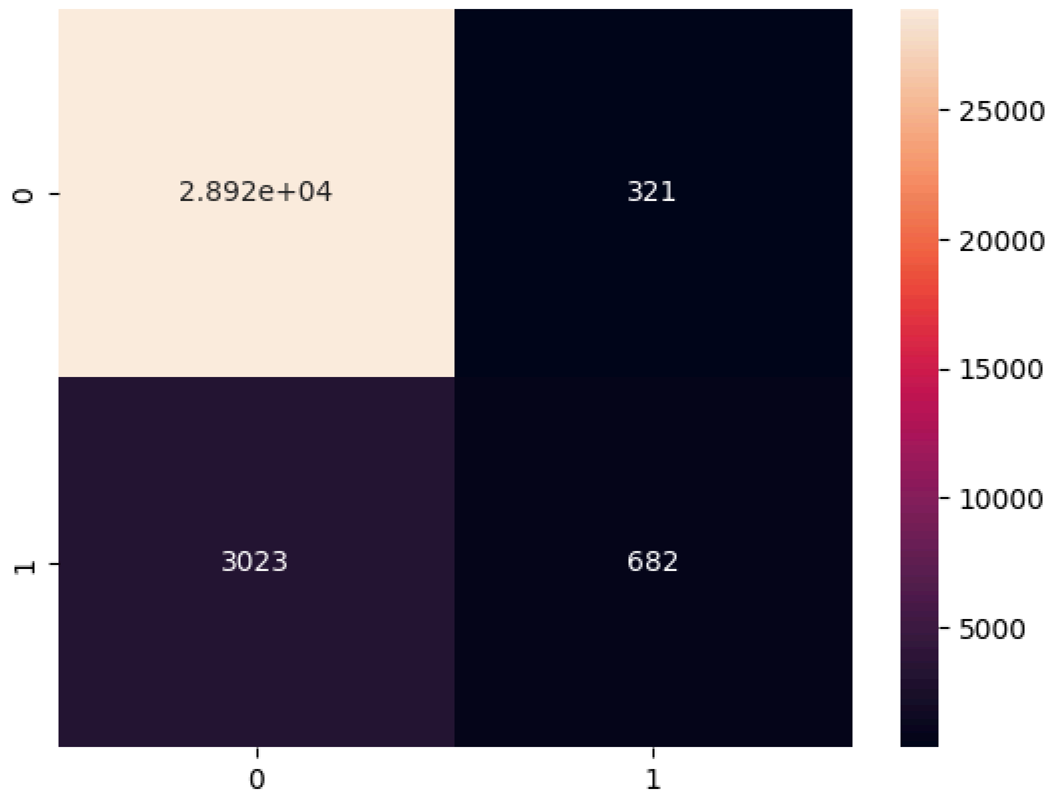
In [40]:
```
y_test_pred_xgb[:3]
```

Out[40]:
```
array([0, 0, 0])
```

results

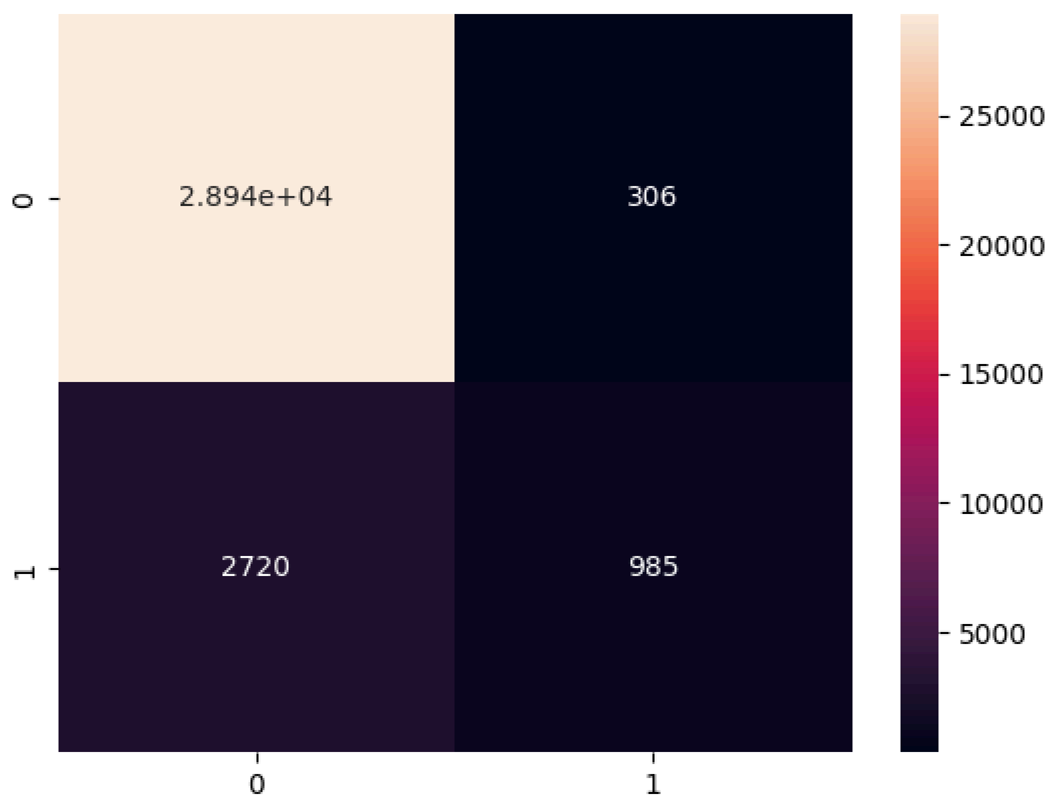
In [41]:
```
sns.heatmap(confusion_matrix(y_train,y_train_pred_lr),annot=True,fmt='.4g')
```

Out[41]: <Axes: >



In [42]:
```
sns.heatmap(confusion_matrix(y_train,y_train_pred_xgb),annot=True,fmt='.4g')
```

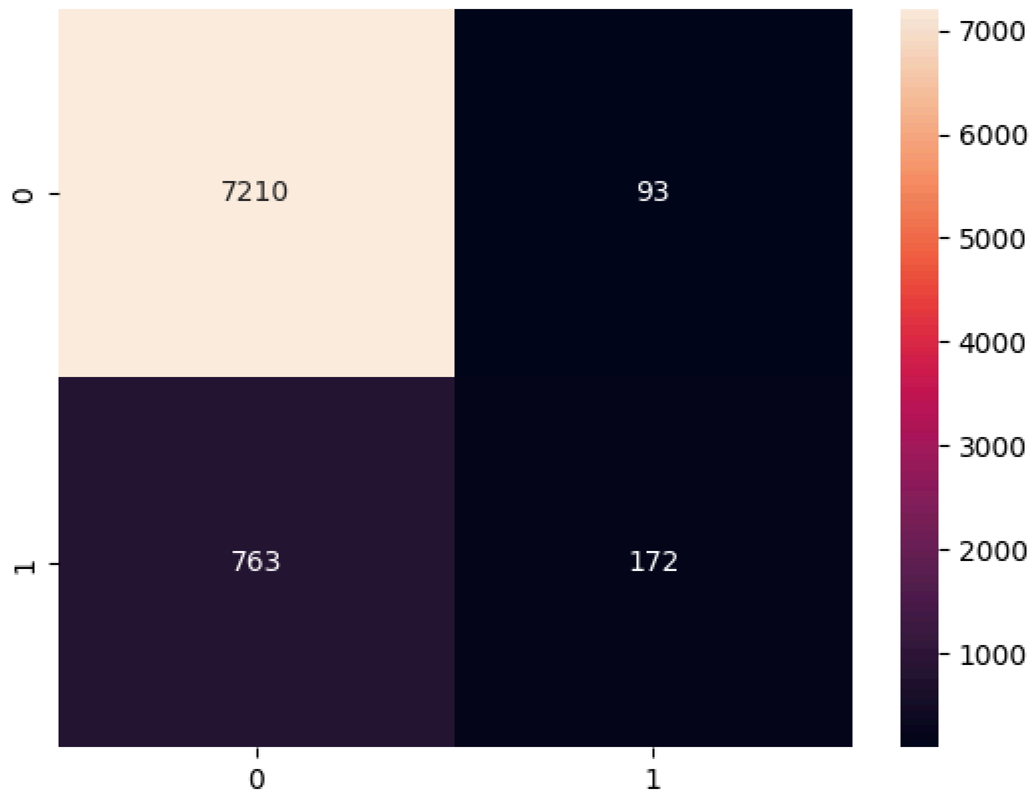
Out[42]: <Axes: >



In [43]:
```
accuracy_score(y_train,y_train_pred_lr)
```
Out[43]:
```
0.8985128983308043
```
In [44]:
```
accuracy_score(y_train,y_train_pred_xgb)
```
Out[44]:
```
0.9081638846737481
```
In [45]:
```
print(classification_report(y_train,y_train_pred_lr))
```
```
              precision    recall  f1-score   support

           0       0.91      0.99      0.95     29245
           1       0.68      0.18      0.29      3705

    accuracy                           0.90     32950
   macro avg       0.79      0.59      0.62     32950
weighted avg       0.88      0.90      0.87     32950
```
In [46]:
```
print(classification_report(y_train,y_train_pred_xgb))
```
```
              precision    recall  f1-score   support

           0       0.91      0.99      0.95     29245
           1       0.76      0.27      0.39      3705

    accuracy                           0.91     32950
   macro avg       0.84      0.63      0.67     32950
weighted avg       0.90      0.91      0.89     32950
```

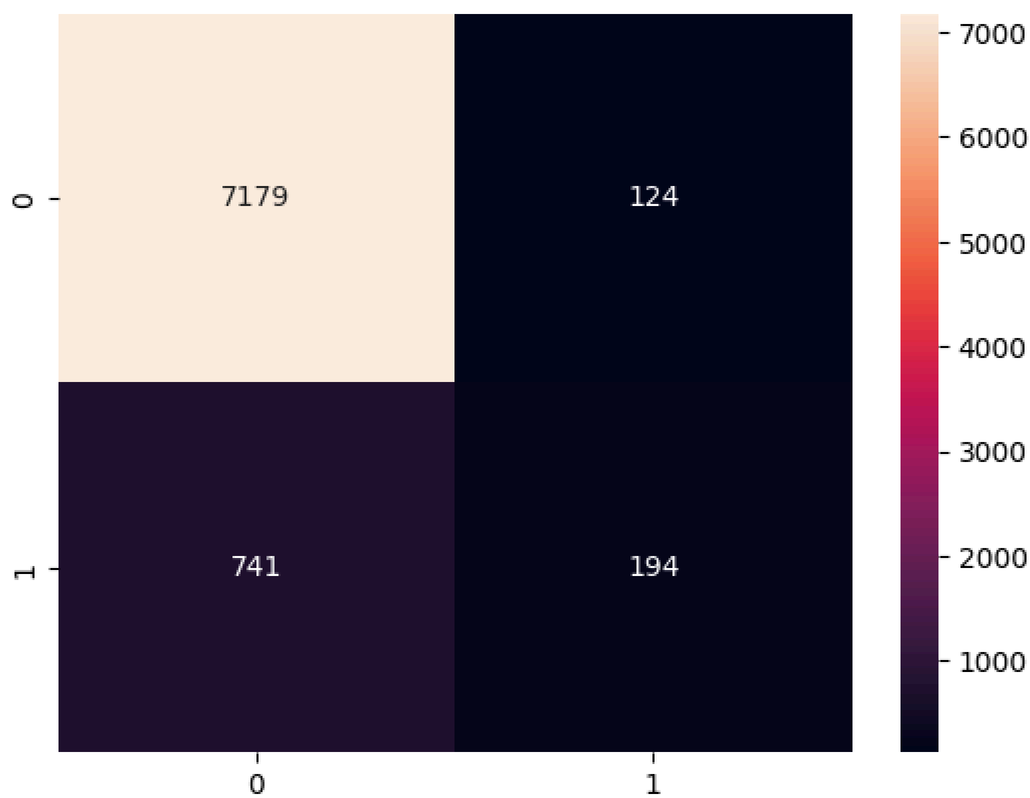
In [47]:
```
sns.heatmap(confusion_matrix(y_test,y_test_pred_lr),annot=True,fmt='.4g')
```

Out[47]: <Axes: >



In [48]:
```
sns.heatmap(confusion_matrix(y_test,y_test_pred_xgb),annot=True,fmt='.4g')
```

Out[48]: <Axes: >



In [49]:
```
accuracy_score(y_test,y_test_pred_xgb)
```
Out[49]:
```
0.8949987861131342
```

In [50]:
```
accuracy_score(y_test,y_test_pred_lr)
```
Out[50]:
```
0.896091284292304
```

In [51]:
```
print(classification_report(y_test,y_test_pred_lr))
```
```
              precision    recall  f1-score   support

           0       0.90      0.99      0.94      7303
           1       0.65      0.18      0.29       935

    accuracy                           0.90      8238
   macro avg       0.78      0.59      0.62      8238
weighted avg       0.88      0.90      0.87      8238
```

In [52]:
```
print(classification_report(y_test,y_test_pred_xgb))
```
```
              precision    recall  f1-score   support

           0       0.91      0.98      0.94      7303
           1       0.61      0.21      0.31       935

    accuracy                           0.89      8238
   macro avg       0.76      0.60      0.63      8238
weighted avg       0.87      0.89      0.87      8238
```

Thus for training set : both xgboost and logistic regression perform with good accuracy but xgboost outperfomed by slight margin

for test set : both had similar accuracy again but xgboost had better F1-score while logistic regression has better recall

while both models performed with good accuracy , for the current purpose , logistic regression could be prefered as it's less computationally expensive than xgboost and also is generally more interpretable .

In [ ]: