Introduction

In this case study I will be working for a fintech company that provides a subscription product to its users, which allows them to manage their bank accounts (saving accounts, credits cards etc.), provides them with personalized coupons, informs them of the latest low-APR loans available in the market and educates them on the best available methods to save money (like videos on saving money on taxes, free courses on financial health etc.).

I am in charge of identifying users who are likely to cancel their subscription so that the company can start building new features that the users may be interested in. These features can increase the engagement and interest of the users towards the product.

Importing Essential Libraries & Our Data

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import random
```

In [2]:
```
dataset = pd.read_csv('churn_data.csv')
```

In [3]:
```
dataset.head()
```

Out[3]:

	user	churn	age	housing	credit_score	deposits	withdrawal	purchases_partners	purchases
0	55409	0	37.0	na	NaN	0	0	0	0
1	23547	0	28.0	R	486.0	0	0	1	0
2	58313	0	35.0	R	561.0	47	2	86	47
3	8095	0	26.0	R	567.0	26	3	38	25
4	61353	1	27.0	na	NaN	0	0	2	0

5 rows × 31 columns

In [4]:
```
dataset.describe()
```

Out[4]:

	user	churn	age	credit_score	deposits	withdrawal	purchas
count	27000.000000	27000.000000	26996.000000	18969.000000	27000.000000	27000.000000	27
mean	35422.702519	0.413852	32.219921	542.944225	3.341556	0.307000	
std	20321.006678	0.492532	9.964838	61.059315	9.131406	1.055416	
min	1.000000	0.000000	17.000000	2.000000	0.000000	0.000000	
25%	17810.500000	0.000000	25.000000	507.000000	0.000000	0.000000	

	user	churn	age	credit_score	deposits	withdrawal	purchas
50%	35749.000000	0.000000	30.000000	542.000000	0.000000	0.000000	
75%	53244.250000	1.000000	37.000000	578.000000	1.000000	0.000000	
max	69658.000000	1.000000	91.000000	838.000000	65.000000	29.000000	

8 rows × 28 columns

In [5]:
```
dataset.isnull().sum()
```

Out[5]:
```
user                       0
churn                      0
age                        4
housing                    0
credit_score            8031
deposits                   0
withdrawal                 0
purchases_partners         0
purchases                  0
cc_taken                   0
cc_recommended             0
cc_disliked                0
cc_liked                   0
cc_application_begin       0
app_downloaded             0
web_user                   0
app_web_user               0
ios_user                   0
android_user               0
registered_phones          0
payment_type               0
waiting_4_loan             0
cancelled_loan             0
received_loan              0
rejected_loan              0
zodiac_sign                0
left_for_two_month_plus    0
left_for_one_month         0
rewards_earned          3227
reward_rate                0
is_referred                0
dtype: int64
```

In [6]:
```
dataset.shape
```

Out[6]:
```
(27000, 31)
```

Since the number of null columns in 'credit_score' and 'rewards_earned' is high, we will not use these columns for our model. Also only 4 rows are null in 'age' column so we can simply remove those rows and keep the age column for the model.

In [7]:
```
dataset = dataset[pd.notnull(dataset['age'])]
```

In [8]:
```
dataset = dataset.drop(columns = ['credit_score', 'rewards_earned'])
```

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

Out[9]:
```
user                    0
```

```
churn                    0
age                      0
housing                  0
deposits                 0
withdrawal               0
purchases_partners       0
purchases                0
cc_taken                 0
cc_recommended           0
cc_disliked              0
cc_liked                 0
cc_application_begin     0
app_downloaded           0
web_user                 0
app_web_user             0
ios_user                 0
android_user             0
registered_phones        0
payment_type             0
waiting_4_loan           0
cancelled_loan           0
received_loan            0
rejected_loan            0
zodiac_sign              0
left_for_two_month_plus  0
left_for_one_month       0
reward_rate              0
is_referred              0
dtype: int64
```

In [10]:

```
dataset.head()
```

Out[10]:

	user	churn	age	housing	deposits	withdrawal	purchases_partners	purchases	cc_taken	cc_ı
0	55409	0	37.0	na	0	0	0	0	0	
1	23547	0	28.0	R	0	0	1	0	0	
2	58313	0	35.0	R	47	2	86	47	0	
3	8095	0	26.0	R	26	3	38	25	0	
4	61353	1	27.0	na	0	0	2	0	0	

5 rows × 29 columns

Visualization & Exploratory Data Analysis

In [11]:

```
dataset.shape
```

Out[11]: (26996, 29)

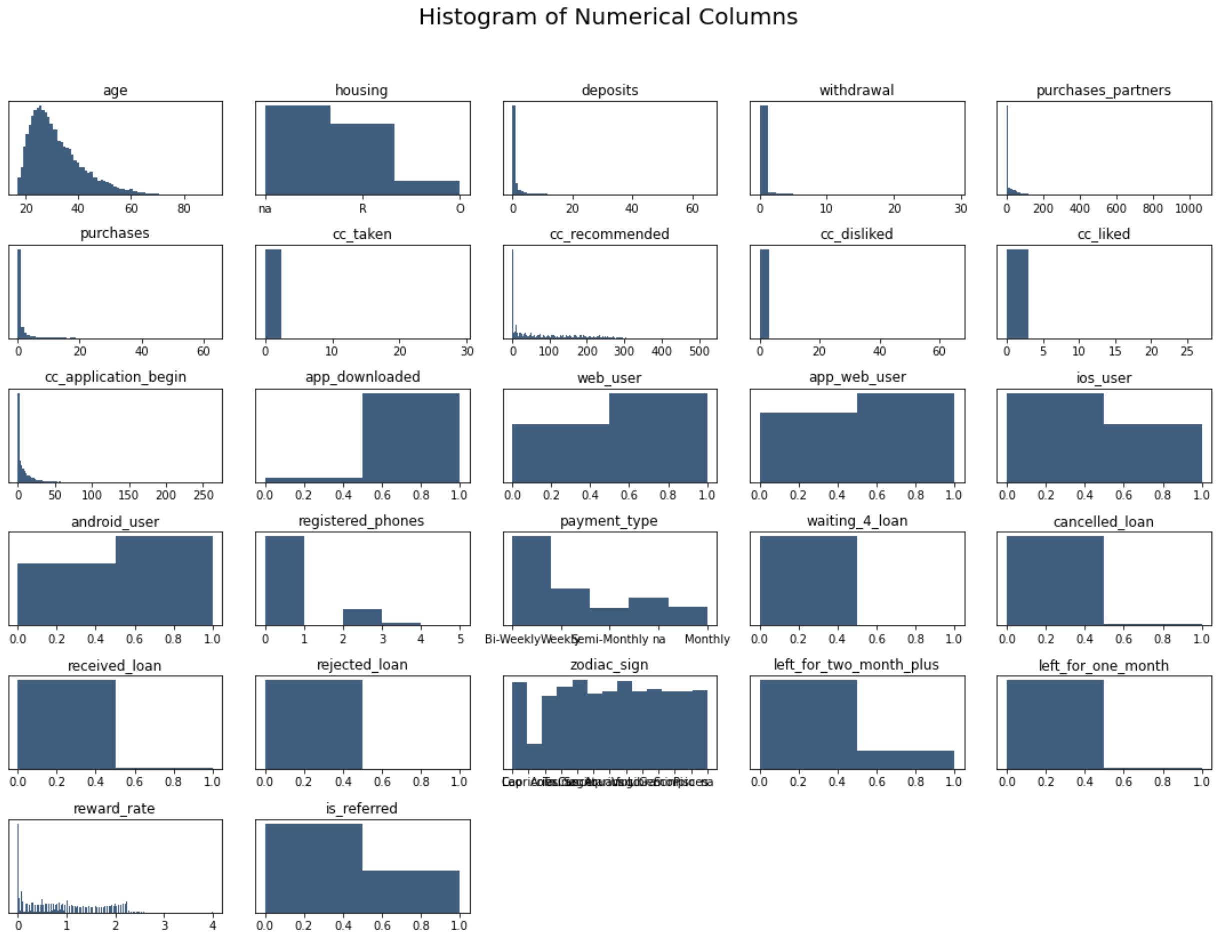
In [12]:

```
dataset2 = dataset.drop(columns = ['user', 'churn'])
```

In [13]:

```
fig = plt.figure(figsize = (15, 12))
plt.suptitle('Histogram of Numerical Columns', fontsize = 20)
for i in range(1, dataset2.shape[1] + 1):
    plt.subplot(6, 5, i)
    f = plt.gca()
    f.axes.get_yaxis().set_visible(False)
    f.set_title(dataset2.columns.values[i - 1])
    vals = np.size(dataset2.iloc[:, i - 1].unique())
    plt.hist(dataset2.iloc[:, i - 1], bins = vals, color = '#3F5D7D')
```

```
plt.tight_layout(rect = [0, 0.03, 1, 0.95])
#plt.savefig('1. Histogram of Numerical Columns.png')
```



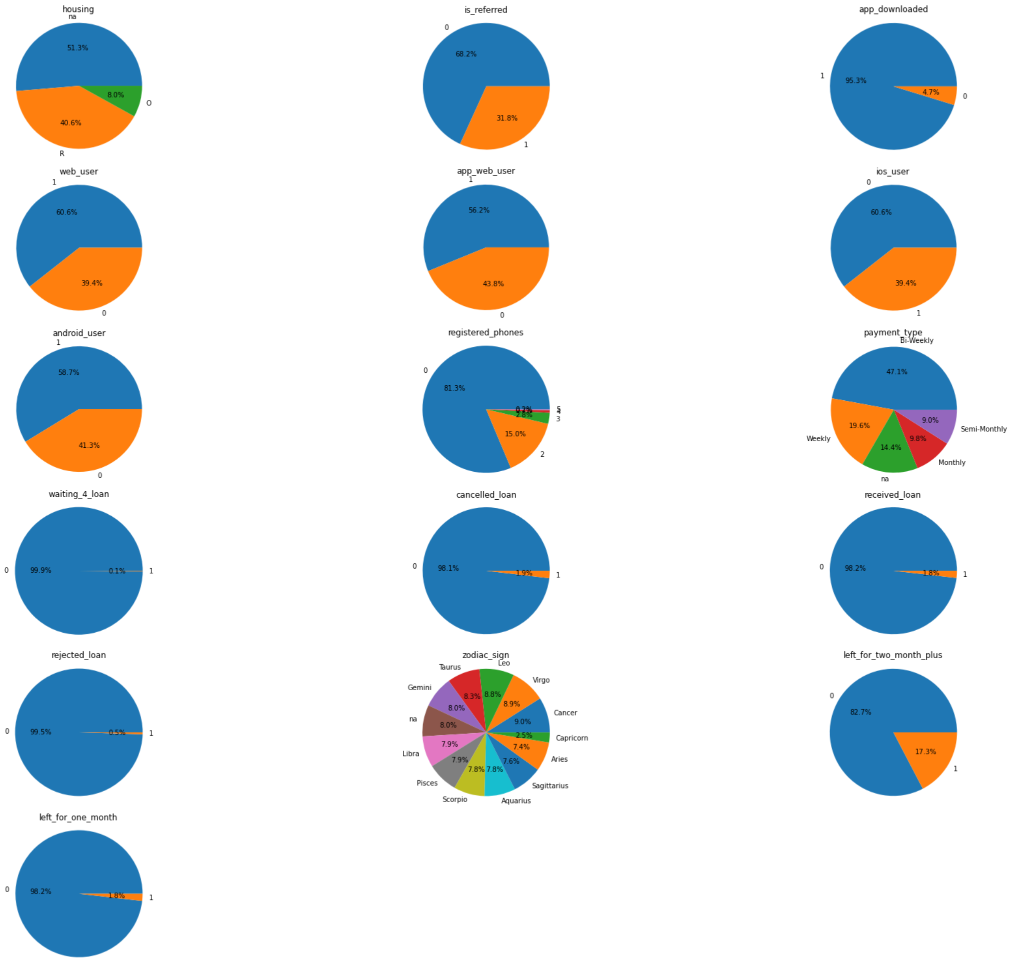
In [14]:
```
dataset2 = dataset[['housing', 'is_referred', 'app_downloaded', 'web_user', 'app_web
                    'registered_phones', 'payment_type', 'waiting_4_loan', 'cancelle
                    'zodiac_sign', 'left_for_two_month_plus', 'left_for_one_month']]
```

In [15]:
```
fig = plt.figure(figsize = (25, 22))
plt.suptitle('Pie Chart Distributions', fontsize = 20)
for i in range(1, dataset2.shape[1] + 1):
    plt.subplot(6, 3, i)
    f = plt.gca()
    f.axes.get_yaxis().set_visible(False)
    f.set_title(dataset2.columns.values[i - 1])

    values = dataset2.iloc[:, i - 1].value_counts().values
    index = dataset2.iloc[:, i - 1].value_counts().index

    plt.pie(values, labels = index, autopct = '%1.1f%%')
    plt.axis('equal')
plt.tight_layout(rect = [0, 0.03, 1, 0.95])
#plt.savefig('2. Pie Chart Distributions.png')
```

Pie Chart Distributions



```
In [16]: dataset[dataset2.waiting_4_loan == 1].churn.value_counts()
```

```
Out[16]: 0    27
         1     8
         Name: churn, dtype: int64
```

```
In [17]: dataset[dataset2.cancelled_loan == 1].churn.value_counts()
```

```
Out[17]: 1    274
         0    234
         Name: churn, dtype: int64
```

```
In [18]: dataset[dataset2.rejected_loan == 1].churn.value_counts()
```

```
Out[18]: 1    107
         0     25
         Name: churn, dtype: int64
```

```
In [19]: dataset[dataset2.received_loan == 1].churn.value_counts()
```

```
Out[19]: 1    292
         0    199
         Name: churn, dtype: int64
```

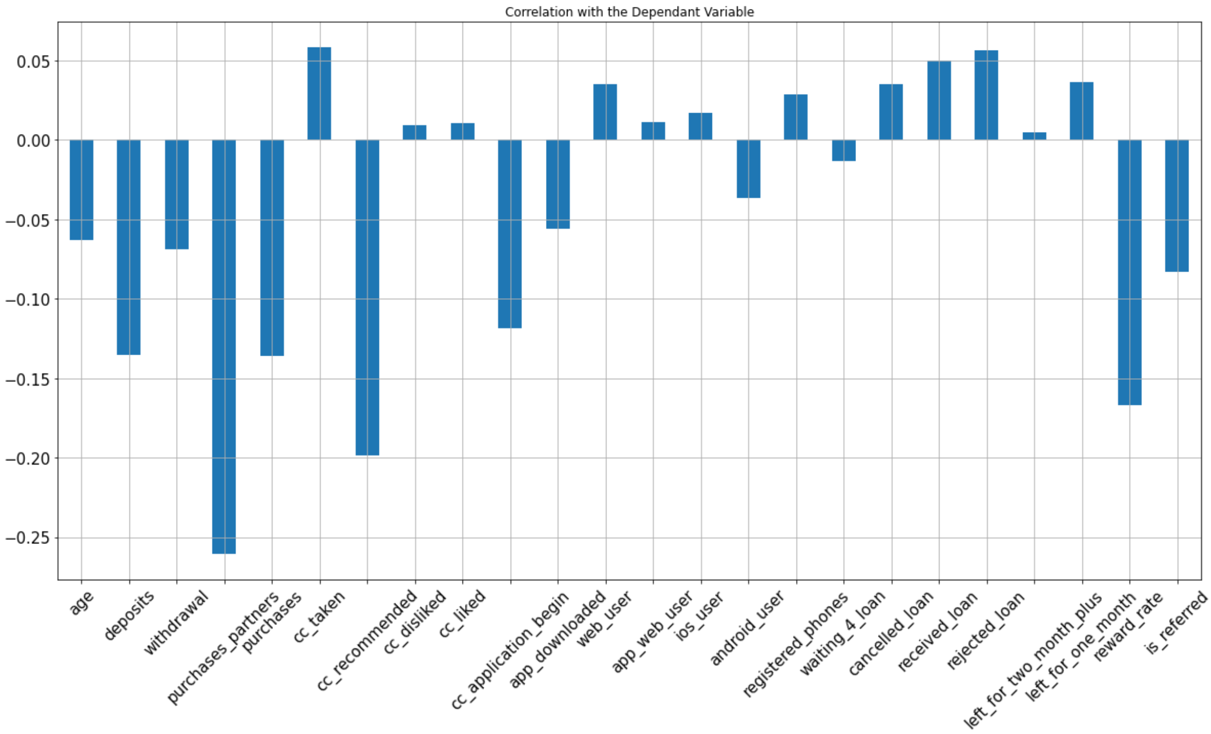
```
In [20]: dataset[dataset2.left_for_one_month == 1].churn.value_counts()
```

```
Out[20]: 1    266
         0    222
         Name: churn, dtype: int64
```

```
In [21]: dataset.drop(columns = ['churn', 'user', 'housing', 'payment_type', 'zodiac_sign']).
         figsize = (20, 10), title = 'Correlation with the Dependant Variable', fontsize = 15
```

```
#plt.savefig('3. Correlation of Independent Variable (churn) with all the dependant
```

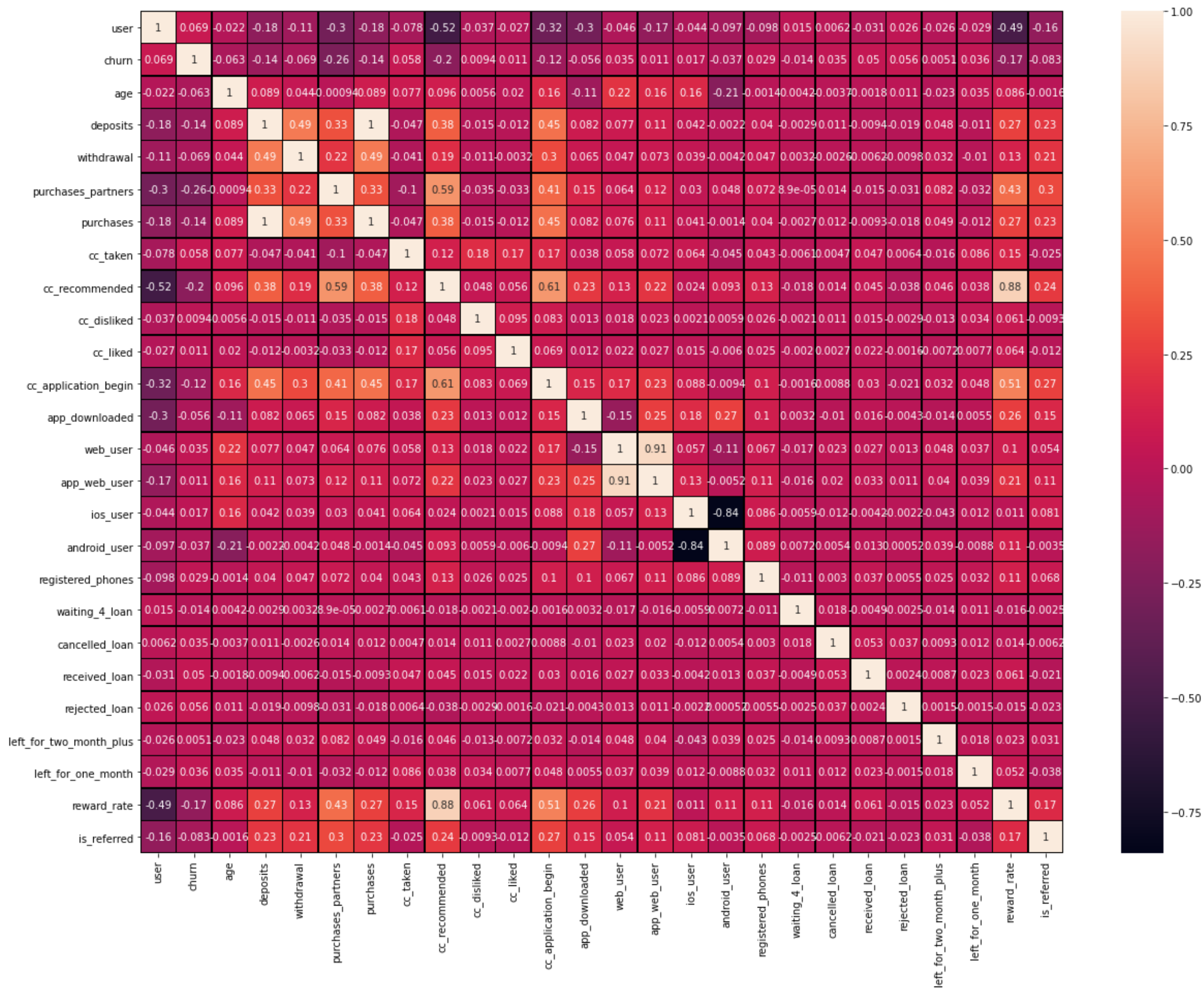
Out[21]: <AxesSubplot:title={'center':'Correlation with the Dependant Variable'}>



In [22]:

```python
plt.figure(figsize = (20, 15))
sns.heatmap(dataset.corr(), annot = True, linewidths = 0.5, linecolor = 'black')
#plt.savefig('4. Heatmap showing Correlation of all vriables with each other.png')
```

Out[22]: <AxesSubplot:>



In [23]:
```
dataset = dataset.drop(columns = ['app_web_user'])
```

In [24]:
```
dataset.to_csv('new_churn_data.csv', index = False)
```

Data Preparation

In [25]:
```
dataset = pd.read_csv('new_churn_data.csv')
```

In [26]:
```
user_identifier = dataset['user']
dataset = dataset.drop(columns = ['user'])
```

In [27]:
```
dataset['housing'].value_counts()
```

Out[27]:
```
na    13856
R     10969
O      2171
Name: housing, dtype: int64
```

In [28]:
```
dataset = pd.get_dummies(dataset)
dataset.columns
```

Out[28]:
```
Index(['churn', 'age', 'deposits', 'withdrawal', 'purchases_partners',
       'purchases', 'cc_taken', 'cc_recommended', 'cc_disliked', 'cc_liked',
       'cc_application_begin', 'app_downloaded', 'web_user', 'ios_user',
       'android_user', 'registered_phones', 'waiting_4_loan', 'cancelled_loan',
       'received_loan', 'rejected_loan', 'left_for_two_month_plus',
       'left_for_one_month', 'reward_rate', 'is_referred', 'housing_O',
       'housing_R', 'housing_na', 'payment_type_Bi-Weekly',
       'payment_type_Monthly', 'payment_type_Semi-Monthly',
       'payment_type_Weekly', 'payment_type_na', 'zodiac_sign_Aquarius',
       'zodiac_sign_Aries', 'zodiac_sign_Cancer', 'zodiac_sign_Capricorn',
       'zodiac_sign_Gemini', 'zodiac_sign_Leo', 'zodiac_sign_Libra',
       'zodiac_sign_Pisces', 'zodiac_sign_Sagittarius', 'zodiac_sign_Scorpio',
       'zodiac_sign_Taurus', 'zodiac_sign_Virgo', 'zodiac_sign_na'],
      dtype='object')
```

In [29]:
```
dataset = dataset.drop(columns = ['housing_na', 'zodiac_sign_na', 'payment_type_na']
```

Splitting the dataset into the Training Set and Test Set

In [30]:
```
X = dataset.drop(columns = 'churn')
y = dataset['churn']
```

In [31]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_st
```

Balancing the Training Set

In [32]:
```
y_train.value_counts()
```

Out[32]:
```
0    12656
1     8940
Name: churn, dtype: int64
```

In [33]:
```
pos_index = y_train[y_train.values == 1].index
neg_index = y_train[y_train.values == 0].index
```

```
if len(pos_index) > len(neg_index):
    higher = pos_index
    lower = neg_index
else:
    higher = neg_index
    lower = pos_index
```

In [34]:
```
random.seed(0)
higher = np.random.choice(higher, size = len(lower))
lower = np.asarray(lower)
new_indexes = np.concatenate((lower, higher))

X_train = X_train.loc[new_indexes, ]
y_train = y_train[new_indexes]
```

Feature Scaling

In [35]:
```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train2 = pd.DataFrame(sc.fit_transform(X_train))
X_test2 = pd.DataFrame(sc.transform(X_test))

X_train2.columns = X_train.columns.values
X_test2.columns = X_test.columns.values

X_train2.index = X_train.index.values
X_test2.index = X_test.index.values

X_train = X_train2
X_test = X_test2
```

In [36]:
```
X_train
```

Out[36]:

	age	deposits	withdrawal	purchases_partners	purchases	cc_taken	cc_recommended
11695	-0.619972	-0.354877	-0.281152	-0.582693	-0.354215	-0.170599	-0.910593
19766	-0.418955	-0.354877	-0.281152	-0.630294	-0.354215	-0.170599	0.317446
8354	0.284606	-0.354877	-0.281152	-0.630294	-0.354215	-0.170599	2.000313
17883	0.586132	-0.354877	-0.281152	0.036120	-0.354215	-0.170599	-0.182866
25149	-0.820989	-0.243187	-0.281152	-0.106683	-0.240408	-0.170599	-0.580842
...	...	...	...	...	...	...	...
7313	-1.022006	-0.354877	-0.281152	-0.630294	-0.354215	-0.170599	-0.956076
25250	0.385114	0.091882	-0.281152	-0.439890	0.101013	-0.170599	1.420406
1323	0.787149	-0.354877	-0.281152	-0.630294	-0.354215	-0.170599	-0.501247
14218	-0.418955	-0.243187	-0.281152	1.511751	-0.240408	-0.170599	0.920094
2565	0.284606	-0.354877	-0.281152	0.321726	-0.354215	-0.170599	-0.057788

17880 rows × 41 columns

Fitting Model to the Training Set

In [37]:
```
from sklearn.linear_model import LogisticRegression
```

```
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
```

Out[37]: LogisticRegression(random_state=0)

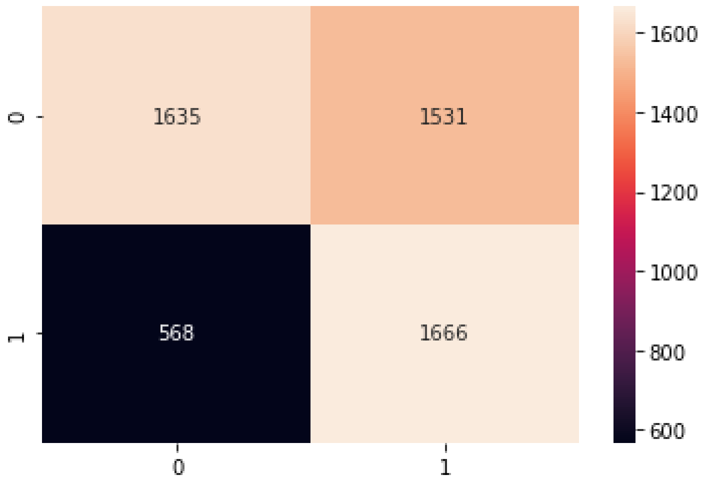
Predicting the Test Set

In [38]:
```
y_pred = classifier.predict(X_test)
```

In [39]:
```
from sklearn.metrics import confusion_matrix, accuracy_score, f1_score, precision_sc
```

In [40]:
```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot = True, fmt = 'g')
print('Test Data Accuracy: %0.4f' %accuracy_score(y_test, y_pred))
#plt.savefig('5. Confusion Matrix Before Feature Engineering.png')
```

```
Test Data Accuracy: 0.6113
```



In [41]:
```
precision_score(y_test, y_pred)
```

Out[41]: 0.5211135439474507

In [42]:
```
f1_score(y_test, y_pred)
```

Out[42]: 0.6135150064444853

In [43]:
```
recall_score(y_test, y_pred)
```

Out[43]: 0.7457475380483438

In [44]:
```
print((classification_report(y_test, y_pred)))
```

```
              precision    recall  f1-score   support

           0       0.74      0.52      0.61      3166
           1       0.52      0.75      0.61      2234

    accuracy                           0.61      5400
   macro avg       0.63      0.63      0.61      5400
weighted avg       0.65      0.61      0.61      5400
```

K-Fold Cross Validation

In [45]:
```
from sklearn.model_selection import cross_val_score
accuracies = cross_val_score(estimator = classifier, X = X_train, y = y_train, cv =
```

In [46]:
```
accuracies
```

Out[46]:
```
array([0.64205817, 0.66498881, 0.651566  , 0.63199105, 0.64149888,
       0.64541387, 0.64765101, 0.65604027, 0.62975391, 0.65100671])
```

In [47]:
```
accuracies.mean()
```

Out[47]:
```
0.6461968680089486
```

In [48]:
```
accuracies.std()
```

Out[48]:
```
0.010080155609311709
```

Analyzing Coefficients

In [49]:
```
pd.concat([pd.DataFrame(X_train.columns, columns = ['features']), pd.DataFrame(np.tr
                                                                                colum
```

Out[49]:

	features	coef
0	age	-0.166823
1	deposits	0.146401
2	withdrawal	0.054753
3	purchases_partners	-0.753717
4	purchases	-0.275242
5	cc_taken	0.064549
6	cc_recommended	0.041492
7	cc_disliked	0.006630
8	cc_liked	0.000965
9	cc_application_begin	0.020635
10	app_downloaded	-0.021762
11	web_user	0.140722
12	ios_user	0.100021
13	android_user	0.021666
14	registered_phones	0.091305
15	waiting_4_loan	-0.031049
16	cancelled_loan	0.063907
17	received_loan	0.110983
18	rejected_loan	0.086127
19	left_for_two_month_plus	0.031455
20	left_for_one_month	0.036311
21	reward_rate	-0.187199
22	is_referred	0.036385
23	housing_O	-0.023197

	features	coef
24	housing_R	0.038735
25	payment_type_Bi-Weekly	-0.034023
26	payment_type_Monthly	-0.009352
27	payment_type_Semi-Monthly	-0.012682
28	payment_type_Weekly	0.047600
29	zodiac_sign_Aquarius	-0.070619
30	zodiac_sign_Aries	-0.026576
31	zodiac_sign_Cancer	-0.017988
32	zodiac_sign_Capricorn	0.012967
33	zodiac_sign_Gemini	-0.057546
34	zodiac_sign_Leo	-0.033866
35	zodiac_sign_Libra	-0.072067
36	zodiac_sign_Pisces	0.003923
37	zodiac_sign_Sagittarius	-0.023210
38	zodiac_sign_Scorpio	-0.071110
39	zodiac_sign_Taurus	-0.046317
40	zodiac_sign_Virgo	-0.026490

Feature Selection

In [50]:
```
X_train.shape
```

Out[50]:
```
(17880, 41)
```

In [51]:
```
from sklearn.feature_selection import RFE
```

In [52]:
```
classifier = LogisticRegression()
rfe = RFE(classifier, 20)
rfe = rfe.fit(X_train, y_train)
```

```
D:\Anaconda\lib\site-packages\sklearn\utils\validation.py:67: FutureWarning: Pass n_
features_to_select=20 as keyword args. From version 0.25 passing these as positional
arguments will result in an error
  warnings.warn("Pass {} as keyword args. From version 0.25 "
```

In [53]:
```
print(rfe.support_)
```

```
[ True  True  True  True  True  True  True False False False False  True
  True False  True False  True  True  True False False  True False False
  True False False False  True  True False False False  True False  True
 False False  True False False]
```

In [54]:
```
X_train.columns[rfe.support_]
```

Out[54]:
```
Index(['age', 'deposits', 'withdrawal', 'purchases_partners', 'purchases',
       'cc_taken', 'cc_recommended', 'web_user', 'ios_user',
       'registered_phones', 'cancelled_loan', 'received_loan', 'rejected_loan',
       'reward_rate', 'housing_R', 'payment_type_Weekly',
```

```
 'zodiac_sign_Aquarius', 'zodiac_sign_Gemini', 'zodiac_sign_Libra',
 'zodiac_sign_Scorpio'],
dtype='object')
```

In [55]:
```
rfe.ranking_
```

Out[55]:
```
array([ 1,  1,  1,  1,  1,  1,  1, 20, 22, 16, 15,  1,  1, 14,  1,  4,  1,
        1,  1,  6,  2,  1,  3,  7,  1,  8, 19, 18,  1,  1, 10, 13, 17,  1,
        9,  1, 21, 12,  1,  5, 11])
```

In [56]:
```
classifier = LogisticRegression(random_state = 0)
classifier.fit(X_train[X_train.columns[rfe.support_]], y_train)
```

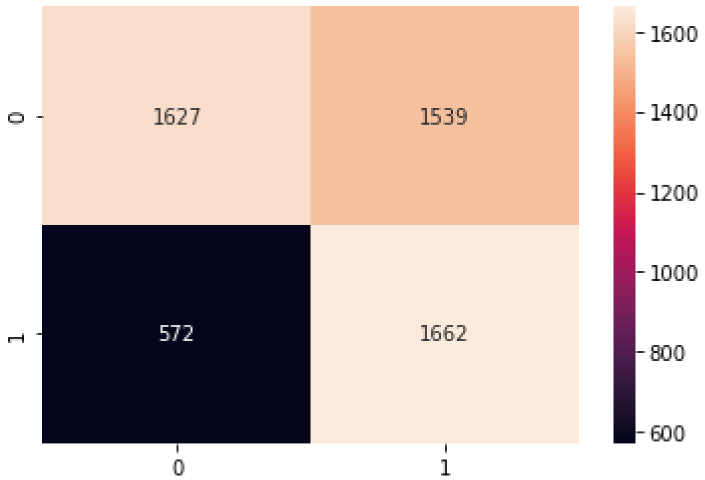
Out[56]:
```
LogisticRegression(random_state=0)
```

Predicting the Test Set on Feature Engineering

In [57]:
```
y_pred = classifier.predict(X_test[X_test.columns[rfe.support_]])
```

In [58]:
```
cm = confusion_matrix(y_test, y_pred)
sns.heatmap(cm, annot = True, fmt = 'g')
print('Test Data Accuracy: %0.4f' %accuracy_score(y_test, y_pred))
#plt.savefig('6. Confusion Matrix Ater Feature Engineering.png')
```

```
Test Data Accuracy: 0.6091
```



In [59]:
```
precision_score(y_test, y_pred)
```

Out[59]:
```
0.5192127460168697
```

In [60]:
```
f1_score(y_test, y_pred)
```

Out[60]:
```
0.6115915363385465
```

In [61]:
```
recall_score(y_test, y_pred)
```

Out[61]:
```
0.7439570277529096
```

In [62]:
```
print((classification_report(y_test, y_pred)))
```

```
              precision    recall  f1-score   support

           0       0.74      0.51      0.61      3166
           1       0.52      0.74      0.61      2234

    accuracy                           0.61      5400
```

```
   macro avg       0.63      0.63      0.61      5400
weighted avg       0.65      0.61      0.61      5400
```

NOTE that our accuracy has slightly decreased but the purpose of doing this was to find the 20 best features.

This showed us the features which were not helping in predicting if a customer would churn or not.

This is useful in putting the model into production because with only so less features, our model is faster and will consume much less time and resources.

Analyzing The Coefficients

In [63]:
```
pd.concat([pd.DataFrame(X_train.columns[rfe.support_], columns = ['features']), pd.D
                                                                                  colum
```

Out[63]:

	features	coef
0	age	-0.163279
1	deposits	0.168174
2	withdrawal	0.060534
3	purchases_partners	-0.741646
4	purchases	-0.290678
5	cc_taken	0.068732
6	cc_recommended	0.053228
7	web_user	0.146408
8	ios_user	0.079578
9	registered_phones	0.096093
10	cancelled_loan	0.063865
11	received_loan	0.109439
12	rejected_loan	0.086455
13	reward_rate	-0.195838
14	housing_R	0.051519
15	payment_type_Weekly	0.069942

	features	coef
16	zodiac_sign_Aquarius	-0.051281
17	zodiac_sign_Gemini	-0.037897
18	zodiac_sign_Libra	-0.053178
19	zodiac_sign_Scorpio	-0.052292

FINAL RESULTS

In [64]:

```
final_results = pd.concat([y_test, user_identifier], axis = 1).dropna()
final_results['churn_prediction'] = y_pred
final_results = final_results[['user', 'churn', 'churn_prediction']].reset_index(dro
```

In [65]:

```
final_results
```

Out[65]:

	user	churn	churn_prediction
0	61353	1.0	1
1	67679	0.0	0
2	21269	0.0	0
3	69531	0.0	1
4	25997	0.0	0
...	...	...	...
5395	22377	0.0	1
5396	24291	1.0	1
5397	23740	0.0	1
5398	47663	1.0	0
5399	52752	1.0	1

5400 rows × 3 columns