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## This code uses Logistic Regression model to predict Churn of a Company.

```
In [1]: import pandas as pd
import numpy as np
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
import pickle
```

```
In [2]: df= pd.read_csv('Train.csv')
print(df.head(15))
```

	user_id	REGION	7	ΓΕΝ	
URE	_				
0 nth	dcf68cc2fb515ccad7d8b9b3bd80ee2a4b270063	SAINT-LOUIS	K > 24	mo	
1 nth	71c44b5ba328db5c4192a80f7cf8f244d9350ed0	NaN	K > 24	mo	
2 nth	ce46411b1526c94f20a383b8cb188f8d27f82a0a	TAMBACOUNDA	K > 24	mo	
3 nth	f467cdb6669818373c26c2bad44e01ba66f97d21	FATICK	K > 24	mo	
4 nth	ec45e1a1888a32b5dcce0954cfec20c6e037db31	FATICK	K > 24	mo	
5 nth	2bd9ab2983615149380a63f44a66780f4fa19a4a	THIES	K > 24	mo	
6 nth	b2d9c4bdceaafe305e8424c97f64e4ba880d0a97	NaN	K > 24	mo	
7 nth	8ebce4e82fa049f96ff1aa460217171af4e4ede1	SAINT-LOUIS	H 15-18	mo	
8	ebfbd28870a7663d49ec79799f9fd59e8c5655ed	TAMBACOUNDA	K > 24	mo	•

```
df Test = pd.read csv('Test.csv')
In [3]:
         print(df Test.head())
                                                user_id REGION
                                                                        TENURE
                                                                                MONT
         ANT \
           af900d87e73b7ff6509d2203df4704a98aa5f2a6
                                                            NaN
                                                                 K > 24 month
         NaN
         1
            5335efd940280b82143272275637d1e65d37eadb
                                                                 K > 24 month
                                                            NaN
         NaN
         2
            a581f4fa08677c26f83f643248c667e241043086
                                                            NaN
                                                                 K > 24 month
                                                                                  190
         0.0
         3
            64f67177d0775262b8087a9e2e3b8061b6324ae6
                                                         DAKAR
                                                                 K > 24 month
                                                                                  300
         0.0
            0d6009a4594c4be22449b8d9cc01a0bcea98faea
                                                         DAKAR
                                                                 K > 24 month
                                                                                3200
         0.0
            FREQUENCE RECH
                            REVENUE
                                       ARPU_SEGMENT
                                                      FREQUENCE
                                                                  DATA VOLUME
                                                                                ON N
         EΤ
         0
                                  NaN
                        NaN
                                                 NaN
                                                             NaN
                                                                           NaN
                                                                                    N
         aN
                                 10.0
                                                             1.0
         1
                        NaN
                                                 3.0
                                                                           NaN
                                                                                    N
         aN
         2
                       15.0
                              2299.0
                                               766.0
                                                            21.0
                                                                         414.0
                                                                                    N
         aN
         3
                        9.0
                              2603.0
                                               868.0
                                                            14.0
                                                                         332.0
         0.0
         4
                             33000.0
                                             11000.0
                                                            47.0
                                                                                  12
                       47.0
                                                                           NaN
         8.0
                                                                           TOP_PACK
            ORANGE
                      TIG0
                            ZONE1
                                    ZONE2 MRG
                                                REGULARITY
         /
         0
               NaN
                       NaN
                                           N0
                                                          1
                              NaN
                                      NaN
                                                                                NaN
         1
               NaN
                       NaN
                              NaN
                                      NaN
                                           N0
                                                          2
                                                                                NaN
         2
               7.0
                       2.0
                                                         27
                                                              Data: 100 F=40MB,24H
                              NaN
                                      NaN
                                           N0
         3
                                                               IVR Echat Daily 50F
              23.0
                       4.0
                              NaN
                                      NaN
                                           N0
                                                         46
         4
             555.0
                     280.0
                              NaN
                                      NaN
                                           N0
                                                         61
                                                             All-net 500F=2000F;5d
            FREQ TOP PACK
         0
                       NaN
         1
                       NaN
         2
                      17.0
         3
                       3.0
         4
                      65.0
```

```
In [4]: print(df.shape)
print(df_Test.shape)

(400000, 19)
```

(100000, 18)

16

17

18

TOP PACK

CHURN

FREQ TOP PACK

memory usage: 58.0+ MB

```
Hackathon logistic regression churn - Jupyter Notebook
In [5]: df.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 400000 entries, 0 to 399999
         Data columns (total 19 columns):
          #
              Column
                               Non-Null Count
                                                  Dtype
         - - -
          0
              user id
                               400000 non-null
                                                  object
          1
              REGION
                               242480 non-null
                                                  object
          2
              TENURE
                               400000 non-null
                                                  object
                               259723 non-null
          3
              MONTANT
                                                  float64
          4
              FREQUENCE RECH
                               259723 non-null
                                                  float64
          5
                               265337 non-null
                                                  float64
              REVENUE
          6
              ARPU SEGMENT
                               265337 non-null
                                                  float64
          7
              FREQUENCE
                               265337 non-null
                                                  float64
          8
              DATA VOLUME
                               203146 non-null
                                                  float64
          9
              ON NET
                               254181 non-null
                                                  float64
          10
              ORANGE
                               233683 non-null
                                                  float64
          11
                               160614 non-null
                                                  float64
              TIG0
          12
              ZONE1
                               31690 non-null
                                                  float64
          13
                                                  float64
              ZONE2
                               25513 non-null
          14
              MRG
                               400000 non-null
                                                  object
          15
              REGULARITY
                               400000 non-null
                                                  int64
```

In [6]: df.columns

232671 non-null

232671 non-null

400000 non-null

dtypes: float64(12), int64(2), object(5)

object

int64

float64

In [7]: df\_Test.describe()

Out[7]:

	MONTANT	FREQUENCE_RECH	REVENUE	ARPU_SEGMENT	FREQUENCE	DATA
count	65049.000000	65049.000000	66510.000000	66510.000000	66510.000000	506
mean	5545.613630	11.545051	5518.341663	1839.453676	13.979973	33
std	7123.955226	13.271270	7177.840304	2392.609422	14.655983	105
min	25.000000	1.000000	1.000000	0.000000	1.000000	
25%	1000.000000	2.000000	1000.000000	333.000000	3.000000	
50%	3000.000000	7.000000	3000.000000	1000.000000	9.000000	2
<b>75</b> %	7400.000000	16.000000	7399.000000	2466.000000	20.000000	29
max	201500.000000	120.000000	181135.000000	60378.000000	91.000000	4742

In [8]: df.describe()

Out[8]:

	MONTANT	FREQUENCE_RECH	REVENUE	ARPU_SEGMENT	FREQUENCE	DAT
count	259723.000000	259723.000000	265337.000000	265337.000000	265337.000000	20:
mean	5522.971346	11.503733	5505.487757	1835.167658	13.951835	;
std	7099.640630	13.275514	7175.802367	2391.929290	14.679943	1:
min	20.000000	1.000000	1.000000	0.000000	1.000000	
25%	1000.000000	2.000000	1000.000000	333.000000	3.000000	
50%	3000.000000	6.000000	3000.000000	1000.000000	9.000000	
75%	7300.000000	15.000000	7340.000000	2447.000000	19.000000	;
max	226550.000000	133.000000	233413.000000	77804.000000	91.000000	934
4						

```
In [9]: df.isna().sum()#checks for number of missing data
 Out[9]: user id
                                  0
         REGION
                             157520
         TENURE
                                  0
         MONTANT
                             140277
         FREQUENCE_RECH
                             140277
         REVENUE
                             134663
         ARPU SEGMENT
                             134663
         FREQUENCE
                             134663
         DATA_VOLUME
                             196854
         ON NET
                             145819
         ORANGE
                             166317
         TIG0
                             239386
         ZONE1
                             368310
         Z0NE2
                             374487
         MRG
         REGULARITY
                                  0
         TOP PACK
                             167329
         FREQ_TOP_PACK
                             167329
         CHURN
                                  0
         dtype: int64
In [10]: df_Test.isna().sum()
Out[10]: user id
                                 0
                             39293
         REGION
         TENURE
         MONTANT
                             34951
         FREQUENCE RECH
                             34951
         REVENUE
                             33490
         ARPU SEGMENT
                             33490
         FREQUENCE
                             33490
         DATA VOLUME
                             49338
         ON NET
                             36383
         ORANGE
                             41200
         TIG0
                             59788
         ZONE1
                             92320
                             93578
         Z0NE2
         MRG
                                 0
         REGULARITY
                                 0
         TOP PACK
                             41703
         FREQ TOP PACK
                             41703
         dtype: int64
In [11]:
         df user = df.pop('user id')
         #df.drop(['user_id'], 1, inplace = True)
In [12]: df_user_Test = df_Test.pop('user_id')
```

```
In [13]: def handle non numerical data(df):
             columns = df.columns.values
             for column in columns:
                 text_digit_vals = {}#Eg here we could have {'NO' : 0, etc}, it (
                 def convert to int(val):
                     return text digit vals[val]
                 if df[column].dtype != np.int64 and df[column].dtype != np.float
                     column_contents = df[column].values.tolist()#we convert to
                     unique elements = set(column contents)#then take the unique
                     x=0
                     for unique in unique elements:
                         if unique not in text digit vals:
                             text digit vals[unique] = x
                             x+=1
                     df[column] = list(map(convert_to_int, df[column]))#we reset
                     #values in first parameter to the 2nd parameter
             return df
         df = handle non numerical data(df)
         print(df.head(15))
         df Test = handle non numerical data(df Test)
         print(df_Test.head())
```

ΕΩ	REGION UENCE \	TENURE	MONTANT	FREQUENCE_RECH	REVENUE	ARPU_SEGMENT	FR
0	14 .0	5	17000.0	32.0	18000.0	6000.0	
1 37	0	5	4300.0	29.0	4427.0	1476.0	
2 3.	6	5	1500.0	3.0	1500.0	500.0	
3 4.	8	5	1500.0	3.0	2497.0	832.0	
4 3.	8	5	NaN	NaN	498.0	166.0	
5	3.0	5	5500.0	9.0	5359.0	1786.0	
6 Na	0	5	NaN	NaN	NaN	NaN	
7 Na	14	7	NaN	NaN	NaN	NaN	
8	6.0	5	22500.0	8.0	22230.0	7410.0	
9 Na	0	6	NaN	NaN	NaN	NaN	
10 Na		5	NaN	NaN	NaN	NaN	
11 3.		5	300.0	3.0	300.0	100.0	
12 10		5	3300.0	9.0	2996.0	999.0	
13 23	.0	5	4550.0	18.0		1483.0	
14	9	5	3800.0	7.0	3500.0	1167.0	

7.0

,	DATA_VOLUME	ON_NET	ORANGE	TIG0	ZONE1	ZONE2	MRG	REGULARITY
\ 0 1 2 3 4 5 6 7 8 9 10 11 12 13 14		97.0 8.0 30.0 159.0 1.0 7.0 NaN NaN 6336.0 NaN 8.0 547.0 34.0	355.0 3.0 30.0 45.0 3.0 12.0 NaN NaN 1017.0 NaN 1.0 9.0 20.0 71.0	0.0 NaN 19.0 NaN 5.0 NaN 185.0 NaN 0.0 0.0	Nan Nan Nan Nan Nan Nan Nan Nan Nan Nan	NaN 2.0 NaN NaN NaN NaN NaN NaN NaN NaN NaN	0 0 0 0 0 0 0 0	62 40 32 18 50 30 7 5 62 1 3 47 54 58 24
14		REQ TOP F		URN	IVAIV	IVAIN	U	24
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14	1 61 1 79 0 22 0 49 0 102 79 16 29		35.0 22.0 3.0 3.0 NaN 7.0 NaN NaN 3.0 NaN NaN 2.0 4.0 11.0	0 0 0 0 0 0 1 0 0 0	DECU. D		ADDU	CECMENT FRE
QUE 0		RE MONTA	ANI FRE NaN	QUENCE_F	RECH RI NaN	evenue	ARPU_	_SEGMENT FRE NaN
NaN 1	0		VaN		NaN	10.0		3.0
1.0 2	0	5 1900		1		2299.0		766.0
21.	9	5 3000	0.0		9.0	2603.0		868.0
14. 4 47.	9	5 32000	0.0	4	17.0 3	3000.0		11000.0
	DATA_VOLUME	ON_NET	ORANGE	TIG0	ZONE1	ZONE2	MRG	REGULARITY
\ 0 1 2 3 4	NaN NaN 414.0 332.0 NaN	NaN NaN NaN 0.0 128.0	NaN NaN 7.0 23.0 555.0	NaN NaN 2.0 4.0 280.0	NaN NaN NaN NaN NaN	NaN NaN NaN NaN NaN	0 0 0 0	1 2 27 46 61

TOP_PACK	FREQ_TOP_PACK
- 0	NaN
Θ	NaN
50	17.0
27	3.0
1	65.0
	- 0 0 50

In [14]: df["CHURN"].value\_counts().values

Out[14]: array([325156, 74844])

In [15]: df.shape

Out[15]: (400000, 18)

In [16]: df.describe()

## Out[16]:

	REGION	TENURE	MONTANT	FREQUENCE_RECH	REVENUE	ARPU_
count	400000.000000	400000.000000	259723.000000	259723.000000	265337.000000	265
mean	4.983425	4.937597	5522.971346	11.503733	5505.487757	1
std	4.884023	0.590715	7099.640630	13.275514	7175.802367	2
min	0.000000	0.000000	20.000000	1.000000	1.000000	
25%	0.000000	5.000000	1000.000000	2.000000	1000.000000	•
50%	3.000000	5.000000	3000.000000	6.000000	3000.000000	10
75%	9.000000	5.000000	7300.000000	15.000000	7340.000000	2
max	14.000000	7.000000	226550.000000	133.000000	233413.000000	77
4						•

In [17]: df\_Test.describe()

## Out[17]:

	REGION	TENURE	MONTANT	FREQUENCE_RECH	REVENUE	ARPU_
count	100000.000000	100000.000000	65049.000000	65049.000000	66510.000000	66!
mean	4.986220	4.936360	5545.613630	11.545051	5518.341663	18
std	4.885387	0.594116	7123.955226	13.271270	7177.840304	2:
min	0.000000	0.000000	25.000000	1.000000	1.000000	
25%	0.000000	5.000000	1000.000000	2.000000	1000.000000	:
50%	3.000000	5.000000	3000.000000	7.000000	3000.000000	1(
75%	9.000000	5.000000	7400.000000	16.000000	7399.000000	24
max	14.000000	7.000000	201500.000000	120.000000	181135.000000	600
4						•

In [18]: df.isnull()

Out[18]:

	REGION	TENURE	MONTANT	FREQUENCE_RECH	REVENUE	ARPU_SEGMENT	FRE	
0	False	False	False	False	False	False		
1	False	False	False	False	False	False		
2	False	False	False	False	False	False		
3	False	False	False	False	False	False		
4	False	False	True	True	False	False		
399995	False	False	False	False	False	False		
399996	False	False	True	True	True	True		
399997	False	False	False	False	False	False		
399998	False	False	True	True	False	False		
399999	False	False	True	True	True	True		
400000 rows × 18 columns								

0			TENURE	MON	TANT	FREQUEN	ICE_RECH		REVENUE	AR	PU_S
1		\ 14	5	17000.00	0000	32	.000000	1800	0.000000	6	000.
2	1	0	5	4300.00	0000	29	.000000	442	7.000000	1	476.
3	2	6	5	1500.00	0000	3	.000000	150	0.000000		500.
1	3	8	5	1500.00	0000	3	.000000	249	7.000000		832.
S   S   S   S   S   S   S   S   S   S	4	8	5	5522.97	1346	11	.503733	49	8.000000		166.
10	5	3	5	5500.00	0000	g	.000000	535	9.000000	1	786.
T	6	0	5	5522.97	1346	11	.503733	550	5.487757	1	835.
8 6 6 5 22500.00000 8.00000 22230.00000 7410.000000 9 0 0 0 6 5522.971346 11.503733 5505.487757 1835.167658 11 3 3 5 5522.971346 11.503733 5505.487757 1835.167658 11 3 3 5 3300.00000 3.000000 300.000000 100.000000 1 2 13 5 3300.000000 9 0.00000 2996.000000 9 0.00000 12 13 9 5 3300.000000 18.000000 3200.00000 1483.000000 1 3 000	7	14	7	5522.97	1346	11	.503733	550	5.487757	1	835.
9   0   6   5522.971346   11.503733   5505.487757   1835.     167658   10   3   5   5522.971346   11.503733   5505.487757   1835.     167658   11   3   5   300.000000   3.000000   300.000000   100.0000000     12   13   5   3300.000000   9.000000   2996.000000   399.000000     13   9   5   4550.000000   18.000000   4450.000000   1483.     14   9   5   3800.0000000   7.000000   3500.000000   1167.     14   9   5   3800.0000000   7.000000   3500.000000   1167.     14   9   5   3800.0000000   7.000000   3550.000000   6.000000   7.8     14   9   34.000000   3369.763441   97.000000   355.000000   6.000000   7.8     74282   1   37.000000   3369.763441   30.000000   30.00000   23.134608   7.8     74282   3   4.000000   3369.763441   30.000000   45.000000   19.000000   7.8     74282   4   3.000000   3.000000   3.000000   23.134608   7.8     74282   5   19.000000   6084.000000   7.000000   12.000000   5.000000   7.8     74282   6   13.951835   3369.763441   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.0000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.0000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.0000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.0000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.0000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.0000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.0000000   275.917586   95.532927   23.134608   7.8     74282   7   13.951835   0.0000000000000000000000000000000000	8	6	5	22500.00	0000	8	3.000000	2223	0.000000	7	410.
10	9	0	6	5522.97	1346	11	.503733	550	5.487757	1	835.
11 3 5 300.000000 3.000000 300.000000 100.0000000000	10	3	5	5522.97	1346	11	.503733	550	5.487757	1	835.
12	11	3	5	300.00	0000	3	.000000	30	0.000000		100.
13 9 5 4550.000000 18.000000 4450.000000 1483.  0000000 14 9 5 3800.0000000 7.0000000 3500.000000 1167.  FREQUENCE DATA_VOLUME ON_NET ORANGE TIGO  20NE1 \ 0 34.000000 3369.763441 97.000000 355.000000 6.000000 7.8  74282 1 37.000000 1764.000000 8.000000 30.000000 0.000000 7.8  74282 2 3.000000 3369.763441 30.000000 30.000000 23.134608 7.8  74282 3 4.000000 1.000000 159.000000 45.000000 19.000000 7.8  74282 4 3.000000 1.000000 1.000000 3.000000 23.134608 7.8  74282 5 19.000000 6084.000000 7.000000 12.000000 5.000000 7.8  74282 6 13.951835 3369.763441 275.917586 95.532927 23.134608 7.8  74282 7 13.951835 0.000000 275.917586 95.532927 23.134608 7.8	12	13	5	3300.00	0000	9	.000000	299	6.000000		999.
14	13	9	5	4550.00	0000	18	.000000	445	0.000000	1	483.
FREQUENCE DATA_VOLUME ON_NET ORANGE TIGO  ZONE1 \ 0	14	9	5	3800.00	0000	7	.000000	350	0.000000	1	167.
ZONE1 \ 0		OHENCI	= DAT.	A VALUME		ON NET	ΛD	ANCE	тт	CO.	
74282         1       37.000000       1764.000000       8.000000       3.000000       0.000000       7.8         74282       3.000000       3369.763441       30.000000       30.000000       23.134608       7.8         74282       3       4.000000       0.000000       159.000000       45.000000       19.000000       7.8         74282       4       3.000000       1.000000       3.000000       23.134608       7.8         74282       5       19.000000       6084.000000       7.000000       12.000000       5.000000       7.8         74282       6       13.951835       3369.763441       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8	ZONE1	\		_	0.7	_					7.0
74282         2       3.000000       3369.763441       30.000000       30.000000       23.134608       7.8         74282       3       4.000000       0.000000       159.000000       45.000000       19.000000       7.8         74282       3.000000       1.000000       1.000000       3.000000       23.134608       7.8         74282       7       19.000000       6084.000000       7.000000       12.000000       5.000000       7.8         74282       7       13.951835       3369.763441       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8	74282										
74282         3       4.000000       0.000000       159.000000       45.000000       19.000000       7.8         74282       4       3.000000       1.000000       1.000000       3.000000       23.134608       7.8         74282       5       19.000000       6084.000000       7.000000       12.000000       5.000000       7.8         74282       6       13.951835       3369.763441       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.0000000       275.917586       95.532927       23.134608       7.8		000000	9 176	4.000000	8	.000000	3.00	0000	0.0000	00	7.8
3       4.000000       0.000000       159.000000       45.000000       19.000000       7.8         74282       4       3.000000       1.000000       1.000000       3.000000       23.134608       7.8         74282       5       19.000000       6084.000000       7.000000       12.000000       5.000000       7.8         74282       6       13.951835       3369.763441       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8		000000	336	9.763441	30	.000000	30.00	0000	23.1346	80	7.8
4       3.000000       1.000000       1.000000       3.000000       23.134608       7.8         74282       5       19.000000       6084.000000       7.000000       12.000000       5.000000       7.8         74282       6       13.951835       3369.763441       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8	3 4.	000000	9	0.000000	159	.000000	45.00	0000	19.0000	00	7.8
5       19.000000       6084.000000       7.000000       12.000000       5.000000       7.8         74282       6       13.951835       3369.763441       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8         74282       7       74282       7.8       7.8       7.8	4 3.	000000	9	1.000000	1	.000000	3.00	0000	23.1346	08	7.8
6       13.951835       3369.763441       275.917586       95.532927       23.134608       7.8         74282       7       13.951835       0.000000       275.917586       95.532927       23.134608       7.8         74282	5 19.	00000	9 608	4.000000	7	.000000	12.00	0000	5.0000	00	7.8
7 13.951835 0.000000 275.917586 95.532927 23.134608 7.8 74282	6 13.	95183	5 336	9.763441	275	.917586	95.53	2927	23.1346	08	7.8
	7 13.	95183	5 (	0.000000	275	.917586	95.53	2927	23.1346	80	7.8
10.000000 14550.000000 0550.000000 1017.000000 105.000000 7.0		000000	9 1495	6.000000	6336	.000000	1017.00	0000	185.0000	00	7.8

		Па	ickatilon_logistic_i	egression_cnum -	- Jupyter Notebook		
742	82						
9	13.951835	33	69.763441	275.917586	95.532927	23.134608	7.8
742							
10	13.951835	33	69.763441	275.917586	95.532927	23.134608	7.8
742							
11	3.000000	1	69.000000	8.000000	1.000000	0.000000	7.8
742							
12			0.000000	547.000000	9.000000	0.000000	7.8
742							
13	23.000000	10	62.000000	34.000000	20.000000	4.000000	7.8
742	_						
14	7.000000	33	69.763441	15.000000	71.000000	5.000000	7.8
742	82						
_	ZONE2	MRG	REGULARITY	TOP_PACK	FREQ_TOP_PACK	CHURN	
0	7.187003	0	62	1	35.000000	0	
1	2.000000	0	40	61	22.000000	0	
2	7.187003	0	32	1	3.000000	0	
3	7.187003	0	18	79	3.000000	0	
4	7.187003	0	50	0	9.254209	0	
5	7.187003	0	30	22	7.000000	0	
6	7.187003	0	7	0	9.254209	0	
7	7.187003	0	5	0	9.254209	1	
8	7.187003	0	62	49	3.000000	0	
9	7.187003	0	1	0	9.254209	0	
10	7.187003	0	3	0	9.254209	0	
11	7.187003	0	47	102	2.000000	0	
12	7.187003	0	54	79	4.000000	0	
13	7.187003	0	58	16	11.000000	0	
14	7.187003	0	24	29	1.000000	0	

```
column means = df Test.mean()
In [20]:
         df Test=df Test.fillna(column means)
          print(df Test.head(5))
                     TENURE
             REGION
                                  MONTANT
                                            FREQUENCE_RECH
                                                                  REVENUE
                                                                            ARPU_SEG
         MENT
                  0
                           5
          0
                               5545.61363
                                                 11.545051
                                                              5518.341663
                                                                             1839.45
          3676
                           5
                               5545.61363
                                                 11.545051
                                                                10.000000
                                                                                3.00
          1
                  0
          0000
          2
                  0
                           5
                               1900.00000
                                                 15.000000
                                                              2299.000000
                                                                              766.00
          0000
                  9
                           5
                               3000.00000
                                                  9.000000
                                                              2603.000000
          3
                                                                              868.00
          0000
                  9
                           5
                              32000.00000
          4
                                                 47.000000
                                                             33000.000000
                                                                            11000.00
          0000
             FREQUENCE
                        DATA VOLUME
                                           ON NET
                                                        ORANGE
                                                                      TIG0
                                                                                ZONE
          1
          0
             13.979973
                        3357.428033
                                      279.370703
                                                    94.900799
                                                                 23.459291
                                                                             8.37330
          7
          1
              1.000000
                        3357.428033
                                      279.370703
                                                    94.900799
                                                                 23.459291
                                                                             8.37330
          7
          2
             21.000000
                          414.000000
                                      279.370703
                                                     7.000000
                                                                  2.000000
                                                                             8.37330
          7
          3
             14.000000
                          332.000000
                                        0.000000
                                                    23.000000
                                                                  4.000000
                                                                             8.37330
          7
          4
             47.000000
                        3357.428033
                                      128.000000
                                                   555.000000
                                                                280.000000
                                                                             8.37330
                                         TOP PACK
                ZONE2
                       MRG
                             REGULARITY
                                                    FREQ TOP PACK
                                                          9.276035
             7.678138
                          0
                                      1
                                                 0
          1
             7.678138
                          0
                                      2
                                                 0
                                                          9.276035
          2
                                     27
             7.678138
                          0
                                                50
                                                         17.000000
          3
             7.678138
                          0
                                     46
                                                27
                                                          3.000000
             7.678138
                          0
                                     61
                                                 1
                                                         65.000000
In [21]: #Create Feature variable X and Target variable y
          y = np.array(df['CHURN'])
In [22]: X = np.array(df.drop(['CHURN'], 1).astype(float))
          #Standardizing/scaling the features
         X = StandardScaler().fit transform(X)
         print(len(X),len(y))
          400000 400000
         x = np.array((df Test).astype(float))
In [23]:
          x = StandardScaler().fit transform(x)
          print(len(x))
```

100000

```
In [24]: #Split the data into 80% training and 20% testing
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =0.1
         # using logistic regression model
         clf = LogisticRegression()
         clf.fit(X train, y train)
Out[24]: LogisticRegression(C=1.0, class weight=None, dual=False, fit intercept
         =True.
                             intercept_scaling=1, l1_ratio=None, max_iter=100,
                             multi class='auto', n jobs=None, penalty='l2',
                             random state=None, solver='lbfgs', tol=0.0001, verb
         ose=0,
                             warm start=False)
In [25]: # evaluating the model
         prediction = clf.predict(X test)
         #printing the predictions
         print(prediction)
         print(len(prediction))
         [0 \ 0 \ 1 \ \dots \ 0 \ 1 \ 0]
         80000
In [26]: #Generate confusion matrix for logistics regression model as it has maxi
         conf mat clf = confusion_matrix(y_test,prediction)
         conf_mat_clf
Out[26]: array([[59012, 5855],
                 [ 4217, 10916]])
In [27]: # Predict the probability of Churn of each customer
         predictions = clf.predict(X)
         print(predictions)
         print(len(predictions))
         [0 0 0 ... 0 0 1]
         400000
In [28]:
         import sklearn
         sklearn.metrics.accuracy score(prediction,y test)
Out[28]: 0.8741
In [29]:
         # Finding precision and recall
         from sklearn.metrics import precision score, recall score
         precision score(prediction, y test)
         recall score(prediction, y test)
Out[29]: 0.6508854570389363
```

```
In [30]: from sklearn.metrics import log loss
         log loss(prediction, y test) # the smaller the logloss(uncertainty), the
Out[30]: 4.348474096898794
In [31]: '''for pickle'''
         with open ('logisticregression.pickle','wb') as f:
             pickle.dump(clf, f)
         '''we use this cell while testing on new data after we have written pic∤
In [32]:
         '''to read the pickle'''
         pickle in = open('logisticregression.pickle','rb')
         '''we renamed classifier here'''
         clf = pickle.load(pickle in)
         solution = clf.predict(x)
In [33]:
         print(solution)
         print(len(solution))
         [1 \ 1 \ 0 \ \dots \ 0 \ 0 \ 0]
         100000
In [34]: df4 = pd.DataFrame(solution) #converting prediction to a dataframe
         df4.rename(columns={0: "CHURN"}) #rename the column from '0' to 'CHURN
Out[34]:
                CHURN
```

	OHOINI
0	1
1	1
2	0
3	0
4	0
99995	0
99996	0
99997	0
99998	0
99999	0

100000 rows × 1 columns

```
In [35]: # Predict the probability of Churn of each customer
         df['Churn'] = predictions
         #print(df['Churn'])
         print(len(df['Churn']))
         #print(df['CHURN'])
         df2 = pd.DataFrame(df['Churn'], columns = ['Churn'])
         print(df2.tail(20))
         400000
                  Churn
         399980
                      0
                      0
         399981
                      0
          399982
         399983
                      0
                      0
         399984
          399985
                      0
         399986
                      0
         399987
                      0
                      0
         399988
         399989
                      0
                      1
         399990
         399991
                      1
          399992
                      0
                      0
         399993
         399994
                      0
         399995
                      0
                      0
         399996
          399997
                      0
         399998
                      0
                      1
         399999
         # Predict the probability of Churn of each customer
In [36]:
          '''df['CHURN'] = pd.Series(solution) #fixed valueerror
         print(len(df['CHURN']))
         print(df['CHURN'])
         df Test = pd.DataFrame(df['CHURN'], columns = ['CHURN'])
         df\overline{4} = df Test.iloc[0:100000]
         print(df4.tail(20))
         print(len(df4))'''
Out[36]: "df['CHURN'] = pd.Series(solution) #fixed valueerror\n\nprint(len(df
          ['CHURN']))\nprint(df['CHURN'])\ndf Test = pd.DataFrame(df['CHURN'], c
         olumns = ['CHURN'])\ndf4 = df Test.iloc[0:100000]\nprint(df4.tail(20))
         \nprint(len(df4))"
```

```
In [37]:
         print(df user)
         df1 = pd.DataFrame(df user, columns = ['user_id'])
         print(df1.tail(20))
         0
                   dcf68cc2fb515ccad7d8b9b3bd80ee2a4b270063
         1
                   71c44b5ba328db5c4192a80f7cf8f244d9350ed0
         2
                   ce46411b1526c94f20a383b8cb188f8d27f82a0a
         3
                   f467cdb6669818373c26c2bad44e01ba66f97d21
                   ec45e1a1888a32b5dcce0954cfec20c6e037db31
         399995
                   a892ad4ed0eda8dc721733200c47147763b183ec
         399996
                   13daa3a651bf0192a413b339c4766aeafc6d1636
                   767f596aee426962f7d92f4de8d7b232cdc17568
         399997
         399998
                   b831e4d3b59a1e294e9e0a2aab391bc12d50845c
                   a80e3a164986e489102cfb538fa62e16ecc28adf
         399999
         Name: user id, Length: 400000, dtype: object
                                                   user id
         399980
                 7b902e808901aceb41731abfb82ac7ec856ca452
         399981
                 186963eda12e9f661af8ce952b36929554de69e7
         399982
                 2f9211523724ec0a6f9da554f1364dc07d49b89e
                 e6464f573cdcfc8d92e3d0c3f96a0925515d9fe8
         399983
         399984
                 f64d8938c3d1ce0401b4d7af4c94a6f8e1a8c85d
         399985
                 a63a501d82db5227001c57fd67fcffb08bcc0fc0
         399986
                 200e23c4639f968fec5b21dadc31cbae61499c1e
         399987
                 e94e33eccf6397d2d111b5eda98c3f00d775957c
         399988
                 0d5ee6f1c0499866f8742351691a29984f79a953
         399989
                 e52db82cb925cdcc6f7cd4bae73b8aa2fb48c383
         399990
                 991f37c6c994daab8ab8c07a2453a43ebb060f53
         399991
                 2a92663555f9c237a0e69462625e8916b8182d5e
         399992
                 6efd8294140f2e410b8cbbbafa77c2b096ca35a5
         399993
                 a708001683c19272a0f7648a61f832a99ae8a3d5
         399994
                 6979ea052669404eae2f58a90df8fd482640915d
         399995
                 a892ad4ed0eda8dc721733200c47147763b183ec
         399996
                 13daa3a651bf0192a413b339c4766aeafc6d1636
         399997
                 767f596aee426962f7d92f4de8d7b232cdc17568
         399998
                 b831e4d3b59a1e294e9e0a2aab391bc12d50845c
         399999
                 a80e3a164986e489102cfb538fa62e16ecc28adf
```

```
In [38]:
          print(df user Test)
          df3 = pd.DataFrame(df user Test, columns = ['user id'])
          print(df3.tail(20))
                    af900d87e73b7ff6509d2203df4704a98aa5f2a6
          0
          1
                    5335efd940280b82143272275637d1e65d37eadb
          2
                    a581f4fa08677c26f83f643248c667e241043086
          3
                    64f67177d0775262b8087a9e2e3b8061b6324ae6
                    0d6009a4594c4be22449b8d9cc01a0bcea98faea
          99995
                    c6bcb3336795a18eb6c0bc7e19078a0704ef4d7e
          99996
                    a44b4e44dc70115ed5bf971ebb4193dd536e87f0
          99997
                    a2f84faffbc995bd0e2d726fa4ffdb93f11646ed
          99998
                    afa76e894df4201fc77eb714de7d1f262299611a
                    c08a2d84b87c1f5d4bb318114f508b77aa8e2663
          99999
          Name: user id, Length: 100000, dtype: object
                                                    user id
          99980
                 501dbe56ea737f87a8c21d711e954bb4f36f2cc3
          99981
                 24838af1f3fbcb95b19ba14e0e977a037cd91bf0
          99982
                 552a68f1fb242bf1c645495fbf7528399050ba0b
          99983
                 7cc53deb9749ff830caa9a5ea1cdb1b21c634540
          99984
                 7bda478c0f7229565bd4d937fcfd53ce37dd71df
          99985
                 64808d2cf540ace5dc242632c75329ad92c558e4
 In [46]:
          print(len(X),len(y))
          result = pd.concat([df1, df2], axis=1)
          print(result)
          400000 400000
                                                     user id
                                                              Churn
          0
                  dcf68cc2fb515ccad7d8b9b3bd80ee2a4b270063
                                                                  0
          1
                                                                  0
                   71c44b5ba328db5c4192a80f7cf8f244d9350ed0
          2
                   ce46411b1526c94f20a383b8cb188f8d27f82a0a
                                                                  0
          3
                   f467cdb6669818373c26c2bad44e01ba66f97d21
                                                                  0
          4
                   ec45e1a1888a32b5dcce0954cfec20c6e037db31
                                                                  0
          399995
                  a892ad4ed0eda8dc721733200c47147763b183ec
                                                                  0
          399996
                  13daa3a651bf0192a413b339c4766aeafc6d1636
                                                                  0
          399997
                  767f596aee426962f7d92f4de8d7b232cdc17568
                                                                  0
          399998
                  b831e4d3b59a1e294e9e0a2aab391bc12d50845c
                                                                  0
          399999
                  a80e3a164986e489102cfb538fa62e16ecc28adf
                                                                  1
          [400000 rows x 2 columns]
          result.to csv('Churn predict file')#to text file
In [165]:
```

```
df5= pd.read csv('sample submission.csv')
           df5.drop(['CHURN'], axis=1, inplace=True)
           Test result=pd.concat([df5,df4], axis=1)
           print(Test result)
           print(len(df5),len(df4))
                                                          user id
                                                                    0
           0
                    af900d87e73b7ff6509d2203df4704a98aa5f2a6
                                                                    1
            1
                    5335efd940280b82143272275637d1e65d37eadb
                                                                    1
            2
                    a581f4fa08677c26f83f643248c667e241043086
                                                                    0
            3
                    64f67177d0775262b8087a9e2e3b8061b6324ae6
                                                                    0
            4
                    0d6009a4594c4be22449b8d9cc01a0bcea98faea
            . . .
                    c6bcb3336795a18eb6c0bc7e19078a0704ef4d7e
           99995
                                                                    0
                    a44b4e44dc70115ed5bf971ebb4193dd536e87f0
           99996
                                                                    0
           99997
                    a2f84faffbc995bd0e2d726fa4ffdb93f11646ed
                                                                    0
           99998
                    afa76e894df4201fc77eb714de7d1f262299611a
                                                                    0
           99999
                    c08a2d84b87c1f5d4bb318114f508b77aa8e2663
                                                                    0
            [100000 \text{ rows } \times 2 \text{ columns}]
            100000 100000
In [167]: Test result.to csv('Eprediction.csv', index=False)
In [168]: Test result
Out[168]:
                                                         0
                                                 user id
                0
                     af900d87e73b7ff6509d2203df4704a98aa5f2a6
                1
                  5335efd940280b82143272275637d1e65d37eadb
                2
                    a581f4fa08677c26f83f643248c667e241043086
                3
                  64f67177d0775262b8087a9e2e3b8061b6324ae6
                                                         0
                   0d6009a4594c4be22449b8d9cc01a0bcea98faea
                                                         0
             99995
                   c6bcb3336795a18eb6c0bc7e19078a0704ef4d7e
                                                         0
             99996
                   a44b4e44dc70115ed5bf971ebb4193dd536e87f0
             99997
                      a2f84faffbc995bd0e2d726fa4ffdb93f11646ed
                                                         0
             99998
                    afa76e894df4201fc77eb714de7d1f262299611a
                                                         0
                   c08a2d84b87c1f5d4bb318114f508b77aa8e2663
             99999
            100000 rows × 2 columns
  In [ ]:
```