

```
In [1]: 1 import numpy as np
        2 import pandas as pd
        3 import matplotlib.pyplot as plt
        4 import seaborn as sns
        5 plt.style.use('fivethirtyeight')
        6 import warnings
        7 warnings.filterwarnings('ignore')
```

```
In [2]: 1 df = pd.read_csv('application_train.csv')
```

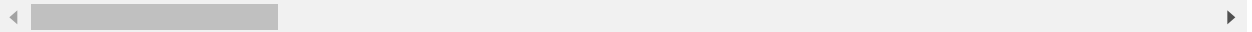
Exploratory data analysis

```
In [3]: 1 df.head()
```

Out[3]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN
0	157876	0	Cash loans	F	N	
1	157878	0	Cash loans	M	Y	
2	157879	0	Revolving loans	M	N	
3	157880	0	Cash loans	F	N	
4	157881	0	Cash loans	F	N	

5 rows × 122 columns



```
In [4]: 1 df.columns.shape
```

Out[4]: (122,)

```
In [5]: 1 len(df)
```

Out[5]: 257512

```
In [6]: 1 df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 257512 entries, 0 to 257511
Columns: 122 entries, SK_ID_CURR to AMT_REQ_CREDIT_BUREAU_YEAR
dtypes: float64(64), int64(42), object(16)
memory usage: 239.7+ MB
```

In [7]: 1 df.describe()

Out[7]:

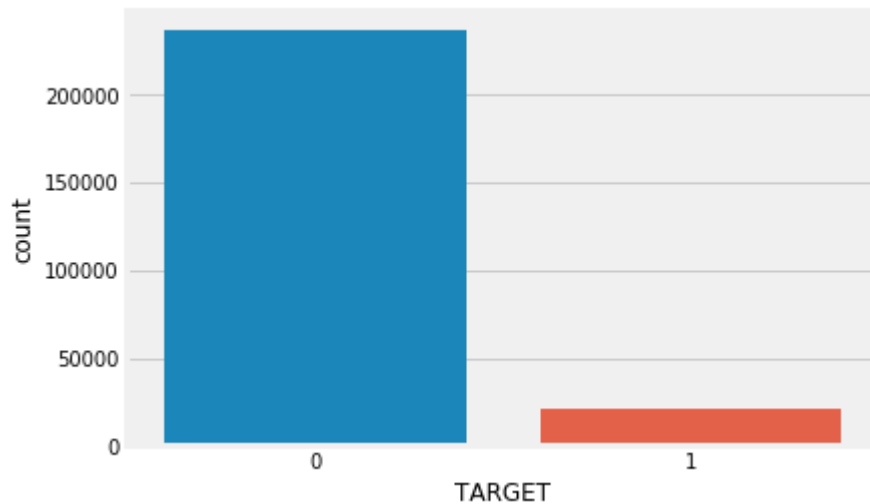
	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_A
count	257512.000000	257512.000000	257512.000000	2.575120e+05	2.575120e+05	257501
mean	307143.115397	0.080769	0.416509	1.684155e+05	5.988950e+05	27108
std	86047.050997	0.272481	0.721749	1.105872e+05	4.025061e+05	14480
min	157876.000000	0.000000	0.000000	2.610000e+04	4.500000e+04	1615
25%	232638.750000	0.000000	0.000000	1.125000e+05	2.700000e+05	16542
50%	307140.500000	0.000000	0.000000	1.476000e+05	5.135310e+05	24903
75%	381476.500000	0.000000	1.000000	2.025000e+05	8.086500e+05	34596
max	456255.000000	1.000000	19.000000	1.800009e+07	4.050000e+06	230161

8 rows × 106 columns

In [8]: 1 df.TARGET.value_counts()

Out[8]: 0 236713
1 20799
Name: TARGET, dtype: int64

In [9]: 1 sns.countplot(x='TARGET', data=df);



Observation : Imbalance data set

```
In [10]: 1 df = df.drop(  
2 ['DAYS_REGISTRATION',  
3 'DAYS_ID_PUBLISH',  
4 'YEARS_BEGINEXPLUATATION_AVG',  
5 'APARTMENTS_MODE',  
6 'BASEMENTAREA_MODE',  
7 'YEARS_BEGINEXPLUATATION_MODE',  
8 'YEARS_BUILD_MODE',  
9 'COMMONAREA_MODE',  
10 'ELEVATORS_MODE',  
11 'ENTRANCES_MODE',  
12 'FLOORSMAX_MODE',  
13 'FLOORSMIN_MODE',  
14 'LANDAREA_MODE',  
15 'LIVINGAPARTMENTS_MODE',  
16 'LIVINGAREA_MODE',  
17 'NONLIVINGAPARTMENTS_MODE',  
18 'NONLIVINGAREA_MODE',  
19 'APARTMENTS_MEDI',  
20 'BASEMENTAREA_MEDI',  
21 'YEARS_BEGINEXPLUATATION_MEDI',  
22 'YEARS_BUILD_MEDI',  
23 'COMMONAREA_MEDI',  
24 'ELEVATORS_MEDI',  
25 'ENTRANCES_MEDI',  
26 'FLOORSMAX_MEDI',  
27 'FLOORSMIN_MEDI',  
28 'LANDAREA_MEDI',  
29 'LIVINGAPARTMENTS_MEDI',  
30 'LIVINGAREA_MEDI',  
31 'NONLIVINGAPARTMENTS_MEDI',  
32 'NONLIVINGAREA_MEDI',  
33 'FONDKAPREMONT_MODE',  
34 'HOUSETYPE_MODE',  
35 'TOTALAREA_MODE',  
36 'WALLSMATERIAL_MODE',  
37 'EMERGENCYSTATE_MODE',  
38 'OBS_30_CNT_SOCIAL_CIRCLE',  
39 'DEF_30_CNT_SOCIAL_CIRCLE',  
40 'OBS_60_CNT_SOCIAL_CIRCLE',  
41 'DEF_60_CNT_SOCIAL_CIRCLE',  
42 'DAYS_LAST_PHONE_CHANGE',  
43 'FLAG_DOCUMENT_2',  
44 'FLAG_DOCUMENT_3',  
45 'FLAG_DOCUMENT_4',  
46 'FLAG_DOCUMENT_5',  
47 'FLAG_DOCUMENT_6',  
48 'FLAG_DOCUMENT_7',  
49 'FLAG_DOCUMENT_8',  
50 'FLAG_DOCUMENT_9',  
51 'FLAG_DOCUMENT_10',  
52 'FLAG_DOCUMENT_11',  
53 'FLAG_DOCUMENT_12',  
54 'FLAG_DOCUMENT_13',  
55 'FLAG_DOCUMENT_14',  
56 'FLAG_DOCUMENT_15',
```

```

57 'FLAG_DOCUMENT_16',
58 'FLAG_DOCUMENT_17',
59 'FLAG_DOCUMENT_18',
60 'FLAG_DOCUMENT_19',
61 'FLAG_DOCUMENT_20',
62 'FLAG_DOCUMENT_21',
63 'AMT_REQ_CREDIT_BUREAU_HOUR',
64 'AMT_REQ_CREDIT_BUREAU_DAY',
65 'AMT_REQ_CREDIT_BUREAU_WEEK',
66 'AMT_REQ_CREDIT_BUREAU_MON',
67 'AMT_REQ_CREDIT_BUREAU_QRT',
68 'AMT_REQ_CREDIT_BUREAU_YEAR'],axis = 1)

```

In [11]:

```

1 sns.heatmap(df.corr(),annot=True,cmap='RdYlGn',linewidths=0.2)
2 fig=plt.gcf()
3 fig.set_size_inches(40,20)
4 plt.show()

```



Observation:

AMT_GOODS_PRICE is highly correlated with AMT_CREDIT ($\rho = 0.98697$)

LIVINGAPARTMENTS_AVG is highly correlated with APARTMENTS_AVG ($\rho = 0.94558$)

LIVINGAREA_AVG is highly correlated with APARTMENTS_AVG ($\rho = 0.91463$)

REGION_RATING_CLIENT_W_CITY is highly correlated with REGION_RATING_CLIENT ($\rho = 0.95087$)

FLAG_MOBIL is having constant value so removing this...

```
In [12]: 1 df = df.drop(['AMT_GOODS_PRICE',  
2                 'FLAG_MOBIL',  
3                 'LIVINGAPARTMENTS_AVG',  
4                 'LIVINGAREA_AVG',  
5                 'REGION_RATING_CLIENT_W_CITY'],axis = 1)
```

Checking for missing values

```
In [13]: 1 df.isnull().sum()
```

```
Out[13]: SK_ID_CURR      0
TARGET      0
NAME_CONTRACT_TYPE      0
CODE_GENDER      0
FLAG_OWN_CAR      0
FLAG_OWN_REALTY      0
CNT_CHILDREN      0
AMT_INCOME_TOTAL      0
AMT_CREDIT      0
AMT_ANNUITY      11
NAME_TYPE_SUITE      1100
NAME_INCOME_TYPE      0
NAME_EDUCATION_TYPE      0
NAME_FAMILY_STATUS      0
NAME_HOUSING_TYPE      0
REGION_POPULATION_RELATIVE      0
DAYS_BIRTH      0
DAYS_EMPLOYED      0
OWN_CAR_AGE      169979
FLAG_EMP_PHONE      0
FLAG_WORK_PHONE      0
FLAG_CONT_MOBILE      0
FLAG_PHONE      0
FLAG_EMAIL      0
OCCUPATION_TYPE      80737
CNT_FAM_MEMBERS      1
REGION_RATING_CLIENT      0
WEEKDAY_APPR_PROCESS_START      0
HOUR_APPR_PROCESS_START      0
REG_REGION_NOT_LIVE_REGION      0
REG_REGION_NOT_WORK_REGION      0
LIVE_REGION_NOT_WORK_REGION      0
REG_CITY_NOT_LIVE_CITY      0
REG_CITY_NOT_WORK_CITY      0
LIVE_CITY_NOT_WORK_CITY      0
ORGANIZATION_TYPE      0
EXT_SOURCE_1      145206
EXT_SOURCE_2      534
EXT_SOURCE_3      51021
APARTMENTS_AVG      130676
BASEMENTAREA_AVG      150744
YEARS_BUILD_AVG      171249
COMMONAREA_AVG      179905
ELEVATORS_AVG      137240
ENTRANCES_AVG      129633
FLOORSMAX_AVG      128145
FLOORSMIN_AVG      174748
LANDAREA_AVG      152869
NONLIVINGAPARTMENTS_AVG      178800
NONLIVINGAREA_AVG      142110
dtype: int64
```

Fill missing values

In [14]:

```
1 df['AMT_ANNUITY'].fillna(df['AMT_ANNUITY'].mean(), inplace=True)
2 df['APARTMENTS_AVG'].fillna(df['APARTMENTS_AVG'].mean(), inplace=True)
3 df['BASEMENTAREA_AVG'].fillna(df['BASEMENTAREA_AVG'].mean(), inplace=True)
4 df['COMMONAREA_AVG'].fillna(df['COMMONAREA_AVG'].mean(), inplace=True)
5
6 df['ELEVATORS_AVG'].fillna(df['ELEVATORS_AVG'].mean(), inplace=True)
7
8 df['ENTRANCES_AVG'].fillna(df['ENTRANCES_AVG'].mean(), inplace=True)
9 df['EXT_SOURCE_1'].fillna(df['EXT_SOURCE_1'].mean(), inplace=True)
10 df['EXT_SOURCE_2'].fillna(df['EXT_SOURCE_2'].mean(), inplace = True)
11 df['EXT_SOURCE_3'].fillna(df['EXT_SOURCE_3'].mean(), inplace=True)
12 df['FLOORSMAX_AVG'].fillna(df['FLOORSMAX_AVG'].mean(), inplace=True)
13 df['FLOORSMIN_AVG'].fillna(df['FLOORSMIN_AVG'].mean(), inplace=True)
14
15
16 df['LANDAREA_AVG'].fillna(df['LANDAREA_AVG'].mean(), inplace = True)
17 df['NONLIVINGAPARTMENTS_AVG'].fillna(df['NONLIVINGAPARTMENTS_AVG'].mean(), i
18 df['NONLIVINGAREA_AVG'].fillna(df['NONLIVINGAREA_AVG'].mean(), inplace=True)
19
20 df['OCCUPATION_TYPE'].fillna(df['OCCUPATION_TYPE'].mode().values[0], inplace
21 df['OWN_CAR_AGE'].fillna(df['OWN_CAR_AGE'].mean(), inplace=True)
22
23
24 df['CNT_FAM_MEMBERS'].fillna(1, inplace=True)
25 df['AMT_ANNUITY'].fillna(df['AMT_ANNUITY'].mean(), inplace=True)
26 df['NAME_TYPE_SUITE'].fillna(df['NAME_TYPE_SUITE'].mode().values[0], inplace
27 df['YEARS_BUILD_AVG'].fillna(df['YEARS_BUILD_AVG'].mean(), inplace=True)
```

```
In [15]: 1 df.isnull().sum()
```

```
Out[15]: SK_ID_CURR          0
TARGET          0
NAME_CONTRACT_TYPE  0
CODE_GENDER      0
FLAG_OWN_CAR      0
FLAG_OWN_REALTY   0
CNT_CHILDREN      0
AMT_INCOME_TOTAL  0
AMT_CREDIT        0
AMT_ANNUITY       0
NAME_TYPE_SUITE   0
NAME_INCOME_TYPE  0
NAME_EDUCATION_TYPE  0
NAME_FAMILY_STATUS  0
NAME_HOUSING_TYPE  0
REGION_POPULATION_RELATIVE  0
DAYS_BIRTH        0
DAYS_EMPLOYED     0
OWN_CAR_AGE       0
FLAG_EMP_PHONE    0
FLAG_WORK_PHONE   0
FLAG_CONT_MOBILE  0
FLAG_PHONE        0
FLAG_EMAIL        0
OCCUPATION_TYPE   0
CNT_FAM_MEMBERS   0
REGION_RATING_CLIENT  0
WEEKDAY_APPR_PROCESS_START  0
HOUR_APPR_PROCESS_START  0
REG_REGION_NOT_LIVE_REGION  0
REG_REGION_NOT_WORK_REGION  0
LIVE_REGION_NOT_WORK_REGION  0
REG_CITY_NOT_LIVE_CITY  0
REG_CITY_NOT_WORK_CITY  0
LIVE_CITY_NOT_WORK_CITY  0
ORGANIZATION_TYPE  0
EXT_SOURCE_1      0
EXT_SOURCE_2      0
EXT_SOURCE_3      0
APARTMENTS_AVG    0
BASEMENTAREA_AVG  0
YEARS_BUILD_AVG   0
COMMONAREA_AVG    0
ELEVATORS_AVG     0
ENTRANCES_AVG     0
FLOORSMAX_AVG     0
FLOORSMIN_AVG     0
LANDAREA_AVG      0
NONLIVINGAPARTMENTS_AVG  0
NONLIVINGAREA_AVG  0
dtype: int64
```

Handle categorical variables


```
In [16]: 1 # Mark all the organization types to appropriate category.
2 def f(x):
3     if (x['ORGANIZATION_TYPE'] != 'Business Entity Type 3' and
4         x['ORGANIZATION_TYPE'] != 'XNA' and
5         x['ORGANIZATION_TYPE'] != 'Self-employed' and
6         x['ORGANIZATION_TYPE'] != 'Medicine' and
7         x['ORGANIZATION_TYPE'] != 'Government' and
8         x['ORGANIZATION_TYPE'] != 'School' and
9         x['ORGANIZATION_TYPE'] != 'Trade: type 7' and
10        x['ORGANIZATION_TYPE'] != 'Kindergarten') : return "Other"
11     else:
12         return x['ORGANIZATION_TYPE']
13
14 df['ORGANIZATION_TYPE'] = df.apply(f, axis=1)
```

one hot encoding

```
In [17]: 1 df = pd.get_dummies(df, columns=['CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REA
2                                     'NAME_CONTRACT_TYPE', 'NAM
3                                     'NAME_FAMILY_STATUS', 'NA
4                                     'NAME_INCOME_TYPE', 'NAME_
5                                     'OCCUPATION_TYPE', 'ORGANI
6                                     'WEEKDAY_APPR_PROCESS_STA
7 df.shape
```

Out[17]: (257512, 101)

Apply pandas profiling to see if anymore colinearity is there or not ?

```
In [18]: 1 #Need not to run again and again. I will update the output file,
2 #import pandas_profiling
3 #profDf = pandas_profiling.ProfileReport(df)
4 #profDf.to_file(outputfile="EDAs.html")
```

Observation:

NAME_INCOME_TYPE_Pensioner and ORGANIZATION_TYPE_XNA need to be deleted since they are causing colinearity

```
In [19]: 1 df = df.drop(['NAME_INCOME_TYPE_Pensioner', 'ORGANIZATION_TYPE_XNA'], axis = 1)
```

Check skewness if any

```
In [20]: 1 df.skew(axis = 0, skipna = True)
```

```
Out[20]: SK_ID_CURR                -0.000818
TARGET                3.077167
CNT_CHILDREN          1.993603
AMT_INCOME_TOTAL      29.963418
AMT_CREDIT            1.236943
AMT_ANNUITY           1.558330
REGION_POPULATION_RELATIVE 1.488825
DAYS_BIRTH            -0.115056
DAYS_EMPLOYED         1.661637
OWN_CAR_AGE           4.697084
FLAG_EMP_PHONE        -1.662176
FLAG_WORK_PHONE        1.504792
FLAG_CONT_MOBILE      -23.268670
FLAG_PHONE            0.970517
FLAG_EMAIL            3.824572
CNT_FAM_MEMBERS        0.994939
REGION_RATING_CLIENT  0.087365
HOUR_APPR_PROCESS_START -0.028260
REG_REGION_NOT_LIVE_REGION 7.932626
REG_REGION_NOT_WORK_REGION 4.085007
LIVE_REGION_NOT_WORK_REGION 4.638841
REG_CITY_NOT_LIVE_CITY 3.151788
REG_CITY_NOT_WORK_CITY 1.282365
LIVE_CITY_NOT_WORK_CITY 1.670053
EXT_SOURCE_1          -0.104457
EXT_SOURCE_2          -0.794435
EXT_SOURCE_3          -0.456820
APARTMENTS_AVG        3.783937
BASEMENTAREA_AVG      5.578418
YEARS_BUILD_AVG       -1.700178
...
OCCUPATION_TYPE_Cleaning staff 7.925194
OCCUPATION_TYPE_Cooking staff  6.978424
OCCUPATION_TYPE_Core staff     2.868653
OCCUPATION_TYPE_Drivers        3.689870
OCCUPATION_TYPE_HR staff       23.545563
OCCUPATION_TYPE_High skill tech staff 4.905667
OCCUPATION_TYPE_IT staff       23.966426
OCCUPATION_TYPE_Laborers       0.027730
OCCUPATION_TYPE_Low-skill Laborers 12.055907
OCCUPATION_TYPE_Managers       3.387534
OCCUPATION_TYPE_Medicine staff  5.755460
OCCUPATION_TYPE_Private service staff 10.667495
OCCUPATION_TYPE_Realty agents  20.175682
OCCUPATION_TYPE_Sales staff    2.583591
OCCUPATION_TYPE_Secretaries    15.251494
OCCUPATION_TYPE_Security staff  6.569893
OCCUPATION_TYPE_Waiters/barmen staff 15.064144
ORGANIZATION_TYPE_Government   5.164803
ORGANIZATION_TYPE_Kindergarten 6.441955
ORGANIZATION_TYPE_Medicine     4.950059
ORGANIZATION_TYPE_Other        0.739920
ORGANIZATION_TYPE_School       5.623879
ORGANIZATION_TYPE_Self-employed 2.268713
ORGANIZATION_TYPE_Trade: type 7 5.993332
```

```

WEEKDAY_APPR_PROCESS_START_MONDAY    1.811169
WEEKDAY_APPR_PROCESS_START_SATURDAY   2.489191
WEEKDAY_APPR_PROCESS_START_SUNDAY     4.004916
WEEKDAY_APPR_PROCESS_START_THURSDAY   1.806866
WEEKDAY_APPR_PROCESS_START_TUESDAY    1.707312
WEEKDAY_APPR_PROCESS_START_WEDNESDAY  1.764320
Length: 99, dtype: float64

```

Find numerical values and plot them to see the distribution

```

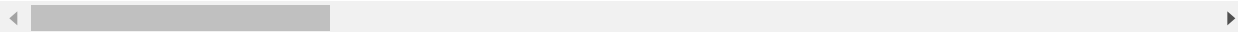
In [21]: 1 df_num = df.select_dtypes(include = ['float64', 'int64'])
          2 df_num.head()

```

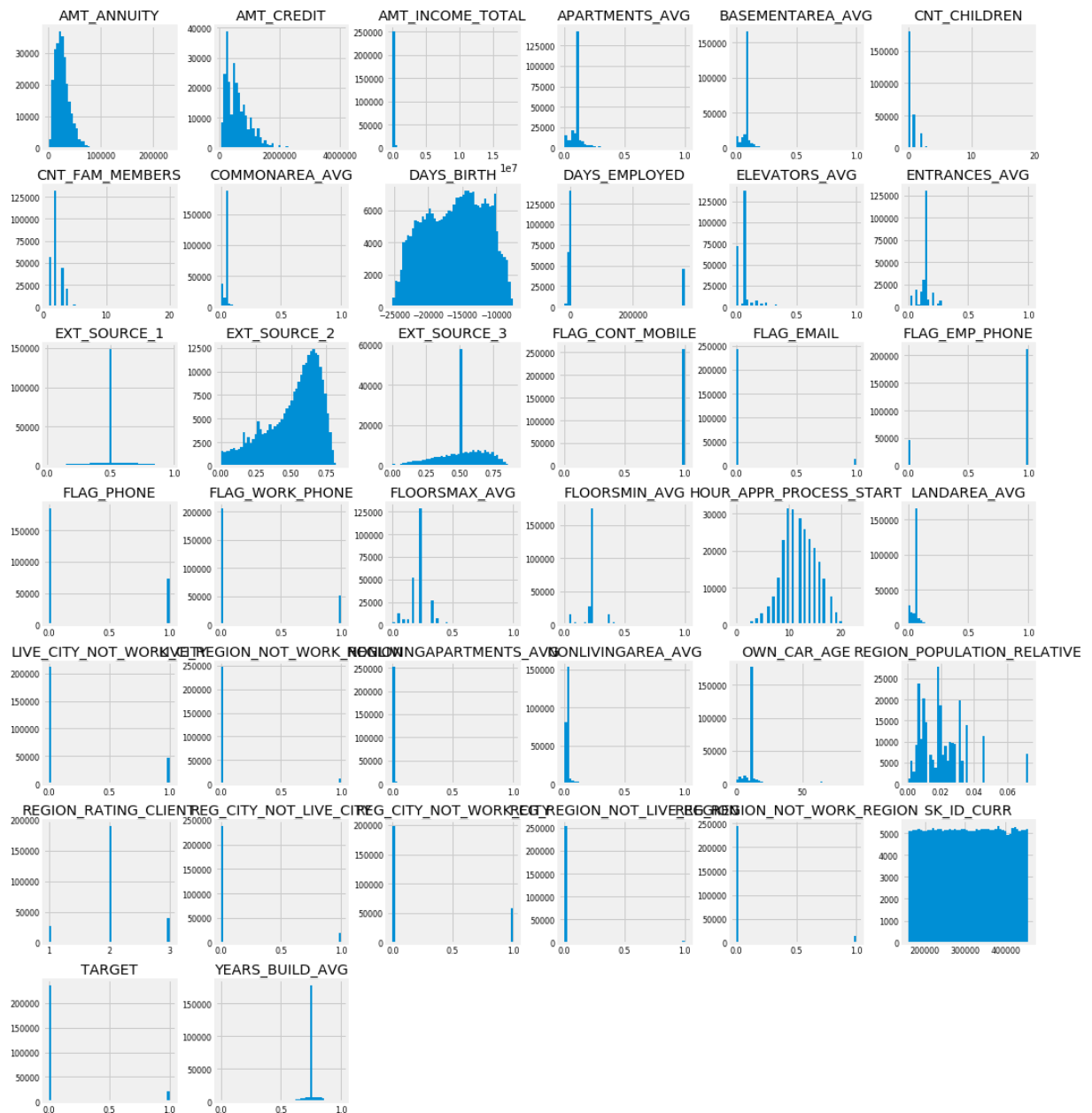
Out[21]:

	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	RI
0	157876	0	0	67500.0	343800.0	16155.0	
1	157878	0	2	247500.0	945000.0	40167.0	
2	157879	0	2	180000.0	540000.0	27000.0	
3	157880	0	0	112500.0	295168.5	16011.0	
4	157881	0	0	63000.0	298512.0	17266.5	

5 rows × 38 columns



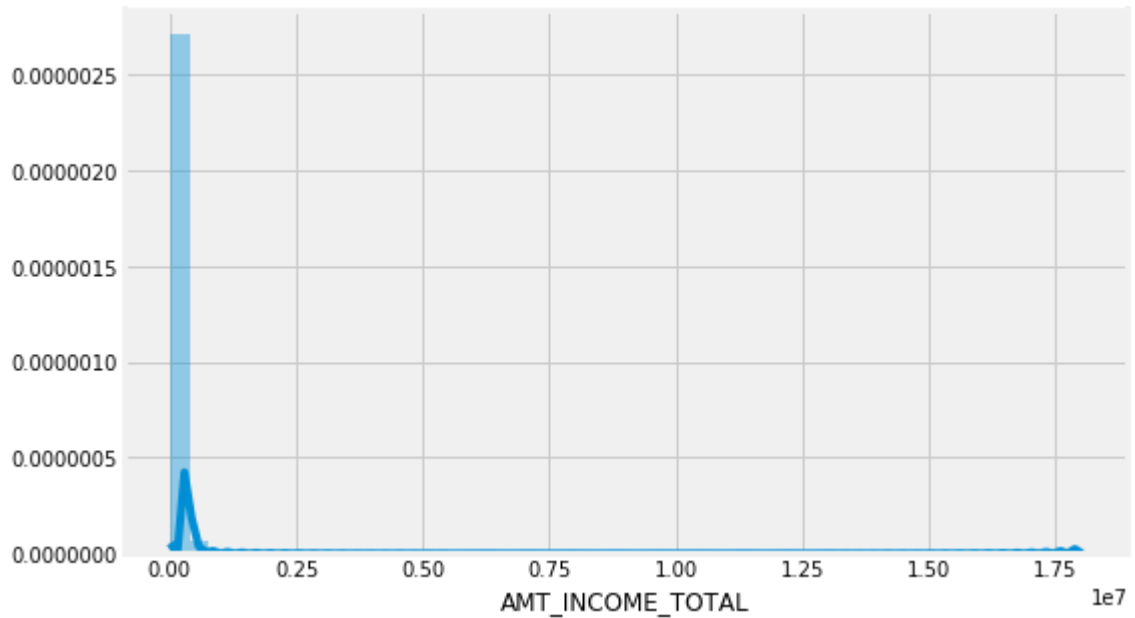
```
In [22]: 1 df_num.hist(figsize=(16, 20), bins=50, xlabelsize=8, ylabelsize=8); # ; avoid
```



Observation : AMT_INCOME_TOTAL and NONLIVINGAPARTMENTS_AVG are highly skewed. Lets normalize them using log normalization.

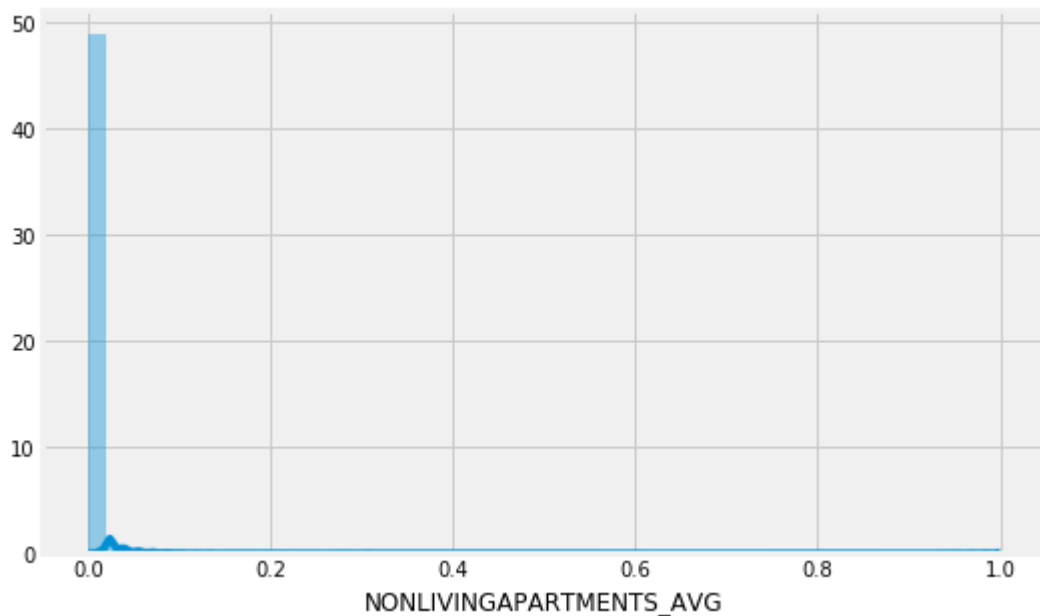
```
In [23]: 1 plt.figure(figsize=(8,5))
          2
          3 sns.distplot(df['AMT_INCOME_TOTAL'])
```

Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x1e0904a8>



```
In [24]: 1 plt.figure(figsize=(8,5))
          2
          3 sns.distplot(df['NONLIVINGAPARTMENTS_AVG'])
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x1eb59588>



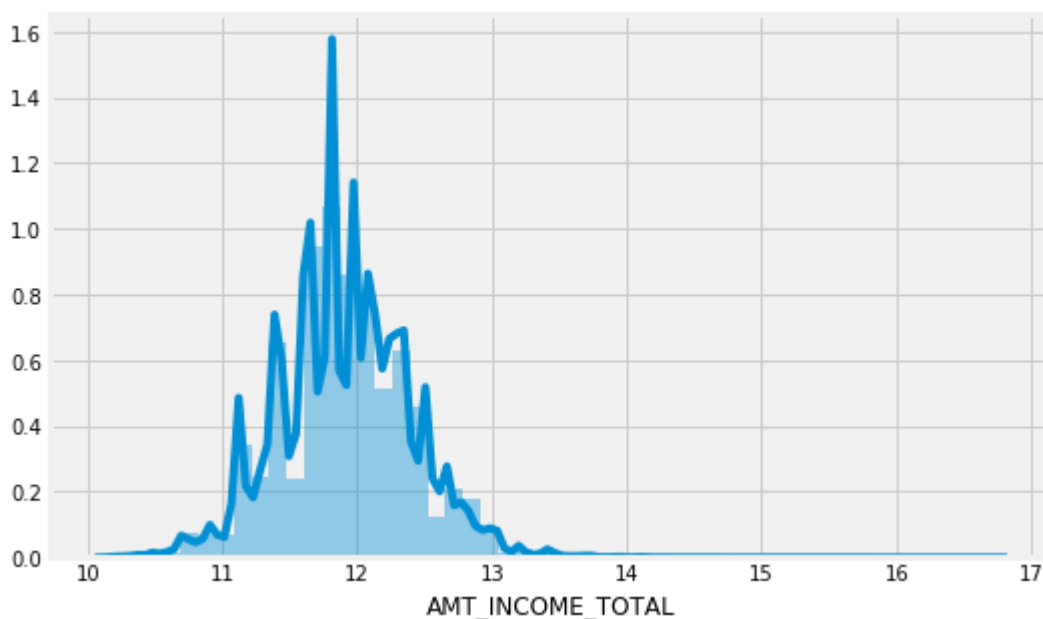
Normalizing the skewed data columns using Log normalization

```
In [25]: 1 temp_df = pd.DataFrame(df['AMT_INCOME_TOTAL'])
2
3 df_log = np.log(temp_df.AMT_INCOME_TOTAL)
4 df_log.describe()
5
6 df = df.drop('AMT_INCOME_TOTAL',axis=1)
7
8 df = df.join(df_log)
```

```
In [26]: 1 temp_df = pd.DataFrame(df['NONLIVINGAPARTMENTS_AVG'])
2
3 df_log = np.log(temp_df.NONLIVINGAPARTMENTS_AVG + 1)
4 df_log.describe()
5
6 df = df.drop('NONLIVINGAPARTMENTS_AVG',axis=1)
7
8 df = df.join(df_log)
```

```
In [27]: 1 plt.figure(figsize=(8,5))
2
3 sns.distplot(df['AMT_INCOME_TOTAL'])
```

Out[27]: <matplotlib.axes._subplots.AxesSubplot at 0x1e3bbba8>



Observation : After normalization the values follow normal distribution

Modeling

```
In [28]: 1 #Perform grid search with lesser number of data points
2 sampled_df = df.sample(frac=0.1, replace=True, random_state=1)
```

```
In [29]: 1 sy = sampledf['TARGET']
2 sX = sampledf.drop(['TARGET', 'SK_ID_CURR'],axis=1)
```

```
In [30]: 1 from sklearn.model_selection import train_test_split
2 from numpy import loadtxt
3 from xgboost import XGBClassifier
4 from sklearn.metrics import accuracy_score
5 from sklearn.model_selection import cross_val_score
6 from collections import Counter
7 from sklearn.metrics import accuracy_score
8 from sklearn.model_selection import cross_validate
9 from sklearn.model_selection import GridSearchCV
10 import warnings
11 warnings.filterwarnings("ignore")
```

Apply grid search CV for hyperparamete tuning

```
In [23]: 1 X_tr, X_t, y_tr, y_t = train_test_split(sX, sy, test_size=0.3)
```

```
In [24]: 1 X_tr, X_cv, y_tr, y_cv = train_test_split(X_tr, y_tr, test_size=0.3)
```

```
In [29]: 1 tuned_parameters = [{'max_depth': [1, 5, 10, 50, 100], 'n_estimators': [10, 50
```

```
In [30]: 1 model = GridSearchCV(XGBClassifier(), tuned_parameters, scoring = 'roc_auc',
2 model.fit(X_tr, y_tr)
3
4 print(model.best_estimator_)
5 print(model.score(X_cv, y_cv))
```

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
               colsample_bynode=1, colsample_bytree=1, gamma=0, learning_rate=0.1,
               max_delta_step=0, max_depth=1, min_child_weight=1, missing=None,
               n_estimators=200, n_jobs=1, nthread=None,
               objective='binary:logistic', random_state=0, reg_alpha=0,
               reg_lambda=1, scale_pos_weight=1, seed=None, silent=None,
               subsample=1, verbosity=1)
0.748401301996768
```

```
In [31]: 1 y = df['TARGET']
2
3 X = df.drop(['TARGET', 'SK_ID_CURR'],axis=1)
```

```
In [32]: 1 from sklearn.model_selection import train_test_split
2 def split_data():
3     return train_test_split(X, y, test_size=0.20, random_state=1)
4 X_train, X_test, y_train, y_test = split_data()
```

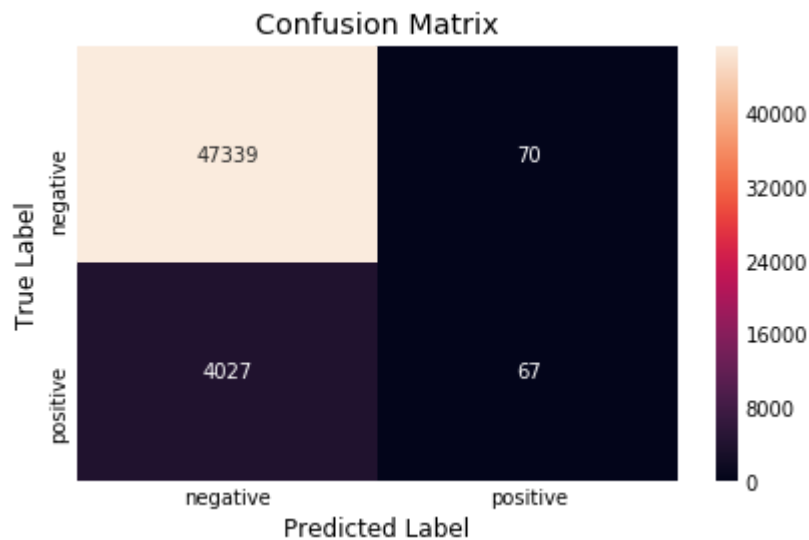
```
In [33]: 1 import xgboost as xgb
```

```
In [34]: 1 gbm = xgb.XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=
2         colsample_bynode=1, colsample_bytree=1, gamma=0,
3         learning_rate=0.1, max_delta_step=0, max_depth=5,
4         min_child_weight=1, missing=None, n_estimators=200, n_jobs=1,
5         nthread=None, objective='binary:logistic', random_state=0,
6         reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
7         silent=None, subsample=1, verbosity=1).fit(X_train, y_train)
8 predictions = gbm.predict(X_test)
```

```
In [35]: 1 def showHeatMap(con_mat):
2         class_label = ["negative", "positive"]
3         df_cm = pd.DataFrame(con_mat, index = class_label, columns = class_label)
4         sns.heatmap(df_cm, annot = True, fmt = "d")
5         plt.title("Confusion Matrix")
6         plt.xlabel("Predicted Label")
7         plt.ylabel("True Label")
8         plt.show()
```

```
In [36]: 1 from sklearn.metrics import confusion_matrix
```

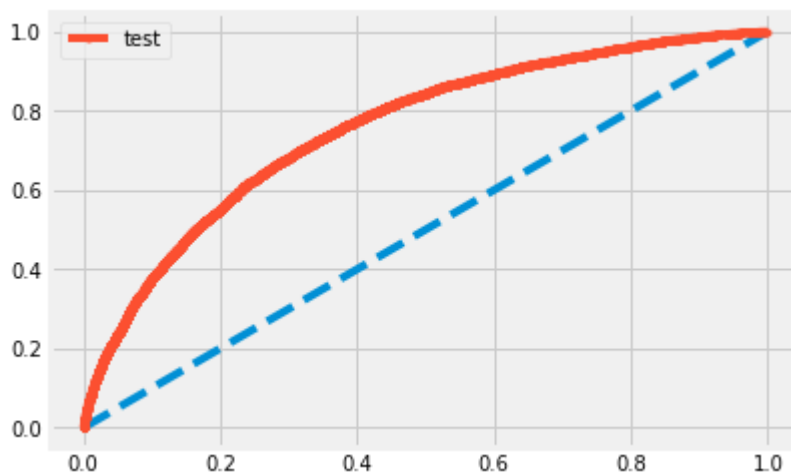
```
In [37]: 1 showHeatMap(confusion_matrix(y_test, predictions, [0, 1]))
```



Observation : My model predicted 4027 + 70 points wrongly.


```
In [38]: 1 from sklearn.metrics import accuracy_score
2 from sklearn.metrics import roc_curve, auc
3 from sklearn.metrics import roc_auc_score
4 acc = accuracy_score(y_test, predictions) * 100
5 print('\nThe accuracy of the RF classifier for %f%%' % (acc))
6 probs = gbm.predict_proba(X_test)
7 probs = probs[:, 1]
8 # calculate AUC
9 auc = roc_auc_score(y_test, probs)
10 print('AUC: %.4f' % auc)
11 # calculate roc curve
12 fpr, tpr, thresholds = roc_curve(y_test, probs)
13
14 # plot no skill
15 plt.plot([0, 1], [0, 1], linestyle='--')
16 # plot the roc curve for the model
17 plt.plot(fpr, tpr, marker='.', label='test')
18 #plt.plot(fpr1, tpr1, marker='*', label='train')
19 plt.legend()
20 # show the plot
21 plt.show()
```

The accuracy of the RF classifier for 92.045124%
AUC: 0.7559



Observation : Model is predicted with AUC: .7559 better than the Dumb model

Preparing test

```
In [39]: 1 test_df = pd.read_csv('application_test.csv')
```

```
In [40]: 1 rm_cols = ['DAYS_REGISTRATION',
2           'DAYS_ID_PUBLISH',
3           'YEARS_BEGINEXPLUATATION_AVG',
4           'APARTMENTS_MODE',
5           'BASEMENTAREA_MODE',
6           'YEARS_BEGINEXPLUATATION_MODE',
7           'YEARS_BUILD_MODE',
8           'COMMONAREA_MODE',
9           'ELEVATORS_MODE',
10          'ENTRANCES_MODE',
11          'FLOORSMAX_MODE',
12          'FLOORSMIN_MODE',
13          'LANDAREA_MODE',
14          'LIVINGAPARTMENTS_MODE',
15          'LIVINGAREA_MODE',
16          'NONLIVINGAPARTMENTS_MODE',
17          'NONLIVINGAREA_MODE',
18          'APARTMENTS_MEDI',
19          'BASEMENTAREA_MEDI',
20          'YEARS_BEGINEXPLUATATION_MEDI',
21          'YEARS_BUILD_MEDI',
22          'COMMONAREA_MEDI',
23          'ELEVATORS_MEDI',
24          'ENTRANCES_MEDI',
25          'FLOORSMAX_MEDI',
26          'FLOORSMIN_MEDI',
27          'LANDAREA_MEDI',
28          'LIVINGAPARTMENTS_MEDI',
29          'LIVINGAREA_MEDI',
30          'NONLIVINGAPARTMENTS_MEDI',
31          'NONLIVINGAREA_MEDI',
32          'FONDKAPREMONT_MODE',
33          'HOUSETYPE_MODE',
34          'TOTALAREA_MODE',
35          'WALLSMATERIAL_MODE',
36          'EMERGENCYSTATE_MODE',
37          'OBS_30_CNT_SOCIAL_CIRCLE',
38          'DEF_30_CNT_SOCIAL_CIRCLE',
39          'OBS_60_CNT_SOCIAL_CIRCLE',
40          'DEF_60_CNT_SOCIAL_CIRCLE',
41          'DAYS_LAST_PHONE_CHANGE',
42          'FLAG_DOCUMENT_2',
43          'FLAG_DOCUMENT_3',
44          'FLAG_DOCUMENT_4',
45          'FLAG_DOCUMENT_5',
46          'FLAG_DOCUMENT_6',
47          'FLAG_DOCUMENT_7',
48          'FLAG_DOCUMENT_8',
49          'FLAG_DOCUMENT_9',
50          'FLAG_DOCUMENT_10',
51          'FLAG_DOCUMENT_11',
52          'FLAG_DOCUMENT_12',
53          'FLAG_DOCUMENT_13',
54          'FLAG_DOCUMENT_14',
55          'FLAG_DOCUMENT_15',
56          'FLAG_DOCUMENT_16',
```

```

57 'FLAG_DOCUMENT_17',
58 'FLAG_DOCUMENT_18',
59 'FLAG_DOCUMENT_19',
60 'FLAG_DOCUMENT_20',
61 'FLAG_DOCUMENT_21',
62 'AMT_REQ_CREDIT_BUREAU_HOUR',
63 'AMT_REQ_CREDIT_BUREAU_DAY',
64 'AMT_REQ_CREDIT_BUREAU_WEEK',
65 'AMT_REQ_CREDIT_BUREAU_MON',
66 'AMT_REQ_CREDIT_BUREAU_QRT',
67 'AMT_REQ_CREDIT_BUREAU_YEAR',
68 'AMT_GOODS_PRICE',
69 'FLAG_MOBIL',
70 'LIVINGAPARTMENTS_AVG',
71 'LIVINGAREA_AVG',
72 'REGION_RATING_CLIENT_W_CITY']
73
74 test_df = test_df.drop(rm_cols,axis=1)

```

In [41]:

```

1 test_df['AMT_ANNUITY'].fillna(test_df['AMT_ANNUITY'].mean(), inplace=True)
2 test_df['APARTMENTS_AVG'].fillna(test_df['APARTMENTS_AVG'].mean(), inplace=True)
3 test_df['BASEMENTAREA_AVG'].fillna(test_df['BASEMENTAREA_AVG'].mean(), inplace=True)
4 test_df['COMMONAREA_AVG'].fillna(test_df['COMMONAREA_AVG'].mean(), inplace=True)
5
6 test_df['ELEVATORS_AVG'].fillna(test_df['ELEVATORS_AVG'].mean(), inplace=True)
7
8 test_df['ENTRANCES_AVG'].fillna(test_df['ENTRANCES_AVG'].mean(), inplace=True)
9 test_df['EXT_SOURCE_1'].fillna(test_df['EXT_SOURCE_1'].mean(), inplace=True)
10 test_df['EXT_SOURCE_2'].fillna(test_df['EXT_SOURCE_2'].mean(), inplace=True)
11 test_df['EXT_SOURCE_3'].fillna(test_df['EXT_SOURCE_3'].mean(), inplace=True)
12 test_df['FLOORSMAX_AVG'].fillna(test_df['FLOORSMAX_AVG'].mean(), inplace=True)
13 test_df['FLOORSMIN_AVG'].fillna(test_df['FLOORSMIN_AVG'].mean(), inplace=True)
14
15
16 test_df['LANDAREA_AVG'].fillna(test_df['LANDAREA_AVG'].mean(), inplace=True)
17 test_df['NONLIVINGAPARTMENTS_AVG'].fillna(test_df['NONLIVINGAPARTMENTS_AVG'].mean(), inplace=True)
18 test_df['NONLIVINGAREA_AVG'].fillna(test_df['NONLIVINGAREA_AVG'].mean(), inplace=True)
19
20 test_df['OCCUPATION_TYPE'].fillna(test_df['OCCUPATION_TYPE'].mode().values[0], inplace=True)
21 test_df['OWN_CAR_AGE'].fillna(test_df['OWN_CAR_AGE'].mean(), inplace=True)
22
23
24 test_df['CNT_FAM_MEMBERS'].fillna(1, inplace=True)
25 test_df['AMT_ANNUITY'].fillna(test_df['AMT_ANNUITY'].mean(), inplace=True)
26 test_df['NAME_TYPE_SUITE'].fillna(test_df['NAME_TYPE_SUITE'].mode().values[0], inplace=True)
27 test_df['YEARS_BUILD_AVG'].fillna(test_df['YEARS_BUILD_AVG'].mean(), inplace=True)

```

```
In [42]: 1 def f(x):
2         if (x['ORGANIZATION_TYPE'] != 'Business Entity Type 3' and
3             x['ORGANIZATION_TYPE'] != 'XNA' and
4             x['ORGANIZATION_TYPE'] != 'Self-employed' and
5             x['ORGANIZATION_TYPE'] != 'Medicine' and
6             x['ORGANIZATION_TYPE'] != 'Government' and
7             x['ORGANIZATION_TYPE'] != 'School' and
8             x['ORGANIZATION_TYPE'] != 'Trade: type 7' and
9             x['ORGANIZATION_TYPE'] != 'Kindergarten') : return "Other"
10        else:
11            return x['ORGANIZATION_TYPE']
12        test_df['ORGANIZATION_TYPE'] = test_df.apply(f, axis=1)
```

```
In [43]: 1 test_df= pd.get_dummies(test_df, columns=['CODE_GENDER', 'FLAG_OWN_CAR', 'FLA
2                                                'NAME_CONTRACT_TYPE', 'NAM
3                                                'NAME_FAMILY_STATUS', 'NA
4                                                'NAME_INCOME_TYPE', 'NAME_
5                                                'OCCUPATION_TYPE', 'ORGANI
6                                                'WEEKDAY_APPR_PROCESS_STA
```

```
In [44]: 1 test_df = test_df.drop(['NAME_INCOME_TYPE_Pensioner', 'ORGANIZATION_TYPE_XNA']
```

```
In [45]: 1 temp_df = pd.DataFrame(test_df['AMT_INCOME_TOTAL'])
2
3         df_log = np.log(temp_df.AMT_INCOME_TOTAL + 1)
4         df_log.describe()
5
6         test_df = test_df.drop('AMT_INCOME_TOTAL',axis=1)
7
8         test_df = test_df.join(df_log)
9
10        temp_df = pd.DataFrame(test_df['NONLIVINGAPARTMENTS_AVG'])
11
12        df_log = np.log(temp_df.NONLIVINGAPARTMENTS_AVG + 1)
13        df_log.describe()
14
15        test_df = test_df.drop('NONLIVINGAPARTMENTS_AVG',axis=1)
16
17        test_df = test_df.join(df_log)
```

```
In [46]: 1 Xtest = test_df.drop(['SK_ID_CURR'],axis=1)
```

```
In [47]: 1 test_pred = gbm.predict(Xtest)
2
3 print(type(test_pred))
4
5 id = test_df['SK_ID_CURR']
6 id_arr = id.as_matrix()
7 tar = test_pred.reshape(-1)
8
9 saved_df = pd.DataFrame({'SK_ID_CURR':id_arr,'TARGET':tar})
10
11 saved_df.to_csv("output_final.csv",index=False)

<class 'numpy.ndarray'>
```

```
In [ ]: 1
```