Home Credit Default Risk

1.Business/Real-world Problem

1.1 Problem Statement

Build a model which can predict how capable each applicant is of repaying a loan.

1.2 Source/Useful Links

https://www.kaggle.com/c/home-credit-default-risk/team (https://www.kaggle.com/c/home-credit-default-risk/team)

1.3 Real-world/Business objectives and constraints.

- No strict latency constraints.
- Interpretability is important.
- Mis-Classification cost is very high.

2. Machine Learning Problem

2.1 Data Description

application_{train|test}.csv

- This is the main table, broken into two files for Train (with TARGET) and Test (without TARGET).
- Static data for all applications. One row represents one loan in our data sample.

bureau.csv

- All client's previous credits provided by other financial institutions that were reported to Credit Bureau (for clients who have a loan in our sample).
- For every loan in our sample, there are as many rows as number of credits the client had in Credit Bureau before the application date.

bureau_balance.csv

- Monthly balances of previous credits in Credit Bureau.
- This table has one row for each month of history of every previous credit reported to Credit Bureau – i.e the table has (#loans in sample * # of relative previous credits * # of months where we have some history observable for the previous credits) rows.

POS_CASH_balance.csv

- Monthly balance snapshots of previous POS (point of sales) and cash loans that the applicant had with Home Credit.
- This table has one row for each month of history of every previous credit in Home Credit (consumer credit and cash loans) related to loans in our sample – i.e. the table has (#loans in sample * # of relative previous credits * # of months in which we have some history observable for the previous credits) rows.

credit_card_balance.csv

- Monthly balance snapshots of previous credit cards that the applicant has with Home Credit.
- This table has one row for each month of history of every previous credit in Home Credit (consumer credit and cash loans) related to loans in our sample – i.e. the table has (#loans in sample * # of relative previous credit cards * # of months where we have some history observable for the previous credit card) rows.

previous_application.csv

- All previous applications for Home Credit loans of clients who have loans in our sample.
- There is one row for each previous application related to loans in our data sample.

installments_payments.csv

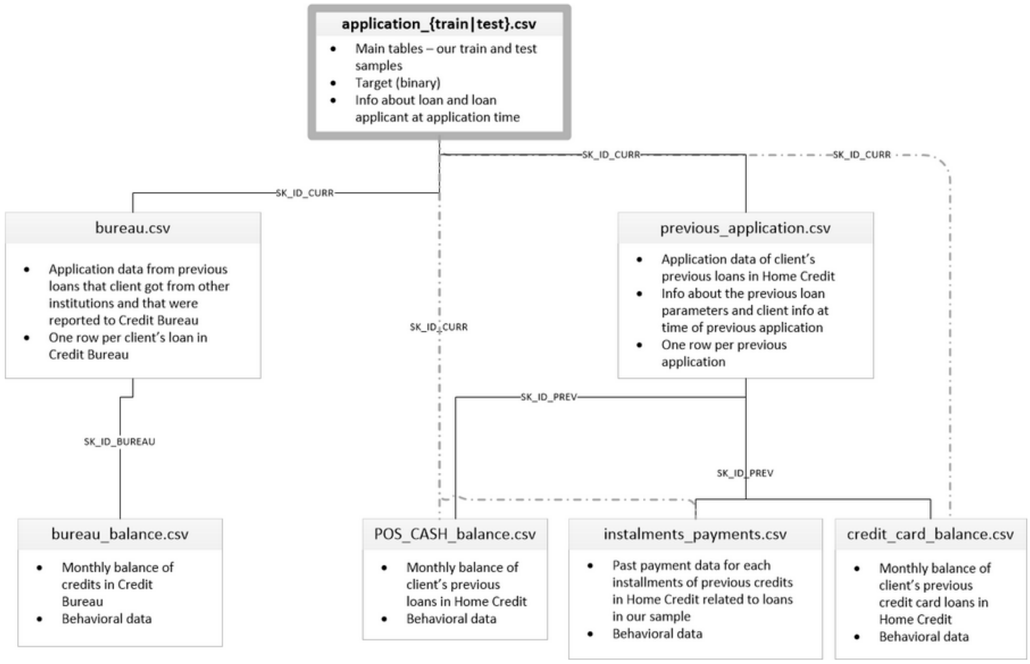
- Repayment history for the previously disturbed credits in Home Credit related to the loans in our sample.
- There is a) one row for every payment that was made plus b) one row each for missed payment.
- One row is equivalent to one payment of one installment OR one installment corresponding to one payment of one previous Home Credit credit related to loans in our sample.

HomeCredit_columns_description.csv

- This file contains descriptions for the columns in the various data files.

In [0]:
```
1 from IPython.display import Image
2 Image(filename='flow.png')
```

Out[1]:



2.2 Type of Machine Learning Problem

It is a binary class classification problem where 0 means person is capable of repaying a loan and 1 means person is not capable of repaying a loan.

2.3 Performance Metric

- AUC
- Confusion matrix

3. Download the dataset

In [1]:
```
1 !wget --header="Host: storage.googleapis.com" --header="User-Agent: Moz
```

```
--2020-02-03 05:19:17--  https://storage.googleapis.com/kaggle-competitions-data/kaggle-v2/9120/860599/bundle/archive.zip?GoogleAccessId=web-data@kaggle-161607.iam.gserviceaccount.com&Expires=1580916655&Signature=N8bGIc9z3FSFcDpTb9x%2FET5xG5B%2FOdlkxUKQ6hWVwr%2FVyoxki6x%2BBtVlyvckcPiP5nLDP5KvqrmlxBkKcIVkYK8JQTe%2BGY6fL2YMQlVht5Fld1wO6cnJikB8Yp2vyuC2RZYt5QSXva6MID%2BpvWI8njIYHMMTpffTXVE8W5ubeaRlt3fUYb2ar8nHUkAfK4fwCjacF14HvGcDYCwKskN3o9YWItM80mY2%2BG1UiQKvDFWsST4lM6hsEKd87xHo09O0OK0WDjFIwGCfpw%2BYgbG0SDn8uZb%2FF4vMKdBZK4vMbpLIEl05Ds1T2%2FOd2I4mkICjVa8ZqFpYIv6jAOtLmdAkFQ%3D%3D&response-content-disposition=attachment%3B+filename%3Dhome-credit-default-risk.zip (https://storage.googleapis.com/kaggle-competitions-data/kaggle-v2/9120/860599/bundle/archive.zip?GoogleAccessId=web-data@kaggle-161607.iam.gserviceaccount.com&Expires=1580916655&Signature=N8bGIc9z3FSFcDpTb9x%2FET5xG5B%2FOdlkxUKQ6hWVwr%2FVyoxki6x%2BBtVlyvckcPiP5nLDP5KvqrmlxBkKcIVkYK8JQTe%2BGY6fL2YMQlVht5Fld1wO6cnJikB8Yp2vyuC2RZYt5QSXva6MID%2BpvWI8njIYHMMTpffTXVE8W5ubeaRlt3fUYb2ar8nHUkAfK4fwCjacF14HvGcDYCwKskN3o9YWItM80mY2%2BG1UiQKvDFWsST4lM6hsEKd87xHo09O0OK0WDjFIwGCfpw%2BYgbG0SDn8uZb%2FF4vMKdBZK4vMbpLIEl05Ds1T2%2FOd2I4mkICjVa8ZqFpYIv6jAOtLmdAkFQ%3D%3D&response-content-disposition=attachment%3B+filename%3Dhome-credit-default-risk.zip)
Resolving storage.googleapis.com (storage.googleapis.com)... 108.177.97.128, 2404:6800:4008:c04::80
Connecting to storage.googleapis.com (storage.googleapis.com)|108.177.97.128|:443... connected.
HTTP request sent, awaiting response... 200 OK
Length: 721616255 (688M) [application/zip]
Saving to: ‘home-credit-default-risk.zip’

home-credit-default 100%[===================>] 688.19M  45.4MB/s    in 14s

2020-02-03 05:19:32 (47.5 MB/s) - ‘home-credit-default-risk.zip’ saved [721616255/721616255]
```

In [2]:
```
1 !unzip /content/home-credit-default-risk.zip
```

```
Archive:  /content/home-credit-default-risk.zip
  inflating: HomeCredit_columns_description.csv
  inflating: POS_CASH_balance.csv
  inflating: application_test.csv
  inflating: application_train.csv
  inflating: bureau.csv
  inflating: bureau_balance.csv
  inflating: credit_card_balance.csv
  inflating: installments_payments.csv
  inflating: previous_application.csv
  inflating: sample_submission.csv
```

4. Include packages

In [0]:
```
import warnings
warnings.filterwarnings("ignore")
import shutil
import os
import pandas as pd
import matplotlib
matplotlib.use(u'nbAgg')
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
import pickle
from sklearn.manifold import TSNE
from sklearn import preprocessing
import pandas as pd
from multiprocessing import Process# this is used for multithreading
import multiprocessing
import codecs# this is used for file operations
import random as r
from xgboost import XGBClassifier
from sklearn.model_selection import RandomizedSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import log_loss
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
import math
from math import log
%matplotlib inline
import gc
import pickle
from lightgbm import LGBMClassifier
from sklearn.metrics import roc_auc_score, roc_curve,auc
from sklearn.model_selection import KFold, StratifiedKFold
import seaborn as sns
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

```

5. Perform EDA

In [0]:
```
Df_application_train=pd.read_csv("application_train.csv")
```

In [0]:
```
1 Df_application_train
```

Out[6]:

	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_I
0	100002	1	Cash loans	M	N	
1	100003	0	Cash loans	F	N	
2	100004	0	Revolving loans	M	Y	
3	100006	0	Cash loans	F	N	
4	100007	0	Cash loans	M	N	
...	...	...	...	...	...	
307506	456251	0	Cash loans	M	N	
307507	456252	0	Cash loans	F	N	
307508	456253	0	Cash loans	F	N	
307509	456254	1	Cash loans	F	N	
307510	456255	0	Cash loans	F	N	

307511 rows × 122 columns

In [0]:
```
1 Df_application_train.TARGET.value_counts()
```

Out[7]:
```
0    282686
1     24825
Name: TARGET, dtype: int64
```

The dataset is highly imbalanced. There are more number of person in the dataset who are capable of giving the loan.

In [0]:
```
1 Df_application_train.columns
```

Out[133]:
```
Index(['SK_ID_CURR', 'TARGET', 'NAME_CONTRACT_TYPE', 'CODE_GENDER',
       'FLAG_OWN_CAR', 'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTA
L',
       'AMT_CREDIT', 'AMT_ANNUITY',
       ...
       'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
       'FLAG_DOCUMENT_21', 'AMT_REQ_CREDIT_BUREAU_HOUR',
       'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
       'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object', length=122)
```

In [0]:
```
1 Df_application_train.NAME_CONTRACT_TYPE.unique()
```

Out[134]:
```
array(['Cash loans', 'Revolving loans'], dtype=object)
```

In [0]:
```
1 Df_application_test=pd.read_csv("application_test.csv")
```

In [0]:
```
Df_application_test.columns
```

Out[11]:
```
Index(['SK_ID_CURR', 'NAME_CONTRACT_TYPE', 'CODE_GENDER', 'FLAG_OWN_CAR',
       'FLAG_OWN_REALTY', 'CNT_CHILDREN', 'AMT_INCOME_TOTAL', 'AMT_CREDIT
',
       'AMT_ANNUITY', 'AMT_GOODS_PRICE',
       ...
       'FLAG_DOCUMENT_18', 'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20',
       'FLAG_DOCUMENT_21', 'AMT_REQ_CREDIT_BUREAU_HOUR',
       'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK',
       'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT',
       'AMT_REQ_CREDIT_BUREAU_YEAR'],
      dtype='object', length=121)
```

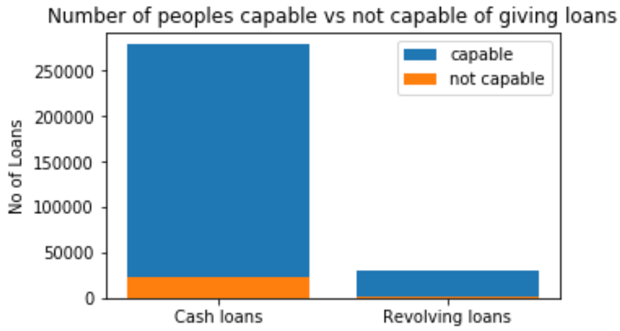
Function to plot bar graph

In [0]:
```
def stack_plot(data, xtick, col2, col3='total'):
    ind = np.arange(data.shape[0])
    %matplotlib inline
    plt.figure(figsize=(10,3))
    p1 = plt.bar(ind, data[col3].values)
    p2 = plt.bar(ind, data[col2].values)
    plt.ylabel('No of Loans')
    plt.title('Number of peoples capable vs not capable of giving loans
    plt.xticks(ind, list(data[xtick].values),rotation=-90)
    plt.legend((p1[0], p2[0]), ('capable', 'not capable'))
    plt.show()
def univariate_barplots(data, col1, col2, top=False):
    # Count number of zeros in dataframe python: https://stackoverflow.
    temp = pd.DataFrame(Df_application_train.groupby(col1)[col2].agg(la

    # Pandas dataframe grouby count: https://stackoverflow.com/a/193855
    temp['total'] = pd.DataFrame(Df_application_train.groupby(col1)[col

    temp['Avg'] = pd.DataFrame(Df_application_train.groupby(col1)[col2]

    temp.sort_values(by=['total'],inplace=True, ascending=False)

    if top:
        temp = temp[0:top]

    stack_plot(temp, xtick=col1, col2=col2, col3='total')

```

6. Analysis on application.csv file

6.1 Identification if loan is cash or revolving

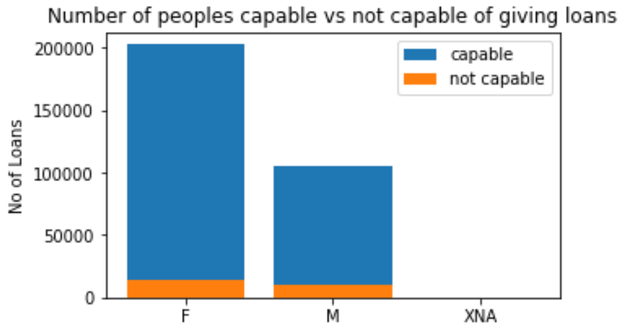
In [0]:
```
univariate_barplots(Df_application_train, 'NAME_CONTRACT_TYPE', 'TARGET
```



observation:Many people took cash loans.

6.2 Gender of the client

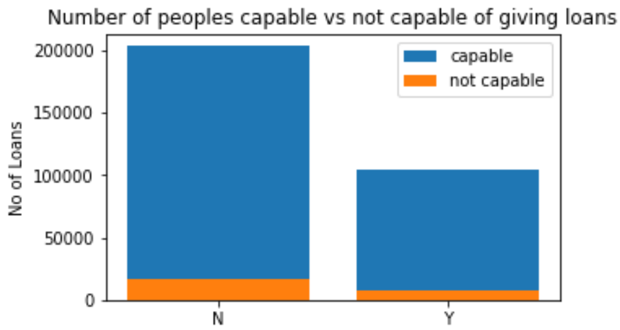
In [0]:
```
1 univariate_barplots(Df_application_train, 'CODE_GENDER', 'TARGET' , top
```



observation : Female took more no of loans then males.

6.3 Flag if the client owns a car

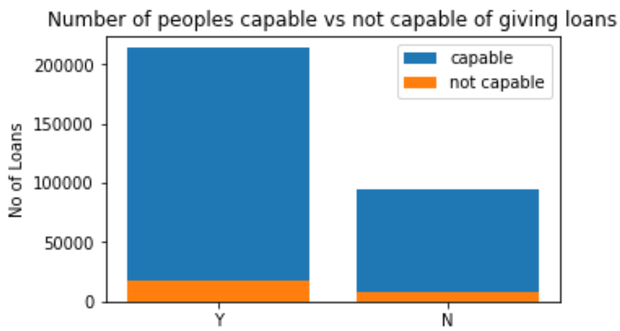
In [0]:
```
1 univariate_barplots(Df_application_train, 'FLAG_OWN_CAR', 'TARGET' , to
```



observation : People who own a car took less no of loan.

6.4 Flag if client owns a house or flat

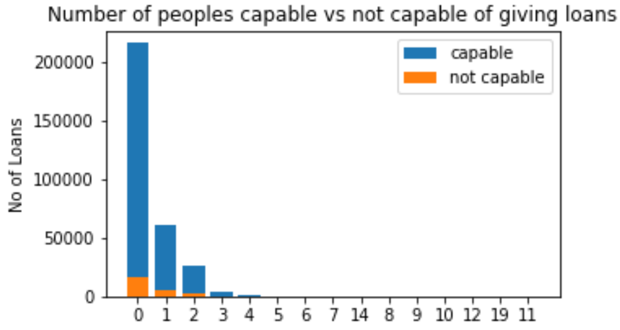
In [0]:
```
1 univariate_barplots(Df_application_train, 'FLAG_OWN_REALTY', 'TARGET' ,
```



observation : People who owns a house or flat takes more no of loans.

6.5 Number of children the client has

In [0]:
```
1 univariate_barplots(Df_application_train, 'CNT_CHILDREN', 'TARGET' , to
```



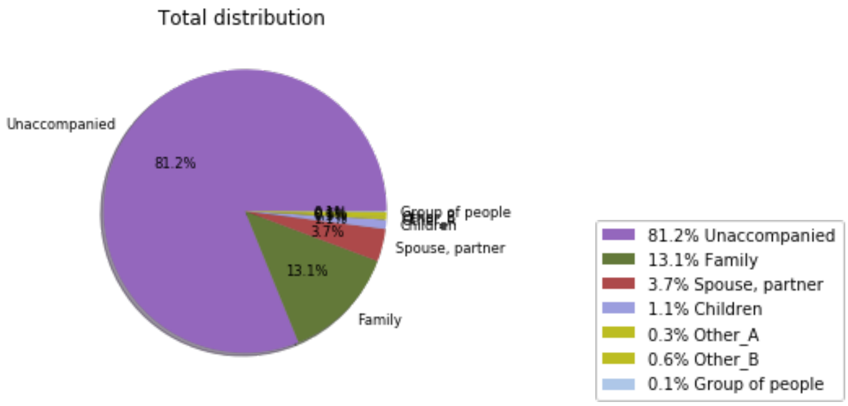
observation : Clients having no child take more no of loans and are also more defaulters.

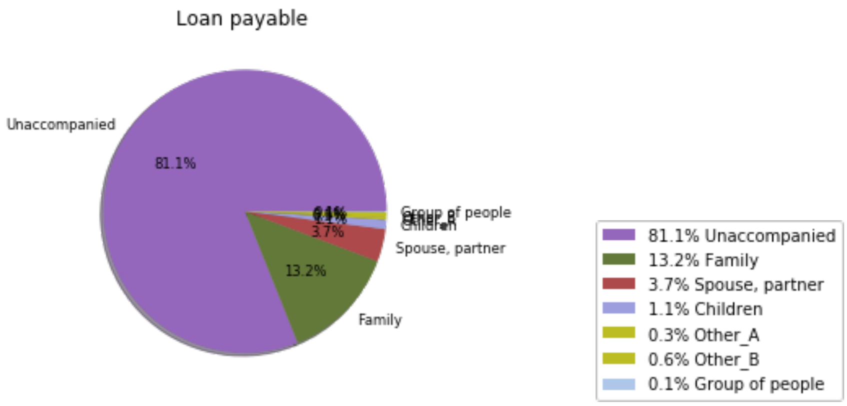
Function to plot pie chart

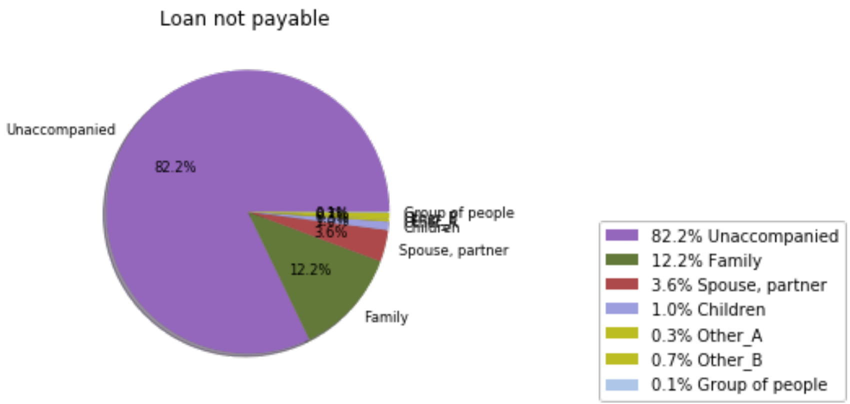
In [0]:
```
def labelupdate(autotexts,labels):
  l=[]
  for i in range(len(labels)):
    l.append(str(autotexts[i]._text) + ' ' + str(labels[i]))
  return(l)

def plotpiechart(s):
  %matplotlib inline
  import random
  labels=list(Df_application_train[s].unique())
  labels=[x for x in labels if (str(x)!='nan')]
  fracs1=[]
  fracs2=[]
  fracs3=[]
  for x in labels:
    count1 = sum(Df_application_train[s]==x)
    fracs1.append(count1)
    count2 = sum(Df_application_train[Df_application_train['TARGET']==0
    fracs2.append(count2)
    count3 = sum(Df_application_train[Df_application_train['TARGET']==1
    fracs3.append(count3)
  colors=["#9c9ede", "#7375b5", "#4a5584", "#cedb9c", "#b5cf6b", "#8ca2
        "#e7cb94", "#e7ba52", "#bd9e39", "#8c6d31", "#e7969c", "#d6616b
        "#843c39", "#de9ed6", "#ce6dbd", "#a55194", "#7b4173","#1f77b4"
        "#ff7f0e", "#ffbb78", "#2ca02c", "#98df8a", "#d62728", "#ff9896
        "#c5b0d5", "#8c564b", "#c49c94", "#e377c2", "#f7b6d2", "#7f7f7f
        "#bcbd22", "#dbdb8d", "#17becf", "#9edae5","#1f77b4", "#ff7f0e"
        "#d62728", "#9467bd", "#8c564b", "#e377c2", "#7f7f7f", "#bcbd22
  colors=random.sample(colors, len(labels))
  plt.title("Total distribution ")

  patches,texts,autotexts=plt.pie(fracs1, labels=labels, colors=colors,
  l=labelupdate(autotexts,labels)
  plt.legend(patches,l, bbox_to_anchor=(1,0.5), loc="best", fontsize=10
  plt.show()
  plt.title("Loan payable ")
  patches,texts,autotexts=plt.pie(fracs2, labels=labels, colors=colors,
  l=labelupdate(autotexts,labels)
  plt.legend(patches,l, bbox_to_anchor=(1,0.5), loc="best", fontsize=10
  plt.show()
  plt.title("Loan not payable ")
  patches,texts,autotexts=plt.pie(fracs3, labels=labels, colors=colors,
  l=labelupdate(autotexts,labels)
  plt.legend(patches,l, bbox_to_anchor=(1,0.5), loc="best", fontsize=10
  plt.show()
```

6.6 Who was accompanying client when he was applying for the loan

In [0]:
```
plotpiechart('NAME_TYPE_SUITE')
```



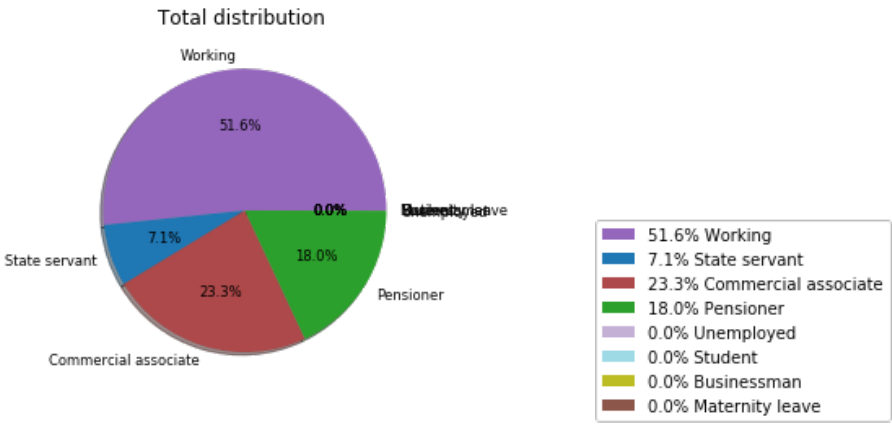


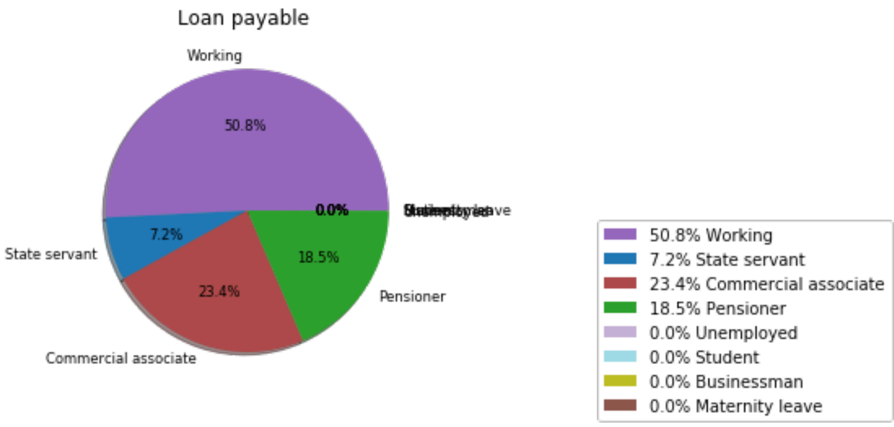


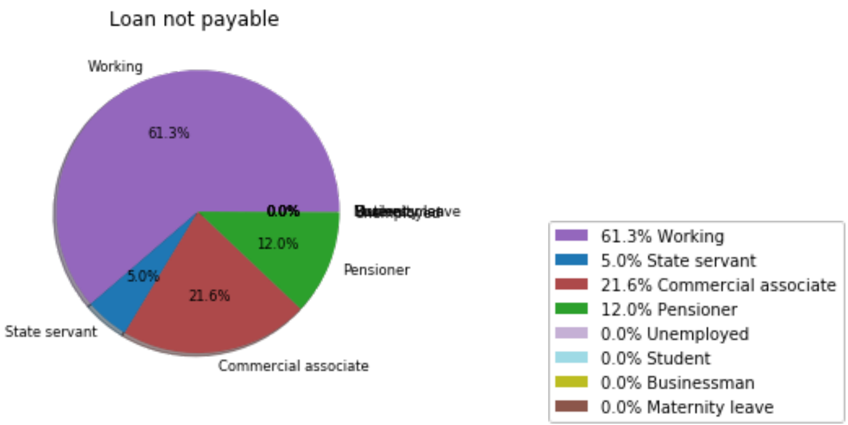
observation : Client who came alone took more loan but also were more defaulters.

6.7 Clients income type (Working,State servant,Commercial associate,Pensioner,Unemployed,Student,Businessman,Maternity leave)

In [0]:
```
plotpiechart('NAME_INCOME_TYPE')
```



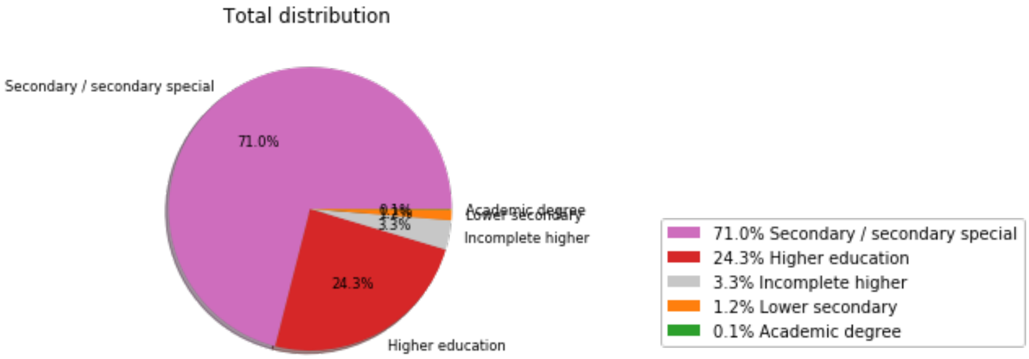


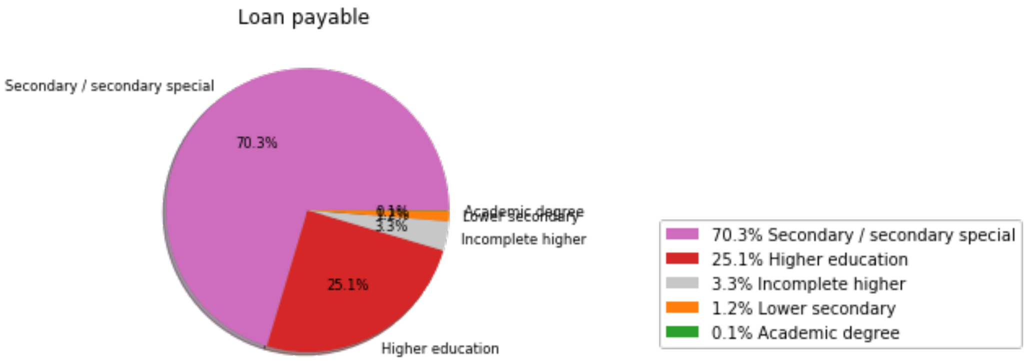


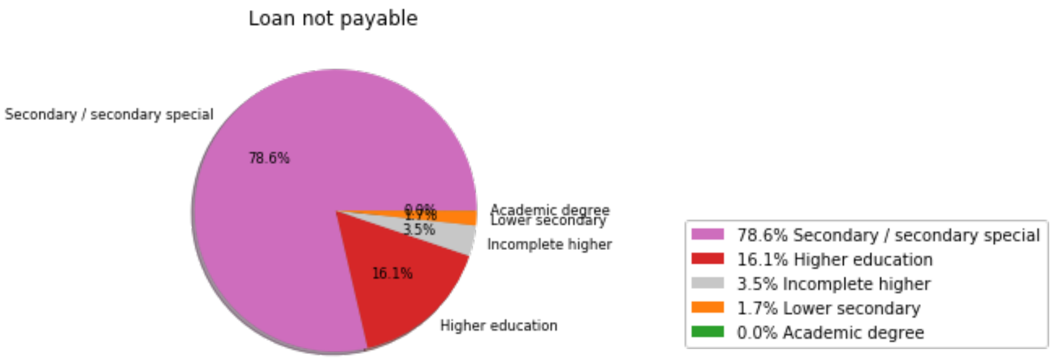
observation : clients with income type working take more no of loans.

6.8 Level of highest education the client achieved.

In [0]:
```
1 plotpiechart('NAME_EDUCATION_TYPE')
```



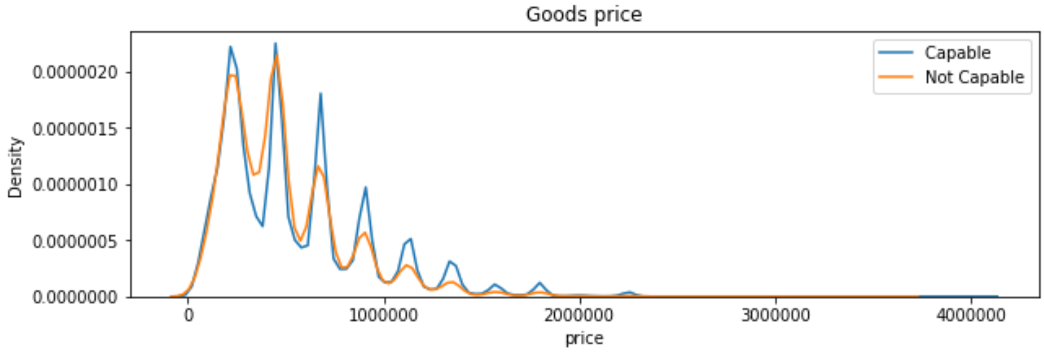




observation : people with highest degree as secondary and secondary special are more no of defaulters compare to people with other degree.

6.9 For consumer loans it is the price of the goods for which the loan is given

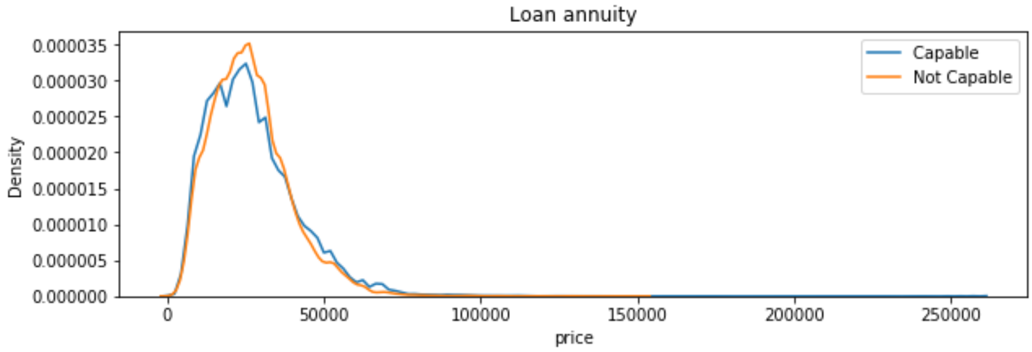
In [0]:
```
from math import log

count1 = Df_application_train[Df_application_train['TARGET']==0]['AMT_G
count1 = count1.values
count1=[x for x in count1 if (str(x)!='nan')]
count2 = Df_application_train[Df_application_train['TARGET']==1]['AMT_G
count2 = count2.values
count2=[x for x in count2 if (str(x)!='nan')]
plt.figure(figsize=(10,3))
sns.distplot(count1, hist=False, label="Capable ")
sns.distplot(count2, hist=False, label="Not Capable")
plt.title('Goods price')
plt.xlabel('price')
plt.ylabel('Density')
plt.legend()
plt.show()
```



Observation: Most no of loans are given for goods price below 10 lakhs

6.10 Loan annuity

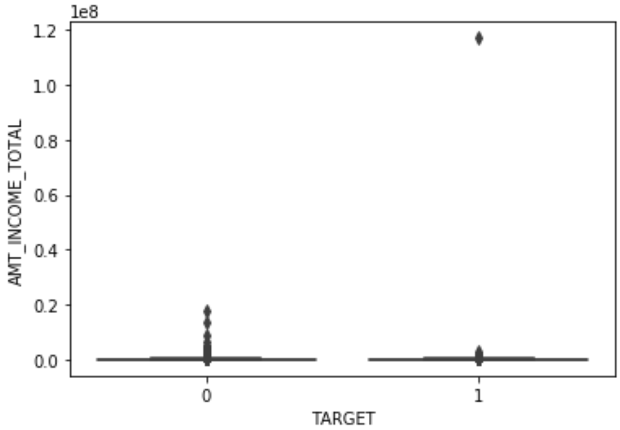
In [5]:
```
from math import log

count1 = Df_application_train[Df_application_train['TARGET']==0]['AMT_A
count1 = count1.values
count1=[x for x in count1 if (str(x)!='nan')]
count2 = Df_application_train[Df_application_train['TARGET']==1]['AMT_A
count2 = count2.values
count2=[x for x in count2 if (str(x)!='nan')]
plt.figure(figsize=(10,3))
sns.distplot(count1, hist=False, label="Capable ")
sns.distplot(count2, hist=False, label="Not Capable")
plt.title('Loan annuity')
plt.xlabel('price')
plt.ylabel('Density')
plt.legend()
plt.show()

```



observation : Most people pay annuity below 50000 for the credit loan

6.11 : Income of the client

In [0]:
```
sns.boxplot(x='TARGET',y='AMT_INCOME_TOTAL', data=Df_application_train)
plt.show()
```



We can't say anything here let's check the percentile

In [0]:
```
v=Df_application_train['AMT_INCOME_TOTAL'].values
v=np.sort(v)
for i in range(0,100,10):
  print(i,'percentile value is',v[int(len(v)*float(i)/100)])
print(100,'percentile value is',v[-1])
```

```
0 percentile value is 25650.0
10 percentile value is 81000.0
20 percentile value is 99000.0
30 percentile value is 112500.0
40 percentile value is 135000.0
50 percentile value is 147150.0
60 percentile value is 162000.0
70 percentile value is 180000.0
80 percentile value is 225000.0
90 percentile value is 270000.0
100 percentile value is 117000000.0
```

In [0]:
```
v=Df_application_train['AMT_INCOME_TOTAL'].values
v=np.sort(v)
for i in range(90,100,1):
  print(i,'percentile value is',v[int(len(v)*float(i)/100)])
print(100,'percentile value is',v[-1])
```

```
90 percentile value is 270000.0
91 percentile value is 270000.0
92 percentile value is 292500.0
93 percentile value is 315000.0
94 percentile value is 315000.0
95 percentile value is 337500.0
96 percentile value is 360000.0
97 percentile value is 382500.0
98 percentile value is 427500.0
99 percentile value is 472500.0
100 percentile value is 117000000.0
```

In [0]:
```
v=Df_application_train['AMT_INCOME_TOTAL'].values
v=np.sort(v)
for i in np.arange(0.0,1.0,0.1):
  print(99+i,'percentile value is',v[int(len(v)*float(99+i)/100)])
print(100,'percentile value is',v[-1])
```

```
99.0 percentile value is 472500.0
99.1 percentile value is 495000.0
99.2 percentile value is 540000.0
99.3 percentile value is 540000.0
99.4 percentile value is 562500.0
99.5 percentile value is 630000.0
99.6 percentile value is 675000.0
99.7 percentile value is 675000.0
99.8 percentile value is 765000.0
99.9 percentile value is 900000.0
100 percentile value is 117000000.0
```

In [0]:

```
v=Df_application_train['AMT_INCOME_TOTAL'].values
v=np.sort(v)
for i in np.arange(0.90,1.0,0.01):
  print(99+i,'percentile value is',v[int(len(v)*float(99+i)/100)])
print(100,'percentile value is',v[-1])
```

```
99.9 percentile value is 900000.0
99.91 percentile value is 909000.0
99.92 percentile value is 1035000.0
99.93 percentile value is 1125000.0
99.94 percentile value is 1125000.0
99.95 percentile value is 1215000.0
99.96 percentile value is 1350000.0
99.97 percentile value is 1350000.0
99.98 percentile value is 1800000.0
99.99 percentile value is 2250000.0
100 percentile value is 117000000.0
```

In [0]:

```
v=Df_application_train['AMT_INCOME_TOTAL'].values
v=np.sort(v)
for i in np.arange(0.99,0.999,0.001):
  print(99+i,'percentile value is',v[int(len(v)*float(99+i)/100)])
print(100,'percentile value is',v[-1])
```

```
99.99 percentile value is 2250000.0
99.991 percentile value is 2250000.0
99.992 percentile value is 2250000.0
99.993 percentile value is 2250000.0
99.994 percentile value is 2700000.0
99.995 percentile value is 3150000.0
99.996 percentile value is 3600000.0
99.997 percentile value is 3950059.5
99.998 percentile value is 4500000.0
99.999 percentile value is 9000000.0
100 percentile value is 117000000.0
```

In [0]:

```
Df_application_train[Df_application_train['AMT_INCOME_TOTAL']>9000000]
```

Out[279]:

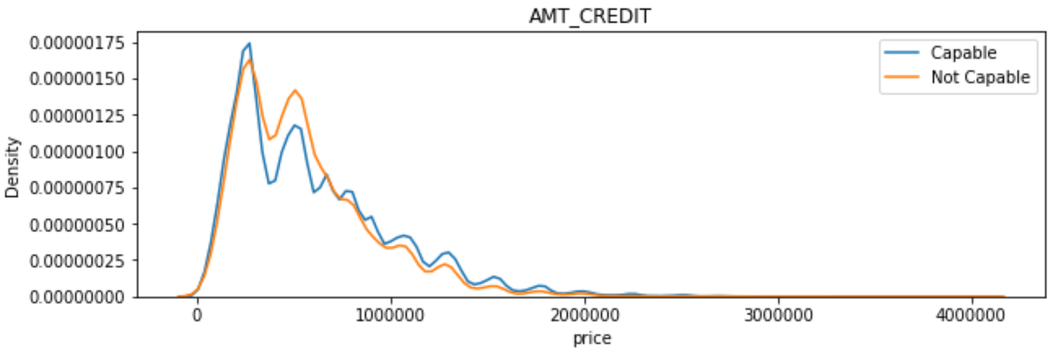
	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_I
12840	114967	1	Cash loans	F	N	
203693	336147	0	Cash loans	M	Y	
246858	385674	0	Cash loans	M	Y	

3 rows × 122 columns

6.12 Credit amount of the loan

In [0]:

```
from math import log
count1 = Df_application_train[Df_application_train['TARGET']==0]['AMT_C
count1 = count1.values
count1=[x for x in count1 if (str(x)!='nan')]
count2 = Df_application_train[Df_application_train['TARGET']==1]['AMT_C
count2 = count2.values
count2=[x for x in count2 if (str(x)!='nan')]
plt.figure(figsize=(10,3))
sns.distplot(count1, hist=False, label="Capable ")
sns.distplot(count2, hist=False, label="Not Capable")
plt.title('AMT_CREDIT')
plt.xlabel('price')
plt.ylabel('Density')
plt.legend()
plt.show()

```

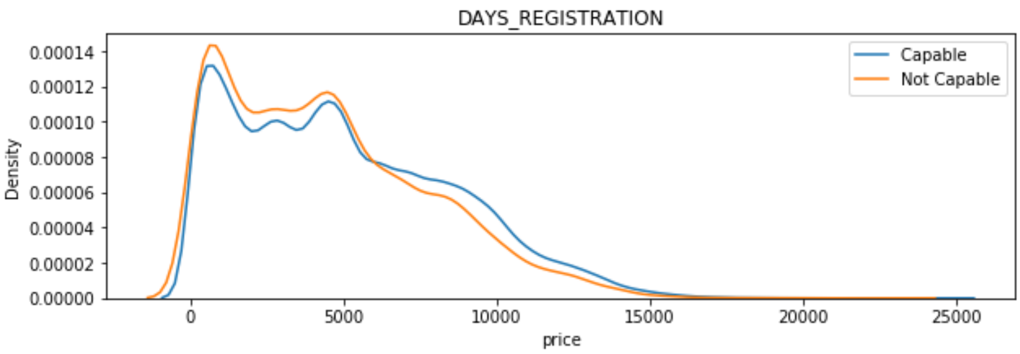


observation : Credit amount of the loan is mostly less then 10 lakhs

6.13 How many days before the application did client change his registration

In [0]:

```
from math import log
count1 = Df_application_train[Df_application_train['TARGET']==0]['DAYS_
count1 = count1.values
count1=[-x for x in count1 if (str(x)!='nan' and x!=0)]
count2 = Df_application_train[Df_application_train['TARGET']==1]['DAYS_
count2 = count2.values
count2=[-x for x in count2 if (str(x)!='nan' and x!=0)]
plt.figure(figsize=(10,3))
sns.distplot(count1, hist=False, label="Capable ")
sns.distplot(count2, hist=False, label="Not Capable")
plt.title('DAYS_REGISTRATION')
plt.xlabel('price')
plt.ylabel('Density')
plt.legend()
plt.show()
```



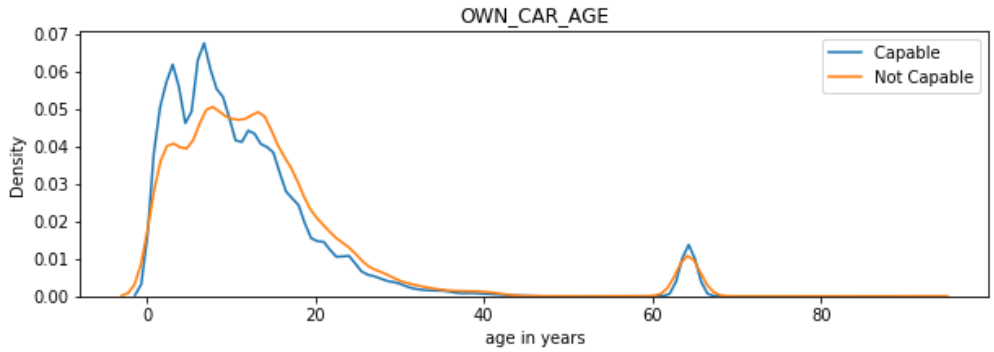
Observation: Most of the applicant changed their registration 15000 days before the application.

6.14 Age of client's car

In [0]:
```
Df_application_train['OWN_CAR_AGE'].describe()
```

Out[201]:
```
count    104582.000000
mean         12.061091
std          11.944812
min           0.000000
25%           5.000000
50%           9.000000
75%          15.000000
max          91.000000
Name: OWN_CAR_AGE, dtype: float64
```

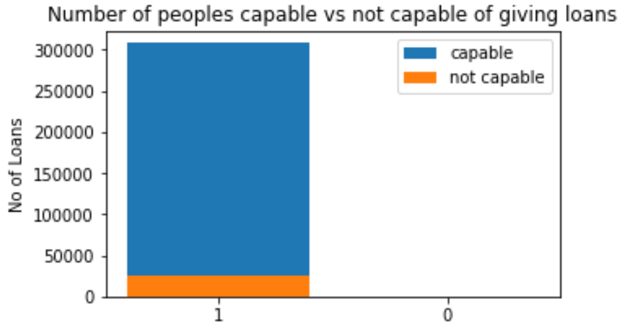
In [0]:
```
from math import log
count1 = Df_application_train[Df_application_train['TARGET']==0]['OWN_C
count1 = count1.values
count1=[x for x in count1 if (str(x)!='nan' and x!=0)]
count2 = Df_application_train[Df_application_train['TARGET']==1]['OWN_C
count2 = count2.values
count2=[x for x in count2 if (str(x)!='nan' and x!=0)]
plt.figure(figsize=(10,3))
sns.distplot(count1, hist=False, label="Capable ")
sns.distplot(count2, hist=False, label="Not Capable")
plt.title('OWN_CAR_AGE')
plt.legend()
plt.xlabel('age in years')
plt.ylabel('Density')
plt.show()
```



observation : Most of the cars are in age group between 0-20 and less between 40-60.

6.15 Did client provide mobile phone (1=YES, 0=NO)

In [0]:
```
univariate_barplots(Df_application_train, 'FLAG_MOBIL', 'TARGET' , top=
```



observation: nearly all applicants have provided their mobile information. Lets check how many applicants are there who have not provided the mobile information.

In [0]:
```
c=Df_application_train.FLAG_MOBIL.values
co=0
for i in c:
  if(i!=1):
    co=co+1
co
```

Out[245]: 1

In [0]:
```
Df_application_train[Df_application_train['FLAG_MOBIL']==0]
```

Out[8]:

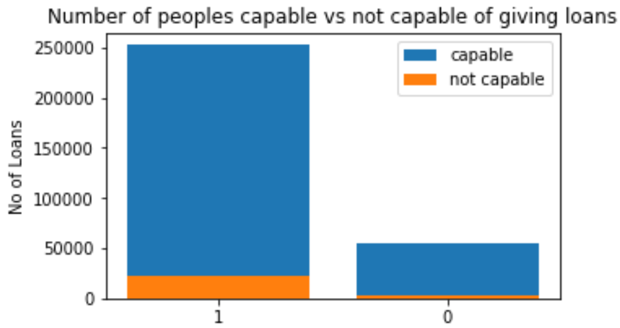
	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_R
15709	118330	0	Cash loans	M	Y	

1 rows × 122 columns

There is only 1 client who did not provide the mobile information.

6.16 Did client provide work phone (1=YES, 0=NO)

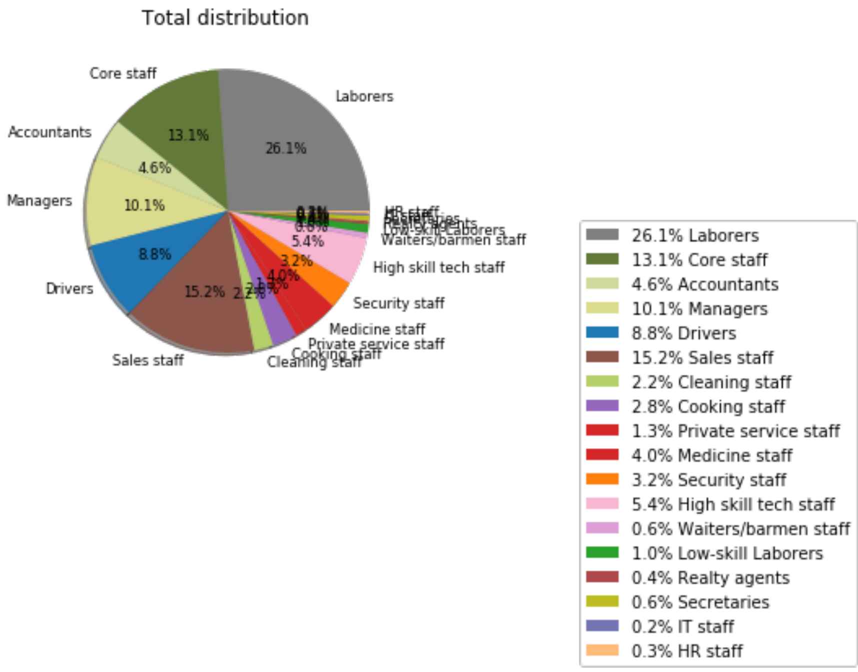
In [0]:
```
univariate_barplots(Df_application_train, 'FLAG_EMP_PHONE', 'TARGET' ,
```

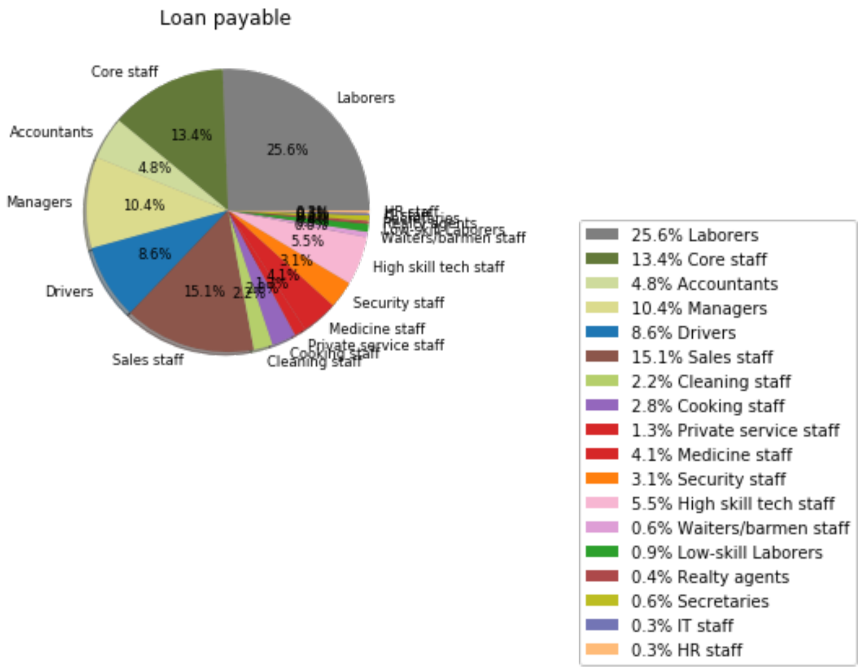


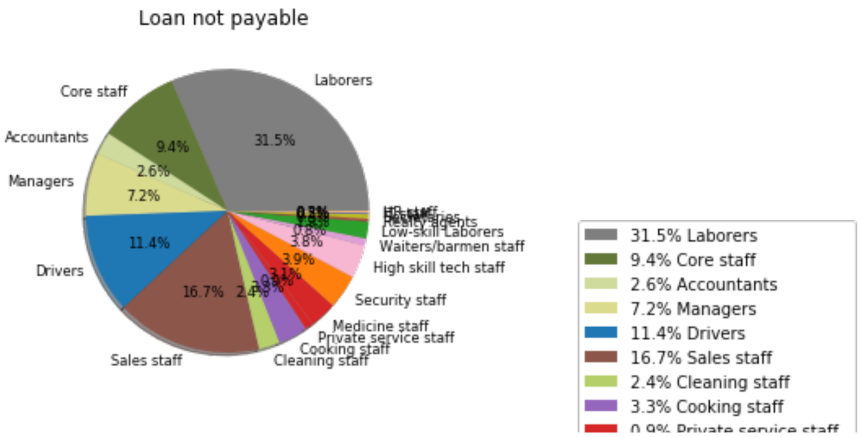
observation : More no of applicants provide work phone.

6.17 What kind of occupation does the client have

In [0]:
```
1 plotpiechart('OCCUPATION TYPE')
```



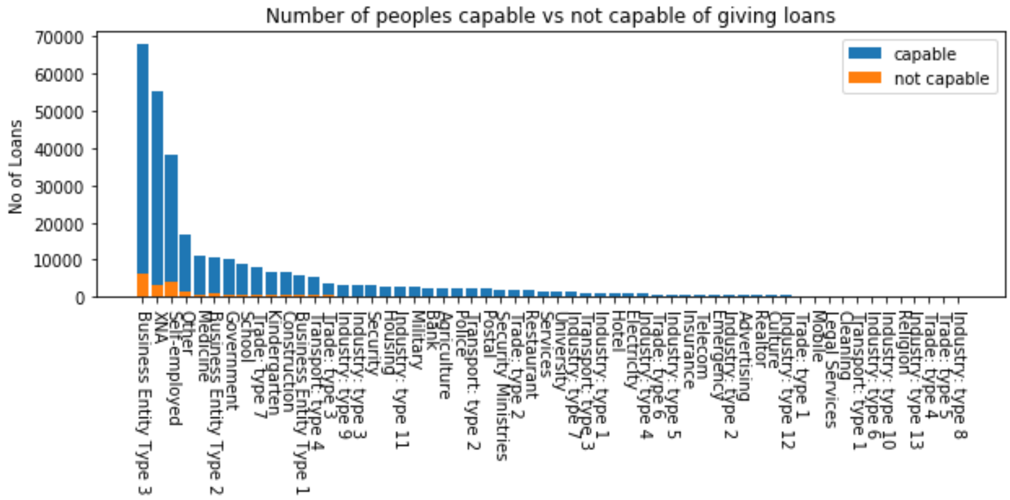




observation : Laborers take more no of loans but also are more no of defaulters.

6.18 Type of organization where client works

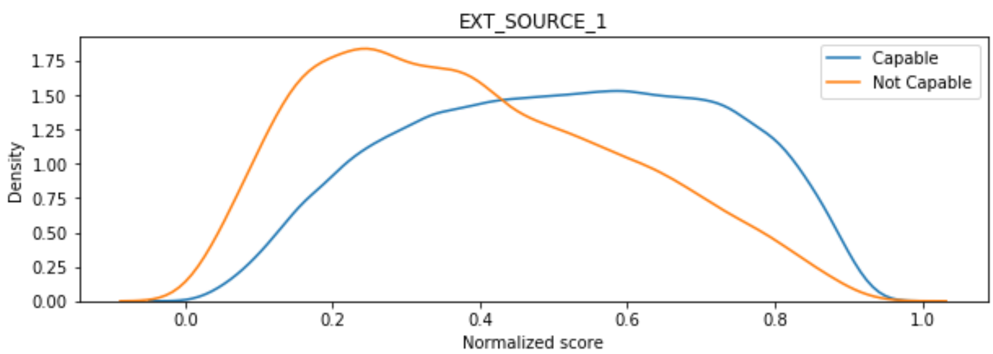
In [0]:
```
univariate_barplots(Df_application_train, 'ORGANIZATION_TYPE', 'TARGET'
```



observation : clients working in business and self employed are more no of defaulters but they also take more no of loan.

6.19 Normalized score from external data source

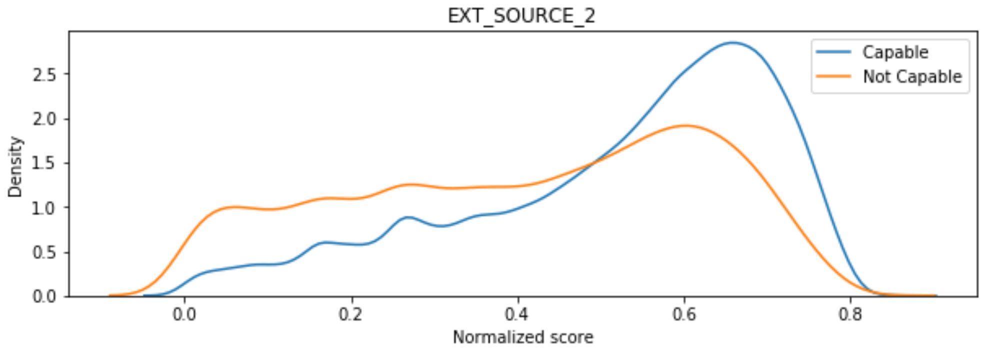
In [0]:
```
from math import log
count1 = Df_application_train[Df_application_train['TARGET']==0]['EXT_S
count1 = count1.values
count1=[x for x in count1 if (str(x)!='nan' and x!=0)]
count2 = Df_application_train[Df_application_train['TARGET']==1]['EXT_S
count2 = count2.values
count2=[x for x in count2 if (str(x)!='nan' and x!=0)]
plt.figure(figsize=(10,3))
sns.distplot(count1, hist=False, label="Capable ")
sns.distplot(count2, hist=False, label="Not Capable")
plt.title('EXT_SOURCE_1')
plt.xlabel('Normalized score')
plt.ylabel('Density')
plt.legend()
plt.show()
```



observation : data is well seperated it will be a important feature.

6.20 Normalized score from external data source

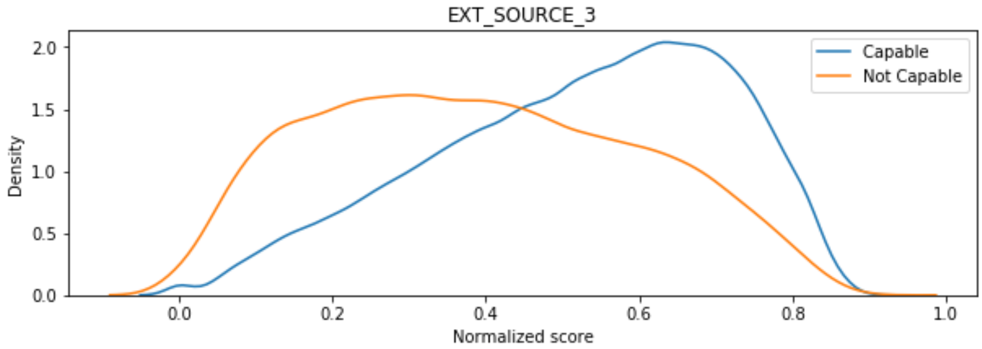
In [0]:
```
from math import log
count1 = Df_application_train[Df_application_train['TARGET']==0]['EXT_S
count1 = count1.values
count1=[x for x in count1 if (str(x)!='nan' and x!=0)]
count2 = Df_application_train[Df_application_train['TARGET']==1]['EXT_S
count2 = count2.values
count2=[x for x in count2 if (str(x)!='nan' and x!=0)]
plt.figure(figsize=(10,3))
sns.distplot(count1, hist=False, label="Capable ")
sns.distplot(count2, hist=False, label="Not Capable")
plt.title('EXT_SOURCE_2')
plt.xlabel('Normalized score')
plt.ylabel('Density')
plt.legend()
plt.show()
```



observation : data is well seperated it will be a important feature

6.21 Normalized score from external data source

In [0]:
```
from math import log
count1 = Df_application_train[Df_application_train['TARGET']==0]['EXT_S
count1 = count1.values
count1=[x for x in count1 if (str(x)!='nan' and x!=0)]
count2 = Df_application_train[Df_application_train['TARGET']==1]['EXT_S
count2 = count2.values
count2=[x for x in count2 if (str(x)!='nan' and x!=0)]
plt.figure(figsize=(10,3))
sns.distplot(count1, hist=False, label="Capable ")
sns.distplot(count2, hist=False, label="Not Capable")
plt.title('EXT_SOURCE_3')
plt.xlabel('Normalized score')
plt.ylabel('Density')
plt.legend()
plt.show()
```



observation : data is well seperated it will be a important feature

Below code will reduce the memory used by the data frame

In [18]:
```
np.iinfo(np.int8).max
```

Out[18]: 127

In [0]:

```
# code takenn from https://www.kaggle.com/gemartin/load-data-reduce-mem
def reduce_mem_usage(df):
    """ iterate through all the columns of a dataframe and modify the d
        to reduce memory usage.
    """
    start_mem = df.memory_usage().sum() / 1024**2
    print('Memory usage of dataframe is {:.2f} MB'.format(start_mem))

    for col in df.columns:
        col_type = df[col].dtype

        if col_type != object:
            c_min = df[col].min()
            c_max = df[col].max()
            if str(col_type)[:3] == 'int':
                if c_min > np.iinfo(np.int8).min and c_max < np.iinfo(n
                    df[col] = df[col].astype(np.int8)
                elif c_min > np.iinfo(np.int16).min and c_max < np.iinf
                    df[col] = df[col].astype(np.int16)
                elif c_min > np.iinfo(np.int32).min and c_max < np.iinf
                    df[col] = df[col].astype(np.int32)
                elif c_min > np.iinfo(np.int64).min and c_max < np.iinf
                    df[col] = df[col].astype(np.int64)
            else:
                if c_min > np.finfo(np.float16).min and c_max < np.finf
                    df[col] = df[col].astype(np.float16)
                elif c_min > np.finfo(np.float32).min and c_max < np.fi
                    df[col] = df[col].astype(np.float32)
                else:
                    df[col] = df[col].astype(np.float64)

    end_mem = df.memory_usage().sum() / 1024**2
    print('Memory usage after optimization is: {:.2f} MB'.format(end_me
    print('Decreased by {:.1f}%'.format(100 * (start_mem - end_mem) / s

    return df

```

Feature engineering for application .csv

Remove outliers

In [0]:

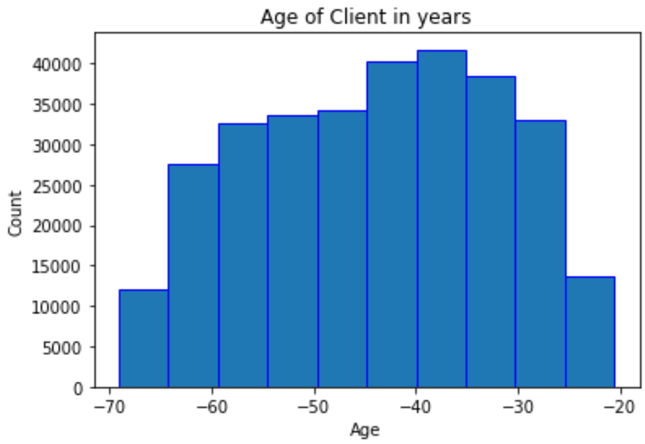
```
(Df_application_train['DAYS_BIRTH'] / -365).describe()
```

Out[33]:

```
count    307511.000000
mean         43.936973
std          11.956133
min          20.517808
25%          34.008219
50%          43.150685
75%          53.923288
max          69.120548
Name: DAYS_BIRTH, dtype: float64
```

The data looks reasonable there is no outliers in DAYS_BIRTH.

In [0]:
```
1 plt.hist(Df_application_train['DAYS_BIRTH'] / 365, edgecolor = 'b', bir
2 plt.title('Age of Client in years'); plt.xlabel('Age'); plt.ylabel('Cou
```



People of age group between 35-40 years takes maximum no of loans.

In [0]:
```
1 (Df_application_train['DAYS_EMPLOYED']).describe()
```

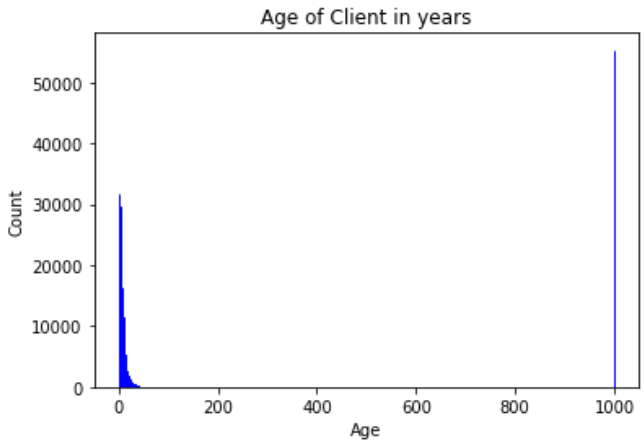
Out[21]:
```
count    307511.000000
mean      63815.045904
std      141275.766519
min      -17912.000000
25%       -2760.000000
50%       -1213.000000
75%        -289.000000
max      365243.000000
Name: DAYS_EMPLOYED, dtype: float64
```

In [0]:
```
1 (Df_application_train['DAYS_EMPLOYED']).max()/365
```

Out[23]:
```
1000.6657534246575
```

365243 is max value for DAYS_EMPLOYED and after dividing it by 365 it gives 1000.66 which is an outlier because how can a employ works for 1000 years.

In [0]:
```
1 plt.hist(abs(Df_application_train['DAYS_EMPLOYED']) / 365, edgecolor =
2 plt.title('Age of Client in years'); plt.xlabel('Age'); plt.ylabel('Cou
```



The person with age 1000 is an outlier

In [0]:
```
Df_application_train['CODE_GENDER'].unique()
```

Out[44]:
```
array(['M', 'F', 'XNA'], dtype=object)
```

XNA is not a gender we should remove it

In [0]:
```
Df_application_train['NAME_INCOME_TYPE'].unique()
```

Out[47]:
```
array(['Working', 'State servant', 'Commercial associate', 'Pensioner',
       'Unemployed', 'Student', 'Businessman', 'Maternity leave'],
      dtype=object)
```

Income type can never be Maternity leave so this should be removed.

In [0]:
```
d = [data for data in Df_application_train.columns if 'FLAG_DOC' in dat

Df_application_train[d]
```

Out[59]:

	FLAG_DOCUMENT_2	FLAG_DOCUMENT_3	FLAG_DOCUMENT_4	FLAG_DOCUMENT_5	FLAG_DOCU
0	0	1	0	0	
1	0	1	0	0	
2	0	0	0	0	
3	0	1	0	0	
4	0	0	0	0	
...	...	...	...	...	
307506	0	0	0	0	
307507	0	1	0	0	
307508	0	1	0	0	
307509	0	1	0	0	
307510	0	1	0	0	

307511 rows × 20 columns

Checking no of 1's in all the flag documents.

In [0]:
```
for i in d:
  a=sum(Df_application_train[i]==1)
  print(i, "contain no of 1's = ",(a*100/307511)," no of 0's =",(307511
```

```
FLAG_DOCUMENT_2 contain no of 1's =  0.004227491049100683  no of 0's = 99.
99577250895089
FLAG_DOCUMENT_3 contain no of 1's =  71.00233812774177  no of 0's = 28.997
661872258227
FLAG_DOCUMENT_4 contain no of 1's =  0.008129790479039774  no of 0's = 99.
99187020952095
FLAG_DOCUMENT_5 contain no of 1's =  1.5114906458630748  no of 0's = 98.48
850935413692
FLAG_DOCUMENT_6 contain no of 1's =  8.80553866365756  no of 0's = 91.1944
6133634244
FLAG_DOCUMENT_7 contain no of 1's =  0.019186305530533868  no of 0's = 99.
98081369446946
FLAG_DOCUMENT_8 contain no of 1's =  8.137595077899652  no of 0's = 91.862
40492210035
FLAG_DOCUMENT_9 contain no of 1's =  0.389579559755586  no of 0's = 99.610
42044024441
FLAG_DOCUMENT_10 contain no of 1's =  0.0022763413341311367  no of 0's = 9
9.99772365866586
FLAG_DOCUMENT_11 contain no of 1's =  0.39120551785139396  no of 0's = 99.
60879448214861
FLAG_DOCUMENT_12 contain no of 1's =  0.000650383238323182  no of 0's = 9
9.99934961676168
FLAG_DOCUMENT_13 contain no of 1's =  0.3525077151711646  no of 0's = 99.6
4749228482883
FLAG_DOCUMENT_14 contain no of 1's =  0.2936480321029166  no of 0's = 99.7
0635196789708
FLAG_DOCUMENT_15 contain no of 1's =  0.12097128232811184  no of 0's = 99.
87902871767189
FLAG_DOCUMENT_16 contain no of 1's =  0.9928100133003372  no of 0's = 99.0
0718998669966
FLAG_DOCUMENT_17 contain no of 1's =  0.02666571277125046  no of 0's = 99.
97333428722875
FLAG_DOCUMENT_18 contain no of 1's =  0.8129790479039775  no of 0's = 99.1
8702095209602
FLAG_DOCUMENT_19 contain no of 1's =  0.059510066306571144  no of 0's = 9
9.94048993369343
FLAG_DOCUMENT_20 contain no of 1's =  0.05072989258920819  no of 0's = 99.
9492701074108
FLAG_DOCUMENT_21 contain no of 1's =  0.03349473677364387  no of 0's = 99.
96650526322635
```

All documents contains very less no of 1's except FLAG_DOCUMENT_3 so we can remove them as they cannot give much information.

In [0]:
```
sum(Df_application_train['AMT_GOODS_PRICE'].isnull())# no of null value
```

Out[75]: 278

In [5]:

```
#https://www.kaggle.com/aantonova/797-lgbm-and-bayesian-optimization
df = reduce_mem_usage(pd.read_csv('application_train.csv'))
test_df = reduce_mem_usage(pd.read_csv('application_test.csv'))
df = df.append(test_df).reset_index()
df = df[df['CODE_GENDER'] != 'XNA']
df = df[df['AMT_GOODS_PRICE'].notnull()]
df = df[df['NAME_INCOME_TYPE'] != 'Maternity leave']
df = df[df['DAYS_LAST_PHONE_CHANGE'].notnull()]
df['DAYS_EMPLOYED'].replace(365243, np.nan, inplace= True)
#If ratio of days birth to days employed is more that means person is l
df['DAYS_BIRTH / DAYS_EMPLOYED'] = df['DAYS_BIRTH'] / df['DAYS_EMPLOYED

df['AMT_CREDIT / AMT_INCOME_TOTAL'] = df['AMT_CREDIT'] / df['AMT_INCOME
df['CNT_FAM_MEMBERS / AMT_INCOME_TOTAL'] = df['CNT_FAM_MEMBERS'] / df['
df['AMT_ANNUITY / AMT_INCOME_TOTAL'] = df['AMT_ANNUITY'] / (1 + df['AMT

df['AMT_CREDIT / AMT_ANNUITY'] = df['AMT_CREDIT'] / df['AMT_ANNUITY']
df['ANNUITY_LENGTH / DAYS_EMPLOYED'] = df['AMT_CREDIT / AMT_ANNUITY'] /
df['CNT_CHILDREN / CNT_FAM_MEMBERS'] = df['CNT_CHILDREN'] / df['CNT_FAM

df['AMT_CREDIT / AMT_GOODS_PRICE'] = df['AMT_CREDIT'] / df['AMT_GOODS_P
df['AMT_CREDIT / AMT_GOODS_PRICE'] = df['AMT_CREDIT'] - df['AMT_GOODS_P
df['DAYS_REGISTRATION / DAYS_ID_PUBLISH'] = df['DAYS_REGISTRATION'] / d
df['DAYS_BIRTH / DAYS_REGISTRATION'] = df['DAYS_BIRTH'] / df['DAYS_REGI
df['DOC_SUM'] = df['FLAG_DOCUMENT_2'] + df['FLAG_DOCUMENT_3'] + df['FLA

df['NAN_AMT_ANNUITY'] = 1.0*np.isnan(df['AMT_ANNUITY'])
df['AGE_FINISH'] = df['DAYS_BIRTH']*(-1.0/365) + (df['AMT_CREDIT']/df['

d = [data for data in df.columns if 'FLAG_DOC' in data]
l = [data for data in df.columns if ('FLAG_' in data) & ('FLAG_DOC' not
df['NEW_DOC_IND_KURT'] = df[d].kurtosis(axis=1)
df['NEW_LIVE_IND_SUM'] = df[l].sum(axis=1)
df['AMT_INCOME_TOTAL / CNT_CHILDREN'] = df['AMT_INCOME_TOTAL'] / (1 + d
org_type = df[['AMT_INCOME_TOTAL', 'ORGANIZATION_TYPE']].groupby('ORGAN
df['NEW_INC_BY_ORG'] = df['ORGANIZATION_TYPE'].map(org_type)
df['AMT_INCOME_TOTAL / NEW_INC_BY_ORG'] = df['AMT_INCOME_TOTAL'] / df['
df['OWN_CAR_AGE / DAYS_BIRTH'] = df['OWN_CAR_AGE'] / df['DAYS_BIRTH']
df['OWN_CAR_AGE / DAYS_EMPLOYED'] = df['OWN_CAR_AGE'] / df['DAYS_EMPLOY
df['DAYS_LAST_PHONE_CHANGE / DAYS_BIRTH'] = df['DAYS_LAST_PHONE_CHANGE'
df['DAYS_LAST_PHONE_CHANGE / DAYS_EMPLOYED'] = df['DAYS_LAST_PHONE_CHAN

for f in ['CODE_GENDER', 'FLAG_OWN_CAR', 'FLAG_OWN_REALTY']:
    df[f], c = pd.factorize(df[f])

cat_col = [i for i in df.columns if df[i].dtype == 'object']
df = pd.get_dummies(df, columns= cat_col)

df= df.drop(['FLAG_DOCUMENT_2','FLAG_DOCUMENT_4','FLAG_DOCUMENT_5','FLA
    'FLAG_DOCUMENT_8','FLAG_DOCUMENT_9','FLAG_DOCUMENT_10', 'FLAG_DOCUM
    'FLAG_DOCUMENT_14','FLAG_DOCUMENT_15','FLAG_DOCUMENT_16','FLAG_DOCU
    'FLAG_DOCUMENT_20','FLAG_DOCUMENT_21'],axis=1)
print(df.shape)
del test_df
gc.collect()

```

```
Memory usage of dataframe is 286.23 MB
Memory usage after optimization is: 92.38 MB
Decreased by 67.7%
Memory usage of dataframe is 45.00 MB
Memory usage after optimization is: 14.60 MB
Decreased by 67.6%
(355967, 244)
```

Out[5]: 0

ONE_HOT Encoding of categorical feaures

In [0]:
```
#one hot encode the categorical data
def one_hot(df):
    original_col = list(df.columns)
    c = [c for c in df.columns if df[c].dtype == 'object']#find categor
    df = pd.get_dummies(df, columns= c, dummy_na= True)#one_hot_encode
    new_col = [c for c in df.columns if c not in original_col]
    return df, new_col
```

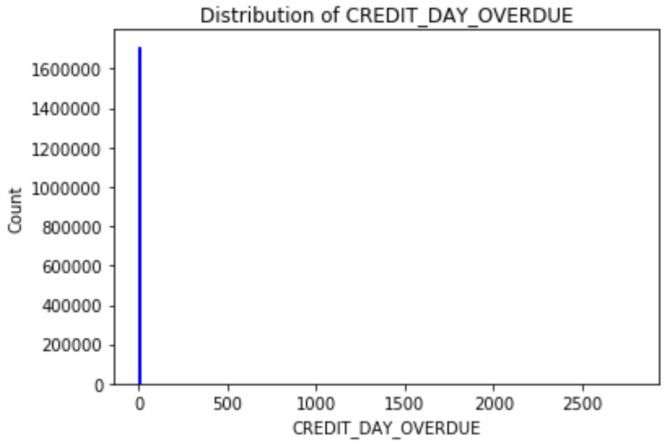
Bureau

In [0]:
```
b=pd.read_csv('bureau.csv')
```

In [0]:
```
b.columns
```

Out[11]:
```
Index(['SK_ID_CURR', 'SK_ID_BUREAU', 'CREDIT_ACTIVE', 'CREDIT_CURRENCY',
       'DAYS_CREDIT', 'CREDIT_DAY_OVERDUE', 'DAYS_CREDIT_ENDDATE',
       'DAYS_ENDDATE_FACT', 'AMT_CREDIT_MAX_OVERDUE', 'CNT_CREDIT_PROLONG
',
       'AMT_CREDIT_SUM', 'AMT_CREDIT_SUM_DEBT', 'AMT_CREDIT_SUM_LIMIT',
       'AMT_CREDIT_SUM_OVERDUE', 'CREDIT_TYPE', 'DAYS_CREDIT_UPDATE',
       'AMT_ANNUITY'],
      dtype='object')
```

In [0]:
```
plt.hist(b['CREDIT_DAY_OVERDUE'], edgecolor = 'b', bins = 1000)
plt.title('Distribution of CREDIT_DAY_OVERDUE'); plt.xlabel('CREDIT_DAY
```



Observation: Most of the credits have close to 0 days overdue

In [0]:
```
b.shape[0] #total no of entries in table
```

Out[20]: 1716428

In [0]:
```
b[b['CREDIT_DAY_OVERDUE']>0].shape[0] #entries which contain non zeroes
```

Out[19]: 4217

In [0]:

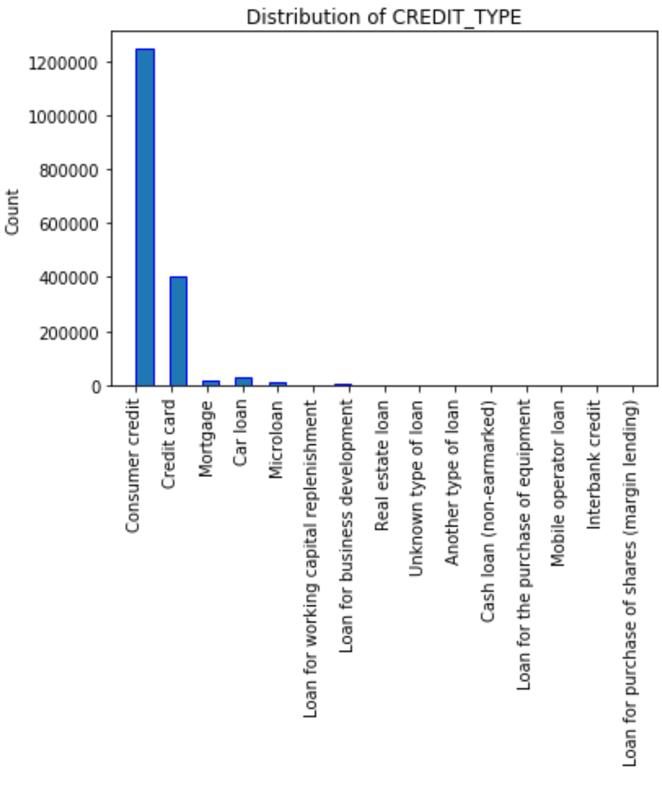
```
v=b['CREDIT_DAY_OVERDUE'].values
v=np.sort(v)
for i in range(99.,100,1):
  print(i,'percentile value is',v[int(len(v)*float(i)/100)])
print(100,'percentile value is',v[-1])
```

```
90 percentile value is 0
91 percentile value is 0
92 percentile value is 0
93 percentile value is 0
94 percentile value is 0
95 percentile value is 0
96 percentile value is 0
97 percentile value is 0
98 percentile value is 0
99 percentile value is 0
100 percentile value is 2792
```

99% of values contain zero value.that means there is no overdue 99% of times.

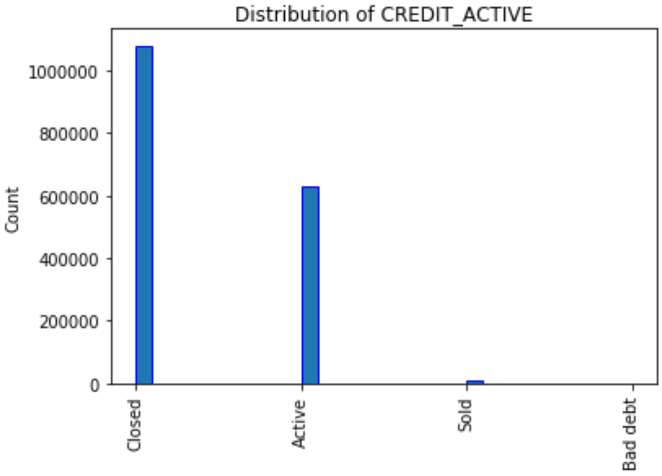
In [0]:

```
plt.hist(b['CREDIT_TYPE'], edgecolor = 'b',stacked=0, bins = 30)
plt.title('Distribution of CREDIT_TYPE')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```



Observation: Consumer credit and Credit card are mostly registered credit in credit bureau.

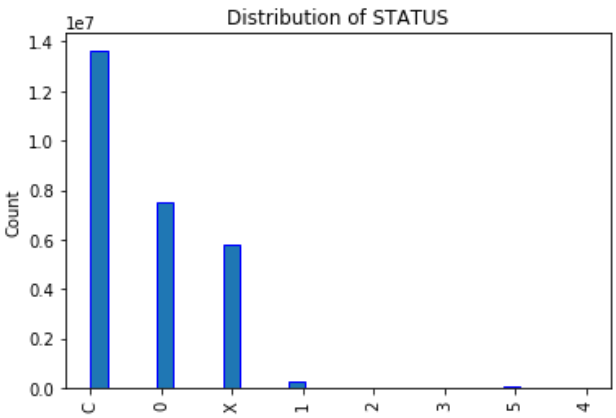
In [0]:
```

plt.hist(b['CREDIT_ACTIVE'], edgecolor = 'b',stacked=0, bins = 30)
plt.title('Distribution of CREDIT_ACTIVE')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```



Observation: Most of the credit registered are in status closed. Sold and bad debt are very few.

In [0]:
```
bb=pd.read_csv('/content/bureau_balance.csv')
```

In [0]:
```
plt.hist(bb['STATUS'], edgecolor = 'b',stacked=0, bins = 30)#Status of
#(active, closed, DPD0-30,à [C means closed, X means status unknown, 0
#1 means maximal did during month between 1-30, 2 means DPD 31-60,à 5 m
plt.title('Distribution of STATUS')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```



Observation: Most of the times credit bureau status is closed for a month

Features extraction in bureau_balance and bureau

In [0]:

```
#function takes the bureau and related dataframe and add aggregated fea
#also merge it with bureau_balance dataframe
#https://www.kaggle.com/jsaguiar/lightgbm-7th-place-solution
#https://www.linkedin.com/pulse/winning-9th-place-kaggles-biggest-compe
def b_new(buro):
    bureau_balance = reduce_mem_usage(pd.read_csv('bureau_balance.csv')
    bureau_balance, col1 = one_hot(bureau_balance)
    bureau, col2= one_hot(buro)

    bureau_balance_agg = {'MONTHS_BALANCE': ['size']}
    for c in col1:
      bureau_balance_agg[c] = ['mean']
    aggregate = bureau_balance.groupby('SK_ID_BUREAU').agg(bureau_balar
    l=[]
    for i in aggregate.columns.tolist():
      l.append(i[0] + "_" + i[1].upper())

    aggregate.columns = pd.Index(l)
    bureau = bureau.join(aggregate, how='left', on='SK_ID_BUREAU')
    bureau.drop(['SK_ID_BUREAU'], axis=1, inplace= True)
    del aggregate
    gc.collect()

    numerical_agg = {'AMT_CREDIT_SUM_DEBT': ['mean', 'sum'],'AMT_CREDIT
        'DAYS_CREDIT': ['mean', 'var'],'DAYS_CREDIT_UPDATE': ['mean'],'
        'DAYS_CREDIT_ENDDATE': ['mean'],'CNT_CREDIT_PROLONG': ['sum'],'
        'AMT_CREDIT_SUM_LIMIT': ['mean', 'sum'],'AMT_CREDIT_MAX_OVERDUE
        'AMT_ANNUITY': ['max', 'mean'],'AMT_CREDIT_SUM': ['mean', 'sum'
      }
    categorical_agg = {}
    for c in col2:
      categorical_agg[c] = ['mean']
    for c in col1:
      categorical_agg[c + "_MEAN"] = ['mean']

    b1 = bureau.groupby('SK_ID_CURR').agg({**numerical_agg, **categoric
    l=[]
    for i in b1.columns.tolist():
      l.append('BU_'+i[0]+'_'+i[1].upper())
    b1.columns = pd.Index(l)

    A = bureau[bureau['CREDIT_ACTIVE_Active'] == 1]
    A_agg = A.groupby('SK_ID_CURR').agg(numerical_agg)
    l=[]
    for i in A_agg.columns.tolist():
      l.append('A_'+i[0]+'_'+i[1].upper())
    A_agg.columns = pd.Index(l)
    b1 = b1.join(A_agg, how='left', on='SK_ID_CURR')
    del A,A_agg
    gc.collect()

    C = bureau[bureau['CREDIT_ACTIVE_Closed'] == 1]
    C_agg = C.groupby('SK_ID_CURR').agg(numerical_agg)
    l=[]
    for i in C_agg.columns.tolist():
      l.append('C_'+i[0]+'_'+i[1].upper())
    C_agg.columns = pd.Index(l)
    b1 = b1.join(C_agg, how='left', on='SK_ID_CURR')
    del C, C_agg
    gc.collect()

    print(b1.shape)
    del bureau
    gc.collect()
    return(b1)

```

In [8]:
```
b=pd.read_csv('bureau.csv')

new = b_new(reduce_mem_usage(b))
df = df.join(new, how='left', on='SK_ID_CURR')
del new
gc.collect()
```

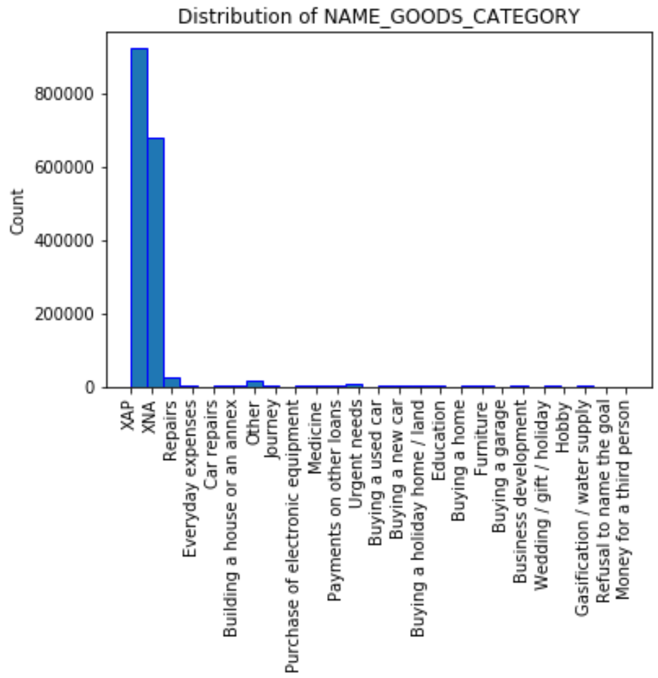
```
Memory usage of dataframe is 222.62 MB
Memory usage after optimization is: 112.95 MB
Decreased by 49.3%
Memory usage of dataframe is 624.85 MB
Memory usage after optimization is: 338.46 MB
Decreased by 45.8%
(305811, 89)
```

Out[8]: 0

Previous application

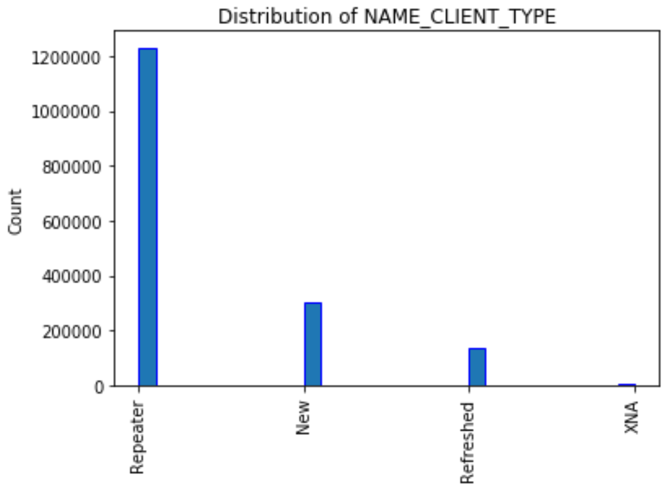
In [0]:
```
p=pd.read_csv('/content/previous_application.csv')
```

In [0]:
```
plt.hist(p['NAME_CASH_LOAN_PURPOSE'], edgecolor = 'b',stacked=0, bins =
plt.title('Distribution of NAME_GOODS_CATEGORY')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```



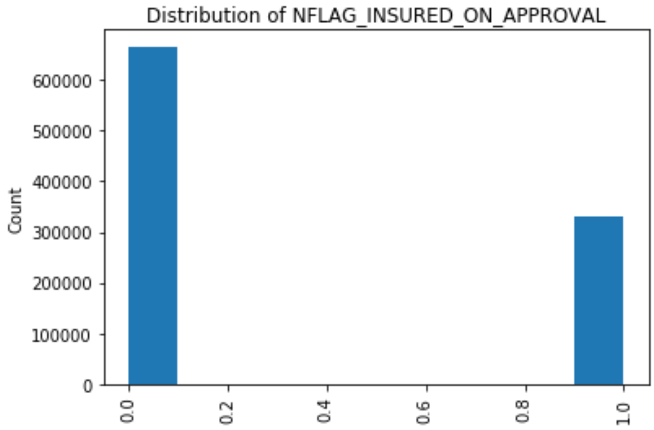
Observation:Most applicant takes cash loans with a purpose of XAP and XNA.

In [0]:
```

plt.hist(p['NAME_CLIENT_TYPE'], edgecolor = 'b',stacked=0, bins = 30)
plt.title('Distribution of NAME_CLIENT_TYPE')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```



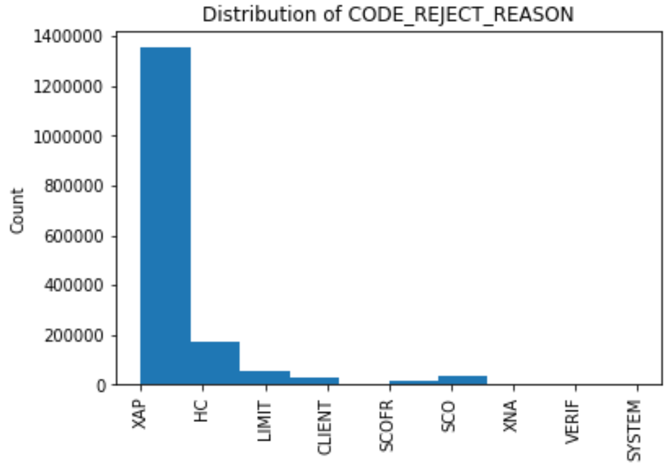
Observation: There are more no of repeaters when applying for the previous application.

In [0]:
```
plt.hist(p['NFLAG_INSURED_ON_APPROVAL'])#Did the client requested insur
plt.title('Distribution of NFLAG_INSURED_ON_APPROVAL')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```



Observation:There are very less client who requested insurance during the previous application.

In [0]:
```
plt.hist(p['CODE_REJECT_REASON'])#Why was the previous application reje
plt.title('Distribution of CODE_REJECT_REASON')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```



Observation: Most of the times bank has given not applicable as the reason for rejecting the loan.

In [0]:
```
p['DAYS_TERMINATION'].describe()
```

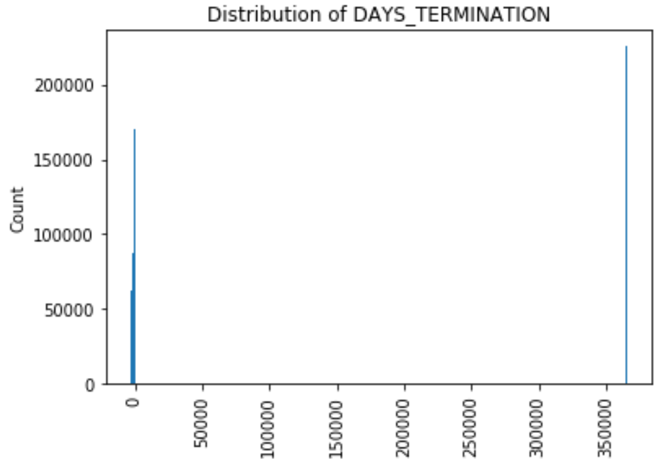
Out[64]:
```
count    997149.000000
mean      81992.343838
std      153303.516729
min       -2874.000000
25%       -1270.000000
50%        -499.000000
75%         -44.000000
max      365243.000000
Name: DAYS_TERMINATION, dtype: float64
```

In [0]:
```
p[p['DAYS_TERMINATION']==365243]['DAYS_TERMINATION']
```

Out[85]:
```
1          365243.0
2          365243.0
17         365243.0
21         365243.0
34         365243.0
             ...
1669925    365243.0
1669945    365243.0
1669960    365243.0
1670192    365243.0
1670199    365243.0
Name: DAYS_TERMINATION, Length: 225913, dtype: float64
```

Observation: nearly 225913 values are outliers here in column DAYS_TERMINATION

In [0]:
```
plt.hist(p['DAYS_TERMINATION'],bins = 1000)#Relative to application dat
plt.title('Distribution of DAYS_TERMINATION')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```

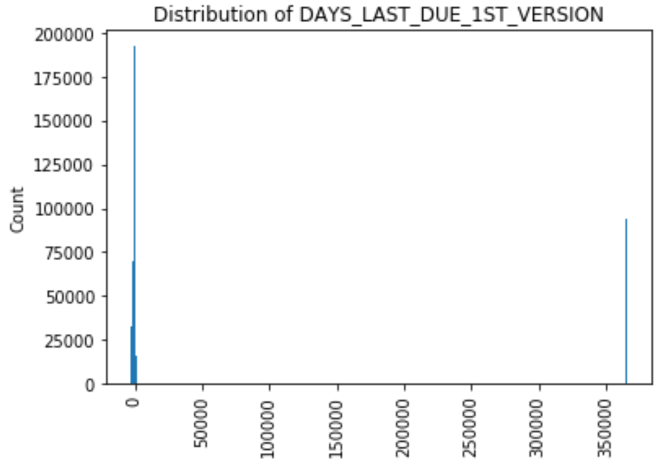


Observation: The min value is -2874 and max value is 365243. 365243 is equal to 1000 years hence it is an outlier.

In [0]:
```

```

In [0]:
```
print(p['DAYS_LAST_DUE_1ST_VERSION'].describe())
plt.hist(p['DAYS_LAST_DUE_1ST_VERSION'],bins = 1000)#Relative to applic
plt.title('Distribution of DAYS_LAST_DUE_1ST_VERSION')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```

```
count    997149.000000
mean      33767.774054
std      106857.034789
min       -2801.000000
25%       -1242.000000
50%        -361.000000
75%         129.000000
max      365243.000000
Name: DAYS_LAST_DUE_1ST_VERSION, dtype: float64
```



Observation: 365243 is an outlier here.

In [0]:
```
1 p['DAYS_FIRST_DRAWING'].describe()
```

Out[84]:
```
count    997149.000000
mean     342209.855039
std       88916.115834
min       -2922.000000
25%      365243.000000
50%      365243.000000
75%      365243.000000
max      365243.000000
Name: DAYS_FIRST_DRAWING, dtype: float64
```

In [0]:
```
1 p[p['DAYS_FIRST_DRAWING']>0]['DAYS_FIRST_DRAWING']
```

Out[81]:
```
0          365243.0
1          365243.0
2          365243.0
3          365243.0
5          365243.0
             ...
1670209    365243.0
1670210    365243.0
1670211    365243.0
1670212    365243.0
1670213    365243.0
Name: DAYS_FIRST_DRAWING, Length: 934444, dtype: float64
```

In [0]:
```
1 p[p['DAYS_FIRST_DRAWING']==365243]['DAYS_FIRST_DRAWING']
```

Out[82]:
```
0          365243.0
1          365243.0
2          365243.0
3          365243.0
5          365243.0
             ...
1670209    365243.0
1670210    365243.0
1670211    365243.0
1670212    365243.0
1670213    365243.0
Name: DAYS_FIRST_DRAWING, Length: 934444, dtype: float64
```

In [0]:
```
1 p[p['DAYS_FIRST_DRAWING']<0]['DAYS_FIRST_DRAWING']
```

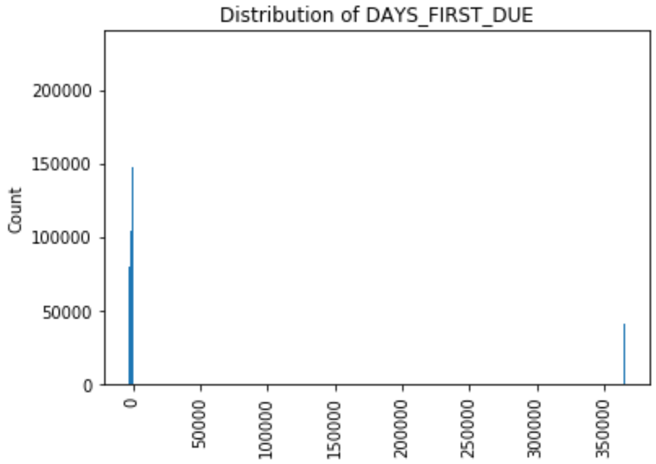
Out[83]:
```
17          -277.0
34          -265.0
82          -479.0
93          -332.0
242         -225.0
             ...
1669788     -863.0
1669830     -453.0
1669833     -596.0
1669960    -1083.0
1670192     -474.0
Name: DAYS_FIRST_DRAWING, Length: 62705, dtype: float64
```

All the values above 0 are 365243 and they all are outliers. Nearly 934444 values in DAYS_FIRST_DRAWING column are outliers except 62705 values which are less than 0.the min value here is -2922

In [0]:
```
p['DAYS_FIRST_DUE'].describe()
```

Out[87]:
```
count    997149.000000
mean      13826.269337
std       72444.869708
min       -2892.000000
25%       -1628.000000
50%        -831.000000
75%        -411.000000
max      365243.000000
Name: DAYS_FIRST_DUE, dtype: float64
```

In [0]:
```
plt.hist(p['DAYS_FIRST_DUE'],bins = 1000)#Relative to application date
plt.title('Distribution of DAYS_FIRST_DUE')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```



Observation: 365243 is outlier here.

In [0]:
```
print('There are',sum(p['DAYS_FIRST_DUE']<0),'reasonable value DAYS_FIR
print("There are",sum(p['DAYS_FIRST_DUE']==365243),"outliers DAYS_FIRST
```

```
There are 956504 reasonable value DAYS_FIRST_DUE
There are 40645 outliers DAYS_FIRST_DUE
```

In [0]:
```
print('There are',sum(p['DAYS_LAST_DUE']<0),'reasonable value in DAYS_L
print("There are",sum(p['DAYS_LAST_DUE']==365243),"outliers in DAYS_LAS
```

```
There are 785928 reasonable value in DAYS_LAST_DUE
There are 211221 outliers in DAYS_LAST_DUE
```

Feature engineering for Previous application

In [0]:
```
#function takes the previous_app and related dataframe and add aggregat
#https://www.kaggle.com/jsaguiar/lightgbm-7th-place-solution
#https://www.linkedin.com/pulse/winning-9th-place-kaggles-biggest-compe
def previous_app(prev):
    p_app, p_app_cols = one_hot(prev)
    p_app['DAYS_TERMINATION'].replace(365243, np.nan, inplace= True)
    p_app['DAYS_LAST_DUE_1ST_VERSION'].replace(365243, np.nan, inplace=
    p_app['DAYS_FIRST_DRAWING'].replace(365243, np.nan, inplace= True)
    p_app['DAYS_FIRST_DUE'].replace(365243, np.nan, inplace= True)
    p_app['DAYS_LAST_DUE'].replace(365243, np.nan, inplace= True)
    p_app['APP_CREDIT_PERC'] = p_app['AMT_APPLICATION'] / p_app['AMT_CR
    num_agg = {'AMT_DOWN_PAYMENT': ['max', 'mean'],'DAYS_DECISION': ['m
                        'AMT_GOODS_PRICE': ['max', 'mean'],'AMT_ANNUITY
        'RATE_DOWN_PAYMENT': ['max', 'mean'],'AMT_APPLICATION': ['max',
        'AMT_CREDIT': ['max', 'mean'],'APP_CREDIT_PERC': ['max', 'mean'

    }
    cat_agg = {}
    for cat in p_app_cols:
        cat_agg[cat] = ['mean']

    P1 = p_app.groupby('SK_ID_CURR').agg({**num_agg, **cat_agg})
    l=[]
    for i in P1.columns.tolist():
      l.append('PR_'+i[0]+'_'+i[1].upper())
    P1.columns = pd.Index(l)
    A = p_app[p_app['NAME_CONTRACT_STATUS_Approved'] == 1]
    A_agg = A.groupby('SK_ID_CURR').agg(num_agg)
    l=[]
    for i in A_agg.columns.tolist():
      l.append('APP_'+i[0]+'_'+i[1].upper())
    A_agg.columns = pd.Index(l)
    P1 = P1.join(A_agg, how='left', on='SK_ID_CURR')
    R = p_app[p_app['NAME_CONTRACT_STATUS_Refused'] == 1]
    R_agg = R.groupby('SK_ID_CURR').agg(num_agg)
    l=[]
    for i in R_agg.columns.tolist():
      l.append('REF_'+i[0]+'_'+i[1].upper())

    R_agg.columns = pd.Index(l)
    P1 = P1.join(R_agg, how='left', on='SK_ID_CURR')
    del R, R_agg, A, A_agg, p_app
    gc.collect()
    print(P1.shape)
    return P1

```

In [11]:

```
# idea refered from https://www.kaggle.com/c/home-credit-default-risk
pr = pd.read_csv('previous_application.csv')

frame = previous_app(reduce_mem_usage(pr))
df = df.join(frame, how='left', on='SK_ID_CURR')
del frame
gc.collect()

frame = reduce_mem_usage(pr[pr.DAYS_DECISION  >=-365].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = previous_app(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_year')
del frame
gc.collect()

frame = reduce_mem_usage(pr[pr.DAYS_DECISION  >=-182].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = previous_app(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_halfyear')
del frame
gc.collect()

frame = reduce_mem_usage(pr[pr.DAYS_DECISION  >=-92].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = previous_app(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_quarter')
del frame
gc.collect()

frame = reduce_mem_usage(pr[pr.DAYS_DECISION  >=-31].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = previous_app(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_month')
del frame
gc.collect()

frame = reduce_mem_usage(pr[pr.DAYS_DECISION  >=-8].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = previous_app(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_week')
del frame
gc.collect()
```

```
Memory usage of dataframe is 471.48 MB
Memory usage after optimization is: 309.01 MB
Decreased by 34.5%
(338857, 219)
Memory usage of dataframe is 110.53 MB
Memory usage after optimization is: 108.34 MB
Decreased by 2.0%
(195522, 216)
Memory usage of dataframe is 42.63 MB
Memory usage after optimization is: 41.78 MB
Decreased by 2.0%
(103914, 213)
Memory usage of dataframe is 17.44 MB
Memory usage after optimization is: 17.01 MB
Decreased by 2.5%
(52584, 210)
Memory usage of dataframe is 7.42 MB
Memory usage after optimization is: 7.23 MB
Decreased by 2.5%
(23184, 208)
Memory usage of dataframe is 1.92 MB
Memory usage after optimization is: 1.88 MB
Decreased by 2.5%
(6135, 206)
```

Out[11]: 0

POS_CASH_balance

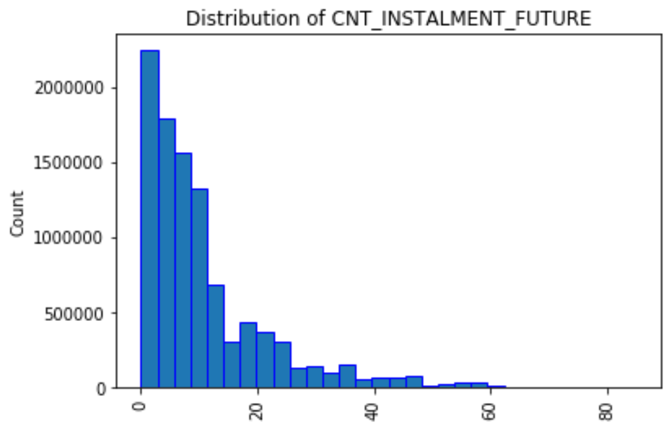
In [0]:
```
pc=pd.read_csv('/content/POS_CASH_balance.csv')
pc
```

Out[51]:

	SK_ID_PREV	SK_ID_CURR	MONTHS_BALANCE	CNT_INSTALMENT	CNT_INSTALMENT_FUTURE
0	1803195	182943	-31	48.0	45.0
1	1715348	367990	-33	36.0	35.0
2	1784872	397406	-32	12.0	9.0
3	1903291	269225	-35	48.0	42.0
4	2341044	334279	-35	36.0	35.0
...	...	...	...	...	...
10001353	2448283	226558	-20	6.0	0.0
10001354	1717234	141565	-19	12.0	0.0
10001355	1283126	315695	-21	10.0	0.0
10001356	1082516	450255	-22	12.0	0.0
10001357	1259607	174278	-52	16.0	0.0

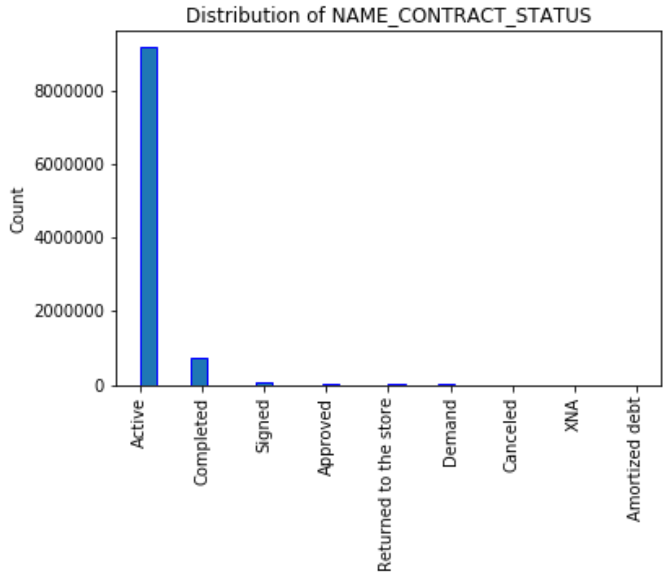
10001358 rows × 8 columns

In [0]:
```
plt.hist(pc['CNT_INSTALMENT_FUTURE'], edgecolor = 'b',stacked=0, bins =
plt.title('Distribution of CNT_INSTALMENT_FUTURE')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```



Observation: installments left to pay mostly falls in the bracket of 0-20.

In [0]:
```
plt.hist(pc['NAME_CONTRACT_STATUS'], edgecolor = 'b',stacked=0, bins =
plt.title('Distribution of NAME_CONTRACT_STATUS')
plt.xticks(rotation='vertical')
a=plt.ylabel('Count')
```



Observation: Most of the time name contract status is Active

Feature engineering on POS_CASH_balance

In [0]:
```
#function takes the posh_cash and related dataframe and add aggregated
#https://www.kaggle.com/jsaguiar/lightgbm-7th-place-solution
#https://www.linkedin.com/pulse/winning-9th-place-kaggles-biggest-compe
def pos_cash(pos):
    pos_ch, col = one_hot(pos)
    aggregate = {'SK_DPD_DEF': ['max', 'mean'],'SK_DPD': ['max', 'mean'
        'MONTHS_BALANCE': ['max', 'mean', 'size']

    }
    for c in col:
        aggregate[c] = ['mean']

    A_agg = pos_ch.groupby('SK_ID_CURR').agg(aggregate)
    l=[]
    for i in A_agg.columns.tolist():
      l.append('POS_'+i[0] + '_' + i[1].upper())
    A_agg.columns = pd.Index(l)
    A_agg['POS_no_COUNT'] = pos_ch.groupby('SK_ID_CURR').size()

    value=pos_ch.groupby('SK_ID_CURR')['MONTHS_BALANCE'].min()
    A_agg['MIN_VALUES']=pos_ch['SK_ID_CURR'].map(value)
    A_agg['MULTIPLIER']=1.00-pos_ch['MONTHS_BALANCE']/A_agg['MIN_VALUES
    print(A_agg.shape)
    del pos_ch
    gc.collect()
    return A_agg
```

In [13]:

```
# idea refered from https://www.kaggle.com/c/home-credit-default-ri
c = reduce_mem_usage(pd.read_csv('POS_CASH_balance.csv'))
frame = pos_cash(c)
df = df.join(frame, how='left', on='SK_ID_CURR')
del frame
gc.collect()

frame = reduce_mem_usage(c[c.MONTHS_BALANCE >=-12].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = pos_cash(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_year')
del frame
gc.collect()

frame = reduce_mem_usage(c[c.MONTHS_BALANCE >=-6].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = pos_cash(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_halfyear')
del frame
gc.collect()

frame = reduce_mem_usage(c[c.MONTHS_BALANCE >=-3].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = pos_cash(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_quarter')
del frame
gc.collect()

frame = reduce_mem_usage(c[c.MONTHS_BALANCE >=-1].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = pos_cash(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_month')
del frame
gc.collect()

```

```
Memory usage of dataframe is 610.43 MB
Memory usage after optimization is: 238.45 MB
Decreased by 60.9%
(337252, 20)
Memory usage of dataframe is 73.51 MB
Memory usage after optimization is: 64.60 MB
Decreased by 12.1%
(240235, 19)
Memory usage of dataframe is 33.01 MB
Memory usage after optimization is: 29.00 MB
Decreased by 12.1%
(192077, 19)
Memory usage of dataframe is 14.10 MB
Memory usage after optimization is: 12.39 MB
Decreased by 12.1%
(161387, 19)
Memory usage of dataframe is 2.99 MB
Memory usage after optimization is: 2.62 MB
Decreased by 12.1%
(79744, 18)
```

Out[13]: 0

Feature engineering on installments payments

In [0]:

```
#function takes the install_payments and related dataframe and add aggr
#https://www.kaggle.com/jsaguiar/lightgbm-7th-place-solution
#https://www.linkedin.com/pulse/winning-9th-place-kaggles-biggest-compe
def inst_pay(ins):
    A, col = one_hot(ins)

    aggregate = {'days_late_on_payment': ['max','mean','min','sum'],'AM
        'NUM_INSTALMENT_VERSION': ['nunique'],'AMT_INSTALMENT': ['max',
        'amount_extra_paid': ['max','mean','min','sum'],'DAYS_ENTRY_PAY
    }
    for c in col:
        aggregate[c] = ['mean']
    A_agg = A.groupby('SK_ID_CURR').agg(aggregate)
    l=[]
    for i in A_agg.columns.tolist():
      l.append('INS_'+i[0]+'_'+i[1].upper())
    A_agg.columns = pd.Index(l)
    A_agg['INSTAL_no_COUNT'] = A.groupby('SK_ID_CURR').size()
    del A
    gc.collect()
    print(A_agg.shape)
    return A_agg
```

In [15]:
```
   # idea refered from https://www.kaggle.com/c/home-credit-default-ri
i=pd.read_csv('installments_payments.csv')
i['DAYS_ENTRY_PAYMENT'].fillna(100, inplace=True)
i['AMT_PAYMENT'].fillna(0.0, inplace=True)
i['days_late_on_payment']=i.DAYS_ENTRY_PAYMENT-i.DAYS_INSTALMENT
i['amount_extra_paid']=i.AMT_PAYMENT-i.AMT_INSTALMENT
i = reduce_mem_usage(i)
frame = inst_pay(i)
df = df.join(frame, how='left', on='SK_ID_CURR')
del frame
gc.collect()

frame = reduce_mem_usage(i[i.DAYS_INSTALMENT  >=-365].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = inst_pay(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_year')
del frame
gc.collect()

frame = reduce_mem_usage(i[i.DAYS_INSTALMENT  >=-182].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = inst_pay(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_halfyear')
del frame
gc.collect()

frame = reduce_mem_usage(i[i.DAYS_INSTALMENT  >=-92].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = inst_pay(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_quarter')
del frame
gc.collect()

frame = reduce_mem_usage(i[i.DAYS_INSTALMENT  >=-31].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = inst_pay(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_month')
del frame
gc.collect()

frame = reduce_mem_usage(i[i.DAYS_INSTALMENT  >=-8].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = inst_pay(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_week')
del frame
gc.collect()

```

```
Memory usage of dataframe is 1038.01 MB
Memory usage after optimization is: 389.25 MB
Decreased by 62.5%
(339587, 20)
Memory usage of dataframe is 124.89 MB
Memory usage after optimization is: 111.74 MB
Decreased by 10.5%
(252761, 20)
Memory usage of dataframe is 60.96 MB
Memory usage after optimization is: 54.54 MB
Decreased by 10.5%
(211804, 20)
Memory usage of dataframe is 28.81 MB
Memory usage after optimization is: 25.78 MB
Decreased by 10.5%
(186521, 20)
Memory usage of dataframe is 8.38 MB
Memory usage after optimization is: 7.50 MB
Decreased by 10.5%
(153389, 20)
Memory usage of dataframe is 1.38 MB
```

credit_card_balance

In [0]:
```
cc=pd.read_csv('credit_card_balance.csv')
```

In [0]:
```
sum(cc['CNT_INSTALMENT_MATURE_CUM']==0)
```

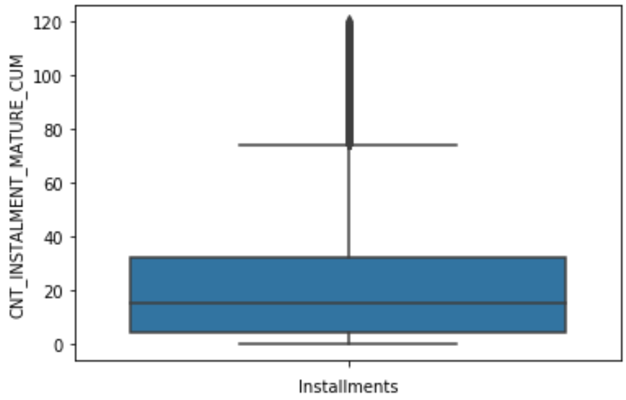
Out[55]:
```
551467
```

551467 times the paid installments are zero on the prrevious credit.

In [0]:
```
print(cc['CNT_INSTALMENT_MATURE_CUM'].describe())
```

```
count    3.535076e+06
mean     2.082508e+01
std      2.005149e+01
min      0.000000e+00
25%      4.000000e+00
50%      1.500000e+01
75%      3.200000e+01
max      1.200000e+02
Name: CNT_INSTALMENT_MATURE_CUM, dtype: float64
```

In [0]:
```
sns.boxplot(y='CNT_INSTALMENT_MATURE_CUM', data=cc)
plt.xlabel('Installments')
plt.show()
```



Observation: 75% of the paid installments on the previous credit are below 40.

Feature engineering on credit credit balance

In [0]:
```
#function takes the credit_card and related dataframe and add aggregate
def credit_card(cre):
    credit_card, col = one_hot(cre)
    credit_card.drop(['SK_ID_PREV'], axis= 1, inplace = True)
    credit_card_agg = credit_card.groupby('SK_ID_CURR').agg(['max', 'me
    l=[]
    for i in credit_card_agg.columns.tolist():
      l.append('CR_'+i[0]+'_'+i[1].upper())
    credit_card_agg.columns = pd.Index(l)
    # Count credit card lines
    credit_card_agg['CR_no_COUNT'] = credit_card.groupby('SK_ID_CURR').
    print(credit_card_agg.shape)
    del credit_card
    gc.collect()
    return credit_card_agg
```

In [17]:
```
  # idea refered from https://www.kaggle.com/c/home-credit-default-ri
cr=pd.read_csv('credit_card_balance.csv')
frame = credit_card(reduce_mem_usage(cr))
df = df.join(frame, how='left', on='SK_ID_CURR')
del frame
gc.collect()

frame = reduce_mem_usage(cr[cr.MONTHS_BALANCE >=-12].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = credit_card(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_year')
del frame
gc.collect()

frame = reduce_mem_usage(cr[cr.MONTHS_BALANCE >=-6].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = credit_card(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_halfyear')
del frame
gc.collect()

frame = reduce_mem_usage(cr[cr.MONTHS_BALANCE >=-3].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = credit_card(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_quarter')
del frame
gc.collect()

frame = reduce_mem_usage(cr[cr.MONTHS_BALANCE >=-1].reset_index())
frame.drop(['index'],axis=1,inplace=True)
frame = credit_card(frame)
df = df.join(frame, how='left', on='SK_ID_CURR',rsuffix='_month')
del frame
gc.collect()
```

```
Memory usage of dataframe is 673.88 MB
Memory usage after optimization is: 289.33 MB
Decreased by 57.1%
(103558, 113)
Memory usage of dataframe is 88.60 MB
Memory usage after optimization is: 84.53 MB
Decreased by 4.6%
(103558, 101)
Memory usage of dataframe is 46.35 MB
Memory usage after optimization is: 44.22 MB
Decreased by 4.6%
(103556, 101)
Memory usage of dataframe is 21.35 MB
Memory usage after optimization is: 20.37 MB
Decreased by 4.6%
(100677, 101)
Memory usage of dataframe is 5.17 MB
Memory usage after optimization is: 4.94 MB
Decreased by 4.6%
(61885, 101)
```

Out[17]: 0

Selecting top 300 features

In [18]:
```
df = reduce_mem_usage(df)

```

```
Memory usage of dataframe is 4718.39 MB
Memory usage after optimization is: 1996.12 MB
Decreased by 57.7%
```

In [0]:
```
import pickle
"""
with open('new_data.pickle', 'wb') as handle:
    pickle.dump(df, handle)
"""
with open('new_data.pickle', 'rb') as handle:
    df = pickle.load(handle)
```

In [0]:
```
train_df = df[df['TARGET'].notnull()]
test_df = df[df['TARGET'].isnull()]
```

In [0]:
```
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import f_classif

Xsp = (train_df.loc[:, train_df.columns != 'TARGET'])
ysp = (train_df['TARGET'] )


```

In [0]:
```
Xsp=np.nan_to_num(Xsp)
```

Splitting the dataset into train, cv and test.

In [0]:
```
from sklearn.model_selection import train_test_split

X_1, X_test, y_1, y_test = train_test_split(Xsp, ysp, test_size=0.10, s

# split the train data set into cross validation train and cross valida
X_tr, X_cv, y_tr, y_cv = train_test_split(X_1, y_1, test_size=0.10, str
```

In [7]:
```
del df,Xsp,train_df
gc.collect()
```

Out[7]: 0

In [42]:
```
print(X_tr.shape, y_tr.shape)
print(X_cv.shape, y_cv.shape)
print(X_test.shape, y_test.shape)
```

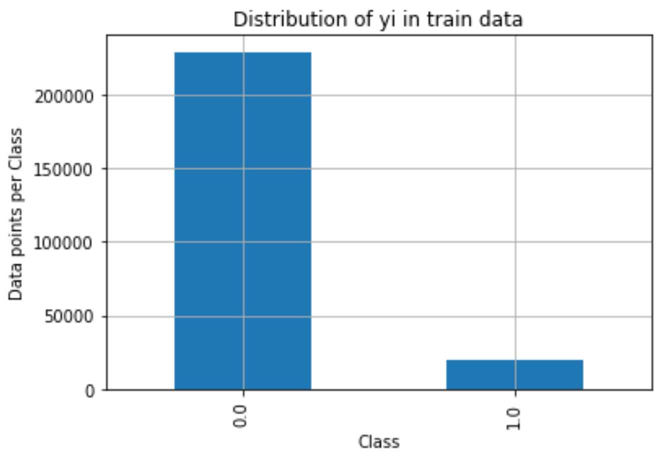
```
(248850, 2336) (248850,)
(27650, 2336) (27650,)
(30723, 2336) (30723,)
```

In [0]:
```
S = SelectKBest(f_classif, k=300)
X_tr=S.fit_transform(X_tr, y_tr)


```

In [0]:
```
X_cv=S.transform(X_cv)
X_test=S.transform(X_test)
```

Checking the distribution of target variable into train,cv and test.

In [0]:
```
# it returns a dict, keys as class labels and values as the number of d
train_class_distribution = y_tr.value_counts()
test_class_distribution = y_test.value_counts()
cv_class_distribution = y_cv.value_counts()

my_colors = 'rgbkymc'
train_class_distribution.plot(kind='bar')
plt.xlabel('Class')
plt.ylabel('Data points per Class')
plt.title('Distribution of yi in train data')
plt.grid()
plt.show()

# ref: argsort https://docs.scipy.org/doc/numpy/reference/generated/num
# -(train_class_distribution.values): the minus sign will give us in de
sorted_yi = np.argsort(-train_class_distribution.values)
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',train_class_distri


print('-'*80)
my_colors = 'rgbkymc'
test_class_distribution.plot(kind='bar')
plt.xlabel('Class')
plt.ylabel('Data points per Class')
plt.title('Distribution of yi in test data')
plt.grid()
plt.show()

# ref: argsort https://docs.scipy.org/doc/numpy/reference/generated/num
# -(train_class_distribution.values): the minus sign will give us in de
sorted_yi = np.argsort(-test_class_distribution.values)
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',test_class_distrib

print('-'*80)
my_colors = 'rgbkymc'
cv_class_distribution.plot(kind='bar')
plt.xlabel('Class')
plt.ylabel('Data points per Class')
plt.title('Distribution of yi in cross validation data')
plt.grid()
plt.show()

# ref: argsort https://docs.scipy.org/doc/numpy/reference/generated/num
# -(train_class_distribution.values): the minus sign will give us in de
sorted_yi = np.argsort(-train_class_distribution.values)
for i in sorted_yi:
    print('Number of data points in class', i+1, ':',cv_class_distribut
```



Logistic Regression

In [0]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(X_tr)
scaler_train = scaler.transform(X_tr)
scaler_cv = scaler.transform(X_cv)
scaler_test = scaler.transform(X_test)
```

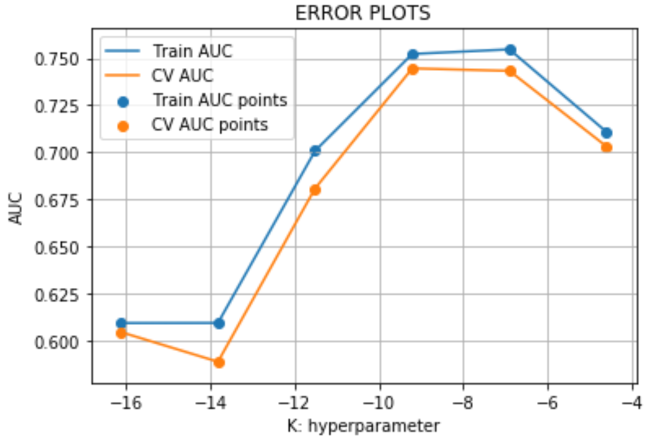
In [0]:
```
def batch_predict(clf, data):
    # roc_auc_score(y_true, y_score) the 2nd parameter should be probab
    # not the predicted outputs

    y_data_pred = []
    tr_loop = data.shape[0] - data.shape[0]%1000
    # consider you X_tr shape is 49041, then your cr_loop will be 49041
    # in this for loop we will iterate unti the last 1000 multiplier
    for i in range(0, tr_loop, 1000):
        y_data_pred.extend(clf.predict_proba(data[i:i+1000])[:,1])
    # we will be predicting for the last data points
    y_data_pred.extend(clf.predict_proba(data[tr_loop:])[:,1])

    return y_data_pred
```

In [0]:
```
from sklearn.metrics import roc_curve, auc
from sklearn.metrics import roc_auc_score
from sklearn import linear_model
from tqdm import tqdm
```

In [0]:

```
train_auc = []
cv_auc = []
K = {'alpha': [10**-7,10**-6,10**-5,10**-4,10**-3,10**-2]}
for i in tqdm(K['alpha']):
    neigh = linear_model.SGDClassifier(loss='log',alpha=i,penalty='l1')
    neigh.fit(scaler_train, y_tr)

    y_train_pred = batch_predict(neigh, scaler_train)
    y_cv_pred = batch_predict(neigh, scaler_cv)

    train_auc.append(roc_auc_score(y_tr,y_train_pred))
    cv_auc.append(roc_auc_score(y_cv, y_cv_pred))
log_K=[]
for l in K['alpha']:
    log_K.append(math.log(l))
plt.plot(log_K, train_auc, label='Train AUC')
plt.plot(log_K, cv_auc, label='CV AUC')

plt.scatter(log_K, train_auc, label='Train AUC points')
plt.scatter(log_K, cv_auc, label='CV AUC points')

plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()
```

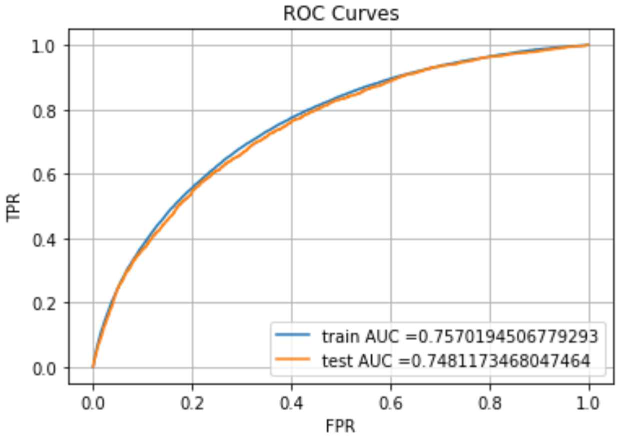
```
100%|██████████| 6/6 [05:52<00:00, 48.31s/it]
```



In [0]:

```
best_par1=10**-3
```

In [33]:
```
from sklearn.metrics import roc_curve, auc

neigh = linear_model.SGDClassifier(loss='log',alpha=best_par1,class_wei
neigh.fit(scaler_train, y_tr)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
# not the predicted outputs

y_train_pred = batch_predict(neigh,  scaler_train)
y_test_pred = batch_predict(neigh, scaler_test)

train_fpr, train_tpr, tr_thresholds = roc_curve(y_tr, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC Curves")
plt.grid()
plt.show()
```



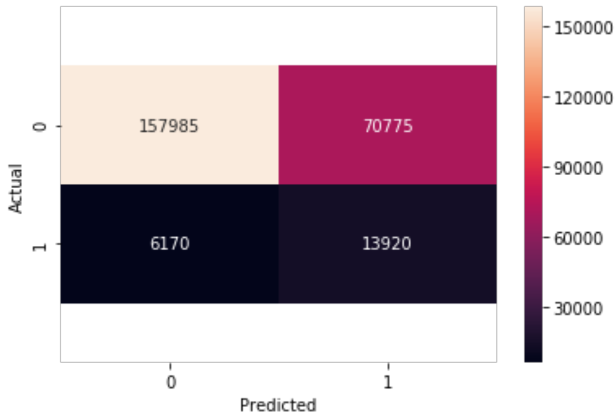
In [0]:
```
def predict(proba, threshould, fpr, tpr):

    t = threshould[np.argmax(tpr*(1-fpr))]

    # (tpr*(1-fpr)) will be maximum if your fpr is very low and tpr is

    # print("the maximum value of tpr*(1-fpr)", max(tpr*(1-fpr)), "for
    predictions = []
    for i in proba:
        if i>=t:
            predictions.append(1)
        else:
            predictions.append(0)
    return predictions
```

Train

In [35]:
```
import seaborn as sns
print("Train confusion matrix")
ax=sns.heatmap(confusion_matrix(y_tr, predict(y_train_pred, tr_threshol
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
plt.xlabel("Predicted")
plt.ylabel("Actual")

```

```
Train confusion matrix
```

Out[35]:
```
Text(33.0, 0.5, 'Actual')
```

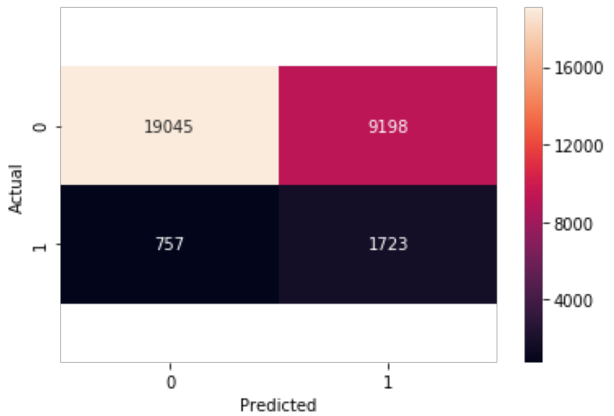


Test

In [36]:
```
import seaborn as sns
print("Train confusion matrix")
ax=sns.heatmap(confusion_matrix(y_test, predict(y_test_pred, te_threshc
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
plt.xlabel("Predicted")
plt.ylabel("Actual")

```

```
Train confusion matrix
```

Out[36]:
```
Text(33.0, 0.5, 'Actual')
```



XGBoost

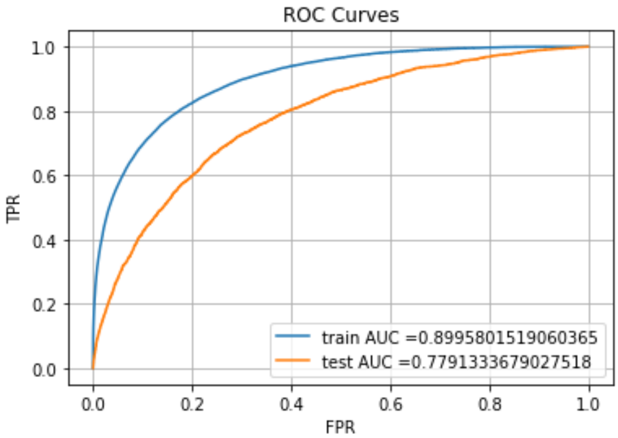
In [1]:
```
from sklearn.model_selection import StratifiedKFold

k=StratifiedKFold(n_splits=3, shuffle=True)
print(k)
```

```
StratifiedKFold(n_splits=3, random_state=None, shuffle=True)
```

In [21]:
```
from xgboost.sklearn import XGBClassifier
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import RandomizedSearchCV
n_estimators = [700,800,900,1000]
learning_rate = [ 0.02,0.05,0.07]
max_depth = [6,7,8,9]

param = dict(learning_rate=learning_rate,n_estimators=n_estimators,max_
xgb = XGBClassifier(nthread=-1)
kfold = StratifiedKFold(n_splits=3, shuffle=True)
random_search_cv = RandomizedSearchCV(xgb, param, scoring="neg_log_loss
result = random_search_cv.fit(scaler_train , y_tr)

print("Best mean_test_score: ", result.best_score_ ,"parameters",result
mean = result.cv_results_['mean_test_score']
std = result.cv_results_['std_test_score']
par = result.cv_results_['params']
for m, s, p in zip(mean, std, par):
    print( 'mean_test_score',m,'std_test_score',s,'params',p)

```

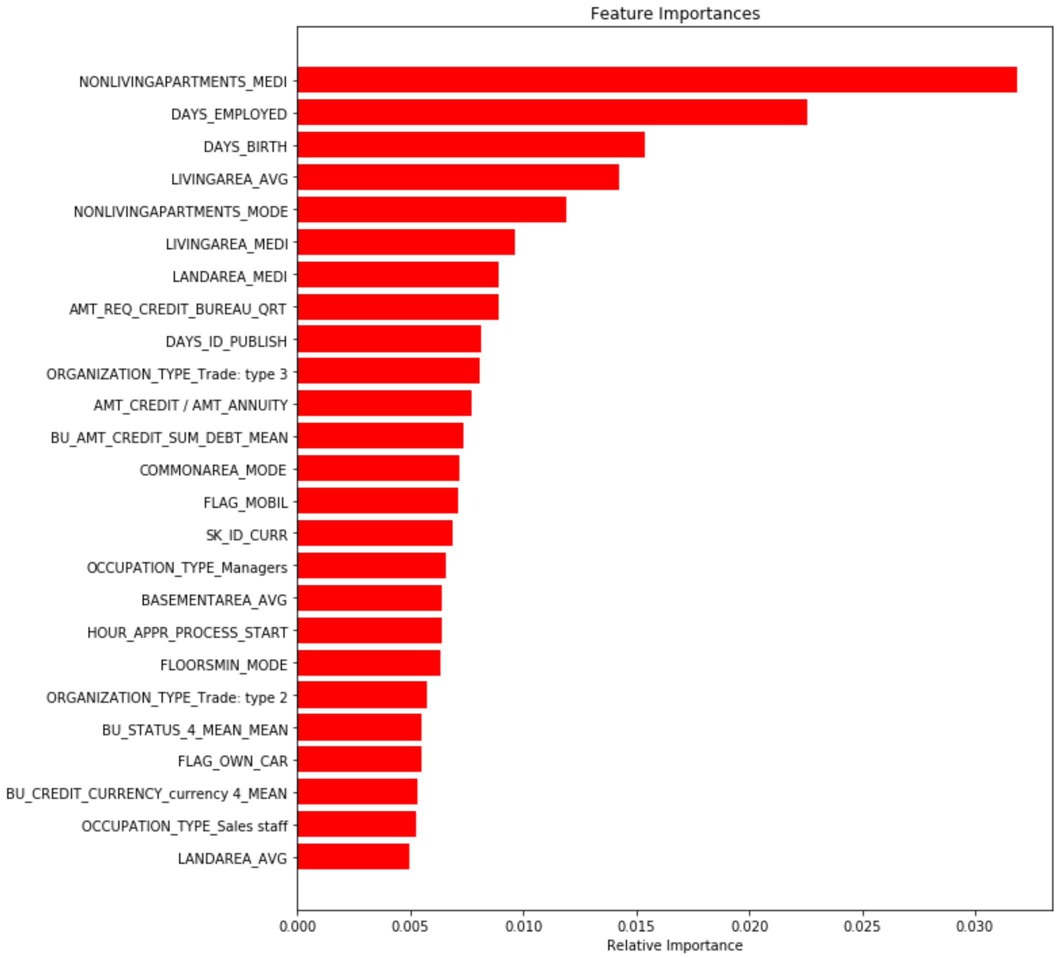
```
Best mean_test_score:  -0.2406262771923414 parameters {'n_estimators': 80
0, 'max_depth': 6, 'learning_rate': 0.05}
mean_test_score -0.24465255370463834 std_test_score 0.0008739492716115714
params {'n_estimators': 700, 'max_depth': 8, 'learning_rate': 0.05}
mean_test_score -0.24186662961652886 std_test_score 0.0007838895703288978
params {'n_estimators': 700, 'max_depth': 7, 'learning_rate': 0.05}
mean_test_score -0.24631985675540405 std_test_score 0.000790347957465164 p
arams {'n_estimators': 800, 'max_depth': 7, 'learning_rate': 0.07}
mean_test_score -0.24428878322120132 std_test_score 0.0007794105997974142
params {'n_estimators': 1000, 'max_depth': 6, 'learning_rate': 0.07}
mean_test_score -0.2448484095207295 std_test_score 0.0007974006162268901 p
arams {'n_estimators': 700, 'max_depth': 7, 'learning_rate': 0.07}
mean_test_score -0.24913924356126568 std_test_score 0.0006932261691023411
params {'n_estimators': 1000, 'max_depth': 8, 'learning_rate': 0.05}
mean_test_score -0.2677679252731944 std_test_score 0.0015705616987893593 p
arams {'n_estimators': 900, 'max_depth': 9, 'learning_rate': 0.07}
mean_test_score -0.2409831330670571 std_test_score 0.0009611824046316707 p
arams {'n_estimators': 900, 'max_depth': 6, 'learning_rate': 0.05}
mean_test_score -0.2406262771923414 std_test_score 0.000906651959100784 pa
rams {'n_estimators': 800, 'max_depth': 6, 'learning_rate': 0.05}
mean_test_score -0.24259295039010853 std_test_score 0.000758119901510508 p
arams {'n_estimators': 800, 'max_depth': 7, 'learning_rate': 0.05}
```

In [30]:
```
from sklearn.metrics import roc_curve, auc
from xgboost.sklearn import XGBClassifier
neigh = XGBClassifier(n_estimators=800,max_depth=6,learning_rate=0.05,
                      )
neigh.fit(scaler_train, y_tr)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
# not the predicted outputs

y_train_pred = batch_predict(neigh, scaler_train)
y_test_pred = batch_predict(neigh, scaler_test)

train_fpr, train_tpr, tr_thresholds = roc_curve(y_tr, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC Curves")
plt.grid()
plt.show()
```



In [19]:

```
import matplotlib.pyplot as plt
features =train_df.columns
importances = neigh.feature_importances_
indices = (np.argsort(importances))[-25:]
plt.figure(figsize=(10,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='c
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```

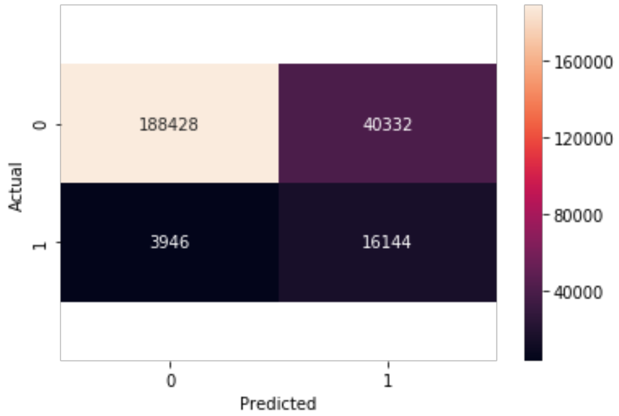


Train

In [20]:
```
import seaborn as sns
print("Train confusion matrix")
ax=sns.heatmap(confusion_matrix(y_tr, predict(y_train_pred, tr_threshol
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
plt.xlabel("Predicted")
plt.ylabel("Actual")

```

```
Train confusion matrix
```

Out[20]:
```
Text(33.0, 0.5, 'Actual')
```

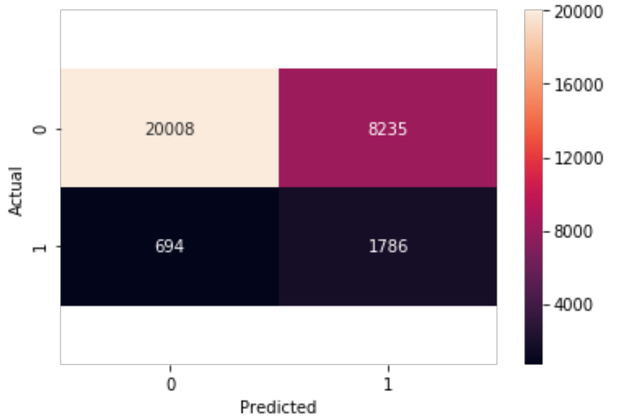


test

In [21]:
```
import seaborn as sns
print("Train confusion matrix")
ax=sns.heatmap(confusion_matrix(y_test, predict(y_test_pred, te_thresho
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
plt.xlabel("Predicted")
plt.ylabel("Actual")

```

```
Train confusion matrix
```

Out[21]:
```
Text(33.0, 0.5, 'Actual')
```



Random Forest

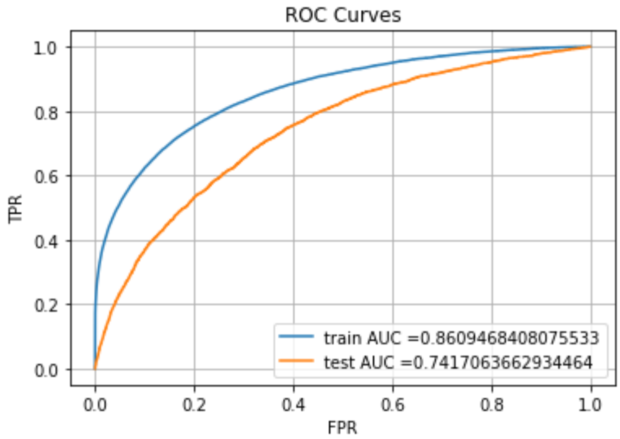
In [23]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import StratifiedKFold
from sklearn.model_selection import RandomizedSearchCV
n_estimators = [500,600,700,800]
max_depth = [9,10,11,12]

param = dict(n_estimators=n_estimators,max_depth=max_depth)
xgb = RandomForestClassifier(n_jobs=-1)
kfold = StratifiedKFold(n_splits=3, shuffle=True)
random_search_cv = RandomizedSearchCV(xgb, param, scoring="neg_log_loss
result = random_search_cv.fit(scaler_train , y_tr)

print("Best mean_test_score: ", result.best_score_ ,"parameters",result
mean = result.cv_results_['mean_test_score']
std = result.cv_results_['std_test_score']
par = result.cv_results_['params']
for m, s, p in zip(mean, std, par):
    print( 'mean_test_score',m,'std_test_score',s,'params',p)

```

```
Best mean_test_score:  -0.2536874293927612 parameters {'n_estimators': 80
0, 'max_depth': 12}
mean_test_score -0.254615364761944 std_test_score 0.0002823405537752798 pa
rams {'n_estimators': 500, 'max_depth': 11}
mean_test_score -0.25651790067081387 std_test_score 0.0001920862401660547
params {'n_estimators': 500, 'max_depth': 9}
mean_test_score -0.2565721240025001 std_test_score 0.0003010964807867514 p
arams {'n_estimators': 600, 'max_depth': 9}
mean_test_score -0.255477673191798 std_test_score 0.0001977923024301139 pa
rams {'n_estimators': 800, 'max_depth': 10}
mean_test_score -0.25376309773251715 std_test_score 0.0002614216605694983
params {'n_estimators': 600, 'max_depth': 12}
mean_test_score -0.2536874293927612 std_test_score 0.000288791520100807 pa
rams {'n_estimators': 800, 'max_depth': 12}
mean_test_score -0.2554554413614863 std_test_score 0.00010584947643292523
params {'n_estimators': 700, 'max_depth': 10}
mean_test_score -0.25379525139531606 std_test_score 0.00021145300208143608
params {'n_estimators': 700, 'max_depth': 12}
mean_test_score -0.25456206385962066 std_test_score 0.00021551356505262402
params {'n_estimators': 600, 'max_depth': 11}
mean_test_score -0.2565865410647776 std_test_score 0.00031073006522073344
params {'n_estimators': 800, 'max_depth': 9}
```

In [24]:

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_curve, auc
neigh = RandomForestClassifier(n_estimators=800,max_depth=12)

neigh.fit(scaler_train, y_tr)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probabilit
# not the predicted outputs

y_train_pred = batch_predict(neigh, scaler_train)
y_test_pred = batch_predict(neigh, scaler_test)

train_fpr, train_tpr, tr_thresholds = roc_curve(y_tr, y_train_pred)
test_fpr, test_tpr, te_thresholds = roc_curve(y_test, y_test_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
plt.legend()
plt.xlabel("FPR")
plt.ylabel("TPR")
plt.title("ROC Curves")
plt.grid()
plt.show()
```



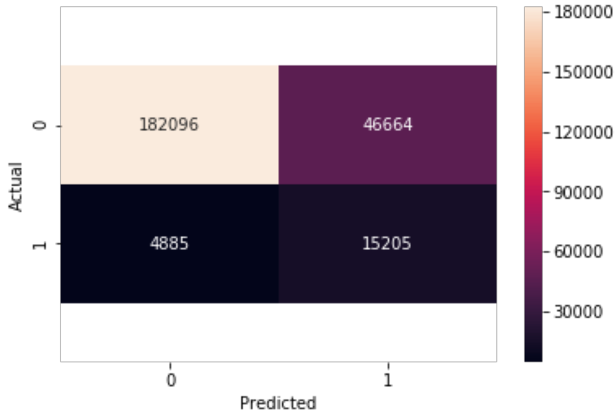
Train

In [25]:

```
import seaborn as sns
print("Train confusion matrix")
ax=sns.heatmap(confusion_matrix(y_tr, predict(y_train_pred, tr_threshol
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
plt.xlabel("Predicted")
plt.ylabel("Actual")

```

```
Train confusion matrix
```

Out[25]: `Text(33.0, 0.5, 'Actual')`



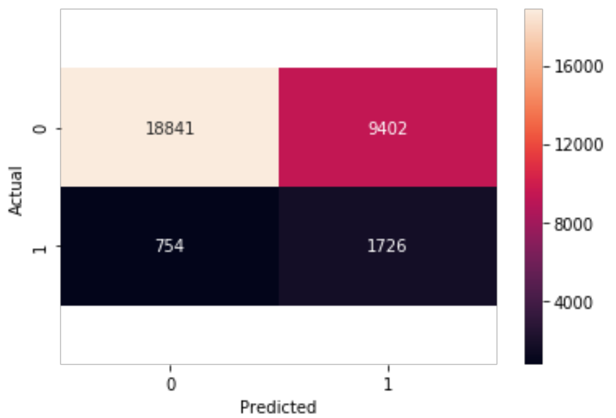
test

In [26]:

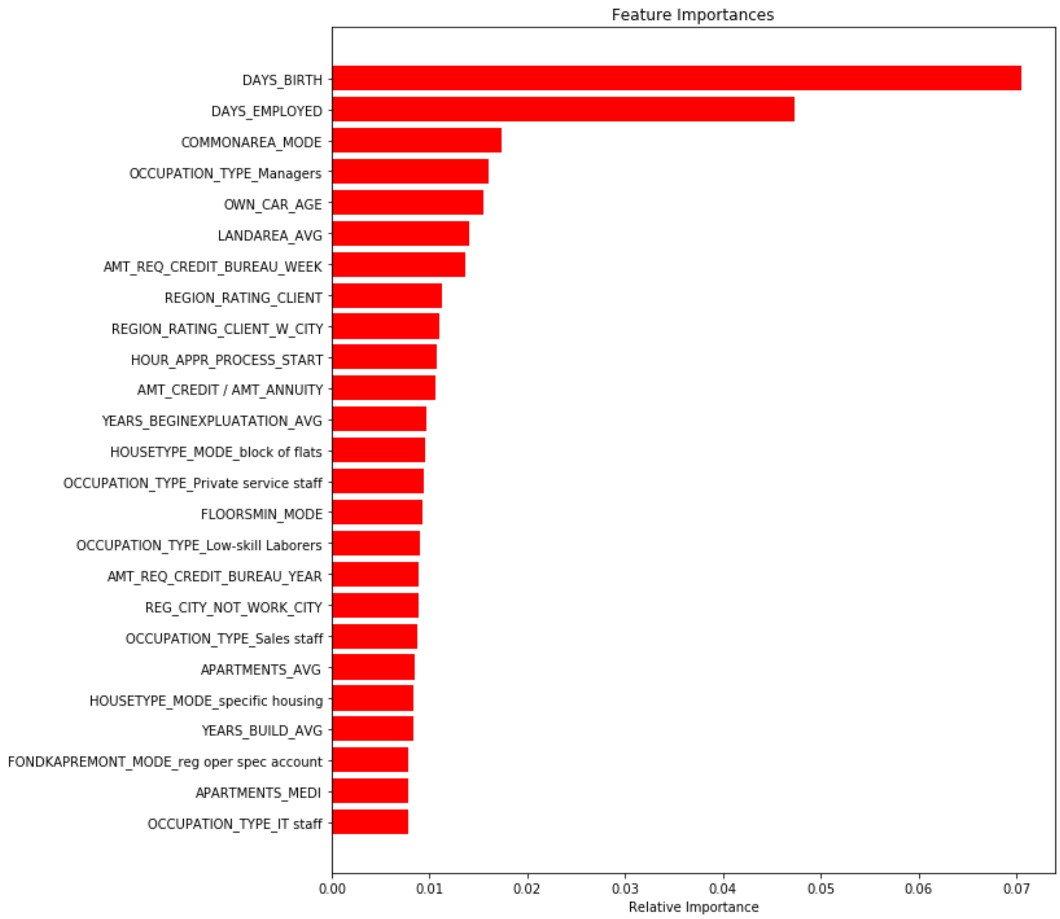
```
import seaborn as sns
print("Train confusion matrix")
ax=sns.heatmap(confusion_matrix(y_test, predict(y_test_pred, te_thresho
bottom, top = ax.get_ylim()
ax.set_ylim(bottom + 0.5, top - 0.5)
plt.xlabel("Predicted")
plt.ylabel("Actual")

```

```
Train confusion matrix
```

Out[26]: `Text(33.0, 0.5, 'Actual')`



In [29]:
```
import matplotlib.pyplot as plt
features = train_df.columns
importances = neigh.feature_importances_
indices = (np.argsort(importances))[-25:]
plt.figure(figsize=(10,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='c
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



Hyper parameter tuning using BayesianOptimization

- Bayesian optimization methods build a probability model of the objective function to propose smarter choices for the next set of hyperparameters to evaluate. hence reduce the tuning time for hyperparameters.

In [22]:
```
!pip install bayesian-optimization
```

```
Collecting bayesian-optimization
  Downloading https://files.pythonhosted.org/packages/72/0c/173ac467d0a53e33e41b521e4ceba74a8ac7c7873d7b857a8fbdca88302d/bayesian-optimization-1.0.1.tar.gz (https://files.pythonhosted.org/packages/72/0c/173ac467d0a53e33e41b521e4ceba74a8ac7c7873d7b857a8fbdca88302d/bayesian-optimization-1.0.1.tar.gz)
Requirement already satisfied: numpy>=1.9.0 in /usr/local/lib/python3.6/dist-packages (from bayesian-optimization) (1.17.5)
Requirement already satisfied: scipy>=0.14.0 in /usr/local/lib/python3.6/dist-packages (from bayesian-optimization) (1.4.1)
Requirement already satisfied: scikit-learn>=0.18.0 in /usr/local/lib/python3.6/dist-packages (from bayesian-optimization) (0.22.1)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-packages (from scikit-learn>=0.18.0->bayesian-optimization) (0.14.1)
Building wheels for collected packages: bayesian-optimization
  Building wheel for bayesian-optimization (setup.py) ... done
  Created wheel for bayesian-optimization: filename=bayesian_optimization-1.0.1-cp36-none-any.whl size=10032 sha256=d476f4cd72ce4ba849bb66887908a3f60d92da283cb0b8d59444dd266ba3fcc4
  Stored in directory: /root/.cache/pip/wheels/1d/0d/3b/6b9d4477a34b3905f246ff4e7acf6aafd4cc9b77d473629b77
Successfully built bayesian-optimization
Installing collected packages: bayesian-optimization
Successfully installed bayesian-optimization-1.0.1
```

In [3]:

```
#https://www.kaggle.com/returnofsputnik/bayes-opt-again/code
#https://www.dlology.com/blog/how-to-do-hyperparameter-search-with-bays
import lightgbm as lgb
from bayes_opt import BayesianOptimization
train_df = df[df['TARGET'].notnull()]
test_df = df[df['TARGET'].isnull()]
y = train_df['TARGET']

data = lgb.Dataset(data=train_df, label=y)

def parameters(num_iterations,num_leaves, feature_fraction, max_depth,
  params = {'application':'binary','early_stopping_round':100, 'metric'
  params['num_iterations']=int(round(num_iterations))
  params["num_leaves"] = int(round(num_leaves))
  params["learning_rate"] = learning_rate
  params['feature_fraction'] = max(min(feature_fraction, 1), 0)
  params['max_depth'] = int(round(max_depth))
  params['min_split_gain'] = min_split_gain
  params['min_child_weight'] = min_child_weight

  cv_result = lgb.cv(params, data, nfold=5,seed=6, stratified=True, met
  return max(cv_result['auc-mean'])

optimizer = BayesianOptimization(parameters, {'num_iterations':(9800,11
                                              'num_leaves':(16,48),
                                              'feature_fraction':(0.1,0.5
                                              'max_depth': (6,12),
                                              'min_split_gain':(0.001,0.1
                                              'min_child_weight': (20,60)
                                              'learning_rate':(0.01,0.07)
                                              })

optimizer.maximize(init_points=30, n_iter=30)

print(optimizer.max)

```

```
|   iter    |  target   | featur... | learni... | max_depth | min_ch... |
min_sp... | num_it... | num_le... |
---------------------------------------------------------------------------
-----------------------------------
|  1        |  1.0      |  0.1895   |  0.03089  |  9.253    |  28.32    |
0.06894   |  1.078e+0 |  28.33    |
|  2        |  1.0      |  0.4026   |  0.05044  |  6.33     |  39.45    |
0.09028   |  1.051e+0 |  26.69    |
|  3        |  1.0      |  0.2039   |  0.03873  |  11.05    |  22.67    |
0.005001  |  1.098e+0 |  26.39    |
|  4        |  1.0      |  0.1684   |  0.03317  |  6.978    |  49.63    |
0.02587   |  9.879e+0 |  27.18    |
|  5        |  1.0      |  0.2845   |  0.03154  |  6.63     |  51.96    |
0.0845    |  1.017e+0 |  33.57    |
|  6        |  1.0      |  0.2323   |  0.04324  |  9.304    |  24.97    |
0.03821   |  1.06e+04 |  28.55    |
|  7        |  1.0      |  0.1349   |  0.0657   |  10.06    |  45.71    |
0.09596   |  1.014e+0 |  38.51    |
|  8        |  1.0      |  0.4099   |  0.01673  |  7.422    |  31.73    |
0.01013   |  1.081e+0 |  23.89    |
|  9        |  1.0      |  0.1966   |  0.04361  |  10.71    |  59.45    |
0.07365   |  1.069e+0 |  33.45    |
|  10       |  1.0      |  0.3293   |  0.03728  |  6.678    |  33.34    |
0.04531   |  9.831e+0 |  17.92    |
|  11       |  1.0      |  0.3723   |  0.02842  |  10.25    |  31.12    |
0.08445   |  1.052e+0 |  19.29    |
|  12       |  1.0      |  0.1611   |  0.02491  |  9.896    |  34.35    |
0.05449   |  1.083e+0 |  27.83    |
|  13       |  1.0      |  0.1106   |  0.06462  |  10.03    |  32.55    |
0.02837   |  1.097e+0 |  36.68    |
|  14       |  1.0      |  0.2265   |  0.04103  |  8.377    |  46.33    |
```

In [0]:
```
#df = reduce_mem_usage(df)
train_df = df[df['TARGET'].notnull()]
test_df = df[df['TARGET'].isnull()]
```

5 k-cross validation

In [0]:
```
f=KFold(n_splits=5,shuffle=True,random_state=101) #K fold cross validat

imp = pd.DataFrame()
y=train_df['TARGET']

```

In [0]:
```
feats = [f for f in train_df.columns if f not in ['TARGET','SK_ID_CURR'
imp['feat']=feats
```

In [0]:
```
#hold outputs of training, testing and cv data
train_predict = np.zeros(train_df.shape[0])
cv_predict = np.zeros(train_df.shape[0])
test_predict = np.zeros(test_df.shape[0])

```

Training on LGBM

Advantages:

- Fast training efficiency because of histogram binning.
- Better accuracy because of leaf wise growth.
- Low memory usage because it replaces continuous values to discrete bins which result in lower memory usage

In [26]:
```

import pickle
a=0
for i,(train, cv) in enumerate(f.split(train_df[feats],y)):
  X_train, Y_train = train_df[feats].iloc[train], y.iloc[train]
  X_valid, Y_valid = train_df[feats].iloc[cv], y.iloc[cv]

  lgb = LGBMClassifier(
            nthread=4,
            n_estimators=10780,
            learning_rate=0.03,
            num_leaves=28,
            feature_fraction=0.1894,#lgbm will select 30 % of the featu
            max_depth=9,
            min_split_gain=0.06,
            min_child_weight=28,
            silent=1,
            verbose=-1, )
  lgb.fit(X_train, Y_train, eval_set=[(X_train, Y_train), (X_valid, Y_v
            eval_metric= 'auc', verbose= 200, early_stopping_rounds= 20
  a=a+1
  train_predict[train] = lgb.predict_proba(X_train, num_iteration=lgb.b
  cv_predict[cv]=lgb.predict_proba(X_valid, num_iteration=lgb.best_iter
  test_predict += lgb.predict_proba(test_df[feats], num_iteration=lgb.b
  with open('model'+ str(a) +'.pickle', 'wb') as handle:
    pickle.dump(lgb, handle)

  #train_fpr, train_tpr, tr_thresholds = roc_curve(Y_train, train_predi
  #test_fpr, test_tpr, te_thresholds = roc_curve(Y_valid, cv_predict)

  imp["imp"] = lgb.feature_importances_
  imp["fold"] = i + 1
  print('Fold ',i + 1,' TRAIN AUC : ',roc_auc_score(Y_train, train_prec
  print('Fold ',i + 1,' CV AUC : ',roc_auc_score(Y_valid, cv_predict[cv


  del lgb, X_train, Y_train, X_valid, Y_valid
  gc.collect()

print('Full TRAIN AUC score ',roc_auc_score(y, train_predict))
print('Full CV AUC score ',roc_auc_score(y, cv_predict))

train_fpr, train_tpr, tr_thresholds = roc_curve(y, train_predict)
test_fpr, test_tpr, te_thresholds = roc_curve(y, cv_predict)

test_df['TARGET'] = test_predict
test_df[['SK_ID_CURR', 'TARGET']].to_csv('gbvh.csv', index= False)

#plot auc curve
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()

#plot imp features
features = imp["feat"]
importances = imp["imp"]
indices = (np.argsort(importances))[-25:]
plt.figure(figsize=(10,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='c
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```

10 K-cross validation

In [0]:
```
#df = reduce_mem_usage(df)
train_df = df[df['TARGET'].notnull()]
test_df = df[df['TARGET'].isnull()]
```

In [0]:
```
f=KFold(n_splits=10,shuffle=True,random_state=101) #K fold cross valida

imp = pd.DataFrame()
y=train_df['TARGET']

```

In [0]:
```
feats = [f for f in train_df.columns if f not in ['TARGET','SK_ID_CURR'
imp['feat']=feats
```

In [0]:
```
#hold outputs of training, testing and cv data
train_predict = np.zeros(train_df.shape[0])
cv_predict = np.zeros(train_df.shape[0])
test_predict = np.zeros(test_df.shape[0])
```

In [10]:

```python

import pickle
a=0
for i,(train, cv) in enumerate(f.split(train_df[feats],y)):
  X_train, Y_train = train_df[feats].iloc[train], y.iloc[train]
  X_valid, Y_valid = train_df[feats].iloc[cv], y.iloc[cv]

  lgb = LGBMClassifier(
            nthread=4,
            n_estimators=10780,
            learning_rate=0.03,
            num_leaves=28,
            feature_fraction=0.1894,#lgbm will select 30 % of the featu
            max_depth=9,
            min_split_gain=0.06,
            min_child_weight=28,
            silent=1,
            verbose=-1, )
  lgb.fit(X_train, Y_train, eval_set=[(X_train, Y_train), (X_valid, Y_v
            eval_metric= 'auc', verbose= 200, early_stopping_rounds= 20
  a=a+1
  train_predict[train] = lgb.predict_proba(X_train, num_iteration=lgb.b
  cv_predict[cv]=lgb.predict_proba(X_valid, num_iteration=lgb.best_iter
  test_predict += lgb.predict_proba(test_df[feats], num_iteration=lgb.b
  with open('model'+ str(a) +'.pickle', 'wb') as handle:
    pickle.dump(lgb, handle)


  imp["imp"] = lgb.feature_importances_
  imp["fold"] = i + 1
  print('Fold ',i + 1,' TRAIN AUC : ',roc_auc_score(Y_train, train_pred
  print('Fold ',i + 1,' CV AUC : ',roc_auc_score(Y_valid, cv_predict[cv


  del lgb, X_train, Y_train, X_valid, Y_valid
  gc.collect()

print('Full TRAIN AUC score ',roc_auc_score(y, train_predict))
print('Full CV AUC score ',roc_auc_score(y, cv_predict))

train_fpr, train_tpr, tr_thresholds = roc_curve(y, train_predict)
test_fpr, test_tpr, te_thresholds = roc_curve(y, cv_predict)

test_df['TARGET'] = test_predict
test_df[['SK_ID_CURR', 'TARGET']].to_csv('gbvh.csv', index= False)

#plot auc curve
plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, t
plt.plot(test_fpr, test_tpr, label="test AUC ="+str(auc(test_fpr, test_
plt.legend()
plt.xlabel("K: hyperparameter")
plt.ylabel("AUC")
plt.title("ERROR PLOTS")
plt.grid()
plt.show()

#plot imp features
features = imp["feat"]
importances = imp["imp"]
indices = (np.argsort(importances))[-25:]
plt.figure(figsize=(10,12))
plt.title('Feature Importances')
plt.barh(range(len(indices)), importances[indices], color='r', align='c
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```

```
Training until validation scores don't improve for 200 rounds.
[200]   training's auc: 0.805515        training's binary_logloss: 0.23332
```

##Conclusion

In [0]:
```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Model", "Metrics",'test score']

x.add_row(['Logistic regression','AUC',0.7480])
x.add_row(['XGBoost','AUC', 0.7710])
x.add_row(['Random forest','AUC', 0.7417])
x.add_row(['lightGBM','AUC',0.7948,])
print(x)
```

Observation:

- **We can see that lightgbm is the clear winner here with 79.48% AUC**

Steps for model

- Download the home credit default risk dataset.
- Perform EDA and data analysis for all the files.
- Extract important features.
- Combine all the file and Prepare data for models.
- Use different models like logistic regression,xgboost, random forest,lgbm.
- Perform hyperparameter tuning to get the best parameter.
- Train models on best hyperparameters.
- Check AUC for various model and give the best model.
- LightGBM performs best among all the models.

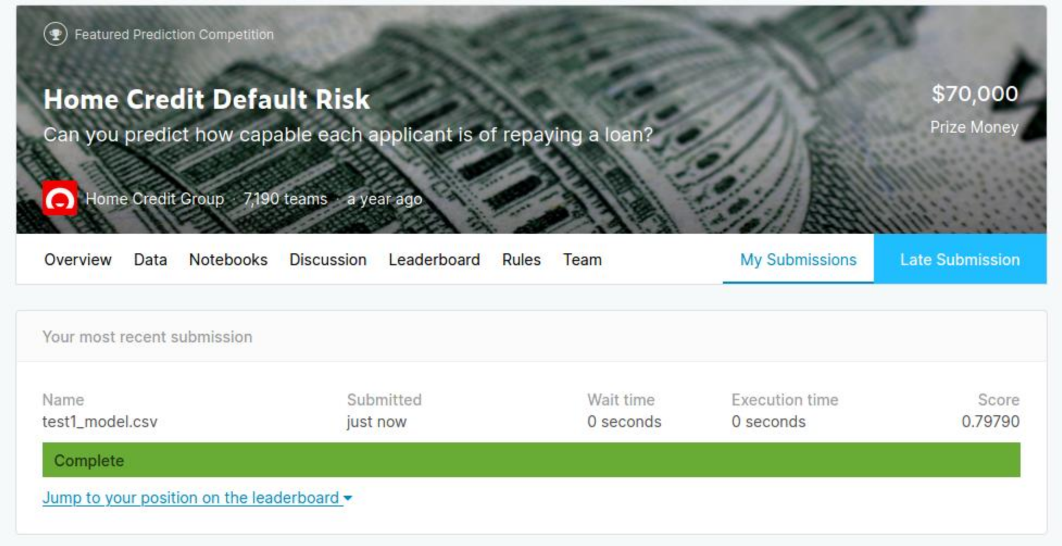
Featurization

- First i used simple domain specific features of application data.
- Then i used aggregation(mean,median,var) on columns for all table except application table.
- I had nearly 750 features and i selected top 300 features.
- Training xgboost on 300 features gave me an AUC of 77%.
- Then i used time related features and bayesian optimization for parameter tuning and lightgbm for training.
- I had 2337 features now and i used bayesian optimization on them and got the best hyperparameters.
- I trained lightgbm on best parameters on all the features and got an AUC of 79.79% on test data.

Refrences

- Bayesian optimization
  https://www.kaggle.com/returnofsputnik/bayes-opt-again/code (https://www.kaggle.com/returnofsputnik/bayes-opt-again/code)
  https://www.dlology.com/blog/how-to-do-hyperparameter-search-with-baysian-optimization-for-keras-model/ (https://www.dlology.com/blog/how-to-do-hyperparameter-search-with-baysian-optimization-for-keras-model/)
- Time related features
  https://www.kaggle.com/c/home-credit-default-risk/discussion/64593 (https://www.kaggle.com/c/home-credit-default-risk/discussion/64593)
- Domain specific features
  https://www.kaggle.com/aantonova/797-lgbm-and-bayesian-optimization (https://www.kaggle.com/aantonova/797-lgbm-and-bayesian-optimization)
- Aggregation featurization
  https://www.kaggle.com/jsaguiar/lightgbm-7th-place-solution (https://www.kaggle.com/jsaguiar/lightgbm-7th-place-solution)
  https://www.linkedin.com/pulse/winning-9th-place-kaggles-biggest-competition-yet-home-levinson/ (https://www.linkedin.com/pulse/winning-9th-place-kaggles-biggest-competition-yet-home-levinson/)
- Reduce dataframe size
  https://www.kaggle.com/gemartin/load-data-reduce-memory-usage (https://www.kaggle.com/gemartin/load-data-reduce-memory-usage)

AUC on the test data




```
In [ ]: 1
```