RESTAURANT SEGMENTATION AND PREDICTION SYSTEM

A.PROBLEM STATEMENT:

The objective of this case study is to build a recommendation engine to predict what restaurants customers are most likely to order from given the customer location, restaurant information, and the customer order history.

B.DATA OVERVIEW:

There are 10,000 customers in the test set. These are the customers you will need to recommend a vendor to. Each customer can order from multiple locations (LOC_NUM).

There are 35,000 customers in the train set. Some of these customers have made orders at at least one of 100 vendors.

There are following datasets which is available to us in this case study.

1. test_customers.csv - customer id’s in the test set.
2. test_locations.csv - latitude and longitude for the different locations of each customer for the test data.
3. train_locations.csv - customer locations details in the train dataset.
4. train_customers.csv - latitude and longitude for the different locations of each customer for the train data.
5. orders.csv - orders that the customers train_customers.csv from made.
6. vendors.csv - vendors that customers can order from and their respective details.
7. VariableDefinitions.txt - Variable definitions for the datasets

C.STRUCTURE OF FINAL SUBMISSION:

1. SampleSubmission.csv - is an example of what your submission file should look like.

The order of the rows does not matter, but the names of CID X LOC_NUM X VENDOR must be correct. The column "target" is your prediction.In the target 1 means The customer CID will have highest chance of taking orders from vendor VENDOR, and 0 means, CID will not order at all from VENDOR.

D. BUSINESS OBJECTIVES AND CONSTRAINTS:

1. No low-latency requirement.
2. Submitted code must run on the original train, test, and other datasets provided.

E. PERFORMANCE METRICS:

The error metric for this competition is the F1 score, which ranges from 0 (total failure) to 1 (perfect score). Hence, the closer your score is to 1, the better your model.

1. Precision :

This is an indicator of the number of items correctly identified as positive out of total items identified as positive. The formula is given as: TP/(TP+FP)

2. Recall / Sensitivity / True Positive Rate (TPR): This is an indicator of the number of items correctly identified as positive out of total actual positives. The formula is given as: TP/(TP+FN)

3. F1 Score: A performance score that combines both precision and recall. It is a harmonic mean of these two variables.

The formula is given as: 2*Recall/(Precision + Recall)

Where:

1. TP=True Positive
2. FP=False Positive
3. TN=True Negative
4. FN=False Negative

1.DATA UPLOADING AND MERGING

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1. Importing packages and files

In [ ]:
```
!pip install geopandas
```

```
Collecting geopandas
  Downloading https://files.pythonhosted.org/packages/d7/bf/e9cefb69d39155d122b6ddca53893b61535fa6ffdad70bf5ef708977f53f/geopandas-0.9.0-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/d7/bf/e9cefb69d39155d122b6ddca53893b61535fa6ffdad70bf5ef708977f53f/geopandas-0.9.0-py2.py3-none-any.whl) (994kB)
     |████████████████████████████████| 1.0MB 3.9MB/s
Requirement already satisfied: pandas>=0.24.0 in /usr/local/lib/python3.7/dist-packages (from geopandas) (1.1.5)
Collecting fiona>=1.8
  Downloading https://files.pythonhosted.org/packages/9c/fc/9807326c37a6bfb2393ae3e1cca147aa74844562c4d5daa782d6e97ad2bc/Fiona-1.8.20-cp37-cp37m-manylinux1_x86_64.whl (https://files.pythonhosted.org/packages/9c/fc/9807326c37a6bfb2393ae3e1cca147aa74844562c4d5daa782d6e97ad2bc/Fiona-1.8.20-cp37-cp37m-manylinux1_x86_64.whl) (15.4MB)
     |████████████████████████████████| 15.4MB 449kB/s
Requirement already satisfied: shapely>=1.6 in /usr/local/lib/python3.7/dist-packages (from geopandas) (1.7.1)
Collecting pyproj>=2.2.0
  Downloading https://files.pythonhosted.org/packages/11/1d/1c54c672c2faf08d28fe78e15d664c048f786225bef95ad87b6c435cf69e/pyproj-3.1.0-cp37-cp37m-manylinux2010_x86_64.whl (https://files.pythonhosted.org/packages/11/1d/1c54c672c2faf08d28fe78e15d664c048f786225bef95ad87b6c435cf69e/pyproj-3.1.0-cp37-cp37m-manylinux2010_x86_64.whl) (6.6MB)
     |████████████████████████████████| 6.6MB 37.0MB/s
Requirement already satisfied: numpy>=1.15.4 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.24.0->geopandas) (1.19.5)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.24.0->geopandas) (2018.9)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python3.7/dist-packages (from pandas>=0.24.0->geopandas) (2.8.1)
Requirement already satisfied: certifi in /usr/local/lib/python3.7/dist-packages (from fiona>=1.8->geopandas) (2020.12.5)
Requirement already satisfied: setuptools in /usr/local/lib/python3.7/dist-packages (from fiona>=1.8->geopandas) (57.0.0)
Collecting cligj>=0.5
  Downloading https://files.pythonhosted.org/packages/73/86/43fa9f15c5b9fb6e82620428827cd3c284aa933431405d1bcf5231ae3d3e/cligj-0.7.2-py3-none-any.whl (https://files.pythonhosted.org/packages/73/86/43fa9f15c5b9fb6e82620428827cd3c284aa933431405d1bcf5231ae3d3e/cligj-0.7.2-py3-none-any.whl)
Requirement already satisfied: click>=4.0 in /usr/local/lib/python3.7/dist-packages (from fiona>=1.8->geopandas) (7.1.2)
Requirement already satisfied: six>=1.7 in /usr/local/lib/python3.7/dist-packages (from fiona>=1.8->geopandas) (1.15.0)
Collecting munch
  Downloading https://files.pythonhosted.org/packages/cc/ab/85d8da5c9a45e072301beb37ad7f833cd344e04c817d97e0cc75681d248f/munch-2.5.0-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/cc/ab/85d8da5c9a45e072301beb37ad7f833cd344e04c817d97e0cc75681d248f/munch-2.5.0-py2.py3-none-any.whl)
Collecting click-plugins>=1.0
  Downloading https://files.pythonhosted.org/packages/e9/da/824b92d9942f4e472702488857914bdd50f73021efea15b4cad9aca8ecef/click_plugins-1.1.1-py2.py3-none-any.whl (https://files.pythonhosted.org/packages/e9/da/824b92d9942f4e472702488857914bdd50f73021efea15b4cad9aca8ecef/click_plugins-1.1.1-py2.py3-none-any.whl)
Requirement already satisfied: attrs>=17 in /usr/local/lib/python3.7/dist-packages (from fiona>=1.8->geopandas) (21.2.0)
```

```
Installing collected packages: cligj, munch, click-plugins, fiona, pyproj, geop
andas
Successfully installed click-plugins-1.1.1 cligj-0.7.2 fiona-1.8.20 geopandas-
0.9.0 munch-2.5.0 pyproj-3.1.0
```

In [ ]:

```
!pip install -U nltk
!pip install plotly
```

```
Collecting nltk
  Downloading https://files.pythonhosted.org/packages/5e/37/9532ddd4b1bbb619333
d5708aaad9bf1742f051a664c3c6fa6632a105fd8/nltk-3.6.2-py3-none-any.whl (https://
files.pythonhosted.org/packages/5e/37/9532ddd4b1bbb619333d5708aaad9bf1742f051a6
64c3c6fa6632a105fd8/nltk-3.6.2-py3-none-any.whl) (1.5MB)
     |████████████████████████████████| 1.5MB 4.0MB/s
Requirement already satisfied, skipping upgrade: regex in /usr/local/lib/python
3.7/dist-packages (from nltk) (2019.12.20)
Requirement already satisfied, skipping upgrade: click in /usr/local/lib/python
3.7/dist-packages (from nltk) (7.1.2)
Requirement already satisfied, skipping upgrade: tqdm in /usr/local/lib/python
3.7/dist-packages (from nltk) (4.41.1)
Requirement already satisfied, skipping upgrade: joblib in /usr/local/lib/pytho
n3.7/dist-packages (from nltk) (1.0.1)
Installing collected packages: nltk
  Found existing installation: nltk 3.2.5
    Uninstalling nltk-3.2.5:
      Successfully uninstalled nltk-3.2.5
Successfully installed nltk-3.6.2
Requirement already satisfied: plotly in /usr/local/lib/python3.7/dist-packages
(4.4.1)
Requirement already satisfied: retrying>=1.3.3 in /usr/local/lib/python3.7/dist
-packages (from plotly) (1.3.3)
Requirement already satisfied: six in /usr/local/lib/python3.7/dist-packages (f
rom plotly) (1.15.0)
```

In [ ]:
```
import pandas as pd
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import geopandas as gpd

import sqlite3
import pandas as pd
import numpy as np
import nltk
import string
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import confusion_matrix
from sklearn import metrics
from sklearn.metrics import roc_curve, auc
from nltk.stem.porter import PorterStemmer
from shapely.geometry import Point,Polygon
import re
import string
from nltk.corpus import stopwords
from nltk.stem import PorterStemmer
from nltk.stem.wordnet import WordNetLemmatizer

import pickle

from tqdm import tqdm
import os

import plotly.offline as offline
import plotly.graph_objs as go
offline.init_notebook_mode()
from collections import Counter
```

In [ ]:
```
orders=pd.read_csv('orders.csv')
tr_customers=pd.read_csv('train_customers.csv')
tr_locations=pd.read_csv('train_locations.csv')
vendors=pd.read_csv('vendors.csv')
sample=pd.read_csv('SampleSubmission.csv')
```

2. File analysis

In [ ]:
```
print('A.The customers data,Top 5 Rows: ')
print('Shape:',tr_customers.shape)
print('='*100)
tr_customers.head(2)
```

```
A.The customers data,Top 5 Rows: 
Shape: (34674, 8)
================================================================================
====================
```

Out[14]:

	akeed_customer_id	gender	dob	status	verified	language	created_at	updated_at
0	TCHWPBT	Male	NaN	1	1	EN	2018-02-07 19:16:23	2018-02-07 19:16:23
1	ZGFSYCZ	Male	NaN	1	1	EN	2018-02-09 12:04:42	2018-02-09 12:04:41

In [ ]:
```
#Preprocessing and removing non-important columns

tr_customers.drop(['dob','created_at','updated_at'], axis=1,inplace=True)
tr_customers.head(2)
```

Out[15]:

	akeed_customer_id	gender	status	verified	language
0	TCHWPBT	Male	1	1	EN
1	ZGFSYCZ	Male	1	1	EN

In [ ]:
```
gendor=pd.DataFrame()
gendor['customer_id']=tr_customers['akeed_customer_id']
gendor['gendor']=tr_customers['gender']
```

In [ ]:
```
print('B.The customers Locations ,Top 5 Rows: ')
print('='*100)
tr_locations.head(5)
```

```
B.The customers Locations ,Top 5 Rows: 
====================================================================================================
```

Out[17]:

	customer_id	location_number	location_type	latitude	longitude
0	02SFNJH	0	NaN	1.682392	-78.789737
1	02SFNJH	1	NaN	1.679137	0.766823
2	02SFNJH	2	NaN	-0.498648	0.661241
3	RU43CXC	0	Home	0.100853	0.438165
4	BDFBPRD	0	NaN	2.523125	0.733464

In [ ]:
```
#Preprocessing and removing non-important columns

tr_locations.drop(['location_type'], axis=1,inplace=True)
tr_locations.head(2)
```

Out[18]:

	customer_id	location_number	latitude	longitude
0	02SFNJH	0	1.682392	-78.789737
1	02SFNJH	1	1.679137	0.766823

In [ ]:
```
print('Total Orders ,Top 5 Rows: ')
print('='*100)
orders.head(2)
```

```
Total Orders ,Top 5 Rows: 
====================================================================================================
```

Out[19]:

	akeed_order_id	customer_id	item_count	grand_total	payment_mode	promo_code	vendor_disc
0	163238.0	92PEE24	1.0	7.6	2	NaN	
1	163240.0	QS68UD8	1.0	8.7	1	NaN	

2 rows × 26 columns

In [ ]:
```
#Preprocessing and removing non-important columns

orders.drop(['akeed_order_id','promo_code','promo_code_discount_percentage','deli
orders.head(2)
```

Out[20]:

	customer_id	item_count	grand_total	payment_mode	vendor_discount_amount	is_favorite	is_r
0	92PEE24	1.0	7.6	2	0.0	NaN	
1	QS68UD8	1.0	8.7	1	0.0	NaN	

2 rows × 21 columns

In [ ]:
```
print('D. Total Vendors ,Top 5 Rows: ')
print('='*100)

vendors['vendor_id']=vendors['id']
vendors.head(2)
```

```
D. Total Vendors ,Top 5 Rows: 
===============================================================================
=====================
```

Out[21]:

	id	authentication_id	latitude	longitude	vendor_category_en	vendor_category_id	delivery_ch
0	4	118597.0	-0.588596	0.754434	Restaurants	2.0	
1	13	118608.0	-0.471654	0.744470	Restaurants	2.0	

2 rows × 60 columns

In [ ]:
```
#creating the final table after
final_df=pd.DataFrame()

final_df['customer_id']=orders['customer_id']
final_df['location_number']=orders['LOCATION_NUMBER']
final_df['vendor_id']=orders['vendor_id']

final_df=pd.merge(final_df,tr_locations,how="outer",on=['customer_id','location_r
final_df=pd.merge(final_df,gendor,how='outer',on=['customer_id'])
```

In [ ]:
```
#dropping unnecessary columns
final_df.drop_duplicates(inplace=True)
final_df['cus_lat']=final_df['latitude']
final_df['cus_long']=final_df['longitude']
final_df.drop(['latitude','longitude'],axis=1,inplace=True)
```

In [ ]:
```
final=pd.merge(final_df,vendors,how="outer",on=['vendor_id'])
final.drop_duplicates(inplace=True)
final=final[['customer_id','location_number','gendor','vendor_id','cus_lat','cus_
             'latitude','longitude','vendor_category_en','delivery_charge','servi
             'prepration_time','is_akeed_delivering','vendor_rating','one_click_v
```

In [ ]:
```
#files saved to again reuse it for exploratory data analysis
final.to_csv('final.csv',index=False)
```

2.EXPLORATORY DATA ANALYSIS

In [ ]:
```
#loading the final data file
final=pd.read_csv('final.csv')
```

In [ ]:
```
final.head(5)
```

Out[28]:

	customer_id	location_number	gendor	vendor_id	cus_lat	cus_long	latitude	longitude	v
0	92PEE24	0	Male	105.0	-0.132100	-78.575297	-0.967769	0.080839	
1	92PEE24	1	Male	105.0	-0.760509	-78.501031	-0.967769	0.080839	
2	I9DNSMJ	0	Male	105.0	-1.801505	-78.378004	-0.967769	0.080839	
3	I9DNSMJ	2	Male	105.0	-1.803343	-0.004722	-0.967769	0.080839	
4	QQEWRHI	0	Male	105.0	0.027163	-78.594119	-0.967769	0.080839	

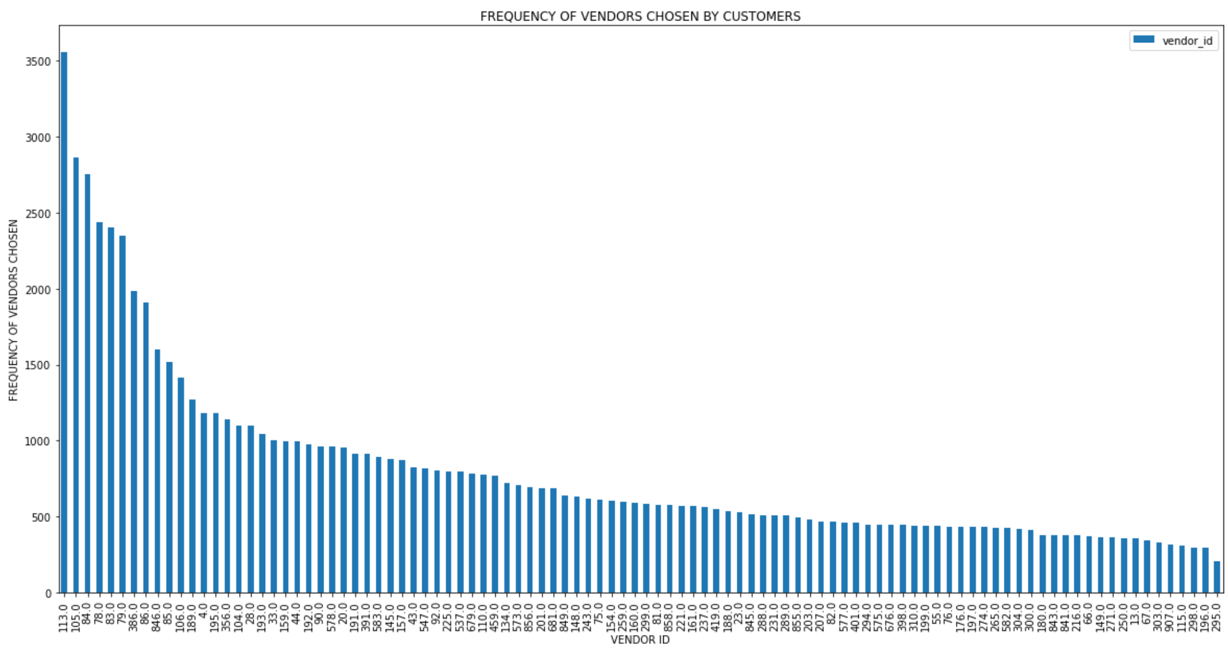
In [ ]:
```
print('Shape of data:',final.shape)
print('='*100)
print('Columns in data:',final.columns)
```

```
Shape of data: (96020, 16)
================================================================================
====================
Columns in data: Index(['customer_id', 'location_number', 'gendor', 'vendor_i
d', 'cus_lat',
       'cus_long', 'latitude', 'longitude', 'vendor_category_en',
       'delivery_charge', 'serving_distance', 'is_open', 'prepration_time',
       'is_akeed_delivering', 'vendor_rating', 'one_click_vendor'],
      dtype='object')
```

A. ANALYSIS ON VENDOR ID's

In [ ]:
```
fig, ax = plt.subplots()
final['vendor_id'].value_counts().plot(ax=ax, kind='bar',figsize=(20, 10))

plt.xlabel('VENDOR ID')
plt.ylabel('FREQUENCY OF VENDORS CHOSEN')
plt.title("FREQUENCY OF VENDORS CHOSEN BY CUSTOMERS")

ax.legend()
```

Out[30]: <matplotlib.legend.Legend at 0x7f0b04803c10>



PLOT DESCRIPTION AND OBSERVATIONS:

1.Here the bar plot showing frequencies of vendors chosen by customers in total period.

2.We can see vendors such as 113,105,84,79,368,86 and 846 contains 25 percentile of total vendors chosen.

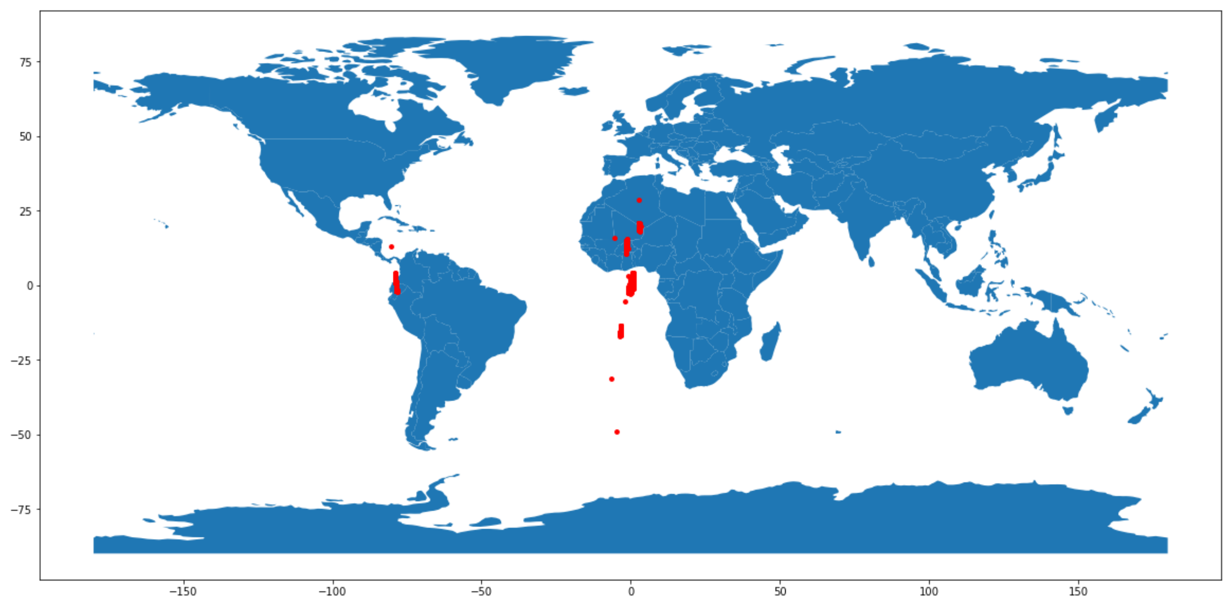
3.In recommendation these vendors will have a high chance of being recommended by customers.

1.Univariate analysis

A. LOCATIONS OF CUSTOMERS-USING LONGITUDES AND LATITUDES

In [ ]:
```
#creating a datframe to analyze customers and vendors locations over map

location_cust=pd.DataFrame()
location_cust['longitude']=final['cus_long']
location_cust['latitude']=final['cus_lat']
location_cust['vendor']=final['vendor_id']
location_cust['ven_lat']=final['latitude']
location_cust['ven_lon']=final['longitude']

#dropping locations with anomalies and using coordinated between (-90,90) for lat
location_cust.drop(location_cust.loc[location_cust['latitude']<-90].index, inplac
location_cust.drop(location_cust.loc[location_cust['latitude']>90].index, inplace
location_cust.drop(location_cust.loc[location_cust['longitude']<-180].index, inpl
location_cust.drop(location_cust.loc[location_cust['longitude']>180].index, inpla
location_cust.drop(location_cust.loc[location_cust['ven_lat']<-90].index, inplace
location_cust.drop(location_cust.loc[location_cust['ven_lat']>90].index, inplace=
location_cust.drop(location_cust.loc[location_cust['ven_lon']<-180].index, inplac
location_cust.drop(location_cust.loc[location_cust['ven_lon']>180].index, inplace
```

In [ ]:
```
#plotting locations of customers over map who ordered anything
#source: geopandas documentations

geo=[Point(x) for x in zip(location_cust['longitude'], location_cust['latitude'])
gdf=gpd.GeoDataFrame(location_cust, geometry=geo)

#this is a simple map that goes with geopandas
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
gdf.plot(ax=world.plot(figsize=(20,20)), marker='o', color='red', markersize=15);
```



PLOT DESCRIPTION AND OBSERVATIONS:

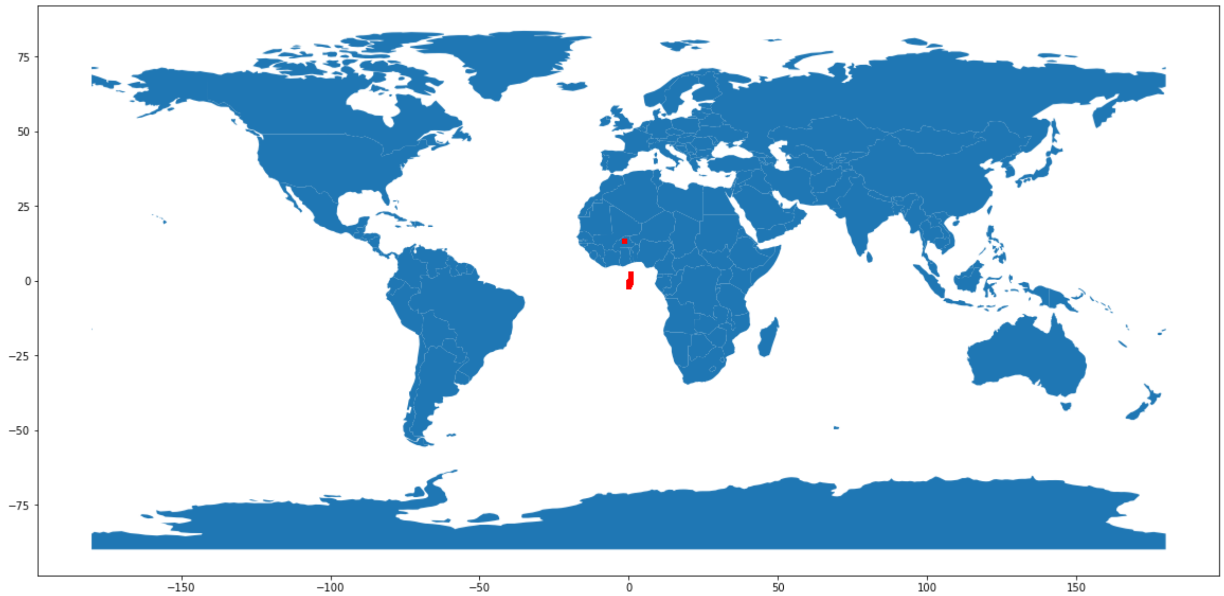
1.Here the locations of all customers who ordered something are shown.

2.There were around 5000 wrong latitudes and longitudes I found and removed them to get shape in the world map(lat:(-90,90) long:(-180,180)). Still some locations are from sea.

3.Most of the customers are from africa and little percentage from south america.

4.This indicates that using just only locations will not be a much use in our recommendation process. We have to see the vendors locations as well.

In [ ]:
```
#plotting locations of vendors over map who received orders
#source: https://towardsdatascience.com/easy-steps-to-plot-geographic-data-on-a-m

geo=[Point(x) for x in zip(location_cust['ven_lon'], location_cust['ven_lat'])]
gdf=gpd.GeoDataFrame(location_cust, geometry=geo)

#this is a simple map that goes with geopandas
world = gpd.read_file(gpd.datasets.get_path('naturalearth_lowres'))
gdf.plot(ax=world.plot(figsize=(20,20)), marker='o', color='red', markersize=15);
```



PLOT DESCRIPTION AND OBSERVATIONS:

1.Here the locations of all vendors who received order from out of all customers.

2.There were around 1000 wrong latitudes and longitudes I found and removed them to get shape in the world map(lat:(-90,90) long:(-180,180)). Still some locations are from sea.

3.All the vendors are from africa, but as we can see using these longitudes and latitudes, finding recommendations are tough. We have to see distance between customers and vendors locations in next approaches.

B. DISTANCE BETWEEN VENDORS AND CUSTOMERS

In [ ]:
```
!pip install geopy
```

```
Collecting geopy
  Downloading geopy-2.1.0-py3-none-any.whl (112 kB)
     |████████████████████████████████| 112 kB 2.8 MB/s eta 0:00:01
Collecting geographiclib<2,>=1.49
  Downloading geographiclib-1.50-py3-none-any.whl (38 kB)
Installing collected packages: geographiclib, geopy
Successfully installed geographiclib-1.50 geopy-2.1.0
```

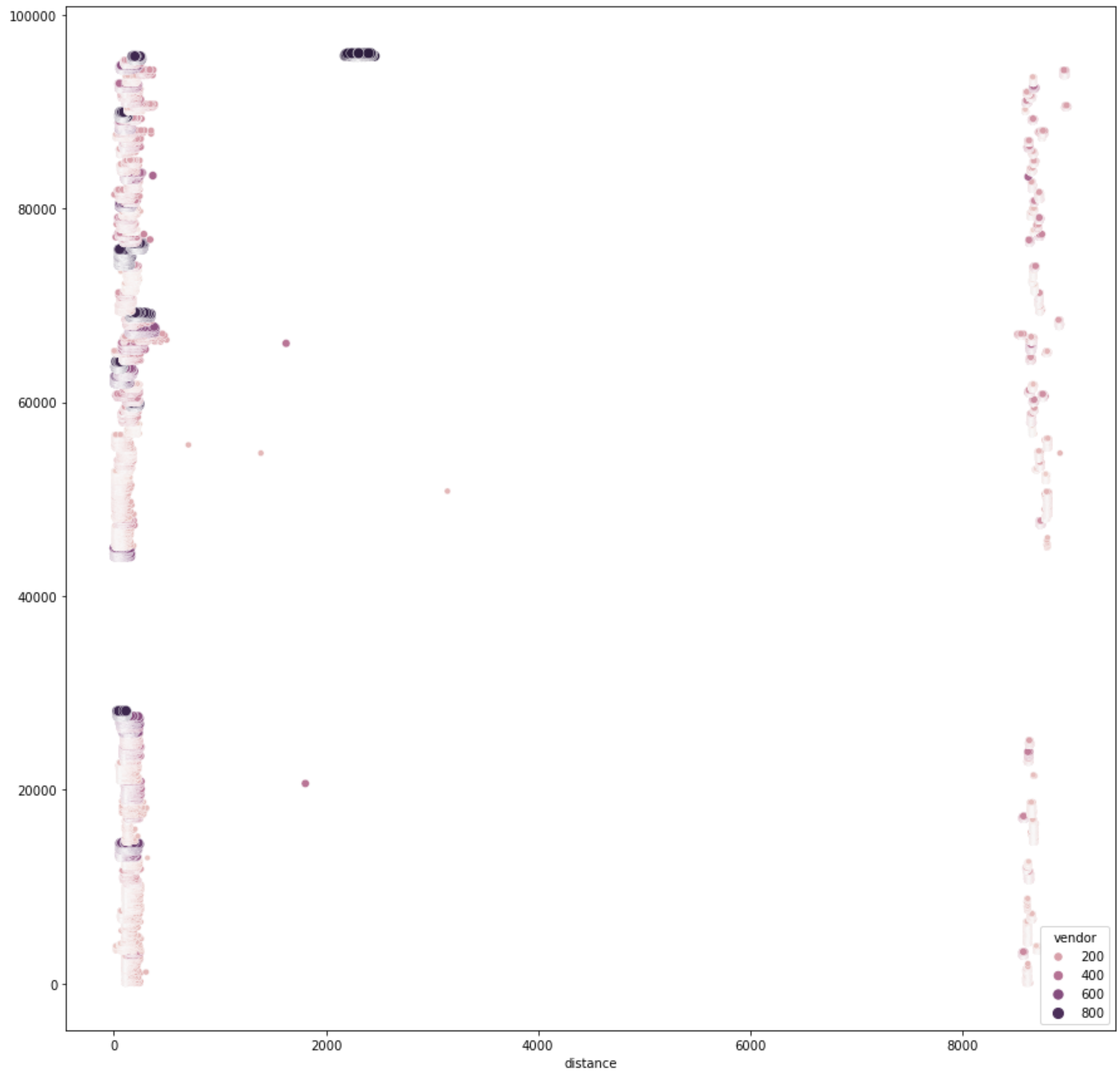
In [ ]:
```
#using these coordinates we can find distances between all vendors
import geopy.distance
#snippet of code reference: https://stackoverflow.com/questions/19412462/getting-

dis=[]
location_cust.dropna(inplace=True)
for i in location_cust.values:

  coords_1 = (i[0],i[1])
  coords_2 = (i[3],i[4])
  dis.append(geopy.distance.geodesic(coords_1, coords_2).km)

location_cust['distance']=dis
location_cust.head(2)
```

Out[48]:

	longitude	latitude	vendor	ven_lat	ven_lon	geometry	distance
0	-78.575297	-0.132100	105.0	-0.967769	0.080839	POINT (0.08084 -0.96777)	8619.063288
1	-78.501031	-0.760509	105.0	-0.967769	0.080839	POINT (0.08084 -0.96777)	8610.903479

In [ ]:
```
fig, ax = plt.subplots(figsize=(15,15))
sns.scatterplot(data=location_cust, x="distance", y=location_cust.index,hue='venc
```

Out[49]: <AxesSubplot:xlabel='distance'>



PLOT DESCRIPTION AND OBSERVATIONS:

1.Here the distances between the vendors and customers are shown using a seaborn plot.

2.There are 2 seperate regions in this, first those ordered from south america whose distances are around 8000 Kms and second who ordered from africa whose distances are under 500 km. Also vendor with id's less than 200 are most favorites.

3.So distance is a feature that drives customers to order, so customers prefer ordering fro vendors in 500 km range most in africa and when you are in south america it is in range 8000km.

4.But why people having distance of more than 8000 are shown, because travelling to a different continent for restaurant is quite different.

C. VENDOR CATEGORIES

In [ ]:
```
final.head(2)
```

Out[50]:

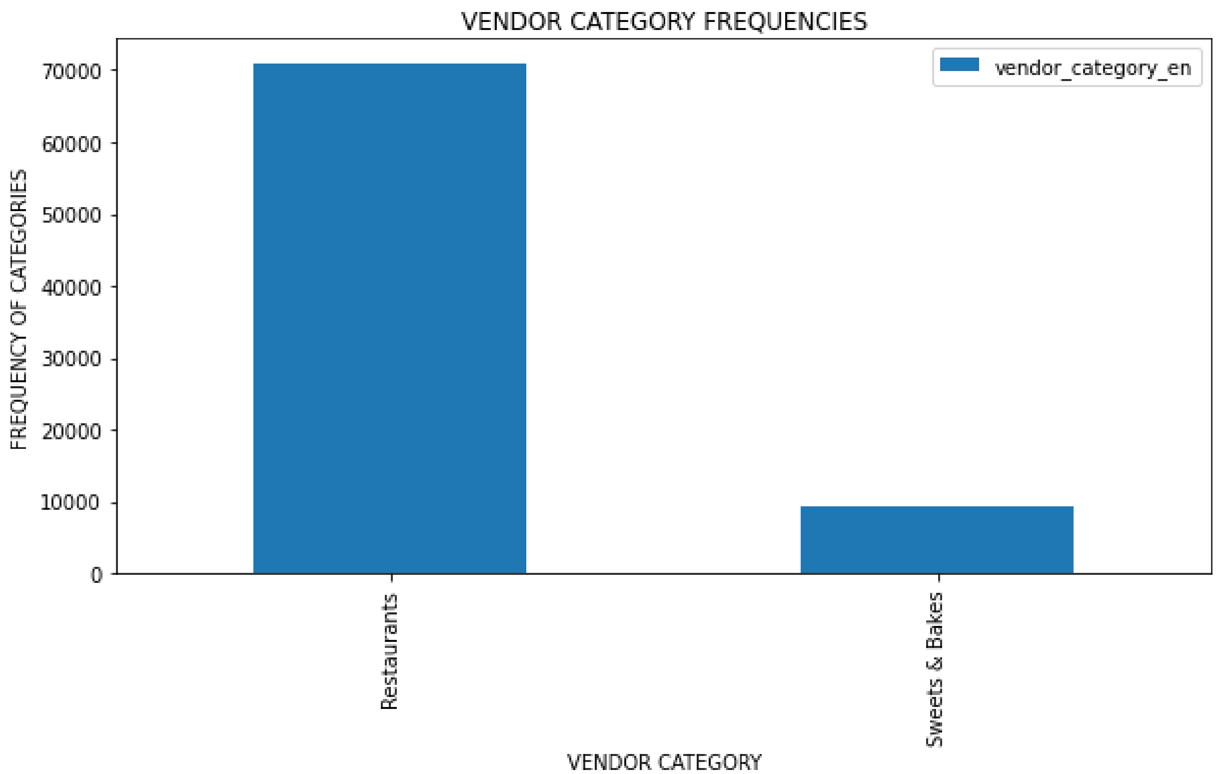
	customer_id	location_number	gendor	vendor_id	cus_lat	cus_long	latitude	longitude	v
0	92PEE24	0	Male	105.0	-0.132100	-78.575297	-0.967769	0.080839	
1	92PEE24	1	Male	105.0	-0.760509	-78.501031	-0.967769	0.080839	

In [ ]:
```
final['vendor_category_en'].value_counts()
#there are only 2 categories seen and most of them were restaurants
```

Out[51]:
```
Restaurants       70854
Sweets & Bakes     9301
Name: vendor_category_en, dtype: int64
```

In [ ]:
```
fig, ax = plt.subplots()
final['vendor_category_en'].value_counts().plot(ax=ax, kind='bar',figsize=(10,5))

plt.xlabel('VENDOR CATEGORY')
plt.ylabel('FREQUENCY OF CATEGORIES')
plt.title("VENDOR CATEGORY FREQUENCIES")

ax.legend()
```

Out[52]: `<matplotlib.legend.Legend at 0x7f0b035152d0>`



PLOT DESCRIPTION AND OBSERVATIONS:

1.Here is the plot of frequencies of vendor_categories

2.There are only 2 broad categories. restaurants and sweets and bakes.

3.Most vendors are from restaurant category and 20k are from sweets and bakes.category is not a much important feature for recommendation it seems.

D. DELIVERY CHARGES ANALYSIS

In [ ]:
```
final.head(2)
```

Out[53]:

	customer_id	location_number	gendor	vendor_id	cus_lat	cus_long	latitude	longitude	v
0	92PEE24	0	Male	105.0	-0.132100	-78.575297	-0.967769	0.080839	
1	92PEE24	1	Male	105.0	-0.760509	-78.501031	-0.967769	0.080839	

In [ ]:
```
final['delivery_charge'].value_counts()
```

Out[54]:
```
0.0    40369
0.7    39786
Name: delivery_charge, dtype: int64
```

PLOT DESCRIPTION AND OBSERVATIONS:

1.From the data we can see that in the presense of delivery charge (0.7) and no delivery charge (0.0), there are same numbers of orders and it dosen't affect the orders.

2.This feature is not important for us in this recommendation.

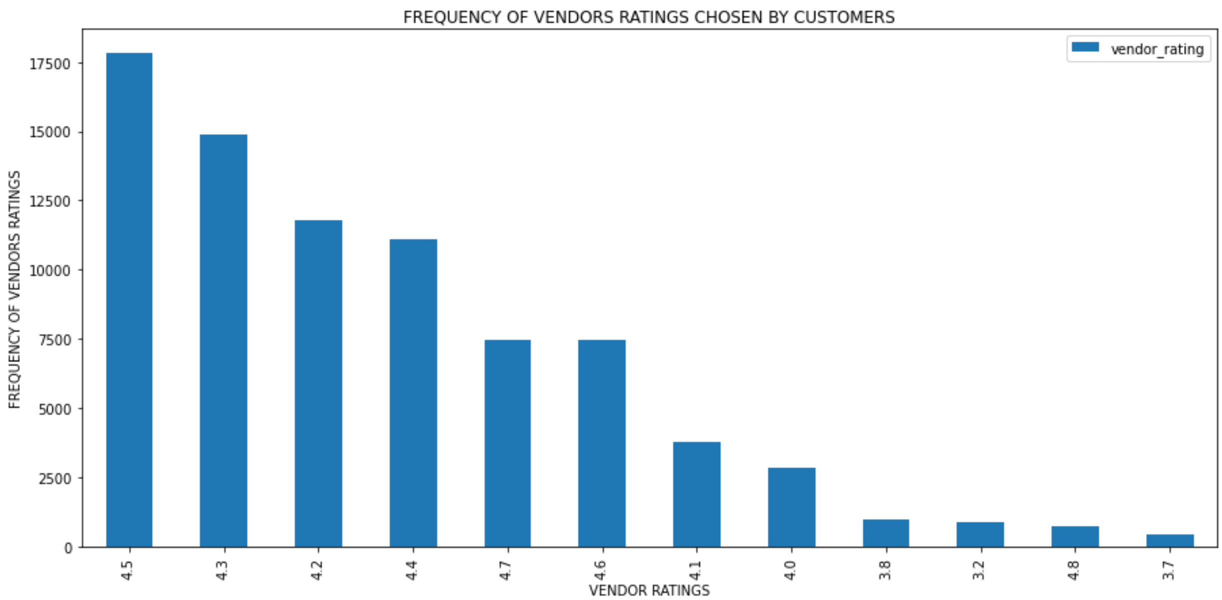
E. VENDOR RATINGS

In [ ]:
```
final['vendor_rating'].value_counts()
```

Out[55]:
```
4.5    17809
4.3    14867
4.2    11784
4.4    11102
4.7     7471
4.6     7462
4.1     3786
4.0     2854
3.8      959
3.2      880
4.8      750
3.7      431
Name: vendor_rating, dtype: int64
```

In [ ]:
```
fig, ax = plt.subplots()
final['vendor_rating'].value_counts().plot(ax=ax, kind='bar',figsize=(15, 7))

plt.xlabel('VENDOR RATINGS')
plt.ylabel('FREQUENCY OF VENDORS RATINGS')
plt.title("FREQUENCY OF VENDORS RATINGS CHOSEN BY CUSTOMERS")

ax.legend()
```

Out[56]:
```
<matplotlib.legend.Legend at 0x7f0b03e30210>
```



PLOT DESCRIPTION AND OBSERVATIONS:

1.We have plotted vendor ratings and their frequencies to find out whether rating can a good feature for recommendation or not.

2.Most of the customers have ordered from the vendors with vendor ratings greater than 4.1.

3.So if ratings are near to 5. chances of ordering is great and that's why rating is very important tool for use.

F. ALL OTHER COLUMNS FREQUENCIES

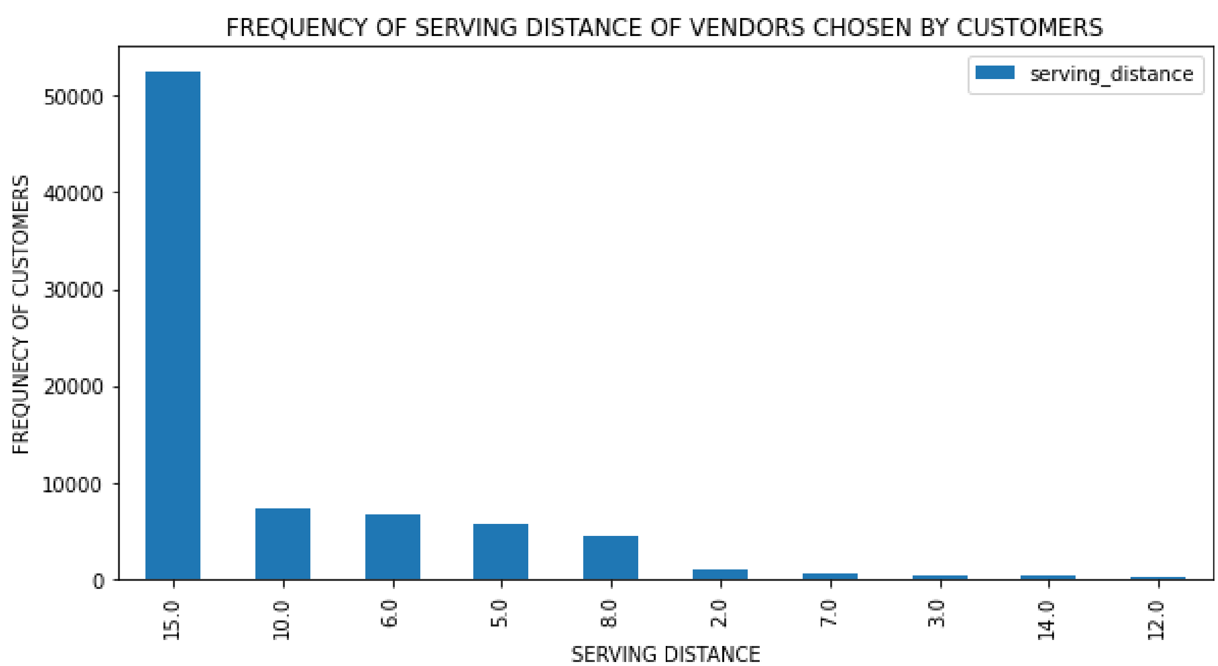
In [ ]:
```
final.head(2)
```

Out[57]:

	customer_id	location_number	gendor	vendor_id	cus_lat	cus_long	latitude	longitude	v
0	92PEE24	0	Male	105.0	-0.132100	-78.575297	-0.967769	0.080839	
1	92PEE24	1	Male	105.0	-0.760509	-78.501031	-0.967769	0.080839	

In [ ]:
```
fig, ax = plt.subplots()
final['serving_distance'].value_counts().plot(ax=ax, kind='bar',figsize=(10,5))

plt.xlabel('SERVING DISTANCE')
plt.ylabel('FREQUNECY OF CUSTOMERS')
plt.title("FREQUENCY OF SERVING DISTANCE OF VENDORS CHOSEN BY CUSTOMERS")

ax.legend()
```

Out[58]: <matplotlib.legend.Legend at 0x7f0b0335a490>



PLOT DESCRIPTION AND OBSERVATIONS:

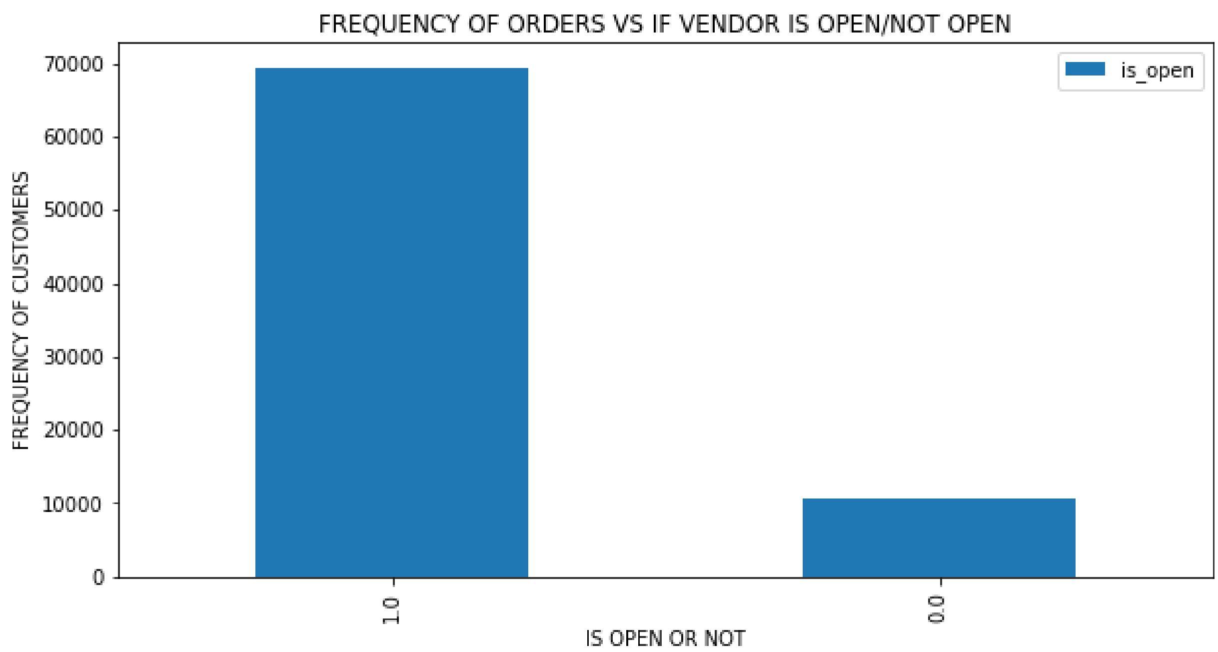
1.We have plotted vendors serving distanec to find if their serving distance affects the chances or getting orders or not.

2.We got to know that if the vendor has a serving distance of 15, chances are high that the customer will have an order from this.

3.Hence this feature is useful for our recommendation.

In [ ]:
```
fig, ax = plt.subplots()
final['is_open'].value_counts().plot(ax=ax, kind='bar',figsize=(10,5))

plt.xlabel('IS OPEN OR NOT')
plt.ylabel('FREQUENCY OF CUSTOMERS')
plt.title("FREQUENCY OF ORDERS VS IF VENDOR IS OPEN/NOT OPEN")

ax.legend()
```

Out[59]:
```
<matplotlib.legend.Legend at 0x7f0b0473d050>
```



PLOT DESCRIPTION AND OBSERVATIONS:

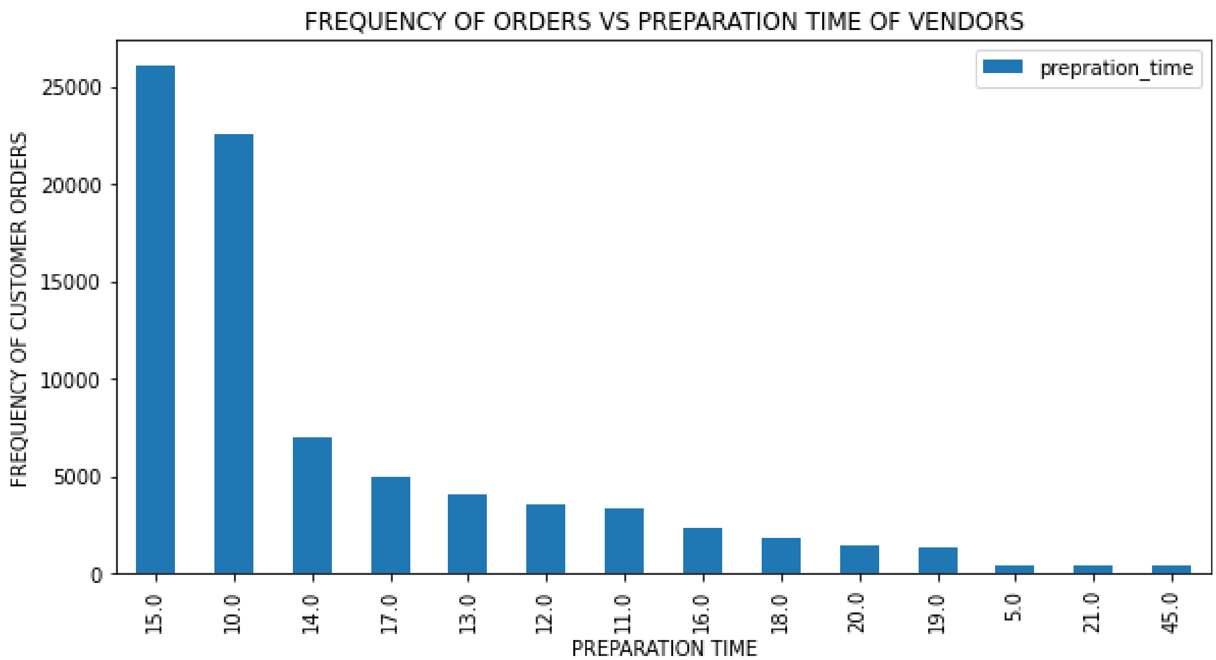
1.We have plotted is_open scatter plot to see if status of vendors affects the chance of getting orders or not.

1.From the data we can see that if it's open then high chance is there but even if it is not open, there are 10000 orders made, that is quite an anomaly.

2.Hence this feature is useful to some extent for our recommendations.

In [ ]:
```
fig, ax = plt.subplots()
final['prepration_time'].value_counts().plot(ax=ax, kind='bar',figsize=(10,5))

plt.xlabel('PREPARATION TIME')
plt.ylabel('FREQUENCY OF CUSTOMER ORDERS')
plt.title("FREQUENCY OF ORDERS VS PREPARATION TIME OF VENDORS")

ax.legend()
```

Out[60]: <matplotlib.legend.Legend at 0x7f0b031f8cd0>



PLOT DESCRIPTION AND OBSERVATIONS:

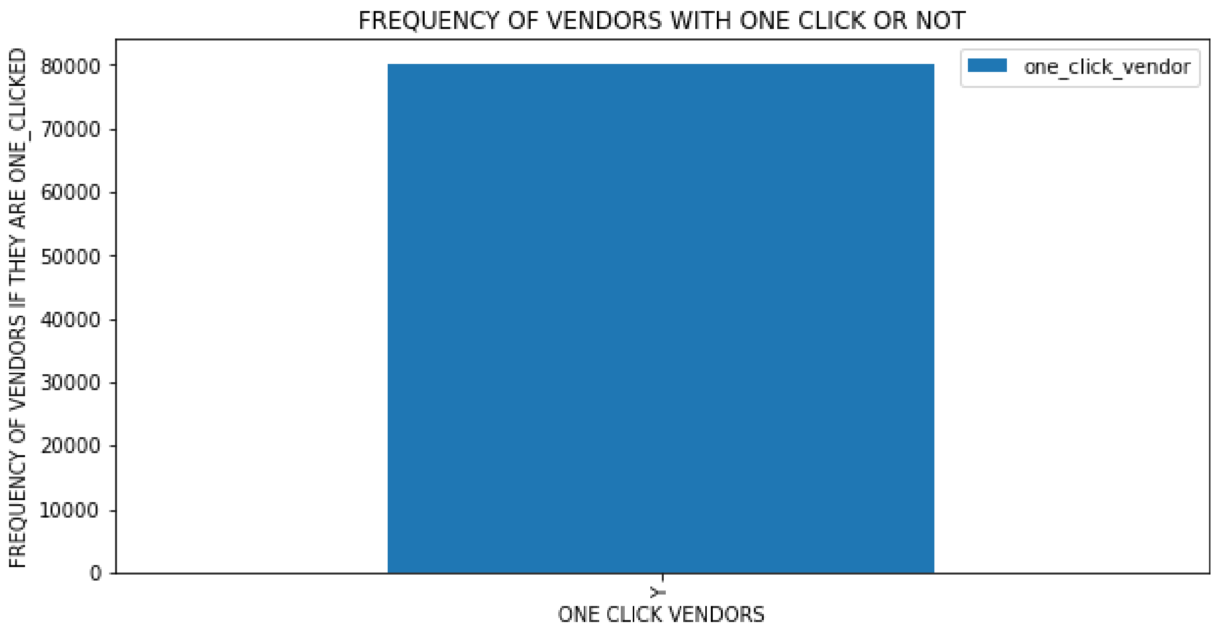
1.We have plotted preparation_time to check if time for preparation is a useful feature or not.

2.We can see that standard time 10 and 15 mins are highly appreciated but also if the time is under 5, there are less orders. So it can depend on orders and type of orders.

3.So this feature can be useful if and if only type of orders taken into account otherwise confusing.

In [ ]:
```
fig, ax = plt.subplots()
final['one_click_vendor'].value_counts().plot(ax=ax, kind='bar',figsize=(10,5))

plt.xlabel('ONE CLICK VENDORS')
plt.ylabel('FREQUENCY OF VENDORS IF THEY ARE ONE_CLICKED')
plt.title("FREQUENCY OF VENDORS WITH ONE CLICK OR NOT")

ax.legend()
```

Out[61]: <matplotlib.legend.Legend at 0x7f0b0341d5d0>



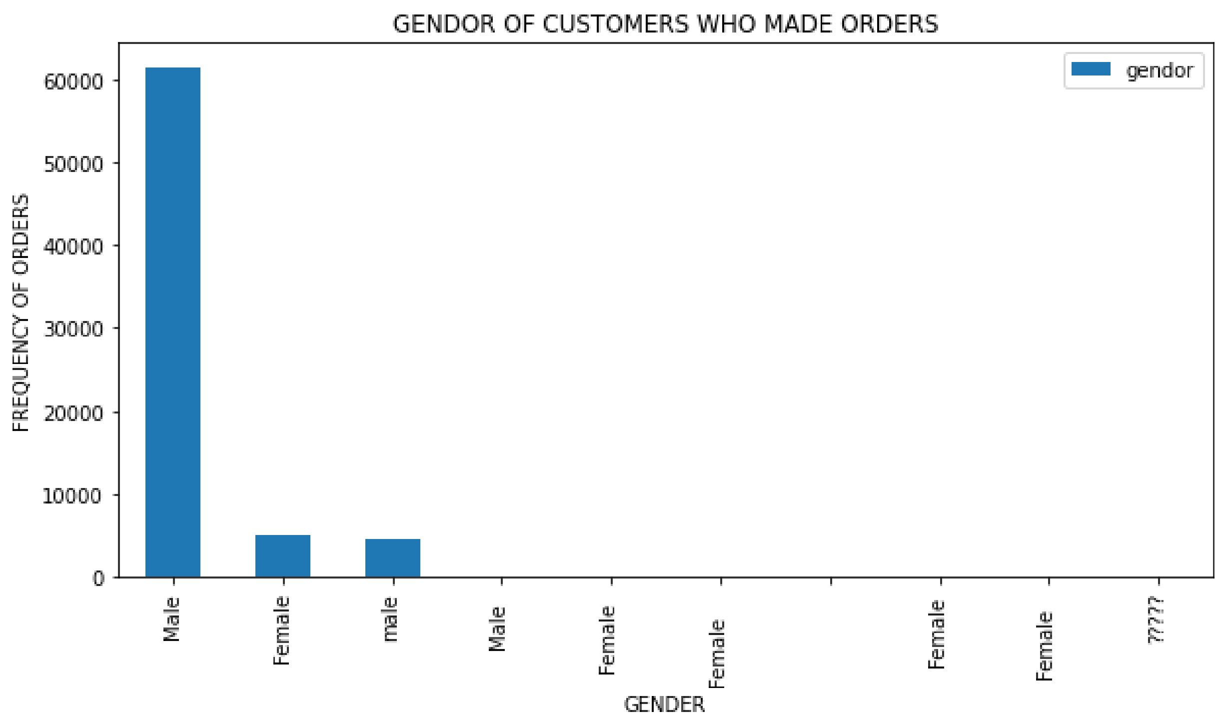
PLOT DESCRIPTION AND OBSERVATIONS:

1.We have plotted whether one_click_vendor to check if vendor is one click process vendor or not that is chosen by customers.

2.All all the customers have chosen vendors with one_click service enables, this feature is not useful for our recommendation.

In [ ]:
```
fig, ax = plt.subplots()
final['gendor'].value_counts().plot(ax=ax, kind='bar',figsize=(10,5))

plt.xlabel('GENDER')
plt.ylabel('FREQUENCY OF ORDERS')
plt.title("GENDOR OF CUSTOMERS WHO MADE ORDERS")

ax.legend()
```

Out[62]: <matplotlib.legend.Legend at 0x7f0b0329a050>



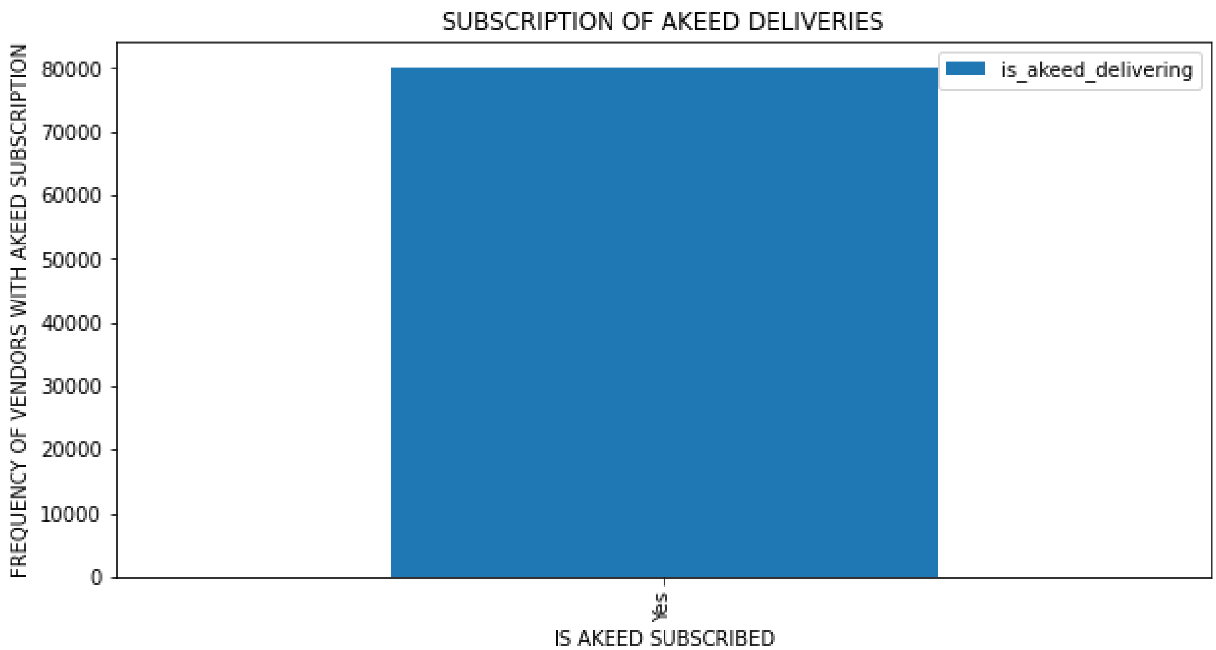
PLOT DESCRIPTION AND OBSERVATIONS:

1.We have plotted gender of customers vs their frequency of orders.

2.As we can see there are 70k, around 80% of the customers as male and 10k as female. This can be a good feature but not to great extent.

In [ ]:
```
fig, ax = plt.subplots()
final['is_akeed_delivering'].value_counts().plot(ax=ax, kind='bar',figsize=(10,5)

plt.xlabel('IS AKEED SUBSCRIBED')
plt.ylabel('FREQUENCY OF VENDORS WITH AKEED SUBSCRIPTION')
plt.title("SUBSCRIPTION OF AKEED DELIVERIES")

ax.legend()
```

Out[63]:
```
<matplotlib.legend.Legend at 0x7f0b03339f10>
```



PLOT DESCRIPTION AND OBSERVATIONS:

1.We have plotted whether is_akeed_delivering to check if vendor is subscribed to akeed.

2.As all the vendors are subscribed, this feature will not affect the recommendation.

2.Bivariate analysis

A. VENDOR VS DISTANCE BETWEEN CUSTOMER AND VENDOR

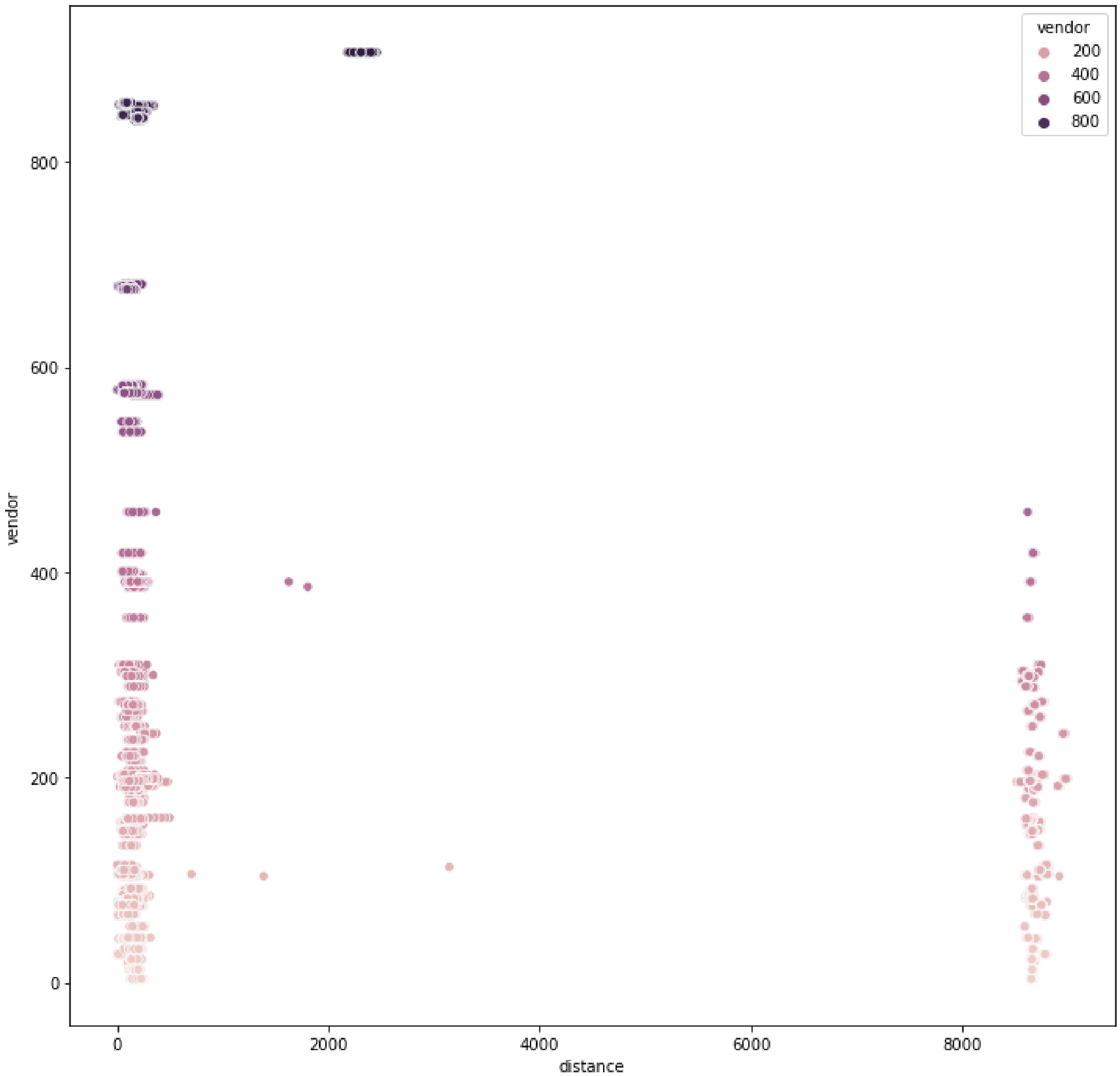
In [ ]:
```
#reading file
final=pd.read_csv('final.csv')
final.head(2)
```

Out[64]:

	customer_id	location_number	gendor	vendor_id	cus_lat	cus_long	latitude	longitude	v
0	92PEE24	0	Male	105.0	-0.132100	-78.575297	-0.967769	0.080839	
1	92PEE24	1	Male	105.0	-0.760509	-78.501031	-0.967769	0.080839	

In [ ]:
```
fig, ax = plt.subplots(figsize=(12,12))
sns.scatterplot(data=location_cust, x="distance", y='vendor',hue='vendor')
```

Out[65]: <AxesSubplot:xlabel='distance', ylabel='vendor'>



PLOT DESCRIPTION AND OBSERVATIONS:

1.I have plotted distance vs vendor chosen by customers. This distance is between the customers(Home or work etc) and the vendor location.

2.This graph shows different clusters and also cluters than are at 2000kms, Here there are 2 different regions, first is people living in south america and second one in left are people living in africa.

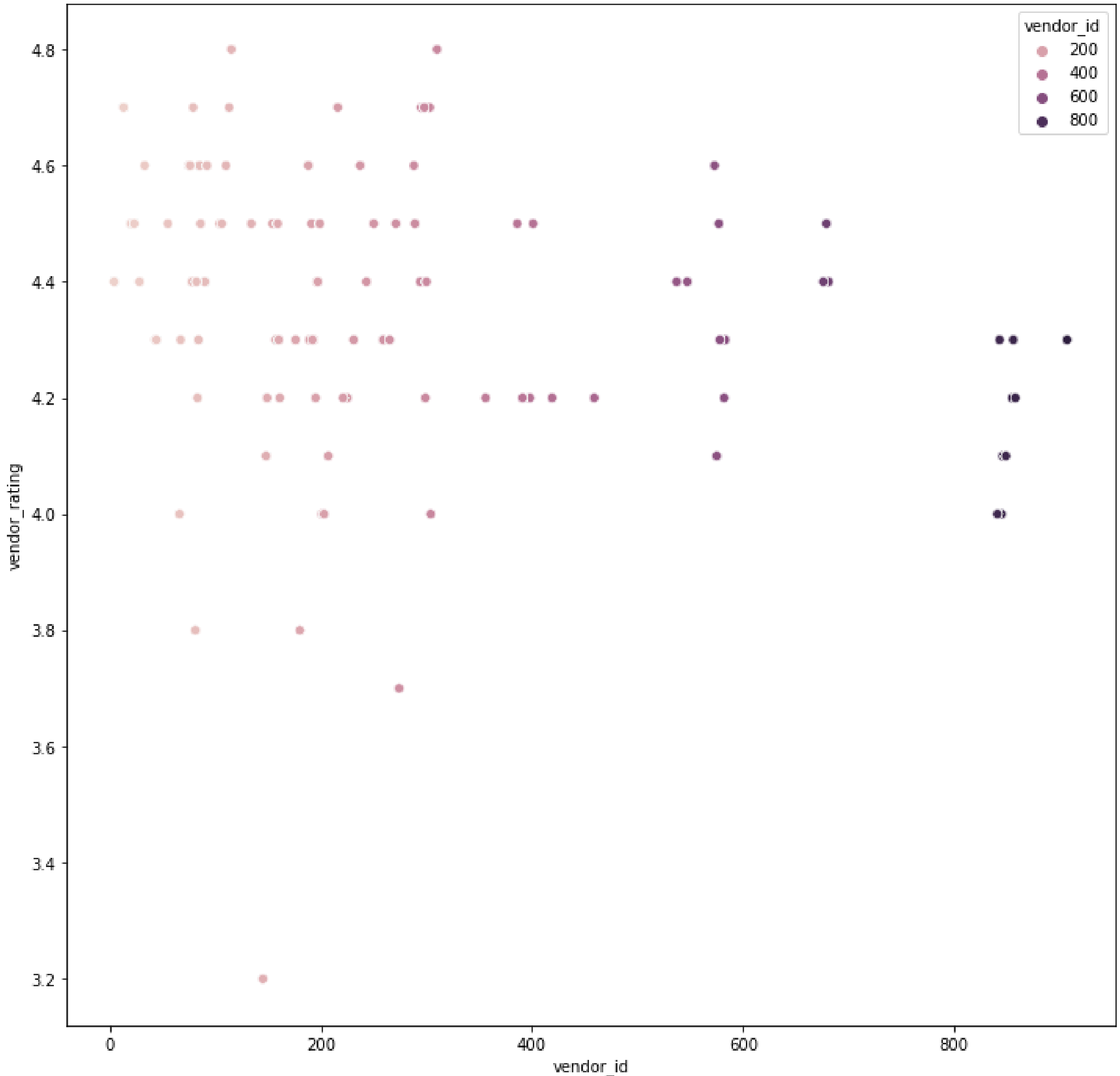
3.Here we can conclude that vendor with id's less than 200 are more favorite for people in south america and for people in africa, there is no such bond.

4.Also distance is a very useful feature to recommend the vendor.

B.VENDOR_RATING VS CUSTOMERS

In [ ]:
```
fig, ax = plt.subplots(figsize=(12,12))
sns.scatterplot(data=final, x="vendor_id", y='vendor_rating',hue='vendor_id')
```

Out[66]: <AxesSubplot:xlabel='vendor_id', ylabel='vendor_rating'>



PLOT DESCRIPTION AND OBSERVATIONS:

1.I have plotted ratings vs vendor chosen by customers.Ratings are of vendors.

2.The range starts from 3.7 to 5 and as close to 5, vendors are more chosen, so this also can be a goof feature for recommendation after distance.

3.FEATURE ENGINEERING

A. Checking Imputations

In [ ]:
```
data=pd.read_csv('train.csv')
```

In [ ]:
```
data.head()
```

Out[75]:

	customer_id	gender	status_x	verified_x	created_at_x	updated_at_x	location_number	locatior
0	TCHWPBT	Male	1	1	2018-02-07 19:16:23	2018-02-07 19:16:23	0	
1	TCHWPBT	Male	1	1	2018-02-07 19:16:23	2018-02-07 19:16:23	0	
2	TCHWPBT	Male	1	1	2018-02-07 19:16:23	2018-02-07 19:16:23	0	
3	TCHWPBT	Male	1	1	2018-02-07 19:16:23	2018-02-07 19:16:23	0	
4	TCHWPBT	Male	1	1	2018-02-07 19:16:23	2018-02-07 19:16:23	0	

5 rows × 73 columns

In [ ]:
```
#removing columns that are not important and relatable

train_df=data[['customer_id','gender','location_number','location_type','latitude
            'longitude_x','id','latitude_y','longitude_y','vendor_category_en','de
            'serving_distance','is_open','prepration_time','vendor_rating',\
            'CID X LOC_NUM X VENDOR','target']]
```

In [ ]:
```
train_df.head(2)
```

Out[77]:

	customer_id	gender	location_number	location_type	latitude_x	longitude_x	id	latitude_y	lor
0	TCHWPBT	Male	0	Work	-96.44	-67.2	4	-0.5884	
1	TCHWPBT	Male	0	Work	-96.44	-67.2	13	-0.4717	

In [ ]:
```
#Here train_df['target'] contains 1-If the particular  (CID X LOC_NUM X VENDOR) c
#0- if the particular customer with location number has not ordered
```

In [ ]:
```
#shape of final train dataset for featurization

train_df.shape
```

Out[79]: (5802400, 17)

In [ ]:
```
#First we will remove those columns which contains more than 25% of null values:
train_df = train_df[train_df.columns[train_df.isnull().mean() < (1-0.25)]]
#So there was no column that contained more than 25% of null values
train_df.shape
```

Out[80]: (5802400, 17)

In [ ]:
```
#We will remove all rows by checking null values column wise, that is to be great

train_df=train_df.loc[train_df.isnull().mean(axis=1) < (1-0.3)]

#similarly all rows are also correct will less null values
train_df.shape
```

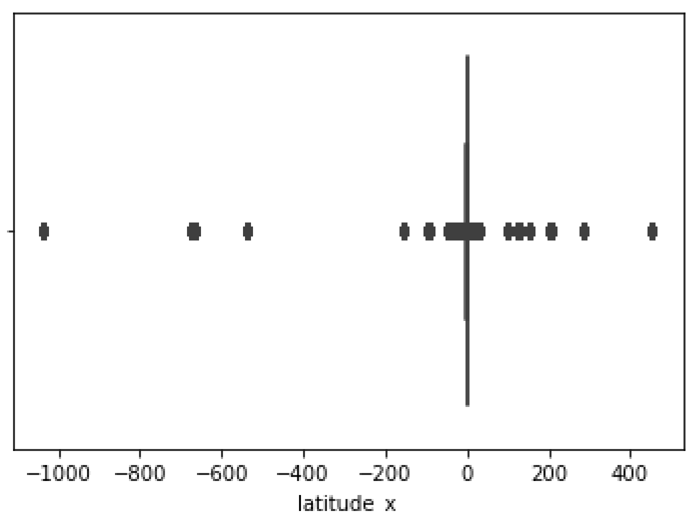
Out[81]: (5802400, 17)

In [ ]:
```
# If there are missing values, We will impute it with medians
train_df = train_df.fillna(train_df.median())
```

B. Visualization of outliers and removal

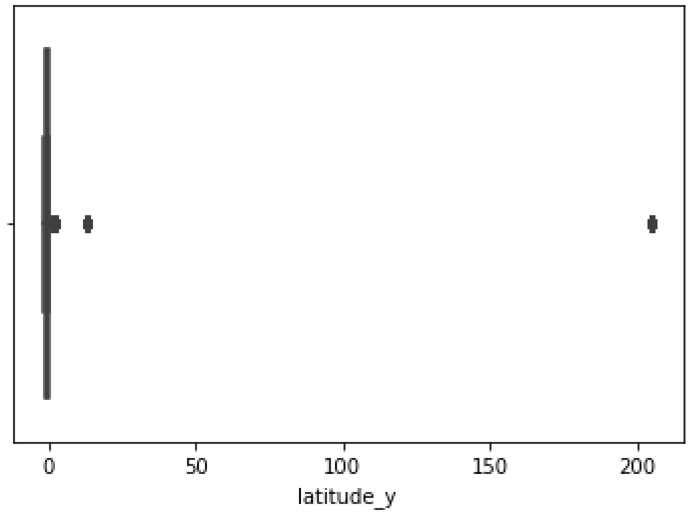
In [ ]:
```
#reference blog: https://towardsdatascience.com/ways-to-detect-and-remove-the-out
#Box plot to detect outliers

sns.boxplot(x=train_df['latitude_x'])
```

Out[83]: <AxesSubplot:xlabel='latitude_x'>



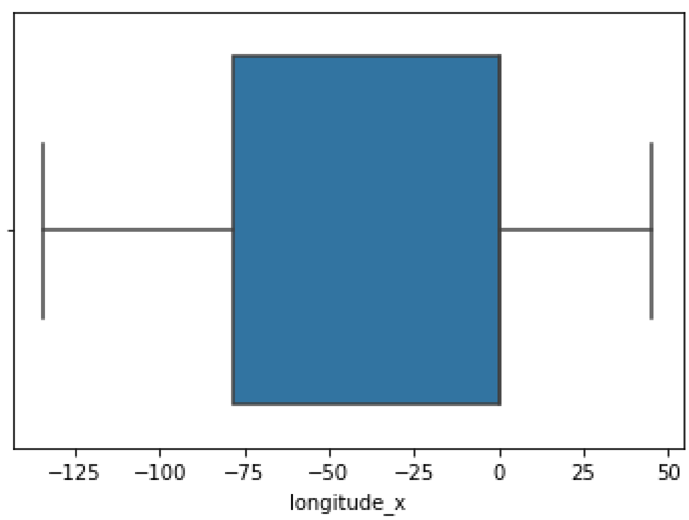
In [ ]:
```
sns.boxplot(x=train_df['latitude_y'])
```

Out[84]: <AxesSubplot:xlabel='latitude_y'>



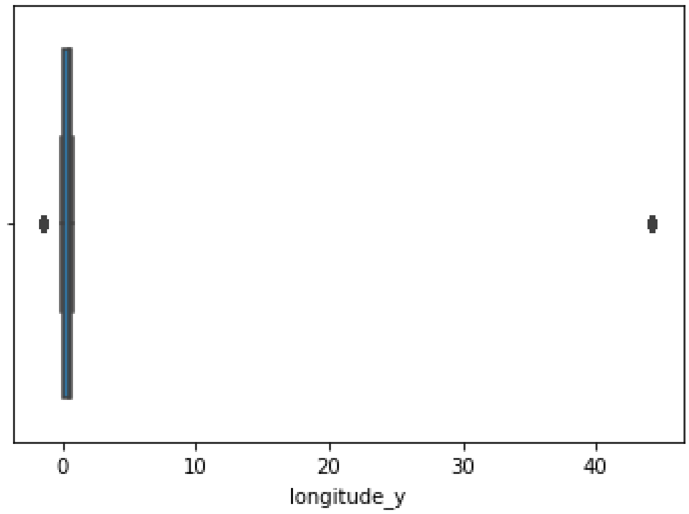
In [ ]:
```
sns.boxplot(x=train_df['longitude_x'])
```

Out[85]: <AxesSubplot:xlabel='longitude_x'>



In [ ]:
```
sns.boxplot(x=train_df['longitude_y'])
```

Out[86]: <AxesSubplot:xlabel='longitude_y'>



In [ ]:
```
#hence we will remove the customers,vendors with wrong latitude and longitude
#The range is from -90 to 90 for latitude and -180 to 180 for longitude.

checked = train_df[(train_df['latitude_x'] < 90) & (train_df['latitude_x'] > -90)
checked1 = checked[(checked['latitude_y'] < 90) & (checked['latitude_y'] > -90)]
checked2 = checked1[(checked1['longitude_x'] < 180) & (checked1['longitude_x'] >
train_df = checked2[(checked2['longitude_y'] < 180) & (checked2['longitude_y'] >

#print final_shape
train_df.shape
```

Out[87]: (5616765, 17)

In [ ]:
```
#saving to start from here
train_df.to_csv('train_data.csv',index=False)
```

In [ ]:
```
train_df=pd.read_csv('train_data.csv')
```

In [ ]:
```
train_df.describe()
```

Out[91]:

	location_number	latitude_x	longitude_x	id	latitude_y	longitude_y
count	5.616765e+06	5.616765e+06	5.616765e+06	5.616765e+06	5.616765e+06	5.616765e+06
mean	7.499956e-01	2.009753e-01	-2.550200e+01	2.894242e+02	-1.786967e-01	3.652483e-01
std	1.297298e+00	2.742297e+00	3.701066e+01	2.422296e+02	1.554850e+00	3.417692e-01
min	0.000000e+00	-4.903000e+01	-8.010000e+01	4.000000e+00	-1.787000e+00	-1.449000e+00
25%	0.000000e+00	-5.073000e-01	-7.850000e+01	1.050000e+02	-8.154000e-01	8.136000e-02
50%	0.000000e+00	-9.520000e-02	3.160000e-02	2.010000e+02	-4.946000e-01	5.270000e-01
75%	1.000000e+00	2.167000e-01	5.160000e-01	3.910000e+02	1.563000e-02	6.445000e-01
max	2.600000e+01	2.873000e+01	3.285000e+00	9.070000e+02	1.333600e+01	7.600000e-01

In [ ]:
```
train_df.head(2)
```

Out[92]:

	customer_id	gender	location_number	location_type	latitude_x	longitude_x	id	latitude_y	lor
0	TCHWPBT	Male	2	NaN	-0.1287	-78.56	4	-0.5884	
1	TCHWPBT	Male	2	NaN	-0.1287	-78.56	13	-0.4717	

C. Binning

There are 5 fields in which we can perform binning to get best results without affecting the performance metrics.

These are:

1.delivery_charge

2.serving_distance

3.is_open

4.prepration_time

5.vendor_rating

In [ ]:
```
train_df['delivery_charge'].value_counts()
```

Out[93]:
```
0.7    3290630
0.0    2326135
Name: delivery_charge, dtype: int64
```

In [ ]:
```
# As there are only 2 categories, I have binned all 0.7 values to 1 and 0.0 value
delivery_charge_en=[]

for i in train_df['delivery_charge'].values:
  if i==0.7:
    delivery_charge_en.append(1)
  else:
    delivery_charge_en.append(0)

train_df['delivery_charge_en']=delivery_charge_en
```

In [ ]:
```
train_df['serving_distance'].value_counts()
```

Out[95]:
```
15.0    3233895
10.0     624085
5.0      567350
6.0      453880
8.0      453880
14.0      56735
3.0       56735
7.0       56735
12.0      56735
2.0       56735
Name: serving_distance, dtype: int64
```

In [ ]:
```
# as there are 4 major ranges, 0-6 , 6-10, 10-12 and above 12. I have binned usir

serving_distance_en=[]

for i in train_df['serving_distance'].values:
  if i<=6:
    serving_distance_en.append(1)
  elif 6<i<=10:
    serving_distance_en.append(2)
  elif 10<i<=12:
    serving_distance_en.append(3)
  else:
    serving_distance_en.append(4)

train_df['serving_distance_en']=serving_distance_en
```

In [ ]:
```
train_df['is_open'].value_counts()
```

Out[97]:
```
1.0    4765740
0.0     851025
Name: is_open, dtype: int64
```

In [ ]:
```
# As there are only 2 categories, I have binned them into 1-Is_open Yes and 0-Is_

is_open_en=[]

for i in train_df['is_open'].values:
  if i==1.0:
    is_open_en.append(1)
  else:
    is_open_en.append(0)

train_df['is_open_en']=is_open_en
```

In [ ]:
```
train_df['prepration_time'].value_counts()
```

Out[99]:
```
15    1985725
10    1418375
14     397145
17     340410
11     283675
13     283675
16     226940
20     170205
12     113470
18     113470
19     113470
5       56735
21      56735
45      56735
Name: prepration_time, dtype: int64
```

In [ ]:
```
# We can see there are major 4 categories of bin ranges, 5-10, 10-15,15-20 and ab

preparation_time_en=[]

for i in train_df['prepration_time'].values:
  if 5<=i<=10:
    preparation_time_en.append(1)
  elif 10<i<=15:
    preparation_time_en.append(2)
  elif 15<i<=20:
    preparation_time_en.append(3)
  else:
    preparation_time_en.append(4)

train_df['preparation_time_en']=preparation_time_en
```

In [ ]:
```
train_df['vendor_rating'].value_counts()
```

Out[101]:
```
4.5    1077965
4.3     964495
4.2     851025
4.4     794290
4.6     567350
4.7     397145
4.0     340410
4.1     283675
4.8     113470
3.8     113470
3.2      56735
3.7      56735
Name: vendor_rating, dtype: int64
```

In [ ]:
```
#Here I can see 5 range of ratings and lets bin them like
#(below 3.7)-->1, (3.7-4.0)-->2, (4.0-4.2)-->3, (4.2-4.5)-->4, (4.5 and above)-->

vendor_rating_en=[]

for i in train_df['vendor_rating'].values:
  if i<=3.7:
    vendor_rating_en.append(1)
  elif 3.7<i<=4.0:
    vendor_rating_en.append(2)
  elif 4.0<i<=4.2:
    vendor_rating_en.append(3)
  elif 4.2<i<=4.5:
    vendor_rating_en.append(4)
  else:
    vendor_rating_en.append(5)

train_df['vendor_rating_en']=vendor_rating_en
```

In [ ]:
```
train_df['gender'].value_counts()
```

Out[103]:
```
Male      3709332
Female     299970
Name: gender, dtype: int64
```

In [ ]:
```
# As there are only 2 categories, I have binned them into Male-0 and Female-1

gender_en=[]

for i in train_df['gender'].values:
  if i=='Male':
    gender_en.append(0)
  else:
    gender_en.append(1)

train_df['gender_en']=gender_en
```

In [ ]:
```
train_df['vendor_category_en'].value_counts()
```

Out[105]:
```
Restaurants       4992680
Sweets & Bakes     624085
Name: vendor_category_en, dtype: int64
```

In [ ]:
```
# As there are only 2 categories, I have binned them into Restuarants: 1 and Swee

vendor_category=[]

for i in train_df['vendor_category_en'].values:
  if i=='Restaurants':
    vendor_category.append(1)
  else:
    vendor_category.append(0)

train_df['vendor_category']=vendor_category
```

In [ ]:
```
# Saving preprocessed file for future use

train_df.to_csv('preprocessed.csv',index=False)
```

In [ ]:
```
train_df=pd.read_csv('preprocessed.csv')
```

In [ ]:
```
train_df.drop(['location_type'],axis=1,inplace=True)
train_df.head()
```

Out[112]:

	customer_id	gender	location_number	latitude_x	longitude_x	id	latitude_y	longitude_y	venc
0	TCHWPBT	Male	2	-0.1287	-78.56	4	-0.5884	0.7544	
1	TCHWPBT	Male	2	-0.1287	-78.56	13	-0.4717	0.7446	
2	TCHWPBT	Male	2	-0.1287	-78.56	20	-0.4075	0.6436	
3	TCHWPBT	Male	2	-0.1287	-78.56	23	-0.5854	0.7540	
4	TCHWPBT	Male	2	-0.1287	-78.56	28	0.4807	0.5527	

5 rows × 23 columns

D. Normalization

As all the data has been binned, the need for normalization or scaling of data has beem reduced, Further we will see the feature importance to find out whether our preprocessed columns have been made a difference or not.

E. Feature Importance and Feature Elimination

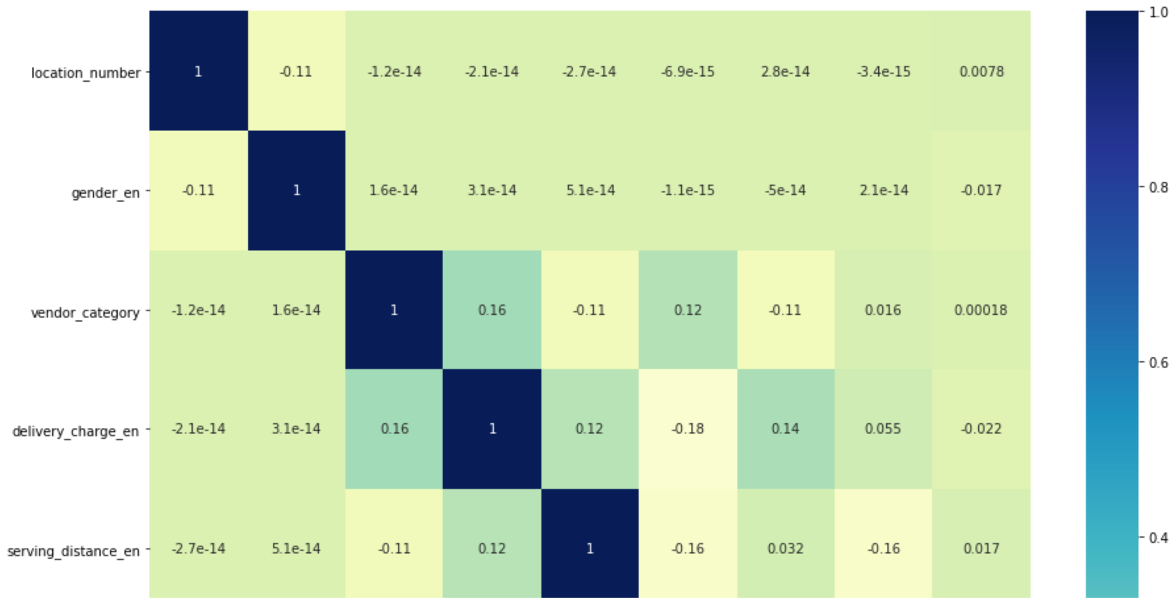
In [ ]:
```
corr=train_df[['location_number','gender_en','vendor_category','delivery_charge_e
             'serving_distance_en','is_open_en','preparation_time_en','vendor_ratir
corr.corr()
```

Out[117]:

	location_number	gender_en	vendor_category	delivery_charge_en	serving_
location_number	1.000000e+00	-1.083937e-01	-1.246404e-14	-2.060277e-14	-2
gender_en	-1.083937e-01	1.000000e+00	1.594191e-14	3.057348e-14	5
vendor_category	-1.246404e-14	1.594191e-14	1.000000e+00	1.595041e-01	-1
delivery_charge_en	-2.060277e-14	3.057348e-14	1.595041e-01	1.000000e+00	1
serving_distance_en	-2.668470e-14	5.140911e-14	-1.074355e-01	1.164292e-01	1
is_open_en	-6.926633e-15	-1.066091e-15	1.195229e-01	-1.837113e-01	-1
preparation_time_en	2.838429e-14	-4.966859e-14	-1.147250e-01	1.411852e-01	3
vendor_rating_en	-3.357673e-15	2.079870e-14	1.553987e-02	5.520680e-02	-1
target	7.797102e-03	-1.657012e-02	1.751520e-04	-2.241130e-02	1

In [ ]:
```
#reference: https://seaborn.pydata.org/generated/seaborn.heatmap.html

fig, ax = plt.subplots(figsize=(15,15))
sns.heatmap(corr.corr(), cmap="YlGnBu", annot=True)
```

Out[118]:
```
<AxesSubplot:>
```



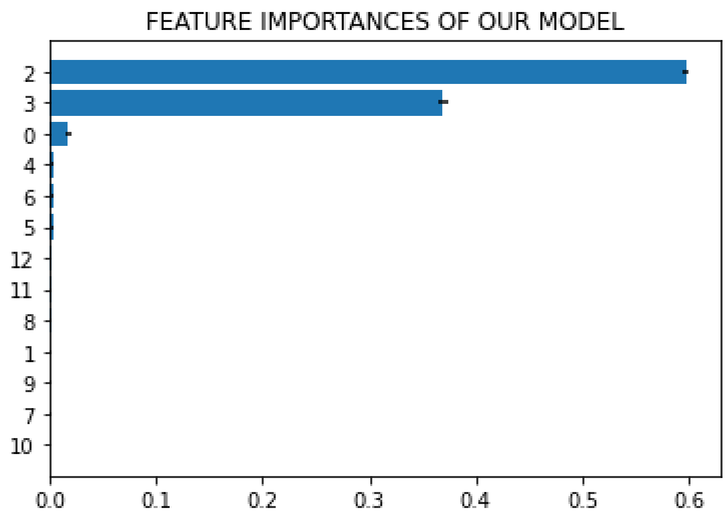
F. Feature Importance and Feature Elimination

In [ ]:
```
feature_x=train_df[['location_number','gender_en','latitude_x',\
           'longitude_x','id','latitude_y','longitude_y','vendor_category','deliv
           'serving_distance_en','is_open_en','preparation_time_en','vendor_ratir
feature_y=train_df['target']
```

In [ ]:
```
#Reference: https://machinelearningmastery.com/feature-selection-in-python-with-s

from sklearn import datasets
from sklearn import metrics
from sklearn.ensemble import ExtraTreesClassifier

model = ExtraTreesClassifier()
model.fit(feature_x,feature_y)
# display the relative importance of each attribute
print(model.feature_importances_)
```

```
[1.75726757e-02 9.51664361e-04 5.96583373e-01 3.68724196e-01
 3.40524530e-03 3.15009961e-03 3.24524415e-03 6.91920362e-04
 1.04077279e-03 9.28178275e-04 5.30188142e-04 1.30292444e-03
 1.87351811e-03]
```

In [ ]:
```
#reference from : https://stackoverflow.com/questions/44511636/matplotlib-plot-fe

feature_imp = model.feature_importances_

std = np.std([x.feature_importances_ for x in model.estimators_],axis=0)
indices = np.argsort(feature_imp)

#plotting festure importances using plt
plt.figure()
plt.title("FEATURE IMPORTANCES OF OUR MODEL")

plt.barh(range(feature_x.shape[1]), feature_imp[indices], xerr=std[indices], alig
plt.yticks(range(feature_x.shape[1]), indices)
plt.ylim([-1, feature_x.shape[1]])
plt.show()
```



PLOT DESCRIPTION AND OBSERVATIONS:

---

1. Here the plot shows the features with their imprtance in predicting the target values.
2. It shows that Gender,Location (latitude and longitude), Location Number is very important features as already seen in EDA.

4.ENCODING TRAIN AND TEST

In [ ]:
```
train=pd.read_csv('/content/drive/MyDrive/CASE STUDY 1/train_full.csv')
```

In [ ]:
```
#taking only important columns
train_df=train[['gender','location_number','location_type','latitude_x',\
           'longitude_x','latitude_y','longitude_y','id','vendor_category_en','de
           'serving_distance','is_open','prepration_time','vendor_rating','target
print('-'*100)
print(train_df.shape)
train_df.head()
```

```
--------------------------------------------------------------------------------
--------------------
(5802400, 15)
```

Out[7]:

	gender	location_number	location_type	latitude_x	longitude_x	latitude_y	longitude_y	id	ver
0	Male	0	Work	-96.44	-67.2	-0.5884	0.7544	4	
1	Male	0	Work	-96.44	-67.2	-0.4717	0.7446	13	
2	Male	0	Work	-96.44	-67.2	-0.4075	0.6436	20	
3	Male	0	Work	-96.44	-67.2	-0.5854	0.7540	23	
4	Male	0	Work	-96.44	-67.2	0.4807	0.5527	28	

In [ ]:
```
import math
#storing distance between points

dist=[]

for i in train_df.values:

  co_1 = (i[6]-i[4])**2
  co_2 = (i[7]-i[5])**2

  di=math.sqrt(co_1+co_2)
  dist.append(di)

train_df['distance']=dist
print(train_df.shape)
print('-'*100)
train_df.head()
```

```
(5802400, 16)
----------------------------------------------------------------------------------------------------
```

Out[8]:

	gender	location_number	location_type	latitude_x	longitude_x	latitude_y	longitude_y	id	ver
0	Male	0	Work	-96.44	-67.2	-0.5884	0.7544	4	
1	Male	0	Work	-96.44	-67.2	-0.4717	0.7446	13	
2	Male	0	Work	-96.44	-67.2	-0.4075	0.6436	20	
3	Male	0	Work	-96.44	-67.2	-0.5854	0.7540	23	
4	Male	0	Work	-96.44	-67.2	0.4807	0.5527	28	

In [ ]:
```
# label encoding the string data
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

train_df['gender']= le.fit_transform(train_df['gender'].astype(str))
train_df['location_type']= le.fit_transform(train_df['location_type'].astype(str)
train_df['vendor_category_en']= le.fit_transform(train_df['vendor_category_en'].a
```

In [ ]:
```
train_df.to_csv('/content/drive/MyDrive/CASE STUDY 1/train_f.csv',index=False)
```

In [ ]:
```
import pandas as pd
train=pd.read_csv('/content/drive/MyDrive/CASE STUDY 1/train_f.csv')
```

In [ ]:
```
print(train.shape)
print('-'*100)
train.head()
```

```
(5802400, 16)
--------------------------------------------------------------------------------
--------------------
```

Out[12]:

	gender	location_number	location_type	latitude_x	longitude_x	latitude_y	longitude_y	id	ver
0	1	0	2	-96.44	-67.2	-0.5884	0.7544	4	
1	1	0	2	-96.44	-67.2	-0.4717	0.7446	13	
2	1	0	2	-96.44	-67.2	-0.4075	0.6436	20	
3	1	0	2	-96.44	-67.2	-0.5854	0.7540	23	
4	1	0	2	-96.44	-67.2	0.4807	0.5527	28	

A. One hot encoding

In [ ]:
```
#applyinh one-hot encoding to all the categorical data
gen = pd.get_dummies(train['gender'])
ltype = pd.get_dummies(train['location_type'])
venc = pd.get_dummies(train['vendor_category_en'])
dev = pd.get_dummies(train['delivery_charge'])
dis = pd.get_dummies(train['serving_distance'])
opn = pd.get_dummies(train['is_open'])
ptime = pd.get_dummies(train['prepration_time'])
rat = pd.get_dummies(train['vendor_rating'])
```

In [ ]:
```
final_train=pd.concat([train[['latitude_x','longitude_x','latitude_y','longitude_
```

In [ ]:
```
final_train.head()
```

Out[15]:

	latitude_x	longitude_x	latitude_y	longitude_y	id	location_number	distance	0	1	2	0	1
0	-96.44	-67.2	-0.5884	0.7544	4	0	68.109132	0	1	0	0	0
1	-96.44	-67.2	-0.4717	0.7446	13	0	69.267275	0	1	0	0	0
2	-96.44	-67.2	-0.4075	0.6436	20	0	70.846455	0	1	0	0	0
3	-96.44	-67.2	-0.5854	0.7540	23	0	71.930642	0	1	0	0	0
4	-96.44	-67.2	0.4807	0.5527	28	0	73.128245	0	1	0	0	0

In [ ]:
```
#encoding the test files
test=pd.read_csv('/content/drive/MyDrive/CASE STUDY 1/test_full.csv')
```

In [ ]:
```
test.head()
```

Out[17]:

	customer_id	gender	status_x	verified_x	created_at_x	updated_at_x	location_number	locatior
0	ICE2DJP	Male	1.0	1.0	2018-02-07 16:45:36	2018-02-07 16:45:36	0.0	
1	ICE2DJP	Male	1.0	1.0	2018-02-07 16:45:36	2018-02-07 16:45:36	0.0	
2	ICE2DJP	Male	1.0	1.0	2018-02-07 16:45:36	2018-02-07 16:45:36	0.0	
3	ICE2DJP	Male	1.0	1.0	2018-02-07 16:45:36	2018-02-07 16:45:36	0.0	
4	ICE2DJP	Male	1.0	1.0	2018-02-07 16:45:36	2018-02-07 16:45:36	0.0	

In [ ]:
```
test_df=test[['gender','location_number','location_type','latitude_x',\
           'longitude_x','latitude_y','longitude_y','id','vendor_category_en','de
           'serving_distance','is_open','prepration_time','vendor_rating']]
print('-'*100)
print(test_df.shape)
test_df.head()
```

```
--------------------------------------------------------------------------------
--------------------
(1672000, 14)
```

Out[18]:

	gender	location_number	location_type	latitude_x	longitude_x	latitude_y	longitude_y	id	v
0	Male	0.0	NaN	-96.44	-67.2	-0.5884	0.7544	4.0	
1	Male	0.0	NaN	-96.44	-67.2	-0.4717	0.7446	13.0	
2	Male	0.0	NaN	-96.44	-67.2	-0.4075	0.6436	20.0	
3	Male	0.0	NaN	-96.44	-67.2	-0.5854	0.7540	23.0	
4	Male	0.0	NaN	-96.44	-67.2	0.4807	0.5527	28.0	

In [ ]:
```
import math
#storing distance between points

dist=[]

for i in test_df.values:

  co_1 = (i[5]-i[3])**2
  co_2 = (i[6]-i[4])**2

  di=math.sqrt(co_1+co_2)
  dist.append(di)

test_df['distance']=dist
print(test_df.shape)
print('-'*100)
test_df.head()
```

```
(1672000, 15)
----------------------------------------------------------------------------------------------------
```

Out[19]:

	gender	location_number	location_type	latitude_x	longitude_x	latitude_y	longitude_y	id	v
0	Male	0.0	NaN	-96.44	-67.2	-0.5884	0.7544	4.0	
1	Male	0.0	NaN	-96.44	-67.2	-0.4717	0.7446	13.0	
2	Male	0.0	NaN	-96.44	-67.2	-0.4075	0.6436	20.0	
3	Male	0.0	NaN	-96.44	-67.2	-0.5854	0.7540	23.0	
4	Male	0.0	NaN	-96.44	-67.2	0.4807	0.5527	28.0	

In [ ]:
```
# label encoding the string data
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

test_df['gender']= le.fit_transform(test_df['gender'].astype(str))
test_df['location_type']= le.fit_transform(test_df['location_type'].astype(str))
test_df['vendor_category_en']= le.fit_transform(test_df['vendor_category_en'].ast
```

In [ ]:
```
test_df.to_csv('/content/drive/MyDrive/CASE STUDY 1/test_f.csv',index=False)
```

In [ ]:
```
import pandas as pd
test=pd.read_csv('/content/drive/MyDrive/CASE STUDY 1/test_f.csv')
```

In [ ]:
```
print(test.shape)
print('-'*100)
test.head()
```

```
(1672000, 15)
----------------------------------------------------------------------------------------------------
```

Out[23]:

	gender	location_number	location_type	latitude_x	longitude_x	latitude_y	longitude_y	id	v
0	1	0.0	3	-96.44	-67.2	-0.5884	0.7544	4.0	
1	1	0.0	3	-96.44	-67.2	-0.4717	0.7446	13.0	
2	1	0.0	3	-96.44	-67.2	-0.4075	0.6436	20.0	
3	1	0.0	3	-96.44	-67.2	-0.5854	0.7540	23.0	
4	1	0.0	3	-96.44	-67.2	0.4807	0.5527	28.0	

In [ ]:
```
gen = pd.get_dummies(test['gender'])
ltype = pd.get_dummies(test['location_type'])
venc = pd.get_dummies(test['vendor_category_en'])
dev = pd.get_dummies(test['delivery_charge'])
dis = pd.get_dummies(test['serving_distance'])
opn = pd.get_dummies(test['is_open'])
ptime = pd.get_dummies(test['prepration_time'])
rat = pd.get_dummies(test['vendor_rating'])
```

In [ ]:
```
final_test=pd.concat([test[['latitude_x','longitude_x','latitude_y','longitude_y'
```

In [ ]:
```
final_test.head()
```

Out[26]:

	latitude_x	longitude_x	latitude_y	longitude_y	id	location_number	distance	0	1	2	0
0	-96.44	-67.2	-0.5884	0.7544	4.0	0.0	117.496084	0	1	0	0
1	-96.44	-67.2	-0.4717	0.7446	13.0	0.0	117.585642	0	1	0	0
2	-96.44	-67.2	-0.4075	0.6436	20.0	0.0	117.579739	0	1	0	0
3	-96.44	-67.2	-0.5854	0.7540	23.0	0.0	117.498300	0	1	0	0
4	-96.44	-67.2	0.4807	0.5527	28.0	0.0	118.254177	0	1	0	0

5.MODELLING

In [24]:

```
!pip install xgboost
```

```
Requirement already satisfied: xgboost in /opt/conda/lib/python3.7/site-package
s (1.4.2)
Requirement already satisfied: numpy in /opt/conda/lib/python3.7/site-packages
(from xgboost) (1.19.5)
Requirement already satisfied: scipy in /opt/conda/lib/python3.7/site-packages
(from xgboost) (1.6.3)
```

In [25]:

```
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
```

In [26]:

```
import pandas as pd
train=pd.read_csv('train_data.csv')
test=pd.read_csv('test_data.csv')
```

In [27]:
```
data=train.copy()
data.head()
```

Out[27]:

	latitude_x	longitude_x	latitude_y	longitude_y	id	location_number	distance	0	1	2	...	4.(
0	-96.44	-67.2	-0.5884	0.7544	4	0	68.109132	0	1	0	...	(
1	-96.44	-67.2	-0.4717	0.7446	13	0	69.267275	0	1	0	...	(
2	-96.44	-67.2	-0.4075	0.6436	20	0	70.846455	0	1	0	...	(
3	-96.44	-67.2	-0.5854	0.7540	23	0	71.930642	0	1	0	...	(
4	-96.44	-67.2	0.4807	0.5527	28	0	73.128245	0	1	0	...	(

5 rows × 57 columns

In [28]:
```
#creating data for training and target

y=data['target'] #target

data.drop(['target'],inplace=True,axis=1)
X=data #dataset

X=X.fillna(0) #filling null values
print('-'*100)
print(X.shape,y.shape)
```

```
----------------------------------------------------------------------------------------------------
(5802400, 56) (5802400,)
```

A. LINEAR REGRESSION

In [ ]:
```
from sklearn import preprocessing, svm
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import confusion_matrix

print('-'*100)
print(X.shape,y.shape)
print('-'*100)

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.4)

lnr = LinearRegression()
lnr.fit(X_train, y_train)
```

```
--------------------------------------------------------------------------------
--------------------
(5802400, 56) (5802400,)
--------------------------------------------------------------------------------
--------------------
```

Out[7]:
```
LinearRegression()
```

In [ ]:
```
import numpy as np
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

#predicting the outputs

y_pred=lnr.predict(X_test)
y_predict=[]

for i in y_pred: #round off values for target data
  if i<=0.5:
    y_predict.append(0)
  else:
    y_predict.append(1)

arr=confusion_matrix(y_test, y_predict)

print('Accuracy Score: ',accuracy_score(y_test, y_predict))
print('-'*100)
print('Precision: ',precision_score(y_test, y_predict))
print('-'*100)
print('Recall: ',recall_score(y_test, y_predict))
print('-'*100)

f1=(2*(precision_score(y_test, y_predict))*(recall_score(y_test, y_predict)))/((r
print('The F1 score:',f1)
```

```
Accuracy Score:  0.9864805942368675
----------------------------------------------------------------------------------------------------
Precision:  0.0
----------------------------------------------------------------------------------------------------
Recall:  0.0
----------------------------------------------------------------------------------------------------
The F1 score: nan
```

B. LOGISTIC REGRESSION

In [ ]:
```
#reference from malware assignment and previous assignments
from sklearn.linear_model import LogisticRegression

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.33)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size = 0.3


alpha = [10 ** x for x in range(-3, 3)]
log_error=[]

#below code hypertune the parameters and do calliberations
#the code structure is referenced from the malware assignment code

for i in alpha: #hyperparameter ALpha tuning
    lor=LogisticRegression(penalty='l2',C=i,class_weight='balanced')

    lor.fit(X_train,y_train)
    clf = CalibratedClassifierCV(lor,method="sigmoid") #caliberation used

    clf.fit(X_train, y_train)
    predict= clf.predict_proba(X_cv)
    log_error.append(log_loss(y_cv, predict, labels=lor.classes_, eps=1e-15)) #pr

for i in range(len(log_error)):
    print ('Log_loss for C = ',alpha[i],'is',log_error[i])

best_alpha = np.argmin(log_error) #choosing best alpha
#--------------------------------------------------------------------------------

fig, ax = plt.subplots()
ax.plot(alpha, log_error,c='g')

for i, txt in enumerate(np.round(log_error,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],log_error[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
```

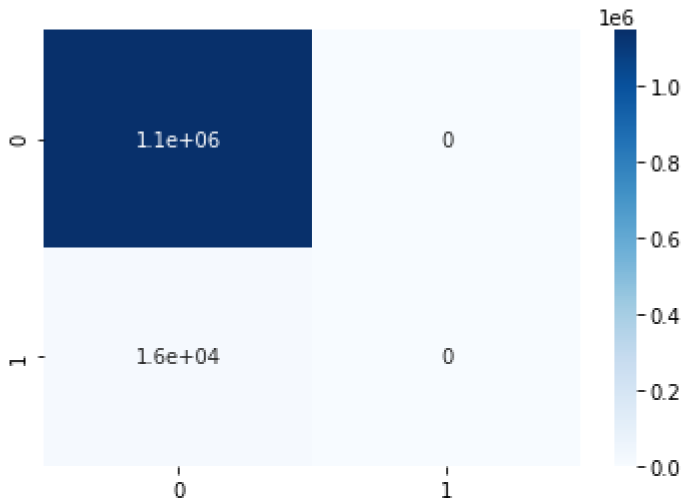
```
Log_loss for C =  0.001 is 0.07082647096390168
Log_loss for C =  0.01 is 0.07082647096390168
Log_loss for C =  0.1 is 0.07082647096390168
Log_loss for C =  1 is 0.07082647096390168
Log_loss for C =  10 is 0.07082647096390168
Log_loss for C =  100 is 0.07082647096390168
```

In [ ]:
```
#Applying hyper-tuned parameter for test data

logistic=LogisticRegression(penalty='l2',C=alpha[best_alpha],class_weight='balanc

#getting final model ready
logistic.fit(X_train,y_train)
clf = CalibratedClassifierCV(logistic, method="sigmoid")
clf.fit(X_train, y_train)

#predicting for F1 score,Precision and Recall
pred=clf.predict(X_test)
```

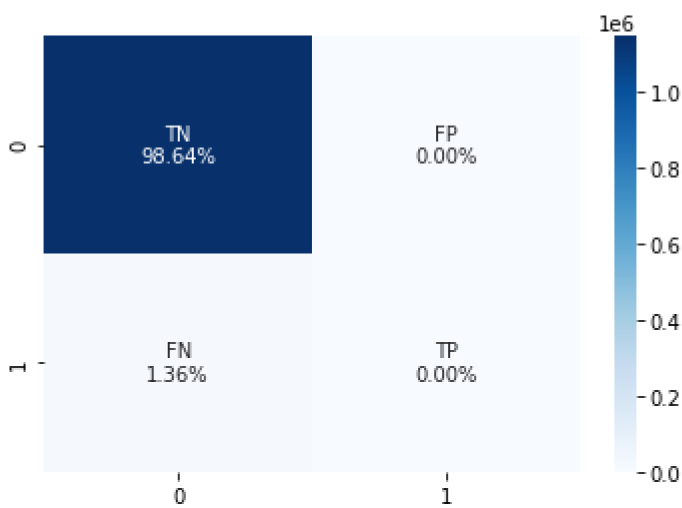
In [ ]:
```
import numpy as np
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

y_predict=[]

for i in pred: #round off values for target data
  if i<=0.5:
    y_predict.append(0)
  else:
    y_predict.append(1)

#printing metrics
print('Accuracy Score: ',accuracy_score(y_test, y_predict))
print('-'*100)
print('Precision: ',precision_score(y_test, y_predict))
print('-'*100)
print('Recall: ',recall_score(y_test, y_predict))
print('-'*100)

f1=(2*(precision_score(y_test, y_predict))*(recall_score(y_test, y_predict)))/((r
print('The F1 score:',f1)
```

```
Accuracy Score:  0.9864211360816214
----------------------------------------------------------------------------------------------------
Precision:  0.0
----------------------------------------------------------------------------------------------------
Recall:  0.0
----------------------------------------------------------------------------------------------------
The F1 score: nan
```

In [ ]:
```
#reference: https://medium.com/@dtuk81/confusion-matrix-visualization-fc31e3f30fe

import matplotlib.pyplot as plt
%matplotlib inline

sns.heatmap(arr, annot=True, cmap='Blues')
plt.show()

gnames = ['TN','FP','FN','TP'] #labeling the map
gper = ["{0:.2%}".format(x) for x in (arr.flatten()/np.sum(arr))] #calculation of

labels = [f"{v1}\n{v2}" for v1, v2 in zip(gnames,gper)] #mapping labels with thei
labels = np.asarray(labels).reshape(2,2) #reshaping the matrix

sns.heatmap(arr, annot=labels, fmt='', cmap='Blues')#printing the confusion m
```



Out[23]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8dda828990>



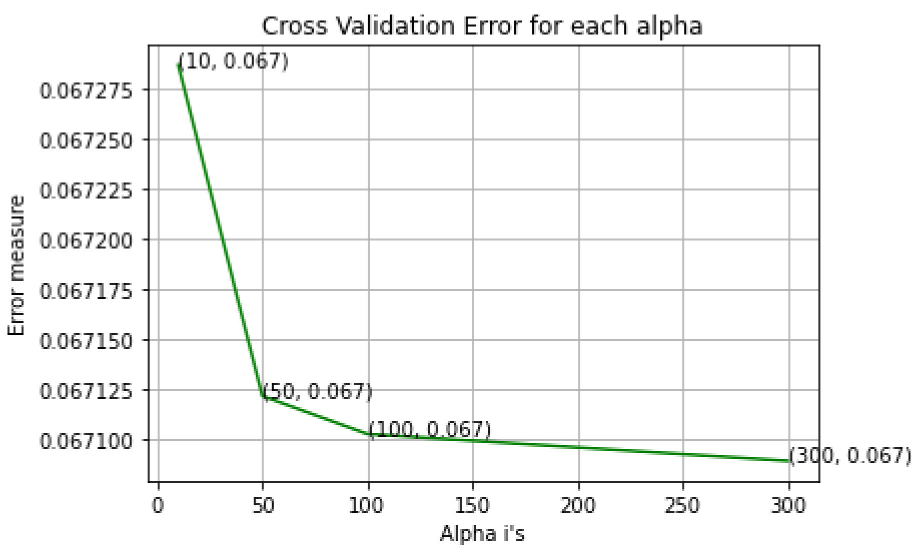
C. RANDOM FOREST

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.calibration import CalibratedClassifierCV
from sklearn.metrics import log_loss
import numpy as np
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.4)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size = 0.4
```

In [ ]:
```
alpha=[10,50,100,300]
cvlog_error=[]
trlog_error=[]

#below code hypertune the parameters and do calliberations
#the code structure is referenced from the malware assignment code
for i in alpha:

    clf=RandomForestClassifier(n_estimators=i,random_state=42,n_jobs=-1)
    clf.fit(X_train,y_train)

    clf1 = CalibratedClassifierCV(clf, method="sigmoid")
    clf1.fit(X_train, y_train)
    pred = clf1.predict_proba(X_cv)
    cvlog_error.append(log_loss(y_cv, pred, labels=clf.classes_, eps=1e-15))
```

In [ ]:
```
%matplotlib inline
from matplotlib import pyplot as plt

for i in range(len(cvlog_error)):
    print ('Log_loss for n_estimator = ',alpha[i],'is',cvlog_error[i])


best_alpha = np.argmin(cvlog_error)

fig, ax = plt.subplots()
ax.plot(alpha, cvlog_error,c='g')

for i, txt in enumerate(np.round(cvlog_error,3)):
    ax.annotate((alpha[i],np.round(txt,3)), (alpha[i],cvlog_error[i]))
plt.grid()
plt.title("Cross Validation Error for each alpha")
plt.xlabel("Alpha i's")
plt.ylabel("Error measure")
plt.show()
```

```
Log_loss for n_estimator =  10 is 0.06728679878785393
Log_loss for n_estimator =  50 is 0.06712139179425688
Log_loss for n_estimator =  100 is 0.06710234680562388
Log_loss for n_estimator =  300 is 0.06708891062571232
```



In [ ]:
```
clf=RandomForestClassifier(n_estimators=10,random_state=42,n_jobs=-1)
clf.fit(X_train,y_train)

#making final model ready
cal_clf = CalibratedClassifierCV(clf, method="sigmoid")
cal_clf.fit(X_train, y_train)

pred = cal_clf.predict_proba(X_train)
```

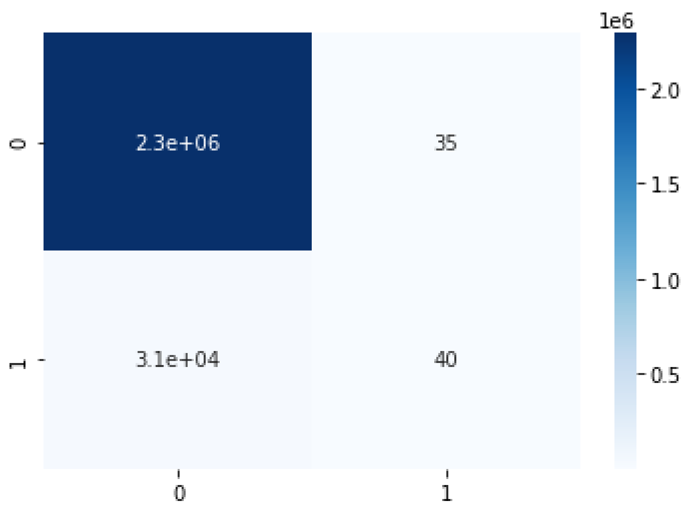
In [ ]:
```
print('For values of best alpha = ', 10, "The train log loss is:",log_loss(y_trai

pred = cal_clf.predict_proba(X_cv)
print('For values of best alpha = ', 10, "The cross validation log loss is:",log_

pred = cal_clf.predict_proba(X_test)
print('For values of best alpha = ', 10, "The test log loss is:",log_loss(y_test,
```

```
For values of best alpha =  10 The train log loss is: 0.035592052103006686
For values of best alpha =  10 The cross validation log loss is: 0.066473537016
49197
For values of best alpha =  10 The test log loss is: 0.06599998051399218
```

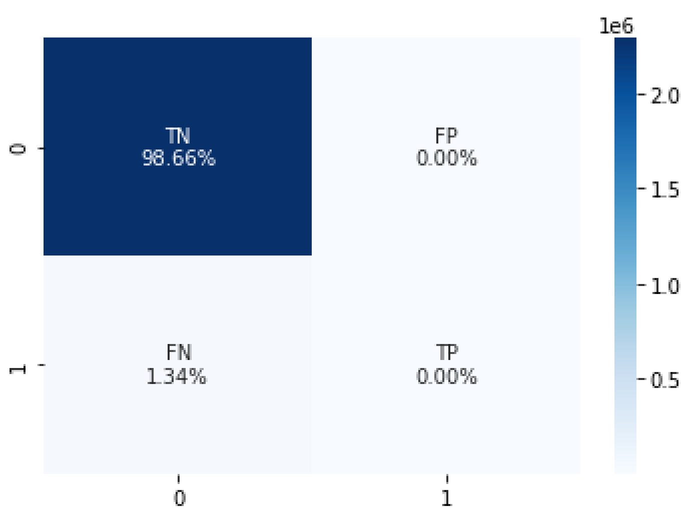
In [ ]:
```
import numpy as np
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

predict=cal_clf.predict(X_test)

#printing metrics
print('Accuracy Score: ',accuracy_score(y_test, predict))
print('-'*100)
print('Precision: ',precision_score(y_test, predict))
prec=precision_score(y_test, predict)
print('-'*100)
print('Recall: ',recall_score(y_test, predict))
rec=recall_score(y_test, predict)
print('-'*100)

f1=(2*prec*rec)/(rec+prec+0.00001)
print('The F1 score:',f1)
```

```
Accuracy Score:  0.9866016648283469
--------------------------------------------------------------------------------
--------------------
Precision:  0.5333333333333333
--------------------------------------------------------------------------------
--------------------
Recall:  0.0012860909266285126
--------------------------------------------------------------------------------
--------------------
The F1 score: 0.002565946166610598
```

In [ ]:
```
#reference: https://medium.com/@dtuk81/confusion-matrix-visualization-fc31e3f30fe
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import seaborn as sns
%matplotlib inline

arr=confusion_matrix(y_test, predict)

sns.heatmap(arr, annot=True, cmap='Blues')
plt.show()

gnames = ['TN','FP','FN','TP'] #labeling the map
gper = ["{0:.2%}".format(x) for x in (arr.flatten()/np.sum(arr))] #calculation of

labels = [f"{v1}\n{v2}" for v1, v2 in zip(gnames,gper)] #mapping labels with thei
labels = np.asarray(labels).reshape(2,2) #reshaping the matrix

sns.heatmap(arr, annot=labels, fmt='', cmap='Blues')#printing the confusion m
```



Out[16]: <AxesSubplot:>



D. XGBOOST

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

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.4)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size = 0.4
```

In [ ]:
```
alpha=[10,50,100,200]

cvlog_error=[]

#below code hypertune the parameters and do calliberations
#the code structure is referenced from the malware assignment code
for i in alpha:
    print('Alpha:',i)
    clf=XGBClassifier(n_estimators=i,nthread=-1)
    clf.fit(X_train,y_train)

    xg_clf = CalibratedClassifierCV(clf, method="sigmoid")
    xg_clf.fit(X_train, y_train)
    pred = xg_clf.predict_proba(X_cv)
    cvlog_error.append(log_loss(y_cv, pred, labels=clf.classes_, eps=1e-15))

for i in range(len(cvlog_error)):
    print ('log_loss for c = ',alpha[i],'is',cvlog_error[i])

best_alpha = np.argmin(cvlog_error)
```

```
Alpha: 10
[14:04:05] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:04:23] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:04:43] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:05:02] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:05:18] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:05:38] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
Alpha: 50
[14:05:59] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:07:08] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:08:06] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
```

```
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:09:03] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:10:01] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:10:58] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
Alpha: 100
[14:12:01] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:14:18] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:16:08] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:17:58] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:19:48] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:21:38] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
Alpha: 200
[14:23:32] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:27:46] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:31:14] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:34:41] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:38:02] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
```

```
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[14:41:32] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
log_loss for c =  10 is 0.06588117303229635
log_loss for c =  50 is 0.06137575082511842
log_loss for c =  100 is 0.0606517038851701
log_loss for c =  200 is 0.060306969242433804
3
```

In [ ]:

```
clf=XGBClassifier(n_estimators=200,nthread=-1)
clf.fit(X_train,y_train)
xg_clf = CalibratedClassifierCV(clf, method="sigmoid")
xg_clf.fit(X_train, y_train)
```

In [ ]:

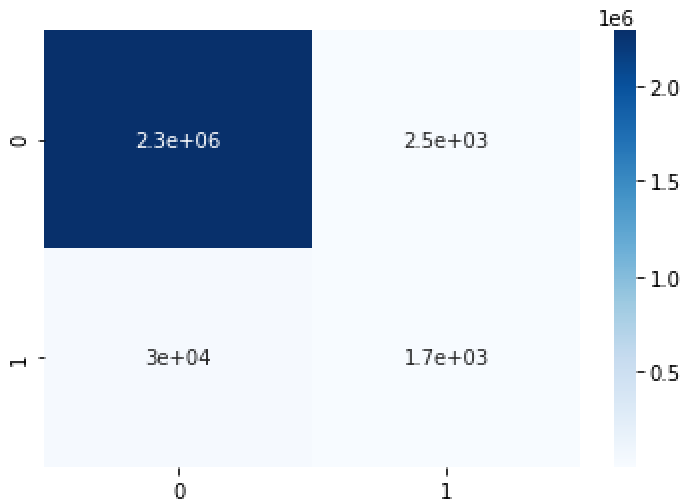
```
predict_y = xg_clf.predict_proba(X_train)
print('For values of best alpha = ', 200, "The train log loss is:",log_loss(y_tra

predict_y = xg_clf.predict_proba(X_cv)
print('For values of best alpha = ',  200, "The cross validation log loss is:",lo

predict_y = xg_clf.predict_proba(X_test)
print('For values of best alpha = ',  200, "The test log loss is:",log_loss(y_tes
```

```
For values of best alpha =  200 The train log loss is: 0.05632387345126351
For values of best alpha =  200 The cross validation log loss is: 0.05985484586
3674525
For values of best alpha =  200 The test log loss is: 0.060016433206268614
```

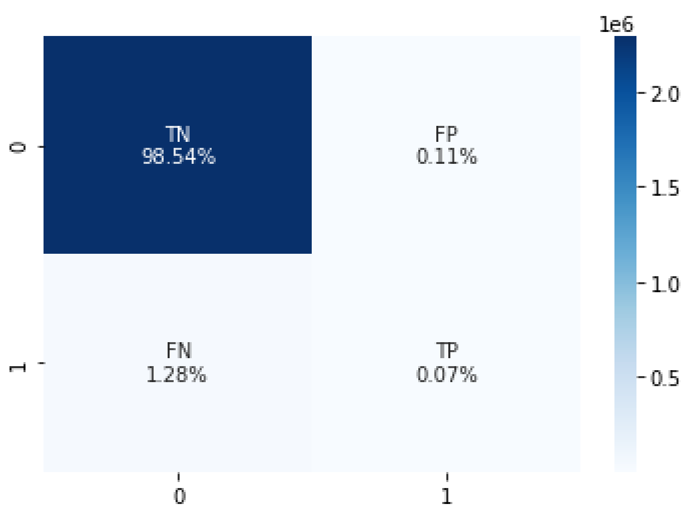
In [ ]:
```
import numpy as np
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

predict=xg_clf.predict(X_test)
#printing metrics

print('Accuracy Score: ',accuracy_score(y_test, predict))
print('-'*100)
print('Precision: ',precision_score(y_test, predict))
prec=precision_score(y_test, predict)
print('-'*100)
print('Recall: ',recall_score(y_test, predict))
rec=recall_score(y_test, predict)
print('-'*100)

f1=(2*prec*rec)/(rec+prec+0.00000001)
print('The F1 score:',f1)
```

```
Accuracy Score:  0.9861514201020267
--------------------------------------------------------------------------------
--------------------
Precision:  0.403125
--------------------------------------------------------------------------------
--------------------
Recall:  0.05351672198110799
--------------------------------------------------------------------------------
--------------------
The F1 score: 0.09448951787668285
```

In [ ]:
```
#reference: https://medium.com/@dtuk81/confusion-matrix-visualization-fc31e3f30fe
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import seaborn as sns
%matplotlib inline

arr=confusion_matrix(y_test, predict)

sns.heatmap(arr, annot=True, cmap='Blues')
plt.show()

gnames = ['TN','FP','FN','TP'] #labeling the map
gper = ["{0:.2%}".format(x) for x in (arr.flatten()/np.sum(arr))] #calculation of
labels = [f"{v1}\n{v2}" for v1, v2 in zip(gnames,gper)] #mapping labels with the
labels = np.asarray(labels).reshape(2,2) #reshaping the matrix

sns.heatmap(arr, annot=labels, fmt='', cmap='Blues')#printing the confusion m
```



Out[14]: <AxesSubplot:>



E. XGBOOST WITH RANDOM SEARCH

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

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.4)
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size = 0.4
```

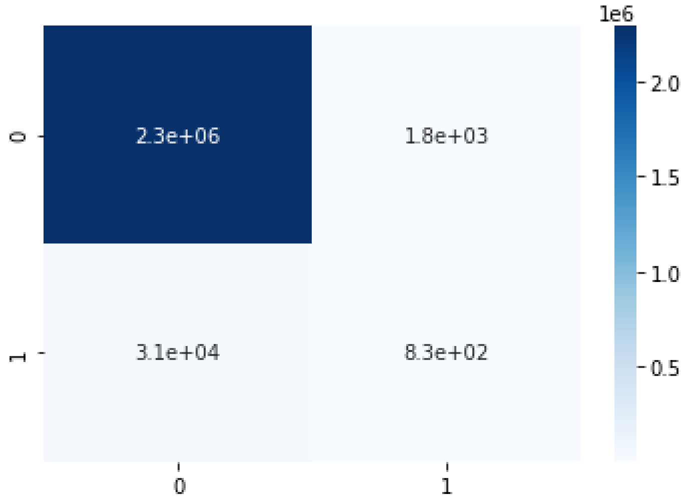
In [ ]:
```
xg_=XGBClassifier(n_estimators=200, learning_rate=0.05, colsample_bytree=1, max_c
xg_.fit(X_train,y_train)

xg=CalibratedClassifierCV(xg_,method='sigmoid')
xg.fit(X_train,y_train)
#below code hypertune the parameters and do calliberations
#the code structure is referenced from the malware assignment code

predict_y = xg.predict_proba(X_train)
print ('train loss',log_loss(y_train, predict_y))

predict_y = xg.predict_proba(X_cv)
print ('cv loss',log_loss(y_cv, predict_y))

predict_y = xg.predict_proba(X_test)
print ('test loss',log_loss(y_test, predict_y))
```

```
[15:28:51] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[15:31:11] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[15:33:07] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[15:35:01] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[15:36:51] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[15:38:44] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
train loss 0.06429010964931357
cv loss 0.06464718700288069
test loss 0.06471846959964107
```

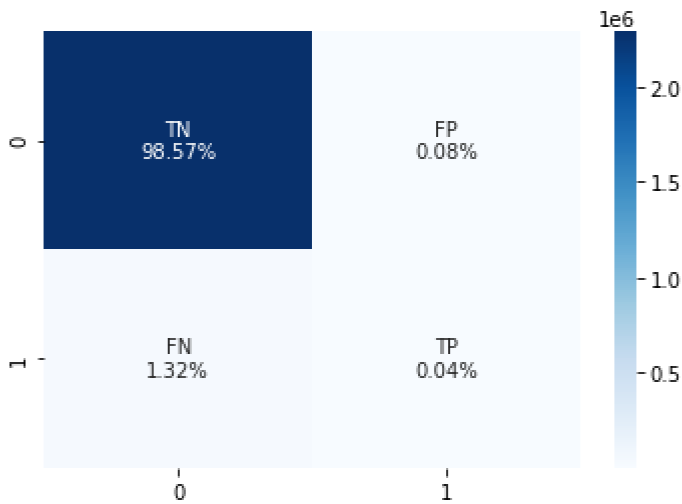
In [ ]:
```
import numpy as np
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

predict=xg.predict(X_test)

print('Accuracy Score: ',accuracy_score(y_test, predict))
print('-'*100)
print('Precision: ',precision_score(y_test, predict))
prec=precision_score(y_test, predict)
print('-'*100)
print('Recall: ',recall_score(y_test, predict))
rec=recall_score(y_test, predict)
print('-'*100)

f1=(2*prec*rec)/(rec+prec+0.00001)
print('The F1 score:',f1)
```

```
Accuracy Score:  0.9860820522542396
----------------------------------------------------------------------------------------------------
Precision:  0.3217324052590874
----------------------------------------------------------------------------------------------------
Recall:  0.026512858098849623
----------------------------------------------------------------------------------------------------
The F1 score: 0.0489873176599693
```

In [ ]:
```
#reference: https://medium.com/@dtuk81/confusion-matrix-visualization-fc31e3f30fe
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import seaborn as sns
%matplotlib inline

arr=confusion_matrix(y_test, predict)

sns.heatmap(arr, annot=True, cmap='Blues')
plt.show()

gnames = ['TN','FP','FN','TP'] #labeling the map
gper = ["{0:.2%}".format(x) for x in (arr.flatten()/np.sum(arr))] #calculation of

labels = [f"{v1}\n{v2}" for v1, v2 in zip(gnames,gper)] #mapping labels with the
labels = np.asarray(labels).reshape(2,2) #reshaping the matrix

sns.heatmap(arr, annot=labels, fmt='', cmap='Blues')#printing the confusion m
```



Out[11]: <AxesSubplot:>



F. USING SMOTE FOR IMBALANCED DATASET

In [9]:
```
!pip install imbalanced-learn
#the data is highly imbalanced, we have to balance it using smote module
```

```
Collecting imbalanced-learn
  Downloading imbalanced_learn-0.8.0-py3-none-any.whl (206 kB)
     |████████████████████████████████| 206 kB 5.2 MB/s eta 0:00:01
Requirement already satisfied: joblib>=0.11 in /opt/conda/lib/python3.7/site-pa
ckages (from imbalanced-learn) (1.0.1)
Requirement already satisfied: scikit-learn>=0.24 in /opt/conda/lib/python3.7/s
ite-packages (from imbalanced-learn) (0.24.2)
Requirement already satisfied: numpy>=1.13.3 in /opt/conda/lib/python3.7/site-p
ackages (from imbalanced-learn) (1.19.5)
Requirement already satisfied: scipy>=0.19.1 in /opt/conda/lib/python3.7/site-p
ackages (from imbalanced-learn) (1.6.3)
Requirement already satisfied: threadpoolctl>=2.0.0 in /opt/conda/lib/python3.
7/site-packages (from scikit-learn>=0.24->imbalanced-learn) (2.1.0)
Installing collected packages: imbalanced-learn
Successfully installed imbalanced-learn-0.8.0
```

In [11]:
```
from collections import Counter
from sklearn.datasets import make_classification
from matplotlib import pyplot
from numpy import where
from imblearn.under_sampling import RandomUnderSampler
from imblearn.over_sampling import SMOTE
from sklearn.pipeline import Pipeline

#printing the counter fucntion to get frequency of classes
counter = Counter(y)
print(counter)
```

```
Counter({0: 5724146, 1: 78254})
```

In [12]:
```
over = SMOTE(sampling_strategy=0.4)
X,y=over.fit_resample(X, y)

#oversampling the lower data
```

In [13]:
```
counter = Counter(y)
print(counter)
```

```
Counter({0: 5724146, 1: 2289658})
```

In [14]:
```
under = RandomUnderSampler(sampling_strategy=0.6)
X,y=under.fit_resample(X,y)
counter = Counter(y)
#undersampling the upper data
print(counter)
```

```
Counter({0: 3816096, 1: 2289658})
```

In [15]:
```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y,test_size =
X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train,stratify=y_trair
```

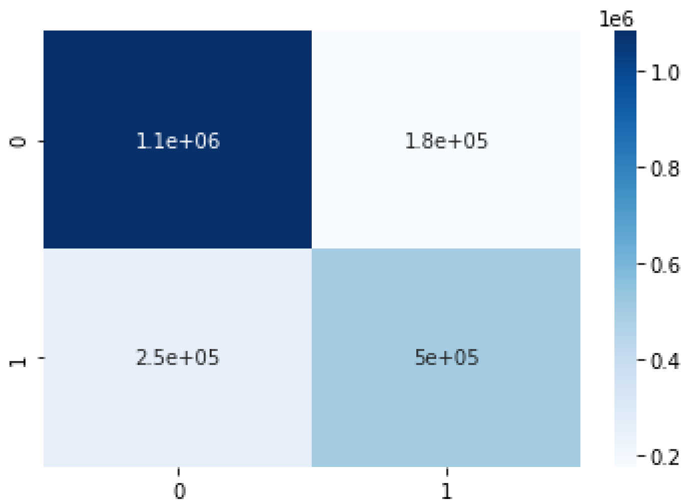
In [16]:
```
xg_=XGBClassifier(n_estimators=250, learning_rate=0.05, colsample_bytree=1, max_c
xg_.fit(X_train,y_train)

#below code hypertune the parameters and do calliberations
#the code structure is referenced from the malware assignment code

xg=CalibratedClassifierCV(xg_,method='sigmoid')
xg.fit(X_train,y_train)

predict_y = xg.predict_proba(X_train)
print ('train loss',log_loss(y_train, predict_y))

predict_y = xg.predict_proba(X_cv)
print ('cv loss',log_loss(y_cv, predict_y))

predict_y = xg.predict_proba(X_test)
print ('test loss',log_loss(y_test, predict_y))
```

```
[08:19:44] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[08:24:07] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[08:27:42] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[08:31:12] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[08:34:39] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
[08:38:13] WARNING: ../src/learner.cc:1095: Starting in XGBoost 1.3.0, the defa
ult evaluation metric used with the objective 'binary:logistic' was changed fro
m 'error' to 'logloss'. Explicitly set eval_metric if you'd like to restore the
old behavior.
train loss 0.44756476392614136
cv loss 0.4486352186922809
test loss 0.44760759486668805
```

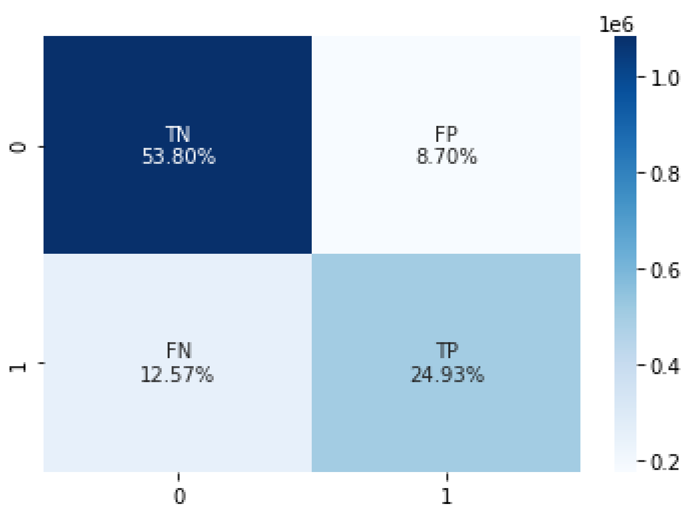
In [17]:
```
import numpy as np
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score

predict=xg.predict(X_test)

#printing metrics
print('Accuracy Score: ',accuracy_score(y_test, predict))
print('-'*100)
print('Precision: ',precision_score(y_test, predict))
prec=precision_score(y_test, predict)
print('-'*100)
print('Recall: ',recall_score(y_test, predict))
rec=recall_score(y_test, predict)
print('-'*100)

f1=(2*prec*rec)/(rec+prec+0.000000000000001)
print('The F1 score:',f1)
```

```
Accuracy Score:  0.78724541527888
--------------------------------------------------------------------------------
--------------------
Precision:  0.741192875798669
--------------------------------------------------------------------------------
--------------------
Recall:  0.6647798334275206
--------------------------------------------------------------------------------
--------------------
The F1 score: 0.7009098729694254
```

In [18]:
```
#reference: https://medium.com/@dtuk81/confusion-matrix-visualization-fc31e3f30fe
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import seaborn as sns
%matplotlib inline

arr=confusion_matrix(y_test, predict)

sns.heatmap(arr, annot=True, cmap='Blues')
plt.show()

gnames = ['TN','FP','FN','TP'] #labeling the map
gper = ["{0:.2%}".format(x) for x in (arr.flatten()/np.sum(arr))] #calculation of

labels = [f"{v1}\n{v2}" for v1, v2 in zip(gnames,gper)] #mapping labels with the
labels = np.asarray(labels).reshape(2,2) #reshaping the matrix

sns.heatmap(arr, annot=labels, fmt='', cmap='Blues')#printing the confusion m
```



Out[18]: <AxesSubplot:>



6.STORING THE MODELS AND VARIABLES

In [23]:
```
import pickle
#finally I am storing the model in a pickle file

pickle.dump(xg, open('/home/abhishek_croblaze/model.pkl', 'wb'))
```