Question 1: Load

Programmatically download and load into your favorite analytical tool the transactions data. This data, which is in line-delimited JSON format, can be found here

Please describe the structure of the data. Number of records and fields in each record?

There are 786363 transactions in the JSON data. It is list of dictionaries. There are a total of 786363 transaction records. For each record, there are 29 fields.

Please provide some additional basic summary statistics for each field. Be sure to include a count of null, minimum, maximum, and unique values where appropriate.

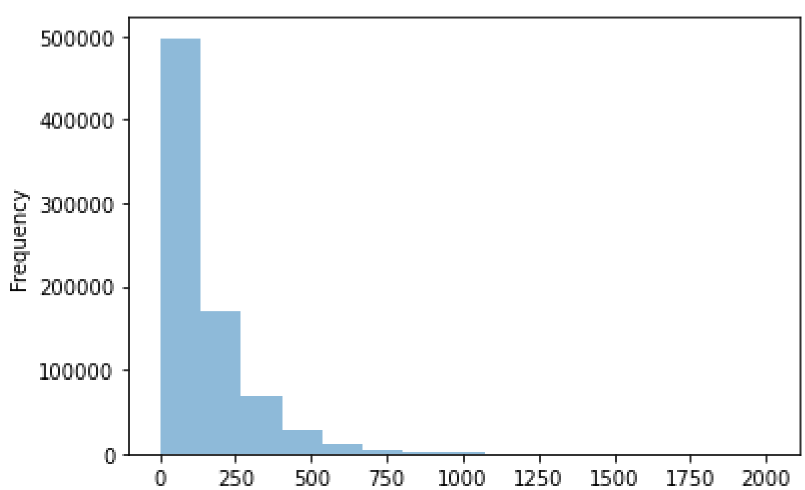
1. There are 4562 missing data in acqCountry,724 in merchantCountryCode, 4054 in posEntryMode, 409 in posConditionCode, 698 in transactionType. There are no data for these 6 categories: echoBuffer, merchantCity, merchantState, merchantZip, posOnPremises, recurringAuthInd.

2. The range for creditLimit is from 250 to 50000. The range for availableMoney is from -1005.63 to 50000. The range for transactionAmount is from 0 to 2011.54. The range for currentBalance is from 0 to 47498.81.

3. There are a total of 5000 unique customer ID in this dataset. For these customers, there are a total of 4 countries recorded (not including NA). There are 19 merchantCategoryCode types, and 3 different transaction types (not including NA).

Question 2: Plot

Plot a histogram of the processed amounts of each transaction, the transactionAmount column.



(histgram for amount of transaction)

Report any structure you find and any hypotheses you have about that structure.

Exponential decay. Number of transations decrease exponentially as the transaction amount increases

Question 3: Data Wrangling - Duplicate Transactions

You will notice a number of what look like duplicated transactions in the data set. One type of duplicated transaction is a reversed transaction, where a purchase is followed by a reversal. Another example is a multi-swipe, where a vendor accidentally charges a customer's card multiple times within a short time span.

Can you programmatically identify reversed and multi-swipe transactions?

Reversed transactions are recorded in reverse_df. They are identified as they have transactionType 'REVERSAL'.

Multi-swipe transactions are recorded in Multi_df_f2. They are identified as multiple trasaction of the same amount, same customer, same merchant, within 2 minutes.

What total number of transactions and total dollar amount do you estimate for the reversed transactions? For the multi-swipe transactions? (please consider the first transaction to be "normal" and exclude it from the number of transaction and dollar amount counts)

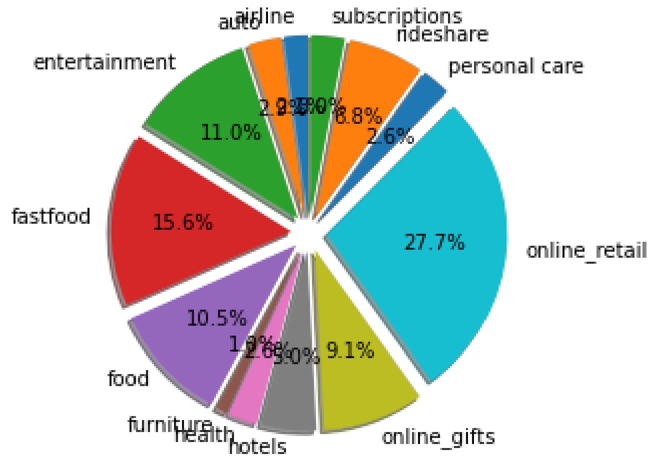
There are a total of 20303 reversed transactions. The total amount for the reversed transactions is 2821792.5.

There are a total of 666 multi-swipe transactions. The total amount for the multi-swipe transactions is 40266.25.

Did you find anything interesting about either kind of transaction?

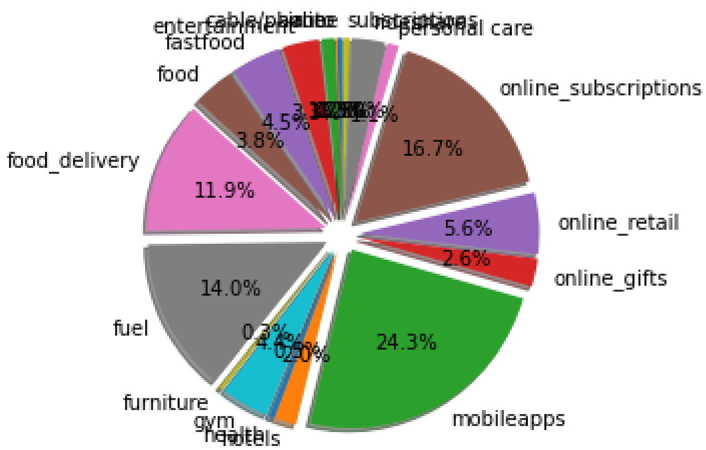
There are a total of 19 type of merchant_Category. Online retail are the merchant_Category that most subject to mistakes.

For reversed transactions, there are only 13 types involved. The most common type is online retail (28%) and fastfood (16%). There are no following type of reversed transcation: 'cable/phone', 'food_delivery', 'fuel', 'gym', 'mobileapps', 'online_subscriptions'. Also, there are higher propotion of transaction in the range of 0-200 compard to that of multi-swipe.



(Reversed Transactions Pie Chart)

For multi-swipe transactions, all 19 types involved. The most common type is online mobileApps (24%) and online subscription (17%). The two most common type are both online payments.



(Multi-swipe Transactions Pie Chart)

Question 4: Model

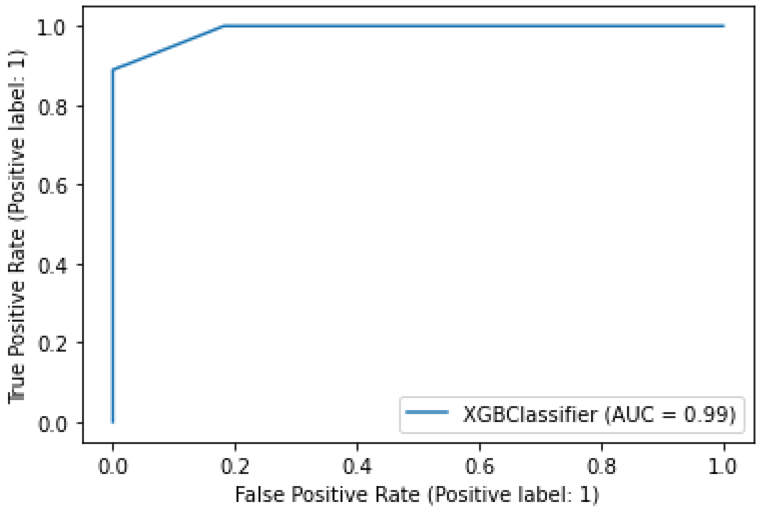
Fraud is a problem for any bank. Fraud can take many forms, whether it is someone stealing a single credit card, to large batches of stolen credit card numbers being used on the web, or even a mass compromise of credit card numbers stolen from a merchant via tools like credit card skimming devices.

Each of the transactions in the dataset has a field called isFraud. Please build a predictive model to determine whether a given transaction will be fraudulent or not. Use as much of the data as you like (or all of it).

Provide an estimate of performance using an appropriate sample, and show your work.

Because a very small proportion of data is positive, I used AUCROC score to evaluate the performance. The data use split at 0.8/0.2 for training/test. Comparing the performace of SVC, Random forest, logistic regression, adaboost and xgboost, it is found that xgboost gives the best AUC of 0.99. The accuracy of xgboost is also the highest among algorithms.

Please explain your methodology (modeling algorithm/method used and why, what features/data you found useful, what questions you have, and what you would do next with more time)



(AUC for xgboost)

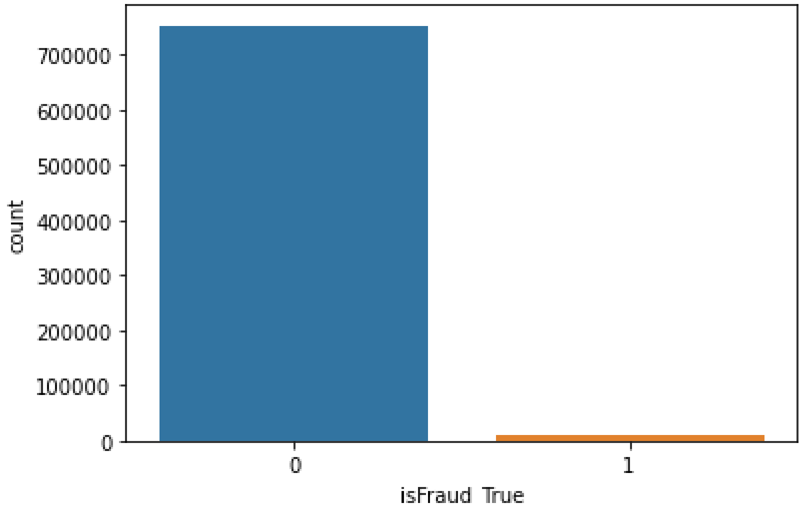
1. Since this is a binary prediction for fraud, I used binary Classification models including SVC, Random forest logistic regression, adaboost and xgboost, it is found that xgboost gives both the best AUC score of 0.99 and the best accuracy of 0.95.

2. Using a parameter analysis on feature importance,the creditLimit data was excluded due to low feature importance. Some of the top important features are: merchantCountryCode_US, cardPresent_True, merchantCategoryCode_online_retail. The following variable is included: 'availableMoney','transactionDateTime' (transformed to months and hours), 'merchantCountryCode', 'transactionAmount', 'merchantCategoryCode', 'transactionType', 'currentBalance', 'cardPresent', 'expirationDateKeyInMatch', 'isFraud'

	features	coef	abs_importance
25	merchantCountryCode_US	-1.442520	1.442520
27	transactionType_PURCHASE	-1.353383	1.353383
28	cardPresent_True	-0.718365	0.718365
17	merchantCategoryCode_online_retail	-0.264183	0.264183
7	merchantCategoryCode_fastfood	-0.222783	0.222783
8	merchantCategoryCode_food	-0.167477	0.167477
6	merchantCategoryCode_entertainment	-0.161233	0.161233
26	transactionType_ADDRESS_VERIFICATION	-0.098699	0.098699
10	merchantCategoryCode_fuel	-0.097059	0.097059
16	merchantCategoryCode_online_gifts	-0.091584	0.091584
15	merchantCategoryCode_mobileapps	-0.077095	0.077095
20	merchantCategoryCode_rideshare	-0.065211	0.065211
18	merchantCategoryCode_online_subscriptions	-0.056763	0.056763
4	merchantCategoryCode_auto	-0.048270	0.048270
14	merchantCategoryCode_hotels	-0.045530	0.045530
13	merchantCategoryCode_health	-0.039057	0.039057
21	merchantCategoryCode_subscriptions	-0.033375	0.033375
19	merchantCategoryCode_personal care	-0.032459	0.032459
9	merchantCategoryCode_food_delivery	-0.021027	0.021027
11	merchantCategoryCode_furniture	-0.011372	0.011372

(list of feature importance)

1. Because there are much more non-fraud cases compared to fraud cases, the more abundant categories seem to have a greater negative impact. A more balanced dataset, i.e a greater proportion of fraud cases included, may change the feature importance and increase prediction rate.



(bar graph of total number of NotFraud and Fraud cases)

1. If given more time, I wish to perform clustering analysis to cluster customers into groups by features, and see if each groups have different fraud rate and prediction accuracy.

Code

In [1]:
```
import json
import pandas as pd
import numpy as np
import datetime as dt
```

In [2]:
```
transactions = []
for line in open('transactions.json', 'r'):
    transactions.append(json.loads(line))
```

In [3]:
```
transactions[0:3]
```

Out[3]:
```
[{'accountNumber': '737265056',
  'customerId': '737265056',
  'creditLimit': 5000.0,
  'availableMoney': 5000.0,
  'transactionDateTime': '2016-08-13T14:27:32',
  'transactionAmount': 98.55,
  'merchantName': 'Uber',
  'acqCountry': 'US',
  'merchantCountryCode': 'US',
  'posEntryMode': '02',
  'posConditionCode': '01',
  'merchantCategoryCode': 'rideshare',
  'currentExpDate': '06/2023',
  'accountOpenDate': '2015-03-14',
  'dateOfLastAddressChange': '2015-03-14',
  'cardCVV': '414',
  'enteredCVV': '414',
  'cardLast4Digits': '1803',
  'transactionType': 'PURCHASE',
  'echoBuffer': '',
```

```
 'currentBalance': 0.0,
 'merchantCity': '',
 'merchantState': '',
 'merchantZip': '',
 'cardPresent': False,
 'posOnPremises': '',
 'recurringAuthInd': '',
 'expirationDateKeyInMatch': False,
 'isFraud': False},
{'accountNumber': '737265056',
 'customerId': '737265056',
 'creditLimit': 5000.0,
 'availableMoney': 5000.0,
 'transactionDateTime': '2016-10-11T05:05:54',
 'transactionAmount': 74.51,
 'merchantName': 'AMC #191138',
 'acqCountry': 'US',
 'merchantCountryCode': 'US',
 'posEntryMode': '09',
 'posConditionCode': '01',
 'merchantCategoryCode': 'entertainment',
 'cardPresent': True,
 'currentExpDate': '02/2024',
 'accountOpenDate': '2015-03-14',
 'dateOfLastAddressChange': '2015-03-14',
 'cardCVV': '486',
 'enteredCVV': '486',
 'cardLast4Digits': '767',
 'transactionType': 'PURCHASE',
 'echoBuffer': '',
 'currentBalance': 0.0,
 'merchantCity': '',
 'merchantState': '',
 'merchantZip': '',
 'posOnPremises': '',
 'recurringAuthInd': '',
 'expirationDateKeyInMatch': False,
 'isFraud': False},
{'accountNumber': '737265056',
 'customerId': '737265056',
 'creditLimit': 5000.0,
 'availableMoney': 5000.0,
 'transactionDateTime': '2016-11-08T09:18:39',
 'transactionAmount': 7.47,
 'merchantName': 'Play Store',
 'acqCountry': 'US',
 'merchantCountryCode': 'US',
 'posEntryMode': '09',
 'posConditionCode': '01',
 'merchantCategoryCode': 'mobileapps',
 'currentExpDate': '08/2025',
 'accountOpenDate': '2015-03-14',
 'dateOfLastAddressChange': '2015-03-14',
 'cardCVV': '486',
 'enteredCVV': '486',
 'cardLast4Digits': '767',
 'transactionType': 'PURCHASE',
 'echoBuffer': '',
 'currentBalance': 0.0,
 'merchantCity': '',
 'merchantState': '',
 'merchantZip': '',
 'cardPresent': False,
 'posOnPremises': '',
 'recurringAuthInd': '',
```

```
 'expirationDateKeyInMatch': False,
 'isFraud': False}]
```

In [4]:
```
len(transactions)
```

Out[4]: 786363

In [5]:
```
print(len(transactions[1].keys()))
```

```
29
```

In [6]:
```
df = pd.DataFrame(transactions)
```

In [7]:
```
df.head(20)
```

Out[7]:

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactionAm
0	737265056	737265056	5000.0	5000.00	2016-08-13T14:27:32	9
1	737265056	737265056	5000.0	5000.00	2016-10-11T05:05:54	7
2	737265056	737265056	5000.0	5000.00	2016-11-08T09:18:39	
3	737265056	737265056	5000.0	5000.00	2016-12-10T02:14:50	
4	830329091	830329091	5000.0	5000.00	2016-03-24T21:04:46	7
5	830329091	830329091	5000.0	5000.00	2016-04-19T16:24:27	3
6	830329091	830329091	5000.0	5000.00	2016-05-21T14:50:35	5
7	830329091	830329091	5000.0	5000.00	2016-06-03T00:31:21	
8	830329091	830329091	5000.0	4990.63	2016-06-10T01:21:46	52
9	830329091	830329091	5000.0	5000.00	2016-07-11T10:47:16	16
10	830329091	830329091	5000.0	5000.00	2016-09-07T20:22:47	16
11	830329091	830329091	5000.0	5000.00	2016-12-07T16:34:04	4
12	830329091	830329091	5000.0	4959.25	2016-12-14T10:00:35	4
13	830329091	830329091	5000.0	4918.50	2016-12-20T18:38:23	4
14	830329091	830329091	5000.0	4877.75	2016-12-28T06:43:01	4
15	574788567	574788567	2500.0	2500.00	2016-01-02T11:19:46	3
16	574788567	574788567	2500.0	2469.92	2016-01-16T01:01:27	4
17	574788567	574788567	2500.0	2428.67	2016-01-26T14:04:22	

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactionAm
18	574788567	574788567	2500.0	2428.67	2016-01-29T07:17:39	12
19	574788567	574788567	2500.0	2304.46	2016-01-29T07:33:15	19

20 rows × 29 columns

In [8]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 786363 entries, 0 to 786362
Data columns (total 29 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   accountNumber             786363 non-null  object 
 1   customerId                786363 non-null  object 
 2   creditLimit               786363 non-null  float64
 3   availableMoney            786363 non-null  float64
 4   transactionDateTime       786363 non-null  object 
 5   transactionAmount         786363 non-null  float64
 6   merchantName              786363 non-null  object 
 7   acqCountry                786363 non-null  object 
 8   merchantCountryCode       786363 non-null  object 
 9   posEntryMode              786363 non-null  object 
 10  posConditionCode          786363 non-null  object 
 11  merchantCategoryCode      786363 non-null  object 
 12  currentExpDate            786363 non-null  object 
 13  accountOpenDate           786363 non-null  object 
 14  dateOfLastAddressChange   786363 non-null  object 
 15  cardCVV                   786363 non-null  object 
 16  enteredCVV                786363 non-null  object 
 17  cardLast4Digits           786363 non-null  object 
 18  transactionType           786363 non-null  object 
 19  echoBuffer                786363 non-null  object 
 20  currentBalance            786363 non-null  float64
 21  merchantCity              786363 non-null  object 
 22  merchantState             786363 non-null  object 
 23  merchantZip               786363 non-null  object 
 24  cardPresent               786363 non-null  bool   
 25  posOnPremises             786363 non-null  object 
 26  recurringAuthInd          786363 non-null  object 
 27  expirationDateKeyInMatch  786363 non-null  bool   
 28  isFraud                   786363 non-null  bool   
dtypes: bool(3), float64(4), object(22)
memory usage: 158.2+ MB
```

In [9]:

```
df.describe()
```

Out[9]:

	creditLimit	availableMoney	transactionAmount	currentBalance
count	786363.000000	786363.000000	786363.000000	786363.000000
mean	10759.464459	6250.725369	136.985791	4508.739089
std	11636.174890	8880.783989	147.725569	6457.442068
min	250.000000	-1005.630000	0.000000	0.000000
25%	5000.000000	1077.420000	33.650000	689.910000

	creditLimit	availableMoney	transactionAmount	currentBalance
50%	7500.000000	3184.860000	87.900000	2451.760000
75%	15000.000000	7500.000000	191.480000	5291.095000
max	50000.000000	50000.000000	2011.540000	47498.810000

In [10]:

```
#check duplicates
len(df)-len(df.drop_duplicates())
```

Out[10]:

```
0
```

In [11]:

```
df.columns
```

Out[11]:

```
Index(['accountNumber', 'customerId', 'creditLimit', 'availableMoney',
       'transactionDateTime', 'transactionAmount', 'merchantName',
       'acqCountry', 'merchantCountryCode', 'posEntryMode', 'posConditionCode',
       'merchantCategoryCode', 'currentExpDate', 'accountOpenDate',
       'dateOfLastAddressChange', 'cardCVV', 'enteredCVV', 'cardLast4Digits',
       'transactionType', 'echoBuffer', 'currentBalance', 'merchantCity',
       'merchantState', 'merchantZip', 'cardPresent', 'posOnPremises',
       'recurringAuthInd', 'expirationDateKeyInMatch', 'isFraud'],
      dtype='object')
```

In [123…

```
#check for unique values
df.nunique()
```

Out[123…

```
accountNumber                 5000
customerId                    5000
creditLimit                     10
availableMoney              521916
transactionDateTime         776637
transactionAmount            66038
merchantName                  2490
acqCountry                       5
merchantCountryCode              5
posEntryMode                     6
posConditionCode                 4
merchantCategoryCode            19
currentExpDate                 165
accountOpenDate               1820
dateOfLastAddressChange       2184
cardCVV                        899
enteredCVV                     976
cardLast4Digits               5246
transactionType                  4
echoBuffer                       1
currentBalance              487318
merchantCity                     1
merchantState                    1
merchantZip                      1
cardPresent                      2
posOnPremises                    1
recurringAuthInd                 1
expirationDateKeyInMatch         2
isFraud                          2
dtype: int64
```

In [13]:
```
df.posConditionCode.unique()
```

Out[13]:
```
array(['01', '08', '99', ''], dtype=object)
```

In [14]:
```
df.posEntryMode.unique()
```

Out[14]:
```
array(['02', '09', '05', '80', '90', ''], dtype=object)
```

In [15]:
```
df.transactionType.unique()
```

Out[15]:
```
array(['PURCHASE', 'ADDRESS_VERIFICATION', 'REVERSAL', ''], dtype=object)
```

In [16]:
```
df2=df.copy()
df2.acqCountry[8]
df2=df2.replace('', np.nan)
df2.acqCountry[8]
```

Out[16]:
```
nan
```

In [17]:
```
#check for null
df2.isna().sum()
```

Out[17]:
```
accountNumber                    0
customerId                       0
creditLimit                      0
availableMoney                   0
transactionDateTime              0
transactionAmount                0
merchantName                     0
acqCountry                    4562
merchantCountryCode            724
posEntryMode                  4054
posConditionCode               409
merchantCategoryCode             0
currentExpDate                   0
accountOpenDate                  0
dateOfLastAddressChange          0
cardCVV                          0
enteredCVV                       0
cardLast4Digits                  0
transactionType                698
echoBuffer                  786363
currentBalance                   0
merchantCity                786363
merchantState               786363
merchantZip                 786363
cardPresent                      0
posOnPremises               786363
recurringAuthInd            786363
expirationDateKeyInMatch         0
isFraud                          0
dtype: int64
```

In [18]:
```
df2.columns
#df2=df2.loc[:,['accountNumber', 'customerId', 'creditLimit', 'availableMoney',
#        'transactionDateTime', 'transactionAmount', 'merchantName',
```

```
#        'acqCountry', 'merchantCountryCode',
#        'merchantCategoryCode', 'currentExpDate', 'accountOpenDate',
#        'dateOfLastAddressChange',
#        'transactionType',  'currentBalance', 'cardPresent', 'expirationDateKeyI

df2=df2.loc[:,['accountNumber', 'customerId', 'creditLimit', 'availableMoney',
        'transactionDateTime', 'transactionAmount',
        'acqCountry', 'merchantCountryCode',
        'merchantCategoryCode', 'currentExpDate', 'accountOpenDate',
        'dateOfLastAddressChange', 'cardCVV', 'enteredCVV',
        'transactionType',  'currentBalance', 'cardPresent', 'expirationDateKeyIn
df2.head(50)
```

Out[18]:

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactionAm
0	737265056	737265056	5000.0	5000.00	2016-08-13T14:27:32	9
1	737265056	737265056	5000.0	5000.00	2016-10-11T05:05:54	1
2	737265056	737265056	5000.0	5000.00	2016-11-08T09:18:39	
3	737265056	737265056	5000.0	5000.00	2016-12-10T02:14:50	
4	830329091	830329091	5000.0	5000.00	2016-03-24T21:04:46	
5	830329091	830329091	5000.0	5000.00	2016-04-19T16:24:27	3
6	830329091	830329091	5000.0	5000.00	2016-05-21T14:50:35	5
7	830329091	830329091	5000.0	5000.00	2016-06-03T00:31:21	
8	830329091	830329091	5000.0	4990.63	2016-06-10T01:21:46	52
9	830329091	830329091	5000.0	5000.00	2016-07-11T10:47:16	16
10	830329091	830329091	5000.0	5000.00	2016-09-07T20:22:47	16
11	830329091	830329091	5000.0	5000.00	2016-12-07T16:34:04	4
12	830329091	830329091	5000.0	4959.25	2016-12-14T10:00:35	4
13	830329091	830329091	5000.0	4918.50	2016-12-20T18:38:23	4
14	830329091	830329091	5000.0	4877.75	2016-12-28T06:43:01	4
15	574788567	574788567	2500.0	2500.00	2016-01-02T11:19:46	3
16	574788567	574788567	2500.0	2469.92	2016-01-16T01:01:27	4
17	574788567	574788567	2500.0	2428.67	2016-01-26T14:04:22	
18	574788567	574788567	2500.0	2428.67	2016-01-29T07:17:39	12
19	574788567	574788567	2500.0	2304.46	2016-01-29T07:33:15	19
20	574788567	574788567	2500.0	2108.39	2016-01-29T21:44:33	
21	574788567	574788567	2500.0	2500.00	2016-02-06T08:16:46	10
22	574788567	574788567	2500.0	2391.14	2016-02-12T03:47:24	2
23	574788567	574788567	2500.0	2362.91	2016-02-22T17:32:13	1
24	574788567	574788567	2500.0	2336.74	2016-02-28T15:53:52	2

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactionAm
25	574788567	574788567	2500.0	2121.58	2016-02-28T16:43:46	1
26	574788567	574788567	2500.0	2500.00	2016-03-02T21:49:24	3
27	574788567	574788567	2500.0	2464.86	2016-03-05T22:24:50	2
28	574788567	574788567	2500.0	2440.42	2016-03-09T14:41:15	13
29	574788567	574788567	2500.0	2300.98	2016-03-10T00:59:51	23
30	574788567	574788567	2500.0	2065.24	2016-03-14T06:24:48	15
31	574788567	574788567	2500.0	2500.00	2016-04-01T20:08:33	3
32	574788567	574788567	2500.0	2465.16	2016-04-05T21:44:57	30
33	574788567	574788567	2500.0	2160.23	2016-04-14T05:00:43	16
34	574788567	574788567	2500.0	1998.84	2016-04-26T04:33:33	6
35	574788567	574788567	2500.0	1930.18	2016-04-28T08:08:33	6
36	574788567	574788567	2500.0	2500.00	2016-05-03T21:11:14	4
37	574788567	574788567	2500.0	2456.36	2016-05-12T00:45:51	4
38	574788567	574788567	2500.0	2416.11	2016-05-24T01:35:33	2
39	574788567	574788567	2500.0	2200.98	2016-05-24T01:38:03	2
40	574788567	574788567	2500.0	2416.11	2016-05-24T19:15:52	28
41	574788567	574788567	2500.0	2129.60	2016-05-26T14:32:39	31
42	574788567	574788567	2500.0	1811.65	2016-05-28T04:42:54	
43	574788567	574788567	2500.0	2500.00	2016-06-04T18:45:39	
44	574788567	574788567	2500.0	2495.54	2016-06-11T04:40:06	14
45	574788567	574788567	2500.0	2355.04	2016-06-15T00:52:10	18
46	574788567	574788567	2500.0	2500.00	2016-07-01T14:55:32	
47	574788567	574788567	2500.0	2491.80	2016-07-03T18:33:35	20
48	574788567	574788567	2500.0	2288.12	2016-07-06T13:08:53	
49	574788567	574788567	2500.0	2283.66	2016-07-16T10:28:25	2

In [19]:
```
df.describe()
```

Out[19]:

	creditLimit	availableMoney	transactionAmount	currentBalance
count	786363.000000	786363.000000	786363.000000	786363.000000
mean	10759.464459	6250.725369	136.985791	4508.739089
std	11636.174890	8880.783989	147.725569	6457.442068
min	250.000000	-1005.630000	0.000000	0.000000
25%	5000.000000	1077.420000	33.650000	689.910000
50%	7500.000000	3184.860000	87.900000	2451.760000
75%	15000.000000	7500.000000	191.480000	5291.095000
max	50000.000000	50000.000000	2011.540000	47498.810000

Question 1: Load

Programmatically download and load into your favorite analytical tool the transactions data. This data, which is in line-delimited JSON format, can be found here

Please describe the structure of the data. Number of records and fields in each record?

There are 786363 transactions in the JSON data. It is list of dictionaries. There are a total of 786363 transaction records. For each record, there are 29 fields.

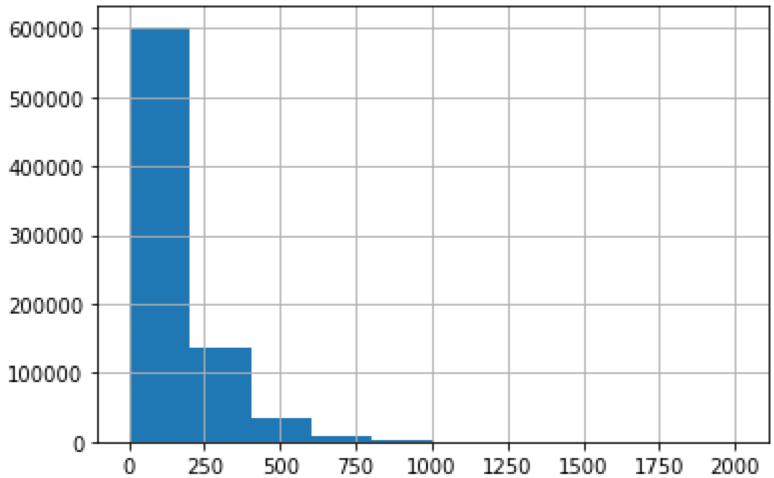
Please provide some additional basic summary statistics for each field. Be sure to include a count of null, minimum, maximum, and unique values where appropriate.

1. There are 4562 missing data in acqCountry,724 in merchantCountryCode, 4054 in posEntryMode, 409 in posConditionCode, 698 in transactionType. There are no data for these 6 categories: echoBuffer, merchantCity, merchantState, merchantZip, posOnPremises, recurringAuthInd.

2. The range for creditLimit is from 250 to 50000. The range for availableMoney is from -1005.63 to 50000. The range for transactionAmount is from 0 to 2011.54. The range for currentBalance is from 0 to 47498.81.

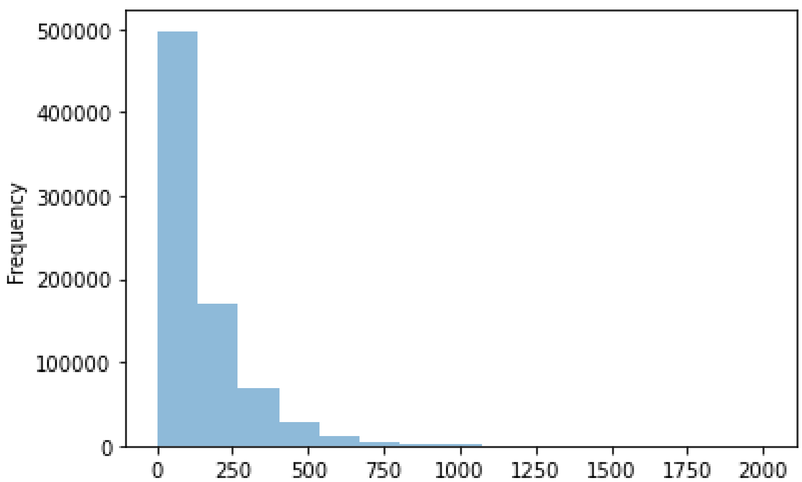
3. There are a total of 5000 unique customer ID in this dataset. For these customers, there are a total of 5 countries recorded.

In [22]:
```
hist = df.transactionAmount.hist(bins=10)
```



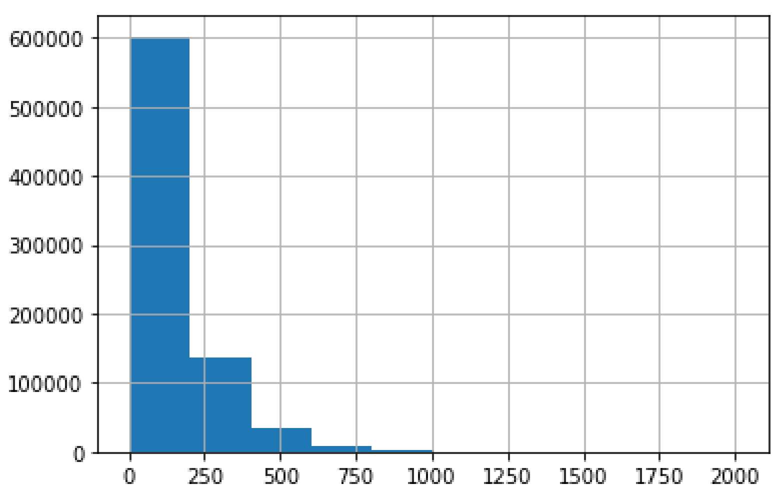
In [23]:

```
ax = df.transactionAmount.plot.hist(bins=15, alpha=0.5)
```



Question 2: Plot

Plot a histogram of the processed amounts of each transaction, the transactionAmount column.



Report any structure you find and any hypotheses you have about that structure.

Exponential decay.

Number of transations decrease exponentially as the transaction amount increases

In [24]:
```
# identification of reverse transaction :
id=df[df.transactionType=='REVERSAL'].index
reverse_df=df2.iloc[id,:]
reverse_df
```

Out[24]:

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactic
39	574788567	574788567	2500.0	2200.98	2016-05-24T01:38:03	
73	574788567	574788567	2500.0	2432.72	2016-10-07T10:23:57	
101	924729945	924729945	50000.0	49831.43	2016-10-19T14:01:45	
133	984504651	984504651	50000.0	46367.41	2016-01-16T09:53:15	
156	984504651	984504651	50000.0	41909.30	2016-01-25T20:39:15	
...	...	...	...	...	...	
786106	899818521	899818521	2500.0	968.33	2016-09-29T02:04:32	
786120	638498773	638498773	10000.0	9798.21	2016-01-01T19:48:03	
786219	638498773	638498773	10000.0	5331.33	2016-11-03T04:23:26	
786225	638498773	638498773	10000.0	4393.10	2016-11-06T22:54:25	
786301	732852505	732852505	50000.0	49860.23	2016-06-22T19:07:55	

20303 rows × 19 columns

In [25]:
```
reverse_df.shape
```

Out[25]: (20303, 19)

In [26]:
```
reverse_df.transactionAmount.sum()
```

Out[26]: 2821792.5

In [27]:
```
from datetime import datetime
```

In [34]:
```
df2['transactionDateTime']=pd.to_datetime(df2['transactionDateTime'],format='%Y-
```

In [35]:
```
df2['transactionDateTime']
```

Out[35]:
```
0         2016-08-13 14:27:32
1         2016-10-11 05:05:54
2         2016-11-08 09:18:39
```

```
3         2016-12-10 02:14:50
4         2016-03-24 21:04:46
                  ...
786358    2016-12-22 18:44:12
786359    2016-12-25 16:20:34
786360    2016-12-27 15:46:24
786361    2016-12-29 00:30:55
786362    2016-12-30 20:10:29
Name: transactionDateTime, Length: 786363, dtype: datetime64[ns]
```

In [36]:

```
customers = df.customerId.unique()
```

In [37]:

```
# initialize dataframe
Multi_df=df2.iloc[1:2,:]  #all multi-swipe transaction
Multi_df2=df2.iloc[1:2,:] #multi-swipe transactions exclude the 1st normal payme
type(Multi_df)
Multi_df
```

Out[37]:

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactionAmou
1	737265056	737265056	5000.0	5000.0	2016-10-11 05:05:54	74

In [38]:

```
# multiple swipe: multiple trasaction of the same amount, same customer, same me
for customer in customers:
    df_cus=df2[df2.customerId==customer]
    for i in range(df_cus.shape[0]-1):
        dff=df2['transactionDateTime'][i+1]-df2['transactionDateTime'][i]
        diff=dff.total_seconds()
        if df_cus.iloc[i,5]==df_cus.iloc[i+1,5] and df_cus.iloc[i,6]==df_cus.ilo
            Multi_df=Multi_df.append(df_cus.iloc[i,:])
            Multi_df=Multi_df.append(df_cus.iloc[i+1,:])
            Multi_df2=Multi_df2.append(df_cus.iloc[i+1,:]) #multi-swipe transact
```

In [41]:

```
Multi_df_f=Multi_df.copy()
Multi_df_f=Multi_df_f.drop(1)
```

In [42]:

```
#all multi-swipe transaction
Multi_df_f.head(20)
```

Out[42]:

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transaction/
3068	101380713	101380713	10000.0	2407.85	2016-11-17 14:32:54	
3069	101380713	101380713	10000.0	2000.18	2016-11-17 14:35:32	
3891	419989841	419989841	5000.0	831.15	2016-03-04 21:26:00	
3892	419989841	419989841	5000.0	517.56	2016-03-04 21:26:53	
4400	281639186	281639186	2500.0	2477.27	2016-06-11 21:55:24	
4401	281639186	281639186	2500.0	2495.20	2016-07-13 01:22:56	
4649	245118458	245118458	15000.0	15000.00	2016-07-04 21:34:49	

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transaction/
4650	245118458	245118458	15000.0	14921.21	2016-07-04 21:37:14	
4902	288118894	288118894	7500.0	7476.05	2016-04-08 02:48:38	
4903	288118894	288118894	7500.0	7493.66	2016-05-08 08:13:42	
5040	988172671	988172671	250.0	213.05	2016-12-02 23:21:34	
5041	988172671	988172671	250.0	189.28	2016-12-16 05:47:41	
5631	935981871	935981871	5000.0	4897.37	2016-04-06 00:38:27	
5632	935981871	935981871	5000.0	4914.29	2016-05-06 19:09:23	
6689	996362843	996362843	1000.0	977.03	2016-03-04 23:21:04	
6690	996362843	996362843	1000.0	878.66	2016-03-04 23:22:29	
8097	687365478	687365478	10000.0	10000.00	2016-10-02 00:15:22	
8098	687365478	687365478	10000.0	10000.00	2016-10-16 11:09:02	
9359	717714059	717714059	15000.0	15000.00	2016-10-08 16:29:31	
9360	717714059	717714059	15000.0	14964.06	2016-10-22 00:01:37	

In [43]:

```
Multi_df_f.shape
```

Out[43]: (1332, 19)

In [44]:

```
Multi_df_f2=Multi_df2.copy()
Multi_df_f2=Multi_df_f2.drop(1)
```

In [45]:

```
#multi-swipe transactions exclude the 1st normal payment
Multi_df_f2.shape
```

Out[45]: (666, 19)

In [46]:

```
Multi_df_f2.head(50)
```

Out[46]:

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactio
3069	101380713	101380713	10000.0	2000.18	2016-11-17 14:35:32	
3892	419989841	419989841	5000.0	517.56	2016-03-04 21:26:53	
4401	281639186	281639186	2500.0	2495.20	2016-07-13 01:22:56	
4650	245118458	245118458	15000.0	14921.21	2016-07-04 21:37:14	
4903	288118894	288118894	7500.0	7493.66	2016-05-08 08:13:42	
5041	988172671	988172671	250.0	189.28	2016-12-16 05:47:41	
5632	935981871	935981871	5000.0	4914.29	2016-05-06 19:09:23	
6690	996362843	996362843	1000.0	878.66	2016-03-04 23:22:29	

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactio
8098	687365478	687365478	10000.0	10000.00	2016-10-16 11:09:02	
9360	717714059	717714059	15000.0	14964.06	2016-10-22 00:01:37	
10525	574212417	574212417	500.0	500.00	2016-11-25 00:12:28	
10922	386732203	386732203	5000.0	1277.50	2016-11-02 23:42:12	
11098	222122504	222122504	15000.0	15000.00	2016-05-19 00:51:02	
13206	393869032	393869032	15000.0	7356.99	2016-11-09 06:48:19	
13375	378369270	378369270	10000.0	10000.00	2016-11-14 15:17:09	
15237	111113489	111113489	15000.0	10954.51	2016-09-21 14:42:10	
15350	364197707	364197707	7500.0	6420.60	2016-11-14 10:53:10	
16669	465894701	465894701	250.0	162.02	2016-11-03 21:27:35	
19082	897665697	897665697	2500.0	2295.20	2016-03-15 21:54:52	
19093	897665697	897665697	2500.0	1790.53	2016-07-04 22:28:07	
19323	543149097	543149097	5000.0	5000.00	2016-09-15 19:35:52	
19453	360564098	360564098	20000.0	19816.50	2016-06-27 23:10:51	
19621	922209733	922209733	2500.0	671.02	2016-10-09 12:19:05	
21110	294270581	294270581	5000.0	5000.00	2016-07-02 05:32:22	
21523	835482161	835482161	7500.0	6359.35	2016-01-19 01:06:04	
22579	368960526	368960526	5000.0	4602.97	2016-12-06 16:25:37	
23650	509526607	509526607	500.0	500.00	2016-09-19 11:20:44	
23896	237944130	237944130	15000.0	14716.52	2016-07-25 11:58:09	
24001	371832344	371832344	50000.0	49985.65	2016-07-04 05:53:01	
24421	722665134	722665134	500.0	330.38	2016-10-26 13:09:48	
24509	605042720	605042720	5000.0	5000.00	2016-07-28 03:05:13	
25004	937999128	937999128	7500.0	6556.23	2016-12-11 06:14:04	
25241	576620175	576620175	5000.0	5000.00	2016-08-27 17:25:36	
25550	888097952	888097952	20000.0	19948.02	2016-06-24 16:01:18	
25561	888097952	888097952	20000.0	19840.42	2016-10-08 21:38:04	
25647	869071202	869071202	500.0	158.92	2016-08-06 23:58:46	
27686	783013155	783013155	500.0	159.09	2016-03-17 03:35:50	
29537	630456222	630456222	250.0	213.10	2016-08-11 05:38:20	
29546	192118573	192118573	7500.0	7253.91	2016-01-02 20:15:15	
29881	192118573	192118573	7500.0	2460.40	2016-05-15 09:34:59	
31221	162576842	162576842	2500.0	2500.00	2016-03-26 05:32:46	
31555	262032771	262032771	7500.0	7138.65	2016-06-05 16:39:24	
31694	739885668	739885668	500.0	292.17	2016-05-27 09:49:14	

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactio
32447	985848672	985848672	5000.0	1666.85	2016-03-02 14:27:48	
33038	593072186	593072186	5000.0	5000.00	2016-06-03 18:24:20	
33327	626983390	626983390	10000.0	9924.03	2016-10-10 01:06:33	
33338	626983390	626983390	10000.0	9772.09	2016-12-25 18:18:25	
35949	256583918	256583918	10000.0	4506.16	2016-04-19 04:01:42	
36439	967020232	967020232	20000.0	20000.00	2016-11-15 10:47:31	
45874	410523603	410523603	5000.0	2800.78	2016-11-29 08:19:12	

In [47]:

```
Multi_df_f2.transactionAmount.sum()
```

Out[47]:

```
40266.25
```

In [48]:

```
Multi_df_f2.merchantCategoryCode.unique()
```

Out[48]:

```
array(['rideshare', 'online_retail', 'mobileapps', 'food', 'fuel',
       'fastfood', 'furniture', 'entertainment', 'food_delivery',
       'hotels', 'health', 'online_subscriptions', 'personal care',
       'airline', 'gym', 'subscriptions', 'cable/phone', 'online_gifts',
       'auto'], dtype=object)
```

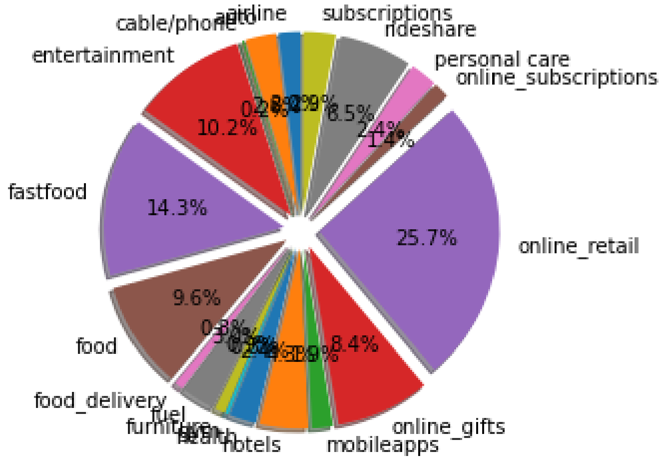
In [49]:

```
# Check for merchantCategoryCode in diffrent transactions
all_pie=df2.groupby(by=["merchantCategoryCode"])["merchantCategoryCode"].count()
reverse_pie=reverse_df.groupby(by=["merchantCategoryCode"])["merchantCategoryCod
multi_pie=Multi_df_f2.groupby(by=["merchantCategoryCode"])["merchantCategoryCode

print(len(all_pie))
print(len(reverse_pie))
print(len(multi_pie))
```

```
19
13
19
```

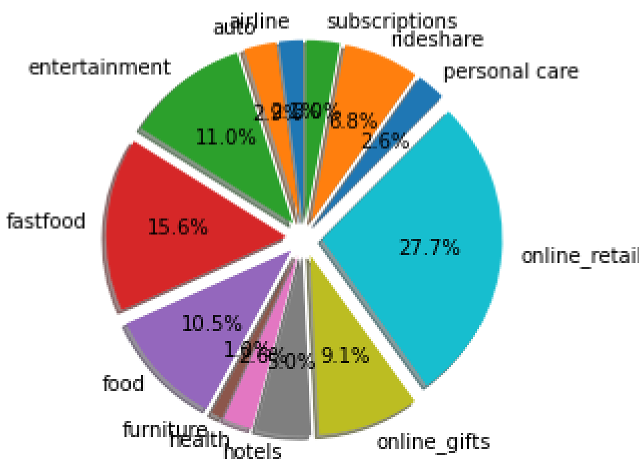
In [50]:

```
import matplotlib.pyplot as plt
# Pie chart, where the slices will be ordered and plotted counter-clockwise:
# Check for merchantCategoryCode in all transactions
labels = all_pie.index
sizes = all_pie.values
explode = (0.1,   0.1,   0.1,  0.1,  0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,  0

fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%',
        shadow=True, startangle=90)
ax1.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.

plt.show()
```



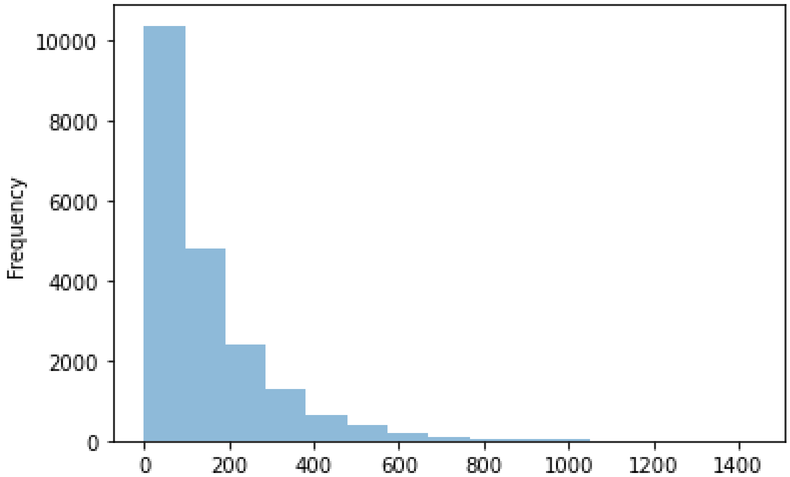
In [51]:

```
# Pie chart, where the slices will be ordered and plotted counter-clockwise:
# Check for merchantCategoryCode in reversed transactions
labels = reverse_pie.index
sizes = reverse_pie.values
explode = (0.1,   0.1,   0.1,  0.1,  0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1)  # onl

fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%',
        shadow=True, startangle=90)
ax1.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.

plt.show()
```



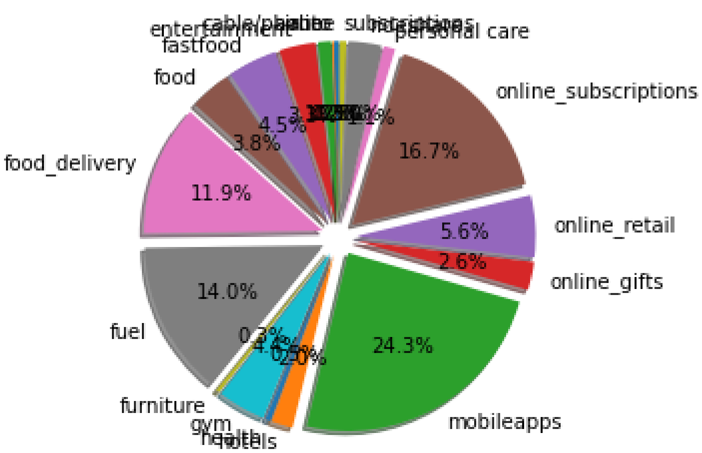
In [52]:

```
#check distribution of transaction amount in reveresd transaction
ax = reverse_df.transactionAmount.plot.hist(bins=15, alpha=0.5)
```



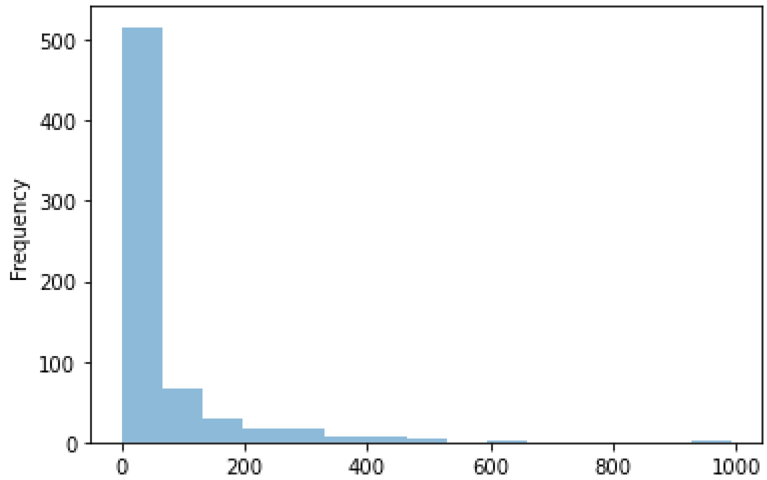
In [53]:

```
# Pie chart, where the slices will be ordered and plotted counter-clockwise:
# Check for merchantCategoryCode in multi-swiped transactions
labels = multi_pie.index
sizes = multi_pie.values
explode = (0.1,   0.1,   0.1,  0.1,  0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,0.1,
        0.1,  0.1, 0.1,0.1,0.1,0.1)  # only "explode" the 2nd slice (i.e. 'Hogs'

fig1, ax1 = plt.subplots()
ax1.pie(sizes, explode=explode, labels=labels, autopct='%1.1f%%',
        shadow=True, startangle=90)
ax1.axis('equal')  # Equal aspect ratio ensures that pie is drawn as a circle.

plt.show()
```



In [54]:

```
#check distribution of transaction amount in multiswiped transaction

ax = Multi_df_f2.transactionAmount.plot.hist(bins=15, alpha=0.5)
```



In [55]:
```
sorted(multi_pie.index)
```

Out[55]:
```
['airline',
 'auto',
 'cable/phone',
 'entertainment',
 'fastfood',
 'food',
 'food_delivery',
 'fuel',
 'furniture',
 'gym',
 'health',
 'hotels',
 'mobileapps',
 'online_gifts',
 'online_retail',
 'online_subscriptions',
 'personal care',
 'rideshare',
 'subscriptions']
```

In [56]:
```
sorted(reverse_pie.index)
```

Out[56]:
```
['airline',
 'auto',
 'entertainment',
 'fastfood',
 'food',
 'furniture',
 'health',
 'hotels',
 'online_gifts',
 'online_retail',
 'personal care',
 'rideshare',
 'subscriptions']
```

In [57]:
```
Rev_id=reverse_df.index
Rev_id
Multi_id=Multi_df_f2.index
Multi_id
bad_id=Rev_id.append(Multi_id)
```

In [58]:
```
df_clean=df2.drop(bad_id)
df_clean.shape
```

Out[58]: (765394, 19)

Question 3: Data Wrangling - Duplicate Transactions

You will notice a number of what look like duplicated transactions in the data set. One type of duplicated transaction is a reversed transaction, where a purchase is followed by a reversal. Another example is a multi-swipe, where a vendor accidentally charges a customer's card multiple times within a short time span.

Can you programmatically identify reversed and multi-swipe transactions?

Reversed transactions are recorded in reverse_df. They are identified as they have transactionType 'REVERSAL'.

Multi-swipe transactions are recorded in Multi_df_f2. They are identified as multiple trasaction of the same amount, same customer, same merchant, within 2 minutes.

What total number of transactions and total dollar amount do you estimate for the reversed transactions? For the multi-swipe transactions? (please consider the first transaction to be "normal" and exclude it from the number of transaction and dollar amount counts)

There are a total of 20303 reversed transactions. The total amount for the reversed transactions is 2821792.5.

There are a total of 666 multi-swipe transactions. The total amount for the multi-swipe transactions is 40266.25.

Did you find anything interesting about either kind of transaction?

There are a total of 19 type of merchant_Category. Online retail are the merchant_Category that most subject to mistakes.

For reversed transactions, there are only 13 types involved. The most common type is online retail (28%) and fastfood (16%). There are no following type of reversed transcation: 'cable/phone', 'food_delivery', 'fuel', 'gym', 'mobileapps', 'online_subscriptions'. Also, there are higher propotion of transaction in the range of 0-200 compard to that of multi-swipe.

For multi-swipe transactions, all 19 types involved. The most common type is online mobileApps (24%) and online subscription (17%). The two most common type are both online payments.

In [59]:
```
#get rid of unwanted/empty columns
df_clean.head()
```

Out[59]:

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactionAmo

	accountNumber	customerId	creditLimit	availableMoney	transactionDateTime	transactionAmo
0	737265056	737265056	5000.0	5000.0	2016-08-13 14:27:32	98
1	737265056	737265056	5000.0	5000.0	2016-10-11 05:05:54	74
2	737265056	737265056	5000.0	5000.0	2016-11-08 09:18:39	7
3	737265056	737265056	5000.0	5000.0	2016-12-10 02:14:50	7
4	830329091	830329091	5000.0	5000.0	2016-03-24 21:04:46	7

In [60]:

```
df_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 765394 entries, 0 to 786362
Data columns (total 19 columns):
 #   Column                    Non-Null Count   Dtype
---  ------                    --------------   -----
 0   accountNumber             765394 non-null  object
 1   customerId                765394 non-null  object
 2   creditLimit               765394 non-null  float64
 3   availableMoney            765394 non-null  float64
 4   transactionDateTime       765394 non-null  datetime64[ns]
 5   transactionAmount         765394 non-null  float64
 6   acqCountry                760958 non-null  object
 7   merchantCountryCode       764690 non-null  object
 8   merchantCategoryCode      765394 non-null  object
 9   currentExpDate            765394 non-null  object
 10  accountOpenDate           765394 non-null  object
 11  dateOfLastAddressChange   765394 non-null  object
 12  cardCVV                   765394 non-null  object
 13  enteredCVV                765394 non-null  object
 14  transactionType           764696 non-null  object
 15  currentBalance            765394 non-null  float64
 16  cardPresent               765394 non-null  bool
 17  expirationDateKeyInMatch  765394 non-null  bool
 18  isFraud                   765394 non-null  bool
dtypes: bool(3), datetime64[ns](1), float64(4), object(11)
memory usage: 101.5+ MB
```

In [101…

```
#get rid of unwanted/empty columns based on later analysis

df_model=df_clean[[#'creditLimit',
                   'availableMoney',
                   #'transactionDateTime',
                   'merchantCountryCode',
                   'transactionAmount',
                   'merchantCategoryCode','transactionType'
                  ,'currentBalance','cardPresent','expirationDateKeyInMatch','is
```

In [102…

```
#df_model['currentExpDate']=pd.to_datetime(df_model['currentExpDate'],format='%m
#df_model.dateOfLastAddressChange=pd.to_datetime(df_model['dateOfLastAddressChan
#df_model.accountOpenDate=pd.to_datetime(df_model['accountOpenDate'],format='%Y-
```

In [62]:

```
## I was going to check if months and hour affect the fraud, but turns out these
## but increased computation significantly.
```

```
#df_model['month']=0
#df_model['hour']=0
#for i in range(df_model.shape[0]):
#    dt=df_model.iloc[i,2]
#    df_model['month']= dt.month
#    df_model['hour']= dt.hour
```

```
<ipython-input-62-679d9187439d>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_model['month']=0
<ipython-input-62-679d9187439d>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_model['hour']=0
<ipython-input-62-679d9187439d>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_model['month']= dt.month
<ipython-input-62-679d9187439d>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy
  df_model['hour']= dt.hour
```

In [103…

```
#df_model.month=df_model.month.astype(str)
#df_model.hour=df_model.hour.astype(str)
df_model.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 765394 entries, 0 to 786362
Data columns (total 9 columns):
 #   Column                    Non-Null Count   Dtype  
---  ------                    --------------   -----  
 0   availableMoney            765394 non-null  float64
 1   merchantCountryCode       764690 non-null  object 
 2   transactionAmount         765394 non-null  float64
 3   merchantCategoryCode      765394 non-null  object 
 4   transactionType           764696 non-null  object 
 5   currentBalance            765394 non-null  float64
 6   cardPresent               765394 non-null  bool   
 7   expirationDateKeyInMatch  765394 non-null  bool   
 8   isFraud                   765394 non-null  bool   
dtypes: bool(3), float64(3), object(3)
memory usage: 59.2+ MB
```

In [104…

```
# creating a copy of the original data frame
df3 = df_model.copy()

# calling the get_dummies method returns the dummies for all categorical columns
df3 = pd.get_dummies(df_model,
```

```
                            columns = ['merchantCategoryCode','merchantCountryCode', 't
df3=df3.drop(['cardPresent_False','expirationDateKeyInMatch_False','isFraud_Fals
display(df3)
```

	availableMoney	transactionAmount	currentBalance	merchantCategoryCode_airline	merc
0	5000.00	98.55	0.00	0	
1	5000.00	74.51	0.00	0	
2	5000.00	7.47	0.00	0	
3	5000.00	7.47	0.00	0	
4	5000.00	71.18	0.00	0	
...	...	...	...	...	
786358	48904.96	119.92	1095.04	0	
786359	48785.04	18.89	1214.96	0	
786360	48766.15	49.43	1233.85	0	
786361	48716.72	49.89	1283.28	0	
786362	48666.83	72.18	1333.17	0	

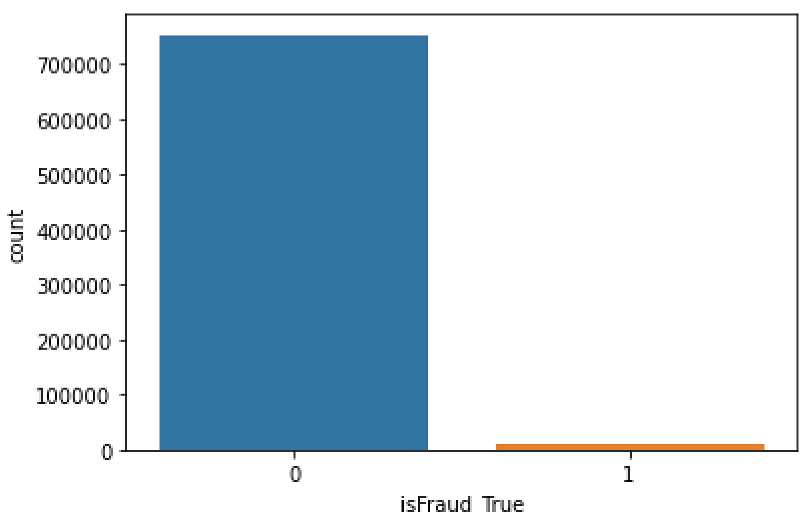
765394 rows × 31 columns

In [105…

```
from sklearn.datasets import make_classification
from sklearn.linear_model import LogisticRegression
from matplotlib import pyplot
```

In [106…

```
#check the fraud outcome distribution
import seaborn as sns
ax=sns.countplot(x=df3['isFraud_True'])
plt.show()
```



Logistic regression to check importance of parameters

In [107…

```
# define dataset
```

```
#y = df['incident_diabetes'][0:500]
y = df3['isFraud_True']
#X=ndf.values[0:500,]
#X=ndf.iloc[0:500,]
X=df3.drop(['isFraud_True'],axis=1)
print(len(y))
X.shape
```

```
765394
```

Out[107…
```
(765394, 30)
```

In [108…
```
# define the model
model = LogisticRegression()
# fit the model
res=model.fit(X, y)
```

In [109…
```
# get importance
importance = model.coef_[0]
```

In [110…
```
FeatureImportance=pd.DataFrame(zip(X.columns,np.transpose(model.coef_.tolist()[0
FeatureImportance['abs_importance']=abs(FeatureImportance.coef)
FeatureImportance.sort_values(by=['abs_importance'],ascending=False)
```

Out[110…

	features	coef	abs_importance
25	merchantCountryCode_US	-1.442520	1.442520
27	transactionType_PURCHASE	-1.353383	1.353383
28	cardPresent_True	-0.718365	0.718365
17	merchantCategoryCode_online_retail	-0.264183	0.264183
7	merchantCategoryCode_fastfood	-0.222783	0.222783
8	merchantCategoryCode_food	-0.167477	0.167477
6	merchantCategoryCode_entertainment	-0.161233	0.161233
26	transactionType_ADDRESS_VERIFICATION	-0.098699	0.098699
10	merchantCategoryCode_fuel	-0.097059	0.097059
16	merchantCategoryCode_online_gifts	-0.091584	0.091584
15	merchantCategoryCode_mobileapps	-0.077095	0.077095
20	merchantCategoryCode_rideshare	-0.065211	0.065211
18	merchantCategoryCode_online_subscriptions	-0.056763	0.056763
4	merchantCategoryCode_auto	-0.048270	0.048270
14	merchantCategoryCode_hotels	-0.045530	0.045530
13	merchantCategoryCode_health	-0.039057	0.039057
21	merchantCategoryCode_subscriptions	-0.033375	0.033375
19	merchantCategoryCode_personal care	-0.032459	0.032459
9	merchantCategoryCode_food_delivery	-0.021027	0.021027

	features	coef	abs_importance
11	merchantCategoryCode_furniture	-0.011372	0.011372
12	merchantCategoryCode_gym	-0.009674	0.009674
3	merchantCategoryCode_airline	-0.005580	0.005580
23	merchantCountryCode_MEX	-0.005118	0.005118
22	merchantCountryCode_CAN	-0.003955	0.003955
5	merchantCategoryCode_cable/phone	-0.003370	0.003370
1	transactionAmount	0.002780	0.002780
24	merchantCountryCode_PR	-0.002779	0.002779
29	expirationDateKeyInMatch_True	-0.002181	0.002181
2	currentBalance	0.000004	0.000004
0	availableMoney	-0.000004	0.000004

ML prediction

In [111…

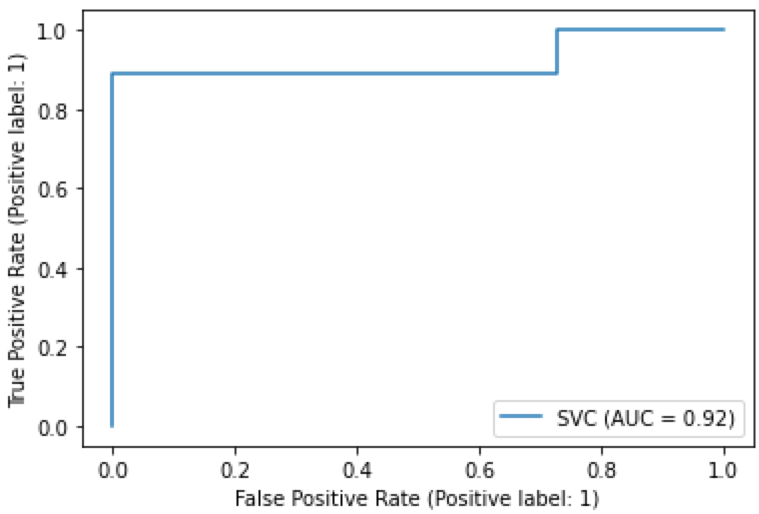
```
import xgboost as xgb
from sklearn.ensemble import AdaBoostClassifier
from sklearn.datasets import make_classification
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_curve, auc,recall_score,precision_score,roc_auc_
```

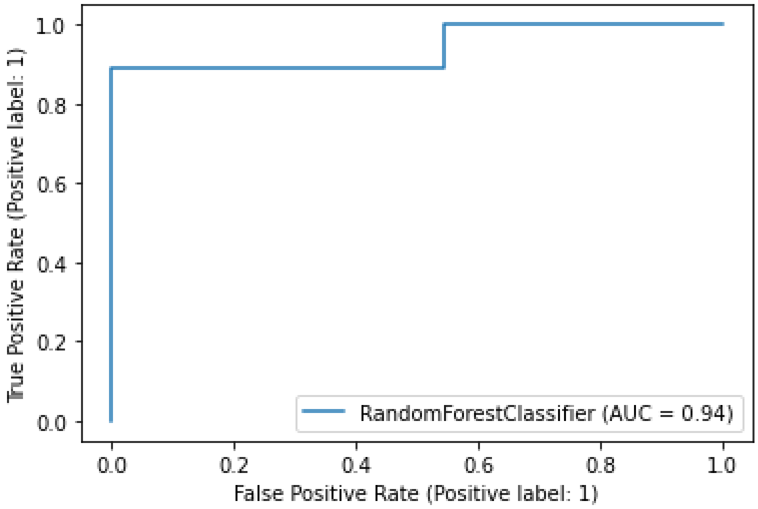
In [112…

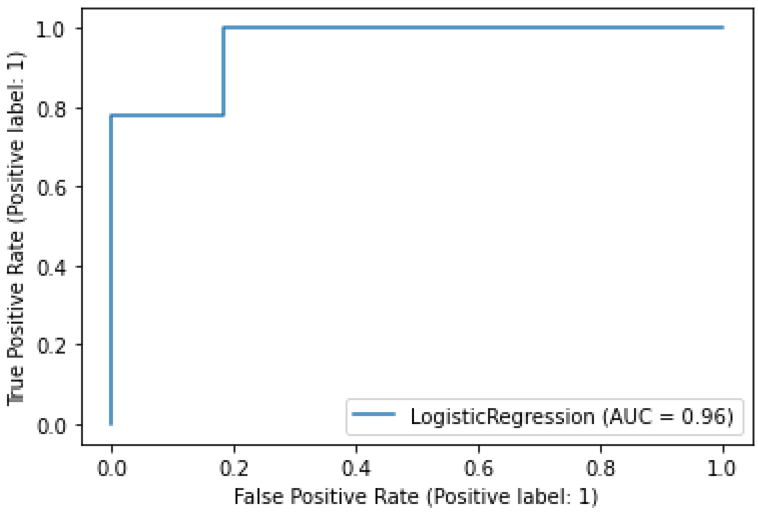
```
#use multiple ml algorithms for model fitting
from sklearn.svm import SVC
from sklearn.metrics import plot_roc_curve
from sklearn.ensemble import RandomForestClassifier

X, y = make_classification(random_state=0)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_

svc = SVC(random_state=42)
svc.fit(X_train, y_train)
#rfc = RandomForestClassifier(random_state=42)
rfc = RandomForestClassifier(max_depth=6, random_state=42)
rfc.fit(X_train, y_train)
logreg=LogisticRegression(random_state=42)
logreg.fit(X_train, y_train)
xg_reg = xgb.XGBClassifier(random_state=42)
xg_reg.fit(X_train, y_train)
adareg=AdaBoostClassifier(n_estimators=100,
                         learning_rate=0.5,random_state=42)
adareg.fit(X_train, y_train)
#xg_reg = xgb.XGBClassifier(random_state=42)
xg_reg = xgb.XGBClassifier(objective ='binary:logistic', colsample_bytree = 0.1,
                max_depth = 25, alpha = 10, n_estimators = 300,booster='gbtree')
xg_reg.fit(X_train, y_train)


svc_disp = plot_roc_curve(svc, X_test, y_test)
rfc_disp = plot_roc_curve(rfc, X_test, y_test)
```

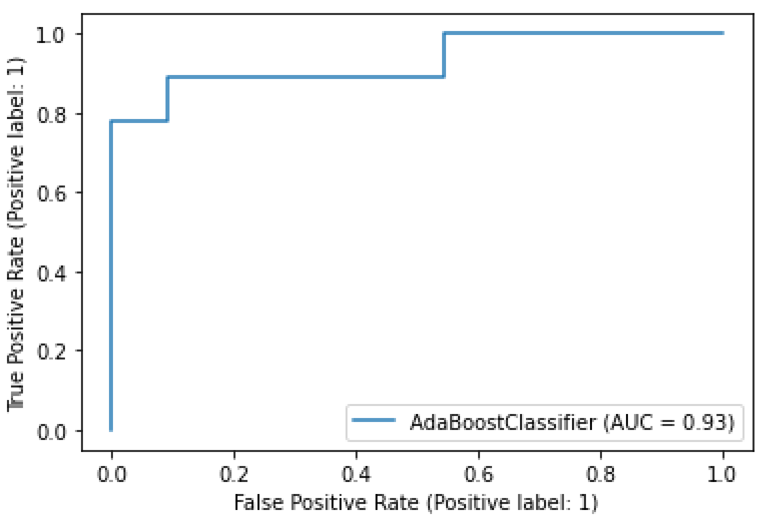
```
logreg_disp = plot_roc_curve(logreg, X_test, y_test)
adareg_disp = plot_roc_curve(adareg, X_test, y_test)
xgbreg_disp = plot_roc_curve(xg_reg, X_test, y_test)
#xgb_disp.figure_.suptitle("ROC curve comparison")

plt.show()
```

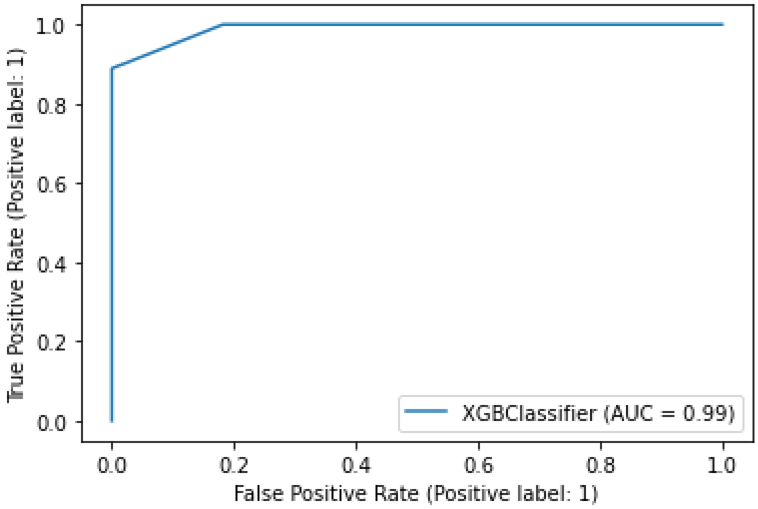
```
/Users/ziye/opt/anaconda3/lib/python3.8/site-packages/xgboost/sklearn.py:888: Us
erWarning: The use of label encoder in XGBClassifier is deprecated and will be r
emoved in a future release. To remove this warning, do the following: 1) Pass op
tion use_label_encoder=False when constructing XGBClassifier object; and 2) Enco
de your labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num_class -
1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
/Users/ziye/opt/anaconda3/lib/python3.8/site-packages/xgboost/sklearn.py:888: Us
erWarning: The use of label encoder in XGBClassifier is deprecated and will be r
emoved in a future release. To remove this warning, do the following: 1) Pass op
tion use_label_encoder=False when constructing XGBClassifier object; and 2) Enco
de your labels (y) as integers starting with 0, i.e. 0, 1, 2, ..., [num_class -
1].
  warnings.warn(label_encoder_deprecation_msg, UserWarning)
[04:28:00] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-4
3e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Startin
g in XGBoost 1.3.0, the default evaluation metric used with the objective 'binar
y:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
[04:28:00] WARNING: /opt/concourse/worker/volumes/live/7a2b9f41-3287-451b-6691-4
3e9a6c0910f/volume/xgboost-split_1619728204606/work/src/learner.cc:1061: Startin
g in XGBoost 1.3.0, the default evaluation metric used with the objective 'binar
y:logistic' was changed from 'error' to 'logloss'. Explicitly set eval_metric if
you'd like to restore the old behavior.
```




True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)
RandomForestClassifier (AUC = 0.94)


True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)
LogisticRegression (AUC = 0.96)


True Positive Rate (Positive label: 1)
False Positive Rate (Positive label: 1)
AdaBoostClassifier (AUC = 0.93)



In [120…

```
svcpreds = svc.predict(X_test)
accuracy=accuracy_score(y_test,svcpreds)
print('The accuracy for SVC is {}'.format(accuracy))

rfcpreds = rfc.predict(X_test)
accuracy=accuracy_score(y_test,rfcpreds)
print('The accuracy for random forest is {}'.format(accuracy))

logregpreds = logreg.predict(X_test)
accuracy=accuracy_score(y_test,logregpreds)
print('The accuracy for logistic regression is {}'.format(accuracy))

adapreds = adareg.predict(X_test)
accuracy=accuracy_score(y_test,adapreds)
print('The accuracy for ada boost is {}'.format(accuracy))

xgpreds = xg_reg.predict(X_test)
accuracy=accuracy_score(y_test,xgpreds)
print('The accuracy for xgboost is {}'.format(accuracy))
```

```
The accuracy for SVC is 0.9
The accuracy for random forest is 0.95
The accuracy for logistic regression is 0.8
The accuracy for ada boost is 0.9
The accuracy for xgboost is 0.95
```

Question 4: Model

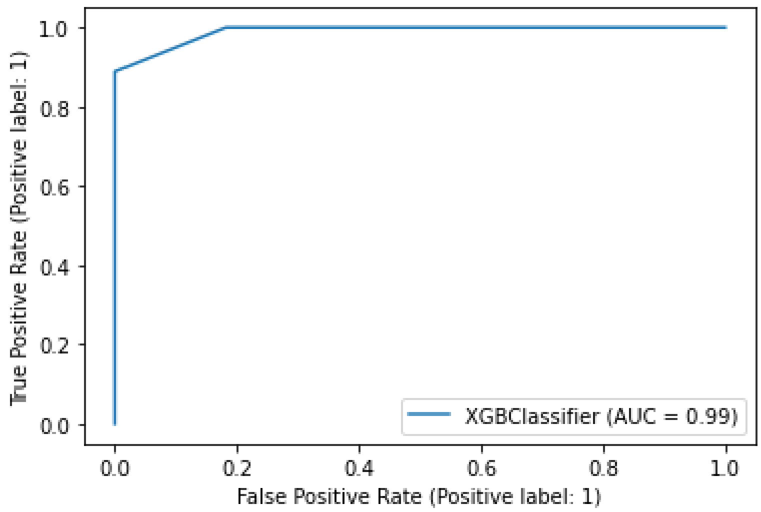
Fraud is a problem for any bank. Fraud can take many forms, whether it is someone stealing a single credit card, to large batches of stolen credit card numbers being used on the web, or even a mass compromise of credit card numbers stolen from a merchant via tools like credit card skimming devices.

Each of the transactions in the dataset has a field called isFraud. Please build a predictive model to determine whether a given transaction will be fraudulent or not. Use as much of the data as you like (or all of it).

Provide an estimate of performance using an appropriate sample, and show your work.

Because a very small proportion of data is positive, I used AUCROC score to evaluate the performance. The data use split at 0.8/0.2 for training/test. Comparing the performace of SVC, Random forest, logistic regression, adaboost and xgboost, it is found that xgboost gives the best AUC of 0.99. The accuracy of xgboost is also the highest among algorithms.

Please explain your methodology (modeling algorithm/method used and why, what features/data you found useful, what questions you have, and what you would do next with more time)

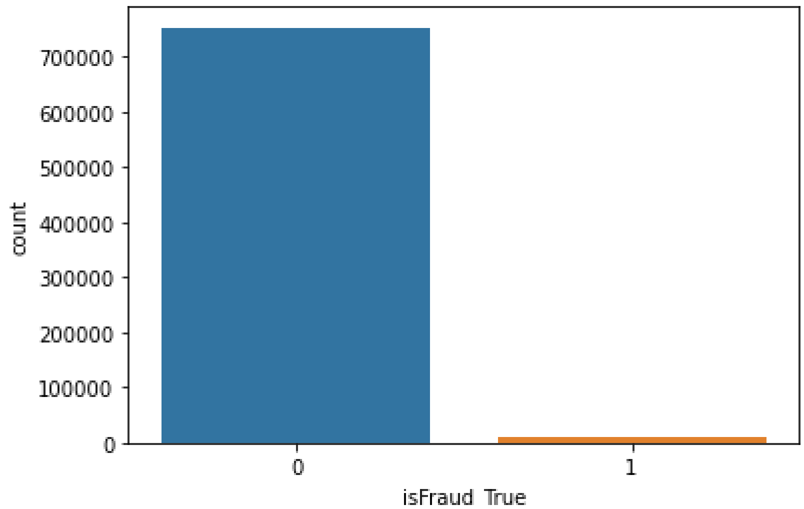


1. Since this is a binary prediction for fraud, I used binary Classification models including SVC, Random forest logistic regression, adaboost and xgboost, it is found that xgboost gives both the best AUC score of 0.99 and the best accuracy of 0.95.

2. Using a parameter analysis on feature importance,the creditLimit data was excluded due to low feature importance. Some of the top important features are: merchantCountryCode_US, cardPresent_True, merchantCategoryCode_online_retail. The following variable is included: 'availableMoney','transactionDateTime' (transformed to months and hours), 'merchantCountryCode', 'transactionAmount', 'merchantCategoryCode', 'transactionType', 'currentBalance', 'cardPresent', 'expirationDateKeyInMatch', 'isFraud'

3. Because there are much more non-fraud cases compared to fraud cases, the more abundant categories seem to have a greater negative impact. A more balanced dataset, i.e

a greater proportion of fraud cases included, may change the feature importance and



increase prediction rate.

4. If given more time, I wish to perform clustering analysis to cluster customers into groups by features, and see if each groups have different fraud rate and prediction accuracy.

In [ ]:

```
```