Importing libraries

In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
# for the Q-Q plots
#import scipy.stats as stats
%matplotlib inline
import pandas as pd
pd.options.display.float_format = '{:.2f}'.format
#from pandas.io.json import json_normalize
```

Loading dataset for receipts

In [2]:

```
receipts = pd.read_excel("receipts.xlsx")
```

In [3]:

```
receipts.info()
```

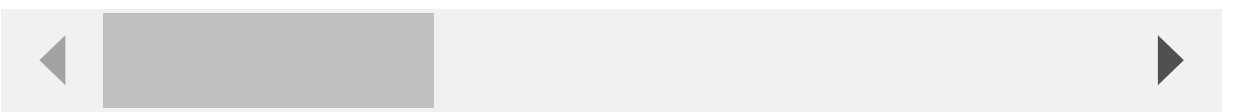
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1119 entries, 0 to 1118
Data columns (total 15 columns):
_id/$oid                    1119 non-null object
bonusPointsEarned           544 non-null float64
bonusPointsEarnedReason     544 non-null object
createDate                  1119 non-null int64
dateScanned                 1119 non-null int64
finishedDate                568 non-null float64
modifyDate                  1119 non-null int64
pointsAwardedDate           537 non-null float64
pointsEarned                609 non-null float64
purchaseDate                671 non-null float64
purchasedItemCount          635 non-null float64
rewardsReceiptItemList      679 non-null object
rewardsReceiptStatus        1119 non-null object
totalSpent                  684 non-null float64
userId                      1119 non-null object
dtypes: float64(7), int64(3), object(5)
memory usage: 131.3+ KB
```

In [4]:

```
receipts.head()
```

Out[4]:

	_id/$oid	bonusPointsEarned	bonusPointsEarnedReason	createDate	d
0	5ff1e1eb0a720f0523000575	500.00	Receipt number 2 completed, bonus point schedu...	1609687531000	160
1	5ff1e1bb0a720f052300056b	150.00	Receipt number 5 completed, bonus point schedu...	1609687483000	160
2	5ff1e1f10a720f052300057a	5.00	All-receipts receipt bonus	1609687537000	160
3	5ff1e1ee0a7214ada100056f	5.00	All-receipts receipt bonus	1609687534000	160
4	5ff1e1d20a7214ada1000561	5.00	All-receipts receipt bonus	1609687506000	160



Identifying numerical and categorical variables

In [5]:

```
# make lists of variable types

temporal = [var for var in receipts.columns if 'date' in var or 'Date' in var]

discrete = [
    var for var in receipts.columns if receipts[var].dtype != 'O'
    and len(receipts[var].unique()) < 20 and var not in temporal
]

continuous = [
    var for var in receipts.columns if receipts[var].dtype != 'O'
    if var not in discrete and var != '_id'
    and var not in temporal
]

categorical = [var for var in receipts.columns if receipts[var].dtype == 'O'
               and var not in temporal and var not in discrete]

print(f'There are {len(continuous)} continuous variables')
print(f'There are {len(discrete)} discrete variables')
print(f'There are {len(temporal)} temporal variables')
print(f'There are {len(categorical)} categorical variables')
```

```
There are 3 continuous variables
There are 1 discrete variables
There are 6 temporal variables
There are 5 categorical variables
```

In [6]:

```
continuous
```

Out[6]:

```
['pointsEarned', 'purchasedItemCount', 'totalSpent']
```

In [7]:

```
discrete
```

Out[7]:

```
['bonusPointsEarned']
```

In [8]:

```
temporal
```

Out[8]:

```
['createDate',
 'dateScanned',
 'finishedDate',
 'modifyDate',
 'pointsAwardedDate',
 'purchaseDate']
```

In [9]:

```
categorical
```

Out[9]:

```
['_id/$oid',
 'bonusPointsEarnedReason',
 'rewardsReceiptItemList',
 'rewardsReceiptStatus',
 'userId']
```

Quantifying missing data

In [10]:

```
receipts.isnull().sum()
```

Out[10]:

```
_id/$oid                    0
bonusPointsEarned         575
bonusPointsEarnedReason   575
createDate                  0
dateScanned                 0
finishedDate              551
modifyDate                  0
pointsAwardedDate         582
pointsEarned              510
purchaseDate              448
purchasedItemCount        484
rewardsReceiptItemList    440
rewardsReceiptStatus        0
totalSpent                435
userId                      0
dtype: int64
```

percentage of missing values in variables

In [11]:

```
# alternatively, we can use the mean() method after isnull() to visualise the percentage o
f missing values for each variable
percentage_null_values= receipts.isnull().mean()
for key,value in percentage_null_values.items():
    if value >0:
        print(key,":",value*100)
```

```
bonusPointsEarned : 51.385165326184094
bonusPointsEarnedReason : 51.385165326184094
finishedDate : 49.240393208221626
pointsAwardedDate : 52.01072386058981
pointsEarned : 45.57640750670242
purchaseDate : 40.03574620196604
purchasedItemCount : 43.25290437890974
rewardsReceiptItemList : 39.32082216264522
totalSpent : 38.8739946380697
```

A considerate fraction of values are missing from the above mentioned variables. Missing values for certain variables are a major concern:

finishedDate- for 49%(almost half) of the receipts we don't know when do they become invalid(assuming that the date on which a receipt finishes processing is the date on which it becomes invalid)

In [12]:

```
receipts["pointsEarned"].unique()
```

Out[12]:

```
array([5.00000e+02, 1.50000e+02, 5.00000e+00, 7.50000e+02, 2.50000e+02,
       1.00000e+02, 8.85000e+03, 3.00000e+02,          nan, 3.89200e+02,
       1.85000e+02, 3.50000e+01, 6.50000e+02, 5.50000e+01, 5.00000e+01,
       3.55000e+02, 6.00000e+02, 1.75000e+03, 3.50000e+02, 2.25000e+02,
       2.75000e+02, 2.50000e+01, 7.55000e+02, 1.80000e+03, 8.10000e+02,
       3.05000e+02, 9.44980e+03, 9.12000e+01, 8.25000e+02, 3.50600e+02,
       1.25000e+02, 7.93100e+02, 2.00000e+02, 3.25000e+03, 0.00000e+00,
       4.00500e+03, 2.00500e+03, 8.41200e+02, 5.75000e+03, 3.75000e+03,
       8.70000e+03, 7.60000e+02, 7.80000e+02, 9.20000e+03, 1.00500e+03,
       1.99960e+03, 1.89200e+02, 8.95000e+03, 8.85000e+02, 8.00000e+02,
       2.95000e+02, 6.82400e+02, 8.37400e+02, 2.37800e+02, 1.60000e+02,
       8.55700e+02, 6.05700e+02, 2.41670e+03, 1.80640e+03, 4.05700e+02,
       1.51690e+03, 1.65830e+03, 2.68580e+03, 8.79100e+02, 3.65940e+03,
       9.34400e+02, 8.77700e+02, 9.22100e+02, 1.54180e+03, 1.00000e+03,
       5.74400e+02, 5.06000e+01, 2.05550e+03, 5.85000e+03, 4.85000e+03,
       1.73600e+02, 9.85000e+03, 5.09000e+01, 2.30000e+03, 6.73000e+02,
       4.05900e+02, 2.14330e+03, 1.55000e+03, 9.86500e+02, 5.83400e+02,
       4.48050e+03, 3.37990e+03, 3.23600e+02, 6.25730e+03, 2.49770e+03,
       1.17870e+03, 1.44700e+03, 1.72950e+03, 1.47620e+03, 1.70800e+03,
       1.07750e+03, 1.13510e+03, 1.04430e+03, 6.40700e+02, 5.23600e+02,
       4.87700e+02, 7.13720e+03, 1.20500e+03, 4.00000e+02, 1.01998e+04,
       8.50000e+02, 9.46000e+01, 1.85000e+03, 8.40000e+02, 1.04980e+03,
       9.40000e+02, 4.94470e+03, 3.75000e+02, 1.49950e+03, 2.09900e+02,
       2.09800e+02, 2.10000e+02, 2.09500e+02, 7.89200e+02, 3.50000e+03])
```

pointsEarned- 45% of the values for the 'pointsEarned' field are missing. If we look at the unique values for 'pointsEarned', we do not have a zero value. This means that points were earned for certain receipts but the data was not captured and that's why the large number of missing values.

purchasedItemCount- large number of missing values will pose problems for deciding if users who bought more than one unit of a product qualify for special offers/bonus points that require them to purchase certain amount of particular products/brands.

totalSpent, rewardsReceiptItemList- Since data for these two fields is missing, it is natural that we don't have information about points earned(pointsEarned field) for those transactions.

Checking for redundant records

In [13]:

```
receipts["_id/$oid"].unique()
```

Out[13]:

```
array(['5ff1e1eb0a720f0523000575', '5ff1e1bb0a720f052300056b',
       '5ff1e1f10a720f052300057a', ..., '603cf5290a720fde10000413',
       '603ce7100a7217c72c000405', '603c4fea0a7217c72c000389'],
      dtype=object)
```

In [14]:

```
receipts["_id/$oid"].duplicated()
```

Out[14]:

```
0       False
1       False
2       False
3       False
4       False
        ...
1114    False
1115    False
1116    False
1117    False
1118    False
Name: _id/$oid, Length: 1119, dtype: bool
```

In [15]:

```
duplicateRowsDF = receipts[receipts.duplicated()]
print("Duplicate Rows except first occurrence based on all columns are :")
print(duplicateRowsDF)
```

```
Duplicate Rows except first occurrence based on all columns are :
Empty DataFrame
Columns: [_id/$oid, bonusPointsEarned, bonusPointsEarnedReason, createDate, d
ateScanned, finishedDate, modifyDate, pointsAwardedDate, pointsEarned, purcha
seDate, purchasedItemCount, rewardsReceiptItemList, rewardsReceiptStatus, tot
alSpent, userId]
Index: []
```

No duplicate records found.

Examining percentage of different category values for categorical variables

Here, the categorical variable of my interest is bonusPointsEarnedReason

In [16]:

```
freq_reasons = 100*(receipts['bonusPointsEarnedReason'].value_counts() / len(receipts))
print(freq_reasons.map('{:,.2f} %'.format))
```

```
All-receipts receipt bonus
16.35 %
Receipt number 1 completed, bonus point schedule DEFAULT (5cefdcacf3693e0b50e
83a36)    10.63 %
COMPLETE_NONPARTNER_RECEIPT
6.34 %
COMPLETE_PARTNER_RECEIPT
3.49 %
Receipt number 3 completed, bonus point schedule DEFAULT (5cefdcacf3693e0b50e
83a36)     2.77 %
Receipt number 2 completed, bonus point schedule DEFAULT (5cefdcacf3693e0b50e
83a36)     2.68 %
Receipt number 5 completed, bonus point schedule DEFAULT (5cefdcacf3693e0b50e
83a36)     2.41 %
Receipt number 4 completed, bonus point schedule DEFAULT (5cefdcacf3693e0b50e
83a36)     2.32 %
Receipt number 6 completed, bonus point schedule DEFAULT (5cefdcacf3693e0b50e
83a36)     1.61 %
Name: bonusPointsEarnedReason, dtype: object
```

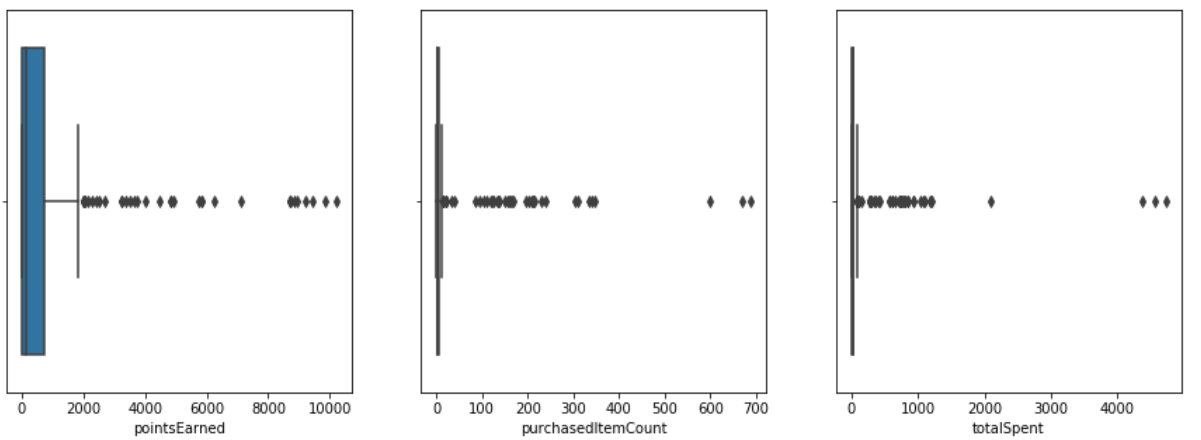
In [ ]:

```

```

Plotting outliers using boxplot

In [17]:

```
fig, axs = plt.subplots(ncols=3, nrows=1,figsize=(15,5))
axs = axs.flatten()

for i, var in enumerate(continuous):
    sns.boxplot(receipts[receipts[var].notnull()][var], ax=axs[i], orient='h');
```

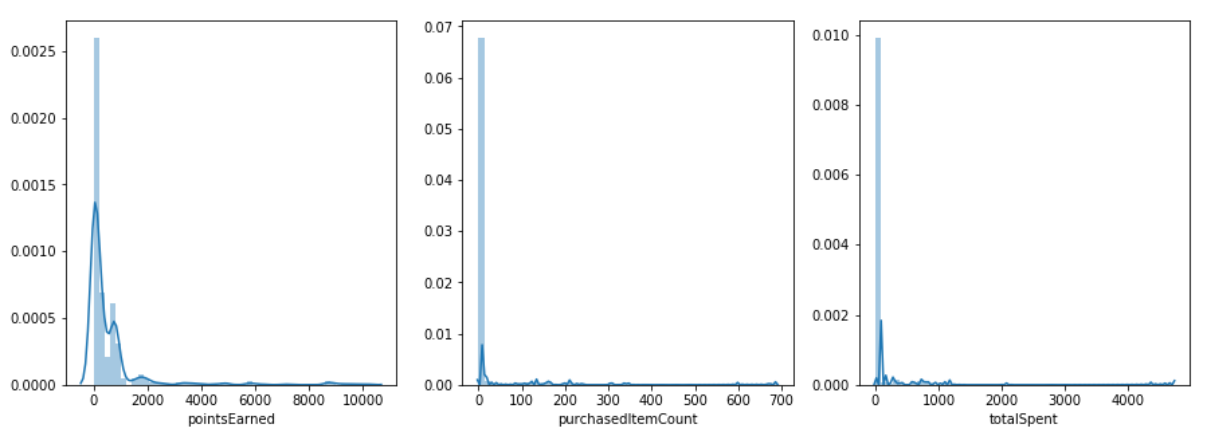


By looking at the boxplots we can say that there is a significantly large range of outliers.

Examining distributions of continuous variables

In [18]:

```
fig, axs = plt.subplots(ncols=3, nrows=1,figsize=(15,5))
axs = axs.flatten()

for i, var in enumerate(continuous):
    sns.distplot(receipts[receipts[var].notnull()][var], ax=axs[i]);
```



The distributions for all the three continuous variables are right-skewed.

Both, the boxplots and value distribution diagrams suggest that there are a lot of outliers, but we can't say anything about the significance of these outliers at this point.

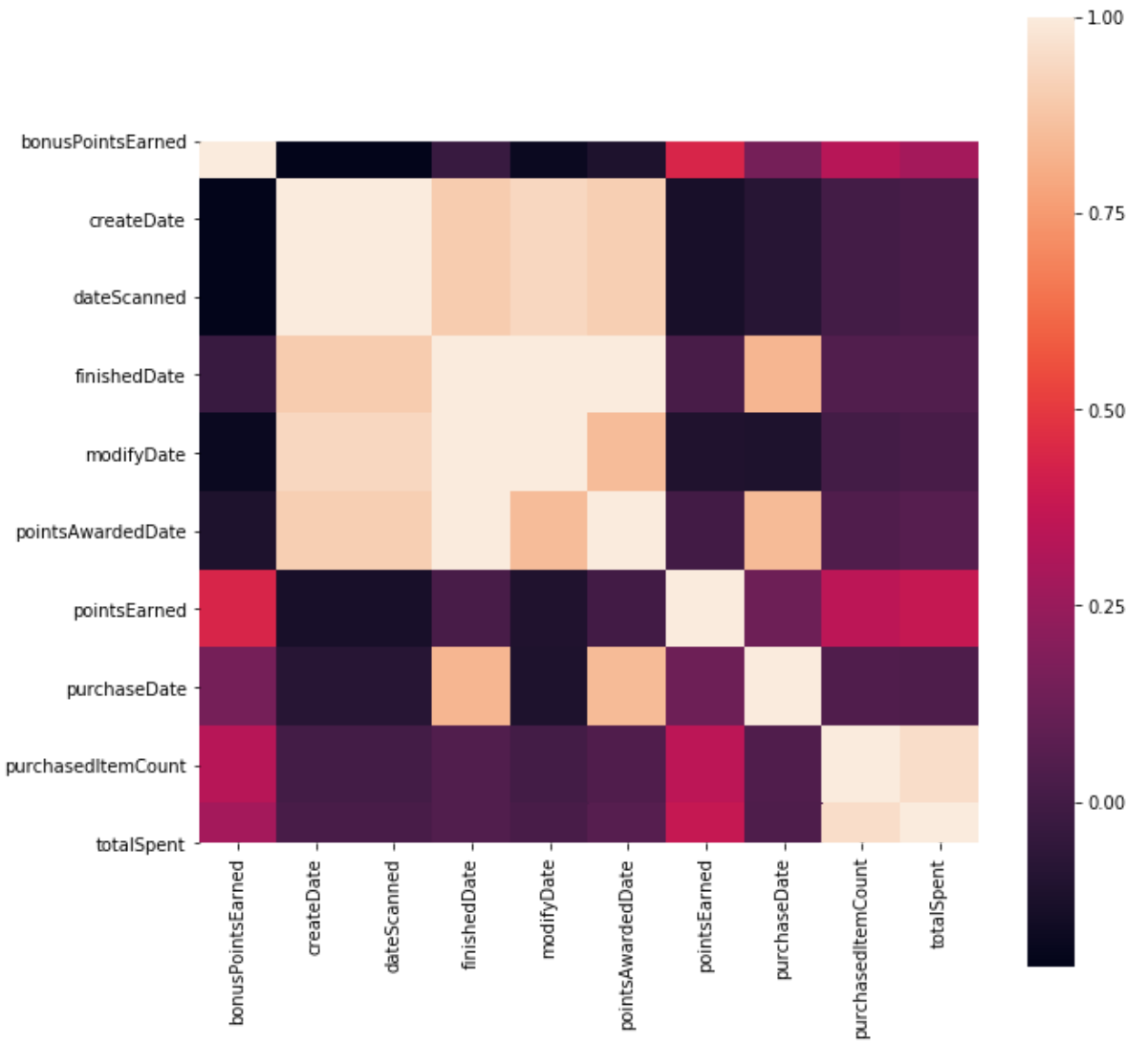
Examining corelation between variables

In [19]:

```
import seaborn as sns
f, ax = plt.subplots(figsize=(10, 10))
corr = receipts.corr()
sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool), square=True, ax=ax
)
```

Out[19]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1d25387a7c8>
```



No significant corelations found.

In [ ]: