Importing libraries

In [16]:

```
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 [17]:

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

In [18]:

```
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 [19]:

```
receipts.head()
```

Out[19]:

	_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 [20]:

```
# 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 [21]:

```
continuous
```

Out[21]:

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

In [22]:

```
discrete
```

Out[22]:

```
['bonusPointsEarned']
```

In [23]:

```
temporal
```

Out[23]:

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

In [24]:

```
categorical
```

Out[24]:

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

Quantifying missing data

In [30]:

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

Out[30]:

```
_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 [32]:

```
# 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:

1. 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 [34]:

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

Out[34]:

```
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])
```

1. 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.

1. 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.

1. 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.

Examining percentage of different category values for categorical variables

Here, the categorical variable of my interest is bonusPointsEarnedReason

In [37]:

```
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
```

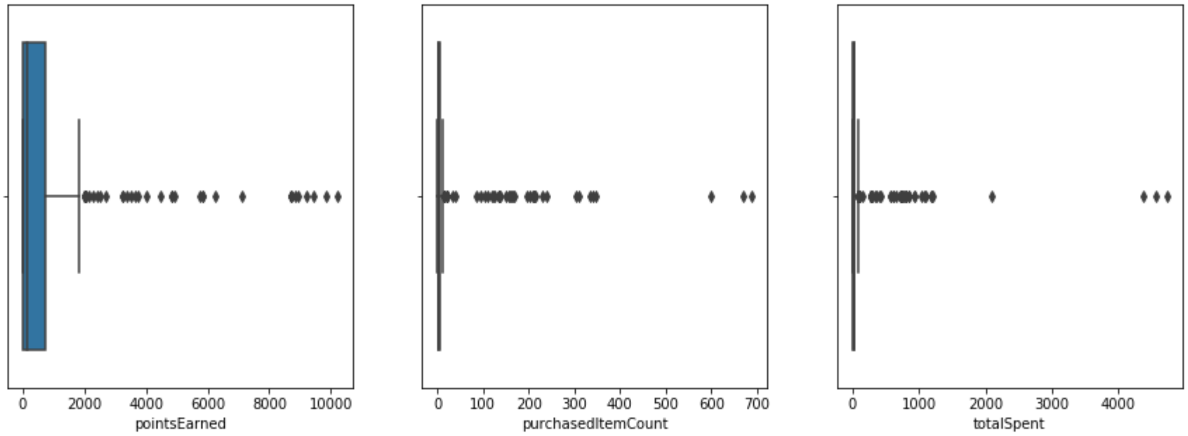
In [ ]:

Plotting outliers using boxplot

In [45]:

```
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');
```



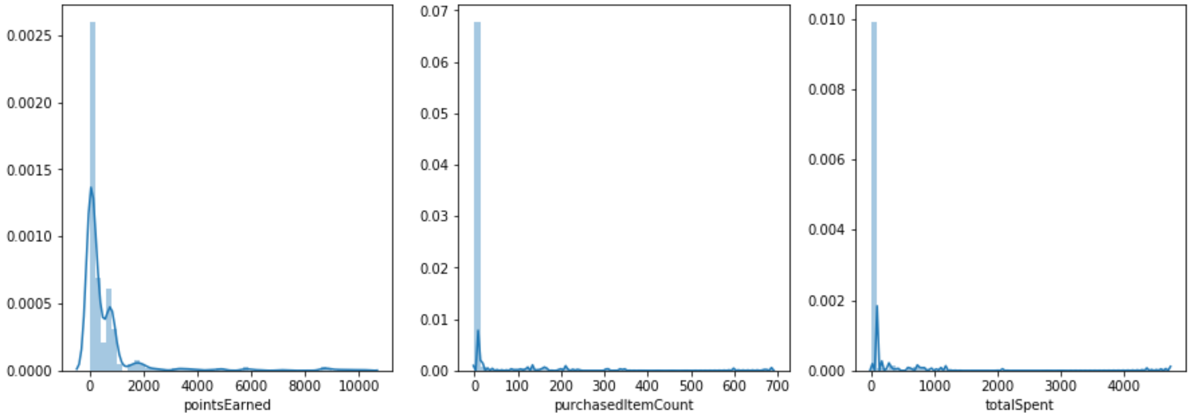
By looking at the boxplots we can say that there is a significantly large range of outliers.

Examining distributions of continuous variables

In [46]:

```
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.

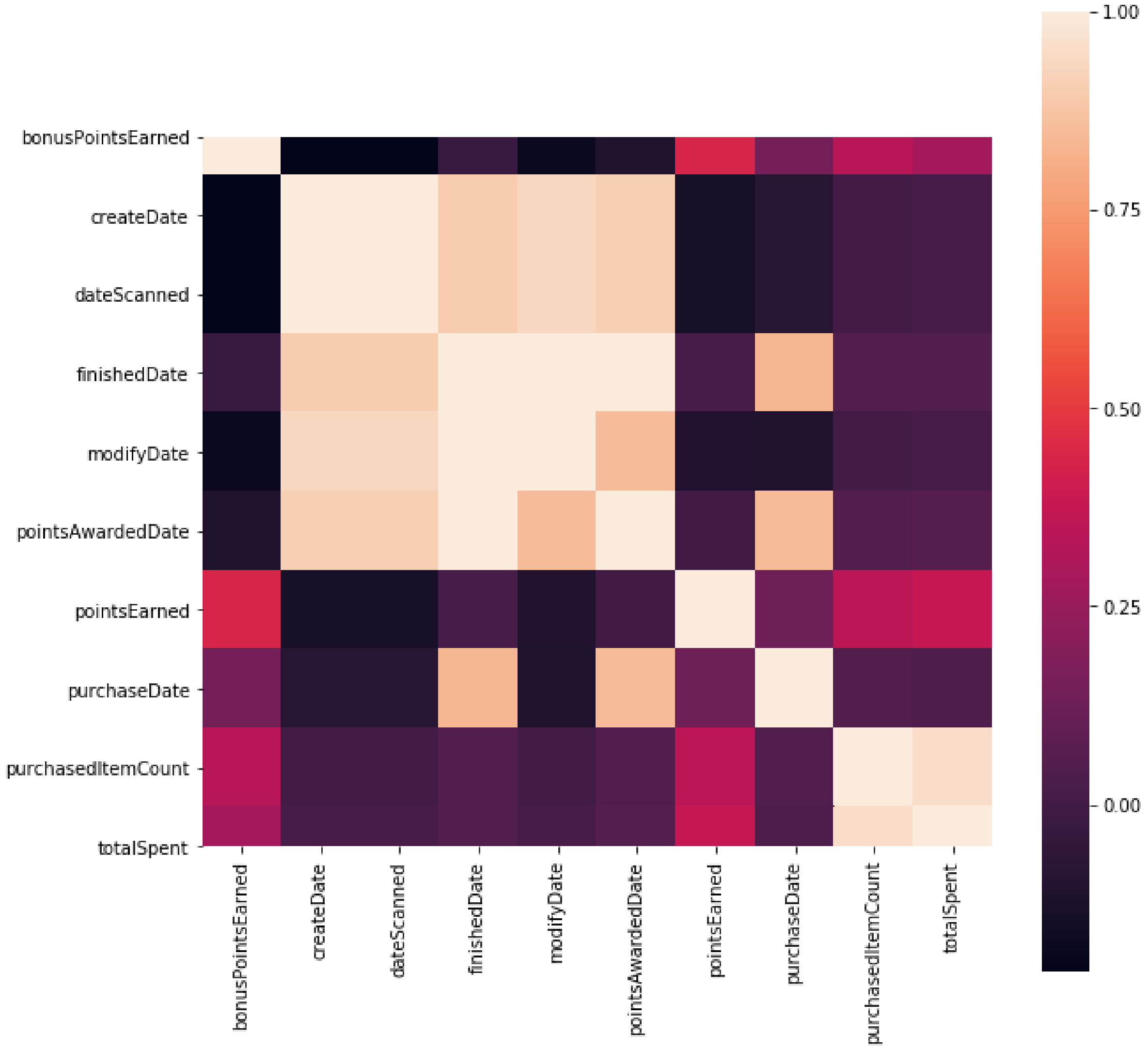
Examining corelation between variables

In [48]:

```
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[48]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1501ba17d88>
```



No significant corelations found.

In [ ]: