Department Name – Computer Science & Engineering

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Subject Name and Code – 2CS702 Big Data Analytics

Practical No – 2

AIM: Identify the data sources for big data. Find the technological limitations of conventional data analysis algorithms to perform analytics on big data. Justify your answer with any one of the applications.

1) Data sources for Big Data

Big Data refers to the accumulation of data in large pools and quantities. It is a collection of organised, semi-structured, and unstructured data gathered by businesses with the objective of improving their services. It provides valuable information that drives the innovation and decision-making in any company in any sector. Few sources of Big Data are as follows:

- **Social Media Platforms**: Billions of people engage with social media daily, sharing their thoughts, experiences, and preferences. It enables the companies to better understand their consumers and accordingly, personalize the plans offered by creating a user profile.

- **Internet of Things (IoT)**: IoT devices, such as smart sensors, wearables, and connected appliances, gather real-time data. From health and fitness data collected by fitness trackers to environmental data like Air Quality Index captured by smart cities' sensors, varied information is generated by IoT devices This data can be analysed to optimize processes, improve efficiency, and enhance overall experiences for individuals and communities.

- **E-Commerce Platforms:** E-Commerce platforms like Amazon and Flipkart have made shopping much easier, everything is available at the click of a thumb. The consumer also demands everything ready and fast. Thus, it is of prime importance to study the user's past preferences for suitable personalized recommendations. Thus, they

analyse the clicks, searches, likes, comments and past purchases plus their trackers also scan other websites.

- **Government Agencies:** Government agencies and public organizations play a crucial role in generating Big Data. Census data, public health records, and administrative data make up a major source of information that helps policymakers in decision-making and resource allocation. Analysing this data assists in identifying societal trends, addressing public issues, and efficient planning for the future.

- **Banks and Financial Institutions**: Banks, credit card companies, and financial service providers collect extensive data on transactions, customer behavior, and economic trends. Analyzing this data helps in detecting fraudulent activities, assessing credit risks, and offering tailored financial solutions to customers.

Dataset Chosen: Market Correlation of Data

Market Segmentation Data involves tracking and recording customer purchase patterns, including the frequency of purchases and which products are often bought together. This information is used to create user profiles and generate relevant product recommendations.

Analyzing Big Data

1) The Clustering algorithm is a widely used technique for association rule mining, but it has certain limitations when applied to Big Data analytics:
2) Scalability: The Clustering algorithm becomes computationally expensive when dealing with large datasets, such as gigabytes (GB) and terabytes (TB) of data. Its performance degrades significantly as the dataset size increases.
3) Diverse Datasets: In the retail domain, shopping malls offer a diverse range of products, with new items continually introduced and old ones phased out. This diversity increases the number of candidate itemsets, making it challenging to generate meaningful rules.
4) Rapid Data Generation: Big Data is generated at an astonishing rate, and the Apriori algorithm may struggle to keep up with the pace of data generation. Real-time processing of such data can be a significant challenge.
5) Rule Quality: The Apriori algorithm generates strong rules based on support and confidence metrics. However, not all strong rules are necessarily interesting. Some rules may appear misleading when

For instance, a high-confidence rule may suggest that customers who purchase bananas are likely to buy apples. Still, in reality, a significant portion of all customers may buy apples, making the rule less valuable.

In summary, while the Apriori algorithm is a valuable tool for association rule mining, it may face scalability and interpretability challenges when dealing with Big Data in dynamic and diverse domains like retail.
Custom implementations and optimizations are often required to address these limitations effectively.

Limitations of Conventional Algorithms on bigdata:

1. Scalability: Conventional algorithms are often designed to work with relatively small datasets. When applied to big data, which can range from terabytes to petabytes in size, these algorithms may become extremely slow or may not even execute due to memory and processing power constraints.

2. Memory Constraints: Many traditional algorithms assume that the entire dataset can fit into memory. In the context of big data, this assumption is often invalid, as the dataset size exceeds available RAM. This limitation can lead to significant performance degradation or even failures.

3. Processing Time: Conventional algorithms may take an impractical amount of time to process big data. For instance, sorting, searching, or aggregating large datasets using traditional algorithms can be extremely time-

consuming, making real-time or near-real-time processing unfeasible.

4. Data Distribution: Big data is often distributed across multiple servers or clusters. Conventional algorithms are not inherently designed to work in a distributed computing environment, requiring significant modifications or new algorithms to harness the full potential of distributed data processing frameworks like Hadoop or Spark.

5. Accuracy vs. Efficiency Trade-off: Traditional algorithms may prioritize accuracy over efficiency. In the big data context, where data volumes are massive, there's often a need to trade off some degree of accuracy for faster processing times. Achieving this balance can be challenging using conventional algorithms.

6. Complexity and Maintainability: Adapting conventional algorithms to big data scenarios can involve complex code modifications and may result in code that is hard to maintain. It can also require a deep understanding of distributed systems, parallel processing, and big data technologies, making it challenging for developers who are not familiar with these concepts.

In summary, while conventional algorithms have their place in traditional computing environments, they often fall short when dealing with big data due to issues related to scalability, memory, processing time, data distribution, and the need for a different balance between accuracy and efficiency. addressing these limitations often requires the development of specialized algorithms and the

use of distributed data processing frameworks.

Load Dependencies and Configuration Settings

We started with the installation of the orange3 package through the command line, since it is not possible to include it through the usual procedure of adding custom packages in the Kernel.

In [ ]:
```
import os
import warnings
warnings.simplefilter(action = 'ignore', category=FutureWarning)
warnings.filterwarnings('ignore')
def ignore_warn(*args, **kwargs):
    pass

warnings.warn = ignore_warn #ignore annoying warning (from sklearn and seaborn)

import pandas as pd
import datetime
import math
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import matplotlib.cm as cm

%matplotlib inline

from pandasql import sqldf
pysqldf = lambda q: sqldf(q, globals())

import seaborn as sns
sns.set(style="ticks", color_codes=True, font_scale=1.5)
color = sns.color_palette()
sns.set_style('darkgrid')

from mpl_toolkits.mplot3d import Axes3D

import plotly as py
import plotly.graph_objs as go
py.offline.init_notebook_mode()

from scipy import stats
from scipy.stats import skew, norm, probplot, boxcox
from sklearn import preprocessing
import math

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples, silhouette_score

# import Orange
# from Orange.data import Domain, DiscreteVariable, ContinuousVariable
# from orangecontrib.associate.fpgrowth import *
```

Load Dataset

In [ ]:
```
cs_df = pd.read_excel(io=r'../input/Online Retail.xlsx')
```

In [ ]:

```
def rstr(df, pred=None):
    obs = df.shape[0]
    types = df.dtypes
    counts = df.apply(lambda x: x.count())
    uniques = df.apply(lambda x: [x.unique()])
    nulls = df.apply(lambda x: x.isnull().sum())
    distincts = df.apply(lambda x: x.unique().shape[0])
    missing_ration = (df.isnull().sum()/ obs) * 100
    skewness = df.skew()
    kurtosis = df.kurt()
    print('Data shape:', df.shape)

    if pred is None:
        cols = ['types', 'counts', 'distincts', 'nulls', 'missing ration', 'uniques
        str = pd.concat([types, counts, distincts, nulls, missing_ration, uniques,

    else:
        corr = df.corr()[pred]
        str = pd.concat([types, counts, distincts, nulls, missing_ration, uniques,
        corr_col = 'corr '  + pred
        cols = ['types', 'counts', 'distincts', 'nulls', 'missing ration', 'uniques

    str.columns = cols
    dtypes = str.types.value_counts()
    print('_____________________________\nData types:\n',str.types.value_counts())
    print('_____________________________')
    return str

details = rstr(cs_df)
display(details.sort_values(by='missing ration', ascending=False))
```

```
Data shape: (541909, 8)
_____________________________
Data types:
 object            4
float64           2
int64             1
datetime64[ns]    1
Name: types, dtype: int64
_____________________________
```

	types	counts	distincts	nulls	missing ration	uniques	skewness	ku
CustomerID	float64	406829	4373	135080	24.926694	[[17850.0, 13047.0, 12583.0, 13748.0, 15100.0,...	0.029835	-1.1
Description	object	540455	4224	1454	0.268311	[[WHITE HANGING HEART T-LIGHT HOLDER, WHITE ME...	NaN	
Country	object	541909	38	0	0.000000	[[United Kingdom, France, Australia, Netherlan...	NaN	
InvoiceDate	datetime64[ns]	541909	23260	0	0.000000	[[2010-12-01 08:26:00, 2010-12-01 08:28:00, 20...	NaN	
InvoiceNo	object	541909	25900	0	0.000000	[[536365, 536366, 536367, 536368, 536369, 5363...	NaN	
Quantity	int64	541909	722	0	0.000000	[[6, 8, 2, 32, 3, 4, 24, 12, 48, 18, 20, 36, 8...	-0.264076	119769.1
StockCode	object	541909	4070	0	0.000000	[[85123A, 71053, 84406B, 84029G, 84029E, 22752...	NaN	
UnitPrice	float64	541909	1630	0	0.000000	[[2.55, 3.39, 2.75, 7.65, 4.25, 1.85, 1.69, 2....	186.506972	59005.7

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

Out[ ]:

	Quantity	UnitPrice	CustomerID
count	541909.000000	541909.000000	406829.000000
mean	9.552250	4.611114	15287.690570
std	218.081158	96.759853	1713.600303
min	-80995.000000	-11062.060000	12346.000000
25%	1.000000	1.250000	13953.000000
50%	3.000000	2.080000	15152.000000
75%	10.000000	4.130000	16791.000000
max	80995.000000	38970.000000	18287.000000

In [ ]:

```
print('Check if we had negative quantity and prices at same register:',
     'No' if cs_df[(cs_df.Quantity<0) & (cs_df.UnitPrice<0)].shape[0] == 0 else 'Ye
print('Check how many register we have where quantity is negative',
      'and prices is 0 or vice-versa:',
      cs_df[(cs_df.Quantity<=0) & (cs_df.UnitPrice<=0)].shape[0])
print('\nWhat is the customer ID of the registers above:',
      cs_df.loc[(cs_df.Quantity<=0) & (cs_df.UnitPrice<=0),
                ['CustomerID']].CustomerID.unique())
print('\n% Negative Quantity: {:3.2%}'.format(cs_df[(cs_df.Quantity<0)].shape[0]/cs
print('\nAll register with negative quantity has Invoice start with:',
      cs_df.loc[(cs_df.Quantity<0) & ~(cs_df.CustomerID.isnull()), 'InvoiceNo'].app
print('\nSee an example of negative quantity and others related records:')
display(cs_df[(cs_df.CustomerID==12472) & (cs_df.StockCode==22244)])
```

```
Check if we had negative quantity and prices at same register: No

Check how many register we have where quantity is negative and prices is 0 or vice
-versa: 1336

What is the customer ID of the registers above: [nan]

% Negative Quantity: 1.96%

All register with negative quantity has Invoice start with: ['C']

See an example of negative quantity and others related records:
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Count
1973	C536548	22244	3 HOOK HANGER MAGIC GARDEN	-4	2010-12-01 14:33:00	1.95	12472.0	Germa
9438	537201	22244	3 HOOK HANGER MAGIC GARDEN	12	2010-12-05 14:19:00	1.95	12472.0	Germa
121980	546843	22244	3 HOOK HANGER MAGIC GARDEN	12	2011-03-17 12:40:00	1.95	12472.0	Germa

In [ ]:

```
print('Check register with UnitPrice negative:')
display(cs_df[(cs_df.UnitPrice<0)])
```

```
print("Sales records with Customer ID and zero in Unit Price:",cs_df[(cs_df.UnitPri
cs_df[(cs_df.UnitPrice==0)  & ~(cs_df.CustomerID.isnull())]
```

```
Check register with UnitPrice negative:
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Count
299983	A563186	B	Adjust bad debt	1	2011-08-12 14:51:00	-11062.06	NaN	Unit Kingdc
299984	A563187	B	Adjust bad debt	1	2011-08-12 14:52:00	-11062.06	NaN	Unit Kingdc

```
Sales records with Customer ID and zero in Unit Price: 40
```

Out[ ]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	C
9302	537197	22841	ROUND CAKE TIN VINTAGE GREEN	1	2010-12-05 14:02:00	0.0	12647.0	G
33576	539263	22580	ADVENT CALENDAR GINGHAM SACK	4	2010-12-16 14:36:00	0.0	16560.0	Ki
40089	539722	22423	REGENCY CAKESTAND 3 TIER	10	2010-12-21 13:45:00	0.0	14911.0	
47068	540372	22090	PAPER BUNTING RETROSPOT	24	2011-01-06 16:41:00	0.0	13081.0	Ki
47070	540372	22553	PLASTERS IN TIN SKULLS	24	2011-01-06 16:41:00	0.0	13081.0	Ki
56674	541109	22168	ORGANISER WOOD ANTIQUE WHITE	1	2011-01-13 15:10:00	0.0	15107.0	Ki
86789	543599	84535B	FAIRY CAKES NOTEBOOK A6 SIZE	16	2011-02-10 13:08:00	0.0	17560.0	Ki
130188	547417	22062	CERAMIC BOWL WITH LOVE HEART DESIGN	36	2011-03-23 10:25:00	0.0	13239.0	Ki
139453	548318	22055	MINI CAKE STAND HANGING STRAWBERY	5	2011-03-30 12:45:00	0.0	13113.0	Ki
145208	548871	22162	HEART GARLAND RUSTIC PADDED	2	2011-04-04 14:42:00	0.0	14410.0	Ki
157042	550188	22636	CHILDS BREAKFAST SET CIRCUS PARADE	1	2011-04-14 18:57:00	0.0	12457.0	Swit
187613	553000	47566	PARTY BUNTING	4	2011-05-12 15:21:00	0.0	17667.0	Ki
198383	554037	22619	SET OF 6 SOLDIER SKITTLES	80	2011-05-20 14:13:00	0.0	12415.0	A
279324	561284	22167	OVAL WALL MIRROR DIAMANTE	1	2011-07-26 12:24:00	0.0	16818.0	Ki
282912	561669	22960	JAM MAKING SET WITH JARS	11	2011-07-28 17:09:00	0.0	12507.0	
285657	561916	M	Manual	1	2011-08-01 11:44:00	0.0	15581.0	Ki

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	C
298054	562973	23157	SET OF 6 NATIVITY MAGNETS	240	2011-08-11 11:42:00	0.0	14911.0	
314745	564651	23270	SET OF 2 CERAMIC PAINTED HEARTS	96	2011-08-26 14:19:00	0.0	14646.0	Neth
314746	564651	23268	SET OF 2 CERAMIC CHRISTMAS REINDEER	192	2011-08-26 14:19:00	0.0	14646.0	Neth
314747	564651	22955	36 FOIL STAR CAKE CASES	144	2011-08-26 14:19:00	0.0	14646.0	Neth
314748	564651	21786	POLKADOT RAIN HAT	144	2011-08-26 14:19:00	0.0	14646.0	Neth
358655	568158	PADS	PADS TO MATCH ALL CUSHIONS	1	2011-09-25 12:22:00	0.0	16133.0	Ki
361825	568384	M	Manual	1	2011-09-27 09:46:00	0.0	12748.0	Ki
379913	569716	22778	GLASS CLOCHE SMALL	2	2011-10-06 08:17:00	0.0	15804.0	Ki
395529	571035	M	Manual	1	2011-10-13 12:50:00	0.0	12446.0	
420404	572893	21208	PASTEL COLOUR HONEYCOMB FAN	5	2011-10-26 14:36:00	0.0	18059.0	Ki
436428	574138	23234	BISCUIT TIN VINTAGE CHRISTMAS	216	2011-11-03 11:26:00	0.0	12415.0	A
436597	574175	22065	CHRISTMAS PUDDING TRINKET POT	12	2011-11-03 11:47:00	0.0	14110.0	Ki
436961	574252	M	Manual	1	2011-11-03 13:24:00	0.0	12437.0	
439361	574469	22385	JUMBO BAG SPACEBOY DESIGN	12	2011-11-04 11:55:00	0.0	12431.0	A
446125	574879	22625	RED KITCHEN SCALES	2	2011-11-07 13:22:00	0.0	13014.0	Ki
446793	574920	22899	CHILDREN'S APRON DOLLY GIRL	1	2011-11-07 16:34:00	0.0	13985.0	Ki
446794	574920	23480	MINI LIGHTS WOODLAND MUSHROOMS	1	2011-11-07 16:34:00	0.0	13985.0	Ki
454463	575579	22437	SET OF 9 BLACK SKULL	20	2011-11-10 11:49:00	0.0	13081.0	Ki

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	C
			BALLOONS					
454464	575579	22089	PAPER BUNTING VINTAGE PAISLEY	24	2011-11-10 11:49:00	0.0	13081.0	Ki
479079	577129	22464	HANGING METAL HEART LANTERN	4	2011-11-17 19:52:00	0.0	15602.0	Ki
479546	577168	M	Manual	1	2011-11-18 10:42:00	0.0	12603.0	G
480649	577314	23407	SET OF 2 TRAYS HOME SWEET HOME	2	2011-11-18 13:23:00	0.0	12444.0	
485985	577696	M	Manual	1	2011-11-21 11:57:00	0.0	16406.0	Ki
502122	578841	84826	ASSTD DESIGN 3D PAPER STICKERS	12540	2011-11-25 15:57:00	0.0	13256.0	Ki

In [ ]:
```
# Remove register withou CustomerID
cs_df = cs_df[~(cs_df.CustomerID.isnull())]

# Remove negative or return transactions
cs_df = cs_df[~(cs_df.Quantity<0)]
cs_df = cs_df[cs_df.UnitPrice>0]

details = rstr(cs_df)
display(details.sort_values(by='distincts', ascending=False))
```

```
Data shape: (397884, 8)
_____________________________
Data types:
 object            4
float64            2
int64              1
datetime64[ns]     1
Name: types, dtype: int64
_____________________________
```

	types	counts	distincts	nulls	missing ration	uniques	skewness	kurtos
InvoiceNo	object	397884	18532	0	0.0	[[536365, 536366, 536367, 536368, 536369, 5363...	-0.178524	-1.20074
InvoiceDate	datetime64[ns]	397884	17282	0	0.0	[[2010-12-01 08:26:00, 2010-12-01 08:28:00, 20...	NaN	Na
CustomerID	float64	397884	4338	0	0.0	[[17850.0, 13047.0, 12583.0, 13748.0, 15100.0,...	0.025729	-1.18082
Description	object	397884	3877	0	0.0	[[WHITE HANGING HEART T-LIGHT HOLDER, WHITE ME...	NaN	Na
StockCode	object	397884	3665	0	0.0	[[85123A, 71053, 84406B, 84029G, 84029E, 22752...	NaN	Na
UnitPrice	float64	397884	440	0	0.0	[[2.55, 3.39, 2.75, 7.65, 4.25, 1.85, 1.69, 2....	204.032727	58140.39667
Quantity	int64	397884	301	0	0.0	[[6, 8, 2, 32, 3, 4, 24, 12, 48, 18, 20, 36, 8...	409.892972	178186.24325
Country	object	397884	37	0	0.0	[[United Kingdom, France, Australia, Netherlan...	NaN	Na

After this first cleanup, note that we still have more description than inventory codes, so we still have some inconsistency on the basis that requires further investigation. Let´s see it:

In [ ]:
```
cat_des_df = cs_df.groupby(["StockCode","Description"]).count().reset_index()
display(cat_des_df.StockCode.value_counts()[cat_des_df.StockCode.value_counts()>1].
cs_df[cs_df['StockCode'] == cat_des_df.StockCode.value_counts()[cat_des_df.StockCo
      .reset_index()['index'][4]]['Description'].unique()
```

	index	StockCode
0	23236	4
1	23196	4
2	23203	3
3	17107D	3
4	23370	3

Out[ ]:
```
array(['SET 36 COLOUR PENCILS DOILEY', 'SET 36 COLOURING PENCILS DOILY',
       'SET 36 COLOURING PENCILS DOILEY'], dtype=object)
```

This gives the multiple descriptions for one of those items and we witness the simple ways in which data quality can be corrupted in any dataset. A simple spelling mistake can end up in reducing data quality and an erroneous analysis.

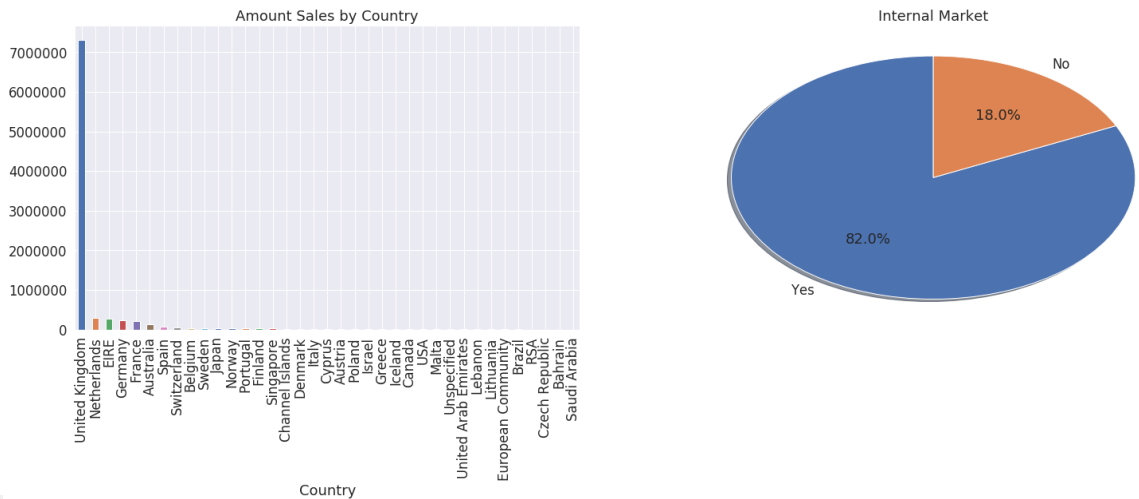
In [ ]:
```
unique_desc = cs_df[["StockCode", "Description"]].groupby(by=["StockCode"]).\
                apply(pd.DataFrame.mode).reset_index(drop=True)
q = '''
select df.InvoiceNo, df.StockCode, un.Description, df.Quantity, df.InvoiceDate,
       df.UnitPrice, df.CustomerID, df.Country
from cs_df as df INNER JOIN
     unique_desc as un on df.StockCode = un.StockCode
'''

cs_df = pysqldf(q)
```

In [ ]:
```
cs_df.InvoiceDate = pd.to_datetime(cs_df.InvoiceDate)
cs_df['amount'] = cs_df.Quantity*cs_df.UnitPrice
cs_df.CustomerID = cs_df.CustomerID.astype('Int64')

details = rstr(cs_df)
display(details.sort_values(by='distincts', ascending=False))
```

```
Data shape: (397884, 9)
_____________________________
Data types:
 object            3
int64              3
float64            2
datetime64[ns]     1
Name: types, dtype: int64
_____________________________
```

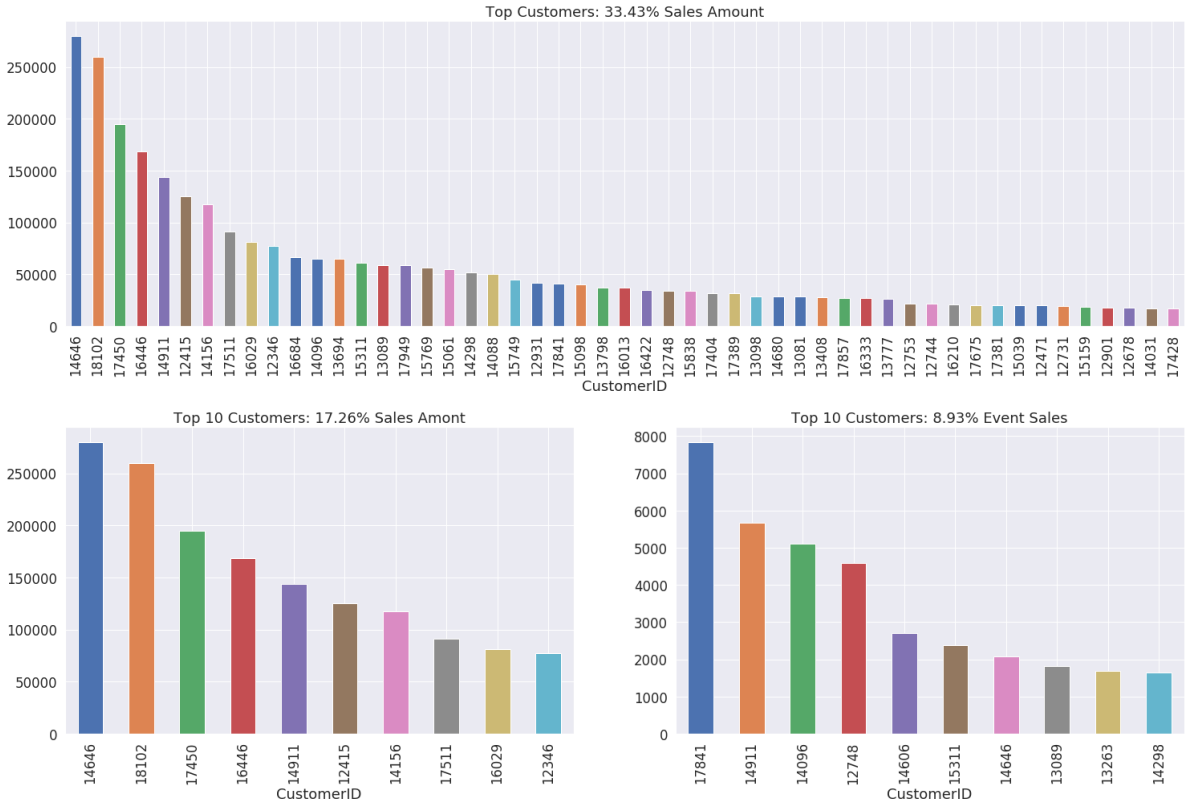
	types	counts	distincts	nulls	missing ration	uniques	skewness	
InvoiceNo	int64	397884	18532	0	0.0	[[536365, 536366, 536367, 536368, 536369, 5363...	-0.178524	
InvoiceDate	datetime64[ns]	397884	17282	0	0.0	[[2010-12-01 08:26:00, 2010-12-01 08:28:00, 20...	NaN	
CustomerID	int64	397884	4338	0	0.0	[[17850, 13047, 12583, 13748, 15100, 15291, 14...	0.025729	
StockCode	object	397884	3665	0	0.0	[[85123A, 71053, 84406B, 84029G, 84029E, 22752...	NaN	
Description	object	397884	3647	0	0.0	[[WHITE HANGING HEART T-LIGHT HOLDER, WHITE ME...	NaN	
amount	float64	397884	2939	0	0.0	[[15.299999999999999, 20.34, 22.0, 15.3, 25.5,...	451.443182	23
UnitPrice	float64	397884	440	0	0.0	[[2.55, 3.39, 2.75, 7.65, 4.25, 1.85, 1.69, 2....	204.032727	5
Quantity	int64	397884	301	0	0.0	[[6, 8, 2, 32, 3, 4, 24, 12, 48, 18, 20, 36, 8...	409.892972	17
Country	object	397884	37	0	0.0	[[United Kingdom, France, Australia, Netherlan...	NaN	

In [ ]:
```
fig = plt.figure(figsize=(25, 7))
f1 = fig.add_subplot(121)
g = cs_df.groupby(["Country"]).amount.sum().sort_values(ascending = False).plot(kir
cs_df['Internal'] = cs_df.Country.apply(lambda x: 'Yes' if x=='United Kingdom' else
f2 = fig.add_subplot(122)
market = cs_df.groupby(["Internal"]).amount.sum().sort_values(ascending = False)
g = plt.pie(market, labels=market.index, autopct='%1.1f%%', shadow=True, startangle
plt.title('Internal Market')
plt.show()
```



In [ ]:
```
fig = plt.figure(figsize=(25, 7))
PercentSales =  np.round((cs_df.groupby(["CustomerID"]).amount.sum().\
```

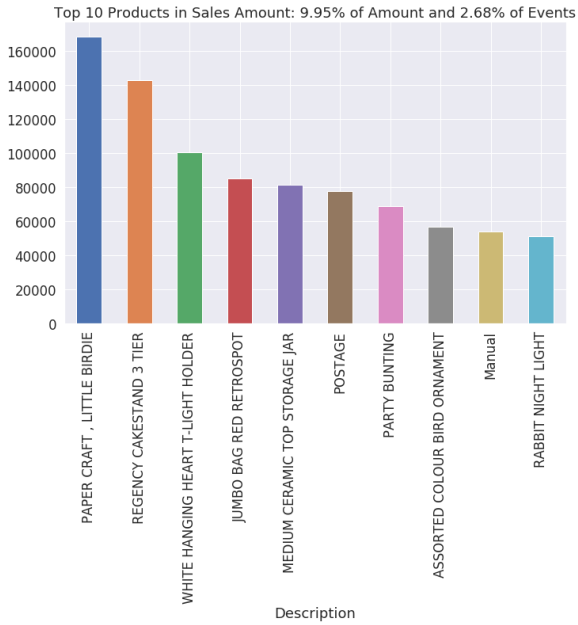
```
                            sort_values(ascending = False)[:51].sum()/cs_df.groupby([
                            amount.sum().sort_values(ascending = False).sum()) * 100,
g = cs_df.groupby(["CustomerID"]).amount.sum().sort_values(ascending = False)[:51].
    plot(kind='bar', title='Top Customers: {:3.2f}% Sales Amount'.format(PercentSal

fig = plt.figure(figsize=(25, 7))
f1 = fig.add_subplot(121)
PercentSales =  np.round((cs_df.groupby(["CustomerID"]).amount.sum().\
                            sort_values(ascending = False)[:10].sum()/cs_df.groupby([
                            amount.sum().sort_values(ascending = False).sum()) * 100,
g = cs_df.groupby(["CustomerID"]).amount.sum().sort_values(ascending = False)[:10]\
    .plot(kind='bar', title='Top 10 Customers: {:3.2f}% Sales Amont'.format(Percent
f1 = fig.add_subplot(122)
PercentSales =  np.round((cs_df.groupby(["CustomerID"]).amount.count().\
                            sort_values(ascending = False)[:10].sum()/cs_df.groupby([
                            amount.count().sort_values(ascending = False).sum()) * 10
g = cs_df.groupby(["CustomerID"]).amount.count().sort_values(ascending = False)[:10
    plot(kind='bar', title='Top 10 Customers: {:3.2f}% Event Sales'.format(PercentS
```

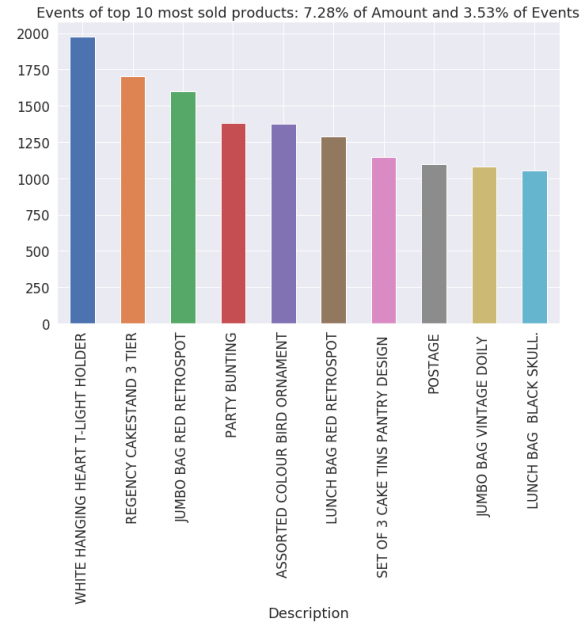


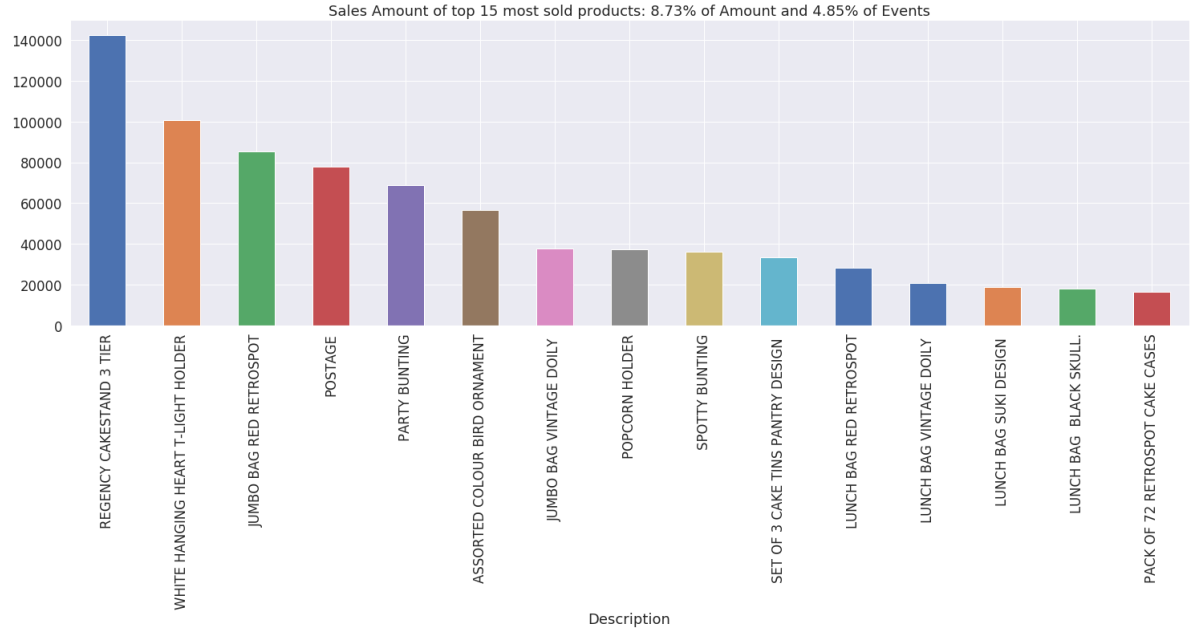
In [ ]:

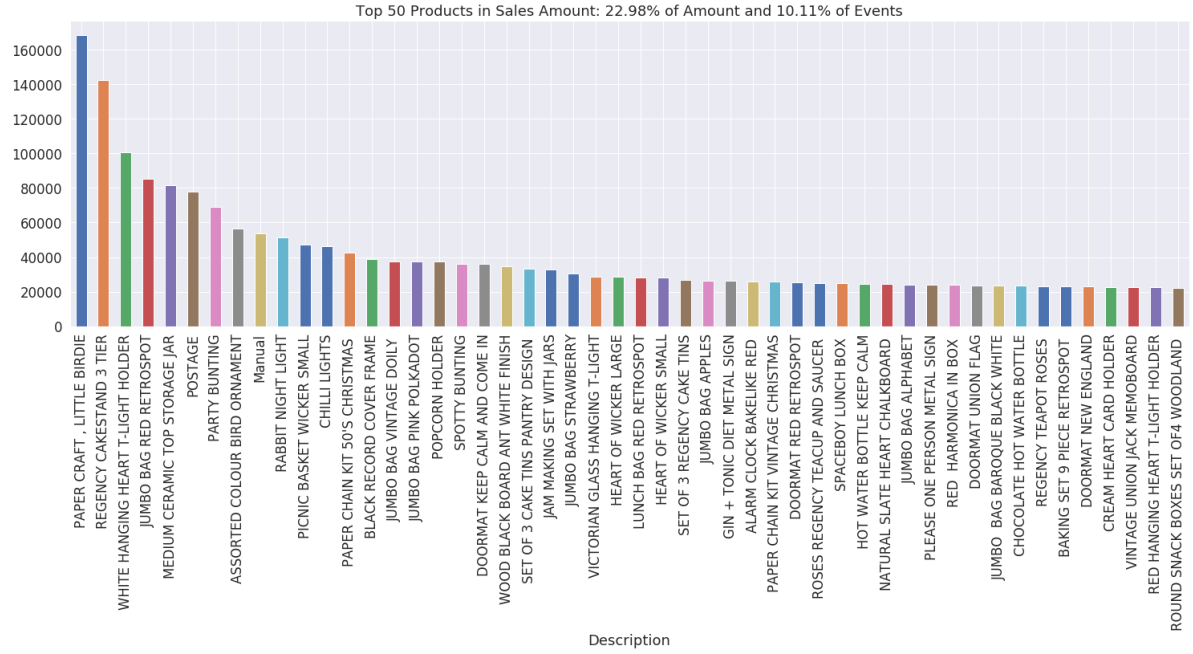
```
AmoutSum = cs_df.groupby(["Description"]).amount.sum().sort_values(ascending = Fals
inv = cs_df[["Description", "InvoiceNo"]].groupby(["Description"]).InvoiceNo.unique
      agg(np.size).sort_values(ascending = False)

fig = plt.figure(figsize=(25, 7))
f1 = fig.add_subplot(121)
Top10 = list(AmoutSum[:10].index)
PercentSales =  np.round((AmoutSum[Top10].sum()/AmoutSum.sum()) * 100, 2)
PercentEvents = np.round((inv[Top10].sum()/inv.sum()) * 100, 2)
g = AmoutSum[Top10].\
    plot(kind='bar', title='Top 10 Products in Sales Amount: {:3.2f}% of Amount and
                        format(PercentSales, PercentEvents))

f1 = fig.add_subplot(122)
Top10Ev = list(inv[:10].index)
PercentSales =  np.round((AmoutSum[Top10Ev].sum()/AmoutSum.sum()) * 100, 2)
PercentEvents = np.round((inv[Top10Ev].sum()/inv.sum()) * 100, 2)
g = inv[Top10Ev].\
    plot(kind='bar', title='Events of top 10 most sold products: {:3.2f}% of Amount
```

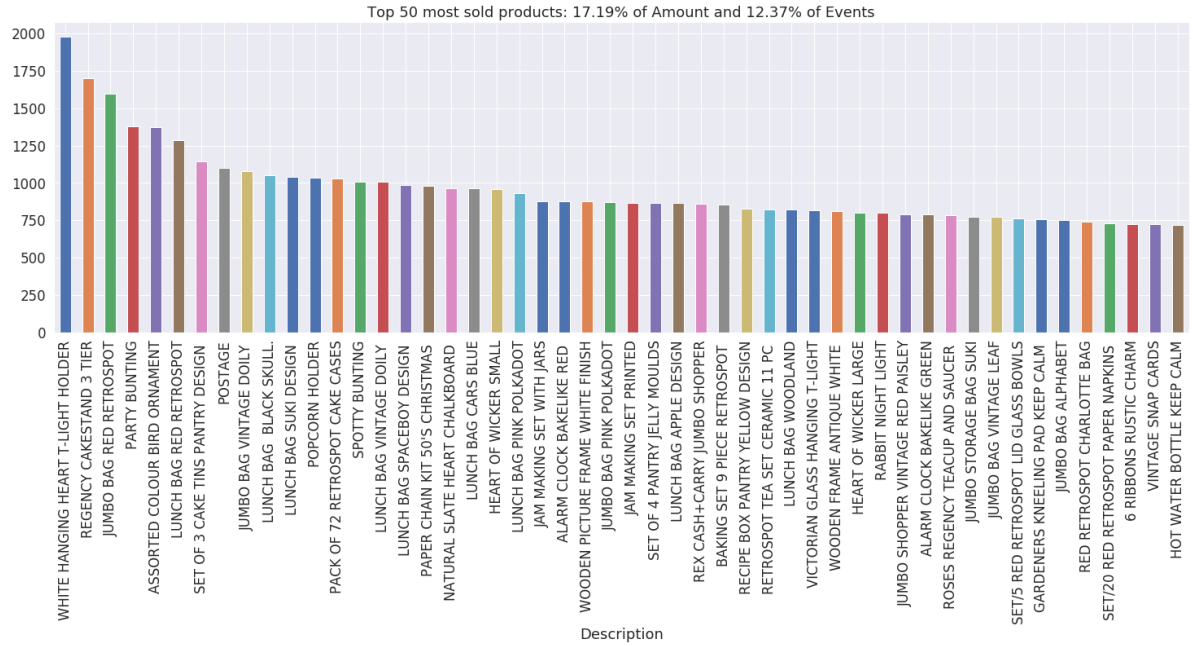
```
                        format(PercentSales, PercentEvents))


fig = plt.figure(figsize=(25, 7))
Top15ev = list(inv[:15].index)
PercentSales =  np.round((AmoutSum[Top15ev].sum()/AmoutSum.sum()) * 100, 2)
PercentEvents = np.round((inv[Top15ev].sum()/inv.sum()) * 100, 2)
g = AmoutSum[Top15ev].sort_values(ascending = False).\
    plot(kind='bar',
         title='Sales Amount of top 15 most sold products: {:3.2f}% of Amount and {
         format(PercentSales, PercentEvents))

fig = plt.figure(figsize=(25, 7))
Top50 = list(AmoutSum[:50].index)
PercentSales =  np.round((AmoutSum[Top50].sum()/AmoutSum.sum()) * 100, 2)
PercentEvents = np.round((inv[Top50].sum()/inv.sum()) * 100, 2)
g = AmoutSum[Top50].\
    plot(kind='bar',
         title='Top 50 Products in Sales Amount: {:3.2f}% of Amount and {:3.2f}% of
         format(PercentSales, PercentEvents))

fig = plt.figure(figsize=(25, 7))
Top50Ev = list(inv[:50].index)
PercentSales =  np.round((AmoutSum[Top50Ev].sum()/AmoutSum.sum()) * 100, 2)
PercentEvents = np.round((inv[Top50Ev].sum()/inv.sum()) * 100, 2)
g = inv[Top50Ev].\
    plot(kind='bar', title='Top 50 most sold products: {:3.2f}% of Amount and {:3.2
                        format(PercentSales, PercentEvents))
```











In [ ]:
```
refrence_date = cs_df.InvoiceDate.max() + datetime.timedelta(days = 1)
print('Reference Date:', refrence_date)
cs_df['days_since_last_purchase'] = (refrence_date - cs_df.InvoiceDate).astype('tir
```

```
customer_history_df =  cs_df[['CustomerID', 'days_since_last_purchase']].groupby("C
customer_history_df.rename(columns={'days_since_last_purchase':'recency'}, inplace=
customer_history_df.describe().transpose()
```

```
Reference Date: 2011-12-10 12:50:00
```

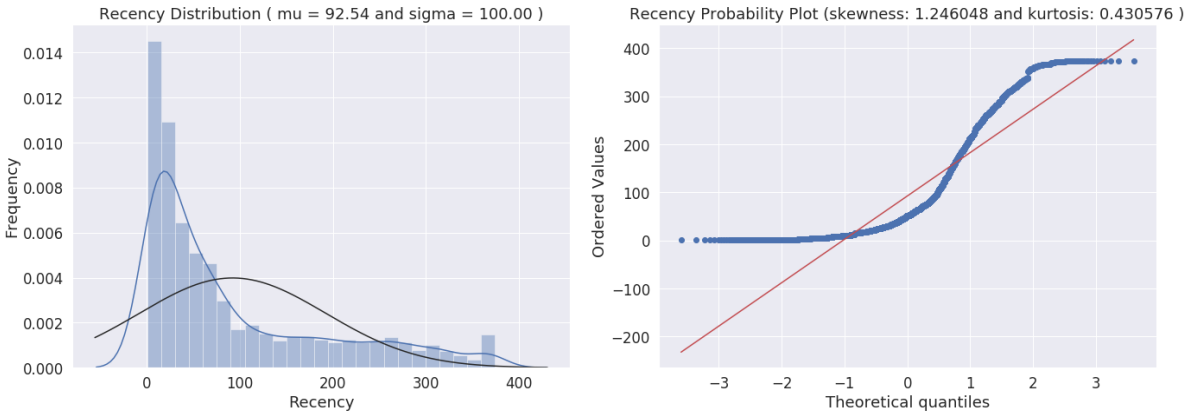
Out[ ]:

	count	mean	std	min	25%	50%	75%	max
CustomerID	4338.0	15300.408022	1721.808492	12346.0	13813.25	15299.5	16778.75	18287.0
recency	4338.0	92.536422	100.014169	1.0	18.00	51.0	142.00	374.0

We will plot the Recency Distribution and QQ-plot to identify substantive departures from normality, likes outliers, skewness and kurtosis.

In [ ]:

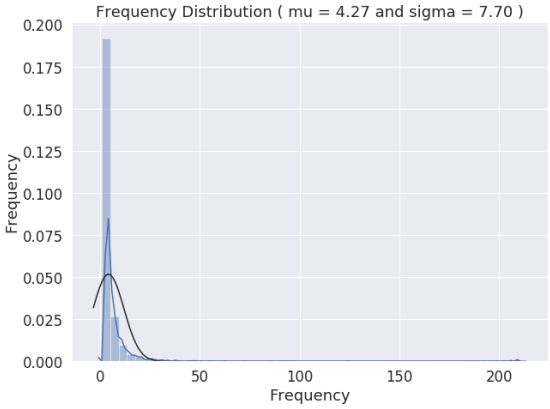
```
def QQ_plot(data, measure):
    fig = plt.figure(figsize=(20,7))

    #Get the fitted parameters used by the function
    (mu, sigma) = norm.fit(data)

    #Kernel Density plot
    fig1 = fig.add_subplot(121)
    sns.distplot(data, fit=norm)
    fig1.set_title(measure + ' Distribution ( mu = {:.2f} and sigma = {:.2f} )'.for
    fig1.set_xlabel(measure)
    fig1.set_ylabel('Frequency')

    #QQ plot
    fig2 = fig.add_subplot(122)
    res = probplot(data, plot=fig2)
    fig2.set_title(measure + ' Probability Plot (skewness: {:.6f} and kurtosis: {:

    plt.tight_layout()
    plt.show()

QQ_plot(customer_history_df.recency, 'Recency')
```

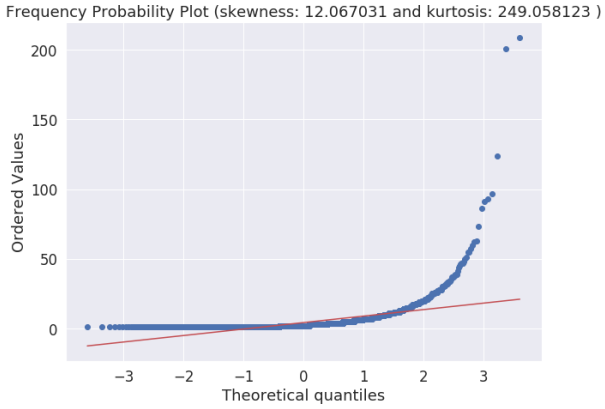


Frequency

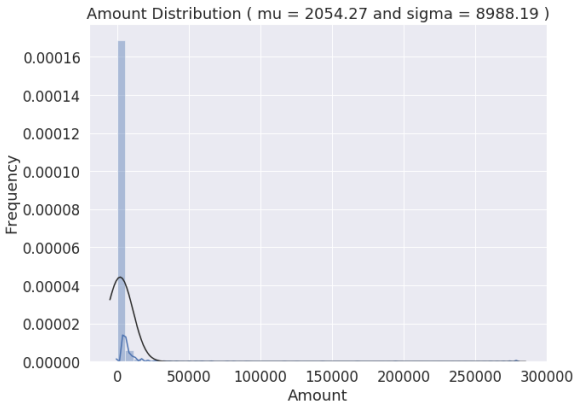
In [ ]:

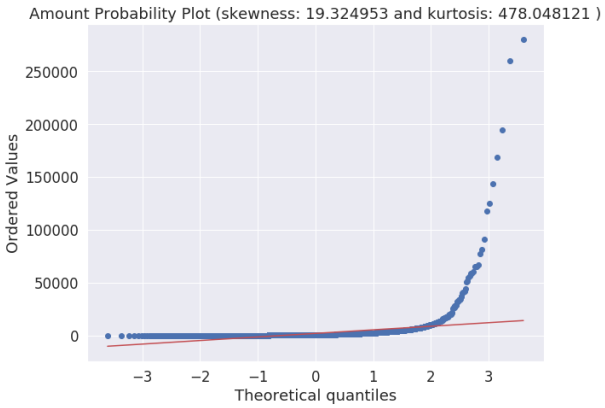
```
customer_freq = (cs_df[['CustomerID', 'InvoiceNo']].groupby(["CustomerID", 'Invoice
                 groupby(["CustomerID"]).count().reset_index()
customer_freq.rename(columns={'InvoiceNo':'frequency'},inplace=True)
customer_history_df = customer_history_df.merge(customer_freq)
QQ_plot(customer_history_df.frequency, 'Frequency')
```





In [ ]:
```
customer_monetary_val = cs_df[['CustomerID', 'amount']].groupby("CustomerID").sum()
customer_history_df = customer_history_df.merge(customer_monetary_val)
QQ_plot(customer_history_df.amount, 'Amount')
```





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

Out[ ]:

	CustomerID	recency	frequency	amount
count	4338.000000	4338.000000	4338.000000	4338.000000
mean	15300.408022	92.536422	4.272015	2054.266460
std	1721.808492	100.014169	7.697998	8989.230441
min	12346.000000	1.000000	1.000000	3.750000
25%	13813.250000	18.000000	1.000000	307.415000
50%	15299.500000	51.000000	2.000000	674.485000
75%	16778.750000	142.000000	5.000000	1661.740000
max	18287.000000	374.000000	209.000000	280206.020000

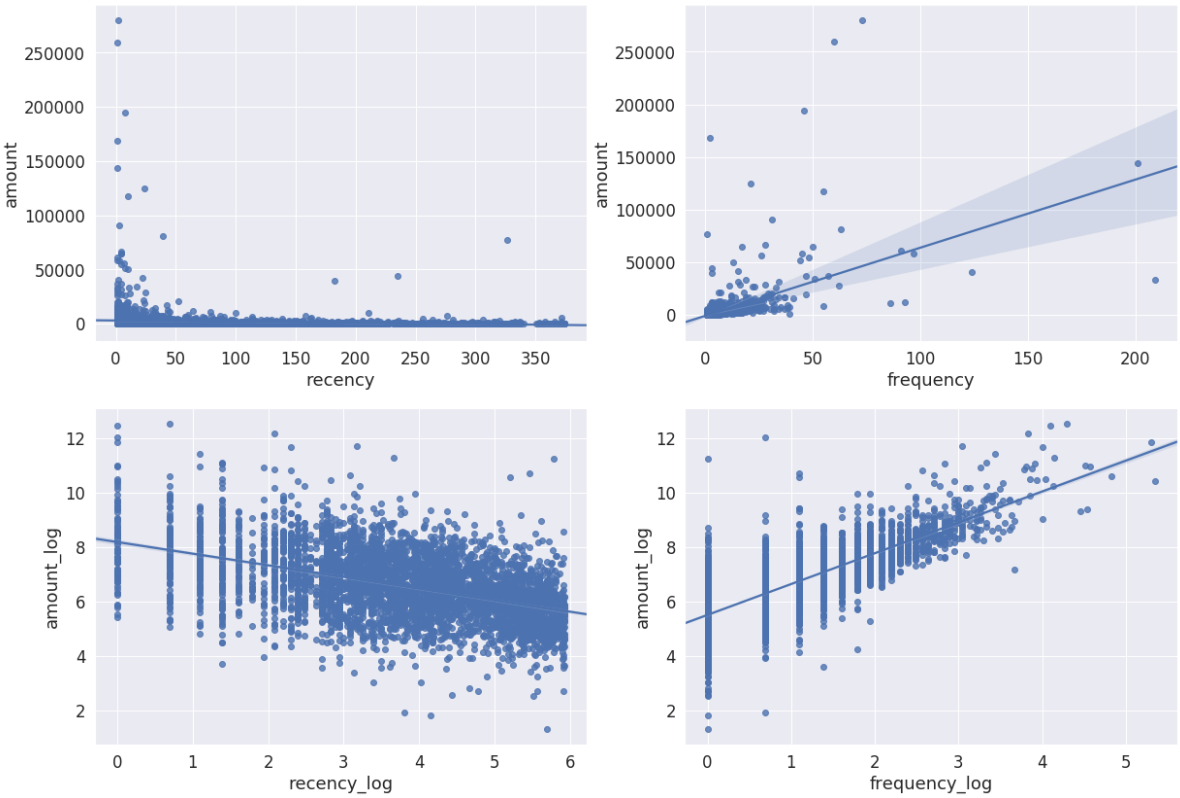
In [ ]:
```
customer_history_df['recency_log'] = customer_history_df['recency'].apply(math.log)
customer_history_df['frequency_log'] = customer_history_df['frequency'].apply(math.
customer_history_df['amount_log'] = customer_history_df['amount'].apply(math.log)
feature_vector = ['amount_log', 'recency_log','frequency_log']
X_subset = customer_history_df[feature_vector] #.as_matrix()
scaler = preprocessing.StandardScaler().fit(X_subset)
X_scaled = scaler.transform(X_subset)
pd.DataFrame(X_scaled, columns=X_subset.columns).describe().T
```

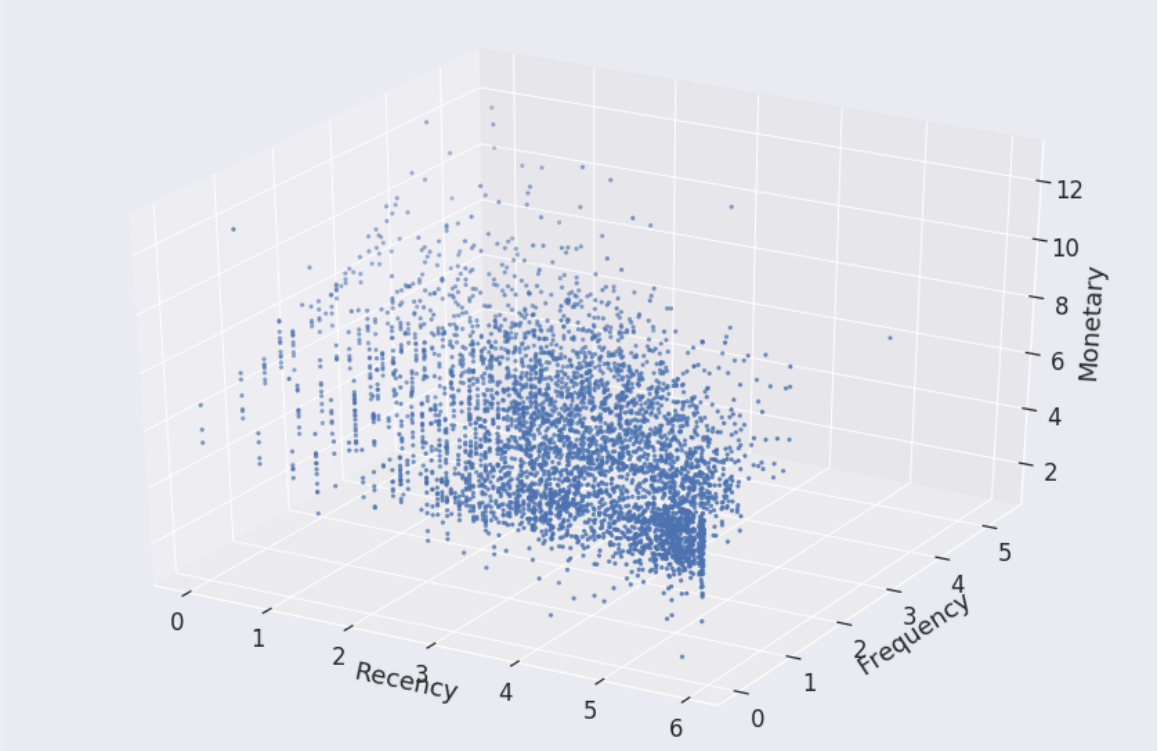
Out[ ]:

	count	mean	std	min	25%	50%	75%	max
amount_log	4338.0	-1.202102e-16	1.000115	-4.179280	-0.684183	-0.060942	0.654244	4.721395
recency_log	4338.0	-1.027980e-16	1.000115	-2.630445	-0.612424	0.114707	0.829652	1.505796
frequency_log	4338.0	-2.355833e-16	1.000115	-1.048610	-1.048610	-0.279044	0.738267	4.882714

In [ ]:

```
fig = plt.figure(figsize=(20,14))
f1 = fig.add_subplot(221); sns.regplot(x='recency', y='amount', data=customer_histo
f1 = fig.add_subplot(222); sns.regplot(x='frequency', y='amount', data=customer_his
f1 = fig.add_subplot(223); sns.regplot(x='recency_log', y='amount_log', data=custor
f1 = fig.add_subplot(224); sns.regplot(x='frequency_log', y='amount_log', data=cust

fig = plt.figure(figsize=(15, 10))
ax = fig.add_subplot(111, projection='3d')

xs =customer_history_df.recency_log
ys = customer_history_df.frequency_log
zs = customer_history_df.amount_log
ax.scatter(xs, ys, zs, s=5)

ax.set_xlabel('Recency')
ax.set_ylabel('Frequency')
ax.set_zlabel('Monetary')

plt.show()
```



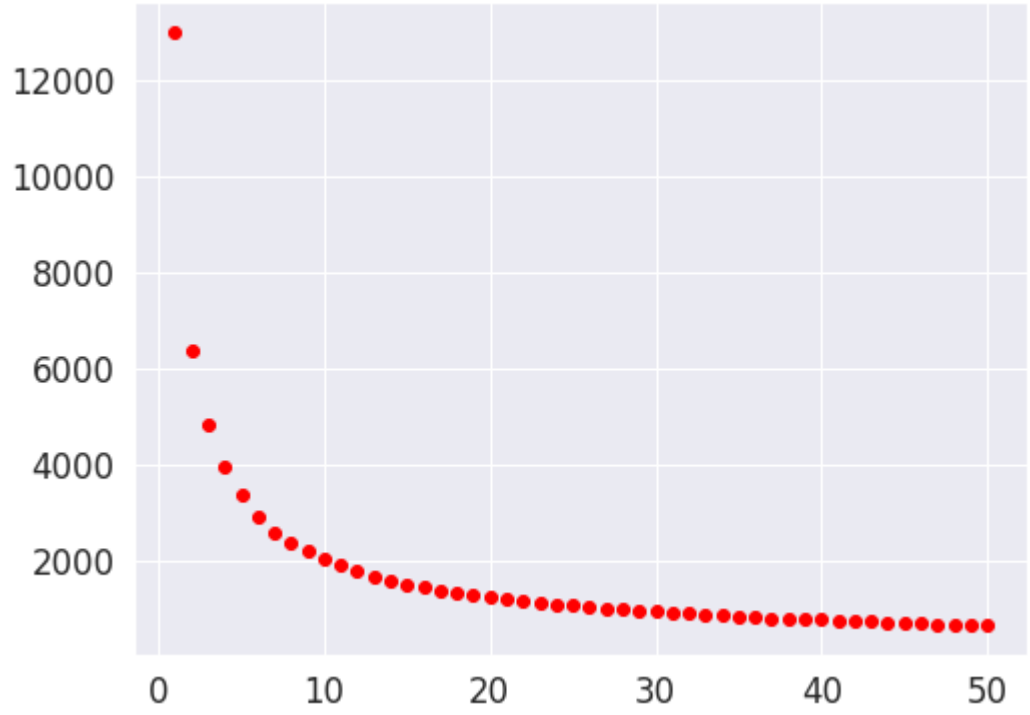


The obvious patterns we can see from the plots above is that costumers who buy with a higher frequency and more recency tend to spend more based on the increasing trend in Monetary (amount value) with a corresponding increasing and decreasing trend for Frequency and Recency, respectively.

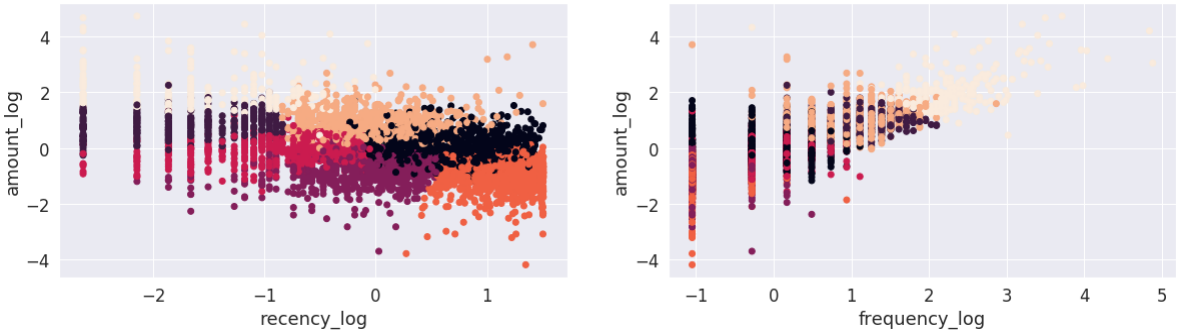
In [ ]:

```
cl = 50
corte = 0.1

anterior = 100000000000000
cost = []
K_best = cl

for k in range (1, cl+1):
    # Create a kmeans model on our data, using k clusters.  random_state helps ensu
    model = KMeans(
        n_clusters=k,
        init='k-means++', #'random',
        n_init=10,
        max_iter=300,
        tol=1e-04,
        random_state=101)

    model = model.fit(X_scaled)

    # These are our fitted labels for clusters -- the first cluster has label 0, ar
    labels = model.labels_

    # Sum of distances of samples to their closest cluster center
    interia = model.inertia_
    if (K_best == cl) and (((anterior - interia)/anterior) < corte): K_best = k - 1
    cost.append(interia)
    anterior = interia

plt.figure(figsize=(8, 6))
plt.scatter(range (1, cl+1), cost, c='red')
plt.show()
```

```
# Create a kmeans model with the best K.
print('The best K sugest: ',K_best)
model = KMeans(n_clusters=K_best, init='k-means++', n_init=10,max_iter=300, tol=1e

# Note I'm scaling the data to normalize it! Important for good results.
model = model.fit(X_scaled)

# These are our fitted labels for clusters -- the first cluster has label 0, and th
labels = model.labels_

# And we'll visualize it:
#plt.scatter(X_scaled[:,0], X_scaled[:,1], c=model.labels_.astype(float))
fig = plt.figure(figsize=(20,5))
ax = fig.add_subplot(121)
plt.scatter(x = X_scaled[:,1], y = X_scaled[:,0], c=model.labels_.astype(float))
ax.set_xlabel(feature_vector[1])
ax.set_ylabel(feature_vector[0])
ax = fig.add_subplot(122)
plt.scatter(x = X_scaled[:,2], y = X_scaled[:,0], c=model.labels_.astype(float))
ax.set_xlabel(feature_vector[2])
ax.set_ylabel(feature_vector[0])

plt.show()
```




```
The best K sugest:  7
```



In [ ]: