Segment customers using RFM analysis and k-means ++ clustering

This script is to segment customers using two methods.

First is RFM analysis. RFM analysis is a behavior-based approach grouping customers into segments. It could help companies provide better service, identify potential customers and do more profitable business.
RFM stands for the three dimensions:
Recency – How recently did the customer purchase?
Frequency – How often do they purchase?
Monetary Value – How much do they spend?
The steps of RFM analysis to segment customers are:
1.Calculate the Recency, Frequency, Monetary values for each customer.
2.Assign a score for each dimension on a scale from 1 to 4 using quartile.
3.Concate all scores in single RFM score
4.Segment customers according to their RFM sore

Second is K-means++. I looked at the elbow curve which helps to find the optimum number of clusters in the K-Means++ algorithm. Then I used sklearn library to complete the K-means++ clustering.

In [20]:

```
import numpy as np
import pandas as pd
import datetime
import math
import matplotlib.pyplot as plt
import matplotlib.mlab as mlab
import matplotlib.cm as cm
from mpl_toolkits.mplot3d import Axes3D
%matplotlib inline

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

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

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_samples, silhouette_score
#from IPython.display import display, HTML
```

In [2]:

```
# Import processed data
df = pd.read_excel("processed data.xlsx",index_col=0, dtype={'CustomerID': str,'InvoiceNo':
df.head()
```

Out[2]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850	United Kingdom

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 397884 entries, 0 to 541908
Data columns (total 13 columns):
InvoiceNo       397884 non-null object
StockCode       397884 non-null object
Description     397884 non-null object
Quantity        397884 non-null int64
InvoiceDate     397884 non-null datetime64[ns]
UnitPrice       397884 non-null float64
CustomerID      397884 non-null object
Country         397884 non-null object
amount          397884 non-null float64
Internal        397884 non-null object
Weekday         397884 non-null int64
weekday_name    397884 non-null object
DAY_OF_WEEK     397884 non-null object
dtypes: datetime64[ns](1), float64(2), int64(2), object(8)
memory usage: 42.5+ MB
```

In [4]:

```
df1 = df.copy()
df1.duplicated().sum()
```

Out[4]:

```
5192
```

In [5]:

```
df1.drop_duplicates(inplace = True)
print(df.shape)
print(df1.shape)
```

```
(397884, 13)
(392692, 13)
```

Part 1 Use RFM score to segement customers

1). Calculate the Recency, Frequency, Monetary values for each customer

- Recency

In [6]:

```
# Set a reference date
reference_date = df1.InvoiceDate.max() + datetime.timedelta(days = 1)
print('reference date: ',reference_date)

# Calculate recency
df1['days_since_referencedate'] = (reference_date - df1.InvoiceDate).astype('timedelta64[D]
customer_history_df =  df1[['CustomerID', 'days_since_referencedate']].groupby("CustomerID"
customer_history_df.rename(columns={'days_since_referencedate':'recency'}, inplace=True)
#customer_history_df.head()
customer_history_df.describe().transpose()
```

```
reference date:  2011-12-10 12:50:00
```

Out[6]:

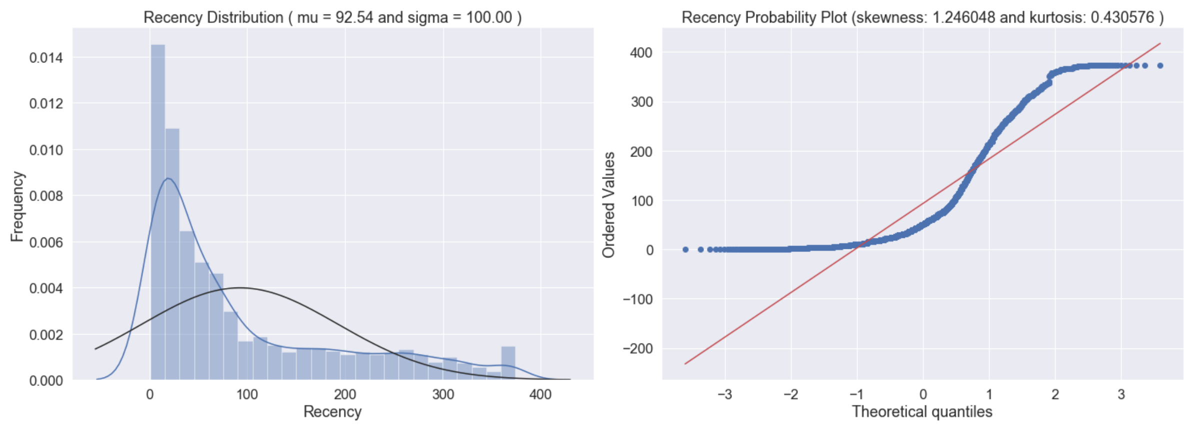
	count	mean	std	min	25%	50%	75%	max
recency	4338.0	92.536422	100.014169	1.0	18.0	51.0	142.0	374.0

In [7]:

```
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} )'.format(mu,
    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: {:.6f} )'.f

    plt.tight_layout()
    plt.show()
```

In [8]:

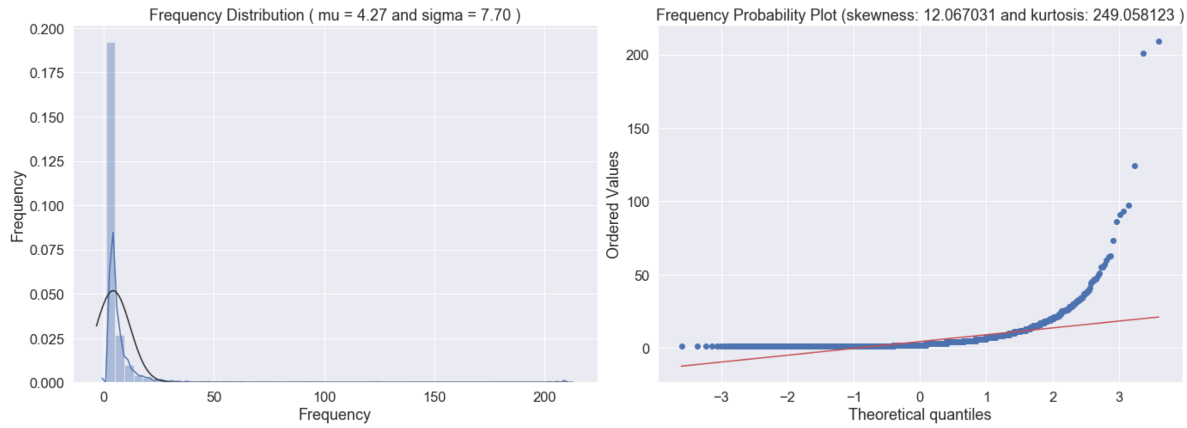
```
QQ_plot(customer_history_df.recency, 'Recency')
```



- Frequency

In [9]:

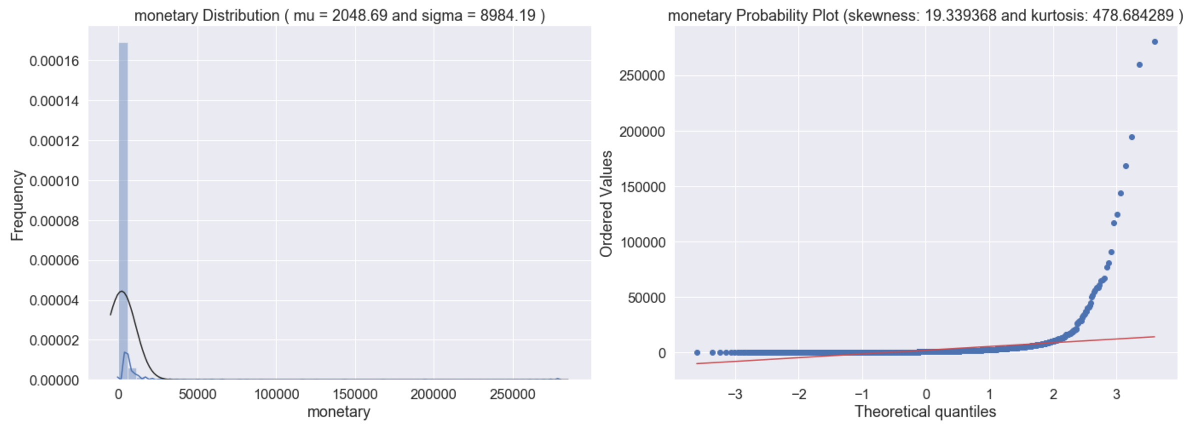
```
customer_freq = (df1[['CustomerID', 'InvoiceNo']].groupby(["CustomerID", 'InvoiceNo']).cour
                 groupby(["CustomerID"]).count().reset_index()
customer_freq.rename(columns={'InvoiceNo':'frequency'},inplace=True)
customer_history_df = customer_history_df.merge(customer_freq)
QQ_plot(customer_history_df.frequency, 'Frequency')
```



- Monetary Value

In [10]:

```

customer_monetary_val = df1[['CustomerID', 'amount']].groupby("CustomerID").sum().reset_inc
customer_history_df = customer_history_df.merge(customer_monetary_val)
customer_history_df.rename(columns={'amount':'monetary'}, inplace=True)
QQ_plot(customer_history_df.monetary, 'monetary')
```



In [11]:

```
customer_history_df.head()
```

Out[11]:

	CustomerID	recency	frequency	monetary
0	12346	326.0	1	77183.60
1	12347	2.0	7	4310.00
2	12348	75.0	4	1797.24
3	12349	19.0	1	1757.55
4	12350	310.0	1	334.40

In [12]:

```
customer_history_df.describe()
```

Out[12]:

	recency	frequency	monetary
count	4338.000000	4338.000000	4338.000000
mean	92.536422	4.272015	2048.688081
std	100.014169	7.697998	8985.230220
min	1.000000	1.000000	3.750000
25%	18.000000	1.000000	306.482500
50%	51.000000	2.000000	668.570000
75%	142.000000	5.000000	1660.597500
max	374.000000	209.000000	280206.020000

2). Assign a score for each dimension on a scale from 1 to 4 using quartile

In [13]:

```
# Use quantile to divide the RFM values
quantiles = customer_history_df.quantile(q=[0.25,0.5,0.75])
quantiles = quantiles.to_dict()
quantiles
```

Out[13]:

```
{'recency': {0.25: 18.0, 0.5: 51.0, 0.75: 142.0},
 'frequency': {0.25: 1.0, 0.5: 2.0, 0.75: 5.0},
 'monetary': {0.25: 306.48249999999996,
  0.5: 668.5699999999999,
  0.75: 1660.5975000000012}}
```

In [14]:

```
def Rscore(x,p,d):
    if x <= d[p][0.25]:
        return 1
    elif x <= d[p][0.50]:
        return 2
    elif x <= d[p][0.75]:
        return 3
    else:
        return 4

def FMscore(x,p,d):
    if x <= d[p][0.25]:
        return 4
    elif x <= d[p][0.50]:
        return 3
    elif x <= d[p][0.75]:
        return 2
    else:
        return 1
```

In [15]:

```
# Divide R,F,M values into four levels in the scale of 1-4
segment_rfm = customer_history_df.copy()
segment_rfm['r_quartile'] = segment_rfm['recency'].apply(Rscore, args=('recency',quantiles,
segment_rfm['f_quartile'] = segment_rfm['frequency'].apply(FMscore, args=('frequency',quant
segment_rfm['m_quartile'] = segment_rfm['monetary'].apply(FMscore, args=('monetary',quantil
segment_rfm.head()
```

Out[15]:

	CustomerID	recency	frequency	monetary	r_quartile	f_quartile	m_quartile
0	12346	326.0	1	77183.60	4	4	1
1	12347	2.0	7	4310.00	1	1	1
2	12348	75.0	4	1797.24	3	2	1
3	12349	19.0	1	1757.55	2	4	1
4	12350	310.0	1	334.40	4	4	3

3). Concate all scores in single RFM score

In [16]:

```
# Calculate RFM score = r*100+f*10+m, 111 is highest RFM score
segment_rfm['RFMScore'] = segment_rfm.r_quartile.map(str) \
                            + segment_rfm.f_quartile.map(str) \
                            + segment_rfm.m_quartile.map(str)

segment_rfm.head()
```

Out[16]:

	CustomerID	recency	frequency	monetary	r_quartile	f_quartile	m_quartile	RFMScore
0	12346	326.0	1	77183.60	4	4	1	441
1	12347	2.0	7	4310.00	1	1	1	111
2	12348	75.0	4	1797.24	3	2	1	321
3	12349	19.0	1	1757.55	2	4	1	241
4	12350	310.0	1	334.40	4	4	3	443

4). Segment customers according to their RFM sore

- 0 - 122, the most valuable customers, who are not very sensitive to the price. so this kind of customers could be selected to promote loyalty projects and new products
- 122 - 223, customers who are gradually lost, so email or channel promotion should be given to them.
- 223 - 333, valuable customers who are not very active recently, need to activate further by giving a discount or email promotion

how to segment customers would be varied mainly depending on company's operational capabilities

In [17]:

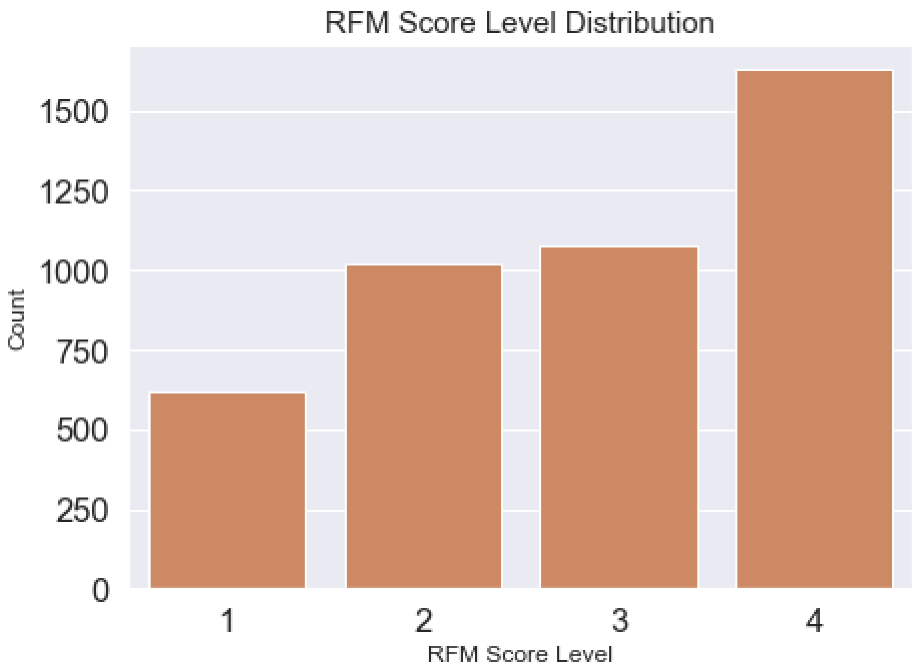
```
segment_rfm['RFMScore'] = segment_rfm['RFMScore'].astype(int)

def rfm_level(RFMScore):
    if (RFMScore >= 0 and RFMScore < 122):
        return '1'
    elif (RFMScore >= 122 and RFMScore < 223):
        return '2'
    elif (RFMScore >= 223 and RFMScore < 333):
        return '3'
    return '4'

segment_rfm['RFMScore_level'] = segment_rfm['RFMScore'].apply(rfm_level).astype(str)
segment_rfm.head()
```

Out[17]:

	CustomerID	recency	frequency	monetary	r_quartile	f_quartile	m_quartile	RFMScore	RFI
0	12346	326.0	1	77183.60	4	4	1	441	
1	12347	2.0	7	4310.00	1	1	1	111	
2	12348	75.0	4	1797.24	3	2	1	321	
3	12349	19.0	1	1757.55	2	4	1	241	
4	12350	310.0	1	334.40	4	4	3	443	

In [18]:

```
# Plot distribution of RFM score
plt.figure(figsize=(7,5))
sns.countplot(x='RFMScore_level',data=segment_rfm, color = color[1])
plt.ylabel('Count',fontsize=12)
plt.xlabel('RFM Score Level', fontsize=12)
plt.xticks()
plt.title('RFM Score Level Distribution',fontsize=15)
plt.show()
```



Part 2 Use K-means++ to segement customers

In [19]:

```
segment_rfm.describe()
```

Out[19]:

	recency	frequency	monetary	r_quartile	f_quartile	m_quartile	RFM
count	4338.000000	4338.000000	4338.000000	4338.000000	4338.000000	4338.000000	4338.0
mean	92.536422	4.272015	2048.688081	2.486169	2.679806	2.500000	277.9
std	100.014169	7.697998	8985.230220	1.126296	1.143825	1.118369	119.6
min	1.000000	1.000000	3.750000	1.000000	1.000000	1.000000	111.0
25%	18.000000	1.000000	306.482500	1.000000	2.000000	1.250000	144.0
50%	51.000000	2.000000	668.570000	2.000000	3.000000	2.500000	244.0
75%	142.000000	5.000000	1660.597500	3.000000	4.000000	3.750000	344.0
max	374.000000	209.000000	280206.020000	4.000000	4.000000	4.000000	444.0

In [23]:

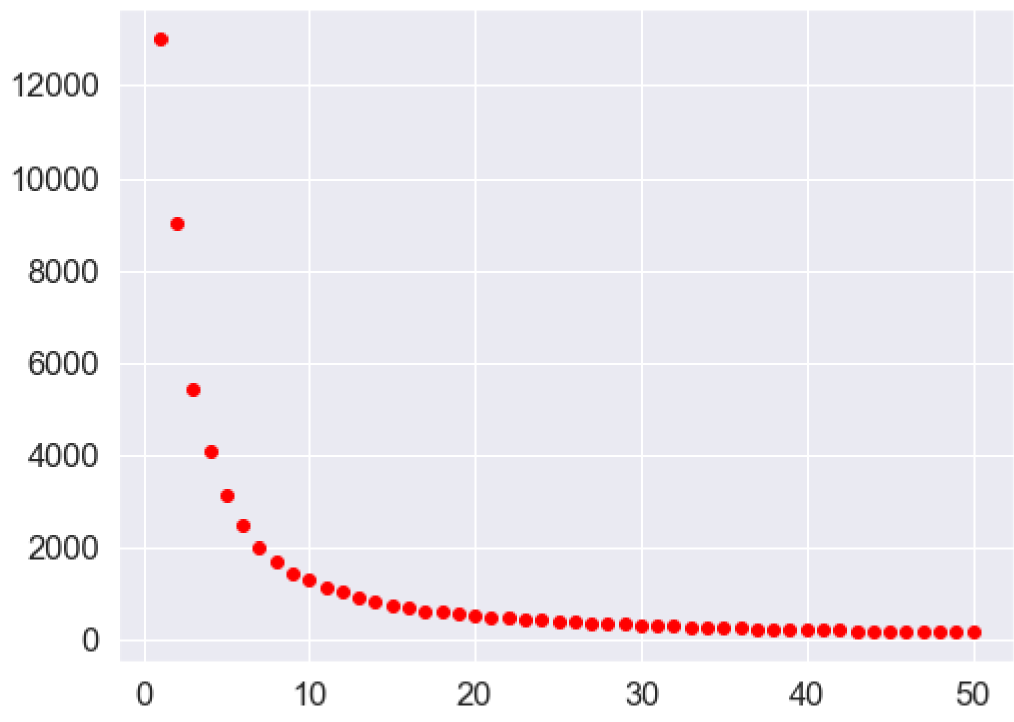
```
# Standardising the data

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
feature_vector = ['recency','frequency','monetary']
X_subset = customer_history_df[feature_vector]
X_scaled = scaler.fit_transform(X_subset)
pd.DataFrame(X_scaled, columns=X_subset.columns).describe()
```

Out[23]:

	recency	frequency	monetary
count	4.338000e+03	4.338000e+03	4.338000e+03
mean	2.702618e-17	1.801745e-17	-6.551800e-18
std	1.000115e+00	1.000115e+00	1.000115e+00
min	-9.153401e-01	-4.250965e-01	-2.276151e-01
25%	-7.453445e-01	-4.250965e-01	-1.939190e-01
50%	-4.153533e-01	-2.951776e-01	-1.536162e-01
75%	4.946227e-01	9.457903e-02	-4.319704e-02
max	2.814561e+00	2.659803e+01	3.096074e+01

In [24]:

```
# Choose the Right Number of Clusters using elbow curve
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 ensure that
    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, and the se
    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()
```



In [25]:

```
K_best
```

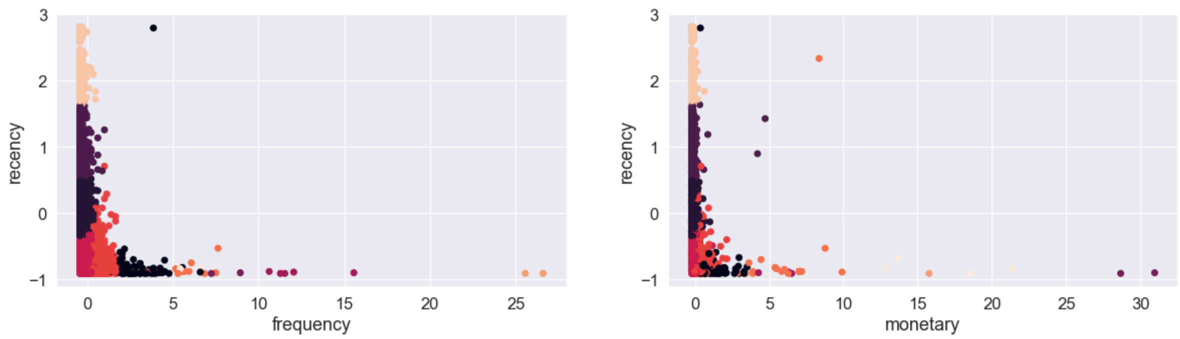
Out[25]:

```
11
```

In [26]:

```
# 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-04, ranc

# Note 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 the seconc
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:  11
```



In [28]:

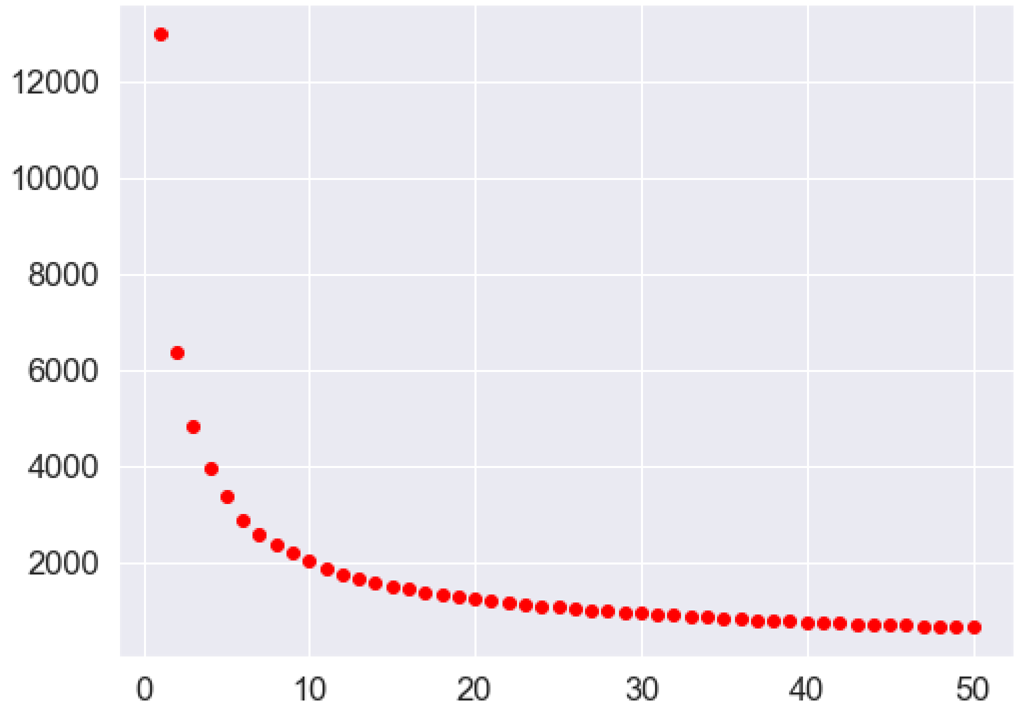
```
segment_rfm['recency_log'] = segment_rfm['recency'].apply(math.log)
segment_rfm['frequency_log'] = segment_rfm['frequency'].apply(math.log)
segment_rfm['monetary_log'] = segment_rfm['monetary'].apply(math.log)
scaler = StandardScaler()
feature_vector = ['recency_log','frequency_log','monetary_log']
X_subset = segment_rfm[feature_vector]
X_scaled = scaler.fit_transform(X_subset)
pd.DataFrame(X_scaled, columns=X_subset.columns).describe()
```

Out[28]:

	recency_log	frequency_log	monetary_log
count	4.338000e+03	4.338000e+03	4.338000e+03
mean	-1.048288e-16	-9.991495e-17	3.275900e-17
std	1.000115e+00	1.000115e+00	1.000115e+00
min	-2.630445e+00	-1.048610e+00	-4.172381e+00
25%	-6.124235e-01	-1.048610e+00	-6.820955e-01
50%	1.147066e-01	-2.790440e-01	-6.385708e-02
75%	8.296516e-01	7.382675e-01	6.572740e-01
max	1.505796e+00	4.882714e+00	4.722173e+00

In [29]:

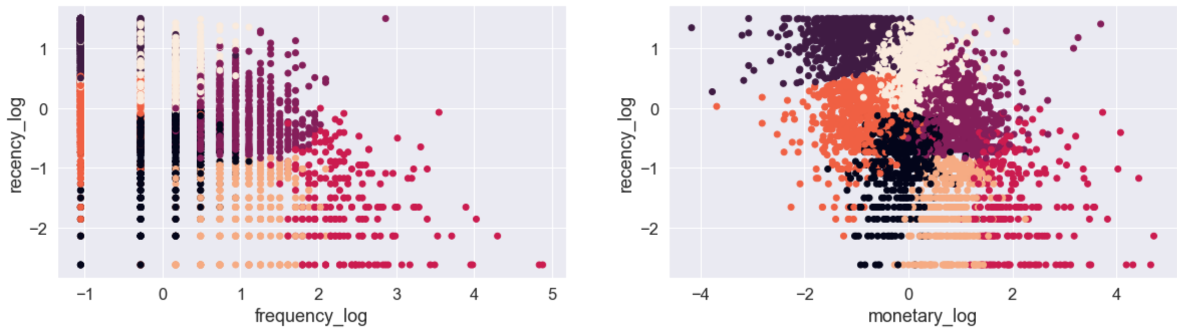
```
cl = 50
corte = 0.1

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 ensure that
    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, and the se
    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()
```



In [30]:

```
# 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-04, ranc

# Note 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 the seconc
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 [ ]: