Customer Behavior Analytics

The importance of customer analytics is rising: because access to customer data became easier for many businesses, and also customers now have easier access to data and information on similar products and contents provided by other competitors, it is critical to many businesses to be able to understand and predict what their customers are likely to purchase or view. The deeper the understanding your company has about its customers, the better competitive power it will have against its competitors.

In [1]:
```
%matplotlib inline
import matplotlib.pyplot as plt
import pandas as pd
```

In [3]:
```
cb_df = pd.read_csv(r'F:\Prthon Programming\Marketing Customer Value\WA_Fn-UseC_-Marketing-Customer-Value-Analysis.csv')
```

In [5]:
```
cb_df.shape
```

Out[5]:
```
(9134, 24)
```

In [6]:
```
cb_df.head()
```

Out[6]:

	Customer	State	Customer Lifetime Value	Response	Coverage	Education	Effective To Date	EmploymentS
0	BU79786	Washington	2763.519279	No	Basic	Bachelor	2/24/11	Em
1	QZ44356	Arizona	6979.535903	No	Extended	Bachelor	1/31/11	Unem
2	AI49188	Nevada	12887.431650	No	Premium	Bachelor	2/19/11	Em
3	WW63253	California	7645.861827	No	Basic	Bachelor	1/20/11	Unem
4	HB64268	Washington	2813.692575	No	Basic	Bachelor	2/3/11	Em

5 rows × 24 columns

In [7]:
```
cb_df.columns
```

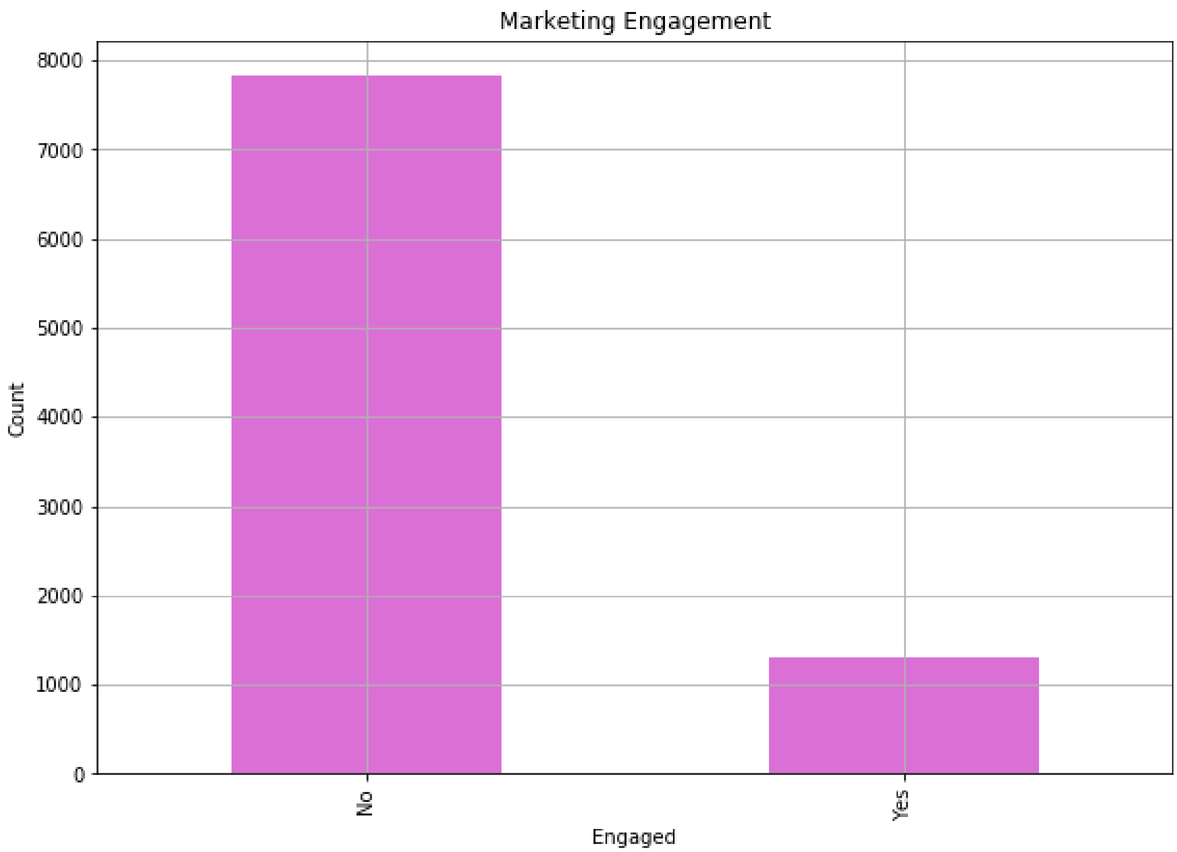
Out[7]:
```
Index(['Customer', 'State', 'Customer Lifetime Value', 'Response', 'Coverag
e',
       'Education', 'Effective To Date', 'EmploymentStatus', 'Gender',
       'Income', 'Location Code', 'Marital Status', 'Monthly Premium Auto',
       'Months Since Last Claim', 'Months Since Policy Inception',
       'Number of Open Complaints', 'Number of Policies', 'Policy Type',
       'Policy', 'Renew Offer Type', 'Sales Channel', 'Total Claim Amount',
       'Vehicle Class', 'Vehicle Size'],
      dtype='object')
```

In [ ]:
```
#We are going to analyze it to understand how different customers behave and r
eact to different marketing strategies.
```

In [8]:
```
cb_df.groupby('Response').count()['Customer'] # Get the total number of custom
ers who have responded
```

Out[8]:
```
Response
No     7826
Yes    1308
Name: Customer, dtype: int64
```

In [13]:
```
# Visualize this in a bar plot
ax = cb_df.groupby('Response').count()['Customer'].plot(
    kind='bar',
    color='orchid',
    grid=True,
    figsize=(10, 7),
    title='Marketing Engagement')

ax.set_xlabel('Engaged')
ax.set_ylabel('Count')
plt.show()
```



In [15]:
```
# Calculate the percentages of the engaged and non-engaged customers
cb_df.groupby('Response').count()['Customer']/df.shape[0]
```

Out[15]:
```
Response
No     0.856799
Yes    0.143201
Name: Customer, dtype: float64
```

From this output and from the plot, we can see that only about 14% of the customers responded to the marketing calls.

The Renew Offer Type column in this DataFrame contains the type of the renewal offer presented to the customers. We are going to look into what types of offers worked best for the engaged customers.

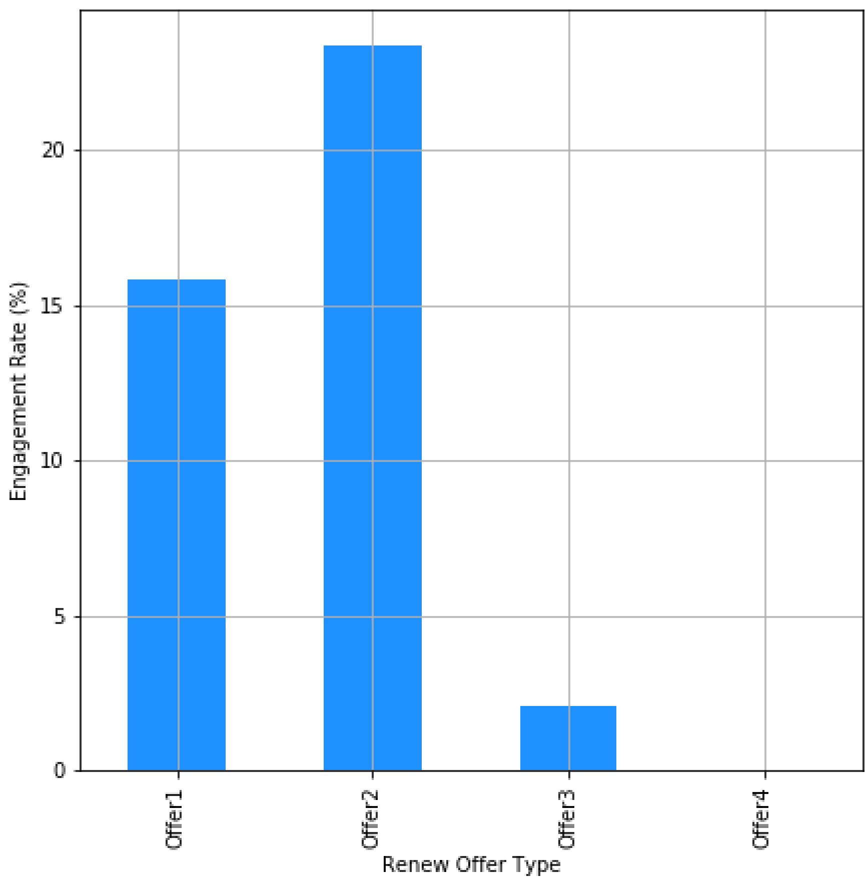
In [22]:

```
# count only engaged customers
# engaged customers grouped by renewal offer type
by_offer_type_df = cb_df.loc[cb_df['Response'] == 'Yes',].groupby(['Renew Offe
r Type']).count()['Customer']
/ cb_df.groupby('Renew Offer Type').count()['Customer']

by_offer_type_df
```

Out[22]:

```
Renew Offer Type
Offer1    0.158316
Offer2    0.233766
Offer3    0.020950
Offer4         NaN
Name: Customer, dtype: float64
```

In [23]:
```
# Visualize it in a bar plot
ax = (by_offer_type_df*100.0).plot(
    kind='bar',
    figsize=(7, 7),
    color='dodgerblue',
    grid=True)

ax.set_ylabel('Engagement Rate (%)')
plt.show()
```



We are going to understand how customers with different attributes respond differently to different marketing messages. We start looking at the engagements rates by each offer type and vehicle class.

In [25]:
```
by_offer_type_df = df.loc[df['Response'] == 'Yes' # engaged customers
                         ].groupby([
                        'Renew Offer Type', 'Vehicle Class' # grouping the dat
a by these two columns
                        ]).count()['Customer'] / df.groupby('Renew Offer Type'
).count()['Customer']# rates for 5
by_offer_type_df
```

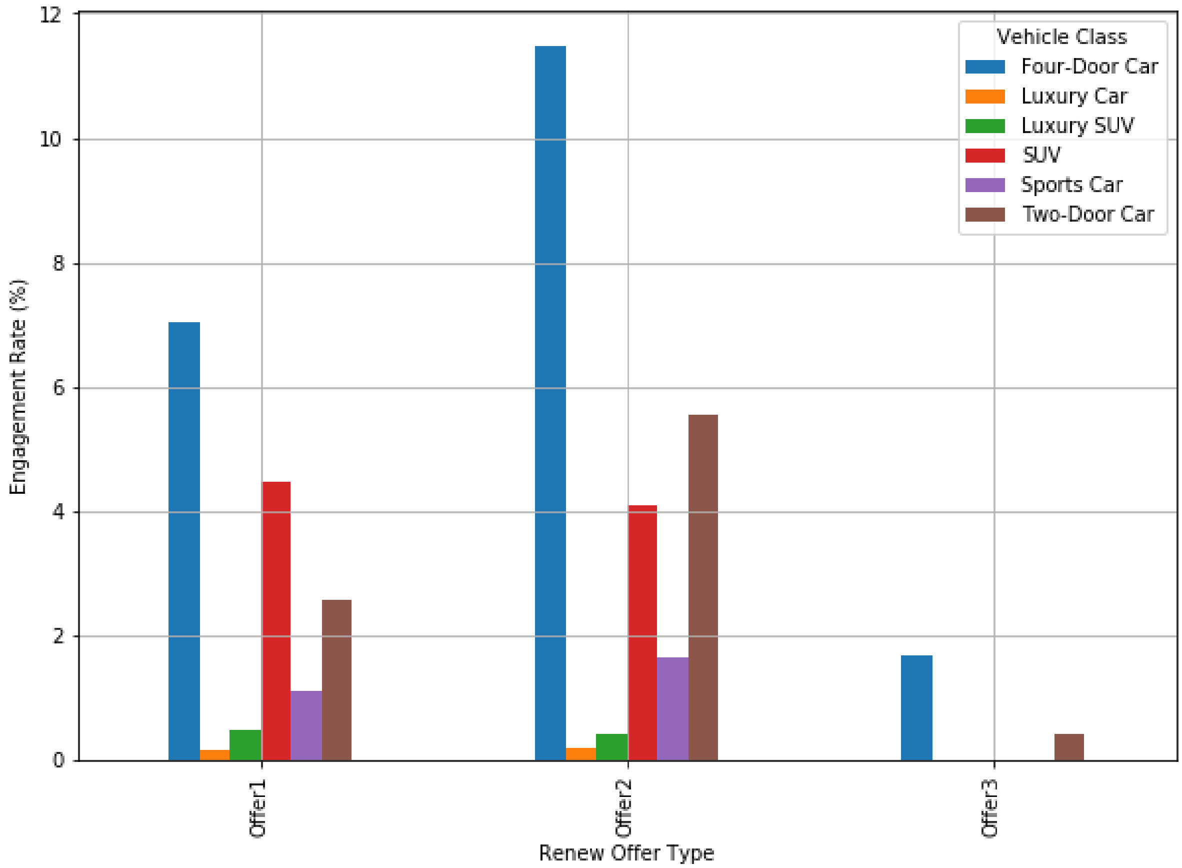
Out[25]:
```
Renew Offer Type  Vehicle Class
Offer1            Four-Door Car    0.070362
                  Luxury Car       0.001599
                  Luxury SUV       0.004797
                  SUV              0.044776
                  Sports Car       0.011194
                  Two-Door Car     0.025586
Offer2            Four-Door Car    0.114833
                  Luxury Car       0.002051
                  Luxury SUV       0.004101
                  SUV              0.041012
                  Sports Car       0.016405
                  Two-Door Car     0.055366
Offer3            Four-Door Car    0.016760
                  Two-Door Car     0.004190
Name: Customer, dtype: float64
```

In [26]:
```
# Make the previous output more readable using unstack function
# to pivot the data and extract and transform the inner-level groups to column
s
by_offer_type_df = by_offer_type_df.unstack().fillna(0)
by_offer_type_df
```

Out[26]:

Vehicle Class Renew Offer Type	Four-Door Car	Luxury Car	Luxury SUV	SUV	Sports Car	Two-Door Car
Offer1	0.070362	0.001599	0.004797	0.044776	0.011194	0.025586
Offer2	0.114833	0.002051	0.004101	0.041012	0.016405	0.055366
Offer3	0.016760	0.000000	0.000000	0.000000	0.000000	0.004190

In [27]:
```
# Visualize this data in bar plot
ax = (by_offer_type_df*100.0).plot(
kind='bar',
figsize=(10, 7),
grid=True
)
ax.set_ylabel('Engagement Rate (%)')
plt.show()
```

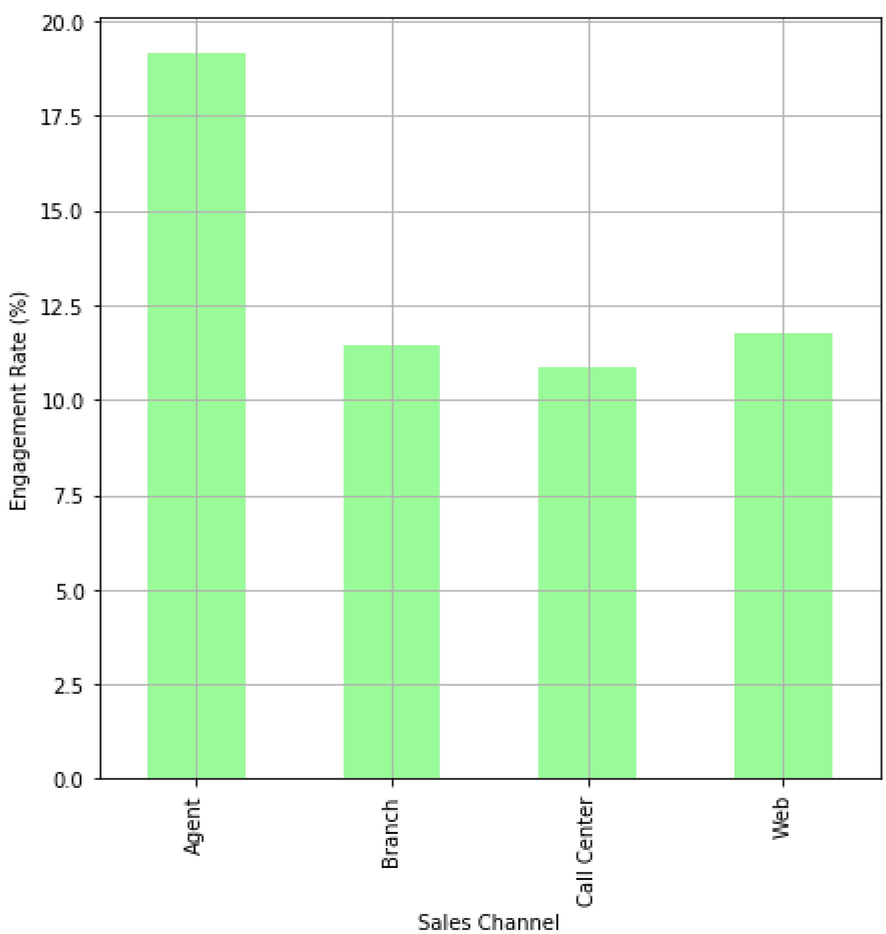


We already knew from the previous section “Engagement Rates by Offer Type” that Offer2 had the highest response rate among customers. Now we can add more insights by having broken down the customer attributes with the category “Vehicle class”: we can notice that customers with Four-Door Car respond more frequently for all offer types and that those with “Luxury SUV” respond with a higher chance to Offer1 than to Offer2. If we have significantly difference in the response rates among different customer rates, we can fine-tune who to target for different set of offers.

In [28]:
```
#We are going to analyze how engagement rates differ by different sales channe
ls.
by_sales_channel_df = df.loc[
df['Response'] == 'Yes'
].groupby([
'Sales Channel'
]).count()['Customer']/df.groupby('Sales Channel').count()['Customer']
by_sales_channel_df
```

Out[28]:
```
Sales Channel
Agent          0.191544
Branch         0.114531
Call Center    0.108782
Web            0.117736
Name: Customer, dtype: float64
```

In [29]:
```
ax = (by_sales_channel_df*100.0).plot(
kind='bar',
figsize=(7, 7),
color='palegreen',
grid=True
)
ax.set_ylabel('Engagement Rate (%)')
plt.show()
```



As we can notice, Agent works better in term of getting responses from the customers, and then sales throughWeb works the second best. Let's go ahead in breaking down this result deeper with different customers' attributes.

In [30]:
```
#We are going to see whether customers with various vehicle sizes respond diff
erently to different sales channels.
by_sales_channel_df = df.loc[
df['Response'] == 'Yes'
].groupby([
'Sales Channel', 'Vehicle Size'
]).count()['Customer'] / df.groupby('Sales Channel').count()['Customer']
by_sales_channel_df
```

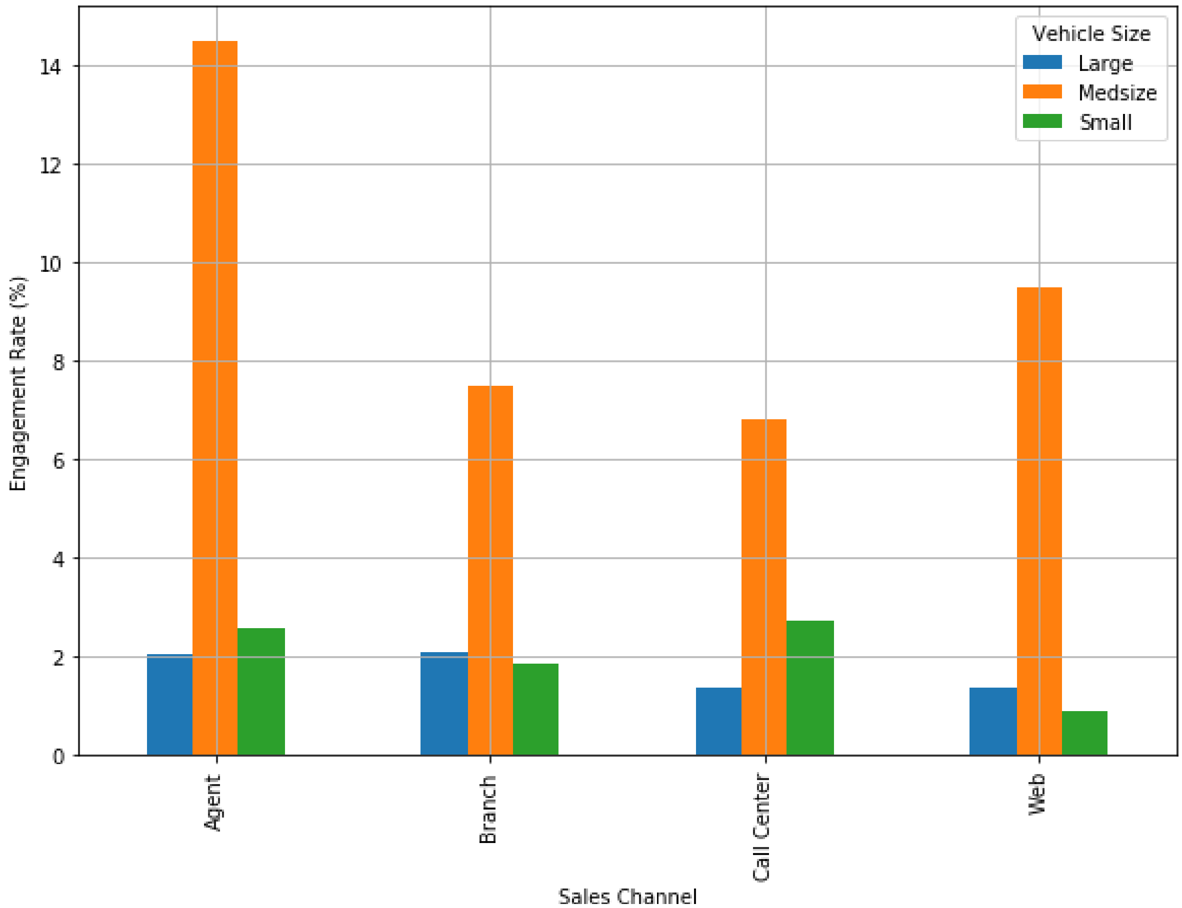
Out[30]:
```
Sales Channel  Vehicle Size
Agent          Large           0.020708
               Medsize         0.144953
               Small           0.025884
Branch         Large           0.021036
               Medsize         0.074795
               Small           0.018699
Call Center    Large           0.013598
               Medsize         0.067989
               Small           0.027195
Web            Large           0.013585
               Medsize         0.095094
               Small           0.009057
Name: Customer, dtype: float64
```

In [31]:
```
# Unstack the data into a more visible format
by_sales_channel_df = by_sales_channel_df.unstack().fillna(0)
by_sales_channel_df
```

Out[31]:

Vehicle Size	Large	Medsize	Small
Sales Channel			
Agent	0.020708	0.144953	0.025884
Branch	0.021036	0.074795	0.018699
Call Center	0.013598	0.067989	0.027195
Web	0.013585	0.095094	0.009057

In [34]:
```
ax = (by_sales_channel_df*100.0).plot(
kind='bar',
figsize=(10, 7),
grid=True
)
ax.set_ylabel('Engagement Rate (%)')
plt.show()
```



As we can see, customers with medium size vehicles respond the best to all sales channels whereas the other customers differs slightly in terms of engagement rates across different sales channels.

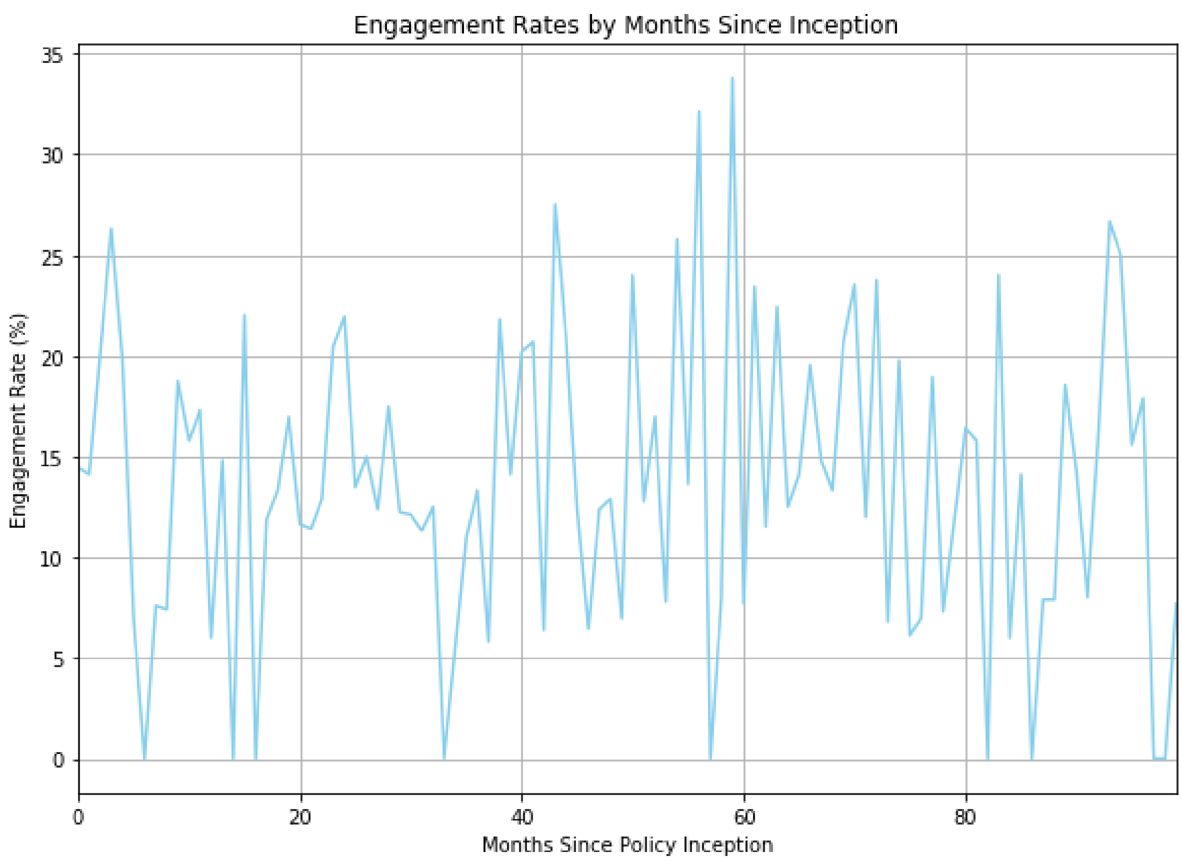
In [35]:
```
#Engagement Rates by Months Since Policy Inception
by_months_since_inception_df = df.loc[
df['Response'] == 'Yes'
].groupby(
by='Months Since Policy Inception'
)['Response'].count() / df.groupby(
by='Months Since Policy Inception'
)['Response'].count() * 100.0
by_months_since_inception_df.fillna(0)
```

Out[35]:

```
Months Since Policy Inception
0     14.457831
1     14.117647
2     20.224719
3     26.315789
4     19.780220
5      6.896552
6      0.000000
7      7.594937
8      7.407407
9     18.750000
10    15.789474
11    17.307692
12     6.000000
13    14.814815
14     0.000000
15    22.018349
16     0.000000
17    11.881188
18    13.333333
19    16.981132
20    11.650485
21    11.428571
22    12.903226
23    20.454545
24    21.951220
25    13.483146
26    15.000000
27    12.371134
28    17.475728
29    12.244898
        ...
70    23.529412
71    12.000000
72    23.762376
73     6.818182
74    19.780220
75     6.122449
76     6.976744
77    18.947368
78     7.317073
79    11.881188
80    16.438356
81    15.789474
82     0.000000
83    24.000000
84     6.000000
85    14.117647
86     0.000000
87     7.894737
88     7.894737
89    18.556701
90    14.285714
91     8.000000
92    16.216216
93    26.666667
94    25.000000
```

```
95    15.584416
96    17.910448
97     0.000000
98     0.000000
99     7.692308
Name: Response, Length: 100, dtype: float64
```

In [36]:
```
ax = by_months_since_inception_df.fillna(0).plot(
figsize=(10, 7),
title='Engagement Rates by Months Since Inception',
grid=True,
color='skyblue'
)
ax.set_xlabel('Months Since Policy Inception')
ax.set_ylabel('Engagement Rate (%)')
plt.show()
```



In [37]:
```
# We are going to segment our customer base by Customer Lifetime Value and Mon
ths Since Policy Inception.
# Take a look at the distribution of the CLV
df['Customer Lifetime Value'].describe()
```

Out[37]:
```
count     9134.000000
mean      8004.940475
std       6870.967608
min       1898.007675
25%       3994.251794
50%       5780.182197
75%       8962.167041
max      83325.381190
Name: Customer Lifetime Value, dtype: float64
```

For the previous output, we are going to define those customers with a CLV higher than the median as high-CLV customers, and those with a CLV lower than the median as low-CLV customers.

In [39]:
```
df['CLV Segment'] = df['Customer Lifetime Value'].apply(lambda x: 'High' if x
> df['Customer Lifetime Value']
                                                   .median() else 'Low')
```

In [40]:
```
# Do the same procedure for Months Since Policy Inception
df['Months Since Policy Inception'].describe()
```

Out[40]:
```
count    9134.000000
mean       48.064594
std        27.905991
min         0.000000
25%        24.000000
50%        48.000000
75%        71.000000
max        99.000000
Name: Months Since Policy Inception, dtype: float64
```

In [41]:
```
df['Policy Age Segment'] = df['Months Since Policy Inception'].apply(lambda x:
'High' if x >
                                                                  df['Month
s Since Policy Inception'].median() else 'Low')
```

In [42]:
```
df.head()
```

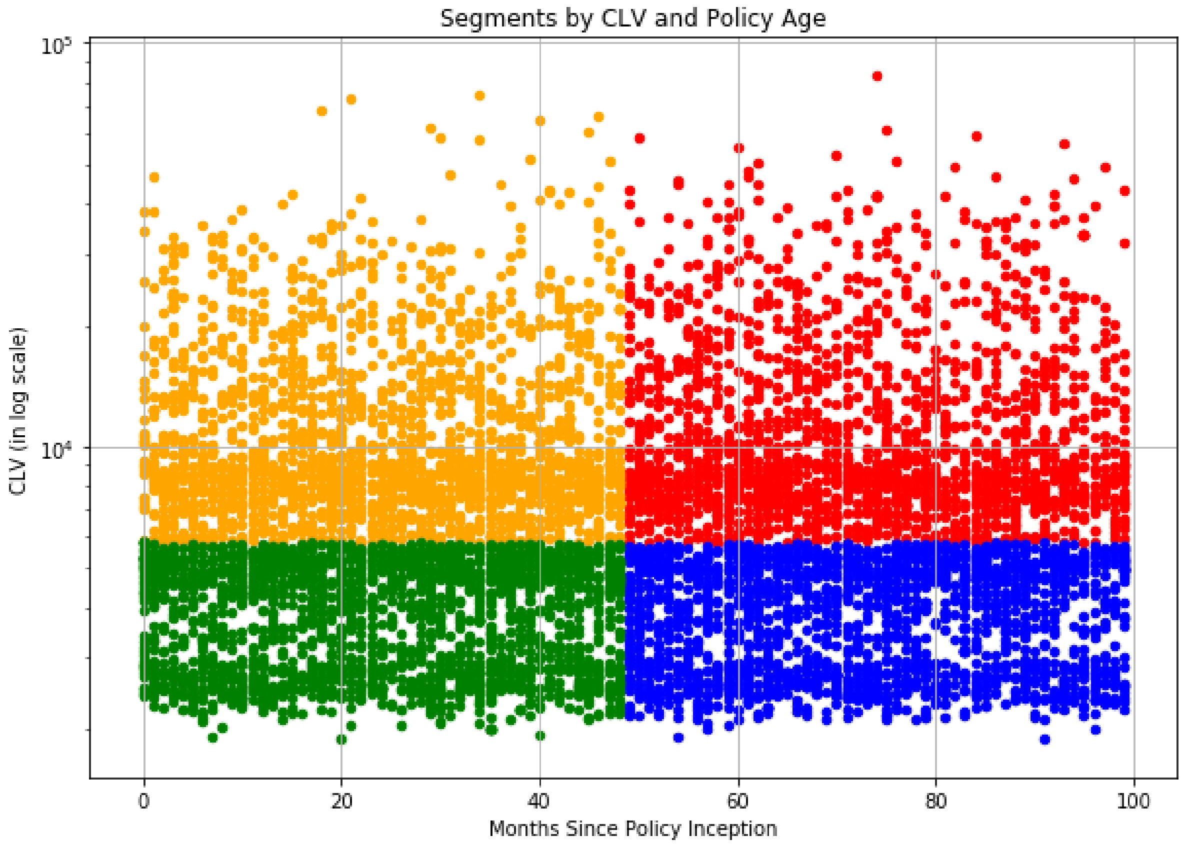
Out[42]:

	Customer	State	Customer Lifetime Value	Response	Coverage	Education	Effective To Date	EmploymentS
0	BU79786	Washington	2763.519279	No	Basic	Bachelor	2/24/11	Em
1	QZ44356	Arizona	6979.535903	No	Extended	Bachelor	1/31/11	Unem
2	AI49188	Nevada	12887.431650	No	Premium	Bachelor	2/19/11	Em
3	WW63253	California	7645.861827	No	Basic	Bachelor	1/20/11	Unem
4	HB64268	Washington	2813.692575	No	Basic	Bachelor	2/3/11	Em

5 rows × 26 columns

In [44]:

```
# Visualize these segments
ax = df.loc[
(df['CLV Segment'] == 'High') & (df['Policy Age Segment'] == 'High')
].plot.scatter(
x='Months Since Policy Inception',
y='Customer Lifetime Value',
logy=True,
color='red')

df.loc[
(df['CLV Segment'] == 'Low') & (df['Policy Age Segment'] == 'High')
].plot.scatter(
ax=ax,
x='Months Since Policy Inception',
y='Customer Lifetime Value',
logy=True,
color='blue')

df.loc[
(df['CLV Segment'] == 'High') & (df['Policy Age Segment'] == 'Low')
].plot.scatter(
ax=ax,
x='Months Since Policy Inception',
y='Customer Lifetime Value',
logy=True,
color='orange')

df.loc[
(df['CLV Segment'] == 'Low') & (df['Policy Age Segment'] == 'Low')
].plot.scatter(
ax=ax,
x='Months Since Policy Inception',
y='Customer Lifetime Value',
logy=True,
color='green',
grid=True,
figsize=(10, 7))

ax.set_ylabel('CLV (in log scale)')
ax.set_xlabel('Months Since Policy Inception')
ax.set_title('Segments by CLV and Policy Age')
plt.show()
```

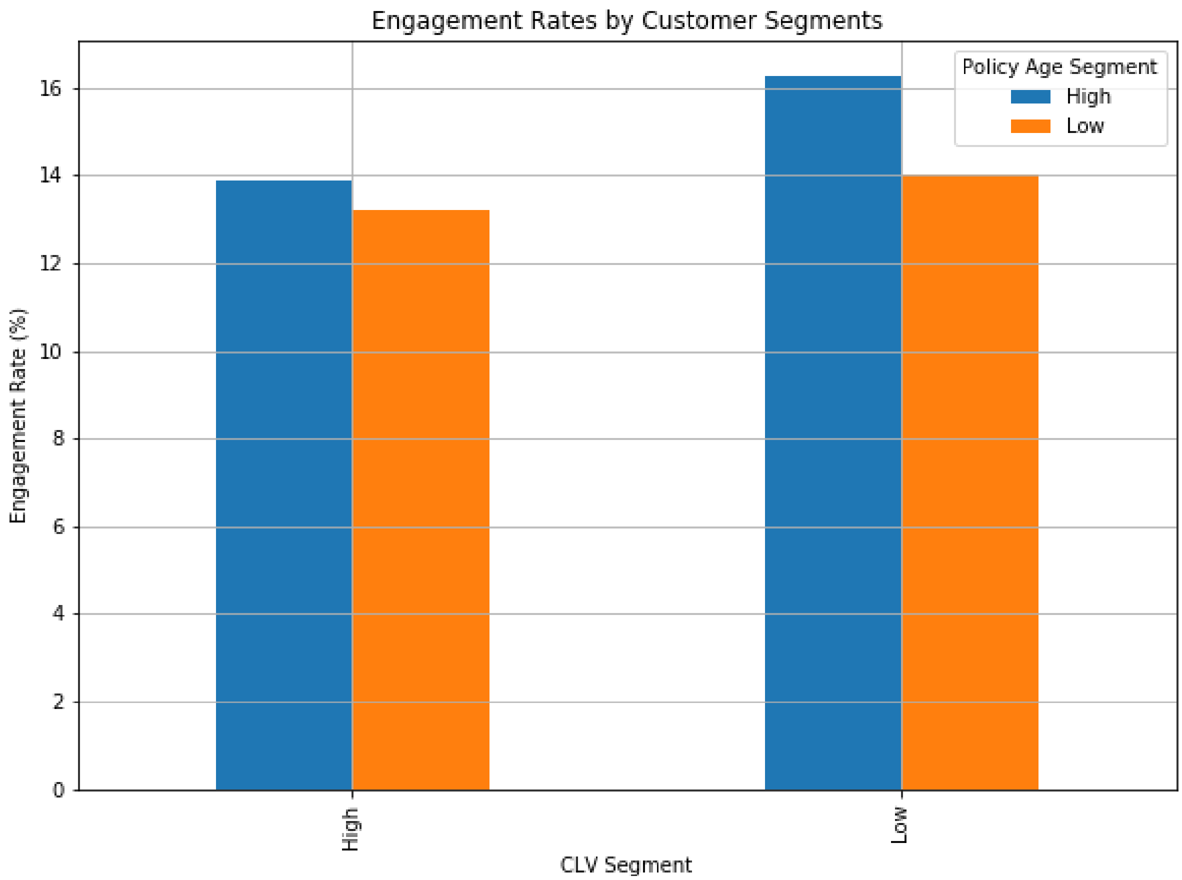


logy=True transform the scale to log scale and it is often used for monetary values as they often have high skewness in their values. We have repeated the code for the plot.scatter 4 times because we have created 4 segments.

In [48]:
```
# See whether there is any noticeable difference in the engagement rates among these four
engagement_rates_by_segment_df = df.loc[
df['Response'] == 'Yes'].groupby([
    'CLV Segment', 'Policy Age Segment']). count()['Customer'] / df.groupby([
'CLV Segment', 'Policy Age Segment'
                                                                          ])
.count()['Customer']
engagement_rates_by_segment_df
```

Out[48]:
```
CLV Segment  Policy Age Segment
High         High                  0.138728
             Low                   0.132067
Low          High                  0.162450
             Low                   0.139957
Name: Customer, dtype: float64
```

In [49]:
```
# Look at these differences in a chart
ax = (engagement_rates_by_segment_df.unstack()*100.0).plot(
kind='bar',
figsize=(10, 7),
grid=True
)
ax.set_ylabel('Engagement Rate (%)')
ax.set_title('Engagement Rates by Customer Segments')
plt.show()
```



As we can notice, High Policy Age Segment has higher engagement than the Low Policy Age Segment. This suggests that those customers who have been insured by this company longer respond better. Moreover, the High Policy Age and Low CLV segment has the highest engagement rate among the four segments. By creating different customer segments based on customer attributes, we can better understand how different groups of customers behave differently, and consequently, use this information to customize the marketing messagges.

In [ ]:

```
```

In [ ]:

```
```