CustomerAnalytics_CustomerBehavior

May 29, 2019

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
```

```
In [2]: import matplotlib.pyplot as plt
        import pandas as pd
```

1 1. Load Data

This data set is one of the publicly available datasets from IBM at the following link: https://https:www.ibm.com/communities/analytics/watson-analytics-blog/marketing-customer-value-analysis/

```
In [3]: df = pd.read_csv('Data/WA_Fn-UseC_-Marketing-Customer-Value-Analysis.csv')
```

```
In [4]: df.shape
```

```
Out[4]: (9134, 24)
```

```
In [5]: df.head()
```

```
Out[5]:   Customer       State  Customer Lifetime Value Response  Coverage Education  \
        0  BU79786  Washington              2763.519279       No     Basic  Bachelor
        1  QZ44356     Arizona              6979.535903       No  Extended  Bachelor
        2  AI49188      Nevada             12887.431650       No   Premium  Bachelor
        3  WW63253  California              7645.861827       No     Basic  Bachelor
        4  HB64268  Washington              2813.692575       No     Basic  Bachelor

          Effective To Date EmploymentStatus Gender  Income  ...  \
        0           2/24/11         Employed      F   56274  ...
        1           1/31/11       Unemployed      F       0  ...
        2           2/19/11         Employed      F   48767  ...
        3           1/20/11       Unemployed      M       0  ...
```

```
4           2/3/11        Employed      M   43836  ...

  Months Since Policy Inception Number of Open Complaints  Number of Policies  \
0                             5                         0                   1
1                            42                         0                   8
2                            38                         0                   2
3                            65                         0                   7
4                            44                         0                   1

      Policy Type        Policy  Renew Offer Type  Sales Channel  \
0  Corporate Auto  Corporate L3            Offer1          Agent
1   Personal Auto   Personal L3            Offer3          Agent
2   Personal Auto   Personal L3            Offer1          Agent
3  Corporate Auto  Corporate L2            Offer1    Call Center
4   Personal Auto   Personal L1            Offer1          Agent

  Total Claim Amount  Vehicle Class Vehicle Size
0         384.811147   Two-Door Car      Medsize
1        1131.464935  Four-Door Car      Medsize
2         566.472247   Two-Door Car      Medsize
3         529.881344            SUV      Medsize
4         138.130879  Four-Door Car      Medsize

[5 rows x 24 columns]
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['Customer', 'State', 'Customer Lifetime Value', 'Response', 'Coverage',
       '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')
```

2 2. Analytics on Engaged Customers

We are going to analyze it to understand how different customers behave and react to different marketing strategies.

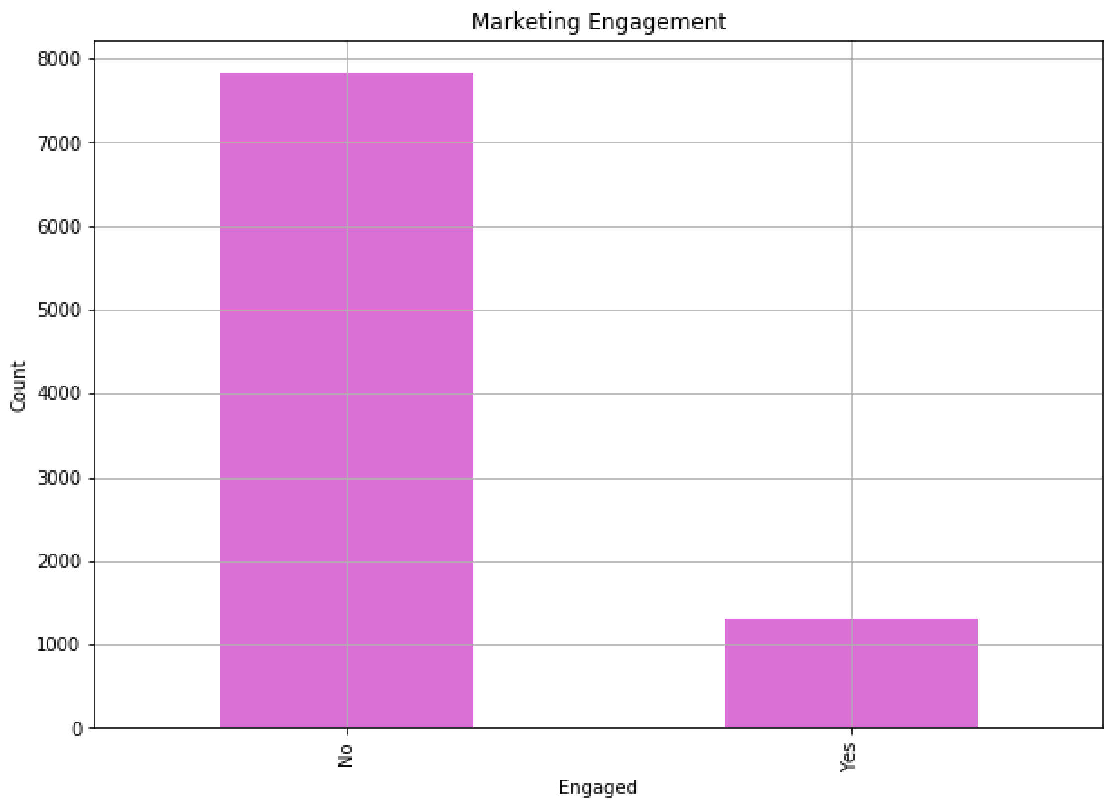
2.1 - Overall Engagement Rate

The Response field contains information about whether a customer responded to the marketing efforts.

In [7]:
```
# Get the total number of customers who have responded

df.groupby('Response').count()['Customer']
```

Out[7]: Response
```
No      7826
Yes     1308
Name: Customer, dtype: int64
```

In [8]:
```
# Visualize this in a bar plot

ax = 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 [9]:
```
# Calculate the percentages of the engaged and non-engaged customers

df.groupby('Response').count()['Customer']/df.shape[0]
```

```
Out[9]: 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.

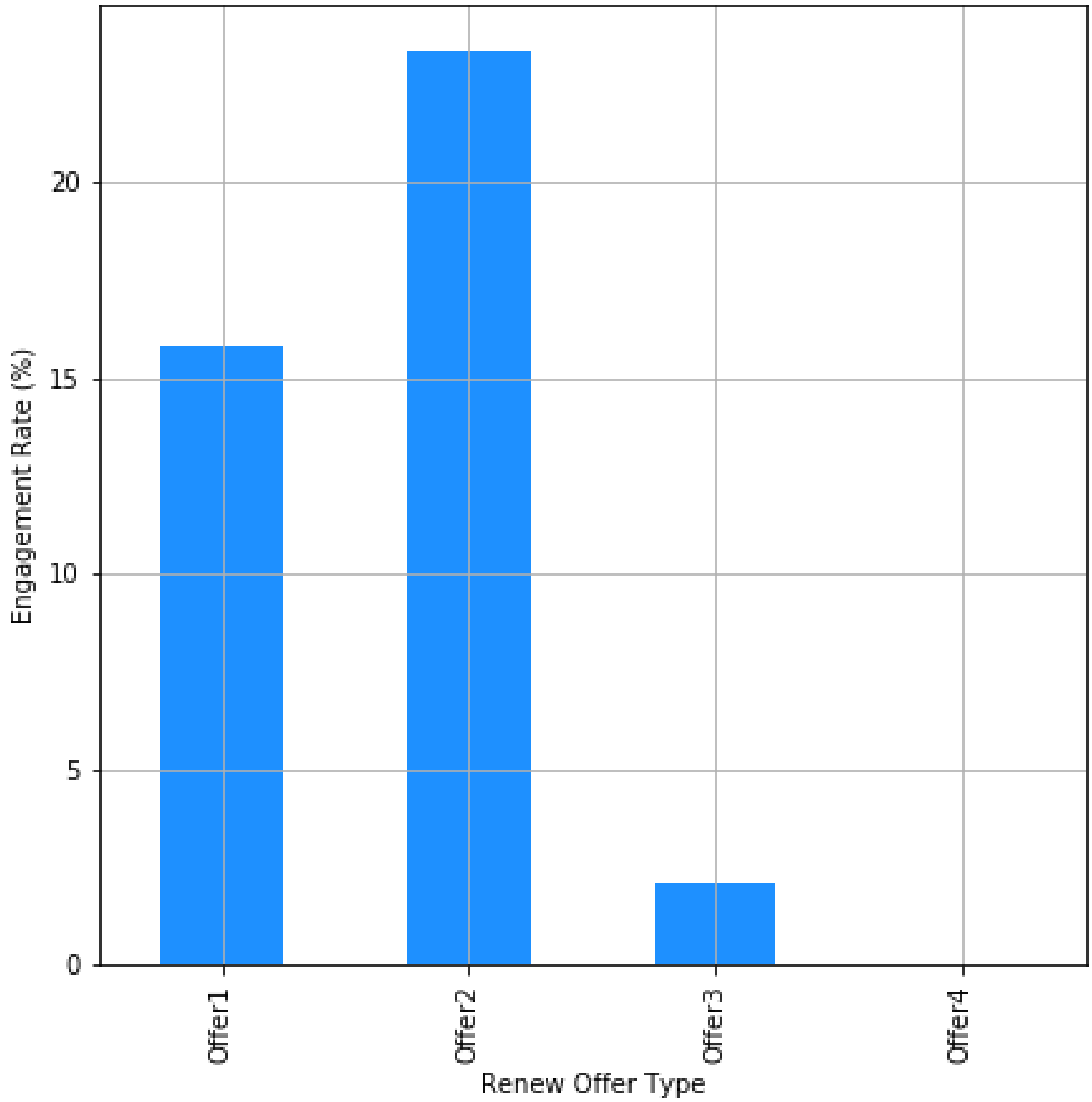
2.2 - Engagement Rates by Offer Type

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 [10]: # Get the engagement rates per renewal offer type

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

         by_offer_type_df
```

```
Out[10]: Renew Offer Type
         Offer1    0.158316
         Offer2    0.233766
         Offer3    0.020950
         Offer4         NaN
         Name: Customer, dtype: float64
```

```
In [11]: # 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()
```



As we can see, **Offer2** had the highest engagement rate among the customers

2.3 - Offer Type & Vehicle Class

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 [12]: by_offer_type_df = df.loc[
             df['Response'] == 'Yes' # engaged customers
         ].groupby([
             'Renew Offer Type', 'Vehicle Class' # grouping the data by these two columns
         ]).count()['Customer']  / df.groupby('Renew Offer Type').count()['Customer']# rates f
```

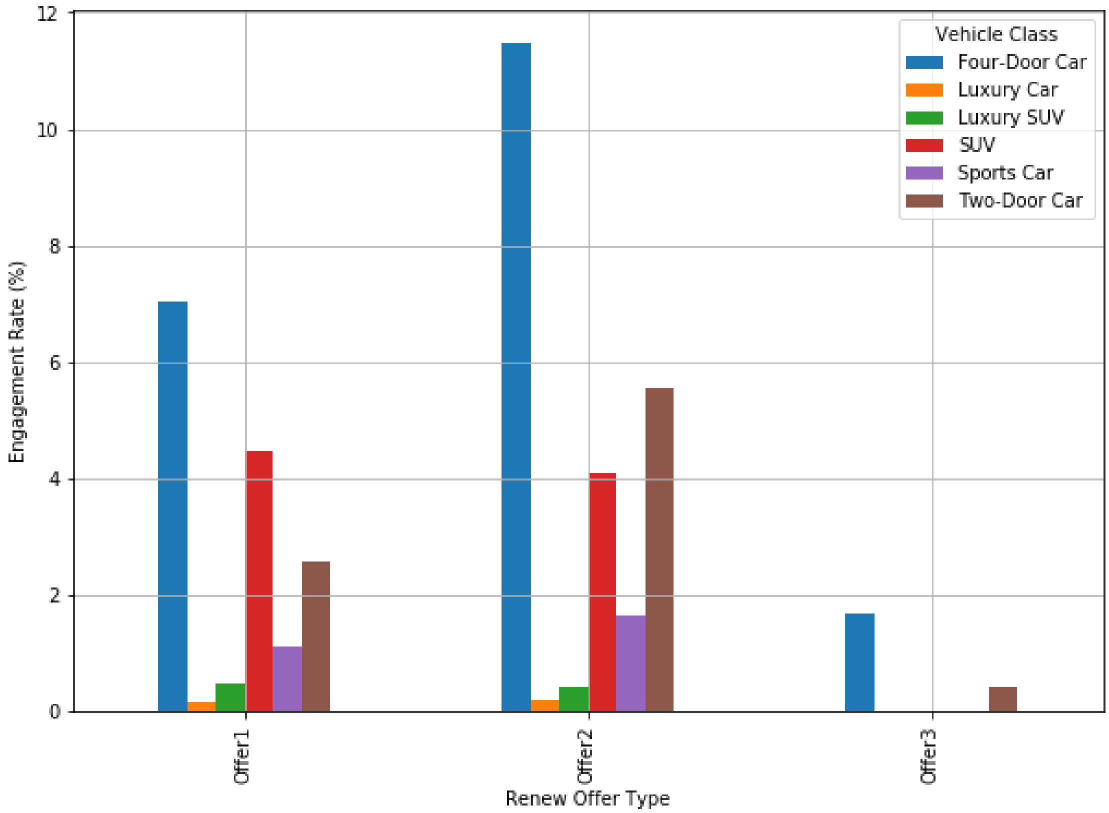
```
by_offer_type_df
```

```
Out[12]: 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 [13]: # Make the previous output more readable using unstack function
         # to pivot the data and extract and transform the inner-level groups to columns

         by_offer_type_df = by_offer_type_df.unstack().fillna(0)
         by_offer_type_df
```

```
Out[13]: Vehicle Class     Four-Door Car  Luxury Car  Luxury SUV       SUV  Sports Car  \
         Renew Offer Type
         Offer1                 0.070362    0.001599    0.004797  0.044776    0.011194
         Offer2                 0.114833    0.002051    0.004101  0.041012    0.016405
         Offer3                 0.016760    0.000000    0.000000  0.000000    0.000000

         Vehicle Class     Two-Door Car
         Renew Offer Type
         Offer1                0.025586
         Offer2                0.055366
         Offer3                0.004190
```

```
In [14]: # 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.**

2.4 - Engagement Rates by Sales Channel

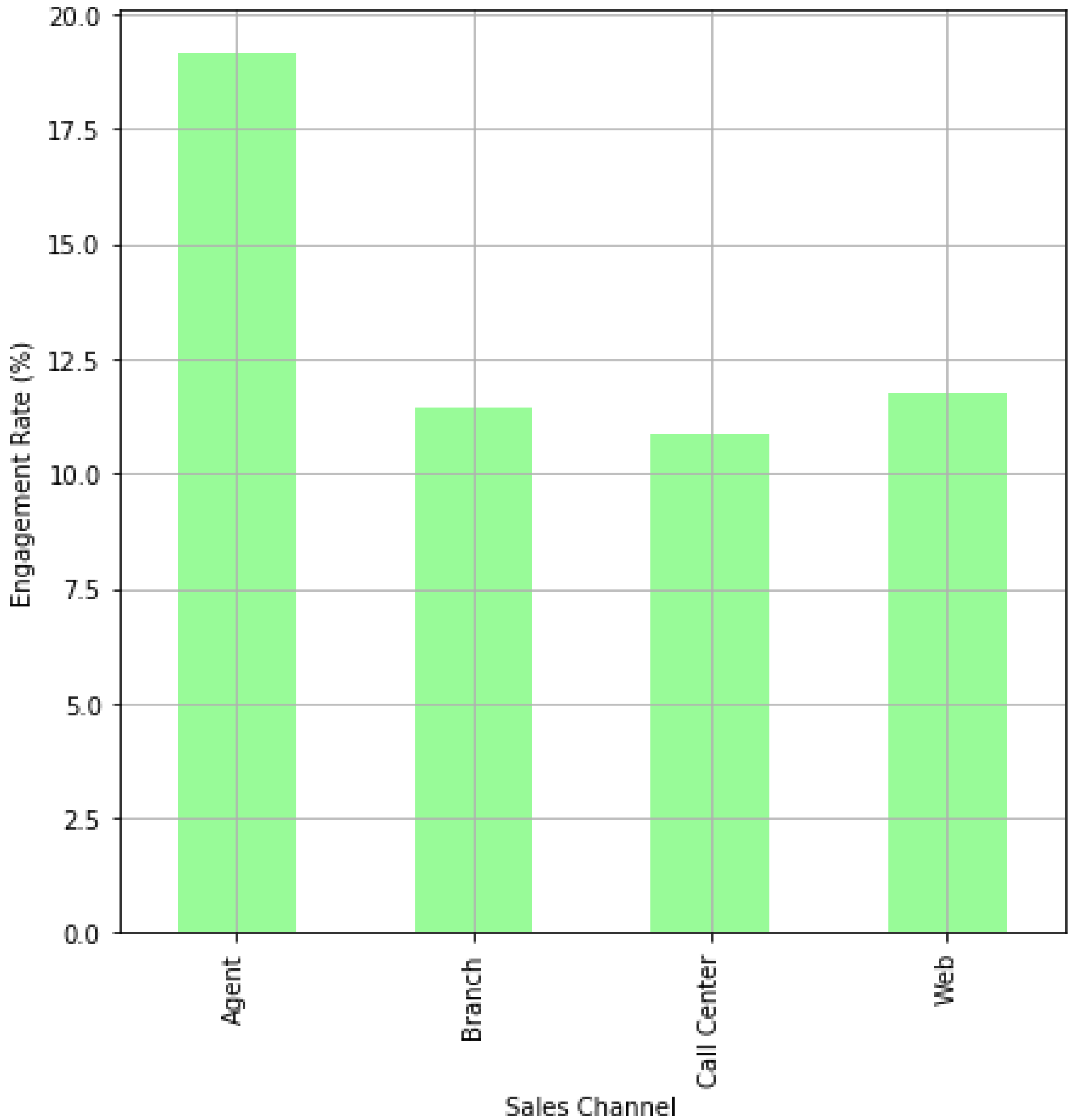
We are going to analyze how engagement rates differ by different sales channels.

```
In [15]: 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[15]: Sales Channel
         Agent          0.191544
```

```
Branch          0.114531
Call Center     0.108782
Web             0.117736
Name: Customer, dtype: float64
```

In [16]:
```
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 through Web works the second best. Let's go ahead in breaking down this result deeper with different customers' attributes.

2.5 - Sales Channel & Vehicle Size

We are going to see whether customers with various vehicle sizes respond differently to different sales channels.

```
In [17]: 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
```

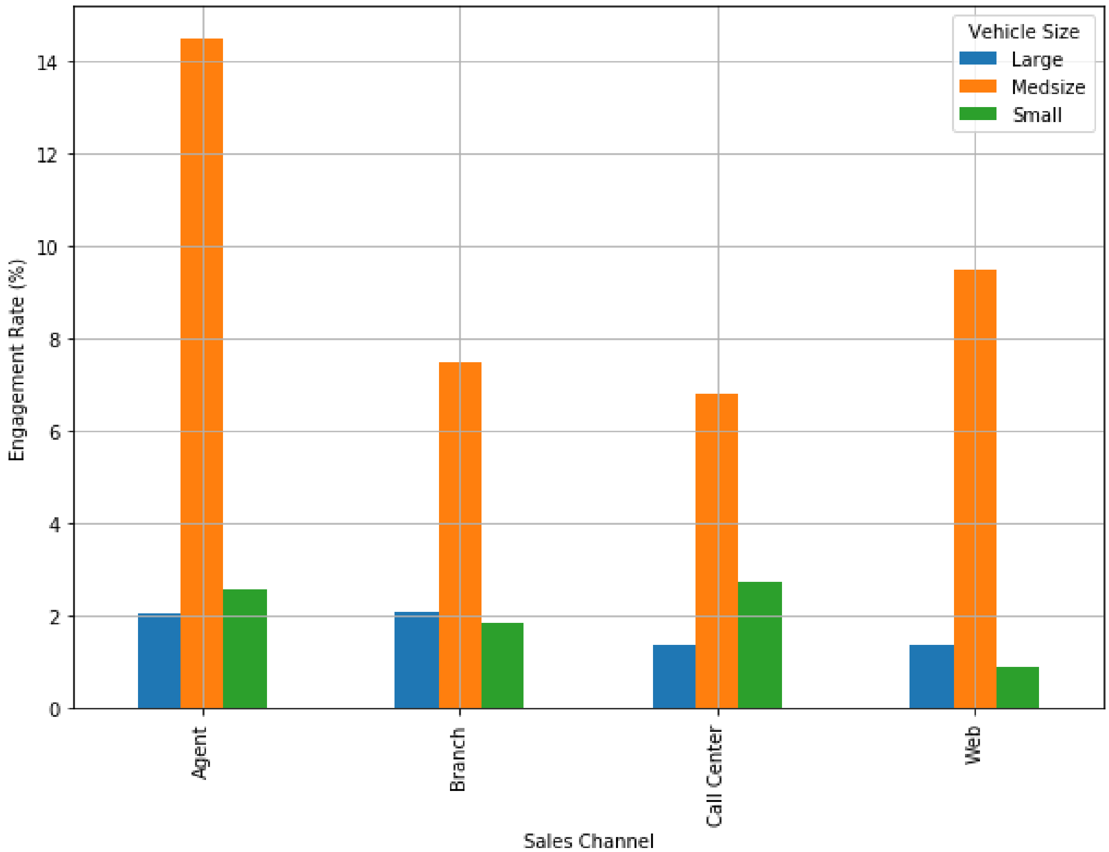
```
Out[17]: Sales Channel  Vehicle Size
         Agent          Large           0.020708
                        Medsize         0.144953
                        Small           0.025884
         Branch         Large           0.021036
                        Medsize         0.074795
                        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 [18]: # Unstack the data into a more visible format

         by_sales_channel_df = by_sales_channel_df.unstack().fillna(0)
         by_sales_channel_df
```

```
Out[18]: 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 [19]: 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.

2.6 - Engagement Rates by Months Since Policy Inception

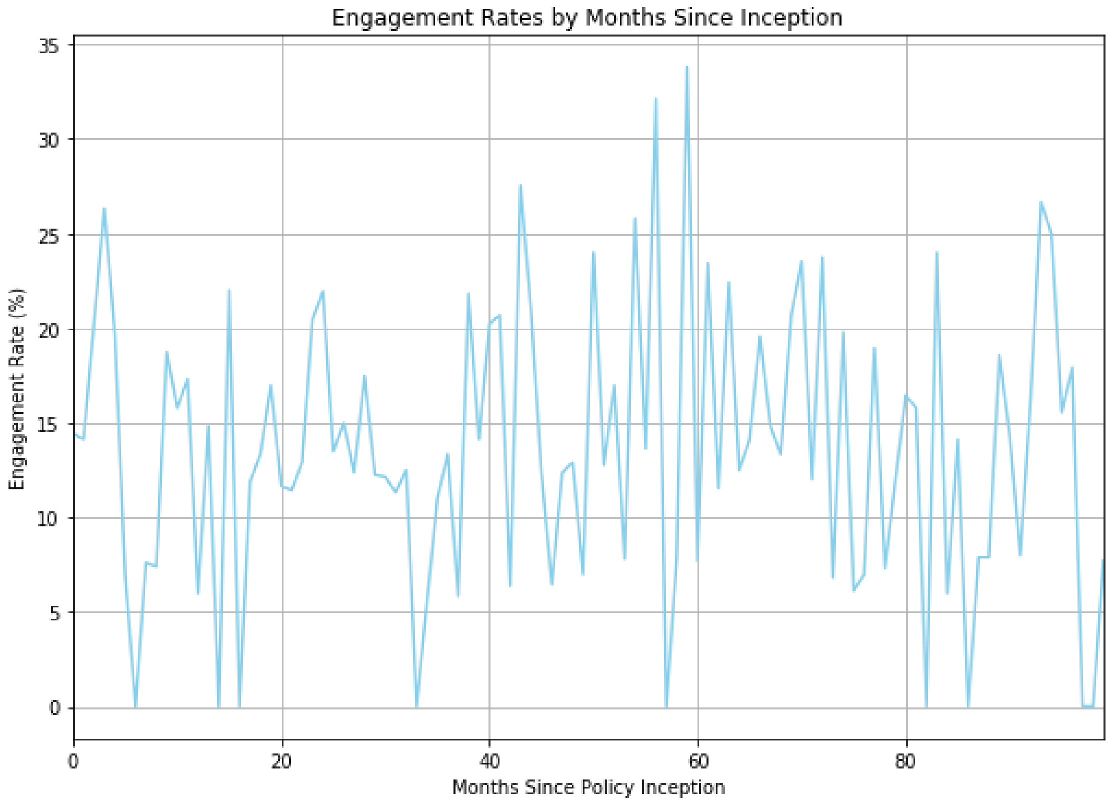
```
In [20]: by_months_since_inception_df = df.loc[
             df['Response'] == 'Yes'
         ].groupby(
             by='Months Since Policy Inception'
         )['Response'].count() / df.groupby(
             by='Months Since Policy Inception'
         )['Response'].count() * 100.0
```

```
by_months_since_inception_df.fillna(0)
```

Out[20]:
```
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 [21]:
```
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()
```



3 3. Customer Segmentation by CLV & Months Since Policy Inception

We are going to segment our customer base by *Customer Lifetime Value* and *Months Since Policy Inception*.

In [22]:
```
# Take a look at the distribution of the CLV

df['Customer Lifetime Value'].describe()
```

Out[22]:
```
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 [23]:
```
df['CLV Segment'] = df['Customer Lifetime Value'].apply(
    lambda x: 'High' if x > df['Customer Lifetime Value'].median() else 'Low'
)
```

In [24]:
```
# Do the same procedure for Months Since Policy Inception

df['Months Since Policy Inception'].describe()
```

Out[24]:
```
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 [25]:
```
df['Policy Age Segment'] = df['Months Since Policy Inception'].apply(
    lambda x: 'High' if x > df['Months Since Policy Inception'].median() else 'Low'
)
```

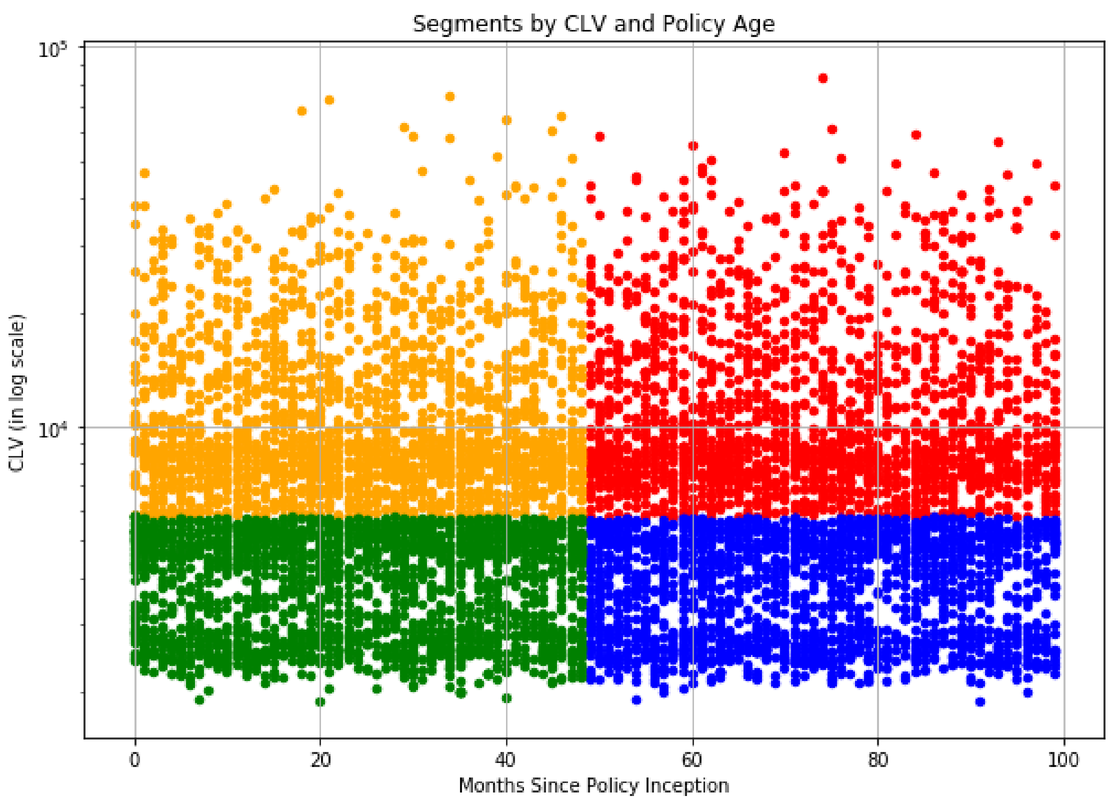
In [26]:
```
df.head()
```

Out[26]:
```
  Customer       State  Customer Lifetime Value Response  Coverage Education  \
0  BU79786  Washington              2763.519279       No     Basic  Bachelor
1  QZ44356     Arizona              6979.535903       No  Extended  Bachelor
2  AI49188      Nevada             12887.431650       No   Premium  Bachelor
3  WW63253  California              7645.861827       No     Basic  Bachelor
4  HB64268  Washington              2813.692575       No     Basic  Bachelor

  Effective To Date EmploymentStatus Gender  Income  ... Number of Policies  \
0           2/24/11         Employed      F   56274  ...                  1
1           1/31/11       Unemployed      F       0  ...                  8
2           2/19/11         Employed      F   48767  ...                  2
3           1/20/11       Unemployed      M       0  ...                  7
4            2/3/11         Employed      M   43836  ...                  1

      Policy Type        Policy  Renew Offer Type  Sales Channel  \
0  Corporate Auto  Corporate L3            Offer1          Agent
1   Personal Auto   Personal L3            Offer3          Agent
2   Personal Auto   Personal L3            Offer1          Agent
3  Corporate Auto  Corporate L2            Offer1    Call Center
4   Personal Auto   Personal L1            Offer1          Agent

   Total Claim Amount  Vehicle Class Vehicle Size CLV Segment  \
0          384.811147   Two-Door Car      Medsize         Low
1         1131.464935  Four-Door Car      Medsize        High
2          566.472247   Two-Door Car      Medsize        High
```

```
3           529.881344            SUV      Medsize        High
4           138.130879  Four-Door Car      Medsize         Low

  Policy Age Segment
0                Low
1                Low
2                Low
3               High
4                Low

[5 rows x 26 columns]
```

In [27]:
```python
# 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 [28]: # See whether there is any noticeable difference in the engagement rates among these

         engagement_rates_by_segment_df = df.loc[
             df['Response'] == 'Yes'
         ].groupby([
```

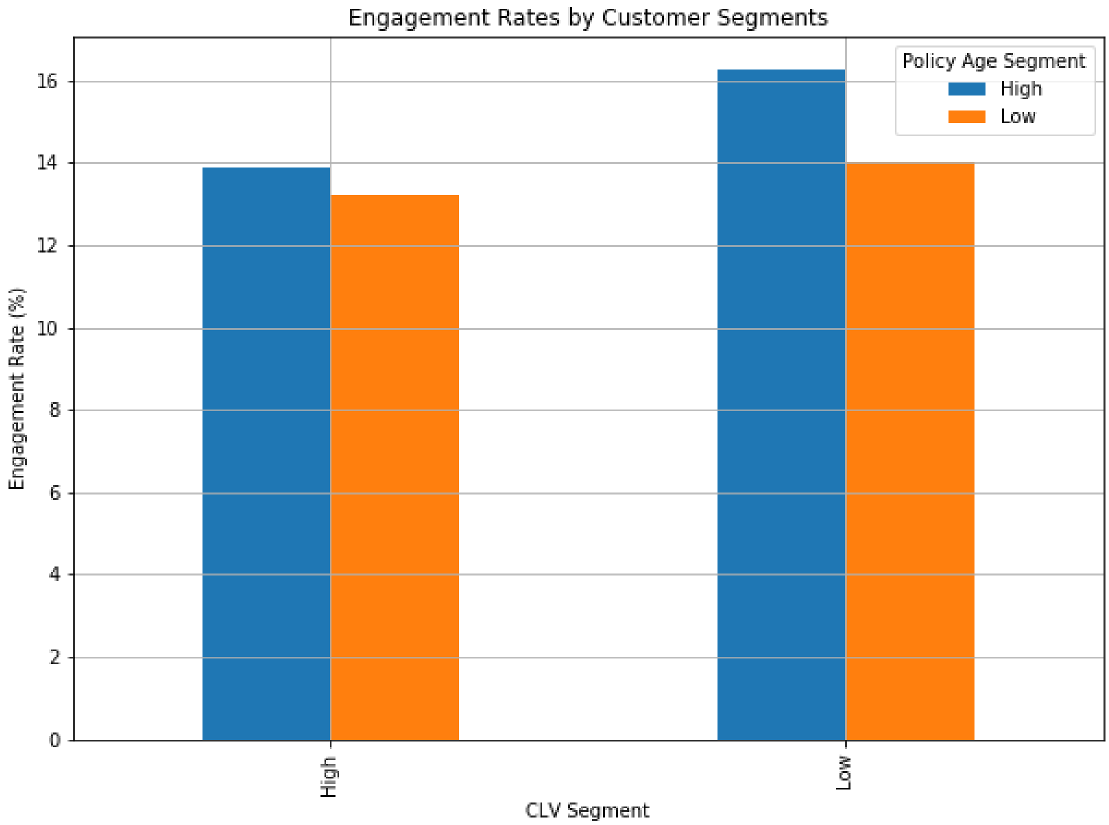
```
    'CLV Segment', 'Policy Age Segment'
]). count()['Customer'] / df.groupby([
    'CLV Segment', 'Policy Age Segment'
]).count()['Customer']

engagement_rates_by_segment_df
```

Out[28]:

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

In [29]:

```
# 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.