2. Using the "Marketing Customer Value Analysis" dataset, complete the following tasks with proper analysis and interpretation:[In Python & R]

i. Load the dataset and explore its structure using basic commands.

```
import matplotlib.pyplot as plt
import pandas as pd
import statsmodels.api as sm

import os

market_df = pd.read_csv("D:\PYTHON\DATA SCIENCE\DATA\WA_Fn-UseC_-Marketing-Customer-Value-Analysis (1).csv")
```

```
<>:1: SyntaxWarning: invalid escape sequence '\P'
<>:1: SyntaxWarning: invalid escape sequence '\P'
C:\Users\AJITH N\AppData\Local\Temp\ipykernel_14680\144760901.py:1:
SyntaxWarning: invalid escape sequence '\P'
  market_df = pd.read_csv("D:\PYTHON\DATA SCIENCE\DATA\WA_Fn-UseC_-Marketing-Customer-Value-Analysis (1).csv")
```

```
market_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9134 entries, 0 to 9133
Data columns (total 24 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   Customer                       9134 non-null   object
 1   State                          9134 non-null   object
 2   Customer Lifetime Value        9134 non-null   float64
 3   Response                       9134 non-null   object
 4   Coverage                       9134 non-null   object
 5   Education                      9134 non-null   object
 6   Effective To Date              9134 non-null   object
 7   EmploymentStatus               9134 non-null   object
 8   Gender                         9134 non-null   object
 9   Income                         9134 non-null   int64
 10  Location Code                  9134 non-null   object
 11  Marital Status                 9134 non-null   object
 12  Monthly Premium Auto           9134 non-null   int64
 13  Months Since Last Claim        9134 non-null   int64
 14  Months Since Policy Inception  9134 non-null   int64
 15  Number of Open Complaints      9134 non-null   int64
 16  Number of Policies             9134 non-null   int64
 17  Policy Type                    9134 non-null   object
 18  Policy                         9134 non-null   object
 19  Renew Offer Type               9134 non-null   object
```

```
 20  Sales Channel                  9134 non-null   object
 21  Total Claim Amount             9134 non-null   float64
 22  Vehicle Class                  9134 non-null   object
 23  Vehicle Size                   9134 non-null   object
dtypes: float64(2), int64(6), object(16)
memory usage: 1.7+ MB
```

```
market_df.head()
```

```
  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]
```

```
market_df.describe()
```

```
       Customer Lifetime Value        Income  Monthly Premium Auto  \
count              9134.000000   9134.000000           9134.000000
mean               8004.940475  37657.380009             93.219291
std                6870.967608  30379.904734             34.407967
min                1898.007675      0.000000             61.000000
25%                3994.251794      0.000000             68.000000
50%                5780.182197  33889.500000             83.000000
75%                8962.167041  62320.000000            109.000000
max               83325.381190  99981.000000            298.000000

       Months Since Last Claim  Months Since Policy Inception  \
count              9134.000000                    9134.000000
mean                 15.097000                      48.064594
std                  10.073257                      27.905991
min                   0.000000                       0.000000
25%                   6.000000                      24.000000
50%                  14.000000                      48.000000
75%                  23.000000                      71.000000
max                  35.000000                      99.000000

       Number of Open Complaints  Number of Policies  Total Claim
Amount
count                9134.000000         9134.000000
9134.000000
mean                    0.384388            2.966170
434.088794
std                     0.910384            2.390182
290.500092
min                     0.000000            1.000000
0.099007
25%                     0.000000            1.000000
272.258244
50%                     0.000000            2.000000
383.945434
75%                     0.000000            4.000000
547.514839
max                     5.000000            9.000000
2893.239678
```

Interpretation:

The `head()` function displays the first five records of the dataset by default.
The `describe()` function provides statistical summaries like count, mean, standard deviation, min, and max for numerical columns.

ii. Create a new column named "Engaged" by transforming the categorical values in the "Response" variable into numerical values. Why is this transformation important?

```
market_df['Engaged'] = market_df['Response'].map({'Yes': 1, 'No': 0})
```

Interpretation:

Creating the "Engaged" column converts "Response" values ('Yes' to 1, 'No' to 0), making them numeric. This improves compatibility with tools and models.

iii. Calculate and interpret the Engagement Rate. How is it computed, and what does it indicate about the customer responses?

```
engagement_rate = market_df['Engaged'].mean()
print(f"Engagement Rate: {engagement_rate:.2%}")
```

```
Engagement Rate: 14.32%
```

Interpretation:

The Engagement Rate of 14.32% means that only 14.32% of customers responded positively ("Yes"). This suggests that customer engagement is relatively low, indicating potential areas for improvement in marketing strategies to boost interactions and responses.

iv. Analyze engagement rate by "Renew Offer Type" and "Sales Channel":

```
renew_offer_engagement = market_df.groupby('Renew Offer Type')
['Engaged'].mean()
renew_offer_engagement
```

```
Renew Offer Type
Offer1    0.158316
Offer2    0.233766
Offer3    0.020950
Offer4    0.000000
Name: Engaged, dtype: float64
```

```
sales_channel_engagement = market_df.groupby('Sales Channel')
['Engaged'].mean()
sales_channel_engagement
```

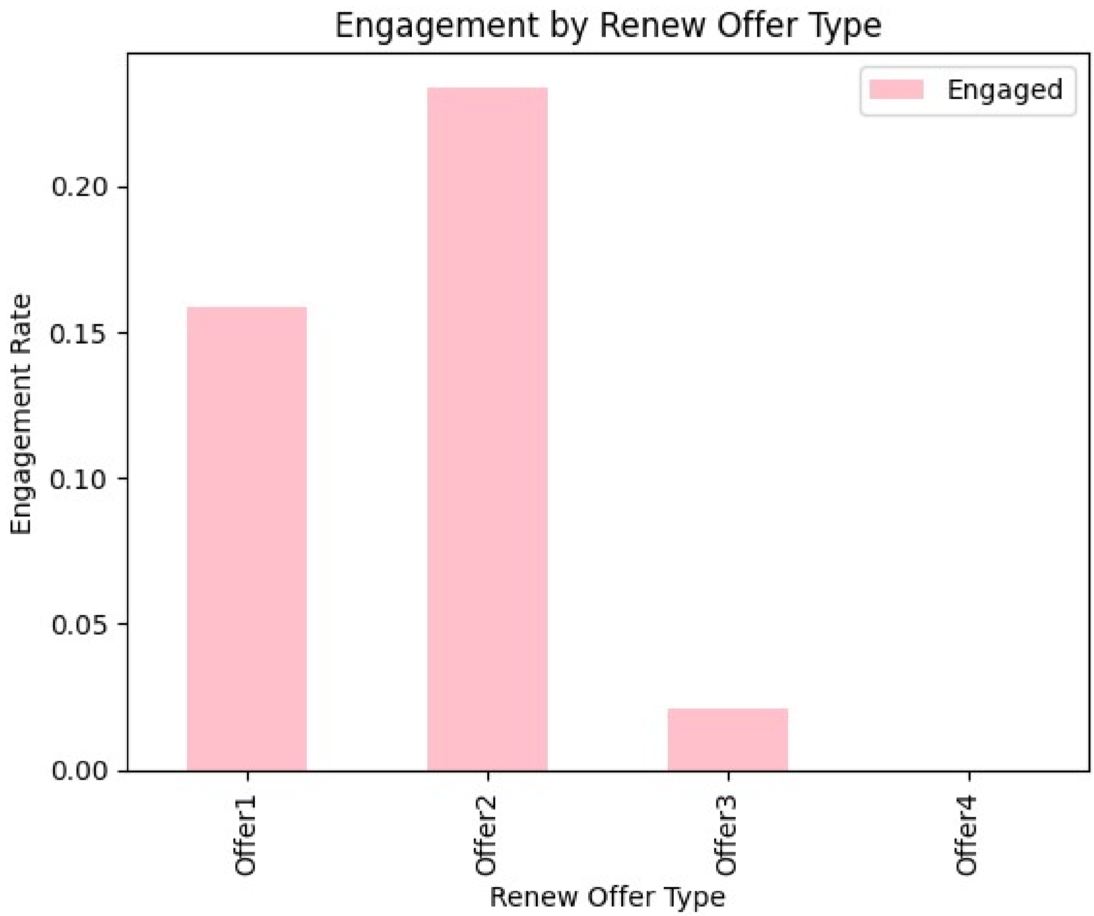
```
Sales Channel
Agent           0.191544
Branch          0.114531
Call Center     0.108782
Web             0.117736
Name: Engaged, dtype: float64
```

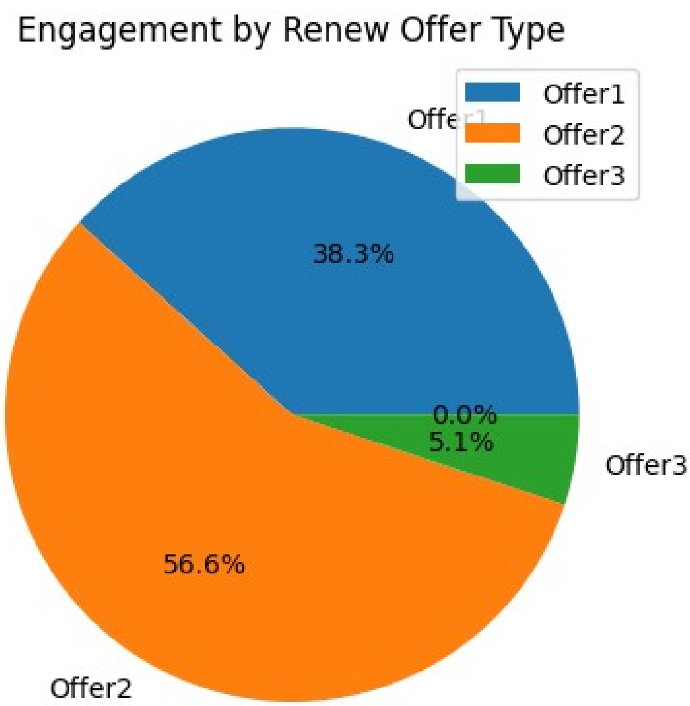
Interpretation:

1. Engagement by Renew Offer Type: Offer 2 (23.38%) has the highest engagement, making it the most effective. Offer 1 (15.83%) performs well but is less effective than Offer 2. Offer 3 (2.10%) has low engagement, while Offer 4 (0%) is completely ineffective.
2. Engagement by Sales Channel: Agents (19.15%) drive the highest engagement, highlighting the power of personal interaction. Branches (11.45%), Web (11.77%), and Call Centers (10.88%) show lower engagement, needing improvements.

v. Use a pivot table to summarize engagement by "Renew Offer Type" and visualize the results using both bar and pie charts. Why are these visualizations helpful in understanding customer engagement patterns?

```
import matplotlib.pyplot as plt

pivot_table = market_df.pivot_table(values='Engaged', index='Renew Offer Type', aggfunc='mean')
pivot_table


                   Engaged
Renew Offer Type
Offer1            0.158316
Offer2            0.233766
Offer3            0.020950
Offer4            0.000000

# Bar chart
pivot_table.plot(kind='bar', color='pink')
plt.title("Engagement by Renew Offer Type")
plt.ylabel("Engagement Rate")
plt.show()

# Pie chart
pivot_table.plot(kind='pie', subplots=True, autopct='%1.1f%%')
plt.title("Engagement by Renew Offer Type")
plt.ylabel("")
plt.show()
```


Engagement by Renew Offer Type
Engaged
Engagement Rate
0.00
0.05
0.10
0.15
0.20
Offer1
Offer2
Offer3
Offer4
Renew Offer Type



Interpretation:

The bar chart compares engagement rates across "Renew Offer Types," highlighting the best performers. The pie chart shows each offer's percentage share of total engagement, illustrating their relative impact.

vi. Explain the purpose of regression analysis in this context. Describe how you would approach regression using (i) continuous variables only, (ii) categorical variables, and (iii) both continuous and categorical variables. How would you interpret the outputs for each approach?

(i)Continuous Variables

```
market_df.describe()

       Customer Lifetime Value        Income  Monthly Premium Auto  \
count              9134.000000   9134.000000           9134.000000
mean               8004.940475  37657.380009             93.219291
std                6870.967608  30379.904734             34.407967
min                1898.007675      0.000000             61.000000
25%                3994.251794      0.000000             68.000000
50%                5780.182197  33889.500000             83.000000
75%                8962.167041  62320.000000            109.000000
max               83325.381190  99981.000000            298.000000
```

```
       Months Since Last Claim  Months Since Policy Inception  \
count              9134.000000                    9134.000000
mean                 15.097000                      48.064594
std                  10.073257                      27.905991
min                   0.000000                       0.000000
25%                   6.000000                      24.000000
50%                  14.000000                      48.000000
75%                  23.000000                      71.000000
max                  35.000000                      99.000000

       Number of Open Complaints  Number of Policies  Total Claim
Amount  \
count                9134.000000         9134.000000
9134.000000
mean                    0.384388            2.966170
434.088794
std                     0.910384            2.390182
290.500092
min                     0.000000            1.000000
0.099007
25%                     0.000000            1.000000
272.258244
50%                     0.000000            2.000000
383.945434
75%                     0.000000            4.000000
547.514839
max                     5.000000            9.000000
2893.239678

           Engaged
count  9134.000000
mean      0.143201
std       0.350297
min       0.000000
25%       0.000000
50%       0.000000
75%       0.000000
max       1.000000
```

```
list(market_df.columns)
```

```
['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',
 'Engaged']
```

```
continous_vars =['Customer Lifetime Value','Income','Monthly Premium
Auto',
 'Months Since Last Claim',
 'Months Since Policy Inception',
 'Number of Open Complaints',
 'Number of Policies','Total Claim Amount']

# Initialize the logistic regression model
logit=sm.Logit(market_df['Engaged'],market_df[continous_vars])

# Fit the model
logit_fit = logit.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.421189
         Iterations 6
```

```
logit_fit.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results

======================================================================
========
Dep. Variable:                Engaged   No. Observations:
9134
Model:                          Logit   Df Residuals:
9126
Method:                           MLE   Df Model:
7
Date:                Mon, 03 Feb 2025   Pseudo R-squ.:
-0.02546
```

```
Time:                             20:39:41   Log-Likelihood:
-3847.1
converged:                            True   LL-Null:
-3751.6
Covariance Type:                 nonrobust   LLR p-value:
1.000
======================================================================
===========================
                                    coef    std err          z
P>|z|      [0.025      0.975]
----------------------------------------------------------------------
---------------------------
Customer Lifetime Value       -6.741e-06   5.04e-06     -1.337
0.181   -1.66e-05    3.14e-06
Income                        -2.857e-06   1.03e-06     -2.766
0.006   -4.88e-06   -8.33e-07
Monthly Premium Auto             -0.0084      0.001     -6.889
0.000      -0.011      -0.006
Months Since Last Claim          -0.0202      0.003     -7.238
0.000      -0.026      -0.015
Months Since Policy Inception    -0.0060      0.001     -6.148
0.000      -0.008      -0.004
Number of Open Complaints        -0.0829      0.034     -2.424
0.015      -0.150      -0.016
Number of Policies               -0.0810      0.013     -6.356
0.000      -0.106      -0.056
Total Claim Amount                0.0001      0.000      0.711
0.477      -0.000       0.000
======================================================================
===========================
"""
```

Interpretation:

The logistic regression model shows that factors like Income, Monthly Premium Auto, Months Since Last Claim, Months Since Policy Inception, Number of Open Complaints, and Number of Policies significantly decrease the likelihood of customer engagement. On the other hand, Customer Lifetime Value and Total Claim Amount do not significantly affect engagement. Generally, higher premiums, more complaints, and longer periods since claims or policy inception are associated with lower engagement.

(ii) Categorical

```
gender_values, gender_lables = market_df['Gender'].factorize()
market_df['genderfactorized'] = gender_values

edu_values, edu_lables = market_df['Education'].factorize()
market_df['educationfactorized'] = edu_values

categorical_vars = ['genderFactorized','educationfactorized']
```

```python
logit = sm.Logit(
    market_df['Engaged'],
    market_df[['genderfactorized','educationfactorized']]
)
logit_fit = logit.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.489140
         Iterations 6
```

```python
logit_fit.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results

======================================================================
========
Dep. Variable:                Engaged   No. Observations:
9134
Model:                          Logit   Df Residuals:
9132
Method:                           MLE   Df Model:
1
Date:                Mon, 03 Feb 2025   Pseudo R-squ.:
-0.1909
Time:                        20:50:59   Log-Likelihood:
-4467.8
converged:                       True   LL-Null:
-3751.6
Covariance Type:            nonrobust   LLR p-value:
1.000
======================================================================
=================
                          coef    std err          z      P>|z|
[0.025      0.975]
----------------------------------------------------------------------
-----------------
genderfactorized       -1.1269      0.046    -24.263      0.000      -
1.218      -1.036
educationfactorized    -0.5536      0.018    -30.560      0.000      -
0.589      -0.518
======================================================================
=================
"""
```

Interpretation:

The logistic regression results show that both **gender** and **education** significantly reduce the likelihood of engagement, with **p-values** of 0.000. The negative coefficients for both variables (**-**

1.1269 for gender and **-0.5536** for education) suggest that changes in gender and higher education levels are associated with lower engagement.

(iii).Both Continous and Categorical

```
logit11 = sm.Logit(
    market_df['Engaged'],
    market_df[[
        'genderfactorized',
        'educationfactorized',
        'Customer Lifetime Value',
        'Income',
        'Monthly Premium Auto',
        'Months Since Last Claim',
        'Months Since Policy Inception',
        'Number of Open Complaints',
        'Number of Policies',
        'Total Claim Amount'
    ]]
)
logit11_fit = logit11.fit()
```

```
Optimization terminated successfully.
         Current function value: 0.420108
         Iterations 6
```

```
logit11_fit.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                           Logit Regression Results

======================================================================
========
Dep. Variable:                Engaged   No. Observations:
9134
Model:                          Logit   Df Residuals:
9124
Method:                           MLE   Df Model:
9
Date:                Mon, 03 Feb 2025   Pseudo R-squ.:
-0.02283
Time:                        20:53:47   Log-Likelihood:
-3837.3
converged:                       True   LL-Null:
-3751.6
Covariance Type:            nonrobust   LLR p-value:
1.000
======================================================================
===========================
                                    coef    std err          z
```

```
P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------------------------
genderfactorized                       -0.1421      0.058     -2.458
0.014      -0.255      -0.029
educationfactorized                    -0.0801      0.022     -3.570
0.000      -0.124      -0.036
Customer Lifetime Value             -6.625e-06   5.02e-06     -1.319
0.187   -1.65e-05    3.22e-06
Income                              -2.275e-06   1.04e-06     -2.188
0.029   -4.31e-06   -2.37e-07
Monthly Premium Auto                   -0.0077      0.001     -6.343
0.000      -0.010      -0.005
Months Since Last Claim                -0.0186      0.003     -6.627
0.000      -0.024      -0.013
Months Since Policy Inception          -0.0054      0.001     -5.559
0.000      -0.007      -0.004
Number of Open Complaints              -0.0811      0.034     -2.375
0.018      -0.148      -0.014
Number of Policies                     -0.0751      0.013     -5.888
0.000      -0.100      -0.050
Total Claim Amount                      0.0002      0.000      1.173
0.241      -0.000       0.000
======================================================================================================
"""
```

Interpretation:

Both numeric and categorical variables are combined to create a comprehensive model. Continuous variables show direct effects on the outcome, while categorical variables are interpreted relative to a reference category.