💻 Question No: 01

⚙️ Setup

- Ensure the Python kernel has the necessary libraries: `pandas` , `seaborn` , `numpy` , `kmeans` , `matplotlib` and `lets-plot`
- Ensure the `Marketing-Customer-Value-Analysis..csv` file is in the `data` folder.

In [56]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

In [57]:
```
# Load the dataset
df = pd.read_csv("D:/Data Science for Marketing-I/dataset/WA_Fn-UseC_-Marketing-Cus
```

i. Perform basic exploratory data analysis (EDA) such as checking dataset shape and previewing the first few rows. What insights can be drawn from this initial exploration?

In [58]:
```
df.shape
```

Out[58]:
```
(9134, 24)
```

💡 The dataset contains 9,134 records and 24 columns.

In [59]:
```
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
```

💡 There are various categorical and numerical variables related to customers and their insurance policies.

ii. Analyze customer engagement by grouping data based on the Response variable. How does this grouping help in understanding customer behavior?

In [60]:
```python
df['Response'] = df['Response'].apply(lambda x: 1 if x == 'Yes' else 0)
```

In [61]:
```python
response_counts = df['Response'].value_counts()
response_counts
```

Out[61]:
```
Response
0    7826
1    1308
Name: count, dtype: int64
```

In [62]:
```python
response_percentage = df['Response'].value_counts(normalize=True) * 100
response_percentage
```

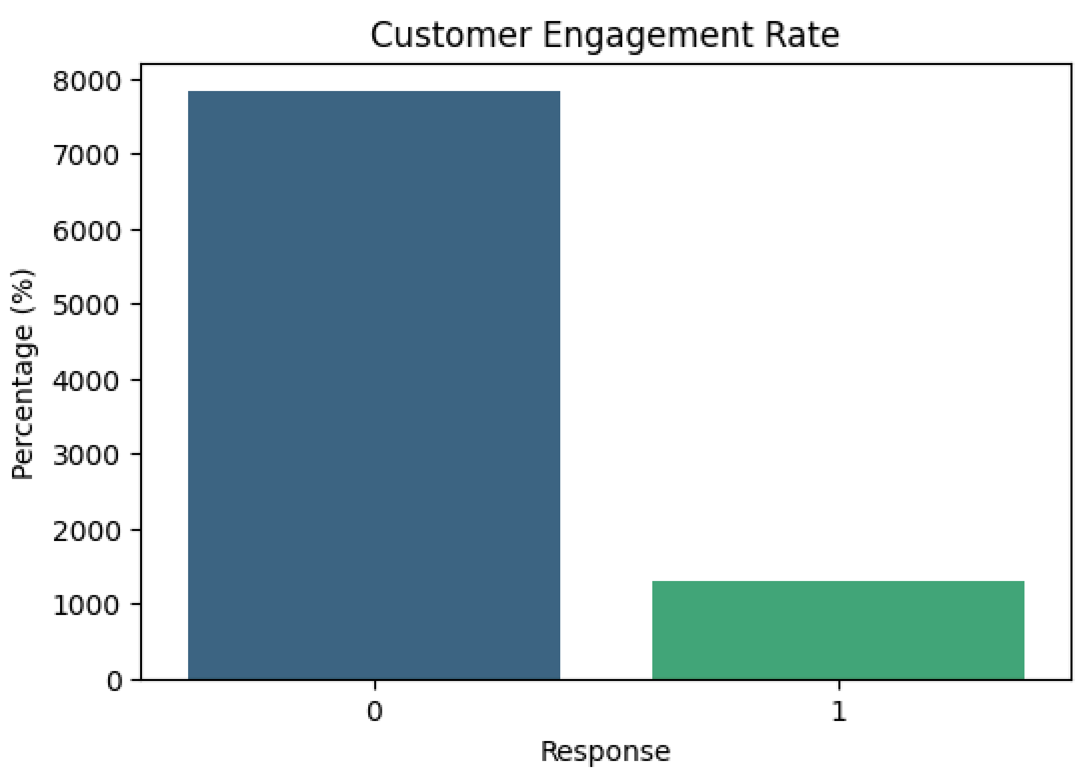
Out[62]:
```
Response
0    85.679877
1    14.320123
Name: proportion, dtype: float64
```

💡

85.68% of customers did not respond, while 14.32% engaged. This suggests that the majority of customers are not engaging with marketing efforts.

iii. Visualize the engagement rate using a bar chart. What is the significance of this visualization, and how does the code achieve it?

In [65]:
```
plt.figure(figsize=(6, 4))
sns.barplot(x=response_counts.index, y=response_counts.values, hue=response_counts.
plt.xlabel("Response")
plt.ylabel("Percentage (%)")
plt.title("Customer Engagement Rate")
plt.show()
```



💡 A bar chart shows a significantly higher percentage of customers who did not respond.This visualization highlights the challenge of low engagement.

iv. Calculate the engagement rate for different renewal offer types and interpret the results. Why is this metric useful?

In [ ]:
```
renew_offer_engagement = df.groupby("Renew Offer Type")["Response"].value_counts(no
```

```
renew_offer_engagement
```

Out[ ]:

Response	0	1
Renew Offer Type		
Offer1	84.168443	15.831557
Offer2	76.623377	23.376623
Offer3	97.905028	2.094972
Offer4	100.000000	NaN

💡 Offer2 has the highest engagement rate (23.38%), while Offer3 and Offer4 show very low engagement.

```
    Offer4 has 0% engagement, indicating it might not be attractive
to customers.
```

v. Extend the analysis by exploring engagement rates segmented by both Renew Offer Type and Vehicle Class. How does this multi-level grouping provide deeper insights?

In [ ]:

```
multi_group = df.groupby(["Renew Offer Type", "Vehicle Class"])["Response"].value_c
print("\nEngagement Rate by Renew Offer Type & Vehicle Class:\n", multi_group)
```

```
Engagement Rate by Renew Offer Type & Vehicle Class:
 Response                                 0          1
Renew Offer Type Vehicle Class
Offer1           Four-Door Car    85.308848  14.691152
                 Luxury Car       91.176471   8.823529
                 Luxury SUV       79.775281  20.224719
                 SUV              81.165919  18.834081
                 Sports Car       81.497797  18.502203
                 Two-Door Car     85.861561  14.138439
Offer2           Four-Door Car    78.082192  21.917808
                 Luxury Car       85.365854  14.634146
                 Luxury SUV       74.468085  25.531915
                 SUV              75.000000  25.000000
                 Sports Car       68.831169  31.168831
                 Two-Door Car     75.856930  24.143070
Offer3           Four-Door Car    96.778523   3.221477
                 Luxury Car      100.000000        NaN
                 Luxury SUV      100.000000        NaN
                 SUV             100.000000        NaN
                 Sports Car      100.000000        NaN
                 Two-Door Car     97.894737   2.105263
Offer4           Four-Door Car   100.000000        NaN
                 Luxury Car      100.000000        NaN
                 Luxury SUV      100.000000        NaN
                 SUV             100.000000        NaN
                 Sports Car      100.000000        NaN
                 Two-Door Car    100.000000        NaN
```

💡 Luxury SUVs and Sports Cars in Offer2 have higher engagement compared to other categories.Offer3 and Offer4 consistently have very low engagement rates across all vehicle classes.

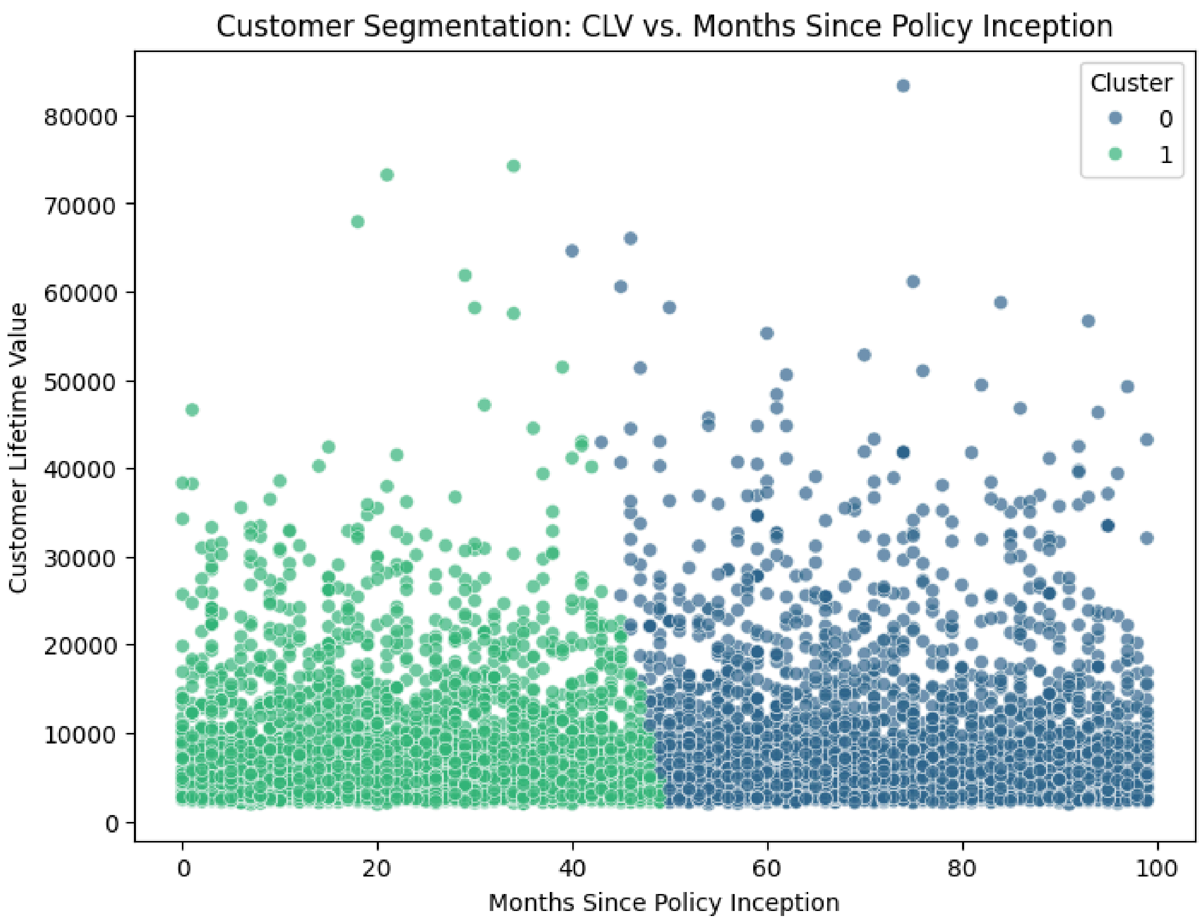
vi. Perform customer segmentation using the variables ‘Customer Lifetime Value (CLV)’ and ‘Months Since Policy Inception’

In [ ]:
```
X = df[["Customer Lifetime Value", "Months Since Policy Inception"]]

# Standardizing the data for better clustering performance
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Applying K-Means clustering with 3 clusters (can be adjusted)
kmeans = KMeans(n_clusters=2, random_state=42, n_init=10)
df["Cluster"] = kmeans.fit_predict(X_scaled)
```

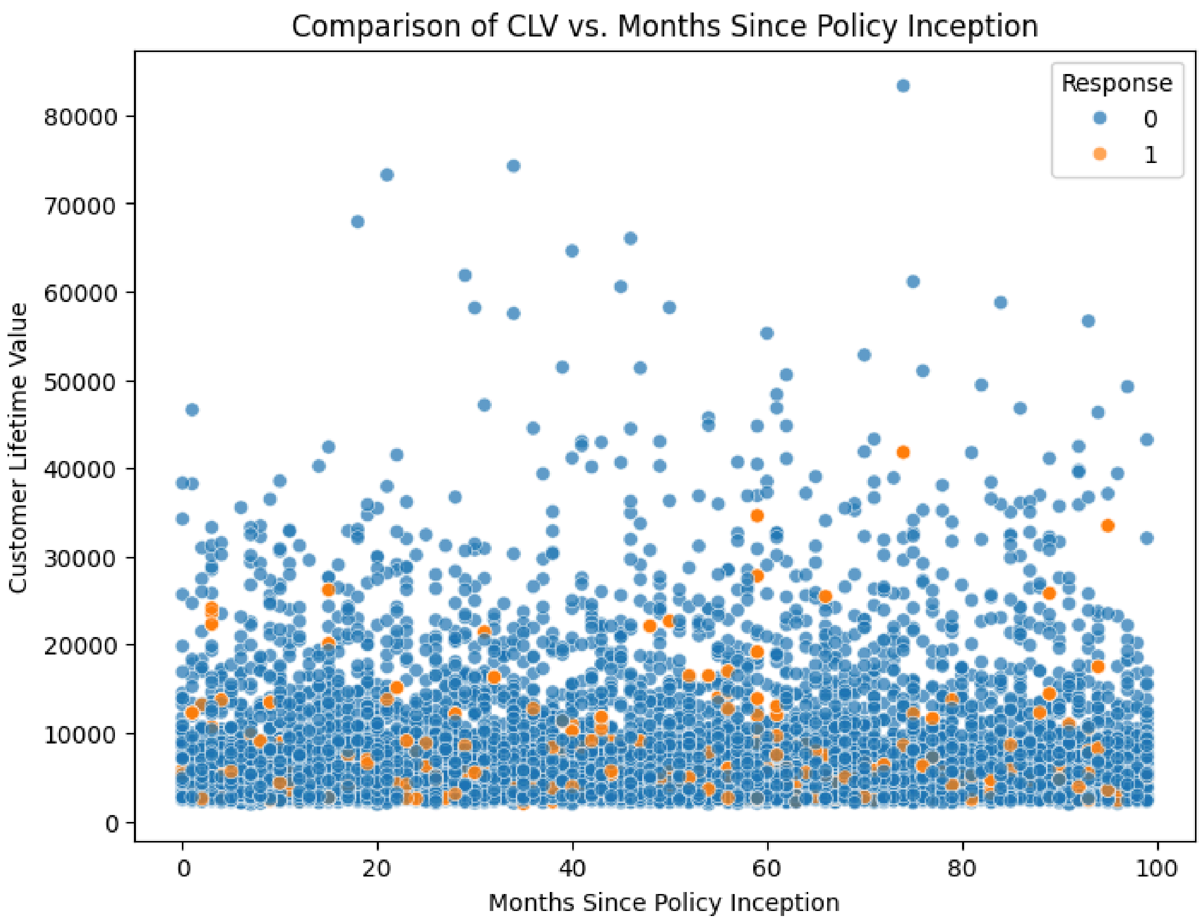
In [ ]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x="Months Since Policy Inception", y="Customer Lifetime Va
plt.xlabel("Months Since Policy Inception")
plt.ylabel("Customer Lifetime Value")
plt.title("Customer Segmentation: CLV vs. Months Since Policy Inception")
plt.legend(title="Cluster")
plt.show()
```



vii. Create a visualization to compare CLV against Months Since Policy Inception

In [ ]:

```
# Visualization: CLV vs. Months Since Policy Inception
plt.figure(figsize=(8, 6))
sns.scatterplot(data=df, x="Months Since Policy Inception", y="Customer Lifetime Va
plt.xlabel("Months Since Policy Inception")
plt.ylabel("Customer Lifetime Value")
plt.title("Comparison of CLV vs. Months Since Policy Inception")
plt.legend(title="Response")
plt.show()
```



💡 The scatter plot suggests no clear pattern, but higher CLV customers might be more engaged.Some high CLV customers have been with the company for a long time,There is no strong linear trend, suggesting CLV is not strictly dependent on policy duration.