Using Machine Learning To Predict Customer Lifetime Value

In [1]:
```
# https://www.kaggle.com/code/narendra123580/insurance-marketing-customer-value-and
```

Customer Lifetime Value Prediction

Customer Lifetime Value represents a customer's value to a company over a period of time. It's a competitive market for insurance companies in 2019, and insurance premium isn't the only determining factor in a customer's decisions. CLV is a customer-centric metric, and a powerful base to build upon to retain valuable customers, increase revenue from less valuable customers, and improve the customer experience overall.

Business Problem

An Auto Insurance company in the USA is facing issues in retaining its customers and wants to advertise promotional offers for its loyal customers. They are considering Customer Lifetime Value CLV as a parameter for this purpose. Customer Lifetime Value represents a customer's value to a company over a period of time. It's a competitive market for insurance companies, and the insurance premium isn't the only determining factor in a customer's decisions. CLV is a customer-centric metric, and a powerful base to build upon to retain valuable customers, increase revenue from less valuable customers, and improve the customer experience overall. Using CLV effectively can improve customer acquisition and customer retention, prevent churn, help the company to plan its marketing budget, measure the performance of their ads in more detail, and much more.

Project Overview

The objective of the problem is to accurately predict the Customer Lifetime Value(CLV) of the customer for an Auto Insurance Company Performed EDA to understand the relation of target variable CLV with the other features. Statistical Analysis techniques like OLS for numerical and Mann–Whitney U and also Kruskal Wallis test for the categorical variables were performed to find the significance of the features with respect to the target. Supervised Regression Models like Linear Regression, Ridge Regression, Lasso Regression, DecisionTree Regression, Random Forest Regression and Adaboost Regression. Using GridSearchCV with Random Forest Regression gave the best RMSE and R^2 score values

Dataset Description

The dataset represents Customer lifetime value of an Auto Insurance Company in the United States, it includes over 24 features and 9134 records to analyze the lifetime value of Customer.

DATASET:- https://docs.google.com/spreadsheets/d/1cltj1nQA2hSM_-BJ2b7S1afMV78hKj9ygd4_P-Aqjqk/edit?usp=sharing

In [2]:
```
#import all packages and liabraries
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import pandas as pd
import seaborn as sns

#To ignore the warnings
import warnings
warnings.filterwarnings('ignore')

#To display all columns and rows
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)


from sklearn.model_selection import train_test_split
from sklearn.model_selection import GridSearchCV


import statsmodels.api as sm
import statsmodels.stats.api as sms
from statsmodels.compat import lzip

from statsmodels.stats import diagnostic as diag
from statsmodels.stats.outliers_influence import variance_inflation_factor

from scipy.stats import normaltest,f_oneway
from scipy.stats import ttest_ind

from mlxtend.feature_selection import SequentialFeatureSelector as SFS
from mlxtend.plotting import plot_sequential_feature_selection as plot_sfs
```

Linear Regression, RidgeRegression, LassoRegression, DecisionTree Regression, Random Forest Regression Adaboost Regression.

Using GridSearchCV with Random Forest Regression gave the best RMSE and R^2 score values

Loading the dataset

In [3]:
```
df=pd.read_csv("AutoInsurance.csv")
```

Understanding the data

In [4]:
```
df.head()
```

Out[4]:

	Customer	State	Customer Lifetime Value	Response	Coverage	Education	Effective To Date	EmploymentSta
0	BU79786	Washington	2763.519279	No	Basic	Bachelor	2/24/11	Emplo
1	QZ44356	Arizona	6979.535903	No	Extended	Bachelor	1/31/11	Unemplo
2	AI49188	Nevada	12887.431650	No	Premium	Bachelor	2/19/11	Emplo
3	WW63253	California	7645.861827	No	Basic	Bachelor	1/20/11	Unemplo
4	HB64268	Washington	2813.692575	No	Basic	Bachelor	3/2/2011	Emplo

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

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

In [6]:
```
df.describe()
```

Out[6]:

	Customer Lifetime Value	Income	Monthly Premium Auto	Months Since Last Claim	Months Since Policy Inception	Number of Open Complaints	Number of Policie
count	9134.000000	9134.000000	9134.000000	9134.000000	9134.000000	9134.000000	9134.00000
mean	8004.940475	37657.380009	93.219291	15.097000	48.064594	0.384388	2.96617
std	6870.967608	30379.904734	34.407967	10.073257	27.905991	0.910384	2.39018
min	1898.007675	0.000000	61.000000	0.000000	0.000000	0.000000	1.00000
25%	3994.251794	0.000000	68.000000	6.000000	24.000000	0.000000	1.00000
50%	5780.182197	33889.500000	83.000000	14.000000	48.000000	0.000000	2.00000
75%	8962.167041	62320.000000	109.000000	23.000000	71.000000	0.000000	4.00000
max	83325.381190	99981.000000	298.000000	35.000000	99.000000	5.000000	9.00000

In [7]:
```
df.describe(include="all").T
```

Out[7]:

	count	unique	top	freq	mean	std	min	
Customer	9134	9134	BU79786	1	NaN	NaN	NaN	
State	9134	5	California	3150	NaN	NaN	NaN	
Customer Lifetime Value	9134.0	NaN	NaN	NaN	8004.940475	6870.967608	1898.007675	399
Response	9134	2	No	7826	NaN	NaN	NaN	
Coverage	9134	3	Basic	5568	NaN	NaN	NaN	
Education	9134	5	Bachelor	2748	NaN	NaN	NaN	
Effective To Date	9134	59	10/1/2011	195	NaN	NaN	NaN	
EmploymentStatus	9134	5	Employed	5698	NaN	NaN	NaN	
Gender	9134	2	F	4658	NaN	NaN	NaN	
Income	9134.0	NaN	NaN	NaN	37657.380009	30379.904734	0.0	
Location Code	9134	3	Suburban	5779	NaN	NaN	NaN	
Marital Status	9134	3	Married	5298	NaN	NaN	NaN	
Monthly Premium Auto	9134.0	NaN	NaN	NaN	93.219291	34.407967	61.0	
Months Since Last Claim	9134.0	NaN	NaN	NaN	15.097	10.073257	0.0	
Months Since Policy Inception	9134.0	NaN	NaN	NaN	48.064594	27.905991	0.0	
Number of Open Complaints	9134.0	NaN	NaN	NaN	0.384388	0.910384	0.0	
Number of Policies	9134.0	NaN	NaN	NaN	2.96617	2.390182	1.0	
Policy Type	9134	3	Personal Auto	6788	NaN	NaN	NaN	
Policy	9134	9	Personal L3	3426	NaN	NaN	NaN	
Renew Offer Type	9134	4	Offer1	3752	NaN	NaN	NaN	
Sales Channel	9134	4	Agent	3477	NaN	NaN	NaN	
Total Claim Amount	9134.0	NaN	NaN	NaN	434.088794	290.500092	0.099007	27
Vehicle Class	9134	6	Four-Door Car	4621	NaN	NaN	NaN	
Vehicle Size	9134	3	Medsize	6424	NaN	NaN	NaN	

In [8]:
```
#Checking missing values
df.isnull().sum()
```

Out[8]:
```
Customer                         0
State                            0
Customer Lifetime Value          0
Response                         0
Coverage                         0
Education                        0
Effective To Date                0
EmploymentStatus                 0
Gender                           0
Income                           0
Location Code                    0
Marital Status                   0
Monthly Premium Auto             0
Months Since Last Claim          0
Months Since Policy Inception    0
Number of Open Complaints        0
Number of Policies               0
Policy Type                      0
Policy                           0
Renew Offer Type                 0
Sales Channel                    0
Total Claim Amount               0
Vehicle Class                    0
Vehicle Size                     0
dtype: int64
```

No missing values

In [9]:
```
df.dtypes
```

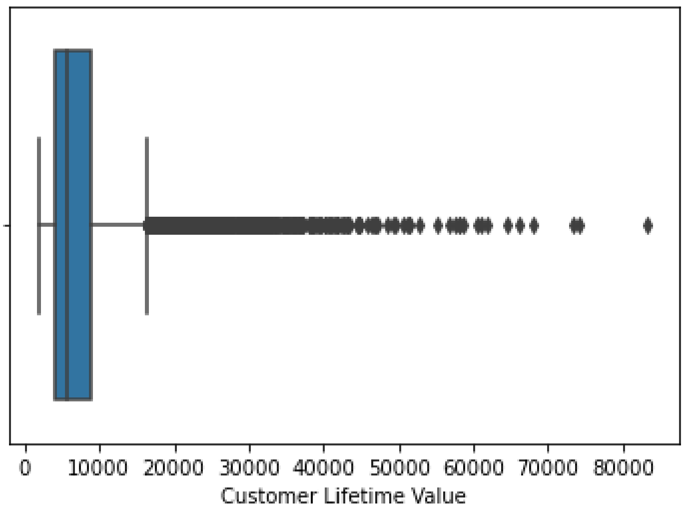
Out[9]:
```
Customer                          object
State                             object
Customer Lifetime Value          float64
Response                          object
Coverage                          object
Education                         object
Effective To Date                 object
EmploymentStatus                  object
Gender                            object
Income                             int64
Location Code                     object
Marital Status                    object
Monthly Premium Auto               int64
Months Since Last Claim            int64
Months Since Policy Inception      int64
Number of Open Complaints          int64
Number of Policies                 int64
Policy Type                       object
Policy                            object
Renew Offer Type                  object
Sales Channel                     object
Total Claim Amount               float64
Vehicle Class                     object
Vehicle Size                      object
dtype: object
```

In [10]:
```
df.isnull().sum()
```

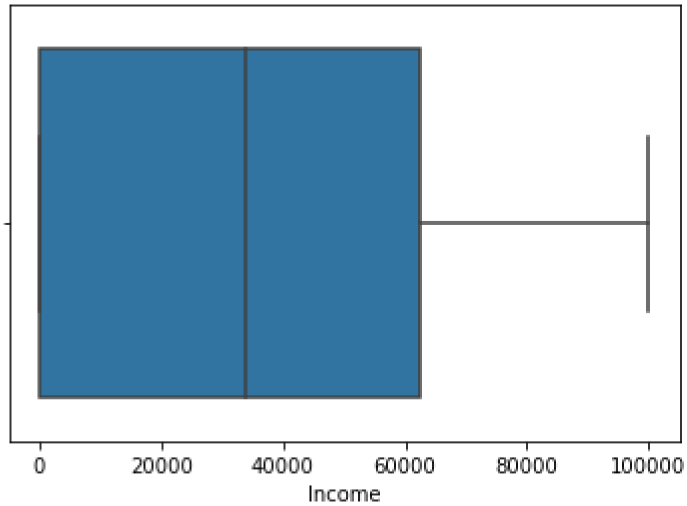
Out[10]:
```
Customer                          0
State                             0
Customer Lifetime Value           0
Response                          0
Coverage                          0
Education                         0
Effective To Date                 0
EmploymentStatus                  0
Gender                            0
Income                            0
Location Code                     0
Marital Status                    0
Monthly Premium Auto              0
Months Since Last Claim           0
Months Since Policy Inception     0
Number of Open Complaints         0
Number of Policies                0
Policy Type                       0
Policy                            0
Renew Offer Type                  0
Sales Channel                     0
Total Claim Amount                0
Vehicle Class                     0
Vehicle Size                      0
dtype: int64
```

In [11]:
```
# Selecting only numerical data to check wheather there are any outliers
for i in df.select_dtypes("number").columns:
    print(sns.boxplot(x=df[i],data=df))
    print(plt.show())
```

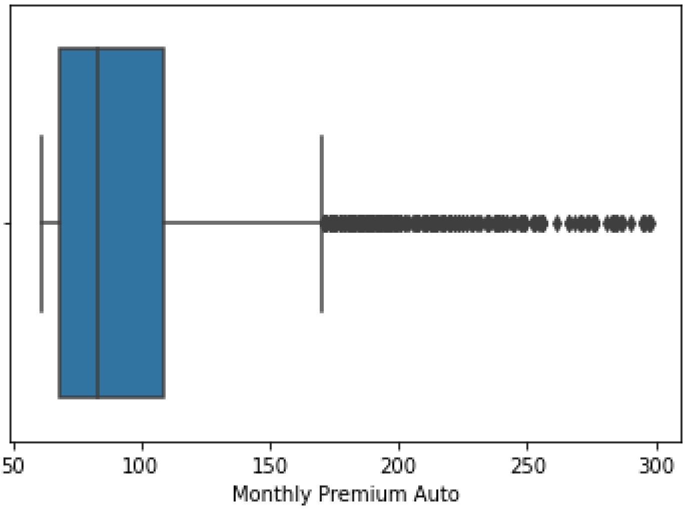
```
AxesSubplot(0.125,0.125;0.775x0.755)
```



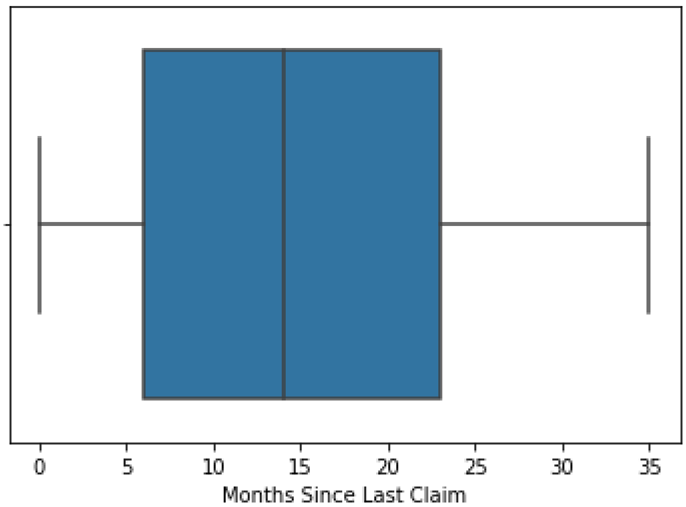

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



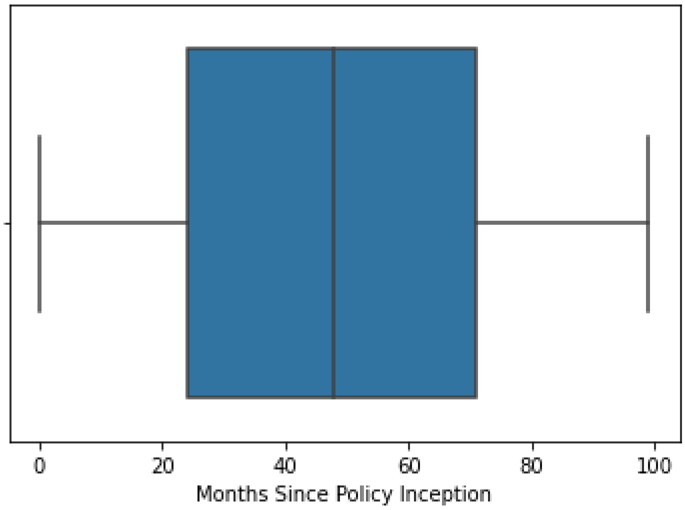

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



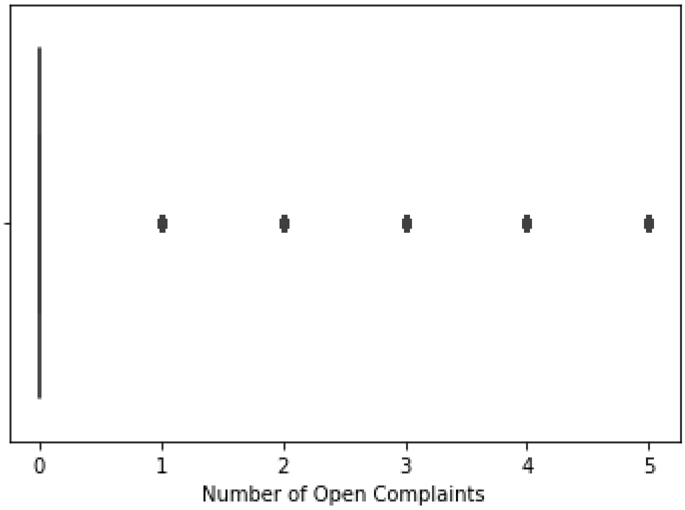

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



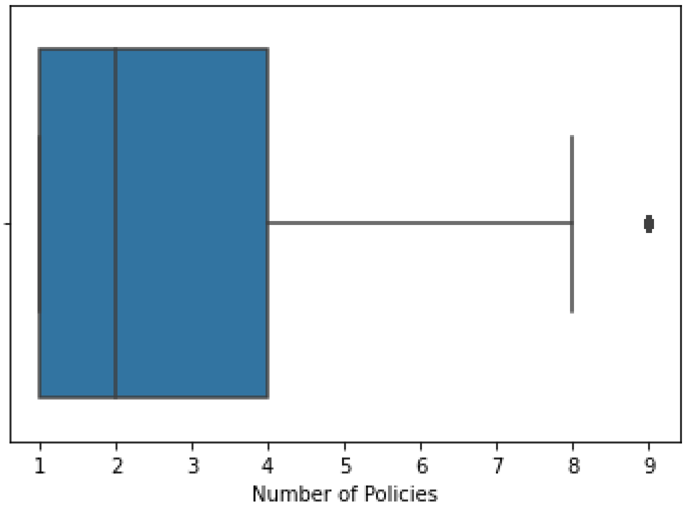

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



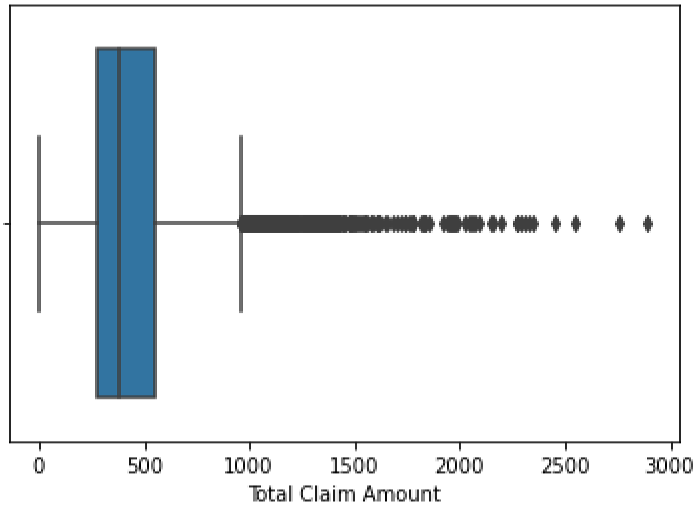

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```




```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```




```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



None

1. As we can see that there are outliers in the 'total claim amount' and also in 'monthly premium auto' , usually we remove the outliers for a better model.

2. since our dataset is related to insurance and banking industry, we must be accept the outliers,as they can be our potential customers.

3. And there are no outliers in the income.

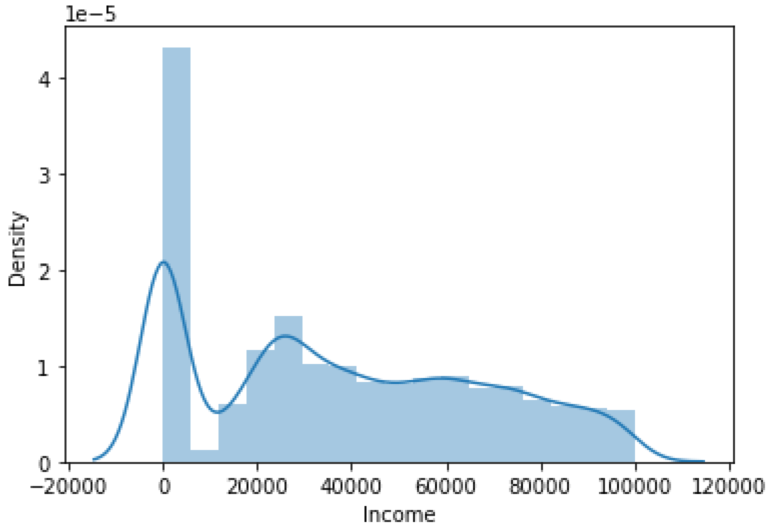
4. Conclusion: No outlier treatment required.

In [12]:
```
#Checking skewness in data
df.skew().sort_values(ascending=False)
```

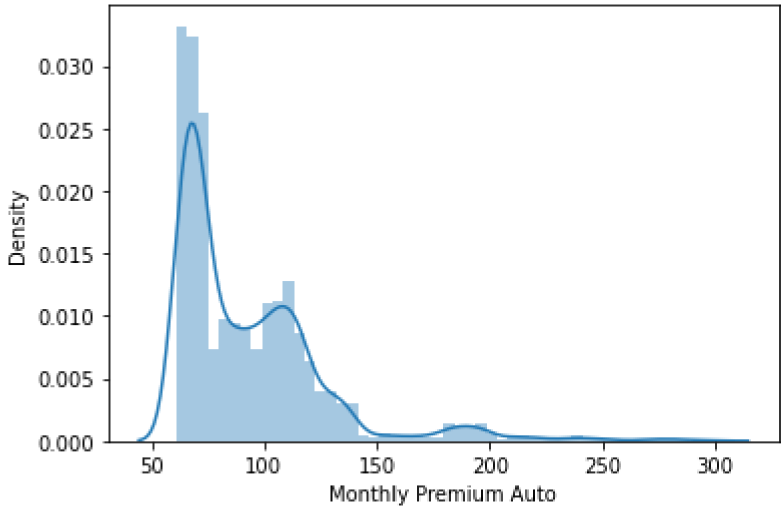
Out[12]:
```
Customer Lifetime Value          3.032280
Number of Open Complaints        2.783263
Monthly Premium Auto             2.123546
Total Claim Amount               1.714966
Number of Policies               1.253333
Income                           0.286887
Months Since Last Claim          0.278586
Months Since Policy Inception    0.040165
dtype: float64
```

We can see data is skewed in features "Customer Lifetime Value", "Number of Open Complaints","Monthly Premium Auto" and "Response"

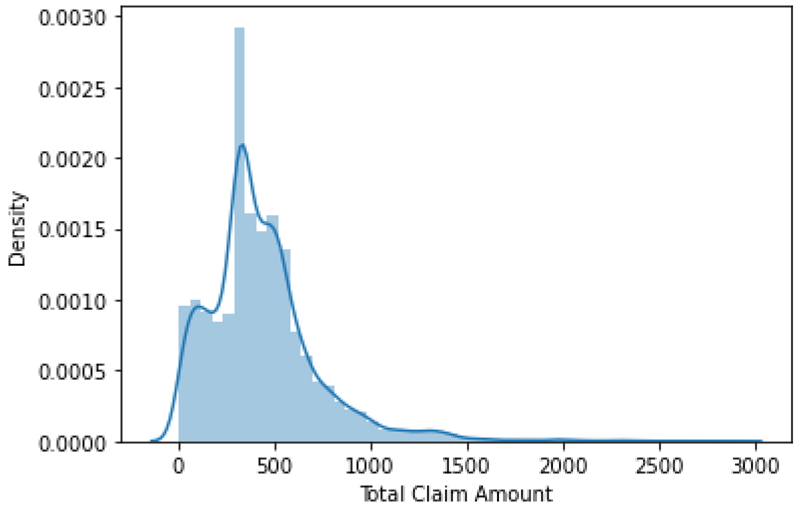
In [13]:
```
sns.distplot(df['Income'])
plt.show()
```



In [14]:
```
sns.distplot(df['Monthly Premium Auto'])
plt.show()
```



In [15]:
```
sns.distplot(df['Total Claim Amount'])
plt.show()
```

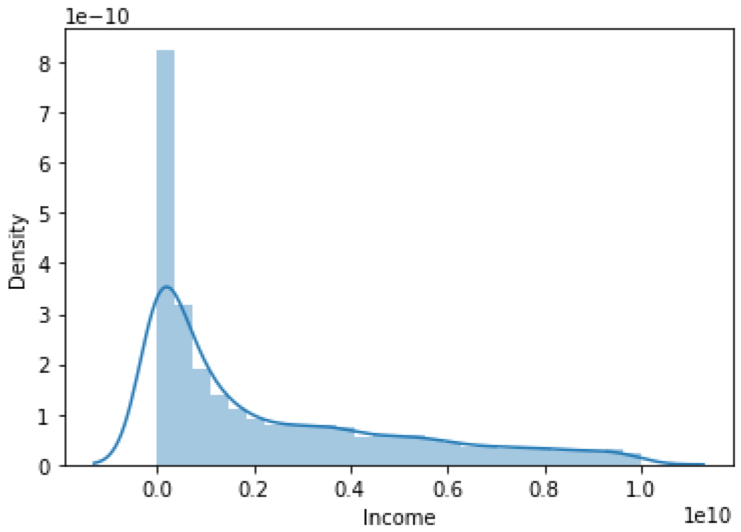


As we can see that none of the continuous variables are normally distributed.

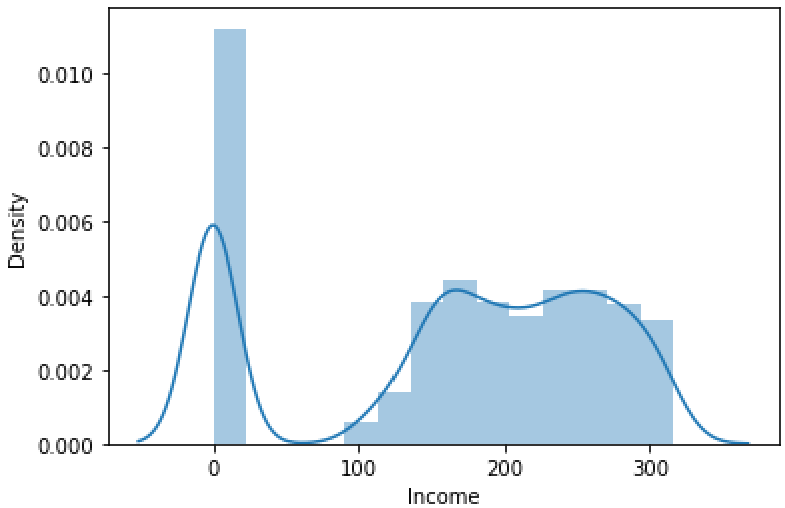
So in our case , we want to make the distributions normal, we can apply some transformations to the data and see if we can achieve a normally distributed variable.

In [16]:
```
# TRANSFORMATION OF THE NUMERICAL VARIABLES
```

In [17]:
```
sns.distplot(df['Income']**2)
plt.show()
```

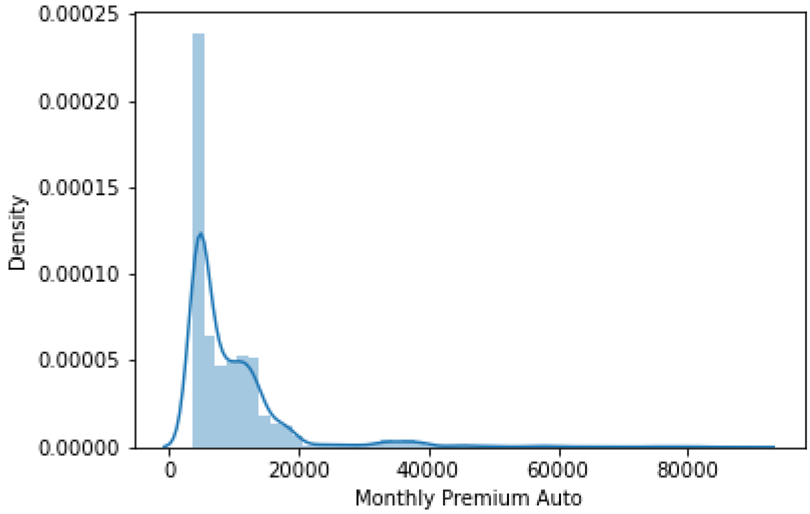


In [18]:
```
sns.distplot(df['Income']**(1/2))
plt.show()
```



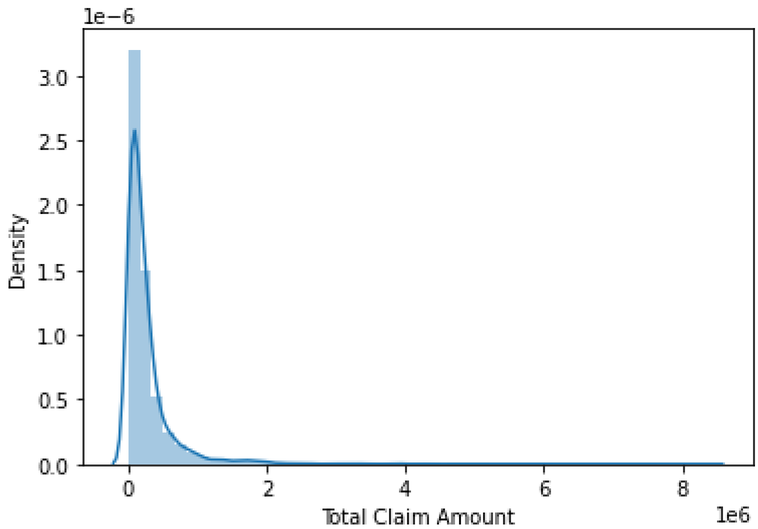
In [19]:
```
# As we can see that while we are trying to transform the data to make it normal,
# rather the distribution is getting skewed, or is having multiple peaks which agai
# is a problem to our model, hence we just stick with the same distribution of the
```

In [20]:
```
sns.distplot(df['Monthly Premium Auto']**(2))
plt.show()
```



In [21]:
```
# The monthly premium auto has multiple peaks,so to remove those peaks we can apply
# of the power transformation (SQUARE / CUBE) but as we can see that after the squa
# the data is getting heavily skewed, so we stick with the actual distribution agai
```

In [22]:
```
sns.distplot(df['Total Claim Amount']**2)
plt.show()
```



In [23]:
```
#' Again for the total claim amount after applying the transformation's the data is
#' and hence we stick to the actual distibution of the data.
#' Conclusion: No matter what power transformation we are applying to the numerical
#' it is still not getting normally distributed, and moreover the data is getting s
#' so rather we will just stick with the actual distribution
```

In [24]:
```
# Selecting only categorical data and assigning it into ObjectData
ObjectData=df.select_dtypes("object")
```

In [25]:
```
ObjectData.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9134 entries, 0 to 9133
Data columns (total 16 columns):
 #   Column              Non-Null Count  Dtype 
---  ------              --------------  ----- 
 0   Customer            9134 non-null   object
 1   State               9134 non-null   object
 2   Response            9134 non-null   object
 3   Coverage            9134 non-null   object
 4   Education           9134 non-null   object
 5   Effective To Date   9134 non-null   object
 6   EmploymentStatus    9134 non-null   object
 7   Gender              9134 non-null   object
 8   Location Code       9134 non-null   object
 9   Marital Status      9134 non-null   object
 10  Policy Type         9134 non-null   object
 11  Policy              9134 non-null   object
 12  Renew Offer Type    9134 non-null   object
 13  Sales Channel       9134 non-null   object
 14  Vehicle Class       9134 non-null   object
 15  Vehicle Size        9134 non-null   object
dtypes: object(16)
memory usage: 1.1+ MB
```

In [26]:
```
ObjectData.columns
```

Out[26]:
```
Index(['Customer', 'State', 'Response', 'Coverage', 'Education',
       'Effective To Date', 'EmploymentStatus', 'Gender', 'Location Code',
       'Marital Status', 'Policy Type', 'Policy', 'Renew Offer Type',
       'Sales Channel', 'Vehicle Class', 'Vehicle Size'],
      dtype='object')
```

In [27]:
```
ObjectData.head()
```

Out[27]:

	Customer	State	Response	Coverage	Education	Effective To Date	EmploymentStatus	Gender
0	BU79786	Washington	No	Basic	Bachelor	2/24/11	Employed	F
1	QZ44356	Arizona	No	Extended	Bachelor	1/31/11	Unemployed	F
2	AI49188	Nevada	No	Premium	Bachelor	2/19/11	Employed	F
3	WW63253	California	No	Basic	Bachelor	1/20/11	Unemployed	M
4	HB64268	Washington	No	Basic	Bachelor	3/2/2011	Employed	M

In [28]:
```
ObjectData.drop(['Customer','Effective To Date'],axis=1,inplace=True)
```

In [29]:
```
for i in ObjectData.columns:
    print(ObjectData[i].value_counts(),"\n")
```

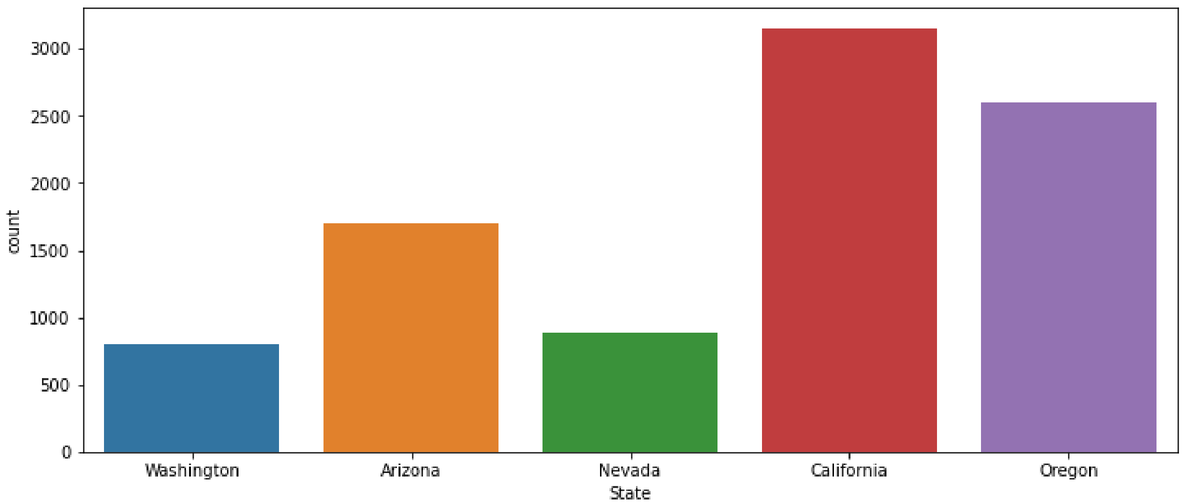
```
California    3150
Oregon        2601
Arizona       1703
Nevada         882
Washington     798
Name: State, dtype: int64

No     7826
Yes    1308
Name: Response, dtype: int64

Basic       5568
Extended    2742
Premium      824
Name: Coverage, dtype: int64

Bachelor                2748
College                 2681
High School or Below    2622
Master                   741
Doctor                   342
Name: Education, dtype: int64

Employed         5698
Unemployed       2317
Medical Leave     432
Disabled          405
Retired           282
Name: EmploymentStatus, dtype: int64

F    4658
M    4476
Name: Gender, dtype: int64

Suburban    5779
Rural       1773
Urban       1582
Name: Location Code, dtype: int64

Married     5298
Single      2467
Divorced    1369
Name: Marital Status, dtype: int64

Personal Auto     6788
Corporate Auto    1968
Special Auto       378
Name: Policy Type, dtype: int64

Personal L3     3426
Personal L2     2122
Personal L1     1240
Corporate L3    1014
Corporate L2     595
Corporate L1     359
Special L2       164
Special L3       148
Special L1        66
Name: Policy, dtype: int64

Offer1    3752
Offer2    2926
Offer3    1432
Offer4    1024
```

```
Name: Renew Offer Type, dtype: int64

Agent           3477
Branch          2567
Call Center     1765
Web             1325
Name: Sales Channel, dtype: int64

Four-Door Car    4621
Two-Door Car     1886
SUV              1796
Sports Car        484
Luxury SUV        184
Luxury Car        163
Name: Vehicle Class, dtype: int64

Medsize    6424
Small      1764
Large       946
Name: Vehicle Size, dtype: int64
```

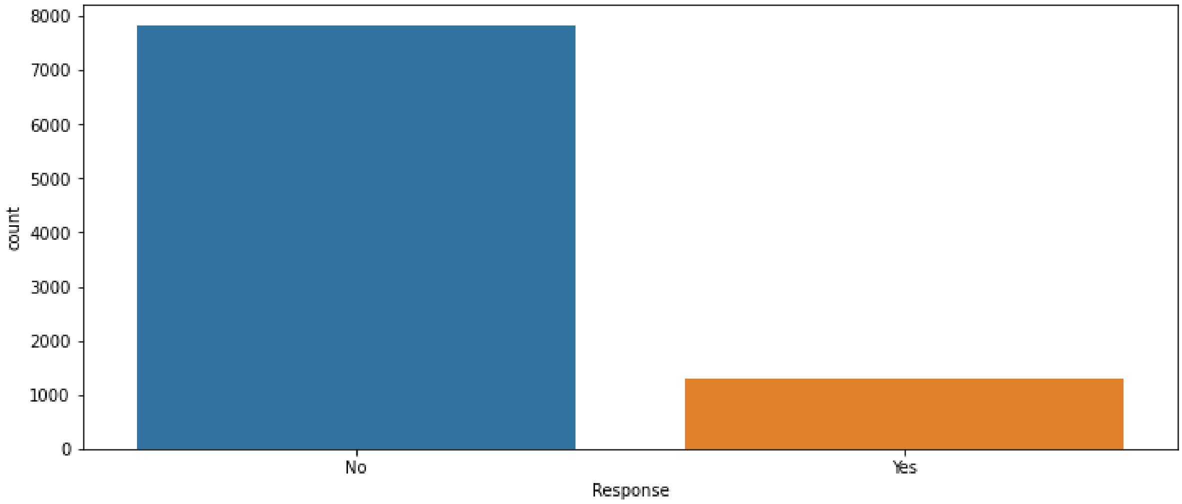
Univariate data visulization

In [30]:
```python
for i in ObjectData.columns:
    plt.figure(figsize=(12, 5))
    print(sns.countplot(x=ObjectData[i],data=ObjectData))
    print(plt.show())

    print(ObjectData[i].value_counts())
```

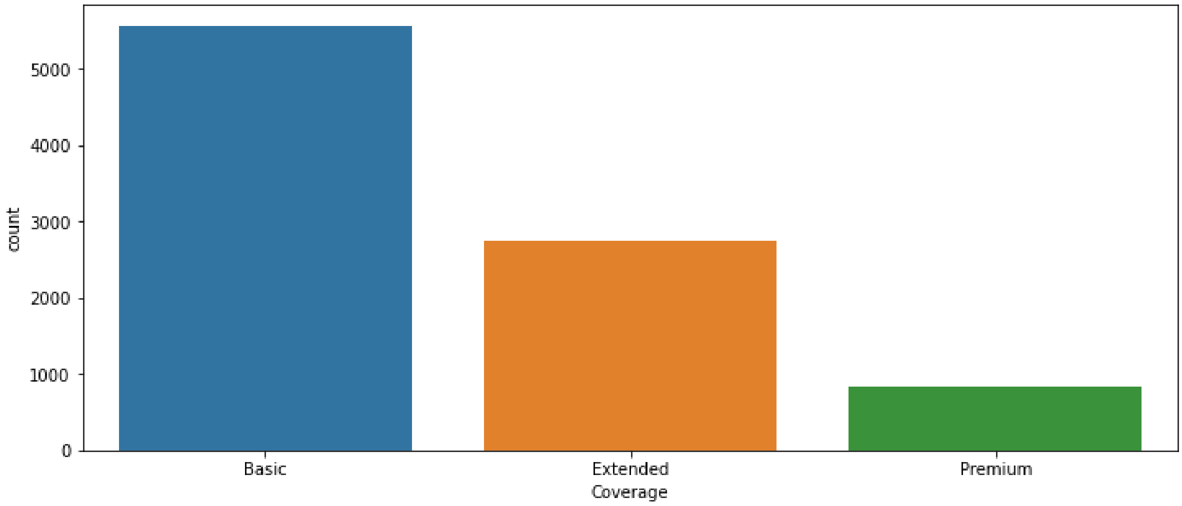
```
AxesSubplot(0.125,0.125;0.775x0.755)
```



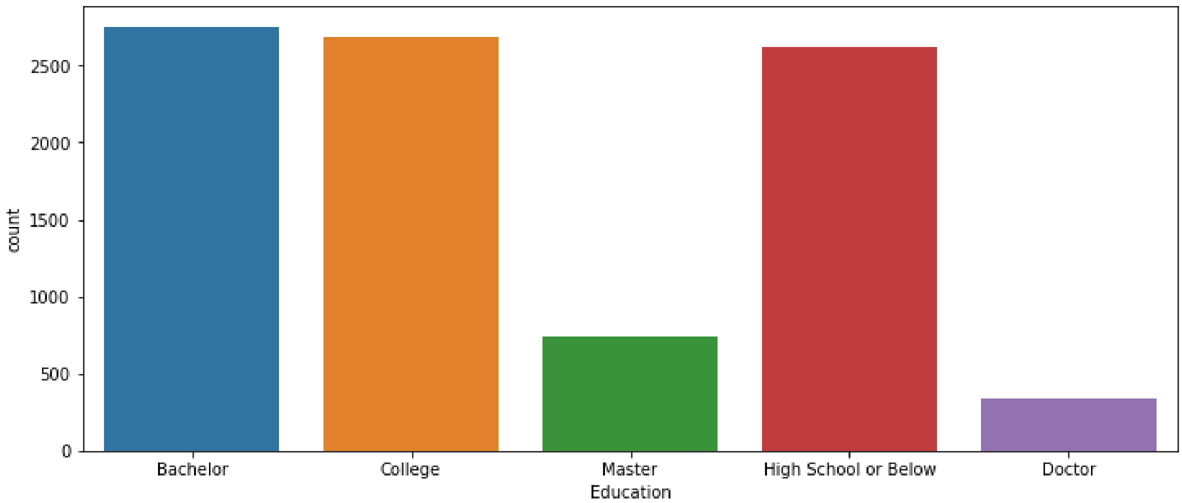

```
None
California    3150
Oregon        2601
Arizona       1703
Nevada         882
Washington     798
Name: State, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



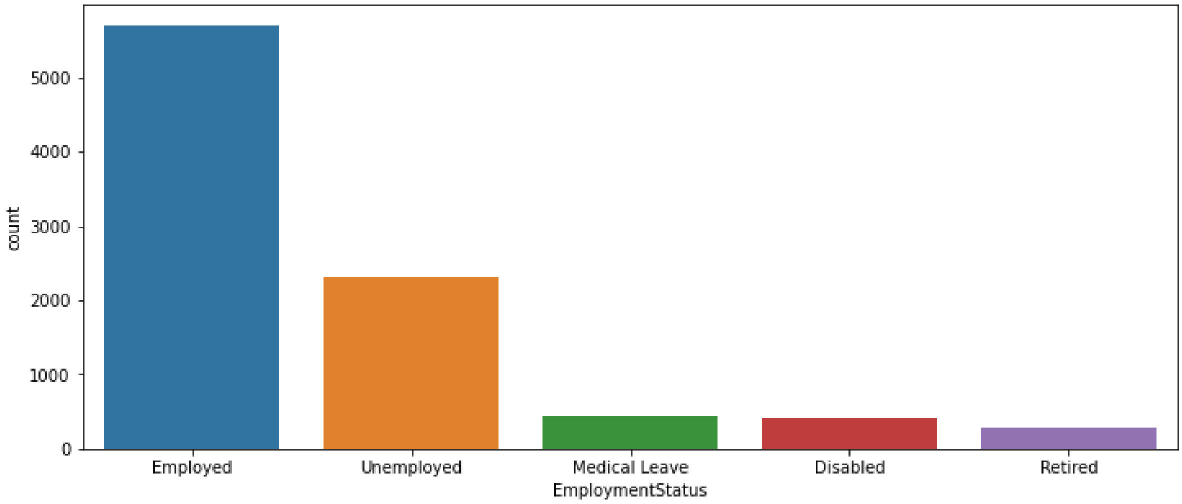

```
None
No     7826
Yes    1308
Name: Response, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



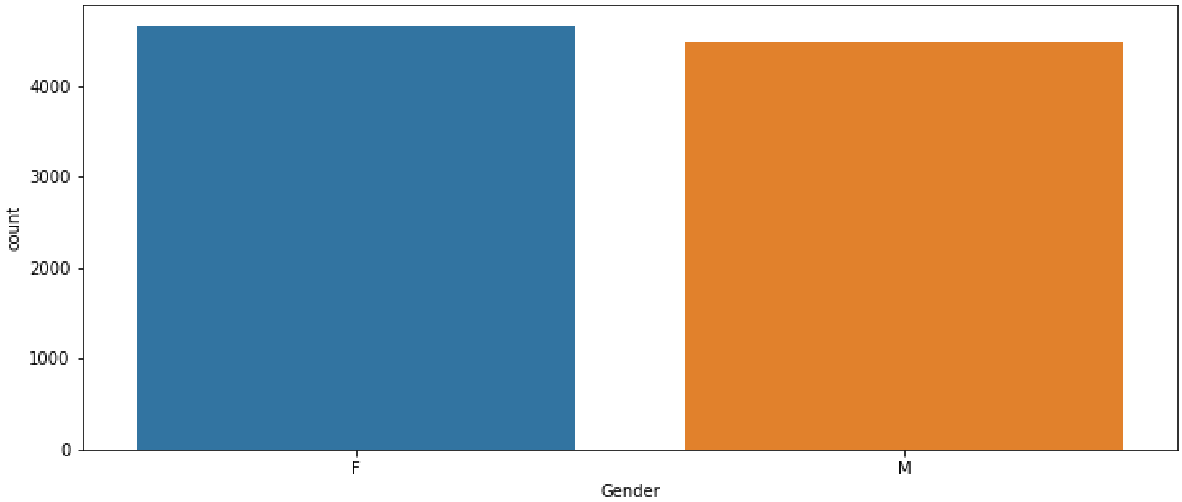

```
None
Basic       5568
Extended    2742
Premium      824
Name: Coverage, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



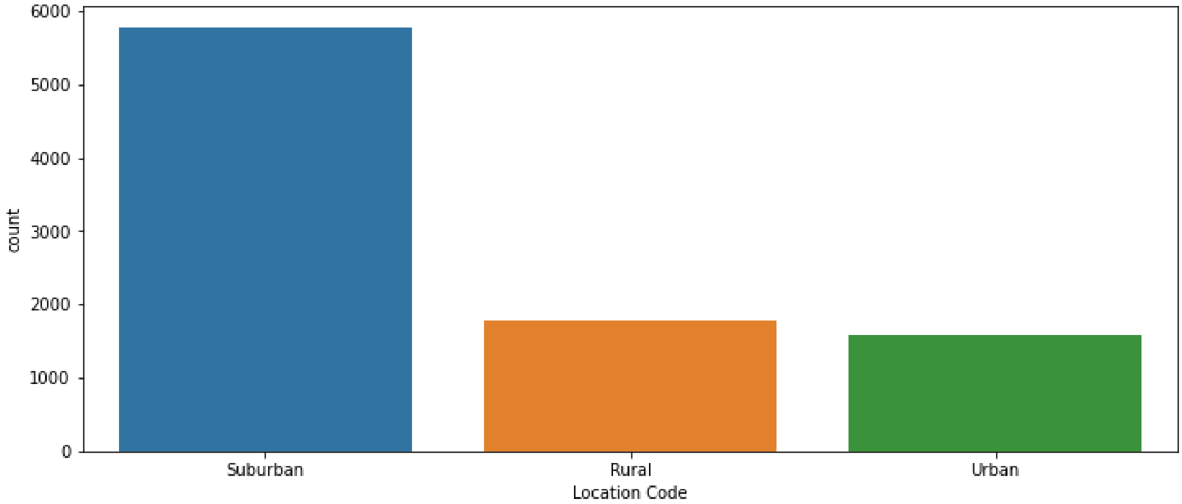
```
None
Bachelor                2748
College                 2681
High School or Below    2622
Master                   741
Doctor                   342
Name: Education, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



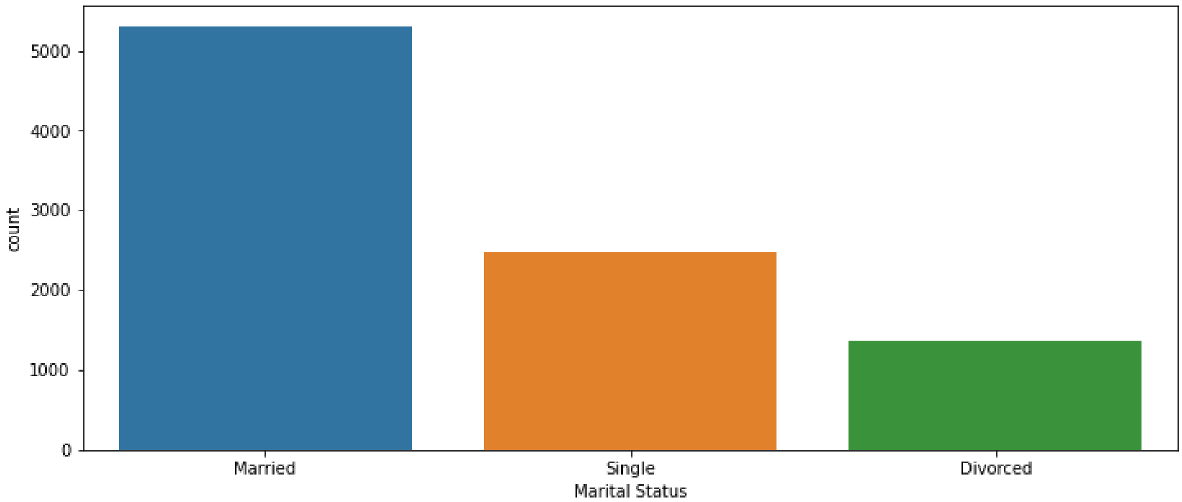

```
None
Employed         5698
Unemployed       2317
Medical Leave     432
Disabled          405
Retired           282
Name: EmploymentStatus, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



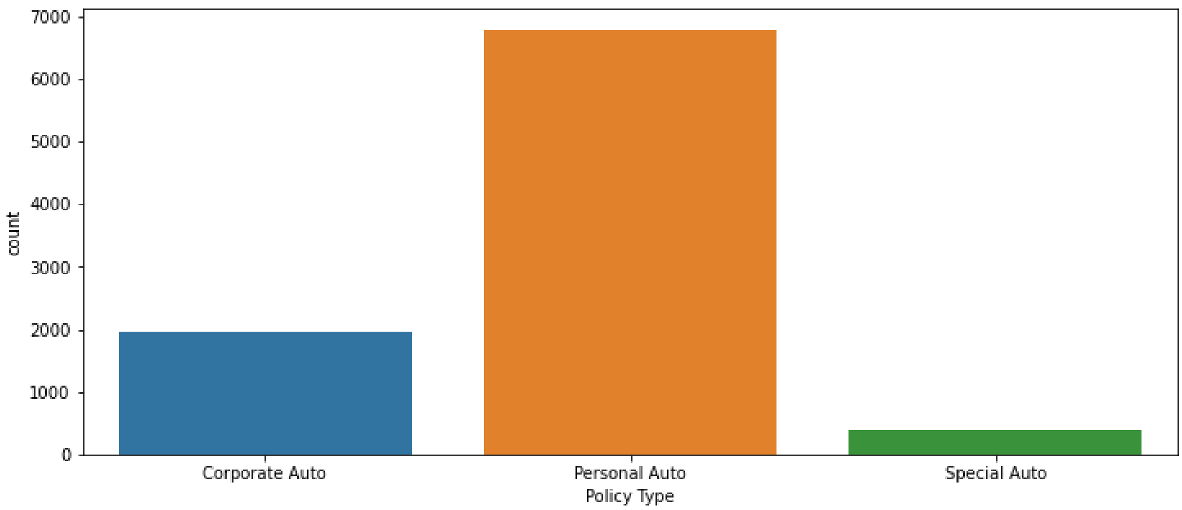

```
None
F    4658
M    4476
Name: Gender, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



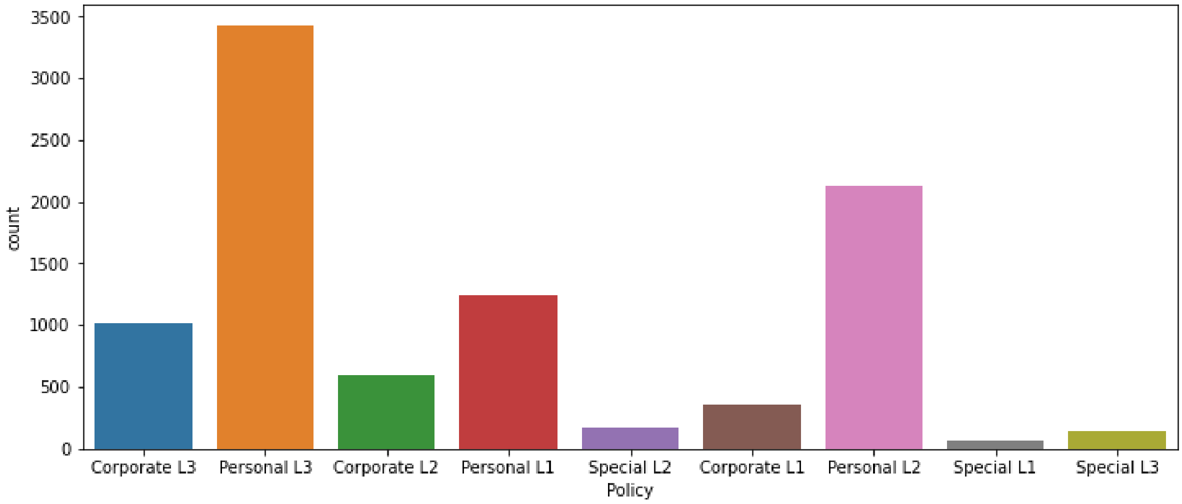

```
None
Suburban    5779
Rural       1773
Urban       1582
Name: Location Code, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



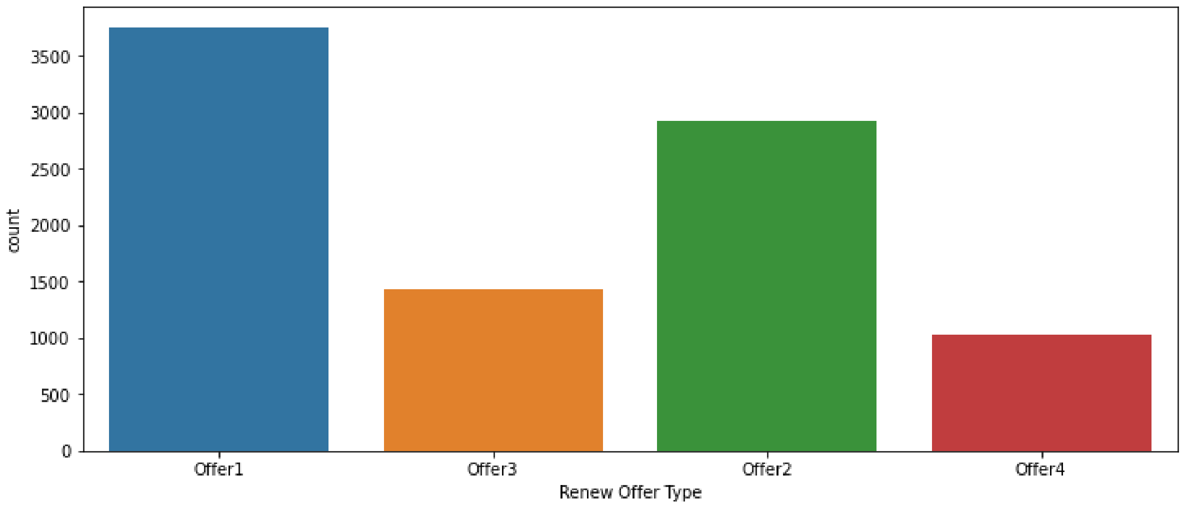

```
None
Married     5298
Single      2467
Divorced    1369
Name: Marital Status, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



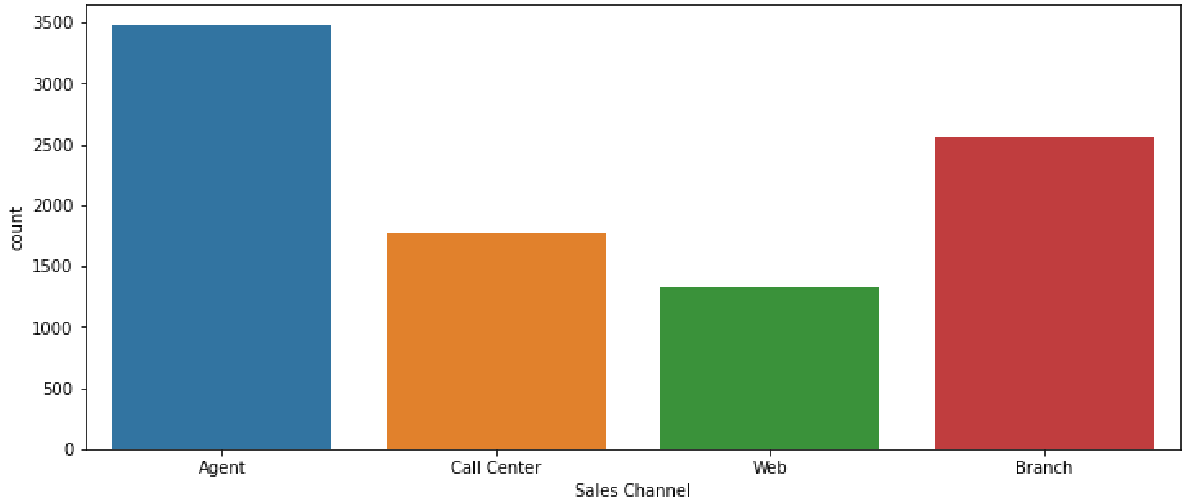
```
None
Personal Auto     6788
Corporate Auto    1968
Special Auto       378
Name: Policy Type, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



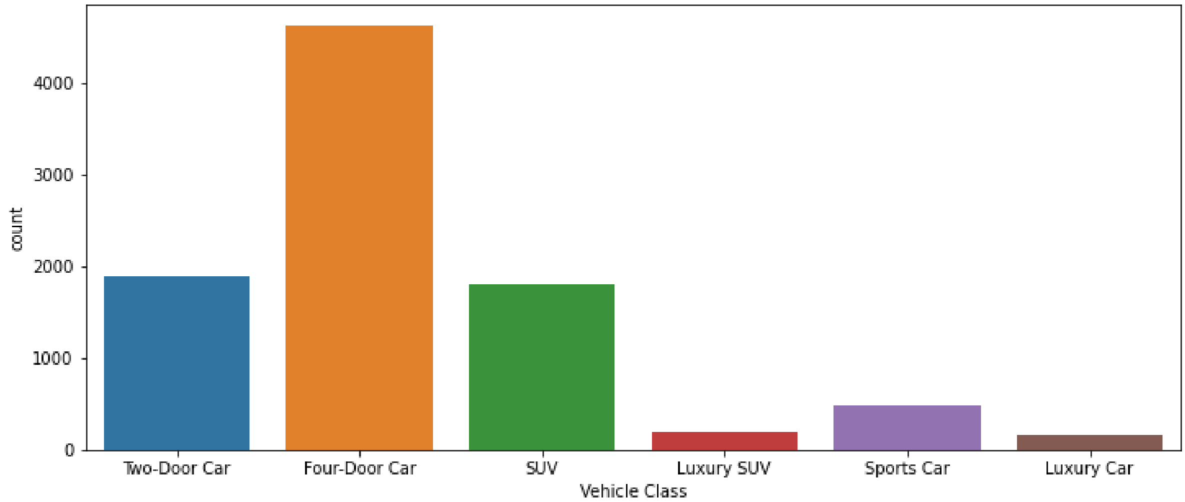

```
None
Personal L3     3426
Personal L2     2122
Personal L1     1240
Corporate L3    1014
Corporate L2     595
Corporate L1     359
Special L2       164
Special L3       148
Special L1        66
Name: Policy, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



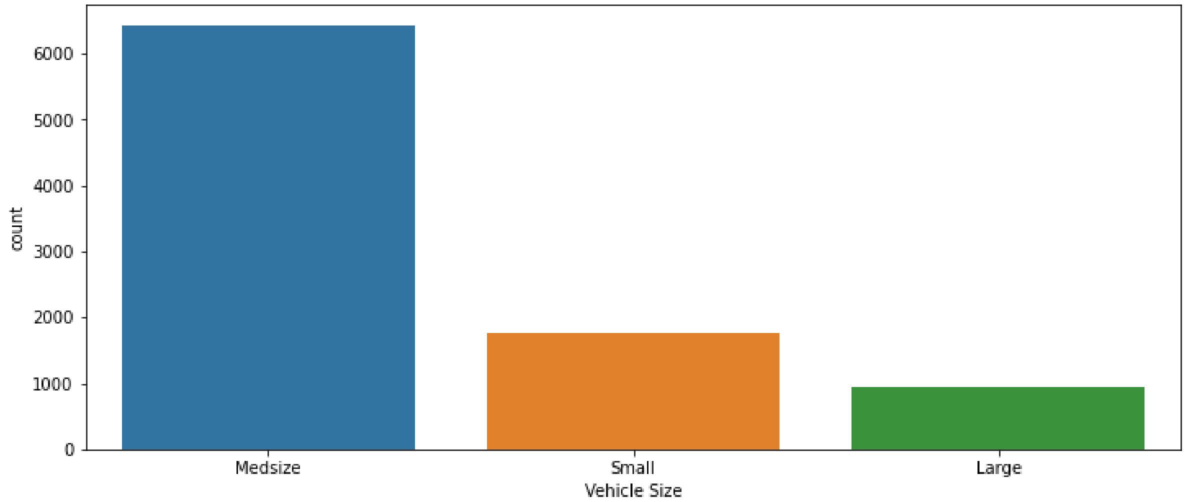

```
None
Offer1    3752
Offer2    2926
Offer3    1432
Offer4    1024
Name: Renew Offer Type, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```




```
None
Agent          3477
Branch         2567
Call Center    1765
Web            1325
Name: Sales Channel, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```




```
None
Four-Door Car    4621
Two-Door Car     1886
SUV              1796
Sports Car        484
Luxury SUV        184
Luxury Car        163
Name: Vehicle Class, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```

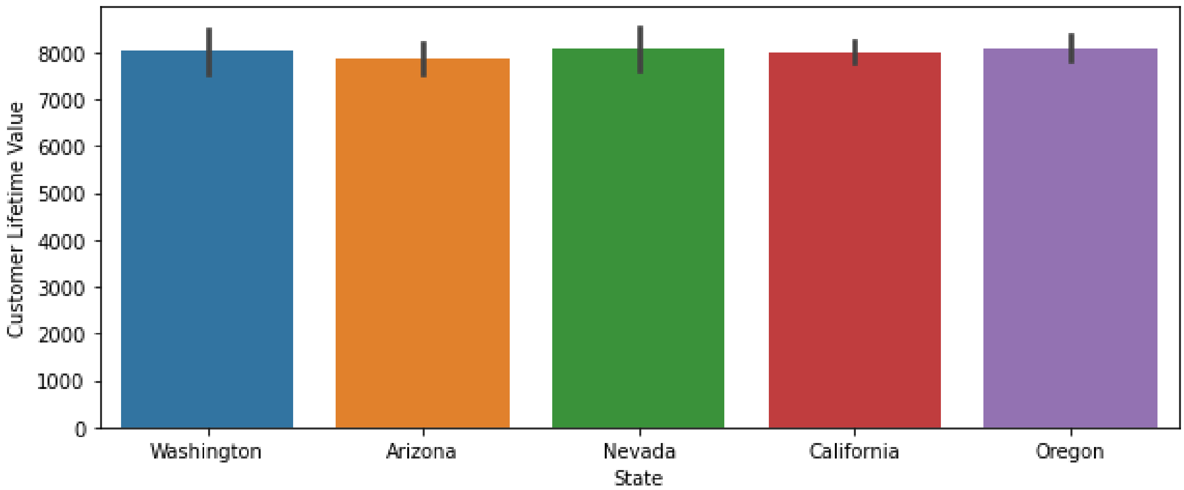



```
None
Medsize    6424
Small      1764
Large       946
Name: Vehicle Size, dtype: int64
```

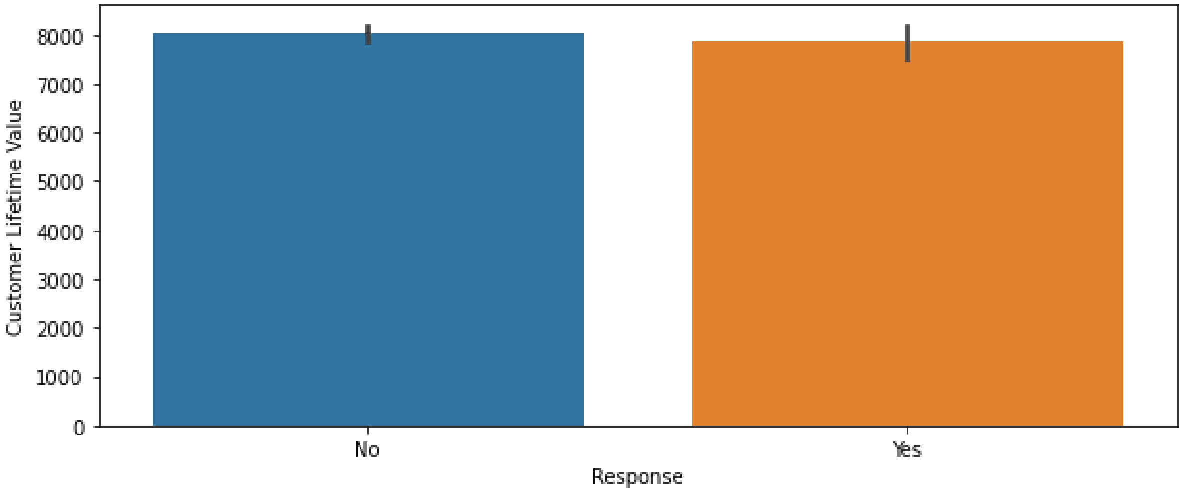
Bivariate Data Visualization

In [31]:
```
for i in ObjectData.columns:
    plt.figure(figsize=(10, 4))
    print(sns.barplot(x=ObjectData[i],y=df['Customer Lifetime Value'], data=ObjectD
    print(plt.show())
```

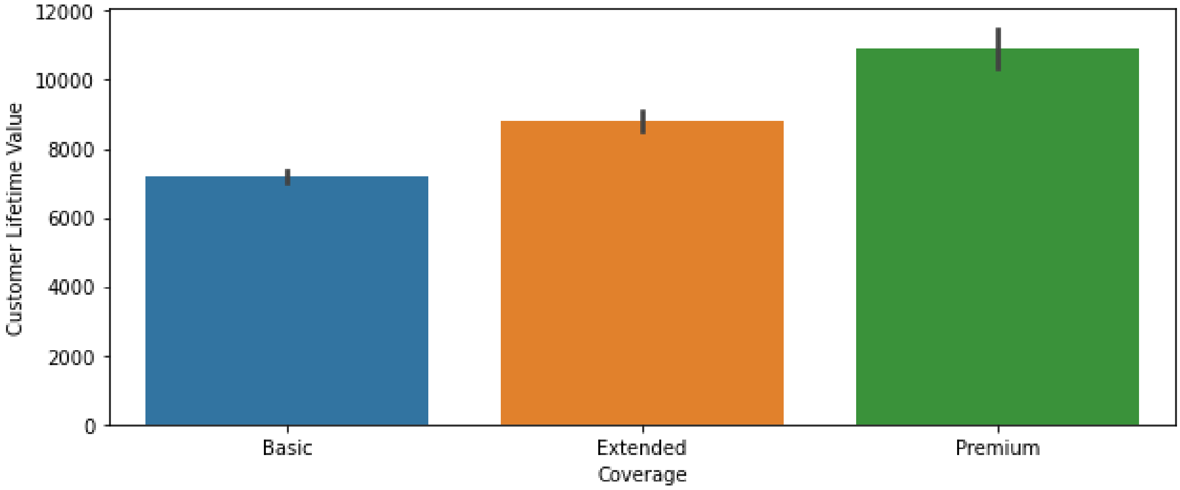
```
AxesSubplot(0.125,0.125;0.775x0.755)
```



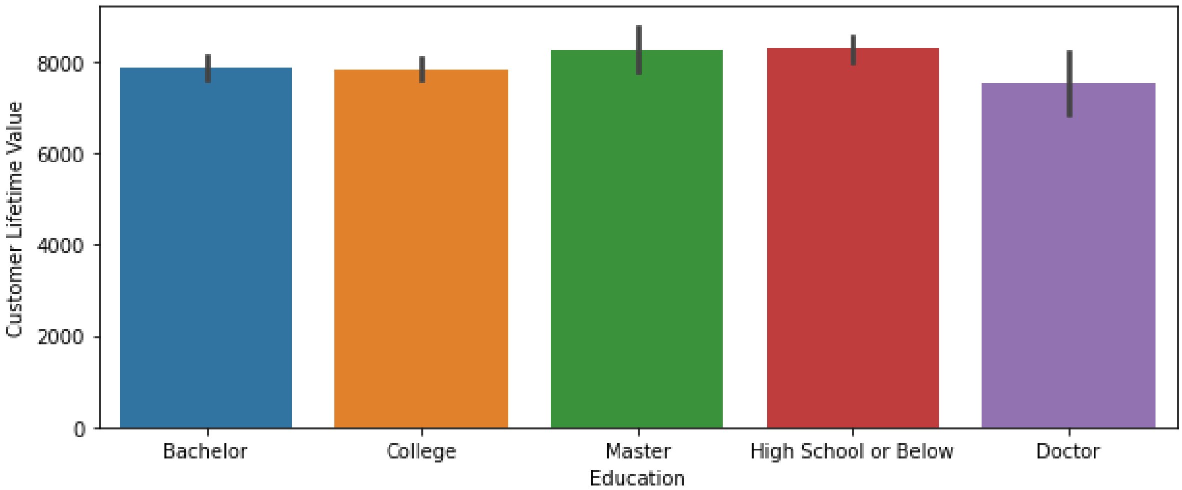

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



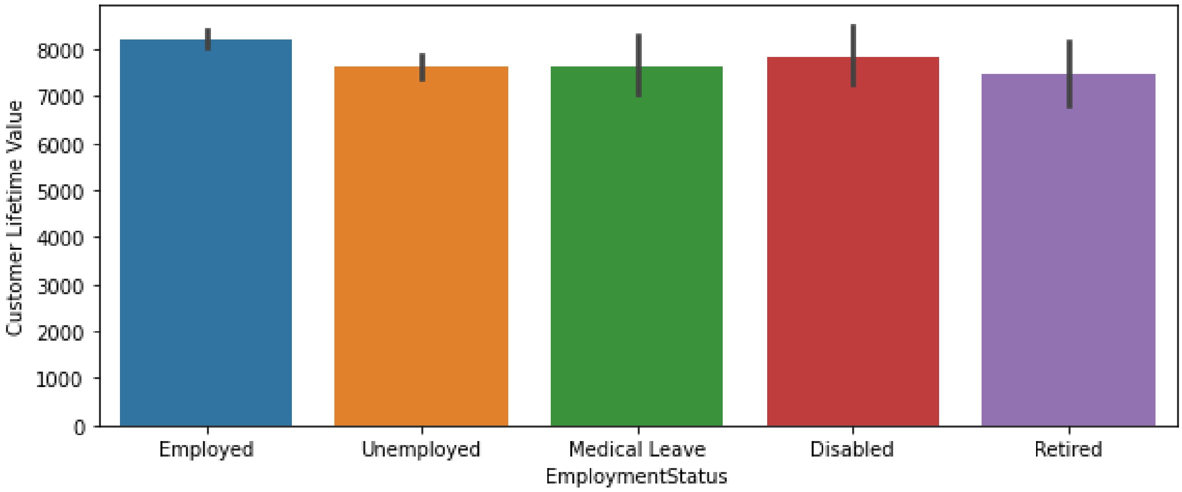

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



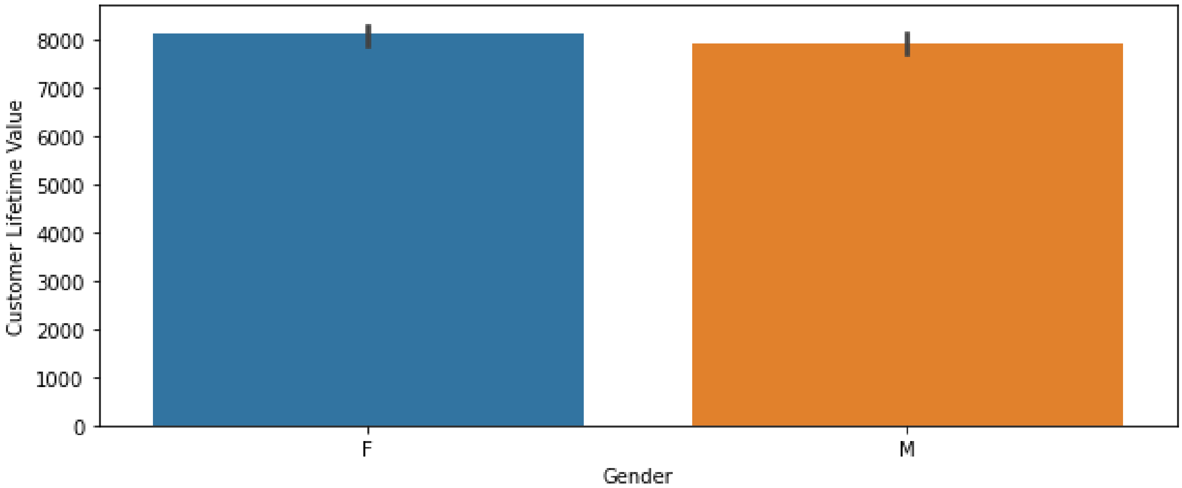

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



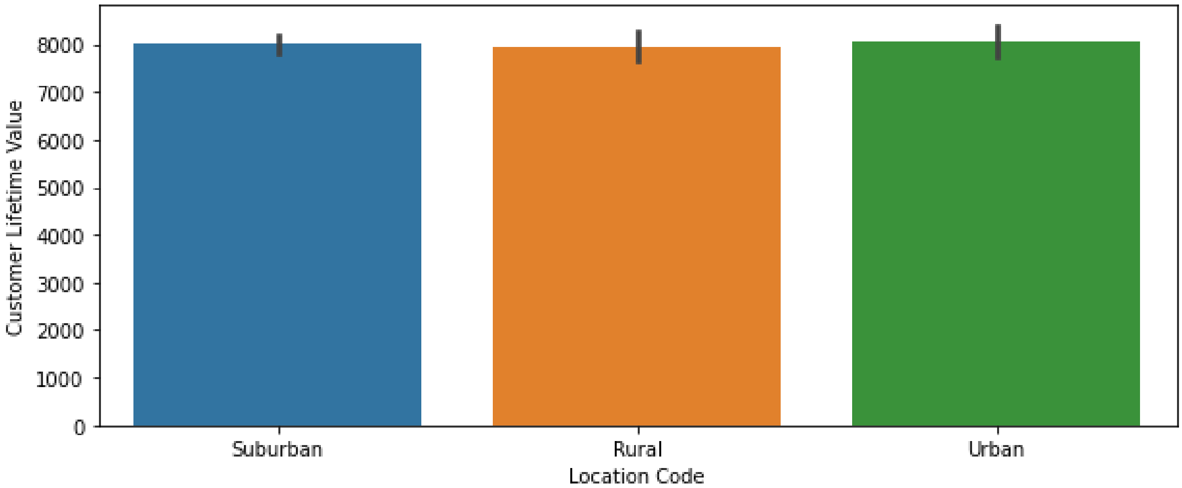

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



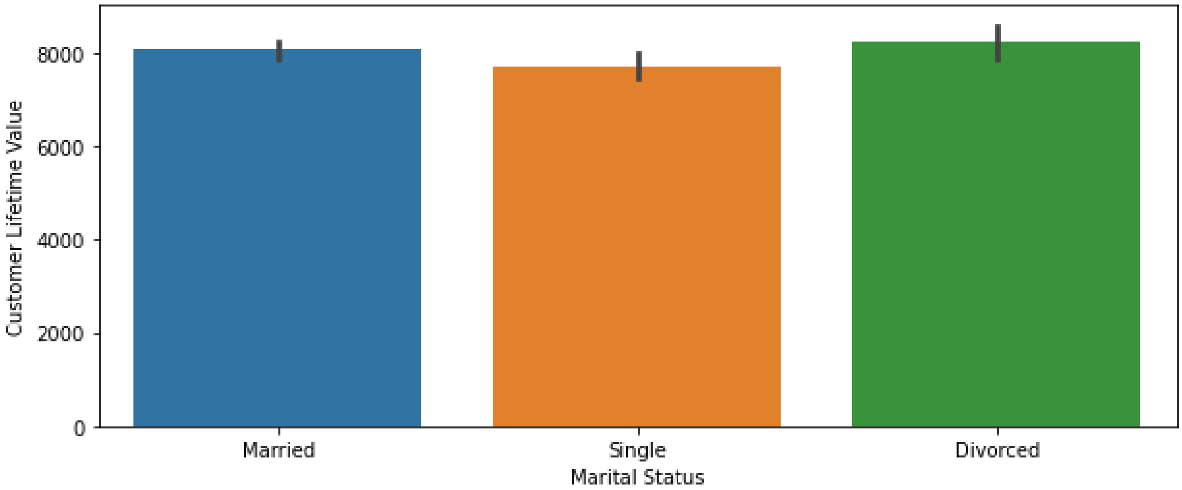

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



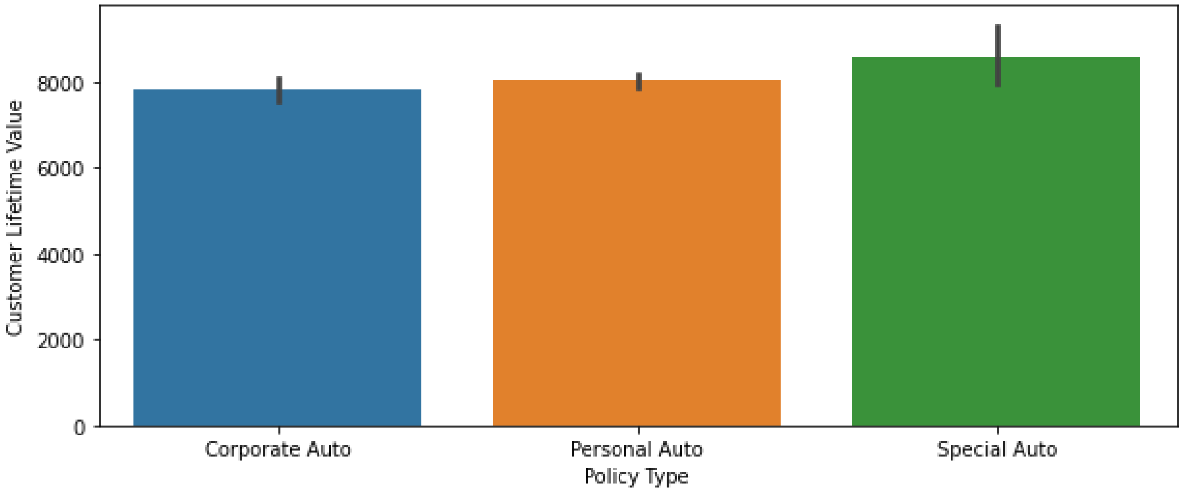

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



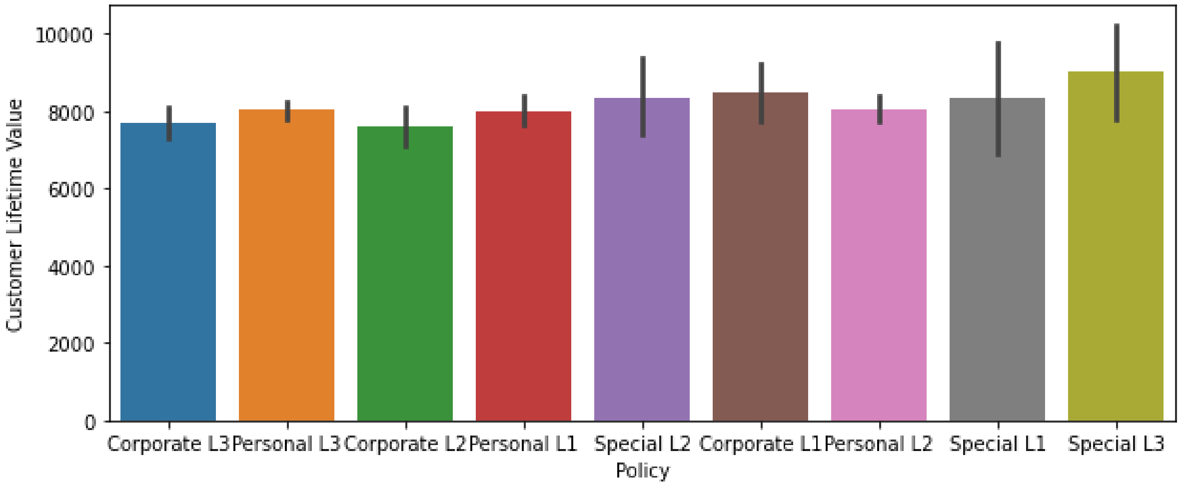

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



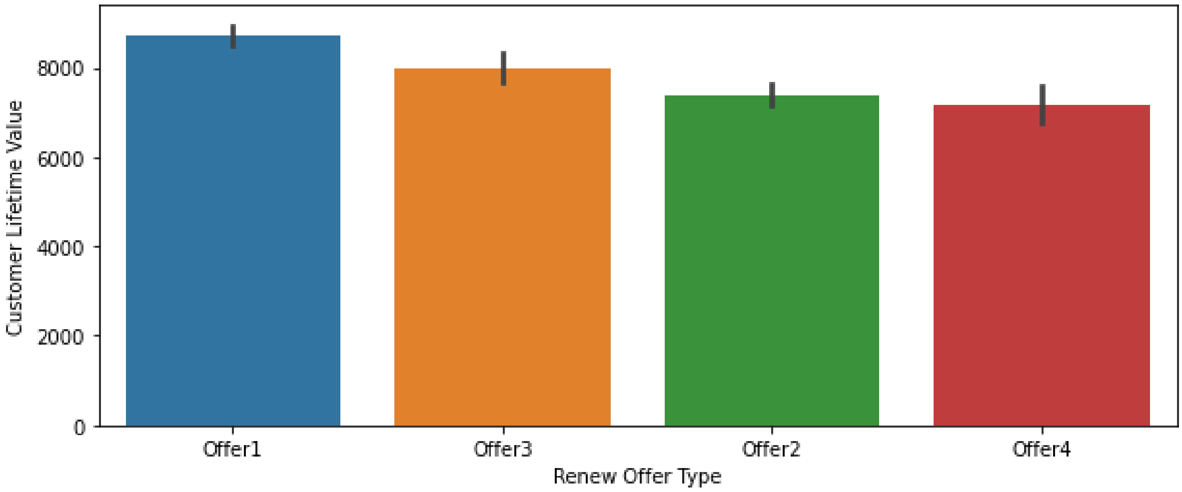

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



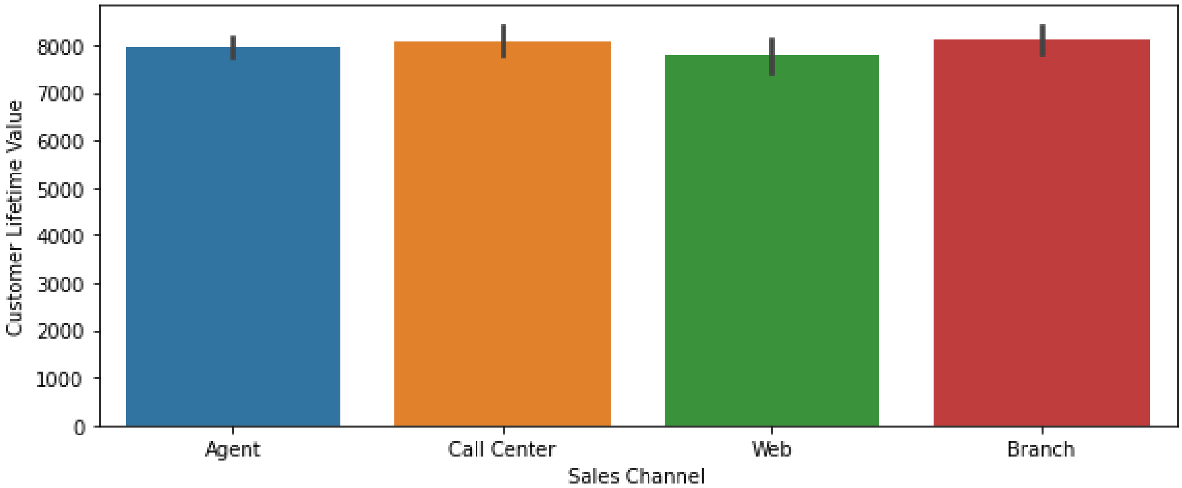

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



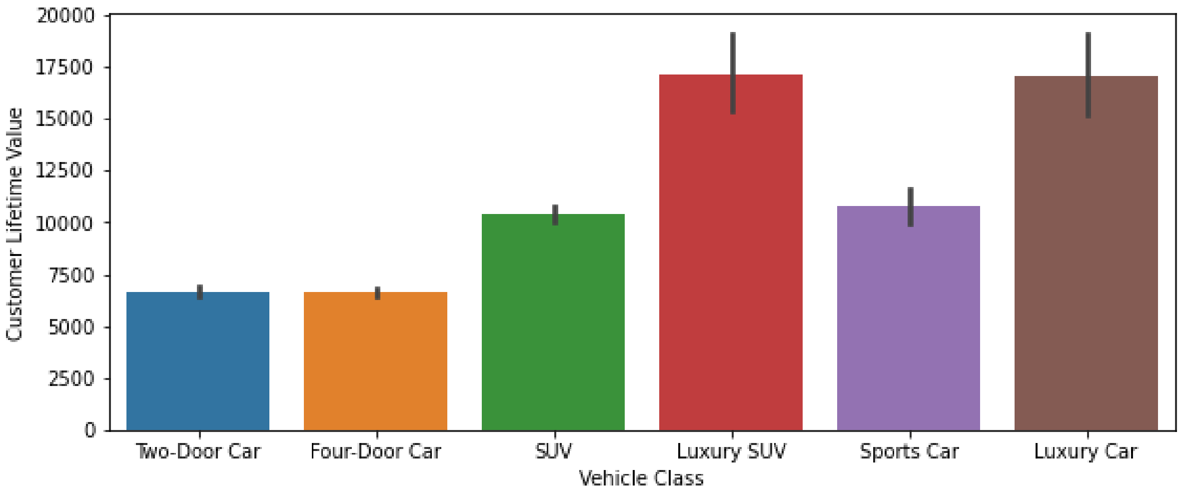

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```



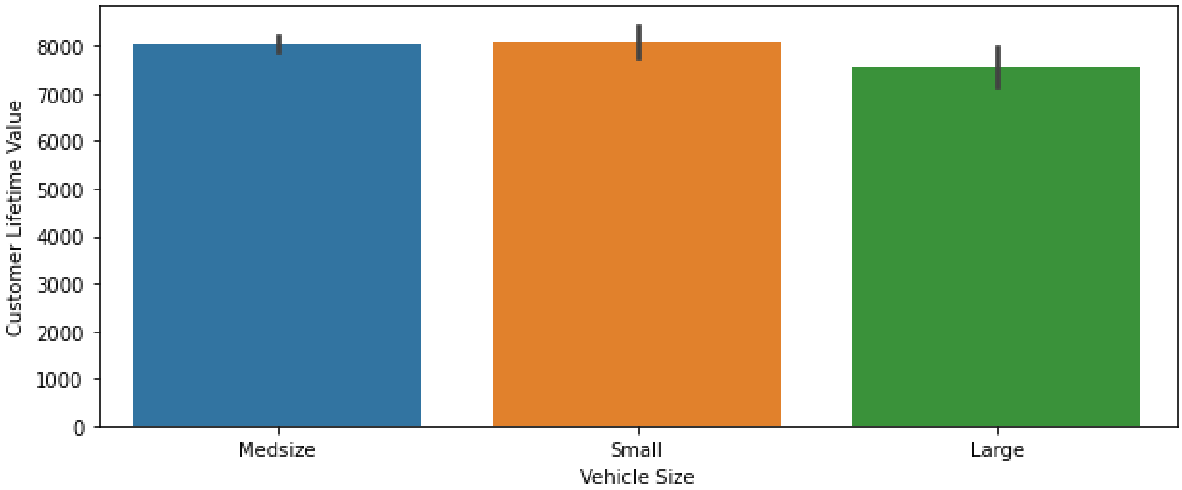

```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```




```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```




```
None
AxesSubplot(0.125,0.125;0.775x0.755)
```

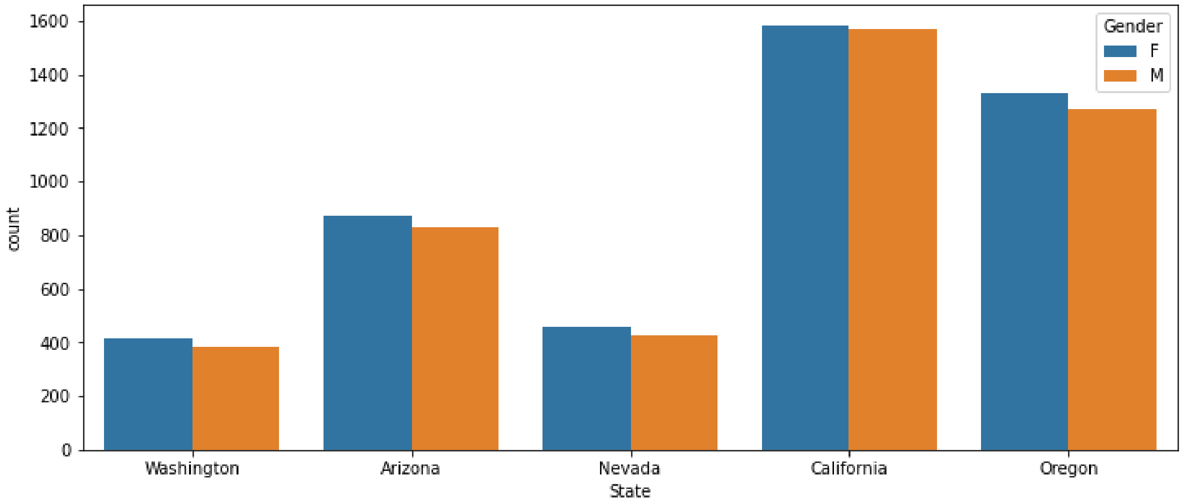



```
None
```

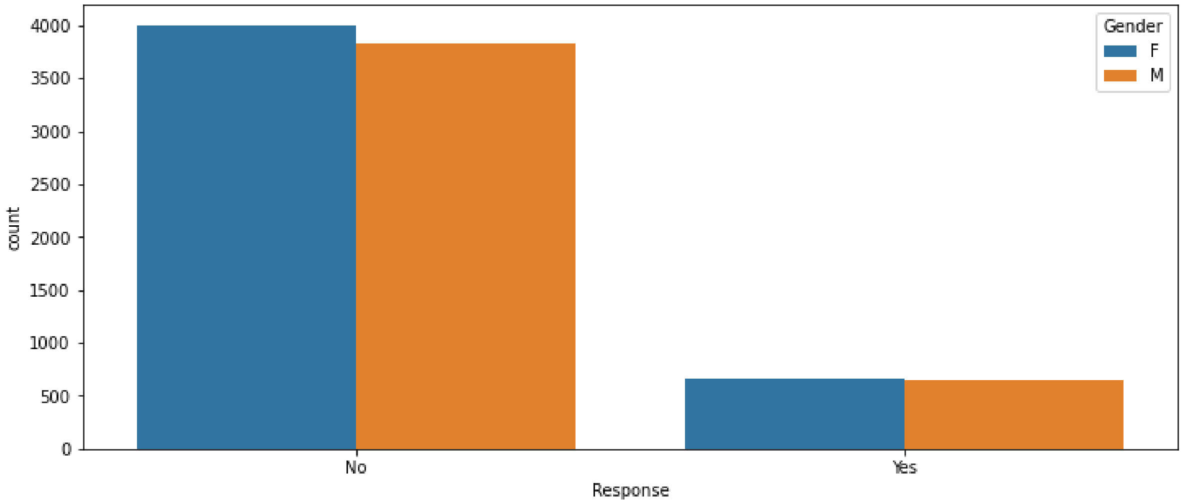
In [32]:
```
# Inferance

# 1. We can see that the average customer lifetime value is same for both male and
```

In [33]:
```
for i in ObjectData.columns:
    plt.figure(figsize=(12, 5))
    print(sns.countplot(x=ObjectData[i],hue=ObjectData['Gender'],data=ObjectData))
    print(plt.show())

    print(ObjectData[i].value_counts())
```

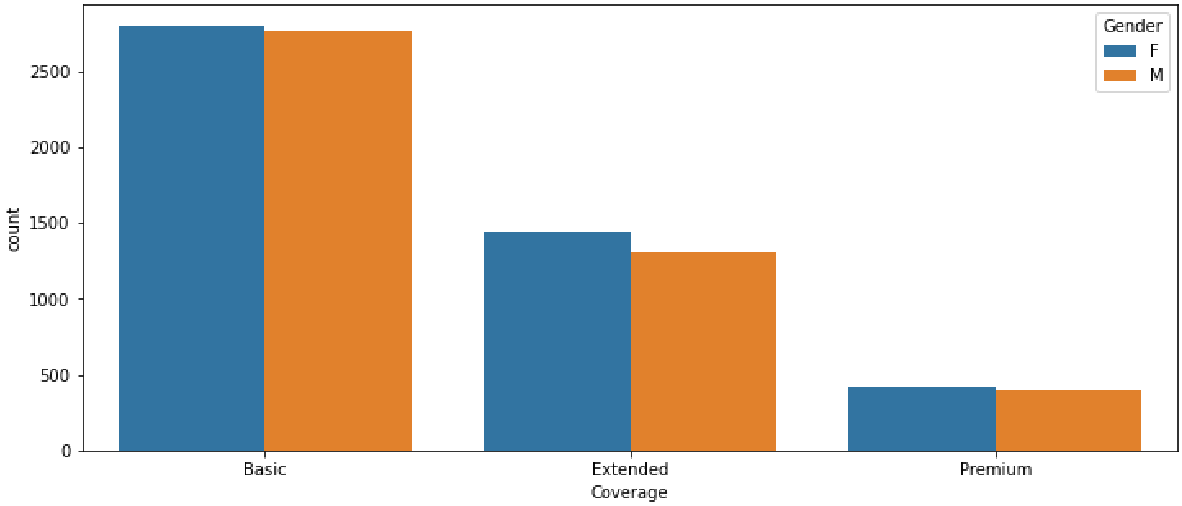
```
AxesSubplot(0.125,0.125;0.775x0.755)
```



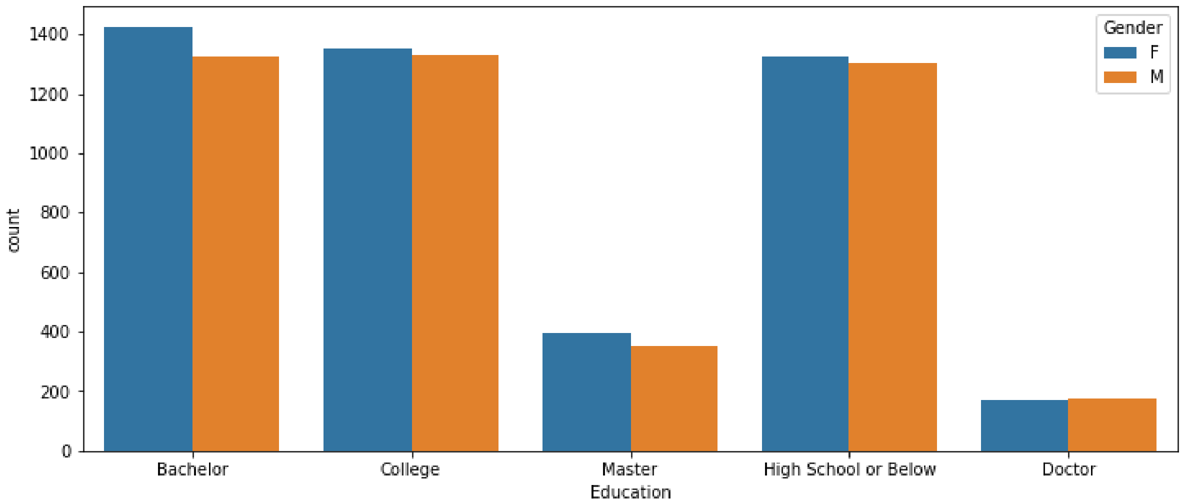

```
None
California    3150
Oregon        2601
Arizona       1703
Nevada         882
Washington     798
Name: State, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



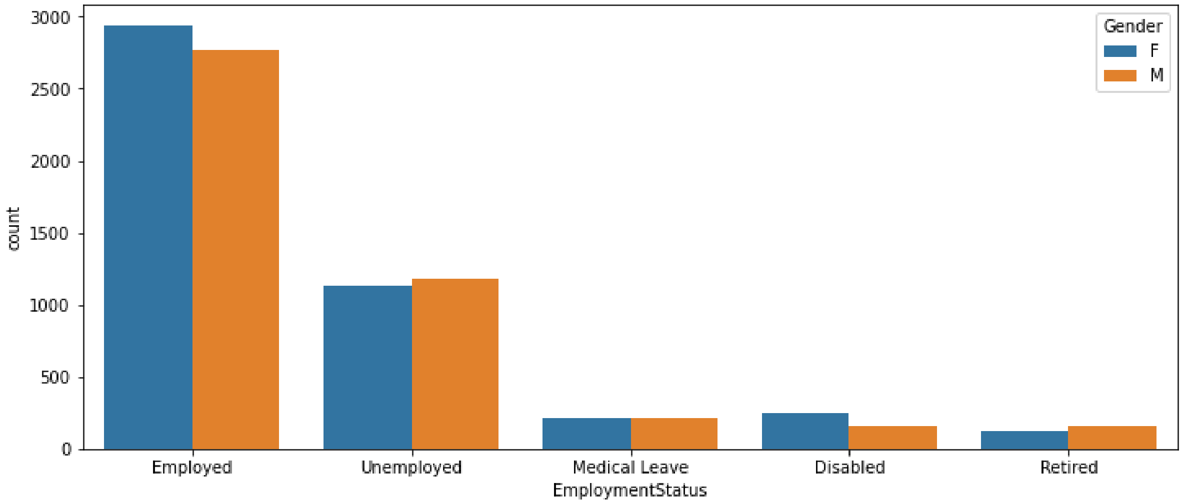

```
None
No      7826
Yes     1308
Name: Response, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



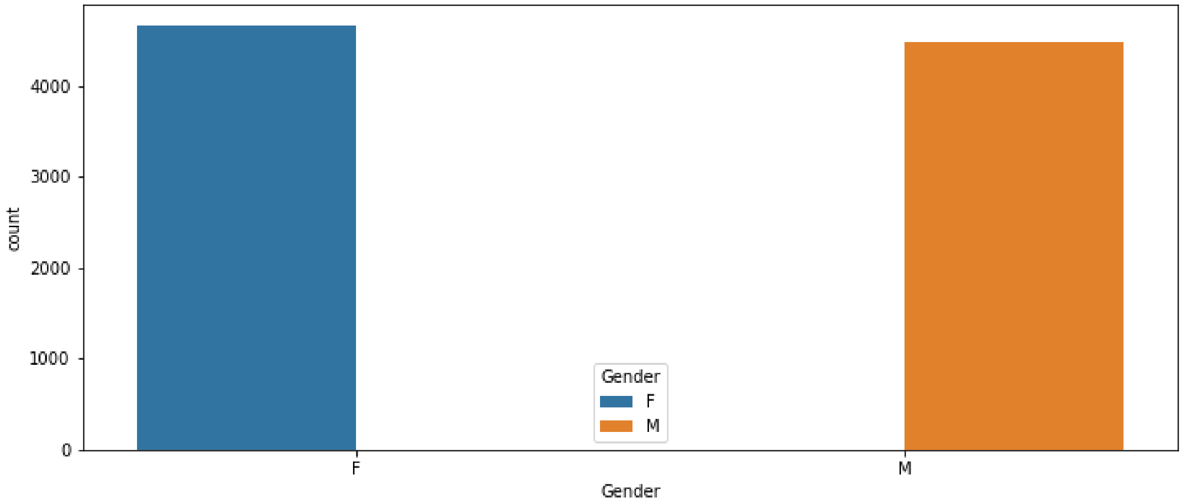

```
None
Basic       5568
Extended    2742
Premium      824
Name: Coverage, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



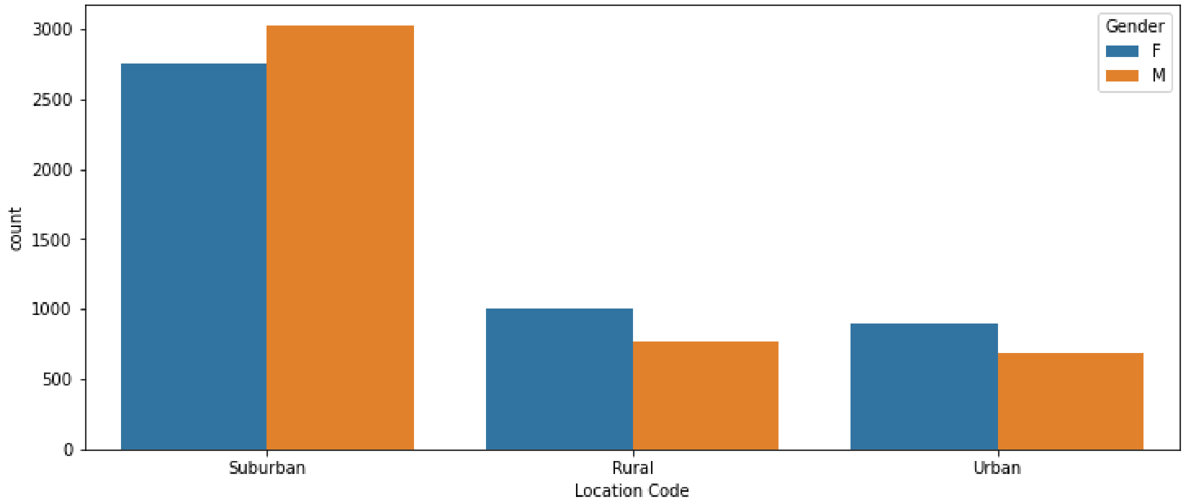
```
None
Bachelor                2748
College                 2681
High School or Below    2622
Master                   741
Doctor                   342
Name: Education, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



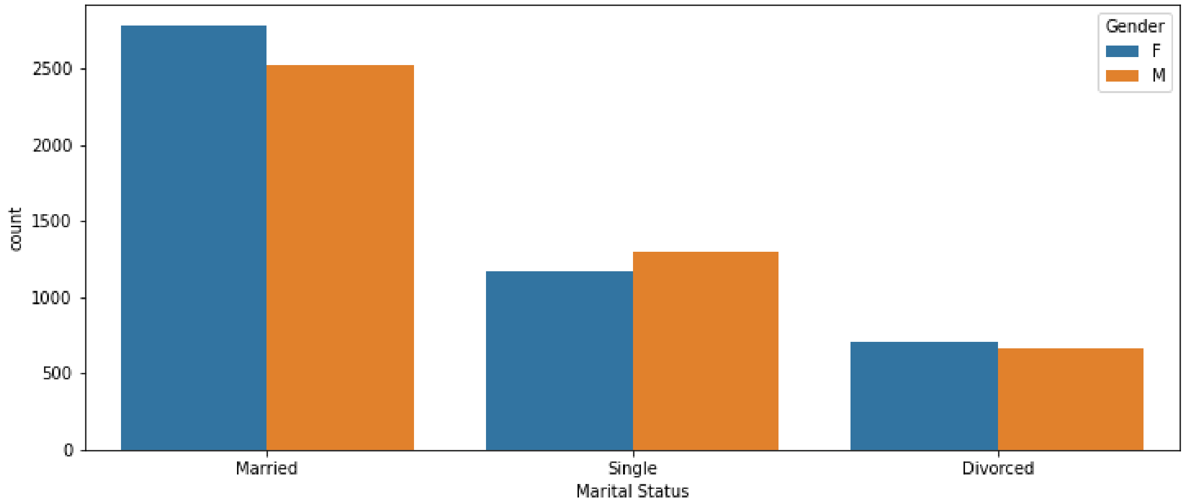

```
None
Employed         5698
Unemployed       2317
Medical Leave     432
Disabled          405
Retired           282
Name: EmploymentStatus, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



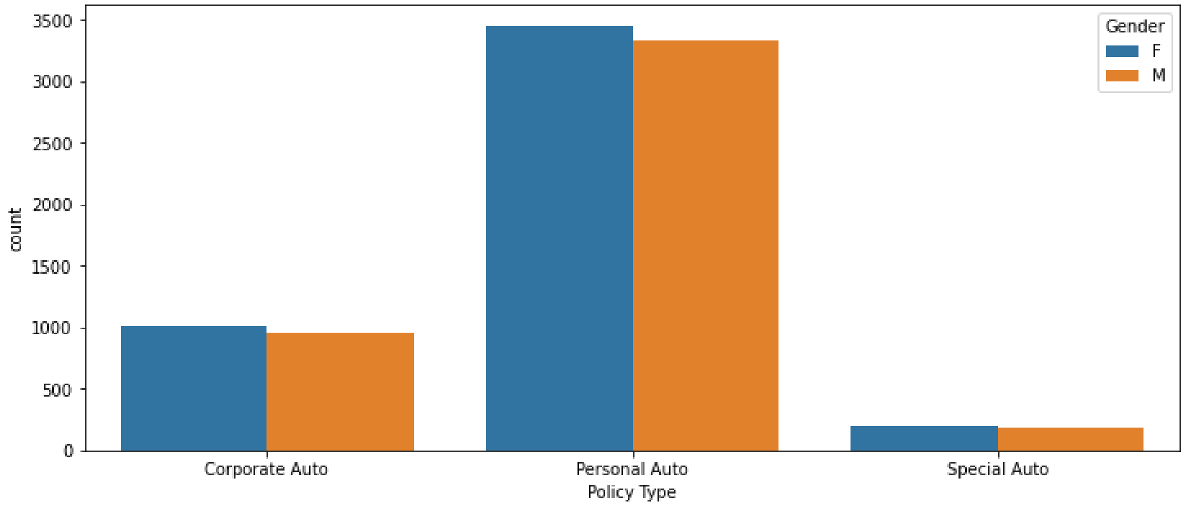

```
None
F    4658
M    4476
Name: Gender, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



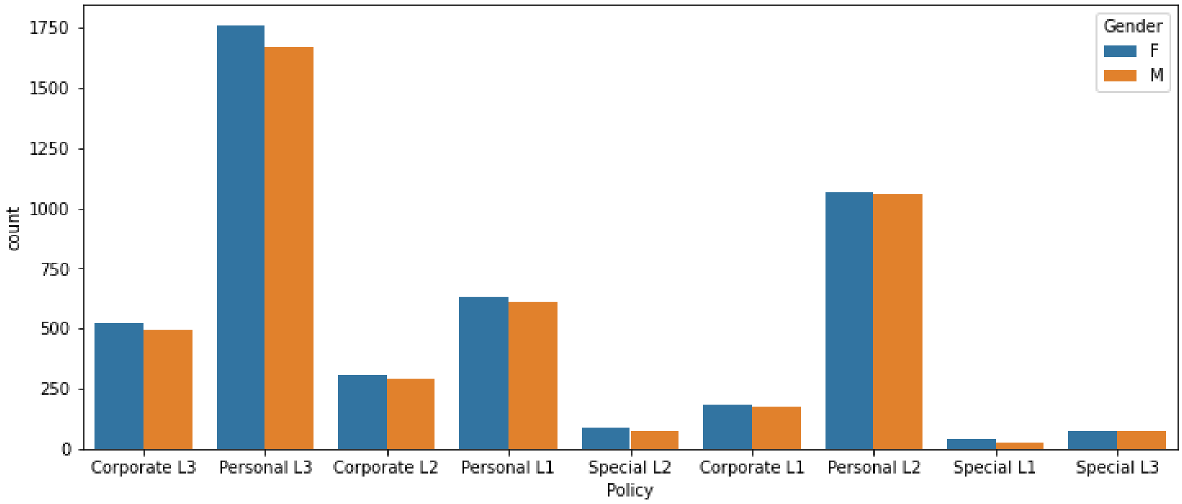

```
None
Suburban     5779
Rural        1773
Urban        1582
Name: Location Code, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



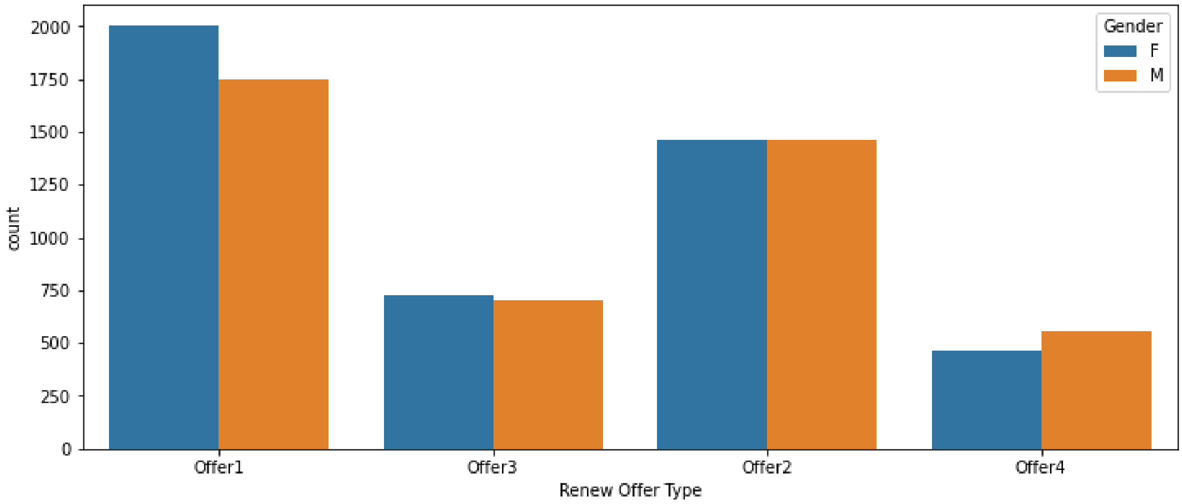

```
None
Married      5298
Single       2467
Divorced     1369
Name: Marital Status, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



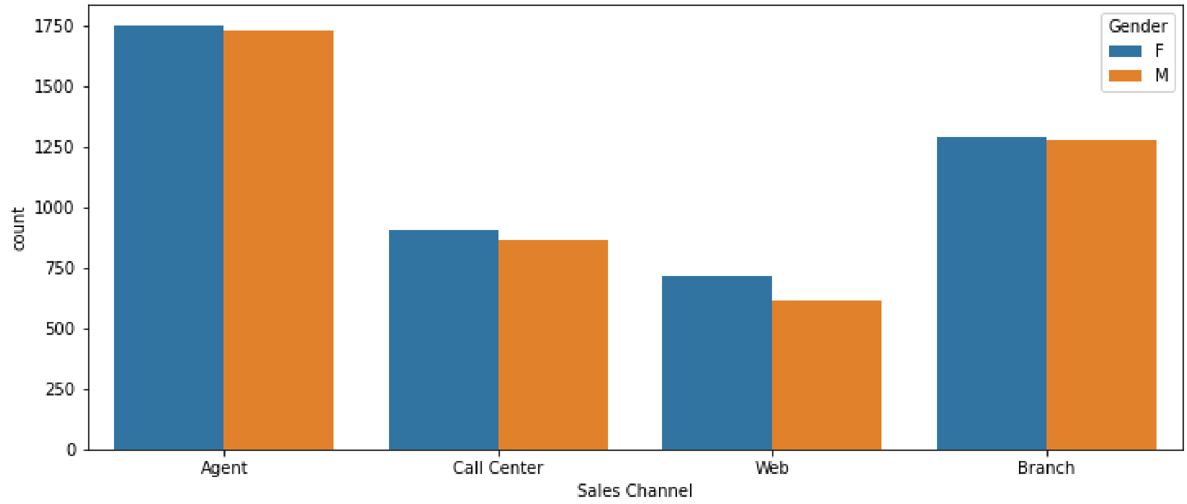
```
None
Personal Auto     6788
Corporate Auto    1968
Special Auto       378
Name: Policy Type, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



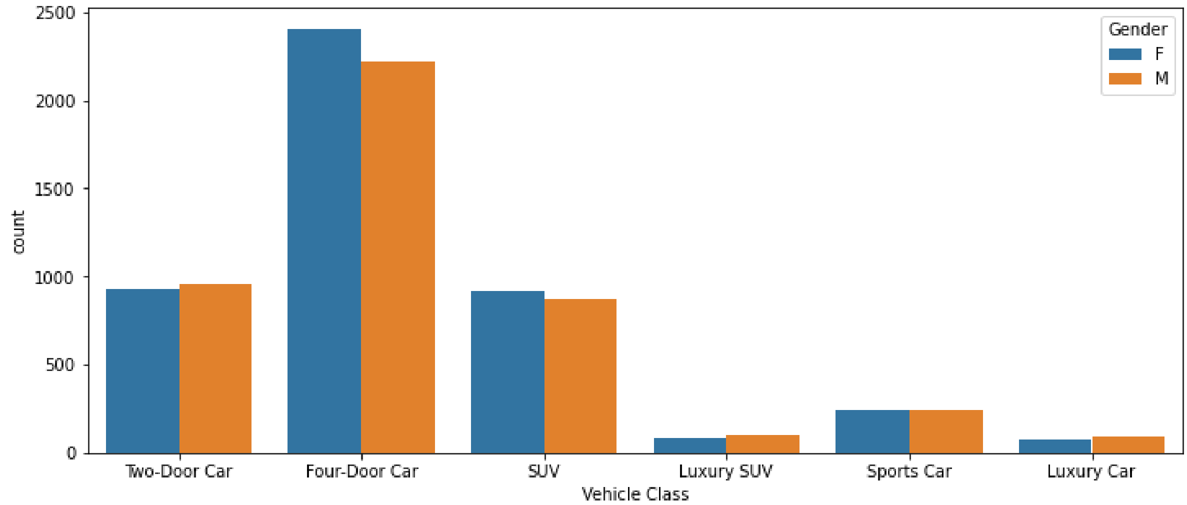

```
None
Personal L3     3426
Personal L2     2122
Personal L1     1240
Corporate L3    1014
Corporate L2     595
Corporate L1     359
Special L2       164
Special L3       148
Special L1        66
Name: Policy, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



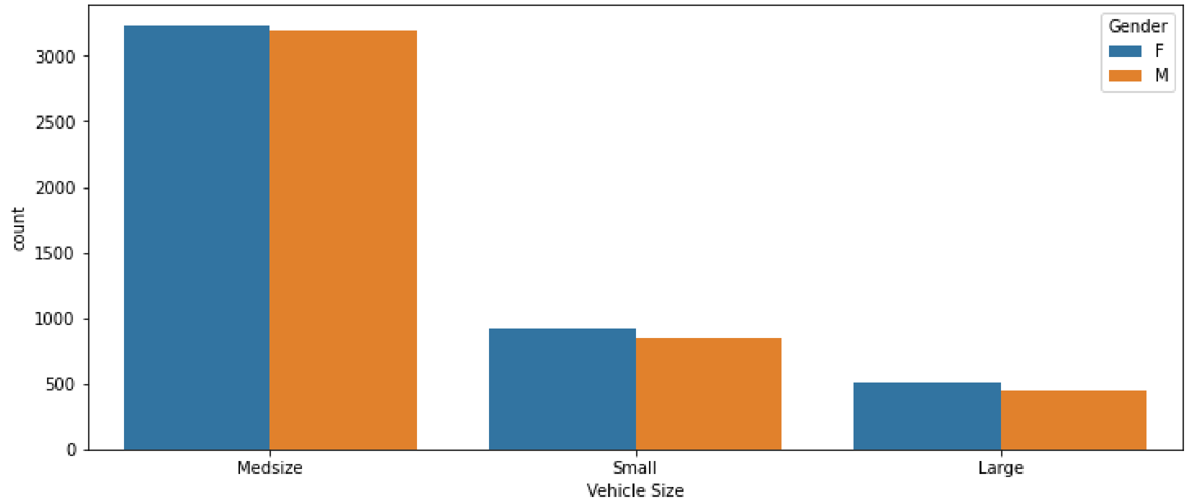

```
None
Offer1    3752
Offer2    2926
Offer3    1432
Offer4    1024
Name: Renew Offer Type, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```




```
None
Agent          3477
Branch         2567
Call Center    1765
Web            1325
Name: Sales Channel, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



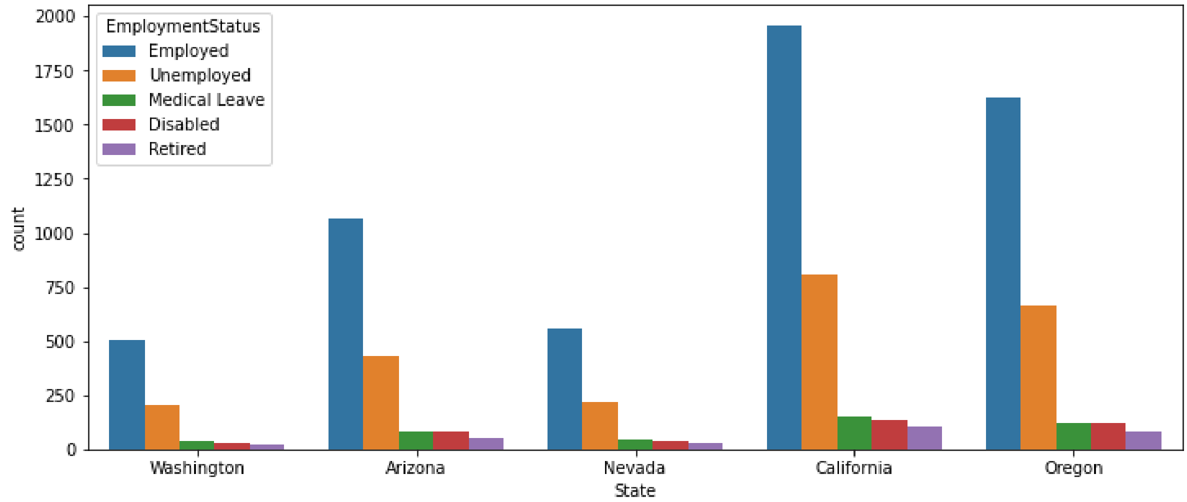

```
None
Four-Door Car    4621
Two-Door Car     1886
SUV              1796
Sports Car        484
Luxury SUV        184
Luxury Car        163
Name: Vehicle Class, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



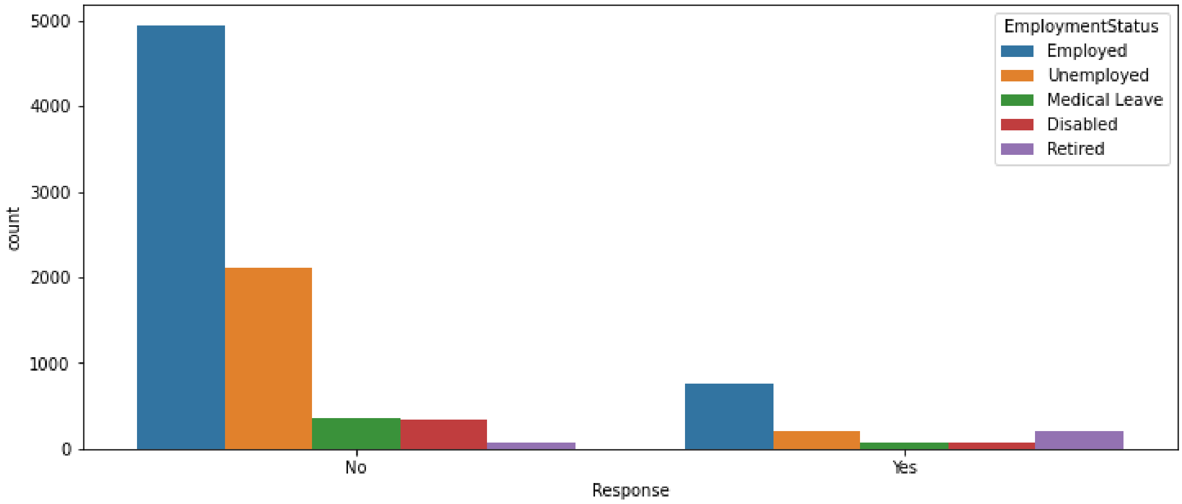

```
None
Medsize    6424
Small      1764
Large       946
Name: Vehicle Size, dtype: int64
```

In [34]:
```
for i in ObjectData.columns:
    plt.figure(figsize=(12, 5))
    print(sns.countplot(x=ObjectData[i],hue=ObjectData['EmploymentStatus'],data=Obj
    print(plt.show())

    print(ObjectData[i].value_counts())
```

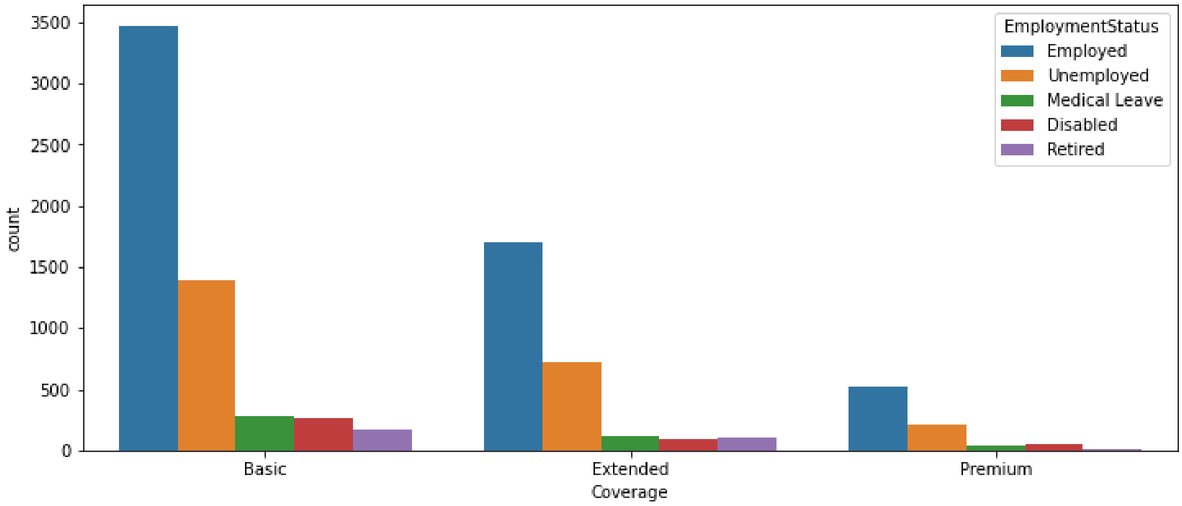
```
AxesSubplot(0.125,0.125;0.775x0.755)
```



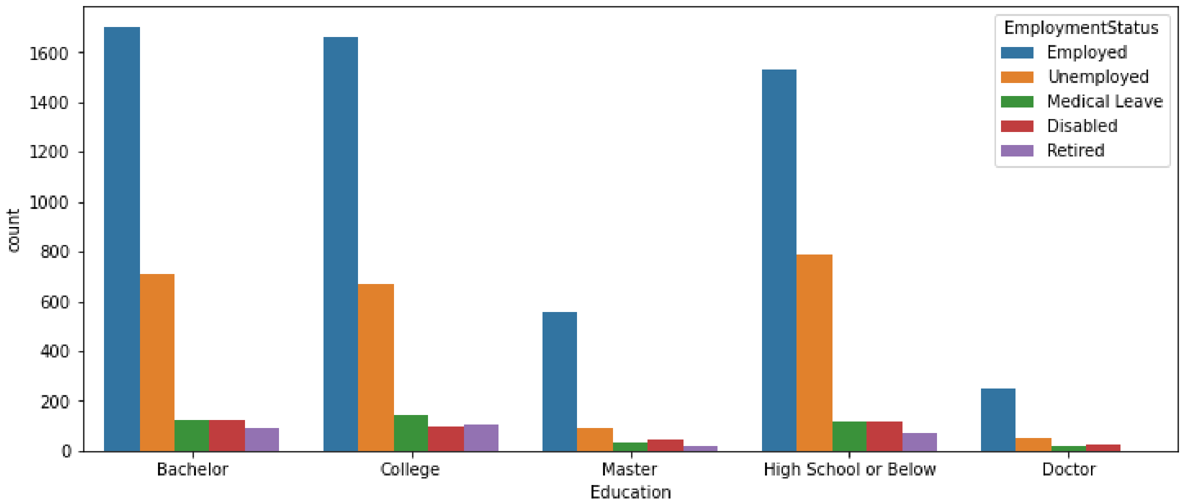

```
None
California    3150
Oregon        2601
Arizona       1703
Nevada         882
Washington     798
Name: State, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



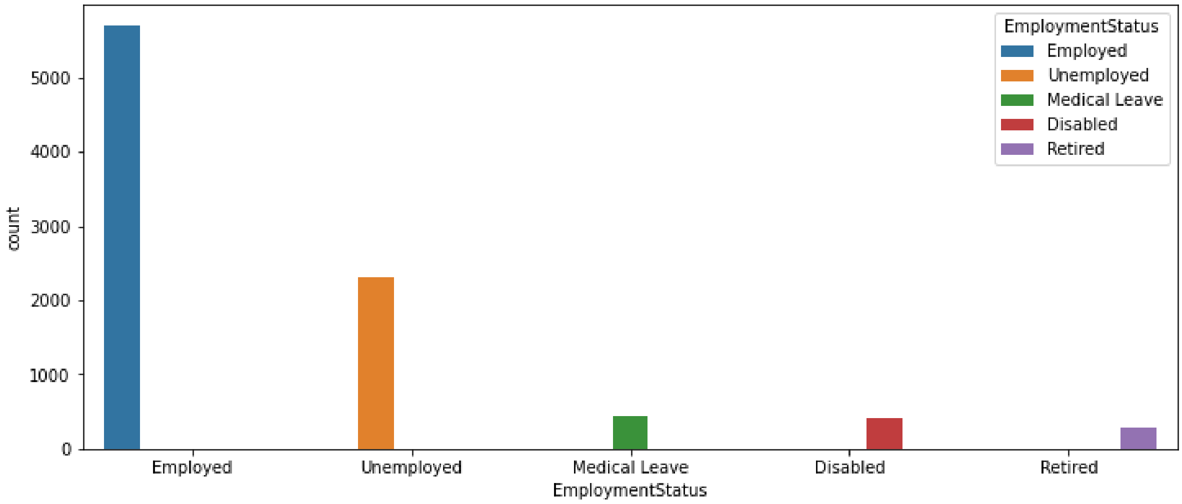

```
None
No      7826
Yes     1308
Name: Response, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



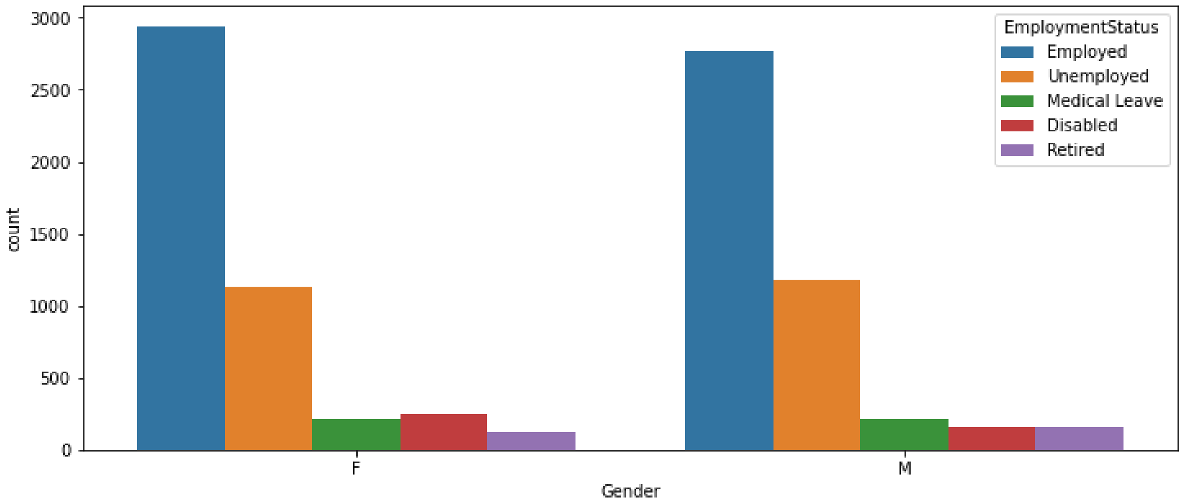

```
None
Basic       5568
Extended    2742
Premium      824
Name: Coverage, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



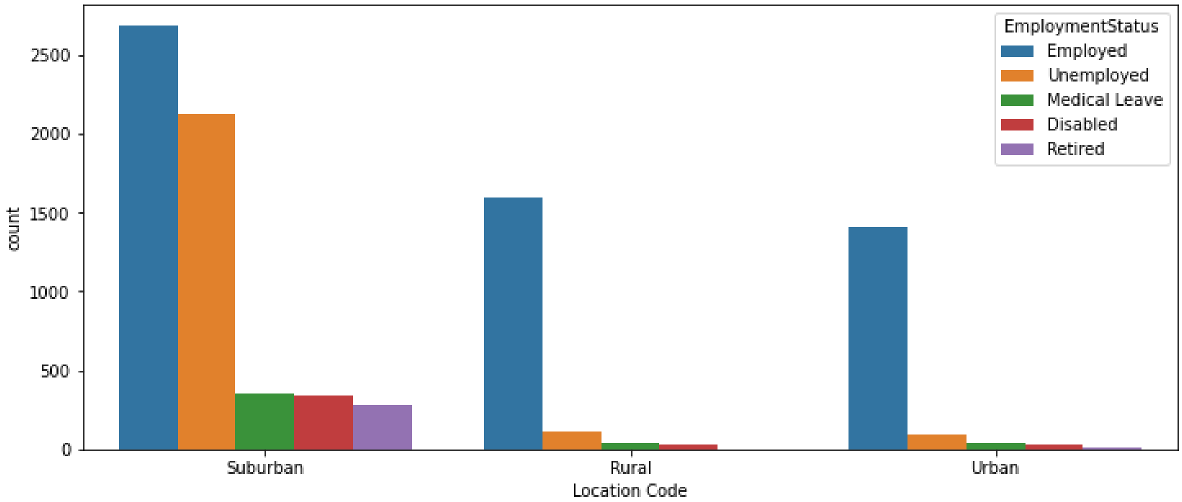
```
None
Bachelor                2748
College                 2681
High School or Below    2622
Master                   741
Doctor                   342
Name: Education, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



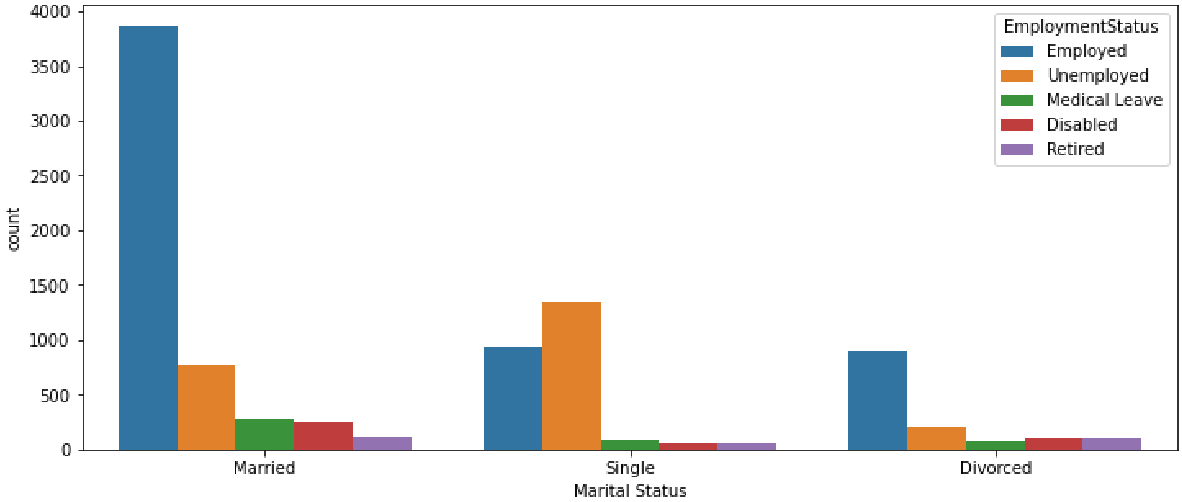

```
None
Employed         5698
Unemployed       2317
Medical Leave     432
Disabled          405
Retired           282
Name: EmploymentStatus, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



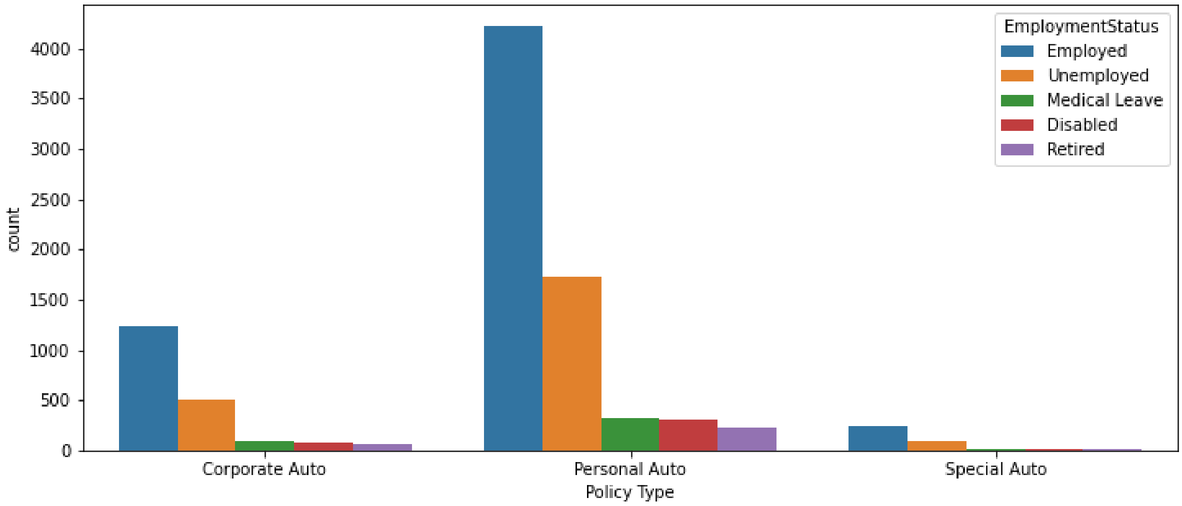

```
None
F    4658
M    4476
Name: Gender, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



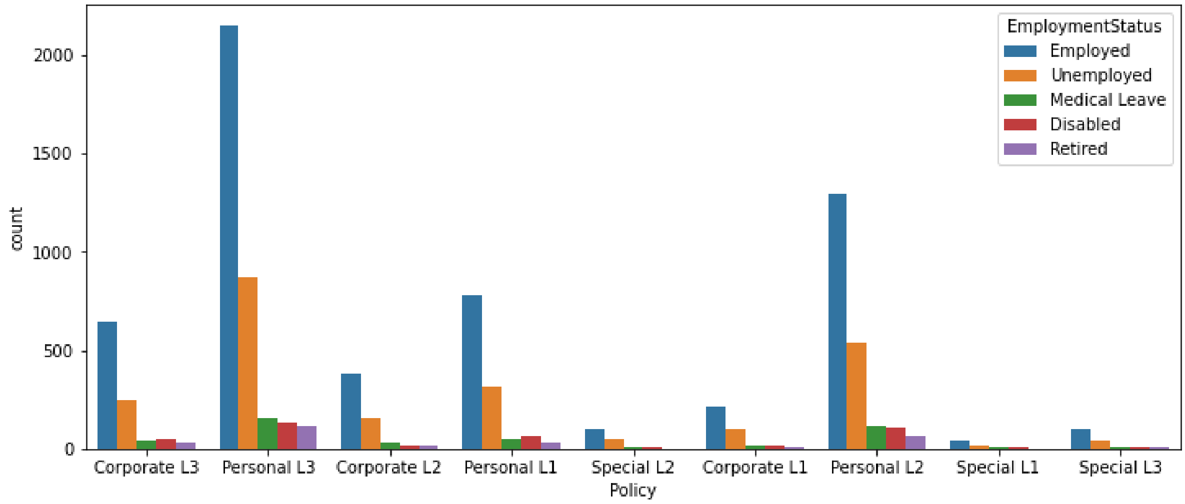

```
None
Suburban     5779
Rural        1773
Urban        1582
Name: Location Code, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



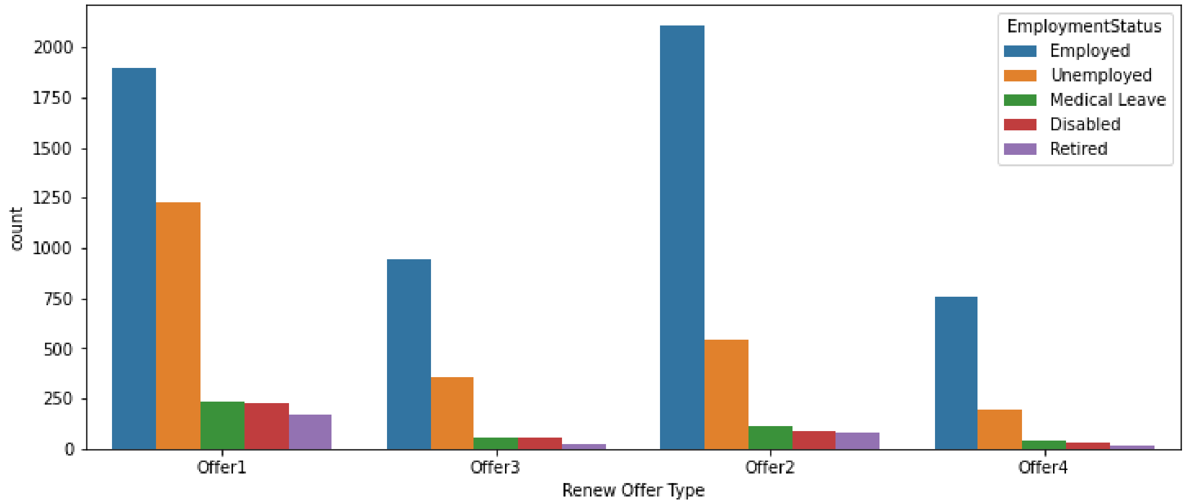

```
None
Married      5298
Single       2467
Divorced     1369
Name: Marital Status, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



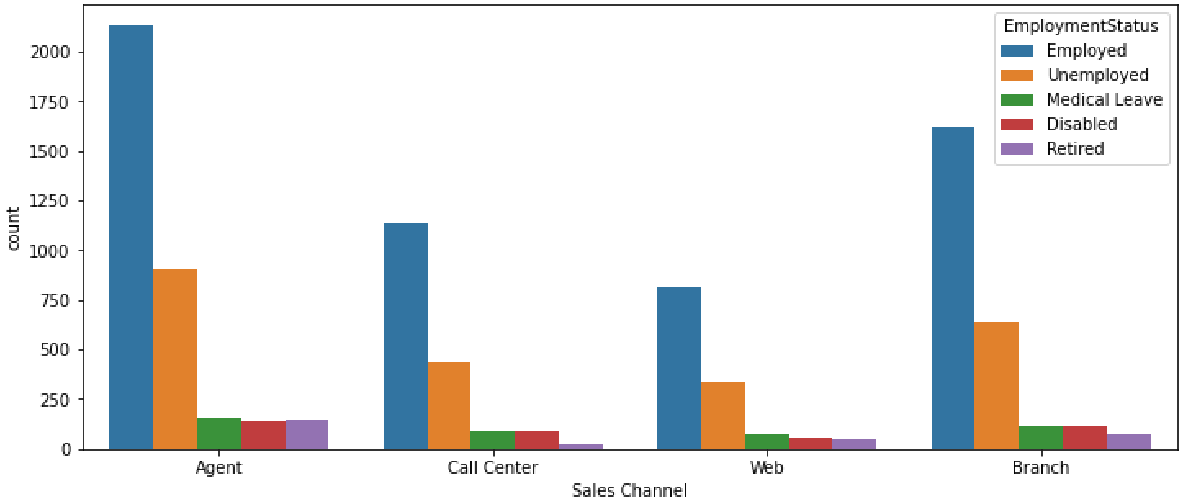
```
None
Personal Auto     6788
Corporate Auto    1968
Special Auto       378
Name: Policy Type, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



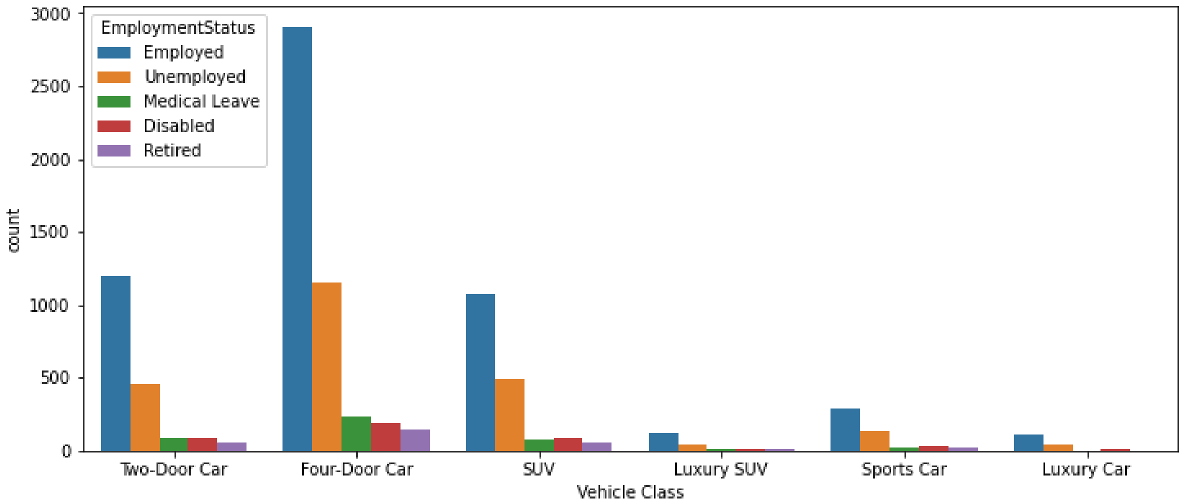

```
None
Personal L3     3426
Personal L2     2122
Personal L1     1240
Corporate L3    1014
Corporate L2     595
Corporate L1     359
Special L2       164
Special L3       148
Special L1        66
Name: Policy, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



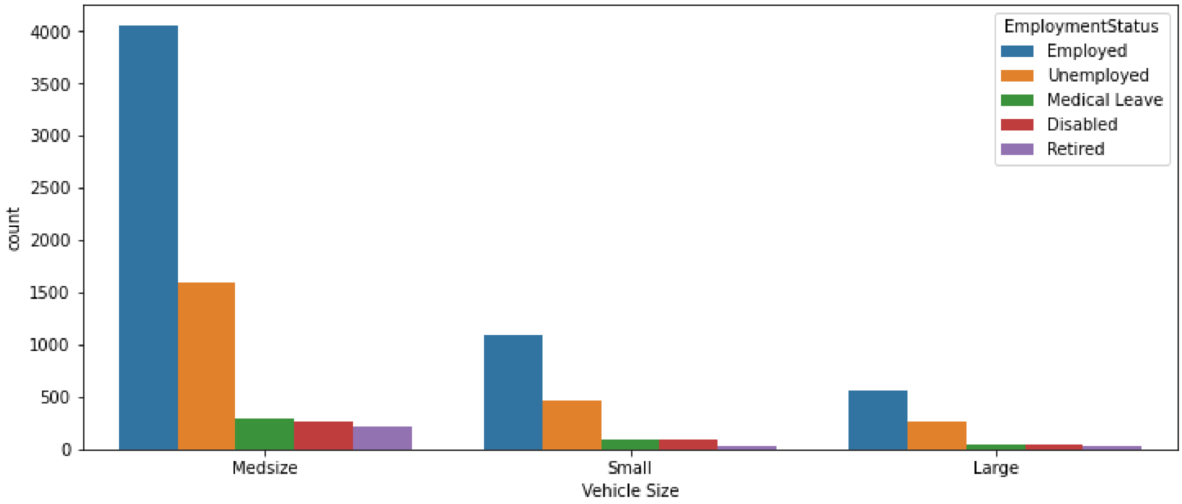

```
None
Offer1    3752
Offer2    2926
Offer3    1432
Offer4    1024
Name: Renew Offer Type, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```




```
None
Agent          3477
Branch         2567
Call Center    1765
Web            1325
Name: Sales Channel, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```




```
None
Four-Door Car    4621
Two-Door Car     1886
SUV              1796
Sports Car        484
Luxury SUV        184
Luxury Car        163
Name: Vehicle Class, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```

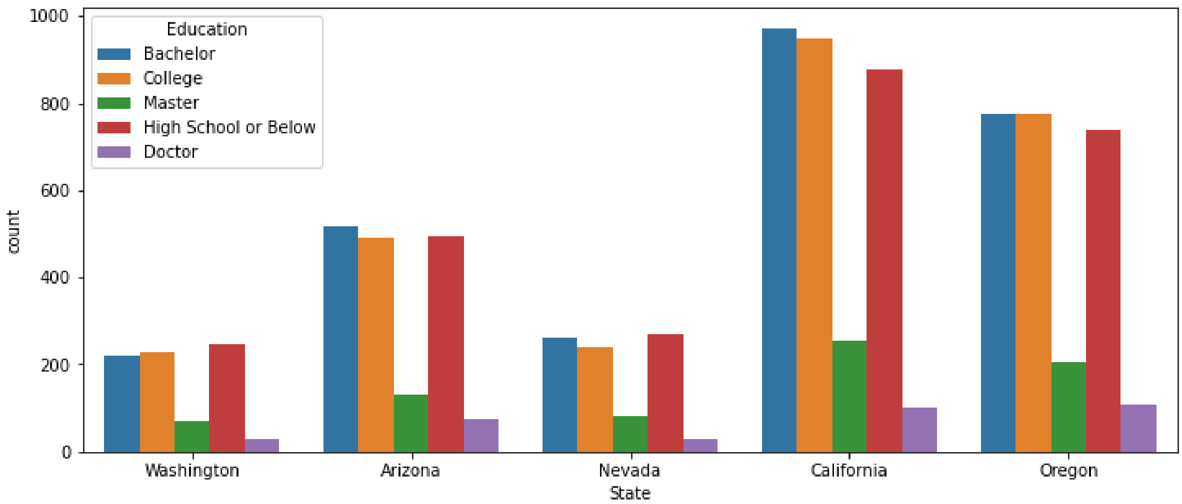



```
None
Medsize    6424
Small      1764
Large       946
Name: Vehicle Size, dtype: int64
```

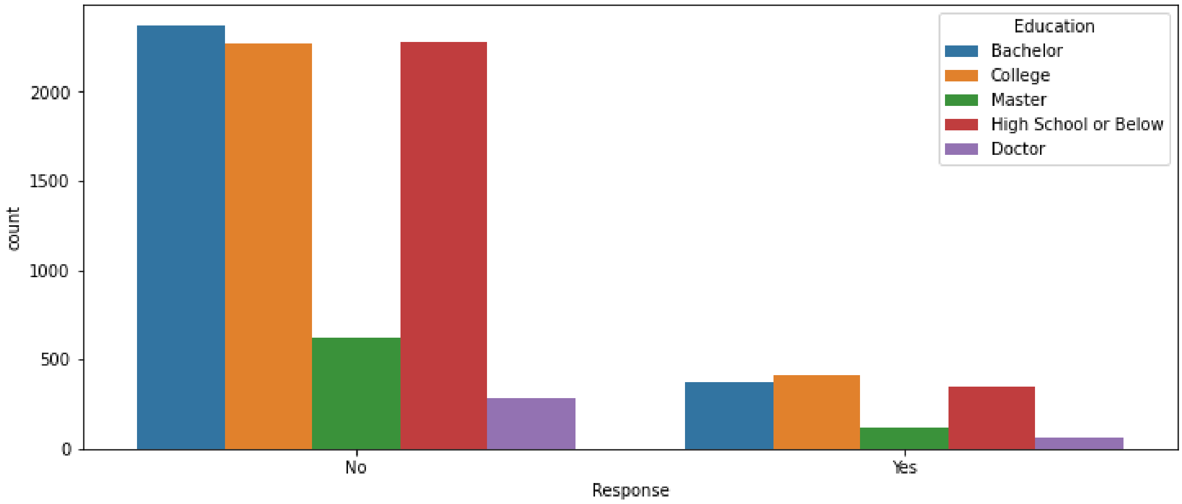
In [ ]:

In [35]:
```
for i in ObjectData.columns:
    sorted(ObjectData[i])
    plt.figure(figsize=(12, 5))
    print(sns.countplot(x=ObjectData[i],hue=ObjectData['Education'],data=ObjectData
    print(plt.show())

    print(ObjectData[i].value_counts())
```

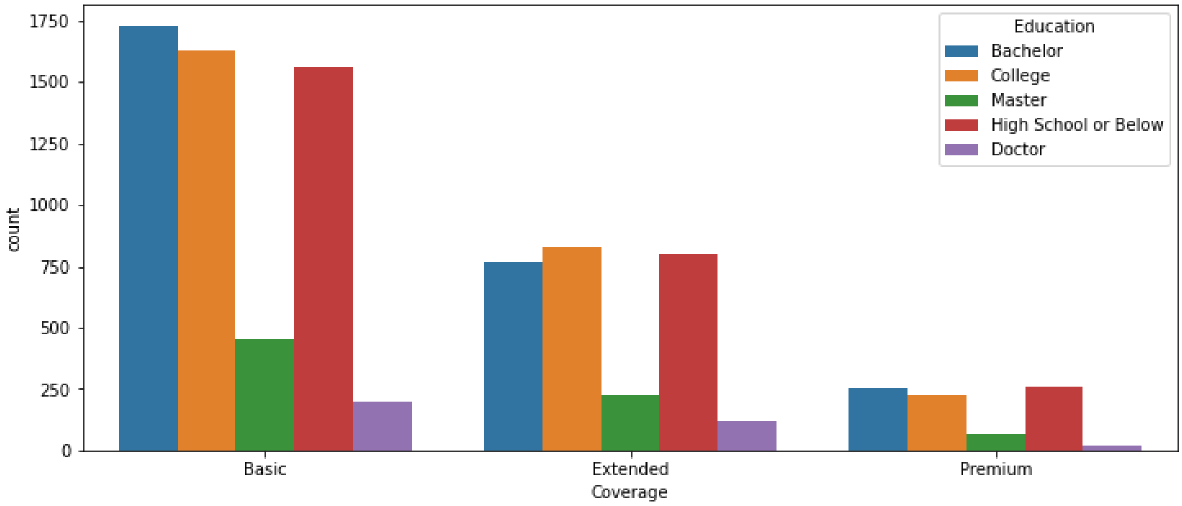
```
AxesSubplot(0.125,0.125;0.775x0.755)
```



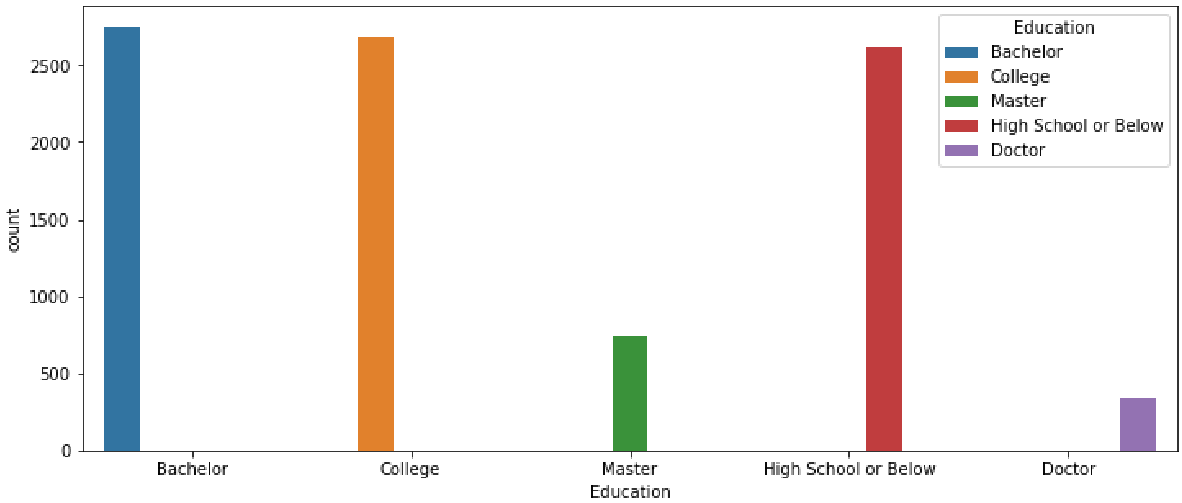

```
None
California    3150
Oregon        2601
Arizona       1703
Nevada         882
Washington     798
Name: State, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



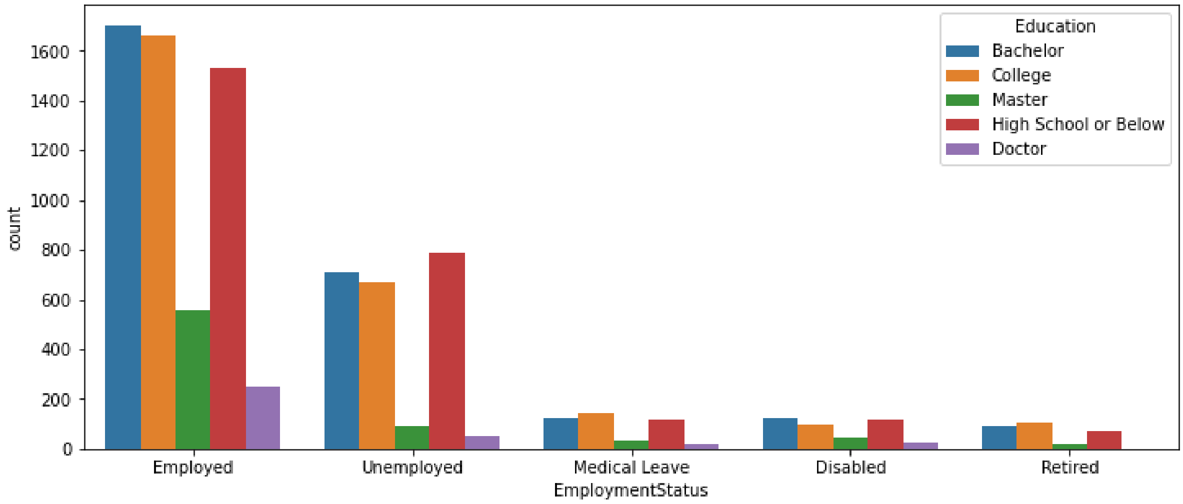

```
None
No     7826
Yes    1308
Name: Response, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



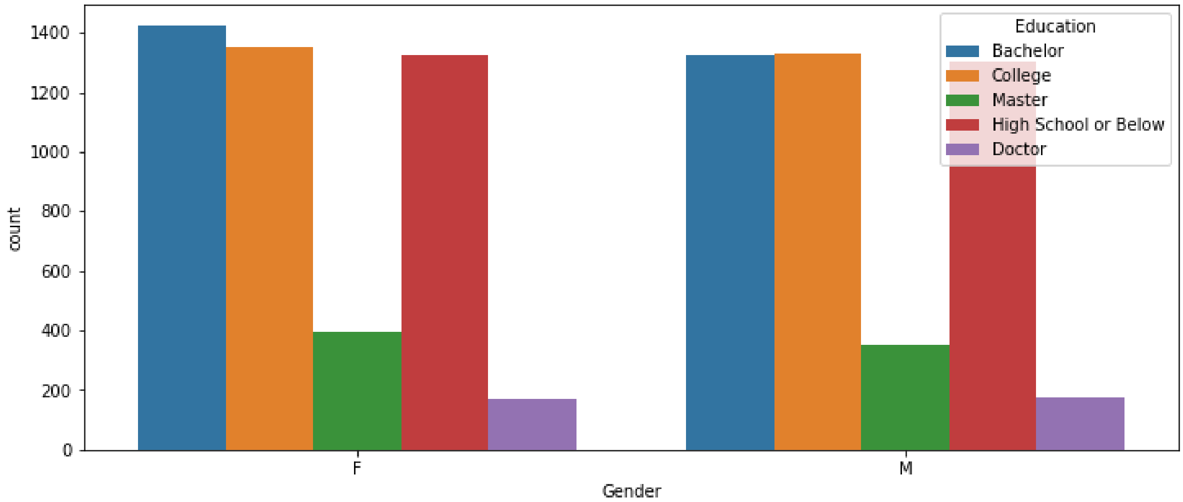

```
None
Basic       5568
Extended    2742
Premium      824
Name: Coverage, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



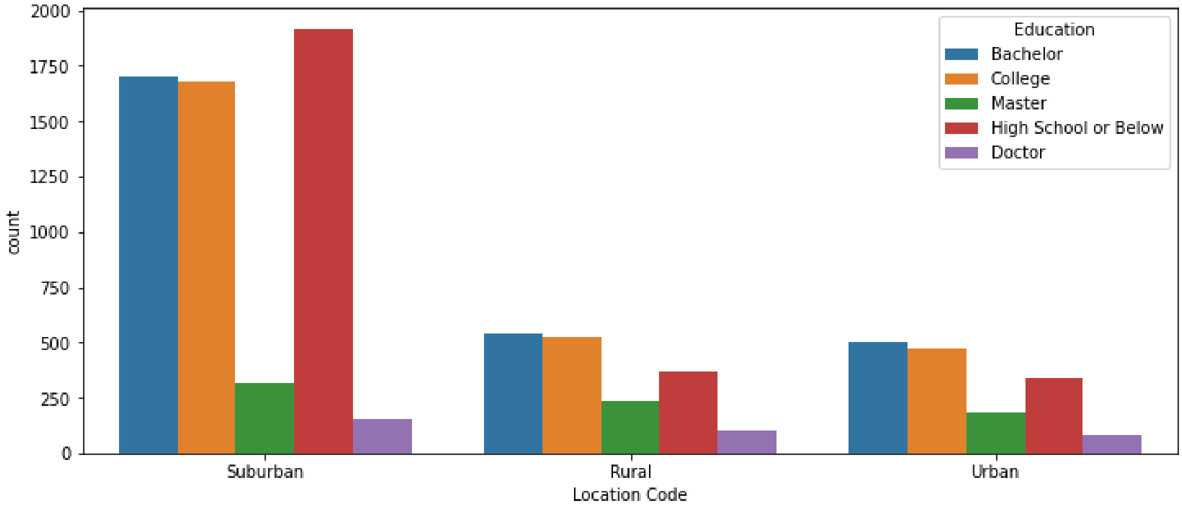
```
None
Bachelor                2748
College                 2681
High School or Below    2622
Master                   741
Doctor                   342
Name: Education, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



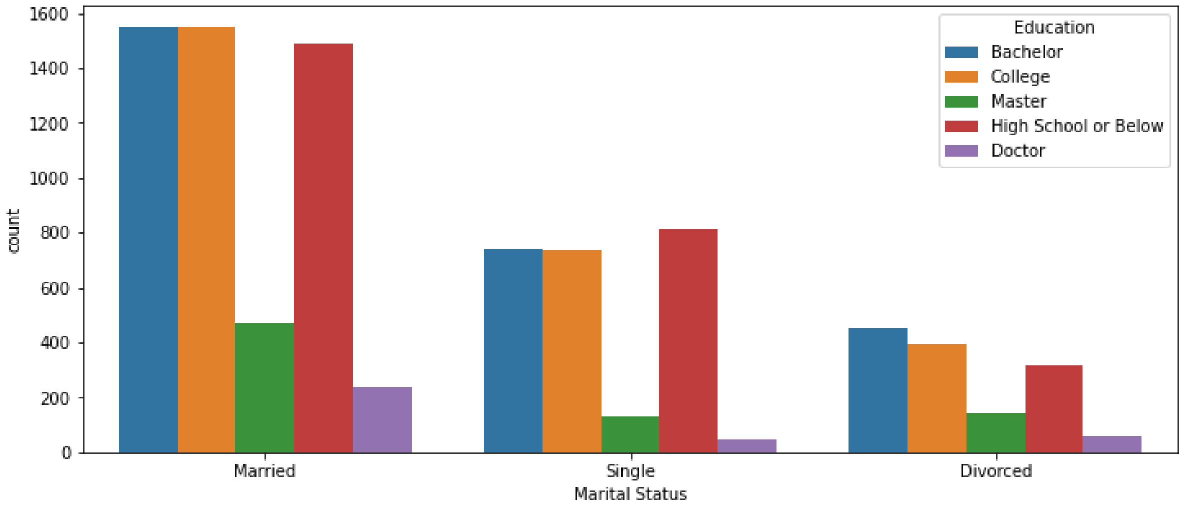

```
None
Employed         5698
Unemployed       2317
Medical Leave     432
Disabled          405
Retired           282
Name: EmploymentStatus, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



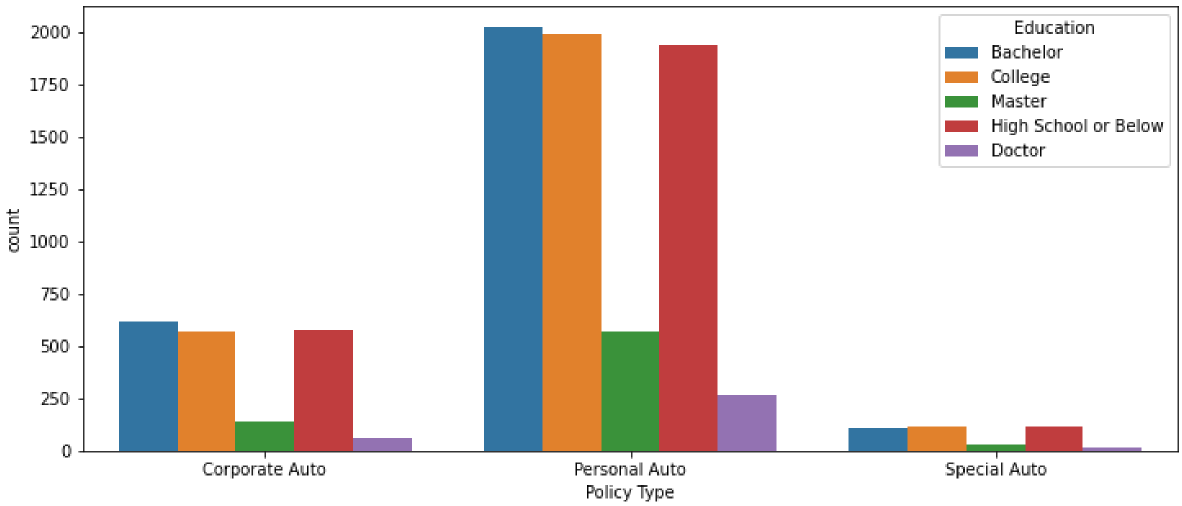

```
None
F    4658
M    4476
Name: Gender, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



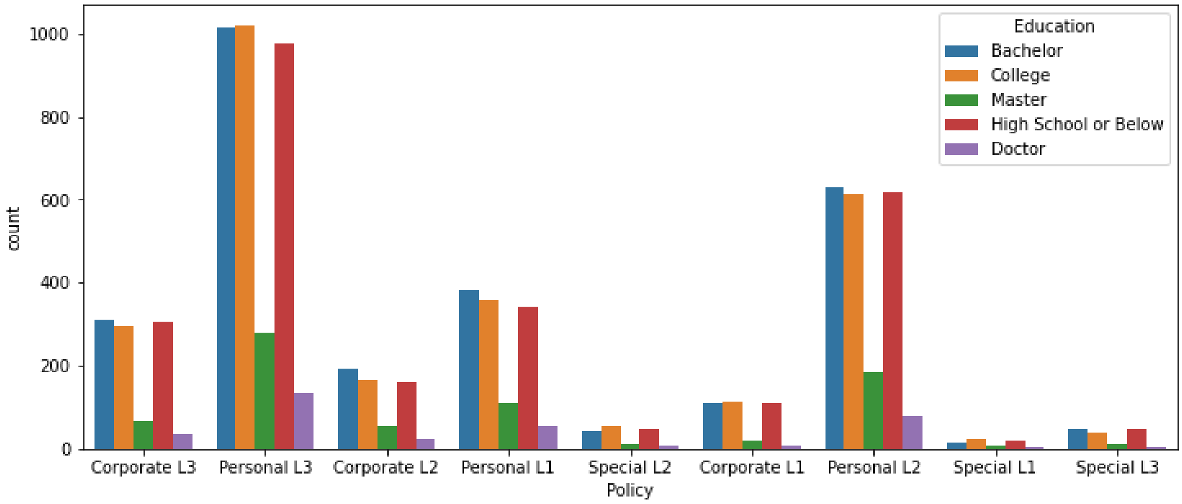

```
None
Suburban    5779
Rural       1773
Urban       1582
Name: Location Code, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



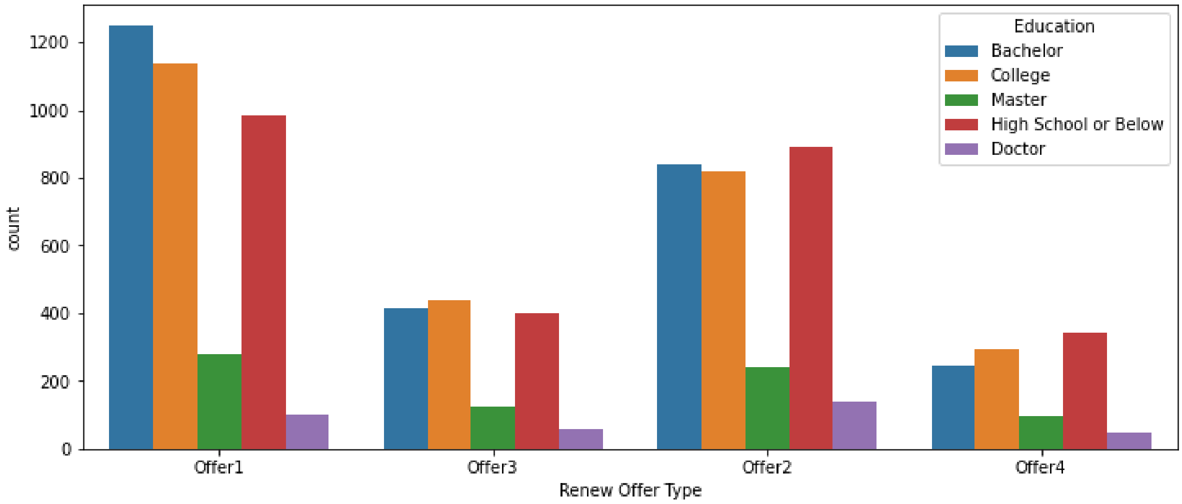

```
None
Married     5298
Single      2467
Divorced    1369
Name: Marital Status, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



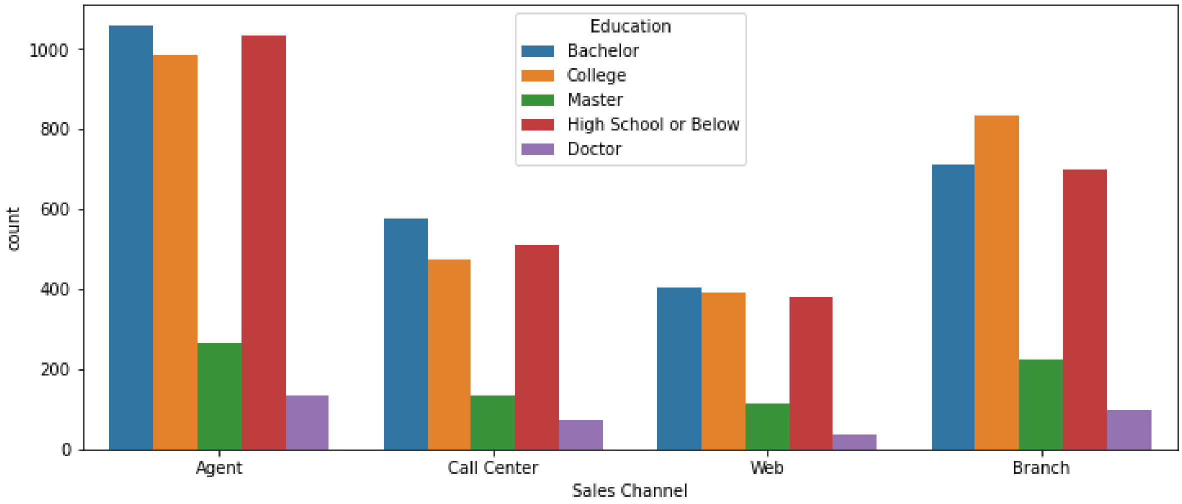
```
None
Personal Auto     6788
Corporate Auto    1968
Special Auto       378
Name: Policy Type, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



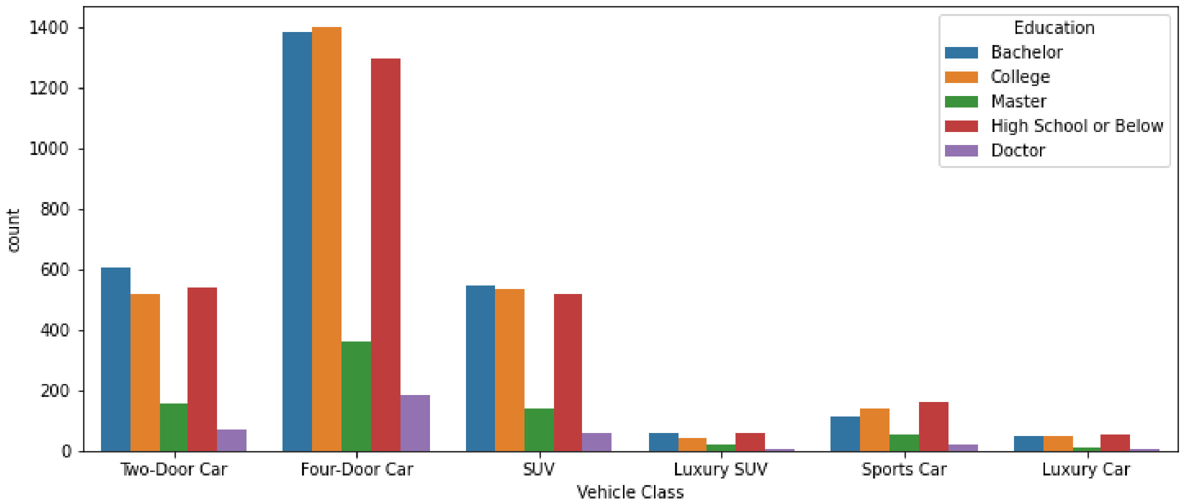

```
None
Personal L3     3426
Personal L2     2122
Personal L1     1240
Corporate L3    1014
Corporate L2     595
Corporate L1     359
Special L2       164
Special L3       148
Special L1        66
Name: Policy, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



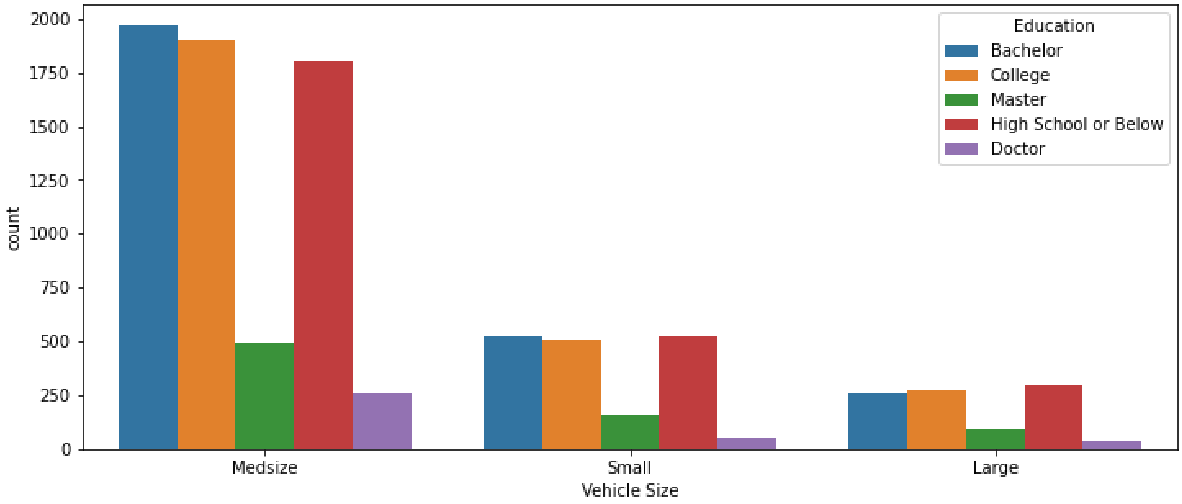

```
None
Offer1    3752
Offer2    2926
Offer3    1432
Offer4    1024
Name: Renew Offer Type, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```




```
None
Agent          3477
Branch         2567
Call Center    1765
Web            1325
Name: Sales Channel, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



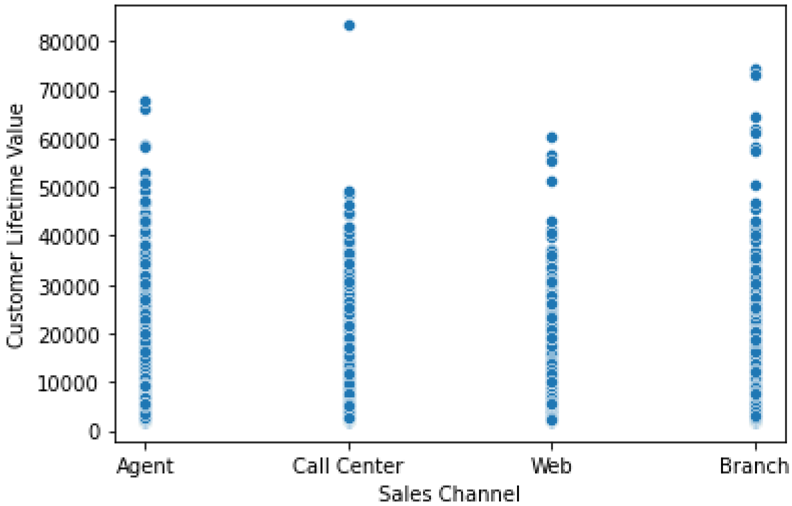

```
None
Four-Door Car    4621
Two-Door Car     1886
SUV              1796
Sports Car        484
Luxury SUV        184
Luxury Car        163
Name: Vehicle Class, dtype: int64
AxesSubplot(0.125,0.125;0.775x0.755)
```



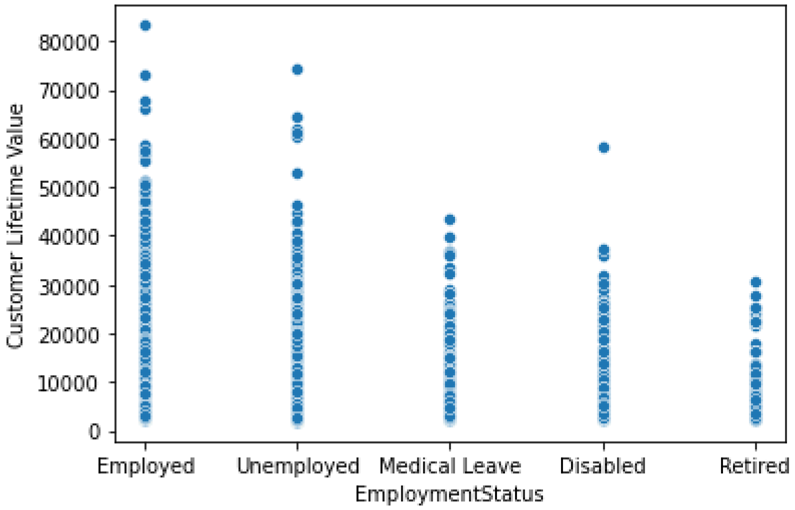

```
None
Medsize    6424
Small      1764
Large       946
Name: Vehicle Size, dtype: int64
```

In [36]:
```
# for i in df.select_dtypes('object').columns:
#     print(sns.scatterplot(x=df[i],y=df['Customer Lifetime Value'],data=df))
#     print(plt.show())
```

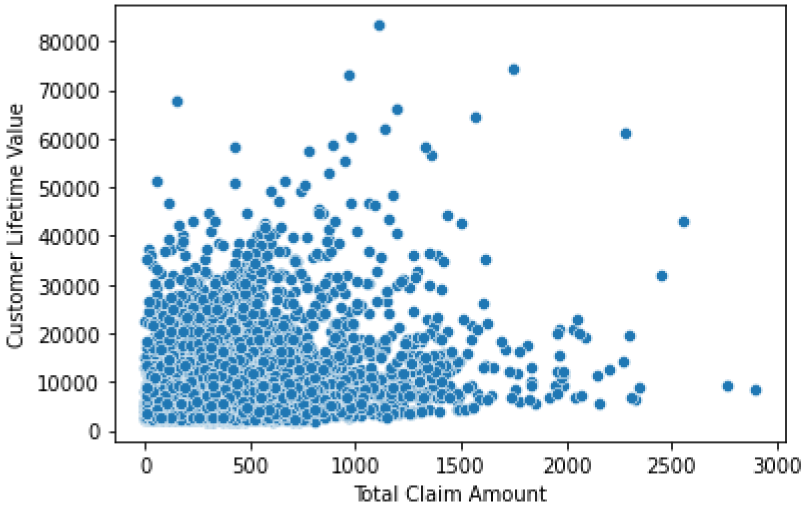
In [37]:
```
sns.scatterplot(x=df['Sales Channel'],y=df['Customer Lifetime Value'],data=df)
plt.show()
```



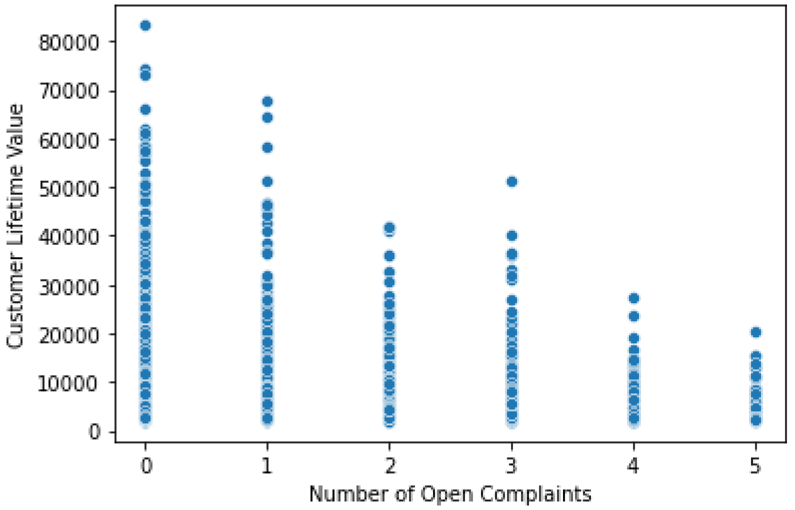
In [38]:
```
sns.scatterplot(x=df['EmploymentStatus'],y=df['Customer Lifetime Value'],data=df)
plt.show()
```



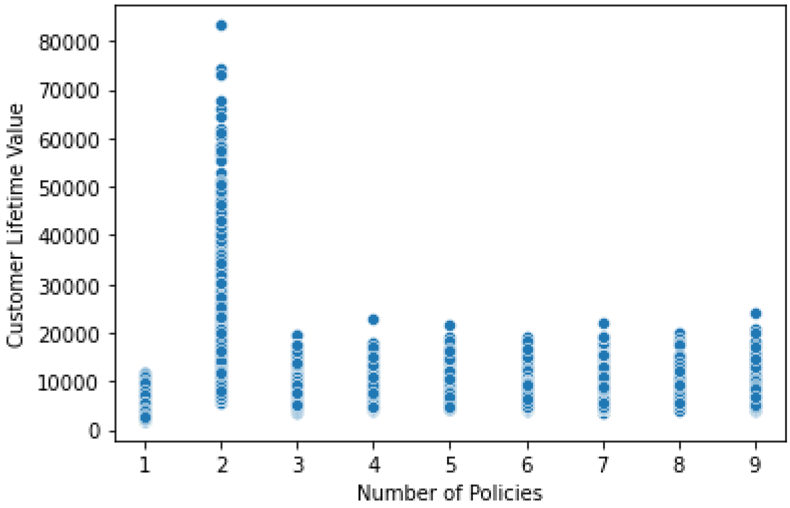
In [39]:
```
sns.scatterplot(x=df['Total Claim Amount'],y=df['Customer Lifetime Value'],data=df)
plt.show()
```



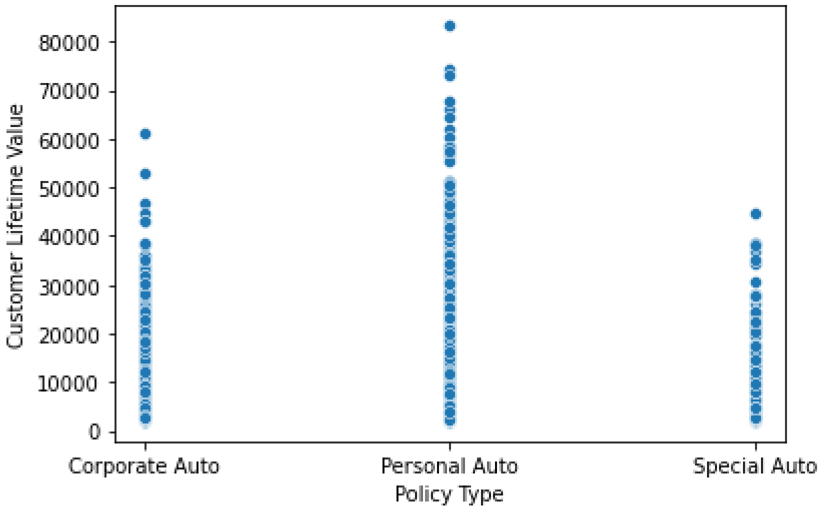
In [40]:
```
sns.scatterplot(x=df['Number of Open Complaints'],y=df['Customer Lifetime Value'],d
plt.show()
```



In [41]:
```
sns.scatterplot(x=df['Number of Policies'],y=df['Customer Lifetime Value'],data=df)
plt.show()
```



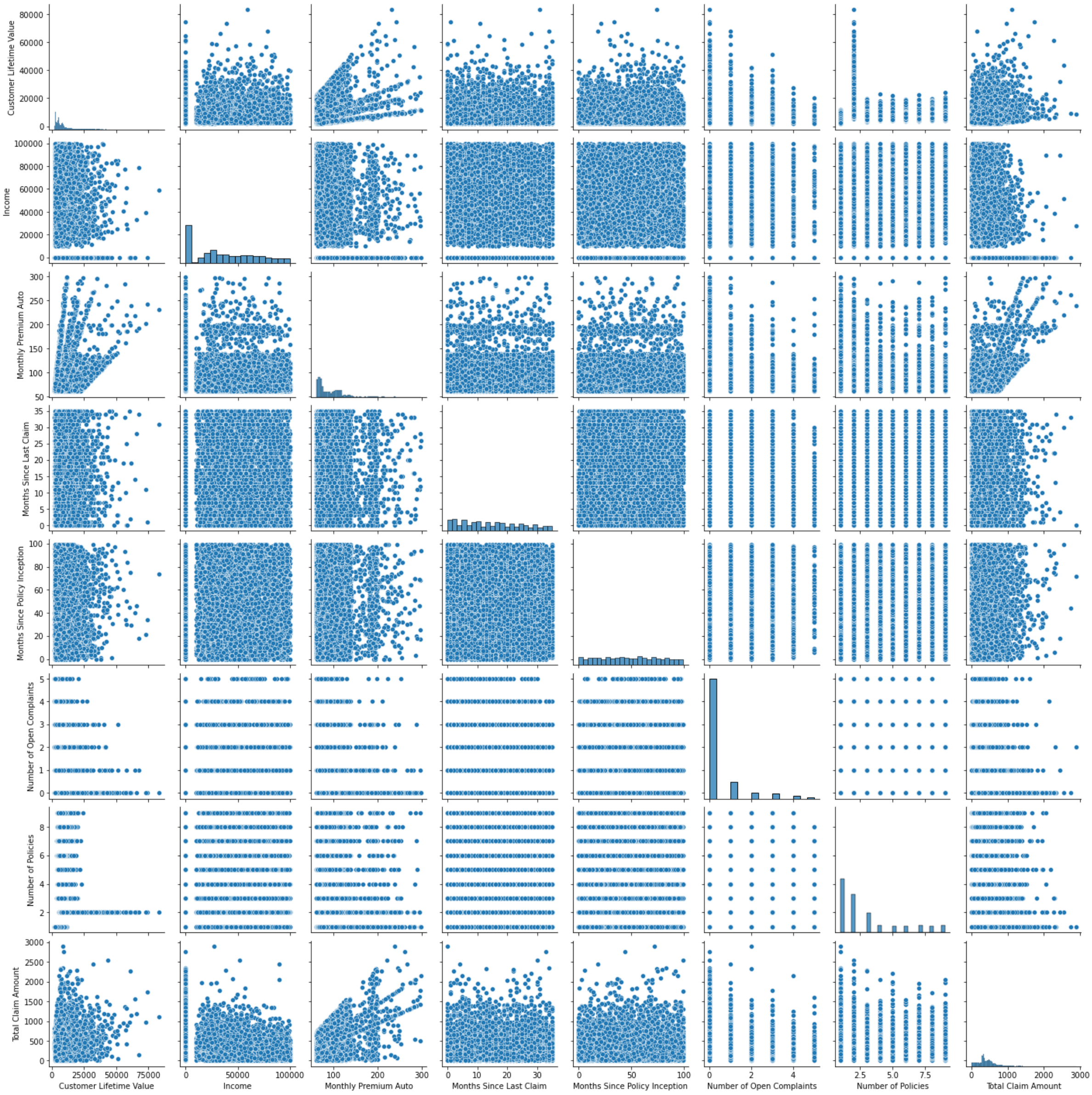
In [42]:
```
sns.scatterplot(x=df['Policy Type'],y=df['Customer Lifetime Value'],data=df)
plt.show()
```



In [43]:
```
df.info()
```

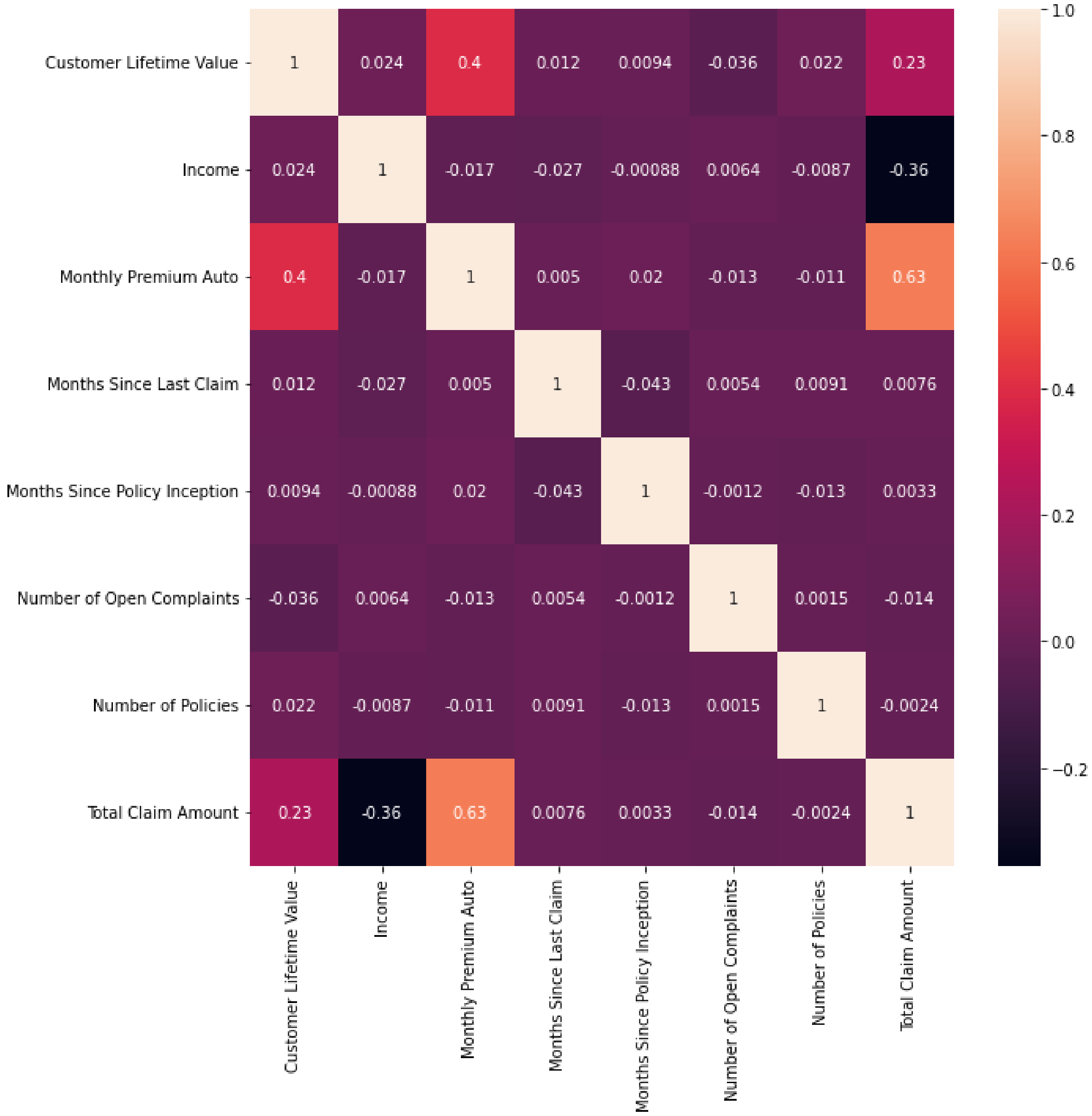
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9134 entries, 0 to 9133
Data columns (total 24 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   Customer                       9134 non-null   object 
 1   State                          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
```

In [44]:
```
#Pairplot
sns.pairplot(df)
plt.show()
```



In [45]:

```
#Correlation between numeric feature
plt.figure(figsize=(10,10))
sns.heatmap(df.corr(),annot=True)
plt.show()
```



And we can clearly see in the correlation map, that customer lifetime value has a

better correlation with monthly premium auto and acceptable co relation with total claim amount,

but it show's no relationship with income, so again with all the visualization's

we can come to the conclusion that we can dis regard the INCOME feature.

Droping the insignificant column

In [46]:
```
df.drop(['Customer'],axis=1,inplace=True)
```

Preprocessing Label Encoding

In [47]:
```
# Import label encoder
from sklearn.preprocessing import  LabelEncoder

# label_encoder object knows
```

```
# how to understand word labels.
label_encoder = LabelEncoder()
```

In [48]:
```
#Selecting only 'Object' feature
df.select_dtypes('object').columns
```

Out[48]:
```
Index(['State', 'Response', 'Coverage', 'Education', 'Effective To Date',
       'EmploymentStatus', 'Gender', 'Location Code', 'Marital Status',
       'Policy Type', 'Policy', 'Renew Offer Type', 'Sales Channel',
       'Vehicle Class', 'Vehicle Size'],
      dtype='object')
```

Encoding all the categorical features

In [49]:
```
for i in df.select_dtypes('object').columns:
    print("Before encoding the unique values of feature:", i)
    print(df[i].value_counts(),"\n\n")

    # Encode labels in column i
    df[i]= label_encoder.fit_transform(df[i])
    print("After encoding the unique values  of feature:", i)

    print(df[i].value_counts(),"\n\n")
```

```
Before encoding the unique values of feature: State
California    3150
Oregon        2601
Arizona       1703
Nevada         882
Washington     798
Name: State, dtype: int64


After encoding the unique values  of feature: State
1    3150
3    2601
0    1703
2     882
4     798
Name: State, dtype: int64


Before encoding the unique values of feature: Response
No     7826
Yes    1308
Name: Response, dtype: int64


After encoding the unique values  of feature: Response
0    7826
1    1308
Name: Response, dtype: int64


Before encoding the unique values of feature: Coverage
Basic       5568
Extended    2742
Premium      824
Name: Coverage, dtype: int64


After encoding the unique values  of feature: Coverage
0    5568
1    2742
2     824
Name: Coverage, dtype: int64


Before encoding the unique values of feature: Education
Bachelor                2748
College                 2681
High School or Below    2622
Master                   741
Doctor                   342
Name: Education, dtype: int64


After encoding the unique values  of feature: Education
0    2748
1    2681
3    2622
4     741
2     342
Name: Education, dtype: int64


Before encoding the unique values of feature: Effective To Date
10/1/2011    195
```

```
1/27/11      194
2/14/11      186
1/26/11      181
1/17/11      180
1/19/11      179
1/31/11      178
3/1/2011     178
1/20/11      173
2/26/11      169
1/28/11      169
2/19/11      168
5/1/2011     167
2/27/11      167
11/1/2011    166
4/2/2011     164
10/2/2011    161
2/28/11      161
2/1/2011     160
1/21/11      160
1/29/11      160
2/22/11      158
5/2/2011     158
3/2/2011     158
7/2/2011     157
12/2/2011    156
1/23/11      155
1/2/2011     154
1/18/11      154
1/15/11      153
1/14/11      152
11/2/2011    151
7/1/2011     151
1/25/11      151
2/25/11      149
8/1/2011     149
2/18/11      149
2/2/2011     149
1/1/2011     148
2/21/11      148
1/24/11      147
9/1/2011     146
1/30/11      145
1/13/11      145
6/2/2011     144
6/1/2011     143
2/23/11      143
1/16/11      142
2/16/11      139
2/13/11      139
2/24/11      139
9/2/2011     137
2/17/11      136
1/22/11      136
8/2/2011     134
2/20/11      132
2/15/11      130
12/1/2011    126
4/1/2011     115
Name: Effective To Date, dtype: int64


After encoding the unique values  of feature: Effective To Date
21    195
16    194
```

```
29    186
15    181
5     180
7     179
20    178
45    178
9     173
42    169
17    169
34    168
49    167
43    167
23    166
48    164
22    161
44    161
27    160
10    160
18    160
38    158
50    158
46    158
54    157
26    156
12    155
8     154
6     154
3     153
2     152
24    151
53    151
14    151
41    149
55    149
33    149
35    149
0     148
37    148
13    147
57    146
19    145
1     145
52    144
51    143
39    143
4     142
31    139
28    139
40    139
58    137
32    136
11    136
56    134
36    132
30    130
25    126
47    115
Name: Effective To Date, dtype: int64


Before encoding the unique values of feature: EmploymentStatus
Employed         5698
Unemployed       2317
Medical Leave     432
```

```
Disabled          405
Retired           282
Name: EmploymentStatus, dtype: int64


After encoding the unique values  of feature: EmploymentStatus
1    5698
4    2317
2     432
0     405
3     282
Name: EmploymentStatus, dtype: int64


Before encoding the unique values of feature: Gender
F    4658
M    4476
Name: Gender, dtype: int64


After encoding the unique values  of feature: Gender
0    4658
1    4476
Name: Gender, dtype: int64


Before encoding the unique values of feature: Location Code
Suburban    5779
Rural       1773
Urban       1582
Name: Location Code, dtype: int64


After encoding the unique values  of feature: Location Code
1    5779
0    1773
2    1582
Name: Location Code, dtype: int64


Before encoding the unique values of feature: Marital Status
Married     5298
Single      2467
Divorced    1369
Name: Marital Status, dtype: int64


After encoding the unique values  of feature: Marital Status
1    5298
2    2467
0    1369
Name: Marital Status, dtype: int64


Before encoding the unique values of feature: Policy Type
Personal Auto     6788
Corporate Auto    1968
Special Auto       378
Name: Policy Type, dtype: int64


After encoding the unique values  of feature: Policy Type
1    6788
0    1968
```

```
2     378
Name: Policy Type, dtype: int64


Before encoding the unique values of feature: Policy
Personal L3     3426
Personal L2     2122
Personal L1     1240
Corporate L3    1014
Corporate L2     595
Corporate L1     359
Special L2       164
Special L3       148
Special L1        66
Name: Policy, dtype: int64


After encoding the unique values  of feature: Policy
5    3426
4    2122
3    1240
2    1014
1     595
0     359
7     164
8     148
6      66
Name: Policy, dtype: int64


Before encoding the unique values of feature: Renew Offer Type
Offer1    3752
Offer2    2926
Offer3    1432
Offer4    1024
Name: Renew Offer Type, dtype: int64


After encoding the unique values  of feature: Renew Offer Type
0    3752
1    2926
2    1432
3    1024
Name: Renew Offer Type, dtype: int64


Before encoding the unique values of feature: Sales Channel
Agent          3477
Branch         2567
Call Center    1765
Web            1325
Name: Sales Channel, dtype: int64


After encoding the unique values  of feature: Sales Channel
0    3477
1    2567
2    1765
3    1325
Name: Sales Channel, dtype: int64


Before encoding the unique values of feature: Vehicle Class
Four-Door Car    4621
```

```
Two-Door Car     1886
SUV              1796
Sports Car        484
Luxury SUV        184
Luxury Car        163
Name: Vehicle Class, dtype: int64


After encoding the unique values  of feature: Vehicle Class
0    4621
5    1886
3    1796
4     484
2     184
1     163
Name: Vehicle Class, dtype: int64


Before encoding the unique values of feature: Vehicle Size
Medsize    6424
Small      1764
Large       946
Name: Vehicle Size, dtype: int64


After encoding the unique values  of feature: Vehicle Size
1    6424
2    1764
0     946
Name: Vehicle Size, dtype: int64
```

Converding the date feature in Day, Month and Year Columns

In [50]:
```
df['Effective To Date'] = pd.to_datetime(df['Effective To Date'])
```

In [51]:
```
df['Effective To Date'].head()
```

Out[51]:
```
0   1970-01-01 00:00:00.000000040
1   1970-01-01 00:00:00.000000020
2   1970-01-01 00:00:00.000000034
3   1970-01-01 00:00:00.000000009
4   1970-01-01 00:00:00.000000046
Name: Effective To Date, dtype: datetime64[ns]
```

In [52]:
```
df['Year'] = df['Effective To Date'].dt.strftime('%Y')
df['Month'] = df['Effective To Date'].dt.strftime('%m')
```

In [53]:
```
df['Date'] = df['Effective To Date'].dt.strftime('%d')
```

In [54]:
```
df['Date'].head()
```

Out[54]:
```
0    01
1    01
2    01
3    01
4    01
Name: Date, dtype: object
```

In [55]:
```
df['Month'].head()
```

Out[55]:
```
0    01
1    01
2    01
3    01
4    01
Name: Month, dtype: object
```

In [56]:
```
df['Year'].head()
```

Out[56]:
```
0    1970
1    1970
2    1970
3    1970
4    1970
Name: Year, dtype: object
```

In [57]:
```
df.drop(['Effective To Date'],axis=1,inplace=True)
```

In [58]:
```
df.head()
```

Out[58]:

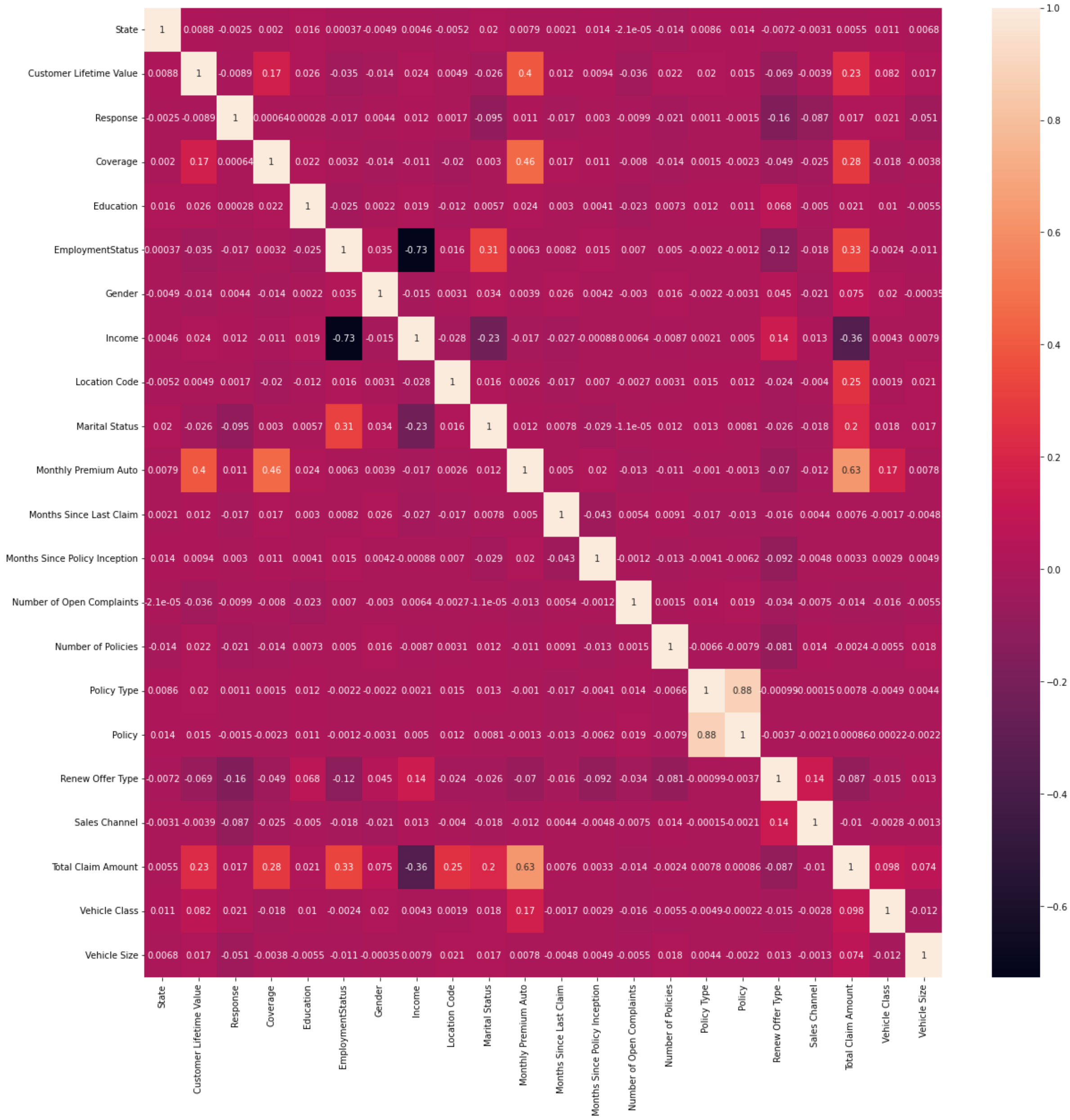
	State	Customer Lifetime Value	Response	Coverage	Education	EmploymentStatus	Gender	Income	Loca
0	4	2763.519279	0	0	0	1	0	56274	
1	0	6979.535903	0	1	0	4	0	0	
2	2	12887.431650	0	2	0	1	0	48767	
3	1	7645.861827	0	0	0	4	1	0	
4	4	2813.692575	0	0	0	1	1	43836	

In [59]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9134 entries, 0 to 9133
Data columns (total 25 columns):
 #   Column                         Non-Null Count  Dtype  
---  ------                         --------------  -----  
 0   State                          9134 non-null   int32  
 1   Customer Lifetime Value        9134 non-null   float64
 2   Response                       9134 non-null   int32  
 3   Coverage                       9134 non-null   int32  
 4   Education                      9134 non-null   int32  
 5   EmploymentStatus               9134 non-null   int32  
 6   Gender                         9134 non-null   int32  
 7   Income                         9134 non-null   int64  
 8   Location Code                  9134 non-null   int32  
 9   Marital Status                 9134 non-null   int32  
 10  Monthly Premium Auto           9134 non-null   int64  
 11  Months Since Last Claim        9134 non-null   int64  
 12  Months Since Policy Inception  9134 non-null   int64  
 13  Number of Open Complaints      9134 non-null   int64  
 14  Number of Policies             9134 non-null   int64  
 15  Policy Type                    9134 non-null   int32  
 16  Policy                         9134 non-null   int32  
 17  Renew Offer Type               9134 non-null   int32  
 18  Sales Channel                  9134 non-null   int32  
 19  Total Claim Amount             9134 non-null   float64
 20  Vehicle Class                  9134 non-null   int32  
 21  Vehicle Size                   9134 non-null   int32  
 22  Year                           9134 non-null   object 
 23  Month                          9134 non-null   object 
 24  Date                           9134 non-null   object 
dtypes: float64(2), int32(14), int64(6), object(3)
memory usage: 1.3+ MB
```

In [60]:
```
#Now all values are in numerical formate and its ready for the training
```

In [61]:
```
plt.figure(figsize=(20,20))
sns.heatmap(df.corr(),annot=True)
plt.show()
```



BASE MODEL

In [62]:
```
#Importing Regression Models
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso


#Importing Ensemble models
from sklearn.ensemble import AdaBoostRegressor
from sklearn.ensemble import BaggingRegressor
from sklearn.ensemble import ExtraTreesRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.ensemble import RandomForestRegressor

lr = LinearRegression()
Ridge=Ridge()
Lasso=Lasso()
dt = DecisionTreeRegressor()
```

```
abr = AdaBoostRegressor()
br = BaggingRegressor()
etr = ExtraTreesRegressor()
gbr = GradientBoostingRegressor()
rfr = RandomForestRegressor()


#Importing the Metrics for Score checking
from sklearn.metrics import r2_score
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
```

In [63]:
```
#Spliting the DV and IDV
```

In [64]:
```
X = df.drop('Customer Lifetime Value',axis=1)
y = df['Customer Lifetime Value']
```

In [65]:
```
#Spliting the data for Train and Test the Models
```

In [66]:
```
from sklearn.model_selection import train_test_split
# train data - 70% and test data - 30%
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.30, random_s
print(X_train.shape)
print(X_test.shape)
print(y_test.shape)
print(y_train.shape)
```

```
(6393, 24)
(2741, 24)
(2741,)
(6393,)
```

1. Linear Regression

In [68]:
```
#Fitting the Linear Regression Models
lin_reg = LinearRegression()
lin_reg.fit(X_train,y_train)

#Check the score of model and
print(f'Coefficients: {lin_reg.coef_}')
print(f'Intercept: {lin_reg.intercept_}')
print(f'R^2 score for train: {lin_reg.score(X_train, y_train)}')
print(f'R^2 score for test: {lin_reg.score(X_test, y_test)}')

# Make predictions
predictions = lin_reg.predict(X_train)

print(f'Mean Squared_Error for Train: {mean_squared_error(y_train,predictions)}')
print(f'R^2 score for Train: {r2_score(y_train,predictions)}')
```

```
Coefficients: [-3.85516872e+01 -7.63683579e+02 -2.16773702e+02  1.50397087e+02
 -1.03136225e+02 -3.19816367e+01  4.15639835e-03 -3.71945324e+01
 -2.18296365e+02  7.78874736e+01  7.94691924e+00  2.55510783e+00
 -2.88968605e+02  6.11092291e+01  1.79231187e+02  3.90721159e+01
 -3.89459500e+02  9.58164982e+01 -2.61848387e-02  5.52992278e+01
  1.08196121e+02  0.00000000e+00  0.00000000e+00  0.00000000e+00]
Intercept: 520.3246976708815
R^2 score for train: 0.1681963201866039
R^2 score for test: 0.15411155333480375
Mean Squared_Error for Train: 37538904.55246068
R^2 score for Train: 0.1681963201866039
```

We can see not a good score in both Train and Test Dataset

2. Decision Tree Regression

In [69]:
```
#Fitting the Models
dt = DecisionTreeRegressor()
dt.fit(X_train,y_train)

#Check the score of model and
print(f'R^2 score for train: {dt.score(X_train, y_train)}')
print(f'R^2 score for test: {dt.score(X_test, y_test)}')
```

```
R^2 score for train: 1.0
R^2 score for test: 0.521667655300103
```

3. AdaBoostRegressor

In [70]:
```
#Fitting the Models
abr =AdaBoostRegressor()
abr.fit(X_train,y_train)

#Check the score of model and
print(f'R^2 score for train: {abr.score(X_train, y_train)}')
print(f'R^2 score for test: {abr.score(X_test, y_test)}')
```

```
R^2 score for train: 0.0011211098471353154
R^2 score for test: 0.10788654145339205
```

4. Bagging Regressor

In [71]:
```
#Fitting the Models
br =BaggingRegressor()
br.fit(X_train,y_train)

#Check the score of model and
print(f'R^2 score for train: {br.score(X_train, y_train)}')
print(f'R^2 score for test: {br.score(X_test, y_test)}')
```

```
R^2 score for train: 0.9429268408369278
R^2 score for test: 0.6933302530959066
```

5. Extra Trees Regressor

In [72]:
```
#Fitting the Models
etr =ExtraTreesRegressor()
etr.fit(X_train,y_train)

#Check the score of model and
print(f'R^2 score for train: {etr.score(X_train, y_train)}')
print(f'R^2 score for test: {etr.score(X_test, y_test)}')
```

```
R^2 score for train: 1.0
R^2 score for test: 0.6971635665656128
```

6. Gradient Boosting Regressor

In [73]:
```
#Fitting the Models
gbr =GradientBoostingRegressor()
gbr.fit(X_train,y_train)

#Check the score of model and
print(f'R^2 score for train: {gbr.score(X_train, y_train)}')
print(f'R^2 score for test: {gbr.score(X_test, y_test)}')
```

```
R^2 score for train: 0.7350168877086709
R^2 score for test: 0.6716872358180188
```

7. Random Forest Regressor

In [74]:
```
#Fitting the Models
rfr =RandomForestRegressor()
rfr.fit(X_train,y_train)

#Check the score of model and
print(f'R^2 score for train: {rfr.score(X_train, y_train)}')
print(f'R^2 score for test: {rfr.score(X_test, y_test)}')
```

```
R^2 score for train: 0.9576544745827726
R^2 score for test: 0.7141868751519352
```

We can see not a good score in all the above Model for both Train and Test Dataset

Let us generate polynomial models reflecting the non-linear interaction between some dimensions

In [75]:
```
from sklearn.preprocessing import PolynomialFeatures
```

In [76]:
```
poly = PolynomialFeatures(degree = 2, interaction_only=True)

#poly = PolynomialFeatures(2)
X_poly = poly.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_poly, y, test_size=0.30, ranc
X_train.shape
```

Out[76]:
```
(6393, 301)
```

In [77]:
```
lin_reg.fit(X_train, y_train)
print(lin_reg.coef_[0])
```

```
-8.72648016979091e-07
```

In [78]:
```
lin_reg.fit(X_train, y_train)
print(lin_reg.score(X_train, y_train))
```

```
0.22459607933004855
```

In [79]:
```
lin_reg.fit(X_train, y_train)
print(lin_reg.score(X_test, y_test))
```

```
0.11765092343686456
```

We can see not a good score in all the above Model for both Train and Test Dataset

Using GridSearchCV with Random Forest Regression

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier

classifier_rf = RandomForestClassifier(random_state=42, n_jobs=-1, max_depth=5,
                                       n_estimators=100, oob_score=True)

classifier_rf.fit(X_train, y_train)
```

In [ ]:
```
# checking the oob score
classifier_rf.oob_score_
```

In [ ]:
```
rf = RandomForestClassifier(random_state=42, n_jobs=-1)

params = {
    'max_depth': [2,3,5,10,20],
    'min_samples_leaf': [5,10,20,50,100,200],
    'n_estimators': [10,25,30,50,100,200]
}

from sklearn.model_selection import GridSearchCV

# Instantiate the grid search model
grid_search = GridSearchCV(estimator=rf,
                           param_grid=params,
                           cv = 4,
                           n_jobs=-1, verbose=1, scoring="accuracy")

#%%time
grid_search.fit(X_train, y_train)
```