Predicting Customer Lifetime Value(CLV)

In [189]:
```
import pandas as pd             #importing libraries
import seaborn as sns
import matplotlib.pyplot as plt
```

In [190]:
```
cust_df = pd.read_csv('Customer-Value-Analysis.csv')  #loading dataset into pand
cust_df.shape
```

Out[190]: (9134, 24)

In [191]:
```
cust_df.head()
```

Out[191]:

	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	2/3/11	Emplo

5 rows × 24 columns

In [192]:
```
cust_df.dtypes  #understanding the datatypes
```

Out[192]:
```
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 [193]:
```
cust_df.isnull().sum()  #nullcheck
```

Out[193]:
```
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
```

Changing Response attribute to 0's and 1's

In [194]:
```
cust_df.Response = cust_df.Response.apply(lambda X : 0 if X == 'No' else 1)
#cust_df.head()
```

Finding correlation between columns

In [195]:
```
cust_df.corr()
```

Out[195]:

	Customer Lifetime Value	Response	Income	Monthly Premium Auto	Months Since Last Claim	Months Since Policy Inception	Number of Open Complaints	Numbe o Policie
Customer Lifetime Value	1.000000	-0.008930	0.024366	0.396262	0.011517	0.009418	-0.036343	0.02195
Response	-0.008930	1.000000	0.011932	0.010966	-0.016597	0.002952	-0.009881	-0.02089
Income	0.024366	0.011932	1.000000	-0.016665	-0.026715	-0.000875	0.006408	-0.00865
Monthly Premium Auto	0.396262	0.010966	-0.016665	1.000000	0.005026	0.020257	-0.013122	-0.01123
Months Since Last Claim	0.011517	-0.016597	-0.026715	0.005026	1.000000	-0.042959	0.005354	0.00913
Months Since Policy Inception	0.009418	0.002952	-0.000875	0.020257	-0.042959	1.000000	-0.001158	-0.01333
Number of Open Complaints	-0.036343	-0.009881	0.006408	-0.013122	0.005354	-0.001158	1.000000	0.00149
Number of Policies	0.021955	-0.020891	-0.008656	-0.011233	0.009136	-0.013333	0.001498	1.00000
Total Claim Amount	0.226451	0.016877	-0.355254	0.632017	0.007563	0.003335	-0.014241	-0.00235

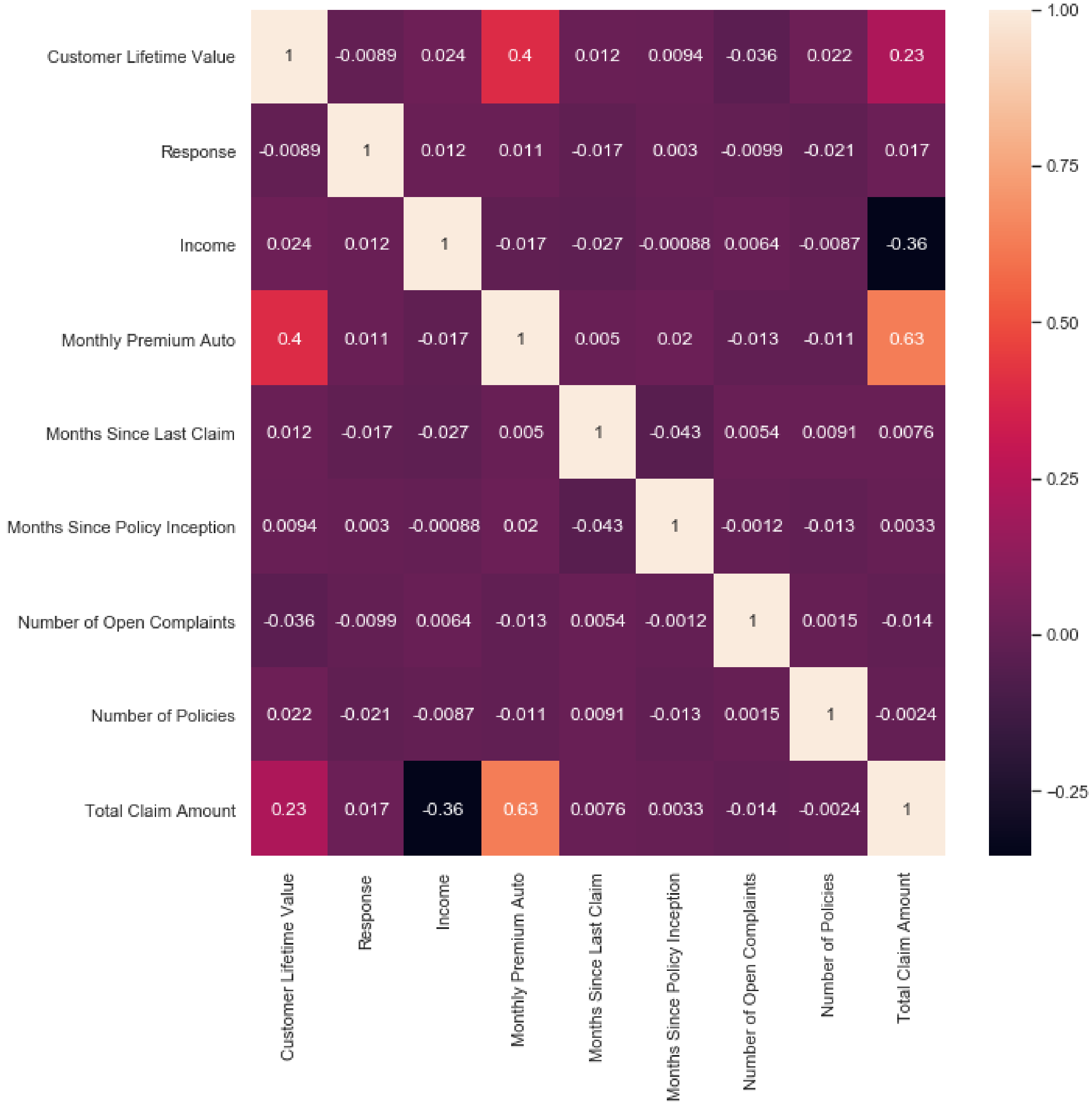
In [196]:
```
corr_matrix = cust_df.corr()['Customer Lifetime Value']    #sorting correlation v
sorted_corr = corr_matrix.sort_values(ascending = False)
sorted_corr
```

Out[196]:
```
Customer Lifetime Value           1.000000
Monthly Premium Auto              0.396262
Total Claim Amount                0.226451
Income                            0.024366
Number of Policies                0.021955
Months Since Last Claim           0.011517
Months Since Policy Inception     0.009418
Response                         -0.008930
Number of Open Complaints        -0.036343
Name: Customer Lifetime Value, dtype: float64
```

Also we can visualize this using heat map

In [197]:
```
sns.set(rc={'figure.figsize':(10,10)})  #heatmap
sns.heatmap(cust_df.corr(),annot = True)
```

Out[197]: <matplotlib.axes._subplots.AxesSubplot at 0x137e2fa20f0>

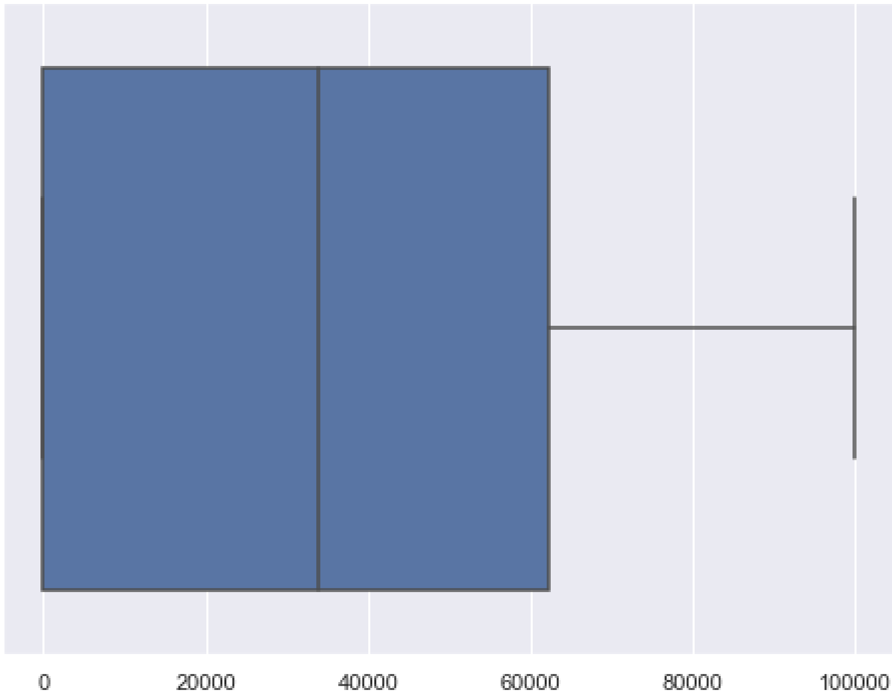


As we can see that the monthly premium auto, total claim amount, and income has an effect on customer lifetime value attribute. Let's work on these attributes

Outliers check

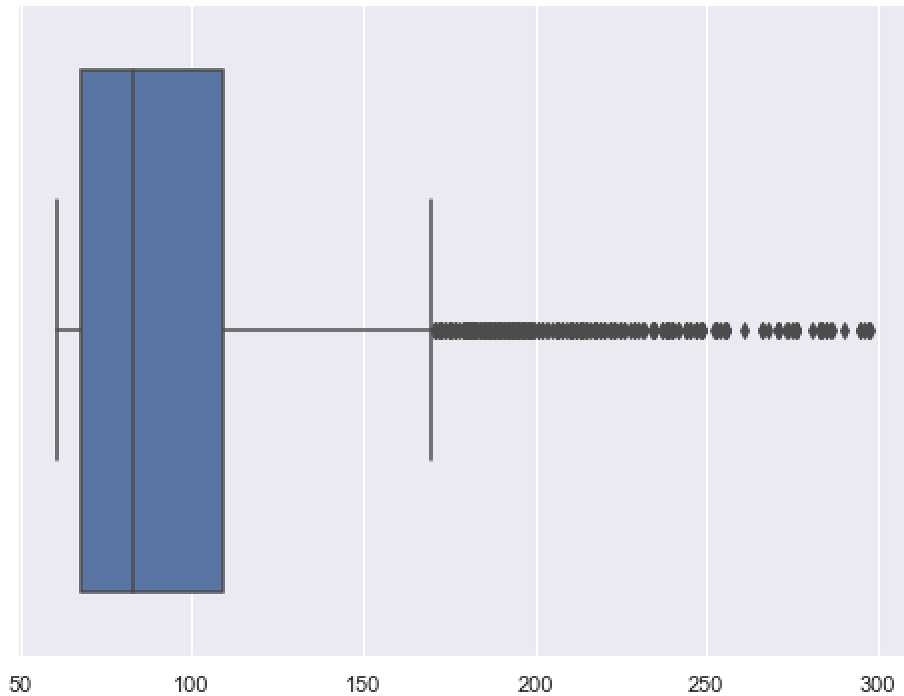
In [198]:
```
sns.set(rc={'figure.figsize':(8,6)})
x = cust_df['Income'].values
ax = sns.boxplot(x)
print('The meadian is: ', cust_df['Income'].median())
```

```
The meadian is:  33889.5
```



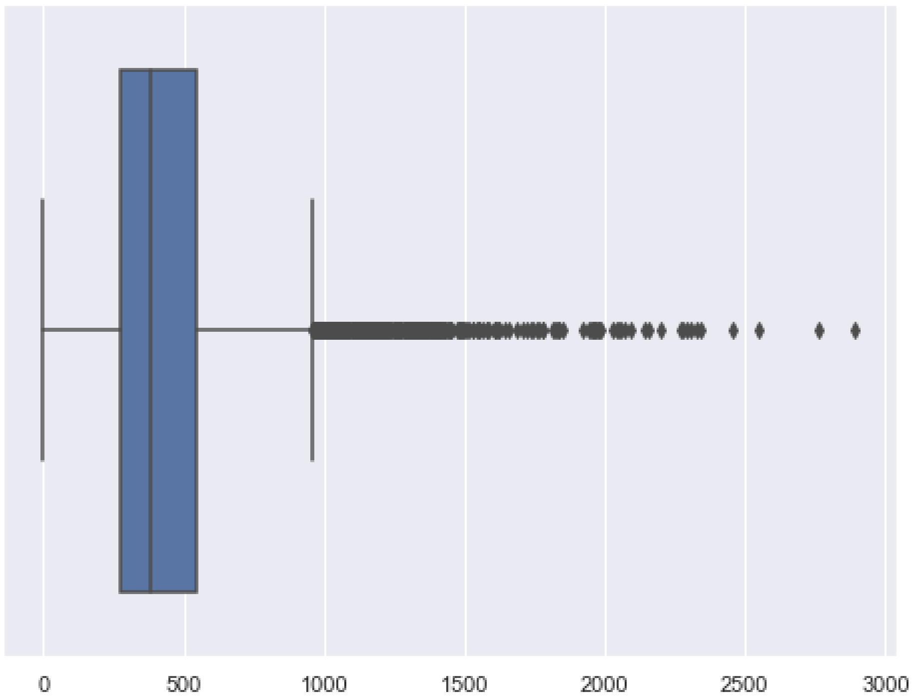
In [199]:
```
sns.set(rc={'figure.figsize':(8,6)})
x = cust_df['Monthly Premium Auto'].values
ax = sns.boxplot(x)
print('The meadian is: ', cust_df['Monthly Premium Auto'].median())
```

```
The meadian is:  83.0
```



In [200]:
```
sns.set(rc={'figure.figsize':(8,6)})
x = cust_df['Total Claim Amount'].values
ax = sns.boxplot(x)
print('The meadian is: ', cust_df['Total Claim Amount'].median())
```

```
The meadian is:  383.94543350000004
```

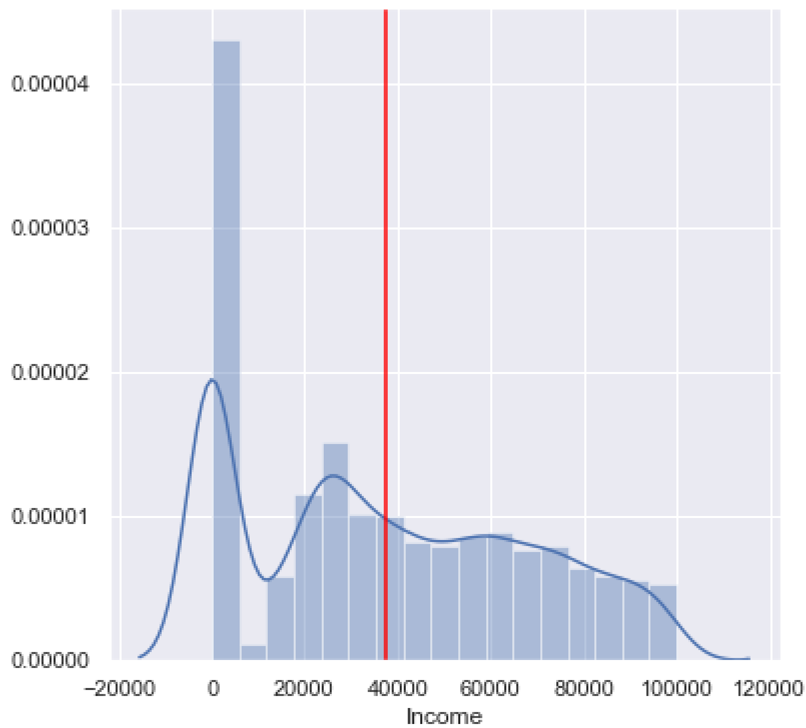


With results above, we can say that there are outliers in total claim amount and monthly premium auto.Usually we remove the outliers but as this data is related to insurance company, the outliers can be our most important customers. So, removing the outliers is not needed.

In [201]:
```
#normal distributions
sns.set(rc = {'figure.figsize': (6,6)})
sns.distplot(cust_df['Income'])
mean = cust_df['Income'].mean()
plt.axvline(mean,0,1,color = 'red')
```

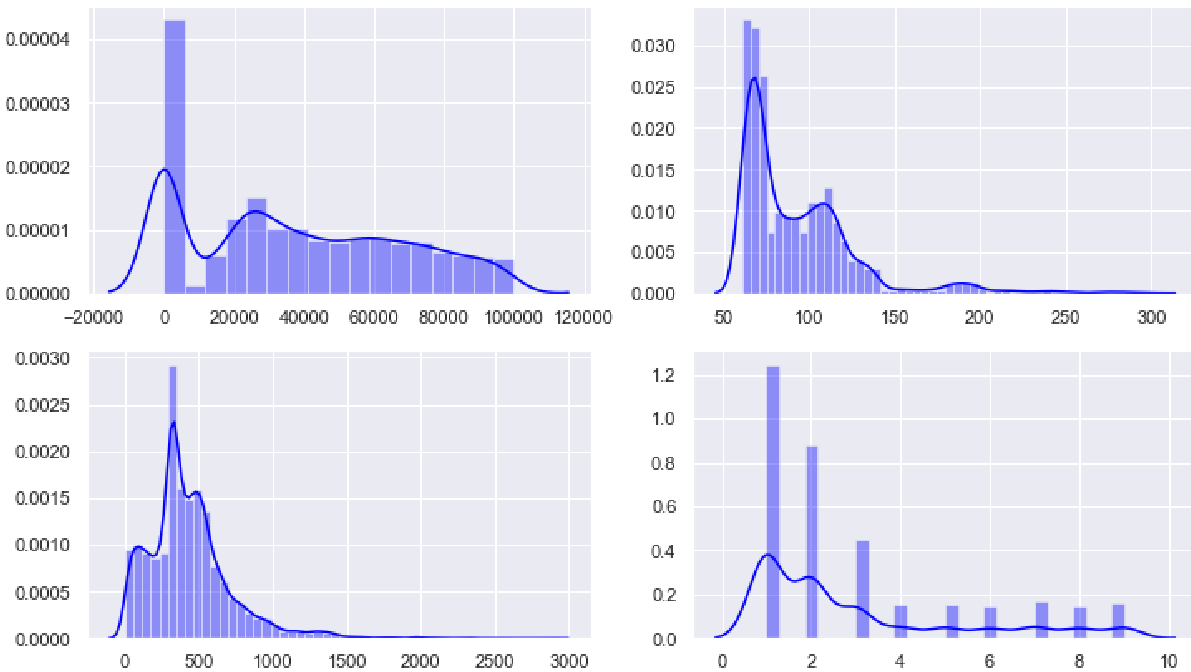
```
C:\ProgramData\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713: FutureWar
ning: Using a non-tuple sequence for multidimensional indexing is deprecated; u
se `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will be interpre
ted as an array index, `arr[np.array(seq)]`, which will result either in an err
or or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

Out[201]: <matplotlib.lines.Line2D at 0x137e2094ef0>



In [202]:
```
fig, axes = plt.subplots(2, 2, figsize=(12, 7))

a = cust_df['Income'].values
b = cust_df['Monthly Premium Auto'].values
c = cust_df['Total Claim Amount'].values
d = cust_df['Number of Policies'].values


# plot 1
sns.distplot(a, color = 'blue', ax=axes[0,0])

# plot 2
sns.distplot(b, color = 'blue', ax=axes[0,1])

# plot 3
sns.distplot(c, color = 'blue', ax=axes[1,0])

#plot 4
sns.distplot(d, color = 'blue', ax=axes[1,1])
```

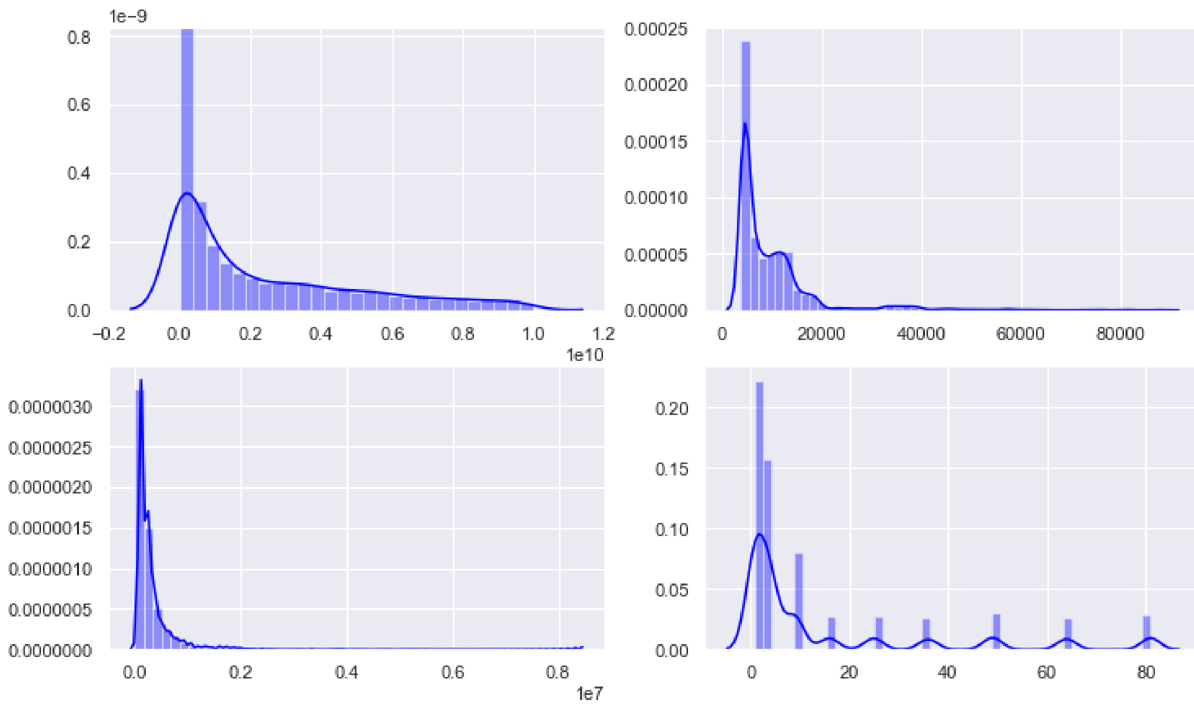
Out[202]: <matplotlib.axes._subplots.AxesSubplot at 0x137df4b83c8>



As the columns are skewed, let's try normalizing it by appying transformations such as square

In [203]:
```
fig, axes = plt.subplots(2, 2, figsize=(12, 7))
at = (cust_df['Income']**2).values
bt = (cust_df['Monthly Premium Auto']**2).values
ct = (cust_df['Total Claim Amount']**2).values
dt = (cust_df['Number of Policies']**2).values

# plot 1
sns.distplot(at, color = 'blue', ax=axes[0,0])

# plot 2
sns.distplot(bt, color = 'blue', ax=axes[0,1])

# plot 3
sns.distplot(ct, color = 'blue', ax=axes[1,0])

# plot 4
sns.distplot(dt, color = 'blue', ax=axes[1,1])
```

Out[203]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x137e3b9dc88>
```



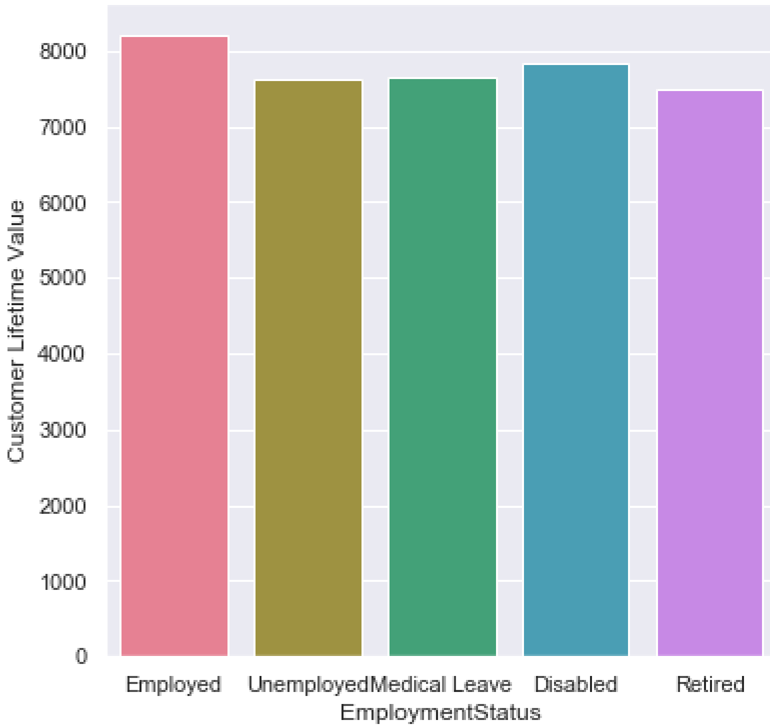
With the transformation of the columns, our data is getting much skewed or the peaks of the distribution are increasing. So, it is better to remain with our original data

visualizations

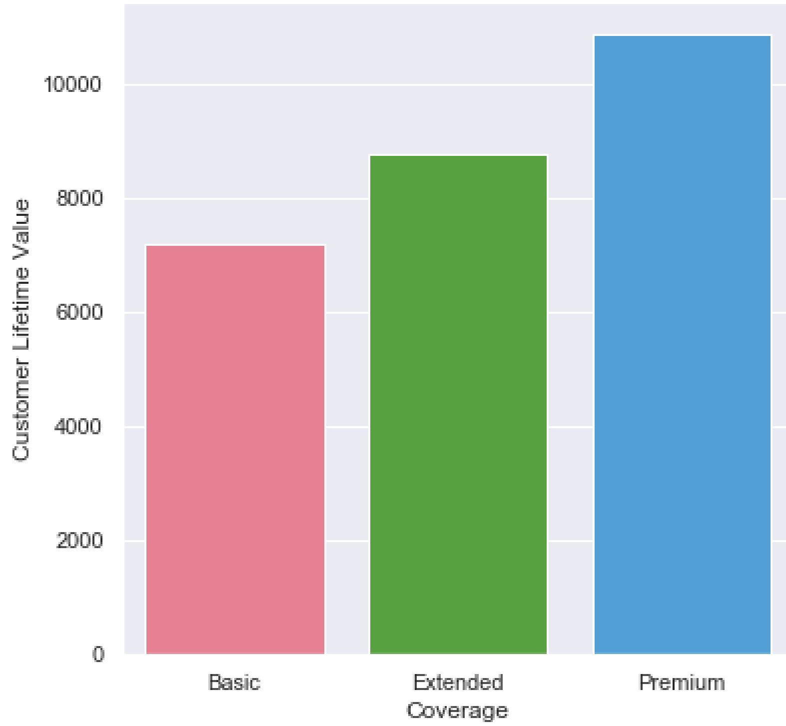
As it is important for the business to understand their customers behavior. some key points can be drawn if we observe the trends in response attribute w.r.t other columns. (Tableau)

Analysis on customer life time value(categorical variables)

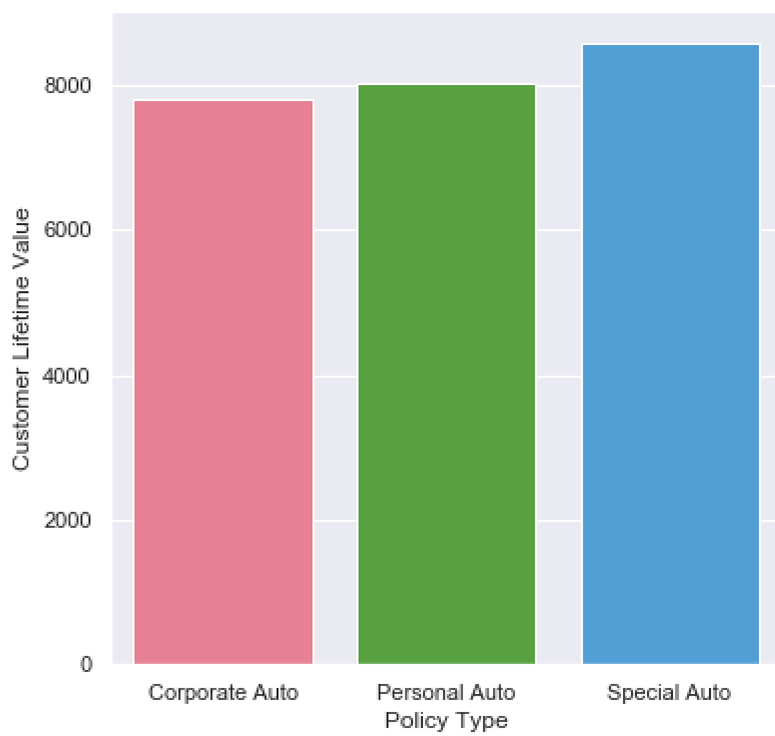
In [204]:
```
# How is customer lifetime value related to employment status of thr customer
ax = sns.barplot(y='Customer Lifetime Value', x='EmploymentStatus',data = cust_d
```



In [205]:
```
#CLV w.r.t coverage
ax = sns.barplot(y='Customer Lifetime Value', x='Coverage',data = cust_df, ci =
```



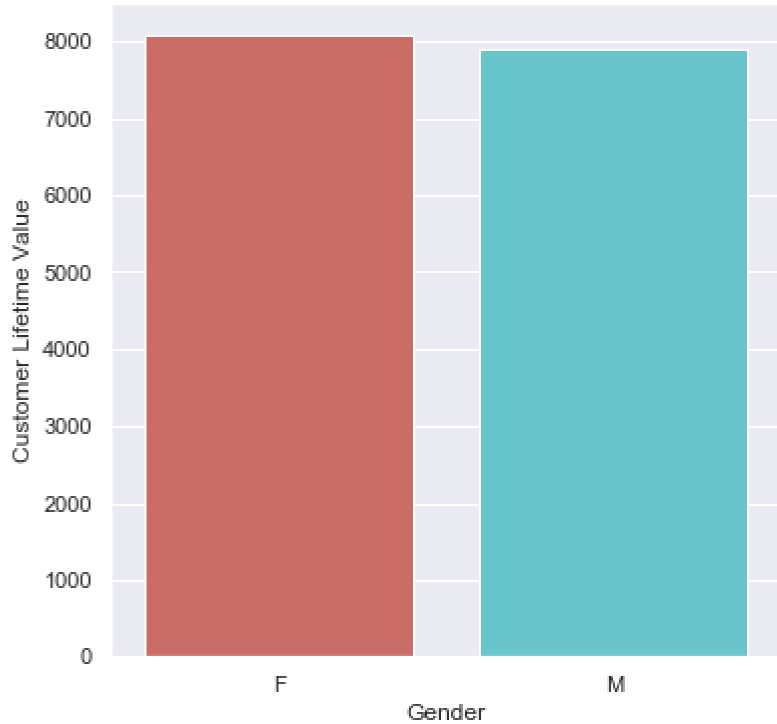
In [206]:
```
#CLV w.r.t policy type
ax = sns.barplot(y='Customer Lifetime Value', x='Policy Type',data = cust_df, ci
```



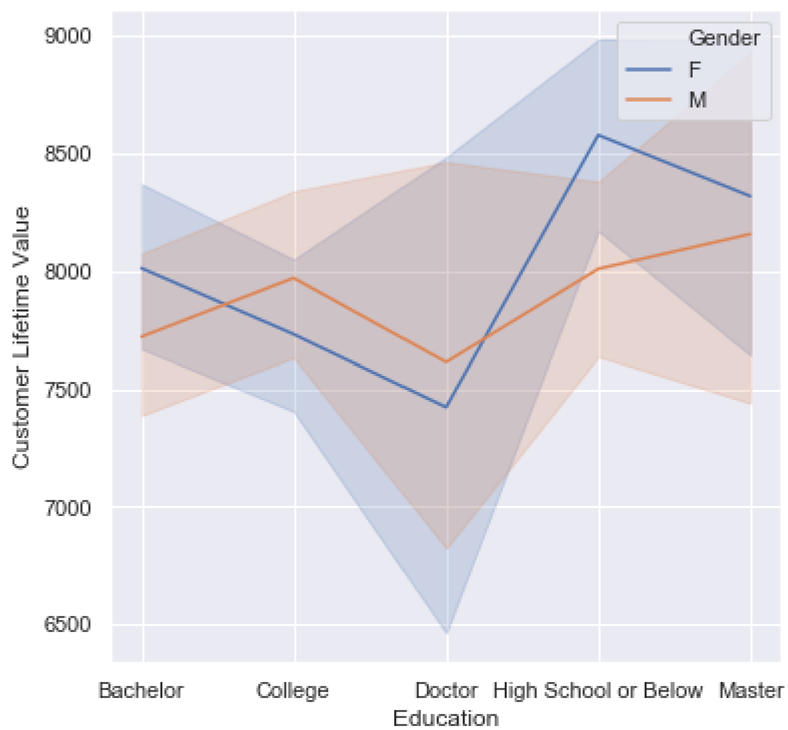
As there is no much variaion in CLV w.r.t whether a customer is employed or not, we can disregard this column.

this column.

In [207]:
```
#CLV w.r.t gender
bx = sns.barplot(y='Customer Lifetime Value', x='Gender',data = cust_df, ci = Fa
```



In [208]:
```
#CLV w.r.t Education and Gender
ax = sns.lineplot(y='Customer Lifetime Value', x='Education',hue = 'Gender',data
```



We can say that people who are educated(doctor) have much less customer lifetime value, when compared to the people who studied high school or below. And also, CLV is slightly high in case of females, than males.

In [209]:
```
rough = cust_df.drop(['State','Customer','Response','EmploymentStatus','Gender',
#cust_df.columns
```

In [210]:
```
rough_cat = cust_df.select_dtypes(include = ['object']).columns
rough_cat
```

Out[210]:
```
Index(['Coverage', 'Marital Status', 'Renew Offer Type', 'Vehicle Class'], dtyp
e='object')
```

In [211]:
```
cols = ['Coverage', 'Marital Status', 'Renew Offer Type', 'Vehicle Class'] #dumm
new = pd.get_dummies(cust_df,columns=['Coverage','Marital Status','Number of Pol
```

In [212]:
```
new.dtypes
```

Out[212]:
```
Customer Lifetime Value          float64
Monthly Premium Auto               int64
Months Since Last Claim            int64
Months Since Policy Inception      int64
Number of Open Complaints          int64
Total Claim Amount               float64
Coverage_Extended                  uint8
Coverage_Premium                   uint8
Marital Status_Married             uint8
Marital Status_Single              uint8
Number of Policies_2               uint8
Number of Policies_3               uint8
Number of Policies_4               uint8
Number of Policies_5               uint8
Number of Policies_6               uint8
Number of Policies_7               uint8
Number of Policies_8               uint8
Number of Policies_9               uint8
Renew Offer Type_Offer2            uint8
Renew Offer Type_Offer3            uint8
Renew Offer Type_Offer4            uint8
Vehicle Class_Luxury Car           uint8
Vehicle Class_Luxury SUV           uint8
Vehicle Class_SUV                  uint8
Vehicle Class_Sports Car           uint8
Vehicle Class_Two-Door Car         uint8
dtype: object
```

In [213]:
```
new.head()
```

Out[213]:

	Customer Lifetime Value	Monthly Premium Auto	Months Since Last Claim	Months Since Policy Inception	Number of Open Complaints	Total Claim Amount	Coverage_Extended	Cover
0	2763.519279	69	32	5	0	384.811147	0	
1	6979.535903	94	13	42	0	1131.464935	1	
2	12887.431650	108	18	38	0	566.472247	0	
3	7645.861827	106	18	65	0	529.881344	0	
4	2813.692575	73	12	44	0	138.130879	0	

5 rows × 26 columns

Model Selection

In [214]:
```
X = new.drop(['Customer Lifetime Value'],axis = 1)
#X.head()
y = new[['Customer Lifetime Value']]
#print(y)
```

In [215]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, rando
```

In [219]:
```
from sklearn.linear_model import LinearRegression
import sklearn.metrics as sm
regressor = LinearRegression()
regressor.fit(X_train, y_train)
y_pred = regressor.predict(X_test)
print(regressor.score(X_test, y_test))
print("R2 score =", round(sm.r2_score(y_test, y_pred), 2))
```

```
0.6335667047027755
R2 score = 0.63
```

In [217]:

```
from sklearn.tree import DecisionTreeRegressor
regr_1 = DecisionTreeRegressor(max_depth = 5,random_state=1)
regr_1.fit(X_train, y_train)
ypred_dt = regr_1.predict(X_test)
print(regr_1.score(X_test, y_test))
print("R2 score =", round(sm.r2_score(y_test, ypred_dt), 2))
```

```
0.6177902611729776
R2 score = 0.62
```