Big Data - Final Assignment

This assignment was written with love and passion *(and a huge ~~lach~~ lack of sleep)* by Benjamin Amar

Delivered for the Big Data elective class Final Assignment in February 2022.

In [1]:
```
#Importing all libraries
import pandas as pd
%pylab inline
import seaborn as sns
```

```
Populating the interactive namespace from numpy and matplotlib
```

Part 1. Exercises

1. For a fraud detection task: Define FP and FN, which mistake costs more?

FP represents **F**alse **P**ositives, meaning that there is no fraud but thinking there is one.
FN represents **F**alse **N**egatives, meaning that there is a fraud but thinking there is none.

This is why in the context of a fraud detection task, a False Negative would cost more to a company than a False Positive.

2. Fraud detection model

```
Recall : TP / (TP + FN) = 0.5
Precision : TP / (TP + FP) = 0.8
Accuracy : (TP + TN) / (P + N) = 0.95
Population : TP + TN + FP + FN = 600
```

We have a 4 variables equation system that can be resolved. First of all, we will isolate **TP**

Recall :

```
TP / (TP + FN) = 0.5
<=> TP = 0.5*TP + 0.5*FN
<=> 0.5*TP = 0.5*FN
<=> TP = FN
```

Precision :

```
TP / (TP + FP) = 0.8
<=> TP = 0.8*TP + 0.8*FP
<=> 0.2*TP = 0.8*FP
<=> FP = 0.25*TP
```

Accuracy :

```
(TP + TN) / (P + N) = 0.95
<=> TP + TN = 0.95*(P + N)  <---(P+N = 600)
<=> TP + TN = 0.95*600
```

Population :

```
TP + TN + FP + FN = 600
<=> 0.95*600 + 0.25*TP + TP = 600
<=> TP = (600*0.95+600) / 1.25
<=> TP = 24
```

Now that we have found the value of TP we can deduce the other values.

```
TP = 24    and    TP = FN    hence    TP = FN = 24
FP = 0.25*TP = 6
TN = 600 - 24 - 24 - 6 = 546
```

We can now build the model's confusion matrix

In [2]:
```
matrix = pd.DataFrame([[546,24],[6,24]])
matrix.loc["Total"] = matrix.sum(axis=0)
matrix["Total"] = matrix.sum(axis=1)
matrix.columns = pd.MultiIndex.from_tuples([("Real","-"),("Real","+"),("","Total")])
matrix.index = pd.MultiIndex.from_tuples([("Predicted","-"),("Predicted","+"),("","Total")])
matrix
```
Out[2]:

		Real		
		-	+	Total
Predicted	-	546	24	570
	+	6	24	30
	Total	552	48	600

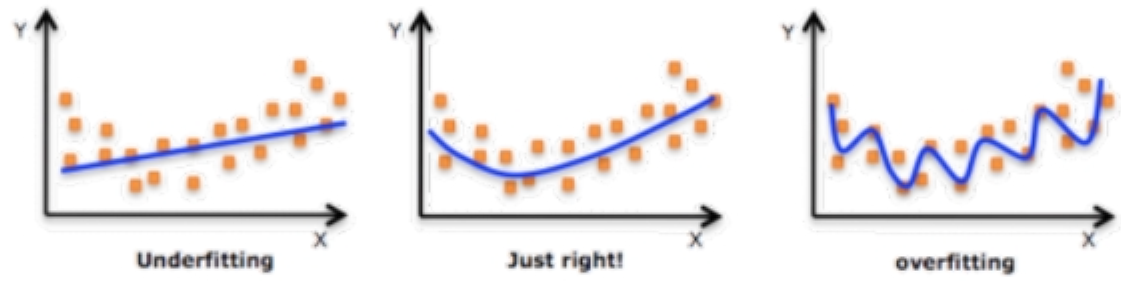
We can interpret that this fraud detection model is not very efficient at **finding all the frauds**, however it is efficient at **detecting real frauds**.

3. Which of the following regressions has a higher risk of overfitting the data?

a. Linear regression using `y=a+b*x` : This model is more likely to be underfitting because it is too simple.
In other words, it is important to avoid too simple models that won't be able to represent the phenomenon we are interested in and won't provide good predictions

b. Linear regression using `y=a+b*x+c*x2` : This model is the less likely to be overfitting since it is the best compromise for bias and variance

c. Linear regression using `y=a+b*x+c*x2+d*x3` : This model is more likely to be overfitting because it is too complex.
Such a model will get really good performances on training data but won't be efficient when facing new data.



A simple model with low variance will be more likely to be underfitting, having a high bias even on the training data.
A complex model with a high variance will be more likely to be overfitting, having a low bias on the training data but high on new data.

The goal here is to find a intermediate model where the prediction bias is the lowest and the generalisation is the best.

```
What Overfitting would look like in real life...
```

Part 2. Insure-Best Dataset

Welcome on this analysis of the Insure-Best dataset where the objective is to train a model that calculates the **CLV** *(Customer's Lifetime Value)*, a value the company needs to score its customers.

The datasets consist of 2 datasets :
`CLV-Training.csv` , a training dataset containing 8637 customer accounts with their respective CLV
`CLV-Test.csv` , a test dataset containing 646 new customer accounts with a CLV to calculate

We are first going to work on the Training dataset, watch an overview, clean it, tailor it and then analyse it.
Next we will create multiple models and train them after tuning their hyperparameters.
Finally we will compare our new results with the training data based on their distribution.

The AzureML experiment can be found at the link below:
https://gallery.cortanaintelligence.com/Experiment/Big-Data-Final-Assignment-Benjamin-Amar

This analysis was performed and written by Benjamin Amar for the Big Data elective final assignment in January and February 2022.

🦊

1.0 Beginning of analysis

In [3]:
```
#Loading the dataset in memory
data = pd.read_csv("CLV-Training.csv")

#Displaying all columns of the dataset
pd.set_option('display.max_columns', None)
data.describe()
```

Out[3]:

	Income	Monthly Premium Auto	Months Since Last Claim	Months Since Policy Inception	Number of Open Complaints	Number of Policies	Total Claim Amount	CLV
count	8637.000000	8637.000000	8637.000000	8637.00000	8637.000000	8637.000000	8637.000000	8637.000000
mean	37670.275906	93.282853	15.152831	48.02744	0.381614	2.967466	434.529481	7999.903842
std	30379.553849	34.526547	10.071044	27.88397	0.907881	2.389180	290.536359	6848.774265
min	0.000000	61.000000	0.000000	0.00000	0.000000	1.000000	0.099007	1898.683686
25%	0.000000	68.000000	6.000000	24.00000	0.000000	1.000000	272.217171	3997.476302
50%	33816.000000	83.000000	14.000000	48.00000	0.000000	2.000000	383.797363	5797.604861
75%	62262.000000	109.000000	23.000000	71.00000	0.000000	4.000000	547.619785	8937.118615
max	99981.000000	298.000000	35.000000	99.00000	5.000000	9.000000	2893.239678	83325.381190

In [4]:
```
#Checking the features in the dataset and their associated type
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8637 entries, 0 to 8636
Data columns (total 23 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   CustomerID                     8637 non-null   object
 1   State                          8637 non-null   object
 2   Response                       8637 non-null   object
 3   Coverage                       8637 non-null   object
 4   Education                      8637 non-null   object
 5   EmploymentStatus               8637 non-null   object
 6   Gender                         8637 non-null   object
 7   Income                         8637 non-null   int64
 8   Location Code                  8637 non-null   object
 9   Marital Status                 8637 non-null   object
 10  Monthly Premium Auto           8637 non-null   int64
 11  Months Since Last Claim        8637 non-null   int64
 12  Months Since Policy Inception  8637 non-null   int64
 13  Number of Open Complaints      8637 non-null   int64
 14  Number of Policies             8637 non-null   int64
 15  Policy Type                    8637 non-null   object
 16  Policy                         8637 non-null   object
 17  Renew Offer Type               8637 non-null   object
 18  Sales Channel                  8637 non-null   object
 19  Total Claim Amount             8637 non-null   float64
 20  Vehicle Class                  8637 non-null   object
 21  Vehicle Size                   8637 non-null   object
 22  CLV                            8637 non-null   float64
dtypes: float64(2), int64(6), object(15)
memory usage: 1.5+ MB
```

The dataset contains 22 features, categorical and numerical. We will need later to encode the categorical features (Dtype = "object") so our model will be able to understand them

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

Out[5]:

	CustomerID	State	Response	Coverage	Education	EmploymentStatus	Gender	Income	Location Code	Marital Status	Monthly Premium Auto	Months Since Last Claim	Months Since Policy Inception	Number of Open Complaints
0	QC35222	California	No	Basic	Bachelor	Employed	F	48269	Urban	Married	69	3	79	3
1	AE98193	Washington	No	Basic	High School or Below	Unemployed	M	0	Suburban	Single	113	19	10	0
2	TM23514	Oregon	No	Extended	College	Employed	M	60145	Urban	Single	132	8	28	0
3	WB38524	California	No	Basic	High School or Below	Employed	M	46131	Suburban	Married	74	27	28	0
4	QZ42725	Washington	No	Basic	Bachelor	Unemployed	F	0	Suburban	Single	64	12	24	0

Deleted useless features 💔

- `CustomerID` : Not bringing any information to the analysis.

Interpretation of features 💡

- `Monthly Premium Auto` : Monthly subscription fee
- `Response` : Whether if the consumer has accepted or not the offer type (`Renew Offer Type`)
- `Months Since Policy Inception` : Months since the beginning of policy/contract

In [6]:
```
data = data.drop("CustomerID", axis = 1)
```

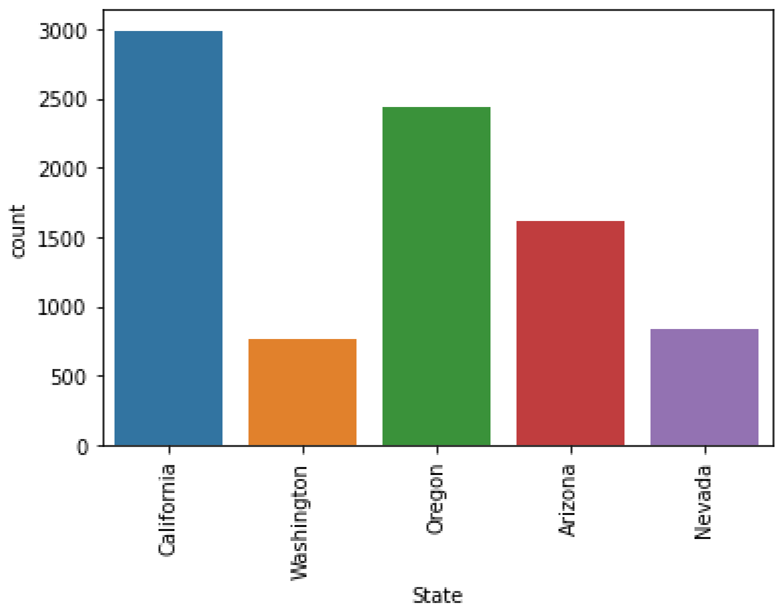
1.1 Univariate descriptive statistics

1.1.a Categorical Features

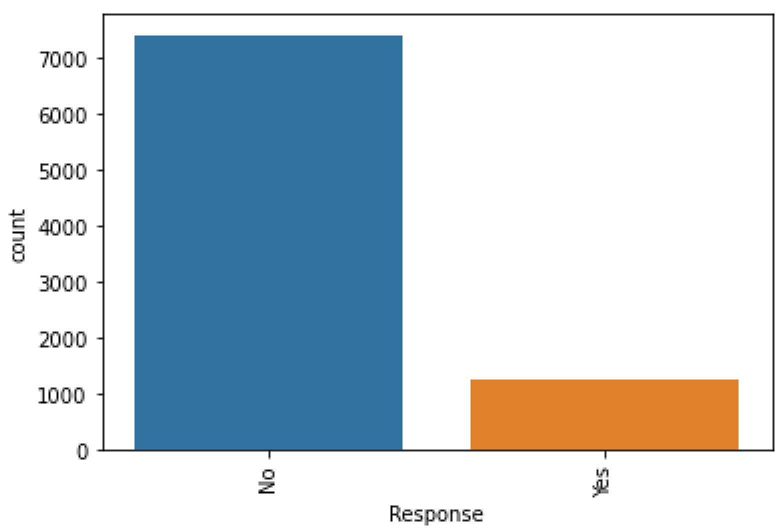
We are starting with categorical features, drawing plots for all of them to find any noticeable information.

In [7]:
```
categorical_features = data.select_dtypes(include='object').columns

for c in categorical_features :
    sns.countplot(data=data,x=c)
    plt.xticks(rotation=90)
    print(c)
    plt.show()
    print(data[c].value_counts().to_dict())
    print("---\n \n \n")
```

```
State
```

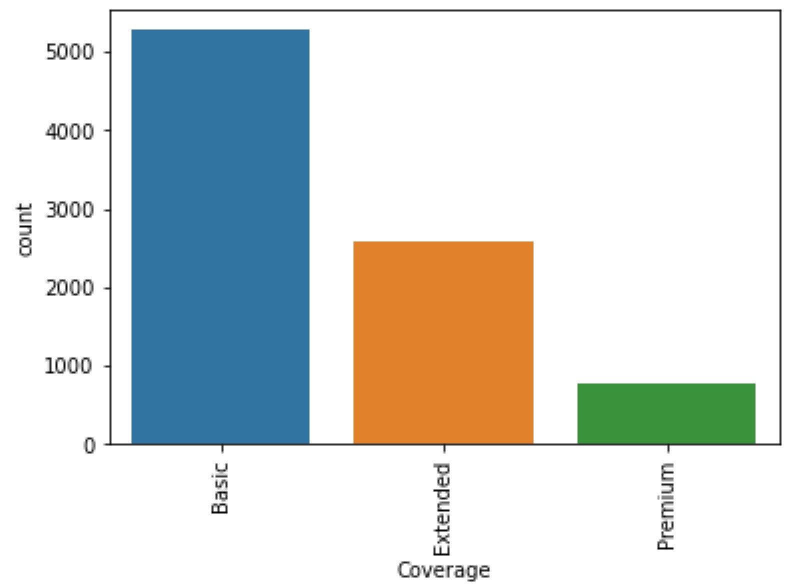



```
{'California': 2990, 'Oregon': 2442, 'Arizona': 1610, 'Nevada': 838, 'Washington': 757}
---


Response
```



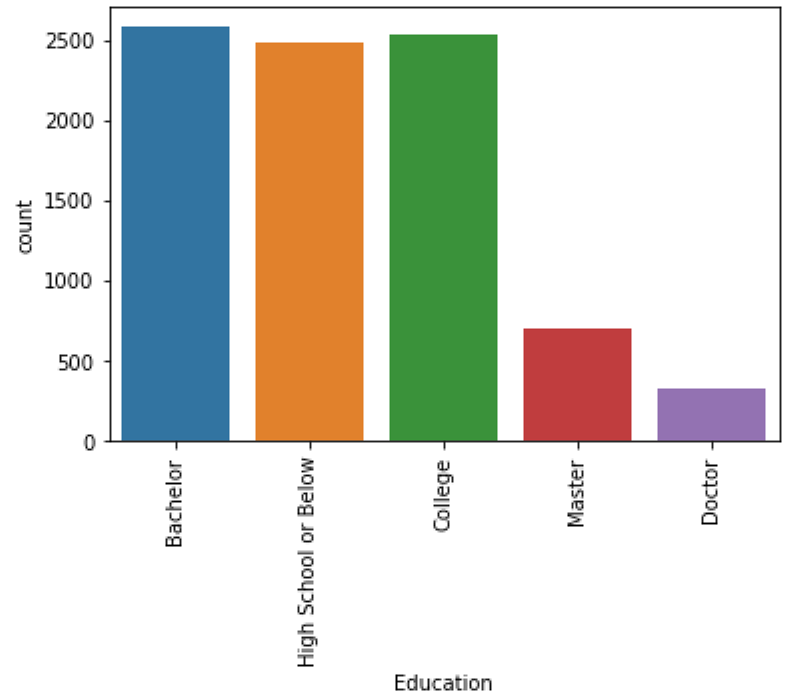

```
{'No': 7407, 'Yes': 1230}
---
```

Coverage



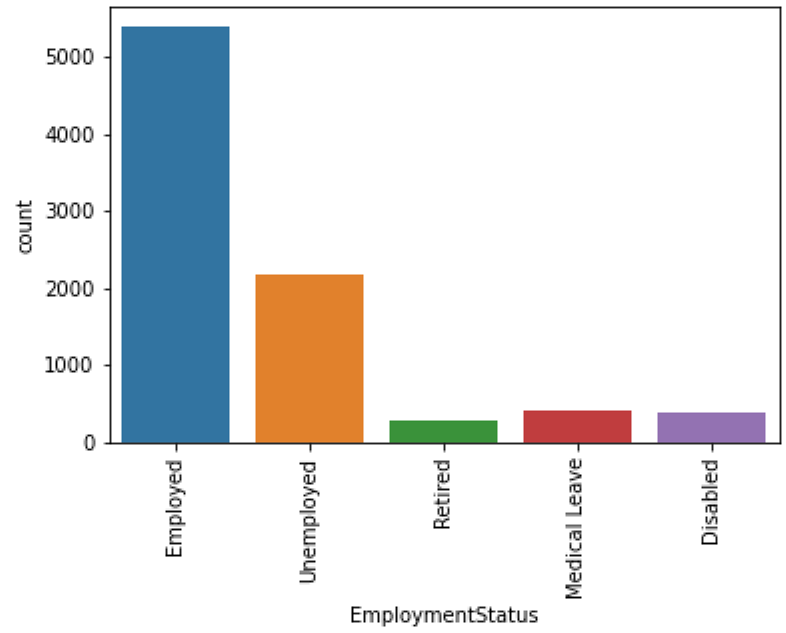
{'Basic': 5274, 'Extended': 2591, 'Premium': 772}

Education



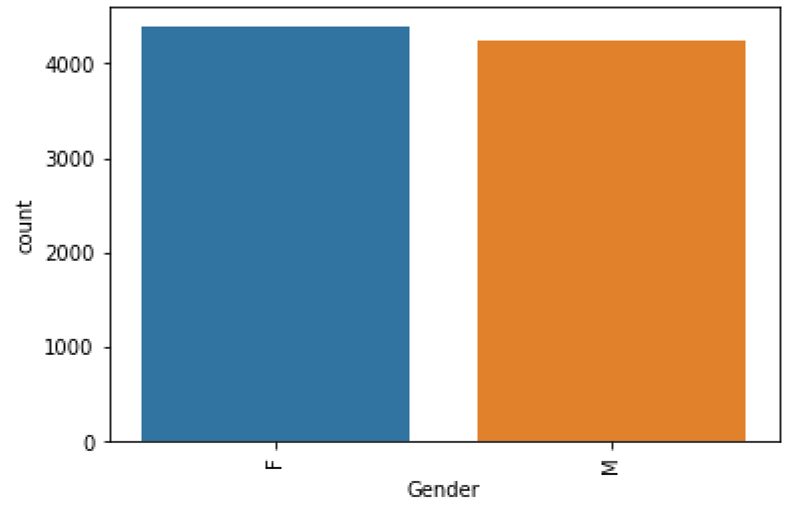
{'Bachelor': 2584, 'College': 2536, 'High School or Below': 2491, 'Master': 701, 'Doctor': 325}

EmploymentStatus



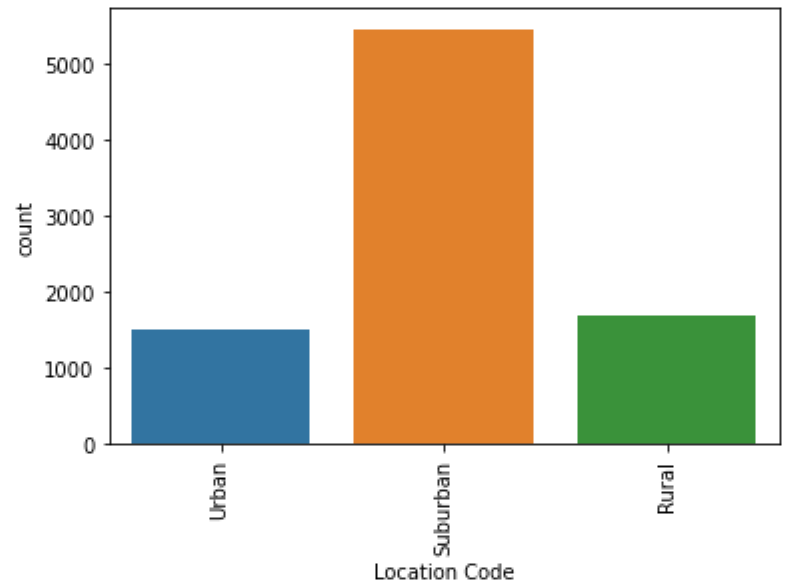
{'Employed': 5386, 'Unemployed': 2184, 'Medical Leave': 414, 'Disabled': 382, 'Retired': 271}

Gender



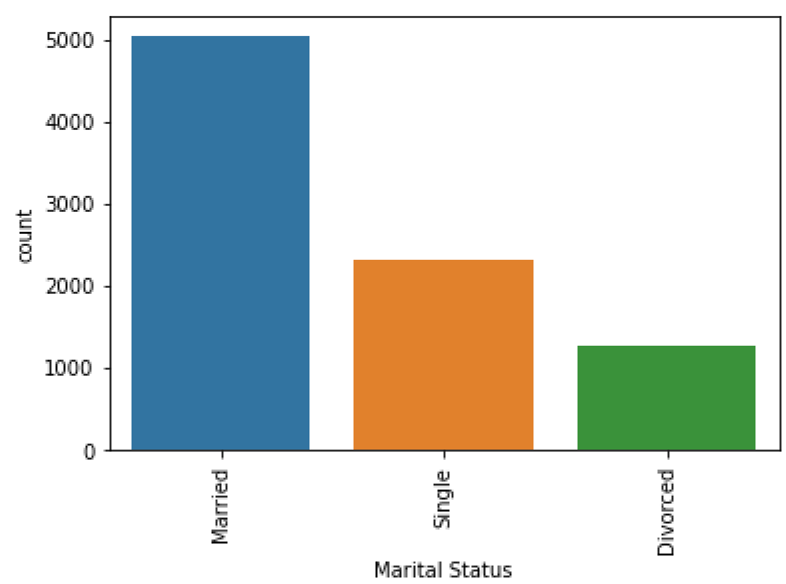

```
{'F': 4388, 'M': 4249}
---
```

Location Code



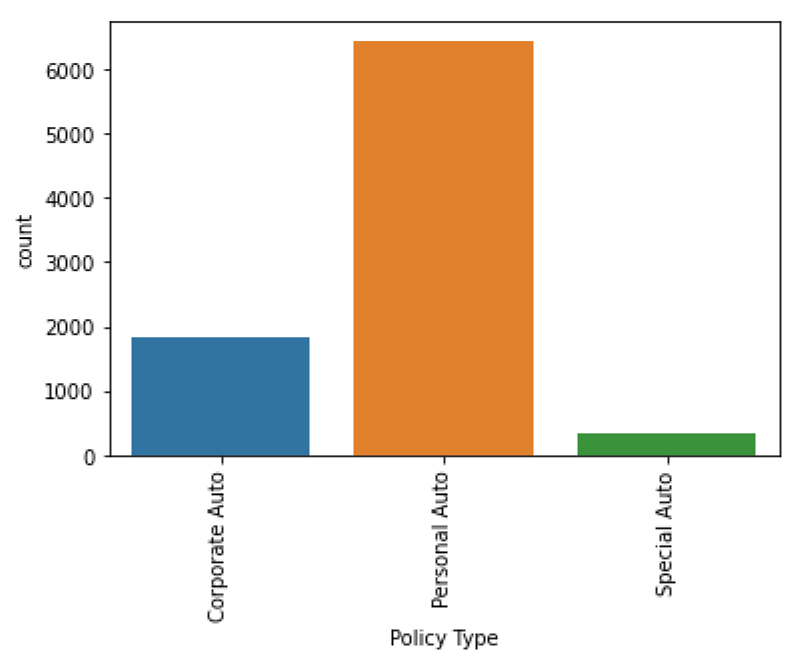

```
{'Suburban': 5459, 'Rural': 1675, 'Urban': 1503}
---
```

Marital Status



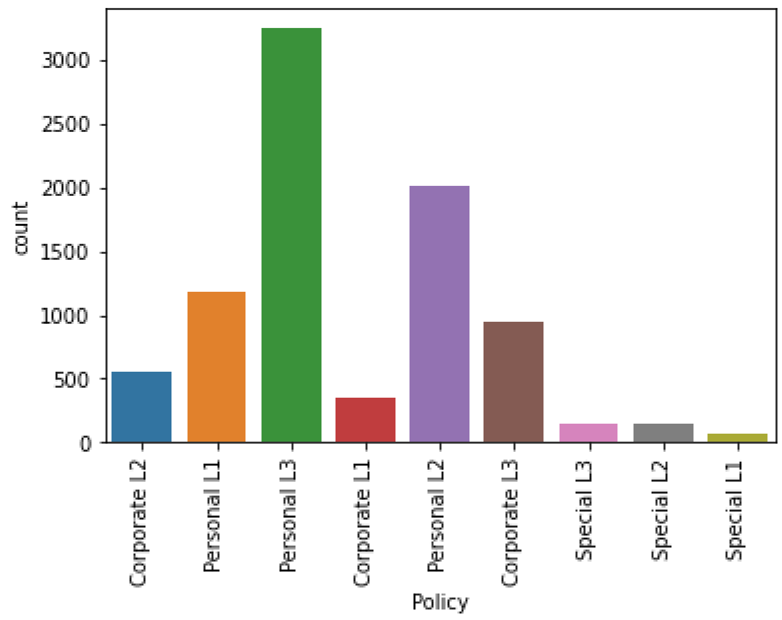

```
{'Married': 5031, 'Single': 2321, 'Divorced': 1285}
---
```

Policy Type



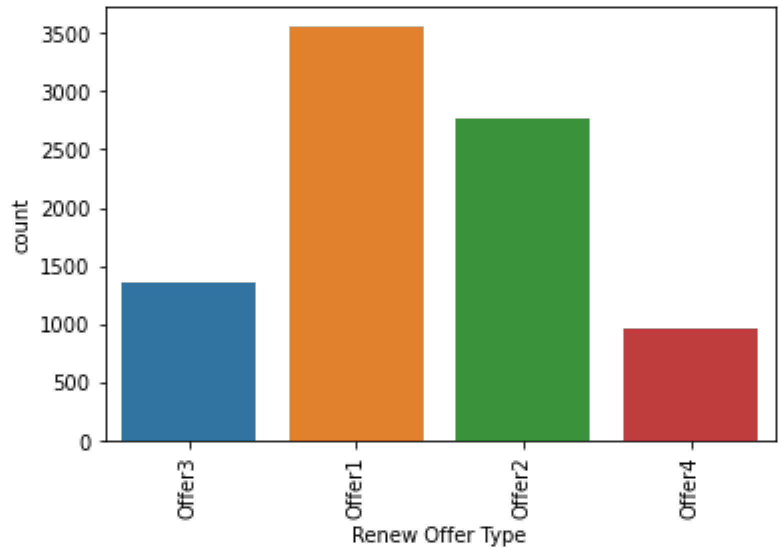
{'Personal Auto': 6434, 'Corporate Auto': 1847, 'Special Auto': 356}

Policy



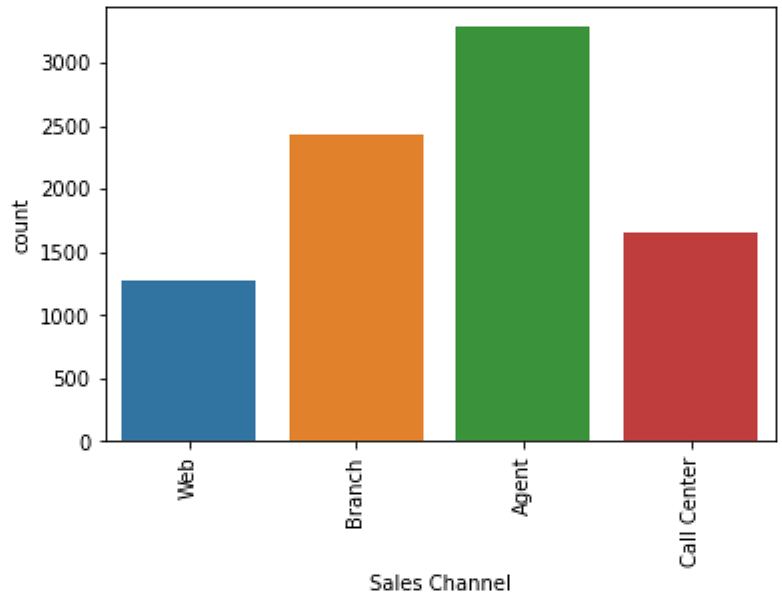
{'Personal L3': 3248, 'Personal L2': 2009, 'Personal L1': 1177, 'Corporate L3': 951, 'Corporate L2': 552, 'Corporate L1': 344, 'Special L2': 149, 'Special L3': 143, 'Special L1': 64}

Renew Offer Type



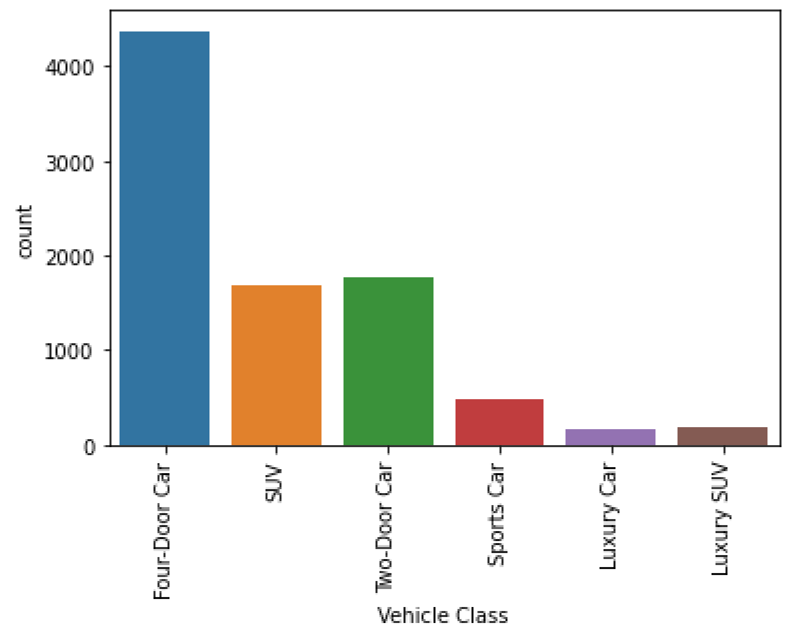
{'Offer1': 3551, 'Offer2': 2761, 'Offer3': 1356, 'Offer4': 969}

Sales Channel



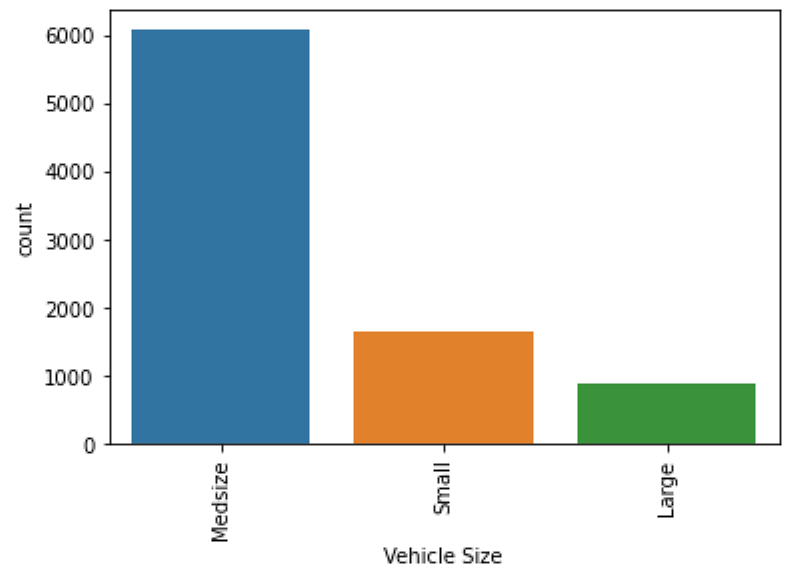
{'Agent': 3283, 'Branch': 2431, 'Call Center': 1655, 'Web': 1268}

```
Vehicle Class
```




```
{'Four-Door Car': 4373, 'Two-Door Car': 1767, 'SUV': 1694, 'Sports Car': 471, 'Luxury SUV': 177, 'Luxury Car': 155}
---
```

```
Vehicle Size
```




```
{'Medsize': 6084, 'Small': 1666, 'Large': 887}
---
```

Interpretation

`State` : The majority of the population is based in California and Oregon

`Response` : Most of the responses are No

`Education` : Bachelor, High School or below and College are approximatively the same amount where Master and Doctor are in a very small amount.

`Gender` : There is an even amount of Females and Males

`Location Code` : The majority of the customers are located in Suburbian areas

`Marital Status` : Majority of Married accounts

`Policy Type` + `Policy` : Majority of Personal Auto L3

`Renew Offer Type` : The most sent renew offers were Offer1 and Offer2 (read *1.2.a* for a contingency table with the offer types and their status)

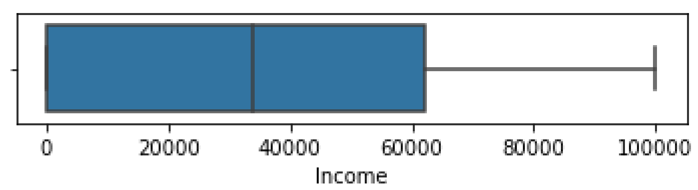
`Vehicle Class` : High majority of Four-Door Cars

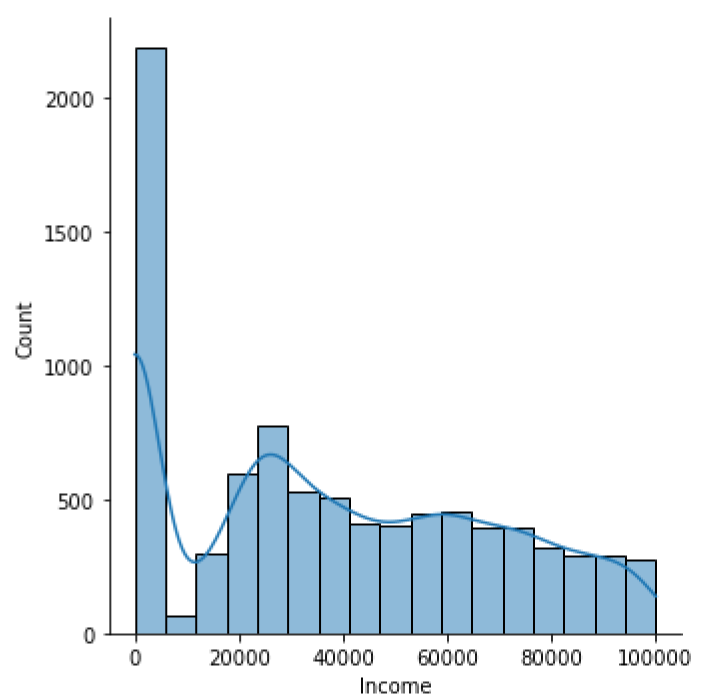
`Vehicle Size` : High Majority of medium sized vehicles

1.1.b Numerical Features

In [8]:
```
numerical_features = data.select_dtypes(include=np.number).columns

for c in numerical_features :
    print(f"Variable : {c}\n")
    print("Central tendency measurement :")
    print(" * Mean: ",data[c].mean())
    print(" * Median: ",data[c].median())
    print("Dispersion measurement :")
    print(" * Variance: ",data[c].var(ddof=0))
    print(" * Standard deviation: ",data[c].std(ddof=0))
    print("Shape measurement :")
    print(" * Skewness: ",data[c].skew())
    print(" * Kurtosis: ",data[c].kurtosis())
    print("P1 and P99 :")
    print(" * P1: ",data[c].quantile(0.01))
    print(" * P25: ",data[c].quantile(0.25))
    print(" * P75: ",data[c].quantile(0.75))
    print(" * P95: ",data[c].quantile(0.95))
    print(" * P99: ",data[c].quantile(0.99))
    plt.figure(figsize=(6, 1))
    sns.boxplot(x=c, data=data)
    plt.xlabel(c)
    plt.show()
    sns.displot(x=c, data=data, kde=True)
    plt.show()
    print("---\n\n\n\n\n")

data[numerical_features].describe()
```

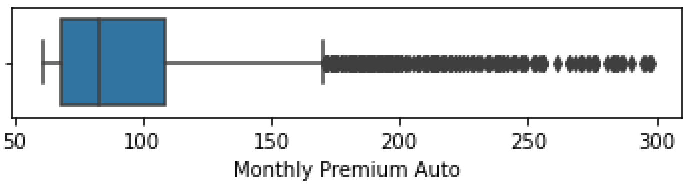
```
Variable : Income

Central tendency measurement :
 * Mean:  37670.27590598587
 * Median:  33816.0
Dispersion measurement :
 * Variance:  922810435.8600599
 * Standard deviation:  30377.79511189151
Shape measurement :
 * Skewness:  0.29011410257692105
 * Kurtosis:  -1.0891946355853834
P1 and P99 :
 * P1:  0.0
 * P25:  0.0
 * P75:  62262.0
 * P95:  90779.0
 * P99:  97861.15999999999
```

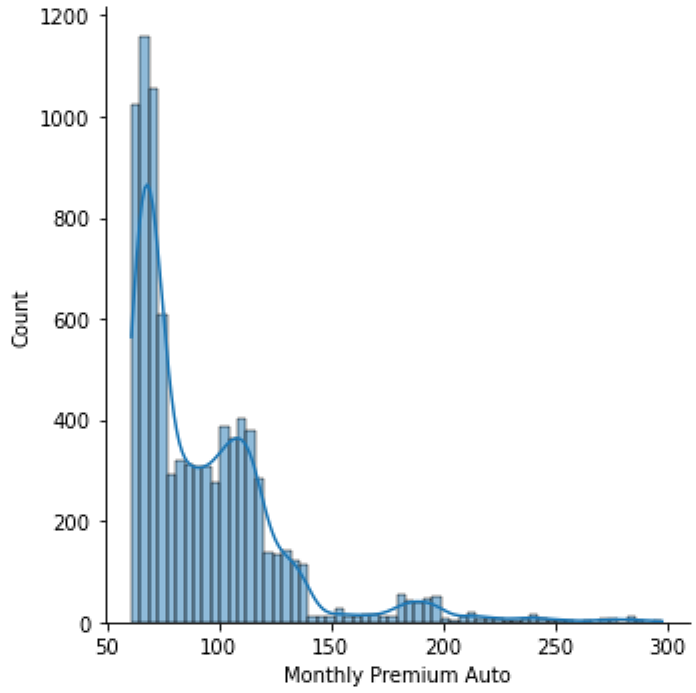




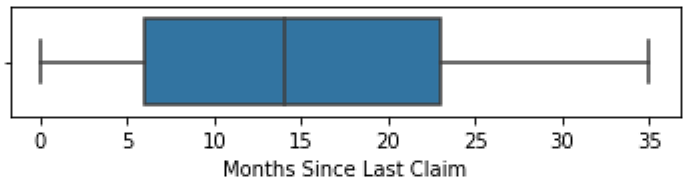

```
---




Variable : Monthly Premium Auto

Central tendency measurement :
 * Mean:  93.2828528424213
 * Median:  83.0
Dispersion measurement :
 * Variance:  1191.9444240483986
 * Standard deviation:  34.52454813677362
Shape measurement :
 * Skewness:  2.1195536219998883
 * Kurtosis:  6.147187703445288
```

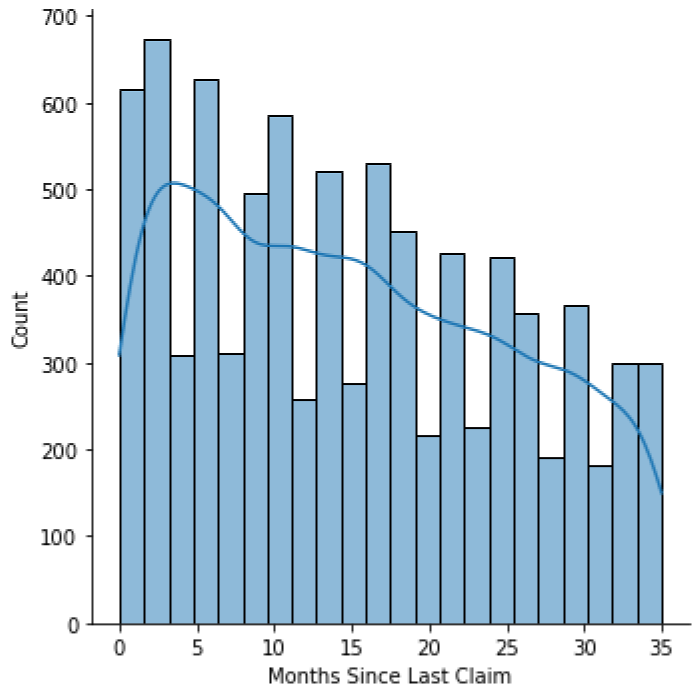
```
P1 and P99 :
 * P1:  61.0
 * P25:  68.0
 * P75:  109.0
 * P95:  165.0
 * P99:  229.0
```



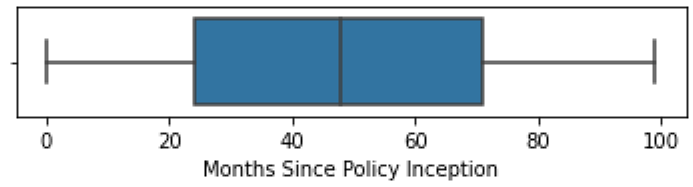


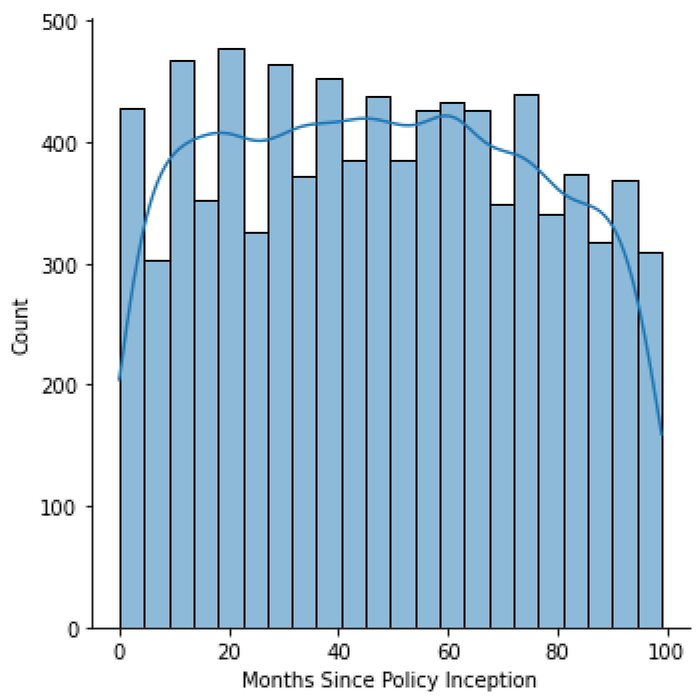
```
Variable : Months Since Last Claim

Central tendency measurement :
 * Mean:  15.15283084404307
 * Median:  14.0
Dispersion measurement :
 * Variance:  101.41417891465221
 * Standard deviation:  10.070460710148877
Shape measurement :
 * Skewness:  0.27208977532080153
 * Kurtosis:  -1.074081653463793
P1 and P99 :
 * P1:  0.0
 * P25:  6.0
 * P75:  23.0
 * P95:  33.0
 * P99:  35.0
```



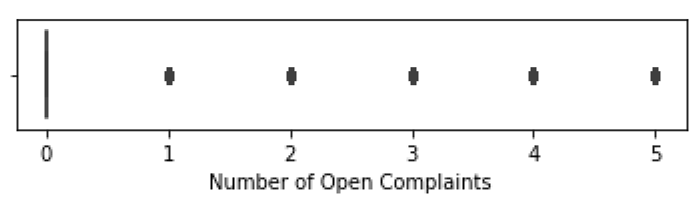


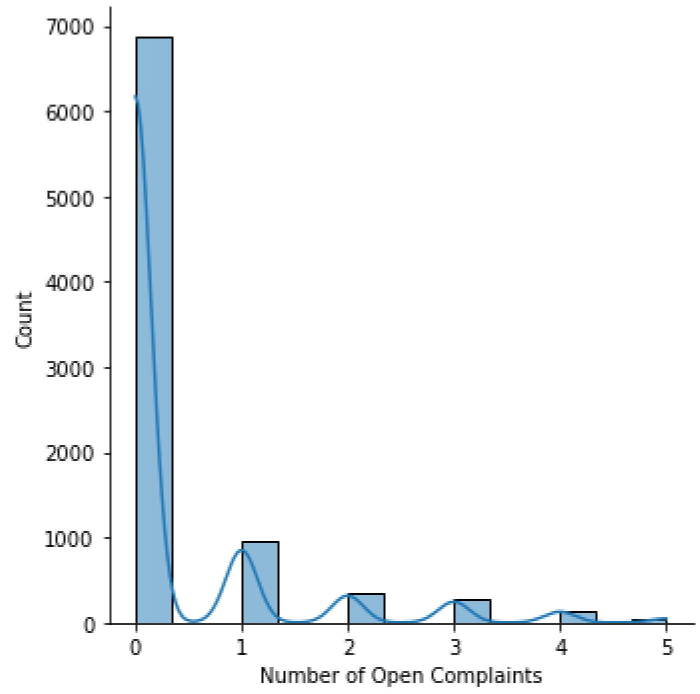
```
Variable : Months Since Policy Inception

Central tendency measurement :
 * Mean:  48.02744008336228
 * Median:  48.0
Dispersion measurement :
 * Variance:  777.4257840338369
 * Standard deviation:  27.882356142080905
Shape measurement :
 * Skewness:  0.04433624691340209
 * Kurtosis:  -1.1349778673084285
P1 and P99 :
 * P1:  1.0
 * P25:  24.0
 * P75:  71.0
 * P95:  93.0
 * P99:  98.0
```





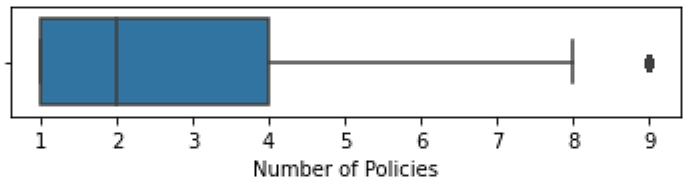
```
Variable : Number of Open Complaints

Central tendency measurement :
 * Mean:  0.38161398633784877
 * Median:  0.0
Dispersion measurement :
 * Variance:  0.8241519394500156
 * Standard deviation:  0.9078281442266568
Shape measurement :
 * Skewness:  2.7962926698994366
 * Kurtosis:  7.826530307528902
P1 and P99 :
 * P1:  0.0
 * P25:  0.0
 * P75:  0.0
 * P95:  3.0
 * P99:  4.0
```

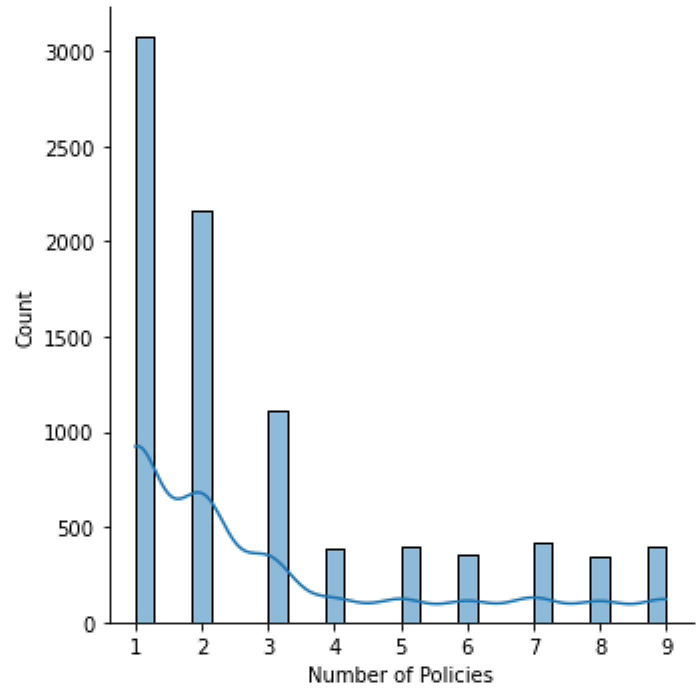




Variable : Number of Policies

Central tendency measurement :
 * Mean: 2.967465555169619
 * Median: 2.0
Dispersion measurement :
 * Variance: 5.707520877735846
 * Standard deviation: 2.3890418325629725
Shape measurement :
 * Skewness: 1.2514265227049022
 * Kurtosis: 0.363066954117353
P1 and P99 :
 * P1: 1.0
 * P25: 1.0
 * P75: 4.0
 * P95: 8.0
 * P99: 9.0

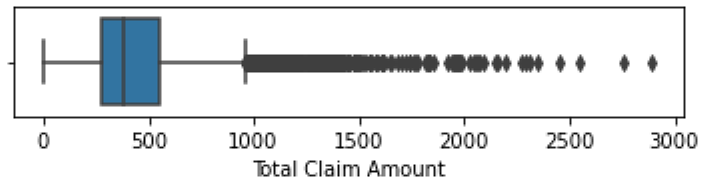


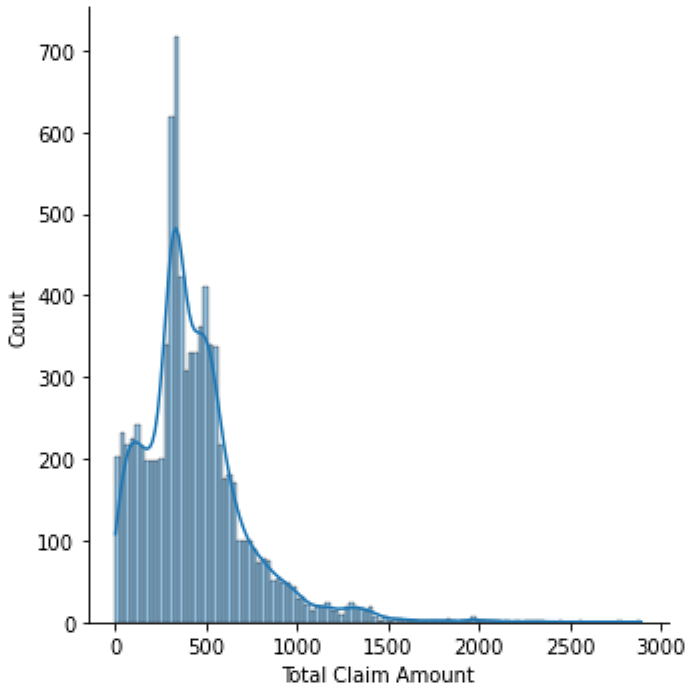


Variable : Total Claim Amount

Central tendency measurement :
 * Mean: 434.5294812961669
 * Median: 383.79736299999996
Dispersion measurement :
 * Variance: 84401.60255904608
 * Standard deviation: 290.51953903144977
Shape measurement :
 * Skewness: 1.7027133163260957
 * Kurtosis: 5.8568568619409955
P1 and P99 :
 * P1: 10.44176324
 * P25: 272.217171
 * P75: 547.619785

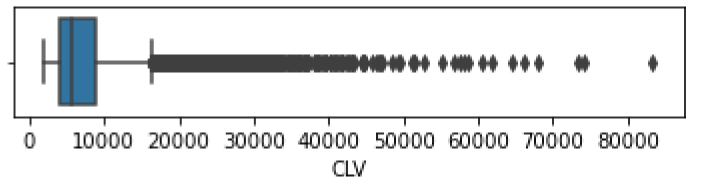
* P95: 962.6306503999974
 * P99: 1405.14020356

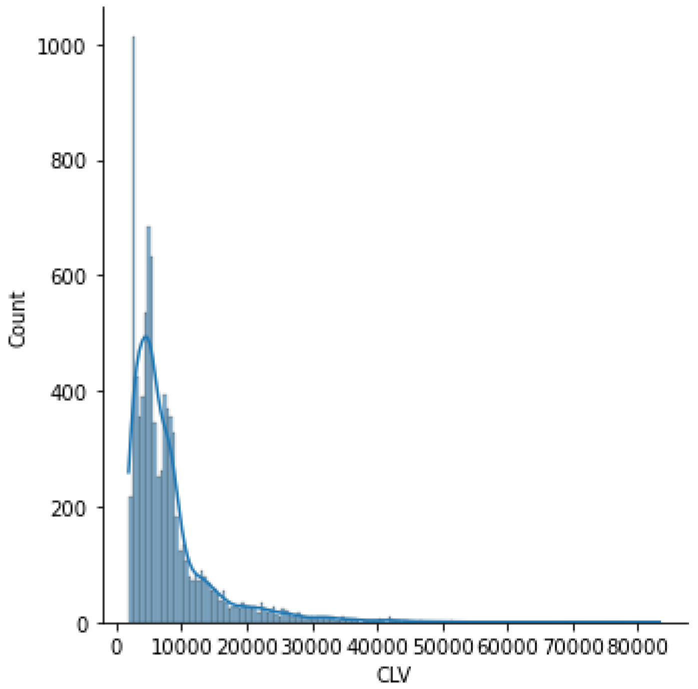




Variable : CLV

Central tendency measurement :
 * Mean: 7999.90384160275
 * Median: 5797.604861
Dispersion measurement :
 * Variance: 46900278.14599537
 * Standard deviation: 6848.3777747723125
Shape measurement :
 * Skewness: 3.0201735252388295
 * Kurtosis: 13.767969612870852
P1 and P99 :
 * P1: 2231.12680436
 * P25: 3997.4763020000005
 * P75: 8937.118615000001
 * P95: 22095.59438399999
 * P99: 35928.64222559998





Out[8]:

	Income	Monthly Premium Auto	Months Since Last Claim	Months Since Policy Inception	Number of Open Complaints	Number of Policies	Total Claim Amount	CLV
count	8637.000000	8637.000000	8637.000000	8637.00000	8637.000000	8637.000000	8637.000000	8637.000000
mean	37670.275906	93.282853	15.152831	48.02744	0.381614	2.967466	434.529481	7999.903842
std	30379.553849	34.526547	10.071044	27.88397	0.907881	2.389180	290.536359	6848.774265
min	0.000000	61.000000	0.000000	0.00000	0.000000	1.000000	0.099007	1898.683686
25%	0.000000	68.000000	6.000000	24.00000	0.000000	1.000000	272.217171	3997.476302
50%	33816.000000	83.000000	14.000000	48.00000	0.000000	2.000000	383.797363	5797.604861
75%	62262.000000	109.000000	23.000000	71.00000	0.000000	4.000000	547.619785	8937.118615
max	99981.000000	298.000000	35.000000	99.00000	5.000000	9.000000	2893.239678	83325.381190

Interpretation

`Income` : Values are mostly distributed between 0$ (unemployed) and 60000$ with a median of 33816$
The amount of Income = 0 is the same as Unemployed customers.

`Monthly Premium Auto` : This data needs to be explained since there is a huge amount of outliers to the right since we can't interpret them with this few amount of information. The mean of monthly subscription fee is 93$ and ranged between 60$ and 300$

`Months since Last Claim` : The majority of claims are happening before 20 months.

`Number of Open Complaints` : The high majority of accounts don't have open complaints, this can be seen on the boxplot where number of complaints higher than 0 are showed as outliers.

`Months since Policy Inception` : Looking at the shape of the slope and metrics, we can see a skewness of 0.04, so the values are symmetrically distributed.
The negative kurtosis means that our slope is platykurtic, hence the flattened shape.

`Number of Policies` : Most of the customers renewed their policies 2 or 3 times.

`Total Claim Amount` : The majority of the claims are between 250$ and 550$, however a huge amount of outliers are visible between 900$ and 3000$
The P95 is 962$ meaning that the outliers are representing 5% of the claims.

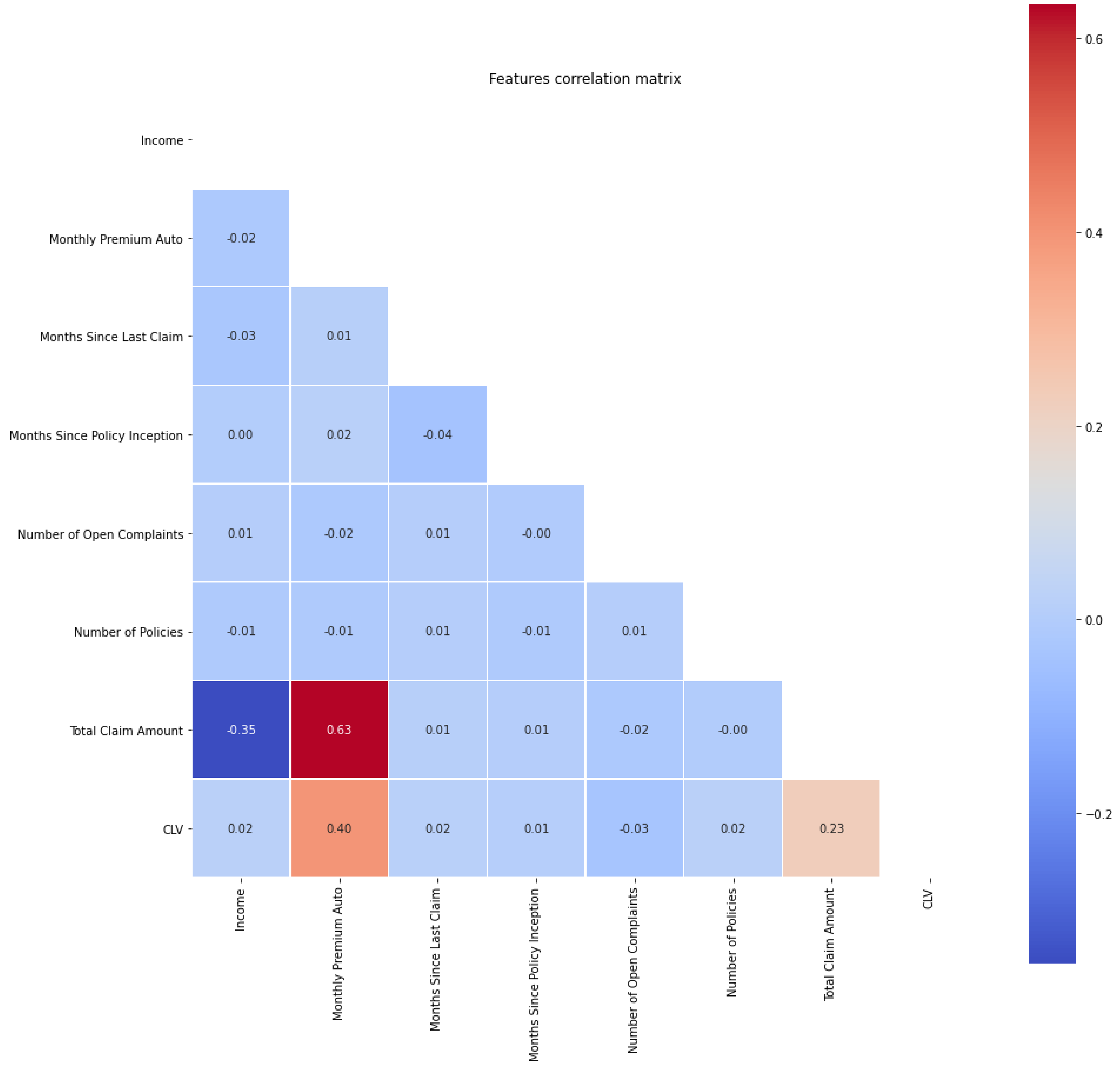
`CLV` : The score feature we need to analyze. **This is the key feature of the dataset.**
The mean is around 8000 correlating with the 8000 default value used in the test dataset.
The median is situated around 5800, and 75% of the values are below 9000.
A high CLV is rare, only 15% of the dataset.
The highest CLV are very rare representing only 5% of the values higher than 22000.

1.2 Bivariate descriptive statistics

1.2.a Numerical Features

In [9]:
```
#Creating a correlation map between the numerical features
corr_matrix = data.corr()
mask = np.triu(corr_matrix)
plt.figure(figsize=(15,15))
sns.heatmap(corr_matrix, cmap='coolwarm', mask=mask, linewidths=.5, cbar=True, square=True, annot=True, fmt=".2f")
plt.title("Features correlation matrix")
```

Out[9]:
```
Text(0.5, 1.0, 'Features correlation matrix')
```



The upper features correlation matrix highlists the correlations that can exist between numerical features.

The table indicates correlations based on an index represented by a temperature color. The warmer the color, the higher the **positive** correlation is. The colder the color, the higher the **negative** correlation is.

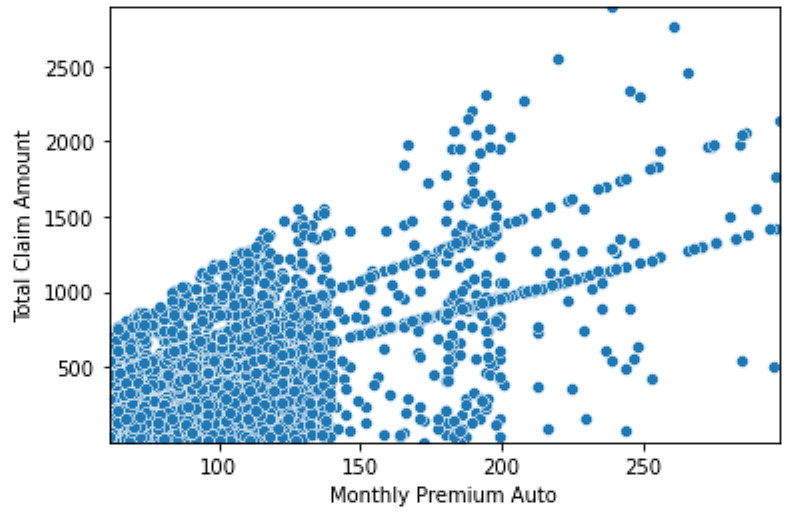
This index is called the Pearson correlation coefficient, r, taking a range from +1 to -1, a value of 0 indicating that there is no association between the two variables.

```
As we can see 4 cells give information about correlations.
```

- A negative correlation between `Total Claim Amount` and `Income`. This means that the higher the customer income is, the less money is going to be claimed when a complaint is opened.
- A small positive correlation between `Total Claim Amount` and `CLV`. We can understand that the calculation method for the CLV is quite dependant on the `Total Claim Amount` since the higher the amount, the higher the CLV.
- A positive correlation between `Monthly Premium Auto` and `CLV`. Exactly like the previous correlation, the higher amount of money the customer will pay for an insurance, the higher the CLV will be.
- A strong correlation between `Total Claim Amount` and `Monthly Premium Auto`. This means that the higher the customer is paying every month for an insurance, the higher the amount of money will be claimed for.

In [10]:
```
#Building scatterplot to find correlations between two numerical features
c1 = "Monthly Premium Auto"
c2 = "Total Claim Amount"

sns.scatterplot(x=c1, y=c2, data=data)
plt.xlim(data[c1].min(), data[c1].max())
plt.ylim(data[c2].min(), data[c2].max())
```

Out[10]:
```
(0.09900700000000001, 2893.239678)
```

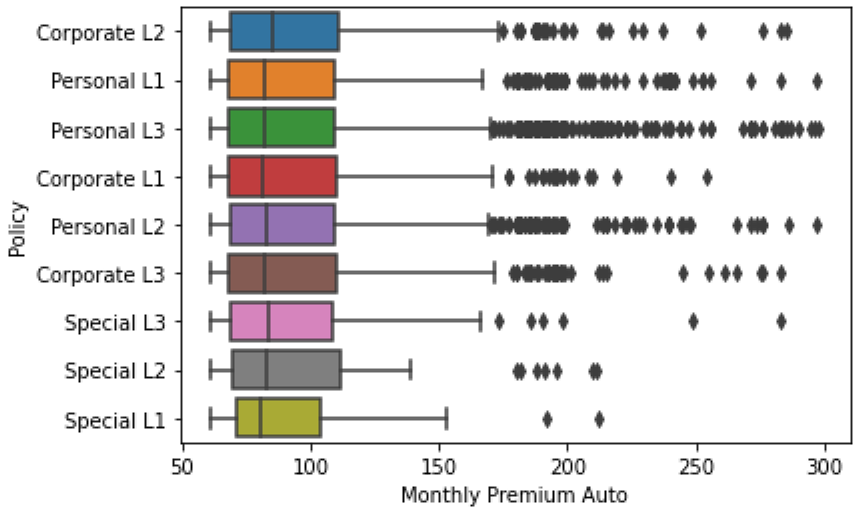


We draw a scatterplot between `Monthly Premium Auto` and `Total Claim Amount` to find any correlations.

We can definitely see two lines in the graph that may represent a subscription model offer for customers.

In [11]:
```
c1 = "Monthly Premium Auto"
c2 = "Policy"

sns.boxplot(x=c1, y=c2, data=data)
plt.xlabel(c1)
plt.ylabel(c2)
```

Out[11]:
```
Text(0, 0.5, 'Policy')
```



We want to see if there is any correlations between `Monthly Premium Auto` and `Policy`.

Interpretation

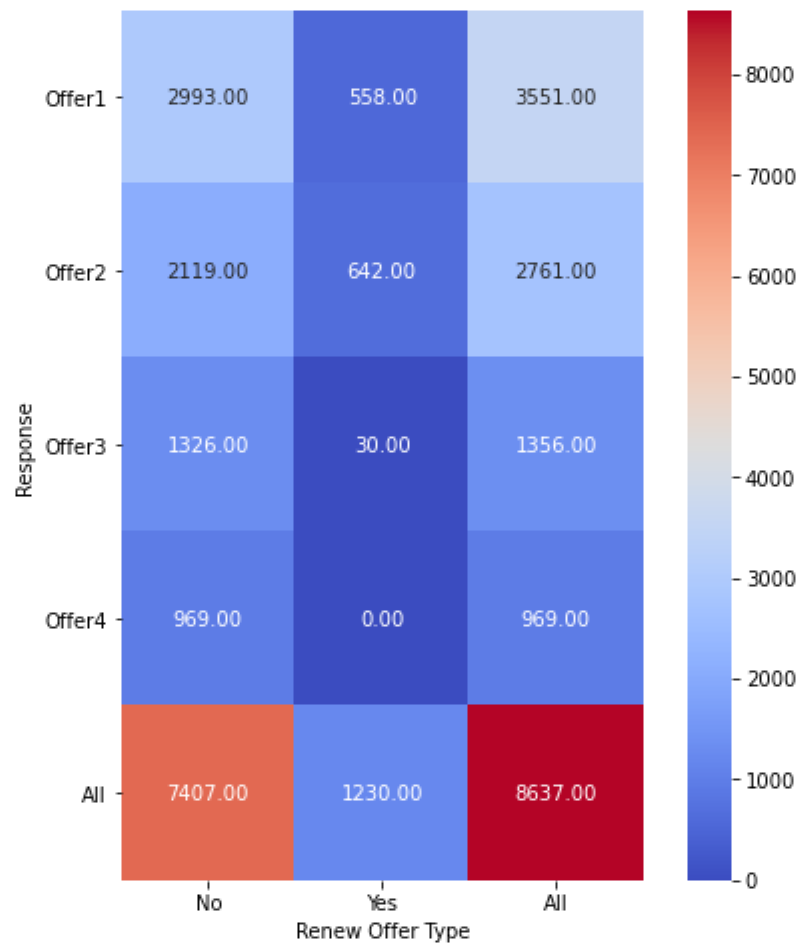
The interesting information can be seen within the outliers.

- Personal L3 contains the most outliers that would represent special monthly insurance prices.
- Special Policies are the one that contain the less outliers, surely because they must be custom made policies for special customers.

1.2.b Categorical Features

In [12]:
```
#Building a contingency table to find correlations between 2 categorical features
c1 = "Renew Offer Type"
c2 = "Response"

contingency = pd.crosstab(index=data[c1], columns=data[c2], margins=True)
plt.figure(figsize=(8,8))
sns.heatmap(contingency, cmap="coolwarm", square=True, annot=True, fmt=".2f")
plt.xlabel(c1)
plt.ylabel(c2)
plt.yticks(rotation=360)
```

Out[12]:
```
(array([0.5, 1.5, 2.5, 3.5, 4.5]),
 [Text(0, 0.5, 'Offer1'),
  Text(0, 1.5, 'Offer2'),
  Text(0, 2.5, 'Offer3'),
  Text(0, 3.5, 'Offer4'),
  Text(0, 4.5, 'All')])
```



Since categorical features can't be added in the features correlation matrix, we need to build a contingency table like the one above.

This table is also showing a temperature color code. The index is the amount of accounts that satisfies both criterias

```
For example : First cell (Offer1 & No) = 2993.
This means that 2993 customers refused the Offer1
```

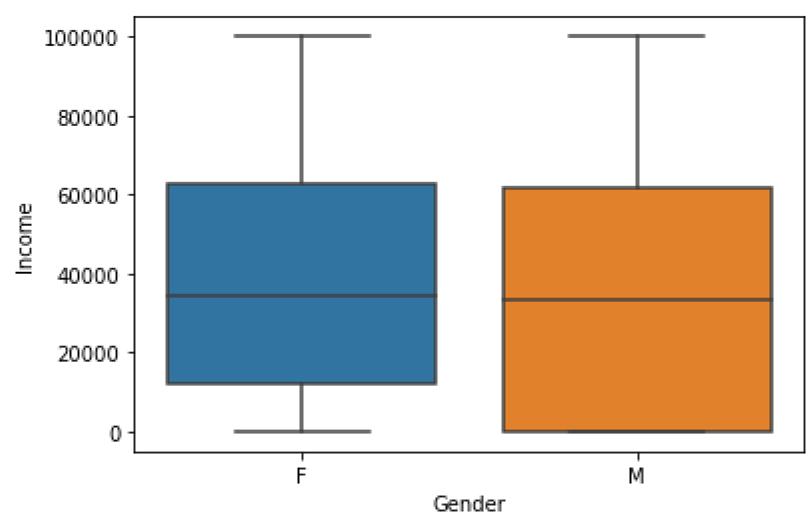
The Offer1 was the most sent with an approval rate of 19%

```
Offer1 : 19% approval rate
Offer2 : 30% approval rate
Offer3 : 2% approval rate
Offer4 : 0% approval rate
```

The Offer2 was the most accepted `Renew Offer Type`.

In [13]:
```
#Building a boxplot to find correlations between one categorical feature and one numerical feature
c1 = "Gender"
c2 = "Income"

sns.boxplot(x=c1, y=c2, data=data)
plt.xlabel(c1)
plt.ylabel(c2)
```

Out[13]: `Text(0, 0.5, 'Income')`



In this test we are comparing `Income` and `Gender` to find correlations or disparities.

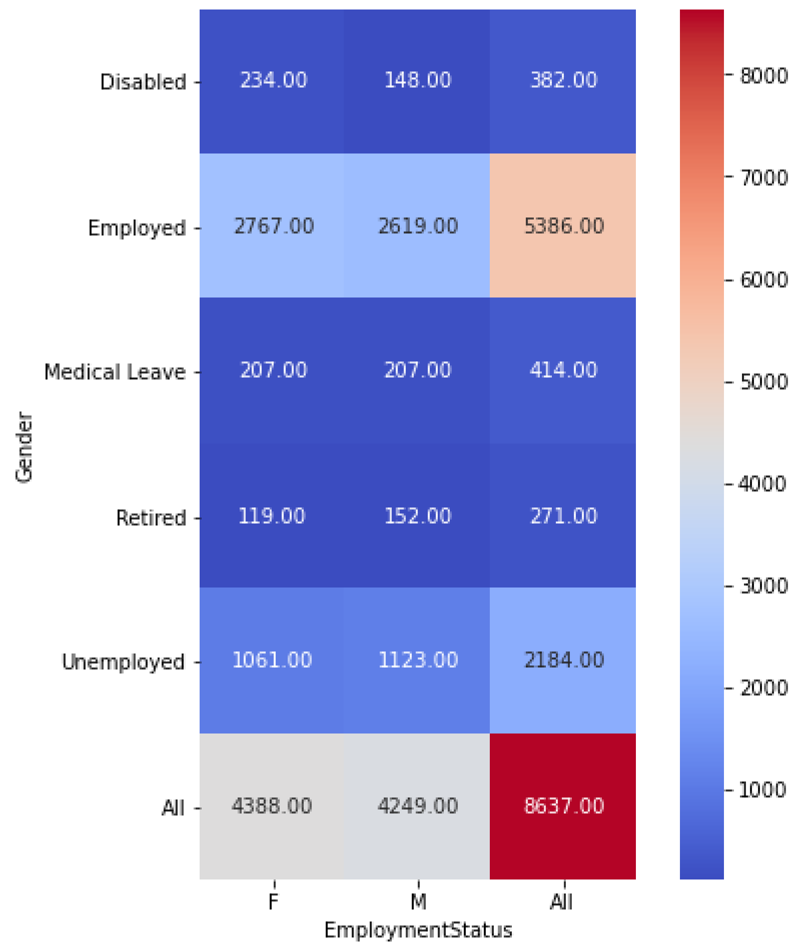
We can see that the amount of Males and Females *(as seen previously in 1.1.a)* is equal, however we can find a difference in `Income` regarding the Male category for low incomes.
The first quartile for Female Income is close to 15000$ whether for the Male Income it is close to 0$

For the high incomes, Males and Females are very close.

Thus, we need to do a deeper analysis by comparing `EmploymentStatus` and `Gender` to find any inconsistencies.

In [14]:
```
c1 = "EmploymentStatus"
c2 = "Gender"

contingency = pd.crosstab(index=data[c1], columns=data[c2], margins=True)
plt.figure(figsize=(8,8))
sns.heatmap(contingency, cmap="coolwarm", square=True, annot=True, fmt=".2f")
plt.xlabel(c1)
plt.ylabel(c2)
plt.yticks(rotation=360)
```

Out[14]:
```
(array([0.5, 1.5, 2.5, 3.5, 4.5, 5.5]),
 [Text(0, 0.5, 'Disabled'),
  Text(0, 1.5, 'Employed'),
  Text(0, 2.5, 'Medical Leave'),
  Text(0, 3.5, 'Retired'),
  Text(0, 4.5, 'Unemployed'),
  Text(0, 5.5, 'All')])
```



We decide to draw a contingency table of `EmploymentStatus` and `Gender`.

Unemployed customers are representing 25% of our sample equally distributed between Males and Females. All the `EmploymentStatus` features are equally distributed between Males and Females except for Disabled customers which are 1.6 times more numerous for Females.

We don't find any explanation about the previous table where the first quartile for Male income was significantly lower than Female's one.

1.3 Claims Verification

We are assessing a claim on our data based on the result of the descriptive analysis. This is done to check any false information that would alter the results of our model.

Our claim is

```
Income == 0 and EmploymentStatus == unemployed
```

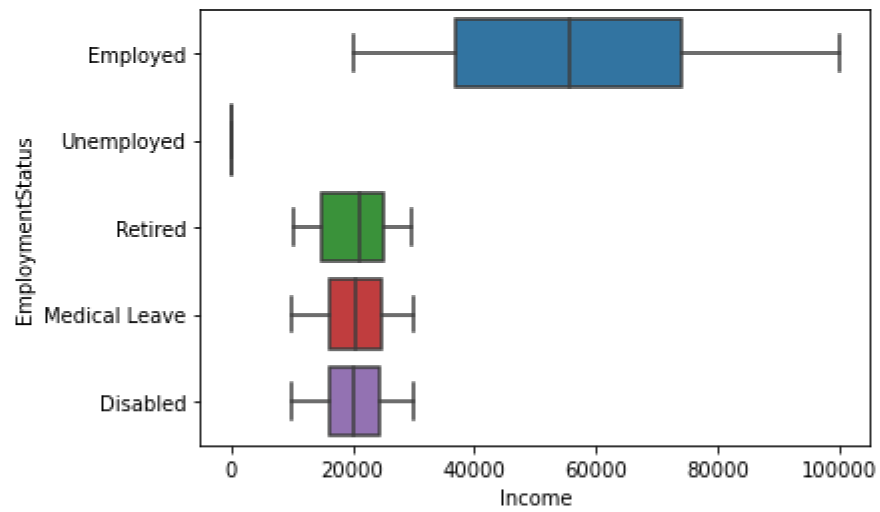
In other words, we need to verify if all acounts displaying an income equal to 0 are also Unemployed and vice versa.

In [15]:
```
#1.3.1 - Income = 0 and EmploymentStatus != unemployed

data[data["Income"] == 0]["EmploymentStatus"].value_counts()
```

Out[15]:
```
Unemployed    2184
Name: EmploymentStatus, dtype: int64
```

In [16]:
```
c1 = "Income"
c2 = "EmploymentStatus"

sns.boxplot(x=c1, y=c2, data=data)
plt.xlabel(c1)
plt.ylabel(c2)

#CLAIM CORRECT NO DROP
```

Out[16]:
```
Text(0, 0.5, 'EmploymentStatus')
```



The claim is verified and correct, all Unemployed accounts have an Income of 0 and vice versa.

Thus, we don't drop any data from the dataset.

2. Data Preprocessing

2.1.a Outliers

During our descriptive analysis, we discovered a high amount of outliers, however we decided to keep them since they bring valuable information in our dataset. Most of the time outliers must be dropped or edited because they alter too much the models, perhaps in this context, outliers represent special customers with special contracts and need to be taken into account.

We decide to keep our outliers because they stand for valued customers by the company.

2.1.b Drops

We don't drop any information outside of the `CustomerID` feature *(dropped in 1.0)* since we find them valuable enough for the model.

In [17]:
```
#Backup of data frame
datac = data.copy()
```

In [18]:
```
datac.head()
```

Out[18]:

	State	Response	Coverage	Education	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	Poli Typ
0	California	No	Basic	Bachelor	Employed	F	48269	Urban	Married	69	3	79	3	1	Cor
1	Washington	No	Basic	High School or Below	Unemployed	M	0	Suburban	Single	113	19	10	0	7	Pe
2	Oregon	No	Extended	College	Employed	M	60145	Urban	Single	132	8	28	0	3	Pe
3	California	No	Basic	High School or Below	Employed	M	46131	Suburban	Married	74	27	28	0	1	Pe
4	Washington	No	Basic	Bachelor	Unemployed	F	0	Suburban	Single	64	12	24	0	1	Pe

2.2 Encoding

Many machine learning algorithms cannot operate on label data directly. They require all input variables and output variables to be numeric.

Since our dataset contains a high amount of categorical features, and leaving them as they are would confuse the model when training it, we have to encode our categorical data into numerical data.

We are using 2 methods, the categorical features that contain only 2 options (`Gender` and `Response`) can be encoded as boolean features.

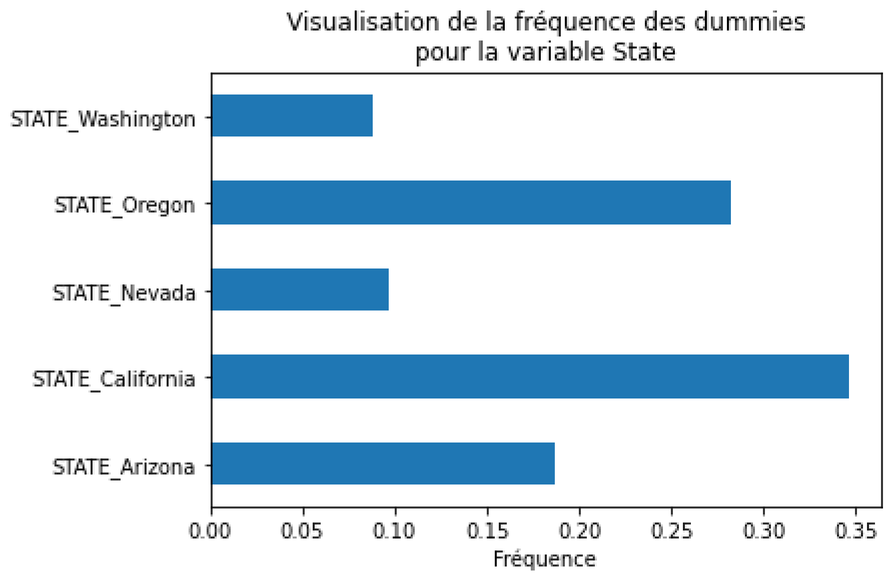
The other features need to be encoded to numerical features using the One Hot Encoding method.
The One Hot Encoding method is used instead of the Integer Encoding method since our data are **nominal categorical** features and **not ordinal**.
We don't want the model to think there is a hierarchy between our values, so this is why the One Hot Encoding method is more suitable.

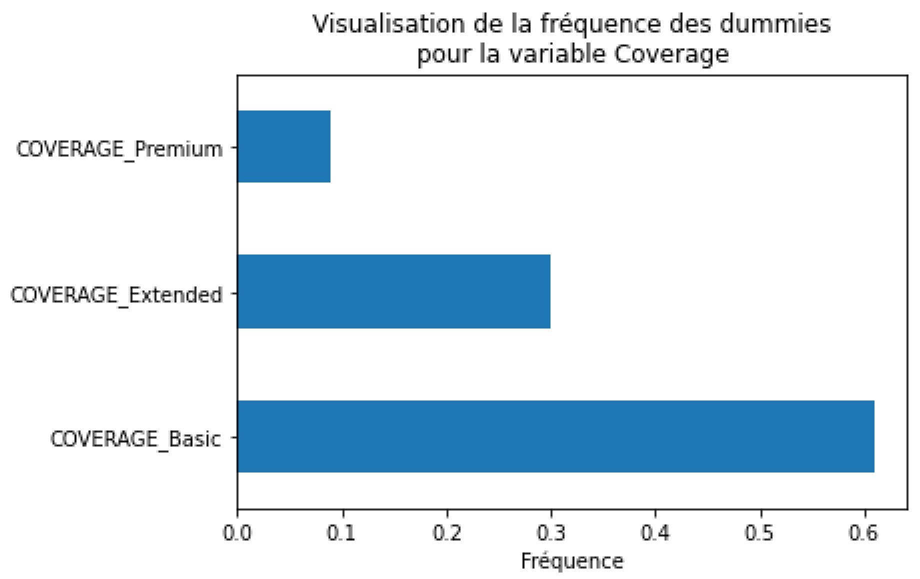
This method replaces a feature by the amount of different options it contains. For example `Marital Status` contains : *Married, Single, Divorced*.
We want to encode them with the One Hot Encoding method.

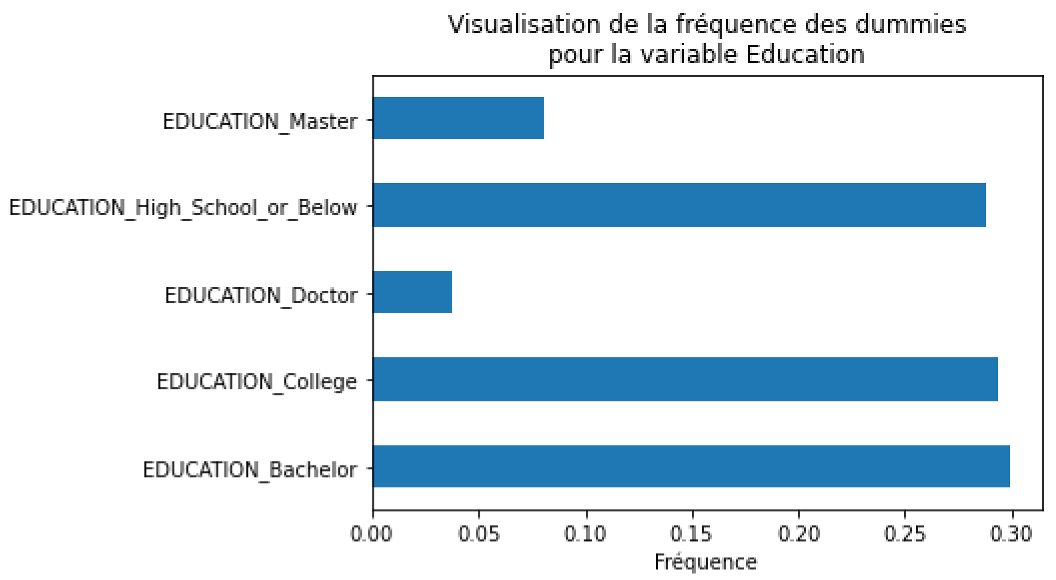
We will replace `Marital Status` by 3 columns with the associated Option as a suffix : `Marital Status_Married` , `Marital Status_Single` , `Marital Status_Divorced` .
These new columns are encoded with Binary values that we can call "dummy variables".
To read how the data are encoded with the One Hot Encoding method, the new processed dataset is displayed below

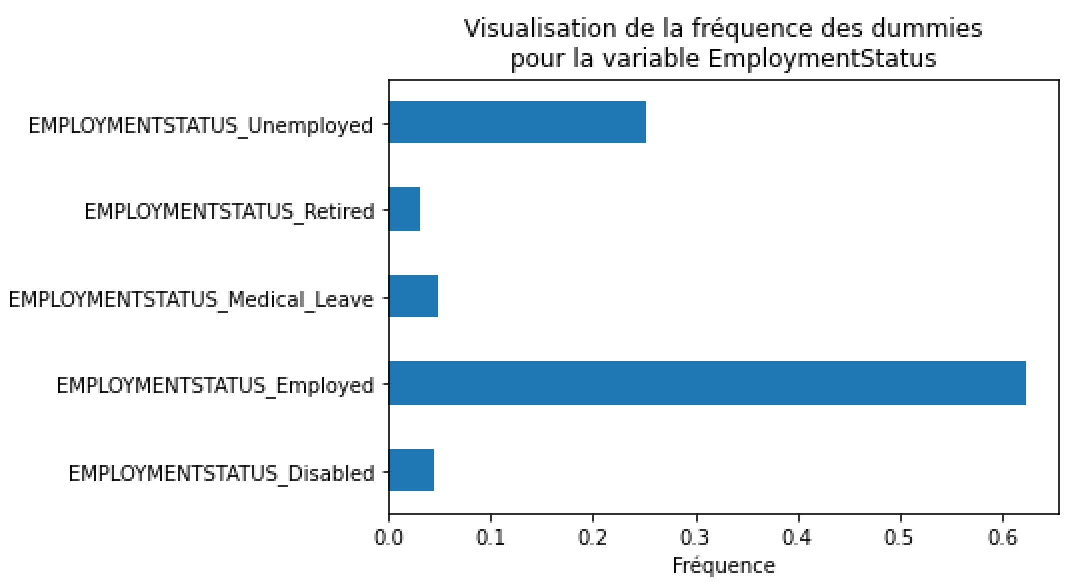
We also need to delete one column every time we encode a feature with this method since we need the sum of the columns to not be 1 to avoid multicolinearity issues.

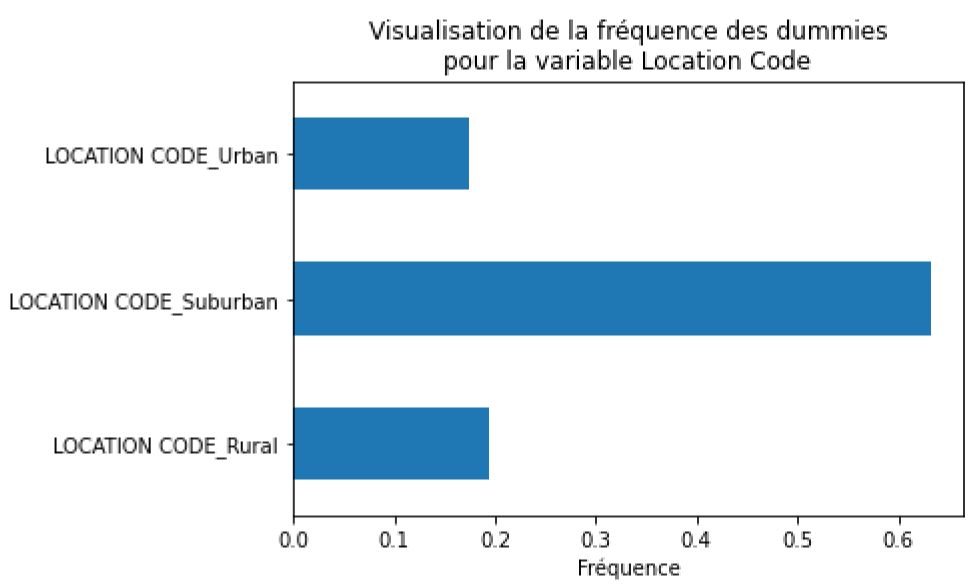
In [19]:
```
#Encoding categorical nominal features with One Hot Encoding method

for column in ['State', 'Coverage', 'Education', 'EmploymentStatus', 'Location Code', 'Marital Status', 'Policy Type', 'Sales Cha
    dummies = pd.get_dummies(datac[column])
    dummies.columns = ['_'.join([column.upper(), str(c).replace(' ', '_')]) for c in dummies.columns]
    plt.figure()
    dummies.mean().plot(kind='barh')
    plt.title(f'Visualisation de la fréquence des dummies\npour la variable {column}')
    plt.xlabel('Fréquence')
    plt.show()
    dummies.drop(dummies.columns[-1], axis=1, inplace=True)
    datac = datac.drop(column, axis=1)
    datac = pd.concat([datac.T, dummies.T]).T
```

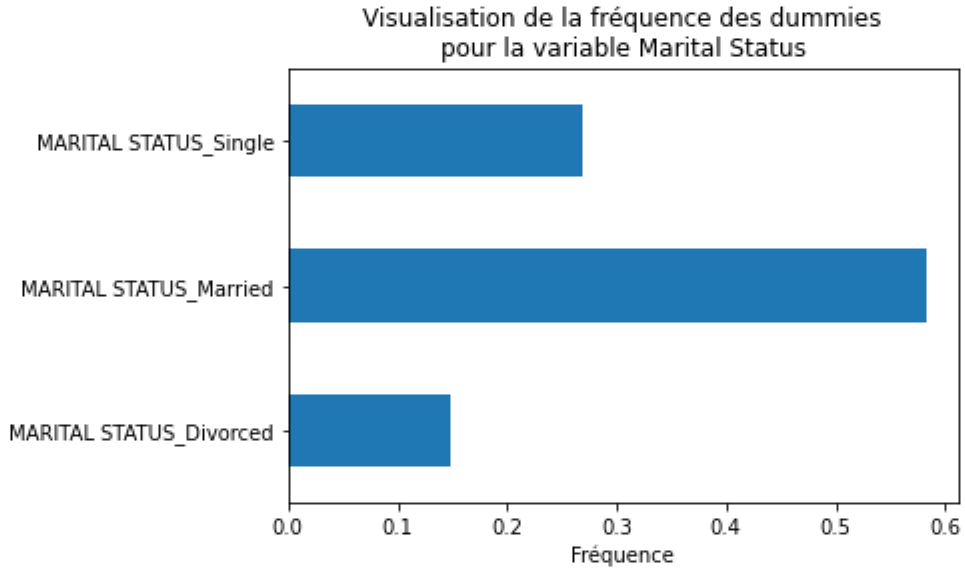

Visualisation de la fréquence des dummies
pour la variable State
STATE_Washington
STATE_Oregon
STATE_Nevada
STATE_California
STATE_Arizona
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
Fréquence

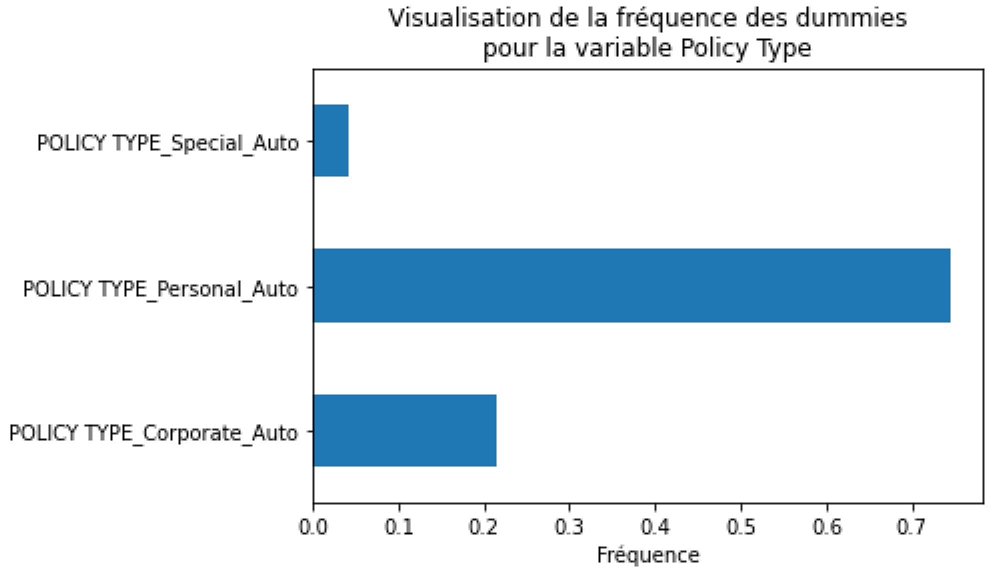

Visualisation de la fréquence des dummies
pour la variable Coverage
COVERAGE_Premium
COVERAGE_Extended
COVERAGE_Basic
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Fréquence

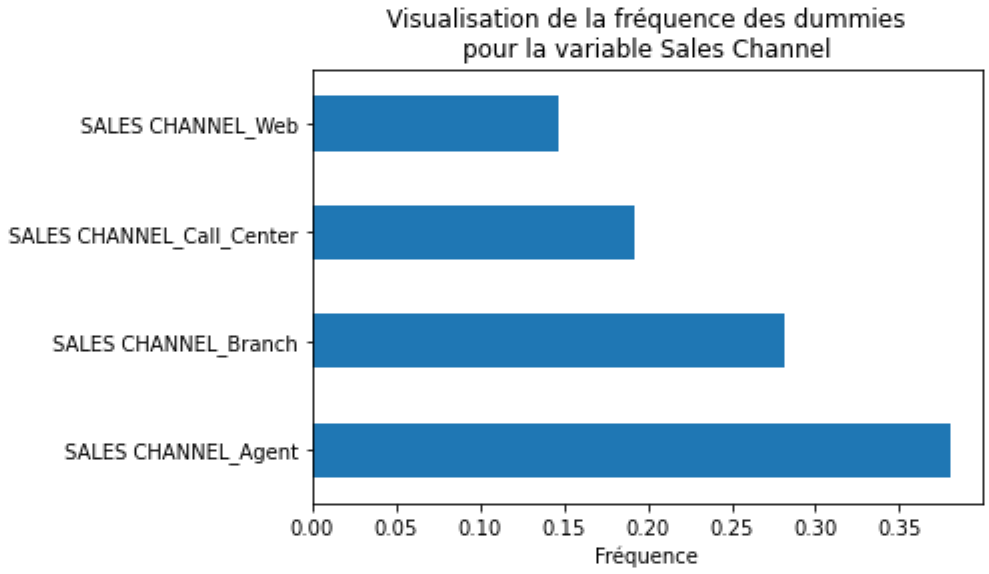

Visualisation de la fréquence des dummies
pour la variable Education
EDUCATION_Master
EDUCATION_High_School_or_Below
EDUCATION_Doctor
EDUCATION_College
EDUCATION_Bachelor
0.00
0.05
0.10
0.15
0.20
0.25
0.30
Fréquence

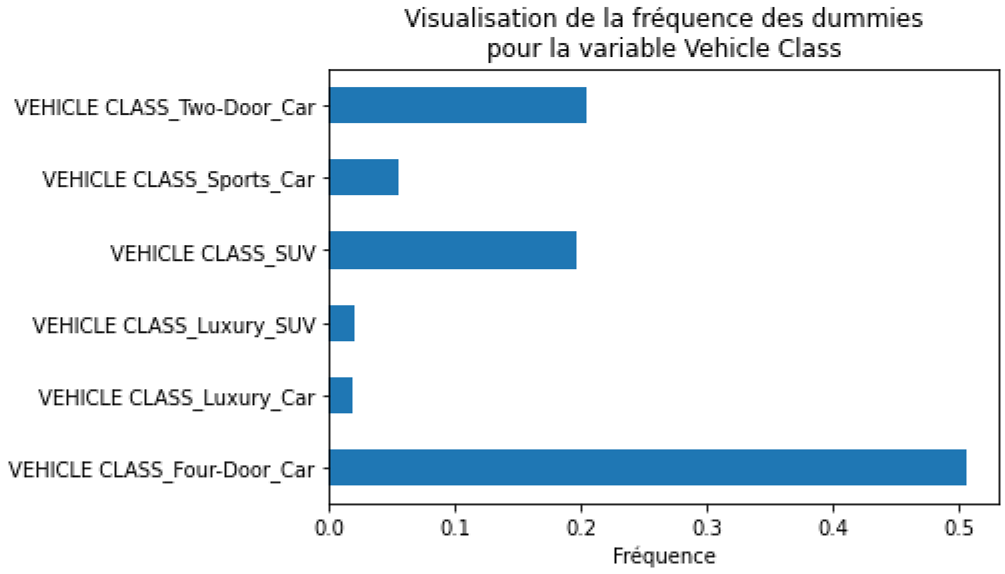

Visualisation de la fréquence des dummies
pour la variable EmploymentStatus
EMPLOYMENTSTATUS_Unemployed
EMPLOYMENTSTATUS_Retired
EMPLOYMENTSTATUS_Medical_Leave
EMPLOYMENTSTATUS_Employed
EMPLOYMENTSTATUS_Disabled
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Fréquence


Visualisation de la fréquence des dummies
pour la variable Location Code
LOCATION CODE_Urban
LOCATION CODE_Suburban
LOCATION CODE_Rural
0.0
0.1
0.2
0.3
0.4
0.5
0.6
Fréquence









In [20]:
```
datac.columns
```

Out[20]:
```
Index(['Response', 'Gender', 'Income', 'Monthly Premium Auto',
       'Months Since Last Claim', 'Months Since Policy Inception',
       'Number of Open Complaints', 'Number of Policies', 'Policy',
       'Renew Offer Type', 'Total Claim Amount', 'Vehicle Size', 'CLV',
       'STATE_Arizona', 'STATE_California', 'STATE_Nevada', 'STATE_Oregon',
       'COVERAGE_Basic', 'COVERAGE_Extended', 'EDUCATION_Bachelor',
       'EDUCATION_College', 'EDUCATION_Doctor',
       'EDUCATION_High_School_or_Below', 'EMPLOYMENTSTATUS_Disabled',
       'EMPLOYMENTSTATUS_Employed', 'EMPLOYMENTSTATUS_Medical_Leave',
       'EMPLOYMENTSTATUS_Retired', 'LOCATION CODE_Rural',
       'LOCATION CODE_Suburban', 'MARITAL STATUS_Divorced',
       'MARITAL STATUS_Married', 'POLICY TYPE_Corporate_Auto',
       'POLICY TYPE_Personal_Auto', 'SALES CHANNEL_Agent',
       'SALES CHANNEL_Branch', 'SALES CHANNEL_Call_Center',
       'VEHICLE CLASS_Four-Door_Car', 'VEHICLE CLASS_Luxury_Car',
       'VEHICLE CLASS_Luxury_SUV', 'VEHICLE CLASS_SUV',
       'VEHICLE CLASS_Sports_Car'],
      dtype='object')
```

Do you know Kristoff? He is a really nice and smart guy! 🧠

In [21]:
```
datac["Response"].value_counts()
```

Out[21]:
```
No     7407
Yes    1230
Name: Response, dtype: int64
```

In [22]:
```
#Encoding boolean categorical features

datac["Response"] = datac["Response"].replace({"Yes":1,"No":0})
datac["Gender"] = datac["Gender"].replace({"M":1,"F":0})
```

In [23]:
```
datac["Response"].value_counts()
```

Out[23]:
```
0    7407
1    1230
Name: Response, dtype: int64
```

In [24]:
```
datac["Gender"].value_counts()
```

Out[24]:
```
0    4388
1    4249
Name: Gender, dtype: int64
```

In [25]:
```
#Encoding ordinal categorical features with label encoding

datac["Vehicle Size"] = datac["Vehicle Size"].replace({"Small":1,"Medsize":2,"Large":3})

#Simplifying this feature by only keeping the "LX" information since the PolicyType is already a feature
datac["Policy"] = datac["Policy"].replace({'Personal L3': 3, 'Personal L2': 2, 'Personal L1': 1, 'Corporate L3': 3, 'Corporate L2

datac["Renew Offer Type"] = datac["Renew Offer Type"].replace({'Offer1': 1, 'Offer2': 2, 'Offer3': 3, 'Offer4': 4})
```

In [26]:
```
#The whole dataset is only containing numerical features for the model training
datac
```

Out[26]:

	Response	Gender	Income	Monthly Premium Auto	Months Since Last Claim	Months Since Policy Inception	Number of Open Complaints	Number of Policies	Policy	Renew Offer Type	Total Claim Amount	Vehicle Size	CLV	STATE_Arizona	STATE_Califor
0	0	0	48269	69	3	79	3	1	2	3	282.151	2	2683.47	0	
1	0	1	0	113	19	10	0	7	1	1	813.6	2	7859.41	0	
2	0	1	60145	132	8	28	0	3	3	3	580.473	2	10272.6	0	
3	0	1	46131	74	27	28	0	1	3	2	355.2	1	2969.59	0	
4	0	0	0	64	12	24	0	1	3	2	460.8	2	2310.88	0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
8632	0	1	0	68	10	48	1	3	3	3	326.4	2	4704.18	0	
8633	0	0	67572	102	7	55	0	2	1	1	296.209	1	24826.9	0	
8634	1	0	25147	101	7	54	0	1	1	1	694.598	2	3600.93	0	
8635	0	0	0	101	17	20	0	3	2	1	978.257	2	7482.85	0	
8636	0	0	74905	72	16	35	0	3	3	1	167.028	2	5714.56	0	

8637 rows × 41 columns

In [27]:
```
datac["CLV"].min()
```

Out[27]:
```
1898.6836859999999
```

2.3 Data Normalization

We decide to normalize the dataset before using it to train the model. The data range value is very wide and there is a strong inertia on the data, so we prefer to normalize them to help the model have a better understanding of them.

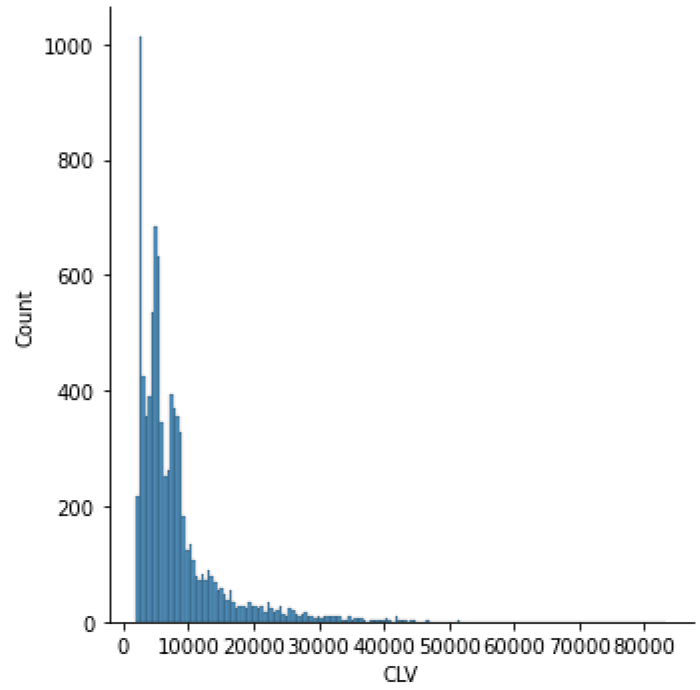
Data normalization is a scaling technique where values are shifted and rescaled to end up between a smaller range.
In this context we normalize based on the Zscore on AzureML.

Moreoever we decide to apply a logarithmic normalization **separately** of the other data on the `CLV` feature for the same reasons as stated before and also because of the asymmetry of the data.
We DO NOT apply the Zscore normalization on the CLV

We don't forget to apply the exponential function to `CLV` before creating the new CSV file.

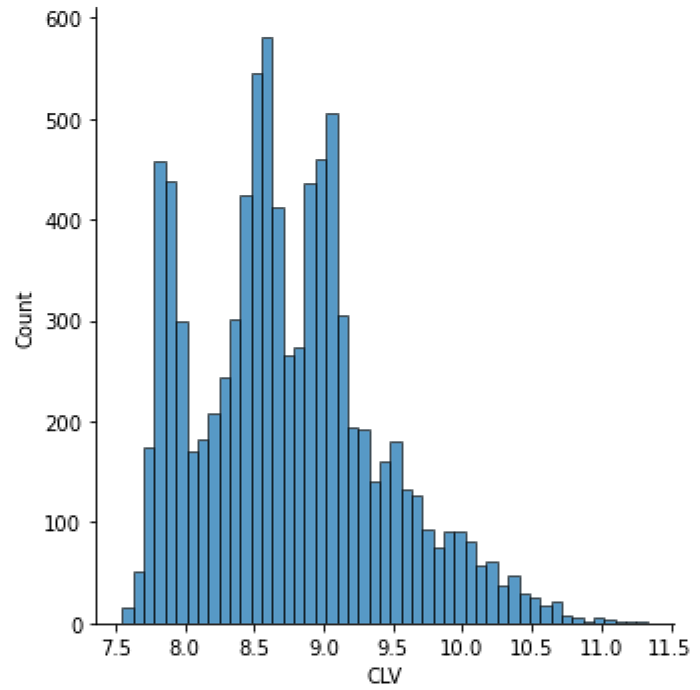
In [28]:
```
#Log normalisation of CLV
sns.displot(datac["CLV"])
```

Out[28]:
```
<seaborn.axisgrid.FacetGrid at 0x2c25eabe490>
```



In [29]:
```
#ONLY RUN IT ONCE!!! ⛔
datac["CLV"] = np.log(datac["CLV"].astype(float))
sns.displot(datac["CLV"])
```

Out[29]: <seaborn.axisgrid.FacetGrid at 0x2c25eabe9d0>



Yoko for the win 🐈

3. Models

3.1 Tested models

We decided to use 5 different regression model types for our dataset.

- Bayesian Linear Regression
  Our baseline model. It is a linear regression using probability distribution rather than point estimates.
  However it is most efficient when dealing with insufficient data or poor distributed data, what is not the case with this dataset.
- Poisson Regression
  An other linear regression model
  Used to tell which X-values work on Y-values.
- Decision Forest Regression
  This regression model consists of an ensemble of decision trees.
  A Random Forest operates by constructing several decision trees during training time and outputting the mean of the classes as the prediction of all the trees.
- Boosted Decision Tree Regression
  Like a Random Forest model, this model also uses boosting methods.
  Each tree is dependent on prior trees.
  The algorithm learns by fitting the residual of the trees that preceded it, tending to improve accuracy with some small risk of less coverage.
- Neural network Regression
  A flexible model structured like a brain nervous system used for classification and regression.

Model	Parameters	Value	Training Data (70%) RMSE	Training Data (70%) R^2	Test Data (30%) RMSE	Test Data (30%) R^2
Underfitting Test	Test with training data		x	x	0.125638	0.963078
Bayesian Linear Regression **Baseline test**	Lambda	1	8.818184	0 negative r^2 = divergent model	8.796151	0 negative r^2 = divergent model
	Min Lambda	1.00E-06				
	Noise Fraction	0.1				
	Noise Variance For Uniform	0.001				
Poisson Regression	Optimization Tolerance	1.00E-07	0.565381	0.24483	0.566920	0.256391
	L1 Weight	0.1				
	L2 Weight	0.1				
	Memory Size	50				
	Quiet	True				
	Use Threads	True				
Decision Forest Regression	Min num of samples per leaf node	1	0.194677	0.910465	0.191036	0.915563
	Number of random splits per node	128				
	Max depth of the decision trees	64				
	Number of decision trees	32				
Boosted Decision Tree Regression	Number of leaves	32	0.209656	0.896157	0.195485	0.911585
	Minimum leaf instances	50				
	Learning rate	0.2				
	Number of trees	500				
Neural Network Regression	Initial Weights Diameter	0.1	0.219088	0.886604	0.217344	0.890706
	Learning rate	0.01				
	Number Of Input Features	40				
	Number of iterations	160				
	LossFunction	SquaredError				
	Data Normalizer Type	MinMax				

3.2 Best Model

Based on our results the best model is the **Decision Forest Regression** with these metrics

RMSE : 0.191036
r^2 : 0.915563
This model fits at **91.56%** to our test data.

Here are the hyperparameters used in this model :

```
Min num of samples per leaf node : 1
The minimum of data points we have allowed in a leaf node.

Number of random splits per node : 128
The amount splits to use when building each node of the tree.

Max depth of the decision trees : 64
Limiting the maxium depth of a decision tree. The higher it is, the better should be the precision but at the risk of so
me overfitting.

Number of decision trees : 32
The amount of decision trees created, the higher the better the coverage.
```

Based on these results, we can assume that this model is the best we have trained in this data analysis and would be the most efficient to find the CLV of the new customers.

4. Results Comparison

We have decided to create two CSV files, the first that will be used below containing the `CLV` calculated by our model and all the features of the dataset. The second CSV file is containing only the `CLV` calculated by our model and the `CustomerID` so the results are easier to read.

The second CSV file will be uploaded for the assignment.

Before claiming that our analysis is finished, we need finally to compare the results we got from our model with the data we had initially in the training dataset. This analysis is not mandatory but will verify our assumptions with the results obtained from the model.
We are going to compare the first dataset `CLV-Training.csv` and `NewCLV-Test.csv` based on their distribution.

In [30]:
```
#Loading the dataset in memory
dataTest = pd.read_csv("NewCLV-Test.csv")

#Displaying all columns of the dataset
pd.set_option('display.max_columns', None)
dataTest.describe()
```

Out[30]:

	Income	Monthly Premium Auto	Months Since Last Claim	Months Since Policy Inception	Number of Open Complaints	Number of Policies	Total Claim Amount	CLV	Scored Label Mean	Scored Label Standard Deviation
count	646.00000	646.000000	646.000000	646.000000	646.000000	646.000000	646.000000	646.0	646.000000	646.000000
mean	37267.80031	93.266254	13.930341	48.982972	0.400929	2.927245	434.001407	8000.0	11067.487103	1.334813
std	30701.95353	32.752873	9.911693	27.307290	0.915973	2.394950	289.401913	0.0	6282.740652	0.212721
min	0.00000	61.000000	0.000000	0.000000	0.000000	1.000000	1.838367	8000.0	4867.267188	1.053273
25%	0.00000	69.000000	6.000000	28.000000	0.000000	1.000000	273.751194	8000.0	5880.975771	1.099571

50%	35862.00000	86.000000	12.000000	50.000000	0.000000	2.000000	386.031248	8000.0	10057.614448	1.327071
75%	63774.00000	109.000000	22.000000	70.000000	0.000000	4.000000	553.800000	8000.0	12772.061558	1.509201
max	99841.00000	295.000000	35.000000	99.000000	5.000000	9.000000	2327.166394	8000.0	38883.461085	1.848631

In [31]:
```python
data.describe()
```

Out[31]:

	Income	Monthly Premium Auto	Months Since Last Claim	Months Since Policy Inception	Number of Open Complaints	Number of Policies	Total Claim Amount	CLV
count	8637.000000	8637.000000	8637.000000	8637.00000	8637.000000	8637.000000	8637.000000	8637.000000
mean	37670.275906	93.282853	15.152831	48.02744	0.381614	2.967466	434.529481	7999.903842
std	30379.553849	34.526547	10.071044	27.88397	0.907881	2.389180	290.536359	6848.774265
min	0.000000	61.000000	0.000000	0.00000	0.000000	1.000000	0.099007	1898.683686
25%	0.000000	68.000000	6.000000	24.00000	0.000000	1.000000	272.217171	3997.476302
50%	33816.000000	83.000000	14.000000	48.00000	0.000000	2.000000	383.797363	5797.604861
75%	62262.000000	109.000000	23.000000	71.00000	0.000000	4.000000	547.619785	8937.118615
max	99981.000000	298.000000	35.000000	99.00000	5.000000	9.000000	2893.239678	83325.381190

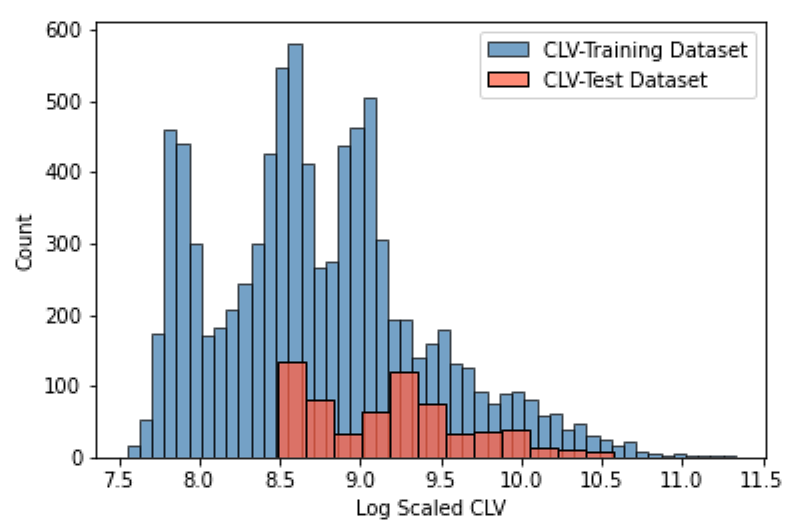
In [32]:
```python
#We drop CLV column containing default CLV (8000) and Scored Label Standard Deviation, since they won't bring any information
dataTest = dataTest.drop(["CLV","Scored Label Standard Deviation"], axis=1)
```

In [33]:
```python
dataTest = dataTest.rename({"Scored Label Mean":"CLV"}, axis=1)
```

4.1 Comparison with `CLV`

We are going to compare the `CLV` distribution between `CLV-Training.csv` and `NewCLV-Test.csv`.

In [34]:
```python
#Display plots separately
#sns.displot(np.log(dataTest["CLV"].astype(float)))
#sns.displot(np.log(data["CLV"].astype(float)))

fig, ax = plt.subplots()
for a,c in [(np.log(data["CLV"].astype(float)),"steelblue"), (np.log(dataTest["CLV"].astype(float)),"tomato")]:
    sns.histplot(a, ax=ax, kde=False, color=c)
plt.legend(["CLV-Training Dataset","CLV-Test Dataset"])
plt.xlabel("Log Scaled CLV")
plt.show()
```



In [35]:
```python
datab = data.copy()

datab = datab[(datab["CLV"] >= dataTest["CLV"].min()) & (datab["CLV"] <= dataTest["CLV"].max())]
```

4.2 Comparison between `Gender` and `CLV`

In [36]:
```python
datab.groupby("Gender").describe()["CLV"]
```

Out[36]:

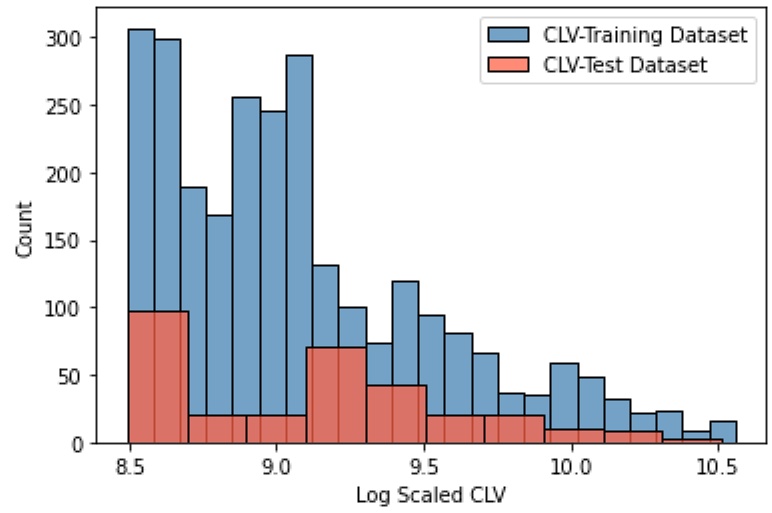
Gender	count	mean	std	min	25%	50%	75%	max
F	2806.0	10263.617243	6356.954470	4867.378203	5884.885390	8085.428783	11619.577798	38496.94701
M	2705.0	9968.858183	5861.059753	4869.596443	6019.960469	8044.872393	11430.588450	38545.70689

In [37]:
```python
dataTest.groupby("Gender").describe()["CLV"]
```

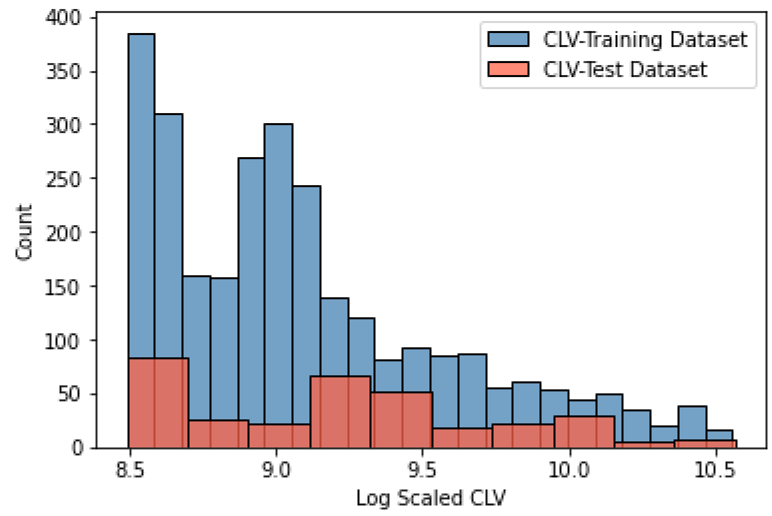
Out[37]:

Gender	count	mean	std	min	25%	50%	75%	max
F	333.0	11650.368170	6716.111635	4867.267188	6012.811743	10292.791172	13699.634130	38883.461085
M	313.0	10447.361241	5732.059211	4889.354819	5856.561826	9462.252457	12108.725439	36758.362070

In [38]:
```python
#Filtering Males
fig, ax = plt.subplots()
df_train = datab[datab["Gender"] == "M"]
df_test = dataTest[dataTest["Gender"] == "M"]

for a,c in [(np.log(df_train["CLV"].astype(float)),"steelblue"), (np.log(df_test["CLV"].astype(float)),"tomato")]:
    sns.histplot(a, ax=ax, kde=False, color=c)
plt.legend(["CLV-Training Dataset","CLV-Test Dataset"])
plt.xlabel("Log Scaled CLV")
plt.show()
```



In [39]:
```python
#Filtering Females
fig, ax = plt.subplots()
df_train = datab[datab["Gender"] == "F"]
df_test = dataTest[dataTest["Gender"] == "F"]

for a,c in [(np.log(df_train["CLV"].astype(float)),"steelblue"), (np.log(df_test["CLV"].astype(float)),"tomato")]:
    sns.histplot(a, ax=ax, kde=False, color=c)
plt.legend(["CLV-Training Dataset","CLV-Test Dataset"])
plt.xlabel("Log Scaled CLV")
plt.show()
```



We can clearly see close distribution between the two datasets.

Male and Female are equally distributed in both datasets

`CLV-Training.csv` : 50.92%
`CLV-Test.csv` : 51.55%

4.3 Comparison between `Income` and `CLV`

In [40]:
```python
datab.groupby("EmploymentStatus").describe()["CLV"]
```

Out[40]:

EmploymentStatus	count	mean	std	min	25%	50%	75%	max
Disabled	239.0	10424.199526	6342.929899	4867.378203	6503.397049	8257.666512	11780.771900	37150.82945
Employed	3622.0	10030.802460	6174.584176	4868.807554	5789.477247	8043.657772	11012.905323	38545.70689
Medical Leave	227.0	10564.006980	6391.845200	4869.596443	6098.229671	8281.740124	12356.156965	36860.90798
Retired	150.0	10869.172063	5848.023970	4873.436612	6273.911874	9310.770644	12168.744920	30591.61257
Unemployed	1273.0	10144.631403	5896.279282	4872.016380	6439.330195	7984.086473	11885.967970	38055.20953

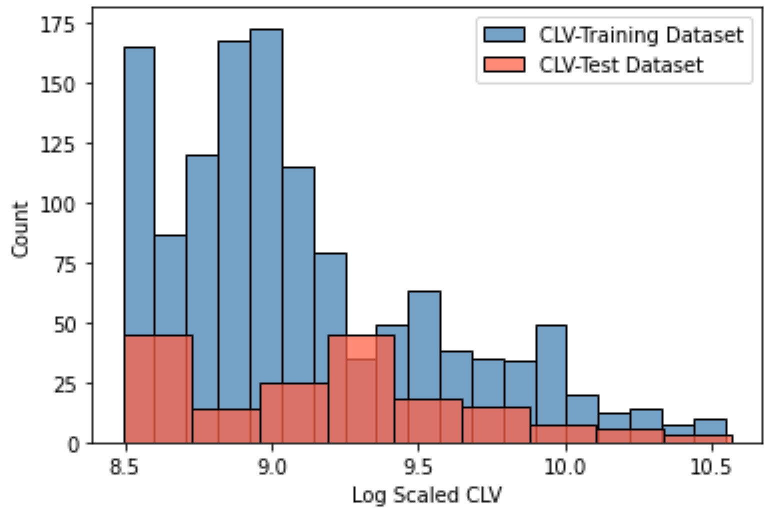
In [41]:
```python
dataTest.groupby("EmploymentStatus").describe()["CLV"]
```

Out[41]:

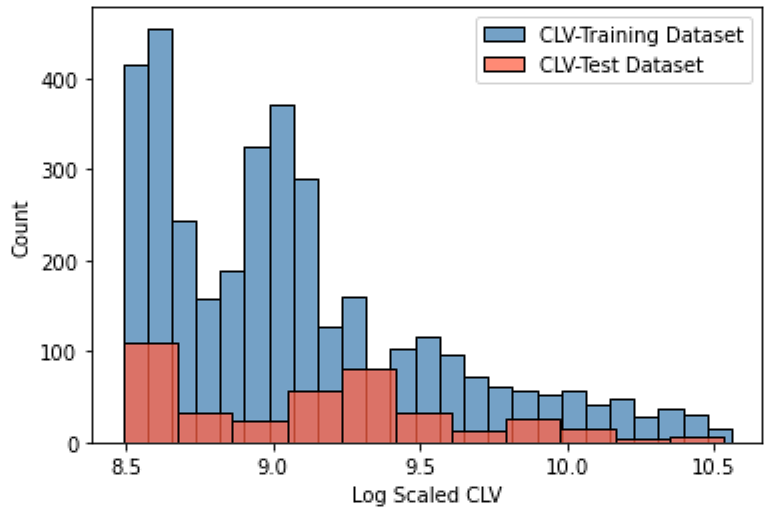
EmploymentStatus	count	mean	std	min	25%	50%	75%	max
Disabled	31.0	12783.184825	6256.092208	4957.917744	9604.974583	11153.477177	18028.192741	29364.950740
Employed	399.0	10721.628507	6202.272394	4867.267188	5796.022598	9618.435102	12195.413600	37636.508584
Medical Leave	20.0	8967.662630	4257.377642	5734.383870	5843.414559	7259.083131	10892.759980	22119.107796
Retired	18.0	16774.004437	5612.832134	5846.913821	15042.063398	17881.063744	21537.454176	22227.313506

Unemployed	178.0	11202.824900	6412.799867	4901.150915	6110.383818	10182.836753	12570.924768	38883.461085

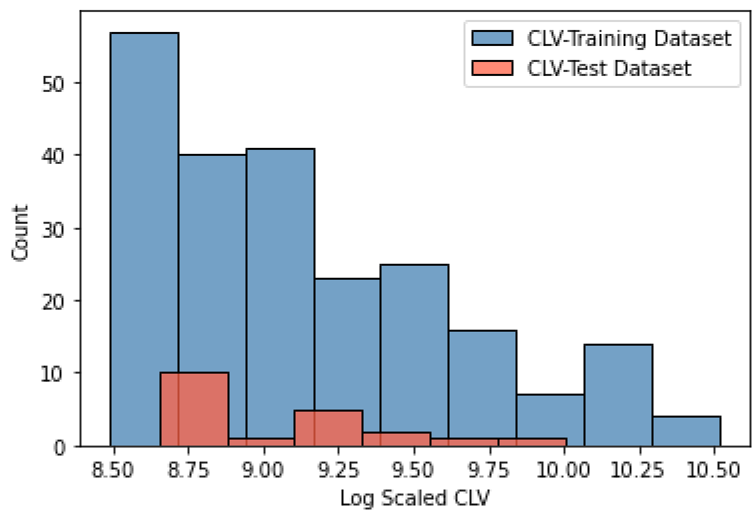
In [42]:
```
#Filtering Unemployed
fig, ax = plt.subplots()
df_train = datab[datab["EmploymentStatus"] == "Unemployed"]
df_test = dataTest[dataTest["EmploymentStatus"] == "Unemployed"]

for a,c in [(np.log(df_train["CLV"].astype(float)),"steelblue"), (np.log(df_test["CLV"].astype(float)),"tomato")]:
    sns.histplot(a, ax=ax, kde=False, color=c)
plt.legend(["CLV-Training Dataset","CLV-Test Dataset"])
plt.xlabel("Log Scaled CLV")
plt.show()
```



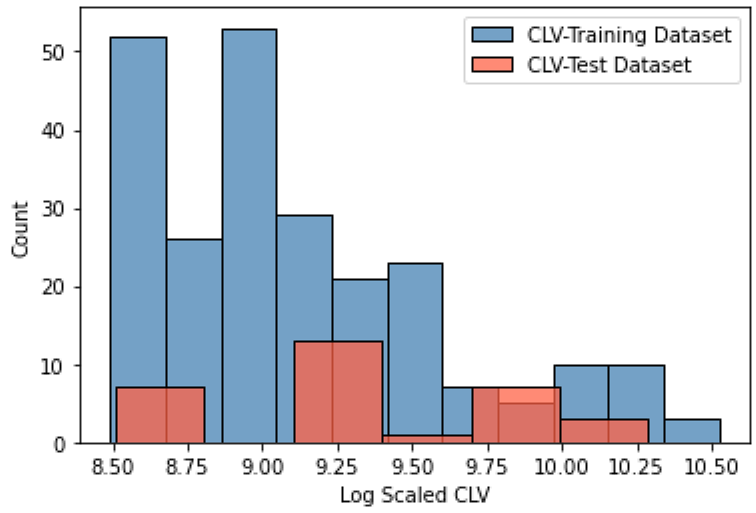
In [43]:
```
#Filtering Employed
fig, ax = plt.subplots()
df_train = datab[datab["EmploymentStatus"] == "Employed"]
df_test = dataTest[dataTest["EmploymentStatus"] == "Employed"]

for a,c in [(np.log(df_train["CLV"].astype(float)),"steelblue"), (np.log(df_test["CLV"].astype(float)),"tomato")]:
    sns.histplot(a, ax=ax, kde=False, color=c)
plt.legend(["CLV-Training Dataset","CLV-Test Dataset"])
plt.xlabel("Log Scaled CLV")
plt.show()
```



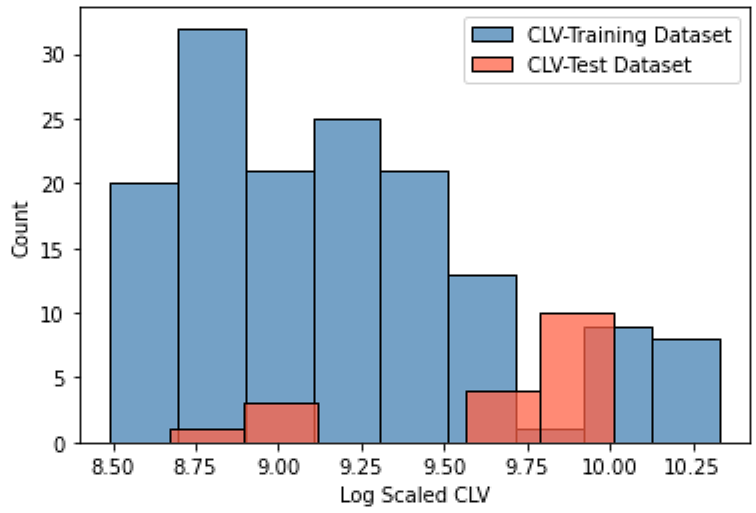
In [44]:
```
#Filtering Medical Leave
fig, ax = plt.subplots()
df_train = datab[datab["EmploymentStatus"] == "Medical Leave"]
df_test = dataTest[dataTest["EmploymentStatus"] == "Medical Leave"]

for a,c in [(np.log(df_train["CLV"].astype(float)),"steelblue"), (np.log(df_test["CLV"].astype(float)),"tomato")]:
    sns.histplot(a, ax=ax, kde=False, color=c)
plt.legend(["CLV-Training Dataset","CLV-Test Dataset"])
plt.xlabel("Log Scaled CLV")
plt.show()
```



In [45]:
```python
#Filtering Disabled
fig, ax = plt.subplots()
df_train = datab[datab["EmploymentStatus"] == "Disabled"]
df_test = dataTest[dataTest["EmploymentStatus"] == "Disabled"]

for a,c in [(np.log(df_train["CLV"].astype(float)),"steelblue"), (np.log(df_test["CLV"].astype(float)),"tomato")]:
    sns.histplot(a, ax=ax, kde=False, color=c)
plt.legend(["CLV-Training Dataset","CLV-Test Dataset"])
plt.xlabel("Log Scaled CLV")
plt.show()
```



In [46]:
```python
#Filtering Retired
fig, ax = plt.subplots()
df_train = datab[datab["EmploymentStatus"] == "Retired"]
df_test = dataTest[dataTest["EmploymentStatus"] == "Retired"]

for a,c in [(np.log(df_train["CLV"].astype(float)),"steelblue"), (np.log(df_test["CLV"].astype(float)),"tomato")]:
    sns.histplot(a, ax=ax, kde=False, color=c)
plt.legend(["CLV-Training Dataset","CLV-Test Dataset"])
plt.xlabel("Log Scaled CLV")
plt.show()
```



4.5 Conclusion

We can see that the model fit well to the training dataset, however it struggled a bit with features with small amount of data.
This may be an improving point on the model we have used.

A more in depth analysis of the features could have been done to improve the results interpretation but was aborted due to a lack of time with the assignment deadline.

Although we have discovered what could be considered as a flaw in our model, it is the proof of an efficient model since it is good at generalizing predictions, **avoiding overfitting**.

Our model is a good compromise between bias and variance, which makes it a pretty good model to predict the `CLV` of future customers.

and voilà.
🦊