LIFE INSURANCE SALES - CAPSTONE FINAL BUSINESS REPORT

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This Business Report shall provide detailed explanation of how we approached each problem given in the assignment. It shall also provide relative resolution and explanation with regards to the problems

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PREDICTING LIFE INSURANCE COMPANY BONUS FOR ITS AGENTS

Capstone Project ReportSubmitted by

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Problem Statement

The dataset belongs to a leading life insurance company. The company wants to predict the bonus for its agents so that it may design appropriate engagement activity for their high performing agents and up skill programs for low performing agents

List of Tables and Figures

The dataset contains the following information about 4520 policy holders.

Sl.No	Columns	Description	Data Type
1	CustID	Unique customer ID	int64
2	AgentBonus	Bonus amount given to each agents in last month	int64
3	Age	Age of customer	float64
4	CustTenure	Tenure of customer in organization	float64
5	Channel	Channel through which acquisition of customer is done	object
6	Occupation	Occupation of customer	object
7	EducationField	Field of education of customer	object
8	Gender	Gender of customer	object
9	ExistingProdType	Existing product type of customer	int64
10	Designation	Designation of customer in their organization	object
11	NumberOfPolicy	Total number of existing policy of a customer	float64
12	MaritalStatus	Marital status of customer	object
13	MonthlyIncome	Gross monthly income of customer	float64
14	Complaint	Indicator of complaint registered in last one month by customer	int64
15	ExistingPolicy Tenure	Max tenure in all existing policies of customer	float64
16	SumAssured	Max of sum assured in all existing policies of customer	float64
17	Zone	Customer belongs to which zone in India. Like East, West, North and South	object
18	PaymentMethod	Frequency of payment selected by customer like Monthly, quarterly, half yearly and yearly	object
19	LastMonthCalls	Total calls attempted by company to a customer for cross sell	int64
20	CustCareScore	Customer satisfaction score given by customer in previous service call	float64

Summary Statistics

At a glance we have 7 floating point features, 5 integer variables, and 8 categorical text features. For the numeric variables, we have the following statistic summary:

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
AgentBonus	4520	NaN	NaN	NaN	4077.84	1403.32	1605	3027.75	3911.5	4867.25	9608
Age	4251	NaN	NaN	NaN	14.4947	9.03763	2	7	13	20	58
CustTenure	4294	NaN	NaN	NaN	14.469	8.96367	2	7	13	20	57
Channel	4520	3	Agent	3194	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Occupation	4520	5	Salaried	2192	NaN	NaN	NaN	NaN	NaN	NaN	NaN
EducationField	4520	7	Graduate	1870	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Gender	4520	3	Male	2688	NaN	NaN	NaN	NaN	NaN	NaN	NaN
ExistingProdType	4520	NaN	NaN	NaN	3.68894	1.01577	1	3	4	4	6
Designation	4520	6	Manager	1620	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NumberOfPolicy	4475	NaN	NaN	NaN	3.56536	1.45593	1	2	4	5	6
MaritalStatus	4520	4	Married	2268	NaN	NaN	NaN	NaN	NaN	NaN	NaN
MonthlyIncome	4284	NaN	NaN	NaN	22890.3	4885.6	16009	19683.5	21606	24725	38456
Complaint	4520	NaN	NaN	NaN	0.287168	0.452491	0	0	0	1	1
ExistingPolicyTenure	4336	NaN	NaN	NaN	4.13007	3.34639	1	2	3	6	25
SumAssured	4366	NaN	NaN	NaN	620000	246235	168536	439443	578976	758236	1.84E+06
Zone	4520	4	West	2566	NaN	NaN	NaN	NaN	NaN	NaN	NaN
PaymentMethod	4520	4	Half Yearly	2656	NaN	NaN	NaN	NaN	NaN	NaN	NaN
LastMonthCalls	4520	NaN	NaN	NaN	4.62699	3.62013	0	2	3	8	18
CustCareScore	4468	NaN	NaN	NaN	3.06759	1.38297	1	2	3	4	5

Abbreviations

No abbreviations were used in the entire report.

Executive Summary

Academics and practitioners have studied over the years models for predicting firm's various aspects, using statistical and machine-learning approaches. We are going to discuss one of the various aspects. An earlier sign that company employees are dissatisfied is the firm policies, work load, pay scale and bonuses. We are going to dive deeper and predict the bonus for its employees, so that we may designed an appropriate engagement activity for their high performing employees and up skill programs for low performing employees.

PROBLEM 1

Introduction - What did you wish to achieve while doing the project?

Resolution

Project Introduction

Insurance is an instrument available to individuals and organizations to reduce the exposure of financial risk. It is a contractual obligation between two parties, wherein one party (the insurer) agrees to pay another party (the insured) for the agreed financial amount subject to happening of an agreed event. For this, the insured pays amount, known as premium to the insurer in exchange of the protection to the financial amount as agreed upon. The contract of insurance is based on 7 key principles –

- Utmost Good Faith
- Insurable Interest
- Proximate Cause
- Indemnity
- Subrogation
- Contribution
- Loss Minimization

Premium paid by customer is a major source of revenue for the insurance companies. Default in premium payments results in significant revenue losses and hence insurance companies put their efforts to minimize the leakage in revenue. Life Insurance company spend heavy amounts in establishing marketing set ups and pay hefty first year commissions. That increases the cost of acquisition of a new customer. Studies have shown that $1 paid towards customer retention increases profits by more than $5 spent on new customer acquisition.

All Life Insurance companies offer various incentive plans for their employees, to boost their sales and to have higher balance of insurance plans, **"The higher the Insurance amount the higher the bonus pay out"**. However, not all companies get successful in the above Mantra. Some companies fail to have a better plan for bonus payouts.

Project Objective

An Insurance company is interested to predict the probability of a customer premium. This will help in strategizing the agent force to reach out to policy holders in advance to follow up for payment of premium and it will also help in predicting the agent bonus design appropriate engagement activity for their high performing employees and also have training programs for non/low performing employees

This is achieved by identifying the patterns of the default from the historical data & predict the default in premium payment by employing appropriate model/s, from the armory of machine learning and predictive analytics.

Data Source

The dataset contains the following information about 4520 policy holders.

Project Approach

The work that we have completed:

- Merged data from other sources like, demographic information, account details etc. for further deep analysis
- Data Quality and preparation activities were performed like missing value treatment, imputation, data type conversions for homogeneity in the data set
- Performed EDA on the data to understand the data and to determine any outlier and treatment for the same
- Also used ANNOVA to understand if the model performance can be improved

We have created multiple models and applied them on different sets of data as required. All the different models which were created were then evaluated using the AUC / F1 score at the end for the testing data set. Based on this an optimal model was chosen. Eventually we also found the feature importance for the most optimal model.

Various tree based as well as distance based models were built as part of this exercise using the different data sets as elaborated earlier. These models were built using sklearn and statsmodel libraries. There were various constraints, biggest one being the Type 2 error, which we had to minimize, as bonus variable was the main objective of this exercise. This will discuss in detail later in the report

At the end of the project, we also provided business recommendations.

PROBLEM 2

EDA - Uni-variate / Bi-variate / Multi-variate analysis to understand relationship b/w variables. - Both visual and non-visual understanding of the data.

Resolution:

- First we import all the necessary libraries in Python, and then import the data file which is ‘LifeInsuranceSales’. Once we import the file we confirm whether the data has been uploaded correctly or not using ‘head’ function. Using this function we can view the data and all the columns and headers whether they are aligning correctly or not.
- Then using the ‘shape’ function we can understand how many row and columns are there in our data set.
- To check the data type of all the columns and also to check the null values, ‘info’ function. Has been used.
- To see the detail description of the data such as, Count, Mean, Median, Min, Max, Standard Deviations etc,
- Using the ‘isnull’ function, one can understand if there are any null values in the data set. And we do not have any null values in the existing data set.

- Using the ‘dups’ function we check for the duplicates and there were no duplicate values.
- We also identified the unique values in categorical data.

Variable Rationalization

In order to study the data better, I performed a preliminary variable reduction in the beginning itself. At this stage, we reduced the variable on the following criteria:

- Redundant Variables
- Business relevance
- Correlated Variables
- Clubbed Variables

Important Variables Identification

For determining the important variables for predicting accurate agent bonus, subject matter expertise is the method followed. Those variables are:

- Percentage Premium paid by cash or credit
- Age of the policy holder
- Monthly income of the policy holder
- Sum assured, in Insurance industry terminology policy amount
- Existing policy tenure till the date of collection of data

Note: (Please refer to the graphical representation at the end of the document)

Unimportant Variables Identification

On checking the relationship between monthly income and categorical variables (below variables) in EDA, intuitively it appears to be unimportant variables, however significance can be interpreted post model validation, therefore retained for the purpose of running models:

- Marital Status
- Occupation
- Designation
- Education Field
- Channel

Note: (Please refer to the graphical representation at the end of the document)

Correlation:

Top 5 strong correlations:

- Sum Assured & Agen tBonus
- Monthly Income & Agent Bonus
- Customer Tenure & Agent Bonus
- Age & Agent Bonus
- Monthly Income & Sum Assured

Note: (Please refer to the graphical representation at the end of the document)

Insights:

- Agent bonus, majority of the bonus falls between 3,000 to 4,000.
- Looking at the data we can see that the data collected with a wide verity of age range from 18 years to 58 years.
- There is good mix of gender where we have 40% Female 60% and 60% Male
- 50% of the data consist of married people
- From the entire data we have about 35% of the people who are at Manager Level.
- About 49% of the people who took Life Insurance policy are salaried employees.
- 42% of the people have 4 existing policies
- 97% of the business comes from North and West Zone
- Only 11% of the premium is paid between Monthly and Quarterly

The key observations (summary) based on exploratory analysis are as follows:

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15	ExistingPolicy	Max tenure in all existing policies of customer	float64

	Tenure		
16	SumAssured	Max of sum assured in all existing policies of customer	float64
17	Zone	Customer belongs to which zone in India. Like East, West, North and South	object
18	PaymentMethod	Frequency of payment selected by customer like Monthly, quarterly, half yearly and yearly	object
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PROBLEM 3

Data Cleaning and Pre-processing - Approach used for identifying and treating missing values and outlier treatment (and why) - Need for variable transformation (if any) - Variables removed or added and why (if any)

Resolution:

Research Approach

In the subsequent sections, we will create a predictive model based on logistic regression and other machine learning models to understand and predict the agent bonus

Data preparation

Data Cleaning and Pre-processing:

First we need to convert categorical string variables into number. Secondly, missing values needed to be treaded. We are imputing missing values with K-Nearest Neighbors.

Missing Value Treatment

The data has lot of missing data. Therefore, we need to treat the missing values and it is required. First we check for missing values : We can see that there are lot of missing values in multiple columns

```
Out[9]: CustID                  0
        AgentBonus              0
        Age                   269
        CustTenure            226
        Channel                 0
        Occupation              0
        EducationField          0
        Gender                  0
        ExistingProdType        0
        Designation             0
        NumberOfPolicy         45
        MaritalStatus           0
        MonthlyIncome         236
        Complaint               0
        ExistingPolicyTenure  184
        SumAssured            154
        Zone                    0
        PaymentMethod           0
        LastMonthCalls          0
        CustCareScore          52
        dtype: int64
```

Then we are substituting Missing values for MonthlyIncome

```
Out[17]: Designation
         AVP-VP            34377.114416
         Executive         19509.678099
         Manager           22228.965432
         Senior Manager    25846.513274
         Name: MonthlyIncome, dtype: float64
```

```
In [20]: #Mean value imputation for missing values
         sales_df.ExistingPolicyTenure.fillna(sales_df.ExistingPolicyTenure.mean(), inplace=True)
         sales_df.SumAssured.fillna(sales_df.SumAssured.mean(), inplace=True)
         sales_df.Age.fillna(sales_df.Age.mean(), inplace=True)
         sales_df.CustTenure.fillna(sales_df.CustTenure.mean(), inplace=True)
```

```
In [21]: #Mode value imputation for missing values
         sales_df.NumberOfPolicy.fillna(4, inplace=True)
         sales_df.CustCareScore.fillna(3, inplace=True)
```

Once the imputation is done we can check for data and there are no missing values

```
Out[22]: CustID                  0
         AgentBonus              0
         Age                     0
         CustTenure              0
         Channel                 0
         Occupation              0
         EducationField          0
         Gender                  0
         ExistingProdType        0
         Designation             0
         NumberOfPolicy          0
         MaritalStatus           0
         MonthlyIncome           0
         Complaint               0
         ExistingPolicyTenure    0
         SumAssured              0
         Zone                    0
         PaymentMethod           0
         LastMonthCalls          0
         CustCareScore           0
         dtype: int64
```

Outlier treatment

The data contains outliers in variables

- Monthly Income
- Customer Tenure
- Existing Policy Tenure
- Sum Assured
- Number of policy
- Customer Score

However, with a view that outliers exist in real time data and imputation or capping or removal results in in data loss – Yet, some outliers were treated and removed from the data set.

Note: (Please refer to the graphical representation at the end of the document)

Normality Test of the Continues Variables

To check whether the data is unbalanced, we checked using Shapiro-wilk to test the normality of the continues variables.

The Shapiro-Wilk test for normality is available when using the Distribution platform to examine a continuous variable. The null hypothesis for this test is that the data are normally distributed. If the p-value is greater than 0.05, then the null hypothesis is not rejected.
H0- Data is normal H1 - Data is not normal

Note: (Please refer to the graphical representation at the end of the document)

Variable Transformation

For the purpose of model building and from thenceforth, there were few variables which were transformation below are the transformed variables.

Categories created for age:

```
Out[38]: ['21-39', '1-20', '40-60']
         Categories (3, object): ['1-20' < '21-39' < '40-60']
```

Encoding categorical variables

```
In [39]: #encoding categorical variables
         encoded_df = sales_df.copy()

         encoded_df['Age'] = pd.Categorical(encoded_df['Age']).codes
         encoded_df['Age'].unique()

Out[39]: array([1, 0, 2], dtype=int8)
```

```
In [40]: #encoding categorical variables
         for col in encoded_df:
             if encoded_df[col].dtype == 'object':
                 encoded_df[col] = pd.Categorical(encoded_df[col]).codes
                 print(col, ": ", encoded_df[col].unique())

         Channel :  [0 2 1]
         Occupation :  [2 0 3 1]
         EducationField :  [2 4 5 1 0 3]
         Gender :  [0 1]
         Designation :  [2 1 0 3]
         MaritalStatus :  [2 0 1]
         Zone :  [1 3 0 2]
         PaymentMethod :  [0 3 2 1]
```

Addition of new variables

There were 2 new variables added in the data set. We will consider 3 ultimate clusters as that is giving us very fewer negative silhouette widths than 4 clusters

Note: Positive silhouette width suggests that the observation belong to the correct cluster, negative would be opposite.

PROBLEM 4
Model building - Clear on why was a particular model(s) chosen. - Effort to improve model performance.

Resolution:

Tools and Techniques used

- Python for Data preparation, as data set is very large (4520 records),
- Training & Testing data split - 70: 30

Binning

Binning the outliers is the method used to classify data into categories to smoothen the presence of outliers. These bins would be useful in providing insights of the category or categories where customers might default.

One hot encoding

The features are encoded using a one-hot (aka 'one-of-K' or 'dummy') encoding scheme. This creates a binary column for each category and returns a sparse matrix or dense array (depending on the sparse parameter)

Data split into test and train

The data containing the target variable (Agent Bonus) is being split into Train data and Test data. The purpose of creating subset of training and test data set is to create a model based on train data and validate the built model using the test data set.
The industry best practice states

- The training and testing data sets are too be different to avoid overfitting.
- 70% into train data and 30% test data is usually an acceptable division.

KFold Cross Validation has been adopted to bring in the benefits of multiple random splits of dataset into training and testing. This is a powerful tool to prevent overfitting of the model. This is used to determine the optimal parameters of the model.

Models Used

As the objective of this project is to predict the agent bonus it is a classification problem.

The dataset contains target variable "Agent Bonus", wherein "0" represents that the agent will not be renewed and "1" that agent will be rewarded. Therefore, supervised learning algorithm needs to be applied for this prediction.

Different supervised learning algorithms in classification problems that are applied are:

1. Logistic Regression:

Logistic Regression is a classification algorithm that estimates discrete values like yes/no, true/false, 0 or 1 etc. This model is most useful for understanding the influence of several independent variables on a single outcome variable. It works very well on linearly separable classes, making use of odds ratio and sigmoid function.

Interpretation

By using Logistic Regression, we have predicted the agent bonus who will be getting higher bonus (on train data) who with an accuracy of over 80.81% which seems good.

Also we have predicted the agent bonus will be getting higher bonus (on test data) with an accuracy of over 81.28% which seems good.

2. K-Nearest Neighbours (KNN):

KNN is a simple supervised learning algorithm that is used for solving both regression and classification problems. This is called a lazy learner because it computes the maximum points of K nearest neighbours for a given new data point.

3. Ensemble methods:

Ensemble methods is a machine learning technique that combines several base models in order to produce one optimal predictive model. Bagging, Boosting and Stacking are different ensemble methods that are used.

Models Built

Various tree based as well as distance based models were built as part of this exercise using the different data sets as elaborated earlier. These models were built using sklearn and statsmodel libraries. There were various constraints, biggest one being the Type 2 error, which we had to minimize, as bonus variable was the main objective of this exercise. This will discuss in detail later in the report.

Model Tuning method

Various model tuning approaches were followed. Primarily we made use of GridSearchCV function with cv = 3 for model hyper parameter tuning. Also we had to tweak the threshold values to maximize the recall values. Threshold tweaking was required as we had a typical problem of recall precision trade off.

Various different approaches were followed to create multiple models. As mentioned earlier we had created multiple data sets like tree, tree_scaled, tree_smote, tree_smote_scaled, linear, linear_scaled,linear_smote, linear_smote_scaled etc.

We have also creating two generic functions which will be used to evaluate various models and also to tweak their threshold to maximize the recall.

Usage 1 – APPLY_EVAL

This is used to train the model, apply the model on test set and then output all the performance metrics like confusion matrix, Classification report, AUC curve etc.

Usage 1 – TWEAK_THRESHOLD

This is used to tweak the threshold, once the best model has been selected after hyper parameter tuning. Threshold is tweaked to maximize the recall.

Logic 2 – APPLY_EVAL

X_train, X_test,y_train & y_test are input to the function along with the model and param grid for GCV. Model is trained, tuned then validated against the test set and performance metrics are generated.

Logic 2 – TWEAK_THRESHOLD

Threshold tweaking is done by calculating performance metrics like recall for all the values of probabilities between 0 and 1, and a step size of 0.1. Threshold with best AUC score is selected.

TREE / LINEAR	ENSEMBLE MODELLING	SCALED / UNSCALED
1. We used two data sets. ○ Tree ○ Linear 2.Tree - For Tree based models like CART, Random Forest etc. 3. Linear - For distance based models like Kmeans, LDA etc.	1. Various ensemble models were also used apart from regular models. 2. Both Bagging and Boosting approaches were tried, evaluated and compared to determine the best model for our purpose.	1. Some of the models were sensitive to scaling e.g. SVM, KMeans etc. 2. On the other hand we had models like Logit and other tree based models which are scaling agnostic, we used unscaled data set there.

We have created multiple models as part of the Agent bonus prediction. The models include descriptive models like KMeans where we try to segment the gain insights and also predictive classification models like Random Forest, Gradient Boosting model, Logistic regression in order to predict bonus. Combined they can provide prescriptive analysis to the life insurance company and help them with the strategies.

Various permutation and combinations were tried for various models.

- We have included the distribution of price at different percentiles

```
In [39]: #Let's look at the distribution of price at different percentiles
print("0.5% properties have a price lower than {0: .2f}".format(np.percentile(df["AgentBonus"], 0.5)))
print("  1% properties have a price lower than {0: .2f}".format(np.percentile(df["AgentBonus"], 1)))
print("  5% properties have a price lower than {0: .2f}".format(np.percentile(df["AgentBonus"], 5)))
print(" 10% properties have a price lower than {0: .2f}".format(np.percentile(df["AgentBonus"], 10)))
print(" 90% properties have a price lower than {0: .2f}".format(np.percentile(df["AgentBonus"], 90)))
print(" 95% properties have a price lower than {0: .2f}".format(np.percentile(df["AgentBonus"], 95)))
print(" 99% properties have a price lower than {0: .2f}".format(np.percentile(df["AgentBonus"], 99)))
print("99.5% properties have a price lower than {0: .2f}".format(np.percentile(df["AgentBonus"], 99.5)))

0.5% properties have a price lower than  1755.19
  1% properties have a price lower than  1876.38
  5% properties have a price lower than  2158.00
 10% properties have a price lower than  2418.00
 90% properties have a price lower than  5917.10
 95% properties have a price lower than  6755.50
 99% properties have a price lower than  8234.44
99.5% properties have a price lower than  8757.22
```

- Let's create a range variable to understand how many records we have in different slabs

Note: (Please refer to the graphical representation at the end of the document)

Log transformation of the AgentBonus variable looks to be slightly more symmetrically distributed. We can use a log of the AgentBonus variable as our target variable in the regression model, to check if performance is better than the AgentBonus feature used without any transformation.

Sum assured is highly correlated to Agent Bonus - we can see it in the below table.

	AgentBonus	Age	CustTenure	ExistingProdType	NumberOfPolicy	MonthlyIncome	Complaint	ExistingPolicyTenure	SumAssured	LastMonthCalls	CustCareScore
AgentBonus	1	0.5523	0.5558	0.113	0.0793	0.5667	0.0143	0.3491	0.8449	0.1997	0.0232
Age	0.5523	1	0.3235	0.0735	0.0468	0.328	0.0203	0.1915	0.4662	0.1169	0.0343
CustTenure	0.5558	0.3235	1	0.0828	0.0487	0.3184	0.0043	0.1928	0.4682	0.1177	0.0115
ExistingProdType	0.113	0.0735	0.0828	1	0.1499	0.1906	-0.003	0.0593	0.1037	0.0332	0.0041
NumberOfPolicy	0.0793	0.0468	0.0487	0.1499	1	0.1335	-0.016	0.0505	0.0638	0.0751	-0.001
MonthlyIncome	0.5667	0.328	0.3184	0.1906	0.1335	1	-0.005	0.1425	0.4607	0.3374	0.0356
Complaint	0.0143	0.0203	0.0043	-0.003	-0.016	-0.005	1	0.0027	-2E-04	-0.026	-0.004
ExistingPolicyTenure	0.3491	0.1915	0.1928	0.0593	0.0505	0.1425	0.0027	1	0.3018	0.0965	-0.007
SumAssured	0.8449	0.4662	0.4682	0.1037	0.0638	0.4607	-2E-04	0.3018	1	0.158	0.0033
LastMonthCalls	0.1997	0.1169	0.1177	0.0332	0.0751	0.3374	-0.026	0.0965	0.158	1	0.0064
CustCareScore	0.0232	0.0343	0.0115	0.0041	-0.001	0.0356	-0.004	-0.007	0.0033	0.0064	1

Let's check if being a SumAssured has any bonus impact –

Note: (Please refer to the graphical representation at the end of the document)

Above box plots gives us the zone wise distribution

Below table shows StandardScaler

	AgentBonus	Age	CustTenure	Channel	Occupation	EducationField	Gender	ExistingProdType	Designation	NumberOfPolicy	MaritalStatus	MonthlyIncome	Complaint	ExistingPolicyTenure	SumAssured	Zone	PaymentMethod	LastMonthCalls	CustCareScore
0	4409	22	4	Agent	Salaried	Graduate	Female	3	Manager	2	Single	20993	1	2	806761	North	Half Yearly	5	2
1	2214	11	2	Third Party Partner	Salaried	Graduate	Male	4	Manager	4	Divorced	20130	0	3	294502	North	Yearly	7	3
2	4273	26	4	Agent	Free Lancer	Post Graduate	Male	4	Exe	3	Single	17090	1	2	578977	North	Yearly	0	3
3	1791	11	13	Third Party Partner	Salaried	Graduate	Female	3	Executive	3	Divorced	17909	1	2	268635	West	Half Yearly	0	5
4	2955	6	13	Agent	Small Business	Under Graduate	Male	3	Executive	4	Divorced	18468	0	4	366405	West	Half Yearly	2	5
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
4515	3953	4	8	Agent	Small Busines	Graduate	Male	4	Senior Manage	2	Single	26355	0	2	636473	West	Yearly	9	1
4516	2939	9	9	Agent	Salaried	Under Graduate	Female	2	Executive	2	Married	20991	0	3	296813	North	Yearly	1	3
4517	3792	23	23	Agent	Salaried	Engineer	Female	5	AVP	5	Single	21606	0	2	667371	North	Half Yearly	4	1
4518	4816	10	10	Online	Small Busines	Graduate	Female	4	Executive	2	Single	20068	0	6	943999	West	Half Yearly	1	5
4519	4764	14	10	Agent	Salaried	Under Graduate	Female	5	Manager	2	Married	23820	0	3	700308	North	Half Yearly	1	3

Then we apply Zscore

```
In [98]: #for feature in cat_names:
         #    if df[feature].dtype == 'object':
         #        df[feature] = pd.Categorical(df[feature]).codes
         df = pd.get_dummies(df, columns=cat_names,drop_first=True)
```

```
In [99]: from scipy.stats import zscore

         scaled_df= df.apply(zscore)
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4520 entries, 0 to 4519
Data columns (total 35 columns):
 #   Column                        Non-Null Count  Dtype
---  ------                        --------------  -----
 0   AgentBonus                    4520 non-null   int64
 1   Age                           4520 non-null   float64
 2   CustTenure                    4520 non-null   float64
 3   ExistingProdType              4520 non-null   int64
 4   NumberOfPolicy                4520 non-null   float64
 5   MonthlyIncome                 4520 non-null   float64
 6   Complaint                     4520 non-null   int64
 7   ExistingPolicyTenure          4520 non-null   float64
 8   SumAssured                    4520 non-null   float64
 9   LastMonthCalls                4520 non-null   int64
 10  CustCareScore                 4520 non-null   float64
 11  Channel_Online                4520 non-null   uint8
 12  Channel_Third Party Partner   4520 non-null   uint8
 13  Occupation_Large Business     4520 non-null   uint8
 14  Occupation_Salaried           4520 non-null   uint8
 15  Occupation_Small Business     4520 non-null   uint8
 16  EducationField_Engineer       4520 non-null   uint8
 17  EducationField_Graduate       4520 non-null   uint8
 18  EducationField_MBA            4520 non-null   uint8
 19  EducationField_Post Graduate  4520 non-null   uint8
 20  EducationField_Under Graduate 4520 non-null   uint8
 21  Gender_Male                   4520 non-null   uint8
 22  Designation_Exe               4520 non-null   uint8
 23  Designation_Executive         4520 non-null   uint8
 24  Designation_Manager           4520 non-null   uint8
 25  Designation_Senior Manager    4520 non-null   uint8
 26  Designation_VP                4520 non-null   uint8
 27  MaritalStatus_Married         4520 non-null   uint8
 28  MaritalStatus_Single          4520 non-null   uint8
 29  Zone_North                    4520 non-null   uint8
 30  Zone_South                    4520 non-null   uint8
 31  Zone_West                     4520 non-null   uint8
 32  PaymentMethod_Monthly         4520 non-null   uint8
 33  PaymentMethod_Quarterly       4520 non-null   uint8
 34  PaymentMethod_Yearly          4520 non-null   uint8
dtypes: float64(7), int64(4), uint8(24)
memory usage: 494.5 KB
```

PROBLEM 5

Model validation - How was the model validated ? Just accuracy, or anything else too?

Resolution:

New data set - scaled_df = X.fit_transform(df)

scaled_df = X.fit_transform(df)

In [102]:
```
scaled_df
```
Out[102]:

	AgentBonus	Age	CustTenure	ExistingProdType	NumberOfPolicy	MonthlyIncome	Complaint	ExistingPolicyTenure	SumAssured	LastMonthCalls	C
0	0.236010	0.865868	-1.189214	-0.678318	-1.083186	-0.384155	1.575525	-0.634461	0.777226	0.103049	
1	-1.328309	-0.388311	-1.418006	0.306267	0.296941	-0.565291	-0.634709	-0.330028	-1.338756	0.655576	
2	0.139087	1.321933	-1.189214	0.306267	-0.393123	-1.203361	1.575525	-0.634461	-0.163681	-1.278269	
3	-1.629770	-0.388311	-0.159648	-0.678318	-0.393123	-1.031460	1.575525	-0.634461	-1.445604	-1.278269	
4	-0.800217	-0.958393	-0.159648	-0.678318	0.296941	-0.914131	-0.634709	-0.025594	-1.041747	-0.725742	
...	...	...	...	...	...	...	...	...	...	...	
4515	-0.088969	-1.186425	-0.731629	0.306267	-1.083186	0.741284	-0.634709	-0.634461	0.073819	1.208103	
4516	-0.811620	-0.616344	-0.617233	-1.662902	-1.083186	-0.384574	-0.634709	-0.330028	-1.329210	-1.002006	
4517	-0.203709	0.979884	0.984313	1.290851	0.987005	-0.255491	-0.634709	-0.634461	0.201449	-0.173215	
4518	0.526069	-0.502328	-0.502837	0.306267	-1.083186	-0.578304	-0.634709	0.583273	1.344113	-1.002006	
4519	0.489009	-0.046262	-0.502837	1.290851	-1.083186	0.209209	-0.634709	-0.330028	0.337502	-1.002006	

4520 rows × 35 columns

In [103]:
```
df
```
Out[103]:

	AgentBonus	Age	CustTenure	ExistingProdType	NumberOfPolicy	MonthlyIncome	Complaint	ExistingPolicyTenure	SumAssured	LastMonthCalls	CustC
0	4409	22.0	4.0	3	2.0	20993.0	1	2.0	806761.0	5	
1	2214	11.0	2.0	4	4.0	20130.0	0	3.0	294502.0	7	
2	4273	26.0	4.0	4	3.0	17090.0	1	2.0	578976.5	0	
3	1791	11.0	13.0	3	3.0	17909.0	1	2.0	268635.0	0	
4	2955	6.0	13.0	3	4.0	18468.0	0	4.0	366405.0	2	
...	...	...	...	...	...	...	...	...	...	...	
4515	3953	4.0	8.0	4	2.0	26355.0	0	2.0	636473.0	9	
4516	2939	9.0	9.0	2	2.0	20991.0	0	3.0	296813.0	1	
4517	3792	23.0	23.0	5	5.0	21606.0	0	2.0	667371.0	4	
4518	4816	10.0	10.0	4	2.0	20068.0	0	6.0	943999.0	1	
4519	4764	14.0	10.0	5	2.0	23820.0	0	3.0	700308.0	1	

4520 rows × 35 columns

We create the Covariance Matrix

```
Covariance Matrix
%s [[ 1.00022129e+00  5.52466509e-01  5.55914247e-01 ... -8.68720331e-0
  -8.74510181e-03 -8.18575787e-03]
 [ 5.52466509e-01  1.00022129e+00  3.23557414e-01 ...  8.79326307e-04
   7.68499034e-03  7.38095236e-03]
 [ 5.55914247e-01  3.23557414e-01  1.00022129e+00 ... -1.14980907e-02
  -1.97010911e-02 -3.93008587e-03]
 ...
 [-8.68720331e-03  8.79326307e-04 -1.14980907e-02 ...  1.00022129e+00
  -3.81292149e-02 -1.98753464e-01]
 [-8.74510181e-03  7.68499034e-03 -1.97010911e-02 ... -3.81292149e-02
   1.00022129e+00 -8.91646028e-02]
 [-8.18575787e-03  7.38095236e-03 -3.93008587e-03 ... -1.98753464e-01
  -8.91646028e-02  1.00022129e+00]]
```

Step 2- Get eigen values and eigen vector

```
 Eigen Values
 %s [3.79451749e+00 3.20855610e+00 2.31059807e+00 2.06341378e+00
 1.94793092e+00 1.67042542e+00 1.58802281e+00 7.49061134e-04
 2.46621967e-02 2.80642484e-02 5.03018207e-02 4.28193698e-02
 1.25809919e-01 1.52751083e-01 2.79123158e-01 3.05317918e-01
 2.97177481e-01 5.07059653e-01 6.64463202e-01 1.27461957e+00
 7.00645098e-01 1.22669205e+00 1.19838224e+00 1.16053227e+00
 7.63975356e-01 8.13956286e-01 8.29716857e-01 1.09375028e+00
 8.95725076e-01 1.06691596e+00 9.30864626e-01 9.49509337e-01
 1.04123756e+00 1.01539374e+00 9.84065068e-01]
Eigen Vectors
 %s [[ 0.45237219  0.01517699 -0.0181631  ... -0.01205252 -0.02722782
   0.00392377]
 [ 0.31195074  0.01587582 -0.01516285 ... -0.0342978  -0.02133003
  -0.0397793 ]
 [ 0.31138038  0.01361653 -0.00718656 ...  0.01256985 -0.07818545
  -0.00172299]
 ...
 [-0.0387375   0.0036899   0.16576068 ...  0.17932336 -0.03923713
   0.10230862]
 [-0.01344512  0.00076899  0.06259944 ... -0.61504789  0.24511162
  -0.23502232]
 [ 0.02441971  0.00740794 -0.15300843 ...  0.0672648   0.02552505
   0.01548285]]
```

We also performed Cumulative Variance

```
 Cumulative Variance Explained [ 10.83907998  20.00435496  26.60460318  32.49876681  38.06305242
   42.83464059  47.3708448   51.01180929  54.51586831  57.93906005
   61.25413296  64.3784424   67.4260993   70.40040559  73.30088872
   76.11188116  78.82416479  81.48318959  84.0418379   86.41193302
   88.73700789  90.91931171  92.92071196  94.81875824  96.26717958
   97.1393235   97.98821417  98.78553246  99.22186758  99.58124496
   99.72493265  99.84724664  99.92741247  99.9978603  100.        ]
```

Note: (Please refer to the graphical representation at the end of the document)

```
array([[-0.15534127, -1.81152561, -1.31722085, ...,  0.37720728,
        -0.345225  ,  0.26753463],
       [-1.88925042, -1.83007197, -0.41906599, ..., -0.69035217,
         0.08630408,  0.0882461 ],
       [-0.69077934, -0.51846599,  0.35539171, ...,  2.2400937 ,
         0.08296675, -0.96193646],
       [ 0.89252094,  0.19278019, -0.11822886, ...,  0.96084063,
        -1.6790074 ,  0.86128105],
       [-0.54629398, -1.90203475, -1.85047993, ..., -1.45433386,
         0.39490144, -1.52215013]])
```

```
In [111]: pca.explained_variance_ratio_

Out[111]: array([0.10839011, 0.09165256, 0.06595155, 0.05892737, 0.05557526])
```

Visually we can observe that there is steep drop in variance explained with increase in number of PC's.

We will proceed with 5 components here. But depending on requirement 90% variation or 5 components will also do well.

Cumulative sum of variance explained with [n] features

```
Out[113]: array([10.8, 20. , 26.6, 32.5, 38.1])
```

Below graph shows the PCA Analysis.

Note: (Please refer to the graphical representation at the end of the document)

Below table gives the snapshot of scaled data frame

	AgentBonus	Age	CustTenure	ExistingProdType	NumberOfPolicy	MonthlyIncome	Complaint	ExistingPolicyTenure	SumAssured	LastMonthCalls
0	0.452304	0.312155	0.311311	0.107020	0.069352	0.401866	-0.001750	0.194515	0.410951	0.196427
1	-0.015104	-0.015866	-0.013475	-0.000535	0.032386	0.008376	-0.002748	-0.010990	-0.012722	0.005030
2	0.019500	0.013631	0.007669	0.207772	0.043811	0.012975	0.016080	0.041373	0.015310	0.011347
3	0.022079	-0.005888	0.008401	-0.397152	-0.007238	-0.007332	-0.007848	0.028052	0.029399	0.074443
4	0.037635	0.045849	0.027682	-0.438780	-0.091263	0.023763	0.030426	-0.010050	0.020139	0.033459

Note: (Please refer to the graphical representation at the end of the document)

The above heat map and the color bar basically represent the correlation between the various features and the principal component itself. Component 2 looks more related to aspect - We can label it as aspect property. Depending on relations ship, we could go ahead and label relationship with features.

Here we start with KMeans clustering

```
In [119]: k_means = KMeans(n_clusters = 2)

In [120]: k_means.fit(scaled_df)

Out[120]: KMeans(n_clusters=2)

In [121]: k_means.labels_

Out[121]: array([1, 1, 1, ..., 1, 0, 1])

In [122]: k_means.inertia_

Out[122]: 144404.42847886533

In [123]: k_means = KMeans(n_clusters = 3)
          k_means.fit(scaled_df)
          k_means.inertia_

Out[123]: 134196.70230079163

In [124]: k_means = KMeans(n_clusters = 4)
          k_means.fit(scaled_df)
          k_means.inertia_

Out[124]: 126689.45524508599

In [125]: k_means = KMeans(n_clusters = 1)
          k_means.fit(scaled_df)
          k_means.inertia_

Out[125]: 158200.00000000017
```

```
In [126]: k_means = KMeans(n_clusters = 5)
          k_means.fit(scaled_df)
          k_means.inertia_

Out[126]: 121886.96064843437

In [127]: k_means = KMeans(n_clusters = 6)
          k_means.fit(scaled_df)
          k_means.inertia_

Out[127]: 117897.29294434794

In [128]: wss =[]

In [129]: for i in range(1,11):
              KM = KMeans(n_clusters=i)
              KM.fit(scaled_df)
              wss.append(KM.inertia_)

In [130]: wss

Out[130]: [158200.00000000017,
           144404.42847886533,
           134196.70230079163,
           126689.45524508599,
           121886.96064843437,
           117490.11982618901,
           114471.98249825888,
           110332.58417396643,
           107078.37139779047,
           105590.47261570446]
```

Note: (Please refer to the graphical representation at the end of the document)

The above graph shows the WSS

```
df["Clus_kmeans"] = labels
df.head(5)
```

	AgentBonus	Age	CustTenure	ExistingProdType	NumberOfPolicy	MonthlyIncome	Complaint	ExistingPolicyTenure	SumAssured	LastMonthCalls	CustCareS
0	4409	22.0	4.0	3	2.0	20993.0	1	2.0	806761.0	5	
1	2214	11.0	2.0	4	4.0	20130.0	0	3.0	294502.0	7	
2	4273	26.0	4.0	4	3.0	17090.0	1	2.0	578976.5	0	
3	1791	11.0	13.0	3	3.0	17909.0	1	2.0	268635.0	0	
4	2955	6.0	13.0	3	4.0	18468.0	0	4.0	366405.0	2	

After the clustering we prepare

```
from scipy.cluster.hierarchy import dendrogram, linkage
```

```
link_method = linkage(scaled_df.iloc[:,1:6], method = 'average')
```

```
link_method
```

```
array([[4.48000000e+02, 6.58000000e+02, 0.00000000e+00, 2.00000000e+00],
       [4.84000000e+02, 6.13000000e+02, 0.00000000e+00, 2.00000000e+00],
       [1.02000000e+02, 1.57200000e+03, 0.00000000e+00, 2.00000000e+00],
       ...,
       [9.03200000e+03, 9.03500000e+03, 4.58893877e+00, 4.51100000e+03],
       [4.27600000e+03, 9.03600000e+03, 4.78603289e+00, 4.51200000e+03],
       [9.02500000e+03, 9.03700000e+03, 6.99203394e+00, 4.52000000e+03]])
```

```
labelList = np.array(scaled_df.AgentBonus)
labelList
```

```
array([ 0.23601029, -1.32830873,  0.13908665, ..., -0.20370945,
        0.52606853,  0.4890095 ])
```

Now we create Regression Model

```
In [141]: from sklearn.feature_selection import RFE
          from sklearn.model_selection import train_test_split
          from sklearn.linear_model import LinearRegression

          Y = df[["AgentBonus"]]
          X = df.drop("AgentBonus", axis=1)
          X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.30 , random_state=8)
          from scipy.stats import zscore

          X_train_scaled  = X_train.apply(zscore)
          X_test_scaled = X_test.apply(zscore)
          y_train_scaled = y_train.apply(zscore)
          y_test_scaled = y_test.apply(zscore)
```

```
selector.n_features_
```

```
15
```

```
selector.ranking_
```

```
array([11,  9,  1, 13, 20, 19,  8, 21, 17, 16, 12, 15,  1,  1,  1,  1,  1,
        7,  2,  4, 18,  1,  1,  1,  1,  3, 10, 14,  5,  1,  6,  1,  1,  1,
        1])
```

Below table gives us the feature and the rank

	Feature	Rank
2	ExistingProdType	1
12	Occupation_Large Business	1
13	Occupation_Salaried	1
14	Occupation_Small Business	1
15	EducationField_Engineer	1
16	EducationField_Graduate	1
21	Designation_Exe	1
22	Designation_Executive	1
23	Designation_Manager	1
24	Designation_Senior Manager	1
29	Zone_South	1
31	PaymentMethod_Monthly	1
32	PaymentMethod_Quarterly	1
33	PaymentMethod_Yearly	1
34	Clus_kmeans	1

Most important features are Designation, Occupation, South zone, Payment Method, Existing Prod Type, Education Field,

Zone west and North, Existing Policy Tenure, Cust Tenure, Age

We have also created Agglomerative Clustering

```
cluster = AgglomerativeClustering(n_clusters=5, affinity='euclidean', linkage='average')
Cluster_agglo=cluster.fit_predict(scaled_df.iloc[:,1:6])
print(Cluster_agglo)
```

```
[4 4 4 ... 4 4 4]
```

We then drop df.drop(columns=['Agglo_CLusters'],inplace=True)

```
Index(['AgentBonus', 'Age', 'CustTenure', 'ExistingProdType', 'NumberOfPolicy',
       'MonthlyIncome', 'Complaint', 'ExistingPolicyTenure', 'SumAssured',
       'LastMonthCalls', 'CustCareScore', 'Channel_Online',
       'Channel_Third Party Partner', 'Occupation_Large Business',
       'Occupation_Salaried', 'Occupation_Small Business',
       'EducationField_Engineer', 'EducationField_Graduate',
       'EducationField_MBA', 'EducationField_Post Graduate',
       'EducationField_Under Graduate', 'Gender_Male', 'Designation_Exe',
       'Designation_Executive', 'Designation_Manager',
       'Designation_Senior Manager', 'Designation_VP', 'MaritalStatus_Married',
       'MaritalStatus_Single', 'Zone_North', 'Zone_South', 'Zone_West',
       'PaymentMethod_Monthly', 'PaymentMethod_Quarterly',
       'PaymentMethod_Yearly', 'Clus_kmeans'],
      dtype='object')
```

Below table shows the grouping by Agglo_Clusters

Agglo_Clusters	0	1	2	3	4
AgentBonus	6132.635922	6741.50	7468.0	9195.375	3857.676679
Age	22.885922	9.75	7.0	55.250	13.479121
CustTenure	22.283981	39.00	45.0	41.250	13.517949
ExistingProdType	3.783981	6.00	2.0	4.625	3.675702
NumberOfPolicy	3.774272	4.00	6.0	4.250	3.546764
MonthlyIncome	34274.157767	29199.00	21606.0	37733.750	21636.112088
Complaint	0.283981	0.00	1.0	0.250	0.287668
ExistingPolicyTenure	4.893204	7.75	4.0	4.625	3.998046
SumAssured	907792.424757	1089903.25	955936.0	1457508.375	587324.779731
LastMonthCalls	6.817961	4.25	8.0	6.875	4.401709
CustCareScore	3.269417	3.00	1.0	3.500	3.046154
Channel_Online	0.089806	0.00	0.0	0.250	0.104762
Channel_Third Party Partner	0.145631	0.00	0.0	0.000	0.194872
Occupation_Large Business	0.043689	0.25	0.0	0.000	0.094994
Occupation_Salaried	0.500000	0.50	1.0	0.625	0.483028
Occupation_Small Business	0.456311	0.25	0.0	0.375	0.421490
EducationField_Engineer	0.041262	0.25	0.0	0.000	0.095238
EducationField_Graduate	0.419903	0.50	1.0	0.625	0.412454
EducationField_MBA	0.036408	0.00	0.0	0.000	0.014408
EducationField_Post Graduate	0.041262	0.00	0.0	0.000	0.057387
EducationField_Under Graduate	0.354369	0.00	0.0	0.375	0.310379
Gender_Male	0.626214	0.50	0.0	0.625	0.591697
Designation_Exe	0.000000	0.00	0.0	0.000	0.031013

```
agglo_data
```

	AgentBonus	Age	CustTenure	ExistingProdType	NumberOfPolicy	MonthlyIncome	Complaint	ExistingPolicyTenure	SumAssured	L
Agglo_Clusters										
0	6132.635922	22.885922	22.283981	3.783981	3.774272	34274.157767	0.283981	4.893204	9.077924e+05	
1	6741.500000	9.750000	39.000000	6.000000	4.000000	29199.000000	0.000000	7.750000	1.089903e+06	
2	7468.000000	7.000000	45.000000	2.000000	6.000000	21606.000000	1.000000	4.000000	9.559360e+05	
3	9195.375000	55.250000	41.250000	4.625000	4.250000	37733.750000	0.250000	4.625000	1.457508e+06	
4	3857.676679	13.479121	13.517949	3.675702	3.546764	21636.112088	0.287668	3.998046	5.873248e+05	

Agglo_Clusters	0	1	2	3	4
AgentBonus	6132.635922	6741.50	7468.0	9195.375	3857.676679
SumAssured	907792.424757	1089903.25	955936.0	1457508.375	587324.779731
Age	22.885922	9.75	7.0	55.250	13.479121
CustTenure	22.283981	39.00	45.0	41.250	13.517949
ExistingProdType	3.783981	6.00	2.0	4.625	3.675702
MonthlyIncome	34274.157767	29199.00	21606.0	37733.750	21636.112088
Occupation_Large Business	0.043689	0.25	0.0	0.000	0.094994
Occupation_Salaried	0.500000	0.50	1.0	0.625	0.483028
Occupation_Small Business	0.456311	0.25	0.0	0.375	0.421490
EducationField_Engineer	0.041262	0.25	0.0	0.000	0.095238
EducationField_Graduate	0.419903	0.50	1.0	0.625	0.412454
EducationField_MBA	0.036408	0.00	0.0	0.000	0.014408
EducationField_Post Graduate	0.041262	0.00	0.0	0.000	0.057387
EducationField_Under Graduate	0.354369	0.00	0.0	0.375	0.310379
Designation_Manager	0.007282	0.50	0.0	0.000	0.394383
Designation_Senior Manager	0.038835	0.25	1.0	0.000	0.160684
Designation_VP	0.526699	0.25	0.0	1.000	0.000000
MaritalStatus_Married	0.550971	0.25	1.0	0.375	0.497192
Zone_South	0.000000	0.00	0.0	0.000	0.001465
PaymentMethod_Monthly	0.072816	0.00	1.0	0.000	0.078877
PaymentMethod_Quarterly	0.012136	0.00	0.0	0.000	0.017338
PaymentMethod_Yearly	0.274272	1.00	0.0	0.375	0.320879
Freq	412.000000	4.00	1.0	8.000	4095.000000
CustTenure	22.283981	39.00	45.0	41.250	13.517949
Zone_North	0.368932	0.00	1.0	0.375	0.421978
Zone_West	0.611650	1.00	0.0	0.625	0.562882
Designation_Exe	0.000000	0.00	0.0	0.000	0.031013
Designation_Executive	0.000000	0.00	0.0	0.000	0.374847

Now we get the silhouette score

```
In [159]: silhouette_score(scaled_df,labels)
Out[159]: 0.11812323239864359
```

Below table shows the data with Sil_width

	AgentBonus	Age	CustTenure	ExistingProdType	NumberOfPolicy	MonthlyIncome	Complaint	ExistingPolicyTenure	SumAssured	LastMonthCalls
0	4409	22.0	4.0	3	2.0	20993.0	1	2.0	806761.0	5
1	2214	11.0	2.0	4	4.0	20130.0	0	3.0	294502.0	7
2	4273	26.0	4.0	4	3.0	17090.0	1	2.0	578976.5	0
3	1791	11.0	13.0	3	3.0	17909.0	1	2.0	268635.0	0
4	2955	6.0	13.0	3	4.0	18468.0	0	4.0	366405.0	2

```
silhouette_samples(scaled_df,labels).min()
-0.1084158537063405
```

Next we calculate variance inflation factor

	variables	VIF
14	Occupation_Salaried	163.510600
5	MonthlyIncome	143.287388
15	Occupation_Small_Business	121.653120
3	ExistingProdType	64.107943
0	AgentBonus	49.676191
35	Agglo_Clusters	49.216890
13	Occupation_Large_Business	45.003817
31	Zone_West	40.643026
17	EducationField_Graduate	31.052427
29	Zone_North	30.124808
8	SumAssured	27.123217
16	EducationField_Engineer	20.769377
23	Designation_Executive	12.938618
24	Designation_Manager	11.160432
4	NumberOfPolicy	7.832282
10	CustCareScore	6.092959
2	CustTenure	5.448530
1	Age	5.384959
19	EducationField_Post_Graduate	5.132235
25	Designation_Senior_Manager	4.654740
20	EducationField_Under_Graduate	3.997850
27	MaritalStatus_Married	3.895606
34	PaymentMethod_Yearly	3.246193
9	LastMonthCalls	3.186624
7	ExistingPolicyTenure	2.960278
28	MaritalStatus_Single	2.871670
21	Gender_Male	2.535430
32	PaymentMethod_Monthly	2.491524
26	Designation_VP	2.364060
18	EducationField_MBA	2.250673
22	Designation_Exe	2.129217
6	Complaint	1.415376
12	Channel_Third_Party_Partner	1.285194
11	Channel_Online	1.168744
33	PaymentMethod_Quarterly	1.124055
30	Zone_South	1.097750

Predict mileage (mpg) for a set of attributes not in the training or test set

Since this is regression, plot the predicted y value vs actual y values for the test data

A good model's prediction will be close to actual leading to high R

Now we get the value of coefficient of determination

```
In [184]: print('The variation in the independent variable which is explained by the dependent variable is',round(model.rsquared*100,4),'%'
```

```
The variation in the independent variable which is explained by the dependent variable is 80.8155 %
```

Then we get the Predictions on test set

```
ypred = model.predict(X_testc)
print(ypred)
```

```
2744    2502.105077
3992    4059.066631
3332    4011.357228
472     3542.932786
1168    3147.634040
           ...
1360    2498.504349
1493    3098.409102
4213    5500.980064
3586    3147.504278
2019    4103.501779
Length: 1356, dtype: float64
```

The Root Mean Square Error

```
In [187]: print("The Root Mean Square Error (RMSE) of the model is for testing set is",np.sqrt(mean_squared_error(y_test,y_pred)))
```

```
The Root Mean Square Error (RMSE) of the model is for testing set is 610.4833684454703
```

```
regression_model = LinearRegression()
regression_model.fit(X_train, y_train)
```

```
LinearRegression()
```

```
print('The coefficient of determination R^2 of the prediction on Train set',regression_model.score(X_train, y_train))
```

```
The coefficient of determination R^2 of the prediction on Train set 0.8081545628073115
```

```
print('The coefficient of determination R^2 of the prediction on Test set',regression_model.score(X_test, y_test))
```

```
The coefficient of determination R^2 of the prediction on Test set 0.8128013867562254
```

```
print("The Root Mean Square Error (RMSE) of the model is for testing set is",np.sqrt(mean_squared_error(y_test,regression_model.p
```

```
The Root Mean Square Error (RMSE) of the model is for testing set is 610.4833684454703
```

Let us explore the coefficients for each of the independent attributes

Now let us check the intercept for the model

```
In [193]: # Let us check the intercept for the model

          intercept = regression_model.intercept_[0]

          print("The intercept for our model is {}".format(intercept))

          The intercept for our model is 1302.718206585811
```

```
In [194]: regression_model.score(X_train, y_train)

Out[194]: 0.8081545628073115
```

```
In [195]: regression_model.score(X_test, y_test)

Out[195]: 0.8128013867562254
```

```
data_train = pd.concat([X_train, y_train], axis=1)
data_train.head()
```

	Age	CustTenure	ExistingProdType	NumberOfPolicy	MonthlyIncome	Complaint	ExistingPolicyTenure	SumAssured	LastMonthCalls	CustCareScore	Cha
4089	21.0	11.0	6	4.0	22165.0	0	1.0	663177.0	5	3.0	
696	13.0	6.0	4	4.0	17743.0	0	1.0	408799.0	2	5.0	
171	18.0	22.0	3	3.0	20296.0	0	1.0	617404.0	7	5.0	
102	3.0	13.0	3	3.0	18161.0	1	3.0	581152.0	0	5.0	
243	25.0	10.0	4	5.0	25266.0	0	6.0	717554.0	11	2.0	

```
In [197]: regression_model_scaled = LinearRegression()
          regression_model_scaled.fit(X_train_scaled, y_train_scaled)

Out[197]: LinearRegression()
```

Let us explore the coefficients for each of the independent attributes

Predict mileage (mpg) for a set of attributes not in the training or test set

Since this is regression, plot the predicted y value vs actual y values for the test data. A good model's prediction will be close to actual leading to high R and R2 values

```
print(grid_search.best_params_)

{'activation': 'relu', 'hidden_layer_sizes': 500, 'solver': 'sgd'}
```

best_params_annr={'activation': 'relu', 'hidden_layer_sizes': 500, 'solver': 'sgd'}

	Train RMSE	Test RMSE	Training Score	Test Score
Linear Regression	611.612103	614.934255	0.808172	0.813200
Decision Tree Regressor	508.120305	597.920356	0.867599	0.823394
Random Forest Regressor	542.802536	620.584032	0.848908	0.809752
ANN Regressor	0.369968	0.424350	0.863124	0.819927

Without tuning

	Train RMSE	Test RMSE	Training Score	Test Score
Linear Regression	613.101894	610.483368	0.808155	0.812801
Decision Tree Regressor	513.260619	593.156926	0.865550	0.823277
Random Forest Regressor	552.781054	625.002852	0.844047	0.803791
ANN Regressor	0.369968	0.424350	0.863124	0.819927

Final Output

	Train RMSE	Test RMSE	Training Score	Test Score
Linear Regression	0.438002	0.432943	0.808155	0.812560
Decision Tree Regressor	0.366675	0.428688	0.865550	0.816227
Random Forest Regressor	0.394837	0.445444	0.844103	0.801580
ANN Regressor	0.369968	0.424350	0.863124	0.819927

Model score - R2 or coeff of determinant

R^2=1–RSS / TSS

0.8131119381670872

We can see that the scaled output has a better score.

Now we see stats model formula

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 1.95e+07. This might indicate that there are

strong multicollinearity or other numerical problems.

The overall P value is less than alpha, so rejecting H0 and accepting Ha that at least 1 regression co-efficient is not 0. Here all regression co-efficients are not 0

PROBLEM 6

Final interpretation / recommendation - Very clear and crisp on what recommendations do you want to give to the management / client.

Resolution:

Actionable Insights and Recommendations

The final interpretation is as follows:

The objective we have here is that an Insurance company is looking for a practicable model to predict the agent bonus for the high performing agents. This will help in strategizing the agent force to reach out to policy holders in advance to follow up for payment of premium

1. Based on the Variable importance of the Logistic Regression model, the insurance company is suggested to orient its agents force to contact policy holders for Renewal premium Monthly and Quarterly.
2. Age between 30-40 years are higher. As we saw in the EDA, the mean age of a policyholder is around 35 years and agent can target these age group.

3. Zones: Business need to focus on expanding their reach in East Zone and South Zone
4. Agents should focus more on AVPs as their number is really high all the metrics.
5. When Age increases by 1 unit, AgentBonus increases by 23.04 units, keeping all other predictors constant. similarly, when MonthlyIncome increases by 1 unit, AgentBonus increases by 0.03 units, keeping all other predictors constant.
6. There are also some negative co-efficient values. Occupation_Large_Business has its corresponding co-efficient as -39.31. This implies, when the Occupation is large business, the AgentBonus decreases by 39.31 units, keeping all other predictors constant.

The End

Thakur Arun Singh

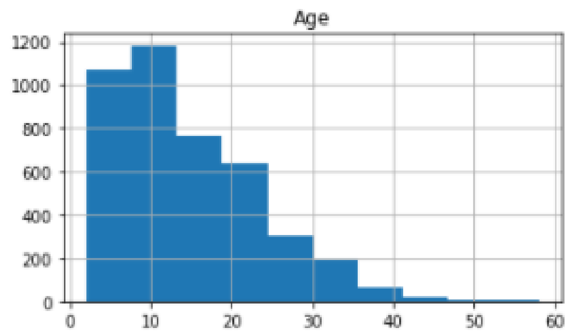
*****************************^^**************************

APPENDIX – GRAPHICAL REPRESENTATIONS

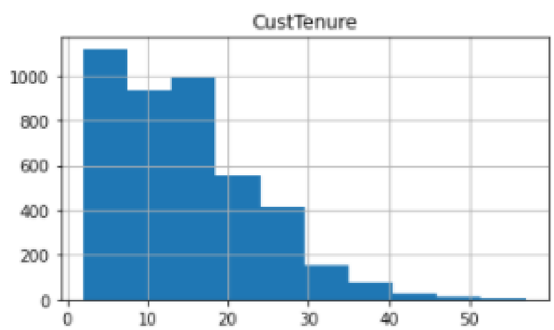
Title	Artifact/Location	Remarks
Source of Data	LifeInsuranceSales.xlsx	Data File for Insurance Premium
Data Dictionary	LifeInsuranceSales.xlsx	Insurance Premium Renewals (provided with dataset)
Modified Data Source(for Model Validation)	AgentBonus.csv	Variable description and rationale behind selection
Project Notes 1	Life Insurance Capstone Business Re	As per Capstone Project guidelines/instructions
Project Notes 2	Life Insurance Capstone Business Re	As per Capstone Project guidelines/instructions
Project Presentation	Life Insurance Capstone PPT Thakur	As per Capstone Project guidelines/instructions
Python Code for Reference	**LifeInsuranceSales-Capstone-Thakur Arun** **Life Insurance Capstone_Thakur Ar**	Complete Python-code used in EDA, Model Building, etc.

Agent Bonus: From the below graph we can see that the majority of the bonus falls between 3,000 to 4,000.

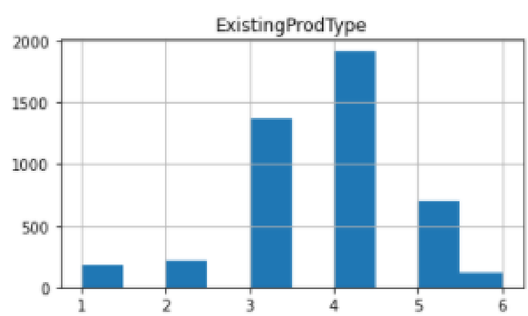
Age: Below the graph shows that the average age of the customer is about 30-35 years.



Customer Tenure: Below graph shows that there are over 1000 customer who are loyal customers for at least 10 years.

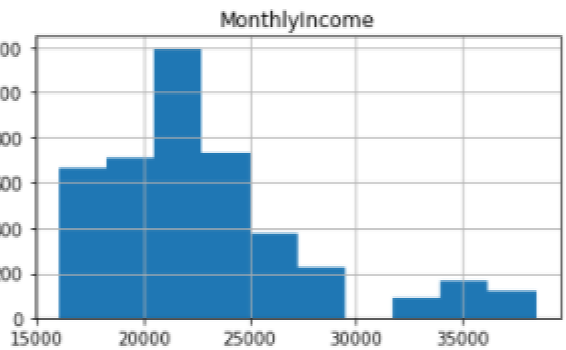


Existing Product Type: Below graph shows that there at about 2000 people who hold at least 4 products

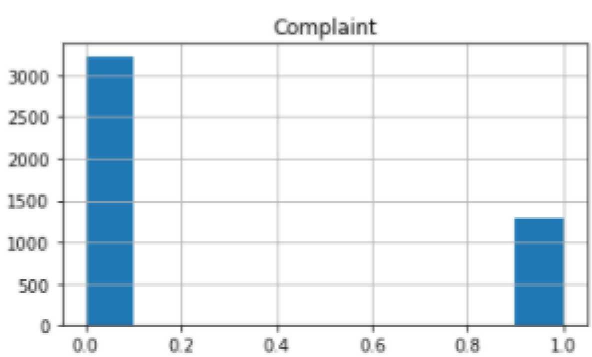


Number of Policies: Below graph shows that at least 1000 people hold 4 policies each.

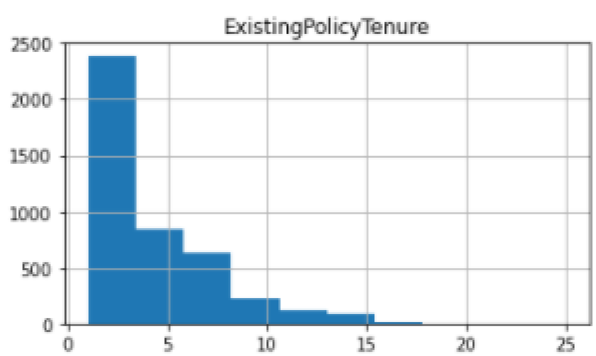
Monthly Income: About 1200 people have a monthly income between 20,000 – 25,000.



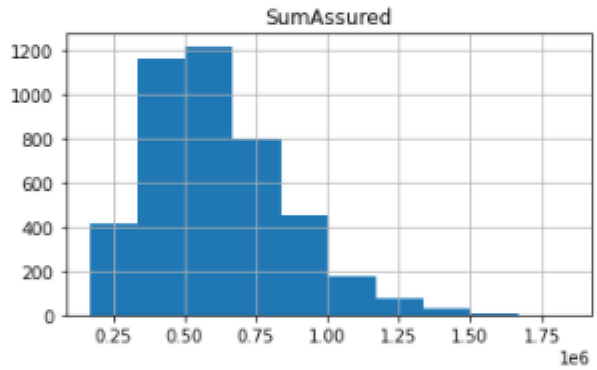
Complaints: There were about 3000+ people who had complained between 0-1 times.



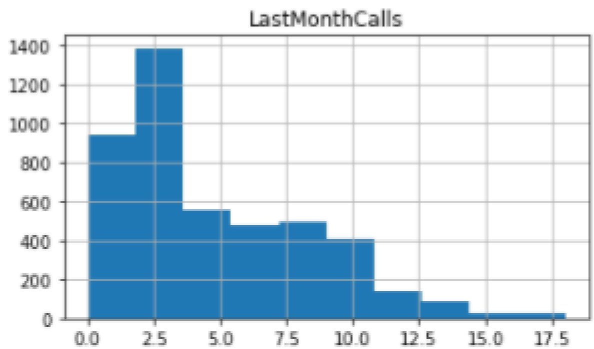
Existing Policy Tenure: There are about 2500 customer who took policies at least a year ago.



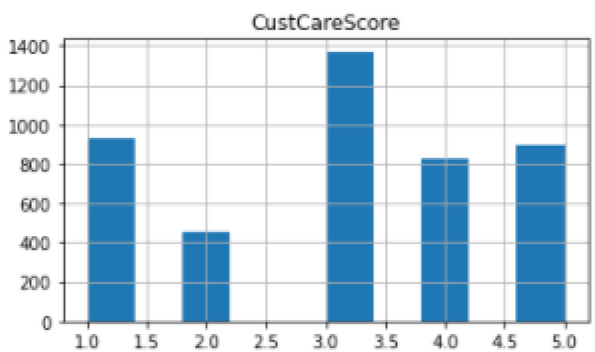
Sum Assured: The major count of the sum assured is between 400K and 600K



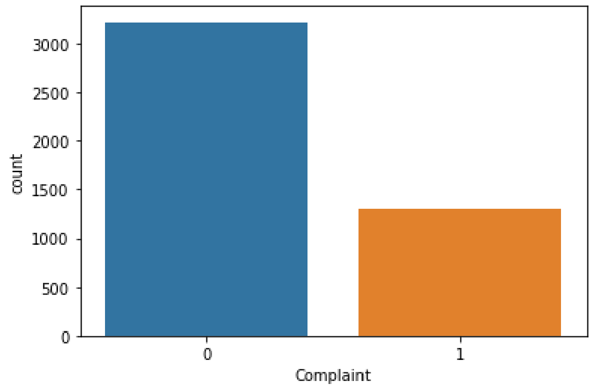
Last Month Calls: We have received at least 2 calls from nearly 1400 customers



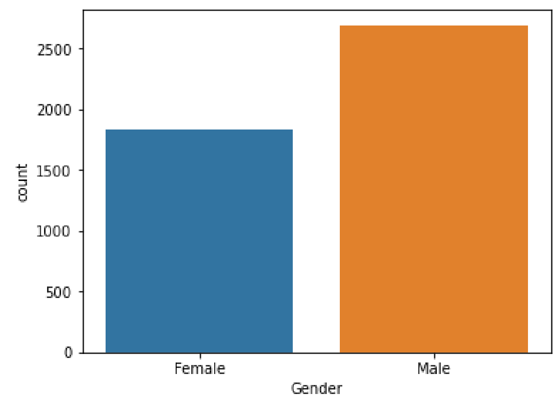
Customer Care Score: Marjory of the customer lies between the Customer care score of 3 – 3.5.



Complaints: Below graph shows the count of the customers who complained and not complained.



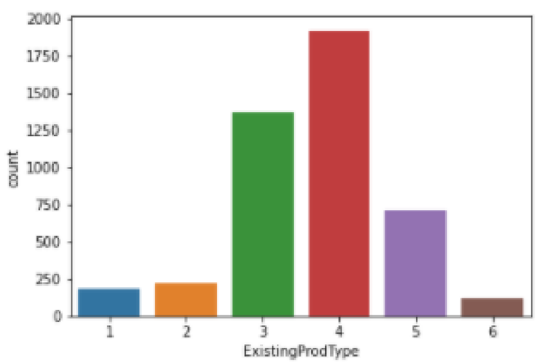

```
0    0.712832
1    0.287168
Name: Complaint, dtype: float64
```




```
Male      0.59469
Female    0.40531
Name: Gender, dtype: float64
```

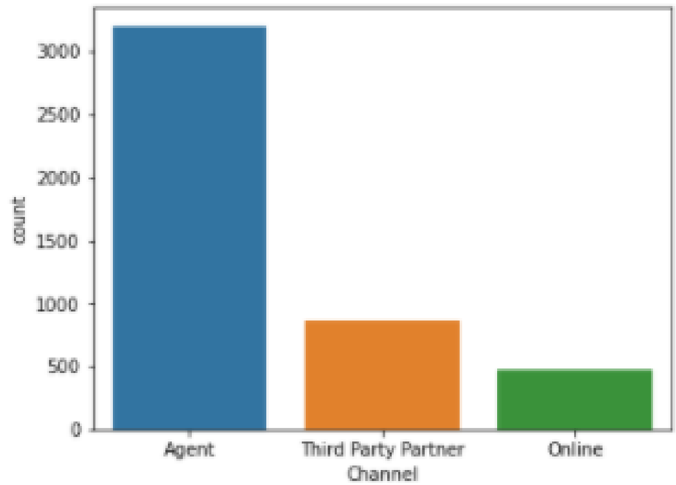
Gender: Below graph gives me the count of Gender

Existing Policy Type: Below Count Plot shows the existing policy types



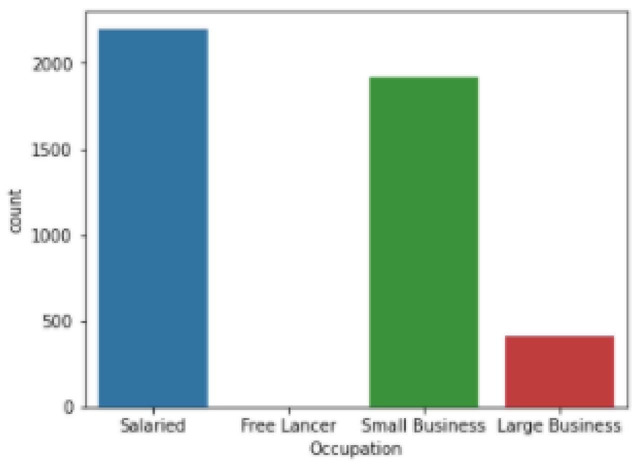

```
4    0.423894
3    0.302876
5    0.156637
2    0.048894
1    0.040487
6    0.027212
Name: ExistingProdType, dtype: float64
```

Blow graph shows the channel data



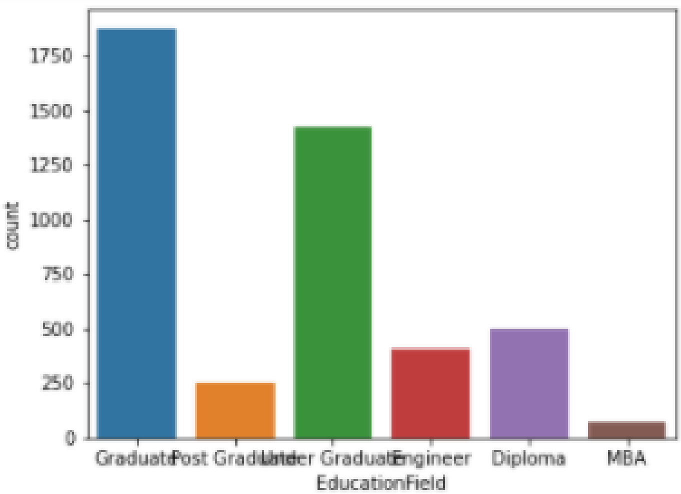

```
Agent                  0.706637
Third Party Partner    0.189823
Online                 0.103540
Name: Channel, dtype: float64
```

Below graph shows the occupation



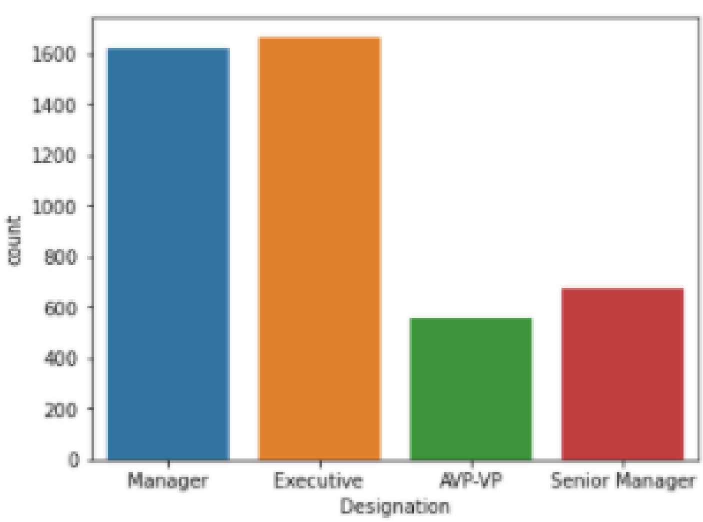

```
Salaried          0.484956
Small Business    0.424336
Large Business    0.090265
Free Lancer       0.000442
Name: Occupation, dtype: float64
```

Below graph shows the education field



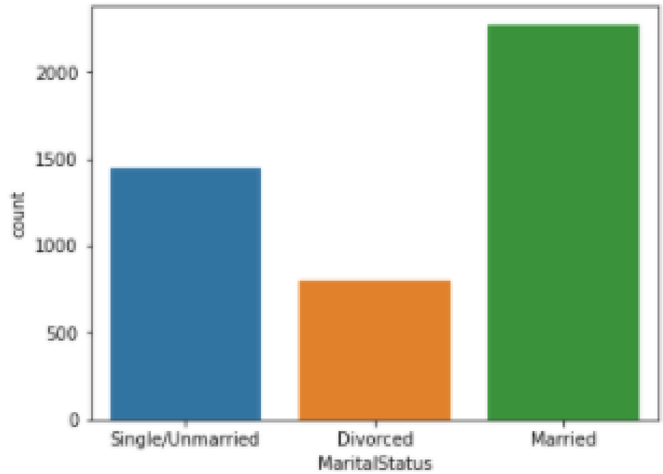

```
Graduate          0.413717
Under Graduate    0.314159
Diploma           0.109735
Engineer          0.090265
Post Graduate     0.055752
MBA               0.016372
Name: EducationField, dtype: float64
```

Below graph shows the designation



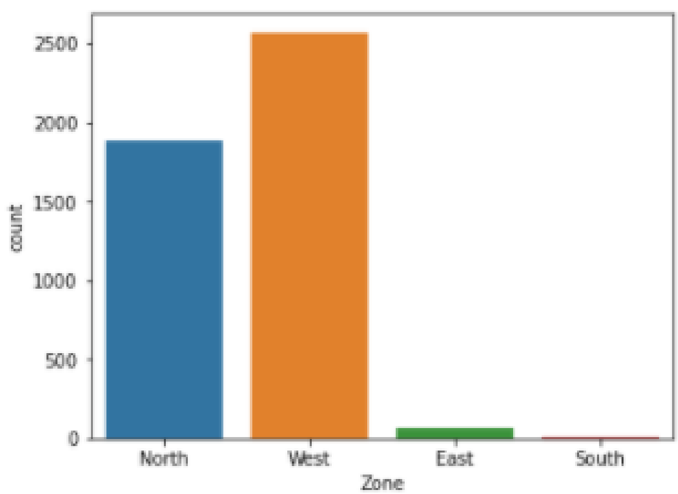

```
Executive         0.367699
Manager           0.358407
Senior Manager    0.149558
AVP-VP            0.124336
Name: Designation, dtype: float64
```

Below graph shows the marital status



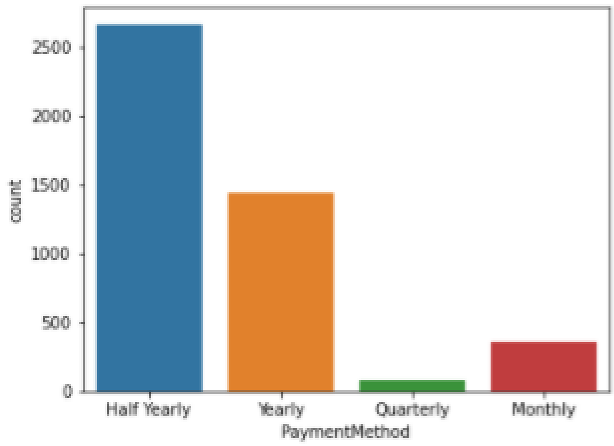

```
Married             0.501770
Single/Unmarried    0.320354
Divorced            0.177876
Name: MaritalStatus, dtype: float64
```

Below graph shows the various Zones




```
West     0.567699
North    0.416814
East     0.014159
South    0.001327
Name: Zone, dtype: float64
```

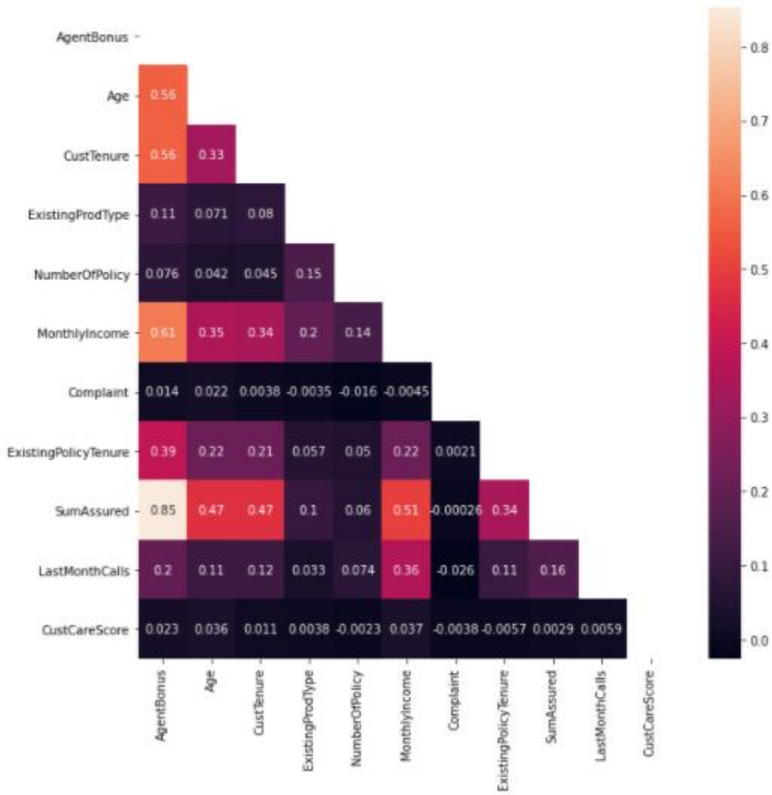
Below graph shows various payment methods



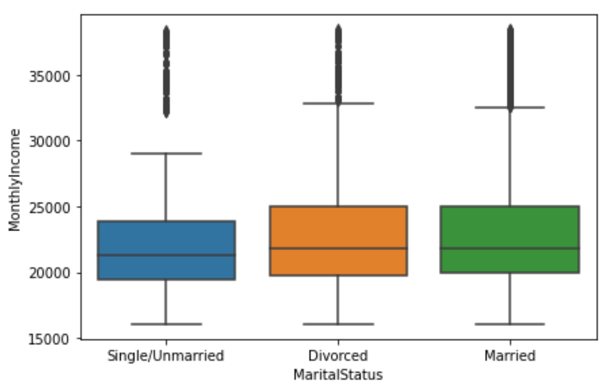

```
Half Yearly    0.587611
Yearly         0.317257
Monthly        0.078319
Quarterly      0.016814
Name: PaymentMethod, dtype: float64
```

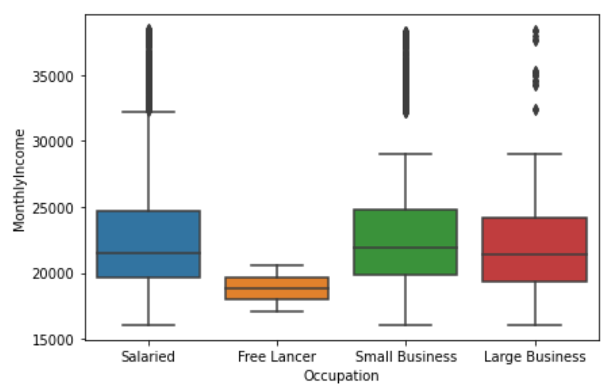
Below Pair plot shows the pairwise relationships in a dataset

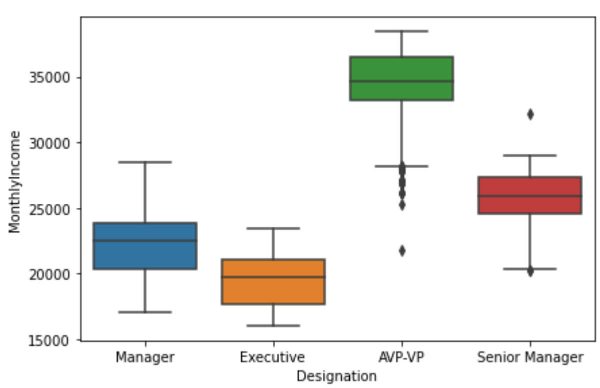
Below Correlation / Heat Map shows Strong Correlation

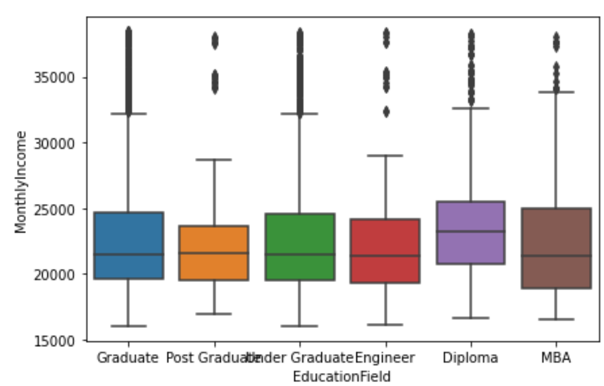


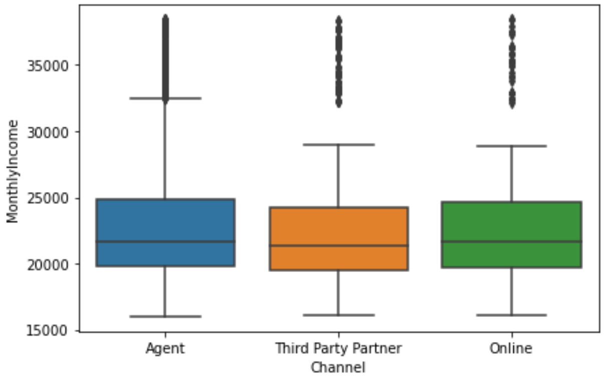
Below box plots shows relationship between MonthlyIncome & categorical variables



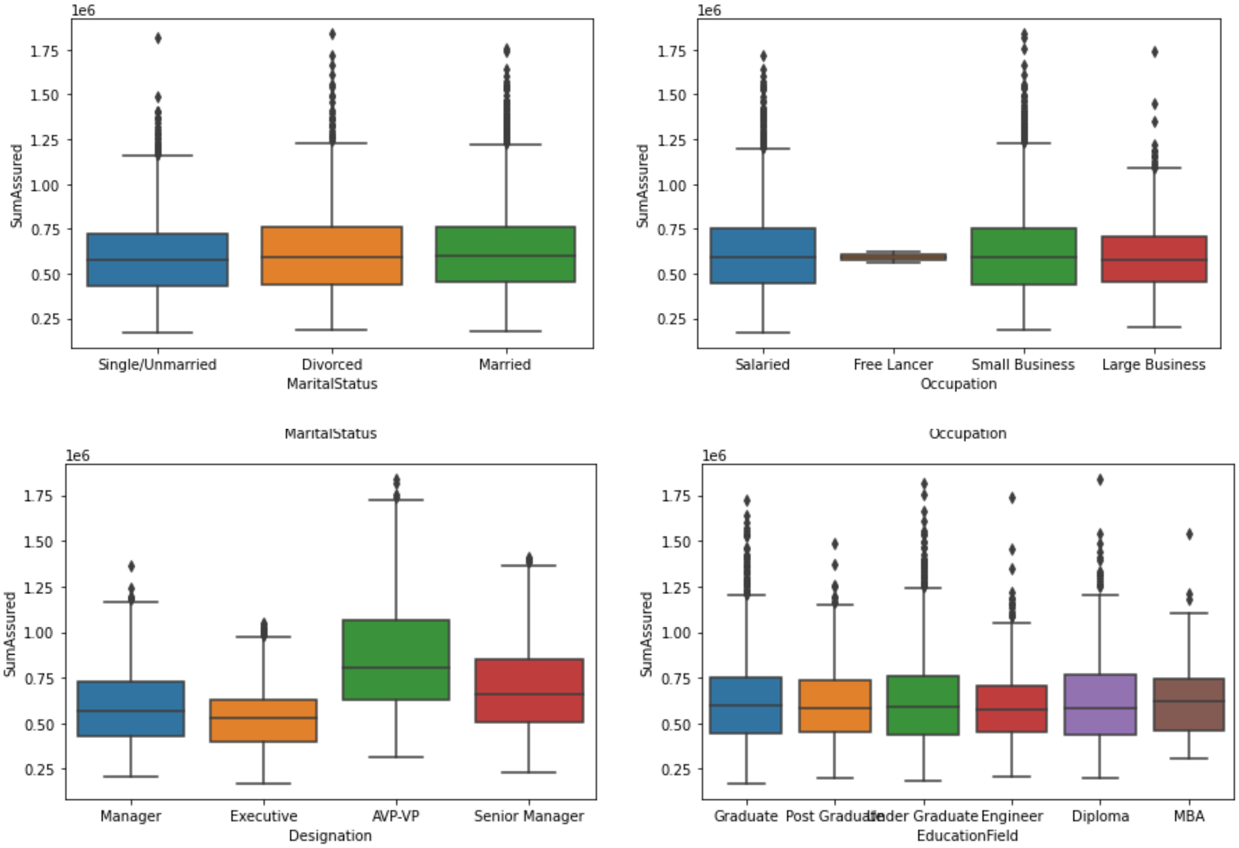


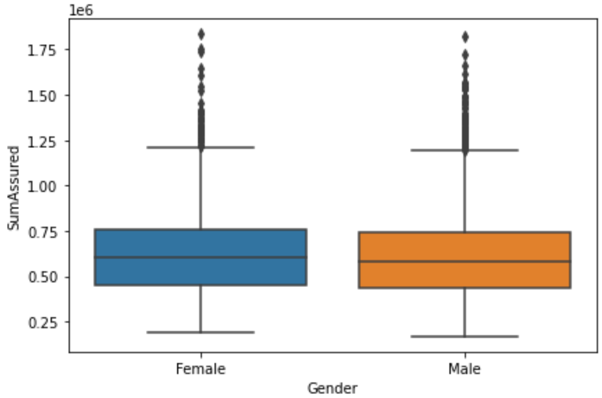


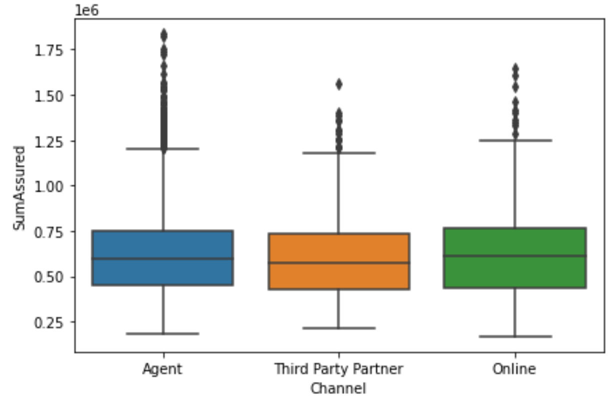




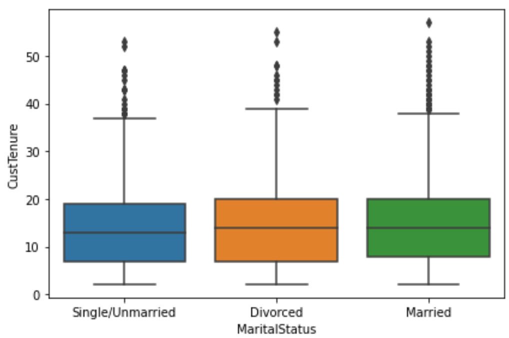
Customer Designation creates clear groups for MonthlyIncome of the customer so Missing Values in MonthlyIncome will be filled considering means of every group

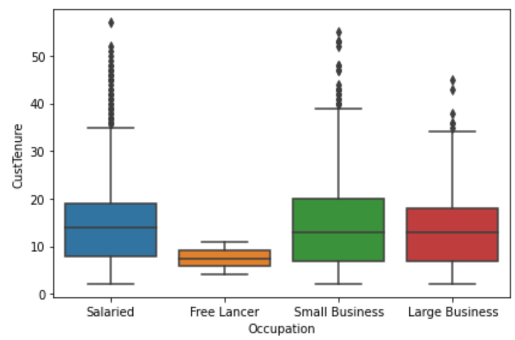


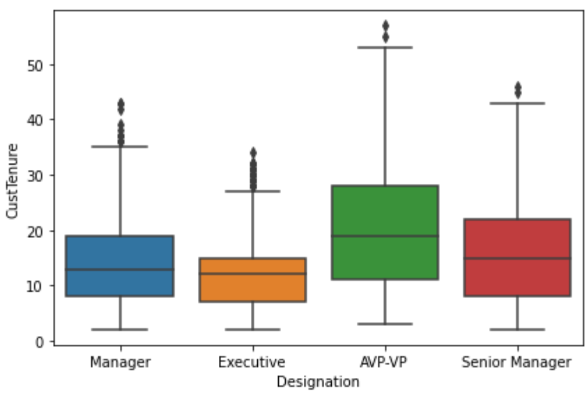


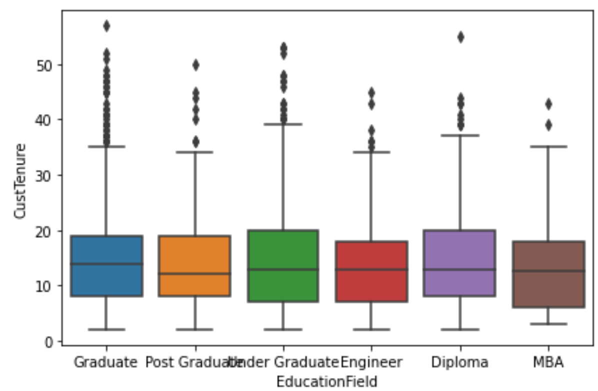


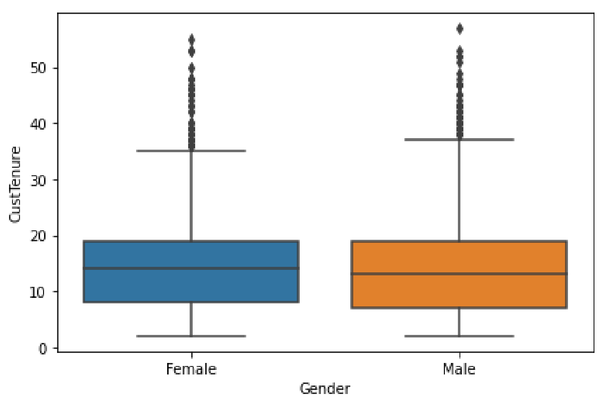
Below box plots shows the relationship between CustTenure & categorical variables

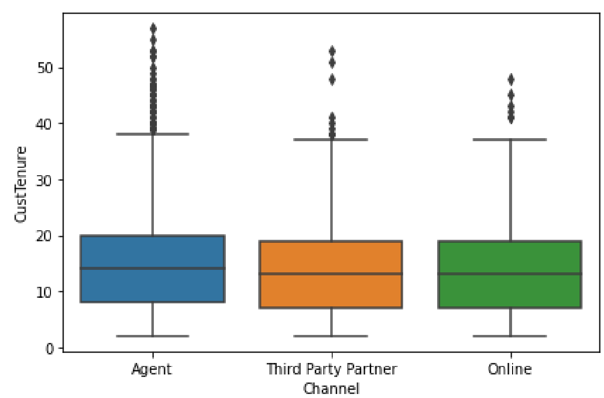




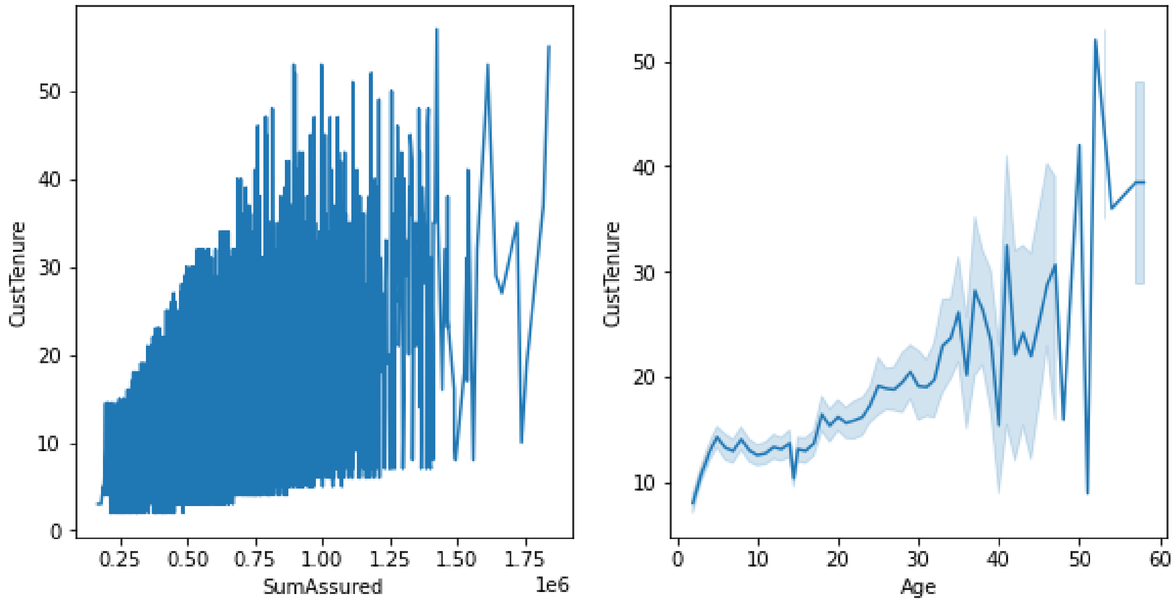




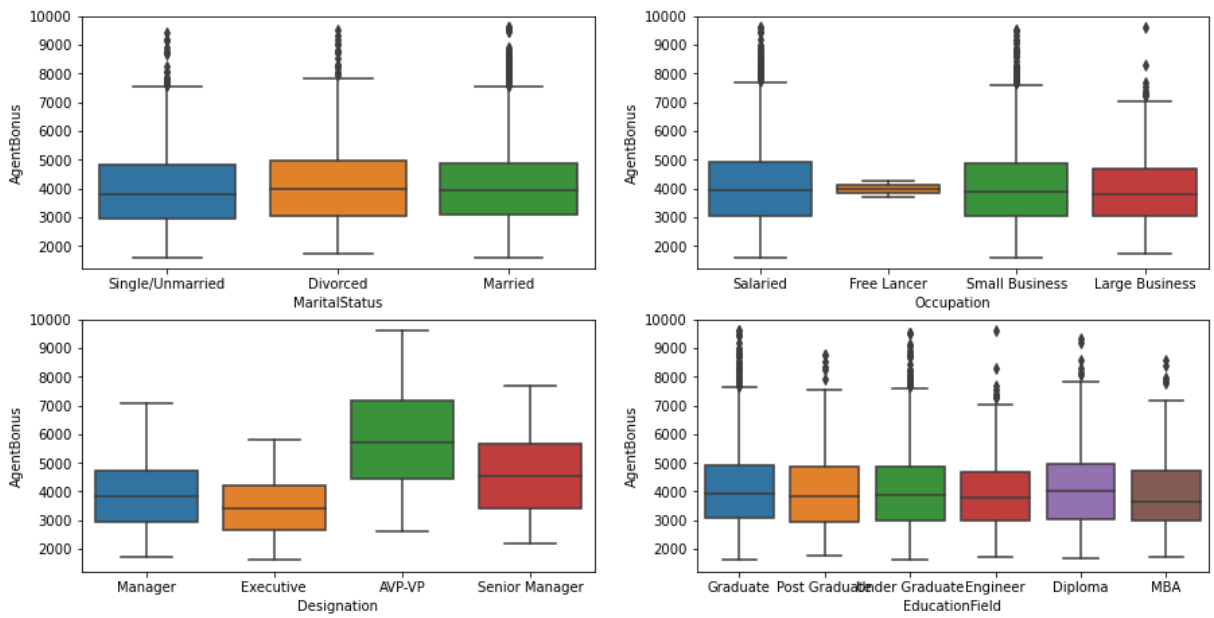


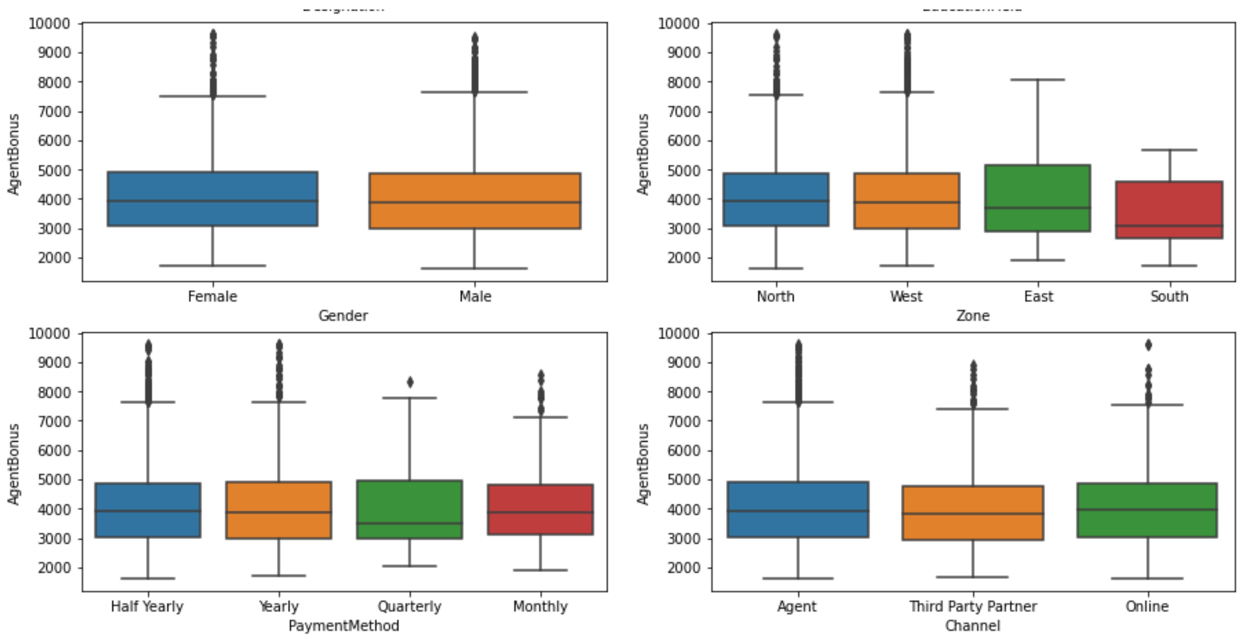


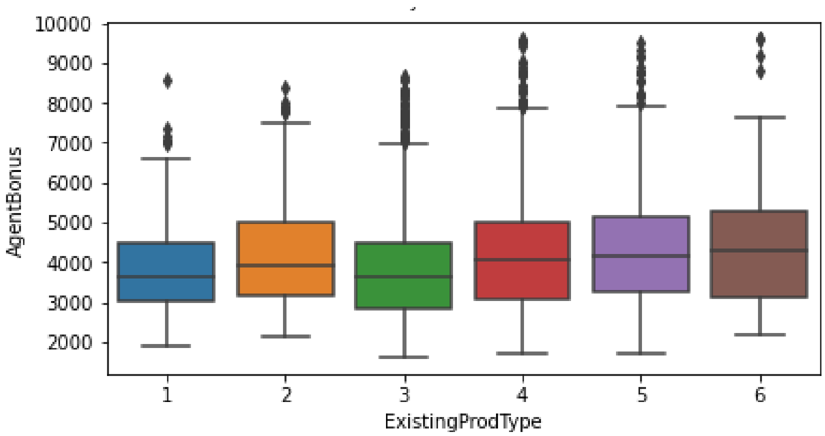
Below graphs shows the relationship between Customer tenure VS Sum Assured and age



Below Box plots shows relationship between AgentBonus & categorical variables

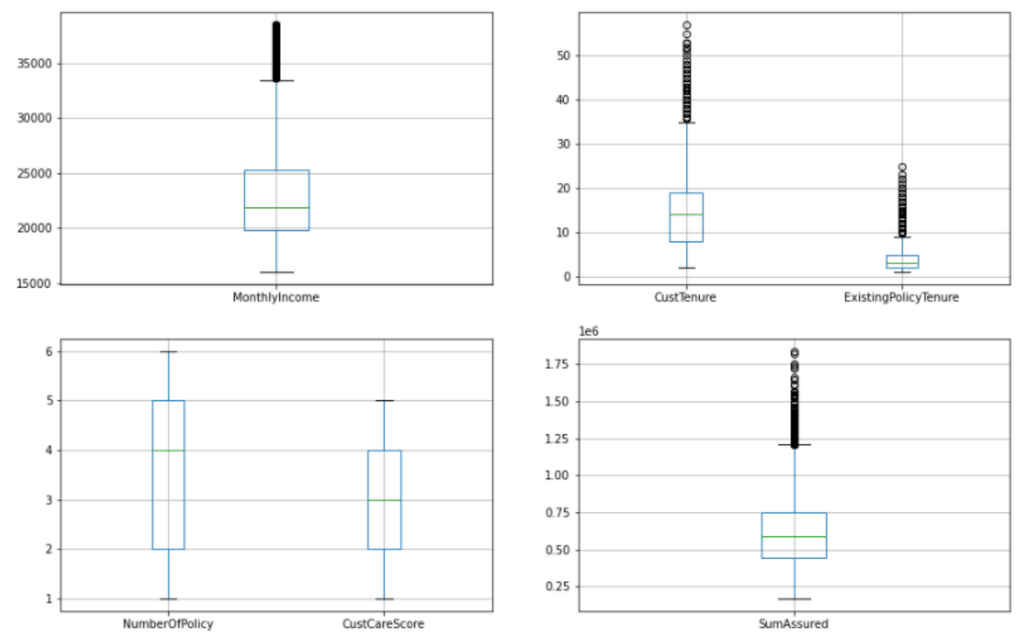






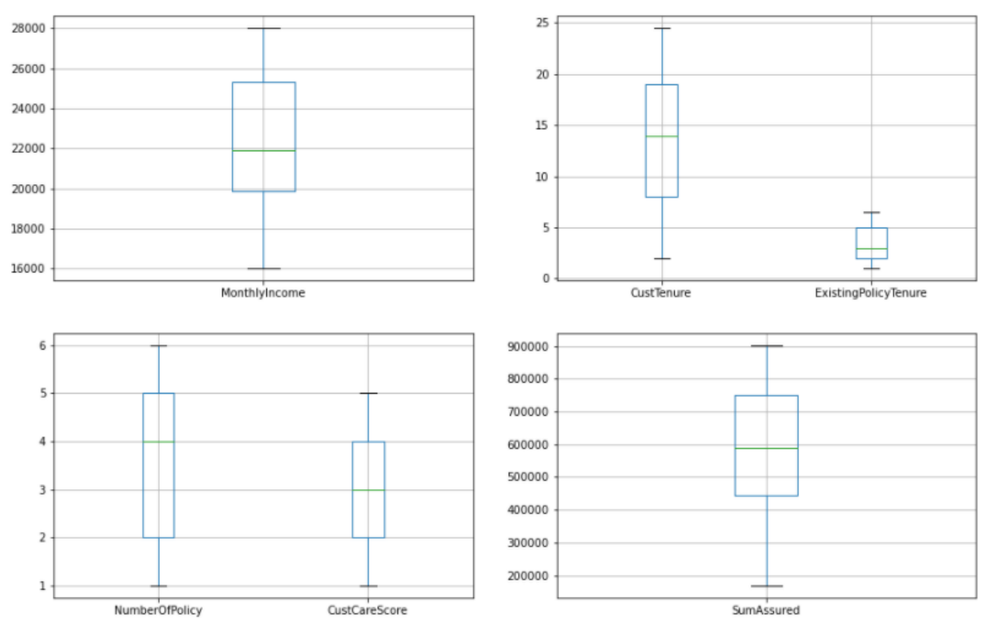
Outlier treatment

First we check for the outliers and box plots shows the outliers

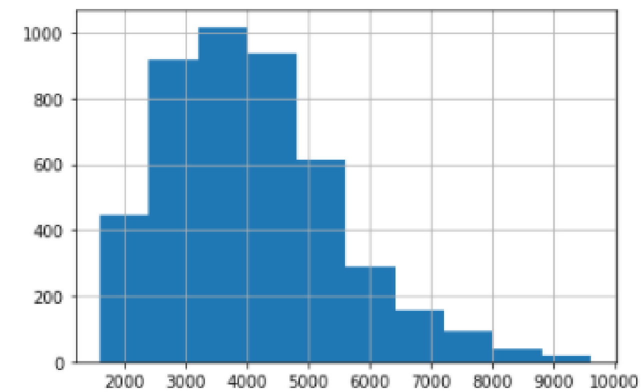


Based on the above graph we remove the below outliers

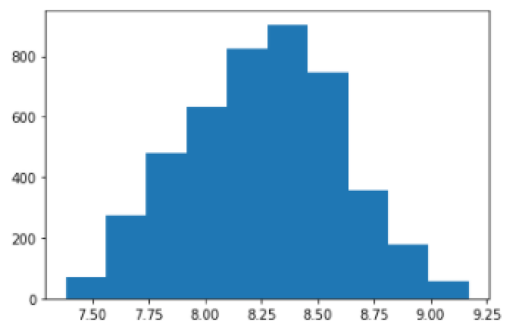
After removing the outliers, we can see from the below box plots that there are no outliers

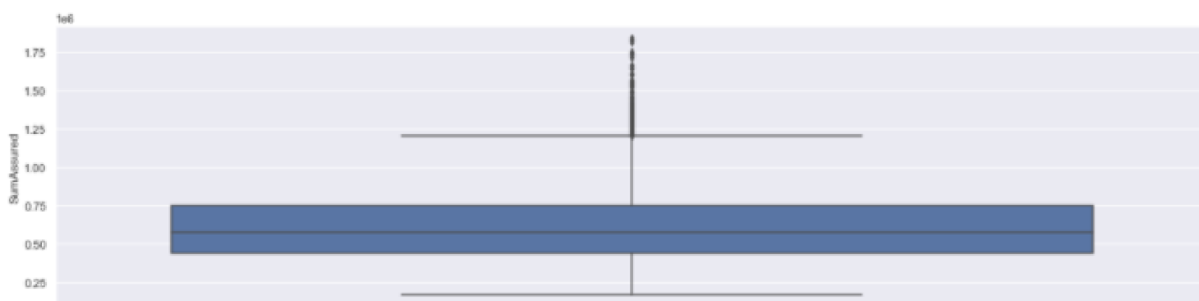


Normality Test of the Continues Variables



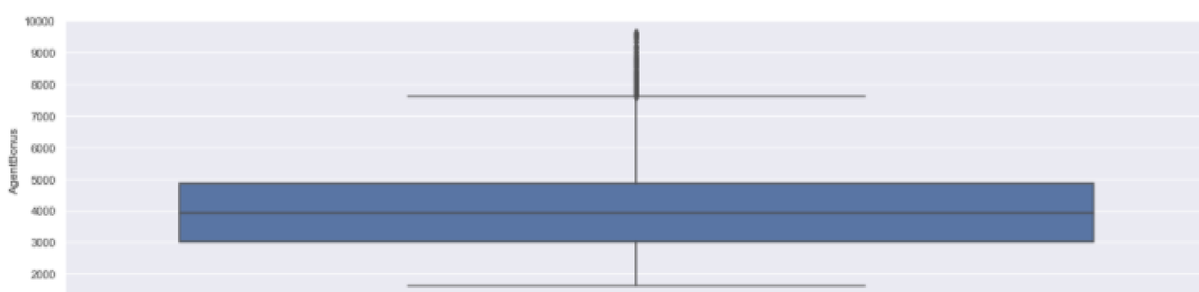

```
(array([ 69., 276., 480., 634., 824., 904., 745., 355., 177.,  56.]),
 array([7.38087904, 7.55982627, 7.7387735 , 7.91772073, 8.09666797,
        8.2756152 , 8.45456243, 8.63350967, 8.8124569 , 8.99140413,
        9.17035136]),
 <BarContainer object of 10 artists>)
```

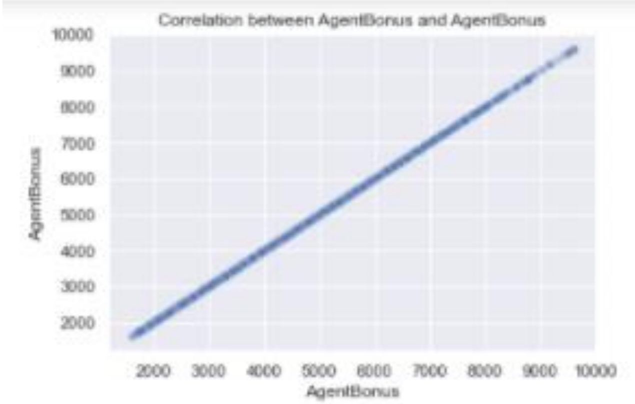




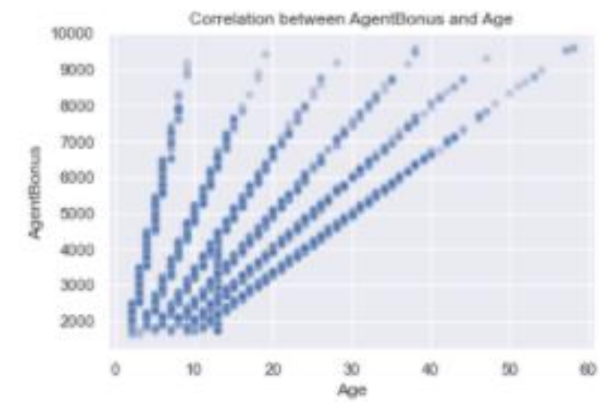

```
plt.figure(figsize=(20,5))
sns.boxplot(y="AgentBonus", data=df)
```

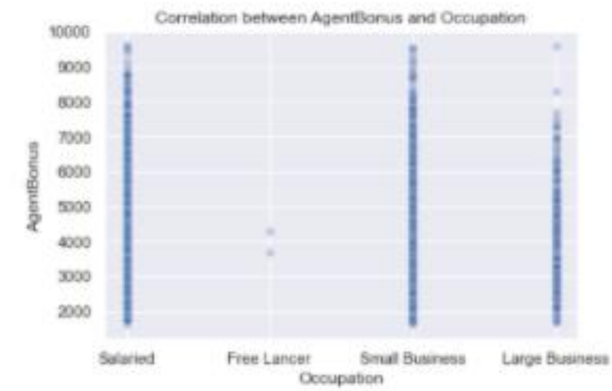
```
<AxesSubplot:ylabel='AgentBonus'>
```

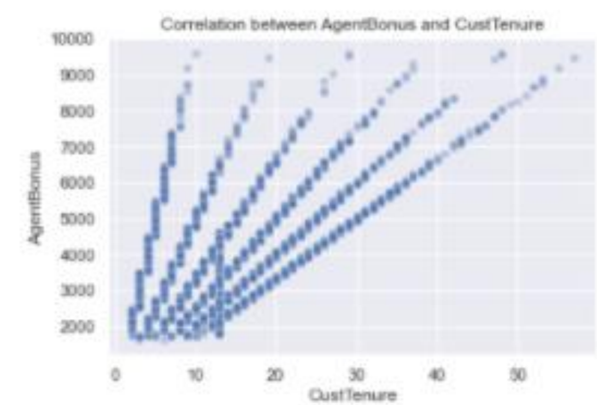


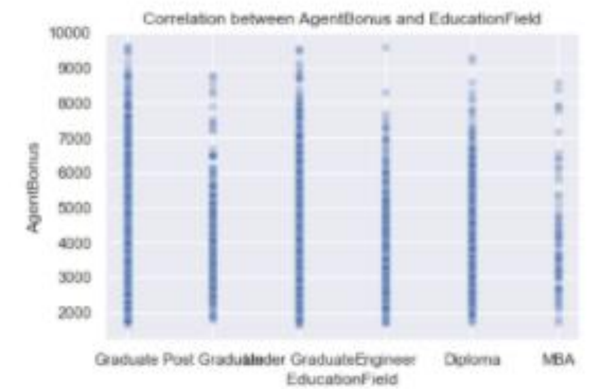

Correlation between AgentBonus and AgentBonus
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
2000 3000 4000 5000 6000 7000 8000 9000 10000
AgentBonus

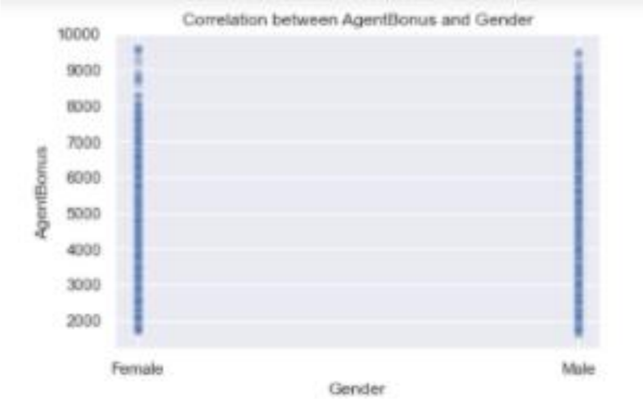

Correlation between AgentBonus and Channel
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
Agent
Third Party Partner
Online
Channel

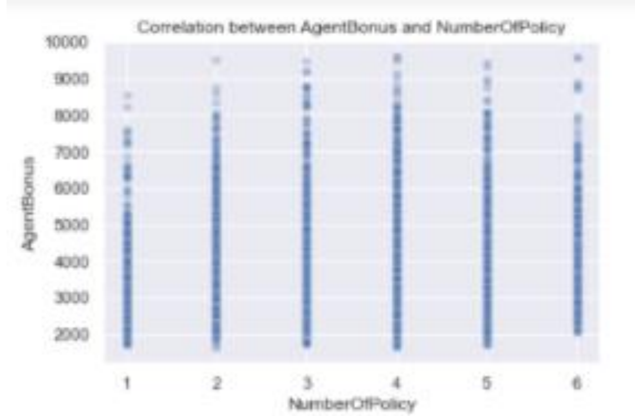

Correlation between AgentBonus and Age
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
0 10 20 30 40 50 60
Age

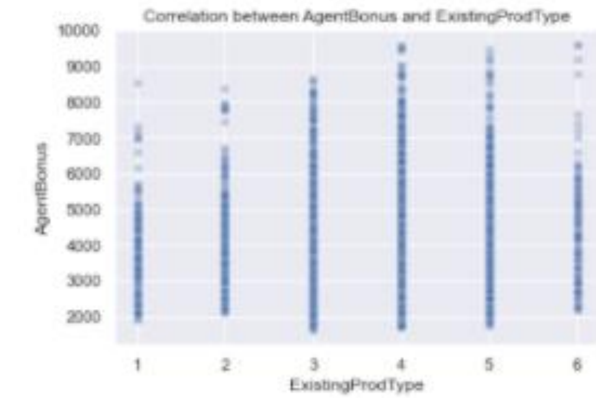

Correlation between AgentBonus and Occupation
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
Salaried
Free Lancer
Small Business
Large Business
Occupation

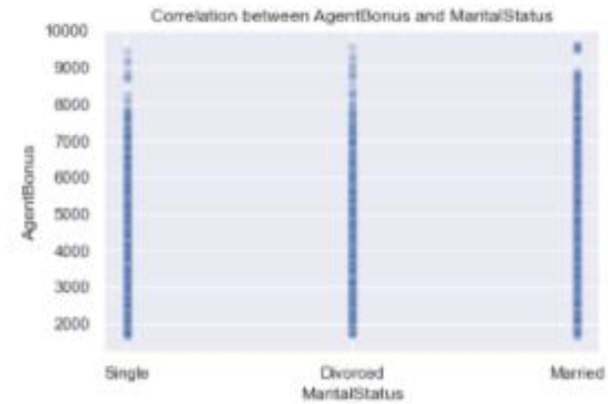

Correlation between AgentBonus and CustTenure
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
0 10 20 30 40 50
CustTenure


Correlation between AgentBonus and EducationField
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
Graduate
Post Graduate
Under Graduate
Engineer
Diploma
MBA
EducationField

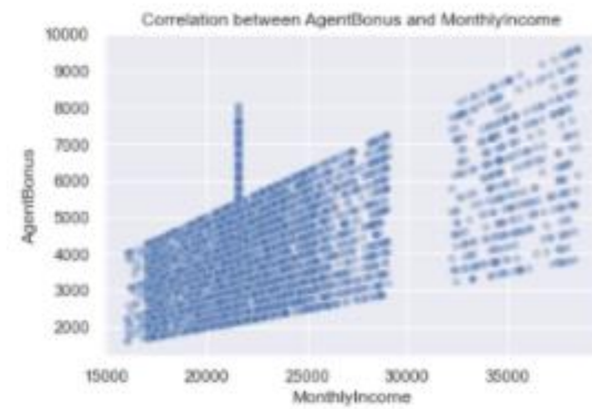

Correlation between AgentBonus and Gender
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
Female
Male
Gender

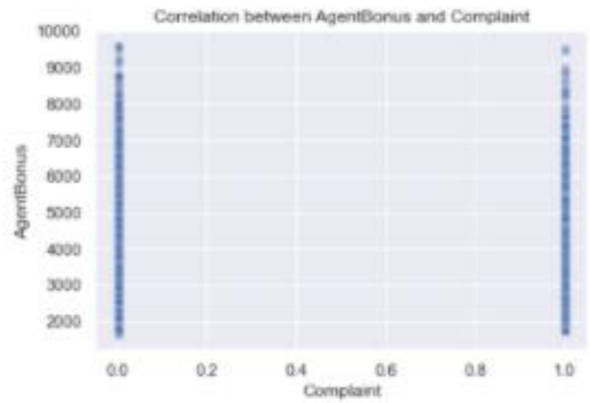

Correlation between AgentBonus and NumberOfPolicy
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
1
2
3
4
5
6
NumberOfPolicy


Correlation between AgentBonus and ExistingProdType
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
1
2
3
4
5
6
ExistingProdType

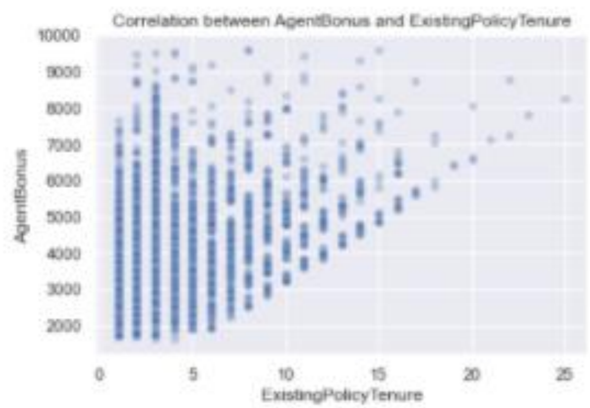

Correlation between AgentBonus and MaritalStatus
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
Single
Divorced
Married
MaritalStatus


Correlation between AgentBonus and Designation
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
Manager
Exe
Executive
VP
AVP
Senior Manager
Designation

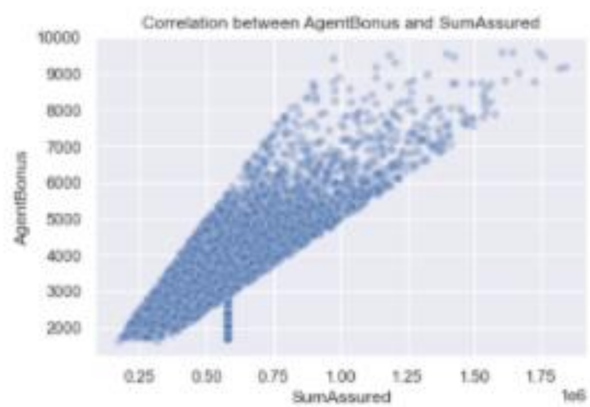

Correlation between AgentBonus and MonthlyIncome
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
15000
20000
25000
30000
35000
MonthlyIncome

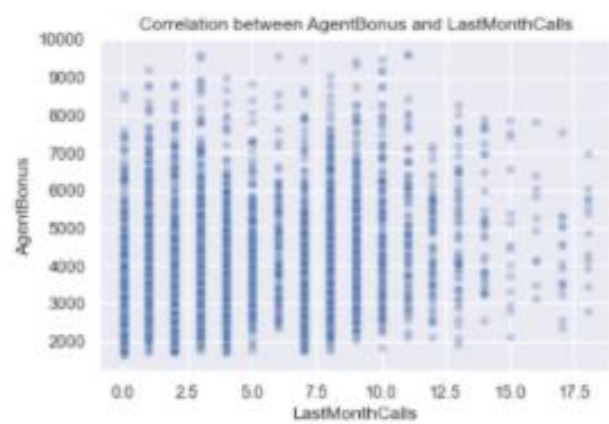

Correlation between AgentBonus and Complaint
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
0.0
0.2
0.4
0.6
0.8
1.0
Complaint

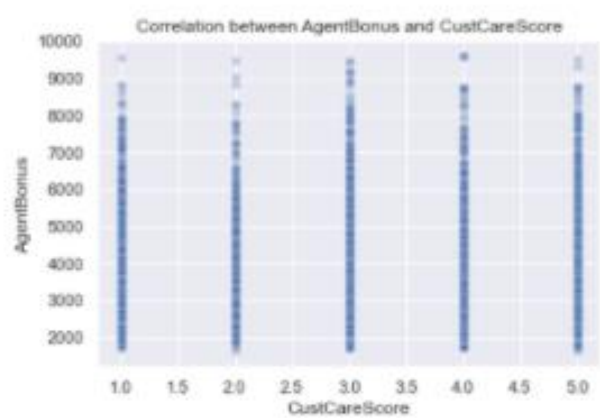

Correlation between AgentBonus and Zone
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
North
West
East
South
Zone

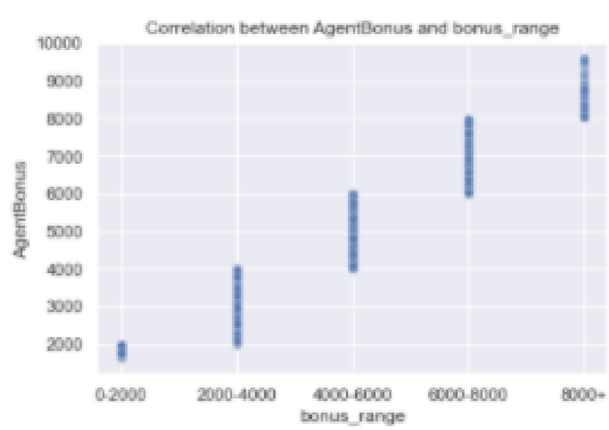

Correlation between AgentBonus and ExistingPolicyTenure
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
0
5
10
15
20
25
ExistingPolicyTenure

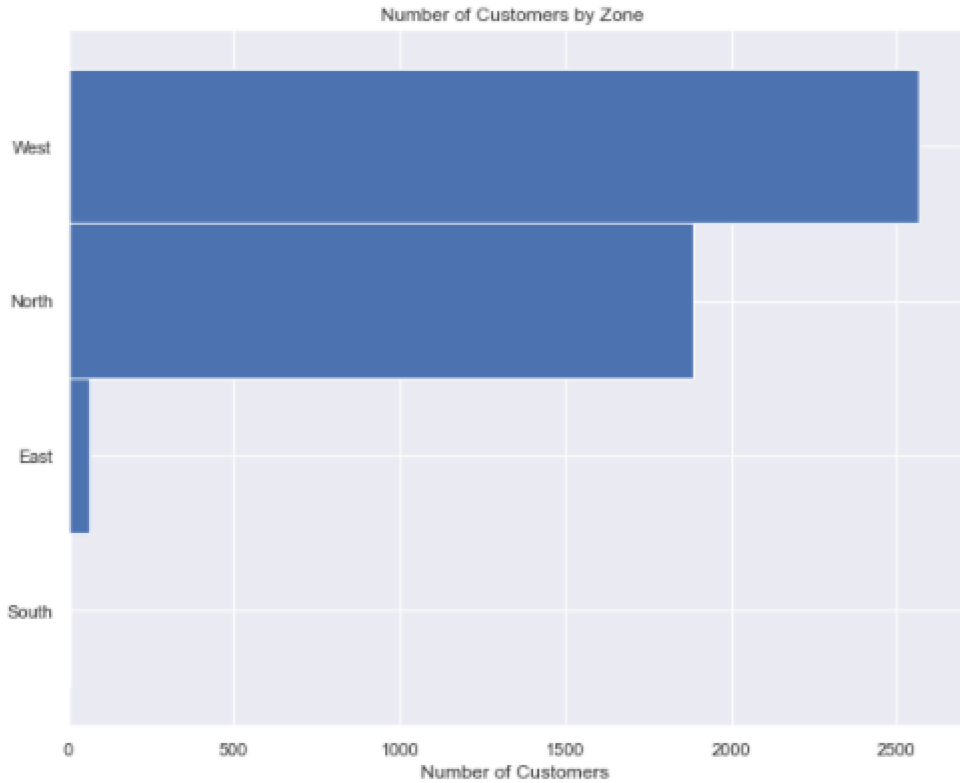

Correlation between AgentBonus and PaymentMethod
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
Half Yearly
Yearly
Quarterly
Monthly
PaymentMethod

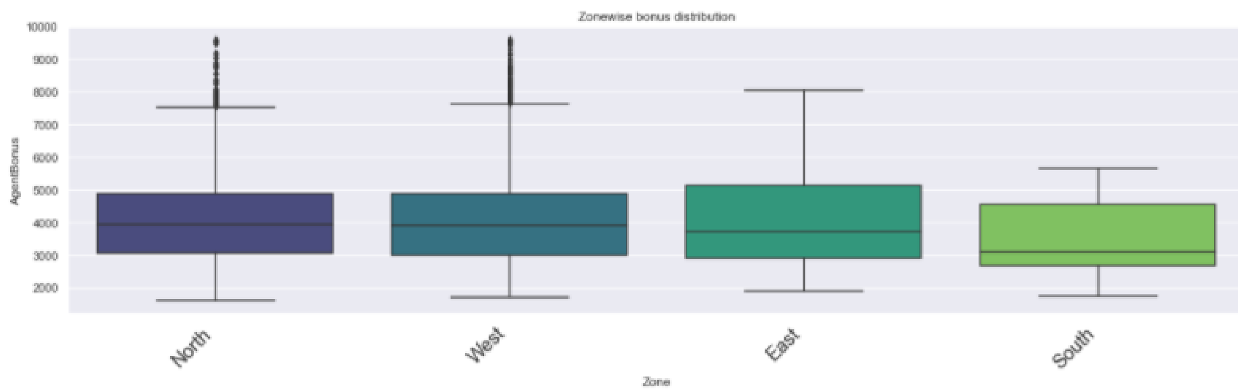

Correlation between AgentBonus and SumAssured
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
SumAssured


Correlation between AgentBonus and LastMonthCalls
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
LastMonthCalls

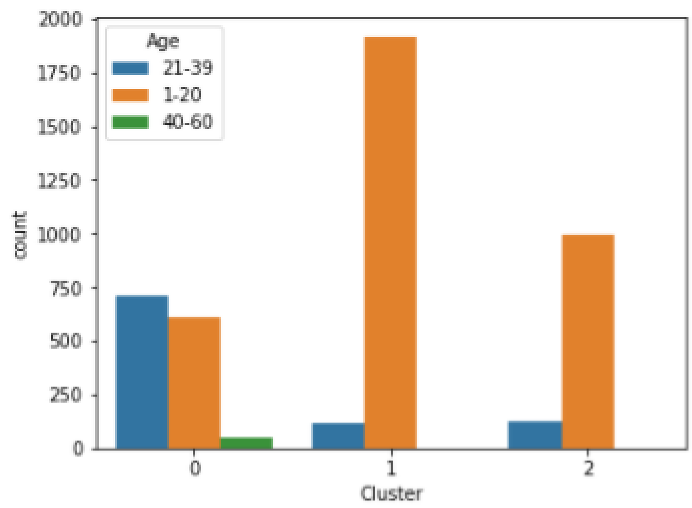

Correlation between AgentBonus and CustCareScore
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
CustCareScore


Correlation between AgentBonus and bonus_range
AgentBonus
10000
9000
8000
7000
6000
5000
4000
3000
2000
0-2000
2000-4000
4000-6000
6000-8000
8000+
bonus_range

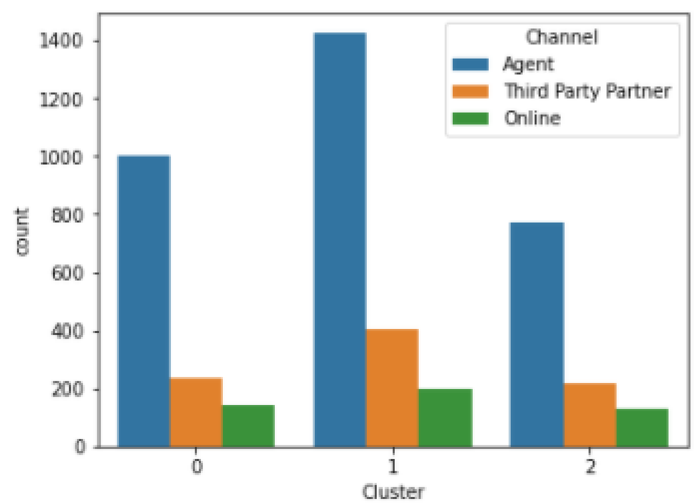




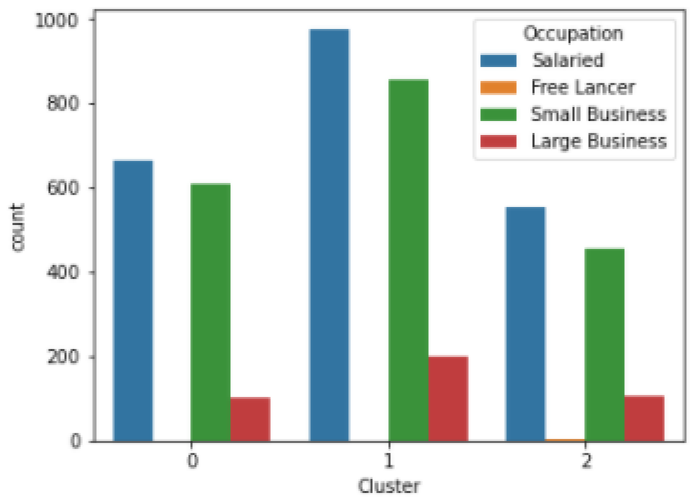
Below graphs shows the findings with variables VS Clusters



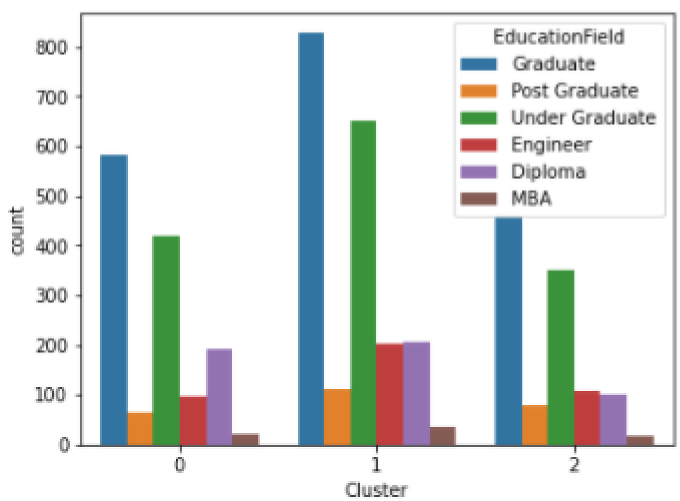

```
1-20     0.778097
21-39    0.210841
40-60    0.011062
Name: Age, dtype: float64
```



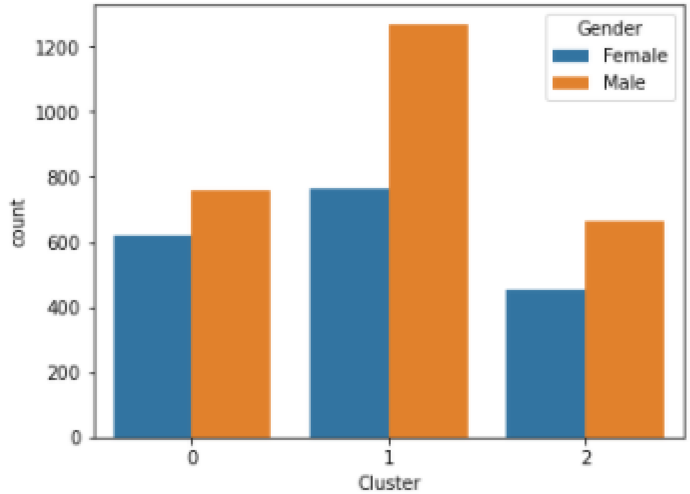

```
Agent                  0.706637
Third Party Partner    0.189823
Online                 0.103540
Name: Channel, dtype: float64
```



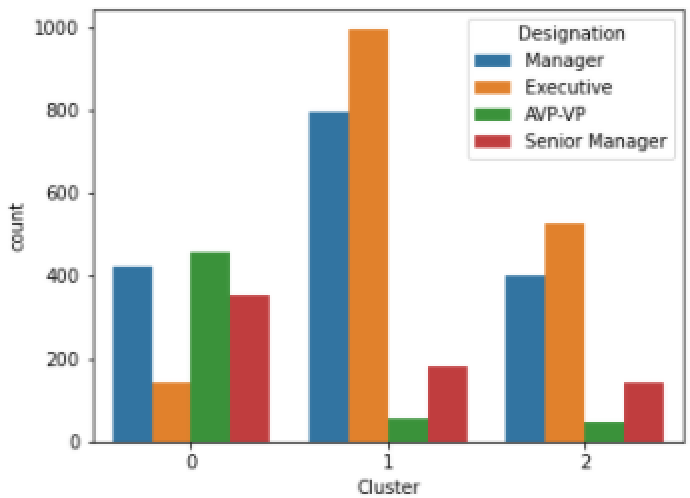

```
Salaried          0.484956
Small Business    0.424336
Large Business    0.090265
Free Lancer       0.000442
Name: Occupation, dtype: float64
```



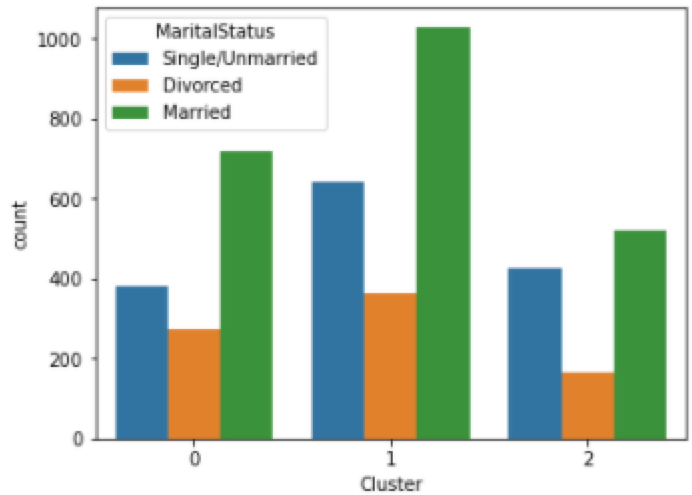

```
Graduate          0.413717
Under Graduate    0.314159
Diploma           0.109735
Engineer          0.090265
Post Graduate     0.055752
MBA               0.016372
Name: EducationField, dtype: float64
```



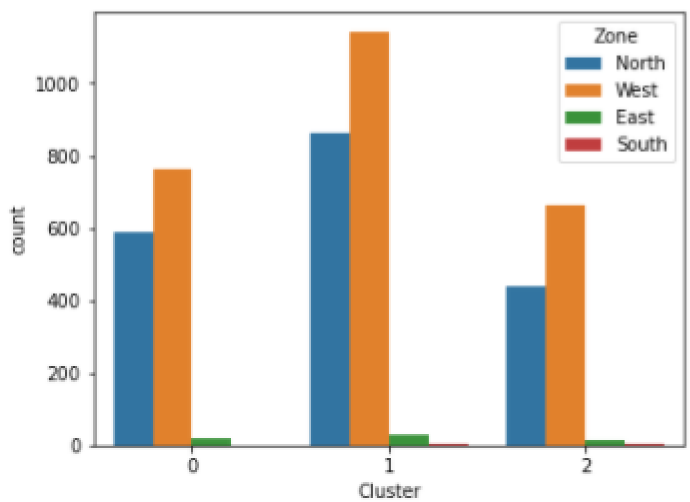

```
Male      0.59469
Female    0.40531
Name: Gender, dtype: float64
```



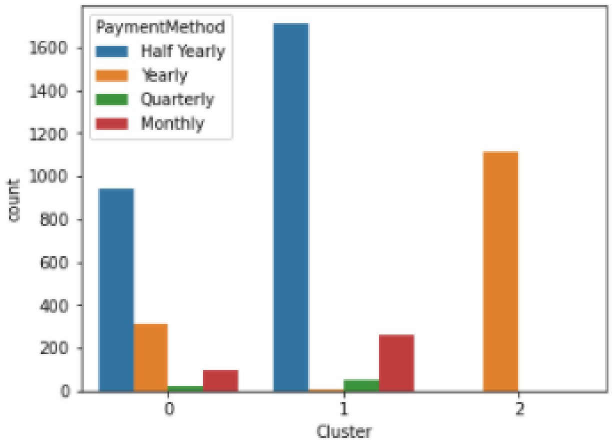

```
Executive         0.367699
Manager           0.358407
Senior Manager    0.149558
AVP-VP            0.124336
Name: Designation, dtype: float64
```




```
Married             0.501770
Single/Unmarried    0.320354
Divorced            0.177876
Name: MaritalStatus, dtype: float64
```



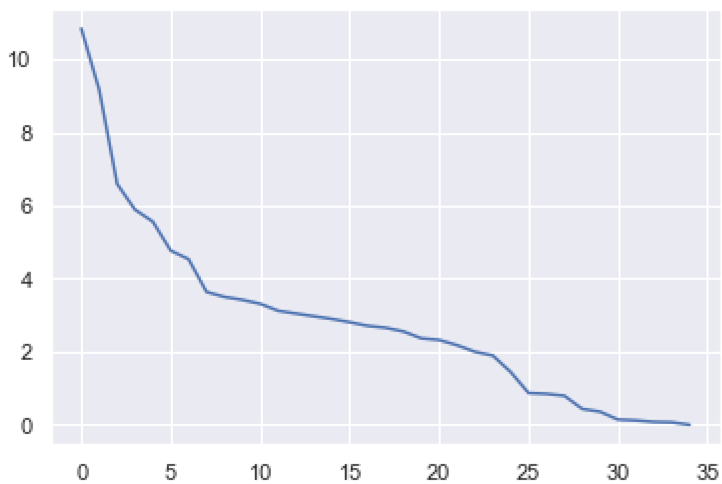

```
West     0.567699
North    0.416814
East     0.014159
South    0.001327
Name: Zone, dtype: float64
```



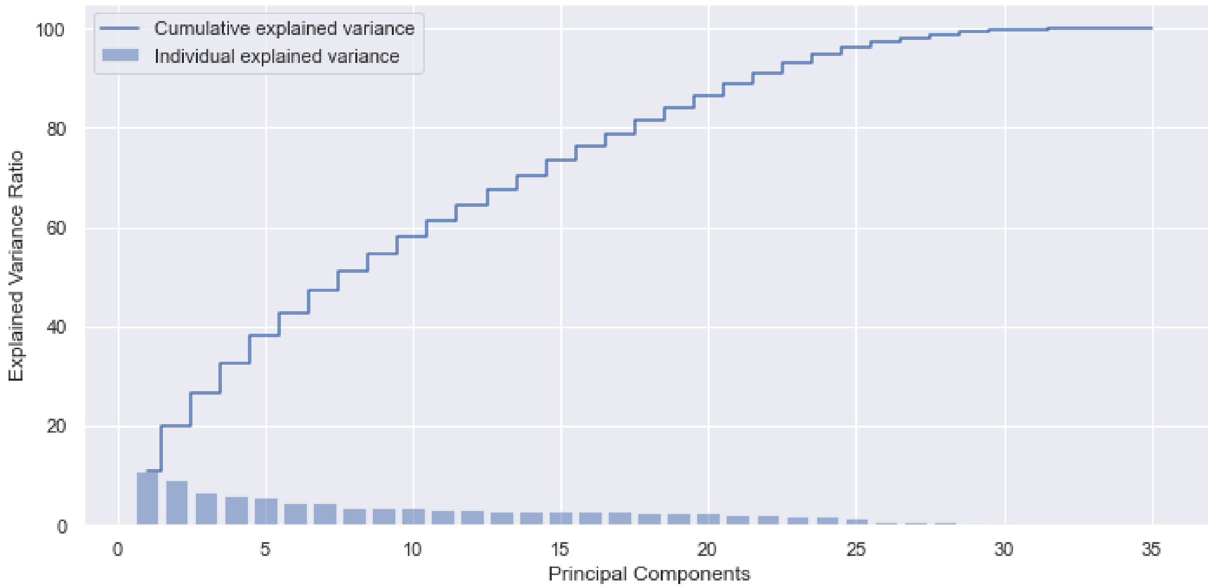

```
Half Yearly    0.587611
Yearly         0.317257
Monthly        0.078319
Quarterly      0.016814
Name: PaymentMethod, dtype: float64
```

Cumulative variance

```
In [107]: plt.plot(var_exp)

Out[107]: [<matplotlib.lines.Line2D at 0x2229cd2a8b0>]
```

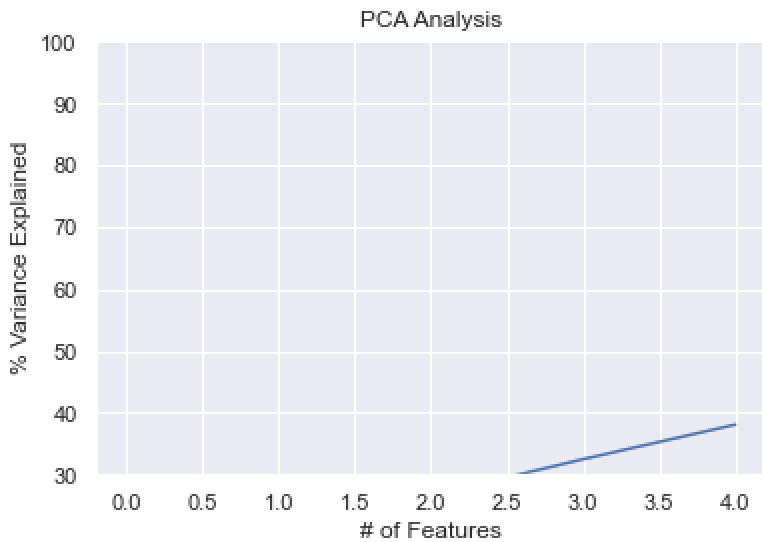


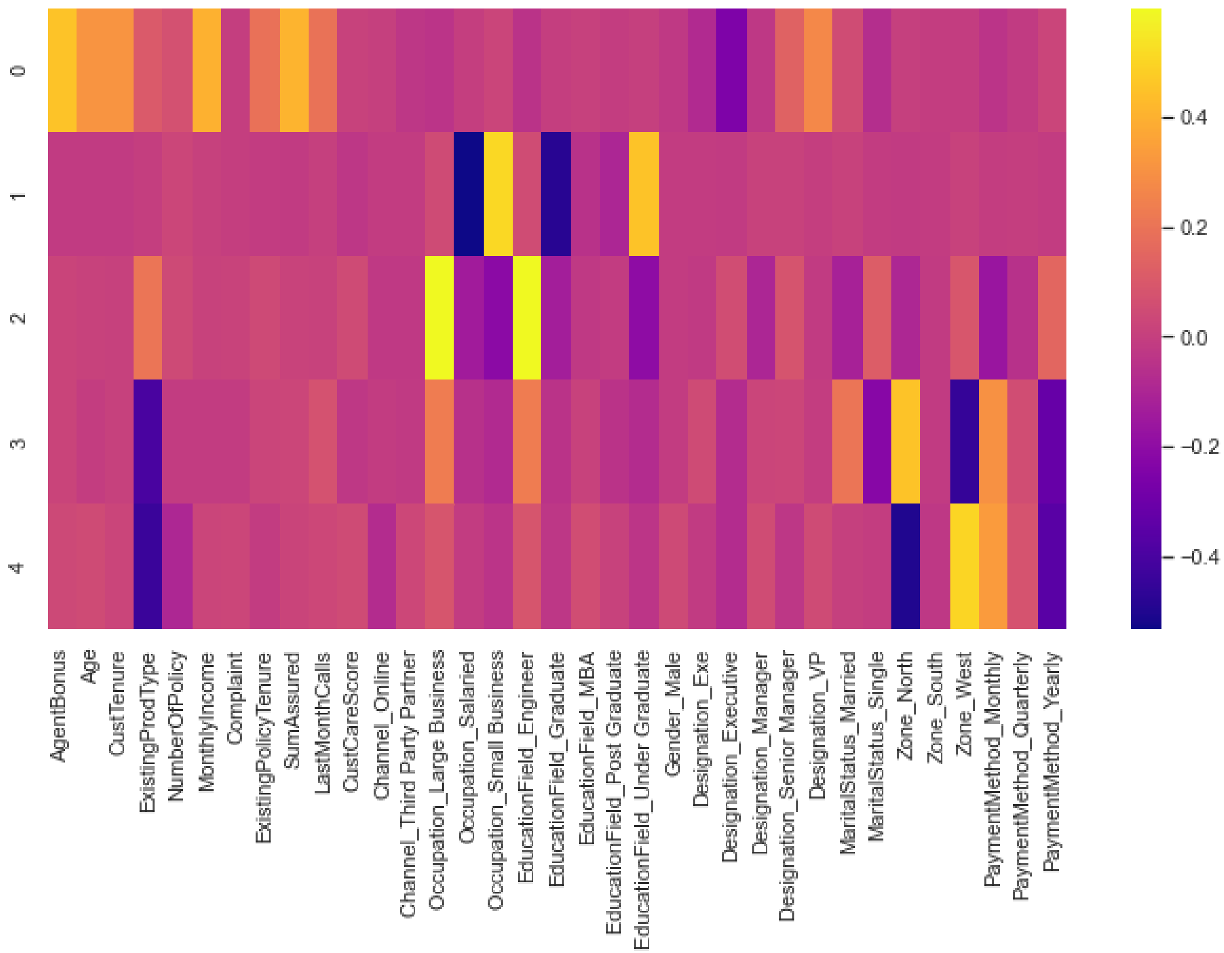
The below figure shows Individual explained variance and Cumulative explained variance plotted against Explained Variance Ratio Principal Components



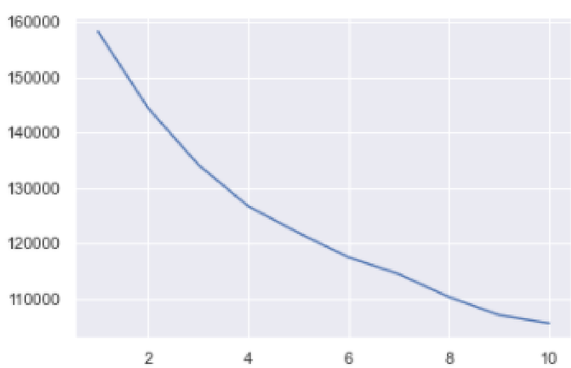
Then using scikit learn PCA. It does all the above steps and maps data to PCA dimensions in one shot

NOTE - we are generating only 4 PCA dimensions (dimensionality reduction from 18 to 4)






```
In [131]: plt.plot(range(1,11), wss)
Out[131]: [<matplotlib.lines.Line2D at 0x2229c6582b0>]
```



Here, we see that the value of VIF is high for many variables. Here, we may drop variables with VIF more than 5 (very high correlation) & build our model

Now we split the data

```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
import statsmodels.api as sm
```

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.30 , random_state=8)
```

```
from scipy.stats import zscore

X_train_scaled  = X_train.apply(zscore)
X_test_scaled = X_test.apply(zscore)
y_train_scaled = y_train.apply(zscore)
y_test_scaled = y_test.apply(zscore)
```

Using Statsmodels OLS

```
model = sm.OLS(y_trainc,X_trainc).fit()
model.summary()
```

OLS Regression Results

Dep. Variable:	AgentBonus	**R-squared:**	0.808
Model:	OLS	**Adj. R-squared:**	0.806
Method:	Least Squares	**F-statistic:**	376.5
Date:	Sun, 16 Jan 2022	**Prob (F-statistic):**	0.00
Time:	13:11:37	**Log-Likelihood:**	-24798.
No. Observations:	3164	**AIC:**	4.967e+04
Df Residuals:	3128	**BIC:**	4.989e+04
Df Model:	35		
Covariance Type:	nonrobust		

Covariance Type:	nonrobust

	coef	std err	t	P>|t|	[0.025	0.975]
const	1302.7182	495.358	2.630	0.009	331.458	2273.978
Age	22.3054	1.470	15.170	0.000	19.423	25.188
CustTenure	23.5837	1.459	16.165	0.000	20.723	26.444
ExistingProdType	37.0125	22.561	1.641	0.101	-7.223	81.248
NumberOfPolicy	3.6064	8.017	0.450	0.653	-12.112	19.325
MonthlyIncome	0.0322	0.006	5.443	0.000	0.021	0.044
Complaint	29.6882	24.275	1.223	0.221	-17.909	77.285
ExistingPolicyTenure	32.7566	3.527	9.288	0.000	25.842	39.672
SumAssured	0.0034	6.05e-05	56.775	0.000	0.003	0.004
LastMonthCalls	-1.7463	3.352	-0.521	0.602	-8.318	4.825
CustCareScore	3.4902	8.067	0.432	0.666	-12.365	19.346
Channel_Online	15.2347	36.443	0.418	0.676	-56.221	86.690
Channel_Third Party Partner	19.2115	28.375	0.677	0.498	-36.424	74.847
Occupation_Large Business	-636.7982	467.077	-1.363	0.173	-1552.606	279.009
Occupation_Salaried	-674.8400	441.006	-1.530	0.126	-1539.531	189.851
Occupation_Small Business	-692.2619	450.606	-1.536	0.125	-1575.775	191.251
EducationField_Engineer	-22.7474	172.628	-0.132	0.895	-361.222	315.727
EducationField_Graduate	-8.0384	97.894	-0.082	0.935	-199.981	183.904
EducationField_MBA	-148.5732	131.765	-1.127	0.260	-406.988	109.822
EducationField_Post Graduate	-40.9633	107.961	-0.379	0.704	-252.645	170.719
EducationField_Under Graduate	0.7167	39.936	0.018	0.986	-77.586	79.019
Gender_Male	9.9057	22.637	0.438	0.662	-34.479	54.290
Designation_Exe	-943.0769	96.711	-9.752	0.000	-1132.700	-753.454
Designation_Executive	-482.5651	68.032	-7.093	0.000	-615.958	-349.174
Designation_Manager	-478.3649	61.472	-7.782	0.000	-598.894	-357.835
Designation_Senior Manager	-288.3461	62.548	-4.610	0.000	-410.986	-165.706
Designation_VP	112.3353	74.772	1.502	0.133	-34.271	258.942
MaritalStatus_Married	0.3029	30.332	0.010	0.992	-59.169	59.775
MaritalStatus_Single	5.7490	32.664	0.176	0.860	-58.297	69.795
Zone_North	-83.1301	96.303	-0.863	0.388	-271.953	105.693
Zone_South	-174.9998	369.820	-0.473	0.636	-900.114	550.115
Zone_West	-79.1350	95.765	-0.826	0.409	-266.942	108.673
PaymentMethod_Monthly	149.5088	61.407	2.435	0.015	29.108	269.910
PaymentMethod_Quarterly	132.0691	90.469	1.460	0.145	-45.355	309.493
PaymentMethod_Yearly	-58.4653	34.522	-1.694	0.090	-126.154	9.223
Agglo_Clusters	35.2088	21.527	1.636	0.102	-7.000	77.416

Omnibus:	190.852	Durbin-Watson:	2.027
Prob(Omnibus):	0.000	Jarque-Bera (JB):	230.138
Skew:	0.606	Prob(JB):	1.06e-50
Kurtosis:	3.527	Cond. No.	5.43e+07

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 5.43e+07. This might indicate that there are

strong multicollinearity or other numerical problems.

Then we create another Regression Model

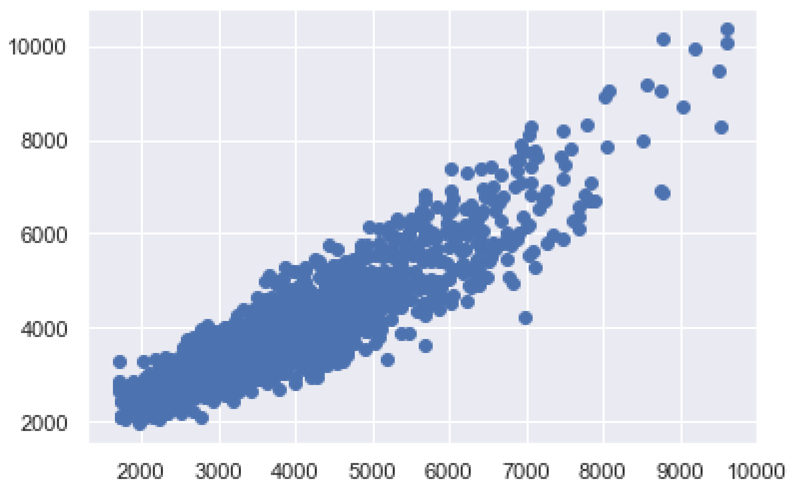
```
regression_model = LinearRegression()
regression_model.fit(X_train, y_train)
```

```
In [178]: mse = np.mean((regression_model.predict(X_test)-y_test)**2)
```

```
In [179]: # underroot of mean_sq_error is standard deviation i.e. avg variance between predicted and actual

          import math

          math.sqrt(mse)

Out[179]: 610.4833684454707
```

```
In [180]: # Model score - R2 or coeff of determinant
          # R^2=1-RSS / TSS

          regression_model.score(X_test, y_test)

Out[180]: 0.8128013867562254
```

```
In [181]: # predict mileage (mpg) for a set of attributes not in the training or test set
          y_pred = regression_model.predict(X_test)
```



```
The coefficient for Age is 22.305433275008976
The coefficient for CustTenure is 23.58367512263337
The coefficient for ExistingProdType is 37.012483187760225
The coefficient for NumberOfPolicy is 3.606394132314583
The coefficient for MonthlyIncome is 0.032234148060110934
The coefficient for Complaint is 29.68818504147072
The coefficient for ExistingPolicyTenure is 32.75681083566654
The coefficient for SumAssured is 0.003434757827044166
The coefficient for LastMonthCalls is -1.7463113487215107
The coefficient for CustCareScore is 3.4901993912915645
The coefficient for Channel_Online is 15.23473926018626 7
The coefficient for Channel_Third_Party_Partner is 19.211451094874846
The coefficient for Occupation_Large_Business is -636.7982076762647
The coefficient for Occupation_Salaried is -674.8400296635879
The coefficient for Occupation_Small_Business is -692.2618592484126
The coefficient for EducationField_Engineer is -22.74738361107367
The coefficient for EducationField_Graduate is -8.038410258729714
The coefficient for EducationField_MBA is -148.57315460426764
The coefficient for EducationField_Post_Graduate is -40.963291955974306
The coefficient for EducationField_Under_Graduate is 0.7167212310898241
The coefficient for Gender_Male is 9.905717143085154
The coefficient for Designation_Exe is -943.0768585468529
The coefficient for Designation_Executive is -482.5650739146594
The coefficient for Designation_Manager is -478.36488278835844
The coefficient for Designation_Senior_Manager is -288.3460989978638
The coefficient for Designation_VP is 112.33525012534695
The coefficient for MaritalStatus_Married is 0.3029246339521265
The coefficient for MaritalStatus_Single is 5.749016483724099
The coefficient for Zone_North is -83.13005166716042
The coefficient for Zone_South is -174.99962343639467
The coefficient for Zone_West is -79.13496496905766
The coefficient for PaymentMethod_Monthly is 149.5088264845823
The coefficient for PaymentMethod_Quarterly is 132.06914121520262
The coefficient for PaymentMethod_Yearly is -58.46534054523914
The coefficient for Agglo_Clusters is 35.208771596169754
```

```
The coefficient for Age is 0.13767054291276307
The coefficient for CustTenure is 0.14673231545576854
The coefficient for ExistingProdType is 0.026583240287272193
The coefficient for NumberOfPolicy is 0.0037266361191006896
The coefficient for MonthlyIncome is 0.11051475089919886
The coefficient for Complaint is 0.009653017910747817
The coefficient for ExistingPolicyTenure is 0.07721280682869969
The coefficient for SumAssured is 0.5911963397769338
The coefficient for LastMonthCalls is -0.004482022077323525
The coefficient for CustCareScore is 0.0034218816627441077
The coefficient for Channel_Online is 0.003357526778051917
The coefficient for Channel_Third_Party_Partner is 0.005414297785330311
The coefficient for Occupation_Large_Business is -0.1289981397245527
The coefficient for Occupation_Salaried is -0.24104793809459416
The coefficient for Occupation_Small_Business is -0.24364887911792552
The coefficient for EducationField_Engineer is -0.004600537950311366
The coefficient for EducationField_Graduate is -0.0028361177496419795
The coefficient for EducationField_MBA is -0.01323705141140738
The coefficient for EducationField_Post_Graduate is -0.006969724212726316
The coefficient for EducationField_Under_Graduate is 0.00023675340244105544
The coefficient for Gender_Male is 0.0034762734938712687
The coefficient for Designation_Exe is -0.10955626710497682
The coefficient for Designation_Executive is -0.16382497709257654
The coefficient for Designation_Manager is -0.163620298237565
The coefficient for Designation_Senior_Manager is -0.07267652783677697
The coefficient for Designation_VP is 0.017791198805611586
The coefficient for MaritalStatus_Married is 0.0001082040270019586
The coefficient for MaritalStatus_Single is 0.0019141209599569647
The coefficient for Zone_North is -0.029258500434660367
The coefficient for Zone_South is -0.0038478363594147275
The coefficient for Zone_West is -0.027982323754654932
The coefficient for PaymentMethod_Monthly is 0.028007029851631345
The coefficient for PaymentMethod_Quarterly is 0.011995805747694384
The coefficient for PaymentMethod_Yearly is -0.01947101649539555
The coefficient for Agglo_Clusters is 0.029369659107792462
```

```
intercept = regression_model_scaled.intercept_[0]

print("The intercept for our model is {}".format(intercept))
```

```
The intercept for our model is 7.798336340434967e-18
```

```
# Model score - R2 or coeff of determinant
# R^2=1-RSS / TSS

regression_model_scaled.score(X_test_scaled, y_test_scaled)
```

```
0.8125601603968964
```

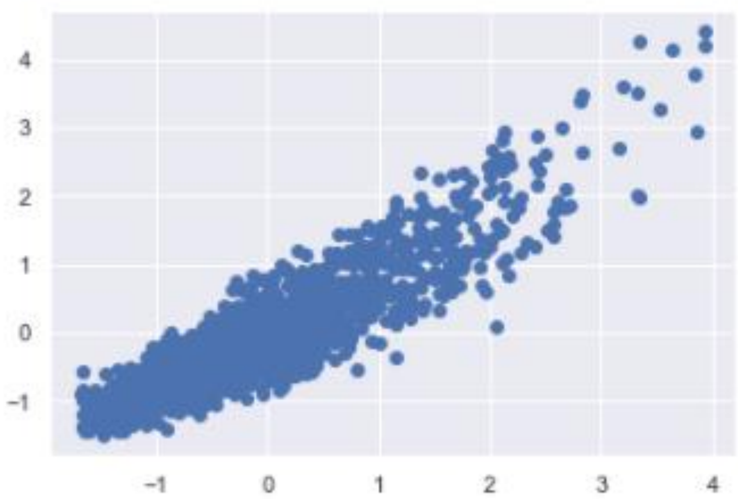
```
# Let us check the sum of squared errors by predicting value of y for training cases and
# subtracting from the actual y for the training cases

mse_scaled = np.mean((regression_model_scaled.predict(X_test_scaled)-y_test_scaled)**2)
```

```
# underroot of mean_sq_error is standard deviation i.e. avg variance between predicted and actual

import math

math.sqrt(mse_scaled)
```

```
0.432943229076404
```

```
# predict mileage (mpg) for a set of attributes not in the training or test set
y_pred_scaled = regression_model_scaled.predict(X_test_scaled)
```

```
<matplotlib.collections.PathCollection at 0x222969876d0>
```



We again check the variance inflation factor

```
Age ---> 4.974204076010754
CustTenure ---> 5.0042780103168765
ExistingProdType ---> 64.01833054809883
NumberOfPolicy ---> 7.8321774219042455
MonthlyIncome ---> 141.82458279669777
Complaint ---> 1.414558834499288
ExistingPolicyTenure ---> 2.8678193653545065
SumAssured ---> 13.290246233456738
LastMonthCalls ---> 3.1858820162173864
CustCareScore ---> 6.091559455568143
Channel_Online ---> 1.1686497715165352
```

Let's invoke the LinearRegression function and find the best fit model on training data.

```
regression_model_out = LinearRegression()
regression_model_out.fit(X_train_no_out, y_train_no_out)
```

```
LinearRegression()
```

Now let us explore the coefficients for each of the independent attributes

```
The coefficient for Age is 21.16035136703995
The coefficient for CustTenure is 22.43803112721254
The coefficient for ExistingProdType is 35.64162751908745
The coefficient for NumberOfPolicy is 4.385210311006258
The coefficient for MonthlyIncome is 0.03218690988832312
The coefficient for Complaint is 25.336989517761737
The coefficient for ExistingPolicyTenure is 35.68936973913441
The coefficient for SumAssured is 0.0035582576401367305
The coefficient for LastMonthCalls is -0.4588578496119094
The coefficient for CustCareScore is 2.40072559100181
The coefficient for Channel_Online is 8.067521549077147
The coefficient for Channel_Third Party Partner is 17.41914062086986
The coefficient for Occupation_Large Business is -624.9404677783616
The coefficient for Occupation_Salaried is -667.5143860777937
The coefficient for Occupation_Small Business is -693.2541275356853
The coefficient for EducationField_Engineer is -38.048640773593306
The coefficient for EducationField_Graduate is -20.382776609002768
The coefficient for EducationField_MBA is -176.00489806226838
The coefficient for EducationField_Post Graduate is -49.2307803636899
The coefficient for EducationField_Under Graduate is 6.275630855759628
The coefficient for Gender_Male is 12.212745365363402
The coefficient for Designation_Exe is -951.6472580695299
The coefficient for Designation_Executive is -479.2809087248839
The coefficient for Designation_Manager is -478.8052227116883
The coefficient for Designation_Senior Manager is -286.382061263671
The coefficient for Designation_VP is 57.25448765074445
The coefficient for MaritalStatus_Married is -7.7643848844325065
The coefficient for MaritalStatus_Single is -0.27209760432839497
The coefficient for Zone_North is -83.64401292733379
The coefficient for Zone_South is -195.50942258990926
The coefficient for Zone_West is -88.35484503904541
The coefficient for PaymentMethod_Monthly is 124.95660663201004
The coefficient for PaymentMethod_Quarterly is 143.22889619995138
The coefficient for PaymentMethod_Yearly is -52.89556145000119
```

```python
intercept = regression_model_out.intercept_[0]

print("The intercept for our model is {}".format(intercept))
```

```
The intercept for our model is 1412.8814770774493
```

```python
# Model score - R2 or coeff of determinant
# R^2=1-RSS / TSS

regression_model_out.score(X_test_no_out, y_test_no_out)
```

```
0.8039846439306599
```

	variables	VIF
30	Zone_South	1.097750
33	PaymentMethod_Quarterly	1.124055
11	Channel_Online	1.168744
12	Channel_Third_Party_Partner	1.285194
6	Complaint	1.415376
22	Designation_Exe	2.129217
18	EducationField_MBA	2.250673
26	Designation_VP	2.364060
32	PaymentMethod_Monthly	2.491524
21	Gender_Male	2.535430
28	MaritalStatus_Single	2.871670
7	ExistingPolicyTenure	2.960278
9	LastMonthCalls	3.186624
34	PaymentMethod_Yearly	3.246193
27	MaritalStatus_Married	3.895606
20	EducationField_Under_Graduate	3.997850
25	Designation_Senior_Manager	4.654740
19	EducationField_Post_Graduate	5.132235
1	Age	5.384959
2	CustTenure	5.448530
10	CustCareScore	6.092959
4	NumberOfPolicy	7.832282
24	Designation_Manager	11.160432
23	Designation_Executive	12.938618
16	EducationField_Engineer	20.769377
8	SumAssured	27.123217
29	Zone_North	30.124808
17	EducationField_Graduate	31.052427
31	Zone_West	40.643026
13	Occupation_Large_Business	45.003817
35	Agglo_Clusters	49.216890
0	AgentBonus	49.676191
3	ExistingProdType	64.107943
15	Occupation_Small_Business	121.653120
5	MonthlyIncome	143.287388
14	Occupation_Salaried	163.510600

The final Linear Regression equation is

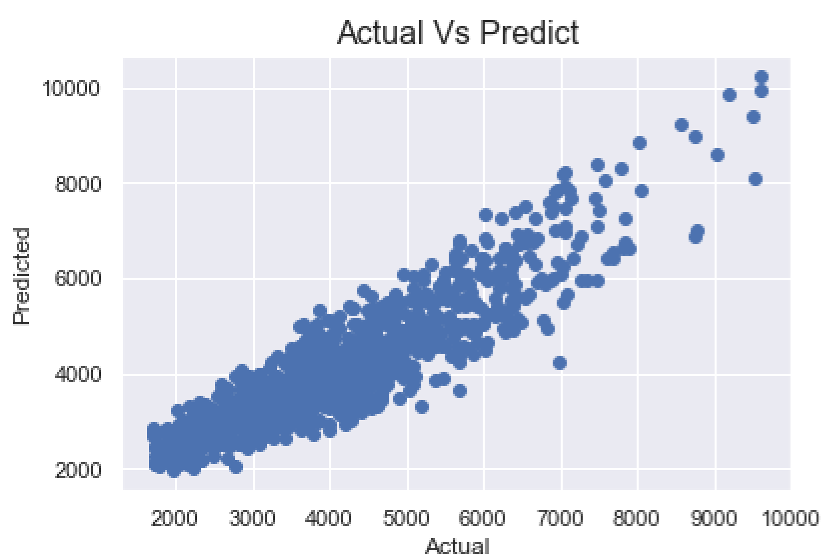
AgentBonus = b0 * Intercept + b1 * Zone_South + b2 * PaymentMethod_Quarterly + b3 * Channel_Online + b4 * Channel_Third_Party_Partner + b5 * Complaint + b6 * Designation_Exe + b7 * Designation_VP + b8 *

EducationField_MBA + b9 * PaymentMethod_Monthly + b10 * Gender_Male + b11 * MaritalStatus_Single + b12 * ExistingPolicyTenure + b13 * LastMonthCalls + b14 * PaymentMethod_Yearly + b15 * Designation_Senior_Manager + b16 * MaritalStatus_Married + b17 * EducationField_Under_Graduate + b18 * EducationField_Post_Graduate + b19 * Age + b20 * CustTenure + b21 * CustCareScore + b22 * NumberOfPolicy + b23 * Designation_Manager + b24 * Designation_Executive + b25 * EducationField_Engineer + b26 * SumAssured + b27 * Zone_North + b28 * EducationField_Graduate + b29 * Occupation_Large_Business + b30 * Zone_West + b31 * ExistingProdType + b32 * MonthlyIncome + b33 * Occupation_Small_Business

AgentBonus = (843.69) * Intercept + (-0.74) * Zone_South + (121.99) * PaymentMethod_Quarterly + (16.45) * Channel_Online + (8.64) * Channel_Third_Party_Partner + (31.43) * Complaint + (-897.0) * Designation_Exe + (19.69) * Designation_VP + (-134.73) * EducationField_MBA + (179.77) * PaymentMethod_Monthly + (3.74) * Gender_Male + (13.12) * MaritalStatus_Single + (35.55) * ExistingPolicyTenure + (-2.62) * LastMonthCalls + (-71.13) * PaymentMethod_Yearly + (-261.65) * Designation_Senior_Manager + (-16.47) * MaritalStatus_Married + (15.54) * EducationField_Under_Graduate + (-76.12) * EducationField_Post_Graduate + (23.04) * Age + (24.0) * CustTenure + (6.01) * CustCareScore + (1.52) * NumberOfPolicy + (-447.69) * Designation_Manager + (-469.53) * Designation_Executive + (-39.86) * EducationField_Engineer + (0.0) * SumAssured + (-44.05) * Zone_North + (-63.73) * EducationField_Graduate + (-39.31) * Occupation_Large_Business + (-44.97) * Zone_West + (54.11) * ExistingProdType + (0.03) * MonthlyIncome + (-92.01) * Occupation_Small_Business

When Age increases by 1 unit, AgentBonus increases by 23.04 units, keeping all other predictors constant. similarly, when MonthlyIncome increases by 1 unit, AgentBonus increases by 0.03 units, keeping all other predictors constant.

There are also some negative co-efficient values. Occupation_Large_Business has its corresponding co-efficient as -39.31. This implies, when the Occupation is Large business, the AgentBonus decreases by 39.31 units, keeping all other predictors constant.



We are scaling the data for ANN. Without scaling it will give very poor results. Computations becomes easier.

	Train RMSE	Test RMSE	Training Score	Test Score
Linear Regression	611.612103	614.934255	0.808172	0.813200
Decision Tree Regressor	0.000000	744.328618	1.000000	0.726316
Random Forest Regressor	200.059407	519.298515	0.979475	0.866785
ANN Regressor	4315.881788	4303.418081	0.969355	0.781622

In [244]:
```
param_grid = {
    'max_depth': [10,15,20,25,30],
    'min_samples_leaf': [3, 15,30],
    'min_samples_split': [15,30,35,40,50],
}

dtr=tree.DecisionTreeRegressor(random_state=8)

grid_search = GridSearchCV(estimator = dtr, param_grid = param_grid, cv = 3)


grid_search.fit(X_train_tun,y_train_tun)

print(grid_search.best_params_)
```

```
{'max_depth': 10, 'min_samples_leaf': 3, 'min_samples_split': 40}
```

In [245]:
```
param_grid = {
    'max_depth': [7,10],
    'max_features': [4, 6],
    'min_samples_leaf': [3, 15,30],
    'min_samples_split': [30, 40,100],
    'n_estimators': [300, 500]
}

rfr = RandomForestRegressor(random_state=8)

grid_search = GridSearchCV(estimator = rfr, param_grid = param_grid, cv = 3)
```

grid_search.fit(X_train_tun,y_train_tun)

```
#best_params_rfr={'max_depth': 10, 'max_features': 6, 'min_samples_leaf': 3, 'min_samples_split': 30, 'n_estimators': 500}
```

Using Grid Search for ANN

```
param_grid = {
    'hidden_layer_sizes':[(500),(100,100)],
    # keeping these simple because it would take too much time to run on low-end computers
    "activation": ["tanh", "relu"],
    "solver": ["sgd", "adam"]}

annr = MLPRegressor(max_iter=1000, random_state=8)

grid_search = GridSearchCV(estimator = annr, param_grid = param_grid, cv = 3)
```

```
Out[250]: GridSearchCV(cv=3, estimator=MLPRegressor(max_iter=1000, random_state=8),
                       param_grid={'activation': ['tanh', 'relu'],
                                   'hidden_layer_sizes': [500, (100, 100)],
                                   'solver': ['sgd', 'adam']})
```

Tuning

```
In [217]: df_vif=df[['Zone_South','PaymentMethod_Quarterly','Channel_Online','Channel_Third_Party_Partner'
              ,'Complaint','Designation_Exe','Designation_VP','EducationField_MBA','PaymentMethod_Monthly'
              ,'Gender_Male','MaritalStatus_Single','ExistingPolicyTenure','LastMonthCalls','PaymentMethod_Yearly'
              ,'Designation_Senior_Manager','MaritalStatus_Married','EducationField_Under_Graduate','AgentBonus','EducationField_Post_Gradua
              ,'Age','CustTenure','CustCareScore','NumberOfPolicy','Designation_Manager','Designation_Executive','EducationField_Engineer'
               ,'SumAssured','Zone_North','EducationField_Graduate','Occupation_Large_Business','Zone_West','ExistingProdType','MonthlyIncom
                     ,'Occupation_Small_Business']]
          #score is max when we remove Occupation_Salaried
```

```
In [218]: df_vif
```

Out[218]:

	Zone_South	PaymentMethod_Quarterly	Channel_Online	Channel_Third_Party_Partner	Complaint	Designation_Exe	Designation_VP	EducationField_MBA
0	0	0	0	0	1	0	0	0
1	0	0	0	1	0	0	0	0
2	0	0	0	0	1	1	0	0
3	0	0	0	1	1	0	0	0
4	0	0	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...
4515	0	0	0	0	0	0	0	0
4516	0	0	0	0	0	0	0	0
4517	0	0	0	0	0	0	0	0
4518	0	0	1	0	0	0	0	0
4519	0	0	0	0	0	0	0	0

4520 rows × 34 columns

We now invoke the LinearRegression function and find the best fit model on training data

```
regression_model_vif = LinearRegression()
regression_model_vif.fit(X_train_vif, y_train_vif)
```

```
LinearRegression()
```

Let us explore the coefficients for each of the independent attributes

```
The coefficient for Zone_South is -177.53074739826755
The coefficient for PaymentMethod_Quarterly is 140.20712725616963
The coefficient for Channel_Online is 13.012341753675729
The coefficient for Channel_Third_Party_Partner is 20.487115418348655
The coefficient for Complaint is 31.685361413976963
The coefficient for Designation_Exe is -914.2840345317121
The coefficient for Designation_VP is 83.61466592603371
The coefficient for EducationField_MBA is -152.46678008724237
The coefficient for PaymentMethod_Monthly is 161.46517974037127
The coefficient for Gender_Male is 10.083903510394341
The coefficient for MaritalStatus_Single is 7.317067441019994
The coefficient for ExistingPolicyTenure is 32.914820300413645
The coefficient for LastMonthCalls is -1.5066627383331075
The coefficient for PaymentMethod_Yearly is -63.09658265704684
The coefficient for Designation_Senior_Manager is -234.90779982050515
The coefficient for MaritalStatus_Married is 0.2273700794131594
The coefficient for EducationField_Under_Graduate is -1.8847983945686386
The coefficient for EducationField_Post_Graduate is -37.79407017070104
The coefficient for Age is 22.158517692104205
The coefficient for CustTenure is 23.395954345736282
The coefficient for CustCareScore is 3.3671519083631627
The coefficient for NumberOfPolicy is 3.8656550571600334
The coefficient for Designation_Manager is -436.56179719317475
The coefficient for Designation_Executive is -452.4643380524982
The coefficient for EducationField_Engineer is -17.317260792697528
The coefficient for SumAssured is 0.003433789096447981
The coefficient for Zone_North is -79.65862392165423
The coefficient for EducationField_Graduate is -11.888898369021842
The coefficient for Occupation_Large_Business is 29.913578690562634
The coefficient for Zone_West is -78.22206217344456
The coefficient for ExistingProdType is 43.98633586581726
The coefficient for MonthlyIncome is 0.02745411921963592
The coefficient for Occupation_Small_Business is -19.367644879940702
The intercept for our model is 810.7915091307291
```

```python
for i,j in np.array(lm1.params.reset_index()):
    print('({}) * {} +'.format(round(j,2),i),end=' ')
```

```
(843.69) * Intercept + (-0.74) * Zone_South + (121.99) * PaymentMethod_Quarterly + (16.45) * Channel_Online + (8.64) * Channel_
Third_Party_Partner + (31.43) * Complaint + (-897.0) * Designation_Exe + (19.69) * Designation_VP + (-134.73) * EducationField_
MBA + (179.77) * PaymentMethod_Monthly + (3.74) * Gender_Male + (13.12) * MaritalStatus_Single + (35.55) * ExistingPolicyTenure
+ (-2.62) * LastMonthCalls + (-71.13) * PaymentMethod_Yearly + (-261.65) * Designation_Senior_Manager + (-16.47) * MaritalStatu
s_Married + (15.54) * EducationField_Under_Graduate + (-76.12) * EducationField_Post_Graduate + (23.04) * Age + (24.0) * CustTe
nure + (6.01) * CustCareScore + (1.52) * NumberOfPolicy + (-447.69) * Designation_Manager + (-469.53) * Designation_Executive +
(-39.86) * EducationField_Engineer + (0.0) * SumAssured + (-44.05) * Zone_North + (-63.73) * EducationField_Graduate + (-39.31)
* Occupation_Large_Business + (-44.97) * Zone_West + (54.11) * ExistingProdType + (0.03) * MonthlyIncome + (-92.01) * Occupatio
n_Small_Business +
```

```python
X_train_tun, X_test_tun, y_train_tun, y_test_tun = train_test_split(X_vif, Y, test_size=0.25, random_state=8)
X_train_scaled_tun  = X_train.apply(zscore)
X_test_scaled_tun = X_test.apply(zscore)
y_train_scaled_tun = y_train.apply(zscore)
y_test_scaled_tun = y_test.apply(zscore)
```

```python
regression_model_tun = LinearRegression()
regression_model_tun.fit(X_train_tun, y_train_tun)
regression_model_tun.score(X_test_tun, y_test_tun)
```

```
0.8132000652084972
```

```python
regression_model_scaled_tun = LinearRegression()
regression_model_scaled_tun.fit(X_train_scaled_tun, y_train_scaled_tun)
regression_model_scaled_tun.score(X_test_scaled_tun, y_test_scaled_tun)
```

```
0.8125601603968964
```

```
Out[226]: Intercept                        843.694069
          Zone_South                        -0.743471
          PaymentMethod_Quarterly          121.985130
          Channel_Online                    16.452712
          Channel_Third_Party_Partner        8.639260
          Complaint                         31.425465
          Designation_Exe                 -896.998779
          Designation_VP                    19.689241
          EducationField_MBA              -134.730077
          PaymentMethod_Monthly            179.770948
          Gender_Male                        3.736511
          MaritalStatus_Single              13.121798
          ExistingPolicyTenure              35.545569
          LastMonthCalls                    -2.622818
          PaymentMethod_Yearly             -71.133166
          Designation_Senior_Manager      -261.650782
          MaritalStatus_Married            -16.469356
          EducationField_Under_Graduate     15.535704
          EducationField_Post_Graduate     -76.117914
          Age                               23.035100
          CustTenure                        24.001376
          CustCareScore                      6.006542
          NumberOfPolicy                     1.516024
          Designation_Manager             -447.692353
          Designation_Executive           -469.527655
          EducationField_Engineer          -39.861369
          SumAssured                         0.003425
          Zone_North                       -44.049140
          EducationField_Graduate          -63.733576
          Occupation_Large_Business        -39.310314
          Zone_West                        -44.965068
          ExistingProdType                  54.113346
          MonthlyIncome                      0.025356
          Occupation_Small_Business        -92.005135
          dtype: float64
```

lm1.summary

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             AgentBonus   R-squared:                       0.810
Model:                            OLS   Adj. R-squared:                  0.809
Method:                 Least Squares   F-statistic:                     579.7
Date:                Sun, 16 Jan 2022   Prob (F-statistic):               0.00
Time:                        13:13:01   Log-Likelihood:                -35414.
No. Observations:                4520   AIC:                         7.090e+04
Df Residuals:                    4486   BIC:                         7.111e+04
Df Model:                          33
Covariance Type:            nonrobust
-----------------------------------------------------------------------------------------------
```

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	843.6941	158.479	5.324	0.000	532.996	1154.392
Zone_South	-0.7435	262.924	-0.003	0.998	-516.204	514.718
PaymentMethod_Quarterly	121.9851	74.532	1.637	0.102	-24.135	268.105
Channel_Online	16.4527	30.665	0.537	0.592	-43.665	76.571
Channel_Third_Party_Partner	8.6393	23.756	0.364	0.716	-37.935	55.213
Complaint	31.4255	20.270	1.550	0.121	-8.314	71.165
Designation_Exe	-896.9988	78.666	-11.403	0.000	-1051.223	-742.775
Designation_VP	19.6892	61.233	0.322	0.748	-100.358	139.736
EducationField_MBA	-134.7301	107.913	-1.249	0.212	-346.292	76.832
PaymentMethod_Monthly	179.7709	51.123	3.516	0.000	79.544	279.997
Gender_Male	3.7365	18.855	0.198	0.843	-33.229	40.702
MaritalStatus_Single	13.1218	27.369	0.479	0.632	-40.534	66.778
ExistingPolicyTenure	35.5456	2.949	12.054	0.000	29.764	41.327
LastMonthCalls	-2.6228	2.771	-0.946	0.344	-8.056	2.810
PaymentMethod_Yearly	-71.1332	29.098	-2.445	0.015	-128.179	-14.087
Designation_Senior_Manager	-261.6508	43.913	-5.958	0.000	-347.742	-175.559
MaritalStatus_Married	-16.4694	25.455	-0.647	0.518	-66.374	33.435
EducationField_Under_Graduate	15.5357	32.617	0.476	0.634	-48.410	79.481
EducationField_Post_Graduate	-76.1179	89.154	-0.854	0.393	-250.903	98.668
Age	23.0351	1.204	19.134	0.000	20.675	25.395
CustTenure	24.0014	1.208	19.865	0.000	21.633	26.370
CustCareScore	6.0065	6.712	0.895	0.371	-7.152	19.165
NumberOfPolicy	1.5160	6.633	0.229	0.819	-11.488	14.520
Designation_Manager	-447.6924	46.393	-9.650	0.000	-538.646	-356.739
Designation_Executive	-469.5277	54.362	-8.637	0.000	-576.104	-362.952
EducationField_Engineer	-39.8614	138.810	-0.287	0.774	-311.997	232.275
SumAssured	0.0034	5.01e-05	68.353	0.000	0.003	0.004
Zone_North	-44.0491	78.644	-0.560	0.575	-198.229	110.131
EducationField_Graduate	-63.7336	80.236	-0.794	0.427	-221.036	93.569
Occupation_Large_Business	-39.3103	129.498	-0.304	0.761	-293.190	214.570
Zone_West	-44.9651	78.229	-0.575	0.565	-198.333	108.402
ExistingProdType	54.1133	18.847	2.871	0.004	17.165	91.062
MonthlyIncome	0.0254	0.004	5.971	0.000	0.017	0.034
Occupation_Small_Business	-92.0051	75.805	-1.214	0.225	-240.621	56.611

Omnibus:	261.417	Durbin-Watson:	2.018
Prob(Omnibus):	0.000	Jarque-Bera (JB):	311.623
Skew:	0.599	Prob(JB):	2.15e-68
Kurtosis:	3.467	Cond. No.	1.95e+07