Life-Insurance Sale Capstone

Final Report

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Problem Statement: Life Insurance Data

- 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 upskill programs for low performing agents.

Need for this Study/Project

- With this problem we want to better understand how the insurance company agents are performing, it's not to underpay or overpay, as the payment is regulated by IRDA.
- With the predictions it's better for the company to understand where they need to focus more as for agents selling less policies the company needs some booster training performs. As the policies are as good as the agents portray it to be to the potential customer.
- While the agents performing good i.e. selling more policies there needs to be a way to reward them, to make their contribution known so that they perform the same and even better in future.

Why is this (agent bonus) important for the business/company?

- A company is as good as their employers.
- For a Life Insurance Company, their agents are the best way to make the companies policies, aims, and perks known to the customer. Once the customer is intrigued by the policy delivery by the agent, it is easier to convince the customer hence improving the sales and thereby motivating the agent as well.
- With this, the market share of the company will gain more ground dominating the potential opponents.
- Moreover, the agents can be classified into categories giving the company better insight where the need to put more effort.
- The customer feedback can help the company develop improved and updated policies/products. Meeting customer needs.
- Hereby, the easiest way to retain their agents.
- Overall, multiplying and adding to company's profit.

Data Report/Dictionary

The following data is provided by Great Learning cover the Life Insurance Sales made by the company, the data dictionary consists of:

Variable	Description
CustID	Unique customer ID
AgentBonus	Bonus amount given to each agents in last month.
Age	Age of customer
CustTenure	Tenure of customer in organization.
Channel	Channel through which acquisition of customer is done.
Occupation	Occupation of customer
EducationField	Field of education of customer
Gender	Gender of customer
ExistingProdType	Existing product type of customer
Designation	Designation of customer in their organization
NumberOfPolicy	Total number of existing policy of a customer
MaritialStatus	Marital status of customer
MonthlyIncome	Gross monthly income of customer
Complaint	Indicator of complaint registered in last one month by customer
ExistingPolicyTenure	Max tenure in all existing policies of customer
SumAssured	Max of sum assured in all existing policies of customer
Zone	Customer belongs to which zone in India. Like East, West, North and South
PaymentMethod	Frequency of payment selected by customer like Monthly, quarterly, half yearly and yearly
LastMonthCalls	Total calls attempted by company to a customer for cross sell
CustCareScore	Customer satisfaction score given by customer in previous service call

Performing Exploratory Data Analysis (EDA).

Head of the Data

	AgentBonus	Age	CustTenure	Channel	Occupation	EducationField	Gender	ExistingProdType	Designation	NumberOfPolicy	MaritalStatus	MonthlyIncome
0	4409	22.0	4.0	Agent	Salaried	Graduate	Female	3	Manager	2.0	Single	20993.0
1	2214	11.0	2.0	Third Party Partner	Salaried	Graduate	Male	4	Manager	4.0	Divorced	20130.0
2	4273	26.0	4.0	Agent	Free Lancer	Post Graduate	Male	4	Exe	3.0	Unmarried	17090.0
3	1791	11.0	NaN	Third Party Partner	Salaried	Graduate	Fe male	3	Executive	3.0	Divorced	17909.0
4	2955	6.0	NaN	Agent	Small Business	UG	Male	3	Executive	4.0	Divorced	18468.0

- I've removed CustID as it is irrelevant to agent bonus.
- Head gives us the idea of what the basic dataset looks like.
- Complete list of all variables is not presented.

Shape of the dataset

Total rows in the dataset: 4520
Total columns in the dataset: 19

Descriptive Statistics of the Columns

	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	1.8385e+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

- The table includes the complete description for all variable with categorical variables included.
- The description includes, variable count, unique values, top frequently occurring categories like Agent-3194, mean, standard deviation, minimum, 25%, 50%(median), 75%, and maximum values present in the respective variables.
- Hence the 'NaN' here is observed for Categorical Variables as a string object cannot have numeric values.
- This we will change by encoding the data in future if needed.
- We can also observe the missing values as the count is not constant for all the variables.
- The unique is only present for categorical variables which hold a specific category
- Example: Gender has male and female hence it should hold unique value of 2 but later we observed some subcategories needs to be renamed.

Info of the parameters

```
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   AgentBonus            4520 non-null   int64  
 1   Age                   4251 non-null   float64
 2   CustTenure            4294 non-null   float64
 3   Channel               4520 non-null   object 
 4   Occupation            4520 non-null   object 
 5   EducationField        4520 non-null   object 
 6   Gender                4520 non-null   object 
 7   ExistingProdType      4520 non-null   int64  
 8   Designation           4520 non-null   object 
 9   NumberOfPolicy        4475 non-null   float64
 10  MaritalStatus         4520 non-null   object 
 11  MonthlyIncome         4284 non-null   float64
 12  Complaint             4520 non-null   int64  
 13  ExistingPolicyTenure  4336 non-null   float64
 14  SumAssured            4366 non-null   float64
 15  Zone                  4520 non-null   object 
 16  PaymentMethod         4520 non-null   object 
 17  LastMonthCalls        4520 non-null   int64  
 18  CustCareScore         4468 non-null   float64
dtypes: float64(7), int64(4), object(8)
memory usage: 671.1+ KB
```

- We have 7 parameters having ‘float’ data type.
- We have 4 parameters having ‘integer’ data type.
- We have 8 parameters having ‘object’ data type.
- Age is shown as float, however we will later observe is its needed to change it to int or not, it won’t make any difference in our observations.
- We can clearly observe some missing values.
- Further count of missing values is provided below.

- 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

- **Number of duplicate rows = 0**
- The **Missing values** can affect the prediction’s hence need to be treated, hence the missing values are imputed with the **median values** in the respective column.

Checking for Unique Categorical Values.

CHANNEL has 3 Unique Values.
Online 468
Third Party Partner 858
Agent 3194
Name: Channel, dtype: int64

OCCUPATION has 5 Unique Values.
Free Lancer 2
Laarge Business 153
Large Business 255
Small Business 1918
Salaried 2192
Name: Occupation, dtype: int64

EDUCATIONFIELD has 7 Unique Values.
MBA 74
UG 230
Post Graduate 252
Engineer 408
Diploma 496
Under Graduate 1190
Graduate 1870
Name: EducationField, dtype: int64

GENDER has 3 Unique Values.
Fe male 325
Female 1507
Male 2688
Name: Gender, dtype: int64

DESIGNATION has 6 Unique Values.
Exe 127
VP 226
AVP 336
Senior Manager 676
Executive 1535
Manager 1620
Name: Designation, dtype: int64

MARITALSTATUS has 4 Unique Values.
Unmarried 194
Divorced 804
Single 1254
Married 2268
Name: MaritalStatus, dtype: int64

ZONE has 4 Unique Values.
South 6
East 64
North 1884
West 2566
Name: Zone, dtype: int64

PAYMENTMETHOD has 4 Unique Values.
Quarterly 76
Monthly 354
Yearly 1434
Half Yearly 2656

- Here it can be observed that subcategories highlighted with a different colour shows an error in naming convention hence have to be renamed.
- Example: ‘Laarge’ and ‘Large’ Business can be put in the same category, the same for ‘UG’ and ‘Under Graduate’, ‘Graduate’ and ‘Post Graduate’, ‘Fe male’ and ‘Female’, and ‘Exe’ and ‘Executive’**.**

<u>Univariate/Bivariate Analysis</u>

AgentBonus

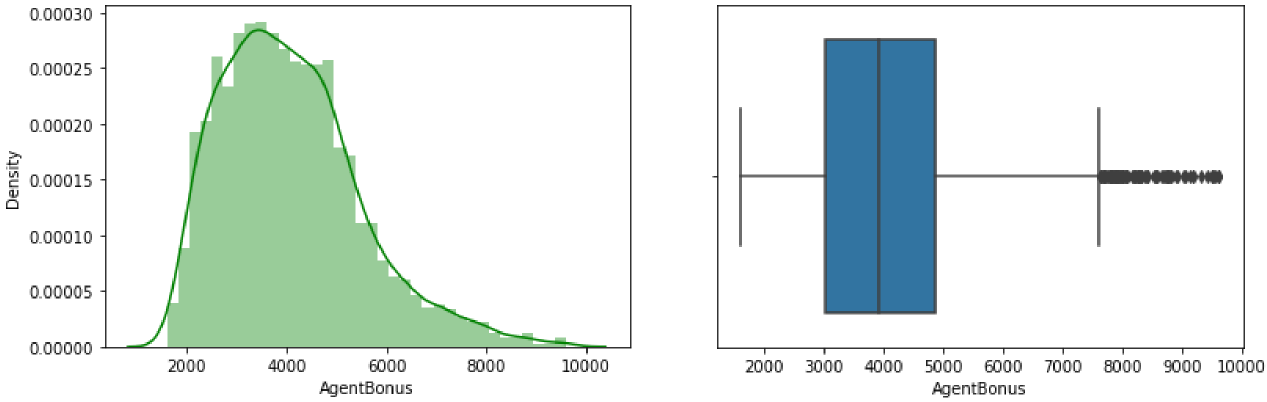

Figure 1(a) Distplot/Histplot - AgentBonus

- **The distribution of "AgentBonus" seems to be positively/right skewed.**
- **The data ranges from 1605 to 9600.**
- **The box plot holds many outliers.**

Age:

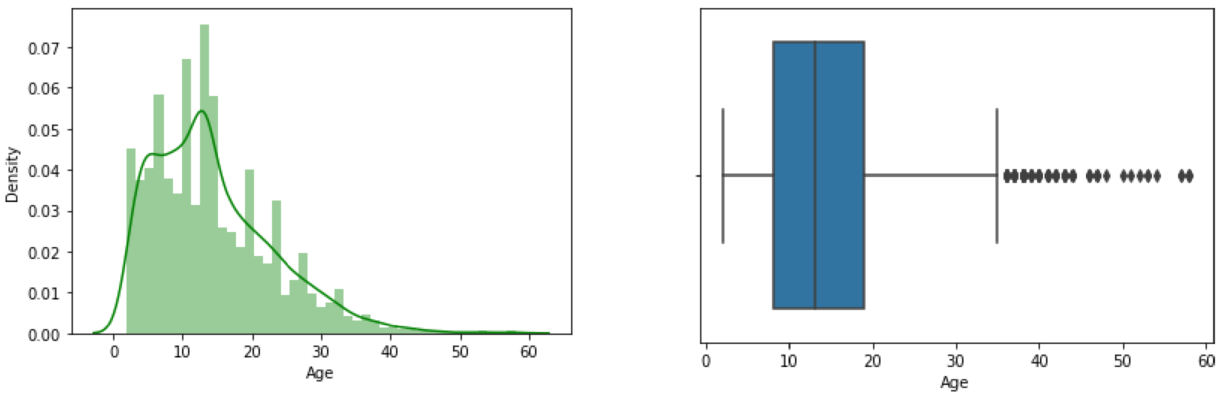

Figure 1(b) Distplot/Histplot - Age

- **The distribution of "Age" seems to be positively/right skewed.**
- **The data ranges from 2 to 58.**
- **The box plot holds many outliers.**

CustTenure:

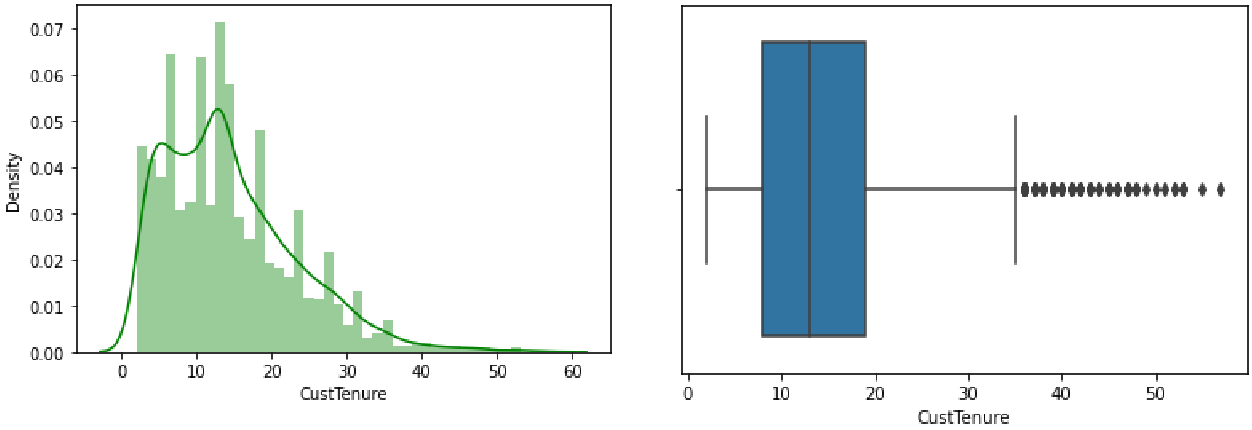

Figure 1(c) Distplot/Histplot - CustTenure

- **The distribution of "CustTenure" seems to be positively/right skewed.**
- **The data ranges from 2 to 57.**
- **The box plot holds many outliers.**

ExistingProdType:

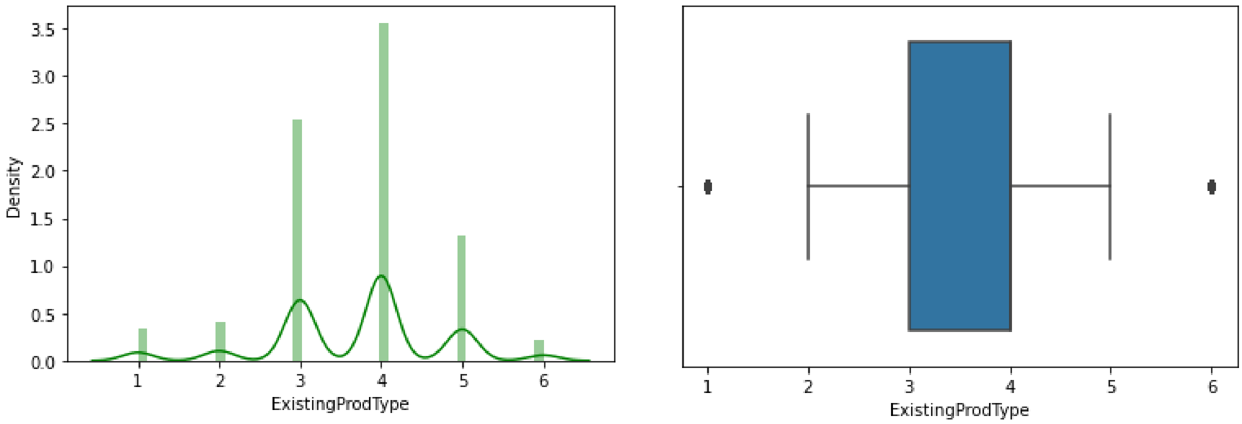

Figure 1(d) Distplot/Histplot - ExistingProdType

- **The distribution of "ExistingProdType" seems to be slightly left skewed.**
- **The data ranges from 1 to 6.**
- **The box plot holds outliers.**

NumberOfPolicy

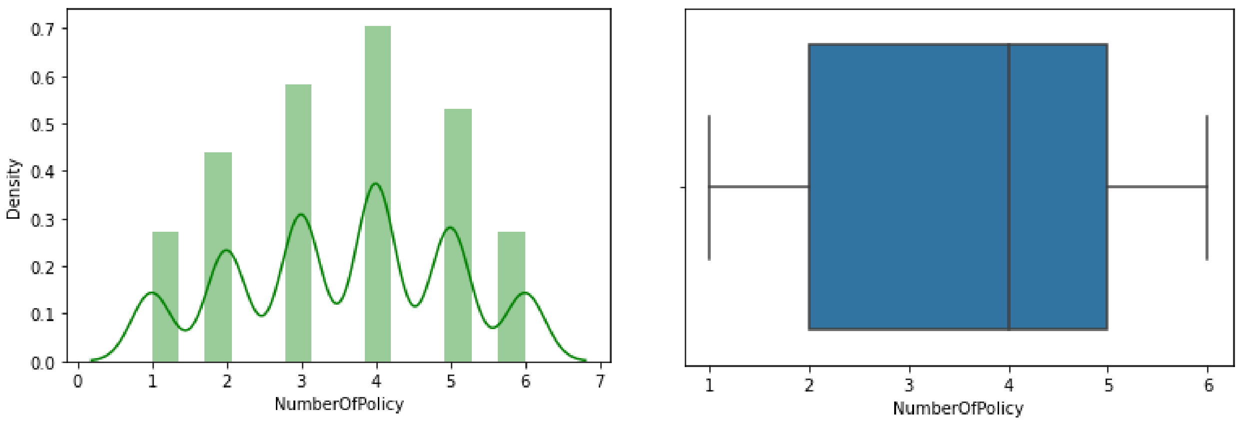

Figure 1(e) Distplot/Histplot - NumberofPolicy

- **The distribution of "NumberOfPolicy" seems to be slightly left skewed.**
- **The data ranges from 1 to 6.**
- **The box plot has no outliers.**

MonthlyIncome

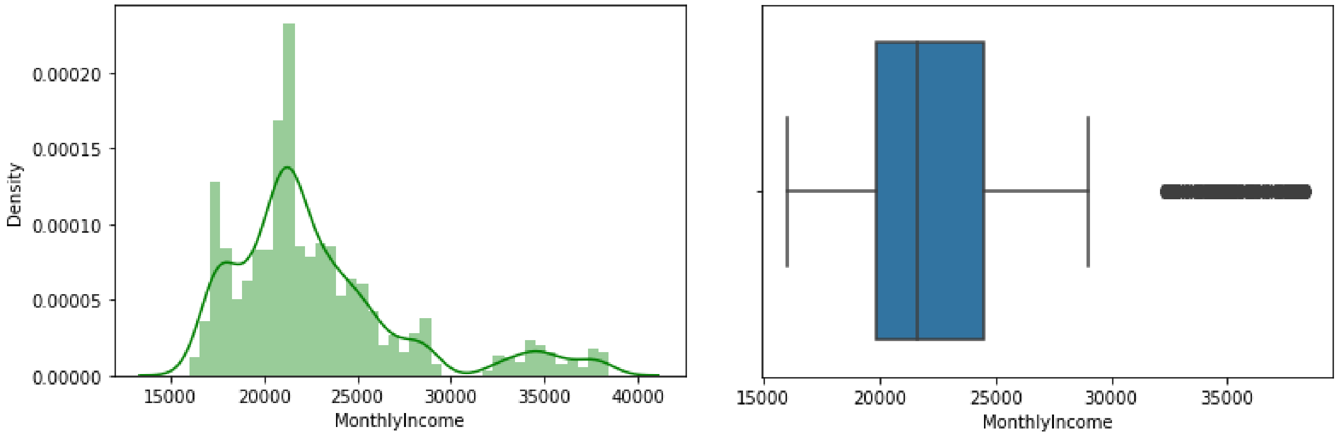

Figure 1(f) Distplot/Histplot - MonthlyIncome

- **The distribution of "MonthlyIncome" seems to be positively/right skewed.**
- **The data ranges from 16000 to 38500.**
- **The box plot holds many outliers.**

Complaint

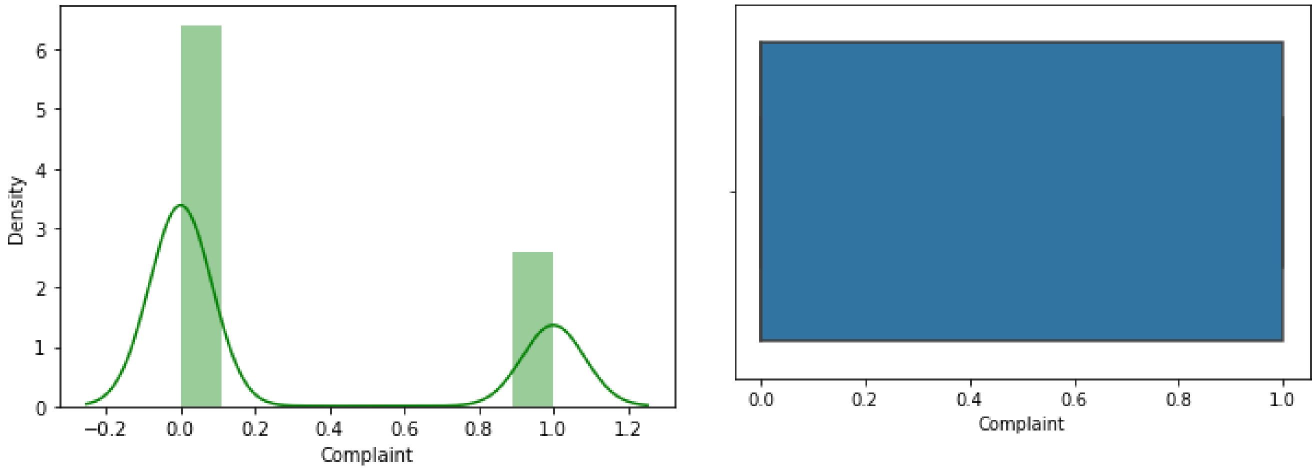

Figure 1(g) Distplot/Histplot - Complaint

- **The distribution of "Complaint" seems to be positively/right skewed.**
- **The data ranges from 0 to 1.**
- **The box plot holds no outliers.**

ExistingPolicyTenure

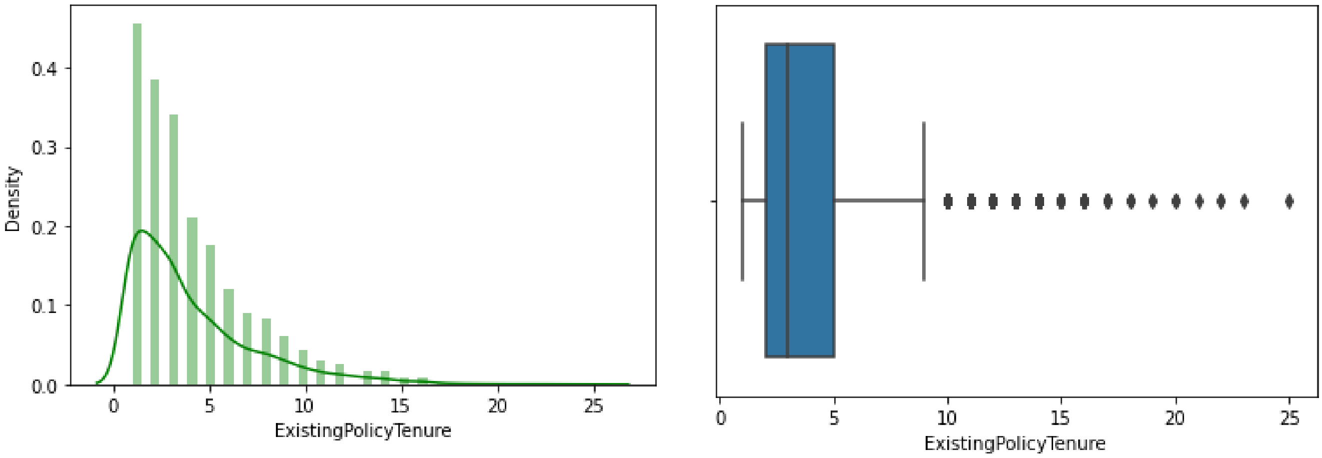

Figure 1(h) Distplot/Histplot - ExistingPolicyTenure

- **The distribution of "ExistingPolicyTenure" seems to be positively/right skewed.**
- **The data ranges from 1 to 25.**
- **The box plot holds many outliers.**

SumAssured

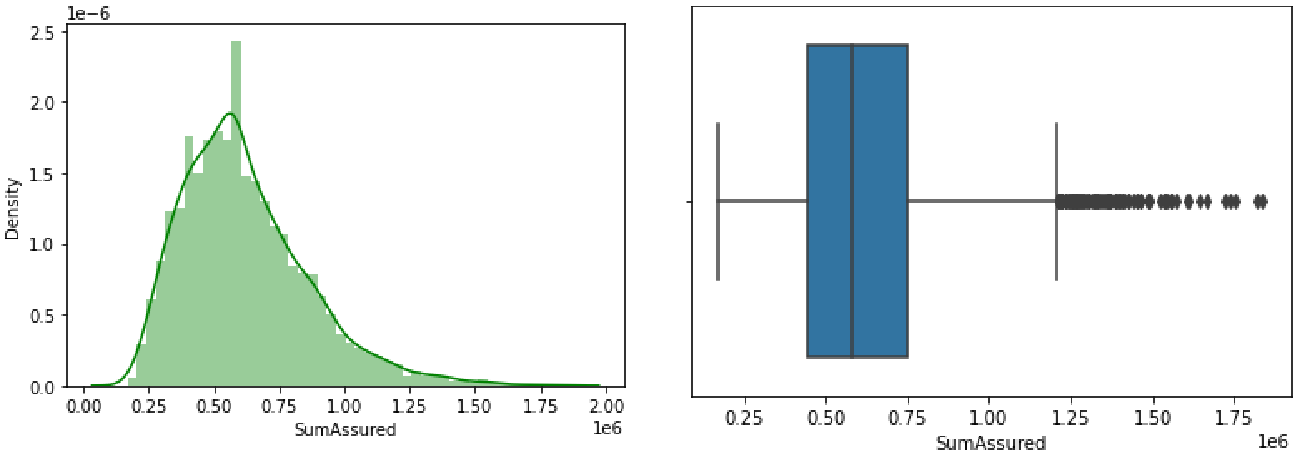

Figure 1(i) Distplot/Histplot - SumAssured

- **The distribution of "SumAssured" seems to be positively/right skewed.**
- **The data ranges from 1.68 * 10^5 to 1.83 * 10^5.**
- **The box plot holds many outliers.**

LastMonthCalls

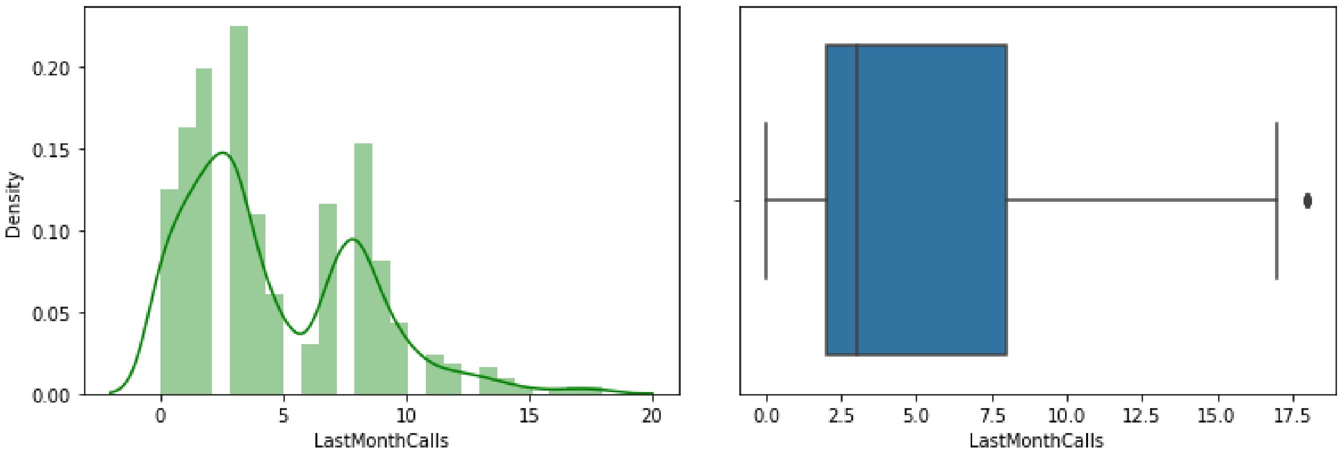

Figure 1(j) Distplot/Histplot - LastMonthCalls

- **The distribution of "LastMonthCalls" seems to be positively/right skewed.**
- **The data ranges from 0 to 18.**
- **The box plot holds outliers.**

CustCareScore

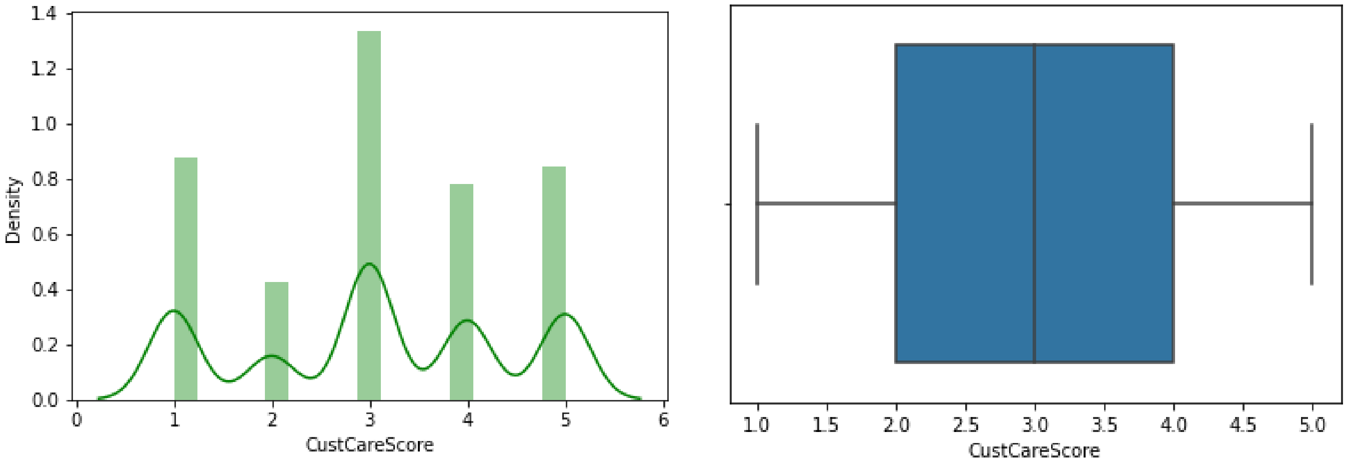

Figure 1(k) Distplot/Histplot – CustCareScore

- **The distribution of "CustCareScore" seems to be slightly left skewed.**
- **The data ranges from 1 to 5.**
- **The box plot holds no outliers**

Skewness

AgentBonus	0.822348
Age	0.998425
CustTenure	0.981002
ExistingProdType	-0.401100
NumberOfPolicy	-0.108161
MonthlyIncome	1.434315
Complaint	0.941129
ExistingPolicyTenure	1.601730
SumAssured	1.002018
LastMonthCalls	0.810417
CustCareScore	-0.138120

- We can observe skewness in the data with ExistingProdType, NumberofPoilicy and CustCareScore being negatively skewed.
- Rest all other parameters holds positive skewness the max being for ExistingPolicyTenure.

Categorical Variable's Univariate Analysis

Education Field

Post Graduate	0.47
Under Graduate	0.31
Diploma	0.11
Engineer	0.09
MBA	0.02

Most Customers approached are Post Graduates having 47% weightage.

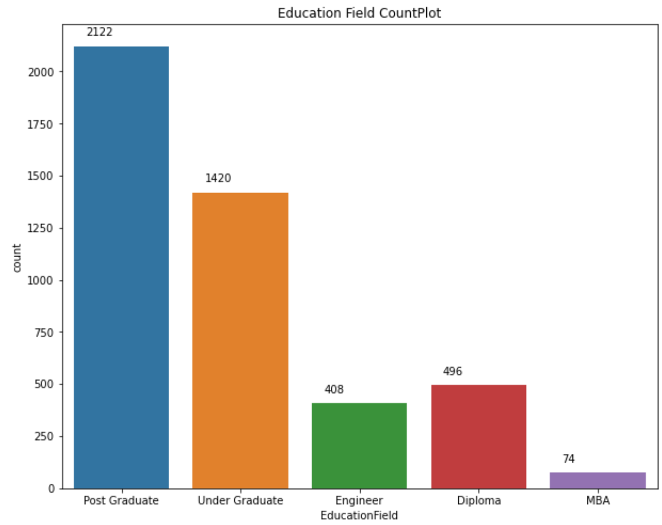

Figure 2(a) Count Plot - EducationField

Channel

Agent	0.71
Third Party Partner	0.19
Online	0.10

Acquisition of a customer is mostly done Via an Agent having 71% weightage.

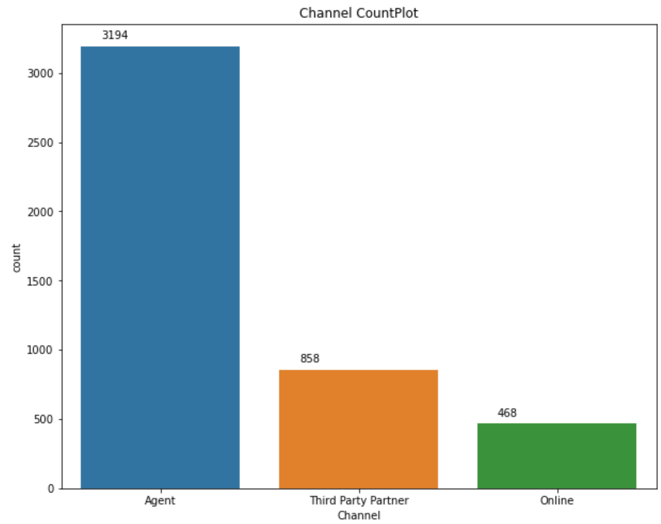

Figure 2(b) Count Plot - Channel

Occupation

Salaried	0.48
Small Business	0.42
Large Business	0.09
Free Lancer	0.00

Most customers have Salaried Occupations Around 48%.
Here freelancers have a minute weightage.

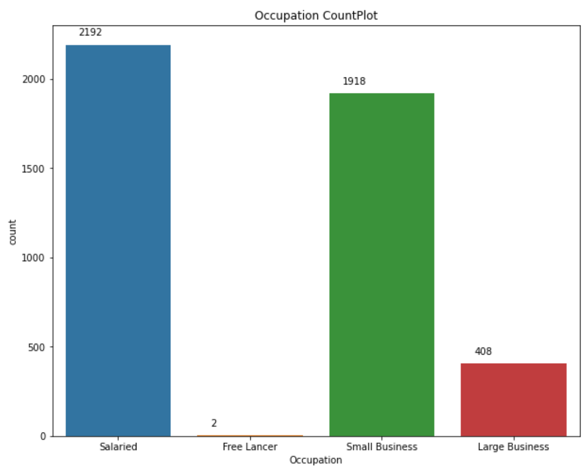

Figure 2(c) Count Plot - Occupation

Gender

Male 0.59
Female 0.41

Approximately 59% of customers
Are males.

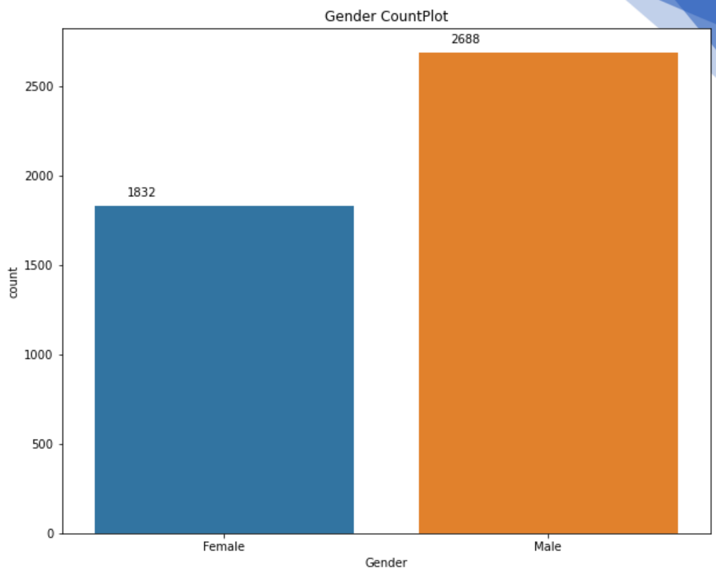

Figure 2(d) Count Plot - Gender

Designation

Executive	0.37
Manager	0.36
Senior Manager	0.15
AVP	0.07
VP	0.05

Most customers are either a
Executive or Managers having
Weightage of 37% and 36%
Respectively.

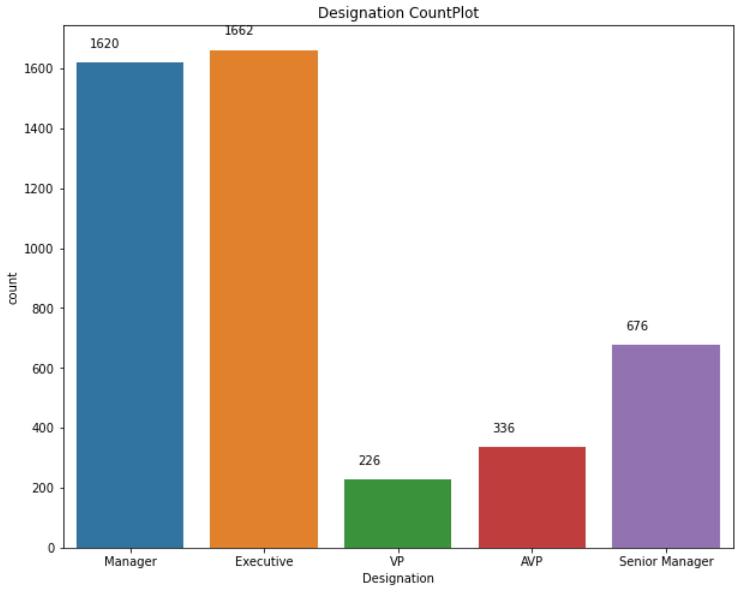

Figure 2(e) Count Plot - Designation

Marital Status

Married	0.50
Single	0.28
Divorced	0.18
Unmarried	0.04

**Around 50% of the customers
Are married.**

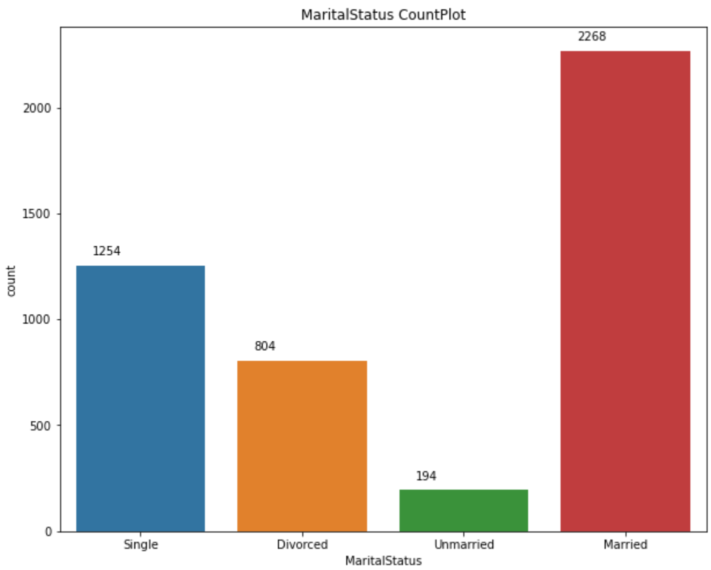

Figure 2(f) Count Plot -Marital Status

Zone

West	0.57
North	0.42
East	0.01
South	0.00

West Zone brings the most Customers with 57% weightage. Here freelancers have a minute weightage.

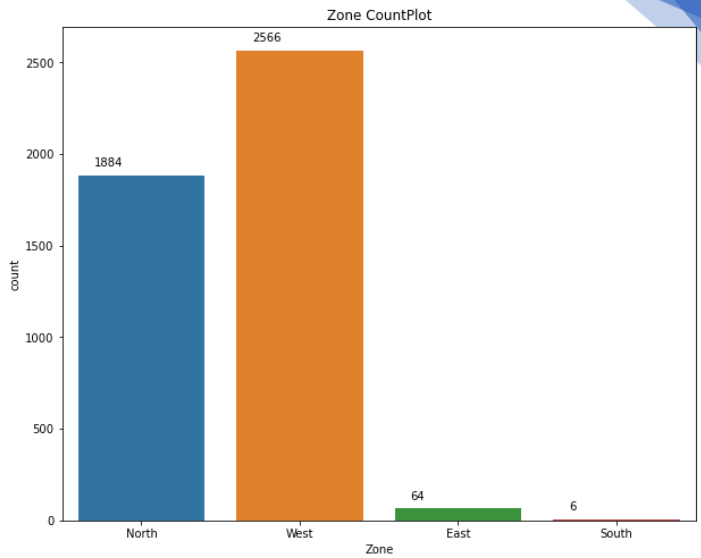

Figure 2(g) Count Plot - Zone

PaymentMethod

Half Yearly	0.59
Yearly	0.32
Monthly	0.08
Quarterly	0.02

Around 59% of Customers went For half-yearly payment plan

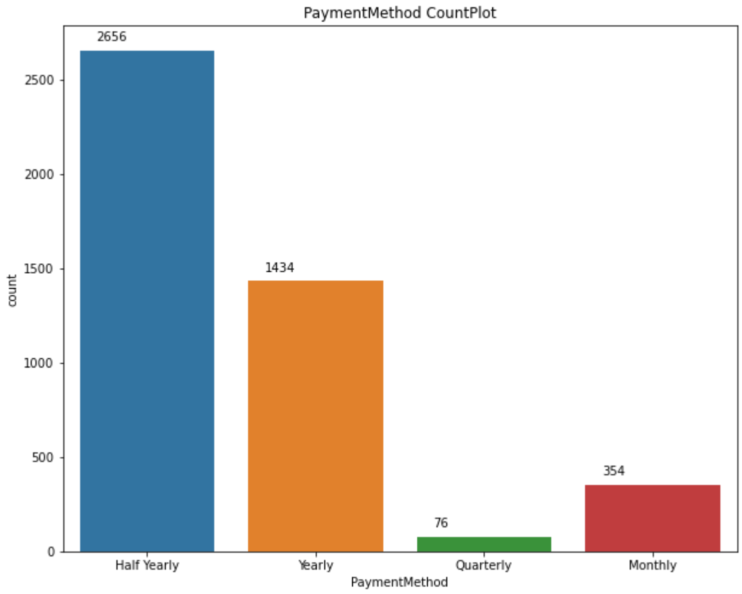

Figure 2(h) Count Plot - PaymentMethod

Categorical Variables Bivariate Analysis w.r.t Agent Bonus

- Agent Bonus has a lot of outlier values for every channel with almost similar mean values for all 3 channels.

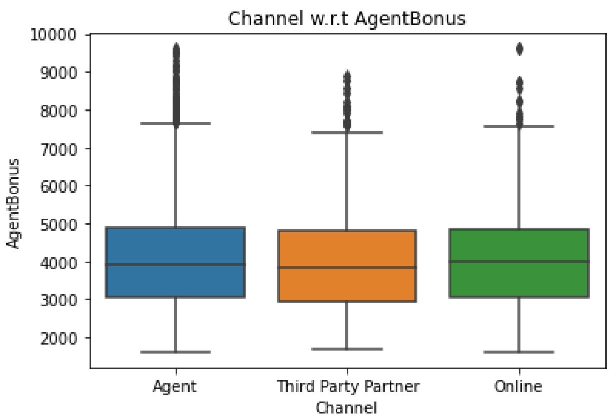

Figure 3(a) Boxplot – Channel w.r.t AgentBonus

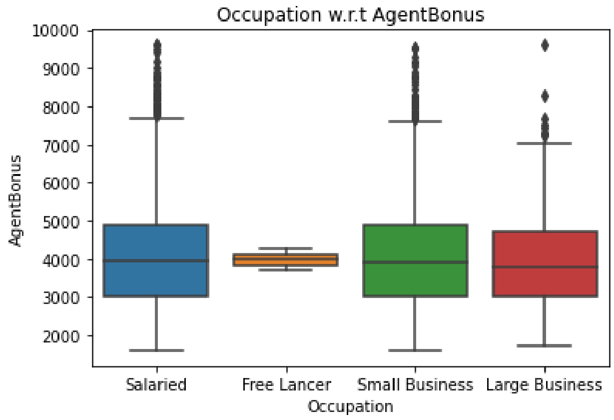

Figure 3(b) Boxplot – Occuapation w.r.t AgentBonus

Almost similar mean value for all Occupations.

NO outliers present for Free Lancer
Could be because we have only 2 data points for Free Lancer.

- Agent Bonus has a lot of outlier values for both Genders with almost similar mean values for b oth Male and Female.

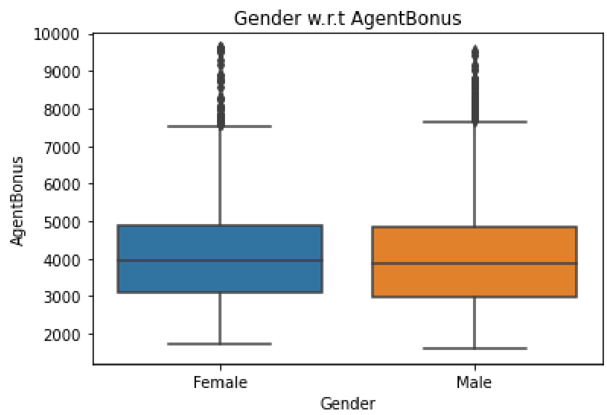

Figure 3(c) Boxplot – Genderl w.r.t AgentBonus

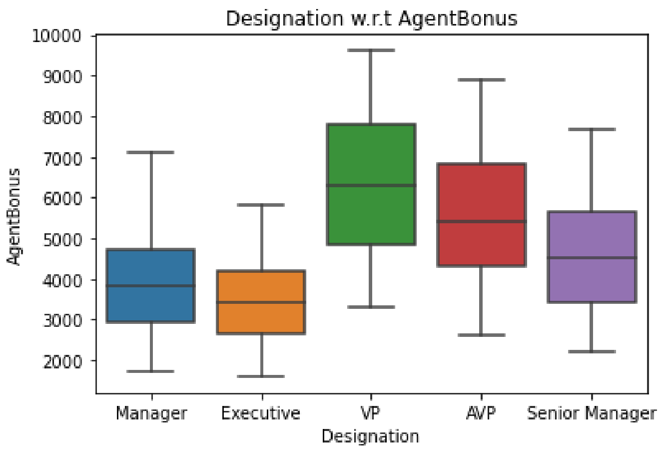

Figure 3(d) Boxplot – Desgnationl w.r.t AgentBonus

No outliers present.

VP Designation has the highest mean
As compared to other Designations.

- Agent Bonus has a lot of outlier values for all MaritalStatus except Unmarried customers.
- With almost similar mean values for all 3 customers except unmarried.

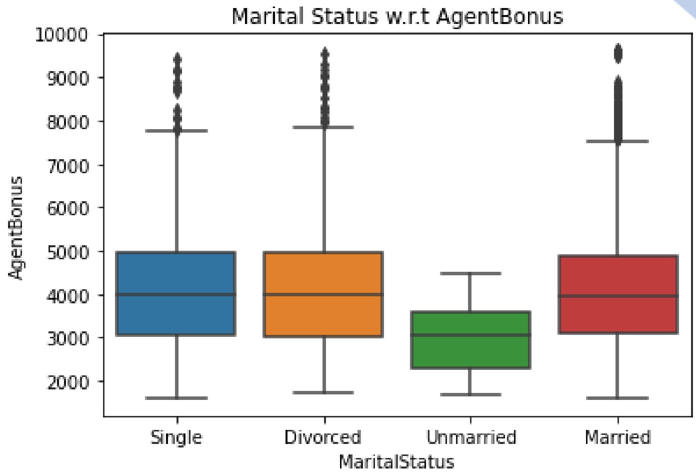

Figure 3(e) Boxplot – MaritalStatus w.r.t AgentBonus

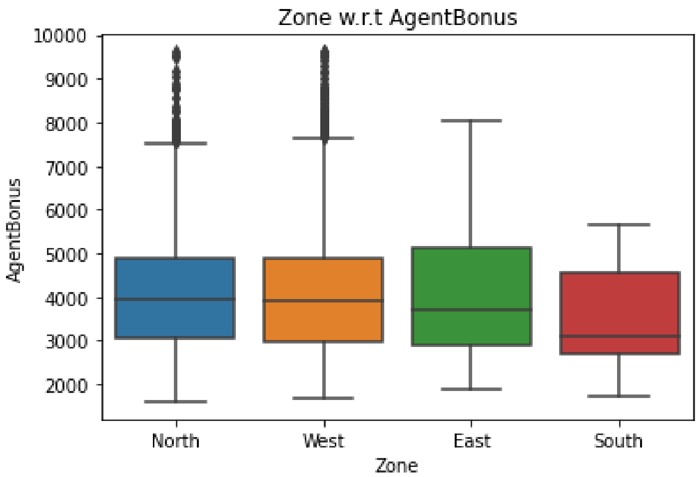

Figure 3(f) Boxplot – Zone w.r.t AgentBonus

Outliers present only for North and West Zones.
Both having almost
Similar means.

No outliers present in East and
South Zones possibly due to less
Customer traffic from those Zones.

- Outliers present for all
Payment methods chosen by the customer.
- Quarterly paying customers having the lowe st mean.

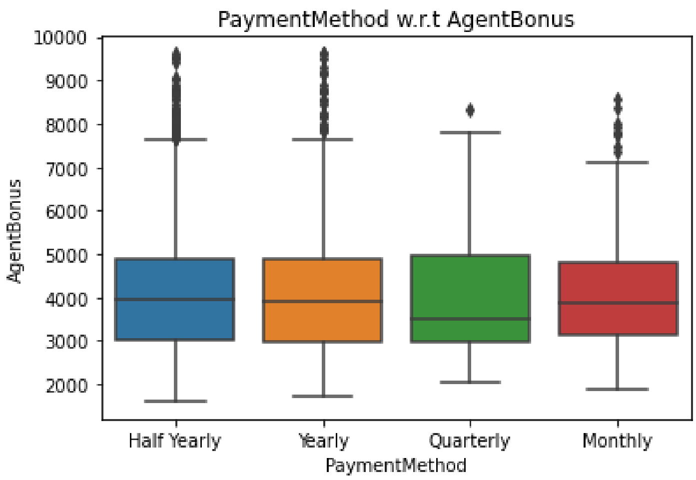

Figure 3(g) Boxplot – Channel w.r.t AgentBonus

Pairplot

A pair plot plots the relationships between all numeric variables in a dataset. The diagonal below is the histogram for each variable and shows the distribution. From the below plot, we can observe if there are relationships between every two pair of variables.

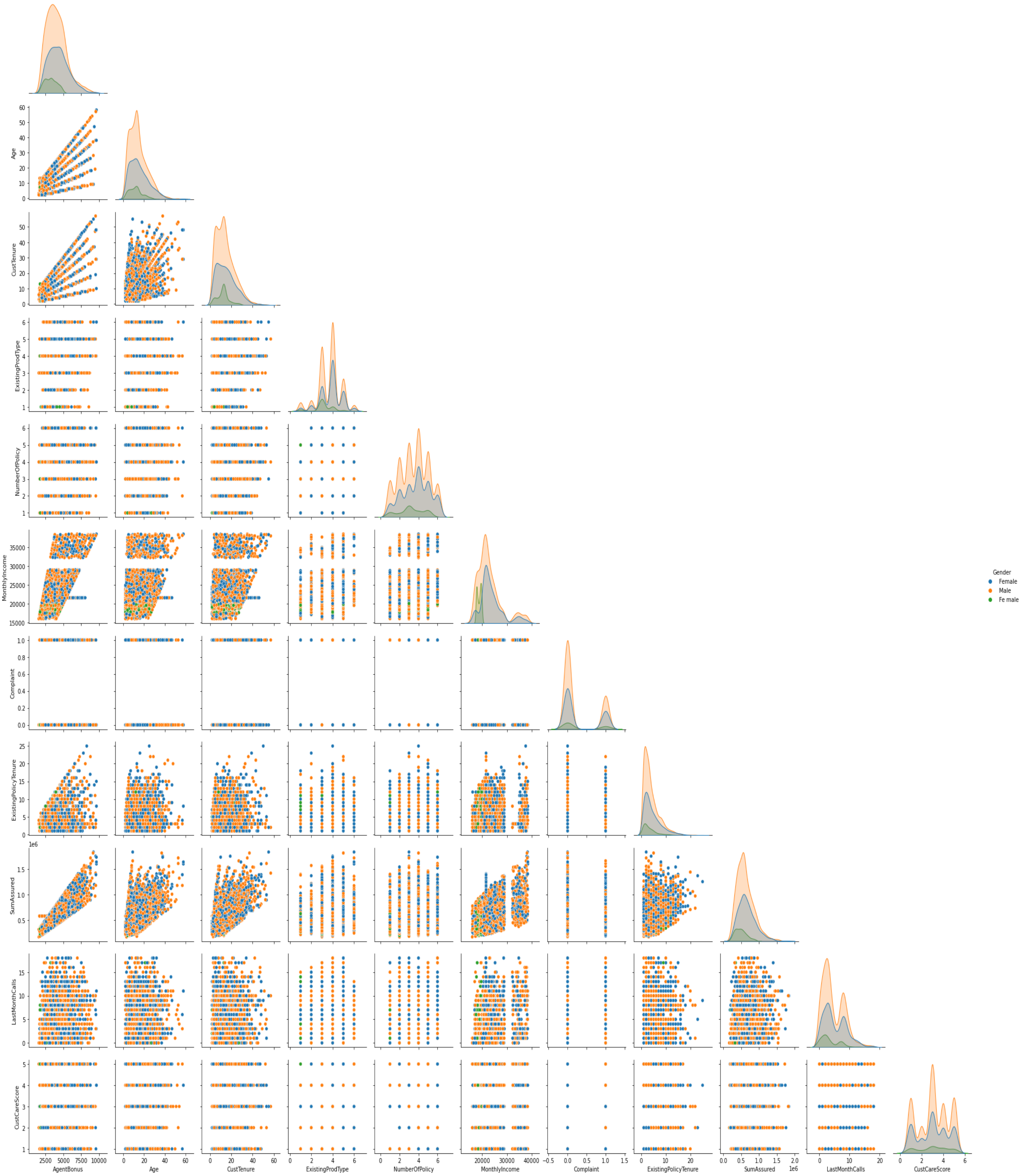

Figure 4 – Pairwise Distribution Plot

Correlation Heatmap.

The correlation coefficient shown in the table below shows the degree of correlation between the two variables represented in X axis and Y axis. It varies between -1 (maximum negative correlation) to +1 (maximum positive correlation).

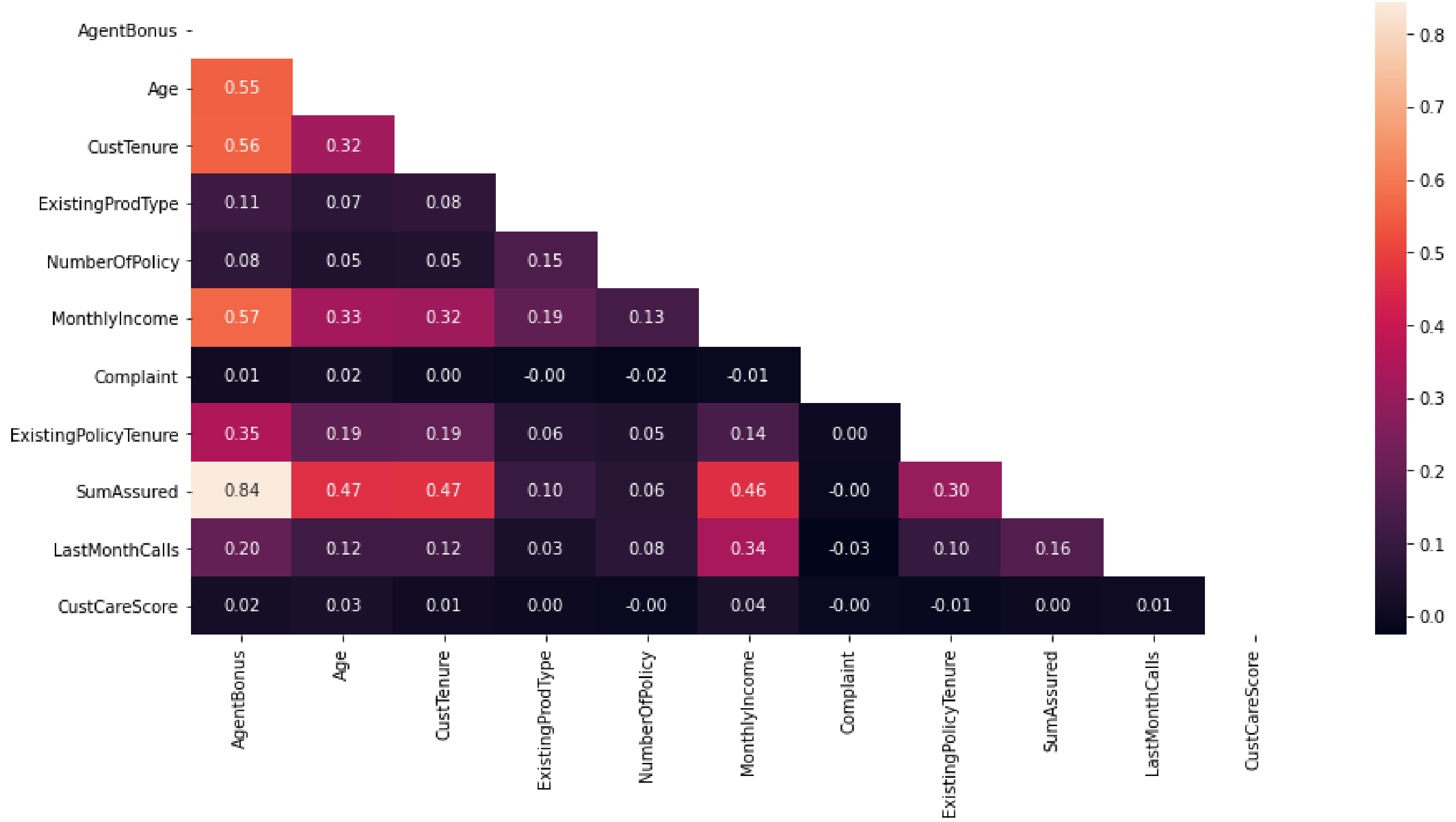

Figure 5 - Correlation Heatmap

- Here the lighter colors depict high correlation and darker colors depict low correlation.
- We can observe that there is almost no multicollinearity in the data.
- Multicollinearity refers to more variables affect our dependant variables, here from the graph above only SumAssured makes the cut as a variable affecting the AgentBonus
- Complaint and CustCareScore have almost no correlation with any other parameter, hence dropping these columns will not make a difference as they hold no weightage in predictions for our dependant variable, i.e AgentBonus where these columns ultimately are ignored in the prediction , hence are removed..
- AgentBonus and SumAssured have high correlation with each other of 0.84.

Business insights from EDA

1. Outlier Removal is performed but it does not seem as the correct approach as some variables like SumAssured are allowed to have some outliers however our model will be affected if outliers are not removed as we will use Linear Regression for our optimal model, where outliers will produce a biase d result with Linear Regression and to prevent that from happening we'll go with the outliers remove d .
2. We can add new variables like Premium which will become another variable having direct correlatio n with AgentBonus and will make it easier to observe the high performing and the low performing agents as the ones who bring in more premium and good for the firm and performing well and those incurring low premium needs to be focused more on.

3. However, adding new variables are not as simple as it sounds as here we have 4520 rows that needs to have a value which will add to the predictions and if we are not careful enough, the new variable introduced will add more variance to our predictions and can be biased too, which ultimately can affect the model, hence it is not recommended unless you have extreme and thorough domain knowledge.
4. With this we've completed the EDA in the coming exercises we'll build the model as this is a Classification problem, Regression Techniques for model building will be our go-to approach.
5. The data from the EDA can be said to be highly unbalanced eg: Zone, South has less weightage similar for Occupation- Freelancer, more data is needed or upscale the data, similar can be the case with EducationField_MBA where we need to have enough data to not make bias decisions which can be done by upscaling the data which will add another problem where the data would be repeatable and not accurate enough to give accurate predictions.

We might have to convert some categorical variables by encoding them into numeric values for out model Building. Stay Tuned to find more.

Model Building and Interpretation

- Regression uses numerical variables,
- But we have a lot of categorical variables we wish to use in our models further,
- And since most of the categorical variables have categories more than 2, therefore applying one-hot encoding.
- One-Hot encoding takes every level of the category and turns it into a variable with two level (yes/no).

The data looks like this after one-hot encoding.

SumAssured	LastMonthCalls	...	Designation_VP	MaritalStatus_Married	MaritalStatus_Single	MaritalStatus_Unmarried	Zone_North	Zone_South	Zone_West
806761.0	5.0	...	0	0	1	0	1	0	0
294502.0	7.0	...	0	0	0	0	1	0	0
578976.5	0.0	...	0	0	0	1	1	0	0
268635.0	0.0	...	0	0	0	0	0	0	1
366405.0	2.0	...	0	0	0	0	0	0	1

- Building our Linear Regression Model with the unprocessed data above.
- Keep in mind, this data holds no outliers as they were removed in EDA – PN1

Split X and y into training and test set in 75:25 ratio

```
The coefficient for Age is                              21.64543636236496
The coefficient for CustTenure is                       22.620905021409023
The coefficient for ExistingProdType is                 46.508784274329514
The coefficient for NumberOfPolicy is                   6.254332127798309
The coefficient for MonthlyIncome is                    0.03188513622751349
The coefficient for Complaint is                        33.0503807570841
The coefficient for ExistingPolicyTenure is             40.22901549596465
The coefficient for SumAssured is                       0.003548018281339438
The coefficient for LastMonthCalls is                   -2.308709717687992
The coefficient for CustCareScore is                    7.559056565466554
The coefficient for Channel_Online is                   22.691900907509453
The coefficient for Channel_Third Party Partner is      3.4952779925482345
The coefficient for Occupation_Large Business is        -616.8600099371561
The coefficient for Occupation_Salaried is              -474.9729637586688
The coefficient for Occupation_Small Business is        -581.6372411869505
The coefficient for EducationField_Engineer is          26.675848148157876
The coefficient for EducationField_MBA is               -177.27368717977166
```

```
The coefficient for EducationField_Post Graduate is      -92.6094978672669
The coefficient for EducationField_Under Graduate is     2.331225272073949
The coefficient for Gender_Male is                       25.187256483000322
The coefficient for Designation_Executive is             -493.36122500604984
The coefficient for Designation_Manager is               -481.4192660702273
The coefficient for Designation_Senior Manager is        -277.42121914512296
The coefficient for Designation_VP is                    -2.956791388368395
The coefficient for MaritalStatus_Married is             -48.20378324641499
The coefficient for MaritalStatus_Single is              29.658243912402032
The coefficient for MaritalStatus_Unmarried is           -188.87907531620797
The coefficient for Zone_North is                        62.35415312785426
The coefficient for Zone_South is                        193.51057687776427
The coefficient for Zone_West is                         49.998087081147155
The coefficient for PaymentMethod_Monthly is             141.95193527244763
The coefficient for PaymentMethod_Quarterly is           112.02879394979776
The coefficient for PaymentMethod_Yearly is              -79.92080455281895
The intercept for our model is 1092.3485100144962
```

	R-Squared	RMSE
Training	0.8068152802160813	600.5900784990952
Testing	0.7825646087670782	621.5274260080358

Checking the same using statsmodel, to get more insights on p-value, r-squared and adjusted r-squared value.

Before we move to statsmodel,

- We need to rename some columns created after encoding as they have some spaces which will not be accepted my statsmodel.

COLUMN NAMES

```
Index(['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_MBA',
       'EducationField_Post Graduate', 'EducationField_Under Graduate',
       'Gender_Male', 'Designation_Executive', 'Designation_Manager',
       'Designation_Senior Manager', 'Designation_VP', 'MaritalStatus_Married',
       'MaritalStatus_Single', 'MaritalStatus_Unmarried', 'Zone_North',
       'Zone_South', 'Zone_West', 'PaymentMethod_Monthly',
       'PaymentMethod_Quarterly', 'PaymentMethod_Yearly', 'AgentBonus'],
```

RENAMED COLUMNS (SPACES REMOVED)

```
Index(['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_MBA',
       'EducationField_Post_Graduate', 'EducationField_Under_Graduate',
       'Gender_Male', 'Designation_Executive', 'Designation_Manager',
       'Designation_Senior_Manager', 'Designation_VP', 'MaritalStatus_Married',
       'MaritalStatus_Single', 'MaritalStatus_Unmarried', 'Zone_North',
       'Zone_South', 'Zone_West', 'PaymentMethod_Monthly',
       'PaymentMethod_Quarterly', 'PaymentMethod_Yearly', 'AgentBonus'],
      dtype='object')
```

Building a Multiple Linear Regression Model, with 'AgentBonus' as the independent variable and all other variables as dependent variables - LINEAR MODEL 1 (LM1)

```
Intercept                        1092.348510
Age                                21.645436
CustTenure                         22.620905
ExistingProdType                   46.508784
NumberOfPolicy                      6.254332
MonthlyIncome                       0.031885
Complaint                          33.050381
ExistingPolicyTenure               40.229015
SumAssured                          0.003548
LastMonthCalls                     -2.308710
CustCareScore                       7.559057
Channel_Online                     22.691901
Channel_Third_Party_Partner         3.495278
Occupation_Large_Business        -616.860010
Occupation_Salaried              -474.972964
Occupation_Small_Business        -581.637241
EducationField_Engineer            26.675848
EducationField_MBA               -177.273687
EducationField_Post_Graduate      -92.609498
EducationField_Under_Graduate       2.331225
Gender_Male                        25.187256
Designation_Executive            -493.361225
Designation_Manager              -481.419266
Designation_Senior_Manager       -277.421219
Designation_VP                     -2.956791
MaritalStatus_Married             -48.203783
MaritalStatus_Single               29.658244
MaritalStatus_Unmarried          -188.879075
Zone_North                         62.354153
Zone_South                        193.510577
Zone_West                          49.998087
PaymentMethod_Monthly             141.951935
PaymentMethod_Quarterly           112.028794
PaymentMethod_Yearly              -79.920805
dtype: float64
```

- **Here the variables with a high value are less significant and do not affect or add to the predictions of dependant variable here AgentBonus.**
- **The variables with low value mean they are highly significant to the predictions hence don't require a high value to balance the weightage it adds to the dependant variable.**
- **And as the value becomes closer to zero the more significant the variable becomes like here SumAssured which we know for a fact is highly significant and is also proved by our EDA.**

More information about variable significance will be provided in the end with the final equation.

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             AgentBonus   R-squared:                       0.807
Model:                            OLS   Adj. R-squared:                  0.805
Method:                 Least Squares   F-statistic:                     424.7
Date:                Sun, 05 Dec 2021   Prob (F-statistic):               0.00
Time:                        23:49:42   Log-Likelihood:                -26499.
No. Observations:                3390   AIC:                         5.307e+04
Df Residuals:                    3356   BIC:                         5.327e+04
Df Model:                          33
Covariance Type:            nonrobust
===================================================================================================
                                      coef    std err          t      P>|t|      [0.025      0.975]
---------------------------------------------------------------------------------------------------
Intercept                        1092.3485    467.264      2.338      0.019     176.198    2008.499
Age                                21.6454      1.420     15.245      0.000      18.862      24.429
CustTenure                         22.6209      1.428     15.840      0.000      19.821      25.421
ExistingProdType                   46.5088     23.229      2.002      0.045       0.964      92.054
NumberOfPolicy                      6.2543      7.560      0.827      0.408      -8.569      21.078
MonthlyIncome                       0.0319      0.005      5.954      0.000       0.021       0.042
Complaint                          33.0504     23.172      1.426      0.154     -12.381      78.482
ExistingPolicyTenure               40.2290      4.066      9.894      0.000      32.257      48.201
SumAssured                          0.0035   5.88e-05     60.294      0.000       0.003       0.004
LastMonthCalls                     -2.3087      3.109     -0.743      0.458      -8.405       3.787
CustCareScore                       7.5591      7.644      0.989      0.323      -7.429      22.547
Channel_Online                     22.6919     34.552      0.657      0.511     -45.054      90.438
Channel_Third_Party_Partner         3.4953     26.973      0.130      0.897     -49.389      56.380
Occupation_Large_Business        -616.8600    453.438     -1.360      0.174   -1505.902     272.182
Occupation_Salaried              -474.9730    428.923     -1.107      0.268   -1315.949     366.003
Occupation_Small_Business        -581.6372    436.329     -1.333      0.183   -1437.134     273.860
EducationField_Engineer            26.6758    155.095      0.172      0.863    -277.414     330.766
EducationField_MBA               -177.2737    123.966     -1.430      0.153    -420.330      65.783
EducationField_Post_Graduate      -92.6095     87.381     -1.060      0.289    -263.934      78.715
EducationField_Under_Graduate       2.3312     36.703      0.064      0.949     -69.631      74.293
Gender_Male                        25.1873     21.339      1.180      0.238     -16.652      67.027
Designation_Executive            -493.3612     59.744     -8.258      0.000    -610.500    -376.222
Designation_Manager              -481.4193     50.448     -9.543      0.000    -580.330    -382.508
Designation_Senior_Manager       -277.4212     48.283     -5.746      0.000    -372.088    -182.755
Designation_VP                     -2.9568     63.911     -0.046      0.963    -128.266     122.352
MaritalStatus_Married             -48.2038     28.749     -1.677      0.094    -104.572       8.164
MaritalStatus_Single               29.6582     31.785      0.933      0.351     -32.662      91.978
MaritalStatus_Unmarried          -188.8791     59.461     -3.177      0.002    -305.462     -72.296
Zone_North                         62.3542     91.992      0.678      0.498    -118.011     242.720
Zone_South                        193.5106    285.551      0.678      0.498    -366.362     753.383
Zone_West                          49.9981     91.518      0.546      0.585    -129.439     229.435
PaymentMethod_Monthly             141.9519     56.403      2.517      0.012      31.363     252.541
PaymentMethod_Quarterly           112.0288     85.052      1.317      0.188     -54.730     278.787
PaymentMethod_Yearly              -79.9208     33.879     -2.359      0.018    -146.346     -13.496
==============================================================================
Omnibus:                      126.575   Durbin-Watson:                   2.005
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              141.177
Skew:                           0.474   Prob(JB):                     2.21e-31
Kurtosis:                       3.315   Cond. No.                     5.53e+07
==============================================================================
```

Here, R-squared (R^2) is a statistical measure that **represents the proportion of the variance for a dependent variable** that's explained by an independent variable or variables in a regression model. Hence a higher R-squared value means the data is capturing maximum variance hence the higher the value, the better the results.

RMSE – value - 600.5900784990948
R squared – value - 0.807
Adjusted R squared – value - 0.805

The variation in R-squared and Adjusted R-squared is not too significant and we have a high value for both, hence a good model.

Variance Inflation Factor(VIF) Value

```
Age  VIF                                        =  1.33
CustTenure  VIF                                 =  1.32
ExistingProdType  VIF                           =  4.36
NumberOfPolicy  VIF                             =  1.12
MonthlyIncome  VIF                              =  4.17
Complaint  VIF                                  =  1.01
ExistingPolicyTenure  VIF                       =  1.11
SumAssured  VIF                                 =  1.73
LastMonthCalls  VIF                             =  1.2
CustCareScore  VIF                              =  1.03
Channel_Online  VIF                             =  1.05
Channel_Third_Party_Partner  VIF                =  1.04
Occupation_Large_Business  VIF                  =  153.84
Occupation_Salaried  VIF                        =  427.21
Occupation_Small_Business  VIF                  =  434.53
EducationField_Engineer  VIF                    =  18.0
EducationField_MBA  VIF                         =  2.0
EducationField_Post_Graduate  VIF               =  17.68
EducationField_Under_Graduate  VIF              =  2.73
Gender_Male  VIF                                =  1.03
Designation_Executive  VIF                      =  7.73
Designation_Manager  VIF                        =  5.43
Designation_Senior_Manager  VIF                 =  2.73
Designation_VP  VIF                             =  1.84
MaritalStatus_Married  VIF                      =  1.92
MaritalStatus_Single  VIF                       =  1.88
MaritalStatus_Unmarried  VIF                    =  1.34
Zone_North  VIF                                 =  19.18
Zone_South  VIF                                 =  1.12
Zone_West  VIF                                  =  19.15
PaymentMethod_Monthly  VIF                      =  2.13
PaymentMethod_Quarterly  VIF                    =  1.11
PaymentMethod_Yearly  VIF                       =  2.31
```

- Wherever VIF score > 5, multicollinearity is present
- Multicollinearity is detected for Occupation_Large_Business, Occupation_Salaried, Occupation_Small_Business, EducationField_Engineer, EducationField_Post_Graduate, Designation_Executive, Designation_Manager(can be omitted), Zone_North, Zone_West.

We still find we have multi collinearity in the dataset, to drop these values to a further lower level we can drop columns after performing stats model.

- **From stats model we can understand the features that do not contribute to the Model**
- ***We can remove those features after that the Vif Values will be reduced. Ideal value of VIF is less than 5%.***

Calculating VIF again after dropping variables having vif>5

```
Age  VIF                                = 1.32
CustTenure  VIF                         = 1.31
ExistingProdType  VIF                   = 3.53
NumberOfPolicy  VIF                     = 1.11
MonthlyIncome  VIF                      = 1.7
Complaint  VIF                          = 1.01
ExistingPolicyTenure  VIF               = 1.11
SumAssured  VIF                         = 1.71
LastMonthCalls  VIF                     = 1.17
CustCareScore  VIF                      = 1.02
Channel_Online  VIF                     = 1.02
EducationField_Engineer  VIF            = 1.11
EducationField_MBA  VIF                 = 1.03
EducationField_Post_Graduate  VIF       = 1.13
Gender_Male  VIF                        = 1.02
Designation_Manager  VIF                = 1.18
Designation_Senior_Manager  VIF         = 1.25
MaritalStatus_Married  VIF              = 1.92
MaritalStatus_Single  VIF               = 1.87
MaritalStatus_Unmarried  VIF            = 1.33
Zone_South  VIF                         = 1.01
Zone_West  VIF                          = 1.02
PaymentMethod_Monthly  VIF              = 1.92
PaymentMethod_Quarterly  VIF            = 1.09
PaymentMethod_Yearly  VIF               = 2.06
```

Running statsmodel again after dropping the necessary variables above - LINEAR MODEL 2 (LM2)

```
Intercept                       -235.677149
Age                               22.256764
CustTenure                        23.459540
ExistingProdType                 -32.270239
NumberOfPolicy                     3.179880
MonthlyIncome                      0.062588
Complaint                         32.347109
ExistingPolicyTenure              40.038106
SumAssured                         0.003593
LastMonthCalls                     1.657254
CustCareScore                      9.045225
Channel_Online                    29.871935
EducationField_Engineer          -20.287296
EducationField_MBA               -97.213875
EducationField_Post_Graduate      10.231469
Gender_Male                       15.950300
Designation_Manager             -124.840296
Designation_Senior_Manager       -24.565951
MaritalStatus_Married            -54.039328
MaritalStatus_Single              16.120937
MaritalStatus_Unmarried         -205.556385
Zone_South                       144.726473
Zone_West                         -5.727819
PaymentMethod_Monthly             13.015562
PaymentMethod_Quarterly           34.504220
PaymentMethod_Yearly               4.557490
dtype: float64
```

This time we are getting a negative intercept

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             AgentBonus   R-squared:                       0.803
Model:                            OLS   Adj. R-squared:                  0.801
Method:                 Least Squares   F-statistic:                     547.2
Date:                Sat, 11 Dec 2021   Prob (F-statistic):               0.00
Time:                        00:31:07   Log-Likelihood:                -26535.
No. Observations:                3390   AIC:                         5.312e+04
Df Residuals:                    3364   BIC:                         5.328e+04
Df Model:                          25
Covariance Type:            nonrobust
===============================================================================================
                                  coef    std err          t      P>|t|      [0.025      0.975]
-----------------------------------------------------------------------------------------------
Intercept                    -235.6771     93.849     -2.511      0.012    -419.684     -51.670
Age                            22.2568      1.431     15.552      0.000      19.451      25.063
CustTenure                     23.4595      1.437     16.323      0.000      20.642      26.277
ExistingProdType              -32.2702     21.099     -1.529      0.126     -73.638       9.097
NumberOfPolicy                  3.1799      7.601      0.418      0.676     -11.723      18.083
MonthlyIncome                   0.0626      0.003     18.138      0.000       0.056       0.069
Complaint                      32.3471     23.352      1.385      0.166     -13.438      78.132
ExistingPolicyTenure           40.0381      4.095      9.777      0.000      32.009      48.067
SumAssured                      0.0036    5.9e-05     60.886      0.000       0.003       0.004
LastMonthCalls                  1.6573      3.097      0.535      0.593      -4.414       7.729
CustCareScore                   9.0452      7.700      1.175      0.240      -6.051      24.142
Channel_Online                 29.8719     34.341      0.870      0.384     -37.460      97.204
EducationField_Engineer       -20.2873     38.882     -0.522      0.602     -96.521      55.947
EducationField_MBA            -97.2139     90.008     -1.080      0.280    -273.689      79.262
EducationField_Post_Graduate   10.2315     22.269      0.459      0.646     -33.430      53.893
Gender_Male                    15.9503     21.457      0.743      0.457     -26.119      58.020
Designation_Manager          -124.8403     23.744     -5.258      0.000    -171.395     -78.286
Designation_Senior_Manager    -24.5660     32.955     -0.745      0.456     -89.180      40.048
MaritalStatus_Married         -54.0393     28.999     -1.864      0.062    -110.896       2.818
MaritalStatus_Single           16.1209     32.012      0.504      0.615     -46.645      78.887
MaritalStatus_Unmarried      -205.5564     59.836     -3.435      0.001    -322.876     -88.237
Zone_South                    144.7265    273.767      0.529      0.597    -392.041     681.493
Zone_West                      -5.7278     21.280     -0.269      0.788     -47.451      35.996
PaymentMethod_Monthly          13.0156     54.141      0.240      0.810     -93.137     119.168
PaymentMethod_Quarterly        34.5042     85.134      0.405      0.685    -132.416     201.425
PaymentMethod_Yearly            4.5575     32.348      0.141      0.888     -58.866      67.981
==============================================================================
Omnibus:                      160.583   Durbin-Watson:                   2.002
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              188.423
Skew:                           0.522   Prob(JB):                     1.21e-41
Kurtosis:                       3.494   Cond. No.                     1.72e+07
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.72e+07. This might indicate that there are
strong multicollinearity or other numerical problems.
```

As it can be observed above the P-value for multiple variables are greater than our alpha i.e 0.05, depicting multicollinearity present therefore we will drop the variables and perform the statsmodel again.

- **To ideally bring down the values to lower levels we can drop one of the variable that is highly correlated.**
- ***Dropping variables would bring down the multi collinearity level down***

	RMSE (LM2)	**RMSE (LM1)**
Training	607.0547411435514	600.5900784990952
Testing	629.0548786960638	621.5274260080358

Since for model 2 our RMSE value has increased, it is not an optimal way to choose the new model. Not a significant change in R-squared either.
Removing variables until all the insignificant variables are removed.

```
                         OLS Regression Results
==============================================================================
Dep. Variable:             AgentBonus   R-squared:                       0.806
Model:                            OLS   Adj. R-squared:                  0.805
Method:                 Least Squares   F-statistic:                     1399.
Date:                Sat, 11 Dec 2021   Prob (F-statistic):               0.00
Time:                        00:44:36   Log-Likelihood:                -26511.
No. Observations:                3390   AIC:                         5.304e+04
Df Residuals:                    3379   BIC:                         5.311e+04
Df Model:                          10
Covariance Type:            nonrobust
===========================================================================================
                                coef    std err          t      P>|t|      [0.025      0.975]
-------------------------------------------------------------------------------------------
Intercept                   643.6161    129.776      4.959      0.000     389.168     898.064
Age                          21.8786      1.416     15.451      0.000      19.102      24.655
CustTenure                   22.7193      1.424     15.955      0.000      19.927      25.511
MonthlyIncome                 0.0372      0.004      8.473      0.000       0.029       0.046
ExistingPolicyTenure         40.1752      4.037      9.951      0.000      32.259      48.091
SumAssured                    0.0036   5.85e-05     60.654      0.000       0.003       0.004
Designation_Executive      -427.4484     52.722     -8.108      0.000    -530.818    -324.079
Designation_Manager        -436.7599     45.193     -9.664      0.000    -525.367    -348.152
Designation_Senior_Manager -258.6449     43.277     -5.977      0.000    -343.496    -173.794
MaritalStatus_Married       -67.6078     21.235     -3.184      0.001    -109.243     -25.973
MaritalStatus_Unmarried    -226.2434     55.495     -4.077      0.000    -335.050    -117.437
==============================================================================
Omnibus:                      128.393   Durbin-Watson:                   1.999
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              143.854
Skew:                           0.475   Prob(JB):                     5.79e-32
Kurtosis:                       3.341   Cond. No.                     9.23e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 9.23e+06. 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 atleast 1 regression co-efficient is not 0. Here all regression co-efficients are not 0

We can see all variables are having p-value < 0.05 and the r-squared value hasn't changes much either

	RMSE (LM2)	**RMSE (LM1)**
Training	602.6246250878111	600.5900784990952
Testing	620.4861930401804	621.5274260080358

Since for model 2 our RMSE value has increased, it is not an optimal way to choose the new model.

- **Modelling approach used here is Linear Regression, which is a machine learning algorithm based on supervised learning. It performs a regression task. Regression models a target prediction value based on independent variables. It is mostly used for finding out the relationship between variables and forecasting.**

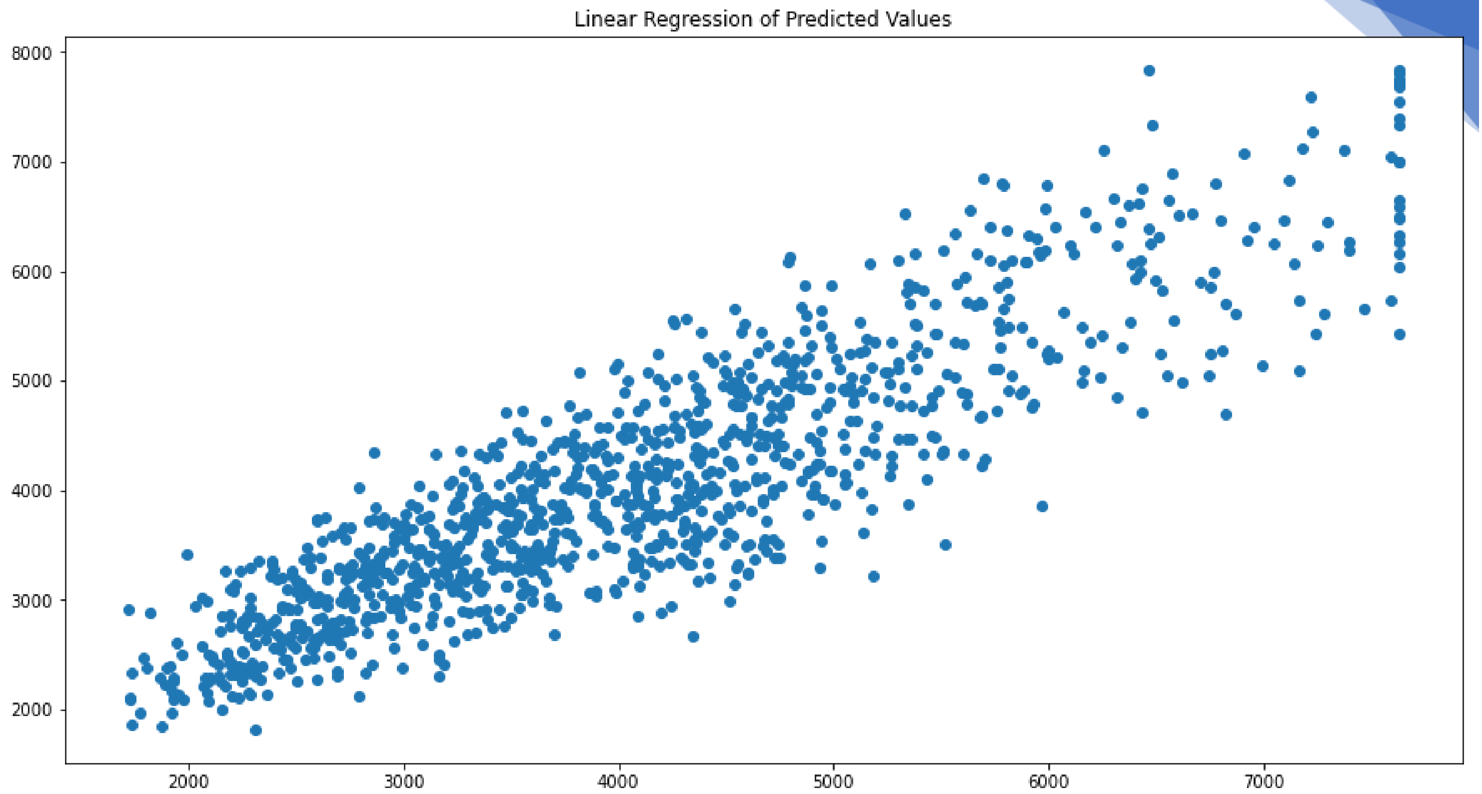

Figure 6 - Linear Regression Scatterplot

The variables are following a linear trend with a little homoscedasticity.

Model Outputs (Without Model Tuning):

Comparing Linear Regression Model with Other models like Random Forest, Artificial Neural Network and Decision Trees – With base parameter values are no hyperparameter tuning the parameters.

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

Scaling is done as some variables with greater weight will affect the predictions more, hence scaling is done to bring all variables in a common range e.g., 0 to 1. Due to which the predictions can be unbiased and not biased to one specific variable with higher weights. For e.g., age and sum assured.

SCALING

- **Scaling can be useful to reduce or check the multi collinearity in the data, so if scaling is not applied, I find the VIF – variance inflation factor values very high. Which indicates presence of multi collinearity**
- ***These values are calculated after building the model of linear regression. To understand the multi collinearity in the model***
- ***The scaling had no impact in model score or coefficients of attributes nor the intercept.***

	Train RMSE	Test RMSE	Training Score	Test Score
Linear Regression	612.550689	585.514819	0.800806	0.801482
Decision Tree Regressor	0.000000	725.006753	1.000000	0.695626
Random Forest Regressor	189.614010	519.044211	0.980913	0.843997
ANN Regressor	225.889011	701.144120	0.972912	0.715332

Here Linear Regression is the best performing model with almost same Training and Testing Accuracies.

On the other hand, we can observe that the other three models namely, Decision Tree, Random Forest, and ANN are Overfitting the model, i.e. the model is performing better while training but poorly while testing.

To fix this we will use Hyperparameter Tuning, this will be done by performing grid search .

Checking if PCA can be applied here.

```
Cumulative Variance Explained [ 99.97511098  99.99912638  99.99999976  99.99999986  99.
99999995
  99.99999997  99.99999998  99.99999999  99.99999999  99.99999999
  99.99999999 100.         100.         100.         100.
 100.         100.         100.         100.         100.
 100.         100.         100.         100.         100.
 100.         100.         100.         100.         100.
 100.         100.         100.         100.        ]
```

Since cumulative variance is almost 99%, hence there is no need to perform PCA

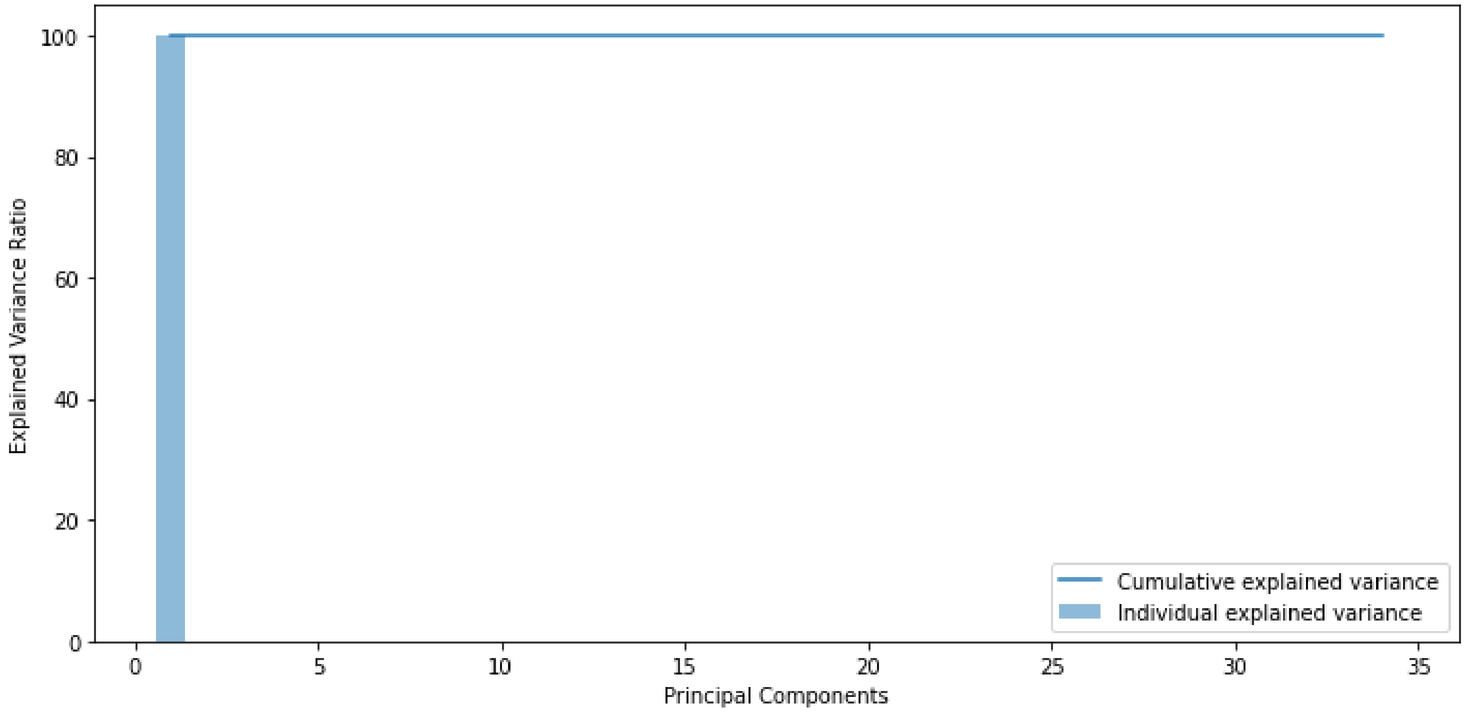

Figure 7 – Principal Components vs Variance Ratio

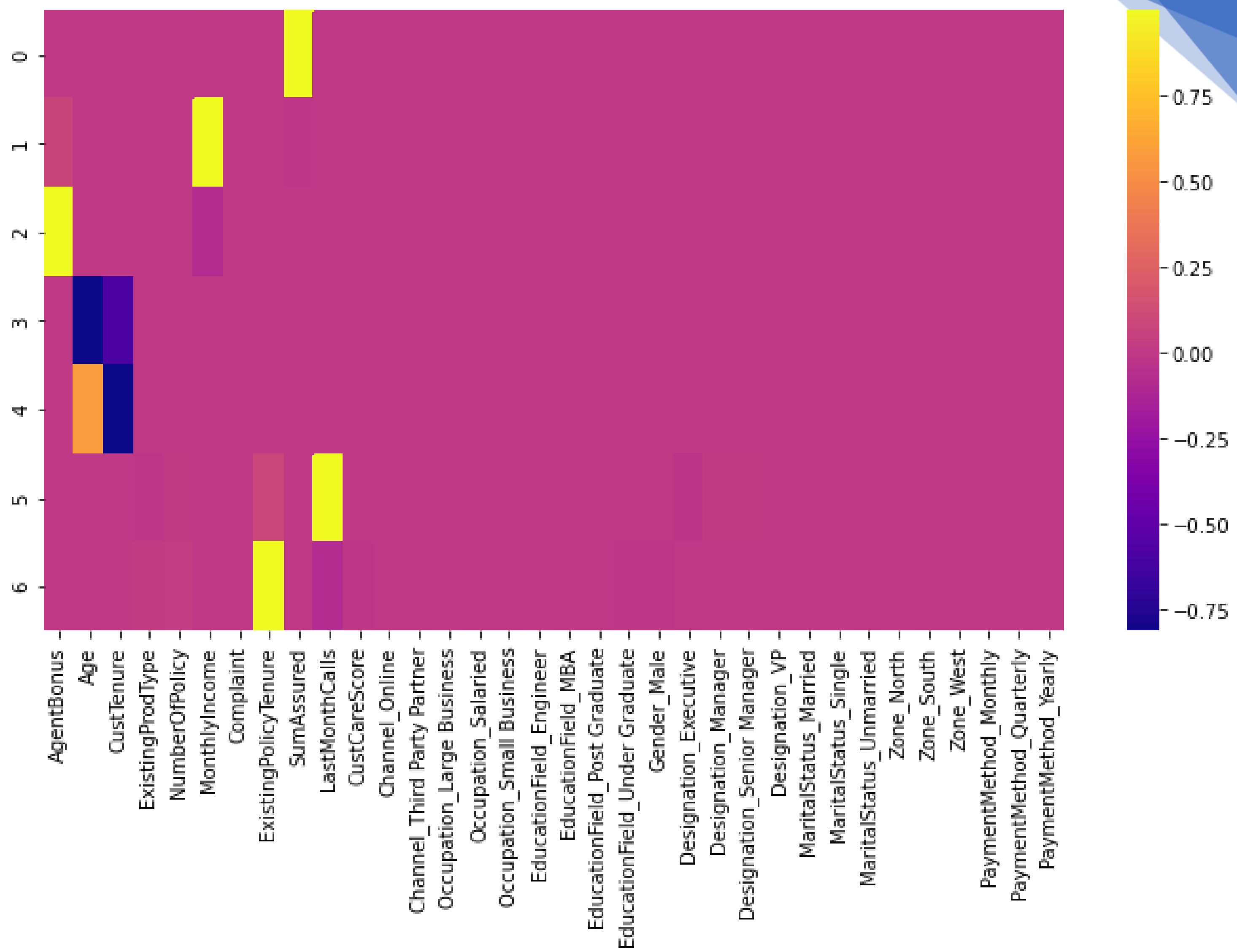

Figure 8 – PCA Heatmap

Not much can be observed about the components from the heatmap, therefore dropping the need to perform PCA as almost all these variables hold a good deal of significance in the predictions.

MODEL TUNING

We will perform grid search for hyperparameter tuning and check if that makes a difference in our accuracies.

Grid Search on Decision Tree

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

Grid Search on Random Forest

```
GridSearchCV(cv=3, estimator=RandomForestRegressor(random_state=123),
             param_grid={'max_depth': [7, 10], 'max_features': [4, 6],
                         'min_samples_leaf': [3, 15, 30],
                         'min_samples_split': [30, 50, 100],
                         'n_estimators': [300, 500]})
```

```
Best Parameters - {'max_depth': 10, 'max_features': 6, 'min_samples_leaf': 3,
                   'min_samples_split': 30, 'n_estimators': 500}
```

Using Grid Search for ANN

```
GridSearchCV(cv=3, estimator=MLPRegressor(max_iter=10000, random_state=123),
             param_grid={'activation': ['tanh', 'relu'],
                         'hidden_layer_sizes': [500, (100, 100)],
                         'solver': ['sgd', 'adam']})

Best parameters - {'activation': 'tanh', 'hidden_layer_sizes': 500, 'solver': 'adam'}
```

Model Outputs (With Model Tuning):

	Train RMSE	Test RMSE	Training Score	Test Score
Linear Regression	612.550689	585.514819	0.800806	0.801482
Decision Tree Regressor	495.463438	569.694730	0.869679	0.812065
Random Forest Regressor	527.410585	572.885614	0.852331	0.809954
ANN Regressor	28.117642	670.444991	0.999580	0.739715

After Hyperparameter tuning it can be observed the problem of overfitting is removed for most of the models however some overfitting can be observed in ANN.

Apart from this, we can observe Linear Regression is still the most stable having not much variation between training and testing sets.

If you’re looking for more stable Model, definitely go for Linear Regression model, else Decision Tree and Random Forest can be chosen for higher accuracy and are good models as the there’s only 5% fluctuations between training and testing model. Random forest is the better choice between the Regressors as random forest is the more advanced version of decision trees where we can further tweak the parameters according to the needs.

Feature Importance from the model can be observed here:

	Imp
SumAssured	0.428155
CustTenure	0.155577
Age	0.144097
MonthlyIncome	0.113766
ExistingPolicyTenure	0.038903
Designation_Executive	0.032743
Designation_VP	0.027304
LastMonthCalls	0.010814
Designation_Manager	0.010730
Designation_Senior Manager	0.007526
ExistingProdType	0.004708
NumberOfPolicy	0.004006
MaritalStatus_Unmarried	0.003666
CustCareScore	0.002908
Zone_North	0.001236
MaritalStatus_Single	0.001231
MaritalStatus_Married	0.001103
Gender_Male	0.001099
Channel_Third Party Partner	0.001056
Complaint	0.001049
Zone_West	0.001029
EducationField_Post Graduate	0.000941

```
Occupation_Salaried            0.000940
EducationField_Under Graduate  0.000844
PaymentMethod_Yearly           0.000832
Occupation_Small Business      0.000793
Channel_Online                 0.000773
PaymentMethod_Monthly          0.000698
EducationField_Engineer        0.000623
Occupation_Large Business      0.000546
PaymentMethod_Quarterly        0.000171
EducationField_MBA             0.000131
Zone_South                     0.000003
```

Sum Assured is the most important feature here, Zone_South being the least important.

MODEL SELECTION

- **From the previous results, it is evident that Linear Regression is a better model.**
- **Why Linear Regression?**
  - **Post removal of variables causing multicollinearity, Linear Regression provided a good R-squared value and similarly a high adjusted R squared value. Hence a good percentage of variance can be successfully explained by our model.**
  - **A very important factor being the train and test set accuracy scores are ~80% and consistent.**
  - **Unlike other models where overfitting and inconsistency in the performance metrics can be observed. Linear Regression model does not show these inconsistencies in the observation.**

(Here by overfitting we mean, the model is performing very good for training set and giving poor results for the testing set)

  - **The LR model makes it easier to understand the model, multicollinearity in the data. Also, unlike other model its computational time is quick therefore we can run it multiple times whereas ANN and Random Forests needs capable machines as they are very time consuming models. Might have to wait for hours and in our case they still don't perform better than LR.**

Note: 100 % accuracy cannot be achieved in real life data as there is always some unexplainable factors and noise that's always present in our data.

MODEL EVALUATION

The Equation

(1092.35) * Intercept + (21.65) * Age + (22.62) * CustTenure + (46.51) * ExistingProdType + **(6.25) * NumberOfPolicy** + **(0.03) * MonthlyIncome** + (33.05) * Complaint + (40.23) * ExistingPolicyTenure + **(0.0) * SumAssured** + **(-2.31) * LastMonthCalls** + **(7.56) * CustCareScore** + (22.69) * Channel_Online + **(3.5) * Channel_Third_Party_Partner** + (-616.86) * Occupation_Large_Business + (-474.97) * Occupation_Salaried + (-581.64) * Occupation_Small_Business + (26.68) * EducationField_Engineer + (-177.27) * EducationField_MBA + (-92.61) * EducationField_Post_Graduate **+ (2.33) * EducationField_Under_Graduate** + (25.19) * Gender_Male + (-493.36) * Designation_Executive + (-481.42) * Designation_Manager + (-277.42) * Designation_Senior_Manager **+ (-2.96) * Designation_VP** + (-48.2) * MaritalStatus_Married + (29.66) * MaritalStatus_Single + (-188.88) * MaritalStatus_Unmarried + (62.35) * Zone_North + (193.51) * Zone_South + (50.0) * Zone_West + (141.95) * PaymentMethod_Monthly + (112.03) * PaymentMethod_Quarterly + (-79.92) * PaymentMethod_Yearly

- **From the equation the variables with a low or no coefficient value depicts that the variable is very important to the independent variable's prediction. As the coefficients value increase it shows the variable has become comparatively less significant.**

The variable significance can be explained using the * method, where * depicts highly significant, ** less significant, and * and **** least significant.**

Variables	Significance
SumAssured, MonthlyIncome	*
LastMonthCalls, CustCareScore, Channel_Third_Party_Partner, EducationField_Under_Graduate, Designation_VP, NumberOfPolicy	**
Age, CustTenure, Channel_Online, EducationField_Engineer, Gender_Male, MaritalStatus_Single, Complaint, ExistingPolicyTenure, MaritalStatus_Married, Zone_West, Zone_North, PaymentMethod_Yearly, EducationField_Post_Graduate	***
Occupation_Large_Business, Occupation_Salaried, Occupation_Small_Business, EducationField_MBA, Designation_Executive, Designation_Manager, Designation_Senior_Manager, MaritalStatus_Unmarried, Zone_South, Paymentmethod_Monthly, PaymentMethod_Quaterly	****

- **R-Squared Obtained from final Linear Regression Model: 0.806**
- **Adjusted R-Squared Obtained from final Linear Regression Model: 0.805**
- **Decision Trees, Random Forest, and ANN (Before Hyperparameter Tuning) :**
  - **It can be observed that all the 3 models have overfitting problems where we have ideal accuracies of ~100% for our training set. However the models are performing poorly on our testing set having accuracies ~70% – 84%. There is a major accuracy difference between the training and testing set which is not acceptable for predictions.**
  - **If the accuracy difference is greater than 6-10% it is advised to not accept the model as the predictions can be unreliable.**
- **Decision Trees, Random Forest, and ANN (After Hyperparameter Tuning) :**
  - **After Hyperparameter Tuning Decision Trees and Random Forest models showed no overfitting errors.**
  - **The training accuracies were ~85% and testing accuracies were ~80%.**
  - **ANN still showed no improvement in results and was still overfitting.**
- **Although the Decision Trees and Random Forest were performing good, I went with Linear Regression as it gave more stable results and Variable importance could be calculated more easily from the Linear Regression Equation and stats-model performed to predict the results.**

Insights from Analysis.

- **Company wants to predict the ideal bonus and what is the engagement for high and low performing agents respectively.**
- **From the model, the high performing agent we will find variable significance, for eg, Sum Assured is highly significant here and highly correlated to our target variable.**
- **SumAssured is highly significant as the agent performing good is the one which is getting more profit for the company selling more or high value policies.**
- **If the Designation is VP the person buys more policy or high value policies.**
- **Therefore, for high and low performing agents, we will train them, suggesting them to purchase or get policies with high sum assured as it is very significant to our model.**
- **Another important feature is Customer tenure where the agents need to focus on the customers who've a tenure ranging between 8-20 this where the majority of the customer are.**
- **Focusing on customers with greater monthly incomes as greater the monthly income, greater is the possibility of the customer buying a higher valued policy.**
- **From the Linear Regression Equation we can find insights and remove all the least significant variables**

Recommendations.

- **For High Performing Agents we can create a healthy contest with a threshold.**
- **Where, if they achieve the desired sum assured, they are eligible for certain incentives like latest gadgets, exotic family vacation packages and some extra perks as well.**
- **For low performing agents, we can introduce certain feedback upskill programs to train them into closing higher sum assured policies, reaching certain people to ultimately becoming top/high performers.**
- **Apart from this, we need more data/predictors like Premium Amount, this will help us to solve the business problem even better as well have more variables to test upon thereby having more accurate results in real time problems like this.**
- **I also feel another predictor can be added as customers geographical location or Region and not just the zones as people living in rural areas are less likely to buy a policy whereas those living in a highly developed location are likely to be belonging to the upper class and should be targeted.**
- **Similarly, another predictor can be AgentID can be introduced which will make it easier to observe the high and low performing agent trend.**