Business Report

(Project Report)

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Content :

1) Introduction of the business problem

a) Problem statement

The major objective of this data set is to extract actionable insights from the leading life insurance company data and make strategic changes to make the company grow. Primary objective is to create Machine Learning models which correctly predicts the bonus for its agents so that it may provide information regarding high performing agents and low performing agents. Once a model is developed then it can extract actionable insights and recommendation, so based of which the company may design appropriate engagement activity and up skill programs for their agents as required.

b) Need of the study/project

Based on their agents to sell the policies, the insurance companies are heavily dependent on their success. So, it becomes very crucial to find and design engagement activity for their high performing agents giving them more and more incentives to keep up their performance and achieve more and also, up skill programs for their low performing agents to get better and perform better, and such that all together their agents are more able to sell the quality insurance to their customers and add more greater value to the company. And through this project with the help of data and its analysis help the insurance company to make data-driven business decisions. It empowers companies with high-level data and information that is leveraged into improved insurance processes and new opportunities.

Basically the need of this data study here is Bonus prediction of the employees. Help the company to conduct proper skill engaging activities for well performing agents. Help the company to conduct proper upskill activities for under performing agents. These programs will help the company to increase skilled employment.

c) Understanding business / social opportunity

Usually businesses benefit to the extent that they stay close to customers. Traditionally, the insurance company has relied on strong networking and trusted relationships. By transforming into social businesses, insurers can tap significant opportunities that enable them to generate more demand, win customer loyalty and maximize returns.

2) Data Report

a) Understanding how data was collected in terms of time, frequency and methodology

The data belongs to a leading life insurance company. The agent's different sales data based on the customers' varied attributes like age, tenure in organization, channel through which acquisition is done, their occupation, education, Designation Marital status, Gender, their location, complaint registered, income, customer satisfaction score, all collected in the course of time they were with the company. Certain attributes leading to the Agent's bonus are also captured.

Variable	Discerption
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
MaritalStatus	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

b) Visual inspection of data (rows, columns, descriptive details)

```
RangeIndex: 4520 entries, 0 to 4519
Data columns (total 20 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   CustID                4520 non-null   int64
 1   AgentBonus            4520 non-null   int64
 2   Age                   4251 non-null   float64
 3   CustTenure            4294 non-null   float64
 4   Channel               4520 non-null   object
 5   Occupation            4520 non-null   object
 6   EducationField        4520 non-null   object
 7   Gender                4520 non-null   object
 8   ExistingProdType      4520 non-null   int64
 9   Designation           4520 non-null   object
```

```
 10  NumberOfPolicy        4475 non-null   float64
 11  MaritalStatus         4520 non-null   object
 12  MonthlyIncome         4284 non-null   float64
 13  Complaint             4520 non-null   int64
 14  ExistingPolicyTenure  4336 non-null   float64
 15  SumAssured            4366 non-null   float64
 16  Zone                  4520 non-null   object
 17  PaymentMethod         4520 non-null   object
 18  LastMonthCalls        4520 non-null   int64
 19  CustCareScore         4468 non-null   float64
dtypes: float64(7), int64(5), object(8)
```

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
CustID	4520.00	NaN	NaN	NaN	7002259.50	1304.96	7000000.00	7001129.75	7002259.50	7003389.25	7004519.00
AgentBonus	4520.00	NaN	NaN	NaN	4077.84	1403.32	1605.00	3027.75	3911.50	4867.25	9608.00
Age	4251.00	NaN	NaN	NaN	14.49	9.04	2.00	7.00	13.00	20.00	58.00
CustTenure	4294.00	NaN	NaN	NaN	14.47	8.96	2.00	7.00	13.00	20.00	57.00
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	4520.00	NaN	NaN	NaN	3.69	1.02	1.00	3.00	4.00	4.00	6.00
Designation	4520	6	Manager	1620	NaN	NaN	NaN	NaN	NaN	NaN	NaN
NumberOfPolicy	4475.00	NaN	NaN	NaN	3.57	1.46	1.00	2.00	4.00	5.00	6.00
MaritalStatus	4520	4	Married	2268	NaN	NaN	NaN	NaN	NaN	NaN	NaN
MonthlyIncome	4284.00	NaN	NaN	NaN	22890.31	4885.60	16009.00	19683.50	21606.00	24725.00	38456.00
Complaint	4520.00	NaN	NaN	NaN	0.29	0.45	0.00	0.00	0.00	1.00	1.00
ExistingPolicyTenure	4336.00	NaN	NaN	NaN	4.13	3.35	1.00	2.00	3.00	6.00	25.00
SumAssured	4366.00	NaN	NaN	NaN	619999.70	246234.82	168536.00	439443.25	578976.50	758236.00	1838496.00
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	4520.00	NaN	NaN	NaN	4.63	3.62	0.00	2.00	3.00	8.00	18.00
CustCareScore	4468.00	NaN	NaN	NaN	3.07	1.38	1.00	2.00	3.00	4.00	5.00

c) Understanding of attributes (variable info, renaming if required)

1. CustID- Unique customer ID
4520 unique customer IDs present ranging from 7000000 to 7004519 (both inclusive).

2. AgentBonus- Bonus amount given to each agents in last month
Amount ranging inclusively between 1605 to 9608. A major difference is seen portraying the gap between high performing agents and low performing agents.

3. Age- Age of customer

Customers' age ranging inclusively between 2 years to 58 years. I found that this column requires missing value treatment.

4. CustTenure- Tenure of customer in organization
Customers' tenure ranging inclusively between 2 years to 57 years. I found that this column requires missing value treatment.

5. Channel- Channel through which acquisition of customer is done
3 Channels are there agent, online, and third party in which agent is the most preferred one.

6. Occupation- Occupation of customer
Salaried customers are the most valued for the company. Also "Laarge Business" values were mistyped so corrected them as "Large Business".

7. EducationField- Field of education of customer
Graduated customers are the most valued for the company followed by undergraduated with minimum being MBA.

8. Gender- Gender of customer
The Number of males is greater than females. Also "Fe male" was mistyped and it was replaced with "Females".

9. ExistingProdType- Existing product type of customer
Here product type could be policy type since it's an insurance company data. Maximum customers have enrolled themselves in policy number 4.

10. Designation- Designation of customer in their organizationNumberOfPolicy- Total number of existing policy of a customer The Number of customers designated as managers is the greatest.

11. NumberOfPolicy- Total number of existing policy of a customer
Customers having 4 existing policies is the maximum.

12. MaritalStatus- Marital status of customer
Married customers are most valuable to the company while unmarried being the least.

13. MonthlyIncome- Gross monthly income of customer
Monthly income of customers is very much scattered.

14. Complaint- Indicator of complaint registered in last one month by customer
Most of the customers have zero complaints while around 1200 have 1 complaint each.

15. ExistingPolicyTenure- Max tenure in all existing policies of customer
Most of the customers prefer a 5 years tenure. Though 25 is the maximum tenure any customer has.

16. SumAssured- Max of sum assured in all existing policies of customer
This column needs missing value treatment. Also the columns' values are scattered within a specific

range.

17. Zone- Customer belongs to which zone in India. Like East, West, North and South
Northern customers are most valuable to the company while southern customers are the minimum.

18. PaymentMethod- Frequency of payment selected by customer like Monthly, quarterly, half yearly and yearly Maximum customers prefer to pay half yearly while very less prefer quarterly.

19. LastMonthCalls- Total calls attempted by company to a customer for cross sell
Maximum customers are attended by agents.

20. CustCareScore- Customer satisfaction score given by customer in previous service call
Maximum customers rated 5/5 for the company.

The name of the columns seems to be fine with no special characters or spaces between them.

Unique values of various Categories :

```
Channel :  3
Online                   468
Third Party Partner      858
Agent                   3194
Name: Channel, dtype: int64


Occupation :  5
Free Lancer           2
Laarge Business     153
Large Business      255
Small Business     1918
Salaried           2192
Name: Occupation, dtype: int64


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


Gender :  3
```

```
Fe male      325
Female      1507
Male        2688
Name: Gender, dtype: int64


Designation :  6
Exe                127
VP                 226
AVP                336
Senior Manager     676
Executive         1535
Manager           1620
Name: Designation, dtype: int64


MaritalStatus :  4
Unmarried     194
Divorced      804
Single       1254
Married      2268
Name: MaritalStatus, dtype: int64


Zone :  4
South       6
East       64
North    1884
West     2566
Name: Zone, dtype: int64


PaymentMethod :  4
Quarterly        76
Monthly         354
Yearly         1434
Half Yearly    2656
Name: PaymentMethod, dtype: int64
```

The highlighted data seems to be recorded incorrectly and required replacement and this was done to ensure the right categories are picked up by the model

```
df['Occupation']=df['Occupation'].replace(to_replace='Laarge Business',value='Large Business')
```

```
df['Gender']=df['Gender'].replace(to_replace='Fe male',value='Female')
```

```
df['Designation']=df['Designation'].replace(to_replace='Exe',value='Executive')
```

```
df['EducationField']=df['EducationField'].replace(to_replace='UG',value='Under Graduate')
```

```
df['MaritalStatus']=df['MaritalStatus'].replace(to_replace='Unmarried',value='Single')
```

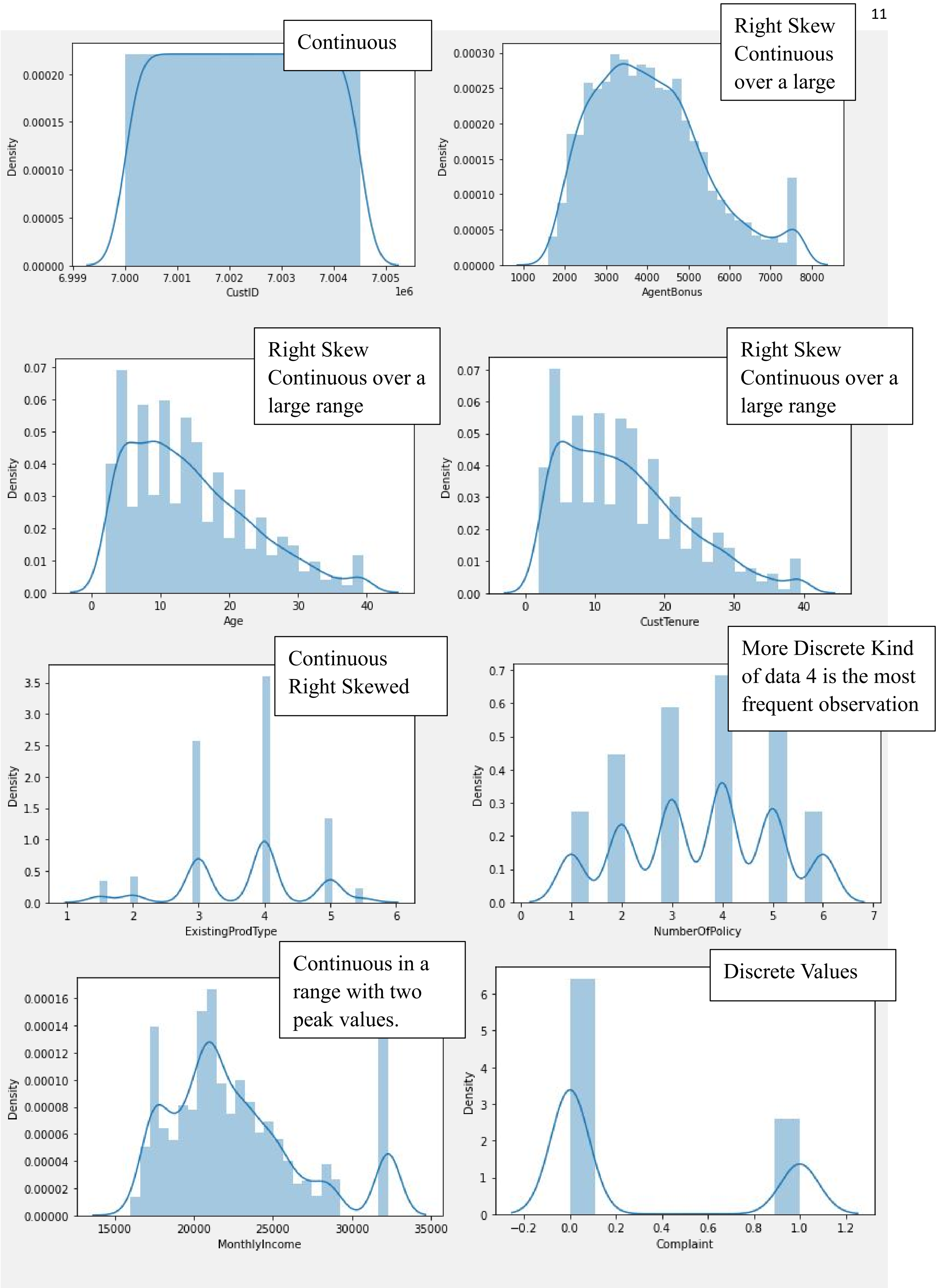
Post fixing of the data :

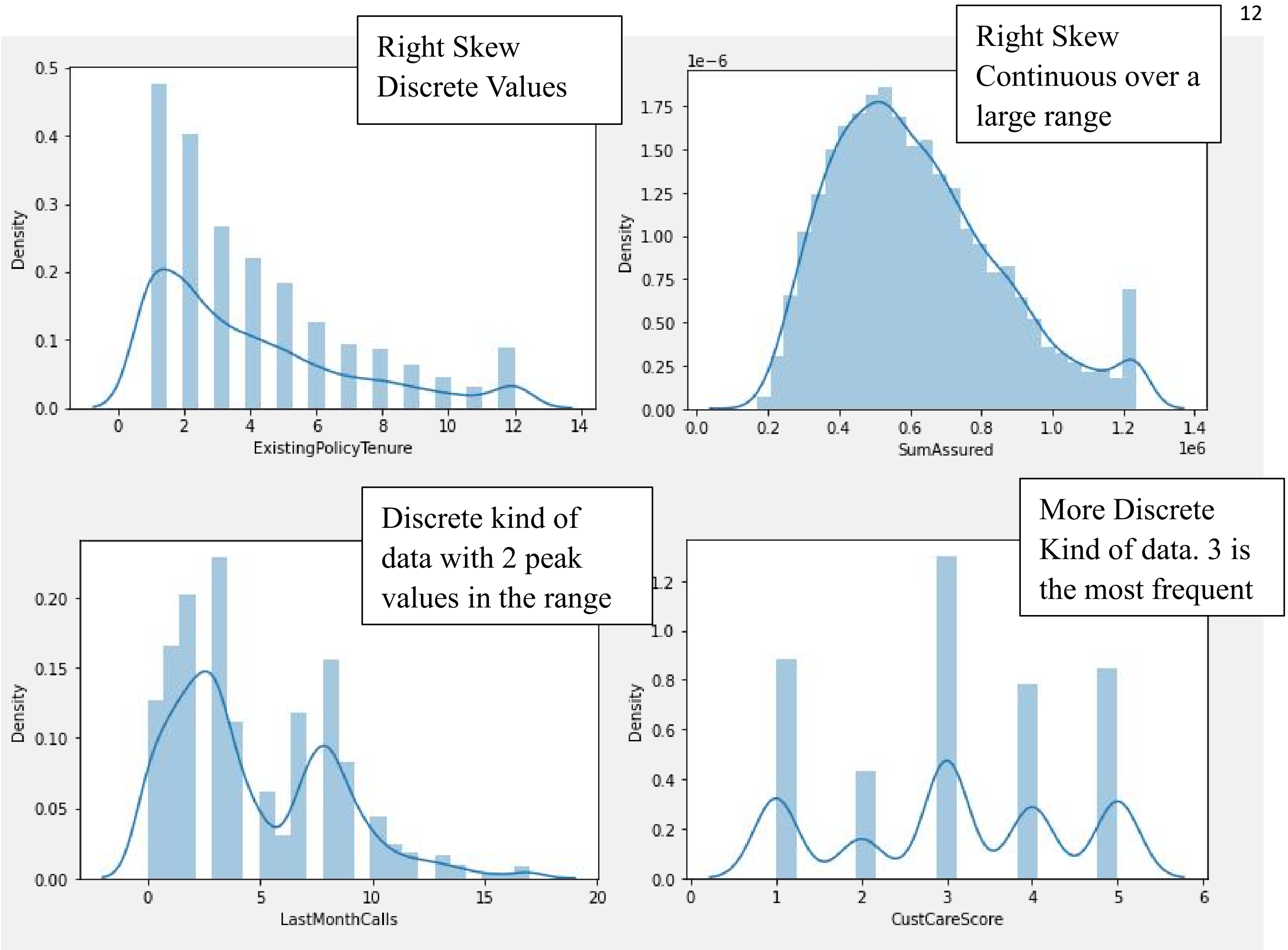
```
Channel :  3
Online                  468
Third Party Partner     858
Agent                  3194
Name: Channel, dtype: int64


Occupation :  4
Free Lancer          2
Large Business     408
Small Business    1918
Salaried          2192
Name: Occupation, dtype: int64


EducationField :  6
MBA                 74
Post Graduate      252
Engineer           408
Diploma            496
Under Graduate    1420
Graduate          1870
Name: EducationField, dtype: int64


Gender :  2
Female    1832
Male      2688
Name: Gender, dtype: int64


Designation :  5
VP                 226
```

```
AVP                336
Senior Manager     676
Manager           1620
Executive         1662
Name: Designation, dtype: int64


MaritalStatus :  3
Divorced     804
Single      1448
Married     2268
Name: MaritalStatus, dtype: int64


Zone :  4
South       6
East       64
North    1884
West     2566
Name: Zone, dtype: int64


PaymentMethod :  4
Quarterly        76
Monthly         354
Yearly         1434
Half Yearly    2656
Name: PaymentMethod, dtype: int64
```

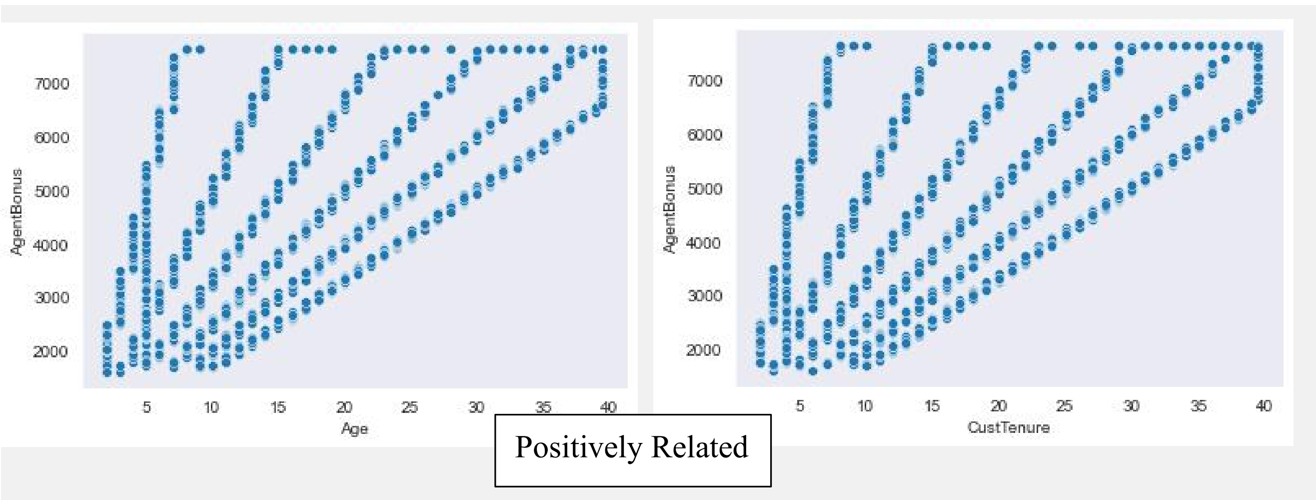
3) Exploratory data analysis

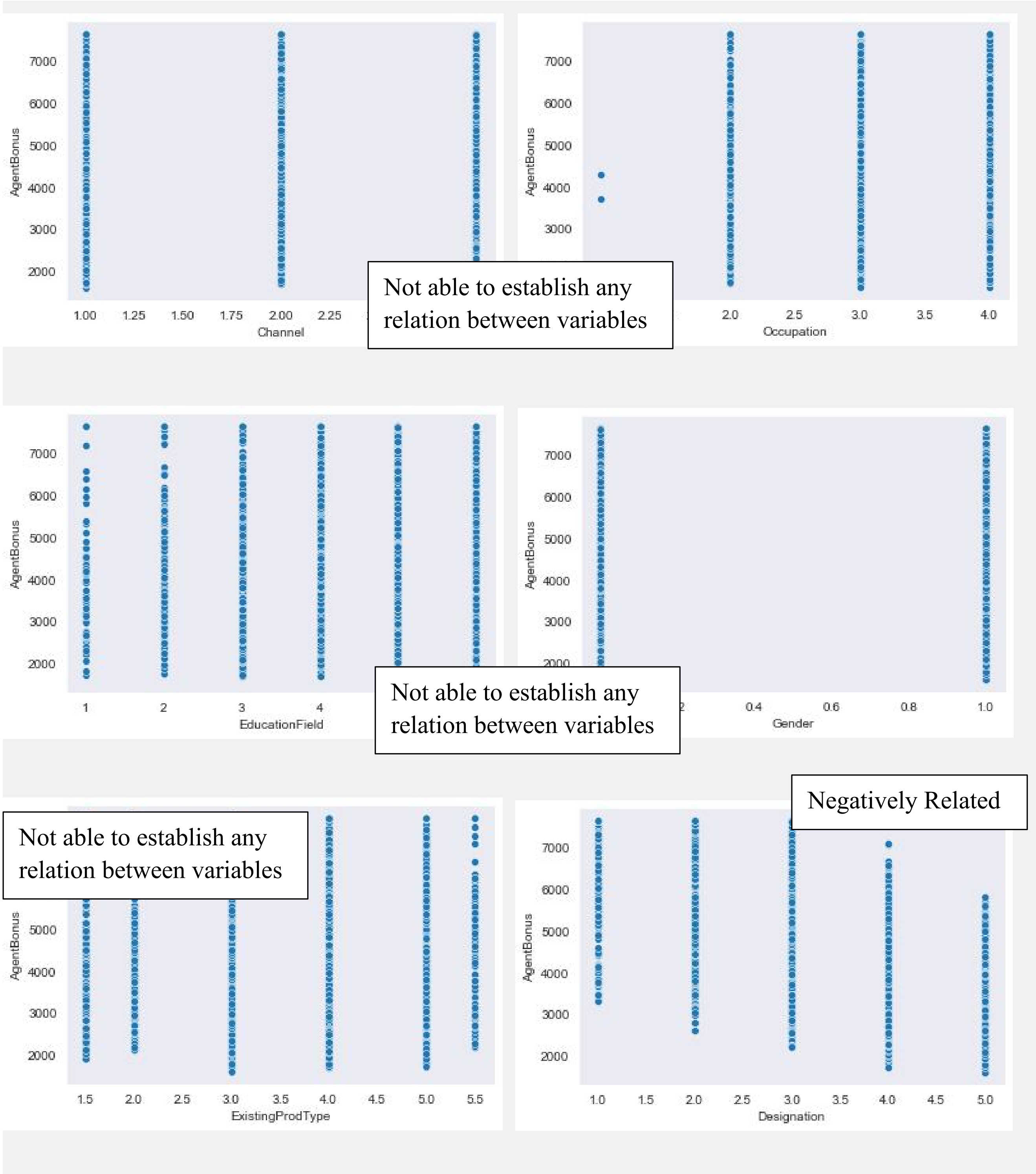
a) Univariate analysis (distribution and spread for every continuous attribute, distribution of data in categories for categorical ones)

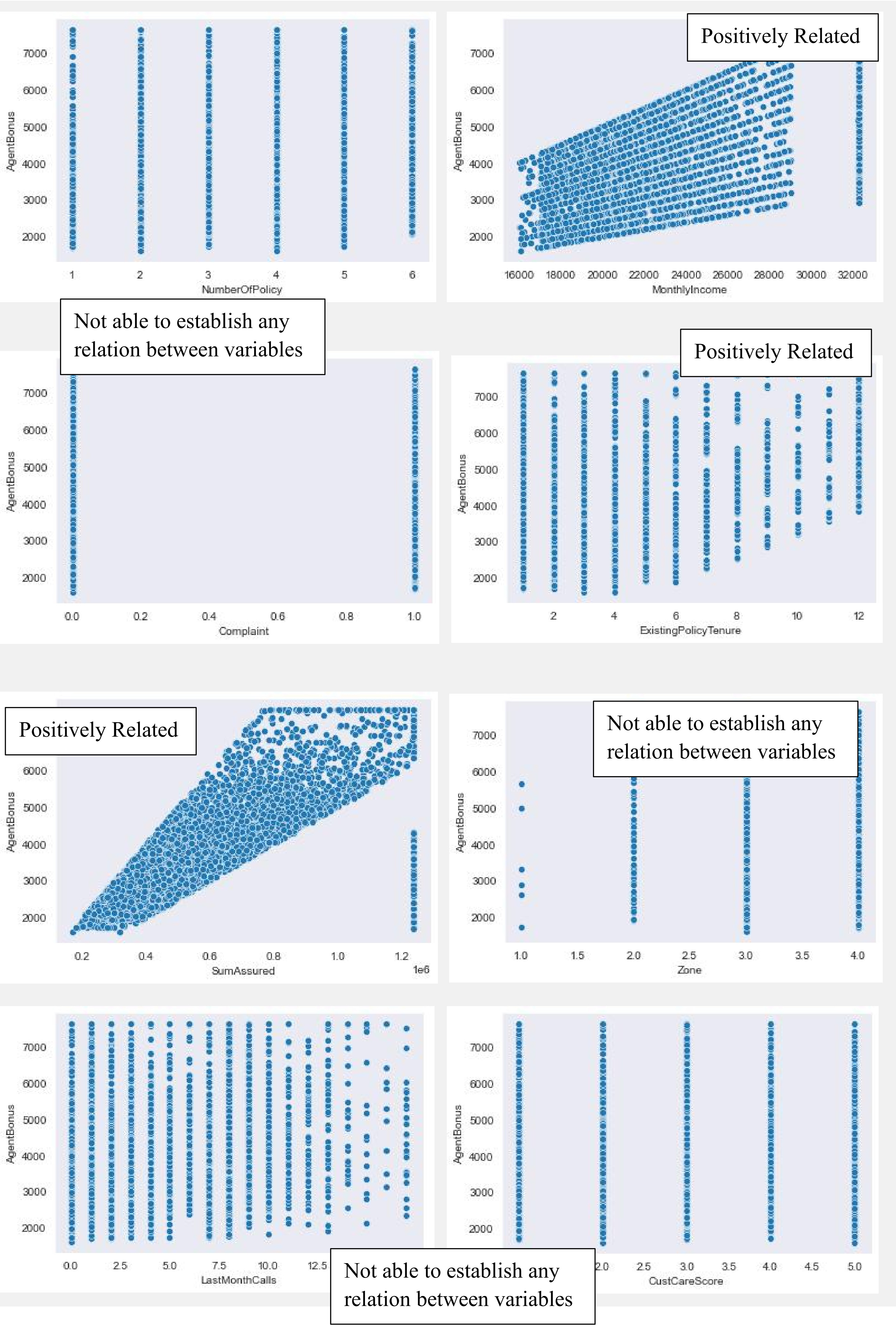

Continuous
Density
CustID
1e6
Right Skew Continuous over a large
Density
AgentBonus
Right Skew Continuous over a large range
Density
Age
Right Skew Continuous over a large range
Density
CustTenure
Continuous Right Skewed
Density
ExistingProdType
More Discrete Kind of data 4 is the most frequent observation
Density
NumberOfPolicy
Continuous in a range with two peak values.
Density
MonthlyIncome
Discrete Values
Density
Complaint



b) Bivariate analysis (relationship between different variables , correlations)

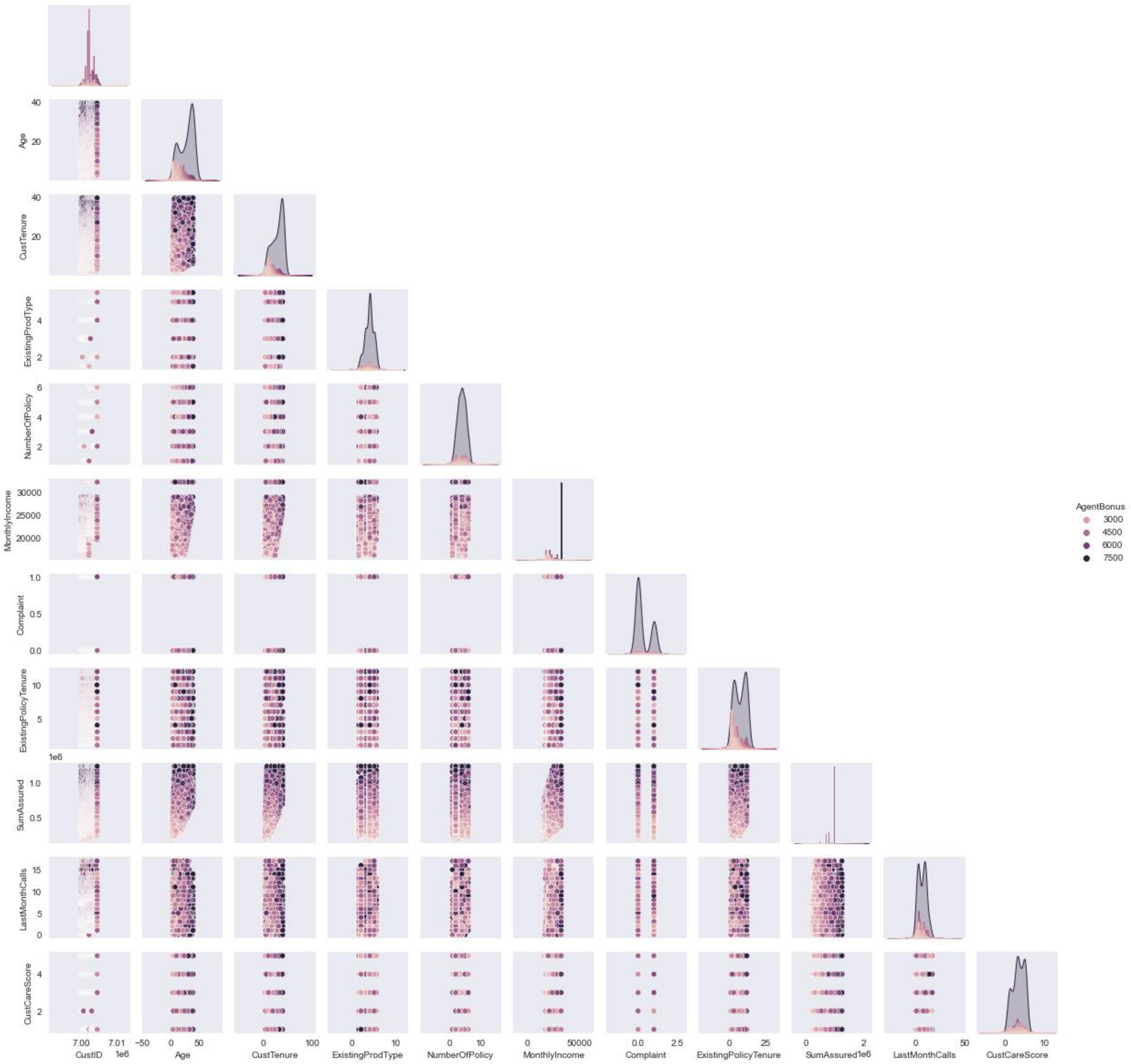



AgentBonus
Channel
Not able to establish any relation between variables
Occupation
EducationField
Not able to establish any relation between variables
Gender
Not able to establish any relation between variables
ExistingProdType
Negatively Related
Designation


AgentBonus
NumberOfPolicy
Positively Related
MonthlyIncome
Not able to establish any relation between variables
Complaint
Positively Related
ExistingPolicyTenure
Positively Related
SumAssured
1e6
Not able to establish any relation between variables
Zone
LastMonthCalls
Not able to establish any relation between variables
CustCareScore

Most of the variables don't seem to be related closely to each other which means there is low multi-collinearity in the data and each feature would have its importance in building the right model . because of this we have not dropped any columns and would want to build the model to see the variable importance.

The pair plot also seems to suggest the same thing . But due to the huge number of columns pair plot was not providing very clear insight and hence resorted to bi variate plots with every combination possible.



c) Removal of unwanted variables

In the dataset CustID, MaritalStatus and PaymentMethod are all redundant columns and thus have been removed. Chose not to remove any other columns and left to the model phase where the variable importance would be judged.

```
df.drop(['CustID','MaritalStatus','PaymentMethod'],axis=1,inplace=True)
```

d) Missing Value treatment

```
There are 1166 missing values in the dataset :

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

The missing values have been treated with most frequent values than median for numeric data including categorical data . The main reason of choosing mode or most frequent entry was it was making more sense considering the sports domain to which the problem belongs . More so as we have been in the various plots as well the numeric data has discrete pattern due to which we treated them as categorical data.

```
null_rows=0
for i in (df.isnull().sum(axis=1)):
    if i>0 :
        null_rows=null_rows+1
print (" Total Missing Rows ",null_rows)
```

```
Total Missing Rows  1073
```

- There can be two options for Missing Value Treatment
  - Either impute the missing values with median or median values for Numeric columns while mode values for categorical columns
  - Drop the rows with missing values but then we are looking at almost 23.74% reduction in data (3447 out of 4520 rows) and hence ruled out

So, Impute the missing values with the mode value of the column.

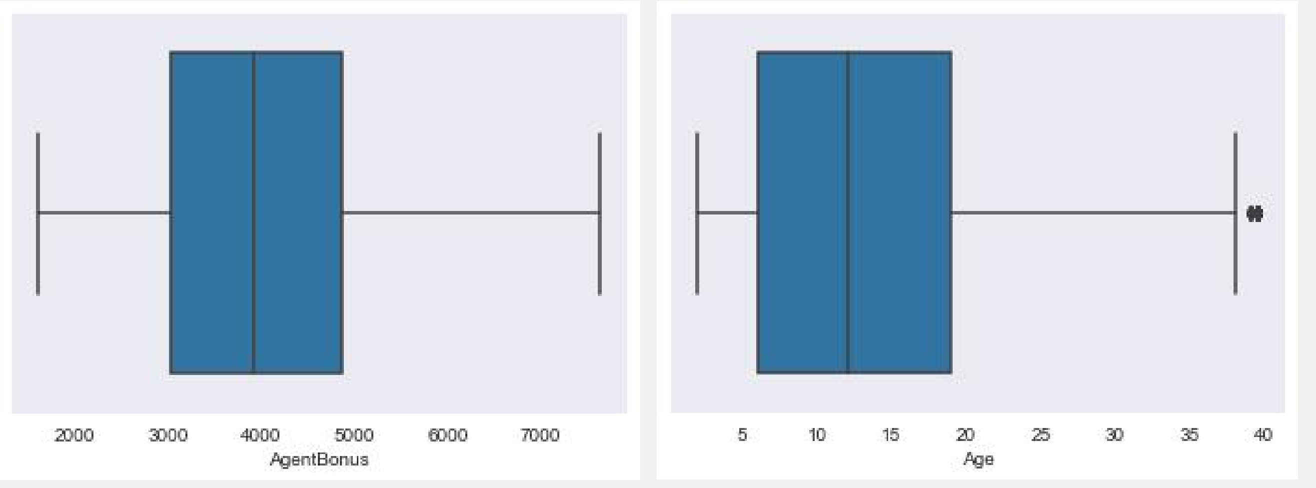
```
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='most_frequent',missing_values=np.nan)
```

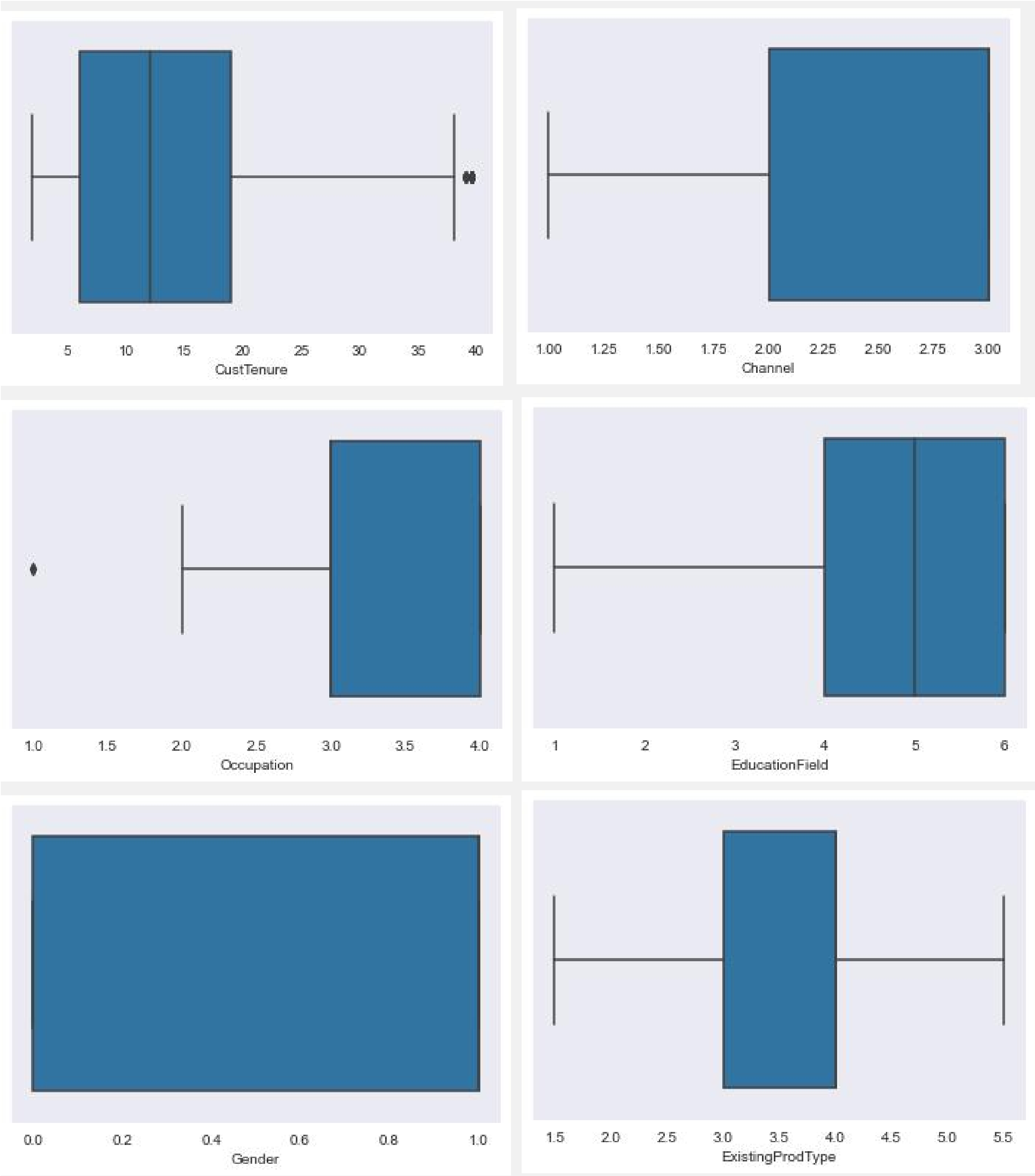
```
for i,col_val in enumerate(list(df.columns)):
    if df[col_val].isnull().sum()>0 :
        df[col_val]=imputer.fit_transform(df[col_val].values.reshape(-1,1))[:,0]
```

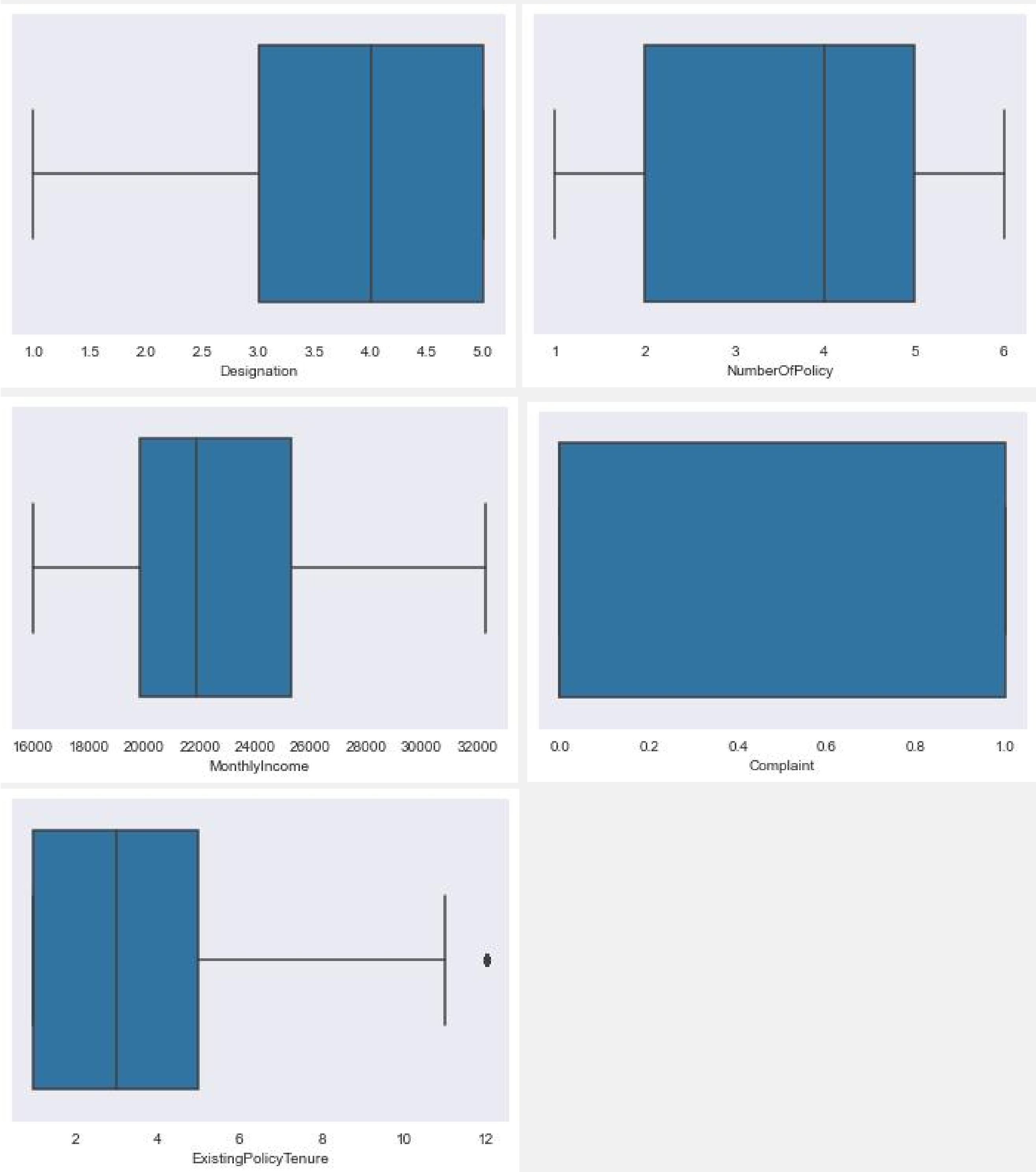
After Treatment of missing value :

```
AgentBonus            0
Age                   0
CustTenure            0
Channel               0
Occupation            0
EducationField        0
Gender                0
ExistingProdType      0
Designation           0
NumberOfPolicy        0
MonthlyIncome         0
Complaint             0
ExistingPolicyTenure  0
SumAssured            0
Zone                  0
LastMonthCalls        0
CustCareScore         0
dtype: int64
```

e) Outlier treatment




5
10
15
20
25
30
35
40
CustTenure
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00
Channel
1.0
1.5
2.0
2.5
3.0
3.5
4.0
Occupation
1
2
3
4
5
6
EducationField
0.0
0.2
0.4
0.6
0.8
1.0
Gender
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
5.5
ExistingProdType



Even though most of the numeric data here is discrete but few of the variables here are playing an important role in predicting the required value for the model which might get affected because of the outlying values, hence the outliers might reduce the value to the model. Like the age and customer tenure with the company which stands out while most of the others are in the right range.

So, in favour of doing the outlier treatment :
Detecting the Outliers

```
col_names = list(df.select_dtypes(exclude=['object']).columns)
fig, ax = plt.subplots(len(col_names), figsize=(5,50)).
for i,col_val in enumerate(col_names):
    sns.boxplot(df[col_val])
    ax[i].set_title('{}'.format(col_val), fontsize=8)
    plt.show()
```

Outlier Treatment :

```
def remove_outlier(col):
    sorted(col)
    Q1,Q3=col.quantile([0.25,0.75])
    IQR=Q3-Q1
    lower_range= Q1-(1.5 * IQR)
    upper_range= Q3+(1.5 * IQR)
    return lower_range, upper_range
```

```
for i,col_val in enumerate(col_names):
    lwr,upr=remove_outlier(df[col_val])
    df[col_val]=np.where(df[col_val]>upr,upr,df[col_val])
    df[col_val]=np.where(df[col_val]<lwr,lwr,df[col_val])
    print("Outlier fixed for ", col_val)
```

```
Outlier fixed for  CustID
Outlier fixed for  AgentBonus
Outlier fixed for  Age
Outlier fixed for  CustTenure
Outlier fixed for  ExistingProdType
Outlier fixed for  NumberOfPolicy
Outlier fixed for  MonthlyIncome
Outlier fixed for  Complaint
Outlier fixed for  ExistingPolicyTenure
Outlier fixed for  SumAssured
Outlier fixed for  LastMonthCalls
Outlier fixed for  CustCareScore
```

f) Variable transformation

The variables has been encoded to numeric values for the following variables :

```
df['Channel'] = df['Channel'].replace(to_replace='Online',value=1)
df['Channel'] = df['Channel'].replace(to_replace='Third Party Partner',value=2)
df['Channel'] = df['Channel'].replace(to_replace='Agent',value=3)
```

```
df['Occupation'] = df['Occupation'].replace(to_replace='Free Lancer',value=1)
df['Occupation'] = df['Occupation'].replace(to_replace='Large Business',value=2)
df['Occupation'] = df['Occupation'].replace(to_replace='Small Business',value=3)
df['Occupation'] = df['Occupation'].replace(to_replace='Salaried',value=4)
```

```
df['EducationField'] = df['EducationField'].replace(to_replace='MBA',value=1)
df['EducationField'] = df['EducationField'].replace(to_replace='Post Graduate',value=2)
df['EducationField'] = df['EducationField'].replace(to_replace='Engineer',value=3)
df['EducationField'] = df['EducationField'].replace(to_replace='Diploma',value=4)
df['EducationField'] = df['EducationField'].replace(to_replace='Under Graduate',value=5)
df['EducationField'] = df['EducationField'].replace(to_replace='Graduate',value=6)
```

```
df['Gender'] = df['Gender'].replace(to_replace='Female',value=0)
df['Gender'] = df['Gender'].replace(to_replace='Male',value=1)
```

```
df['Designation'] = df['Designation'].replace(to_replace='VP',value=1)
df['Designation'] = df['Designation'].replace(to_replace='AVP',value=2)
df['Designation'] = df['Designation'].replace(to_replace='Senior Manager',value=3)
df['Designation'] = df['Designation'].replace(to_replace='Manager',value=4)
df['Designation'] = df['Designation'].replace(to_replace='Executive',value=5)
```

```
df['Zone'] = df['Zone'].replace(to_replace='South',value=1)
df['Zone'] = df['Zone'].replace(to_replace='East',value=2)
df['Zone'] = df['Zone'].replace(to_replace='North',value=3)
df['Zone'] = df['Zone'].replace(to_replace='West',value=4)
```

g) Addition of new variables

No new variables were added at this stage . But before proceeding with the model one hot encoding would be required on few categories which would increase the number of column not essentially the number of variables.

4) Business insights from EDA

a) Is the data unbalanced? If so, what can be done? Please explain in the context of the business

The data is balanced for most of the attributes given in the given data set, but for the remaining attributes the target variable has more observations in one specific class than the others. Our goal is to use techniques to cluster the sample into natural groups or to describe the relationship of the minority class with the features (independent variables), then this doesn't pose a "huge" problem. It only becomes an issue when this "property" affects the performance of the algorithms or the models that you could obtain. If the classes are separable using the available features, then the distribution of the classes between them is not problematic.

To rectify this we can take following steps in the situation :

1. Resample the dataset:

- ***Undersampling***

The idea is to reduce the ratio of instances in the majority and minority levels. You can randomly select observations in the desired ratio

- ***Oversampling***

We can create synthetical observations of the minority class based on the available data.

- ***VAE***

Variational Autoencoders allows us to explore variations in the current data, not just in a random way, but in the desired direction. For this task, VAE is a powerful method.

2. Collect more data from the minority class

This option appears trivial, but it solves the problem when it is applicable.

3. Use the "adequate" correct algorithm

Some algorithms are more robust than others. A mastery of the theory behind each algorithm will help us understand their strengths and weaknesses in various situations.

4. Change your approach

nstead of building a classifier, sometimes it is beneficial to change your approach and the scope ; one option would be to analyze your data from the 'anomaly detection' point of view.

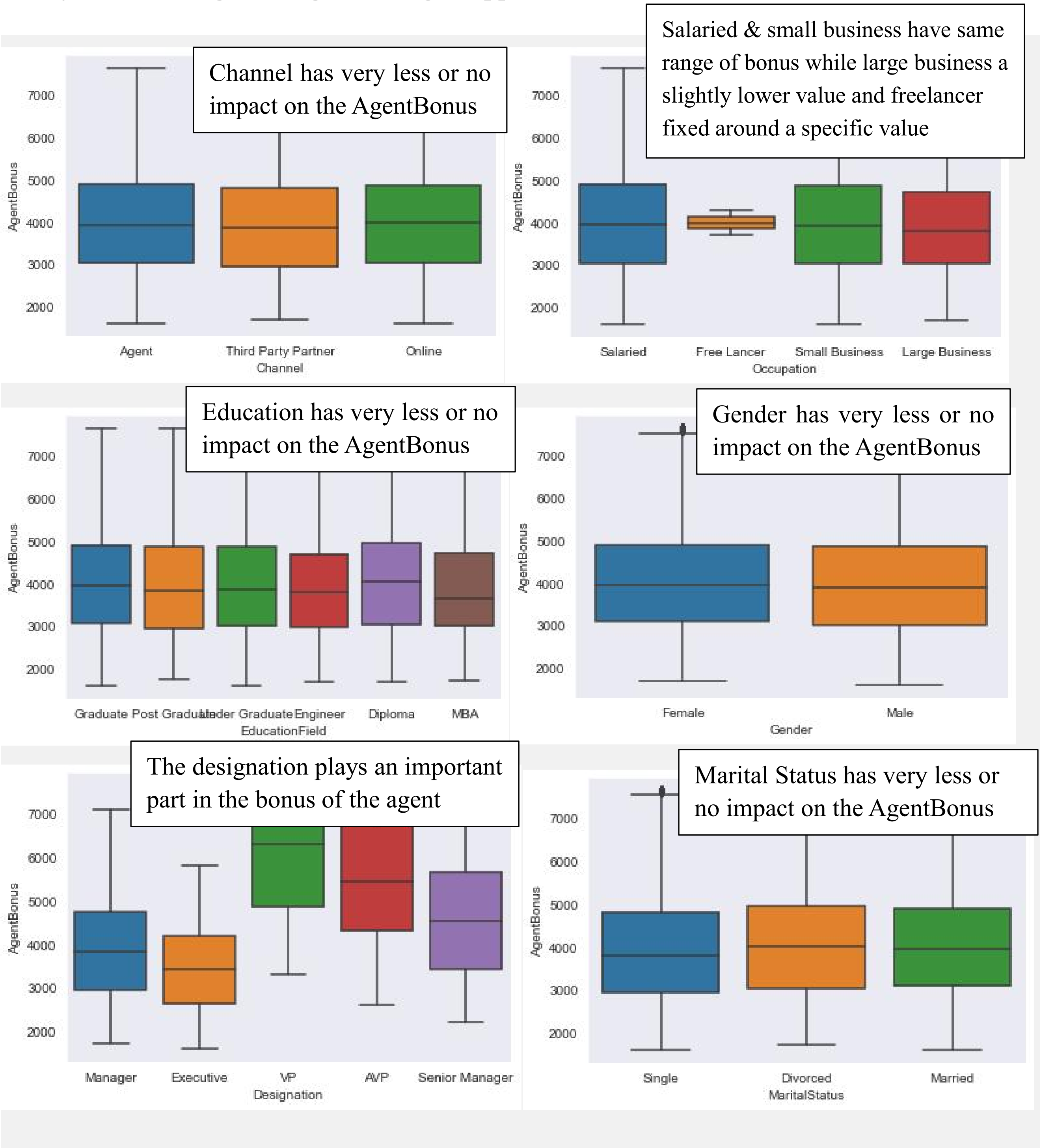
5. Use penalized models

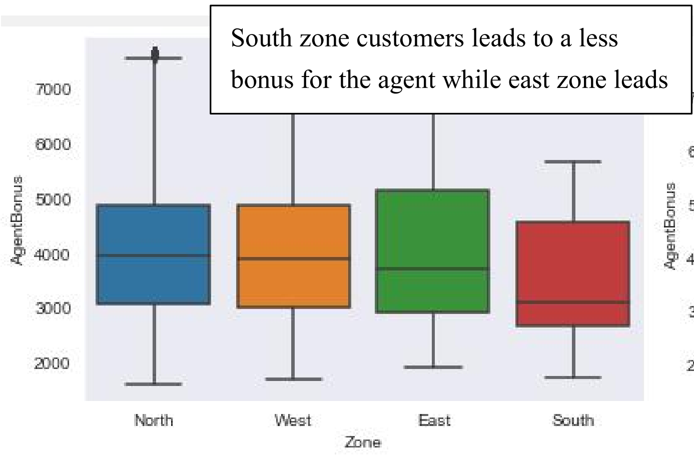
Many algorithms have their own penalized version. Usually, algorithms treat all misclassifications the same, so the idea is to penalize misclassifications from the minority class more than the majority.

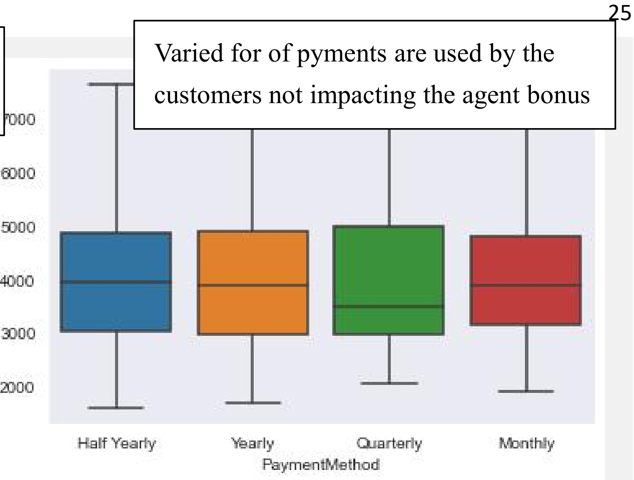
Also based on the data given we can predict the high performing agents and the low performing agents and the company could take any required option like upskilling them or to give more incentives and bonuses to the agents, for various attributes given to us in the dataset are corelated to the agent bonuses and hence performance. Through which the company could benefit a great value.

I think there should be more data for agent by which we can find which agent has more bonus and whose performance is high or low. Because in the dataset the given information are all about customers.

b) Any business insights using clustering (if applicable)

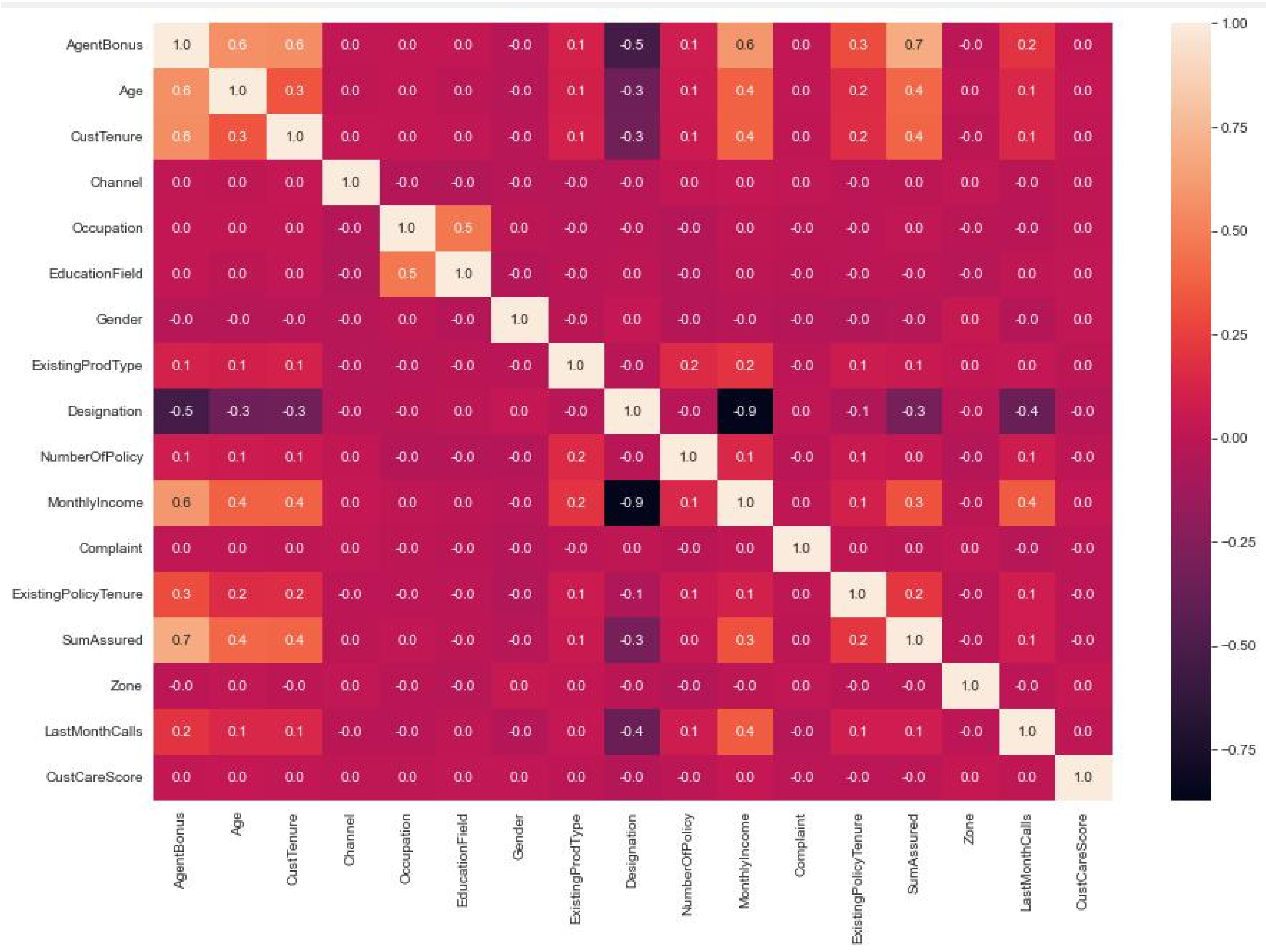






We can make clusters of high performing agents and groups of low performing agents and put each agent in one of these group by collecting the data of their performance and can predict their bonus by which company can decide which group can take bonus and which group needs upskill program. Age, CustTenure, monthlyIncome, SumAssured seems to be correlated with AgentBonus which means with increase in age and then tenure of customer also increase in sumAssured and monthlyincome brings the best performance in an Agent, but may not be true for the everyone. Designation plays an negative role on the Agents Bonus as well. Various attributes like Marital status, gender have less or no impact on Agent performance.

d) Any other business insights



- Age, CustTenure, monthlyIncome, SumAssured seems to be correlated with AgentBonus which means with increase in age and then tenure of customer also increase in sumAssured and monthlyincome brings the best performance in an Agent, but may not be true for the everyone.
- Designation plays an negative role on the Agents Bonus as well as at monthlyIncome which means as move from VP towards Executive the Bonus and monthy income decreases.