Problem 1: Clustering

A leading bank wants to develop a customer segmentation to give promotional offers to its customers. They collected a sample that summarizes the activities of users during the past few months. You are given the task to identify the segments based on credit card usage.

Data Dictionary for Market Segmentation:

- **spending**: Amount spent by the customer per month (in 1000s)
- **advance_payments**: Amount paid by the customer in advance by cash (in 100s)
- **probability_of_full_payment**: Probability of payment done in full by the customer to the bank
- **current_balance**: Balance amount left in the account to make purchases (in 1000s)
- **credit_limit**: Limit of the amount in credit card (10000s)
- **min_payment_amt** : minimum paid by the customer while making payments for purchases made monthly (in 100s)
- **max_spent_in_single_shopping**: Maximum amount spent in one purchase (in 1000s)

1.1 Read the data, do the necessary initial steps, and exploratory data analysis (Univariate, Bi-variate, and multivariate analysis).

Reading the Dataset

We will be loading the EDA cars excel file using pandas. For this we will be using read_excel file.

Basic Data Exploration

In this step, we will perform the below operations to check what the data set comprises of. We will check the below things:

- **head of the dataset**
- **shape of the dataset**
- **info of the dataset**
- **summary of the dataset**

Out[3]:

	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent_in_single_shopping
0	19.94	16.92	0.8752	6.675	3.763	3.252	6.550
1	15.99	14.89	0.9064	5.363	3.582	3.336	5.144
2	18.95	16.42	0.8829	6.248	3.755	3.368	6.148
3	10.83	12.96	0.8099	5.278	2.641	5.182	5.185
4	17.99	15.86	0.8992	5.890	3.694	2.068	5.837

head function will tell you the top records in the data set. By default python shows you only top 5 records.

```
The total number of rows present in the dataset above is :   210
The total number of columns/variables present in the dataset above is :   7
```

Shape attribute tells us number of observations and variables we have in the data set. It is used to check the dimension of data. The data set has 210 observations and 7 variables in the data set.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 210 entries, 0 to 209
Data columns (total 7 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   spending                      210 non-null    float64
 1   advance_payments              210 non-null    float64
 2   probability_of_full_payment   210 non-null    float64
 3   current_balance               210 non-null    float64
 4   credit_limit                  210 non-null    float64
 5   min_payment_amt               210 non-null    float64
 6   max_spent_in_single_shopping  210 non-null    float64
dtypes: float64(7)
memory usage: 11.6 KB
```

info() is used to check the Information about the data and the datatypes of each respective attributes.

We have data for 210 rows with neither any null values nor any missing entries.

All columns are numerical

Out[6]:
```
spending                        0
advance_payments                0
probability_of_full_payment     0
current_balance                 0
credit_limit                    0
min_payment_amt                 0
max_spent_in_single_shopping    0
dtype: int64
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
spending	210.0	14.847524	2.909699	10.5900	12.27000	14.35500	17.305000	21.1800
advance_payments	210.0	14.559286	1.305959	12.4100	13.45000	14.32000	15.715000	17.2500
probability_of_full_payment	210.0	0.870999	0.023629	0.8081	0.85690	0.87345	0.887775	0.9183
current_balance	210.0	5.628533	0.443063	4.8990	5.26225	5.52350	5.979750	6.6750
credit_limit	210.0	3.258605	0.377714	2.6300	2.94400	3.23700	3.561750	4.0330
min_payment_amt	210.0	3.700201	1.503557	0.7651	2.56150	3.59900	4.768750	8.4560
max_spent_in_single_shopping	210.0	5.408071	0.491480	4.5190	5.04500	5.22300	5.877000	6.5500

The describe method will help to see how data has been spread for the numerical values. We can clearly see the minimum value, mean values, different percentile values and maximum values.

Check for Duplicate records

```
Number of duplicate rows = 0
```

Now, we can clearly see that there are no duplicate records in the data set.

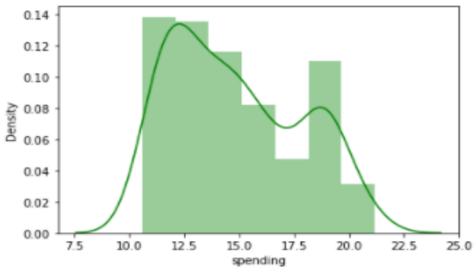
Performing Exploratory Data Analysis

Univariate Analysis

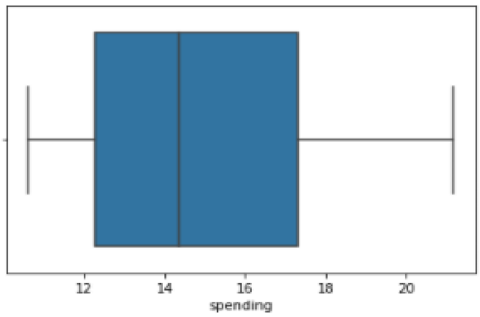
Let us define a function **'univariateAnalysis_numeric'** to display information as part of univariate analysis of numeric variables. The function will accept coulmn name and number of bins as arguments.

The function will display the statistical description of the the numeric variable, histogram or distplot to view the distribution and the box plot to view 5 point summary and outliers if any.

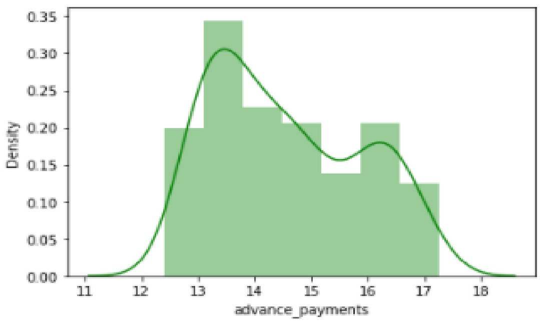
```
Total Numerical Columns =  7

Description of spending
----------------------------------------------------------------------------
count    210.000000
mean      14.847524
std        2.909699
min       10.590000
25%       12.270000
50%       14.355000
75%       17.305000
max       21.180000
Name: spending, dtype: float64

Distribution of spending
----------------------------------------------------------------------------
```



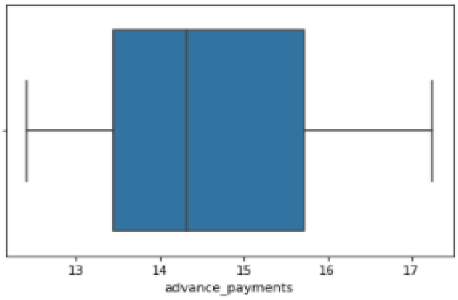

```
BoxPlot of spending
----------------------------------------------------------------------------
```



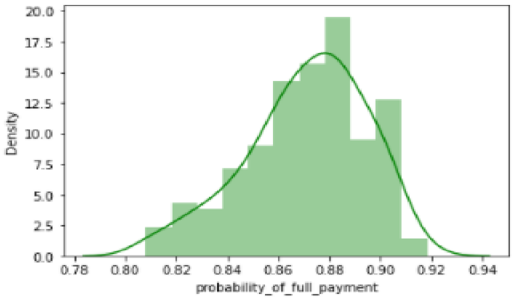

```
Description of advance_payments
----------------------------------------------------------------------------
count    210.000000
mean      14.559286
std        1.305959
min       12.410000
25%       13.450000
50%       14.320000
75%       15.715000
max       17.250000
Name: advance_payments, dtype: float64

Distribution of advance_payments
----------------------------------------------------------------------------
```



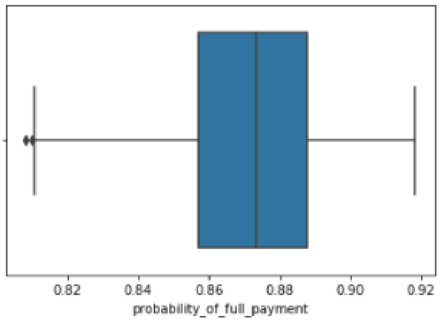
```
BoxPlot of advance_payments
----------------------------------------------------------------------------
```



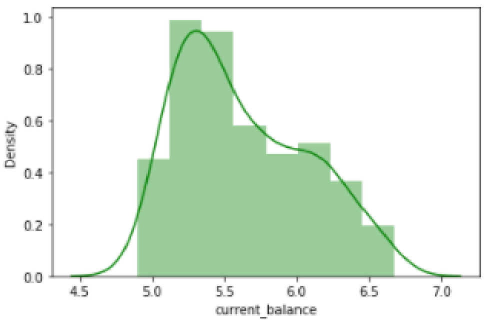

```
Description of probability_of_full_payment
----------------------------------------------------------------------------
count    210.000000
mean       0.870999
std        0.023629
min        0.808100
25%        0.856900
50%        0.873450
75%        0.887775
max        0.918300
Name: probability_of_full_payment, dtype: float64

Distribution of probability_of_full_payment
----------------------------------------------------------------------------
```



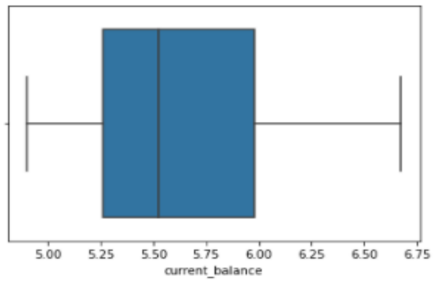
```
BoxPlot of probability_of_full_payment
----------------------------------------------------------------------------
```




```
Description of current_balance
----------------------------------------------------------------------------
count    210.000000
mean       5.628533
std        0.443063
min        4.899000
25%        5.262250
50%        5.523500
75%        5.979750
max        6.675000
Name: current_balance, dtype: float64

Distribution of current_balance
----------------------------------------------------------------------------
```

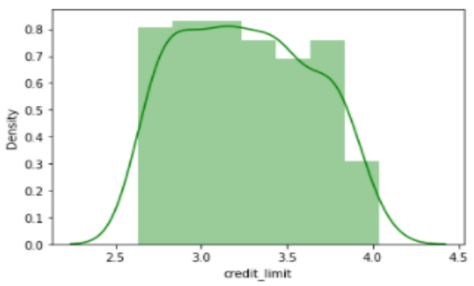


```
BoxPlot of current_balance
--------------------------------------------------------------------------------
```

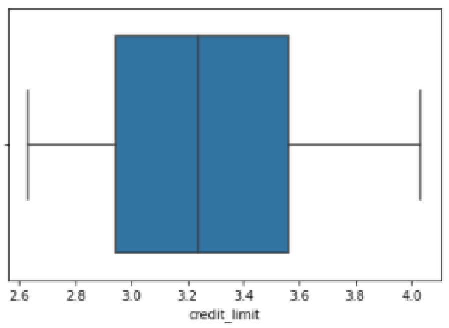



```
Description of credit_limit
--------------------------------------------------------------------------------
count    210.000000
mean       3.258605
std        0.377714
min        2.630000
25%        2.944000
50%        3.237000
75%        3.561750
max        4.033000
Name: credit_limit, dtype: float64
```

```
Distribution of credit_limit
--------------------------------------------------------------------------------
```

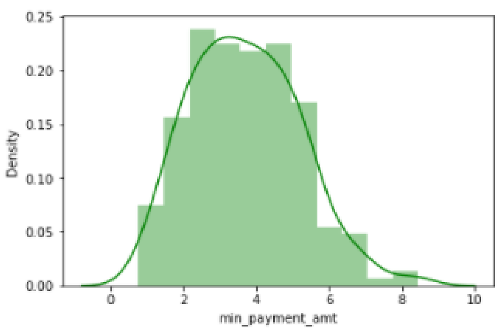



```
BoxPlot of credit_limit
--------------------------------------------------------------------------------
```

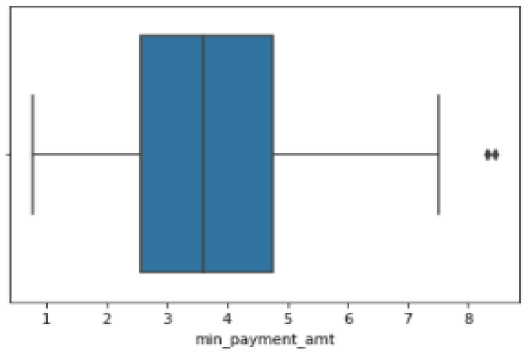



```
Description of min_payment_amt
--------------------------------------------------------------------------------
count    210.000000
mean       3.700201
std        1.503557
min        0.765100
25%        2.561500
50%        3.599000
75%        4.768750
max        8.456000
Name: min_payment_amt, dtype: float64
```

```
Distribution of min_payment_amt
--------------------------------------------------------------------------------
```



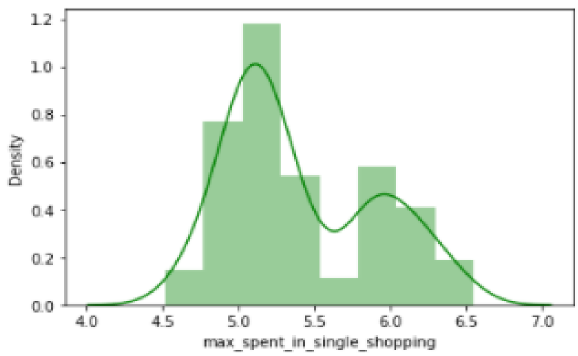
BoxPlot of min_payment_amt



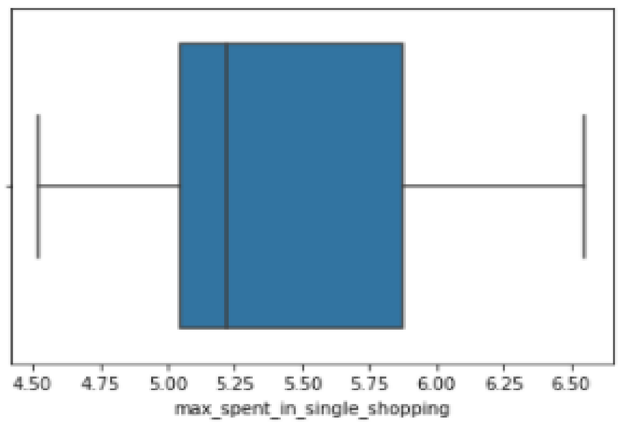
Description of max_spent_in_single_shopping

```
count    210.000000
mean       5.408071
std        0.491480
min        4.519000
25%        5.045000
50%        5.223000
75%        5.877000
max        6.550000
Name: max_spent_in_single_shopping, dtype: float64
```

Distribution of max_spent_in_single_shopping



BoxPlot of max_spent_in_single_shopping



Bivariate Analysis

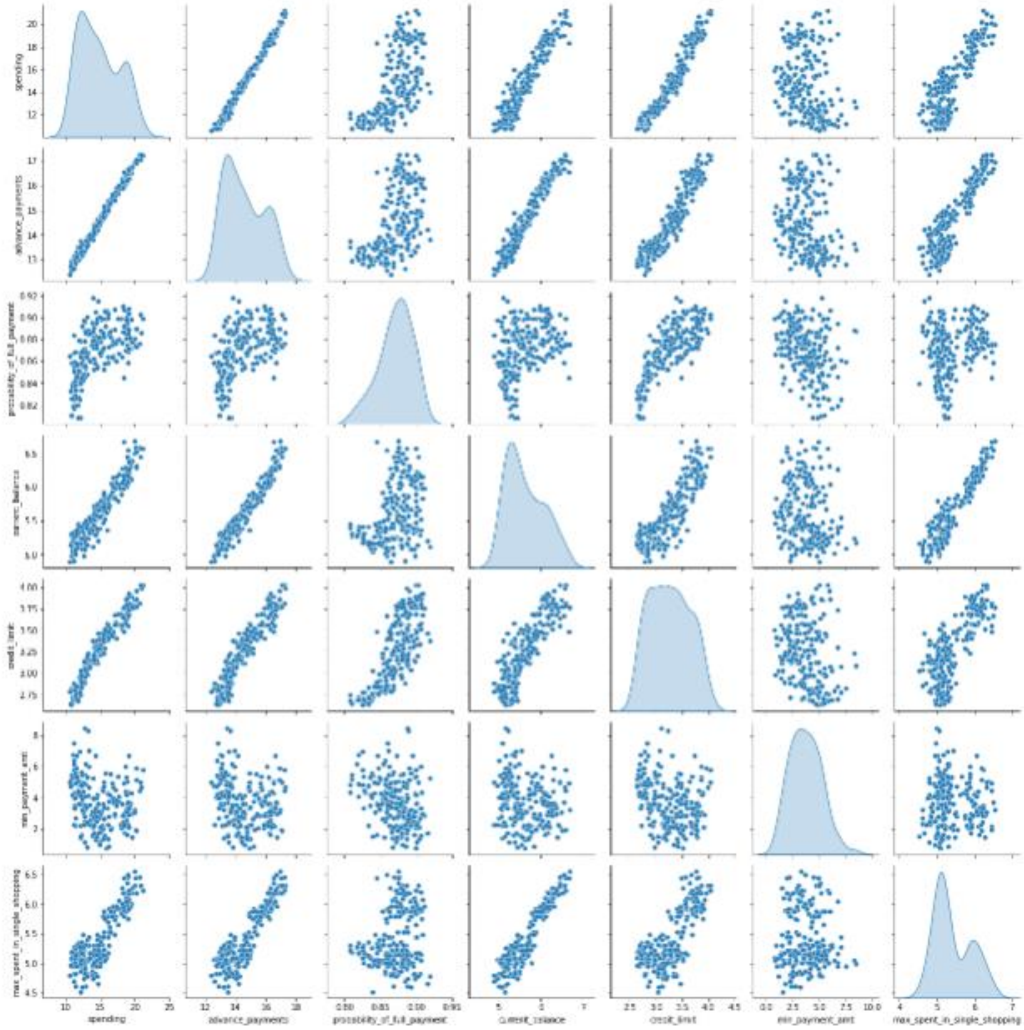
The following Bivariate Analysis will be performed by

- Calculating the correlation between variable for better understanding of how variables are correlated with each other, and
- Calculating the corresponding pairplot.

Correlation Plot

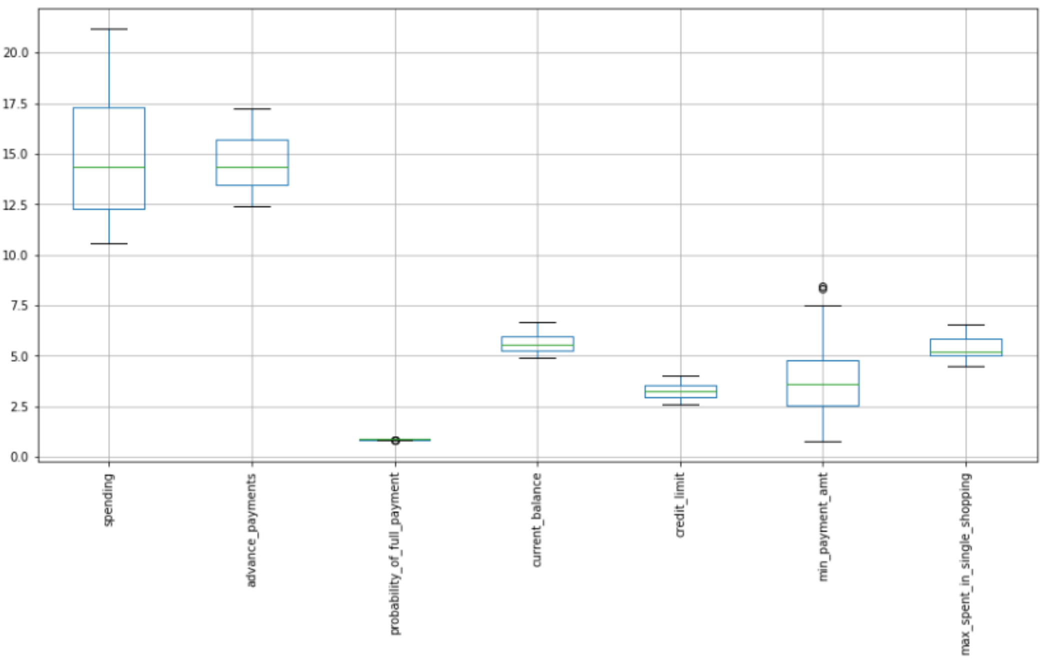
There are mostly positive correlations between variables, and very few negative correlations.Overall the magnitude of correlations between the variables are very less.

Pairplot



In the above plot scatter diagrams are plotted for all the numerical columns in the dataset. A scatter plot is a visual representation of the degree of correlation between any two columns. The pair plot function in seaborn makes it very easy to generate joint scatter plots for all the columns in the data.

Checking for Outlier and Outlier Treatment



- As it can be observed, out of the 7 variables, only probability_of_full_payment and min_payment_amt have outlies present in them.
- However they dont seem that significant, therefore we wont treat them until its asked for.

1.2 Do you think scaling is necessary for clustering in this case? Justify

Often the variables of the data set are of different scales i.e. one variable is in millions and other in only 100. For e.g. in our dataset some variables like,spending, current balance, credit limit max spent are having values in thousands, while others are having values in hundreds and probability values which are less than 1 or 100%. Since the data in these variables are of different scales, it is tough to compare these variables.

Feature scaling (also known as data normalization) is the method used to standardize the range of features of data. Since, the range of values of data may vary widely, it becomes a necessary step in data preprocessing while using machine learning algorithms.

In this method, we convert variables with different scales of measurements into a single scale.

StandardScaler normalizes the data using the formula (x-mean)/standard deviation.

We will be doing this only for the numerical variables.

Scaling the Data

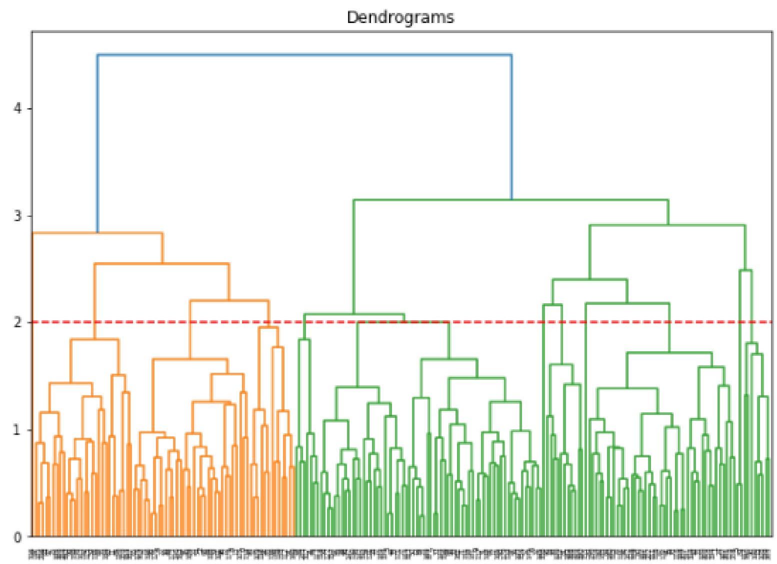
Out[19]:

	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent_in_single_shopping
0	1.754355	1.811968	0.178230	2.367533	1.338579	-0.298806	2.328998
1	0.393582	0.253840	1.501773	-0.600744	0.858236	-0.242805	-0.538582
2	1.413300	1.428192	0.504874	1.401485	1.317348	-0.221471	1.509107
3	-1.384034	-1.227533	-2.591878	-0.793049	-1.639017	0.987884	-0.454961
4	1.082581	0.998364	1.196340	0.591544	1.155464	-1.088154	0.874813

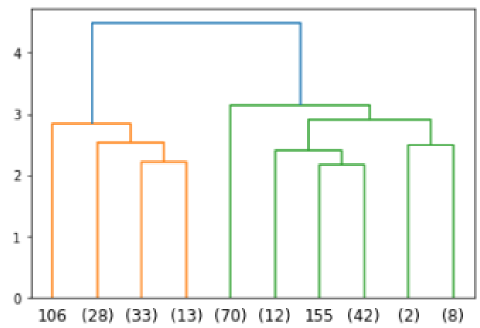
1.3 Apply hierarchical clustering to scaled data. Identify the number of optimum clusters using Dendrogram and briefly describe them

Choosing Linking Method "average"

Creating the Dendogram



Cutting the Dendrogram with suitable clusters



Creating Clusters Using fcluster

Out[24]:
```
array([1, 3, 1, 2, 1, 3, 2, 2, 1, 2, 1, 1, 2, 1, 3, 3, 3, 2, 2, 2, 2, 2,
       1, 2, 3, 1, 3, 2, 2, 2, 2, 2, 2, 3, 2, 2, 2, 2, 2, 1, 1, 3, 1, 1,
       2, 2, 3, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 2, 2, 1, 3, 2, 2, 1, 3, 1,
       1, 3, 1, 2, 3, 2, 1, 1, 2, 1, 3, 2, 1, 3, 3, 3, 3, 1, 2, 1, 1, 1,
       1, 3, 3, 1, 3, 2, 2, 1, 1, 1, 2, 1, 3, 1, 3, 1, 3, 1, 1, 2, 3, 1,
       1, 3, 1, 2, 2, 1, 3, 3, 2, 1, 3, 2, 2, 2, 3, 3, 1, 2, 3, 3, 2, 3,
       3, 1, 2, 1, 1, 2, 1, 3, 3, 3, 2, 2, 2, 2, 1, 2, 3, 2, 3, 2, 3, 1,
       3, 3, 2, 2, 3, 1, 1, 2, 1, 1, 1, 2, 1, 3, 3, 2, 3, 2, 3, 1, 1, 1,
       3, 2, 3, 2, 3, 2, 3, 3, 1, 1, 3, 1, 3, 2, 3, 3, 2, 1, 3, 1, 1, 2,
       1, 2, 3, 3, 3, 2, 1, 3, 1, 3, 3, 1], dtype=int32)
```

Concatenating the clusters as a seperate column to our dataset

Out[26]:

	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent_in_single_shopping	clusters
0	19.94	16.92	0.8752	6.675	3.763	3.252	6.550	1
1	15.99	14.89	0.9064	5.363	3.582	3.336	5.144	3
2	18.95	16.42	0.8829	6.248	3.755	3.368	6.148	1
3	10.83	12.96	0.8099	5.278	2.641	5.182	5.185	2
4	17.99	15.86	0.8992	5.890	3.694	2.068	5.837	1

Cluster Frequency

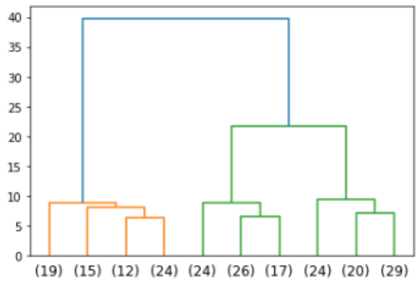
Out[27]:
```
1    75
2    70
3    65
Name: clusters, dtype: int64
```

Cluster Profiles

Out[28]:

clusters	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent_in_single_shopping	Freq
1	18.129200	16.058000	0.881595	6.135747	3.648120	3.650200	5.987040	75
2	11.916857	13.291000	0.846766	5.258300	2.846000	4.619000	5.115071	70
3	14.217077	14.195846	0.884869	5.442000	3.253508	2.768418	5.055569	65

Choosing method as "ward"



Out[31]:
```
array([1, 3, 1, 2, 1, 2, 2, 3, 1, 2, 1, 3, 2, 1, 3, 2, 3, 2, 3, 2, 2, 2,
       1, 2, 3, 1, 3, 2, 2, 2, 3, 2, 2, 3, 2, 2, 2, 2, 2, 1, 1, 3, 1, 1,
       2, 2, 3, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 2, 2, 1, 3, 2, 2, 3, 3, 1,
       1, 3, 1, 2, 3, 2, 1, 1, 2, 1, 3, 2, 1, 3, 3, 3, 3, 1, 2, 3, 3, 1,
       1, 2, 3, 1, 3, 2, 2, 1, 1, 1, 2, 1, 2, 1, 3, 1, 3, 1, 1, 2, 2, 1,
       3, 3, 1, 2, 2, 1, 3, 3, 2, 1, 3, 2, 2, 2, 3, 3, 1, 2, 3, 3, 2, 3,
       3, 1, 2, 1, 1, 2, 1, 3, 3, 3, 2, 2, 3, 2, 1, 2, 3, 2, 3, 2, 3, 3,
       3, 3, 3, 2, 3, 1, 1, 2, 1, 1, 1, 2, 1, 3, 3, 3, 3, 2, 3, 1, 1, 1,
       3, 3, 1, 2, 3, 3, 3, 3, 1, 1, 3, 3, 3, 2, 3, 3, 2, 1, 3, 1, 1, 2,
       1, 2, 3, 1, 3, 2, 1, 3, 1, 3, 1, 3], dtype=int32)
```

Out[32]:

	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent_in_single_shopping	Ward_clusters
0	19.94	16.92	0.8752	6.675	3.763	3.252	6.550	1
1	15.99	14.89	0.9064	5.363	3.582	3.336	5.144	3
2	18.95	16.42	0.8829	6.248	3.755	3.368	6.148	1
3	10.83	12.96	0.8099	5.278	2.641	5.182	5.185	2
4	17.99	15.86	0.8992	5.890	3.694	2.068	5.837	1

Out[33]:
```
1    70
2    67
3    73
Name: Ward_clusters, dtype: int64
```

Out[34]:

Ward_clusters	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent_in_single_shopping	Freq
1	18.371429	16.145429	0.884400	6.158171	3.684629	3.639157	6.017371	70
2	11.872388	13.257015	0.848072	5.238940	2.848537	4.949433	5.122209	67
3	14.199041	14.233562	0.879190	5.478233	3.226452	2.612181	5.086178	73

Perfroming Agglomerative Clustering technique as well to check if any significant variation in clusters is present.

Clusters

```
[1 0 1 2 1 0 2 2 1 2 1 1 2 1 0 0 0 2 2 2 2 2 1 2 0 1 0 2 2 2 2 2 2 0 2 2 2
 2 2 1 1 0 1 1 2 2 0 1 1 1 2 1 1 1 1 1 2 2 2 1 0 2 2 1 0 1 1 0 1 2 0 2 1 1
 2 1 0 2 1 0 0 0 0 1 2 1 1 1 1 0 0 1 0 2 2 1 1 1 2 1 0 1 0 1 0 1 1 2 0 1 1
 0 1 2 2 1 0 0 2 1 0 2 2 2 0 0 1 2 0 0 2 0 0 1 2 1 1 2 1 0 0 0 2 2 2 2 1 2
 0 2 0 2 0 1 0 0 2 2 0 1 1 2 1 1 1 2 1 0 0 2 0 2 0 1 1 1 0 2 0 2 0 2 0 0 1
 1 0 1 0 2 0 0 2 1 0 1 1 2 1 2 0 0 0 2 1 0 1 0 0 1]
```

Analyzing the frequency of the clusters wrt to the dataset.

Out[38]:

Agglo_CLusters	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_amt	max_spent_in_single_shopping	Freq
0	14.217077	14.195846	0.884869	5.442000	3.253508	2.768418	5.055569	65
1	18.129200	16.058000	0.881595	6.135747	3.648120	3.650200	5.987040	75
2	11.916857	13.291000	0.846766	5.258300	2.846000	4.619000	5.115071	70

Observation

- Both the method are almost similar with only minor variations, which we know are expected to occur while using different techniques, but it does not affect our data as the difference is not that significantly large.
- Choosing 3 or 4 clusters seems like a better option as only 2 clusters are meaningless and does not portral much information. After further analysis based on the dataset grouping into 3 clusters is a better option using heirarchial clustering.
- Also in real time, there could have been more variables value captured - tenure, balance, purchase but we will not dwell much on that since its not present in the dataset.
- The **'three'** group cluster solution gives a pattern based on high/medium/low spending patterns with max_spent_in_single_shopping (high value item) and probability_of_full_payment(payment made).

1.4 Apply K-Means clustering on scaled data and determine optimum clusters. Apply elbow curve and silhouette score. Explain the results properly. Interpret and write inferences on the finalized clusters.

Applying k-means technique choosing 3 as the number of clusters with random state=0

Out[40]:
```
KMeans(n_clusters=3, random_state=0)
```

Extracting the labels post clustering

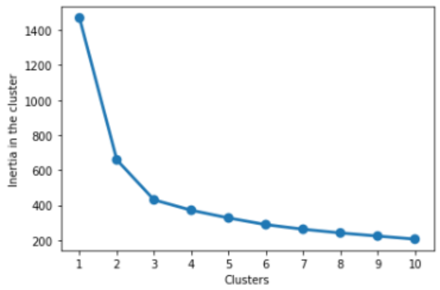
Out[41]:
```
array([2, 1, 2, 0, 2, 0, 0, 1, 2, 0, 2, 1, 0, 2, 1, 0, 1, 0, 0, 0, 0, 0,
       2, 0, 1, 2, 1, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 2, 2, 1, 2, 2,
       0, 0, 1, 2, 2, 2, 0, 2, 2, 2, 2, 2, 0, 0, 0, 2, 1, 0, 0, 1, 1, 2,
       2, 1, 2, 0, 1, 0, 2, 2, 0, 2, 1, 0, 2, 1, 1, 1, 1, 2, 0, 1, 2, 1,
       2, 0, 1, 2, 1, 0, 0, 2, 2, 2, 0, 2, 1, 2, 1, 2, 1, 2, 2, 0, 0, 2,
       1, 1, 2, 0, 0, 2, 1, 1, 0, 2, 1, 0, 0, 0, 1, 1, 2, 0, 1, 1, 0, 1,
       1, 2, 0, 2, 2, 0, 2, 1, 1, 1, 0, 0, 1, 0, 2, 0, 1, 0, 1, 0, 1, 1,
       0, 1, 1, 0, 1, 2, 2, 0, 2, 2, 2, 0, 1, 1, 1, 0, 1, 0, 1, 2, 2, 2,
       1, 0, 1, 0, 1, 1, 1, 1, 2, 2, 0, 1, 1, 0, 0, 1, 0, 2, 1, 2, 2, 0,
       2, 0, 1, 2, 1, 0, 2, 1, 2, 1, 1, 1])
```

Calculating the sum of distances between the points and the corresponding centroids for each cluster ranging from 1 to 10.

```
WSS value for  1  clusters is =  1469.9999999999998
WSS value for  2  clusters is =  659.171754487041
WSS value for  3  clusters is =  430.6589731513006
WSS value for  4  clusters is =  371.38509060801096
WSS value for  5  clusters is =  327.21278165661346
WSS value for  6  clusters is =  289.31599538959495
WSS value for  7  clusters is =  262.98186570162267
WSS value for  8  clusters is =  241.81894656086033
WSS value for  9  clusters is =  223.91254221002725
WSS value for  10  clusters is =  206.39612184786694
```

- As it can be observed the WSS value show significant change until cluster 3, and from 4 cluster onwards, we can observe minimal change therefore **we will choose 3 clusters** as 2 and 1 clusters instead of having high values doesn't make sense as we need to distinguish the data better. The same can be better observed from the elbow curve below.

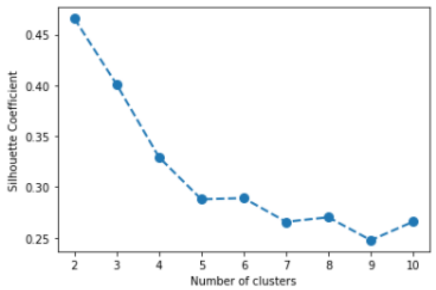
Elbow-curve for better understanding of the clusters formed.



Calculating silhouette_score for multiple clusters ranging from 2 to 10

```
The Silhouette Score/coefficient for  2  clusters is =  0.46577247686580914
The Silhouette Score/coefficient for  3  clusters is =  0.4007270552751299
The Silhouette Score/coefficient for  4  clusters is =  0.3291966792017613
The Silhouette Score/coefficient for  5  clusters is =  0.2878322312678646
The Silhouette Score/coefficient for  6  clusters is =  0.2890450980368358
The Silhouette Score/coefficient for  7  clusters is =  0.2656984649780521
The Silhouette Score/coefficient for  8  clusters is =  0.2701675870182155
The Silhouette Score/coefficient for  9  clusters is =  0.24760490111901076
The Silhouette Score/coefficient for  10  clusters is =  0.2658701603565836
```

Visualizing the Silhoutte score values



Cluster Frequency

Out[53]:
```
0    72
1    71
2    67
dtype: int64
```

Changing the cluster numbering with 1 instead of 0 and adding it to the dataset.

Out[55]:

cluster	1	2	3
spending	18.5	11.9	14.4
advance_payments	16.2	13.2	14.3
probability_of_full_payment	0.9	0.8	0.9
current_balance	6.2	5.2	5.5
credit_limit	3.7	2.8	3.3
min_payment_amt	3.6	4.7	2.7
max_spent_in_single_shopping	6.0	5.1	5.1
Ward_clusters	1.0	2.1	2.9
Agglo_CLusters	1.0	1.8	0.3

Cluster Percentage wrt to Cluster Size

Out[57]:

	Cluster_Size	Cluster_Percentage
1	67	31.90
2	72	34.29
3	71	33.81

- The Silhouette Scores are also used to determine the number of clusters which we should choose by their value (high is better). From list of silhouette scores we can **observe 2 and 3 cluster score have significant difference between them**.

- After 4 the score doesn't vary much, and since 2 clusters does not give better insights on the data, therefore **we will choose 3 as the optimal clusters.**

1.5 Describe cluster profiles for the clusters defined. Recommend different promotional strategies for different clusters.

___________________K_Means Clusters________________________________

Out[58]:

cluster	1	2	3
spending	18.5	11.9	14.4
advance_payments	16.2	13.2	14.3
probability_of_full_payment	0.9	0.8	0.9
current_balance	6.2	5.2	5.5
credit_limit	3.7	2.8	3.3
min_payment_amt	3.6	4.7	2.7
max_spent_in_single_shopping	6.0	5.1	5.1
Ward_clusters	1.0	2.1	2.9
Agglo_CLusters	1.0	1.8	0.3

___________________Heirarchial Clustering________________________________

Out[59]:

Ward_clusters	1	2	3
spending	18.371429	11.872388	14.199041
advance_payments	16.145429	13.257015	14.233562
probability_of_full_payment	0.884400	0.848072	0.879190
current_balance	6.158171	5.238940	5.478233
credit_limit	3.684629	2.848537	3.226452
min_payment_amt	3.639157	4.949433	2.612181
max_spent_in_single_shopping	6.017371	5.122209	5.086178
Freq	70.000000	67.000000	73.000000

Cluster Group Profiles

Group 1 : High Spending

Group 3 : Medium Spending

Group 2 : Low Spending

Promotional strategies for each cluster are as follows:-

Group 1 : High Spending Group

- Giving any reward points might increase their purchases.
- maximum max_spent_in_single_shopping is high for this group, so can be offered discount/offer on next transactions upon full payment
- Increase there credit limit and
- Increase spending habits
- Give loan against the credit card, as they are customers with good repayment record.
- Tie up with luxury brands, which will drive more one_time_maximun spending

Group 3 : Medium Spending Group

- They are potential target customers who are paying bills and doing purchases and maintaining comparatively good credit score. So we can increase credit limit or can lower down interest rate.
- Promote premium cards/loyality cars to increase transcations.
- Increase spending habits by trying with premium ecommerce sites, travel portal, travel airlines/hotel, as this will encourge them to spend more.

Group 2 : Low Spending Group

- Customers should be often given reminders for payments.
- Offers can be provided on early payments to improve their payment rate thus decreasing the default rate as well.
- Increase there spending habits by tieing up with grocery stores, utlities (electricity, phone, gas, others)and other daily essentials and other inexpensive ammenities.

Problem 2: CART-RF-ANN

An Insurance firm providing tour insurance is facing higher claim frequency. The management decides to collect data from the past few years. You are assigned the task to make a model which predicts the claim status and provide recommendations to management. Use CART, RF & ANN and compare the models' performances in train and test sets.

Attribute Information:

- 1. Target: Claim Status (**Claimed**)
- 1. Code of tour firm (**Agency_Code**)
- 1. Type of tour insurance firms (**Type**)
- 1. Distribution channel of tour insurance agencies (**Channel**)
- 1. Name of the tour insurance products (**Product**)
- 1. Duration of the tour (**Duration**)
- 1. Destination of the tour (**Destination**)
- 1. Amount of sales of tour insurance policies (**Sales**)
- 1. The commission received for tour insurance firm (**Commission**)
- 1. Age of insured (**Age**)

Importing the required Libraries

2.1 Read the data, do the necessary initial steps, and exploratory data analysis (Univariate, Bi-variate, and multivariate analysis).

Reading the Data

Basic Data Exploration

In this step, we will perform the below operations to check what the data set comprises of. We will check the below things:

- **head of the dataset**
- **shape of the dataset**
- **info of the dataset**
- **summary of the dataset**

Out[10]:

	Age	Agency_Code	Type	Claimed	Commision	Channel	Duration	Sales	Product Name	Destination
0	48	C2B	Airlines	No	0.70	Online	7	2.51	Customised Plan	ASIA
1	36	EPX	Travel Agency	No	0.00	Online	34	20.00	Customised Plan	ASIA
2	39	CWT	Travel Agency	No	5.94	Online	3	9.90	Customised Plan	Americas
3	36	EPX	Travel Agency	No	0.00	Online	4	26.00	Cancellation Plan	ASIA
4	33	JZI	Airlines	No	6.30	Online	53	18.00	Bronze Plan	ASIA

head function will tell you the top records in the data set. By default python shows you only top 5 records.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Age           3000 non-null   int64  
 1   Agency_Code   3000 non-null   object 
 2   Type          3000 non-null   object 
 3   Claimed       3000 non-null   object 
 4   Commision     3000 non-null   float64
 5   Channel       3000 non-null   object 
 6   Duration      3000 non-null   int64  
 7   Sales         3000 non-null   float64
 8   Product Name  3000 non-null   object 
 9   Destination   3000 non-null   object 
dtypes: float64(2), int64(2), object(6)
memory usage: 234.5+ KB
```

info() is used to check the Information about the data and the datatypes of each respective attributes.

Observation

- We have data for 3000 rows with neither any null values nor any missing entries.
- 10 variables present, out of which
- Age, Commision, Duration, Sales are numeric in nature, while
- rest are categorial variables
- 9 independent variable and one target variable - Clamied

Descriptive Statistics Summary

Out[65]:

	count	mean	std	min	25%	50%	75%	max
Age	3000.0	38.091000	10.463518	8.0	32.0	36.00	42.000	84.00
Commision	3000.0	14.529203	25.481455	0.0	0.0	4.63	17.235	210.21
Duration	3000.0	70.001333	134.053313	-1.0	11.0	26.50	63.000	4580.00
Sales	3000.0	60.249913	70.733954	0.0	20.0	33.00	69.000	539.00

The describe method will help to see how data has been spread for the numerical values. We can clearly see the minimum value, mean values, different percentile values and maximum values.

Observation

- Duraction has negetive value which is not possible, therefore deemed as a Wrong entry.
- Mean and Median value varies signficantly with Commision & Sales.
- But CART and RF models treat outliers therefore not removing them manually.
- As for ANN we will scare the data which will remove the outliers.

Out[66]:

	count	unique	top	freq	mean	std	min	25%	50%	75%	max
Age	3000	NaN	NaN	NaN	38.091	10.4635	8	32	36	42	84
Agency_Code	3000	4	EPX	1365	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Type	3000	2	Travel Agency	1837	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Claimed	3000	2	No	2076	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Commision	3000	NaN	NaN	NaN	14.5292	25.4815	0	0	4.63	17.235	210.21
Channel	3000	2	Online	2954	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Duration	3000	NaN	NaN	NaN	70.0013	134.053	-1	11	26.5	63	4580
Sales	3000	NaN	NaN	NaN	60.2499	70.734	0	20	33	69	539
Product Name	3000	5	Customised Plan	1136	NaN	NaN	NaN	NaN	NaN	NaN	NaN
Destination	3000	3	ASIA	2465	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Observation

- For Categorial variables maximun unique count is 5.

Geting unique counts of all Nominal/Categorical Variables

```
AGENCY_CODE :  4
JZI     239
CWT     472
C2B     924
EPX    1365
Name: Agency_Code, dtype: int64


TYPE :  2
Airlines         1163
Travel Agency    1837
Name: Type, dtype: int64


CLAIMED :  2
Yes     924
No     2076
Name: Claimed, dtype: int64


CHANNEL :  2
Offline      46
Online     2954
Name: Channel, dtype: int64


PRODUCT NAME :  5
Gold Plan             109
Silver Plan           427
Bronze Plan           650
Cancellation Plan     678
Customised Plan      1136
Name: Product Name, dtype: int64


DESTINATION :  3
EUROPE       215
Americas     320
ASIA        2465
Name: Destination, dtype: int64
```

Check for duplicate data

```
Number of duplicate rows = 139
```

Out[68]:

	Age	Agency_Code	Type	Claimed	Commision	Channel	Duration	Sales	Product Name	Destination
63	30	C2B	Airlines	Yes	15.0	Online	27	60.0	Bronze Plan	ASIA
329	36	EPX	Travel Agency	No	0.0	Online	5	20.0	Customised Plan	ASIA
407	36	EPX	Travel Agency	No	0.0	Online	11	19.0	Cancellation Plan	ASIA
411	35	EPX	Travel Agency	No	0.0	Online	2	20.0	Customised Plan	ASIA
422	36	EPX	Travel Agency	No	0.0	Online	5	20.0	Customised Plan	ASIA
...	...	...	...	...	...	...	...	...	...	...
2940	36	EPX	Travel Agency	No	0.0	Online	8	10.0	Cancellation Plan	ASIA
2947	36	EPX	Travel Agency	No	0.0	Online	10	28.0	Customised Plan	ASIA
2952	36	EPX	Travel Agency	No	0.0	Online	2	10.0	Cancellation Plan	ASIA
2962	36	EPX	Travel Agency	No	0.0	Online	4	20.0	Customised Plan	ASIA
2984	36	EPX	Travel Agency	No	0.0	Online	1	20.0	Customised Plan	ASIA

139 rows × 10 columns

Duplicates -

- Not removing the duplicates as we have no unique identifier to .
- Though it shows there are 139 records, but there is no customer ID or any unique identifier to distinguish the customers as it can be different customer, so I am not dropping them off. ### We can say it would be great is we had knowledge of more variables for better understanding of the data.

Performing Exploratory Data Analysis

Univariate Analysis

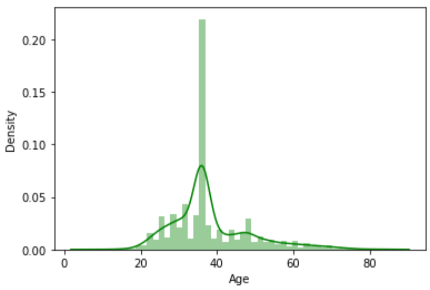
Let us define a function **'univariateAnalysis_numeric'** to display information as part of univariate analysis of numeric variables. The function will accept coulmn name and number of bins as arguments.

The function will display the statistical description of the the numeric variable, histogram or distplot to view the distribution and the box plot to view 5 point summary and outliers if any.

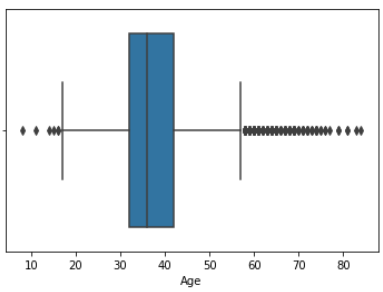
```
Total Numerical Columns =  4

Total Categorical Columns =  6
```

Analysis using Numerical Data

```
Description of Age
----------------------------------------------------------------------------
count    3000.000000
mean       38.091000
std        10.463518
min         8.000000
25%        32.000000
50%        36.000000
75%        42.000000
max        84.000000
Name: Age, dtype: float64

Distribution of Age
----------------------------------------------------------------------------
```

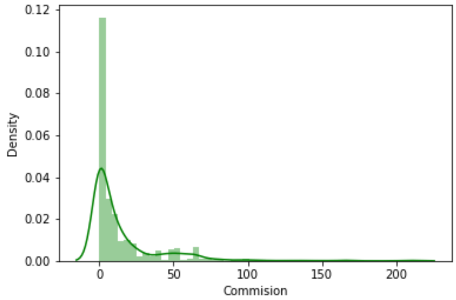



```
BoxPlot of Age
----------------------------------------------------------------------------
```

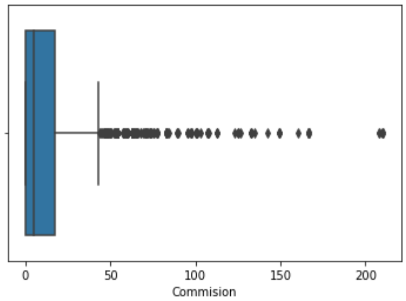


```
Description of Commision
--------------------------------------------------------------------------------
count    3000.000000
mean       14.529203
std        25.481455
min         0.000000
25%         0.000000
50%         4.630000
75%        17.235000
max       210.210000
Name: Commision, dtype: float64
```

```
Distribution of Commision
--------------------------------------------------------------------------------
```

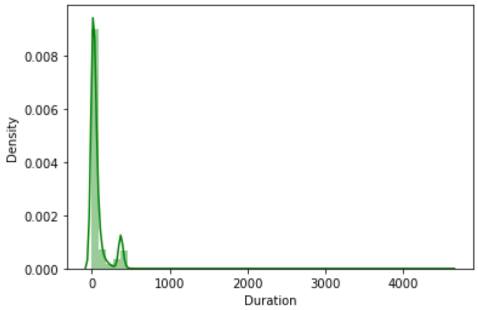



```
BoxPlot of Commision
--------------------------------------------------------------------------------
```

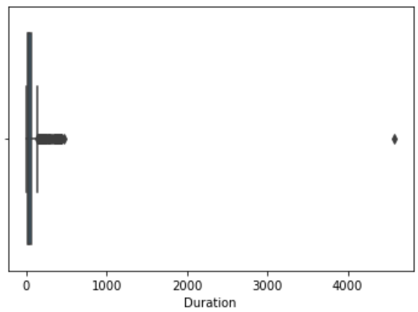



```
Description of Duration
--------------------------------------------------------------------------------
count    3000.000000
mean       70.001333
std       134.053313
min        -1.000000
25%        11.000000
50%        26.500000
75%        63.000000
max      4580.000000
Name: Duration, dtype: float64
```

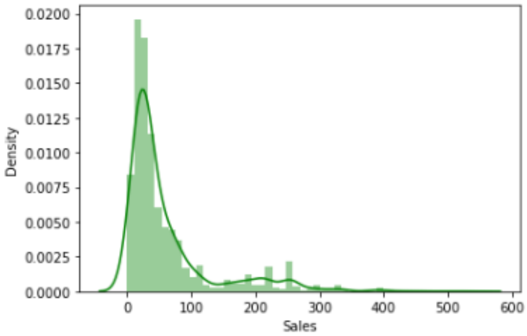
```
Distribution of Duration
--------------------------------------------------------------------------------
```



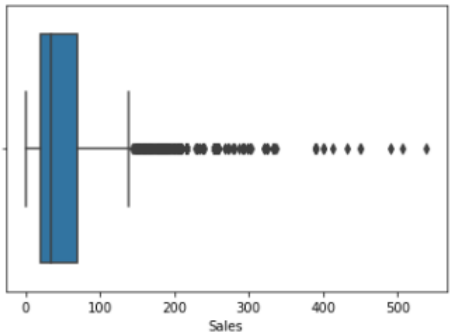

```
BoxPlot of Duration
--------------------------------------------------------------------------------
```



```
Description of Sales
----------------------------------------------------------------------------
count    3000.000000
mean       60.249913
std        70.733954
min         0.000000
25%        20.000000
50%        33.000000
75%        69.000000
max       539.000000
Name: Sales, dtype: float64

Distribution of Sales
----------------------------------------------------------------------------
```



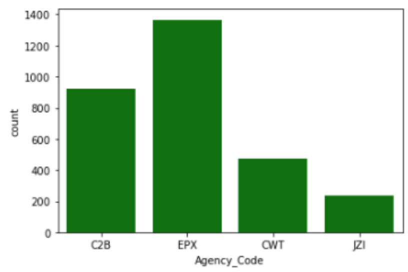

```
BoxPlot of Sales
----------------------------------------------------------------------------
```



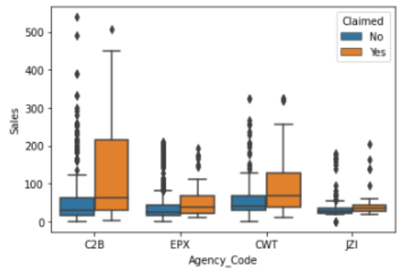
- There are outliers in all the variables, but the sales and commision can be a genuine business value as there can be some exceptional sales and comparative commision received.
- Furthermore, Random Forest and CART can handle the outliers. Hence, Outliers are not treated for now, we will keep the data as it is.
- We will treat the outliers by scaling the Data for predictions using ANN model.

Analysis using Categorical Data

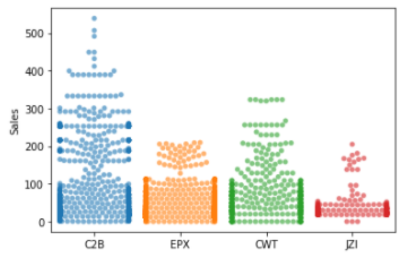
```
Countplot of Agency_Code
----------------------------------------------------------------------------
```



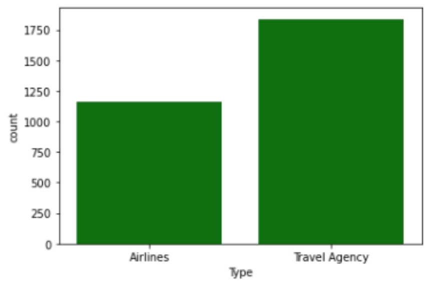

```
BoxPlot of Agency_Code
----------------------------------------------------------------------------
```



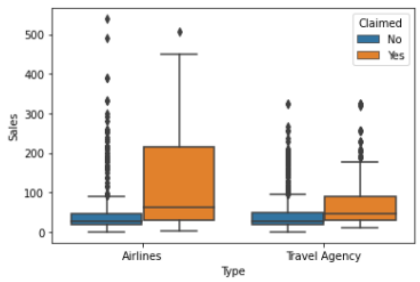

```
Swarmplot of Agency_Code
----------------------------------------------------------------------------
```



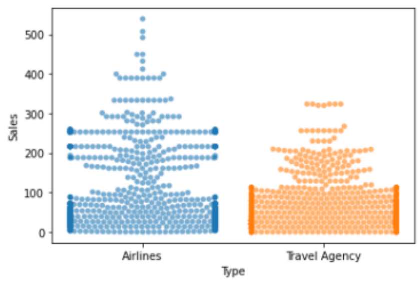

```
Countplot of Type
----------------------------------------------------------------------------
```



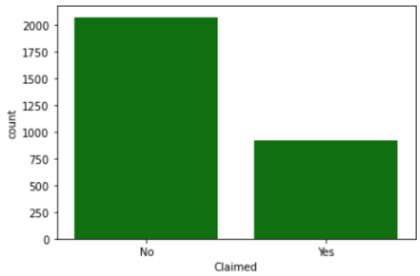

```
BoxPlot of Type
----------------------------------------------------------------------------
```



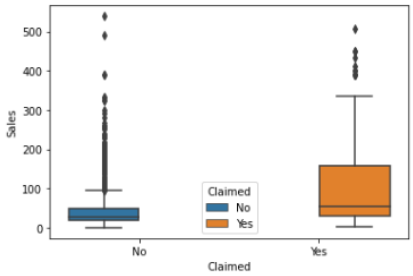

```
Swarmplot of Type
----------------------------------------------------------------------------
```



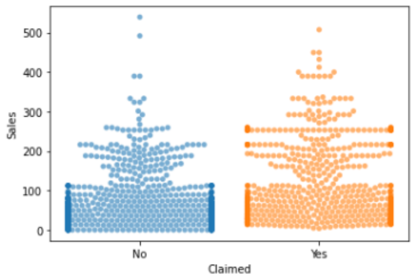
Countplot of Claimed



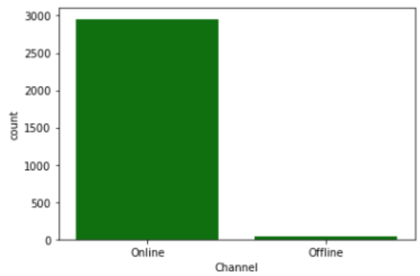
BoxPlot of Claimed



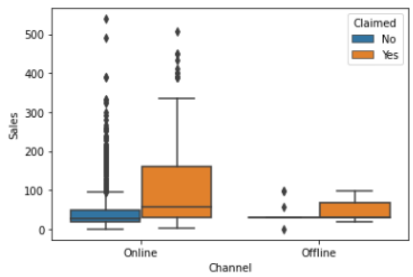
Swarmplot of Claimed



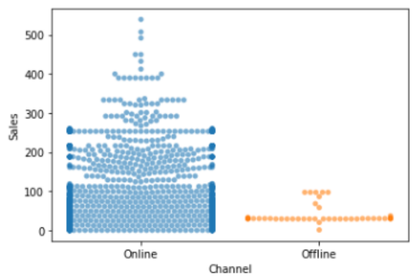
Countplot of Channel



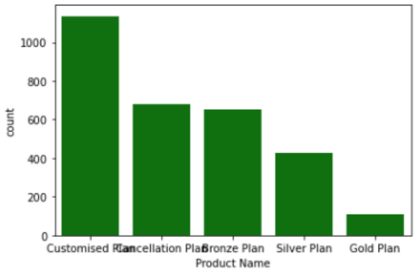
BoxPlot of Channel



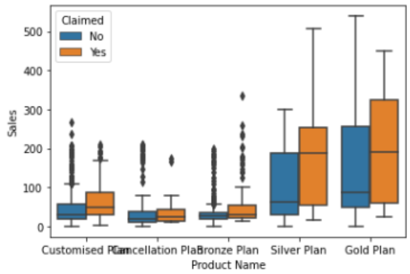
Swarmplot of Channel



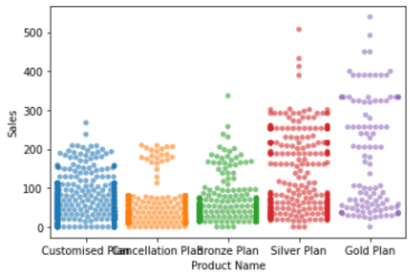
Countplot of Product Name



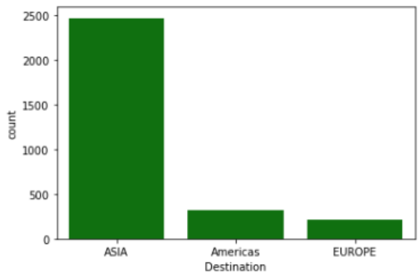
BoxPlot of Product Name



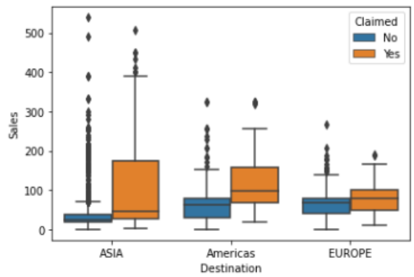
Swarmplot of Product Name



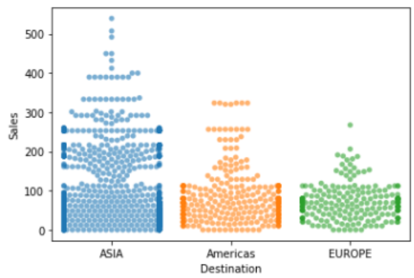
Countplot of Destination



BoxPlot of Destination



Swarmplot of Destination

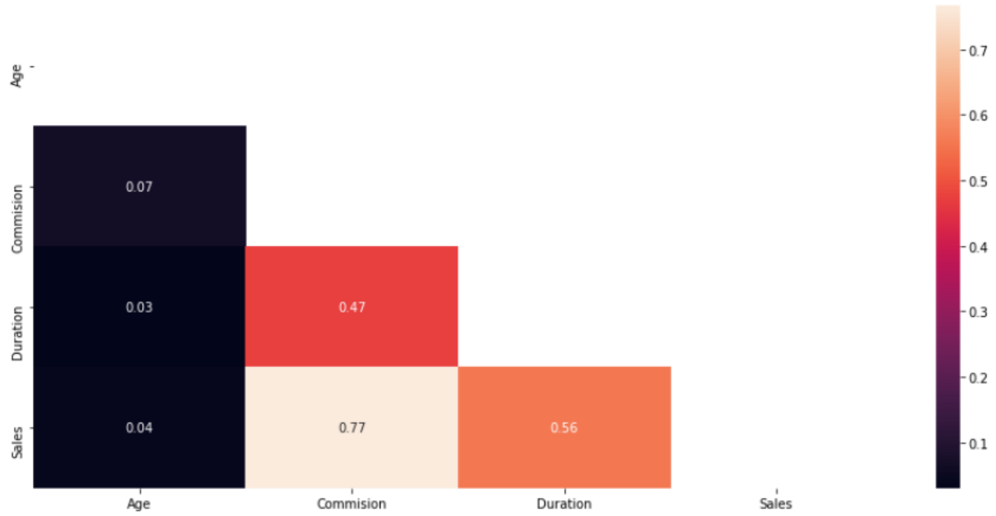


Bivariate Analysis

The following Bivariate Analysis will be performed by

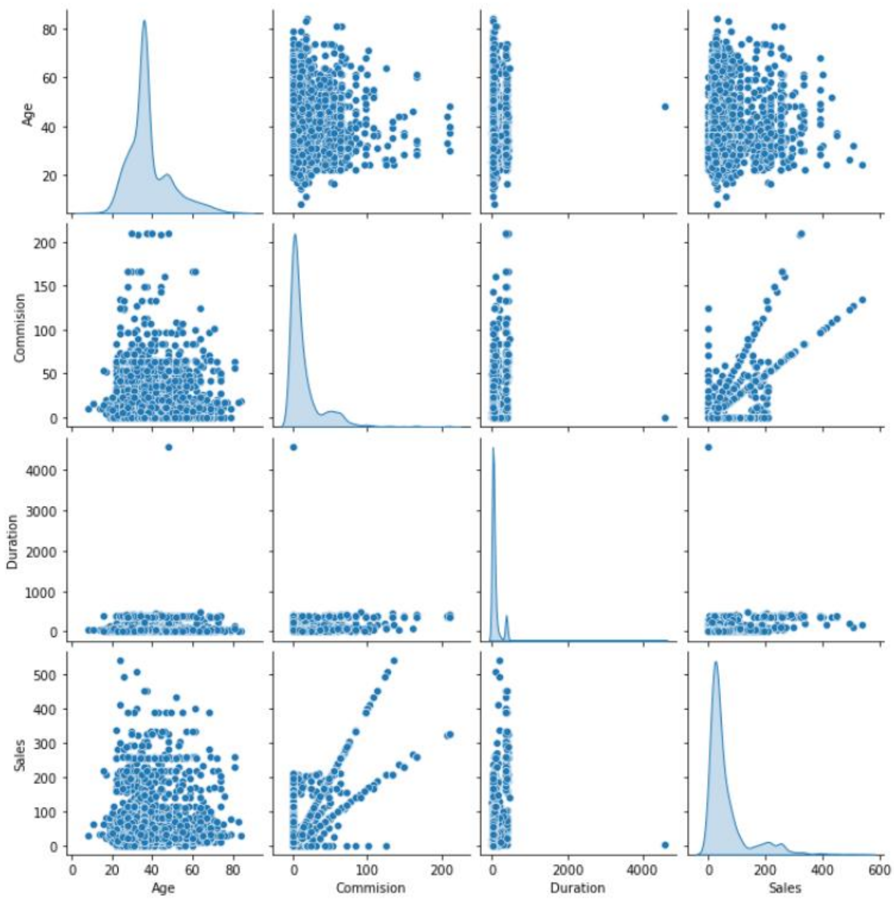
- Calculating the correlation between variable for better understanding of how variables are correlated with each other, and
- Calculating the corresponding pairplot.

Checking for Correlations ¶



Sales and Commision have the highest correlation whereas Age has the Lowest correlation with every variable

Generating a Pairplot



In the above plot scatter diagrams are plotted for all the numerical columns in the dataset. A scatter plot is a visual representation of the degree of correlation between any two columns. The pair plot function in seaborn makes it very easy to generate joint scatter plots for all the columns in the data.¶

***Converting all objects to categorical codes and checking the info of the data.**

```
feature: Agency_Code
[C2B, EPX, CWT, JZI]
Categories (4, object): [C2B, CWT, EPX, JZI]
[0 2 1 3]


feature: Type
[Airlines, Travel Agency]
Categories (2, object): [Airlines, Travel Agency]
[0 1]


feature: Claimed
[No, Yes]
Categories (2, object): [No, Yes]
[0 1]


feature: Channel
[Online, Offline]
Categories (2, object): [Offline, Online]
[1 0]


feature: Product Name
[Customised Plan, Cancellation Plan, Bronze Plan, Silver Plan, Gold Plan]
Categories (5, object): [Bronze Plan, Cancellation Plan, Customised Plan, Gold Plan, Silver Plan]
[2 1 0 4 3]


feature: Destination
[ASIA, Americas, EUROPE]
Categories (3, object): [ASIA, Americas, EUROPE]
[0 1 2]
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3000 entries, 0 to 2999
Data columns (total 10 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Age           3000 non-null   int64  
 1   Agency_Code   3000 non-null   int8   
 2   Type          3000 non-null   int8   
 3   Claimed       3000 non-null   int8   
 4   Commision     3000 non-null   float64
 5   Channel       3000 non-null   int8   
 6   Duration      3000 non-null   int64  
 7   Sales         3000 non-null   float64
 8   Product Name  3000 non-null   int8   
 9   Destination   3000 non-null   int8   
dtypes: float64(2), int64(2), int8(6)
memory usage: 111.5 KB
```

- As we can see all the categorical values are now converted to numerical data.
- The head function below makes it easier to notice the change.

Out[79]:

	Age	Agency_Code	Type	Claimed	Commision	Channel	Duration	Sales	Product Name	Destination
0	48	0	0	0	0.70	1	7	2.51	2	0
1	36	2	1	0	0.00	1	34	20.00	2	0
2	39	1	1	0	5.94	1	3	9.90	2	1
3	36	2	1	0	0.00	1	4	26.00	1	0
4	33	3	0	0	6.30	1	53	18.00	0	0

Proportion of 0's and 1's

Out[80]:

```
0    0.692
1    0.308
Name: Claimed, dtype: float64
```

2.2 Data Split: Split the data into test and train, build classification model CART, Random Forest, Artificial Neural Network

Extracting the target column into separate vectors for training set and test set

```
______Training Dataset_____
```

Out[81]:

	Age	Agency_Code	Type	Commision	Channel	Duration	Sales	Product Name	Destination
0	48	0	0	0.70	1	7	2.51	2	0
1	36	2	1	0.00	1	34	20.00	2	0
2	39	1	1	5.94	1	3	9.90	2	1
3	36	2	1	0.00	1	4	26.00	1	0
4	33	3	0	6.30	1	53	18.00	0	0

- Since we can observe that in the training dataset, some variable hold more weightage than others, therefore it may affect our observations.
- To prevent this we will perform scaling of the dataset when creating the Neural Network model so that each variable falls under a certain range.

Splitting data into training and test set

Checking the dimensions of the training and test data

```
X_train (2100, 9)
X_test (900, 9)
train_labels (2100,)
test_labels (900,)
```

Building a Decision Tree Classifier (CART)

- Regularizing the decision tree and adding a range of tuning parameters

```
Best Parameters:  {'criterion': 'gini', 'max_depth': 5, 'min_samples_leaf': 30, 'min_samples_split': 120}
Best Estimator:  DecisionTreeClassifier(max_depth=5, min_samples_leaf=30, min_samples_split=120,
                       random_state=1)
```

Generating the tree

Use the url given below and copy all the data from the dot file created above and paste in the following url to visualize the generated Decision Tree which will look like the figure given below.

- http://www.jdolivet.byethost13.com/Logiciels/WebGraphviz/

Variable Importance - Decision Tree Classifier

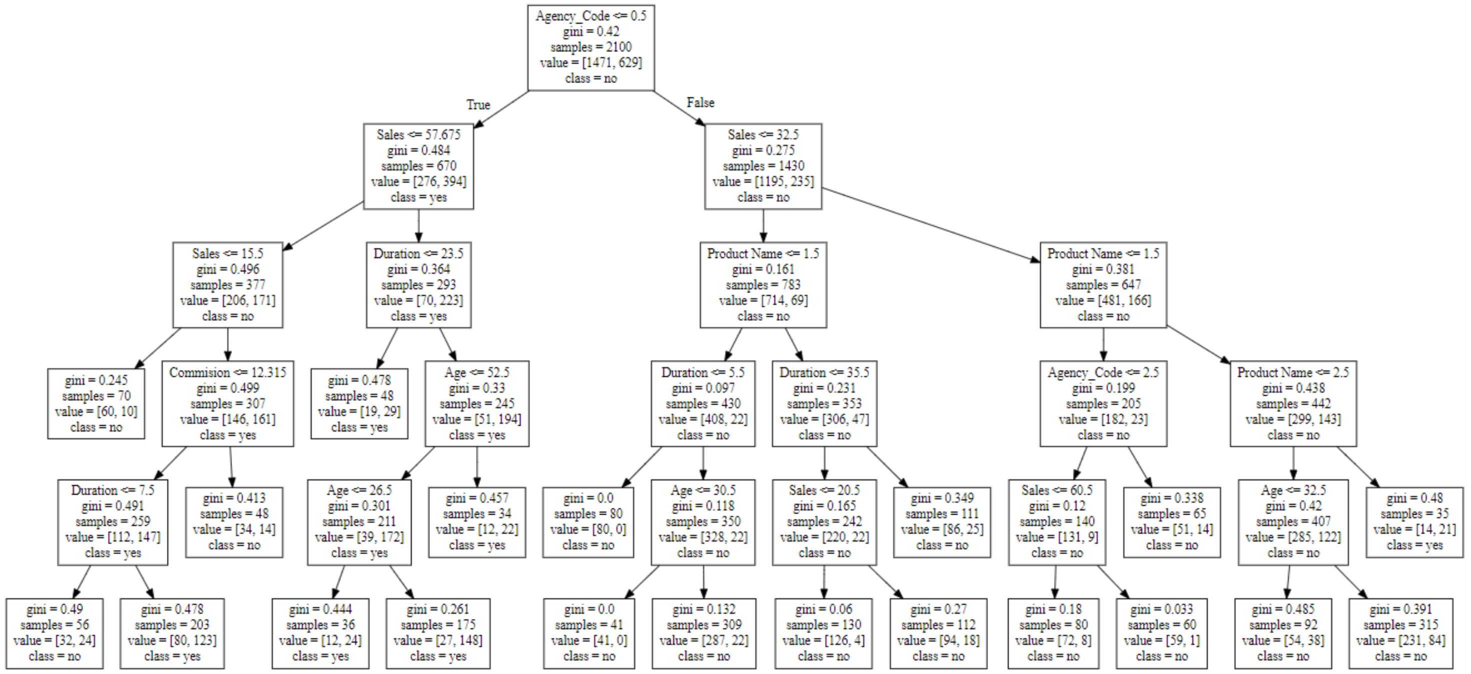
```
                   Imp
Agency_Code   0.594092
Sales         0.252143
Product Name  0.074957
Duration      0.031694
Age           0.025030
Commision     0.022083
Type          0.000000
Channel       0.000000
Destination   0.000000
```

Predicting on Training and Test dataset

Extracting the Predicted Classes and Probabilities

Out[90]:

	0	1
0	0.983333	0.016667
1	0.394089	0.605911
2	0.394089	0.605911
3	0.154286	0.845714
4	0.928803	0.071197



Ensemble RandomForest Classifier

Building the RandomForest Classifier

Importance of Random State

The important thing is that everytime you use any natural number, you will always get the same output the first time you make the model which is similar to random state while train test split

```
Best Parameters:  {'max_depth': 7, 'max_features': 4, 'min_samples_leaf': 10, 'min_samples_split': 30, 'n_estimators': 200}
Best Estimator:  RandomForestClassifier(max_depth=7, max_features=4, min_samples_leaf=10,
                       min_samples_split=30, n_estimators=200, random_state=1)
```

Predicting the Training and Testing data

Getting the Predicted Classes and Probs

Out[94]:

	0	1
0	0.742785	0.257215
1	0.455185	0.544815
2	0.422682	0.577318
3	0.260157	0.739843
4	0.938409	0.061591

Variable Importance - Random Forest

```
                  Imp
Agency_Code   0.291965
Product Name  0.192573
Sales         0.179281
Commision     0.129381
Duration      0.083125
Age           0.063843
Type          0.049477
Destination   0.009756
Channel       0.000599
```

Building a Neural Network Classifier

- It is important that we scale the data while performing a Neural Network Classifier, this however is not a necessary condition for other models like CART and Random Forest.
- Scaling is done so that each variable holds same weightage in the output so that the model is not affected by one variable having significantly high weights than the others.
- Scaling converts the all the variables in the same scale range.

```
________________________________Scaled Train Dataset__________________________________
```

Out[137]:
```
array([[-0.19192502,  0.72815922,  0.80520286, ..., -0.5730663 ,
         0.24642411, -0.43926017],
       [-0.19192502,  0.72815922,  0.80520286, ..., -0.26910565,
         0.24642411,  1.27851702],
       [-0.97188154, -1.28518425, -1.24192306, ...,  1.74601534,
         1.83381865, -0.43926017],
       ...,
       [-0.19192502,  0.72815922,  0.80520286, ...,  0.02103862,
         0.24642411, -0.43926017],
       [ 0.58803151,  1.73483096, -1.24192306, ..., -0.60069909,
        -1.34097044, -0.43926017],
       [-0.19192502, -1.28518425, -1.24192306, ..., -0.53852532,
         1.83381865, -0.43926017]])
```

```
________________________________Scaled Test Dataset__________________________________
```

Out[138]:
```
array([[-1.55684893, -0.27851251,  0.80520286, ...,  0.18683534,
        -1.34097044,  2.99629421],
       [ 1.66047173, -1.28518425, -1.24192306, ..., -0.48325974,
        -1.34097044, -0.43926017],
       [-0.87438698, -1.28518425, -1.24192306, ..., -0.62833187,
        -1.34097044, -0.43926017],
       ...,
       [-0.19192502, -1.28518425, -1.24192306, ..., -0.47635155,
        -1.34097044, -0.43926017],
       [ 1.07550434,  1.73483096, -1.24192306, ..., -0.43490237,
        -1.34097044, -0.43926017],
       [-0.28941958,  1.73483096, -1.24192306, ..., -0.49016794,
        -1.34097044, -0.43926017]])
```

Performing ANN Classification

```
Best parameters:  {'hidden_layer_sizes': 500, 'max_iter': 100, 'solver': 'adam', 'tol': 0.001}
Best Estimator:  MLPClassifier(hidden_layer_sizes=500, max_iter=100, random_state=1, tol=0.001)
```

Predicting the Training and Testing data

Getting the Predicted Classes and Probabilities

Out[140]:

	0	1
0	0.932492	0.067508
1	0.553721	0.446279
2	0.555950	0.444050
3	0.293352	0.706648
4	0.942679	0.057321

2.3 Performance Metrics: Comment and Check the performance of Predictions on Train and Test sets using Accuracy, Confusion Matrix, Plot ROC curve and get ROC_AUC score, classification reports for each model.

CART Confusion Matrix and Classification Report for the Training data

```
________________Confusion Matrix for Training Dataset_________________
```

Out[145]:
```
array([[1307,  164],
       [ 262,  367]], dtype=int64)
```

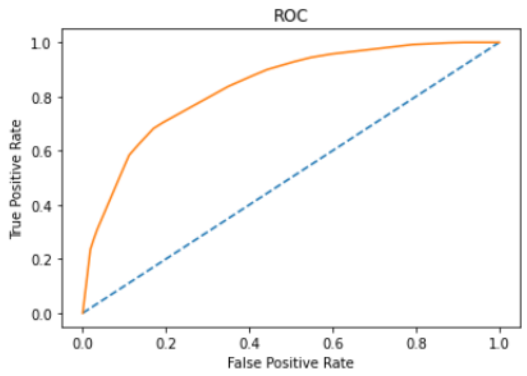
```
Accuracy of Training Dataset:  0.797

___________________________Classification Report___________________________

              precision    recall  f1-score   support

           0       0.83      0.89      0.86      1471
           1       0.69      0.58      0.63       629

    accuracy                           0.80      2100
   macro avg       0.76      0.74      0.75      2100
weighted avg       0.79      0.80      0.79      2100
```

Training Data Metrics

```
cart_train_precision  0.69
cart_train_recall  0.58
cart_train_f1  0.63
```

CART - AUC and ROC for the Training data

```
Area Under Curve : 0.837
```



CART Confusion Matrix and Classification Report for the Testing data

```
_______________Confusion Matrix for Testing Dataset________________
```

```
Out[150]: array([[549,  56],
                 [155, 140]], dtype=int64)

Accuracy of Testing Data:  0.766
```

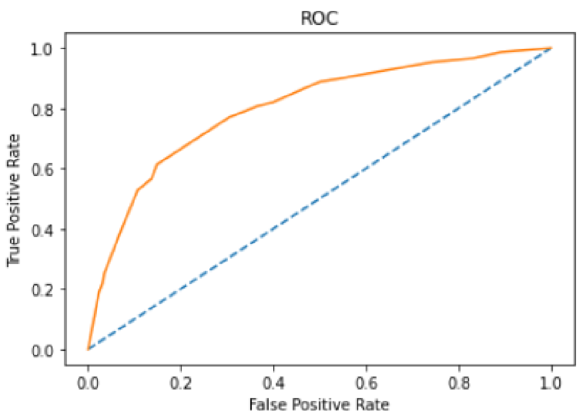
```
____________________________Classification Report_____________________________

              precision    recall  f1-score   support

           0       0.78      0.91      0.84       605
           1       0.71      0.47      0.57       295

    accuracy                           0.77       900
   macro avg       0.75      0.69      0.70       900
weighted avg       0.76      0.77      0.75       900
```

Testing Dataset Metrics

```
cart_test_precision  0.71
cart_test_recall  0.47
cart_test_f1  0.57
```

CART -AUC and ROC for the Test data

```
Area Under Curve: 0.800
```



CART Conclusion

Train Data:

- AUC: 83.7%
- Accuracy: 80%
- Precision: 69%
- f1-Score: 63%
- Recall: 58%

Test Data:

- AUC: 80%
- Accuracy: 77%
- Precision: 71%
- f1-Score: 57%
- Recall: 47%

- Training and Testing dataset results are almost similar, with the overall measures having high values
- Therefore it is safe to conclude, the model is a good model.

RandomForest Model Performance Evaluation on Training data

```
________________Confusion Matrix for Training Dataset_________________
```

```
Out[158]: array([[1331,  140],
                 [ 243,  386]], dtype=int64)
```

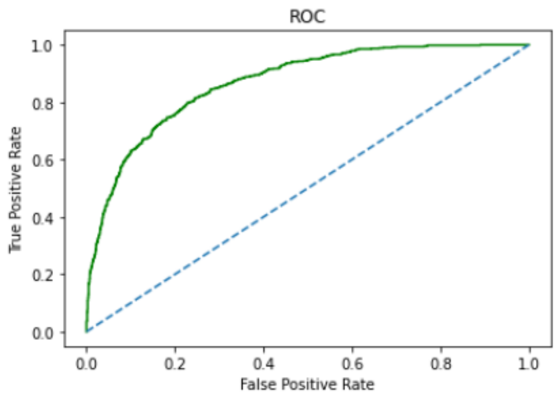
```
Accuracy of Training Dataset:  0.818

___________________________Classification Report___________________________

              precision    recall  f1-score   support

           0       0.85      0.90      0.87      1471
           1       0.73      0.61      0.67       629

    accuracy                           0.82      2100
   macro avg       0.79      0.76      0.77      2100
weighted avg       0.81      0.82      0.81      2100
```

Training Data Metrics

```
rf_train_precision  0.73
rf_train_recall  0.61
rf_train_f1  0.67
```

RF- AUC and ROC for the Training data

```
Area Under Curve: 0.869
```



RF Model Performance Evaluation on Test data

```
________________Confusion Matrix for Testing Dataset_________________
```

```
Out[159]: array([[555,  50],
                 [153, 142]], dtype=int64)
```

```
Accuarcy of Testing Data:  0.774
```

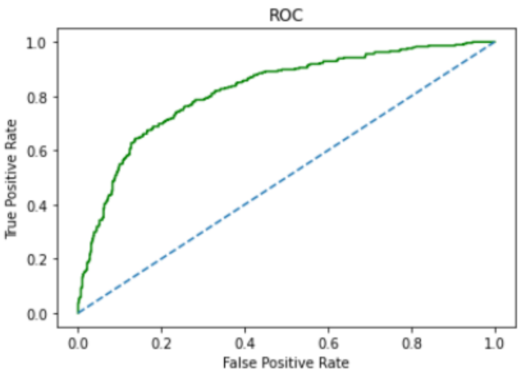
```
__________________________Classification Report__________________________

              precision    recall  f1-score   support

           0       0.78      0.92      0.85       605
           1       0.74      0.48      0.58       295

    accuracy                           0.77       900
   macro avg       0.76      0.70      0.71       900
weighted avg       0.77      0.77      0.76       900
```

Testing Data Metrics

```
rf_test_precision  0.74
rf_test_recall  0.48
rf_test_f1  0.58
```

RF- AUC and ROC for the Testing data

```
Area under Curve : 0.821
```



Random Forest Conclusion

Train Data:

- AUC: 87%
- Accuracy: 82%
- Precision: 73%
- f1-Score: 67%
- Recall: 61%

Test Data:

- AUC: 82%
- Accuracy: 77.4%
- Precision: 74%
- f1-Score: 58%
- Recall: 48%

- Training and Testing dataset results are almost similar, with the overall measures having high values
- Therefore it is safe to conclude, the model is a good model.

Artificial Neural Network Model Performance Evaluation on Training data

```
________________Confusion Matrix for Training Dataset________________
```

```
Out[171]: array([[1329,  142],
                 [ 296,  333]], dtype=int64)
```

```
Accuracy of Training Data: 0.791
```

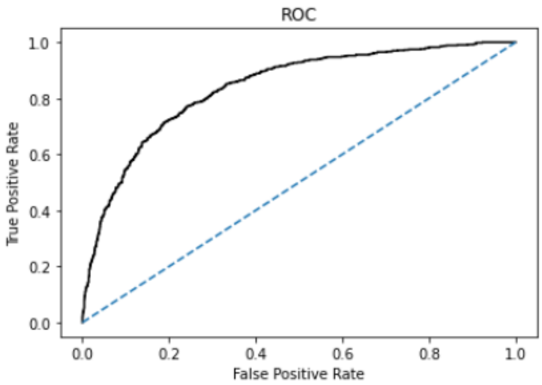
```
___________________________Classification Report___________________________

              precision    recall  f1-score   support

           0       0.82      0.90      0.86      1471
           1       0.70      0.53      0.60       629

    accuracy                           0.79      2100
   macro avg       0.76      0.72      0.73      2100
weighted avg       0.78      0.79      0.78      2100
```

Training Data Metrics

```
nn_train_precision  0.7
nn_train_recall  0.53
nn_train_f1  0.6
```

ANN - AUC and ROC for the Training data

```
Area Under Curve 0.839
```



Artificial Neural Network Model Performance Evaluation on Testing data

```
_______________Confusion Matrix for Testing Dataset________________
```

Out[172]:
```
array([[555,  50],
       [165, 130]], dtype=int64)
```

```
Accuracy of Testing Dataset: 0.761
```

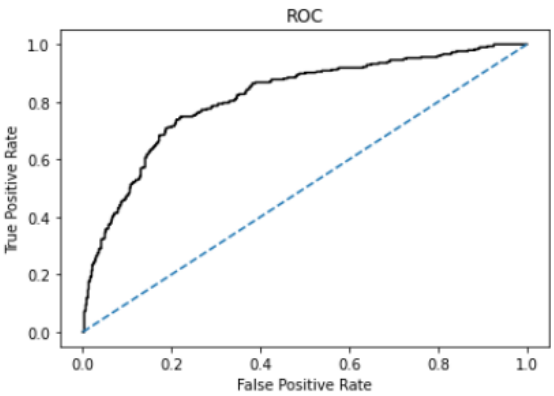
```
___________________________Classification Report____________________________

              precision    recall  f1-score   support

           0       0.77      0.92      0.84       605
           1       0.72      0.44      0.55       295

    accuracy                           0.76       900
   macro avg       0.75      0.68      0.69       900
weighted avg       0.75      0.76      0.74       900
```

Testing Data Metrics

```
nn_test_precision  0.72
nn_test_recall  0.44
nn_test_f1  0.55
```

ANN - AUC and ROC for the Testing data

```
Area under Curve 0.815
```



Neural Network Conclusion

Train Data:

- AUC: 84%
- Accuracy: 79%
- Precision: 70%
- f1-Score: 60%
- Recall: 53%

Test Data:

- AUC: 81.5%
- Accuracy: 76%
- Precision: 72%
- f1-Score: 55%
- Recall: 44%

- Training and Testing dataset results are almost similar, with the overall measures having high values
- Therefore it is safe to conclude, the model is a good model.

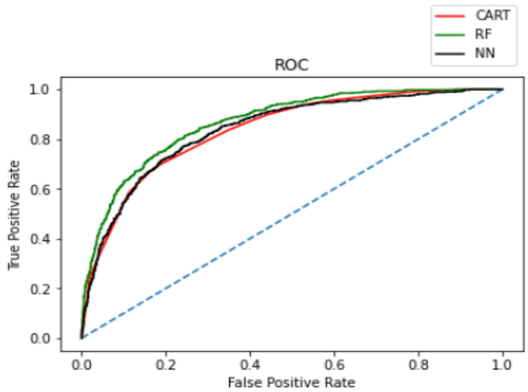
2.4 Final Model: Compare all the model and write an inference which model is best/optimized.

Comparison of the performance metrics from the 3 models

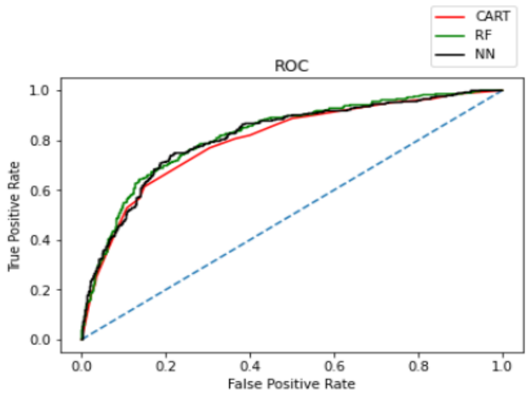
Out[133]:

	CART Train	CART Test	Random Forest Train	Random Forest Test	Neural Network Train	Neural Network Test
Accuracy	0.80	0.77	0.82	0.77	0.79	0.76
AUC	0.84	0.80	0.87	0.82	0.84	0.81
Recall	0.58	0.47	0.61	0.48	0.53	0.44
Precision	0.69	0.71	0.73	0.74	0.70	0.72
F1 Score	0.63	0.57	0.67	0.58	0.60	0.55

ROC Curve for the 3 models on the Training data



ROC Curve for the 3 models on the Test data



CONCLUSION :

*** All of the three models are performing very good having high accuracy, AUC and precision values.**

*** Random Forest model is the one which is performing the best as compared to CART and ANN therefore that is the model we will use for better predictions.**

*** This can also be oberved from the ROC curves of all 3 models.**

2.5 Inference: Basis on these predictions, what are the business insights and recommendations

- I strongly recommended we collect more real time unstructured data and past data if possible.
- This is understood by looking at the insurance data by drawing relations between different variables such as day of the incident, time, age group, and associating it with other external information such as location, behavior patterns, weather information, airline/vehicle types, etc., we can grad more insights from the data leading to better predictions hence improving the accuracy and precision of the model.
- • Streamlining online experiences benefitted customers, leading to an increase in conversions, which subsequently raised profits. • As per the data 90% of insurance is done by online channel. • Other interesting fact, is almost all the offline business has a claimed associated, need to find why? • Need to train the JZI agency resources to pick up sales as they are in bottom, need to run promotional marketing campaign or evaluate if we need to tie up with alternate agency • Also based on the model we are getting 80%accuracy, so we need customer books airline tickets or plans, cross sell the insurance based on the claim data pattern. • Other interesting fact is more sales happen via Agency than Airlines and the trend shows the claim are processed more at Airline. So we may need to deep dive into the process to understand the workflow and why?
- Key performance indicators (KPI) The KPI's of insurance claims are: • Reduce claims cycle time • Increase customer satisfaction • Combat fraud • Optimize claims recovery • Reduce claim handling costs Insights gained from data and AI-powered analytics could expand the boundaries of insurability, extend existing products, and give rise to new risk transfer solutions in areas like a non-damage business interruption and reputational damage.

By: TUSHAR BABBAR