DATA MINING REPORT

CLUSTERING, CART, RF, ANN

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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.

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

Read Data first 5 row:

Spending	Advance_ payments	Probability_ of_full_paym ent	Current_ balance	Credit_ limit	Min_payment _amt	Max_spent_in_s ingle_shopping
19.94	16.92	0.8752	6.675	3.763	3.252	6.55
15.99	14.89	0.9064	5.363	3.582	3.336	5.144
18.95	16.42	0.8829	6.248	3.755	3.368	6.148
10.83	12.96	0.8099	5.278	2.641	5.182	5.185
17.99	15.86	0.8992	5.89	3.694	2.068	5.837

Data information:

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

Interpretation:

* The data has 210 rows and 7 columns with Float as the data type for each.

We have continuous, non-null data with 7 variables.

Describe the data:

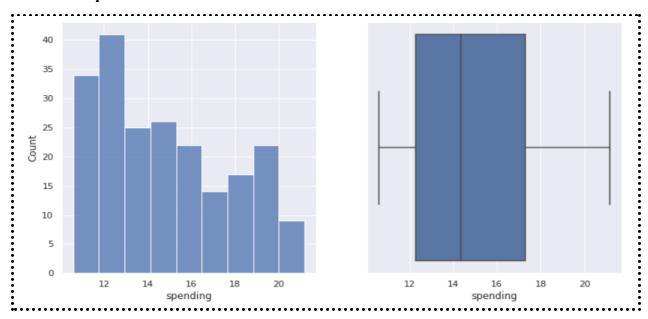
	Count	Mean	STD	MIN	25.00%	50.00%	75.00%	MAX
Spending	210	14.847524	2.909699	10.59	12.27	14.355	17.305	21.18
Advance_paymen ts	210	14.559286	1.305959	12.41	13.45	14.32	15.715	17.25
Probability_of_fu ll_payment	210	0.870999	0.023629	0.8081	0.8569	0.87345	0.887775	0.9183
Current_balance	210	5.628533	0.443063	4.899	5.26225	5.5235	5.97975	6.675
Credit_limit	210	3.258605	0.377714	2.63	2.944	3.237	3.56175	4.033
Min_payment_a mt	210	3.700201	1.503557	0.7651	2.5615	3.599	4.76875	8.456
Max_spent_in_si ngle_shopping	210	5.408071	0.49148	4.519	5.045	5.223	5.877	6.55

- ❖ The summary stats: average spending is approximate 14800/-
- The average advance payment done by a customer is approximate 1400/- which is almost 10% of the monthly spend.
- The average max spend in one purchase is approximate 5400/- and the minimum paid amount by customer during purchase is approximate 370/-

EDA - Univariate Analysis

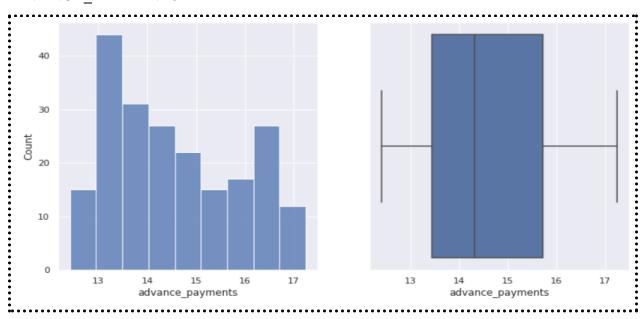
> Our objective is to derive the data, define and analyze the pattern present in each variable separately.

Dist and boxplot of all variables: SPENDING



- > The Boxplot tells us there are no outliers Spending distribution.
- > The distribution can be said to be slightly left skewed. Skewness(spending) is 0.397. The distribution ranges between 11 to 20.

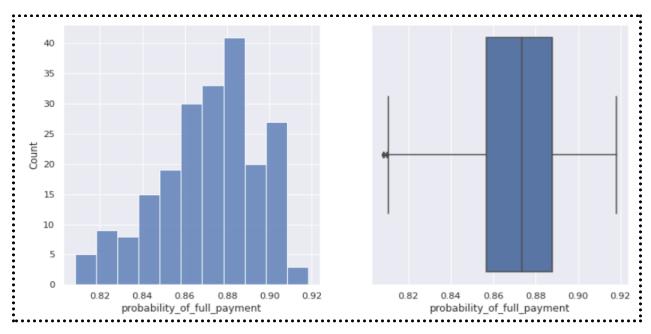
ADVANCE PAYMENTS



> The Boxplot tells us there are no outliers advance_payments distribution.

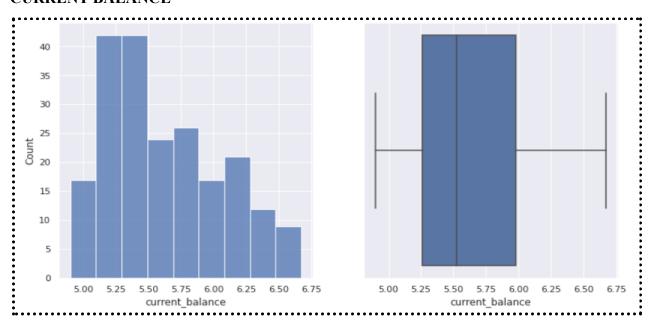
> The distribution can be said to be slightly left skewed. Skewness(advance payments) is 0.384. The distribution ranges between 12 to 17(100s).

PROBABILITY OF FULL PAYMENT



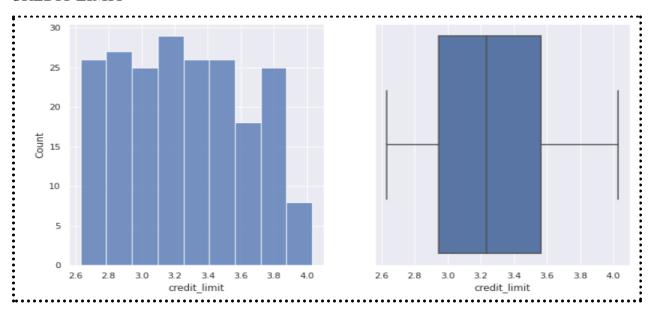
- > The Boxplot tells us there are few outliers for probability_of_full_payment distribution.
- > The distribution can be said to be slightly right skewed. Skewness (probability_of_full_payment) is -0.534. The distribution ranges between 0.80 to 0.92.

CURRENT BALANCE



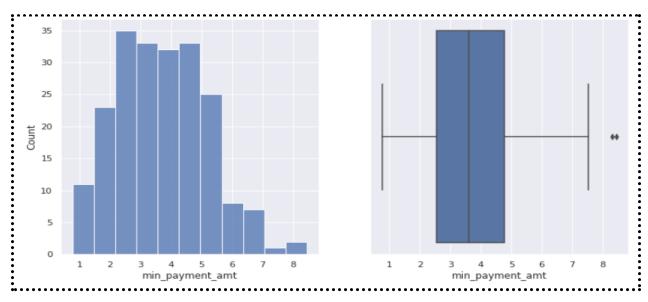
- > The Boxplot tells us there are no outliers for current balance distribution.
- > The distribution can be said to be slightly left skewed. Skewness (current_balance) is 0.522. The distribution ranges between 5 to 6.7(1000s).

CREDIT LIMIT



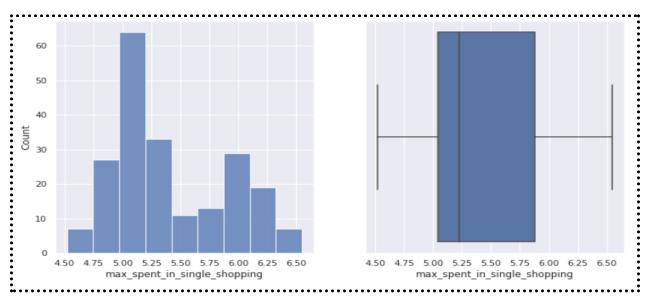
- > The Boxplot tells us there are no outliers for credit limit distribution.
- > The distribution can be said to be normally distributed. Skewness (credit_limit) is 0.133. The distribution ranges between 2.6 to 4 (10000s)

MIN PAYMENT AMT



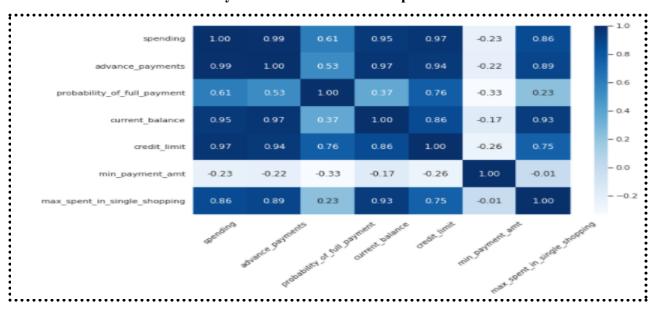
- > The Boxplot tells us there are few outliers for min payment amt distribution.
- > The distribution can be said to be slightly left skewed. Skewness (min_payment_amt) is 0.399. The distribution ranges between 1 to 8 (100s)

MAX SPEND IN SINGLE SHOPPING



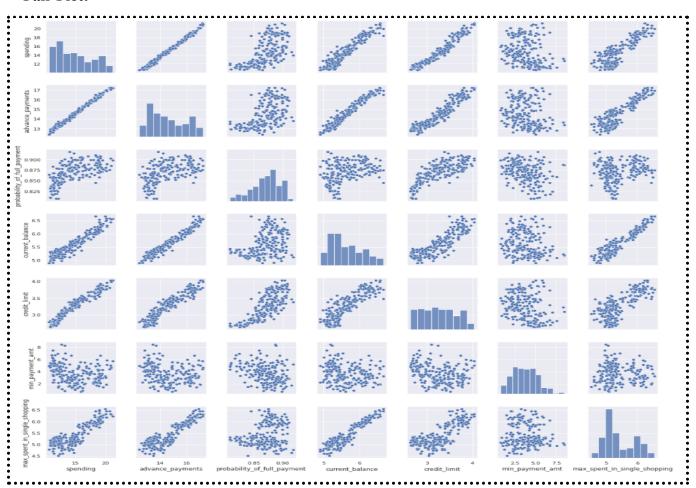
- > The Boxplot tells us there are no outliers for max_spent_in_single_shopping distribution.
- > The distribution can be said to be slightly left skewed. Skewness (max_spent_in_single_shopping) is 0.558. The distribution ranges between 4.5 to 6.5 (1000s)

Bivariate and Multivariate Analysis - Correlation Heatmap:



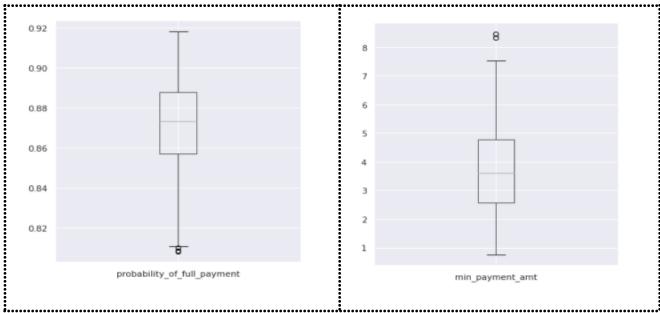
- > The relation between pairs of numeric variables is given by the heatmap.
- > The correlation between the following variables are highly positive: (variable are directly proportional)
 - Spending and Advance Payment
 - Current Balance and Advance Payment
 - Spending and Credit Limit
 - Spending and Current Balance
- > The correlation between the following variables are negative: (variable are inversely proportional)
 - Min Payment Amt and Probability Of Full Payment
 - Min Payment Amt and Credit Limit
 - Min Payment Amt and Spending
 - Min Payment Amt and Advance Payment

Pair Plot:



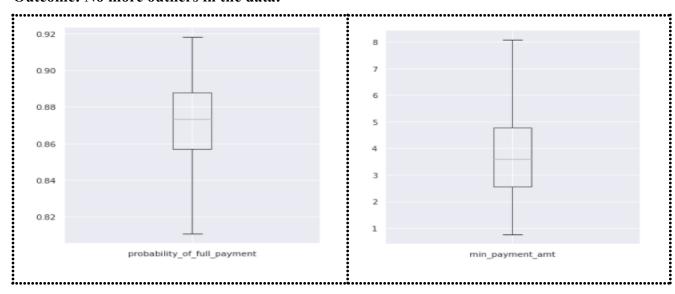
- > We can see the same relation pattern(Strong correlation) between the variables in the Pair Plot above.
- > Spending & Advance payment by cash increases with credit card amount limit and current balance amount left in the account to make purchases.
- > We can see outliers in only two variables: Probability_of_full_payment and Min payment amt.

Probability of full payment and Min payment amt with Outliers:



> As we have few outliers, we will replace the outlier values for each variable using the IQR(Q1 and Q3) respectively.

Outcome: No more outliers in the data:



- 1.2 Do you think scaling is necessary for clustering in this case? Justify.
 - Scaling is used to eliminate redundancy in data during clustering and ensures that good quality clusters are generated.
 - * As in this case, we see that though numeric, our variables vary in dimension (having different weight), which would lead some variables to have more weightage on the outcome than others.
 - * For example if we look at our data summary we see:
 - > Standard Deviation(std) of Spending and Advance_Payments and Min payment amt is high (2.91, 1.30 and 1.50) when compared to others.
 - > Probability of full payment(std) being the lowest. (0.023)
 - **Same** if we look at the variance:

> spending	<i>8.43</i>
> advance_payments	1.70
<pre>probability_of_full_payment</pre>	0.00
> current_balance	0.20
> credit_limit	0.14
> min_payment_amt	2.22
> max spent in single shopping	0.24

- As we do have large variance data, we do scale our variables. So as to avoid(creating a bias), the variables with largest variance have disproportionately more influence on cluster outcome.
- Hence before clustering all the variables should be scales to have the same weight(unit). Can be done by:
 - Z-score method
 - Min-Max method
- **❖** Using Min-Max method method to scale the 7 variables here:
- ♦ Min-Max method has now brought the data closer and decreased the variance between them: We can see the change in std and variance after scaling. (between 0 & 1)
- **❖** We look at the variance after scaling:

> spending	0.08
<pre>advance_payments</pre>	0.07
<pre>probability_of_full_payment</pre>	0.05
<pre>current_balance</pre>	0.06
> credit_limit	0.07
> min_payment_amt	0.04
> max_spent_in_single_shopping	0.06

5-Point summary stat of scaled data:

	Count	Mean	STD	MIN	25.00%	50.00%	75.00%	MAX
Spending	210	0.4	0.27	0	0.16	0.36	0.63	1
Advance_payments	210	0.44	0.27	0	0.21	0.39	0.68	1
Probability_of_full_payment	210	0.56	0.22	0	0.43	0.58	0.72	1
Current_balance	210	0.41	0.25	0	0.2	0.35	0.61	1
Credit_limit	210	0.45	0.27	0	0.22	0.43	0.66	1
Min_payment_amt	210	0.4	0.2	0	0.25	0.39	0.55	1
Max_spent_in_singl e_shopping	210	0.44	0.24	0	0.26	0.35	0.67	1

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

Clustering is a method of grouping similar objects into classes.

It is used to convert data into structures that can be easily understood and manipulated.

There are two types:

- > Hierarchical clustering
- > Partitioning clustering

We will be using Hierarchical clustering.

> It groups similar objects into groups called clusters, where each cluster is distinct from each other cluster, and the objects within each cluster are broadly similar to each other.

It has a Bottom Up approach: We start by treating each object as a separate cluster. Then, repeatedly executes the following two steps:

- (1) Identify the two clusters that are closest to each other
- (2) Merge the two most similar clusters.

For the 1st step we measure distance - hierarchical clustering, including the following:

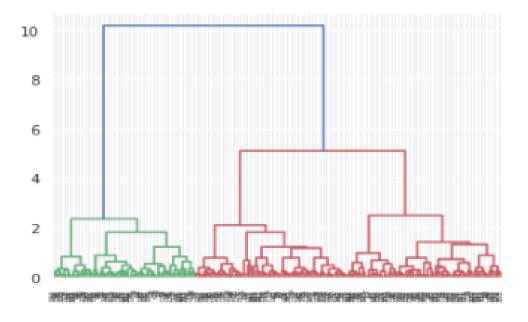
- > Euclidean Distance
 - It follows pythagoras theorem to find shortest distance between two points: x1(i, j) and x2(v,u), then distance = $\sqrt{(i-v)^2+(j-u)^2}$
- > Manhattan distance
 - It is a distance between the projection of points(modulus): x1(i, j) and x2(v,u), then distance = |i-v|+|j-u|

For the 2nd step we merge clusters by similarity - Using linkage methods:

- > Single Linkage
 - Two clusters with the closest minimum distance are merged
- > Complete Linkage
 - Two clusters with the closest maximum distance are merged
- > Centroid Linkage
 - Two clusters with the lowest centroid distance are merged.
- ➤ Ward's Linkage
 - Two clusters are merged based on their error sum of square values.
- > Average Linkage
 - Average linkage method uses the average pairwise proximity among all pairs of objects in different clusters. Clusters are merged based on their lowest average distances.

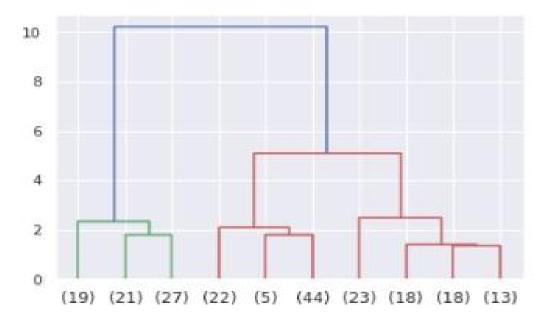
I will be using Ward's Linkage method for merge on scaled data. And Euclidean to find the shortest distance, as that is one of the commonly used and default.

Here is the Dendrogram for visualization:



- Next step would be to choose the number of clusters to go with.
- ❖ By using 'lastp' where p=10, we get a clear picture of our structure above:

 Dendrogram after Trimming:



❖ We can conclude by getting 2 main clusters, however as 2 clusters are not optimal for industrial use, we go with 3 clusters here as our optimal clusters count.

* Proceeding with Hierarchical Clustering implementation:

- > Using Fclusters to proceed:
- > Number of clusters: 3, Affinity: 'Euclidean' and Linkage: 'Ward'

Fclusters Cluster Added to database:

	spending	advance_payments	<pre>probability_of_full_payment</pre>	current_balance	credit_limit	min_payment_amt	max_spent_in_single_shopping	clusters
0	0.88	0.93	0.60	1.00	0.81	0.34	1.00	
1	0.51	0.51	0.89	0.26	0.68	0.35	0.31	
2	0.79	0.83	0.67	0.76	0.80	0.36	0.80	
3	0.02	0.11	0.00	0.21	0.01	0.60	0.33	
4	0.70	0.71	0.82	0.56	0.76	0.18	0.65	

Fclusters Cluster Frequency:

1 67

2 71

3 72

Name: clusters, dtype: int64

Fclusters Cluster Profiling:

Clusters	Spending	Advance_ payments	Probability _of_full_p ayment	Curren t_balan ce	Credit _limit	Min_pay ment_amt	Max_spent _in_single_ shopping	Freq
1	0.74	0.78	0.68	0.72	0.76	0.4	0.75	67
2	0.13	0.19	0.36	0.2	0.17	0.56	0.29	71
3	0.35	0.39	0.65	0.34	0.43	0.24	0.29	72

- * For banks Tier 1 users are high spenders, as well as their Maximum amount spent in one purchase, along with their probability of payment done in full by the customer to the bank is high.
- ❖ For banks Tier 2 users are low monthly spend, their Credit limit, probability of payment done in full by the customer to the bank is also on the lower end, when compared to other clusters.
- ❖ For banks Tier 3 users are medium monthly spend, their probability of payment done in full by the customer to the bank is high.
- * Following the same for Agglomerative Clustering we get equal outcome:

Cluster Frequency:

0 72

1 67

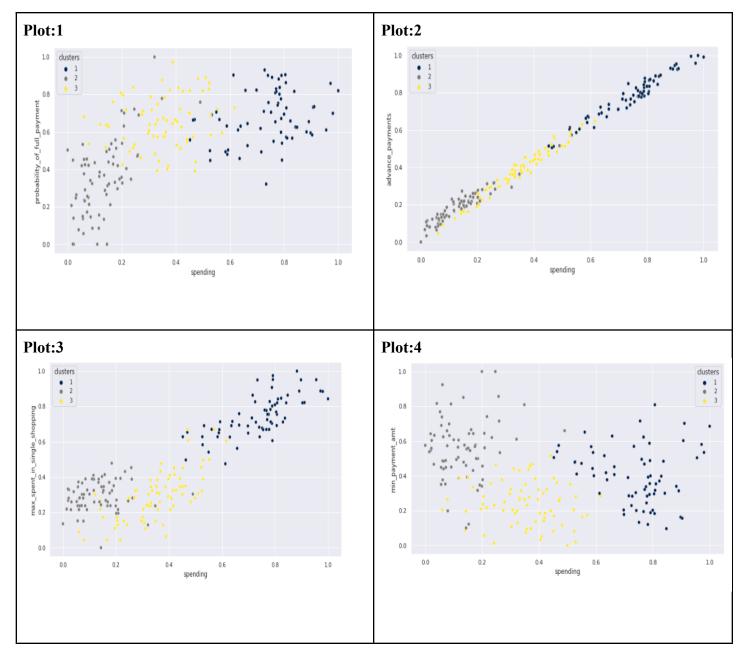
2 71

Name: Agglo_CLusters, dtype: int64

Agglomerative Clustering Cluster Profiling:

A.	Agglo_ Luster s	Spendin g	Advance _paymen ts	Probabil ity_of_fu ll_payme nt	Current_ balance	Credit_li mit	Min_pay ment_am t	Max_spe nt_in_sin gle_shop ping	Freq
	0	0.13	0.19	0.36	0.2	0.17	0.56	0.29	71
	1	0.74	0.78	0.68	0.72	0.76	0.4	0.75	67
	2	0.35	0.39	0.65	0.34	0.43	0.24	0.29	72

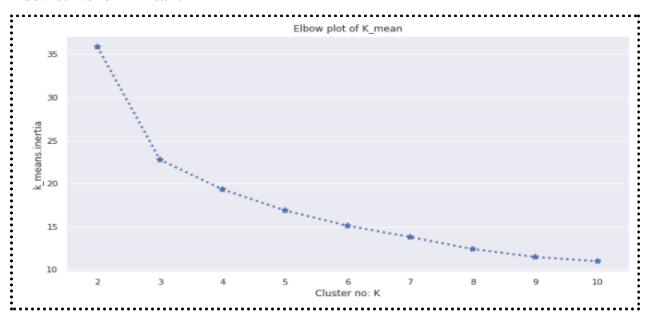
Fclusters Cluster Plots:



- ❖ We are able to make out the variance in each cluster plot and identify the cluster groups.
- ❖ The cluster follows the same path as all the plots, 1 being on the higher end of the spectrum and 2 on the lower end.
- This can be used by the bank to narrow down user behavior in each cluster group.

- 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.
 - * K-means clustering uses "centroids", K different randomly-initiated points in the data, and assigns every data point to the nearest centroid.
 - ❖ In this case, will start with K=3 to proceed.
 - ➤ It's Within Cluster Sum of Squares as: 22.770013026036565
 - ***** Calculating WSS for other values of K:
 - > K=2 k mean inertia is 35.86521074048986
 - > K=3 k mean inertia is 22.770013026036565
 - > K=4 k mean inertia is 19.323702051792594
 - > K=5 k mean inertia is 16.88519118531759
 - > K=6 k mean inertia is 15.1045576826233
 - > K=7 k mean inertia is 13.802943437508269
 - > K=8 k mean inertia is 12.40244683471637
 - > K=9 k mean inertia is 11.480004867341448
 - > K=10 k mean inertia is 10.995733610492227
 - ❖ To find the optimum K value I have created an elbow curve.

Elbow curve for K-mean:



- > We can see that after 3, there is an almost constant decrease in K_mean inertia value.
- > Hence will take 3 as the optimum number of clusters for the given data.

Silhouette Score:

- > Silhouette Score is a metric used to calculate the goodness of a clustering technique.
- > Its value ranges from -1 to 1.
- ➤ Silhouette Score for our optimal K=3 is: 0.41888372435617
- **Cluster evaluation for all above k values, the silhouette score:**
 - > K=2 silhouette score is 0.5000644323521964
 - > K=3 silhouette score is 0.41888372435617
 - > K=4 silhouette score is 0.336795122525894
 - > K=5 silhouette score is 0.28630579552105506
 - > K=6 silhouette_score is 0.2894420745589243
 - > K=7 silhouette_score is 0.26322890706145396
 - > K=8 silhouette_score is 0.25966810176636784
 - > K=9 silhouette score is 0.26177716346826413
 - > K=10 silhouette score is 0.24801301630025002
- * As 2 clusters with the highest score, cannot be used for industrial application, will select the next high score value as we got above.

Append cluster labels from K-means into the original data: first 5 rows:

Spending	Advance _payment s	Probability _of_full_p ayment	Current_ balance	Credit_ limit	Min_pay ment_amt	Max_spent_i n_single_sho pping	KMCluster
19.94	16.92	0.8752	6.675	3.763	3.252	6.55	1
15.99	14.89	0.9064	5.363	3.582	3.336	5.144	0
18.95	16.42	0.8829	6.248	3.755	3.368	6.148	1
10.83	12.96	0.810588	5.278	2.641	5.182	5.185	2
17.99	15.86	0.8992	5.89	3.694	2.068	5.837	1

Cluster Frequency:

0 69

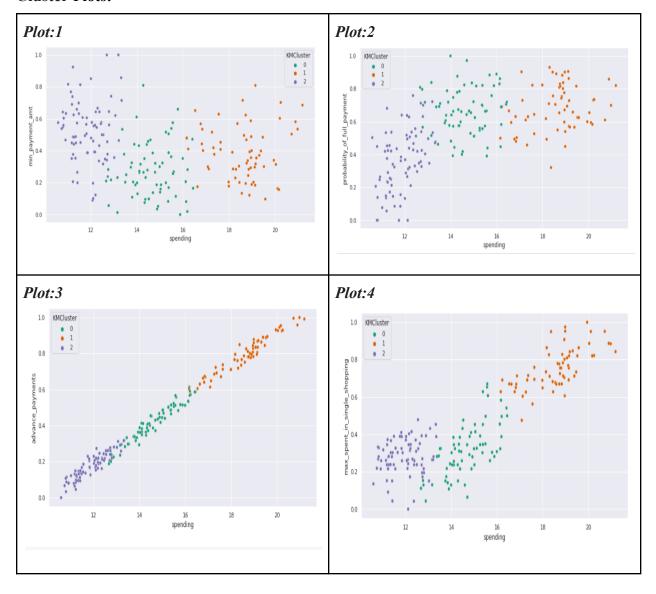
1 64

2 77

Name: KMCluster, dtype: int64

- * K mean has divided our data into 3 clusters.
- ❖ The data is distributed almost equally. Cluster 2 having more data compared to the other two.

Cluster Plots:



Inference:

- ❖ We get three cluster and if we look at the cluster profiling we can see that:
 - > Tier 0 is has 69 users
 - > Tier 1 is has 64 users
 - > Tier 2 is has the highest 77 users
- * The graph results are similar from our earlier model.
- The above plots show a pattern format followed in each pair graph, with Tier 2 on the lower end and Tier end at the high end.
- ❖ We can conclude the data is properly clustered, benefiting further analysis.
- 1.5 Describe cluster profiles for the clusters defined. Recommend different promotional strategies for different clusters.
 - Now performing Cluster Profiling for our K_mean cluster data that we appended to the original data.

Cluster Profiling: (K mean cluster data that we appended to the original data)

KMCluster	Spending	Advance_ payments	Probabilit y_of_full _payment	Current_ balance	Credit _limit		Max_spent_ in_single_s hopping	Freq
0	14.65	14.44	0.88	5.55	3.29	2.8	5.17	69
1	18.61	16.25	0.88	6.2	3.71	3.59	6.06	64
2	11.9	13.26	0.85	5.23	2.86	4.59	5.09	77

- ❖ We have three groups with their frequencies displayed in the above table.
 - > Tier 0 is (medium)
 - > Tier 1 is (high)
 - > Tier 2 is (low)

❖ By viewing the above data and analyzing it mean there is a pattern, which is similar to the pattern one sees during Fcluster.

Inferences:

- ❖ The Group 1 or Tier 1 data has of Kmean:
 - > High Spending, High Advance_payments, High Probability_of_full_payment, High Current_balance, High Credit_limit, Medium Min_payment_amt and High Max spent in single shopping.
 - > This pattern matched Agglomerative Cluster's Group 1 or Tier 1 data.
- ❖ The Group 0 or Tier 0 data has of Kmean:
 - Medium Spending, Medium Advance_payments, High Probability_of_full_payment, Medium Current_balance, Medium Credit_limit, Low Min_payment_amt_and Medium Max_spent_in_single_shopping.
 - > This pattern matched Agglomerative Cluster's Group 2 or Tier 2 data.
- * The Group 2 or Tier 2 data has of Kmean:
 - > Low Spending, Low Advance_payments, Low Probability_of_full_payment, Low Current_balance, Low Credit_limit, High Min_payment_amt and Low Max spent in single shopping.
 - > This pattern matched Agglomerative Cluster's Group 0 or Tier 0 data.
- ***** Kmean Group 0 = Agglomerative Group 2
- **❖** Kmean Group 1 = Agglomerative Group 1
- ***** Kmean Group 2 = Agglomerative Group 0

Recommendation:

- ❖ For Group 1 -
 - > High Spenders give purchase credit points(Loyal customer base)
 - > Medium Min_payment_amt, High Advance_payments offer premium on credit card.
 - > High Current_balance offer higher credit limits, would encourage purchases.
 - > High Probability_of_full_payment offer membership & exclusive promotion on loyalty.
 - > High Max_spent_in_single_shopping pitching more brands and products would benefit, as they have higher conversion rate.

❖ For Group 0

- > Medium Spending, Medium Advance_payments offering promotions, price match offers.
- > Medium Credit_limit, Low Min_payment_amt offering membership deals, cashbacks and low interest loans, credit purchases.
- ➤ Medium Max_spent_in_single_shopping.
- > High Probability_of_full_payment rewarding loyalty points, keeping them updates on upcoming offers and detail, would encourage customers to make more purchases.

* For Group 2

- > High Min_payment_amt and low on every other variable, shows the customer is not spending though the bank much.
- > Need to maintain timely engagements with the customer to let them know about new offers and deals.
- > Reward on purchase and repayment of the credit would improve engagements.
- > Customers here in this group have to be given extra attention, as they are more likely to churn.

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.

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

Data Shape:

Rows and columns: (3000, 10)

Data information:

#	Column	Non-Null Count	Dtype
0	Age	3000 non-null	int64
1	Agency_Code	3000 non-null	object
2	Туре	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

Read Data first 5 row:

Age	Agency_ Code	Type	Claimed	Commis s-ion	Chann -el	Durati -on	Sales	Product Name	Destination
48	C2B	Airlines	No	0.7	Online	7	2.51	Customi sed Plan	ASIA
36	EPX	Travel Agency	No	0	Online	34	20	Customi sed Plan	ASIA
39	CWT	Travel Agency	No	5.94	Online	3	9.9	Customi sed Plan	Americas
36	EPX	Travel Agency	No	0	Online	4	26	Cancella tion Plan	ASIA
33	JZI	Airlines	No	6.3	Online	53	18	Bronze Plan	ASIA

Interpretation:

- The data has 3000 rows and 10 columns with 2 floats, 2 int and 6 object as the data type.
- There are no null values.
- Independent variable:

- ➤ We have 4 continuous variables (Age, Commission, Duration, Sales)
- > 5 categorical variables (Agency_Code, Type, Channel, Product Name, Destination).

Describe the data: Numeric data:

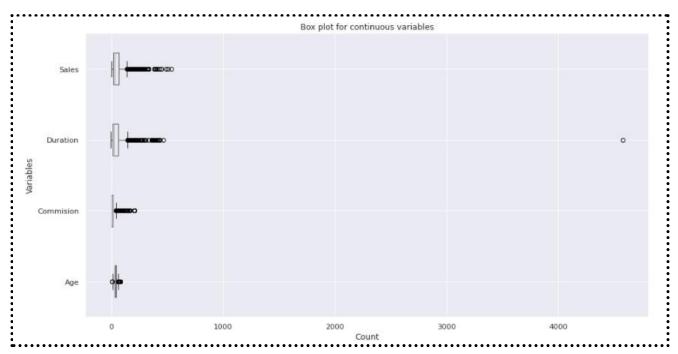
	Count	Mean	STD	MIN	25.00%	50.00%	75.00%	MAX
Age	3000	38.091	10.463518	8	32	36	42	84
Commision	3000	14.529203	25.481455	0	0	4.63	17.235	210.21
Duration	3000	70.001333	134.053313	-1	11	26.5	63	4580
Sales	3000	60.249913	70.733954	0	20	33	69	539

Describe the data: Categorical data:

	Count	Unique	Тор	Freq
Agency_Code	3000	4	EPX	1365
Type	3000	2	Travel Agency	1837
Claimed	3000	2	No	2076
Channel	3000	2	Online	2954
Product Name	3000	5	Customised Plan	1136
Destination	3000	3	ASIA	2465

- ***** Claimed is our Dependent variable:
 - > We see majority is 'No' and it's frequence is 2076
- ❖ Most types are Travel Agency frequency: 1365 and most prefer Channel is Online.
- ❖ There are 139 duplicate rows. Will be dropping them, there is a possibility that the data would be from different customers. As there is no unique Identifier to check this and we have 3000 rows, for this case. I will be dropping the duplicate.
- * The data shape is now: (2861, 10).

Outliers: All the four continuous variables have outliers:



- ❖ Would need to treat outliers during Neural Networks.
- **❖** Value counts of Categorical Variables

JZI 239

CWT 471

C2B 913

EPX 1238

Name: Agency Code, dtype: int64

> TYPE: 2

Airlines 1152

Travel Agency 1709

Name: Type, dtype: int64

> CLAIMED: 2

Yes 914

No 1947

Name: Claimed, dtype: int64

> CHANNEL: 2

Offline 46

Online 2815

Name: Channel, dtype: int64

> PRODUCT NAME: 5

Gold Plan 109

Silver Plan 421

Cancellation Plan 615

Bronze Plan 645

Customised Plan 1071

Name: Product Name, dtype: int64

> DESTINATION: 3

EUROPE 215

Americas 319

ASIA 2327

Name: Destination, dtype: int64

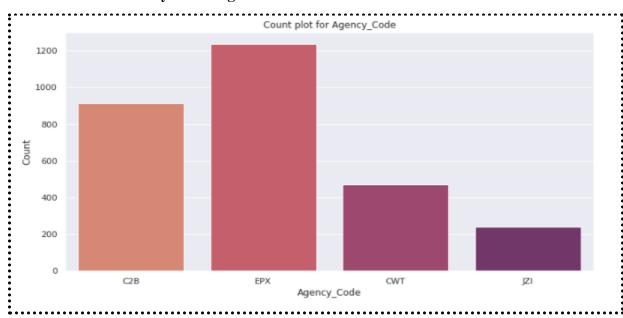
❖ The data is okay to proceed. Target Data: Spread is 30 & 70%, it no unbalanced.

> No 0.680531

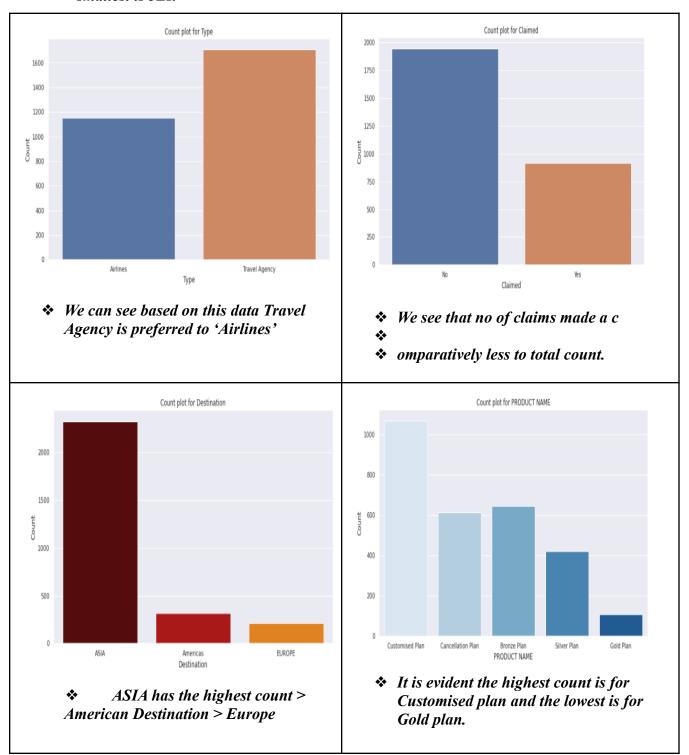
> Yes 0.319469

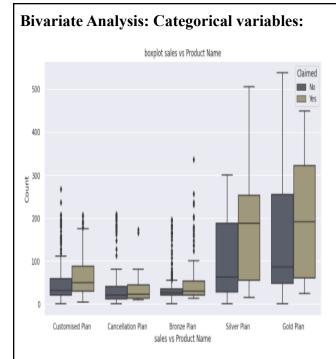
Name: Claimed, dtype: float64

EDA - Univariate Analysis: Categorical variables:

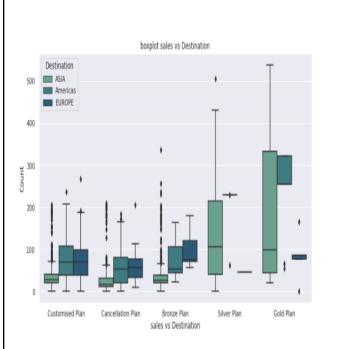


❖ From the above countplot it is clear that the data count of EPX > C2B > CWT and the smallest is JZI.

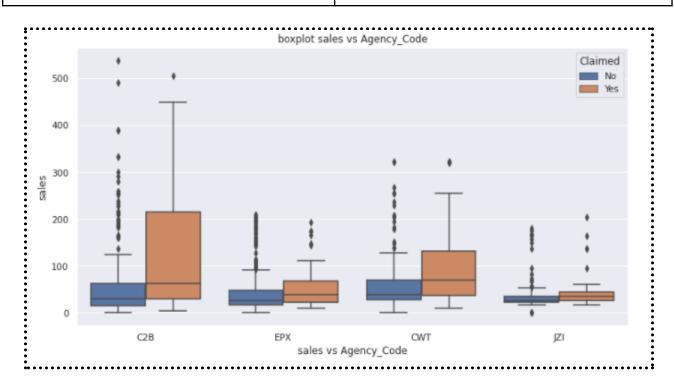




* Based on the figure we can see that most sales and claims are made for Gold and Silver plans.



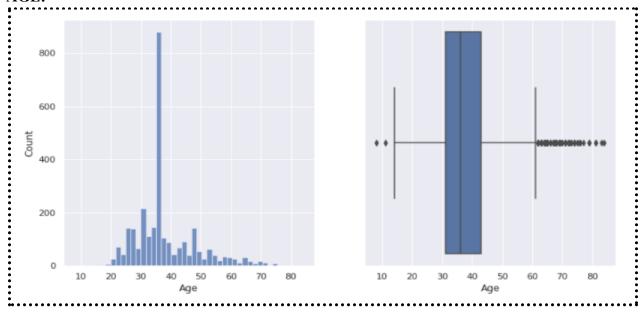
We can conclude that Gold and Silver plan sale are highest in ASIA



The highest number of Claims are recorded at C2B agency for sales.

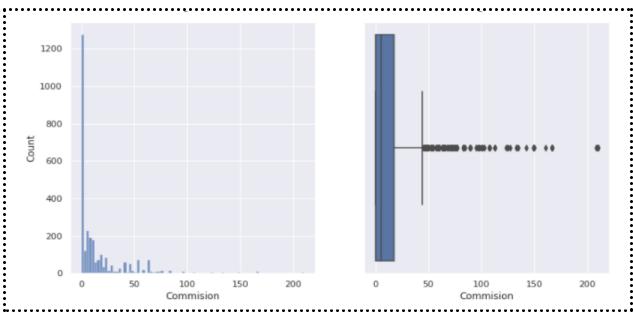
Numerical Variable: Univariate Analysis

AGE:



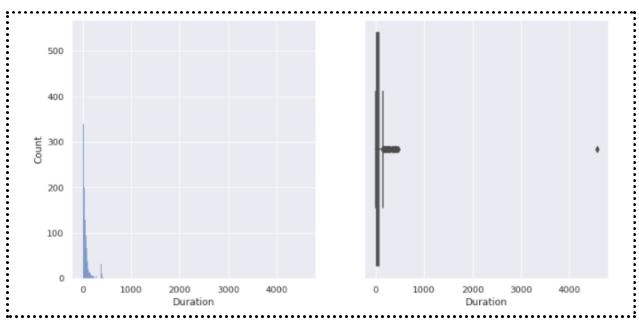
- * The Boxplot tells us there are outliers for Age distribution.
- ❖ The distribution can be said to be normally distributed. Skewness (Age) is 1.103. The distribution ranges between 20 to 75

COMMISION:



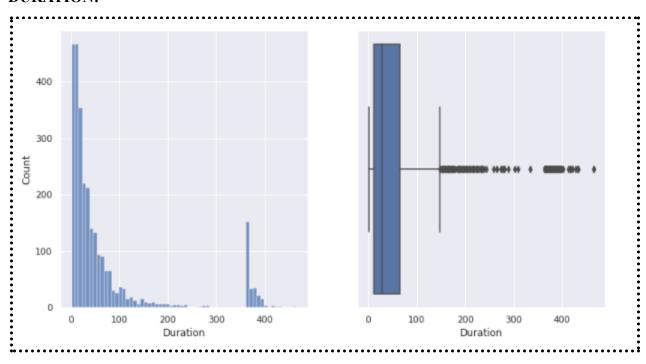
- * Boxplot tells us there are outliers for Commission distribution.
- ❖ The distribution can be said to be normally distributed. Skewness (Commission) is 3.103. The distribution ranges between 0 to 50

DURATION:



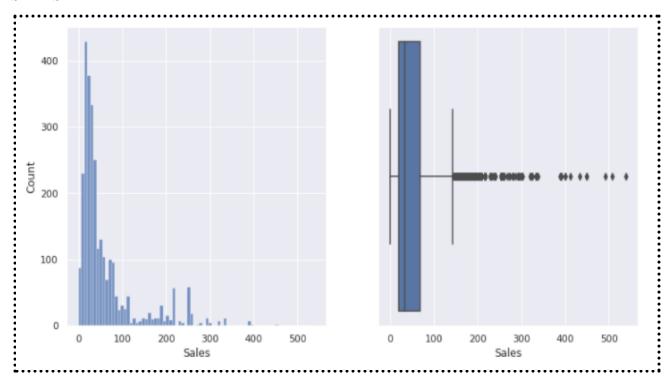
- * The Boxplot tells us there are outliers for Duration distribution.
- * The distribution can be said to be normally distributed. Skewness (Duration) is 13.779.
- ❖ As the min Duration shows -1 and time can't be negation or 0, we will treat it.

DURATION:



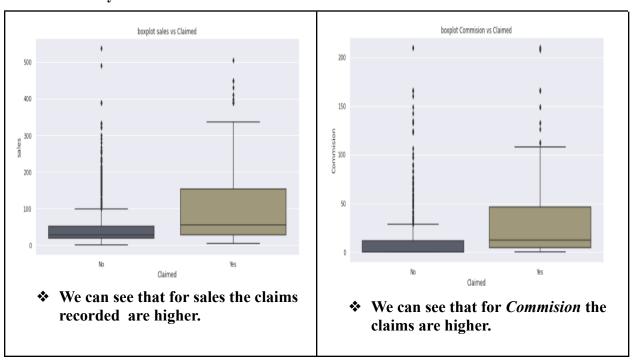
- The new Duration boxplot after removing -1, 0 and the single entry of 4580.
- ❖ Skewness (Duration) is reduced to 2.19.

SALES

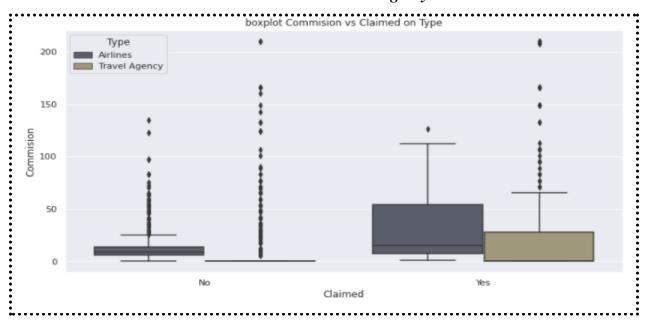


- * The Boxplot tells us there are outliers for Sales distribution.
- ❖ The distribution can be said to be normally distributed. Skewness (Sales) is 2.343. The distribution ranges between 0 to 500

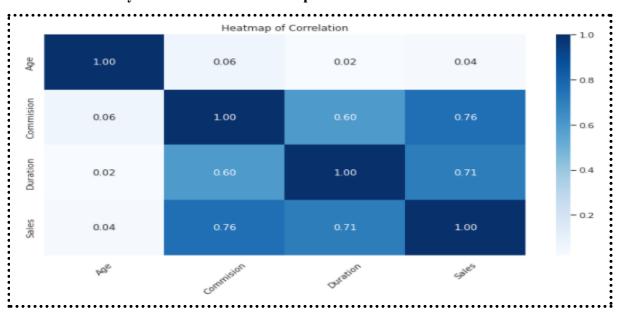
Bivariate Analysis:



❖ We see that Airlines has more claims than Travel Agency.



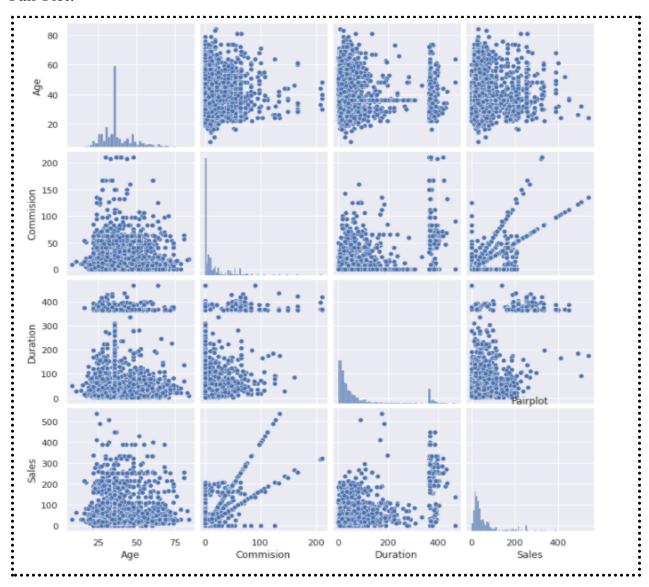
Multivariate Analysis - Correlation Heatmap:



- > The relation between pairs of numeric variables is given by the heatmap.
- > The correlation between the following variables are highly positive: (variable are directly proportional)
 - Sales and Commission (0.76)
 - Duration and Commission (0.60)
 - Sales and Duration(0.71)

- > We can conclude that these three variables are related to each other. Whereas we have Age that has a weak relation with all variables.
- > Sales and Commission have the highest value of correlation, as sales increase the commission also increases.
- > As for Age we can understand that is not a major factor affecting or interacting with the other variables so far.

Pair Plot:



❖ In this plot we can see direct relations between Duration, Commission and Sales.

- 2.2 Data Split: Split the data into test and train, build classification model CART, Random Forest, Artificial Neural Network.
 - ❖ Splitting data into Train and Test at the default radio of 30:70% with random state as 123.
 - ❖ We have object data type, which we will convert to categorical codes:

Data info after conversion:

#	Column	Non-Null Count	Dtype
0	Age	2861 non-null	int64
1	Agency_Code	2861 non-null	int8
2	Type	2861 non-null	int8
3	Claimed	2861 non-null	int8
4	Commision	2861 non-null	float64
5	Channel	2861 non-null	int8
6	Duration	2861 non-null	int64
7	Sales	2861 non-null	float64
8	Product Name	2861 non-null	int8
9	Destination	2861 non-null	int8
dty	pes: float64(2)), int64(2), int	8 (6)
memo	ory usage: 208	.5 KB	

* Target variable class distribution.

> Yes: 31.95%

> No: 68.05%

❖ After splitting the data into test and train, distribution is:

```
> X_train (2002, 9)
```

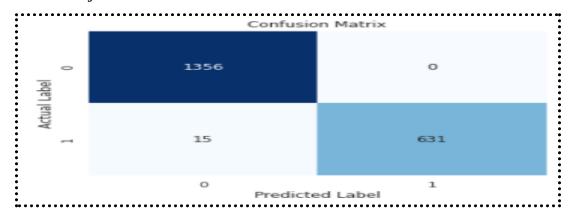
- > X_test (859, 9)
- train_labels (2002,)
- > test labels (859,)
- ***** Variable Importance:

> Duration 0.273646

> Sales	0.210878
<pre>Agency_Code</pre>	0.179736
➤ Age	0.167237
> Commision	0.091713
> Product Name	0.049420
> Destination	0.023208
➢ Channel	0.004161
> Type	0.000000

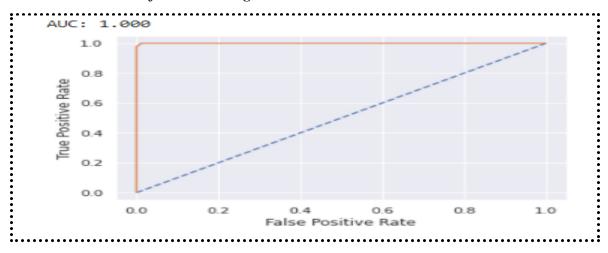
Decision Tree Classifier

- Creating a model with default feature value with criterion as Gini (It is calculated by subtracting the sum of squared probabilities of each class from one.)
- The parameters are: {'criterion': 'gini', 'max_depth': None, 'min_samples_leaf': 1, 'min_samples_split': 2, random_state=123}
- * CART: Confusion Matrix Train data:

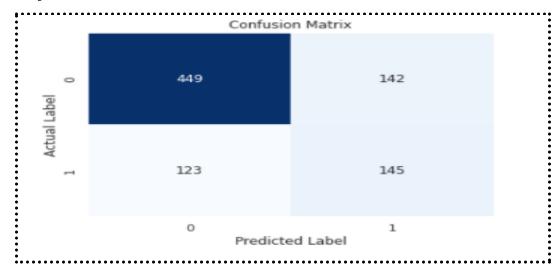


	precision	recall	f1-score	support	•
0	0.99	1.00	0.99	1356	
1	1.00	0.98	0.99	646	
accuracy			0.99	2002	
macro avg	0.99	0.99	0.99	2002	
weighted avg	0.99	0.99	0.99	2002	•

* AUC and ROC curve for the training data:



- * Training data Accuracy Score:
 - > 0.9925074925074925
- * Confusion Matrix Test data:



	precision	recall	f1-score	support	
0	0.78	0.76	0.77	591	
1	0.51	0.54	0.52	268	
accuracy			0.69	859	
macro avg	0.65	0.65	0.65	859	
weighted avg	0.70	0.69	0.69	859	,

* AUC and ROC curve for the testing data:



- * Testing data Accuracy Score:
 - > 0.6915017462165308
- **From the data above we can say that the model with default values is over fitted:**
 - > Accuracy from the Training data is: 1.0
 - > Accuracy from the Test data is: 0.65
- ❖ As we see, the accuracy of training and test results are very different. Training data being 1, concludes that the model is Overfitted.
- Next we will perform a Grid search that will help us in Tuning the model and address overfitting.
- ***** The Tuning Parameters used are:
 - > Max_depth: The maximum depth of the tree. If None, then nodes are expanded until all leaves are pure.
 - Min_samples_leaf: The minimum number of samples required to be at a leaf node.
 - Min_samples_split: The minimum number of samples required to split an internal node.
- The best parameters for Grid search are: DecisionTreeClassifier(max_depth=5, min_samples_leaf=20, min_samples_split=200, random_state=123)
- ***** The most important variables are:

> Agency Code

0.587848

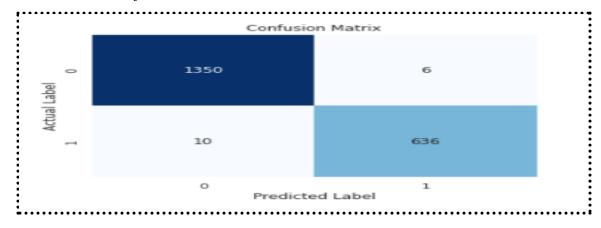
> Sales

0.219399

➤ Product Name	0.109473
➤ Age	0.032647
> Duration	0.021835
> Commision	0.020183
> Destination	0.008615
> Type, Channel	0.000000

Random Forest:

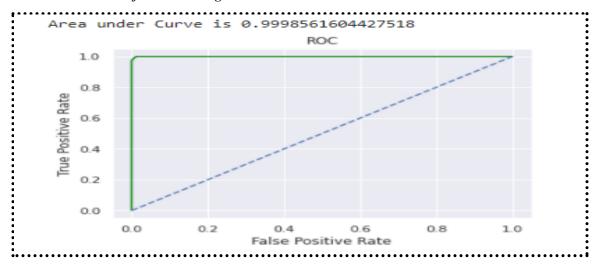
- ❖ We start with Default parameters to implement random forest to our split data of 30:70
- The parameters are: {'criterion': 'gini', 'n_estimators'=100, 'max_depth': None, 'Min_samples_leaf': 1, 'min_samples_split': 2, max_features="auto", random_state=123}
- ***** Variable Importance:
 - > Duration 0.262404 > Sales 0.203511 ➤ Age 0.172830 > Commision 0.121100 > Agency Code 0.100321 > Product Name 0.095428 > Destination 0.022865 > Type 0.014934 > Channel 0.006606
- * Random Forest: Confusion Matrix Train data:



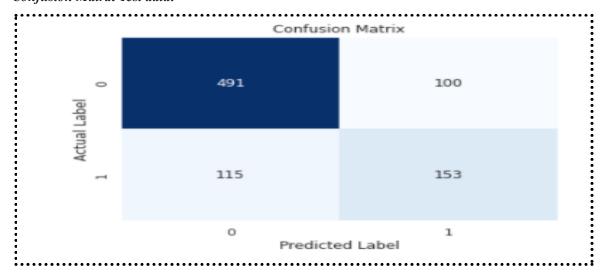
Classification_report:

•••••	precision	recall	f1-score	support	•••••
0	0.99	1.00	0.99	1356	
1	0.99	0.98	0.99	646	
accuracy			0.99	2002	
macro avg	0.99	0.99	0.99	2002	
weighted avg	0.99	0.99	0.99	2002	

- Training data Accuracy Score:
 - > 0.9920079920079921
- **AUC** and ROC curve for the training data:

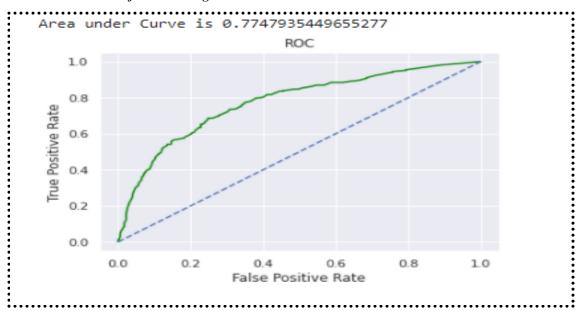


* Confusion Matrix Test data:



; · · · · · · · · · · · · · · · · · · ·	precision	recall	f1-score	support
0	0.81	0.83	0.82	591
1	0.60	0.57	0.59	268
accuracy			0.75	859
macro avg	0.71	0.70	0.70	859
weighted avg	0.75	0.75	0.75	859

- * Testing data Accuracy Score:
 - > 0.7497089639115251
- * AUC and ROC curve for the testing data:



- **From the data above we can say that the model with default values is over fitted:**
 - > Accuracy from the Training data is: 0.99
 - > Accuracy from the Test data is: 0.77
- ❖ As we see, the accuracy of training and test results are very different. Training data being 0.99 almost 1, concludes that the model is Overfitted.
- * Next we will perform a Grid search that will help us in Tuning the model and address overfitting.

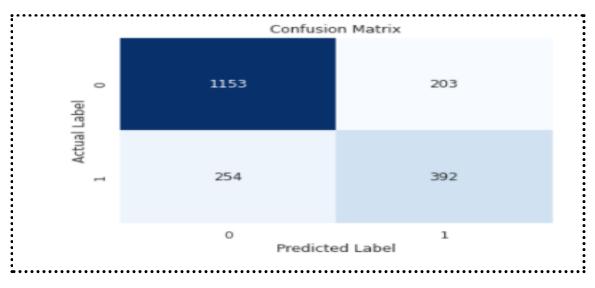
- ***** The Tuning Parameters used are:
 - > Max_depth: The maximum depth of the tree. If None, then nodes are expanded until all leaves are pure.
 - Min_samples_leaf: The minimum number of samples required to be at a leaf node.
 - > Min_samples_split: The minimum number of samples required to split an internal node.
 - > n_estimators : The number of trees in the forest.
 - > max_features : default="auto" The number of features to consider when looking for the best split.
- The best parameters for Grid search are: RandomForestClassifier(max_depth=10, max_features=5, min_samples_leaf=50, min_samples_split=20, n_estimators=50, random_state=123)
- ***** The most important variables are:

<pre>Agency_Code</pre>	0.416913
> Product Name	0.256784
> Sales	0.169993
➤ Commision	0.062347
> Duration	0.042298
➤ Age	0.024639
≻ туре	0.022198
> Destination	0.004829
➤ Channel	0.000000

Artificial Neural Network:

- We start with Default parameters to implement artificial neural network to our split data of 30:70
- The parameters are: {'hidden_layer_sizes': 100, 'max_iter': 200, 'solver': 'adam', 'Tol': 0.1, random state=123}

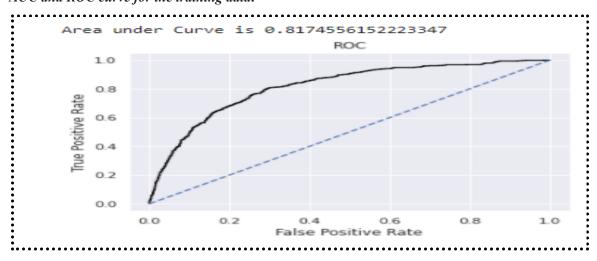
* Artificial Neural Network: Confusion Matrix Train data:



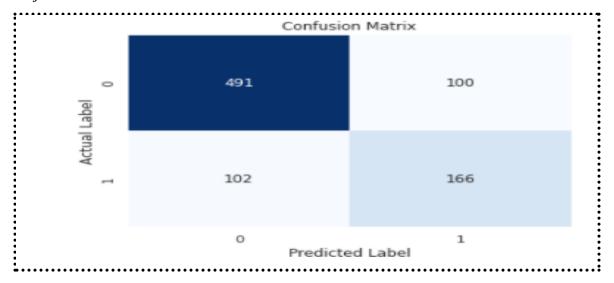
- * Training data Accuracy Score:
 - > 0.7717282717282717
- Classification_report:

	• • • • • • • • • • • • • • • • • • • •		• • • • • • • • • • • • • • • • • • • •	•••••	• • • • •
	precision	recall	f1-score	support	
0	0.82	0.85	0.83	1356	
1	0.66	0.61	0.63	646	
accuracy			0.77	2002	
macro avg	0.74	0.73	0.73	2002	:
weighted avg	0.77	0.77	0.77	2002	

AUC and ROC curve for the training data:



* Confusion Matrix Test data:

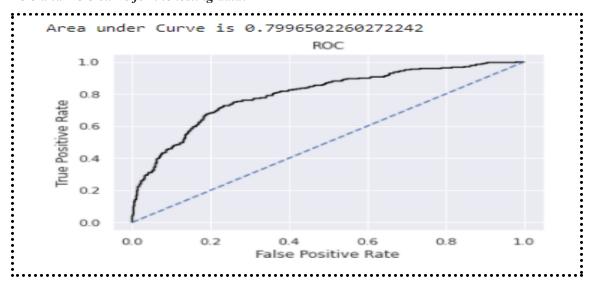


- * Testing data Accuracy Score:
 - > 0.7648428405122235

Classification_report:

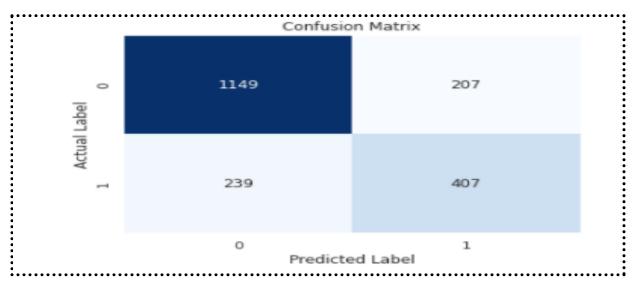
	precision	recall	f1-score	support	
0 1	0.83 0.62	0.83 0.62	0.83 0.62	591 268	
accuracy macro avg weighted avg	0.73 0.76	0.73 0.76	0.76 0.73 0.76	859 859 859	

* AUC and ROC curve for the testing data:



- **From the data above we can say that the model with default values is over fitted:**
 - > Accuracy from the Training data is: 0.77
 - > Accuracy from the Test data is: 0.76
- ❖ As we see, the accuracy of training and test results are very close.
- Next we will perform a Grid search that will help us in Tuning the model and address overfitting.
- * The Tuning Parameters used are:
 - > Hidden_layer_sizes: The ith element represents the number of neurons in the ith hidden layer.
 - > Solver: The solver for weight optimization.
 - > tol: Tolerance for the optimization.
 - > Max iter: Maximum number of iterations.
- The best parameters for Grid search are: MLPClassifier(hidden_layer_sizes=200, max_iter=2500, random_state=123, tol=0.001)
- 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.

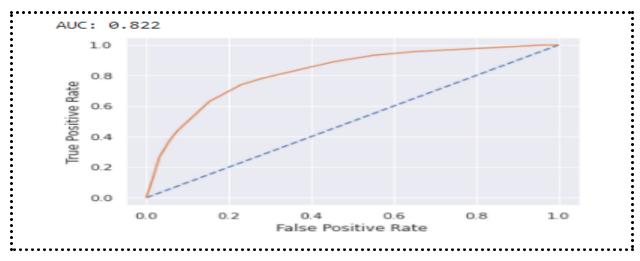
CART: Confusion Matrix Train data:



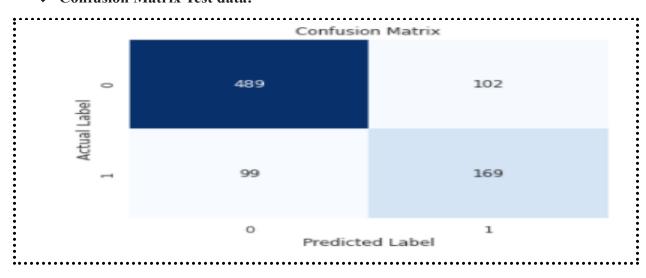
Classification_report:

support	f1-score	recall	precision	
1356	0.84	0.85	0.83	0
646	0.65	0.63	0.66	1
2002 2002 2002	0.78 0.74 0.78	0.74 0.78	0.75 0.77	accuracy macro avg weighted avg

- ***** Training data Accuracy Score:
 - > 0.7772227772227772
- **AUC** and ROC curve for the training data:



Confusion Matrix Test data:



	precision	recall	f1-score	support
0	0.83	0.83	0.83	591
1	0.62	0.63	0.63	268
accuracy			0.77	859
macro avg	0.73	0.73	0.73	859
weighted avg	0.77	0.77	0.77	859
1 1 1				

- * Testing data Accuracy Score:
 - > 0.7660069848661234
- **❖** AUC and ROC curve for the testing data:

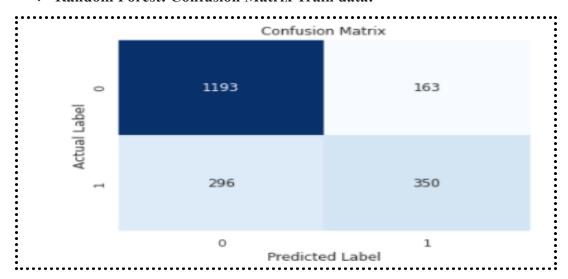


- The best parameters are: DecisionTreeClassifier(max_depth=5, min_samples_leaf=20, min_samples_split=200, random_state=123)
- * From the data above we can say we were able to build a good model:
 - > Accuracy from the Training data is: 0.77
 - > Accuracy from the Test data is: 0.76
 - > Which is close, we had addressed the over-fitting issue scenario here.
 - > There is still room for improvement.
 - > Though the model can be used.

* The most important variables are:

- > Agency_Code 0.587848
- > Sales 0.219399
- > Product Name 0.109473
- > Age 0.032647
- > Duration 0.021835
- > Commision 0.020183
- Training: cart_train_precision 0.66, cart_train_recall 0.63,
 cart_train_f1 0.65
- * Testing: cart_test_precision 0.62, cart_test_recall 0.63,
 cart_test_f1 0.63

A Random Forest: Confusion Matrix Train data:

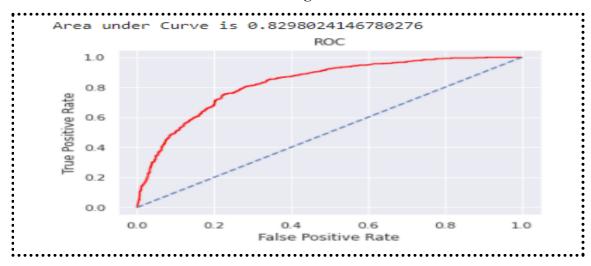


	precision	recall	f1-score	support
0	0.80	0.88	0.84	1356
1	0.68	0.54	0.60	646
accuracy			0.77	2002
macro avg	0.74	0.71	0.72	2002
weighted avg	0.76	0.77	0.76	2002
:				

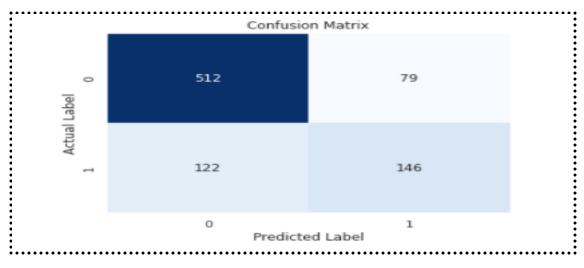
* Training data Accuracy Score:

> 0.7707292707292708

AUC and ROC curve for the training data:

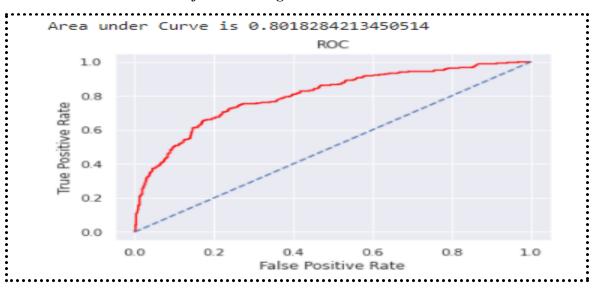


Confusion Matrix Test data:



	precision	recall	f1-score	support
0	0.81	0.87	0.84	591
1	0.65	0.54	0.59	268
accuracy macro avg weighted avg	0.73 0.76	0.71 0.77	0.77 0.71 0.76	859 859 859

AUC and ROC curve for the testing data:



- * Testing data Accuracy Score:
 - > 0.7660069848661234

Inference -

- **There was an overfitting issue, after Hyperparameter tuning. We can further work on it to improve.**
- * The best parameters are: RandomForestClassifier(max_depth=10, max_features=5, min samples leaf=50, min samples split=20, n estimators=50, random state=123)
- From the data above we can say we were able to build a good model:
 - > Accuracy from the Training data is: 0.77
 - > Area under Curve is 0.8174556152223347
 - > Accuracy from the Test data is: 0.76
 - > Area under Curve is 0.8018284213450514
 - > Which is close, we had addressed the over-fitting issue scenario here.
 - > There is still room for improvement.
 - > Though the model can be used.
- ***** The most important variables are:
 - ➤ Agency_Code 0.416913
 - > Product Name 0.256784
 - > Sales 0.169993
 - > Commision 0.062347

> Duration 0.042298

> Age 0.024639

> Type 0.022198

> Destination 0.004829

> Channel 0.000000

* Training: rf_train_precision 0.68, rf_train_recall 0.54,
rf_train_f1 0.6

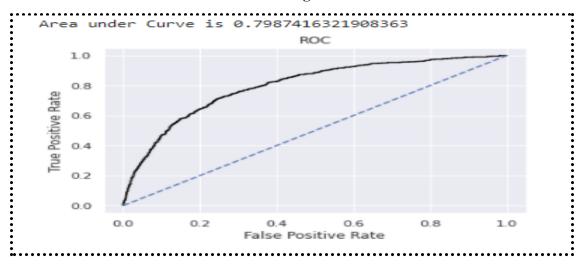
Testing: rf_test_precision 0.65, rf_test_recall 0.54, rf_test_f1
0.59

Neural Network Classifier: Confusion Matrix Train data:

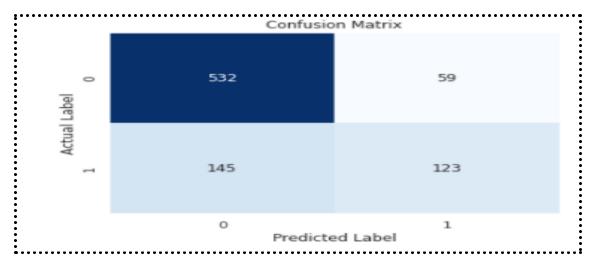


	precision	recall	f1-score	support	
0	0.78	0.89	0.83	1356	
1	0.67	0.48	0.56	646	
accuracy			0.76	2002	
macro avg	0.73	0.68	0.69	2002	
weighted avg	0.75	0.76	0.74	2002	

AUC and ROC curve for the training data:

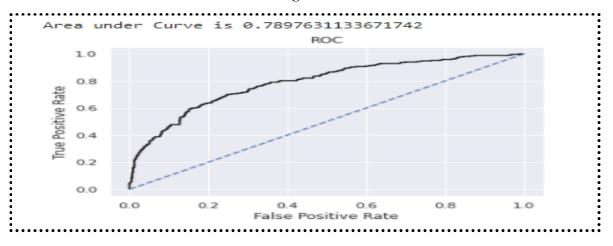


- ***** Training data Accuracy Score:
 - > 0.7562437562437563
- **Confusion Matrix Test data:**



	precision	recall	f1-score	support
0 1	0.79 0.64	0.88 0.48	0.83 0.55	591 268
accuracy macro avg weighted avg	0.72 0.74	0.68 0.75	0.75 0.69 0.74	859 859 859

AUC and ROC curve for the testing data:



- * Testing data Accuracy Score:
 - > 0.7543655413271245

Inference:

- ***** The model behaviour was the same before and after tuning. We can further work on it to improve.
- * The best parameters are: Neural Network Classifier >> MLPClassifier(hidden_layer_sizes=100, max_iter=2500, random_state=123, tol=0.01)
- * From the data above we can say we were able to build a good model:
 - > Accuracy from the Training data is: 0.77
 - > Area under Curve is 0.7987416321908363
 - > Accuracy from the Test data is: 0.76
 - > Area under Curve is 0.7897631133671742
 - > The accuracy is very close to each other suggesting this model can be used for further analysis. (Same as we saw above in default parameter)
 - > Of Course there is still room for improvement.
 - > Though the model can be used.
- ***** Training:
 - > nn train precision 0.67
 - > nn train recall 0.48
 - > nn train f1 0.56

***** Testing:

- > nn_test_precision 0.64
- > nn test recall 0.48
- > nn test f1 0.55
- 2.4 Final Model: Compare all the models and write an inference which model is best/optimized.
- 3 Model Tuned table: The overall Tuned Models output table..

	CART Train	CART Test	Random Forest Train	Random Forest Test	Neural Network Train	Neural Network Test
Accuracy	0.78	0.77	0.77	0.77	0.76	0.75
AUC	0.82	0.78	0.83	0.8	0.8	0.79
Recall	0.63	0.63	0.54	0.54	0.48	0.48
Precision	0.66	0.62	0.68	0.65	0.67	0.64
F1 Score	0.65	0.63	0.6	0.59	0.56	0.55

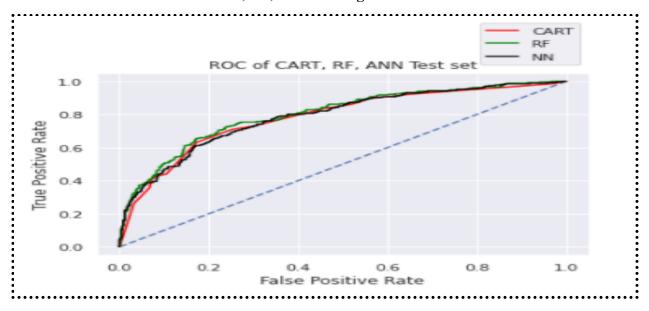
❖ We can see that the 'Artificial neural network' model gives us the best result, both AUC and neural network test set result at the tolerance rate of 0.01.

ROC curves: CART, RF, ANN Training model:



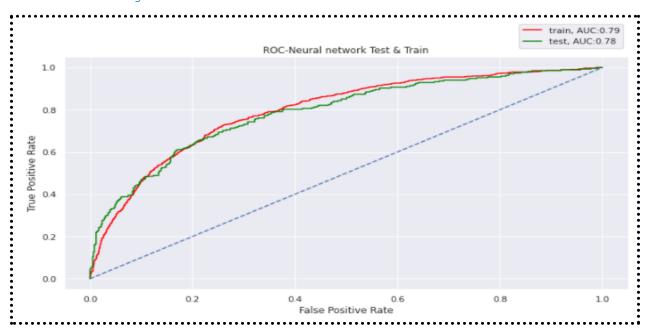
❖ From the above graph we can conclude that the Neural Network Classifier is the best model, when compared with other two.

ROC curves: CART, RF, ANN Testing model:



❖ From the above graph we can conclude that the Neural Network Classifier is the best model, when compared with other two.

2.5 Inference: Based on the whole Analysis, what are the business insights and recommendations



- ❖ Looking at the Artificial neural network model data we were able to predict better, 80% accuracy for test sets.
- * The models give us around 80 or close to 80% accuracy for both test and train model, though it can still be improved, with tuning.
- ❖ We see that more sales happen in Travel Agency than Airlines.
- ❖ We see that the Airlines has more claims, more attention has to be given.
- * Tuning and making changes to the model gave better results.
- ❖ As per the data we can see that insurance is done online and so are the claims.
- ❖ Increasing customer satisfaction will help me revenue and also less claims.
- * Reducing claim handling cost.
- Need to pay more attention to the JZI agency as the most claims were reported there, and also need more sales.
- ❖ Improvement in Customer Service requests will reduce he claims.

END!