DATA MINING ASSIGNMENT

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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.

Question 1.1

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

spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_
19.94	16.92	0.8752	6.675	3.763	3.252
15.99	14.89	0.9064	5.363	3.582	3.336
18.95	16.42	0.8829	6.248	3.755	3.368
10.83	12.96	0.8099	5.278	2.641	5.182
17.99	15.86	0.8992	5.890	3.694	2.068

BANK MARKETING DATA

Column Names	Understanding of each Column
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)

Data Dictionary

- There are a total of 210 rows and 7 columns

	count	mean	std	min	25%	50%	75%	max
spending	210.0	14.848	2.910	10.590	12.270	14.355	17.305	21.180
advance_payments	210.0	14.559	1.306	12.410	13.450	14.320	15.715	17.250
probability_of_full_payment	210.0	0.871	0.024	0.808	0.857	0.873	0.888	0.918
current_balance	210.0	5.629	0.443	4.899	5.262	5.524	5.980	6.675
credit_limit	210.0	3.259	0.378	2.630	2.944	3.237	3.562	4.033
min_payment_amt	210.0	3.700	1.504	0.765	2.561	3.599	4.769	8.456
max_spent_in_single_shopping	210.0	5.408	0.491	4.519	5.045	5.223	5.877	6.550

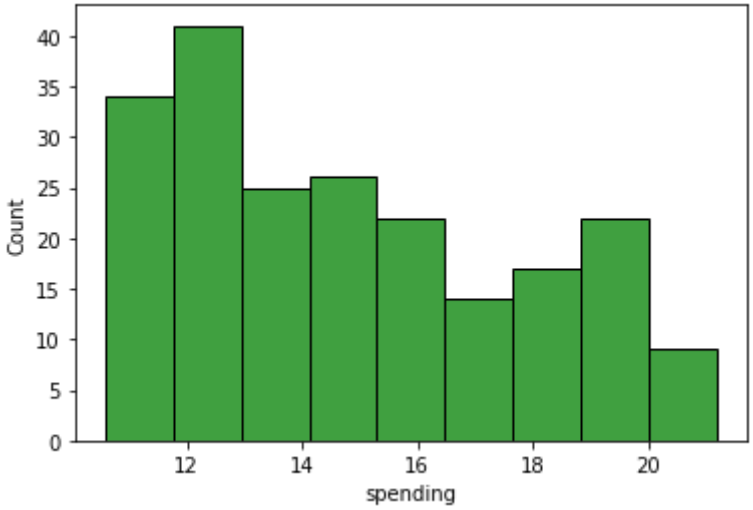
#	Column	Non-Null Count	Dtype
0	spending	210 non-null	float64
1	advance_payments	210 non-null	float64
2	probability_of_full_payment	210 non-null	float64
4	credit_limit	210 non-null	float64
5	min_payment_amt	210 non-null	float64
6	max_spent_in_single_shopping	210 non-null	float64

dtypes: float64(7)

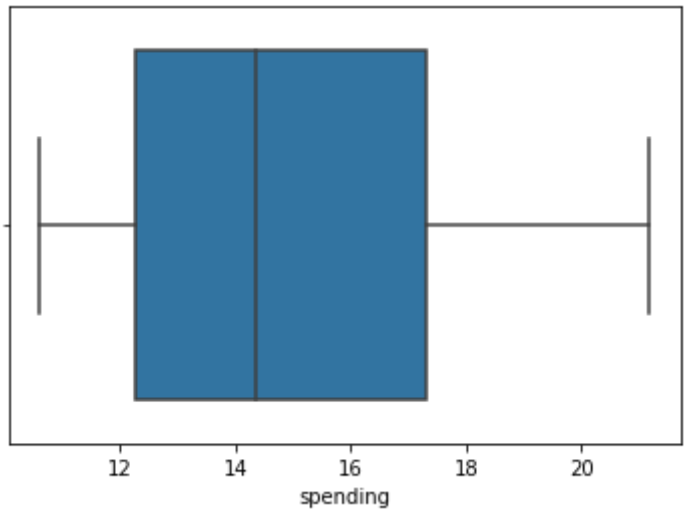
- No missing or unique characters within then data
- There are **NO** Duplicate Rows within the data

UNIVARIATE ANALYSIS

	Descrpition of spending
mean	14.847524
std	2.909699
min	10.590000
25%	12.270000
50%	14.355000
75%	17.305000
max	21.180000



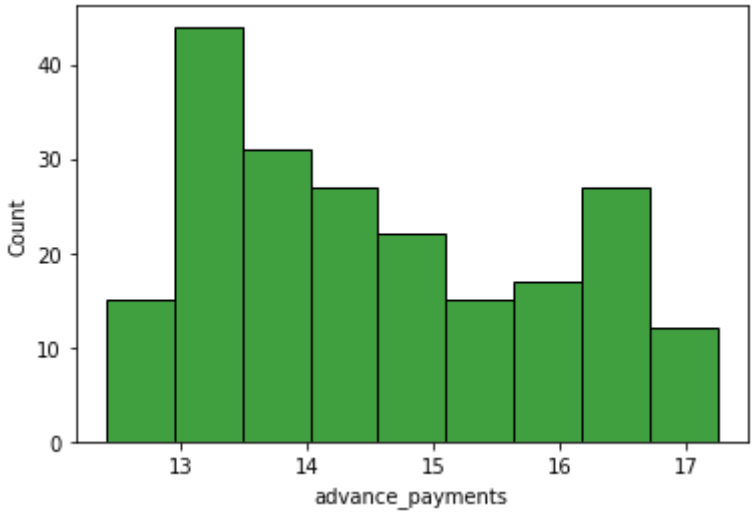
Distribution of spending



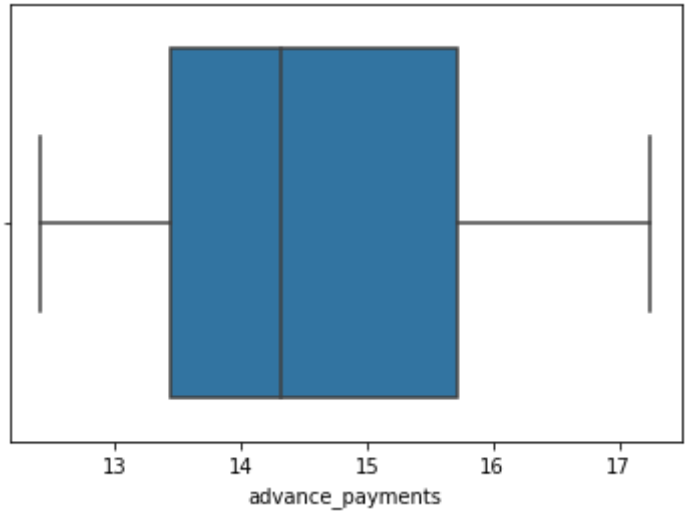
BoxPlot of spending

	Description of advance_payments
mean	14.559286
std	1.305959
min	12.410000
25%	13.450000
50%	14.320000
75%	15.715000
max	17.250000

Distribution of advance_payments

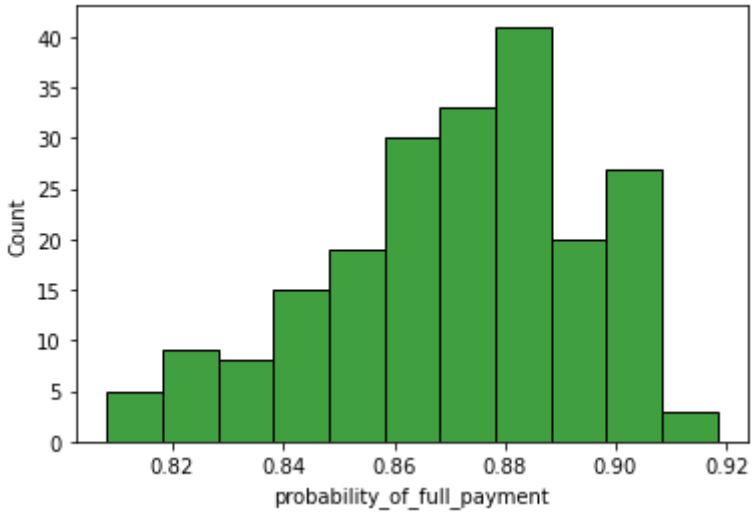


BoxPlot of advance_payments

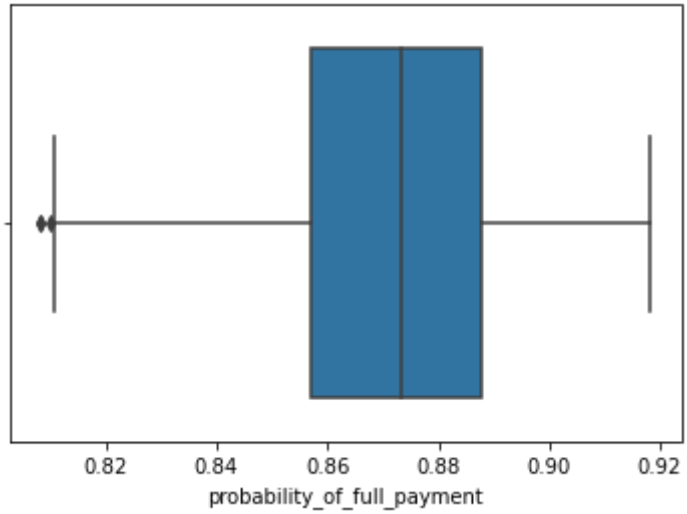


	Description of probability_of_full_payment
mean	0.870999
std	0.023629
min	0.808100
25%	0.856900
50%	0.873450
75%	0.887775
max	0.918300

Distribution of probability_of_full_payment



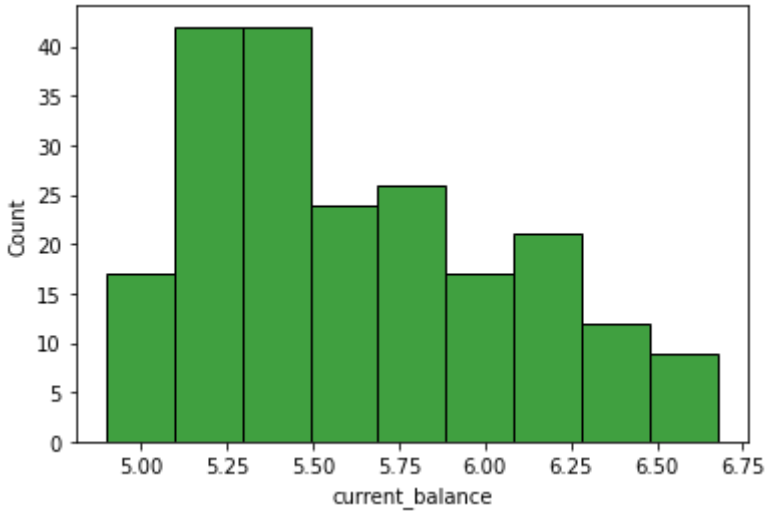
BoxPlot of



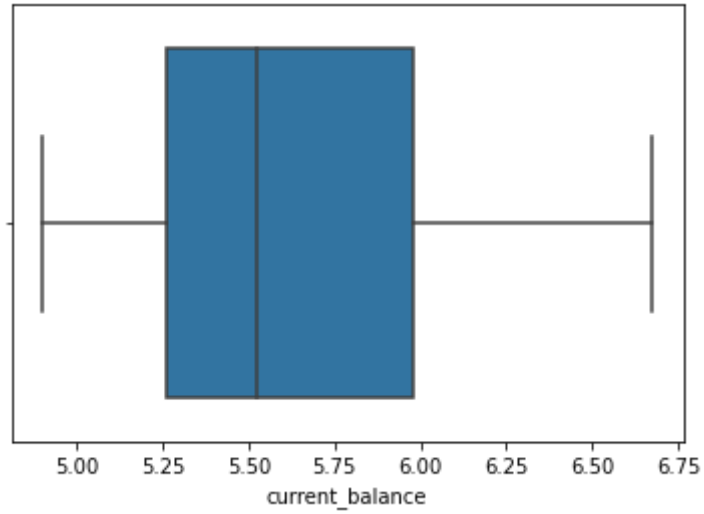
probability_of_full_payment

	Description of current_balance
mean	5.628533
std	0.443063
min	4.899000
25%	5.262250
50%	5.523500
75%	5.979750
max	6.675000

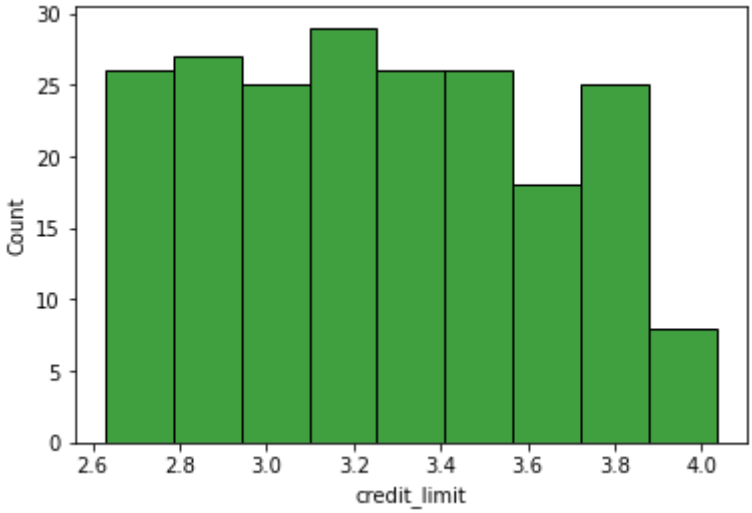
Distribution of current_balance



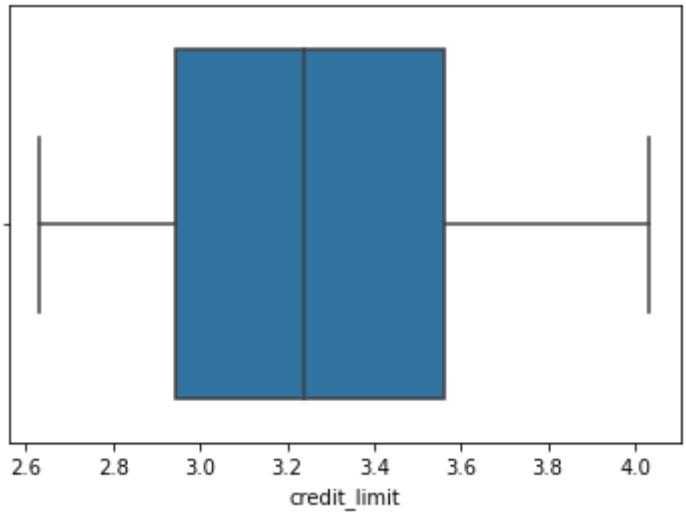
BoxPlot of current_balance



	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



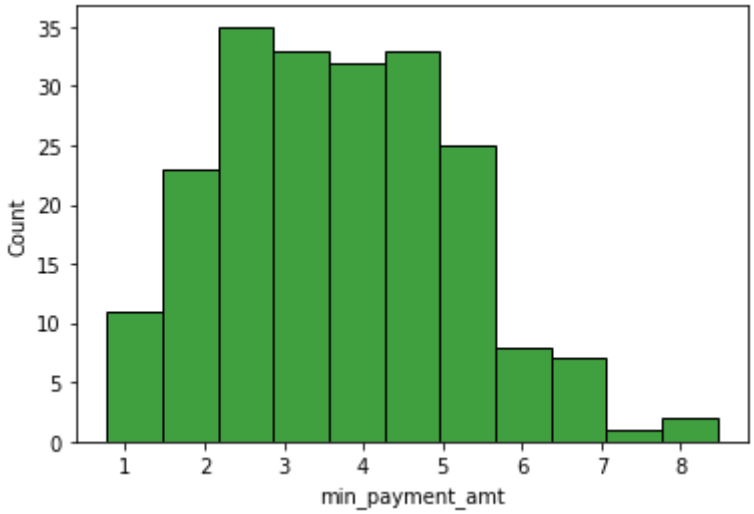
Distribution of credit_limit



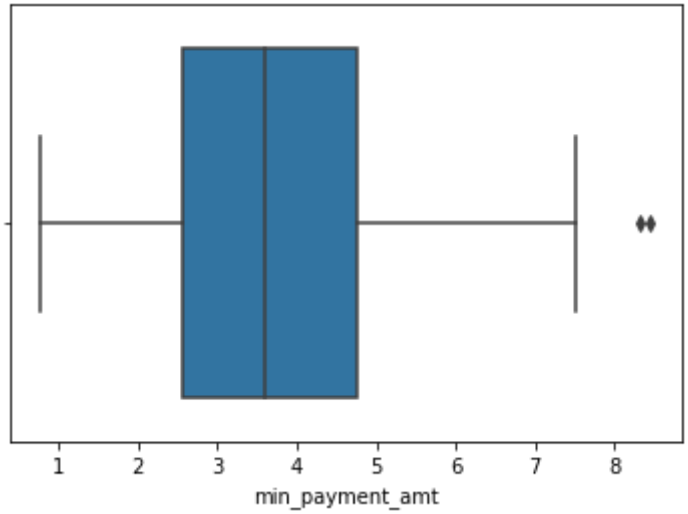
BoxPlot of credit_limit

	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

Distribution of min_payment_amt

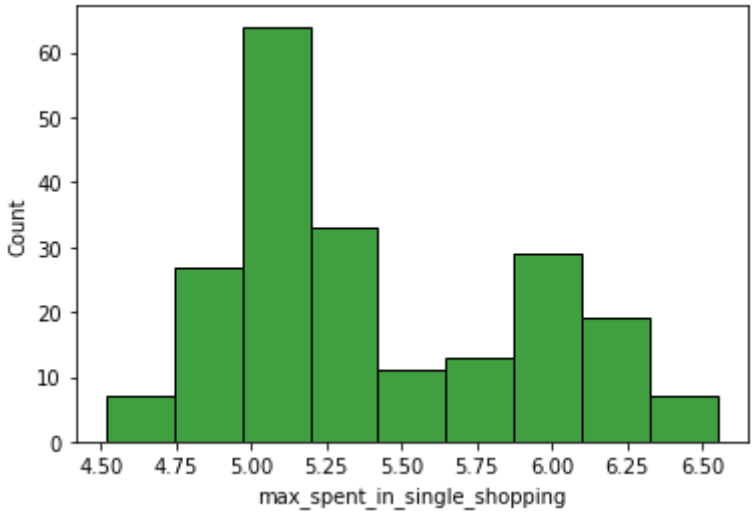


BoxPlot of min_payment_amt

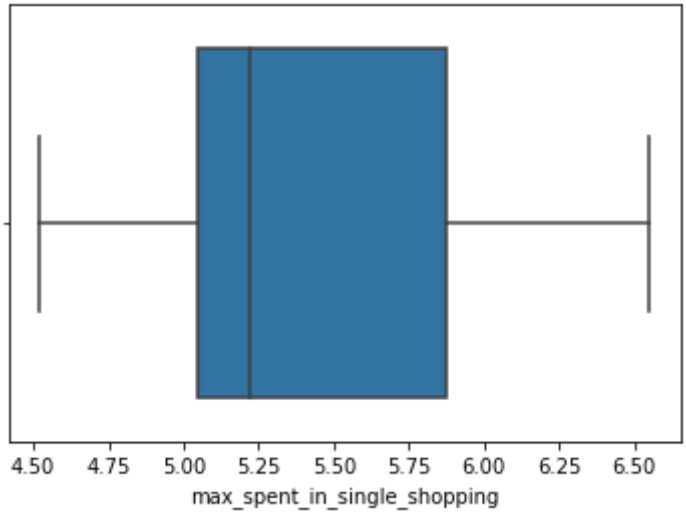


	Description of max_spent_in_single_shopping
count	210.000000
mean	5.408071
std	0.491480
min	4.519000
25%	5.045000
50%	5.223000
75%	5.877000
max	6.550000

Distribution of max_spent_in_single_shopping

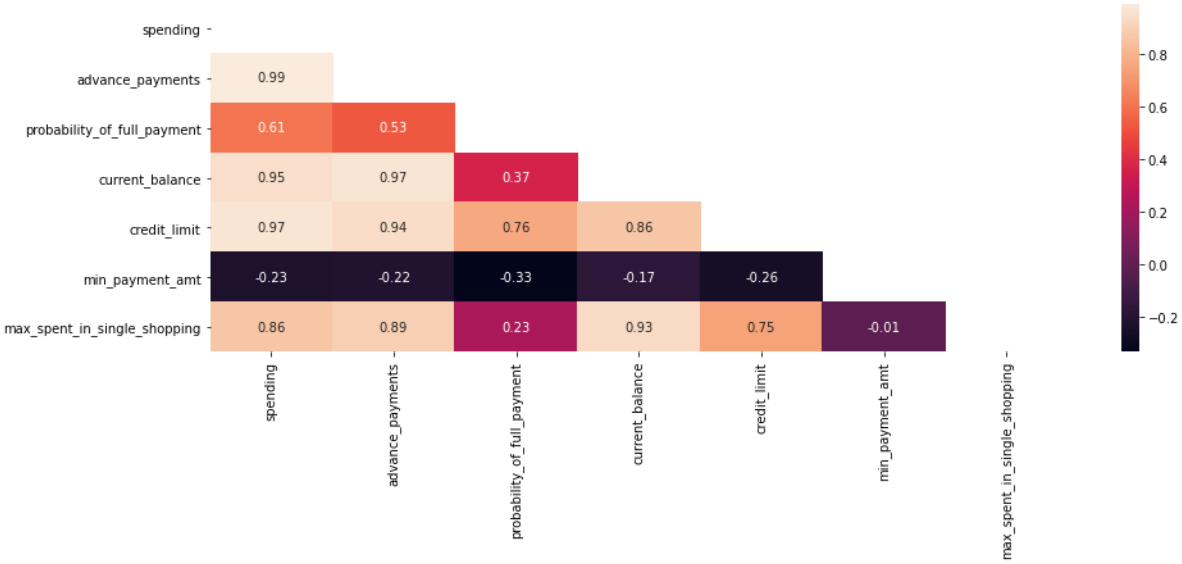


BoxPlot of



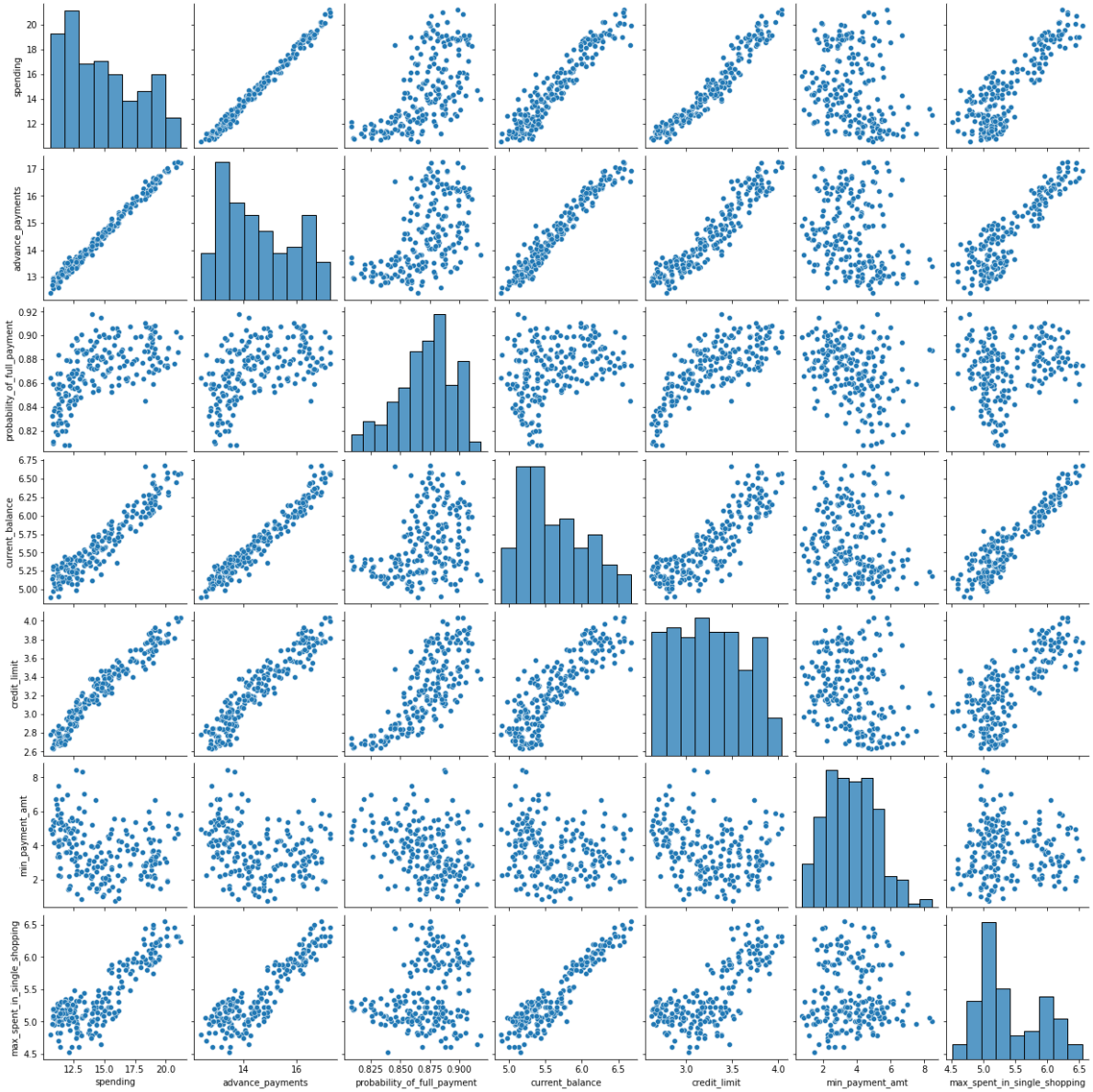
max_spent_in_single_shopping

Bi-Variate Analysis



Heat Map of the Data showing Coorelations between Variables

Multi-Variate Analysis



PAirPlot Among Variables

Question 1.2

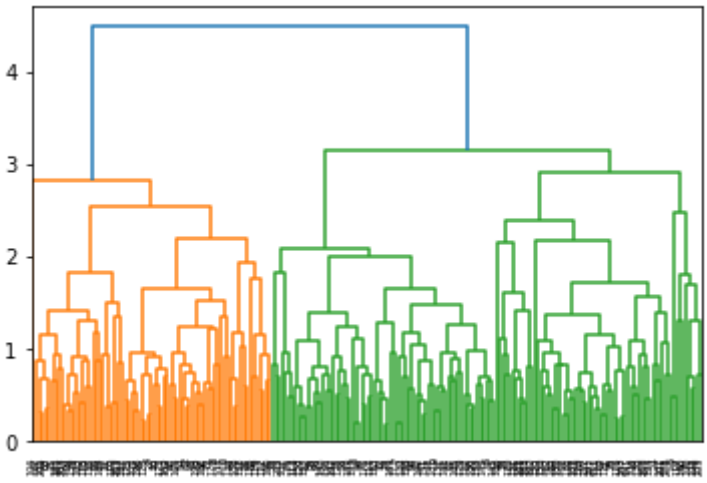
Do you think scaling is necessary for clustering in this case? Justify

- Scaling is necessary in this case as Dataset has features with different "weights".
- As per the Data Dictionary we see that each column is not measured / observed with the same Weights as the other. So when Data is considered without scaling then more weightage will go to the data with more value even thought its of less importance in some case.
- Here we use Standard Scalare from Sk Learn Preprocessing. StandardScaler removes the mean and scales each feature/variable to unit variance.

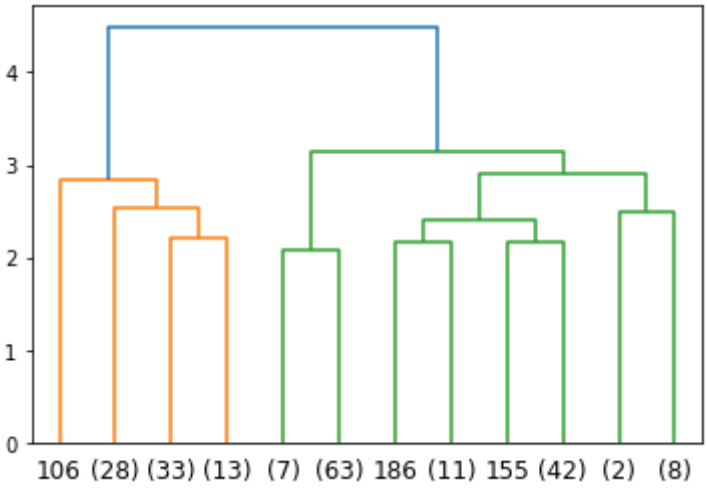
Question 1.3

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

Creating the Dendrogram



Dendogram without Trancating



Dendogram after Trancating

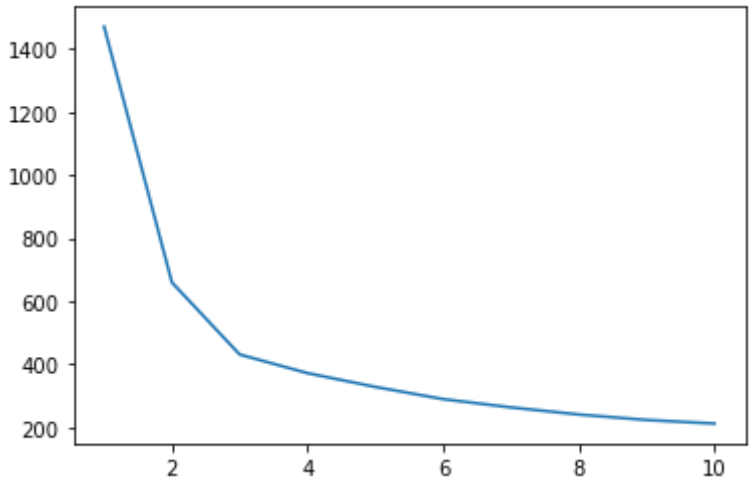
- To create Dendrogram & use linkage method, we have used the package scipy.cluster.hierarchy.
- Linkage method used is the Average linkage.
- The Dendrogram formed by using this method is as shown above and also Dendrogram image after truncating is also shown.
- From the Dendrogram we see that there are 2 colored clusters formed and hence we split the data into 2 clusters. With Green Color having the maximum number of data points and Orange Cluster having the minimum number data points
- To Split the data we use Fcluster from package scipy.cluster.hierarchy and when calling function we use criterion as maxclust
- Once the data is split we will then include this in out orginal data
- Original data with Clusters column included is as shown below

	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_paym
0	19.94	16.92	0.8752	6.675	3.763	3.252
1	15.99	14.89	0.9064	5.363	3.582	3.336
2	18.95	16.42	0.8829	6.248	3.755	3.368
3	10.83	12.96	0.8099	5.278	2.641	5.182
4	17.99	15.86	0.8992	5.890	3.694	2.068
5	12.70	13.41	0.8874	5.183	3.091	8.456
6	12.02	13.33	0.8503	5.350	2.810	4.271

	spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_paym
7	13.74	14.05	0.8744	5.482	3.114	2.932

Question 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.



KMeans Inertia Values Plot

- The Above plot will help us to identify number of Clusters that can be considered
- From the Above plot we see that we can use 3 Cluster as the there is no significant change if cluster size is taken as 4 or more

spending	advance_payments	probability_of_full_payment	current_balance	credit_limit	min_payment_
19.94	16.92	0.8752	6.675	3.763	3.252
15.99	14.89	0.9064	5.363	3.582	3.336
18.95	16.42	0.8829	6.248	3.755	3.368
10.83	12.96	0.8099	5.278	2.641	5.182
17.99	15.86	0.8992	5.890	3.694	2.068

- All the Clusters on an average have a Silhouette Score of 0.4.
- The minimum value of Silhouette score is 0.002. This indicates that all the Samples are correctly mapped to their clusters.
- The Sil_Width and the Clusters are added to the original Data and is as shown above.

Question 1.5

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

	spending	advance_payments	prob_of_full_payment	current_balance	credit_limit	min_paym
Clusters						
0	18.495373	16.203433	0.884210	6.175687	3.697537	3.632373

	spending	advance_payments	prob_of_full_payment	current_balance	credit_limit	min_paym
1	11.856944	13.247778	0.848253	5.231750	2.849542	4.742389
2	14.437887	14.337746	0.881597	5.514577	3.259225	2.707341

Cluster 0: Highest Spending, Advance Payments,highest probability of full payment, current balance, credit limit and max spending in single shopping

Cluster 1: Lowest Spending, advance payments probability of full payment, current balance, credit limit and max spent in single shopping but has the highest mini payment amount

Cluster 2: The intermidiate range Customers belong to this Cluster but has the lowest mini-payment amount.

- Cluster 0 are the high end Customers who spend good amount every month. Securing them within Cluster 0 is top priority. So offers are to be made in such a way that they do not end up thinking otherwise.
- Cluster 1 is the the low end Customer who doesn't want to spend much. they maintain a low credit balance which indicate majority of the amount they spend through Credit card rather than paying with Cash. about 84 % of the Customer pay back to Bank which indicates that the they have a steady income. Cluster 1 has the highest number of Customer who pay a minimum amount to bank every month. Targeted Offers are to be made to them so that they can be observed in Cluster 2 (Intermediate Range)
- Cluster 2 are the Intermidiate Group of Customer. They have an Average spending and maintain average Credit limit. More offers are to be given to them so that they end up in Cluster 0 or High end Customers.
- Cluster 2 has least amount of customers that end up paying minimum amount to bank and also 88% of this group pay in full payment to bank.

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.

Question 2.1

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

	Age	Agency_Code	Type	Claimed	Commision	Channel	Duration	Sales	Product Name	Destina
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	America

	Age	Agency_Code	Type	Claimed	Commision	Channel	Duration	Sales	Product Name	Destina
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

Part of Insurance Data that is being Worked on

1. Target: Claim Status (Claimed)
2. Code of tour firm (Agency_Code)
3. Type of tour insurance firms (Type)
4. Distribution channel of tour insurance agencies (Channel)
5. Name of the tour insurance products (Product)
6. Duration of the tour (Duration)
7. Destination of the tour (Destination)
8. Amount of sales of tour insurance policies (Sales)
9. The commission received for tour insurance firm (Commission)
10. Age of insured (Age)

Above is the Dataset Columns and its understandings

- There are over 3000 Rows and 10 Columns in the given Data

	Columns	Non-Null values	Datatypes
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

Data columns (total 10 columns)

dtypes: float64(2), int64(2), object(6)

	count	mean	std	min	25%	50%	75%	max
Age	3000.0	38.09	10.46	8.0	32.0	36.00	42.00	84.00
Commision	3000.0	14.53	25.48	0.0	0.0	4.63	17.24	210.21
Duration	3000.0	70.00	134.05	-1.0	11.0	26.50	63.00	4580.00
Sales	3000.0	60.25	70.73	0.0	20.0	33.00	69.00	539.00

</t > **Description of the Numeric data**

- There are a total of 139 Duplicate Rows present in the Dataset given.
- We need to drop them before proceeding with implementing Machine Learning Models
- Now the Dataset will have 139 less values than it's original
- We can also see that there is a negative value in the Duration which is false. We will also need to treat that Anomaly

	Age	Agency_Code	Type	Claimed	Commision	Channel	Duration	Sales	Product Name	Destinat
1508	25	JZI	Airlines	No	6.3	Online	-1	18.0	Bronze Plan	ASIA

- We observe a negative duration at row 1508. We will replace the median value

	Columns	Non-Null values	Datatypes
0	Age	2861 non-null	int64
1	Agency_Code	2861 non-null	object
2	Type	2861 non-null	object
3	Claimed	2861 non-null	object
4	Commision	2861 non-null	float64
5	Channel	2861 non-null	object
6	Duration	2861 non-null	int64
7	Sales	2861 non-null	float64
8	Product Name	2861 non-null	object
9	Destination	2861 non-null	object

- **Data columns (total 10 columns)**
- **2861 Non Null Values in total**
- **dtypes: float64(2), int64(2), object(6)**

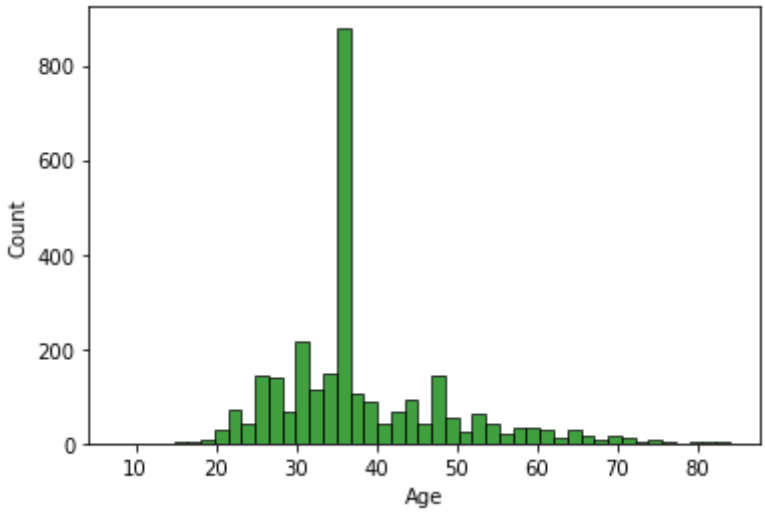
	count	mean	std	min	25%	50%	75%	max
Age	2861.0	38.20	10.68	8.0	31.0	36.00	43.00	84.00
Commision	2861.0	15.08	25.83	0.0	0.0	5.63	17.82	210.21
Duration	2861.0	72.12	135.98	0.0	12.0	28.00	66.00	4580.00
Sales	2861.0	61.76	71.40	0.0	20.0	33.50	69.30	539.00

Description of numeric part of Data after Duplicate rows are Dropped

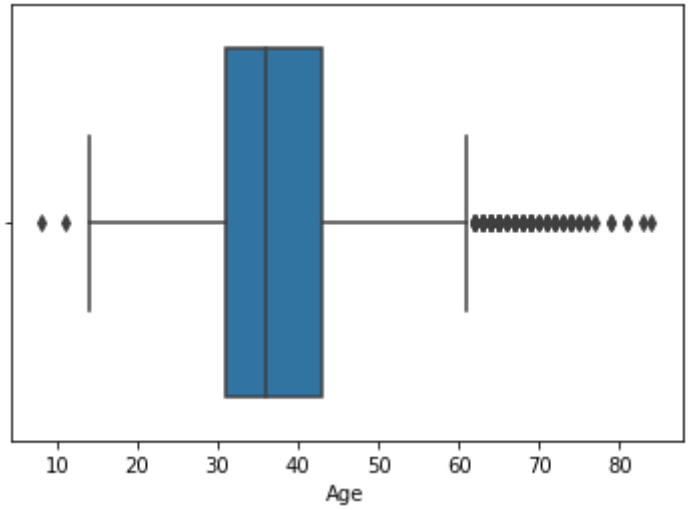
- After dropping the Duplicate rows, mean values increased compared to when duplicated rows were still part of data.
- Change of means will sometimes significantly impact model building Hence we need to drop the duplicate rows

UNIVARIATE ANALYSIS

	Description of Age
mean	38.204124
std	10.678106
min	8.000000
25%	31.000000
50%	36.000000
75%	43.000000
max	84.000000



Distribution of Age



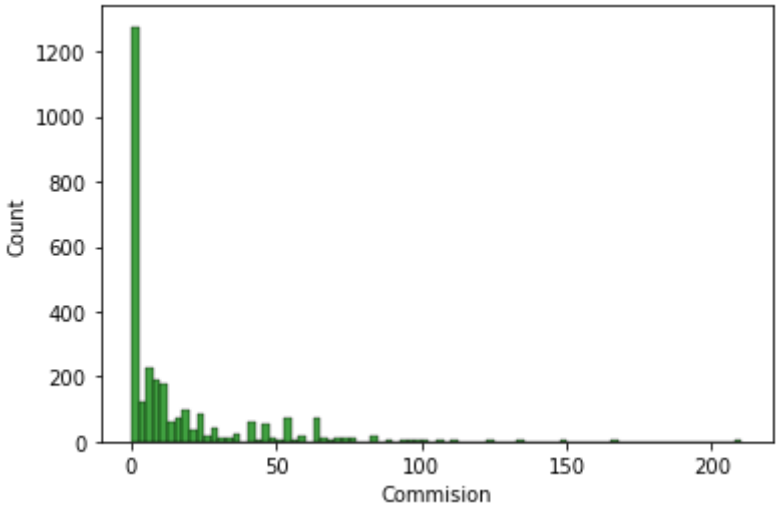
BoxPlot of Age

We observe the follow from the Distribution plot and Bloxplot of Age

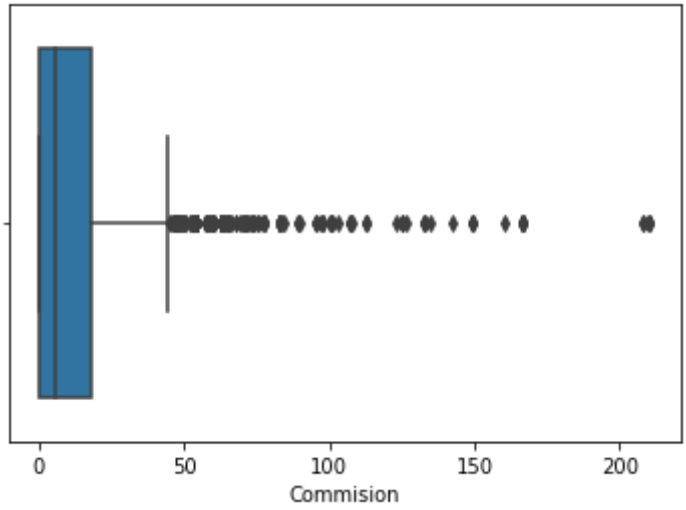
- 75% of the Group falls under 45 years old.
- We observe a large number of Outliers.

	Description of Commision
mean	15.080996
std	25.826834
min	0.000000
25%	0.000000
50%	5.630000

	Description of Commision
75%	17.820000
max	210.210000



Distribution of Commision

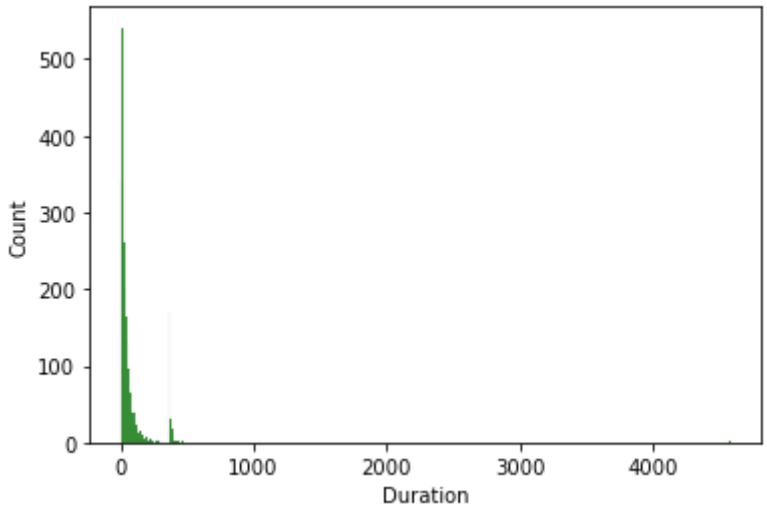


BoxPlot of Commision

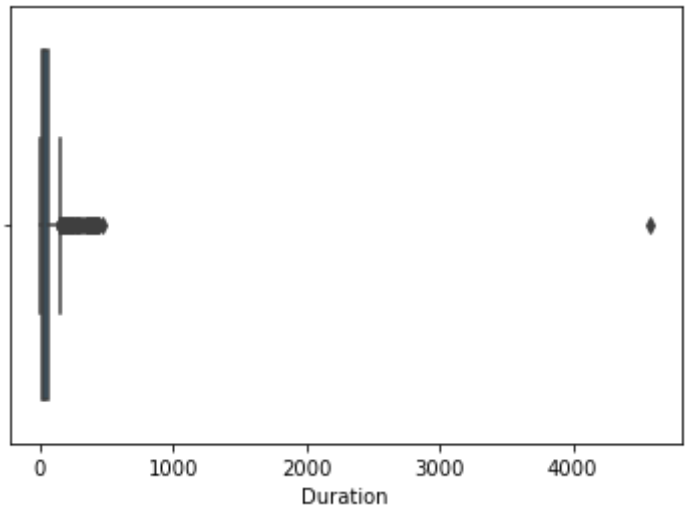
We observe the follow from the Distribution plot and Bloxplot of Commision

- We observed that on an average Commission of 15.08 units were taken and 75% of the crowd claims receive less than 17.62 units
- We observed that the data for Commission is Right Skewed.

	Description of Duration
mean	72.120238
std	135.977200
min	0.000000
25%	12.000000
50%	28.000000
75%	66.000000
max	4580.000000



Distribution of Duration

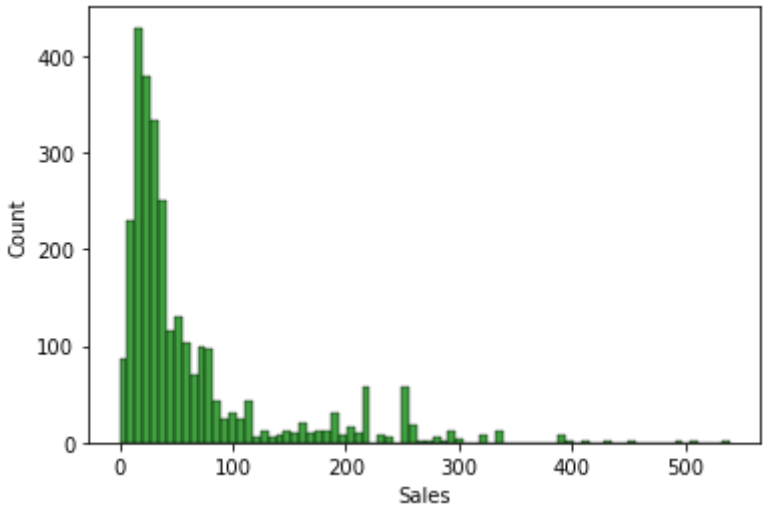


BoxPlot of Duration

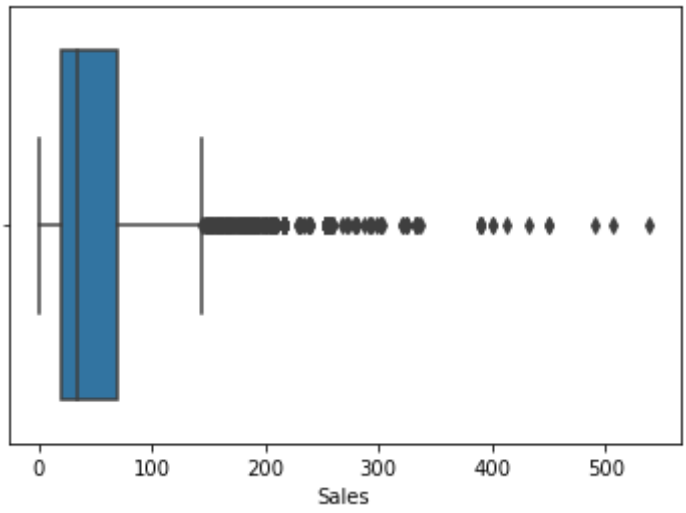
We observe the follow from the Distribution plot and Bloxplot of Duration

- We observed that on an average Duration spent is approximately 72 days
- We See only one Outlier(one Customer) who's travel duration is 4580 days.

	Description of Sales
mean	61.757878
std	71.399740
min	0.000000
25%	20.000000
50%	33.500000
75%	69.300000
max	539.000000



Distribution of Sales

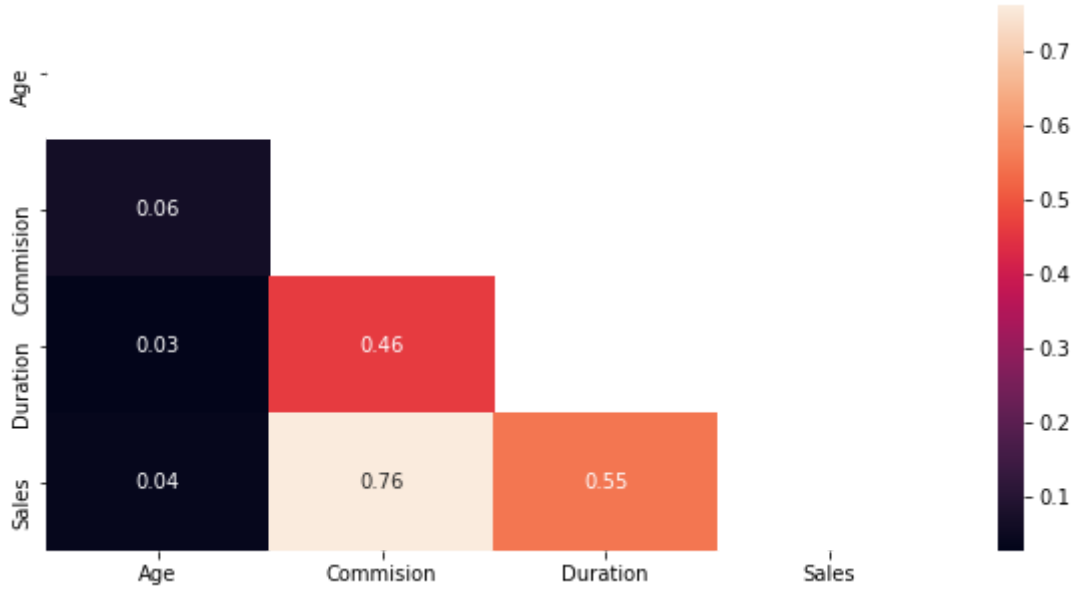


BoxPlot of Sales

We observe the follow from the Distribution plot and Bloxplot of Sales

- We observed that the average Sales on tour insurance policies is approx 71.4 units.
- Data on Sales is Right Skewed

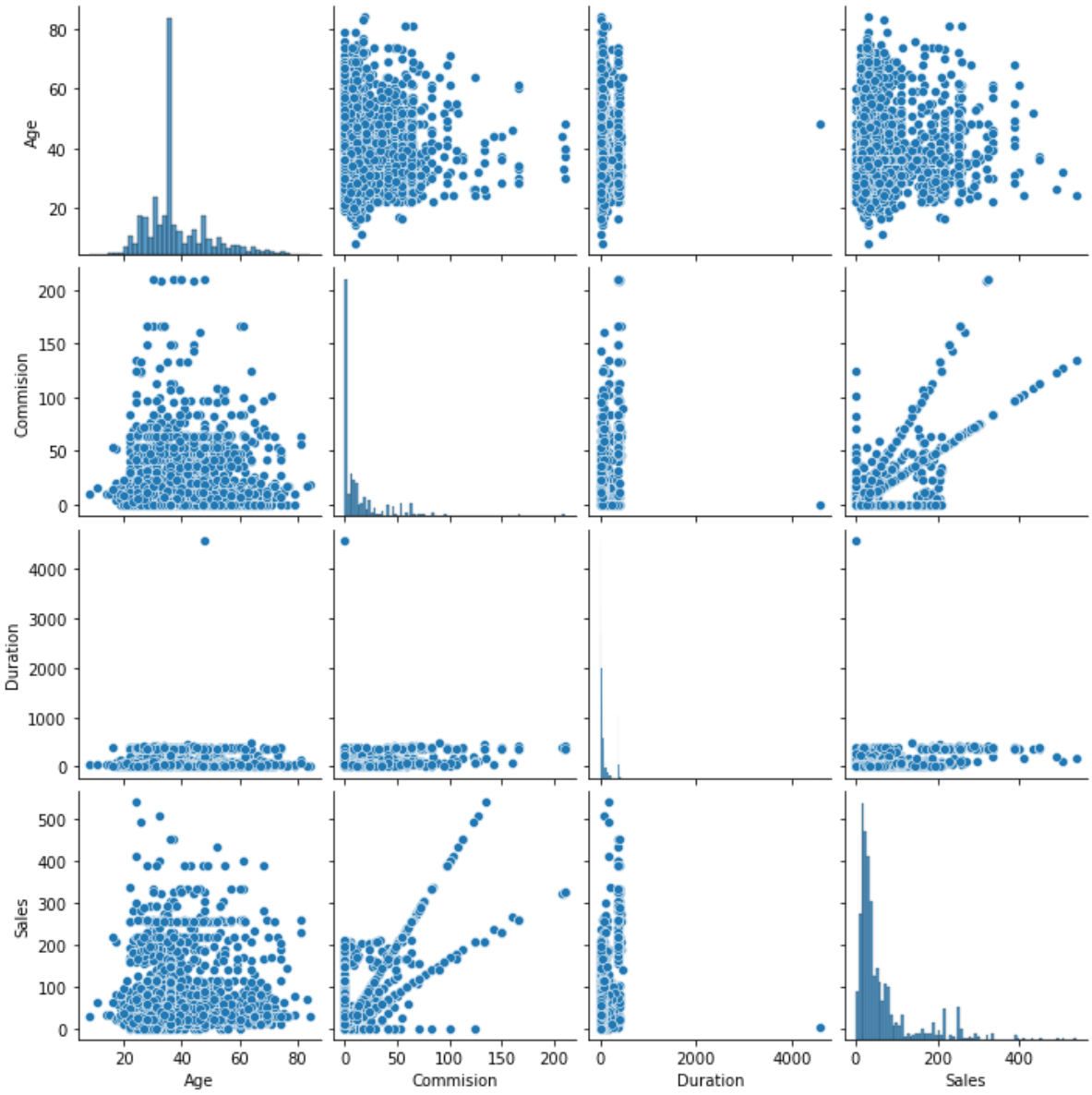
BI-VARIATE ANALYSIS



Heat Map

- We observe from the above data that there is high coorelation between Sales and Commission & Sales and Duration
- There is very little or no coorelation between Age and any of the other numeric factors

MULTI-VARIATE ANALYSIS



Pair Plot of the Numberic Data

Question 2.2

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

	Age	Agency_Code	Type	Claimed	Commision	Channel	Duration	Sales	Product Name	Destination
0	48	0	0	0	0.70	1	7.0	2.51	2	0
1	36	2	1	0	0.00	1	34.0	20.00	2	0
2	39	1	1	0	5.94	1	3.0	9.90	2	1
3	36	2	1	0	0.00	1	4.0	26.00	1	0
4	33	3	0	0	6.30	1	53.0	18.00	0	0

- Decision tree in Python can take only numerical / categorical colums. It cannot take string / object types.
- We convert each column and checks if the column type is object then converts those columns into categorical with each distinct value becoming a category or code.
- Once converting, the dataset is as shown above.
- Data types of the columns will be changed and is as shown below.

	Columns	Non-Null values	Datatypes
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	float64
7	Sales	2861 non-null	float64
8	Product Name	2861 non-null	int8
9	Destination	2861 non-null	int8

- **Data columns (total 10 columns)**
- **2861 Non Null Values in total**
- **dtypes: float64(3), int64(1), int8(6)**

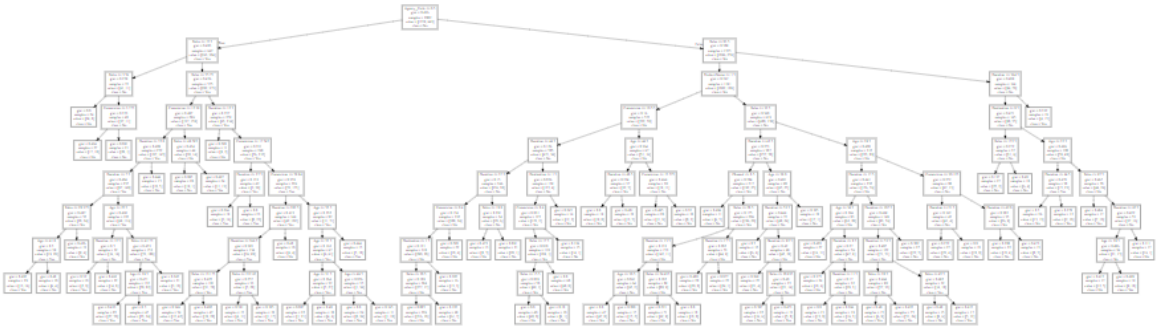
- The Dataset has been Split in to Train Set and Test set.
- I have choosen the test size as 30% and train set as 70% of the Data set.
- Random state being used is 1

CLASSIFICATION MODEL - CART

Over grown Decision Tree is as shown

Regularising the Decision Tree

Pruned Decision Tree with Max depth of 9



	Precision	Recall	F1-Score	Support
0	0.84	0.88	0.86	1359
1	0.72	0.65	0.68	643
accuracy			0.80	2002
macro avg	0.78	0.76	0.77	2002
weighted avg	0.80	0.80	0.80	2002

Classification Table for CART model on Train set using max_depth=9, min_samples_leaf=10, min_samples_split=30

- We see Precision is 72% and Recall is 65% and Fscore is .68

	Precision	Recall	F1-Score	Support
0	0.83	0.84	0.84	588
1	0.65	0.62	0.63	271
accuracy			0.77	859
macro avg	0.74	0.73	0.73	859
weighted avg	0.77	0.77	0.77	859

Classification Table for CART model on Test set using max_depth=9, min_samples_leaf=10, min_samples_split=30

- We see Precision is 64% and Recall is 57% and Fscore is .61

After applying Grid search, the best parameters are max_depth': 8, 'min_samples_leaf': 20, 'min_samples_split': 60

	Precision	Recall	F1-Score	Support
0	0.82	0.88	0.85	1359
1	0.70	0.59	0.64	643
accuracy			0.79	2002
macro avg	0.76	0.74	0.75	2002
weighted avg	0.78	0.79	0.78	2002

Classification Table for CART model on Train set using Grid Search

	Precision	Recall	F1-Score	Support
0	0.80	0.86	0.83	588
1	0.64	0.54	0.58	271
accuracy			0.76	859
macro avg	0.72	0.70	0.71	859
weighted avg	0.75	0.76	0.75	859

Classification Table for CART model on Test set using Grid Search

- We see Precision is 64% and Recall is 54% and Fscore is 58%

RANDOM FOREST CLASSIFIER

	Precision	Recall	F1-Score	Support
0	0.80	0.89	0.84	1359
1	0.69	0.51	0.59	643
accuracy			0.77	2002
macro avg	0.74	0.70	0.71	2002
weighted avg	0.76	0.77	0.76	2002

Classification Table for Random Forest method on Train Dataset

	Precision	Recall	F1-Score	Support
0	0.80	0.90	0.84	588
1	0.69	0.51	0.59	271
accuracy			0.78	859
macro avg	0.74	0.70	0.72	859
weighted avg	0.77	0.78	0.76	859

Classification Table for Random Forest method on Test Dataset

	Precision	Recall	F1-Score	Support
0	0.80	0.90	0.85	1359
1	0.71	0.52	0.60	643
accuracy			0.78	2002
macro avg	0.75	0.71	0.72	2002
weighted avg	0.77	0.78	0.77	2002

Classification Table for Random Forest method using Grid Search on Train Dataset

	Precision	Recall	F1-Score	Support
0	0.80	0.90	0.84	588
1	0.70	0.50	0.58	271
accuracy			0.77	859
macro avg	0.75	0.70	0.71	859
weighted avg	0.76	0.77	0.76	859

Classification Table for Random Forest method using Grid Search on Test Dataset

- We see that Precision is 70% and recoil is 50% and Fscore is at 0.58

MLP CLASSIFIER (ARTIFICIAL NEURAL NETWORKS- ANN)

	Precision	Recall	F1-Score	Support
0	0.69	0.99	0.81	1359
1	0.73	0.07	0.12	643
accuracy			0.68	2002
macro avg	0.71	0.53	0.47	2002
weighted avg	0.70	0.69	0.59	2002

Classification Table for MLP Classifier on Train Set

	Precision	Recall	F1-Score	Support
0	0.80	0.90	0.85	588
1	0.69	0.51	0.59	271
accuracy			0.77	859
macro avg	0.75	0.70	0.72	859
weighted avg	0.77	0.78	0.76	859

Classification Table for MLP Classifier on Test Set

- Precision is 69% and Recoil is 51% and F1-score is 0.59

	Precision	Recall	F1-Score	Support
0	0.80	0.89	0.84	1359
1	0.69	0.51	0.59	643
accuracy			0.77	2002
macro avg	0.74	0.70	0.71	2002
weighted avg	0.76	0.77	0.76	2002

Classification Report for MLP Classifier using Grid Search on Train Set

	Precision	Recall	F1-Score	Support
0	0.80	0.90	0.85	588
1	0.69	0.51	0.59	271
accuracy			0.78	859
macro avg	0.75	0.70	0.72	859
weighted avg	0.77	0.78	0.76	859

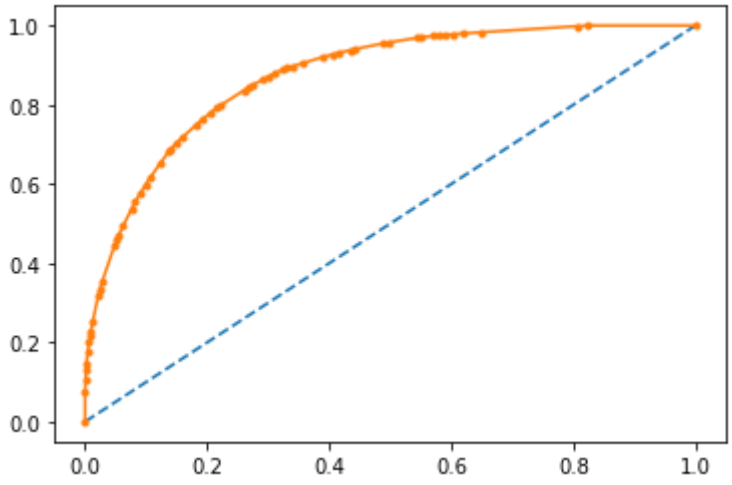
Classification Report for MLP Classifier using Grid Search on Test Set

Question 2.3

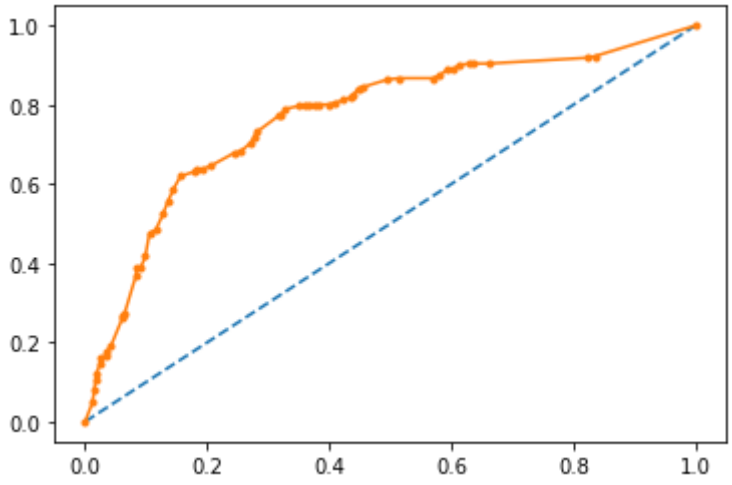
Performance Metrics: Comment and Check the performance of Predictions on Train and Test sets using Accuracy, Confusion Matrix, Plot ROC curve and get ROC_AUC score, classification reports for each model.

Model Evaluation

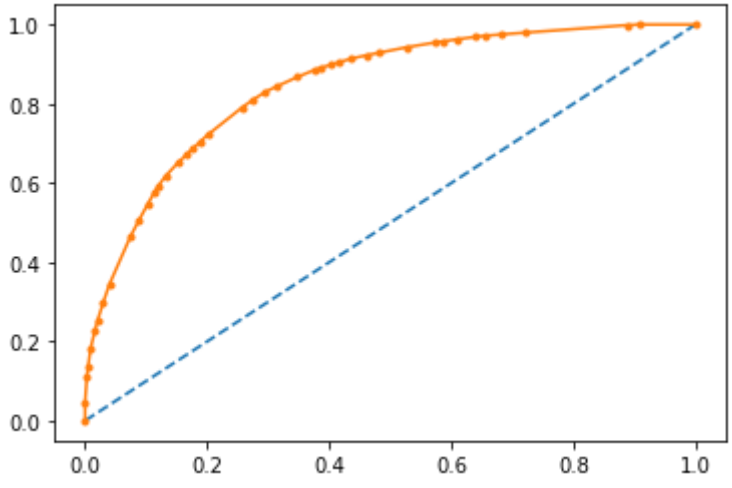
Measuring AUC-ROC Curve for CART model



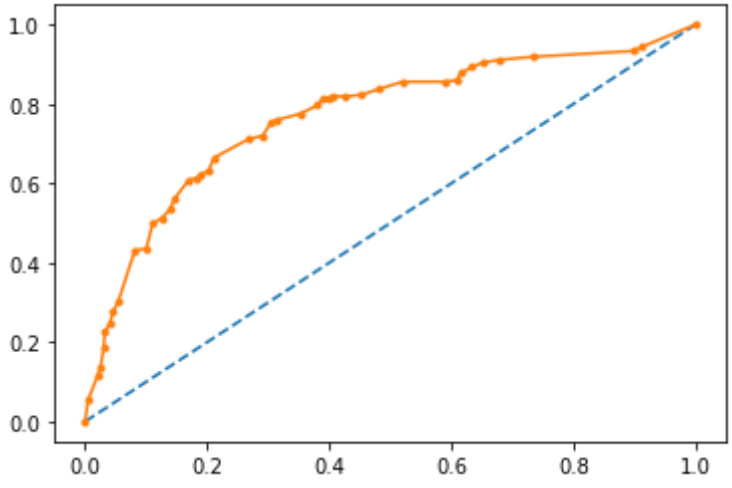
AUC Score on Train Set for CART model is 0.874



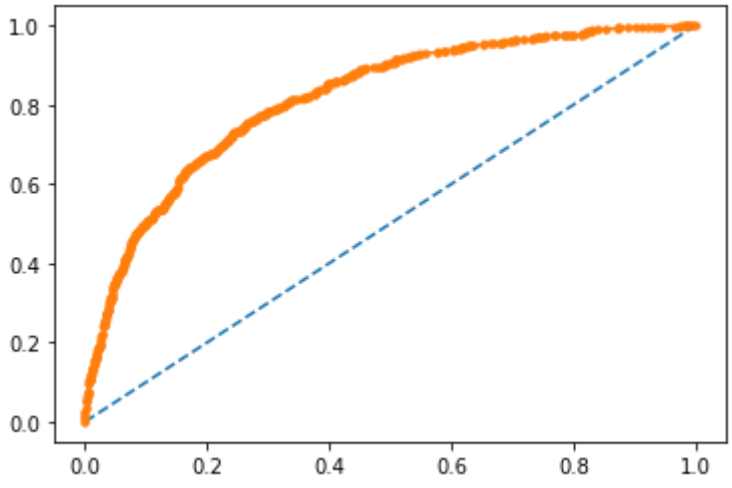
AUC Score of CART model on test set is 0.771



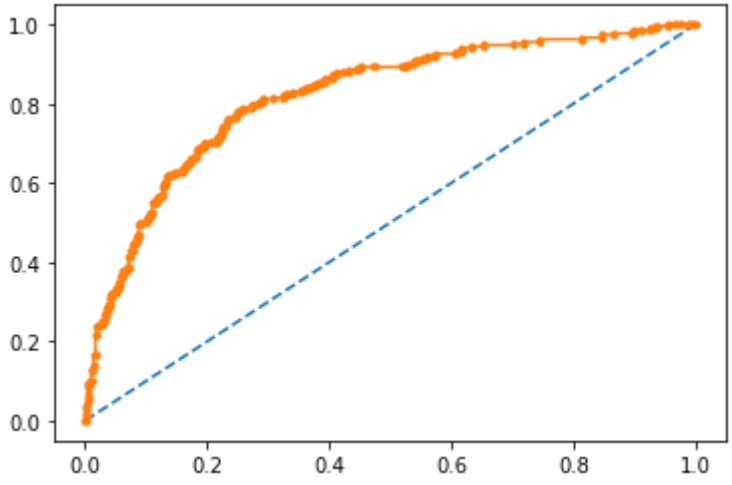
AUC Score on Train Set for CART model using Grid Search is 0.847



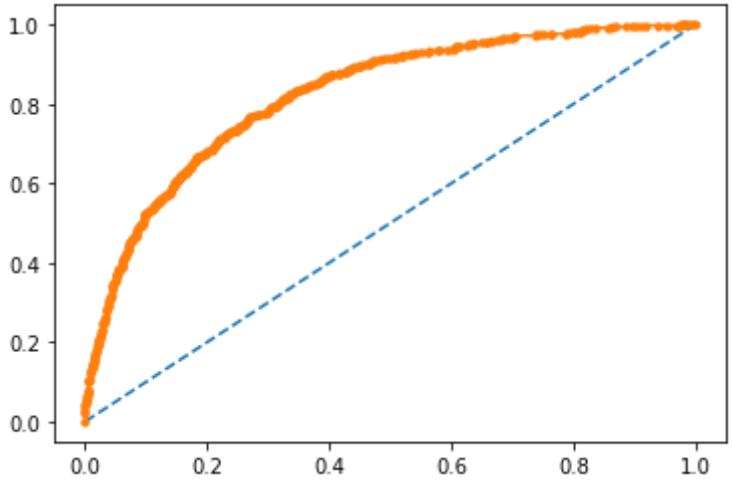
AUC Score on Test Set for CART model using Grid Search is 0.77



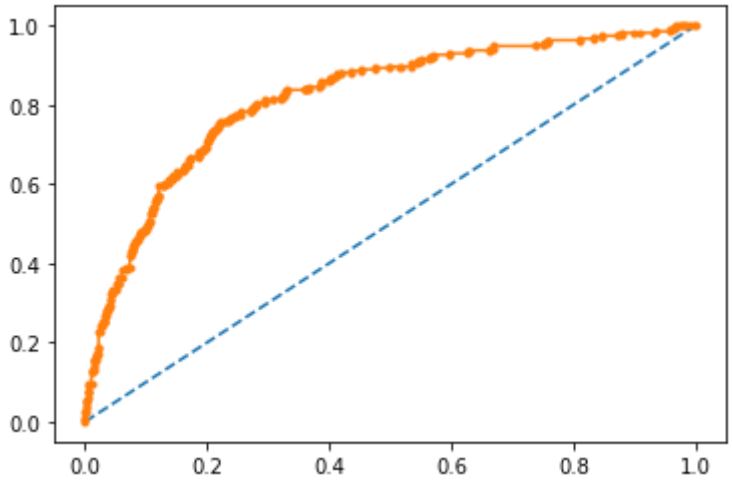
AUC Score on Train Set for Random Forest model is 0.818



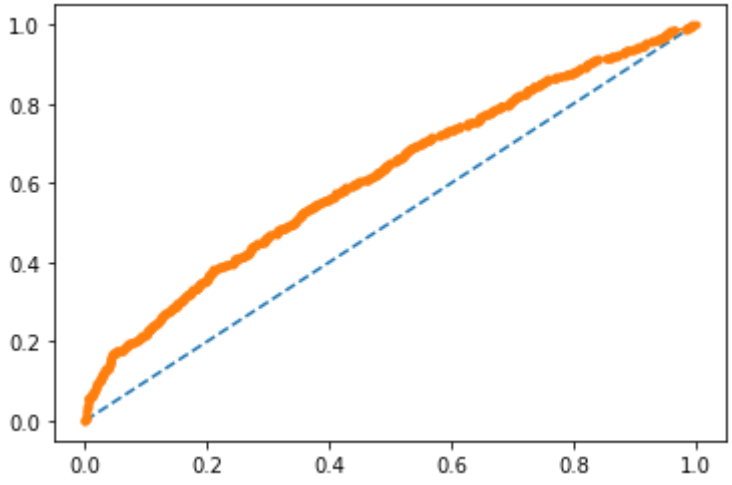
AUC Score on Test Set for Random Forest model is 0.82



AUC Score on Train Set for Random Forest model when used Grid Search is 0.825

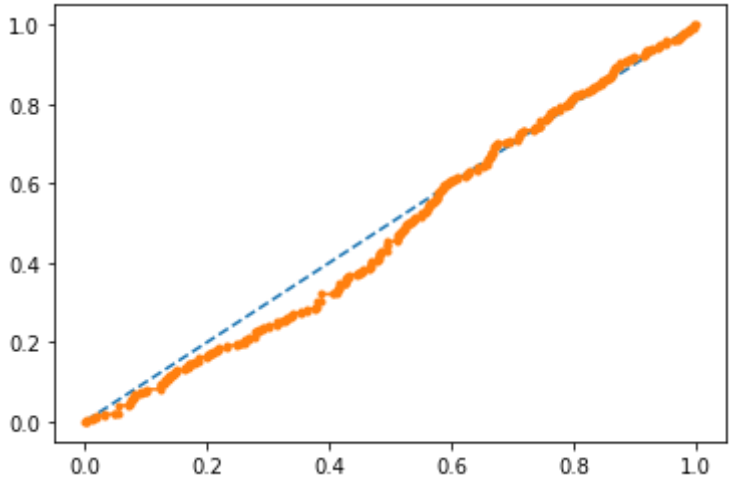


AUC Score on Test Set for Random Forest model when used Grid Search is 0.819



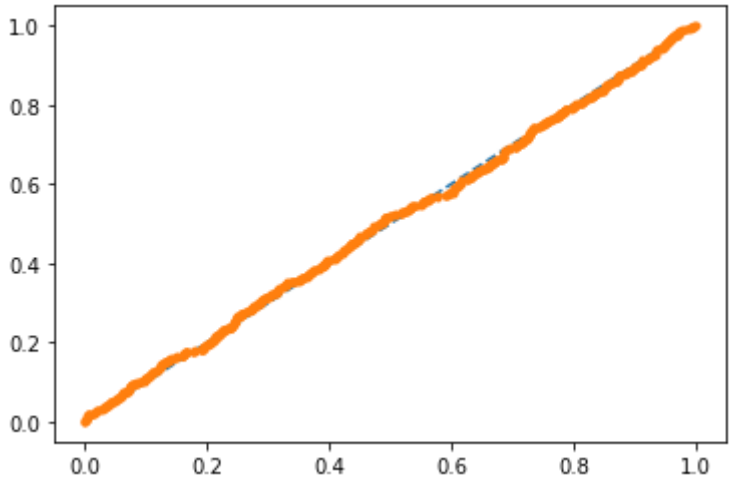
AUC Score on Train Set for MLP

Processor is 0.617



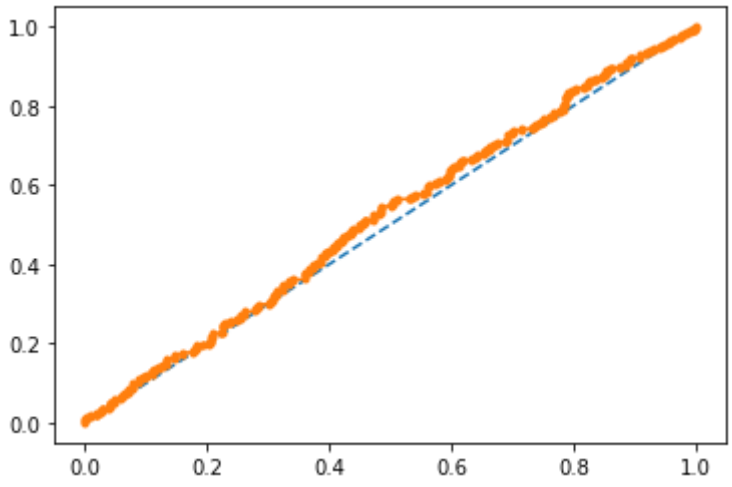
AUC Score on Test Set for MLP

Processor is 0.477



AUC Score on Train Set for MLP

Processor using Grid Search is 0.503



AUC Score on Train Set for MLP Processor using Grid Search is 0.522

Question 2.4

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

Classification Table of Test Dataset without Grid Search

Model	Accuracy	Precision	Recall	F1 Score	AUC Score
CART	0.77	0.65	0.62	0.63	0.771
Random Forest	0.78	0.69	0.51	0.59	0.82
MLP Processor	0.77	0.69	0.51	0.59	0. 477

Classification Table of Test Dataset with Grid Search

Model	Accuracy	Precision	Recall	F1 Score	AUC Score
CART	0.76	0.64	0.54	0.58	0.77
Random Forest	0.77	0.70	0.50	0.58	0.819
MLP Processor	0.78	0.69	0.51	0.59	0. 522

- From the above Table we can concure that Precision of any model considered is equal to 70 or less than 70.
- Recall is close to 0.50. Accuracy of the model is close to 80%.
- We know that higher the F1 score , Better the model. But we see that F1 Score is same for all the models.
- AUC score is calculated for all the models and we see that AUC score for Random Forest Model is the Highest. Which indicates Stong Model.
- We can prefer Random Forest Model since it has the highest AUC score and has the highest Precision value.

Question 2.5

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

- We observe that the Accuracy is approximately 77% for all the models. This could be increased with more information and Robust Model.
- since that the dataset is unbalanced, and so we have a class imbalance problem.

- With Treating Outliers, Model Robustness can be increased but will have to enquire with the company before treating outliers.
- To build a more robust classification model, this class imbalance needs to be addressed before building the model. This will be applicable to any kind of classification model. Once this issue is addressed and the model is built, further model tuning/optimization using grid search will result in improved performance. This Class imbalance will also be be need to discussed with Company and if access to more data to build a better model.

THE END