DataCO MARKET ANALYSIS

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Introduction

In recent years, the rise of the Internet of things (IoT) as an emerging technology has been unbelievable, more companies are moving towards the adoption of these technologies and many IoT sensors are being deployed to share information in real-time which leads to the generation of a huge amount of data. This data when used correctly, will be very helpful to the company to discover hidden patterns for better decision making in the future. For example, with the DataCo company, dataset customer segmentation analysis was performed in this project which helps the company to better understand its customers and target them to increase customer responsiveness and the company's revenue. With a lot of options available to analyze data, it is very difficult to decide which method and machine learning model to use since the performance of the model vary on the parameters available in the data.

This project aims to compare 10 popular machine learning classifiers, and measure their performance to find out which machine learning model performs better. Since the dataset used is related to supply chain important parameters are identified and the machine learning models are trained with the dataset for detection of fraud transactions, late delivery of orders, sales revenue and quantity of products which customer orders.

he machine learning classifiers used in this project are Logistic Regression, K-Nearest Neighbor Classiifer, Random Forest Classifier , Decision Tree Classifier, Naïve Bayes Classifier, Bagging, Boosting.

Data Collection

The dataset consists of roughly 180k transactions from supply chains used by the company DataCo Global for 3 years.

The continuous columns are:
['Days for shipping (real)', 'Days for shipment (scheduled)', 'Benefit per order', 'Sales per customer', 'Late_delivery_risk', 'Category Id', 'Customer Id', 'Customer Zipcode', 'Department Id', 'Latitude', 'Longitude', 'Order Customer Id', 'Order Id', 'Order Item Cardprod Id', 'Order Item Discount', 'Order Item Discount Rate', 'Order Item Id', 'Order Item Product Price', 'Order Item Profit Ratio', 'Order Item Quantity', 'Sales', 'Order Item Total', 'Order Profit Per Order', 'Order Zipcode', 'Product Card Id', 'Product Category Id', 'Product Description', 'Product Price', 'Product Status']

The Categorical Columns are:
['Type', 'Delivery Status', 'Category Name', 'Customer City', 'Customer Country', 'Customer Email', 'Customer Fname', 'Customer Lname', 'Customer Password', 'Customer Segment', 'Customer State', 'Customer Street', 'Department Name', 'Market', 'Order City', 'Order Country', 'order date (DateOrders)', 'Order Region', 'Order State', 'Order Status', 'Product Image', 'Product Name', 'shipping date (DateOrders)', 'Shipping Mode']

In Total there are 53 Columns Initially in the dataset

Data Cleaning

The total data set consists of 180519 records and 53 columns

Only the below Columns has null values in the dataset:

Order Zipcode	86.239676
Product Description	100.000000

Order Zipcode and order description both have highest null values, and for the given problem the Zipcode is not required and also the description column is empty, so dropping the two columns.

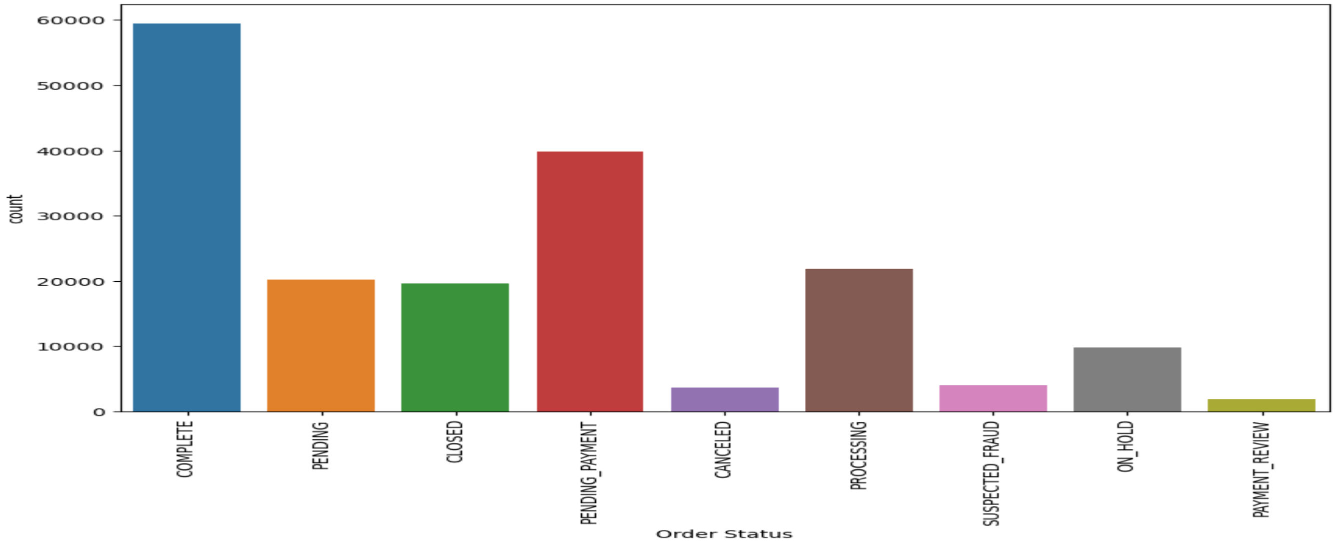
To make it easier for analysis some unimportant columns are dropped

Customer Zipcode,Product Status,Late_delivery_risk,Customer Email,Customer Password,Customer Fname ,Customer Lname,Product Image,shipping date (DateOrders), Order Profit Per Order.

The target variable for our problem is Order Status Column.
The unique categories present for the order status are:
['COMPLETE' 'PENDING' 'CLOSED' 'PENDING_PAYMENT' 'CANCELED' 'PROCESSING'
'SUSPECTED_FRAUD' 'ON_HOLD' 'PAYMENT_REVIEW']

This is the distribution of each category in the Order Status Column:

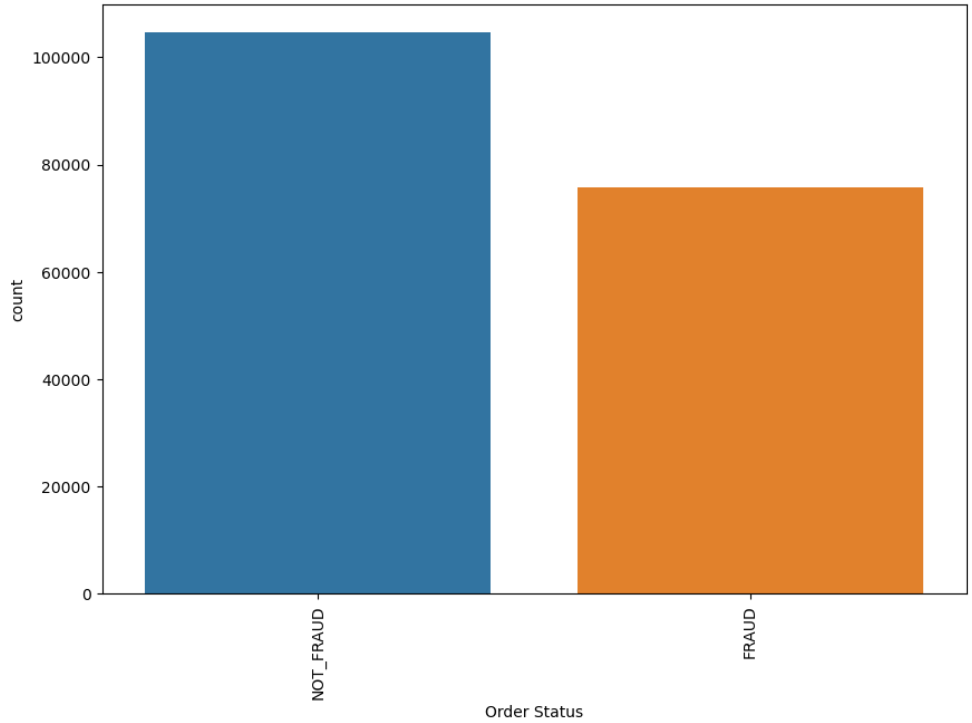
COMPLETE	32.955534
PENDING_PAYMENT	22.065267
PROCESSING	12.132795
PENDING	11.204915
CLOSED	10.866446
ON_HOLD	5.431007
SUSPECTED_FRAUD	2.250179
CANCELED	2.045214
PAYMENT_REVIEW	1.048643



The Categories Complete, Processing, Closed, Cancelled can be categorised as NON-FRAUD as the order is processed or in processing state. The Categories PENDING_PAYMENT, PENDING, ON_HOLD, SUSPECTED-FRAUD, PAYMENT_REVIEW can be categorised as FRAUDULANT as the order is on hold, or on review.

After the change these are the categories in the Order Status column and there weightage:

NOT_FRAUD	57.999989
FRAUD	42.000011



Days for shipping(real) and Days for shipping(scheduled) are telling the number of days it took to deliver the order, why not create 1 column telling if the order shipment was delayed, on-time or before-time

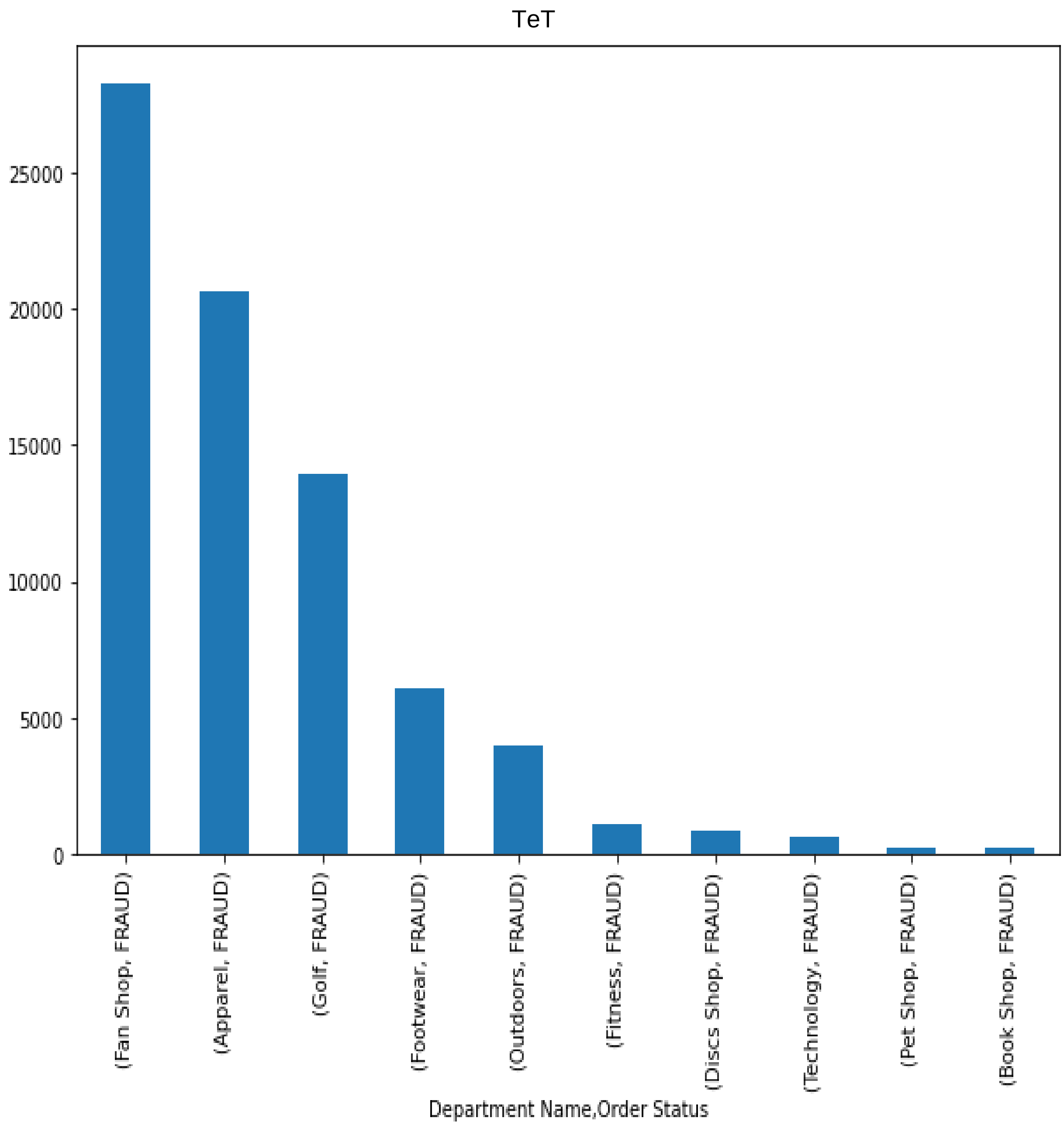
After the necessary changes we where able to create a new column Order Shipment, with the below categories and weightages:

DELAY	57.279289
BEFORE_TIME	24.022956
ON_TIME	18.697755

Data Visualization

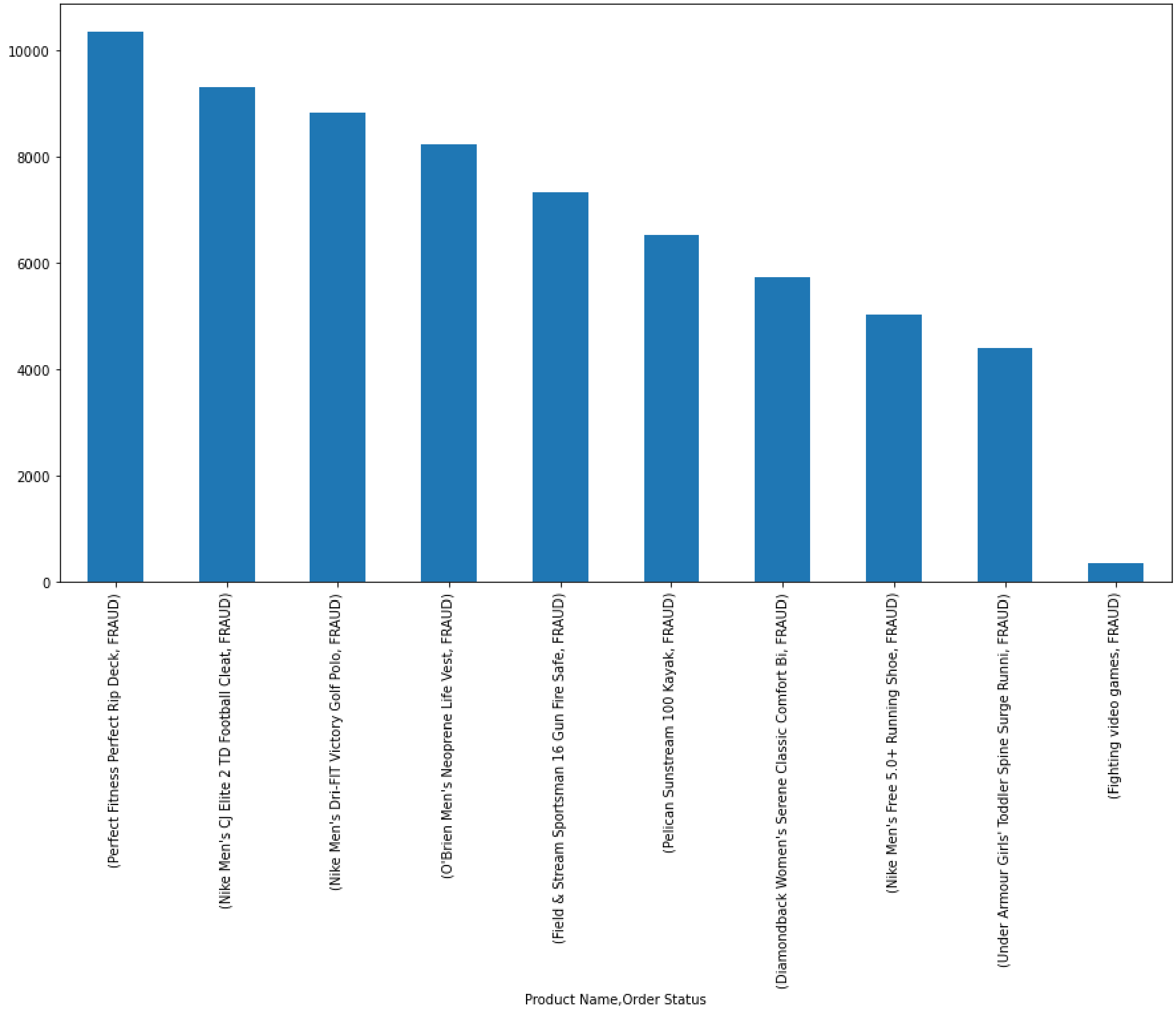
Univariate and Bivariate Analysis:

1. Top 10 departments which have the highest Fraud:



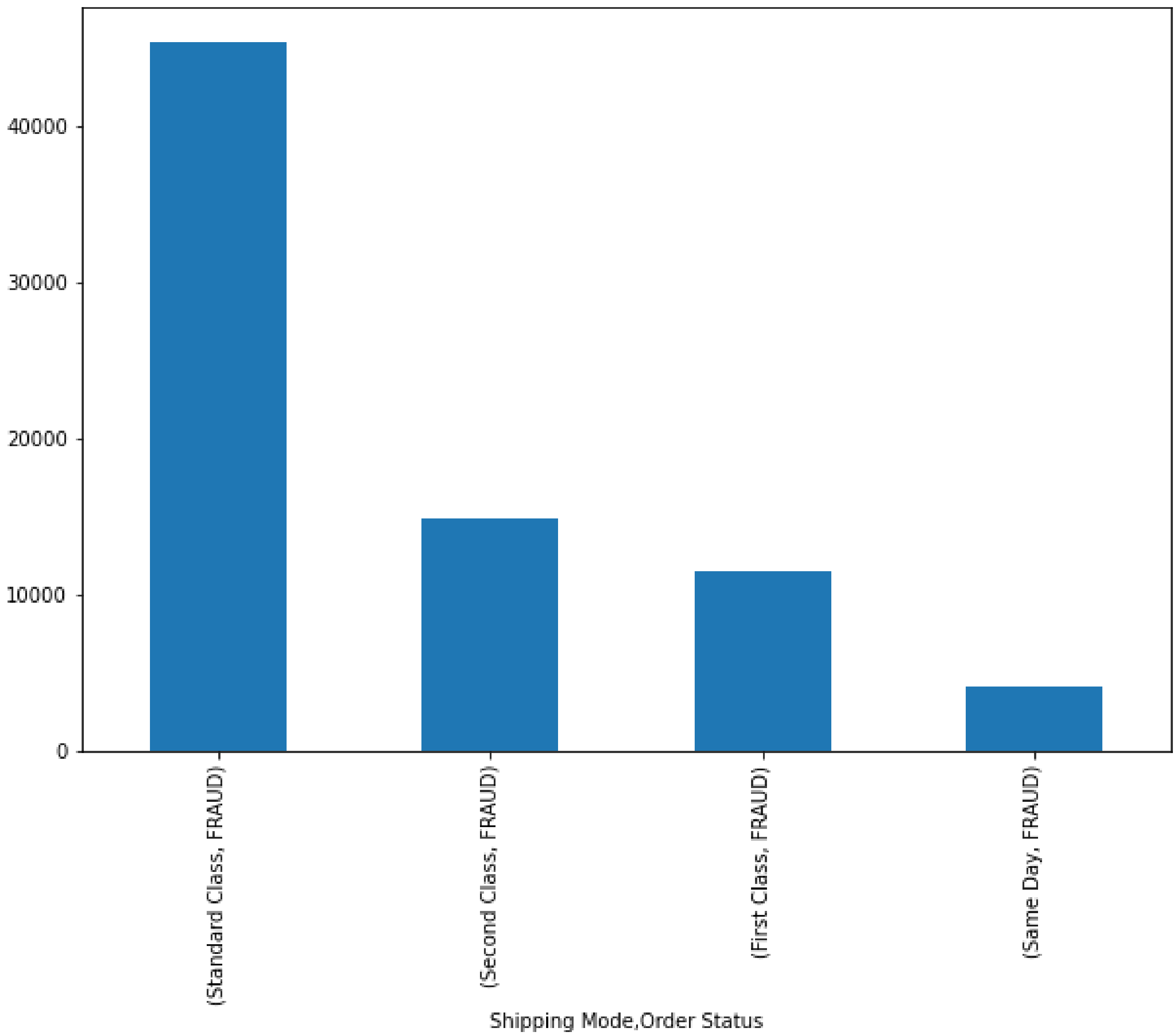
The above plot shows the top 10 Departments that are effected by fraud.

2. Top 10 Products which have the he highest fraud:



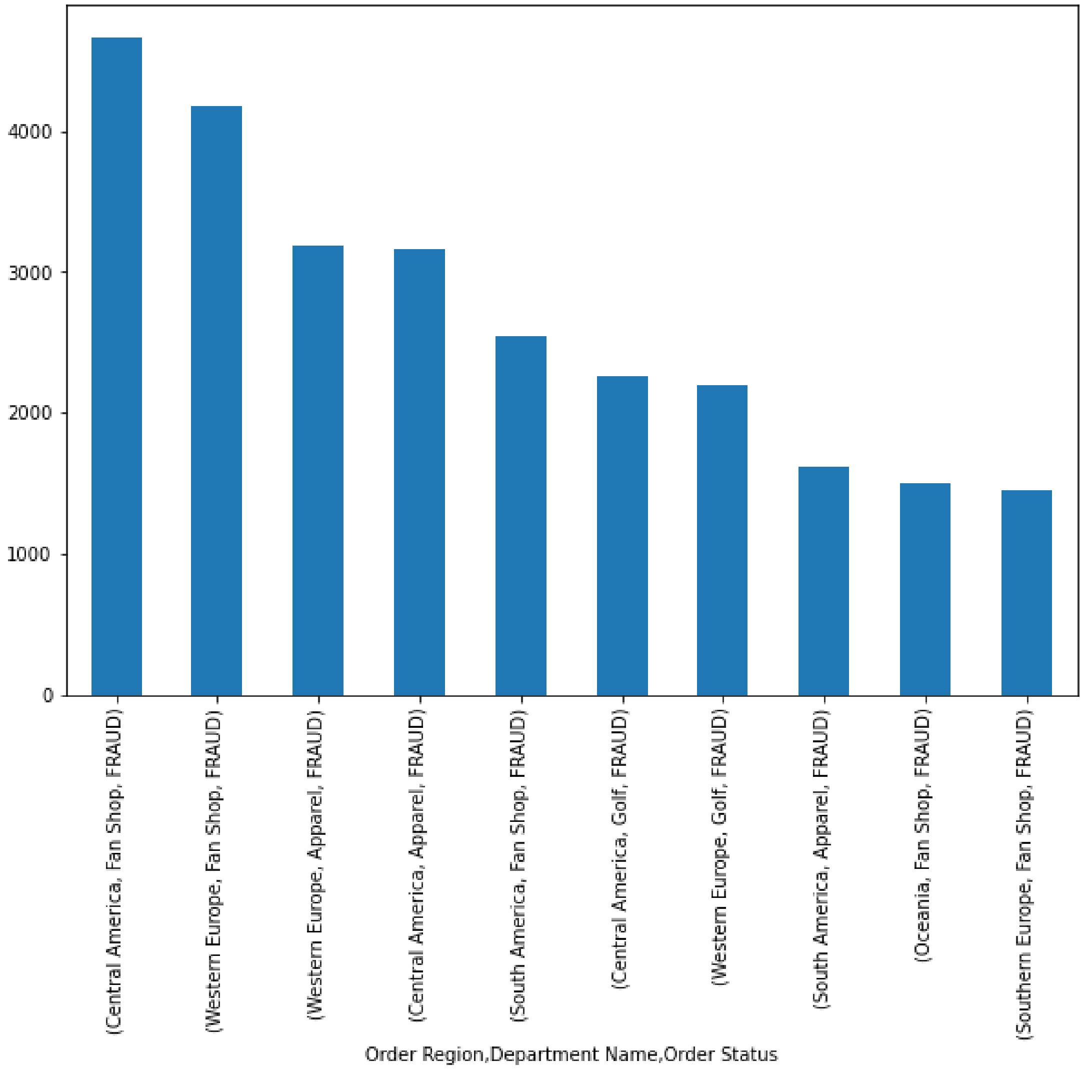
The above plot shows the top 10 products that are effected by fraud.

3. Shipping Mode which have the highest fraud:



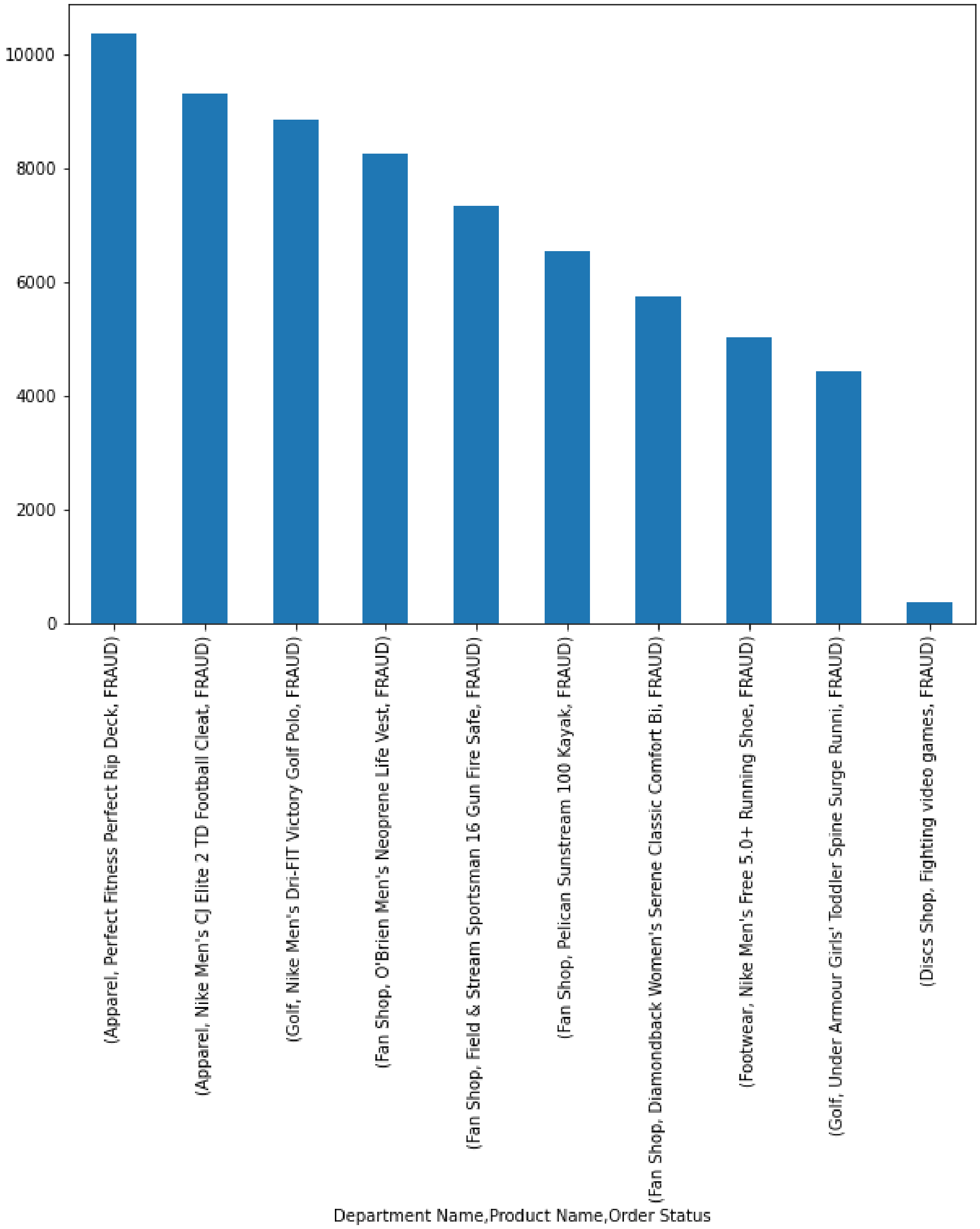
The above plot shows which type of shipping mode does a fraud order go through.

4. Region wise analysis for the departments:



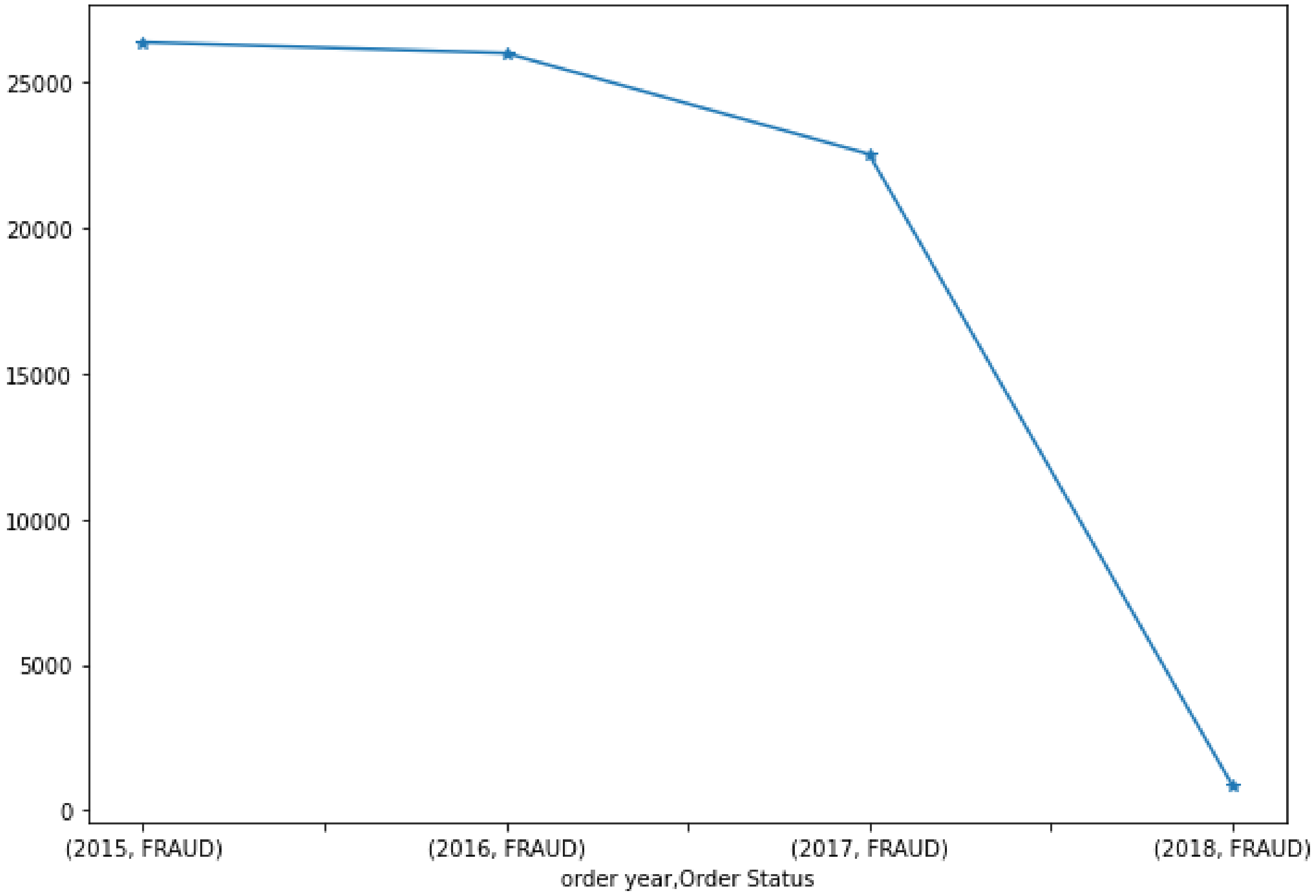
The above plot shows the fraud order trend region wise.

5. Top 10 product s effected by fraud:



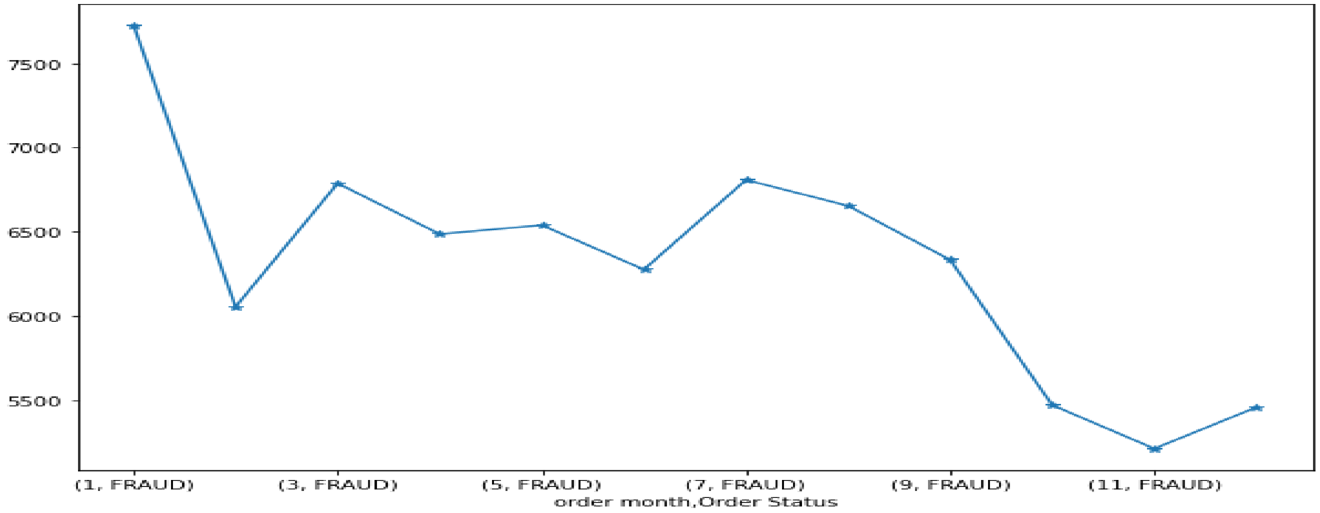
The above plot shows the worst effected products for fraud orders.

6. Year wise analysis for fraud orders:

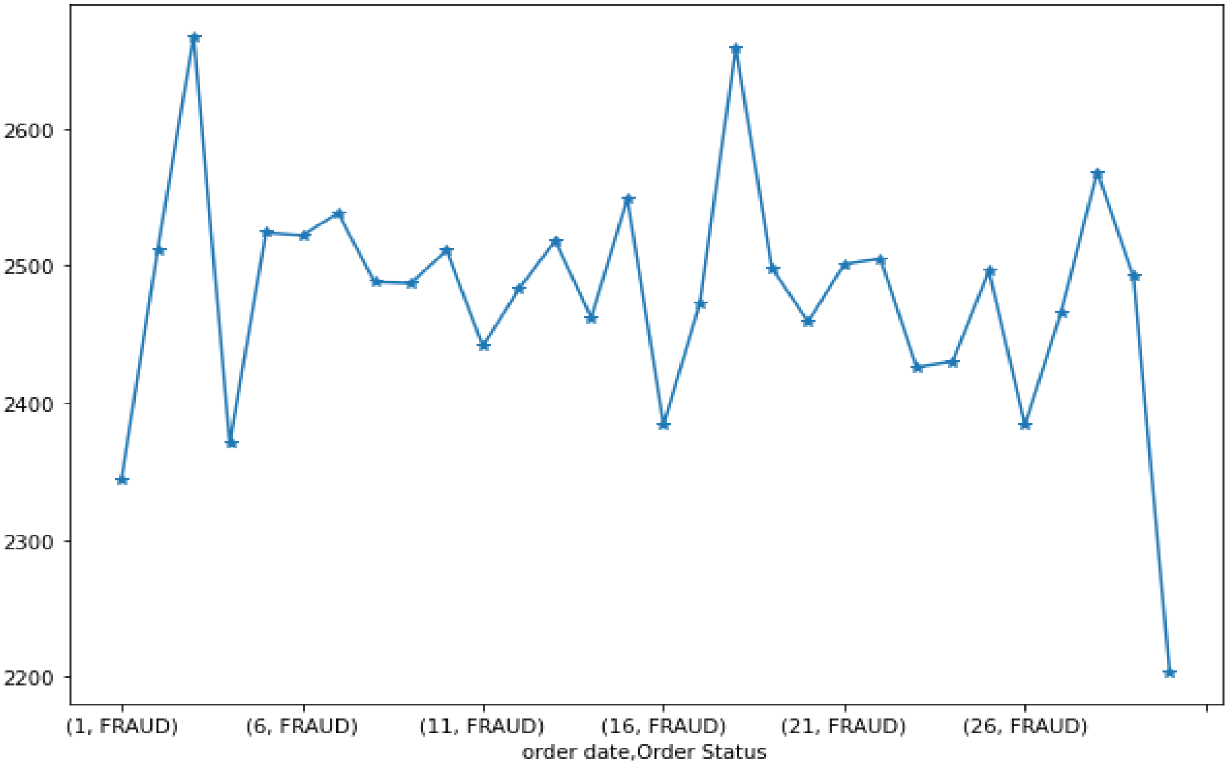


Year wise and month wise trend for fraud orders placed

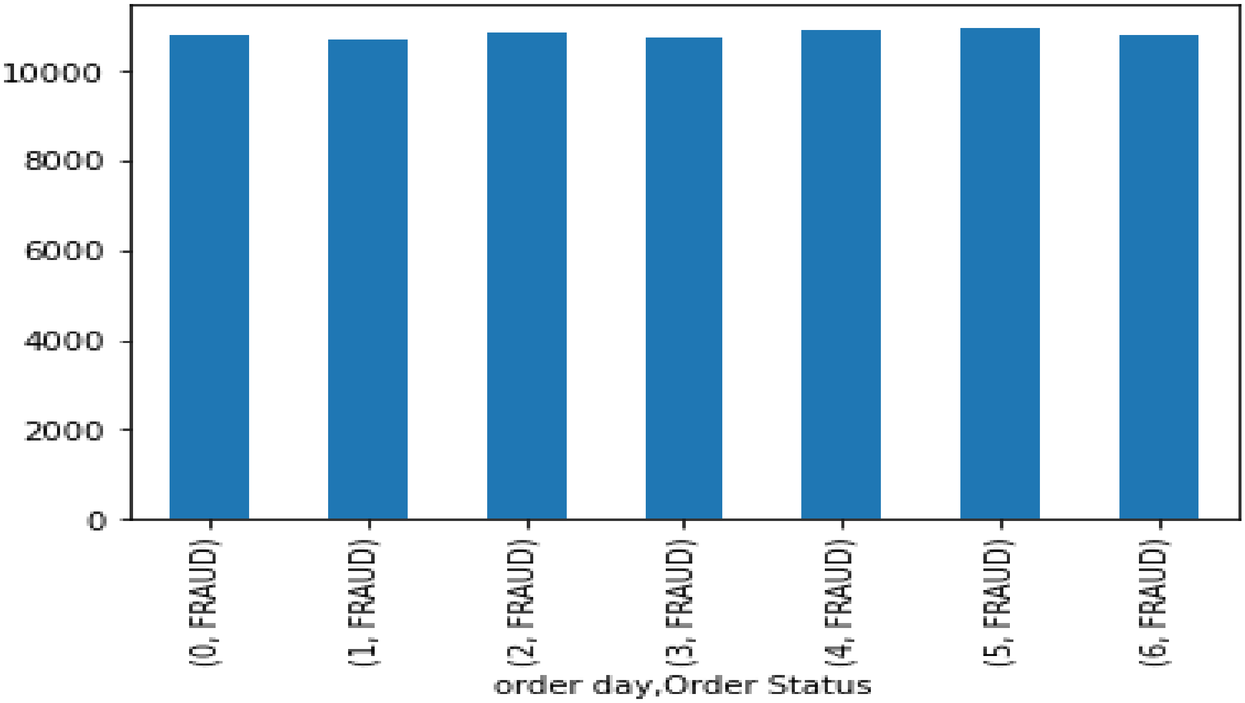
7. Month wise analysis for fraud orders:



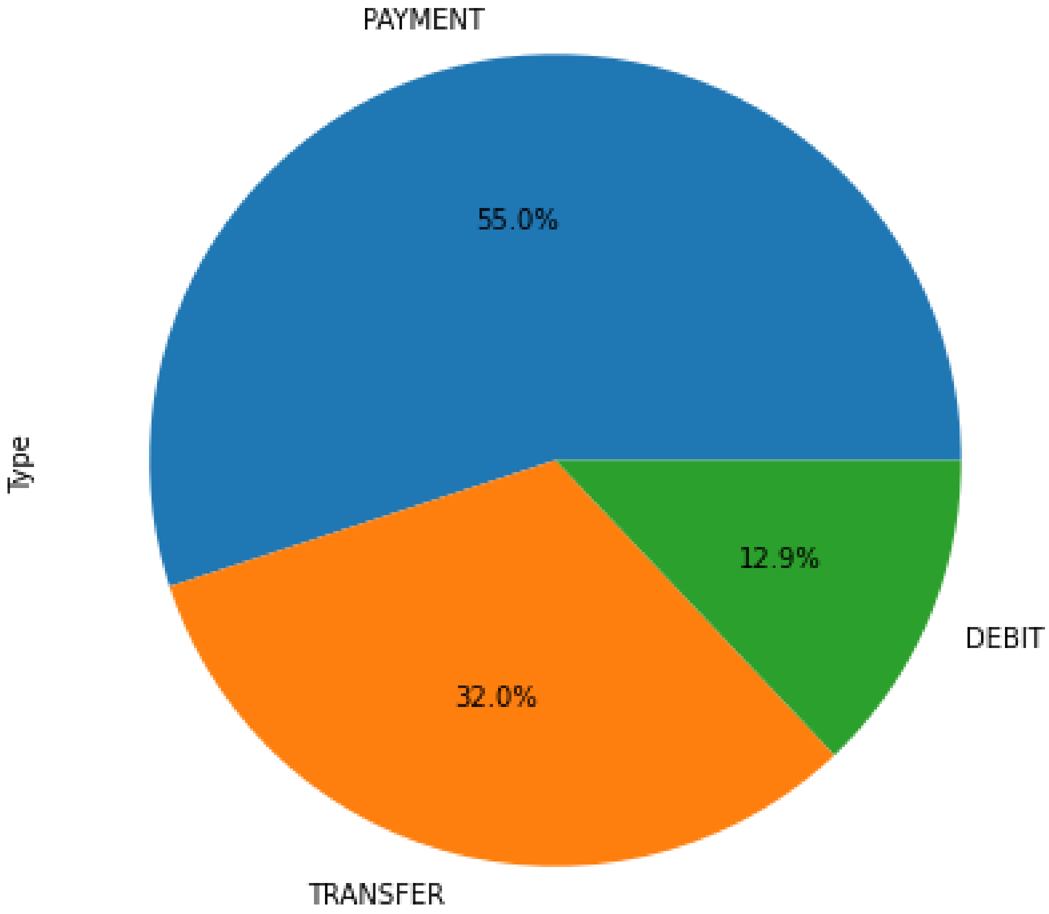
8. Date wise analysis for fraud orders:



9. Day wise analysis for fraud orders:

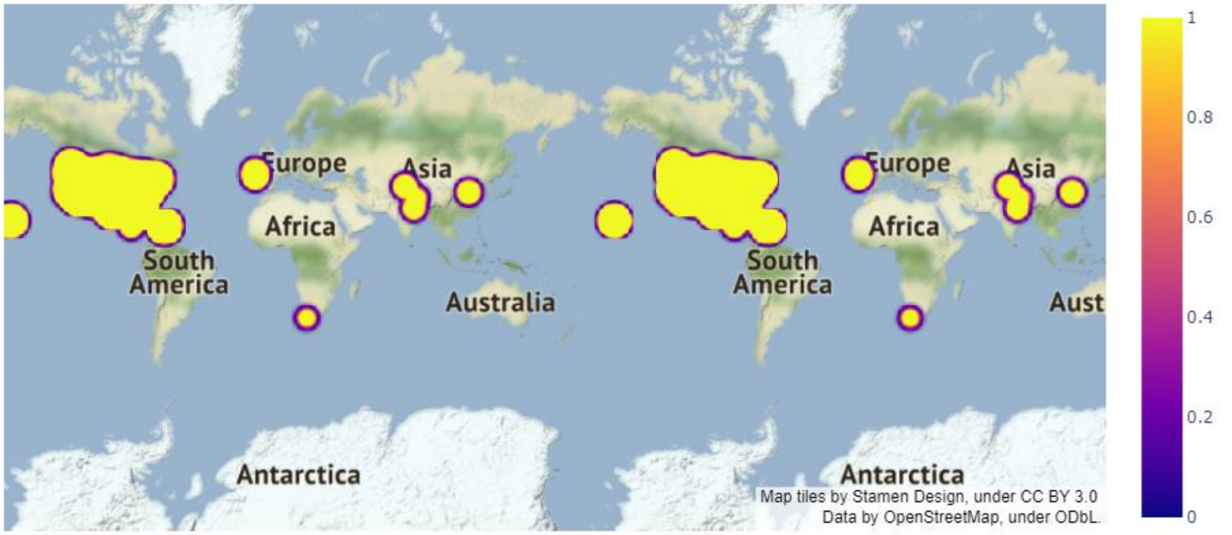


10. Weightage of payment methods used by customers:



The above pie chart shows the weightage of payments methods in the dataset.

11. Visualizing the customers location present in the dataset via Portly:



Outler Treatment

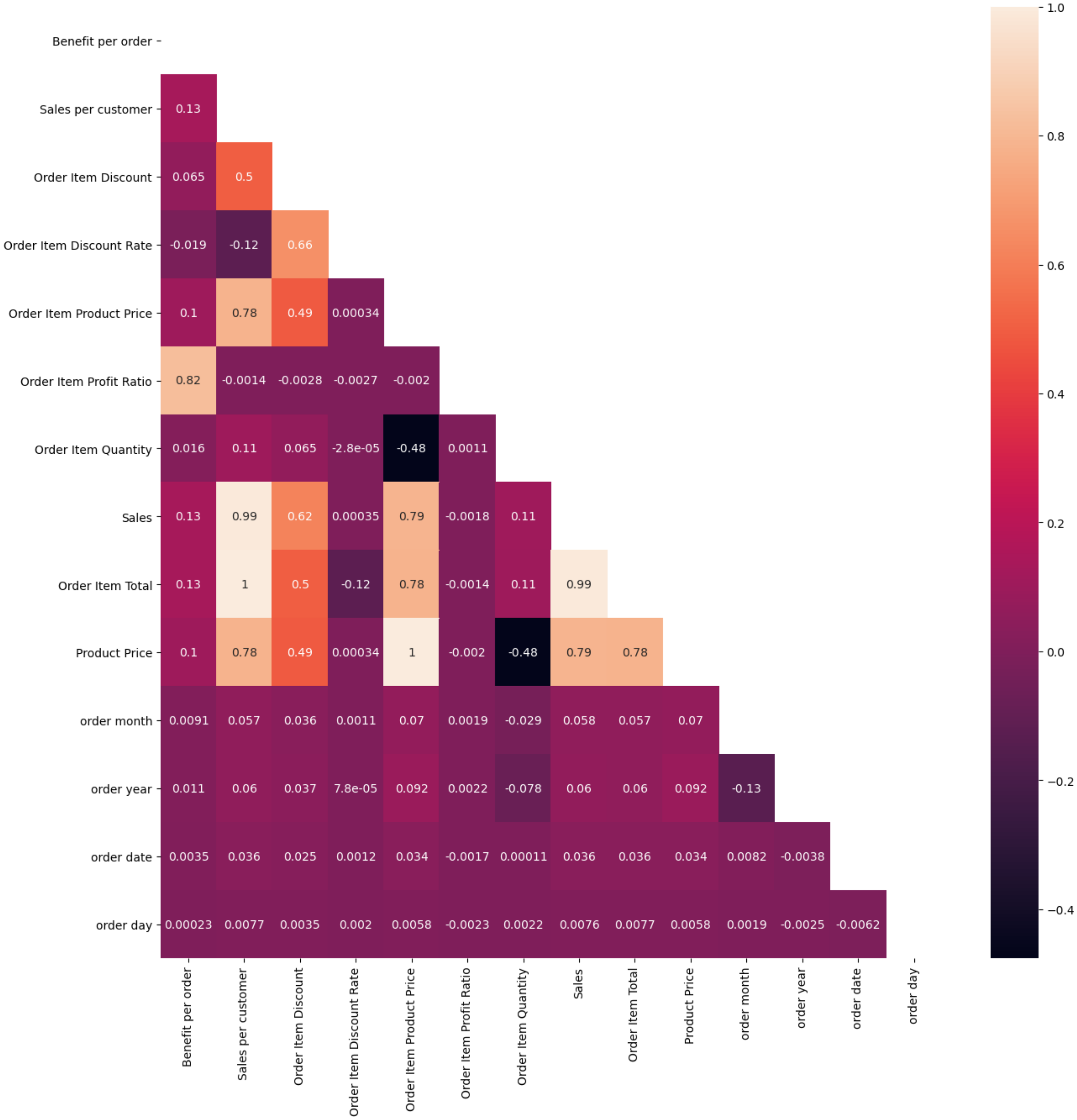
Below shows the percentage of outliers in each column:

```
Benefit per order            10.493078
Category Id                   0.000000
Category Name                 0.000000
Customer City                 0.000000
Customer Country              0.000000
Customer Id                   0.663642
Customer Segment              0.000000
Customer State                0.000000
Customer Street               0.000000
Delivery Status               0.000000
Department Id                 0.200533
Department Name               0.000000
Market                        0.000000
Order City                    0.000000
Order Country                 0.000000
Order Customer Id             0.663642
Order Id                      0.000000
Order Item Cardprod Id        0.000000
Order Item Discount           4.175184
Order Item Discount Rate      0.000000
Order Item Id                 0.000000
Order Item Product Price      1.134507
Order Item Profit Ratio       9.583479
Order Item Quantity           0.000000
Order Item Total              1.076341
Order Region                  0.000000
Order Shipment                0.000000
Order State                   0.000000
Order Status                  0.000000
Product Card Id               0.000000
Product Category Id           0.000000
Product Name                  0.000000
Product Price                 1.134507
Sales                         0.270332
Sales per customer            1.076341
Shipping Mode                 0.000000
Type                          0.000000
order date                    0.000000
order day                     0.000000
order month                   0.000000
order year                    0.000000
```

% of loss of data from the original data set is: 17.40% Since the percentage of removal is very high we will not be removing the outliers from the original dataset as data loss is very high

Checking for Multi-Collinearity

We can visualize the multi-collinearity of the dataset via a Heatmap

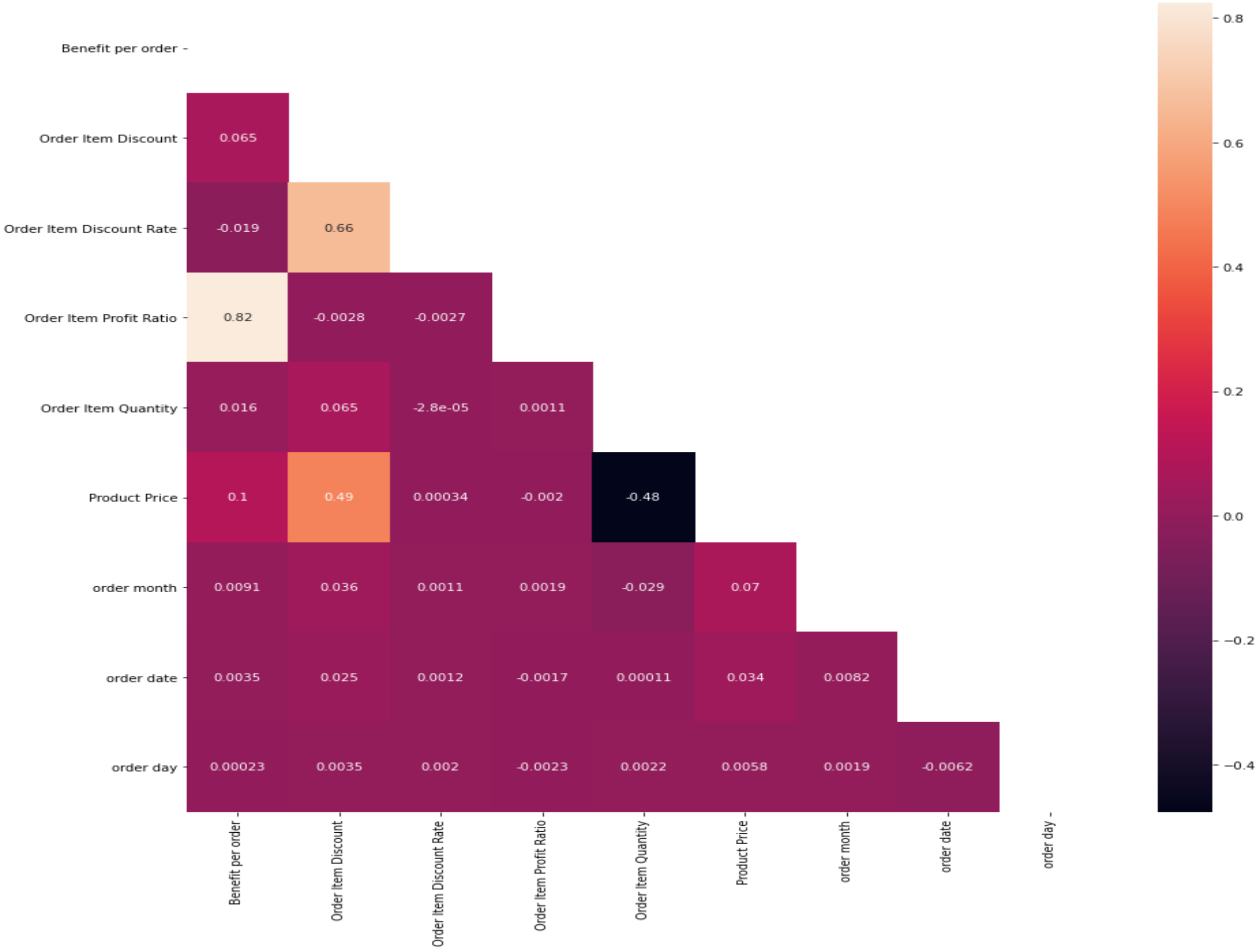


There is high multi-collinearity present in the data, we will be treating the same using VIF(Variance Inflation Factor).

After calculating VIF and via Backward elimination keeping only features with VIF less that 10, we have the below features:

```
    VIF_Factor                   Features
0     3.407359           Benefit per order
1     3.840572           Order Customer Id
2     7.183878         Order Item Discount
3     6.882066    Order Item Discount Rate
4     4.272494               Order Item Id
5     3.414860     Order Item Profit Ratio
6     3.809974         Order Item Quantity
7     6.938691         Product Category Id
8     6.216378               Product Price
9     4.259147                 order month
10    3.787456                  order date
11    3.013430                   order day
```

And, now after removing the multi-collinearity from the dataset the heatmap is as shown below:



Checking for Model Assumptions:

Assumption 1:
The target variable i.e., Order Status is a categorical variable.
The datatype of Order Status column is: object and it has 2 categories.

Assumption 2:
As shown in the above heatmap we have removed the multicollinearity from all the numeric columns of the dataset

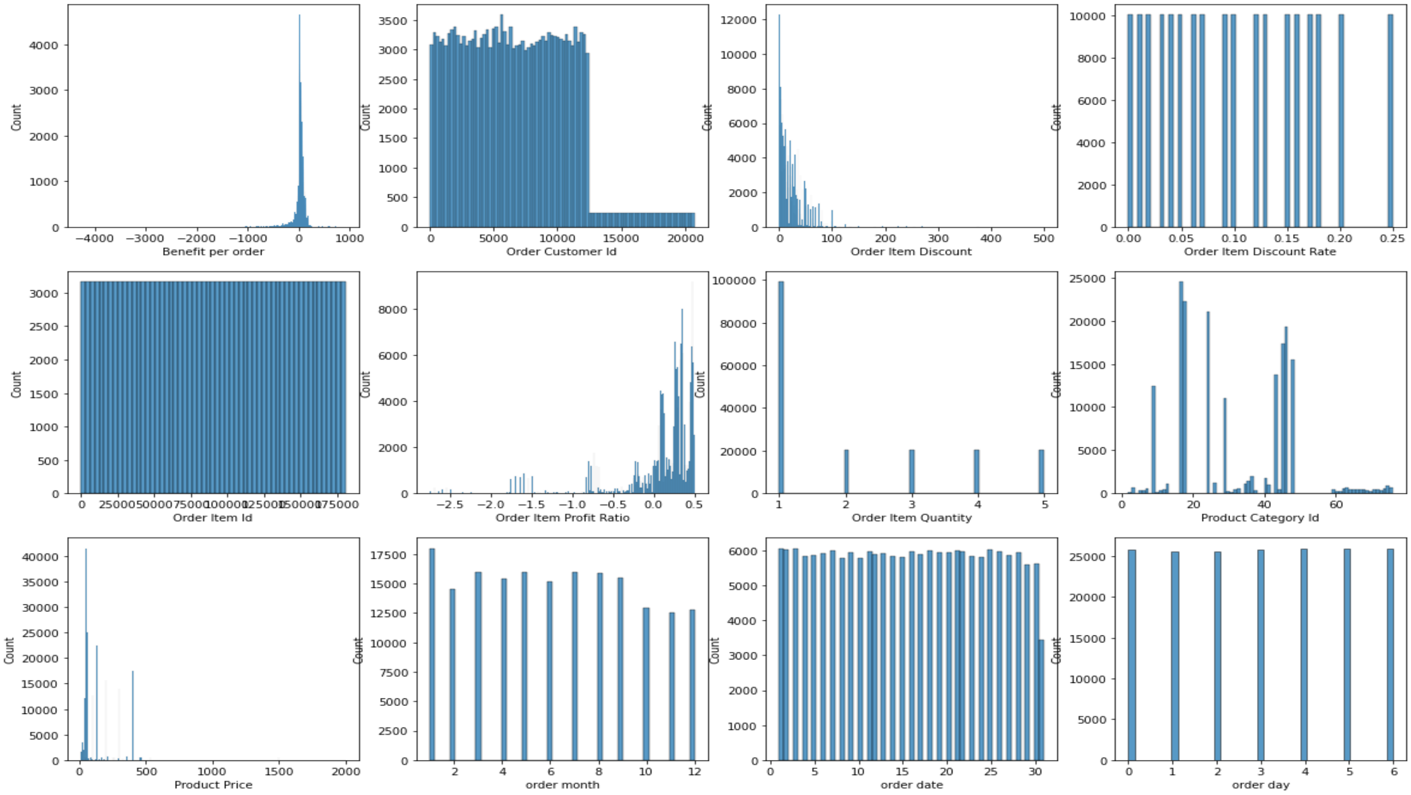
Final Data-Set Details:

The total number of continuous columns now that can be used in the dataset are: 12
The total number of categorical columns that can be used in the dataset are 18

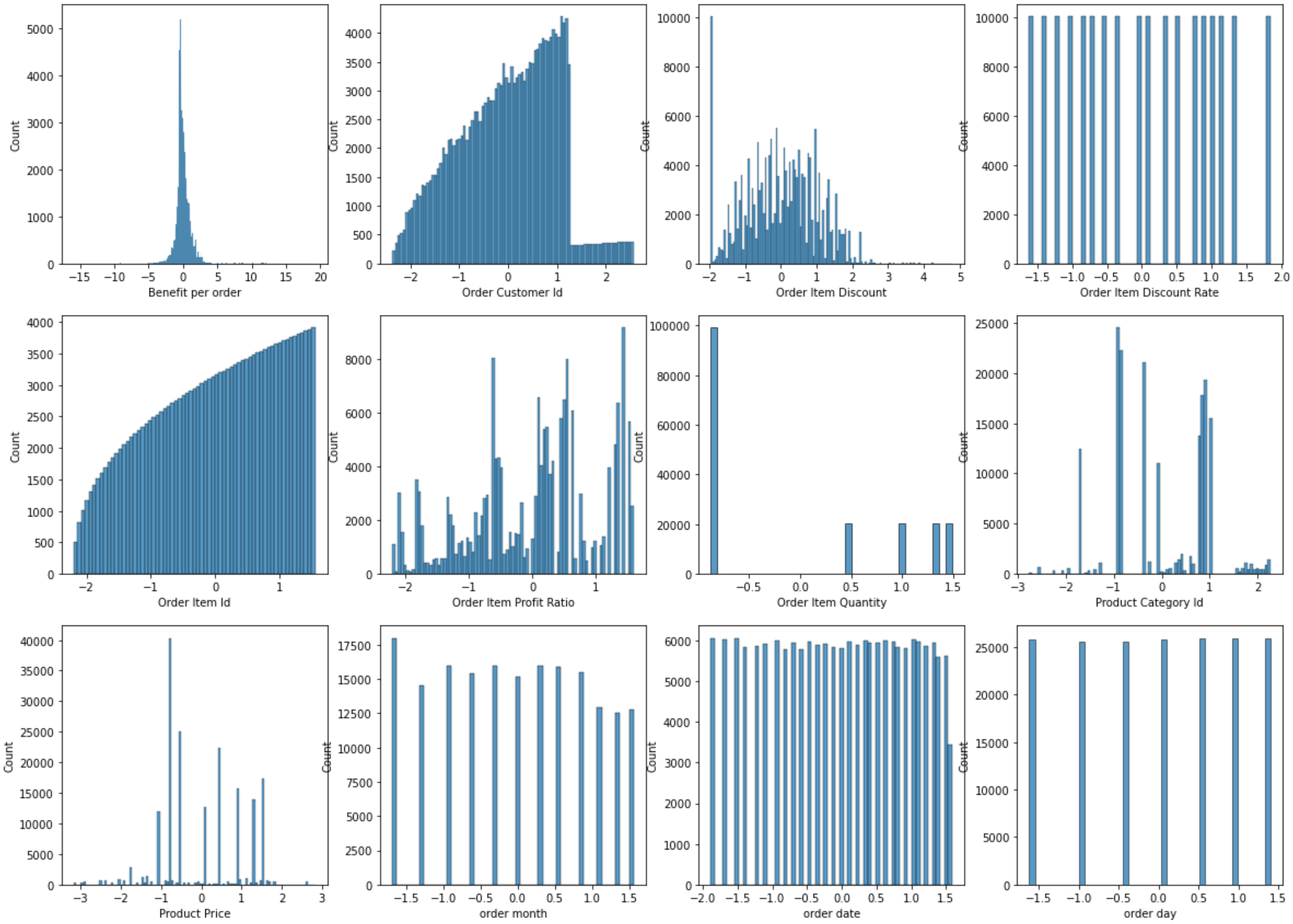
Feature Engineering:

For feature engineering we have decided to normalize the continuous columns using PowerTransformer to make it normally distributed, and for the categorical columns we used LabelEncoder.

Distribution of numerical columns before applying PowerTransformer:



Distribution of numerical columns after applying PowerTransformer:



Statistically checking the significance of each variable:

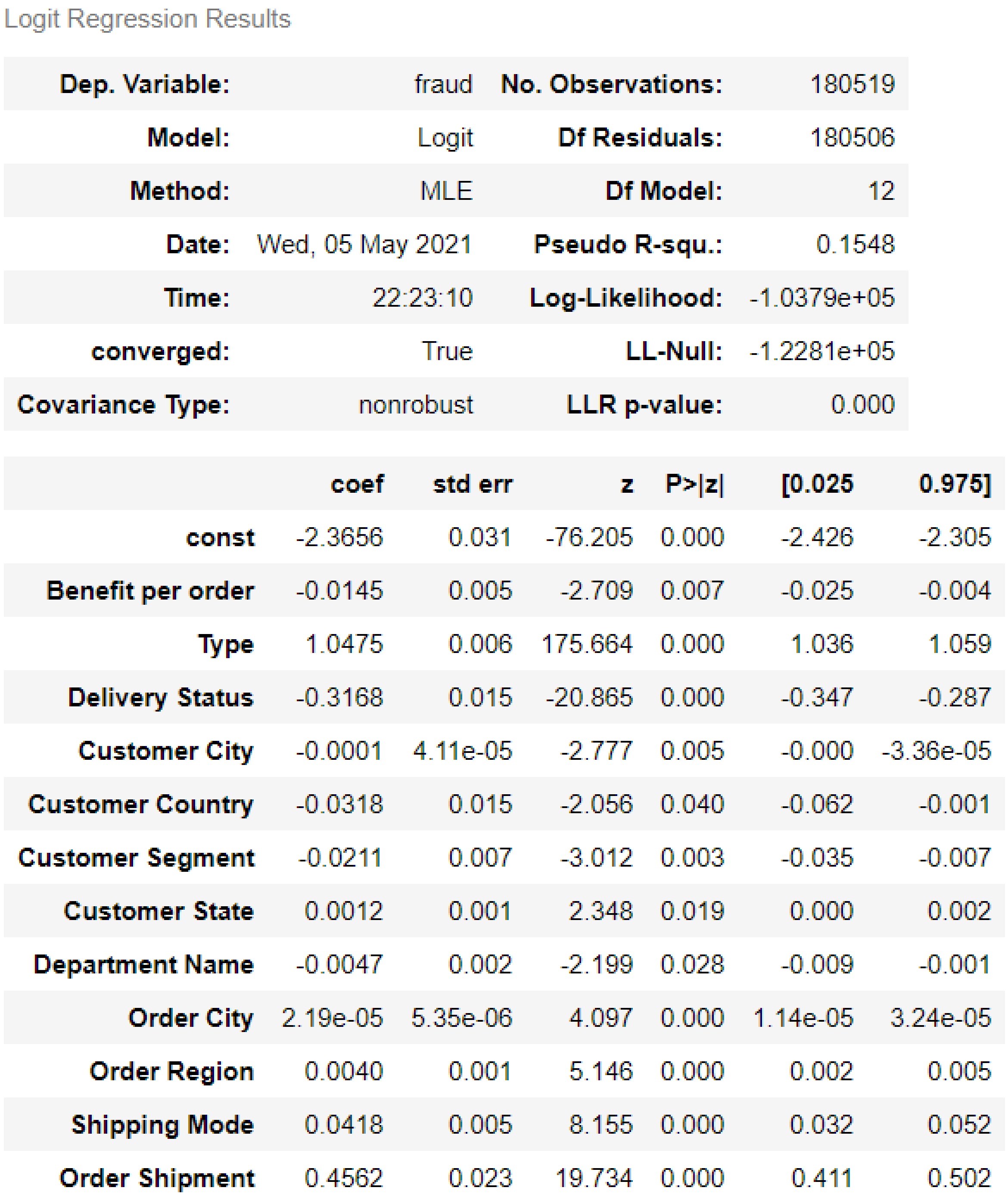
We applied the StatsModel Logit() model in our dataset to get features which have p-value < 0.05.

To select the significant variables we will selected them based on the p-values of the same, the hypothesis is such that:

H0: Feature is significant where p-value < 0.05

H1: Feature is not significant where p-Value > 0.05

And after getting the base model, we have applied backward elimination to get the best features from the dataset so that we can proceed with the model making and predict the target. The best features are listed below:



Logit Regression Results

Dep. Variable:	fraud	**No. Observations:**	180519
Model:	Logit	**Df Residuals:**	180506
Method:	MLE	**Df Model:**	12
Date:	Wed, 05 May 2021	**Pseudo R-squ.:**	0.1548
Time:	22:23:10	**Log-Likelihood:**	-1.0379e+05
converged:	True	**LL-Null:**	-1.2281e+05
Covariance Type:	nonrobust	**LLR p-value:**	0.000

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-2.3656	0.031	-76.205	0.000	-2.426	-2.305
Benefit per order	-0.0145	0.005	-2.709	0.007	-0.025	-0.004
Type	1.0475	0.006	175.664	0.000	1.036	1.059
Delivery Status	-0.3168	0.015	-20.865	0.000	-0.347	-0.287
Customer City	-0.0001	4.11e-05	-2.777	0.005	-0.000	-3.36e-05
Customer Country	-0.0318	0.015	-2.056	0.040	-0.062	-0.001
Customer Segment	-0.0211	0.007	-3.012	0.003	-0.035	-0.007
Customer State	0.0012	0.001	2.348	0.019	0.000	0.002
Department Name	-0.0047	0.002	-2.199	0.028	-0.009	-0.001
Order City	2.19e-05	5.35e-06	4.097	0.000	1.14e-05	3.24e-05
Order Region	0.0040	0.001	5.146	0.000	0.002	0.005
Shipping Mode	0.0418	0.005	8.155	0.000	0.032	0.052
Order Shipment	0.4562	0.023	19.734	0.000	0.411	0.502

Using the above features we created a dataset so that we proceed with the final model building.

Data Modelling

To measure the performance of different models the machine learning models are trained to detect fraud. And the different measures used to measure the performance of a Regression model are:

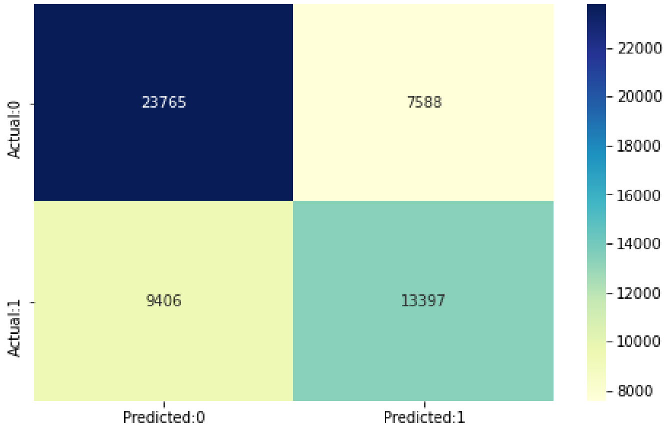
Accuracy: Accuracy refers to how close a measurement is to the true or accepted value.

Precision: Precision talks about how precise/accurate your model is out of those predicted positive, how many of them are actual positive.

Re-call: Recall actually calculates how many of the Actual Positives our model capture through labeling it as Positive (True Positive).

F1-Score F1 which is a function of Precision and Recall.

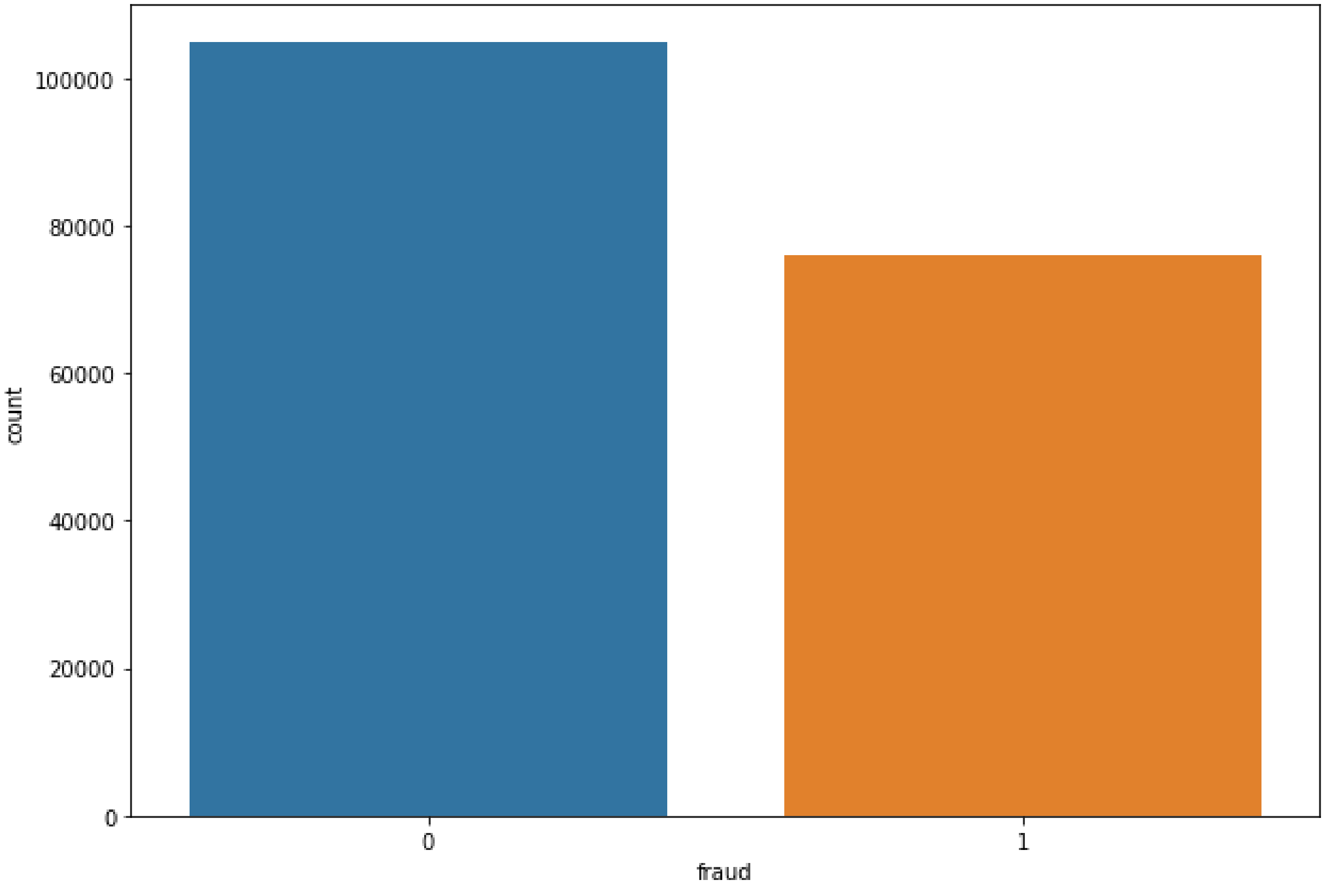
1. Base Model (Logistic regression):



True negative: 23765
True Positive: 13397
False Negative: 9406
False Positive: 7588
The accuracy of the base model is: 68.62028214786912
The precision of the base model is: 63.84083869430546
The re-call value of the base mode is: 58.75104152962329
The f1-score of the base model is: 61.19028044213026

This is the Benchmark that we set for future Machine Learning models, we would be using advanced regression models, tune the same using hyperparameter tuning and get the best model from the same.

Before we proceeded, we checked if there is any im-balance in the target variable:



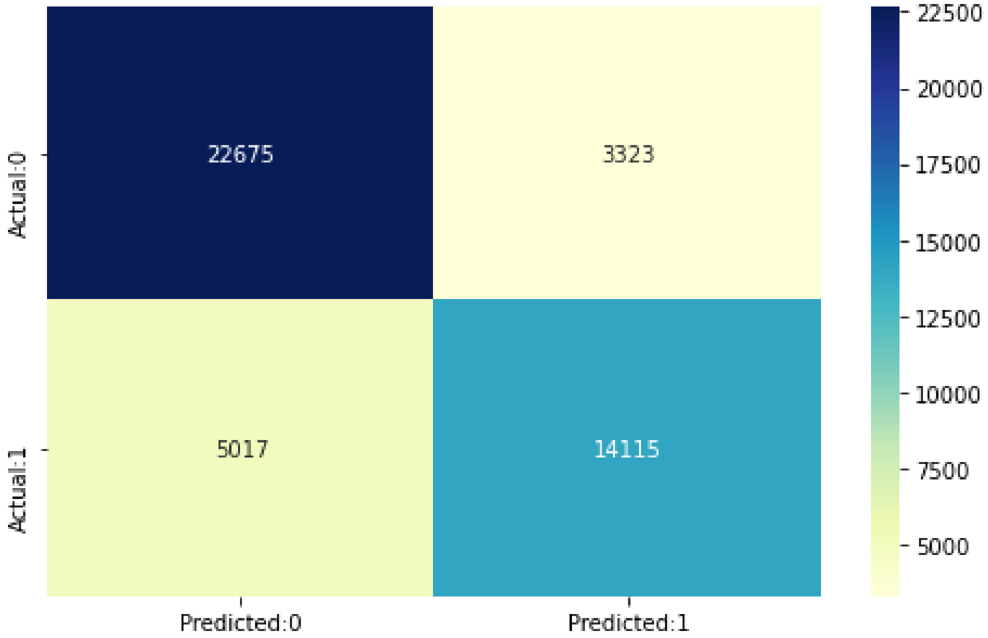
From the above plot we see that there is no in-balance present in the target variable.

So going ahead with model building:

First, we will do base model and then tune the same using hyperparameter tuning.

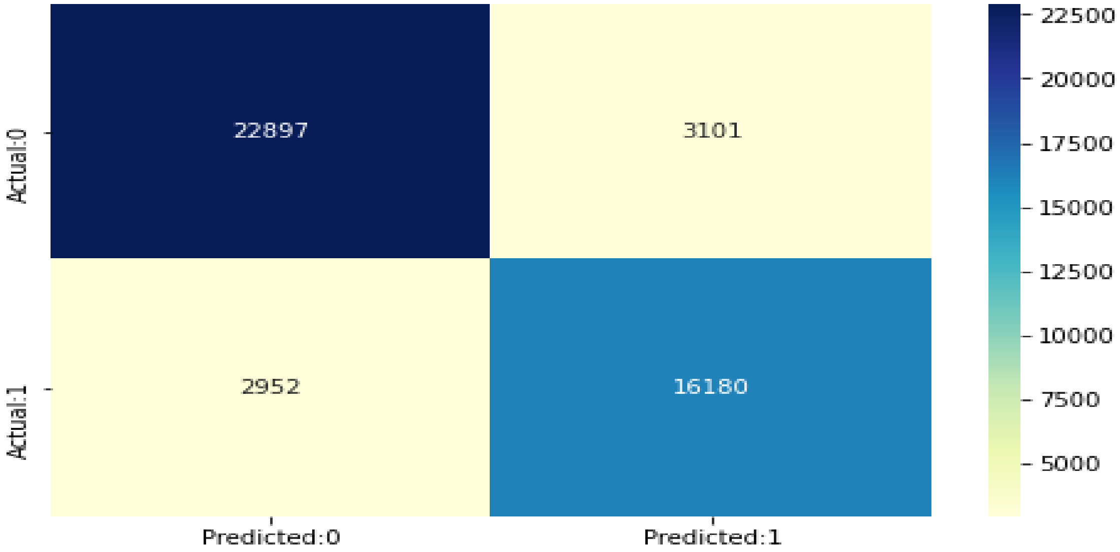
We also split the data to train and test dataset using train_test_split, and kept the test size as 0.25

2. **Prediction using KNN:**



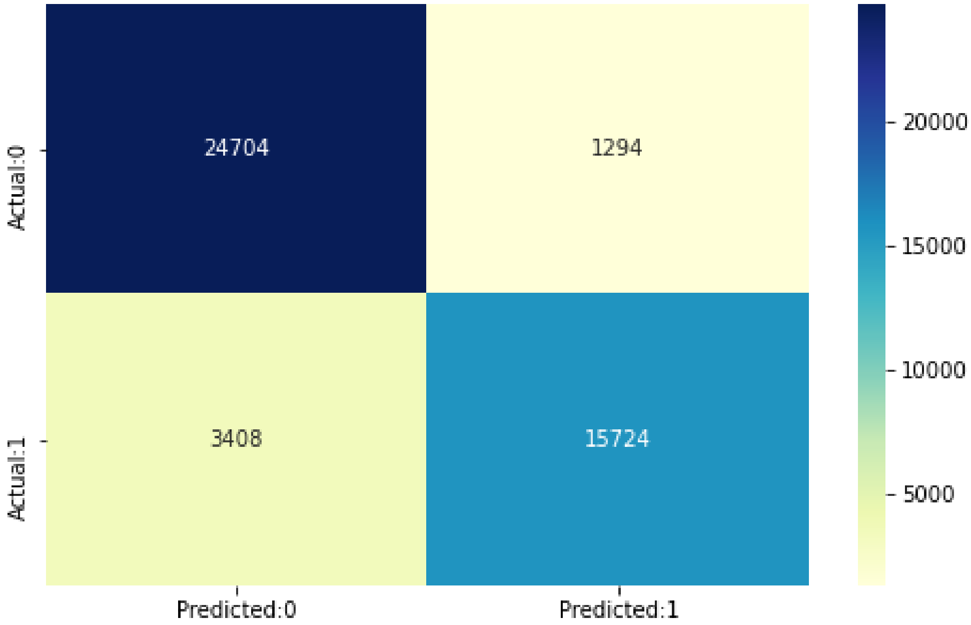
True negative: 22675
True Positive: 14115
False Negative: 5017
False Positive: 3323
The accuracy of the base model is: 81.52005317970308
The precision of the base model is: 80.94391558664985
The re-call calue of the base mode is: 73.776918252143
The f1-score of the base model is: 77.19442165709597

3. **Prediction using Decision Tree:**



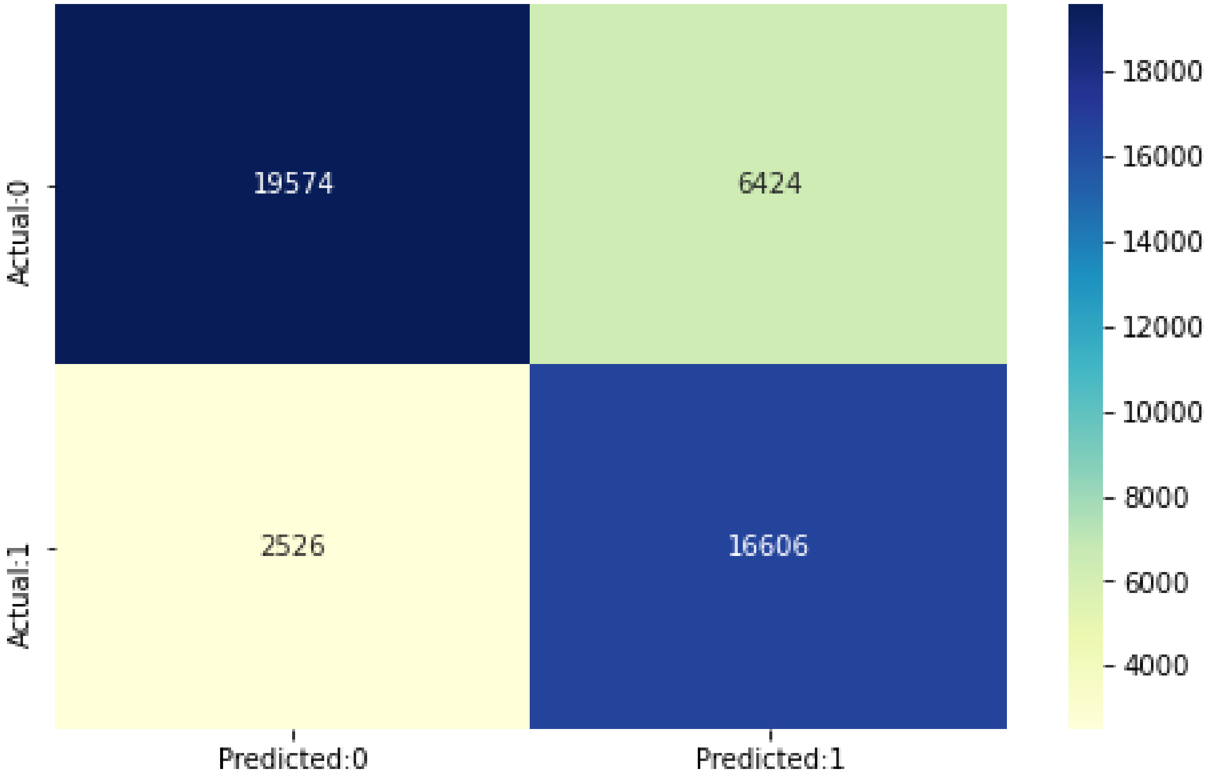
True negative: 22897
True Positive: 16180
False Negative: 2952
False Positive: 3101
The accuracy of the base model is: 86.58763571903391
The precision of the base model is: 83.91680929412375
The re-call calue of the base mode is: 84.57035333472716
The f1-score of the base model is: 84.24231380001562

4. **Prediction using Random Forest:**



True negative: 24704
True Positive: 15724
False Negative: 3408
False Positive: 1294
The accuracy of the base model is: 89.58120983824507
The precision of the base model is: 92.39628628510988
The re-call calue of the base mode is: 82.18691197992891
The f1-score of the base model is: 86.99308437067772

5. **Prediction using Naïve Bayes:**

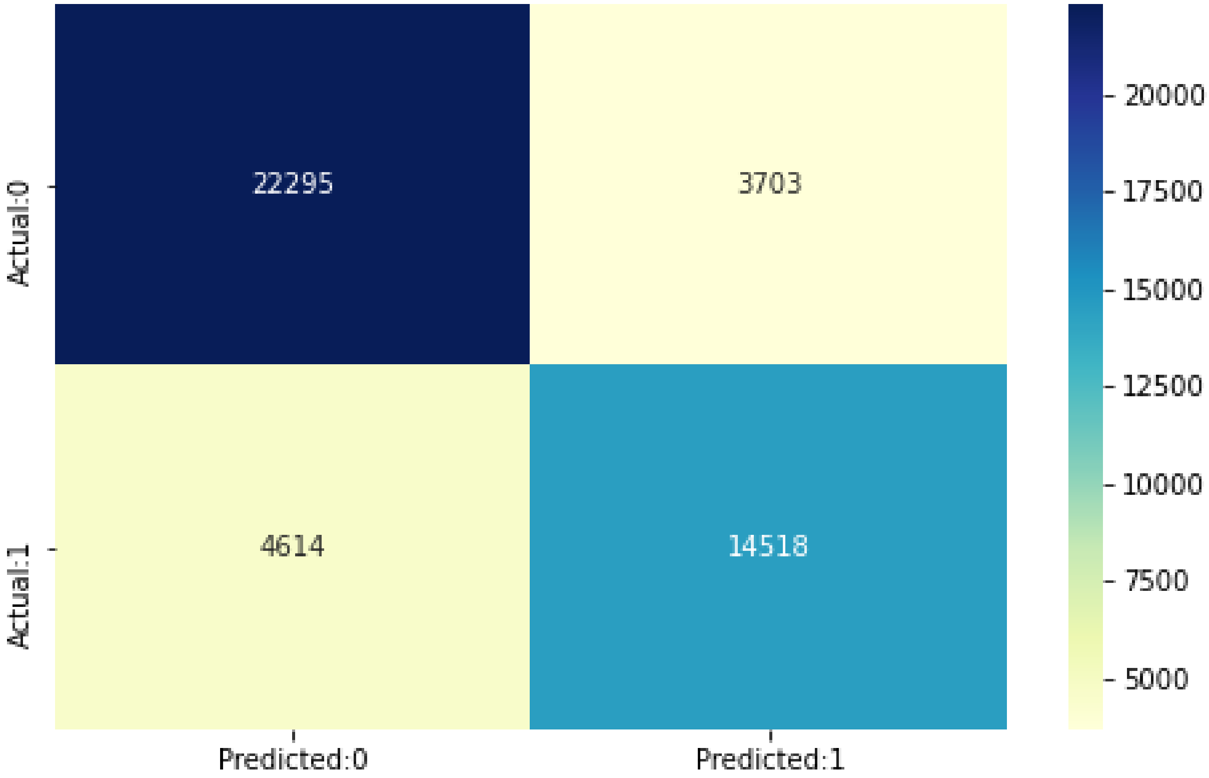


True negative: 19574
True Positive: 16606
False Negative: 2526
False Positive: 6424
The accuracy of the base model is: 80.16840239308664
The precision of the base model is: 72.10594876248372
The re-call calue of the base mode is: 86.79698933723604
The f1-score of the base model is: 78.77235425264456

We now will apply Hyperparameter tuning and using the best parameters for the same.

6. Hyperparameter tuning for KNN

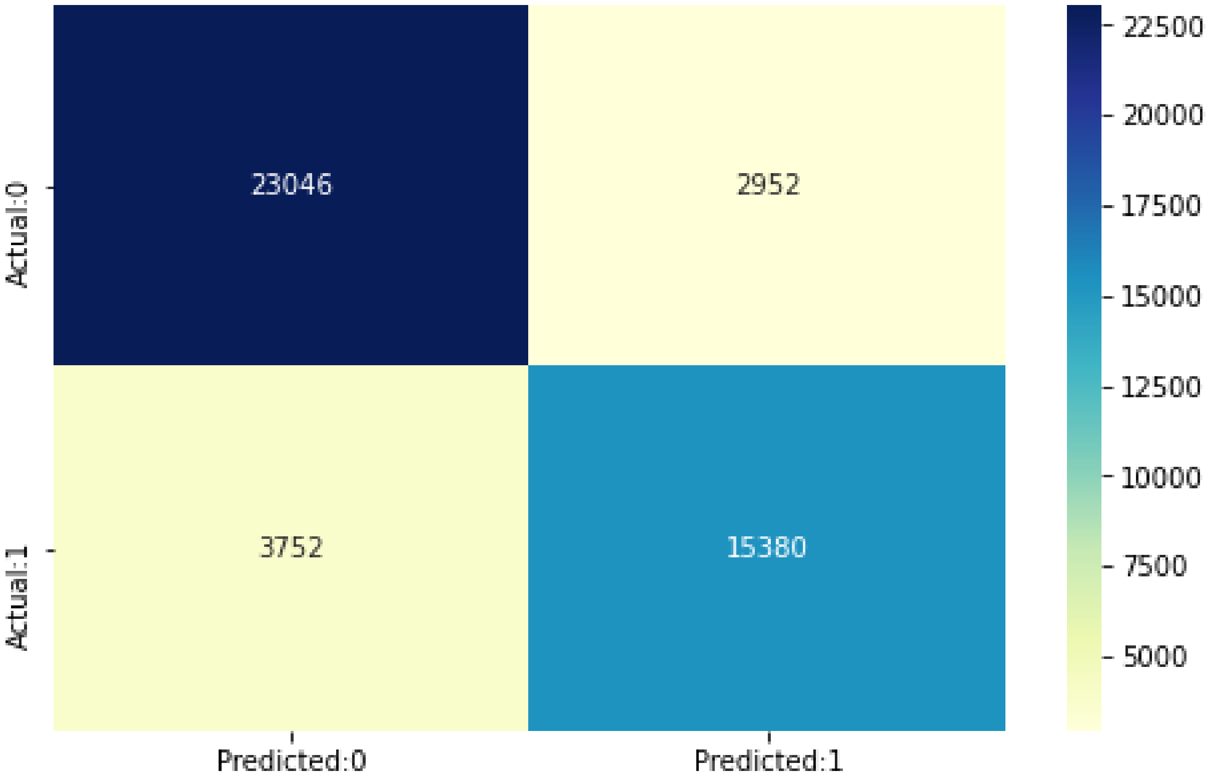
Best Parameters for KNN {'n_neighbors': 25, 'p': 2}



True negative: 22295
True Positive: 14518
False Negative: 4614
False Positive: 3703
The accuracy of the base model is: 81.57101706182141
The precision of the base model is: 79.6772954283519
The re-call calue of the base mode is: 75.88333681789672
The f1-score of the base model is: 77.73405081251842

7. Hyperparameter Tuning for Random Forest:

```
Best parameters for Random Forest:
 {'criterion': 'gini',
 'max_depth': 13,
 'max_features': 3,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'n_estimators': 165}
```

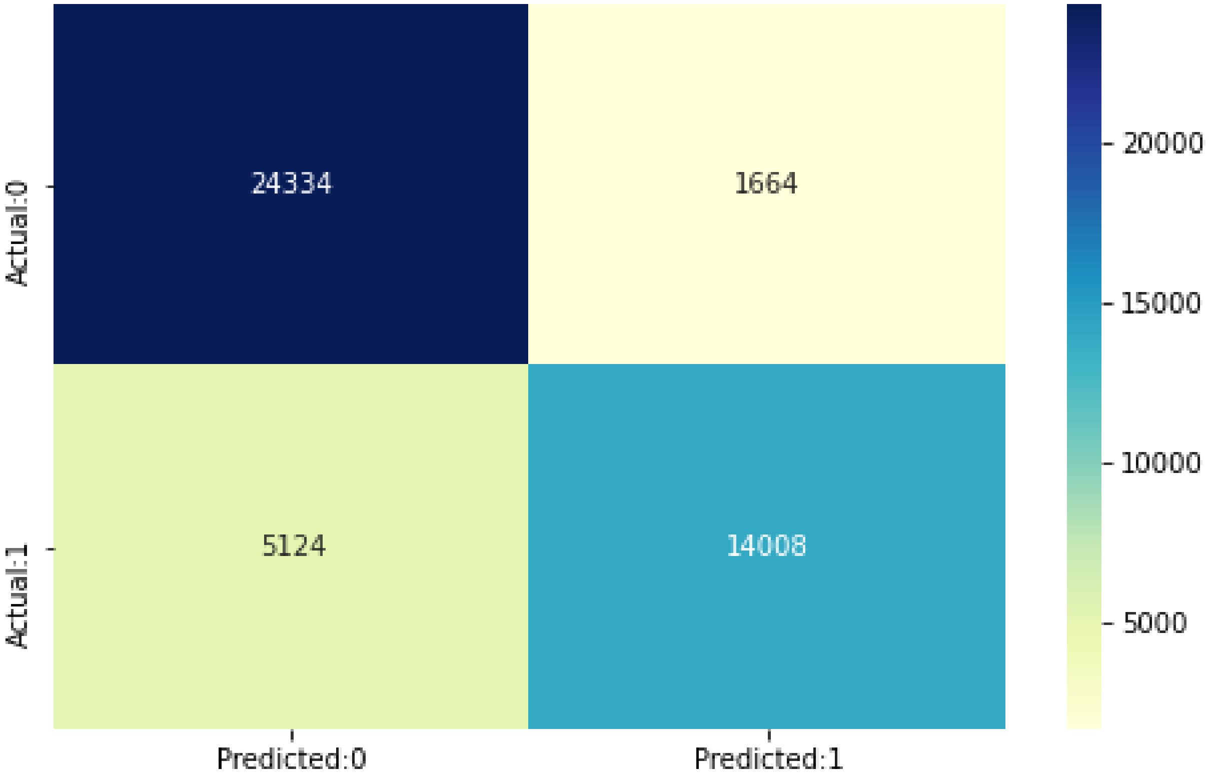


```
True negative: 23046
True Positive: 15380
False Negative: 3752
False Positive: 2952
The accuracy of the base model is:  85.14513627298913
The precision of the base model is:  83.89701069168667
The re-call calue of the base mode is:  80.38887727367761
The f1-score of the base model is:  82.10548793508434
```

8. **Hyper Parameter tuning for Decision tree:**

Best parameters for Decision tree are:

```
{'criterion': 'gini',
 'max_depth': 19,
 'max_features': 6,
 'min_samples_leaf': 26,
 'min_samples_split': 15}
```



True negative: 24334

True Positive: 14008

False Negative: 5124

False Positive: 1664

The accuracy of the base model is: 84.95900731220918

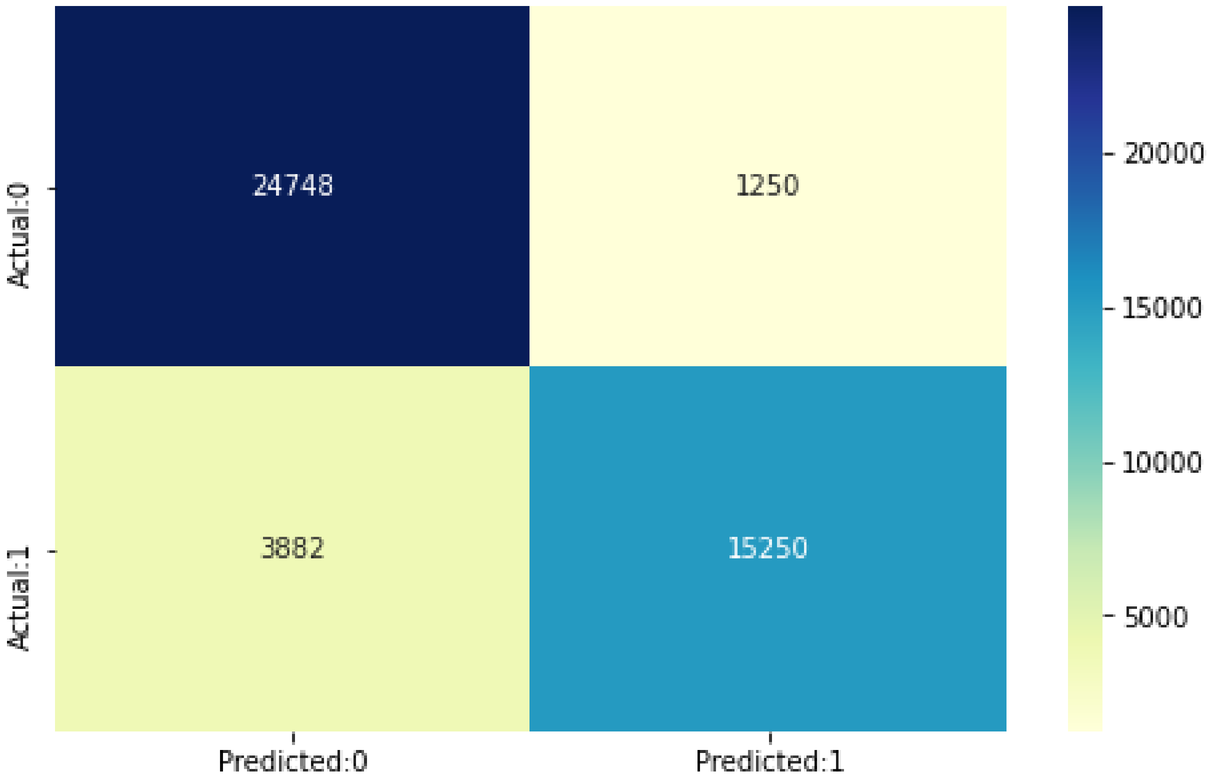
The precision of the base model is: 89.38233792751403

The re-call value of the base mode is: 73.21764582897762

The f1-score of the base model is: 80.49649465578669

9. Prediction using Bagging:

First we applied bagging without any base estimators:

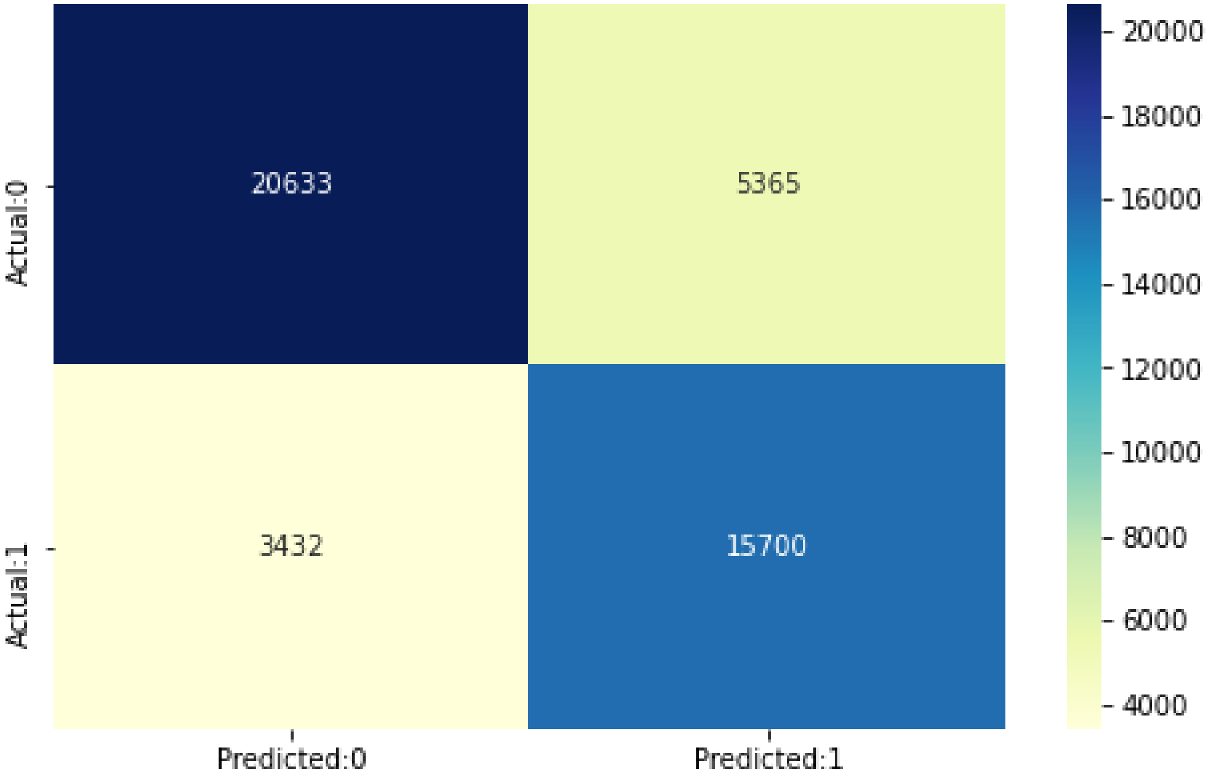


True negative: 24748
True Positive: 15250
False Negative: 3882
False Positive: 1250
The accuracy of the base model is: 88.62840682472857
The precision of the base model is: 92.42424242424242
The re-call value of the base mode is: 79.70938741375706
The f1-score of the base model is: 85.5972159856309

10. Bagging with Hyperparameter tuning:

Now, for hyperparameter tuning for bagging we have used the base estimators we got for knn, decision tree and random forest with the best parameters.

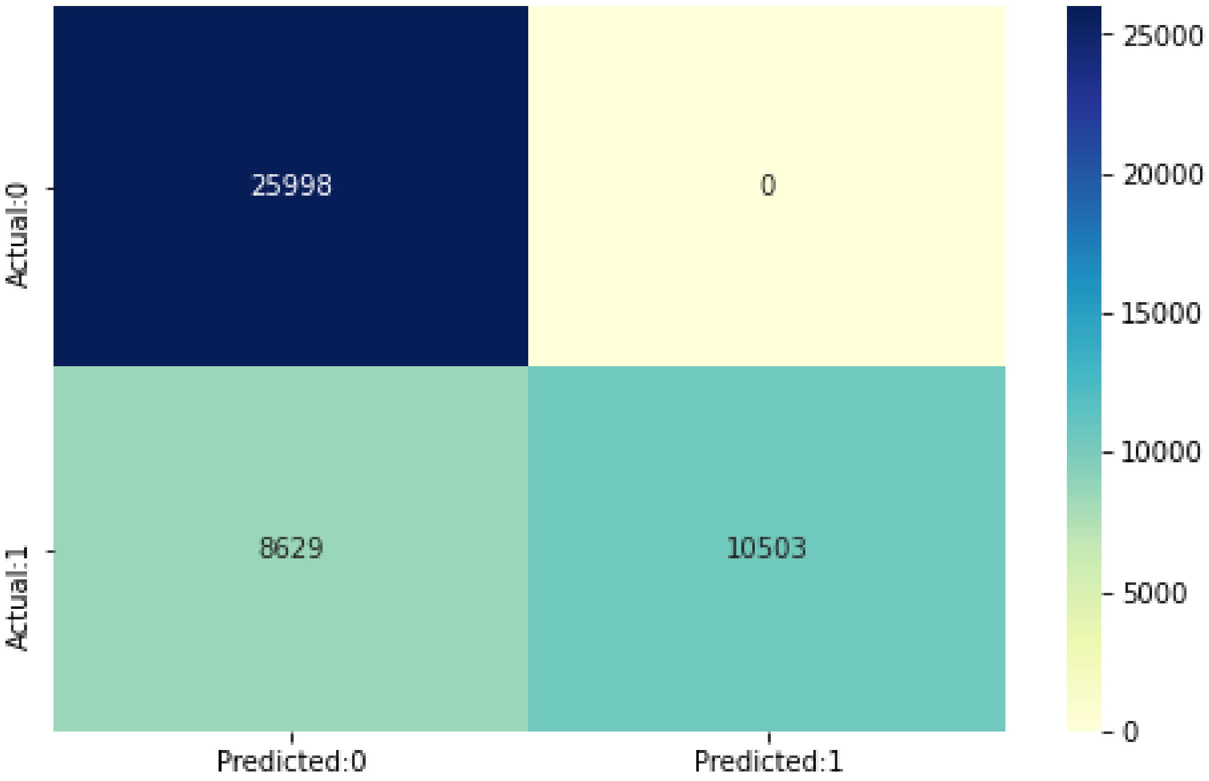
```
Best Parameters for Bagging:
{'base_estimator': RandomizedSearchCV(cv=3, estimator=DecisionTreeClassifier(random_state=0),
                   n_jobs=-1,
                   param_distributions={'criterion': ['gini', 'entropy'],
                   random_state=0, scoring='roc_auc'),
 'max_features': 9,
 'max_samples': 42,
 'n_estimators': 120}
```



True negative: 20633
True Positive: 15700
False Negative: 3432
False Positive: 5365
The accuracy of the base model is: 80.50742300022158
The precision of the base model is: 74.53121291241396
The re-call value of the base mode is: 82.06146769809742
The f1-score of the base model is: 78.11528223499266

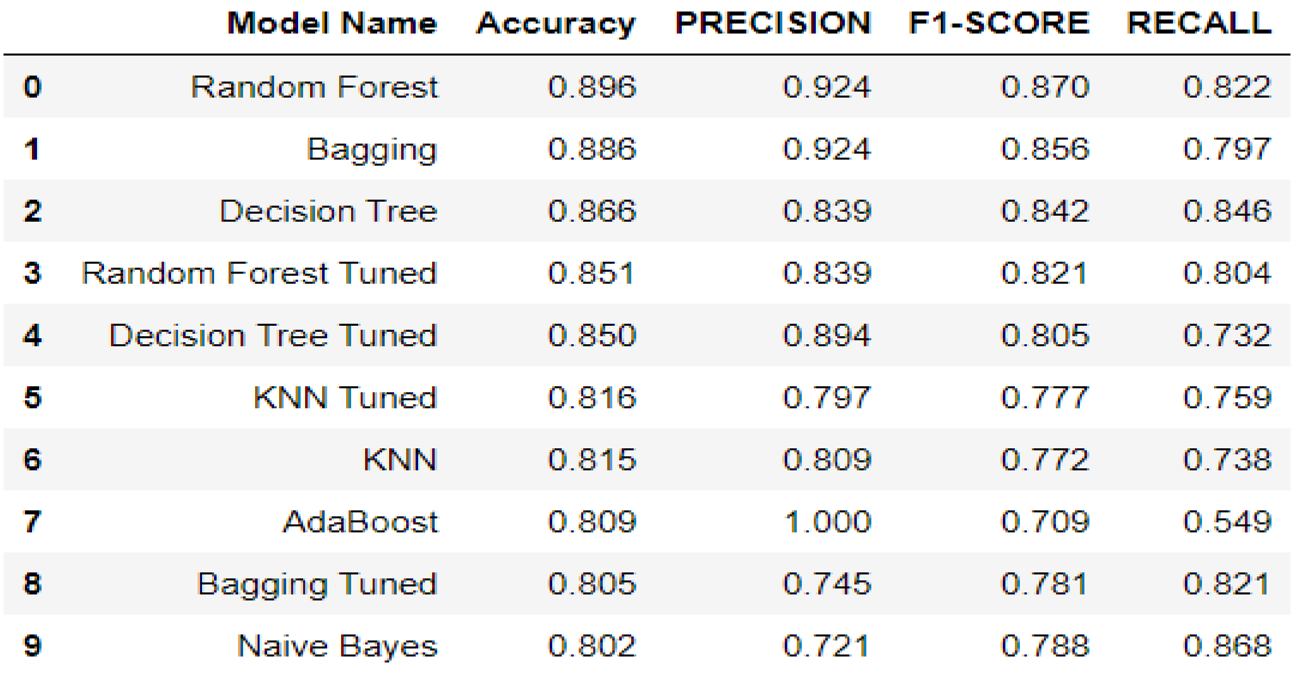
11. Boosting using AdaBoost:

We, have used base model for AdaBoost.



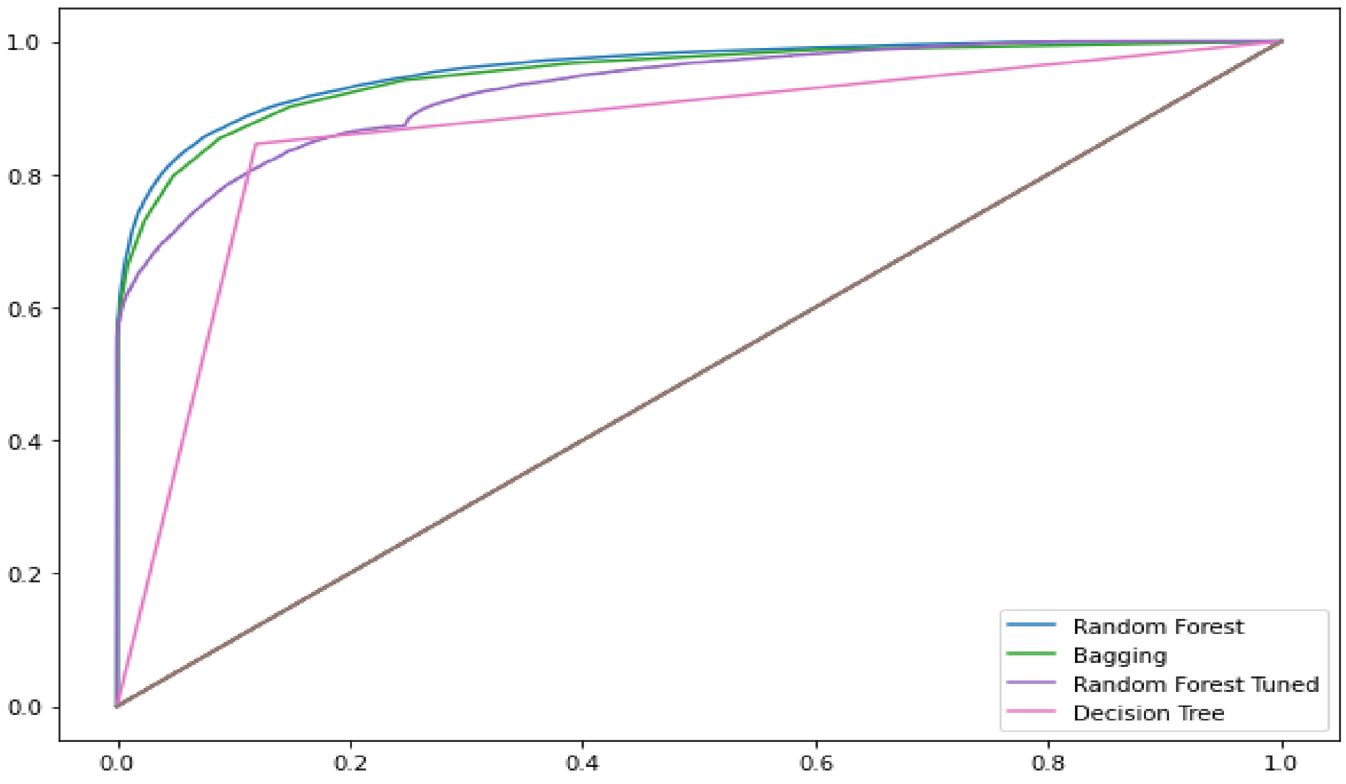
True negative: 25998
True Positive: 10503
False Negative: 8629
False Positive: 0
The accuracy of the base model is: 80.87968092178151
The precision of the base model is: 100.0
The re-call value of the base mode is: 54.89755383650429
The f1-score of the base model is: 70.88240256453518

Final Results:



	Model Name	Accuracy	PRECISION	F1-SCORE	RECALL
0	Random Forest	0.896	0.924	0.870	0.822
1	Bagging	0.886	0.924	0.856	0.797
2	Decision Tree	0.866	0.839	0.842	0.846
3	Random Forest Tuned	0.851	0.839	0.821	0.804
4	Decision Tree Tuned	0.850	0.894	0.805	0.732
5	KNN Tuned	0.816	0.797	0.777	0.759
6	KNN	0.815	0.809	0.772	0.738
7	AdaBoost	0.809	1.000	0.709	0.549
8	Bagging Tuned	0.805	0.745	0.781	0.821
9	Naive Bayes	0.802	0.721	0.788	0.868

ROC Curve for the top 4 performing models:



From the above table and the results that we have achieved here, we see that **RANDOM FOREST** will give us the best accuracy to detect a FRAUD activity.

Model Implications

We see that Random Forest is the best model among all the models that have been built here. Compared to the base model which only gave us a accuracy of 68%, we are getting a accuracy of 89% through random forest.

Some details about the base model:

The accuracy of the model = TP+TN / (TP+TN+FP+FN) = 0.6862028214786912
The Miss-classification = 1-Accuracy = 0.31379717852130884
Sensitivity or True Positive Rate = TP / (TP+FN) = 0.5875104152962329
Specificity or True Negative Rate = TN / (TN+FP) = 0.7579816923420406
Positive Predictive value = TP / (TP+FP) = 0.6384083869430546
Negative predictive Value = TN / (TN+FN) = 0.7164390582134997
Positive Likelihood Ratio = Sensitivity / (1-Specificity) = 2.427545341431575
Negative likelihood Ratio = (1-Sensitivity) / Specificity = 0.5441946538698594

From the above statistics it is clear that the model has a very high difference between sensitivity and specificity.

Some details about the model built using random forest

The accuracy of the model = TP+TN / (TP+TN+FP+FN) = 0.8958120983824507
The Miss-classification = 1-Accuracy = 0.10418790161754932
Sensitivity or True Positive Rate = TP / (TP+FN) = 0.8218691197992891
Specificity or True Negative Rate = TN / (TN+FP) = 0.9502269405338872
Positive Predictive value = TP / (TP+FP) = 0.9239628628510989
Negative predictive Value = TN / (TN+FN) = 0.8787706317586795
Positive Likelihood Ratio = Sensitivity / (1-Specificity) = 2.427545341431575
Negative likelihood Ratio = (1-Sensitivity) / Specificity = 0.5441946538698594

From the above statistics it is clear that the model has reduced the difference between sensitivity and specificity, that was seen in the base model.

Inconclusion, we see that if the company has to predict fraud accurately, a model with better accuracy, precision is required.

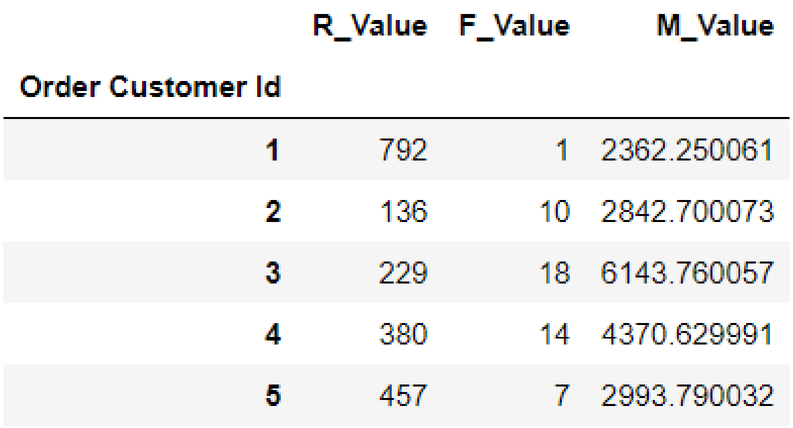
To improve the model performance, since there are many categorical columns present in the dataset, with many categories in each, we can for further better model building apply some technique to segment the categories into smaller categories and then proceed with better mode building to get more accurate results.

RFM ANALYSIS TO ANALIZE CUSTOMER RETENTION

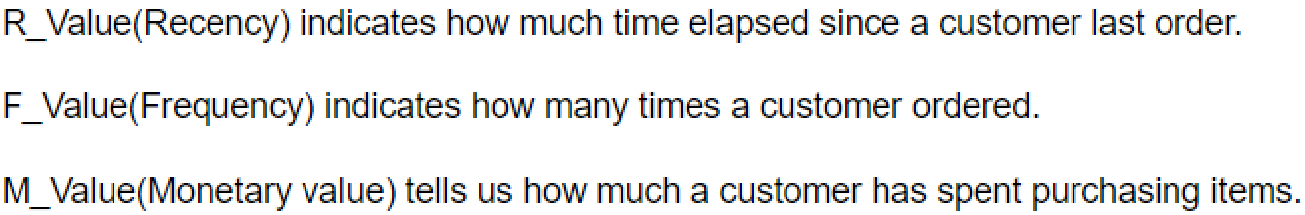
We have used the original dataset to analyse the RFM for the DataCO company.

Understanding customer needs and targeting specific clusters of customers based on their need is one way for a supply chain company to increase number of customers and also to gain more profits.Since,purchase history of customers is already available in the dataset, it can use RFM analysis for customer segmentation. Even though there are so many different methods for customer segmentation, RFM analysis is being used because it utilizes numerical values to show Customer recency,frequency and monetary values and also the output results are easy to interpret

After analysis we get the below table:



	R_Value	F_Value	M_Value
Order Customer Id			
1	792	1	2362.250061
2	136	10	2842.700073
3	229	18	6143.760057
4	380	14	4370.629991
5	457	7	2993.790032

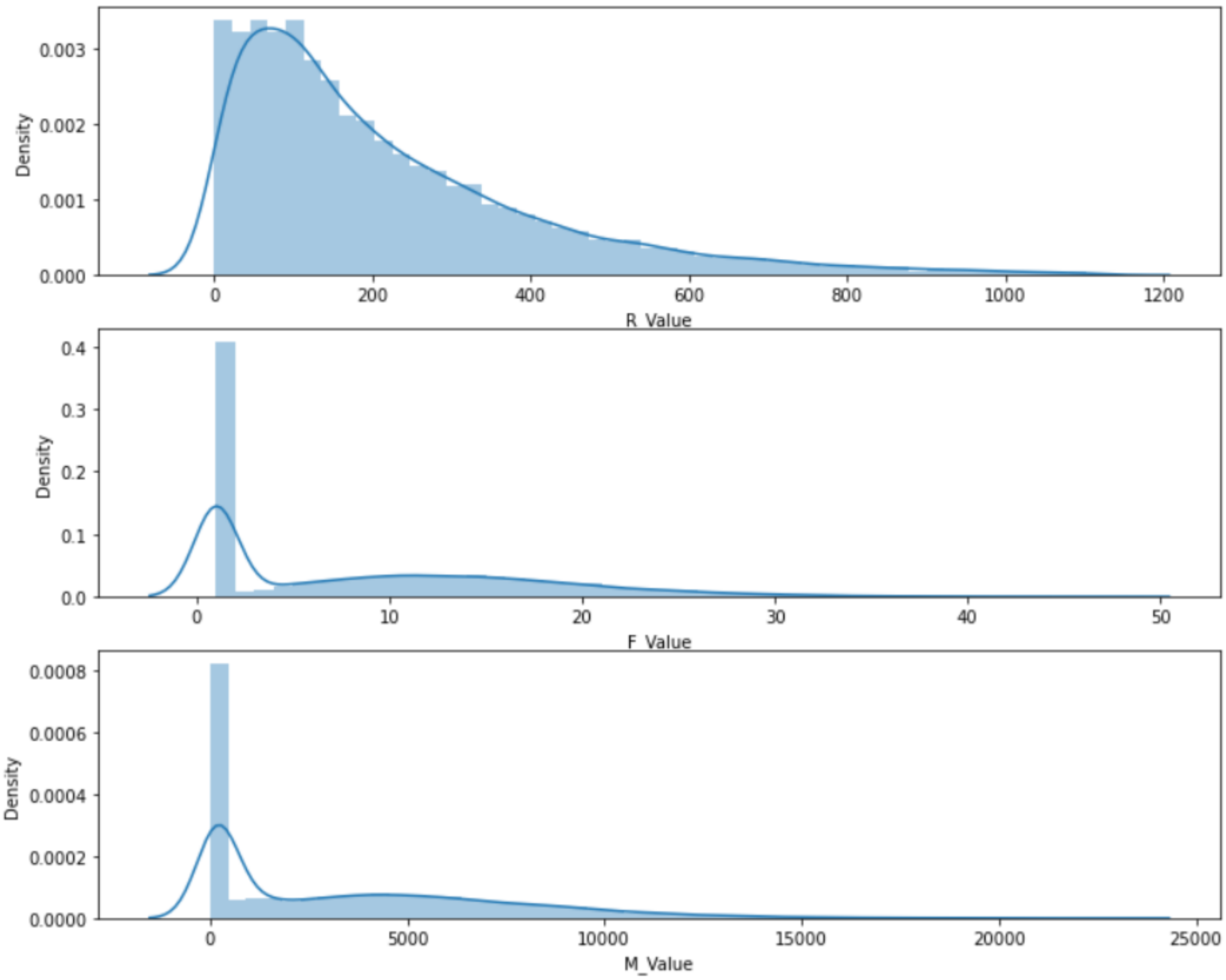


R_Value(Recency) indicates how much time elapsed since a customer last order.

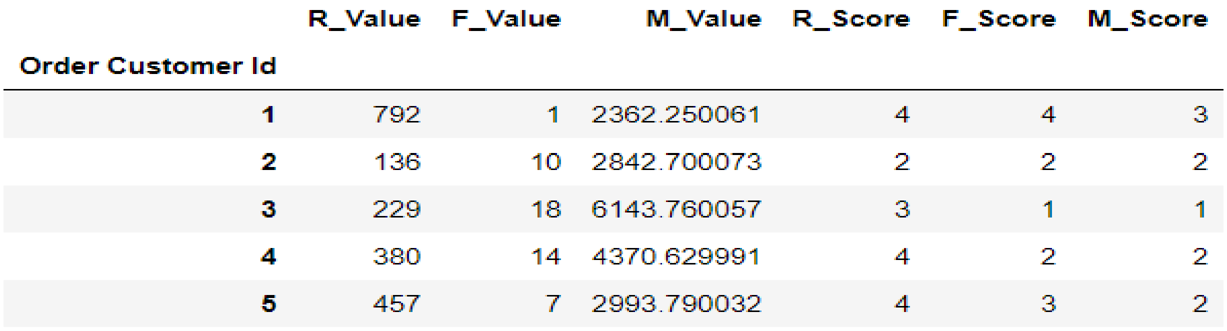
F_Value(Frequency) indicates how many times a customer ordered.

M_Value(Monetary value) tells us how much a customer has spent purchasing items.

Plotting the distribution for Recency, Frequency and Monetary value:



The total data is divided into 4 quantiles. The R_Value should be low because it indicates recent customer activity and F_value, M_Value should be high since they indicate frequency and total value of purchase. Function is defined to indicate quantiles as numerical values.



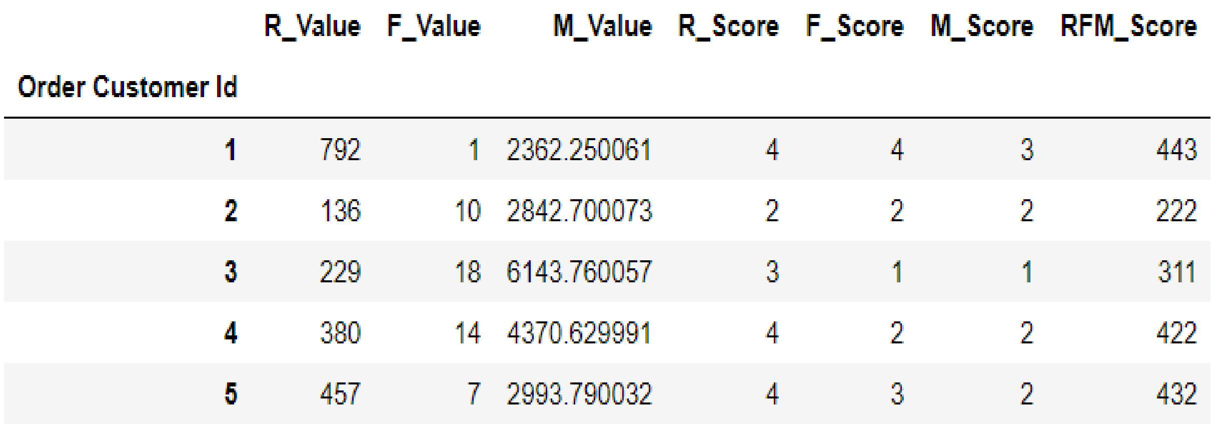
	R_Value	F_Value	M_Value	R_Score	F_Score	M_Score
Order Customer Id						
1	792	1	2362.250061	4	4	3
2	136	10	2842.700073	2	2	2
3	229	18	6143.760057	3	1	1
4	380	14	4370.629991	4	2	2
5	457	7	2993.790032	4	3	2

The individual scores of R,F,M are known.A column for combined RFM score is created.

The RFM score is then calculated from the above table:

#Adding R,F,M Scores to one new column

Customer_seg['RFM_Score'] = Customer_seg.R_Score.astype(str)+
Customer_seg.F_Score.astype(str)+Customer_seg.M_Score.astype(str)

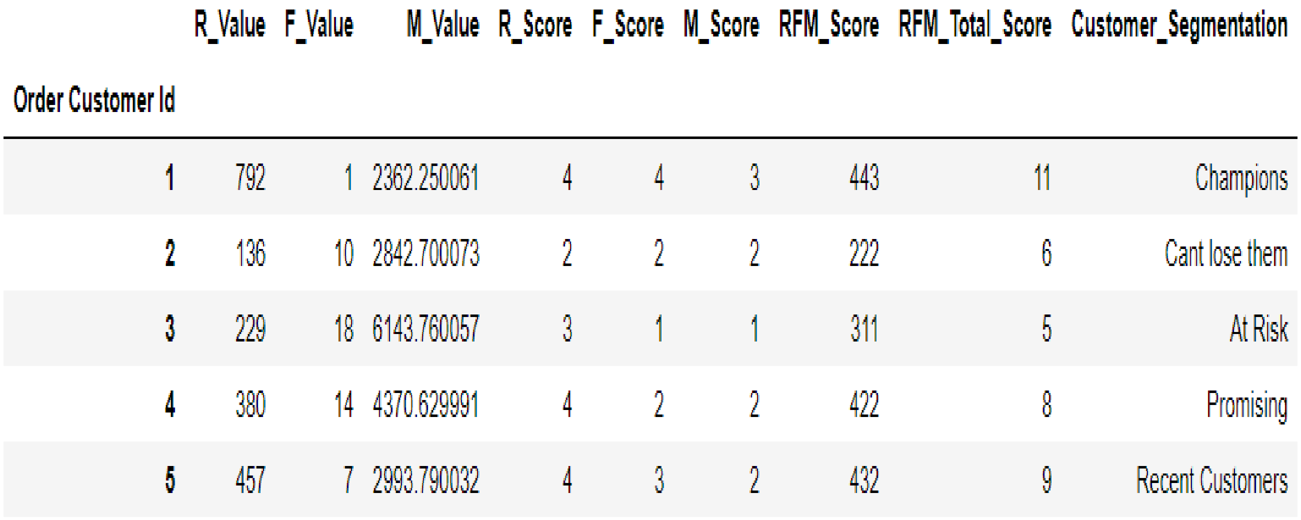


	R_Value	F_Value	M_Value	R_Score	F_Score	M_Score	RFM_Score
Order Customer Id							
1	792	1	2362.250061	4	4	3	443
2	136	10	2842.700073	2	2	2	222
3	229	18	6143.760057	3	1	1	311
4	380	14	4370.629991	4	2	2	422
5	457	7	2993.790032	4	3	2	432

It can be seen that there are 33 different customer segments. To make it easier for segmentation individual R,F,M scores are added together

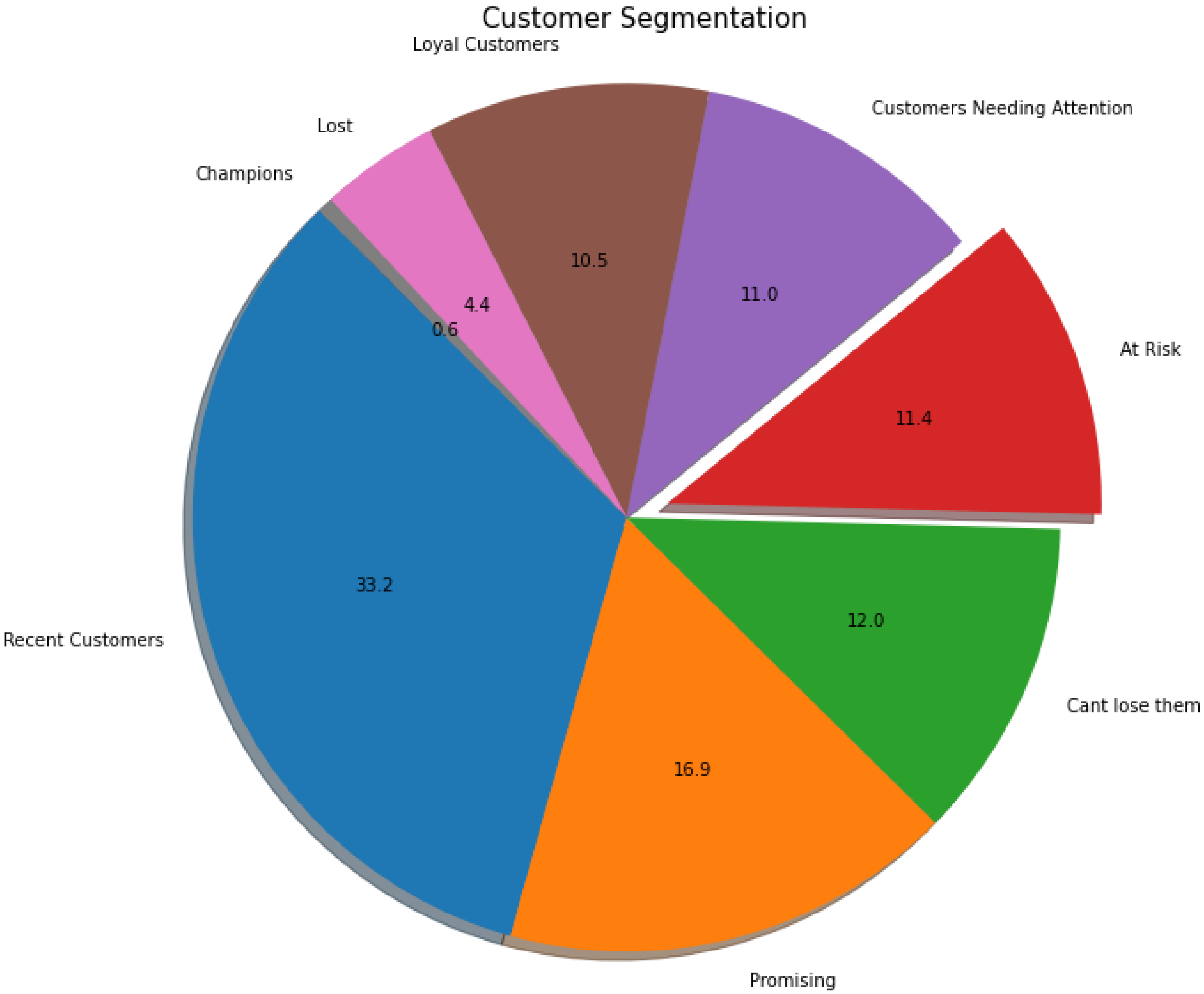
Customer_seg['RFM_Total_Score'] = Customer_seg[['R_Score','F_Score','M_Score']].sum(axis=1)

There are 9 values in total for customer segmentation. Appropriate names were assigned for each value separately.



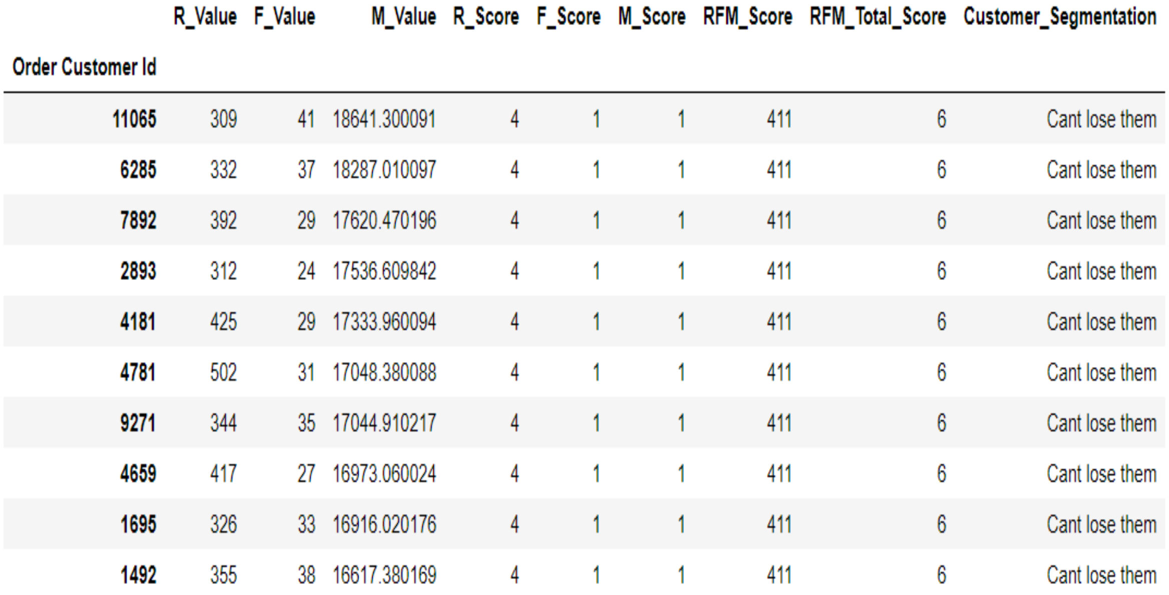
	R_Value	F_Value	M_Value	R_Score	F_Score	M_Score	RFM_Score	RFM_Total_Score	Customer_Segmentation
Order Customer Id									
1	792	1	2362.250061	4	4	3	443	11	Champions
2	136	10	2842.700073	2	2	2	222	6	Cant lose them
3	229	18	6143.760057	3	1	1	311	5	At Risk
4	380	14	4370.629991	4	2	2	422	8	Promising
5	457	7	2993.790032	4	3	2	432	9	Recent Customers

Visually, checking the segmentation, using pie chart.



Since total customers are divided into 9 segments it can be seen that, 11.4% customers are at risk of losing them as customers and 11% customers needs attention else even they will be lost eventually.It can be seen that 4.4% of customers are already lost.

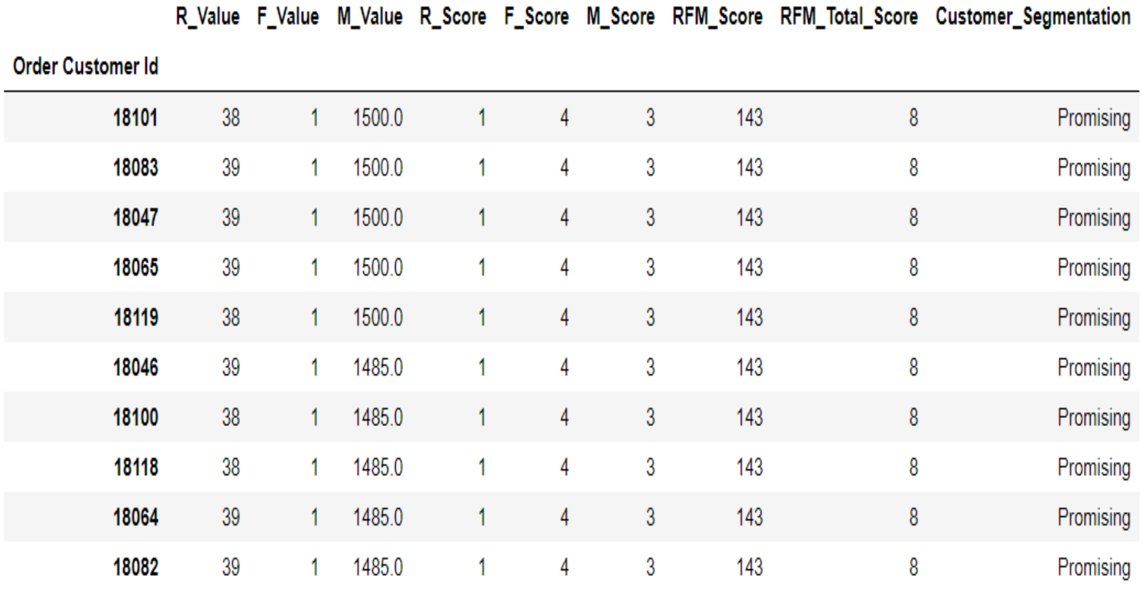
Our Top 10 Churned best customers who has not purchased anything in a while



	R_Value	F_Value	M_Value	R_Score	F_Score	M_Score	RFM_Score	RFM_Total_Score	Customer_Segmentation
Order Customer Id									
11065	309	41	18641.300091	4	1	1	411	6	Cant lose them
6285	332	37	18287.010097	4	1	1	411	6	Cant lose them
7892	392	29	17620.470196	4	1	1	411	6	Cant lose them
2893	312	24	17536.609842	4	1	1	411	6	Cant lose them
4181	425	29	17333.960094	4	1	1	411	6	Cant lose them
4781	502	31	17048.380088	4	1	1	411	6	Cant lose them
9271	344	35	17044.910217	4	1	1	411	6	Cant lose them
4659	417	27	16973.060024	4	1	1	411	6	Cant lose them
1695	326	33	16916.020176	4	1	1	411	6	Cant lose them
1492	355	38	16617.380169	4	1	1	411	6	Cant lose them

These customers used to place orders with huge amounts very frequently but they did not place orders from almost a year which means they are purchasing from other companies. These groups of people should be targeted with offers to gain them back.

Top 10 new best customers who place costly orders often.



	R_Value	F_Value	M_Value	R_Score	F_Score	M_Score	RFM_Score	RFM_Total_Score	Customer_Segmentation
Order Customer Id									
18101	38	1	1500.0	1	4	3	143	8	Promising
18083	39	1	1500.0	1	4	3	143	8	Promising
18047	39	1	1500.0	1	4	3	143	8	Promising
18065	39	1	1500.0	1	4	3	143	8	Promising
18119	38	1	1500.0	1	4	3	143	8	Promising
18046	39	1	1485.0	1	4	3	143	8	Promising
18100	38	1	1485.0	1	4	3	143	8	Promising
18118	38	1	1485.0	1	4	3	143	8	Promising
18064	39	1	1485.0	1	4	3	143	8	Promising
18082	39	1	1485.0	1	4	3	143	8	Promising

The above customers has the potential to become best customers this people should be targeted to convert them into loyal customers.All these different segment of customers should be targeted with different tailored advertisments and rewards for increased profits and more responsiveness from customers.

THANK YOU!!