Unlocking Future Transactions: Predicting Customer's Next Purchase in E-commerce through Machine Learning Analysis.

Rohit Kc[1], Shashikesh Shandilya[2], Manikesh Shandilya[3], Rajashree[4]

[1, 2 ,3] Student, ISE, Department of Information, AMCEC, Karnataka, India
[4] Professor, ISE, Department of Information, AMCEC, Karnataka, India

ABSTRACT

The exponential growth of the E-commerce industry has created a need for accurate sales predictions to drive effective business strategies. This abstract presents a data-driven approach to predict e-commerce sales by leveraging machine learning techniques. To develop the prediction model, historical sales data from various e-commerce platforms was collected and preprocessed to ensure data quality. Feature engineering techniques were applied to extract relevant information from the data, including customer demographics, product attributes, pricing, promotions, and seasonal trends. Several machine learning algorithms, including regression models, ensemble methods, and deep learning models, were implemented and evaluated to identify the most accurate prediction model.

Keyword: - *Prediction, E-commerce*

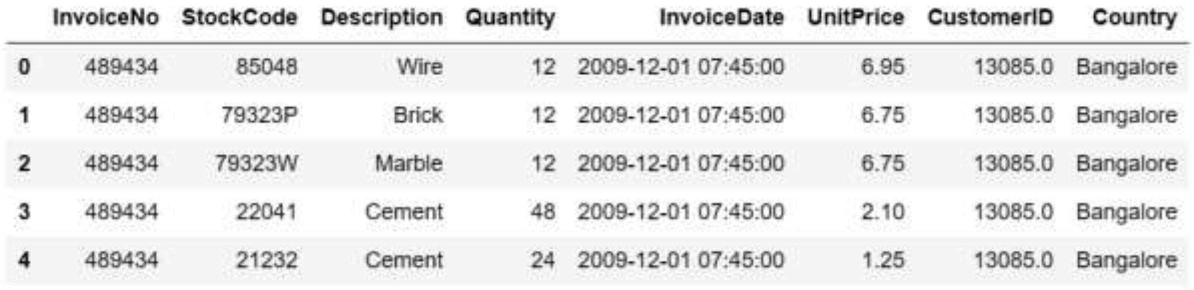
1. Introduction

The rapid growth of the e-commerce industry has revolutionized the way businesses operate and consumers shop. With the increasing prevalence of online shopping, e-commerce companies face the challenge of accurately predicting sales to optimize their operations, enhance customer satisfaction, and maximize profitability. Accurate sales predictions enable businesses to effectively manage inventory, allocate resources, plan marketing strategies, and meet customer demands in a timely manner. Sales prediction is a critical component of e-commerce business strategy, enabling companies to forecast consumer demand, optimize pricing, promotions, and inventory management, and identify growth opportunities. Accurate sales predictions can help businesses allocate resources effectively, reduce costs, and improve profitability. Machine learning techniques have emerged as a powerful tool for predicting e-commerce sales by leveraging the vast amounts of data generated by online transactions. By analyzing customer behavior, product attributes, pricing, and seasonality trends, machine learning algorithms can identify patterns and predict future sales performance with high accuracy.

1.1 Data Wrangling

Data wrangling encompasses various tasks, including data collection, data cleaning, data integration, data transformation, and feature engineering. These tasks are necessary to address issues such as missing values, inconsistencies, outliers, and incompatible data formats, among others.

```
# Rename the following columns:
#    Invoice to InvoiceNo
#    Customer ID to CustomerID
#    Price to UnitPrice
df.rename(columns={'Invoice':'InvoiceNo', 'Customer ID':'CustomerID',
                'Price':'UnitPrice'},
        inplace=True)
```



	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	489434	85048	Wire	12	2009-12-01 07:45:00	6.95	13085.0	Bangalore
1	489434	79323P	Brick	12	2009-12-01 07:45:00	6.75	13085.0	Bangalore
2	489434	79323W	Marble	12	2009-12-01 07:45:00	6.75	13085.0	Bangalore
3	489434	22041	Cement	48	2009-12-01 07:45:00	2.10	13085.0	Bangalore
4	489434	21232	Cement	24	2009-12-01 07:45:00	1.25	13085.0	Bangalore

Fig 1:-First Five Entries of the Dataset

1.2 Feature Engineering

To enhance customer segmentation and gain insights into their future purchase behavior, feature engineering techniques, specifically using the RFM segmentation method, were applied to the dataframe ctm_dt. RFM stands for Recency, Frequency, and Monetary Value/Revenue, which are key indicators used to segment customers.

Recency represents how recently a customer made a purchase, Frequency indicates the number of times a customer has made purchases, and Monetary Value/Revenue measures the amount of money a customer spends during a purchase. By combining these three features, an RFM score system was created to group customers based on their behavior and potential future purchase decisions.The RFM scores were calculated, providing a comprehensive understanding of each customer's purchasing patterns. These scores were then utilized in applying unsupervised machine learning algorithms to identify distinct customer groups or clusters. The resulting cluster assignments were added as additional features to the ctm_dt dataframe.

1.2.1 Recency

The length of time a customer has been inactive after their last purchase provides insights into their likelihood of engaging in a new transaction. Customers who have recently made a purchase are more likely to make another purchase soon compared to those who have not bought anything for an extended period.

Important to note that the sales generated by a customer who has made a recent purchase hold greater value compared to a customer who has been inactive for a significant duration. By focusing on the recency feature, businesses can prioritize their marketing efforts towards customers who have recently engaged in a transaction, as they are more likely to convert and contribute to revenue generation.

```
# Get the maximum purchase date of each customer and create a dataframe with it together with the
customer's id.
ctm_max_purchase = ctm_bhvr_dt.groupby('CustomerID').InvoiceDate.max().reset_index()
ctm_max_purchase.columns = ['CustomerID','MaxPurchaseDate']
# Find the recency of each customer in days
ctm_max_purchase['Recency'] = (ctm_max_purchase['MaxPurchaseDate'].max() -
ctm_max_purchase['MaxPurchaseDate']).dt.days
# Merge the dataframes ctm_dt and ctm_max_purchase[['CustomerID', 'Recency']] on the CustomerID column.
ctm_dt = pd.merge(ctm_dt, ctm_max_purchase[['CustomerID', 'Recency']], on='CustomerID')
```

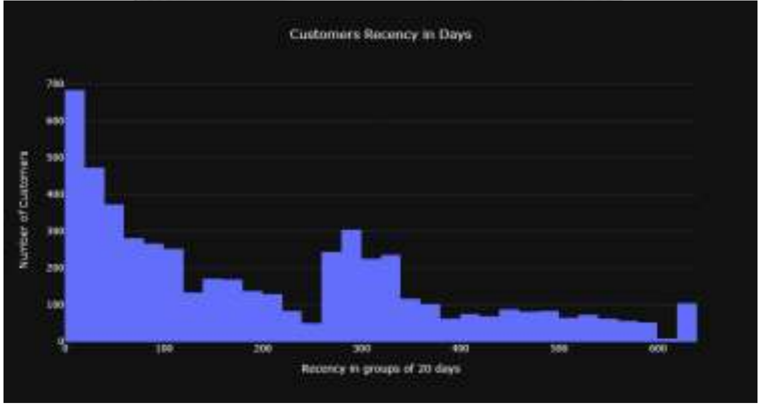


Fig 2:-Below gives a visual presentation of the recency data of the online customers.

1.2.2 Frequency

The frequency characteristic provides valuable insights into a customer's loyalty and engagement with a specific company or brand. It helps the company understand the level of commitment and alliance that customers have towards their products or services. By analyzing the frequency of customer purchases, businesses can gain a deeper understanding of customer behavior and preferences

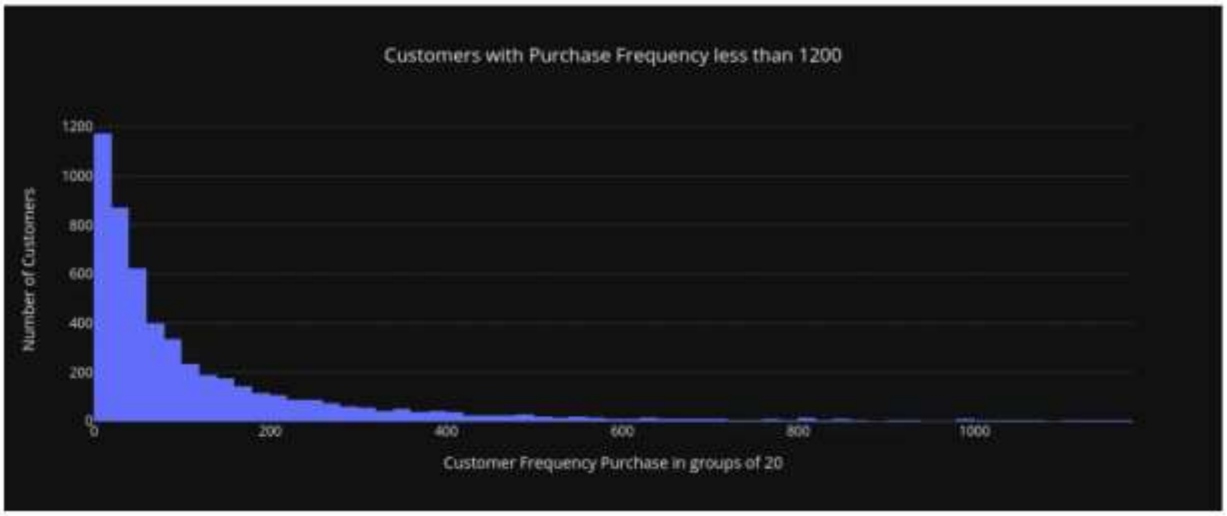
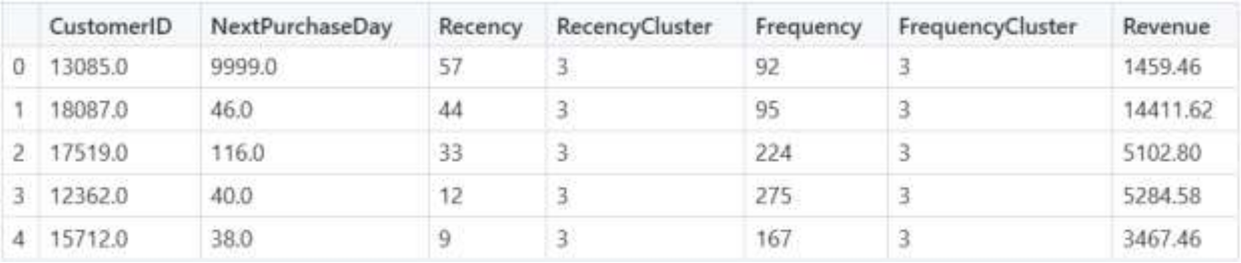


Fig 3:- Customer Frequency

1.2.3 Monetary Value/Revenue

The Monetary Value or revenue characteristic provides insights into the amount of money a customer typically spends during a purchase at any given point in time. This feature focuses on understanding the customer's spending behavior and allows businesses to estimate the potential revenue that can be generated when the customer engages in a transaction.While the Monetary Value feature does not directly predict the timing of the customer's next purchase, it is valuable in assessing the potential financial impact when the customer does make a transaction. By analyzing the historical spending patterns of customers, businesses can gain an understanding of their purchasing power and tailor their marketing and sales strategies accordingly.

```
# Create a new label, Revenue of each item bought
df_data['Revenue'] = df_data.UnitPrice * df_data.Quantity
# Get the revenue from each customer and sum them.
ctm_revenue = df_data.groupby('CustomerID').Revenue.sum().reset_index()
# Merge the dataframe ctm_revenue with ctm_dt
ctm_dt = pd.merge(ctm_dt, ctm_revenue, on='CustomerID')
ctm_dt.head()
```



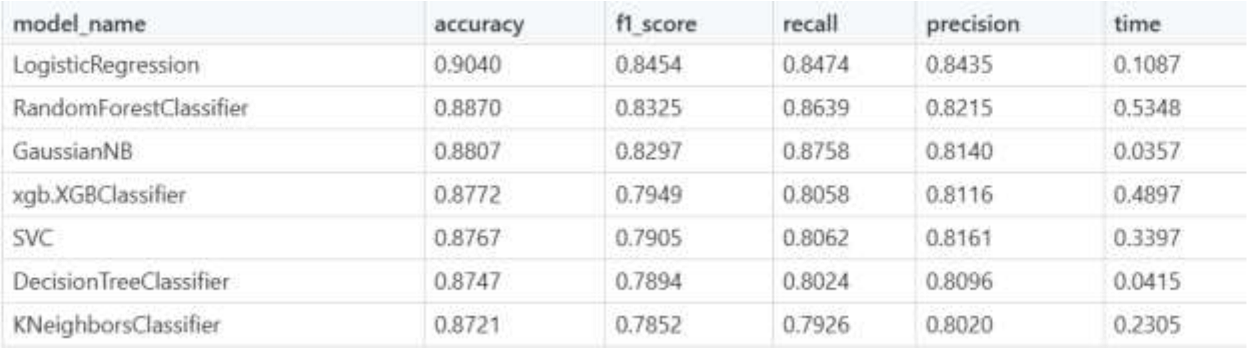
	CustomerID	NextPurchaseDay	Recency	RecencyCluster	Frequency	FrequencyCluster	Revenue
0	13085.0	9999.0	57	3	92	3	1459.46
1	18087.0	46.0	44	3	95	3	14411.62
2	17519.0	116.0	33	3	224	3	5102.80
3	12362.0	40.0	12	3	275	3	5284.58
4	15712.0	38.0	9	3	167	3	3467.46

Fig 4:-First five entries of the main dataset with Revenue

1.3 Building Machine Learning Models

In this section, we discuss the essential prerequisites for building the machine learning model. To begin, the provided code snippet demonstrates the process of preparing the necessary data for model training. The dataframe `ctm_class` is split into two parts: X features (independent variables) and the target variable y (dependent variable).Following the separation of X and y, the dataset is further divided into training and test sets. This step ensures that the model is trained on a subset of the data and evaluated on unseen data, enabling an assessment of its generalization capabilities.To evaluate the performance of the different models, several metrics are employed, including accuracy, F_1-score, recall, and precision. These metrics provide insights into the model's ability to accurately classify and predict the target variable based on the given features. Accuracy measures the overall correctness of the model's predictions, while the F_1-score takes into account both precision and recall, providing a balanced evaluation of the model's performance.

These steps ensure the availability of a well-prepared dataset for model training and evaluation. By measuring the performance of the models using appropriate metrics, the efficacy of each model can be assessed and compared. This information is crucial for selecting the most suitable model for the given task, contributing to the advancement of machine learning methodologies and their applications.



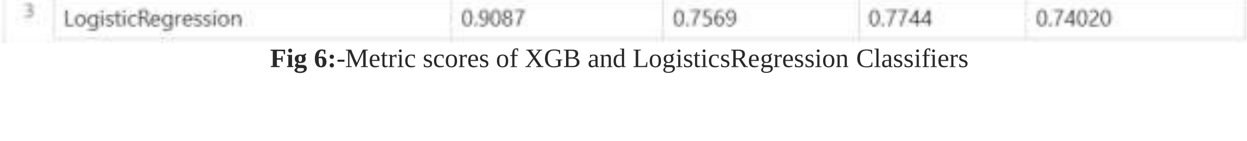
model_name	accuracy	f1_score	recall	precision	time
LogisticRegression	0.9040	0.8454	0.8474	0.8435	0.1087
RandomForestClassifier	0.8870	0.8325	0.8639	0.8215	0.5348
GaussianNB	0.8807	0.8297	0.8758	0.8140	0.0357
xgb.XGBClassifier	0.8772	0.7949	0.8058	0.8116	0.4897
SVC	0.8767	0.7905	0.8062	0.8161	0.3397
DecisionTreeClassifier	0.8747	0.7894	0.8024	0.8096	0.0415
KNeighborsClassifier	0.8721	0.7852	0.7926	0.8020	0.2305

Fig 5:-Metric of all models

1.4 Selecting Model

In this section, a detailed demonstration is provided on building a machine learning model to predict the likelihood of an online customer from a retail shop making their next purchase within a 90-day period from their last purchase. Various models were utilized, and special emphasis was given to improving the performance of the XGB classifier model through hyperparameter tuning.Initially, the XGB classifier model was compared to the LogisticRegression model to establish a baseline for performance evaluation. However, the initial results of the XGB classifier model, with max_depth and min_child_weight set to 3, did not surpass the performance of the LogisticRegression model.

To enhance the XGB classifier model's performance, an iterative process of hyperparameter tuning was conducted. The values of max_depth and min_child_weight were further adjusted heuristically to find the optimal configuration that would outperform the LogisticRegression model.



1	model_name	accuracy	f1_score	recall	precision
2	xgb.XGBClassifier	0.9200	0.7848	0.7949	0.7750
3	LogisticRegression	0.9087	0.7569	0.7744	0.74020

Fig 6:-Metric scores of XGB and LogisticsRegression Classifiers

4. CONCLUSIONS

In conclusion, the prediction of a customer's next purchase in the online retail domain holds significant value for businesses. By leveraging machine learning techniques and analyzing key customer behavior features such as recency, frequency, and monetary value, accurate predictions can be made regarding whether a customer is likely to make a purchase within a specified timeframe.

Through the application of RFM segmentation and feature engineering, valuable insights into customer segmentation and purchase patterns can be obtained. This information enables businesses to tailor their marketing strategies and allocate resources effectively, focusing on high-value customers and maximizing customer retention and revenue generation.

In the process of building the machine learning model, various algorithms were explored, including the XGB classifier and LogisticRegression models. Through hyperparameter tuning, the performance of the XGB classifier model was optimized to outperform the LogisticRegression model, showcasing the importance of fine-tuning model parameters for enhanced accuracy and predictive capabilities.

5. REFERENCES

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