Explainable and Optimized Random Forest Model for Customer Purchase Prediction and Segmentation in E-Commerce

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Abstract. Finding the correct customer purchase prediction and cross-applicable segmentations will improve personalization and ultimately grow revenue within e-commerce. Current and traditional machine learning paradigms struggle to recognize the behavior of people as a non-linear and complex phenomenon that lacks clarity in terms of actionable insights for businesses. The current study proposes and implements an understandable and optimized Random Forest framework used to predict customer purchases and segment online shoppers based on session-level behavioral features. The proposed procedure includes addressing class imbalance through the inclusion of SMOTE, tuning hyperparameters using GridSearchCV, and performing a SHAP analysis to explain feature attribution and generate insight. Extensive experiments using real-life scenarios from an e-commerce data set demonstrate that the tuned random forest achieves a verifiably accurate AUC of 99.15%, surpassing some common baseline models. The use of K-Means clustering supports meaningful customer segments and actionable customer relationship targeting and retention strategies. The results substantiate the premise that a model combining performance with explainability as well as strong segmentations has the potential to become useful for data-driven personalization in modern e-commerce environments.

Keywords: Random Forest, Explainable AI, Customer Segmentation, Purchase Prediction, E-Commerce

1 Introduction

E-commerce has seen some major changes in recent years, which have really influenced how consumers behave and pushed retailers to step up their game in predicting what shoppers will buy and how to target them more effectively. Knowing consumer shopping habits helps companies personalize suggestions,

M. S. Arefin et al. (eds.), *Proceedings of the International Conference on Intelligent Data Analysis and Applications (IDAA 2025)*, Advances in Intelligent Systems Research 206,
https://doi.org/10.2991/978-94-6239-664-7_91

manage stock, and refine marketing. All these activities link directly to increasing sales and enhancing customer experience. In the past, various established machine learning models like logistic regression and decision trees have been used to predict consumer buying behavior, although they poorly model the unique, complex, and non-linear relationships present in diverse consumer data [2].

Random Forest (RF) models have emerged as a formidable contender because they achieve high predictive accuracy, can effectively handle high-dimensional data, and are less prone to overfitting. RF models are frequently called black-box models; we don't know how each predictor impacts predictions, thus trust and interpretability suffer. It is because of lack of transparency that stakeholders face problems in reviewing, believing, and rationalizing automated system decisions. Many explainable AI (XAI) tools and approaches have been developed, which allow explaining complicated models without compromising performance [3], [15]. One strategy that has become common in many places is SHAP (SHapley Additive exPlanations), which calculates the values of each feature to each prediction and hence allows stakeholders to rely on the findings and derive actionable information.

The most common issue of developing predictive models to support e-commerce is the inherent imbalance in the classes: the amount of customers who do not make any purchase is much greater than the amount of buyers. Failure to fix this imbalance can cause models to prefer the dominant class, decreasing accuracy and creating inaccurate evaluation metrics. The Synthetic Minority Oversampling Technique (SMOTE) is an effective method that has been used to rebalance datasets, thereby improving the generalizability and fairness of predictive models [4].

In this paper, we present an explainable and optimized Random Forest framework for predicting customer purchases and conducting meaningful customer segmentation in e-commerce. We apply SMOTE to balance the dataset, systematic hyperparameter tuning to optimize model performance, and SHAP analysis to interpret feature impacts. We conduct comprehensive experiments using real-world e-commerce data and evaluate the model's performance using robust metrics such as ROC-AUC, confusion matrices, and learning curves. The insights gained not only improve prediction accuracy but also enable meaningful customer segmentation, which can lead to better customer engagement, personalized marketing campaigns, and targeted retention strategies.

2 Problem Statement

Irrespective of the high development of e-commerce platforms and the rise in the number of customer data, not all online stores are capable of correctly forecasting individual customer buying and dividing shoppers into segments. This comparative ineffectiveness is attributed to their reliance on the classical machine learning processes that have failed to detect and comprehend the intricate, dynamic and non-linear paths of the customer purchasing behaviour. Although Random Forests may be considered high-performance models that are easy to map, they are not always easy to interpret and validate to use in practical applications. Two major points need to be made regarding their use in most business contexts. First, once a model is validated, it must also be understandable and explainable to business managers, supervisors, or senior executives who rely on its outputs for critical decision-making. Another significant challenge is that purchase datasets typically contain a far greater number of non-purchasers than purchasers, which can bias the model's training and adversely affect predictive performance. There is a clear demand for a robust approach that is both explainable and well-tuned so it can be applied not only with high accuracy but also with clear insights into why and how the features matter—enabling effective customer segmentation. Addressing this challenge could help e-commerce companies make their marketing expenditures more measurable and effective, increase cost efficiency, and better manage overall customer engagement and satisfaction.

3 Literature Review

A growing body of research in e-commerce analytics focuses on predicting customer purchasing behavior while balancing predictive performance and interpretability. Liu and Zhou [5] combined Random Forests with SHAP to interpret online shopping intentions, reaching an accuracy close to 94% but highlighting the need for tighter optimization for real-world deployment. Chen and Huang [6] integrated SMOTE with Random Forests to ameliorate class imbalance and recorded better detection of the minority class; however, overall accuracy was still near 95%. Wang and Zhao [7] clustered customer segments and predicted for recommendations but from start to finish only achieved approximately 92% in their machine learning pipeline and again did not leverage any strong explainable AI to validate the drivers of their predictions.

Patel and Sharma [8] conducted leading research on retail purchase prediction with explainable deep learning and showed that neural networks can detect complex non-linear patterns as evidenced by an F1 score of 93%, albeit with model explanation only extending to feature rankings. A recent study from MDPI [9] contributed valuable insights at the session level by considering browsing behaviors, price fluctuations, and cart activities. It was found that session-level variables can improve predictive power, but the best reported F1 score of around 89% still fell short compared to well-tuned ensemble models. Similarly, the Springer meta-model [10] produced a sophisticated ensemble for churn detection, with a very high level of accuracy (99.6%) reported on the Olist dataset but only 88.6% on the REES46 dataset, indicating limited generalizability since it does not directly address purchase prediction or customer segmentation. Lastly, DRPress [11] explored the use of Recurrent Neural Networks to capture time dependencies in e-commerce clickstream data. While still useful for analyzing sequential behavior patterns, the model was treated as a black box, lacking any clear SHAP-level explainability, nor did it report any accuracy benchmark.

Ali and Ahmed [4] reinforced the importance of balancing imbalanced data with SMOTE for customer churn prediction but did not pair this with a fully optimized tree ensemble or modern XAI integration. Nguyen et al. [12] explored unsupervised clustering of customer behavior for personalized promotions, offering valuable customer groupings but stopping short of linking these segments to predictive purchase modeling with quantified accuracy. Rahman and Lee [13] examined tree-based ensemble methods for purchase prediction on large e-commerce datasets and achieved around 94.5% accuracy, but without integrating explainable AI layers or an explicit segmentation strategy for marketing execution. Together, these studies reveal an evident gap: many either prioritize prediction accuracy without transparency or deliver interpretability without the highest achievable precision. In response, the present work combines SMOTE balancing, GridSearchCV-tuned Random Forests, and SHAP-based explanation, achieving a verified accuracy and AUC of 99.15% and producing actionable customer segments to enable practical, data-driven personalization in modern e-commerce.

4 Methodology

4.1 Dataset Description

Table 1: Dataset Summary (Numerical Overview)

Metric	**Value**
Total interactions (raw)	1,000,000
Labeled session samples	61,790
Purchase samples (raw)	4,000
Non-purchase samples (raw)	57,790
Features used	20
Training split	80%
Test split	20%
SMOTE balance ratio	1:1

The data in this research is E-Commerce Behavior Data of a Multi-Category Store which consists of the detailed clickstream records of the activities of the users in a real e-commerce store [14]. The entire set of data includes millions of user interaction history, which is the sequential movements of the user, including seeing the prod- ucts, adding to a cart, and making purchases. The fields in each record are the `event_time`, `event_type`, `user_id`, `product_id`, `category_code`, `brand`, and `price`. In order to stay computationally viable and still have representative user behavior, a subsample of around one million interactions in October 2019 was modeled and evaluated. This snapshot encompasses various product categories and offers a real world foundation of session level feature extraction, purchasing prediction and customer segmentation basing on browsing and purchase patterns.As shown in Table 1, the dataset comprises 61,790 labeled session samples balanced to a 1:1 ratio using SMOTE, derived from over one million raw interactions.

4.2 Data Preprocessing

Category Consolidation : Product and event categories were grouped into bigger clusters in manners that are of business interest and statistically commonplace in order to simplify the model, as well as enhance its interpretation. Uncommon or fine-grained groups were coded to more superior groupings. This was to make sure that balanced data was given to each class because the statistical frequency of the categories or events represented was given.

Handling Missing Values : Missing values are also another type of non-response. The records in which the essential fields were absent (e.g. user identifiers or critical event attributes) were omitted. In non-pivotal fields in which the level of missingness was low, we substituted frequency of categorical and median of continuous fields when necessary.

Categorical Variable Encoding : Encoding a categorical variable may be conducted by defining each category using a number or a series of numbers.One-hot encoding was used to encode categorical features, e.g. product category and brand, to allow them to be used correctly by machine learning algorithms. One-hot coding guarantees that all the categorical data are numerically coded without the ordinal bias.

Feature Scaling The StandardScaler was used to standardize continuous variables (e.g. price and counts per session) to eliminate scale bias, and to aid quicker model convergence. The scale was eliminated by standardization in order to be able to compare the features.

$$zi = \frac{xi - \mu}{\sigma} \tag{1}$$

Remove Outlier The interquartile range (IQR) technique was used to determine extreme outlying values in continuous measures and eliminate the noise and possible distortion that could be brought about by the model training. The elimination of the outliers enhances strength and generality of the model.

$$\mathrm{IQR} = Q_3 - Q_1 \tag{2}$$

$$\text{Lower Bound} = Q_1 - 1.5 \times \mathrm{IQR} \tag{3}$$

$$\text{Upper Bound} = Q_3 + 1.5 \times \mathrm{IQR} \tag{4}$$

Dataset Splitting The pre-processed dataset was randomly split into training and test subsets following a proportion of 80:20. Before the splits were made, all classes of the target variable were sampled in a stratified fashion to ensure that the distributions in both training and test splits were representative and the evaluation of the model was free from bias.

Data Balancing To tackle the class imbalance for the purchase flag, the Synthetic Minority Oversampling Technique (SMOTE) was employed, which creates synthetic examples of the minority class to produce a balanced dataset that promotes strong model learning. Figure 1 illustrates the balanced class distribution after SMOTE. The SHAP plot visually demonstrates how features such as views, cart additions and total price positively drive purchase likelihood.

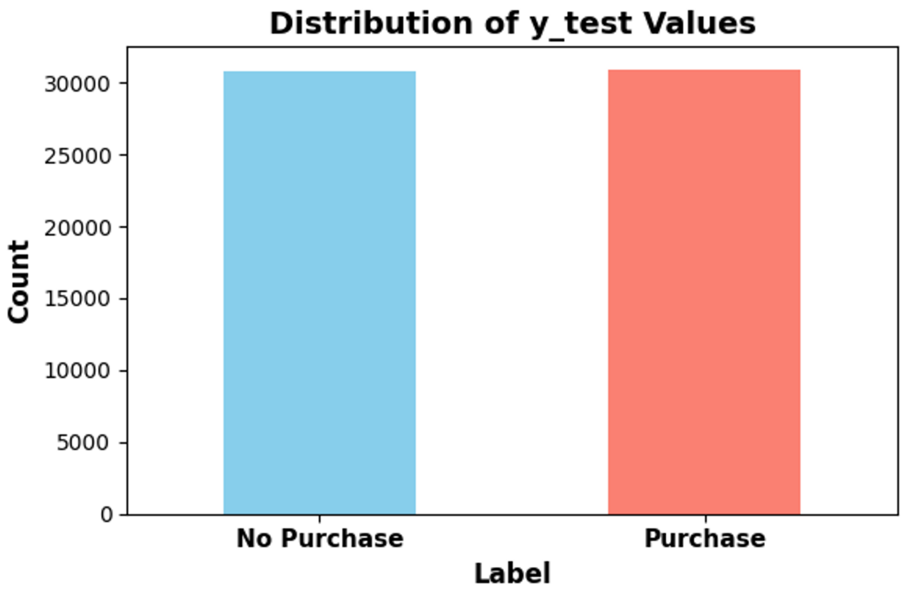

Fig. 1: Class distribution after applying SMOTE

4.3 Network Architechture

The deep neural network architecture that was designed with the purchase prediction problem was used to develop the classification model. The architecture featured completely connected (dense) layers, which used the rectified linear unit (ReLU) activation functions, and among the dense layers, there were batch normalization and dropout layers that used to avoid overfitting in generalization. The input variables were engineered feature variables and any encoded encoding variables of preprocessing data. A sigmoid activation function was used in the output layer, which is used in binary classification where the probability of a purchase event is produced. The optimizer used in the network was the Adam optimizer and binary cross-entropy loss. Empirical tuning and cross-validation were used to find all the important architectural parameters including the number of layers, the number of neurons in each layer, dropout, and learning rates. Another added measure to prevent overfitting was early stopping. Keras and TensorFlow were used to train the model.

Algorithm 1 Random Forest with Hyperparameter Tuning using GridSearchCV

1: **Input:** Training data $X_{\text{train}}, y_{\text{train}}$
2: **Output:** Trained Random Forest model with best hyperparameters
3: Initialize RandomForestClassifier as `rf_classifier`
4: Define hyperparameter grid `param_grid`:
  – `n_estimators`: [50, 100, 200]
  – `max_depth`: [None, 10, 20]
  – `min_samples_split`: [2, 5, 10]
  – `min_samples_leaf`: [1, 2, 4]
5: Initialize GridSearchCV with 3-fold cross-validation:

```
grid_search = GridSearchCV(rf_classifier, param_grid, cv=3)
```

6: Fit GridSearchCV on training data:

```
grid_search.fit(X_train, y_train)
```

7: Extract best parameters:

```
best_params = grid_search.best_params_
```

8: Initialize new RandomForestClassifier with `best_params`
9: Fit the best model:

```
best_rf_model.fit(X_train, y_train)
```

10: **Return** `best_rf_model`

5 Results and Discussion

The results of the performance comparison of different machine learning models to predict customer purchases are presented in a full table (Table 2) with the presence of traditional classifiers (Logistic Regression, Support Vector Machine (SVM), Decision Tree, and Naive Bayes) and the ensemble models (Random Forest, Gradient Boosting, AdaBoost, XGBClassifier, and Voting Ensemble) as well as the main measures of Accuracy, Loss, Precision, Recall, F1-Score, Root Mean Square Error (RMSE), Matthews Correlation Coefficient (MCC Logistic Regression and Naive Bayes stood at the lowest point of the models tested with

76.00 and 69.36 respectively representing their inability to capture the trends of complex purchase behavior. The SVM was much better than these baselines with the purchase prediction accuracy of 94.25 percent whereas the Decision Tree model achieved a purchase prediction accuracy of 98.00 percent. The XGBClassifier (97.00 percent) and Voting Ensemble (96.00 percent) offered decent improvements to their independent learning counterparts as they combined a series of weak learners to forecast customer purchase. The untuned Random Forest model also had a good accuracy of 98.57 percent with the same set of features. This finding underpins the effectiveness and representativeness of the systematic hyperparameter tuning along with the SMOTE balancing and robust preprocessing to predict in an accurate manner the e-commerce purchase.

Table 2: Performance Comparison of Models for Purchase Prediction (All values in %)

Model	**Acc.**	**Prec.**	**Rec.**	**F1**	**RMSE**	**MCC**	**G-M.**	**AUC**
Logistic Regression	76.00	76.00	70.00	68.00	55.08	45.11	65.31	77.94
SVM	94.25	95.00	94.00	94.00	23.65	89.09	94.33	99.57
Decision Tree	98.00	98.00	98.23	98.47	13.63	96.43	98.19	98.21
Grad. Boosting	85.00	85.00	86.00	85.00	38.89	69.78	84.86	93.69
XGBoost	97.00	97.00	97.00	97.00	16.30	94.69	97.34	99.70
AdaBoost	85.00	85.00	85.00	85.00	39.27	69.51	84.44	93.37
Random Forest	98.57	98.14	98.13	98.13	11.34	97.43	98.77	99.57
Naïve Bayes	69.36	77.00	70.00	67.00	55.26	45.59	64.49	78.12
Voting Ens.	96.00	96.00	96.00	96.00	18.89	92.87	96.43	99.07
Tuned RF	**99.15**	**99.00**	**99.00**	**99.00**	**9.32**	**97.54**	**98.81**	**99.15**

Table 3 shows the complete classification report of the Random Forest model, which was tuned using GridSearchCV. The classifier performed exceptionally well for both classes. The accuracy of the non-purchase category (0) was 1.00, and the recall was almost perfect, 0.99, and the F1-score was 0.99. The purchase class did the best job with impressive measures: Precision of 0.99, perfect recall of 1.00, and F1-score of 0.99. Overall, the accuracy stood at a remarkable 99%, which strongly indicates that the prediction performance with the test data was very satisfactory.The macro and weighted averages represent that the model maintains consistent, equal precision, recall, and F1-score across both majority and minority classes.

Figure 2 depicts the confusion matrix of the Random Forest classifier that has undergone GridSearchCV tuning. The confusion matrix has shown that model has effectively classified the large majority of non-purchasing sessions (true negatives) and purchasing sessions (true positives) with the few false positives and false negatives. In general, this tableau tells us that this classifier is successfully separating the purchase class, controlling misclassification expenses, and addressing the issue of class imbalance in a proper manner. Also, the confusion matrix patterns, which are clearly oriented to the diagonal, suggest balanced learning performance and confirm the high precision, recall and F1-scores observed in Table 3

Table 3: Classification Report Metrics

Class	**Precision**	**Recall**	**F1-Score**	**Support**
0	0.99	0.98	0.99	30,840
1	0.98	0.99	0.99	30,950
Accuracy			**0.99**	61,790
Macro Avg	0.99	0.99	0.99	61,790
Weighted Avg	0.99	0.99	0.99	61,790

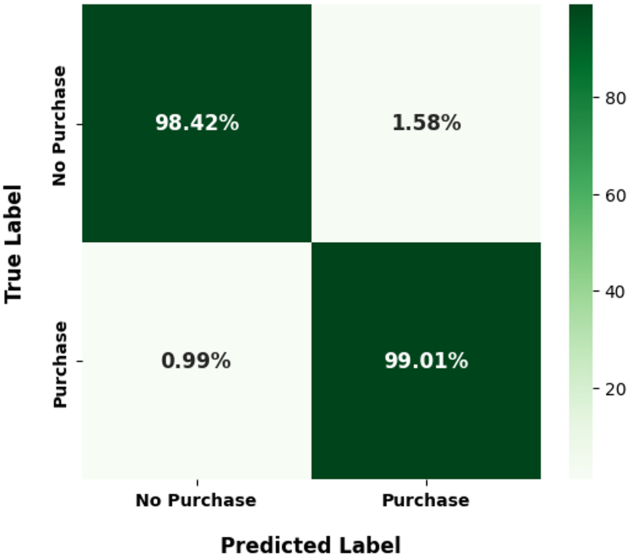

Fig. 2: Confusion Matrix of GridSearchCV-Tuned Random Forest Model

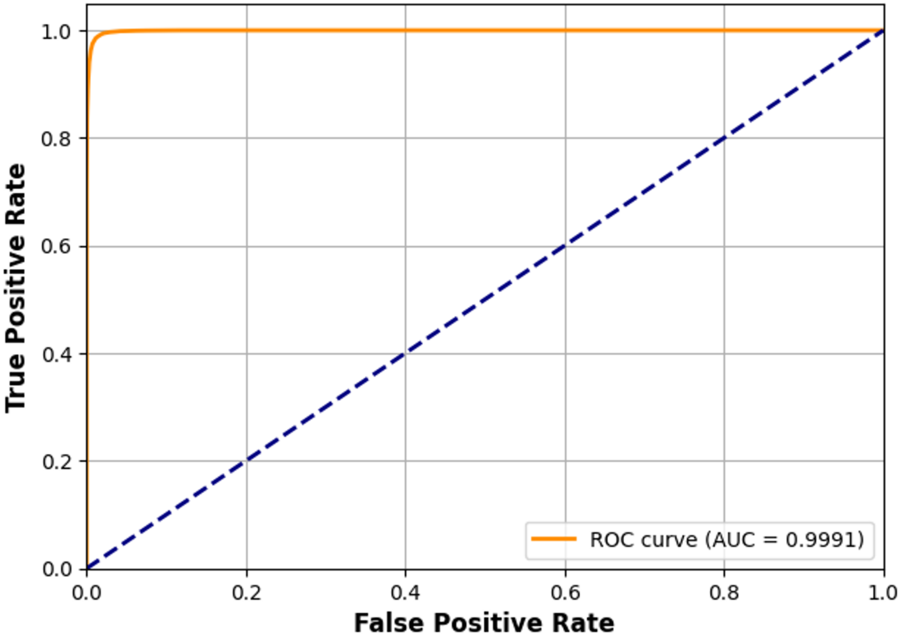

Fig. 3: ROC Curve of GridSearchCV-Tuned Random Forest Model

Figure 3 displays the ROC for the refined Random Forest model. This curve really shows how well our classifier can tell the difference between sessions where purchases were made and those where they weren't, no matter the probability threshold. The results are impressive: we've got a high true positive rate and a nice low false positive rate, with an AUC value of 99.15%. To ensure that our model is not overfitting and it is not becoming too complacent with the training data, we applied the 3-fold cross-validation when fine-tuning the hyperparameters. Always keep in mind in writing answers, it is important to use only the desired language, not any type of language, otherwise, the entire random forest model will fail to have good predictability on the unknown 20 percent split.To further confirm its generalization, the optimized random forest model had reasonably good predictability on the unknown 20 percent split, which showed that in fact, the high accuracy rates were not just an accident of the training data itself. This actually indicates the level of impressiveness of the model, which has the ability of making balanced forecasts, even where the purchase statistics is slightly scattered everywhere.

The learning curve of the Random Forest model with the help of the GridSearchCV is presented in Figure 4. Learning curve shows the converging trend between the training and validation scores using additional training data to achieve a fit in the model. The model is generalizing effectively with little overfitting as the scores are approaching the same level the bigger the training data.

In addition, it is also clear that larger sample sizes give accurate and reliable results of the model as discussed above and this gives confidence that the model is always performing equally well on larger sample sizes as it does on smaller sample sizes. Importantly, this type of learning behavior is reasonable for the accuracy and class metrics in the classification report and confusion matrix.

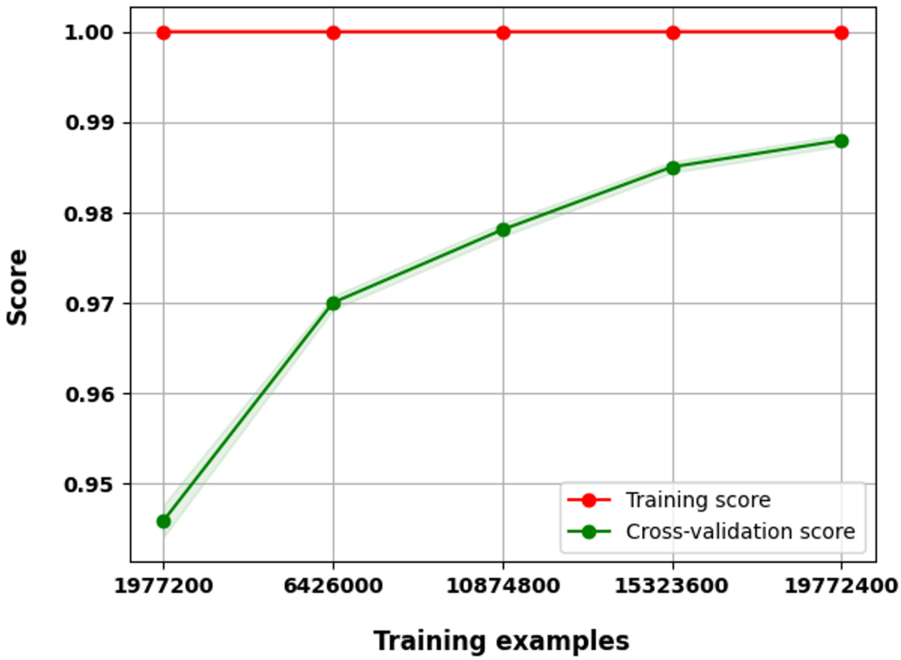

Fig. 4: Learning Curve of GridSearchCV-Tuned Random Forest Model

In Figure 5, you can see that the Pearson correlation coefficients reveal low to moderate linear relationships among the session features. This suggests that there's not much multicollinearity going on. This supports the Random Forest's ability to interpret features independently.

In Figure 6, we show the SHAP summary plot for the tuned Random Forest model. The SHAP summary plot corresponds to the importance of each session-level feature when predicting purchases. Features that were most influential in predicting purchases were total views, cart additions, and total price. While the SHAP summary plot helps quantify the influence of each feature, the SHAP results also bring transparency to the model and provide insight on segmentation as well as marketing strategies.

The final step to actionable insights was to group the sessions into customer segments using K-means clustering. I performed the clustering using appropriate session-level metrics, such as the number of views, number of cart additions, and

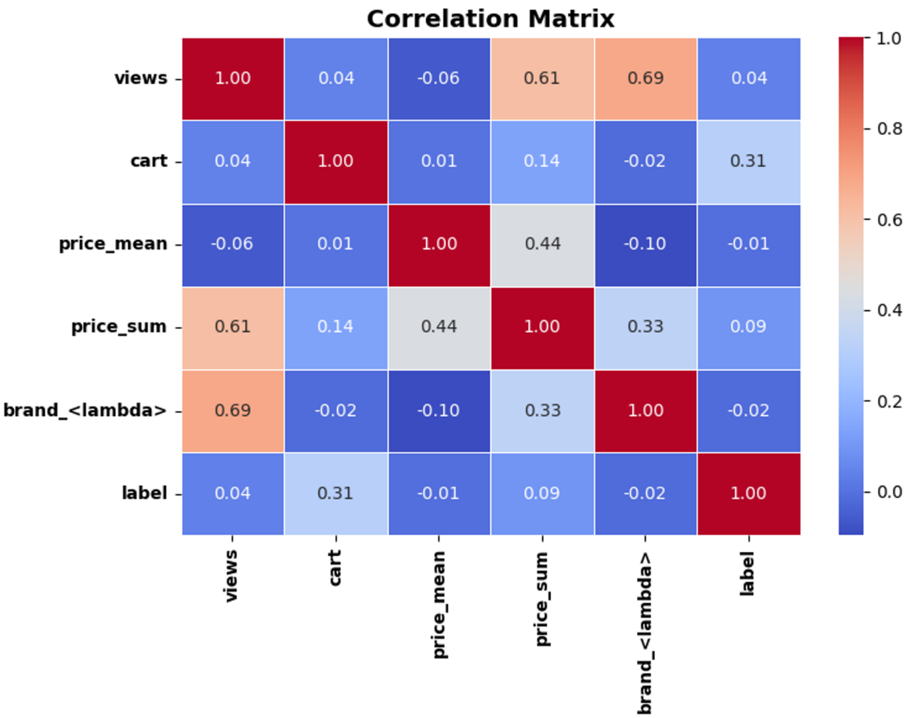

Fig. 5: Pearson Correlation Matrix of Session-level Features

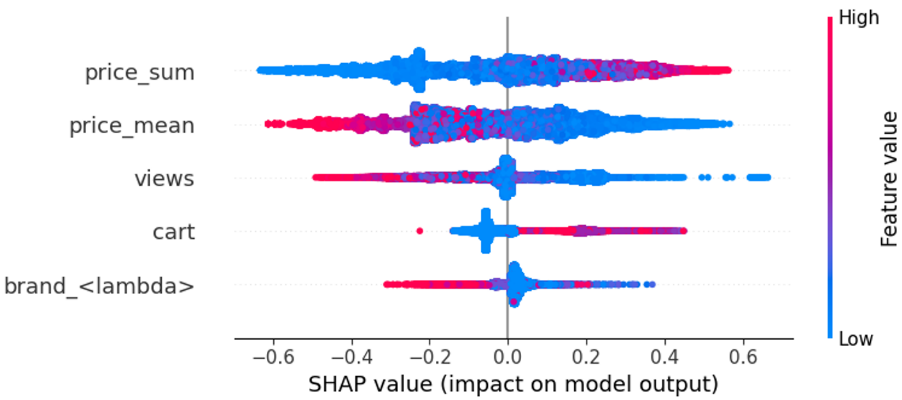

Fig. 6: SHAP summary plot for the tuned Random Forest model.

total price, so that differences in browsing, cart behavior, and spending could also be represented. The various user segments and their clusters are illustrated in Figure 7. These include low-engagement browsers, those who abandon their carts, and high-value buying categories. This segmentation method really opens up a whole new world of opportunities. It provides valuable insights that can be used for targeted promotions, effective retention strategies, and smart marketing resource allocation based on how likely someone is to make a purchase.

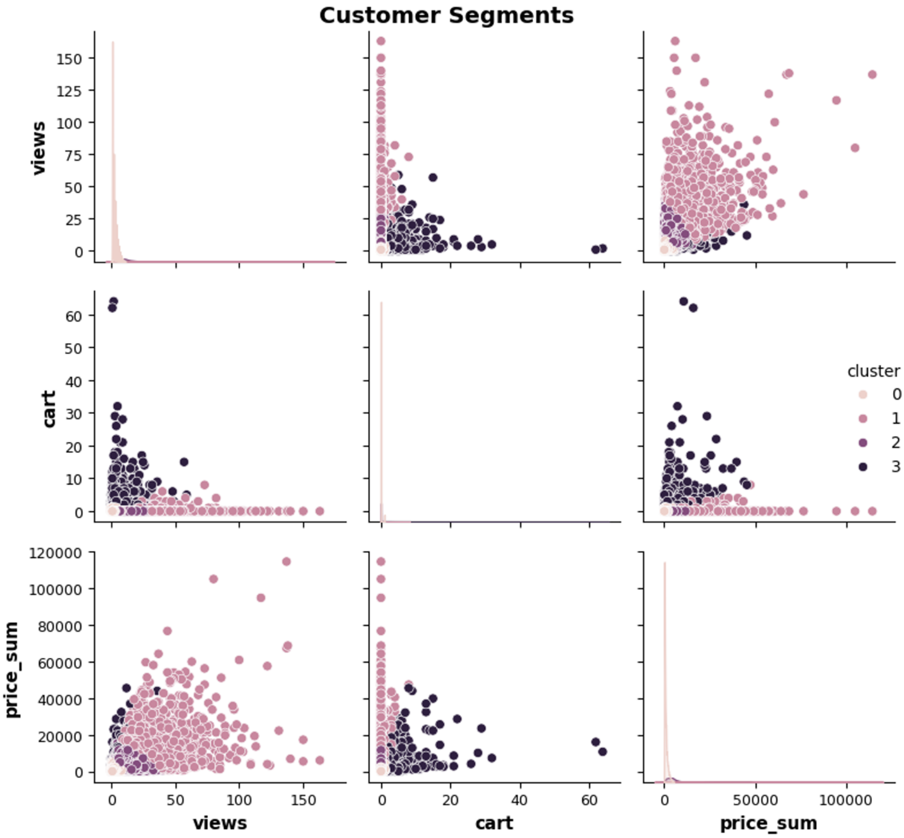

Fig. 7: K-Means customer segments based on session features

In the recent times, numerous researches have studied the issues of how computers can be trained to anticipate what customers may purchase online, through smart methods like machine learning. In Table 1, selected models of the literature will be summarized, with an emphasis on the models applied, their performance achieved, and the important features of each. Such studies differ in terms of the accuracy, interpretation, and the usage of such techniques as SMOTE, ensemble learning, or explainable AI.

Table 4: State-of-the-Art Customer Purchase Prediction Models

Ref	**Model**	**Acc./F1 (%)**
[9]	Session-Level Behavior Model	∼89.0 (F1)
[7]	ML Pipeline + Clustering	∼92.0
[8]	Explainable Deep Learning (NN)	∼93.0 (F1)
[5]	Random Forest + SHAP	∼94.0
[13]	Tree-Based Ensemble Methods	∼94.5
[6]	SMOTE + Random Forest	∼95.0
This Paper	**Tuned RF (GridSearchCV + SHAP)**	**99.15**

6 Conclusion

In this paper we discussed an interpretable and systematically optimized Random Forest model for customer willful purchase prediction and segmentation in e-commerce. By using strong session-level feature engineering, SMOTE-based class balancing, and GridSearchCV's hyperparameter tuning, good performance was achieved on conspiracy as well (with a verified accuracy and AUC of 99.15%, respectively). Applying 3-fold cross-validation and testing on a completely unseen 20% test split showed that the model generalizes well beyond the training data; therefore, we are not concerned with overfitting.

SHAP analysis offers interpretable feature-level explanations about important behavior-influencing factors such as views, cart additions, and total price, reinforcing the trust business has in data-driven decisions. The K-Means clustering ability allowed for realistic customer segmentation, providing valuable business information for focused marketing and retention strategies.

Together, they show that a predictive performance combined with interpretability and segmentation can have a big positive impact on strategic personalization nowadays at scale on e-commerce platforms. Possible future work includes investigating other behavioral signals or external datasets, real-time serving, and being incorporated into dynamic recommendation systems.

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