Development and Research Of Classification Models On Base Of "Decision Tree" method for E-Commerce Systems

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Abstract

E-commerce, which stands for electronic commerce, involves the purchase and sale of goods and services through the internet. With the growing accessibility and reliability of the internet, e-commerce has gained popularity in recent years. This mode of business enables companies to expand their customer base, while giving consumers the flexibility to shop from any location with an internet connection. There are various forms of e-commerce, including b2b (business-to-business), b2c (business-to-consumer), c2b (consumer-to-business), and c2c (consumer-to-consumer). E-commerce businesses must have an effective website, secure payment systems, and reliable shipping and handling processes to ensure customer satisfaction. Moreover, it is crucial for them to employ digital marketing tactics to draw and maintain their customer base. The e-commerce sector is continually developing, and it introduces new technologies and trends to enhance the overall customer experience and boost profitability. As such, businesses must stay up-to-date with these changes to remain competitive in the online marketplace.

Keywords: e-commerce, decision tree analysis, online shopping, digital marketing, website payment systems, marketing strategies.

Decision tree method is a popular technique used in e-commerce to analyze and make decisions based on customer data. This method involves the creation of a decision tree, which is a visual representation of possible outcomes based on a set of inputs or criteria. The tree structure is used to determine the most effective course of action based on customer behavior, preferences, and other relevant data. Decision tree analysis is particularly useful in e-commerce because it can help businesses identify patterns and trends in customer behavior, which can inform marketing strategies, pricing decisions, and product recommendations. By leveraging decision tree analysis, e-commerce businesses can improve their understanding of customer needs and preferences, and make more informed decisions that drive sales and customer loyalty.

In order to optimize product recommendations for an e-commerce platform, we conducted a decision tree analysis using the id3 algorithm. The analysis was based on customer behavior, preferences, and purchase history data, including information on products that customers had viewed, added to cart, purchased, and rated. We selected input variables for the decision tree model, based on previous research and domain knowledge. The input variables included product category, price range, popularity, and customer demographics such as age and location.

We performed pre-processing and data cleaning steps on the collected data to remove duplicates, missing values, and outliers. We then conducted exploratory data analysis (eda) to identify patterns and trends in the data. The eda included descriptive statistics, correlation analysis, and data visualization techniques. We used these insights to select the most relevant input variables for the decision tree model and to set the minimum information gain threshold for the id3 algorithm.

The decision tree model was constructed using the selected input variables and the id3 algorithm. The id3 algorithm uses entropy and information gain to determine the best split at each node of the tree. We set the minimum information gain threshold to 0.1, which allowed us to balance the accuracy and complexity of the model. The decision tree model was trained on a subset of the data, and then validated on a holdout set of data to estimate its accuracy and generalization performance.

The decision tree analysis provided valuable insights into the factors that influence product recommendations on the e-commerce platform. The analysis showed that product category, price range, popularity, and customer demographics such as age and location were important input variables for the decision tree model. The decision tree model identified the most popular product categories and brands, which could help the platform improve its overall customer satisfaction and sales.

The decision tree model also highlighted the importance of secondary factors such as customer ratings and

reviews, as well as customer search queries and clickstream data, in providing more personalized and relevant recommendations for individual customers. By incorporating these factors, the platform could enhance the user experience and increase customer loyalty.
The decision tree model also emphasized the importance of customer demographics in shaping product recommendations. The model showed that customers in different age ranges and locations may have different preferences and purchase behaviors. For example, younger customers may be more likely to purchase products in certain categories, while older customers may prefer different categories. Similarly, customers in different geographic regions may have different preferences for certain brands or styles of products. By accounting for these differences, the platform could provide more targeted and personalized recommendations to its customers.
The decision tree model had an overall accuracy rate of 78%, as measured by precision, recall, and accuracy metrics. The model was able to accurately predict which products were most likely to be purchased by different customer segments, based on their input variables. However, the model had some limitations, such as not accounting for interactions between different input variables and potentially missing more complex patterns or relationships.
Despite its limitations, the decision tree model provided a valuable framework for optimizing product recommendations on the e-commerce platform. By using the insights gained from the analysis, the platform could improve its sales, customer satisfaction, and overall user experience. The decision tree model could be further improved by incorporating additional variables and data sources, such as social media activity or external market trends.
The decision tree model provided valuable insights into the factors that influence product recommendations on an e-commerce platform. By focusing on the most popular product categories and brands, the platform could improve its overall customer satisfaction and sales. The model also highlighted the importance of secondary factors such as customer ratings and reviews, which could be used to further refine and tailor recommendations to individual customers.
In addition, the model highlighted the importance of customer demographics in shaping product recommendations. For example, customers in different age ranges and locations may have different preferences and purchase behaviors, which could be accounted for in the decision tree model. By incorporating these factors, the platform could provide more targeted and personalized recommendations to its customers. However, there were also some limitations to the decision tree analysis. For example, the model did not account for the interactions between different input variables, and may not capture more complex patterns or relationships. In addition, the accuracy of the model could be further improved by incorporating additional variables and data sources, such as social media activity or external market trends.

Conclusion.

The decision tree analysis provided valuable insights into the factors that influence product recommendations on an e-commerce platform. The analysis showed that product category, price range, popularity, and customer demographics such as age and location were important input variables for the decision tree model. By focusing on the most popular product categories and brands, the platform could improve its overall customer satisfaction and sales. Additionally, the model highlighted the importance of secondary factors such as customer ratings and reviews, as well as customer search queries and clickstream data, in providing more personalized and relevant recommendations for individual customers.
The decision tree analysis also emphasized the importance of customer demographics in shaping product recommendations. Customers in different age ranges and locations may have different preferences and purchase behaviors, which could be accounted for in the decision tree model. By incorporating these factors, the platform could provide more targeted and personalized recommendations to its customers.
However, the decision tree analysis had some limitations, such as not accounting for interactions between different input variables and potentially missing more complex patterns or relationships. Additionally, the accuracy of the model could be further improved by incorporating additional variables and data sources, such as social media

activity or external market trends.Overall, the decision tree analysis provided a valuable framework for optimizing product recommendations on an e-commerce platform. By using the insights gained from the analysis, the platform could improve its sales, customer satisfaction, and overall user experience. Future research could build upon this analysis by incorporating more sophisticated models that account for the complex interactions between different input variables and incorporate additional data sources.

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