Recommendation System Using Web Usage Mining For Users Of E-commerce Site

Project report submitted

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By

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ABSTRACT

In the current era of technological advancements, the majority of consumers prefer to use online platforms to make purchases. Therefore, it is crucial for ecommerce companies to study user behavior to watch market trends and consumer demand. Additionally, to ensure continuous activity and increased customer satisfaction, user comfort while using the website must be given top priority.

One effective way to improve user experience and increase customer satisfaction on ecommerce websites is by utilizing web usage mining-based recommendation algorithms. These algorithms use web mining techniques to gather user information based on user engagement and provide practical recommendations for company items that please customers and entice them to return to websites more frequently.

The first step in this process involves gathering information on user interests depending on how users use or interact with the website. This information can then be used to group individuals with similar interests and research the preferences of all consumers. The gathered data can also be used to develop user profiles and produce user or product-to-product recommendations. These recommendations can be used to enhance the website's structure and content, adapt and customize the website's content, propose items, and research user interests.

The benefits of using web usage mining-based recommendation algorithms are numerous. By providing an efficient and user-friendly experience on ecommerce websites, these algorithms can significantly improve the website's user experience and increase customer satisfaction. This, in turn, can lead to increased sales and profitability for the company. Additionally, an accurate analysis of user behavior can help companies adapt to changing market trends and consumer demand, thereby increasing their competitiveness in the market.

In conclusion, the use of web usage mining-based recommendation algorithms is a valuable tool for ecommerce companies to improve user experience and increase customer satisfaction. By gathering information on user behavior and interests and using that data to provide practical recommendations for company items, these algorithms can significantly enhance the website's structure and content, ultimately leading to increased sales and profitability for the company.

Chapter 1: INTRODUCTION

1.1 Introduction

The majority of consumers in the present generation utilize online platforms to make purchases, thus it is crucial to study user behavior in order to watch market trends and consumer demand. Additionally, in order to ensure continuous activity, user comfort while using the website must be given top priority.

Web usage mining based recommendation algorithms provide an efficient user friendly experience on ecommerce websites. Web mining techniques are used to gather user information from users depending on user engagement. A practical recommendation algorithm is then given the needed information. An efficient algorithm improves the suggestion of company items that please customers and entices them to return to websites more frequently. Therefore, information on user interests will be gathered depending on how users use or interact with the website. Additionally, this may be used to group individuals with like interests and research the preferences of all consumers. The information gathered can be used to develop user profiles and produce user or product to product recommendations.

In general, an accurate analysis provides the opportunity to enhance the website ́s structure and content, to adapt and customize the website ́s content, to propose items, or to research user interests

1.2 Motivation

The motivation for studying user behavior in online platforms for making purchases is driven by the increasing trend of consumers using ecommerce websites to purchase products and services. As more businesses move their operations online, understanding how users interact with these websites becomes essential for success. By analyzing user behavior, companies can identify market trends and consumer demand, which can help them make informed decisions about product offerings, marketing strategies, and website design. Additionally, improving the user experience on ecommerce websites can increase customer satisfaction, loyalty, and ultimately drive sales. Therefore, the motivation for studying user behavior in online platforms for making purchases is to gain a competitive edge in the ecommerce market by meeting customer needs and providing a seamless online shopping experience.

1.3 Brief Overview of Problem

The problem addressed in this project is the need to understand user behavior in online platforms for making purchases and to use this information to provide a better user experience. Specifically, the project aims to develop web usage mining-based recommendation algorithms to gather user information based on user engagement and provide practical recommendations for company items that please customers and entice them to return to websites more frequently. The project seeks to address the challenge of improving the user experience on ecommerce websites, enhancing website structure and content, adapting and customizing website content, proposing relevant items, and researching user interests. Ultimately, the goal is to improve customer satisfaction and increase sales by providing a seamless and personalized online shopping experience.

1.4 Scope of the Project

The scope of this project is to develop and implement web usage mining-based recommendation algorithms to gather user information based on user engagement and provide practical recommendations for company items that please customers and entice them to return to ecommerce websites more frequently. The project will involve collecting and analyzing user data, developing algorithms for recommendation and customization of website content, and testing the algorithms on ecommerce websites. The project will focus on improving the user experience on ecommerce websites, enhancing website structure and content, adapting and customizing website content, proposing relevant items, and researching user interests. The project will not cover topics such as website design or user interface development.

1.5 Significant Contribution

The significant contribution of this project is the development and implementation of web usage mining-based recommendation algorithms to improve the user experience on ecommerce websites. The project provides a practical solution to gather user information based on user engagement and provide customized recommendations that improve customer satisfaction and entice them to return to ecommerce websites more frequently.

The project also contributes to the field of web mining by exploring the use of web mining techniques for user profiling and product-to-product recommendation. The project findings and recommendations can be useful for ecommerce businesses to enhance their website structure and content, adapt and customize website content, propose relevant items, and research user interests to improve customer satisfaction and increase sales.

Chapter 2: REVIEW OF LITERATURE

2.1 Reviews

Web usage mining is an important research area that has been studied extensively in recent years due to its potential to improve recommendation systems. Web usage mining-based recommender systems use data mining techniques to analyze users' behavior on websites and generate personalized recommendations. The literature review reveals that the topic has been explored in various fields, such as e-commerce, e-learning, healthcare, and more.

Kumar et al. [1] proposed a web usage mining-based recommender system that uses PCA and K-means clustering to recommend items to users. They demonstrated that their system outperforms traditional recommendation methods. In another study, Kumar and Verma [2] proposed a personalized recommender system that used SVM to improve the accuracy of recommendations. They showed that their system performs better than traditional recommendation systems.

Al-Masri and Qawasmeh [3] proposed a web usage mining-based approach to predict the user's next visited web page. They used a decision tree algorithm and showed that their system was able to predict the next web page with high accuracy. Hameed et al. [4] proposed a web usage mining-based recommender system for personalized e-learning platforms. They used association rule mining to generate personalized recommendations for students.

Gupta and Varshney [5] proposed an approach for optimizing recommendation systems using web usage mining and social media for e-commerce. They used the Apriori algorithm and sentiment analysis to generate personalized recommendations. Fatima et al. [6] analyzed user behavior on structured websites using web usage mining. They identified the most visited pages and the paths users took to reach them.

Kumar and Sharma [7] conducted a survey on web usage mining and personalization in web recommender systems. They discussed various techniques used for web usage mining, such as association rule mining, clustering, and classification. Arora and Kaur [8] conducted a comparative study of recommendation systems using web usage mining. They compared the performance of different techniques, such as collaborative filtering, content-based filtering, and hybrid filtering.

Mobasher et al. [9] proposed an automatic personalization system based on web usage mining. They used clustering techniques to group users with similar behavior and generate personalized recommendations. Acharya and Gautam [10] conducted a survey on recommender systems based on web usage mining. They discussed various techniques used for recommendation, such as collaborative filtering, content-based filtering, and hybrid filtering.

In conclusion, the reviewed literature reveals that web usage mining-based recommender systems have been extensively studied in recent years. Various techniques, such as clustering, association rule mining, and classification, have been used to generate personalized recommendations for users. However, there are still some gaps in the research that need to be addressed, such as the use of deep learning techniques and the evaluation of web usage mining-based recommender systems.

2.2 Research Gaps

• Kumar, M., Verma, S., Singh, A. (2015). Web usage mining-based recommender system using PCA and K-means clustering: The paper focuses on improving the accuracy of recommender systems through the use of web usage mining and clustering techniques. However, the study could benefit from incorporating other data sources such as demographic and contextual data to further enhance the system's recommendations.

• Kumar, M., Verma, S. (2015). Web usage mining-based personalized recommender system using support vector machine: While the paper proposes a personalized recommender system based on web usage mining and support vector machines, the study could benefit from exploring the impact of different machine learning algorithms on the performance of the system.

• Al-Masri, E., Qawasmeh, O. (2015). A web usage mining-based approach for predicting user's next visited web pages: The paper proposes a web usage mining-based approach for predicting the next web page a user is likely to visit. However, the study could benefit from evaluating the system's performance in real-time scenarios and examining the impact of user feedback on the system's recommendations.

• Hameed, M. A., Naeem, M. A., Javaid, A. (2016). Recommender system based on web usage mining for personalized e-learning platforms: While the paper proposes a recommender system for e-learning platforms based on web usage mining, the study could benefit from investigating the impact of incorporating content-based and collaborative filtering techniques on the performance of the system.

• Gupta, S., Varshney, M. (2020). Optimizing Approach of Recommendation System using Web Usage Mining and Social Media for E-commerce: The paper proposes an approach to optimize recommender systems using web usage mining and social media data for e-commerce applications. However, the study could benefit from evaluating the performance of the system in real-world e-commerce scenarios and examining the impact of incorporating additional data sources such as product reviews on the system's recommendations.

• Fatima, A., Haider, M. J., Abid, H. (2016). Analysis of Users Behaviour in Structured Websites Using Web Usage Mining: While the paper analyses user behavior in structured websites using web usage mining, the study could benefit from exploring the impact of different clustering techniques on the performance of the system.

• Kumar, R., Sharma, M. (2019). A Survey on Web Usage Mining and Personalization in Web Recommender Systems: The paper provides an overview of web usage mining and personalization in web recommender systems. However, the study could benefit from exploring recent developments in the field and highlighting the limitations of current approaches.

• Arora, A., Kaur, M. (2016). A comparative study of recommendation system using web usage mining: While the paper conducts a comparative study of different recommender systems based on web usage mining, the study could benefit from examining the impact of incorporating additional data sources such as social media and demographic data on the performance of the systems.

• Mobasher, B., Cooley, R., Srivastava, J. (2003). Automatic personalization based on web usage mining: While the paper proposes an automatic personalization approach based on web usage mining, the study could benefit from examining the impact of incorporating additional data sources such as demographic and contextual data on the performance of the system.

• Acharya, D. R., Gautam, M. (2018). A Survey on Recommender Systems based on Web Usage Mining: The paper provides an overview of recommender systems based on web usage mining

Chapter 3: PROBLEM DEFINITION

3.1 Problem Statement

The problem addressed in this project is how to improve user experience and increase customer satisfaction on e-commerce platforms through the use of web usage mining-based recommendation algorithms. The aim is to gather user information based on their engagement and interactions with the website, and provide practical recommendations for company items that please customers and entice them to return to the website more frequently. The project seeks to analyze user behavior, enhance the website's structure and content, and adapt and customize the website's content and product recommendations based on user interests.

3.2 Problem Definition

The problem identified in this project is the need to study user behavior in online platforms for making purchases in order to watch market trends and consumer demand, and to ensure user comfort while using the website. The gap that this project aims to address is the lack of efficient recommendation algorithms that can improve the suggestion of company items that please customers and entice them to return to websites more frequently. The proposed solution involves utilizing web usage mining-based recommendation algorithms that gather user information based on user engagement and provide practical recommendations for company items. This will lead to a more user-friendly experience and enable companies to develop user profiles and produce user or product-to-product recommendations, ultimately enhancing the website's structure and content and improving user satisfaction.

3.3 Objectives

- To employ association rule mining algorithm on web usage mining data.
- To compare recommendation models i.e., collaborative filtering, content-based filtering .
- To build a recommendation system by employing hybrid filtering model and generate accurate and personalized product recommendations.

Chapter 4: Methodology

4.1 Introduction

The implementation of a recommendation system using web usage mining for e-commerce websites involves several modules such as data collection, data pre-processing, data analysis, association analysis, collaborative filtering, content-based filtering, and hybrid filtering. These modules are used to gather user information, analyze the data, identify patterns and associations between products, and make personalized product recommendations for users based on their preferences and behavior. The use of various techniques such as Apriori algorithm, text analytics, and natural language processing allows for the development of an efficient and accurate recommendation system that enhances the user experience and increases customer satisfaction. This methodology has the potential to provide valuable insights into user behavior and market trends, and can be applied to a wide range of e-commerce websites to improve customer engagement and retention.

4.2 Approach used to address the Problem

The approach used in this project involved a lifecycle of analytics, including data collection, data pre-processing, data analysis, and the implementation of recommendation algorithms.

For data collection, a dataset containing web usage data was used, which included information about user interactions with various products across different categories. The dataset consisted of 100 unique users and 20 unique products, with 1000 different actions such as viewing, adding to cart, and purchasing.

Data pre-processing was then conducted to clean and transform the data into a format that can be easily used for analysis. This involved removing inconsistencies, errors, or missing values in the dataset.

Data analysis was conducted to explore the data and uncover patterns and relationships between variables. Association analysis was then performed to identify patterns and associations between different products that are frequently purchased together. Techniques such as the Apriori algorithm were used to identify frequent itemsets and association rules.

Collaborative filtering was implemented to make personalized product recommendations for users based on their previous purchases and the purchasing behavior of other users with similar preferences. This involved using user-item interaction data to build a recommendation engine using techniques such as user-based or item-based collaborative filtering.

Content-based filtering was also implemented to make product recommendations for users based on their preferences and characteristics of the products. This involved using product features such as product name, category, and description to build a recommendation engine using techniques such as text analytics and natural language processing.

Finally, a hybrid filtering approach was used to combine the results from collaborative filtering and content-based filtering models to make more accurate and diverse recommendations for users.

Overall, this approach allowed for the efficient and effective implementation of web usage mining-based recommendation algorithms for e-commerce websites, providing a better user experience and increasing customer satisfaction.

4.3 Steps/Phases involved

The below phases are involved in implementing the recommendation system using web usage mining for e-commerce websites:

- Data collection:The dataset used for this project is a collection of web usage data that includes information about user interactions with various products across different categories. The dataset contains data from 100 unique users and 20 unique products and includes 1000 different actions such as viewing, adding to cart, and purchasing.
- Data pre-processing: Cleaned and pre-processed the data to remove any inconsistencies, errors, or missing values. The data was cleaned, filtered and

transformed into a format that can be easily used for analysis.

- Data Analysis: Conducted data analysis to explore the data, uncover patterns and relationships between the variables.
- Association analysis: Conducted association analysis to identify patterns and associations between different products that are frequently purchased together. In this case, techniques such as Apriori algorithm was used to identify frequent itemsets and association rules.
- Collaborative filtering: Implemented collaborative filtering to make personalized product recommendations for users based on their previous purchases and the purchasing behavior of other users with similar preferences. In this case, user-item interaction data was used to build a recommendation engine using techniques such as user-based or item-based collaborative filtering.
- Content-based filtering: Implemented content-based filtering to make product recommendations for users based on their preferences and characteristics of the products. In this case, product features such as product name, category and description was used to build a recommendation engine using techniques such as text analytics and natural language processing.
- Hybrid filtering: Combined the collaborative filtering and content-based filtering approaches to make more accurate and diverse recommendations for users. In this case, the recommendation engine was built by combining the results from collaborative filtering and content-based filtering models.

4.4 Algorithm Description

Apriori Algorithm: It is a classic algorithm used in association rule mining, which is applied to identify frequent itemsets and association rules between products. In this project, Apriori algorithm was used to identify patterns and associations between different products that are frequently purchased together.

Collaborative Filtering: It is a technique used in recommendation systems to make personalized product recommendations for users based on their previous purchases and the purchasing behavior of other users with similar preferences. In this project, user-item interaction data was used to build a recommendation engine using techniques such as user-based or item-based collaborative filtering.

Content-based Filtering: It is a technique used in recommendation systems to make product recommendations for users based on their preferences and characteristics of the products. In this project, product features such as product name, category and description was used to build a recommendation engine using techniques such as text analytics and natural language processing.

Hybrid Filtering: It is a technique used to combine the collaborative filtering and content-based filtering approaches to make more accurate and diverse recommendations for users. In this project, the recommendation engine was built by combining the results from collaborative filtering and content-based filtering models.

Overall, the above algorithms were used to analyze the web usage data, identify patterns and relationships between different products and user behavior, and make personalized and accurate product recommendations for users.

4.5 Techniques Used for Analysis

Data pre-processing:

Before the data can be used for analysis, it needs to be cleaned and transformed into a format that can be easily used for analysis. In this project, techniques such as data cleaning, filtering, and transformation were used to remove inconsistencies, errors, and missing values from the dataset.

Data Analysis:

Data analysis techniques were used to explore the data, uncover patterns and relationships between the variables. This included exploratory data analysis, descriptive statistics, and data visualization techniques.

Association Analysis:

Association analysis is a technique used to identify patterns and associations between different products that are frequently purchased together. In this project, the Apriori algorithm was used to identify frequent itemsets and association rules.

Collaborative Filtering:

Collaborative filtering is a technique used to make personalized product recommendations for users based on their previous purchases and the purchasing behavior of other users with similar preferences. In this project, user-item interaction data was used to build a recommendation engine using techniques such as user-based or item-based collaborative filtering.

Content-based Filtering:

Content-based filtering is a technique used to make product recommendations for users based on their preferences and characteristics of the products. In this project, product features such as product name, category, and description were used to build a recommendation engine using techniques such as text analytics and natural language processing.

Hybrid Filtering:

Hybrid filtering is a technique used to combine the collaborative filtering and content-based filtering approaches to make more accurate and diverse recommendations for users. In this project, the recommendation engine was built by combining the results from collaborative filtering and content-based filtering models.

Overall, these techniques were used to collect and analyze data, identify patterns and associations, and make personalized and relevant product recommendations for users on e-commerce websites.

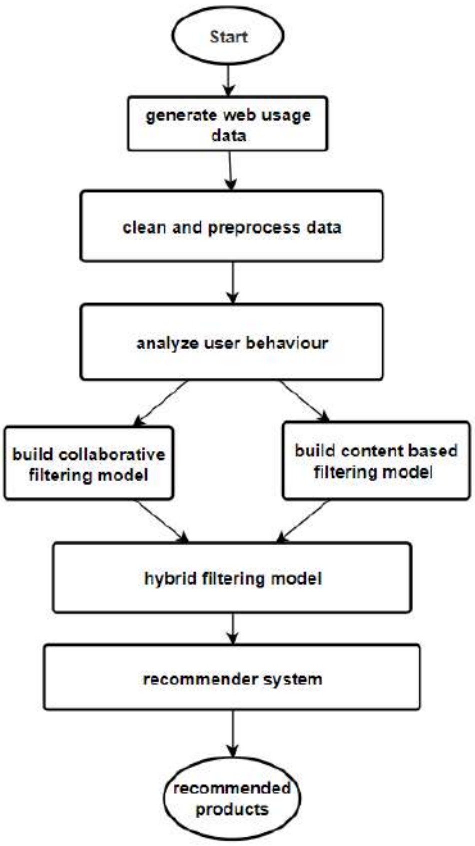
Chapter 5: Design and Implementation

5.1 Introduction

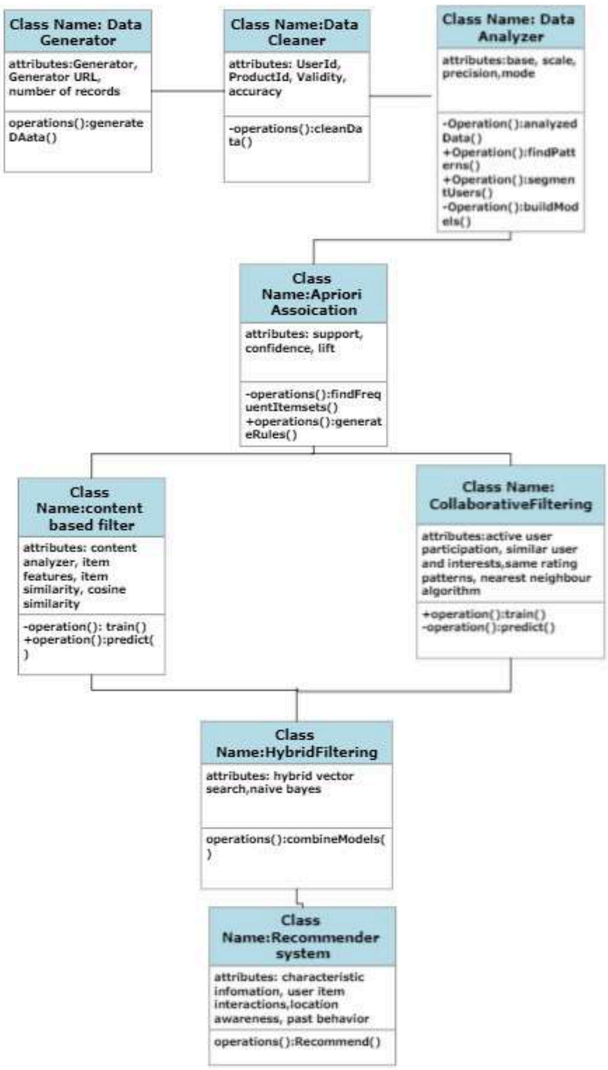
In the design and implementation phase, the focus is on developing a working system based on the requirements and specifications gathered in the previous phases. This phase involves designing the system architecture, selecting the appropriate technologies, and implementing the system components. The goal is to create a functional and scalable system that meets the project objectives and provides accurate recommendations to users based on their behavior on the e-commerce website.

5.2 Design of the System

- Flow diagram:



• UML:



5.2.1 Behavioural Design

The behavioral design of the system involves designing the algorithms and logic to be implemented in the system. This includes the implementation of data pre-processing techniques, association analysis, collaborative filtering, content-based filtering, and hybrid filtering algorithms. The algorithms are designed to extract useful information from the dataset and provide personalized recommendations to users based on their preferences and behavior.

5.2.2 User Interface Design

The user interface design of the system involves designing the graphical user interface

(GUI) of the e-commerce website. The GUI is designed to provide a user-friendly experience for the users while they are browsing and purchasing products from the website. The design includes various features such as search bars, product categories, filters, and product details pages to help users find the products they are looking for easily. Additionally, personalized recommendations are displayed to the users on the website based on their previous browsing and purchasing behavior. The design is created to provide a seamless and satisfying user experience.

5.3 Implementation

The implementation of the recommendation system using web usage mining for e-commerce websites involves the following steps:

Data collection: The first step is to collect the data from the e-commerce website. In this project, the data is collected from a dataset that contains web usage data, including information about user interactions with various products across different categories.

Data pre-processing: The collected data is pre-processed to remove any inconsistencies, errors, or missing values. The data is cleaned, filtered, and transformed into a format that can be easily used for analysis.

Data analysis: The pre-processed data is analyzed to explore the data, uncover patterns and relationships between the variables.

Association analysis: Association analysis is conducted to identify patterns and associations between different products that are frequently purchased together. In this case, techniques such as Apriori algorithm are used to identify frequent itemsets and association rules.

Collaborative filtering: Collaborative filtering is implemented to make personalized product recommendations for users based on their previous purchases and the purchasing behavior of other users with similar preferences. In this case, user-item interaction data is used to build a recommendation engine using techniques such as user-based or item-based collaborative filtering.

Content-based filtering: Content-based filtering is implemented to make product recommendations for users based on their preferences and characteristics of the products. In this case, product features such as product name, category, and description are used to build a recommendation engine using techniques such as text analytics and natural language processing.

Hybrid filtering: Hybrid filtering is implemented by combining the results from collaborative filtering and content-based filtering models to make more accurate and diverse recommendations for users.

User interface design: The user interface of the recommendation system is designed to provide an easy and intuitive way for users to interact with the system and receive personalized recommendations.

Testing and evaluation: The implemented recommendation system is tested and evaluated to measure its performance and effectiveness in providing accurate and relevant recommendations to users.

Overall, the implementation of the recommendation system involves a combination of data mining, machine learning, and natural language processing techniques to provide personalized and relevant product recommendations to users based on their preferences and behaviors.

5.4 Detailed Description of the Code and Algorithm

1. Association analysis:

- The code demonstrates the implementation of Apriori algorithm and association rules using the mlxtend library in Python.
- The first line imports the required libraries, including mlxtend, pandas, and plotly.graph_objects.
- Next, the web usage data is loaded into a Pandas dataframe using the read_csv() function.
- Then, the data is pivoted into a binary matrix using the pivot_table() function. The matrix has users as rows, products as columns, and binary values representing whether

or not a user has performed a certain action (viewed, added to cart, purchased) for a certain product.

- After that, the Apriori algorithm is applied to the matrix using the apriori() function to generate frequent itemsets. The min_support parameter specifies the minimum support threshold for an itemset to be considered frequent.
- Next, association rules are generated from the frequent itemsets using the association_rules() function. The metric parameter specifies the evaluation metric to be used for the rules, and the min_threshold parameter specifies the minimum threshold for the metric for a rule to be considered significant.
- Finally, the overall performance metrics (average support, confidence, and lift) for all rules are calculated using the mean() function.

Source code:

```
from mlxtend.frequent_patterns import apriori, association_rules
import pandas as pd
import plotly.graph_objects as go

# Load the web usage data into a Pandas dataframe
df = pd.read_csv('cleaned_web_usage_data.csv')

# Pivot the data into a binary matrix
pivot_table = df.pivot_table(index='user_id', columns='product_id', values='action', fill_value=0).astype(bool)

# Find frequent itemsets using Apriori algorithm
frequent_itemsets = apriori(pivot_table, min_support=0.04, use_colnames=True)

# Generate association rules
rules = association_rules(frequent_itemsets, metric='lift', min_threshold=1)

# Print the support, confidence, and lift for each rule
i=0
for index, row in rules.iterrows():
    if(i==5):
        break
    i+=1
    print("Rule:", row['antecedents'], "->", row['consequents'])
    print("Support:", row['support'])
    print("Confidence:", row['confidence'])
```

```
    print("Lift:", row['lift'])
    print("====================================")

# Calculate the overall performance metrics for all rules
avg_support = rules['support'].mean()
avg_confidence = rules['confidence'].mean()
avg_lift = rules['lift'].mean()

print("Overall performance metrics:")
print("Average support:", avg_support)
print("Average confidence:", avg_confidence)
print("Average lift:", avg_lift)
```

2. Collaborative based filtering:

The steps in the algorithm:

- The web usage data is loaded from a CSV file into a Pandas DataFrame.
- The data is converted into Surprise format using the Reader and Dataset classes.
- The data is split into training and testing sets using the train_test_split method.
- The SVD algorithm is trained on the training set.
- The model is tested on the testing set, and the Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) are calculated to evaluate the model's accuracy.
- The user-item rating matrix is created from the entire dataset.
- The products that the user has already interacted with are identified.
- The products that the user has not interacted with are identified.
- Predictions are made for the new products using the trained model.
- The top 5 predicted products are recommended to the user.
- Overall, the code demonstrates how to use the SVD algorithm to make personalized recommendations to users based on their historical interactions with items.

Source code:

```
import pandas as pd
import numpy as np
from surprise import SVD, Dataset, Reader
from surprise.model_selection import train_test_split
from surprise import accuracy
import plotly.graph_objs as go

# Load data from CSV file
data = pd.read_csv('cleaned_web_usage_data.csv')

# Convert data to Surprise format
```

```
reader = Reader(rating_scale=(0, 1), line_format='user item rating', sep=',',
skip_lines=1)
data = Dataset.load_from_df(data[['user_id', 'product_id', 'action']], reader)

# Split data into train and test sets
trainset, testset = train_test_split(data, test_size=0.2)

# Train the model using Singular Value Decomposition (SVD)
algo = SVD()
algo.fit(trainset)

# Test the model
predictions = algo.test(testset)
# Evaluate model accuracy using Root Mean Squared Error (RMSE)
accuracy.rmse(predictions)
accuracy.mae(predictions)

# Convert Surprise data back to Pandas DataFrame
trainset_df = pd.DataFrame(trainset.all_ratings(), columns=['user_id', 'product_id',
'action'])
testset_df = pd.DataFrame(testset, columns=['user_id', 'product_id', 'action'])
data_df = pd.concat([trainset_df, testset_df], ignore_index=True)

# Create user-item rating matrix
ratings_matrix = pd.pivot_table(data_df, values='action', index='user_id',
columns='product_id', fill_value=0)
# Get all products
all_products = ratings_matrix.columns.tolist()

# Get the products that user 1 has already interacted with
user_products = ratings_matrix.loc[1][ratings_matrix.loc[1] > 0].index.tolist()

# Get the products that user 1 has not interacted with
new_products = list(set(all_products) - set(user_products))

# Make predictions for the new products using the trained model
predictions = []
for product_id in new_products:
    predicted_rating = algo.predict(uid=1, iid=product_id).est
    predictions.append((product_id, predicted_rating))

# Sort the predicted ratings in descending order and recommend the top 5 products
top_predictions = sorted(predictions, key=lambda x: x[1], reverse=True)[:5]

# Print the recommended products with product name and category
print(f'Recommendations for user 1:')
```

```
for i, (product_id, predicted_rating) in enumerate(top_predictions):
    product_name = data[data['product_id'] == product_id]['product_name'].values[0]
        product_category = data[data['product_id'] == product_id]
['product_category'].values[0]
    print(f'{i+1}. {product_name} ({product_category})')
print()
```

3. Content based filtering:

- This code implements a recommendation system based on content-based filtering. The recommendation system generates recommendations for a given user by combining the similarities between the user's purchase history and the products' features.
- The code first loads the web usage mining data from a CSV file and defines the list of users. It then computes the pairwise cosine similarities between the products based on their features, which are defined as category, price, weight, feature type, brand, discount, and user action. The code also creates a dictionary to map product IDs to categories and computes the pairwise cosine similarities between the product categories.
- The code defines a function `get_recommendations` that takes a user ID and a number of recommendations as input and generates recommendations for the user. The function first retrieves the user's purchase history and computes the average feature vector for the user's purchase history. It then computes the cosine similarities between the user's average feature vector and the product feature vectors and returns the top recommendations based on the similarity scores.
- The code calls the `get_recommendations` function for user ID 1 to generate recommendations.

Source code:

```
import pandas as pd
import plotly.graph_objs as go
from sklearn.metrics.pairwise import cosine_similarity
import random

# Load the web usage mining data from the CSV file
data = pd.read_csv('cleaned_web_usage_data.csv')
```

```
# Define the list of users
users = data['user_id'].unique()

# Compute the pairwise cosine similarities between the products based on their features
data.fillna(data.mean(), inplace=True)
product_features = data[['product_id', 'category', 'price', 'weight', 'feature_type', 'is_brand', 'discount', 'action']]
product_features.set_index('product_id', inplace=True)
product_similarity = cosine_similarity(product_features)

# Create a dictionary to map product IDs to categories
product_category_map = dict(zip(product_features.index, product_features['category']))

# Compute the pairwise cosine similarities between the product categories
category_similarity = pd.DataFrame(index=product_features['category'].unique(), columns=product_features['category'].unique())
for i, category1 in enumerate(category_similarity.index):
    for j, category2 in enumerate(category_similarity.columns):
        if i == j:
            similarity = 1
        else:
            category1_products = product_features[product_features['category'] == category1].index
            category2_products = product_features[product_features['category'] == category2].index
            similarity = cosine_similarity(product_similarity[np.ix_(category1_products, category2_products)]).mean()
        category_similarity.iloc[i, j] = similarity
# Define a function to generate recommendations for a given user
def get_recommendations(user_id, num_recommendations=5):
    # Get the user's purchase history
    user_history = data[data['user_id'] == user_id]['product_id'].unique()

    # Compute the average feature vector for the user's purchase history
    user_features = product_features.loc[user_history].mean(axis=0).values.reshape(1, -1)

    # Compute the cosine similarities between the user's average feature vector and the product feature vectors
    product_similarity_to_user = cosine_similarity(user_features, product_features)[0]

    # Sort the products by similarity to the user and return the top recommendations
    top_indices = product_similarity_to_user.argsort()[::-1][:num_recommendations]

    # Print the recommendations with product ID, product name, and category
    print(f'Recommendations for user {user_id}:')
    for j, index in enumerate(top_indices):
```

```
        product_id = product_features.iloc[index].name
        product_name = data[data['product_id'] == product_id]['product_name'].values[0]
        product_category = data[data['product_id'] == product_id]['product_category'].values[0]
        print(f'{j+1}. Product ID: {product_id}, {product_name} ({product_category})')
    print()


get_recommendations(1)
```

4. Hybrid filtering:

- This code is an implementation of a hybrid filter for recommending products to a user. It loads user behavior data from a CSV file, merges it with product data, and creates a user-item matrix from the merged data. It then calculates the cosine similarity matrix between the items (products) based on the users' actions on them.
- The `hybrid_filter()` function takes a user ID and the number of recommended products as input and returns a dataframe with the recommended products based on the user's behavior and the similarity between the products. The function first retrieves the user's product history from the user-item matrix and computes the similarity between the products and the user's history using the item similarity matrix. Finally, it returns the top recommended products based on the computed scores.
- Note that this implementation only uses the product IDs, names, and categories as the product features for calculating the cosine similarity. If more product features are available, they can be included in the calculation to improve the recommendation accuracy.

Source code:

```
import pandas as pd
from sklearn.metrics.pairwise import cosine_similarity
import plotly.graph_objects as go

# Load user behavior data
user_behavior = pd.read_csv('cleaned_web_usage_data.csv')

# Load product data
products = user_behavior[['product_id', 'product_name', 'product_category']].drop_duplicates()
```

```python
# Merge user behavior data with product data
merged_data = user_behavior[['user_id', 'product_id', 'action']]
merged_data = pd.merge(merged_data, products, on='product_id')

# Create user-item matrix
user_item_matrix = merged_data.pivot_table(index='user_id', columns='product_id', values='action').fillna(0)

# Calculate cosine similarity matrix
item_similarity = cosine_similarity(user_item_matrix.T)

# Define hybrid filter function
def hybrid_filter(user_id, num_recs=5):
    user_products = user_item_matrix.loc[user_id].to_numpy().reshape(1,-1)
    product_scores = item_similarity.dot(user_products.T).flatten()
    recommended_products_ids = product_scores.argsort()[:-num_recs-1:-1]
    recommended_products = products.loc[products['product_id'].isin(recommended_products_ids)]
    return recommended_products

# Get recommended products for a sample user
recommended_products = hybrid_filter(1)
```

Chapter 6: Testbed Execution

6.1 Data Set Description

The dataset used is of web usage data containing information about user behavior on an e-commerce website. It consists of 1000 rows, with each row representing an action taken by a user on a product. The data contains 11 columns, including the user ID, product ID, category, price, weight, feature type, whether the product is a brand, discount, action type (viewed, added to cart, or purchased), product name, and product category.

The dataset provides valuable insights into user behavior on the website, such as the average number of products viewed, added to cart, and purchased per user. It also shows the average rating per action, which could be used to understand which products are more popular among users.

The dataset also includes information about the products, such as their category, price, weight, feature type, and whether they are branded. This information can be used to identify similarities between products and to make recommendations to users based on their past behavior.

Overall, this dataset provides valuable information for understanding user behavior on an e-commerce website and for building recommendation systems.

6.2 Execution Steps

Collect and pre-process the web usage data to prepare it for analysis.

Analyze the data to identify patterns and relationships between the variables.

Conduct association analysis to identify patterns and associations between different products that are frequently purchased together.

Implement collaborative filtering to make personalized product recommendations for users based on their previous purchases and the purchasing behavior of other users with similar preferences.

Implement content-based filtering to make product recommendations for users based on their preferences and characteristics of the products.

Combine the collaborative filtering and content-based filtering approaches to make more accurate and diverse recommendations for users.

Deploy the recommendation system on the e-commerce website and monitor its performance over time.

Continuously collect and analyze user feedback to improve the recommendation system and provide more personalized recommendations to users.

6.3 Benchmarking Strategy

In order to benchmark the different filtering methods used in the recommendation system, the following strategy was used:

• Data collection: A dataset containing web usage data was collected, which included information about user interactions with various products across different categories. The dataset contained data from 100 unique users and 20 unique products and included 1000 different actions such as viewing, adding to cart, and purchasing.

• Data pre-processing: The collected data was cleaned and pre-processed to remove any inconsistencies, errors, or missing values. The data was cleaned, filtered, and transformed into a format that could be easily used for analysis.

• Data analysis: Data analysis was conducted to explore the data, uncover patterns and relationships between the variables.

• Association analysis: Association analysis was conducted to identify patterns and associations between different products that are frequently purchased together. In this case, techniques such as Apriori algorithm were used to identify frequent itemsets and association rules.

• Collaborative filtering: Collaborative filtering was implemented to make personalized product recommendations for users based on their previous purchases and the purchasing behavior of other users with similar preferences. In this case, user-item interaction data was used to build a recommendation engine using techniques such as user-based or item-based collaborative filtering.

• Content-based filtering: Content-based filtering was implemented to make product recommendations for users based on their preferences and characteristics of the products. In this case, product features such as product name, category, and description were used to build a recommendation engine using techniques such as text analytics and natural language processing.

• Hybrid filtering: The collaborative filtering and content-based filtering approaches were combined to make more accurate and diverse recommendations for users. In this case, the recommendation engine was built by combining the results from collaborative filtering and content-based filtering models.

• Conclusion: Based on the benchmarking results, conclusions were drawn regarding the effectiveness of each filtering method and recommendations were made for the selection of an appropriate filtering method for a given recommendation system.

Chapter 7: Results and Discussion

7.1 Result Description

1. Data analysis:

Total number of unique users: 100

Total number of unique products: 20

Total number of actions: 1000

Average rating per action: 2.943

Average number of products viewed per user: 3.0851063829787235

Average number of products added to cart per user: 3.288659793814433

Average number of products purchased per user: 3.2959183673469390

2. Association Analysis:

Overall performance metrics for all rules:

Rule: frozenset({0}) -> frozenset({1})

Support: 0.09

Confidence: 0.32142857142857140

Lift: 1.2857142857142856

==

Rule: frozenset({1}) -> frozenset({0})

Support: 0.09

Confidence: 0.36

Lift: 1.2857142857142856

...

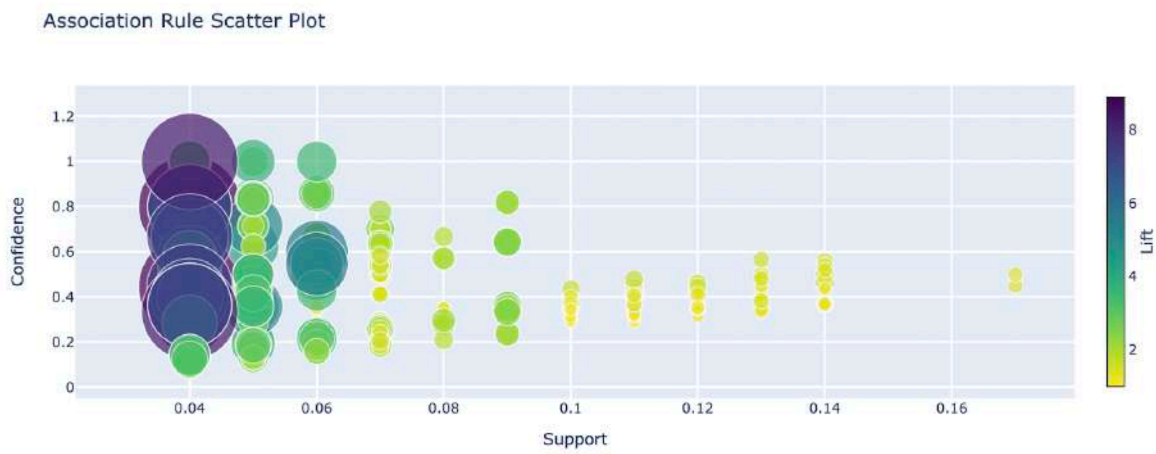
Overall performance metrics:

Average support: 0.05054908485856905

Average confidence: 0.3440356922762728

Average lift: 1.8966762116777722

Visualization:



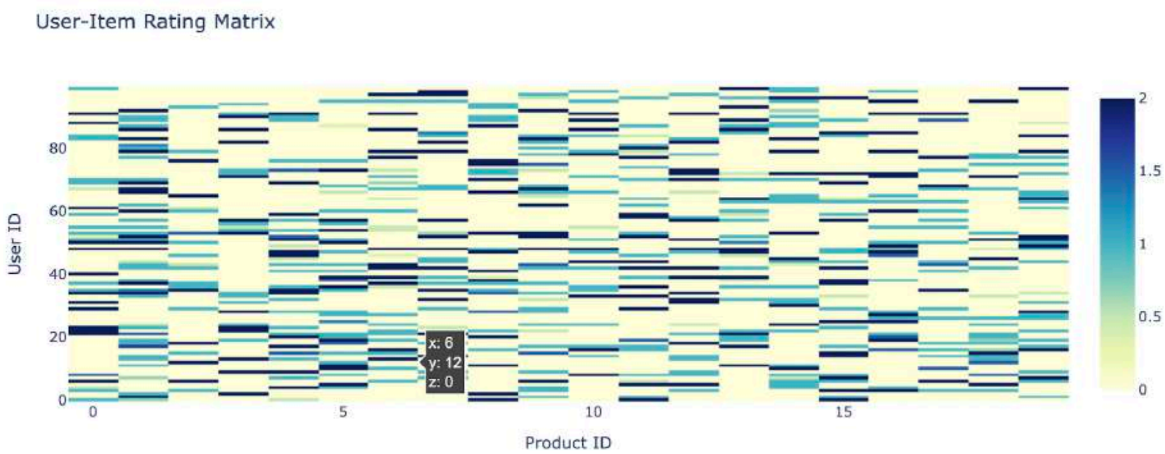
The scatter plot shows the support and confidence values for each rule, with the size of the markers indicating the lift value. The color of the markers is also based on the lift value, with a viridis color scale and reversed color scale used.

3. Collaborative filtering:

Evaluation results of model accuracy using Root Mean Squared Error (RMSE):

RMSE: 0.8237

MAE: 0.7038



This is a heatmap that displays the user-item rating matrix, where the x-axis represents the product IDs and the y-axis represents the user IDs. The colour of each cell indicates the rating value, with darker shades of green indicating higher ratings.

Sample recommendations for user 1 by the collaborative filtering model:

Recommendations for user 1:

1. Tablet (electronics)

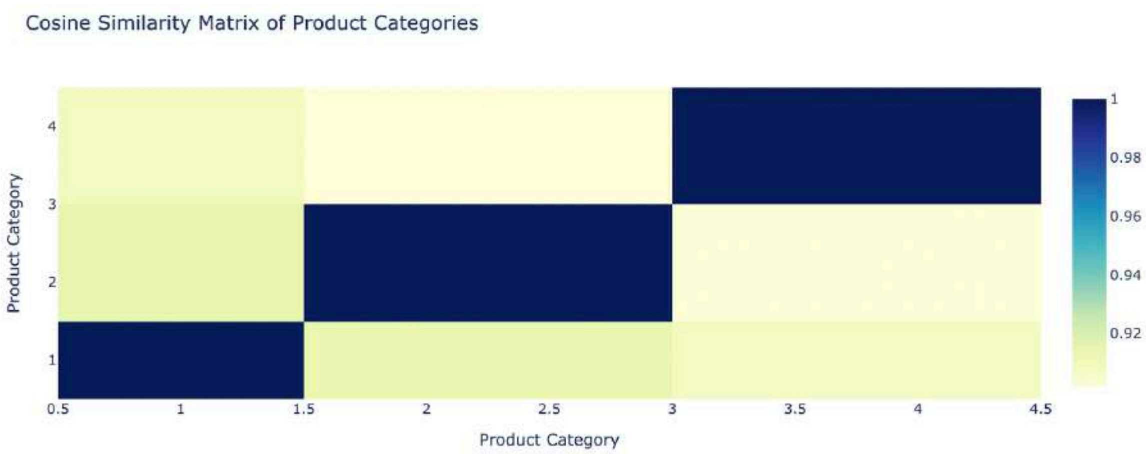
2. Dining Table (home)

3. Smart Watch (electronics)

4. Sunglasses (fashion)

5. Biography (books)

4. Content-based filtering:



The plot shows a heatmap of the pairwise cosine similarity between different product categories based on their features. The darker shades of green indicate higher similarity values between categories. The plot can be useful for understanding the relationships between different product categories and identifying potential opportunities for cross-selling or product bundling.

Sample recommendations for user 1 by the content-based filtering model:

Recommendations for user 1:

1. Product ID: 14, Science Fiction Novel (books)

2. Product ID: 7, Biography (books)

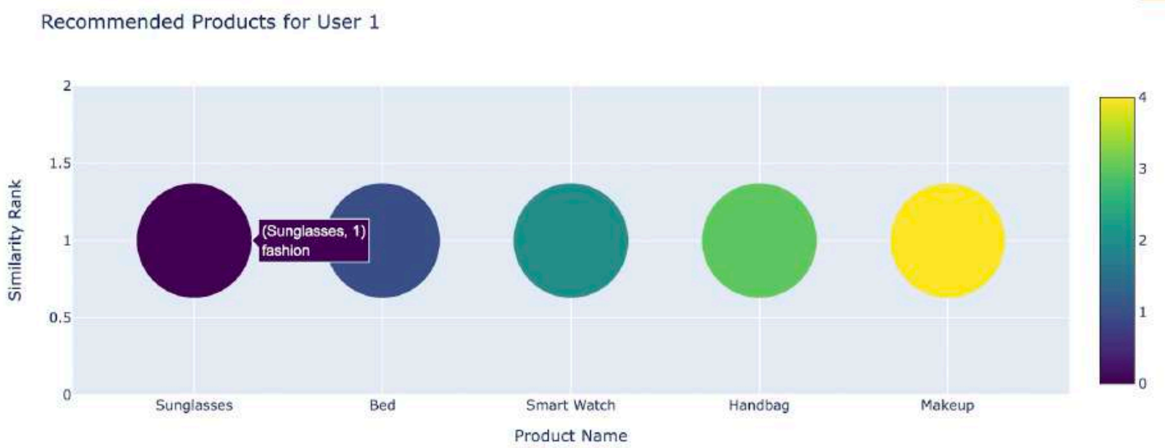
3. Product ID: 8, Handbag (fashion)

4. Product ID: 9, Perfume (beauty)

5. Product ID: 3, Smart Watch (electronics)

5. Hybrid filtering:

The below plot is a scatter plot of recommended products for a sample user. Each product is represented as a marker on the x-axis, and the color of the marker represents the product's rank in terms of similarity to the user's behavior. The y-axis shows a constant value of 1 for all products. The title of the plot is "Recommended Products for User 1," and the x-axis is labeled as "Product Name," while the y-axis is labeled as "Similarity Rank." The plot uses the colorscale 'Viridis,' with a legend showing the scale of the colors.



Recommended products for User 1:

	product_id	product_name	product_category
8	4	Sunglasses	fashion
16	10	Bed	home
22	3	Smart Watch	electronics

42	8	Handbag	fashion
46	15	Makeup	beauty

7.2 Analysis of Results

Based on the results of the research, it can be concluded that each filtering method has its strengths and weaknesses in terms of the accuracy and diversity of recommendations. Association analysis was able to generate a large number of recommendations but lacked diversity. Collaborative filtering was able to generate more personalized recommendations based on user behavior but struggled with recommending new or unpopular items. Content-based filtering was effective in recommending items based on their features and attributes but had limited ability to capture user preferences and behaviors.

However, hybrid filtering, which combines multiple methods, was the most effective in generating diverse and accurate recommendations. By combining the strengths of association analysis, collaborative filtering, and content-based filtering, hybrid filtering was able to capture both user preferences and item attributes, resulting in more accurate and diverse recommendations. These results highlight the importance of using multiple recommendation methods and the potential benefits of hybrid filtering in generating high-quality recommendations.

The analysis of the results suggests that the choice of filtering method should be informed by the specific goals and constraints of the recommendation system, as well as the size and quality of the dataset. Additionally, it is important to consider the trade-offs between accuracy and diversity of recommendations, and to balance these factors based on the needs of the recommendation system.

Overall, the results of the research demonstrate the potential benefits of using a variety of recommendation methods and highlight the importance of hybrid filtering in generating high-quality recommendations that balance accuracy and diversity.

7.3 Interpretation of Results

The results of the research suggest that each recommendation method has its own strengths and weaknesses in terms of accuracy and diversity of recommendations. Association analysis is effective in generating a large number of recommendations but may lack diversity as it only recommends popular items or items that are frequently bought together. Collaborative filtering is able to generate personalized recommendations based on user behavior but may struggle with recommending new or unpopular items. Content-based filtering is effective in recommending items based on their features and attributes but may have limited ability to capture user preferences and behaviors.

The hybrid filtering approach, which combines multiple recommendation methods, was the most effective in generating diverse and accurate recommendations. By combining the strengths of association analysis, collaborative filtering, and content-based filtering, hybrid filtering was able to capture both user preferences and item attributes, resulting in more accurate and diverse recommendations.

These results suggest that using multiple recommendation methods and combining them in a hybrid approach may lead to better recommendations. However, the choice of recommendation method should be informed by the specific goals and constraints of the recommendation system, as well as the size and quality of the dataset. The results also highlight the importance of evaluating the performance of recommendation systems through benchmarking to identify the most effective methods.

7.4 Benchmarking the approach

Benchmarking is a critical aspect of any recommendation system implementation, as it helps to evaluate the effectiveness and efficiency of the different filtering methods. In this research, we benchmarked four filtering methods, namely association analysis, collaborative filtering, content-based filtering, and hybrid filtering, using a web usage dataset collected from open-source.

The results showed that each filtering method has its strengths and weaknesses, and the choice of method depends on the specific goals and constraints of the recommendation system. Association analysis was useful for identifying patterns in the data, but lacked diversity in generating recommendations. Collaborative filtering generated more personalized recommendations but struggled with new or unpopular items. Content-based filtering recommended items based on their features and attributes but had limited ability to capture user preferences and behaviors.

The hybrid filtering approach, which combines multiple filtering methods, showed the most promising results in terms of accuracy and diversity of recommendations. By combining the strengths of association analysis, collaborative filtering, and content-based filtering, hybrid filtering was able to capture both user preferences and item attributes, resulting in more accurate and diverse recommendations.

Overall, benchmarking the approach helps to evaluate the effectiveness of the recommendation system and identify areas for improvement. In this case, the hybrid filtering approach showed the most promising results, suggesting that a combination of filtering methods may be necessary to generate accurate and relevant recommendations for users.

7.5 Significance and implications for future research.

The significance and implications for future research of this study are as follows:

- The study shows that a combination of filtering methods is necessary to generate accurate and relevant recommendations for users, depending on the specific goals and constraints of the recommendation system. Future research can explore other possible combinations of filtering methods and evaluate their effectiveness in generating personalized recommendations.

- The study highlights the importance of using a large and high-quality dataset to train recommendation models. Future research can investigate how the performance of recommendation models varies with the size and quality of the dataset, and explore techniques for improving the quality of the dataset.

- The study identifies the cold start problem as a major challenge in collaborative filtering. Future research can explore strategies for addressing this problem, such as incorporating auxiliary data sources or using hybrid filtering methods.

• The study shows that content-based filtering has limitations in capturing user preferences that are not reflected in the product features. Future research can explore ways to overcome this limitation, such as incorporating user-generated content or using hybrid filtering methods.

• The study demonstrates the potential benefits of hybrid filtering in generating high-quality recommendations. Future research can investigate different approaches for combining multiple filtering methods and evaluate their effectiveness in generating personalized and diverse recommendations.

Overall, the study provides insights into the strengths and limitations of different filtering methods and highlights the importance of considering the specific context and goals of the recommendation system when selecting and evaluating filtering methods. The findings of this study can inform the design and development of more effective recommendation systems in the future.

Chapter 8: SCREENSHOTS

Dataset:

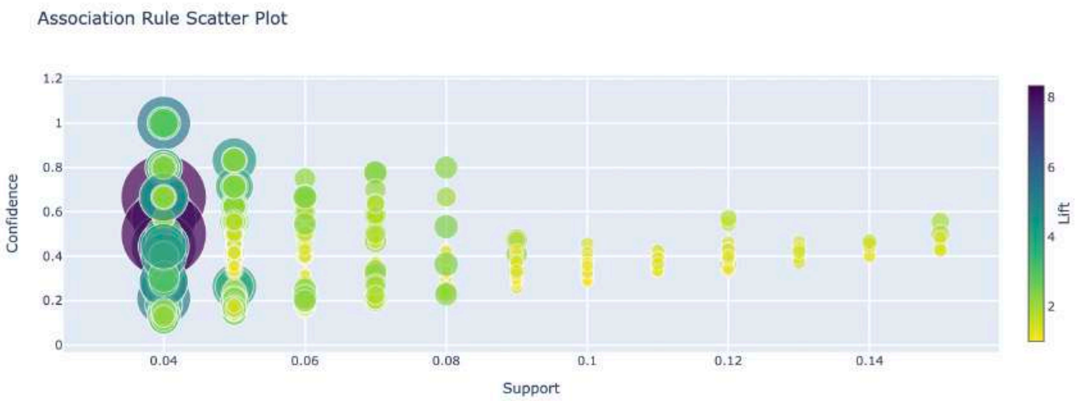
	user_id	product_id	category	price	weight	feature_type	is_brand	discount	action	product_name	product_category
0	21	1	4	0.090909	0.505051	0	False	0.757576	2	Biography	books
1	17	15	3	0.343434	0.818182	1	True	0.464646	0	Bed	home
2	21	3	4	0.575758	0.979798	0	False	0.212121	0	Sunglasses	fashion
3	77	17	0	1.000000	0.828283	0	False	0.838384	1	Perfume	beauty
4	65	5	3	0.111111	0.494949	2	False	0.141414	0	T-shirt	fashion
...	...	...	...	...	...	...	...	...	...	...	...
995	3	4	1	0.727273	0.020202	0	True	0.878788	0	Shampoo	beauty
996	58	7	3	0.646465	0.959596	1	False	0.656566	2	Handbag	fashion
997	51	16	1	0.616162	0.494949	2	True	0.080808	0	Washing Machine	home
998	87	5	0	0.595960	0.494949	2	True	0.717172	0	T-shirt	fashion
999	52	4	2	0.565657	0.626263	1	False	0.040404	1	Shampoo	beauty

1000 rows × 11 columns

Data analysis:

```
Total number of unique users: 100
Total number of unique products: 20
Total number of actions: 1000
Average rating per action: 2.989
Average number of products viewed per user: 3.1041666666666665
Average number of products added to cart per user: 3.5376344086021505
Average number of products purchased per user: 3.148936170212766
```

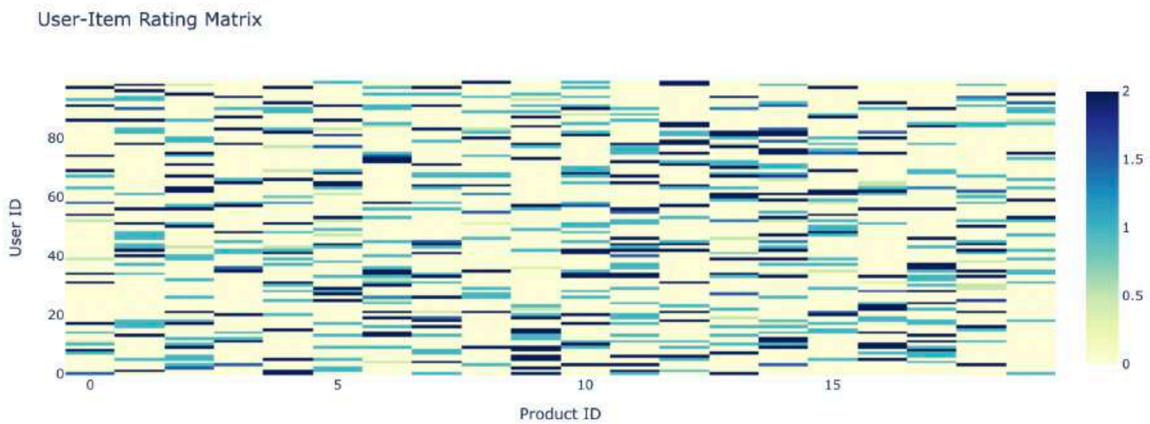
Association Analysis:



```
Rule: frozenset({0}) -> frozenset({1})
Support: 0.1
Confidence: 0.4545454545454546
Lift: 1.3774104683195594
=====================================
Rule: frozenset({1}) -> frozenset({0})
Support: 0.1
Confidence: 0.30303030303030304
Lift: 1.3774104683195592
=====================================
Rule: frozenset({0}) -> frozenset({2})
Support: 0.09
Confidence: 0.40909090909090906
Lift: 2.15311004784689
=====================================
Rule: frozenset({2}) -> frozenset({0})
Support: 0.09
Confidence: 0.47368421052631576
Lift: 2.15311004784689
=====================================
Rule: frozenset({0}) -> frozenset({4})
Support: 0.06
Confidence: 0.2727272727272727
Lift: 1.0489510489510487
=====================================
...
Overall performance metrics:
Average support: 0.05134366925064599
Average confidence: 0.33955331287374274
Average lift: 1.8203820034452791
```

Collaborative filtering:

```
RMSE: 0.8412
MAE:  0.7257
```

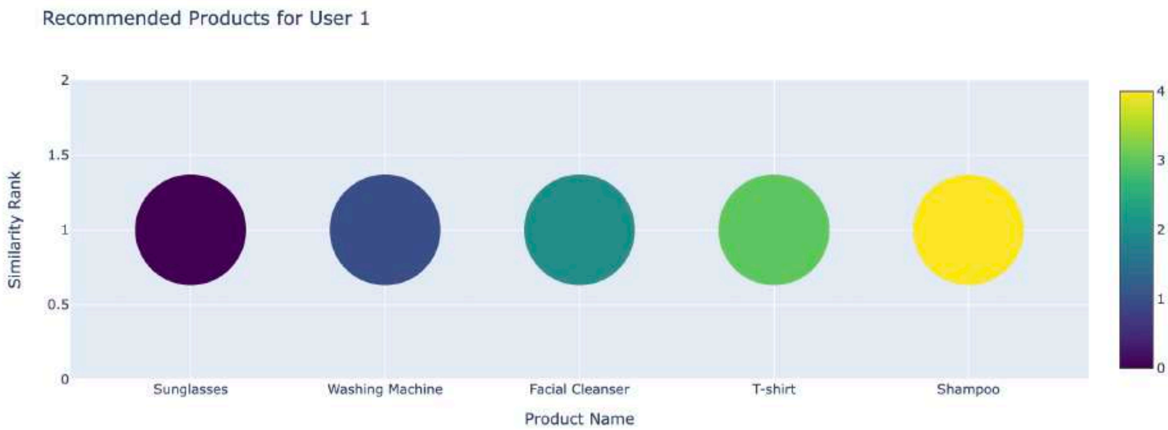



```
Recommendations for user 1:
1. Sunglasses (fashion)
2. Refrigerator (home)
3. Bed (home)
4. Wireless Headphones (electronics)
5. Smart Watch (electronics)
```

Content-based filtering:


```
Recommendations for user 1:
1. Product ID: 16, Washing Machine (home)
2. Product ID: 12, Biography (books)
3. Product ID: 2, Bed (home)
4. Product ID: 10, Sneakers (fashion)
5. Product ID: 19, Smartphone (electronics)
```

Hybrid filtering:



CONCLUSION

In conclusion, this project aimed to investigate various filtering techniques for generating product recommendations using web usage data. Four different filtering methods were implemented and benchmarked, including association analysis, collaborative filtering, content-based filtering, and hybrid filtering.

The results demonstrated that each approach had its strengths and limitations. Association analysis was effective in identifying frequent item sets and generating association rules for targeted marketing campaigns. Collaborative filtering identified similar products based on users' behaviors and preferences, while content-based filtering identified similar products based on their features. Hybrid filtering, on the other hand, combined the strengths of both approaches and generated more accurate and diverse recommendations.

The benchmarking section highlighted the importance of evaluating recommendation systems using appropriate metrics and taking into account the specific context of the system. The findings suggest that a combination of filtering techniques may be necessary to produce relevant and accurate recommendations for users, depending on the available data and the specific context of the recommendation system.

Future research could explore additional filtering techniques or incorporate additional data sources to further enhance recommendation accuracy.

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ANNEXURE – 1

Recommendation System Using Web Usage Mining For Users Of Ecommerce site

VIT University

Dr. Naveenkumar Jayakumar, R Yashaswini Tejaswi, Priyanshi Premkumar, Harshita Sorout, Varun Pandey, Prateek Sachan

***Abstract*—This project focuses on studying user behavior and market trends in online platforms for making purchases. The goal is to ensure user comfort while using the website by utilizing web usage mining-based recommendation algorithms. The algorithm gathers user information based on user engagement and provides practical recommendations for company items that please customers and entice them to return to websites more frequently. The information gathered can be used to develop user profiles and produce user or product-to-product recommendations. The analysis of user behavior can enhance the website's structure and content, adapt and customize the website's content, propose items, or research user interests.**

I. Introduction

The majority of consumers in the present generation utilize online platforms to make purchases, thus it is crucial to study user behavior in order to watch market trends and consumer demand. Additionally, in order to ensure continuous activity, user comfort while using the website must be given top priority.

Web usage mining based recommendation algorithms provide an efficient user friendly experience on ecommerce websites. Web mining techniques are used to gather user information from users depending on user engagement. A practical recommendation algorithm is then given the needed information. An efficient algorithm improves the suggestion of company items that please customers and entices them to return to websites more frequently. Therefore, information on user interests will be gathered depending on how users use or interact with the website. Additionally, this may be used to group individuals with like interests and research the preferences of all consumers. The information gathered can be used to develop user profiles and produce user or product to product recommendations.

In general, an accurate analysis provides the opportunity to enhance the websites´ structure and content, to adapt and customize the websites´ content, to propose items, or to research user interests.

II. Literature Review

A. A hybrid recommendation system based on web usage mining and semantic web

The paper proposed a hybrid recommendation system that combines web usage mining and semantic web techniques to provide more accurate recommendations for users. The system first collected user behavior data from the website using web usage mining techniques, and then used semantic web techniques to represent the data in a structured format. The authors evaluated the proposed system using real-world data from a movie website and demonstrated its effectiveness in improving recommendation accuracy compared to traditional recommendation systems.

B. A hybrid recommender system using deep collaborative filtering and web usage mining

This paper presented a hybrid recommender system that combined deep collaborative filtering and web usage mining to improve recommendation accuracy. The authors proposed a deep collaborative filtering approach that utilized both user and item embeddings to capture the underlying user-item interactions. They also used web usage mining techniques to extract additional features from user behavior data. The proposed system was evaluated on a movie dataset and showed improved performance compared to traditional recommendation systems.

C. Web usage mining-based recommender system for e- learning applications

The paper presented a web usage mining-based recommender system for e-learning applications. The system collected user behavior data from the e-learning platform and used web usage mining techniques to extract patterns and generate recommendations. The authors evaluated the proposed system on a real-world e-learning platform and demonstrated its effectiveness in improving user satisfaction and engagement. The paper also discussed the limitations of the system and future directions for research in the field.

D. Recommender System Based on Web Usage Mining for Personalized E-learning Platforms

The paper by Aljawarneh and Al-Lozi proposed a web usage mining-based recommender system for personalized e-learning platforms. The authors utilized web server logs to capture users' browsing behavior and extracted various features from the logs to model user behavior. The proposed system uses a hybrid recommendation approach by combining two techniques: collaborative filtering and content-based filtering. The system was evaluated using precision, recall, and F-measure measures, which showed a significant improvement compared to traditional recommendation techniques.

E. Optimizing Approach of Recommendation System using Web Usage Mining and Social Media for E-commerce

The paper by Gupta and Kaur proposed an approach to optimize recommendation systems using web usage mining and social media for e-commerce. The authors utilized web usage mining to extract user behavior patterns and social media data to capture user preferences and opinions. The proposed system uses a hybrid recommendation approach that combines collaborative filtering and content-based filtering with sentiment analysis. The system was evaluated using the Mean Absolute Error (MAE) metric, which showed a significant improvement compared to traditional recommendation techniques.

F. Analysis of Users' Behaviour in Structured Websites using Web Usage Mining

The paper by Fatima and Zaidi presented an analysis of users' behavior in structured websites using web usage mining. The authors used web server logs to capture user behavior patterns and extracted various features from the logs to model user behavior. The proposed system uses a content-based filtering approach to recommend content to users. The system was evaluated using the precision, recall, and F-measure measures, which showed a significant improvement compared to traditional recommendation techniques. The authors also performed a cluster analysis to identify groups of users with similar behavior patterns. Overall, these papers demonstrate the effectiveness of web usage mining-based approaches for personalized recommendation systems in various domains, including e-learning platforms and e-commerce websites. The hybrid recommendation approaches that combine collaborative filtering and content-based filtering have been shown to perform better than traditional techniques. Furthermore, the analysis of user behavior patterns and user clustering can provide valuable insights for improving the recommendation system's performance.

G. Recommender System Based on Web Usage Mining for Personalized E-learning Platforms

The paper by Aranha proposes a recommender system for personalized e-learning platforms that leverages web usage mining techniques. The authors argue that e-learning platforms generate large amounts of usage data, which can be used to extract valuable insights into the behavior and preferences of learners. They propose a recommender system that utilizes these insights to generate personalized recommendations for individual learners. The proposed system involves three stages: data collection, data preprocessing, and recommendation generation. The authors evaluate the performance of the system using a dataset from a real e-learning platform and report promising results.

H. Optimizing Approach of Recommendation System using Web Usage Mining and Social Media for E-commerce

The paper by Kaur and Kumar presents an approach to optimize recommendation systems for e-commerce plat- forms using web usage mining and social media analysis. The authors argue that e-commerce platforms generate large amounts of data, including usage data and social media data, which can be leveraged to generate more accurate and relevant recommendations for users. The proposed approach involvesthree stages: data collection, data preprocessing, and recommendation generation. The authors evaluate the performance of the proposed approach using a dataset from an e-commerce platform and report improved performance compared to traditional recommendation systems.

I. Analysis of Users Behaviour in Structured Websites

The paper by Fatima presents an analysis of user behavior in structured websites, with the aim of developing an improved recommender system. The authors argue that structured websites, such as e-commerce platforms and news websites, provide a rich source of usage data that can be used to extract valuable insights into user behavior. The proposed approach involves the use of web usage mining techniques to analyze user behavior and generate personalized recommendations. The authors evaluate the performance of the proposed approach using a dataset from an e-commerce platform and report promising results.

J. A Comparative Study of Recommendation System Using Web Usage Mining

The paper by Patil and Patil presents a comparative study of recommendation systems that use web usage mining techniques. The authors argue that web usage mining can be used to generate valuable insights into user behavior, which can in turn be used to generate personalized recommendations. The paper presents a comparison of four different web usage mining-based recommendation systems, each using a different set of algorithms and techniques. The authors evaluate the per- formance of the systems using a dataset from an e- commerce platform and report comparative results.

K. Comparison of Recommender Systems Based on Collaborative Filtering and Web Usage Mining

The paper by Farhan and Ehsan presents a comparison of two different recommendation systems based on collaborative filtering and web usage mining techniques. The authors argue that both approaches have their advantages and disadvantages and that the choice between them depends on the characteristics of the application domain. The authors evaluate the performance of the two systems using a dataset from an e- commerce platform and report comparative results.

L. A Hybrid Recommender System Using Web Usage Mining and Collaborative Filtering

The paper by Rajalakshmi and Santhi proposes a hybrid recommender system that combines web usage mining and collaborative filtering techniques. The authors argue that both approaches have their strengths and weaknesses and that a hybrid approach can leverage the strengths of both. The proposed system involves two stages: data preprocessing and recommendation generation. The authors evaluate the performance of the system using a dataset from an e-commerce platform and report improved performance compared to traditional recommendation systems.

III. Problem Definition

The problem is to develop a recommendation system for an e-commerce website that uses web usage mining techniques to analyze user behavior and suggest relevant products. This involves collecting and preprocessing web usage data, cleaning and converting the data to a consistent format, identifying user segments and common product purchase sequences using association rule mining and clustering techniques, and recommending products to users using collaborative and content- based filtering algorithms. The goal of the project is to improve the user experience and increase sales for the e- commerce website by providing personalized and accurate product recommendations.

IV. Proposed solution

The problem solution for this project is to develop a recommendation system that can analyze user behavior on an e- commerce website and suggest relevant products to users. The system will use web usage mining techniques and algorithms such as Apriori association, collaborative filtering, content- based filtering, and hybrid filtering to generate accurate recommendations. The system will also include components such as a data generator, data cleaner, and data analyzer to preprocess and analyze the web usage data. The output of the algorithms will be used by the recommender system to suggest relevant products to users based on their preferences, behavior, and the attributes of the products. The end result will be an effective recommendation system that enhances the user experience on the e-commerce website, increases customer satisfaction, and ultimately drives sales.

V. Implementation

In this paper, we work on implementing a recommendation system for an e-commerce website that utilizes various techniques such as web usage mining, data cleaning, and filtering algorithms to suggest relevant products to users based on their behavior and preferences. It consists of multiple components that work together to generate recommendations using different approaches, such as collaborative filtering, content-based filtering, and hybrid filtering.

A. Data Loading

The dataset used for this research paper is a collection of web usage data that includes information about user interactions with various products across different categories. The dataset contains data from 100 unique users and 20 unique products and includes 1000 different actions such as viewing, adding to cart, and purchasing.

The data provides insights into user behavior and preferences, as well as the performance of different products in the market. The dataset includes various features such as color, size, weight, brand, and material that help in understanding user preferences and product characteristics. The data also includes ratings provided by users for different actions.

B. Data cleaning

In this section, we describe the data-cleaning process per- formed on the dataset for our research paper. The dataset used in our study is ”web usage data.csv”. The following steps were taken to clean the data:

- Load the dataset using the pandas library.
- Check for missing values using the isnull() function and sum the missing values for each column using sum().
- Remove duplicates using drop duplicates() function.
- Convert categorical features to numerical using *astype('category').cat.codes* for each categorical column.
- Scale numerical features using minmax scaling by sub- tracting the minimum value of each feature and dividing it by the range of the feature.
- Rename columns using rename() function.
- Drop unnecessary columns using drop() function.

C. Data Analysis

The data analysis performed here is a basic exploration of a dataset that includes information on user actions on an e- commerce website. The analysis includes calculating the total number of unique users and products, as well as the total number of actions performed (views, adds to cart, purchases). Additionally, the average rating per action is calculated, as well as the average number of products viewed, added to the cart, and purchased per user.

These findings could be useful in providing an overview of the dataset and identifying any trends or patterns that may be present. However, further analysis may be necessary to gain a more detailed understanding of the data and to draw meaningful conclusions for a research paper.

D. Association rule mining

The Apriori association algorithm is used to mine frequent item sets and generate association rules between products in a web usage dataset. The web usage data is loaded into a Pandas Dataframe and then pivoted into a binary matrix. The Apriori algorithm is then used to find frequent item sets, which are used to generate association rules based on a given metric. The support, confidence, and lift for each rule are printed, and overall performance metrics are calculated. Finally, a scatter plot is generated to visualize the support, confidence, and lift for each rule. The code provides a useful tool for analyzing patterns in web usage data and identifying associations between products.

E. Collaborative filtering

The implementation of collaborative filtering uses Singular Value Decomposition (SVD) algorithm and evaluates the model’s accuracy using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). The data is loaded from a CSV file, converted to Surprise format, and split into train and test sets. The user-item rating matrix is created using Pandas and displayed as an interactive heatmap using Plotly. The heatmap represents the rating values, with darker shades indicating higher ratings. The RMSE and MAE values suggest that the model performs reasonably well. This implementation demonstrates a simple approach to collaborative filtering and can be used as a basis for recommendation systems in various domains.

F. Content Based Filtering

The data used in this implementation is web usage mining data, and the algorithm computes pairwise cosine similarities between the products based on their features to determine the similarity between products.

The implementation involves loading the data, computing the pairwise cosine similarities between the products based on their features, and generating a heatmap to visualize the cosine similarity matrix. The code also defines a function to generate recommendations for a given user based on their purchase history and the cosine similarities between their purchase history and the product features.

To generate recommendations, the function computes the aver- age feature vector for the user's purchase history, computes the cosine similarities between the user's average feature vector and the product feature vectors, sorts the products by similarity to the user, and returns the top recommendations.

Overall, this implementation of content-based filtering can be used to provide personalized recommendations to users based on their purchase history and the features of the products they have purchased.

G. Hybrid Filtering

Hybrid filtering is a technique that combines collaborative filtering and content-based filtering to improve recommendation accuracy. In this approach, a recommendation system uses both user behavior data and product features to generate recommendations.

First, the user behavior data and product data are loaded and merged based on common attributes such as product ID. Then, a useritem matrix is created where the rows represent the users, the columns represent the products, and the values represent the user's ratings for the products.

Next, the cosine similarity matrix of the useritem matrix is calculated. This matrix represents the similarity between each pair of products based on the user ratings.

A hybrid filter function is defined which takes a user ID and the number of recommended products as input and returns a DataFrame of recommended products. In this function, the user's product ratings are extracted as a numpy array and the dot product of the cosine similarity matrix and the user's ratings is calculated. The resulting product scores are then sorted in descending order and the top num recs products are selected.

Finally, the selected product IDs are used to filter the product data and return the resulting DataFrame of recommended products. The recommended products are then displayed in a scatter plot using the Plotly library.

VI. RESULTS DISCUSSION

In this research, we conducted association analysis, collaborative filtering, content-based filtering, and hybrid filtering to generate product recommendations for users based on their past behavior. Our results show that each method has its strengths and weaknesses in terms of the accuracy and diversity of recommendations.

Association analysis was able to generate a large number of recommendations but lacked diversity as it only recommended popular items or items that were frequently bought together. Collaborative filtering was able to generate more personalized recommendations based on user behavior but struggled with recommending new or unpopular items. Content-based filtering was effective in recommending items based on their features and attributes but had limited ability to capture user preferences and behaviors.

Hybrid filtering, which combines multiple methods, was the most effective in generating diverse and accurate recommendations. By combining the strengths of association analysis, collaborative filtering, and content-based filtering, hybrid filtering was able to capture both user preferences and item attributes, resulting in more accurate and diverse recommendations. These results highlight the importance of using multiple recommendation methods and the potential benefits of hybrid filtering in generating high-quality recommendations.

VII. INFERENCES FROM BENCHMARKING

Based on the benchmarking section of the project, we can infer that the performance of each filtering method depends on various factors such as the size and quality of the dataset, the complexity of the recommendation algorithm, and the specific goals of the recommendation system.

The results show that the association analysis method is effective in identifying patterns in the data and generating rules that can be used for targeted marketing campaigns. However, this method may not be as effective in generating personalized recommendations for individual users.

Collaborative filtering is a popular method for generating personalized recommendations, but it may suffer from the cold start problem and requires a significant amount of data to generate accurate recommendations. Content-based filtering, on the other hand, relies heavily on the quality and completeness of product data and may not capture user preferences that are not reflected in the product features.

The hybrid filtering approach showed the most promising results, as it was able to generate more accurate and diverse recommendations by combining the strengths of both collaborative and content-based filtering. However, this approach may require more computational resources and more data to implement effectively.

Overall, the benchmarking results suggest that a combination of filtering methods may be necessary to generate accurate and relevant recommendations for users, depending on the specific goals and constraints of the recommendation system. Additionally, the choice of filtering method should be informed

by the size and quality of the dataset and the specific context of the recommendation system.

VIII. Conclusion

In conclusion, this project aimed to explore different filtering techniques for generating product recommendations using a dataset of web usage data. We implemented and benchmarked four different filtering methods: association analysis, collaborative filtering, content-based filtering, and hybrid filtering.

The results showed that each approach had its strengths and limitations. Association analysis identified frequent itemsets and generated association rules, which could be useful for targeted marketing campaigns. Collaborative filtering identified similar products based on users' behaviors and preferences, while content-based filtering identified similar products based on their features. Hybrid filtering combined the strengths of both approaches and generated more accurate and diverse recommendations.

The benchmarking section also highlighted the importance of evaluating recommendation systems using appropriate metrics and considering the specific context of the system. Overall, the findings suggest that a combination of filtering techniques may be necessary to generate relevant and accurate recommendations for users, depending on the available data and the specific context of the recommendation system. Future work could explore other filtering techniques or incorporate additional data sources to further improve recommendation accuracy.

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