A PROJECT REPORT ON

[RECCOKART] PRODUCT PRODUCT RECOMMENDATION SYSTEM

SUBMITTED TO THE SAVITRIBAI PHULE PUNE UNIVERSITY, PUNE
IN THE PARTIAL FULFILLMENT FOR THE AWARD OF THE DEGREE

OF

BACHELOR OF ENGINEERING
IN
INFORMATION TECHNOLOGY

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DEPARTMENT OF INFORMATION TECHNOLOGY
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2022-23

CERTIFICATE

This is to certify that project report entitled

(Reccokart) PRODUCT RECOMMENDATION SYSTEM

Submitted By

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is a bonafide work carried out by them under the supervision of Prof.NALE.R.K and it is approved for the partial fulfillment of the requirement of Savitribai Phule Pune University for the award of the Degree of **Bachelor of Engineering** (Information Technology) during the academic year **2022-23**

This project report has not been earlier submitted to any other Institute or University for the award of any degree or diploma.

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Abstract

Any cutting-edge social networking or on line retail platform need to have a advice device. A product advice is basically a filtering system that seeks to predict and show the gadgets that a consumer would really like to purchase. it may now not be completely accurate, but if it indicates you what you like then it's miles doing its process proper. As an average instance of a legacy recommendation device, the product advice machine has two good sized drawbacks: advice repetition and unpredictability about new objects (cold begin). because the older recommendation algorithms best use the consumer's preceding shopping history when making tips, these boundaries exist. The cold start and recommendation redundancy may be lessened by way of incorporating the consumer's social attributes, which include character traits and regions of hobby. In mild of this, we gift MetaInterest, a personality- aware product advice device constructed on consumer hobby mining and metapath discovery. The counseled technique includes the person's personality characteristics to forecast his or her issues of hobby and to link the consumer's personality facets with the applicable things, making it character-aware from views. The recommended gadget was evaluated towards cutting-edge recommendation strategies, which include session- based and deep-getting to know-based totally systems. according to experimental findings, the counseled strategy can improve the advice gadget's reminiscence and precision, especially in bloodless-begin situations.

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Chapter 1

Introduction

A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase.The product recommendation system as a typical example of the legacy recommendation systems suffers from two major drawbacks:recommendation redundancy and unpredictability concerning new items (coldstart). These limitations take place because the legacy recommendation systems rely only on the users previous buying behaviour to recommend new items. In personality- aware recommendation system, the similarity between the users is computing based on their personality trait similarity or using a hybrid personality-rating similarity measurement, and the resulting set of neighbors are similar in terms of personality traits to the studied user.

1.1 Aim of Project

The aim of a recommender system is to estimate the utility of a set of objects belonging to a given domain, starting from the information available about users and objects.

1.2 Motivation

To Motivate the users Product recommendation engines analyze data about shoppers to learn exactly what types of products and offerings interest them. Based on search behavior and product preferences, they serve up contextually relevant offers and product options that appeal to individual shoppers — and help drive sales.

1.3 Project Objectives

The objective of Personality aware product recommendation system is to provide recommendation based on recorded information on the users buying similarity. Increase performance while working with huge data. Provide 24x7 access system.

1.4 Application

A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase. It may not be entirely accurate, but if it shows you what you like then it is doing its job right

Chapter 2

Literature Survey

Reference No: 1. Title: Study of E-commerce recommender system based on Big data Publication: Oxbridge college, kunning university Author: Xuesong Zhao Summary: Recommender system algorithms are widely used in e-commerce to provide personalized and more accurate recommendations to online users and enhance the sales and user stickiness of e-commerce. This study aims to build a product recommendation system on e-commerce platform according to user needs.

Reference No: 2 Title: Collaborative Filtering for Recommender Systems Publication: 2014 Second International Conference on Advanced Cloud and Big Data Author: Michael D. Ekstrand, John T. Riedl and Joseph A. Konstan Summary: The report also highlights the discussion of the types of the recommender systems as general and types of CF such as; memory based, model based and hybrid model. In addition, this report discusses how to choose an appropriate type of CF.

Reference No: 3 Title:Content-Based Filtering: Techniques and Applications Publication: 2017 International Conference on Communication, Control, Computing and Electronics Engineering (ICCCCEE) Author: Khartoum, Sudan Summary: Content-based recommender systems make recommendations by analysing the content of textual information and finding regularities in the content. The major difference between CF and content-based recommender systems is that CF only uses the user-item ratings data to make predictions and recommendations, while content-based recommender systems rely on the features of users and items for predictions. Both content-based recommender systems and CF systems have limitations. While CF systems do not explicitly incorporate feature information, content-based systems do not necessarily incorporate the information in preference similarity across individuals.

Reference No: 4 Title: Automatiic Personality Recognition of Authors using Big Five Factor model Publication: Jacques Author: k. Pramodh, Y. Vijayalata Summary: The paper focuses on an approach developed to recognize the personality of the author by evaluating their writings. The score for each of the Big-Five personality traits is computed programmatically.

2.0.1 Summary of Literature survey

Reference No	Title	Author	Summary
1	Study of E-commerce recommender system based on Big data	Michael D. Ekstrand, John T. Riedl	Recommender system algorithms are widely used in e-commerce to provide personalized and more accurate recommendations to online users
2	Collaborative Filtering for Recommender System	Michael D. Ekstrand, John T. Riedl and Joseph A. Konstan	It discusses how to choose an appropriate type of CF. The evaluation methods of the CF systems.
3	Content-Based Filtering: Techniques and Applications	Khartoum, Sudan	Content-based recommender systems make recommendations by analyzing the content of textual information and finding regularities in the content.

4	Recommender System Based on Consumer Product Reviews	k. Pramodh, Y. Vijayalata	The proposed approach is illustrated using the case study of a recommender system for digital cameras

2.1 Related Work Done

In this related work, we review the recent advances of personality-aware recommendation system and interest mining schemes as well.

2.1.1 Personality and Recommendation Systems : Many works have discussed the importance of incorporating the users personality traits in the recommendation systems. Haf shejani proposed a CF system that clusters the users based on their big-five personality.traits using the K-means algorithm. Following that, the unknown ratings of the sparse user item matrix are estimated based on the clustered users. Ning proposed a friend recommendation system that incorporates the big-five personalitytraits model and hybrid filtering, where the friend recommended process is based on personality traits and the users harmony rating.

2.1.2 Interest Mining : Far from personality, many previous works have discussed user interest mining from social media content. Piao surveyed the literature of user interest mining from social networks, and the authors reviewed all the previous works by emphasizing the following on four aspects: 1) data collection; 2) representation of user interest profiles; 3) construction and refinement of user interest profiles; and 4) the evaluation measures of the constructed profiles. Zarrinkalam presented a graph-based link prediction scheme that operates over a representation model built from three categories of information.

2.2 Existing System

Name of System: Friend recommendation (persoNet) Developer: Ning Explanation: Personality-aware friend recommendation system named persoNet that leverages Big-Five personality traits to enhance the hybrid filtering friend selection process

Advantages: good precision and recall values in cold start phase Disadvantages: complex algorithm because it is hybrid algorithm. Name of System: Moves recommendation (Roppsa) Developer: Asabere Explanation:a personality aware TV program recommendation system that leverage normalization and folksonomy procedures to generate group recommendations for viewers with similar personality traits.

Name of System: Image recommendation (Flickr) Developer: Guntuku Explanation:Associating images features and personality traits is twofold: known the feature of the image can help to infer the personality of users who interact with the image, and know the personality traits of the users could help to recommend relevant images. Advantages:offer a personality-aware multi-task framework for generic as well as personalizedimage aesthetics assessment Disadvantages: need for using high-level user understandable features and illustrate the effectiveness.

2.2.1 Comparison between Existing and Proposed system

Classification	Existing System	Proposed System
Main techniques	• Information retrieval • classifier • decision trees	• neighbour based • Graph theory • Clustering
Type of Algorithm	Hybrid	CF, COF, Hybrid, Meta path
working principle	this systems require product rating or users previous history	without knowing user history still we can recommend product

Table 2.1: Existing system vs proposed system

2.3 Feasibility Study

A feasibility study aims to objectively and rationally uncover the strengths and weaknesses of an existing business or proposed venture, opportunities and threats present in the environment, the resources required to carry through, and ultimately the prospects for success. In its simplest terms, the two criteria to judge feasibility are the cost required and the value to be attained. A well-designed feasibility study should provide a historical background of the business or project, a description of the product or service, accounting statements, details of the operations and management, marketing research and policies, financial data, legal requirements, and tax obligations. Generally, feasibility studies precede technical development and project implementation. A feasibility study evaluates the project's potential for success; therefore, perceived objectivity is an important factor in the credibility of the study for potential investors and lending institutions. It must therefore be conducted with an objective, unbiased approach to provide information upon which decisions can be based.

The key consideration in feasibility

1. Economic Feasibility
2. Technical Feasibility
3. Operational Feasibility
4. Legal Feasibility

Economic feasibility

The purpose of the economic feasibility assessment is to determine the positive economic benefits to the organization that the proposed system will provide. It includes quantification and identification of all the benefits expected. This assessment typically involves a cost/ benefits analysis. We know that Python implementations are open-source. We can get all the things related to Python and anaconda from the internet. All the software required to develop this project is available on the internet. So that, we can easily get this software to develop our system. We did not require buying any software for this project. So that, our system is economically feasible.

Operational Feasibility

Operational feasibility is a measure of how well a proposed system solves problems and takes advantage of the opportunities identified during scope definition and how it satisfies the requirements identified in the requirements analysis phase of system development. The operational feasibility assessment focuses on the degree to which the proposed development projects fit in with the existing business environment and objectives with regard to the development schedule, delivery date, corporate culture, and existing business processes. To develop this project we are using the windows operating system. All operations are done by using Anaconda or Python language. Operationally this project is feasible because it can handle all problems related to the existing system.

Technical Feasibility

This assessment is based on an outline design of system requirements, to determine whether the company has the technical expertise to handle the completion of the project. When writing a feasibility report, the following should be taken into consideration:

1. A brief description of the business to assess more possible factors which could affect the study
2. The part of the business being examined
3. The human and economic factor
4. The possible solutions to the problem

To develop our system, we required knowledge of Python. We know the Python language. Python is an object-oriented language. There are easily available all the related software to develop this project. Python and anaconda is easy to implement. So that, our system is technically feasible.

Chapter 3

Problem Statement

In the recommendation system the problem is trying to forecast the opion the users will have on the dissimilar substance and be able to recommends the finest items to each user. Write here Project Statement

3.1 What is to be developed?

In this work, we propose a product recommendation system that predicts the user's needs and the associated items, even if his/her history does not contain these items or similar ones. This is done by analyzing the user's topical interest and, eventually, recommending the items associated with the theses interest. The proposed system is personality-aware from two aspects; it incorporates the user's personality traits to predict his/her topics of interest and to match the user's personality facets with the associated items.

3.2 Scope of Project

Recommendation system have been all the rage the last couple of years in many different fields, and it appears that they are also helpful for solving recommendation system problems. One of the benefits of Personality aware recommendation system is similar to matrix factorization, in that there is an ability to derive latent attributes.

3.3 Project Constraints

Dataset is the main constraint.

3.4 Technology Used

Python3

Python is a high-level, general-purpose programming language. Its design philosophy emphasizes code readability with the use of significant indentation. Python is dynamically-typed and garbage-collected. It supports multiple programming paradigms, including structured, object-oriented and functional programming. Designed by: Guido van Rossum. First appeared: 20 February 1991; 31 years ago OS: Windows

Anaconda

Anaconda is a distribution of the Python programming language for scientific computing, that aims to simplify package management and deployment. The distribution includes data-science packages suitable for Windows. Developer of Continuum analytics
License: Freemium (Miniconda and the Individual Edition are free software, but the other editions are software as a service)
Programming language: Python

3.5 Parameters

Recommendation System uses several technologies to check the response of user which are as follows:-

Content-Based Filtering : Content-based filtering uses the features of product to recommend similar items for what the user is interested, based on their previous experience and as well as the feedback of the user

Collaborative-based filtering : uses the interactions and data gathered by the system from other users. It makes recommendations based on user preferences for product features. For example, if a user is interested in a watch then the system should recommend the watch which is liked by most of the users.

Hybrid filtering : uses both content-based filtering and collaborating-based filtering. Hybrid filtering recommends the items to the user of his/her interest as well as the items which are liked by most of the user i.e. the highest rating items.

3.6 Mathematical Model

3.6.1 Users Representation

The proposed system incorporates the user's personality traits and their associated facets to detect the user's interest and recommend products accordingly.By measuring similarity between its vertices, users' graph GU = (Vu, Eu) is constructed. There are three types of similarities, which we denote as SimT, SimI, and SimP, respectively: topic interest, product interest, and personality traits. Informally, let U = [u1, u2,..., un] represent all users, and Pi = [PO, PC, PE, PA, PN] represent the user's big five personality traits; Ti = [t1,t2,...,tm] represents UI's topical interests, and Ii = [i1,i2,...,ik] represents previously viewed items.
The interface of a given client are spoken to within the frame of a set of themes. The subject space is spoken to by the chart GT = (Vt, Et), where the vertices speak to the points and the edges speak to the semantic similitude relationship between these subjects. To relate these themes with thing chart hubs, each theme hub is related with a category of open directory project (ODP).

3.6.2 Item Representation:

Formally, let Cx : c0, c1,..., cn and Cy : c0, c1,..., cm signify the substance labels of thing Px and Py , individually, and Vx and Vy speak to the sets of their viewing/buying clients. The similarity between things is computed from two likeness measures, content closeness and collaborative likeness. The content similarity is measured by common item's metadata labels, while the collaborative similitude is calculated by measuring the ratio of common buyers/viewers between the two things to the total buyers/viewers of each thing.Comparable Comparable to the clients and interest topics, the things are spoken to as a chart information structure GP = (Vp, Ep), where the hubs speak to the things and the edges speak.

$$\vartheta\left(P_x,\ P_y\right) = \beta\left\|\frac{2|C_x \bigcap C_y|}{|C_x| + |C_y|}\right\| + (1-\beta)\left(\left\|\frac{2|V_x \bigcap V_y|}{|V_x| + |V_y|}\right\|\right).$$

Figure 3.1: Item representation.

3.6.3 Metapath Discovery

The link prediction score between user ui and item p j with the metapath maximum link constrain as lmax = l is computed using the score between the user and the item.In In order to predict a possible recommendation for a given user node, we explore all the instances of metapath with a maximum path length lmax = 3. Therefore, we prioritize shorter metapath by considaering that the contribution of a path weight to the overall link prediction score is inversely proportional to the meta-path length Pl . Because short metapaths are more semantically significant compared with longer meta-paths.

$$\delta_{i,j}^{l} = \sum_{k=2}^{l} \frac{\sum_{r \in P_{i,j}(k)} w_r}{k-1}.$$

Figure 3.2: Metapath Discovery.

Chapter 4

Software Requirement Specification

4.1 Software Requirements Specification

Product recommendation systems play a vital role in helping users discover relevant and interesting products in today's digital landscape. Traditional recommendation approaches, such as collaborative filtering (CF) and content-based filtering (CB), have their own strengths and limitations. CF relies on user behavior data, such as ratings and purchase history, to find similarities between users and recommend products based on their collective preferences. CB, on the other hand, leverages product attributes, such as descriptions and features, to recommend similar items based on content similarity.

4.1.1 purpose:

The Product Recommendation System aims to overcome the limitations of individual filtering techniques by combining CF and CB approaches. By integrating the two techniques, the system can provide more accurate and diverse recommendations to users. It takes advantage of the collaborative nature of CF to capture user preferences and behavior, while also incorporating content-based analysis to consider the intrinsic characteristics of products.

4.1.2 Document Conventions

The purpose of SRS and it covers the designing purpose and the documents of this report training period of project.

Overview of responsibilities of Developer

If you are considering a job as Software Developer here is a list of the most standard responsibilities and duties for the Software Developer position.

1. Evaluate, assess and recommend software and hardware solutions.
2. Develop software, architecture, specifications and technical interfaces.
3. Develop user interfaces and client displays.
4. Design, initiate and handle technical designs and complex application features.
5. Develop, deliver and test software prototypes.
6. Assist software personnel in handling ongoing tasks as required.
7. Build flexible data models and seamless integration points.
8. Innovate and develop high-value technology solutions to streamline processes.
9. Initiate and drive major changes in programs, procedures and methodology.

4.1.3 Project Scope

The recommendation system will be developed for an online platform that offers various products, services, or content. It will analyze user data such as browsing history, purchase history, ratings, and preferences to generate relevant recommendations. Making accurate forecasts will be possible because it will employ machine learning algorithms to identify patterns and trends in the data.

4.2 Overall Description

Product recommendation systems play a vital role in helping users discover relevant and interesting products in today's digital landscape. Traditional recommendation approaches, such as collaborative filtering (CF) and content-based filtering (CB), have their own strengths and limitations. product recommendation system will analyze user preferences and behavior to provide personalized product recommendations across various categories. The project will use machine learning algorithms to analyze real-time data and provide accurate predictions.

4.2.1 Product Perspective

The product recommendation system will be a standalone application that integrates with an existing e-commerce platform. It will receive user data and transaction history from the platform's database and provide recommendations based on that data.

4.2.2 Product Features

1. User registration and profile management
2. Data collection and analysis of user preferences.
3. Recommendation generation based on user behavior and preferences.
4. Integration with e-commerce platform to display recommendations.

4.3 System Features

The Product Recommendation System includes the following key features:

1. User Profiling: The system collects and maintains user profiles that capture their preferences, behavior, and demographic information.

2. Data Collection: It gathers user data, such as ratings, purchase history, and browsing behavior, to build a comprehensive user profile.

3. Collaborative Filtering: The system applies CF algorithms to identify similarities among users and recommend products based on the preferences of similar users.

4. Content-Based Filtering: It leverages CB techniques to analyze product attributes, such as descriptions, categories, and specifications, to recommend items similar to the ones users have shown interest in.

5. Hybrid Recommendation Generation: The system combines the results of CF and CB to generate hybrid recommendations that provide a balance between

collaborative and content-based approaches.

6. Recommendation Presentation: The system presents the recommendations to users through a user-friendly interface, such as a web page or mobile app, ensuring seamless integration with the platform's existing user experience.

4.4 Software and Hardware Requirements

4.4.1 Server side:

Sr.No	Tools	Requirement
1	Processor	Intel
2	RAM	1 GB(min)
3	Hard Disk	4GB
4	Operating System	Windows
5	Database	NOSQL
6	Tool	Anaconda
7	IDE	visual Studio

4.4.2 Client side:

Sr.No	Tools	Requirement
1	Processor	Intel
2	RAM	500MB(min)
3	Hard Disk	Minimum 2GB of free space
4	Operating System	Windows
5	Browser	Chrome

4.5 Functional Requirements:

1. User Registration and Profile Management :

- The system should allow users to create accounts and maintain profiles.
- Users should be able to update their profile information, including preferences and demographics.

2. Data Collection :

- The system should collect user data, including browsing history, purchase history, and ratings.
- Data collection should be performed in real-time or near real-time.

3. Recommendation Generation :

- The system should analyze user data to generate personalized recommendations.
- The recommendations should be based on user preferences, browsing history, and other relevant factors.

4. Recommendation Presentation :

- The system should present the recommendations to users through a user interface component.
- The recommendations should be displayed in a user-friendly and intuitive manner.

4.6 Non-Functional Requirements:

1. Performance :

- The recommendation system should respond to user requests in a timely manner.
- The system should be capable of handling concurrent user requests without significant degradation in performance.

2. Security and Privacy :

- The system should ensure the confidentiality and integrity of user data.
- User data should be stored securely and protected from unauthorized access.

3. Scalability :

- The system should be able to scale horizontally or vertically to accommodate increasing user and data loads.

4. Usability :

- The user interface should be intuitive and easy to navigate.
- The system should provide clear and helpful recommendations to users.

5. Reliability :

- The recommendation system should be reliable and available for use at all times.
- The system should have mechanisms to handle failures and errors gracefully.

Chapter 5

5. Flowchart

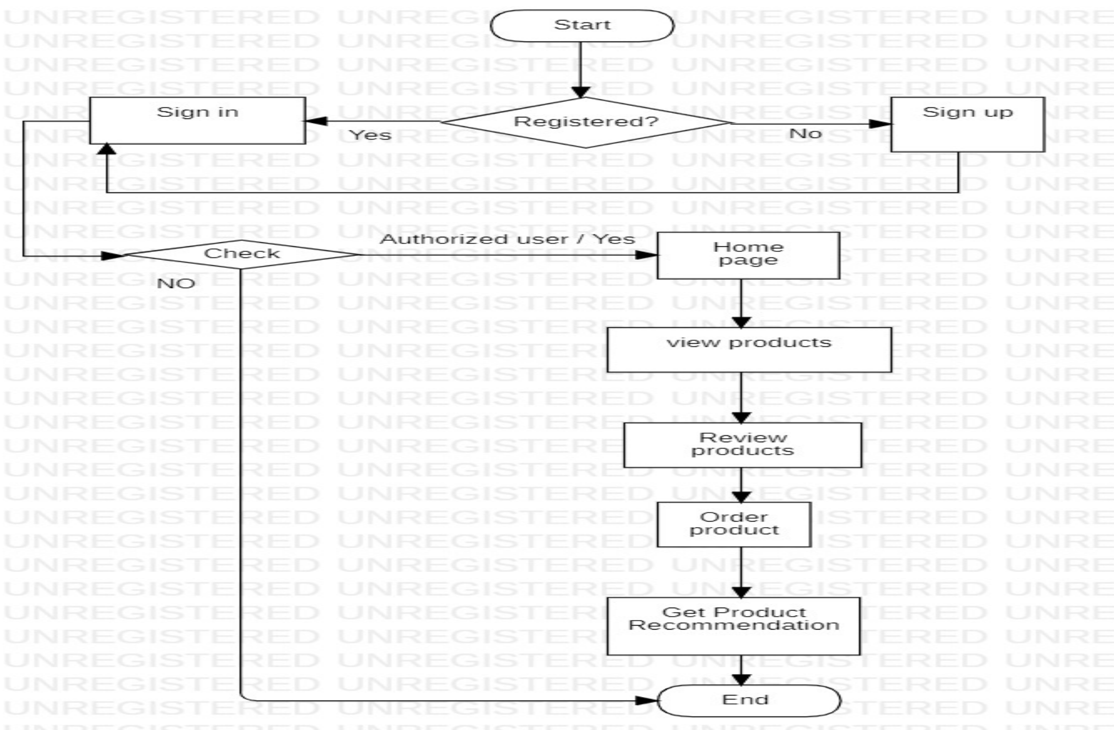


Figure 5.1: User Flowchart Diagram.

5.1 Description of Flowchart

- Sign in: if the user credentials (Username and password) match with the data records stored in the database then the user can log in and go to the Home page which is the welcome page. otherwise, the system throws an error message.

- Sign up: if the user does not have an account in the system user can register information and carate one. after carting the account user can log in using a username and password.

- Home page: this page contains all the information about the project and all other content.

- View Products: display the product information. user can select the required product and buy it.

- Order product: if the user wants they can buy products and add into cart.

- Get product recommendations: after gating the user profile and required information using the system. The system will generate and produce recommendations

Chapter 6

Project Requirement Specification

6.1 Project Overview

A recommendation system is an integral part of any modern online shopping or social network platform.A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase.the purpose of a personality aware product recommendation system is to recommend product based on user interest mining and metapath discovery. Meta-Interest predicts the user's interest and the items associated with these interests, even if the user's history does not contain these items or similar ones. The purpose of personality-aware product recommendation system hat predicts the user's needs and the associated items, even if his/her history does not contain these items or similar ones

6.1.1 Objectives

- The objective of Personality aware product recommendation system is to provide recommendation based on recorded information on the users buying similarity.
- increaser performance while working with huge datasets 11
- Achieve maximum accuracy

6.1.2 Scope

Recommendation system have been all the rage the last couple of years in many different fields, and it appears that they are also helpful for solving recommendation system problems. One of the benefits of Personality aware recommendation system is similar to matrix factorization, in that there is an ability to derive latent attributes.

6.1.3 Timeframe

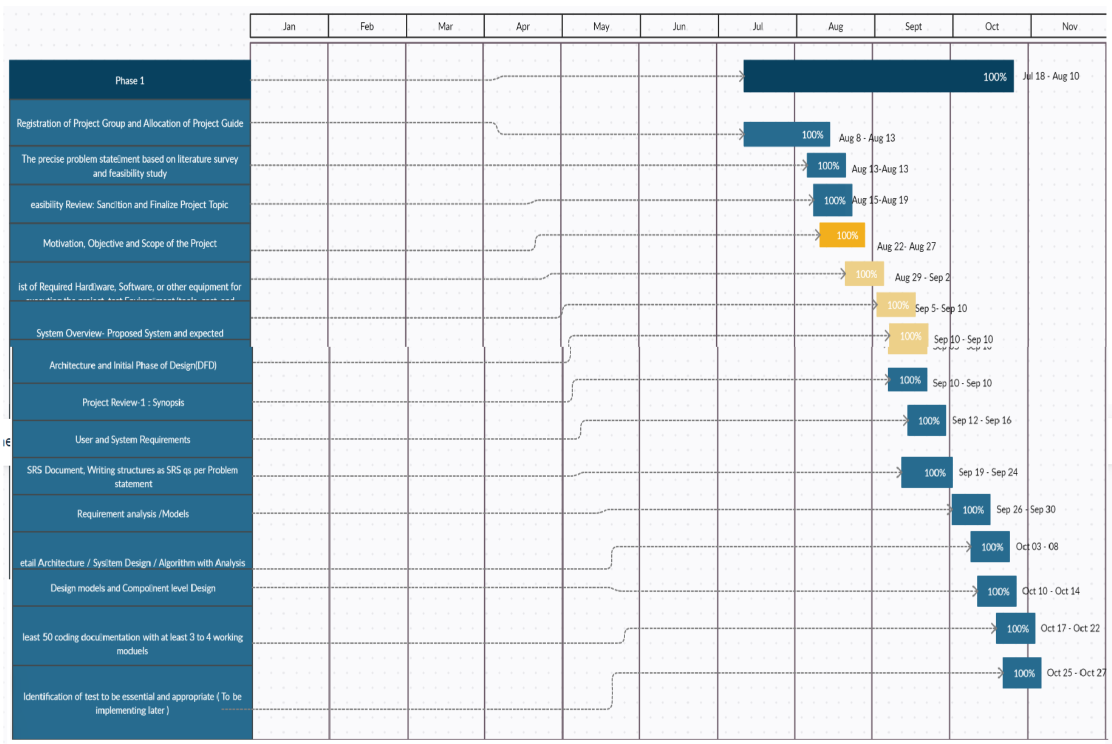


Figure 6.1: Timeframe

6.2 Project Requirements

6.2.1 Project Category

Scope and significance this Product based recommendation system is used in many organizations. It is an International level project. According to the Project, this is an industrial project which is undertaken with a view to developing the economy. It is High-Tech Project if we want to deploy it on a large scale Huge investments are made in technology in this type of project. this is small scale project which can be completed within a period of 1 to 2 years.

6.2.2 Functional Requirements

Requirements that the end user specifically demands as basic facilities that the system should offer. All these functionalities need to be necessarily incorporated into the system as a part of the project. These are represented or stated in the form of input to be given to the system, the operation performed and the output expected. They are basically the requirements stated by the user which one can see directly in the final product, unlike the non-functional requirements.

Features

Feature Title	Feature Description
Interface	Web
Login	User should enter username and password to use this system
Knowledge base	Deep Learning

Table 6.1: Requirements as per IEE

6.2.3 Design Requirements

Screens/GUI

Provide GUI design, wireframe or screen mock-ups to be built. Think about how users will interact with each page (UX) and how the site should perform (behavior, load time etc.) Also think of Aesthetic design (look and feel), Content layout, Navigation design etc

Chapter 7

Proposed System Architecture

7.1 Overview of System Architecture

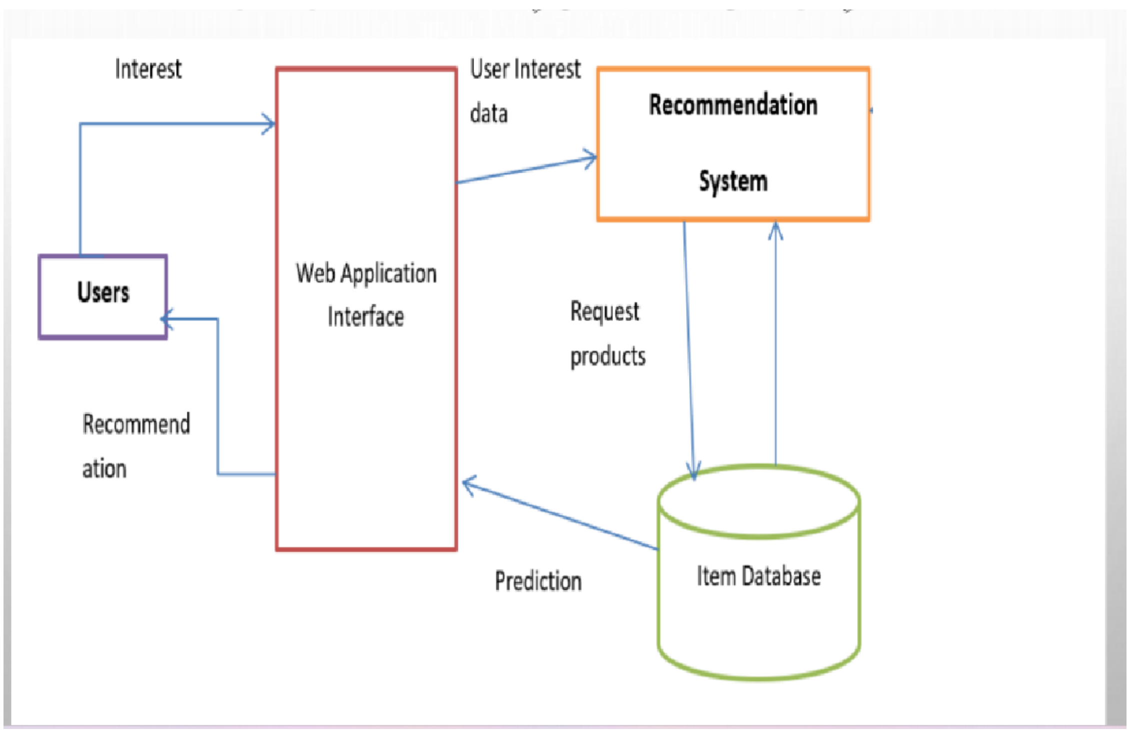


Figure 7.1: System architecture.

7.2 User

In this module, there are n numbers of users are present. User should register before performing any operations. Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. In the user module, first the new user should register to login and access the portal. For registration, user needs to provide their details and then get login to the system. Once if the user logged into the system, the user can see "Products", "Recommended Products". In products option, the products which are all available in the portal are shown to the user with the details and review. In the Recommendation section user will get recommended products.

7.3 Hybrid Filtering

The hybrid filtering module combines collaborative filtering and content-based filtering techniques to provide more accurate and diverse recommendations. It leverages the strengths of both approaches to overcome limitations and improve recommendation quality. Hybrid filtering intelligently merges the results from collaborative and content-based filtering, producing hybrid recommendations that offer a balanced approach.

7.4 Data Collection

The data collection module gathers and organizes data from various sources, including user interactions, product information, and other relevant data points. It involves retrieving and processing data in real-time or near real-time, ensuring the availability of up-to-date information for recommendation generation.

7.5 Recommendation Generation

The recommendation generation module takes inputs from user profiles, data collection, collaborative filtering, content-based filtering, and potentially other sources. It applies algorithms and techniques to generate personalized recommendations for users. The recommendation generation module considers user preferences, historical behavior, item characteristics, and any additional business rules or constraints to generate relevant and accurate recommendations.

7.6 Recommendation Presentation/UI

The recommendation presentation module focuses on delivering recommendations to users through a user-friendly interface. It involves designing and implementing user interfaces, such as web pages or mobile apps, to display recommendations effectively. The presentation module ensures that the recommendations are presented in an intuitive and appealing manner, facilitating user engagement and interaction.

Chapter 8

High-Level Design of the Project

8.1 Overview

This can be taken from the specifications and modified as necessary. For a design document, you can assume the reader has a technical background. For your projects assume a background of a class member.

8.2 Data Flow Diagrams

8.2.1 DFD Level-0

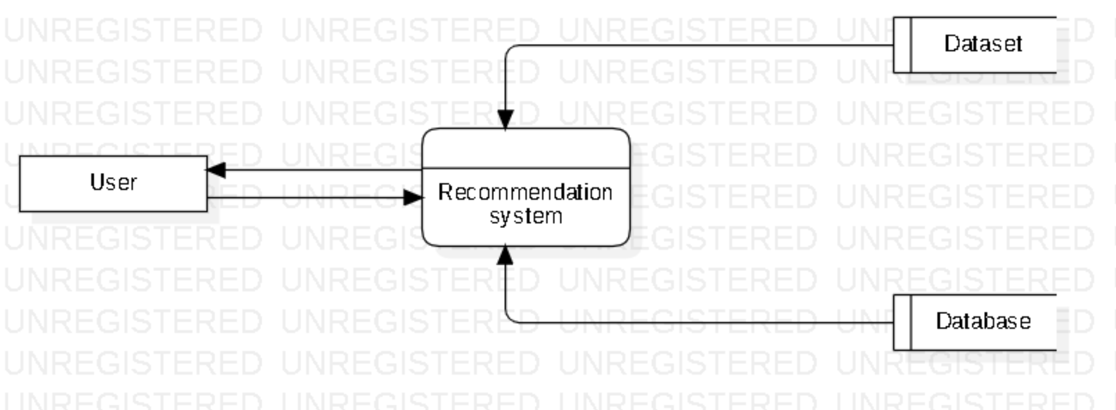


Figure 8.1: DFD 0.

8.2.2 DFD Level-1

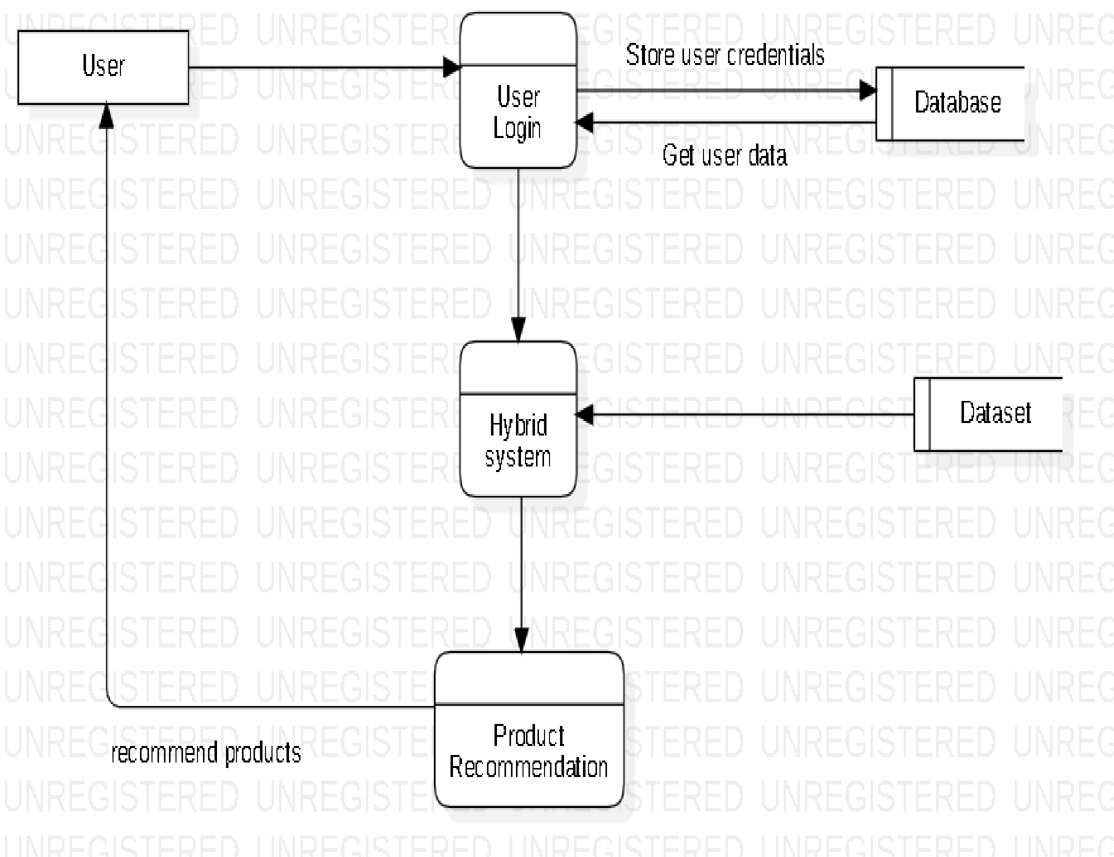


Figure 8.2: DFD 1.

8.2.3 DFD Level-2

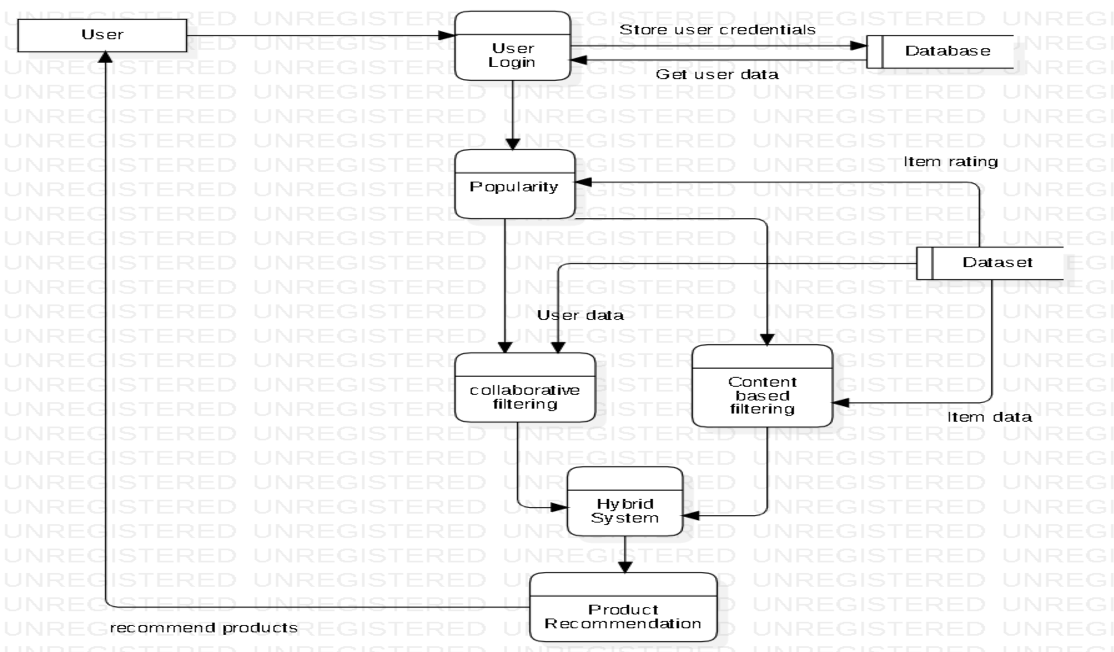


Figure 8.3: DFD 2.

8.3 UML Diagrams

8.3.1 Use Case Diagram

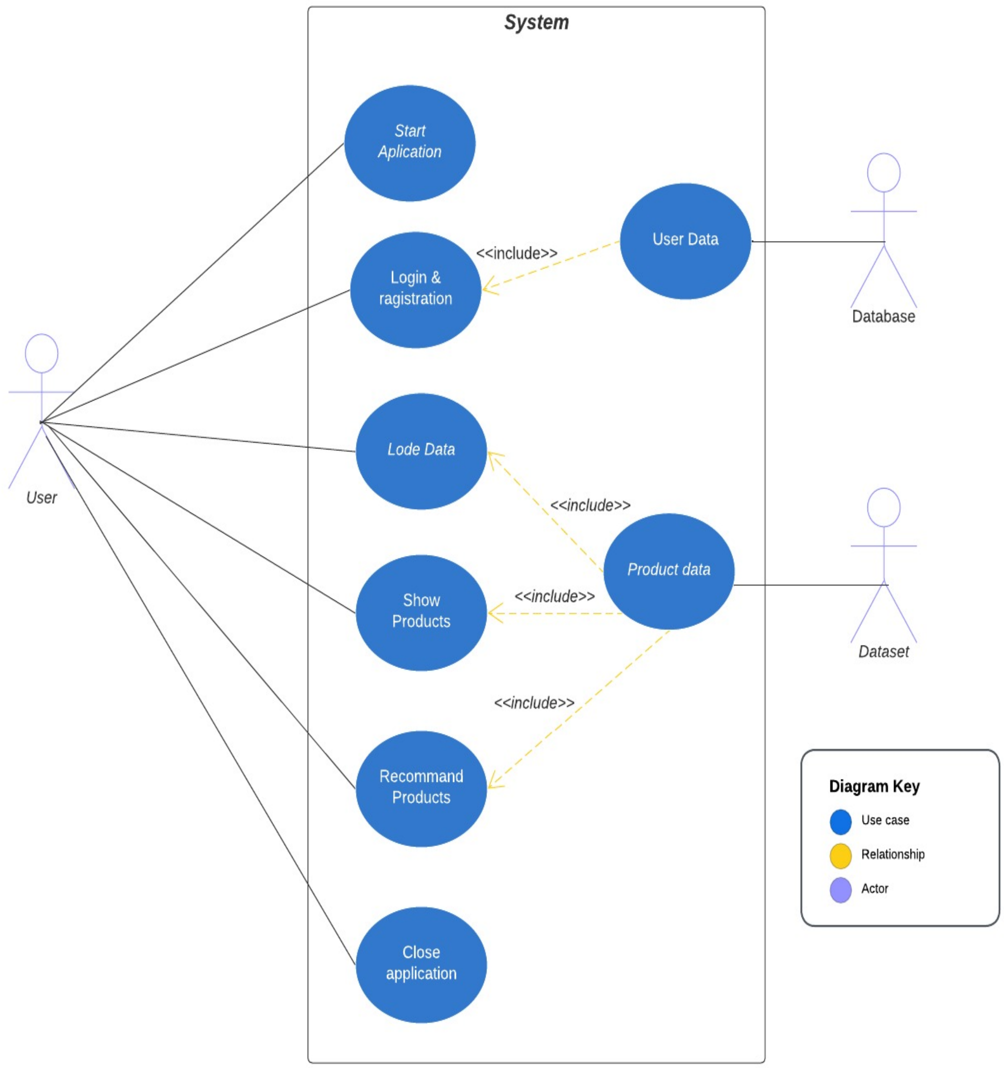


Figure 8.4: Use Case Diagram.

8.3.2 Class Diagram

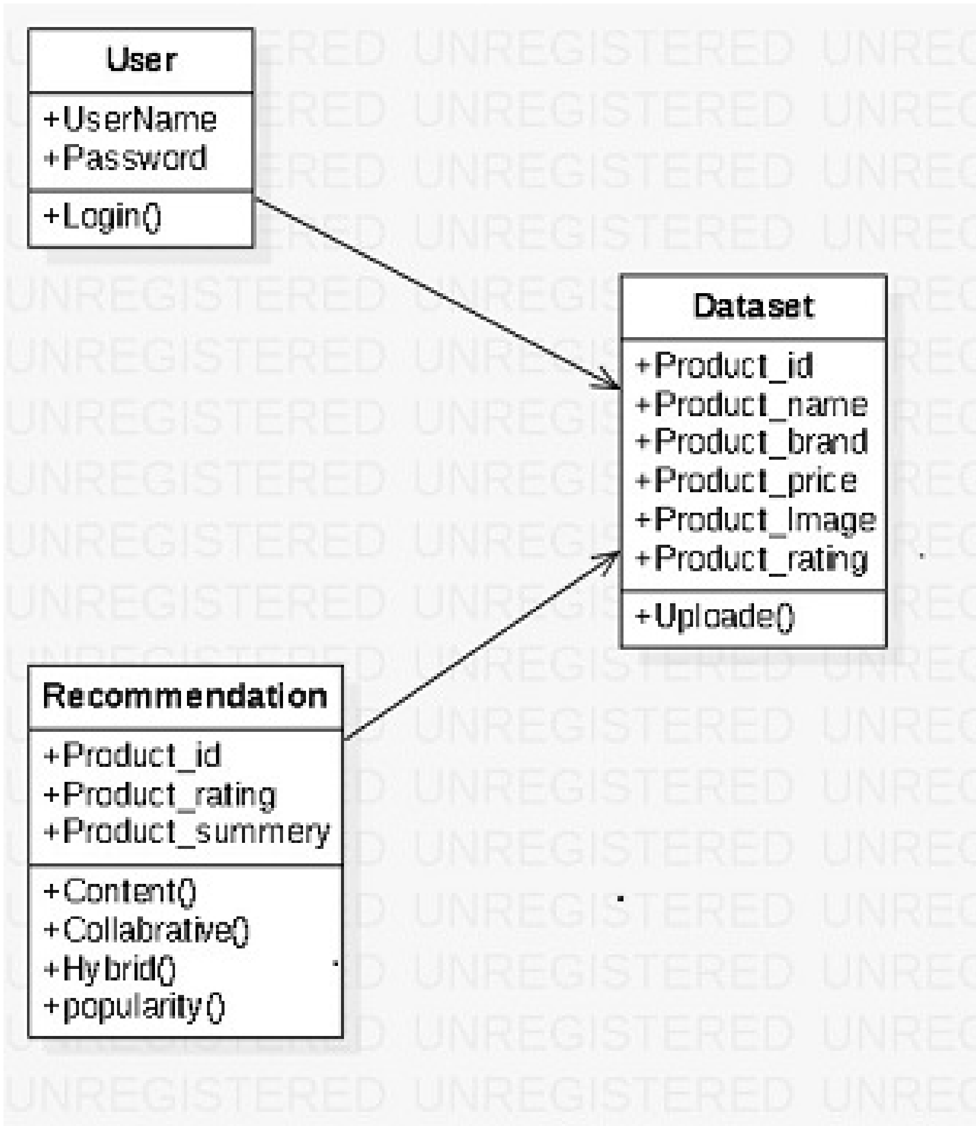


Figure 8.5: Class Diagram.

8.3.3 Sequence Diagram

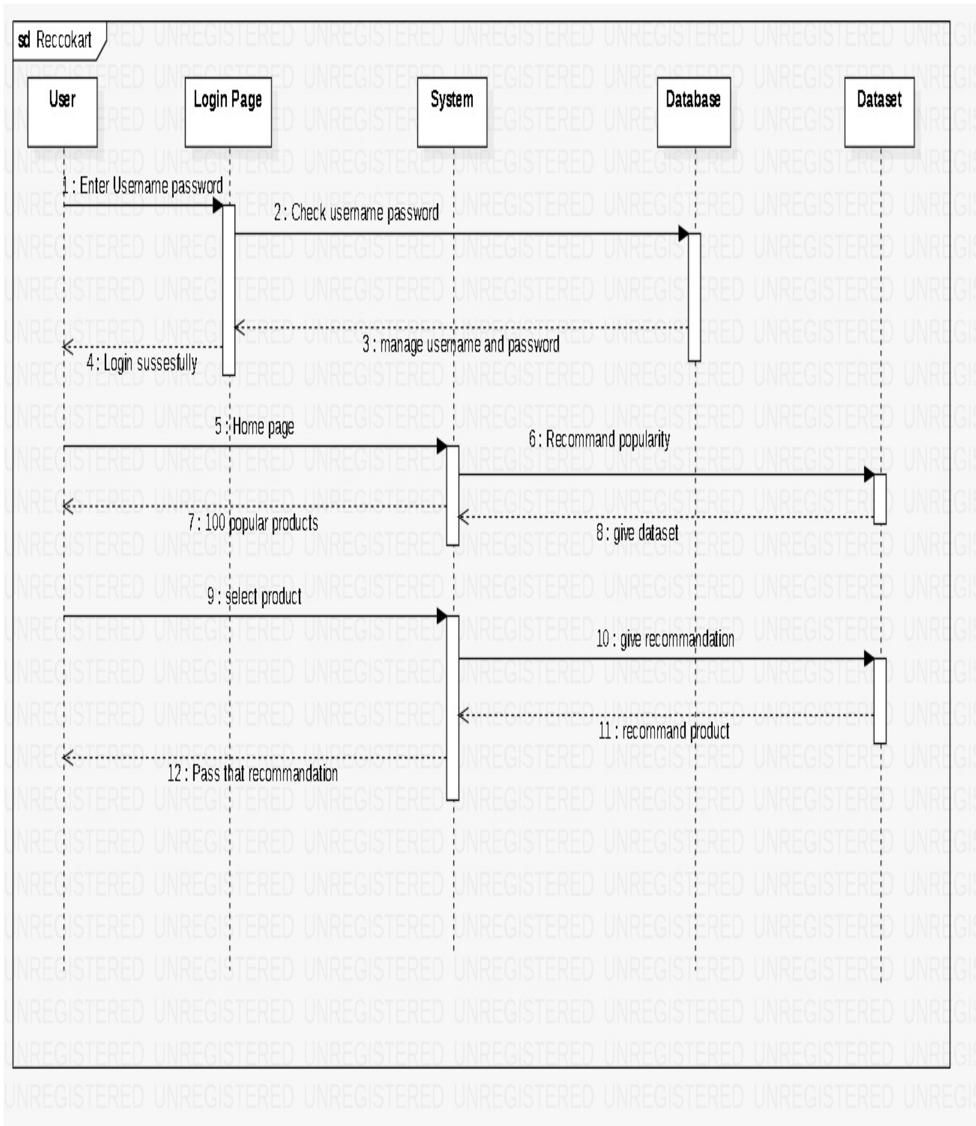


Figure 8.6: Sequence Diagram.

8.3.4 Activity Diagram

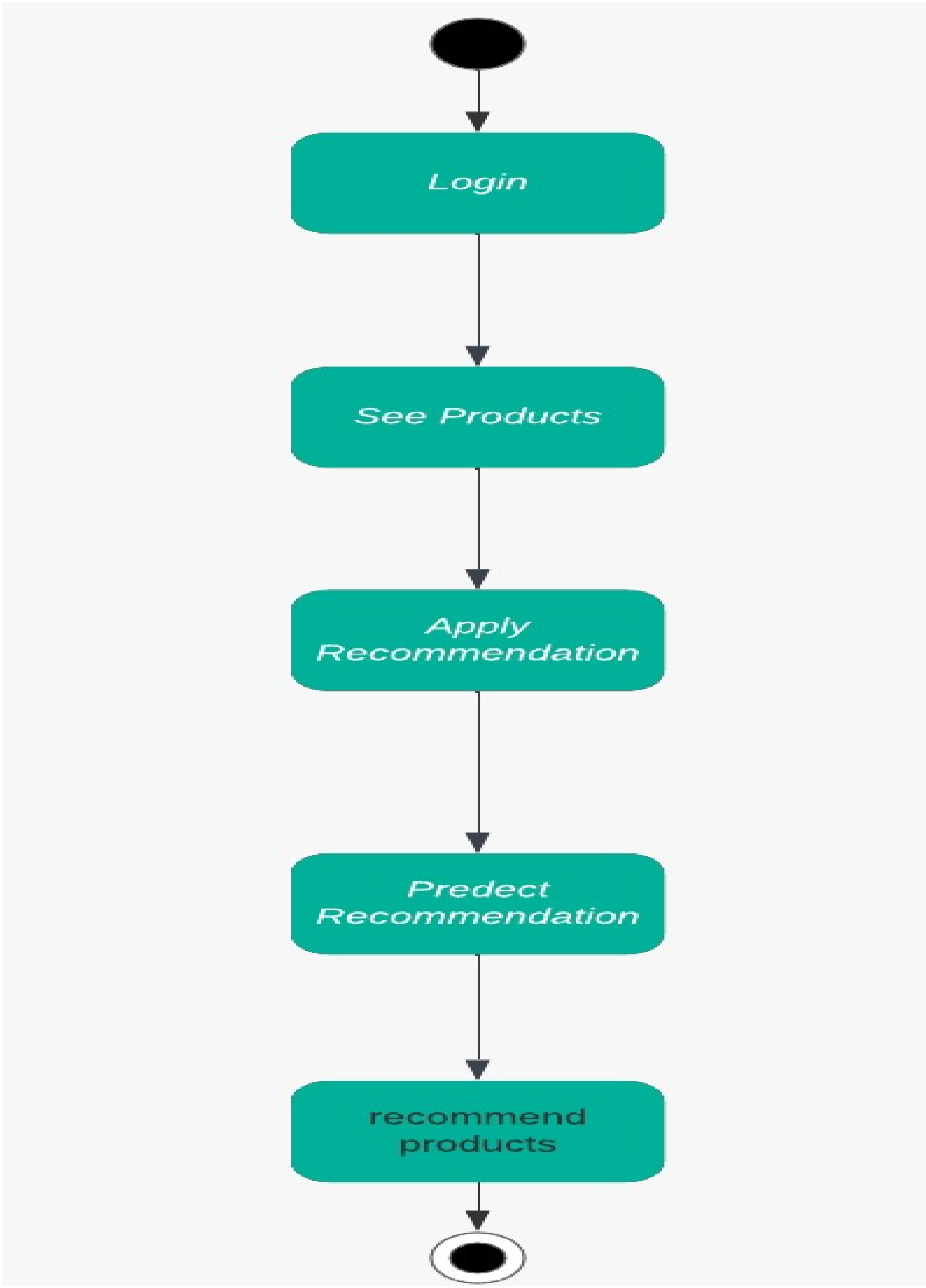


Figure 8.7: Activity Diagram.

8.3.5 Object Diagram

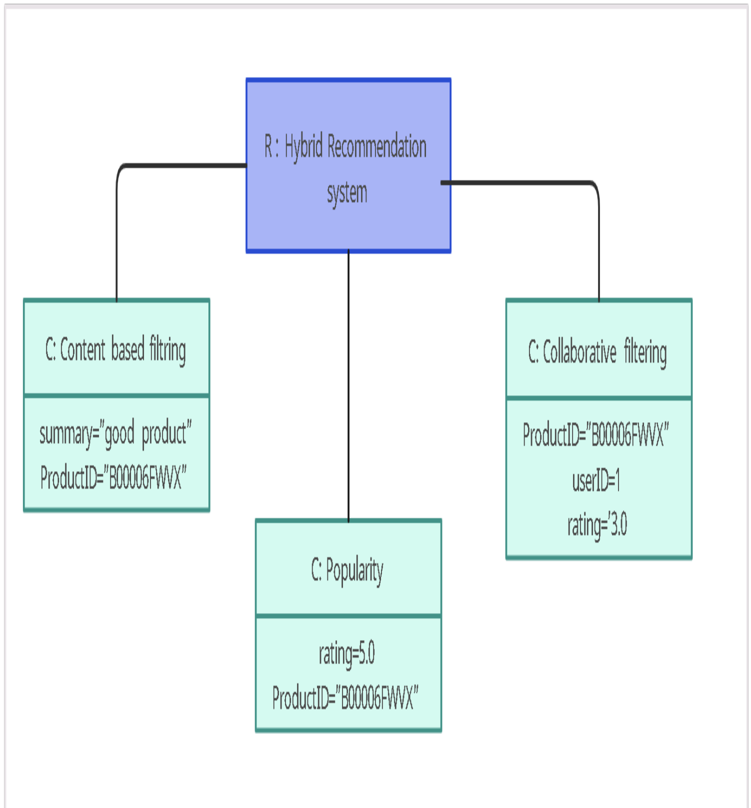


Figure 8.8: Object Diagram

8.3.6 ER Diagram

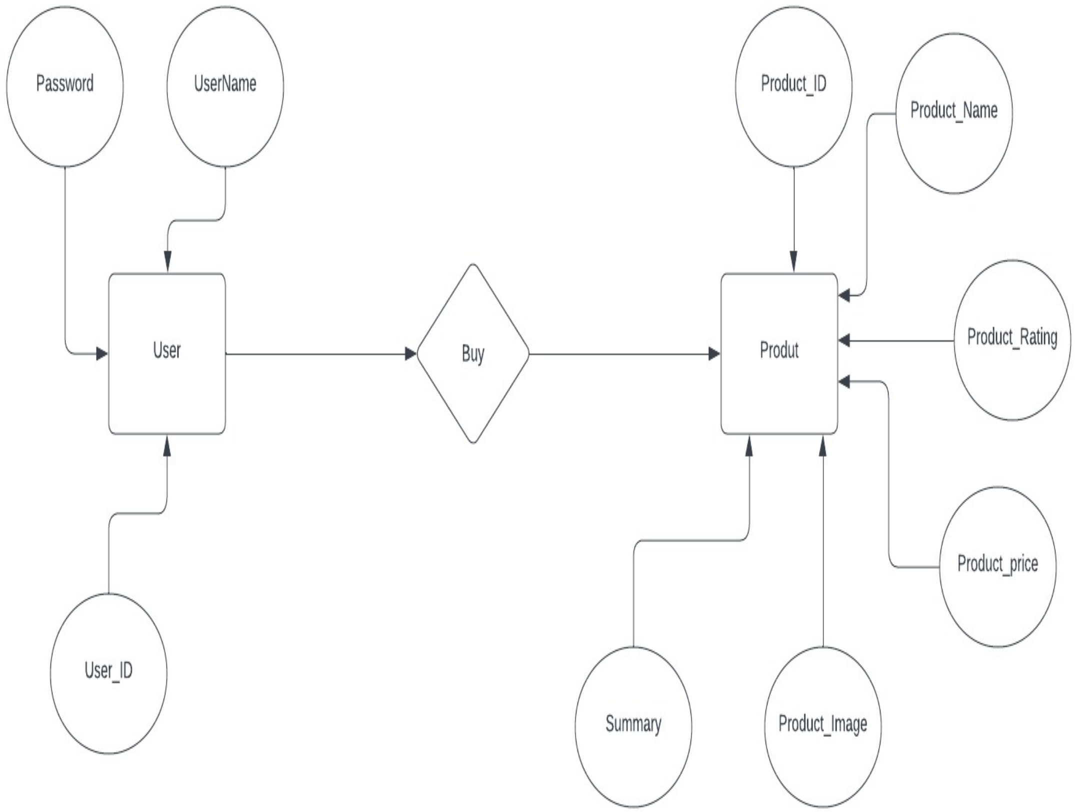


Figure 8.9: ER Diagram.

Chapter 9

System Implementation

9.1 Algorithm

9.1.1 Collaborative Based Filtering

Collaborative filtering (CF) is a technique used by recommender systems. Collaborative filtering has two senses, a narrow one and a more general one.In the newer, narrower sense, collaborative filtering is a method of making automatic predictions (filtering) about the interests of a user by collecting preferences or taste information from many users (collaborating). The underlying assumption of the collaborative filtering approach is that if a person A has the same opinion as a person B on an issue, A is more likely to have B's opinion on a different issue than that of a randomly chosen person. For example, a collaborative filtering recommendation system for preferences in television programming could make predictions about which television show a user should like given a partial list of that user's tastes (likes or dislikes).

Collaborative filtering approaches often suffer from three problems: cold start, scalability, and scarcity. • Cold start: For a new user or item, there isn't enough data to make accurate recommendations. Note: one commonly implemented solution to this problem is the Multi-armed bandit algorithm. • Scalability: There are millions of users and products in many of the environments in which these systems make recommendations. Thus, a large amount of computation power is often necessary to calculate recommendations.

9.1.2 Content Based Filtering

Another common approach when designing recommender systems is content-based filtering. Content-based filtering methods are based on a description of the item and a profile of the user's preferences. These methods are best suited to situations where there is known data on an item (name, location, description, etc.), but not on the user. Content-based recommenders treat recommendation as a user-specific classification problem and learn a classifier for the user's likes and dislikes based on an item's features. In this system, keywords are used to describe the items, and a user profile is built to indicate the type of item this user likes. In other words, these algorithms try to recommend items similar to those that a user liked in the past or is examining in the present.

The system creates a content-based profile of users based on a weighted vector of item features. The weights denote the importance of each feature to the user and can be computed from individually rated content vectors using a variety of techniques. Simple approaches use the average values of the rated item vector while other sophisticated methods use machine learning techniques such as Bayesian Classifiers, cluster analysis, decision trees, and artificial neural networks in order to estimate the probability that the user is going to like the item.

9.1.3 Hybrid Based Filtering

After working with both approaches this is the approach in which the machine learning model is trained in such a way that it has both the functionality of content-based and collaborative filtering approaches. The above two approaches have their problem for a recommendation, this method faces the problem when there is less amount or not enough data to learn the relation between users and items. To overcome this issue there is hybrid approach is discovered, in this approach, we add the power of content and collaborative filtering.

The hybrid recommendation system is a special type of system that used data of both collaborative data and content-based data simultaneously which helps to suggest a similar or close item to the users. Combining the two above approaches helps to resolve the big problems in more effective cases sometimes. In this, the system suggests similar items which are already used by the user or suggests the items which are likely to be used by another user with some similarities

9.2 Methodologies

Scoping and planning : This phase focuses on the planning of the project's overall direction, including the definition of the project's scope, objectives, and timelines. The deliverable from this phase is this Design Plan.

Conceptual design and research : In this phase, the conceptual design of the methodology is developed and research on existing methodologies is conducted. Research is performed from independent research firms, such as the Gartner Group, Forrester Research, and CIO.com. These research firms sometimes publish the methodologies that consulting firms use. Consulting firms' websites are another source for researching E-commerce strategy methodologies.

Development of methodology : The actual methodology is developed in this phase. Detailed descriptions of each task in the methodology are documented, including the objectives, inputs, approach, relevant models, applicable tools and techniques, outputs, and any references. The methodology is to be documented in an appropriate format, be it a Word document or HTML pages.

Implementation of methodology : The methodology will be implemented with a client. This phase includes the marketing of E-commerce strategy development services and the closing of the sale, followed by the actual implementation.

Revision of methodology : Final touches and revisions to the methodology are made in this phase. The majority of these revisions come from experiences on the client project. Sample reports and any additional references are added to the methodology.

9.3 Code Documentation

Content.py

```
import pandas as pd
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.metrics.pairwise import cosine_similarity
import nltk # It is the Natural Language Toolkit library, which provides various    functionalities for working with human language data.
from nltk.stem import PorterStemmer # It applies a set of rules to remove common suffixes from words to obtain their root form. This can be useful in tasks such as text analysis, information retrieval, and language modeling
from nltk.corpus import stopwords

nltk.download('stopwords')
stopwords = stopwords.words('english')
stemmer = PorterStemmer()
Item_df = pd.read_pickle('Grocary.pkl')
Item_df['summary'] = Item_df['summary'].apply(lambda x: x.lower())
Item_df['summary'] = Item_df['summary'].apply(lambda x: ' '.join([word for word in x.split() if word not in stopwords]))
Item_df['summary'] = Item_df['summary'].apply(lambda x: stemmer.stem(x))
vectorizer = TfidfVectorizer()
summary_vectors = vectorizer.fit_transform(Item_df['summary'])
cosine_similarities = cosine_similarity(summary_vectors, summary_vectors)
def recommend_products(title, n_recommendations=10): # The function first retrieves the index of the input title from the DataFrame. Then it calculates the Cosine similarity and compare with existing product.
    movie_idx = Item_df[Item_df['ProductID'] == title].index[0]
    sim_scores = list(enumerate(cosine_similarities[movie_idx]))
    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)
    sim_scores = sim_scores[1:n_recommendations+1]
    movie_indices = [i[0] for i in sim_scores]

    return Item_df.iloc[movie_indices]['ProductID'].head(10) #return 10 similar products

#print(recommend_products('BJ-6 3-Pack Jerky Spice Works'))
```

Collabrative.py

```
import pandas as pd #It provides easy-to-use of DataFrame
from sklearn.metrics.pairwise import cosine_similarity #calculates the cosine similarity between pairs of samples
#building and analyzing recommender systems
from surprise import SVD
from surprise import Dataset
from surprise import Reader
from surprise.model_selection import cross_validate

def collaborative_filtering(UserID,productId): # function that performs     collaborative filtering-based recommendation using the Surprise library
        df =pd.read_pickle('Grocary.pkl')

        df=df[['UserID','ProductID','rating']]
        print("-------------------------------------------")
        print(df.iloc[0])
        print("-------------------------------------------")
        print(df.head)

        new_row = {'UserID': UserID, 'ProductID': productId, 'rating': 5.0}
```

```
    df = df.append(new_row, ignore_index=True)

    #print(df.index[df['UserID']==UserID].tolist())
    reader = Reader(rating_scale=(0.5, 5))
    data = Dataset.load_from_df(df, reader)
    algo = SVD()
    cross_validate(algo, data, measures=['RMSE', 'MAE'], cv=5, verbose=True)
    trainset = data.build_full_trainset()
    algo.fit(trainset)
    user_id = 2
    for i in df.index[df['UserID']==UserID].tolist():
        user_id=i
    items_to_recommend = []
    for item_id in df['ProductID'].unique():
        items_to_recommend.append((item_id, algo.predict(user_id, item_id).est))
    items_to_recommend.sort(key=lambda x: x[1], reverse=True)
    return items_to_recommend[:10] #return 10 product by similar user

#print(collaborative_filtering('A2R0EBFJFCNSZM'))
```

Hibrid.py

```
#popularity and hibrid system local files
from popularity.popularity import Rec_pop
from endResult import result

from werkzeug.security import generate_password_hash, check_password_hash #create Password hash
from flask_sqlalchemy import SQLAlchemy
from sqlalchemy import * #Database
from flask import Flask, request, render_template, redirect, url_for, session # imaport tamplet and
required fask methods
from sqlalchemy.orm import sessionmaker #A session is a way to interact with a database using
SQLAlchemy.
from sqlalchemy.ext.declarative import declarative_base #It provides a way to define database models
using Python classes.
from sqlalchemy.exc import IntegrityError #This module contains an exception class for integrity-
related errors
import pandas as pd

app = Flask(__name__)
app.secret_key = 'ravi_mane'
engine = create_engine('sqlite:///mydatabase.db', echo=True) #database name
Session_db = sessionmaker(bind=engine)
Base = declarative_base()

class User(Base): #tabel structure
    __tablename__ = 'users'
    id = Column(Integer, primary_key=True, autoincrement=True )
    username = Column(String(50), unique=True)
    password = Column(String(100))
    liked = Column(String(700))

Base.metadata.create_all(engine)
session_main = Session_db() # create session

users = [
    {'username': 'john', 'password': generate_password_hash('password')},
    {'username': 'jane', 'password': generate_password_hash('1234')}
]

@app.route('/', methods=['GET', 'POST'])
```

```
def home(): # Main index screen
    if 'username' in session:
        df2=Rec_pop()
        df=pd.read_pickle('Grocary.pkl')
        df = df[df['ProductID'].isin(df2)]
        names=df['brand'].drop_duplicates(keep='first').tolist()
        brand =names
        print(df.iloc[0])
        return render_template(
            "view.html",data=df.to_dict(orient="records"),
            languages=brand
        )
    else:
        return redirect(url_for('login'))

@app.route('/login', methods=['GET', 'POST'])
def login(): #login screen
    img_url = url_for('static', filename='login.webp')

    if request.method == 'POST':
        username = request.form['username']
        password = request.form['password']
        user2 = session_main.query(User).filter_by(username=username,password=password).first()
        user = next((user for user in users if user['username'] == username), None)
        if user and check_password_hash(user['password'], password): #check username and password
and login into system
            session['username'] = username
            return redirect(url_for('home'))
        elif user2:
            session['username'] = username
            return redirect(url_for('home'))
        else:
            return render_template('login.html', error='Invalid username or password',img=img_url)
    else:
        return render_template('login.html',img=img_url)

@app.route('/signup', methods=['GET', 'POST'])
def signup(): #signup screen
    img_url = url_for('static', filename='login.webp')

    if request.method == 'POST':
        username = request.form['username']
        password = request.form['password']

        if next((user for user in users if user['username'] == username), None) is None:

            new_user = User(username=username, password=password)
            try:
                session_main.add(new_user)  #add user to database
                session_main.commit()
            except IntegrityError:
                session_main.rollback()

            users.append({'username': username, 'password': generate_password_hash(password)})
            session['username'] = username

            return redirect(url_for('login'))
        else:
            return render_template('signup.html', error='Username already taken',img=img_url)
    else:
```

```
        return render_template('signup.html',img=img_url)

@app.route('/logout')
def logout(): #logout function
    session.pop('username', None)
    return redirect(url_for('home'))

@app.route('/single', methods=['GET', 'POST'])
def single(): #display single item
    if 'username' in session:
        id = request.args.get('param')
        Pname = request.args.get('name')
        user = session_main.query(User).filter(User.id == 1).first()
        user.liked = 'raj '
        session_main.commit()
        brand = request.args.get('brand')
        uname= session['username']
        df=pd.read_pickle('Grocary.pkl')

        passData=df[df['ProductID'] == 'B00006FWVX']
        df2=result(session['username'],id)

        return render_template(
            "single.html",
            images=df2.to_dict(orient="records"),
            name=id,
            brand=Pname,
        )
    else:
        return redirect(url_for('single'))
@app.route('/Bsingle', methods=['GET', 'POST'])
def Bsingle():#display scarched item
    if 'username' in session:
        id = request.args.get('param')
        Pname = request.args.get('name')
        user = session_main.query(User).filter(User.id == 1).first()
        user.liked = 'raj '
        session_main.commit()
        brand = request.args.get('brand')
        uname= session['username']
        df=pd.read_pickle('Grocary.pkl')
        passData=df[df['ProductID'] == 'B00006FWVX']
        df2=result(session['username'],id)
        df2 = df[df['brand'] == brand][:10]
        return render_template(
            "Bsingle.html",
            images=df.to_dict(orient="records"),
            name=id,
            brand=brand,
            images2=df2.to_dict(orient="records"),
        )
    else:
        return redirect(url_for('Bsingle'))

app.run(port=8080)
```

Chapter 10

Test Cases

10.1 Testing Environment

UnitTest
The unittest unit testing framework was originally inspired by JUnit and has a similar flavor as major unit testing frameworks in other languages. It supports test automation, sharing of setup and shutdown code for tests, aggregation of tests into collections, and independence of the tests from the reporting framework.

The purpose of this report is to provide an overview of the unit testing process conducted for the recommendation system. The recommendation system is designed to generate personalized recommendations for users based on their preferences and behaviors.
Test Environment:
Programming Language: Python
Unit Testing Framework: unittest
Test Runner: TestRunner

10.2 Testing Report

Project	Product Recommandation system
Module	Login

ID	Description	ID	Description	Test Steps	Expected Result	Actual Result	Status
TS_H_01	Verify buttons functionality	TC_01	Check buttons functionality	Click on buttons if they are working or not	UI should be perfect	UI is perfect	Pass
		TC_02	Check Login Button's Functionality	Click on login button if it is working or not	User should be able to see the second page	User is able to see the second page	Pass
		TC_03	Check Registration link Functionality	Click on registration link if it is working or not	User should be able to see the second page	User is able to see the second page	Pass

Module	Registration

ID	Description	ID	Description	Test Steps	Expected Result	Actual Result	Status
TS_R_01	Verify buttons functionality	TC_01	Check buttons functionality	Click on buttons if they are working or not	UI should be perfect	UI is perfect	Pass
		TC_02	Check Registration Button's Functionality	Click on registration button if it is working or not	User should be able to see the registration page	User is able to see the registration page	Pass
		TC_03	Check login link Functionality	Click on login link if it is working or not	User should be able to see the second page	User is able to see the second page	Pass

Module	Home

ID	Description	ID	Description	Test Steps	Expected Result	Actual Result	Status
	100 popular		Check all 100	after click on login	It should display 100	It is showing 100	

TS_FDR_01	100 popular items Functionality	TC_01	popular item is display	display top 100 popular items	popular items	popular item	Pass
TS_FDR_02	brand search field auto saggest functionality	TC_02	Check it display suggetions	enter any character it diplay related brand if exist	It will be showing the saggeation	It is showing the saggetion	Pass

Module	Brand

ID	Description	ID	Description	Test Steps	Expected Result	Actual Result	Status
TS_SWR_01	Verify brand Functionality	TC_01	Check displayed data is belong similar brand	enter brand in search fileld and than click enter	It will be showing the similar brands	It is showing the similar brands	Pass
TS_SWR_02	Recommand button functionality	TC_02	Check Recommand buttons functionality	Click on buttons if they are working or not	User should be able to see the second page with	User is able to see the second page with recommandation	Pass

Module	Single

ID	Description	ID	Description	Test Steps	Expected Result	Actual Result	Status
TS_SWR_01	Verify brand Functionality	TC_01	Check displayed data is belong similar brand	enter brand in search fileld and than click enter	It will be showing the similar brands	It is showing the similar brands	Pass
		TC_02	Check Recommand buttons functionality	Click on buttons if they are working or not	User should be able to see the second page with recommandation	User is able to see the second page with recommandation	Pass

Module	Content based

ID	Description	ID	Description	Test Steps	Expected Result	Actual Result	Status
TS_FDL_01	Verify Functionality	TC_01	Check recommend_products function	pass product ID as argument to funtion and display releated product list	It will be showing the Product list as output	It is showing the Product list as output	Pass

Module	Collabrative

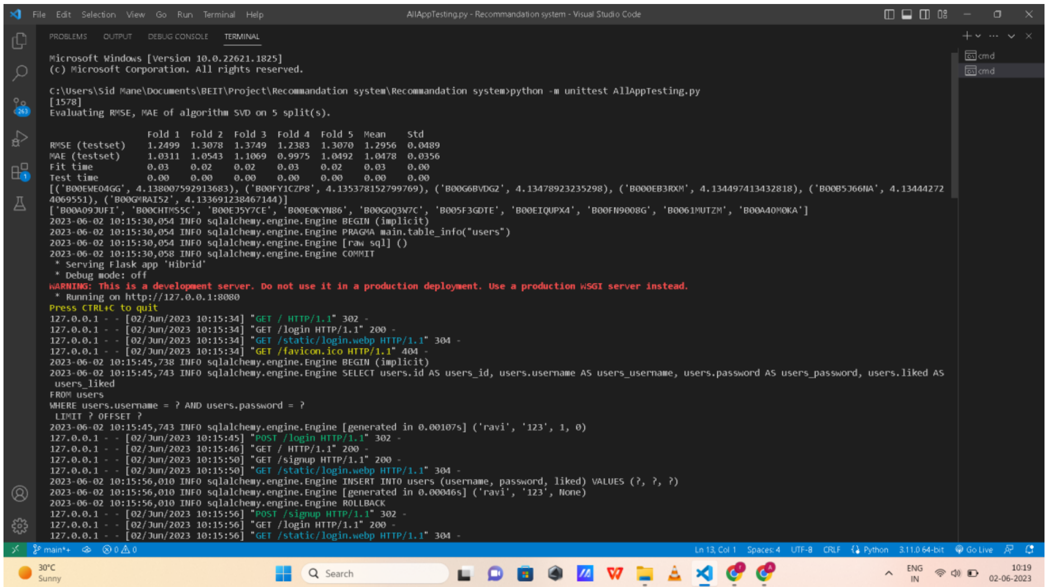
ID	Description	ID	Description	Test Steps	Expected Result	Actual Result	Status
TS_FDL_01	Verify Functionality	TC_01	Check collaborative_filtering function	pass product ID and userID as argument to funtion and display releated product list	It will be showing the Product list as output	It is showing the Product list as output	Pass

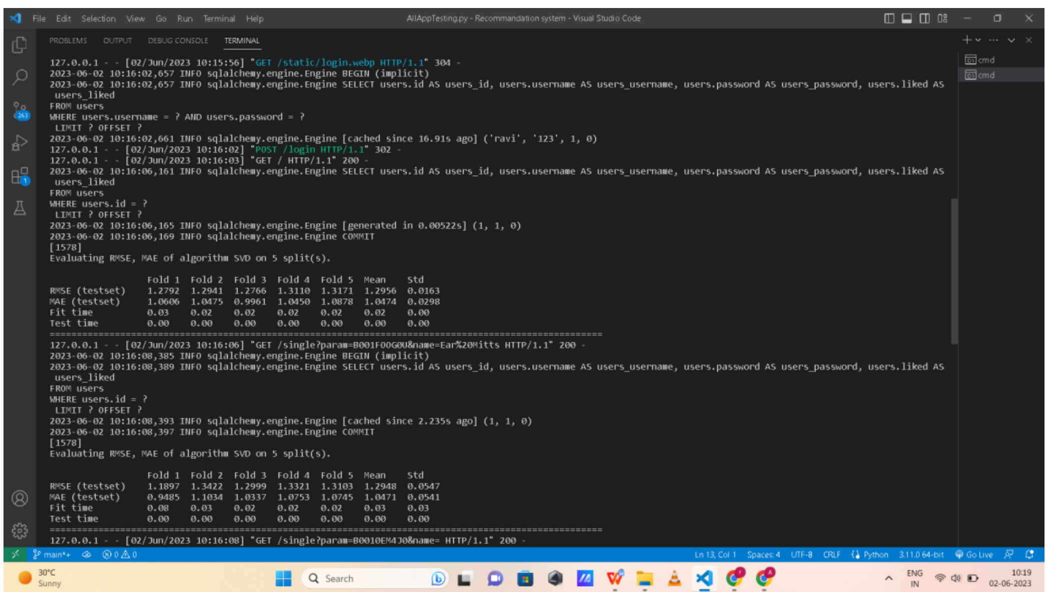
Module	Popularity

ID	Description	ID	Description	Test Steps	Expected Result	Actual Result	Status
TS_FDL_01	Verify Functionality	TC_01	Check Rec_pop function	call the function rec_pop	It will be showing the Product list as output	It is showing the Product list as output	Pass

Module	Hybrid

ID	Description	ID	Description	Test Steps	Expected Result	Actual Result	Status
TS_FDL_01	Verify Functionality	TC_01	Check result function	pass product ID and userID as argument to funtion and display releated product list	It will be showing the Product list as output	It is showing the Product list as output	Pass


AllAppTesting.py - Recommandation system - Visual Studio Code
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL
Microsoft Windows [Version 10.0.22621.1825]
(c) Microsoft Corporation. All rights reserved.
C:\Users\Sid Mane\Documents\BEIT\Project\Recommandation system\Recommandation system>python -m unittest AllAppTesting.py
[1578]
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).
Fold 1 Fold 2 Fold 3 Fold 4 Fold 5 Mean Std
RMSE (testset) 1.2499 1.3078 1.3749 1.2383 1.3070 1.2956 0.0489
MAE (testset) 1.0311 1.0543 1.1069 0.9975 1.0492 1.0478 0.0356
Fit time 0.03 0.02 0.02 0.03 0.02 0.03 0.00
Test time 0.00 0.00 0.00 0.00 0.00 0.00 0.00
[('B00EWE04GG', 4.138007592913683), ('B00FY1CZP8', 4.135378152799769), ('B00G6BVDG2', 4.13478923235298), ('B000EB3RXM', 4.134497413432818), ('B00B5J66NA', 4.134442724069551), ('B00GMRAI52', 4.133691238467144)]
['B00A09JUFI', 'B00CHTMS5C', 'B00EJ5Y7CE', 'B00E0KYN86', 'B00G0Q3W7C', 'B005F3GDTE', 'B00EIQUPX4', 'B00FN9008G', 'B0061MUTZM', 'B00A40M0KA']
2023-06-02 10:15:30,054 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-06-02 10:15:30,054 INFO sqlalchemy.engine.Engine PRAGMA main.table_info("users")
2023-06-02 10:15:30,054 INFO sqlalchemy.engine.Engine [raw sql] ()
2023-06-02 10:15:30,058 INFO sqlalchemy.engine.Engine COMMIT
* Serving Flask app 'Hibrid'
* Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
* Running on http://127.0.0.1:8080
Press CTRL+C to quit
127.0.0.1 - - [02/Jun/2023 10:15:34] "GET / HTTP/1.1" 302 -
127.0.0.1 - - [02/Jun/2023 10:15:34] "GET /login HTTP/1.1" 200 -
127.0.0.1 - - [02/Jun/2023 10:15:34] "GET /static/login.webp HTTP/1.1" 304 -
127.0.0.1 - - [02/Jun/2023 10:15:34] "GET /favicon.ico HTTP/1.1" 404 -
2023-06-02 10:15:45,738 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-06-02 10:15:45,743 INFO sqlalchemy.engine.Engine SELECT users.id AS users_id, users.username AS users_username, users.password AS users_password, users.liked AS users_liked
FROM users
WHERE users.username = ? AND users.password = ?
LIMIT ? OFFSET ?
2023-06-02 10:15:45,743 INFO sqlalchemy.engine.Engine [generated in 0.00107s] ('ravi', '123', 1, 0)
127.0.0.1 - - [02/Jun/2023 10:15:45] "POST /login HTTP/1.1" 302 -
127.0.0.1 - - [02/Jun/2023 10:15:46] "GET / HTTP/1.1" 200 -
127.0.0.1 - - [02/Jun/2023 10:15:50] "GET /signup HTTP/1.1" 200 -
127.0.0.1 - - [02/Jun/2023 10:15:50] "GET /static/login.webp HTTP/1.1" 304 -
2023-06-02 10:15:56,010 INFO sqlalchemy.engine.Engine INSERT INTO users (username, password, liked) VALUES (?, ?, ?)
2023-06-02 10:15:56,010 INFO sqlalchemy.engine.Engine [generated in 0.00046s] ('ravi', '123', None)
2023-06-02 10:15:56,010 INFO sqlalchemy.engine.Engine ROLLBACK
127.0.0.1 - - [02/Jun/2023 10:15:56] "POST /signup HTTP/1.1" 302 -
127.0.0.1 - - [02/Jun/2023 10:15:56] "GET /login HTTP/1.1" 200 -
127.0.0.1 - - [02/Jun/2023 10:15:56] "GET /static/login.webp HTTP/1.1" 304 -
Ln 13, Col 1 Spaces: 4 UTF-8 CRLF Python 3.11.0 64-bit Go Live
30°C Sunny
Search
ENG IN
10:19 02-06-2023


AllAppTesting.py - Recommandation system - Visual Studio Code
PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL
127.0.0.1 - - [02/Jun/2023 10:15:56] "GET /static/login.webp HTTP/1.1" 304 -
2023-06-02 10:16:02,657 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-06-02 10:16:02,657 INFO sqlalchemy.engine.Engine SELECT users.id AS users_id, users.username AS users_username, users.password AS users_password, users.liked AS users_liked
FROM users
WHERE users.username = ? AND users.password = ?
LIMIT ? OFFSET ?
2023-06-02 10:16:02,661 INFO sqlalchemy.engine.Engine [cached since 16.91s ago] ('ravi', '123', 1, 0)
127.0.0.1 - - [02/Jun/2023 10:16:02] "POST /login HTTP/1.1" 302 -
127.0.0.1 - - [02/Jun/2023 10:16:03] "GET / HTTP/1.1" 200 -
2023-06-02 10:16:06,161 INFO sqlalchemy.engine.Engine SELECT users.id AS users_id, users.username AS users_username, users.password AS users_password, users.liked AS users_liked
FROM users
WHERE users.id = ?
LIMIT ? OFFSET ?
2023-06-02 10:16:06,165 INFO sqlalchemy.engine.Engine [generated in 0.00522s] (1, 1, 0)
2023-06-02 10:16:06,169 INFO sqlalchemy.engine.Engine COMMIT
[1578]
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).
Fold 1 Fold 2 Fold 3 Fold 4 Fold 5 Mean Std
RMSE (testset) 1.2792 1.2941 1.2766 1.3110 1.3171 1.2956 0.0163
MAE (testset) 1.0606 1.0475 0.9961 1.0450 1.0878 1.0474 0.0298
Fit time 0.03 0.02 0.02 0.02 0.02 0.02 0.00
Test time 0.00 0.00 0.00 0.00 0.00 0.00 0.00
127.0.0.1 - - [02/Jun/2023 10:16:06] "GET /single?param=B001F00G0U&name=Ear%20Mitts HTTP/1.1" 200 -
2023-06-02 10:16:08,385 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-06-02 10:16:08,389 INFO sqlalchemy.engine.Engine SELECT users.id AS users_id, users.username AS users_username, users.password AS users_password, users.liked AS users_liked
FROM users
WHERE users.id = ?
LIMIT ? OFFSET ?
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2023-06-02 10:16:08,397 INFO sqlalchemy.engine.Engine COMMIT
[1578]
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).
Fold 1 Fold 2 Fold 3 Fold 4 Fold 5 Mean Std
RMSE (testset) 1.1897 1.3422 1.2999 1.3321 1.3103 1.2948 0.0547
MAE (testset) 0.9485 1.1034 1.0337 1.0753 1.0745 1.0471 0.0541
Fit time 0.08 0.03 0.02 0.02 0.02 0.03 0.03
Test time 0.00 0.00 0.00 0.00 0.00 0.00 0.00
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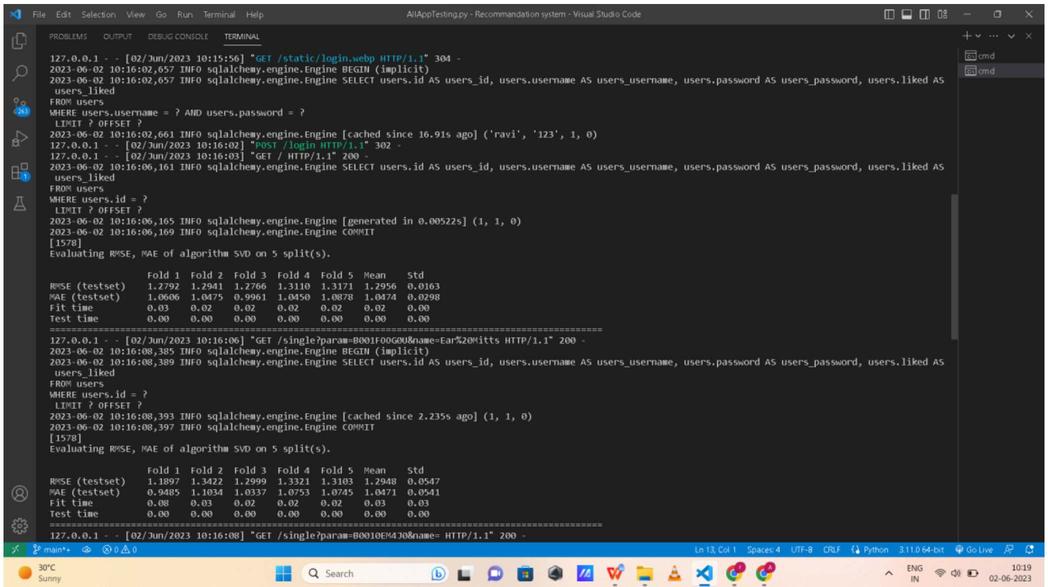
30°C Sunny
Search
ENG IN
10:19 02-06-2023


AllAppTesting.py - Recommandation system - Visual Studio Code
127.0.0.1 - - [02/Jun/2023 10:15:56] "GET /static/login.webp HTTP/1.1" 304 -
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FROM users
WHERE users.username = ? AND users.password = ?
LIMIT ? OFFSET ?
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127.0.0.1 - - [02/Jun/2023 10:16:03] "GET / HTTP/1.1" 200 -
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FROM users
WHERE users.id = ?
LIMIT ? OFFSET ?
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2023-06-02 10:16:06,169 INFO sqlalchemy.engine.Engine COMMIT
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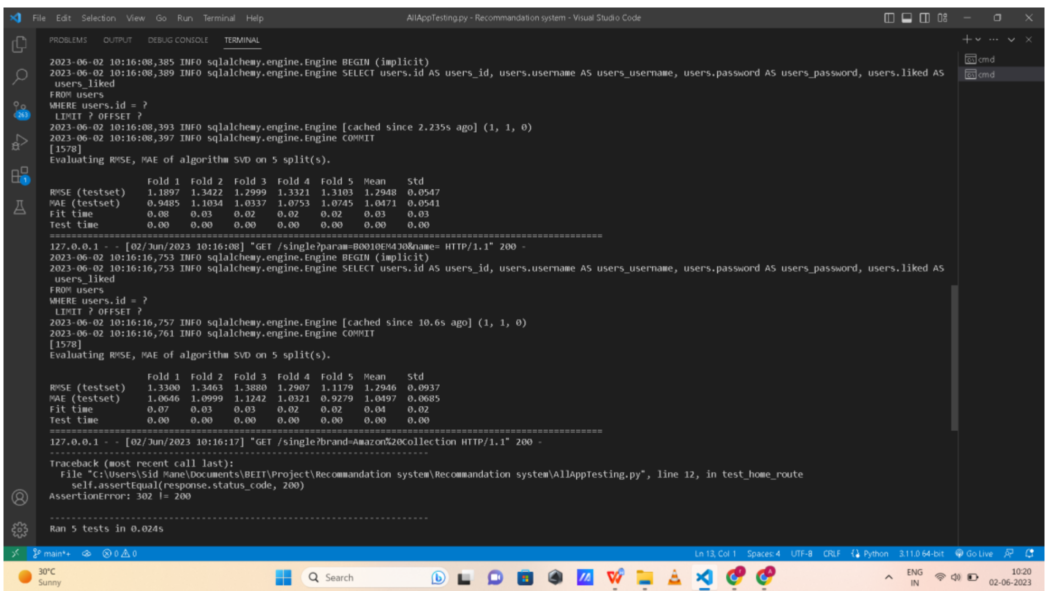
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).
Fold 1 Fold 2 Fold 3 Fold 4 Fold 5 Mean Std
RMSE (testset) 1.2792 1.2941 1.2766 1.3110 1.3171 1.2956 0.0163
MAE (testset) 1.0606 1.0475 0.9961 1.0450 1.0878 1.0474 0.0298
Fit time 0.03 0.02 0.02 0.02 0.02 0.02 0.00
Test time 0.00 0.00 0.00 0.00 0.00 0.00 0.00
127.0.0.1 - - [02/Jun/2023 10:16:06] "GET /single?param=B001F00G0U&name=Ear%20Mitts HTTP/1.1" 200 -
2023-06-02 10:16:08,385 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-06-02 10:16:08,389 INFO sqlalchemy.engine.Engine SELECT users.id AS users_id, users.username AS users_username, users.password AS users_password, users.liked AS users_liked
FROM users
WHERE users.id = ?
LIMIT ? OFFSET ?
2023-06-02 10:16:08,393 INFO sqlalchemy.engine.Engine [cached since 2.235s ago] (1, 1, 0)
2023-06-02 10:16:08,397 INFO sqlalchemy.engine.Engine COMMIT
[1578]
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).
Fold 1 Fold 2 Fold 3 Fold 4 Fold 5 Mean Std
RMSE (testset) 1.1897 1.3422 1.2999 1.3321 1.3103 1.2948 0.0547
MAE (testset) 0.9485 1.1034 1.0337 1.0753 1.0745 1.0471 0.0541
Fit time 0.08 0.03 0.02 0.02 0.02 0.03 0.03
Test time 0.00 0.00 0.00 0.00 0.00 0.00 0.00
127.0.0.1 - - [02/Jun/2023 10:16:08] "GET /single?param=B0010EM4J0&name= HTTP/1.1" 200 -


AllAppTesting.py - Recommandation system - Visual Studio Code
2023-06-02 10:16:08,385 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-06-02 10:16:08,389 INFO sqlalchemy.engine.Engine SELECT users.id AS users_id, users.username AS users_username, users.password AS users_password, users.liked AS users_liked
FROM users
WHERE users.id = ?
LIMIT ? OFFSET ?
2023-06-02 10:16:08,393 INFO sqlalchemy.engine.Engine [cached since 2.235s ago] (1, 1, 0)
2023-06-02 10:16:08,397 INFO sqlalchemy.engine.Engine COMMIT
[1578]
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).
Fold 1 Fold 2 Fold 3 Fold 4 Fold 5 Mean Std
RMSE (testset) 1.1897 1.3422 1.2999 1.3321 1.3103 1.2948 0.0547
MAE (testset) 0.9485 1.1034 1.0337 1.0753 1.0745 1.0471 0.0541
Fit time 0.08 0.03 0.02 0.02 0.02 0.03 0.03
Test time 0.00 0.00 0.00 0.00 0.00 0.00 0.00
127.0.0.1 - - [02/Jun/2023 10:16:08] "GET /single?param=B0010EM4J0&name= HTTP/1.1" 200 -
2023-06-02 10:16:16,753 INFO sqlalchemy.engine.Engine BEGIN (implicit)
2023-06-02 10:16:16,753 INFO sqlalchemy.engine.Engine SELECT users.id AS users_id, users.username AS users_username, users.password AS users_password, users.liked AS users_liked
FROM users
WHERE users.id = ?
LIMIT ? OFFSET ?
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[1578]
Evaluating RMSE, MAE of algorithm SVD on 5 split(s).
Fold 1 Fold 2 Fold 3 Fold 4 Fold 5 Mean Std
RMSE (testset) 1.3300 1.3463 1.3880 1.2907 1.1179 1.2946 0.0937
MAE (testset) 1.0646 1.0999 1.1242 1.0321 0.9279 1.0497 0.0685
Fit time 0.07 0.03 0.03 0.02 0.02 0.04 0.02
Test time 0.00 0.00 0.00 0.00 0.00 0.00 0.00
127.0.0.1 - - [02/Jun/2023 10:16:17] "GET /single?brand=Amazon%20Collection HTTP/1.1" 200 -
Traceback (most recent call last):
File "C:\Users\Sid Mane\Documents\BEIT\Project\Recommandation system\Recommandation system\AllAppTesting.py", line 12, in test_home_route
self.assertEqual(response.status_code, 200)
AssertionError: 302 != 200
Ran 5 tests in 0.024s

Chapter 11

Experimental Results

11.1 GUI

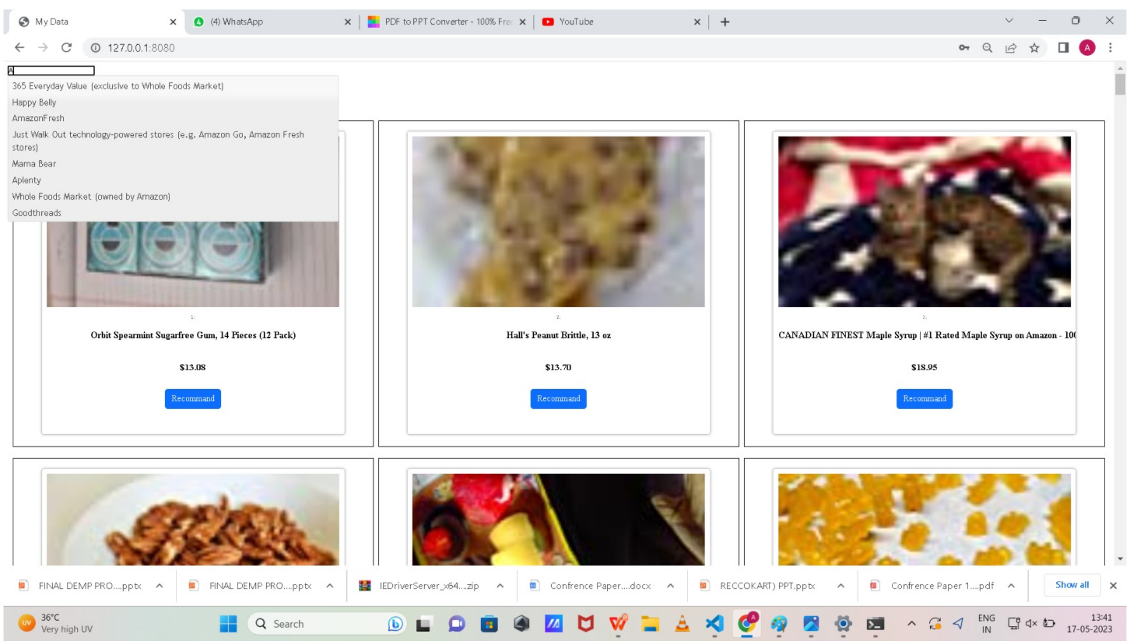


Figure 11.1: User Side.

User Side: User can see products,perches them.View recommended products generated by system. view ordered products.

11.2 Working Modules

User side 1. Home: When user click on home than home page of the system will display to the user.

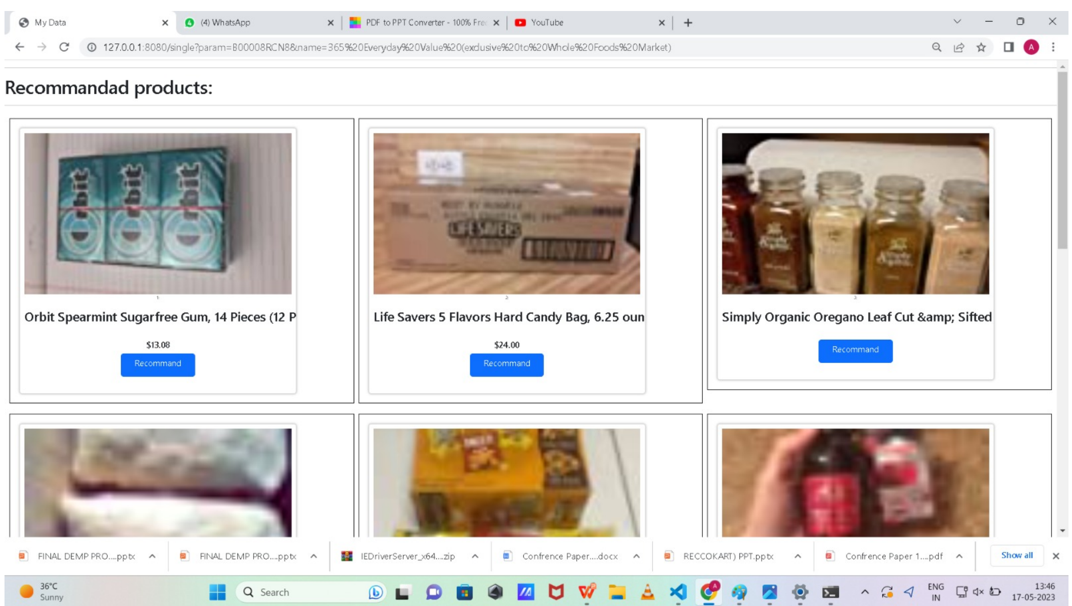
2. Products: When user can click on products display the list of products. user can order witch over product he wants.

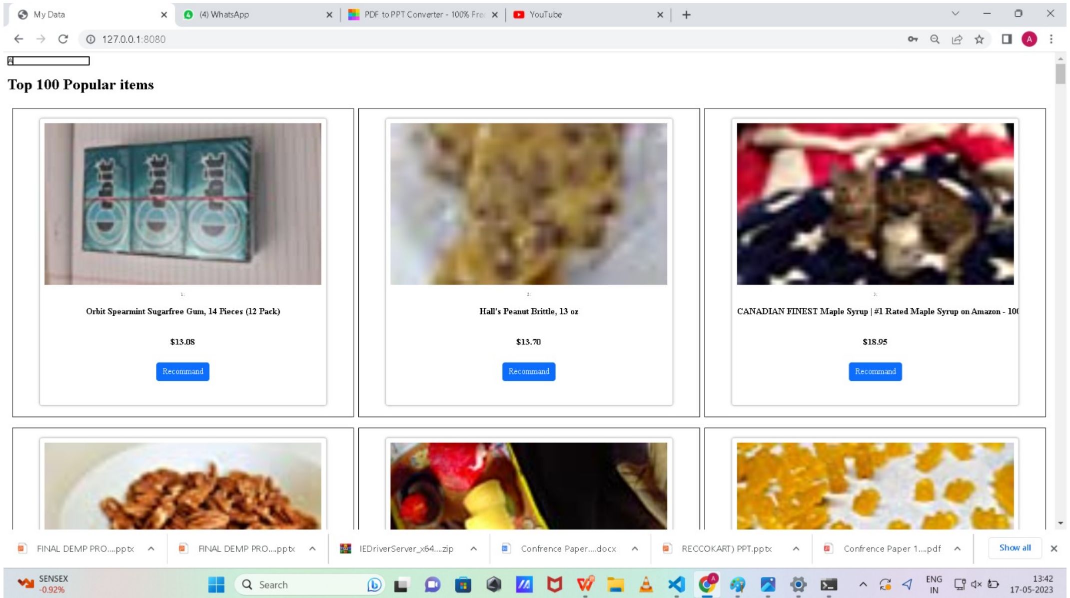
3.Recommender products: this is the section which show user the recommendation as per his opening.

4.Your order: When user order product then his order is placed her.

11.3 Experimental Results and Discussions

As show abow the design phase of the main project is completed and the output is as shown.her user login in to the system user login to system using conditionals than see products buy it and than system Recommends product to user




My Data
(4) WhatsApp
PDF to PPT Converter - 100% Fre
YouTube
127.0.0.1:8080
Top 100 Popular items
Orbit Spearmint Sugarfree Gum, 14 Pieces (12 Pack)
$13.08
Recommend
Hall's Peanut Brittle, 13 oz
$13.70
Recommend
CANADIAN FINEST Maple Syrup | #1 Rated Maple Syrup on Amazon - 10(
$18.95
Recommend
FINAL DEMP PRO....pptx
IEDriverServer_x64....zip
Confrence Paper....docx
RECCOKART) PPT.pptx
Confrence Paper 1....pdf
Show all
SENSEX
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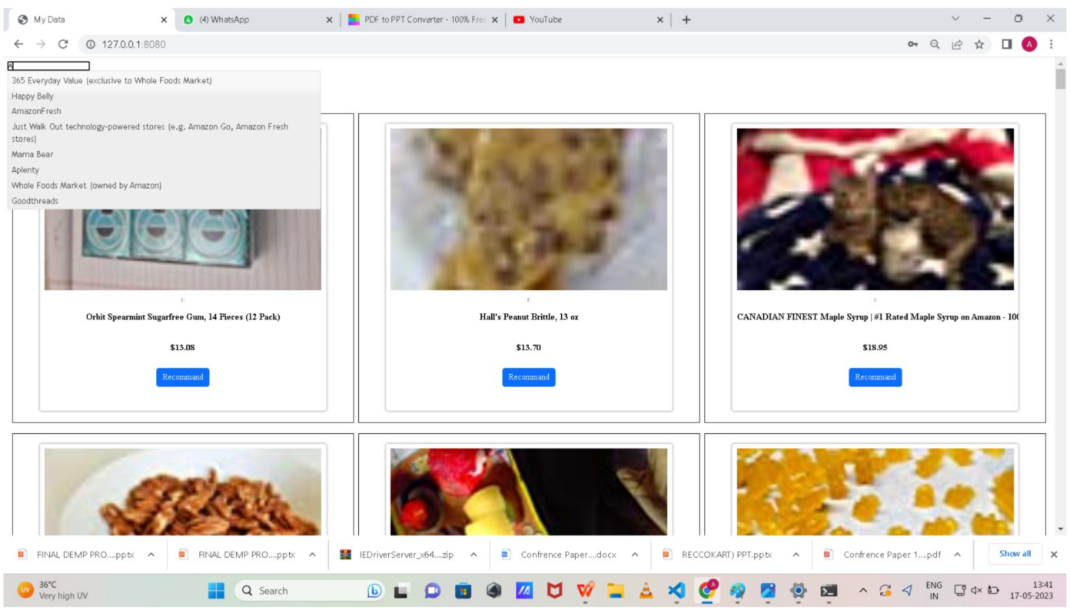
IN
13:42
17-05-2023


My Data
(4) WhatsApp
PDF to PPT Converter - 100% Fre
YouTube
127.0.0.1:8080
365 Everyday Value (exclusive to Whole Foods Market)
Happy Belly
AmazonFresh
Just Walk Out technology-powered stores (e.g. Amazon Go, Amazon Fresh stores)
Mama Bear
Aplenty
Whole Foods Market (owned by Amazon)
Goodthreads
Orbit Spearmint Sugarfree Gum, 14 Pieces (12 Pack)
$13.08
Recommend
Hall's Peanut Brittle, 13 oz
$13.70
Recommend
CANADIAN FINEST Maple Syrup | #1 Rated Maple Syrup on Amazon - 10(
$18.95
Recommend
FINAL DEMP PRO....pptx
IEDriverServer_x64....zip
Confrence Paper....docx
RECCOKART) PPT.pptx
Confrence Paper 1....pdf
Show all
36°C
Very high UV
Search
ENG
IN
13:41
17-05-2023

Chapter 12

Project Plan

Project Stage-1

Sr No	**Task Name**	**Start Date**	**Finish Date**
1	Registration of Project Group and Allocation of Project Guide	18-07-2022	05-08-2022
2	The precise problem statement based on literature survey and feasibility study	08-08-2022	13-08-2022
3	Feasibility Review: Sanction and Finalize Project Topic	13-08-2022	13-08-2022
4	Motivation, Objective and Scope of the Project	15-08-2022	19-08-2022
5	List of Required Hardware, Software, or other equipment for executing the project, test Environment/tools, cost, and software measurement/human efforts in hours.	22-08-2022	27-08-2022
6	System Overview- Proposed System and expected outcomes	29-08-2022	02-09-2022

Sr No	Task Name	Start Date	Finish Date
7	Architecture and Initial Phase of Design(DFD)	05-09-2022	10-09-2022
8	Project Review-1 : Synopsis	10-09-2022	10-09-2022
9	User and System Requirements	12-09-2022	16-09-2022
10	SRS Document, Writing structures as SRS qs per Problem statement	19-09-2022	24-09-2022
11	Requirement analysis /Models	26-09-2022	30-09-2022
12	Detail Architecture / System Design / Algorithm with Analysis / Methods / Techniques	03-10-2022	08-10-2022
13	Design models and Component level Design	10-10-2022	14-10-2022
14	At least 50 coding documentation with at least 3 to 4 working moduels	17-10-2022	22-10-2022
15	Identification of test to be essential and appropriate (To be implementing later)	25-10-2022	27-10-2022

Table 12.1: Project Plan 1.0

Project Stage-2

Sr No	Task Name	Start Date	Finish Date
1	100% Implementation	23/01/2023	23/02/2023
2	Project Review-3: Implementation	24/02/2023	24/02/2023
3	100% Testing and Result Analysis	25/02/2023	09/03/2023
4	Project Review-4 : Testing and Result Analysis	10/03/2023	10/03/2023
5	Project Report Writing	13/03/2023	16/03/2023
6	Project Report Review	17/03/2023	17/03/2023
7	Submission of Project Report	20/03/2023	29/03/2023
8	Internal Project Exam	31/03/2023	31/03/2023

Table 12.2: Project Plan 2.0

12.1 Project Estimates

COCOMO MODEL

The project cost can be found using any one of the model.
COCOMO-1 Model
COCOMO-2 Model
Model -1: The basic COCOMO model computes software development efforts as a function of program size expressed in estimated lines of code.
Model-2: The intermediate COCOMO model computes software development efforts as a function of program size and a set of cost drivers that include subjective assessment of the product, hardware, personnel, project attributes
Model-3: The advanced COCOMO model incorporates all characteristics of the intermediate version with a assessment of the cost drivers impact on each step of the software engineering process. Following is the basic COCOMO -2 model.
The basic COCOMO -2 model equations take form:
E=A(b)KLOCB(b)
D=C(b)ED(b)

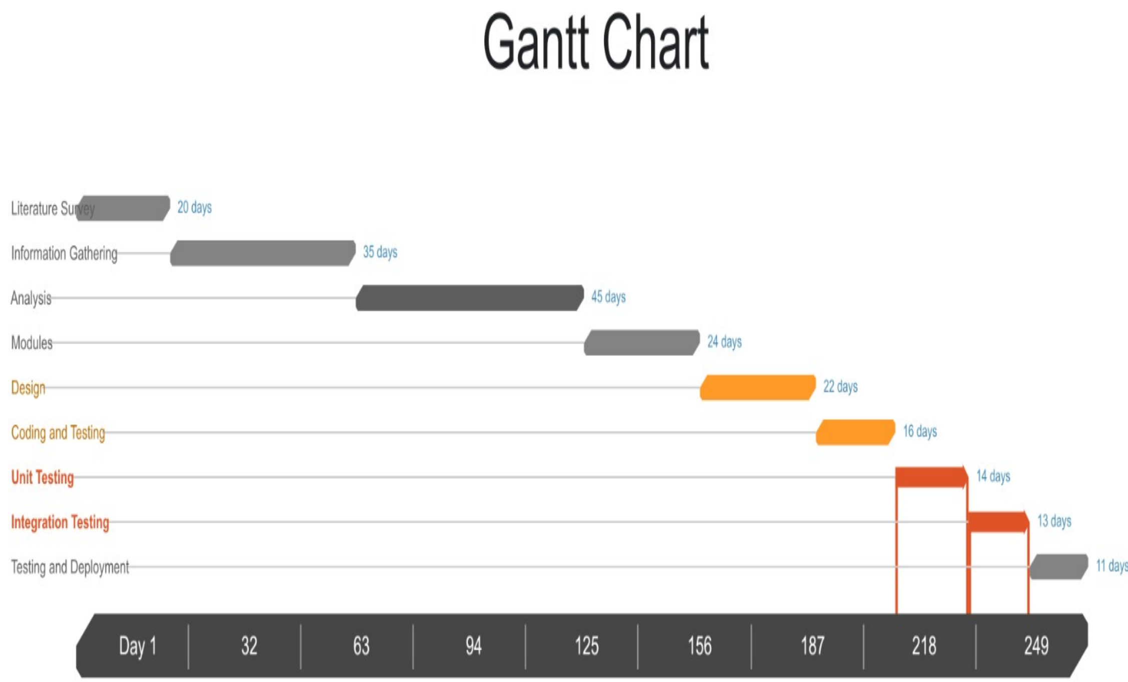
Where E is the effort applied in person months. D is development time in chronological month. KLOC is estimated number of delivered lines of code for the project. This project can be classified as Semidetached software project. The rough estimate of number of lines of this project is 9.072k.Applying the above formula
E=3.0*(9.072)1.22
= 44.20 person- months
D=2.5* 44.35 = 9.40 months
Hence according COCOMO -2 model the time required for completion of the project is 9 (9.40) months.

12.2 Team Structure and Responsibilities

Name of Team Member	Role
Umesh Patil	• Requirement Gathering – Dataset Collection – Case Study • Requirement Analysis
Bobade Ganesh	Front End Design
Raviraj Mane	Python Code Development
RohitKhomane	Testing & Implementation

Table 12.3: project Responsibilities

12.3 Gant Chart



Chapter 13

Conclusions

In this article, we have proposed a product recommendation system based on interest mining and metapath discovery, and the system predicts the user's needs and the associated items. Products' recommendation is computed by analyzing the user's topical interest and, eventually, recommending the items associated with those interests. The proposed system is personality-aware from two aspects: first, because it incorporates the user's personality traits to predict his topics of interest; second, it matches the user's personality facets with the associated items. Experimental results show that the proposed system outperforms the state-of-art schemes in terms of precision and recall especially in the cold-start phase for new items and users. However, Meta-Interest could be improved in different aspects.

1) In this work, the users' hobbys' measurement was conducted through questionnaires. Integrating an automatic personality recognition system, which can detect the users' personality traits based on their shared data, into Meta-Interest is one of our future directions.

2) The proposed system uses big-five to model the user's personality. Extending Meta-Interest to include other personality traits models, such as the Myers–Briggs type indicator, is a future direction.

3) The proposed system could be further improved by integrating a knowledge graph and infer topic–item association using semantic reasoning.

Bibliography

[1] G. Piao and J. G. Breslin, "Inferring user interests in microblogging social networks: A survey," User Model. User-Adapted Interact., *vol. 28, no. 3, pp. 277–329, Aug. 2018.* [Online]. Available: http://link.springer.com/10.1007/s11257-018-9207-8.

[2] Vinciarelli and G. Mohammadi, "A survey of personality computing," IEEE Trans. Affect. Comput., *vol. 5, no. 3, pp. 273–291, Jul. 2014.*[Online]. Available: http://ieeexplore.ieee.org/ document/6834774/

[3] L. Sebastia, I. Garc´ıa, E. Onaindia, and C. Guzman Alvarez, ´e-Tourism: A tourist recommendation and planning application, International Journal on Artificial Intelligence Tools, vol. 18, no. 5, pp. 717–738, 2009.

[4] F. Ricci, L. Rokach, and B. Shapira, Introduction to recommender systems handbook, in Recommender Systems Handbook, F. Ricci, L. Rokach, B. Shapira, and P. Kantor, eds. Boston, MA, USA: Springer, 2011, pp. 1–35.

[5] G. Adomavicius and A. Tuzhilin, Toward the next generation of recommender systems: A survey of the stateof-the-art and possible extensions, IEEE Transactions on Knowledge and Data Engineering, vol. 17, no. 6, pp. 734– 749, 2005.

[6] M. de Gemmis, P. Lops, C. Musto, F. Narducci, and G.Semeraro, Semantics-aware content-based recommender systems, in Recommender Systems Handbook, F. Ricci, L. Rokach, and B. Shapira, eds. Boston, MA, USA: Springer, 2015, pp. 119–159

Appendix A

Plagiarism Report

A.1 Plagiarism Report of Paper

PLAGIARISM SCAN REPORT

Report Generation Date: 29-11-22

Words: 185

Characters: 1312

Excluded URL : N/A

0% Plagiarism	100% Unique
0 Plagiarized Sentences	9 Unique Sentences

Content Checked for Plagiarism

Any contemporary social network or online store must include a recommendation system. An example of this would be the product suggestion system.
Redundancy in recommendations and the unpredictable nature of new items are two significant flaws with historical recommendation systems (cold start). Because the older recommendation algorithms only use the user's prior purchasing history when making recommendations, these restrictions exist. It may be possible to reduce the cold start and eliminate redundant recommendations by including the user's social characteristics, such as personality traits and areas of interest. As a result, we suggest Meta-Interest in this study, a personality-aware product recommendation system based on user interest mining and meta-path discovery. Even if the user's history does not contain these or comparable things, Meta-Interest may forecast the user's interests and the items related to those interests. This is accomplished by examining the user's subject-specific interests and ultimately recommending products related to those interests.
The suggested system uses the user's personality qualities to forecast his themes of interest and to link the user's personality facets with the associated things, making it personality aware in two different ways.

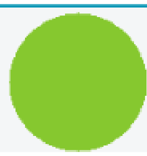
Congrats! Your Content is 100% Unique.

A.2 Plagiarism Report of Project report

Check Plagiarism

PLAGIARISM SCAN REPORT

Date	May 23, 2023
Exclude URL:	NO



Unique Content	100
Plagiarized Content	0
Word Count	222
Records Found	0

CONTENT CHECKED FOR PLAGIARISM:

Any cutting-edge social networking or on line retail platform need to have a advice device. A product advice is

basically a filtering system that seeks to predict and show the gadgets that a consumer would really like to purchase. it may now not be completely accurate, but if it indicates you what you like then it's miles doing its process proper. As an average instance of a legacy recommendation device, the product advice machine has two good sized drawbacks: advice repetition and unpredictability about new objects (cold begin). because the older recommendation algorithms best use the consumer's preceding shopping history when making tips, these boundaries exist. The cold start and recommendation redundancy may be lessened by way of incorporating the consumer's social attributes, which include character traits and regions of hobby. In mild of this, we gift MetaInterest, a personality- aware product advice device constructed on consumer hobby mining and metapath discovery. The counseled technique includes the person's personality characteristics to forecast his or her issues of hobby and to link the consumer's personality facets with the applicable things, making it character-aware from views. The recommended gadget was evaluated towards cutting-edge recommendation strategies, which include session- based and deep-getting to know-based totally systems. according to experimental findings, the counseled strategy can improve the advice gadget's reminiscence and precision, especially in bloodless-begin situations.

MATCHED SOURCES:

Appendix B

Base Paper

Personality-Aware Product Recommendation System Based on User Interests Mining and Metapath Discovery

Sahraoui Dhelim, *Member, IEEE*, Huansheng Ning, *Senior Member, IEEE*, Nyothiri Aung, Runhe Huang, *Senior Member, IEEE*, and Jianhua Ma, *Member, IEEE*

***Abstract*—A recommendation system is an integral part of any modern online shopping or social network platform. The product recommendation system as a typical example of the legacy recommendation systems suffers from two major drawbacks: recommendation redundancy and unpredictability concerning new items (cold start). These limitations take place because the legacy recommendation systems rely only on the user's previous buying behavior to recommend new items. Incorporating the user's social features, such as personality traits and topical interest, might help alleviate the cold start and remove recommendation redundancy. Therefore, in this article, we propose Meta-Interest, a personality-aware product recommendation system based on user interest mining and metapath discovery. Meta-Interest predicts the user's interest and the items associated with these interests, even if the user's history does not contain these items or similar ones. This is done by analyzing the user's topical interests and, eventually, recommending the items associated with the user's interest. The proposed system is personality-aware from two aspects; it incorporates the user's personality traits to predict his/her topics of interest and to match the user's personality facets with the associated items. The proposed system was compared against recent recommendation methods, such as deep-learning-based recommendation system and session-based recommendation systems. Experimental results show that the proposed method can increase the precision and recall of the recommendation system, especially in cold-start settings.**

***Index Terms*—Big-five model, personality computing, product recommendation, recommendation system, social networks, social computing, user interest mining, user modeling.**

I. Introduction

With the widespread of personal mobile devices and the ubiquitous access to the internet, the global number of digital buyers is expected to reach 2.14 billion people within the next few years, which accounts for one-fourth of the world population. With such a huge number of buyers and the wide variety of available products, the efficiency of an online store is measured by their ability to match the right user with the right product; here comes the usefulness of product recommendation systems. Generally speaking, product recommendation systems are divided into two main classes.

1) *Collaborative Filtering (CF):* CF systems recommend new products to a given user based on his/her previous (rating/viewing/buying) history and his/her neighbors (similar users). For example, as shown in Fig. 1(a), most of the people previously bought a football jersey, and they have also bought a football; thus, the system predicates that the user might be interested in buying a football.
2) *Content Filtering or Content-Based Filtering (CBF):* CBF systems recommend new items by measuring their similarity with the previously (rated/viewed/bought) products. For example, as shown in Fig. 1(b), football is recommended because it is semantically similar to the football jersey.

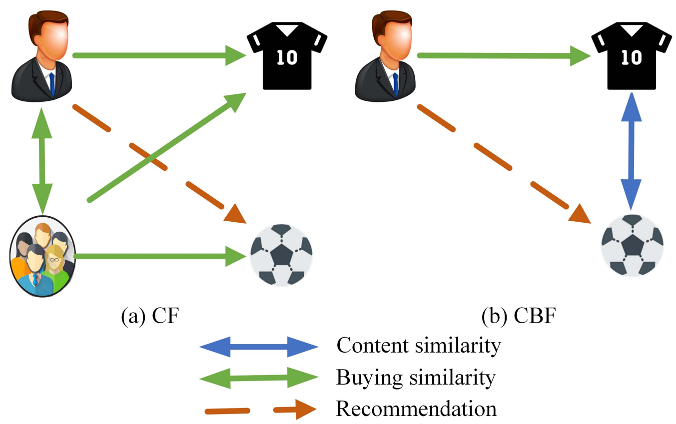


Fig. 1. Collabortive filtering and content filtering.

Far from that, with the popularity of online social networks, such as Facebook, Twitter, and Instagram, many users use social media to express their feeling or opinions about different topics or even explicitly expressing their desire to buy a specific product in some cases, which made social media content a rich resource to understand the users' needs and interests [1]. On the other hand, the emerging of personality computing [2] has offered new opportunities to improve the efficiency of user modeling in general and particularly recommendation systems by incorporating the user's personality traits in the recommendation process. In this work, we propose a product recommen-

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Sahraoui Dhelim, Huansheng Ning, and Nyothiri Aung are with the School of Computer and Communication Engineering, University of Science and Technology Beijing, Beijing 100083, China (e-mail: ninghuansheng@ustb.edu.cn).

Runhe Huang and Jianhua Ma are with the Faculty of Computer and Information Sciences, Hosei University, Tokyo 184-8584, Japan.

Digital Object Identifier 10.1109/TCSS.2020.3037040

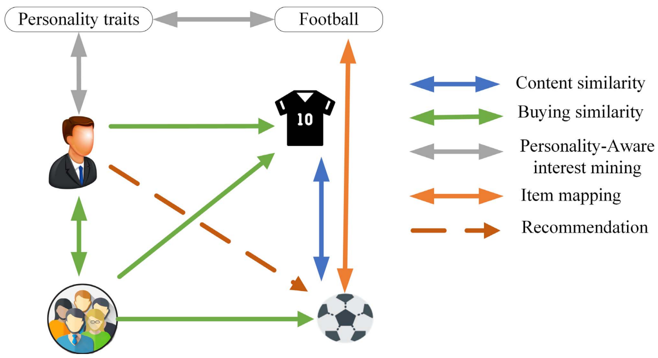


Fig. 2. Interest mining-based product recommendations.

dation system that predicts the user's needs and the associated items, even if his/her history does not contain these items or similar ones. This is done by analyzing the user's topical interest and, eventually, recommending the items associated with the theses interest. The proposed system is personality-aware from two aspects; it incorporates the user's personality traits to predict his/her topics of interest and to match the user's personality facets with the associated items. As shown in Fig. 2, the proposed system is based on a hybrid filtering approach (CF and CBF) and personality-aware interest mining.

Since we have multiple types of nodes (users, items, and topics), the system is modeled as a heterogeneous information network (HIN), which includes multiple types of nodes and links. In our case, product recommendation could be formulated as link prediction in HIN [3]. For example, in Fig. 2, given the user's previous rating and topical interest represented in an HIN, the problem is to predict whether or not a link exists between the user and the product (the ball). One of the main challenges of link prediction in HIN is how to maintain a reasonable balance between the size of information considered to make the prediction and the algorithm complexity of the techniques required to collect that information. Since, in practice, the networks are usually composed out of hundreds of thousands or even millions of nodes, the method used to perform link prediction in HIN must be highly efficient. However, computing only local information could lead to poor predictions, especially in very sparse networks. Therefore, in our approach, we make use of metapaths that start from user nodes and end up in the predicted node (product nodes in our case), and we try to fuse the information from these metapaths to make the prediction.

The contributions of this work are summarized as follows.

1) Propose a product recommendation system that infers the user's needs based on his/her topical interests.
2) The proposed system incorporates the user's big-five personality traits to enhance the interest mining process and perform personality-aware product filtering.
3) The relationship between the users and products is predicted using a graph-based metapath discovery; therefore, the system can predict implicit and explicit interests.

The remainder of this article is organized as follows. In Section II, we review the related works. In Section III, the system design of the proposed system is presented. In Section IV, we evaluate the proposed system. Finally, in Section V, we conclude the work and state some of the future directions.

II. RELATED WORKS

In this section, we review the recent advances of personality-aware recommendation system and interest mining schemes as well.

A. Personality and Recommendation Systems

Many works have discussed the importance of incorporating the user's personality traits in the recommendation systems. Yang *et al.* [4] proposed a recommendation system of computer games to players based on their personality traits. They have applied text mining techniques to measure the players' Big-five personality traits and classified a list of games according to their matching with each dominant trait. They have tested their proposed system on 2050 games and 63 players from the Steam gaming network. While Wu *et al.* [5] presented a personality-based greedy reranking algorithm that generates the recommended list, where the personality is used to estimate the users' diversity preferences, Ning *et al.* [6] proposed a friend recommendation system that incorporates the big-five personality traits model and hybrid filtering, where the friend recommended process is based on personality traits and the users' harmony rating. Ferwerda *et al.* [7] studied the relationship between the user's personality traits and music genre preferences; they have analyzed a data set that contains personality test scores and music listening histories of 1415 Last.fm users. Similarly, in [8], they conducted an online user survey where the participants were asked to interact with an application named Tune-A-Find and measured taxonomy choice (i.e., activity, mood, or genre), individual differences (e.g., music expertise factors and personality traits), and different user experience factors. Similarly, Hafshejani *et al.* [9] proposed a CF system that clusters the users based on their big-five personality traits using the K-means algorithm. Following that, the unknown ratings of the sparse user–item matrix are estimated based on the clustered users. Dhelim *et al.* [10] discussed the benefits of capturing the user's social feature, such as personality traits that are represented as cyberentities in cyberspace. Similarly, Khelloufi *et al.* [11] showed the advantages of leveraging the user's social features in the context of service recommendation in the Social Internet of Things (SIoT).

B. Interest Mining

Far from personality, many previous works have discussed user interest mining from social media content. Piao *et al.* [1] surveyed the literature of user interest mining from social networks, and the authors reviewed all the previous works by emphasizing the following on four aspects: 1) data collection; 2) representation of user interest profiles; 3) construction and refinement of user interest profiles; and 4) the evaluation measures of the constructed profiles. Zarrinkalam *et al.* [12] presented a graph-based link prediction scheme that operates over a representation model built from three categories of information: user explicit and implicit contributions to topics, relationships between users, and the similarity among topics.

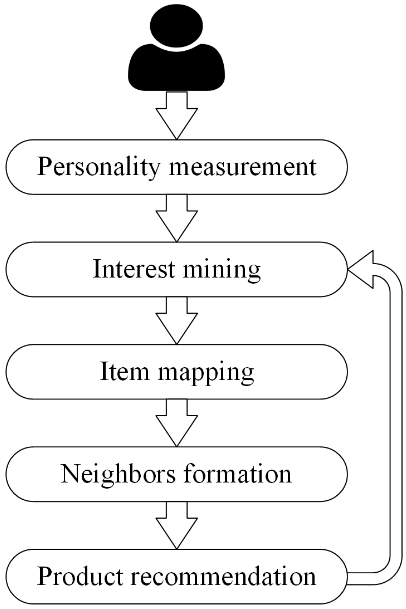


Fig. 3. Meta-Interest recommendations process.

keywords that reflect its topical interests. Implicit interest mining involves a more complex analysis of the social network structure and other latent factors that may influence the user's topical interests. In Step 3, Meta-Interest matches the items with the corresponding topics. The matching is in the form of a many-to-many relationship that is to say that a topic might be related to many items. Similarly, an item might be related to more than one topic. In Step 4, the set of most similar users (neighbors) to the subject user is determined. In this context, Meta-Interest uses three similarity measures, personality similarity, viewing/buying/rating similarity, and common interest similarity. Finally, Step 5 is the item recommendation phase, and the recommendation is refined by updating the neighbors' set and the user's topical interest profile and topics–items matching.

B. Notations

The notations and symbols used in the current work are explained in Table III.

C. Representational Model

Let $U = \{u_1, u_2, \ldots, u_n\}$ be the set of users, $T = \{t_1, t_2, \ldots, t_m\}$ the set of topics, and $P = \{p_1, p_2, \ldots, p_k\}$ the set of all items. The system is modeled as a heterogenous graph that consists of three subgraphs $G = (G_U, G_T, G_P)$, as shown in Fig. 4. $G_U = (V_u,\ E_u)$ is undirected graph where its node set V_u is the users set U, and the edges set E_u represents the similarity relationship between users. In addition to online behaviors similarity, such as posting and follower/followee similarities, the personality traits' similarity between users is also considered to compute the overall similarity between users. Similarly, the graphs $G_T = (V_t,\ E_t)$ and $G_P = (V_p,\ E_p)$ represent the nodes and relationship between topics and items, respectively.

TABLE III
NOTATIONS AND SYMBOLS

Symbol	Meaning
U	The set of all users
u_x	The user x
T	The set of all topics
t_y	The topic t
$\varphi(u_x,\ u_y)$	The similarity measure between users x and y
$\vartheta(P_x,\ P_y)$	The similarity measure between item P_x and item P_y
$\overrightarrow{P_x}$	User u_x's personality traits vector
α	User similarity weight parameter
β	Item relatedness weight parameter
Γv	Denotes the set of neighbors of node v
P_l	Meta-path length
w_p	The weight of meta-path P
l_{max}	The maximum length of a meta-path
$\delta^l_{i,j}$	The score between user u_i and item p_j with the meta-path maximum link constrain as $l_{max} = l$
ε	Link prediction score threshold

1) Users' Representation: As mention earlier, one of the most important aspects of the proposed system is that it incorporates the user's personality traits and their related facets to detect the user's interest and eventually in product recommendations. The users' graph $G_U = (V_u,\ E_u)$ is constructed by measuring the similarity between its vertices. In this regard, we consider three types of similarities: topic interest similarity, product interest similarity, and personality traits' similarity, which we denote as SimT, SimI, and SimP, respectively. Formally, let $U = \{u_1, u_2, \ldots, u_n\}$ be the set of all users and $P_i = \{P_O, P_C, P_E, P_A, P_N\}$ be the big-five personality trait vector of the user u_i; $T_i = \{t_1, t_2, \ldots, t_m\}$ is the set of topical interest of u_i, and $I_i = \{i_1, i_2, \ldots, i_k\}$ is the set of items that were previously viewed by u_i

$$\varphi(u_x,\ u_y) = \alpha \frac{\sum_i \left(p_x^i - \overline{p_x}\right)\left(p_y^i - \overline{p_y}\right)}{\sqrt{\sum_i \left(p_x^i - \overline{p_x}\right)^2 \sum_i \left(p_y^i - \overline{p_y}\right)^2}} + (1-\alpha)\left(\left\| \frac{2|T_x \bigcap T_y|}{|T_x| + |T_y|} \right\| \left\| \frac{2|I_x \bigcap I_y|}{|I_x| + |I_y|} \right\|\right) \quad (1)$$

where $\overline{p_x}$ and $\overline{p_y}$ is the average value of the personality traits vector for user u_x and u_y, respectively, and p_x^i and p_y^i are the ith trait in the personality traits vector of user u_x and u_y respectively. α is the user similarity weight parameter that tunes the contribution of item-topic similarity and personality similarity in the total similarity measure.

2) Topics Representation: The interests of a given user are represented in the form of a set of topics. The topic space is represented by the graph $G_T = (V_t,\ E_t)$, where the vertices represent the topics and the edges represent the semantic similarity relationship between these topics. To associate these topics with items graph nodes, each topic node is associated with a category of open directory project (ODP) [26] (see Fig. 5). ODP is a public open directory for web sites' classifications. Currently, it contains 3.8 million websites that have been categorized into 1 031 722 categories by 91 929 human editors. We have used the four-level subcategories to construct the topics graph; these categories are used to match the interest topics with the related items from the item graph.

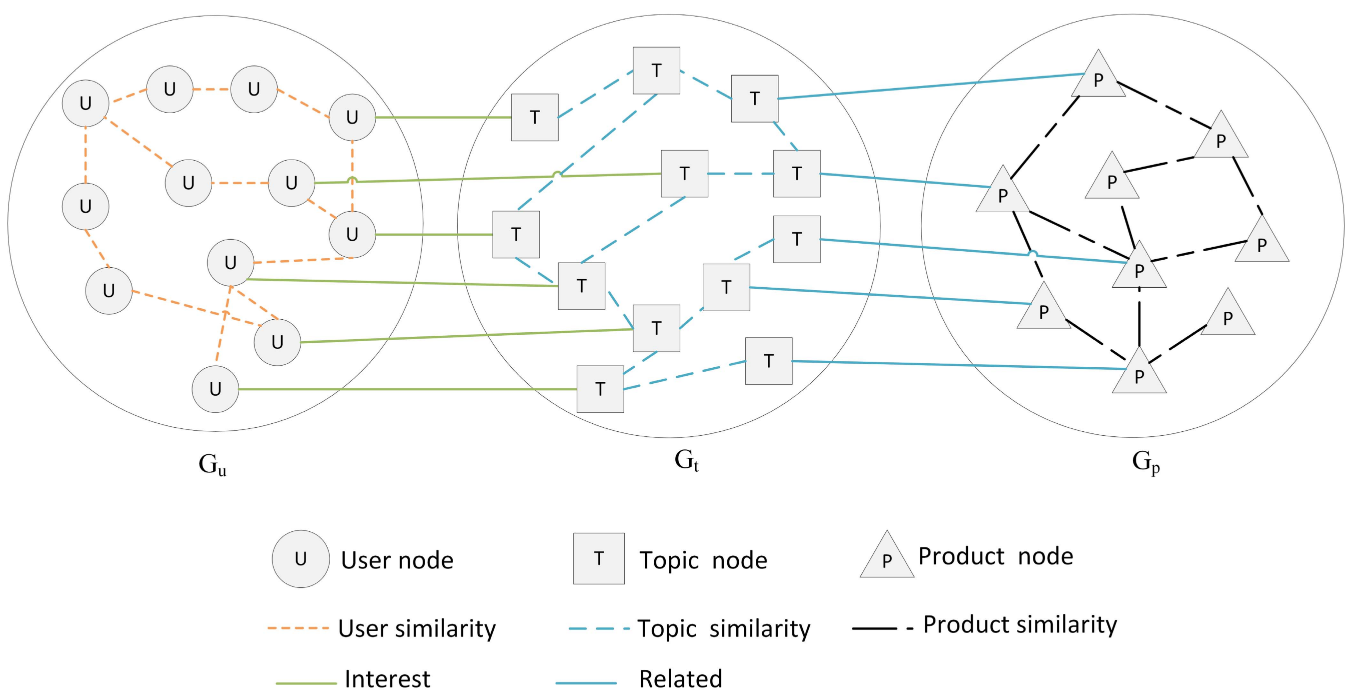


Fig. 4. User–topic–item heterogeneous information network.

Fig. 5. OPD root categories.

3) Item Representation: Similar to the users and interest topics, the items are represented as a graph data structure $G_P = (V_p,\ E_p)$, where the nodes represent the items and the edges represent the similarity between the items. The similarity between items is computed from two similarity measures, content similarity and collaborative similarity. The content similarity is measured by common item's metadata tags, while the collaborative similarity is calculated by measuring the ratio of common buyers/viewers between the two items to the total buyers/viewers of each item. Formally, let $C_x : \{c_0, c_1, \ldots, c_n\}$ and $C_y : \{c_0, c_1, \ldots, c_m\}$ denote the content tags of item P_x and P_y, respectively, and V_x and V_y represent the sets of their viewing/buying users. The similarly between P_x and P_y is computed using the function ϑ, as shown in (2), where β is the item similarity threshold, and it is used to tune the contribution of content similarity and collaborative similarity to the overall

Algorithm 1 Interest_mining

Input u_x, s_x, F_x **Output** I_x

```
if (s_x > CS) then
    Semantic_Annotation(s_x)
    Topics_Extraction(s_x)
else
    for f ∈ F_x do
        I_x ← I_x ∪ {Personality_facet_topics(f)}
    end for
end if
```

similarity measure, $\beta = 0$, when the item has no views and never been bought before (item cold start)

$$\vartheta(P_x,\ P_y) = \beta \left\| \frac{2|C_x \bigcap C_y|}{|C_x| + |C_y|} \right\| + (1-\beta)\left(\left\| \frac{2|V_x \bigcap V_y|}{|V_x| + |V_y|} \right\| \right). \quad (2)$$

D. Interest Mining

The main advantage of our approach is that the proposed system makes use of the user's interests along with the user's personality information to optimize the accuracy of system recommendations and alleviate the cold-start effects. By analyzing the user's social network posted data, we can infer his/her topical interests. The task can be achieved by applying automatic topic extraction techniques, such as latent Dirichlet allocation (LDA) [27] or frequency-inverse category frequency (TFICF) [28]. However, such techniques are supposed to be applied to long articles, and they do not yield good results if applied on the user's short sparse noisy posts, such as tweets [29]. Therefore, to overcome this problem, we have enriched each post from the user's data using semantic annotators, which could help to reduce the noise and alleviate

Algorithm 2 Item_mapping

Input p_z, U_{p_z}
Output I_{p_z}
if $(views(p_z) > CS)$ **then**
  $I_{p_z} \leftarrow OPD\_Topics(p_z)$
else
  for $f \in F_x$ and $u_x \in U_{p_z}$ **do**
    if $(|u_y, f \in F_y| > \frac{|U_{p_z}|}{2})$ **then**
      $I_{p_z} \leftarrow I_{p_z} \cup \{Personality\_facet\_topics(f)\}$
    end if
  end for
end if

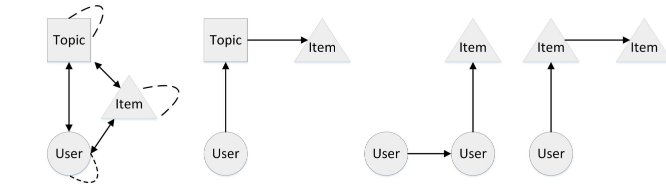
ambiguity of the post and increase the topic detection accuracy, as shown in the proposed framework in [18]. Algorithm 1 shows the pseudocode of interest mining steps. When the user is during the cold-start phase or completely did not view any articles (lines 1–4), Meta-Interest estimates the topical interest based on the interests of users with similar personality facets. Otherwise, it crawls the viewed news articles and extracts the labels of each news article to serve as the topical interest of the user, as we will see in the experimental section.

E. Item Mapping

After populating the topics public space using ODP ontology categories, the items are matched with these topics. Each item is associated with one or more topics and, subsequently, recommended for users that have these topics within their topical interests. Algorithm 2 shows the pseudocode of the item interest mapping process. With newly added items that have not been viewed by any user, the item is directly associated with the corresponding topic category in ODP ontology, whereas items that have passed the cold-start phase are associated with the interest of those that are related to the personality facets that are shared among the users who bought this item.

F. Metapath Discovery

After building the users–topics–items heterogeneous graph $G = (G_U, G_T, G_P)$ that incorporates the users, topics, and items subgraphs and their interrelationships. At this stage, the objective is to predict for a given user the N-most recommended items that match his/her topical interests and previous buying/viewing behaviors. Predicting the users' recommended items is formulated as a graph-based link prediction problem. Link prediction problem has been investigated in many works before, and many schemes have been proven to achieve high accuracy in their predictions, such as Adamic/Adar [30], Katz [31], and Jaccard [32]. However, these schemes are supposed to work on homogeneous graphs where all nodes represent the same type of entities and all the edges are connecting these entities, which is not the case with our heterogeneous graph. Since, in our representation model $G = (G_U, G_T, G_P)$, nodes can represent different entities (users, topics, and items) and the links can connect different nodes (user–user, user–topic, user–item, topic–item, item–item, and topic–topic). We use



(a) Network Scheme (b) Meta-Path U-T-P (c) Meta-Path U-U-P (d) Meta-Path U-P-P

Fig. 6. Network scheme and length 2 metapath samples.

metapaths [21] to predict the matching score between a given user node in G_U and an item node in G_P.

A metapath is a sequence of relations between nodes defined over a heterogeneous network, which can be used to define a topological structure with various semantics. In our case, we investigate the metapaths that start from a user node and end with an item node $P : \{u \rightarrow x \rightarrow \cdots \rightarrow x \rightarrow i\}$. Each metapath is characterized by the number of links between the source and destination nodes, and it is called the path length P_l. For example, the possible metapath with path length P_2 from a user node to an item node is presented in Fig. 6. For a given metapath $P : \{s \rightarrow x \rightarrow \cdots \rightarrow x \rightarrow d\}$, any path in the network that connects nodes s and d following the same intermediate node types as defined by P is called a path instance of P. For a given metapath P, the path count is the number of all path instances $P_c = |\{p : p \in P\}|$. In our case, we consider all metapaths that start with a user node and end with an item node with maximum metapath length to $l_{\max} = 2$. We have made the maximum length to 3 because short metapaths are semantically more important than long ones, and they are good enough for capturing the structure of the network. Besides that, it is computationally expensive to explore longer metapath because the path count increases exponentially with the increase in the path length P_l [33].

By exploring all metapaths with length constraint, we could holistically extract all relationships between nodes with different filtering combinations. We are interested in three types of metapaths: first, the interest metapaths (IP) of the format ⟨U-T-P⟩ [see Fig. 6(b)] that represents metapaths that are based on interest mining and item matching; second, the friendship metapaths (FP) of the format ⟨U-U-P⟩ [see Fig. 6(c)] that represents metapaths that are based on CF (users' similarity); and finally, content metapaths (CP) of the format ⟨U-P-P⟩ [see Fig. 6(d)] that represents metapaths that are based on the content filtering (items similarity). Similarly, by exploring longer metapath, we get more hybrid filtering paths (based on both CF and CBF, in addition to interest mining and item mapping); for example, metapaths of length $P_l = 3$ could be based on CBF (i.e., ⟨U-P-P-P⟩), CF (i.e., ⟨U-U-U-P⟩), hybrid filtering (i.e., ⟨U-U-P-P⟩), or a combination of filtering and interest mining (i.e., ⟨U-T-T-P⟩, ⟨U-T-P-P⟩, and ⟨U-U-T-P⟩).

The importance of each metapath is characterized by its weight w_p. The path weight is computed by the sum of its edges' weight over its length P_l. Formally, let $P^n : \{v_1, v_1, \ldots, v_n\}$ be a metapath with a length of $P_l = n$, and the path weight of P is denoted as w_p, which is the sum of all the links' weights within P, as shown in (3), where $w_{v_i, v_{i+1}}$ represents the weight of link that connects the nodes

Algorithm 3 DiscoverMetaPaths

Input $u_s, l_{max}, \varepsilon$
Output FNL
1: $VIST \leftarrow \emptyset$
2: $P \leftarrow \emptyset$
3: $FNL \leftarrow \emptyset$
4: **for** $i = 1$ to l_{max} **do**
5: **if** $(i = 1)$ **then**
6: $VIST \leftarrow VIST \cup \{u_s\}$
7: **for** $NGB \in \Gamma u_s$ **do**
8: $P \leftarrow P \cup \{u_s \rightarrow NGB\}$
9: $VIST \leftarrow VIST \cup \{NGB\}$
10: **end for**
11: **else**
12: $TEMP \leftarrow \emptyset$
13: **for** $CURN \in P$ **do**
14: $NODE \leftarrow p_c[i]$
15: **if** $(NODE = item)$ **and** $(w_{p_c} > \varepsilon)$ **then**
16: $FNL \leftarrow FNL \cup \{p_c\}$
17: **end if**
18: **if** $(\Gamma NODE - VIST \neq \emptyset)$ **then**
19: **for** $NGB \in \Gamma NODE - VIST$ **do**
20: $TEMP \leftarrow TEMP \cup \{CURN \rightarrow NGB\}$
21: $VIST \leftarrow VIST \cup \{NGB\}$
22: **end for**
23: **end if**
24: $P \leftarrow P - CURN$
25: **end for**
26: $P \leftarrow TEMP$
27: **end if**
28: **end for**

v_i and v_{i+1}

$$w_p = \frac{\sum_{i=1}^{n} w_{v_i, v_{i+1}}}{P_l}. \quad (3)$$

In order to predict a possible recommendation for a given user node, we explore all the instances of metapath with a maximum path length $l_{\max} = 3$. Because short metapaths are more semantically significant compared with longer metapaths. Therefore, we prioritize shorter metapath by considering that the contribution of a path weight to the overall link prediction score is inversely proportional to the metapath length P_l. The link prediction score between user u_i and item p_j with the metapath maximum link constrain as $l_{\max} = l$ is computed using (4). To predict the N-most recommended items for a given user, we extract all metapaths by exploring the interest graph with a fixed length and link prediction score constraints

$$\delta_{i,j}^{l} = \sum_{k=2}^{l} \frac{\sum_{r \in P_{i,j}(k)} w_r}{k-1}. \quad (4)$$

To compute the recommended items for a given user, we extract all metapaths instances between the user and potential recommended items by exploring the user–interest–item graph with a fixed length and link prediction score constraints. The pseudocode shown in Algorithm 3 presents the steps of metapath discovery. The algorithm takes as input the user source node u_s, the maximum metapath length to explore $l_{\max}$, and the link prediction score threshold ε. We denote P as the set of the temporarily explored metapaths, P is updated by adding new explored paths or removing dead paths (paths that have no neighbors or paths that do not end with an item node), and FNL is the set of the final metapaths. The set of visited nodes is denoted as VIST, and Γv denotes the set of neighbors of node v. NODE and CURN are temporary variables used to denote the current node and current path respectively in each iteration. In Lines 5–11, a path from the source node u_s to every neighbor node is created and inserted into the set of metapaths P, and node u_s and its neighbors are marked as visited nodes VIST. In lines 13—25, for each path CURN from P, the last node of these paths is visited and added to the final metapaths if it is an item node, and recursively, all the nodes that have not been visited before are added as a potential metapaths. Algorithm 4 shows the pseudocode of recommendation process. Initially, if the user is still in the cold-start phase (lines 2–7), the recommended items are to be filtered based on the topical interests that were extracted from the user's social media data and by associating these topics with the related items according to their OPD categories. Otherwise, the metapaths starting from the source user u_s are discovered and grouped according to the metapath types (interest metapath, friendship metapath, and content metapath), and the items that are in the intersection of these metapaths sets are given propriety in the recommended items' set.

Lines 7–10 enumerate all the neighbors of the source node and lines 13–25 (and eventually lines 19–22) are the primary computational blocks in Algorithm 3. If we study the worst case graph structure, which is a complete graph (fully connected graph), where every user is similar to all other users and interested in all topics and also connected to all the available products (even though, in this case, we do not have to run Algorithm 3, there is no unknown link that we need to predict). Algorithm 3 still runs in linear time complexity. Let G be a complete graph (fully connected) with n nodes and $n = x + y + z$ (x: user nodes; y: topic nodes; and z: product node). The run time of the block (lines 7–10) is $O(x+y+z-1)$ to add all the graph nodes to the visited nodes group VIST and their generated paths to P. The block (12–25) also runs in linear time of $O(x + y + z - 1)$ as well; Even, it includes a nested loop (lines 19–22) that could result a quadratic time, lines 19–22 will never be reached due to the if-condition block in lines 18–23 (as the studied graph is a complete graph, and VIST will contain all the graph nodes [added in block (7–10)]; therefore, $\Gamma\text{NODE} - \text{VIST} = \emptyset$). Hence, the overall time complexity of Algorithm 3 is $O(n)$.

IV. System Evaluation

In this section, we present the details of the collected data set, evaluation metrics and baselines, and the analysis of the obtained results.

A. Baselines

To evaluate the performance of the proposed product recommendation system, we have compared it with different

Algorithm 4 RecommendProducts

Input u_s, l_s
Output R
$R \leftarrow \emptyset$
if $(CS(u_s))$ **then**
  for $t \in I_s$ **do**
    $PR \leftarrow Product\_interest(t)$
    $R \leftarrow R \cup PR$
  end for
else
  $P = DiscoverMetaPath(u_s)$
  $IP = InterestPaths(P)$
  $FP = FriendPaths(P)$
  $CP = ContentPaths(P)$
  $RecPaths = TopNPaths(IP \cap FP \cap CP, FP \cap CP, CP \cap IP)$
  for $Path \in RecPaths$ **do**
    $PR \leftarrow Path[last_node]$
    $R \leftarrow R \cup PR$
  end for
end if

baselines that use various recommendation techniques, such as deep learning, metapath analysis, network embedding, and session-based. The proposed system is compared with the following baselines:

1) GNN-SEAL (Graph Neural Networks) [22]: GNN-SEAL is a link prediction framework that formulates link prediction problem as a subgraph classification problem. For every predicted link (user–item link in our case), GNN-SEAL determines its h-hop enclosing subgraph A and computes its node information matrix X (which contains structural labels, latent embeddings, and the explicit attributes of nodes). After that, the framework feeds (A, X) into a graph neural network (GNN) to classify the link existence so that it can learn from both graph structure features (from A) and latent/explicit features (from X) simultaneously for link prediction. The framework is open source, and the code is available on GitHub.[1]

2) metapath2vec (Metapath and Network Embedding) [20]: metapath2vec formalizes metapath-based random walks to build the heterogeneous neighborhood of a node and then uses the heterogeneous skip-gram model to perform node embeddings and, subsequently, user–item link prediction. metapath2vec is open source, and its implementation code is available on Github.[2]

3) DGRec (Session-Based) [23]: DGRec is a session-based recommendations' framework that employs dynamic-graph-attention neural network to model the context-dependent social influence and recurrent neural network to model dynamic user interest. Finally, DGRec gives the recommendation by merging the user's interests and preferences and his/her social influence. DGRec is open source, and its implementation code is available on Github.[3]

4) LightFM (Cold Start) [34]: LightFM is a cold-start alleviation framework that uses a hybrid matrix factorization model to represent items (products in our case) and users as linear combinations of their content features' latent factors. LightFM is parameterized in terms of d-dimensional user and item feature embeddings e U f and e I f for each feature f. Every feature is also modeled by a scalar bias term (b U f for user and b I f for item features). The model's prediction for user u and item i is then given by the dot product of user and item representations, adjusted by the user and item feature biases. LightFM is open source, and the implementation code is available on GitHub.[4]

5) CF-CBF: This is the hybrid filtering system that combines the users' viewing similarity and product similarity to determine the neighborhood set and recommends new items.

B. Evaluation Metrics

Any product recommendation system is evaluated by measuring the accuracy and coverage of its recommended items. To test the efficiency of Meta-Interest and compare it to the afore-mentioned baselines, we determine the recommended items by each baseline, display it in the user's feed along with other irrelevant items, and measure the accuracy rate of the relevant items. Formally, let $F = R \cup I$ be the set that represents all items in user u's feeds, where $R = \{p_1, p_2, \ldots, p_r\}$ is the set relevant items, and $I = \{p_1, p_2, \ldots, p_i\}$ is the set of irrelevant items. After showing F in user u's feeds, we denote $V = \{p_1, p_2, \ldots, p_v\}$ as the set of viewed items. In this context, we are interested in the following values: 1) true positives: the group of relevant items that have been viewed by the user $\mathrm{TP} = \{x \,/\, x \in R \bigcap V\}$; 2) false positives: the group of irrelevant items that have been viewed by the user $\mathrm{FP} = \{x \,/\, x \in I \bigcap V\}$; and 3) false negatives: the group of relevant items that have not been viewed by the user $\mathrm{FN} = \{x \,/\, x \in R,\ x \notin V\}$. We have used the following metrics.

Precision: The portion of relevant viewed items in the total viewed items, and it is computed as follows:

$$\text{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}. \quad (5)$$

Recall: The portion of relevant viewed items in the total relevant items, and it is computed as follows:

$$\text{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}. \quad (6)$$

F-Measure: It is also called the balanced F-Score; it is the harmonic average of the precision and recall; and it is computed as follows:

$$F = \frac{2\ P\ R}{P + R}. \quad (7)$$

[1]github.com/muhanzhang/SEAL
[2]ericdongyx.github.io/metapath2vec/m2v.html
[3]github.com/DeepGraphLearning/RecommenderSystems/tree/master/socialRec
[4]github.com/lyst/lightfm

TABLE IV
DATA SET STATISTICS

Parameter	Value
Number of users	2228
Number of articles	25873
Number of items	6230
Cold start users	575
Cold start items	1520

C. Data Set Description

We have integrated the Meta-Interest product recommendation system with a social network platform called Newsfulness[5] that we have implemented earlier for automatic personality recognition projects. Newsfulness enables the user to view and shares news articles from various news publishers. During registration, the users go through the TIPI Big-Five personality questionnaire [35] to capture their personality traits. Newsfullness collects published articles from different English-speaking news websites, and the collected articles are from the following outlets (BBC, CNN, Aljazeera, France24, Russia-Today, Reuters, The Guardian, and The New York Times). The gathered articles are from all the news classes (politics, business, sports, health, travel, education, entertainment, art, science, and technology) from different geographic regions categories. The products' recommendation system was implemented by fetching products from different online stores (mainly JD, Banggood, and Amazon). The statistical details of the used data set are presented in Table IV.

D. Result Discussion

To tune the optimal value of the users' similarity parameter α and products' similarity parameter β, we observe the optimal value of α and β that maximize the F-Measure of the proposed system. Figs. 7 and 8 show the optimal value of α and β in different topics of interest count and viewed items count, respectively. As we can observe from Fig. 7, during the cold-start phase with no topic of interest at all, $\alpha = 1$, and at this point, the users' similarity is based only on personality similarity measurement. With the increase in previously detected topics of interest, the value of α gradually decreases and finally stabilizes with $\alpha = 0.2$ when the user passes the cold-start phase and had enough topical interest and previously viewed items. Similarly, the optimal value of β during the cold-start phase for the new item with no views is $\beta = 1$, and with the increase in the number of views, the value of β decreases to finally stabilize with $\beta = 0.5$, as shown in Fig. 8. For the size of Top-n recommended products, in our experiment, we set $N = 20$, as choosing a larger value will lead to uncertainty of whether the users did not view the products' feed because they are not interested in them, or they did not view them because there are too many items in the products' feed. If we ignore this uncertainty and just consider that the user did not view the product out of his disinterest, this will lead to an increase in false positives and false negatives as well, hence the decrease in the overall system performance. As we can observe from Fig. 9, the

[5]www.newsfullness.live/data set

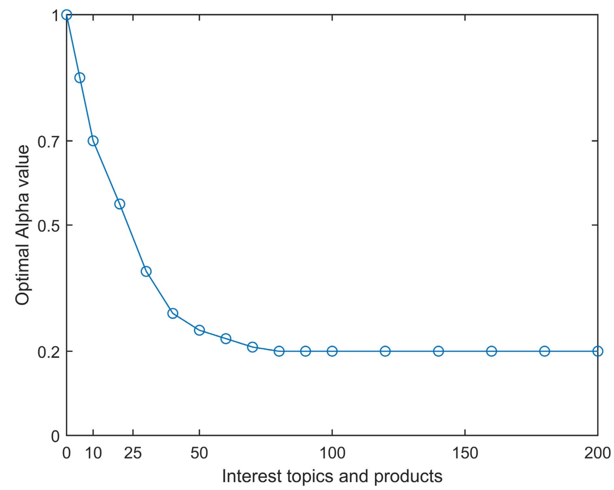


Fig. 7. Users' similarity parameter tuning.

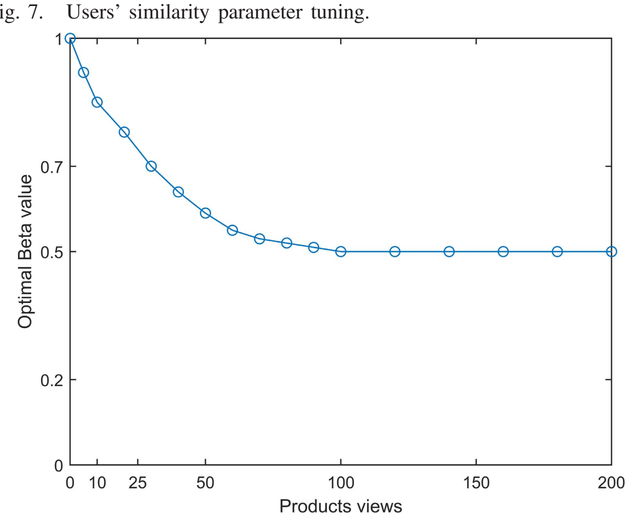


Fig. 8. Products' similarity parameter tuning.

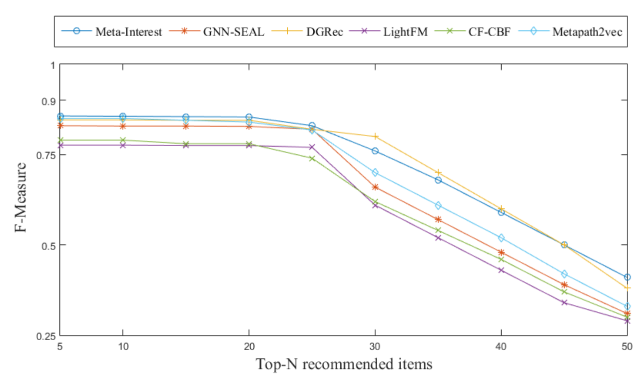


Fig. 9. Top-n recommendation parameter tuning.

F-Measure of the proposed system and all the studied baselines have decreased dramatically when the value of N is over 22.

The precision, recall, and F-measure of Meta-Interest compared with the baseline schemes are shown in Fig. 10. As we can observe, the proposed system, Meta-Interest, and the session-based system, DGRec, clearly have the highest precision (0.854 and 0.845) and recall (0.868 and 0.855), respectively. The superiority of the proposed system is because of the personality biased approach that filters the relevant

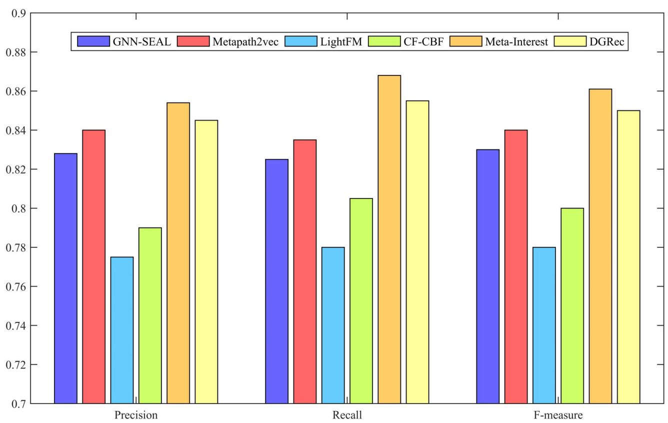


Fig. 10. Overall system evaluation.

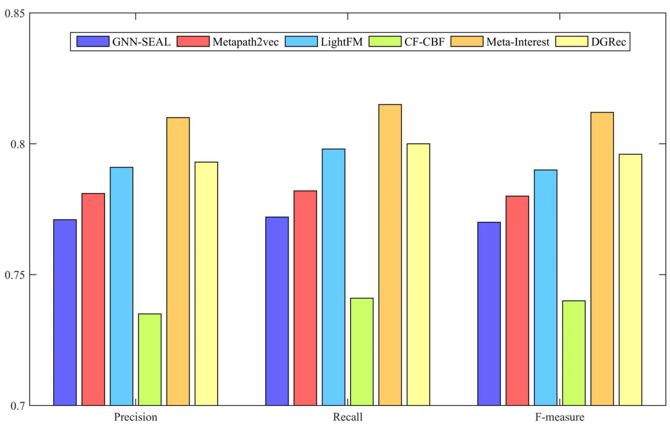


Fig. 11. System evaluation under cold start (new users).

items that are related to the personality facets of the user, while other approaches view the user's personality traits just as additional information that helps find the similarity and construct the network embeddings or features. The second reason for the superiority of Meta-Interest (and also DGRec compared with other baselines) is the ability of Meta-Interest and DGRec to alleviate the cold-start effects, and hence maintain stable precision, and recall values all over the phases. Unlike the network representation method, metapath2vec, and the deep-learning method, GNN-SEAL, that come third and fourth with 0.84 and 0.828 of precision value and 0.835 and 0.825 of recall value, respectively, LightFM performs quite well in the cold-start phase (as we will see later in other figures); however, it fails to cope with a large amount of diverse data in later stages, which leads to a drop in its precision and recall values.

One of the main reasons for incorporating the user's personality in the product recommendation systems and interest mining schemes is to alleviate the effects of the cold-start problem [6]. In this regard, we have tested the performance of Meta-Interest and the studied baselines under the cold-start settings. The cold-start settings include two tests.

1) Cold-start users' test, in which only the new users are considered in the precision and recall measurements. In our experiment, a user is considered in the cold-start phase if the number of viewed articles and items is less than 20.

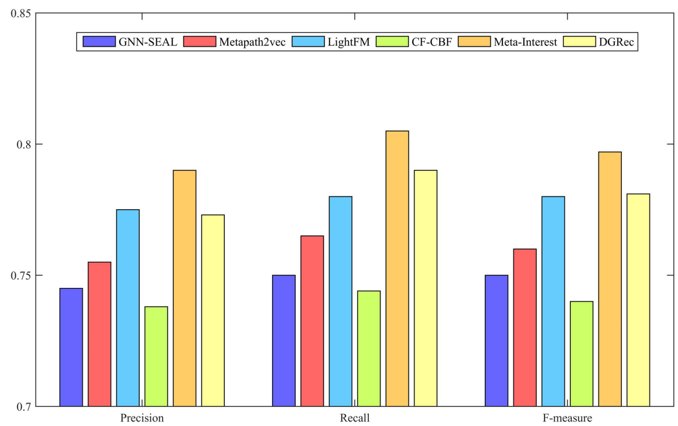


Fig. 12. System evaluation under cold start (new items).

2) Cold-start items' test, in which we consider only the new items that have not been viewed or rated by any user. Figs. 11 and 12 show the results of the cold-start users' test and cold-start items' test, respectively.

As we can observe, the proposed system and the session-based system, DGRec, still have the upper hand even in the cold-start phase as both systems are robust in cold-start settings, as explained early. However, we can notice that the LightFM is ranked third and obviously outperforms metapath2vec and GNN-SEAL because LightFM was originally designed to mitigate the cold-start effects, and as mentioned early, LightFM has a poor performance when the amount of the data increases. To further study the relationship between the amount of available data and the performance of the proposed system compared with the baselines, we measure the performance of Meta-Interest and the other baseline systems while changing the percentage of training set size from 10% to 100%. Fig. 13 shows the precision, recall, and F-measure values of the studied systems with different training set sizes. We can clearly observe that Meta-Interest outperforms the other baselines with only a small training set size, with only 10% of the training set and Meta-Interest scores 0.768 and 0.765 in precision and recall, respectively. With the increase in training set size, Meta-Interest steadily improves to reach 0.854 and 0.868 in precision and recall using 100% of the training set (around 10.07% improvement compared with 10% training). LightFM ranks second in terms of precision and recall with 10% of the training set; however, it ends in the fifth place (better only than the conventional CF-CBF) with full training set 100%, whereas deep-learning-based schemes (GNN-SEAL) and network embeddings approach (metapath2vec) have a low performance with small training data. When trained with 10% of the data set, GNN-SEAL scores 0.63 and 0.64 in precision and recall, respectively. However, GNN-SEAL and metapath2vec performance increase dramatically with the increase in the training data size. For instance, when trained with the full training data, metapath2vec scores 0.84 and 0.835 (around 23% improvement compared with 10% training). That is because metapath2vec uses network embedding, which requires the presence of dense node links to capture the network structure.

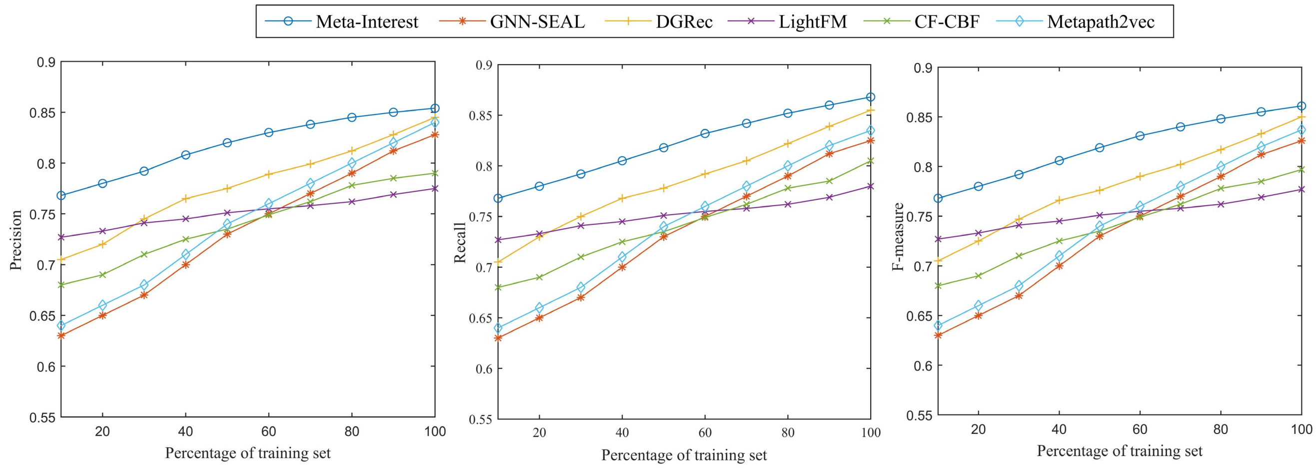


Fig. 13. System evaluation with different sizes of the training set.

TABLE V
SPEED COMPARISON (s)

System	Total computational time	Update computational time
Meta-Interest	16.05	3.56
metapath2vec	14.6	14.6
GNN-SEAL	15.5	15.5
DGRec	16.2	4.66
LightFM	19.04	5.92
CF-CBF	16.15	5.41

In a practical situation with a large graph of millions of nodes and links that require intensive computational power, the speed of the recommendation system is crucial to keep a reasonable response time. Therefore, it is important to analyze the speed and time complexity of the proposed system compared with the compared baselines. Table V shows the time complexity of the proposed system compared with the studied baselines. The shown values in Table V are the average of 100 times testing. The time complexity of Meta-Interest and all the baselines were tested on Dell Inspiron 173000 Laptop, with tenth-generation Intel Core i7-1065G7 Processor (8-MB Cache, up to 3.9 GHz) and 16-GB RAM (2×8 GB, DDR4, 2666 MHz), running Ubuntu 19.04 operating system. As we can observe from Table V, when it comes to the total computational time required for the system to compute the recommendation for all users, Meta-Interest is not the fastest system, metapath2vec has the lowest computational time of 14.6 s, and GNN-SEAL ranks second with 15.5. However, for the update operation where we add a new block of users and items and compute the time required for the system to compute the recommendation of these new users, metapath2vec needs to recalculate the network embeddings in lower dimensional space all over again, which costs as high as the initial time required to compute all the recommendations, which is not the case with Meta-Interest, as we just need to recalculate the weights of the newly added metapaths.

V. CONCLUSION

In this article, we have proposed a personality-aware product recommendation system based on interest mining and metapath discovery, and the system predicts the user's needs and the associated items. Products' recommendation is computed by analyzing the user's topical interest and, eventually, recommending the items associated with those interests. The proposed system is personality-aware from two aspects: first, because it incorporates the user's personality traits to predict his topics of interest; second, it matches the user's personality facets with the associated items. Experimental results show that the proposed system outperforms the state-of-art schemes in terms of precision and recall especially in the cold-start phase for new items and users.

However, Meta-Interest could be improved in different aspects.

1) In this work, the users' personality traits' measurement was conducted through questionnaires. Integrating an automatic personality recognition system, which can detect the users' personality traits based on their shared data, into Meta-Interest is one of our future directions.
2) The proposed system uses big-five to model the user's personality. Extending Meta-Interest to include other personality traits models, such as the Myers–Briggs type indicator, is a future direction.
3) The proposed system could be further improved by integrating a knowledge graph and infer topic–item association using semantic reasoning.

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The authors would like to thank all the active users of Newsfullness that agreed to be a part of the Meta-Interest experiment.

REFERENCES

[1] G. Piao and J. G. Breslin, "Inferring user interests in microblogging social networks: A survey," *User Model. User-Adapted Interact.*, vol. 28, no. 3, pp. 277–329, Aug. 2018. [Online]. Available: http://link.springer.com/10.1007/s11257-018-9207-8
[2] A. Vinciarelli and G. Mohammadi, "A survey of personality computing," *IEEE Trans. Affect. Comput.*, vol. 5, no. 3, pp. 273–291, Jul. 2014. [Online]. Available: http://ieeexplore.ieee.org/document/6834774/

Appendix C

Papers Published and Certificates

Sr. No.	Title of Paper	Authors	Name of Conference/ Journal	Date	Vol. Issue	ISSN
1	Personality-aware Product Recommendation System	Ganesh Bobade, Umesh Patil, Raviraj Mane, Rohit Khomane	International Journal of Novel Research and Development	Dec 2022	Volume: 07 Issue: 12	2456-4184
2	[Reccokart]-Product Recommendation System	Ganesh Bobade, Umesh Patil, Raviraj Mane, Rohit Khomane	International Journal of Scientific Research and Engineering Development	May 2023	Volume: 06 Issue: 03	2581-7175

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Personality Aware Product Recommendation System (RECCOKART)

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Abstract:

Any modern social networking or online retail platform must have a recommendation system. A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase. It may not be entirely accurate, but if it shows you what you like then it is doing its job right. As a typical illustration of a legacy recommendation system, the product recommendation system has two significant drawbacks: recommendation repetition and unpredictability about new items (cold start). Because the older recommendation algorithms only use the user's previous purchasing history when making recommendations, these limitations exist. The cold start and recommendation redundancy may be lessened by incorporating the user's social attributes, such as personality traits and areas of interest. In light of this, we present Meta-Interest, a personality- aware product recommendation system built on user interest mining and metapath discovery. The suggested method incorporates the user's personality qualities to forecast his or her themes of interest and to link the user's personality facets with the relevant things, making it personality-aware from two perspectives. The suggested system was evaluated against current recommendation techniques, including session- based and deep-learning-based systems. According to experimental findings, the suggested strategy can improve the recommendation system's memory and precision, particularly in cold-start conditions.

Keywords:; social networks; social computing; user interest mining; user modeling personality computing; product recommendation; recommendation system.

1.INTRODUCTION

A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase.The product recommendation system as a typical example of the legacy recommendation systems suffers from two major drawbacks:recommendation redundancy and unpredictability concerning new items (coldstart). These limitations take place because the legacy recommendation systems rely only on the users previous buying behaviour to recommend new items. In personality- aware recommendation system, the similarity between the users is computing based on their personality trait similarity or using a hybrid personality-rating similarity measurement, and the resulting set of neighbors are similar in terms of personality traits to the studied user.

AimofProject

The aim of a recommender system is to estimate the utility of a set of objects belonging to a given domain,starting from the information available about users and objects.

1.1 Motivation

To Motivate the users Product recommendation engines analyze data about shoppers to learn exactly what types of products and offerings interest them. Based on search behavior and product preferences, they serve up contextually relevant offers and product options that appeal to individual shoppers — and help drive sales.

1.3 ProjectObjectives

The objective of Personality aware product recommendation system is to provide recommendation based on recorded information on the users buying similarity. Increase performance while working with huge data. Provide 24x7 access system.

1.4Application

A product recommendation is basically a filtering system that seeks to predict and show the items that a user would like to purchase. It may not be entirely accurate, but if it shows you what you like then it is doing its job right.

2.LITERATURESURVEY

Reference No: 1.

Title: Study of E-commerce recommender system based on Big data Publication: Oxbridge college, kunning university Author: Xuesong Zhao Summary: In this paper they In this era of web, they have a huge amount of information overloaded over Internet. It becomes a big task for the user to get the relevant 1 information. To some extent, the problem is being solved by the search engines, but they do not provide the personalization of data.Recommender system algorithms are widely used in e-commerce to provide personalized and more accurate recommendations to online users and enhance the sales and user stickiness of e-commerce. This study aims to build a product recommendation system on ecommerce platform according to user needs.

Reference No: 2

Title: Collaborative Filtering for Recommender Systems Publication: 2014 Second International Conference on Advanced Cloud and Big Data Author: Michael D. Ekstrand, John T. Riedl and Joseph A. Konstan Summary: The report also highlights the discussion of the types of the recommender systems as general and types of CF such as; memory based, model based and hybrid model. In addition, this report discusses how to choose an appropriate type of CF. The evaluation methods of the CF systems are also provided throughout the paper However, there are several limitations for the memory-based CF techniques, such as the fact that the similarity values are based on common items and therefore are unreliable when data are sparse and the common items are therefore few. To achieve better prediction performance and overcome shortcomings of memory-based CF algorithms, model-based CF approaches have been investigated.

Reference No: 3

Title:Content-Based Filtering: Techniques and Applications Publication: 2017 International Conference on Communication, Control, Computing and Electronics Engineering (ICCCCEE) Author: Khartoum, Sudan Summary: Besides collaborative filtering, content-based filtering is another important class of recommender systems. Content-based recommender systems make recommendations by analysing the content of textual information and finding regularities in the content. The major difference between CF and content-based recommender systems is that CF only uses the user-item ratings data to make predictions and recommendations, while content-based recommender systems rely on the features of users and items for predictions. Both content-based recommender systems and CF systems have limitations. While CF systems do not explicitly incorporate feature information, content-based systems do not necessarily incorporate the information in preference similarity across individuals. collaborative filtering models which are based on assumption that people like things similar to other things they like, and things that are liked by other people with similar taste.

Reference No: 4

Title: Automatiic Personality Recognition of Authors using Big Five Factor model Publication: Jacques Author: k. Pramodh, Y. Vijayalata Summary: The paper focuses on an approach developed to recognize the personality of the author by evaluating their writings. The score for each of the Big-Five personality traits is computed programmatically.

3.SYSTEMARCHITECTURE:

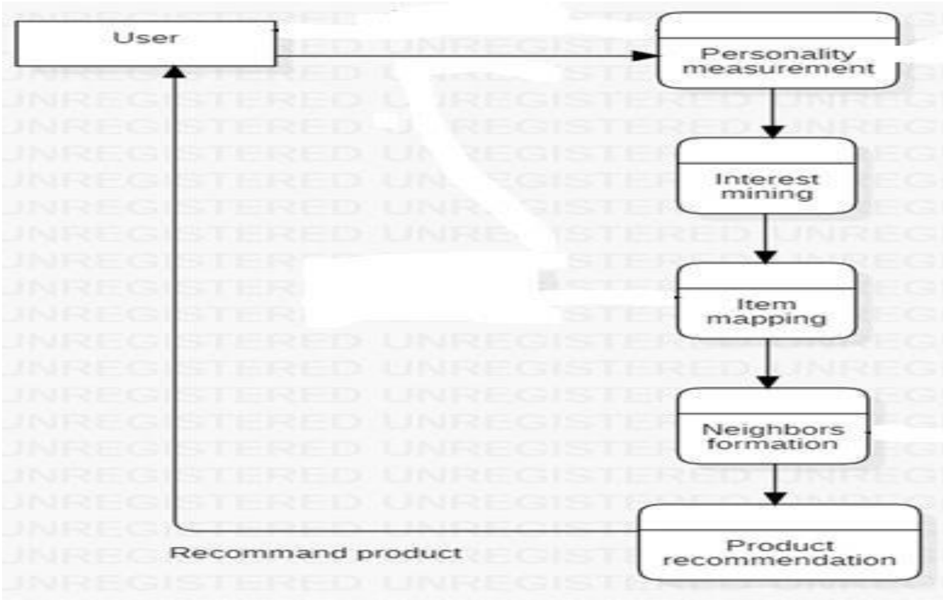
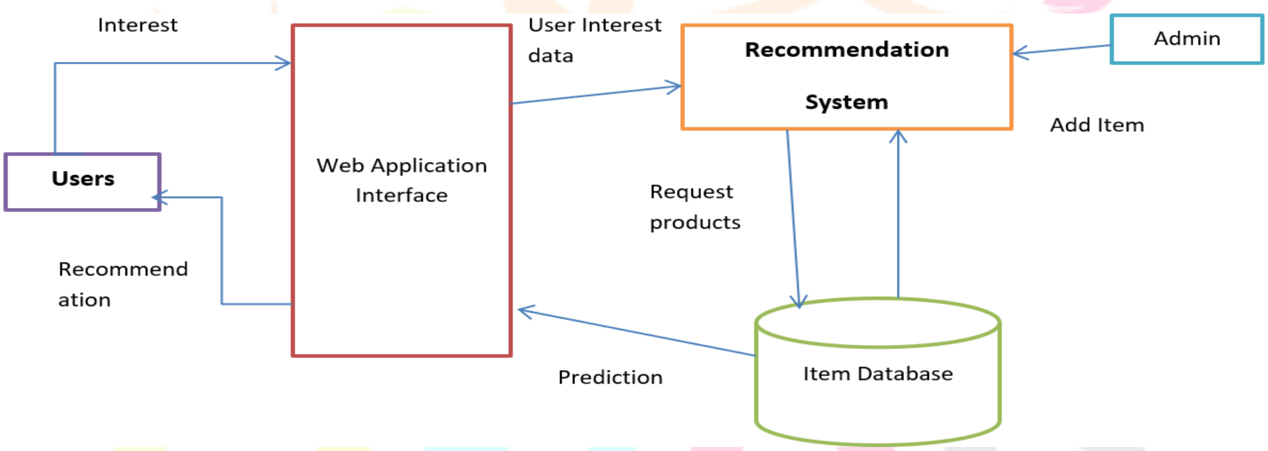


Fig. Meta-interest recommendations process.



In this section, we will present the theoretical framework of the proposed system. The purpose of Meta- Interest is to recommend the most relevant items by detecting the user's topical interests from its social networking data. Fig. 1 shows the general system framework of Meta-Interest. The recommendation process includes five steps. Step 1 is the personality traits' measurement, which can be obtained by asking the user to take a personality measurement questionnaire or using automatic personality recognition by analyzing the subject's social network data. The personality measurement phase is the only static part of the system, which isbecause personality traits have been proven to be relatively stable over time. Step 2 is mining the user's topicalinterests, including explicit and implicit interest mining. Explicit interest mining is performed by analyzing the text shared by the user in social networks in order to detect keywords that reflect its topical interests. Implicit interest mining involves a more complex analysis of the social network structure and other latent factors that may influence the user's topical interests. In Step 3, Meta-Interest matches the items with the corresponding topics. The matching is in the form of a many-to-many relationship that is to say that a topic might be related to many items. Similarly, an item might be related to more than one topic. In Step 4, the set of most similar users (neighbors) to the subject user is determined. In this context, Meta-Interest uses three similarity measures, personality similarity, viewing/buying/rating similarity, and common interest similarity. Finally, Step 5 is the item recommendation phase, and the recommendation is refined by updating theneighbors' set and the user's topical interest profile and topics–items matching.

Big-Five Personality Traits

The big five personality traits constitute a unique combination of an individual's behaviour, preferences and mannerisms. It can influence their friendships, relationships, hobbies and careers. Psychologists use objective tests and projective measures to break down an individual's personality into different components. Objective measures use self-reporting tests and tools, where an individual responds to a series of queries in a questionnaire. Projective measures use psychoanalytic theories that reveal inner aspects of an individual's personality. The big five tests or the five-factor model uses questionnaires and tests to rank the following five traits that can affect an individual's behavior and attributes:

Openness: If you score highly on openness, you are likely to prefer new, exciting situations. You value knowledge, and friends and family are likely to describe you as curious and intellectual.

Conscientiousness: If you're a conscientious person, you have a lot of self-discipline and exceed others' expectations. You have a strong focus and prefer order and planned activities over spontaneity.

Extroversion: Extroverts thrive in social situations. If you have a high score in extroversion, you are action- oriented and appreciate the opportunity to work with others.

Agreeableness: A high score in agreeableness shows that you're considerate, kind and sympathetic to others. As an agreeable person, friends and colleagues likely seek you out to participate in group activities since you're adept at compromise and helping others.

Neuroticism: Although this measure typically indicates anxiety and pessimism, some tests focus on low scores, which researchers call emotional stability. This measure can mean you have a more hopeful view of your circumstances.

Representation Model:

Let U = {u1, u2,..., un} be the set of users, T = {t1,t2,...,tm} the set of topics, and P = {p1, p2,..., pk} the set of all items. The system is modeled as a heterogenous graph that consists of three subgraphs G = (GU , GT , GP), GU =(Vu, Eu) is undirected graph where its node set Vu is the users set U, and the edges set Eu represents the similarity relationship between users. In addition to online behaviors similarity, such as posting and follower/followed similarities, the personality traits' similarity between users is also considered to compute the overall similarity between users. Similarly, the graphs GT = (Vt, Et) and GP = (Vp, Ep) represent the nodes and relationship between topics and items, respectively. The users' graph GU = (Vu, Eu) is constructed by measuring the similarity between its vertices. In this regard, we consider three types of similarities: topic interest similarity, product interest similarity, and personality traits' similarity, which we denote as SimT, SimI, and SimP, respectively.

3.1 ALGORITHM

Interest Mining:

The main advantage of our approach is that the proposed system makes use of the user's interests along with the user's personality information to optimize the accuracy of system recommendations and alleviate the cold-start effects. By analyzing the user's social network posted data, we can infer his/her topical interests. The task can be achieved by applying automatic topic extraction techniques.

Algorithm 1 Interest_mining
Input ux,sx, Fx Output Ix 1: if (sx > CS) then
2: Semantic_Annotation(sx)
3: Topics_Extraction(sx)
4: else
5: for f ∈ Fx do
6: Ix ← Ix ∪{Personality_facet_topics(f)} 7: end for
8: end if

The pseudocode shown in Algorithm 1 presents the steps of Interest Mining.

Item Mapping:

After populating the topics public space using ODP ontology categories, the items are matched with these topics. Each item is associated with one or more topics and, subsequently, recommended for users that have these topics within their topical interests. With newly added items that have not been viewed by any user, the item is directly associated with the corresponding topic category in ODP ontology, whereas items that have passed the cold-start phase are associated with the interest of those that are related to the personality facets that are shared among the users who bought this item.

Algorithm 2 Item_mapping
Input pz,Upz Output Ipz 1: if (views(pz)>CS) then 2: Ipz ← OPD_Topics(pz) 3: else
4: for f ∈ Fx and ux ∈Upz do
5: if (|uy, f ∈ Fy|> |Upz| 2) then
6: Ipz ← Ipz ∪{Personality_facet_topics(f)} 7: end if
8: end for
9: end if

The pseudocode shown in Algorithm 2 presents the steps of Item Mapping.

Meta Path Discovery:

After building the users–topics–items heterogeneous graph G = (GU , GT , GP) that incorporates the users, topics, and items subgraphs and their interrelationships. At this stage, the objective is to predict for a given user the N-most recommended items that match his/her topical interests and previous buying/viewing behaviors. Predicting the users' recommended items is formulated as a graph-based link prediction problem.

Algorithm 3 DiscoverMetaPaths
Input us,lmax,ε Output FNL 1: VIST←Ø
2: P ←Ø
3: FNL←Ø
4: for i =1 tolmax do
5: if (i =1) then
6: VIST← VIST∪{us}
7: for NGB∈ us do
8: P ← P ∪{us → NGB}
9: VIST← VIST∪{NGB}
10: end for
11: else
12: TEMP←Ø
13: for CURN ∈ P do 14: NODE← pc[i]
15: if (NODE=item) and (wpc >ε) then 16: FNL← FNL∪{pc}
17: end if
18: if (NODE−VIST =Ø) then

Figure : User Side.

RESULTS

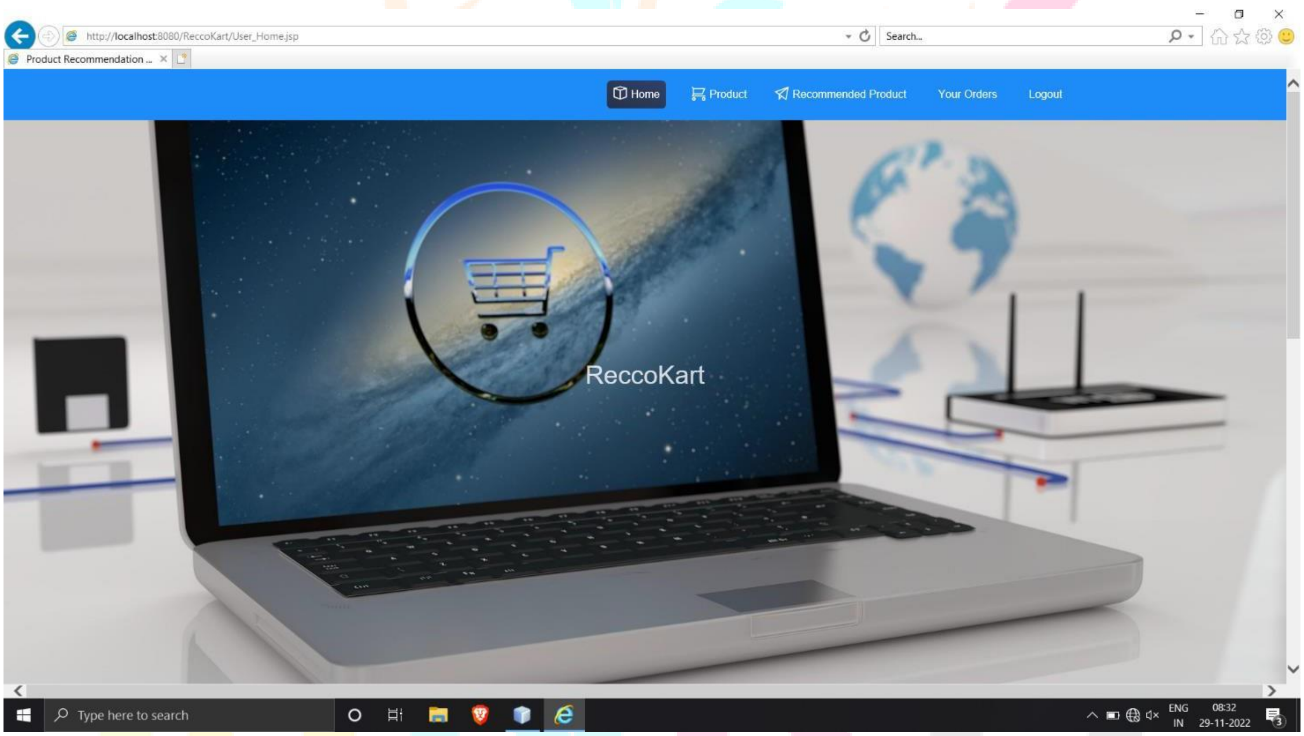
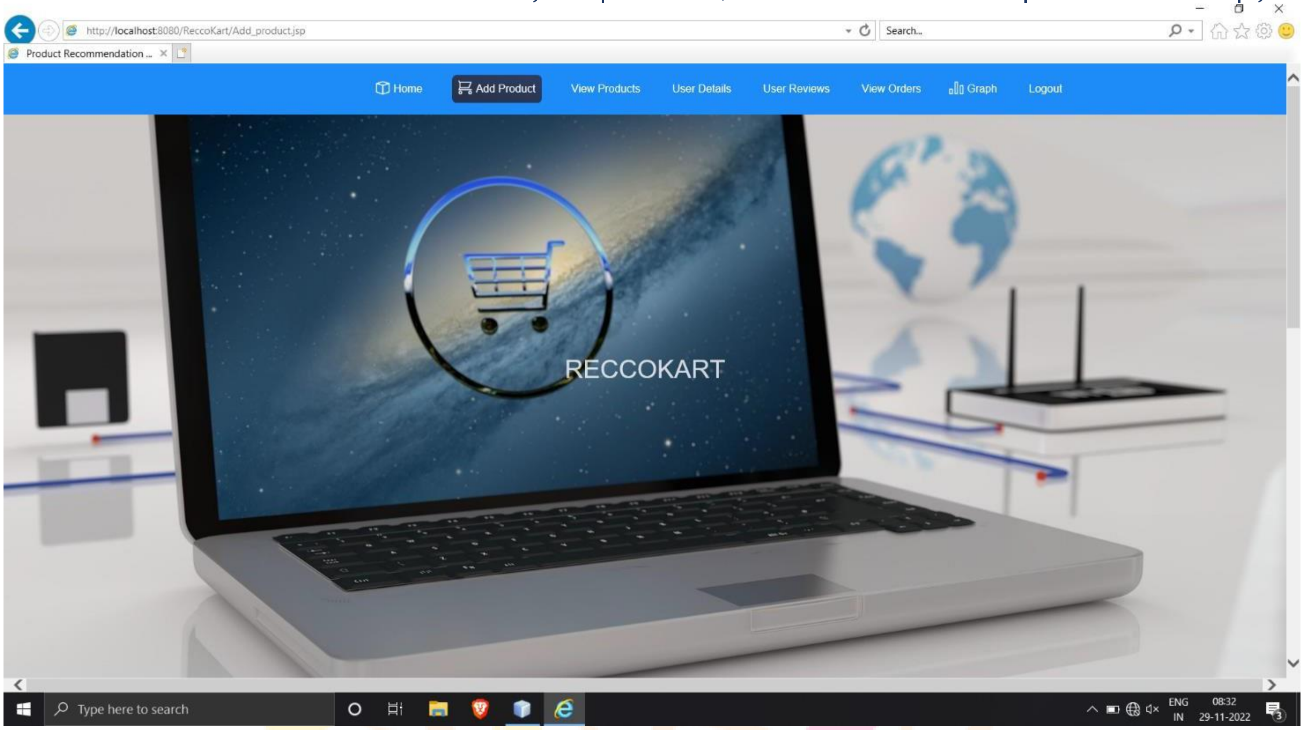


Fig 1 : User Home Page

Description: In the figure 1 Homepage , there are 2 modules ,one is user and other is admin. Admin Loginwith the authorized



user id and password.

Fig.2 Admin Page

Description: In the figure 2, After successful login the admin can add Domain, add Products, Viewall Recommended posts, View all user reviews, View Post's rank results view user's search history and view all recommended Posts.

4.CONCLUSION

In this paper, we propose a personality-aware product recommendation system based on interest mining and meta route discovery, which predicts the user's wants and the related objects. The suggestion of products is calculated by examining the user's subject interests and then recommending the goods related to those interests. The proposed system is personality-aware in two ways: first, it uses the user's personality features to forecast his interests in topics; and second, it links the user's personality facets with the things that are connected with those facets. The suggested approach outperforms state-of-the-art systems in terms of precision and recall, particularly during the cold-start phase for new items and users, as per experimental results. However, Meta-Interest could be improved in different aspects.

5.REFERENCES

[1] http://link. springer.com/10.1007/s11257-018-9207-8

[2] G. Piao and J. G. Breslin, "Inferring user interests in microblogging social networks: A survey," User Model. User-Adapted Interact., vol. 28, no. 3, pp. 277–329, Aug. 2018. [Online]. Available: http://link. springer.com/10.1007/s11257-018-9207-8

[3] A. Vinciarelli and G. Mohammadi, "A survey of personality computing," IEEE Trans. Affect. Comput., vol. 5, no. 3, pp. 273–291, Jul. 2014. [Online]. Available: http://ieeexplore.ieee.org/ document/6834774/

[4] V. Martínez, F. Berzal, and J.-C. Cubero, "A survey of link prediction in complex networks," ACM Comput. Surv., vol. 49, no. 4, pp. 1–33, Feb. 2017.

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Personality Aware Product Recommendation System [Reccokart]

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CONFERENCE ARTICLE OPEN ACCESS

(RECCOKART) Product Recommendation System

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Abstract:

Any cutting-edge social networking or on line retail platform need to have a advice device. A product advice is basically a filtering system that seeks to predict and show the gadgets that a consumer would really like to purchase. it may now not be completely accurate, but if it indicates you what you like then it's miles doing its process proper. As an average instance of a legacy recommendation device, the product advice machine has two good sized drawbacks: advice repetition and unpredictability about new objects (cold begin). because the older recommendation algorithms best use the consumer's preceding shopping history when making tips, these boundaries exist. The cold start and recommendation redundancy may be lessened by way of incorporating the consumer's social attributes, which include character traits and regions of hobby. In mild of this, we gift MetaInterest, a personality- aware product advice device constructed on consumer hobby mining and metapath discovery. The counseled technique includes the person's personality characteristics to forecast his or her issues of hobby and to link the consumer's personality facets with the applicable things, making it character-aware from views. The recommended gadget was evaluated towards cutting-edge recommendation strategies, which include session- based and deep-getting to know-based totally systems. according to experimental findings, the counseled strategy can improve the advice gadget's reminiscence and precision, especially in bloodless-begin situations.

Keywords: social networks; social computing; user interest mining; user modeling personality computing; product recommendation; recommendation system.

I. INTRODUCTION

A product advice is essentially a filtering system that seeks to are expecting and show the objects that a user would like to purchase.The product advice gadget as a typical instance of the legacy advice systems suffers from Fore most drawbacks:recommendation redundancy and unpredictability regarding new system (coldstart). thoseobstacles take place because the legacy recommendation structures rely handiest on the users preceding shopping for behaviour to suggest new objects. In personality- conscious recommendation system, the similarity among the users is computing based on their character trait similarity or the use of a hybrid persona-rating similarity dimension, and the ensuing set of pals are similar in phrases of personality developments to the studied person.

Aim of Project:-

The goal of a recommender system is to estimate the utility of a set of system belonging to a given area,beginning from the facts to be had about users and items.

Motivation :-

To motivate the customers Product advice engines examine data approximately buyers to analyze exactly what kinds of merchandise and offerings hobby them. based totally on seek conduct and product preferences, they serve up contextually relevant gives and product options that attraction to individual consumers — and help power income.

Algorithms

Interest Mining:

The primary gain of our method is that the proposed device uses the user's pastimes along side the consumer's personality facts to optimize the accuracy of machine suggestions and alleviate the bloodless-begin outcomes. by using studying the consumer's social network posted information, we are able to infer his/her topical interests. The project can be done via

Algorithm 1 Interest_mining Input ux,sx, Fx Output Ix 1: if (sx> CS) then 2: Semantic_Annotation(sx) 3: Topics_Extraction(sx) 4: else 5: for f ∈Fx do 6: Ix ← Ix ∪{Personality_facet_topics(f)} 7: end for 8: end if

Item Mapping:

After populating the subjects public space the usage of ODP ontology classes, the gadgets are matched with these subjects. each object is related to one or extra topics and, subsequently, advocated for users which have those topics within their topical

interests. With newly introduced gadgets which have no longer been regarded with the aid of any consumer, the object is without delay related to the corresponding subject matter class in ODP ontology, while gadgets which have exceeded the cold-begin section are associated with the hobby of these which are associated with the character facets which are shared the various customers who offered this item.

Algorithm 2 Item_mapping Input pz,Upz Output Ipz 1: if (views(pz)>CS) then 2: Ipz ← OPD_Topics(pz) 3: else 4: for f ∈Fx and ux∈Upz do 5: if (|uy, f ∈Fy|> |Upz| 2) then 6: Ipz ← Ipz∪{Personality_facet_topics(f)} 7: end if 8: end for 9: end if

Meta path Discovery:

After building the customers–subjects–objects heterogeneous graph G = (GU , GT , GP) that incorporates the customers, topics, and gadgets subgraphs and their interrelationships. At this level, the objective is to are expecting for a given person the N-maximum recommended items that in shape his/her topical interests and former buying/viewing behaviors. Predicting the customers' recommended gadgets is formulated as a graph-based hyperlink prediction trouble.

Algorithm 3 DiscoverMetaPaths Input us,lmax,ε Output FNL 1: VIST←Ø 2: P ←Ø 3: FNL←Ø 4: for i =1 tolmax do 5: if (i =1) then 6: VIST← VIST∪{us} 7: for NGB∈ us do 8: P ← P ∪{us → NGB} 9: VIST← VIST∪{NGB} 10: end for 11: else 12: TEMP←Ø 13: for CURN ∈ P do 14: NODE← pc[i] 15: if (NODE=item) and (wpc>ε) then 16: FNL← FNL∪{pc} 17: end if 18: if (NODE−VIST =Ø) then19: for NGB∈ NODE−VIST do 20: TEMP← TEMP∪{CURN → NGB} 21: VIST← VIST∪{NGB} 22: end for 23: end if 24: P ← P −CURN 25: end for 26: P ← TEMP 27: end if 28: end for

Recommend Products:

Algorithm 4 Recommend Products Input us,ls Output R 1: R ←Ø 2: if (CS(us)) then 3: for t∈ Is do 4: PR← Product_interest(t) 5: R ← R∪ PR 6: end for 7: else 8: P = DiscoverMetaPath(us) 9: IP= InterestPaths(P) 10: FP= FriendPaths(P) 11: CP=ContentPaths(P) 12: RecPaths = TopNPaths(IP∩ FP ∩ CP, FP ∩ CP,CP ∩ IP) 13: for Path∈RecPaths do 14: PR← Path[lastnode] 15: R ← R∪ PR 16: end for 17: end if The pseudocode shown in Algorithm 4 presents the steps of Product Recommendation.

II. LITERATURE SURVEY

Reference No: 1.

Title: look at of E-commerce recommender device based on big information e-book: Oxbridge university, kunning university

writer: Xuesong Zhao summary: in this paper they In this period of net, they have got a huge amount of facts overloaded over internet. It will become a huge task for the user to get the applicable 1 information. to some extent, the problem is being solved through the search engines like google, however they do not provide the personalization of records.Recommender gadget algorithms are extensively used in e-commerce to provide personalized and greater accurate hints to online users and enhance the sales and consumer stickiness of e-trade. This have a look at targets to build a product advice machine on ecommerce platform in line with user wishes.

Reference No: 2

Title: Collaborative Filtering for Recommender structures book: 2014 second worldwide convention on superior

Cloud and huge facts author: Michael D. Ekstrand, John T. Riedl and Joseph A. Konstan summary: The record additionally highlights the dialogue of the types of the recommender systems as fashionable and forms of CF consisting of; memory primarily based, version primarily based and hybrid version. similarly, this record discusses the way to pick the best form of CF. The assessment techniques of the CF systems are also provided throughout the paper however, there are numerous boundaries for the memory-based CF strategies, inclusive of the reality that the similarity values are primarily based on common objects and therefore are unreliable while statistics are sparse and the commonplace items are therefore few. To attain higher prediction overall performance and overcome shortcomings of memory based CF algorithms, version-based totally CF approaches had been investigated.

Reference No: 3

Title:content material-based totally Filtering: strategies and programs book: 2017 worldwide conference on conversation,

control, Computing and Electronics Engineering (ICCCCEE) creator: Khartoum, Sudan precis: besides collaborative filtering, content-based filtering is another vital magnificence of recommender structures. content material-primarily based recommender systems make suggestions by analysing the content of textual statistics and locating regularities within the content. The essential distinction between CF and content-based totally recommender structures is that CF most effective makes use of the person-object rankings information to make predictions and suggestions, while content material-based recommender systems rely upon the capabilities of users and items for predictions. both content-primarily based recommender systems and CF systems have obstacles. even as CF systems do now not explicitly include function records, content material-based structures do no longer always incorporate the information in preference similarity across individuals. collaborative filtering models which can be based totally on assumption that human beings like things just like other matters they prefer, and things which can be appreciated through other people with similar taste.

Reference No: 4

Title: Automatiic personality reputation of Authors the use of big five issue model booklet: Jacques writer: k. Pramodh, Y. Vijayalataprecis: The paper makes a speciality of an technique developed to understand the character of the writer with the aid of comparing their writings. The rating for each of the big-five persona traits is computed programmatically.

III. OBJECTIVE

Product recommendation systems aim to improve the user experience by suggesting products that are likely to be of interest to a particular user. The objectives of a product recommendation system are as follows:

1)Increase sales: The primary objective of a product recommendation system is to increase sales. By suggesting products that a user is likely to buy, the system can increase the likelihood that the user will make a purchase.

2)Improve user experience: A product recommendation system can improve the user experience by suggesting products that are relevant to the user's interests. This can save users time and effort when searching for products, and can help them discover new products they may not have found otherwise.

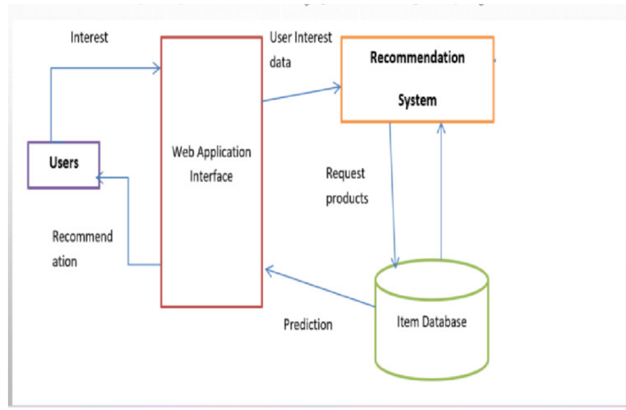
3)Increase customer loyalty: By providing personalized recommendations, a product recommendation system can improve customer satisfaction and increase customer loyalty. This can lead to repeat business and positive word-of-mouth recommendations.

4)Optimize inventory: A product recommendation system can help optimize inventory by suggesting products that are popular and likely to sell. This can help reduce the amount of unsold inventory and improve profitability.

5)Reduce returns: By suggesting products that are relevant to the user's interests, a product recommendation system can reduce the likelihood of returns. When users receive personalized recommendations, they are more likely to be satisfied with their purchases and less likely to return items.

Overall, the main objective of a product recommendation system is to provide a better shopping experience for users and to increase sales for the business.

IV. ARCHITECTURE



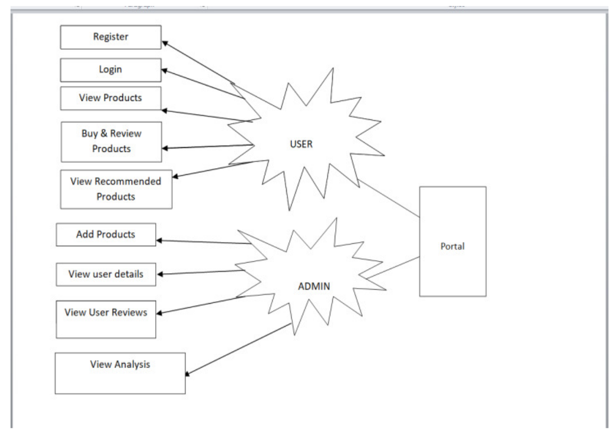


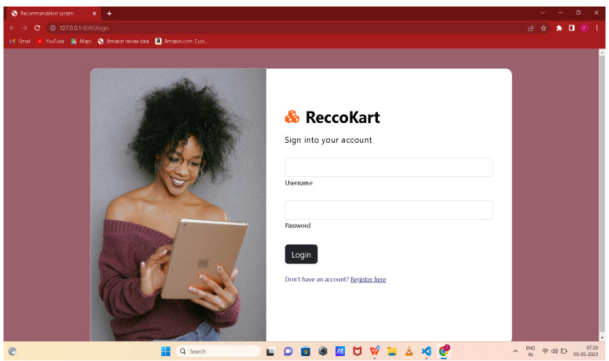
Fig1: System Architecture

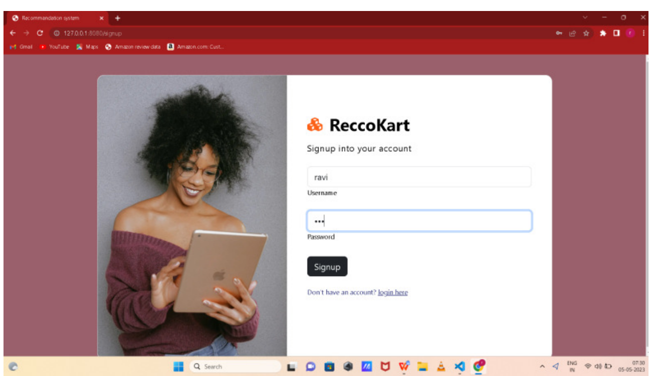
on this segment, we can present the theoretical framework of the proposed device. The motive of Meta-interest is to

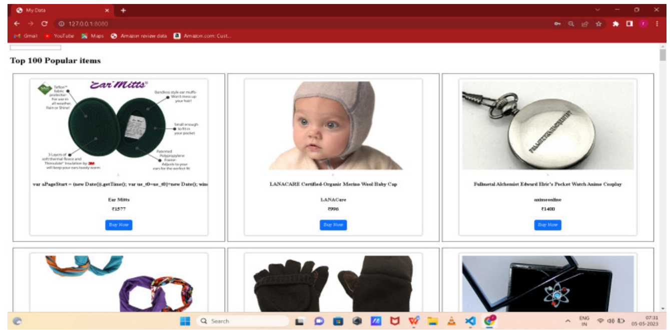
propose the maximum applicable items by means of detecting the consumer’s topical pastimes from its social networking facts. Fig. 1 shows the general device framework of Meta-interest. the advice technique includes five steps. Step 1 is the personality tendencies’ dimension, which can be received by way of asking the consumer to take a persona dimension questionnaire or the usage of automated character reputation by analyzing the subject’s social network information. The character measurement segment is the best static a part of the device, which isbecause persona developments were confirmed to be fairly strong over time. Step 2 is mining the user’s topicalinterests, such as express and implicit interest mining. explicit interest mining is achieved by way of reading the textual content shared by way of the person in social networks so that it will come across keywords that replicate its topical hobbies.Implicit hobby mining includes a more complex analysis of the social community shape and other latent factors thatcan also have an effect on the user's topical hobbies. In Step three, Meta-hobby fits the items with the corresponding topics. Thematching is inside the form of a many-to-many dating this is to mention that a topic might be related to many items. further, an object might be associated with multiple topic. In Step 4, the set of maximum comparable customers (pals) to the concern person isdecided. in this context, Meta-interest makes use of 3 similarity measures, character similarity, viewing/buying/score

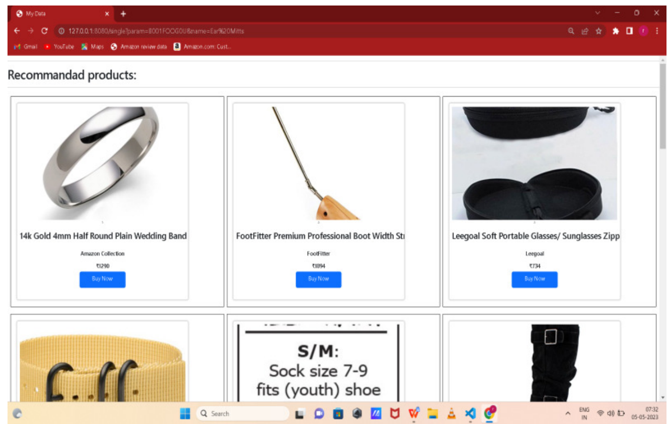
similarity, and commonplace interest similarity. eventually, Step five is the item recommendation section, and the recommendation isrefined by way of updating theneighbors' set and the person's topical hobby profile and topics–items matching.

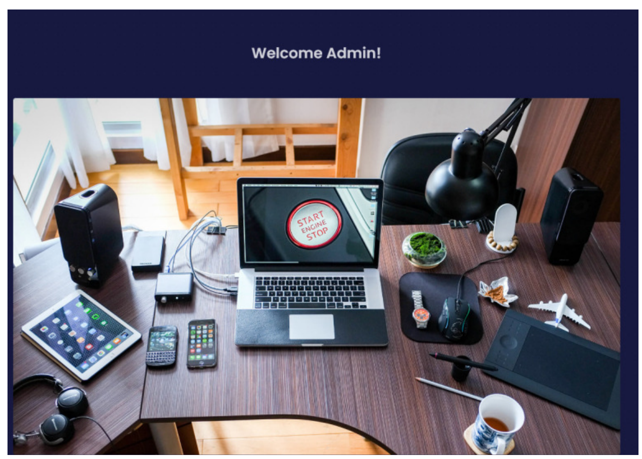
V. RESULT











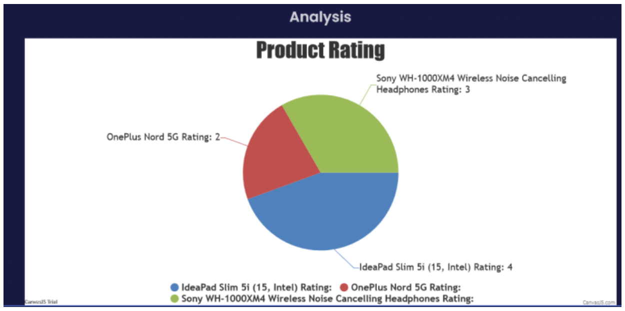


Fig 3: Result

VI. CONCLUSION

In this paper, we recommend a personality-conscious product advice machine based on hobby mining and meta direction discovery, which predicts the consumer's wants and the related gadgets. The proposal today's merchandise is calculated with the aid of examining the consumer's concern pastimes and then recommending the goods related to those hobbies. The proposed system is persona-aware in ways: first, it uses the user's persona capabilities to forecast his interests in topics; and second, it links the user's character facets with the things which are connected with those sides. The recommended approach outperforms systems in terms today's precision and recollect, specially in the course of the bloodless-start section for brand spanking new items and customers, as in line with experimental consequences. however, Meta-interest might be advanced in specific elements.

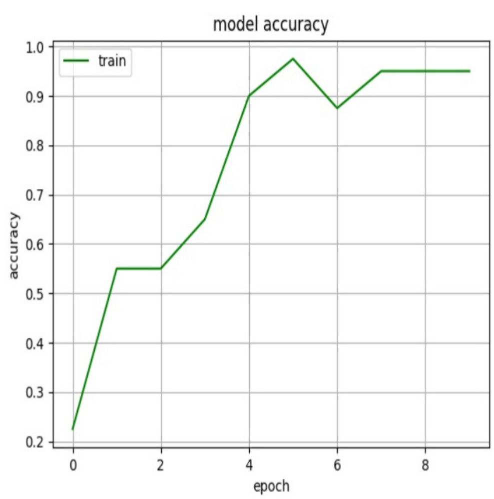


Fig 4: Model Accuracy

VII. ACKNOWLEDGMENT

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VIII. REFERENCES

[1] Islam, S., Ahmed Foysal, M. F., &Jahan, N. (2020). A Computer Vision Approach to Classify Local Flower using Convolutional Neural Network. 2020 4th International Conference on Intelligent Computing and Control Systems (ICICCS). doi:10.1109/iciccs48265.2020.9121143 Sarma, P., &Talukdar, J. K. (2020). Digital Image Processing based proposed approach to Identify Different Bamboo Species. 2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA). doi:10.1109/icirca48905.2020.9182932

[2] R. Shaparia, N. Patel and Z. Shah," Flower classification using texture and color features", vol. 2, pp. 113-118, 2017.M. Wegmuller, J. P. von der Weid, P. Oberson, and N. Gisin, "High resolution fiber distributed measurements with coherent OFDR," in Proc. ECOC'00, 2000, paper 11.3.4, p. 109.

[3] Hu, F., Yao, F., &Pu, C. (2020). Learning Salient Features for Flower Classification Using Convolutional Neural Network. 2020 IEEE International Conference on Artificial Intelligence and Information Systems (ICAIIS). doi:10.1109/icaiis49377.2020.9194931

[4] Shah, S. S., & Sheppard, J. W. (2020). Evaluating Explanations of Convolutional Neural Network Image Classifications. 2020 International Joint Conference on Neural Networks (IJCNN). doi:10.1109/ijcnn48605.2020.9207129

[5] Giraddi, S., Seeri, S., Hiremath, P. S., & G.N, J. (2020). Flower Classification using Deep Learning models. 2020 International Conference on Smart Technologies in Computing, Electrical and Electronics (ICSTCEE). doi:10.1109/icstcee49637.2020.9277041

[6] Das, M., Manmatha, R., Riseman, E.: 'Indexing flower patent images using domain knowledge', IEEE Intell. Syst. Appl., 1999, 14, , pp. 24–33

[7] Larson, R. (Ed.): 'Introduction to floriculture(Academic Press, San Diego,CA, USA, 1992, 2nd edn.)

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Appendix D

Project Competition and Certificates

Sr. No.	Title of Project	Name of Participants	Name of Competition	Organizer of Competition	Date	Location
1	Personality Aware Product Recommendation System	Ganesh Bobade, Raviraj Mane, Umesh Patil,Rohit Khomane	AVISHKAR-2022	SVPM's COE Malegaon	15-Sep-2022	Malegaon (Bk)
2	Reccokart Product Recommendation System	Ganesh Bobade, Raviraj Mane, Umesh Patil,Rohit Khomane	CRE-TECHNOVA-2023	SVPM's COE Malegaon	21-Apr-2023	Malegaon (Bk)

Shivnagar Vidya Prasarak Mandal's

College Of Engineering Malegaon (Bk.)

Tal -Baramati, Dist - Pune 413115

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A National Level Technical Symposium

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Prof. B. S. Kamble	Prof. S. B. Dixit	Dr. S. M. Mukane
Co-Convener	Convener	PRINCIPAL

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Dr. Devendra P. Agrawal	Dr. Shailendra M. Mukane
Academic Research Coordinator	PRINCIPAL

Shivnagar Vidya Prasarak Mandal's

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(Institute Level Research Project Competition
In association with Savitribai Phule Pune University, Pune)

This is to certify that Mr. / ~~Ms.~~ ...Patil Umesh.........................

has participated in **AVISHKAR -2022**. A Institute Level Research Project Competition organized by SVPM's College of Engineering, Malegaon Bk., Baramati in association with Savitribai Phule Pune University, Pune at UG/~~PG~~/~~Ph.D.~~/~~Teacher level~~ under Commerce, Managment & Law category held at SVPM's College of Engineering, Malegaon Bk., Baramati on 15th September, 2022.

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PRINCIPAL