A Model Creation Tool for Recommendation System (InterestHub)

SPL-3 Final Report

Course

Software Project Lab -3
Course Code: SE 801

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Letter of Transmittal

December 17, 2023,

BSSE 4th Year Exam Committee

Institute of Information Technology,

University of Dhaka

Subject: **Technical report on “A Model Creation Tool for Recommendation System (InterestHub)”.**

Sir,

With due respect and immense pleasure, I am pleased to submit the technical report on “A Model Creation Tool for Recommendation System (InterestHub)”. I have tried my level best to produce an acceptable technical report, although this report may have some shortcomings. I would be highly grateful if you overlooked the mistakes and accepted the efforts that have been put into this report.

Sincerely,

Md. Inzamam-Ul Haque Sobuz

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Documentation Authentication

This project document has been approved by the following person.

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Acknowledgment

I am grateful to the Institute of Information Technology for giving me the chance to work on “A Model Creation Tool for Recommendation System (InterestHub). I would like to express my gratitude to my supervisor, Dr. Naushin Nower, a professor at the Institute of Information Technology, University of Dhaka, for providing me with guidelines on the preparation of this document and completing this project. Lastly, I would like to thank my classmates. They have always been helpful and provided valuable insights from time to time.

Abstract

This project presents InterestHub, a user-friendly tool for building recommendation systems utilizing Machine Learning. The system employs Neural Collaborative Filtering (NCF) to construct personalized models based on user datasets. Users can seamlessly submit, integrate, and share datasets, fostering a collaborative environment. Noteworthy features include a comprehensive movie search functionality and the incorporation of user ratings for continual model refinement. This report outlines the development and implementation of InterestHub, highlighting the efficacy of NCF in enhancing user-specific recommendations within a dynamic platform.

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Chapter 1: Introduction

In an era characterized by information abundance, the need for personalized recommendation systems has become paramount. The ubiquity of vast datasets, coupled with the potential of machine learning (ML) techniques, has opened avenues for creating intelligent tools that cater to individual preferences. This project introduces "InterestHub," a pioneering Model Creation Tool for Recommendation Systems, designed to empower users to construct and integrate personalized recommendation models seamlessly.

InterestHub responds to the growing demand for a user-friendly platform that not only allows the submission and integration of diverse datasets but also fosters collaboration by enabling data sharing with the public. The heart of this project lies in the implementation of Neural Collaborative Filtering (NCF), a state-of-the-art ML model, to construct personalized recommendation models. NCF, with its ability to capture intricate user-item interactions, forms the backbone of InterestHub, ensuring the delivery of accurate and relevant recommendations tailored to individual preferences.

This introduction sets the stage for the exploration of InterestHub, detailing its core objectives, features, and the innovative use of NCF. As we delve into the subsequent sections, a comprehensive understanding of the project's significance in the realm of recommendation systems will unfold, shedding light on its potential impact and contributions to this evolving field.

1.1 Purpose

The purpose of this work is -

Enhance User Engagement:

- ☐ Foster increased user engagement by establishing connections with content that aligns with individual preferences.

Improve Content Discovery:

- Optimize content discovery through effective filtering and tailored suggestions, ensuring users encounter content that resonates with their interests.

Empower User Personalization:

- Enable users to refine and personalize their profiles, enhancing the precision of content recommendations based on their unique preferences.

User-Friendly Content Exploration:

- Develop a user-friendly platform for the exploration and discovery of diverse content, spanning books, movies, and courses.

Practical Learning Opportunity:

- It serves as a practical learning opportunity in both machine learning and web development and is specifically designed to contribute to academic pursuits.

1.2 Scope

The scope encompasses ease of use, model creation, integration, community collaboration, and dynamic adaptation to user preferences, establishing InterestHub as a versatile and evolving recommendation system solution.

1.3 Motivation

InterestHub is motivated by a desire to simplify recommendation model creation, making it accessible to a wider audience. The project encourages collaboration by allowing users to share datasets, fostering diversity and robust model development. Prioritizing personalized user experiences, InterestHub tailors recommendations based on interactions and feedback. The platform ensures continuous model improvement through a feedback loop driven by user ratings. By streamlining integration into personal projects, InterestHub promotes widespread adoption. Additionally, it addresses the need for diverse testing data with a comprehensive movie database of around 10,000 movies, enhancing the effectiveness of recommendation models.

Chapter 2: Project Description

In this chapter, we delve into the Quality Function Deployment (QFD) and explore the usage scenarios for the "A Model Creation Tool for Recommendation System (InterestHub)".

2.1 Quality Function Deployment

QFD is a technique employed to translate customer needs into technical requirements for the software. Within the context of our project, we have identified the following categories of requirements.

2.1.1 Normal Requirements

NR1: User-friendly Interface

The system must feature an intuitive and user-friendly interface to ensure ease of use for individuals with varying levels of technical expertise.

NR2: Dataset Submission Functionality

The platform should allow users to seamlessly submit datasets, providing a straightforward mechanism for incorporating their data into the recommendation model.

NR3: NCF-based Model Creation

The system must employ Neutral Collaboration Filtering (NCF) as the core technique for creating recommendation models, leveraging user-item interactions to generate accurate and personalized suggestions.

NR4: Stability and Reliability

The recommendation system must operate with high stability and reliability, ensuring consistent performance and minimizing disruptions.

2.1.2 Expected Requirements

ER1: Collaboration Features

The platform is expected to include collaboration features, enabling users to share datasets and fostering a community-driven environment for the improvement of recommendation models.

ER2: Personalized Movie Recommendations

Users should anticipate receiving personalized movie recommendations based on their interactions with the system, enhancing the overall user experience.

ER3: Seamless Integration into Personal Projects

The system is expected to facilitate the seamless integration of recommendation models into personal projects, allowing users to incorporate the models effortlessly.

2.1.3 Exciting Requirements

ExcR1: Continuous Model Improvement through Feedback Loop

The system will offer an exciting feature of continuous model improvement through a feedback loop, where user ratings and interactions contribute to refining and enhancing the recommendation models over time.

ExcR2: Comprehensive Movie Database (10,000+ entries)

Users can look forward to accessing a vast and comprehensive movie database, comprising over 10,000 entries, ensuring a diverse and extensive selection for testing and refining recommendation models.

ExcR3: Efficient Search Functionality

An exciting requirement is the implementation of an efficient search functionality, allowing users to quickly and accurately retrieve information from the extensive movie database.

2.2 Usage Scenario

A User Profile: Alice is an avid movie enthusiast who wants to enhance her movie-watching experience by receiving personalized recommendations.

- ☐ **User Registration and Dataset Submission:**

  Action: Alice registers on InterestHub and navigates to the dataset submission section.

  Interaction: She submits her personal movie-watching history dataset to the platform.

- ☐ **Exploring the Movie Database:**

  Action: After dataset submission, Alice explores the extensive movie database containing over 10,000 entries.

  Interaction: She searches for movies in her favorite genres and discovers new releases.

- ☐ **Building a Recommendation Model:**

  Action: Intrigued by the movie database, Alice decides to build a recommendation model.

  Interaction: She selects the NCF-based model creation option and customizes it based on her preferences and viewing history.

- ☐ **Integration into Personal Project:**

  Action: With the recommendation model created, Alice plans to integrate it into her personal movie-watching app.

  Interaction: InterestHub provides a seamless integration process, and Alice successfully incorporates the recommendation model into her app.

- ☐ **Receiving Personalized Recommendations:**

  Action: Alice starts using her personalized movie recommendation system within her app.

Interaction: She receives real-time movie suggestions tailored to her viewing habits, enhancing her overall movie-watching experience.

- **Rating and Feedback Loop:**

  Action: After watching a recommended movie, Alice rates it within her app.

  Interaction: The rating is sent back to InterestHub, contributing to the continuous improvement of the recommendation model through the feedback loop.

- **Collaboration and Dataset Sharing:**

  Action: Impressed with the system, Alice decides to share her dataset with the InterestHub community.

  Interaction: She accesses the collaboration features, contributing to the diversity of datasets available for model creation.

- **Exploring Others' Recommendations:**

  Action: Curious about what others are watching, Alice explores recommendations from the community.

  Interaction: She discovers new movies and refines her preferences based on collaborative suggestions.

This usage scenario highlights the user journey on InterestHub, from dataset submission to building a personalized recommendation model, integrating it into a personal project, and actively participating in the collaborative ecosystem by sharing feedback and exploring recommendations from the community.

Chapter 3: Timeline

A 5-month timeline has been planned for this project.

Activities	Months				
	1st	2nd	3rd	4th	5th
Literature Review	✓	✓	✓		
Experiments and Study		✓	✓		
Design			✓		
Development and Testing			✓	✓	✓

Chapter 4: Scenario-Based Modeling

This chapter presents the quality function deployment and usage scenario of the "**Interest-Based Content Recommender (InterestHub)**".

4.1 Use Case Diagram

Use Case diagrams of Interest-Based Content Recommender (InterestHub) are given below:

4.1.1 Level-0: Use case of Interest-Based Content Recommender

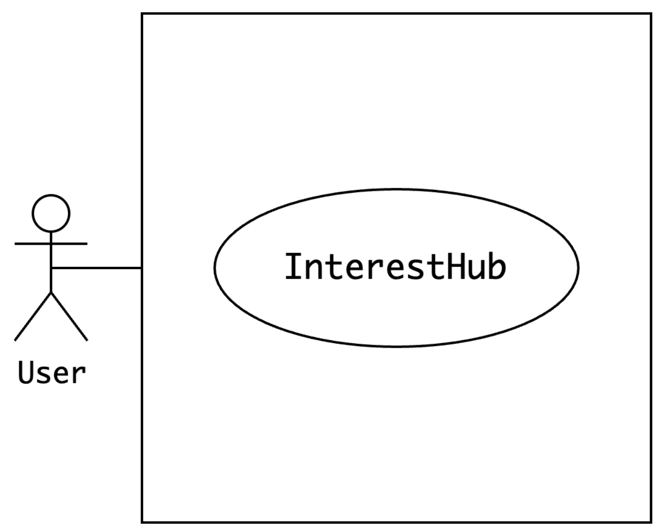

Figure 1: *Level-0 Use case diagram of InterestHub*

Primary actors: User.

Secondary actors: None.

Goal in context: Top-level view of the Interest-Based Content Recommender (InterestHub).

4.1.2 Level-1: Modules of InterestHub

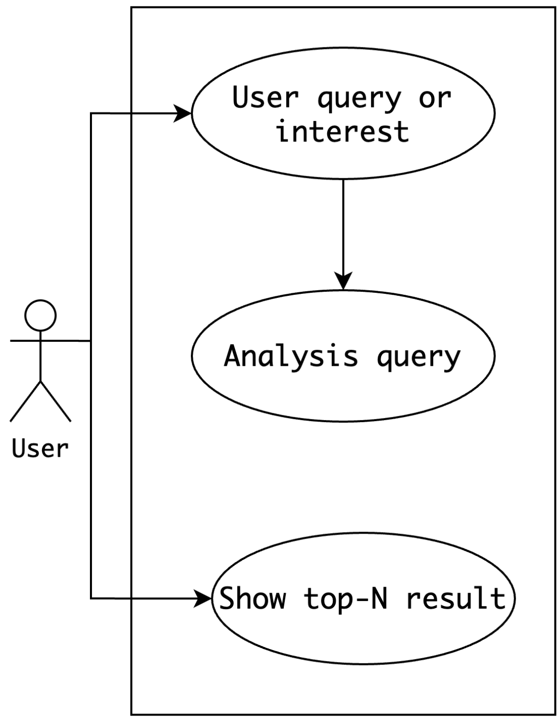

Figure 2: Level-1 Use-case Diagram of IntersetHub

Primary actors: User.

Secondary actors: None.

Goal in context: Module-wise view of the Interest-Based Content Recommender (InterestHub).

4.1.2.1 User query or interest

The User Interest Module is responsible for capturing and managing user interests. Users can input their interests, which may include academic topics and entertainment preferences. This module allows users to refine their interests over time, ensuring that recommendations stay aligned with their evolving preferences.

4.1.2.2 Query Analysis Module

The Query Analysis Module focuses on processing user queries effectively. Whether users are searching for academic courses or entertainment content, this module interprets their queries, identifies key terms, and matches them to relevant content categories. It plays a crucial role in ensuring that users receive accurate and personalized recommendations.

4.1.2.3 Show Top-N results

The Show Result Module is responsible for presenting content recommendations to users. It takes into account the user's interests and query analysis to generate personalized content lists. Users can explore recommended books, movies, or courses based on their preferences, ultimately enhancing their content discovery experience.

Chapter 5: Data-Based Modeling

Any kind of database or data storage system is not used for this tool. So, this section is not relevant.

Chapter 6: Class-Based Modeling

After identifying nouns from the scenario, I filtered nouns belonging to the solution domain using General Classification criteria (External entities, Things, Events, Roles, Organizational units, Places, and Structures). Nouns selected as potential classes were filtered using Selection Criteria (Retained information, Needed services, Multiple attributes, Common attributes, Common operations, and Essential requirements). After performing an analysis of potential classes, I have finalized the following classes:

- ☐ **Query Handler**
- ☐ **Trained Data Manager**
- ☐ **Model Controller**
- ☐ **Output Generator**
- ☐ **Analysis Controller**

6.1 Class Cards

The class cards of the above-mentioned classes are given below –

Query Handler	
Attribute	**Method**
-queryType -queryText -listSize	+getQueryType() +getQueryText() +getListSize() +setQueryType() +setQueryText()

	+setListSize() +checkQueryValidation()
Responsibilities	**Collaborator**
• Taking input from user • Make sure valid query for the model.	- Output Generator

Table 1: Class Card for Query Handler

Model Controller	
Attribute	**Method**
-trainData[]	+getModel()
Responsibilities	**Collaborator**
• Preprocess datasets • Instantiate Models	- Query Handler

Table 2: Class Card for Model Controller

Trained Data Manager	
Attribute	**Method**
-topNSuggestion[]	+resultUsingCF() +resultUsingMF() +resultUsingNCF() +calculateAccuracy()

Responsibilities	Collaborator
• Get suggestions for query	- Model Controller

Table 3: Class Card for Train Data Manager

Output Generator	
Attribute	**Method**
-topNSuggestion[] -ratingOfResult	+getTopNSuggestion() +setRaringOfResult()
Responsibilities	**Collaborator**
• Show Top N suggestion based on query	- Train Data Manager

Table 4: Class Card for Output Generator

Analysis Handler	
Attribute	**Method**
-testData[] -results[] -errors[]	+getResult() +getError() +comparisonScoreOfResult() +comparisonErrorScore()
Responsibilities	**Collaborator**
• Show a comparison of collaborating filtering and neural collaborating	-Train Data Manager

filtering. ● Show evaluation of the result.	

Table 5: Class Card for Output Generator

6.2 Class Responsibility and Collaboration Diagram

The Class Responsibility and Collaboration Diagram of the above-mentioned classes are given below –

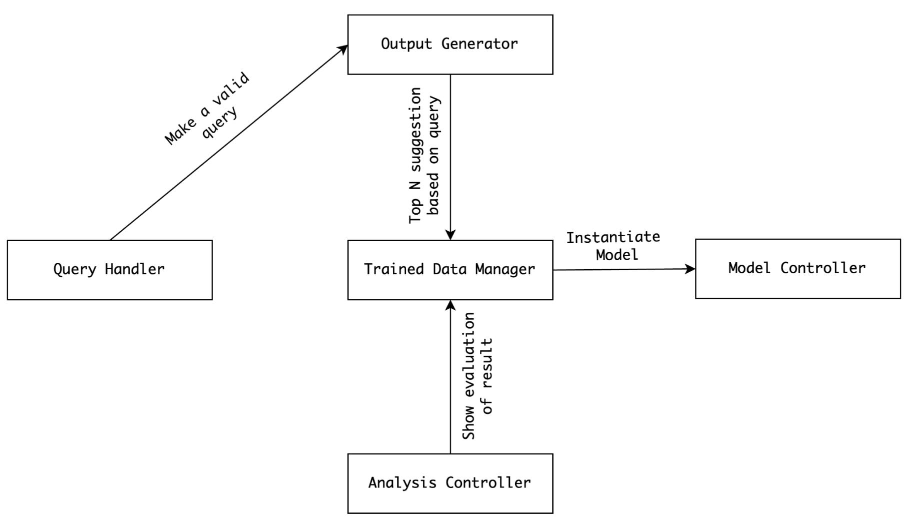

Figure 3: Class Responsibility and Collaboration Diagram of InterestHub

Chapter 7: Architectural Design

This chapter describes the architectural overview and architectural context diagram of the **Interest-Based Content Recommender (InterestHub).**

7.1 Architectural Context Diagram

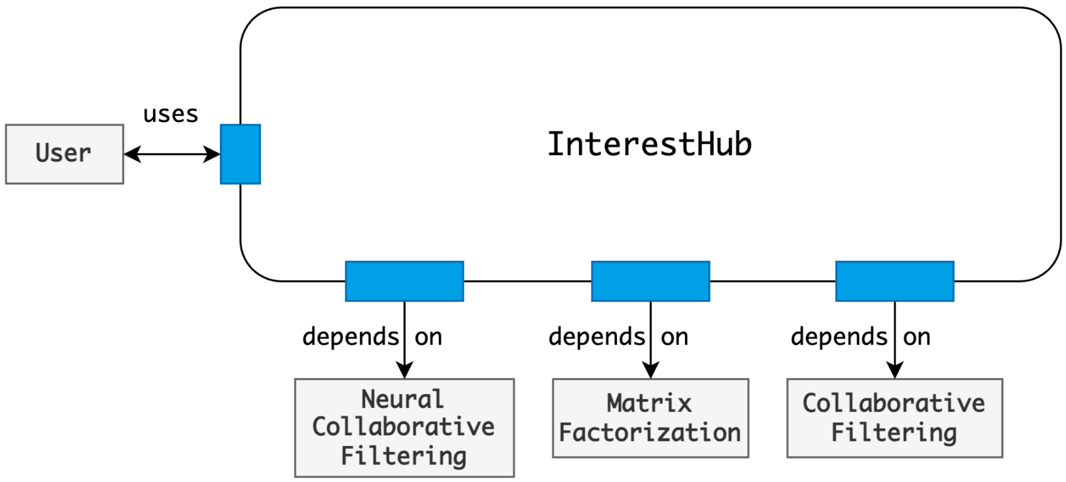

Figure 4: Architectural Context Diagram

The Architectural context diagram of the recommended system depicted above illustrates the following external entities:

- **Subordinate Systems:** Those systems that are used by the Recommend System. Here the app uses 3 models to process query results and generate Top-N best suggestions of the query.

  Collaborative Filtering, Matrix Factorization, Neural Collaborative Filtering.

- **Actors:** Entities that interact with the app. Here Users are the sole actors of the app.

7.2 Defining Archetypes

An archetype is a class or pattern representing a core abstraction critical to the design of an architecture for the target system. Archetypes are the abstract building blocks of an architectural design. In many cases, archetypes can be derived by examining the analysis classes defined as part of the requirements model. An archetype is a generic, idealized model of a person, object, or concept from which similar instances are derived, copied, patterned, or emulated.

The following picture delineates the archetypes of the InterestHub.

Model View Controller(MVC) Architecture

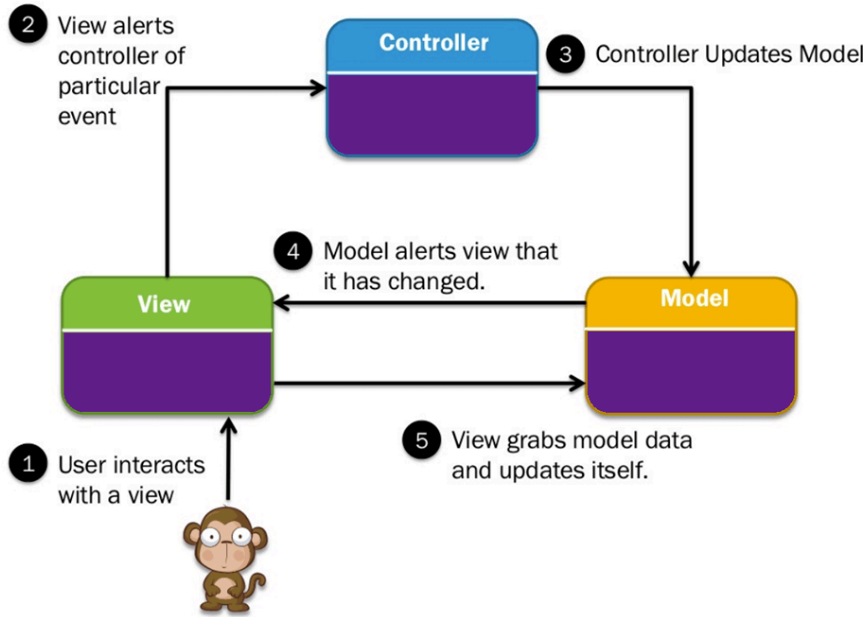

Figure 5: *MVC Architecture*

The MVC architecture is chosen to accommodate the front end of the tool that will be shown to the user and the business logic.

7.3 Instantiation of Software Architectural Components

The diagram of the architectural components of the Recommendation System is given below –

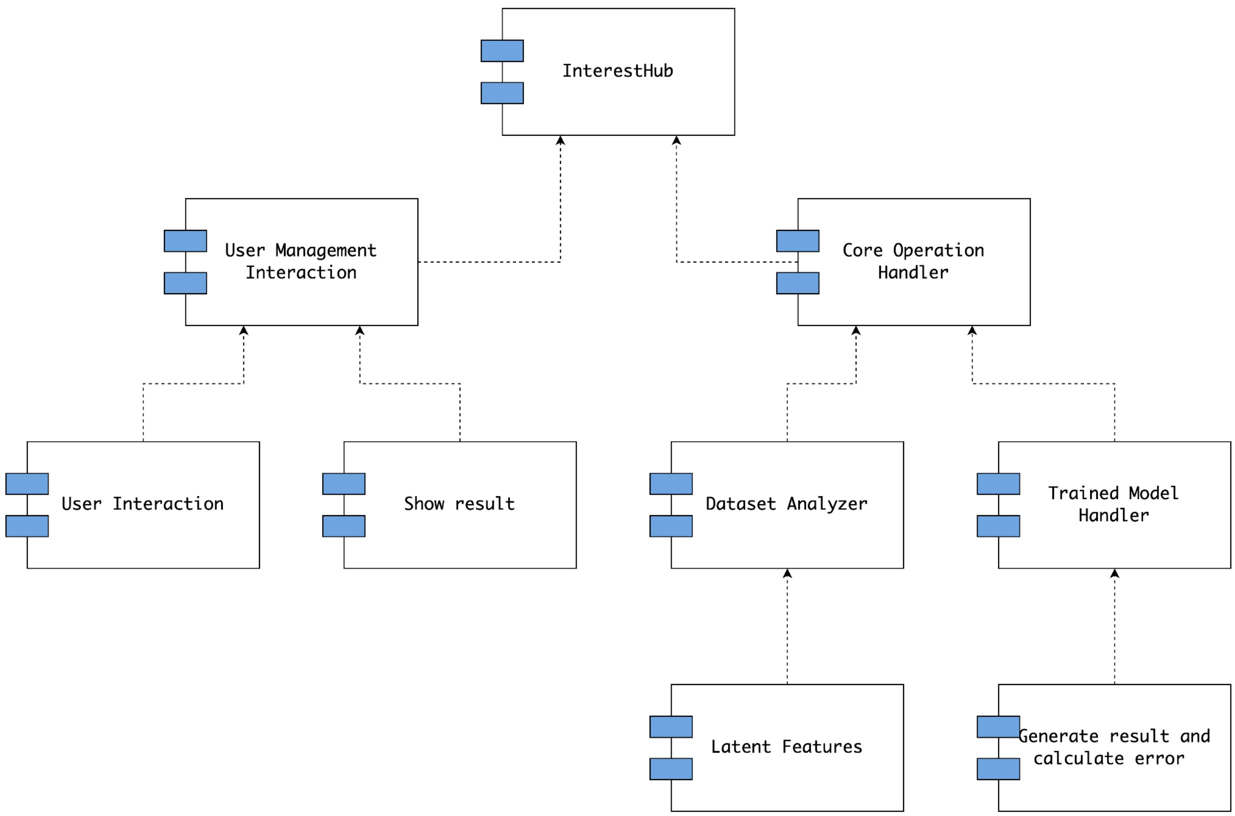

Figure 6: Instantiation of Software Architectural Components

7.4 Mapping Requirements for Software Architecture

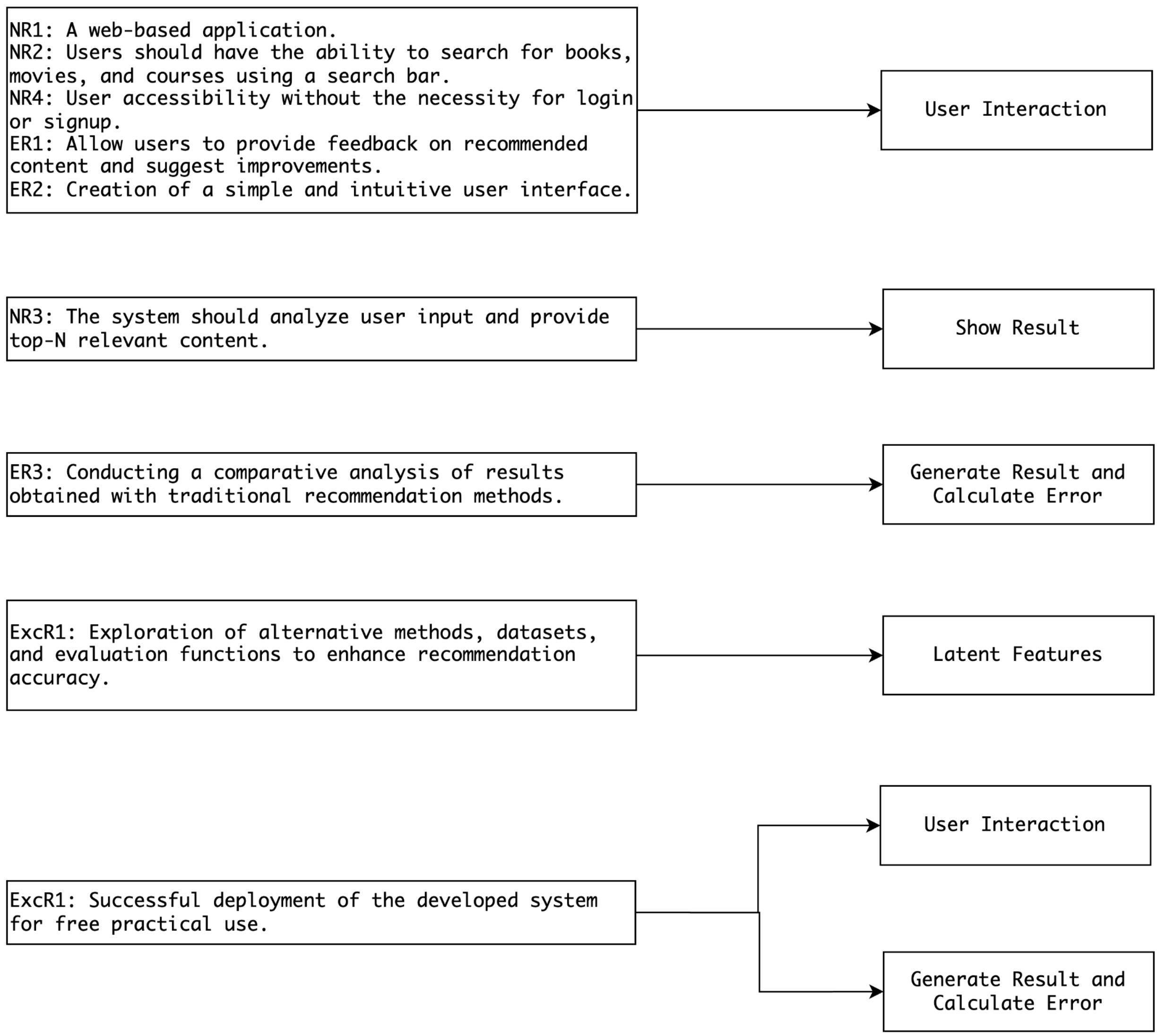

Figure 7: *Mapping Requirements to Software Architecture*

Chapter 8: Preliminary Test Plan

In this chapter, a high-level description of testing goals and a summary of features to be tested are presented.

8.1 High-Level Description of Testing Goals

Testing goals for this application are represented below from a high level:

- ☐ To demonstrate that the system meets its requirements.
- ☐ To verify the accuracy of the recommendation.
- ☐ To validate the effectiveness of the user satisfaction.
- ☐ To ensure proper searching.
- ☐ To ensure compatibility with different web browsers and devices.
- ☐ To find any existing bugs.
- ☐ To ensure that the system runs smoothly.

8.2 Test Cases

Test cases for the testing of this tool are documented below -

Test ID: T1
Test Case: Recommendation Accuracy Test
Input Test Data: A user with specified interests.
Steps To Be Executed:

1. Input the user's interests into the system.
2. Retrieve content recommendations for books, movies, and courses.
3. Review the recommendations and compare them with the user's specified interests.

Expected Result: The recommendations accurately align with the user's interests.
Target Item: Recommendation algorithm and personalization.

Pass/Fail: Passed

Test ID: T2
Test Case: Search Query Accuracy Test
Input Test Data: User search query for "Machine Learning Courses."
Steps To Be Executed:

1. Input the search query into the system.
2. Execute the search and retrieve course recommendations.
3. Analyze the search results to ensure they are relevant to the query.

Expected Result: The search results display relevant machine learning courses.
Target Item: Query analysis and content retrieval.

Pass/Fail: Passed

Test ID: T3
Test Case: Content Rating and Feedback Test
Input Test Data: User interaction with recommended content.
Steps To Be Executed:

1. The user rates and provides feedback for a recommended movie.
2. Check if the rating and feedback are properly recorded and associated with the user.

Expected Result: The user's rating and feedback are successfully recorded and used to improve future recommendations.
Target Item: User engagement and feedback system.

Pass/Fail: Passed

Chapter 9: Methodology

This section outlines the systematic approach taken to develop and implement InterestHub, ensuring a structured and effective process.

9.1 Data Collection:

Description: The project initiated with the collection of diverse datasets to serve as a foundation for recommendation model creation. This involved acquiring datasets with varied user interactions and movie preferences to enhance the model's adaptability.

Process: Datasets were obtained from publicly available sources, and efforts were made to ensure representativeness across different genres and user demographics.

9.2 Model Development with Neutral Collaboration Filtering (NCF):

Description: The recommendation system's core model was developed using Neutral Collaboration Filtering (NCF), a technique known for its ability to provide accurate and personalized recommendations based on user interactions.

Implementation: NCF algorithms were integrated into the system, allowing for the creation of recommendation models tailored to individual user preferences.

9.3 User Interface Design:

Description: An iterative design process was employed to create an intuitive and user-friendly interface for InterestHub. User feedback and usability testing played a crucial role in refining the design to enhance accessibility.

Tools: UI/UX design tools were utilized, and feedback from prototype testing sessions was incorporated to optimize the interface.

9.4 Integration Mechanism:

Description: The development included the design and implementation of a seamless integration mechanism, allowing users to effortlessly incorporate recommendation models into their personal projects or applications.

Testing: Integration features were extensively tested to ensure compatibility with various project structures and frameworks.

9.5 Continuous Model Improvement Feedback Loop:

Description: A feedback loop was established to gather user ratings and interactions, contributing to the continuous improvement of recommendation models. This iterative process ensures that the system evolves to meet changing user preferences.

Implementation: User ratings and feedback are systematically collected, and periodic model updates are triggered based on this input.

9.6 Community Collaboration Features:

Description: Collaboration features were integrated to facilitate the community-driven enhancement of recommendation models. Users can share datasets, contributing to the diversity of available data for model training.

Community Engagement: Forums and community engagement initiatives were established to encourage knowledge-sharing and collaboration among users.

9.7 Comprehensive Movie Database:

Description: A comprehensive movie database containing around 10,000 entries was curated to provide users with a diverse set of choices for testing and refining recommendation models.

Curation: The database was curated to ensure coverage across genres, release years, and popularity metrics.

By adopting this methodology, InterestHub was systematically developed to meet user needs, provide personalized recommendations, and foster a collaborative community. The approach considered data diversity, model effectiveness, user experience, and community engagement, ensuring a well-rounded and impactful recommendation system.

Chapter 10: Implementation Details

10.1 Frontend: Angular

Here is the file structure -

Figure 8: *Frontend File Structure*

10.2 Backend: Java Spring Boot

Here is the file structure -

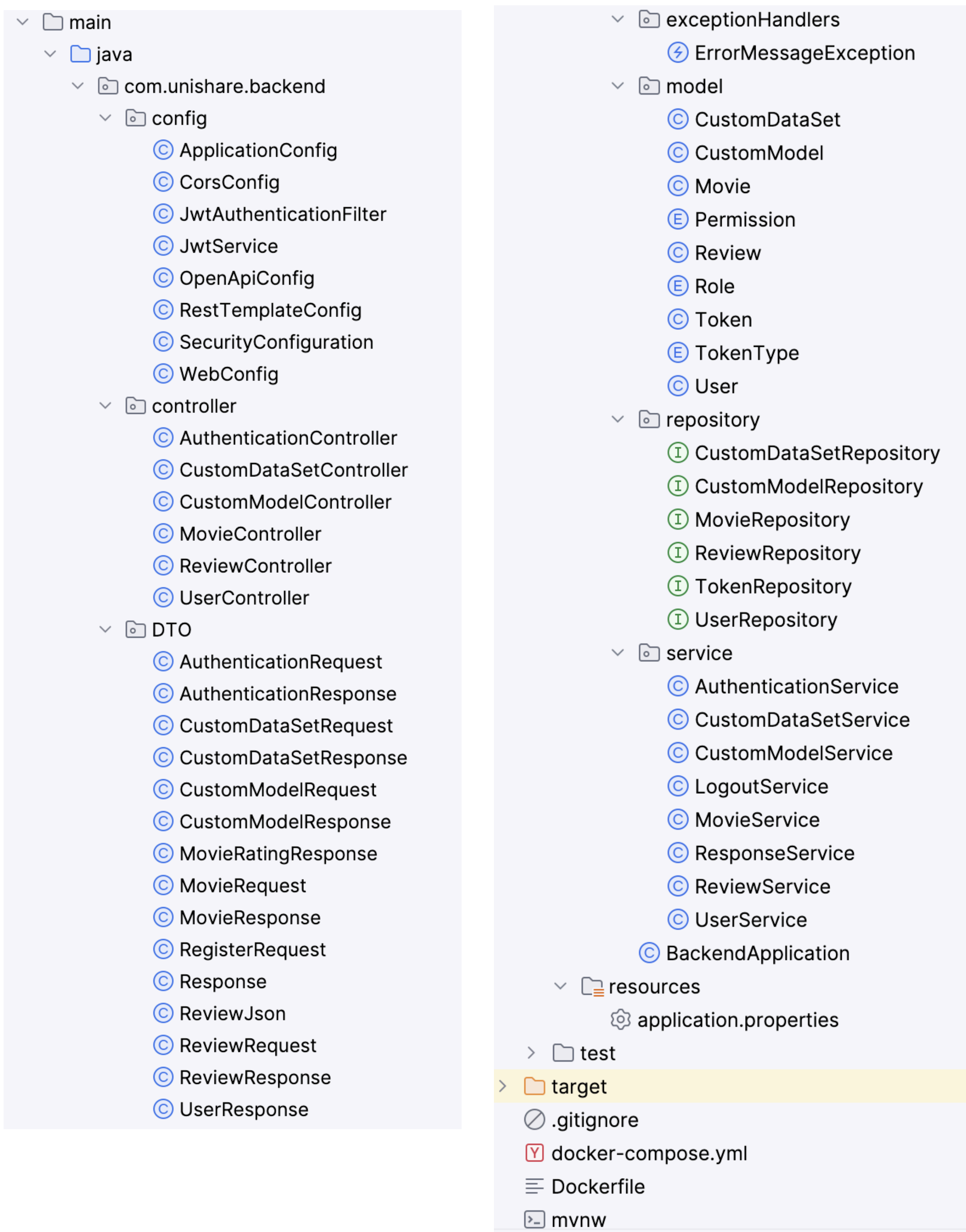

***Figure 9**: Backend File Structure*

10.3 Database: Postgresql

PostgreSQL is a powerful open-source relational database management system (RDBMS) known for its robustness, extensibility, and adherence to SQL standards. Renowned for its ACID compliance, PostgreSQL supports complex queries, indexing, and advanced data types. Its active community and continuous development make it a popular choice for a wide range of applications, from small-scale projects to large enterprise solutions.

10.4 Model: Neural Collaborative Filtering (NCF)

The process of Neural Collaborative Filtering (NCF)

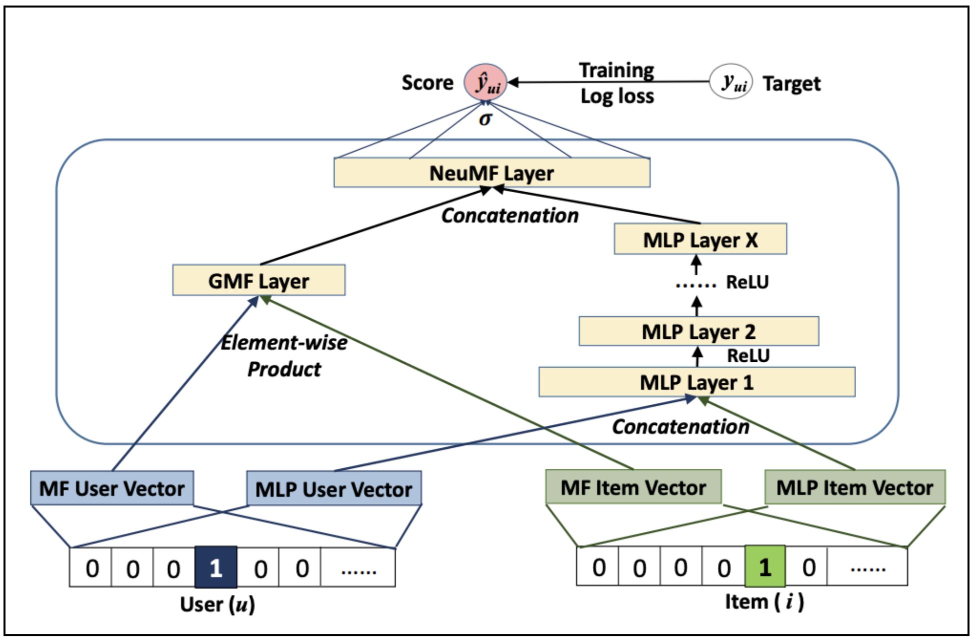

Figure 9: *Neutral Collaborative Filtering* (NCF)

Neutral Collaborative Filtering (NCF) is a machine-learning approach commonly used in recommendation systems. It combines the strengths of collaborative filtering with neural network models to provide accurate and personalized recommendations. NCF leverages user-item interactions to learn latent factors and predict user preferences for unrated items. This model's flexibility allows it to handle sparse data efficiently, making it well-suited for scenarios with incomplete user feedback. NCF's ability to capture intricate patterns in user behavior has contributed to its widespread adoption in building recommendation systems across various domains.

The details implementation of Neural Collaborative Filtering (NCF) in Python using Keras:

```
# Define inputs
movie_input = Input(shape=[1], name='movie-input')
user_input = Input(shape=[1], name='user-input')

# MLP Embeddings
movie_embedding_mlp = Embedding(num_movies + 1, latent_dim, name='movie-embedding-mlp')(movie_input)
movie_vec_mlp = Flatten(name='flatten-movie-mlp')(movie_embedding_mlp)
user_embedding_mlp = Embedding(num_users + 1, latent_dim, name='user-embedding-mlp')(user_input)
user_vec_mlp = Flatten(name='flatten-user-mlp')(user_embedding_mlp)

# MF Embeddings
movie_embedding_mf = Embedding(num_movies + 1, latent_dim, name='movie-embedding-mf')(movie_input)
movie_vec_mf = Flatten(name='flatten-movie-mf')(movie_embedding_mf)
user_embedding_mf = Embedding(num_users + 1, latent_dim, name='user-embedding-mf')(user_input)
user_vec_mf = Flatten(name='flatten-user-mf')(user_embedding_mf)

# MLP layers
concat_mlp = Concatenate(name='concat-mlp')([movie_vec_mlp, user_vec_mlp])
fc_1_mlp = Dense( units: 2000, name='fc-1-mlp', activation='relu')(concat_mlp)
fc_2_mlp = Dense( units: 500, name='fc-2-mlp', activation='relu')(fc_1_mlp)
fc_3_mlp = Dense( units: 20, name='fc-3-mlp', activation='relu')(fc_2_mlp)

# Prediction from MLP
pred_mlp = Dense( units: 10, name='pred-mlp', activation='relu')(fc_3_mlp)

# Prediction from MF
pred_mf = Dot(axes=1, name='pred-mf')([movie_vec_mf, user_vec_mf])

# Combine predictions from both MLP and MF
combine_mlp_mf = Concatenate(name='combine-mlp-mf')([pred_mlp, pred_mf])

# Final result
result = Dense( units: 1, name='result', activation='relu')(combine_mlp_mf)
```

Figure 10: *Implementation*

Chapter 11: User Manual

11.1 Sign Up

To start exploring the features of InterestHub, you'll need to create an account. Click on the "Sign Up" button on the homepage, and you'll be prompted to provide your full name, email address, and a secure password. Once you've filled in the required information, click "Sign Up" to successfully create your account.

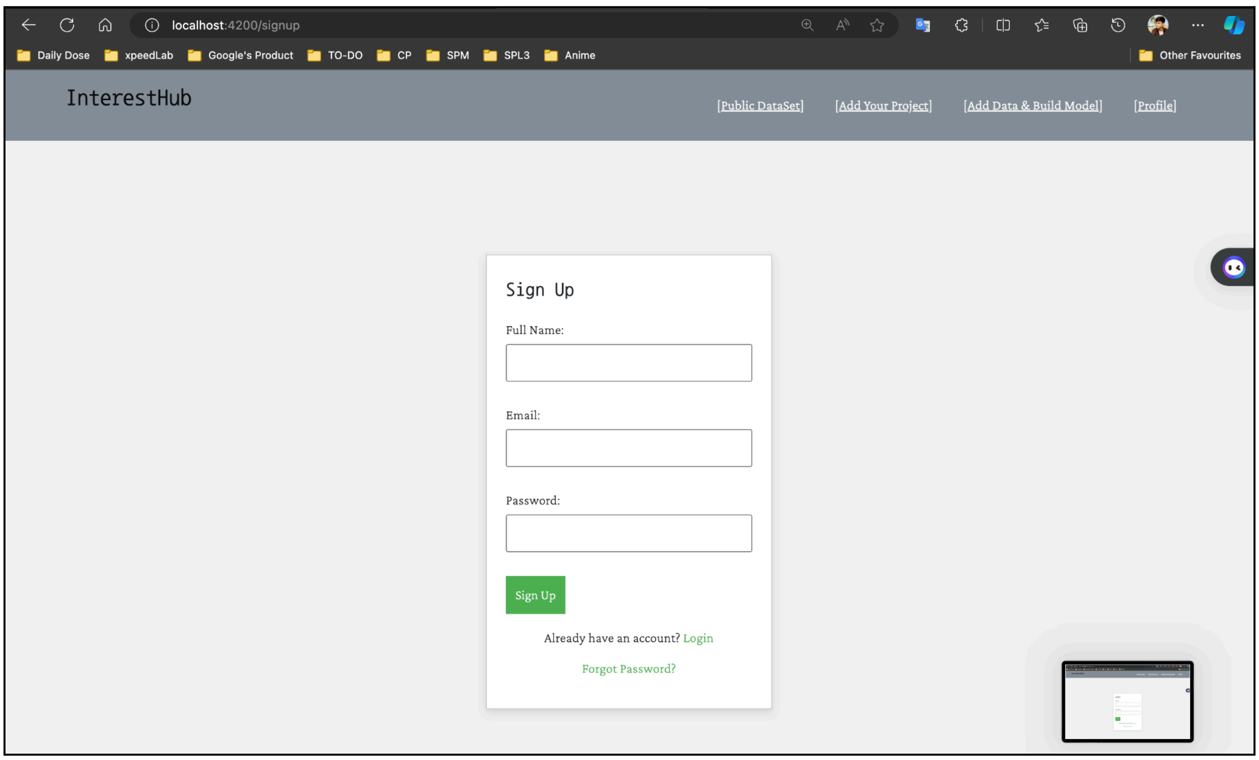

Figure 11: *Sign Up Page*

11.2 Log In

For returning users, the login process is straightforward. Click on the "Log In" button, enter your registered email address, along with your password, and click "Log In" to access your existing InterestHub account.

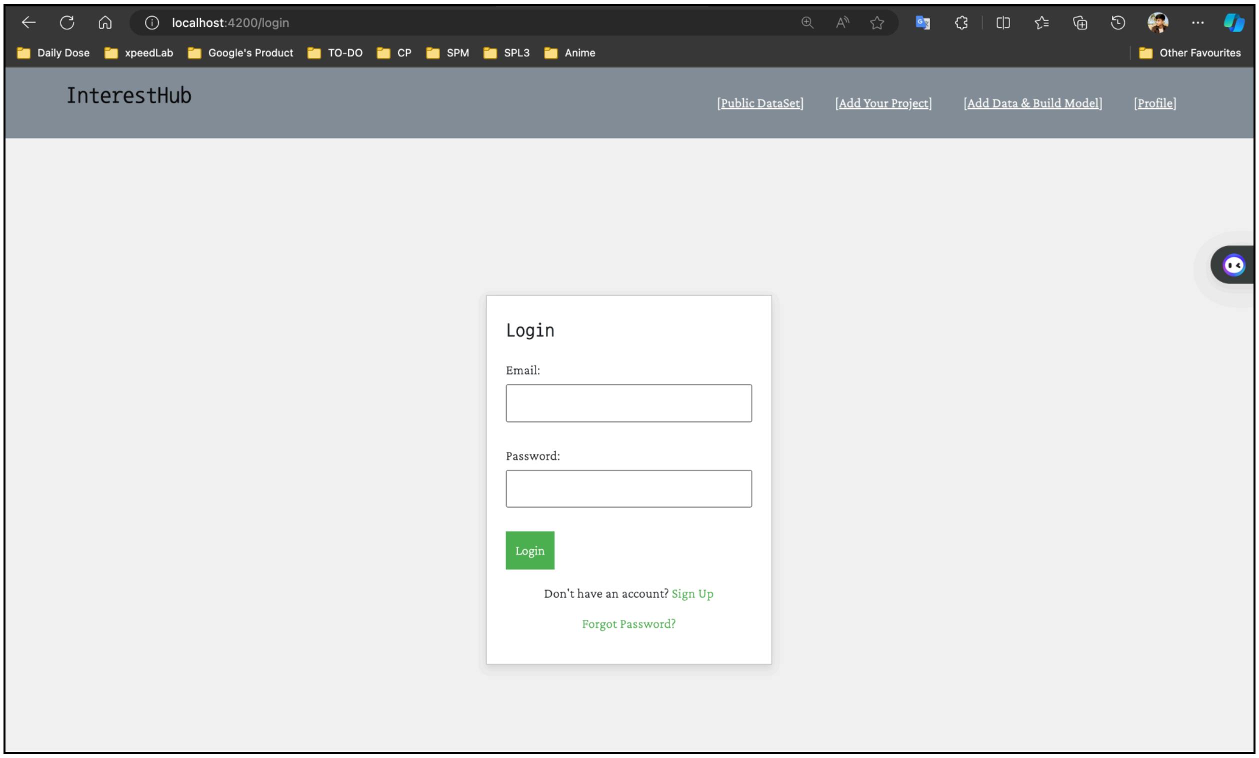

Figure 12: *Log In Page*

11.3 User Information and Control

InterestHub user profile is the control center for your experience. Review your past activities, from dataset submissions to movie ratings, and explore personalized recommendations aligned with your preferences. Actively shape the recommendation system by providing feedback through ratings, and seamlessly integrate your latest preferences by rebuilding the system. Your engagement not only refines your own recommendations but contributes to the collaborative community insights. Customize your settings and connect with others through community forums, making your user profile the dynamic heart of your InterestHub journey.

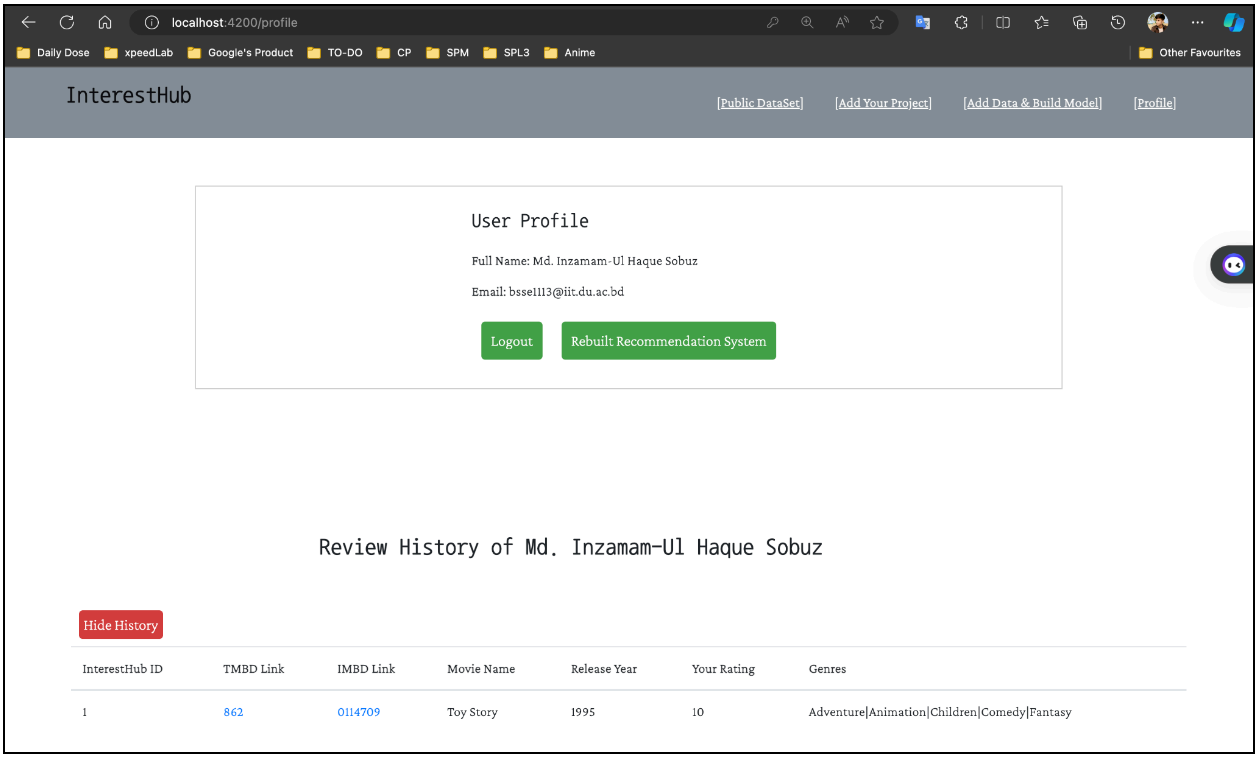

Figure 13: *User Profile Page*

11.4 Add Project

Within your InterestHub user profile, you can take charge of your recommendation experience by adding your own projects. Simply enter a project name and title, and initiate the creation of a personalized model tailored to your preferences. This feature empowers users to contribute to the InterestHub community by publicly sharing their datasets, fostering collaboration and diversity in model development. Whether you're refining your own recommendations or enriching the collective dataset, your user profile becomes a dynamic space for both personalization and community engagement in the realm of InterestHub projects.

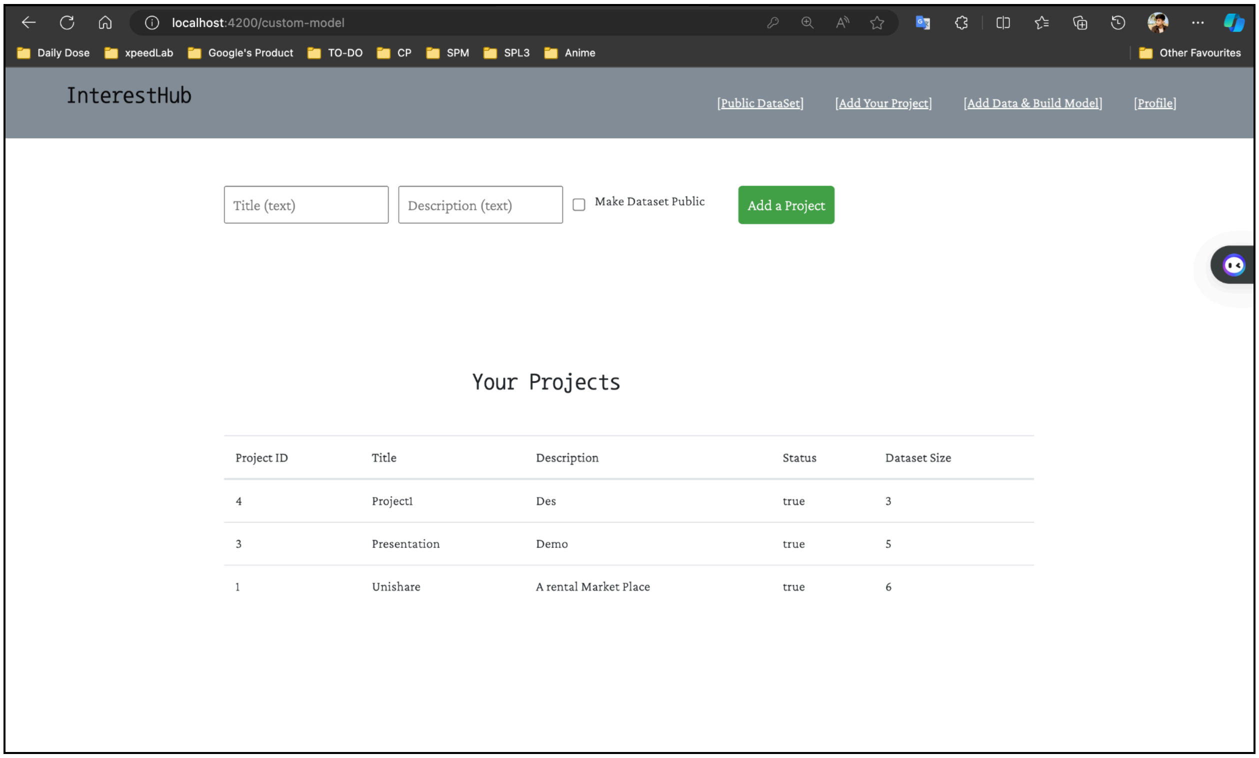

Figure 14: *Add Project*

11.5 Adding Datasets to Your Project

Enrich your InterestHub project by seamlessly adding datasets to tailor your recommendation model. Users have the flexibility to upload CSV files or manually enter data, allowing for diverse and personalized dataset contributions. Navigate to your existing project, choose the "Add Dataset" option, and effortlessly enhance your model's capabilities. This user-friendly feature empowers you to refine recommendations based on your unique dataset, contributing to the collaborative and dynamic environment of InterestHub.

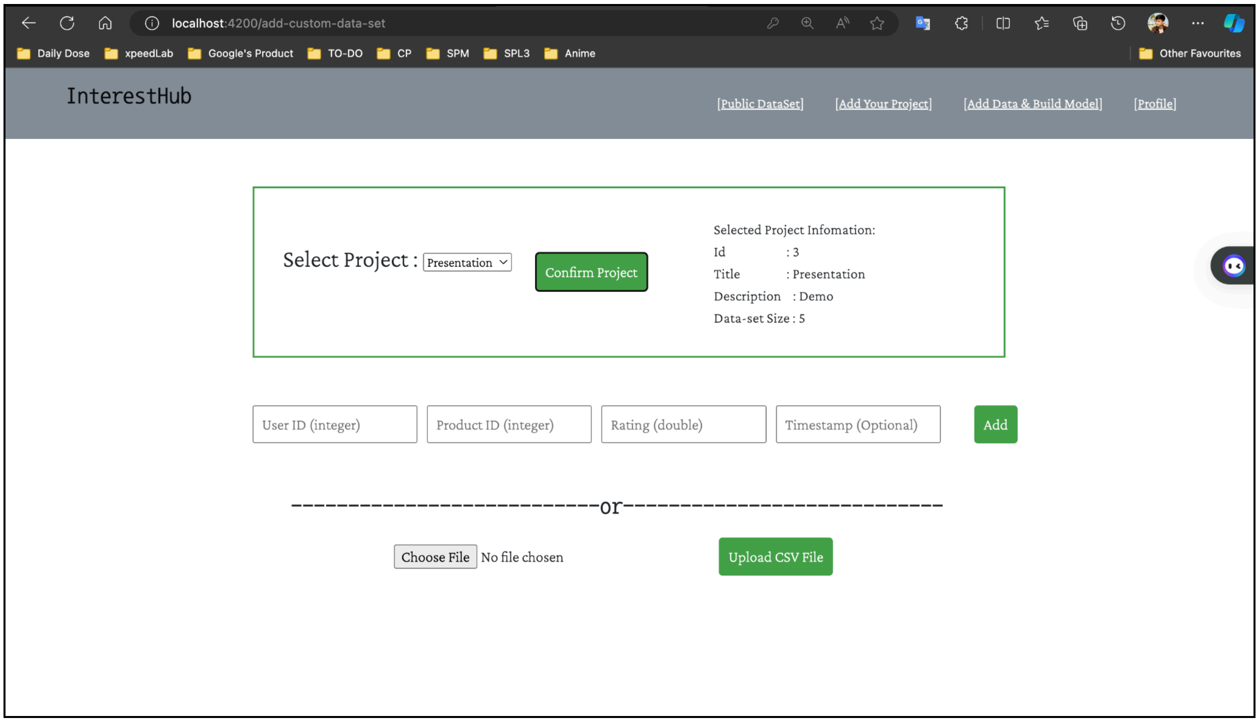

***Figure 15**: Add Dataset for a project*

11.6 Building and Downloading Models

Empowering users with control, InterestHub enables the creation of personalized models for any project. Simply initiate the model-building process for your dataset within the project interface. Once the model is generated, users have the convenience of downloading it, putting the power of recommendation customization directly in their hands. This seamless process ensures that users can refine, experiment, and integrate their models into personal projects effortlessly, embodying the user-centric approach of InterestHub.

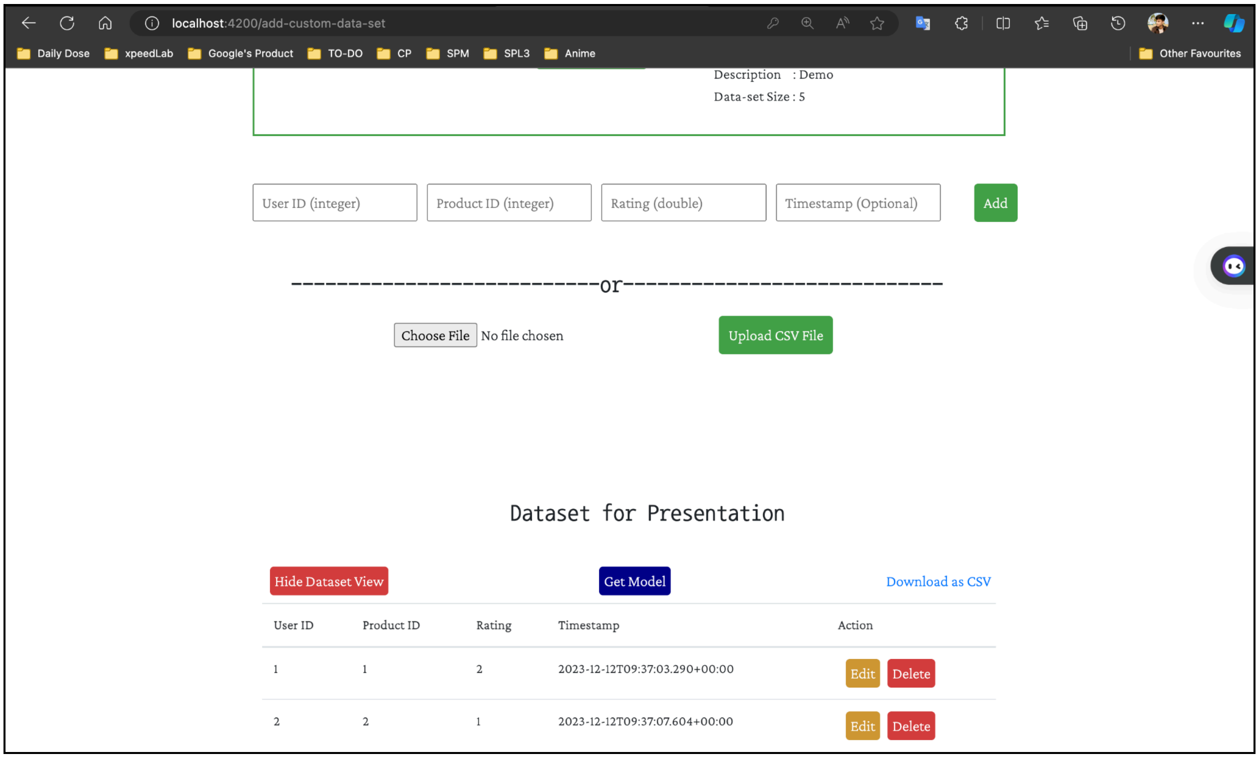

Figure 16: *Get a Model for a project*

11.7 Viewing and Downloading Public Datasets

Explore the wealth of diverse datasets within InterestHub by seamlessly viewing and downloading public datasets contributed by the community. Navigate to the "Public Datasets" section to discover a curated collection of datasets. Users can preview the contents of each dataset, gaining valuable insights before deciding to download. This user-friendly feature encourages knowledge-sharing and collaborative model development, making it easy for users to access and integrate public datasets into their projects for enhanced recommendation system customization.

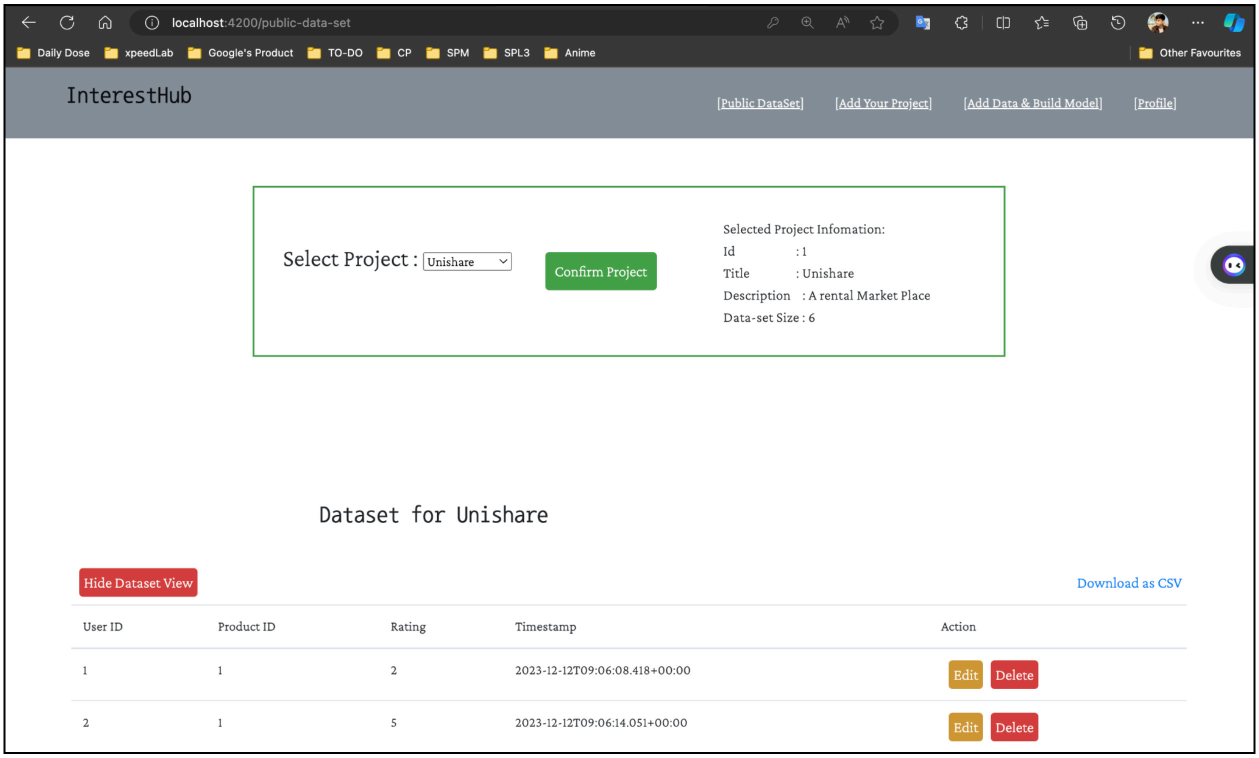

Figure 17: *Public Dataset*

11.8 Movie Discovery and Personalized Recommendations

Discover over 10,000 movies effortlessly with InterestHub's intuitive exploration and search features. Receive personalized movie recommendations based on your preferences, powered by the advanced Neutral Collaborative Filtering (NCF) model. Rate movies for valuable feedback, actively shaping your unique cinematic experience within the vibrant InterestHub community.

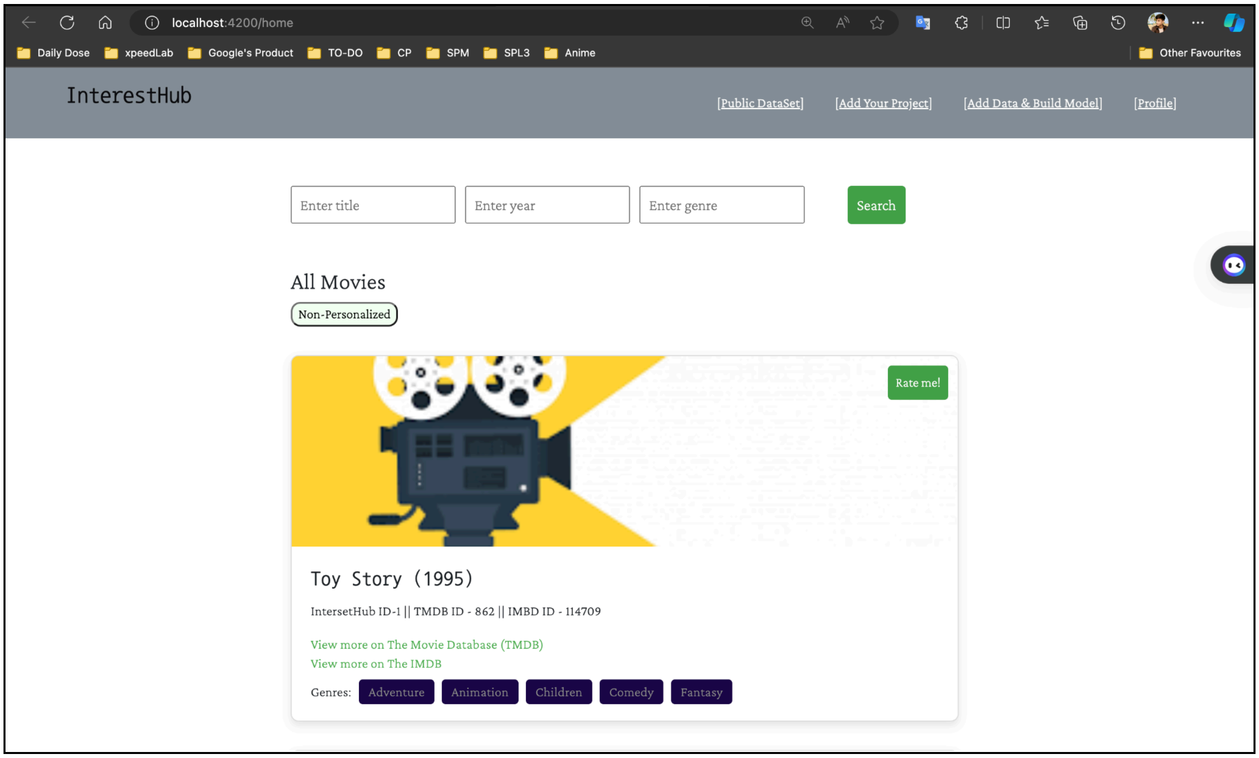

***Figure 18**: All Movies*

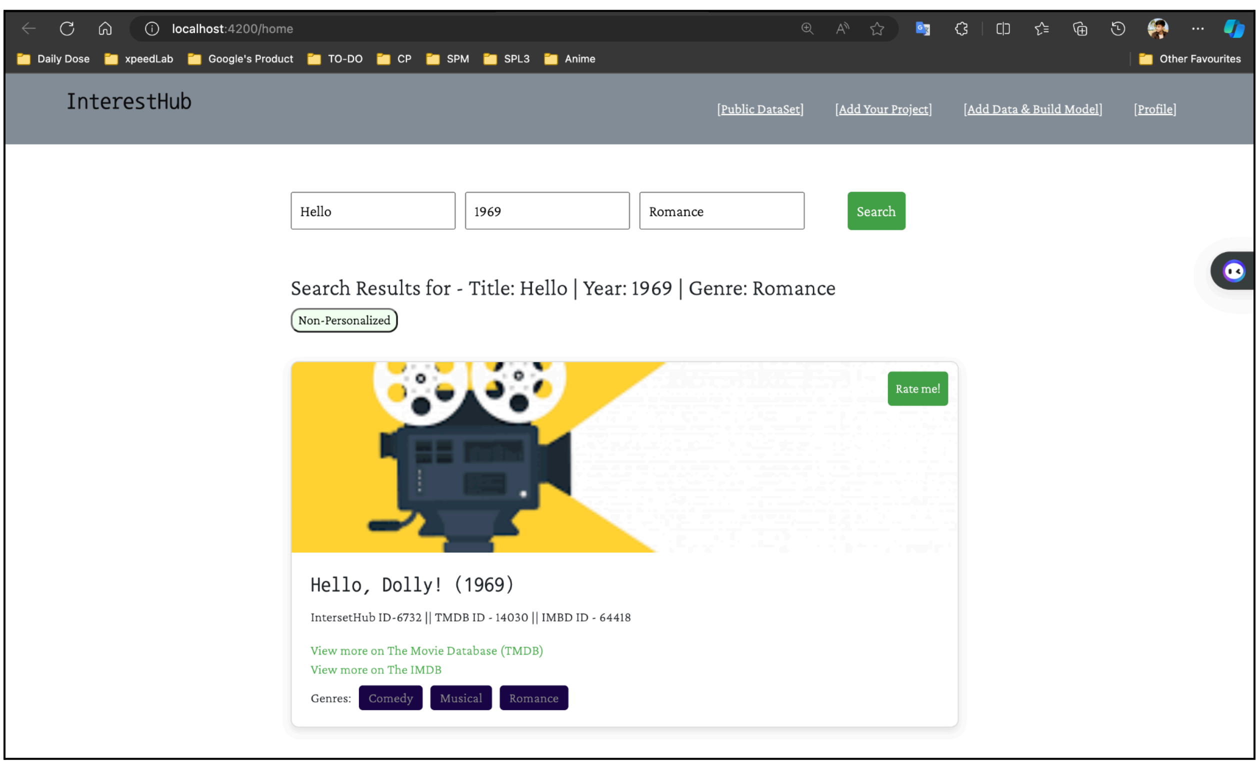

***Figure 19**: Movies based on search*

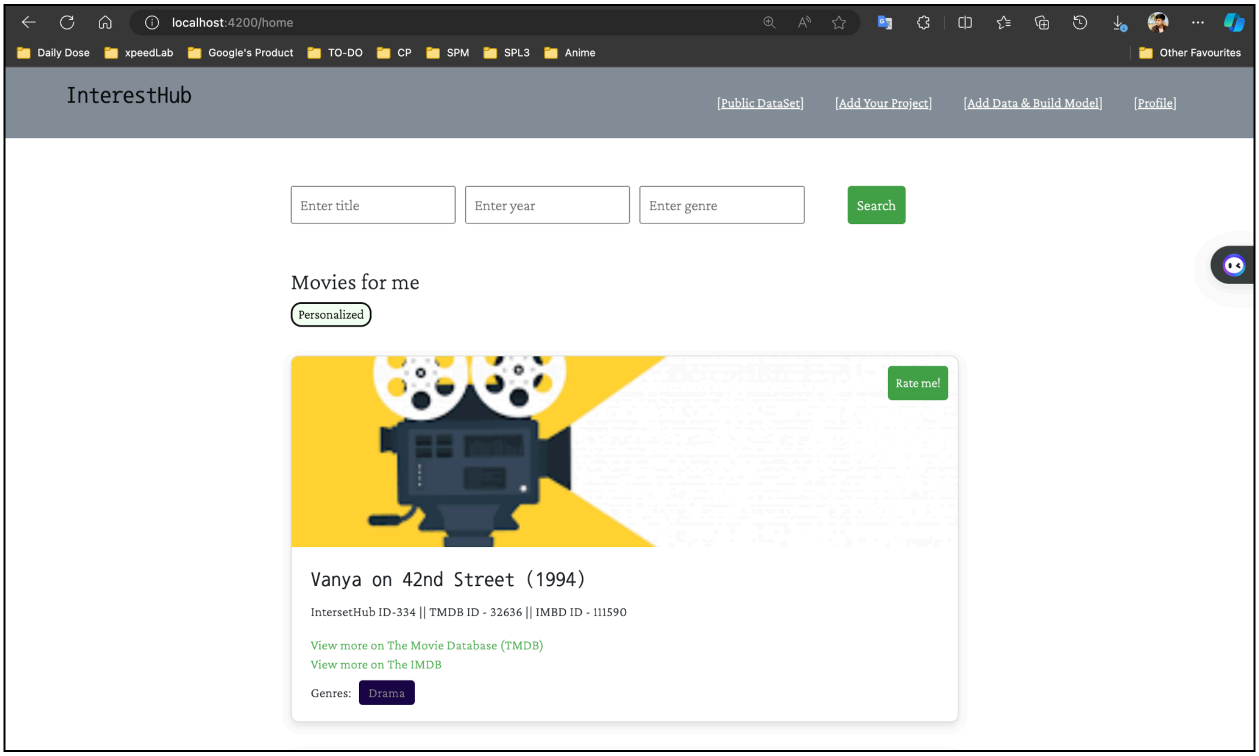

Figure 20: *Personalised movie recommendation*

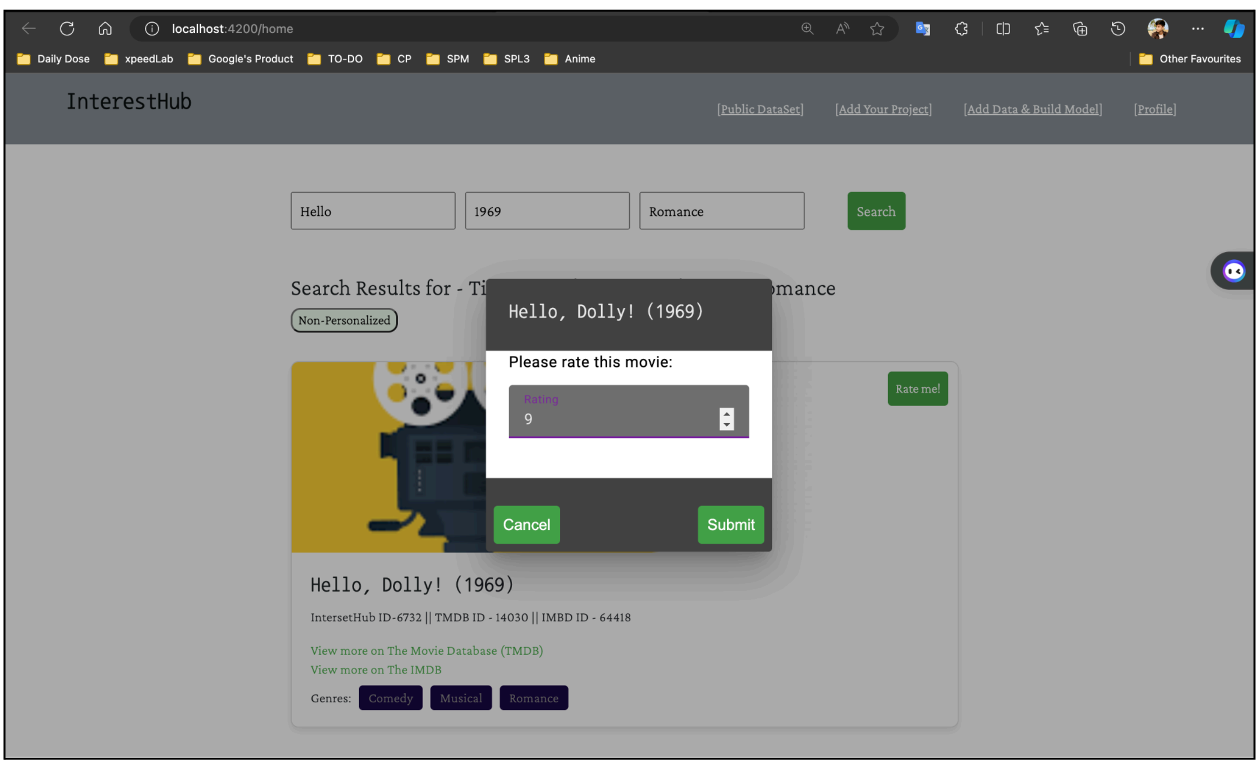

Figure 21: *Collect User Feedback*

Chapter 12: Conclusion

InterestHub emerges as a pivotal tool in the realm of recommendation systems, offering a seamless and user-centric experience. The platform's intuitive interface and reliance on Neutral Collaboration Filtering (NCF) fulfill basic user needs, ensuring accessibility and accurate model creation. Beyond stability and dataset submission, InterestHub introduces exciting elements, such as continuous model improvement and a comprehensive movie database, exceeding user expectations.

The tool's value extends beyond individual use, fostering a collaborative environment where users can share datasets and contribute to the refinement of recommendation models. By seamlessly integrating these models into personal projects, InterestHub becomes not just a recommendation system but an integral part of users' applications, enhancing their overall experience.

As we look ahead, InterestHub's potential for growth remains significant. Exploring real-time model updates, additional recommendation algorithms, and enhanced collaboration features could further elevate the platform. In conclusion, InterestHub is more than a tool; it's a dynamic platform driving innovation and collaboration, poised to adapt and thrive in the evolving landscape of personalized recommendations.

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