# Recommender Systems: A Comprehensive Review of Models, Techniques, and Emerging Trends

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## Section I: Abstract

Recommendation systems' main goal is to provide a consumer with relevant objects based solely on historical data. A movie that has received a high rating from a customer who has also seen the film you are currently viewing may appear in the suggestions. It's likely that almost everyone will enjoy the movies with the highest total scores. CineMatch is the name of the algorithm that performs all of these functions. Regarding individual users, it also gains insight from their behavior to enhance the likelihood that they will find a film engaging. Here, we need to apply cutting-edge collaborative filtering approaches to boost our CineMatch algorithm by 10%.
Keywords: Sparse matrix, Similarity matrix, Movies, Ratings, Machine learning models.

## Section II: Introduction

1. INTRODUCTION

The dynamic landscape of cinema consumption has made it imperative for entertainment platforms to provide consumers with personalized movie recommendations for the digital era. embracing a paradigm similar to that of outcome-based education (OBE), in which the mainstay of educational efficacy is the achievement of outcomes, The goal of the movie recommender system is to improve the cinematic experience by anticipating viewer preferences. Similar to how results are the concrete expressions of students' abilities and proficiencies in the classroom, movie suggestions are the tangible results of tailored entertainment viewing experiences.

Navigating the Cinematic Maze:

The movie recommender system, with its foundation in a pre-planned garland of expected results, is a lighthouse of knowledge in the field of cinematic suggestion, giving the procedure direction and clarity. Organization and clarity are essential components of this framework, creating an environment where viewers' contentment with suggested films is seen as the primary goal. The validation of viewer engagement with suggested movies assumes paramount significance, as elucidated by the astute insights of machine learning algorithms, the keepers of recommendation intelligence, as demonstrated by the body of data-driven insights existing in the history of recommendation systems.

A Call to Action:

A cry goes out across the film industry for platforms to re-calibrate their recommendation algorithms to conform to the principles of viewer-centric recommendation in light of the demands of personalized recommendation. However, in the clamor of entertainment talk, the shadow of uncertainty hangs large, demanding a deliberate attempt to make sense of the maze-like pathways of suggestion optimization. Platforms are urged to steer towards recommendation enlightenment by using data-driven knowledge and analytical research as a prism. In this scenario, recommendations work as the lodestar, pointing viewers in the direction of immersive experiences and satisfying cinematic moments.

A. Motivation and Scope

The era of facts is ending and the era of recommendations is beginning. A recommender system bases its prediction, like many other device mastering approaches, on users' past behavior. It is specifically to anticipate that a user will select a defined set of products solely on the basis of prior experience.

B. Need to study

The importance of recommendation systems is growing in the incredibly hectic world of today. Due to the numerous tasks that people have to complete in the limited 24-hour period, people are never on schedule. As a result, the recommendation structures are essential since they enable them to make wise decisions without depleting their mental energy. A recommendation system's primary function is to find content that would excite a particular user. Additionally, it has several features that allow for the creation of personalized lists of interesting and helpful stuff for each user or individual. Artificial intelligence-driven algorithms, known as recommendation structures, scan through all of the options to generate a personalized list of items that may be interesting and pertinent to a given person.

C. Literature Survey/Review of Literature

• Rate predictions and ratings are the two main tasks that collaborative filtering algorithms address. On the other hand, ranking fashions make advantage of implicit input (such as Clicks) to provide the user with a personalized ranked list of recommended things [1].

• Privacy-preserving collaborative filtering has drawn more attention as the requirement to protect confidential statistics while also providing guidance grows. Numerous strategies were put up to estimate pointers without seriously endangering privacy, hence improving the comfort level of statistics proprietors even as they communicate forecasts. By using excellent privacy-retaining procedures, these technologies eliminate or lessen the private, financial, and legal issues of data proprietors [2].

• The ability to swiftly choose one's favorite movie from a vast array of options becomes crucial in the dissemination of information. Especially when a person lacks a clear goal movie, customized recommendation engines might be quite important. [3].

• In this study, we learn about the KNN method and the collaborative filtering method and use them to create and implement a prototype movie recommendation machine that combines user preferences with real movie recommendations [4].

• In this paper, we investigate a randomized reaction methodology, which is a privacy-preserving collaborative filtering technique for basic facts. We create a technique centered on the second privacy concern to determine fake binary rankings through the use of auxiliary and public data [5].

• If privacy safeguards are offered, they can choose to become concerned about the techniques used in prediction generation. In order to eliminate e-commerce sites' privacy issues, we support privacy-maintaining techniques that provide predictions based on allocated data [6].

• The recommendation engine has become increasingly popular as e-commerce and the Internet have developed. This research examines how the electronic commerce recommendation system uses the collaborative filtering algorithm as a specialization in the personalized film recommendation system [7].

II. RESEARCH GAP

In addition to a prediction accuracy bar that is 10% higher than what the Cinematch algorithm can achieve on an equivalent training data set, the data set included a good deal of rating information. (Accuracy is a metric used to quantify how closely real rankings follow closely predicted movie scores. Additionally, we need to estimate the rating a customer will give a film that they haven't yet given a score for. Minimize the discrepancy between the predicted and real score as well.

## Section III: Methodology

Given the prevalence of information overload in the present digital era, sophisticated recommendation systems have become indispensable. Content-based recommender systems leverage natural language processing and machine learning to provide a customized recommendation based on user preferences. This provides a comprehensive overview of the strategy, its advantages, and its impact on people's lives as well as the entertainment sector:

• Need in the Modern Era: Users are sometimes faced with an abundance of options because to the vast amount of content that is available on many platforms, such as social networking, e-commerce sites, and streaming services. Traditional web browsing and content search methods are becoming more time-consuming and ineffective. Thus, there is a growing need for recommendation systems that can effectively filter and present relevant content based on users' interests and past interactions.

• Advantages: - Customization: Item attributes and previous user interactions are used by content-based recommender systems to generate recommendations that are specific to each user. This customisation boosts user happiness and engagement by showing content that aligns with their preferences and interests. Reduced Information Overload: By eliminating irrelevant content and providing users with a well curated list of recommendations, content-based recommender systems assist in reducing information overload. Users can discover new material that interests them without being inundated with irrelevant options.

- Enhanced User Experience: Personalized recommendations improve the user experience in general by expediting the process of finding relevant information and making it easy to obtain products, services, or entertainment options. This leads to higher levels of user engagement and loyalty.

- Efficient use of Resources: information-based recommender systems efficiently use resources by directing users to information that is likely to resonate with them. Consequently, this leads to a more efficient allocation of resources, such as server capacity and marketing campaigns, saving businesses money and increasing return on investment. impact on both the entertainment industry and lives.

- material-based recommender systems empower users by allowing them to select material that aligns with their interests and generate customized recommendations, so providing them a feeling of control and authority over their digital interactions.

- Diversification of information Consumption: Individualized recommendations increase the likelihood that users will find a greater range of information than they otherwise might. This diversity improves their entertainment experiences, exposes them to new ideas, and fosters cross-cultural dialogue.

- Assisting Content Creators: Content-based recommendation systems play a crucial role in providing assistance to content creators by streamlining the process of finding content and reaching a wider audience. These technologies contribute to the growth and longevity of the entertainment industry by enabling the interaction between content providers and relevant viewers.

- Encouraging Innovation: As content-based recommender systems gain traction, fresh approaches to the creation, usage, and sharing of material are welcomed. material makers and platforms put in a lot of effort to encourage creativity and innovation in the entertainment sector so that they may produce unique and captivating material that resonates with their target viewers.

In conclusion, modern content-based recommender systems can efficiently handle the issues of information overload and content discovery in the digital age. The ability of these systems to offer customized recommendations enhances user experiences, encourages engagement, and promotes innovation across various sectors, including the field of entertainment. By employing state-of-the-art machine learning techniques, information-based recommender systems have the potential to profoundly impact people's interactions with and consumption of information in the future.

1. Dataset Collection

A complete collection of data must be obtained from numerous sources, including Kaggle and The Movie Database (TMDb), in order to provide information for a content-based recommender system. On Kaggle, you may find a multitude of datasets spanning a wide range of subjects, including music, movies, literature, and more. It provides structured data sets with descriptive information about items, user preferences, and interactions. The specialized movie website TMDb has an abundance of information, including cast, genres, plots, movie titles, and user ratings. By using both Kaggle and TMDb, a wide range of data points can be collected and utilized to train the recommender system, ensuring the system's effectiveness in generating personalized recommendations tailored to individual preferences and interests.

With almost 5000 movies, we gathered a sizable dataset for our research. This dataset includes extensive information on every film, such as storyline synopses, actor bios, genres, and user reviews. The casting data provides details about the actors and actresses in each film, allowing for an analysis of how their selections impact the preferences of the audience. Insightful sentiment data is provided by customer reviews, which express the opinions and feelings of viewers about the movies. Genres categorize films into distinct thematic categories, making them suitable for use in genre-based recommendation systems. Storyline descriptions include textual summaries of movie plots, enabling content analysis and recommendation using natural language processing techniques.

- Points Considered

In addition to the extensive collection of almost 5000 films, we have considered a crucial aspect: the audience's inclinations towards specific actors. When collecting data, we considered the fact that, regardless of the film's ultimate rating, fans usually watch movies starring their favorite stars. This entails compiling data on the celebrities that feature in each movie and acknowledging that, despite a film's low rating, viewers may prioritize seeing films starring their favorite actors. By considering viewers' affinities for specific actors, we enhance the relevance and accuracy of our content-based recommender system, making it more in line with users' individual preferences and watching habits.

When collecting data, we have considered the impact of directors and their unique styles. We recognize that many directors have a reputation for consistently delivering a particular type of picture over an extended period of time, which is why we have assembled information on directors' filmographies and the genres or subjects that are associated with them. Based on the understanding that audiences often develop preferences for directors whose aesthetic appeals to them, this acknowledgement is made. Because our recommender system considers directors' preferences for specific genres or subjects, it may be able to suit viewers with specific tastes in filmmaking. This guarantees that the recommendations closely align with the audience's expectations and interests.

Most practical machine learning research focuses on preparing and organizing data such that it is suitable for machine learning algorithms. Preprocessing data has a direct bearing on the specific problem at hand, such categorizing text or photos. Whereas text classification focuses on extracting features from the text, image classification places more emphasis on identifying relevant aspects within the images. Once the data is prepared, researchers typically use multiple machine learning algorithms in trials to determine which is most effective for the given problem. The effectiveness of these algorithms is often dependent on the nature of the dataset, which varies according on the task.
Many research publications start their preprocessing stages with traditional machine learning methods designed for single-label data. When dealing with problems involving several labels and classes, two main categories of methods are commonly applied:

1. **Problem Formulation for Recommender Systems (PMRS) through Problem Transformation (PT):**

By defining the suggestion problem as a multi-label multi-class situation, our technique handles both multi-label and multi-class scenarios. In multi-label recommendation, a movie can be linked to many genres or subjects, with a desired cardinality of less than two (0 or 1) for each category. with contrast, with multi-class recommendation, a single target with a target cardinality more than two indicates the expected genre in a predefined set.

When working with datasets that contain multi-label multi-class or multi-output multi-class information, problem transformation techniques are used since movies may be associated with several genres or subjects with a target cardinality greater than 2. A multi-label recommendation system, for instance, might simulate relationships between multiple movie genres using methods like Monte Carlo procedures to increase prediction accuracy. Frequently used techniques such as binary relevance are used to convert multi-label recommendation problems into single-label classification data, where each movie instance is associated with a single projected genre label. During formulation, each genre is considered as a distinct input for the learning process, and binary classification techniques are used to each genre independently. After the transformation is finished, binary classification techniques can be used to predict the right genre labels for each film.

## 2. Algorithm Selection and Evaluation for Recommender Systems (AEMRS):

The optimal method for addressing the movie recommendation problem is selected and assessed in AEMRS. It is required to assess the performance of multiple alternative recommendation algorithms in order to determine which one performs the best in terms of accurately projecting movie genres. The former approach applies its methodology differently from the later in the setting of movie recommender systems, drawing inspiration from both PMRS and AEMRS.

In PMRS, the multi-label movie dataset is constructed to fit the recommended recommendation algorithms, whereas in AEMRS, the recommendation algorithms are updated to fit the multi-label movie dataset so as to select the most effective one. Our recommended movie recommender system uses advanced algorithms designed to handle multi-label movie genre classification datasets in order to address the unique challenges posed by movie recommendation jobs.

In summary, the preprocessing stage of a movie recommender system project often involves modifying traditional machine learning algorithms to handle multi-label and multi-class movie genre prediction tasks through problem transformation techniques, like binary relevance, in order to enable effective recommendation and prediction processes.

1. Identification of Movie Distribution Across Genres (IMDAG): Understanding the number of movies in each genre category is crucial for optimizing the performance of movie suggestion algorithms. By analyzing the distribution of movies within categories, recommender systems can fine-tune their algorithms to better suit user interests and improve the quality of recommendations. The quantity of movies in each genre group directly affects how well the system learns to predict user preferences and enhances the overall user experience.

2. Classification of Movie Features (CMF): A film is categorized based on a number of factors, such as its genre, director, ensemble of performers, and story aspects. Every movie has at least two features associated with it in order to paint a complete picture of its attributes. Sample videos with a range of feature combinations are included in the collection. Recommender systems can leverage a wide range of film aspects to give users a customized and engaging viewing experience with the aid of this classification system.

3. Number of Genres in Each Film: Every movie is distinct and belongs to a specific genre based on its underlying themes. The quantity of genres a film includes directly affects its appeal and audience participation. A movie recommendation engine that considers the tastes of a broad audience may suggest more films that straddle many genres than it would films with less category associations. The range of genres a film explores influences both its overall appeal and the enjoyment of its audience.

In conclusion, the number of genres associated with a given film has a considerable impact on both viewer preferences and the effectiveness of recommendation systems. Possibilities to enhance viewer satisfaction through personalized recommendations and targeted initiatives aimed at improving the quality of the film content expand in line with the diversity of genres.

Rating Distribution: The rating distribution is derived from the total user-assigned ratings for each film. As Table 3 shows, ratings might be high, above average, average, below normal, or poor. Options for enhancing users' movie-watching experiences rely on the application of a binary feature technique for user categorization. This strategy operates in the following ways:

Determine the mean value µ10 for each characteristic to get the user category feature δ. A 60% total success percentage is the rating mechanism's success level. The algorithm below is used to determine the user category feature using the mean value µ10.

Films are assigned a rating score based on the type of potential mechanism that is explained. To encourage

$$\text{User Category } \delta = \begin{cases} 0, & \text{if } \delta < 60 \text{ (Poor User)} \\ 1, & \text{if } \delta \geq 60 \text{ (Satisfied User)} \end{cases}$$

suggestions for enhancing the movie recommendation system, the total number of users in each rating category is calculated.

### 5. Movie Watching Outcomes (MWOs):

These are the observable reactions that viewers are expected to display after watching a movie. Considering their viewing experience and newly acquired knowledge, these results show what audiences can utilize in real life. A few of the elements that make up MWOs are comprehension, emotional response, critical thinking, and involvement with the movie's content. The MWOs, or clearly defined statements, encompass the specific knowledge, feelings, critical thinking abilities, and overall engagement with the film subject that viewers are expected to gain and demonstrate by the conclusion of their movie-watching experience.

Various actions might be required for every Movie Watching Outcome (MWO) to enhance viewer satisfaction and engagement. After calculating each MWO's achievement percentage, the Movie Recommender (MR) algorithm makes a number of recommendations aimed at improving the caliber of the movie recommendation and the viewing experience. These could be recommendations for relevant movies, content that is specifically catered to, or adjustments made to the recommendation algorithm to better accommodate audience preferences and standards.

- **PREPROCESSING OF DATA**

In applied machine learning research, a lot of work goes into organizing and preparing data to satisfy the requirements of machine learning algorithms. Preprocessing is a crucial stage that varies depending on the kind of issue (e.g., text or picture categorization). In the case of a movie recommender system, which is analogous to text classification in which text characteristics are extracted, the key issue lies in identifying relevant features to extract from movie data. Machine learning research has traditionally focused on preprocessing for single-label data. However, as multi-label problems have emerged, such as recommending movies from various genres, new categorization strategies have been adjusted to accommodate multiple class labels.

Multi-label multi-class challenges in movie recommendation systems are usually solved in two ways:

**1. Problem Transformation (PT):**

The recommendation problem is rewritten using this way as a scenario with many labels and classes. In this arrangement, a movie may have various target audiences (multi-class) and multiple genres (multi-label). Monte-Carlo algorithms are among the strategies used to capture the dependencies between different movie genres. Following that, each movie is given a single genre label, and the multi-label multi-class data is condensed into smaller single-label classification data. Binary relevance is used to convert the multi-label problem into single-label classification data, allowing binary classification methods to be used to predict suitable movie suggestions.

2. **Binary Relevance for Multi-Label Classification:**

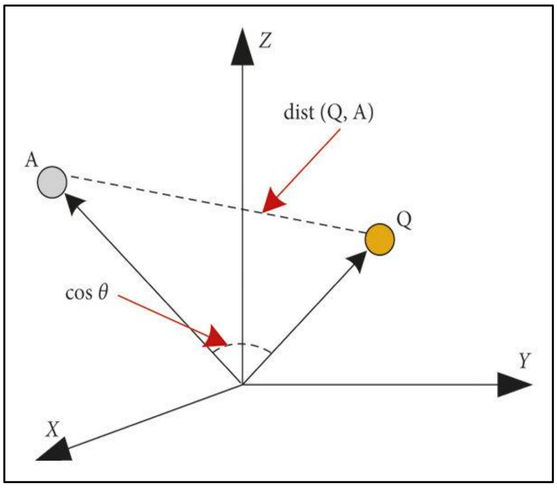
This method involves assigning multiple genre labels to each movie and then going through a binary classification process for each category. This enables the prediction of suggested films according to individual preferences for various genres. Once modified, a binary classification system can be used to generate tailored movie suggestions that take into account each user's tastes and watching habits. The performance of these algorithms depends on the nature and quality of the movie dataset, and several strategies are employed to effectively handle the multi-label component of the recommendation task.

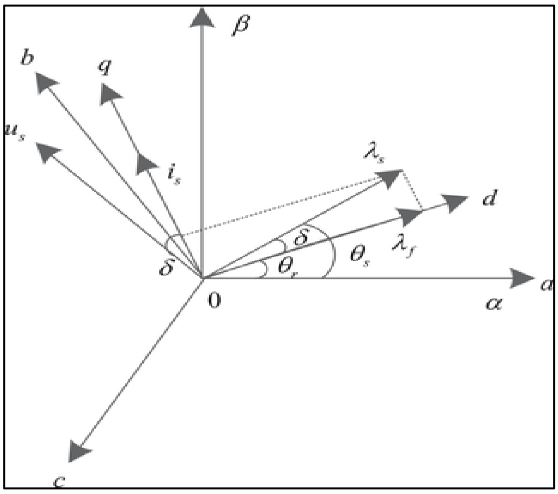
**Data Filtering in Recommender Systems:**

Data filtering is a crucial step in enhancing the dataset so that movie recommender systems perform better. It means getting rid of information that is unneeded or unnecessary and doesn't really affect how good the recommendations are overall.

In relation to movie recommendation systems, input from users can be processed based on multiple characteristics to improve system efficiency. Users could be divided into different groups based on, for instance, how they interact with the system. By categorizing customers based on their interaction patterns, movie recommender systems can enhance user happiness by making recommendations that are more tailored to the preferences of the user. This filtering process helps improve the dataset and guarantees that only relevant user data is used to provide personalized movie recommendations. Our recommendation for the results is based on cosine similarity.

Cosine similarity is a commonly used metric in recommendation and text mining systems that measures the degree of similarity between two vectors by calculating the cosine of the angle that separates them. Packages like NumPy or Scikit-learn, which aid in tasks like collaborative filtering and document clustering, are frequently used to compute it in Python. The two vectors' alignment on a two-dimensional plane is represented graphically by the cosine of the angle between them, which varies from -1 (different directions) to 1 (same




direction) and 0 (orthogonal). This geometric interpretation contributes to a coherent explanation of vector similarity in high-dimensional domains.

1) **Handling Missing Values in Recommender Systems:**

The movie recommender systems dataset's missing values are handled with a methodical approach. Null values in numerical fields are replaced with 0 in order to preserve consistency and prevent computational errors. Null fields that indicate recommended actions are likewise set to 1 in order to distinguish between missing values and the absence of recommendations. This preparation step ensures that the dataset is suitably formatted and ready for analysis and suggestion development.

**2) Mapping activities to Recommendations in Recommender Systems:**

The nine categories of suggested activities by the movie recommender system are as follows. Table 4 enumerates these acts and plots them on a scale of 0 to 8, with 1 representing "no action." Each activity in the dataset is associated with a unique number of samples, totaling 304 samples. The recommendations are derived from user-generated film summaries at the end of every screening. An analysis of user preferences and behavior leads to recommendations for actions to enhance the entire movie-watching experience. Actions such as "add more runtime to the movie" that are unnecessary or impractical are eliminated at the preprocessing stage.

The movie recommender system's final input data after preparation. Every recommended movie has a set of activities associated with it, based on user preferences and interactions. These class actions aim to improve the quality of the movie suggestion process while ensuring that clients have a personalized and enjoyable viewing experience.

In this part, we discuss different issue transformation approaches in the context of a movie recommender system. We also discuss an adaptive strategy that we apply to five base classifier algorithms. Multi-label learning is a crucial step in the supervised learning process that addresses scenarios with multiple labels. Unlike traditional systems that learn from single-label data, multi-label learning involves training datasets associated with multi-label multi-class binary classification.

As seen in Figure 1, the framework has training as well as testing protocols. The training dataset is utilized to fit pre-processed data into preset issue transformation algorithms, while the testing dataset remains independent. However, if the dataset has already been fitted in the training dataset, then the characteristics of the testing dataset are also fitted and selected suitably.

The test dataset is used to evaluate the trained models, while the training dataset is used to explore different approaches to issue transformation through the application of machine learning methods. The Movie Recommender System (MRS) selects the top-performing model to serve as the final prediction model. During the problem transformation process, multi-label movie data is converted into several binary classification datasets. The four issue transformation approaches employed are One-vs-All (OvA), Binary Relevance (BR), Label Powerset (LP), Classifier Chains (CC), and an adaptive classifier based on the ML-KNN classifier.

This comprehensive approach can be used to evaluate and select the optimal model for generating personalized movie recommendations based on user preferences and viewing habits. By turning the multi-label movie data into binary classification datasets, the system can effectively handle the complexity of recommending movies across many genres while ensuring accurate and relevant suggestions for customers.

## Section IV. IMPLEMENTATION

### A. Reading and Storing Data

The dataset I am working with is downloaded from Kaggle .https://www.kaggle.com/Netflix-inc/Netflix-prize data.

It consists of four .txt files and we have to convert the four .txt files to .csv file. And the .csv file consists of the following attributes.

MovieID: Unique identifier for the movie.

CustID: Unique identifier for the Customer.

Ratings - 1 to 5: Rating between 1 to 5.

Date: Date on which customer had watched the movie and given rating.

Following the completion of the statistical analysis, we must check the records set for empty values. using the null characteristic. We designate missing values as NaN when using Python, particularly with Pandas, NumPy, and Scikit-Learn. Values that have a NaN cost are not included in operations such as count, sum, etc. Using the replace () function on a subset of the columns we are interested in, we can easily designate values as NaN with the Pandas Data Frame.

## Section V: WEBSITE DESIGN

System design is the process of specifying the armature, components, modules, connections, and data so that the system satisfies specific requirements. In summary, this is how systems proposition to product development operates. Building computer systems with object-oriented design and analysis techniques is quickly becoming the most common option.

System design is the process of establishing the fundamental components of a system, such as its modules, armature, factors, and data, based on the criteria that have been established for the system. It is the process of identifying, creating, and designing systems that satisfy the particular needs and specifications of an organization or business. Synopsis An efficient and harmonious system

The nethermost-up or top-down method is required to take into account all relevant system variables. A developer can represent data and knowledge in a methodical framework with well-defined rules and delineations by using modeling languages. Modeling languages that are verbal or visual can be used to define plans. Examples of graphical modeling languages include

a) A graphic memo using the Unified Modeling Language (UML) to describe the structural and functional aspects of software.
b) A flowchart, which is an algorithm's schematic or step-by-step description.c. A process modeling language that uses the business-specific Business Process Modeling Memorandum (BPMN). SysML, or the Systems Modeling Language, is used to design systems.

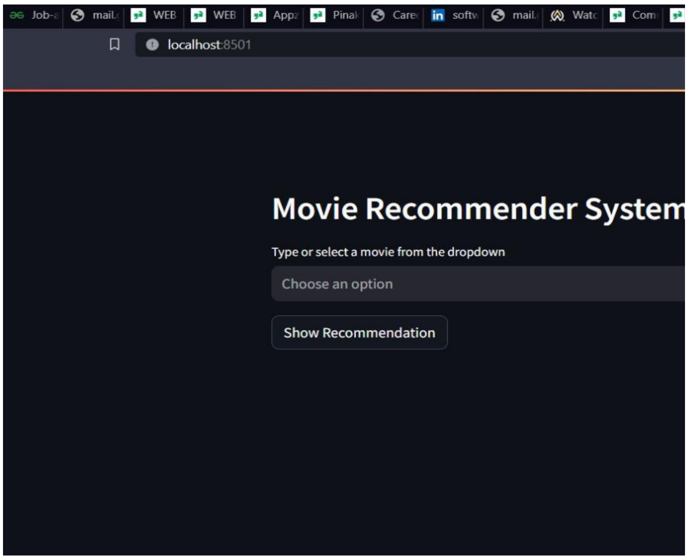
c) Design styles
   1) The perspectives, models, gestures, and system structure are all described by architectural design.
   2) The system's labors, inputs, and information intake are represented through logical design. example reality relationship plates, or ER plates.
   3) Physical design is described as follows:

i) how users contribute data to the system and how the system provides the user with data.
ii) The system's modeling and storage of data.
iii) The way information enters and exits the system, as well as how it is verified, guarded, and/or transformed.

## Section VI: RESULTS / OUTPUTS & TESTING

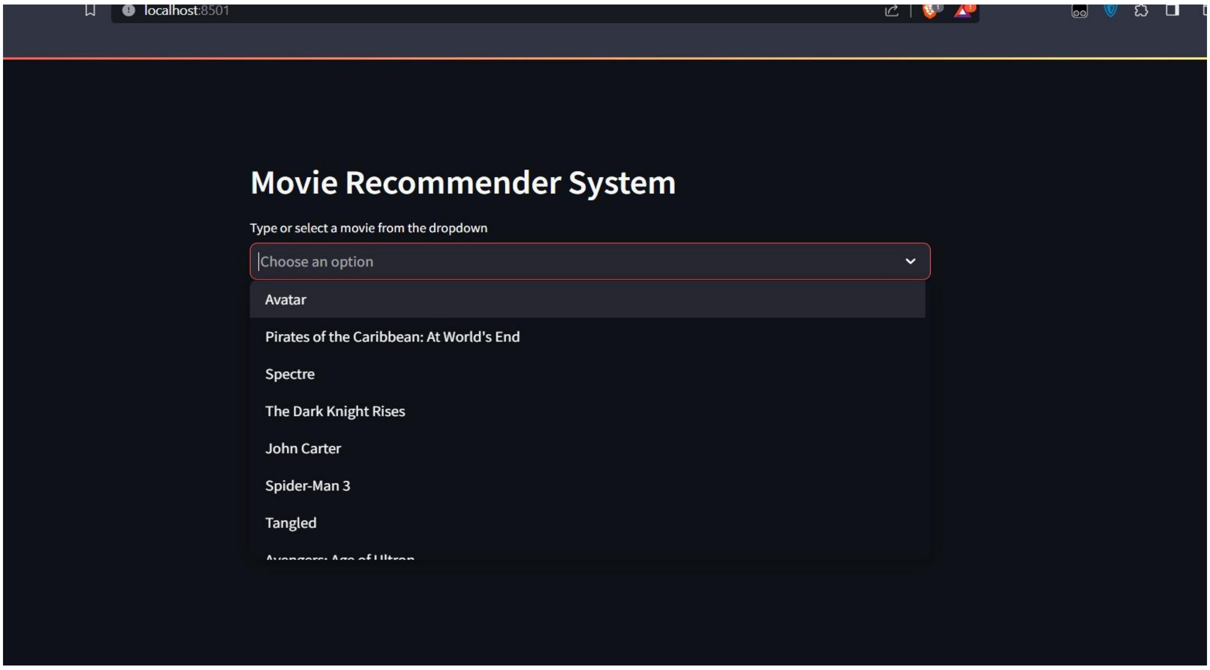
### 7.1 ALL USER INTERFACES AND OUTPUT SCREENS

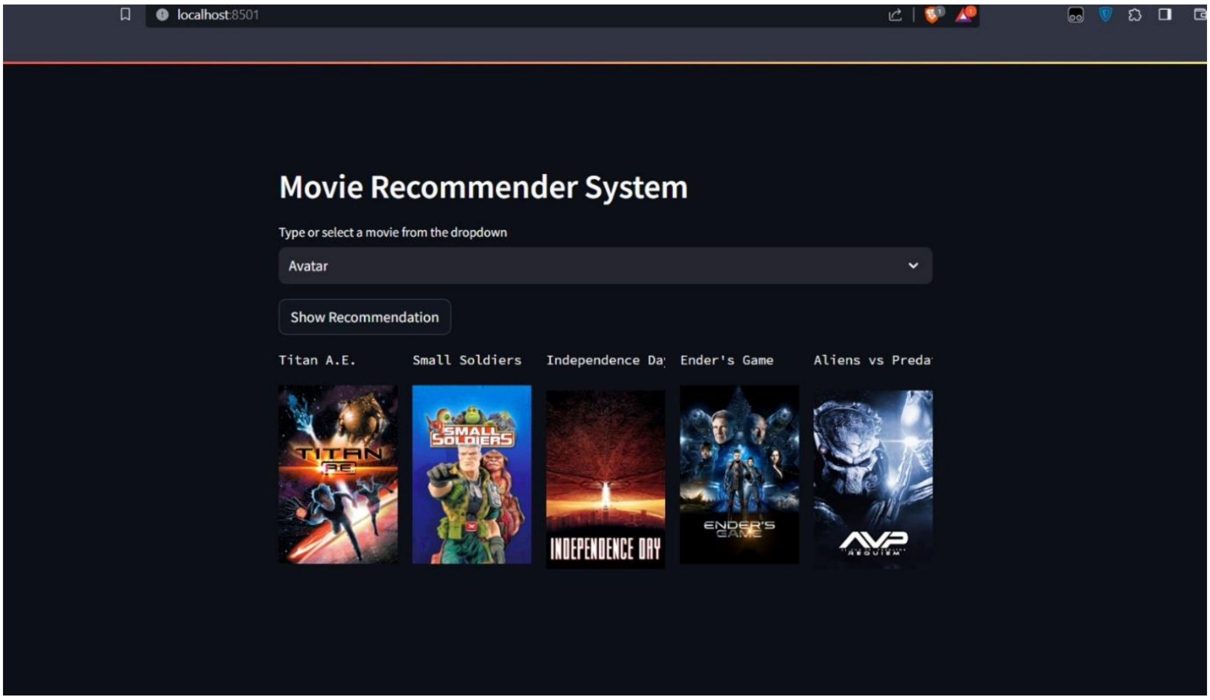
Landing Page




Result (Recommended Movies)

**User Input**






## REFERENCES

[1] Davidsson C, Moritz S. Utilizing implicit feedback and context to recommend mobile applications from first use. DOI: 10.1051/,04008 (2017) 712012ITA 2017 ITM Web of Conferences itmconf/201 40084 In: Proc. of the Ca RR 2011. New York: ACM Press, 2011. 19 22.http://dl.acm.org/citation.cfm?id=1961639[doi:10.1145/1961 634.1961

[2] Bilge, A., Kaleli, C., Yakut, I., Gunes, I., Polat, H.: A survey of privacy-preserving collaborative filtering schemes. Int. J. Softw. Eng. Knowl. Eng. 23(08), 1085–1108 (2013)CrossRefGoogle Scholar.

[3] Calandrino, J.A., Kilzer, A., Narayanan, A., Felten, E.W., Shmatikov, V.: You might also like: privacy risks of collaborative filtering. In: Proceedings of the IEEE Symposium on Security and Privacy, pp. 231–246, Oakland, CA.

[4] Okkalioglu, M., Koc, M., Polat, H.: On the discovery of fake binary ratings. In: Proceedings of the 30th Annual ACM Symposium on Applied Computing, SAC 2015, pp. 901–907. ACM, USA (2015).

[5] Kaleli, C., Polat, H.: Privacy–preserving naïve bayesian classifier based recommendations on distributed data. Comput. Intell. 31(1), 47–68(2015).

[6] Munoz-Organero, Mario, Gustavo A. Ramíez-González, Pedro J. Munoz-Merino, and Carlos Delgado Kloos. "A Collaborative Recommender System Based on Space-Time Similarities", IEEE Pervasive Computing, 2010.

[7] Peng, Xiao, Shao Liangshan, and Li Xiuran. "Improved Collaborative Filtering

Algorithm in the Research and Application of Personalized Movie.