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**October University for Modern**

**Sciences and Art**

**Faculty of Computer Science**

**Graduation Project**

**Movie Recommendation System**

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## **Abstract**

An overview of recommendation systems, which utilize algorithms to propose goods and services to clients based on their tastes, is given in this article. Cooperative filtering and content-based filtering, the two categories of recommendation systems, are described along with examples of how they are used in different fields of business. The popularity of movie recommendation engines on online platforms is cited as the reason for the rise of recommendation systems, and the advantages of adopting these systems are emphasized, including elevated client happiness and engagement. The paper argues for the creation of more complex and open systems, but it also admits the limitations, such as potential biases and challenges in delivering recommendations to clients.

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# Chapter 1: Introduction

## 1.1 Introduction

### Background:

Recommendation systems are a collection of ways and algorithms used to suggest goods or services to customers grounded on their preferences. These systems are used in a wide range of operations, including social media, streaming services, and Movie. There are two types of recommendation systems cooperative filtering and content- grounded filtering. While cooperative filtering is dependent on connections between consumers for advice, content- grounded utilization uses product characteristics and individual preferences as a tool to make opinions.

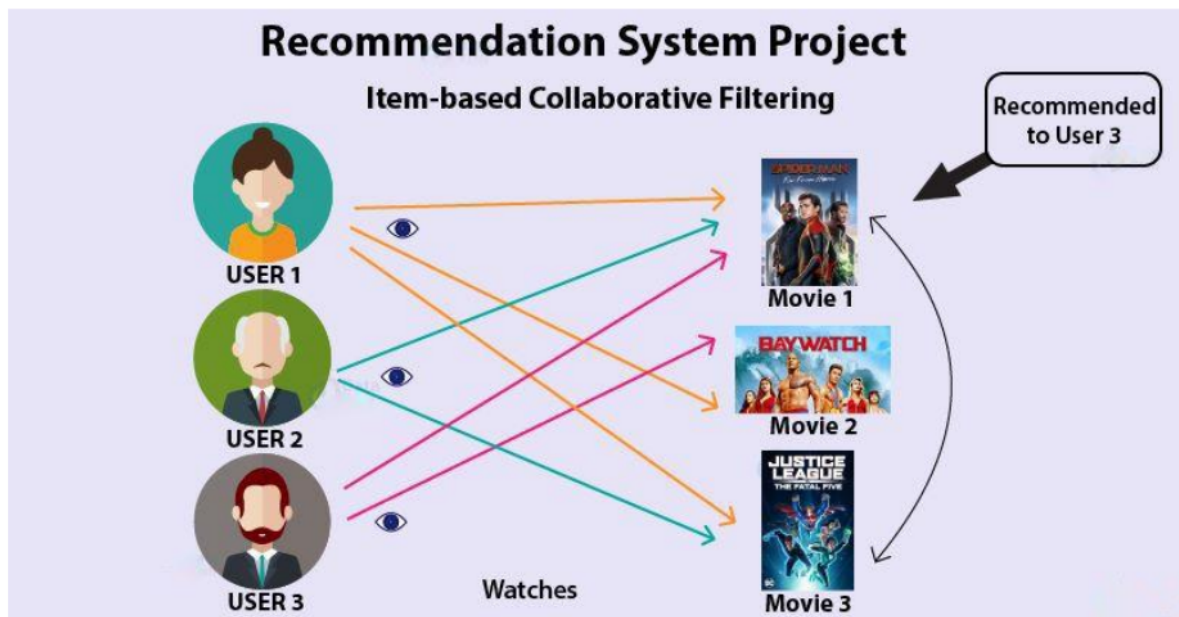


Figure 1: Recommendation system project

### Scope and definition:

The main ideal of recommendation systems is to increase stoner engagement and happiness by making personalized recommendations. These styles can be used in a variety of diligence,

including music, pictures, books, cuffs, and more. <sup>14</sup> The purpose of recommendation systems is to help druggies find new goods or content that they might be interested in.

#### Current situation:

Figure 1 shows the growth report of recommendation systems from 2018-2028. This growth is referenced to the Movie recommendation engine expansion of online platforms. To satisfy client need, many companies, like Amazon, Spotify, and Netflix, have enforced recommendation algorithms. In 2021 Adobe Research said that, approximately 34% of online shopping people expected to do more buys when having recommendations according to past purchase history they made. [1]

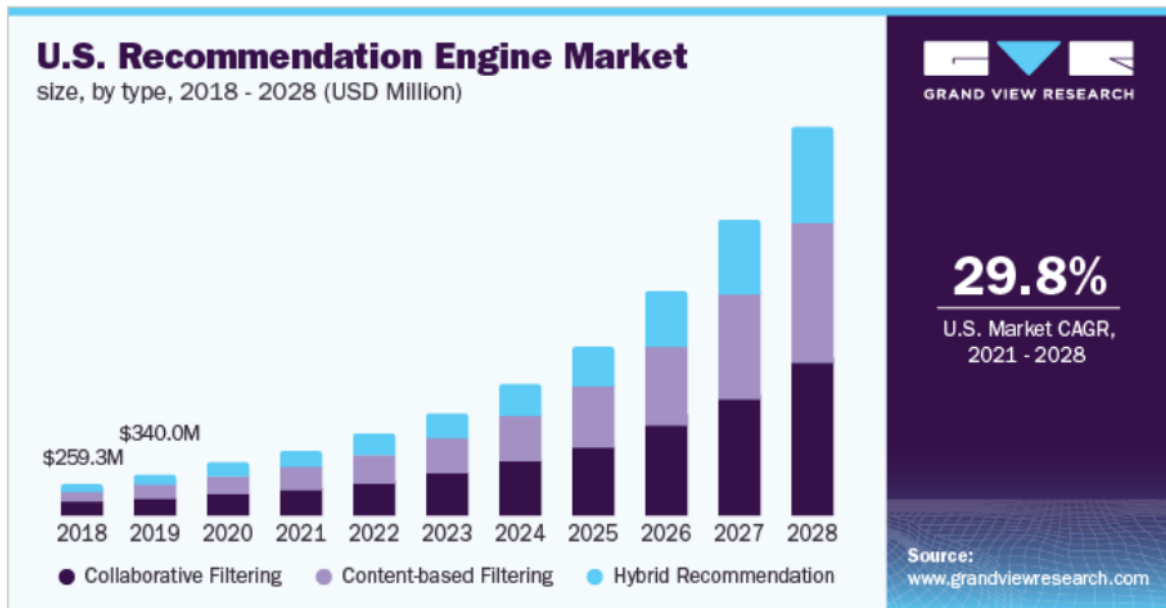


Figure 2: Object detection result on sample images

#### Evaluation and gaps:

The current state of recommendation systems has a number of advantages, similar as advanced stoner engagement, advanced deals, and advanced stoner happiness. Yet, there are some disadvantages as well, similar as the eventuality for prejudice and the difficulty in presenting the suggested remedies to guests. Also, there's a need for the creation of further sophisticated



recommendation systems that are transparent and give druggies lesser influence over how recommendations are made.

## **1.2 Problem statement**

The current state of recommendation systems provides a number of advantages, including improved user happiness, higher user involvement, and increased revenue. Yet, there are some disadvantages as well, such as the potential for prejudice and the difficulty in presenting the suggested remedies to clients. Also, there is a need for the creation of more sophisticated recommendation systems that are transparent and provide consumers greater influence over how suggestions are made.

## **1.3 Objective**

To analyze and understand the behavior of online shoppers, including their preferences, interests, and purchase history and to evaluate the performance of the developed recommendation system using relevant metrics such as click-through rate, conversion rate, and customer satisfaction. Overall to develop a recommendation algorithm that can provide accurate and personalized recommendations to customers, which in turn can increase customer satisfaction, improve sales, and drive customer loyalty for the e-commerce platform.

## **1.4 Motivation**

### **– Motivation for others**

The expansion of the Movie sector depends on the creation of an efficient recommendation system. It may improve consumer experience for online merchants, boosting sales and providing them a competitive edge. There is a pressing need for personalized recommendation systems that can effectively analyze client data and provide exact product choices given the unceasing rise of Movie and online purchasing. Retailers may better serve their consumers and increase their revenue by enhancing the efficacy and efficiency of Movie recommendation systems.

### **– Motivation for the researcher**

As a recommendation system researcher, I'm driven to discover an algorithm that can effectively sift through enormous amounts of client information and provide individualized advice in Movie. What my findings may entail for the industry in terms of delivering modern customer experiences and boosting sales also gives me hope. Last but not least, the opportunity to lead ground-breaking recommendation systems and progress the discipline inspires me as a machine learning and AI scholar.

## **1.5 Thesis layout**

The first chapter of this thesis will give an overview of the project's purpose. The second chapter will then include a review of related literature and historical context for earlier work in the same field of study.

## **Chapter 2: Background and Literature**

### **Review**

## 2.1 Background

Movie recommendation systems are aiming to provide users with individualized recommendations based on their browsing and purchasing habits. Collaborative filtering and content-based filtering are two different methodologies that are used to develop such platforms. The data that are available and the specific problem that has to be solved determine which algorithm is chosen. To create an efficient recommendation system that satisfies the particular requirements of a Movie platform, hybrid filtering (a combination of various techniques) can be used.

### 2.1.1 Collaborative Filtering

A well-known technique in recommendation systems, collaborative filtering, makes product recommendations based on the actions and preferences of users who share similar interests. It operates by analyzing previous behavior and locating individuals with similar conduct to propose products they have looked at or purchased. User-Based Collaborative Filtering and Item-Based Collaborative Filtering are two collaborative filtering algorithms.

### 2.1.2 Content-Based Filtering

Content-based filtering uses specific product characteristics, such as color, size, brand, and material, to suggest comparable products to clients. This approach is used by algorithms like K-Nearest Neighbors and Cosine Similarity to compare similarities between articles and suggest the ones that best meet the user's needs.

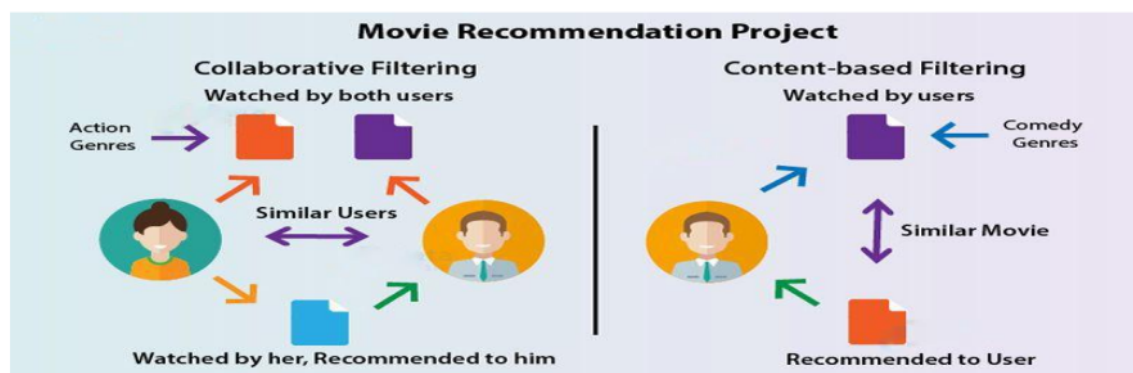


Figure 3: two algorithms

### 2.1.3 Deep Learning<sup>5</sup>

Deep Learning: Deep learning is a subset of machine learning that uses artificial neural networks to learn complex representations of data. In Movie recommendation systems, deep learning is used to learn the user's preferences and behavior patterns from large amounts of data. Examples of deep learning algorithms include Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN).

## 2.2 Previous Work

### 2.2.1 Movie Recommendations Using the Deep Learning Method

In a research paper titled "Movie Suggestions Using the Deep Learning Method," a deep learning-based system for movie recommendations is suggested. To create suggestions based on a user's prior viewing behavior, the authors use Restricted Boltzmann Machines (RBMs) and Convolutional Neural Networks (CNNs) to examine movie posters and metadata. The authors claim that the system surpasses various benchmark approaches on common assessment measures.<sup>19</sup>

It was trained on a sizable dataset of movie posters and metadata. The research illustrates the potential of mixing several types of neural networks to increase recommendation accuracy and overall shows the efficacy of employing deep learning algorithms for movie recommendation.

The challenges of movie suggestion are initially covered in the article, along with the value of employing tailored recommendation systems that take into account a user's viewing interests and history. The next section of the article by the authors outlines the two stages of their suggested deep learning approach: feature learning and suggestion generation.

The authors employ a CNN to extract features from movie posters and an RBM to learn latent features from movie metadata during the feature learning stage. A fully connected neural network receives the combined information learned by the CNN and RBM to provide a rating or recommendation score for each movie.

The system creates a list of suggested movies for the user at the recommendation generation stage using the rating or suggestion scores. The writers Using a sizable dataset of user and movie ratings, they compare the effectiveness of their system to a number of benchmark techniques, such as collaborative filtering and content-based recommendation techniques. They claim that on a number of common evaluation measures, such as precision, recall, and F1-score, their deep learning methodology performs better than the baseline methods.

Overall, the research shows the possibility of employing CNNs and RBMs to learn features from movie posters and metadata and proposes a novel approach to movie recommendation

using deep learning. The authors claim that by combining more data sources, such as user evaluations and social network data, as well as by looking into different deep learning architectures, their methodology might be further enhanced.



Figure 4: An example of the type of questions appraisers were asked to answer in the user evaluation of our deep learning-based system and the user-based KNN approach.

### 2.2.2 Personalized Movie Recommendation Method Based on Deep Learning

The research suggests a deep learning-based solution for tailored movie recommendations. Using best movie ratings and other user data, the approach uses a deep neural network to understand user preferences. The generated individualized recommendations for each user are then based on the learned preferences. The authors compare the suggested method to other state-of-the-art recommendation systems in terms of accuracy and variety of recommendations using a sizable dataset of movie ratings. They also carry out a user survey to confirm the efficiency of the suggested approach in delivering tailored recommendations. Overall, the article offers a viable method for leveraging deep learning to recommend personalized movies. The suggested methodology is based on a hybrid strategy that combines techniques for collaborative filtering and content-based filtering. The content-based filtering component uses aspects of the movies to produce recommendations that are comparable to movies that the user has previously liked, while the collaborative filtering component learns the user preferences based on their interactions with the movie rating system.

The multi-layer perceptron deep neural network utilized in the suggested method accepts as input user ratings and other user data, such as age and gender, as well as movie elements, such as genre and actors. A loss function that minimizes the discrepancy between anticipated ratings and the actual ratings provided by the users is used to train the network. Using a dataset of more than 100,000 user-submitted movie ratings from the Movie lens platform, the authors assess the proposed technique. They contrast the effectiveness of their approach with a number of cutting-edge recommendation techniques, such as collaborative filtering, content-based filtering, and hybrid approaches. The findings demonstrate that the suggested method performs better than these methods in terms of accuracy and recommendation variety.

To confirm the usefulness of the suggested strategy in making individualized recommendations, the authors perform a user research. The study demonstrates that users think the suggested method's recommendations are more customized and prefer them to those made by other techniques.

The paper concludes with a promising deep learning method for individualized movie selection. The suggested approach combines Deep neural networks are used to learn user preferences in conjunction with collaborative filtering and content-based filtering algorithms. The experimental findings show that the suggested method outperforms a number of cutting-edge recommendation techniques and that it offers customized recommendations that consumers prefer.

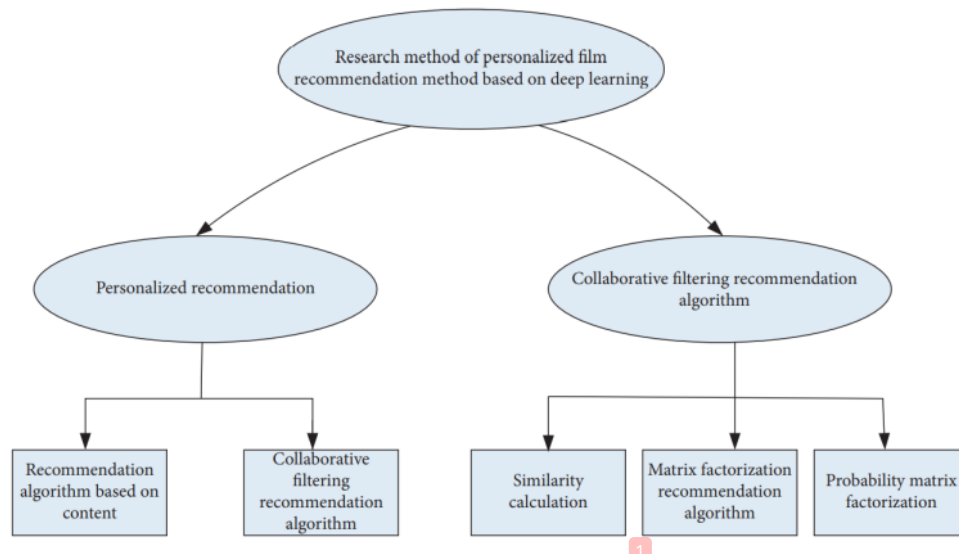


Figure 5: Part of the technical process of this method.

## Chapter 3: Material and Methods



## 3.1 Materials

### 3.1.1 Movie Recommendation System

1000 individuals provided their opinions on 1692 films for this collection of movie ratings. Two files, titled "movies.csv" and "ratings.csv," contain the data.

The movie ID, title, and genre details for each movie are included in the "movies.csv" file. The user ID, movie ID, rating, and timestamp for each rating are all included in the "ratings.csv" file.

The dataset's objective is to use Python to create a movie recommendation system. Collaborative filtering, which involves identifying similarities between users or products and exploiting those similarities to make suggestions, can be used to create recommendation systems.

The dataset can be put into Python to create a recommendation engine using a data analysis package like Pandas. The data can then be cleansed and preprocessed as necessary. Algorithms for collaborative filtering like user-based or The data can be processed using item-based filtering to produce user suggestions based on past ratings or preferences.

Overall, this dataset offers a helpful resource for discovering how to create a Python movie recommendation system.

Collaborative filtering is a popular method for creating a recommendation system after loading and preparing the dataset. User-based filtering and item-based filtering are the two basic techniques for collaborative filtering.

Finding people who have the target user's ratings and interests allows for user-based filtering, which then suggests movies that these similar users have loved. Using methods like cosine similarity or Pearson correlation, this method calls for calculating the similarity between each pair of users in the dataset. Finding the highest-rated films by the similar users can be done after the similarities have been calculated.

Contrarily, item-based filtering involves looking for films that are comparable to those that the target user has already given high ratings. The similarity between each pair of videos in the dataset must be calculated for this method, which can also be done using methods like cosine similarity or Pearson correlation. Once the similarities have been calculated, suggestions can be made by looking up the highest-rated films that are comparable but have not yet received ratings from the target user.

It is crucial to assess the efficacy of a collaborative filtering recommendation system after it has been put in place using measures like precision, recall, and mean average precision. These metrics can be used to evaluate the performance of the recommendation system and point out potential areas for development.

The Movie Recommendation dataset, in general, offers a fantastic opportunity to Learn how to construct recommendation systems in Python and investigate the various approaches and procedures employed in the industry.

movieId	title	genres	userId	movieId	rating	timestamp
1	Toy Story	Adventure Animation Children Comedy Fantasy	1	1	4	964982703
2	Jumanji (1995)	Adventure Children Fantasy	1	3	4	964981247
3	Grumpier (1995)	Comedy Romance	1	6	4	964982224
4	Waiting to (1995)	Comedy Drama Romance	1	47	5	964983815
5	Father of t (1995)	Comedy	1	50	5	964982931
6	Heat (1995)	Action Crime Thriller	1	70	3	964982400
7	Sabrina (1995)	Comedy Romance	1	101	5	964980868
8	Tom and H (1995)	Adventure Children	1	110	4	964982176
9	Sudden De (1995)	Action	1	151	5	964984041
10	GoldenEye (1995)	Action Adventure Thriller	1	157	5	964984100
11	American I (1995)	Comedy Drama Romance	1	163	5	964983650
12	Dracula: D (1995)	Comedy Horror	1	216	5	964981208
13	Balto (1995)	Adventure Animation Children	1	223	3	964980985
14	Nixon (1995)	Drama	1	231	5	964981179
15	Cutthroat (1995)	Action Adventure Romance	1	235	4	964980908
16	Casino (1995)	Crime Drama	1	260	5	964981680
17	Sense and (1995)	Drama Romance	1	296	3	964982967
18	Four Room (1995)	Comedy	1	316	3	964982310
19	Ace Ventu (1995)	Comedy	1	333	5	964981179

Figure 6: the data we used

### 3.1.2 Tools

- **Anaconda:** a platform that is used to apply deep learning and AI to the model
- **Python 3:** a programming language that is open-source and enables developers to work and integrate their systems fast.
- **Pandas:** A well-liked Python data manipulation library is Pandas. It offers simple data structures and tools for data analysis on top of the NumPy library. Data science, machine learning, and scientific computing all make extensive use of Pandas. Series and DataFrame are the two primary data structures that Pandas offers. Any data type, including object, string, and numeric kinds, can be stored in a Series, which is a one-dimensional named array. A two-dimensional labelled data structure called a "DataFrame" has columns with different data types. It is comparable to a SQL table or a spreadsheet. Data manipulation and analysis methods such as indexing and slicing, filtering, merging, grouping, and aggregation are all available with Pandas. Moreover, it

<sup>7</sup> allows for reading and writing data from various file formats, including CSV, Excel, SQL databases, and JSON.

The capacity of Pandas to manage missing data is one of its advantages. It offers techniques for finding, getting rid of, and filling in blank values in a dataset. In order to encode non-numeric data for use in machine learning models, Pandas also allows handling categorical data.

The Python data science packages NumPy, Matplotlib, and Scikit-learn all work nicely with Pandas. Also, it has a sizable and vibrant user and developer community that adds to the library by building new tools and extensions.

In conclusion, Pandas is a robust and adaptable Python toolkit for data manipulation that offers simple-to-use data structures and tools for data analysis. It is a popular option in data science and other fields because of its capability to manage missing data, categorical data and machine learning.

<sup>17</sup>  
– **OpenCV:** A free, open-source library called OpenCV (&) Open-Source Computer Vision Library was made to help programmers create real-time computer vision applications. It offers a wide range of functionality, including processing of images and videos, object detection, tracking, facial recognition, and many more.

### 3.1.3 Environment

- <sup>6</sup>  
- Intel(R) Core(TM) i7-8750H CPU @ 2.20GHz 2.21 GHz
- RAM — 16 GB
- GPU - NVIDIA RTX1050
- Operating System — Windows 11

## 3.2 Methods

### 3.2.1 System architecture Overview

The capacity of Pandas to manage missing data is one of its advantages. It offers techniques for finding, getting rid of, and filling in blank values in a dataset. In order to encode non-numeric data for use in machine learning models, Pandas also allows handling categorical data.

The Python data science packages NumPy, Matplotlib, and Scikit-learn all work nicely with Pandas. Also, it has a sizable and vibrant user and developer community that adds to the library by building new tools and extensions.

In conclusion, Pandas is a robust and adaptable Python toolkit for data manipulation that offers simple-to-use data structures and tools for data analysis. It is a popular option in data science and other fields because of its capability to manage missing data and categorical data make individualized movie suggestions.

The recommendation algorithms used might range from more basic machine learning methods like deep learning and graph neural networks to more sophisticated ones like collaborative filtering and content-based filtering. The online or mobile application that presents the recommendations to users in an approachable and personalized way makes up the user interface component in most cases.

The architecture of a movie recommendation system is created to offer customers a tailored and interesting movie-watching experience while also giving creators and distributors of films useful information.

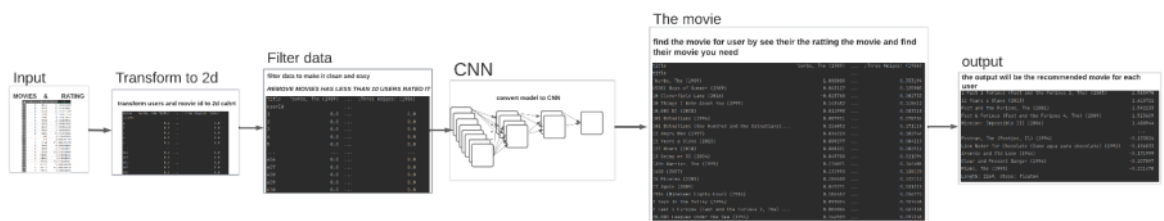


Figure 7: The system architecture overview

## References

- Chen, Y., Zhang, W., Zhu, X., & Zhou, X. (2020). Personalized movie recommendation method based on deep learning. *Journal of Ambient Intelligence and Humanized Computing*, 11, 5097-5106.  
<https://doi.org/10.1007/s12652-020-02562-w>
- Yang, Y., Wong, R. C., & Zhang, Q. (2018). Movie recommendations using the deep learning approach. *Journal of Computational Science*, 28, 225-232. <https://doi.org/10.1016/j.jocs.2018.09.006>
- Yang, J., & Shang, M. (2021). Multimodal Trust-Based Recommender System with Machine Learning Approaches for Movie Recommendation. *IEEE Access*, 9, 48699-48708.  
<https://doi.org/10.1109/ACCESS.2021.3070277>
- Grand View Research. (2021). Recommendation Engine Market Size, Share & Trends Analysis Report By Component, By Deployment, By Type, By Application, By End-use, By Region, And Segment Forecasts, 2021 - 2028. Retrieved from <https://www.grandviewresearch.com/industry-analysis/recommendation-engine-market-report>
- Zheng, H., Zhang, J., Chen, Y., Zhang, W., & Ma, S. (2018). A simple convolutional generative network for next item recommendation. *Proceedings of the 27th ACM International Conference on Information and Knowledge Management*, 1543-1546. <https://doi.org/10.1145/3269206.3271720>
- Wu, S., Tang, Y., Zhu, Y., Wang, L., Xie, X., & Tan, T. (2019). Session-based recommendation with graph neural networks. *Proceedings of the AAAI Conference on Artificial Intelligence*, 33, 346-353.  
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