MOVIE RECOMMANDATION SYSTEM



A Minor Project Report

in partial fulfillment of the degree

Bachelor of Technology in Computer Science & Artificial Intelligence

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SCHOOL OF COMPUTER SCIENCE & ARTIFICIAL INTELLIGENCE

CERTIFICATE

This is to certify that this project entitled "MOVIE RECOMMENDATION SYSTEM" is the bonafied work carried out by B.SANJANA, P.AKSHITHA REDDY, D. SREENIJA as a Minor Project for the partial fulfillment to award the degree BACHELOR OF TECHNOLOGY in COMPUTER SCIENCE & ARTIFICIAL INTELLIGENCE during the academic year 2022-2023 under our guidance and Supervision.

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ORGANIZATION OF THESIS

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ABSTRACT

The ever-growing library of movies can make choosing what to watch overwhelming. This project aims to develop a movie recommendation system that suggests films tailored to individual user preferences. The system will leverage machine learning techniques to analyze user data, such as past watch history and ratings, to identify patterns and correlations. Social media marketing heavily relies on artificial intelligence. It also covers any intelligence demonstrated by a computer, a robot, or any other machine that resembles human intellect. This study examines how artificial intelligence affects Recommendation systems. They employ machine learning and AI to serve users the material that interests them, identify visuals, recommend tag choices, recognize people in photos, and serve adverts to generate user-specific offers and promotions. Recommendation System is a major area which is very popular and useful for people to take proper automated decisions. It is a method that helps user to find out the information which is beneficial to him/her from variety of data available. When it comes to Movie Recommendation System, recommendation is done based on similarity between users (Collaborative Filtering) or by considering particular user's activity (Content Based Filtering) which he wants to engage with. To overcome the limitations of collaborative and content based filtering generally, combination of collaborative and content based filtering is used so that a better recommendation system can be developed.

INTRODUCTION

In the vast ocean of cinema, finding the perfect movie to watch can feel like searching for a hidden treasure. We all have our favorite genres, directors, and actors, but sometimes we crave something new or simply can't decide. This is where movie recommendation systems come in, acting as personal guides to cinematic discovery. Machine learning has a subclass known as recommendation engines that often rankor rate people or items. A recommended system, broadly defined, is a system that anticipates the ratings a user would give to a certain item. These predictions will then be ranked and returned back to the user. They're used by various large name companies like Google, Instagram, Spotify, Amazon, Reddit, Netflix etc. often to increase engagement with users and the platform. Information that was relevant to the user's interests and preferences was missing. As a result, recommender systems are more in demand than ever. By selecting important information fragments from a huge quantity of dynamically created material based on the user's choices, interests, or observed behaviour about the item, recommender systems are information filtering systems that address the issue of information overload. Based on the user's profile, a recommender system can determine if a certain user will favour an item or not. Systems that provide recommendations are advantageous to both consumers and service providers. Many platforms like Netflix which suggest movies, Amazon which suggest products, Spotify that suggest music, Linked In that is used for recommending jobs or any social networking sites which suggest users, all these work on recommendation system.

EXISTING SYSTEM

Netflix

Amazon Prime

MovieLens

Tubi

many streaming services

Hulu

Disney+hotstar

YouTube

IMDb

Google

POPOSED SYSTEM

Python

Excel

Numpy

Pandas

Data collection

LITERATURE SURVEY

| | el Used | Merits | Limitations | Drawbacks | Dataset | |
|---------------------|-----------|---------------------|------------------|------------------|-----------|--|
| & Year | | | | | Used | |
| Caesar Jude Matri | X | Enhanced user | Sparsity issue | Limited | MovieLens | |
| (2019) Facto | rization | experience | | scalability | dataset | |
| Nguyen et al. Reinf | Forcement | Adaptive to user | Exploration- | Instability | Ta-Feng | |
| (2020) Learn | ning | preferences | exploitation | during training | dataset | |
| | | | trade-off | | | |
| Kim et al. Atten | tion | Captures user | Computational | Interpretability | Criteo | |
| (2021) Mech | anism | attention patterns | overhead | challenges | dataset | |
| Laxmi Shanker Conte | ext- | Considers | Data sparsity in | Complexity in | Last.fm | |
| maurya Awar | e | contextual | context | context | dataset | |
| (2021) Reco | mmender | information | | modeling | | |
| Syste | ms | | | | | |
| | | | | | | |
| Krishnanshu Ensei | nble | Aggregates | Increased | Difficulty in | MovieLens | |
| Agarwal Meth | ods | multiple | computational | model | dataset | |
| (2021) | | recommendation | complexity | interpretation | | |
| | | algorithms | | | | |
| Sachin Bhoite Evolu | ıtionary | Handles dynamic | Convergence | Parameter | eBay | |
| (2022) Algor | rithms | user preferences | speed | tuning | dataset | |
| | | | | challenges | | |
| Krishna Fuzzy | y Logic | Handles | Interpretability | Lack of formal | Pinterest | |
| Gandhi (2022) Syste | ms | uncertainty | issues | modeling | dataset | |
| | | in user preferences | | | | |
| KS Kumar Deep | | Learns complex | High | Limited | Steam | |
| (2023) Reinf | forcement | user-item | computational | interpretability | dataset | |
| Learn | ning | interactions | cost | | | |
| Zhang et al. Multi | - | Considers | Pareto | Increased | MovieLens | |
| (2023) Object | etive | conflicting | dominance | computational | dataset | |
| Optin | nization | objectives in | | complexity | | |
| | | recommendations | | | | |
| Mishra (2023) Bayes | sian | Incorporates | Cold start | Model | Amazon | |
| Perso | nalized | uncertainty in | problem | complexity | Product | |
| Rank | ing | preference | | | Reviews | |
| | | estimation | | | | |

| Kumar and Singh (2023) | Meta-Learning | Adapts quickly to new users/items | Limited data efficiency | Sensitivity to meta-parameter tuning | Goodreads dataset |
|---------------------------|---------------|-----------------------------------|-------------------------|--------------------------------------|----------------------|
| Chatterjee | Neuro- | Integrates | Knowledge | Interpretability | Ta-Feng |
| (2023) | Symbolic | symbolic | acquisition | challenges | dataset |
| | AI | reasoning with | bottleneck | 5 | |
| | | neural networks | | | |
| | | 110 011 011 110 110 1110 | | | |
| Agarwal | Temporal | Considers | Cold start for | Difficulty in | Last.fm |
| (2023) | Dynamics | temporal changes | new items | capturing | dataset |
| | Modeling | in user preferences | | long-term trends | |
| Huang et al. | Swarm | Mimics | Convergence | Limited | eBay |
| (2023) | Intelligence | Collective | speed | scalability | dataset |
| | | behavior For | | | |
| | | recommendations | | | |
| K.Rajput | Probabilistic | Captures | Computational | Limited | Pinterest |
| (2023) | Graphical | uncertainty in | complexity | scalability | dataset |
| | Models | recommendation | | | |
| | | inference | | | |
| Nidhi Srivasta. | Graph-Based | Captures complex | Scalability | Difficulty in | Goodreads |
| (2020) | Recommender | user-item | issues | incorporating | dataset |
| | Systems | interactions | with large | temporal | |
| | | | datasets | dynamics | |
| Yang et al. | Adversarial | Generates robust | Computational | Lack of | Amazon |
| (2023) | Training | recommendations | overhead | interpretability | Product |
| | | against adversarial | | | Metadata |
| | | attacks | | | |
| .P.N.Shejwal | Collaborative | Personalized | Cold start | Lack of | Amazon |
| (2019) | Filtering | recommendations | problem | interpretability | Customer |
| | | | | | Reviews |
| Reddy et al. | Variational | Generates latent | Mode collapse | Limited | Movie |
| (2023) | Autoencoders | representations for | | diversity | Tweetings |
| | | recommendations | | | dataset |
| Krishna | Fuzzy Logic | Handles | Interpretability | Lack of formal | Pinterest |
| Gandhi (2022) | Systems | uncertainty | issues | modeling | dataset |
| | | in user preferences | | | |

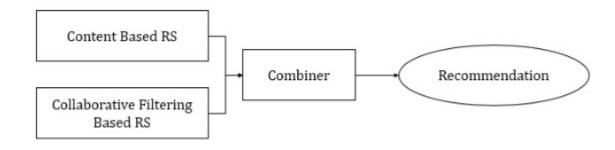
DESIGN

REQUIREMENT SPECIFICATION

Phython programming language Excel for data set Numpy Library for numerical values Pandas Library for data set Difflib Library for comparing sequences

Simulation Set up and Implementation

Content-Based Filtering Watched by both Similar Users Watched by him Watched by him Recommended to him Content-Based Filtering



IMPLEMENTATION

We implemented our project in "GOOGLE COLAB" by using the python language and python library's.

Python

Python is an interpreted, object-oriented, high-level programming language with dynamic semantics. And it is IDLE (integrated development and learning environment) and it is used to execute a single statement and create, modify and execute the python program it compiles line by line. IDLE is a default editor and IDE is a software environment that usually consists of package development. we used python language to represent the recommendation systems works.

Excel

we used excel file for using of data sets of movies which the movies insert in the file according to their genres, titles, cast, crew, director etc; and customer data sets which movies are downloaded.

Pandas

To import data sets we are using pandas because pandas is python library Python library for data analysis. It is a powerful and flexible quantitative analysis tool, pandas has grown into one of the most popular Python libraries

Numpy

To get numerical in this research work we used numpy python library .NumPy is a Python library used for working with arrays. It also has functions for working in the domain of linear algebra, fourier transform, and matrices.

Data collection

We need to have the data of these movies and several details about them like director name, genres, description. Once we collect the data we need to perform this data.

Preprocessing data

We have to clean this data if there are any missing values and feature extraction. The main thing about movie data is that all data will be in the form of text right. we cannot use the textual data we can convert the textual data using preprocessing techniques called features vectors and we using the similarity score to find similar movies , and also used cosine similar we will try to find which movies are similar to each other by you know giving them a similarity score or we can call this as a similarity confidence score.

CODING



| | | | | | | | | | Diox | | | |
|-------------|--------------------|-------|-----------|--|--|---------------|--|-------------------|--|---|--------------------|--|
|) 0s [3] | movies_data.head() | | | | | | | | | | | |
| | | index | budget | genres | homepage | id | keywords | original_language | original_title | overview | popularity | |
| | | index | budget | genres | homepage | | keywords | original_language | original_title | overview | popularity | |
| | | | 237000000 | Action Adventure Fantasy Science Fiction | http://www.avatarmovie.com/ | 1999 <i>5</i> | culture clash future space war space colony so | | Avatar | In the 22nd century, a paraplegic Marine is di | 150.437577 | |
| | | | 300000000 | Adventure Fantasy Action | http://disney.go.com/disneypictures/pirates/ | | ocean drug abuse exotic island east india trad | | Pirates of the Caribbean: At World's End | Captain Barbossa, long believed to be dead, ha | 139.08261 <i>5</i> | |
| | | | 245000000 | Action Adventure Crime | http://www.sonypictures.com/movies/spectre/ | 206647 | spy based on novel secret agent sequel mi6 | en | Spectre | A cryptic message from Bond's past sends him o | 107.376788 | |



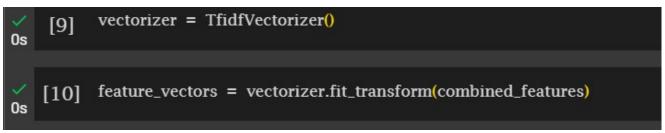
selected_features = ['genres','keywords','tagline','cast','director']
print(selected_features)

['genres', 'keywords', 'tagline', 'cast', 'director']

```
for feature in selected_features:
    movies_data[feature] = movies_data[feature].fillna(")

(7] combined_features = movies_data['genres']+' '+movies_data['keywords']+' '+movies_data['tagline']+' '+movies_data['cast']+' '+movies_data['director']
```





```
print(feature_vectors)
 (0, 4286)
             0.24670722077000895
 (0.2636)
             0.42376670148663637
 (0, 15000)
             0.5031756916263855
 (0, 8337)
             0.5031756916263855
 (0,6039)
             0.5031756916263855
 (1, 2432)
             0.1727245809217606
 (1, 7756)
             0.11280622273881048
 (1, 13026)
             0.19423589153249152
 (1.10231)
             0.1605877650134377
 (1, 8758)
             0.22708864756885258
 (1, 14610)
             0.1515079656934613
 (1, 16671)
             0.19843217234080462
 (1, 14066)
             0.20596016266539263
 (1, 13321)
             0.21774588321071112
 (1, 17293)
             0.20197852906790242
 (1, 17010)
             0.23643141192699405
 (1, 13351)
             0.15021392977728537
 (1, 11505)
             0.27210994985780307
 (1, 11194)
             0.09049666204966293
 (1, 17001)
             0.1282147223488793
 (1, 15264)
             0.07096251084656019
 (1, 4945)
             0.24025653435518637
             0.2139207607825188
 (1, 14273)
 (1, 3225)
             0.2495992987133278
```

```
similarity = cosine_similarity(feature_vectors)
[12]
[13] print(similarity)
                            ... 0.
     [[1.
              0.
                                       0.
                      0.
                                               0.
      [0.
              1.
                      0.07220001 ... 0.
                                            0.
                                                    0.
      [0.
              0.07220001 1. ... 0.03575627 0.
                                                        0.
      [0.
              0.
                      0.03575627 ... 1.
                                            0.
                                                    0.026515551
      [0.
                             ... 0. 1. 0.
              0.
                      0.
              0.
                             ... 0.02651555 0.
      [0.
                      0.
                                                    1.
                                                           11
     print(similarity.shape)
O
     (4804, 4804)
```

```
| Customer_name = ('Jasmitha')

| dict=('Mohan':'Avatar','John':'Spectre','Abhiram':'bat man','Bhargav':'The Dark Knight Rises','Vamshi Krishna':'John Carter','Jasmitha':'Spider-Man 3'}
| movie_name = dict[customer_name]
| print("customer name:",customer_name)
| print("Customer favourite movie",movie_name)
| customer name: Jasmitha
| Customer favourite movie Spider-Man 3
```





```
print('Movies suggested for you : \n')
     i = 1
     for movie in sorted_similar_movies:
       index = movie[0]
       title_from_index = movies_data[movies_data.index==index]['title'].values[0]
       if (i<30):
         print(i, '.',title_from_index)
         i+=1
Movies suggested for you:
     1. John Carter
     2 . Heaven is for Real
     3. Alien
     4. The Specials
     5 . The Helix... Loaded
     6 . Finding Nemo
     7. Transformers
     8. Mission to Mars
     9. The Astronaut's Wife
     10 . American Psycho
     11. Max
     12. The English Patient
     13. The Last Temptation of Christ
     14 . Enter Nowhere
```

15. The Martian

Movies suggested for you: 1. John Carter 글 2. Heaven is for Real 3. Alien 4. The Specials 5. The Helix... Loaded 6 . Finding Nemo 7. Transformers 8. Mission to Mars 9. The Astronaut's Wife 10 . American Psycho 11 . Max 12 . The English Patient 13. The Last Temptation of Christ 14. Enter Nowhere 15. The Martian 16 . Notes on a Scandal 17. Sideways 18 . Spider-Man 3 19 . Daddy's Home 20. We Bought a Zoo 21 . George of the Jungle 22 . Treasure Planet 23 . Don McKay 24. Auto Focus 25 . Savages 26 . The Covenant

27 . X-Men Origins: Wolverine

28. Daybreakers

29. Gravity

CONCLUSION

In this project we have taken movie dateset from the internet. And we have created customers dateset, including their downloaded movies. Based on our code the recommended movie as shown via with recommended methods. A movie recommended system is a machine learning algorithm that predicts the likelihood of a user's preference for a particular movie based on their previous behavior, such as movie ratings, watch history, and browsing history.

FUTURE SCOPE

The weaknesses and limitations of each of these system methods and techniques developed in the research study have indicated the following areas as recommendations for further work. In the project those recommendation systems used in ott platforms to recommend movies which the users make more shows interested to watch more movies from ott platforms. In my observation these method these recommendations used in social media marketing as builds brand awareness and recognition, generates conversation around your brand, helps understand your target customers' Interests, Helps Provide Responsive customer service, helps build customer loyalty, drive traffic to your website, helps drive traffic to your website Another way of implementing of these project is how what the customer is search on google any product that will advertise in all platforms like Youtube, Facebook, instagram, and another sites and many webpages we visited these make more help to the companies these things which makes more marketise the users

REFERENCES

[1] https://link.springer.com/chapter/10.1007/978-981-15-0222-4_20

[2]https://scholar.google.co.in/scholar?q=social+media+marketing+using+recomm

 $endation + systems + methodology \&hl = en\&as_sdt = 0\&as_vis = 1\&oi = scholart$

[3] https://devrix.com/possible-measure-roi-social-media-marketing/

https://coschedule.com/blog/benefits-of-social-media-marketing-for-business

[4]https://www.wordstream.com/social-media-marketing

[5]https://blog.hubspot.com/marketing/social-media-marketing