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Kernel Optimization Based Enhanced Preference Learning for Online Movie Recommendation

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Abstract: Recommendation systems have wide range of applications in today's digital life. Recommendation is performed on books, products, dresses, movies, music and so on. Promotion of movies are rapidly increasing much better than past decades. Movie recommendation is an area for promoting movies to users. Traditional systems are based on batch training techniques. These techniques are expensive for arrival of new ratings and also did not handle dynamic changes of user preferences. The proposed system is a movie recommendation system which related on user preferences or interests. This system produces an accurate movie recommendation to users. In this system the basic idea for recommending movies to users are loss values and social similarities. Frank Wolfe optimization algorithm is used to recommend movies. The proposed system also reducing nonlinearity in ratings using Monte Carlo uncertainty propagation method. In addition to optimization algorithm system uses a classification method SVM for recommendation. Also system provides the facility for online movie ticket booking.
Keywords: Recommendation, Loss function, Social similarity, Optimization, Uncertainty, Preference.

I. INTRODUCTION

In our digital world, an unbounded number of contents will be used by users such as books, videos, articles, products, movies and so on. Therefore, finding their interests on content are the key issue. At the meantime, content providers need to boost up customers to use their services for the maximum period of time. This causes the implementation of recommendation system. Content providers recommend contents to users depends on their interests or preferences. The recommendation system or recommender system (RS) is a sub-category of the information filtering system that attempts to predict the interest or preference provided by the customer to an item. This is a revolutionary technology that can transform applications from content-based to customer-based. The efficient as well as accurate collection and calculation of information leads to the emergence of recommended technologies, and these technologies provide an improved understanding of users. The innovation behind the recommendation framework has developed into a rich accumulation of tools in recent years that has attracted researchers and scientists to create accurate referrers [5]. Fig.1 shows simple concept of recommendation system.

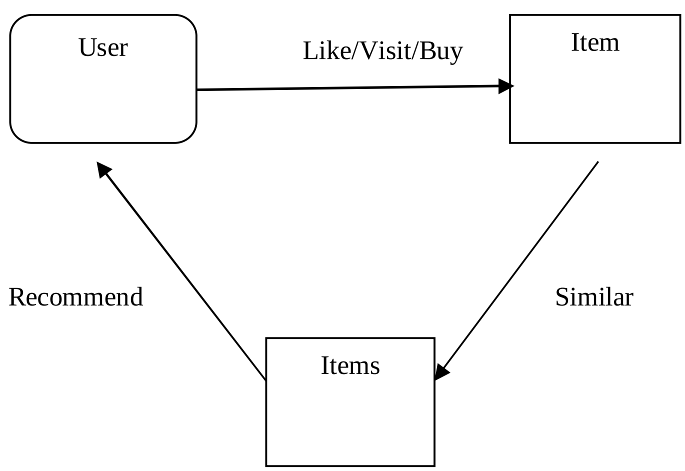

Fig.1 Simple concept of recommendation system

The recommender system provides list of recommendations basically in three ways: Content Based Filtering, Collaborative Filtering and Mixed Approach (Hybrid method). In content based filtering, content is the basis for building a recommended application. The content based filtering method is based on the details of the item or content and the user's preferred profile. This algorithm try to recommend something similar to what the user used to enjoy (or what is being considered now). Also various contents are compared with contents which are previously liked or viewed by that user. Then the best matching contents are recommended to that user. Another common method of widely used recommendation system design is collaborative filtering [7]. The idea based on collaborative filtering is it collects and evaluating massive size of information about user's activities, views, searches or likes and predicting the preference of customer based on the similarity with other customers. In some cases, a hybrid approach that combines collaborative filtering and content-based filtering may be more effective [7]. The hybrid recommendation system is adjusted to add content-based and collaborative filtering controlled by a framework, and to increase the benefits and reduce the weaknesses of both technologies. Therefore, the mixed recommendation system is suitable for the characteristics associated with both. It can give more correct recommendation than pure methods [7].

Movie recommendations are an open area of research, unresolved issues and growing social network data. It will helps to connect different information about data from different sources of movies and users in order to improve the quality of recommendations. These recommendation systems help people to provide general idea about latest movies and also capture more details about movies. Likewise, providing movies to users that are rated by different users. Movie recommendation system helps to improve the promotion of movies.

Many recommendation systems were introduced in the early days. Most of the existing recommendation systems are related on batch training methods. In this technique, sequentially collects ratings from users. Whenever a new rating reaches, the training procedure consuming more time. Additionally, if the size of the data is too large, it is a big challenge to process all the data in batch mode. In an actual online application, user preferences also change over time, making it impossible for the batch learning process to dynamically capture these changes [1]. To overcome these problems introduce a new movie recommendation system which is based on user preference. This system is a mixed approach which combines content based and collaborative filtering methods. Proposed system takes rating as input and accurately recommend movies to users. In this system loss function and social similarity are the key values for recommendation. Also reduces nonlinearity (uncertainty) in ratings using Monte Carlo uncertainty method. And a classification method, SVM is used for recommendation. Also users can book tickets for movies through online. Recommendation system is based on user's preferences or likes. User's preference will be changed over time so it will greatly affects the recommendation system [1]. A good recommendation system is always take care of that. The main goals of this method are:

A. To provide more accurate movie recommendation to users.
B. To recommend movies to customers based on changing nature of customer's interests or preferences.
C. To develop a new platform of movie recommendation related on online graph regularized user preference which is based on an optimization algorithm.
D. Irregularities or uncertainties in ratings make the recommendation worst. The proposed system reduces the uncertainty in ratings and recommend movies.
E. To recommend movies to users based on a classification method.
F. To provide the facility of movie ticket booking through online so that users can book movie tickets based on ratings.

II. RELATED WORKS

In the early periods, many movie recommendation systems were developed. Most movie recommendation systems are based on content-based filtering and collaborative filtering. The basic idea about content-based recommendation is user's previous history or content description. MovieOracle [6] is based on content-based filtering. Collaborative filtering uses similarities or likeness between users. For example, MOVREC [3] is a collaborative filtering based recommendation system. Some methods use hybrid approach which integrates collaborative and content-based filtering. ORBIT [4] is an example of a mixed recommendation. Most recommendation systems are created on the basis of these three types. The variation of these systems are related on different procedures used to recommend different items. There are also some recommendation systems based on batch training techniques. In batch processing, all data is processed in batch mode [1].

P. Li and S. Yamada [2] proposed a new structure of movie recommendation based on content-based filtering. This recommendation system is based on genre description about movies rather than similarity of other users. Recommended movies are similar to users who rated, visited, browsed and liked movies in the past. In movie recommendations, the number of feature factors, such as actors, directors, stories, song sequences, etc., may be considered, which may be used to recommend movies based on user interests. Assume that two feature factors, romantic and action, classify the movie. Comparing the user profile's interest and feature factors, the movie can be recommended to the user. For example: User X prefers romantic movies more than action movies. X has rated

Movie2 and Movie3 as 5 also Movie1 and Movie5 as 0. Movie4 can be recommended to X by comparing feature values, because it is marked as a romantic movie. The main limitations of content-based filtering are the same set of elements characterize two different items and therefore cannot be distinguished. This method does not recommend anything distinct from what the user had previously seen and also cold start problem which means items are not recommended because of lack of information about users and contents.

Manoj Kumar, D. Yadav, Ankur Singh and Vijay Kr. Gupta [3] suggested a recommendation system for movies which is named as MOVREC. It is based on a collaborative filtering method that uses user-supplied information, analyses them, after that best movies which are recommended to the user at the time. The list of recommended movies are sorted by the previous user's ratings to these movies. In this method recommendation is performed based on K-means algorithm. Due to the simplicity, flexibility and computational efficiency of the K-means algorithm, especially considering a large amount of data, this algorithm is mainly used clustering method. K-means repetitively computes k cluster centers and allocates items to the nearby cluster based on distance metrics. When there is no more change in the center point, the clustering algorithm will converge. However, K-means lacks the ability to select suitable initial seeds and may result in an inaccurate classification. Randomly select the initial seed it may be the reason for local optimal solution to be worse than the global optimal solution. MOVREC can also beneficial for users to find movies of their choice based on the movie experience of other users in an efficient and effective way, without wasting maximum time for unusable browsing. The main contribution of the system is that it has been tested by a small group of people and the system has received their positive response. Keep the system simple and interactive. In order to recommend movies to the user accurately, a K-means clustering algorithm and a pre-filter are applied. To give weight to attributes and give them priority, they surveyed a group of people and prioritized attributes related on the outcomes obtained. However, this method has some problems due to the use of collaborative filtering such as if a user's profile does not match with other users in terms of items then recommendation of items to other users based on that user is not possible. Lack of sufficient amount of data is also a problem. Lack of variation is a problem of K-means algorithm.

D. Pathak, S. Matharia and C. N. S. Murthy [4] suggested a movie recommendation system called ORBIT. Today, users will get so many movie recommendation websites for obtaining best movies to themselves based on their comforts. All of these sites implement one of the traditional content, context and collaboration recommendation algorithms. Alone, these algorithms fail to recommend the best and effective recommendations to the user. Therefore, it is essential to determine a unique algorithm that combines the features of traditional algorithms with their new features. ORBIT is a recommendation system for movies which are related on a unique hybrid recommendation algorithm that satisfies user's needs by providing optimal and effective recommendations. It also contains context-based input. This context-based input determines time or behavior-oriented data, such as date, weather, taste, mood, etc. In general, context-based recommendations are in such inputs. It provides an easy-to-use graphical user interface for user profile and movie information management. ORBIT offers the best recommendations for users those without having sufficient personal experience or ability to assess the number of alternatives offered by the site. The core limitation of this system is that it is very difficult to find relevant information from a huge volume of available data, the computational complexity is high and also the cost for implementing this system is expensive.

III. SYSTEM OVERVIEW

The social recommendation system has recently attracted much attention in the research community. Existing recommendation methods are usually based on batch machine learning methods. Batch training techniques which are affected by several significant limitations. For example, the cost of model retraining, which is extremely expensive whenever user ratings are arrived newly and cannot capture user's likes or interests over time. Therefore, it is important to adapt social recommendation system to the real-world online applications where data arrives consecutively and user preferences or interests may change dynamically and rapidly. Existing systems have some problems which are:

A. The same set of attributes represent two different items and therefore cannot be distinguished.
B. The system does not recommend anything different from what the user had previously seen. This can sometimes be a problem because the user may need to use something new and the system will never attained it.
C. When new users enter the system, there will not be any previous information, such as browsing history, items of interest, etc. In this case, it is hard to recommend items to users.
D. There is no rating for new items entering the system and may not be recommended.
E. The amount of contents exceeds the amount of users. It's hard to find contents with enough people to rate.

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F. Ratings are often arrive, whenever a new rating reaches the critical training method requires more time to train the data.
G. If the size of the data is too large, it is very difficult to process all the data in batch mode.
H. Ratings are given by users. The user's preferences will change over time. Dynamic changes in user preferences will make the system poorest and existing systems will not deal with this change.

The proposed system is a new framework of online social movie recommendation from the perception of online graph regularized user preference learning (OGRPL), which combines both content-based filtering and collaborative filtering. This method overcomes the problem of overfitting data [1]. System takes ratings from users as input. This rating is stored in a matrix called rating matrix. However this rating matrix contains error data or noisy data. This noise causes overfitting problem. To overcome this problem introduce loss function. The system implements an online learning for recommendation of movies. Recommendation is based on loss values and social similarity. This system considers an optimization problem from loss function and solve by using an optimization algorithm. Frank Wolfe algorithm is used as an optimization algorithm for recommendation [9].
However this method doesn't handle uncertain ratings which contains irregularities. That means large differences in ratings given by different users will affect the performance. Uncertainty in ratings makes recommendation worst. Monte Carlo uncertainty propagation method is used to handle uncertain data in recommendation [10]. The level of uncertainty is measured and also reduces uncertainty in ratings. After reducing uncertainty, movies are recommended to users. Frank Wolfe optimization method and Monte Carlo uncertainty propagation method are used to recommend movies to users based on similarity ranking between users. Cosine similarity and similarity in demographic details are used to compute similarity or likeness between users. Also SVM (Support Vector Machine) can be used to predict the user preference by learning [11]. SVM is a classification algorithm used to classify or predict the test data based on training data. A training set may be created and kept for offline process. An SVM library is used to learn the test data using training data. Based on prediction, movies are classified to different classes. When user gives rating for a movie then predict in which class that movie belongs and recommend other movies which are in that class. Also analysing the performance of recommendation based on different algorithms used in the proposed system. The proposed system also provides the facility for online movie ticket booking. Users can book movie tickets based on other user's ratings. Fig.2 shows the architecture of the proposed system.

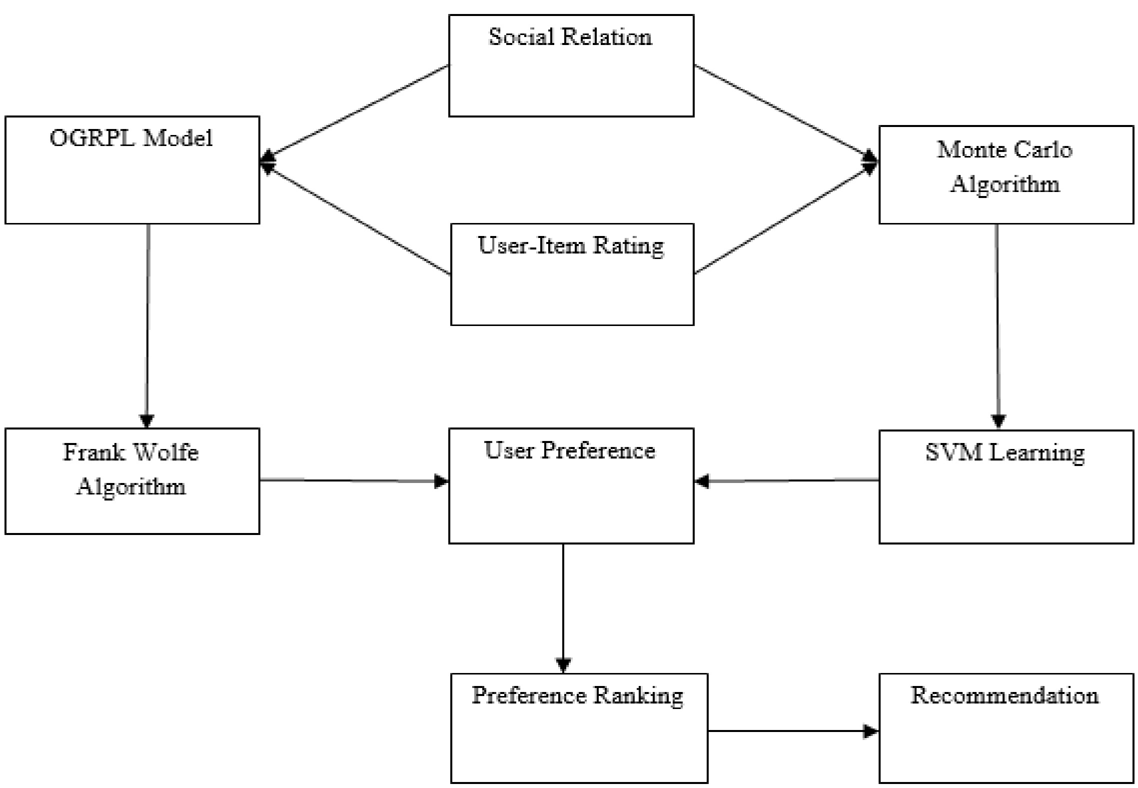

Fig.2 Architecture of the proposed system

IV. SYSTEM DESIGN

A. Modules and Their Functionalities

The proposed system Kernel Optimization Based Enhanced Preference Learning for Online Movie Recommendation consists of the following modules.

1) *Admin Module:* The main part of the proposed system is admin module. Admin controls overall process of the system. Users are giving ratings to movies. This ratings are stored in movie-user matrix. Movie-user matrix consists of ratings which are given by users to different movies. If user did not provide ratings to movies that field contains zero value. Also use another matrix called preference matrix which contains preference values obtained from rating matrix. User preference will change frequently based on their likes or interests. Users are given ratings to movies in such situation error may be occurred because humans are prone to make error rating. So recommendation which is directly obtained from user ratings is not an accurate method. To avoid such situation loss function is calculated. Loss function is a calculation which is obtained from rating matrix and preference matrix [1].
2) *Loss Function:* Loss function is obtained from ratings and preferences. Preferences are values which are obtained from ratings. Calculate the difference between rating matrix and preference matrix which is saved in another matrix called difference matrix. Then obtaining ratings given by different users to a movie from this matrix which is stored as an array. Similarly obtaining each movies and its ratings. Then calculate the total of ratings which are obtained from the array. Then divide the total of a movie by average rating of that movie. This value is the loss value of that movie
3) *Social Relation:* After calculating loss function, social relation can be calculated for missing values in rating matrix. Social relations are well recognized in social recommendation systems. Based on the property of social relation it's assume that like users have same preference in rating matrix consider as similar users. In this system cosine similarity and demographic similarity can be used to compute the similarity or likeness between users .Social similarity can be calculated depends on ratings given by users. For example, If X is a user who gives ratings to movies. Y is another user also gives ratings to other movies. Similarity is based on ratings which are given by users. If X and Y are giving nearly similar ratings in any movies then these users are considered as similar users. Also consider demographic details of users for similarity calculation. Demographic details are obtained from user's profiles. This system uses gender, place and favourite actor as demographic details. Here demographic details obtained from user registration. Initially calculate cosine similarity which is depends on ratings provided by customers and calculate demographic similarity between customers then aggregate demographic similarities to rating similarities. Proposed system calculated cosine similarity by the ratio of number of ratings which are common by the total number of ratings given by two users. The cosine similarity matrix finds the dot product of two attributes [8]. It can be obtained by using the following formula:

$$Similarity = \frac{Number\ of\ common\ attributes}{Total\ number\ of\ attributes}$$

Demographic similarity is determined by finding users those having similar demographic details. Similarity values are ranging from 0 to 1. If the similarity value is close to 1 which means that users have higher similarity. If it is close to 0 similarity is very low. Proposed system takes high similarity values between users.

4) *Frank Wolfe Algorithm*: Loss function and similarity calculation can be treated as an optimization problem [1]. Optimization problems are very easy to design and have higher understand ability. This is the reason for loss function and similarity can be evaluated as an optimization problem. Optimization problem can be solved by either minimizing the function or maximizing the function. This optimization problem can be solved by an optimization algorithm. Frank Wolfe algorithm [9] which is also known as conditional gradient method is an optimization algorithm which is used to minimize the loss function. And update the preference value. Here minimization is achieved by dividing the loss function of a movie by the last round. Then update the round for obtaining the latest preference of users. After solving optimization problem using Frank Wolfe algorithm, recommending movies to users. Initially use the similarity between users. If X is a user then find users those are similar to X. Suppose Y and Z are users similar to X then choose movies which are rated by Y and Z with higher loss function values. Movies which are rated by highest similarity user are recommended significantly based on loss values
5) *Monte Carlo Uncertainty Propagation*: However Frank Wolfe algorithm does not handle uncertainty in data rating. Uncertainty means irregularities or nonlinearity in ratings. Ratings that contain uncertainty produces recommendation inaccurate. Uncertainty reduction in ratings increase the perfection of recommendation. Monte Carlo uncertainty propagation method [10] is used to measure uncertainty in ratings and reduces uncertainty. Monte Carlo is a stochastic method. In this system three

inputs are passed to Monte Carlo algorithm. Rating matrix, preference matrix and loss function which is calculated from rating and preference. Here the input domain is these matrices. Then process each rows in the matrix as arrays. So that iterations are performed in Monte Carlo algorithm is related on the product of number of rows and number of columns. In the rating matrix, consider each rows and perform deterministic calculation. This system calculate mean value of items in the first row. Then this aggregated result is consider as an output of the first movie that means rating of the first movie. This output is given as an input to the next row. Then compute the sum of second row and add previous stage output to this sum and calculate the mean value. Then this aggregated result is passed as an input to next row. Similarly this process is repeated until it reaches the iterative condition. This process reduces the nonlinearity in rating. Similarly preference value is calculated in the similar fashion in order to reduce the uncertainty in preference vales. After performing Monte Carlo algorithm reduced uncertainty in ratings can be used to calculate loss function. This loss function value is more accurate than previously calculated loss values. Then based on similarity values, movies are recommended to users. Movies which are recommended to users are highly depend on similar user's ratings. For example, If X is a user who gives ratings to movies. Y is another user also gives ratings to other movies. Similarity is based on ratings which are given by users. If X and Y are giving nearly similar ratings to any movies then these users are considered as similar users. Then recommend movies to X which are rated by Y. Monte Carlo algorithm uses random numbers to produce results. This method is useful for different applications. Depends on applications method will be vary, but has a tendency to follow a specific pattern

6) *SVM (Support Vector Machine)*: After reducing uncertainty in ratings using Monte Carlo simulation, movies are recommended to users based on loss function and social similarities. Then use SVM (Support Vector Machine) to group movies in to different classes. SVM is a classification method used to predict the user preference by model learning method [11]. It is used to categorise or predict test data based on training data. A training set may be created and kept for training purpose. An SVM library is used to learn the test data using training data. Based on prediction movies are classified and when the user gives ratings to movie then predict the class of that movie and recommend other movies in that class. In the proposed system training data can be created by admin. The criteria for creating training set is based on average ratings of movies. Training set is classified as class 5, class 4, class 3, class 2, class 1 and class 0 based on the values of average ratings of movies for example, movies having average rate greater than or equal to 8 is treated as class 5. Whenever the test data is obtained from user that means user gives rating to a movie calculate the average rate and predict in which class that movie belongs. For that initially training and prediction must be completed and classify movies based on prediction. Training and prediction of movies are done by using commands. Then based on prediction other movies in that class are recommend to users. In this system recommendation is performed using SVM depends on the genre of the rated movie. Recommending other movies having the same type (genre) of rated movie by user.
7) *Online Movie Booking*: The proposed system also provides an opportunity of ticket booking through online. For that admin create a virtual bank for storing account details of users. Details which are stored in the virtual bank are bank name, IFSC code, account number, pin number and balance. Also admin can provide different theatres for movie booking. If a user wants to book movies through online admin check whether it is a genuine user who has sufficient balance for ticket booking. If it is not like then users can't booking ticket.
8) *Movie Maker Module :* In the proposed system movie makers give the details of different movies to the system. Different movie makers post their movie details. Admin can give permission to movie makers for posting their movies. Then they can edit details, delete details what they are posted. Also they can view user's preferences to different movies. They can view their movies with loss function which is acquired from ratings. In this system movies from different languages are stored. Languages such as Malayalam, English, Tamil, Hindi and Telugu. Their main responsibility is to promote their movies to users or viewers. This promotion is done by posting their movies to the system and view their movie's ratings and other movie maker's movie ratings.
9) *User Module:* The main part of the system is user module. Result of all processing performed in the system are shown by users. Users give only ratings to the system and based this input recommend movies to users. Users can search movies by using movie title, year, director, actors, languages, country and genre. Main problem of recommendation system is cold start problem. The proposed system overcomes the cold start problem. This system provides the facility to view new movies to users which are posted by movie makers currently or recently. Also movies are recommended to new user who is entered to the system. If a registered user didn't give ratings to movies in such case movies are recommended based on demographic details. Likewise users those are not registered to the system can view movies based on average ratings. Users can view movies by different manners such as popular movies, top rated movies, low rated movies etc. They can also view ratings given by other users. A

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user can rated only once to a particular movie. So it will reduce false rating of movies. Then recommending movies to users based on Frank Wolfe algorithm, Monte Carlo algorithm and SVM classification. Also users can booking tickets through online. Users can view latest movies and their ratings so it will help users to ticket booking. They can book ticket for movies having highest rate.

V. RESULTS AND ANALYSIS

A. Results

The experimental results of the proposed system, kernel optimization based enhanced preference learning for online movie recommendation are discussed in this section. The system here using the operating system of version Windows 10 and platform using is C# .net. And the database created is SQL server. Proposed system using synthetic data and real data for result evaluation. Synthetic data are data which are created. Synthetic data are created for obtaining specific requirements or certain criteria that could not be found in the original data. Synthetic data are very useful for developing system of any type because it can be used as a model. Real time data is an online dataset. Here IMDb (Internet Movie Database) dataset is used for the result evaluation. The proposed system implemented on both synthetic data and IMDb dataset. IMDb is an online database of movies, television shows, the actors/actresses that star in them, and the people that make them. Proposed system uses IMDb dataset of movies.

Proposed system implemented by using many modules and sub modules. The input of the system is ratings which are given by users to different movies. All processes are applied on this input. Loss function and similarity are calculated based on ratings. And this two functions can be treated as an optimization problem. The Frank Wolfe optimization algorithm is used to resolve optimization problem and recommend movies to users based on similarity and loss values. Nonlinearity in ratings make recommendation inaccurate. Monte Carlo uncertainty propagation is used to reduce uncertainty and recommendation is performed accurately. Finally recommendation is performed based on a classification method. SVM is used for recommendation. Classification method accurately classifies movies into different classes depending on ratings. When user gives rating to a movie after the completion of training, predict the class for that movie and recommend more movies which are in that class based on genre of that movie. All these methods are applied on synthetic data as well as IMDb dataset. Also system uses demographic details of users for recommendation. When registered user did not give ratings to movies such case demographic details are used. Results of recommendations using various methods are discussed below.

1) *Recommendation Based on Frank Wolfe Algorithm*

Fig.3 Recommendation based on Frank Wolfe algorithm

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2) Recommendation Based on Monte Carlo Algorithm

Fig.4 Recommendation based on Monte Carlo algorithm

3) Recommendation Based on SVM Classification

Fig.5 Recommendation based on SVM classification

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4) Recommendation Based on Demographic Details

	Movie ID	Title	Language	Actor 1	Actor 2	Director	Year	Country
	1	Minnaram	Malayalam	Mohanlal	Sobhana	Priyadharshan	1994	India
	102	Lady Bird	English	Saoirse Ronan	Laurie Metcalf	Greta Gerwig	2017	USA
	103	Magnolia	English	Jeemy Blackman	Tom Cruise	Paul Thomas Anderson	1999	USA
	109	Independence Day	English	Will Smith	Bill Pullman	Roland Emmerich	1996	USA

Fig.6 Recommendation based on demographic details

5) Online Movie Booking

	Movie ID	Name	Cast	Director	Language	Country	year	Rating
	12	Adu 2	Jayasoorya	Midhun Manual	Malayalam	India	2018	6.000
	4	Padmavath	Deepika Padukone	Sanjay Leela	Hindi	India	2018	6.500
	140	Saaho	Prabhas	Sujeeth Reddy	Telungu	India	2018	0.000
	141	Bhaagamathie	Anushka Shetty	G. Ashok	Telungu	India	2018	7.250
	143	Mahanubhavudu	Sharwanand	Maruthi Dasari	Telungu	India	2017	0.000

Theater	Timing	Number of Seat	Movie Name	Amount/Ticket	
RP mall	9.00am-12.00pm	50	Ira	150	BOOK
RP mall	2.00 pm-5.00pm	50	Shadow	150	BOOK
RP mall	9.00 pm-12.00 am	50	Naachiyar	150	BOOK

Fig.7 Online movie ticket booking

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B. Analysis

This system shows an accurate movie recommendation to customers based on their interests or likes. It also shows analysis based on algorithms which are used in the system. Likewise shows different movies and their ratings. And analyses loss values of movies before Monte Carlo and after Monte Carlo algorithm. The algorithms are Frank Wolfe, Monte Carlo, and SVM. Analysis performed on both data which are created and on IMDb dataset.

1) *Analysis: Movies, Ratings and Loss value:* This analysis shows different movies and ratings of that movies. Ratings lies between 0-10. In the proposed system 10 features of movies are considered for ratings. These 10 features have rating values ranges from 0-10. Fig.8 shows movies and their ratings produced by users. Fig.9 shows movies and their loss values calculated from ratings. Loss values of movies lies between 0-1.

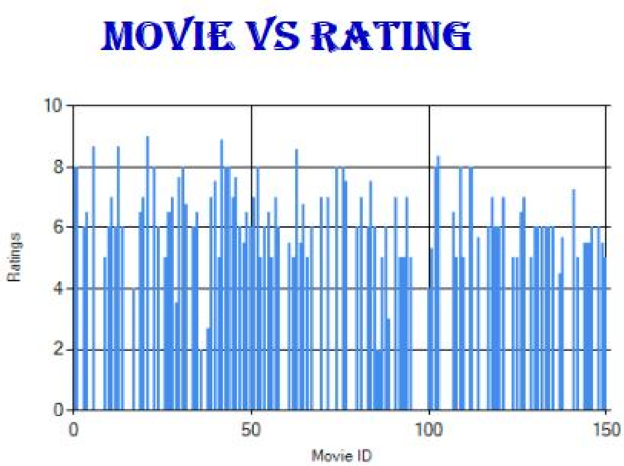

Fig.8 Movies and their ratings

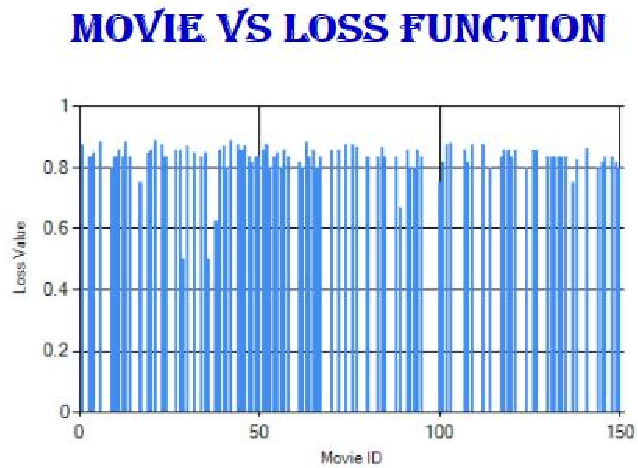

Fig.9 Movies and their loss values

2) *Analysis of Loss values before and after Monte Carlo Uncertainty Propagation:* This analysis gives loss values of different movies before uncertainty measure and after uncertainty measure using Monte Carlo. Nonlinearity calculation related on ratings and after measuring uncertainty in ratings, loss values can be calculated. Fig.10 shows movies with loss values before and after uncertainty measure calculated in ratings. This analysis shows that loss values calculated from ratings with reduced uncertainty are lower than ratings without measuring uncertainty. This means that Monte Carlo reducing error ratings of movies.

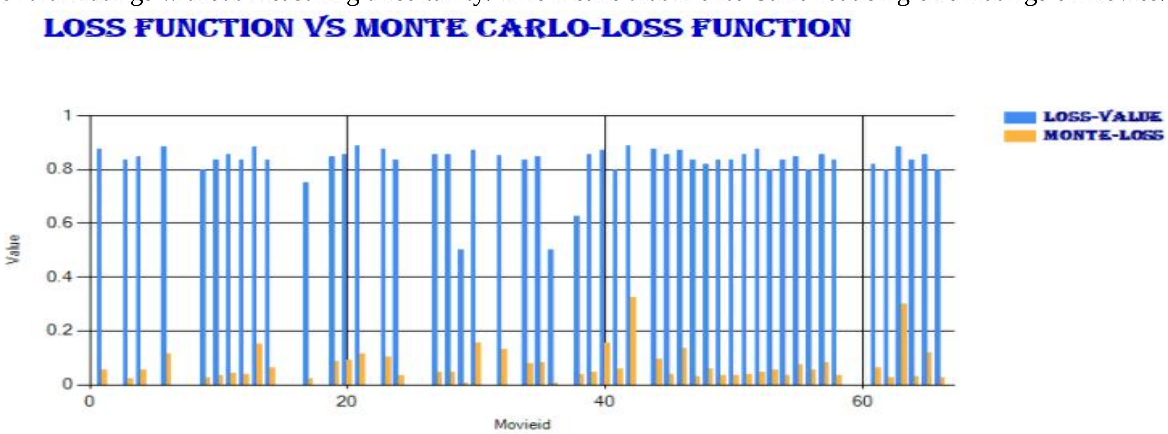

Fig.10 Movies with loss values before and after uncertainty measure

3) *Analysis between Frank Wolfe and Monte Carlo Recommendation:* The graph shows number of recommended movies using both Frank Wolfe and Monte Carlo. Here trial number represents how many times each user will view the recommendations using both algorithms. In this analysis each bar shows number of movies recommended to a user using Frank Wolfe and Monte Carlo. Frank Wolfe algorithm recommend movies without reducing nonlinearity in ratings. So that recommendation using Frank Wolfe recommend large number of movies to users. Monte Carlo reducing uncertainty in ratings from that loss values are

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calculated for movies. Uncertainty measure reducing error ratings. So loss values obtained from that ratings also reduces errors of loss values. Then recommendation using Monte Carlo provide an accurate recommendation than Frank Wolfe algorithm. Monte Carlo uncertainty propagation reducing the count of movies which are recommended. Fig.11 shows recommendation using Frank Wolfe and Monte Carlo.

Fig.11 Recommendation using Frank Wolfe and Monte Carlo

4) *Analysis between Frank Wolfe and SVM Recommendation:* Frank Wolfe algorithm is an optimization algorithm used to recommend movies to users based on their preferences. SVM is a classification method used to recommend movies. SVM classifies movies to different classes based on ratings. Then training data is used to predict in which class test data is included. SVM is an efficient classification method. Recommendation based on classification is also an accurate recommendation. Fig.12 shows recommendation using Frank Wolfe and SVM.

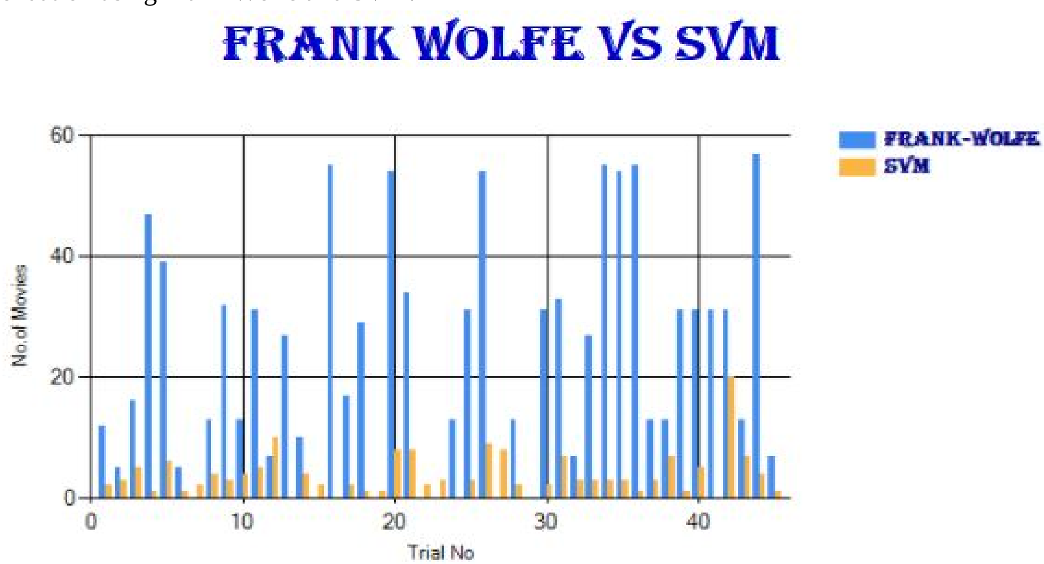

Fig.12 Recommendation using Frank Wolfe and SVM

VI. CONCLUSION AND FUTURE WORKS

Recommendation system is an area having widespread applications in nowadays. The proposed system is a platform for movie recommendation which is related on user preferences or interests. The important intention of this method is to provide an accurate recommendation based on user's interest. Proposed system introduced Frank Wolfe algorithm for movie recommendation. For reducing uncertainty in rating Monte Carlo method is used and recommend movies more accurately than Frank Wolfe algorithm. Also use a classification method for recommendation. System uses SVM for classification. SVM classifies movies and recommend movies to users based on class. This system also gives an opportunity for movie ticket booking through online. This facility will helps users for ticket booking based on user's ratings or preferences.This also provides new opportunities for future work. To use another time efficient method for measuring uncertainty in ratings. To introduce another classification method for better recommendation. To implement movie booking facility based on preference of users.

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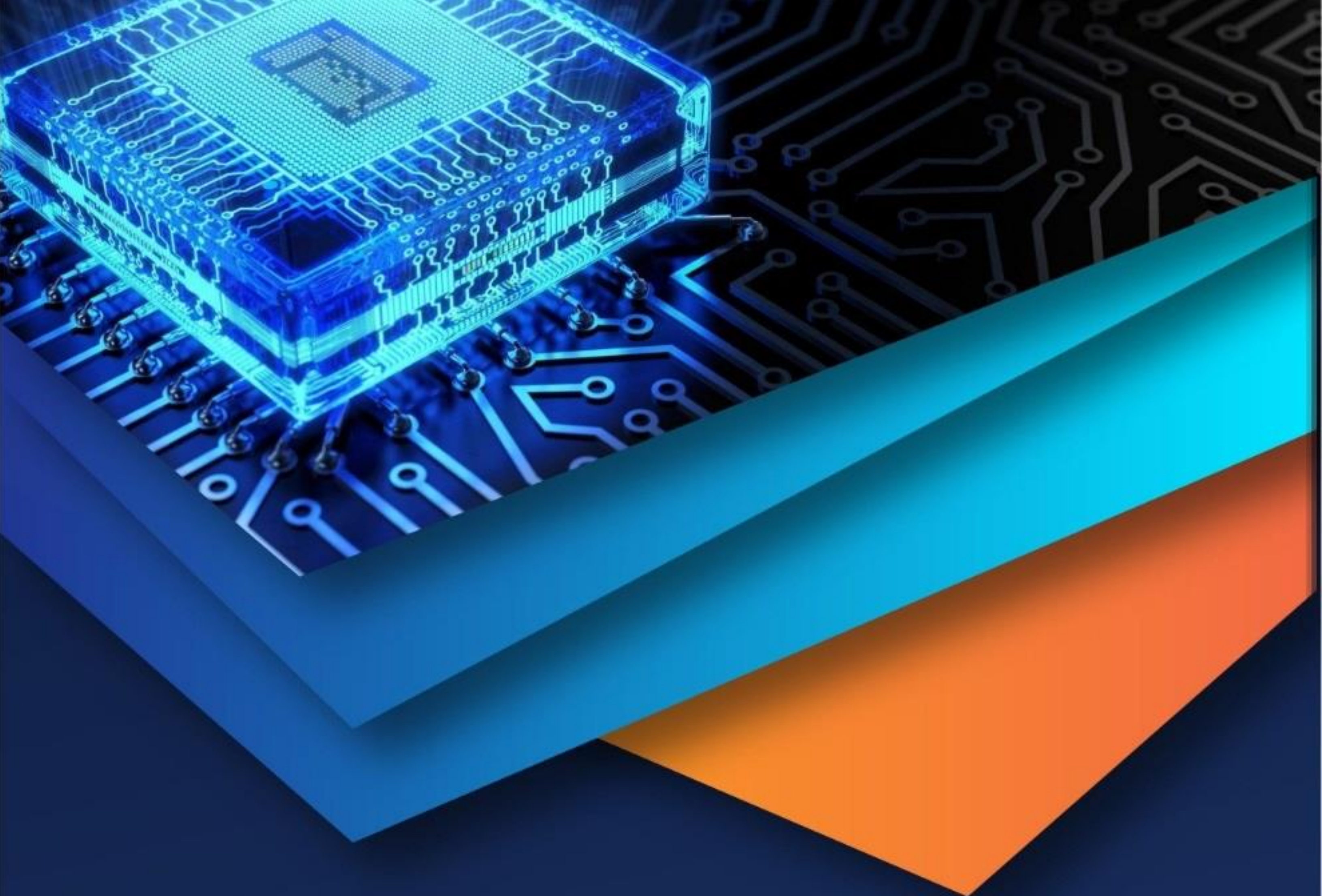

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