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ORIGINAL ARTICLE

Comparative study of recommender system approaches and movie recommendation using collaborative filtering

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Abstract The increasing demand for personalized information has resulted in the development of the Recommender System (RS). RS has been widely utilized and broadly studied to suggest the interests of users and make an appropriate recommendation. This paper gives an overview of several types of recommendation approaches based on user preferences, ratings, domain knowledge, users demographic data, users context and also lists the advantages and disadvantages of each RS approach. In this paper, we also proposed the movie recommendation based on collaborative filtering and singular value decomposition plus-plus (SVD++). The proposed approach is compared with well-known machine learning approaches namely k nearest neighbor (K-NN), singular value decomposition (SVD) and Co-clustering. The proposed approach is experimentally verified using MovieLens 100 K datasets and error of the RS is measured using Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The result shows that the proposed approach gives a lesser error rate with RMSE (0.9201) and MAE (0.7219). This approach also overcomes cold-start, data sparsity problems and provides them relevant items and services.

Keywords Recommender system · Knowledge based · Context based · Hybrid · Content based · Collaborative filtering · Intelligent · Demographic

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1 Introduction

Recommender systems are information filtering tools and whose main aim is to provide personalized recommendations. Nowadays exponential growth of information systems, increase in number of users and data have become challenging problems in obtaining essential information. RS helps users to overcome the information overload problem and easily find products and services. RS generally helps users to find the products and services that fit their personal needs and preferences. Millions of users throughout the globe interact with a wide variety of RS on a daily basis Anwar and Uma (2019c, 2020a).

Increasing trends in internet usage have affected almost every aspect of life. Dependency on the internet in performing online shopping, online booking and using social networking websites etc. is increasing day by day. Through RS, users effortlessly get required information from the enormous amount of data in lesser time. RS predicts the interest and preferences of users. RS is widely accepted approach which is earning continuous attention in recent years. RS is mostly used in various fields such as e-government, e-learning, e-commerce, social media and tourism Premalatha et al. (2018). A large number of researches are being carried out on RS using various methods with the aim of selecting out relevant information from the huge amount of data. In the current scenario many approaches for recommendation have been proposed in several domains such as information retrieval, artificial intelligence and data mining. In Fig. 1, shows the simple model of recommendation system.

The highlights of this paper are as follows:

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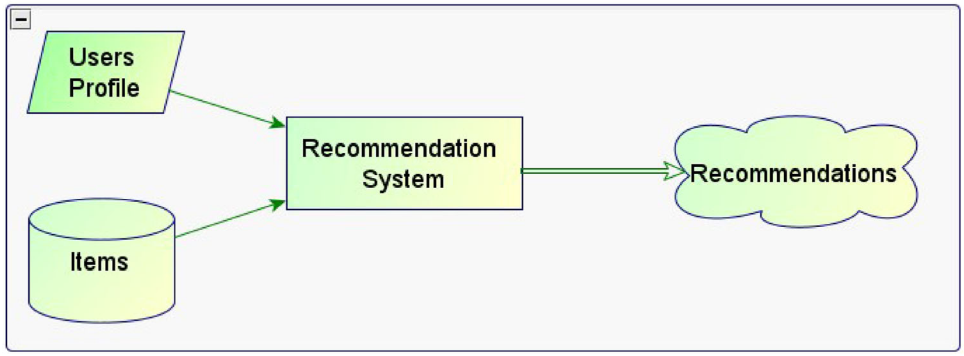

Fig. 1 Simple model of recommendation system

(a) Overview of several recommendations approaches based on user preferences, user ratings, item ratings, domain knowledge, users demographic data, user context, user reviews, knowledge representation, and reasoning methods are provided extensively.
(b) The advantages and disadvantages of each RS approach is provided.
(c) The advantage of the proposed approach that combines collaborative filtering with SVD++ is compared with well-known machine learning approaches namely K-NN (k nearest neighbor), SVD (singular value decomposition) and Co-clustering.

The remainder of the article is structured as follows: Sect. 2 explains various types of RS approaches. In Sect. 3, comparison of RS approaches is presented and the conceptual goals and various inputs to be given to RS are explained. Section 4 provides details about the experimental analysis and Sect. 5 concludes the paper.

2 Types of recommender system

In Fig. 2, various types of Recommender systems are presented.

2.1 Content-based recommender system (CBRS)

CBRS mainly works by analyzing the features of an item preferred by a user and tries to identify the similarity between them. The preference of user is calculated based on his/her choice in the past. Similar items are identified based on the characteristics of compared items Pazzani and Billsus (2007). CBRS system can start recommending items as soon as information about items are available. For appropriate recommendations in CBRS, a large amount of information about the items is required Kumar and Thakur (2018).

CBRS is categorized into attribute based approach Felfernig and Burke (2008) and case based reasoning approach Adomavicius and Tuzhilin (2005). Attribute based approach suggests items on the basis of matching their features to the related learner profile Klašnja-Milićević et al. (2015) and case based reasoning approach

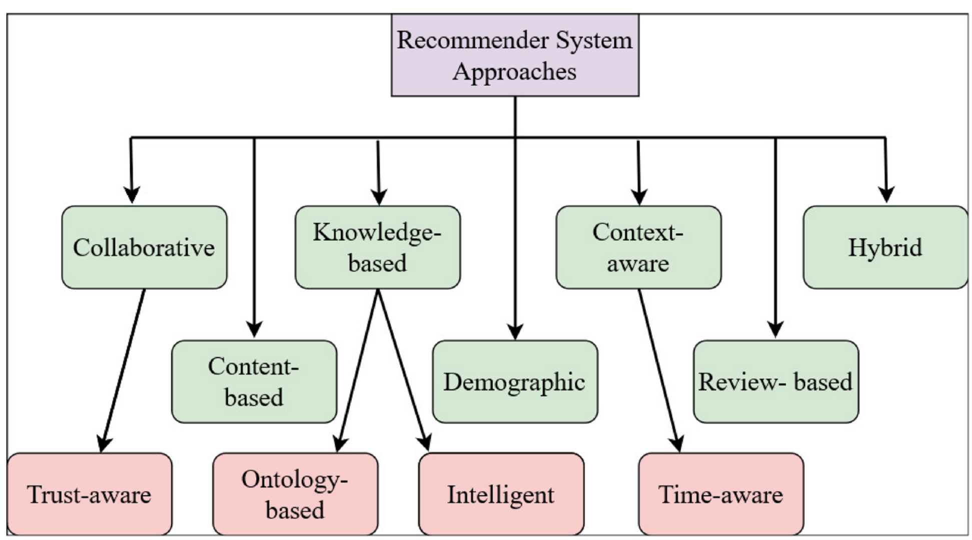

Fig. 2 Types of recommender systems

suggests items which are correlated to user interest. In general CBRS approach mostly uses simple retrieval models like Term Frequency-Inverse Document Frequency (TF- IDF) weighting, keyword matching and Vector Space Model (VSM).

Deldjoo et al. (2016) proposed an innovative CBRS that automatically checks the video contents and collects a set of unique characteristics (motion, color and lighting). The result shows that the approaches gave more appropriate recommendations. The proposed approach performs better not only when visual characteristics are extracted but also with small-length videos (movie trailers).

2.2 Collaborative recommender system (CRS)

CRS is a prevalent RS approach, which uses past rating data, comments, and review to make appropriate recommendations. This technique works based on the users' similarity and without asking for exogenous information Kant and Mahara (2018); Anwar and Uma (2019a). For finding similarity between items, widely used matrices are cosine and correlation based similarity. The standard CRS approaches are model-based and memory based, which are mostly used in various fields such as social networks (e.g., Instagram, Facebook), review sites (e.g., Google news, Movielens) and e-commerce (e.g., Flipkart, Amazon). One of the most important benefits of memory based CRS approach is that their natural idea makes it convenient to understand and yields convenient results. Besides, the main strength and backbone of pure CRS approaches is that frequent data addition can be done without any problem. This is because, no tagging of items is required when compared to CBRS recommendations Anwar and Uma (2019b). The process involved in CRS is shown in Fig. 3.

CRS has some limitations such as cold start Lillegraven and Wolden (2010) Yan et al. (2020),data sparsity Ahmadian et al. (2019) and scalability Koshti et al. (2019). Cold start problem exists when a new user and new item enters the system and there is no rating available. CRS can't recommend in the absence of initial ratings and therefore, it is very tough to make accurate recommendations (Anwar and Uma 2020b).

Aciar et al. (2016) proposed a recommendation based on novel similarity computation (i.e., ratio-based method) for computing similarity. This system can easily calculate similarity between items or between users using the attribute values directly. On the basis of similarity, a new approach has been proposed for predicting unknown values. A large data set of real web services is used for checking the performance of proposed method. The results show that computation time is less, mean absolute error is less and prediction precision is higher.

2.2.1 Trust aware recommender system (TARS)

This is an extension of conventional Collaborative based RS.Trust is a commitment to a person and an action on the basis of faith such that the future hopes for good outcome. This approach only examines the trust association between users in order to make the recommendation Hassan (2019). TARS are more robust and can easily overcome cold start and data sparsity problem because trust can be generated in the network. Generally, trust is of two types implicit and explicit. Implicit trust is the information of the trust that is implicitly gathered from user behavior and explicit trust is the value of the trust that is explicitly given by users.

Golbeck and handler Golbeck and Hendler (2006) said that trust is a commitment related to an activity on the basis of hope such that the future activity starts with a good result. The main aim of this approach is to produce a personalized recommendation from trust relation and known opinions. TARS are extensively used in e-commerce, e-learning and social network where trust plays essential aspect to improve the relationship between users.

2.3 Knowledge based recommender system (KBRS)

KBRS works on the basis of domain knowledge about user and items. This recommending approach is based on reasoning as to what items are related to the user's interest Tarus et al. (2017b). Mainly three types of information are required; knowledge about the items, users and the similarity between users and items. KBRS approaches are mainly used for complex domains where items are not bought regularly. KBRS approaches support hybridization with some other recommendation approach. An important advantage of KBRS is the nonexistence of cold start (startup or ramp up) problems. The main limitation of KBRS is the necessity of knowledge and engineering skills Ricci et al. (2011).

Aciar et al. (2016) proposed a recommender system on the basis of the degree of domain knowledge that provided

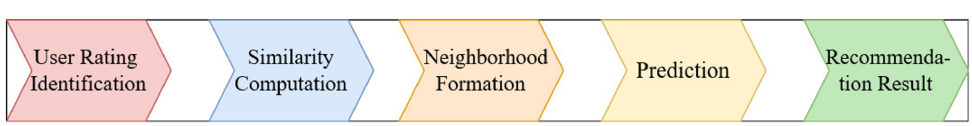

Fig. 3 Process involved in collaborative recommendation system

a convenient question-answering facility. In this paper, new method has been added to find the reputation of the candidate users in the group. Result shows that the proposed approach gave high degree of effectiveness and proper recommendations.

2.3.1 Ontology based recommender system (OBRS)

OBRS works on the basis of ideal knowledge about the users, items, and domain knowledge. In OBRS, ontology is mainly used for knowledge representation George and Lal (2019). OBRS is mainly related to KBRS that uses ontology for knowledge representation. OBRS also alleviates some limitations related to traditional RS, such as Data sparsity Zhao et al. (2015) Ramp Up and overspecialization. Meanwhile, OBRS relies more on domain knowledge rather than ratings. This striking characteristic makes OBRS most useful and suitable for e-commerce, e-learning and tourism-related field. On the other side, development of ontologies is complex and costly process.

John Tarus et.al Tarus et al. (2017a) presented a recommendation approach for e-learning using CBF and ontology. Ontology is used to combine recommendation process into the learner features. Result shows that OBRS outperforms than CRS. The proposed approach also overcome start-up limitations in the initial steps of recommendation through ontological knowledge.

2.3.2 Intelligent recommender system (IRS)

The extension of knowledge-based RS is the IRS. The IRS adventures knowledge, learns, explores new information from reviews and identifies preferences. IRS is described by the components: learning methods, knowledge representation model and reasoning mechanisms. Furthermore, IRS has five Knowledge models in the distinct context such as items, users, context, criticisms and domain, that can be considered during the recommendation.It also alleviates cold-start problem because it does not depend upon user rating and knowledge engineering processes is not required. IRS also utilizes the information about users through learning mechanism to increase its performance.

Aguilar et al. (2016) proposed IRS which enhances the degree of the recommendations through its knowledge representation, learning and reasoning techniques. It also overcomes some conventional problems of the recommender system, i.e., cold start problem as recommendations do not depend on the previous user ratings. Implementation of IRS has been done using the fuzzy cognitive map. The main features of IRS are representation of diverse knowledge, reasoning and learning capabilities.

2.4 Demographics based recommender system (DBRS)

DBRS works on the basis of user demographic data. The main goal of this RS approach is to classify the user on the basis of attributes and user's demographic data stored in their profiles (i.e. gender, age, location etc.) for suggesting the item. Unlike CRS and CBRS demographic approach doesn't need previous user ratings.

DBRS works on three steps: Collecting input data, similarity computation and recommendation prediction. Collecting input data is the first step that includes new target user's demographic information (the user who wants recommendations) and also demographic information and rating of other users. Similarity Computation step uses user demographic information to retrieve users having related demographic interest thus creating a neighborhood. Ultimately, recommendation computation stage recommends items that are generally positively rated by surrounding users. The process involved in DBRS is shown in Fig. 4.

Zhao et al. (2015) proposed a DBRS for product recommendations which identify users buying plans from microblogs and make recommendations on the basis of matching user demographic data. Conventional Product RS are generally designed for some particular e-commerce websites, which provides suggestions when users are carrying out some e-commerce activities. For experimental testing data crawled from Sina Weibo microblog is used. The result shows that effectiveness and feasibility are better in terms of recommendations.

2.5 Context aware recommender system (CARS)

CARS make better suggestions using particular contextual condition of the user Aghdam (2019). Preferences of the user may change according to context (mood, season, time of day, location, companion, occasion etc.). For example, while watching a movie (location, time, companion etc.), traveling (location, time, weather, transport condition etc.) and listening to music (time, location, emotions, occasions etc.) Thaduri et al. (2017). CARS collects the context of the user at the time of making recommendations. There are generally three types of architecture for building CARS: Contextual Modeling, Contextual Pre-filtering, and Contextual Post-filtering.

Mazloom et al. (2017) proposed a technique to analyze the collaboration between item and user for suggesting the prevalence of posts associated with a particular user and item in social media. The result shows that relational improvement in user specific and item-specific post popularity recommendation increased.

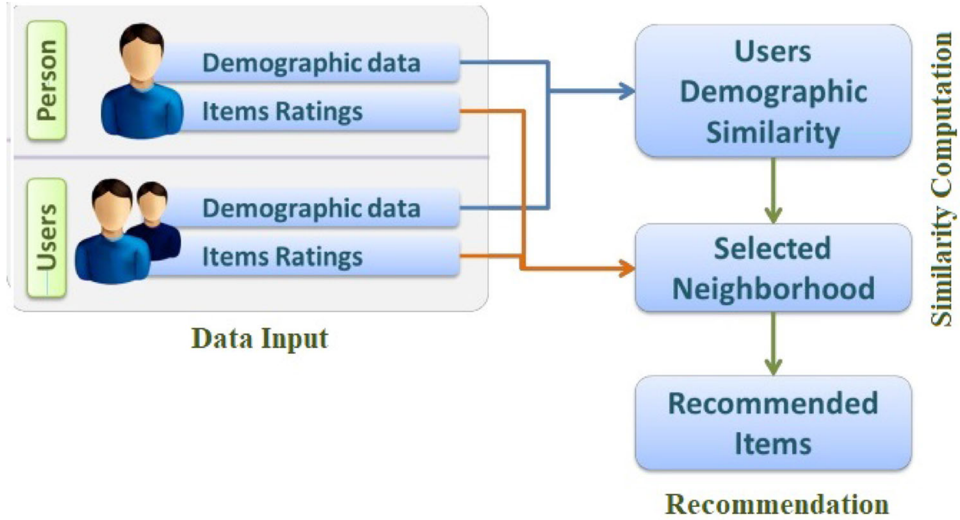

Fig. 4 Process involved in demographic based recommendation system

2.5.1 Time aware recommender systems (TiARS)

TiARS is a specialized form of CARS, and it mainly focuses on utilizing time as contextual information. The interest of users might change time to time, and this is mainly considered in this RS. Managing the temporally changing preference of the user in RS leads to new hurdles because each particular user interests are distinct due to the concept drift problem Tsymbal (2004). In the social network, numerous items and users with multiple attributes are changing at the same time and move towards each other.

Rezaeimehr et al. (2018) presented a unique TiARS on the basis of finding overlapping community structure within users. The suggested algorithm finds overlapping community structures within the users and assists in reducing the effect of sparsity. The suggested method uses two real-world datasets and achieves better precision than various state-of-the-art approaches.

2.6 Review based recommender system (RBRS)

This RS has the capability to reduce and remove cold start and data sparsity problems. Basically, RBRS works on the basis of product profile and user profile which are reviewed. This approach, analyzes and classifies the reviews using different methods like opinion mining and text analysis. It is then divided based on user and product profile, and then recommend of items is done similar to CBRS and Rating-based CRS. The process involved in RBRS is shown in Fig. 5.

Aciar et al. (2007) proposed the RBRS based on consumer product reviews. This proposed approach was based on a case study considering digital cameras. In this technique domain ontology is used to interpret the information.

2.7 Hybrid recommender system (HRS)-approaches

The HRS approach merges characteristics of multiple filtering approaches e.g. CBRS and CRS approach, by adding advantages of each approach there by achieving better performance Ghauth and Abdullah (2010). This also alleviate various issues of RS such as ramp-up, data sparsity and overspecialization. HF approach is widely accepted and very helpful as it reduces the limitations of conventional recommender system (Anwar et al. 2021). Firstly in 2002, Burke suggested a taxonomy of seven hybridization techniques Mobasher (2007). He divided hybridization technique into seven types. This is shown in Fig. 6 and the explanation of each technique is given in Table 1 (Fig. 7).

Gordillo et al. (2017) proposed an idea about HRS for Learning Object Repositories (LORs) that merges demographic based RS, content based RS and context aware RS approaches, including the use of popularity and quality metrics. This paper also explains how to use the model for implementing two RSs for two real Learning Object Repositories: Europeana and ViSH. The experimental result shows that the presented technique had high user acceptance in terms of satisfaction, usability and utility.

Aslanian et al. (2016) proposed a HRS algorithm by analyzing the similarity among content characteristics. This relationship is inserted in HRS to increase their accuracy. At first, a novel approach is used to obtain the content characteristic relation matrix. Then the CRS is revised so that relation matrix can be efficiently merged with the algorithm. This algorithm alleviates the ramp-up

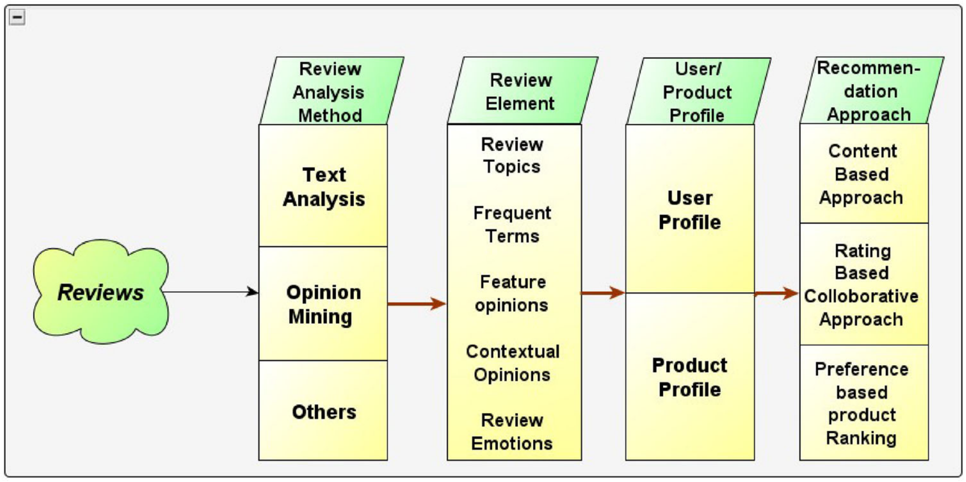

Fig. 5 Review based recommender system process

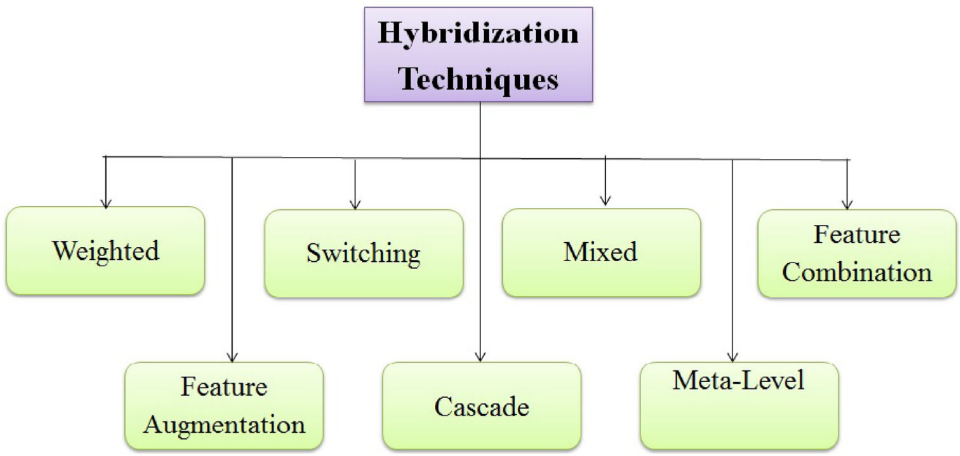

Fig. 6 Hybridization technique

Table 1 Taxonomy of hybridization techniques

Sr. No.	Technique name	Function
1	Weighted	Merge several RS component numerically
2	Switching	System switches among RS depending upon the current situation
3	Mixed	Several recommenders are presented together
4	Feature Combination	Combine the different features and given to a single method
5	Feature Augmentation	Output from one approach is used as an input characteristic to another approach
6	Cascade	Applies a repetitive refinement.One recommendation refines the recommendation given by other
7	Meta-level	One approach is used for producing some small model, which is given to input as another approach

problem. In this paper, content based hybrid recommender system showed better results in terms of novelty and accuracy.

Zhang et al. (2015) presented a HRS on the basis of user recommender interaction and calculated its performance with diversity metrics and true positive rate (recall). At first, user recommender interaction is set. Second, merging of HRS with K- nearest neighbor and random forest is introduced. After that, the diversity and true positive rate on the basis of the new situation is redefined to evaluate the RS. The experiment is done using the MovieLens dataset. The result shows that hybrid algorithm makes more efficient and appropriate recommendation than non-hybrid one.

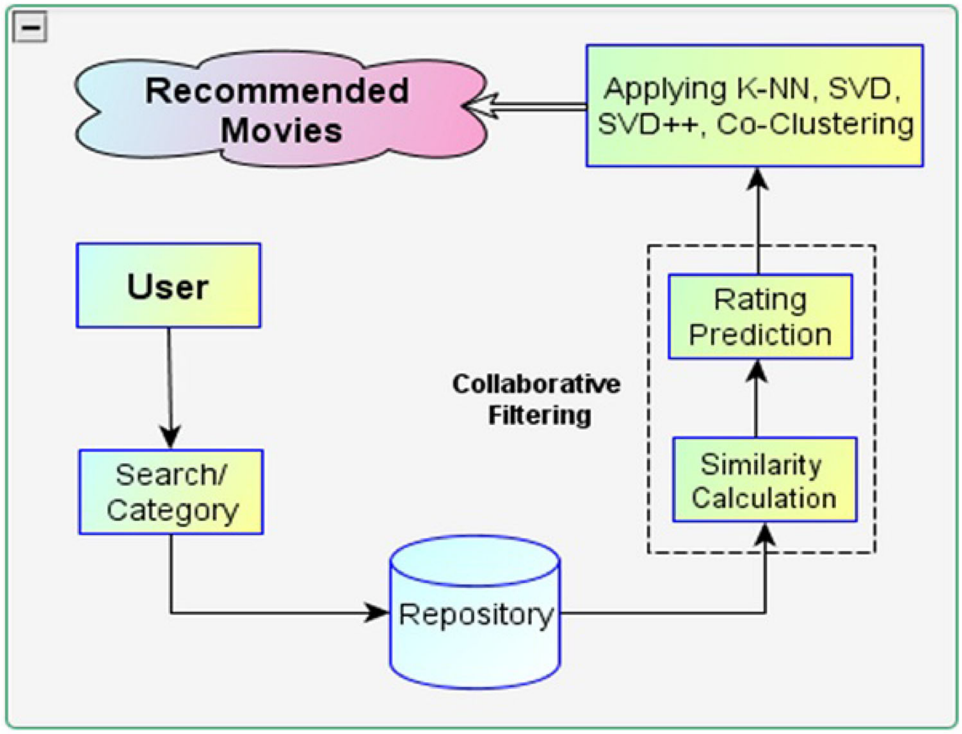

Fig. 7 Recommendation System model for movie recommendation

3 Comparison of RS approaches

3.1 Table 2 provides details about the advantages and disadvantages of various Recommendation system approaches.

3.2 Table 3 provides details about conceptual goals and various input to be given to various Recommendation system approaches.

4 Experiments and result

4.1 Dataset description

We have used the openly available MovieLens 100 K dataset related to Movie domain which contains 100,000 ratings (1-5) of 1682 movies given by 943 users. Each user has rated at least twenty movies. The details such as User id, Movie id, Movie name, rating, genre are obtained[1].

[1] https://grouplens.org/datasets/movielens/100k/.

4.2 Proposed system

In the basic collaborative recommender system, the recommendation is done by (1) Finding similarity between items and users (2) Neighborhood formation (3) Predicting the rating matrix and (4) Recommendation of top-N items. But, in the proposed movie recommendation model, the recommendation is done using collaborative filtering with Singular Value Decomposition (SVD)++. The proposed model is divided into five modules which are explained below.

(1) Data pre-processing.
(2) Calculating similarity between movies and users using the Cosine similarity using Eq. 1.
(3) Finding the Prediction Matrix using the formula in Eq. 2.
(4) Applying the SVD++ approach
(5) Recommending Top-N movies.

At first, user-movie ratings are used for generating the rating matrix. Then cosine similarity is found for generating similarity between movie and user. The prediction matrix is evaluated using Eq. 2. Then the SVD++ approach is applied and finally, Top-N items are recommended.

$$Cosine = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sum_{i=1}^{n} A_i^2 B_i^2} \quad (1)$$

A and B are features of the movies or items. A dot (.)

Table 2 Advantages and disadvantages of Recommendation method

Recommendation methods	Advantages	Disadvantages
Collaborative filtering	It does not depend on the analysis of the information given by the user. The information which is being used for recommendation is domain independent. Does not require analysis of the items (features). Better at qualitative judgments. Adaptability(Requirement of a user may change over time) better at qualitative judgments	Cold start or ramp-up problem (can't handle new items or new users). Unpopular items are not strongly recommended.Bootstrapping. Ratings required. Critical mass required. Not as transparent in their recommendations. Need substantially more user data to work wel
Content-based	Useful in solving cold start problem when a user in the new community. Characteristics of the user profile are matched with characteristics of the items. Domain knowledge is not required. Independent of other users. Provide transparency (easily understandable,explanations). Easy to explain and understand	The item which is highly correlated with user interest or profile is only recommended (Overspecialization problem occurs). Learning item/content must be in the category. Need category maintenance and modeling.New user problem. Limited content analysis(insufficient keywords, content may not be automatically extractable)
Knowledge based	Grey sheep and Cold start problems are avoided because the domain knowledge is used for recommendation. Provides noise-free and more reliable recommendation. Great precision is possible. Easily mapping is possible from user need to products	Necessity of knowledge and engineering skills. Construction of the knowledge base is a difficult task that demands expertise in knowledge representation and considerable domain knowledge
Ontology based	It alleviates some limitations related to traditional RS, such as Data sparsity, ramp up and overspecialization. The main advantage of applying ontologies are pointed recommendation	Ontologies creation is a difficult process. Construction of ontology is expensive and time-consuming
Demographics based	Feedback is not needed. No cold start problem. Metadata engineering is not needed	Cannot provide personalization. Low accuracy. Too general
Context aware	Context-aware is more of a real-time nature. More advanced than content based RS because this system continuously in synchronization with user movement and generate recommendation as per user current context	Contextual factor identification. May lead too much sparsity. Categorical (Time Morning. Evening) Vs. (Time 6:30,2PM) Numeric context information.Serendipity and surprise
Trust-aware	The decision-making process can become easy. Reduces the sparsity problem. More relevant recommendation than the traditional approach	In explicit trust user have an extra burden for giving trust information apart from the rating. Sparsity problem in Explicit Trust Information because no trust information is less than no of ratings
Intelligent RS	An inference is used for inferring interesting information. Alleviates cold-start problem because do not depend upon user rating. Knowledge engineering process is not required	Large knowledge about context and domain are required
Utility based	No cold start problem. Non-product features can include. Preferences changes by sensitively possible	Utility function must be added by the user. The ability of suggestion is static (doesn't learn)
Time aware	Minimizing the sparsity effects. Better precision also possible	collecting implicit feedback
Hybrid	Combining CF with other RS in attempt to overcome cold-start, scalability, and data-sparsity problem. Prediction performance is improved	External information required that easily not available. Compare between various recommendation paradigms (rating, domain knowledge, item features, critiques, requirements etc.) not allowed because all are rarely available in a dataset. Have increased expense of and complexity

represents vector dot product $\|A\|$ and $\|B\|$ shows the length of the vector.

$$P_{u,i} = \frac{\sum_{t \varepsilon N}\left(sim(i,t) \times R_{u,t}\right)}{\sum_{t \varepsilon N}(sim(i,t))} \tag{2}$$

In this equation, n is the neighborhood of most related movies rated by user u and sim (i,t) is the similarity between movies i and t.

In this section, Collaborative filtering is performed with four well-known approaches namely K-NN (k nearest neighbor), SVD (singular value decomposition), SVD++ (singular value decomposition plusplus), Co-clustering and the results are analyzed. The comparative analysis shows that SVD++ gives a lesser error rate.

K-NN is a machine learning approach to find clusters of similar users on the basis of common item ratings, and is

Table 3 The conceptual goals of various recommender systems

Methodology	Objective	Input
Content-based	Recommendations based on the content of item	User ratings + item attributes
Collaborative	Recommendations based on past behavior of user	User ratings + item attributes
Knowledge-based	Based on domain knowledge of item and user	knowledge of items + knowledge of user + Similarity between users and items
Ontology based	OBRS more trust on domain knowledge instead of ratings	Model knowledge of items + Model knowledge of user + Domain knowledge
Hybrid	HRS reduces the limitations of conventional recommendation system	User ratings + item attributes + domain Knowledge etc
Demographics	DBRS approach is to classify the user on the basis of attributes doesn't need previous user ratings like CRS and CBRS	User demographic data (gender, age, location etc)
Context aware	Works based on CARS preferences of the user (mood, season, time of day, location, companion, occasion etc)	Context of User (location + time + mood + companion etc)
Trust-aware	TARS use social media and trust information to make a recommendation. Main goal is to improve the accuracy of recommendation	Trust value + ~ Trust metric
Intelligent RS	The IRS adventures knowledge, learns, explores new information also concludes reviews and preferences among other things	User profile + item profile

Table 4 RMSE and MAE comparison using MovieLens 100K dataset

	RMSE	MAE
K-NN	0.979	0.7732
SVD	0.9358	0.737
SVD++	0.9201	0.7219
Co-Clustering	0.9675	0.7582

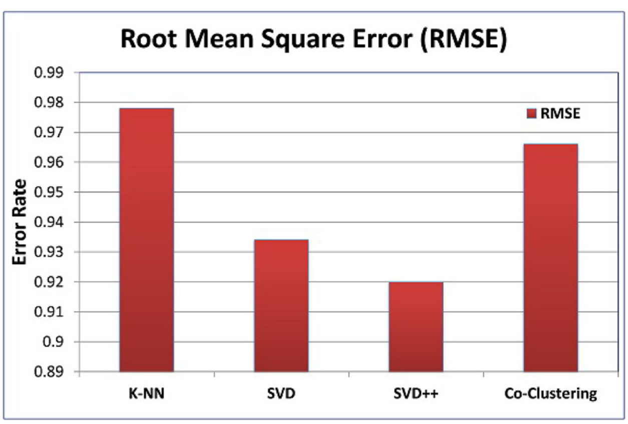

Fig. 8 RMSE Comparison graph

used to make predictions applying the average rating of top-k nearest neighbors. SVD finds the latent factors associated with matrices. It is a matrix decomposition approach that reduces the user-item rating matrix as the product of two lower-dimensional matrices. The first one has a row for each user, while the second has a column for each item. But, the SVD++ model tries to mix the strengths of the latent model and the neighborhood model. Co-clustering is a data mining approach that allows simultaneous clustering of the rows and columns of a matrix.

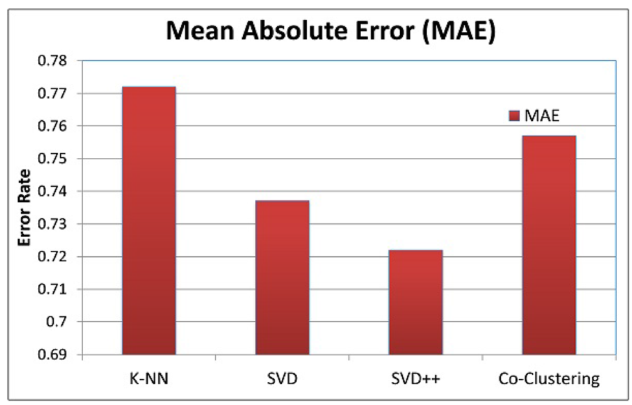

Fig. 9 MAE Comparison graph

For implementing the proposed approach python language has been used. For implementing various machine learning approaches scikit-learn and surprise module were used. For performing comparative analysis on dataset, packages such as numpy, pandas and matplotlib were used (Table 4).

4.3 Result analysis

Our experiment shows that collaborative filtering based K-NN gives highest Root Mean Square Error (RMSE) of

0.978 and highest Mean Absolute Error (MAE) of 0.772. In terms of the lesser error rate, collaborative filtering based SVD++ gives lowest RMSE of 0.9201 and MAE of 0.7219 (Figs. 8, 9).

5 Conclusion

This paper discusses the different RS approaches and provides a comparison between them. Various recommender approaches have been developed for several reasons but they have some limitations. So, it is essential to develop RS that is both precise and efficient. This paper proposed a movie recommendation system using collaborative filtering and SVD++ (singular value decomposition plus-plus) approaches. The proposed approach is compared with well-known machine learning approaches namely K-NN (k nearest neighbor), SVD (singular value decomposition) and Co-clustering. The recommender system error is evaluated considering RMSE (Root Mean Square Error) and MAE (Mean Absolute Error). The result shows that the Collaborative filtering with SVD++ gives a lesser error rate with RMSE (0.9201) and MAE (0.7219). This approach also overcome with cold-start and data sparsity problems to some extent.

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