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# Comparative Analysis of Functionality and Aspects for Hybrid Recommender Systems

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**Abstract**—Recommender systems are gradually becoming the backbone of profitable business which interact with users mainly on the web stack. These systems are privileged to have large amounts of user interaction data used to improve them. The systems utilize machine learning and data mining techniques to determine products and features to suggest different users correctly. This is an essential function since offering the right product at the right time might result in increased revenue. This paper gives focus on the importance of different kinds of hybrid recommenders. First, by explaining the various types of recommenders in use, then showing the need for hybrid systems and the multiple kinds before giving a comparative analysis of each of these. Keeping in mind that content-based, as well as collaborative filtering systems, are widely used, research is comparatively done with a keen interest on how this measures up to hybrid recommender systems.

**Keywords**-Hybrid Recommender System; Content based filtering; Collaborative filtering; Neural networks.

## I. INTRODUCTION

As the name suggests, hybrid recommender engines are a result of the implementation of systems using a fusion of various methods.[1] Recommender engines, too, must get better, and what way to do so than using hybrids? These are the future. Comparative analysis of hybrid systems is the fundamental purpose of this paper. While it's not fathomable to do an in-depth review of each implementation, the much that shall be covered shall suffice.

In a study [6] author outlines six common types of hybrid recommender systems. These are based on their functionality and include weighted, mixed, switching, feature combination, feature augmentation, cascade, and meta-level. While all these have engaging means of giving desired results, the focus of this paper will be on those among these that can best utilize collaboration and content-based filtering. This is because these two forms of recommenders can be used within most of the hybrid paradigms of filtration using K-Nearest Neighbours (KNN) and Latent Dirichlet Allocation (LDA), which are both excellent for large scale systems and relatively straightforward to implement. Hybrid systems are used to overcome limitations posed by using some of the other recommenders as stand-alone systems. Incorporating a hybrid solution drives one to ask themselves more questions like whether the answer derived is optimal. This inherently is followed by the analysis of algorithms and inner workings of hybrid recommenders.

### *A. Types of Recommender Systems*

There are various types of Recommender Systems that can be used according to users, items, and interaction among them. Some of the popular recommendation system with their functionalities are discussed in next section. [3] These recommender systems have some changes that can differentiate them. These “changes” involves the evolution of new system or enhancement of existing systems[2].

### *B. Content-Based RSs*

These are recommender engines that utilize profiles generated using user preferences. The selections are passed through keyword analysis algorithms before being parsed to implement the desired effect in this process [2].

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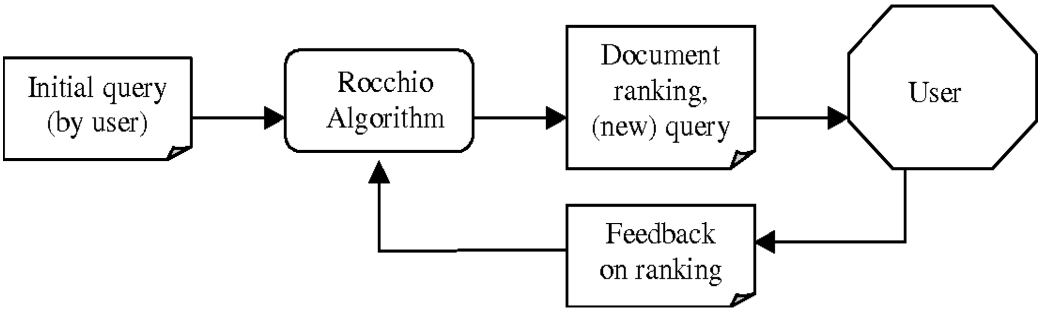


Figure 1. Content -Based Recommendation [28]

In Figure 1. Initial Query is passed through keyword analysis algorithm like Rocchio Algorithm and provides ranking to the results based on user profiles and then user provides the feedback for the same so that the ranking can be improved. A ranking system for semantic web documents that compares the documents' semantic similarity to the user-specified query[26].

*C. Collaborative-Filtering*

The assumption of collaborative filtering is that the people who had similar tastes of some item in the past will also have similar tastes for that item in the future.[4, 5] To handle several the restrictions of content based filtering, it uses similarities between users and things at the same time to produce recommendations. It rarely supports the assumptions that folks like things almost like different things they like and things that are liked by people with similar style. Consider the Figure 2 for the example showing two similar users based on their liking will be recommend the things of each other by the system.[7-10]

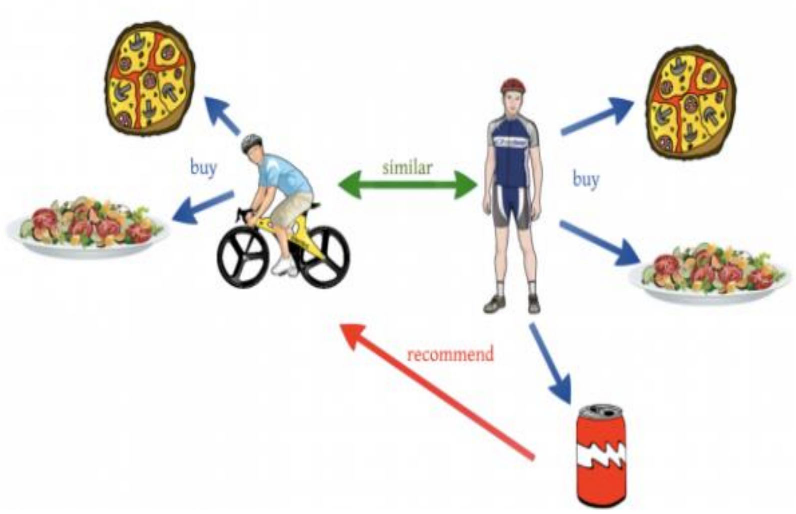


Figure 2. Example of Collaborative Filtering [29]

*D. Demographic-Based RSs*

Demographic-based RSs utilize the information which users provide while first joining the website. Data on demographics helps the engine deliver recommendations that are not user-specific to give the system more time to learn about the user's preferences. This is especially useful when the system is starting up. The way demographic-based RSs work makes them a perfect fit for a hybrid solution that needs to input many functional users' information that could only be obtained from real users, thus giving the other method some data while demographics are used [2].

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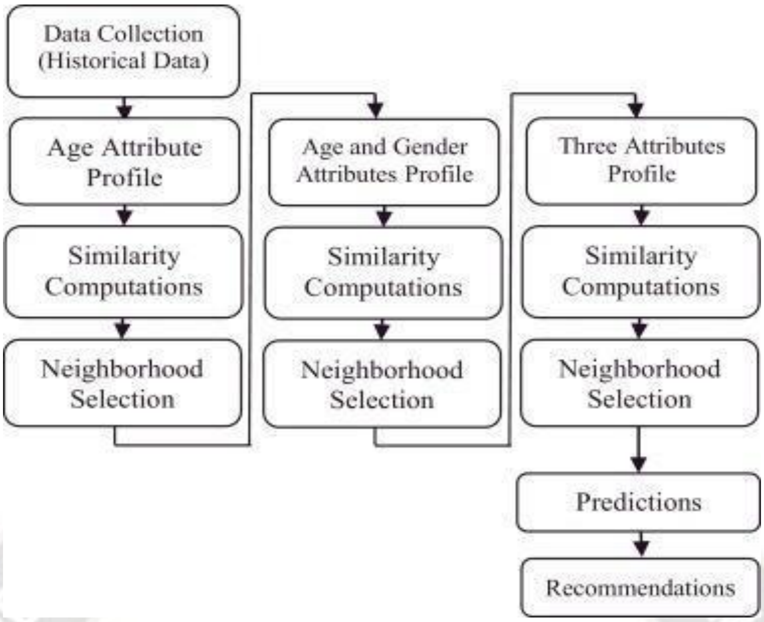


Figure 3.Demographic-Based RSs

*E. Knowledge- Based RSs*

Such recommender engines need to develop recommendation knowledge before being able to work [2]. This has nothing to do with ratings, and one aspect that must be considered is that they utilize information from both users and products. Their functionality could be seen as a limitation or an upside, depending on the perspective. Figure 3 shows that Demographic-Based RSs

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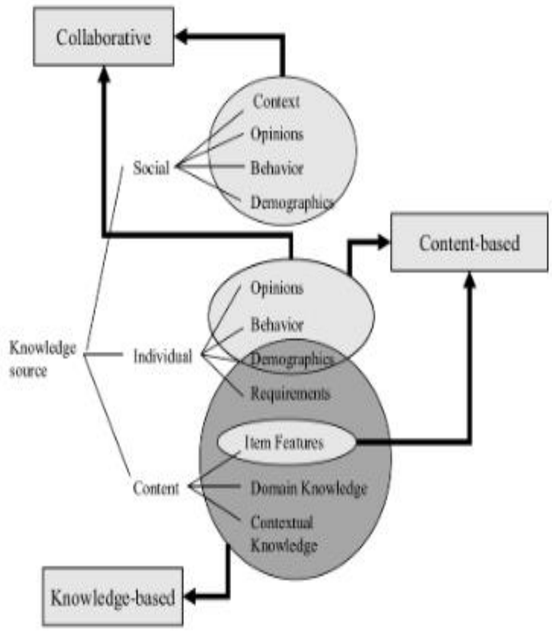


Figure 4. Knowledge- Based RSs

*F. Utility-Based RSs*

These are recommendation engines that generate suggestions for the perceived value of each item by a user [2]. There are various algorithms for the measurement of utility, such as implicit and genetic utility. Figure 4 shows that Knowledge- Based RSs

The use of only a single recommendation system exposes the implementation to some of the disadvantages that come with the help of different RS techniques. These limitations can give the results in very limited form and sometimes not accurate as shown in Table I.

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TABLE I. LIMITATIONS AND ADVANTAGES OF A MODULAR USE OF RSS

| Method | Advantages | Limitations |
|---|---|---|
| Collaborative Filtering | -Can identify niches in-between genres. -Knowledge of the domain is not necessary. -Improves quality with time. -Indirect feedback works | -Liable to user build-up issue -susceptible to item build-up issue -Cannot handle users who lie in the grey areas on ratings -Quality is contingent upon documented data set. -Trade-off between stability and plasticity |
| Content-based | -Knowledge of the domain is not necessary. -Improves quality with time. -Improves quality with time. | -Liable to user build-up issue -Quality is contingent upon documented data set. -Trade-off between stability and plasticity |
| Demographic | -Can identify niches in-between genres. -Knowledge of the domain is not necessary. -Improves quality with time. C | -Liable to user build-up issue -Cannot handle users who lie in the grey areas on ratings -Quality is contingent upon documented data set. -Trade-off between stability and plasticity -Requires acquisition of data on demographics. |
| Utility-based | -No user build-up issue -Affected by a change in user preferences -Might include features that are not about the product | -Requires users contribution before the function works -Learning ability is moderated |
| Knowledge-based | -No user build-up issue -Affected by a change in user preferences -Might include features that are not about the product | -Learning ability is moderated -must incorporate knowledge engineering |

To overcome these set of drawbacks that comes due to use of single technique hybrid recommender systems are designed.

### *G. Hybrid recommender designs*

There are different approaches for designing hybrid recommenders. These approaches guide us towards an understanding of how each hybrid recommender engine works. The three main types of hybrid recommenders include the use of Monolithic, Parallel and Pipeline techniques. Each of these is divided further to give rise to the commonly known seven hybrid recommenders collectively

### *H. Monolithic hybrid recommenders*

Monolithic recommendation systems use only one component to generate suggestions. They, however, integrate several algorithms and amalgamate a couple of knowledge sources or features for use as source data. There are two ways to use the monolithic approach. One is feature combination hybrid, and the other is feature augmentation [2].

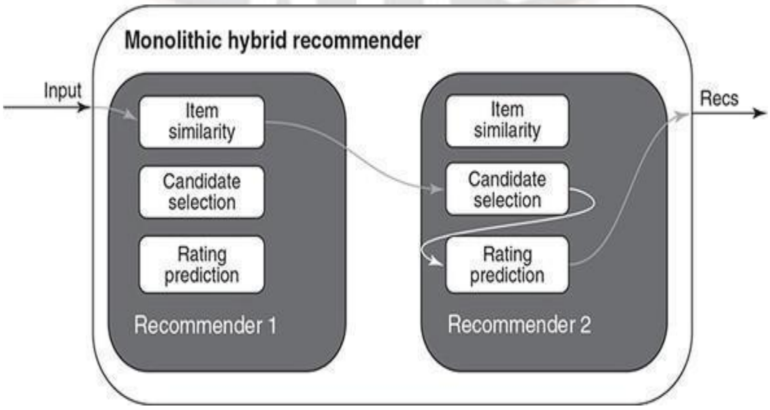


Figure 5. Monolithic Hybrid Recommender

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*I. Feature combination*

The term combination signifies the use of several knowledge sources as if they were one. The system uses all the individual recommender systems separately then joins the resultant data source into one. Figure 5 shows that Monolithic Hybrid Recommender

*J. Feature augmentation*

Such recommenders usually utilize the individual ones to create a learning model. The model is then used to generate output which can be combined to create a basis for the recommendation.

*K. Parallel hybrid recommenders.*

These recommenders utilize the output of more than one implementation; combine it before using some form of ratio determination to generate a recommendation. Examples include weighted hybrid recommenders, switched hybrid recommender engines, and mixed hybrid recommenders. Each of these types of parallel hybrids has its form of implementation.

**1) Weighted hybrid:**

Such platforms use the score of each technique used within the hybrid engine to calculate a weighted score.

**2) Switched hybrid**

The method is inbuilt with mechanisms for determining when and how to switch from one recommender to another.

**3) Mixed hybrid**

Mixed Hybrid RSs provide recommendations by allowing each recommendation technique chosen for the hybrid system to run. After this, results for all recommender engines are presented as one without any further manipulation of the data. Figure 6 shows that Mixed Hybrid Recommender

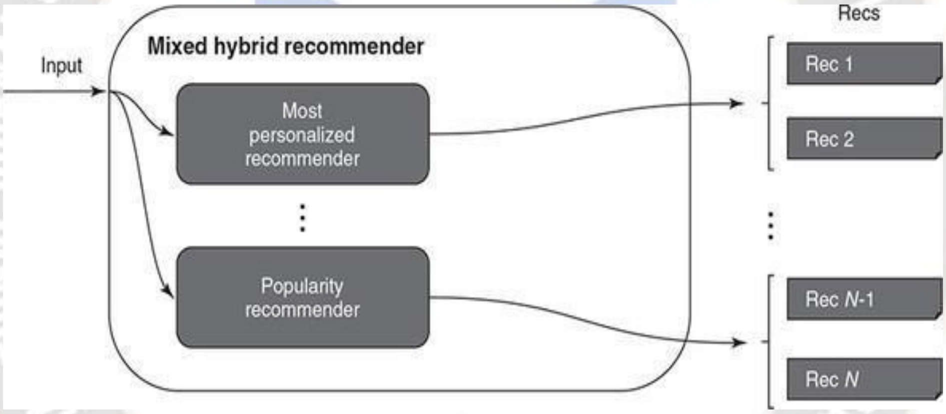


Figure 6. Mixed Hybrid Recommender

*L. Pipeline Hybrid RSs*

In a nutshell, these recommenders work as any industrial pipeline would. One of the recommender engines prepares the data for the other, but this is different for each of the pipeline hybrid RSs. Examples include Cascade hybrid recommendation engine and Meta-level hybrid RS.

*1) Cascade RSs*

The recommendations for the next RS are subject to the constraints suggested by the previous recommender. Therefore, the list of suggestions keeps on shrinking. The first one could incorporate a knowledge-based algorithm to remove obvious itemsand then assign a score to the remaining items.

*2) Meta-level RSs*

Meta level RS uses the first recommender in the pipeline to generate a model to generate output used by the second RS in the hybrid pipeline as input data to create recommendations.

In this paper, initially recommender system its type advantages and disadvantages were introduced. To overcome the limitations of individual system various hybrid model types were defined in the introduction part. In the next section a thorough review of research papers in the last 4 years is done. This Literature review is entirely focussed on recent publications in hybrid recommender system. We have picked three digital libraries that represent our primary source for computer science resources. These libraries are Springer, Science Direct and IEEEXplore. After that the various metrices are defined that can be utilized for calculation of the efficiency of various hybrid models. In the last sections results of singular technique and hybrid

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technique are compared and conclusion of the study is given.

## II. LITERATURE REVIEW

There are vast numbers of research articles had been written in the past decades regarding recommender systems. In the last several years for improving accuracy hybridisation is used in large number. In this paper, we have considered research articles and papers from last 4 years i.e., 2018 to 2021 as before that systematic review have been already done in various studies. The study is strictly based on hybrid recommender systems only.

For the Conventional techniques like using only matrix factorization in collaborative filtering can cause the data sparsity problem. To overcome that, in [15, 16] authors gave the Probabilistic Matrix Factorization (PMF) framework a hybrid framework that blends textual bias with rating bias, which increases the interpretability of the model from the perspective of probability. Each item might have a specific word representation thanks to the proposed model, which could also yield a more precise set of latent components [25]. By comparing RMSE and recall@M to traditional algorithms, the results improved as compared with singular recommendation techniques.

Recently, Deep learning models have shown effective representation while exploring in the fields of recommender system. In [23], a novel model that use Non-Linear Factorization Machine (NLFM) for modelling user-item interaction function and hybrid deep model named AE-NLFM (Auto Encoder Base Non – Linear Factorization Machine) for collaborative recommendation. The Authors have experimented it on three real-world datasets and concludes that their model outperforms the state-of-the art methods.

A hybrid strategy that combines pair wise ranking-based collaborative filtering and collaborative variational ranking model (CVRank) was proposed in the work given in [17]**.** The model creates suggestions by learning unobserved variables of items and people from information gathered through rating by computing the dot products between people and items. The proposed strategy performs well in experiments at different sparsity levels, and neural collaborative filtering techniques can greatly improve recommendation accuracy when compared to pure collaborative filtering.

In [18] the author gave a practical method for increasing diversity and long tail item suggestions. Movie Lens and Netflix datasets are used in the research. The author of this research presented HyReCF, or Hybrid Reranking Framework in Collaborative Filtering, as a method to enhance variety and long tail item recommendations. With a slight loss in accuracy, various statistics of the rating information and suggested items are merged to increase diversity. Comparing the proposed approach to the state-of-the-art, the diversity is significantly improved. The long tail goods are more prevalent in the suggested framework than the cutting edge, which keeps the system engaging for users and boosts financial success for company organisations.

An analysis on a system that recommended courses to users in [8] is based on Content-based RS evaluated using f-measures, precision, recall, and sensitivity as the metrics for evaluation. By implementing query expansion and n-gram classification, it was discovered that perhaps using a dataset with users of similar tastes could help improve the model, especially during learning.

The analysis using the IFF book-crossing dataset done in [10] evaluated the performance of a hybrid recommender using RMSE and MSE. The implementation was enabled using KNN, Pearson-based similarity, and cosine-based similarity. It can be observed from this that categorization of items needs to be improvised, if not random, to some extent.

For academic teams, the authors suggested a hybrid recommendation model based on temporal dimension [11]. The algorithm combines the three factors (user and team similarity, excellent friends, and hot teams), and creates a list of teams it recommends based on various weights assigned by the team's formation date. Studies using the SCHOLAT data set demonstrate that the suggested model can significantly increase recommendation accuracy and coverage while partially resolving the cold start issue.

A study on Content-based Recommenders using the Persian blog as the source of data is given in [12]. The technique used for this was by HITs ranking and page rank. Evaluation of performance through Coverage and MAE metrics was done. It can be observed that such a model's performance depends on the placement and number of links on a page. This is also termed link density.

In their research in [13] authors used logistic regression and suggested a new recommendation algorithm based on a bipartite graph. First, the weights and user similarity of the bipartite graph are established. The bipartite graph is then used to create a suggestion list. The categorization results of the logistic regression are then used to reorganise the suggestions in the list. To evaluate a recommender system's accuracy and variety in its whole, a balancing factor is also recommended. Results of experiments show that the suggested algorithm produces good recommendation results.

A generalised neural network-based recommender architecture that is easily expandable by new networks was introduced in [14]**.** Neural Hybrid Recommender, or NHR for short, is a framework that enables us to include more detailed data from the same and various data sources. The

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authors tested their strategy on benchmark datasets and datasets that had not yet undergone experiments to assess the impact of such a framework. The outcomes in these real-world datasets demonstrate the approach's improved performance in contrast to leading-edge techniques.

To fill in the gaps in Collaborative Filtering systems and obtain the highest predicted accuracy possible using deep learning, a unique deep learning hybrid recommender system in [19] is proposed. To overcome the cold start problem and latent factor linearity, the authors presented a novel hybrid recommender system that makes use of deep learning [27]. Several datasets, including Movie Lens 100k, Film Trust, Book-Crossing, and Movie Lens 1M, were used in the research. Results indicated a considerable improvement over the previous algorithms.

In their study[20]authors introduced a monolithic hybrid recommender system called Predictory. It combines a fuzzy expert system, a content-based system, and a collaborative filtering system (using the SVD algorithm) into a single recommender module. The recommended system is utilised to make recommendations for suitable films. The approach considers both the user's favourite and rare genres, and the final list of suggested movies is generated using a fuzzy expert system that evaluates the films' importance. Over 80% of the results of system verification using popular metrics (precision, recall, and F1-measure) are achieved. A hybrid movie recommendation system is created, which has been assessed against existing traditional recommender systems and tested on a sample of users using the Movie Lens dataset.

A new recommender system is provided by in [21] a study that has three parts: content-based, collaborative, and hybrid filtering. The suggested recommender system uses the tagging functionalities to generate more useful suggestions for discussion groups. To do this, the semantic significance of tags is retrieved from the Word Net lexical database, and the tags are then organised hierarchically according to their semantic relevance. Relevant postings are located using a hierarchical structure in the region for content-based filtering, and the user's query is broadened using relevant semantic tags. In the collaborative filtering stage, similarity measures are used to determine the implicit ratings of the participants. The hybrid filtering component of this section combines the outcomes of these two phases. Experimental results show that the proposed approach is more accurate than earlier recommender systems.

In [22] the author in their work focussed on the issue of social network as very less work in suggestion had been done. The proposed a hybrid model with combination of Collaborative and content base – filtering. They named the model as SNHF (Social Neural Hybrid Filtering) consists of combining Generalize Matrix Factorization (GMF); and Hybrid Multilayer Perceptron (HybMLP). The Experiments were performed on two datasets and results in better improvement in Cold Start problem in compare of experiment algorithm [23].

## III. COMPARITIVE ANALYSIS

There are a variety of ways to know the performance of a hybrid recommender system. In [1] the author focuses on the following areas in evaluating recommender systems: Scalability, robustness & stability, Diversity, uncertainty, novelty, confidence & trust, coverage, & accuracy..

### A. *Evaluation Metrics*

For this paper, the comparative analysis of recommender systems will be focused on evaluation using statistical accuracy metrics such as MAE and RMSE; Decision support accuracy metrics such as Precision, recall, and f-measure; coverage; and Diversity

### B. *Statistical accuracy metrics*

These are metrics used in determining how close the predicted value is to the actual rating. They include Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

**RMSE** is used to calculate the average value of the squared difference between ratings predicted by the recommender and the actual values. Then the square root of the resultant answer is found.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(d_i - \hat{d}_i)^2} \quad (1)$$

We can discover and filter out significant errors through this, especially when the desired result is to avoid them. This metric is therefore very sensitive to increased errors and the presence of outliers [24].

**MAE** is used to calculate the absolute mean difference between ratings predicted by our recommender and the actual values. Mathematical representation for this could be:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|d_i| - |\hat{d}_i| \quad (2)$$

where: $d_i = actual\ rating, \widehat{d_\imath} = prediction, \&\ n = no\ of\ ratings$

A high MAE value implies that the accuracy of our implementation is wanting. Lower values are preferred.

### C. *Decision support accuracy metrics*

Some of the decisions support accuracy metrics often used include reversal rate, weighted errors, Receiver Operating Characteristics (ROC), Precision-Recall Curve

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(PRC), f-measure, recall, and precision. This paper gives a focus to the last three.

$$Precision(P) = \frac{Correctly\ recommended\ items}{total\ recommended\ items}$$

$$Recall(R) = \frac{Correctly\ recommended\ items}{Total\ useful\ recommended\ items}$$

$$F - measure = \frac{2PR}{P+R} \quad (3)$$

*D. Coverage*

This metric puts into perspective the ratio of items as well as users for which the engine can provide suggestions.

$$CC = \frac{|\cup_{u=1}^{m} T_u|}{n} \quad (4)$$

where:

CC= Fraction of items recommended to at least one user

Tu = A list of top-k items recommended to users $u \in \{1 \ldots m\}$

.

n = no of items

This is a measure of how equality has been considered in the inclusion of various items during recommendations. It works best when the data set consists of users' historical preferences.

*E. Diversity*

$$Diversity = \frac{1}{2}\sum_{i,\in_u}^{j}\sum_{i,\in_u}^{k} Sim(ij, ik) \quad (5)$$

where$sim(ij, ik)$ is a measure of similarity

## IV. RESULTS

In the recent studies that are done in the paper the findings that the common research gaps to overcome in the Recommender system scenarios are Cold Start Problems, Long tail phenomenon and Diversity issue. The hybridisation improves the accuracy of the system, and the various combinations can lead to increase the reliability of the system. The experiment results conducted in [20] gave a performance metrics for various type of recommender system on Movie Lens dataset.

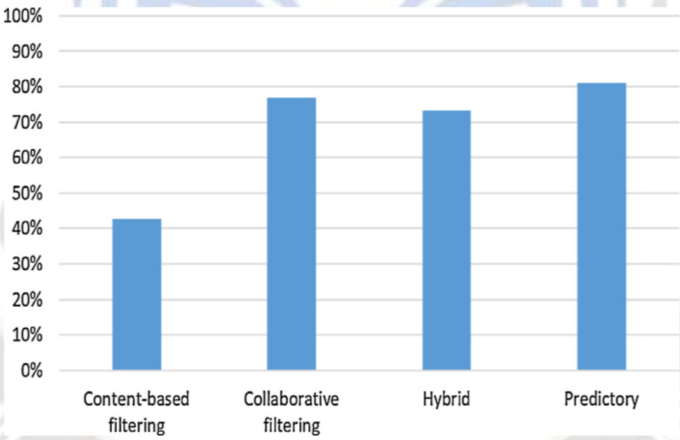


Figure 7. Comparison of Various techniques [20]

In Figure 7 the experimental results show that even enhancing the feature of Hybrid could also lead to better results. Other studies also refer to improvements in system by using various evaluation metrics.

## V. CONCLUSION AND FUTURE SCOPE

This paper has shown that recommender system deal with solution for optimum performance by the platform. In general, this means that the one choosing might end up with a hybrid of one or more basic recommenders to avoid some limitations here and there. The paper compares various hybrid recommender systems along with various designs in the recent time. In the various studies for hybrids, peak performance is ensured by choosing the right combinations and algorithms for implementation for recommenders. To add to this, the choice of varieties for recommenders often involves analyzing the base environment to see the variables that might affect the alternative, for example, knowledge source and system limitations. Better algorithms could be developed to be able to surpass the performance of those which are there currently. However, all we might need to do to reach the desired optimum is to fine-tune the knowledge we have and brainstorm on ways to improve on current implementations through testing, research, and more testing.

In future Studies more work on Cross Domain dataset can be done with the help of Hybrid models. As Hybridisation deals far better in dealing with conventional problems like Cold Start Problems, Diversity, and Long-term phenomenon more experiments can be conducted for getting more accurate results.

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