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HYBRID RECOMMENDATION SYSTEM TO SOLVE COLD START PROBLEM

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ABSTRACT

The recommendation system has been very vital in the field of research. The objective of the recommendation system is to recommend items to users, but it is difficult when the user's purchase history, ratings, personal information are not available. Though many recommendation systems are available to recommend products, it is a big problem for new users because there is no available information that helps to recommend the appropriate products to the new users. To get better enactment of recommendation systems, solving the cold start problem is an important issue for researchers. Many recommendation techniques are available for the last couple of years. It has been overwhelming for the new researchers, merchants, web application developers and etc. to know each of them very quickly. Commonly used possible solutions of coldstart problem, frequently used datasets for the specific domain have not been found. So, various techniques are summarized in this article like hybridization methods, data collection approaches, most commonly used possible solutions of cold start, frequently used datasets, algorithms, evaluation methods etc. This study examines how the cold start problem can be solved by the existing hybrid approaches that may help researchers to get a direction for solving the cold start problem.

Keywords: *Content-Based-Filtering, Collaborative-Filtering, Cold-Start, Hybrid, Recommendation Systems*.

1. INTRODUCTION

We live in an era of online information technology. Data is the key to this technology. In recent-years, recommender systems(RS) have been used in various field including commercial websites like Netflix, Movielens, Amazon, eBay, Linkedln, MovieFinder, Jinni, Myspace, Facebook, and etc [1], [2]. The recommendation system is to access users' profiles to find out their interests and gather their opinion either implicitly or explicitly or combine them both to find the relevant or most similar item to suggest them[1]. Recommender system is extensively used in YouTube, Amazon, and Netflix in the online industry. Collaborative-filtering(CF) and content-based-filtering(CBF) are the two basic approaches or parts to developing recommender systems as well as hybrid recommender system is created by combining the two methodologies [3].

One of the main issues which hamper the performance of the recommendation system (RS) is known as "cold-start". It can be either for new users or new items. If the user profile is new or does not contain a sufficient rating, the user gets a non-personalized recommendation until the user profile is enriched with information [4]. In recommendation system, the solution of cold-start problem is still a challenge for researchers. There have been many solutions of cold start using content-based filtering, collaborative-filtering, and hybrid approaches. But most of the papers are used hybrid approach which is given a better result than content-based filtering and collaborative-filtering approaches. After reviewing the papers, it has been found that some papers have discussed recommendation type, hybridization methods, and data collection techniques [156], but has not been found any discussion about datasets, cold start solutions. Another author discussed recommendation types and data collection approaches [6] but not discussed the all information in one paper. So, a possible summarize information in one paper has been created which help a researcher to get every possible and common suggestion on this field for getting better solution.

Many research papers have been found after the review where the authors have solved coldstart problem but have not found the proper solution. They are still working to get better solution of the cold start problem. To get a proper idea to solve cold start problem, some information like full details about the recommendation system, cold start solution, data collection techniques, hybridization methods, and etc. are found in one paper is helpful. But this full information in one paper has not been found. So, the main objective of this paper is to give an informative overview of the recommendation system, the solution of cold start, data collection technique as well as give a future direction for solving the cold-start problem in a hybrid approach. For this purpose, more than a hundred papers have been collected. Papers have been excluded and included based on some criteria. Then the papers have been read and tried to find out every single thing like how the cold start problem is solved using hybrid approach, algorithms, datasets, data collection process, and etc. Every piece of information is listed in the statistical process.

The structure of the paper is as follows. The brief of the recommendation system is described in section 2, section 3 demonstrates the full procedure which is followed to write this review, section 4 describes the data collection techniques section 5 describes the most commonly used solutions of cold-start, section 6 shows the result, and at the end, section 7 concludes the paper.

2. RECOMMENDATION SYSTEM

On the social or online platform, a feature is shown that gives suggestions of various items. This feature generates the list of tips according to user personal information, likes, dislikes, past preferences etc. This feature is called the Recommendation System. The suggestion generated by the feature is unique to the user and will be different from user to user. Recommender systems use user profiles or preferences to filter information and provide predictions [5]. Recommendation systems typically generate a list of suggestions using one of the strategies available. In the following Fig. 1, the full recommendation systems are represented at a glance.

Personalized Recommendation system is a sort of recommender system that aims to recommend users desired things based on their previous behavior as well as interpersonal relationships in social networks by taking three views into account: 1) Interpersonal influence, which refers to somebody you would trust. 2) Interest circle derivation, which indicates who shares your interests, and 3) User individual interest, which influences what things you would be interested in[6]. In Fig. 1, it is shown that personalized recommendation systems are divided into some categories based on how they provide recommendations [6].

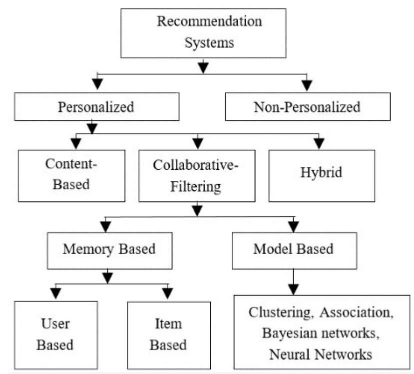

Figure 1. Recommendation Systems

Content-Based-Filtering(CBF) is based on the users' past preference and the item's descriptions that help in recommending similar things to the users' according to their past choice [1]. CBF algorithms basically work on user past preference, likes, dislikes etc. It does not compare others' choices or similarities to recommend a user. It does not take other users' similarity data to recommend items to a user. How content-based-filtering works is shown in Fig. 2.

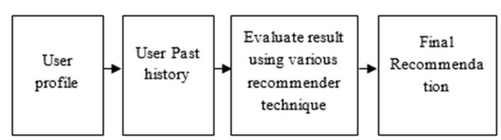

Figure 2. Content-Based-Filtering

Collaborative-filtering (CF) strategies create a model based on a user's previous behavior like their purchased or selected items in the past, ratings given to those items, as well as similar decisions made by other users[7]. It does compare others' choices or similarities to recommend a user. It takes other users' similarity data to recommend products to a user. How collaborative-filtering works is shown in Fig. 3.

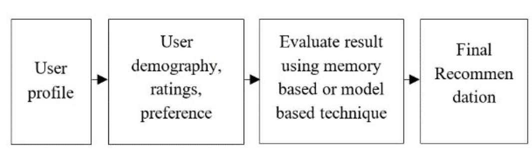

Figure 3. Collaborative-filtering

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Hybrid recommender systems combine many recommender systems to provide a more robust framework [6]. This approach is more helpful to solve the 'cold-start' problem. In CF recommendation system, the full process is based on domain dependency [8]. In CBF recommendation systems, the full process is about people past preferences [8]. The process of hybrid recommendation system is shown in Fig. 4.

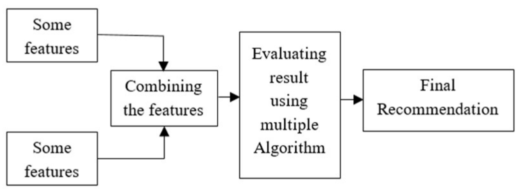

Figure 4. Hybrid Recommendation System

There are seven type of hybridization methods. Weighted hybridization integrates the findings of various recommenders to build a suggestion list or forecast by using a linear formula to incorporate the scores from each of the approaches in use [156].

The switching hybrid chooses a single recommendation system. The model is utilized to build for the item-level sensitive dataset, and we should set the recommender selection criteria based on the user profile or other factors. DailyLearner is the Example of a switching hybrid [156]. In Fig 5, switching hybridization method is shown.

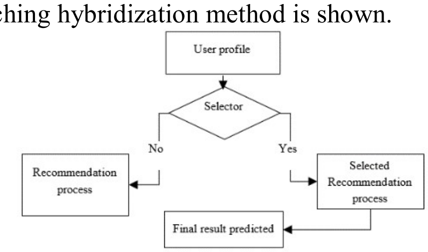

Figure 5. Switching Recommendation System

Instead of having only one suggestion per item, mixed hybrids simultaneously incorporate the findings of many recommendation algorithms.[156]. Each item has several requests from various recommendation techniques connected with it. Individual results do not necessarily affect a particular region's overall performance in mixed hybridization. The PTV system is an example of mixed hybridization[157]. Fig. 6 shows the mixed hybrid scenario.

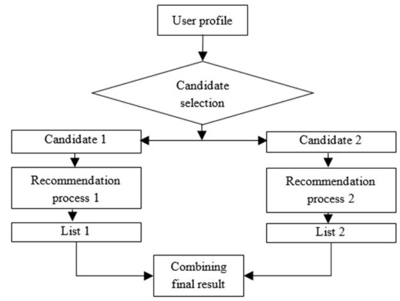

Figure 6. Mixed Hybridization Method

The feature combination hybrid allows the system to analyze cooperative data without depending only on it; the system's susceptibility to the number of user who have been rated a product is reduced [157]. In turn, it provides information to the system regarding the intrinsic similarity of things that would otherwise be unavailable to a collaborative approach. In Fig. 7, feature combination hybrid scenario is shown.

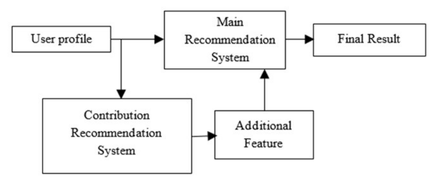

Figure 7. Feature Combination Hybridization Method

In this method, one recommendation methodology is used to provide a coarse rating of candidates, while a second technique is used to refine the suggestion from the candidate set. It is used in sparse dataset. Cascade hybridization permits systems to avoid using the 2nd, lower-priority strategy on things that have already been well differentiated by the 1st or are so less-rated that they will never be suggested [157].

In comparison to feature-combination approaches, feature augmentation hybrids add a modest number of characteristics to the primary recommender [156]. This method is used to improve the performance of CBF. It generates a ratio on the classification of the use or item profile. The approach takes advantage of the preceding recommender's ratings and other data, and it also necessitates new capability from the recommender systems. In Fig. 8, the feature-augmentation process is showed.

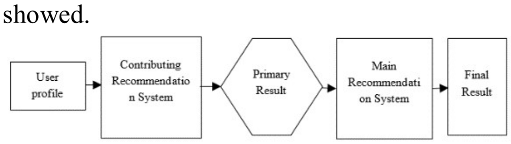

Figure 8. Feature Augmentation Hybridization Method

Instead of using the actual dataset, the meta-level employs a learned structure from the contributing structure to the original recommendation model. We can see the summarization of the Hybridization method at a glance in Table 1.

Table 1. Hybridization Methods[157]

Hybridization Method	Description
Weighted	Multiple recommendation methods' scores (or votes) are merged to generate a single suggestion.
Switching	Depending on the current scenario, the system shifts between recommendation methods.
Mixed	Simultaneously, recommendations from multiple different recommenders are provided.
Feature Combination	A single recommendation algorithm is developed by integrating various recommendation data sources features.
Cascade	One recommender builds on the recommendations provided by another.
Feature Augmentation	One technique's output is employed as a feature in another's input.
Meta-Level	One recommender's model gets fed into another's algorithm.

3. THE WORKING PROCEDURE

To start the paper, some research questions are defined. After settings the questions, the papers are collected from various data sources like Scopus, IEEE, ACM and, Web of Science. So, the full writing process of literature review are given below:

- Step-01: Defining research questions.
- Step-02: Collect paper from various databases according to criteria
- Step-03: Paper inclusion and exclusion
- Step-04: Reading the selected paper
- Step-05: Find out the data collection approaches
- Step-06: Find out hybridization methods
- Step-07: Find the frequent solution of cold Start
- Step-08: Evaluate result

The questions which help to write the review paper are given below:

Q-1: Does the use of hybrid technique create any improvement for solving the cold start problem?

Q-2: Which data collection techniques give a better result to solve cold start problem using hybrid approaches?

Three criteria are followed to collect papers which are shown in Fig. 9. First of all, a search string is created. Based on this search string, the papers have been collected. Then the snowballing method is used. Finally, the forwarding process is used to collect paper. Papers are collected from Google Scholar which are indexed in various database like Scopus, IEEE, ACM and, Web of Science.

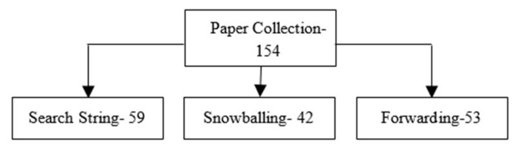

Figure 9. Paper Collection Process

For executing the first step, a search string has been created. The string is ("hybrid recommendation" OR "content and collaborative filtering" OR "combined recommendation system" OR "cross recommendation" OR "content and collaborative base recommendation") AND ("cold start recommendation" OR "new user recommendation system" OR "newcomer recommendation"). Almost 59 papers are collected using this searching string which is shown in Table 2.

Table 2. Collecting Papers Using Search String

Publishing year	No of paper	Reference
2010	0	-
2011	2	[9], [10]
2012	1	[11]
2013	1	[12]
2014	3	[13], [14], [15],
2015	4	[16], [17], [18], [18]
2016	5	[19], [20], [21], [22], [23], [24], [25]
2017	9	[26], [27], [28], [29], [2], [30], [31], [32], [33],
2018	10	[34], [35], [36], [37], [38], [39], [8], [40], [41], [42]
2019	8	[43], [44], [45], [46], [47], [48], [49], [50],
2020	8	[5], [51], [1], [3], [52], [53], [54], [55]
2021	8	[56], [57], [58], [59], [60], [61], [62], [63],

After collecting papers using search string, the next process is going to be executed which is called snowballing process. Almost 42 papers have been collected from snowballing. Papers are collected from snowballing has been shown in Table 3.

Table 3. Collecting Papers Using Snowballing

Publishing year	No of paper	Reference
2010	3	[64], [65], [66]
2011	2	[67], [68]
2012	1	[69]
2013	6	[12], [70], [71], [72], [73], [74]
2014	12	[75], [76], [77], [24], [78], [79], [80], [81], [82], [83], [84], [85]
2015	6	[86], [87], [88], [89], [90], [91]
2016	5	[92], [93], [94], [50], [95]
2017	2	[96], [97]
2018	2	[98], [99]
2019	4	[100], [43], [101], [102]
2020	1	[103],
2021	0	-

Finally, forwarding process is applied for collecting rest of the papers. Using forwarding process almost 53 papers has been collected. Papers are collected from forwarding has been enlisted in Table 4.

Table 4. Collecting Papers Using Forwarding

Publishing year	No of paper	Reference
2013	1	[4]
2014	1	[104]
2015	3	[105], [106], [107]
2016	4	[108], [109], [110], [111]
2017	9	[112], [113], [114], [115], [116], [117], [51], [118], [119]
2018	5	[2], [120], [121], [83], [122]
2019	6	[123], [124], [125], [126], [127], [128]
2020	11	[129], [130], [131], [132], [133], [134], [135], [136], [137], [138], [139]
2021	13	[140], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [152]

After collecting all the papers, the vital process has been executed for picking up the most relevant papers from the paper collection. This step is called paper inclusion and exclusion, which is shown in Fig. 10. For paper inclusion and exclusion, some steps are followed. These steps are described below.

Step-01: After collecting all the papers from various databases, it is defined whether the paper is written in English. If it is not written in English, the papers are excluded.

Step-02: After this, the title, abstract, introduction and, the conclusion of the paper is read.

Step-03: After reading, we try to find if these papers solve any cold start problem. If yes, then go to the next step. Otherwise, exclude the paper.

Step-04: After finding the Cold start, we try to find out if there are any uses of hybrid approaches? If yes, then choose the paper for work. Otherwise, the paper is discarded.

Fig. 10 is shown to present the whole process of our paper exclusion and inclusion.

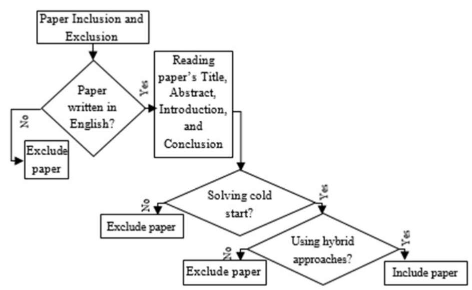

Figure 10. Paper Inclusion and Exclusion Criteria

According to the above criteria, some papers has been picked up for review. A list of papers is shown in Table 5.

Table 5. Total Papers after Inclusion and Exclusion

Publishing Year	**No of relevant paper**	**References**
2010	2	[64], [65]
2011	1	[9]
2012	1	[11]
2013	2	[4], [153]
2014	1	[13]
2015	4	[17], [18], [16], [19]
2016	4	[21], [20], [22], [110]
2017	5	[26], [29], [28], [32], [27]
2018	7	[34], [35], [36], [8], [2], [98], [40]
2019	7	[46], [43], [45], [44], [127], [39], [47]
2020	7	[37], [3], [1], [5], [52], [51], [7]
2021	2	[56], [154]

According to the Table. 5 a graph is created. How many papers have been got as most relevant to work is shown in Fig. 11.

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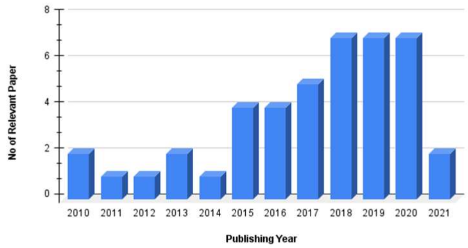

Figure 11. No of Relevant Paper VS Publishing Year

In the above Fig. 11, The X-axis defines publication year, and the Y-axis depicts the number of papers collected based on the search string, snowballing and forwarding process. Within 2018-2020, most of the papers are found for the relevant work.

4. DATA COLLECTION APPROCHES

In recommendation systems, data is the most important thing. Data can be collected either implicitly or explicitly or combined both in an RS which is known as "Information-Feedback" [6]. The core function of an RS is data or information feedback, which provides the information or data that RS needs to make appropriate recommendations to customers based on their choice or preferences [6]. In general, there are three sorts of feedback mechanisms which is reflected in Fig: 12.

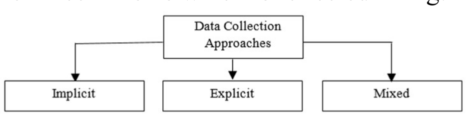

Figure 12. Data Collection Approaches

This approach obtains information without the user's knowledge but is based on the user's actions during the process. Without the user's agreement, the user's preferences are assessed. An Implicit Technique uses applications tools and procedures to record and evaluate the user input. This form of Implicit Technique could be found in a variety of apps, including browser history, web consumption or purchasing record, and even search history or user's behavior.

Users are asked to offer either a number or a score-evaluation while assessing the product, in this method. An organized continuous scale is used to fulfil the usual situation of explicit evaluations (example-Mark out ten). Ratings on various measures enable statistical analysis of these judgments, such as distributions, averages, and so on. The Explicit Technique assists people in expressing their desire and taste for a certain thing [155].

Both Implicit and Explicit Techniques are combined in Mixed Techniques. To anticipate things of interest and choice to users, this technique uses a combination of numerical rating, scores and human nature [6].

5. MOST COMMONLY USED SOLUTIONS OF COLD START

The solution of cold start is one of the main challenges in the Recommendation Systems. The cold start problem occurs when recommenders are unable to make conclusions about users or goods due to a lack of data[4]. It can be either for new products or new users. Some frequent solutions of cold start is given below in Fig 13.

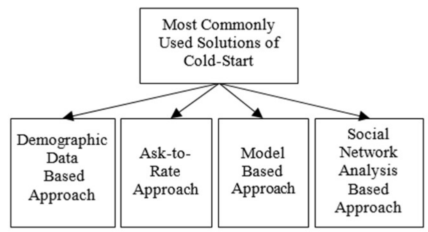

Figure 13. Frequent Solution of Cold-Start

The demographical based approach is based on user demographical characteristics or personal attributes. The RS suggests a list of goods that have received positive feedback from customers with demographics comparable to the target customer [18]. When no user rating record is available, this method produces suggestions. This method is quick, easy, and straightforward in creating findings based on a few observations.

Until there are enough rated products, a new user is explicitly requested to give rate the selected items. In RS, asking a set of questions regarding user's preferences or proposing certain goods to obtain any rating that would irritate the consumer. It's also a time-consuming and inconvenient activity.

Build a model based on the rating database first when using the model-based method. The model then generates a suggestion without consulting the entire database each time.

To increase suggestion accuracy, this recommender system incorporates social networking aspects. The practice of examining social structures using network and graph theory concepts is known as social network analysis (SNA). Nodes (individual actors or persons inside the network) and edges (relationships) illustrate the social network.

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6. RESULT AND DISCISSION

The main purpose of this literature review is to display the full overview of the possible solution of Cold-Start problem using hybridization approaches as well as showing the suitable data collection process for solving coldstart. Some tables and graphs are created for showcasing the results.

There are three type of data collection techniques. They are implicit, explicate and mixed approaches. After reviewing the papers, it is found that the mixed method is the most used data collection approach among all which is the answer of Q-2. The result is shown in the following Fig: 14.

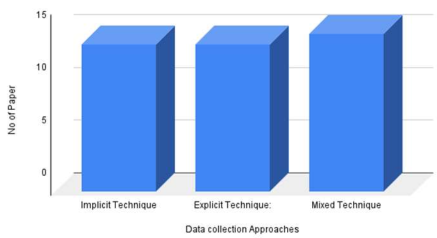

Figure 14. No of Paper VS Data Collection Approaches

In the above Fig: 14, the X-axis depicts the data collection process. On the other hand, the Y-axis defines the number of papers. According to Fig: 14, most of the authors used this mixed technique to get a better result.

There are seven types of hybridization methods. But weighted, mixed, feature combination and Feature Argumentation are the most commonly used hybridization methods used in recommendation systems. In Fig. 15, which hybrid methods are broadly used for solving cold start problem is shown. In the following pie chart, the percentage of the hybridization methods are shown. In our finding, the weighted hybridization method is a highly used method. About 28.9% of our collected paper's authors used this method. On the other hand, cascade hybridization is a rarely used method. About 2.6% of collected paper used this method which is so low in the count.

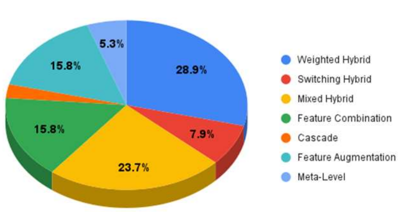

Figure 15. Hybridization Methods

The most frequently used solutions to cold start problems are Demographic Data Based, Ask-to-rate, Model based and, Social network analysis based. But after the survey, we can find out that demographic data based solutions are the most commonly used approaches. In Fig. 16, the frequently used cold start solutions in practical field are shown.

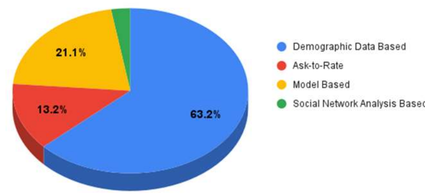

Figure 16. Frequent Solutions of Cold-Start

In the above pie chart, the demographic-based solution has been highlighted. According to the collected paper, about 63.2% of authors used this solution to solve cold start problem.

In this paper, five types of domain's papers like Movies, Books, Tourism, Music and, E-commerce are reviewed. After reviewing, some commonly used datasets are found. The datasets are shown in Table 6.

Table 6. Datasets

Paper Domain	Datasets
Movie	MovieLens [4], [1], [2], [21], MovieLens 1M [18], [37], [154], [110], [65], MovieLens 100K [37], [127], [154]
Books	Using historical data of Southwest University Library [17], DBook [13], Book-Crossing community [26], Twitter platform [44], Amazon/LibraryThing (A/LT) corpus [45]
Tourism	TripAdvisor [28], [27], [39], Tongcheng [20], Flickr [51]
Music	Last.fm [11], [32], [32], Million Song, Yahoo Music [52], Spotify [40]
E-commerce	Amazon [35], [56]

After analysis, according to collected paper it can be said that MovieLens dataset is the most commonly used dataset for movie domain, as well as TripAdvisor for tourism, Last.fm for music and Amazon for the e-commerce sector.

There are many papers where the authors used their own proposed algorithms. But most of the papers are used some common algorithms which are enlisted in Table 7.

Table 7. Commonly Used Algorithms

Algorithm Name	No of papers	Reference
K Nearest Neighbor (KNN)	6	[26], [29], [28], [7], [65], [98]

K- means Clustering	8	[4], [9], [13], [43], [127], [8], [153], [40]
Jaccard Similarity	3	[4], [18], [110]
Pearson's Correlation Coefficient	4	[18], [16], [8], [110]
Cosine Similarity	5	[18], [1], [7], [5], [110]
Euclidean Distance	4	[18], [45], [127], [28]
Singular Value Decomposition (SVD)	2	[43], [7]
Matrix Factorization (MF)	4	[43], [34], [32], [110]
Associate Rule Mining	3	[4], [37], [65]
TF-IDF	2	[21], [5]
Decision Tree	2	[9], [28]

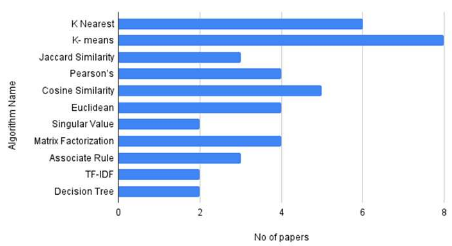

Figure 17. Commonly Used Algorithms VS No of papers.

In Fig. 17, X-axis illustrates the number of papers, and the Y-axis defines the name of the commonly used algorithms. From the collected paper, K- means clustering algorithm, K-Nearest Neighbor (KNN), Cosine Similarity etc. are the most widely used algorithms.

There are a lot of evaluation metrics but after reviewing some common evaluation metrics are found. They are

$$MAE = \frac{1}{N}\sum_{u,i}\left|p_{u,i} - r_{u,i}\right| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{u,i}\left(p_{u,i} - r_{u,i}\right)^2} \quad (2)$$

$$MAP = \frac{1}{U^T}\sum_{u \in U^T}\sum_{N=1}^{\left|I_u^T\right|}\frac{1}{N}\sum_{k=1}^{N}\delta\left(i_u^k \in I_u^T\right) \quad (3)$$

Different forms of measurements, such as accuracy or coverage, can be used to evaluate the importance of a recommendation system. The metrics utilized are determined by the filtering process. The metrics are shown below in Table 8.

Table 8. Commonly Used Evaluation Metrics

Evaluation Metrics	No of paper	Reference
MAE (Mean Absolute Error)	12	[18], [9], [16], [45], [28], [1], [2], [7], [46], [32], [52], [20]
RMSE (Root Mean Square Error)	10	[18], [13], [34], [43], [3], [28], [2], [7], [20], [158]
Precision	7	[4], [17], [44], [154], [5], [52], [98]
Recall	5	[44], [154], [5], [51], [98]
MAP (Mean Average Precision)	3	[154], [22], [51]

According to the Table 8, Fig. 18 has been created where the commonly used evaluation metrics are shown.

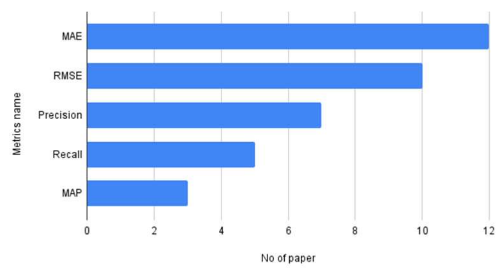

Figure 18. No of paper VS Evaluation Metrics

In Fig. 18, X-axis represents the evaluation metrics and Y-axis depicts the number of papers which used this metrics According to collected paper, only 12 papers are used MAE (Mean Absolute Error), 10 papers used RMSE (Root Mean Square Error), 7 papers used Precision, 5 papers used Recall and 3 papers used MAP (Mean Average Precision).

After the survey, some important information like the most useable data collection techniques, hybridization methods, commonly used solutions of coldstart problems, algorithms, evaluation matrices, etc. has been found. Besides this, some common datasets are found for a specific domain. In the future, implementing the combination of this survey result will give a possible better solution in these domains as well as other domains.

7. CONCLUSION

The coldstart problem is the existing barrier in the recommender system. It is the most challenging issue to solve. Another problematic issue is to get accurate available data. A lot of researchers are working on it. As a result, various types of possible solutions have been found. But

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still, they are working on it to get a more accurate solution. It is a vast research platform. Many new methods will be proposed to solve the problem in the future. This paper reviewed the recommendation approaches and hybrid approaches to solving the cold start problem. According to the writing procedure, the papers has been collected. Then the papers are included and excluded based on exclusion and inclusion criteria. Then the vital information is evaluated for solving cold start. Every author solves cold start problem in their own way. But the common methods which had been used from 2010 to 2021 in the field of cold start solutions using hybrid approaches are shown here. An informative overview of the recommendation system, the solution of cold start, data collection techniques, and a future direction for solving the coldstart problem in a hybridization approach are given. It will help the researchers by providing ideas. It will be improved in other domains of recommendation systems in the future. Above all, this paper will inspire researchers and provide a future roadmap for improving current recommendation approaches for solving cold-start problems.

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