Hybrid Recommendation Systems: A State of Art

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Abstract: Recommendation systems have become more important and popular in many application areas such as music, movies, e-commerce, advertisement and social networks. Recommendation systems use either collaborative filtering, content-based filtering or hybrid filtering in order to propose items to users, and each type has its weaknesses and strengths. In this paper, we present the results of a literature review that focuses specifically on hybrid recommendation systems. The objective of this review is to identify the problems that hybrid filtering tends to solve and the different techniques used to this end.

1 INTRODUCTION

Recommendation systems are techniques that propose products and services that are likely to interest the users of a platform, a website or an application. Nowadays, the demand for recommendation systems has increased in many areas such as movies, music, news, e-commerce, advertisement, tourism and social networks (Pandey and Rajpoot, 2016). Those systems are analyzing several characteristics of the online users, such as their reviews and their purchase history to make suggestions to other users based on the assumption that users with similar profiles tend to make the same choices (Tsolakidis et al., 2016).

In real life, when going for online products, people first always look for those items that are of their preferences. For that reason, recommendation systems, by the virtue of their nature, are used as a remedy that helps users choose between the immense variety of items (services and products) that Websites offer (Pandey and Rajpoot, 2016). Recommendation systems usually needs to consider many factors, including accuracy, diversity, novelty, coverage, user satisfaction and so on, to provide satisfactory recommendations for users (Cai et al., 2020). Typically, there are three major recommendation methods: collaborative, content-based and hybrid (Prakash et al., 2019).

Collaborative filtering is the most widely-used technique in recommendation systems because it is a method that makes predictions about a given user's interests by collecting a number of other users' appreciations (Duzen and Aktas, 2016), and this method can be either user-based recommendation or item-based recommendation. Content-based recommendation is also a very important type of filtering, because it computes recommendations according to the features of items that the user preferred in the past (Do et al., 2020). Recommendation can be for books, movies, music, news, articles, documents, etc. In order to have better recommendations for users, a new recommendation technique was proposed in the literature by combining both the collaborative filtering and the content-based filtering, which helps to benefit from the advantages of each method and overcome their drawbacks. This type of combination is known as the hybrid recommendation and aims at providing more accurate and effective recommendations by merging different algorithms (Ammar et al., 2020)(Tian et al., 2019)(Mansur et al., 2017)(Pandey and Rajpoot, 2016).

In this paper, we summarize the state of the art of hybrid recommendation systems in the last five years. For this, we have conducted a literature review whose objective is to collect the different problems of recommendation addressed by hybrid approaches and to identify the techniques used to solve these problems.

The remaining of this paper is organized as follows. Section 2 gives an overview of the background of our work. Section 3 presents the research methodology followed in the review. Section 4 answers the research questions by analysing and discussing the results of the review. Finally, Section 5 concludes the paper.

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2 BACKGROUND

Because of the rapid development of social network, recommendation systems appear to sort through and find what is desired by users (Prakash et al., 2019), in order to satisfy their needs. The first works in the field were based only on the two known types of recommendation, which are content-based filtering (Shah et al., 2017) (Kumar et al., 2018) (Najmani et al., 2019) and collaborative filtering (Song et al., 2016) (Patel et al., 2017) (Maihami et al., 2019). And since these two techniques have their strengths and weaknesses, researchers started to shift to hybridization between the two filtering techniques in order to exploit the advantages of both of them (Dhawan, 2019).

2.1 Content-based Recommendation

Content-based filtering methods (Burke, 2002) are based on a description of the item and the profile of the user's preferences. These algorithms try to recommend items that are similar to those that a user liked in the past (Tian et al., 2019)(Nikzad–Khasmakhi et al., 2019). Indeed, a content-based recommendation system tracks user preferences in terms of items consumed and liked, and from that data, it creates a user profile. Then, the system matches items from users' profile to those other items in the database and recommend the items the user has not consumed in the past and that are similar to user's preferences (Wairegi et al., 2020).

2.2 Collaborative Recommendation

Collaborative filtering method (Wairegi et al., 2020) is based on opinion shared between users and their taste. We recommend to a user an item appreciated by another with common interests (Ammar et al., 2020) (Chen et al., 2018). The fact of being capable of making predictions, without asking for more data from the users or items, gives more utility and importance for the filtering. However, there are many problems related to this type of systems, namely sparsity, scalability and the cold start problem (Duzen and Aktas, 2016). This filtering is divided into two categories: user-based and item-based filtering (Burke, 2002).

In the user-based approach, the algorithm produces a rating for each item using similar users (Li et al., 2018a). That means if **User 1** is interested in Items A, B and C, and **User 2** is interested in Items A and B, then the system recommends Item C to **User 2**.

The item-based technique computes recommendation using the similarity between items and not between users (Patel et al., 2017). In other words, if a user likes the Items A, B and C, and Item D is similar to C, the system proposes Item D to this user.

2.3 Hybrid Recommendation

Hybrid recommendation systems (Burke, 2002) can produce outputs that outperform single component systems by combining multiple techniques of different types, such as mixing content-based and collaborative filtering methods, which is the most common combination (Wairegi et al., 2020). Furthermore, it is also possible to mix different techniques of the same type (Cano and Morisio, 2017).

The collaborative recommendation approach and the one based on the content are considered as complementary, because the collaborative recommendation does only recommend items already evaluated, meanwhile, the content-based recommendation is able to recommend new items not evaluated yet by the user.

In addition, the content of the item is either inadequate or difficult to extract. There is no need for the content in the collaborative recommendation; in contrast, this is very necessary in the second type of filtering.

To reach the best performance, we need an approach that deals with the different weaknesses of individual technique, benefits from their advantages and relies on multiple sources in order to use the most appropriate ones. In this vein, the hybridisation of the two types of filtering have been proposed. There are many available hybridization techniques such as mixing, switching, weighted approach, feature combination among others. By using these techniques, the system combines various recommendation approaches to a single hybrid recommending system (Wairegi et al., 2020).

3 RESEARCH METHODOLOGY

Several studies related to the hybrid recommendation systems have been proposed by researchers and practitioners. To analyse these studies, we have conducted a review of the literature by following the same protocol of a Systematic Literature Review (SLR) described in Kitchenham's guidelines (Kitchenham and Charters, 2007). This protocol contains the following steps : 1) Identification of research questions, 2) Research in Databases, 3) Data Selection which includes the definition of Inclusion and Exclusion criteria, 4) Data Extraction, and 5) Data Analysis. The rest of this section focuses on the first four steps, while the data analysis step is detailed in Section 4.

3.1 Search Questions

The objective of our review is to find the different contributions proposed in literature in relation with hybrid recommendation systems and to discuss the different criteria of hybridisation used by these approaches. We thus formulated the three following questions :

- **RQ1.** What are the different approaches proposed regarding hybrid recommendation systems?
- **RQ2.** What are the types of problems that the hybridization techniques tend to solve?
- **RQ3.** What are the different techniques of hybridization used to enhance the functioning of recommendation systems?

In order to answer the research questions defined above, we have constructed the research string using the keywords related to our topic. The basic keywords are: Recommendation, System, Hybridization and Filtering. To make the research more efficient, we defined a set of synonyms and alternatives for the different keywords. To link the alternative keywords, we used the Boolean “OR” and to interconnect the different parts of the string, we used the Boolean “AND”. As a consequence, we obtained the research string presented below:

*(hybrid **OR** hybridization **OR** collaborative **OR** content-based) **AND** (recommender **OR** recommending **OR** recommendation) **AND** (system **OR** systems **OR** filtering **OR** technique)*

3.2 Research in Databases

Using the keywords above, we considered publications retrieved from IEEE Xplore, ACM Digital Library, ScienceDirect and Springer Link.

- **IEEE Xplore:** This database is very easy to manipulate. First, we entered the search string, and then we filtered the first result by date to obtain only the papers corresponding to our review.
- **ACM Digital Library:** In this database, we had to be more specific in the notation by adding two quotes to the keywords, otherwise, we come up with a big number of studies that have nothing to do with our topic.
- **ScienceDirect – Elsevier:** This database works in the same way as the ACM Digital Library in using the quotes. In ScienceDirect, we can refine our search through many filters like date, publication title, article type, etc.
- **Springer Link:** Springer link is also a database known for its diversity in studies. The only complicated issue we had to deal with in this database is the interconnection between some filters.

3.3 Data Selection

To perform a successful literature review, the inclusion and exclusion criteria must be carefully defined in order to keep only the articles that are relevant to our search.

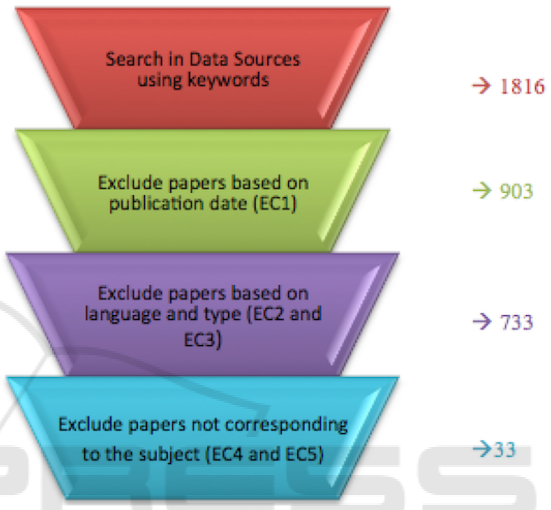

Figure 1: Papers Selection Process.

The inclusion criteria we have defined are the following:

- **IC1:** The paper is a full article, a book, a chapter, a report, a thesis, a presentation.
- **IC2:** The title or the abstract of the paper contains the keywords of the search.
- **IC3:** The paper addresses the hybrid recommendation systems.
- **IC4:** The paper addresses at least one problem of recommendation or proposes at least one technique of hybridization.

And the exclusion criteria are the following:

- **EC1:** The publication date is previous to 2016.
- **EC2:** The paper is written in a language other than English.
- **EC3:** The paper is a short article, a standard, a poster, an editorial, or a tutorial.
- **EC4:** The title, the keywords and the abstract do not correspond to the research subject.
- **EC5:** The paper does not discuss the hybrid recommendation systems.

The total number of papers initially retrieved is 1816, divided as follows: 1046 from IEEE Xplore, 431 from ACM Digital Library, 245 from ScienceDirect and 94 from SpringerLink. After applying all the exclusion criteria, we kept only 33 papers at the end of the selection process.

3.4 Data Extraction

In order to make a synthesis of the data collected and to be able to answer the predefined research questions above, we extracted a number of attributes from each selected paper, as described in Table 1 (Kitchenham, 2007),

Table 1: Attributes used in data extraction.

Title	Title of the paper
Year	Publication year of the paper
Type	e. g. Journal paper, conference paper, thesis, book, chapter
Database	e. g. IEEE, ACM, SpringerLink, ScienceDirect (Elsevier)
Keywords	Keywords specified in the paper
Methodology	Methodology followed in the study
Contribution	e. g. Model, Framework, Tools, Method, Algorithm

4 RESULTS AND DISCUSSION

The objective of this step is to answer the research questions defined in the last section. The different papers we have judged relevant for our review were studied from different perspectives.

4.1 Metadata Analysis

In our review, we analyzed many types of articles metadata, but we present in this article two main types, which are the Data Source and the Publication Year.

Data Source. Figure 2 presents the percentage of papers from the four digital databases. The distribution of papers is the following : 39% of the selected papers belong to IEEE Explore (13 papers), 23% of papers from Springer (8 papers) and the lowest percentage of papers were retrieved from both ScienceDirect and ACM 19% (6 papers).

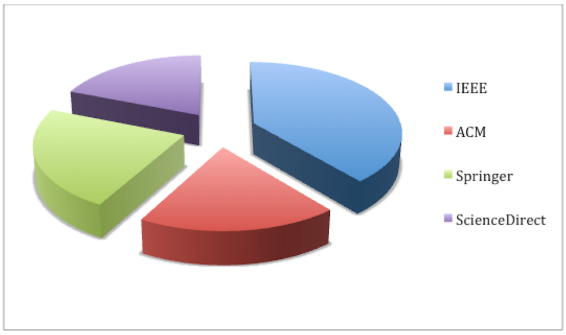

Figure 2: Percentage of papers in databases.

Publication Year. As mentioned earlier, the review was conducted for the period 2016-2020. Figure 3 shows the number of papers published in each year. The highest number of papers were published in 2019 with 12 papers. 7 of the selected papers were published in 2017, 6 papers were published in 2020, 4 papers in 2018 and 4 papers in 2016.

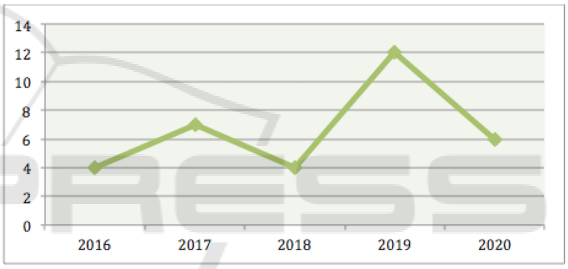

Figure 3: Number of papers per year.

4.2 Problems Addressed by Hybridisation

To answer the question RQ2 asked above, we summarized the main problems that the selected papers try to avoid by using the hybridization. A total of 12 problems were found, and each problem has a degree of importance. This section defined the four more common problems:

- **Cold-start:** This problem is caused when the system is unable to recommend an item to any user because there is no rating for that item, or when a new user enters in the system and has no rating record, the system is unable to recommend items to him (Wang et al., 2019).
- **Data Sparsity:** This problem is caused by the rate of users, which means if the user do not rate some item, the system suffers from the paucity of data and becomes unable to recommend items to him because it has no idea about the user taste (Dhawan, 2019).

Table 2: Problems Addressed per Paper.

Paper	Cold-Start	Sparsity	Scalability	Diversity	Others
(Pandey and Rajpoot, 2016)	X	X	X	X	X
(Dhawan, 2019)	X	X			
(Patel et al., 2017)	X	X	X		
(Duzen and Aktas, 2016)	X	X			
(Mansur et al., 2017)	X				
(Tian et al., 2019)	X	X	X	X	X
(Nikzad–Khasmakhi et al., 2019)	X	X	X	X	
(Idrissi et al., 2019a)	X	X	X		
(Wairegi et al., 2020)	X	X	X		
(Agner et al., 2020)	X	X			
(Cai et al., 2020)	X	X			
(Ammar et al., 2020)	X	X	X	X	X
(Tsolakidis et al., 2016)	X	X	X	X	X
(Kumar et al., 2018)	X	X	X		
(Cano and Morisio, 2017)	X	X	X	X	X
(Tang and Wang, 2016)	X	X	X	X	
(Prakash et al., 2019)	X				
(Gong et al., 2020)	X	X			
(Cao et al., 2018)	X		X		
(Zhang et al., 2018)	X	X	X	X	
(Alamdari et al., 2017)	X	X	X	X	X
(Chen et al., 2017)	X	X	X		
(Gulzar et al., 2018)	X				
(Do et al., 2020)	X				
(Chen et al., 2018)		X			
(Wang et al., 2019)		X			
(Li et al., 2018a)		X		X	
(Maihami et al., 2019)	X	X			
(Shah et al., 2017)	X	X	X		
(Song et al., 2016)					X
(Najmani et al., 2019)	X	X	X	X	X
(Çakır et al., 2019)		X			
(Idrissi et al., 2019b)	X				

- **Scalability:** It is the increase of number of rated items by users, which increases also the complexity. Thus, the recommendation system is unable to handle such amount of data (Alamdari et al., 2017).
- **Diversity:** Diversity is recommending the same item many times that are presented with different names but represent the same product or item. In this case, the system is unable to identify the item with the other name affected to it (Burke, 2002). Diversity is one of the optimization objectives, and it is related to the accuracy (Cai et al., 2020). Diversity of recommended items decreases while accuracy improves.

There are other problems appearing in few studies, like accuracy, gray sheep, shilling attacks, black sheep, Changing user preferences, privacy, trust.

Figure 4 shows the total of papers that treat each problem. It is very notable that the cold-start issue is the main problem treated in this area, With 28 papers out of the total of papers (85%). The second most addressed issue is data sparsity with 26 papers (79%). Scalability, as discussed before, is also an interesting issue in the field of hybrid recommendation and is covered by 17 papers selected in this review (52%).

And finally, some of these studies addressed data diversity with 11 papers (33%), but, not all of them, seeing that the over-specialization of data is still causing problem in some of type of hybridization.

The figure also shows that the other different issues, mentioned separately in few papers, are presented in less than 25% out of 33 papers with 8 papers.

Table 2 presents the Problems addressed and the different papers that deal with them.

Table 3: Problems vs. hybridisation techniques.

	Cold-start	Diversity	Sparcity	Scalability
Weighting	YES	YES	YES	YES
Switching	YES	NO	YES	YES
Mixture	YES	NO	YES	YES
Feature combination	YES	NO	YES	YES
Feature augmentation	YES	YES	YES	YES
Meta-level	YES	YES	YES	YES

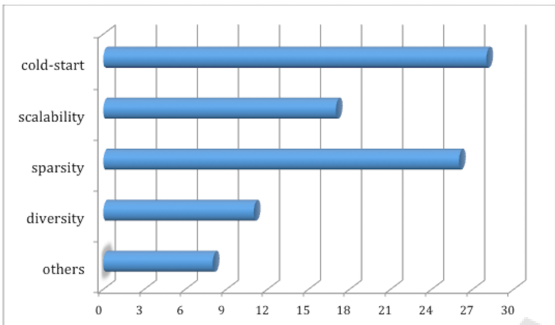

Figure 4: Number of papers per Recommendation Problem.

4.3 Hybridisation Techniques

The quality of recommendation is the main topic of all the papers. Quality has many definitions, but generally it is the ability of a product to satisfy defined requirements [18]. Based on the selected papers, we collected the different hybridisation techniques used to solve the recommendation problems.

- **Weighting:** In the weighted hybrid recommendation, score or weight of a recommended item is calculated from the results of all available recommendation techniques implemented in the system (Burke, 2002). In this sense, (Li et al., 2018a) have worked on the recommendation system based on weighted linear regression models to establish the model between the user's scores for the items and the user's highest frequency scores.
- **Switching:** By using this technique, the system switches between recommendation techniques depending on the current situation (Burke, 2002). This technique has been used by many papers. For example, (Prakash et al., 2019) proposed a system that optimizes the results by incorporating dual hybridization techniques, meta-level and switching.
- **Cascade:** Cascade technique selects candidate completely with the main recommendation, and uses the other recommendation to refine product or item scores (Burke, 2002). An example of systems that use this technique is the mobile music cascade recommender that combines SVM genre classification with collaborative user personality (Cano and Morisio, 2017).
- **Feature Combination:** Features from different recommendation data sources are thrown together into a single recommendation algorithm (Burke, 2002). This technique is used by (Wairegi et al., 2020) to come up with an hybrid recommender system that combines both content-based and collaborative filtering approaches to recommend items to the users.
- **Mixture:** Mixed hybrids combine recommendation results of different recommendation techniques at the same time instead of having just one recommendation per item (Burke, 2002). In this contexte, (Gulzar et al., 2018) proposed a system based on a mixed combination of three individual techniques used in recommender information retrieval systems.
- **Feature Augmentation:** The output from one technique is used as an input feature to another (Burke, 2002). For instance, (Cano and Morisio, 2017) mentioned an hybrid method that combines multidimensional clustering and Collaborative filtering to increase recommendation diversity.
- **Meta-level:** The meta-level technique seeks to input the result obtained by collaborative filtering into the content-based system to get a more refined recommendation set (Burke, 2002). Among papers applying this technique, (Sattar et al., 2017) proposed meta-level hybrid recommendation algorithms by combining item-based collaborative filtering with content-based filtering and build content-based filtering model on the content of K-nearest neighbors of items.

4.4 Discussion

Table 3 presents the techniques used to solve the different recommendation problems addressed by the selected papers. From the table, we can see clearly that hybridization techniques in most papers had for objective to overcome the cold-start problem, data sparsity and scalability. The problem then is with the diversity of data or the problem of over-specialization of data which is still existing in Switching Hybrid Recommenders. Indeed, (Ghazanfar and Prugel-Bennett, 2010a) talks about the four issues of a hybrid recommender system, but the switching hybridization proposed in the paper is only able to deal with with the cold-start, sparsity and scalability problems. A good quality is also saving the users' valuable time by recommending the best items that are related to their preferences and choices and a weighted system has shown the ability to make consolidated decisions (Do et al., 2020) and to overcome the problem of data diversity or the over-specialization besides the cold-start issue, data sparsity and scalability (Cano and Morisio, 2017). As for mixed hybridization, it has shown its ability to avoid cold-start, sparsity and scalability issues (Santos, 2014) but seems to have still the data over-specialization issue since multiple recommenders present their results at once.

Hybridization based on feature combination treats information as simply additional feature data (Burke, 2002), which explains why the combination type is facing the same problem of data diversity as the weighted and switching types. In cascading hybrid recommender systems, a recommendation technique is applied to produce a coarse candidate list of items for recommendation that are refined by applying other recommendation techniques (Ghazanfar and Prugel-Bennett, 2010b). This means that the cascading type does not suffer from the over-specialization issue due to the enhancement that does on the other previous techniques. Hybridization based on feature augmentation is also able to deal with data over-specialization issue (Li et al., 2018b), because it is employed to produce a rating or classification of items before recommending them to the users. Finally, the meta-level technique gives a compressed representation of user's interest, which explains how it deals with diversity problem and data sparsity too.

5 CONCLUSION

Today, recommender systems play an important role in our daily life. It have become an essential tool for users to navigate the vast number of options for content and products, because it enables users to make the most appropriate choices from the immense variety of items that are available by predicting the preferences that users would give to an item (Tang and Wang, 2016).

In this papers, we have presented the results of a review that focuses especially on hybrid recommendation systems. The objective of this review was to investigate the different approaches proposed in the subject between 2016 and 2020. As a result of searching papers in four digital libraries, we identified at the beginning 1816 papers. By applying a set of inclusion and exclusion criteria, 33 relevant papers were selected.

Many conclusions have been drawn from this review. The most important constraint addressed by hybrid approaches is the cold start problem because it appears in almost 75% of papers.

The analysis has also shown that data sparsity is another important issue in recommendation, while the scalability problem comes in the third place. There are other issues found in studies such as accuracy, gray sheep, shilling attacks, black sheep, Changing user preferences, privacy and trust, that are also important but do not have the same impact on recommendation.

From the results, we can conclude that despite of representing an important issue in recommendation systems, data diversity or also known as the over-specialization of information is not as current as the other issues. It is slightly studied or just mentioned in some papers. Therefore, we have found out that this issue is not addressed by some hybridization techniques, namely the weighting, the switching and the feature combination techniques.

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