Exploring Strategies to Mitigate Cold Start in Recommender Systems: A Systematic Literature Mapping

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Abstract: Recommender Systems are designed to provide personalized item recommendations to users based on their preferences and behavioral patterns, aiming to suggest items that align with their interests and profile. In Recommender Systems, a common issue arises when the user's profile is not adequately characterized, particularly at the initial stages of using the system. This issue has persisted in Recommender Systems since its inception, commonly known as Cold Start. The Cold Start issue, which impacts new users, is called User Cold Start. Through a systematic literature mapping, this paper identifies strategies to minimize User Cold Start without reliance on external sources (such as social networks) or user demographic data for initializing the profile of new users. The systematic literature mapping results present strategies aimed at mitigating the User Cold Start Problem, serving as a foundational resource for further enhancements or novel proposals beyond those identified in the review. Thus, the goal of this work is to understand how to create an initial user profile before any prior interaction and without using external sources in the recommender system.

1 INTRODUCTION

Recommender systems provide suggestions for items with a higher probability of interest to a user (Ricci et al., 2015). An "item" refers to what the system recommends to users (Jannach et al., 2010), which can be movies, books, music, tourist spots, products, scientific papers, etc.

Since the inception of Recommender Systems, various algorithms/approaches have been devised to produce recommendations. Traditionally, three approaches are mainly cited: (a) Content-Based, where the user receives recommendations for items similar to those they preferred in the past; (b) Collaborative Filtering, where the system recommends items to the user that users evaluated with a similar profile; and (c) Hybrid, where approaches are combined to recommend items, aiming to reduce disadvantages present in a single approach (Burke, 2002). Other approaches can be cited, like the demographic approach where sociodemographic attributes such as age are used (Ricci et al., 2015).

Despite the advancements in Recommender Systems, with numerous published works and the application of these systems in various domains, there is still much to explore, especially regarding some known problems of these systems (Alyari and Jafari Navimipour, 2018). One of the most well-known issues is the Cold Start problem. Despite the approach employed, Recommender Systems grapple with the Cold Start problem (Ricci et al., 2015). The Cold Start problem can be defined as the inability to create reliable recommendations due to a lack of data about a new user or a new item (Monti et al., 2021). Thus, there are two types of Cold Start: User Cold Start and Item Cold Start. New User Cold Start is related to the fact that a user who has interacted little with the system and made a few item evaluations will not initially receive quality recommendations since little is known about this user. New Item Cold Start refers to the fact that items evaluated by few users or not evaluated at all will not be recommended, something that occurs in some of the approaches used in Recommender Systems, specially in Collaborative Filtering.

The Cold Start poses serious challenges to the value of Recommender Systems, as users who do not

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receive appropriate recommendations for their profile may, in some cases, cease using the system (Panda and Ray, 2022). In (Panda and Ray, 2022), the authors emphasize that Cold Start problems represent serious challenges to the commercial value of Recommender Systems, where New users who do not find the recommendations useful would stop using the system, affecting user engagement and sales.

In the work of (Abdullah et al., 2021), the authors conclude that little research has been carried out in academia about the Could Start problem. However, they found that cold start user recommendation has frequently been researched in the entertainment domain, typically using music and movie data.

Thus, this work aims to identify attempts to minimize the Cold Start problem described in academic literature through a systematic literature mapping.

The focus is on the User Cold Start problem. This choice was made since User Cold Start is the more crucial characteristic for user engagement and retention of new users, and it is not a highlighted problem in a more significant number of approaches used in Recommender Systems (see Section 2). Also, the number of these approaches used to create the users's profiles using some prior interaction and using external sources for the recommendation system is extensive. Consequently, this paper brings a comprehensive analysis to understand how to create this profile without those approaches.

This paper is structured as follows. Section 2 presents more details about the Cold Start problem, along with papers describing how Recommender Systems has obtained data to identify user preferences and build their profiles. Section 3 presents the systematic mapping carried out. Considering the results of systematic mapping, Section 4 indicates future works. Section 5 presents the final considerations.

2 USER PROFILE CONSTRUCTION AND COLD START

The user cold start problem is linked to the creation of user profiles. Understanding the process of creating user profiles requires knowledge about how to build and represent these profiles. The user profile representation depends on the chosen approach within Recommender Systems. It is also important the way to gather data for building robust user profiles. The subsequent sections explore these aspects.

2.1 User Profile Representation and Recommender Systems Approaches

Cold Start presents itself differently for each recommendation approach employed. In the Content-Based approach, where the user receives recommendations for items similar to those they liked in the past, the problem is particularly pronounced for new users ((New User Cold Start) (Pazzani and Billsus, 2007). In Collaborative Filtering, in addition to User Cold Start, there is also the presence of New Item Cold Start, which is related to the fact that items not evaluated by any user will not be recommended (Lika et al., 2014)

The issue lies in the Content-Based approach Notably, the Content-Based approach is closely linked to the field of Information Retrieval, where items are often characterized by textual descriptions (papers, books, etc.) (Adomavicius and Tuzhilin, 2005).

In the Content-Based approach, the user's profile is represented by a set of keywords (Adomavicius and Tuzhilin, 2005). In many Recommender Systems, this set of keywords in the user profile is compared with items (papers, books, for example) using a similarity function, like cosine. Furthermore, in Content-Based Recommender Systems, TF-IDF - Term Frequency-Inverse Document Frequency is employed (TF-IDF is frequently used in Information Retrieval Systems). The TF-IDF measures the importance of a term/word to a document in a collection. The TF-IDF assigns a weight to term i in document d. Here, $tf_{i,d}$ represents the number of occurrences of term i in document d, and idf_i, known as the Inverse Document Frequency of term i, emphasizes the effect of terms that frequently occur in an item and are significant for determining the relevance of that item. In Recommender Systems, a numerical value is assigned to each term/word in a user profile to indicate the significance of each term in defining the user's interests (Manning et al., 2009).

In Collaborative Filtering, the system typically identifies the utility of an item based on user ratings and ratings from other users for existing items. In (Adomavicius and Tuzhilin, 2005), it is mentioned that this allows the system to handle any type of item (often, there is no representation/characterization of items, or it is not used in the recommendation process, making it unnecessary). The problem arises in systems where Collaborative Filtering is used, as an item to be recommended needs to be evaluated by users, giving rise to the New Item Problem or Item Cold Start.

One of the most widely used algorithms in Recommender Systems employing Collaborative Filtering is the Neighborhood-Based approach, with the most commonly used variation being User-User if the system has more items than users. This variation assesses which users have similar tastes (evaluated the same items and provided similar ratings) compared to a particular user (Ning et al., 2015).

One of the steps in this approach involves calculating similarity using the Pearson Coefficient and comparing a user with others based on the ratings they gave to items. The Pearson Coefficient measures the strength of the relationship between two variables. Considering this, in the Collaborative Filtering approach, the user's profile is represented by a set of item ratings (Resnick et al., 1994).

When the Recommender System uses a Hybrid Approach (a mix of Content Based and Collaborative approaches), the way of representing the user profile will depend on the kind of item to be recommended. If an item consists of a textual item (e.g., scientific papers), it is possible to use a set of words and a set of ratings to represent the user profile (Burke, 2002).

In a Demographic Approach, data about the user, like age, will be necessary. In this case, a pair attribute-value will represent the user profile. The problem is that in many contexts, demographic data will be irrelevant. This is the case of a Recommender System that recommends scientific papers, for example, (Tintarev and Masthoff, 2015; Adomavicius and Tuzhilin, 2015). Considering that User Cold Start is present in more approaches, the emphasis of the work is on this problem, which involves acquiring user preferences.

2.2 User Preference Acquisition

Considering the insights from (Knijnenburg and Willemsen, 2015), four methods can be regarded as the most commonly used by Recommendation Systems to acquire these user preferences: item evaluation through scales, assignment of weights to item attributes, textual reviews of items, and implicit feedback.

The method of item evaluation through rating scales is the most commonly used explicit evaluation method, where users employ scales (usually a 5-point Likert scale) to assign ratings to items according to their preferences (Cena et al., 2010),(Cosley et al., 2003),(Dooms et al., 2011),(Gena et al., 2011),(Sparling and Sen, 2011). Sometimes, binary evaluations are made where users are simply asked if they liked an item or not (Goldberg et al., 2001; Schafer et al., 2007). On the other hand, assigning weights to item attributes originates from the field of decision analysis, where multi-attribute utility is used as a standard for decision-making (Bettman et al., 1998). In this case, a degree of importance is assigned to each attribute of the item to be recommended, requiring the user to indicate the degree of importance for each item. There is a strong dependence on the type of item to be recommended, as different classes of items present different attributes (e.g., for a computer, the amount of memory, processor, and price are attributes that may have distinct weights for different users). The values of these attributes can be discrete values arranged on a scale indicating from the best value to the worst value, e.g., for the cost attribute of an item, the values could be "very high, high, medium, low, very low" (Bettman et al., 1998).

Another method of eliciting user preferences is through a critique/comment made for the item. For example, this comment can even be processed automatically to determine whether the critique was positive or negative. Finally, considering that users may not always be willing to provide evaluations, indicate which attributes are most important to them in an item, or elaborate on comments, many Recommendation Systems seek to observe user behavior, i.e., their actions, which does not require extra effort from the user (Ricci et al., 2015; Amatriain and Basilico, 2015). Thus, actions such as viewing item details, purchasing/consuming, and selecting items for purchase, among others, indicate interest in the item.

Furthermore, user demographic data such as age, gender, and occupation can be considered for profile formation (Adomavicius and Tuzhilin, 2015) and the creation of stereotypes that are associated with preferences for specific items. Demographic data significantly mitigates issues related to User Cold Start. Still, this data may not always be available, and its use may not be suitable for recommending certain items (e.g., recommender systems for scientific papers). Some recommender systems utilize user data obtained from social networks (Son, 2016). However, the challenge lies in the fact that these data are not always available. It is important to note that regardless of the approach used, these ways to acquire information can be useful. In this sense, even in the Content-Based approach, ratings given to items can be utilized. It is possible, for example, to assign greater weight to terms in the user's profile that belong to well-rated documents.

3 SYSTEMATIC LITERATURE MAPPING

The Systematic Literature Mapping aims to identify approaches to minimize User Cold Start presented in the literature, excluding approaches that use external sources to the Recommender System (e.g., Social Networks) and considering only the information obtained during the user's initial access to the system. The Systematic Literature Mapping was based on (Petersen et al., 2008).

The expected results for the review include (a) Identifying techniques/strategies to minimize the Cold Start for new users in Recommender Systems; (b) Identifying the approaches of Recommender Systems (predominantly Content-Based, Collaborative, or Hybrid) where these techniques/strategies have been employed; (c) Identifying the application domains of Recommender Systems where these techniques/strategies have been utilized; and (d) Identifying the types of user profile representations employed in the identified works.

3.1 Research Questions

Given the objectives, we have formulated a main research question (MRQ) and secondary research questions (SRQ). The following section presents these questions: **MRQ** What techniques have been employed to reduce the user Cold Start problem? **SRQ1:** How is the initial user profile created in these works? **SRQ2:** What approaches are used in Recommender Systems in these works? **SRQ3:** What are the application domains of these works? **SRQ4:** How has the evolution of strategies to minimize Cold Start been over time?

3.2 Search and Selection of Papers

Through an initial search on works related to the research questions, keywords were identified to form the search query based initially on two terms: (1) Recommendation Systems and (2) Cold-Start. The term User Cold-Start was added as the focus was on new users. Thus, the works should meet the search query argument ***ALL(recommender systems or recommendation systems) AND ALL(user cold start) AND ABS(cold start)***, considering the terms "recommender systems" or "recommendation systems" and the term "user cold start" anywhere in the paper.

The term "cold start" should be in the paper's abstract ("ABS") to identify papers that address the Cold Start problem and not just mention the term. In this sense, it was assumed from some preliminary searches that papers proposing ways to minimize Cold Start mention the expression "Cold Start" in their abstract.

Thus, the search strings are defined considering these criteria and the search engine available in each digital library. The searches were conducted in January 2023 on the following sources: ACM Digital Library - https://dl.acm.org/; IEEE - https://www.ieee.org/ and Scopus - https://www.scopus.com/.

Scopus was considered since its database contains several other scientific bases (Buchinger et al., 2014). The number of papers returned by each engine is: ACM returned 90 papers, Scopus returned 374 and IEEE returned 44. Out of the 508 documents obtained, an analysis of information in the attributes of title, abstract, and keywords was conducted, applying inclusion and exclusion criteria.

The Inclusion Criteria (IC) used were: **IC1:** The publication is written in the English; and **IC2:** The publication has more than four pages.Out of the 508 documents returned by the search, 469 papers met the inclusion criteria.

Subsequently, Exclusion Criteria (EC) were applied, initially consisting of four criteria: **EC1:** The publication is not available for fully open access through the portal; [1]; **EC2:** The publication does not describe a technique to minimize User Cold Start; **EC3:** The publication is not a primary scientific paper; **EC4:** The publication is duplicated (i.e., with the same Digital Object Identifier - DOI).

It was necessary to read the works to apply some of the exclusion criteria. To expedite the process, this reading was conducted in three phases: (1) Reading of the title, abstract, and keywords; (2) Reading of the introduction and conclusion; and (3) Complete reading of the paper. If it was impossible to identify whether the exclusion criterion was met after the first phase, the second phase was carried out. When still insufficient, the third phase was executed. After completing this process and considering the four exclusion criteria, 324 papers remained. However, it was noted that several works created the user profile through the analysis of the user's interaction history (here, there is no reference to the user's initial interaction, that is, the one made on the first access to the system, but rather interactions recorded after multiple accesses); several works used demographic data; and several works used external data sources such as Social Networks from which the data was extracted.

As the objective of this work is to understand how to create this profile before any prior interaction and without using external sources to the recommendation system, that is, at the moment when the user registers, a fifth exclusion criterion **EC5** was defined.

The **EC5** defines: the publication uses the user's system access history (not only the initial access), external source (e.g., user's social networks), or user demographic data as a way to initiate the profile of a new

[1] A free access portal promoted by the government.

user.

Thus, the EC5 was applied. In the ACM database, 54 papers were identified that used user history, 9 papers used demographic data, and 3 papers used some external source. In the IEEE database, 22 papers used history, 6 papers used demographic data, and 5 papers used some external source. Finally, in the SCOPUS database, 168 papers used user history, 33 papers used demographic data, and 5 papers used some external source. After applying CE5 and removing duplicate papers, only 19 works were selected for analysis (see Table 1.

Table 1: Number of papers returned per EC.

Exclusion Criteria	ACM	SCOPUS	IEEE	Total
Total	83	345	41	469
EC 1	83	249	41	373
EC 2	74	231	39	344
EC 3	73	216	39	326
EC 4	73	212	39	324
EC 5	7	6	6	19

3.3 Selected Papers: Solutions to Minimize the Cold Start (RQ)

As achieved statistical data, papers are distributed across the search engines used. The majority of studies were obtained from ACM, around 36.84%. Finally, IEEE and Scopus contribute with 31.57% each to the total result of papers per search engine.

Considering the way to create the initial user profile from the analysis of the works (**Creation of the Initial User Profile (SRQ1)**), it is possible to identify the following strategies: **Strategy 1** Requesting the user to answer questions; **Strategy 2** Requesting the user's evaluation for a set of items; **Strategy 3** Requesting the user to select items; **Strategy 4** Requesting the user to select/register keywords/tags; and **Strategy 5** Using popular items among older users (or users considered experts) of the Recommender System.

Strategy 1 consists of asking the users some question(s) as soon as they enter the system to identify their preferences. This is used by (Christakopoulou et al., 2016), (Walunj et al., 2022), (Okada et al., 2021). Questions include "What genres of movies do you enjoy?" or "What places do you enjoy to visit?".

In the case of Strategy 2, the user is asked to rate some items at their first entry into the system. This is used by (Felício et al., 2017), (Lazemi and Ebrahimpour-Komleh, 2017), (He et al., 2020), (van der Velde et al., 2021)

Strategy 3 is used by (Hristakeva et al., 2017), (Crawford, 2012), (Felício et al., 2016), (Khan et al., 2021), (Martins et al., 2013), (Fernández et al., 2020).

The technique of selecting/registering keywords/tags (Strategy 4) is used by(Shi et al., 2021), (Hristakeva et al., 2017).

Finally, using popular items (Strategy 5) involves items highly rated by active users or called experts. This strategy is used by (Chao and Guangcai, 2020), (Lin et al., 2012), (Amatriain et al., 2009), (Zhang et al., 2020), (Darshna, 2018).

Approaches Used **(SRQ2)** - In the ACM database, 6 selected papers are Collaborative Filtering, and 1 is Hybrid Approach. In the IEEE database, the three main recommendation approaches, Collaborative Filtering (CF), Content-Based (CB), and Hybrid (HB), are found. In the SCOPUS database, the three main recommendation approaches are also present.

The application Domains **(SRQ3)** are presented in the Table 2.

Table 2: Selected papers per application domains.

Paper	Recommended items
(Shi et al., 2021)	News
(Christakopoulou et al., 2016)	Restaurants
(Felício et al., 2017)	Movies
(Hristakeva et al., 2017)	Documents
(Chao and Guangcai, 2020)	Movies
(Lin et al., 2012)	News
(Amatriain et al., 2009)	Movies
(Crawford, 2012)	Movies
(Walunj et al., 2022)	Hotels, restaurants e tourist spots
(Okada et al., 2021)	Songs
(Felício et al., 2016)	Art paintings and clothes
(Zhang et al., 2020)	Movies
(Khan et al., 2021)	Food recipes
(Lazemi and Ebrahimpour-Komleh, 2017)	Jokes
(Martins et al., 2013)	Videos and songs
(He et al., 2020)	Movies
(Darshna, 2018)	Songs and movies
(van der Velde et al., 2021)	Learning objects
(Fernández et al., 2020)	Movies

Regarding the Evolution of Solutions to Minimize Cold Start Over Time **(SRQ4)**, over the years of publication of the selected papers, the techniques of requesting user evaluation for a set of items and asking the user to select items are present in a significant number of years (Felício et al., 2017), (Lazemi and Ebrahimpour-Komleh, 2017), (He et al., 2020), (van der Velde et al., 2021), (Hristakeva et al., 2017), (Crawford, 2012), (Felício et al., 2016), (Khan et al., 2021), (Martins et al., 2013), (Fernández et al., 2020). From 2016 onward, the technique of asking the user to answer questions or questionnaires (Christakopoulou et al., 2016), (Walunj et al., 2022), (Okada et al., 2021) starts to be seen in publications, and from 2018 onward, the technique of using popular items becomes present in the papers (Chao and Guangcai, 2020), (Lin et al., 2012), (Amatriain et al., 2009), (Zhang et al., 2020), (Darshna, 2018). In 2021, the technique of asking the user to select or register keywords/tags were noticed (Shi et al., 2021), (Hristakeva et al., 2017). Over the years, there is also a growing diversity of techniques, with not just one technique present in all papers published in the same year.

4 FINAL CONSIDERATIONS

The systematic literature mapping allowed us to identify strategies to reduce the User Cold Start problem. Based on the mapping, it is possible to define future works related to the User Cold Start Problem. Five strategies were identified: Strategy 1, Requesting the user to answer questions; Strategy 2, Requesting the user's evaluation for a set of items; Strategy 3, Requesting the user to select items; Strategy 4, Requesting the user to select/register keywords/tags; and Strategy 5, Using items popular among older users (or users considered experts) of the Recommendation System.

These strategies do not involve the user's previous interaction with the system, i.e., a user history or the use of external sources to build the profile (e.g., user data from social networks) so that the Recommender System can construct an initial user profile.

Over the years of publication of the selected papers, the techniques of asking the user to evaluate a set of items and requesting the user to select items are present in many papers. From 2016 onwards, the strategy of requesting the user to respond to questions/questionnaires started to appear in publications, and from 2018 onwards, the popular item strategy became prevalent in the papers. Over the years, there has also been a noticeable increase in the diversity of strategies, with not just one strategy present in all papers published in the same year (**SRQ3**).

Some considerations can be made about these strategies, aiming for future works. Firstly, many of these strategies still involve evaluations from other users, as the new user is not always treated as the first user when using the system. Therefore, strategies that can be applied to a new user should be considered, considering that the new user does not require evaluations from other users. There is a research gap regarding works that use these strategies that do not require any previous user information before the user enters the system, as well as not needing a user network like the above strategy of evaluations from other users. It can also be noted that a limited number of works deal with the new user problem in Recommender Systems that use content-based filtering. This fact had been observed before the mapping through searches in digital libraries. Few works bring this approach to minimize the Cold Start associated with the identified gap; the works found with this approach use strategies of requesting user responses to questions/questionnaires or selecting items.

Strategy 1 requires the definition of a questionnaire. This is not easy because it requires knowledge about the domain. Besides, Users may not be willing to spend time filling out a questionnaire; they might respond inadequately and even choose not to use the system. Strategy 5 can be considered suitable only if the items consist of texts or are described in textual format. Thus, it is more suitable for the Recommender System, which uses a Content-based approach. Besides, defining how the user will give keywords/tags is necessary. For example: Will the user write keywords? How many keywords/tags will the user select? In the last case, how many keywords/tags will be presented by the user selected, and which keywords/tags will be shown to the user? A similar issue is presented in strategy 2 and in strategy 3. How many items will the user select/evaluate? How many items will be presented by the user selected, and which items will be shown to the user?

Show random items, like in (Crawford, 2012), are not an ideal solution. The problem is that the user profile can be limited to part of Recommender System items, and the user profile does not reflect all users' interests. Thus, in future works, a need arises to apply item diversity before generating recommendations in the user profile formation. In this sense, to develop an initial profile that enables recommending items encompassing all user preferences, one possibility would be to present diversified items to the user, allowing them to select what they like.

This study aimed to identify, through a Systematic Literature Mapping, papers addressing the minimization of the *Cold Start* problem without access to external sources. As a result, 19 papers presenting strategies for reducing the *Cold Start* problem were identified (**MRQ**).

The strategies are identified by requesting that the user responds to questions/questionnaires, asking for the user's evaluation of a set of items, requesting the user to select items, keyword/tag selection/registration, and finally, popular item strategies (**SRQ1**). Additionally, it was observed that most studies focus on the movie domain and domains such as gastronomy, learning objects, humor entertainment items, videos, restaurants, papers, news, hotels, music, and art items (**SRQ3**). Hence, it is noteworthy to highlight that, for future works, certain aspects elucidated in the current study can be considered when formulating a strategy to mitigate the Cold Start challenge in Recommender Systems of any domain.

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