Journal of Intelligent Information Systems (2022) 59:341–366
https://doi.org/10.1007/s10844-022-00698-5

Approaches and algorithms to mitigate cold start problems in recommender systems: a systematic literature review

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Received: 31 August 2021 / Revised: 17 February 2022 / Accepted: 23 February 2022 /
Published online: 23 April 2022

Abstract

Cold Start problems in recommender systems pose various challenges in the adoption and use of recommender systems, especially for new item uptake and new user engagement. This restricts organizations to realize the business value of recommender systems as they have to incur marketing and operations costs to engage new users and promote new items. Owing to this, several studies have been done by recommender systems researchers to address the cold start problems. However, there has been very limited recent research done on collating these approaches and algorithms. To address this gap, the paper conducts a systematic literature review of various strategies and approaches proposed by researchers in the last decade, from January 2010 to December 2021, and synthesizes the same into two categories: data-driven strategies and approach-driven strategies. Furthermore, the approach-driven strategies are categorized into five main clusters based on deep learning, matrix factorization, hybrid approaches, or other novel approaches in collaborative filtering and content-based algorithms. The scope of this study is limited to a systematic literature review and it does not include an experimental study to benchmark and recommend the best approaches and their context of use in cold start scenarios.

Keywords Recommender systems · Cold start problems · New user problem · New item problem · Systematic literature review

1 Introduction

With an immense increase in the availability of information, the users suffer from the cognitive load of multiple choices. Recommender System solves this problem by recommending items to users based on their preferences. There are different types of recommender systems which could be classified based on techniques used in filtering of items for recommendation or based on the source or type of data that they use. Based on the techniques in filtering of items for recommendations, the recommender systems algorithms can be of three types:

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collaborative filtering, content-based, and hybrid recommender systems (Richa, 2020; Viktoratos et al., 2018). Similarly based on the type or source of data, the recommender systems can also be classified into social network-based recommender system, knowledge-based recommender systems, utility-based recommender systems, context-aware recommender systems, and demographic-based recommender systems (Rodríguez et al., 2010; Viktoratos et al., 2018). Apart from these well-established classifications, the evolving research has led to the development of several other types of recommender systems such as critiquing-based recommender systems and constraint-based recommender systems that are variations of knowledge-based recommender systems with use of different form of data sources to derive knowledge for modelling the recommender system. Critiquing-based recommender systems uses users' feedback as critiques to make item recommendations (Chen & Pu, 2012). Constraint-based recommender systems uses constraints that are modelled from specific item properties and their relationship with user requirements (Felfernig & Burke, 2008).

Of all the recommender systems, the most widely adopted and classic recommendation techniques are collaborative filtering and content-based approached (Rodríguez et al., 2010; Viktoratos et al., 2018). The collaborative filtering method makes use of past collaborative preferences between the items and users to generate top N item recommendations for users. It can be further classified based on collaborating entities into three types: user-based collaborative filtering or the traditional collaborative filtering model, item-based collaborative filtering, and latent factor-based models that use matrix factorization (Puthiya Parambath & Chawla, 2020). The user-based collaborative filtering method makes use of the item rating pattern of a user and recommends the items to the neighboring users who have similar item rating patterns or liking preferences. Item-based collaborative filtering methods identify nearest neighbors of items and then provide item recommendations to users based on the user's past item interactions and item preferences. Latent factor-based matrix factorization models make use of latent features of users and items along with user-item rating matrix to predict missing ratings in the User-item rating matrix for generating top N recommendations that are predicted to have higher ratings corresponding to the user (Zhang et al., 2018). These collaborative filtering techniques are known for higher accuracy but suffer from both cold start user and cold start item problems when these recommender systems are subjected to new users and new items respectively (Ferdaous et al., 2018). These problems affect the prediction accuracy and quality of recommendations. Content-based recommender systems overcome these cold-start scenarios by analyzing the item metadata and finding similarities but in absence of user interaction data, it still faces challenges to provide reliable recommendations (Rohani et al., 2014).

Cold Start problems also pose serious challenges to the business value of recommender systems. New users who will not find recommendations useful would stop using the system thereby affecting user engagement (Zhang et al., 2017). New item cold start problems also disrupt business as it takes a lot of marketing and operations cost for businesses to promote new items in absence of an organic method of recommendation (Liu et al., 2014b). Thus, to mitigate these challenges posed by a new user or new item cold start, several researchers both in the academic and practice community have been actively involved in designing, developing, and suggesting novel strategies. Many such strategies are advancements on the existing collaborative filtering methods that suggest the use of item-specific data instead of the user data in the collaborative filtering to enhance the quality of recommendations and demonstrate better recommender system performance (Sarwar et al., 2001). Advanced content-based approaches have also been suggested that make use of content information, tagging information, and cross-domain information to tackle the cold start problems (Liu et al., 2014b). Context-aware recommender systems that use context data such as location, time, social information, similar groups, and events information, have also been designed for the remediation of these cold start scenarios. Even hybridization techniques such as weighted hybridization, switching, feature combination, cascade, feature augmentation, cascade, and meta-level hybridization, have been proven to be effective against the cold start problems (Mobasher et al., 2007).

2 Research objectives and related works

The challenge posed by cold start problems affects the effectiveness and performance of recommender systems. Hence, there have been several approaches and algorithms proposed by various researchers in both academia and industry. However, to the best of our knowledge, there has been very limited research done on collating these approaches and algorithms together to synthesize various strategies that can be adapted for the cold start problem. This research observes few notable works in this area.

First, Son (2016) have taken the attempt to present a comparative review of algorithms that can alleviate cold start problems. There are multiple gaps in this research. The research is not based on systematic literature review. Hence, the research work does not present exhaustive set of research methods done in the cold start domain. The research just identifies and considers four algorithms such as MIPFGWS-CS by Son (2014a), NHSM by Liu et al. (2014b), FARAMS Leung et al. (2008), and HU-FCF by Son (2014b). It discusses their advantages and disadvantages and does a comparative study on them using MovieLens and Jester datasets to propose that NHSM is the most effective algorithm in cold start scenarios based on comparative MAE and RMSE values.

Second, Suryana and Basari (2018) who have tried to do a literature study to identify important components, existing approaches, and how their effectiveness has been measured. The research has considered papers from 2006 to 2016 and has not adopted a systematic literature review approach. Thus, the strategies mentioned may not have exhaustive consideration of all possible approaches and algorithms and may miss out on some of the latest research findings as the field has evolved since 2016. Also, the authors have acknowledged that the research has not considered all application domains of recommender systems and might have missed out on certain domains like online shopping applications (Suryana & Basari, 2018).

Third, Camacho and Alves-Souza (2018) have also done a systematic review on how social network data could be leveraged to alleviate cold start problems. But, the research is specific to collaborative filtering based recommender systems and in that context, they have tried to study whether the use of social network data in various collaborative filtering approaches has helped in mitigating the cold start problem.

Lastly, Abdullah et al. (2021) have also attempted to do a literature survey on approaches and techniques used by researchers in deriving and making use of auxiliary information for addressing cold start problems. The scope in this study to assess and study the use of auxiliary information in recommender system models, especially adaptive traditional filtering models and matrix factorization techniques.

The present study acknowledges these research works and aims to build on their limitations and gaps and study the extant research conducted on the cold start problems so as to collate the various approaches and algorithms that have been proposed to mitigate these problems in new user and new item scenarios. Thus, the research objectives of this study are: (1) To perform an exhaustive study using a systematic literature review to identify the existing approaches and algorithms that have been used to alleviate cold start problems.

(2) To synthesize the various strategies such as benchmark algorithms, information types and their features, computing techniques, and their effectiveness that have been adopted by various recommender system researchers across different domains.

The remaining part of the paper is organized as follows. Section 3 of the paper discusses the methodology of a systematic literature review followed in this research. The descriptive statistics and synthesis of the literature review are further discussed in Sections 4 and 5 respectively. The qualitative synthesis also compiles and clusters the strategies and approaches that have been suggested by researchers to address cold start problems. Section 6 discusses the synthesized approaches further and provides recommendations for future research. Section 7 concludes the paper by summarizing the research findings, contributions, and limitations of the paper.

3 Methodology

The paper has adopted a systematic literature review methodology to systematically identify the available literature, review the key concepts on various approaches and algorithms recommended by the research to mitigate the cold start problems, analyze the diverse perspectives present in the literature, collate and synthesize the strategies and approaches to contribute towards the recommender systems research on cold starts. This systematic approach has been recommended by researchers to garner key perspectives to answer research questions, reconceptualize the topics, and add knowledge to the scholarly discussion on the topic (Torraco, 2016). The systematic literature review is different from a standalone literature review that reviews and analyses the literature in the field of research in a journal-length paper without having any empirical aspects to it. The systematic literature review is a more rigorous, systematic, and methodological approach such that it could be reproduced by other researchers (Okoli, 2015).

A well-defined scope is also an important aspect of a systematic literature review as the systematic literature review will not be appropriate if the research topic is too vague or broad or even too narrow (Okoli, 2015). The scope of the paper is limited to study the approaches and algorithms proposed in the recommender systems research area to address the cold start problems. With this scope in the purview, the paper has used the keywords 'cold start', 'recommender system', 'recommendation system', and 'collaborative filtering' for the search and discovery of the literature. The search string thus used: "cold start" AND ("recommender system" OR "recommendation system" OR "collaborative filtering". The research has considered four scientific databases: EBSCO – Business Source Complete, ACM Digital Library, Web of Science, and ProQuest in this regard. All these scientific databases are well-acknowledged among the research community and provide wide access to most published literature in the major journals and conferences (Okoli, 2015). From the identified literature, to shortlist the relevant literature, the research has used additional exclusion or inclusion criteria set as follow: (1) the paper has considered 'English' as the publication language for the retrieved literature based on the proficiency of the reviewers (2) the paper has considered only peer-reviewed articles from scholarly journals and conferences and has excluded other types of artifacts to ensure that the literature review is done on high-quality credible literature; (3) the paper has considered a specific time frame of January 2010 – December 2021 for the date of publication of the articles to ensure the review encompasses all major research contributions in the last decade in the area of cold starts in recommender systems. The retrieved articles were further reviewed, first on the title and abstract, and second on the entire article content. Any duplicates are removed. The journal titles that are considered

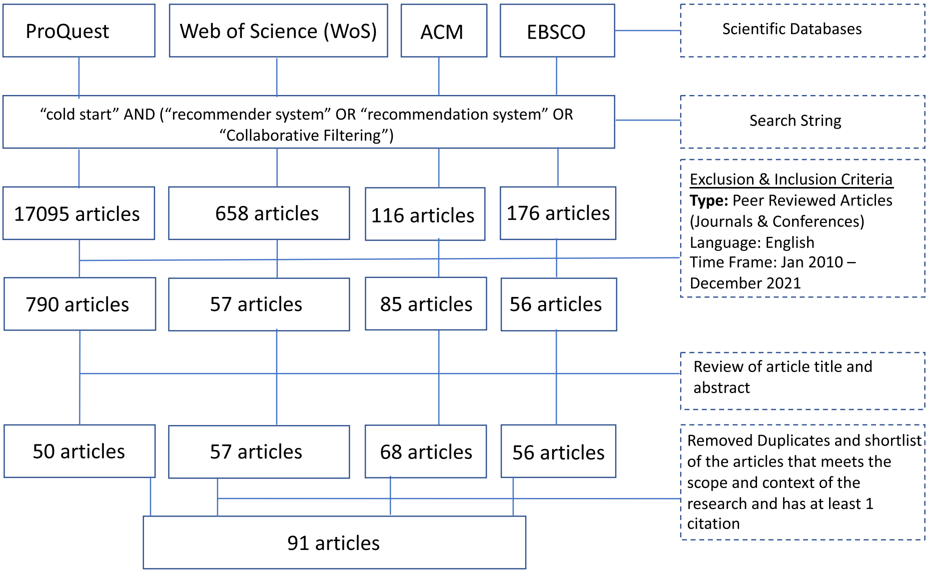

Fig. 1 Articles shortlisting procedure for the systematic literature review

are either part of ABDC journal quality list or SCImago Journal and Country Rank (SJR) are considered in order to ensure the quality of journal articles. Lastly, the articles that has at least one or more citation has been considered into the final shortlist of 91 articles. Citations is an indicator of the quality of the article, its scientific relevance, and credibility as perceived by other research scholars (Aksnes et al., 2019). The article selection procedure along with the inclusion and exclusion process is represented systematically in Fig. 1.

The shortlisted articles are downloaded and imported into Mendeley Reference Manager to form a collection for the literature review. The shortlisted articles are also exported as list into Google spreadsheet for systematic capturing of the notes on the proposed strategy to address cold start problem, baseline algorithms used, and metrics used for evaluation.

4 Descriptive statistics of the literature

The 91 selected articles for the research are published across 57 different peer-reviewed journals (refer to Table 1). Most of these journals are from the area of information systems, computer science, and allied areas such as mathematics, statistical applications, e-commerce, mobile networks, sensors, and geo-information science. "User Modelling and User-Adapted Interaction" and "Knowledge-Based Systems" has the maximum number of articles with the count of 5, followed by "IEEE Access" and "Expert Systems with Applications" with the count of 4 each.

It is observed that the publication of articles on the strategies that can alleviate cold start problems has been steadily increasing with a brief anomalous drop in 2016, 2018, and 2021. The maximum articles has been published in the last year 2020 (refer to Fig. 2). This shows that the cognizance about the cold start being a significant challenge affecting the user engagement in recommender systems has been increasing. This is leading to more research in the area.

Table 1 Distribution of Selected Articles by Journals

Journal Titles	Count of Articles
"ACM Transactions on Information Systems"	3
"ACM Transactions on Intelligent Systems and Technology"	1
"ACM Transactions on Knowledge Discovery from Data"	2
"ACM Transactions on the Web"	1
"Applied Intelligence"	3
"Applied Sciences"	2
"Big Data and Cognitive Computing"	1
"Cluster Computing"	1
"Computing Archives for Informatics and Numerical Computation"	1
"Data Mining and Knowledge Discovery"	1
"Decision Support Systems"	3
"Education and Information Technologies"	1
"Electronic Commerce Research"	1
"Electronic Commerce Research and Applications"	2
"Engineering Applications of Artificial Intelligence"	1
"Enterprise Information Systems"	1
"EUREKA Physics and Engineering"	1
"Europhysics Letters"	1
"Evolutionary Intelligence"	1
"Expert Systems with Applications"	4
"Future Generation Computer Systems"	2
"IEEE Access"	4
"IEEE Transactions on Computational Social Systems"	1
"IEEE TRANSACTIONS ON ENGINEERING MANAGEMENT"	1
"IEICE Transactions on Information and Systems"	1
"Information Processing and Management"	1
"Information Retrieval Journal"	2
"Information Sciences"	3
"Information Systems"	1
"Intelligent Data Analysis"	1
"International Journal of Machine Learning and Cybernetics"	1
"International Arab Journal of Information Technology"	1
"International Journal of Computational Intelligence Systems"	1
"International Journal of Web Information Systems"	1
"Internet Research"	1
"ISPRS International Journal of Geo-Information"	1
"Journal of Computational Science"	1
"Journal of Computer Science and Technology"	1
"Journal of Information Science"	2
"Journal of Intelligent and Fuzzy Systems"	2
"Journal of Intelligent Information Systems"	1
"Journal of Network and Computer Applications"	1
"Journal of the American Statistical Association"	1

Table 1 (continued)

Journal Titles	Count of Articles
"Knowledge and Information Systems"	2
"Knowledge-Based Systems"	5
"KSII Transactions on Internet and Information Systems"	1
"Machine Learning"	1
"Mathematical Problems in Engineering"	2
"Mobile Information Systems"	1
"Mobile Networks and Applications"	1
"Multimedia Tools and Applications"	2
"Neurocomputing"	2
"PLoS One"	2
"Sensors"	1
"The Scientific World Journal"	1
"User Modeling and User-Adapted Interaction"	5

In the next section, the paper will synthesize the findings that the reviewers have drawn from the literature. Synthesis of literature helps in organizing the existing research for building up a taxonomy on the topic, reconceptualizing the topic, developing constructs or meta-theories, proposing research agenda or research questions for future research (Torraco, 2016). The paper tries to develop research clusters from the synthesized information that can be used in further sections for discussion.

5 Qualitative synthesis of the literature

The in-depth review of the 91 shortlisted articles provides a holistic purview of various approaches that have been proposed and experimentally proven to have tackled the cold start

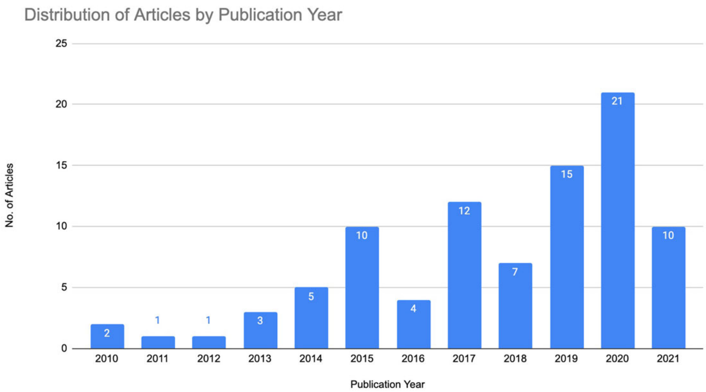

Fig. 2 Distribution of Journal Articles by Publication Year

scenarios in recommender systems. This section attempts to effectively synthesize these approaches by primarily dividing them into two categories:

1. Data-driven Strategies: This category includes papers that propose strategies around the effective use of different types of data and their relationships with user and item attributes to alleviate new user and new item problems. This research observes the use of data such as location data, social network data, trust data, and cross-domain data by various researchers to propose novel methods that address cold start problems.
2. Approach-driven Strategies: This category includes papers that propose strategies around defining new algorithms, using a combination of methods, and recommender system approaches to alleviate the cold start problems. This research further classifies them into five clusters:

   (a) Deep Learning-Based Approaches: The approaches that have relied on deep learning algorithms to tackle the new user and new item problems.
   (b) Matrix Factorization Based Approaches: The approaches that have used various matrix factorization techniques to better the algorithm performance in cold start scenarios.
   (c) Hybrid Recommender System Based Approaches: The approaches that have used a combination of different content-based and collaborative filtering methods to address the cold start problems.
   (d) Novel Approaches in Collaborative Filtering: The approaches that have proposed novel approaches and algorithms using clustering, KNN, and genetic algorithms on top of the basic user and item-based collaborative filtering to address the cold start problems.
   (e) Novel Approaches in Content-based Recommender Systems: The approaches that have built on the base of content-based recommender systems and proposed novel strategies around semantic relationships, use of semantic tags, derive personality characteristics, and use of other item feature spaces to tackle the cold start problems.

In the following sections, we will discuss these strategies in detail. It must also be noted that although the categorization has segregated the data-driven approaches from approach-driven strategies, the researchers in most articles have used a combination of the method. The categorization is based on whether the primary influence in the approach is data or novelty of the method.

5.1 Data-driven strategies

Data-driven strategies proposed by various researchers have used unique methods to use different types of data such as social network, trust, location, and cross-domain data to handle the cold start problems.

Social Network data of users are typically used in the context of recommender systems to enhance the rating profiles of users that do not have sufficient ratings and trust information. It is used to determine the reliability of users and their trust networks. A similar approach has been used by Abel et al. (2013) who have tried to aggregate the form-based and tag-based user profile information from the social web, especially from social tagging activities which to perform semantic enrichment. They have thus proposed an approach called Mypes, a cross-system user modelling that uses the semantic enrichment coming from the social network data to improve the quality of the recommendations and effectively address cold start problems. “Biased Random Walk on Coupled Social Network”, a random walk algorithm has been proposed by Nie et al. (2014) that makes use of various features of social networks such as social interests, social influence, and user preferences into account to successfully alleviate the cold start user problem and providing recommendations with higher accuracy. Ahmadian et al. (2019) have proposed a “Reputation-based Trust-Aware Recommender System (RTARS)” that makes use of social information of users to enhance the rating profiles of users that do not have sufficient ratings and trust information. Social Information is used to determine the reliability of users and their trust networks. This is further modelled to determine user reputation to predict virtual ratings. These ratings are then used for generating recommendations. This approach not only helps in addressing the cold start and data sparsity problem but also improves the quality, reliability, and diversity of the recommender system.

Researchers have also coupled social network data with other data attributes to effectively remediate new user cold start problems. A user similarity detection engine (USDE) that makes use of user’s personal smart devices to extract their social information to garner the user similarities for generating recommendations has been suggested by Ojagh et al. (2020). This approach uses a user clustering algorithm for clustering users with this similarity and contextual information and then makes use of these clusters in the recommendation algorithm to personalize the recommendations. The approach was found to have better performance than traditional algorithms in cold start and data sparsity issues. Liu and Meng (2015) have proposed the use of a region-based location graph (RLG) that connects region nodes with the user and business information nodes. RLG utilizes the short-range and long-range mobility information formed by the social network of users to generate location-based recommendations on business information. This approach argues that human movements are short-ranged spatially and temporally and hence proposes that location-based recommendations sensitive to user’s movement help in alleviating the cold start problems. The evaluation of this approach shows that RLG when combined with user-based and item-based collaborative filtering alleviates the cold start problem and demonstrates an 80 percent improvement in the Hit ratio. Rosli et al. (2015) proposed an approach that combines similarity values from Facebook pages to compute users’ similarity to address cold start problem. The proposed approach by Herce-Zelaya et al. (2020) uses social media data to create behavioural profile to classify users and then make predictions for these users using classification trees and random forests.

Trust data and user trust networks have also been leveraged by various researchers to overcome cold start and data sparsity issues in recommender systems. Ghavipour and Meybodi (2019) have used trust networks enriched by trust (popular users with high reputation) and interest similarity for a stochastic trust-based propagation method, LTRS to enhance the quality and coverage of recommendations while addressing cold start and data sparsity issues. Zou et al. (2015) have developed a novel recommender system, TrustRank by leveraging the trust relationships in user-trust networks to generate recommendations with improved accuracy. The TrustRank algorithm handles the cold-start user problems, which also pose a critical challenge of not having extensive user-trust networks, by applying the PageRank algorithm to extend the network to friends or friends of friends based on user-user similarity computation. The algorithm does an iterative computation to handle scalability especially for large user network propagation. Chen et al. (2013) have proposed an approach leverages the trust and distrust networks of users and models it further to identify trustworthy users and then makes use of suggestions of these users to provide recommendations in cold start scenarios. A novel approach called “Merge” has been proposed by Guo et al.

(2014) that uses social trust information to identify trusted neighbours and then use that for generating recommendations of similar new users.

Cross-domain recommender systems are also adopted by various recommender system researchers to improve the performance and accuracy of recommender systems while mitigating the cold start problem. Richa (2020) have proposed Cross-Domain Recommender Systems (CDRS) that contextualizes and profiles the target user and based on the user rating tries to find the neighbourhood. If the user ratings are not available as is the case with data sparsity and cold start scenario, it does the cross-domain computation with rating available in source domain with the mediation of user modelling data based on trust, influence, and reputation computation to solve the data sparsity and cold start problem in the target domain. This approach improves the accuracy measures with better precision and means absolute error scores. Zhang et al. (2017) have used a cross-domain recommender system with consistent information transfer (CIT) to elicit knowledge consistency between the user and item groups and transfer information and the learning process between the domains to generate recommendations. The approach uses a domain adaptation method to maintain information consistency between two domains on the item and user groups and then devises an adaptive knowledge transfer method, CIT, to facilitate cross-domain recommendations with improved accuracy. The proposed knowledge transfer based CDRS is also found effective in alleviating the cold start problems, both while research experimentation and in real-world application with Smart Bizseeker, a B2B recommender system. Zhang et al. (2018) have proposed CrossRec, a cross-domain recommender system (three models for CF-based cross-domain recommendation: i) fusion-auxiliary-similarity CF (FAS-CF), ii) fusion-auxiliary-result CF (FAR-CF) and iii) global-fusion CF(GF-CF)) based on multi-source social big data with the use of social-tag-based association rule mining. The proposed recommender system analyses the social tag as an item's semantic attribute and develops an association rule based on these tags in the auxiliary domain which is then used for tag discovery in the target domain to generate recommendations. This addresses the cold start user problems, provides more diverse recommendations, and was observed to have a significant improvement over the information fusion based cross-domain collaborative filtering algorithms.

Li et al. (2018) have proposed a novel cross domain recommendation system models based on partial least squares regression analysis, PLSR-CrossRec and PLSR-Latent. These use source-domain rating to predict the ratings for new users in cold start scenarios for target domains. A cross-domain latent feature mapping model has been proposed by Wang et al. (2020) that takes user rating behaviour from source domain and perform matrix factorization to alleviate cold start problem in the target domain. Feature mapping of users and other linked users in neighbourhood is taken into account with adoption of gradient boosting trees and multiplayer perceptron to model the CDLFM. Clustering-based matrix factorization leveraging cross domain data has been proposed by Mirbakhsh and Ling (2015) that utlizies data from auxiliary domains to provide better recommendations in cold start scenarios. Weighted Irregular Tensor Factorization (WITF) model to leverage multi-domain explicit and implicit feedback data of users in cross-domain context to learn informative priors and address cold start problems (Hu et al., 2016).

5.2 Approach-driven strategies

Approach-driven strategies encapsulate the novel approaches, algorithms, methods, and a combination of all of the above to remediate the cold start problems. The review observes the extant literature to have used deep learning, matrix factorization, hybrid recommender systems, and other novel approaches developed over basic collaborative and content-based filtering algorithms.

5.2.1 Deep learning based approaches

Deep learning techniques have been used by various recommender system researchers to enhance the quality, precision, and accuracy of recommender systems and these methods have also been found to help overcome the cold start problems.

Yue et al. (2018) have improved the accuracy and performance of the recommender system and solved the cold start problem with the use of deep learning techniques. They have developed a deep learning based denoising autoencoder called, SemRe-DCF, that learns from the semantic descriptions of items, auxiliary information of users, and captures granular similarities between them using vector arithmetic to generate accurate recommendations.

Guan et al. (2019) have proposed a deep learning based model called "Deep Multi-view Information Integration (Deep - MINE)" that factors in information from multiple sources such as product images, descriptions, and reviews mapped in auto-encoder networks to map multi-view information in an end-to-end recommendation model. A cognition layer understands this multi-view information in liaison with the consumer's heterogenous cognition styles to generate recommendations with higher accuracy, even in the cold start scenarios.

The proposed approach by Ma et al. (2021) is a deep neural network based multiplex interaction-oriented service recommendation approach, MSIR to address cold start service recommendations. The approach utilizes representational learning abilities of deep learning to extract latent structures and features from three different types of interactions between mashups and services. A two-stage neural network based item recommender system has been proposed by Tsai et al. (2021) which has two major components: denoising autoencoder based cold start item rating (DACR) and neural network-based collaborative filtering (NNCF) predictor. DACR uses the textual description and auxiliary content information of the item to extract the content features that presents derived ratings and NNCF predictor predicts ratings in sparse user-item matrix. Lastly, the latent vectors are put into the multi-player perceptron for user-item matrix learning. Two recommendation models are proposed by Wei et al. (2017) based on collaborative filtering and deep learning neural network. SADE, a deep neural network, extracts the content features of items and timeSVD++ is a CF model that models and utilizes temporal features of users and items to predict ratings in cold start scenarios. Meta-User2Vec model proposed by Misztal-Radecka et al. (2021) using metadata embeddings along with item representations to address cold start problem. Meta-Learning embedding ensemble (ML2E) is proposed by Wang and Zhao (2020) that forecasts new users' preference to address new user cold start problem and generate desirable initial embedding for new items to address new item cold start scenarios. ConTS model, Conversational Thompson Sampling, is proposed by Li et al. (2021) that unifies attributes and items in same arm space and the uses the Thompson sampling framework to generate conversational recommendations in cold start contexts. Neural Semantic Personalized Ranking (NSPR) is proposed by Ebesu and Fang (2017) that uses deep neural network and pairwise learning to develop a latent factor model and a robust feature representational learning from implicit feedback and item content to generate recommendations in cold start scenarios.

5.2.2 Matrix factorization based approaches

Matrix factorization models in recommender systems decompose user-item interaction matrix in lower-dimensional latent space and make use of the latent features to generate recommendations. These techniques have been found effective over the basic collaborative filtering models and several researchers have adopted variations of matrix factorization models for addressing cold start issues.

Zhang and Liu (2015) developed a social network factored matrix factorization model, TrustSeqMF, to generate recommendations for users in a social network. The model utilizes the latent feature space using the temporal information and user trust relations in a social network to constrain the objective function that helps in enhancing the quality of recommendations and overcoming the cold start user problem.

Yu et al. (2017) have tried to leverage the matrix factorization method of collaborative filtering and incorporate item-attribute information coupled with item similarity information to enhance recommendations quality while addressing the cold start problems. The approach is observed to be better performant for the cold start item problem.

Fernández-Tobías et al. (2019) have proposed a matrix factorization model that addresses the gap in the cross-domain recommender systems that does not factor the items and its content heterogeneity between the domains. This matrix factorization model for cross-domain recommender system uses Linked Open Data project to extract the items between three different domains and find item similarities between these domains by developing a knowledge graph with direct and indirect linkages. This approach improves the item ranking accuracy and diversity of recommendations and overcomes the cold start user problems.

Puthiya Parambath and Chawla (2020) have developed a matrix factorization model with a two-stage soft-cluster embedding algorithm that makes use of side information of the items to provide an effective solution to the cold start item problem. The method relies on the collaborative matrix factorization framework and tries to make use of conventional user-item rating matrix and item-side information matrix to develop soft clusters of items to generate recommendations. The authors have also proposed a metric, Cold Items Precision (CIP) that can be used alongside NDCG and MAP to measure the effectiveness of a recommender system algorithm, especially in the cold start scenarios. The approach was compared to three deep learning based algorithms: Neural Graph Collaborative Filtering (NGCF), Graph Convolutional Matrix Completion (GCMC), and Hybrid Collaborative Filtering with Autoencoders (HCFA). The proposed algorithm performed superiorly to these deep learning algorithms in terms of the Cold Items Precision (CIP) score.

The proposed strategy by Ji and Shen (2015) uses content-based information about users and items such as tags and keywords and does a mapping of users' tags to items' keywords hence forming tag-keyword relation matrix. This is further used in the context of ratings by applying 3-factor matrix factorization for users' interest vector based on extracted tags with respect to items' correlation for extracted keywords to make recommendations. Zhang et al. (2020) incorporate Bipartite network into user-based collaborative filtering to address cold start problem. The approach uses a new weighted bipartite modularity index by merging normalized rating and then building community partition with co-clustering of users and items. The approach further applies localized low-rank matrix factorization on clusters to predict rating scores of new users for providing recommendations. Chen and Chen (2019) improve the existing MF-based approach by regularization weight on the norms of the latent factors of both users and items. LambdaMART, a novel matrix factorization based technique has been proposed by Nguyen et al. (2016) that learns latent representations of both users and items with gradient boosted trees to address the cold start problem. A novel interview-based model called local representative-based matrix factorization is proposed by Shi et al. (2017) that creates meaningful user groups with decision trees for new user recommendations. mrf-MF, N-dimensional Markov random field in prior to matrix factorization, is proposed by Peng et al. (2016) that uses user attributes such as age, occupation, preferred genre, release year of items along with latent features in markov random field and uses it prior to matrix factorization to generate recommendations to address cold-start problems.

5.2.3 Hybrid recommender system based approaches

Hybrid recommender systems deploy a mix of multiple techniques and leverage the best of both collaborative filtering and content-based methods to provide a high degree of robustness to the recommender systems. Many researchers have also proposed different types of hybridization techniques that have proven effective in cold start scenarios.

Ferdaous et al. (2018) have proposed the Hybrid Features Selection Method (HFSM) that uses a content-based clustering algorithm that combines statistical and semantic features of the item and then passes it through the classical collaborative filtering module and a hybrid module with a linear combination of content and collaborative filtering techniques. This helps in tackling the cold start problems and improves the recommender system performance.

Tarus et al. (2017) have proposed a hybrid knowledge-based recommender system that uses ontology and sequential pattern mining to recommend e-learning to learners. The algorithm uses a four-step approach, first to create ontology-based on learning resources, second to compute similarity ratings between learning resources based on ontology and domain knowledge, thirdly use of collaborative filtering to generate top N learning items, and lastly to apply sequential pattern mining on top N learning items to generate final recommendations. The systematic use of ontology, domain knowledge, and sequential pattern mining alleviates the cold start problems with improved accuracy of recommendations for new users that translates into a learning satisfaction score of 94 precent.

Deldjoo et al. (2019) have developed a new movie recommender system that can address the new item cold start problem in the movie domain. The recommender system integrates the movie genome that is automatically extracted from the audio and video descriptors and exploited using the canonical correlation analysis. This two-step hybrid model also referred to as the collaboratively-enriched content-based filtering model demonstrates enhanced recommendation quality for cold start items.

“DISCOVER, a social network analysis and contextual similarity analysis based recommender system” has been proposed by Pradhan and Pal (2020) for recommending the venue to scholars which have also proven to be effective in cold start scenarios. This algorithm integrates social network analysis constituting citation and co-citation analysis, centrality measure calculation, topic modelling based contextual similarity computation, and key route based main path analysis. This hybrid approach makes use of multiple facets of content and metadata analysis and collaborative filtering to address the data sparsity and cold start problems.

Pappas and Popescu-Belis (2015) have approached the cold start problem by combining collaborative filtering and content based algorithms with item-based similarity to generate recommendations for TED lectures. The generated recommendations are cross-validated with keyword-based and semantic vector space-based methods for quality enhancement. It is observed that the semantic vector space-based methods improve the quality and accuracy of recommendations in cold start settings.

Bahrani et al. (2020) have proposed an ontological hybrid recommender system where ontology is used in the content filtering part of the recommender system and the structure of the ontology is used in the collaborative filtering part and this is combined with the demographic similarity and cosine similarity between the users to deliver high-quality recommendations. This approach uses the combination of demographic and cosine similarity between users to solve the cold start user problem and it combines ontological similarity and cosine similarity between items to solve the cold start item problems.

Kolahkaj et al. (2020) while designing a recommender system for a personalized travel package in the context of e-tourism have used a hybrid approach by combining Collaborative Filtering (CF), Context-Aware algorithms (CA), Demographic-Based recommender systems (DB), and Sequential Pattern Mining (SPM) in a dynamic contextual model to generate high-quality recommendations. The approach incorporates context incorporation with pre and post-filtering of the same and also makes use of multidimensional data and asymmetric similarity scoring functions to overcome both cold start and data sparsity problems. The approach has been proven effective against eight other popular baseline recommendation methods.

Nouh et al. (2019) in their endeavor to develop a smart recommender system of hybrid learning have combined hybrid filtering methods with machine learning algorithms to address the cold start problem. The model suggestively switches between the content-based and collaborative filtering methods, identifies user context with dynamic filtering, and learns from the profile screening and processing to recommend items. The method has a reflective feedback loop to mitigate the cold-start problems.

Tahmasebi et al. (2021) propose a hybrid recommender system model using profile expansion technique to tackle the cold start problem. For profile expansion, this approach uses the demographic data of user alongside user ratings to build a denser user-item matrix with expanded rating profiles by calculating the similarity values between users and predict unseen items. A hybrid ontology-based content recommender system is proposed by Jeevamol and Renumol (2021) that uses ontology to model learner and learning objects in order to generate top N recommendations. A hybrid approach LA-ALS is proposed by Paleti et al. (2021) that makes use of Louvain's algorithm and alternating least square algorithm to predict recommendations in cold start scenarios.

Viktoratos et al. (2018) propose to use community-based knowledge with associate rule mining to suggest a hybrid approach called context aware recommender system. A new context aware recommender system, CSSVD is proposed by Rodpysh et al. (2021) that uses IFPCC (Item Features Pearson Correlation Coefficient) and DPCC (Demographic Pearson Correlation Coefficient) similarity criteria to form SSVD (similarity singular value decomposition) matrix and the the matrix is put through CWP similarity criterion to generate the context matrix which is used for addressing cold start problem.

Hong et al. (2019) propose a new crowd-enabled framework, called CrowdStart, that integrates human-machine collaboration by combining two-step crowdsourcing with a hybrid machine learning model. A hybrid framework, HRS-CE is proposed by Anwaar et al. (2018) that integrate content embeddings with Word2Vec in recommender systems for cold start items. A hybrid method, HU-FCF++ is proposed by Son (2015) integrating demographic data with representative ratings and then computing similarity values for prediction of recommendations in cold start scenarios. Zheng et al. (2016) propose a hybrid model using opinion mining that refines user preferences and item opinions is proposed as tourism destination recommender system. A hybrid model combining collaborative filtering and knowledge-based system and using linguistic incomplete preference relations is proposed by Rodríguez et al. (2010) to address cold start problems. SCOAL is a hybrid recommender system model proposed by Pereira and Hruschka (2015) that combines collaborative filtering with demographic information to do simultaneous co-clustering and learning. A hybrid CF ranking model is proposed by Feng et al. (2021) that combines rating-oriented probabilistic matrix factorization (PMF) and a pairwise ranking-oriented Bayesian personalized ranking (BPR) together to address the cold start scenarios.

5.2.4 Novel approaches in collaborative filtering

Researchers have also tried to improve the collaborative technique and bring about novelty in the methods to overcome cold start problems.

Wu et al. (2013) have proposed Div-clustering, a collaborative recommendation technique that relies on active users in the social network who can share and accept recommendations to enhance the data clustering. The method is an improvement on the k-means clustering algorithm and clusters both items and users and identifies active users in each cluster to generate recommendations while addressing the cold start problems.

Liu et al. (2014b) have tackled the cold start problem for new items by using bipartite network representation on item-based collaborative filtering algorithms such as top-k nearest neighbors.

Nguyen et al. (2017) have proposed a new collaborative filtering technique that deciphers soft ratings by modelling community preferences with subjective and qualitative preference information about users and then integrates with the social network of users to overcome the data sparsity and cold start problems with significant improvements in the accuracy of the recommendations.

Bi et al. (2017) have developed a group recommender system drawing similar characteristics from users and items using a singular value decomposition framework. The approach performs betters on cold start users and items as it incorporates the missing attributes of new users and items by drawing on the similarity patterns and the group-specific features through clustering. They have suggested a new back-fitting algorithm into alternating least squares that is computationally scalable as it avoids large matrix operations or intensive memory storage.

Alhijawi and Kilani (2020) have developed a novel genetic recommendation algorithm, BLI(GA) that factors historical rating and semantic information to generate recommendations of the best list of items. The recommendation list generated from historical rating and item's semantic information is passed through three filtering levels: first with semantic correlation, second based on user satisfaction based similarity between the active user and other users with at least one rating, and lastly the algorithmic prediction of item ratings to identify the best list of items. The performance of BLI (GA) in cold start situations in terms of accuracy and quality of recommendations is better than other recommender system algorithms such as Cosine-based CF, Pearson-based CF, GA1 genetic-based CF by Bobadilla et al. (2011), Item CFGA by Xiao et al. (2015), SimGen by Alhijawi and Kilani (2016), and Hybrid MC-SeCF by Shambour and Lu (2011).

Kim et al. (2011) have developed an error prediction method that first predicts actual ratings and then identifies prediction errors for each user which is further factored into an error-reflective model to generate recommendations. This model helps to overcome the cold-start problems inherent to collaborative filtering methods.

Fernández et al. (2019) have combined different high order profile expansion techniques to develop a high order profile expansion algorithm that increases the size of a user profile by using traditional profile expansion algorithms and user-based kNN algorithm. The authors have used serial profile expansion and parallel profile expansion as two techniques wherein the case of serial the user profile is first expanded by expansion algorithms in a serial manner followed by passing it through the user-based kNN algorithms and in the case of parallel approach the user profile expansion by expansion algorithms happen in parallel and are combined before passing it through the user-based kNN algorithms. The serial algorithm is observed to be better performant whereas both the high order profile expansion methods help in remediating the new user cold start problem.

Pan et al. (2020) propose a new similarity model called Popularity-Mean Squared Difference, that considers the influence of popular items, average difference between tow user's common ratings, and non-numerical information of ratings. The strategy considers the deviation degree between two popular items between two users and distributes the similarity degree of the co-ratings between two users as weight to adjust the deviation degree. The proposed strategy by Hernando et al. (2017) tries to cater to the cold start recommendation problem of non-registered users by using a natural inference based probabilistic model that depends on the uncertainty rules and factors them for simulated forward reasoning. Han et al. (2019) in their endeavour to address cold start problem of app usage for new users on mobile operating systems, propose a Predictor based on dynamic CF fusion algorithm that uses the app usage periodicity of new users and combines with app preferences and app usage of similar users through conditional combination to predict appropriate app launch and usage expectations addressing the cold start problem. The proposed strategy by Zhang et al. (2019) is interrelationship mining to extract binary relations between item attributes and leveraging these interrelated attributes to define commonalities between items and new items to address the new item cold-start problem.

Hasan and Roy (2019) propose two item-bases similarity measures, one by determining the degree of asymmetric correlation and the other one by determining relative interconnection using transitive inference. These similarity measures are used along with an enhanced prediction algorithm to address the cold start recommendation problem. The proposed approach by Guo et al. (2019) combines the attribute information of item with historical rating matrix to predict preferences of cold start users and then using a matrix decomposition model it provides recommendations to these users. The approach tries to address cold start problems of new items. A Point-of-Interest (POI) approach proposed by Mazumdar et al. (2020) crowdsources the POIs and then recommends the top-K POIs consisting of new and existing POIs in cold start scenarios.

Polohakul et al. (2021) proposed an approach uses weighted cosine based similar approach to compute nearest neighbour by modifying session-based recommender systems and using contextual information of items' attributes. Covering reduction collaborative filtering is proposed by Zhang et al. (2020) as a novel collaborative filtering method that defines and analyses the interconnections between redundant users and reduce the redundant elements in covering-based rough sets and then use the information of candidate neighbours to generate recommendations. An improvement on existing covering-based CF has been proposed by Zhang et al. (2020) that analyses the characteristics of new users, reconstructs decision class, and utilizes the covering reduction algorithm to generate recommendations for new users. Coverage maximization techniques such as Max-coverage and Category-exploration are proposed by Silva et al. (2019).

Joint Personalized Markov Chains (JPMC) is proposed by Zhang et al. (2020), Shi et al. (2020) that utilizes user embedding to generate network neighbours that can represent similar users to generate recommend items to new users in cold start scenarios. A new user similarity model has been proposed by Mansoury and Shajari (2016) using disagreements of commonly rated items to address cold start problems. Temporal constraints using time stamp data is leveraged by Chalyi et al. (2019) for generating recommendations in cyclic cold start scenarios. Recommender System with Linked Open Data (RS-LOD) model is proposed by Natarajan et al. (2020) to address cold start problems in collaborative filtering. The proposed approach by Zahid et al. (2020) uses normalization technique to model user feedback, their involvement, and liking to the items in neighbourhood models to generate recommendations in cold start scenarios.

5.2.5 Novel Approaches in Content-based Recommender Systems

Several researchers have improved classic content-based filtering models by using semantic relationships, semantic tags, derived personality characteristics, and other item feature spaces to solve the cold start problems.

ECSN proposed by Rohani et al. (2014), is an enhanced content-based algorithm with the social network, that uses social network information of users and the user preferences to overcome the cold start problem and improve the prediction accuracy of recommendations. The suggested approach creates a preference tree based on the interaction data of the user and its social circle and then computes a preference score based on the attributes of the preference tree. This preference score is further attributed to predicting item recommendations. Hence, in the case of a new user when the user's interaction data is absent, the preference score is computed with the interactions data of friends and social circle to generate recommendations.

Semantic information in the data of users and items and tagging patterns have been used by various researchers to enrich the user and item profile data for tackling the cold start issues. Movahedian and Khayyambashi (2014b) have leveraged the similarities in the tagging patterns between users and items, and subsequently profiling and segregating them into user preference-based relevant patterns to generate recommendations. During profiling, the algorithm translates the tag-based profiles to semantic profiles that are further enriched by the semantic spread mechanism and then by inheriting the preferences of similar users. This helps in irradicating the cold start and overspecialization problem. In another paper by these authors, they have suggested a semantic-based recommender system that uses user-generated tag patterns to find similarities between the user and item profiles and then upgrade these tag-based profiles to semantic-based profiles with the use of external knowledge bases such as WordNet, Wikipedia, and W3C Linking Open Data initiative. These semantic profiles are further enriched with a semantic spread mechanism that is factored in for generating recommendations. The approach performs significantly better in terms of generating recommendations based on the user interest with more precision and accuracy and also remediates the cold start problems (Movahedian & Khayyambashi, 2014a).

Ralph et al. (2020) has proposed the "Transitive Semantic Relationships (TSR) model" that derives relationships from the text content of user and item and few labeled examples to address the cold start problems in the big data that are sparsely labeled. The authors have recommended TSR as a recommender system approach in domains where similar content indicates similar relationships between the items. TSR demonstrated a hit-rate@10 of over 75 percent for sparse data overcoming the negative effects of data sparsity and cold starts.

Cai et al. (2017) have developed a fuzzy item-based prototype classifier by utilizing the social circle preferences for pattern classification. The classified patterns are further used to construct feature space for generating recommendations with the use of information gain and OWA aggregator.

Wu et al. (2018) have developed a dynamic personality-based greedy re-ranking system that uses user's diversity preferences to determine personality and uses it alongside collaborative filtering to generate recommendations while overcoming the cold start problems. The approach suggests five diversity preferences such as openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism, and then based on these preferences it does a scoring on both preferences and personality which is further used in re-ranking of the recommendations list. The approach shows statistically significant improvements in recommendation quality and accuracy in cold start scenarios.

Choi et al. (2020) address the item-side cold start problem with a new process of feature identification based on representative reviewers in rater-group and then put it through a predictive method of defining expected preferences for new items by combining content-based filtering with preferences of representative users. The proposed approach by Yadav et al. (2020) combines Linked Open Data and Social Network Features to develop an ontology based similarity in recommendation model to address the cold start problem. MFS-LDA is proposed by Masood et al. (2017) based on Latent Dirichlet allocation model using multiple feature spaces such as title, content, and tags to generate tag based recommendations in cold start scenarios. Social-tag based recommender algorithm is proposed by Zhang et al. (2010) that uses user-tag-object tripartite graphs to solve the cold start problem.

6 Discussion and recommendations for future research

Recommender systems usually suffer from two key problems that affect the precision and accuracy of recommendations: (1) Data Sparsity; (2) Cold Start. Data Sparsity is caused by a lack of item ratings whereas cold start problems arise from new users or items that cannot be profiled by the recommender system (Richa, 2020). Cold Start problems are most challenging of the two as it affects new user engagement with the recommender system. Cold Start problems arise from the presence of new users or new items in the recommendation data set. These new users or new items have problems concerning recommendations as to the rating data and the new user interaction data is not available (Rohani et al., 2014). Collaborative filtering based recommender systems is more prone to both new user and new item cold start problems than content-based recommender systems. However, traditional content-based recommender systems algorithms usually demonstrate low accuracy. And, because cold start scenarios affect the performance of recommender systems and do not help businesses realize the value of these systems. Many researchers have attempted to develop several approaches and algorithms to cater to these problems. Web 2.0 and Web 3.0 evolution of the recommender systems have aided in this regard overcoming the limitations of the first-generation recommender systems such as collaborative filtering and content-based recommender systems relied on user's demographic data, user's purchase preferences, and the metadata of purchased products. With Web 2.0, the recommender systems evolved to gather more social information and trust data to personalize the recommendations and with Web 3.0 the recommender systems are now adopting hybrid ensemble algorithms using location information and a wide array of other data collected from devices and sensors that provide real-time health information, food habits, and data on daily routines and habits (Bobadilla et al., 2013). Advancements in computing with developments in machine learning and deep learning algorithms have also aided the cause.

This literature review tries to collate these approaches and algorithms proposed by various researchers in the extant research. The study observes that the researchers have made use of two types of strategies to tackle the cold start problems: data-driven strategies and approach-driven strategies. The data-driven strategies have primarily harnessed different forms of data such as social information, trust data, location data, cross-domain and cross-system data to define novel recommender system methods that can perform efficiently and effectively in cold start scenarios. The approach-driven strategies encapsulate the research inventions of novel approaches and algorithms that can be further grouped into five key clusters: deep learning-based approaches, matrix factorization-based approaches, hybrid recommender system-based approaches, novel approaches in collaborative filtering, and novel approaches in content-based recommender systems.

Developments in Machine Learning and Deep Learning has been put to effective use by many researchers who have built on the KNN algorithms, clustering, and matrix factorization to develop profile expansion strategies, make use of latent feature spaces, derive trust relations, and soft clusters for tackling new user and new item problems. Deep Learning has also led to deep learning based autoencoder algorithms, and deep multi-view information integration approaches. The hybrid approaches use a combination of methods in both content-based filtering and collaborative filtering with the added use of ontology, sequential pattern mining, network analysis, main path analysis, clustering, and semantic vector space-based methods to address the problem. The semantic and tag-based approaches use social tagging activities, semantic relationships, semantic spread mechanisms, and semantic and tag-based profile enrichment for improving the accuracy and quality of recommendations. The social information-based approaches use the social network analysis for developing preference trees, trust networks, or user similarity detection and reputation engine. Some approaches leveraging social networks have also developed network-based pattern classification, latent feature-based matrix factorization, and random walk algorithms using social influence and social interest to alleviate the cold start scenarios. Cross domain recommender systems have also been proposed with consistent information transfer and context awareness approaches to use the data available in the source domain to generate recommendations in the target domain. A few of these approaches have also been used alongside social-tag based association mining, matrix factorization, and knowledge graph development. Novel approaches using region-based location graphs, reflective error models, personality-based greedy re-ranking, bipartite network-based item collaborative filtering, clustering with matrix factorization-based approaches, and novel genetic recommendation algorithms have been developed by several researchers which are observed to be better performant in the cold start problems.

Thus, the present study has effectively collated a multitude of different recommender system approaches that have been developed and experimentally validated to yield better results in new user and new item cold start problems. The review has systematically identified and captured the approaches and algorithms used by researchers for cold start problems, the benchmark algorithms that they have used to compare the effectiveness of these approaches, and the metrics that authors have used to evaluate the efficacy of the algorithms. The study observes that basic collaborative filtering algorithms such as user-based CF and item-based CF are commonly used as benchmark algorithms by many researchers. However, the researchers have also used a wide variety of algorithms and there is no common pattern that has been noted in this study. In terms of the use of metrics for evaluation of the effectiveness of proposed algorithms and methods, Mean Absolute Error (MAE), Precision, and Recall are most widely used by different researchers followed by Root Mean Square Error (RMSE). This presents an opportunity for future recommender systems scholars to research and report on which all key benchmark algorithms and metrics should be considered for evaluation of the algorithm performance in cold start scenarios.

The study has also tried to report the domains of the cold start research that has been conducted thus far. This intends to help the recommender system researchers and practitioners who are working on cold start problems in any particular domain can refer to, use, and build on the works in the extant research. The study observes that movies, music, and books are the most popular domains due to publicly available datasets that researchers have made use of. These domains are followed by shopping and e-commerce as shopping and item review datasets from various sites such as epinions.com are easily available. E-learning and Supply Chain are two key domains that have not seen much research. Also, not many novel ideas have been presented on Travel, Tourism, Food, and Hospitality domains to tackle the cold start problems. This presents future research avenues for the recommender system scholars to propose novel algorithms that can improve the recommender system performance and alleviate cold start problems in these domains. The researchers can also look beyond these domains and bring in the novelty of recommender system applications in other business domains.

7 Conclusion and limitations

To conclude, the review presents a collection of different approaches and algorithms that the recommender systems researchers have adopted in the last decade to address the new user and new item cold start problems. The main contribution of this research is the exhaustive study and synthesis of 91 articles on recommender systems that propose approaches and algorithms to mitigate cold-start problems. The study effectively synthesizes the various strategies into two broad categories: data-driven strategies and approach-driven strategies and further the approach-driven strategies are categorized into five main clusters depending upon the method adopted by the researchers. The study also captures details such as the domain of recommender system research, benchmark algorithms used for comparison, and metrics used for evaluation. Hence, this study can be used by future recommender system researchers as a comprehensive guide and ready reckoner to understand the research that has been thus far on cold start problems and the future avenues of research that can be conducted further as stated above. Practitioners can also use this study as a guide to effectively identify various algorithms and approaches that could be easily applied in their recommender system domain to mitigate the cold start problems.

The research also acknowledges that it has certain limitations. The research presented in this paper is limited to a systematic literature review of 91 journal articles published in scholarly peer-reviewed journals. Although the research to the best of its ability has tried to collate the various approaches and algorithms that are proposed by various researchers to mitigate the cold start problems, it has not done a comparative analysis or an experimental study to benchmark and recommends the best approaches and their context of use for practitioners to adopt in these cold start scenarios. This limitation of the paper is also the scope for recommender system researchers to take up future research in the cold start domain.

Funding The authors did not receive any funding or financial support from any organization for the submitted work.

Data Availability Statement Data sharing is not applicable to this article as no data-sets were generated or analysed during the current study.

Code Availability Code Availability is not applicable to this article.

Declarations

Ethics approval and consent to participate The authors confirm that they have abided to the ethical guidelines required of an author as per Committee on Publication Ethics (COPE). The authors confirm of their consent to participate.

Consent for Publication The authors confirm of their consent for publication

Conflict of Interests The authors have no conflicts of interest to declare that are relevant to the content of this article.

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