A Review of Tag-aware Recommender Systems

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Abstract
Due to the recent growth in online data about customers and the growing social web content due to the ever-increasing popularity of social media services, tag-aware recommendation systems are attracting more attention. Tag-aware recommendation systems effectively reveal user preferences and extract latent semantic information of items through social tag information. Therefore, a review of the present status of the literature on tag-aware recommendation systems is necessary to identify future research possibilities and directions. This article reviews the research direction in terms of approaches used, application domains, challenges and problems related to developing a system of recommendations, and evaluation metrics used to evaluate performance. In addition, we offer a thorough quantitative evaluation of the research in this field. Finally, we discuss the insights gained and potential directions for further research.
Keywords:
Tag-aware, Recommender Systems, Social Tagging System.

1. Introduction

The information and content in our time are increase in the amount . And that becuase of extensively used by the users [1]. Thus, access to appropriate and effective content from the vast amount of information has become a problem [2]. And for this, recommendation systems (RS) have appeared, which have provided an appropriate and effective solution [3], [4]. A recommendation system deals with the overload of information problem. which is a filtering tool of information that providing it as indicative and importance in a highly personalized way. And this by filtering the vital information part from a large amount of information which generated dynamically according to user preferences or interests or its observed behavior around the element [3], [4]. These systems not only display preferences similar to the user's preferences, but also those that are unknown and of interest to the user. Techniques for creating personalized recommendations have been developed and suggested, such as Tag-aware Recommendation Systems (TRS). TRS helps find items that are important and reflect the user's personal preferences by using random words or phrases, which are freely sets by the user [2], [5]. Through their labeling behavior, these systems provide complementary information to the recommender systems[5] . This type of recommendation system showed effective work, as were made recommendation systems based on deep reinforcement learning as in the paper [4], and recommendation systems based on deep learning - Intelligent computing systems as in the paper [2] , and through the fusion of collaborative filtering algorithms as in paper [6].

From our view, the field of recommender systems suffers from a lack of research papers in it. There may be some scientific papers on recommendation systems, but not especially on tag-aware recommender systems. From this direction, this paper contributes to publishing a new value to scientific papers and is a starting point for publishing specialized scientific papers in tag-aware recommender systems. From this, this paper aims to present a survey of the tag-aware recommender systems. This paper will differ from previous papers in this field, which will first present a survey in recommender systems and then specialize more in tag-aware recommender systems.

The remainder of this paper is structured as follows. Section presents the background information about recommender systems generations and tag-aware recommender systems. In section 4 we briefly review the related work of recommender systems and tag-aware recommender systems. Section 4 is about tag-aware recommender systems. We present a quantitative assessment of the comprehensive literature in section 5. Insights and discussions in section 6. Finally, a conclusion is given in section 7.

2. Background

Due to the abundance of information on the web nowadays, people are becoming increasingly confused, making it challenging and time-consuming to choose a specific product or item or locate a particular product [7]. And in order not to take the task for a long time, the solution is the recommendation systems [3], [4]. Recommendation systems appeared in the 1990s and have evolved more over the days for the algorithms used and for deploying applications that use these systems [8]. And as we said earlier, recommendation systems are filtering tools to guide the user to preference or interest objects from the vast information and play an essential role in finding relevant information to help online users [9]. Recommender systems are in their development stages and have been

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developed from the first generation to the third generation [7].

First-generation recommendation systems deal with e-commerce [7]. Objects and users are the two basic blocks of this generation, and they have a binary relationship [7]. Based on their preferences, users rate the items. The rating could be binary or on a scale from 1 to 5. Researchers have classified this generation into 11 approaches according to [7]. In the second generation, recommendation systems are used in the social network and social contextual information [7]. Social tagging sites have grown, and thus tag recommendation has become a topic of interest in this generation of recommending systems. Social tagging systems rely on three building blocks: Users, Items, and Tags to create recommendations, and these blocks have relationships with each other. According to [7], there are nine approaches for this generation. The third generation appeared after the increase in the use of mobile devices, as this generation uses location-based information or the Internet of Things to create recommendations. Location-based recommendation systems and RFID tags are examples that used in this generation. There are two approaches to this generation according to [7], where it was used Collaborative recommender with space and time similarity in [10], and Location-aware recommender system (LARS) which was used in [11].

Recommendation systems were developed from the first generation to the third generation through the second generation [7]. As the available options increased and with the increase in its applications, topics related to recommendation systems appeared, including social tagging systems (STS) [9], [12]. Where items can be social entities such as people or a group of people [7]. Tags are generally a way to make it easier to display content by topic, and this content is grouped by category [13]. The interested content of the user can be found by used this approach. [13]. Social recommendations include tag recommendations, people recommendations, and content recommendations [7].

The tag recommendation system is a system that recommends tags to the user, and these tags are defined as words that the user freely adds to an object [12]. The tag recommendation system uses a database that contains the objects, which in turn contains the tags that organize and describe them, and thus it is easy to search in this database for objects [12]. Through this database, the user can create tags on objects or add tags to new objects [12]. And because the Internet of things technologies are used in social networks such as NFC and RFID, which are used in [10] and others, tag recommendation systems fall under the third generation. It is one of the most successful approaches of increasing the level of relevant content as more content is available on the Internet.

3. LITERATURE REVIEW

Recommendation Systems (RS) have improved many different services in various fields. A systematic literature review [14] discussed RS from 2005 and compared the different algorithms and limitations. RS techniques have also been categorized into five main categories: content-based model, collaborative filtering, demographic filtering, knowledge-based recommendation, and hybrid filtering approaches, each category is discussed in detail. As a result, the classic recommendations approaches play a dominant role in almost all types of applications. Still, hybrid RS is more popular than a recommendation based on a single-recommendation technique to avoid the drawbacks of the single-recommendation approach. The results are consistent with the survey in[15]. as a results , some new techniques of recommendation in recent applications are played an essential role in the development it . Some Example of these techniques are social networking, Computational intelligence-based, demographics-based, and group-based techniques.

Although the classic approaches of RS have been successful, they still suffer from many problems. Based on this, authors in [16] presented a systematic literature review of deep learning-based learning resources that can better guide researchers and practitioners to understand trends and new challenges in this field. The results indicate that the most widely exploited deep learning architectures for RS are autoencoder (AE) models, followed by Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) models. As for the datasets most used to evaluate RS based on deep learning, the two datasets are Movie Lenses, followed by Amazon. The review results also indicated that the most common domains in the recommendation systems are movies and e-commerce. Finally, the performance of the deep learning-based RSs is evaluated by the Root Mean Squared Error and precision measures which are the most widely used in evaluation.

In[17], they presented a survey study of deep learning-based recommendation system approaches, categorized into four main aspects. Firstly, they categorized the studies based on the different models of deep learning used to understand their suitability to the problem of creating recommendations. Secondly, they investigate how deep learning approaches address current challenges to recommender systems research. Thirdly, the application domains were evaluated. Finally, the relationship between deep learning techniques and the purposeful characteristics of recommender systems was analyzed. Furthermore, they provide a quantitative assessment of the literature and a discussion of the insights gained. As a result’s review, the promising and encouraging results can be seen from the deep learning recommender system. In addition, scalability and accuracy consedred as challenges for this review for improvement and future work.

The study [18], provides a reference for developing and reviewing the limitations of deep learning-based recommendation systems that provide appropriate tools to assist quickly in the information search process. which from the massve data it learn learn latent representations of users and items. Then, the recommendation model is builded . After that , an effective list of recommendation user is build. Then the main tasks of how to organize large multi-source heterogeneous data, build more appropriate user models according to the requirements of user preferences, improve performance, and user satisfaction was then identified. Deep learning-based recommendation systems have shown many advantages over traditional recommendation systems as they learn latent features of the user and item automatically by integrating different types of heterogeneous data from multiple sources, modeling hierarchical patterns of user behavior, and more effectively reflecting different user preferences, and improving the accuracy of recommendations.

Furthermore in [19], they presented a recommender system survey focusing on deep learning approaches and application systems. Whereas the deep learning neural network is customized to the recommendation system to extract the users and items features or latent and explicit features. The results showed that the Deep Belief Network (DBN) is usually used to create a user profile, the CNN is usually used to extract the image or visual features, and the autoencoder model is usually used to find latent or implicit features.

Due to the recent growth in online customer data, tag-aware RS is attracting more attention. Based on this, A systematic review are conducted [20] provides the challenges and problems that motivate researchers to develop new recommendation systems and methodologies. They covered the tag-aware recommendation systems, which include the challenges and problems related to developing the recommendations system, the application areas, the proposed methodologies, the evaluation criteria used to evaluate performance, limitations, and defects that require investigation and improvement. The results indicate that CNN significantly outperforms traditional approaches of tag capture. The precision, f1-score, mean absolute error and recall are the four most important criteria for evaluation. However, the majority of papers use a set of criteria to improve their performance evaluation. Moreover, several research directions have been presented as dealing with a huge amount of constantly updated data.

The authors presented [21] a review of the challenges to address the tag recommendation problem. Moreover, the overall performance of ontology-based recommender systems was compared favorably with other systems in the literature. As a result, researchers were directed to focus in future work on defining hierarchies between tag sets and adding3 a more semantic layer by extracting tags from the contents of a source file.

The progress on tag-aware RS has been summarized [5], focusing on contributions from three main perspectives and approaches: network-based, tensor-based, and topic-based, and then identifying future challenges for tag-aware recommendation algorithms. The results of the review showed that there is no single method that can completely address all the problems found in RS. Network-based and tensor-based approaches can be used to design efficient algorithms as they can overcome large-scale data asymmetry. However, they focus only on the network structure, while lacking considerations of relationships between tags. Topic-based approaches can also distinguish tags on relatively different topics. Moreover, most of the topic-based approaches use machine learning to improve results iteratively, they require highly efficient hardware for computation, and thus consume more computational time. Tensor-based approaches have a similar problem in the dimensionality reduction process. As a future work they propose a standardized model to take full advantage of its advantages and provide a more promising approach in tag-aware recommendation systems.

In conclusion, the tag-aware RS is witnessing the interest of researchers in recent years and given the lack of literature reviews that have been conducted in this field, from our point of view, the field requires more studies to summarize the progress made, including the approaches used from 2004 to 2022 and their application domains. In addition, to the advantages, problems, and evaluation metrics of the TRS. Thus, quantitatively assessing and discussing the findings and inferences that we reached to contribute to TRS development and provide new research directions in the future.

4. TAG-AWARE RECOMMENDER SYSTEM

Tags allow information to be retrieved and shared in the future to determine user preferences. In this section, we will review suggested approaches for establishing a tag-aware recommendation system, application areas, evaluation metrics used to evaluate the performance of the proposed model, advantages and problems related to the development of the recommendations system.

A. Tag-aware Recommender System Approaches:

The approaches analyze user data based on tags to help users find the items they want by producing a predicted likelihood score or a list of top-N recommended items [22]. In this part, the techniques used will be reviewed and categorized into traditional approaches and deep learning approaches.

1) Traditional Approaches: Traditional approaches have played a key role in helping users to make decisions, such as collaborative filtering, content-based models, and hybrid filtering approaches.

a) Collaborative filtering: To Taking users' preferences advantage, Collaborative filtering (CF) approach is used. Which is the most widely used by assume the same intrest of usres. . CF is categorized into memory-based and model-based methods. User-based and item-based methods are Memory-based methods. based on similar ratings of users the user-based methods are depend on the target , while item-based methods depend on ratings of similar items given by the user. *[20]*.

b) Content-based filtering: Content-based recommendation systems use information about the items stored in tags. The similarity between items consumed by the user and other available items are measured by the system to find item similar to the item liked by the user *.[23]*.

c) Hybrid Approaches: Different recommendation algorithms are collected to create a recommendation algorithm that can take advantage of the algorithms' strengths and mitigate their weaknesses, as clustering-based methods deal with redundancy in tags and ease ambiguity when there is a vague word *[24]*.

2) Artificial Intelligence Approaches: Machine learning and deep learning plays a significant role in extracting hidden patterns from data for building effective and dynamic behavior modeling in RSs. Convolutional neural network (CNN), recurrent neural network (RNN), and attention models are an examples of neural networks. Which have been used recently to deal with tag-aware recommendation systems problems. In additioon to address the traditional approaches limitations *[20].*

B. Applications of Tag-aware Recommender System:

There are many areas of application of the tag recommendation system to provide improvements that help users in making decisions, which we will review in this section:

1) E-learning: A tag-based recommendation system assists e-learning that helps in providing suggestions to users, such as finding relevant educational materials that match the time and content based on the availability of information [25].

In [25], a web-based learning system model based on collaborative filtering and data clustering are developed, to provide intelligent and adaptive recommendations based on system feedback of learners' activities throughout their learning period and the cumulative assessments made by learners.

2) Social Media: The popularity of social content published online is significantly influenced by tags. Tag suggestion systems assist users in tagging their submitted photographs, increasing the likelihood that they will become popular[26].

Many studies have been conducted to improve the accuracy of social media recommendations based on tags. A framework based on collaborative filtering has been proposed [23], and several machine learning models have been developed [26] and [27]. Furthermore, studies have been conducted to develop models based on deep learning and neural network [28], [29].

To improve the performance of systems, machine learning models have been proposed [30] and [27], also the deep learning [31].

On the other hand, studies have been conducted to recommend images using collaborative filtering in [32], and recommend images and videos based on tag-aware deep learning in [12]. In addition, to recommending restaurants and food, the cooperative liquidation model in [33].

3) Movies: The tags are used to develop recommendation systems to help movie and series providers to make recommendations appropriate to users' interests[34].

Tag-aware movies recommendations are an active research domain, as both traditional and deep learning approaches have been used. A new model has been proposed for the collaborative filtering approach, which is one of the famous traditional methods [35], [36]. While in [34] a hybrid framework has been proposed.

The tag-aware based on deep learning enhances the movies recommendation system to overcome the problems of traditional approaches, as many studies have been conducted to present proposals to achieve this goal [2], [31] and [37]. Furthermore, a Tag-aware recommender system based on a deep reinforcement learning model is proposed in [4].

4) Music: Social tagging is one of the most important sources of essential information for developing recommendation systems in music. Moreover, they are considered the cornerstone of the algorithms of recommendation systems based on the similarity of tags, taking into account several considerations such as time periods, the name of the band or singer, etc. [38].

Collaborative filtering is the most widely used approach based on tag-aware music recommendation systems [6],[39]–[40] and [41], and a hybrid approach has been proposed in [42]. Moreover, the machine learning approach has been applied in [30] and the deep learning approach in [37] and [31].

5) Tourism: Photographs displaying motion and paths shared by photographers can be utilized to make route recommendations based on geo-tagging, as they contain sequential spatial-temporal information and implicitly contain spatial semantics [43].

C. Advantages of Tag-aware Recommender System:

Tag recommendation Systems help users with the manual commenting effort of tagging by recommending tags to them. Tags are helpful because they give RS useful supplemental information as a flexible and effective method of managing information by summarizing item characteristics and reflecting user desire. Tags act as a bridge to create an implicit relationship between users and items by assigning several personal tags [31].

D. The Problems of Tag-aware Recommender System:

There are two main sub-problems with tag recommendations. There are the object-centric problem and the personal problem [12].

The object-centric approach in recommender systems aims to suggest relevant tags to an object and then recommend the same tags to another object regardless of the user [12]. This problem revolves around parsing a specific object. As for the other problem, the system will also consider the user. This means that different users will get different recommendations for the same object depending on the history of interactions with the recommendation system [12].

Another problem related to the tag recommendation system that must be solved separately is the cold start problem [12]. It is a common problem in this type of system and is also called an out-of-matrix recommendation problem. Indicates that the element does not have tags already added [7]. This is a problem in associative tag recommendation systems that rely on pre-added tags. A cold start problem can also refer to a person who hasn't rated anything yet, or to a new item that no one has rated yet [7], [13].

E. Evaluation Metrics:

Numerous metrics may be determined depending on the characteristics of the issue at hand and the suggested model to assess how well various methods for developing a tag-aware recommendation system operate. The performance evaluation measures are reviewed in this section in the manner listed below:

$$recall@N = \frac{\#\ of\ recommended\ resources\ @N\ that\ are\ relevant}{total\ \#\ of\ relevant\ resources} \quad (1)$$

By recommending tags to users, tag suggestion systems make it easier for users to tag items without having to manually remark on them. Tags are advantageous as they provide valuable supplementary information to RS as a flexible and efficient approach to information management by summarizing the properties of items and reflecting user preferences. Tags act as a bridge to create an implicit relationship between users and items by assigning several personal tags [31].

Equation (1) is recall@N, representing the proportion of relevant resources found in the top-N recommendations [30].

$$precision@N = \frac{\#\ of\ recommended\ resources\ @N\ that\ are\ relevant}{\#\ of\ recommended\ resources\ @N} \quad (2)$$

Equation (2) is precision@N which is the proportion of recommended resources in the top-N set that are relevant [30].

$$F1@N = \frac{2\ .\ precision@N\ .recall@N}{precision@N + recall@N} \, (3)$$

Equation (3) is F1- measure@N, which is a harmonic mean of recall@N and precision@N and becomes a comprehensive indicator [30].

$$MRR = max_{q \in Q} Q \frac{1}{C_q} \, (4)$$

Equation (4) is The system's capacity to return relevant tags at the top of the ranking (or the quality of top suggested tags) is demonstrated by Mean Reciprocal Rank (MRR), where C_q indicates the rank attained by relevant tag q [32].

$$RK(u)@k = \sum_{i \in Test(u) \cap Top-k(u)} \frac{1}{rank(i)} \, (5)$$

Equation (5) is the Ranking accuracy of user u at top-k ranking, RK(u)@k, is a metric that is used to demonstrate if a tag with a better rank is actually more relevant, where rank(i) denotes the rank of item i in top-k list [36].

$$S@k = \begin{cases} 1 & if\ Q \cap C_k \neq \emptyset \\ 0 & otherwise \end{cases} \quad (6)$$

Equation (6) is Success at Rank k (S@k) is the probability of finding a relevant tag, q ∈ Q, in a set of top-k recommended tags, Ck [32].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - p_i)^2} (7)$$

Εθυατιον (7) ισ Ροοτ Μεαν Σθυαρεδ Ερρορ (ΡΜΣΕ), Ωηερε t_i ισ τηε τεστ ρατινγ ϖαλυε ανδ p_i ισ τηε πρεδ ιχτεδ ρατινγ ϖαλυε [35].

$$MSE = \frac{1}{n}\sum_{i=1}^{n}|t_i - p_i| (8)$$

Equation (8) is Mean Absolute Error (MSE).

To return recommendations as important evaluation metrics when facing a real-time application problem or when there is a large amount of data to computation, it considers the computation time and cost for a system . [44].

5. QUANTITATIVE ASSESSMENT

This section will present a comprehensive evaluation of the scientific papers in the field of the Tag-Aware Recommender System, which were collected in a certain period of years, from 2004 to 2022. The number of collected papers reached 33 scientific papers. We will display the papers and evaluate them according to different categories, including the domain, the type of publication, a journal, a conference, or periodicals. Also, the dataset, the technology used in each paper, and another category. Table

1 presents the papers and assessments for each paper in detail for all categories.

We started by presenting the types of papers over the years in Fig. 1. Through the assessment, we note that the actual increase in the publication of scientific papers starts from 2014, and before this year the publication of papers is considered very few. Most papers have been published in the journal type, with the fewest being periodicals. Where the percentage of journal papers reaches 73%, and the percentage of papers published from the conference type reaches 23%, and the percentage of periodical papers is 4%, and this is illustrated in Fig. 2.

Next, we examined the papers according to the techniques used in the papers. Several techniques appeared through our analysis in Table 1, which are Deep Learning, Collaborative Filtering, Machine Learning, Deep Reinforcement Learning, and Hybrid approach. The result showed that the most used techniques in scientific papers are three techniques, which there is a slight percentage among them, they are Collaborative Filtering, where the percentage reaches 29%, followed by Deep Learning by 25%, and then Machine Learning by 21%. The other techniques are little in use compared to the three mentioned techniques shown in Fig. 3 as a pie chart.

After that, we examined the papers in different fields. The number of fields has reached 12 different fields covered by scientific papers. The most covered fields are music with 26%, followed by movies with 19%, then social media with 17%. Fig. 4 illustrates this with the other percentages of other fields as a pie chart.

Finally, we examined the papers in terms of the databases used. Fig. 5 illustrates the distribution of the datasets used as a pie chart. It appears that the frequently used datasets are Last.FM and MovieLens, as it appears that 20% of the papers use Last.FM, and 17% use MovieLens.

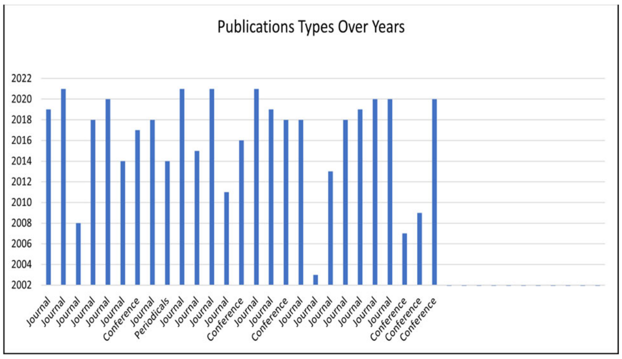

Figure 1. Types of Publications Over Years

Figure 1. Distribution of Publications by Their Types

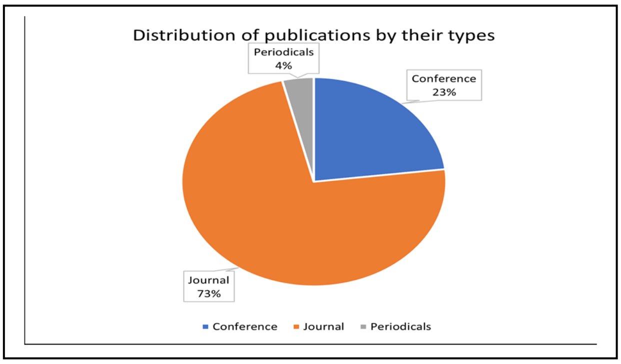

Figure 2. Distribution of Techniques

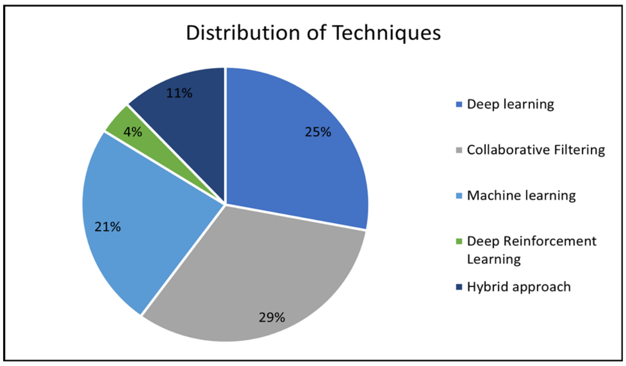

Figure 3 Distribution of Publications by Their Types

TABLE 1 COMPREHENSIVE LITERATURE

Ref	Type of Paper	Domain	Techniques	Model	Dataset used	FINDING/ RESULTS
[12]	Journal	Videos Images	Deep Learning	Deep learning model (a deep learning hybrid (content- and tag cooccurrence-based) tag recommender system) and a baseline model (a hybrid model combining content and tag cooccurrence.)	Flickr	Deep learning can be used to successfully model tag co-occurrence both separately and jointly together with content information.
[4]	Journal	Movies	Deep Reinforcement Learning	Proposed a tag-aware recommender system based on deep reinforcement learning without complex function design	MovieLens	The experiment proves that the recommendation algorithm used in this study has smaller errors, and it also has a beneficial effect on the overfit problem
[6]	Journal	Radio Music	Collaborative Filtering	Propose a generic method that allows tags to be incorporated into standard CF algorithms	Last.fm	Adapted fusion method has successfully captured the relationships between users, items, and tags
[2]	Journal	Movies	Deep Learning	Tag-aware recommender system based on deep learning (TRSDL) for rating prediction task	MovieLens	TRSDL is effective and competitive for rating prediction tasks. It improves traditional collaborative filtering methods and performs better than the state-of-the-art models on this dataset.
[45]	Journal	Libraries	Deep Learning	Propose a hybrid approach that leverages deep semantic representation of research papers based on social tags assigned by users.	CiteULike	The proposed approach outperforms state-of-the-art collaborative filtering-based tech - proposed model shows the effectiveness of integrating deep semantic representation of research papers based on social tags with collaborative filtering.
[34]	Journal	Movies	Hybrid Approach	Hybrid item recommendation and a recommendation framework for social tagging systems	MovieLens	For less active users, as we expected, the hybrid approach performs better than other methods.
[26]	Conference	Social media	Machine Learning	Proposed two tag ranking algorithms, Document Frequency-Weights from regression and Folk Popularity Rank	Flickr	1- FP-Rank makes better recommendations with a higher level of influence on popularity boosting over the other three tag recommendation methods. 2- FP-Rank has better effect on popularity boosting in the unpopular test set.
[23]	Journal	Social media	Collaborative Filtering	Propose a tag-based recommender system framework, a unified profile model (UPM) for social bookmarking websites	Delicious, BibSonomy	The experiment results show that the proposed recommender framework achieves higher performances than the baselines and it is more flexible and scalable.
[46]	Conference	Bookmarks	Collaborative Filtering	a new recommender system is proposed based on the similarities between user and item profiles	Del.icio.us	Experimental result s demonstrate that the proposed approach provides a better representation of user interests and achieves better recommendation results in terms of precision and ranking accuracy as compared to existing methods
[39]	Journal	Radio Music		Propose a novel tag-aware top-n recommendation model AIRec	Last.Fm, Delicious	The result shows significant improvements of AIRec over state-of-the-art methods for tag-aware top-n recommendation.

[44]	Periodicals	Music	Collaborative Filtering	Deeply analyze the impact of a tag recommendation system in the folksonomy of Freesound	Freesound	The results are that tag recommendation effectively increases vocabulary sharing among users of the platform. - tag recommendation is shown to contribute to the convergence of the vocabulary as well as to a partial increase in the quality of annotations.
[47]	Journal	Sentence Representation	Deep Learning	Novel neural network model (TagHyperTreeLSTM)	Stanford Sentiment Treebank (SST2), Movie Reviews (MR), Sentences grouped as being either subjective or objective (SUBJ), TREC, SICK	The experiment results show that the proposed recommender framework achieves higher performances than the baselines and it is more flexible and scalable.
[36]	Journal	Movies	Collaborative Filtering	Propose a new collaborative approach to user modeling that can be exploited to recommender systems.	The Internet Movie Database (IMDb)	Experimental results show that the proposed model achieves superior or competitive performance in text classification and text semantic matching based on six benchmark datasets when compared against previous tree-structured models.
[35]	Journal	Movies	Collaborative Filtering	Collective Matrix Factorization using Tag Embedding	MovieLens	The experimental results have shown the proposed model provides a better representation in user interests and achieves better recommendation results in terms of accuracy and ranking.
[30]	Journal	Movie Bookmarks Music	Machine Learning	New social tag expansion model (STEM)	MovieLens, Del.icio.us, Last.fm, BibSonomy	The analysis and experimental results showed that the new STEM technique was able to correctly find a sufficient set of tags and to improve the recommendation accuracy by solving the tag sparsity problem. At this point, this technique has consistently outperformed state-of-art tag-aware recommendation methods in these extensive experiments.
[32]	Journal	Restaurants and Food	Collaborative Filtering	Propose the Extended Category-based Collaborative Filtering (ECCF) recommender	Yelp	The evaluation showed that ECCF outperforms User-to-User Collaborative Filtering in accuracy, MRR, intra-list diversity and user coverage. - ECCS also obtains higher accuracy and diversity than the SVD++ recommender system, based on Matrix Factorization
[28]	Conference	Social media	Deep Learning	Propose a reconstruction method of tag-based profiles of users and items to enhance tag-aware recommendations	Delicious, Last.fm	The results show our method can achieve improvement of recommendation performance by leveraging reconstructive profiles of users and items.
[27]	Journal	Social Media Bookmarking	Machine Learning	Proposed an effective ontological similarity measure that uses ontologies to solve the tag ambiguity problem and to semantically measure the similarity between user and document profiles.	Delicious	The experiments show that the proposed ontological similarity is semantically more accurate than the state-of-the-art similarity metrics
[25]	Journal	E-learning	Collaborative Filtering	propose an evolving web-based learning system which can adapt itself not only to its users, but also to the open Web in response to the usage of its learning materials	CiteSeer	The system can retrieve relevant information related to users and their situated learning characteristics.

[33]	Journal	Images	Collaborative Filtering	A novel personalized tag recommendation system that discovers and exploits generalized association rules, that is, tag correlations held at different abstraction levels, to identify additional pertinent tags to suggest.	MIR Flickr 2008	The effectiveness of the proposed approach has been validated against a recently proposed tag recommendation system. Experiments show that the use of the generalizations in rule-based tag recommendation yields significant performance improvements.
[42]	Journal	Music	Hybrid Approach	A Gaussian state-space model coupled with low-rank matrix factorization	Last.fm	Experiments have been conducted over a large-scale real-world music data set and demonstrate the effectiveness of the proposed music recommendation framework.
[40]	Journal	Music	Collaborative Filtering	Propose a novel tag-aware recommendation framework by incorporating tag mapping scheme into ranking-based collaborative filtering model.	Lastfm, Citeulike	Experiments on real-world recommendation datasets show that the proposed recommendation method outperformed competing methods on ranking-oriented recommendation performance.
[37]	Journal	Movies, music	Deep Learning	Propose a novel tag-aware recommendation model named Tag Graph Convolutional Network (TGCN)	MovieLens, Last.fm, Delicious	Extensive experiments demonstrate that TGCN achieves remarkable performance improvement compared with state-of-the-art models.
[31]	Journal	Bookmarks Music Movies	Deep Learning	Tag-aware Neural Attention Model	Del.icio.us, Last.fm,MovieLens	Experiment results demonstrate that TNAM significantly outperforms the state-of-the-art baselines in Top-N recommendation on the evaluation metrics of HR and NDCG.
[41]	Conference	Bookmarks Music	Collaborative Filtering	-	Del.icio.us, Last.fm,BibSonomy	The straightforward collaborative filtering adaptation based on projections and an adaptation of the well-known PageRank algorithm named FolkRank.
[48]	Conference	Bookmarks	Hybrid Approach	The hybrid recommender can surpass the effective graph-based approaches while retaining the efficiency of its parts.	Bibsonomy	Alone these recommenders perform poorly; together they achieve a cooperation which proves to be as e active as state-of-the-art tag recommenders. The hybrid recommender can surpass the effective graph-based approaches while retaining the efficiency of its parts.
[29]	Conference	Social media	Deep Learning	Proposed a graph neural networks boosted personalized tag recommendation model (GNN-PTR)	Last.fm, ML10M	Experimental results show that our proposed method outperforms the state-of-the-art personalized tag recommendation methods.

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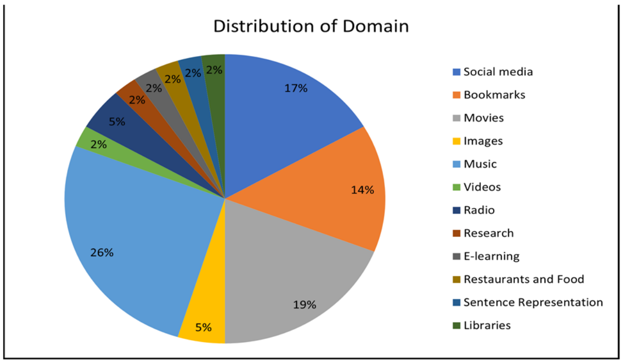

Figure 4 Distribution of Domain

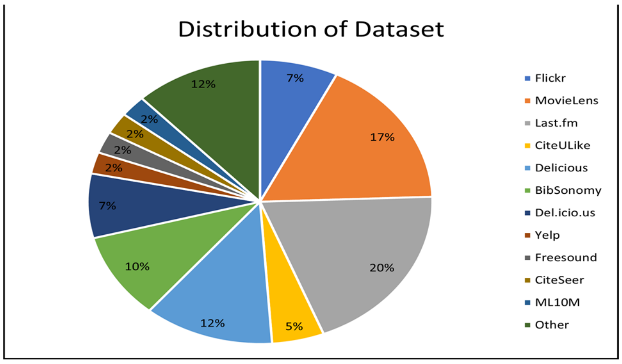

Figure 5 Distribution of Datasets

6. INSIGHTS AND DISCUSSIONS

The approaches used for tag-aware recommendation systems varied in different fields and on various data sets. This section discusses our findings and conclusions and provides the reader with insights based on the general analysis of the tag-aware recommendation systems throughout the study period.

- There has been an increase in studies from 2014 until now, but it is still not noticeable and fastly. Therefore, the field still needs more attention from researchers.
- We noticed no diversity in the type of publication, as most papers are published in journals or conferences, while other types are almost non-existent or non-existent.
- The domains of application of the tag recommendations systems varied, but some domains witnessed more bias than others, such as music, movies, and social media.
- Collaborative filtering is one of the most used methods until now in tag recommendation systems. Enriching the user profile by collaborating with user profiles and other similar tags contributes to recommending new items.
- In recent years, tag-aware recommendation systems have witnessed great interest in developing deep and machine learning models to overcome the problems and challenges facing traditional approaches and improve accuracy.
- Deep learning techniques deal with cold start problems of tag recommender systems by extracting features from profile information and integrating them into the user's item preferences.
- Neural networks are a deep learning technique that has recently emerged in tag-recommendation systems by using tag-based profiles of users and objects to improve tag-aware recommendations.
- In neural network training, neural network methods need to be measured more effectively to balance tag-based profiles and abstract representations to improve the item recommendation further.
- One of the challenges facing tag-recommendation systems is users' unwillingness to share tags, leading to tag scattering. Therefore, the accuracy of recommendations is significantly at risk when few tags are attached to users or resources. Creating a dynamic user profile is a solution to improve the performance of the recommendation.

7. CONCLUSION

Tag-aware recommendation system addresses the problem of extracting appropriate information and content from the vast amount of information on the Internet. And that helps users to find essential elements and reflect their personal preferences through words or phrases that users specify freely. This survey aims to present the scientific papers related to TRS that were published from 2004 to 2022 and then analyze them to provide an overview and purposeful for readers on this subject. This study, 33 scientific papers were evaluated based on the field, type of publication, dataset, techniques, model, and results. As a result of the evaluation, the papers began to increase in 2014; before that, the publication was little. 73% of the papers were published as a journal, and 29% of papers used collaborative filtering as a technique. The most covered area being music with 26%. And the most used dataset is Last.FM with 20%. Although TRS is a flexible approach to managing information by summarizing it and reflecting user preferences, the research related to it is few, and the number of publications has been few over the years. Also, scientific publications do not vary; they are limited to specific datasets and types of publications and focus on a specific field more than others. This does not help expand the publication and cover the field of TRS in different respects.

REFERENCES

[1] J. A. Konstan and J. Riedl, “Recommender systems: from algorithms to user experience,” *User Model User-Adap Inter*, vol. 22, no. 1, pp. 101–123, Apr. 2012, doi: 10.1007/s11257-011-9112-x.

[2] N. Liang, H. Zheng, J.-Y. Chen, A. K. Sangaiah, and C.-Z. Zhao, “TRSDL: Tag-Aware Recommender System Based on Deep Learning–Intelligent Computing Systems,” 2018, doi: 10.3390/APP8050799.

[3] F. O. Isinkaye, Y. O. Folajimi, and B. A. Ojokoh, “Recommendation systems: Principles, methods and evaluation,” *Egyptian Informatics Journal*, vol. 16, no. 3, pp. 261–273, Nov. 2015, doi: 10.1016/j.eij.2015.06.005.

[4] Z. Zhao, X. Chen, Z. Xu, and L. Cao, “Tag-Aware Recommender System Based on Deep Reinforcement Learning,” *Mathematical Problems in Engineering*, pp. 1–12, May 2021, doi: 10.1155/2021/5564234.

[5] Z.-K. Zhang, T. Zhou, and Y.-C. Zhang, “Tag-Aware Recommender Systems: A State-of-the-art Survey,” *J. Comput. Sci. Technol.*, vol. 26, no. 5, pp. 767–777, Sep. 2012, doi: 10.1007/s11390-011-0176-1.

[6] K. Tso, L. Marinho, and L. Schmidt-Thieme, *Tag-aware recommender systems by fusion of collaborative filtering algorithms*. 2008, p. 1999. doi: 10.1145/1363686.1364171.

[7] R. Singh, K. Chuchra, and A. Rani, “A Survey on the Generation of Recommender Systems,” *International Journal of Information Engineering and Electronic Business*, vol. 9, pp. 26–35, May 2017, doi: 10.5815/ijieeb.2017.03.04.

[8] A. Felfernig, M. Jeran, G. Ninaus, and F. Reinfrank, “Toward the Next Generation of Recommender Systems: Applications and Research Challenges,” in *Smart Innovation, Systems and Technologies*, vol. 24, 2013, pp. 81–98. doi: 10.1007/978-3-319-00372-6_5.

[9] J. Tang, X. Hu, and H. Liu, “Social recommendation: a review,” *Soc. Netw. Anal. Min.*, vol. 3, no. 4, pp. 1113–1133, Dec. 2013, doi: 10.1007/s13278-013-0141-9.

[10] M. Organero, G. Ramirez-Gonzalez, P. Merino, and C. Delgado-Kloos, “A Collaborative Recommender System Based on Space-Time Similarities,” *IEEE Pervasive Computing*, vol. 9, pp. 81–87, Jul. 2010, doi: 10.1109/MPRV.2010.56.

[11] J. Levandoski, M. Sarwat, A. Eldawy, and M. Mokbel, “LARS: A location-aware recommender system,” *Proceedings - International Conference on Data Engineering*, pp. 450–461, Apr. 2012, doi: 10.1109/ICDE.2012.54.

[12] D. Malmström, *Automatic tag suggestions using a deep learning recommender system*. 2019. Accessed: Mar. 29, 2022. [Online]. Available: http://urn.kb.se/resolve?urn=urn:nbn:se:kth:diva-271215

[13] F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, Eds., *Recommender Systems Handbook*. Boston, MA: Springer US, 2011. doi: 10.1007/978-0-387-85820-3.

[14] F. Alyari and N. Jafari Navimipour, “Recommender systems: A systematic review of the state of the art literature and suggestions for future research,” *Kybernetes*, vol. 47, no. 5, pp. 985–1017, Jan. 2018, doi: 10.1108/K-06-2017-0196.

[15] S. Malik, A. Rana, and M. Bansal, “A Survey of Recommendation Systems,” *IRMJ*, vol. 33, no. 4, pp. 53–73, Oct. 2020, doi: 10.4018/IRMJ.2020100104.

[16] A. Da’u and N. Salim, “Recommendation system based on deep learning methods: a systematic review and new directions,” *Artif Intell Rev*, vol. 53, no. 4, pp. 2709–2748, Apr. 2020, doi: 10.1007/s10462-019-09744-1.

[17] Z. Batmaz, A. Yurekli, A. Bilge, and C. Kaleli, “A review on deep learning for recommender systems: challenges and remedies,” *Artif Intell Rev*, vol. 52, no. 1, pp. 1–37, Jun. 2019, doi: 10.1007/s10462-018-9654-y.

[18] R. Mu, “A Survey of Recommender Systems Based on Deep Learning,” *IEEE Access*, vol. 6, pp. 69009–69022, 2018, doi: 10.1109/ACCESS.2018.2880197.

[19] J. Y. Liu, “A Survey of Deep Learning Approaches for Recommendation Systems,” *J. Phys.: Conf. Ser.*, vol. 1087, p. 062022, Sep. 2018, doi: 10.1088/1742-6596/1087/6/062022.

[20] B. M. Shoja and N. Tabrizi, “Tags-Aware Recommender Systems: A Systematic Review,” in *2019 IEEE International Conference on Big Data, Cloud Computing, Data Science Engineering (BCD)*, 2019, pp. 11–18. doi: 10.1109/BCD.2019.8884850.

[21] V. Subramaniyaswamy, V. Vijayakumar, and V. Indragandhi, “A Review of Ontology-Based Tag Recommendation Approaches,” *International Journal of Intelligent Systems*, vol. 28, no. 11, pp. 1054–1071, 2013, doi: 10.1002/int.21616.

[22] T. Bogers, “Tag-Based Recommendation,” in *Social Information Access: Systems and Technologies*, P. Brusilovsky and D. He, Eds. Cham: Springer International Publishing, 2018, pp. 441–479. doi: 10.1007/978-3-319-90092-6_12.

[23] H. Liu, “A tag-based recommender system framework for social bookmarking websites,” *International Journal of Web Based Communities*, vol. 14, no. 3, pp. 303–322, Jan. 2018, doi: 10.1504/IJWBC.2018.094916.

[24] A. Shepitsen, J. Gemmell, B. Mobasher, and R. Burke, “Personalized recommendation in social tagging systems using hierarchical clustering,” in *Proceedings of the 2008 ACM conference on Recommender systems*, New York, NY, USA, 2008, pp. 259–266. doi: 10.1145/1454008.1454048.

[25] T. Tang and G. McCalla, “Smart Recommendation for an Evolving E-Learning System: Architecture and Experiment,” presented at the International Journal on E-Learning, 2005, vol. 4, no. 1, pp. 105–129. Accessed: Dec. 27, 2022. [Online]. Available: https://www.learntechlib.org/primary/p/5822/

[26] Y. Zhang, J. Hu, S. Sano, T. Yamasaki, and K. Aizawa, “A Tag Recommendation System for Popularity Boosting,” in *Proceedings of the 25th ACM international conference on Multimedia*, New York, NY, USA, 2017, pp. 1227–1228. doi: 10.1145/3123266.3127913.

[27] Z. Xu, O. Tifrea, T. Lukasiewicz, M. V. Martinez, G. Simari, and C. Chen, “Lightweight Tag-Aware Personalized Recommendation on the Social Web Using Ontological Similarity,” *IEEE Access*, vol. PP, pp. 1–1, Jun. 2018, doi: 10.1109/ACCESS.2018.2850762.

[28] Z. Li, J. Huang, and N. Zhong, “Leveraging Reconstructive Profiles of Users and Items for Tag-Aware Recommendation,” in *2018 IEEE International Conference on Data Mining Workshops (ICDMW)*, 2018, pp. 1294–1299. doi: 10.1109/ICDMW.2018.00184.

[29] X. Chen, Y. Yu, F. Jiang, L. Zhang, R. Gao, and H. Gao, “Graph Neural Networks Boosted Personalized Tag Recommendation Algorithm,” in *2020 International Joint Conference on Neural Networks (IJCNN)*, Jul. 2020, pp. 1–8. doi: 10.1109/IJCNN48605.2020.9207610.

[30] Y. Pan, Y. Huo, J. Tang, Y. Zeng, and B. Chen, “Exploiting relational tag expansion for dynamic user profile in a tag-aware ranking recommender system,” *Information Sciences*, vol. 545, pp. 448–464, Feb. 2021, doi: 10.1016/j.ins.2020.09.001.

[31] R. Huang, N. Wang, C. Han, F. Yu, and L. Cui, “TNAM: A tag-aware neural attention model for Top-N recommendation,” *Neurocomputing*, vol. 385, pp. 1–12, Apr. 2020, doi: 10.1016/j.neucom.2019.11.095.

[32] N. Mauro and L. Ardissono, “Extending a Tag-based Collaborative Recommender with Co-occurring Information Interests,” in *Proceedings of the 27th ACM Conference on User Modeling, Adaptation and Personalization*, New York, NY, USA: Association for Computing Machinery, 2019, pp. 181–190. Accessed: Mar. 29, 2022. [Online]. Available: https://doi.org/10.1145/3320435.3320458

[33] L. Cagliero, A. Fiori, and L. Grimaudo, “Personalized tag recommendation based on generalized rules,” *ACM Trans. Intell. Syst. Technol.*, vol. 5, no. 1, p. 12:1-12:22, 2014, doi: 10.1145/2542182.2542194.

[34] H. Kim and H.-J. Kim, "A framework for tag-aware recommender systems," *Expert Systems with Applications*, vol. 41, no. 8, pp. 4000–4009, Jun. 2014, doi: 10.1016/j.eswa.2013.12.019.
[35] H. Bang and J.-H. Lee, "Collective Matrix Factorization Using Tag Embedding for Effective Recommender System," in *2016 Joint 8th International Conference on Soft Computing and Intelligent Systems (SCIS) and 17th International Symposium on Advanced Intelligent Systems (ISIS)*, Aug. 2016, pp. 846–850. doi: 10.1109/SCIS-ISIS.2016.0183.
[36] H.-N. Kim, A. Alkhaldi, A. El Saddik, and G.-S. Jo, "Collaborative user modeling with user-generated tags for social recommender systems," *Expert Systems with Applications*, vol. 38, no. 7, pp. 8488–8496, Jul. 2011, doi: 10.1016/j.eswa.2011.01.048.
[37] B. Chen *et al.*, "TGCN: Tag Graph Convolutional Network for Tag-Aware Recommendation," in *Proceedings of the 29th ACM International Conference on Information & Knowledge Management*, New York, NY, USA, 2020, pp. 155–164. doi: 10.1145/3340531.3411927.
[38] A. van den Oord, S. Dieleman, and B. Schrauwen, "Deep content-based music recommendation," in *Advances in Neural Information Processing Systems*, 2013, vol. 26. Accessed: Apr. 02, 2022. [Online]. Available: https://proceedings.neurips.cc/paper/2013/hash/b3ba8f1bee1238a2f37603d90b58898d-Abstract.html
[39] B. Chen, Y. Ding, X. Xin, Y. Li, Y. Wang, and D. Wang, "AIRec: Attentive intersection model for tag-aware recommendation," *Neurocomputing*, vol. 421, pp. 105–114, Jan. 2021, doi: 10.1016/j.neucom.2020.08.018.
[40] H. Li, X. Diao, J. Cao, L. Zhang, and Q. Feng, "Tag-aware recommendation based on Bayesian personalized ranking and feature mapping," *Intelligent Data Analysis*, vol. 23, no. 3, pp. 641–659, Jan. 2019, doi: 10.3233/IDA-193982.
[41] R. Jäschke, L. Marinho, A. Hotho, L. Schmidt-Thieme, and G. Stumme, "Tag Recommendations in Folksonomies," in *Knowledge Discovery in Databases: PKDD 2007*, Berlin, Heidelberg, 2007, pp. 506–514. doi: 10.1007/978-3-540-74976-9_52.
[42] E. Zheng, G. Y. Kondo, S. Zilora, and Q. Yu, "Tag-aware dynamic music recommendation," *Expert Systems with Applications*, vol. 106, pp. 244–251, Sep. 2018, doi: 10.1016/j.eswa.2018.04.014.
[43] G. Cai, K. Lee, and I. Lee, "Itinerary recommender system with semantic trajectory pattern mining from geo-tagged photos," *Expert Systems with Applications*, vol. 94, pp. 32–40, Mar. 2018, doi: 10.1016/j.eswa.2017.10.049.
[44] F. Font, J. Serrà, and X. Serra, "Analysis of the Impact of a Tag Recommendation System in a Real-World Folksonomy," *ACM Trans. Intell. Syst. Technol.*, vol. 7, no. 1, p. 6:1-6:27, 2015, doi: 10.1145/2743026.
[45] H. A. Mohamed Hassan, G. Sansonetti, and A. Micarelli, *Tag-Aware Document Representation for Research Paper Recommendation*. 2020.
[46] H. Movahedian and M. R. Khayyambashi, "A tag-based recommender system using rule-based collaborative profile enrichment," *Intelligent Data Analysis*, vol. 18, no. 5, pp. 953–972, Oct. 2014, doi: 10.3233/IDA-140677.
[47] C. Xu, H. Wang, S. Wu, and Z. Lin, "TreeLSTM with tag-aware hypernetwork for sentence representation," *Neurocomputing*, vol. 434, pp. 11–20, Apr. 2021, doi: 10.1016/j.neucom.2020.12.074.
[48] J. Gemmell, M. Ramezani, T. Schimoler, L. Christiansen, and B. Mobasher, "A Fast Effective Multi-Channeled Tag Recommender," in *Proceedings of ECML PKDD (The European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases) Discovery Challenge 2009, Bled, Slovenia, September 7, 2009*, 2009, vol. 497. Accessed: Dec. 27, 2022. [Online]. Available: http://ceur-ws.org/Vol-497/paper_25.pdf

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