A Review of Tag-aware Recommender Systems for Future Applications in Research and Development

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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(TRS) 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. It also, presents the insights gained and potential directions for further research. We evaluated 33 scientific papers thorough quantitative evaluation. Although TRS is a flexible approach to managing information, we found that the number of publications are few over the years. Also, scientific publications are limited to specific datasets and types of publications and focus on a specific field more than others. 73% of the papers were published as a journal, and 29% of papers used collaborative filtering approach. The most covered domin was the music domain with 26%, and the most used dataset was Last.FM with 20%.

KEY WORDS: TAG-AWARE, RECOMMENDER SYSTEMS, SOCIAL TAGGING SYSTEM.

INTRODUCTION

The information and content in our time are increase in the amount . And that becuase of extensively used by the users. Thus, access to appropriate and effective content from the vast amount of information has become a problem (Konstan and Riedl, 2012), (Isinkaye, Folajimi and Ojokoh, 2015), (Liang et al., 2018), (Zhao et al., 2021). And for this, recommendation systems (RS) have appeared which is a filtering tool that 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 in a highly personalized way (Isinkaye, Folajimi and Ojokoh, 2015), (Zhao et al., 2021).

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 (Liang et al., 2018). Through their labeling behavior, these systems provide complementary information to the recommender systems (Zhang, Zhou and Zhang, 2012). This type of recommendation system showed effective work, as were made recommendation systems through the fusion of collaborative filtering algorithms as in paper (Tso, Marinho and Schmidt-Thieme, 2008), and recommendation systems based on deep learning - Intelligent computing systems as in the paper (Liang et al., 2018). Also, based on deep reinforcement learning as in the paper (Zhao et al., 2021).

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 review article differs from previous ones as it provides more recent information on the tag-aware recommender systems.

The remainder of this paper is structured as follows. Section 2 presents the background information about recommender

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systems generations and tag-aware recommender systems. In section 3 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.

Background

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 (Felfernig et al., 2013). Recommender systems are in their development stages and have been developed from the first generation to the third generation (Singh, Chuchra and Rani, 2017). First-generation recommendation systems deal with e-commerce (Singh, Chuchra and Rani, 2017). Objects and users are the two basic blocks of this generation, and they have a binary relationship (Singh, Chuchra and Rani, 2017). 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 (Singh, Chuchra and Rani, 2017). In the second generation, recommendation systems are used in the social network and social contextual information (Singh, Chuchra and Rani, 2017).

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 (Singh, Chuchra and Rani, 2017), 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 (Singh, Chuchra and Rani, 2017), where it was used Collaborative recommender with space and time similarity in (Organero et al., 2010), and Location-aware recommender system (LARS) which was used in (Levandoski et al., 2012).

Recommendation systems were developed from the first generation to the third generation through the second generation (Singh, Chuchra and Rani, 2017). As the available options increased and with the increase in its applications, topics related to recommendation systems appeared, including social tagging systems (STS) (Tang, Hu and Liu, 2013), (Malmström, 2019). Where items can be social entities such as people or a group of people (Singh, Chuchra and Rani, 2017). Tags are generally a way to make it easier to display content by topic, and this content is grouped by category (Ricci et al., 2011). The interested content of the user can be found by used this approach. (Ricci et al., 2011). Social recommendations include tag recommendations, people recommendations, and content recommendations (Singh, Chuchra and Rani, 2017).

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 (Malmström, 2019). 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 (Malmström, 2019). Through this database, the user can create tags on objects or add tags to new objects (Malmström, 2019). And because the Internet of things technologies are used in social networks such as NFC and RFID, which are used in (Organero et al., 2010) 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.

Literature Review

Recommendation Systems (RS) have improved many different services in various fields. A systematic literature review (Alyari and Jafari Navimipour, 2018) discussed RS from 2005 and compared the different algorithms and limitations. They concluded 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 (Malik, Rana and Bansal, 2020).

Although the classic approaches of RS have been successful, they still suffer from many problems. Based on this, authors in (Da'u and Salim, 2020) 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. In(Batmaz et al., 2019), they presented a survey study of deep learning-based recommendation system approaches, categorized into four main aspects. 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 (Mu, 2018) provides a reference for developing and reviewing the limitations of deep learning-based recommendation systems. Furthermore, exploration of the advantages of deep learning over traditional recommendation systems, 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 (J. Y. Liu, 2018), 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 (Shoja and Tabrizi, 2019) provides 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. 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 and 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.

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 (Bogers, 2018). 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. (Shoja and Tabrizi, 2019).

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 .(H. Liu, 2018).

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 (Shepitsen et al., 2008).

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 (Shoja and Tabrizi, 2019).

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 (Tang and McCalla, 2005). In (Tang and McCalla, 2005), 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.

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(Zhang et al., 2017). 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 (H. Liu, 2018), and several machine learning models have been developed (Zhang et al., 2017) and (Xu et al., 2018). Furthermore, studies have been conducted to develop models based on deep learning and neural network (Li, Huang and Zhong, 2018), (X. Chen et al., 2020). To improve the performance of systems, machine learning models have been proposed (Pan et al., 2021) and (Xu et al., 2018), also the deep learning (Huang et al., 2020). On the other hand, studies have been conducted to recommend images using collaborative filtering in (Mauro and Ardissono, 2019), and recommend images and videos based on tag-aware deep learning in (Malmström, 2019). In addition, to recommending restaurants and food, the cooperative liquidation model in (Cagliero, Fiori and Grimaudo, 2014).

3). Movies: The tags are used to develop recommendation systems to help movie and series providers to make recommendations appropriate to users' interests (Kim and Kim, 2014). 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 (Bang and Lee, 2016), (Kim et al., 2011). While in (Kim and Kim, 2014) 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 (Liang et al., 2018), (Huang et al., 2020) and (B. Chen et al., 2020). Furthermore, a Tag-aware recommender system based on a deep reinforcement learning model is proposed in (Zhao et al., 2021).

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. (van den Oord, Dieleman and Schrauwen, 2013). Collaborative filtering is the most widely used approach based on tag-aware music recommendation systems (Tso, Marinho and Schmidt-Thieme, 2008),(Chen et al., 2021)–(Li et al., 2019) and (Jäschke et al., 2007), and a hybrid approach has been proposed in (Zheng et al., 2018). Moreover, the machine learning approach has been applied in (Pan et al., 2021) and the deep learning approach in (B. Chen et al., 2020) and (Huang et al., 2020).

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 (Cai, Lee and Lee, 2018).

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 (Huang et al., 2020).

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 (Malmström, 2019). 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 (Malmström, 2019). 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 (Malmström, 2019).

Another problem related to the tag recommendation system that must be solved separately is the cold start problem (Malmström, 2019). 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 (Singh, Chuchra and Rani, 2017). 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 (Singh, Chuchra and Rani, 2017), (Ricci et al., 2011).

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 (Huang et al., 2020). Equation (1) is recall@N, representing the proportion of relevant resources found in the top-N recommendations (Pan et al., 2021).

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

Equation (2) is precision@N which is the proportion of recommended resources in the top-N set that are relevant (Pan et al., 2021).

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

Equation (3) is F1- measure@N, which is a harmonic mean of recall@N and precision@N and becomes a comprehensive indicator (Pan et al., 2021).

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

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 (Mauro and Ardissono, 2019).

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

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 (Kim et al., 2011).

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

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 (Cagliero, Fiori and Grimaudo, 2014).

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

Equation (7) is Root Mean Squared Error (RMSE) , Where t_i is the test rating value and p_i is the predicted rating value (Kim and Kim, 2014).

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

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 . (Font, Serrà and Serra, 2015).

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 2: Distribution of Publications by Their Types

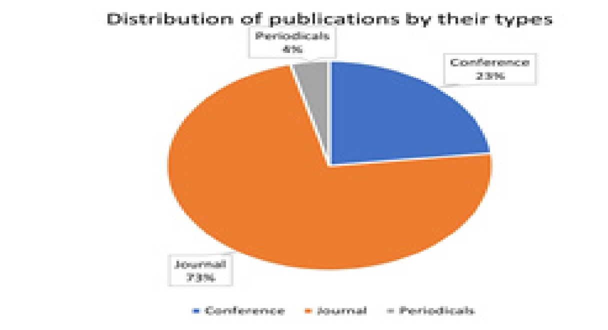


Figure 3: Distribution of Techniques

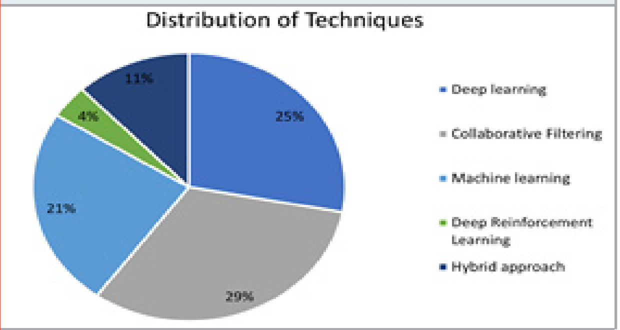


Figure 4: Distribution of Domain

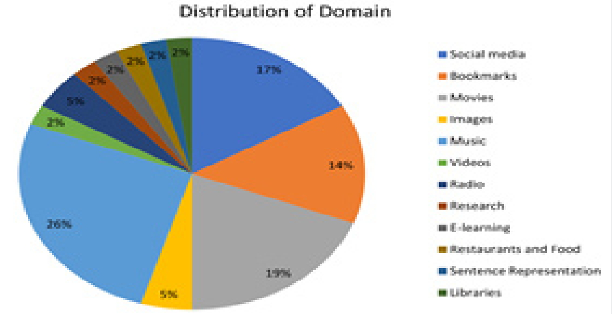
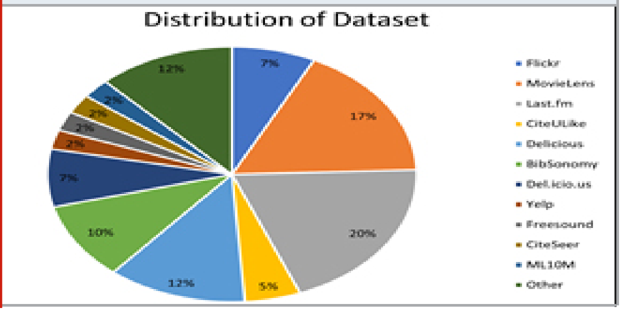


Figure 5: Distribution of Datasets



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.

Table 1. Comprehensive Literature

Ref	Type of Paper	Domain	Techniques	Model	Dataset used	FINDING/ RESULTS
(Malmströ m, 2019)	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.
(Zhao *et al.*, 2021)	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
(Tso, Marinho and Schmidt-Thieme, 2008)	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
(Liang *et al.*, 2018)	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.
(A. Mohamed Hassan, Sansonetti and Micarelli, 2020)	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.
(Kim and Kim, 2014)	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.
(Zhang *et al.*, 2017)	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.

Continue Table 1

(H. Liu, 2018)	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.
(Movahedian and Khayyambashi, 2014)	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
(Chen *et al.*, 2021)	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.
(Font, Serrà and Serra, 2015)	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.
(Xu *et al.*, 2021)	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.
(Kim *et al.*, 2011)	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.
(Bang and Lee, 2016)	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.
(Pan *et al.*, 2021)	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.
(Mauro and Ardissono, 2019)	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
(Li, Huang and Zhong, 2018)	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.
(Xu *et al.*, 2018)	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
(Tang and McCalla, 2005)	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.

Continue Table 1

(Cagliero, Fiori and Grimaudo , 2014)	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.
(Zheng *et al.*, 2018)	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.
(Li *et al.*, 2019)	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.
(B. Chen *et al.*, 2020)	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.
(Huang *et al.*, 2020)	Journal	Bookmarks Music Movies	Deep Learning	Tag-aware Neural Attention Model	Del.icio.us, Last.fm,Movie Lens	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.
(Jäschke *et al.*, 2007)	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.
(Gemmell *et al.*, 2009)	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.
(X. Chen *et al.*, 2020)	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.

- 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.

CONCLUSION

This survey aims to present the scientific papers related to TRS. 33 scientific papers were evaluated based on the field, type of publication, dataset, techniques, model, and results. As a result, the papers began to increase in 2014. 73% of the papers were published as a journal, and 29% of papers used collaborative filtering. The most covered area being music with 26%. And the most used dataset is Last. FM with 20%. The research related to TRS is few, and the number of publications has been few over the years. Also, scientific publications do not vary; it focus on a specific field more than others.

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