Science in Information Technology Letters
Vol. 2., No. 1, May 2021, pp. 28-42
ISSN 2722-4139
http://pubs2.ascee.org/index.php/sitech

Location-aware recommender system: a review of application domains and current developmental processes

Khalid Haruna [a], Zayyanu Yunusa [a], Nur Bala Rabiu [a], Aminu Musa [b,2,*], Yakubu Ibrahim [c], Fa'iz Ibrahim Jibia [d]

[a] Department of Computer Science, Bayero University Kano, Nigeria
[b] Department of Computer Science, Federal University Dutse, Jigawa, Nigeria
[c] Department of Computer Science, Yobe State University, Yobe, Nigeria
[d] Department of Computer Science, Federal Polytechnic Bauchi, Nigeria
[2] musa.aminu@fud.edu.ng
* Corresponding Author

ARTICLE INFO

Article history
Received March 12, 2021
Revised April 20, 2021
Accepted May 15, 2021

Keywords
Context-aware
Collaborative Filtering
Location-aware
Recommender

ABSTRACT

Recommender systems (RS) have been widely used to extract relevant and meaningful information from a vast body of data, to make appropriate suggestions to users with different preferences in various domains of applications. However, despite the success of the early recommendation systems, they suffer from two major challenges of cold start and data sparsity. Traditional RS consider an interaction between user and item (2D), neglecting contextual information such as location, until fairly recently. The contexts extend traditional RS to multi-dimension interaction and provides a useful information that allow recommendations to be more personalized. Surprisingly, taking these contexts such as location, into consideration eliminates the challenges of traditional RS. Location-Aware Recommender System (LARS) takes user's location into account as an additional context. The combination allows the prediction of spatial items, items closest to the users, to reduce information overload and was proved to be more effective than earlier RS. In this research, we provide a systematic literature of the existing literature in LARS from 2010 to 2021, focusing on the state-of-the-art methodologies, the domain of applications, and trends of publications in LARS. The paper proposed several models of LARS based on the traditional RS methodologies, providing future directions to researchers. Despite numerous reviews available on LARS, a review that proposed several LARS techniques were not found in the literature. The results indicated that the trend of publication in LARS is growing exponentially and that the field is getting attention rapidly with the number of publications on the rise every year.

1. Introduction

The volume of information that is been generated around us every day is enormous. Mobile computing has made it possible to bring everything to our fingertips in a limitless volume. This vast nature of information needs filter to scale down the voluminous information to be more relevant and more useful to the user. The demand for what is relevant is important to save time and resources. The process of filtering relevant information to cut down the search overhead led to the development of the Recommender System (RS). Recommender systems are a subclass of information filtering system and are widely used in several domains such as e-commerce, restaurants, entertainment, hotels, and so on [1]. These kinds of systems filter a huge amount of information to provide personalized recommendations for services or products to individuals based on their preference. They used prior knowledge or user interaction history to identify the best items that will be of interest to the user. With the view that a similar item might be of interest to the user. But that alone cannot describe the preference of the user and makes accurate recommendations, therefore contextual information was added to make the recommendation more personalized. Most of the traditional approaches of recommender systems do not take into account contextual information such as weather, day, time, distance, and location to provide recommendations. Several research works have shown that the RS can be extended to include contextual information in addition to the classical two-dimensional approach of user and item to provide better-personalized recommendations. This gives birth to a context-aware recommender system.

The earliest theoretical formulation of Context-aware recommender systems was seen in the work of [2], as a way of extending the capabilities of traditional RS. In their work they provided general overview of current the recommender system processes, limitation of each, and the way forward. The author claims that contextual information can extend the traditional formulation of a recommender system by incorporating the third dimension to the user-item interactions.

In line with that, [3]proved that contexts can be used to provide better recommendation and eliminates the challenges of traditional RS such as problem of cold start. In their paper, the authors described how to extract the user context rather than using keyword. In traditional text-based recommender systems keywords are used to extract relevant information, without bothering much about their meaning. Here, the word context means that the text that is related with the target word was also used to extract the opinion of the user review.

However, recent researches have proved that location is an important contextual information that can be tailored with RS to provide relevant and filtered information happening around us and reduce information overload. These kinds of information filtering led to the development of a location-aware recommender system.

The work of [1] provides a survey of LARS in mobile environment. In their work they gave an overview of RS and LARS and discussed several approaches to LARS. However, their work was conducted in 2015. In this rapidly technological changing world, a lot must have happened in this five-year period, which is why another review in LARS is critical. Additionally, their work is only limited to mobile computing environment.

Similarly, [4] provides a survey of LARS methodologies and their respective performances. The authors compared several methodologies of LARS and assess the performance of each in an effort to exploit the strength and weakness of each method, the sole aim was to discuss different methodologies of LARS and various evaluation metrics to compare these methodologies. While their work is astonishing, they completely ignored domain of application of the discussed methodologies.

Another survey on LARS was the work of [5] who considered LARS based on social media technology alone. While most of the LARS uses social media to extract the location context of the user, some make use of other technologies. [6]make use of volunteer geographic information to collect location context of the users and used it along with rest of the contexts to provide LARS. Still there are tons of LARS that uses a number of different technologies to collect user's location apart from social media, which was not captured in the work, as such limiting the scope of their work.

It is noteworthy that none of the above discussed surveys provide a review that combines the general overview of LARS, domain of applications, trends of publications, as well as thorough discussion about methodologies used. Therefore, this research aimed at providing a thorough review about LARS that addressed all the drawbacks associated with previous reviews. It gives an analysis on trend of publication in LARS, it discussed several methodologies used in formulating LARS, and it also uncovers several domains of application where LARS have been used. The survey covers top five research databases, as a sources of literature from 2010-2021.

The rest of the paper is organized as follows: Section II gives general overview of recommender systems, Section III entails the research methodology adopted, and Section IV concludes the paper.

2. Method

Recommender systems history of development can be traced back to information filtering systems; techniques which remove redundant or unwanted information from Information stream using semi-automated or computerized methods before presentation to a human user [7]. The purpose of this technique is to reduce information overload. The user's profile is compared with some information characteristics for refinement and extraction. This technique evolved and gave rise to the modern recommender system. With the inception of the formal term Recommender system in the 1990s, two-dimensional RS were the only approaches in predicting users' interest until recently, researchers aimed at developing systems with the ability to recommend items to users in certain circumstances considering contextual information to provide context-aware recommendation system .

The authors in [8] reported that the concept of context-aware was first introduced by the work of [9] and has significantly evolved since then. Context-aware recommender systems (CARS) extend the traditional formulation of a recommender system problem by incorporating the third dimension to the user-item interactions. It is widely accepted that there can be diverse kinds of contextual information that can be used in the formulation of CARS. These contexts can be classified into three main categories: device context, user context, and physical context depending on the perspective adopted, application, or user side [10]. Over the years, various types of recommender system have been proposed by many researchers with various techniques, such as context-aware, location-aware, demographic-based and knowledge-based recommender systems which have been developed and deployed in different applications areas [11]–[17]

2.1. Traditional Methodologies

The methodogies discussed below, are considered traditional methodologies of developing RS. With the rise of aritificial intelligence and machine learning, new methodologies have emerged.

2.1.1. Collaborative Filtering:

In this approach or methodology user is intimated with items consumed in the past by other users who have similar tastes or preferences. Additionally, it is used to suggest items based on the similarity with other items that the user has liked in the past, where the similarities are computed by analyzing the ratings given to the items by the users [18]. Collaborative filtering is further subdivided into two main categories that is model-based and memory-based techniques. With memory based been classified as either user-based or item-based.

According to [19], User-based usually take place in four steps, first step is user-to-user correlations to find common users on a target. Second step deals with collection of items rating by user. In third step a preference score is computed to determine the likelihood of future actions by the user. Step four, respective prediction scores are ranked and a list of recommendations comprising the items with the highest ranks is generated. On other hand, Item-based collaborative filtering is more accurate than user-based, especially in a situation where the number of items is larger than the number of users, such as in e-commerce services.

2.1.2. Content-Based Filtering:

This method of recommendation is based on the similarity between the searched item and another item the user liked in the past, where the similarity is computed by comparing the contents (features) of the items [4]. Content-based recommendation methods can be formulated as: having a user U, and item I, then a utility function can be given as in equation (1).

$$F\ (u, i)\ =\ score\ (user\ profile\ (P), contents(c)) \tag{1}$$

The utility function of an item I, for user U, is a value of rating assigned by user U to items I which is similar to previous item I.

2.1.3. Hybrid Approach:

As described by [59], hybrid approach is a technique that combines both the collaborative and content-based algorithms. It leverages the advantage of each approach and eliminates their drawbacks. The hybrid technique improves the recommendation performance of either content or collaborative filtering approach by overcoming their drawbacks.

2.2. Location-Aware Recommender System (LARS)

A location-based recommendation is a type of recommender system, which selectively returns items to a user with the consideration of relevant spatial information (locations) and personal preferences [5]. LARS can be considered as an extension of traditional recommendation systems, and an important subset of CARS that focuses on the dimension location in the multidimensional context. These locations can be of three types, the physical position of the user, the location of an item, or both. According to [20] location-based ratings is categorized into three:

a) Spatial ratings for non-spatial items: Represented by the tuple (user; location; rating; item), where location is the user's location and is the only location that is considered.

b) Non-spatial ratings for spatial items: Stated by the tuple (user; rating; item; location), where location represents an item's location.

c) Spatial ratings for spatial items: Represented by the tuple (user; location; rating; item; location). In this case, the location of the user and the location of the item are both relevant

2.2.1. Selecting the relevant Databases

To provide a thorough and comprehensive search of the literature, we cover the top five academic bibliographic databases namely, ACM, Springer link, Science Direct, IEEExplore, and web of science library with the intention of finding relevant literature to guide our work.

2.2.2. Finding related works from the databases

From each database, the searching process was performed based on the Boolean search criteria "(Location OR Location-aware) AND (Recommender System OR Recommendation System)". The desired articles which matched the criteria were extracted, that is papers that mentioned Location-aware and recommender system in either title or abstract. Table 1 presents the retrieved papers from each database. The inclusion and exclusion criteria were then applied to the returned articles in order to extract the most relevant papers.

The inclusion and exclusion criteria are:

- Journal article in which location-aware and recommender system were mentioned in either abstract or title.
- Conference proceedings in which location-aware and recommender systems were mentioned in either abstract or title.
- Papers are written from 2010 to date.
- The paper must not be a survey paper.
- The paper must not be published in another language apart from English Language.
- The paper must reflect location-aware from its abstract.

Table 1. Papers returned from the databases

S/N	Database	Papers returned
1	ACM Digital Library	26,202
2	IEEExplore Library	149
3	Springer Link	412
4	Science Direct	2,427
5	Web of Science	298
	Total	29,488

Table 1 presents the frequency of the returned articles from each of the academic library consulted. The papers were thoroughly refined and screened to come up with the most relevant ones suitable for the work as depicted in Fig. 1. A total of 50 papers were finally selected (See Table 2), which were critically reviewed to identify the publication trends, techniques or methodology used, and application domain.

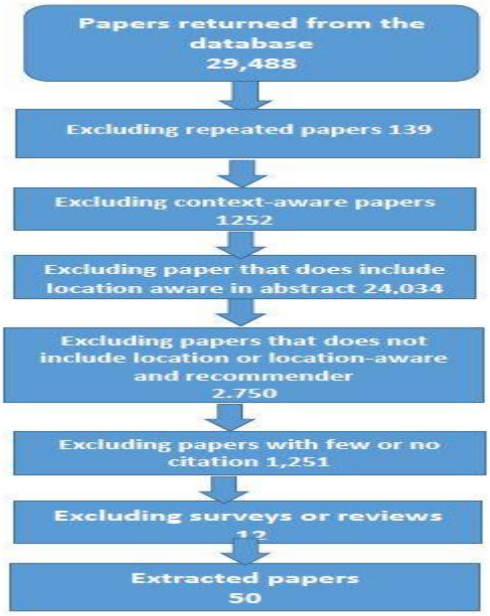

Fig. 1. Paper Extraction process

After applying inclusion and exclusion criteria on the returned papers from the databases, the refinement procedure allow us to select only 50 papers across the entire databases as presented in Table 2.

Table 2. Showing distribution extracted papers across databases

S/N	Database	Papers returned
1	ACM Digital Library	24
2	IEEExplore Library	5
3	Springer Link	11
4	Science Direct	7
5	Web of Science	3
	Total	50

3. Results and Discussion

3.1. Publication Trends

The selected papers were first examined based on the year of publications to justify the trends of the research. The result of the analysis shows that the location-aware recommender system was not given much attention until recently as demonstrated by Fig. 2. For instance, total number of papers written from 2010 to 2015 were few in number than the number of papers found from 2015 onward. And were not as much as papers published in 2019 alone. This also indicates that research in this area is growing with time. LARS is an active area of research that is getting popularity. Despite huge growth of LARS publications from 2017-2019, the trend began to descend drastically in 2020 and 2021 with fewer publications which might results from the covid-19 pandemic that disrupted every aspect of life in these years, but we are hoping to see the trend go up again when order is restored and normal lifestyle continues.

Fig. 2.LARS Publication Trends

3.2. Application Domains

This section describes the results from analysis with respect to domain of application of LARS. The papers were analyzed based on the domain of applications in order to discover areas in which LARS were implemented and used. The domain of applications found in literature after the analysis are e-commerce, entertainment, social network, news, tourism, and place of interest as presented in Table 3.

Table 3. Area of applications in LARS

Application domain	Papers
Point of interest (POI)	[8], [20], [21], [22], [23], [24], [21], [25], [26],[27], [28],[29], [30], [31], [32], [33], [34], [35], [36], [37], [9], [37]
E-commerce	[38], [39], [40], [34], [41], [21], [22], [24], [42], [43], [3]
Travel and tourism	[24], [44], [45], [46], [47], [48], [6], [49]
Entertainment	[48], [50], [31], [24]
Others	[51], [18], [8], [52], [53], [6], [54], [49], [55], [23], [50], [56]

3.2.1. Electronic-commerce (e- commerce)

e-commerce is a process of buying and selling products/services electronically with aid of a computer or a smartphone over the Internet. Examples of e-commerce platforms are Amazon, Alibaba, Jumia, and so on. According to [53], modern electronic commerce typically uses the

World Wide Web for at least one part of the transaction's life cycle although it may also use other technologies such as e-mail.

Major areas of e-commerce include online retailing, electronic marketing, and online auctions. Location aware has become more prominent in e-commerce systems in order to better understand the customer's preferences and items that suits a specific customer in a given location. E-commerce giants such as Alibaba uses location context in their recommendation system to provide recommendations such as summer sales or winter offers as these seasons varies from one location to another.

3.2.2. Entertainments

Entertainments are range of activities that capture the attention and interest of audience to provide pleasure and satisfaction. Entertainment can be delivered in the form of storytelling, music, dramatization, and dance. Various types of performance exist in all societies for entertainment purpose, they are usually upheld in imperial courts, formed into complex structures, and over the long run opened up to all residents [7]. The entertainment industry has seen dramatic growth and significant changes with the popularity of digital computers in the '90s. The process has been accelerated in modern fashion by an entertainment industry that records and sells entertainment products. Technology changes the dynamics of the industry in all aspect, from the way contents are created, developed, and distributed to the audience. Nowadays, audience enjoyed entertainments contents such as music, films, and concerts, from the comfort of their homes.

3.2.3. Point of Interest (POI)

This is another domain of application of LARS, which are a collection of locations that someone may find useful, or interesting. The traditional RS used in POI recommendation uses users' check-ins and suggested locations that are closer to where the user checking. With the inception of LARS POI recommendation becomes popular, they used GPS technology to continuously suggest location of interest to user based on user's current location, places such as a coffee shop, restaurants, and the rest. POI recommendation is important to travelers who found themselves in a new place, as it helps them navigate easily and find places that they might be looking for without asking a question or getting lost [34].

3.2.4. Travelling and Tourism

According to Oxford Dictionary [57], tourism is an activity that involves people traveling to and staying in places outside their usual environment for not more than one consecutive year for leisure and not less than 24 hours, for business and other purposes. It could be domestic (within the traveler's own country) or international (outside one's country). The role LARS is playing in this sector is that it guides the travelers in finding nearby businesses, finding places to stay such as hotels and motels, and much more.

The above-mentioned domain of applications of LARS are the major application areas where LARS have been used, which are found in the consulted literatures with few that do not fall on these categories which we termed as others as presented Table 3.

Table 3 shows all the consulted literature and their domain of applications. It describes the major areas of application of LARS which are categorized into five major categories. Point of interest (POI) is the most widely used application area of LARS, with almost half of the consulted literature focused on using LARS to recommend nearby places such as restaurants, hotels, and news. The second most widely used area is the E-commerce with more works than the rest of the areas, for instances [38], [41], [30] proposed location-aware recommender systems for retail services, which recommend products for a specific retail store to customers that are located close to them. [31], [42] proposed LARS for online marketing platforms and [22], [24], [53] and [3] focused on building LARS that aid in advertisement aspect of E-commerce. Their systems recommend various businesses based on the location of the user.

The next category is travel and tourism [58], [59], [33], [47], [48], [50], [51] proposed LARS to improve travel and tourism experiences by suggesting interesting destination and places to the users. The rest of the categories are entertainment and education accordingly with fewer works done on the areas.

The last category is termed as others, which grouped papers that do not have a direct application area but rather explanatory papers or an improvement upon an existing method. For example, the work of [56] use a form of LARS to recommend drunk drivers to authorities. The system has the capability of detecting the alcohol concentration of the driver, upon exceeding a threshold, that driver is recommended to authorities as potential threat. Looking at the domain of this work, it does not fall directly into any of the above works therefore, it is put into others category.

3.3. Proposed Lars Models

The advent of smartphones, wireless network technology, and Global Positioning System (GPS) paved the way for user's location to be collected easily in real-time and extract useful information such as frequent user check-ins and user behaviors. For example, a place where user usually check-in in the morning, where user frequent check-in in the evening, in working days and weekends. This user behavior can be used to provide automatic recommendations to the user without explicitly collecting check-in at real time. The location context will be used to develop location-based context-aware recommender system.

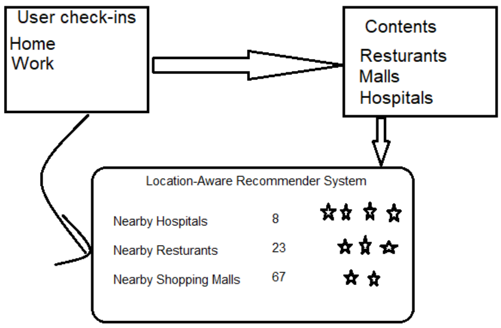

Fig. 3.LARS Publication Trends

This paper proposed several models of LARS based on the traditional RS techniques. The models were proposed by extending traditional methodologies and techniques of RS to include a location context.

In Fig.3 the model will utilize user check-in from a smartphone device, and search history to build a corpus of frequent user locations and search items. This can be used to recommend service based on user current location. For example, a user can check-in at home and search for nearby hospital, or check-in at new hotel and search for nearby restaurants, the recommender will then recommend all the nearby hospitals or restaurant in proximity with user location. In the Fig.3 it can be seen that the user has favorite locations; home and work, and the most frequent search services from history are restaurants, malls, and hospitals. Therefore, in the proposed model, these two contexts will be tailored together to provide a personalized recommendations to the user based on his location. If the user is at work, a very close restaurant will recommend saving a lot of transport time, when compared with distant one.

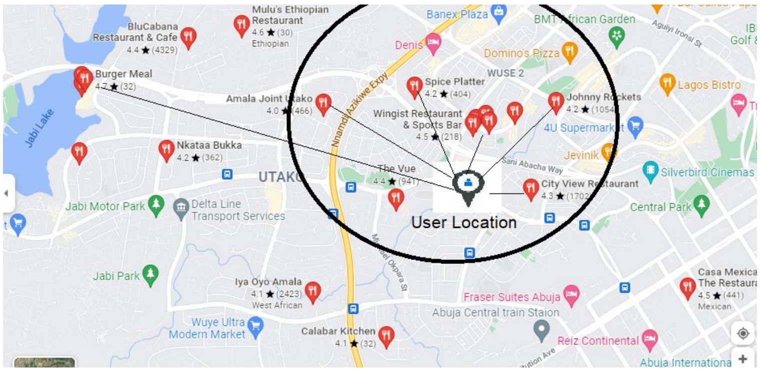

Fig. 4. Displaying nearest restaurants based on user location

Fig.4 provides a simulation of typical scenario of LARS; a user was recommended a restaurant based on the user locations and his proximity to these restaurants.

The section below described all the proposed models of LARS proposed in this paper, the paper present four techniques, LARS based on collaborative filtering, LARS based on Matrix factorization, LARS based on content-based filtering and LARS based Machine learning technology.

3.3.1. Collaborative Filtering LARS (CF-LARS)

It is a method used in traditional recommender system to make a prediction of user interest by collecting preference of many users with the intention that if user like item A, then a similar user will automatically like item A [3]. The intuition can be extended to LARS by integrating location as a contextual information, the collaborative filtering LARS can be formulated as follows:

Given location l for item and user (x, y), then

$$\exists sim(x, y) \tag{2}$$

$$\Omega\eta\varepsilon\rho\varepsilon\text{:}\ x, y \in l \tag{3}$$

This means we can define a similarity function on x, y with respect to l or which belongs to same location l. using Pearson correlation the similarity can be computed as:

$$sim_{l(x,y,i)} = \sum_{u=1}^{n} \frac{\left(r_{u,i,x_l} - r_{\bar{i}}\right)}{\sigma x_l} . \frac{r_{u,i,y_l} - \check{r}_i}{\sigma y_l} \tag{4}$$

Where: sim_ (l(x, y, i)) compute the similarity of item to user with respect to its location l.

3.3.2. Matrix Factorization (MF-LARS)

Despites the fact that MF can be categorized as machine learning technique, it differs from ML technique in the sense that it does not use a classifier to predict ratings, or make recommendations, but rather a predefined objective function by simple matrix multiplication. According to [42] matrix factorization is a technique used to develop LARS by finding out two or more sub-matrices from the factorization of a larger matrix, such that multiplying smaller matrices will approximately get the large matrix. In LARS, Matrix factorization is used to derive matrices of user's preferences and locations from a general matrix that comprises as a whole. It discovers features underlying the interactions between two different kinds of entities which help in predicting ratings.

Given user embedding matrix: $U \in R^{m,\,d}$

Item embedding matrix: $V \in R^{n,\,d}$

Location embedding matrix: $Z \in R^{s,d}$

Therefore, feedback matrix: A= U.V.Z^T
Where A, will give approximate estimation of similar items.
The objective function for the LARS can be given as:

$$\sum_{i,j,k}(A_{i,j,k} - (U_i, V_j, Z_k)^2 \quad (5)$$

3.3.3. Content-Based LARS (CB-LARS):

Content-based filtering is another category of LARS technique that leverages machine learning algorithms power to measure similarities in features to make recommendations. [12, 14, 16, 23, 45] proposed LARS based on CBF techniques, and it differs from the ML technique in the sense that it does not make full use of the algorithms to make the recommendation but rather it calculates item features and compare them to user interests. Simply put, it uses item features to recommend other items similar to what users like.

The recommender can be formulated in 3D problem space, with user U, item I and location L. the recommendation space can be given as:

S=U×I×L

And the rating prediction function can be defined as:

$$R_{user,content,location=}\text{U×I×L}\ \text{ratings} \quad (6)$$

To obtain a rating for user about an item on a certain location using content information, equation (6) can be modified to:

R_ (user, content,location)= R_(user,content,location)= R_(U×C r)

Where r= ratings.

The function calculates the ratings of user on a particular item at a given location, for example, user A may rate item B high in location C, and rate it differently on another location.

3.3.4. Machine Learning (ML-LARS)

Machine learning and deep learning techniques were used to develop RS as in the cases of [51], [30], [33], [40], [35], [37], [21], [42] who proposed LARS with several machine learning models such as Neural Networks, K-nearest Neighbor, and associative data mining algorithms. It was reported by [60] that majority of works in recommender systems use a form of statistics or machine learning to predict the most favorites items to customers. Despite the success rate of this approaches which have proven to be accurate in many domains, the approaches suffer from a major drawback of, it can only work well with a large volume of data. In a situation where there is not enough data, this approach must make some assumed approximate calculations to create the recommendations.

The most popular approach in this statistical way of building recommender system is deep learning, where, softmax embedding is used.

The probability of items can be given as:

$$P_{j=}\ e^{\frac{x,Vj}{z}} \quad (7)$$

Where x: output of the last hidden layer
V: is the matrix of weights of the softmax layer
Z: is the normalization function

The probability function can be simplified as

$$log\ (P_j) = (x, V_j) - \log\ (z) \quad (8)$$

In section 3.3 three LARS models were proposed based on Collaborative filtering, Content Filtering, Matrix factorization and Deep learning techniques. These models were extension of traditional RS techniques to include location as a contextual information to provide personalized recommendation service with greater performance.

The advantage of using deep neural network (DNN) is to overcome the limitations of matrix factorization methods of failure to incorporates query features. CNN can easily incorporate query features and item features (because of flexible input layer), which can help capture the specific interests of a user and improve the relevance of recommendations.

Each of the above models has its strength and weakness, starting with simplest technique CF. According to [20], collaborative filtering is the most popular method used to develop a recommender system because of its capabilities of finding the structure of nonlinear shape in density-based clusters. Moreover [41], mentioned that CF is the most employed method of recommending web services, in their paper they proposed an improvement to RS by adding location context and proposed LARS for recommending web services.

Content based approach is more accurate and robust, it makes recommendation irrespective of other users, unlike the collaborative filtering, and it also consider a little inner relationship between items. The model recommendations are specific to a user which makes it easier to scale to many users.

3.4. Benefit of Lars

In general, LARS improves traditional RS by eliminating most of its drawbacks. In LARS the problem of cold start was completely eliminated. The system enabled new items to be recommended to users even without been rated. As the system gather all items that are tailored to user location rated and unrated. The sparsity problem was also neutralized, the problem arises if some items were rated by few people, then they won't be recommended more often despites their quality. With integration of location context, the items that are rated by few people gets to be recommended as long as they belong to that location. Therefore, LARS actually improve RS recommendations, solves many issues associated with it and provides more personalized and accurate recommendations.

3.5. Challenges of Lars

Despite the huge benefits of LARS, it also has some drawbacks. The success of LARS relies heavily on user check-ins, when locations information of some users or items are hidden, then LARS cannot recommend those items, as they won't be listed in the items to be recommended. This shows that the performance of LARS is reduced with fewer user check-ins. Another problem of LARS is over-generalization. For example. If a person uses LARS for restaurant recommendation, the system will always recommend nearby restaurants to the user, irrespective of his cuisine taste. Chinese person will not receive a recommendation about Chinese restaurant which is not located in the user location. Even though the recommended restaurants might not offer Chinese food.

4. Conclusion

In this review paper, we give a general overview about Location-aware recommender system (LARS). LARS is an extension of traditional RS which came into existence to eliminate the problems of traditional RS, by integrating location contextual information to extend the dimension of RS from 2D to 3D. The review provided an exhaustive discussion about different methodologies of RS available in literature from (2010-2021). It discussed several domains and trend of publication from 2010 to 2021. The paper bridges the knowledge gap missing in previous reviews, by proposing several models of LARS based on the traditional methodologies. It also presents an in-depth discussion about LARS methodologies showcasing their benefits and drawbacks. The paper uncovers that, while LARS eliminates some of the problems of RS such as cold start, sparsity, it still suffers from the problem of over generalization and lack of check-ins by the users. It exposes opportunities and challenges in the field. The paper will serve as a guide to new researchers who want to contribute to the field of LARS.

It is recommended that LARS be improved with the addition of other contexts from user profile such as time, weather and so on. It is also recommended that future research should investigate several performance measures of LARS in order to discover the best performing techniques.

References

[1] Maria del et all, "Location-aware recommendation systems: Where we are and where we recommend to go", Accessed: Apr. 12, 2023. Available at: researchgate.net.

[2] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *IEEE Trans. Knowl. Data Eng.*, vol. 17, no. 6, pp. 734–749, Jun. 2005, doi: 10.1109/TKDE.2005.99.

[3] A. Razia Sulthana and S. Ramasamy, "Context Based Classification of Reviews Using Association Rule Mining, Fuzzy Logics and Ontology," *Bull. Electr. Eng. Informatics*, vol. 6, no. 3, pp. 250–255, Sep. 2017, doi: 10.11591/EEI.V6I3.682.

[4] "Networks in Business -- Research Starters Business | EBSCO | XanEdu Customization Platform.", Availabe at : academicpub.

[5] C. M. Chen, "An intelligent mobile location-aware book recommendation system that enhances problem-based learning in libraries," vol. 21, no. 5, pp. 469–495, Oct. 2013, doi: 10.1080/10494820.2011.593525.

[6] Ughade and A. Arun, "Personalized Location Recommendation System Personalized Location Recommendation System: A Review,", vol. 10, no. 1, pp. 49–58, Jan. 1AD, doi: 10.4018/IJAEC.2019010104.

[7] U. Hanani, B. Shapira, and P. Shoval, "Information filtering: Overview of issues, research and systems," *User Model. User-adapt. Interact.*, vol. 11, no. 3, pp. 203–259, 2001, doi: 10.1023/A:1011196000674.

[8] S. Sharma and D. Kaur, "Location based context aware recommender system through user defined rules," *Int. Conf. Comput. Commun. Autom. ICCCA 2015*, pp. 257–261, Jul. 2015, doi: 10.1109/CCAA.2015.7148384.

[9] H. Tyagi, "An Effective and Accessible Location Aware Recommender System," *Proc. - 2016 8th Int. Conf. Comput. Intell. Commun. Networks, CICN 2016*, pp. 620–622, Oct. 2017, doi: 10.1109/CICN.2016.127.

[10] K. Haruna, M. Ismail, and S. Shuhidan, "Domain of application in context-aware recommender systems: a review," 2016. Available at : researchgate.net.

[11] K. Haruna, M. A. Ismail, A. B. Bichi, V. Chang, S. Wibawa, and T. Herawan, "A citation-based recommender system for scholarly paper recommendation," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10960 LNCS, pp. 514–525, 2018, doi: 10.1007/978-3-319-95162-1_35.

[12] A. Qazi, R. G. Raj, G. Hardaker, and C. Standing, "A systematic literature review on opinion types and sentiment analysis techniques: Tasks and challenges," *Internet Res.*, vol. 27, no. 3, pp. 608–630, 2017, doi: 10.1108/INTR-04-2016-0086.

[13] K. Haruna *et al.*, "Research paper recommender system based on public contextual metadata," *Scientometrics*, vol. 125, no. 1, pp. 101–114, Oct. 2020, doi: 10.1007/S11192-020-03642-Y.

[14] K. Haruna, M. A. Ismail, D. Damiasih, H. Chiroma, and T. Herawan, "A Comprehensive Survey on Comparisons across Contextual Pre-filtering, Contextual Post-filtering and Contextual Modelling Approaches," *TELKOMNIKA (Telecommunication Comput. Electron. Control.*, vol. 15, no. 4, pp. 1865–1874, Dec. 2017, doi: 10.12928/TELKOMNIKA.V15I4.6875.

[15] N. Sakib, R. B. Ahmad, and K. Haruna, “A Collaborative Approach Toward Scientific Paper Recommendation Using Citation Context,” *IEEE Access*, vol. 8, pp. 51246–51255, 2020, doi: 10.1109/ACCESS.2020.2980589.

[16] K. Haruna and M. A. Ismail, “Research paper recommender system evaluation using collaborative filtering,” *AIP Conf. Proc.*, vol. 1974, no. 1, p. 020052, Jun. 2018, doi: 10.1063/1.5041583.

[17] A. Qazi, G. Hardaker, I. S. Ahmad, M. Darwich, J. Z. Maitama, and A. Dayani, “The Role of Information Communication Technology in Elearning Environments: A Systematic Review,” *IEEE Access*, vol. 9, pp. 45539–45551, 2021, doi: 10.1109/ACCESS.2021.3067042.

[18] J. Bao and Y. Zheng, “Location-Based Recommendation Systems,” *Encycl. GIS*, pp. 1145–1153, 2017, doi: 10.1007/978-3-319-17885-1_1580.

[19] M. R. B. M. Razali, S. Ahmad, and N. M. Diah, “Collaborative filtering content for parental control in mobile application chatting,” *Bull. Electr. Eng. Informatics*, vol. 8, no. 4, pp. 1517–1524, Dec. 2019, doi: 10.11591/EEI.V8I4.1634.

[20] R. Vinodha and R. Parvathi, “Location Based Point-Of-Interest Recommendation System Using Co-Pear Similarity Measure,” *Int. J. Sci. Technol. Res.*, vol. 8, 2019, Accessed: Apr. 14, 2023. [Online]. Available: ijstr.org.

[21] N. C. Khalid K and S. K. P, “Personalized and Location aware Online Product Recommendation System,” *Int. J. Sci. Res.*, vol. 6, pp. 2319–7064, 2015, Accessed: Apr. 14, 2023. [Online]. Available: ijsr.net.

[22] H. Ahn and K. J. Kim, “Context-Aware Recommender System for Location-Based Advertising,” *Key Eng. Mater.*, vol. 467–469, pp. 2091–2096, 2011, doi: 10.4028/WWW.SCIENTIFIC.NET/KEM.467-469.2091.

[23] H. Liao, X. Zhang, Z. Long, A. Vidmer, M. Liu, and M. Zhou, “Diffusion-based location-aware recommender systems,” *J. Stat. Mech. Theory Exp.*, vol. 2020, no. 4, p. 043401, Apr. 2020, doi: 10.1088/1742-5468/AB74C5.

[24] W. S. Yang, H. C. Cheng, and J. Ben Dia, “A location-aware recommender system for mobile shopping environments,” *Expert Syst. Appl.*, vol. 34, no. 1, pp. 437–445, Jan. 2008, doi: 10.1016/J.ESWA.2006.09.033.

[25] H. Wang, Y. Fu, Q. Wang, H. Yin, C. Du, and H. Xiong, “A location-sentiment-aware recommender system for both home-town and out-of-town users,” *Proc. ACM SIGKDD Int. Conf. Knowl. Discov. Data Min.*, vol. Part F129685, pp. 1135–1143, Aug. 2017, doi: 10.1145/3097983.3098122.

[26] L. Massai, P. Nesi, and G. Pantaleo, “PAVAL: A location-aware virtual personal assistant for retrieving geolocated points of interest and location-based services,” *Eng. Appl. Artif. Intell.*, vol. 77, pp. 70–85, Jan. 2019, doi: 10.1016/J.ENGAPPAI.2018.09.013.

[27] S. Honarparvar, R. Forouzandeh Jonaghani, A. A. Alesheikh, and B. Atazadeh, “Improvement of a location-aware recommender system using volunteered geographic information,”, vol. 34, no. 13, pp. 1496–1513, Nov. 2018, doi: 10.1080/10106049.2018.1493155.

[28] L. Chen, D. Lyu, Z. Xu, H. Long, and G. Chen, “A content-location-aware public welfare activity information push system based on microblog,” *Inf. Process. Manag.*, vol. 57, no. 1, p. 102137, Jan. 2020, doi: 10.1016/J.IPM.2019.102137.

[29] J. Li and L. Li, “A Location Recommender Based on a Hidden Markov Model: Mobile Social Networks,”, vol. 24, no. 2–3, pp. 257–270, 2014, doi: 10.1080/10919392.2014.896730.

[30] TuZhen, FanYali, LiYong, ChenXiang, SuLi, and JinDepeng, “From Fingerprint to Footprint,” *Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol.*, vol. 3, no. 1, pp. 1–22, Mar. 2019, doi: 10.1145/3314413.

[31] S. Ojagh, M. R. Malek, S. Saeedi, and S. Liang, “A location-based orientation-aware recommender system using IoT smart devices and Social Networks,” *Futur. Gener. Comput. Syst.*, vol. 108, pp. 97–118, Jul. 2020, doi: 10.1016/J.FUTURE.2020.02.041.

[32] Y. Wang, L. Zhu, J. Ma, G. Hu, J. Liu, and Y. Qiao, "Knowledge Graph-Based Spatial-Aware User Community Preference Query Algorithm for LBSNs," *Big Data Res.*, vol. 23, p. 100169, Feb. 2021, doi: 10.1016/J.BDR.2020.100169.

[33] T. Y. Qian, B. Liu, L. Hong, and Z. N. You, "Time and Location Aware Points of Interest Recommendation in Location-Based Social Networks," *J. Comput. Sci. Technol.*, vol. 33, no. 6, pp. 1219–1230, Nov. 2018, doi: 10.1007/S11390-018-1883-7.

[34] S. Xing, F. Liu, X. Zhao, and T. Li, "Points-of-interest recommendation based on convolution matrix factorization," *Appl. Intell.*, vol. 48, no. 8, pp. 2458–2469, Aug. 2018, doi: 10.1007/S10489-017-1103-0.

[35] M. Chen, W. Z. Li, L. Qian, S. L. Lu, and D. X. Chen, "Next POI Recommendation Based on Location Interest Mining with Recurrent Neural Networks," *J. Comput. Sci. Technol.*, vol. 35, no. 3, pp. 603–616, May 2020, doi: 10.1007/S11390-020-9107-3.

[36] S. Chakraverty and A. Mithal, "IoT Based Weather and Location Aware Recommender System," *Proc. 8th Int. Conf. Conflu. 2018 Cloud Comput. Data Sci. Eng. Conflu. 2018*, pp. 610–617, Aug. 2018, doi: 10.1109/CONFLUENCE.2018.8442454.

[37] M. Habayeb, B. Soltanifar, B. Caglayan, and A. Bener, "A Novel Point of Interest (POI) Location Based Recommender System Utilizing User Location and Web Interactions," *Proc. - 2016 IEEE 2nd Int. Conf. Big Data Comput. Serv. Appl. BigDataService 2016*, pp. 121–130, May 2016, doi: 10.1109/BIGDATASERVICE.2016.42.

[38] T. Chatzidimitris *et al.*, "A location history-aware recommender system for smart retail environments," *Pers. Ubiquitous Comput.*, vol. 24, no. 5, pp. 683–694, Oct. 2020, doi: 10.1007/S00779-020-01374-7.

[39] S. Saeed, M. Asim, T. Baker, and Z. Maamar, "A location-sensitive and network-aware broker for recommending Web services," *Computing*, vol. 101, no. 5, pp. 455–475, Mar. 2019, doi: 10.1007/S00607-019-00708-5.

[40] C. Yin, S. Ding, and J. Wang, "Mobile marketing recommendation method based on user location feedback," *Human-centric Comput. Inf. Sci.*, vol. 9, no. 1, pp. 1–17, Dec. 2019, doi: 10.1186/S13673-019-0177-6.

[41] J. Liu, M. Tang, Z. Zheng, X. F. Liu, and S. Lyu, "Location-Aware and Personalized Collaborative Filtering for Web Service Recommendation," *IEEE Trans. Serv. Comput.*, vol. 9, no. 5, pp. 686–699, Sep. 2016, doi: 10.1109/TSC.2015.2433251.

[42] S. B. Aher and L. M. R. J. Lobo, "Combination of machine learning algorithms for recommendation of courses in E-Learning System based on historical data," *Knowledge-Based Syst.*, vol. 51, pp. 1–14, Oct. 2013, doi: 10.1016/J.KNOSYS.2013.04.015.

[43] K. Madadipouya, "A Location-Based Movie Recommender System Using Collaborative Filtering," *Int. J. Found. Comput. Sci. Technol.*, vol. 5, no. 4, pp. 13–19, Aug. 2015, doi: 10.5121/ijfcst.2015.5402.

[44] Q. Fang, C. Xu, M. S. Hossain, and G. Muhammad, "STCAPLRS," *ACM Trans. Intell. Syst. Technol.*, vol. 7, no. 4, Mar. 2016, doi: 10.1145/2842631.

[45] GaoChen, HuangChao, YuYue, WangHuandong, LiYong, and JinDepeng, "Privacy-preserving Cross-domain Location Recommendation," *Proc. ACM Interactive, Mobile, Wearable Ubiquitous Technol.*, vol. 3, no. 1, pp. 1–21, Mar. 2019, doi: 10.1145/3314398.

[46] W. Shafqat and Y. C. Byun, "A Context-Aware Location Recommendation System for Tourists Using Hierarchical LSTM Model," *Sustain. 2020, Vol. 12, Page 4107*, vol. 12, no. 10, p. 4107, May 2020, doi: 10.3390/SU12104107.

[47] C. P S and D. G. H A, "Hybrid Approach for Location Based Customized POI Travel Recommendation System," *Int. J. Eng. Comput. Sci.*, May 2016, doi: 10.18535/IJECS/V5I4.52.

[48] M. Tuteja, "Flight Recommendation System based on user feedback, weighting technique and context aware recommendation system," *Int. J. Eng. Comput. Sci.*, Sep. 2016, doi: 10.18535/IJECS/V5I9.31.

[49] H. Huang, "Context-Aware Location Recommendation Using Geotagged Photos in Social Media," *ISPRS Int. J. Geo-Information 2016, Vol. 5, Page 195*, vol. 5, no. 11, p. 195, Oct. 2016, doi: 10.3390/IJGI5110195.

[50] Y. Li, D. Kim, and B. S. Shin, "Geohashed Spatial Index Method for a Location-Aware WBAN Data Monitoring System Based on NoSQL," *J. Inf. Process. Syst.*, vol. 12, no. 2, pp. 263–274, Jun. 2016, doi: 10.3745/JIPS.04.0025.

[51] C. Chen, T. Lukasiewicz, X. Meng, and Z. Xu, "Location-aware news recommendation using deep localized semantic analysis," *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 10177 LNCS, pp. 507–524, 2017, doi: 10.1007/978-3-319-55753-3_32.

[52] B. Jueajan, K. Naleg, L. Pipanmekaporn, and S. Kamolsantiroj, "Development of location-aware place recommendation system on Android smart phones," *Proc. 2016 5th ICT Int. Student Proj. Conf. ICT-ISPC 2016*, pp. 125–128, Jul. 2016, doi: 10.1109/ICT-ISPC.2016.7519252.

[53] M. Sarwat, J. J. Levandoski, A. Eldawy, and M. F. Mokbel, "LARS*: An efficient and scalable location-aware recommender system," *IEEE Trans. Knowl. Data Eng.*, vol. 26, no. 6, pp. 1384–1399, 2014, doi: 10.1109/TKDE.2013.29.

[54] F. Rehman, O. Khalid, and S. A. Madani, "A comparative study of location-based recommendation systems," *Knowl. Eng. Rev.*, vol. 32, p. e7, Aug. 2017, doi: 10.1017/S0269888916000308.

[55] W. Lin *et al.*, "Location-Aware Service Recommendations with Privacy-Preservation in the Internet of Things," *IEEE Trans. Comput. Soc. Syst.*, vol. 8, no. 1, pp. 227–235, Feb. 2021, doi: 10.1109/TCSS.2020.2965234.

[56] S. L. A. Muthukarpan *et al.*, "Drunken drive detection with smart ignition lock," *Bull. Electr. Eng. Informatics*, vol. 10, no. 1, pp. 501–507, Feb. 2021, doi: 10.11591/EEI.V10I1.2241.

[57] "Oxford Learner's Dictionaries | Find definitions, translations, and grammar explanations at Oxford Learner's Dictionaries." Available at : oxfordlearnersdictionaries .

[58] L. Ravi, V. Subramaniyaswamy, V. Vijayakumar, S. Chen, A. Karmel, and M. Devarajan, "Hybrid Location-based Recommender System for Mobility and Travel Planning," *Mob. Networks Appl.*, vol. 24, no. 4, pp. 1226–1239, Aug. 2019, doi: 10.1007/S11036-019-01260-4.

[59] L. Ravi, S. Vairavasundaram, S. Palani, and M. Devarajan, "Location-based personalized recommender system in the internet of cultural things," *J. Intell. Fuzzy Syst.*, vol. 36, no. 5, pp. 4141–4152, Jan. 2019, doi: 10.3233/JIFS-169973.

[60] N. N. Qomariyah, D. Kazakov, and A. N. Fajar, "On the benefit of logic-based machine learning to learn pairwise comparisons," *Bull. Electr. Eng. Informatics*, vol. 9, no. 6, pp. 2637–2649, Dec. 2020, doi: 10.11591/EEI.V9I6.2384.