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A Comprehensive Literature Survey of Context-Aware Recommender Systems

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Abstract— Recommender systems are tools that assist users in finding products and services on the web and personalize the recommendation accordingly. Collaborative filtering (CF) is the most widely used traditional technique of recommender systems that predict preference of users based on user-item rating model and make proper recommendations. However, many research findings believed that beyond user-item ratings, enhancing the recommendation process by incorporating contextual information, such as location, time, emotions etc, helps to generate accurate recommendations and these are called Context-Aware Recommender Systems (CARS). This paper surveyed the background, the framework, the types of algorithms and other contribution of state-of-the-art researchers in the area of Context-Aware Recommender Systems.

Keywords— Recommender System; Context; Context-Aware Recommender systems; Literature reviews; Context-Aware Recommender systems Framework.

I. INTRODUCTION

Availability of immense amount of digital information makes it difficult for users to find their desired content (e.g., movies, books, music, tourist destinations) in a reasonable time. The contemporary society today has entered the era of Big Data [34] because of the increasing amount of available digital information. Hence, such problem of excessive information prompted a phenomenon called information overload that deter the timely access of right information leading to incorrect decision making [45]. Recommender systems solves this problem by searching through a dynamically generated large volume of information to provide content and services based on user's personal taste and preferences [42].

Given profile of user and a target item, the task of recommender systems is to predict users' rating for that item that reflects the degree of his/her preference towards the item. Particularly, the task of a recommender system is to estimate the rating function: R: User × Item → Ratings that maps user-item pairs to an ordered set of rating values. However, in providing the most relevant items to users, the classic recommender systems center their recommendation decision by relying on user profiles that reflect their personal preference and taste but ignore the importance of understanding the situation in which users consume the items called context. In other words, user preferences for items are a function of items themselves as well as a function of the context in which items are being considered [10].

According to [2], context is any information that characterizes the situation of an entity. Such entity might be a place, person, or object that is considered essential to the interaction between a system and the user. Here, the context considers every aspect of the time, location, activity and preferences of each of the entities. Incorporating relevant contextual information when generating or providing recommendations improve the accuracy of prediction and efficiency of the recommendation. A type of recommender system that utilizes contextual information to adopt its recommendations to users' contextual situations is known as context-aware [44]. A context-aware recommendation system labels each action of the user with an appropriate context and effectively adopts the system output to the user in that given context [10].

This paper is organized in the following way. Section II presents some of the recent literatures surveyed on context-aware recommender systems and section III presents its framework based on those reviewed literatures. The main phases of a typical context-aware recommender system algorithm are discussed in this section. In Section IV, the three typical context-aware recommender system algorithms are identified and elaborated. Finally, Section V concludes the paper.

II. CONTEXT-AWARE RECOMMENDER SYSTEMS (CARS) AND APPLICATIONS

A context-aware recommender system (CARS) model and predict the long-term tastes and preferences of users, expressed as ratings, by integrating existing contextual information into the recommendation process as supplemented category of data [9], [10]. Such users' preferences and tastes are modelled as a function of users, items and context and defined with the rating function R: User × Item × Context → Rating.

Various recommender approaches that boosted with contextual information have been developed for several application domains to enhance recommendation results making use of domain-specific context variables selected based on those applications. To mention some, a context-aware recommender system is proposed by Bogers [48] that suggests context-based relevant movies based on a technique called Markov random walk in which the movie actors, genre and ratings are taken as contextual information for the experiment. Hyung et al. [54] developed a context-based recommender system that suggests music based on textual inputs. The authors applied latent semantic analysis and probabilistic latent semantic analysis for the recommendation process. Kothari et al. [1], proposed a context-based trip advising recommender system by utilizing both context dependent and context independent user preferences data by integrating Support Vector Machine (SVM) classifier model to the recommendation process. They argue that their reason to integrate this classifier model into their proposed contextual recommender system was that SVM has performed consistently well in amplifying the accuracy of the recommendations in maximum domains and has worked towards reducing the errors.

Yoon et al. [31] implemented a personalized context-aware recommender system for music recommendation using selected features, context information and listening history in which feature extraction is applied to find the context of content or the context of users. Cai et al. [43] present a novel contextual music recommendation approach to suggest music when users read Web documents such as Weblogs. The authors extract emotion tags from the online documents to match them with a set of musical lyrics. Similarly, the authors in [52] and [15] mine the mobile logs for context-aware preferences.

Generally, various research attempts are made to build context-aware recommendation systems for several domains of applications to demonstrate its effectiveness in improving the performance of recommendation such as movies [39], [24], restaurants [34], e-commerce [26], [22], travels [40], [18], educational learning [13] etc.

III. FRAMEWORK OF CONTEXT-AWARE RECOMMENDER SYSTEMS

The general framework of a typical context-aware recommender system is depicted in Figure 1. In this framework, firstly, users rating data as well as his/her context information are collected. Then, it is imperative to combine these two data's and generate either by adopting a hierarchical or a multidimensional rating model which captures the user-item interactions and the contextual information. Based on this rating model, the recommendation module is built to predict user interests and recommend related items. All these processes are elaborated as follows.

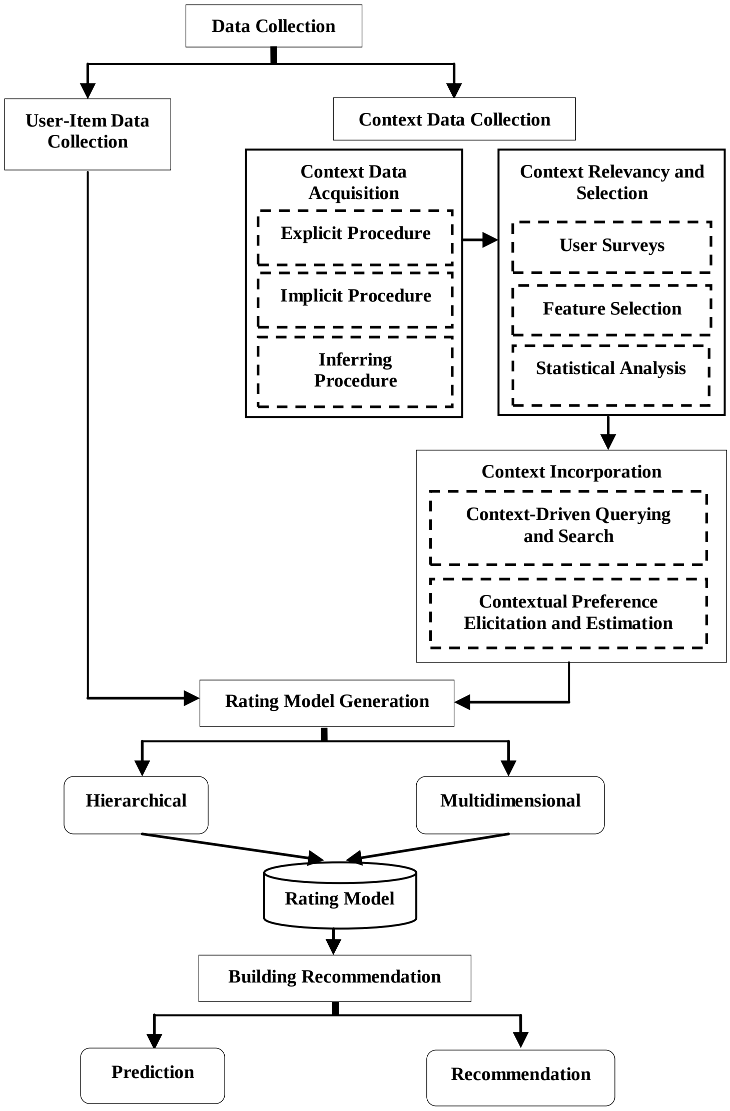

Figure 1 Framework of CARS

A. *Data Collection*

Data collection phase is the fundamental of the entire framework of context-aware recommender systems that mainly fall into two categories: user-item data and context data. The user-item data collection is related to collecting information regarding the preferences (e.g., ratings) of users for the items the system wishes to recommend. On the other hand, the context data collection is simply about capturing the contextual information of the users while expressing their preferences. Furthermore, the context data collection phase is categorized into the following three processes.

1) Context Acquisition

In a context-aware recommender system, relevant contextual information's are collected to generate a context-aware user profile for the prediction tasks. The contextual user profiling is a new paradigm of user profiling, formally proposed by Adomavicus et al. [10] that emerged from context-aware recommendation systems to address the limitations of the traditional user profiling techniques which focus only on the interests of users and how much they express it. The authors researched approaches where such traditional user/ item paradigm was extended to support additional dimensions capturing the context in which recommendations are made. Accordingly, context-aware profiling techniques consider a multidimensional approach to accommodate the user, his/her preferences and the context where user expresses such interests/preferences and this is represented as $R: User \times Items \times Context \rightarrow Rating$ where R is the rating function, *User* and *Items* are the domains of the user and items respectively, and *Context* specifies the contextual information that defines the user and the item domains.

The type of contextual information acquired for user profiling is categorized according to studies conducted by different researchers. In this paper, the authors gathered the common contextual information's utilized for context-aware recommender system and they divided them into the following categories.

User Context

This category of contextual information represents the user's profile, location, their demography, current activity, emotions and the people nearby.

Physical Context

This is the second category of contextual information that represents the time, position, and activity of the user. When the system performs the recommendation, the physical context also includes the weather, light, and temperature information's of the surroundings.

Social Context

This is the third category of contextual information that refers to interactions wherein people react to events differently, depending on their immediate situation. The social context information provides contents such as the presence and role of other people around the user, and whether the user is alone or in a group when using the recommender system.

Interaction media context

This is a type of contextual information that describe the device used to access the system such as a mobile phone, or the type of media, such as ordinary text, music, images, movies, or queries made to the recommender system, that are browsed and personalized.

Modal context

This last category of context type is modal context that represent the user goal, experience, mood, and cognitive capabilities. Generally, it represents the current state of mind of the user while using the recommendation service.

After pinpointing the type of contextual information utilized for the recommender system, the following step is the acquisition techniques that direct how such contextual information can be obtained. According to Adomavicius et al. [10] and Verbert et al. [41], contextual information can be acquired in the following ways.

Explicit

The explicit procedure involves capturing the context information by relying on manual input from the user. This is by explicitly gathering the context by asking direct questions or eliciting information through other means.

Implicit

The implicit procedure involves observing user behaviour and captures the contextual information automatically from the environment such as obtaining the current location or device type. As well, the temporal contextual information, for instance, can be obtained implicitly from the timestamp of a transaction. Unlike the explicit one, this type of context data capturing technique doesn't involve the direct interaction of users with the recommender system; rather the source of the implicit contextual information is accessed directly and the data is extracted from it.

Inferred

The inferring of contextual information for recommender systems can be done by simply analyzing user interactions with tools and resources and the context is acquired by using statistical or data mining methods. This technique is used, for instance, to estimate the current task of the user.

2) Context Relevancy and Selection

The type and extent to which relevant contextual information is incorporated determines the prediction accuracy of CARS. The personalization of recommendation system would be inefficient, inaccurate and its performance degraded if there is an inclusion of irrelevant context information which acts as noise. So, selecting the most relevant context information and ignore the irrelevant one is essential for recommendation performance [3].

Though a vast variety of contextual attributes can be considered during data acquisition based on the particular recommendation application, they are screened and filtered to remove noise and redundancy. Hence, different methodologies for context relevance analysis and selection are investigated by various researchers in the literature. To mention some, Sarwar et al. [46] describes the technique of applying user surveys for relevancy assessment and detection of relevant context using statistical testing. This is to identify the context dimension that would be important for the particular domain of problem that the recommender system trying to solve. Adomavicius et al. [10] also argued that important contextual attributes can be identified by applying statistical testes such as pairwise t-tests. Here the authors added that, the involvement of domain experts in selecting the initial contextual attributes as possible candidates for the application is vital. Then, by calculating the significant deviations in ratings across different values of a contextual attribute, significant contextual attributes can be identified for the recommendation process.

The bayes classifier methodology and the singular value decomposition (SVD) techniques are also applied by Verbert et al. [30] to decide on the context relevancy and select the relevant context dimension for predicting recommendation. Specifically, the application of dimensionality reduction techniques such as SVD and PCA as well as usage of statistical methods for relevant context selection is mostly mentioned by different researches such as [37], [38], [3]. Kim et al. [35] and Kumaravel et al. [3] in their research describes the various concepts related to context-aware recommender system along with the importance of selecting relevant context dimensions through applying the Weighted Principal Component (WPC) and the Principal Component Analysis (PCA) feature selection techniques.

In general, context relevancy as well as relevant context selection can be performed by applying user surveys, feature selection techniques and statistical analysis on contextual ratings [10].

3) Context Incorporation

According to the pioneering researches done by Adomavicius et al. [9], [10], [11] on context-aware recommender system, two of the most applied approaches for context incorporation are *Context-Driven Querying and Search* and *Contextual Preference Elicitation and Estimation* approaches.

In the former approach, the recommendation process obtain the relevant contextual information when users explicitly specified their current situations, for instance their current mood or interest, or by implicitly obtain the current location of the user, the local time and weather information from the environment. Such implicit and explicit user's information is specified as queries to search and present the best matching preferred resource to the user based on their interest. Some applications that utilize this approach are presented in [12], [14].

On the other hand, in the case of contextual preference elicitation and estimation approach, user preferences can be learned and modelled by getting information from their interaction with the system, for instance by getting their feedback on recommended items. In this approach, either traditional recommender system algorithms, such as collaborative filtering, content-based, or their hybrid approach, or intelligent data analysis techniques from data mining or machine learning research, such as Bayesian classifiers or support vector machines, can be adopted to model and recommend users' context-based preferences [10]. This approach is the most adopted technique in many recent CARS literatures [3], [28], [49].

B. Rating Model Generation

According to [10], [9], the rating model generation in context-aware recommender systems can be represented in two forms: as a *hierarchical structure* or *multi-dimensional* model. In the first case, the contextual information is modelled as a hierarchical structure, represented as a tree, to generate the model. This representation defined as a set of contextual dimensions, each having a set of attributes in which each attributes in the set has a hierarchical structure having a particular type of context.

Adomavicius et al. [9] suggested that the second way of generating the rating model is by defining the contextual information as a multi-dimensional model by referring its dimensions. These dimensions are defined in a way that the first two dimensions are User and Item and the rest of the dimensions are contextual information in which each dimension is a subset of a Cartesian product of some attributes (fields) having a single or domain of values. According to the authors, if the model assumes K_1, K_2 . . . ,K_m be dimensions, since this model handle the dimensions as a Cartesian product, the rating function, $R\colon User \times Item \times Context \rightarrow Rating$, can be defined over the space of these dimensions as $R\colon K_1 \times K_2 \times \ldots K_m \rightarrow Rating$.

C. Building Recommendation

The recommendations that are produced by context-aware recommender systems can be of either prediction or recommendation. Prediction is a numerical value, expressing the predicted score of an item for the user based on the contextual information given, while Recommendation is a list of top N items that the user will like the most. In other word, it is generating a short list of recommendations for users by predicting missing values based on his/her contextual settings, ranking the items according to the predicted ratings and finally selecting Top-N of them as recommendations.

D. Evaluation Metrics of Context-Aware Recommender Systems

Once a context-aware recommender system is established, the next challenge is how to evaluate its performance since the quality of a recommender system can be decided on the result of evaluation. Like the traditional collaborative filtering recommender algorithms, most of the context-aware recommender system algorithms perform two vital recommendation tasks; the rating prediction task and item recommendation task as mentioned in section 3.3. Various researches has pointed out the importance of using appropriate evaluation metrics for the two tasks of different formats, and the potential of misleading evaluation results if inappropriate metrics are used. However, unlike the traditional ones, the evaluation of context-aware recommendation algorithms is different since contexts are embedded into the evaluation process as additional inputs.

Typically, the most adopted metrics for evaluating the rating prediction task are by using different prediction errors, such as the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) [24]. These metrics measure the quality of proximity to the truth or the true value achieved by the recommender system. The item recommendation task of the traditional as well as the context-aware recommender systems, on the other hand, can be evaluated through adopting relevance metrics, such as precision and recall, and ranking metrics, such as mean reciprocal rank (MMR), mean average precision (MAP), and normalized discounted cumulative gain (NDCG) [17].

IV. TYPICAL CONTEXT-AWARE RECOMMENDER ALGORITHMS

As explained in section 2, partial user preferences in context-aware recommender systems modelled with data records of the form <user, item, context, rating> where each record define how much a particular item is liked by a user in a specific context. Three types of algorithms are identified by Adomavicius et al. [10] to work on such record of context-based user-preferences namely, contextual prefiltering, contextual postfiltering and contextual modelling.

The contextual prefiltering approach uses the current context information to select the ratings. Then, the ratings on the selected data can be predicted by applying any traditional two-dimensional recommender system algorithm. On the other hand, the contextual postfiltering algorithm initially ignores the contextual information but predict the ratings using any traditional two-dimensional recommender system algorithm on the whole data set. Finally, the contextual information is used to adjust the output of the recommendation for each user.

The contextual modelling approach is a third type of algorithm that directly utilizes the contextual information to predict the rating for an item by formulating a multidimensional recommendation functions. This function represents predictive models that are built using probabilistic models, decision trees, regression or heuristic-based calculations by using the rating as well as the contextual information.

There are several studies that manifest the possibility of employing the combined approaches of the three algorithmic paradigms for context-aware recommender systems just like combining the functionality of traditional recommender system algorithms to achieve a higher predictive performance [51], [32], [42]. Adomavicius et al. [10], for instance, suggest a model that combines the functionality of different contextual pre-filters.

V. CONCLUSION

This article discusses context-aware recommender systems (CARS) employed for different domain of applications. A framework is firstly presented in order to express the main phases of a typical context-aware recommender system, i.e., data collection (which further separated into user-item data collection and context data collection), rating model generation, and building recommendation. The context data collection phase further categorized into three essential processes: context acquisition, context relevancy and selection and context incorporation. In this phase, features of common contextual information's, how to captured and incorporate them into the rating model are analyzed in detail. Evaluation Metrics of Context-Aware Recommender Systems are also discussed where those metrics are adopted in the traditional recommender algorithms as well. Typical context-aware recommender algorithms including contextual prefiltering, contextual postfiltering and contextual modeling are also introduced and their common features are elaborated. Overall, the study found that the application of context-aware recommendation approach seems to increase dramatically in providing users with context-aware services. It is believed that the continuously improved context-aware recommender systems can greatly help users find proper items based on their contextual settings without much effort in the era of Big Data. The authors believe that the CARS framework which is developed and suggested in this paper offers a general development guideline and on the basis of this framework and the literature provided, this paper open the opportunities for future research to be conducted on context-aware recommender systems and its applications.

REFERENCES

[1] A.A. Kothari and W.D. Patel, "A Novel Approach Towards Context Based Recommendations Using Support Vector Machine Methodology," In *Proc.* Recent Trends in Computing, 2015, pp. 1171 – 1178.

[2] A. Dey, G. Abowd, and D. Salber, "A Conceptual Framework and a Toolkit for Supporting the Rapid Prototyping of Context-Aware Applications," *Journal of Human-Computer Interaction*, vol.16, pp. 97–166, 2001.

[3] A. Kumaravel and Pallab D., "Application of PCA for Context Selection for Collaborative Filtering," *Middle-East Journal of Scientific Research*, vol. 20, pp. 88-93, 2014.

[4] Adomavicius, G. and Tuzhilin, A., "Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions," *IEEE Knowledge and Data Engineering*, vol.17, pp. 734– 749, 2005.

[5] Adomavicius, G. and A. Tuzhilin, *Context-aware recommender systems*, in Recommender Systems Handbook, F. Ricci, et al., Ed. New York, USA: Springer, 2011.

[6] F.O. Isinkaye, Y.O. Folajimi, B.A. Ojokoh, "Recommendation systems: Principles, methods and evaluation," *Egyptian Journal of Informatics*, vol.16, pp.261–273, 2015.

[7] G. Adomavicius, R. Sankaranarayanan, S. Sen, and A. Tuzhilin, "Incorporating contextual information in recommender systems using a multidimensional approach," in *Proc. TOIS*, 2005, pp. 103–145.

[8] D. Gallego, E. Barra, P. Rodriguez, and G. Huecas, "Incorporating Proactivity to Context-Aware Recommender Systems for E-Learning," in *Proc.WCCIT*, 2013.

[9] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions," *IEEE Knowledge and Data Engineering*, vol.17, pp. 734 -749, 2005.

[10] G. Adomavicius and A. Tuzhilin, "*Context-Aware Recommender Systems*," Recommender Systems Handbook: A Complete Guide for Research Scientists and Practitioners, L. Rokach, B. Shapira, P. Kantor, and F. Ricci, Ed. Springer, 2011.

[11] G. Adomavicius, A. Tuzhilin, Shlomo Berkovsky, E. W. Luca and Alan Said, "Context-awareness in recommender systems: Research workshop and movie recommendation challenge," in *Proc. Recommender systems*, ACM, 2010, pp. 385–386.

[12] G. D. Abowd, C. G. Atkeson, J. Hong, S. Long, R. Kooper, and M. Pinkerton, "Cyberguide: A mobile context-aware tour guide," *ACM Wireless Networks*, vol.3, pp. 421–433, 1997.

[13] G. Salton and M.McGill, "*Introduction to Modern Information Retrieval*," New York, NY, USA: McGraw-Hill, 1983.

[14] F. Cena, L. Console, C. Gena, A. Goy, G. Levi, S. Modeo, and I. Torre, "Integrating heterogeneous adaptation techniques to build a flexible and usable mobile tourist guide," *ACM AI Communications*, vol.19, pp. 369–384, 2006.

[15] H. Zhu, E. Chen, H. Xiong, K. Yu, H. Cao, and J. Tian, "Mining mobile user preferences for personalized context-aware recommendation," *ACM Intelligent Systems and Technology (TIST)*, vol.5, p. 58, 2014.

[16] I. Bartolini, Z. Zhang, and D. Papadias, "Collaborative filtering with personalized skylines," *IEEE Knowledge Data Engineering*, vol.23, pp. 190-203, 2011.

[17] J. Breese, D. Heckerman, and C. Kadie, "Empirical analysis of predictive algorithms for collaborative filtering," In *Proc. UAI '98*, 1998, pp, 43-52.

[18] J. D. M. Rennie and N. Srebro, "Fast maximum margin matrix factorization for collaborative prediction," In *Proc. ICML '05*, 2005, pp. 713-719.

[19] J. Hong *, E. Suh, S. Kim, "Context-aware systems: A literature review and classification," *Elsevier Expert Systems with Applications*, vol.36, pp. 8509 – 8522, 2008.

[20] J. Kwon, "A Study on Effective Proactive Service in Pervasive Computing Environment," *International Journal of Computer Science and Network Security (IJCSNS)*, vol.12, pp. 35-39, 2012.

[21] J. L. Herlocker, J. A. Konstan, L. G. Terveen, and J. T. Riedl, "Evaluating collaborative filtering recommender systems," *ACM Information Systems*, vol.22, pp.5–53, 2004.

[22] J. L. Herlocker, J. A. Konstan, A. Borchers, and J. Riedl, "An algorithmic framework for performing collaborative filtering," In *Proc. Research and development in information retrieval*, 1999, pp. 230-237.

[23] J. Herlocker, J. A. Konstan, and J. Riedl, "An empirical analysis of design choices in neighborhood-based collaborative filtering algorithms," *Journal of Information Retrieval*, vol.5, pp. 287–310, 2002.

[24] J. L. Herlocker, J. A. Konstan, L. G. Terveen, and J. T. Riedl, "Evaluating collaborative filtering recommender systems," *ACM Information Systems*, vol.22, pp.5–53, 2004.

[25] J. Madhusudanan, A. Selvakumar, and R.Sudha, "Framework for Context aware Applications," In *Proc. ICCCNT*, 2010.

[26] Jennings A, Higuchi H., "A personal news service based on a user model neural network," *IEICE Information and System*, vol.E75- D, pp.198–209, 1992.

[27] K. F. Yeung and Y. Yang, "A Proactive Personalized Mobile News Recommender System," In *Proc. DESE*, 2010, pp. 207-212.

[28] K. Oku, S. Nakajima, J. Miyazaki, and S. Uemura, "Context-aware SVM for context-dependent information recommendation," In Proc. MDM, 2006, p.109.

[29] K. Verbert, N. Manouselis, X. Ochoa, M. Wolpers, H. Drachsler, I. Bosnic and E. Duval. "Context-Aware Recommender Systems for Learning: A Survey and Future Challenges," *IEEE Learning Technologies*, vol.5, pp. 318-335, 2012.

[30] K. Verbert, N. Manouselis, X. Ochoa, M. Wolpers, H. Drachsler, I. Bosnic and E. "Duval - Context-Aware Recommender Systems for Learning: A Survey and Future Challenges," *IEEE Learning Technologies*, vol.5, pp. 318-335, 2012.

[31] K. Yoon, J. Lee, and M.-U. Kim, "Music recommendation system using emotion triggering low-level features," *IEEE Consumer Electronics*, vol.58, pp. 612–618, 2012.

[32] K. Yu, B. Zhang, H. Zhu, H. Cao, and J. Tian, "Towards personalized context-aware recommendation by mining context logs through topic models," In *Proc. Advance Knowledge Discovery Data Mining*, 2012, pp. 431–443.

[33] K. Zheng, Z. Yang, K. Zhang, P. Chatzimisios, K. Yang, and W. Xiang, "Big data-driven optimization for mobile networks toward 5G," *IEEE Network*, vol.30, pp. 44 -51, 2016.

[34] Kim, S. B. and Rattakorn, P., "Unsupervised feature selection using weighted principal components," *Journal of Expert Systems with Applications*, vol.38, pp. 5704 -5710, 2011.

[35] Kumaravel, "A Layered Approach for Predicting Protein Subcellular Localization in Yeast Microarray Data," *Indian Journal of Science and Technology*, vol.6, pp. 4568 - 4571, 2013.

[36] Kumaravel, “A Efficient Molecule Reduction for Drug Design by Intelligent Search Methods,” *International Journal of Pharmacy and Bio Sciences*, vol.4, pp. 1023-1029, 2013.
[37] Kumaravel, “A Construction of Meta Classifiers for Apple Scab Infections,” *International Journal of Pharmacy and Bio Sciences*, vol.4, pp. 1207-1213, 2013.
[38] L. Yao, Q. Z. Sheng, A. H. H. Ngu, J. Yu, and A. Segev, “Unified collaborative and content-based Web service recommendation,” *IEEE Services Computing*, vol.8, pp. 453 - 466, 2014.
[39] M. Gates, H. Anzt, J. Kurzak, and J. Dongarra, “Accelerating collaborative filtering using concepts from high performance computing,” In *Proc. Big Data*, 2015, pp. 667- 676.
[40] N. Y. Asabere, “Towards a Viewpoint of Context-Aware Recommender Systems (CARS) and Services,” *International Journal of Computer Science and Telecommunications*, vol.4, pp. 19 -29, 2013.
[41] R. Burke, “Hybrid Recommender Systems: Survey and Experiments”, *Journal of User Modeling and User-Adapted Interaction*, vol.12, pp. 331-37, 2002.
[42] R. Cai, C. Zhang, C. Wang, L. Zhang, and W.-Y. Ma, “MusicSense: Contextual music recommendation using emotional allocation modeling,” In *Proc. Multimedia*, 2007, pp. 553–556.
[43] B. Sarwar, G. Karypis, J. Konstan and J. Riedl, “Analysis of recommendation algorithms for e-commerce,” In *Proc. Electronic Commerce*, ACM, 2000, pp. 158-167.
[44] S. Gao, H. Luo, D. Chen, S. Li, P. Gallinari, Z. Ma, and J. Guo, “A cross-domain recommendation model for cyber-physical systems,” *IEEE Emerging Topics in Computing*, vol.1, pp. 384-393, 2013.
[45] Sarwar B., Karypis G., Konstan J., and Riedl J., “Application of Dimensionality Reduction in Recommender System – A case Study,” In *Proc. ACM Web KDD Workshop*, 2000.
[46] Suchman, L., “*Plans and Situated Actions*,” Cambridge University Press, Cambridge, UK, 1987.
[47] T. Bogers, “Movie recommendation using random walks over the contextual graph,” In *Proc. Context-Aware Recommender Systems*, 2010.
[48] U. Panniello, A. Tuzhilin, M. Gorgoglione, C. Palmisano, and A. Pedone., “Experimental comparison of pre vs. post-filtering approaches in context-aware recommender systems,” In *Proc. Recommender systems*, 2009, pp.265 –268.
[49] Unger M, Bar A, Shapira B, Rokach L., “Towards latent context-aware recommendation systems,” *Journal of Knowledge-Based Systems*, vol.104, pp. 165–178, 2016.
[50] X. Su and T. M. Khoshgoftaar, “A Survey of Collaborative Filtering Techniques” *ACM Advances in Artificial Intelligence*, vol.4, pp. 1-19, 2009.
[51] X. Su and T. M. Khoshgoftaar, “Collaborative Filtering for Multi-class Data Using belief Nets Algorithms,” In *Proc. ICTAI ’06*, 2006, pp. 497–504.
[52] Y. Shi, A. Karatzoglou, L. Baltrunas, M. Larson, A. Hanjalic, and N. Oliver, “TFMAP: Optimizing map for top-n context-aware recommendation,” *In Proc.Research and Development in Information Retrieval*, 2012, pp. 155 – 164.
[53] Z. Hyung, K. Lee, and K. Lee, “Music recommendation using text analysis on song requests to radio stations,” *Journal of Expert System Applications*, vol.41, pp. 2608–2618, 2013.

