

A Framework for Cognitive Recommender Systems in the Internet of Things (IoT)

Kamran Gholizadeh HamlAbadi

Faculty of Computer and Information Technology
Engineering
Qazvin Branch, Islamic Azad University
Qazvin, Iran
K.gholizadeh@qiau.ac.ir

Ali Mohammad Saghiri

Computer Engineering and Information Technology
Department
AmirKabir University of Technology
Hafez Ave., Tehran, 15914, Iran
Saghiri@aut.ac.ir

Monireh Vahdati

Faculty of Computer and Information Technology
Engineering
Qazvin Branch, Islamic Azad University
Qazvin, Iran
Vahdati.monireh@gmail.com

Mehdi Dehghan TakhtFooladi

Computer Engineering and Information Technology
Department
AmirKabir University of Technology
Hafez Ave., Tehran, 15914, Iran
Dehghan@aut.ac.ir

Mohammad Reza Meybodi

Computer Engineering and Information Technology Department
AmirKabir University of Technology
Hafez Ave., Tehran, 15914, Iran
mmeybodi@aut.ac.ir

Abstract— Internet of Things (IoT) will be emerged over many of devices that are dynamically networked. Because of distributed and dynamic nature of IoT, designing a recommender system for them is a challenging problem. Recently, cognitive systems are used to design modern frameworks in different types of computer applications such as cognitive radio networks and cognitive peer-to-peer networks. A cognitive system can learn to improve its performance while operating under its unknown environment. In this paper, we propose a framework for cognitive recommender systems in IoT. To the best of our knowledge, there is no recommender system based on cognitive systems in the IoT. The proposed algorithm is compared with the existing recommender systems.

Keywords-component; *Internet of Things(IoT), recommender systems, cognitive recommender systems, cognitive system.*

I. INTRODUCTION

Internet of Things (IoT) will be emerged over many of devices that are dynamically networked. In these systems, the devices communicate, sense, and interact with their environment. Recommender systems represent user preferences for the purpose of suggesting items to purchase or examine[1]. Because of distributed and dynamic nature of IoT, designing a recommender system for them is a challenging problem.

Different approaches are used to design recommender systems in IoT [2].

Recent approaches for designing recommender systems in IoT based applications invest in context-aware computations. Context-aware recommender systems (CARS) generate relevant recommendations by adapting to the specific contextual situation of the user[3]. In [4], a context-aware recommender system framework deployed in urban space to engage anonymous viewer is reported. In other study, [5] presents a Multi-Agent System (MAS) based solution for generating personalized recommendations on mobile devices with the use of contextual data acquired from the IoT. Note that, in IoT, the computational power of computers is not limited to consume contextual information and every computer is able to execute a wide range of machine learning algorithms. Therefore, it seems that we need a new framework for future generation of recommender systems.

Recently, the cognitive systems are used to design modern frameworks in different types of computer applications such as cognitive radio networks and cognitive peer-to-peer networks[6-8]. Cognitive systems can learn to improve their performance while operating under their unknown environment. It seems that the cognitive systems have high

potential to be used in designing next generation of recommender systems in IoT.

In this paper, we propose a framework for cognitive recommender systems in IoT. A cognitive recommender system learns from the experiences that happen in the past to improve the decisions about recommendations. To the best of our knowledge, there is no recommender system based on cognitive systems in the IoT.

The rest of the paper is organized as follows. Section II and section III introduces related work and preliminary. In Section IV, a framework for cognitive recommender systems is suggested. Section V is dedicated to discussion and comparison. Section VI concludes the paper.

II. RELATED WORK

Recent approaches for designing recommender systems in IoT focus on context-aware computations and personalization methods such as those reported in [4, 5]. Note that cognitive systems has not been used to design recommender systems in IoT but cognitive IoT has been reported in [9]. A main drawback of existing recommender systems is that they do not use a general framework. Therefore, a designer cannot analyze and extend them easily. It seems that the cognitive systems can be used to design a general purpose cognitive framework which is not application dependent. All of existing recommender systems reported in [4, 5] and [10-24] are not based on cognitive systems.

In other hand, as it was previously mentioned, the computational power of computers of things is not limited to consume contextual information and every computer is able to execute a wide range of machine learning algorithms. Therefore, it seems that we need a new framework for future generation of recommender systems. In this paper, we suggested a general framework for cognitive recommender systems for IoT. The suggested framework can be used as a standard framework for the next generation of recommender systems in IoT.

III. PRELIMINARIES

In this section, in order to provide basic information for the remainder of the paper, we present a brief overview of cognitive systems and recommender systems.

A. Cognitive Systems

A cognitive system can learn to improve its performance while operating under its unknown environment. Many theories are reported in the literature to model a cognitive system[10]. In this paper, we use a three-layer model for a learning system which is widely used to model a cognitive system in artificial intelligence. The layers are described as bellow.

- A layer to determine the goals and behavior for the system.
- A layer to analyses the status of the environment and making appropriated decisions considering the goals of the system.

- A layer consisting sensors to observe the environment. This layer also consists modifiable elements for changing the environment of the cognitive system.

This model was used to define modern frameworks for managing computer networks such as those reported in[7, 8]. We will customize it in our suggested framework for the cognitive recommender systems.

B. Recommender Systems

Recommender systems are tools which provide users suggestions by analyzing their behaviors to help them make a good decision [11]. The Recommender systems can be classified into five different techniques: Content-based recommender systems which analyze item descriptions in order to identify items that are particular interest to users [12]. Collaborative filtering recommender systems use ratings data provided by the user. User similarity is based on user rating[13]. Demographic recommender systems recommend items based on the identification of the demographic enumeration which the user fits better according to a personal demographic profile [14]. Knowledge-based recommender systems recommend items based on specific domain knowledge regarding how items meet user references [15]. Hybrid recommender systems are based on the combination of the aforementioned techniques.

IV. A FRAMEWORK FOR COGNITIVE RECOMMENDER SYSTEM

In this section, we present a framework for cognitive recommender system. The goal of the cognitive recommender system is to provide an appropriate set of recommendation list to users. This framework consists of three layers: Requirement Layer(RL), Cognitive Process Layer(CPL), and Things System Layer(TSL). Note that, we borrowed some concepts from framework of the cognitive networks introduced by [6, 7] and present a framework for cognitive recommender system. The structure of the framework is shown in figure 1.

A. Requirement Layer

In the requirement layer, the goal and behavior of the network are described by a Cognitive Specification Language (CSL). Each thing finds a file called configuration file that is shared in the IoT. In the configuration file, the CLS is used to determine the goals of the cognitive recommender systems. Each thing finds the goals of the cognitive recommender system from the configuration file and then transfers them to the CPL. This layer enables the manager to change the goals of the cognitive recommender engine by sharing a new file as configuration file. It should be noted that, changing the goals of the cognitive recommender system in the RL leads to changing the optimizing functions in the CPL.

Several approach considering distributed nature of IoT for sharing the configuration things are suggested below.

- **Centralized approach:** In this approach, the configuration file will be saved in a server. Each thing connects to the server and then finds the last version of the configuration file.

- **Semi-centralized approach:** In this approach, the configuration file will be saved in multiple servers in the IoT.
- **Fully-distributed approach:** In this approach, the configuration file can be saved in every thing of the IoT. Each thing periodically download the last version of the configuration file from its neighboring things and then update its configuration file considering the downloaded configuration file.

B. Things System Layer

In the Things System Layer (TSL), the things sensors and recommendation list are designated based on local configurations of the things in the IoT. In other words, cognitive recommender engine uses its IoT's sensors for gathering local information about its corresponding thing in the network to observe things. The things sensors can be considered in different vision based on technologies such as Near Field Communication(NFC), wireless sensor, Actuator Network(WSAN), RFID and etc.[16]. cognitive recommender engine also acts on its recommendation list. During design of the TSL, a list of required functions for the things sensors. and recommendation list must be prepared. In the rest of this subsection, we describe about the required functions.

- The required functions for the things sensors are defined based on goals of the cognitive recommender system. The things sensors must be able to execute appropriate functions to find local and global information about the environment of the things.
- The required functions for representing the recommendation list. If the recommendation algorithm is in charge of tuning a parameter for representing the recommendations, we must have techniques for tuning the recommender system.

C. Cognitive Process Layer

The Cognitive Process Layer(CPL) is implemented using the cognitive engine resided in the cognitive recommender engine. The cognitive recommender engine observes things from the things sensor in the TSL. This layer executes the recommendation algorithm and act on the recommendation list. Because of distributed nature of IoT, the cognitive recommender engine can be implemented using one of the following methods.

- **Centralized cognitive engine:** In this type, the cognitive engine is implemented in one server.
- **Semi-centralized cognitive engine:** In this type, the cognitive engine is implemented in multiple servers.
- **Fully-distributed cognitive engine:** In this type, every thing has its own cognitive engine.

In all of above methods, the information about the things is shared in the cognitive engines.

During implementation of the CPL, several decisions should be made which some of them are explained as below.

- Decision about selecting the goal of the cognitive recommender system that determines which objective function should be optimized.
- Decision about selecting things sensors considering the goal of the cognitive recommender engine.
- Decision about selecting recommendation list which can be used in the cognitive recommendation processes in order to improve the performance of the cognitive recommender engine.
- Decision about selecting appropriate learning mechanism considering the status of recommender system. Because of distributed and dynamic nature of recommender system, the artificial intelligence technique which can use distributed information about things of the network is a good candidate for designing learning mechanism of the cognitive recommender engines in IoT[17].

Note that, we can use every learning mechanism considering the conditions of the cognitive recommender engine in the proposed framework.

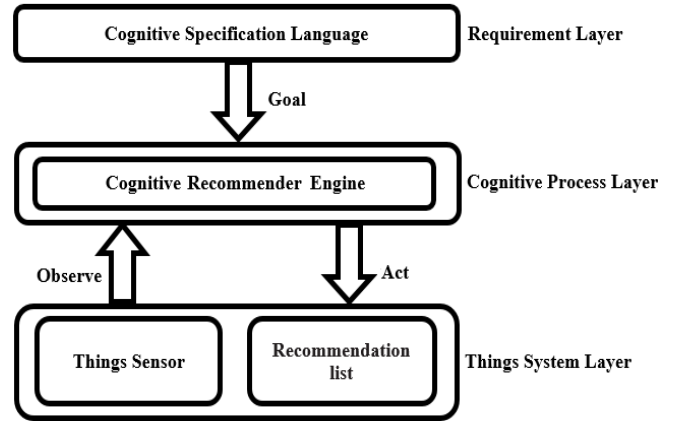


Figure 1. A framework for cognitive recommender system

V. DISCUSSION AND COMPARISON

In this section, first, we summarize the features of the proposed framework and then compare it with other studies. the features of the proposed framework are listed below.

- The proposed framework is a **general purpose** framework which is not limited to a specific application.
- The proposed framework is based on **cognitive systems**. A cognitive system can learn to improve its performance while operating under its unknown environment. Note that, the proposed framework is self-adaptive. This is because of existing a feedback loop which enable the system to reorganize itself considering the feedbacks.
- The proposed framework is **flexible**. In this framework, the designer (or system admin) using the

cognitive specification language is able to change the configurations/objectives of the system during operation of the system.

- The proposed framework enables the **information sharing** among things using cognitive engine. Information sharing among things enable the things to execute their management problems in collaborative manner.

The mentioned metrics were used to compare the proposed framework with other studies reported in the literature. Table I shown the compared our framework with other studies

TABLE I. THE DETAILS OF ALGORITHMS REPORTED IN THE LITRITURE

Reference	Evaluation Metrics			
	General Purpos	Cognitive	Flexible	Information sharing
(Frey et al., 2015) [18]	✓	✗	✓	✓
(Mashal et al., 2015) [19]	✗	✗	✓	✓
(Twardowski and Ryzko, 2015) [5]	✗	✗	✗	✓
(Cha et al., 2016) [20]	✗	✗	✗	✓
(Chirila et al., 2016) [21]	✗	✗	✗	✓
(Tu et al., 2016) [4]	✗	✗	✗	✓
(Le and Co., 2016) [22]	✓	✗	✗	✓
(Yavari et al., 2016) [23]	✗	✗	✗	✓
(Saleem et al., 2016) [24]	✓	✗	✓	✓
(Sewak and Singh, 2016) [25]	✓	✗	✗	✓
(Noirie et al., 2017) [26]	✓	✗	✓	✓
(Nizamkari, 2017) [27]	✗	✗	✗	✓
(Forestiero, 2017) [28]	✓	✗	✗	✓
(Matsui and Choi, 2017) [29]	✗	✗	✗	✓
(Palaokrassas et al., 2017) [30]	✓	✗	✗	✓
(Asthana et al., 2017) [31]	✗	✗	✓	✓
Proposed framework	✓	✓	✓	✓

To the best of our knowledge, our work is novel and there hasn't been any prior study on designing cognitive framework for recommender system in the IoT.

VI. CONCLUSION

In this paper, we proposed a framework for the cognitive recommender system in Internet of Things (IoT). This framework is the first framework based on cognitive systems for the recommender systems in the IoT. In this framework, the recommender engine observes the things sensor. Then, the

information about users and items are used to solve user/item prediction problem. This framework can be a reference framework for future research in the field of the recommender systems. The proposed framework was compared with other existing solutions with respect to four metrics. For future research we can implement an IoT platform for a real-time recommender system.

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REFERENCES

- [1] R. Burke, "Hybrid recommender systems: Survey and experiments," *User modeling and user-adapted interaction*, vol. 12, pp. 331-370, 2002.
- [2] J. Kwon and S. Kim, "Study on Recommendation in Internet of Things Environment," in *Multimedia, Computer Graphics and Broadcasting (MulGraB), 2015 7th International Conference on*, Jeju, South Korea, 2015, pp. 13-14.
- [3] G. Adomavicius and A. Tuzhilin, "Context-aware recommender systems," in *Recommender systems handbook*, ed: Springer, 2011, pp. 217-253.
- [4] M. Tu, Y.-K. Chang, and Y.-T. Chen, "A Context-Aware Recommender System Framework for IoT based Interactive Digital Signage in Urban Space," in *Proceedings of the Second International Conference on IoT in Urban Space*, Tokyo, Japan, 2016, pp. 39-42.
- [5] B. Twardowski and D. Ryzko, "IoT and context-aware mobile recommendations using Multi-Agent Systems," in *Web Intelligence and Intelligent Agent Technology (WI-IAT), 2015 IEEE/WIC/ACM International Conference on*, Singapore, Singapore, 2015, pp. 33-40.
- [6] R. Thomas, D. Friend, L. DaSilva, and A. Mackenzie, "Cognitive Radio, Software Defined Radio, and Adaptive Wireless Systems, chapter Cognitive Networks," ed: Springer, 2007.
- [7] R. W. Thomas, D. H. Friend, L. A. Dasilva, and A. B. Mackenzie, "Cognitive networks: adaptation and learning to achieve end-to-end performance objectives," *IEEE Communications Magazine*, vol. 44, pp. 51-57, 2006.
- [8] A. M. Saghir and M. R. Meybodi, "An approach for designing cognitive engines in cognitive peer-to-peer networks," *Journal of Network and Computer Applications*, vol. 70, pp. 17-40, 2016.
- [9] F. M. Al-Turjman, "Information-centric sensor networks for cognitive IoT: an overview," *Annals of Telecommunications*, vol. 72, pp. 3-18, 2017.
- [10] P. N. Johnson-Laird, *The computer and the mind: An introduction to cognitive science*: Harvard University Press, 1988.
- [11] L. Lü, M. Medo, C. H. Yeung, Y.-C. Zhang, Z.-K. Zhang, and T. Zhou, "Recommender systems," *Physics Reports*, vol. 519, pp. 1-49, 2012.
- [12] M. J. Pazzani and D. Billsus, "Content-based recommendation systems," in *The adaptive web*, ed: Springer, 2007, pp. 325-341.
- [13] C. W.-k. Leung, S. C.-f. Chan, and F.-l. Chung, "An empirical study of a cross-level association rule mining approach to cold-start recommendations," *Knowledge-Based Systems*, vol. 21, pp. 515-529, 2008.
- [14] L. O. Colombo-Mendoza, R. Valencia-García, A. Rodríguez-González, G. Alor-Hernández, and J. J. Samper-Zapater, "RecomMetz: A context-aware knowledge-based mobile recommender system for movie showtimes," *Expert Systems with Applications*, vol. 42, pp. 1202-1222, 2015.
- [15] F. Ricci, L. Rokach, and B. Shapira, "Introduction to recommender systems handbook," in *Recommender systems handbook*, ed: Springer, 2011, pp. 1-35.
- [16] L. Atzori, A. Iera, and G. Morabito, "The internet of things: A survey," *Computer networks*, vol. 54, pp. 2787-2805, 2010.
- [17] G. Adomavicius and A. Tuzhilin, "Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions," *IEEE transactions on knowledge and data engineering*, vol. 17, pp. 734-749, 2005.
- [18] R. M. Frey, R. Xu, and A. Ilic, "A novel recommender system in IoT," presented at the 5th International Conference on the Internet of Things (IoT), Seoul, South Korea, 2015.

- [19] I. Mashal, T.-Y. Chung, and O. Alsaryrah, "Toward service recommendation in Internet of Things," in *Ubiquitous and Future Networks (ICUFN), 2015 Seventh International Conference on*, Sapporo, Japan, 2015, pp. 328-331.
- [20] S. Cha, M. P. Ruiz, M. Wachowicz, L. H. Tran, H. Cao, and I. Maduako, "The role of an IoT platform in the design of real-time recommender systems," in *Internet of Things (WF-IoT), 2016 IEEE 3rd World Forum on*, Reston, VA, USA, 2016, pp. 448-453.
- [21] S. Chirila, C. Lemnaru, and M. Dinsoreanu, "Semantic-based IoT device discovery and recommendation mechanism," in *Intelligent Computer Communication and Processing (ICCP), 2016 IEEE 12th International Conference on*, Cluj-Napoca, Romania, 2016, pp. 111-116.
- [22] J.-S. Lee and I.-Y. Ko, "Service Recommendation for User Groups in Internet of Things Environments Using Member Organization-Based Group Similarity Measures," in *Web Services (ICWS), 2016 IEEE International Conference on*, San Francisco, CA, USA, 2016, pp. 276-283.
- [23] A. Yavari, P. P. Jayaraman, and D. Georgakopoulos, "Contextualised service delivery in the Internet of Things: Parking recommender for smart cities," in *Internet of Things (WF-IoT), 2016 IEEE 3rd World Forum on*, Reston, VA, USA, 2016, pp. 454-459.
- [24] Y. Saleem, N. Crespi, M. H. Rehmani, R. Copeland, D. Hussein, and E. Bertin, "Exploitation of social IoT for recommendation services," in *Internet of Things (WF-IoT), 2016 IEEE 3rd World Forum on*, Reston, VA, USA, 2016, pp. 359-364.
- [25] M. Sewak and S. Singh, "IoT and distributed machine learning powered optimal state recommender solution," in *Internet of Things and Applications (IOTA), International Conference on*, Pune, India, 2016, pp. 101-106.
- [26] L. Noirie, M. Le Pallec, and N. Ammar, "Towards automated IoT service recommendation," in *Innovations in Clouds, Internet and Networks (ICIN), 2017 20th Conference on*, Paris, France, 2017, pp. 103-106.
- [27] N. S. Nizamkari, "A graph-based trust-enhanced recommender system for service selection in IOT," in *Inventive Systems and Control (ICISC), 2017 International Conference on*, Coimbatore, India, 2017, pp. 1-5.
- [28] A. Forestiero, "Multi-agent recommendation system in Internet of Things," in *Proceedings of the 17th IEEE/ACM International Symposium on Cluster, Cloud and Grid Computing*, Madrid, Spain, 2017, pp. 772-775.
- [29] K. Matsui and H. Choi, "A recommendation system with secondary usage of HEMS data for products based on IoT technology," in *Networks, Computers and Communications (ISNCC), 2017 International Symposium on*, Marrakech, Morocco, 2017, pp. 1-6.
- [30] G. Palaiokrassas, I. Karlis, A. Litke, V. Charlaftis, and T. Varvarigou, "An IoT architecture for personalized recommendations over big data oriented applications," in *Computer Software and Applications Conference (COMPSAC), 2017 IEEE 41st Annual*, Turin, Italy, 2017, pp. 475-480.
- [31] S. Asthana, A. Megahed, and R. Strong, "A Recommendation System for Proactive Health Monitoring Using IoT and Wearable Technologies," in *AI & Mobile Services (AIMS), 2017 IEEE International Conference on*, Honolulu, Hawaii, USA, 2017, pp. 14-21.
- [32] L. M. De Campos, J. M. Fernández-Luna, J. F. Huete, and M. A. Rueda-Morales, "Combining content-based and collaborative recommendations: A hybrid approach based on Bayesian networks," *International Journal of Approximate Reasoning*, vol. 51, pp. 785-799, 2010.

VII. APPENDX

In this section, in order to study the applicability of the proposed framework, a collaborative algorithm is given using the proposed framework. The performance of the proposed algorithm shows that its performance with respect to precision, recall, and F1-measure is better than other algorithms when the number of recommendations are limited. In other word, the proposed algorithm is appropriate for devices with small screens. Note that, In IoT based applications, the screens of devices are limited. In the rest of this section, at first an

algorithm based on the proposed framework is given and then its performance is studied.

A. An approach based on hybrid recommendation for designing cognitive recommender system

In this section, we propose an algorithm based on suggested recommender system. In this part, the recommender engine input includes several elements such as user profile, user preferences and product specifications, which are observe from the things sensors. The recommender engine implements a hybrid recommendation algorithm with combining the collaborative filtering and content-based algorithms. The collaborative filtering predicts a user's interests by collecting data onto a great number of other users especially those whose rating trends towards the items which are similar to the target user's. The content based algorithm is the similarity between items which is used instead of the similarity between users. The recommender engine can predict user ratings through a collaborative mechanism which includes content-based estimations and acts a list of recommendations to the user.

In the things sensor component, once a user selects a thing, the information transferred into the things sensor component. All users have IDs, and user profile has been saved into user profile database in the recommendation engine. In the recommendation list component, the result of recommender system is transferred into user mobile phones and displayed in the user mobile phone screen.

Algorithm cognitive recommender engine

Inputs

User status from the things sensor
The goal and behavior of the network are described by Cognitive Specification Language

Output

Recommender engine act the recommendation list to present the users.

01: Begin

02: Compute the user and item scores in the matrix score.

03: Implement the *hybrid recommender system technique* with combining the *collaborative filtering* and *content-based techniques*.

04: Defined the hybrid correlation weight which determines the significance of the *collaborative filtering* and *content-based techniques* in the *hybrid algorithm*.

05: Compute the Pearson correlation with respect to a significance weight factor.

06: **IF** number of common items greater than **50** **Then**
cross it with **1**.

07: Compute self-weighting factor reflects the confidence in the *content-based algorithm*.

08: End.

B. Experimental results

In this section, the dataset used in this study is introduced first; we examined the hybrid algorithm by obtaining the results of collaborative filtering and content-based algorithms in order to predict the ranks. Finally, we compared the performance of the proposed recommender system with other studies.

1) Datasets

There is no dataset for the retails in the fields of the IoT. According to this limitation, we validated our algorithm through experiments on the Movie lens data set. Movie Lens

data sets were collected by the Group Lens Research Project at the University of Minnesota. This data set consists of: 1) 100,000 ratings (1-5) from 943 users on 1682 movies. 2) Each user has rated at least 20 movies and 3) Simple demographic info for the users (age, gender, occupation, zip).

The data was collected through the Movie Lens web site. (movielens.umn.edu) during the seven-month period from September 19th, 1997 through April 22nd, 1998. This data has been cleaned up – users who had less than 20 ratings or did not have complete demographic information were removed from this data set¹.

2) Results

a) Experiments

In the algorithm proposed to this study, a specific time was considered for providing recommendations. The ratings given before that time were considered to be the train file, and the ratings after that time was called the test matrix. To compare the results of each paper, the precision, recall and F1-measure criteria were used.

In this section, the results of the proposed algorithm were compared with those obtained from other study on recommender systems in order to compare the efficiency of the proposed algorithm. In [32], a Bayesian network was first introduced to calculate the likelihood that a user would give a specific rating to an item. Using this network, the ratings pertaining to the content-based and collaborative filtering algorithms were obtained, and then combined.

According to figure 2, the value of precision in the algorithm proposed here performed better for fewer recommendations in comparison with those in the other study. However, as the number of recommendations increased, the precision of the results of the current study decreased and then remained unchanged. According to figure 3, the results of the Recall criterion, we conclude that this value would be increased with increasing the number of recommendations. Our proposed recommendation is a good performance when the number of recommendations are limited in with compare the [32]. According to figure 4, The results of F1-Measure indicated that if the number of recommendations increased, this value would also be increased.

It is natural that the quality of the above criteria shall increase as the number of recommendations increased. However, as things have limitations displaying information, the number of recommendations displayed on things should also be limited.

According to the results obtained as the Precision, Recall, and F1-Measure criteria, the proposed algorithm showed a better

performance for fewer recommendations in comparison with other study.

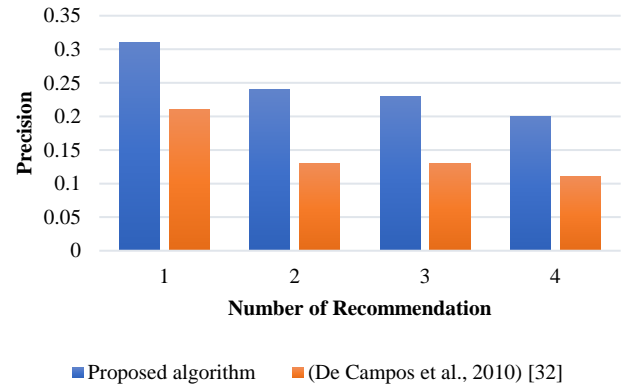


Figure 2. Comparison cognitive recommendation with other study of with Precision

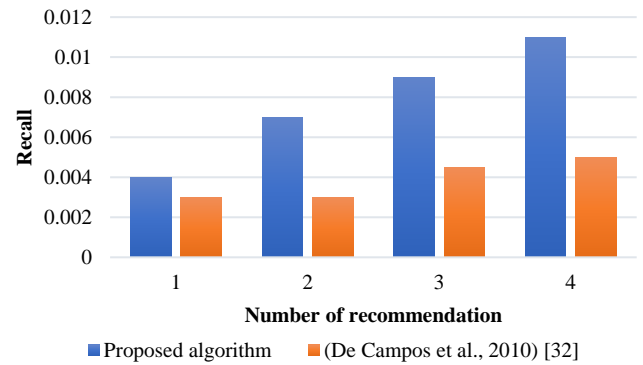


Figure 3. Comparison cognitive recommendation with other study of with Recall

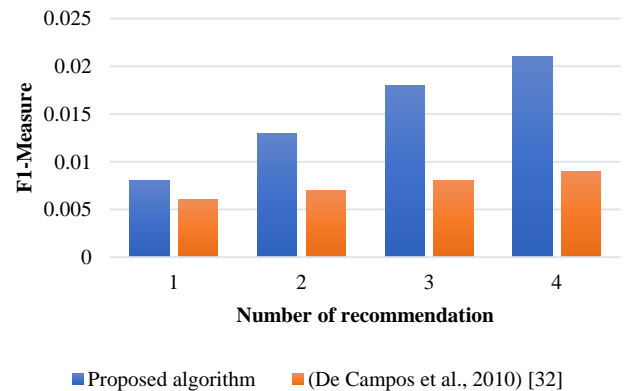


Figure 4. Comparison cognitive recommendation with other study of with F1-Measure

¹ Available at <http://www.grouplens.org/node/73>