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A personalized recommendation procedure with contextual information*

Hyun Sil Moon
School of Management and Management Research Institute, Kyunghee University
(pahunter@khu.ac.kr)

Il Young Choi
School of Dance and Culture Item Factory Center, Kyunghee University
(choice102@khu.ac.kr)

Jae Kyeong Kim
School of Management and Management Research Institute, Kyunghee University
(jaek@khu.ac.kr)

As personal devices and pervasive technologies for interacting with networked objects continue to proliferate, there is an unprecedented world of scattered pieces of contextualized information available. However, the explosive growth and variety of information ironically lead users and service providers to make poor decision. In this situation, recommender systems may be a valuable alternative for dealing with these information overload. But they failed to utilize various types of contextual information. In this study, we suggest a methodology for context-aware recommender systems based on the concept of contextual boundary. First, as we suggest contextual boundary-based profiling which reflects contextual data with proper interpretation and structure, we attempt to solve complexity problem in context-aware recommender systems. Second, in neighbor formation with contextual information, our methodology can be expected to solve sparsity and cold-start problem in traditional recommender systems. Finally, we suggest a methodology about context support score-based recommendation generation. Consequently, our methodology can be first step for expanding application of researches on recommender systems. Moreover, as we suggest a flexible model with consideration of new technological development, it will show high performance regardless of their domains. Therefore, we expect that marketers or service providers can easily adopt according to their technical support.

Keywords : context-aware recommender system; recommender system; collaborative filtering; contextual information; contextual boundary

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1. Introduction

As personal devices (e.g., smart phone or wearable devices) and pervasive technologies for interacting with networked objects in IoT (Internet of Things) environments continue to proliferate, there is an unprecedented world of scattered pieces of contextualized information available (Gershenfeld

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et al., 2004; Lee and Hong, 2011). However, the explosive growth and variety of information with these technologies ironically lead users and service providers to make poor decision because they are hard to be interpreted and structured (Zhang et al., 2011).

In this situation, recommender systems may be a valuable alternative for dealing with these information overload of them (Mulvenna et al., 2000; Garcia-Molina et al., 2011). But they failed to utilize various types of contextual information as traditional recommender systems (e.g., collaborative filtering systems, and so on) only consider user explicit or implicit ratings (Konstan, 2004; Adomavicius et al., 2005). Therefore, such environments offer unique challenges to researcher of recommender systems which do not typically consider information about where and when a particular user accesses (Adomavicius and Tuzhilin, 2005). Recently, as it is important to cope with challenges to use these contextual information into the recommendation system in order to make a recommendation list under certain situation of the user, many applications called context-aware recommender systems (CARS) have been attempted.

With the evolution of computing paradigm, we should consider some important things in context-aware recommender systems. First, the propagation of personal devices such as wearable devices and the development of sensing technologies extremely increase the amount of data dealing with. Context-aware recommender systems are performed based on not only preferences of users and item profiles in their generation of recommendation, but also contextual information such as location, time, or weather. Moreover, these data need suitable interpretation based on knowledge from experts and taxonomies. Therefore, with the development of technologies, studies for context-aware recommender systems should solve complexity problem for composing user profiles. Second, in IoT environment, their devices spontaneously interact with each other. Therefore, each interaction in an efficient manner gradually updates the current users' context. That is, as they track users' behavior in real-time, recommendations should be consistently fitted by users' current context and systems should be activate interactively in real-time. Lastly, plentiful data set related with users such as contextual information can be utilized to infer their preferences. Therefore, as we suggest a novel user model with consideration of contextual information, our methodology is also expected to solve sparsity and cold-start problem in traditional recommender systems.

Consequently, in this study, we suggest a methodology for context-aware recommender systems based on the concept of contextual boundary. First, as we suggest contextual boundary-based profiling which reflects contextual data with proper interpretation and structure, we attempt to solve complexity problem in context-aware recommender systems. Second, in neighbor formation with contextual information, our methodology can be expected to solve sparsity and cold-start problem in traditional recommender systems. Because, with contextual boundary of the target user in recommendation process, our methodology decide candidate neighbor set of the target user before neighbor formation stage, it can recommend items even their users have no purchase records or their data set is sparse. Finally, we suggest a methodology about context support score-based recommendation generation. Although typical recommender systems generate recommendation lists based on similarity between neighbors, we attempt to consider interactivity in our methodology as it regenerates recommendation lists according to the target user's current context.

2. Related Work

As a kind of personalization technics, recommender systems traditionally are performed based upon a two-dimensional matrix representation of preferences ($N \times M$; N users by M products). However, Adomavicius et al.(2005) suggest that each users under various situations may have different preferences and needs according to their context. Therefore, with the development of technologies, contextual information recently is considered as additional valuable information sources to inference the user preference. Context in recommender systems refers to any information which express the current situation of an entity including the user (Kim et al., 2007). Although it have been defined by various researchers in recommendation studies such as Table 1, the definition of context in this study is derived from Dey et al.(1998).

In the last decades, there are many attempts to using these contextual information in their generation of a recommendation list. Especially, Adomavicius and Tuzhilin(2005) suggest three paradigms for context-aware recommender systems such as Figure 1.

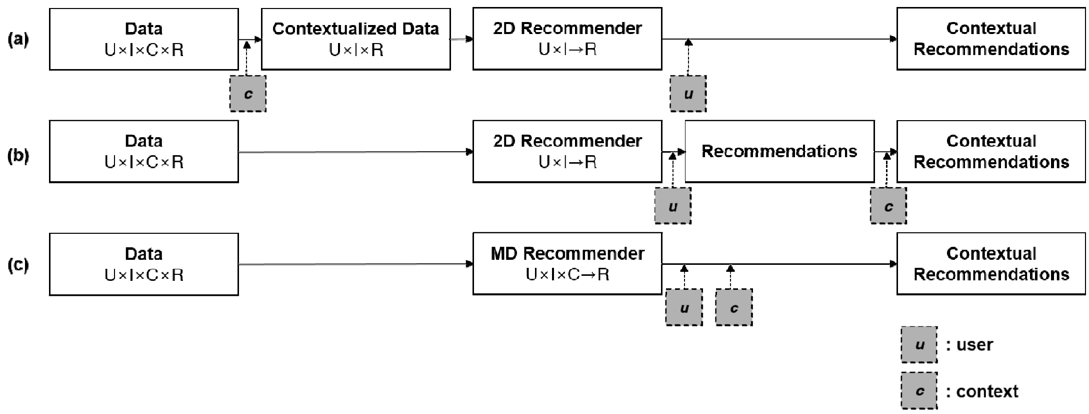
(a) *Contextual pre-filtering* : contextual information is used to make contextualized data set which is filtered data set according to the specific context of users

(b) *Contextual post-filtering* : although contextual information is ignored in initial stage of recommendation process, the initial recommendation list though recommender systems is adjusted according to each user's situation (i.e., context)

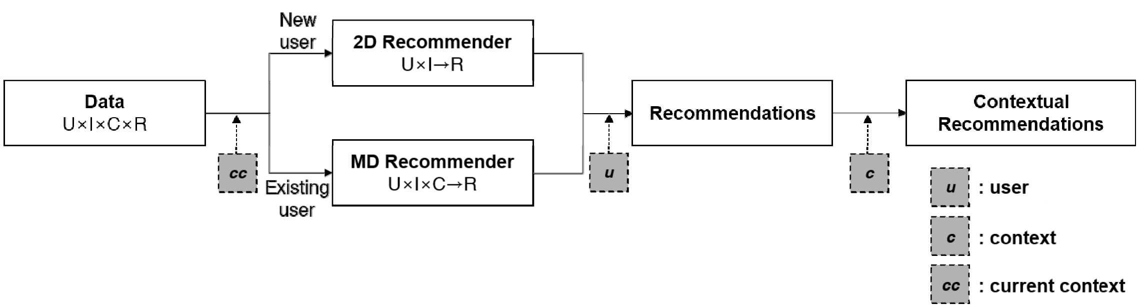
(c) *Contextual modeling* : using contextual

〈Table 1〉 Definition of context

	Definition
Brown et al.(1997)	location, who they are with, time of day, season of the year, temperature, and so fourth
Ryan et al.(1998)	location, time, temperature, user identity
Dey(1998)	information the user is attending to, emotional state, focus of attention, location and orientation, date and time of day, objects and people in the user's environment
Dey et al.(1998)	any information about the user and the environment that can be used to enhance the user's experiences



〈Figure 1〉 Paradigms for CARS



〈Figure 2〉 Conceptual model for methodology

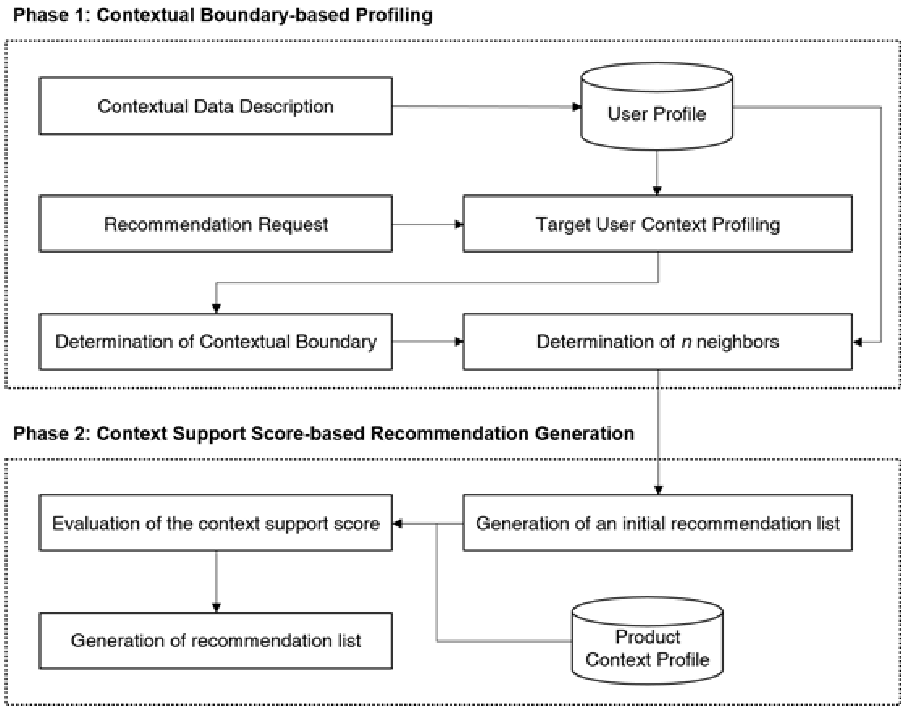
model for recommendation process as a factor to estimate preference, they directly use contextual information to generate a recommendation list.

In this study, such as Figure 2, we attempt to combine three paradigms as mentioned above. First, in the case of existing user, we adopted contextual modeling concept with a user model based on contextual boundary for his/her recommendations. On the other hand, in the case of new user, we adopted contextual pre-filtering based on the current context boundary of the user. Second, in the perspective of contextual post-filtering, our methodology filters initial recommendation lists according to the target user's contextual boundary in the contextual space.

3. Methodology

2.1. Overall Procedure

Based on conceptual model, an overall procedure of our methodology is composed of two phases; contextual boundary-based profiling and context support score-based recommendation generation. In contextual boundary-based profiling



〈Figure 3〉 Overall procedure

phase, according to the current context of the target user, we determine *n*-minded neighbors utilizing contextual boundary of the target user and existing user profile. And then we generate a recommendation list utilizing context support score and neighbors' opinion for products in context support score-based recommendation generation phase. Detailed procedure of our methodology is shown as Figure 3.

Before description of our methodology, we first define user profile and product context profile. According to contextual data description based on the knowledge of experts and taxonomies, a user profile is defined as a collection of his/her sensing data from various devices and purchasing records. Therefore, our user profile is composed of two parts; the matrix of product preference ratings $\forall R(u_i, i_j) \in U \times I$ and context preference ratings $\forall C(u_i, c_{pq}) \in U \times C$. First, the product preference ratings are defined as

$$R(u_i, i_j) = \begin{cases} 1, \text{if the user } u_i \text{ purchases the product } i_j \\ 0, \text{otherwise} \end{cases} \tag{1}$$

where u_i means the i^{th} user and i_j means the j^{th} product. Hence, when user u_i purchases the product i_j, the user ratings is 1. Second, the context preference ratings are defined as

$$R(u_i, i_j) = \begin{cases} 1, if\ the\ user\ u_i\ purchases\ the\ product\ i_j \\ 0, otherwise \end{cases} \quad (2)$$

where p means p^{th} context dimension and q means q^{th} context in p^{th} context dimension. Therefore, each context description is involved in a certain context dimension. Namely, the context preference ratings are in a contextual space of each user.

On the other hand, a product context profile is a collection of sensing data which is obtained when users purchased it. Likewise the context preference rating of users, the product context profiles are defined as

$$R(u_i, i_j) = \begin{cases} 1, if\ the\ user\ u_i\ purchases\ the\ product\ i_j \\ 0, otherwise \end{cases} \quad (3)$$

These profiles are utilized as source of recommendations. Especially, in the case of new user, user profile is narrowly used.

2.2. Phase 1: Contextual Boundary-based Profiling

When the target user requests a recommendation list, we first update his/her context preference ratings with a current context $C_{current} = \{c_{1a}, c_{2b}, \cdots, c_{pq}\}$. If the target user u_T requests a recommendation list at $C_{current}$, context preference rating of the target user u_T will be temporarily updated following as

$$C(u_T, c_{pq}) = \begin{cases} \frac{(\#\ of\ purchases\ in\ the\ context\ c_{pq}) + 1}{(\#\ of\ purchases\ in\ the\ context\ dimension\ p) + 1} & (c_{pq} \in C_{current}) \\ \frac{(\#\ of\ purchases\ in\ the\ context\ c_{pq})}{(\#\ of\ purchases\ in\ the\ context\ dimension\ p) + 1} & (c_{pq} \notin C_{current}) \end{cases} \quad (4)$$

As mentioned above, in the case of new user which does not have user profile, its context preference rating is defined as

$$C(u_T, c_{pq}) = \begin{cases} 1 & (c_{pq} \in C_{current}) \\ 0 & (c_{pq} \notin C_{current}) \end{cases} \quad (5)$$

After updating the target user profile, we determine the centroid and range of contextual boundary of the target user. Contextual boundary refers to approximate preference for each context. In our methodology, the centroid of contextual boundary $C_{centroid}$ is equal with the updated context preference rating $C(u_T, c_{pq}) \in C_{current}$. That is, we use only context preference ratings related with the current context of the target user. And the range of contextual boundary is defined as $(C_{centroid} \pm \gamma)$ where γ is a parameter for the range $(0 \leq \gamma \leq 1)$. Therefore, the bigger mean the more indifferent of context preference ratings.

As a last step of contextual boundary-based profiling, we determine *n* neighbors for the target user. In this step, we first find candidate neighbors of the target user utilizing context preference ratings and boundary. Candidate neighbors means users in the condition of

$$(C_{centroid} - \gamma) \leq \forall C(u_n, c_{pq}) \leq (C_{centroid} + \gamma) \quad (6)$$

where $C(u_n, c_{pq}) \in C_{current}$. That is, candidate neighbors refer to users who have similar context preference with the target user in the current context. After finding candidate neighbors, we calculate the similarity between the target user and candidate neighbors. But if the target user is new user, we will not calculate the similarity and *n* neighbors are equal with candidate neighbors. Similarity between the target user u_T and the candidate neighbor u_n is calculated as

$$sim\,(u_T, u_n) = corr_{u_T u_i} = \frac{\sum_{j=1}^{n}\left(R(u_T, i_j) - \overline{R(u_T)}\right)\left(R(u_n, i_j) - \overline{R(u_n)}\right)}{\sqrt{\sum_{j=1}^{n}\left(R(u_T, i_j) - \overline{R(u_T)}\right)^2 \sum_{j=1}^{n}\left(R(u_n, i_j) - \overline{R(u_n)}\right)^2}} \quad (7)$$

where similarity denotes Pearson correlation which is well-known approach in collaborative filtering systems. According to the similarity between users, we can determine top-*n* neighbors in candidate neighbors.

2.3. Phase 2: Context Support Score-based Recommendation Generation

In phase 2, we generate a recommendation list based on context support score. For this purpose, we first generate an initial recommendation list for the target user. The initial recommendation list is created along with the purchase likelihood score (PLS) (Adomavicius and Tuzhilin, 2005). We suggest two ways to calculate the PLS whether the target user is new or existing user.

$$PLS\,(u_T, i_j) = \frac{\sum_{n \in neighbors} R(u_n, i_j)}{\#\ of\ neighbors} \quad (8)$$

$$PLS\,(u_T, i_j) = \frac{\sum_{n \in neighbors} R(u_n, i_j) \times sim(u_T, u_n)}{\sum_{n \in neighbors} sim(u_T, u_n)} \quad (9)$$

Here, equation (8) is the simplest case which has some drawbacks that the similarity measure is not considered and it is easily affected deviation of ratings. But because new user has not similarity value, equation (8) is utilized for new user. In the case of existing user, with the similarity measure, equation (9) is utilized. As the higher the purchase likelihood score mean the higher probability that the target user will purchase the product, we generate top-*k* initial recommendation list according to their purchase likelihood score.

Before generating the recommendation list, for contextual post-filtering, we evaluate the context support score of products in the initial recommendation list. The context support score of the target user u_T to the product i_j is defined as

$$Context\ support\ score(u_T, i_j) = \sum_{c_{pq} \in C_{current}} C(i_j, c_{pq}) \quad (10)$$

Finally, as the higher context support score mean the more purchases in the current context of the target user, we sort the products according to their context support score and return *N* products with the high context support score among the initial recommendation list.

4. An Illustrative Example

To help readers understating better, we now

〈Table 2〉 Raw data for an example

weather			time			date		
sunny	cloudy	rain	09～12	12～15	15～18	weekday	weekend	holiday
4	0	6	8	2	0	5	5	0
2	3	0	0	3	2	0	1	4
1	4	5	2	2	6	3	3	4

〈Table 3〉 Contextual data description

Context(c_{pq})								
weather(c_{1q})			time(c_{2q})			date(c_{3q})		
sunny (c_{11})	cloudy (c_{12})	rain (c_{13})	09～12 (c_{21})	12～15 (c_{22})	15～18 (c_{23})	weekday (c_{31})	weekend (c_{32})	holiday (c_{33})
0.4	0	0.6	0.8	0.2	0	0.5	0.5	0
0.4	0.6	0	0	0.6	0.4	0	0.2	0.8
0.1	0.4	0.5	0.2	0.2	0.6	0.3	0.3	0.4

〈Table 4〉 Target use rprofile

	weather(c_{1q})			time(c_{2q})			date(c_{3q})		
	sunny (c_{11})	cloudy (c_{12})	rain (c_{13})	09～12 (c_{21})	12～15 (c_{22})	15～18 (c_{23})	weekday (c_{31})	weekend (c_{32})	holiday (c_{33})
u_T	1	2	6	3	4	2	0	1	8

present an example. Especially, as our methodology takes account of the contextual space concept and is based on traditional collaborative filtering technics, we explain with an illustrative example to show. Table 2 represents raw data description for contextual data description in this section.

In Table 2, a value in raw data means the number of purchases at each context which is classified by a taxonomy. Using this raw data, we make a user profile according to contextual data description such as Table 3.

According to a taxonomy, our example has three contextual dimension; weather(c_{1q}), time (c_{1q}), and date(c_{1q}). And each dimension has three contexts in it. A value in Table 3 means the context preference rating of each user. For example, the context rating of sunny c_{11} for user u_1 is evaluated as

$$C(u_1, c_{11}) = \frac{\#\ of\ purchases\ in\ the\ context\ c_{11}}{\#\ of\ purchases\ in\ the\ context\ dimension\ 1}$$

$$= \frac{4}{4+0+6} = 0.4$$

Based on contextual data description, suppose that the target user requests a recommendation in {sunny(c_{11}); 12~15(c_{22}); weekend(c_{32})}. So the

〈Table 5〉 Updated profile of the target user

	weather(c_{1q})			time(c_{2q})			date(c_{3q})		
	sunny (c_{11})	cloudy (c_{12})	rain (c_{13})	09～12 (c_{21})	12～15 (c_{22})	15～18 (c_{23})	weekday (c_{31})	weekend (c_{32})	holiday (c_{33})
u_T	0.2	0.2	0.6	0.3	0.5	0.2	0	0.2	0.8

〈Table 6〉 Contextual space of the target user

	weather(c_{1q})	time(c_{2q})	date(c_{3q})
	sunny (c_{11})	12～15 (c_{22})	weekend (c_{32})
$C_{centroid}$	0.2	0.5	0.2
u_1	0.4	0.2	0.5
u_2	0.4	0.6	0.2
u_3	0.1	0.2	0.3

current context of the target user is $C_{current} = \{c_{11}, c_{22}, c_{32}\}$. If the target user u_T has a user profile like Table 4, his/her context preference ratings are updated following as Table 5 when the target user request a recommendation list.

That is, a context such as sunny(c_{11}) which includes in $C_{current}$ is updated by

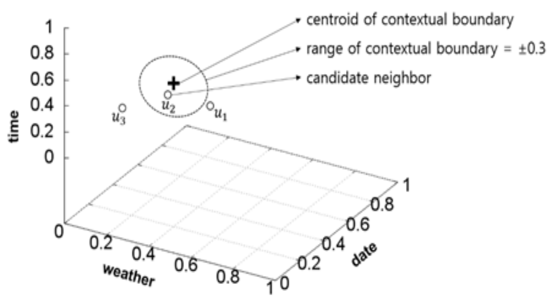
$$\frac{(\#\ of\ purchases\ in\ the\ context\ c_{pq}) + 1}{(\#\ of\ purchases\ in\ the\ context\ dimension\ p) + 1}$$

like $c_{11} = \frac{(1+1)}{(9+1)} = 0.2$, otherwise they are updated by

$$\frac{(\#\ of\ purchases\ in\ the\ context\ c_{pq})}{(\#\ of\ purchases\ in\ the\ context\ dimension\ p) + 1}$$

like $c_{12} = \frac{2}{(9+1)} = 0.2$.

Based on this updated profile, we composed of the contextual space of the target user according to the current context. In this example, three context dimension and the contextual space are composed such as Table 6 according to $C_{current}$ and the centroid of the target user is $C_{cetroid} = \{0.2, 0.5, 0.2\}$. If we set a range parameter γ to 0.3, the contextual boundary of the target user is $C_{cetroid} \pm 0.3$. The shaded areas in Table 6 mean that the value is located in the contextual boundary. Figure 4 represents a conceptual graphic of the contextual boundary.



〈Figure 4〉 Conceptual graphic of the contextual boundary

〈Table 7〉 Product context profile

	weather(c_{1q})			time(c_{2q})			date(c_{3q})		
	sunny (c_{11})	cloudy (c_{12})	rain (c_{13})	09～12 (c_{21})	12～15 (c_{22})	15～18 (c_{23})	weekday (c_{31})	weekend (c_{32})	holiday (c_{33})
p_1	0.4	0.6	0	0	0.6	0.4	0	02	0.8
p_2	0.1	0.4	0.5	0.2	0.2	0.6	0.3	0.3	0.4

Therefore, u_2 is only selected as a candidate neighbor. Until now we only explain the concept of context awareness in our methodology, we leave similarity calculation and neighbor selection out of this section. That is, candidate neighbors are equal to neighbor list of the target user.

To simplify the recommendation generation process, suppose that u_2 only purchased two products and their purchase likelihood scores are equal. That is, we only consider context support scores of products in this example. Therefore, an initial recommendation list is composed of products p_1 and p_2. An example of product context profile is represented as Table 7.

For generation of a recommendation list, we evaluate the context support score of products based on product context profile and the current context of the target user. Shaded areas in Table 7 means contexts which are satisfied by $C_{current}$. In this example, the context support score of each product is following as

$$Context\ support\ score(u_T, p_1) = \sum_{c_{pq} \in C_{current}} C(p_1, c_{pq})$$

$$= 0.4 + 0.6 + 0.2 = 1.2$$

$$Context\ support\ score(u_T, p_2) = \sum_{c_{pq} \in C_{current}} C(p_2, c_{pq})$$

$$= 0.1 + 0.2 + 0.3 = 0.6$$

Consequently, our methodology recommends a product p_1 to the target user u_T according to the context support score.

5. Conclusion

In this study, we propose a novel approach for context-aware recommender systems (CARS). Technological development has made us enhance our life, but the explosive growth and variety of data and information sometimes lead us to make wrong decision due to information overload problem. Fortunately, from information retrieval, recommender systems as a kind of personalization technics are alternatives for coping with this problem (Kim et al., 2009). Over a decade, as it has being important to use the contextual information as valuable inference sources, context-aware recommender systems receive attentions from researchers. Especially, thanks to the development of information technologies such as IoT, there is data everywhere and it is useful source of generating a recommendation. However, with the evolution of computing paradigm, we should consider three things for improving context-aware recommender systems. First of all, as context-aware recommender systems for the current age should use various type of contextual information, they needs suitable interpretation and to solve complexity problem for composing user profiles. Second, interaction between devices play a key role to update the current users' prediction in real-time. Therefore, their recommendation technics should be designed that they can track users' current context and active interactively in real-time. Finally, using plentiful data set related with users, recommender systems should solve sparsity and cold-start problem.

Based on these considerations, we suggest a methodology for based on the concept of contextual boundary. Contextual boundary means the approximate preferences for their contexts in user profile. Through this concept, we first attempt to solve complexity problem dealing with descriptive value of contexts by taxonomies of experts. Moreover, with this concept, our methodology also tries to solve sparsity and cold-start problem in the traditional collaborative filtering systems. Second, although typical recommender systems generate recommendation lists based on similarity between neighbors, we also attempt to consider interactivity and real-time computation in our methodology as it regenerates recommendation lists according to the target user's current context.

In the perspective of application for recommender systems, their applications have been restricted in e-commerce due to several limitations. However, as new technologies available, researchers in recommender systems have recognized real-world market (e.g., department store, exhibition, or tourism) as a new opportunity. Therefore our methodology can be first step for expanding application of researches on recommender systems. Moreover, as we suggest a flexible model with consideration of new technological development, it will show high performance regardless of their domains. Therefore, we expect that marketers or service providers can easily adopt according to their technical support.

However, there are some limitations of our study. In the determination of the centroid and the range for contextual boundary, we just determine them with a parameter settings. And we assume that a user has approximate preferences for contexts. Therefore, for future works, with the in-depth consideration of precise user models, we will expand and develop our methodology.

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국문요약

상황 정보를 이용한 개인화 추천 방법 개발*

문현실** · 최일영*** · 김재경**†

최근 개인 단말기의 보급과 객체간의 네트워크 연결이 확산됨에 따라 방대한 양의 상황 정보들이 수집되고 있지만 역설적으로 사용자들과 서비스 제공자들은 정보의 홍수 속에서 종종 잘못된 의사결정을 내리고 있다. 이러한 정보 과부하 문제를 해결하기 위해 추천 시스템은 좋은 대안이 될 수 있지만 전통적인 추천 시스템은 다양한 형태의 상황 정보 사용에 한계를 보이고 있다. 또한 획득 가능한 상황 정보가 다양해지고 방대해짐에 따라 이를 활용한 추천 시스템은 복잡성의 문제를 해결해야 하며 지속적으로 변화되는 사용자 선호 및 상황에 부합할 수 있도록 실시간 서비스가 가능하도록 설계되어야 한다. 따라서 본 연구에서는 상황 영역의 개념을 기반으로 한 상황 인식 추천 서비스 방법론을 제안하여 추천 시스템에서 상황정보를 활용하는 한편 복잡성 및 실시간 서비스 제공의 문제를 해결하려 한다. 먼저 적절한 해석과 구조로 상황 데이터를 사용자 프로필에 반영할 수 있도록 상황 영역 개념에 기반한 프로파일링을 제안함에 따라 기존의 상황 인식 추천 시스템이 가지고 있던 복잡성의 한계를 해결하고자 한다. 다음으로 목표 사용자의 상황 영역에 기반한 이웃 집단 탐색으로 추천 시스템의 희박성과 신규 사용자 문제를 해결하는 한편 현재의 상황 정보에 대한 해석으로 도출되는 상황 지지 점수를 기반으로 한 추천 목록을 생성하여 실시간 서비스가 가능한 방법론을 제안한다. 결론적으로 본 연구에서 제안하는 방법론은 추천 시스템의 적용 영역을 확장하는 연구가 될 것으로 기대되며 새로운 기술 출현을 고려한 유연한 모델을 제안함에 따라 마케팅 담당자나 서비스 제공자들이 쉽게 본 연구에서 제안하는 방법론을 적용할 수 있으리라 판단된다.

주제어 : 상황 인식 추천 시스템; 추천 시스템; 협업 필터링; 상황 정보; 상황 영역

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** 경영대학 & 경영연구소, 경희대학교, 서울특별시 동대문구 경희대로 26, 130-701, Tel: +82-2-961-9355, Fax: +82-2-961-0515, email: {pahunter, jaek}@khu.ac.kr
*** 무용학부 &문화아이템팩토리연구센터, 경희대학교
**† Corresponding Author: Jae Kyeong Kim
School of Management and Management Research Institute, Kyunghee University,
26 Kyunghee-daero, Dongdaemun-gu, Seoul 130-701, Korea
Tel: +82-2-961-9355, Fax: +82-2-961-0515, E-mail: jaek@khu.ac.kr

저 자 소 개

Hyun Sil Moon

Hyun Sil Moon obtained his M.S. and Ph.D. in Management Information Science (MIS), and his B.S. in Business Administration from Kyung Hee University. His current research interests focus on big data analysis, recommender systems, social network analysis, and a complex systems. He has published numerous papers which have appeared in International Journal of Information Management, Journal of Intelligence and Information Systems, Journal of Information Technology Services, and Journal of Information Technology Applications and Management.

Il Young Choi

Il Young Choi(choice102@khu.ac.kr) is a PhD at School of Management, Kyunghee University. He obtained his MS in MIS, and his BS in Economics from Kyung Hee University. His current research interests focus on Recommender Systems, green business/IT, and business intelligence. He has published numerous papers which have appeared in International Journal of Internet and Enterprise Management, Journal of the Korean Society for Management, Korean Management Science Review, Journal of Intelligence and Information Systems, and Information Systems Review.

Jae Kyeong Kim

Jae Kyeong Kim(jaek@khu.ac.kr) is a professor at School of Management, Kyunghee University. He obtained his MS and PhD in Management Information Systems (MIS) from KAIST (Korea Advanced Institute of Science and Technology), and his BS in Industrial Engineering from Seoul National University. His current research interests focus on business intelligence, network management, and green business/IT. He has published numerous papers which have appeared in Artificial Intelligence Review, Electronic Commerce Research and Applications, European Journal of Operational Research, Expert Systems with Applications, Group Decision and Negotiations, IEEE transactions on services computing, International Journal of Human-Computer Studies, International Journal of Information Management, Technological Forecasting and Social Change.