Journal of Knowledge Information Technology and Systems

ISSN 1975-7700

http://www.kkits.or.kr

Design of User Profile-based Personalized Recommendation Service for Sport Commerce

Chul-Moo Heo*

Department of Physical Educations, Sungkyul University

ABSTRACT

Nowadays, many business embed recommendation systems in their web sites, in order to study the tastes of their customers, and achieve some business objectives. Personalized Recommender Service is necessary to latent tendency to optimize service for each user's unique needs and characteristics. This service is to offer user to customize their service, as well as provide information from their past behaviors. These events have many functions what do they want/need to behaviors and preferences with commerce. Especially, most diversity of commerce serve users with product contents by self-adapting computer system. However, many users don't always know what they want and need, and when their behaviors occasionally change preferences. Besides, users don't find out their purchased history that they want to buy with required product on commerce. After all, personalized recommender service aims to provide with associated services of user's preference or purchase pattern from the unexpected product information of commercial market. Accordingly, we propose strategies for adaptive personalized recommender service in this paper. Finally, we need to design for adaptable recommender service (tag-based ranking) to support sport commerce. In addition, we make use of adaptive service design, detecting service with user's data modeling.

KEYWORDS: Personalized recommender service, Commercial market, User behavior and preference, Adaptive service design, Personalized recommender service (PRS)

ARTICLE INFO: Received 21 March 2017, Revised 3 April 2017, Accepted 7 April 2017.

*First author is with the Department of Physical Educations Sungkyul University, Sunkyul University-ro 53, Manan-gu, Anyang-city, Gyeonggi-do, Korea

E-mail address: chulmoo@sungkyul.ac.kr

1. Introduction

Smart platforms, computers and smart devices have become an essential part of our lives. Many users use them both for their work and in their personal life cycle. Information consumption has moved from offline and online that it relies on the internet for the news, education, and for keeping in touch with users, as well as many commerce market promote with interact for the various service policies on online [1]. Nevertheless, increasing amount of online content competing for attention has created, some web services reorganize already existing information, created in the context of the service itself. Eventually, what all of commercial services have in common is that they serve as a gateway to information for users, presented through the platform they operate[2-3]. To understand this complicated recommendation system, it's important to understand the main participants and their motivations. In case, sport online market seller earn money proportional to user click streams, rates, and gain popularity through sport product sometimes [4]. Accordingly, there are service providers who, beyond wanting to keep their users contents, have a clear economic incentive to find out the content their users are most likely to consume. To content to each user, web services have started implementing personalization algorithms. Such as, Google search returns results user's IP address or coordinates and Amazon recommends products to a user based on user's similarity for online shopping histories as well as Naver. Most data the online market/shopping mall have about a user, the better they can predict their preferences. This leads to content providers collecting information with purchased data, tracking user behaviour on their online market. It has become easier to come by user data since user's smart device and computers essentially act as sensors that gather data every time. To deal with the vast amount of data, operators use machine learning algorithms for Big Data. The following sections give a more precise description of the context of the research, along with an overview of related work and modelling. We proposed architecture design and algorithm for personalized recommender service of sport commerce.

2. Related Works

2.1 GroupLens

GroupLens provide to alleviate the problem of information overload by applying Collaborative Filtering (CF) techniques to Usenet news and other internet resources [5]. Information Filtering (IF) refers to techniques for selecting valuable information from the wealth of available information. As the amount of information in the world increases, information filtering is becoming more and more important from many fields including information retrieval, artificial intelligence, user interface, and collaborative filtering system. Collaborative filtering systems make use of the reactions and options of user that have already seen a piece of information to make predictions about the value of that piece of

information for user that have not seen it yet. In the GroupLens collaborative filtering system users enter their ratings of net-based news messages through the user interface. These ratings are stored in database along with their ids. A separate database is used for each newsgroup [6-8].

2.2 Keyword Based Filtering

Keyword Based Filtering System (KFS) form a representation of a document based on information extracted from the document. This representation often takes the form of a vector of the keyword found in the document along with other features such as the author and source. Keyword based analysis compares the document vector against another vector which represent the user's profile of interests to determine whether the user is likely to find the document interesting. Keyword techniques can be effective at selecting text documents on a desired subject [9]. But, keyword-based information retrieval systems as well as the user who use these systems suffer from a tremendous information overload.

2.3 User Modeling of Social Web System

In order to information system of social web adapt functionality to users, this systems require personalized information such as purchased product, collected product, and so on [10-12]. Social web provides opportunities to gather such information that users leave of traces on the web. Also, distributed user modeling is to provide/aggregate user and context information from the different sources available on the social web [13]. This user model used contextual information by means of tag-based profile that represent the same entity in different services , as well as a user might have tag-based profiles can thus be computed by accumulating the profiles provided by the different services.

3. Proposed System

Information like visited locations, web-searches, purchases, smart platform, and even sport equipment handling are collected and stored without any clear benefit for the user. Consequently, it is being defined the need for personal models to manage and exploit these large amounts of data. It is taking place the idea of the personal data store that is a personal, digital controlled by an individual where each user can choose.

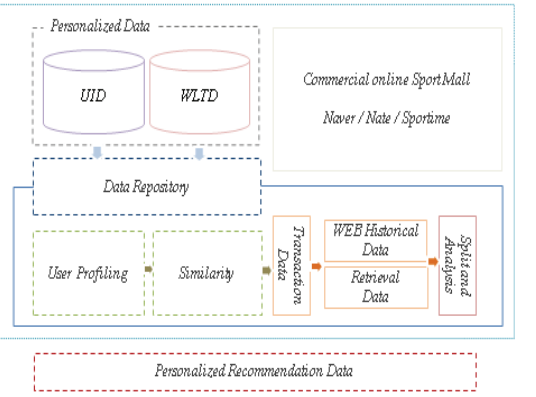

그림 1. 개인화 추천 서비스 아키텍처

Figure 1. Architecture of Personalized Recommender Service (UID is User ID, and WLTD is Web-based Logical Tag Data)

We show <Figure 1> in such a service personalized recommender service for user data model in our research paper. User profile have automatically extracted through personal data mining. Personal data mining refers to autofocus methods able to build subjective and adaptive with themselves. These methods are able to automatically detect and extract the repetitive and valuable patterns delineating the user's systematic behaviors.

3.1 Personalized Data Modeling

In our research paper, we approach personalized data models contextual user interaction in our system as tag-based profiles. Based on the traditional this model specified in definition 1. that can be computed for specific context as bellow.

Definition 1.
A tag-based profile is a set of weighted tags where the weight of a tag t is computed by a certain strategy w with respect to a given context c.

$$P(c) = \{(t, w(c,t)) | t \in T, c \in U \cup T \cup R \cup \{\varepsilon\}\} \quad (1)$$

U,T,R are finite sets of instances of users, tags, and resources.
w(c,t) computes the weight that is associated with tag t in a given context c. $\in$ *describes the context.*

Personalized search and personalized content exploration is adapt the search result computed by the historical strategies to the given user and the user's context. We proposed different strategies for inferring contextual user profiles from user interactions with sport commerce. Such as, a keyword query issued by a user can be enriched with further keyword that described the user's personal needs in the given context. The personalized search algorithms should thus generate a search result that respects the query as well as the context given by means of personalized recommender service with user-oriented profile [14]. In our recommender service scenario above the query was given as single tag, that means web-based URL information, clicked on a tag to retrieve both a ranked list of resources and a clicked list of users [15-17]. A user query might however also consist of multiple tags and can there with be interpreted of user profiles.

3.2 PRS Algorithm for Service Scenario

In definition 2., we design a generic algorithm for computing personalized rankings that requires a domain-driven ranking strategy *s* as input. Given a query *P(a)* and contextual information about the user *P(c)* the ranking strategy s is applied to generate two rankings *Rq* and *Rc* by using *P(q)* and *P(c)* respectively as query. Using a common mixture approach both rankings are then combined to produce the ranking *Rr* that is finally returned as output. A contextualized ranking is thus the weighted average of the query

and context ranking [18-20].

Definition 2.
The generic algorithm for computing contextualized rankings combines the ranking computed with respect to the query with the one computed for the tagging context profile.

1. Input: *query P(q), user P(c), ranking algorithm s, context influence d∈ [0..1].*

2. Compute a ranking Rq based on the query tagging profile, Rq <- s.rank(P(q)), and a ranking Rc based on the context tagging profiles, Rc <- s.rank(P(c)). Rq and Rc are sets of weighted entities (e_1, w_1), and (e_1, w_2) respectively.

3. Compute the result ranking R, by average Rc_1 and Rc_2. R contains weighted entities, where w = (1-d)·w + d·w and d specifies the influence of the ranking scores computed via the context profile.

4. ***Output:*** *R, the set of weighted entities (e,w), where w denotes the weight assigned to the entities.*

<Figure 2> we show that this tag usage reminds of a URL pattern distribution as there are a lot of tags. For example, when user search sport product at Naver shopping mall (sport.naver.com), we could collect many tags on web log (user query) and identify with tag usage of Naver shopping mall. We can make a set with tag-based context profile of Naver shopping mall, then we compute the result ranking of log data.

http://shopping.naver.com/search/category.nhn?**pagingIndex=1&pagingSize=40&productSet=total&viewType=list&sort=rel&cat_id=50001104&frm=NVSHPRC**

http://shopping.naver.com/search/category.nhn?**color=64&pagingIndex=1&pagingSize=40&productSet=total&viewType=list&sort=rel&cat_id=50001104&frm=NVSHPRC**

http://shopping.naver.com/search/category.nhn?**brand=235&color=64&pagingIndex=1&pagingSize=40&productSet=model&viewType=list&sort=rel&cat_id=50001104&frm=NVSHBRD**

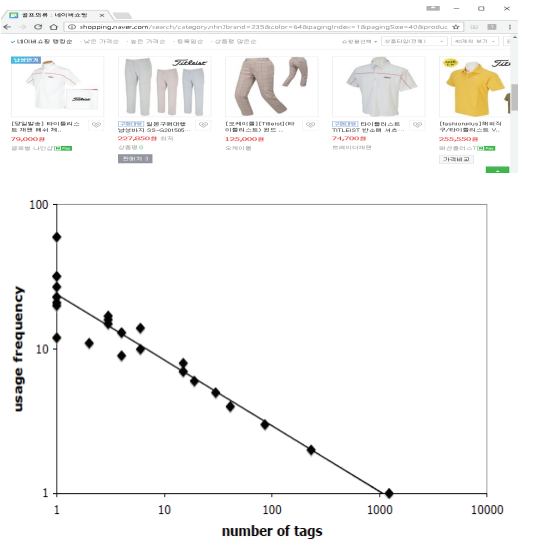

그림 2. 네이버 스포츠 마켓에서의 사용자 태그 빈도수
Figure 2. Tag Usage in the Naver Sport Commerce.

We ran the experiments for each the 100 users, who actively contributed tags in Naver shopping mall. By the proposed both Definition 1. and Definition 2., we reduce the computation retrieval time required for each users. And we have the size of the tag-based profiles to 100 entries, more user profile information results in a better performance of the tag recommendation as following <Figure 3>.

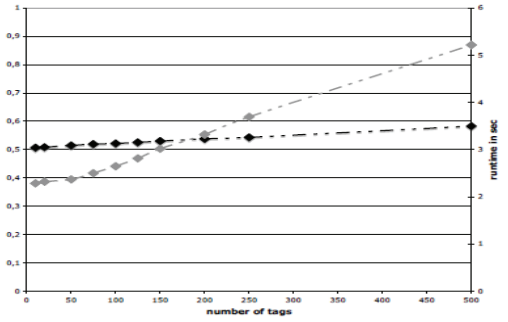

그림 3. 태그 기반 사용자 프로파일 추천

Figure 3. Tag-based User Profile Recommendation
(Reduce the computation retrieval time of users)

4. Conclusions

In our paper, we have proposed a simply web-based personalized recommender service scenario modified that user profile would serve tag-based user's characteristics. As the possibilities to analysis each user's tag/click behaviour individually, a thorough modelling of this context and preferences enables dynamic composition of suitable web contents. Accordingly, this paper contributes to research on information retrieval as well as user modeling and personalized recommender service on Social Web. We had a simple contextualization model of Naver sport commerce to improve user-oriented search. Although, it is difficult to experiment with various methodologies, we anticipate to develop a context-based user modeling and personalized recommender service framework for between the Big Data and the social web environments.

References

[1] J.S. Ancker, M. Silver, M. C. Miller, and R. Kaushal, *Consumer experience with and attributes toward health information technology: A nationwide survey.* Journal of the American Medical Informatics Association Vol. 20, No. 1, pp. 152-156, 2013.

[2] J-H. Kim, B-H. Ahn, and D. Jeong, *A recommender system using mixed filtering for health products,* The Journal of Internet Electronic Commerce Research, Vol. 12, No. 2. pp. 109-124. 2012.

[3] K. H. Kim, and S. R. Oh, *Methodology for applying text mining techniques to analyzing online customer reviews for market segmentation*, Journal of the Korea Contents Association, Vol. 9, No. 8. pp. 272-284. 2009.

[4] J. Beel, S. Langer, A. Nürnberger, and M. Genzmehr, *Persistence in recommender systems: Giving the same recommendations to the same users multiple times.* Valletta, Malta, Springer, pp. 390-394, 2013.

[5] A. Ankolenkar, M. Burstein, J. R. Hobbs, O. Lassila, D. L. Martin, D. McDermott, S. A. McIlraith, S. Narayanan, M. Paolucci, T. R. Payne, and K. Sycara, *The DAML services coalition, DAML-S: Web service description for the semantic Web*, The First International Semantic Web Conference (ISWC), Sardinia, Italy, Jun. 2012.

[6] H. Lu, *Semantic web services discovery and ranking.* The 2015 IEEE/WIC/ACM International Conference on Web Intelligence, pp. 19-22. Sep. 2015

[7] J. Bao, Y. Zheng, and M. F. Mokbel, *Location-based and Preference-aware recommendation using sparse geo-social networking data.* ICAGIS, 2012.

[8] F. Emekci, O. D. Sahin, D. Agrawal, and A. El Abbadi, *A peer-to-peer framework for web service discovery with ranking,* Proceedings of the IEEE International Conference on Web Services (ICWS04), San Diego, USA Jul. 2014.

[9] H. Lu, A. Sajjanhar, *Meaningful UDDI semantics description*, International Conference on Computer Applications in Industry and Engineering, Las Vegas, USA, Nov. 2013.

[10] J. Gennari, M. A. Musen, R. W. Fergerson, W. E. Grosso, M. Crubezy, H. Eriksson, N. F. Noy, and S. W. Tu. *The evolution of protege: An environment for knowledge-based systems development*. 2012.

[11] M. Ge, C. Delagado-Battenfeld, and D. Jannach. *Beyond accuracy: Evaluating recommender systems by coverage and serendipity,* ACM Conference on Recommender Systems, RecSys'10. pp. 257-260. 2010.

[12] J. Scicluna, C. Abela, and M. Montebello. *Visual modeling of owl-s services.* In Proceedings of the IADIS International Conference WWW/Internet, Oct. 2004.

[13] D. H. Park, H. K. Kim, I. Y. Choi, and J. K. Kim, *A literature review and classification of recommender systems research.* Expert Systems with Applications, Vol. 39, No. 11, pp. 10059-10072. 2012.

[14] J. R. Drake, D. J. Hall, C. Cegielski, and T. A. Byrd, *An exploratory look at early online auction decisions: Extending signal theory,* Journal of Theoretical and Applied Electronic Commerce Research, Vol. 10, No. 1, pp. 35-48. 2015.

[15] P. Melville, and V. Sindhwani. *Recommender systems*, Springer US, Boston, pp. 829−838, Mar. 2010.

[16] J. Liu, X. Jin, and Y. Wang. *Agent-based load balancing on homogeneous minigrids: Macroscopic modeling and characterization.* IEEE Transactions on Parallel and Distributed Systems, Vol. 16, No. 7, pp. 586-598, 2005.

[17] F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, *Introduction to recommender systems handbook. In: F. Ricci, L. Rokach and S. Bracha, eds. recommender systems handbook.* 1 ed. Springer US, pp. 1-35. 2011.

[18] K. Krstovski, D. A. Smith, H. M. Wallach, and A. McGregor. *Efficient nearest-neighbor search in the probability simplex,* In Proceedings of the 2013 Conference on the Theory of Information Retrieval, ICTIR '13, pp. 101−22:108, NY, USA, 2013. ACM.

[19] N. Gude, T. Koponen, J. Pettit, B. Pfa, M. Casado, N. McKeown, and S. Shenker. *NOX: Towards an operating system for networks.* In SIGCOMM CCR, Jul. 2008.

[20] N. Barbieri, G. Manco, and E. Ritacco, *Probabilistic approaches to recommendations.* In: J. Han, et al. eds. Synthesis Lectures on Data Mining and Knowledge Discovery. San Rafael, California: Morgan & Claypool Publishers. 2014.

스포츠 상거래를 위한 사용자 프로파일 기반 개인화 추천 서비스

허철무

성결대학교 체육교육과

요 약

오늘날, 개인화 추천 서비스는 사용자의 각 사용자들의 요구와 특성에 따라 최적화할 필요가 있다. 이러한 서비스는 그들의 서비스에 따라 제공되며, 과거의 행위로부터 정보를 제공받는다. 이러한 이벤트는 언제 사용자가 원하는지, 무엇을 원하고 필요로 하는지에 따라 다양한 기능들이 수행된다. 특히, 상거래의 다양성은 자가적응 컴퓨터 시스템에 의해 컨텐츠들이 제공된다. 하지만, 많은 사용자들은 경우에 따라 그들의 관심이 바뀜에 따라, 무엇을 원하고 필요로 하는지 알지 못한다. 또한, 사용자들은 상거래 통해 필요한 상품을 사기를 원하지만, 그들의 이전 히스토리를 알지 못한다. 결국, 개인화 추천 서비스는 예상치 못한 상품 정보로부터 사용자의 구매 패턴 및 사용자의 선호에 따른 관련 상품을 제공하는 것이 그 목표이다. 따라서, 본 논문에서는 적응형 개인화 추천 시스템을 제안한다. 원활한 상거래 시스템의 활성화를 위해 서비스 상호작용 방법 및 온라인 스포츠 마켓에서 제공되는 서비스에 대해 제안한다. 또한, 사용자의 데이터 모델링과 적응형 서비스를 설계하고자 한다.

Chul-Moo Heo received the bachelor's degree and the M.S. degree in the Department of Physical Education from the Korea National Sport University in 2001 and 2003. He received the Ph.D. degree in the Department of Physical Education from Kon-Kuk University in 2012. He has been a professor in the Department of Physical Education at Sungkyul University since 2014. His current research interests include Sport marketing, Sport management. He is a life member of the KAHPERD, KSSM, KSGS, KSSLS.

E-mail address: chulmoo@sungkyul.ac.kr