AN OVERVIEW ON CONTEXT AWARE RECOMMENDER SYSTEM IN MOBILE ENVIRONMENT

Jun Zeng Feng Li, Yinghua Li, Junhao Wen, Yingbo Wu
The school of Software, Chongqing University
{ zengjun@, lifeng@, yinghuali@, jhwen@, wyb@}cqu.edu.cn

Abstract

With the rapid development of wireless communication and mobile internet, it is impossible to obtain high-quality recommendation just depending on traditional user-item binary relation. How to use multi-context to generate satisfying recommendation in such a complicated environment has been a hot pot in some fields like e-commerce, tourism, music and video. Context aware recommender system (CARS) import multi-context into recommender to generate recommendation with ubiquitousness and personalization. This paper presents an overview of the development status of CARS in recent years. We detail the definition of context, usage, process of CARS and evaluation. We also analyze some challenging research extension.

Keywords: context aware recommender system, mobile environment, personalized recommender

In recent years, with the development of mobile internet and the rising popularity of mobile intelligent devices, a large number of services are released on the mobile network. The contents of these services are no longer limited to traditional Web services, but cover all aspects of life, such as taking a taxi, catering service, shopping, tourism, etc. However, when mobile services bring us convenience, it also give us great burden of information for mobile users, namely, mobile information overload (Meng et al., 2014; Wang et al., 2013; Ricci et al., 2011). As one of the effective means to relieve information overload, recommender system (RS) has won wide attention in academia and industry. However, different from the traditional application scene, the mobile environment is dynamic and changing. User's behavior and preference change with surrounding environment. Using traditional RS into mobile environment directly is unreasonable because of multiple mobile environment. Therefore, more and more researchers focus on mobile recommender system (Wang et al., 2011; Liu et al., 2014; 2015). Compared with traditional RS, mobile recommender systems must be ubiquitous and personalized (Meng et al., 2013). That is, users can get service meeting their requirements anywhere, anytime and in any ways. In this case, some researchers study context aware recommender system (CARS) using contexts, such as position, time, demographic information and weather, to generate good recommendation in a specific scenario by analyzing user's preference.

Many research institutes have developed CARS for a long term, such as Beijing University of Post and Telecommunications, University of Science and Technology of China, Microsoft Research Asia, Nanyang Technological University and University of Minnesota. The ACM Recommender Systems conference (RecSys) was held from 2007. Workshop on Context-Aware Recommender Systems were held from 2009 to 2012 in which lots of works about CARS are published, which greatly promotes the development of CARS. Especially, in recent years, some researches about emotions, personality and deep learning give CARS more energy (Gao et al., 2015; Gao et al., 2015; Oord et al., 2013; Elkahky et al., 2015). At present, many overviews mainly concentrate on traditional recommenders (Adomavicius et al., 2005). There is a relatively few works about CARS in mobile environment. Considering the great value and attraction of CARS, it is significant to summarize and analyze its development status.

The rest of this paper is organized as follows: in section 1, we introduce mobile recommender system, including new features and CARS in mobile environment; in section 2, we detail the definition and classification of context, the usage of context and evaluation in mobile CARS, respectively; section 3 present the developments and challenges; finally, section 4 concludes this paper.

1. MOBILE RECOMMENDER SYSTEM

1.1 New features of mobile environment

At present, the mobile Internet is leading a new wave of the Internet revolution. Mobile devices are used more and more widely in people's daily life. Users can read news, shop and mail when they are on their way to work. Mobile devices have been able to replace traditional PC devices in some ways, which mainly concentrate on the continuous development of basic functions and the utilization of multi resources.

Compared with traditional desktop environment, mobile environment is more complex. On the one hand, mobile devices are small and portable. Rich components make it has a strong ability of collecting data. For example, mobile device can get users' environment information in real-time, such as location, weather, audio/video information, using camera sensor, Bluetooth sensor, the color sensor, temperature sensor, gravity sensor, range sensor and so on (Baldauf et al., 2010). Vital signs even can be available by means of infrared vision. We can use these hardware devices to get multi aspects and unstructured data that

tradition desktop environment can't acquire easily. One the other hand, mobile device has small screen and inadequate computational ability. Wireless network is not always stable. In this case, mobile devices cannot accomplish large scale data processing. Collaborating with desktop devices can supply good service for users. Therefore, the recommendation in mobile environment has a very high demand to the time and accuracy.

Another important characteristic of mobile environment is decentralization. Every users, not only some specific ones as before, can create lots of data, such as applications' usage records, the location information, the using period of the specific application and messages in social network. This information implies users' daily routines. That is, using information from these data, we can get more personalized recommendation.

1.2 CARS in mobile environment

CARS in mobile environment is developing continuously through the basis of the traditional recommender systems, mobile devices and a lot of contexts. Convenience of mobile devices make all kinds of service access to people's daily life more easily. CARS in mobile environment has great flexibility and extensibility depending on abounding data. It can generate more accurate recommendation in complicated environment, which has great prospect and values. However, the traditional recommendation methods are not capable of solving some big challenges that too much worthless information, complex application scenario and the rea-time capability give us. Therefore, designing an effective CARS in mobile environment is the long-term and wonderful work.

2. CONTEXT AWARE RECOMMENDER SYSTEM IN MOBILE ENVIRONMENT

2.1 Context information

2.1.1 The definition of context

All users' behaviors occur in a particular scenario containing a series of context information sequence. These contexts describe users' current status, such as activity, surrounding, companion, location. Different combination of contexts formed different session scenarios. Dividing scenario into different context sequences is helpful for analyzing the role of different contexts under the different scenarios.

At present, the definition of context is still not clear. Some researchers refer to context as locations, identities of nearby people and items and their changes (Dey, 2001). These definitions that define context by example are difficult to apply to all scenarios. The most widely used definition is the one Dey gave. **Context is any information that can be used to characterize the situation of an entity.** An entity is a person, place, or object that is considered relevant to the interaction between a user and an application,

including the user and applications themselves." Compared with previous enumerative definition, this definition has a high level abstract. Many Contexts can be captured by our mobile phone, such as time, place, human vital signs, temperature, pressure, motion state, the weather. Different contexts constitute an application scenario in which user preferences change gradually. In order to make full use of the contexts in a more fine-grained way to provide users with accurate recommendations, recognizing valid and invalid context in different scenario is very important.

2.1.2 Classification of contexts

According to the different fields, mobile contexts are divided into different types. Gwizdka J (Gwizdka, 2000) think context can be divided into internal part and external part. The external part refer to the context information which can be measured with sensors, such as position, temperature, lighting levels and mobile condition. The Internal part is specified by users or captured from users' interaction record, such as the user's goals, tasks, scheduling. Schilit (Schilit et al., 1994) divide context into computing context (such as network connectivity, communication cost, communication bandwidth, nearby resources like printers), user context (such as user profile, position, the people around as well as the social status), physical context (like sound, light, temperature). Guanling Chen and David Kotz (Chen et al., 1970) consider that time is also a kind of important information. Jonna Hakkila and Mantyjarvi J. (Hakkila et al., 2005) divide context into physical environment, user goals, device application, local ad-hoc connections and connections to infrastructure. Meng et al.(Meng et al., 2014) divide mobile context into user context, computing context and environment context according to users' status and behavior, the properties of terminal equipment and users' surroundings.

2.1.3 The role of mobile context in CARS

Since there are lots of contexts can be collected, how to utilize them for high-quality recommendation is worth investigating. Researchers use context in their study as follows:

(1) **Filtering.** Filtering process (Ahn et al., 2011; Baltrunas et al., 2009) is divided into pre-filtering and post-filtering. Pre-filtering method filters context which doesn't match the current situation and import the rest valid context into recommendation algorithm or model, as shown in figure 1. Post-filtering (Panniello et al., 2009) ignore context at first and use traditional methods to predict user preference, then filter unrelated recommendation, as shown in figure 2. These two methods can effectively reduce the computational complexity. But they ignore the relationship between contexts, which has much influence upon recommendation.

(2) **Modeling.** Modeling methods import contexts into detailed algorithm, not just filter unrelated information, as shown in Fig.3. The effect of different contexts in different scenarios perform differently in the way and the degree it

functions, even the same context. Plenty of modeling methods have been studied, such as the nearest neighbor algorithm (Yuan et al., 2013), tree structure model (Bao et al., 2012), matrix decomposition (Gao et al., 2013; 2015; Lian et al., 2014), graph model (Yuan et al., 2014), probability distribution model (Cheng et al., 2014; Liu et al., 2013), Bayesian model (Park et al., 2007), the SVM model (Wang et al., 2014). For example, when making a point of interest recommendation (POI recommendation), considering POI properties, user interest and sentiment indications in comment, Huiji Gao (Gao et al., 2015) use matrix decomposition to provide recommendation. Modeling methods can improve the preference of recommender, while it greatly increases time and space complexity. Using demographic information (e.g. birthday, birthplace, gender, occupation) and web logs and application logs, we can get user behavior records (such as user ratings, reviews, behavior information and applications using time) and communication and social network information. For example, by importing the concept of trust in sociology, Shudong Liu (Liu et al., 2014) calculate the trust between two users according to their communication.

Fig 1. Context pre-filter in CARS

Fig 2. Context post-filtering in CARS

2.2 The process of CARS

As shown in Fig. 4, in general, the process of context aware recommender system can be divided into four parts: context recognition & collection, data preprocessing, model & recommendation algorithm and evaluations. In order to get more satisfying performance, we need to optimize the algorithm in time according to the evaluation.

(1) Context recognition and collection. Researchers acquire context information by means of implicit and explicit way. In explicit way, we collect contexts

Fig 3. Context modeling in CARS

information using device directly. For example, mobile phone can get our detailed position using GPS. In implicit way, we try to analyze lots of behavior logs to find or deduce latent contexts. For example, we can analyze the time of using APPs to deduce whether users stay at home or company or not. Finally, users' behavior information, current contexts, social network and item information all are available. In this process, it is necessary to study how to detect real-time contexts, find out missing or false contexts, define valid contexts, reduce computational complexity and improve computational performance.

(2) Data preprocessing. There is always too much noise data in initial data. It is important to remove the noise data and reduce the effect of invalid data. For example, when making location recommendation using collaborative filtering method, we need remove those users who have a few followers and follow a few users (Yuan et al., 2013). On the other hand, a variety of data is directly collected by various equipment, these raw data may not meet the input of recommendation algorithm. In order to conveniently store and use the data, researchers always transform the data into normalization form, such as check-in text data (Cho et al., 2011; Zheng et al., 2009), user-location-time matrix (Gao et al., 2013).

(3) Generating recommendation. We get users' behavior rule and preference with the preprocessed data, such as rating (Liu et al. 2013), check in or not/the frequency of check-in (Liu et al., 2013; Hu et al. 2014), mobile trajectory (Liu et al. 2013). We could get recommendation using designed model and algorithm.

(4) Evaluation and optimization. When users get the recommendation list, the interpretability of recommendation list must be distinct. Although users don't have to understand the detailed algorithm, it is important to let users know the recommendation list is reasonable, not wild guesswork. The works about the evaluation of CARS mainly focus on offline evaluation. Researchers and service providers evaluate the performance with traditional metrics, such as precision, recall, coverage and diversity. Because of the high real-time in mobile Internet, Real-time capability is a promising metric. Only evaluating the performance of RS

is still far from enough. Optimizing the algorithm according to evaluating result is the key to get more satisfying result.

Fig 4. The process of CARS

2.3 CARS in mobile environments

2.3.1 Location-based recommendation

Location aware recommendation system (LARS) are among the hottest and the fastest-growing mobile applications now, such as location-based social recommendation (Liu et al. 2015), restaurant (Li et al., 2015; Zeng et al. 2016), activity, urban computing (Zheng et al., 2011; 2014), point of interest recommendation (POI recommendation) (Costa et al., 2012; Li et al., 2015). In LARS, the rating is modeled as a function f in terms of the item, user and location (41), as shown in formula (1).

$$f: U \times I \times L \rightarrow R \quad (1)$$

The first step of LARS is to acquire users' location. At present, mobile device can get this context using GPS/COMPASS, AGPS, IP/WIFI positioning, Cell-Id, Bluetooth/RFID. Then, the most significant work is the recognition and mining of important location, the semantic annotation, mining users' trajectory pattern and the relationship between users' behavior and location. In POI recommendation, researchers get users' location and trajectory and then try to find out human movement rule (Liu et al., 2013).

Shudong Liu(Liu et al., 2014) proposed an approach of location-based network services recommendation. This paper regarded tuple (location, service) as users' preference, computing mobile user's preferences based on location and trust value according to the concept of trust in sociology, and mixing them into the process of generating recommendation. Finally the proposed algorithm is proved to be more accurate and feasible in experiments by using the public dataset MIT. Emanuel Lacic(Lacic et al., 2015) presented IPS-based recommender approach based on collaborative filtering that exploits user's location information using indoor positioning system (IPS). When computing the similarity between two users based on raw location data and user-location network, this approach can

provide more accurate recommendations for "extreme" cold-start users. Girardello et al. (Girardello et al., 2010) introduced a way of finding new apps, taking location into consideration and analyzing what applications are being installed right now around the location. They recommended the most frequently used application. Jeong-Woo Son(Son et al., 2013) proposed a new article recommendation using the location context of the user and a method for the topical representation of documents, Explicit Localized semantic Analysis (ELSA), an extension of Explicit semantic Analysis (ESA). ELSA represented contents of news articles as topic vectors considering the geographical context, that is, ELSA represented not only articles but also locations, because the topics expressing the user location come from a set of geo-tagged documents retrieved with that location. Zhiyong Cheng(Cheng et al., 2014) proposed an adaptive personalization system. In this model, the three-way aspect model (music content, music popularity detection, and users' listening records) is extended to incorporate the location contexts and global music popularity trends via analyzing music-related tweets. They gave a tuple as (user, location, song and audio content) to show users' preference.

2.3.2 Time-based recommendation

Considering users' behavior and preference change over time, many researchers study temporal factor in analyzing users' daily behavior. Anastasios(Anastasios et al., 2011) present large-scale study of user behavior in Foursquare. Their findings suggest that activity varies within the course of a day and of a week, with meaningful patterns closely related to human activity from a temporal and spatial point of view. That is, temporal influence plays an important role in analyzing users' daily activities. Quan Yuan(Yuan et al., 2013) develop a collaborative recommendation model that is able to incorporate temporal information. They split a day into multiple equal time slots based on hour, and smoothing the missing check-in data. Result on real dataset show the proposed approach works very well. Then, they propose the Geographical-Temporal influences Aware Graph (GTAG) to model check-in records, geographical and temporal influence and develop a preference propagation algorithm named Breadth-first Preference Propagation (BPP) to return recommendation results (Yuan et al., 2014). Huiji Gao(Gao et al., 2013) analyze the consecutiveness and non-consecutiveness of check-in behavior hourly in location-based social network (LBSN). They introduce four temporal aggregation strategies (max, sum, mean, voting) to integrate a user's check-in preferences of different temporal states. The experiment result exhibit the power of temporal effects for capturing a user's mobile behavior. Users' interest vary with time. They think other time patterns (like day of week, weekday/weekend, monthly, yearly) could provide the model with potential power to predict the future. Empirically, users' preference change gradually with different effect of time. How to model time influence in real applications is still a valuable problem.

2.3.3 Multi-dimensional context-based recommendation

Some researchers consider that user's decision process is affected by multiple contexts, not just one kind of context (Vico et al., 2011; Karatzoglou et al., 2010; Zou et al., 2014; Park et al., 2007; Hosseini-Pozveh et al., 2009; Ahn et al., 2006). In fact, users' behavior always occur in complicated scenario including many valid contexts and invalid contexts. Hosseini-Pozveh (Hosseini-Pozveh et al., 2009) proposes a novel multidimensional approach for CARS in mobile commerce. The approach represents users, items, context information and the relationship between them in a multidimensional space. It then determines the usage patterns of each user under different contextual situations and creates a new two dimensional recommendation space and does the final recommendation in that space. Vico (Vico et al., 2011) design a proactivity two-phase model with user context, temporal context, geographical context, social context. They decides when to make a recommendation after calculating the score by weighted combination of these contexts in Phase I and which item to recommend in Phase II. Some researchers use tensor factorization to solve the multi-dimensional problem in CARS (Karatzoglou et al., 2010; Zou et al., 2014). They decompose the multi-dimensional tensor into the product of a core tensor and multiple factor matrices. These factor matrices can be regard as the principal component in every dimension.

2.4 Evaluation on CARS

Evaluation and optimization on CARS is indispensable to valid the recommendation quality, locate the shortage and get better recommendation. We detail the evaluation in terms of dataset and metric.

2.4.1 Dataset

It is obviously inappropriate to run an algorithm for CARS in traditional datasets which hardly include contexts. Now, the public multi-context datasets is seldom. For one thing, collecting sufficient data including contexts is difficult because of privacy and security. For another thing, considering copyright and commercial value, some researchers don't release their datasets for download freely. So we just introduce part of datasets.

(1) Geolife dataset. This GPS trajectory dataset was collected in Geolife project from Microsoft Research Asia by 182 users in a period of over three years (from April 2007 to August 2012). A GPS trajectory of this dataset is represented by a sequence of time-stamped points, each of which contains the information of latitude, longitude and altitude. This dataset contains 17,621 trajectories with a total distance of about 1.2 million kilometers and a total duration of 48,000+ hours. This dataset recoded a broad range of users' outdoor movements, including not only life

routines like go home and go to work but also some entertainments and sports activities, such as shopping, sightseeing, dining, hiking, and cycling. This trajectory dataset can be used in many research fields, such as mobility pattern mining, user activity recognition, location-based social networks, location privacy, and location recommendation (Zheng et al., 2008; 2009; 2010).

(2) SNAP dataset for LBSN. E. Cho et al. (Cho et al., 2011) collected all the public check-in data between Feb. 2009 and Oct. 2010 for Gowalla and Apr. 2008 to Oct. 2010 for Brightkite. The total number of check-ins for Gowalla is 6.4 million and 4.5million for Brightkite. Gowalla and Brightkite also contain an explicit social network. In Gowalla the friendships are undirected and in Brightkite they are directed. For simplicity, they consider Brightkite as an undirected friendship network by only considering bi-directional edges. There are 196,591 nodes, 950,327 edges in Gowalla and 58,228 nodes, 214,078 edges in Brightkite.

(3) Reality Mining Dataset. The information collected includes call logs, Bluetooth devices in proximity, cell tower IDs, application usage, and phone status (such as charging and idle), which comes primarily from the Context application. The study generated data collected by one hundred human subjects over the course of nine months and represent approximately 500,000 hours of data on users' location, communication and device usage behavior.

2.4.2 Evaluation

Evaluation on CARS can be divide into two parts: online and offline evaluation (Zhu et al., 2012). In online evaluation, we evaluate the recommendation quality according to their real-time feedback or questionnaire after volunteers experiencing the recommender online. The common way is A/B test. Using this way, we can get the satisfaction of users for the recommender, but the cost is very high. In this case, many researchers choose offline evaluation. Offline evaluation measure the quality of recommender, which mainly depend on a series of metric from traditional recommender, such as MAE, Precision, Recall, P@N, MAP, AUC, ROC, RSME, nDCG, MRR. But these metrics couldn't measure the quality of recommendation sufficiently. Coverage, diversity, real-time capability and other are good supplementary choices (Liu et al., 2013). The last but not the least, maybe an algorithm perform well in offline environment, but perform worse in online environment because of complicated context, which demonstrate how to evaluate recommender in an effective way is really a hot pot.

3. THE DEVELOPMENT AND CHALLENGE OF CARS

Although researchers and scientists has study CARS for a long time and make outstanding achievements in the fields of e-commerce, tour, advertisement, music/video, POI recommendation and so on, many challenges is worthy

being studied intensively. Some topics are listed for reference.

(1) The recognition and combination of valid context. Users in different fields have different requirements. Multi contexts need be considered in different scenario. Simple context maybe lost some important information, and too much contexts maybe increase the computational complexity. So the recognition and combination of valid contexts is an urgent issue.

(2) Privacy and security. The more information users supply, the more satisfying recommendation will be. Paradoxically, on the one hand, worried about privacy and security, users are not willing to contribute more personal information. On the other hand, users desire to acquire accurate recommendation. Meanwhile, some attackers deceive users with shilling attack. All of these has been a huge challenge in CARS.

(3) User interface for CARS. Users are always concerned about the recommendation result, not the process. Under the limitation of mobile device, how to show friendlier user interface, guide users join CARS and help them to make decision quickly is really necessary.

(4) Cold start and data sparsity. CARSs generate recommendation for users depend on users' history data. In multidimensional environment, maybe users are not in some specific scenarios, which result in missing value. To recommend items for those new users that has a little or no information is a difficult problem. Capturing Users' preference in specific scenarios is more difficult than in traditional circumstance. In this case, using limited information to generating good recommendation is really a hard work.

(5) Deep learning. 1st workshop on Deep Learning for Recommender Systems has been held in RecSys 2016. As one of the next promising technology in RS, the past few years have seen the tremendous success of deep neural networks in a number of complex tasks such as computer vision, natural language processing and speech recognition. Despite this, only little work has been published on deep learning methods for the recommender systems. Aaron van den Oord(Oord et al., 2013) think sound of a song play a very big role in determining whether or not users enjoy listening to it. They predict listening preferences from audio signals by training a regression model to predict the latent representations of songs that were obtained from a collaborative filtering model. The proposed method could predict the representation of a song in the collaborative filtering space, even if no usage data was available. The regression model in question was a deep neural network. Elkahky(Elkahky et al., 2015) introduce their achievements in news, application and movie/TV recommendation using deep learning in WWW2015. We anticipate that the strong computational ability of deep learning will make a great achievement in CARS.

(6) Social network. Users in social network share their experience with their followers, which has been a new life

style. Social network give us a new way to connect users who maybe are really not related at all previously. Users of social network often explicitly express what they are doing in somewhere or implicitly express preferences through their interactions with other users by tagging or rating. Finding relevant and interesting content in the network including much information according to these abounding information is a challenge for existing recommender approaches.

(7) Emotion and personality. Users' emotion and personality also affects the user's preferences, decisions and actions. since ACM RecSys held EMPIRE from 2013, researchers start to turn to more user-centric descriptors of content and services. The advances made in affective computing, especially in automatic emotion detection techniques, paved the way for the exploitation of emotions and personality as descriptors that account for a larger part of variance in user behavior than the generic descriptors (e.g. genre of a multimedia content) used so far. Personality and emotions shape our daily lives by having a strong influence on our preferences, decisions and behavior in general. In recent years, emotions and personality have shown to play an important role in various aspects of recommender systems. Quanli Gao(Gao et al., 2015) propose a preference collecting method based on users' cognition, and extract user preference in single and multiple dimension. Inspired by the model of level of processing and the theory of distributed cognition, Licai Wang(Wang et al., 2011) propose a cognitive psychology-based approach to user preferences elicitation for mobile network services. Huiji Gao(Gao et al., 2015) capture users real interest for a place according to the sentiment score in comments and make location recommendation using matrix factorization, result on real dataset reveals emotions play a great role on CARS. Researchers import emotions from sociology, which result in the difficulty of quantifying them effectively. With machine learning and natural language processing, users' preference can be understood more precise.

4. CONCLUSIONS

Under complicated scenario including multiple contexts, traditional recommender can't meet users' requirements perfectly. As a new way of relieving information overload, CARS has been a hot pot and improve the quality and satisfaction of recommender. But there still are some challenges remained to be settled. We summarize the updated development status about CARS in this paper. We hope that our work can help researchers promote the development of the field.

5. ACKNOWLEDGMENT

This research is supported by the National Natural Science Foundation of China (Grant No. 61502062, Grant No. 61379158 and Grant No. 71301177), the China Postdoctoral Science Foundation under Grant

2014M560704, the Scientific Research Foundation for the Returned Overseas Chinese Scholars (State Education Ministry), and the Fundamental Research Funds for the Central Universities Project No. 2015CDJXY.

6. REFERENCES

- Gediminas Adomavicius and Alexander Tuzhilin. 2005. Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. *IEEE Trans. on Knowl. and Data Eng.* 17, 6 (June 2005), 734-749.
- Dey A K. Understanding and Using Context Personal and Ubiquitous Computing Journal. *Personal & Ubiquitous Computing*, 2001, 5(1):4-7.
- Gwizdzka J. What's in the context? *Computer Human Interaction*. 2000, 2000.
- Schilit B, Adams N, Want R. Context-Aware Computing Applications, The Workshop on Mobile Computing Systems & Applications. *IEEE Computer Society*, 1994:85-90.
- Chen G, Kotz D. A Survey of Context-Aware Mobile Computing Research. *Dartmouth College*, 1970.
- Hakkila J, Mantyjarvi J. Collaboration in Context-Aware Mobile Phone Applications. 2005, 1(2):33a-33a.
- Meng XW, Wang F, ShiYC, Zhang Y J. Mobile user requirements acquisition techniques and their applications. *Ruan Jian Xue Bao/Journal of Software*, 2014, 25(3): 439-456(in Chinese) .
- Wang LC, Meng XW, Zhang YJ. Context-Aware recommender systems: A survey of the state-of-the-art and possible extension. *Ruan Jian Xue Bao/Journal of Software*, 2012, 23(1):1-20 (in Chinese).
- Yu Z, Zhou X, Zhang D, et al. Supporting Context-Aware Media Recommendations for Smart Phones. *IEEE Pervasive Computing*, 2006, 5(3):68-75.
- Cho E, Myers S A, Leskovec J. Friendship and mobility: user movement in location-based social networks, *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Diego, Ca, Usa, August. 2011:1082-1090.
- Zheng Y, Zhang L, Xie X, et al. Mining interesting locations and travel sequences from GPS trajectories, *International Conference on World Wide Web*, WWW 2009, Madrid, Spain, April. 2009:791-800.
- Meng XW, Hu X, Wang LC, Zhang YJ. Mobile recommender systems and their applications. *Ruanjian Xuebao/Journal of Software*, 2013, 24(1):91-108 (in Chinese).
- Quanli Gao, Ling Gao, Jianfeng Yang, Hai Wang. A preference elicitation method based on users' cognitive behavior for context-aware recommender system. *Chinese Journal of Computers*, 2015, 38(9): 1767-1776 (in Chinese)
- Vico DG, Woerndl W, Bader R. A study on proactive delivery of restaurant recommendations for Android Smartphones. In: *Proc. of the RecSys 2011 Workshop on PeMA 2011*. Chicago, 2011.
- Licai wang, Xiangwu Meng, Yujie Zhang. A cognitive psychology-based approach to user preference elicitation for mobile network service. *Acta Electronica Sinica*, 2011, 39(11): 2547-2553(in Chinese)
- Shudong Liu, Xiangwu Meng. Recommender system in location-based social networks. *Chinese Journal of Computers*, 2015, 38(2): 322-336 (in Chinese)
- Liu Q, Ma H, Chen E, et al. A survey of context-aware mobile recommendations. *International Journal of Information Technology & Decision Making*, 2013, 12(01): 139-172.
- Yu Zheng, Yanchi Liu, Jing Yuan, and Xing Xie, Urban computing with taxicabs. In *Proceedings of the 13th international conference on Ubiquitous computing (UbiComp '11)*, 2011, pp. 89-98.
- Zheng Y, Capra L, Wolfson O, H Yang, Urban Computing: Concepts, Methodologies, and Applications, *Acm Transactions on Intelligent Systems & Technology*, 2014, 5(3), pp. 222-235.
- Quan Yuan, Gao Cong, Zongyang Ma, Aixin Sun, and Nadia Magnenat-Thalmann. 2013. Time-aware point-of-interest recommendation. In *Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval (SIGIR '13)*. ACM, New York, NY, USA, 363-372.
- Liu SD, Meng XW. Approach to network services recommendation based on mobile users' location. *Ruan Jian Xue Bao/Journal of Software*, 2014, 25(11):2556-2574 (in Chinese).
- Lacic E, Kowald D, Traub M, et al. Tackling Cold-Start Users in Recommender Systems with Indoor Positioning Systems. *ACM Recsys*. 2015.
- Andrea Girardello and Florian Michahelles. 2010. AppAware: which mobile applications are hot?. In *Proceedings of the 12th international conference on Human computer interaction with mobile devices and services (MobileHCI '10)*, 431-434.
- Son J W, Kim A Y, Park S B. A location-based news article recommendation with explicit localized semantic analysis. *International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2013:293-302.
- Zhiyong Cheng and Jialie Shen. 2014. Just-for-Me: An Adaptive Personalization System for Location-Aware Social Music Recommendation. In *Proceedings of International Conference on Multimedia Retrieval (ICMR '14)*. ACM, New York, NY, USA, Pages 185-192.
- Noulas A, Scellato S, Mascolo C, et al. An Empirical Study of Geographic User Activity Patterns in Foursquare, *International Conference on Weblogs and Social Media*, Barcelona, Catalonia, Spain, July. 2011.
- Karatzoglou A, Amatriain X, Baltrunas L. Multiverse recommendation: n-dimensional tensor factorization for context-aware collaborative filtering , *Proceedings of the fourth ACM conference on Recommender systems*. ACM, 2010: 79-86
- Zou BY, Li CP, Tan LW, Chen H, Wang SQ. Social recommendations based on user trust and tensor factorization. *Ruan Jian Xue Bao/Journal of Software*, 2014, 25(12):2852-2864 (in Chinese).
- Xibin Wang , Junhao Wen , Shafiq Alam , Zhuo Jiang , Jun Zeng , Sales growth rate forecasting using Improved PSO and SVM , *Mathematical Problems in Engineering* , 2014 , 2014 (2014) : 1-13
- Park, MH, Hong JH, Cho SB. Location-Based recommendation system using Bayesian user's preference model in mobile devices. In: *Proc. of the Ubiquitous Intelligence and Computing 2007*. LNCS 4611, Berlin: Springer-Verlag, 2007. 1130-1139.
- Bao J, Zheng Y, Mokbel M F. Location-based and preference-aware recommendation using sparse geo-social networking data. *Gis*, 2012:199-208.
- Liu B, Fu Y, Yao Z, et al. Learning geographical preferences for point-of-interest recommendation, *ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 2013:1043-1051.
- Gao H, Tang J, Hu X, et al. Exploring temporal effects for location recommendation on location-based social networks, *Proceedings of the 7th ACM conference on Recommender systems*. ACM, 2013: 93-100.
- Gao H, Tang J, Hu X, et al. Content-Aware Point of Interest Recommendation on Location-Based Social Networks, *AAAI*. 2015: 1721-1727.
- Lian D, Zhao C, Xie X, et al. GeoMF: joint geographical modeling and matrix factorization for point-of-interest recommendation, *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM, 2014: 831-840.

Yuan Q, Cong G, Ma Z, et al. Time-aware point-of-interest recommendation, Proceedings of the 36th international ACM SIGIR conference on Research and development in information retrieval. ACM, 2013: 363-372.

Yuan Q, Cong G, Sun A. Graph-based point-of-interest recommendation with geographical and temporal influences, Proceedings of the 23rd ACM International Conference on Conference on Information and Knowledge Management. ACM, 2014: 659-668.

Costa H, Furtado B, Pires D, et al. Context and intention-awareness in pois recommender systems, 6th ACM Conf. on Recommender Systems, 4th Workshop on Context-Aware Recommender Systems, RecSys. 2012, 12: 5.

Li X, Xu G, Chen E, et al. MARS: A multi-aspect Recommender system for Point-of-Interest, 2015 IEEE 31st International Conference on Data Engineering. IEEE, 2015: 1436-1439.

Zeng J, Li F, Liu H, et al. A Restaurant Recommender System Based on User Preference and Location in Mobile Environment, Advanced Applied Informatics (IIAI-AAI), 2016 5th IIAI International Congress on. IEEE, 2016: 55-60.

del Carmen M, Ilarri S, Trillo-Lado R, et al. Location-Aware Recommendation Systems: Where We Are and Where We Recommend to Go.

Yu Zheng, Quannan Li, Yukun Chen, Xing Xie, Wei-Ying Ma. Understanding Mobility Based on GPS Data. In Proceedings of ACM conference on Ubiquitous Computing (UbiComp 2008), Seoul, Korea. ACM Press: 312-321.

Yu Zheng, Xing Xie, Wei-Ying Ma, GeoLife: A Collaborative Social Networking Service among User, location and trajectory. Invited paper, in IEEE Data Engineering Bulletin. 33, 2, 2010:32-40.

Oord A V D, Dieleman S, Schrauwen B. Deep content-based music recommendation, Neural Information Processing Systems Conference (NIPS 2013). Neural Information Processing Systems Foundation (NIPS), 2013:2643-2651.

Elkahky A M, Song Y, He X. A Multi-View Deep Learning Approach for Cross Domain User Modeling in Recommendation Systems, International Conference on World Wide Web. ACM, 2015.

Baldauf B M. et al. "A survey on context-aware systems, Int. J. Ad Hoc Ubiquitous Comput. 2010.

Yuxiao Zhu, Linyuan Lv. Evaluation metrics for recommender system. Journal of University of Electronic Science and Technology of China. 2012 41(2):163-175(in Chinese)

Ahn HC, Kim KJ. Context-Aware recommender system for location-based advertising. Key Engineering Materials, 2011, 467-469:2091-2096.

Ricci F, Rokach L, Shapira B, Kantor PB. Recommender Systems Handbook. Berlin: Springer-Verlag, 2011. 1-842.

Baltrunas L, Amatriain X. Towards time-dependant recommendation based on implicit feedback, Workshop on context-aware recommender systems (CARS'09). 2009.

Panniello U, Tuzhilin A, Gorgoglione M, Palmisano C, Pedone A. Experimental comparison of pre- vs. post-filtering approaches in context-aware recommender systems. In: Proc. of the RecSys 2009. New York: ACM Press, 2009. 265-268.

Hu B, Ester M. Social Topic Modeling for Point-of-Interest Recommendation in Location-Based Social Networks, IEEE International Conference on Data Mining. 2014:845-850.

Lee TQ, Park Y, Park YT. A time-based approach to effective recommender systems using implicit feedback. Expert Systems with Applications, 2008, 34(4):3055-3062

Hosseini-Pozveh M, Nematbakhsh MA, Movahhedinia N. A multidimensional approach for context-aware recommendation in mobile commerce. Int'l Journal of Computer Science and Information Security, 2009, 3(1):86-91

Ahn H, Kim KJ, Han I. Mobile advertisement recommender system using collaborative filtering: Mar-cf. In: Proc. of the 2006 Conf. of the Korea Society of Management Information Systems. The Korea Society of Management Information Systems, 2006.709-715.

Authors

Jun Zeng received the BS and MS degree in software engineering from Chongqing University in 2007 and 2010. He received PhD degree in advanced information technology of Kyushu University in 2013. Since 2013, he has been a lecturer in the school of software engineering in Chongqing University. His research interest includes service computing and data mining.

Feng Li, postgraduate. He received the BE degree in software engineering from Chongqing University. His current research mainly focus on recommender system, data mining and machine learning.

Yinghua Li, postgraduate, member of CCF. He received the BE degree from Sichuan Normal University. His current research mainly concentrates on service computing, data mining, social network analysis and recommender system.

Junhao Wen, Ph.D., professor, vice dean of the school of software engineering. Vice chairman of Chongqing Branch of CCF, fellow of CCF. His research interest includes service computing and data mining.

Yingbo Wu, ph.D, associate professor/the supervisor, Vice Department Director, member of CCF, AC commissioner of CCF YOCSEF of Chongqing Branch. His research interest includes distributed and intelligent computing, service system engineering, domain engineering and industry informatization.