A Context-Aware Recommender System Based on Social Media

Chia-Chi Wu[1], and Meng-Jung Shih[2]

Abstract**—**Context-aware recommender systems, which recommend products, content, or learning resource to users according to not only user preference and item characteristics but also contextual information, have received much attention in recent years. However, many existing systems collect only limited amount of user rating without any contextual information. That brings these systems into a crisis of cold starting. In this paper, we propose a framework which collects information from social media. By analyzing user reviews from a forum, our framework extracts contextual features, such as date, time, and motivation, for each user review, and recommends items to users according to reviews with similar contextual features. We also developed a modified collaborative filtering algorithm to integrate different contextual features. To sum it up, this study proposes a new framework which integrates rich information on social media to ease the lack of contextual information of context-aware recommender systems.

Keywords**—**Context-Aware Recommender Systems, Personalization, Recommendation, Social Network

I. Introduction

SINCE the publication of the first papers on collaborative filtering, recommender systems, which aim to recommend products, content, or learning resource to users based on user behavior or preference, have become an important issue and received a lot of study[3]. There have been many approaches of recommender systems proposed by academia and industry including: Content-Based Filtering [10], [14], [17], Collaborative Filtering [10], [11], [14], [19], [20], Knowledge-based Filtering [8], [9], [18], and Hybrid approaches [10], [14]. There are also some reviews about recommender systems [3], [20].

Traditional recommender systems mentioned above consider only user preference and item characteristics, and try to train a recommender function ($User \times Item \rightarrow Rating$). Using this function, recommender systems estimate ratings for all (user, item) pairs which have not been rated by users and generate recommendation lists with high-rated items as the output [5], [7]. However, in many applications, it may not be enough to consider only user and item. Contextual information, such as time, location, or motivation, is also critical and has to be considered into a recommendation process. For example, in the case of travel recommender system, users may prefer hot springs tours in winter, and vice versa interested in water activities in summer.

Much attention has been given to context-aware recommender systems in recent years. Adomavicius and Tuzhilin (2011) provide a comprehensive literature review about context-aware recommender systems. They classify context-aware recommender systems into three categories, contextual pre-filtering, contextual post-filtering, and contextual modeling. Contextual pre-filtering approaches, such as [2], [6], [12], [13], use contextual information to select relevant set of records or to filter irrelevant ones. Contextual post-filtering approaches ignore contextual information first, and then adjust recommendation list for each user according to the contextual information. Panniello et al. (2009) compared the performance of pre-filtering approaches and post-filtering approaches, and the result showed that none of the two approaches dominates another in all applications. Contextual modeling approaches, such as [1], [4], [15], use contextual information directly in their modeling technique.

Most approaches mentioned above generate context-aware recommendations based on user ratings and corresponding contextual information. However, many systems collect only limited amount of user rating without any contextual information. That brings these systems into a crisis of cold starting. Therefore, additional external data source is needed to enrich the data of user rating and contextual information. In this paper, we propose a new framework of context-aware recommender system. This framework extracts contextual information from social media, which is a treasure of information in the big data era. By collecting and analyzing user reviews, our framework extracts contextual features, such as date, time, and motivation, and recommends items to users according to reviews with similar contextual features. For integrating contextual features with different characteristics, we also developed a modified collaborative filtering algorithm named context-aware collaborative filtering (CCF) which combines contextual pre-filtering and contextual post-filtering approaches.

The remainder of this paper is organized as follows. We first introduce the framework of our new context-aware recommender system in section II. A prototype of our system is then shown in section III. Finally, conclusion and possible future work are presented in section IV.

Chia-Chi Wu[1] is with the Advanced Research Institute, Institute for Information Industry, Taipei City 105, Taiwan, R.O.C. (phone: 886-2-6607-2963; e-mail: arthurwu@iii.org.tw).

Meng Jung Shih[2] is with the Advanced Research Institute, Institute for Information Industry, Taipei City 105, Taiwan, R.O.C. (e-mail: mengjungshih@iii.org.tw).

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II. System Framework

The Framework of our new context-aware recommender system is shown in Fig. 1.

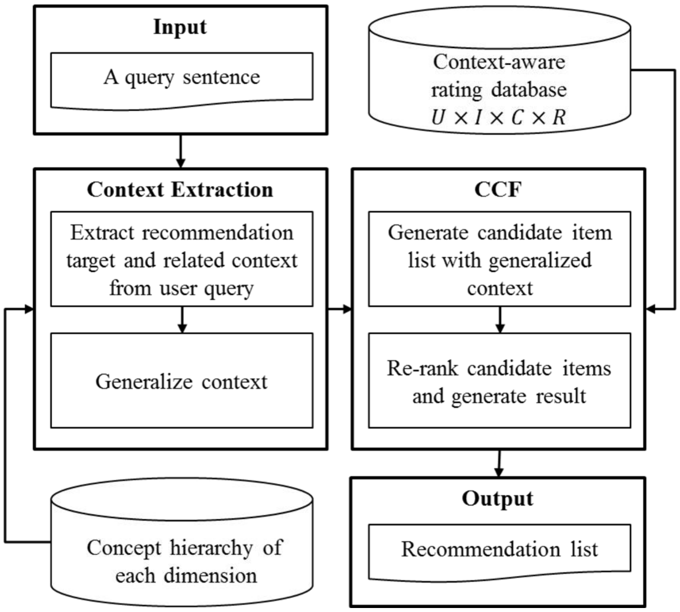

Fig. 1 System framework

In Fig. 1, the input of our system is a query sentence which can be composed of natural language. There are two main partitions in the framework. One is context extraction, which identifies search target of users and related contextual information according to a set of concept hierarchy, another is recommender, which selects candidate items and re-ranks them based on user query and a context-aware rating database. The re-ranking result is then used to generate a recommendation list as the output of our system. Details of each procedure and database will be interpreted in the remainder of this section.

A. Context Extraction

In this partition, we first extract search target and related contextual information from a query sentence. We define some contextual features belonging to different dimensions, such as time, location, or motivation. For presenting all possible values of contextual features and relationships between them, a concept hierarchy is built for each contextual feature. An example of concept hierarchy of "Week" is shown in Fig. 2.

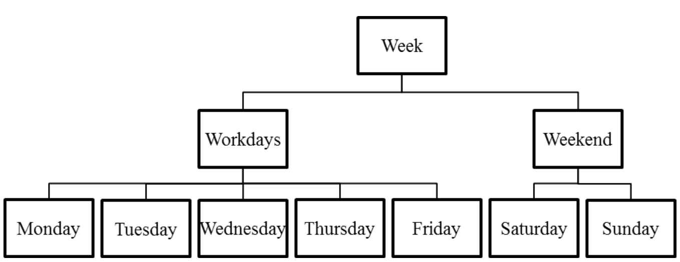

Fig. 2 A concept hierarchy of "Week"

By comparing each word (including synonyms) among the query sentence and each item in each concept hierarchy, all contextual information mentioned by this query can be identified and classified into corresponding features. For example, the contextual information extracted from the query "Eat Korean food with family in Taipei on Saturday" is shown in Table I. Not all dimensions of contextual information can be found from user query. In this example, we can not identify the gender of this user with the query submitted. Therefore, the value of "Gender" in Table I is set to "Null".

TABLE I
Contextual Information Extracted from User Query

Gender	Location	Week	Motivation	Category
Null	Taipei	Saturday	Family meal	Korean cuisine

The contextual information extracted from query can be too narrow to be significant. For example, user's restaurant preferences on Saturday may be totally the same as on Sunday, but different from Monday's. Therefore, using a more general concept, such as Weekend instead of Saturday, may be more appropriate. After extracting context from queries, we then generalize some context features according to concept hierarchies. The result of the example is shown in Table II.

TABLE II
Contextual Information after Generalized

Gender	Location	Week	Motivation	Category
Null	Taipei	Weekend	Family meal	Korean cuisine

B. Context-aware rating database

The system generates recommendation lists by comparing contextual features of input query with contextual features of user ratings. User ratings and corresponding contextual features can be collected by retrieving and analyzing user reviews in social media. Fig. 3 is a review which comments on an Italian cuisine restaurant located in Taipei. The rating score was five stars, the rating time was on Aug. 17, 2013, and the common was "A good place for having dinner with colleagues".

Fig. 3 A review in social media

Thus, the contextual information extracted from the review in Fig. 3 is shown in Table III

TABLE III
Contextual Information of The Review in Fig. 3

Gender	Location	Week	Motivation	Category
Male	Taipei	Weekend	Colleague meal	Korean cuisine

C. Context-aware collaborative filtering

After getting search target and related contextual information of input query, the system conducts a modified collaborative filtering algorithm, context-aware collaborative

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filtering (CCF), to generate final recommendation list.

CCF divides all contextual features into two groups, necessary features and priority features. For a recommended target, i.e. a restaurant, some features, such as “Location” and “Target”, are fixed and are therefore more suitable to be necessary conditions, while others, such as “Gender”, “Week”, and “Motivation”, are different among distinct ratings and are therefore more suitable to be priority conditions.

There are two steps involved in CCF:

Step1. Generate a list of candidates by filtering out items that are irrelevant with necessary features.

Step2. Re-rank items within the candidate list with priority features.

Assume $nf_i(q)$ be the value of the ith necessary context feature of input query q and $nf_j(x)$ be the value of the jth necessary context feature of an item x. For an input query q, a list of candidates $C(q)$ is generated in step 1, where an item x is selected into $C(q)$ if and only if $\forall i, \exists j, nf_j(x) \subseteq nf_i(q)$.

After generating the list of candidates $C(q)$, CCF estimates the rating of each item in $C(q)$ for a target user u. A traditional collaborative filtering recommender estimates the rating $r(u, x)$ of item x for user u by equation (1)

$$r(u,x) = k\sum_{v\in V} sim(u,v) r(v,x) \tag{1}$$

where V is the set of all users who have given a rating to x, k is a normalizing factor which is usually selected as $k=1/\sum_{v\in V} sim(u,v)$, and $sim(u, v)$ is the similarity between the two users u and v.

Most approaches define the similarity between two users based on their ratings of items which both of them have rated. However, many systems collect only limited amount of user rating, and therefore result in a crisis of cold starting. For easing the problem of cold starting and applying contextual information at recommendation process, our CCF algorithm defines the similarity between a user and a rating based on contextual features.

CCF estimates the rating $r(q, x)$ of an item x for a user query q by equation (2)

$$r(q,x) = k\sum_{w\in W(x)} sim(q,w) r(w,x) \tag{2}$$

where $W(x)$ is the set of all reviews rating on item x, k is a normalizing factor which is selected as $k=1/\sum_{w\in W(x)} sim(q,w)$, and $sim(q, w)$, the similarity of context features between user query q and review w, is defined in equation (3).

$$\begin{aligned} sim(q,w) &= \frac{1}{|PF|}\sum_{pf_i\in PF} sim(pf_i(q), pf_i(w)) \\ sim(pf_i(q), pf_i(w)) &= \begin{cases} 1 & \text{if } pf_i(w) \subseteq pf_i(q) \\ 1 & \text{if } pf_i(q) = \text{"null"} \\ 0 & \text{if } pf_i(w) \not\subset pf_i(q) \end{cases} \end{aligned} \tag{3}$$

In equation (3), PF is the set of all priority features, and pf_i is the ith priority feature. The values of pf_i in user query q and in review w are denoted by $pf_i(q)$ and $pf_i(w)$, respectively. For example, suppose “Gender”, “Week”, and “Motivation” are all the priority features, and all related values of user query q and review w are listed in Table II and Table III, respectively. The similarity between q and w $sim(q, w) = 2/3$.

After estimating the rating $r(q, x)$ for all items belonged to $C(q)$, CCF sorts the items in $C(q)$ by estimated ratings and generates the recommendation list.

III. A Prototype of Context-Aware Recommender System

We constructed a prototype of our context-aware recommender system to evaluate our framework and the CCF algorithm. This prototype recommends points of interest (POIs) and restaurants in Taiwan. In this prototype, the contextual features and the related concept hierarchies are defined as:

- Gender: Male/Female
- Nationality: Nationality of user
- Location: Business district $\rightarrow$ District $\rightarrow$ City
- Season: Month $\rightarrow$ Season
- Week: DayofWeek $\rightarrow$ Workdays/Weekend
- Motivation: Motivation of user
- Category: Category of POI or restaurant

After submitting a query, such as “Eat Korean food with family in Taipei on Saturday”, the system generates a recommendation list and outputs this list as shown in Fig. 4. In Fig. 4, the system lists POIs and related information in the order of estimated rating of POIs. Information offered for each POI includes photo, name, description, and hot issues which extracted from user reviews.

IV. Conclusion

In this paper, we propose a new framework of context-aware recommender system. For easing the problem of cold starting and utilizing rich resources of user generated content, this framework collects ratings and extracts related contextual information from a social media. We also propose a modified collaborative filtering algorithm, context-aware collaborative filtering (CCF), to integrate different context features. In future, we will involve the mechanism of context inferring into our framework to infer contextual information which can not be extracted from query sentences.

Fig. 4 Recommendation list

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