Personalized Multimedia Recommendation with Social Tags and Context Awareness

Che Kao-Li, Tsung-Hsien Yang, and Wei-Po Lee

Abstract—**The large amount of multimedia contents often cause the problem of information overload. To tackle this problem, it is necessary to develop personalization techniques to recommend most suitable contents to users. In this work, we develop a new social tag-based method for the recommendation of multimedia items, and compare it with several often-used methods. A context-aware platform is also implemented that takes into account different environment situations in order to make the most sensible recommendations.**

Index Terms— **personalization, social tagging, collaborative recommendation, context awareness**

I. Introduction

Following the advances of communication techniques, digital broadcasting systems can now conveniently deliver different types of multimedia contents to end-users. However, the large amount of multimedia content leads to the problem of information overload. To mediate this problem, it becomes important to develop personalization techniques to recommend most suitable contents to users [1][2].

In general, the recommendation techniques can be categorized into two types: content-based and collaborative ones. The content-based approach is to predict the user's preference on unknown items from his historical records. Therefore, the most important issue is to construct a computational model for prediction. Many machine learning approaches have been applied to construct user models, for example, [3][4]. But it should be noted that the content-based approach largely relies on the sufficient examples used for model construction. Also, this type of approach inevitably recommends items within some specific scopes, and thus loses item diversity (i.e., ignoring items of the unfamiliar classes). One the other hand, a collaborative approach recommends items to the user according to the evaluations from other users with similar tastes. In other words, it does not analyze what a user likes but taking the opinions of others. In this type of approach, the most important issue is to the measure of similarity between users. With a certain correlation criterion, the system can employ a *k*-nearest neighbor method to find most similar users to perform recommendation. The prediction of an unknown item for a user is thus based on the combination of the ratings of his nearest neighbors. This type of approach has been widely used in different applications.

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It has generally been agreed that the collaboration-based approach can provide better performance than the content-based approach. Yet, with the current trend of organizing and sharing digital content through user-created metadata (i.e., social tags), the performance and effectiveness of collaborative recommendation can be improved by using such metadata to further recognize how the users likes specific items. Social tags are brief descriptions of items and they are freely supplied by a community of internet users to aid the access of large collections of media [5][6]. The use of social tags provides an interesting alternative to current efforts at semantic web ontologies in content annotation [7][8]. As tagging is neither exclusive nor hierarchical and therefore can in some circumstances have an advantage over hierarchical taxonomies. In this work, we adopt this way for multimedia annotation, use the tag information to analyze how the user likes specific items, and exploit such user information to perform collaborative recommendation.

In addition to the above-mentioned approach that focuses on the items, another issue needs to consider in personalized recommendation is the context. Context awareness is about capturing a broad range of contextual attributes (such as the user's current positions, activities, and their surrounding environments) to better understand what the user is trying to accomplish, and what content suits the user the most in that context [9][10]. Any contextual changes may cause a user to select a different item. By integrating context information into the service, a recommendation system can satisfy the user's need more efficiently and practically.

In this paper, we compare different computational methods for making personalized recommendation on multimedia items. Considering the current trend of community-based information sharing, we also propose to use social tags as item annotation to improve recommendation performance. The experimental results show that the tag-based method outperforms other often used methods. In addition to the user preference, context can also influence a user's decision in accessing information services. Therefore, we also implement a context-aware platform and present how to take the environmental situations into consideration to perform item recommendation accordingly.

II. Tag-based Collaborative Filtering for Multimedia Recommendation

A. User Profiling

The first important step to perform personalized recommendation is the creation of personal profile that provides a common reference point in delivering certain

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information services. Therefore, it is critical to collect profile data explicitly or implicitly and keep it up-to-date with a user's changing needs and contexts. In this work, the recorded information is quantified as a set of instances with user preferences in the profile. That is, each item (i.e., multimedia instance) is transferred into a symbolic feature form. This involves extracting and modeling semantic information about the multimedia content. Modeling multimedia content is a time-consuming and laborious process, and researchers have been adopting various methods to achieve it. Traditionally, video segmentation or clustering is first performed for content interpretation and modeling in which video segments or clusters with similar low-level features or frame-level static features are grouped together. The segments are then mapped into a hierarchical structure with incremental semantic granularity from top to bottom. However, using the decomposed segments as features to represent a multimedia item is a computationally expansive way and the meaning of the original video sequential can easily be lost [11].

Instead of directly analyzing the video sequence, this system uses an efficient way to capture the semantic of a multimedia program: it extracts some features to represent a program from relevant electronic text-based information. Our previous study has shown that this is a promising approach to capture the meanings of multimedia items [4]. In our work, a multimedia item is transferred into a feature vector of genre, director, cast, and plot, because these features normally imply some semantic characteristics of this program. The plot here means a set of keywords obtained from the content provider to describe the content of a program. All terms appearing in the training examples are defined as candidate features in the learning procedure and used to construct the user models.

Different from the above representation that mainly describes the content of item, in this work we propose to take the way of social tagging that records how a user like/dislike an item from different dimensions. This method has been a very popular technique in Web 2.0 applications. It allows individual users to arbitrarily attach different tags to annotate items (or contents). These tags not only describe item characteristics but also reflect what the users feel about the items personally. By analyzing the tags used to annotate items, we can extract a user's preference and furthermore make prediction for him on unknown items accordingly.

B. *Content-based Recommendation*

Once the personal information has been collected (or updated), the next step is to model the user's preference from the information obtained. Two recommendation methods mentioned previously (learning method and collaboration method) are developed for user modeling. The learning module takes the responsibility of building a classifier by using the most recent items collected and recorded in the personal profile as training examples. Different machine learning approaches can be applied to construct the user model. The choice of learning approach completely depends on the considerations of service providers and the characteristics of application domains. In this work, we experience three information theory-based inductive methods that are computational efficient and thus more practical for user modeling. They are decision tree method, Naïve Bayes method, and support vector machine (SVM) method to build predictive classifiers. Their prediction performance is presented in the experimental section.

C. *Collaborative Recommendation*

Collaborative recommendation (or collaborative filtering, CF) performs predictions for a specific user according to the evaluations (ratings) from other users with similar tastes. For a user u_a, the most similar users are selected as a neighbor set $Neig(u_a)$, and their combined opinion on a certain item m_{recom} is used to predict whether u_a will like this item. The rating of preference of a specific item m_{recom} is defined as:

$$R_{pre}(u_a, m_{recom}) = \bar{R}_{pre}(u_a) + z_1 \times \sum_{u_n \in Neig(u_a)} Sim(u_a, u_n) \cdot (R_{pre}(u_n, m_{recom}) - \bar{R}_{pre}(u_n))$$

In the above equation, $R_{pre}(u, m)$ represents the preference of user u on item m; $\bar{R}_{pre}(u)$ is the average preference rating of user u on all items he has rated; $Sim(u_a, u_n)$ is the similarity between two users u_a and u_n; z_1 is the normalized factor and can be calculated as $z_1 = 1 \Big/ \sum_{u_n \in Neig(u_a)} |Sim(u_a, u_n)|$.

There are several methods to calculate the similarity mentioned above, and the most often used method is the Pearson correlation coefficient. Here, we adopt this method to measure the similarity between two users u_a and u_n as:

$$Sim_{CF} = \frac{\sum_{m_l \in Com(u_a,u_n)} (R_{pre}(u_a, m_l) - \bar{R}_{pre}(u_a)) \times (R_{pre}(u_n, m_l) - \bar{R}_{pre}(u_n))}{\sqrt{\sum_{m_l \in Com(u_a,u_n)} (R_{pre}(u_a, m_l) - \bar{R}_{pre}(u_a))^2} \sqrt{\sum_{m_l \in Com(u_a,u_n)} (R_{pre}(u_n, m_l) - \bar{R}_{pre}(u_n))^2}}$$

In the above equation, $Com(u_a, u_n)$ is the set of items that both users u_a and u_n have already rated. This coefficient is between 1 (the preferences of both users are exactly the same) and -1 (their preferences are opposite each other); and a value 0 means that their preferences are not correlated.

D. *Tag-based Collaborative Recommendation*

Folksonomy (i.e., community-based method) is a very popular technique nowadays to annotate items (or contents). To exploit the current trend in adding metadata in shared contents, we develop a new approach that incorporates user-specific tags into CF to conduct item recommendation.

To enable users to share tags and keep the annotation consistent, in this work we adopt the method of suggestive-tagging that collects and provides a table of popular tags (as shown in Table 1) for multimedia annotation. The user can select tags from the table and give a value from 1 (lowest) to 5 on each tag to explicitly express his evaluation.

Similar to the collaborative recommendation method described above, Tag-CF also measures the similarity between users and finds a neighbor set $Neig(u_a)$ for a specific user u_a to predict the user preference on a certain item m_{recom}. The same equation for measuring rating preference in CF is used here to calculate $R_{pre}(u, m)$. But it should be noted that the Tag-CF method uses tags to look for similar users rather than item preference as in the traditional CF method.

To show the importance of using tags and how the tag-based CF differs from CF, we take an illustrate example as following. Suppose there are three users ($u_1 \sim u_3$) and five items ($m_1 \sim m_5$) in the recommendation system, and Figs 1 and 2 describe the preference ratings and the corresponding tag

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evaluations of the three users on the five items, respectively. The goal here is to predict the rating of user u_1 on item m_5, based on the information recorded in the two tables. As can be seen in Fig 1, if the system uses CF method is for prediction, it will find the most similar user u_2 and take his opinion. On the contrary, if tags are taken into consideration, the most similar user is now u_3 because from Fig 2 we can observe that u_3 takes the similar perspectives (i.e., they use the same tags) as u_1 to rate items and gives similar evaluation results. Therefore, the system shall take u_3's opinion to predict whether u_1 likes m_5 or not. In this example, using tags for prediction is in fact more reasonable and precise than that of preference rating. But it should be noted that this is not a general situation. It is possible that the user may give high remarks in some feature dimensions (tags) on the items he does not like.

TABLE I: THE SUGGESTED TAGS FOR ANNOTATION

story	climax	originality	profundity	dialogue	pace
thinking	portraying	role	popularization	horror	music
touchingness	satire	humor	entertainment	cast	acting
visual	action	stunt	characteristic	atmosphere	director

	Multimedia m_1				Multimedia m_2				Multimedia m_3				Multimedia m_4				Multimedia m_5			
	Pre	t_1	t_2	t_3	Pre	t_1	t_2	t_3	Pre	t_1	t_2	t_3	Pre	t_1	t_2	t_3	Pre	t_1	t_2	t_3
User u_1	5	5		5	4		4	5	2	2			2	1			?	-	-	-
User u_2	5		5		4		5		2		2		2	3			4		5	3
User u_3	4	4		5	5		4	5	1	1			2	1			1	1		2

Fig. 1. The preference ratings of three users on five items.

	Multimedia m_1				Multimedia m_2				Multimedia m_3				Multimedia m_4				Multimedia m_5			
	Pre	t_1	t_2	t_3	Pre	t_1	t_2	t_3	Pre	t_1	t_2	t_3	Pre	t_1	t_2	t_3	Pre	t_1	t_2	t_3
User u_1	5	5		5	4		4	5	2	2			2	1			?	-	-	-
User u_2	5		5		4		5		2		2		2	3			4		5	3
User u_3	4	4		5	5		4	5	1	1			2	1			1	1		2

Fig. 2. The tag evaluations of three users on five items.

To consider the two factors of user preference and tag evaluation, we combine both of them to develop a new method for the calculation of similarity between two users and use it to work with collaborative recommendation. The user similarity is now described as:

Sim_{TagCF} =

(1) $$\frac{z_2 \times \sum_{m_l \in Com_{LL}(u_a,u_n)} TC(u_a,u_n,m_l) + z_3 \times \sum_{m_l \in Com_{DD}(u_a,u_n)} TC(u_a,u_n,m_l)}{2} - z_4 \times \sum_{m_l \in Com_{LD}(u_a,u_n)} TC(u_a,u_n,m_l)$$

if $Com_{LL}(u_a, u_n) \neq \phi$ and $Com_{DD}(u_a, u_n) \neq \phi$;

(2) $z_2 \times \sum_{m_l \in Com_{LL}(u_a,u_n)} TC(u_a,u_n,m_l) - z_4 \times \sum_{m_l \in Com_{LD}(u_a,u_n)} TC(u_a,u_n,m_l)$ if $Com_{DD}(u_a, u_n) \neq \phi$;

(3) 0 if $Com_{LL}(u_a, u_n) \neq \phi$

In the above equations, $Com_{LL}(u_a, u_n)$ represents the set of items that u_a and u_n have evaluated and the two users both like them; $Com_{DD}(u_a, u_n)$ includes the items that both users do not like them; and $Com_{LD}(u_a, u_n)$ includes the items that one of the two users like them. In addition, the normalized factors z_2, z_3, and z_4 are $1 \Big/ \sum_{m_l \in Com_{LL}(u_a,u_n)} \left|TC(u_a,u_n,m_l)\right|$, $1 \Big/ \sum_{m_l \in Com_{DD}(u_a,u_n)} \left|TC(u_a,u_n,m_l)\right|$, and $1 \Big/ \sum_{m_l \in Com_{LD}(u_a,u_n)} \left|TC(u_a,u_n,m_l)\right|$, respectively. As can be observed, these equations accumulate tag evaluations of those items that both users have the same preference ratings, and then decrease the effect caused from the items they have different preferences.

$TC(u_a, u_n, m_l)$ measures the similarity of tag evaluation on item m_l between u_a and u_n, based on the calculation of Tanimoto coefficient, an extended Jaccard coefficient that is often used to calculate the similarity of vectors with asymmetric binary attributes. In our case, for the tags that are only used (evaluated) by one user, a default value of 3 will be automatically inserted as the evaluation result by the other user. But for the tags that are not used by any of the users, they are simply ignored (not taken into consideration). In this way, the $TC(u_a, u_n, m_l)$ is defined as:

$$TC(u_a,u_n,m_l) = TC(\vec{E}_{u_a,m_l}, \vec{E}_{u_n,m_l})$$

$$= \frac{\sum_g R_{tag}(u_a,m_l,t_g) \cdot R_{tag}(u_n,m_l,t_g)}{\sum_g R_{tag}(u_a,m_l,t_g)^2 + \sum_g R_{tag}(u_n,m_l,t_g)^2 - \sum_g R_{tag}(u_a,m_l,t_g) \cdot R_{tag}(u_n,m_l,t_g)}$$

in which $R_{tag}(u, m, t_g)$ means the evaluation result of user u on tag t_g that is used to annotate item m_l.

E. Context Awareness

As mentioned above, the mobile internet has become increasingly popular, and a variety of environmental contexts that do not happen in the stationary internet now needed to be taken into account in the deployment of recommendation service. This section describes the contexts considered in our work, including user location, audience, mobile device, and network condition. They have been used to develop a set of rules to re-rank the recommendation list derived from the user preference.

A location-aware service can be described as an application that is dependent on a certain geographical location. Location information can be used either on its own or integrated with other information sources to provide business advantages for companies. One way is to use the location of a mobile user as parameter for service provision, for example, using handset-based positioning solution (such as global positioning system, GPS) or network-based positioning solution (such as GSM cellular system). Here, we do not use the detailed location parameters but instead categorize the location context into two types, public and private, and use this information to restrict the playing of multimedia contents. According to the MPAA (Motion Picture Association of America) rating systems, we rank multimedia products into five levels-G (general audiences), PG (parental guidance suggested), PG-13 (parental strongly cautioned), R (restricted), and NC-17 (only people 17 and older are admitted), and associate them to appropriate location types. This is to consider the impression of the people around the user who is accessing the multimedia by a mobile device.

The social context means that sometimes a user may invite other people to access multimedia content (e.g., watch movie) together. Similar to the situation in the above location context, the recommendation list needs to be adjusted and some contents need to be filtered out from the list. In this work, we use the above MPAA rating criterion to remove the ones not

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suitable for many viewers, and re-rank the rest items in the list according to their popularity.

As can be observed, it is now very popular to use powerful mobile devices, such as mobile phones, slim notebooks, or portable TVs, to listen to music or watch movie in the mobile environment. Devices used by mobile users are diverse and heterogeneous. They have different screen size, memory, media support, connection speed, and perhaps the most important capability—computational power, to deal with the multimedia content. For the high resolution media content, a more powerful computational mechanism is needed to prevent the delay of video and audio in media playing. Battery power is another important issue needed to be aware because accessing multimedia through mobile devices is a very power-consuming application. Under such circumstances, some contents can not be supported by mobile devices with more hardware limitations. Therefore, the system must take the device context into consideration in making recommendation.

In addition to the hardware devices, the communication condition is also a critical factor that decides service quality directly. High resolution online contents are generally preferred, but they require the support of high network bandwidth. Multimedia products can therefore be produced in different modes to fit in the available network bandwidth. For example, YouTube started to supports high resolution films since 2008 when the network condition was largely improved. It allows the user to choose appropriate resolution mode for the multimedia he is playing, depending on the network and device conditions.

III. Experiments and Results

After presenting our framework with the corresponding methodology in recommendation, in this section we describe the experiments conducted for the comparison of different recommendation methods. Then we embed the most efficient method to the framework and illustrate the implementation details of our context-aware recommendation system.

A. Performance Evaluation on Recommendation

In the recommendation experiments, the dataset was collected from 40 individual users. Each participant was asked to provide at least 40 movie items (chosen from a default list with 320 items, or specified by user manually) he has evaluated before. To avoid the data imbalanced problem and to produce more objective evaluations for different methods, we asked the user to give roughly the same number of example items for each class (like or dislike). For each item, the user needed to further express his degree of preference from the common five-scale values measurement (the degree of preference decreases from 5 to 1). This value will be used to predict user preference in the collaboration-based approach as indicated. In addition to the overall preference on the items, in the data collection process, the users were also asked to arbitrarily pick some tags from a suggested list and then indicate his preferences on these tags. In the collected dataset, the user gave 12 tag-evaluations on each movie item on average.

With the above dataset, the first set of experiment is to evaluate the performance of the proposed tag-based method for the situation in which a content-based strategy is adopted for recommendation. In the experiment, the traditional keyword-based method and the tag-based method were used to represent the multimedia content, respectively. For the keyword-based method, the publicly available online database Internet Movie Database (IMDb) was used, and the keywords for each movie were extracted to represent the movie accordingly. On the other hand, the tags listed in Table 1 were provided to users and they can arbitrarily use the tags to annotate the movies. These tags were then collected and used to build user model for preference prediction.

To compare which of the above representations can deliver better performance, three machine learning techniques widely used in prediction, including decision tree, support vector machine, and naïve Bayes classifier, have been used to work with the two representations for recommendation. To obtain a more objective assessment, the 10-fold cross validation evaluation method was employed. Fig. 3 presents the results, in which the details of three popular performance measurements in classification—accuracy, precision and recall are provided. As can be seen, in all measurements the tag-based method outperforms the keyword-based method when the above three machine learning techniques were used for user modeling. It shows that the proposed method can more pertinently capture user characteristics in movie recommendation.

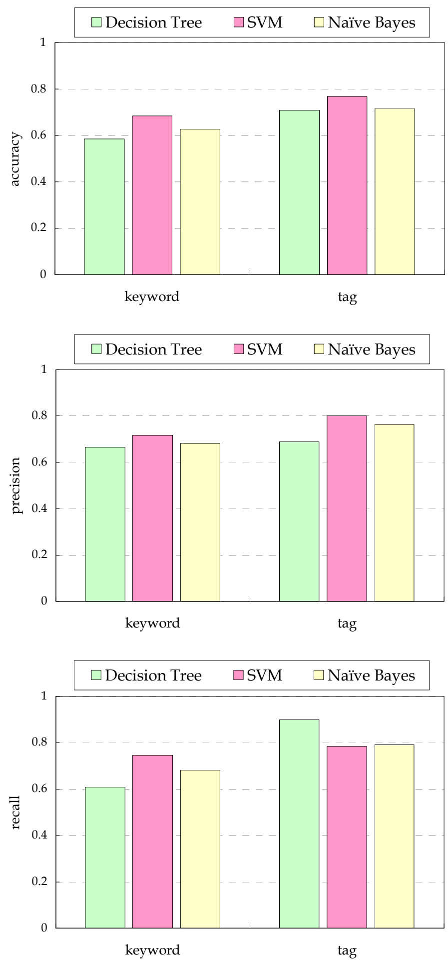

Fig. 3. Comparison of using keywords and tags with different machine learning methods for content-based recommendation.

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In addition to the content-based strategy, the other strategy often adopted in recommendation is based on user-collaboration. Therefore, the second set of experiments was conducted to examine the efficiency of tag-based method when it works with the collaborative filtering strategy. In this set of experiments, we firstly employed the methods described in section 2.C and 2.D to measure the similarity between users. If this measuring result exceeds a certain threshold, their preferences are considered to be similar, and by which the nearest neighbors of a certain user can be determined. To examine the effect of information sharing by the traditional collaborative filtering method and the proposed tag-based collaboration method, we conducted three sets of experiments with different user-similarity thresholds (0.7, 0.6 and 0.5, respectively).

Fig. 4 presents the test results in which three criteria are used for performance measurement as in the content-based strategy. From this figure, we can observe that the tag-based method can offer better recommendations than the traditional CF method in accuracy, precision and recall for the situation of threshold 0.7. And the results of the two methods have significant difference (t-test, $\alpha < 0.05$). As can be seen in the figure, the tag-based method also has better performance when a similarity threshold 0.6 was used (and therefore more user opinions were taken into consideration), and the results obtained from the two methods have significant difference. But when lower thresholds (0.5 or less) were used, there is no significant difference between the two methods with a statistical examination (t-test, $\alpha < 0.05$). These results indicate that social tags are better media to capture user characteristics and more precisely measure user similarity. Therefore, the method based on tag measurement can deliver better performance in preference prediction.

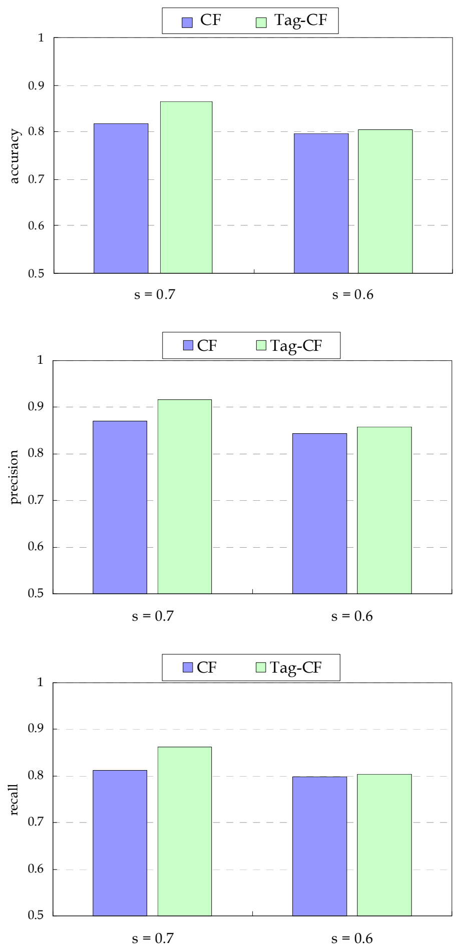

Fig. 4. Comparison of the tag-based CF and the traditional CF method.

B. *System Implementation*

To realize the personalized movie recommendation in a context-aware environment, we have implemented a system with client-server architecture as shown in Fig. 5. In this system, the tag-based collaborative method has been used to develop the recommendation module, as it has been shown to give the best performance in the above section. To identify the networking condition, the system on the server sends certain packets to the client and waits for its responses, and the system can then estimates the bandwidth available for the user. On the other hand, the system also retrieves information recorded in the HTTP header received from the client, to classify the operating system embedded in the most popular client devices (currently including Windows NT, Mac OS, Linux and Solaris for non-mobile devices, and Windows CE, iPhone Mac OS, Palm OS, Pocket PC, EPOC, and Linux Operation for the mobile devices), and to recognize the type of the user device accordingly. Based on the above information of network condition and user device, our system can then suggest the most suitable type of resolution to the user.

As mentioned in section 2.E, the GPS or GSM cellular system can be used (with the electronic map) to provide detailed location context. However, as the handheld device with embedded positioning system has not been commonly used in our local area, therefore, for practical reason, in our current implementation we have not integrated the positioning system-based location information to our system. Instead, we ask the user to to provide his environmental context to the system by making some selections from some predefined choices on the interface (as shown below).

Fig. 6 shows two screenshots of the system presents to the user. As is illustrated, the upper-left icons provide predefined options of social and location contexts. The social context here tries to capture the social condition around the user. The user can tell the system whether he is alone (signle user) or with other people (multiple users). Similarily, the user can tell the system whether he is in a public or private place. The recommended movies is listed below the icons according to the user's specification on the above contexts. Below the interface window are the recommendation results for two different situations in which "multiple users" and "public place" are selected for the first situation, and "single user" and "private place" are selected for the second situation, respectively. The frame for showing the movie is allocated on the middle area of the interface window. The information of the user device, currently including the kind of operation system and the network bandwidth, is detected and provided on the right hand side, and the resolution for viewing the

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movie is suggested accordingly. Fig. 7 presents an example of recommendation for considering device and network conditions. In additoin, the tags used to annotate the movie are also provided below the movie frame. The user can give his feedback through the evaluation of these tags.

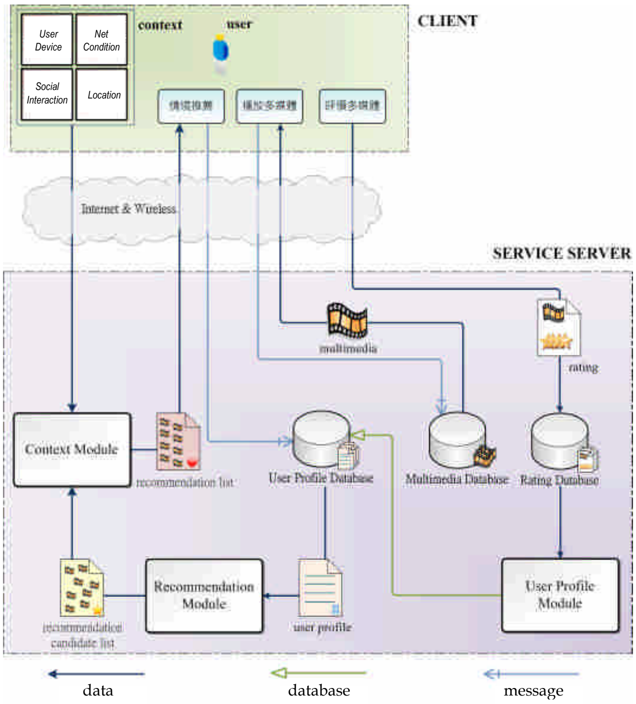

Fig. 5. System implementation of our context-aware personalized recommendation.

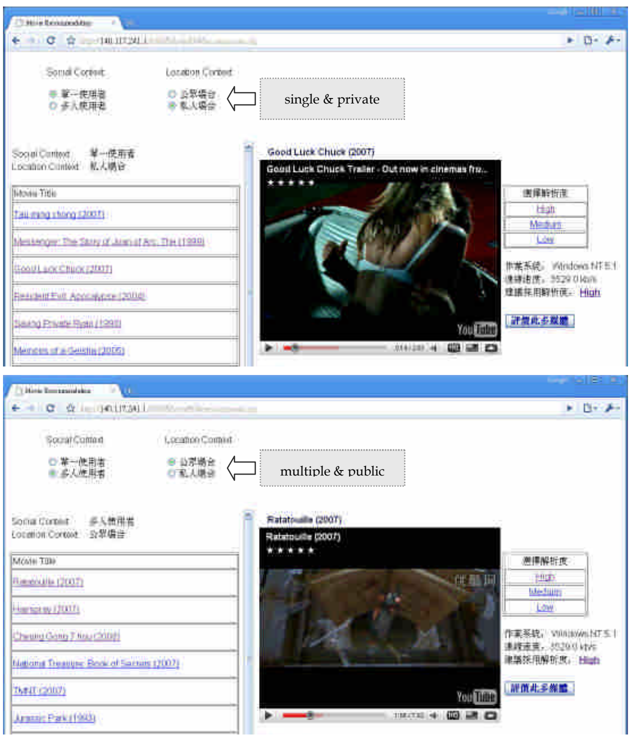

Fig. 6. The results presented to the user with different context situations.

Fig. 7. The device information is shown and the suggestion is provided.

IV. Conclusions

In this paper, we have indicated the need of developing personalized recommendation service to help end-users to access most suitable digital content. Considering the current trend of organizing and sharing digital content through user-created metadata, we have proposed a new recommendation method that exploits social tags to annotate multimedia items. To verify the proposed method, experiments have been conducted to compare different methods and the results present that the proposed method can give better performance on movie recommendations than others. In addition to the user preference, we have also considered different environmental conditions, including user location, audience, device, and network connection, to implement a context-aware system platform. The experiments show that with the proposed social tag-based method and the context-aware platform, more efficient recommendation service can be obtained.

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