Using Online Media Sharing Behavior as implicit feedback for Collaborative Filtering

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***Abstract*— In many practical recommender systems, it is found difficult to obtain explicit feedback from users about the preference for a specific item, such as music, book, movie, etc. Most researches up to this point has focused on tracking various sources of implicit feedback from user behavior including purchase history, browsing patterns, and watching habits, in order to model user preference. In this paper, we investigate a method that uses information exploited from a user's online media sharing activities as a novel source of implicit feedback for recommendation system. We look into elements of media sharing behavior and suggest whether behaviors have the potentiality that could play a role as a predictor of users' preference. Then in a specific domain, we choose appropriate behaviors by two criteria: abundance and observability. As a representative case, we focus on YouTube, one of the most popular social video sharing sites. By criteria we suggest, we select three behaviors including favorite, upload and view and formulate the simple item-based algorithm based on those behaviors. Through a series of experiments, we evaluate recommendation results obtained from our dataset by comparison with those from other reference algorithms. The results show that favorite and upload have possibility to be used as implicit feedback.**

Keywords- recommender systems, collaborative filtering, social media, implicit feedback

I. INTRODUCTION

The collaborative filtering, one of the most widely adapted approaches for recommender systems, basically characterize users' interest by using explicit ratings for items as an input set. Explicit ratings, however, are acquired by a time-consuming process and require laborious human efforts to be generated. Therefore the recommender system using explicit data usually suffers from so-called sparsity problem. As a result of the drawback in data, using explicit ratings as input set decreases the quality of recommendation systems. To deal with the limitation of explicit data, there have been attempts to extract *implicit feedback* of user preference from various user behaviors. Implementing such techniques, however, needs to embed behavior tracking tools either on sever-level or in a user's personal system. As a result, there remain possibilities to incur additional costs and violate users' privacy.

In this paper, we suggest a methodology to utilize the behavior of users on social media as implicit feedback, which does not require an additional cost except for a simple web mining. Due to the rapid growth of social media today, many researchers and practitioners have realized the potential and possibility of application development. In an academic conference[1], social media is roughly categorized into six kinds: weblogs (including comments), social networking sites, microblogs, wikies, forums/usenet, and community media sites. The sixth category, community media sites, also called as media sharing sites, are one of social media that provide users with the opportunity of sharing various media, such as video clips for YouTube[2] and pictures for Flickr[3]. The sites also have the common features of web-based social networks [1], such as posting comments or making relationships between users, but the core feature is the posting and sharing media segments among users. This kind of user behavior data is accumulated as use of social media rapidly grows and can be accessed publicly.

Our research question is twofold: First, what are elements of online media sharing behaviors that could be used as implicit feedback? To address this, we categorized online media sharing behaviors and selected behaviors that can be used as implicit feedback by two criteria – *abundance* and *observability*, on YouTube, the largest community media sites in the world. We, then, based on these observable behaviors, formulated a simple item-based collaborative filtering algorithm. Second, Could those behaviors be used as a predictor of users' preference? To address this, we conducted experimental comparison of the quality of the recommendation results based on media sharing behavior to those obtained from other algorithms.

II. RELATED WORK

In the early stage of *implicit feedback* related studies, Konstan et al. [2] and Morita and Shinoda [3] found that the elapsed time for reading a news article could be a predictor of users' interest on the article. Nichols [4] suggested 13 types of implicit actions including purchasing, assessing and repeated using, etc. Recently, several studies showed that implicit feedback has positive relationship with explicit ratings in the context of web recommender systems: i.e. time spent on web pages and scrolling patterns [5], click through [6], users' requests to a web server [7], and query text [8, 9]. Especially, Fox et al. [10] evaluated the relationship between implicit measures and explicit ratings, and found that there is a

[1] From 4th Int'l AAAI Conference on Weblogs and Social Media, www.icwsm.org/2010/cfp.shtml
[2] www.youtube.com
[3] www.flickr.com

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relationship between 30 implicit measures and explicit judgments of user satisfaction.

Some studies imply that sharing behavior could be a predictor of users' preference. Wang and Soergel [11] explained the relationship between value assessment and increasing information accessibility in context of academic paper citation. Brown et al. [12] suggested that music sharing behaviors promoted the exchange of taste about music. In the context of recommender systems, few attempts have been made at using information from online media sharing behavior as implicit feedback, including favorite lists [13, 14] and video co-view statistics [15]. To the best of our knowledge, however, there have been no attempts to systematically approach on the possibility of using online media sharing behavior for implicit feedback. In other word, this study takes a top-down approach on using media sharing behavior as implicit feedback by observing the entire aspects of the behavior first.

III. MODELING IMPLICIT FEEDBACK FROM ONLINE MEDIA SHARING BEHAVIOR

A. *Sharing Behavior and Implicit Feedback*

Using the sharing behavior, this study proposes a methodology to infer user preferences of contents by observing the media sharing behavior of users in community media sites. This starts from a simple idea that people share because they prefer more. It means if a user shares certain content with other users, it implies the user's preference on the content exceed the effort that required for sharing the content, and the preferences on other contents that the user has not shared. If this rationale is accepted, it might be possible to use sharing behavior of users as a proxy of the users' preference to the contents in real world.

This argument is inherently connected to the implicit feedback of user behavior. That is, we can manipulate the sharing behavior on community media sites as implicit ratings to enhance the quality of recommender systems. For the first step, we classified online media sharing behaviors that can be implicit feedback. Tables 1 shows the classification developed based on the framework from Oard and Kim [16, 17] and Kelly and Teevan [18]. Our classification also has two axis, behavior category and minimum scope, and all the sharing-related user behaviors are assigned to each cell. We use the same classification for minimum scope, however the behavior category is revised for better understanding of sharing behavior.

For the revision of behavior category, we firstly define the range of online media sharing behavior. The scope of online media sharing behavior in this study is not only the direct sharing behavior allowing other users to consume some contents, but also the indirect sharing behavior that can implicitly give influence on the consumption of other users. Basically, there are six categories of online media sharing behavior that users can employ in social media:

- *Generation*: users can create contents on sites by uploading media segments, which can be comprised of text, pictures, or video. Moreover, they add meta-information to media segments such as title or tagging.
- *Consumption*: users can consume contents by using the features of searching, browsing, watching or viewing public content.
- *Evaluation*: users can express their evaluation or opinion by posting comments or rating.
- *Scrapping*: users can implicitly express their preference by scrapping media segment in the form of favorite list or playlist.
- *Forwarding*: users can forward media segments to other users. They send their favorite contents via e-mail, or even embedding to other social network service.
- *Networking*: users can network with other users with social oriented features such as sending message, making friends, or subscribing to other users or group of users.

Almost sharing behavior categories we propose in this study, except networking, can be mapped to one of behavior category of previous studies. The process of revising behavior category enables us to better understand the nature of media sharing behavior, and more appropriate for assigning specific actions on media sharing sites.

TABLE I. CLASSIFICATION OF ONLINE SHARING BEHAVIOR

Behavior Category			**Minimum Scope**	
Previous	***Ours***		***Segment/Object***	***Class***
Create	Generate	→	Upload Adding meta-data	
Examine	Consume	→	Watch View Listen	Search Browsing
Annotate	Evaluate	→	Rating Add Comments	
Retain	Scrap	→	Add to favorite list	Playlist
Reference	Forward	→	Link Embed	
	Network	→		Subscribe

Unfortunately, it is rarely possible to use all the behavior data as implicit feedback due to both in economic and performance issues. Therefore, we additionally propose the following criteria for online media sharing behavior to be appropriate for implicit feedback:

- *Abundance*: it should be plentiful enough for accurate user preference modeling and avoiding sparsity problem of explicit rating.
- *Observability*: it should be able to be acquired from publicly open space with simple mining technique, and without laborious human effort and privacy violation.

Moreover, there could be an argument on the degree of *observability*. For example, it is possible to observe the popularity of an item, even though we do not know which users actually contributed to the popularity by consuming the item. Therefore, we additionally propose there are two kinds of observable behaviors:

- *Observable Personal Behavior*: it is possible to observe the interaction between specific user and specific item by directly tracking the behavior of each user.
- *Observable Collective Behavior*: it is possible to observe the interaction between multiple users and specific item from collective usage statistics.

B. Modeling Sharing Behavior on YouTube

1) Research Domain

YouTube is one of the most popular online video sharing community and social networking services. It serves about 4.67 million video streams monthly and has approximately 96.1 million unique monthly views. Therefore, we test and evaluate our methodology that use of media sharing behavior as implicit rating for recommender systems on this platform. Specifically, we focus on 'music' category on YouTube because it is (1) one of the most active and easy-to-observe the behavior of media sharing on YouTube, and (2) easy to share due to the relatively shorter playing time.

The basic service provided by YouTube is letting users publicize and share video clips. Users can upload any kind of video clip with any length, but usually a video belongs to one of 14 categories[4]. Moreover, actions taken by a user are not restricted to consuming video clip. They are allowed to make a number of actions for evaluation and sharing, and networking with other users. Specifically, they post comments, rate, and register the video clip to their favorite list to express how they are satisfied with the video. It is also possible for users actively share video clip via e-mail or other social networking services, such as Facebook or Twitter. On the other hand, users can freely access the information of video uploaders, and make new connection friend with them via subscribing to the channels continuously be informed of the activities..

2) Behavior Selection

The foremost step to modeling the media sharing behavior on YouTube to implicit feedback, we have to select appropriate user behaviors. As mentioned in the previous part, we conduct the procedure with the two criteria:

a) Abundance

Users are more likely to view or save videos rather than to upload their own media. Previous studies statistically show that 'view' is the most active user behavior on YouTube. View is about 88 times more frequently observed than 'upload' per average user. 'Favorite' is the secondly most behavior, and it is about 1.4 times more than upload behavior [19]. Maia et al. [20] also showed that the dominant behavior of view (view is 177 times more than upload). In short, the top three mostly common behaviors on YouTube are view, favorite, and upload. On the other hand, there are several features that the site provides to users for social networking such as, subscription, channel, or friends. However, the inactive user behavior of networking reported from several previous studies [19, 20] fade the possibility. Therefore, we choose view (consume), favorite (scrap), upload (generate) for implicit feedback on YouTube in the criteria of *abundance*.

b) Observability

Among the three behaviors, both favorite and upload are clearly observable because users must log-in to make the actions. Viewing, which is mostly conducted while logged out status, is almost unable to directly observe without implementing tracking tools on the server or users' system. This is same for searching or browsing behavior. That means viewing behavior does not have *direct observability*. Instead, there is possibility for *indirect observability* using the publicly provided statistics, derived from those behaviors such as view count, rating, and number of adding to favorite list of a video. Those data represent the collective preference tendency of users and it is possible to manipulate those for implicit feedback.

In summary, our strategy for measurement of sharing behavior on YouTube is based on the premise that all the user behaviors are for sharing. We select two main elements to capture users' sharing behavior from all the features provided by YouTube: favorite and upload. In addition, we use the collective usage statistics, especially view count for the representative behavior of examine.

C. Collaborative Filtering based on Media Sharing Behavior

1) Item-Based Collaborative Filtering Algorithm

The main purpose of this study is to prove that the dataset from media sharing behavior actually reflect user preferences. To formulate a collaborative algorithm using implicit feedback derived from online media sharing behavior, we choose the item-based algorithm from Sarwar et al. [21]. Unlike the most traditional user-based algorithms, the competitive advantage of item-based algorithm is the possibility of easy comparison to other dataset from other domain with pre-computed model. Among various sorts of item-based models, our research employs a simple algorithm since the most important contribution of this study is to present a potential implicit dataset, not algorithm development.

2) Favorite and Upload

The first step of the item-based collaborative filtering algorithm is computing the similarity between items for prediction. The similarity between items i and j is given by

$$sim(i,j) = \frac{\Sigma_{u \in U}(R_{u,i}-\overline{R}_u)(R_{u,j}-\overline{R}_u)}{\sqrt{\Sigma_{u \in U}(R_{u,i}-\overline{R}_u)}\sqrt{\Sigma_{u \in U}(R_{u,j}-\overline{R}_u)}} \quad (1)$$

Here U denotes the set of users who both rated item i and j, $R_{u,i}$ denotes the rating of user u on item i, and $\overline{R}_u$ is the average of the u-th user's rating. If the behavior of upload or favorite is a sort of preference expression, we might be able to suppose two different videos which are uploaded or added to favorite list by a user are similar. Meanwhile, in the case of favorite and upload, interactions between items and users can be expressed by binary data rather than multi-graded rating. Therefore, we can apply the sharing behavior to the above similarity computation as the following:

$$R_{u,i} = \begin{cases} 1 & , if\ a\ user\ u \frac{upload}{favorite} item\ i \\ 0 & otherwise \end{cases} \quad (2)$$

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[4] www.youtube.com/videos

where $\overline{R}_u$ is the average frequency of the u-th user's interaction.

3) View Count

One of the main concerns of collaborative filtering is to reduce the effect of universally popular items. This is because the information of the items preferred by most if the users is not as useful to capture the individual preference and characteristics. Breese et al.[22] suggested user-item matrix transformation by multiplying each entry with inverse user frequency. Inverse item frequency $f(i)$ is denoted by $f(i) = log(n/n_j)$, where n_j is the number of users who have favorite or uploaded item *i,* and n is the total number of users. This method, however, is just an applying of the user's popularity who upload or favorite some particular items. Thus, we take an alternative approach which can take other media sharing behavior into account.

Using view count that can be implicit feedback as we discussed in the earlier section, we suggest inverse view count of item *i, vc(i)*, which is given by

$$vc(i) = log(\frac{VC}{\sum_{v \in V} VC_{v,i}}) \tag{3}$$

where V denotes the set of all videos, $VC_{v,i}$ denotes view count of video v which are related to item *i,* and VC denotes the sum of view count of all videos. Then, we can denote the popularity weighted prediction score $P_{u,i}$ as

$$P_{u,i} = \frac{\sum_j vc(i) \times sim(i,j) \times R_{u,j}}{\sum_j |vc(i) \times sim(i,j)|} \tag{4}$$

IV. EXPERIMENTAL EVALUATION

A. Dataset

For experiments, we carried out a crawl of meta-information about music-related videos using YouTube Data API[5], from 2nd to 20th of April in 2010. First of all, we constructed the initial user set and collected meta-information about all music-related videos favorited or uploaded by each of chosen users. The users in other categories than 'standard' such as 'guru', 'director', 'reporter', and especially 'musician' are excluded from our dataset because it is controversy to assume that such users' favorite or upload really reflect their preference. There could be other reason than mere sharing, for example advertisement. In addition, we filtered out the users who uploaded less than two video clips for music category.

Then, we compared titles of the videos to musician's name and their song titles to assign each video to a specific musician. For example, if the video title contained words 'Beatles' and 'Help!', we identified that this video was related to the musician 'The Beatles'. For reasonable density level of interaction matrix, we limited target artists in terms of their popularity provided by Last.fm[6], which is one of the most popular web-based social radio services. As a result, our dataset consists of 3.8 million favorited-videos from 177,206 users and 0.9 million uploaded-videos from 152,874 users related to 10,399 musicians. Table 2 shows the descriptive statistics of the data. The data indicates that favorite videos are more abundant as 3.6 times than uploaded videos.

TABLE II. DESCRIPTIVE STATISTICS OF DATASET

Category	Favorite	Upload
# of users	146,534	89,010
# of videos	3,694,850	829,346
Avg. # of videos/a user	21.56	5.98
Video published date	4th of May 2005 ~ 20th of Apr. 2010	
# of musicians	10,399	
Avg. # of musicians/a user	12.73	3.02
Density Level(%)	0.1224	0.0290

B. Evaluation Metrics

To verify the availability of online media sharing behaviors for implicit feedback, we measured the prediction accuracy on a test set based on predictions generated from item-item similarity computed using a training set. We adopted four metrics that are most commonly used for recommender system performance evaluation: precision, recall, F-measure, and rank score [23].

- Precision is a fraction of recommended items that are relevant to items actually used by a user u in the test set.

$$P_u = \frac{\#(relevant\ items\ recommended)}{\#(recommended\ item)} \tag{5}$$

- Recall is a ratio of the number of matched items to the number of all items used by a user u.

$$R_u = \frac{\#(relevant\ items\ recommended)}{\#(all\ items\ used)} \tag{6}$$

- F-measure combines these two measures into a single metric. It is computed by giving equal weight to two metrics mentioned above.

$$F_u = \frac{2 \times P_u \times R_u}{P_u + R_u} \tag{7}$$

- Rank score measures prediction accuracy of the order of recommended items. The rank score of user u is given by

$$RS_u = \sum_j \frac{r_{u,j}}{2^{(j-1)/(\alpha-1)}} \tag{8}$$

where j is the index for the ranked list, α is the viewing half-life. The half-life is the index of the item on the list such that there is the probability of .5 that the user would view that item.

The overall metric for precision, recall and the F-measure was an average over all users in the test set. For the rank score, we derived an aggregated score over the entire dataset:

$$RS = 100 \frac{\sum_u RS_u}{\sum_u RS_u^{max}} \tag{9}$$

[5] code.google.com/apis/youtube
[6] www.last.fm

where RS_u^{max} is the best possible rank score for user u if all observed items occupied at the top of the ranked list. We set the length of recommendations at $N = 10$ and the rank score's half-life at $\alpha = 5$.

C. Experimental Procedure

Overall evaluation procedure is comprised of three experiments. In the first experiment, we attempted to confirm the existence of relationship between users' preference and the observable personal behaviors**,** favorite and upload. We divided the users from YouTube into two sets: a training set constitutes 80% of the users, and a test set accounts for remaining 20% for each data set: that of favorite and that of upload. From the training set, we constructed the user-musician interaction matrix of each behavior and computed similarity between musicians by (1). For each user in the test set, we generate a rank list of N musicians by using the 'Given N' method of Breese et al. [22]. In particular, we randomly selected 50% of each test user's interaction data, and attempt to predict the remaining data. Finally, we compared prediction accuracy of these results to results generated from the benchmark algorithm. As a baseline performance, we used 'top-N most popular' algorithm that recommends the top-N musicians who were frequently observed in whole dataset.

In the second experiment, we endeavored to figure out which sharing behavior among favorite and upload is stronger predictor of user preference. On account of potential bias between the training set and the test set from same dataset, we measured the prediction accuracy of each behavior over a test set from other online platform. To construct a new test set, we used Last.fm data that contained information about users' preference for musicians. Specifically, we collected lists of top 15 most-listened-to musicians from randomly selected 116,334 Last.fm users. We computed similarity between musicians based on the training set from YouTube favorite and upload behaviors, and measured the prediction accuracy over the test set from Last.fm. For a benchmark, we used results from top-N popular musicians in Last.fm and the training set was constructed based on the remaining 80% data of Last.fm users. In addition, we conducted correlation analysis on item-item similarity between the YouTube training set and the Last.fm training set to compare how user preferences are reflected in both platforms.

In the final experiment, we aimed to assess the feasibility of the observable collective behavior, viewing, for a predictor of item popularity. We computed inverse view count for each musician in the dataset and compared it to other item popularity indicator used in the previous research. As a reference, we adopted inverse user frequency suggested by Breese et al. [22] Then, with the same training sets as in the prior experiment, we used (4) at the prediction stage and measure prediction accuracy for comparison with results from the algorithm using inverse user frequency. In addition, we compared prediction accuracy of this algorithm to that of other algorithms used in the prior experiment to evaluate the competence of inverse view count related to prediction quality improvement.

V. Results and Discussion

Fig. 1 shows the results from the three experimental configurations. The former illustrates the prediction accuracy of algorithms with the training and test set from YouTube favorite/upload dataset, and the latter presents the configuration of using Last.fm dataset as a test set. The top-N most popular algorithm and item-based collaborative filtering algorithm are each labeled 'Top-N popular' and 'Item-based'. The algorithm labeled 'Item-based, *f(i)*' and 'Item-based, *vc(i)*' refer to use of the collaborative filtering algorithm with popularity indicator, inverse user frequency and inverse view count. Numbers in parentheses show the relative recall, precision, F-measure and rank score to Top-N popular algorithm.

Expected findings in each experiment configuration are as following:

- Experiment 1: Prediction accuracy of recommendation results generated from the favorite/upload training set should be higher than the base-case performance over the favorite/upload test set.
- Experiment 2: Prediction accuracy of recommendation results generated from the favorite/upload training set should be higher than the base-case performance over the Last.fm test set. In addition, the similarity between items computed based on from the favorite/upload training set should be highly correlated with the similarity from the Last.fm training set.
- Experiment 3: The item-based algorithm with inverse view count should perform better than an algorithm without an item popularity indicator and the base-case performance.

A. Experiment 1 & 2 : favorite / upload training set on YouTube/Last.fm test set

As Fig.1 (a) shows, prediction accuracy measures of algorithms over the favorite / upload test set are generally with the favorite / upload training set than with the list of top-N popular artists. Over the Last.fm test set, the algorithm with favorite test set performed better than the base case performance. However, precision and rank score of the algorithm with upload training set were lower than the base-case performance although recall and F-measure were slightly higher.

Furthermore, the Pearson correlation coefficient between item similarities over YouTube and Last.fm training sets indicates similarity between listening behavior and favorite/upload behavior. The correlation coefficient between item similarities from favorite data and Last.fm data is 0.8064 and the coefficient between item similarities from upload data and Last.fm data is 0.8276 at significance level $p < 0.05$. If listening behavior could be used as implicit feedback for

From these findings, we suggest that favorite and upload can be implicit feedback of users' preference about musicians. Moreover favorite is stronger predictor than upload, but not enough to overcome bias between a training and test set from the same original set. We can identify the effect of this bias from the superiority of the Last.fm training set in the Experiment 2.

(a) YouTube Test Set

Training /Test Set	Algorithm	P	R	F	RS
Favorite	Top-N popular	0.0537	0.0526	0.0531	5.9260
	Item-based	**0.0842**	**0.0633**	**0.0723**	**9.8959**
		(1.56)	(1.20)	(1.36)	(1.66)
	Item-based, f(i)	0.0681	0.0469	0.0555	7.6967
		(1.81)	(1.37)	(1.64)	(1.92)
	Item-based, vc(i)	0.0586	0.0406	0.0479	6.5690
		(1.97)	(1.45)	(1.80)	(2.09)
Upload	Top-N popular	0.0098	0.0266	0.0143	1.0637
	Item-based	**0.0238**	**0.0471**	**0.0316**	**2.8240**
		(2.42)	(1.77)	(2.20)	(2.65)
	Item-based, f(i)	0.0178	0.0350	0.0236	2.0425
		(1.26)	(0.89)	(1.04)	(1.29)
	Item-based, vc(i)	0.0194	0.0387	0.0258	2.2244
		(1.09)	(0.77)	(0.90)	(1.10)

(b) Last.fm Test Set

Training Set	Algorithm	P	R	F	RS
Last.fm	Top-N popular	0.0613	0.0501	0.0551	7.2817
	Item-based	0.1233	0.1085	0.1154	14.721
		(2.01)	(2.16)	(2.09)	(2.02)
Favorite	Item-based	**0.0926**	**0.08**	**0.0858**	**10.960**
		(1.51)	(1.59)	(1.55)	(1.50)
	Item-based, f(i)	0.0737	0.0646	0.0689	8.2424
		(1.20)	(1.29)	(1.25)	(1.13)
	Item-based, vc(i)	0.0718	0.0630	0.0671	8.0456
		(1.17)	(1.25)	(1.21)	(1.10)
Upload	Item-based	0.0601	0.0518	0.0556	6.729
		(0.98)	(1.03)	(1.01)	(0.92)
	Item-based, f(i)	0.0354	0.0322	0.0337	3.8103
		(0.57)	(0.64)	(0.61)	(0.52)
	Item-based, vc(i)	0.0442	0.0392	0.0416	4.7910
		(0.72)	(0.78)	(0.75)	(0.65)

Figure 1. Prediction Accuracy with YouTube and Last.fm Test Set

B. *Experiment 3: inverse view count as a predictor of item popularity*

In experiment 3, we drew comparisons of prediction accuracy between two algorithms using different popularity indicator over three test sets. Prediction accuracy of algorithms that label contains '*f(i)*' or '*vc(i)*' in Fig. 1 illustrates results from these comparisons. Especially, we focus on the effectiveness of *vc(i)*, inverse view count describe above.

Over the YouTube test set, the algorithms with popularity indicators generally performed better than the base-case algorithm, but worse than the item-based algorithm without using any indicator. The same tendency was found in the case of the Last.fm test set. Moreover, the two algorithms with the item popularity predictor have less predication accuracy than the base-case performance. In the case of favorite test set, the performance was better than base-case, but the prediction accuracy is lower than the algorithm without any indicators or with inverse user frequency. These results imply that view count might be not an appropriate indicator to predict the popularity of items.

VI. CONCLUSIONS

Our research aimed to verify availability of using online media sharing behavior as implicit feedback for a collaborative filtering. Specifically, we analyzed and categorized online media sharing behaviors that have possibilities to be implicit feedback. In community media sites domain, we selected favorite, upload and view by criteria of abundance and observability. Then, we formulated the simple item-based collaborative filtering algorithm based on those behaviors. In the similarity computation phase of collaborative filtering, we constructed a user-item interaction matrix and computed item similarity based on favorite and upload. Also we suggested inverse view count, which could be used as an item popularity indicator. For validation, we evaluated prediction accuracy of algorithms with favorite, upload and view over musician-related video sharing behavior in YouTube. As a result, favorite and upload have possibility to be used as implicit feedback, while view has not enough competence to predict item popularity. In addition, the results also shows favorite is stronger predictor for users' preference than upload.

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