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A Novel Social Situation Analytics-Based Recommendation Algorithm for Multimedia Social Networks

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ABSTRACT Due to the increasing popularity of multimedia social networks (MSNs), the ability to mine users' interests in different contexts on such networks is crucial in recommendation systems. It is, however, challenging to mine users' current preferences based on session on MSNs. In this study, we propose a novel recommendation algorithm based on both social situation analytics and collaborative filtering for session-based recommendation. Specifically, the algorithm predicts the rating for target users based on their nearest neighbors and historical behaviors. First, for the purpose of mining users' current intentions, the session-level behavioral sequences of target user are analyzed based on *SocialSitu (t)*. Then, the recommended contents are generated for target users based on their behaviors and perceived session-based intentions and identity. We evaluate the performance of the proposed algorithm using real-world social media dataset from Shareteches. Findings demonstrate that our algorithm outperforms two classical algorithms and a state-of-the-art method.

INDEX TERMS Multimedia social networks, situation analytics, behavior analysis, recommendation algorithm, prototype.

I. INTRODUCTION

The amount of online content and data has increased significantly in our digitalized society, and one particular challenge facing content or service providers is the (in) ability to help users overcome (multimedia) information overload. Recommendation systems play an important role in helping users find multimedia content of interest or relevance quickly. In other words, an effective recommendation method or algorithm will facilitate distribution and sharing of multimedia content among social users. Conventional recommendation systems mine online resources (e.g. multimedia content) that might be of interest to users or satisfy user requirements based on an analysis of the user's browsing/searching history and/or recommendation lists of their friends. Some new recommendation techniques, such as context awareness-based recommender system, have played an increasingly important role in recent application developments [1], [2]. Generally, conventional recommendation methods are not capable of capturing user's real time requirements that might change over time in a timely manner.

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In other words, the recommended contents are not always what the users are really interested in.

Existing recommendation systems generally focus on mining the two-dimensional relationship model of the user–item, and recommend the most relevant resource(s) to different users without considering user's behavior, the current intention, and other social situation and contexts [3]. In a real-world social domain or any virtual multimedia social networks, the user's intention, preference and interest can vary over time or in different contexts [4]. The dynamic changes in user requirements and behaviors reflect intentions changing constantly. As explained by Cui *et al.* [5], fully understanding and predicting the true requirements and intentions of social users in different situations and contexts remain a research challenge.

More specifically, session-based requirements and intentions of users in a social networks are closely related to the constant changes in current identity, group and role of users, along with their desires, actions and surrounding physical/online environment. These and other factors can be used to determine a user's true and dynamic preferences.

Hence, in this paper, we seek to determine user preferences using these factors in order to provide them with more accurate personalized services. It is also known that conventional algorithms suffer from data sparseness, cold boot and other limitations [6]. Thus, in this paper, we leverage the SocialSitu, our previously proposed real-time social situation analytical technique [7], to facilitate the analysis and mining of the true and dynamic preferences of target users (i.e. leverage behavioral pattern analysis and intention prediction for the social domain, prior to recommending potential and possible relevant videos to any user). First, we predict the target user's possible preferences by combining his/her behaviors on the item and preferences of similar users. Then session-based interests are determined found by predicting the intention of the target user on the current item. In other words, the proposed recommendation algorithm in this paper allows us to identify the target user's current preferences based on their behaviors and real-time intentions of current session.

The key contribution of this paper is demonstrating the potential to predict the rating of the target user for an item more effectively, by combining the target user's behaviors on the item, as user behavior is a real reflection of their interests that can vary with time and their predicted rating on an item in online social networks to facilitate recommendation. In other words, we determine user preferences and hidden needs more accurately by understanding their intention and identity of current session. In doing so, we also address the cold start challenges in recommendation systems, by focusing on session-based user behaviors and intentions in online social networks.

The rest of this paper is organized as follows. Related literature is presented in the next section. Sections III and IV present our proposed algorithm and its evaluation as well as a comparative summary, respectively. Conclusion is presented in the last section.

II. RELATED WORKS

Limitations such as scalability and data sparseness are common in mainstream collaborative filtering recommendation algorithms. For example, a number of recommendation algorithms proposed in recent times analyze users' behaviors and relationships in social networks based on user-based collaborative recommendation [8]–[10]. Guan *et al.* [11] proposed a recommendation algorithm based on item quality and rating preferences, which is designed to decrease computing complexity and deal with data sparseness limitation. Deldjoo *et al.* [12] combined a variety of features, both meta-data as well low-level visual and audio features, in a recommender system for movies. Wang *et al.* [13] designed a joint social-content recommendation framework that suggests to users which videos to import or re-share in the online social network. In their work, a user-content matrix update approach that updates and fills in cold user-video entries to provide the foundations for the recommendation was proposed. Then, based on the updated user-content matrix, they constructed a joint social-content space to measure the relevance between users and videos. This is designed to provide a high accuracy for video importing and re-sharing recommendation. To fully utilize user-contributed / user-generated information online, Kim *et al.* [14] used the fast diffusion and information sharing capability of a large customer network to develop a recommendation method. The authors in [15] utilized multi-dimensional QoS (quality-of-service) data (e.g., time and location, and the structural relationships among the multi-dimensional QoS data) for service recommendation. While most of these approaches follow the collaborative filtering principle, they perform distributed and local searches for similar neighbors over a customer network in order to generate a recommendation list.

User preferences vary between contexts and times. For example, some users prefer horror or thrilling movies normally or when they are by themselves, but may prefer light-hearted and humorous movies when they are under pressure or in a group. Users are also more likely to be interested in pubs, restaurants, shopping malls and even unsavory venues (e.g. adult shops) during evenings (e.g. around dinner time) rather than working hours.

Thus, situation analytic recommendation system is fast becoming a popular research topic. A novel context-aware recommendation algorithm was proposed based on combination of the SVD algorithm and time filtering by Cui *et al.* [16]. More recently in 2016, Alhamid *et al.* [17] noted that context-aware recommendations offer the potential of leveraging social content and utilizing related tags and rating information to personalize the search for context-specific content. The authors then proposed a personalized recommendation model, which improves user experience by analyzing the context a user accesses. Song *et al.* [18] utilized context-awareness to provide user-centered personalized IPTV services and personalization, by introducing context-awareness on top of IPTV architecture to gather different information about the user and his/her environment.

Existing context preference-capturing algorithms generally acquire user preference via quantitative analysis of user behavior information in a specific context, without considering their cognitive psychology. Such algorithms also analyze the inherent relationship between the cognitive behavior of different users for different context information and user preferences. Consequently, this leads to low accuracy of preference prediction [4]. With the understanding that group recommendation plays a significant role in contemporary popular social networks, Sun *et al.* [19] introduced a video recommendation algorithm for online social groups based on group preference model. Mizgajski and Morzy [20] based on a set of affective item features, a multi-dimensional model of emotions for news item recommendation is proposed. Zhao *et al.* [21] proposed a user-service rating prediction approach through the analysis of the social users' rating behaviors, and attempted to predict user-service rating. Shin *et al.* [22] combined multimodal approach, integrating classification-based and keyword-based similarity predictions, in order to present a user with a limited subset of relevant content.

Observable user behaviors can be helpful in describing users, and a relation-based similarity measure can be used to improve categorized content rating precision. Not surprisingly, Zhang *et al.* [7] determined the behavioral sequence model of users through the analysis of their historical context information in multimedia social networks. In their approach, a four-tuple {ID, d, A, E}t was defined to represent a *SocialSitu(t)* which is a user's situational data at t. Here, ID refers to user's identity represented by a two-tuple {Group, Role}, d and A respectively denote user's desire at t and user's behavior corresponding to d at the moment, and E refers to environment information, including the terminal information which the user utilized.

Existing popular social media platforms, such as Tecent Videos and Aiqiyi in China, rely on recommended content to attract a large number of users. Such recommendations are in line with the user's preferences. However, a user's interests may be narrowly focused, and existing recommender systems may not be able to find the user's hidden interests, actual needs and the users' precise preferences, in real time.

One literature gap observed is the lack of focus on user real time intentions in online social networks, as most existing research make recommendations based on users' inherent attributes. We posit that using user real time intentions to facilitate recommendation will help enhance the accuracy or precision of user varying preferences. Thus, a recommendation algorithm for multimedia content based on user context analysis in multimedia social network is proposed in this paper. The algorithm is designed to recommend relevant content to target users in a timely manner through the analysis of the identity, behavior, real time intentions, and environmental (big) data associated with users in existing social networks and related content of users similar to the target users.

III. PROPOSED RECOMMENDATION ALGORITHM

Generally, multimedia social network (MSNs) users have their individual habits for multimedia access, usage and scoring, and conventional recommendation algorithms use similar users' scores to predict target user's movie preferences. However, some users may rate contents randomly or maliciously in multimedia social networks, and these "users" might even be socialbots. Therefore, it is not sufficient to only consider users' rates and attributes. We posit that interactions between users and system are a more accurate reflection of a real user's preference(s). Thus, we adopt user behavior analytics for multimedia social networks to dynamically determine user current video preferences (as a user's preference can change over time or in different context). The SocialSitu recommendation system model is shown in Figure 1. Social situation big data is used to analyse the target user's historical behavior sequences and intentions (interests) in the current session, and then SocialSitu recommendation algorithm is executed. We present the relevant definitions as follow:

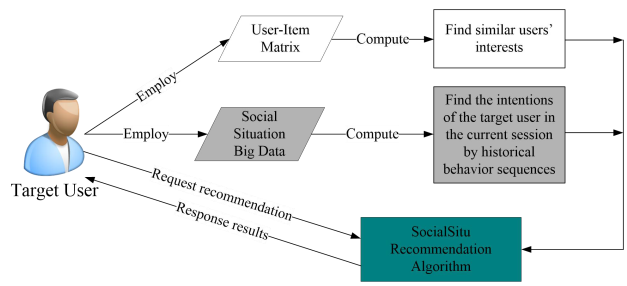

FIGURE 1. SocialSitu recommendation system model employing social situation analytics.

Definition 1 [7]: Desire: It refers to what users want to achieve when using a social media service, namely, the user's purpose. It consists of a series of atom-desire (d), namely $\{d_1, d_2, \ldots, d_n\}$, $d_i (1 \leq i \leq n)$ refers to user's desire at *i*. For example, a user want to add friends of MSNs, so he/she has to login in the system, find friends he/she wants to add and send requests, the Desire is add friends, and it is composed of a series of atom-desire{Login in, Find friends. Send request}.

Definition 2 [7]: SocialSitu(t): It refers to the situation at time *t* which is the extensional *Situation(t)* for the social domain. SocialSitu(t) is a four-tuple *SocialSitu(t) = {ID, d, A, E}*. Here, *ID* refers to user's identity information; *d* refers to user's desire at *t*; *A* refers to user's behavior corresponding to *d* at the moment; and *E* refers to context information of current session, including the terminal information which the user utilized, here we consider it is a mobile terminal or a computer, in a session user uses the same terminal, but in different sessions the user may use different devices (e.g., the target user starts with a smart phone and ends up with the smart phone in this session, but in the next session the user may use computer.).

Definition 3 [7]: ID: *ID* refers to the two-tuple user's identity information, *ID = {Group, Role}*. In MSNs, there is a corresponding relationship between the user's role and group. User may be with different roles in different groups. For example, in a manuscript submission system, a user may be an author when he/she submits an paper, but may be an reviewer when he/she reviews a paper. At some given time, a user only belongs to a specific group. In a group, a user has only a single role. When a user's role is changed, the user's behavior may also change.

Definition 4 [7]: Intention: It refers to the *SocialSitu(t)* sequence of user from starting point to target achievement, namely *I = {SocialSitu(1), SocialSitu(2),},..., SocialSitu(n)}*, $n \in N$, *SocialSitu(1)* refers to the starting point; and *SocialSitu(n)* refers to the ending point when the target is achieved. Here, *SocialSitu(t)* sequence is directly correlated to the target achievement. If one of the elements of *SocialSitu(t)* changes, the intention may different. For example, a user may want to watch a video using the computer, but it is more probable for the user to listen to a music rather than watching a video when he/she uses a mobile device access. We used the association rule to find the *SocialSitu(t)* sequence of a intention. A detailed calculating process is shown in [7].

Definition 5: User Intention Interest Degree: To quantitatively describe the user's intention, we define the user intention interest degree. It refers to the user's intention on a content in the MSNs which reflects the user's interest in the content (contents in the MSNs are various kinds of videos and audios), which also let $W_{intention}$ be the total interest degree of the content, where $W_{intention} = \{\text{Share}(W_{Share}), \text{Collection}(W_{Collection}), \text{Download}(W_{Download}), \text{Play}(W_{Play}), \text{Skip}(W_{Skip})\}$. In other words, W_{Share}, $W_{Collection}$, $W_{Download}$, W_{Play}, W_{Skip} are the interest degree of intentions (Share, Collection, Download, Play, Skip) respectively. For instant, if a user want to share a content to his/her friends, it reflects the user likes the content. And the share is his/her intention. Not every system takes the same weight of these intentions, and it could be customized, depending on the application. User's behaviors reflects his/her intention [23], the quantification is the same as the quantification of Definition 5.

Definition 6 : Behavior = {Share, Collection, Download, Complete play, and Skip}, and the score of each behavior is S_{Share}, $S_{Collection}$, $S_{Download}$, S_{Play}, and S_{Skip} respectively, and in a real scenario these behavior scores can statistically processed, $S_{Share} > S_{Collection} > S_{Download} > S_{Play} > S_{Skip}$. $\text{Behavior}_{i,j}$ refers to set of behaviors of user i to content j. In the database, there are more than one records about the user i to the content j.

Having introducing the relevant definitions, we present our recommendation algorithm for video content, based on both user situation analytics and collaborative filtering recommendation. The algorithm analyzes the user's identity, desire, action and prior data generated by the user in the social media network. Then, we filter relevant content of neighbor-nearest similar users and recommend them to the target user in real time. The procedures are presented as follows:

Step1: Gather the historical records of users and construct a user–item playing matrix, as shown in Equation (1).

$$R(m,n) = \begin{bmatrix} R_{11}, & R_{12}, & \cdots, & R_{1n} \\ R_{21}, & R_{22}, & \cdots, & R_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ R_{m1}, & R_{m2}, & \cdots, & R_{mn} \end{bmatrix} \tag{1}$$

In Equation (1), m denotes the user's historical records in row m, n denotes the multimedia content in column n, and each line denotes the playing record of one user on all multimedia contents. If a user record of a certain content is in the browsing (accessing) records, then the position of the content matching the user is 1; otherwise, 0.

Step 2: Search for similar users to the target user u. Calculate the similarity of the target user with other users by applying cosine similarity, as shown in Equation (2). We use $\cos(u, v)$ to quantify the similarity between user u and user v:

$$\cos(u, v) = \frac{A_u \times A_v}{|A_u| \times |A_v|} \tag{2}$$

In the above equation, A_u denotes the playing record of user u, A_v denotes the playing record of user v, and $\cos(u, v)$ denotes the cosine similarity between users u and v. The bigger the cosine, the more similar are these two users. We then perform sorting in descending order of similarity, and take the first K users as the similar users to the target user.

Step 3: Quantify user behavior using the score of each behavior b marked as S_b.

User behavior can reflect the degree of the actual user preference in content browsing. These behaviors are directly related to the browsed multimedia content, Behavior = {Share, Collection, Download, Complete play, and Skip}, and the score of each behavior is S_{Share}, $S_{Collection}$, $S_{Download}$, S_{Play}, and S_{Skip} and respectively.

Step 4: Build a user interest model, as shown in Steps 4.1 and 4.2.

Step 4.1: Predict the scores of multimedia contents that are not browsed by the target user.

$$P_{u,i} = \overline{R}_u + \frac{\sum\limits_{v \in U} (R_{v,i} - \overline{R}_v) \bullet \cos(u, v) \bullet \overline{Behavior_{v,i}}}{\sum\limits_{v=1}^{K} |\cos(u, v)| \bullet \overline{Behavior_{v,i}}} \tag{3}$$

According to the score of similar user v on content i and his/her behavioral information $\text{Behavior}_{v,i}$ as defined in the Definition 5, predicts the degree $P_{u,i}$ of target user u for content i, as shown in Equation (3). In the equation, $\text{Behavior}_{v,i}$ denotes the operation behavior of the similar user v for content i. $\overline{Behavior_{v,i}}$ represents the average operation behavior of user v for content i, for example, there are three behavior records (e.g. Share, Download, Play) about the user v for content i, $\overline{Behavior_{v,i}} = \frac{S_{Share}+S_{Download}+S_{Play}}{3}$. If only one behavior record (e.g. Share) about the user v on content i, $\overline{Behavior_{v,i}} = S_{Share}$. $\overline{R_u}$ and $\overline{R_v}$ represent the average score of target user u and similar user v according to the all scores that he has made, respectively. We use $R_{v,i}$ to quantify the scoring of similar user v on content i. Sorting is carried out in descending order of $P_{u,i}$, and let I_1 represents the set of top L(L≥N) contents that are candidate recommended.

Step 4.2: The content collections to be recommended are obtained in the situation analytic analysis (situation awareness analysis) based on target users. The specific processes are as follows:

Step 4.2.1: Through the analysis of the historical *SocialSitu(t)* sequences of users in the MSN, user behavioral sequences are obtained using the situation analytics-based discovery algorithm for behavioral models [7].

Step 4.2.2: Now, we will predict the target user intention based on his/her current behavioral sequence. When the similarity of the current user sequence *SocialSitu(t)* and the behavioral sequence under some intention, $Intention_i$, is high, his/her current intention is considered to be $Intention_i$, $Intention_i \in Intention$. User intentions in MSNs are finally presented in the user behavioral manner. In Step 3, the Intention that the behavior corresponds to is an intention that is directly associated with the browsed multimedia content. Different weights are assigned to these Intentions in the quantization of user behaviors in Step 3 represent the degree of the target user preference for the current content as defined in Definition 4 – i.e. $Intention = \{\text{Share}(W_{Share}), \text{Collection}(W_{Collection}), \text{Download}(W_{Download}), \text{Play}(W_{Play}), \text{Skip}(W_{Skip})\}$.

Step 4.2.3: Set a threshold $\overline{W}$ according to the average intention weight of the target user for the contents that he/she has accessed as the average weight of intentions, as Equation (4), M is the number all contents' intentions. The threshold $\overline{W}$ reflects the general interest level of the target user. When the weight of the target user intention is $W_i \geq \overline{W}$, the user is extremely interested in the content being browsed. According to two properties of copyright owner and type of the content, which are the most salient attributes of the content. For instant, the copyright of a movie in our paper is the director or the actors of the movie, the type of a movie refers to what kind of the movie is (e.g. action, love or comedy). We calculate the weight of the two properties of the other multimedia contents which hasn't been accessed, carry out sorting based on weights, and determine the collection of multimedia contents that are to be recommended. Let I_2 represents candidate recommended set of the top L of the sorting list.

$$\overline{W} = \frac{\sum_{n=1}^{M} W_{intention_n}}{M} \tag{4}$$

Step 5: Generate collections of content to be recommended to target users.

In the collection of content to be recommended $I = I_1 \cap I_2$, I is the intersection of I_1 and I_2, we sort I by number of clicks of contents, select TOP-N in I for recommendation. If $|I| \leq N$, then the content to be recommended is $I = (I_1 \cap I_2) \cup I'$, where $I' \subset I_2 - (I_1 \cap I_2)$ is the subset that removing the intersection of I_1 and I_2 from I_2. That is, if the number of intersection of I_1 and I_2 is less than N, we select the candidate set from I' to supplement I.

The flowchart of the proposed recommendation algorithm is shown in Figure 2, and its pseudo code is presented in Algorithm 1.

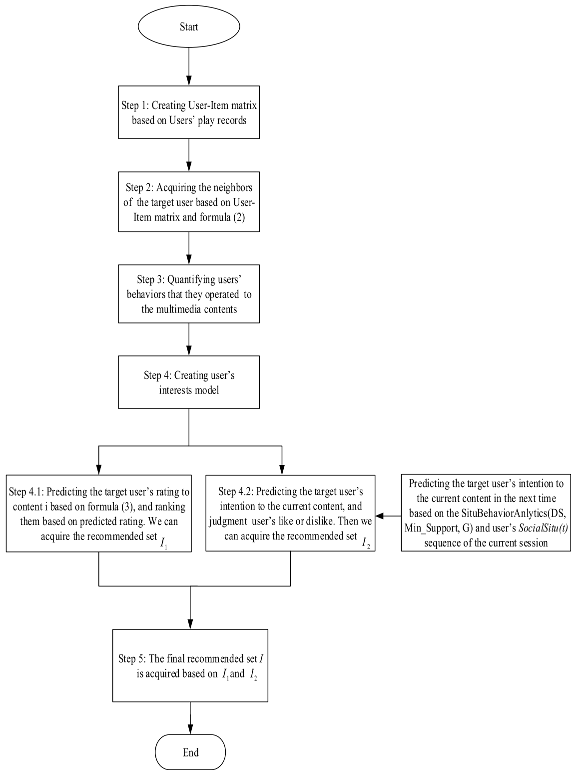

FIGURE 2. Flowchart of the proposed video content recommendation based on social situation analytics.

The function SituBehaviorAnlytics (DS, Min_Support, G) in Algorithm 1 is an intention serialization algorithm proposed in [7], which is used to find the user's behavior mode in a specific intention. DS represents the item set of user's history *SocialSitu(t)*, Min_Support refers to the value of minimum support in the function, and G represents the final goal corresponding to DS of the user. The $intention_{u,i}$ denotes the behavioral pattern of the ith intention of user u.

The user's frequent intention sequence mode is obtained through the intention serialization algorithm. The function Compare represents the comparison between the behavior sequence of the user's current session and the user's behavior patterns of the user-specific intentions in the database. If the comparison result is greater than a certain threshold, then the user's intention of the current session is the intention of the behavior pattern. The function *Weight()* represents the weight of the director or singer and type of the current browsing content in the content that the target user has viewed; thus, we can compute the weight of content that the target user has not access. The function *max()* is the maximum

Algorithm 1 Proposed Recommendation Algorithm for Video Content Based on Both the User Situation Analytics and Collaborative Filtering Recommendation

Input: User play records: $R(U_k, M_j)$, user collection: U, item collection: M, user context information: $SocialSitu\ (t)$
Output: multimedia content to be recommended MediaID
Recommend (R, $SocialSitu(t)_v$)
Begin
for each $r_{kj} \in R$ **and** $k \leftarrow 0$ **to** m − 1 **and** $j \leftarrow 0$ **to** n − 1
$R(U_k, M_j) = 1$; //Construct user-item matrix R(m,n) for user play
end for
$\cos(u, v) = \frac{A_u \times A_v}{|A_u| \times |A_v|}$; //According to R(m,n), use cosine similarity to calculate the similarity between users
for $v \in U$ **and** $v \neq u$ and $i \in M$
$P_{u,i} = \overline{R}_u + \frac{\sum_{v \in U} (R_{v,i} - \overline{R}_v) \bullet \cos(u,v) \bullet \overline{Behavior_{v,i}}}{\sum_{v=1}^{n} |\cos(u,v)| \bullet \overline{Behavior_{v,i}}}$ //Predict the scoring of the target user u on audio and video content
$I_1 = Sort(P_{u,i})$; //Carry out sequencing according to scores, and generate the collection I_1 to be recommended
end for
for $u \in U$
  for $i \leftarrow 0$ **to** n − 1 **and** $intention_i \in Intention$ //Calculate the behavioral model for the specific intention of the target user
$intention_{u,i}$ = SituBehaviorAnlytics(DS,Min_Support,G);
  endfor
endfor
$s \leftarrow Compare((SocialSitu(0)_u, SocialSitu(1)_u, \ldots, SocialSitu(t-1)_u), intention_{u,i})$
max(s); //The maximum of s
$intention_{u,t} = intention_{u,i}$
if $intention_{u,t} \in \{Share, Collection, Download, Play, Skip\}$ **and** $W_{intention_{u,t}} > \overline{W}$
for $m \in M$
$W_m = Weight(a.Author + a.Type)$ //According to the weights of the two properties of copyright owner and type of the currently browsed content a, calculate the weight of the multimedia content that have not been browsed by the other target users
  end for
$I_2 = Sort(W_m)$ //Sort the W_m of contents the target user hasn't accessed
end if
$I = I_1 \cap I_2$ //Audio and video sets to be recommended
if $|I|$ <N
$I = (I_1 \cap I_2) \cup I'_{\text{and}} I' \subset I_2 - (I_1 \cap I_2)$
endif
for $i \in I$
return $i.MusicID$
endfor
End

of similarity between the current behavior sequence and the behavior patterns of the target user.

In MSNs, user's intention may vary when they are in different roles [7], partly due to the increased attention on copyright protection of media content in publicly accessible and subscriber based MSNs. Therefore, differences in user permissions to view multimedia content under different identities are considered. The design of a recommendation algorithm that takes this into consideration is as follows: When generating the set I2 to be recommended, we take into account the content's authority that the user is viewing under the current identity. The proposed context analysis-based collaborative filtering recommendation algorithm with user identify for multimedia content is Algorithm 2.

IV. EVALUATION

TOP-N is an evaluation index of recommendation systems and is used to assess the performance of any recommendation system through the number of user interests included in the recommendation list. Precision and recall are the two common indicators, where precision refers to the proportion of user interests included in the recommendation list, and recall refers to the proportion of user interests included in the recommendation list of the preferred items of the users in the entire system. In approaches using precision and recall as the assessment indicators, a comprehensive indicator F (F-measure) is frequently used to consider Precision and Recall synthetically. For the recommendation list R_u of user u, Tu represents the collection of products preferred by users in the test set, and the three indicators are expressed mathematically as follows:

$$Precision = \frac{\sum_u |R_u \cap T_u|}{\sum_u |R_u|} \tag{5}$$

$$Recall = \frac{\sum_u |R_u \cap T_u|}{\sum_u |T_u|} \tag{6}$$

$$F - measure = \frac{2 * precision * recall}{precision + recall} \tag{7}$$

In this study, an experiment was conducted on the short video clips-oriented MSN platform named as Shareteches (formerly CyVOD) [24]. The platform architecture is integrated with multimedia content management, sociality, copyright protection and situation analytics function, as illustrated in Figure 3. Registered users can access the platform via different devices (e.g. Android and iOS devices, and smart TVs), and the server would recommend relevant contents to the target user using our proposed recommendation algorithm.

By using the real-world dataset from the platform, we conducted experiments to evaluate the precision, recall and F-measure (see Algorithm 1), trust-based collaborative filter recommendation [9], user-based collaborative filter recommendation and popular recommendation, as shown in Figures 4(a), (b), and (c). In our dataset, there are 738 users and 8890 videos, as well as 7439 playing history records, in which 6136 records are used as training set and 1303 as

TABLE 1. Comparisons between our recommender algorithms and others.

	Algorithm 1	Algorithm 2	Ref. [8]	Ref.[9]	Ref. [10]	Ref. [16]	Ref. [19]	Collaborative Filtering
User Behavior	Yes	Yes	Yes	No	No	No	Yes	No
User Identity	No	Yes	No	No	No	No	No	No
User Intention	Yes	Yes	No	No	No	No	No	No
Content Attributes	Yes	Yes	Yes	Yes	Yes	No	No	Yes
Context Aware	Yes	Yes	No	No	No	Yes	Yes	No

TABLE 2. Impact of different $\overline{W}$ on recommendation for user 161#.

Evaluation / Length / Threshold	Accuracy				Recall				F-measure			
	5	10	15	20	5	10	15	20	5	10	15	20
0.3	0.600	0.500	0.333	0.400	0.100	0.167	0.167	0.267	0.171	0.250	0.222	0.320
0.4	0.600	0.500	0.333	0.400	0.100	0.167	0.167	0.267	0.171	0.250	0.222	0.320
0.5	0.600	0.500	0.333	0.400	0.100	0.167	0.167	0.267	0.171	0.250	0.222	0.320
0.6	0.600	0.500	0.333	0.400	0.100	0.167	0.167	0.267	0.171	0.250	0.222	0.320
0.7	0.400	0.300	0.267	0.200	0.067	0.100	0.133	0.133	0.115	0.150	0.178	0.160

TABLE 3. Comparison of accuracy, recall and F-measure in the different thresholds of user 2#.

Evaluation / Length / Threshold	Accuracy				Recall				F-measure			
	5	10	15	20	5	10	15	20	5	10	15	20
0.3	0.200	0.600	0.533	0.500	0.021	0.128	0.170	0.213	0.038	0.211	0.259	0.299
0.4	0.200	0.600	0.533	0.500	0.021	0.128	0.170	0.213	0.038	0.211	0.259	0.299
0.5	0.400	0.500	0.533	0.500	0.043	0.106	0.170	0.213	0.078	0.175	0.259	0.299
0.6	0.400	0.500	0.533	0.500	0.043	0.106	0.170	0.213	0.078	0.175	0.259	0.299
0.7	0.400	0.500	0.533	0.500	0.043	0.106	0.170	0.213	0.078	0.175	0.259	0.299

test set. In which we conduct the data processing to remove the noisy data, such as the videos which the target user is open and close immediately.

When a new registered user logs in the platform, the server is responsible for discovering the user's possible intention by comparing the behavior sequence of the user's current session with all the behavior sequence patterns in the database. This allows us to determine the user's interests.

Figure 4 shows that Algorithm 1 achieves better performance than the two classical algorithms (i.e. user-based

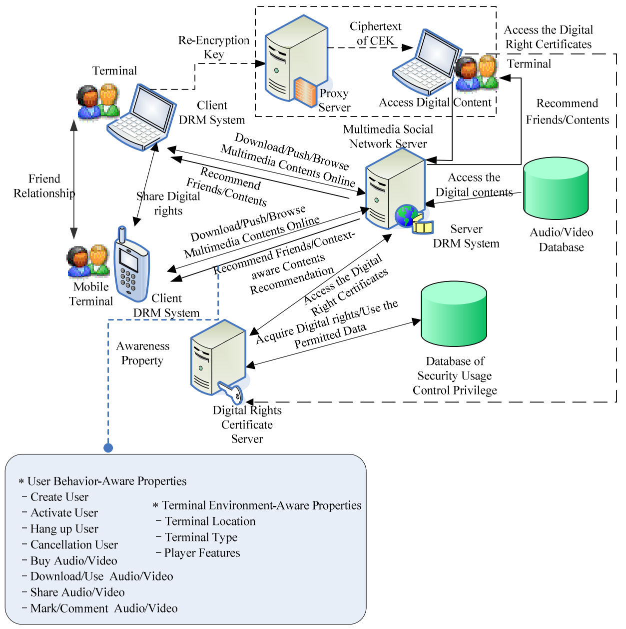

FIGURE 3. **Shareteches architecture with the social situation analytics function.**

collaborative filtering recommendation and popularity-based recommendation) and the trust-based collaborative filtering algorithm presented by Chen *et al.* [9]. The inclusion of the trust-based collaborative filtering algorithm presented by Chen *et al.* [9] in the comparison is due to the fact that both our proposed algorithm and the trust-based collaborative filtering algorithm are based on user-based collaborative filtering recommendation. Popularity-based recommendation is a basic recommendation algorithm, and we observed that our algorithm has a better performance than this basic algorithm.

As shown in Figures 4(a) and 4(b), as the length of the recommendation lists increases, the recall of the recommendation algorithm for Algorithm 1 will also increase and the precision will decrease after reaching a certain value. However, F-measure in the proposed algorithm increases with the number of recommendations and is much better than the trust-based method– see Figure 4(c). From Figure 4, it can be concluded that with a recommendation list of more than 10, our recommendation algorithm outperforms two classical algorithms and a state-of-the-art method, in terms of precision, recall and F-measure.

Given that a user may have different roles (e.g. ordinary registered user and VIP user), the permissions for the content that can be browsed can also differ. For example, ordinary registered users can only play content without copyright protection, and VIP users can play all content with or without copyright protection. Algorithm 2 was designed with this consideration in mind. We used 80% of the historical record data for 161# user as the training set and the remaining 20% as the test set. The precision, recall, and F-measure for Algorithms 1 and 2, trust-based collaborative filtering recommendation algorithm, user-based collaborative filtering

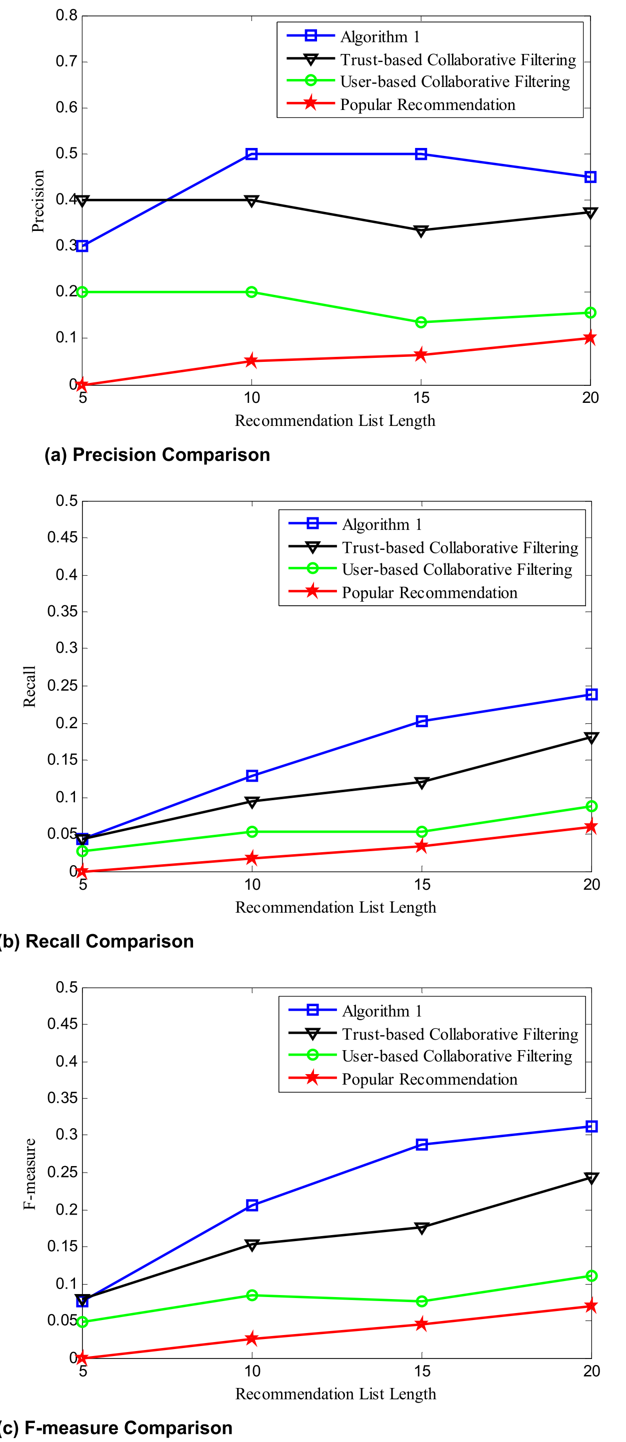

FIGURE 4. **Performance between proposed Algorithm 1 and three other algorithms: A comparative summary.**

recommendation algorithm, and another popular algorithm are shown in Figures 5(a), (b), and (c), respectively.

As shown in Figure 5, for 161# user, Algorithm 2 performs better than Algorithm 1 and other algorithms in terms of precision, recall, and F-measure. The reason why Algorithm 2 outperforms Algorithm 1 is because user role

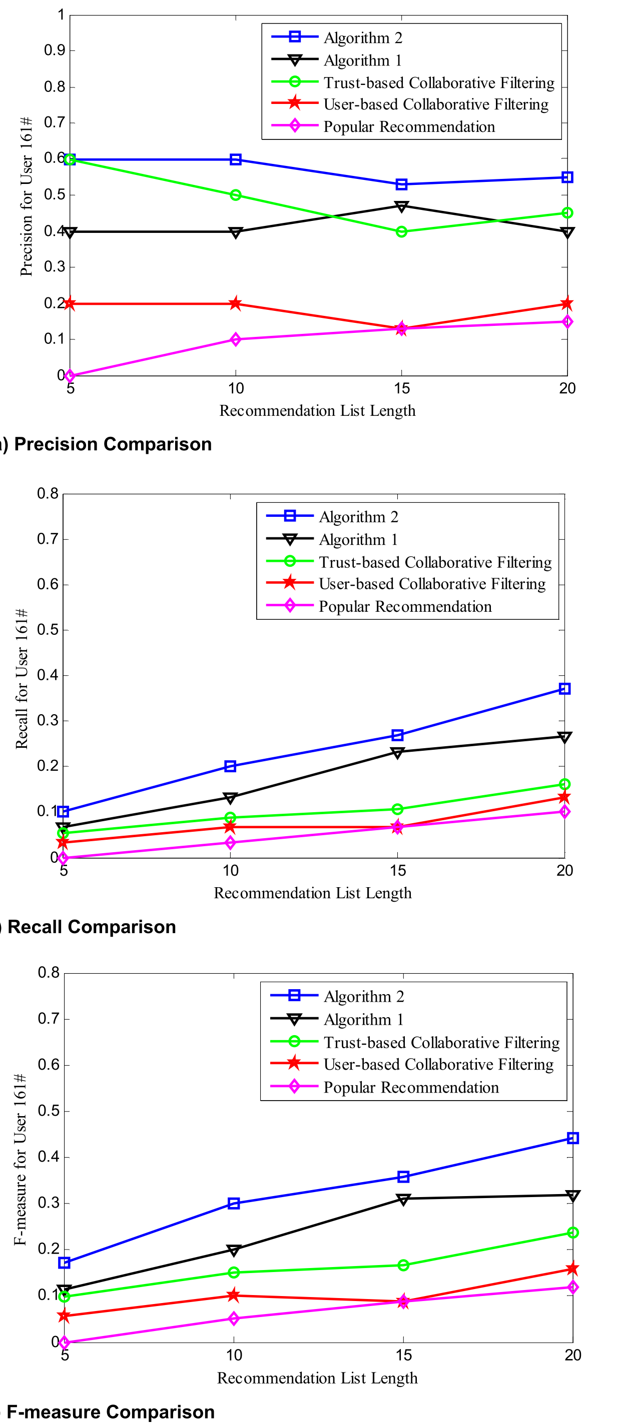

FIGURE 5. Comparison and analysis between the proposed Algorithm 1, Algorithm 2 and others when user u has the different identities in social domain.

is considered in Algorithm 2 but not Algorithm 1. But trust-based can result better than Algorithm 1 for 161# user in terms of precision from Figure 5 (a). It is also observed from Figure 5 (c) that Algorithm 2 has an improved performance of approximately 10% compared to Algorithm 1 for F-measure. Hence, we posit that user identities can facilitate the identification of user-personalized requirements that will allow us to understand user preference better.

Also we have made a qualitative comparison between recommendation algorithms of references [8]–[10], [16], [19] and our work. As shown in Table 1. From the comparison we can see that the algorithms in this paper have considered many factors to find users interests, and the others only take one of the elements in consideration. In addition, from Figure 4 and Figure 5 we can see that a comprehensive consideration of these elements is much better than that only one. However, our methods are not perfect.

The threshold $\overline{W}$ used in both Algorithms 1 and 2 is the average intention weight of the target user for the content he/she has accessed (i.e. average preference of the target user for all viewed content). In order to analyze the impact of different thresholds $\overline{W}$ on the performance of recommendation, we carried out two experiments using Algorithm 2. The precision, recall and F-measure of the recommendation for users 161 # and 2 # at different thresholds were analyzed. The results are shown in Tables 2 and 3. As presented in both tables, even though we used the same threshold for different users, accuracy, recall rate and F-measure may differ. When the recommendation list length is constant, the thresholds for users 161 # and 2 # to achieve optimal recommendation are not the same. Thus, we set different threshold values for different users.

V. CONCLUSION

Multimedia social networks are likely to continue to be a trend in our society, particularly with advances in multimedia capturing and sharing technologies, as well as communications technologies. Thus, the ability to help users to find the current media content of interest and relevance based on current session is crucial for service and content providers.

In this paper, we considered the realistic situation where user preferences and intentions may vary due to factors such as context (e.g. using a work computer vs using a mobile device alone at home) and time (e.g. daytime vs nighttime). Thus, to provide users with more accurate personalized services and to recommend content of interest and relevance, we proposed a user situation analytics-based recommendation algorithm for video content taking into consideration time-varying user intentions. The algorithm predicts and analyzes users' preferences according to the user's transaction history and the neighbor-nearest similar users, as well as the behavior sequences and referred of intentions of the target user. We then demonstrated the efficacy and efficiency of the proposed algorithm using a real-world dataset from Shareteches platform.

Future research includes collaborating with a real-world multimedia social network provider that can provide a larger data set to implement our proposed algorithms for evaluation and fine-tuning (if necessary). In addition, determining which factor plays a more important role in our algorithms, user's behaviors, similarity users, user's role, or user's intention.

Algorithm 2 Improved Recommendation Algorithm With User Identity for Multimedia Content Based on Algorithm 1

Input: User play records: $R(U_k, M_j)$, user collection: U, item collection: M, user context information: $SocialSitu\ (t)$
Output: multimedia content to be recommended MediaID
Recommend (R, $SocialSitu(t)_v$)
Begin
for each $r_{kj} \in R$ **and** $k \leftarrow 0$ **to** m − 1 **and** $j \leftarrow 0$ **to** n − 1
$R(U_k, M_j) = 1$; //Construct user-item matrix R(m,n) for user play
end for
$\cos(u, v) = \frac{A_u \times A_v}{|A_u| \times |A_v|}$; //According to R(m,n), use cosine similarity to calculate the similarity between users
for $v \in U$ **and** $v \neq u$ and $i \in M$
$P_{u,i} = \overline{R}_u + \frac{\sum_{v\in U} (R_{v,i}-\overline{R}_v)\bullet\cos(u,v)\bullet\overline{Behavior_{v,i}}}{\sum_{v=1}^{n} |\cos(u,v)|\bullet\overline{Behavior_{v,i}}}$ //Predict the scoring of the target user u on audio and video content
$I_1 = Sort(P_{u,i})$; //Carry out sequencing according to scores, and generate the collection I_1 to be recommended
end for
for $u \in U$
for $i \leftarrow 0$ **to** n − 1 **and** $intention_i \in Intention$
//Calculate the behavioral model for the specific intention of the target user
$intention_{u,i}$ = SituBehaviorAnlytics(DS,Min_Support,G);
endfor
endfor
$s \leftarrow Compare((SocialSitu(0)_u, SocialSitu(1)_u, \ldots, SocialSitu(t-1)_u), intention_{u,i})$
max(s); //The maximum of s
$intention_{u,t} = intention_{u,i}$
if $intention_{u,t} \in \{Share, Collection, Download, Play, Skip\}$ **and** $W_{intention_{u,t}} > \overline{W}$
for $m \in M$
$W_m = Weight(a.Author + a.Type + a.Authority)$//According to the weights of the three properties of content a, calculate the weight of the multimedia content that have not been browsed by the other target users
end for
$I_2 = Sort(W_m)$//Sort the $W_m$of contents the target user hasn't accessed
end if
$I = I_1 \cap I_2$ //Audio and video sets to be recommended
if $|I| <$ N
$I = (I_1 \cap I_2) \cup I'_{\text{and}} I' \subset I_2 - (I_1 \cap I_2)$
endif
for $i \in I$
return $i.MusicID$
endfor
End

APPENDIX

See Algorithm 2.

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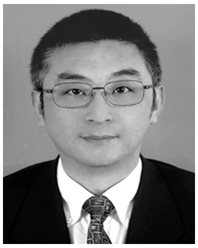

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