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# SOS: A multimedia recommender System for Online Social networks

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## HIGHLIGHTS

- We propose a novel recommending system for big data applications.
- We design an user-centered recommendation approach for online social networks.
- Modern social networking applications can take the more important advantages of the proposed framework.
- Experimental results encourage further research in this direction.

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## ABSTRACT

The use of Online Social Networks has been rapidly increased over the last years. In particular, Social Media Networks allow people to communicate, share, comment and observe different types of multimedia content. This phenomenon produces a huge amount of data showing Big Data features, mainly due to their high change rate, large volume and intrinsic heterogeneity. In this perspective, in the last decade Recommender Systems have been introduced to support the browsing of such data collections, assisting users to find "what they really need" within this ocean of information. In this research work, we propose and describe a novel recommending system for big data applications able to provide recommendations on the base of the interactions among users and the generated multimedia contents in one or more social media networks. The proposed system relies on a "user-centered" approach. An experimental campaign, using data coming from many social media networks, has been performed in order to assess the proposed approach also showing how it can obtain very promising results.



## 1. Introduction

Nowadays, multimedia data allow fast and effective communication and sharing of information about peoples' lives, their behaviors, works and interests; these data can be also considered as the digital testimony of facts, objects, and locations. In such a context, *Online Social Networks* (OSNs)—and more in general *Social Media Networks* (SNMs)—actually represent the most natural environment where users can create and share multimedia content such as text, image, video, audio, and so on. Just as a real example, each minute thousands of tweets are sent on Twitter, several hundreds of hours of videos are uploaded to YouTube, and a huge quantity of photos are shared on Instagram or uploaded to Flickr.

Indeed, using multimedia content each user interacts with the others generating "social links" that can effectively characterize their behaviors within the network. In particular, links in a social media network could represent anything from intimate friendships to common interests for a given multimedia object (e.g., tweet, post, video, photo, etc.).

Here, multimedia data seems to play a"key-role" especially if we consider the *Social Network Analysis* (SNA) perspective: representing and understanding user-multimedia interaction mechanisms and multimedia items' characteristics can be useful to predict user behavior and, especially, to design human-centric multimedia applications and services.

*Recommender Systems* are surely the applications that can take the most immediate and evident advantages by leveraging in different ways user experiences and interactions within a social community in order to suggest multimedia objects of interest.

In fact, in many cases social media repositories include a large amount of multimedia contents available to a wide population of users with rich and different metadata, showing *Big Data* features,

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mainly due to their high change rate, their huge volume and intrinsic heterogeneity. Thus, recommendation facilities should be very useful to assist users while search the desired information (e.g. an user living the photography art would like to see the last published images depicting a sunset).

Nowadays, recommender applications and services have been introduced to support in an effective and efficient way the intelligent browsing of items' collections, assisting users to find "what they need" within this ocean of information and thus realizing the well known transition in the Web from the "search" to the "discovery" paradigm.

Generally, they help people in retrieving information that match their preferences by recommending products or services from a large number of candidates [1], and have been proposed over the last years to support people in making decisions in various contexts: what items to buy [2], which photo or movie to watch [3,4], which music to listen [5], what travels to do [6], who they can invite to their social network [7], which artwork could be interesting within an art collection or even to suggest visiting paths in Cultural Heritage applications [8–12], just to make some examples.

One of the most interesting open research challenge is to provide recommendation techniques for multimedia data in one or more social media environments, exploiting at the same time (low-level) features, (high-level) metadata description (together with the attached semantics) and users' community behaviors in the different networks, trying to match user needs and eventually considering the *context* information [3,13].

Formally, a recommender system deals with a set of *users* $U = \{u_1 \ldots, u_m\}$ and a set of *items* $O = \{o_1, \ldots, o_n\}$. For each pair $(u_i, o_j)$, a recommender can compute a *score* (or a *rank*) $r_{i,j}$ that measures the expected interest of user $u_i$ in item $o_j$ (or the expected utility of item $o_j$ for user $u_i$), using a *knowledge base* and a *ranking* algorithm that generally could consider different combinations of the following characteristics: (i) user preferences and past behavior, (ii) preferences and behavior of the user community, (iii) items' features and how they can match user preferences, (iv) user feedbacks, (v) context information and how recommendations can change together with the context (see [14] for more details).

In turn, from the architectural point of view, the last generation of recommender systems is usually composed by one or more of the following components [1,6].

- A *pre-filtering* module that selects for each user $u_i$ a subset $O_i^c \subset O$ containing items that are good candidates to be recommended; such items usually match user preferences and needs [15].
- A *ranking* module that assigns w.r.t. user $u_i$ a rank $r_{i,j}$ to each candidate item $o_j$ in $O_i^c$ using the well-known recommendation techniques (i.e., *content-based*, *collaborative filtering* and *hybrid* approaches) that can exploit in several ways items' features and users' preferences, feedbacks (in the majority of cases in terms of *ratings*) moods (by opinion or sentiment analysis) and behavior [1].
- A *post-filtering* module that dynamically excludes, for each user $u_i$, some items from the recommendations' list; in this way, a new set $O_i^f \subseteq O_i^c$ is obtained on the base of user feedbacks and other contextual information (such as data coming from the interactions between the user and the application). Eventually, depending on applications, recommended items can be arranged in *groups* according to additional constraints [6].

According to the described scenario, in this paper we propose a novel *user-centered* approach able to provide multimedia recommendations based on several aspects related to users of one or more social media networks.

In particular, *preferences* (usually coded in the shape of items' metadata), *opinions* (textual comments to which it is possible to associate a particular sentiment), *behavior* (in the majority of cases logs of past items' observations and actions made by users in the environment), *feedbacks* (usually expressed in the form of ratings)—are considered and integrated together with *items' features* and *context information* within a general and unique framework that can support the development of recommender applications of multimedia items within several and heterogeneous social media networks.

Summarizing, the main research contribution of the work lies from one hand in the definition of a novel user-centered recommendation approach (with the set of characteristics described above) and, from the other one, in its application within one or more social media networks (e.g. Flickr, Youtube, Last.FM, etc.) to automatically suggest multimedia objects of interest for a specific user according to her/his preferences and needs.

The rest of the paper is organized as follows. Section 2 illustrates a motivating example for our work. Section 3 reports the state of the art of the most diffused recommendation approaches and their applications for online social networks. Section 4 describes the proposed strategy for recommendation. Section 5 reports a functional overview of the proposed recommender system with some implementation details. Section 6 reports some experimental results and Section 7 gives some concluding remarks and discusses future works.

## 2. Motivating example

In the following, we are describing a typical scenario where an effective social recommender system would be desirable. We can consider a situation in which a newbie user of Flickr – that loves photography, and in particular images depicting landscapes – desires to watch the most recent available photos of sunsets published and shared by other users with the social community. In order to obtain the requested multimedia information, the user could exploit the search functionality provided by Flickr and browse the set of pictures proposed by the system to retrieve the most interesting ones with respect to her/his preferences. Indeed, the quality of results, and consequently user satisfaction, will depend on the chosen search keywords (e.g. landscape, sunset) and moreover images that are of real interest for the user could be excluded form the result set. Eventually, the user can spent much time to collect the desired data on the basis of the number of returned images.

By using our Recommender System, the user retrieval task can be considerably simplified and the related experience significantly improved. In fact, leveraging user profile (containing information about her/his preferences or needs), in a first step, the recommender can filter and select from the entire multimedia collection only images depicting a landscape, and mainly, sunsets (as for example specified in the profile). Successively, using a proper ranking strategy the filtered images are ordered according to a "popularity" (a sort of relevance measure in the social community) based criterion. As soon as user choose to watch a particular photo, or marks it as favorite, the set of proposed images can be further refined, leveraging multimedia content and metadata of the selected pictures. Thus, the recommender system dynamically changes the list of candidate objects, exploiting user preferences, the most relevant images in the social community and, finally, user interaction with the system and eventually context (e.g. user position can be exploited to give more importance to picture that were taken in near places). Fig. 1 illustrates the described process.

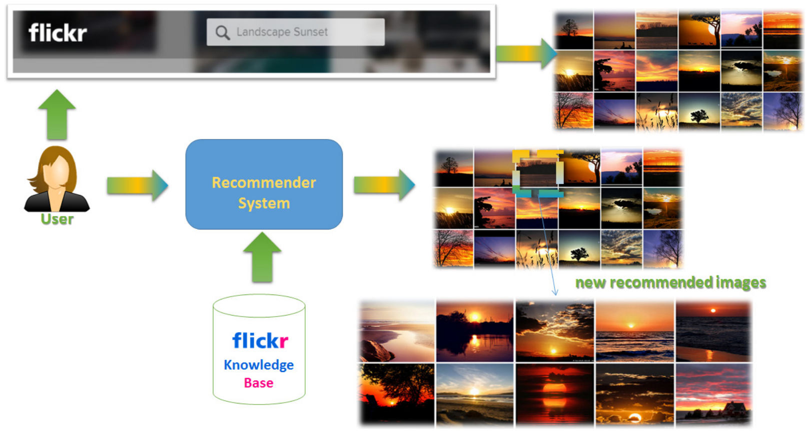



**Fig. 1.** Motivating example.

## 3. Related work

Recommender Systems are more and more playing an important role in our life, representing useful tools helping users to find "what they need" from a very large number of candidates. They represent a meaningful response to the problem of *information overload*, having as the main goal to predict user's preferences providing suggestions about items that could be of interest [1,16]. The most diffused classification for recommender system leverages five broad categories.

In the *content-based* approach, recommended items to a user are based on the ratings made by the user himself for *similar* items in the past [17]. A critical drawback of this kind of technique is *overspecialization*, since a system can only recommend items similar to those already rated by the user. In addition, we have the problem of defining an effective similarity criterion between two items on the base of the related features, especially if we consider complex data as multimedia information.

In a *collaborative filtering* strategy [18], the recommendation is in turn performed by filtering and evaluating items with respect to ratings from other users. Typically, users are asked to rate items and a similarity between their profiles is also computed to choose among highly rated items. Thus, the major challenge faced by collaborative filtering is the need to associate each user to a set of other users having similar profiles. In order to make any recommendations, the system has to collect data either asking for explicit ratings from users, or through non-intrusive profiling algorithms implicitly logging actions performed by users[19]. An important limitation of collaborative filtering systems is the *cold start problem*, that describes situations in which a recommender is unable to provide meaningful recommendations due to an initial lack of ratings.

Content-based filtering and collaborative filtering are then manually or automatically combined in the so called *hybrid* approaches [1] that help to overcome some limitations of each method. Different ways to combine collaborative and content-based methods into a hybrid recommender system can be classified as follows: (i) implementing collaborative and content-based methods separately and combining their predictions; (ii) incorporating some content-based characteristics into a collaborative approach; (iii) incorporating some collaborative characteristics into a content-based approach; (iv) constructing a general unifying model that incorporates both content-based and collaborative characteristics.

Eventually, a recommendation strategy should be able to provide users with relevant information depending on the *context* [20,9,21] (i.e. user location, observed items, etc.) as in *Context Aware Recommender Systems*. In the *Contextual Pre-filtering* techniques context information is used to initially select the set of relevant items, while a classic recommender is used to predict ratings. In *Contextual Post-filtering* approaches context is used in the last step of the recommending process to contextualize the output of a traditional recommender.

Finally, a category of recommender systems, named *Large Scale Recommender Systems* [21], calls for new capabilities of such applications to deal with very large amount of data with respect to scalability and efficiency issues.

More recently, all the above discussed strategies have been extended to multimedia realm (e.g. multimedia repositories, digital libraries, multimedia sharing system, etc.) with the aim of considering in the more effective way the multimedia content of recommended objects, both in terms of low-level and high-level characteristics (i.e. multimedia features and semantics) in the recommendation process together with user's social behavior and preferences [3,9]. From an other hand, recommendation techniques have been extended to provide useful recommendations for *groups* of users, and not only for the single ones [22,23].

Performance of classical recommender systems is strictly related to the *availability* and *quality* of user profiles and ratings: the density of the available ratings in commercial systems is often less than 1% and the proliferation of *fake* users can arise *malicious ratings*. An important improvement for traditional recommender systems to overcome such problems lies in the possibility to embed *social* elements into a recommendation strategy [24,25]. In fact, the great increase of user-generated content in social networks, such as product reviews, tags, forum discussions and blogs, has been followed by a bunch of valuable user opinions, perspectives or tastes toward items or other users, that are useful to build enhanced user profiles. In such a context, customer *opinion summarization* and *sentiment analysis* [26] techniques represent effective augmentations to traditional recommendation strategy, for example by not recommending items that receive a lot of negative feedbacks [27,24].

In the context of recommendation in the Online Social Networks, a lot of proposals have been presented in the last years [28,29] and interesting surveys are available [7,24].

In particular, social recommender applications can profitably exploit heterogeneous information extracted by one or more social networks to improve the accuracy of traditional recommendation approaches and provide new types of suggestions. As an example, they can recommend not only items but also groups, friends, events, tags, etc. to users, using particular algorithms [30,31].

As it will be evident later in the article, our approach can be classified as a hybrid user-centered strategy for a social network that incorporates some content-based characteristics into a collaborative strategy. It exploits from one hand logs from heterogeneous social networks to implicitly derive information about individual users and the community of users as a whole, considering their past browsing sessions as a sort of unary ratings. From the other one, user profiles in terms of item features are exploited to perform a first data filtering. Similarly to some collaborative filtering techniques, it is a kind of active filtering strategy in which past browsing sessions, modeled as a directed graph, determine the most suitable items to be recommended. In according to other collaborative approaches, transitive relationships among items are considered in computing the importance of an object. Similarly to some content based approaches, our approach gives high importance to the characteristics of the object a user is currently watching, in order to effectively compute the utility of other items. Finally, we assume the existence of a priori knowledge about metadata values and their relationships and consider both low and high-level information together with social elements as opinions and ratings, such that they contribute to determine the utility of an object in the recommendation process.

## 4. The recommendation strategy

The basic idea behind our proposal is that when a user is browsing a particular items' collection in a social media network, the recommender system:

1. determines a set of useful *candidate* items for the recommendation, on the base of user actual needs and preferences (*pre-filtering* stage);
2. opportunely assigns to these items a rank, previously computed exploiting items' intrinsic features and users' past behaviors, and using as refinement, other social elements in the shape of users' opinions and feedbacks (*ranking* stage);
3. dynamically, when a user "selects" as interesting one or more of the candidate items, determines the list of most suitable items (*post-filtering* stage), also considering other context information expressed by users in the shape of constraints on items' features;
4. eventually, final recommended items can be arranged in specific "groups" of objects considering further constraints (*presentation* stage).

The proposed idea takes its roots from our previous works, where we considered as user behaviors only the simple access to a single multimedia item [6,3]. Here, we have extended our approach considering all the possible user-to-content relationships that can occur in a social network.

In our recommendation process, items to be recommended are multimedia data (i.e. texts, images, videos, audio) related to specific social items (e.g. tweet, post, photo, etc. shared in a given social network). As in the majority of multimedia systems, items are described at two different levels:

- from an "high-level" perspective, by one or more set of *symbolic features* (i.e. keywords, tags and other metadata) that do not depend on the type of multimedia object, but can depended on the particular social network;
- from a "low-level" perspective, by a set of *intrinsic* or *content-based features* that are different for each kind of multimedia object (e.g. for an image we can choose descriptors based on color or texture information) but independent on the particular social network.

In the following, we are detailing all the described stages.

### 4.1. Pre-filtering stage using user features

In the *pre-filtering* stage, our aim is to select for a given user $u_h$ a subset $O_h^c \subset O$ containing items that are good "candidates" to be recommended: such items usually have to match some (static) user preferences and (dynamic) actual needs.

Considering high-level perspective, each item subjected to recommendation may be represented in different and heterogeneous feature spaces. For instance, in Flickr a given photo may be described by a set of metadata as title, tags, location and author, by the number of visualizations and favorites and the users' comments, by the photo-camera characteristics, by users' albums, galleries and groups in which it is present, and so on.

The first step consists in clustering together "similar" items, where the similarity should consider all (or subsets of) the different spaces of features. To this purpose, we employ *high-order star-structured co-clustering* techniques – that some of the authors have adopted in previous work [15,9] – to address the problem of heterogeneous data pre-filtering.

In this context, the same set of items is represented in different feature spaces. Such data represent items of a certain type, connected to other types of data, the features, so that the overall data schema forms a star structure of inter-relationships. The co-clustering task consists in clustering simultaneously the set of items and the set of values in the different feature spaces. In this way we obtain a partition of the items influenced by each of the feature spaces and at the same time a partition of each feature space.

The pre-filtering stage leverages the clustering results to select a set of items by using the user's profile, which is modeled as sets of descriptors in the same spaces as the items' descriptors. User profiles can be acquired in an explicit manner through proper questionnaires or learned in an implicit way considering user past behavior [32].

Let $O = \{o_1, \ldots, o_n\}$ be the set of items and $\mathcal{F} = \{F^1, \ldots, F^l\}$ a set of $l$ feature spaces. In our recommendation problem, a user $u_h$ is represented as a set of vectors in the same $l$ feature spaces describing the items.

To provide a first candidate list of items to be recommended, we measure the *cosine distance* of the user vectors associated to the $k$th space, with the centroids of each item clusters in the $k$th space. For each space, the most similar item cluster is chosen leading to $l$ clusters $\{X_1^c, \ldots, X_l^c\}$ of candidate items. Then, two different strategies can be adopted to provide the pre-filtered list of candidate items $O_h^c$: (i) *set-union strategy* – the items belonging to the union of all clusters are retained, i.e., $O_h^c = \bigcup_k X_k^c$; (ii) *threshold strategy* – the items that appears in at least *ths* clusters ($ths \in \{1 \ldots l\}$) are retained. The first strategy is suitable when user's vectors are associated to very small clusters. In any other situation, the second strategy is the most appropriate. As a final step, items already visited/liked/browsed by the user can be eventually filtered out.

Notice that, thanks to this approach, users are not described by set of items, but by sets of features that characterize the objects they visit, like or browse.

### 4.2. Ranking stage using user behavior and items similarity

The main goal of this stage is to automatically rank the set of items $O$ embedding in a collaborative learning context (user preferences are represented modeling the choice process in recommender system and learn by users' *browsing behaviors*) their *features* (those on the top of which it is possible to introduce a *similarity* notion).

In particular, we use a novel technique that some of the authors have proposed in previous works – combining in a

**Table 1**
User-to-content relationships in online social networks.

| | Twitter | Facebook | Instagram | Google+ | Last.FM | Flickr |
|---|---|---|---|---|---|---|
| Publishing | × | × | × | × | × | × |
| Tagging | × | × | × | × | × | × |
| Comment | × | × | × | × | × | × |
| Like | × | × | × | × | | × |
| Resharing | × | × | | × | | |
| Favorites | × | | | | × | × |
| Visualization | | × | × | | × | × |

novel manner low and high level features of items, possible past behavior of individual users and overall behavior of the whole user "community" [19,3] – to provide useful recommendations during the browsing of multimedia collections.

### 4.2.1. Modeling user behavior in a social media network

In our model we assume the existence of a finite set of *Action Symbols* ($S$) coding all the possible "interactions" among the set of *Users* ($U$) and the set of *Objects* ($O$) in one ore more social media networks, which can be properly captured during several browsing sessions exploiting log information [33,34].

In such a context, we can consider different examples of actions: users' reactions or comments to published contents (e.g., a post or photo), user visualization or rating of a given content, and so on. Table 1 summarizes the available user-to-content relationships in the most diffused social networks.

We introduce the following definitions.

**Definition 4.1** (*Log Tuple*)**.** A *log tuple* can be defined by the information $l = (s, u, o, \lambda_1, \dots, \lambda_k)$, where $s \in S$, $u \in U$, $o \in O$ and $\lambda_1, \dots, \lambda_k$, are particular attributes (e.g., timestamp, type of reaction, text and tags of a comment, etc.) used to describe a particular action.

**Definition 4.2** (*Log*)**.** A *Log* ($L$) is a finite sequence of log tuples.

Intuitively, a log tuple corresponds to an observation of $l.s$ performed by the user $l.u$ on a given object $l.o$ along with the associated attributes of the observation $\lambda_1, \dots, \lambda_k$. By convention, if action $a_2$ occurs after $a_1$ in a log, then the action $a_2$ occurred temporally after $a_1$.

Starting from a log, it is possible to model interactions among users and the generated multimedia contents in social media networks as a particular labeled graph as in the following definition.

**Definition 4.3** (*User-Content Social Graph*)**.** We define a *User-Content Social Graph* as a couple $(G, \gamma)$, where: $G = (O, E)$ is a *directed graph*; $\gamma : E \rightarrow \{pattern, sim\} \times R^+$ is a *labeling function* that associates each edge in $E \subseteq O \times O$ with a pair $(t, w)$, $t$ being the type of the edge which can assume two enumerative values (*pattern* and *similarity*) and $w$ is the weight of the edge.

In our model, we list two different cases:

- a *pattern label* for an edge $(o_j, o_i)$ denotes the fact that an item $o_i$ was accessed immediately after an item $o_j$ by any user in a given browser session and, in this case, the weight $w_j^i$ is the number of times $o_i$ was accessed immediately after $o_j$;
- a *similarity label* for an edge $(o_j, o_i)$ denotes the fact that an item $o_i$ is similar to $o_j$ and, in this case, the weight $w_j^i$ is the "similarity" between the two items. Thus, a link from $o_j$ to $o_i$ indicates that part of the importance of $o_j$ is transferred to $o_i$.

A user-content social graph can be *local* if it is related to a given user or *global* if it concerns an entire social community.

Summarizing, our basic idea is to assume that when an item $o_i$ is chosen after an item $o_j$ in the same user browsing session, this event means that $o_i$ "is voting" for $o_j$. Similarly, the fact that an item $o_i$ is "very similar" in terms of some intrinsic features to $o_j$ can also be interpreted as $o_j$ "recommending" $o_i$ (and vice versa). Leveraging log information in the graph building process, we have to choose for each kind of social media network:

- the list of "consecutive" actions in the log with the related attributes that can instantiate an edge, as an example:
  - a user visualized/published two objects in consecutive temporal instants of the same browsing session,
  - a user provided two positive reactions or comments to two different objective in successive times of the same browsing session;
  - a user marked two objects as "favorite" in consecutive temporal instants of the same browsing session,
  - etc.
- the particular attributes (e.g. tags, keywords or other relevant information extracted from an annotation text) describing user actions on different objects that can be used in the similarity computation together with high-level and low-level features of multimedia contents.

Fig. 2 describes an example of log and the related global user-content social graph.

### 4.2.2. Items ranking

On the basis of the user-content social graph, each object can be opportunely *ranked*. In particular, a *recommendation grade* is computed for each item.

**Definition 4.4** (*Recommendation Grade*)**.** Given an item $o_i \in O$, its *recommendation grade* $\rho(o_i)$ is defined as follows:

$$\rho(o_i) = \sum_{o_j \in P_G(o_i)} \hat{w}_{ij} \cdot \rho(o_j) \tag{1}$$

where $P_G(o_i) = \{o_j \in O | (o_j, o_i) \in E\}$ is the set of predecessors of $o_i$ in $G$, and $\hat{w}_{ij}$ is the normalized weight of the edge from $o_j$ to $o_i$. We note that for each $o_j \in O$ $\sum_{o_i \in S_G(o_j)} \hat{w}_{ij} = 1$ must hold, where $S_G(o_j) = \{o_i \in O | (o_j, o_i) \in E\}$ is the set of successors of $o_j$ in $G$.

In [19], it has been shown that the ranking vector $R = [\rho(o_1) \dots \rho(o_n)]^T$ of all the items can be computed as the solution to the equation $R = C \cdot R$, where $C = \{\hat{w}_{ij}\}$ is an ad-hoc matrix that defines how the importance of each item is transferred to other items.

The matrix can be seen as a linear combination of:

- a *local browsing matrix* $A_h = \{a_{ij}^h\}$ for each user $u_h$, where its generic element $a_{ij}^l$ is defined as the ratio of the number of times item $o_i$ has been chosen by user $u_h$ immediately after $o_j$ to the number of times any item in $O$ has been chosen by $u_h$ immediately after $o_j$;
- a *global browsing matrix* $A = \{a_{ij}\}$, where its generic element $a_{ij}$ is defined as the ratio of the number of times item $o_i$ has been chosen by any user immediately after $o_j$ to the number of times any item in $O$ has been chosen immediately after $o_j$;
- a *similarity matrix* $B = \{b_{ij}\}$ such that $b_{ij}$ denotes the similarity between two items $o_i$ and $o_j$ (in the next subsection we are providing more details).

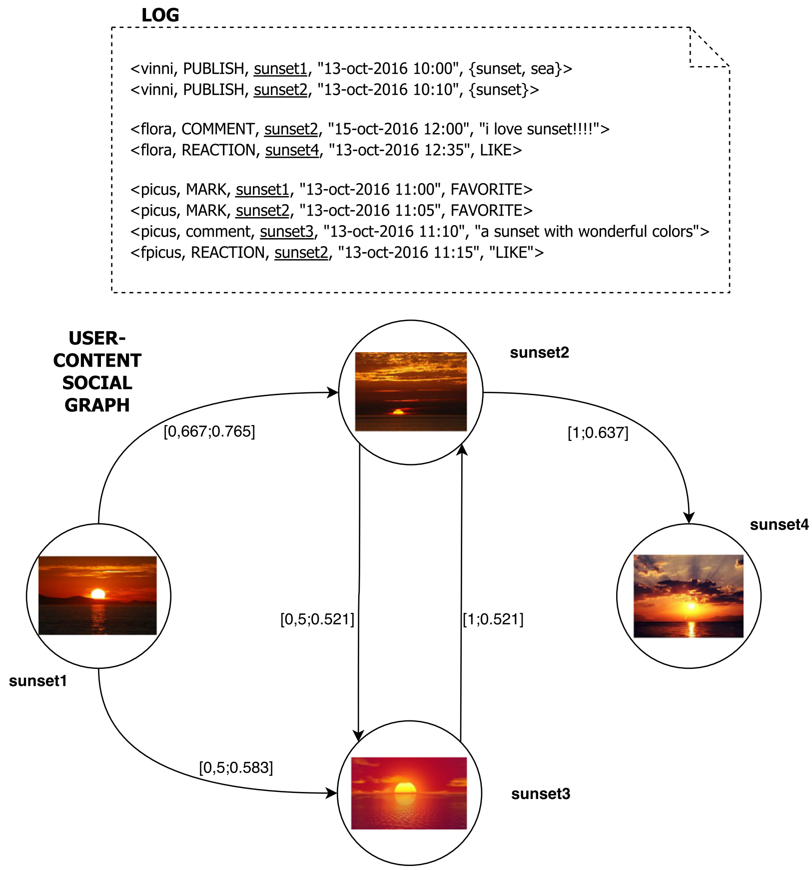



**Fig. 2.** Log with the related user-content social graph.

The successive step is to compute *customized* rankings for each individual user. In this case, we can rewrite previous equation considering the ranking for each user as $R_h = C \cdot R_h$, where $R_h$ is the vector of preference grades, customized for a user $u_h$ considering only items in the related $O^c_h$. We note that solving the discussed equation corresponds to finding the stationary vector of $C$, i.e., the eigenvector with eigenvalue equal to 1. In [3], it has been demonstrated that $C$, under certain assumptions and transformations, is a real square matrix having positive elements, with a unique largest real eigenvalue and the corresponding eigenvector has strictly positive components. In such conditions, the equation can be solved using the *Power Method* algorithm.

Rank can be finally refined using user attached *sentiments* and ratings (*popularity*) using the strategy that some of the authors proposed in [6].

#### 4.2.3. Computing items similarity

The items' similarity [35] has been computed taking into account:

- a semantic relatedness[36,37] based on a set of available ontologies, taxonomies and vocabularies using some high-level features values (i.e. *ontological* attributes [38]) combined with a "tag-based" similarity;
- a low-level features comparison[1] using multimedia descriptors [39].

### 4.3. Post-filtering stage using context information

We have introduced a *post-filtering* method for generating the final set of "real" candidates for recommendation using *context* information. The context is represented by means of the well-known *key-value* model [40] using as dimensions some of the different feature spaces related to items.

In our system, context features can be expressed either directly using some *target items* (e.g. objects that have positively captured user attention) or specifying the related values in the shape of *constraints* that recommended items have to satisfy.

Assume that a user $u_h$ is currently interested in a target item $o_j$. We can define the set of candidate recommendations as follows:

$$O^f_{h,j} = \bigcup_{k=1}^{M} \{o_i \in O^c_h \mid a^k_{ij} > 0\} \cup \{o_i \in NNQ(o_j, O^c_h)\}. \tag{2}$$

The set of candidates includes the items that have been accessed by at least one user within $k$ steps from $o_j$, with $k$ between 1 and $M$, and the items that are most similar to $o_j$ according to the results of a *Nearest Neighbor Query* ($NNQ(o_j, O^c_h)$) functionality.[2] The ranked list of recommendations is then generated by ranking the items in $O^f_{h,j}$, for each item $o_j$ selected as interesting by user $u_h$, using the ranking vector $R_h$ thus obtaining the final set $O^f_h$.

Finally, for each user all the items that do not respect possible context constraints are removed from the final list.

[1] The low-level similarity is computed only for multimedia items of the same type.

[2] Note that a positive element $a^k_{ij}$ of $A^k$ indicates that $o_i$ was accessed exactly $k$ steps after $o_j$ at least once.

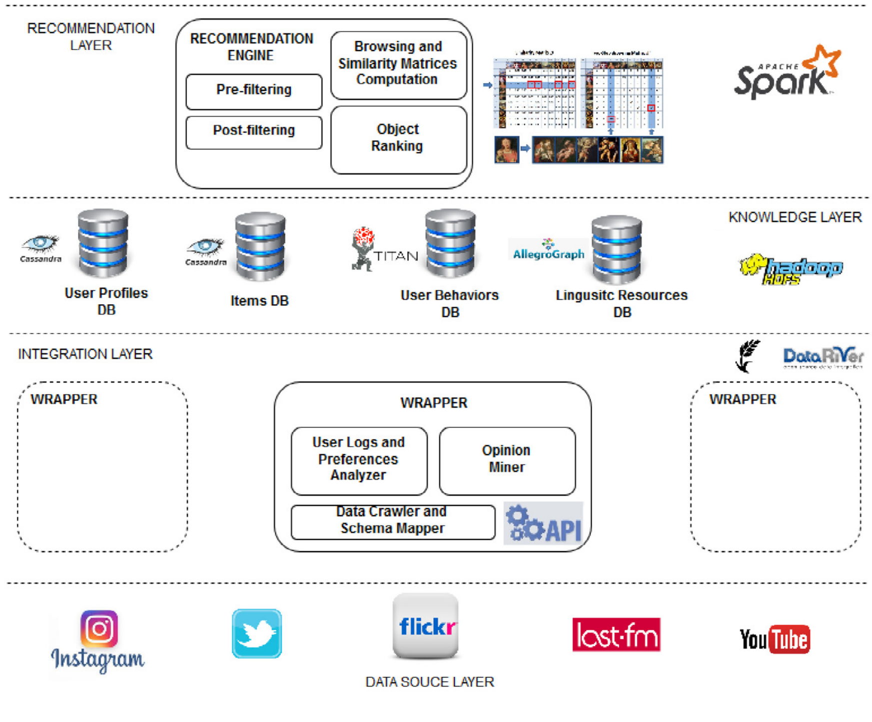



**Fig. 3.** System overview.

### 4.4. *Presentation stage*

Multimedia objects that are good candidates for the recommendation can be eventually arranged in groups of items in according to some system configuration parameters and user preferences.

## 5. The recommender system overview

Fig. 3 describes at a glance an overview of the proposed system in terms of its main components, which we are describing in the following.

Data to be recommended are retrieved by a *Wrapper* component that is composed by several modules. The *Data Crawler and Schema Mapper* is responsible of: (i) periodically accessing to the items' repositories (e.g., Twitter, Flickr, Youtube, Instagram, etc.) using the proper API, (ii) extracting for each item all the *features* (e.g., metadata, possible ratings and reviews, etc.) and other information of interest (e.g. user preferences, time-stamped items' observations, etc.), (iii) performing a mapping w.r.t. a global schema. A part of such information will be then exploited by the *User Logs and Preferences Analyzer* and *Opinion Miner* modules to determine the user-content social graph with the related user profiles and the users' mood on the different items.

After the wrapping phase, all the information will be stored in the *Knowledge Base* of the system. In particular, it is composed by: (i) the *User Behaviors DB* containing the user-content social graph related to the users' browsing sessions, (ii) the *Items DB* containing items with all the related features, (iii) *User Profiles DB* containing user preferences in terms of items' features, (iv) *Linguistic Resources DB* with the available ontologies, taxonomies and vocabularies [41].

The *Recommender Engine* provides a set of recommendation facilities for multi-dimensional and interactive browsing of items. Exploiting user preferences, the *Pre-filtering* module selects a set of *candidate* items for recommendation; successively, the *Object Ranking* module assigns a ranking of such candidates exploiting a proper social strategy (that uses the *Users and Similarity Matrices Computation* module and information on users' opinions).

Finally, the *Post-filtering* module dynamically selects a subset of candidates, exploiting the item that a user is currently watching and context information.

In particular, we designed and implemented a first prototype for the recommender system that builds and manages different multimedia collections, providing the basic facilities for querying and recommendation, using data from several social media network repositories.

The system was realized on the top of the Apache Spark engine based on the Hadoop technological stack to meet Big Data issues. More in details, the log files and multimedia raw data are stored on HDFS while user and object descriptions are managed by Cassandra. In turn, linguistic resource are managed by the AllegroGraph triplestore. Co-clustering, ranking and post-filtering techniques were implemented on the top Spark machine learning and graph analysis libraries and leveraging SPARK SQL facilities; multimedia similarities were computed using Windsurf library [39]. Wrapping functionalities were implemented using DataRiver[3] solution (based on the MOMIS system) and leveraging Social Harvest[4] facilities.

In addition, the system provides some REST API that can be dynamically invoked by the social network applications to suggest a set of items that can be of interest for a particular user browsing multimedia collections.

## 6. Experimental results

Recommender Systems are very complex applications and their evaluation is a challenging task, in addition, results are hardly generalizable as reported in the literature [42].

3 http://www.datariver.it/it/.
4 http://www.socialharvest.io/.

The majority of research efforts on recommender system evaluation have mainly focused on prediction *accuracy* and *stability* [42]. More recently, researchers began examining issues related to users' subjective opinions and developing additional criteria to evaluate recommender systems. In particular, they suggest that *user satisfaction* does not always (or, at least, not only) correlate with the overall recommender's accuracy. Moreover, characterizing and evaluating the quality of a user's experience and subjective attitude toward the acceptance of recommender technology is an important issue [3].

Starting from these considerations and on the basis of current trends in the literature, we decided to perform an evaluation of our recommendation algorithm in terms of ranking effectiveness both with respect to a human observer and based on well-established accuracy metrics, in the last case also reporting a comparison with two of the most diffused recommendation approaches.

### 6.1. Dataset

We used a subset of the *Yahoo Flickr Creative Commons 100 Million Data* (YFCC100M)[5] multimedia collection (containing about 500,000 images), provided by Yahoo in 2014.

In particular, we exploited users' social interactions (friendships, tags, publishing, comments, favorites) with the related multimedia data.

Images and user actions necessary to build our user-content graph[6] were retrieved using Flickr API[7] and are related to several domains and topics (e.g., animal, landscape, nature, etc.).

### 6.2. Ranking effectiveness

In such a kind of experiments, we have analyzed the correlations existing among our social multimedia ranking, other ranking approaches and a human ground truth. In particular, we defined a human-generated ranking (representing the unique gold standard), asking a group of about 20 students to rank the top-100 results of different multimedia queries with respect to the relevance of the retrieved images, in terms of topics and low-level content. Then, we used two classes of ranking methods: *Popularity* (PR)[43]—based on popularity of images computed by a linear combination of number of favorites, comments and likes—and *Collaborative* (CR)[44]—based on the user feedbacks and interactions among users.

Table 2 shows the results of ranking comparison using the *Kendall's Tau* ($\tau$) and *Spearman's Rank Correlation* ($\rho$) coefficients obtained by comparing in pairs the following methods: Social Multimedia Ranking (SMR), Human Ranking (HR), Popularity Ranking (PR) and Collaborative Ranking (CR).

It is possible to note that our ranking presents the most similar behavior with respect to the human ground truth.

### 6.3. Recommender accuracy

For this second type of experiments, we used a collection of about 2000 images (for which a consistent number of comments are available), rated by a subset of 100 users. We consider as rating the number of favorites opportunely normalized bu assigning each image a score between 1 (*"Awful"*) and 5 (*"Must see"*).

**Table 2**
Ranking comparison (Social Ranking (SMR), Human Ranking (HR), Popularity Ranking (PR) and Collaborative Ranking (CR)).

| | $\tau$ | $\rho$ |
|---|---|---|
| SMR–HR | 0.69 | 0.80 |
| PR–HR | 0.55 | 0.61 |
| CR–HR | 0.68 | 0.74 |
| SMR–PR | 0.51 | 0.60 |
| SMR–CR | 0.68 | 0.73 |
| PR–CR | 0.54 | 0.78 |

We used the *Mean Absolute Error* (*MAE*) and the *Root Mean Square Error* (*RMSE*) as metrics in our experiments. In our case, *MAE* and *RMSE* are defined as:

$$MAE = \frac{1}{N}\sum_{u,i,j} |r_{ui}^j - \hat{r}_{ui}^j|$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{u,i,j}(r_{ui}^j - \hat{r}_{ui}^j)^2}$$

where $r_{ui}^j$ is the actual rating that the user $u$ has given to item $i$ for the item $j$, $\hat{r}_{ui}^j$ is the system predicted rating (the recommendation grades were also normalized on a scale from 1 to 5), and $N$ is the total number of test ratings. Both *MAE* and *RMSE* thus attempt to measure the prediction error (accuracy of the recommendation): *RMSE* is considered as a stronger measure than *MAE* as larger prediction errors are penalized more. For both the metrics, smaller values indicate better performances.

We compared the accuracy in terms of *Root Mean Square Error* of the predictions computed by our recommender system with the *UPCC* and *IPCC* [45] approaches (which reliable implementation can be obtained leveraging machine learning libraries provided by the *Apache Mahout* framework). In particular, we selected 50 test users and computed the average accuracy for 50 predictions on a subset of the most recently observed items, increasing data sparsity for the same users. In the case of our system, we used the last observed item in the test users' browsing sessions as the query item for post-filtering stage, and normalized the recommendation grade on a scale ranging from 1 to 5.

Fig. 4 shows the trend of RMSE for our system as well as for the UPCC and IPCC algorithms, as the sparsity of the rating matrix increases. Our approach outperforms UPPC and IPPC ones for each value of items' sparsity – and especially for higher values – showing as social information can improve recommendations.

However, our approach is more accurate when the sparsity of the rating matrix is high. This is due to the use of the *similarity matrix*, which provides useful information to the algorithm, in order to compute meaningful predictions even if a user's browsing session data is not available.

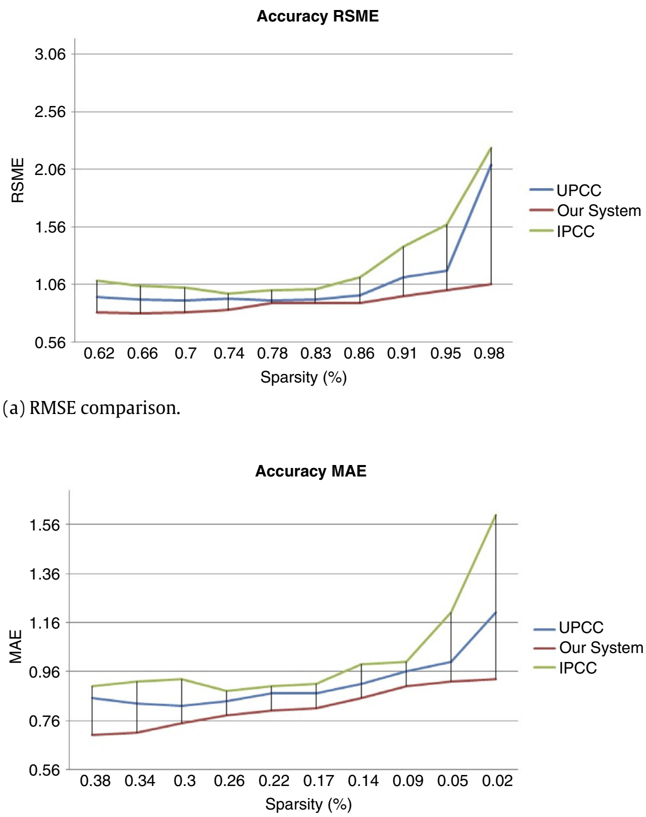
## 7. Conclusions and future works

In this paper a novel user-centered recommendation approach for online social networks has been proposed and discussed. Several aspects related to users – i.e. *preferences* (usually in the shape of items' metadata), *opinions* (textual comments to which it is possible to associate a sentiment), *behavior* (in the majority of cases logs of past items' observations made by users), *feedbacks* (usually expressed in the form of ratings) – have been considered and integrated together with *items' features* and *context information* within a general framework that can support different applications using proper customizations. In particular, modern social networking applications can take the more important advantages of our framework that can be adopted as the recommendation engine for a variety of items (news to

5 https://webscope.sandbox.yahoo.com.

6 An edge is created when a user visualized/published two objects in consecutive temporal instants of the same browsing session, or when she/he marked two objects as "favorite" in consecutive temporal instants of the same browsing session. The action timestamps provide the needed temporal information.

7 https://www.flickr.com/services/api.




(a) RMSE comparison.



(b) MAE comparison.

**Fig. 4.** Comparison in terms of MAE and RMSE between our approach and UPCC and IPCC respectively.

read, movie to watch, music to listen, etc.) embedded in a social environment. In addition, the system can be easily used to provide recommendations of more than one category of items. In this case, mechanisms for grouping different items in a unique object are necessary. The experimental results have shown that our approach is promising and encourage further research in this direction. The current major limitations of this work are represented by the necessity of action timestamps' information (that is not always available for all the social media networks) and the relatively not very large size of the datasets used for the experiments, both in terms of number of items and in terms of number of users involved in the current evaluation. Future efforts will be devoted to: (i) extending the experimental evaluation to a larger multimedia dataset, also considering the *stability* of recommendations, (iii) applying our approach to other kinds of data from heterogeneous collections and compare it with other more recent approaches of the literature.

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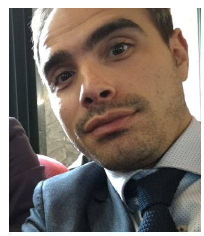

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