Ontology-based Recommendation in Multimedia Sharing Systems

Katarzyna Musiał, Krzysztof Juszczyszyn, Przemysław Kazienko
katarzyna.musial@pwr.wroc.pl, krzysztof@pwr.wroc.pl, kazienko@pwr.wroc.pl

In this paper, a new framework for recommendation of multimedia objects in the environment of the multimedia sharing system was proposed. It uses two kinds of individual ontologies one is created for multimedia objects and the second one for system users. The final recommendation process takes into account similarities calculated both between objects' and users' ontologies. These individual ontologies respect all the social and semantic features existing in the system. The entire recommender framework was developed for the use in Flickr, a typical photo sharing system.

1. Introduction

The typical examples of recent Web 2.0 applications are multimedia sharing systems like *Flickr* or *YouTube*. that enable their users to upload, download, manage, and browse multimedia contents such as photos, videos, animations called in this paper multimedia objects (MOs). Each of the multimedia object can be tagged by its author what is equivalent to indexing with keywords in typical systems with Information Retrieval functionality. The main difference is lack of common set of tags available for users. In other words, users can describe their MO with one or more short phrases that are most meaningful for the authors and usually describe the content of this element. However, the tags are proposed by authors on their own even though they can observe achievements of others. For that reason, tags do not have to be understandable for all other users. It includes especially colloquial tags and tags expressed in other languages. The process of autonomous creation and assignment of tags to multimedia objects performed by their authors is often called *folksonomy*.

In the multimedia sharing system, users simultaneously interact, collaborate and influence one another forming a kind of social community in this way. Hence, users can not only tag multimedia objects they have published but also comment the items added by others, include them to their favorites, etc. Additionally, users have the opportunity to set up new, direct relationships with other system users as well as establish groups of collective interests and directly enumerate their friends or acquaintances.

This diverse and vast amount of data about both multimedia objects and user activities gives the opportunity to complex analysis. It can also be exploited to create complex ontologies that would provide the comprehensive view onto both the multimedia objects existing within the system, the relationships between them as well as the users operations connected with these multimedia objects. Next, the knowledge built into these ontologies can be utilized by the recommender system to suggest to the active user the items, which are the most suitable for them.

2. Related Work

Nowadays, recommender systems became more and more popular and often constitute the integral part of the recent web sites. They help people to make decision, what items to buy, which news to read [21], which movie to watch or even who they can invite to their social network [13]. On the other hand, especially in e-commerce these kind of system provide the powerful tool to maintain the loyalty of the customers and increase the sales [11]. Recommender systems are especially useful in environments with vast amount of information since they cope with selection of a small subset of items that appears to fit to the users' preferences

[1, 15, 20, 22]. Overall, the recommender systems are usually divided into three main categories: collaborative filtering, content-based filtering, and hybrid recommendation [1]. The collaborative filtering technique relies on opinions about items delivered by users. The system recommends products or people that have been positively evaluated by other people, whose ratings and tastes are similar to the preferences of the user who will receive recommendation [1, 7, 21]. In the content-based filtering the items that are recommended to the user are similar to the items that user had picked and rate high in the past [19]. The hybrid method combines two previously enumerated approaches [8, 11, 21].

However, in some cases, especially in Web 2.0 applications, we can use available knowledge about application domains in order to generate recommendations [23]. An ontology is a conceptualisation of a domain into a machine-readable format typically in the form of a structure consisting of concepts, attributes, relationships, and axioms [6]. The problem of finding similarities between ontology elements and also between entire ontologies as complex structures plays important and growing role in shaping online user communities and managing the content of Web portals [10] such as Flickr.

There exist numerous researches that applied the idea of ontology in the recommendation process. One of the first examples were Quickstep and Foxtrot systems proposed in [17], where the collections of research papers were classified using ontological classes. The advantage of such methods is that they allow to take into account the relations between commonly used search terms and their possible role in the application domain under consideration. The similar approach, using ontologically grounded user profiles, was proven to be successful in [3]. Another example where the view-based search method developed within the information retrieval community was combined with the ontology-based annotations and search was presented in [9]. As a result the authors worked out the ontology and vie-based image retrieval and recommendation browser Ontogator.

Ontologies were also utilized to address the cold-start problem as well as interest acquisition problem [16]. It was performed by integrating the Quickstep recommender system, AKT ontology and OntoCoPI. Furthermore, the ontologies were applied in the recommender system for business collaboration [18]. The goal of the system was to facilitate knowledge workers to find the most relevant resources that enable to complete the given task. This process was performed based on continuous monitoring of worker's context and anticipating the person's potential requirements.

3. Problem Description

The typical multimedia sharing system accumulates vast amount of data about the published multimedia objects, relationships between them, tags and various types of user activities. However, the information hidden in this data is poorly structuralized and do not provide any comprehensive view onto the relationships between MOs nor the system users. Besides, due to open and flexible profile of the multimedia sharing system users often utilize the language, which is not really comprehensible for the others. It regards especially tags and descriptions containing colloquial and improperly used terms. Moreover, users often assign to the MOs they want to publish only few relevant tags or no tags at all. Hence, many multimedia objects do not possess any appropriate and verified descriptions or tags. As a result, there are many MOs that contain similar multimedia content and completely divergent tags and textual description.

On the other hand, the ontology concept appears to be suitable for this kind of data but acquiring such knowledge and keeping it up to date is not a trivial task.

Typical recommender framework process data gathered by the system and generate some suggestions to users. However, the users have no influence on the recommendation process.

Sometimes, in the systems based on demographic filtering, users can only provide information about themselves: their interests, gender, age and other demographic data. This kind of data is usually inserted once at registration and never updated. The character of multimedia sharing systems requires a new method of recommendation, in which users would be able to change relationships between multimedia objects generated by the system. However, these relationships result from many different either semantic or social links. The former include common tags and similar descriptions, whereas the latter are consequences of relations between system users and can be derived from lists of favourites, groups, contact lists and comments to the same MOs. The exaggerated independence of the recommender system can be weakened by introduction of the automatically created individual ontologies that could be manually changed by the users.

4. Ontology-based Recommendation in Multimedia Sharing Systems

4.1. General Concept

The main goal of the recommendation process in multimedia sharing system such as Flickr is to provide users the MOs that they would be interested in and in consequence they will watch and comment them or even add to their list of favourites. The suggestions generated by the recommender system respect the current context, i.e. the user and the individual MOs recently viewed by this given user.

The general concept of the recommendation process for user u_x while viewing multimedia object a_i is presented in Fig.1. It consists of four main steps: user context monitoring (user u_x and the viewed MO a_i), ontology-based similarities calculation, integration of knowledge provided by ontologies and finally creation and presentation of the recommendation list for the current user u_x.

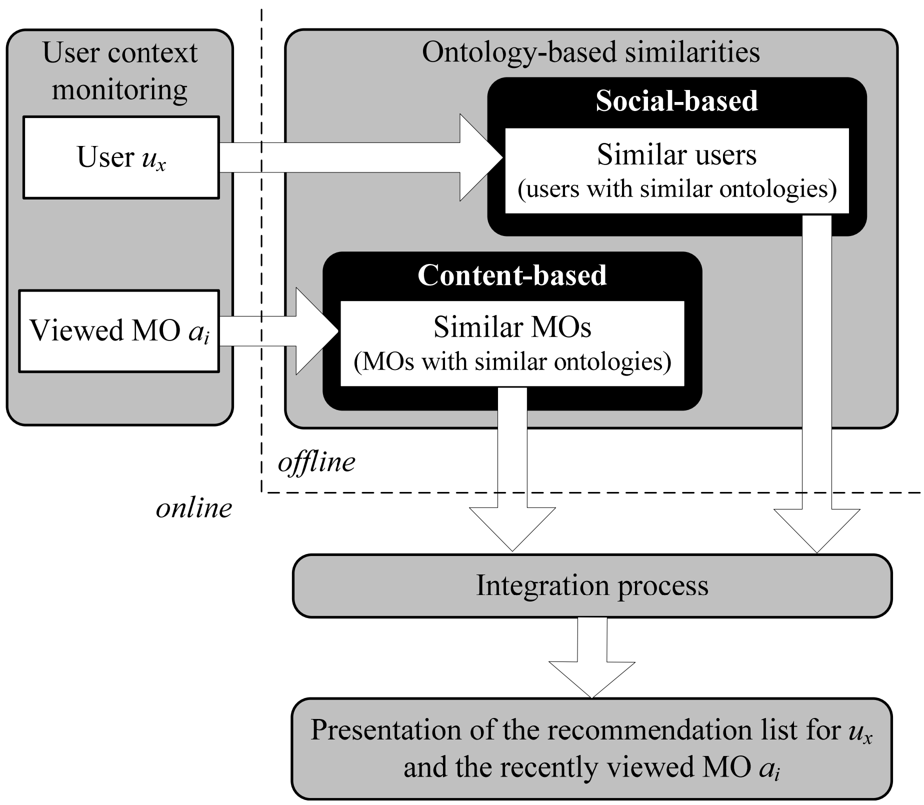

Fig. 1 The general concept of ontology-based recommendation process in MSS

The first step, user context monitoring, is incorporated into basic function of the web server. It provides the data about current user u_x and the MO a_i that is just requested by this user to the rest of the recommender engine. Both user u_x and MO a_i possess their own individual ontologies (see sec. 4.2) that serve as the input to the second element of the framework, i.e. ontology-based similarities calculation (see sec. 4.4). In this phase, user u_x is compared to all other users that are registered in the system by means of similarity function between their individual ontologies. As a result, we obtain the ranking list of users – potential authors of MOs ordered by their similarity to user u_x. The similar procedure with is launched for MO a_i, although only k MOs closest to the given MO a_i are selected. The number k limits the length of the MO list and is used to reduce the number of necessary calculations performed online during the next step - integration. In the integration process, the list of k-nearest MOs is verified according to the closest of their authors. It means, that for each of k MOs from the list its author is identified in the list of users with ontologies similar to person u_x. The basic concept of final recommendation list creation is to confront the similarity to MOs with similarity to their authors: the weight of the close MO is enriched by the weight of its author if it is on the list of the users close to u_x. Note that the weights reflect the level of similarity, i.e. the greater weight, the greater similarity. This regards also pairs of MOs. Finally, the top N multimedia objects are chosen from the enhanced list and presented to user u_x as recommendations.

4.2. Individual Ontologies

Domain Knowledge consists of the two types of ontologies, representing knowledge about users and multimedia objects. Both define the domain concepts and the basic relations met in our system. Their basic structure is predefined (Fig. 2a and Fig. 3a), however the individual set of concepts for each user and multimedia object may differ depending on the users' actions and their history. The examples that are presented in Fig. 2b and Fig. 3b provide better insight into how the individual ontologies can look like. Nevertheless, it should be emphasized that these ontologies used all extracted concepts whereas in the real system every individual ontology can contain different types of concepts. Moreover, most of the concepts are optional, so for example the user does not have to possess favourite MOs or be a member of any group. The same situation appears regarding the multimedia object that e.g. does not have to belong to any group and in consequence the concept "groups" is not relevant for this particular object.

The individual user ontology represents knowledge about users and covers five main aspects of user activity (Fig.2):

- authored, favourite and commented MOs. Note that, these three activities can overlap. It means, that one user can e.g. both adds the given MO to the favourites and in the same time comments it,
- the tags used by the user to annotate MOs. These tags also called keywords usually reflect the content of the MO,
- the descriptions made by users in order to provide more information about their objects,
- users included in contact list as well as the fact of being included in someone's contact list,
- the fact of being a member or an administrator of user group.

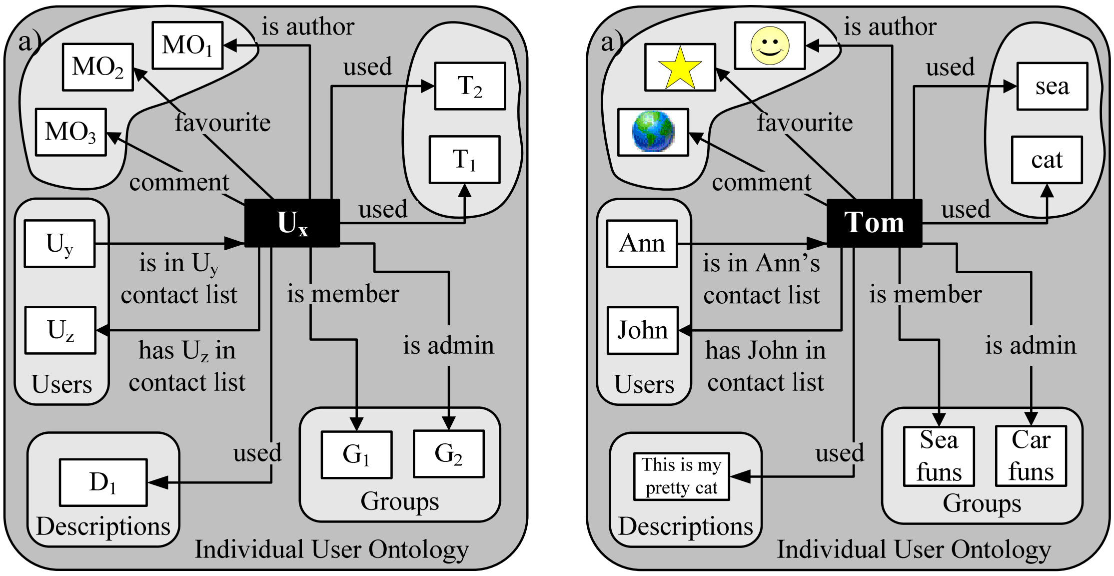

Fig. 2 The individual user ontology

On the other hand, the concepts within the individual multimedia object ontology reflect the knowledge about MOs uploaded to the system (Fig.3):

- the users who authored, favourite or commented given object.
- description attached to MO by the author,
- the tags which describe a MO,
- the groups to which this MO belongs to.

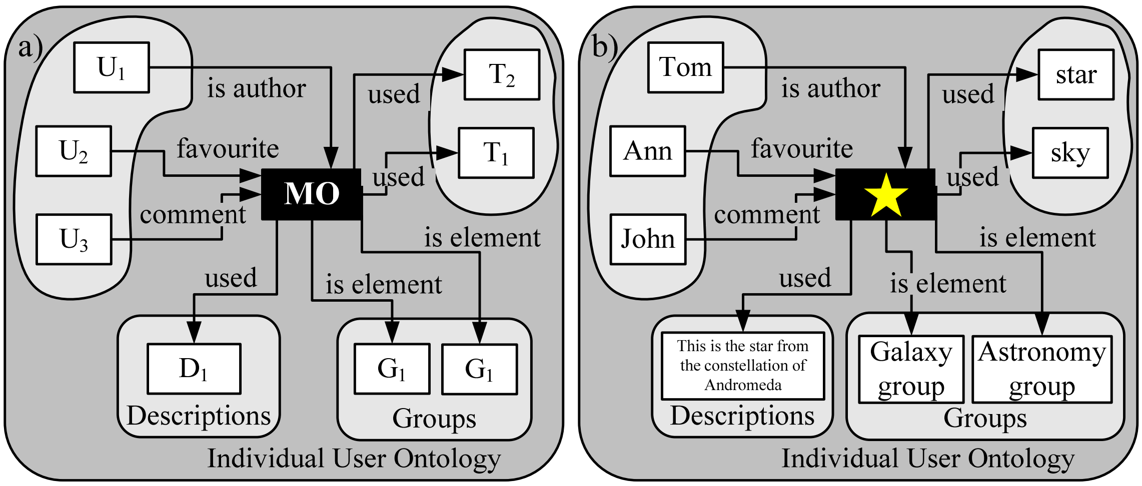

Fig. 3 The individual multimedia object ontology

The ontologies are created in the moment when the user or multimedia object appears in the system for the first time. When the MO is added by the user then the individual MO's ontology is created based on such information as tags, description and author of the photo. On the other hand, when new user registers to the system then the empty ontology for this person is created.

Of course the ontologies must be revised continuously. The changes will come both from the users who like to update their ontologies and from the system. Such considerations provokes the formation of two layers of ontology: the system and the user ontology. The former one will be managed by the system itself and the latter one will be changed by the user of multimedia sharing system. Moreover, each person can maintain only own ontology and the ontologies of this users' photos. However, the particular user cannot directly influence other users' ontologies. The ontology that will be presented in the system is the product of these two enumerated ontologies. The user ontology is stored in the system as the set of facts that denote the elements that user has changed, which one were added, modified or deleted.

In order to facilitate the process of updating the individual user ontology the appropriate mechanisms that support the users in their activities ought to be developed. One of them is to guarantee the user the access to the dictionaries such as WordNet, which enable to introduce the unified tags as the keywords for their photos. Furthermore some visualization tools ought to be available in order to support users in their actions regarding their ontologies.

4.3. Ontology Similarity Measure

It is assumed that in order to compute ontology-based similarities between users and Multimedia Objects (see Fig.1), an *ontology similarity measure* will be developed and applied to individual user's and MO's ontologies comparison. It should be noted that in majority of researches, addressing problems of ontology similarity, merging and alignment of ontologies, only similarity between the elements of ontological structures (typically: concepts and relations) is considered [2]. There are only few works which deal with comparing ontologies as a whole knowledge structures [4, 14].

In our approach we use a *Taxonomic Precision* (*TP*), a similarity measure based on the notion of *semantic cotopy* (see def. 2) recently presented and analysed in [5]. The reason to chose this measure was its ability to compare ontologies as whole structures and along multiple dimensions. The legal values of *TP* are from the range [0,1]. As stated in [5] this definition of taxonomic precision may be influenced by the lexical term layer in the case of significant differences in domain models (ambiguous use of terms). However, in our approach, most of the concepts used in individual ontologies (both users' and MOs') come from global sets (user, group and object names, also – to some extend – tags), so this issue is not expected to appear. In our approach terms like tags, user names etc. are directly identified with concepts. Moreover, we do not distinguish between relations in our ontologies, when applying similarity measures we treat them as taxonomies with root concepts *user* and MO.

Now we introduce the basic definitions needed to formulate the notion of *Taxonomic Precision*.

Definition 1. The ontology O is a structure $O := (C, root, \leq_X)$ where C is a set of concept identifiers and *root* is a designated root concept for the partial order $\leq_X$ on C.

Definition 2. *Semantic Cotopy* $sc(c,O)$ of a concept c from ontology O is a set containing c and all super- and subconcepts of c in O, excluding root concept $root(O)$.

Note: the above modification from standard definition (exclusion of the root concept) comes from the specific features of our system. In our case when comparing ontologies, the root concepts will always be different.

Definition 3. *Taxonomic Precision* of a concept c and the two ontologies O_1 and O_2 such that $c \in O_1$ and $c \in O_2$ is defined as:

$$tp(c,O_1,O_2) = \frac{|sc(c,O_1) \cap sc(c,O_2)|}{|sc(c,O_1)|} \quad (1)$$

Definition 4. *Global Taxonomic Precision* TP(O_1,O_2)of the two ontologies O_1 and O_2 is defined as:

$$TP(O_1,O_2)=\frac{1}{|C_1|}\sum_{c\in C_1}\begin{cases} tp(c,O_1,O_2) & if \quad c\in C_2 \\ 0 & if \quad c\notin C_2 \end{cases}, \qquad \textbf{(2)}$$

where:
C_1, C_2 – the sets of concepts of O_1 and O_2 respectively.

4.4. Ontology Similarity Assessment

In order to decide if the given user or multimedia object is similar to another one their individual ontologies need to be processed. Intuitively, people *similar* to the given individual will be users who are utilizing the same sets of tags, are dealing with the same or alike MOs, are participating in the same groups, etc.. The same concerns MOs. Because individual ontologies of the users do not represent information about the features of processed MOs or users in the contact list (the same concerns MOs' ontologies) we postulate their extension by adding relevant subconcepts. This action is temporary and performed only for the purpose of computing similarities.

The similarity assessment algorithm called OSA (Ontology Similarity Algorithm) for the two users' or MOs' ontologies (from here on denoted as O_1 and O_2) looks as follows:

The ontology similarity algorithm – OSA

Input:

- Ontologies O_1 and O_2 to be compared.

Note: we assume that they are both of the same type (i.e. user's or MO's individual ontologies, as defined in sec 4.2).

Output:

- The value of similarity between O_1 and O_2 from the range [0,1].

1. begin
2. /* create extensions O_1^* and O_2^* of O_1 and O_2 */
3. O_1^* = O_1 O_2^* = O_2
4. for (each *user* concept $C_i \leq_X$ *root* in O_1^*) do
5. begin
6. find ontology O_i such that *root*(O_i) = C_i
7. attach all subconcepts of C_i from O_i as subconcepts of C_i in O_1^*
8. end
9. for (each MO concept $C_j \leq_X$ *root* in O_1^*) do
10. begin
11. find ontology O_j such that *root*(O_j) = C_i
12. attach all subconcepts of C_j from O_j as subconcepts of C_j in O_1^*
13. end
14. repeat steps 4-13 for O_2^*
15. calculate $TP(O_1^*, O_2^*)$ according to Def. 4.
16. return $TP(O_1^*, O_2^*)$
17. end

In order to compute the similarities between the O_1 and O_2, they will be extended by attaching concepts from individual ontologies of users and MOs met in O_1 and O_2. The motivation is to take into account their characteristic features, which could be omitted otherwise. For example, two different MOs in ontologies of two users are not signs of their similarity, but if they are tagged in the same way, by the same users and have similar descriptions – it should have positive influence on similarity between these users.

4.5. Recommendation Process

Based on the gathered information from the individual users and multimedia objects ontologies we have built the recommendation framework that enables users to view, comment, add to the list of favourites the MOs that they will be keenly interested in. Moreover, if one finds the recommended MO interesting then this person can find the author of the photo and set up a new relationship with this user. The main goal of the system is to provide the most relevant recommendations to users. Moreover, by combining the several, different sources of data, the method facilities a bootstrap user to find interesting content in the multimedia sharing system and fulfil their expectations.

The overall view of the recommendation framework for the multimedia sharing system is presented in Fig. 4.

Before the recommendation process for the given person is launched the individual ontologies for all people as well as for all MOs are created. Note that these ontologies can be changed by both the system itself as well as each user can maintain their own ontology as well as ontologies of MOs added by them to the system (see sec. 4.2)

The first step of the recommendation process is to capture the user context, i.e. that both the user who browse the MOs and the MO selected by this person to browse are identified. In order to facilitate the further explanation of the process let's assume that the user u_x is watching MO a_i.

The individual ontologies for the users and the MOs serve as the input data for the whole process and are utilized in the ontology-based similarities calculation phase. Note that these ontologies are periodically recalculated in order to assure their validity. Based on individual multimedia object ontologies the k-nearest MOs that are close to MO a_i are selected and list L_{MO} of these objects is established. List L_{MO} contains the weights that reflects the level of similarity between MO a_i and k-nearest MOs. This element can be seen as the content-based filtering, whereas the method of list L_U creation is also called social-based filtering.

List L_U is obtained by comparing the given user u_x's ontology with all other users' ontologies registered in the system. In this list the weights that reflects the level of similarity between user u_x and all other users are stored.

After that, the user context filtering is performed. During the recommendation process some of the multimedia objects must be rejected from the list of candidates (L_{MO}) in order to avoid the situation in which the user have already seen the particular multimedia object. The MOs that ought to be omitted and in consequence rejected from the list L_{MO} are: the objects owned by user u_x as well as the objects that have already been commented or added to favourites by user u_x. Moreover, the weight of MOs that have been already viewed by user u_x should be made smaller. The level of reduction basically depends on two elements, i.e. how often was the particular MO viewed in the past and the second one when was this object browsed for the last time by the given user. Obviously, the MOs that were viewed several times and in the nearest past will have much lower weight than these that were viewed once and it was few months ago.

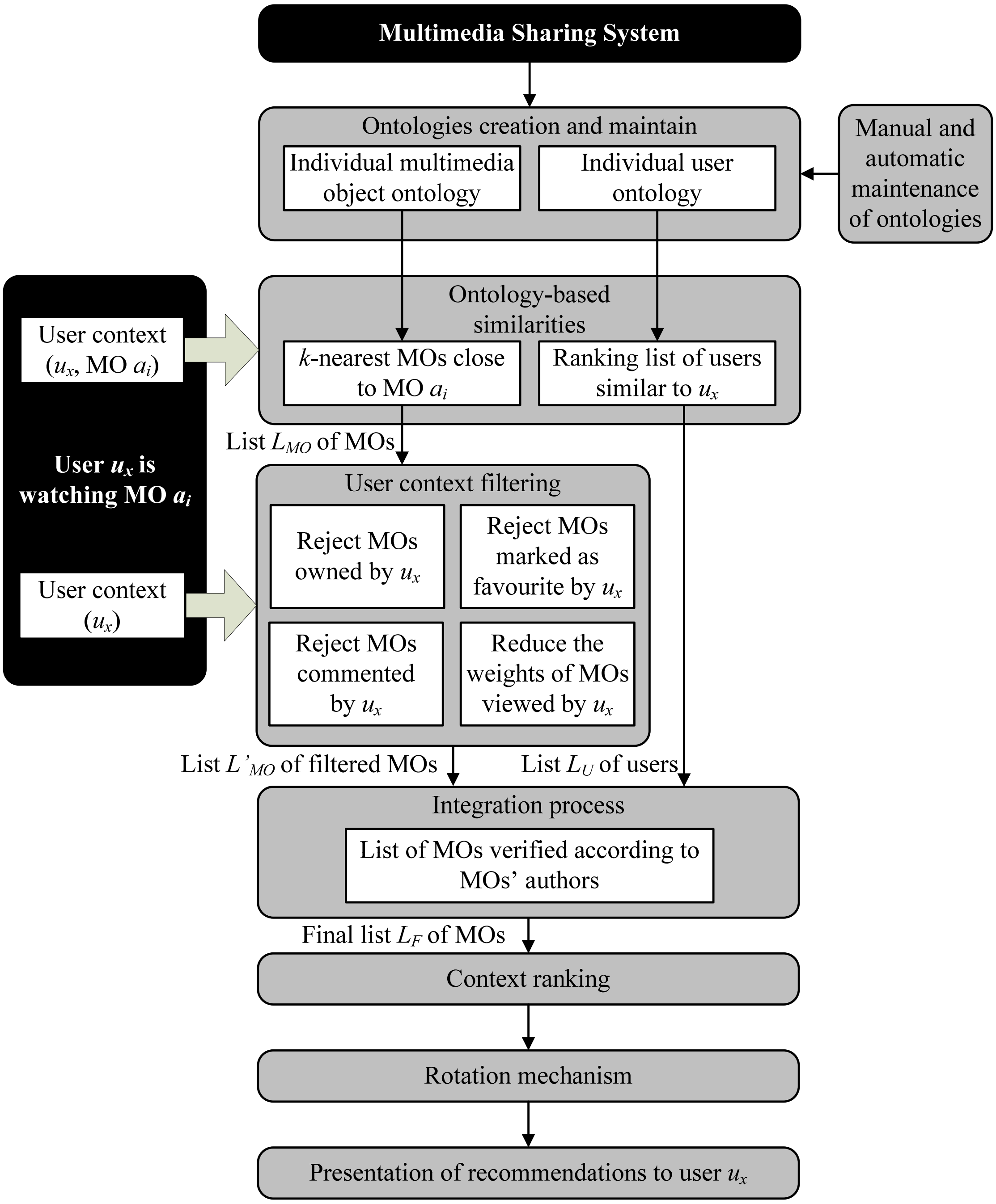

Fig. 4 Ontology-based Recommendation Process in Multimedia Sharing Systems

The next step is the integration of lists L_{MO} and L_U. The main idea here is to create the final recommendation list L_F and top N elements from this list are presented to the user u_x. List L_F is obtained by verifying list L_{MO} according to MOs' authors. It means, that for each MO from list L_{MO} its author's weight from list L_U is taken and these weights are summed up. Note that for both of these weights the importance coefficients is assigned (see formula 3).

$$w^{\text{final}}(a_i, a_j, u_x) = \alpha \cdot w^{\text{MO}}(a_i, a_j) + \beta \cdot w^{\text{A}}(u_x, u_j), \qquad \textbf{(3)}$$

where:
$w^{\text{final}}(a_i, a_j, u_x)$ – the final weight for the MO a_j from the list L_{MO} of items most similar to MO a_i viewed by u_x,

$w^{MO}(a_i, a_j)$ – the weight for the MO a_j from the list L_{MO} of items most similar to MO a_i from the range [0,1],
$w^{A}(u_x, u_j)$ – the weight for the author u_j of MO a_j from the list L_U of users most similar to u_i from the range [0,1],
α, β – importance coefficients with values from the range [0,1]. They are used to simulate and adjust the influence of the weights from lists L_1 and filtered L_2. For example, if α is low and β is high then the author's weight is more significant than MO's weight.

Since values of both components are from the range [0,1], the value of final weight belongs to the range [0,2].

After the integration process the list L_F is sorted and finally top N selected MOs from L_{MO} are suggested to person u_x. The rotary mechanism is used, to prevent the same MOs to be recommended to user u_x all the time [12].

The recommender system described above can be split into several processes (Fig. 5). Such division provides deeper insight and enables better understanding of the whole framework. The processes within the ontology-based recommender systems can be grouped into two sets: the users and system elements. The former ones are these in which the users modify their ontologies as well as the MOs' ontologies that belong to them. The latter ones are performed directly by the system itself. The system is responsible for creation and maintenance of the both users' and multimedia objects' ontologies (see sec. 4.2). All enumerated and described above processes support the idea of ontology maintenance.

The system performs also all processes strictly connected with the generation of the recommendations. It creates and update recommendation lists both for each MO and for every single user. Furthermore, the system is responsible for user context-based list selection, i.e. the appropriate lists for the user u_x that is watching MO a_i must be picked from the whole sets. Finally, the system creates the final recommendation list L_F and by selecting N top elements from this list, recommends them to the user.

Moreover, the processes can be split into these performed offline and online (Fig. 5). The former set contains: the maintenance of the individual ontologies made by the system and periodical calculation of the ranking lists based on the ontologies similarities. The phase of periodical calculation of the ranking lists is the most time-consuming element of the whole recommendation framework. This is caused by the fact that the user is compared to all other users within the system as well as each MO is compared to all other MOs. In such a big and complex system as Flickr this can be a very significant problem. On the other hand, the online operations are maintenance of the individual ontologies made by the user ,user context-based list selection, integration process during which the final recommendation list is created, and presentation of the suggestions to the user.

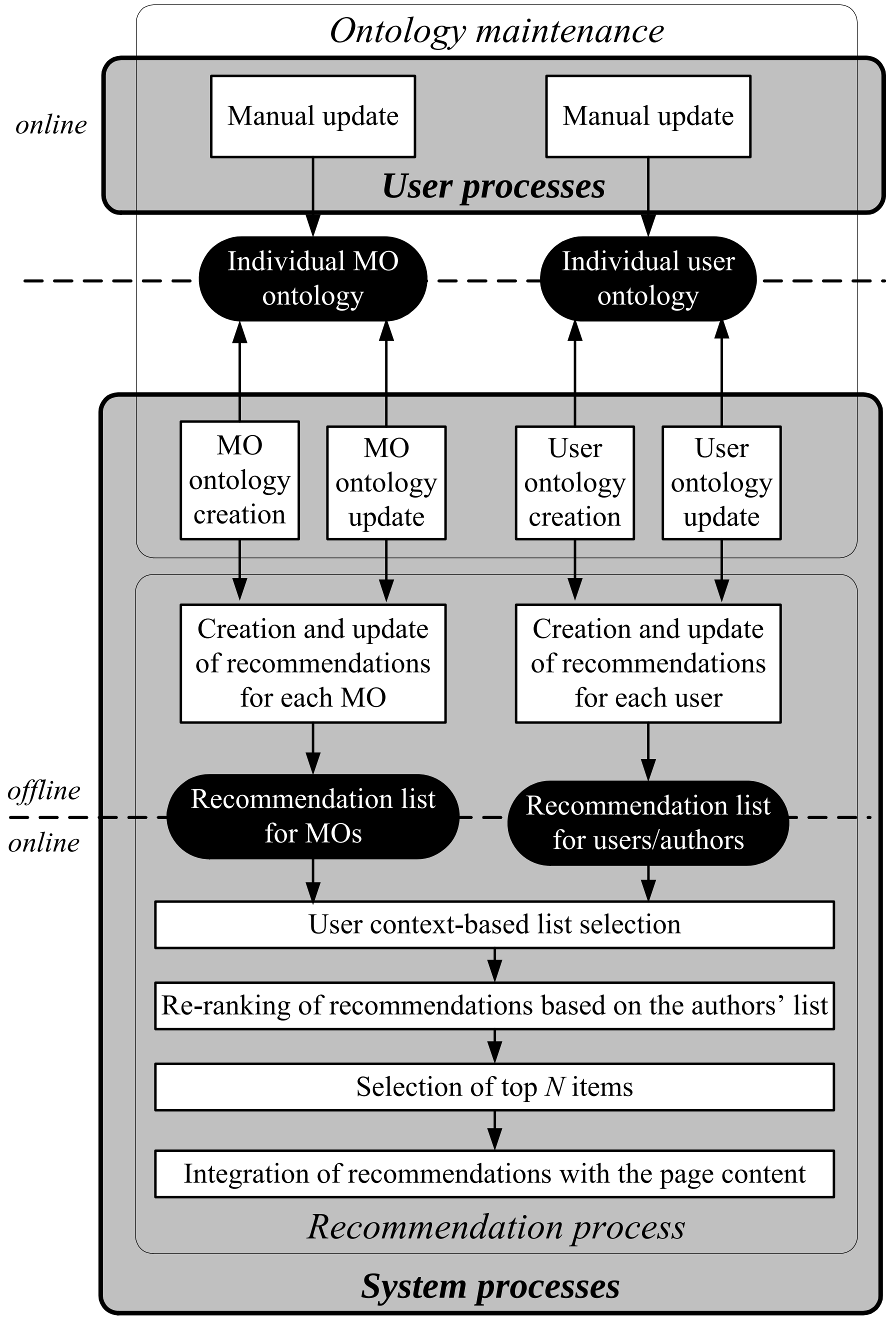

Fig. 5 Processes that exist within the recommender system

5. Discussion

During the development of the recommender process several issues, which need to be addressed, have appeared. Let us just enumerate few of them. One of the most important concerns is the high complexity of the performed calculations. In order to cope with that issue the processes that were established during the research (see sec. 4.4) can be divided into two sets, i.e. these that can be executed offline and these that ought to be performed online as it was presented in Fig. 5.

Next thing that is connected with the efficiency issue is that the whole list of similar authors to the given one (L_U) is stored in the system. This list ought to be shortened, i.e. only *m*-nearest authors and their weights should be remembered and for the rest users one system weight should be assigned. This issue is especially significant in the multimedia sharing systems with large number of users and vast amount of data that describes these users, what in consequence leads to storing in the system the list of even few million of weights for each user. If the list is shortened only to *m*-nearest users then the integration process is faster because only *m* elements is searched through.

Another element that can be discussed is the integration process in which list of MOs is verified according to MOs' authors. In the proposed method the two weights, one for the MO that is in the list L_{MO} and another one for the author of this object from L_U, are summed up. Nevertheless, another approaches can be applied in this phase. For example, one weight can be multiply by the second one. However, note that in this case the outcome will be much more diversified as well as the weights cannot equal zero. This problem can be addressed by establishing the minimal non-zero value of the weight or by adding small number ε to each weight.

The descriptions which are represented in MOs' and users' ontologies are written in the natural language that must be properly processed. One of the method is to abstract the most important words as well as to create the proper stop list of such words as personal pronouns, articles, etc. In our case we plan to use a chosen text comparing tool; the concepts *Description* from different ontologies will be considered the same if the tool returns text similarity value above given threshold.

The thing that should be also emphasized is that the cold-start problem, which appears in recommender systems based on collaborative or content-based filtering, do not exist in the proposed recommendation process. This is caused by the fact that the proposed recommender framework presents the hybrid approach and if new user registers to the system then only the similarity between the MO that this user is being viewed and other object from the system is calculated. On the other hand, if new MO is added then the system automatically creates the individual ontology for this object.

6. Conclusions and Future Work

The proposed approach utilizes the technique that compares ontologies as a whole structures to assess similarity between multidimensional profiles of users and multimedia objects in the recommender system. The ontologies provide the comprehensive view of the information gathered in the multimedia sharing system. As a result, we can execute the recommendation process, which takes into account many distinct features of system users and multimedia objects created and annotated by them.

Future work will include research on Flickr – the photo sharing system in order to prove the effectiveness of ontology-based recommendation and show the synergy effect that results from the joint use of recommender system with ontology-based user and multimedia object assessment. Note, that there are many ways of further developments of the proposed scheme. They lay in more sophisticated mechanisms of ontology extension before similarity computation (see sec. 4.4), providing users with advanced visual interfaces and conversational modules, which will use the underlying ontological structures.

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