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multimedia content recommendation**

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# CONTEXT REPRESENTATION FOR CONTEXT-AWARE MOBILE MULTIMEDIA CONTENT RECOMMENDATION

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## ABSTRACT

Very few of the current solutions for content recommendation take into consideration the context of usage when analyzing the preferences of the user and issuing recommendations. Nonetheless, context can be extremely useful to help identify appropriate content for the specific situation or activity the user is in, while consuming the content. In this paper, we present a solution to allow content-based recommendation systems to take full potential of contextual data, by defining a standards-based representation model which accounts for possible relationships among low-level contexts. The MPEG-7 and MPEG-21 standards are used for content description and low-level context representation. OWL/RDF ontologies are used to capture contextual concepts and, together with SWRL to establish relationships and perform reasoning to derive high-level concepts the way humans do. This knowledge is then used to drive the recommendation and content adaptation processes. As a side achievement, an extension to the MPEG-21 specification was developed to accommodate the description of user activities, which we believe have a great impact on the type of content to be recommended.

## KEY WORDS

Context, recommendation, adaptation, mobile multimedia, knowledge-based.

## 1. Introduction

The sheer size of on-line multimedia content and the widespread offer of multimedia-enabled mobile devices are stimulating the development of content recommendation systems to help users to find what they want. Traditional recommender systems offer recommendations based on explicit user rating and/or usage history, building user profiles. However, user's preferences or consumption habits are most likely to change according to external factors such as current time, day of the week, location or activity the user is engaged in. It is our belief that activity of a user plays a vital role in the type of content he/she consumes. Low-level contextual information, such as the type of terminal or the time or location, should be taken into consideration when analyzing candidate content and selecting recommendations [1]. From this low-level data it is

possible to obtain additional knowledge by establishing relationships and applying reasoning mechanisms. This additional information can help the system to understand the situation the user is in and thus may enable more accurate and useful recommendations to be issued. In particular, additional knowledge could be extracted to describe the activity the user is engaged in while consuming the content. This knowledge can be used to filter the universe of possible candidates of a content recommendation system. Moreover, the reasoning mechanisms can also be used to derive additional user's preferences, different but somehow related to his/her consumption habits, enabling to diversify the recommendations and thus to overcome the "over-specialization" problem of Content Based Recommendation (CBR) approaches. Although recently, contextual information has started to be incorporated in recommendation systems, very few provide a comprehensive context representation model with capability for capturing low-level context data in a standardized way while expressing high-level semantic knowledge inferred from reasoning mechanisms.

Additionally, given the heterogeneity in a device's capabilities, network conditions and characteristics of the surrounding environments, this contextual data could also be used to adapt the recommended content to the identified consumption constraints. It is very possible that different recommended content from the list of possible candidates might not have the technical characteristics suitable to be presented to the user [2].

In this paper, we present, as part of our context-aware CBR solution targeting mobile users, the development of a context representation framework combining recommender and adaptation engines, based on MPEG-21 [3], MPEG-7 Multimedia Description Schemes (MDS) [4] and OWL ontology [5]. We focus on representing contexts of user activities, such as location, time, device capabilities as well as user preferences using MPEG-21 and the content characteristics using MPEG-7. The use of an ontological model helps in abstracting concepts and inferring additional knowledge that better describes the activity the user is engaged in. In our approach, we believe that the preferences of the user are intuitively influenced by the user's context, namely, the activity he/she is engaged in at that point in time. Hence, we integrate the activity concept and representation into the MPEG-21 standard metadata.

In section 2, we provide a brief description of other works and technologies that served as motivation and which are related to our work. In section 3, we present the context-based content filtering approach as well as user and media profile models. In section 4 the context metadata framework, including the ontology model, are presented. Section 5 presents the system approach and architecture together with a set of usage scenarios that demonstrate the usefulness of the approach. Finally, section 6 concludes the paper, with on-going and future work.

## 2. Previous Work

Traditional recommender systems adopt one of three approaches [6]: 1) based on opinions and preferences of other users, designated by Collaborative Filtering (CF); 2) based on the previous user's consumption history and available content descriptions, referred to as Content Based Recommendation (CBR); and 3) a mixture of CF and CBR denoted as Hybrid Recommenders (HR) [7]. Recently, contextual information is being integrated with these approaches to enhance the recommendation decision process [6], [8].

In [7], Adomavicus et al present a multidimensional recommendation model, integrating context as one of the model dimensions. In [9], the authors use location, environment information and user mood, as contextual data to recommend user-generated content on a social network. The work presented in [10] uses mass collaboration and contextual data related to the content only for performing context sensitive ranking of contents. In [11], a recommender system using the users' context built from their log files is presented. In [12], an approach based on Support Vector Machine (SVM) was extended to include context data in its feature space to take into account the user context in the recommendation process. The work presented in [13], uses contextual information in recommending services to tourists. However, none of these solutions proposes a formal and standardized framework for representing contexts nor do they explain how high-level context is obtained. Moreover, they only address the recommendation itself and not the need to adapt the recommended content to constraints imposed by the sensed contexts.

Various standard tools for context representation have been developed in the last decade. Tools such as Composite Capabilities/Preference Profiles (CC/PP) [14], UAProf [15], CONNEG [16] and MPEG-21 [3] are the popular standards for representing contextual information. Part 7 of MPEG-21, the Digital Item Adaptation (DIA) [11], which seems to be the most complete, provides several tools, among which the Usage Environment Description (UED) tool, for describing user information, natural environment context, network and terminal characteristics. It also provides tools for adaptation decision taking. These standardized frameworks have been used by some authors to personalize and adapt content. An example is the work presented by Tseng,

which uses MPEG-7 and MPEG-21 for personalizing video [17]. Steiger et al in [18] use MPEG-21 for content delivery. Chen in [19] proposes a context aware collaborative filtering algorithm for recommending similar items to users in similar contexts. However, these approaches fail to establish relationships among low-level context, which could enable them to provide more effective and reliable adaptation/recommendation decisions.

MPEG-21 does not provide a rich semantic description support and alone cannot establish meaning and relationships between low-level context information [20]. Ontology engineering, on the other hand, enables one to establish relationships among low-level context information and perform reasoning to infer high-level concepts [21]. In [22], Qin Wijun et al presented an ontology based context middleware for smart spaces, allowing unambiguous definition of context concepts and enriching them in cases where the context data is incomplete or inaccurate due to sensing error. In [23] and [24], contextual information was represented using ontologies. In [25], Barbosa et al present a multimedia context aware ontology (MULTICAO) combined with MPEG-21 for content adaptation decision. In [26], ontology was explored in the design of context aware media recommendation for smart phones. With the exception of MULTICAO, which nevertheless does not address recommendations, these systems do not rely on standards for low-level context representation.

The novelty brought by our work comes from the definition of a comprehensive standards and knowledge-based description framework, whilst combining recommendation with adaptation. New concepts, such as the activity the user is engaged in, are introduced and formally specified within the MPEG-21 schema.

## 3. User and Media Item Profiles and Relevance calculation

Our approach is based on the Vector Space Model, using one vector to represent the user preferences under specific contexts and another one to represent the importance of media features in candidate media items.

### 3.1 User profile

A user profile is built based on data initially collected from the user and then enriched and updated from the user actions. A tree structure is used to represent the user profile. Figure 1 illustrates the general structure of the user profile tree. The root of the tree is the user  $u_i$  containing the user information such as age, sex, and role. The direct children of the root node are the media item category nodes such as Movies, Music and News. The next levels' nodes represent the features of each media item category. These features are further characterized by the high-level context under which the user consumed that type of content. This context information constitutes the

leaves of the tree and weights are assigned at this level.

The weights describe the user preference for each category-feature under a specific context.

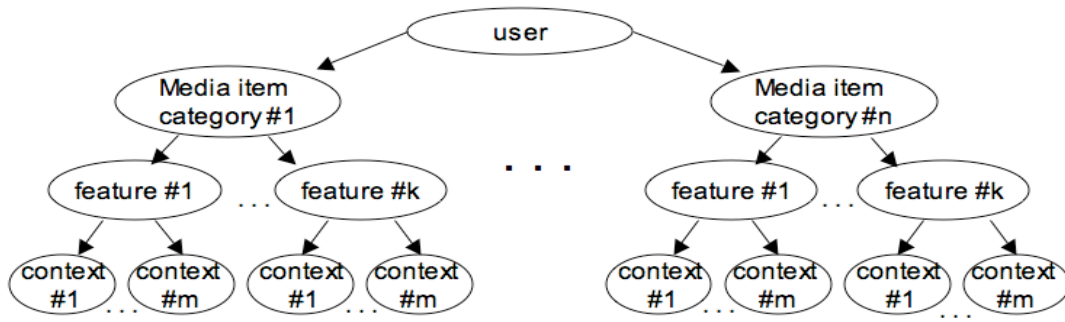


Figure 1 - General tree structure for the user profile

Multiple levels of the “features” nodes can be hierarchically nested. There is no restriction on the tree structure, such that it can be unbalanced with leaves at different levels and can dynamically grow. Figure 2 represents a possible User profile adopting this structure. Each leaf is assigned a weight and a “lifetime” parameter (explained in section 3.4), which are accordingly updated when the user consumes an item of that category-feature under the corresponding context. For each node upwards in the tree, a weight can be computed as the sum of the weights of all its children in a recursive way. This allows issuing recommendations at different levels.

The user preferences are captured in a vector  $U = \{(feature_1, wc_{1,1}), (feature_1, wc_{1,2}), \dots, (feature_2, wc_{2,1}), (feature_2, wc_{2,2}), \dots, (feature_n, wc_{n,1}), \dots, (feature_n, wc_{nn})\}$ ,

consisting of the weights extracted from the user profile for each feature that appears in the profile. The user profile vector  $U$  can be built for a specific context  $CI_k$  but it may also be built without considering the context. In the latter case,  $U$  will have a number of elements equal to the number of different features that appear in the user profile tree. In the former case,  $U$  will have a number of elements that is equal to the number of different features that appear in the user profile tree associated to the specific context under consideration. We call this vector, a contextualized user vector  $UC$ . In the example of figure 2,  $U$  would have 12 elements, whereas  $UC$  for context  $CI_1$  would have only 5 (corresponding to the features “country=UK”, “actor=Leo\_Capri”, “actor=Denzel\_Wash”, “genre=drama” and “genre=action”).

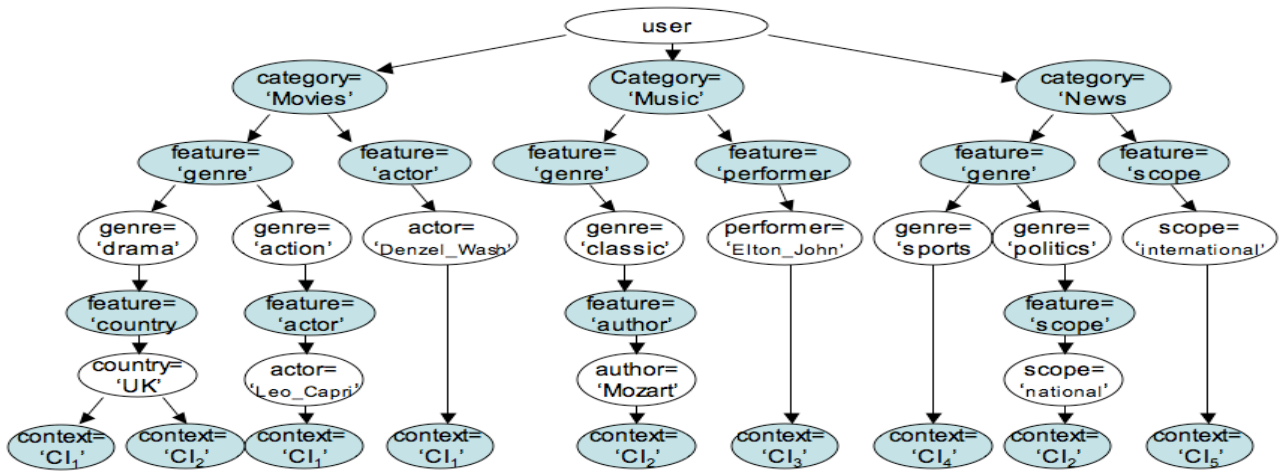


Figure 2 - Example Tree Structure of a User Profile

### 3.2 Media profile

The attributes of media items that are used to build the media vector  $M$  are extracted from MPEG-7 MDS. An importance factor is assigned to each attribute taking into consideration its importance to the user, by inspecting the weights of corresponding media features in the user profile. We borrow the idea from [1] but implement it in a different way, without defining an additional vector of

attributes and weights. Instead we use directly the user profile vector built for the current context the user is in. For each attribute that appears in the MPEG-7 metadata of the media item under inspection, we check whether it appears also in the user profile; if it does, an element in the media vector is created with a value equal to the weight in the user profile; if it does not, an element is created with value zero.

Let us assume we have a contextualized user vector generated for context  $CI_1$  from the example of the user

profile tree in figure 2.,  $UC=\{(drama,0.5), (UK,0.2), (USA,0.3),(action,0.8),(Leo\_Capri,0.4),Denzel\_Wash,0.4)\}$  and the MPEG-7 metadata of a candidate media item as in Listing 1. This will produce a media vector  $M = \{0.5, 0, 0, 0.8,0,0\}$ . Any of the features not in the metadata is assigned 0. Like this, we form the media item vector.

Listing 1: An extract of MPEG-7 Media Item Metadata

```
<Title>Cry Freedom</Title>
<Genre>Action</Genre>
<Genre>Drama</Genre>
<Genre>Biography</Genre>
<Keyword>Biography</Keyword>
<Keyword>Freedom</Keyword>...
```

### 3.3 Calculating media item relevance

Having formulated the two vectors representing the contextualized user and the media item profiles, equation (1) below, which is a classical cosine distance measure, is used to find the degree of similarity of candidate media items. If they are similar based on a threshold  $\gamma$ , then the media item is recommended to the user.

The denominator of this equation is the normalization factor, which allows minimizing the occurrence of false positives due to media features that appear many times in the media item metadata.

$$Sim(U, M) = \cos(\Theta) = \frac{U \cdot M}{U \times M} = \frac{\sum_{i=1}^n u_i \cdot \sum_{i=1}^n m_i}{\sqrt{\sum_{i=1}^n u_i^2} \cdot \sqrt{\sum_{i=1}^n m_i^2}}$$

### 3.4 Updating the User profile

Apart from assigning or updating weights of category-features-context nodes in the user profile every time the user consumes some content, we also define a “lifetime”,  $L$ , parameter attached to profile nodes which is used to measure and update user preference over time, similar to the “vitality” representation used in [9] and defined as indicated below.

$$L_i^k = (1 + \alpha) \cdot L_i^{k-1}, \quad \text{if } sim(u_i, m_i) \leq \gamma$$

$$L_i^k = 0, \quad \text{if } sim(u_i, m_i) > \gamma$$

$L_i^k$  and  $L_i^{k-1}$  are the lifetime values of node  $i$  at time  $k$  and  $k-1$  respectively;  $\alpha$  is an incremental factor,  $sim(u_i, m_i)$  is the similarity between the vectors that contain the current user profile  $u_i$  and the media profile  $m_i$  being considered;  $\gamma$  is the similarity threshold. This controls the life span of the user interest or preference. Therefore, each time a consumption belonging to a category-genre-context node is newly registered by the system, the value of the parameter is set to zero. Its value is then automatically increased periodically. This procedure is applied in the same way for all of the user profile nodes. When

analyzing the user profile tree to build a user profile vector, the weight of each node is multiplied by  $(1 - \text{lifetime parameter})$ . In this way, the nodes that have smaller values of  $L$  will be assigned a greater importance, indicating that the user has had a more recent interest in items belonging to that node.

## 4. Metadata Representation and Ontological Model

### 4.1 MPEG-7 and MPEG-21 Metadata Representations

MPEG-7 MDS is used for describing the media items. MPEG-7 semantic descriptions are essential to allow the identification of candidate content and consequent generation of user and media profiles. MPEG-7 technical characteristics or encoding parameters such as bit rate or spatial and temporal resolution are also essential to tailor the contents to the constraints imposed by the context of usage namely terminal capabilities and network conditions.

All contextual metadata is represented using the MPEG-21 tools, namely the UED tool. However, the standard was defined to allow the adaptation of content according to constraints of the consumption environment and user preferences and not to assist recommendation of content. As such, we have identified the need to extend the specification to support the description of the activity the user is engaged in while receiving the content Listing 2 presents an excerpt from the extended schema, adopting MPEG-7 and MPEG-21 conventions.

Listing 2: Extended MPEG-21 UED Schema accommodating User Activity

```
<complexType name = "UserActivity">
  <complexContent>
    <extension base = "UserInfoType">
      <sequence>
        <element name = "UserActivity"
          TypeMpeg7:agentType minOccurs="0"/>
      </sequence>
    </extension>
  </complexContent>
</complexType>
```

### 4.2 The Knowledge-based approach

Ontology is a formal representation of a set of concepts within a domain and the relationships between these concepts [21]. Among others, the advantage of using ontology to model contextual information is its ability to provide complex but efficient inference mechanisms to deduce high-level contexts from low-level context data [25]. The core concepts defined in the ontology used in our solution are represented in figure 3, whereas listings 3 and 4 provide example rules. Five of these concepts are

borrowed directly from MPEG-21 and MPEG-7. Two additional concepts, Activity and Time, have been defined:

- Activity: Six classes of activities were defined, namely, Home, Study, Office, Sporting, Leisure, and Transit. Sporting activities occur when the user is not at home and is practicing some kind of sport activity, either indoors or outdoors. Transit activities include traveling in a bus, train or car. Leisure activities involve things like sightseeing or going to a concert. These activities are derived from low-level users' location and time data.
- Time: The time concept is primarily used to capture the "when question" of the other concepts. Time duration, start time, end time etc, are some of the elements of this concept. These elements of time concept are used to infer, for instance, high-level time information such as weekdays or weekends that are subsequently used in addition to location information to infer the activity a user might be engaged in.

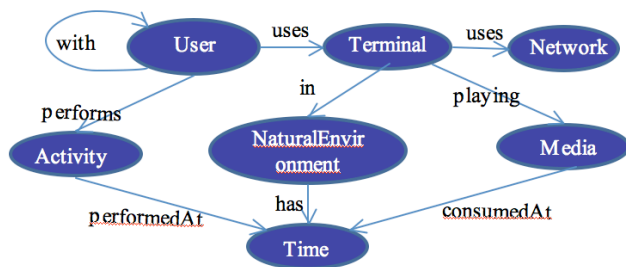


Figure 3 – Ontology Model

Listings 3 and 4: Example rules

```

hasLatitude(?loc, ?lat) ^ hasLongitude(?loc,
?long) ^ describes(?loc, ?buildingloc) ^
inIndoorLocation(?user, ?boolean) ^
swrlb:notEqual(?boolean, "true") ->
OutdoorLocation(?user)

```

```

OutdoorLocation(?user) ^ Weekend(?day) ^
Afternoon(?time) -> LeisureActivity(?user)

```

The knowledge-based model incorporates reasoning mechanisms based on two methods. The first method is the inherent ontology reasoning mechanism that is responsible for checking class consistency and implied relationships. This method uses the inference engine Pellet [27] for inference purposes. The second method is based on the Semantic Web Rule Language (SWRL) [28]. It extends OWL with rules to allow inferring new knowledge from multiple facts or conditions at the same time. For example, by combining time and location data, together with information on the type of device being used and whether the user is accompanied or not, the system may be able to infer the activity the user is engaged in. It can then decide the type of content to recommend to the user based on his previous preferences under such context/activity.

## 5. Context-aware Recommendation and Adaptation Framework

### 5.1 System Approach

Our platform provides the functional support to deliver adapted recommendations adopting a phased approach, where metadata captured inside the defined data models is used to generate additional knowledge to drive both the recommendation and the adaptation decision processes. The platform thus serves two purposes: 1) building a recommendation list matching user interests in specific contexts; and 2) deciding if an adaptation is needed and identifying appropriate adaptation parameters for the item selected by the user from the list of recommended items. One of the important aspects to retain concerning the platform and the overall approach is the fact that it is the realization of the context of the user that dictates the type of content that is going to be recommended. Accordingly, the first objective is to infer the usage context. The other aspect is that once a recommendation list has been issued and the user has selected from that list one single item for consumption, the inferred context is once again used to drive the adaptation decision process.

#### 5.1.1 Context-aware recommendation process

The adopted recommendation strategy comprehends two main processes, namely the creation/update of the user profile and the recommendation itself. The user profile is initially built using personal data explicitly supplied by the user such as age, gender, nationality, preferred language, etc. It is then continuously updated and enriched using information concerning the items consumed by the, as described in section 3.3. The recommendation process can be decomposed in two phases: 1) in a first phase the current usage context is inferred and used to create a filtered version of the user profile, the contextualized User profile vector; 2) in a second phase, the similarity between the contextualized User profile and candidate Media profiles is calculated in order to determine the category and features of items that should be recommended to the user. During this process, the output of the first phase is therefore a representation of the user preferences constrained to the inferred context of usage. The high-level context description is inferred from the sensed low-level context descriptions using the knowledge-based mechanisms described in section 4. The second phase is performed as described in section 3. These two phases are to be performed during the service lifetime and typically are triggered by a change in the usage context conditions, or alternatively, may be initiated by the user himself.

In both processes, it is necessary to obtain descriptions of the media item and of the context. To update the profile whenever the user consumes a media item, it is necessary to identify the category and features of the item being consumed by the user and the specific context under

which the consumption occurs. With this information it is possible to increase the weight of the corresponding “category-feature-context” node in the user profile and to re-set its “importance” value (thus reflecting the recent interest of the user for that category-feature under the specific context). To identify candidate items suitable to be recommended to the user, it is also necessary to obtain a characterization of each media item in terms of category-features following the process explained in section 3.

### 5.1.2 Context-aware content adaptation decision

Once the recommendation list is issued and the user selects one specific item for consumption from that list, the adaptation decision process is initiated. Using the inferred context and MPEG-7 content descriptions such as the bit rate, the spatial dimensions or encoding format, the system decides the type of adaptation to be performed to satisfy the current context constraints.

Figure 4 illustrates the high-level architecture of the system envisaged to support context-aware recommendations and adaptation decisions. The system consists of two major parts: i) the client component that runs on a mobile device or any other device such as laptop and which delivers low-level contextual information, as well as an indication of the user actions; and ii) the middleware, which consists of context, knowledge, recommendation and adaptation decision engines. This part can be located at the server side or in any intermediate node. The platform also relies on the availability of media item descriptions in the form of MPEG-7 metadata. Generation of content metadata is outside the scope of our work.

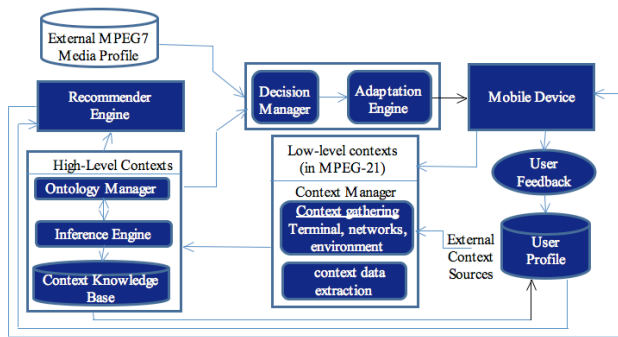


Figure 4 – System Architecture

## 6. Typical Usage Scenarios

*Susan* enjoys listening to sport news in the morning before leaving for school. Later in the evening, when doing her daily exercise, she likes listening to a summary of previous day soccer result with her mobile device using a headset. She also enjoys listening to music. However, *Susan*’s device supports only a few audio codecs.

*Andrew* enjoys watching his subscribed video podcast when he is on transit (train/bus) going to school or when

coming back from school using his headset. The system presents him with appropriate video podcasts, but it detects that his device has a low battery level. Accordingly it decides to adapt the video to a lower resolution, grey scale version. These two brief scenarios explain the applicability of our system.

Steps below summarize the system’s operations and how it handles the first of the two scenarios, Normally, basic personal information is supplied by the user upon registration and optionally the user may also provide the indication of preferred categories-genres for a limited number of pre-identified contexts/situations. This information is used to build an initial user profile, which is updated during the service lifetime, whenever the user consumes new items. In these scenarios it is thus assumed that that a user profile already exists for each user.

#### a) User profile acquisition:

The information contained in *Susan*’s profiles together with terminal device information is sent to the platform in MPEG-21 UED format. Data is extracted and instantiated in the ontology.

#### b) Context capturing:

When *Susan* starts consuming content or when her context changes, current low-level context information is acquired into the system in the form of MPEG-21 UED files. Context values extracted from the UEDs are instantiated into the context ontology model. The ontology manager consequently infers high-level context using the mechanisms described in section 4, and sends that data to the recommender engine. Example is inferring from *Susan* GPS data, the knowledge that she is at home, and also inferring that it is morning/afternoon/evening time during a weekday/weekend from low-level time information

#### c) User profile update:

Whenever *Susan* starts consuming a given content, that content is identified and described with a given category and features and is associated to the inferred context. In the user profile tree, the system searches for the combination “category-feature-context” just identified; if it finds a match, it updates the weight and lifetime parameter of the corresponding leave; if it does not find a match, then it creates the required nodes and assigns an initial value to the just created leave.

#### d) Filtering/Recommendation:

The high-level context information from b) is used to find a match between currently inferred high-level context and contexts that have already been inserted in the user profile.

*d-1)* if it finds a match (i. e., is, if *Susan* has already consumed something under that context), it generates the corresponding contextualized user profile vector and retrieves category-feature values preferred by *Susan* under that context. The system then initiates a search on the Web using the pairs “category-feature” as keywords to find candidate content; upon receiving the results, it builds the media profile vector for each item and

computes the similarity with the contextualized user vector. It recommends to Susan, items with similarity values above threshold, filtering the initial list of results.

*d-2)* if it does not find a match (i. e., is, if Susan had never consumed anything under that particular context), it ignores the context information and builds a complete user profile vector. It identifies the pair “category-feature” with the largest weight to initiate a search on the Web as in step *d-1*). If a given “category-feature” pair appears multiple times in Susan’s profile associated to different contexts, then the weight of that pair will be computed as the sum of the weights of all occurrences.

*d-3)* Susan is presented with a recommended list, from which she selects one specific item.

*e) Adaptation Decision:*

The indication of the selected content is then forwarded to the adaptation decision engine to check if the modality, frame rate, frame size, format etc of the recommended content satisfy the constraints imposed by the current usage context, namely the device capabilities and network conditions. If not, the item is subjected to adaptation before it is finally delivered and rendered. In the case of Susan’s selected music, the system discovers the incompatibility in the music format. Accordingly, it identifies the need for trans-coding the media item, selecting the appropriate adaptation parameters.

## 7. Conclusion

This paper proposes a context representation framework using an ontology model approach and MPEG-7 and MPEG-21 tools for context-aware content-based recommendation. The objective of the work is to deliver content recommendations taking into account the context in which the user is in and to adapt the recommended content to suit possible constraints of the context of usage. Moreover, the aim is to use high-level descriptions of the context, in a similar way the humans do, inferred from low-level context data. The benefits of this strategy are the interoperability provided by the standards and the expressiveness provided by the ontology, with its ability to provide complex but efficient inference mechanisms to deduce high-level contexts from low-level, raw context data. Additionally, it provides the support to take decisions on the need to adapt the recommended content to suit constraints of the context of usage. We are currently working on extending the CBR approach with traditional filtering based approach. This will be tested using data set being collected from mobile phone users. The algorithm will then be evaluated and compared with such work as the one presented in [1], using precision and recall of recommendation aided by high-level contextual information. Future work will also include the extension of the described CBR approach with the use of the already existing reasoning mechanisms to predict user preferences, different from the ones registered in his/her profile. These additional preferences will enable issuing

diversified recommendations to the user, thus overcoming the “over-specialization” problem of CBR approaches.

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