Use of Granularity and Coverage in a User Profile Model to Personalise Visual Content Retrieval

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***Abstract*— the enormous volume of visual content available from cameras and from recordings stored in data centres and the phenomenal number of users presents a major challenge to the research community. This major challenge is the use of adaptive techniques for *personalised* retrieval and filtering mechanisms in order to find relevant visual content appropriate to individual needs but without overloading users by retrieving uninteresting content. This paper presents a user modelling framework, which integrates a statistic model based upon Latent Semantic Indexing (LSI) and a First-order Logic (FOL) type knowledge-based technique, in order to acquire static and dynamic user preferences. Consequently, the framework is able to detect shifts in user interests. The framework is also able to construct a user profile at appropriate levels of granularity and coverage by taking advantage of concept properties, relations and the distance between nodes in users' model of a domain with respect to a common or global domain model. In addition, terminological problems such as ambiguities are solved by exploiting an external lexical reference system, WordNet.**

Keywords-user-oriented ontology; personalised information retrieval; user modeling and personalisation;

I. INTRODUCTION

Personalisation has multiple benefits for accessing visual content [1][2][3]. It can be used to automatically filter content. It can simplify the user interaction needed to select the content of interest. It can reduce the level of understanding of a domain needed users and applications. Personalisation involves matching a definition or profile of the user's preferences against some abstraction or summary description of the visual content – the content metadata. Conventionally, raw text keywords and multimedia descriptors generated via image processing have been used as content metadata to match to user queries and preferences. However, human preferences can be complex, multi-valued, heterogeneous, dynamic and contradictory. Increasingly, semantic representations such as Ontologies are being investigated to enhance these raw descriptions to match complex personal preferences because of their higher expressivity and precision [1][3][4].

Ontology-based techniques tend to conceptualise an idea, single global view, of the world. In contrast, user preferences can be regarded as relative, multi-dimensional, time-dependent, task dependent and involve different degrees, which are dynamic and relative to a wide variety of contextual factors [3]. However, in current ontology-based visual content retrieval (VCR) systems, user preferences tend to be not modelled very simply, leading to the delivery of some irrelevant information to users. We propose to integrate a domain Ontology model and a user model, a statistic model (LSI [5]) in order to flexibly handle different terms and conceptualisations in user preferences. This integration gives the VCR system more flexibility, and greater user modelling power. In order to illustrate the application of this method, we consider its use to filter pre-recorded sports visual content, to identify video frames or even images, via text annotation frames, as part of the My-e-Director 2012 [6] project.

The rest of this paper is organized as follows. In Section II, state-of-the-art frameworks are surveyed and their limitations are analysed. In Section III, the design of the proposed framework infrastructure is described. Section IV discusses the application of the framework within the sports domain. Section V presents our conclusions.

II. RELATED WORK

This survey of models of users' preferences focuses on ontology-based one. Gauch [1] focused on automatically creating user profiles based on Ontologies that are created automatically and implicitly as users browse web pages. Gondra [7] present a technique to retrieve images based on low-level features and users' relevance feedback. The system of Mylonas [3] detects user-preference patterns by analyzing a large set of recorded user actions and requests called a 'persistent user preference'. Since user interests are not static, the authors described ad-hoc user preferences, which are dependent on the live context within which the user engages in content-retrieval tasks. User interests are learnt implicitly to form the ontological-based user's preferences [8]. This is similar to our idea in this paper as keywords are mapped to concepts in ontology model. However, those methods did not support user profiles with different view of the domain ontology model.

TABLE I. COMPARISON OF USER PREFERENCE ACQUISITION METHODS

Surveyed systems	Automatic acquisition	Dynamic user's profile representation	Semantic & inference	Granularity	Coverage
Gauch [1]	✓	P	✓	?	?
Gondra [7]	✓	✓	P	?	?
Daoud [8]	✓	✓	✓	?	?
Mylonas [3]	✓	✓	✓	?	?

✓= full support; P= partial support; ? = not stated explicitly

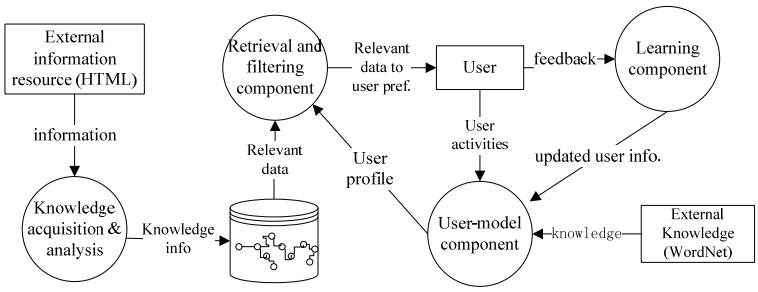

Figure 1. An overview of a framework for personalized VCR

The requirements for user preference models to personalise visual content are as follows:

- *Semantic inference*: user preferences are encoded in Ontologies which define term descriptions and interrelationships and support logic inferencing supporting much richer retrieval than keyword based searches
- *Dynamic user profile representation*: some user preferences may be static, e.g., an interest in athletes with the same nationality as the viewer. Some preferences may be dynamic vary with respect to different contexts, e.g., an interest in athletes with the same nationality as the viewer but only if the athlete competes well (the winner or losing context) or an interest in female or male athletes but only in particular sports. Therefore, user profiles need to be dynamic.
- *Information heterogeneity*: different users have different levels of understanding, with respect to the granularity and coverage of a domain Ontology. Coverage identifies user interest in a subset of the domain concepts, e.g., someone interested in concepts of improving the performance of a specific athlete themselves or a trainer) versus someone interested in seeing who wins a sub-set of sports such as individual athletics and swimming. Granularity describes the level of specification used for these concepts, e.g., someone being interested in any kind of swimming versus a particular style of swimming. Different terms may be used (*terminology heterogeneity).*

The framework presented here addresses these requirements and represents the main novelty and contribution of this paper. Most frameworks aim to automatically create models of user profiles because manually user profile creation is impossible for a large scale system. Table I shows the comparison of various user modelling methods with respect to the requirements. From the analysis of the existing solutions, we can draw the limitations of them as follows:

1) There is a lack of representations of user's profile at an appropriate level of granularity and coverage;

2) Methods lack support for the terminology heterogeneity problem e.g. terms in user's interest may not appear in existing ontologies.

III. Personalised Visual Content Access

The objective of this framework is to represent user's interests in a formal way, such that different user models can form customised views of, and can be checked to be valid, with respect to the global ontology based domain model generate the flexible indexing structure for different users. In addition, we integrate the domain Ontology model and user model, with a statistic model (LSI) in order to flexibly handle different terms and conceptualisations in user preferences.

A. Framework Overview

A personalised VCR system uses four basic components (Fig. 1): knowledge acquisition and analysis component; a user-model component; a learning component; and the retrieval and filtering component. Further details about each component are given in subsequent sections.

The knowledge acquisition and analysis component obtains or collects data from text-based visual content captions. The textual information is analyzed and represented in an ontology representation language e.g., RDF or OWL. In this research, we select OWL because it supports RDF(S) for range and domain constraints, cardinality constraints, and transitive, inverse and symmetrical properties.

The user-model component implicitly gathers information about the users and their interests, and constructs user profiles. The user-model is also input to the information retrieval component.

The learning component is used to adapt to changes in users' interests. The retrieval process must include a learning process that detects shifts in user's interests and updates the user profiles. Otherwise, inaccuracies occur in profiles that affect the retrieval results.

The retrieval and filtering component matches the user profile with the information in KB and decides whether or not the data is relevant to the user. The decision is not binary i.e. relevant or not relevant but it is probabilistic i.e. information receives a relevance rank.

B. Knowledge acquisition and analysis

Text and visual content are two distinct types of information from different modalities. However, there are some close, implicit connections between textual and visual information. Text-based annotation can be used to enhance visual content retrieval by supplementing visual content with

textual information associated with it. We presented our technique to acquire knowledge from content captions in [9] and this technique is exploited in this paper within the Olympics games domain. In summary, textual information from text captions (HTML format) are parsed in order to extract textual information using the Natural Language Processing (NLP) framework. In this research, we deploy an established NLP framework named ESpotter[1]. ESpotter adapts lexicon and patterns to individual domains for efficient Named Entity Recognition (NER) and generates an initial version of the semantic metadata in the form of relational database (RDBMS). To be able to use this data in a semantic context, it will be exposed to the ontology from which the data is given a well defined meaning. The initial metadata will be restructured from RDBMS' tables to a hierarchical structure which is so-called the *domain ontology* using the Jena[2] API. In this framework, users' profiles are generated based upon the domain ontology.

C. User preference acqusition

Users' preferences are represented in the form of user profiles. A hybrid method is used for acquiring knowledge about users which combine a statistic calculation and an ontological KB model. The ontological-based users' profiles are constructed from unstructured textual data of image captions which user have accessed. An external lexical reference system, WordNet [10], and domain ontology are exploited into the process to achieve a higher degree of automation. Because some users' interests may change over time, the system, which only relies on user's profile, might become worse when user changes his/her interest. For example, Bob is a fan of British swimming team but British swimming team's performance is very poor and more likely to lose the match. Then, Bob changes his interest to another team which has a potential to win the match. Thus, the system should be dynamic by continuous and incremental refining, extending, and updating during system operation in order to cope with new facts and evidence about users' viewing preferences. This requirement led to the development of a learning model with respect to two dimensions of users' profiles: dynamic versus static, single-shot versus multiple-shot.

1) Dynamic Single-shot User Profiles

To create dynamic user profiles, the usage information is collected from a user search session. An initial profile for a new user will be created after a user enters a query to the system. Ontologies enable an initial user profile to be matched with existing concepts in the domain ontology and with relationships between these concepts. The method in this paper is inspired by the method of Gauch *et al* [1]. Whereas Gauch maps a visited page onto five categories in the Open Directory Project, we map a user interest into domain ontology and employ text captions associated with the visual content. Building an Ontological model of a user's interest may cause inconsistencies if the domain ontology does not contain any of the words that form a given user's preferences (terminological problem). To solve this problem, after processing with the NLP technique, text captions can be augmented by adding a few semantically similarity or related terms. WordNet is exploited as a lexical reference system in order to find these additional related terms. Hence, the similarity between terms and concepts in the domain ontology are computed to determine the best match category to users' preferences. The concept which has highest similarity value will be selected in order to construct the user profile. Then, the user profile consists of all concepts resulting from the previous step and is constructed based upon the domain ontology. The main advantage of this technique over existing learning algorithms is that it does not require a large number of training sets to identify a strong pattern. This is suitable for modelling dynamic user's preferences. Figure 2 shows the algorithm for generating user profiles. The result of this step is that the initial user's profile ($\mathcal{P}$) is created. All concepts in $\mathcal{P}$ are called the user interest concepts (c).

1. *Extract words from image caption using NLP algorithm;*
2. *Get set of keywords {K} by remove stop words and stemming;*
3. *Get keywords {C} from class labels in domain ontology;*
4. *For each keyword pairs $\{K_i,C_i\}$*
   a. *Look up all word senses in WordNet;*
   b. *Compute similarity between $\{K_i,C_i\}$;*
   c. *Select the concept (c_i) which has the highest similarity value of word sense.*
5. *Construct the user's profile (c);*

Figure 2. User modeling algorithm that exploits WordNet

After creating $\mathcal{P}$, the presented system will recommend other relevant concepts (c') to users. We hypothesise that the lower the concept is in the hierarchical-based user profile, the more relevant concepts to user interests, or higher the level of concepts, the more general they are. Therefore, the proposed system will implicitly recommend content based on the leaf nodes (LNs) in c. For example, a user accesses a visual content for the text caption '*Beijing 2008, Michael Phelps stretching before jumping in to the freestyle 100m men*' as a caption. The user profile is constructed using the domain ontology and WordNet. Hence, we can acquire the following information:

1. $swimming \supseteq freestyle \supseteq individual \supseteq 100m$
2. Micheal Phelps – <*participate*>-Beijing 2008
3. Beijing-<*hostCountry*>-Chaina
4. Micheal Phelps-<*hasNationality*>-USA

where $\supseteq$ is the 'hypernym' relationship. The hierarchical model of user profile is depicted in Fig 3. In this example, the LN is the '100m men'. The system will recommend only two types of relevant concepts to users by adding c' to $\mathcal{P}$ based on the similarity to LN; *Sibling Similarity nodes (SS)* (i.e. 200m and 400m men), and its parents, the so-called *Parent Similarity node (PS)*, e.g., Relay. The similarity

[1] ESpotter- Adaptive Named Entity Recognition for Web Browsing; http://people.kmi.open.ac.uk/jianhan/ESpotter

[2] Jena library, See http://jena.sourceforge.net

degrees between c' and LN are measures based upon a distance vector, the number of nodes and their properties. For instance, the '200m men' and '400m men' nodes (distance is 2 from LN) have a higher semantic relevance than the 'Relay' node (distance is 3 from LN). For those concepts which have same parents with LN, the similarity is calculated from the properties between siblings. For instance, the '200m men' has a higher degree of similarity than the '400m men' in terms of the *distance* property as 200m is close to 100m than to 400m. Another example is if 'Freestyle' is LN, the presented system will recommend 'Backstroke', 'Breaststroke', and 'Butterfly' to the user profile. Among these concepts, 'Backstroke' is more similar to 'Freestyle' than 'Breaststroke' and 'Butterfly' in term of arms and legs movement property (arms and legs movement of Freestyle and Backstroke are synchronous whereas Breaststroke and Butterfly are asynchronous). By this technique, the presented system is able to model the taxonomy of users' profiles at an appropriate granularity and coverage more than the surveyed frameworks.

Let $\mathbb{C}$ be the set of concepts in domain ontology $\mathcal{O}$, $\mathbb{R}$ be the set of all semantic relations in $\mathcal{O}$. Then, the structure of user profile can be defined as follows:

$$u = c \cup c' \cup r \tag{1}$$

where c is the user interested concepts captured from his current activities, $c \in \mathbb{C}$, c' is the set of recommended concepts, $c' \in \mathbb{C}$, and r is the set of semantic relationships of c and c', $r \in \mathbb{R}$.

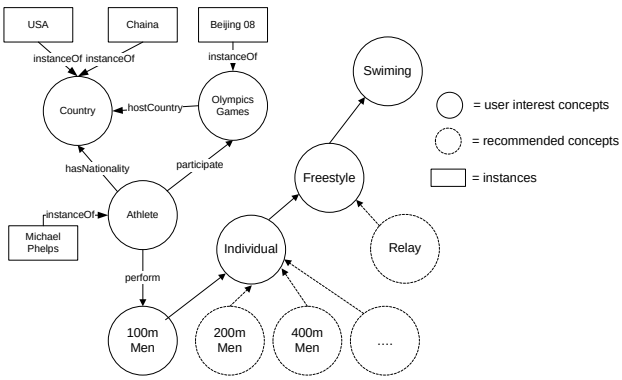

Figure 3. The Ontology model of part of a user's profile.

The advantage of this technique is that users' profiles can be assigned a well-defined meaning using the global Ontology domain model. Ontologies consist of term descriptions and their interrelationships and support for logical inferences such that content retrieval can extend beyond the capability of keyword-based searches, e.g., knowledge-based searches can find the relevant information even the searching keyword in the query does not appear in text document (captions). This approach can enhance the personalisation system.

2) Static Multi-shot User Profiles

User profiles can be learnt from multiple user activities, referred to as multi-shot or multi-session user profiles which are recorded by the user-model component using the statistical model. The aim is to derive a reliable feature set that retains the original meaning of terms and to help to remove noise from free text data. Usage data (text captions) of user can be accumulated from previous usage history to form two metrics: Visual Content Term (VCT) and Concept-Term (CT) metrics (Fig. 4.). The VCT matrix holds the relationships between the content and text caption key-terms. Stop words have been removed and Porter stemming has been performed before constructing the VCT matrix. The CT matrix derives information from the VCT matrix and stores the relationships between concepts, from WordNet, and the key-terms. The value in each cell in *CT(i,j)* is a weighted value of each term which measures the *important degree* between the key-terms and concepts. We apply LSI to calculate the weight of each term. We select this weight scheme because it is simple and effective. It can be scaled to a large dataset.

Content/Term	Football	Backstroke	100m men	Long jump
C1	1	0	0	0
C2	0	1	1	0
C3	0	0	0	1

(a) Visual Content Term matrix (VCT)

Concept/Term	Football	Backstroke	100m men	Long jump
Field game	0.855	0	0	0.855
Contact sport	0.577	0	0	0
Swimming	0	0.855	0.707	0

(b) Concept Term matrix (CT)

Figure 4. Matrix representation of a user's usage history

Some studies argue that only keywords and their frequencies (weights) are insufficient data for an accurate model of the user in semantic manner. Hence, we try to solve the above problem by inferring high-level knowledge about the user preference by transforming *CT* matrix to the ontological-based model. The mapping process from the key-terms to the concepts in the domain ontology is defined as follows:

1) Selection of key-terms and their relevant concepts from *CT*. The result sets are grouped by a key-term.
2) Creation of instances and identifiers: the Jena API is deployed to create the Ontology concept instances and their properties, corresponding to the domain ontology model.
3) Mapping of the grouped record set metadata to properties of instances: The grouped record set metadata is assigned to the ontology entities created in step 2.

However, this static multi-shot user model relies on previous usage data. This can result in a failure to filter irrelevant visual content because users' interests are dynamic and are likely to change over time. Therefore, multi-shot interests are not always reliable and not always accurately reflect the user's interests. Therefore, a dynamic model is needed to cope with this problem.

D. Leaning and updating user profile

The learning component is needed in order to improve further retrieval results by detecting user's interest shifts and updating the user profile, updating weight of terms, and removing existing knowledge about users. User profiles can be updated implicitly during and after the retrieval process. Here, we adopted an adaptive learning algorithm proposed in [2] as follows:

$$M(i,j)^t = \frac{N_i^{t-1}}{N_i^t} M(i,j)^{t-1} + \frac{1}{N_i^t} \sum_k VCT(k,j) * CT(k,i) \quad (2)$$

where M^t is the modified user profile at time t; N_i^t is the number of visual contents which are related to the i-th concept that have been accumulated from time zero to time t; the second term on right hand side of (2) is the sum of the weight of the j-th term in the text captions that are related to the i-th concept and obtained between time t-1 and time t divided by N_i^t. This approach allows the system to learn and update users' interests rapidly and makes user profile more *dynamic* than the previous frameworks.

E. Retrieval and filtering

Once knowledge-based and user profiles are obtained, semantic retrieval will be performed. The retrieval component applies the Ontology model in order to support semantic queries on text captions. Again there are several sub-processes involved: eliminating stopwords within captions, processing query, and semantic measurement etc.

1) Query processing and word sense disambiguities

Keywords in users' queries could be ambiguous by containing more than one word meaning. Hence, word sense or meaning disambiguation is necessarily. The system expands those keywords to other relevant concepts implicitly e.g., finding hypernymy (is-a-kind-of) concept and other synonyms from WordNet. The algorithm to disambiguate the word sense of user keywords is similar to the algorithm in Figure 3. Firstly, the user's query process to remove stopwords and to stem these in order to get a set of query keywords $\{Q\}$. Secondly, another set of keywords $\{U\}$ is acquired from the class labels in users' profiles. For each keyword pair $\{Q_i,U_i\}$, a look up of all word senses in WordNet is done. Then, the similarity between $\{Q_i,U_i\}$ is computed. The highest similarity value of word sense will be selected. Finally, a semantic search is performed.

2) Semantic search and measures

After disambiguating the word sense, the system will automatically formulate queries to be represented as SPARQL queries[3]. The SPARQL query performs a semantic search on the KB and returns results to a user. SPARQL returns a list of instance tuples that satisfies the query. If the tuples only comprise domain concepts, the visual contents that are annotated with these instances can simply be retrieved.

To ensure that the results are relevant to the query, a statistical computation, in the form of a *cosine similarity* measurement, is performed. Equation (3) defines the cosine similarity formula. The similarity between the query (q) and a weighted keyword associated with visual content (p) in the KB is measured using the following inner product:

$$sim(p,q) = \frac{p \cdot q}{\|p\|\|q\|} \quad (3)$$

The results obtained from the cosine similarity measure are further filtered according to the user profile. A *Personal relevance measure* has been proposed in [11]. We adopt this formula to calculate the similarity between a user preference (u) and a weighted keyword associated with visual content (p) in the KB. The personal relevance measure is defined as:

$$prm(u,p) = \frac{u \cdot p}{\|u\|\|p\|} \quad (4)$$

3) Similarity aggregation

To calculate the similarity between a user preference, query and the visual content, integrating the *cosine similarity* and the *personal relevance measure* a so-called combSum model is needed. The combSum model merges the two rankings using a linear combination of the relevance scores.

$$score(d,q,u) = \lambda \cdot prm(u,p) + (1-\lambda) sim(p,q) \quad (5)$$

where $\lambda \in [0,1]$. More detail about the combSum model can be found in [11]. The searching results are presented to user in descending order according to the value of the score.

IV. Discussion

Key issues for ontology-based personalised visual information retrieval systems include the acquisition method of user interests, the dynamic representation of user interests based on text captions, and the exploitation of user preferences. In this section, we will analyse the advantages of the ontological-based user profile with respect to these key issues and compare it to the traditional user models.

Integrating statistical computation into a personalisation model enables the use of more user-centred terminology in user models. However, the fact that the statistical technique relies solely on numeric data can result in a failure to understanding the *meaning* of users' interests. For instance, Bob has accessed a picture of Beijing's Olympics games. Use of only a statistical model, however, fails to capture the context of the story in the visual content that has is of interest. This feature is not supported by usage mining techniques, but a knowledge-based model. In this framework, the context of visual content can be captured by NLP technique from text captions and then, restructures that information to form a KB in a hierarchical structure in order to keep relationships between concepts found in the visual information. Consequently, the KB structure is able to share the concept-based representation proposed for retrieval, and the expressiveness of ontologies to define user interests on the basis of the same concept space used to describe the visual information content. The main difference from the previous frameworks is that text captions are augmented by

[3] SPARQL query, See http://www.w3.org/TR/rdf-sparql-query

adding a few semantically similarity or related terms obtained from WordNet (Section III-C). Hence, the presented system tolerates the uncertainty when the domain ontology does not contain any of the words in user's interest.

The rich concept descriptions in the KB provide useful information for disambiguating the meaning of natural language described in text captions. For instance, in a traditional user's profile, it is difficult to distinguish users' interests between "Athletes from China participating in the Olympics games in the USA" and "Athletes from USA participating in Olympics games in China". This can be distinguished using an ontological-based model. In addition, this information can be relatively easily retrieved using a semantic query because a structured query (SPARQL) can express more precise information, leading to more accurate answers. In this framework, the personalised semantic search is achieved by exploiting an external knowledgebase (WordNet), a domain-specific ontology, and a user profile model. This can be seen as a form of query expansion leading to a more effective search mechanism.

Semantic searches are able to find the relevant visual content when querying class instance even if keyword(s) in the query are not present in the text captions or as concepts in users' profiles. For example, Bob might want to find visual content about 'Aquatics' sports. This is because the KB contains semantic relationships with sub-concepts of sports. The proposed system is thus able to recognize visual content annotated with a sport genre which belongs to the 'Aquatics' concept even if the 'Aquatics' word does not appear in the text caption whereas the tradition type of user profile cannot. This means that the personalised search obtains better precision and recall than previous user profile models.

Using an Ontology representation for the domain knowledge and users' profiles allows inference mechanisms to find more relevant information effectively. For example, Bob can view the visual contents for Freestyle, Backstroke, Butterfly, and Breaststroke swimming. With a knowledge-based model, the system can infer that Bob is interested in Aquatics sport (generalisation). In addition, using *inference* and *reasoning* mechanisms, it is possible to predict the 'Aquatics sport' as a 'general' interest of Bob. This information can be represented in users' profile using a hierarchical structure at an appropriate level of granularity and coverage. As a result, the user model is represented with richer information than conventional methods. Learning dynamic user preferences from only the most recent observation leads to a user model that can adjust more rapidly to a user's changing interest. This makes a user profile more dynamic than previous frameworks [3][7][8].

However, the cases where the proposed technique performed worse were due to the lack of information in the domain ontology and in a user's profile - ontology imperfection [9]. As a result, the system cannot find visual content which is related to the certain user preferences.

V. CONCLUSIONS

The main contribution of this research is the development of a user model that exploits a statistical technique (LSI) and WordNet in order to represent users' preferences in the semantic model as well as using the KB derived from text captions. An Ontology with taxonomic relations provides the ability to represent users' interests and preferences in a richer, more precise, and less ambiguous manner than using traditional models e.g., matrix or simple concept network. In addition, the ontology model is also able to present user preferences at appropriate levels of details (granularity) and to use portions of the KB (coverage) to simplify usage. To retrieve relevant information, the system implements the query expansion engine in order to find the most suitable meaning of a query which is best matched to users' profiles by exploiting WordNet. Additionally, personalisation is achieved by ranking the search results where the cosine similarity is combined with the personal relevant score yielded by the similarity between users' profiles and visual content.

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