Personalized Open-Vocabulary Image Retrieval via Semantic and SRSiM-Based Social Features

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The large scale of image databases opens up new challenges for storing, organizing, and searching for data. The common challenge of image retrieval systems is to emphasize object detection and recognition from images to bridge the semantic gap between the Open-Vocabulary and Visual Content. This paper proposes a framework for a personalized image retrieval system which selects the most relevant images according to the specified query, the user interest, and the semantic interpretation. Our framework is composed of three major modules: (1) Users processing using Movielens as a social database. (2) Query processing and personalization. (3) Images processing by semantic annotation and clustering based on a new semantic similarity measure named SRSiM (Statistical Retina Similarity Measure) using statistical and knowledge-based approaches. The experimental study is performed on the NUS-WIDE dataset, a list of queries covering several social subjects and various user profiles extracted from the MovieLens database. The evaluation of the overall system shows promising results going up to 0.675 in terms of MAP (Mean Average Precision) measurement, which overcomes the score of other works established in the same conditions and using the same databases. The SRSiM measurement also reaches an accuracy of 77.77% compared to Wordnet, Wikipedia, and Retina-based measurements

Povzetek: Raziskava predstavlja personaliziran sistem za iskanje slik, ki združuje semantično analizo in SRSiM merilo za kvalitetno prilagoditev rezultatov uporabniškim interesom.

1 Introduction

With the popularity of Web 2.0, which is characterized by its social property, there is an explosive large range of applications and services. These services allow the user to become more interactive with Web resources, generating a lot of information that concerns both users and resources. The classical models of information retrieval are blind to this social context that surrounds both users and resources. They model documents (text, image, video) as a static representation using classical indexing schemas where the ranking algorithms are basically based on query-document similarity available from the existing hypertext links that connect webpages containing similar resources. On the contrary, the social information retrieval models extend conventional information retrieval models in order to incorporate social information to satisfy the information need.

In the literature, there are several social information retrieval approaches that differs depending on the manner the social information is used. There are mainly three categories of social information retrieval [32]:

(1) Social Search, is associated with platforms defined as search engines specifically dedicated to social data management, such as Facebook and Twitter. The main ingredient to perform a social search is the user interactions, including social content (comments and tweets) and social relations (friends, followers). Hence, social search systems index either social content or social relations and offer a means for users to search the content likely to respond to specific needs. [6].

(2) Social Recommendation, is a set of techniques that attempt to suggest items (movies, music, books, news, webpages...) or social entities (people, events, groups, topics of interest...) to the user. There are two major approaches to recommendation: Content-based recommendation and collaborative filtering. In a content-based recommender system, if a user is interested in document X and Y is similar to X, Y can be recommended to this user. In collaborative filtering, if two users X and Y have similar interests, documents that interest X are predicted to be interesting for Y. [36], [27], [42], [34], [38].

(3) Social Web Search, in existing information retrieval systems, queries are usually interpreted and processed using document indexes and/or ontologies, which are hidden for users. Documents are returned as results and may not necessarily be relevant to the user's need despite the ranking process performed by the search engine [35].

A study released by American Customer Satisfaction Index about an internet search engines and information shows that the satisfaction rate related to the 2016 scores ranges from 69% for About.com to 84% for Google. Despite the simplicity and efficiency of several search engines, performing keyword-based search is far from satisfying. This is because of two reasons. First,the queries introduced by users are short and nonspecific. For example, for the query "java" there are several interpretations which can the island java, the programming language java or either the coffee brand java. Second, users may have different intentions for the same query. For example, searching for "mouse" by an animal specialist has a different meaning from searching by a computer scientist searching for a mouse as a computer peripheral. One solution to address these problems is to personalize the search process.

In personalized image retrieval, we use user-specific information and context information to differentiate the exact intentions that impact search results. Generating results for a personalized image search involves not only providing relevant results based on query terms but also tailoring them to the user's search history and preferences [9], which are inferred from their previous activities on the social web. There are three improvement tracks dealing with the personalization of image retrieval: personalization social query understanding, personalization ranking based on the user profile or context and personalization indexing documents.

Personalization and semantic analysis converge to enhance the effectiveness of information retrieval process. We approve this convergence because personalization would not be meaningful if we do not correctly explore the semantic fields associated with the query. Conversely, investigating the user's preferences would resolve the semantic gap between the input queries and the user intentions [22]. The specificity of the user's profile impact the results according to the selected semantic field of the query.

In this paper, we investigate the association between semantic analysis and personalization when searching for social images. For this purpose, we propose a semantic similarity measure SRSiM. We apply this measurement in various steps of the personalized image retrieval system: query analysis, query to concept mapping, and user profile modeling.

So, our framework consists of three major modules: (1) Users process using the social database of Movielens. (2) Query processing and personalization. (3) Images processing by semantic annotation and clustering based on a new semantic similarity measure SRSiM (Statistical Retina Similarity Measure) using the statistical and knowledge-based approaches.

This paper is structured as follows:
In section 2, we will present the related works that deal with the semantic-based information retrieval system, where the semantic aspect affects various stages of retrieval, such as query understanding and document indexing. We will focus also on existent personalization techniques used in information retrieval in the literature.
In Section 3, we will present our user-centric social image retrieval pre-processing. This section will showcase our proposed similarity measure used for interpreting the input query and the query to concept mapping. We will present also our approach for user profile modelling according to information about the user extracted from the MovieLens social Site. Finally, we will present the pre-processing of users' and images databases using the clustering techniques.
Section 4 will focus on presenting the experimental results obtained throughout the retrieval system's different steps, namely, the accuracy of the proposed similarity measure and the precision of the image retrieval system using Average Precision and Mean Average Precision metrics.
The discussion of results is reserved for Section 5, followed by the conclusion in the final section.

2 Related works

In this section, we reviews the existing related works through two aspects: semantic-based information retrieval and personalization techniques used in the context of information retrieval.

2.1 Semantic impact on information retrieval: techniques and approaches

In information retrieval, fetching the precise semantic interpretation of documents and queries is the most important task, admitting that the search results depend directly on it. To address this challenge, researchers in information retrieval have taken efforts to enhance document indexing and query processing by using semantic annotation techniques and semantic ontologies.

2.1.1 Semantic annotation

Semantic annotation is a fundamental issue in multimedia content analysis. It aims to find the most appropriate labels that can identify the multimedia content. This task presents a tricky phase that can involve awful consequences with inaccurate choice of labels. In the literature, some researchers have oriented the problem of semantic annotation for a problem of visual object detection from the questioned image and guess the concept list that can be inferred. In this context authors in [24] proposed a machine learning based algorithm where they adopt a convolutional neural networks model (CNN). The CNN shows more effectiveness compared to the feed-forward neural networks with similarly-sized layers. The advantage of the use of CNN is to have less connections and parameters that impact the training phase in an effective way.
Authors in [33] adopted another technique for semantic image annotation. They believe that the click through data (images) can provide valuable information for developing an automatic concept detector that is useful for image retrieval. By utilizing search logs, the researchers gather images from web search engines and use them to assign a

Table 1: Approaches for semantic annotation

	Methodology applied	State of the art	Approach
Semantic image annotation	Extract labels by processing a CNN-based object detection	[24] Krizhevsky et al, 2012	Imagenet classification
	Attributing a relevance score for images according to the search logs from the search engines	[33] Sarafis et al, 2015	SVM concept detectors from clickthrough data
Semantic query processing	Context query understanding	[12] Ghali et al, 2017	Latent Semantic Analyses (LSA)
		[37] Tekli et al, 2022	Xml data - based
		[30] Rivas et al, 2014	Biomedical information
	Knowledge structure based Query disambiguation	[40] Witten et al, 2010	Wikipedia-links based
		[13] Elberrichi et al , 2008	Wordnet-based
		[39] Webber et al, 2016	Retina-based
	Merging between knowledge structures-based approach and statistical based approach for query interpretation	Proposed SRSiM	latent semantic analyses + Latent Dirichlet Allocation (LDA)

relevance score to the training samples. They also incorporate these images at the classifier level to enhance the effectiveness of the concept detector. The similarity measurement between visual or textual queries and queries from the search logs of image search engines estimates this relevance score.

2.1.2 Semantic query processing

For query processing, using only keywords from the intitial query is not usually efficient. Indeed, the same keyword can imply different topics, and the initial keywords cannot infer such an adequate interpretation. The query understanding tools present an effective manner to guess the adequate searched topics. [30]. The major techniques for query understanding are based on the investigation of new concepts related to terms and context of the query. Authors in [12] propose an approach to enrich the user's queries by additional interpretation using the language model to build the query context. The context is composed of similar queries which are used for query understanding. Query understanding aims to raise up all contexts surrounding query terms to overcome the queries ambiguity. The query understanding is usually based on an external data information resource. This latter, is investigated to sort the list of proposed contexts for a term according to the used knowledge structure. Knowledge structures [37], [19],[20] provide methods for capturing a term context which cover other semantically related terms such as finding Similar Context using the Wikipedia [40], Retina [39] and WordNet [13]…

Table 1 summarize the information cited above noting that the proposed SRSiM Measure is created as we deal with textual queries interpretation. The idea of merging knowledge structures-based approach and statistical based approach arises after testing the other methods cited in the state of the art [13][39][40] and noticing the complications with the use of Wikipedia in term of memory and hard-drive space needs. SRSiM takes the advantages of the online API Cortical.io's Retina and the mathematical calculation method of LSA which shows an improvement in term of real time responding.

2.2 Social image retrieval personalization: techniques and approaches

Information retrieval personalazation was shown as an effective tool to improve the system effectiveness. Personalization can affect three tracks of information retrieval process: query understanding , documents ranking and items indexing. In what follows we expose the main works within each way [7] .

2.2.1 Personalization for social open-vocabulary query understanding

Query understanding is the process that consists in transforming the initial query written in open-vocabulary by the user .It forms the best way to fit the real user need. Query understanding aims to enhance the initial query by injecting additional information predictable to be occurring in relevant documents. However, providing the same understanding concept to all users is not efficient nor suitable since the relative aspect of the items's relevance judgments varies from one user to another [28]. Therefore, a uniform query understanding is not efficient to provide suitable search results for all users. The personalization of query understanding is solved by adding possible tags related to the original tags of the initial query having a higher similarity with it. [4] propose an adaptation of the PageRank algorithm named Tag Rank algorithm which automatically define tags which best expand the tags list of the initial query. This is achieved by creating and maintaining a Tag Map matrix which captures the personalized relationships between tags and items. [8] propose to use ranking terms for personalized query understanding and takes into account the semantic similarity between tags from the initial query and the social proximity between the query and the user [46]. [5] propose a personalized query understanding strategy where meta-data retrieved from social bookmarking services is used to enhance the co-occurrence matrix terms in document. This matrix is used for providing personalized search results according to the user interests and the user is able to select tags which are suitable for the understanding. Proposed tags belong to different semantic field and the final result are grouped in different blocks identified through keywords to facilitate for the user the choice of the most suitable result with his interests.

2.2.2 Personalization for ranking

In information retrieval, ranking is defined as the process of quantifying and sorting similarities between items and queries. For social ranking, there are two categories of using the social information: by adding a social relevance to the ranking process or by using the social information to personalize search results [5]. SocialPageRank algorithm [3],[43] belongs to the first category by using the social relevance to compute the importance of items according to the mutual enhancement relation among resources, users and tags. In second category, personalized ranking approaches are usually applied in the context of folksonomy systems where users are able to apply public tags to online items. These tags are used in the ranking process to aid the system in finding relevant items. The ranking score of a retrieved item is driven by two scores which are merged to generate a final ranking score. First, the term matching score which represent the similarity between query and item. Second, the interest matching score which represent the similarity between the user and the item. A personalized PageRank algorithm is proposed also by [**?**] as a modification of the global PageRank algorithm to achieve a personalized ranking. This algorithm assigns a score to each node in the graph which represent an item. This score reflects the degree of interest that show the user on the item

2.2.3 Personalization for item indexing

For the document indexing using social information, there are two ways of representation: either by adding social meta-data to the content of the document, or by personalization the representation of documents, following the intuition of the user assuming that each user has his own interpretation of the content of a given document. Therefore, a user can annotate a document with different structure of words from another user to describe the document content. The social annotation is essentially based on matrix factorization which allow a personal representation of a given document that varies from one user to another.

This personal representation is used for query processing. For the same purpose of personalization [1] have used personalized indexing techniques and personalized ranking at the same time. This model aims to compute for each user and for each document a personalized document profile which summarizes the user perception about the document by taking into account the similarity between users and documents.
In summary, personalization has an impact on various aspects of information retrieval, including query understanding, ranking, and indexing. The selection of relevant concepts heavily relies on the semantic meaning of the query. This problem is the main focus of a lot of literature. Evaluation metrics such as MAP and NDCG, recall and precision are commonly used to assess the effectiveness of the information retrieval system. Various datasets, including Flickr, Flickr51, NUS-WIDE, LETOR, are utilized for personalized search. The methodologies, datasets, and best results achieved in the presented literature works are summarized in Table 2

3 Proposed approach for open-vocablurary image retrieval personalization

This section deals with the pre-processing phases that precede the performance of the personalized retrieval process, as well as, the inference of these pre-treatment for performing the personalized retrieval. Indeed, we treat three major phases of pre-treatment.

We first, introduce our manner for semantic similarity measure calculation which will be used for concept mapping and query analysis. Second, we present our approach for user profile modelling where data about the user are extracted from MovieLens database. Finally, we illustrate the pre-treatment of the image database and the constructed user profile database that consists in classifying these databases into clusters. We used the clustering techniques to assembly items sharing similar content. The clustering has a direct impact on the retrieval process by considering time constraint. Then we expose our approach of user-centric image retrieval processing which take advantages of the previous pre-treatment.

3.1 SRSiM: proposed statistical retina similarity measure

Semantic similarity measure is a milestone which has a direct impact on various domain efficiency like natural language processing, artificial intelligence, data mining and

Table 2: Approaches for social retrieval personalization

	Applied Methodology	Datasets	Results
[3] Bao et al, 2007	Integrating social annotations into web search	3000 queries generated from Delicious corpus 1,736,268 web pages 269,566 social annotations	Map = 0.4724 NGDC = 0.16
[4] Bertier et al, 2009	Inferring automatically personalised connections between users and provides them with semantically related tags as companions to their queries.	CiteULike dataset	Recall =0.47
[8] Bouadjenek et al, 2011	Personalized social query expansion using social bookmarking systems by taking into account the similarity between terms and user profile	Delecious corpus $150 * 10^3$ bookmarks 1000 queries	Map =0.45
[43] Yeh et al, 2022	Graph-based feature selection method for learning to rank using spectral clustering for redundancy minimization and biased PageRank for relevance analysis.	LETOR datasets: HP2004, NP2004, OHSUMED, MQ2008	Result for MQ2008 : Map = 0.4776 NDCG@10= 0.2318
[26] Li et al, 2016	image tag assignment, refinement and retrieval	Mir Flickr Flickr51 NUS-WIDE Dataet	Map =0.583 Map = 0.672

information retrieval. There are two main approaches for computing inter-concept similarity. The first approach is based on the use of a knowledge structures like ontologies or thesaurus[41]. Wordnet and Wikipedia are considered as knowledge structures. The second approach is based on statistics [25] deducted from a large corpus like Latent Semantic Analysis (LSA) and Latent Dirichlet Allocation (LDA) [45]. In our system, we merge between these two approaches. As knowledge structure, we based on Cortical.io's Retina [39] which present a huge amount of text (structured and unstructured).

Concepts in Cortical.io's Retina are presented as Semantic Fingerprint. This latter resumes the description of the concept as a vector of positions in the space. Each position represents individual clusters of meaning and their contexts in the Retina. The combination of these fingerprint positions forms the semantic meaning of the concept. The advantage of this representation is to reduce the meaning and the operations on meaning to a mathematically computable representation. The compute of semantic similarity between two concepts leads to the compute of the distance between the two vectors containing the fingerprint positions. Each concept is represented as a binary features vector sized of 16K and characterized by its sparsity. We rely on Cortical.io's Retina as a knowledge structure due to its online accessibility promoting a response in real-time, in addition to its lexical richness which cover the English language.

Our proposed measure is called SRSiM (Statistical Retina Similarity Measure). It is based on merging the Retina Fingerprint as an ontology and the Latent Semantic Indexing (LSI) techniques as a statistical approach to provide hybrid similarity measure. Actually, LSI is used as statistical approach for analyzing documents to find the underlying meaning of concepts or documents and it is also used to rank a list of documents according to a specified query. The major advantage of the use of LSI is the dimensionality reduction. Since, the fingerprint vector deriving from Cortical.io's Retina is a voluminous vector, we employ the dimensionality reduction through LSI techniques. As first step, we construct the term-term matrix A and query matrix q basing on the retina Fingerprint representation. Second, we decompose matrix A by processing the singular value decomposition, then, we implement a rank 2 approximation

of the matrix A and find the new representation of terms in the reduced 2-dimensional space. The same process is applied for the query q. Finally, we rank terms in decreasing order of query-term using cosine similarity measure.
In this step we focus on the study of temporal complexity of our SRSiM measure which will be compared to wikipedia-based measure complexity.
For our SRSiM measure, the temporal complexity refers to the complexity of LSA algorithm. noting that the SVD computation denote the dominant factor in the time complexity of the LSA algorithm. SVD decomposes the matrix into three matrices. The time complexity of computing the SVD of an $(n \times m)$ matrix where: (n) the number of terms and (m) the number of documents is generally $(O(n^2))$. In practice, this can be quite computationally intensive, especially for large matrices and large datasets. Thus, the overall complexity of SRSiM is around $(O(n^2))$.
For Wikipedia-based measure (WikiRelate) often involves constructing a graph where nodes represent articles and edges represent semantic relationships. If there are (n) articles, the time complexity for constructing this graph is $(O(n^2))$. The second step of WikiRelate is the semantic similarity computation between articles. The complexity for this step can vary widely based on the method used but can be approximated as $(O(n^2))$ for pairwise comparisons. Thus, the overall complexity of WikiRelate is $(O(n^2))$ as it is influenced by the graph construction and similarity computation steps.
In summary the temporal complexity of the two semantic measure SRSiM and Wikipedia-based is $(O(n^2))$. They can be differentiated in terms of spatial complexity which allows to quantify memory usage. In this context Wikipedia-based measure require more memory space as it needs to load the hole dump of Wikipedia for each use contrary to SRSiM which will perform the SVD computation only one time.
We contribute in semantic similarity measure, as we deal with social retrieval context where the performance at real time and results' accuracy are both required as they affect the entire retrieval process

3.2 User profile modelling

In this section we identify two steps for user profile modelling: construction of user profile from MovieLens and mapping the issued profile from genres to preferences.

3.2.1 MovieLens as source of social information

MovieLens dataset is widely used in the field of recommender systems. We have used this dataset in the context of image retrieval by the construction of user profile database. We used MovieLens dataset as a source of social information about users as it is characterized by its accessibility, structuration and essentially do not violate the user's privacy. This database is used to predict the shape of the user preferences which will be used to improve the personalization of the image search engine.

MovieLens dataset includes movie features, user ratings, and user demographic information. It is composed of 20 million ratings made on a 5-star scale and 465,000 tags applied by 138,000 users on 27,000 movies. This dataset gives information about which user has rated, which movies with how many stars and each movie is assigned to which genres. It should be noted that a movie can hold in more than one genre and genres are ranked in decreasing order according to its relevance. Movies are described according to 18 genres including Action, Adventure, Animation, Children's, Comedy, Crime, Documentary, Drama, Fantasy, Film-Noir, Horror, Musical, Mystery, Romance, Sci-Fi, Thriller, War and Western. Genres in the MovieLens dataset are represented with binary values [17],[15],[44]. The user preferences prediction of the user U is calculated according to movies he was rated and genres emerging from these movies. Thus, a score RG is assigned for each genre. RG is calculated and normalized following equation (1).

$$RG = \frac{\sum_{i=0}^{n} \frac{rk*ri}{1.5^{\sqrt{(\alpha*Li*(rk-1)}}}}{5*NG}. \quad (1)$$

Where:

- n: number of rated movies by the user U
- ri: rate assigned to movie i by user U
- rk: rank of the genre per movie.
- Li: number of genres per movie
- α :a constant equal to 2.5
- NG: Total number of genre G in all rated movies by user U

The coefficient rk is added to more distinguish the global genre of a movie.

3.2.2 Genres to preferences mapping

The movie genres used in MovieLens dataset form a specific jargon for cinema world which cannot bypass all the interest centers of users. In real life, a person can be interested in other fields that reflect his personality known as user preferences. The contradiction between what a user is actually interested in and its projection on the movie jargon can present an intention gap. To bridge this gap, we employ a mapping between MovieLens genres and user preferences. Many search engine and recommender systems propose some subjects for the user that assist the search process even the user has some trouble in wording his information need. These subjects are expected to cover all users interests without regard to exceptional intentions. Alike the same principle, we try to select the more significant topics that represent the user need when interacting with a social information retrieval system. The selected topics as well as

Table 3: Various Search engine recommended subjects

Yahoo	Bing	Youtube	Dailymotion	Selected Topics
News	Animals	Music	News	Science
Sport	Anime	Comedy	Comedy	Politics
Finance	Architecture	Film	Entertainment	Technology
People	Arts and Crafts	Gaming	Movies	Sport
Style-Beauty	Beauty	Fashion	Music	Arts
Cinema	Cars-Motorcycles	Automotive	Cars	Nature
Auto	Celebrity	Animation	Travel	Travel
	Comics	Sports	Creative	Society
	Fitness	Tech	Gaming	Music
	Food and Drink	Science	Sports	Entertainment
	Gardening	Cooking	Animals	
	Marine Life	Health	Celebrity	
	Fashion	News	Tech	
	Nature	Education	Lifestyle	
	Photography	Politics	Kids	
	Snow	Entertainment		
	Tattoo			
	Travel			
	Video Games			
	Wedding			

an example of proposed subjects by the famous search engines yahoo, Bing, Dailymotion and Youtube are reported in Table 3.

The mapping between MovieLens genres and the selected user preferences is performed using an automatic process as shown in equation (2). We calculate the semantic similarity measure SRSiM between each genre and each concept in user preferences set. If we assume that the genre j is fixed in the initial iteration, the combination having the highest score between this genre j and user preference i is returned as the nearest meaning to the genre j as shown in equation (3).

$$Genrej \leftarrow UserPreferenceX \tag{2}$$

$$UserPreferenceX = Max(SRSiM) \tag{3}$$

The mapping is approved by an expert who manage the semantic relatedness between concepts. This is noticed in Figure 1

In this context, the expert assumes that a user who is interested in “comedy” movies, is predicted to be interested in “entertainment” and then the obtained score assigned to the genre “comedy” is inferred to the “entertainment” preference. In the case where the selected user preference refers to more than one genre, the returned score is the average of all genres score inferring this user preference.

3.3 Clustering of images and users' databases

In this section we focus on clustering steps for images from NUS-WIDE dataset based on a semantic analysis and for users based on community grouping.

3.3.1 Semantic-based NUS-WIDE clustering

We take the advantage of the semantic-based annotation of images for the clustering the dataset NUS-Wide into clusters according to the content of the image. The clustering process requires the categorization of images under semantic classes which demand a substantial work of learning and training which have a big work on objects recognition behind.

Our system were based on the semantic annotation the image dataset which is performed thanks to the tools of caffe demos [23]. This library is based on a deep learning framework. It is developed by the Berkeley Vision and Learning Center (BVLC). Thanks to advanced techniques of convolutional neural networks and objects recognition, it allows to detect objects in a given image. It gives also a score for each object presenting its accuracy. Figure 2 shows an example of processing the Caffe tools and the obtained results. We have used K-means algorithm for clustering images in Nus-wide dataset into k clusters according to their semantic annotation. Each image in Nus-wide dataset is annotated by one or more concepts from a list of concepts defined right from the beginning. The n concepts are classified into k clusters in which each concept belongs to the cluster having the nearest meaning. Cluster's number is equal to the number of preference to reduce the overall burden during the retrieval process. This process is more explained in Figure 3.

3.3.2 Community-based users clustering

For users clustering, we used Pearson correlation coefficient as a measurement to estimate the user-user similarity. This coefficient is employed actually for converting sim-

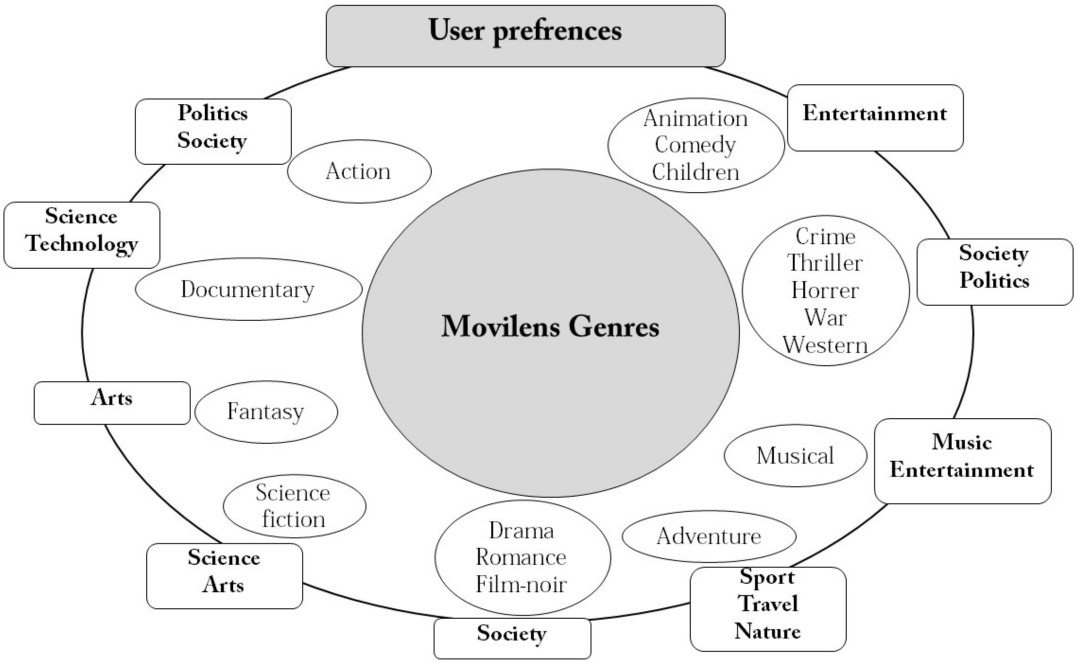

Figure 1: MovieLens genres to user preferences mapping

Figure 2: Example of image classification using Caffe demos

ilarity between two users by computing obliquity of two preferences' sets and comparing them using linear manner. This measure tries to find each user' derivations deducted from his average of preference scores while identifying a linear adjustment between two users. Given two users U and V, the Pearson correlation similarity between U and V is calculated as follow in equation (4).

$$Sim(U,V) = \frac{\sum_i (P_{U,i} - \overline{P_U})(P_{V,i} - \overline{P_V})}{\sqrt{\sum_i (P_{U,i} - \overline{P_U})^2 \sum_i (P_{V,i} - \overline{P_V})^2}}. \quad (4)$$

Where:

- i: a preference
- $P_{U,i}$: Score of the preference i for the user U
- $P_{V,i}$: Score of the preference i for the user V
- $\overline{P_U}$: Average preferences for user U
- $\overline{P_V}$: Average preferences for user V

We have used Fuzzy C-mean algorithm for the clustering of users and joining profiles having similar preferences together. Users clustering lead to communities' construction in a manner where the number of communities is equal to

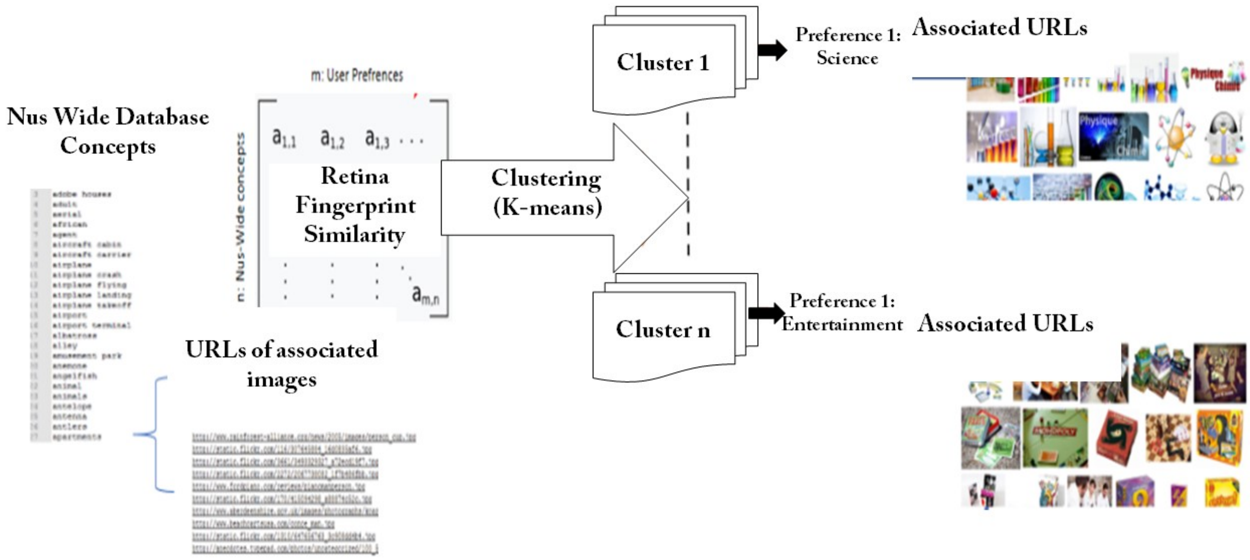

Figure 3: Semantic clustering of Nus-wide dataset

the number of selected preferences. By the way, each community refer to users who are interested in preference i and a user can belong to one or more than one community.

3.4 User-centric image retrieval processing

Our overall framework of a personalized image retrieval system is composed of 3 major modules:

- ***Users processing:*** users are divided into community that joins users having similar interests which are discovered through managing information available in the social database of Movielens.

- ***Query processing:***query introduced by the user is treated and mapped to be represented as concepts known by the system [18]. For the refinement of the query according to user preferences, all contexts related to extracted concepts are also searched and stocked for further uses of personalization.

- ***Images processing:*** images in the data set collection are annotated semantically using Caffe demos tool and clustered in a predefined number of sets equal to the number of concepts taken into consideration by the system.

Figure 4 shows an overview of image retrieval system including the three major modules: query processing, images processing, users processing and the link between them.

3.4.1 Personalized query processing

In our system, the query processing module is composed of two major steps: query analysis and query understanding.

Query analysis: it depends on the nature of the query that can be textual or visual and each modality has its specific techniques as treatment. In previous work [16], we proposed a concept-based query refinement architecture for image retrieval enhancement. We are interested in textual queries which are pre-processed to remove the stop-words that contain high-frequency used words in the language such as prepositions. Only representative keywords are conserved to be mapped to the nearest concepts from the selected concepts known by our image retrieval system. These concepts are taken as the clusters label of Nus-wide dataset. Among these concepts, we can mention (actor, airplane, city, moon, fruit, desert, night, police, vehicle, water, zoos…)
The semantic similarity measure between query keywords and the identified concepts is determined by computing the SRSiM measure between them. The returned concept refers to the highest score accorded to the couple (keyword, concept).

Query understanding: In natural language, there are several ambiguous words which can be understood in more than one context. When a user introduces a query using one of these words, we should predict all contexts of the word. According to user preference, one context will be more significant which will have the highest score. Selecting a term context is performed using the command “get Contexts for Term” of retina API which provides the capability of ob-

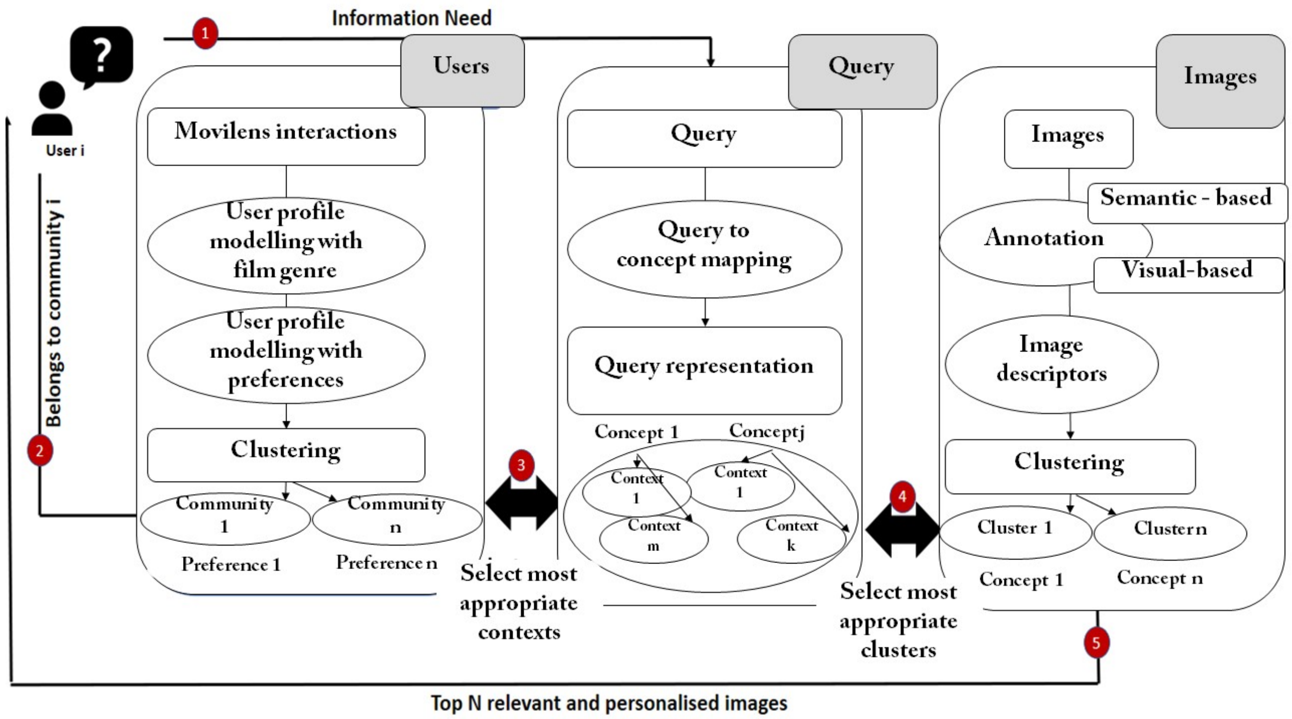

Figure 4: Workflow of user-centric image retrieval system

Table 4: Query understanding by contexts

Query	Query understanding
Apple	Software, fruit, hardware, labels, tree, ipod
Bride	Marriage, woman, Princess, film, groom, daughter
Jaguar	Chassis, race, species, software, aircraft, logo
Sky	Planets, channel, angels, orange, heavens, week

taining contexts associated to a term. Table 4 shows some examples of query understanding by searching the different context of a term.

Term contexts are compared to user preferences (Science, Politics, Technology, Sport, Arts, Nature, Travel, Society, Music, Entertainment) by computing the semantic similarity measure SRSiM and the closest meaning is assigned to the term context from the user preferences list. For a user i, the context referred to the preference having the highest score will be taken into consideration for the refinement of the next step "relevance ranking". Table 5 shows an example of query understanding refinement with context.

The query expansion is processed in a way where the initial query Q is adjusted according to the user and his preferences recorded in vector P. Q and P are combined respecting the algorithm below to obtain a new expanded query denoted Q':

Let's denote:

- C {c1, c2, …, cn}: The initial semantic concept list.
- Preferences {Society, Entertainment, Politics, Music, Sport, Nature, Science, Arts, Technology}: The selected preferences list
- Q {q1, q2, …, qn}: the binary representation of each concept in the query: 1 if the concept exists and 0 otherwise.
- Q' {q'1, q'2, …, q'n}: the representation of the optimized query
- P {p1, p2, …, pm}: the user profile representation where pm the value of each preference according to the user i

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Algorithm:
User preferences-based query processing

For each user
    For each x in Preferences
        If $px > 0.5$,
        select Cj concepts derived from x
        For each c in Cj
            If $qc = 0$, $q'c = px$
            else $q'c = 1$
        Next c
    Next x
    Return Q'
Next user

Table 5: ”Apple” query understanding enhancement with the query personalization

Query	Contexts	Preference Mapping	Personalization
Apple	Software Hardware Ipod	Technology	
Apple	Labels	Music	
Apple	Fruit Tree	Nature	

The obtained query Q’ is matched with images in the dataset and the top N images will be selected and ranked .

3.4.2 Personalized relevance ranking

The relevance ranking algorithm in conventional retrieval process aim to order images in the dataset collection according to a ranking function. Images are sorted in a decreasing order depending on the relevance score known through the query-image similarity. Finally, the top k relevant images will be returned.

Contrary to the principle of personalized search, a personalization factor intervenes to refine the relevance score according to the user profile.
First, contexts delivered from the keyword in the query are investigated to assign a score to each context according to the user preference.
Second images derived from the relevance-based ranking are refined according to the context score. The context having the higher score is treated firstly in a way where the tags issued from the semantic annotation of images concur with it.

This process is more explained in Figure 5 applied for the ambiguous query ‘Apple’. Details of the example are presented of the red color.

4 Experimental Results

This section provides the experimental evaluation of our proposed image retrieval system. We present firstly the used evaluation dataset covering queries, users and image database. Then, we present the evaluations metrics popularly used in the context of information retrieval. Thereafter, we give an overview of our proposed platform for image retrieval. The accuracy evaluation of the proposed SRSiM measure is presented in the next section. Then, we move to the effectiveness evaluation of the proposed architecture for retrieval in classical and personalized ways.

4.1 Evaluation data Set

For the evaluation of our approaches, we have tested our algorithms on a list of queries used by [26] in the task ‘tag retrieval’. The goal of this task is to retrieve relevant images with respect to a tag of interest from a collection of images. The image collection used is NUS-WIDE database which contain about 260 thousand images organized in clusters according to its semantic presentation.
We have also tested our approaches by focusing on the retrieving diverse social images task proposed by Mediaeval 2016 competition.In this context, experiments are carried out on data provided by MediaEval 2016 benchmarks [19]. Test set consists of 65 queries and 19017 photos (crawled from Flickr using the ”relevance” default algorithm). The following data are provided with every query:

- A ranked list of 300 photos retrieved from Flickr (jpeg format)
- Convolutional neural network based descriptors based on the reference convolutional neural network (CNN) model provided along with the Caffe framework (this model is learned with the 1,000 ImageNet classes used during the ImageNet challenge)
- Solr xml containing metadata from Flickr for all the retrieved photos (e.g., photo title, photo id, photo description, tags, Creative Common license type, the url link of the photo location from Flickr, user id, the photo owner’s name, the number of times the photo has been displayed, etc)

The personalization approach focusing on the selection of relevant images which responds the user need as well as the user interest is tested on users from MovieLens datasets. MovieLens 20M is generated basing on the intervention of about 138 thousand users. Each user has a personal profile reflecting his interests.
Table 6 summarizes the different resources used for the evaluation task.
The accuracy of SRSiM, the semantic similarity measure for concept tags and phrases, is evaluated by comparing it with other measures based on Wordnet ontology, Wikipedia dump, and Retina fingerprints.

4.2 Evaluation metrics

Evaluation of information retrieval system is a sensitive issue which revolves around the judgment if a document is relevant or not with respect to the user requirements. There are several measures used for this issue as performance indicator such as precision, recall and mean average precision which remain the most popular evaluation metrics for

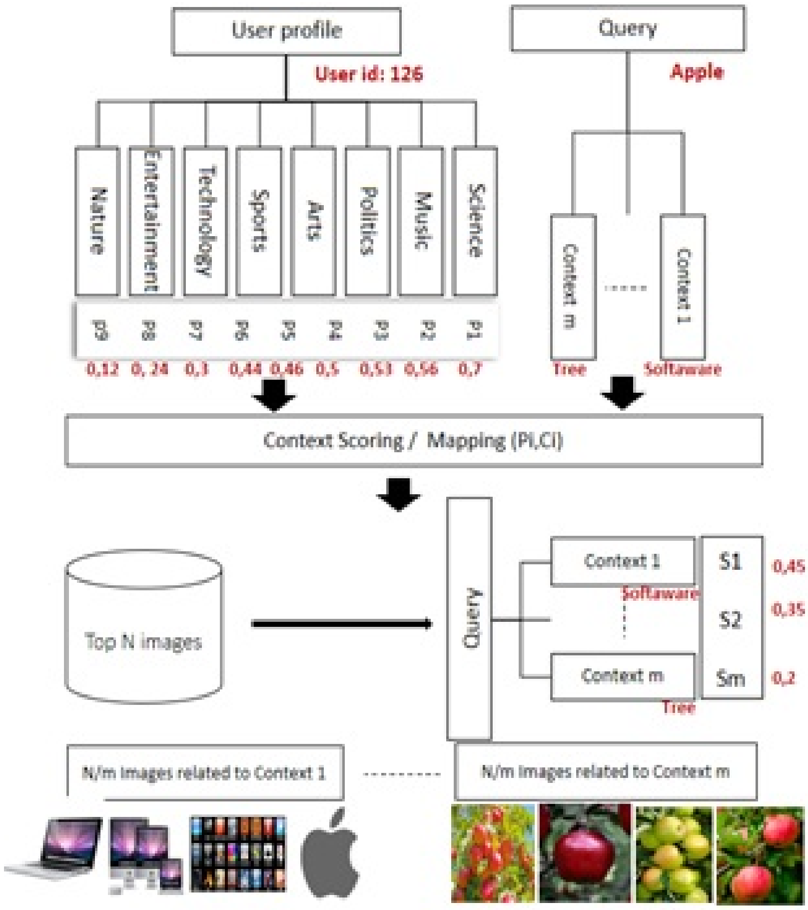

Figure 5: Personalized ranking process

Table 6: Evaluation datasets

	Number	Data
Queries	51	X.Li et al. [26]
	65	Mediaeval 2016
Images	269 648	NUS-WIDE
	19 017	Flickr
Users	138 493	MovieLens
Concepts	704	NUS-WIDE
Preferences	10	Our selected topics

information retrieval and recommender systems. Table 7 contains the most used evaluation metrics in the field of information retrieval with the associated formulation.
We used average precision and mean average precision (MAP) metrics as evaluation metrics to report the performance of our image retrieval system.

4.3 Proposed platform

Our proposed framework for image retrieval system is illustrated in Figure 6. It is composed of three main modules:

– ***Query specification module:*** the user is able to specify his information need in form of a query.

– ***User specification module:*** used for the identification of the user to correctly load his profile from user preference database.

– ***Retrieval module:*** focuses on the personalized ranking of the images in database according to the user preferences and the information need. Here one context will be intensively promoted for the user according to his profile and the raking will be adapted to his interest. Images dealing with this context will be ranked in first rank.

Table 7: Evaluation metrics for information retrieval

Metric	Formula	Description
Recall: R@n	$\frac{A}{A \cup C}$	C: list of relevant but not retrieved images A: list of relevant and retrieved images $A \cup C$: all retrieved images
Precision:P@n	$\frac{A}{A \cup B}$	@n: The number of relevant documents retrieved by rank n, divided by n. B: list of irrelevant but retrieved images $A \cup B$: all relevant images (retrieved and not retrieved)
F1 score F-measure	$2 \times \frac{Recall \times Precision}{Recall + Precision}$	
Average-Precision	$\frac{\sum_1^n P@i \times Rel(i)}{Numberofrelevantdocument}$ $\sum_1^n P@i \times ChangeinR@i$	P@i: Precision@i Change in R@i: the change in recall that happened between cutoff k-1 and cutoff k Rel(i): is equal to 1 if the item at rank i is a relevant document, zero otherwise
Mean Average Precision MAP@n	$\frac{\sum_1^x AP@n}{x}$	x: Total number of queries
Normalized Discounted Cumulative Gain	$NDCG@n = Z_n \frac{\sum_1^n 2^{r_i - 1}}{log(i+1)}$	r_i=$\{Bad = 0, Good = 2, Excellent = 3\}$ the manually judged relevance for each image with respect to the query Z_n is a normalizer factor which make the score for n excellent retrieved images to 1

4.4 SRSiM semantic similarity measure evaluation

The accuracy evaluation of a semantic similarity measure is not an easy process, given that the notion of inter concepts similarity measurement is a subjective human judgment. A set of selected experts are selected to judge in objective way the accuracy of the detailed techniques applied for the mapping between MovieLens genre and the chosen preferences in section 3. Our measure SRSiM is compared to measures obtained using wordnet ontology, Wikipedia dump and retina fingerprints. Wordnet [13] is used as a large lexical database of English language regrouping concepts defined as synsets in hierarchical structure where nodes are arranged depending on the relation figuring between two sysnset. The most frequently used relations among synsets are synonymy, hyperonymy, hyponymy and ISA relation. The semantic similarity measure between two concepts is calculated depending on the shortest path separating the two questioned concepts.

Our proposed measure is compared to similarity measures offered by Wikipedia which presents the largest free online encyclopedia characterized by its richness of English vocabulary words. It provides different techniques to compute the semantic similarity basing on its hyperlink structure. The mainly proposed Wikipedia-based measures [40] [27] are WikiRelate, WLM Wikipedia Link-based Measure and ESA Explicit Semantic Analysis.

The obtained results are summarized in Figure7. It shows that our measure SRSiM out performs the previous measures cited above. The SRSiM gives an accuracy percentage equal to 77,77% which is very close to the results obtained using Wikipedia-based measure. However, we have to notice that running Wikipedia-based similarity measure on local requires the access to the whole Wikipedia dump containing a copy of Wikipedia's content which forms a big file, sizing about 31 G. As a result, the run of Wikipedia tool seems to be memory intensive and needs lots of harddrive space. Besides the intensive requirement on hardware devices performance, the call for Wikipedia functions requires previously high response time, thing which is undesired even the tool shows good results in predicting the semantic similarity measure between concepts. The compute of semantic similarity measure of a couple of words basing on Wikipedia-dump and using a computer characterized by

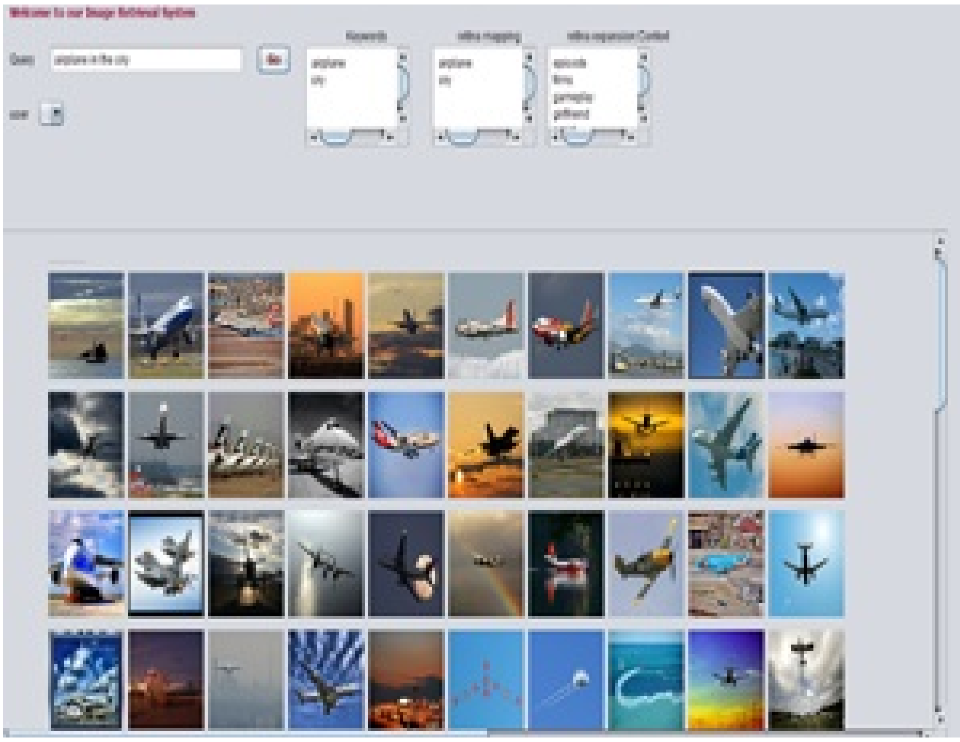

Figure 6: Screenshot of proposed platform

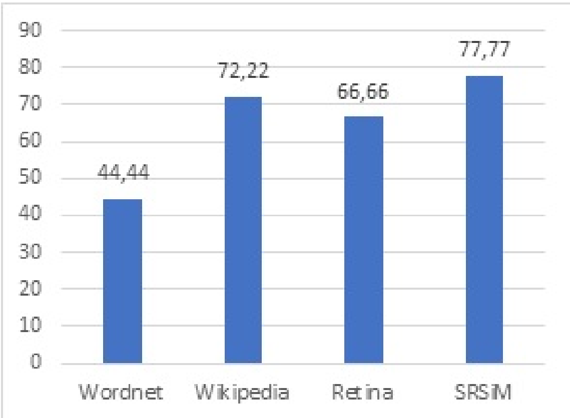

Figure 7: Semantic mapping tools accuracy

12G of memory and i7 processor takes about 3 minutes to be processed. However, processing the semantic SRSiM measure on a couple of words takes only 7 seconds. The computation of SRSiM measure takes the advantages of the online API Cortical.io's Retina and the mathematical calculation method of LSA. Retina API has the ability to respond in real time with significant result when comparing the semantic of two concepts and predicting the nearest meaning for a term. The application of the mathematical calculation method of LSA on the inter-terms Matrix increase the accuracy of the similarity measure since it is considered as a run-time method. It only involves the decomposition of the term-term matrix which is faster than other dimensionality reduction models.

4.5 Retrieval process effectiveness evaluation

Figure 8 shows the retrieval performance of our system tested on NUS-WIDE Data-set. For 34 out of the 51 queries used for the test, our system exhibits average precision higher than 0.7.

The MAP calculated for the 51 queries is 0.675 while the corresponding numbers for [26] using the Semantic Field and RelExample methods are 0.583 and 0.672 respectively. The details of MAP values are represented in the Table 8.

SemanticField method is introduced by [47]. This method measures tag relevance in terms of an averaged semantic similarity between the tag (in our case the query) and

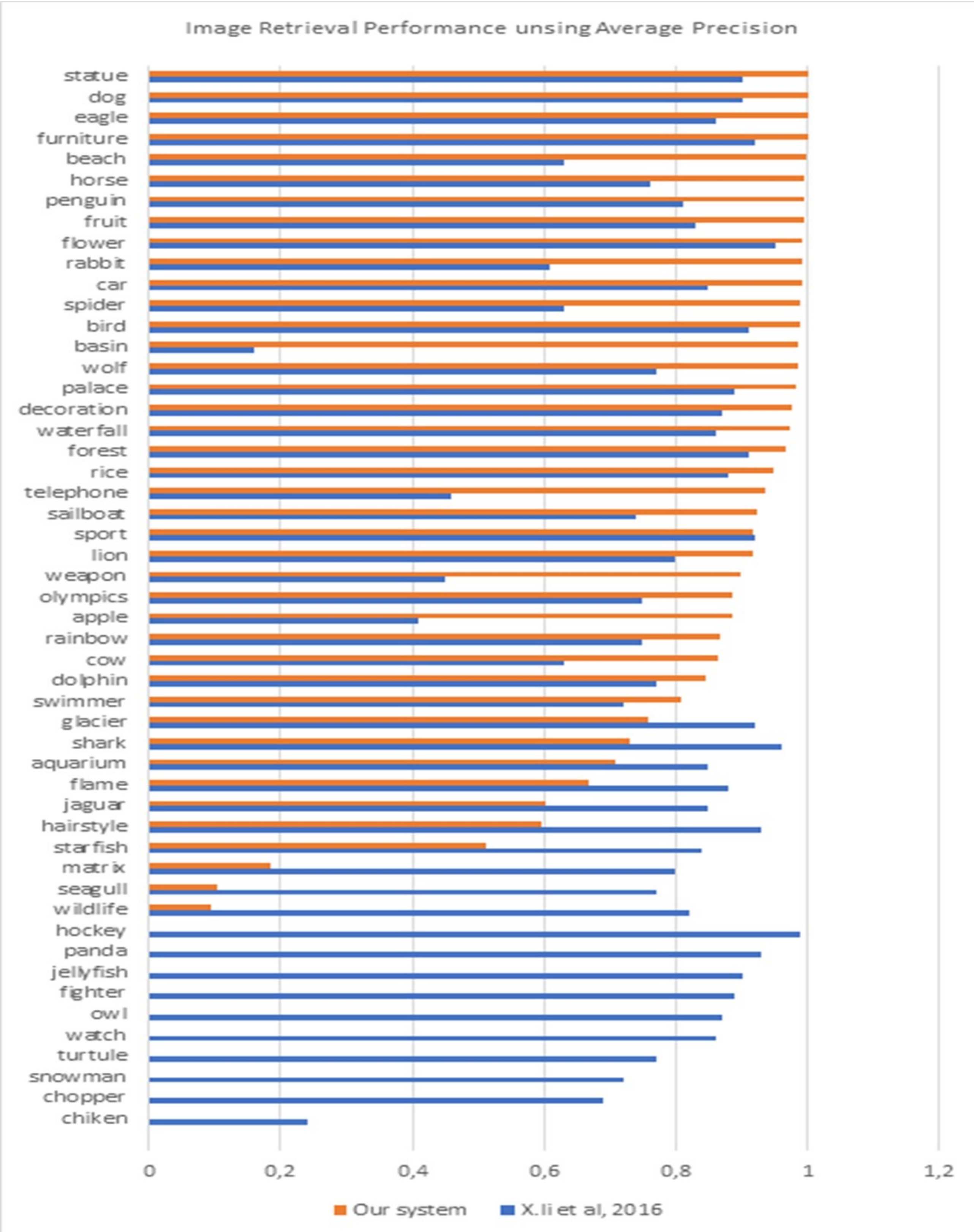

Figure 8: Retrieval performance per query on Nus wide dataset using RelExample of X.Li et al. [26] and our system. Queries have been sorted in descending order by the performance of our system

the other tags assigned to the image. RelExample method is introduced by [26]. RelExample learns from tagged images and exploits positive and negative training examples which are deemed to be more relevant with respect to the query.

Table 8: Mean Average Precision of our system compared to X.Li et al. [26] applied on NUS-WIDE and tested for 51 queries

Team	Approch	MAP
X.Li et al. [26]	SemanticField	0.583
X.Li et al. [26]	RelExample	0.672
Our	SRSiM-based	0.675

Figure 9: Retrieval evaluation on Flickr dataset: Example of ”Birthday candles” query

In particular, relevant positive examples are selected from the collection. We have to note that the average precision for 10 tested queries is null. This score is hereby approved by the misunderstanding of the query by the system noticed in the query to concept mapping.

A second experiment is carried out on data provided by MediaEval 2016 benchmarks [19]. Here we focus on the context of diversity-based image retrieval according to the 2016 retrieving diverse social images task proposed by mediaeval 2016 competition. Compared with the top ranked list of up to 300 photos retrieved from Flickr, our approaches enhance the diversity rate by reducing the number of redundant images. For example, for ”Birthday Candles” query, applying Flickr Baseline approach returns two duplicates' images (with red color) out of 10 first returned images. Applying our approach discard all redundant images and return a diverse search as showed in Figure 9.

In the same context of the retrieving diverse social images task, we compared our approach to [21] and [10]. Noting that [21] approach is performed according to 3 steps: First, it re-ranks the initial list provided by Flickr using the textual information. Second, it aggregates re-ranked lists by several text-based descriptors using genetic programming. Finally, it uses agglomerative with centroid and average link linkage methods on Color Layout which are used for distance computing and Birch approaches to enhance diversity.[10]: First, the relevance of every image to the query is estimated with an initial visual probability scores. Next, the hierarchical agglomerative clustering is used on textual description. Combined with the formal concept analysis, it detects latent topics and then textual clusters are generated to diversify images according to the detected topics.

Experiments show that the comparison of these methods with our approach demonstrates an approximate curve shape in terms of Cluster Recall and F1-measure but in term of precision the difference is significant. Figure 10 (a) illustrates the important variation especially with the unexpected drop in the precision values achieved by the approach of [10]. We notice that our approach outperforms the other approaches for the cut off points 10, 20 and 30. The precision of our top five images is extremely better than the precision of [21] . However, for the cut off points 40 and 50, this approach overcomes this shortage and provides better precision values.

Figure 10 show also the evolution curves in term of Cluster Recall (b) and F1-measure (c) of the three aforementioned approaches. These illustrations demonstrate that all of the approaches have similar behavior and confirm the degradation of the performance of the approach of [10] when increasing the number of returned images.

4.6 Conventional search vs Personalized search

Our approach for personalization is tested on random queries introduced by the user. the following Table shows the different runs assigned to 5 queries applied by the conventional search process and the personalized process. The chosen queries used for the test are: bride, airplane in the sky, train station, funny baby and animal in snow. These runs prove a good level of personalization. Personalization depends on user preference having the highest score. In these cases, we take some examples where the first ranked preference scale is higher than 0.7. These results are illustrated in Table 9.

To more evaluate the user satisfaction, we focus on a list of users (30) from Flickr ‘users having different profiles in term of preferences and we observe the top ranked images according to a query. The personalization of the suggestions sort ensures that the top ranked ones are those that align with the user's preferences. We estimate the AP@n

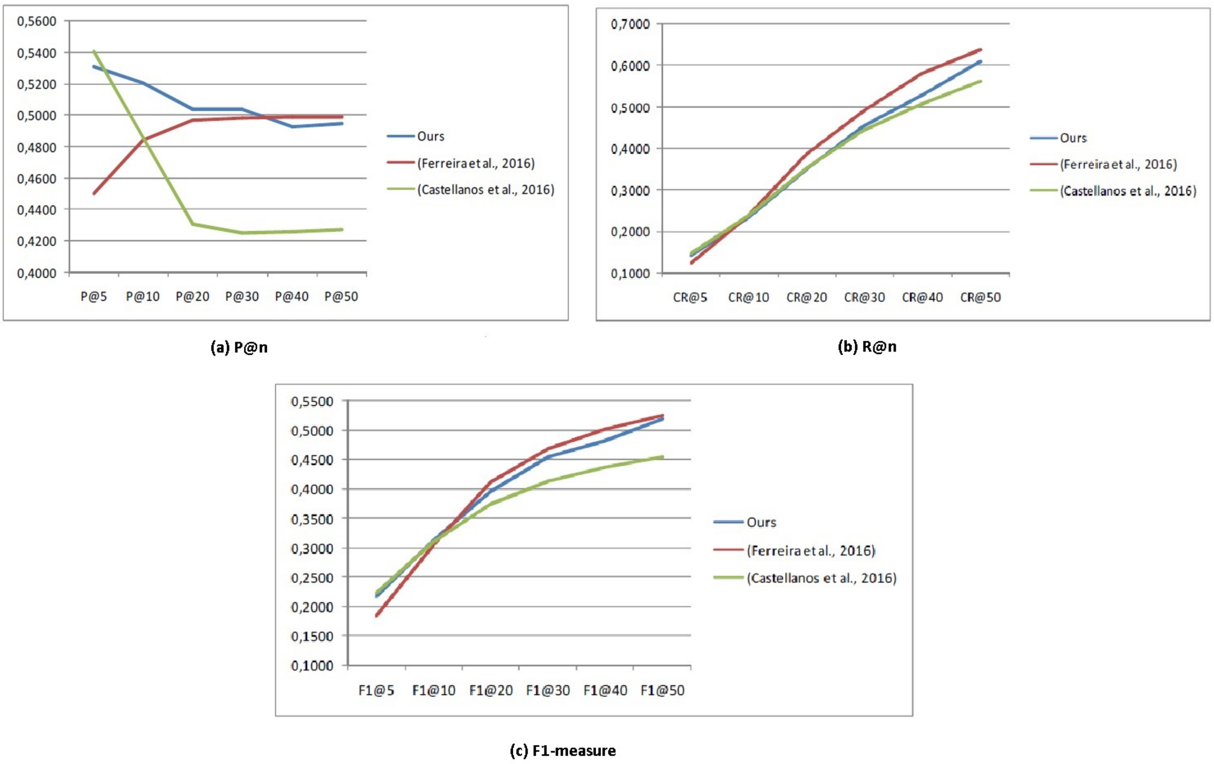

Figure 10: P@n, R@n and F1-measure of our system compared to [10] and [21]

Table 9: Conventional search vs Personalized search

Query	Personalized vs Conventional Results
Bride	Personalized with Social preference $\succ$ 75%
	Personalized with Entertainment preference $\succ$80%
Airplane in the sky	Personalized with Technology preference $\succ$80%
	Personalized with Nature preference $\succ$65%
Train station	Personalized with Travel preference $\succ$90%
Funny baby	Personalized with Social preference $\succ$70%
	Personalized with Sport preference $\succ$30%
Animal in snow	Personalized with Nature preference $\succ$65%

with and without the personalization aspect of each query for different users as shown in Figure 11 (a)(b)(c). Then, we generate the score P@n for each user to illustrate its satisfaction rate. As illustrated by the figure11 (d), the relevance of the top five returned suggestions is enhanced by performing the personalized process. In fact, we focus on the five first suggestions since the personalization step aims to help the user to find the most likely query expansion.

5 Results discussion

Finding the relevant user need from processing the query is a critical skill in information retrieval.For this purpose we used the SRSiM as an hybrid similarity measure based on Retina Fingerprint as an ontology and the Latent Semantic Indexing (LSI) techniques as a statistical approach.The online API provided by Cortical.io improve response times and generate a semantic Fingerprint for each concept instantly in contrast to Wikipedia-based measurements, which take longer time since they must scan the entire dump, which is very huge. As mentioned in the previous section SRSiM show a competitive results compared to measures based on wikipedia,Retina and wordnet.(77.77% of accuracy vs 72.22% 66.66% and 44.44%).

SRSiM outperforms Wikipedia measures not only in term of time, but also in term of accuracy as it depends on Retina, which has a rich structure covering the English language in contrast to Wikipedia measures which depends on inks between Wikipedia pages.

The evaluation of semantic similarity measure is applied on concepts from lexical field of Movilens Database. We aim in the future work to test this measure on a more general Lexical field.

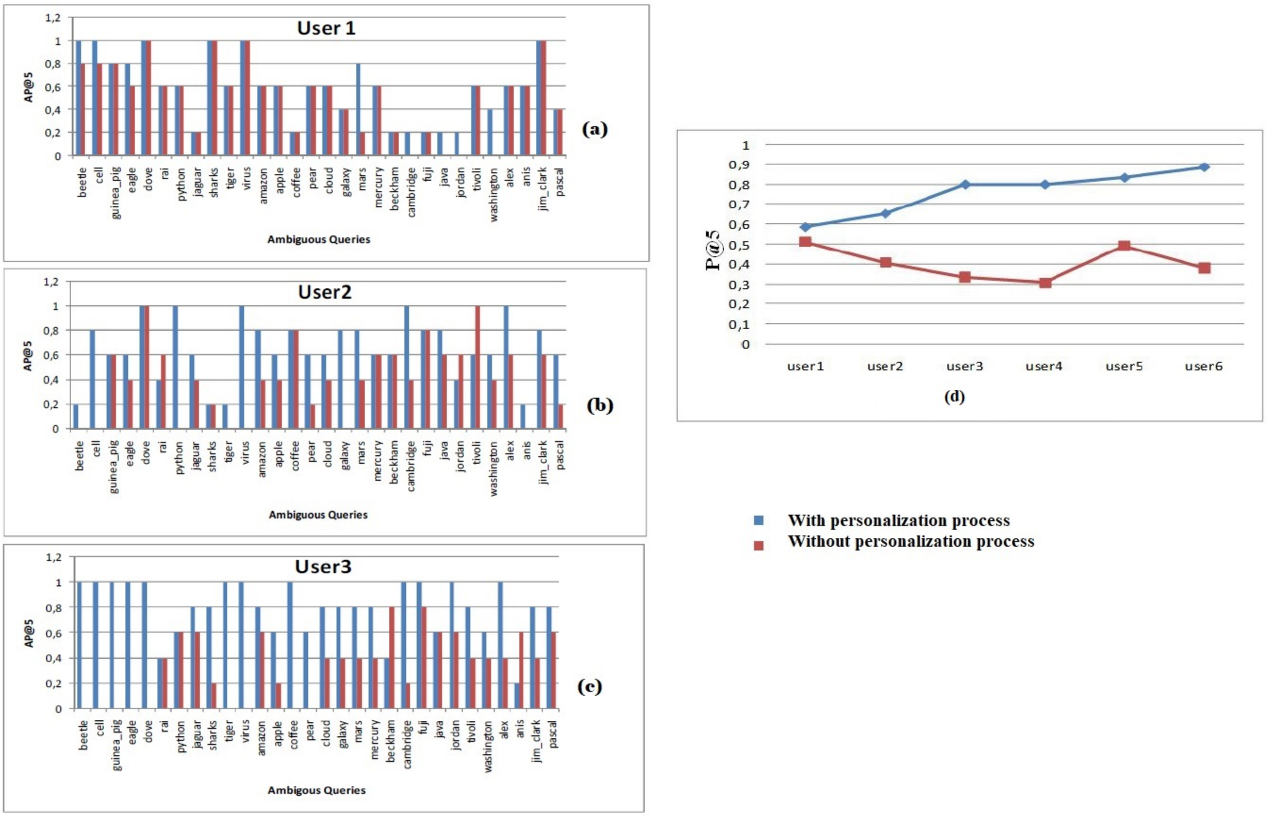

Figure 11: User satisfaction evaluation

Our second contribution focuses on a personalized retrieval process. We proposed a system for personalized image retrieval that handles queries written in open-vocabulary. User preferences are obtained from MovieLens, specifically through data on movie ratings and reviews. The evaluation of the retrieval system indicates that our system demonstrates an AP$>$ 0.7 for $2/3$ of the queries, with a MAP reaching 0.675. Approximately 20% of queries have an almost negligible AP. this, is explained by the misunderstanding of user queries reached from the first step of retrieval process (query-to-concept mapping) and the use of inaccurate concepts to define their needs. The user query does not arrange the user intent although we perform a personalized search via profiles from Movielens .This is witnessed in several cases where the user queries concept are not covered by user preferences from MovieLens dataset (Exp: for the queries ”jellyfish” and ” chicken” there is no preferences that deal with them in our database) In this way, the personalized search can be improved by:

. Tailoring user preferences from other social networks with increased activity and interaction among users. The use of information shared in social network can improve the results as users spent more time in consulting social networks and various methods dealing with context awareness, artificial intelligence and machine learning techniques are conducted to more improve the deduction of preferences [14]. In this case, performance can be improved by using the Graph Convolutional Network used as AI technology to determine personal preferences or by applying techniques for context awareness. The use of this information require to overcome problems and challenges of data protection, privacy and confidentiality imposed by Social Media Platforms [11] [29] [2] [31].

. Applying a user behavior analysis to understand user preferences, needs, and interests. This can be reached by tailoring search History, search engines track click-through rates (CTR) on search results, browsing Behavior of user, time spent on each visited page, social Media interactions, location Data, device

. Optimizing Results by continuously refining personalization algorithms based on user feedback.

6 Conclusion

In this paper, we have presented our architecture of a personalized image retrieval system which is composed of three major modules: (1) Users processing using the social database of Movielens. (2) Query processing and personalization. (3) Images processing by semantic annotation and clustering based on a new semantic similarity measure SRSiM (Statistical Retina Similarity Measure) using the statistical and knowledge-based approaches. For this purpose and in a first step, we have performed different tasks of pre-processing in which we introduced our proposed similarity measure used for the interpretation of the input query and the query to concept mapping. We have modeled the user profile according to information about the user extracted from the MovieLens databases. Users and images databases are pre-processed by using the clustering techniques to divide them into clusters having similar content. Finally, we have presented our approach for personalizing the image retrieval system. The evaluation of the different system parts showed a good results related in term of the accuracy of the proposed similarity measure SRSiM, the Average Precision AP and the Mean Average Precision MAP of the image retrieval system.

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