Fuzzy User Profile Modeling for Information Retrieval

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Abstract: Given the continued growth in the number of documents available in the social Web, it becomes increasingly difficult for a user to find relevant resources satisfying his information need. Personalization seems to be an efficient manner to improve the retrieval engine effectiveness. In this paper we introduce a personalized image retrieval system based on user profile modeling depending on user's context. The context includes user comments, rates, tags and preferences extracted from social network. We adopt a fuzzy logic-based user profile modeling due to its flexibility in decision making since user preference are always imprecise. The user has to specify his initial need description by rating concepts and contexts he is interested in. Concepts and contexts are weighted by the user by associating a score and these scores will infer in our fuzzy model to predict the preference degree related to each concept for such context and return the preference degree. Relying on the score affected for each concept and context we deduce its importance to apply then the appropriate fuzzy rule. As for as the experiments, the advanced user profile modeling with fuzzy logic shows more flexibility in the interpretation of the query.

1 INTRODUCTION

Internet growth has trained various types of social networks with big scale, which are now recognized as an important means for the information diffusion. With this social dimension that enriches the content of web resources, user's information needs have been emerged for new contexts. But the classic information retrieval does not seem to be suitable to this dimension, involving users and their interactions within social networks. The emergences of Social Information Retrieval which is a recent approach that take into account the information extracted from social networks and adapt models and algorithms of classical information retrieval to exploit the convenient social information in the retrieval process according to the conventional measures of Recall and Precision.

Social information retrieval has the objective of improving the information retrieval process by exploiting social information and customizing the user search according to its social context. The main issues of this theme are to identify, exploit and combine social information from social networks to improve and possibly customize the information retrieval. There are two approaches in the state of the art related to social information retrieval. The first category consists in exploiting social information about the content like the annotations (Gemmell et al., 2011) (Gemmell et al., 2010). The second category combines this content with social relations between users of social networks and then the orientation towards personalized information retrieval in which the relevant documents for a given query may be different from one user to another (Sharma et al., 2012)(Shen et al., 2005).

Therefore, we focus on the issues of the impact of social information on information retrieval whose purpose is to improve the classical information results. Social information including social relationships between users, annotations, clicks, profiles etc. can be exploited in the process of information retrieval in the step of the query analysis and interpretation, the matching and finally in the ranking of the results list.

In a personalized information retrieval system, the user is the core of the entire system as the results depend on his profile and his preferences hence the importance of modeling the user profile which must follow the changing in preferences and user interest over the time. The user modeling can have different representation, namely the representation of the user profile can be a vector where the profile is composed of one or more vectors defined in an indexing terms

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space , hierarchical where the characteristics of a user are organized in a hierarchical structure of concepts representing the fields of interest, or multidimensional where the profile is represented by a structured model of predefined dimensions such as personal data, area of interest and preferences .

The static manipulation of user profile can affect the decision making of the results in a wrong way. In fact, this representation requires the processing of data in a fixed manner ie a user can be endowed with a precise theme or not while this logic does not satisfy the human nature of the individual who can change his mind across the time and context. In this context, fuzzy logic provides a theoretical framework for the representation and the processing of these data with their imperfections. Its purpose is to make the framework of representation and knowledge processing flexible which is inspired from human mental processes and therefore the tendency for fuzzy modelling of the user profile used for the improvement of personalized retrieval systems, and systems recommendations.

2 RELATED WORK

User preferences discovery research aim to enhance the effectiveness of personalized information systems. User preferences are learnt by following the user interaction with retrieval engine. This can be reached either by asking the user his behaviors directly in an explicit elicitation via filling out forms or by observing their behaviors in implicit way by extracting automatically his interaction with his browser of from the social networks.

Discovering user preferences basing on implicit elicitation requires less user involvement and this is more efficient in retrieval process. Implicit information can be extracted from social networks and aims to find the importance of a user in the social network and thus the importance of a document in the collection database. The importance of a user in social networks can be measured thanks to social network analysis methods. In this context researchers think on modeling information retrieval system which can be enhanced by the document relevance ranking based on centrality measures of social networks. There are three elementary steps in this model which are: social Network extraction, social network analysis and document relevance ranking (Kirchhoff, 2010). Enhancing retrieval effectiveness using social networks is based on finding structural information from the documentation collection about social relationships and exploiting it in retrieval process like recommender systems, information filtering, information retrieval, user modeling and personalized agents (Pitsilis et al., 2009).

The richness of information that can be extracted from social network has a grand impact for enhancing the quality and the effectiveness of multimedia information retrieval solutions. The new trend of multimedia information retrieval is to converge between multimedia content analysis and social media which have a complementary role and each one can affect the other. In (Hanjalic, 2012) researchers show that social media complement multimedia content analysis by expanding the opportunities of the content access or also in confirming or correcting the low-confidence of multimedia content analysis techniques. This can be done thanks to information extracted from social networks through tags, ratings and comments provided by the user. In other hand, multimedia content analysis can be used to improve the effectiveness and efficiency of the tagging process. In fact, techniques of multimedia content analysis can identify the content items and this latter can be refined and enriched by the interaction of the user on online social platforms through tagging, rating and recommending of the items. Due to the complexity of Information extracted from social networks, this last can be structured in hypergraph structure. (Yang et al., 2013) propose an hypergraph spectral hashing for image retrieval with heterogeneous social contexts. This hypergraph model the various relationships among images and other contexts in social media (tags, locations, users, communities).

3 FUZZY USER PROFILE MODELING

3.1 Fuzzy Logic in Information Retrieval

The uses of fuzzy logic in the field of information retrieval have emerged due to its nature allowing the bridge of the gap between the soft logic of human-understandable and hard logic of machine readable. Indeed, fuzzy logic is used in ontology which define a new theoretical paradigm known as Fuzzy Ontology that aim to improve the semantic documents retrieval by handling the trade off between the fixed definition of a term in the ontology structure, and the actual meaning desired by individuals. In (Silvia and Elie, 2007), Fuzzy logic is used also as model of information retrieval instead of the probabilistic model due to its perfection shown by obtaining a comprehensive treatment of imprecision and uncertainty pervading the information retrieval process (Nowacka et al., 2008) (Oussalah and Eltigani, 2005). With the emergence of social networks and user profiling, in the field of information retrieval the fuzzy logic is used in the interpretation of the user profile like (Ghaderi et al., 2012) who propose an approach that aim to predict users' preferences and use it for movie recommendation basing on the theory of the representation of knowledge preferences discovery by identifying types of subjectivity, vagueness and uncertainty existing in the user preferences due to developing a fuzzy model that provides a formalism to quantify how much a user likes, dislikes or be indifferent to an element given and its characteristics based on the fuzzy set theory, it enriches the results of discovered preferences including positive fuzzy categories, negative, neutral and unknown preferences.

The uses of fuzzy logic in information retrieval have proven a great efficiency for various research fields. In this context, we aim to apply fuzzy logic for user profile modeling which is useful in the process of information retrieval and go with the characteristic of user preferences which are often ambiguous and imprecise.

3.2 Fuzzy Logic for Profiling in Information Retrieval

Our purpose is to reach a fuzzy user profile modeling extracted from social network and operate this profile for improving the information retrieval process. Alike each information retrieval system, an image retrieval system comprises four essential modules: an image processor (Feki et al., 2013) (Ksibi et al., 2013), a query processor (Fakhfakh et al, 2012) (Fakhfakh et al 2013), a search and matching function and a ranking capability (Feki et al., 2012). As shown in Figure1, in an offline way we construct an hypergraph that manage all information extracted from the social network that relate users, images and concepts. Information related to each user are stocked in the hypergraph structure and then used for query analysis step to inform us about the user interest. The user profile is used also in ranking process to sort the more relevant images related to each user in first order.
In information retrieval, user profile is defined as a collection of data about the user of the system, which the system collects and maintains in order to

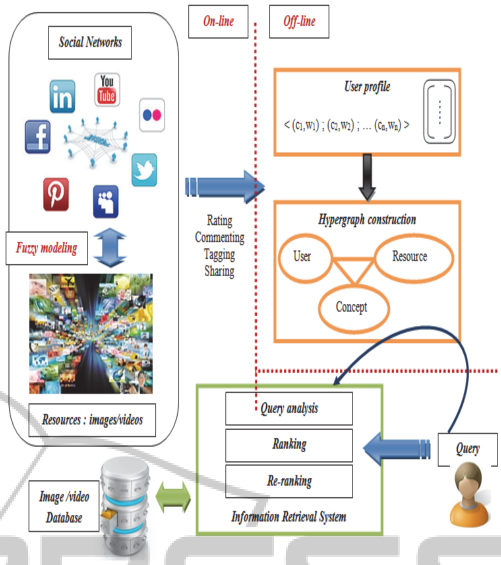


Figure 1: Fuzzy logic for information retrieval.

improve the quality of information access. These data are divided in two major parts which are: personal information like age, gender, location, etc … and his interest known among his interaction on the social network through commenting, sharing, rating and other activities that can be done on the resources available in the network. In addition to user profile, there is another factor that can influence the effectiveness of retrieval process which is the context of research. We mean by context the spatiotemporal data like location, time and devices (laptop, mobile…) used for information search that handle the user needs. Table1 shows how the search context can impact the search result.

Table 1: Context influence on query interpretation.

Query	Context	User need suggestions
Food	Device: laptop Location: at home	Recipes
	Device: laptop Location: at work	Online order for meal
	Device: mobile Location: in the car	Address of the nearest restaurant, menu, prices …

In our case, the user interacts with the image retrieval system in two ways: explicitly and implicitly as shown in figure 2.

- Explicit information based on rating technique: the user gives his feedback after the evaluation of system’s results and mention if he like or dislike the results by giving a degree ranging from 0 to 5.

- Implicit information extracted from the social network. These data can be about personal information (age, gender, occupation...) or about user interest known through user interaction by tagging, commenting or rating.

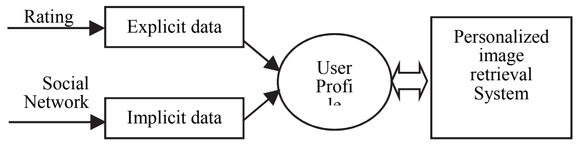


Figure 2: Data for user profile constriction.

With video search engine Youtube, the opinion of a user about a video can only be: I like or I dislike this video. This representation does not reflect the reality of user preferences. There certainly intermediate states between these two expressions.

Our contribution aims to give more flexibility in the expression of user preference by choosing one of the following classes of choice depending on the rating value : Poor, Fair, Average, Good and Excellent.

We adopt a multidimensional representation of user interests and fuzzy logic approach to compute the satisfaction degrees of the user rather than the usual evaluation known as like or dislike (1 or 0) that represent the boolean logic. In our fuzzy user model, we have two inputs and one output. As inputs the user will be asked to give a value to concepts and contexts he is interested in. The relevant concepts and contexts will be rated as 4 or 5 value for example, against the disliked ones have a score of 0 or 1.

Let's denote:

- n the value associated to concept's rate where $n \in [0\ 5]$. The interpretation of this value follows the next rules:Poor : if $n \in [0\ 1]$, Fair : if $n \in]1\ 2]$, Average : if $n \in]2\ 3]$, Good : if $n \in]3\ 4]$ and Excellent : if $n \in]4\ 5]$

- m the value associated to the context's rate where $m \in [0\ 5]$. The interpretation of this value is as follows: Not Relevant: if $m \in [0\ 1]$, average: if $m \in]1\ 4]$, Relevant: if $m \in]4\ 5]$.

The output of our user' fuzzy logic model is the preference degree p $\in [0\ 1]$ that merge between the concepts and contexts rated. The interpretation of the preference degree can be as follows Not Relevant: if p $\in [0\ 0{,}25]$, Neutral: if p $\in]0{,}25\ 0{,}75]$, Relevant: if p $\in]0{,}75\ 1]$

Figure 4 displays the representation of inputs and the output of our fuzzy user preferences model.

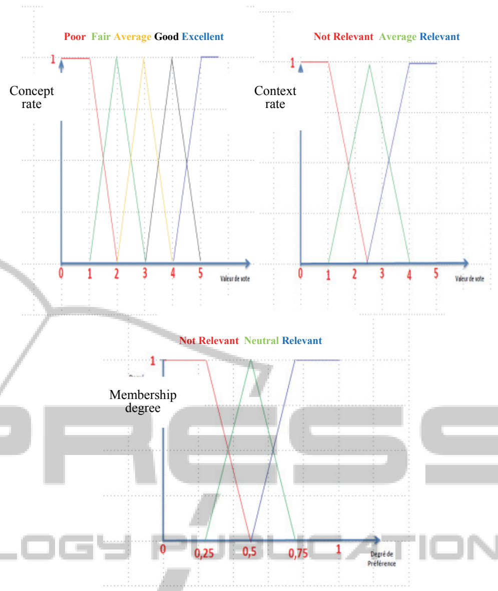


Figure 3: Fuzzy representation of user preferences.

There are 15 fuzzy rules that identify our fuzzy logic user preferences model due to the 15 possible combinations that link the different value of inputs representing concept rate and context rate.

To solve decision problems of the output we are based on fuzzy inference system which is a way of mapping an input space to an output space using fuzzy logic. We try to formalize the reasoning process of user preferences interpretation by means of fuzzy logic. The fuzzy rule is presented as:

"IF (Concept rate is x) AND (Context rate is y) THEN (preference degree is z)".

The different combination of x,y and z are shown in Table2.

Table 2: Fuzzy rules of user preferences.

		Context Rate		
		Not Relevant	*Average*	*Relevant*
Concept Rate	*Poor*	Not Relevant	Not Relevant	Not Relevant
	Fair	Not Relevant	Neutral	Neutral
	Average	Not Relevant	Relevant	Relevant
	Good	Not Relevant	Relevant	Relevant
	Excellent	Not Relevant	Relevant	Relevant

The different combination of x,y and z are shown in Table2.

We used Mamdani's method as inference method to predict the preference degree. The conjunction AND and the implication THEN are presented by the operator "MIN. MAX is used as the fuzzy aggregation operator. The defuzzification method used is the Middle of Maximum.

Figure 5 shows an example of defuzzification where n=3.25 and m=1.

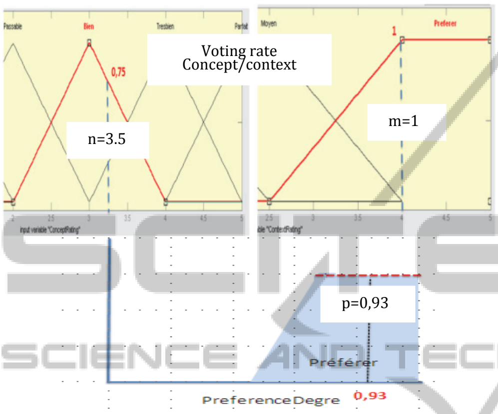


Figure 4: Preference degree prediction (n=3.25, m=1).

4 EXPERIMENTS

Concepts used for user profile construction are 130 concepts extracted from the ontology LSCOM (Large Scale Concept Ontology for Multimedia) like actor, adult, airplane, animal, sports, plant ....

Based on the selected concepts we generate randomly our queries. Example of queries: Adult person, Olympic athlete, gift flower, ...

As for as the evaluation we are based on the measurement P@5 and P@10 witch express the user satisfaction related to the top 5 or 10 relevant documents and MAP (Mean Average Precision) that expresses the model ability in selecting relevant documents in response to all tested queries.

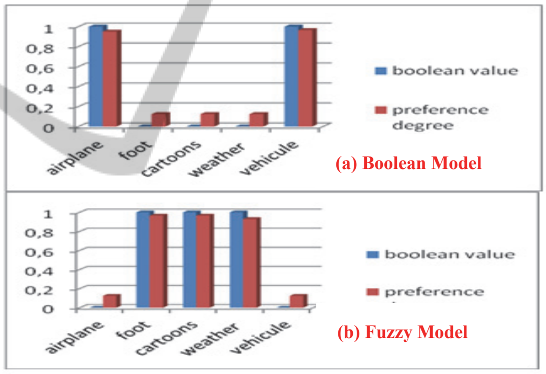
We can observe from these results shown in Table 3 that with the integration of fuzzy model user preferences realize a significant improvement in performance compared to standard Boolean model (Kalervo et al.,2002) especially in values clarification P@5 and P@10 and consequently an improvement in MAP.

The fuzzy user preference modeling has earned us great flexibility with regard to the degree of preference of a particular concept. For example: In the context "at home", the Boolean representation of

Table 3: result comparison for the context "At home".

Query	Boolean model			Fuzzy model		
	Precision					
	@5	@10	MAP	@5	@10	MAP
Olympic athlete	0.71	1	0,85	0,83	1	0,91
French bike tour	0,38	0,769	0,57	0,45	0,9	0,67
Bird singing	0,83	1	0,91	0,83	1	0,91
University professor	0,5	1	0,75	1	1	1

user preferences will cause the elimination of concepts preference values equal to 0 and will limit choices only for concepts having rate 1. While in the reality, we have the possibility of gradual and flexible expression, for example by giving a preference value equal to 0.7 which is allowed by the fuzzy user preferences modeling is closer to the user's choices and this representation can eliminate the rigid decision of the system. This is more displayed in figure 6.



(a) standard boolean model (b) fuzzy model.
Figure 5: Boolean vs fuzzy modelling.

In our case, the context represents the spatiotemporal representation of the user and the equipment used for the research that can has an impact on the result of the image retrieval system depending on the characteristics of the used hardware like the size of the screen, the ability of memory, processor speed etc… Figure 7 shows the impact of the context on the preferences decision using the fuzzy interpretation. This representation shows that the shape of the fuzzy preferences curve (in green) is depending on the changes of context rating (in Red). For example, when the concept has a rate equal to 4.5 / 5 with a linguistic value: perfect), the fuzzy preferences will 0.5 / 1 (Middle linguistic value). This is due to the context score: less than 1.

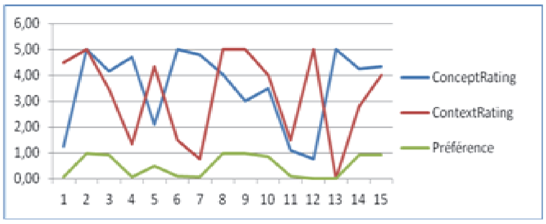


Figure 6: Context impact on user preferences decision.

5 CONCLUSION

In this paper we present our personalized image retrieval system based on user profile modeling depending on user's context. We adopt a fuzzy logic-based user profile modeling due to its flexibility in decision making. This model work with a list of concept and context where the user is asked to rate them according to his interest and these rates help in predicting the preference degree related to each concept for such context. As for as the experiments, the advanced user profile modeling with fuzzy logic shows more flexibility in the interpretation of the query compared with the standard boolean model. For future work, we aim to make the context detection automatic without user intervention and the same thing for the concept rating where the rate value will be deduced from the user profile extracted from social network.

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