Building Topic Profiles Based on Expert Profile Aggregation

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Abstract. In this work, we present a method to characterize a given topic on an Information Retrieval System based on expert user profiles. We start from a set of documents from which a set of characteristic terms is extracted. The presence of any term in each document is known and we want to establish the most significant ones in order to select relevant documents about a given topic Π. For that purpose, a group of experts are required to assess the set of documents. The experts can query with the same terms (an unique query) to the system or with different terms (several queries). By aggregating these assessments with the weight associated to the terms, a topic profile can be obtained. An overview of these different situations and an experimental example are also presented.

1 Introduction

In the last decade, research in the field of Information Retrieval has helped users looking for information in Internet. Optimization mechanisms at query and indexing stages, as well as filtering tasks and user profile construction, have contributed to enhance the retrieval process. The problems of surfing through the web include not only the browsing of sites, but also the query in search engines. Besides the amount of information that the user can find in the web, sometimes the user do not know how to query due to the lack of knowledge about the topic, due to a lack of vocabulary in the field or just because the suitable words do not come to user's mind at query moment.

In the literature, some approaches have been presented to solve this problem called in general querying expansion or query refinement (good reviews in the field can be found in (Efthimiadis, 1996) and (Bodner and Song, 1996). In all of them, the general idea is to obtain a list of additional terms to be added to the original query terms to improve the system answer. The addition of these terms can be made automatically (without the intervention of the user) or semi-automatically (the user sees the list and chooses the most suitable terms for the query).

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In our approach, we suppose that expert users[1] query the system and their profiles are available. Profiles contain terms representing user preferences, and can be used to query the system. These profiles represent queries about a certain topic, and can be used as starting point for other queries coming from non-expert users. In this sense, our approach can be considered automatic, since the information stored in the constructed profile can be used automatically as profile for a novel user looking for information in the same topic. Moreover, a list of terms from this profile could be shown to the user who can select the most interesting terms and learn new vocabulary about the topic. This fact represents an advantage above other approaches in the literature (Harman, 1992), since the user can see the expert profiles and can use the system in automatic way or can select the most appropriated terms in a semi-automatic one.

This approach is inspired in the Collaborative Filtering (Foltz and Dumais, 1992), (Goldberg et al., 1992), where a shared decision-making process is carried out. When users look for information in a data source, the time and knowledge spent in searching can be useful for other users looking for documents in the same field. Collaborative Filtering deals with this problem. A filter process is performed in the search, and the resulting filtered information is shared with other users. The knowledge about user preferences and relevance feedback is stored in user profiles. In a Collaborative Filtering framework, the evaluation of documents from users is utilized to filter retrieved documents when other users query the IRS[2]. In our work, we use not only the document evaluation from users, but also the information stored in the profiles.

The vagueness and uncertainty inherently present in the Information Retrieval tasks, specially in the query construction and user evaluation processes make Fuzzy Logic be one of the best tools to give flexibility and facility when dealing with imprecision (Buell and Kraft, 1981), (Bookstein, 1980), (Bordogna & Pasi, 1993), (Kraft et al., 1997), (Martín-Bautista et al., 2000a), (Martín-Bautista et al., 2000b). Fuzzy logic has also been applied to collaborative filtering based on fuzzy preference relations, as is presented in (Perny and Zucker, 1999). We apply fuzzy logic to profile representation, as well as to the aggregation of expert profiles and opinions to help non-expert users to query an IRS.

In this paper, we start with a presentation of the problem of constructing topic profiles. In Sect. 3, a model for the aggregation of expert profiles to obtain an unique topic profile is exposed. Different cases based on the fact that the experts can make the same or different queries are considered in this section. An experimental example with one of these cases is explained in Sect. 4. Finally, some concluding remarks and future lines of work can be found in Sect. 5.

[1] By expert users, we understand users with background knowledge about the topic and its vocabulary. Moreover, an extension of the proposed approach could have different confidence levels for the experts. So the profiles could be weighted based on these knowledge levels.

[2] We use the term IRS referring to a general Information Retrieval System, including the filtering systems, which are sometimes referred as IFS (Information Filtering Systems) in the literature (Belkin and Croft, 1992).

2 Construction of a Topic Profile

Let us suppose a user looks for relevant documents about a certain topic Π on an IRS. When this search is represented by a query, the user try to express her/his needs by a set or terms which are usually not very specific due to the lack of background knowledge of the user about the topic or just because in the moment of the query, the terms do not come to the user's mind. To help the user with the query construction, terms related to the words of a first query may be added to the query. These words are usually extracted from the documents retrieved in the first query (Harman, 1992).

For instance, let us consider a very common situation in any research group: a beginner is asked by a senior researcher to read and comment some papers or works about Machine Learning. If the user formulates a query using the terms “Machine Learning”, it is quite possible that she/he fails to obtain certain interesting papers about “sub-symbolic models”, that are useful tools in Machine Learning (and thus a term very relevant for this topic), a fact surely unknown for the beginner.

To cope with this situation, we propose a model for a search help tool based on the construction of a profile for the topic Π. We present here a methodology where an aggregation of the opinions of a set of experts is carried out to obtain what we call the “topic-profile”. Roughly speaking, this profile may be characterized as a set of terms with an associated weight. This is important both for the characterization of the topic and for constructing efficient queries about it.

Once the expert profiles are constructed, as a result of a filtering process, both the term in profiles and the expert opinions have to be aggregated and combined to obtain a global assessment for each term to take part of the topic profile.

We can deal with two different cases in our model. On the one hand, each expert can query the system with different terms, so a set of documents would be obtained as a response to each expert query. An expert profile is built for each expert. We can aggregate these profiles that represent queries about the topic Π. On the other hand, if experts make an unique query with the same terms, the retrieved set of documents will be the same. However, as the evaluation of the experts over the documents is different, the expert profiles would contain different terms with different evaluations. We can aggregate these profiles to obtain the topic profile.

We combine evaluation of documents from different experts (before the profile construction), or terms in the expert profiles once they have been obtained. The result of this aggregation is a profile that characterizes Π. For this purpose, we need the following elements:

- A given topic Π.
- A set $\{D_1,...,D_m\}$ of documents related to Π. This set of documents could be obtained in a different way based on the framework (information retrieval or filtering one). In our case, we are dealing with a filtering framework.
- A set $T=\{t_1,...t_n\}$ of terms obtained from the abovementioned documents. For each term t_i and document D_j, there exists the “representation of t_i in D_j”, i.e. a pair $(t_i, D_j(t_i))$ where $D_j(t_i) = f_{ij}$ assesses, in some way, the weight of t_i in D_j, $i=1,\dots,n$; $j=1,\dots,m$. In classical models, f_{ij} is some frequency scheme (generally the relative frequency) measuring the occurrences of t_i in D_j, $i=1,\dots,n$; $j=1,\dots,m$, but some other very interesting representations for these weights have been introduced in the

last years, mainly by using fuzzy numbers to obtain a more expressive representation (see (Martín-Bautista, 2000) for details).

- A set of experts $\{E_1,...,E_P\}$, where each of them is asked to evaluate the relevance of any document in relation with Π. Let us suppose that an expert E_k is able to assess the relevance of the document D_j for the topic Π represented by s_{kj}, $k=1, \ldots, P$; $j=1, \ldots, M$.
- A set of profiles $Z = \{z_1,...,z_p\}$, where each profile z_k corresponds to the expert E_k.

2.1 Concept of User Profile

In a filtering process, the users can feedback the system by evaluating some of the retrieved documents. This evaluation allows the construction of profiles, where the terms appearing in the most relevant documents, as well as terms presented in non-relevant documents expressing what users do not like (Martín-Bautista et al., 2000a).

A user profile consists of a set of terms and a weight indicating the strength of each term in relation to the topic for that user. Terms in the profiles can be extracted from both previous queries and index terms in relevant documents retrieved in response to those queries for the considered user. In a fuzzy framework, each term in a profile has associated a fuzzy value signifying the strength of user interest in the topic(s) represented by that term (Martín-Bautista et al., 2000b).

We start from a given set of user profiles $Z = \{z_1,...,z_p\}$, with p the number of profiles (we suppose the number of profiles equal to the number of experts), and where $z_i = \{t'_{i1},...,t'_{ia}\}$ $t'_{ij} \in T$, $1 \le i \le p$, $1 \le j \le a$, being a the number of terms in the profile. We can define a function analogous to the indexing function defined in (Buell and Kraft, 1981) for the extended Boolean model, but for user profiles where the representation of the terms is expressed by a fuzzy degree of membership of the term to the profile (Martín-Bautista et al., 2002a):

$$G\colon ZxT \rightarrow [0,1] \ \forall \ z \in Z, \ t \in T \quad G(z,t) = \mu_z(t)\ . \tag{1}$$

This presence value of terms in the profiles can be calculated as is suggested in (Martín-Bautista et al., 2000a), and is based in both the presence of the term in a document and in the relevance that the user gives to the document where the term is.

This profile representation differs from other approaches where the evaluation of documents from the user is stored in the profiles, but the evaluation corresponding to each term is not calculated. Therefore, our profiles are in a term level, and not in a document one, although the evaluation of the documents can be also stored in the profiles. The main advantage of representing the profiles at the term level is the use of terms in the profiles as possible queries. This storage of user preferences in the low level, allows us to compare the terms to other terms in documents, queries, user profiles, etc.

Taking into account that users querying a system can be considered 'experts' in different fields, we can obtain a set of expert profiles after the filtering process. The knowledge extracted from these expert profiles can be used to help non-expert users to query an IRS. In this way, the non-expert user can take advantage of the expert awareness about a certain topic, besides of the time spent in the document evaluation.

3 Aggregation of Expert Profiles

When an expert user queries a system, a filtering process can be carried out, and a user profile can be generated. We call this profile *expert profile*. We can assume that expert profiles have some advantageous features. On the one hand, the documents evaluated by the expert about a topic, that can be stored in the profile, have a guarantee, in some way, above documents evaluated by non-expert users in the topic. On the other hand, the terms representative from those documents to be stored in the profiles, can be terms extracted from the query of the expert or from the retrieved documents (title, abstract, keywords, indexing terms, body, etc.). These terms, besides coming from documents evaluated as relevant from expert users in the topic, can be valuable for non-expert users and can suggest query terms that do not come to the non-expert user's mind in a natural way. This is generally due to a lack of knowledge about the technical words, or about translating words into other language related to the queried topic.

When we deal with a group of experts $\{E_1, \dots, E_p\}$, we can consider two different situations for this model:

- **A Unique Query:** This situation is the simplest because all the experts query the system using the same terms. The set of retrieved documents is the same for all the experts, assuming that the system for all of them has the same document collection. The evaluation of the documents from all the experts can be aggregated for each document. From the overall aggregation of the documents, we can extract the terms to be part of the 'topic profile'. Another possibility is to obtain first the different profiles of the experts by extracting terms from documents on the basis of documents' relevance (according to the expert's evaluation). The topic profile can be obtained from the aggregation of these expert profiles.
- **Several Queries:** In this case, the experts make different queries to the system, which implies to retrieve different sets of documents for each query. As the experts evaluate different sets of retrieved documents, the best way to aggregate this information is to aggregate the corresponding profiles. Therefore, we first construct the profiles for each expert, and then we can aggregate them to obtain the topic profile. Another possibility is to combine previously the document sets obtained by each expert in order to obtain an unique ranked list of documents based on the reliability of each expert.

In the following, we present some ideas to face with the problem when an unique or several queries are performed by the experts. In all the cases, we assume that the expert opinions are numerically expressed. Further considerations and proposals where expert opinions are given by symbolic statements or by pure ordinal opinions can be found in (Delgado et al., 2001).

3.1.1 Expert Profile Aggregation with a Unique Query

Let $q = (t_1 r_1, ..., t_h r_h)$ be the query formulated by the experts $\{E_1, \ldots, E_p\}$, where $(r_1, \ldots, r_k)$ are importance weights associated to the terms in the query (Bordogna et al., 1995), which can be given by the experts. An unique document set $\{D_1, \ldots, D_M\}$ is retrieved as a response to the query q.

Thus, let assume that the expert E_k is able to assess the relevance of the document D_j for the topic Π to be $u_{kj} \in [0,1]$, $k=1,\ldots, P$; $j=1,\ldots, M$. Then the experts' opinions may be summarized into the matrix:

$$U = (u_{kj})_{k=1,\ldots,P;\, j=1,\ldots,M} \; . \tag{2}$$

Two different situations arise at this point:

- We can first aggregate experts opinions (the rows in U) into a only global evaluation vector $(u_1, ..., u_M)$ and then, obtain a topic profile as in a filtering problem, where starting from a set of documents and their evaluations by the user, we can obtain the user profile. The topic profile is a set of terms selected from the evaluated documents, and importance weights that can be utilized in future queries by non-expert users. We represent the topic profile by $\Pi = (t_1 w_1, ..., t_n w_n)$.
- We can first construct the profile $z_i = (t_{i1} w_{i1}, \ldots, t_{ik} w_{ik}), 1 \le i \le p$, $1 \le k \le n$ for each expert as the result of the filtering process with the document evaluations of each expert, and then aggregate the weights related to each profile into an unique topic profile $\Pi = (t_1 w_1, ..., t_k w_k)$.

As in the first model, approaches to solve group decision and/or consensus problems can be used (Delgado et al., 1998).

3.1.2 Expert Profile Aggregation with Several Queries

In this case, each expert E_k formulates a query $q_k = (t_1 r_{k1}, ..., t_h r_{kh})$, $1 \le k \le P$, $1 \le h \le N$, where $(r_1, \ldots, r_k)$ are again the weights associated to the term queries, that can be different for each term and expert (a simplification of the model would be the consideration of the query without these importance degrees). A set of documents $\{D_{k1}, \ldots, D_{kM}\}$ is retrieved as a response to each query q_k formulated by the expert E_k. Each expert evaluates the document set, given an evaluation vector $\{U_{k1}, \ldots, U_{kM}\}$. A profile $z_k = (t_{k1} w_{k1}, ..., t_{kh} w_{kh})$, $1 \le k \le p, 1 \le h \le N$ defined as a set of terms with associated importance weights related to the topic Π is constructed for each expert. Once all the expert profiles $\{z_1, ..., z_p\}$ have been obtained, an aggregation process is needed in order to obtain an overall topic profile.

4 An Experimental Example

In order to test the proposed model, we have considered a system for constructing user profiles based on previous research, where genetic algorithms are utilized (Martín-Bautista et al., 2002b). In this system, a profile is constructed based on the feedback of the user over a previous set of documents retrieved as a result of a query to an IRS. Initially, the population of the genetic algorithm is initialized with indexing terms from the first set of retrieved documents. With the evaluation given by the user over some of the retrieved documents, the weights of terms in the population are recalculated and the population evolves towards the space of terms that best represents the user's preferences. Each chromosome of the population is a possible query representing the user's preferences. When the profile is an expert one, the queries (chromosomes) in the population can be considered as 'high-quality' possible queries about the topic the expert asked.

In previous experiments, all the population has been considered as user profile, since the profile as a whole is used to initialize the population again when a new query in the same channel is carried out. The size and the chromosome length considered for the population was 80 chromosomes and 10 terms each chromosome, respectively. We have to take into account that a term can appear more than once in a chromosome. The chromosomes represented in Table 4 contain only different terms within each chromosome.

The simulation of the process is made considering the first model where an unique query is formulated for all the experts. A query with the terms "genetic algorithms" is performed using *Google*. The first set of documents retrieved from this query is shown in Table 1. In a second step, the experts see the documents and feedback the system by an interface that allows us to assign a label to each document. The labels are (*very high*, *high*, *medium*, *low*, *very low*). The feedback of the experts for the top ten documents is detailed in Table 2.

Table 1. Top 10 results of Google to the query 'genetic algorithms'

Document Id.	Document address
D_1	http://www.aic.nrl.navy.mil/galist
D_2	http://gal4.ge.uiuc.edu/illegal.home.html
D_3	http://www.cs.cmu.edu/Groups/AI/html/fqas/ai/genetic/top.html
D_4	http://cs.gmu.edu/research/gag/
D_5	http://www.scs.carleton.ca/~csgs/resources/gaal.html
D_6	http://www.fqas.org/fqas/ai-faq/genetic/
D_7	http://lancet.mit.edu.ga/
D_8	http://www.mat.sbg.ac.at/~uhl/GA.html
D_9	http://www.cs.bgu.ac.il/~omri/NNUGA/
D_{10}	http://www.aridolan.com/ga/gaa/gaa.html

Table 2. Evaluations of experts to the top 10 results of Google to the query 'genetic algorithms'

Document Id	Expert 1	Expert 2	Expert 3	Expert 4
D_1	*very high*	---	---	*high*
D_2	---	*very high*	---	---
D_3	*very high*	---	---	*medium*
D_4	*High*	*very high*	*medium*	---
D_5	---	*very high*	---	*Very high*
D_6	*very high*	---	---	*medium*
D_7	---	---	*very high*	---
D_8	*very high*	---	---	*medium*
D_9	---	*Low*	---	---
D_{10}	---	---	*very high*	---

As we have explained above, the experiments have been performed according to the first model explained in Sect. 3.1.1 where all the experts query the system with the same terms and the opinions of the experts are first aggregated and then the profile of the aggregation is generated. Supposing we aggregate using the AND operator, the results of the aggregation over the expert evaluations can be seen in Table 3. If a document is not evaluated by all the experts, the aggregation will be only over the available evaluation given by some of the experts.

The best first chromosomes generated by these aggregated evaluations are shown in Table 4. The complete population can be used as a starting point for a new query. From this population, a list of terms with their weights is extracted to form the topic profile. Any of them may be used as user guide to retrieve information about the topic, with the suggestion of new terms related to the original query ones.

Table 3. Aggregation of expert evaluations

Doc. Id.	D_1	D_2	D_3	D_4	D_5	D_6	D_7	D_8	D_9	D_{10}
Expert Aggreg.	*me-dium*	*very high*	*me-dium*	*me-dium*	*high*	*me-dium*	*very high*	*me-dium*	*low*	*very high*

Table 4. Chromosomes of the population of the genetic algorithm to construct the topic profile 'genetic algorithms'

Valuation	Chromosome
Very high	(schwefel, org, Pollack, algorithms, illegal, kinds, purpose, traveling, multi)
Very high	(programming, rastrigin, ziv, galib, algorithms, implemented, faq, optimization)
Very high	(witty, modal, nature, laboratory, search, algorithms, omri)
Very high	(neural, org, Pollack, algorithms, Alabama, index, matthew, java, algorithms, page)
Very high	(traveling, unconventional, reference, urbana, technology, nnuga, introductory, web, algorithms)
Very high	(nnuga, algorithms, ackley, related, Alabama, experiments, playground, rastrigin, links)

Table 4. (Continuation)

Valuation	Chromosome
Very high	(evolutionary, unconventional, free, references, rosenbrock, algorithms, Pollack, bibliographies, examples)
High	(tools, online, designed, references, rosenbrock, search, life, final, experiments, algorithms)
High	(faq, sphere, active, algorithms, applied, resources, Pollack, neural, ep)
High	(links, online, experiments, life, diverse, lab, algorithms, griewank, list, programming)

5 Concluding Remarks and Future Work

We have presented a system that allows us to construct a topic profile when expert profiles about queries related to the topic are available. The resulting topic profile can be used in two different ways: on the one hand, a list of terms with associated importance weights can be shown to novel users for suggesting queries that do not come naturally to users' mind. On the other hand, the topic profile in its original form of chromosomes of a genetic algorithm can be used as starting population for future queries of novel users.

Several situations arise based on the way experts query the system (by an unique query or several queries), and the aggregation method: we can aggregate first the experts opinions over the top documents and then obtain a topic profile, or we can first obtain the experts profiles based on their evaluations, and then aggregate them to generate the topic profile.

We have to point out the dynamical aspect of the system. The topic profile may be incrementally constructed by aggregating the opinion of several users, when the users are the experts themselves.

In the future, other aggregation operators that incorporate the existence of weights measuring the importance or reliability assigned to each expert opinion will be considered. Further experiments where each expert asks the system about the same topic but with different queries will be performed as well.

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