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Image Based Personalized Search from the Picture Sharing Websites

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Abstract
Although search has become a popular feature in many search engines, including Yahoo!, MSN, Google, etc., the majority of image searches use very little, if any, image information. Due to the success of text-based search of Web pages and, in part, to the difficulty and expense of using image based signals, most search engines return images solely based on the text of the pages from which the images are linked.Web search engines help users find useful information on the World Wide Web (WWW). However, when the same query is submitted by different users, typical search engines return the same result regardless of who submitted the query. Users are increasingly pursuing complex task oriented goals on the Web, such as making travel arrangements, managing finances or planning purchases. Searchers create and use external records of their actions and the corresponding results by writing/typing notes, using copy and paste functions, and making printouts. The social media sites, such as Flickr and del.icio.us, allow users to upload content and annotate it with descriptive labels known as tags, join special-interest groups, etc. We believe user-generated metadata expresses user's tastes and interests and can be used to modified information to an individual user. Specifically, we describe a machine learning method that analyzes a corpus of tagged content to find hidden topics. We then these learned topics to select content that matches user's interests. We empirically validated this approach on the social picture-allocation site Flickr, which allows users to annotate icon s with freely chosen tags and to search for icon s labeled with a certain tag. We use metadata associated with icon s tagged with an ambiguous query term to identify topics corresponding to different senses of the term, and then modified results of icon search by displaying to the user only those icon s that are of interest to her.

Keywords
Modified D Icon Search, Information Search (IS). Web Revolution, Topic Model, Social Annotation, Data Mining

I. Introduction
The research overview described focuses on the design of search history displays to support information Search (IS). Web personalization refers to the process of customizing. It is used by advertising firms to target ads to a particular user. Search personalization has also been studied as a way to improve the quality of Web search by disambiguating query terms based on user's browsing history or by eliminating irrelevant documents from search results. Personalizing icon search is an especially challenging problem, because, unlike documents, icon s generally contain little text that can be used for disambiguating terms. Consider, for example, a user searching for pictures of "jaguars." Should the system return icon s of luxury cars or spotted felines to the user? In this context, personalization can help disambiguate query keywords used in icon search or to weed out irrelevant icon s from search results. Therefore, if a user is interested in wildlife, the system will show her icon s of the predatory cat of South America and not of an automobile.

However, when the same query is submitted by different users, most search engines return the same results regardless of who submits the query. In general, each user has different information needs for his/her query.

In order to predict such information needs, there are several approaches applying data mining techniques to extract usage patterns from Web logs. However, the discovery of patterns from usage data by itself is not sufficient for performing the personalization tasks. Furthermore, Shahabad and Chen [37] have pointed out that the item association generated from Web server logs might be wrong because Web usage data from the server side are not reliable. Therefore, these techniques are not so appropriate for Web personalization.

As far as we know, three types of Web search systems provide such information One of information-Search tasks often performed by students is Information Gathering, which is the extracting, evaluating, and organizing relevant information for a given topic. One important step towards enabling services and features that can help users during their complex search quests online is the capability to identify and group related queries together. Recently, some of the major search engines have introduced a new "Search History" feature, which allows users to track their online searches by recording their queries and clicks. The user's past (implicit) indication of document relevance we can predict his/her reaction to the current retrieved documents.

For example, if the user searched with the same query "python" before and clicked on Python language website's link, we have high confidence that the user would do it again this time, and it makes good sense to list that webpage in the top. Even when there is no exact occurrence of the current query in history, we may still find similar queries like "python doc" helpful (e.g., discovering that the user prefers results from the www.python.org site). Recommendations for search history displays and two search history based user interface tools are described here, which take advantage of automatically recorded information. In fact, identifying groups of related queries has applications beyond helping the users to make sense and keep track of queries and clicks in their search history[5]. First and foremost, query grouping allows the search engine to better understand a user's session and potentially tailor that user's search experience according to her needs. Once query groups have been identified, search engines can have a good representation of the search context behind the current query using queries and clicks in the corresponding query group.

In this paper, we study the problem of organizing a user's search history into a set of query groups in an automated and dynamic fashion. Each query group is a collection of queries by the same user that are relevant to each other around a common informational need. These query groups are dynamically updated as the user issues new queries, and new query groups may be created over time. Existing click through-based user profiling strategies can be categorized into document-based and concept based approaches. They both assume that user clicks can be used to infer users' interests, although their inference methods and the outcomes of the inference are different.

II. Motivation

A. Information Search (IS)

The Information Search Process (ISP) presents a holistic view of information Search from the user's perspective in six stages: task initiation, selection, exploration, focus formulation, collection and presentation. The six stage model of the ISP incorporates three realms of experience: the affective (feelings) the cognitive (thoughts) and the physical (actions) common to each stage (1). The ISP reveals information Search as a process of construction influenced by Kelly's personal construct theory (2) with information increasing uncertainty in the early stages of the ISP.

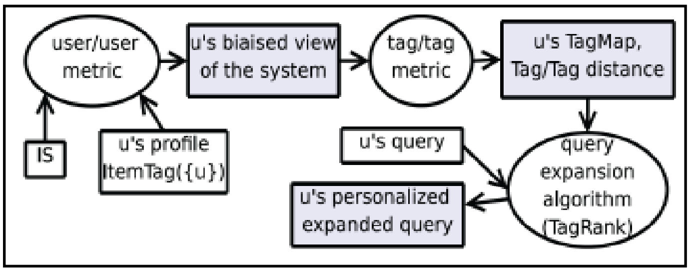

Fig. 1: Information Search (IS)

The development of the ISP as a conceptual framework is the result of more than two decades of empirical research that began with a qualitative study of secondary school students and the emergence of an initial model, that was verified and refined through quantitative and longitudinal methods of diverse library users and further developed in case studies of people in the workplace. To summarize the findings of these studies of the user's perspective of the ISP, the affective symptoms of uncertainty, confusion and frustration prevalent in the early stages are associated with vague, unclear thoughts about a topic or problem. As knowledge states shifted to clearer, more focused thoughts a corresponding shift was noted in feelings of increased confidence and certainty. Affective aspects, such as uncertainty and confusion can influence relevance judgments as much as cognitive aspects, such as personal knowledge and information content. Central in the model of the ISP is uncertainty described formally as a principle of uncertainty for information Search. Increased uncertainty in the exploration stage of the ISP indicates a zone of intervention for intermediaries and system designers

B. The Web Revolution

The Web has turned from a read-only infrastructure with passive participants into a read-write platform with active players. The language: instead of subject indexing with a controlled vocabulary, freely chosen keywords are used to tag billions of items, e.g. URL (Delicious). The user- generated taxonomy is called folksonomy (folk + tax- anomy) and is used to label and share user-generated content (e.g picturegraphs), or to collaboratively label existing content (e.g Web sites, books, or blog entries). Part of the appeal of a folksonomy is its inherent subversiveness: folksonomies can be seen as a rejection of the traditional search engine status quo in favors of tools that are created by the community. In theory, precisely because folksonomies develop Internet-mediated modified d environments, one could dynamically discover the tag sets of another user who tends to interpret and tag content in a similar manner. The result could be a rewarding gain in the user's capacity to related content, a practice known as "pivot browsing".

C. Modified d Web Sites

Link topology and the structure and contents of Web pages are often used in the construction of a modified d Web site. In this section, we review the framework of these systems with regard to "Link Personalization," and "Content Personalization."

1. Link Personalization

This scheme involves selecting the links that are more relevant to the user and changing the original navigation space by reducing or improving the relationships between Web pages. E-commerce applications use link personalization to recommend items based on the buying history of clients or some categorization of clients based on ratings and opinions. Users who give similar ratings to similar objects are presumed to have similar preferences, so when a user seeks recommendations about a certain product, the site suggests those recommendations that are most popular for his/her class or those that best correlate with the given product for that class. At the E-commerce site for Amazon.com2, this approach has been taken to an extreme by constructing a "New for you" home page and presenting it to each user, with new products that the user may be interested in. Additionally, Amazon.com uses implicit recommendations via purchase history and/or explicit recommendations via "rate it" features to generate recommendations of products to purchase. In a recent study, Sundials and Schaefer [46] proposed a system that automatically adapts links in the browsed pages based on their relevance to the weighted topics specified by sliders that users can manipulate.

2. Content Personalization

In general, content personalization is done when pages present different information to different users. The difference between this and "Link Personalization" described because part of the contents (i.e., the link anchors) presents different information when links are modified d. However, content personalization is referred to when substantial information in a Web page is modified d, unlike link anchors. For example, Bharat et al. presented "Krakatau Chronicle", an interactive modified d newspaper on theWWWthat allows for interactive personalization, browsing and layout control. Moreover, My Yahoo! or My Netscape4 filters the information that is relevant to the user, showing only sections and details in which the user may be interested. The user may explicitly indicate his/her preferences, or preferences may be inferred (semi-) automatically from his/her profile or from his/her navigation activity. At these sites, users choose a set of "modules" from a large set including weather, news, music and so on, and further modified these modules by choosing a set of attributes of the module to be perceived.

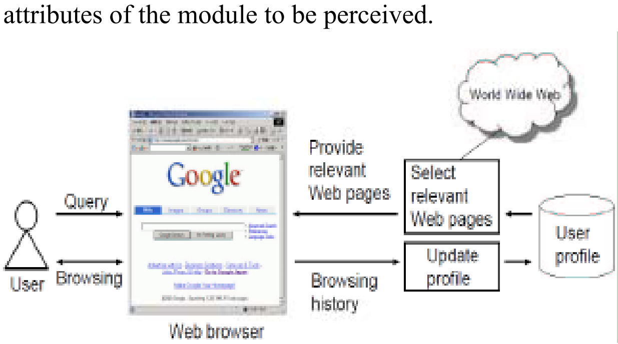

Fig. 2: System Overview

III. Existing System

In Existing System, Users may have different intentions for the same query, e.g., searching for "jaguar" by a car fan has a completely

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different meaning from searching by an animal specialist. One solution to address these problems is modified d search, where user-specific information is considered to distinguish the exact intentions of the user queries and re-rank the list results. Given the large and growing importance of search engines, modified d search has the potential to significantly improve searching experience

Fig. 3: Results for the Query "Jaguar"

IV. Proposed System

A. Leveraging User-Generated Metadata for Personalization

An explosion not only in user-generated content, but also in user-generated metadata. This "data about data" is expressed in a number of ways on the Social Web sites: through tags (descriptive labels chosen by the user), ratings, comments and discussion about its, items that users mark as their favorite, and through the social networks users create and the special-interest groups they participate in. This metadata provides a wealth of information about individual user's tastes, preferences and interests. Social Web sites currently don't make much use of this data, except perhaps to target advertisement to individual users or groups. However, this data has the potential to transform how users discover, process and use information. For example, Web browsing and search can be tuned to an individual user based on his or her expressed interests. Rather than requiring the user disambiguate query terms, e.g., through query expansion, in order to improve results of Web search, a personalization system would infer a user's meaning based on the rich trace of content and metadata the user has created. Such metadata could also filter the vast stream of new content created daily on the Web and recommend to the user only that content the user would find relevant or interesting. Personalization, recommendation and filtering are just some of the applications of user-generated metadata that have recently been explored by researchers.

B. Issues, Controversies, Problems

The distinguishing feature of tagging systems is that they use an uncontrolled vocabulary, and that the user is free to highlight any one of the object's properties. From an algorithmic point of view, tagging systems offer many challenges that arise when users try to attach semantics to objects through keywords. These challenges are homonymy (the same tag may have different meanings), polysemy (tag has multiple related meanings), synonymy (multiple tags have the same meaning), and "basic level" variation (users describe an item by terms at different levels of specificity, e.g., "beagle" vs "dog"). Despite these challenges, tagging is a light weight, flexible categorization system. In a small case study we show how tags on the social picture-allocation site Flickr can be used to modified results of icon search.

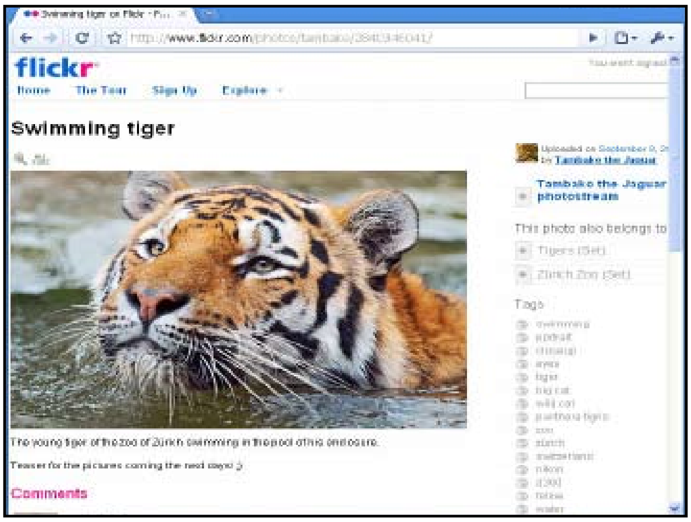

Fig. 4: Screen Shot of an Icon Page of Flickr User Tambako the Jaguar Showing the Icon and the Tags He Attached to the Icon

Flickr consists of a collection of interlinked user, picture, tag and group pages. A typical Flickr picture page, shown in fig. 1, provides a variety of information about the icon : who uploaded it and when, what groups it has been submitted to, its tags, who commented on the icon and when, how many times the icon was viewed or bookmarked as a "favorite." The user calling himself (user's may reveal their gender in their profile, as this user has chosen to do) "Tambako the Jaguar" posted a picturegraph of a swimming tiger at a Swiss zoo. To the right of the icon is a list of keywords, tags, the user has associated with the icon .1 These tags include "tiger," "big cat," "wild cat," "panther tigris," and "feline," all useful terms for describing this particular sense of the word "tiger." Clicking on a user's name

brings up that user's picture stream, which shows the latest pictures he uploaded, the icon s he marked as "favorite," and his profile, which gives information about the user, including a list of his social network (contacts) and groups he belong to. Clicking on the tag shows user's icon s that have been tagged with that keyword, or all public icon s that have been similarly tagged.

Fig. 5: Tag Cloud View of the Tags the Owner of the Icon in fig. 1, used to annotate his icon s. The bigger the font, the more Frequently that Tag was Used by the User

These tags clearly show that the user is interested in wildlife (big cat, cat, lion, cheetah, tiger, tiger, wildcat) and nature (clouds, mountains) picturegraphy. They also show that he shoots with a Nikon (Nikon, d300) and has traveled extensively in Europe (Switzerland, Germany, France) and parts of Africa (Kenya). These interests are further reflected in the groups the user joined, which are listed on his profile page, that include such ad-hoc groups as “Horns and Antlers,” “Exotic cats,” “Cheetah Collection,” and many others. In this work, we view group names just as we treat tags themselves. In fact, group names can be viewed as publicly agreed-upon tags. Flickr allows users to search for pictures that contain specified keywords in their descriptions (including titles) or tags. A user can search all public pictures, or restrict the search to pictures from her contacts, her own pictures, or pictures she marked as her favorite. Search results are by default displayed in reverse chronological order of being uploaded, with the most recent icon s on top. Another option is to display icon s by their “interestingness”, 2 with the most “interesting” icon s on top. Suppose a user is interested in wildlife picturegraphy and wants to see icon s of tigers on Flickr.

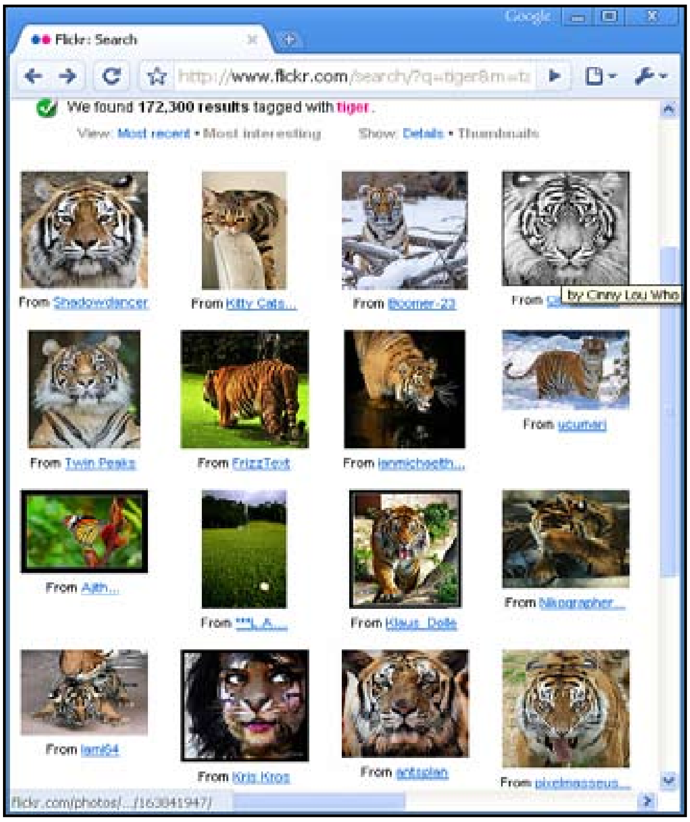

Fig. 6: Results of Icon Search on Flickr for Icon s Tagged with Tiger”

We assume that when a search term is ambiguous, the sense that the user has in mind is related to his or her interests. A wildlife picturegrapher searching for “tiger” icon s is probably not interested in picturegraphs of children with face paint. Similarly, a child picturegrapher searching for pictures of “Newborns” is most likely interested in icon s of human babies, not kittens or tiger cubs. In this chapter we show that we can improve the relevance of icon search by personalizing icon search results on Flickr. We use user-generated metadata, in the form of tags and the groups, for this purpose. Inferring personal interests from tags, however, is problematic, since this data is sparse (few tags per icon) and noisy (idiosyncratic vocabulary use, synonyms, etc). Machine learning methods, which try to find statistical correlations in the data, directly address some of these challenges. In the section below, we describe a machine learning-based method that exploits information contained in user-generated metadata, specifically tags, to modified icon search results to an individual user.

V. Probabilistic Model for Tag-based Personalization

We outline a probabilistic model that takes advantage of the icon s’ tag and group information to discover latent topics contained in a set of icon s. If the dataset is a result of a search for icon s that have been tagged with the query term, the topics correspond to different senses of the query term. The users’ interests can similarly be described by collections of tags they used to describe their own icon s. The latent topics found by the model can be used to modified search results by finding icon s on topics that are of interest to the user.

We consider four types of entities in the model: a set of users U={u1, ... ,un}, a set of icon s or pictures I={i1, ... ,im}, a set of tags T={t1, ... ,to}, and a set of groups G={g1, ... , gp}. A picture ix posted by user (icon owner) ux is described by a set of tags {tx1, tx2, ...} and submitted to several groups {gx1, gx2, ...}. This post could be viewed as a tuple <ix, ux, {tx1, tx2, ...},{gx1, gx2, ...}>. We assume that there are n users, m posted pictures and p groups in Flickr. Meanwhile, the vocabulary size of tags is q. In order to filter icon s retrieved by Flickr in response to tag search and modified them for a user u, we compute the conditional probability p(i|u), that describes the probability that the picture i is relevant to u based on her interests. Icon s with high enough p(i|u) are then presented to the user as relevant icon s. As mentioned earlier, users choose tags from an uncontrolled vocabulary according to their styles and interests. Icon s of the same subject could be tagged with different keywords although they have similar meaning. Meanwhile, the same keyword could be used to tag icon s of different subjects. In addition, a particular tag frequently used by one user may have a different meaning to another user. Probabilistic models offer a mechanism for addressing the issues of synonymy, homonymy and tag sparseness that arise in tagging systems.

We use a probabilistic topic model (Rosen-Zvi, 2004) to model user’s icon posting behaviour. As in a typical probabilistic topic model, topics are hidden variables, representing knowledge categories. In our case, topics are equivalent to icon owner’s interests. The process of picture posting by a particular user could be described as a stochastic process:

- User u decides to post a picture i.
- Based on user u’s interests and the subject of the picture, a set of topics z are chosen.
- Tag t is then selected based on the set of topics chosen in the previous state.
- In case that u decides to expose her picture to some groups, a group g is then selected according to the chosen topics.

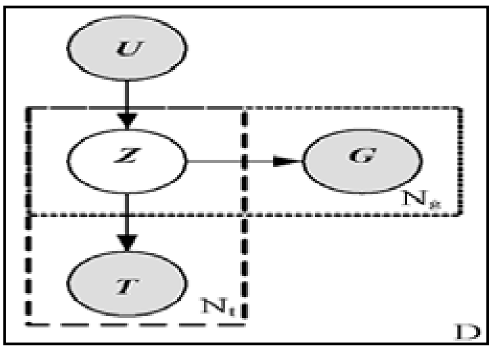

Fig. 7: Graphical Representation for Model-Based Information Filtering. U, T, G and Z Denote Variables

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"User", "Tag", "Group", and "Topic" respectively. Nt represents a number of tag occurrences for a one picture (by the picture owner); D represents a number of all pictures on Flickr. Meanwhile, Ng denotes a number of groups for a particular picture.

The process is depicted in a graphical. We do not treat the icon i as a variable in the model but view it as a co-occurrence of a user, a set of tags and a set of groups. From the process described above, we can represent the joint probability of user, tag and group for a particular picture as

$$p(i) = p(u_i, T_i, G_i) = p(u_i)\left(\prod_{n_t}\left[\sum_k p(z \mid u_i)p(t_i \mid z)\right]^{n_i(t)}\right)\cdot\left(\prod_{n_g}\left[\sum_k p(z \mid u_i)p(g_i \mid z)\right]^{n_i(g)}\right)$$

nt and ng are the numbers of all possible tags and groups respectively in the data set. Meanwhile, ni(t) and ni(g) act as indicator functions: ni(t)=1 if an icon i is tagged with tag t; otherwise, it is 0. Similarly, ni(g)=1 if an icon i is submitted to group g; otherwise, it is 0. k is the predefined number of topics. Note that it is straightforward to exclude picture's group information from the above equation simply by omitting the terms relevant to g. In order to estimate parameters p(z|ui), p(ti|z), and p(gi|z), we define a log likelihood L=log((ip(i)), which measures how the estimated parameters fit the observed data, in our case all the pictures in the dataset. L is used as an objective function to estimate all parameters. In the expectation step (E-step), the joint probability of the hidden variable Z given all observations is computed from the following equations:

$$p(z \mid t,u) \propto p(z \mid u)\cdot p(t \mid z)$$
$$p(z \mid g,u) \propto p(z \mid u)\cdot p(g \mid z)$$

L cannot be maximized easily, since the summation over the hidden variable Z appears inside the logarithm. We instead maximize the expected complete data log-likelihood over the hidden variable, E[Lc], which is defined as

$$\begin{aligned} E[L^c] &= \sum_m \log(p(u) \\ &+ \sum_m\sum_t n_i(t)\cdot\sum_z \mathrm{p(z \mid u,t)\log(p(z \mid u)\cdot p(t \mid z))} \\ &+ \sum_m\sum_g n_i(g)\cdot\sum_z \mathrm{p(z \mid u,g)\log(p(z \mid u)\cdot p(g \mid z))} \end{aligned}$$

Since the term log (p(u) is not relevant to parameters and can be computed directly from the observed data, we discard this term from the expected complete data log likelihood.

$$\begin{aligned} H = E[L^c] &+ \sum_z \tau_z\left(1-\sum_t p(t \mid z)\right) \\ &+ \sum_z \rho_z\left(1-\sum_t p(g \mid z)\right) \\ &+ \sum_u \psi_u\left(1-\sum_z p(z \mid u)\right) \end{aligned}$$

We maximize H with respect to p(t|z), p(g|z), and p(z|u), and then eliminate the Lagrange multipliers to obtain the following equations for the maximization step:

$$p(t \mid z) \propto \sum_i n_i(t)\cdot p(z \mid t,u)$$
$$p(g \mid z) \propto \sum_i n_i(g)\cdot p(z \mid g,u)$$
$$p(z \mid u) \propto \sum_i\left(\sum_t n_i(t)\cdot p(z \mid t,u)+\sum_g n_i(g)\cdot p(z \mid g,u)\right)$$

The algorithm iterates between E and M step until the log likelihood for all parameter values converges. Additional details about model derivation and inference method can be found. We can use the parameters inferred from the dataset to find the icon s i most relevant to the interests of a particular user u'. We do so by computing the conditional probability p(i|u'):

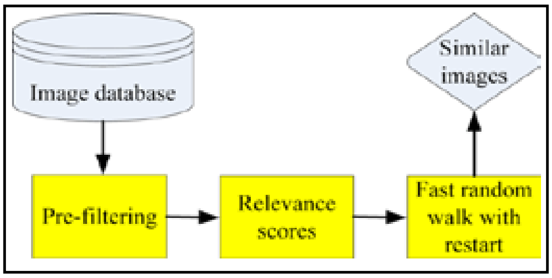
$$p(i \mid u') = \sum_z p(u_i, T_i, G_i \mid z)\cdot p(z \mid u')$$

Where ui is the owner of icon i in the data set, and Ti and Gi are, respectively, the set of all the tags and groups for the icon i.

We represent the interests of user u' as an aggregate of the tags she used in the past for tagging her own icon s. This information is used to to approximate p(z|u'):

$$p(z \mid u') \propto \sum_t n(t'=t)\cdot p(z \mid t)$$

where n(t'=t) is a frequency (or weight) of tag t' used by u'. Here we view n(t'=t) as proportional to p(t'|u'). Note that we can use either all the tags u' had applied to the icon s in her picturestream, or a subset of these tags, e.g., only those that co-occur with some tag in user's icon s.



VI. Conclusion

In addition to creating content, users of Web sites generate large quantities of metadata, or data about data, that describe their interests, tastes and preferences. These metadata, in the form of tags and social networks, are created mainly to help users organize and manage their own content. These types of metadata can also be used to target relevant content to the user through recommendation or personalization. This describes a machine learning-based method for personalizing results of icon search on Flickr. Our method relies on metadata created by users through their everyday activities on Flickr, namely the tags they used for annotating their icon s and the groups to which they submitted these icon s. This information captures user's tastes and preferences in picturegraphy and can be used to modified icon search results to the individual user. We validated our approach by showing that it can be used to improve precision of icon search on Flickr for three ambiguous terms: "newborn," "tiger," and "beetle." In addition to improving search precision, the tag-based approach can also be used to expand the search by suggesting other relevant keywords (e.g., "pantheratigris," "big cat" and "cub" for the query "tiger").

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