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Stipulated Ranking Technique for Image Search Engines

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Abstract -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 personalize 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 photo-sharing site Flickr, which allows users to annotate images with freely chosen tags and to search for images labeled with a certain tag. We use metadata associated with images tagged with an ambiguous query term to identify topics corresponding to different senses of the term, and then personalize results of image search by displaying to the user only those images that are of interest to her.

Keywords: Social Annotation, Personalized Search, Tagging, Collaborative Filtering, Metadata, RMTF, User preference, User Specific topic, Query relevance

INTRODUCTION

The rise of the Social Web underscores a fundamental transformation of the Web. Rather than simply searching for, and passively consuming, information, users of blogs, wikis and social media sites like del.icio.us, Flickr and digg, are creating, evaluating, and distributing information. In the process of using these sites, users are generating not only content that could be of interest to other users, but also a large quantity of meta data in the form of tags and ratings, which can be used to improve Web search and personalization.

Web personalization refers to the process of customizing Web experience to an individual user (Mobasher, 2000). Personalization is used by online stores to recommend relevant products to a particular user and to customize a user's shopping experience. 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 (Ma, 2007) by disambiguating query terms based on user's browsing history or by eliminating irrelevant documents from search results.

Personalizing image search is an especially challenging problem, because, unlike documents, images generally contain little text that can be used for disambiguating terms. Consider, for example, a user searching for photos of "jaguars." Should the system return images of luxury cars or spotted felines to the user? In this context, personalization can help disambiguate query keywords used in image search or to weed out irrelevant images from search results. Therefore, if a user is Interested in wildlife, the system will show her images of the predatory cat of South America and not of an automobile.

In this chapter we explore a novel source of evidence – user-generated meta data – that can be used to personalize image search results. We perform a case study of the technique on the social photo sharing site Flickr, which allows users to upload images and label them with freely-chosen keywords, known as tags. Tags are meant to help users organize content and make it searchable by themselves and others. In addition to describing and categorizing images, tags also capture user's photography interests. We use a machine learning method to find topics of a large corpus of tagged images returned by image search on Flickr. We then use the learned topics to match images to an individual user's interests. This appears to be a promising method for improving the quality of image search results.

BACKGROUND

Traditionally,personalization techniques fall in one of two categories: collaborative-filtering or profile based. The first, collaborative filtering (Breese, 1998; Schafer, 2007), aggregates opinions of many users to recommend new items to like-minded users. In these systems, users are asked to rate items on a universal scale. The system then analyses ratings from many users to identify those sharing similar opinions about items and recommends new items that these users liked. Netflix uses collaborative filtering to recommend movies to its subscribers. Amazon uses a similar technology to display other products that users who purchased a given product were also interested in. Since users are asked to rate items on a universal scale, the questions of how to design the rating system and how to elicit high quality ratings from users are very important. Despite the early concern that users lack incentives for making recommendations and, therefore, will be reluctant to make the extra effort, there is new evidence (Schafer, 2007) that this does not appear to be the case. It appears that, at the very least, users find value in a collaborative rating system as an extension of their memory.

The second class of personalization systems uses a profile of user's interests to target items for user's attention. The profile can be created explicitly by the user (Ma, 2007), or mined from data about user's behaviour. Examples of the latter include data about user's Web browsing (Mobasher, 2000) and purchasing (Agrawal, 1994) behaviour. One problem with this approach is that it is time-consuming for users to keep their explicit profiles current. Another problem is that while data mining methods have proven effective and commercially successful, in most cases they use proprietary data, which is not easily accessible to researchers.

Machine learning has played an increasingly important role in personalization. (Popescul, 2001) proposed a probabilistic generative model that describes co-occurrences of users and items of interest. In particular, the model assumes a user generates her topics of interest; then the topics generate documents and words in those documents if the user prefers those documents. The author-topic model (Rosen-Zvi, 2004) is also used to find latent topics in a collection of documents and group documents according to topic. If a user prefers one document (or topic), this method can be used to recommend other relevant documents. These models, however, do not carry any information about individual users, their tastes and interests. However, a recent work this area described a mixture model for collaborative filtering that takes into account users' intrinsic preferences about items (Jin, 2006). In this model, item rating is generated from both the item type and user's individual preference for that type. Intuitively, like-minded users provide similar ratings on similar types of items (e.g., movie genres). When predicting a rating of an item for a certain user, the user's previous ratings on other items will be used to infer a like-minded group of users, and then the "common" rating of that group is used in the prediction. This type of model can conceivably be adapted to social metadata and be used to personalize results of image search.

LEVERAGINGUSER-GENERATED METADATA FOR PERSONALIZATION

The Web 2.0 has created 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.

Issues, Controversies, Problems

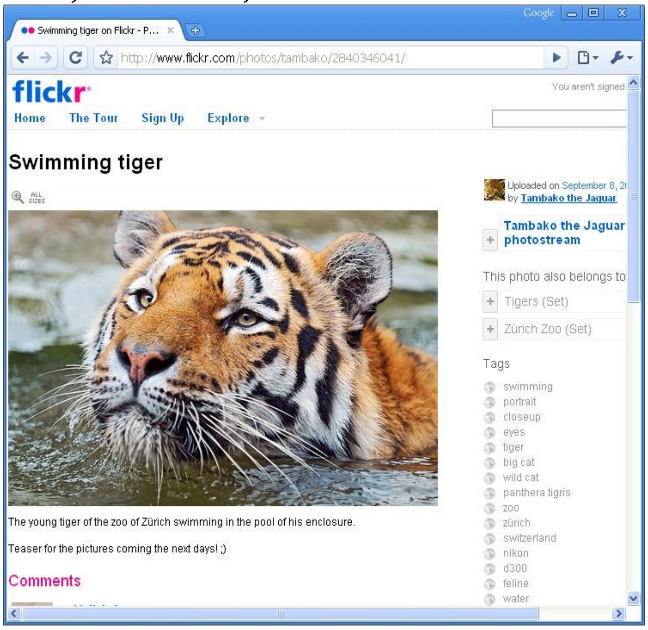


Figure 1

In this chapter we focus on tags, although the analysis can be easily expanded to include other types of metadata, including social networks (Lerman et al., 2007). Tags are freely-chosen keywords users associate with content. Tagging was introduced as a means for users to organize their own content in order to facilitate searching and browsing for relevant information. 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 (Golder, 2006). 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. The growing amount of tagged content provides evidence that users are adopting tagging on Flickr (Marlow, 2006), Del.icio.us and other collaborative tagging systems. In a small case study we show how tags on the social photo-sharing site Flickr can be used to personalize results of image search.

Flickr consists of a collection of interlinked user, photo, tag and group pages. A typical Flickr photo page, shown in Figure 1, provides a variety of information about the image: who uploaded it and when, what groups it has been submitted to, its tags, who commented on the image and when, how many times the image 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 photograph of a swimming tiger at a Swiss zoo. To the right of the image is a list of keywords, tags, the user has associated with the image.1 These tags include "tiger," "big cat," "wild cat," "panthera 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 photo stream, which shows the latest photos he uploaded, the images he marked as "favourite," 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 images that have been tagged with that keyword, or all public images that have been similarly tagged.

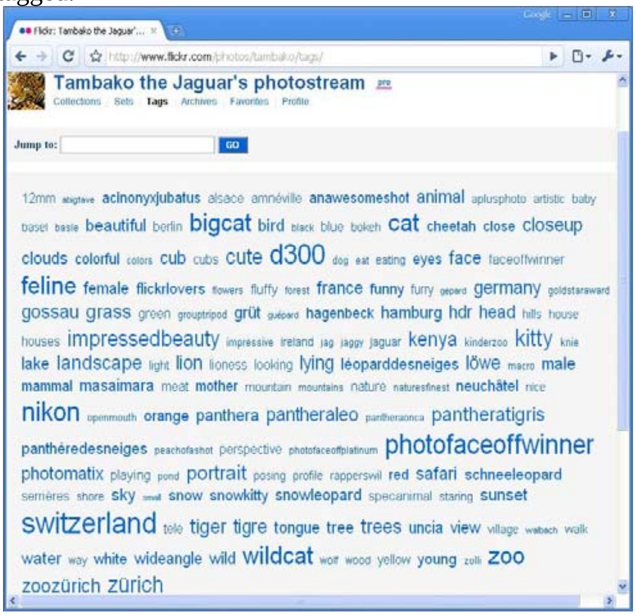


Figure 2

Information about a user's photography tastes and interests is contained in the rich metadata he creates in his everyday activities on Flickr. He expresses these interests through the contacts he adds to his social networks, the groups he joins, the images of other photographers he marks as his favourite or comments on, as well as through tags he adds to his own images. Figure 2 shows a tag cloud view of the tags that "Tamboko the Jaguar" used to annotate his images on Flickr. The bigger the font, the more frequently that keyword was used. These tags clearly show that the user is interested in wildlife (big cat, cat, lion, cheetah, tiger, tigre, wildcat) and nature (clouds, mountains) photography. 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.

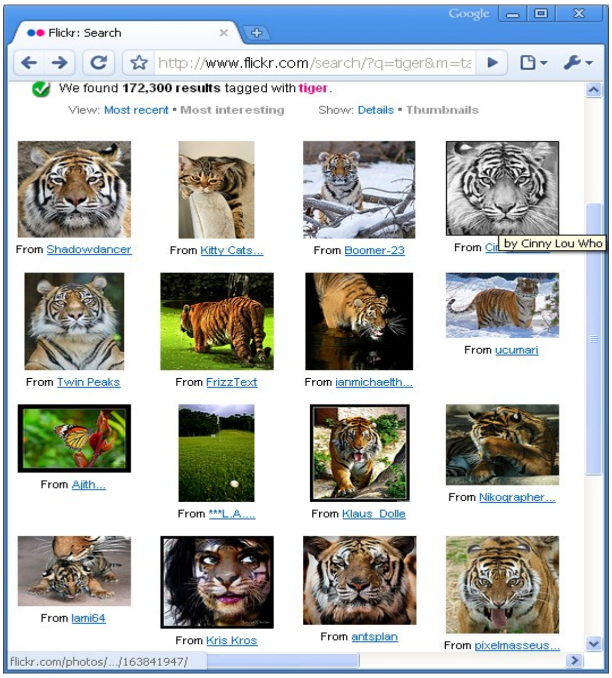


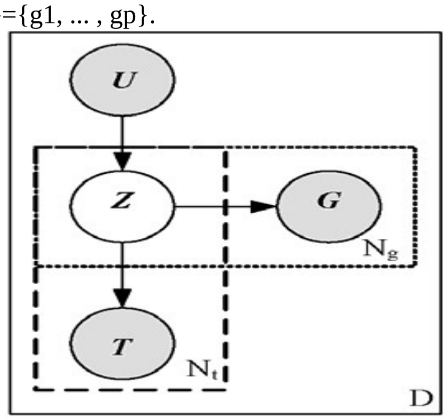
Figure 3

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 personalize image search results to an individual user.

PROBABILISTIC MODEL FOR TAG-BASED PERSONALIZATION

We outline a probabilistic model that takes advantage of the images' tag and group information to discover latent topics contained in a set of images. If the dataset is a result of a search for images 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 images. The latent topics found by the model can be used to personalize search results by finding images 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 images or photos I={i1, ... ,im}, a set of tags T={t1, ... ,to}, and a set of groups G={g1, ... , gp}.



Future Research Directions

User-generated metadata is a rich source of information about user's tastes and preferences that can be leveraged to personalize information to an individual user. This personalization can be applied to browsing and search. In this chapter we explored the use of tags and groups (which were also viewed as publicly agreed-upon tags) for representing user's interests. In addition to tags, users express their interests in other ways, e.g., through the social networks they join and through the content they mark as their favorite. It is important to develop algorithmic approaches that combine multiple heterogeneous sources of metadata to succinctly represent user's information preferences.

The personalization method described in this chapter will fail if a user makes a query in a domain in which she has not previously expressed any interest. For example, suppose that a child portrait photographer wants to find beautiful mountain scenery. If she has never created tags relating to mountains landscape photography in general, the personalization method described above will fail. However, the Flickr community as a whole has generated a significant amount of data about nature and landscape photography and mountains in particular. Analysis of community-generated data can help the user discover mountain imagery the community has identified as being good. We need algorithms to mine community-generated metadata and knowledge to identify community-specific topics of interest, vocabulary, authorities within the communities and community-vetted content.

CONCLUSION

In addition to creating content, users of Web 2.0 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 chapter describes a machine learning-based method for personalizing results of image 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 images and the groups to which they submitted these images. This information captures user's tastes and preferences in photography and can be used to personalize image search results to the individual user. We validated our approach by showing that it can be used to improve precision of image 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," "bigcat" and "cub" for the query "tiger").

REFERENCES

Agrawal, R., & Srikant, R. (1994). Fast algorithms for mining association rules. In Bocca, J. B., Jarke, M.& Zaniolo, C. (Eds.), *Proceedings of the 20th Int. Conf. Very Large Data Bases, VLDB* (pp. 487— 499). Morgan Kaufmann.

Breese, J., Heckerman, D.& Kadie, C. (1998). Empirical analysis of predictive algorithms for collaborative filtering. In *Proceedings of the 14th Annual Conference on Uncertainty in Artificial Intelligence* (pp. 43—52). San Francisco, CA: Morgan Kaufmann.

Dempster, A. P., Laird, N.M. & Rubin, D.B. (1977). Maximum likelihood from incomplete data via the em algorithm. *Journal of the Royal Statistical Society. Series B (Methodological)39*(1), 1-38.

Golder, S.A. & Huberman, B.A.(2006). The structure of collaborative tagging systems. *Journal of Information Science 32*(2), 198-208.

Jin, R., Si, L., & Zhai, C. (2006) A study of mixture models for collaborative filtering. *Information Retrieval* 9(3):357–382.

Lerman, K., Plangprasopchok, A. & Wong, C. (2007). Personalizing Image Search Results on Flickr. In *Proceedings of AAAI workshop on Intelligent Techniques for Information Personalization.* Vancouver, Canada, AAAI Press.

Ma, Z., Pant, G.& Liu-Sheng, O.R. (2007). Interest-based personalized search. *ACM Trans. Inf. Syst. 25*(1).

Marlow, C., Naaman, M., boyd, d. & Davis, M. (2006). Ht06, tagging paper, taxonomy, flickr, academic article, toread. *Proceedings of Hypertext 2006*. New York: ACM.

Mobasher, B., Cooley, R. & Srivastava, J. (2000). Automatic personalization based on web usage mining. *Commun. ACM43*(8), 142-151.

Popescul, A., Ungar, L., Pennock, D. & Lawrence, S. (2001). Probabilistic models for unified collaborative and content-based recommendation in sparse-data environments. In *17th Conference on Uncertainty in Artificial Intelligence* (pp. 437-444).

Rosen-Zvi, M., Griffiths, T., Steyvers, M. & Smyth, P. (2004). The author-topic model for authors and documents. In *Proceedings of the 20th conference on Uncertainty in artificial intelligence* (pp. 487—494). Arlington, Virginia, United States: AUAI Press.

Schafer, J., Frankowski, D., Herlocker, J. & Sen, S. (2007). Collaborative filtering recommender systems. *The Adaptive Web*, 291-324.

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