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AN INTELLIGENT & ENHANCED HYDRA: A WEB RECOMMENDER SYSTEM

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ABSTRACT: Recommender systems provide personalized information by learning the user's interests from traces of interaction with that user. In order for a recommender system to make predictions about a user's interests it has to learn a user model. A user model contains data about the user and should be represented in such a way that the data can be matched to the items in the collection. The question is, what kind of data can be used to construct a user profile. Obviously the items that users have seen in the past are important but other information such as the content of the items, the perception of users of the items or information about users themselves could also be used.

I. INTRODUCTION

The next question is how to represent this data. The words in the texts should be represented in such a way that they can be used to differentiate between documents about different topics. Another important issue is how time influences the user profile. The interests of users usually do not remain the same but change over time. The data in the user model should therefore be constantly adjusted so that it remains in accordance with the user's interests.

Most recommender systems focus on the task of information filtering, which deals with the delivery of items selected from a large collection that the user is likely to find interesting or useful. Recommender systems are special types of information filtering systems that suggest items to users. Some of the largest e-commerce sites are using recommender systems and apply a marketing strategy that is referred to as mass customization.

There are two main approaches to information filtering: Collaborative filtering and content-based filtering. Collaborative filtering select items based on the similarities between the preferences of different users. Content-based filtering selects items based on the similarities between the content description of an item and the user's preferences. A hybrid approach, combining collaborative filtering and content-based filtering also exists.

A content-based filtering system often uses many of the same techniques as an information retrieval system (such as a search engine), because both systems require a content description of the items in their domain. A recommender system also requires the modeling of the user's preferences for a longer period of time which is not needed in an information retrieval system. There are several techniques that can be used to improve recommender systems in different ways. These techniques fall in the category of web mining, a research field that is closely related to data mining. Web mining is the application of algorithms for extraction knowledge from internet data sources such as server log files and large document collections.

Recommender systems have begun attracting major research interest during the early nineties. Nowadays, commercial and industrial systems are rife and wide-spread, detailed comparisons concerning features and approaches are given in. Recommender systems differ from each other mainly through their filtering method. Hereby, distinctions between three types of filtering systems are made, namely collaborative, content-based and economic. Collaborative filtering systems generate recommendations obtained from persons having similar interests. Content-based filtering only takes into account the content of products, based upon metadata and extracted features. Economic filtering has seen little practical application until now and exerts marginal impact only. Modern recommender systems are hybrid, combining both content-based and collaborative filtering facilities in one single framework. Our filtering approach, comprising taxonomy-based profile generation and similarity computation, also exploits both content-based and collaborative filtering facilities. Trust networks add another supplementary level of filtering.

Initial attempts have been taken towards transplanting recommender systems into decentralized scenarios. Olsson offers an extensive overview of existing approaches. Montaner, and

Chen et al devise agent-based approaches, where agents acquire knowledge about other peers from interaction experience. Hereby, reputation evolves over time and simple trust relationships become tied.
Our past efforts have mainly focused on designing suitable trust metrics for computing trust neighborhoods, and conceiving metrics for making collaborative filtering applicable to decentralized architectures. Moreover, we have shaped and synthesized an extensive infrastructure based upon "real-world" data from various communities and online stores. Until now, analysis has been largely confined to the book domain only. Future research will also include movies and other specific product groups and investigate intrinsic differences between these groups. For instance, Amazon's taxonomy for DVD classification contains more topics than its book counterpart, though being less deep. We would like to better understand the impact that taxonomy structure may have upon profile generation and similarity computation. Furthermore, we are currently investigating applicability of taxonomy-based profile generation for automated stereotype generation and efficient behavior modeling. Efforts for extracting rife usage and profile information from various other communities are well under way.
Merging ranks from both filtering paradigms into one metric and recommendation generation have remained untouched until now. Thorough empirical analysis will be required for selecting most appropriate alternatives and integrating them into our recommender application.

As the World Wide Web continues to grow at an exponential rate, the size and complexity of many web sites grow along with it. For the users of these web sites it becomes increasingly difficult and time consuming to find the information they are looking for. User interfaces could help users find the information that is in accordance with their interests by personalizing a web site.
Some web sites present users with personalized information by letting them choose from a set of predefined topics of interest. Users however do not always know what they are interested in beforehand and their interests may change overtime which would require them to change their selection frequently.

APPROACH TO THE PROBLEM EXPLAINING THE METHODOLOGY AND TECHNIQUES TO EMPLOYED

Recommendation Approach	**Recommendation Technique**	
	Heuristic-based	**Model-based**
Content-based	Commonly used techniques: • TF-IDF (information retrieval) • Clustering Representative research examples: • Lang 1995 • Balabanovic & Shoham 1997 • Pazzani & Billsus 1997	Commonly used techniques: • Bayesian classifiers • Clustering • Decision trees • Artificial neural networks Representative research examples: • Pazzani & Billsus 1997 • Mooney et al. 1998 • Mooney & Roy 1999 • Billsus & Pazzani 1999, 2000 • Zhang et al. 2002

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Collaborative	Commonly used techniques: • Nearest neighbor (cosine, correlation) • Clustering • Graph theory Representative research examples: • Resnick et al. 1994 • Hill et al. 1995 • Shardanand & Maes 1995 • Breese et al. 1998 • Nakamura & Abe 1998 • Aggarwal et al. 1999 • Delgado & Ishii 1999 • Pennock & Horwitz 1999 • Sarwar et al. 2001	Commonly used techniques: • Bayesian networks • Clustering • Artificial neural networks • Linear regression • Probablistic models Representative research examples: • Billsus & Pazzani 1998 • Breese et al. 1998 • Ungar & Foster 1998 • Chien & George 1999 • Getoor & Sahami 1999 • Pennock & Horwitz 1999 • Goldberg et al. 2001 • Kumar et al. 2001 • Pavlov & Pennock 2002 • Shani et al. 2002 • Yu et al. 2002, 2004 • Hofmann 2003, 2004 • Marlin 2003 • Si & Jin 2003
Hybrid	Combining content-based and collaborative components using: • Linear combination of predicted ratings • Various voting schemes • Incorporating one component as a part of the heuristic for the other Representative research examples: • Balabanovic & Shoham 1997 • Claypool et al. 1999 • Good et al. 1999 • Pazzani 1999 • Billsus & Pazzani 2000 • Tran & Cohen 2000 • Melville et al. 2002	Combining content-based and collaborative components by: • Incorporating one component as a part of the model for the other • Building one unifying model Representative research examples: • Basu et al. 1998 • Condliff et al. 1999 • Soboroff & Nicholas 1999 • Ansari et al. 2000 • Popescul et al. 2001 • Schein et al. 2002

II. CONCLUSION

Recommender systems are an integral part of how we experience the Web today and they have become so ubiquitous that we do not even notice them anymore. However, today's recommender systems mostly treat items they recommend as black boxes and primarily focus on extracting correlations and co-counts from user behavior data. So, next generation recommender systems will require deep understanding of items being recommended as well as modeling the relationships between those items.

These all existed method has their own kind of limitations. So, I propose hybridization of many existing model to provide better, intelligent and enhanced model to handle faster, volumes and irredundant result.

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