



**UNIVERSITI PUTRA MALAYSIA**

**IMPROVED REINFORCEMENT-BASED PROFILE LEARNING FOR  
DOCUMENT FILTERING**

**YAHYA MOHAMMED ALMURTADHA**

**FSKTM 2007 13**



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DOCUMENT FILTERING**

**By**

**YAHYA MOHAMMED ALMURTADHA**

**Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia,  
in Fulfilment of the Requirements for the Degree of Master of Science**

**June 2007**



**Dedicated to**  
*my parents, my wife,*  
*my brothers, and my sisters*



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Master of Science

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**Chairman : Associate Professor Hj. Md. Nasir Sulaiman, PhD**

**Faculty : Computer Science and Information Technology**

Today the amount of accessible information is overwhelming. A personalized information filtering system must be able to tailor to current interests of the user and to adapt as they change over time. This system has to monitor a stream of incoming documents to learn the user's information requirements, which is the user profile.

The research has proposed a content-based personal information system learns the user's preferences by analyzing the document contents and building a user profile. This system is called RePLS; an agent-based Reinforcement Profile Learning System with adaptive information filtering. The research focuses on an improved terms weighting to measure the importance of the terms represent each profile called "purity term weighting". The top selected terms are then used to filter the incoming documents to the learned user profiles. The agent approach is used because of its autonomous and adaptive capabilities to perform the filtering.



The proposed method was evaluated and compared with three Information Filtering methods, namely Rocchio, Okapi/BSS Basic Search System and Reinf, the incremental profile learning method. Based on the proposed method, a profile learning system is developed using Microsoft VC++ connected to Microsoft Access database through an ODBC. AFC kit is used to implement the proposed agents under RETSINA architecture. The experiments are carried out on the TREC 2002 Filtering Track dataset provided by the National Institute of Standards and Technology (NIST).

This research has proven that RePLS is able to filter the stream of incoming documents according to the user interests (profiles) learned by the proposed Purity term weighting method. Based on the experiments results, Purity weighting shows better terms weighting and profile learning than the other methods. The outcome of a considerably good accuracy is mainly due to the right weighting of the profile's terms during the learning phase.

This research opens a wide range of future works to be considered, including the investigation of the dependency between the selected terms for each profile, investigating the quality of the method on different datasets, and finally, the possibility to apply the proposed method in other area like the recommendation systems.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Master Sains

**PENAMBAHBAIKAN PEMBELAJARAN BERASASKAN PENGUKUHAN  
PROFIL BAGI PENYARINGAN DOKUMEN**

Oleh

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Dewasa ini jumlah maklumat yang sedia diperoleh adalah sangat memberangsangkan. Sesebuah sistem penyaringan maklumat peribadi mestilah berupaya disesuaikan dengan kehendak individu pengguna, serta mampu berubah sejajar mengikut perubahan masa. Sistem tersebut perlu mengawasi aliran masuk dokumen-dokumen pengguna bagi mempelajari keperluan maklumat mereka, iaitu profil pengguna.

Kajian ini mencadangkan sebuah sistem maklumat peribadi berasaskan kandungan, yang berupaya mempelajari kecenderungan pengguna melalui analisa kandungan dokumen beserta profil pengguna. Sistem ini dinamakan RePLS, iaitu sistem pembelajaran profil berasaskan pengukuhan melalui agen. Kajian ini tertumpu ke arah penambahbaikan pemberat terma yang digunakan bagi mengukur kepentingan sesuatu terma yang wujud dalam setiap profil. Terma-



terma terbaik yang terpilih akan digunakan bagi menyaring kemasukan dokumen dalam proses mempelajari profil pengguna. Pendekatan berasaskan agen digunakan kerana sifatnya yang autonomi dan boleh diadaptasi dalam menjalankan proses penyaringan.

Kaedah yang dicadangkan ini telah dinilai dan dibandingkan dengan tiga buah algoritma penyaringan maklumat yang lain, iaitu *Rocchio's Algorithm*, *Okapi/BSS Basic Search System* dan *Reinf*, sebuah kaedah pembelajaran profil berperingkat. Berdasarkan kaedah yang dicadangkan ini, sebuah sistem pembelajaran profil telah dibangunkan dengan menggunakan Microsoft VC++ dan dihubungkan kepada pangkalan data Microsoft Access melalui ODBC. Kit AFC digunakan bagi membangunkan agen yang tersebut di bawah kerangka RETSINA. Eksperimen yang dibuat adalah menggunakan set data *TREC 2002 Filtering Track* oleh *National Institute of Standards and Technology* (NIST).

Kajian ini telah membuktikan bahawa RePLS berupaya menyaring sesebuah aliran masuk dokumen mengikut kehendak atau profil pengguna. Berdasarkan keputusan eksperimen, RePLS menunjukkan prestasi yang lebih baik berbanding dengan kaedah-kaedah yang lain. Ketepatan keputusan yang menggalakkan adalah hasil daripada pemberat yang berpadanan dengan terma-terma sesuatu profil sewaktu proses pembelajaran.



Kajian ini membuka banyak ruang bagi kajian masa hadapan, termasuk pemeriksaan ke atas kebergantungan antara terma-terma tertentu dalam setiap profil, kualiti kaedah ini pada set data yang pelbagai, dan akhir sekali, penggunaan kaedah yang dicadangkan ini dalam bidang lain seperti sistem pencadangan.



## ACKNOWLEDGEMENTS

In the name of Allah, the most Merciful, Gracious and most Compassionate, Creator of all knowledge for eternity. We beg for peace and blessing upon our Master the beloved Prophet Mohammed (Peace and Blessing be Upon Him) and his progeny, companions and followers.

I wish to extend my deepest appreciation and gratitude to the supervisory committee led by Assoc. Prof. Dr. Hj. Md. Nasir bin Sulaiman and committee member Pn. Hj. Zaiton Muda for the various guidance, sharing of intellectual experiences and in giving me the vital to undertake the numerous of this study. Thanks to Pn. Aida Mustafa for her appreciated help.

I would like to thank Prof. Mohand Boughanem the Professor at Université Paul Sabatier of Toulouse, France for providing comments on the profile learning. I would also like to thank Lori R Price from Robotics Institute at Carnegie Mellon University, USA, for help with providing the AFC kit.

Also special thanks to my parents and my wife for making the best of my situation. May thanks are also extended to the Quraan teachers, my friends and the colleagues for sharing experiences throughout the years.



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## **DECLARATION**

I hereby declare that the thesis is based on my original work except for quotation and citation which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any degree at UPM or other institution.

---

**YAHYA MOHAMMED AL MURTADHA**

Date: 6 August 2007



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## LIST OF ABBREVIATIONS

AFC	Agent Foundation Classes
ANS	Agent Name Server
IDF	Inverse Document Frequency
IF	Information Filtering
IR	Information Retrieval
MAS	Multi Agent System
ML	Machine Learning
NIST	National Institute of Standards and Technology
Okapi/BSS	Okapi Basic Search System
ODBC	Open Database Connectivity
PMA	Profile Manager Agent
RCV	Reuters Corpus Volume
RePLS	Reinforcement Profile Learning System
Reinf.	Reinforcement Incremental Profile Learning
SA	Software Agents
TREC	Text Retrieval Conference
VSM	Vector Space Model
XML	Extended Markup Language



# CHAPTER 1

## INTRODUCTION

### Background

There are numerous text documents available in electronic form. More and more are becoming available every day. Such documents represent a massive amount of information. In addition, the information sources set a dynamic and unorganized environment where the information appear and disappear at any time. Gathering information from such environment is similar to drinking water from a fire hose metaphorically. Hence, there are many occasions when users are not able to get the information they require. Seeking values in this huge collection requires organization, and much of the work of organizing documents can be automated through text classification (Rennie, 2001).

To alleviate this problem, the solution of Information Filtering (IF) and user profiling is introduced. Filters are tools to help people find the most valuable information, so that the limited time spent on locating the information can be maximized on finding the most interesting and valuable documents. Filters are also used to organize and structure information. IF monitors the incoming documents and filter only those matches the user's information need, which are called profile. A typical case is a newsfeed, where the producer is a news agency



and the consumer is a newspaper. In this case, the filtering system should block the delivery of the documents that readers are not interested in (e.g., all news not concerning sports, in the case of a sports newspaper). Filtering is done by applying filtering rules to attributes of the documents to be filtered. The attributes of these documents, are mainly words in the titles, abstracts, or the whole document. Filtering can be seen as a case of single-label Text Categorization, which is the classification of incoming documents into two disjoint categories: the relevant and the irrelevant.

The uncertainties in the filtering environments especially the dynamic nature of the user's interests and the documents stream have made it extremely difficult to gather and maintain accurate information necessary for filtering (Mostafa *et al.*, 1997). Viewed from the perspective of the filtering system, rapid changes introduced in the environment are sources of uncertainty. Managing such uncertainties require a high level of adaptivity on the system's part. This adaptivity can be achieved by applying various machine learning techniques. The overall problem of the IF may then be interpreted as learning the mapping from a space of documents to the space of real-valued user relevance factors.

Profile learning is the heart of a filtering process. It aims to collect the user preferences and modify the filtering behavior according to the preferences. To identify whether a document is relevant to the user or not, a score that measures the similarity between the document and the profile is computed. When the score



is higher than the similarity threshold then the document is selected, otherwise the document is rejected. Profile learning has been studied by two communities, Information Filtering and Machine Learning (Tebri *et al.*, 2005). In machine Learning (ML) paradigm, a general inductive process will automatically build an automatic document classifier by learning from a set of pre-classified documents. The advantages of this approach are; (1) the accuracy is comparable to the accuracy achieved by human experts, and (2) a considerable saving in terms of expert labor power, since no intervention from either the knowledge engineers or the domain experts is needed for construction of the classifier or for porting to a different set of categories (Sebastian, 2002).

Most of the IF researches is based on the Rocchio's algorithm (Rocchio, 1971). It is based on the Vector Space Model (VSM) methodology that allows for partial matching by assigning non-binary (as opposed to the Boolean method) weights to index terms in both profiles and documents. These weights indicate the importance of the terms in describing the semantic of the document and profiles. Terms weights are used to calculate the degree of similarity between each document stored in the system and the user profiles. This method however, does not cover text mining, which has another focus compared to text retrieval (Boertjes *et al.*, 2001). In general, text mining aims at finding implicit correlations in texts by trying to discover previously unknown information. Text retrieval on the other hand, focuses on finding information that is already present explicitly in texts.

IF systems must acquire and maintain accurate knowledge regarding the documents as well as the users. The dynamic nature of the user interests and the document streams makes the maintenance of such knowledge quite complex. Acquiring correct user interest profiles is difficult; users may not be sure of their interests or even do not wish to invest an effort in creating such a profile. Acquiring information regarding documents is equally difficult, due to the size of the document stream and the computational cost associated with parsing huge texts. At any time, new topics may be introduced in the document stream, or user interests related to topics may change. Furthermore, a sufficiently represented document may not be available to facilitate a prior analysis or training.

### **The Problem Statement**

As the amount of accessible information is overwhelming, an intelligent and personalized filtration of available information is a big challenge (Albayrak *et al.*, 2005). The accumulative number of information containers, the users and their increasing demands for the information are the main cause of the retrieval of huge and irrelevant information. IF monitors a stream of incoming document to find those match the user's information need, known as the profile. Profile learning is fundamental in the filtering process; the goal is to collect the user preference on the judged documents and modify the filtering behavior accordingly.



The capability of modeling and learning the user preferences is at the heart of a personalized information filtering system. The main problem with all the personalized filtering is how to measure and select the most suitable terms (attributes) that will help to discriminate between the filtered classes, and learn the user's interests to build their profiles.

Most of the researches in IF use an incremental version of Rocchio's algorithm (Salton and Buckley, 1990; Singhal *et al.*, 1997) to propose different profile learning methods. Microsoft Research Laboratory in Cambridge has developed an evaluation environment called Keenbow for a wide range of IR experiments. One component in Keenbow is Okapi/BSS (Robertson and Walker[a], 2000) which uses terms weighting in addition to the Query Expansion. Reinf, the incremental profile learning based on reinforcement method (Tebri *et al.*, 2005) is an IF profile learning method based on the terms weighting. These methods weigh the terms according to the frequency of term occurrence in the documents and the profiles, without considering the pure occurrence in either the relevant or irrelevant documents.

With the growing need for a sufficient learning of user interests, there also exists a growing urgency to achieve this without an additional effort from the user by adapting the software agent approach. Software agents are software entities that





array out some set of operations on behalf of a user or another program with some degree of independence or autonomy (IBM Agent<sup>1</sup>).

### **Objectives of the Research**

The main goal of this research is to improve the document filtering based on user interests. To fulfill this, the following objectives must be achieved:

- Improving the filtering engine at the terms weighting stage of the reinforcement-based profile learning, in order to select the best terms to aid for building the user profiles based on the user preference.
- Implementing an agent-based document filtering system that works as a user assistant to help building the user profiles based on his preferences.

### **Scope of the Research**

This research focuses on improving terms weighting for learning the user preferences and building the user profile. The learning method is an incremental profile learning based on the reinforcement method. A user profile learning agent that is able to help learning the user preferences without any user intervention is also implemented. The data used for testing is TREC 2002 filtering track, which is a Reuter's news stories in XML format. The output of the learning stage is a list of selected terms for each user profile stored in database tables. The list is then

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<sup>1</sup> <http://activist.gpl.ibm.com:81/WhitePaper/ptc2.htm>

