Bayesian Graphical Models for Adaptive Filtering

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Abstract

A personal information filtering system monitors an incoming document stream to find the documents that match information needs specified by user profiles. The most challenging aspect in adaptive filtering is to develop a system to learn user profiles efficiently and effectively from very limited user supervision.

In order to overcome this challenge, the system needs to do the following: use a robust learning algorithm that can work reasonably well when the amount of training data is small and be more effective with more training data; explore what a user likes while satisfying the user's immediate information need and trade off exploration and exploitation; consider many aspects of a document besides relevance, such as novelty, readability and authority; use multiple forms of evidence, such as user context and implicit feedback from the user, while interacting with a user; and handle various scenarios, such as missing data, in an operational environment robustly.

This dissertation uses the Bayesian graphical modelling approach as a *unified* framework for filtering. We customize the framework to the filtering domain and develop a set of solutions that enable us to build a filtering system with the desired characteristics in a *principled way*. We evaluate and justify these solutions on a large and diverse set of standard and new adaptive filtering test collections. Firstly, we develop a novel technique to incorporate an IR expert's heuristic algorithm as a Bayesian prior into a machine learning classifier to improve the robustness of a filtering system. Secondly, we derive a novel model quality measure based on the uncertainty of model parameters to trade off exploration and exploitation and do active learning. Thirdly, we carry out a user study with a real web-based personal news filtering system and more than 20 users. With the data collected in the user study, we explore how to use existing graphical modeling algorithms to learn the causal relationships between multiple forms of evidence and improve the filtering system's performance using this evidence.

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&

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Chapter 1

Introduction

1.1 What is filtering

An agent working in the Homeland Security Department wants to be alerted of any information related to potential terror attacks; a customer call center representative wants the phone routing system to route a customer call reporting a specific product problem to him if the problem matches his expertise; a student wants to be alerted of fellowship or financial aid opportunities appropriate for her/his circumstances; and a financial analyst wants to be alerted of any information that may affect the price of the stock he is tracking.

In these examples, the user preferences are comparatively stable and represent a long term information need, the information source is dynamic, information arrives sequentially over time, and the information needs to be delivered to the user as soon as possible. Traditional ad hoc search engines, which are designed to help the users to pull out information from a comparatively static information source, are inadequate to fulfill the requirements of these tasks. Instead, a filtering system can serve the user better. A filtering system is an autonomous agent that delivers good information to the user in a dynamic environment. As opposed to forming a ranked list, it estimates whether a piece of information matches the user needs as soon as the information arrives and pushes the information to the user if the answer is "yes". So a user can be alerted of any important information on time.

A typical information filtering system is shown in Figure 1.1.* In this figure, a piece of information is a document.† A user's information needs are represented in a user profile. The profile contains one or more classes, such as "stock" or "music", and each class corresponds to one information need. When a user has a new information need, he/she sends to the system an initial request, such as a query or some sample documents of what he/she wants. Then the system initializes and creates a new online classifier in the user's profile to serve this information need. As more future documents arrive, the system delivers documents the classifier considered good to the user. The user may read delivered documents and provide explicit feedback,

*A filtering system can serve many users, although only one user is shown in the figure.
†Information can be documents, images, or videos. This dissertation focuses on documents.

such as identifying a document as "good" or "bad". The user also provides some implicit feedback, such as deleting a document without reading it or saving a document. The filtering system uses the user feedback accumulated over time to update the user profile and classifiers frequently.

Standard ad hoc retrieval systems, such as search engines, let user use short queries to pull out information and treat users the same given the query words. However, users are different and are not good at describing their information needs using ad hoc queries. If the information need of a user is more or less stable over a long period of time, a filtering system has a good environment to learn user profiles (also called user models) from a fair amount of user feedback that can be accumulated over time. In other words, the system can serve the user better by learning user profiles while interacting with the user, thus information delivered to the user can be personalized and catered to individual user's information needs automatically. Even if the user's interest drifts or changes, the system can still adapt to the user's new interest by constantly updating the user profile from training data, creating new classes automatically [50], or letting the user create/delete classes.

While learning user profiles is an advantage of a filtering system, it is also a major research challenge in the adaptive filtering research community. Common learning algorithms require a significant amount of training data. However, a real-world filtering system must work as soon as the user uses the system, when the amount of training is extremely small or zero. [‡] How should a good filtering system learn user profiles efficiently and effectively with limited user supervision while filtering? In order to solve this problem, the system needs to do the following efficiently: use a robust learning algorithm that can work reasonably well when the amount of training data is small and more effective with more training data; explore what the user likes while satisfying a user immediate information need and trade off exploration and exploitation; consider many aspects of a document besides relevance, such as novelty, readability and authority; use multiple forms of evidence, such as user context and implicit feedback from the user, while interacting with a user; and handle various scenarios, such as missing data, robustly.

1.2 Bayesian graphical models for adaptive filtering

We hypothesize that Bayesian graphical modelling (BGM) is a useful and unified framework to guide us building a filtering system with the above desired characteristics in a principled way. This dissertation tests the hypothesis and studies how to customize the Bayesian graphical modelling approach into the filtering domain to build filtering systems with the desired characteristics.

[‡]It is possible the system needs to begin working given a short user query and no positive instance.

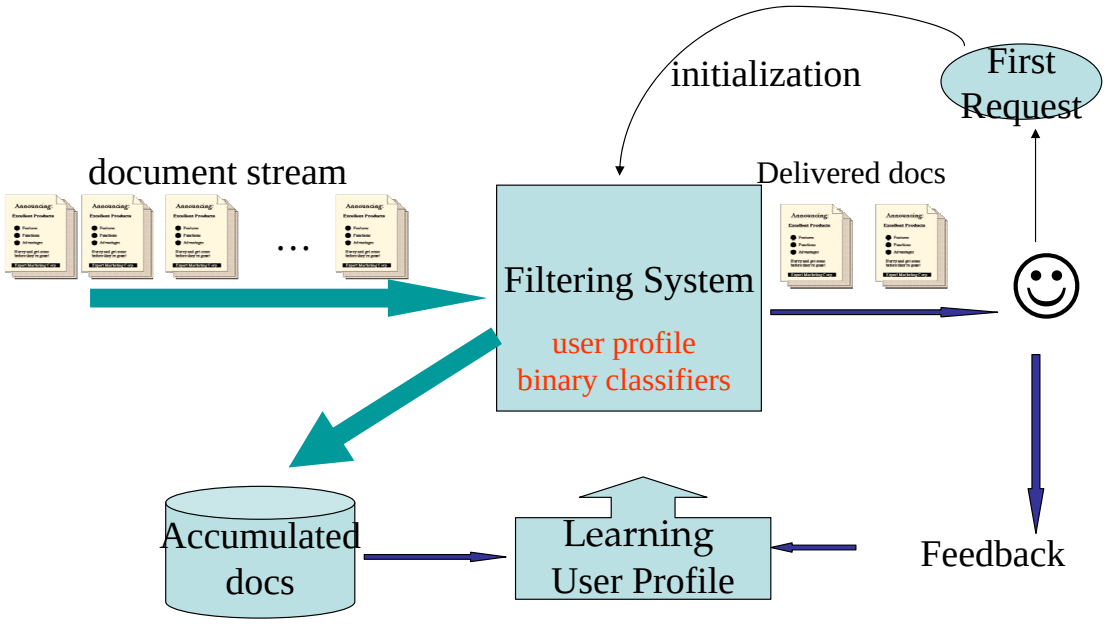


Figure 1.1: A typical filtering system.

Bayesian graphical modeling is based on Bayesian decision theory and graph theory, both of which have been successfully used in other domains, such as image modeling [59][16], Error correcting coding [100] bioinformatics [28][3], computer software user modeling [64], and other social phenomena modeling [101]. These two theories complement each other and combine nicely, so we propose to combine them together as a unified framework for filtering task. This framework contains the following three major components.

Representation tools: The framework provides a set of representation tools that enable researchers to build a personalized information filtering system, which can combine multiple forms of evidence such as relevance, novelty, readability, authority, and explicit and implicit feedback;

Bayesian axiom: In this framework, maximizing the expectation of a user defined utility function is the

only decision criterion;

Inference tools: Statistical inference algorithms introduced in Section 2.3.4 are the tools that enable us to estimate probability distributions that can be used to achieve the goal of maximizing the utility.

Compared with other commonly used text classification algorithms, the proposed framework has five major advantages.

First, the goal of a system is clearly defined in a broader way. Most filtering systems only optimize for a very narrow definition of topical relevance, while we want to optimize for a broader, more realistic set of criteria that can be expressed as a utility function. This utility function is defined based on whether the user likes a document or not, and can be influenced by relevance,[§] novelty, authority and readability of a document. It is very natural to understand and optimize this utility function according to the Bayesian axiom.

Second, the filtering system models the uncertainty explicitly using probabilities. Researchers in the information retrieval community often estimate the uncertainty of relevance, and talk about the uncertainty about a user profiles. However, the uncertainty about a user profile is not modeled explicitly. Existing filtering systems usually use a point estimator of the parameter, such as maximum likelihood estimation or max posterior estimation, to make predictions and decisions. In the Bayesian framework, the uncertainty about a user profile is modeled explicitly as a probabilistic distribution of model parameters, and the filtering system can estimate a user profile quality and do active learning based on the distribution.

Third, the framework helps us to understand the causal relationships in the domain and further improve the design of the filtering system. For example, knowing whether a user likes a document may cause the user to spend more time reading the document can help the system designer decide whether to collect the time spent on a page as an implicit feedback. Understanding the causal relationships can also help us to predict the consequences of intervention. For example, we may want to know if system gives a document a high score, whether the user's rating of the document will be influenced. The representation tools, especially the causal structure learning algorithm, can help us to answer these questions.

Fourth, the framework enables us to combine prior domain knowledge or heuristics with training data. Prior domain knowledge or heuristics are very important when the training data is scarce or expensive to get. Bayes' theorem makes it natural to encode this information as a prior distribution of the parameter

[§]The word "relevant" was used ambiguously, either as a narrow definition of "related to the matter at hand (aboutness)" or a broader definition of "having the ability to satisfy the needs of the user". When it is used by the second definition, researchers were usually studying what this dissertation refers to as *user likes*. In this dissertation, we use "relevant" as is defined in the first definition and use the phrase "user likes" for the second definition.

to be estimated, and graph structure learning algorithms also provide the mechanism to encode the prior knowledge for the task of causal discovery (Section 2.3.3).

Fifth, the framework handles situations of missing data naturally based on the conditional dependencies encoded in the graph structure. The unpredictability of user behaviors and system glitches make it difficult to collect all the information one intends to collect. Training data with missing entries is very common in the real world, and a robust system needs to learn and make predictions with partial observations. In the BGM framework, missing data means some nodes are hidden. The inference tools discussed in detail in Section 2.3.4 can estimate the conditional probability of unknown nodes given whatever known.

With the above five advantages, we hypothesize Bayesian graphical modelling is a good unified framework to guide us developing a filtering system with the desired characteristics and solve the limited training data problem.

1.3 The goal of this dissertation and overview of the solutions

The Bayesian graphical modeling framework is not a universal solution to all filtering problems. Instead, it is a set of general tools and design principles. Knowing the functionalities provided by the tools and a good understanding of the filtering problem domain are both important in order to build a good filtering system under the framework.

The goal of this dissertation is to explore how to customize Bayesian graphical models to the task of filtering and help solve the limited user supervision problem (limited training data).

The approach we take is considering what humans may do to solve the same filtering problem, identifying desirable characteristics of a filtering system motivated from humans, and then developing solutions that enable the system to behave as desired using tools or principles provided by the Bayesian graphical modeling framework.

First, humans may solve the problem by consulting with domain experts and using heuristics. Motivated by this, we use simple heuristic models developed by an IR expert to influence the learning of statistical models using a Bayesian prior.

Second, humans may do active learning by carefully picking the right document to ask the user for feedback so that the answer can provide the most valuable information. Motivated by this, we measure the utility gain of delivering a document (asking the user for feedback) explicitly based on Bayesian decision theory. Using this measure, exploitation (making the user happy right now) and exploration (asking the user for feedback) can be combined in a unified framework to optimize a user utility function.

Third, humans may use multiple forms of evidence, such as the user's context and implicit user feedback, to learn about the user's information needs. Motivated by this, we use Bayesian graphical models to combine whatever information available to learn detailed data driven probabilistic user models while filtering.

1.4 Contributions of the dissertation

Up to the time of this dissertation, most of the existing filtering works haven't tried to build a filtering system with desired characteristics using a general theoretical paradigm. The notion of uncertainty about user was mentioned but never explicitly modelled in filtering task.

This thesis is the most comprehensive study of the filtering problem to date. The solutions developed in this thesis are both theoretical and practical. The most important contribution is providing a *unified framework* to build a filtering system in a *principled way*. The framework is general and powerful.

To demonstrate the power of the proposed framework, the dissertation presents examples of how to develop novel techniques as well as how to use existing techniques to build a filtering system with the desired characteristics. This leads to the following three specific filtering solutions, which we evaluate on several large and diverse standard and new data sets.

- The thesis develops a constrained maximum likelihood estimation technique to integrate an expert's heuristic algorithm into machine learning algorithms. Based on the assumption that Rocchio works better than norm-2 regularized logistic regression when the number of training data is small, [¶] we use the technique to integrate IR expert Rocchio's algorithm as a Bayesian prior of the logistic regression algorithm. The new algorithm works like a human being in the sense that it uses the IR expert's heuristic algorithm to learn user interests when the amount of training data is small, and gradually shifts to a more complex learning algorithm to update its believes about user interests as more training data are available. The new algorithm automatically controls its model complexity based on the amount of training data. This leads to a filtering system that works robustly with limited training data and learns efficiently as more training data are available. When there is an initial query, the new algorithm is much better than both Rocchio algorithm and logistic regression algorithm, comparable to the best official result in the TREC-9 adaptive filtering task, and much better than the best official result in the TREC-11 adaptive filtering task. When there is no initial query, it is similar to logistic regression and among the best on TDT 2005 supervised tracking task.

[¶] which is likely to be true when an initial user query is provided by the user.

- The thesis derives utility divergence as a model quality measure for exploration and exploitation based on Bayesian decision theory. This leads to a filtering learning system with an active learning capacity that can choose to deliver a document the user may not like but the system believes it can learn a lot from the users' feedback and work better in the long run. Most importantly, exploitation (making the user happy right now) and exploration (asking for user feedback) are combined in a unified framework to optimize a user utility function. The experimental results demonstrate the algorithm can improve results on favorable data set (TREC-10) and has little effect on unfavorable data set (TREC-9).

- The thesis explores how to integrate multiple forms of evidence using existing graphical modeling algorithms while filtering. More importantly, the research goes beyond relevance filtering, considers other criteria, such as novelty, authority and implicit feedback of a documents, and models these criteria explicitly as hidden variables. We find the system can predict user preference better with more evidence than using relevance information alone. Furthermore, the graphical modelling approach handles the problem of missing data naturally and efficiently. The more information a system tries to collect, the more likely the system will fail to collect all the information for each individual case. Humans usually try to guess the missing information, and graphical models solve the problem in a similar way by estimating the probabilistic distribution of the missing values from the known using inference algorithms.

The first two are novel techniques in the context of information filtering arising from Bayesian theory and the representation power of the graphical models. Although they are developed for filtering, they can also be applied to solve similar problems in other domains. The third demonstrates how to customize the existing graphical modeling algorithms to the domain of filtering, and it leads to some new findings about the filtering problem.

With the first technique, a filtering system now can work robustly initially with heuristics, and continue to improve over time with training data. With the second technique, a filtering system now won't be too aggressive while exploring user characteristics or too conservative because of the fear of exploitation. With the third technique, a filtering system now goes beyond relevance and develop more interesting and detailed data driven user models and handles various problems like missing data in an operational environment robustly. The dissertation changes the view of filtering by going beyond relevance, includes active learning, novelty, authority, readability, implicit user feedback and other user context.

The dissertation also changes the way of designing filtering solutions from ad hoc or inflexible methods to a principled way under a unified framework. Although the framework does not give "always better"

algorithms, it provides guidance on a wide ranges of problems. This is a more general and scientific way to develop filtering solutions with desired characteristics. There are some prior work on developing filtering systems with one or two of the desired characteristics. However, early research was not under a unified theoretical framework and the solutions were rather ad hoc. We are not aware of any work that considers all of these problems under a unified framework.

1.5 Outline

The dissertation is organized as follows. Chapter 2 gives a literature review, including the general evaluation schema for the adaptive filtering task, several standard evaluation data sets, traditional IR models, and Bayesian graphical models. This knowledge helps the user to understand the remaining of the dissertation. Chapter 3 describes how we integrate an IR expert's heuristic algorithm into model building as a Bayesian prior, Chapter 4 describes how we trade off exploration and exploitation to optimize a utility while active learning based on Bayesian decision theory. Chapter 6 describes how we combine multiple forms of evidence, including a user study we carried to collect a new evaluation data set, and data analysis using graphical models. Chapter 7 summarizes the contributions of the thesis, discusses the limitation of the work, and proposes some future directions.

Each chapter is relatively self-contained. Readers familiar with information filtering and Bayesian graphical models can skip Chapter 2. Readers interested in the general idea can read Chapter 7 only. Readers interested in specific filtering techniques developed can read Chapter 3, Chapter 4 and Chapter 6 respectively.

Parts of the thesis have been published in conferences. Chapter 3 is based on a paper published in the International ACM SIGIR Conference on Research and Development in Information Retrieval in 2004, Chapter 4 is based on a paper published in the International Conference on Machine Learning 2003.

The author also researched several other important filtering issues during her graduate study. The filtering system only receives user feedback for documents delivered to the user, which causes a sampling bias problem while learning. We studied how to correct this sampling bias while learning a user profile threshold [164]. We identified the importance of novelty/redunancy detection while filtering, proposed several measures to estimate the redundancy/novelty, collected an evaluation data set, and evaluated the proposed measures [166]. We also found an exact and efficient solution to a class of commonly used language models [167] and evaluated the language models for the filtering task [165]. These works are not included in this dissertation, because they were done before the proposal of the thesis and are beyond the scope of this dissertation. Readers interested in these works are referred to the author's other papers for more information.

Chapter 2

Literature Review and Background Knowledge

In order to help the readers better understand the discussions in the later chapters, this chapter provides necessary background knowledge. We first introduce some standard evaluation measures and several evaluation data sets to be used to evaluate the proposed solutions (Section 2.1). Then we introduce existing information retrieval models to provide the theoretical motivation for the thesis work in the context of prior works (Section 2.2). Finally, the Bayesian graphical modelling approach is introduced to help the readers understand the principles and tools provided by the proposed framework, which is used to solve the filtering problems later(Section 2.3).

2.1 Adaptive filtering standards

An ***information filtering*** system monitors a document stream to find the documents that satisfy users' information needs. As the system filters, an ***adaptive*** filtering system also updates its knowledge about the user's information needs frequently based on observations of the document stream and periodic explicit or implicit user feedback from the user. One major focus of adaptive information filtering is to learn user profile.

There is much prior work in the area of adaptive filtering [51]. The Filtering Track [121][120][124] at the Text REtrieval Conference (TREC) is the best known forum for this study, and the adaptive filtering task is the most important task evaluated in the Filtering Track [149].

This chapter first introduces some standard evaluation measures and evaluation data sets used in the TREC adaptive filtering task [121]. These were selected by researchers working in adaptive filtering area over the last several years, and the benchmark performance of different systems on these standard data sets are publicly available at http://trec.nist.gov. The reported benchmark performance will be used in our experiments as baselines to evaluate the empirical performance of the filtering system built based on the Bayesian graphical models.

The supervised tracking task at the Topic Detection and Tracking (TDT) workshop is a forum closely related to information filtering [7][151]. TDT research focuses on discovering topically related material in streams of data. TDT is different from adaptive filtering in several aspects. In TDT, a topic is user independent and defined as an event or activity, along with all directly related events and activities. In TREC-style adaptive filtering, an information need is user specific and has a broader definition. A user information needs may be a topic about a specific subject, such as "2004 presidential election", or not, such as "weird stories".

However, TDT-style topic tracking and TREC-style adaptive filtering have much in common, especially if we treat a topic as a form of user information need. To study the effectiveness of the filtering solutions we developed for a different but similar task, we will also use the TDT data for evaluation in this thesis. The most recent TDT data set is introduced in this section.

2.1.1 Evaluation measures

The Text REtrieval Conference (TREC), co-sponsored by the National Institute of Standards and Technology (NIST) and the Defense Advanced Research Projects Agency (DARPA), was started in 1992 and held annually to support research within the information retrieval community by "providing the infrastructure necessary for large-scale evaluation of text retrieval methodologies".

A TREC conference consists of a set of tracks. Each track is an area of focus in which particular retrieval tasks are defined. The Filtering Track* is one of them. In the Filtering Track, the most important research task is the adaptive filtering task, which is designed to model the text filtering process from the moment of profile construction. In this task, the user's information need is stable while the incoming new document stream is dynamic. For each user profile, a random sample of a small amount (2 or 3) of known relevant documents were given to the participating systems, and no relevance judgments for other documents in the training set were available. When a new document arrives, the system needs to decide whether to deliver it to the user or not. If the document is delivered, the user's relevance judgment for it will be released to the system immediately to simulate the scenario that an explicit user feedback is provided to the filtering system by the user. If the document is not delivered, the relevance judgment will never be released to the system. Once the system makes the decision of whether to deliver the document or not, the decision is final [121]. This is strict and not always necessary in a real filtering system, however it is a simple, reasonable and implementable scenario where comparison of the performance between laboratory systems is possible.

In each Filtering Track, NIST provides a test set of documents and relevance judgments. The judgement

*The Filtering Track was last run in TREC 2002

Table 2.1: The values assigned to relevant and non-relevant documents that the filtering system did and did not deliver. R^-, R^+, N^+ and N^- correspond to the number of documents that fall into the corresponding category. A_R, A_N, B_R and B_N correspond to the credit/penalty for each element in the category.

	Relevant	*Non-Relevant*
Delivered	R^+, A_R	N^+, A_N
Not Delivered	R^-, B_R	N^-, B_N

of relevance is based on topical relevance only. Participants run their own filtering systems on the data, and return to NIST their results. Thus different systems' performance on the set of standard Filtering Track evaluation data sets are publicly available for cross system comparison.

In the information retrieval community, the performance of an ad hoc retrieval system is typically evaluated using relevance-based recall, precision at a certain cut-off of the ranked result. Taking a 20-document cut-off as an example:

$$precision = \frac{the\ number\ of\ relevant\ documents\ among\ the\ top\ 20}{20} \tag{2.1}$$

$$recall = \frac{the\ number\ of\ relevant\ documents\ in\ the\ top\ 20}{all\ relevant\ documents\ in\ the\ corpus} \tag{2.2}$$

What is a good cut off number is unknown. In order to compare different algorithms without specify a cut off, mean average precision (MAP) at different cut off number is often used (Appendix).

However, the above evaluation measures are not appropriate for filtering. Instead of a ranking list, a filtering system makes an explicit binary decision of whether accept or reject a document for each profile. So a *utility function* is usually used to model user satisfaction and evaluate a system. A general form of the linear utility function used in the recent TREC Filtering Track is shown below [119].

$$Utility_{relevant} = A_R \cdot R^+ + A_N \cdot N^+ + B_R \cdot R^- + B_N \cdot N^- \tag{2.3}$$

This model corresponds to assigning a positive or negative value to each element in the categories of Table 2.1, where R^-, R^+, N^+ and N^- correspond to the number of documents that fall into the corresponding category, A_R, A_N, B_R and B_N correspond to the credit/penalty for each element in the category. Usually, A_R is positive, and A_N is negative. Assigning a negative weight for a non-relevant document delivered is reasonable considering the fact that retrieving non-relevant documents have a much worse impact than not retrieving relevant ones [19]. B_N and B_R are set to zero in TREC to avoid the dominance of undelivered

documents on the final evaluation results, because the number of undelivered documents is usually extremely large and a user satisfaction is mostly influenced by what the user has seen. The total number of relevant documents $R^+ + R^-$ is a constant for a user profile. Thus a non-zero $A_R \cdot R^+$ already implicitly encodes the influence of R^- undelivered relevant documents in the final evaluation measure. [†]

In the TREC-9, TREC-10 and TREC-11 Filtering Tracks, the following utility function was used:

$$T9U = T10U = T11U = 2R^+ - N^+ \tag{2.4}$$

In the supervised tracking task at the Topic Detection and Tracking (TDT5), another utility function that emphasizes recall was used:

$$TDT5U = 10R^+ - N^+ \tag{2.5}$$

If we use the T9U utility measure directly and average over the utilities across user profiles to evaluate a filtering system, profiles with many documents delivered to the user will dominate the result. So a normalized version T11SU was also used in TREC-11:

$$T11SU = \frac{max(\frac{T11U}{MaxU}, MinNU) - MinNU}{1 - MinNU} \tag{2.6}$$

where $MaxU = 2 * (R^+ + R^-)$ is the maximum possible utility, [‡] and $MinNU = -0.5$. If the score is below $MinNU$, the $MinNU$ is used, which simulates the scenario that the users stop using the system when the performance is too bad. [§]

Similarly, the TDT track also used a normalized version of the TDT5U utility measure. Two normalized versions were used:

$$TDT5NU = \frac{TDT5U}{MaxU} \tag{2.7}$$

$$TDT5SU = \frac{max(\frac{TDT5U}{MaxU}, MinNU) - MinNU}{1 - MinNU} \tag{2.8}$$

where the definitions of MaxU and MinNU are the same as used in TREC. The definition of TDT5SU is very

[†]Some other evaluation measure, such as the normalized utility measure described in the following paragraphs, also considers N^+ implicitly.

[‡]Notice the normalized version does take into consideration relevant documents not delivered. Thus it also provides some information about the recall of the system implicitly.

[§]It's not exactly the same, since in TREC and also in the thesis, we only evaluate the system at the very end of filtering process.

similar to T11SU. The major difference between TDT5NU and TDT5SU is: profiles with many non-relevant documents delivered to the user may dominate the final results if using TDT5NU measure, but not if using TDT5SU measure.

In general, when we average across user profiles to evaluate a filtering system, we can view T11U and TDT5U as micro average measures, while the normalized utility T11SU, TDT5NU and TDT5SU as macro average measures.

Notice that in a real scenario, the choice of A_R, A_N, B_R and B_N depends on the user and/or the task. For example, when a user is reading news using a wireless phone, he may have less tolerance for non-relevant documents delivered and prefer higher precision, and thus use a utility function with larger penalty for non-relevant documents delivered, such as $TU_{Wireless} = R^+ - 3N^+$. When a user is doing research about a certain topic, he may have a high tolerance for non-relevant documents delivered and prefer high recall, and thus use a utility function with less penalty for non-relevant documents delivered, such as $TU_{Research} = R^+ - 0.5N^+$. When monitoring potential terrorist activities, missing information might be crucial and B_R may be a big non-zero negative value. We could define user-specific utility functions to model user satisfaction and evaluate filtering systems. Because most of the TREC and TDT benchmark results were produced by systems optimized for different variations of the linear utility measures, the TREC linear utility measure is used to evaluate our solutions in this dissertation. The specific utility measures are different for different data sets, and the standard measure for each data set will be used in our evaluation. Which one is used depends on the context.

The choice of evaluation measure influences the decision of the filtering system a lot, since optimizing the measure is the goal of a good system. In addition to the linear utility measure, other measures such as F-beta [121] defined by van Rijsbergen and DET curves [96], are also used in the research community.

2.1.2 Evaluation data sets

In this dissertation, several standard and new data sets are used to test the effectiveness of the Bayesian graphical modeling approach for information filtering and study some of the important aspects of the filtering solutions we developed. The standard data sets include three latest TREC adaptive filtering data sets and one latest TDT data set. The basic information about these data sets are provided in this section. We also created a new data set through a user study. More details about it will be provided in Section 5.

TREC9 OHSUMED Data

The OHSUMED data set is a collection from the US National Library of Medicine's bibliographic database [63]. It was used by the TREC-9 Filtering Track [119]. It consists of 348,566 references derived from a subset of 270 journals covering the years 1987 to 1991. Sixty three OHSUMED queries were used to simulate user profiles. The following is an example of a user profile specification:

Number OHSU1

Title 60 year old menopausal woman without hormone replacement therapy

Description Are there adverse effects on lipids when progesterone is given with estrogen replacement therapy

The relevance judgments for the OHSUMED queries were made by medical librarians and physicians based on the results of interactive searches. In the TREC-9 adaptive filtering task, it is assumed that the user profile specifications arrive at the beginning of 1988, so the 54,709 articles from 1987 can be used to learn word occurrence statistics (e.g., idf) and corpus statistics (e.g., average document length). However, each participating filtering system only begins with a profile description, two relevant documents, and zero non-relevant document for each profile. In the OHSUMED profiles, the average number of relevant articles per profile in the testing data is about 51.

TREC10 Reuter's Data The Reuter's 2001 corpus (also called the RCV1 corpus) provided by Reuter's is a collection of about 806,791 news stories from August 1996 to 1997. This corpus was used by the TREC-10 and TREC-11 Filtering Tracks [120][121].

In the TREC-10 adaptive filtering task, 84 Reuter's categories were used to simulate user profiles. The documents in the first 12 days from 20 August through 31 August 1996 are used as training data. However, each participating filtering system only begins with a category name, 2 relevant documents, and zero non-relevant document for each profile. The initial training data is very limited and not particularly representative of the variety of the large number of relevant documents in the test data. Thus this is considered a very difficult data set.

The average number of relevant articles in the testing data is about 9,795 documents per profile, which is much larger than other standard filtering data set.

TREC-11 Reuter's Data The Reuter's 2001 corpus was also used in TREC11. Compared to TREC10, a different set of 100 topics was used to simulate user profiles.

The first fifty profiles were constructed in the traditional TREC fashion by assessors at NIST. The following is an example of a profile specification:

Number 101

Title Economic espionage

Description What is being done to counter economic espionage internationally?

The relevance judgments were created based on extensive searches using multiple rounds of multiple retrieval classification systems after an initial definition of the profiles [121]. For these 50 profiles, the documents from 20 August through 20 September 1996 are used as training data. However, only 3 relevant documents per user profile are provided for the filtering system to begin with, while other documents in the training set are unlabeled. The documents after 20 September 1996 are the testing set. The overall number of relevant articles in the testing data is about 9 to 599 documents per profile.

The remaining fifty profiles were constructed as intersections of pairs of Reuter's categories. Creation of these 50 profiles was for the experiment on the intersection method of building profiles, which would be considerably cheaper than the usual assessor method. The experimental results from participants indicates that the intersection method is not useful, as the performance of the filtering systems differed significantly on the two sets of user profiles. Researchers think the first human created 50 profiles simulate the real user scenario in a more realistic way. Although intersection categories represent a task that is similar to the traditional text classification task, only the first 50 profiles will be used in this dissertation since we are focusing on the filtering task.

TDT5 Multi-lingual Data

Topic Detection and Tracking (TDT) under the DARPA Translingual Information Detection, Extraction, and Summarization (TIDES) program try to automatically organize news stories by the events that they discuss. TDT includes several tasks. In the TDT supervised tracking task, each participating system was given one on topic story, and must process the incoming document stream in chronological order. For each <story, topic> test pair, if the system decision on the story is *on topic*, the relevance feedback information of the story may be used for adaptation, otherwise not. If we consider each topic as a user profile, the supervised tracking task is very similar to adaptive filtering task. So the data set namely "TDT5" used in TDT 2004 is also an interesting data set for evaluation.

This corpus contains English, Mandarin and Arabic news from April 2003 to September 2003 [2]. For Arabic and Mandarin sources, we have both the original language character stream and an English translation

produced automatically. The English translations will be used by the filtering system in our experiments. 126 topics are used to simulate user profiles. The filtering system begins with one labeled on topic document. Compared with TREC adaptive filtering data sets, TDT5 is different in two aspects: 1) A TDT system has no initial description of each topic to begin with; 2) TDT5 data annotation is far from complete. [¶] On average, there are 71 relevant documents per profile.

A formal description about the TDT task contains much jargon. However, we use simpler terminology in this section to make it easier for readers to understand in the filtering context. Readers interested in the exact definition of TDT data set, such as the exact definition of "topic" in TDT, are referred to official TDT publications [7][2][1].

2.2 Existing retrieval models and filtering approaches

In this section, we first review some existing information retrieval models since most of them are also used, or will be used, in information filtering. Then we review two common filtering approaches for learning user profiles from explicit user feedback.

We introduce these existing approaches and their drawbacks here, so that the readers can get a better understanding of the theoretical motivation of the thesis work. As there is a large amount of literature about these in early work, we will only review them concisely. For more detail about these models, the readers are referred to [71, 128][122][147][17][146][44][8][29][91][10][40][139][51][86][30][15][121][139][102][154][85].

2.2.1 Existing retrieval models

Information filtering has a long history dating back to the 1970s. It was created as a subfield of the more general Information Retrieval (IR) field, which was originally established to solve the ad hoc retrieval task. [‖] For this reason, early work tended to view filtering and retrieval as "two sides of the same coin" [20]. The duality argument is based on the assumptions that documents and queries are interchangeable. This dual view has been questioned [117][29] by challenging the interchangeability of documents and queries due to their asymmetries of representation, ranking, evaluation, iteration, history and statistics. However, the influence of retrieval models on filtering is still large, because the retrieval models were comparatively well studied and the two tasks share many common issues, such as how to handle words and tokens, how to

[¶] This is because annotators have a fixed time allocated for each topic in TDT5. TREC annotation is not complete either, however the chance of a missing annotation on TREC data is much smaller because of the way annotation was gathered.

[‖] Historically, information retrieval was first used to refer to the ad hoc retrieval task, and then was expanded to refer to the broader information seeking scenario that includes filtering, text classification, question answering and more.

represent a document, how to represent a user query, how to understand relevance, and how to use relevance feedback. So it is worthwhile to look at various models used in IR and how relevance feedback is used in these models.

In the last several decades, many different retrieval models have been developed to solve the ad hoc retrieval task. In general, there are three major classes of IR models:

Boolean models The *Boolean model* is the simplest retrieval model and the concept is very intuitive. The drawbacks of the Boolean model are in three aspects: 1) the users may have difficulty to express their information needs using Boolean expressions; 2) the retrieval system can hardly rank documents that matches the Boolean query. Nevertheless, the Boolean model is widely used in commercial search engines because of its simplicity and efficiency. How to use relevance feedback from the user to refine a Boolean query is not straightforward, so the Boolean model was extended for this purposes [90].

Vector space models *The vector space model* is a well implemented IR model, most famously built in the SMART system [128]. It represents documents and user queries in a high dimensional space indexed by "indexing terms", and assumes that the relevance of a document can be measured by the similarity between it and the query in the high dimensional space [127]. In the vector space framework, relevance feedback is used to reformulate query vector so that it is closer to the relevant documents, or for query expansion so that additional terms from the relevant documents are added to the original query. The most famous algorithm is the Rocchio algorithm [125], which represents a user query using a linear combination of the original query vector, the relevant documents centroid, and the non-relevant documents centroid.

A major criticism for the vector space model is that its performance highly depends on the representation, while the choice of representation is heuristic because the vector space model itself does not provide a theoretical framework on how to select key terms and how to set weights of terms.

Probabilistic models *Traditional probabilistic models*, such as the *Binary Independence Model (BIM)* ([122]), provide direct guidance on term weighting and term selection based on probability theory. In these probabilistic models the retrieval task is treated as a two-category (relevant vs. non-relevant) classification problem, and the probability of relevance is modelled explicitly [116][122][55]. Using relevance feedback to improve parameter estimation in probabilistic models is straightforward according to the definition of the models, because they presuppose relevance information.

In the last decades many researchers proposed IR models that are more general, while also explaining already existing IR models. *Inference networks* have been successfully implemented in the INQUERY

retrieval system [146], and Bayesian networks extend the view of inference networks. Both models represent documents and queries using acyclic graphs. Unfortunately, both models do not provide a sound theoretical framework to learn the structure of the graph or estimate the conditional probabilities defined on the graphs, and thus the model structure and parameter estimations are rather ad hoc [57].

A common drawback of the above models is that most of them are focused on "relevance" based retrieval. This is probably due to the task at focus when these models were proposed (ad hoc retrieval), the nature of evaluation data sets, and the limitation of computational power. It is hard to extend the already existing models to model more complex user scenario where relevance is not the only aspect of documents we need to consider, or if we have explicit and implicit relevance feedback. Another common drawback is that although most of them estimate the uncertainty of relevance, they do not estimate the uncertainty of the model itself. So these models do not provide guidance on how to solve problems, such as exploration, where the uncertainty of the model is the key. The third drawback is that they do not provide a convenient way to integrate domain knowledge, which is very important while building a practical system.

Inference networks and Bayesian networks have the potential to be extended to avoid these drawbacks to model more complex problems such as going beyond relevance, integrating domain knowledge, and active learning. Unfortunately, researchers were more focused on efficient algorithms that work in simple scenarios such as the ad hoc retrieval task, perhaps due to the limitation of the computation power of machines and the IR task in hand. When researchers first introduced these improved models, they steered their direction away from modeling complex scenarios, and usually limited their methods to associating random variables with user query, terms, and documents. Later researchers also followed the same direction, thus expansion beyond relevance based retrieval is not well studied, empirically or theoretically.

Although simplification of IR models was reasonable in early years, the IR community now has a broader definition of information seeking tasks. More complex IR scenarios are becoming interesting topics, and different training and testing data sets are available for the IR community. In addition, the computational power of machines is much stronger than before. Some researchers have tried to handle complex scenarios that need to consider multiple forms of evidence during retrieval. For example, [137] proposes using Bayesian network to combine information extracted from the content of the documents (terms) with information derived from the cross-references among the documents. However, neither the parameters nor the structure of their network are learned using Bayesian inference, and the combination function is manually set to a disjoint operation between the two pieces of evidence. Their approach is reasonable in the ad hoc scenario where no training data is available, however, it is not appropriate for filtering task where the system has some training data. Another example is using the linear or polynomial regression models to combine multiple

document features, such as term frequency, authorship and co-citations [56][52]. All these approaches can be viewed as special cases of the Bayesian graphical modeling approach. Unfortunately, some of the models are simplified so much that some of the powerful tools provided by BGM, which is discussed in Section 2.3, are ignored by IR researchers.

Language modeling, a statistical approach that models the document generation process, becomes a very active research area in the IR community since late 90s [44]. Some researchers have tried to extend this model for more complex scenarios [45]. Because language modeling itself is more focused on the text of the document, it does not provide formal guidance on how to model user scenarios with non textual information, such as implicit user feedback. So researchers need to introduce new techniques and go beyond the language modeling approach itself in order to handle more complex scenarios.

To summarize, existing IR models are inadequate for modeling adaptive information filtering, which is more complex than the traditional ad hoc retrieval task.

2.2.2 Existing adaptive filtering approaches

In the early research work as well as some recent commercial filtering systems, a user profile is represented as a Boolean logic [65]. With the growing computation power and the advance of research in the information retrieval community in the last 20 years, filtering systems have gone beyond simple Boolean queries and represent a profile as a vector, a statistical distribution of words or something else. Much of the research on filtering is focused on learning a user profile from explicit user feedback on whether he/she likes a document or not while interacting with the user. In general, there are two major approaches:

Retrieval + thresholding Ad hoc Information Retrieval is an extensively studied information seeking task. A typical retrieval system has a static information source, and the task is to return a ranking of documents for a short-term user request. Commonly used web search engines, such as Google.com, Lycos.com and Altavista.com, are examples of ad hoc information retrieval systems. Because of the influence of the retrieval models, some existing filtering systems use "retrieval scoring+thresholding" approach for filtering and build adaptive filtering based on algorithms originally designed for the retrieval task. Some examples are Rocchio, language models, Okapi, and pseudo relevance feedback [8][29][91][10][40][139]. A filtering system uses a retrieval algorithm to score each incoming document and delivers the document to the user if and only if the score is higher than a threshold. Because setting thresholds is not a problem in the retrieval task, where the system only needs to return a ranked list of documents, a major research topic in the adaptive filtering community is on how to set dissemination thresholds [123][12][157][11][164][15][25][161].

Text classification *Text classification* is another well studied area similar to filtering. A typical classification system learns a classifier from a labeled training data set, and then classifies unlabeled testing documents into different classes. Another popular approach is to treat filtering as a text classification task by defining two classes: relevant vs. non-relevant. The filtering system learns a user profile as a classifier and delivers a document to the user if the classifier *thinks* it is relevant or the probability of relevance is high. The state of the art text classification algorithms, such as Support Vector Machine (SVM), K nearest neighbors (K-NN), neural network, logistic regression and Winnow, have been used to solve this binary classification task [86][30][15][121][158] [163][139][102][154][85][140]. Some approaches, such as logistic regression or neural network, estimate the probability of relevance directly, which makes the task of setting dissemination threshold easier.

Both of the above approaches are focused on identifying relevant documents using distance measures defined in a document space indexed by text features such as keywords. This is a very simple and limited view of user modeling, without considering user context or other property of a document, such as whether a document is authoritative or whether it is novel to the user. However, even this simplest filtering task is still very hard, and existing filtering systems can't work effectively.

2.3 Bayesian Graphical Models

This section is a tutorial about Bayesian graphical models. Most of the content covered here is based on [72][142][34] and [22]. Readers familiar with Bayesian theory and graphical modelling theory can skip the rest of this chapter.

In the Bayesian graphical models framework, the Bayesian axiom of "maximizing the utility" together with the probabilistic inference tools provide the general guidance on what is the goal of a filtering system and how to make decisions to achieve this goal. This enables the system to choose the right action under uncertain situations.

The basic methodology underlying graphical models is to represent related knowledge about the task as a graph that summarizes the conditional independence relationships between different variables. Finite mixture models, Factor Analysis, Hidden Markov models, Kalman filters, and Hierarchical models are commonly-used examples of specific graphical models. Once a specific graphical model is created, most of the tasks are recast as probabilistic inference: Computing a conditional probability distribution over the values of the unobserved hidden nodes given the values of observed evidence nodes. What is hidden or observed depends. For example, when we train the relevance model in Figure 2.1, the node θ (the model parameters)

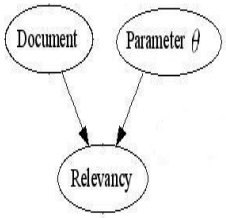


Figure 2.1: A graphical model for relevance filtering.

is hidden while the nodes *Relevant* (the user assessment) and d_i (the document) are observed. While testing (predicting whether a document is relevant or not), the node *Relevant* is hidden while the nodes θ (or the distribution of θ) and d_i are observed. Thus a system based on this framework can do learning and inference in a unified framework. **

Besides learning (representing beliefs) and doing inference, the main goal of a system is to choose actions in situations of uncertainty. For example, a filtering system should choose whether it should deliver a document to the user or not. Bayesian theory says that the criterion of maximizing expected utility is the only decision criterion that a system should use to decide which action to take. We can estimate the probability distribution of each variable, and then optimize the utility accordingly.

Bayesian theory and graph theory are two well studied areas. They have been applied and investigated in many fields, such as computer science, engineering, physics, neuroscience, cognitive science. There are many published papers about related work, and this section only summarizes Bayes' theorem, graph structure learning, inference, and Bayesian experimental design, since these techniques will be used throughout the dissertation. Other important work in the graphical field, such as the triangulation of a graph, will not be covered here because they are not used in the dissertation. Readers interested in these areas are referred to [68][110][42][68][73].

2.3.1 Bayes' theorem

Bayes' theorem can be summarized with a simple mathematical form shown below:

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)} \tag{2.9}$$

The most important application of Bayes' theorem is to update the beliefs about the unobservable based on new information. This could be prediction or parametric inference. Let $y = y_1, y_2, .., y_m$ denote future

**Some people also refer to learning and inference as training and testing.

or unobserved quantities, and $x = x_1, x_2, ..., x_n$ denote the observed quantities, and let θ the denote model parameter. We have:

$$P(x) = \int_\theta P(x|\theta)P(\theta)d\theta \tag{2.10}$$

$$P(y|x) = \int_\theta P(y|\theta)P(\theta|x)d\theta \tag{2.11}$$

$$P(\theta|x) = \frac{P(x|\theta)P(\theta)}{P(x)} \tag{2.12}$$

In above equations, the distribution of θ explicitly models our uncertainty of the model. To learn from the data, a learning system usually begins with a prior $P(\theta)$. We can view $P(\theta)$ as our prior belief about the parameters before we see the data x. The prior benefits us in two aspects: 1) it provides a tool for introducing human knowledge into model building; and 2) it acts as a regularizer to control the model complexity and avoid overfitting. Equation 2.12 shows how to estimate $P(\theta|x)$, the posterior belief about the parameters, after seeing the data x.

In many cases, estimating $P(x)$ can be computationally expensive because of the integration over θ in Equation 2.10. Fortunately, it is not always necessary to do that. Given a set of training data x, $P(x)$ is the same for all models. If the goal is to compare different values of θ to maximize $P(\theta|x)$, we can drop $P(x)$ in Equation 2.12 without affecting the final result:

$$P(\theta|x) \propto P(x|\theta)P(\theta) \tag{2.13}$$

This means the posterior distribution of the model θ is proportional to the prior distribution of θ multiplied by the data likelihood given the θ. It can be more computationally efficient if we use Equation 2.13 instead of Equation 2.12. For example, the following formula derived from Equation 2.13 is often used to estimate the maximum a posteriori (MAP) estimation of θ without estimating $P(x)$.

$$\theta_{MAP} = argmax_\theta P(x|\theta)P(\theta) \tag{2.14}$$

2.3.2 Graphical models

The basic methodology behind graphical modeling is to represent related knowledge about the task as a graph that summarizes the conditional independence relationships between different variables. The nodes in the graph are random variables, such as *parameter*, *document* and *relevant* in Figure 2.1. The missing

arcs in the graph represent conditional independence between variables. A graphical model includes the definition of the graph structure and a collection of local distributions. The graph can be either directed, such as Bayesian Networks, or undirected, such as Markov Random Fields.

Let's first begin with the DAG (directed acyclic graph). We will focus on the most widely used DAG: The Bayesian network. A DAG is represented by $G(V, E)$, where V is a set of nodes and E is a set of edges of the graph. We use V to represent the set of nodes, or the set of random variables indexed by the nodes of the graph. Which one it refers to depends on the context. Similarly, each $X \in V$ corresponds to a node in the graph, or the random variable indexed by that node. Each node is associated with a conditional probability distribution $P(X|pa(X))$, where $pa(X)$ denotes the parents of node X. The structure of the graph defines conditional independence relationships between random variables. We can use graphical manipulation to find such independence relationships [110]. Generally speaking, each variable is independent of its non-descendants given its parents. A *plate* can be used to represent the replication in graphical models (Figure 2.2).

One simple graphical model is illustrated in Figure 2.3 where each x_i is independent of all $x_{j\neq i}$. This graph can be used to represent a logistic regression model

$$P(Y|X_1, X_2, ..X_N) = \frac{1}{1 + exp^{\sum_{i=1}^{N} w_i X_i}}$$

where $w_i : i = 1...N$ is the logistic regression weight of X_i.

The same graph can also represent a linear regression model:

$$P(Y|X_1, X_2, ..X_N) = AX = \sum_{i=1}^{N} a_i X_i$$

where $a_i : i = 1...N$ is the linear regression weight of X_i.

The joint probability over the set of all variables V can be calculated by the product of the probability of each variable conditioned on its parents over all nodes:

$$P(V) = \prod_{X \in V} P(X|pa(X)) \tag{2.15}$$

For example, for the graphical model in Figure 2.4, the joint probability is:

$$P(A, B, C, D, E) = P(A)P(B)P(C|A, B)P(D|A)P(E|D, C)$$

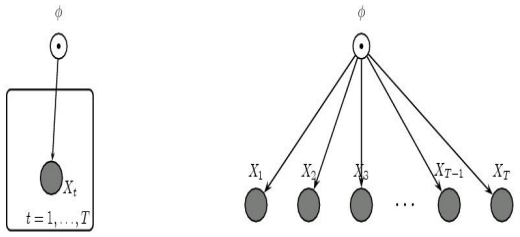


Figure 2.2: The representation of plate. The diagram on the left is a different representation for the graphical model on the right. The shorthand representation on the left means variables X_t are conditionally independent and identically distributed given ϕ.

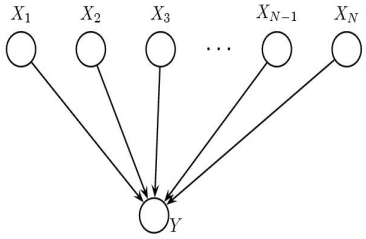


Figure 2.3: A graphical model representation for logistic regression or linear regression.

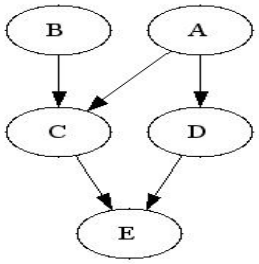


Figure 2.4: An example of directed acyclic graph with five nodes.

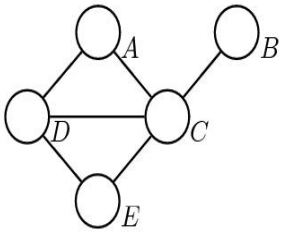


Figure 2.5: An undirected graph: (A,D,C), (C,B), and (D,E,C) are cliques.

Now let us consider the undirected graph. We will still use $G(V, E)$ to represent the graph and corresponding random variables, except the edges do not have directions now.

Clique A fully connected subset of nodes, usually denoted using C. We use C to represent a collection of cliques of the graph. For example in Figure 2.5, C=(A,D,C),(C,B),(D,C,E).

In an undirected graph we usually use nonnegative *potential functions* instead of conditional probability functions $P(X|pa(X))$ to represent the relationships between random variables [73]. Let $\psi_C(X_C)$ be a nonnegative *potential function* associated with each maximal clique C. Then the joint probability of the variables represented in the graph is the normalized product over all potential functions:

$$P(V) = \frac{1}{Z} \prod_{C \in C} \psi_C(X_C) \tag{2.16}$$

where Z is the normalization factor:

$$Z = \int_X \prod_{C \in C} \psi_C(X_C)$$

.

We can always convert a DAG to an undirected graph by treating Equation 2.15 as a special case of Equation 2.16. In order to do that, we need to force $pa(X) \bigcup X$ to be a clique by adding undirected edges between all of the parents of node X [72].

2.3.3 Algorithms for structure learning

A graphical model is a combination of its graph structure and a set of local conditional probability functions or potential functions. Structure learning and probabilistic inference are the two key techniques. We will use both of them later in this dissertation to learn graphical models from the data and make predictions about unknowns. This section and the following section briefly cover these two topics.

[42] gives a good introduction for Bayesian network structure learning algorithms, and [138]. In general, there are two major approaches to learn graph structure from the data:

Scoring based structure learning In this approach, the algorithm assigns a score, such as the likelihood of the training data given the structure, to each candidate graph. Usually a structure with the best score is selected.

Constraint based structure learning In this approach, the algorithm finds some constraints, and usually the structure(s) consistent with these constraints are kept as valid. Besides the constraints au-

Table 2.2: PC algorithm.

FUNCTION : Derive a model structure consistent with the data
INPUT : A set of data; V: the set of nodes in the graph
OUTPUT : A graphical model structure
NOTES: ADJ_X is the set of adjacent nodes of node X;
$|S|$ is the number of nodes in set S;
$I(X, Y|S)$ is the independence relationships between node X and Y condition on a set of nodes S.
ALGORITHM:
Start with a complete undirected graph gp
(or a less than complete graph with unlikely links removed by domain experts):
i=0
Repeat
  For each $X \in V$
    For each $Y \in ADJ_X$
      Determine if there is $S \subseteq ADJ_X - Y$ with $|S| = i$ and $I(X, Y|S)$
      If this set exists: Make $S_{XY} = S$, Remove link $X - Y$ from the graph
i=i+1;
Until $|ADJ_X| \leq i$ for $\forall X$
For each uncoupled meeting X-Z-Y, if $Z \notin\in S_{XY}$, Orient $X - Z - Y$ as $X \rightarrow Z \leftarrow Y$
Repeat
  For each $X \leftarrow Y - Z$, if X and Z are not adjacent, orient $Z - Y$ as $Y \leftarrow Z$
  For each $X - Y$, if there is a directed path from X to Y, orient $X - Y$ as $X \leftarrow Y$.
Until no edges can be oriented

tomatically generated by the algorithm, a person can also specify prior constraints based on domain knowledge.

In a graph, if there is an arc from node X to node Y if and only if X is a direct cause of Y, we call the graph a *causal graph*. One of the major goals and advantages of structure learning is the ability to automatically learn the *causal graph* that encodes the causal relationships between variables. This will help us to understand the problem domain and answer questions, such as whether a user liking a document causes increased reading time, or whether the authority of a page is important to the user. Some structure learning algorithms try to achieve the goal of causal discovery directly. They are new and subject to criticisms. However, because of the potential of these algorithms, their success in some domains [101][111][138], and the lack of causality based analysis in the information retrieval community, we decided to introduce this important technique to the IR community and apply it to the task of filtering in this thesis.

As an example, let's look at a simple constraint based causal learning algorithm that will be used later in Section 6.1: PC algorithm (Table 2.2).

To learn the causal structure, the PC algorithm begins with a complete graph, then removes edges

that contradict zero order conditional independence relations, then remove edges that contradict first order conditional independence relations, and so on. Finally, the algorithm finds some head to head links and orient the links without producing cycles. The algorithm finds a set of models that can't be rejected on the basis of the data. A major step in this algorithm is to do statistical tests about independence relationships of the form $I(X, Y|S)$ using the data, and thus the final results are subject to the error of the statistical test.

This algorithm is computationally efficient with polynomial time complexity. It assumes no hidden common causes, the causal relationships are acyclic, the direct causal effect of a variable into another is linear and the distribution is normal. These assumptions, especially the assumption of no hidden variables, may not hold in the real scenario. Some algorithms make fewer assumptions. For example, the Fast Causal Inference algorithm (FCI [138]) handles unmeasured hidden variables. [111] and [138] provide extensive detailed descriptions about learning structures with causal meanings, including hidden variables, circles, and undirected graphs. More details of causal structure discovery are beyond the scope of this dissertation, we refer the reader to these books for more information on this topic.

2.3.4 Algorithms for probabilistic inference

A system based on graphical modelling treats training and testing in a unified framework, both as probabilistic inference problems. Thus the most important computation problem for graphical modelling is probabilistic inference: computing the conditional probabilities $P(x_F|x_E)$, where E are observable variables, and F are unobservable variables we need to estimate. Usually the set of variables represented by the graph are $V = E \bigcup F \bigcup H$, where H are other variables.

There are several different algorithms for probabilistic inference, such as exact algorithms ([110]), sampling based algorithms ([142][143][92]), variational algorithms ([67][74]), most likely configuration, parametric approximations ([105][159]), and heuristic methods ([61]). These algorithms were developed by researchers working in Bayesian theory and graph theory. Different algorithms have different trade-offs between computational speed, implementation complexity, generality and accuracy. In order to do statistical inference on a graphical model, we can combine different algorithms together. For example, we can do exact inference algorithms locally in addition to an overall sampling framework [108].

This section discusses the exact inference algorithms, the sampling based algorithms and the most likely configuration approach, since they will be used later in the dissertation. As there is a large amount of literature about these algorithms, we will only review them concisely. For more detail about these models, the readers are refereed to [110][73].

Exact inference

Let's consider the graph in Figure 2.5, and suppose we want to compute the marginal probability $P(B)$. We will obtain this by integrating out other variables (A, C, D, E):

$$\begin{aligned} P(B) &= \int_A \int_C \int_D \int_E \frac{1}{Z}\psi(A,D,C)\psi(D,E,C)\psi(B,C)dAdEdDdC \\ &= \frac{1}{Z}\int_C \psi(B,C)\int_D \int_E \psi(D,E,C)\int_A \psi(A,D,C)dAdEdDdC \\ &= \frac{1}{Z}\int_C \psi(B,C)\int_D \int_E \psi(D,E,C)m_A(D,C)dEdDdC \\ &= \frac{1}{Z}\int_C \psi(B,C)\int_D m_E(D,C)dDdC \\ &= \frac{1}{Z}\int_C \psi(B,C)m_D(C)dC \\ &= \frac{1}{Z}m_C(B) \end{aligned}$$

where the intermediate factors $m_x = \int_x ...dx$ $(x \in (A, D, C, E))$ are defined in an obvious notation. We can view these intermediate factors as messages passed from variables that have been integrated.

Note that the elimination order is very important here. This is a classical graph-theoretic problem and can be solved by the triangulation algorithm; readers are referred to [110] for more detail.

The problem is NP-hard for an arbitrary graph, so exact inference is often used only for simple graph structure, such as trees, which exhibit less complexity in calculating the marginals. Beside, each step can be computationally expensive because of the integration involved. Fortunately, the computation can be affordable for certain simple graphical models. For example, the integration can be reduced to a very simple form if we use Gaussian networks. Even for certain more complex graphical models, there are good approximation based algorithms, such as the most likely configuration, sampling based algorithms, variational methods, parametric approximation, and heuristic methods, as discussed below.

Most likely configuration

While doing exact inference we get the marginal probability by integrating out unobserved variables. We can view the intermediate factors (m_A, m_D, m_C, m_E) in Equation 2.17 as messages passed from variables that have been integrated out by averaging all possible configurations of these variables. Instead of averaging all possible configurations, we can also use the best configuration of these variables and then pass out the

message. This approach is called *most likely configuration*.

The most likely configuration approach has been widely used. Maximum likelihood estimation (MLE) and maximum a posteriori (MAP) are special cases of using the most likely configuration approach to estimate the parameters while learning. The Viterbi algorithm used for Hidden Markov Model decoding is a special case of using the most likely configuration approach to find the best label of data while testing.

Monte Carlo methods

Given a set of known variables X_E, Monte Carlo methods use samples of one or more values of the unobserved variables X_F. In these methods messages passed from a set of nodes are in the form of samples.

Commonly used Monte Carlo methods, such as importance sampling, rejection sampling, the Metropolis method and Gibbs sampling, can be used to obtain a sample of values, $(x_1, x_2, .., x_N)$, from the probability distribution $P(x)$. [††] Then, these samples can be used to answer virtually any question ϕ about the distribution P(x) by formulating the question in the form:

$$\int \phi(x)P(x)dx \simeq \frac{1}{N}\sum_{i=1}^{N}\phi(x_i) \tag{2.17}$$

For example, we can estimate some function of the posterior probability distribution, such as mean, variance, divergence using Equation 2.17.

Among these Monte Carlo methods, the Metropolis method and Gibbs sampling can be practical in high dimensional spaces. For more detail of Monte Carlo methods, please refer to [142][143][92].

2.3.5 Bayesian experimental design and sequential decision problem

For most tasks, model estimation is only an intermediate step in the whole process, and the task of a system is usually to make a decision on which action to take. A good system chooses the best action (such as delivering or not delivering a document to the user) to maximize some expected utility function, such as the linear utility function defined in Equation 2.4. A decision is usually made based on the current belief about the parameters. A comparatively formal description about how to make the decision is:

> Let $A = a_i, i \in I$ be the set of alternative actions available to the system. For each a_i, based on the initial belief about the parameter $P(\theta)$ and additional information obtained after observing data X, we can estimate the possible consequences C_{ij} that may occur after action

[††] In Bayesian graphical modeling framework $P(x)$ could be the posterior distribution $P(X_F|X_E)$. Here we use $P(x)$ for representational convenience.

a_i. Let $U(C_{ij})$ be the utility corresponding to the consequences if action a_i (such as delivering a document) is taken and we get a consequence C_{ij} (such as the user likes the document). Then, action a_1 is to be preferred over action a_2 if and only if:

$$E(U(a_1|X)) > E(U(a_2|X)) \tag{2.18}$$

where

$$E(U(a_i|X)) = \sum_j U(C_{ij})P(C_{ij}|a_i, P(\theta), X)$$

.

So, in order to decide which action to take, one very important part is to specify a utility function that reflects accurately the purpose of the system.

For example, if the filtering system's objective is to maximize the immediate $T9U$ utility, system needs to decide whether to deliver a document or not, and the possible consequences are either the document is relevant or not, then we have: $A = a_1, a_2$, $a_1 = deliver$, $a_2 = notdeliver$, $C_{1,1} = relevant$, $C_{1,2} = non-relevant$, $C_{2,1} = relevant$, $C_{2,2} = non-relevant$, $UC_{1,1} = 2$, $UC_{1,2} = -1$, and $UC_{2,1} = UC2, 2 = 0$.

According to Equation 2.18, the action $a_1 = deliver$ is preferred over action $a_2 =$"not deliver" if and only if:

$$\begin{aligned}
0 &< E(U(a_1|X)) - E(U(a_2|X)) \\
&= U(C_{1,1})P(C_{1,1,}|a_1, P(\theta), X) + U(C_{1,2})P(C_{1,2,}|a_1, P(\theta), X) \\
&\quad +U(C_{2,1})P(C_{2,1,}|a_2, P(\theta), X) + U(C_{2,2})P(C_{2,2,}|a_2, P(\theta), X) \\
&= 2 * P(relevant|delivered, P(\theta), X) - P(non\text{-}relevant|delivered, P(\theta), X) \\
&= 2 * P(relevant|P(\theta), X) - P(non\text{-}relevant|P(\theta), X)
\end{aligned}$$

The last step is based on the assumption that whether to deliver or not to deliver a document does not affect the relevance of a document. So the system should deliver a document to the user if and only if the probability of relevance is higher than 1/3 based on current belief about θ.

However, an online system, such as a filtering system, needs to make sequential decisions to optimize a long term objective function instead of the immediate utility in the previous simple example. To do that, the system first takes an action based on information learned from the old data, and gets the consequence

together with more information after the action. Then the system revises its belief and chooses another action, and gets a consequence with further information. The whole online process keeps on until the end when the final evaluation is made. This is a *sequential decision problem* where successive interdependent decisions are to be made. An important area, *Bayesian Experimental Design*, is devoted to solving such problems.

A Bayesian decision theory approach to this problem can be summarized as follows [88][34].

Bayesian Experimental Design: An experiment/action a must be chosen from some set $A = a_i, i \in I$ after which a data y ($\in Y$) will be observed. The unknown parameter are θ and the parameter space is Θ. $P(y|a)$ can usually be estimated based on an initial belief about the parameter $P(\theta)$ and additional information X obtained before the action a is taken. There are two decision problems: The selection of action a and the selection of terminal decision $d(\in D)$. A general utility function is of the form $U(d, \theta, a, y)$. For any action a, the expected utility of the best decision function is given by

$$U(a) = \int_y max_{d \in D} \int_\Theta U(d, \theta, a, y) P(\theta|y, a) P(y|a) d\theta dy \tag{2.19}$$

The utility function defined here is not necessarily to be the same as defined in Equation 6.1, even if the global objective function is Equation 6.1. There are many alternative utility functions used by other researchers for sequential decision problems. Detailed discussion about these various utility functions is available in [34]. In Section 4.1.2, we will derive a utility function to maximize the global objective function.

In *finite states finite horizon* sequential decision problem, if the number of possible scenarios (states) at any given time is finite and if the number of decision nodes to be considered is finite, backward induction can be used to find the global optimal action [23]. This means that if we know when the user will stop using the filtering system, theoretically we can find the optimal active learning strategy. Unfortunately, usually this condition does not hold for the adaptive filtering task. Even if it holds, an exact optimal solution may not be practical because the computation is usually very expensive. Filtering can be modeled as a *continuous multi-bandits problem* [93], a branch of a more general *optimal stopping problem*. Although the solution described in [93] probably can't be applied to the adaptive filtering task because of its computational complexity, it does provide some useful guidance for us to solve the adaptive filtering task. For example, the exploration and exploitation we will discuss in Section 4.1.2 can be viewed as one special approximate solution in this framework.

Chapter 3

Integrating Expert's Heuristics using Bayesian Priors

As mentioned before, the filtering task shares some common problems, such as document representation and query representation, with the text classification task and the ad hoc retrieval task. Thus algorithms used for text classification tasks or the ad hoc retrieval relevant feedback task such as SVMs, logistic regression models, Naive Bayes, decision trees, language modeling, or Rocchio can be used for profile updating (Section 2.2.2). Although a large literature about these algorithms exists, there is no conclusion about which algorithm works best. The purpose of profile learning is to find a classifier with the least generalization error on future data using the *training data available*, thus the answer usually depends on the data set. In order to understand which algorithm works better under what kinds of situations, we can decompose the generalization error of a learning algorithm into 3 parts:

- Bias: Measure of how closely the learning algorithm is able to approximate the best solution.
- Variance: Measure of how sensitive the learning algorithm is to the training sample.
- Noise: Measure of the inherently irreducible uncertainty of the problem. For example, for a given x there are more than one possible y.

A high variance means the learning algorithm converges to its asymptotical classifier very slowly. A high bias means the asymptotical classifier is far from the theoretically optimal classifier. For problems with many training samples, the bias can be the dominant contributor to the generalization error, while for problems with very few training samples, the variance may be a dominant contributor. One may want to use a learning algorithm with both low bias and low variance. However, there is a natural "bias-variance trade-off" for any learning algorithm [58].

Bias-Variance Dilemma As the complexity of the learning algorithm increases, the bias goes down, but the variance goes up.

Because of this dilemma, some complex learning algorithms, such as SVM or logistic regression, may work well when the amount of training data is large, but some simple algorithms, such as naive Bayesian or Rocchio, may work better when the amount of training data is very small.

At the early stage of filtering, we have very few training data, thus a low variance learning algorithm could be a better choice. When we have enough training data later based on long term interaction with the user, a low bias learning algorithm may work better. However, an adaptive filtering system needs to work consistently well in the whole filtering process.

We hypothesize that using a Bayesian prior to combine two different algorithms may solve this problem. In this chapter, we develop a new technique to use the decision boundary of the low variance algorithm as prior knowledge to set the prior distribution of a low bias model, and then use the data to learn the posterior distribution of the low bias model. The combined algorithm may get a good bias-variance trade-off based on the size of the training set, thus achieving a consistent good performance at different stages of filtering. We apply the proposed technique to combine Rocchio, a heuristic algorithm proposed by an IR expert, with logistic regression, a widely used statistical machine learning algorithm. An adaptive filtering system using the new algorithm behaves similar to Rocchio at the early stage of filtering, and becomes more similar to logistic regression as more user feedback is available. When a user profile contains an initial query, the proposed algorithm is significantly better than both Rocchio and logistic regression, and compares favorably with the best methods in the TREC-9 and TREC-11 adaptive filtering tasks. On the TDT5 data set where no initial query is available, the new algorithm is similar to logistic regression and among the best on TDT 2005 supervised tracking task.

This chapter describes how we develop and evaluate the proposed solution. It is organized as follows: Section 3.1 introduces the definition of the Rocchio algorithm, logistic regression algorithm. A new algorithm Logistic_Rocchio that combines the Rocchio algorithm and logistic regression is introduced in Section 3.2. Section 3.3 and Section 3.4 describes our experimental methodology and results. Further discussion and some related works are provided in Section 3.5. Section 3.6 concludes.

3.1 Existing algorithms

At a certain point in the adaptive filtering process, suppose we have t training documents with user feedback $D_t = (X, Y)_t = [(\mathbf{x_1}, y_1), (\mathbf{x_2}, y_2), ..., (\mathbf{x_t}, y_t)]$, where $\mathbf{x_i}$ $(i = 1$ to $t)$ is a vector that represents the document d_i in a K dimensional space indexed by K keywords*. y=1 if the document $\mathbf{x}$ is relevant, otherwise y=-1.

*Any weighting schema, such as $TF \cdot IDF$, can be used to convert a document d_i into its vector representation $\mathbf{x_i}$.

The core problem in relevance filtering is estimating the posterior probability of relevance of document $\mathbf{x}$ based on the training data: $P(y = 1|\mathbf{x}, D_t)$. [†]

As mentioned before, many algorithms can be used for profile learning. This section introduces two very representative algorithms: the Rocchio algorithm and logistic regression.

3.1.1 Rocchio algorithm

A widely used profile updating methods in the information retrieval community are different variations of the incremental Rocchio algorithm [6][29][132][15], which can be generalized as:

$$\mathbf{Q}^{'} = \alpha \cdot \mathbf{Q} + \beta \frac{\sum_{\mathbf{x_i} \in R} \mathbf{x_i}}{|R|} - \gamma \frac{\sum_{\mathbf{x_i} \in NR} \mathbf{x_i}}{|NR|} \tag{3.1}$$

where $\mathbf{Q}$ is the initial profile vector, $\mathbf{Q}^{'} = (w_{r1}, .., w_{rK})$ is the new profile vector, R is the set of relevant documents, and NR is the set of non-relevant documents. When there is no relevant or non-relevant documents, the corresponding component in Equation 3.1 is deleted. The Rocchio algorithm also works reasonably under such kind of conditions.

When a document arrives, the Rocchio algorithm only provides a score indicating how well the document matches each user profile. [‡] The score is calculated by measuring the distance between the document vector and the user profile $Q^{'}$. Since an adaptive system needs to make a binary decision for each incoming document (e.g., choose from action "deliver" or "not deliver"), researchers usually have to use another module to learn the dissemination thresholds [155][164]. The filtering system will deliver document $\mathbf{x}$ to the user if and only if its score is above the dissemination threshold. The corresponding decision rule is:

$$\text{deliver if and only if } (w_{r1}, .., w_{rK})^T \mathbf{x} >= threshold \tag{3.2}$$

Let $w_{r0} = -threshold$, $\mathbf{w_R^T} = (w_{r0}, w_{r1}, .., w_{rK})$. If we make $\mathbf{x}$ a K+1 dimension vector with the first dimension corresponding to a pseudo-feature which is always equal to 1, the above equation can be rewritten

[†]Through out this dissertation, we use a symbol in bold font to represent a vector.
[‡]The same is true for many other statistical retrieval algorithms that were originally designed for ad hoc retrieval, where a ranking of documents is sufficient.

as: [§]

$$\text{deliver iff } \mathbf{w_R^T x} >= 0 \tag{3.3}$$

The Rocchio algorithm is popular for two reasons. First, it is computationally efficient for online learning [6]. Second, compared to many other algorithms, it works well empirically [15][164]. However, the Rocchio algorithm is not based on a strong probabilistic framework and there is no guarantee about whether it will provide the optimal decision boundary in the high dimensional document space asymptotically, with infinite training data. In other words, the Rocchio algorithm is a simple heuristic algorithm that works empirically well.

3.1.2 Logistic regression

Logistic regression is one widely used statistical algorithm that can provide an estimation of the posterior probability $P(y|\mathbf{x})$ of an unobserved variable y given an observed variable $\mathbf{x}$. It has been widely used in the statistical and machine learning community.

A logistic regression model estimates the posterior probability of y via a log linear function of observed document $\mathbf{x}$.

$$P(y = \pm 1|\mathbf{x}, \mathbf{w}) = \sigma(y\mathbf{w}^T\mathbf{x}) = \frac{1}{1 + \exp(-y\mathbf{w}^T\mathbf{x})}$$

where $\mathbf{w}$ is the K dimensional logistic regression model parameter learned from the training data.

Before filtering, the Bayesian based learning system usually begins with a certain prior belief $p(\mathbf{w})$ about the distribution of the logistic regression parameter $\mathbf{w}$ (Section 2.3.1).

A Gaussian distribution $p(\mathbf{w}) = N(\mathbf{w}; \mathbf{m_w}, v_w)$ is often used as the prior distribution for logistic regression weights, where $\mathbf{m_w}$ is the mean of the Gaussian distribution in the K dimensional parameter space and v_w^{-1} is a $(K+1)\cdot(K+1)$ covariance matrix of the Gaussian distribution.

If there is no obvious correlation between the different dimensions of $\mathbf{w}$, or if we can't tell what the correlations are, the off-diagonal values in the matrix v_w^{-1} are usually set to zero. If we are not very confident about whether the true value of $\mathbf{w}$ is $\mathbf{m_w}$, the diagonal variables of the matrix v_w^{-1} are usually set to a small number. If all items in matrix v_w^{-1} are zero, $p(\mathbf{w})$ is a non-informative prior: all values of $\mathbf{w}$ have the same probability. A non-informative prior may seem *objective* as it represents the idea of *letting the data speak for themselves*. However, a classifier learned using a non-informative prior usually over fits

[§]For convenience, depending on the context, we use $\mathbf{x}$ to represent K dimensional vector or K+1 dimensional vector in the dissertation.

the data. So, v_w^{-1} is usually set to a diagonal matrix with a small non-zero positive number on the diagonal to act as a regularizer. The effect is the same as smoothing techniques used while building language models [162]. [162] presents smoothing with priors for generative models, while we are regularizing with priors for discriminative models.

At a certain point in the adaptive filtering process, we can update our belief about the logistic regression parameter $\mathbf{w}$ conditional on the training data D_t using Bayesian theorem.

$$\begin{aligned} P(\mathbf{w}|D_t) &= \frac{P(D_t|\mathbf{w})P(\mathbf{w})}{\int_{\mathbf{w}} P(D_t|\mathbf{w})P(\mathbf{w})} \\ &= \frac{\prod_{i=1}^{t} P(y_i|\mathbf{w},\mathbf{x_i})P(\mathbf{w})}{\int_{\mathbf{w}} \prod_{i=1}^{t} P(y_i|\mathbf{w},\mathbf{x_i})P(\mathbf{w})} \end{aligned}$$

With a Gaussian prior $N(\mathbf{w};\mathbf{m_w},v_w))$, the maximum a posteriori MAP estimation of $\mathbf{w}$ is:

$$\begin{aligned} \mathbf{w}_{MAP_t} &= argmax_{\mathbf{w}} P(\mathbf{w}|D_t) \\ &= argmax_{\mathbf{w}} \prod_{i=1}^{t} P(y_i|\mathbf{w},\mathbf{x_i})P(\mathbf{w}) \\ &= argmax_{\mathbf{w}} \sum_{i=1}^{t} log(1+\exp(-y_i\mathbf{w}^T\mathbf{x_i})) - v_w(\mathbf{w}-\mathbf{m_w})^2 \end{aligned}$$

Equation 3.4 can be viewed as a special form of regularized logistic regression, where v_w controls the strength of the regularizer. There is no closed form solution for $\mathbf{w}_{MAP_t}$, so greedy search algorithms, such as conjugate gradient descent, are often used to find the $\mathbf{w}_{MAP_t}$. In most of the cases where we have no prior knowledge about what the logistic regression parameter is, we usually set $\mathbf{w} = (0,...,0)$ and v_w^{-1} to a very small value. Then, we get a norm-2 regularized logistic regression model:

$$\mathbf{w}_{MAP_t} = argmax_{\mathbf{w}} \sum_{i}^{t} log(1+\exp(-y_i\mathbf{w}^T\mathbf{x_i})) - v_w\mathbf{w}^2 \tag{3.4}$$

When a new document $\mathbf{x}$ arrives, we can estimate the probability of relevance for this document:

$$P(y=1|\mathbf{x}) = P(y=1|\mathbf{x},\mathbf{w}_{MAP_t}) \tag{3.5}$$

3.2 New algorithm: LR_Rocchio

At the early stage of filtering when the system has very few training data, a simple profile learning algorithm with low variance, such as the Rocchio algorithm with a good thresholding method, is likely to be a good choice. At the later stage of filtering when the system has enough training data, a complex profile learning algorithm with low bias, such as logistic regression, may be better. How do we get an algorithm that works well consistently over the whole filtering process? One possible approach is to use the Rocchio algorithm first, then switch to logistic regression later when the amount of training data is enough. Another approach is to combine the Rocchio algorithm and logistic regression together to get a natural and smooth trade-off between variance and bias. The second approach, which will be explored further in this section, is the motivation for the new algorithm, a combination of Rocchio and logistic regression based on a Bayesian prior.

As mentioned before, Bayesian priors are a widely used tool for introducing human knowledge into model building; and it is also a regularizing tool for controlling the model complexity and avoiding overfitting. An adaptive filtering task begins with a very small amount of training data, thus a stable prior that works well with little training data is very important for building a good filtering system. Since the Rocchio algorithm is designed by researchers in IR community and works well empirically in the adaptive filtering task, using it to set a Bayesian prior of the logistic regression model parameter may help us to achieve stable performance at the early stage of filtering.

Usually, a logistic regression prior is a Gaussian distribution $N(\mathbf{m_w}, v_w)$. How does one find the prior mean $\mathbf{m_w}$ from Rocchio? A new technique is proposed here to solve this problem.

Let $\mathbf{w_R} = (w_{r0}, w_{r1}, w_{r2}, w_{r3}..., w_{rK})$ be the profile vector calculated based on the Rocchio algorithm (Equation 3.3).

For logistic regression, we use the same representation as Rocchio for documents: the same set of keywords with the same weighting schema, plus a pseudo-dimension, which is always 1, as features. The probability of relevance of a given document $\mathbf{x}$ based on logistic regression model w is:

$$P(y = 1|\mathbf{x}, \mathbf{w}) = \frac{1}{1 + \exp(-\mathbf{w}^T\mathbf{x})}$$

If the goal is to minimize classification error, a filtering system using the logistic regression model will:

$$\text{deliver if and only if } \mathbf{w}^T\mathbf{x} >= 0 \tag{3.6}$$

Equation 3.3 and Equation 3.6 are very similar. If the threshold of a Rocchio learner is set to minimize classification error too, both algorithms are trying to find a linear decision boundary in the high dimensional space indexed by the set of keywords for the same objective. A Gaussian prior $N(\mathbf{w}; \mathbf{m_w}, v_w)$ for logistic regression encodes the belief that the true decision boundary is around the one defined by $\mathbf{m_w}$. Instead of setting $\mathbf{m_w} = (0, ..., 0)$, if we set $\mathbf{m_w}$ so that the decision boundary of it is the same as the one found by Rocchio, $N(\mathbf{w}; \mathbf{m_w}, v_w)$ may be better than the commonly used non-informative prior or zero mean Gaussian prior.

A prior $\mathbf{m_w}$ that encodes Rocchio's suggestion about decision boundary can be learned via constrained maximum likelihood estimation:

$$\mathbf{m_w} = argmax_{\mathbf{w}} \sum_{i=1}^{t} log(\frac{1}{1 + \exp(-y_i \mathbf{w^T x_i})}) \tag{3.7}$$

$$\text{under the constraint: } \cos(\mathbf{w}, \mathbf{w_R}) = 0 \tag{3.8}$$

The resulting logistic regression parameter $\mathbf{m_w}$ maximizes the likelihood of the data (Equation 3.7) under the constraint that it corresponds to the same decision boundary as the Rocchio algorithm (Equation 3.8). This is an optimization problem, and the solution is in a simple form that can be calculated efficiently:

$$\mathbf{m_w} = \alpha^* \cdot \mathbf{w_R} \tag{3.9}$$

where α is a scalar:

$$\alpha^* = argmax_{\alpha} \sum_{i=1}^{t} \frac{1}{1 + \exp(-y_i \alpha \mathbf{w_R^T x_i})}$$

This is a one dimensional optimization problem, and the solution can be found quickly using gradient descent algorithms.

The Rocchio algorithm tends to be more stable at the early stage of filtering, especially given an initial query. The decision boundary found by Rocchio is likely to be better than the one found by logistic regression. As an extreme example, if the system has only an initial query without training data, Rocchio can still provide reasonable performance, while we can't learn a logistic regression model. At the early stage of filtering when the amount of training data is small, the prior is very important, thus the influence of the Rocchio algorithm on the logistic regression model is strong. When the system gets more and more training data, the prior is less important, and logistic regression dominates. This technique automatically manages the trade-off between bias and variance based on the amount of training data available. With the Bayesian prior estimated using Rocchio, the logistic regression parameter estimated has a higher bias but lower variance than without a

prior. As more and more training data are available, the bias decreases. Asymptotically, the learned classifier converges to the optimal linear decision boundary in the high dimensional document space.

3.3 Experimental methodology

Some experiments are carried out to understand the proposed new algorithm and compare it with the Rocchio algorithm (Equation 3.1), Norm 2 regularized logistic regression algorithm 3.4, logistic regression with unscaled Rocchio weights $\mathbf{w_r}$ as the prior mean, and the best methods in TREC-9 and TREC-11 adaptive filtering tasks. We set the variance of the prior according to our confidence about the prior distribution. For example, we feel more confident about the prior mean set by the scaled Rocchio weight $\alpha^* w_R$, thus we set the variance of the prior mean to a comparatively smaller number, 10I, where I is an identity matrix (also known as unit matrix). While using other prior means, such as zero used in the Norm 2 regularized logistic regression model, we are less confident about whether they are close to the optimal or not, thus we set the variance of the prior mean to a larger number, 100I. The Rocchio weights $(\alpha, \gamma, \lambda)$ is set to $(1, 3.5, 2)$ as [164].

The experiments follow the requirements specified by TREC adaptive filtering tasks [119][121]. The whole task models the text filtering process from the moment user arrives with a small amount of identified relevant documents and a natural language description of the information need. Documents arrive before user profile construction, among which only 2 or 3 are labeled, can be used as training data to learn word occurrence (e.g., idf) statistics, corpus statistics (e.g., average document length), and the initial profile representation. Remaining documents in the incoming documents stream are testing data. As soon as a new document arrives, the system makes a binary decision about whether or not deliver it to the user. If it is delivered, the relevance judgment for that document is released to the system and added to the training data set for profile updating.

The system treats the initial user profile description, which includes the title and description fields of the corresponding topic provided by NIST, as a relevant document while training logistic regression models. As a TREC adaptive filtering run begins with no non-relevant documents, our system randomly samples a small number (<= 3) documents and uses them as non-relevant documents to train logistic regression and Logistic_Rocchio models. Documents are represented as vectors using a variation of INQUERY's $TF \cdot IDF$ weighting [6]. ¶

¶We set $x_{i,d} = tfbel_{i,d} \cdot idf_i$, where $tfbel_{i,d} = \frac{tf_{i,d}}{tf_{i,d}+0.5+1.5\frac{len_d}{avgDocLen}}$, $idf_i = \log(\frac{N+0.5}{df_i}/\log(N+1))$, $tf_{i,d}$ is the number of times term i occurs in document d, len_d is the length of document d, $avgDocLen$ is the average length of documents processed, N is the number of documents processed, and df_i is the number of documents that contain term i.

Table 3.1: A comparison of different algorithms on the TREC-9 OHSUMED data set.

	Rocchio	LR1	LR2	LR_Rocchio
Prior Mean	NA	0	$\mathbf{w}_R$	$\alpha_* \mathbf{w}_R$
T11SU	0.37	0.36	0.12	**0.39**
T9U	11.38	10.43	-24.54	**15.03**
Precision	0.37	0.30	0.10	0.37
Recall	0.19	0.21	0.20	0.23
Doc/Profile	20.10	24.67	62.87	23.78

Three different text corpora are used to evaluated the proposed algorithms in our experiments: the OHSUMED data set used in the TREC-9 Filtering Track (Section 2.1.2), the Reuter's 2001 data set used in the TREC-11 Filtering Track (Section 2.1.2), and the multi lingual data set used in the TDT5 supervised tracking task (Section 2.1.2).

3.4 Experimental results

The experimental results on the OHSUMED data set are in Table 3.1. The Rocchio algorithm has reasonable performance, among the best compared to other filtering systems that participated in the TREC-9 adaptive filtering task [119]. [‖] Logistic regression with a prior $N(\mathbf{w}; 0, 100I)$ (LR1) is a little worse, but still good. Logistic regression using the prior $N(\mathbf{w}; \mathbf{w_R}, 10I)$ (LR2) is bad. This indicates using w_R directly estimated by the Rocchio algorithm as the prior mean is very misleading. However, after scaling using Equation 3.9 and setting the prior to $N(\mathbf{w}; \alpha^* \mathbf{w}_R, 10I)$ (LR_Rocchio), we get a significant improvement. This confirms our hypothesis that combining Rocchio with logistic regression will work well. This is not surprising since using a low variance classifier to set the prior for a low bias classifier may provide a nice trade-off between variance and bias.

The experimental results on Reuter's data set are in Table 3.2 and Table 3.3. [**] The Rocchio algorithm gets reasonable performance. Logistic regression with the prior with zero mean is a little better. Logistic regression using the Gaussian prior with w_R as the mean performs poorly. Using the scaled Rocchio weight (Equation 3.9) as the prior performs the best.

Figures 3.1 and Figure 3.2 compare the performance of the new algorithm with the Rocchio and logistic regression algorithms on each individual profile using T11U measure to get an idea of how significant the improvement is on a query by query basis. We can see that for most of the profiles, the new algorithm works

[‖]The T9U values of the top 3 TREC participants on this data set are: 17.3, 10.7 and 10.1.

[**]The final relevance judgments used in Table 3.2 are a little better than the old relevance judgments used in Table 3.3 (Section 2.1.2.).

Table 3.2: A comparison of different algorithms on the TREC-11 Reuter's data set.

	Rocchio	LR1	LR2	LR_Rocchio
Prior Mean	NA	0	$\mathbf{w}_R$	$\alpha_*\mathbf{w}_R$
T11SU	0.46	0.49	0.16	**0.52**
T11U	63.06	76.60	-25.86	**83.10**
Precision	0.53	0.48	0.20	0.56
Recall	0.33	0.41	0.46	0.41
Doc/Profile	69.36	88.28	223.32	84.12

Table 3.3: A comparison of different algorithms on the TREC-11 Reuter's data set using the old relevance judgments.

	Rocchio	LR1	LR2	LR_Rocchio
Prior Mean	NA	0	$\mathbf{w}_R$	$\alpha_*\mathbf{w}_R$
T11SU	0.46	0.49	0.11	**0.54**
T11U	40.20	54.66	-32.38	**61.68**
Precision	0.51	0.46	0.18	0.54
Recall	0.35	0.49	0.50	0.50
Doc/Profile	47.22	69.96	165.04	66.18

better (above the horizontal line). A statistical test (sign test) indicates that the new algorithm is significant better than the Rocchio algorithm and logistic algorithm.

Figure 3.3 compares the performance of our system with other systems that participated in the TREC11 adaptive filtering task. In TREC11, each participant submitted 1-4 runs to NIST, and the best run of each individual participant is reported here. A system that delivers nothing will get T11SU=0.33, and some TREC-11 participating systems are lower than that. The logistic regression and the Rocchio algorithm are among the best of TREC participants, while the proposed algorithm (Logistic_Rocchio) is much better than the best runs submitted by the TREC-11 adaptive filtering task participants. In Section 2.3.1, we mentioned that a prior helps us to control model complexity as well as introduce prior knowledge into model building. Both *LR_Rocchio* and logistic regression models benefit from the use of prior to control model complexity, thus work well. *LR_Rocchio* also benefits from the prior knowledge/heuristics, thus works the best.

We also compare the accumulated performance of different profile learning algorithms *over time* on the TREC-11 adaptive filtering task (Figure 3.4). Rocchio works better than logistic regression at the early stage of filtering, but worse at later stages. Logistic regression with a Rocchio prior is the best at any time. This is not surprising based on the bias-variance analysis. The new algorithm Logistic_Rocchio, is consistently much better than the other two.

To study the effectiveness of the proposed algorithm filtering solution to a similar but different task where

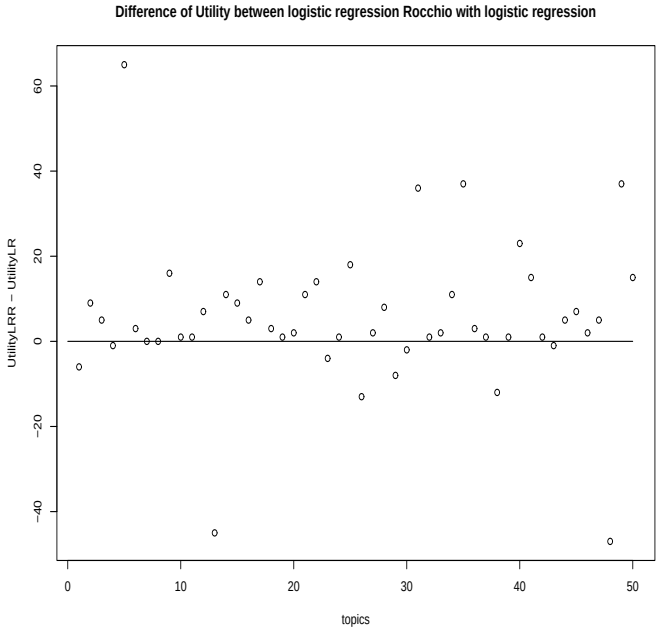


Figure 3.1: Comparison of the performance on individual profile: T11U of Logistic_Rocchio - T11U of LogisticRegression.

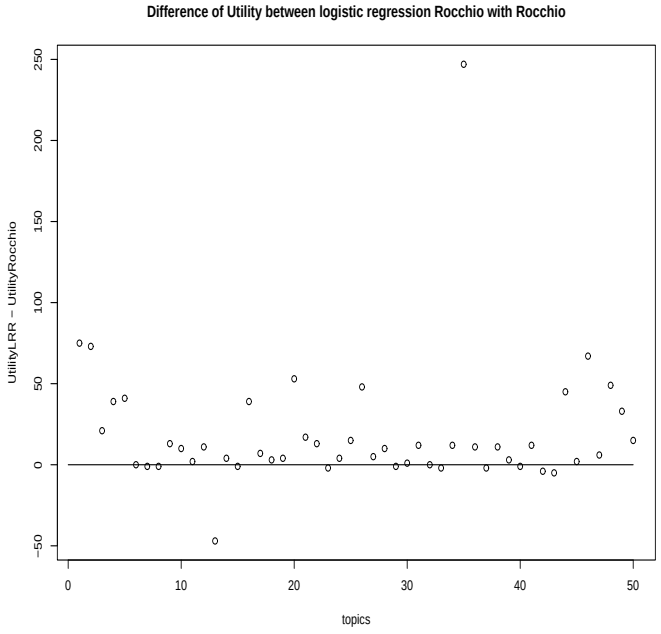


Figure 3.2: Comparison of the performance on individual profile: T11U of Logistic_Rocchio - T11U of Rocchio.

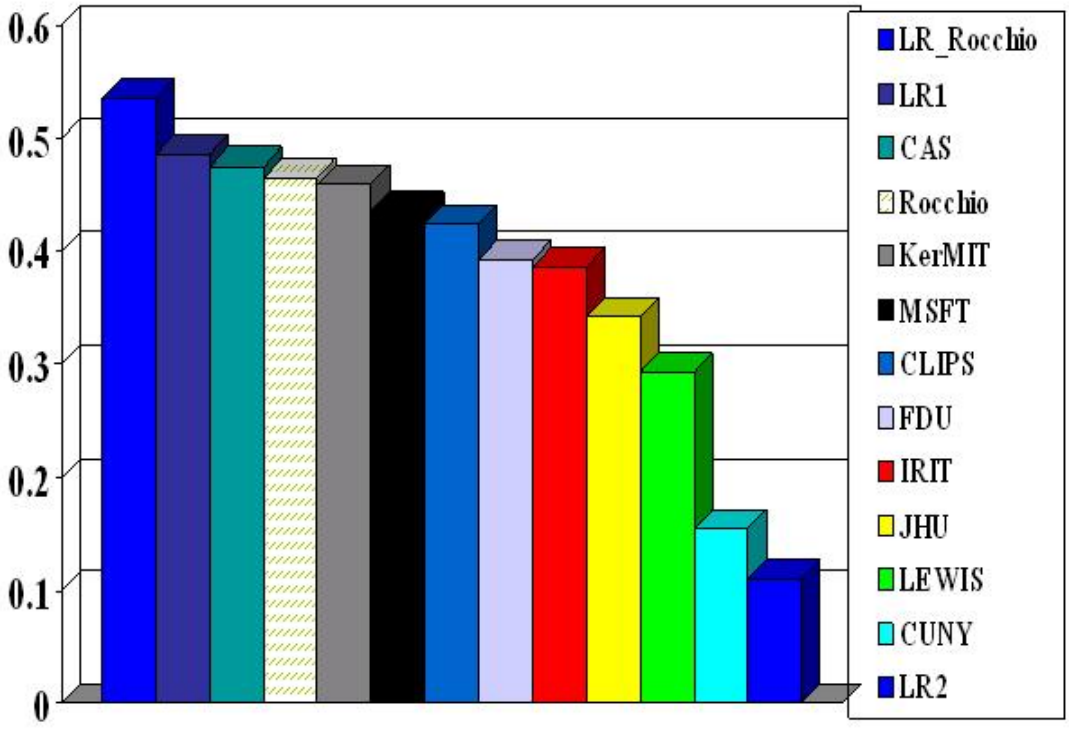


Figure 3.3: Comparison with other TREC participants. The T11SU values of different runs on the TREC-11 adaptive filtering task are reported in this figure. Systems in the legend from top to bottom correspond to bars from left to right. Our results and the results of TREC-11 participants are not directly comparable, because we have had greater experience with the dataset. The figure is provided only to give context for the results reported in this dissertation.

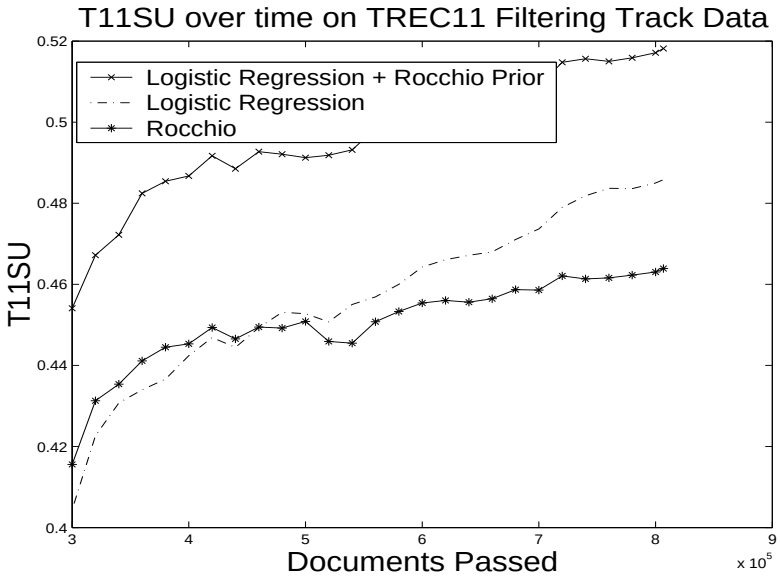


Figure 3.4: A comparison of the performance of different profile learning algorithms over time on the TREC-11 adaptive filtering task. This figure is the average of 50 user profiles.

RUN	Utility	TDT5NU: Utility Normalized	TDT5SU: Utility Scaled
team1_run1	-4964.58	-70.3956	0.0270
team1_run2	-1248.07	-20.1269	0.1091
team1_run3	317.37	0.3390	0.6917
team1_run4	-1665.99	-11.5721	0.0985
team1_run5	-504.75	-21.4876	0.2723
team1_run6	161.32	-6.0389	0.4532
CMU7_debug	459.92	0.1037	0.5911
CMU8:LR_Rocchio	449.17	0.5921	***0.7281***
Team2_run1	261.81	-1.8287	0.3820
team2_run2	233.64	-1.4206	0.3575
team3_run1	340.52	0.4019	0.6104
team3_run2	-614.56	-14.9671	0.1924
team3_run3	391.95	0.4934	0.6672
team3_run4	384.10	0.4148	0.6264

Table 3.4: The utilities of submitted supervised adaptation topic tracking results reported by NIST. CMU7 and CMU8 are our runs. Besides us, three other teams submitted their results of several runs.

we don't have much knowledge about the characteristics of the data set, we participated in the supervised tracking task in TDT5 held in the Fall of 2004. The utilities of all submitted supervised adaptation topic tracking results released by NIST are in Table 3.4. Our run CMU8:LR_Rocchio is among the best by different utility measures. [††]

When we compare logistic regression with Logistic_Rocchio on the TDT5 data set (Table 3.5), we find that the *LR_Rocchio* is better than logistic regression if evaluated using normalized utility measure TDT5SU, but worse if evaluated using unnormalized utility measure TDT5U. Why does *LR_Rocchio* work much better than logistic regression on TREC9 and TREC11 data set, but not obviously on the TDT5 data set? One major difference between these data sets is that TREC filtering data sets have initial profile description (as initial queries for the system to begin with), while the TDT data set does not. The lack of initial query in TDT5 data set may hurt the quality of the Rocchio prior. This suggests that a major reason that Rocchio is a good prior is that Rocchio uses the initial query well when the amount of training data is small. When there is an initial query, *LR_Rocchio* begins with a *good* prior. When there is no initial query, the advantage of *LR_Rocchio* is not as big.

Based on the experimental results, we hypothesize that

- If LR baseline is lower than Rocchio, a Rocchio prior helps, otherwise it may not help;
- Using the query in the Rocchio is a major reason for the improved performance;

[††]In TDT5 workshop, team1 reported a even better performance (TDT5SU=0.7328) using regularized logistic regression on this data set.

Table 3.5: A comparison of logistic regression (LR) with Logistic_Rocchio on the TDT5 Multilingual data set.

	LR1	LR_Rocchio
Prior Mean	0	$\alpha_* \mathbf{w}_R$
TDT5SU	0.687	0.72
TDT5U	435	399
Precision	0.19	0.32
Recall	0.92	0.77
Doc/Profile	162.3	99.7

- Using the query in other ways may also help. However, one needs to be careful about how to use the query, since using it as one training example as in logistic regression (LR1) or using it in as in unscaled Rocchio prior (LR2) have not help as much as in LR_Rocchio.

It's worth mentioning that the Rocchio algorithm itself is rather heuristic. Different implementations of the algorithm may perform differently. Because the Rocchio algorithm does not provide the guidance on other components, such how to set dissemination threshold or how to set term weights and do feature selection, while these compenents also influence the final result. In TREC adaptive filtering track, Rocchio is used for profile learning by some of the top ranking systems, as well as some lower ranking systems [119]. Similarly, the logistic regression algorithm may perform differently. So one may want to test whether the assumptions hold before using *LR_Rocchio*.

3.5 Related work and further discussion

Although our detailed analysis is focused on combining Rocchio and logistic regression, the proposed technique can also be applied to combining other learning algorithms. One may ask, how can we tell which algorithms we should combine? In other words, how can we tell which algorithm has a lower bias, and which algorithm has a lower variance?

We do not have a good answer to this question. The Bias-Variance Dilemma tells us that the complexity of the learning algorithm grows, the bias goes down, while the variance goes up. Unfortunately the complexity of classification algorithms are difficulty to measure, thus it is hard to use this dilemma empirically. In order to get a better answer to this question, we can compare the following two more general probabilistic approaches.

Discriminant approach: The posterior distribution $P(y|\mathbf{x})$ is modeled directly. For example, SVM [70]

and logistic regression are popular discriminative models. In this approach, systems directly model the boundary between classes.

Generative approach: The distributions $P(\mathbf{x}|y)$ and $P(y)$ are modeled, and the posterior distribution $P(y|\mathbf{x})$ is derived using the Bayes rule:

$$P(y=1|\mathbf{x}) = \frac{P(y=1,\mathbf{x})}{P(\mathbf{x})} = \frac{P(y=1,\mathbf{x})}{\sum_y P(\mathbf{x}|y)}$$

For example, language models [83], Naive Bayes [98], and BIM [122] are popular generative models used in IR. In this approach, systems first model the characteristics of each classes, and then derive the boundary between classes. The non-probabilistic Rocchio algorithm has some generative model flavor in the sense that the centroid of relevant and non-relevant documents are estimated [69, 125].

Some early work suggests that the generative models may have a low variance and work well with few training data, and comparable discriminative models may have a low bias and work better when the amount of training data is large [109][126]. Although there is no strong theoretical justification on which discriminative-generative pairs are low bias/low variance pairs, and the answer may also depend on the empirical task, combining comparable generative-discriminative models using the technique proposed in this chapter is likely to give a good performance in adaptive filtering system.

Besides statistical models, systems sometimes also use heuristic approaches or domain knowledge to make decisions. If we view the Rocchio classifier's decision boundary or the initial query from the user as domain knowledge, the proposed solution is a mechanism to integrate the domain knowledge into learning algorithms. Other domain knowledge can also be integrated into a machine learning algorithm in a similar way by first converting the domain knowledge into a decision boundary, then converting the decision boundary into a prior distribution of the model parameters. If the decision boundary derived from the domain knowledge works well, the final classifier will work well with little training data.

The technique proposed in this chapter has the flavor of a Bayesian analysis. However it is not a strict Bayesian approach, because the prior is estimated using the data. This is similar to Empirical Bayes methods [95].

There has been much research on combining different text classification algorithms or retrieval algorithms in the IR community [80][156][66][18][82]. [80] picks up different classifiers for different categories using categorical features; [66] [156] and [18] combine the output or transformation of the output of different

classifiers using linear combinations; [21] combines out put of classifiers with probabilistic learning based on some reliability indicators.

In contrast to the previous research on text classification or retrieval task, our work is different in three aspects:

- The focus of our work is adaptive filtering task, where the amount of training data changes over time.
- The previous work combines the output of various text classifiers, while the proposed techniques combines the classifiers based on better understanding of the variance, bias properties of the classifiers to be combined.
- By using a low variance classifier to set the prior for a low bias classifier, the proposed technique automatically gets a nice trade-off between variance and bias based on the size of the training data set. The combined classifier has a low variance when the amount of training data is small, and has a low bias when the amount of training data is large.

We also noticed a recent independent work that combines generative/discriminative models [115] and they found the hybrid model is significantly better than either the generative model or the discriminative counterparts. However, they focused on text classification instead of the adaptive filtering task. The combination technique and the effects of their algorithm are very different from ours. For example, their classifier does not converge to logistic regression's optimal estimation when the amount of training data goes to infinity.

Besides the Bayesian's way of using domain expert's knowledge or heuristics as a prior distribution of the parameters to be learned, there are alternative approaches to encode the prior. We can introduce the prior as constraints for learning a classifier under the maximum entropy or minimum divergence framework. For example, we can use a regularized logistic regression, with regularizer derived from initial user query, to achieve similar effect. This alternative approach can be explained under the Bayesian framework as in Equation 3.4, and different regularizer usually can be converted to different prior distribution.

3.6 Summary

An empirical filtering system needs to works well consistently at all stages of filtering process. Motivated by Bayes' theorem, we have developed a new technique to combine two classifiers, using a constrained maximum likelihood approach to learn a Bayesian prior for one classifier from another classifier. If the classifier used to learn the prior should have less variance, and if the classifier that uses the prior should have less bias, the proposed approach provides a reasonable trade-off between variance and bias based on the amount of

training data. Thus the combined algorithm may achieve a consistent good performance at different stages of filtering.

We developed a new algorithm to incorporate the Rocchio algorithm into logistic regression models using the proposed technique. Under certain assumptions, the new algorithm is likely to be better than LR and Rocchio, but not better otherwise. The experimental results show that the performance is much better than both the Rocchio algorithm and the logistic regression algorithm, comparable to the best in the TREC-9 adaptive filtering task, much better than the best in the TREC-11 adaptive filtering task. The algorithm is among the best on the TDT 2005 supervised tracking task. The experimental results suggest how the original query is used in the Rocchio algorithm is a major reason for the improved performance.

Although we focused on combining Rocchio with logistic regression, the proposed technique can also be applied to combine other classifiers or use domain knowledge. Early research work that compares generative models and discriminative models suggest that generative models may have lower bias and higher variance than their discriminative counterparts [109][126]. So using a generative model to set a Bayesian prior for its discriminative counterpart may get a good performance. If domain knowledge is available, one can first convert it into a decision boundary in the document space, and then use the proposed technique to convert the boundary into a prior.

Chapter 4

Exploration and Exploitation Trade-off using Bayesian Active Learning

As a system filters, it also refines its knowledge about the user's information need based on relevance feedback from the user. Delivering a document has two effects: 1) it satisfies the user's information need immediately, and 2) it helps the system better satisfy the user in the future by learning from the relevance feedback about this document provided by the user. Traditional approaches for adaptive information filtering, including the filtering experiments we did in the previous chapter, fail to recognize and model this second effect.

The goal of a filtering system is to maximize the utility in the long run. In order to do that, traditional approaches deliver a document if and only if the expected immediate utility of delivering it is greater than the expected utility of not delivering it. The expected immediate utility can be calculated from the probability that the document is relevant. For example, for the utility function used by the TREC-9, TREC-10 and TREC-11 Filtering Tracks (Equation 2.4), TREC participants usually set the threshold at t where $P(relevant|document\ score = t) = 1/3$ because the expected utility at that point is 0 [12, 164, 118]. In fact, delivering a document if and only if $P(relevant|\text{document score}) \geq 1/3$ was written explicitly in the guidelines of some TREC adaptive filtering tasks [119].

The work in the previous section is also an example of the traditional method that only focuses on the immediate utility. The system first estimates the *uncertainty of the relevant node* in Figure 2.1: the probability of relevance of a document. Then the system estimates the utility (credit or penalty) it can get immediately after delivering this document. Existing filtering approaches, including what we have done in previous chapter, do not consider the possibility that the system can improve its knowledge about the user's information need based on the feedback from the user so that it can better serve the user in the future. Especially in the early stage of filtering, when the system's knowledge about the user's information need is very limited, the potential gain from improving the user model can be substantial.

In this section, we go further to study the second aspect and model the long term benefit of delivering a document. The Bayesian graphical modeling approach provides a principled way to do that because of the explicit modeling of *uncertainty*. In Figure 2.1, *uncertainty* is not only related to the "relevant" node, but

also associated with other nodes, such as the "parameter θ" node. So we can also estimate the *uncertainty of the "θ" node*: the probability distribution of the model parameter. The notion of *uncertainty of* θ enables us to measure the improvement of the user profiles after learning from the user feedback on the delivered documents.

Maximizing the accumulated utility over a period of time is the objective of a filtering system. To achieve this goal, we derived a new model quality measure, utility divergence (Section 4.1.2), to help the filtering measure the quality of a user profile. Unlike measures of model quality used in most active learning methods, utility divergence has the advantage of having the same scale as the traditional utility model adaptive filtering systems try to optimize. Thus we can combine the expected immediate utility with the expected improvement on model quality to get a single quantity that measures the short-term and long-term value of a document in the document stream. This combined measure is the basis for deciding whether to deliver the document.

The following subsections describe our research on exploration and exploitation while filtering based on uncertainty of the model parameters. Section 4.1 describes the general theoretical framework of optimizing the utility based on the trade-off between exploration and exploitation using Bayesian theory. Sections 4.2 and Section 4.3 describe our experimental methodology and results. Section 4.4 discusses related work and Section 4.5 concludes this chapter.

4.1 Algorithm

In order to maximize the overall utility of a system, we propose to have two modules for the system: The exploitation module and the exploration module. The exploitation module estimates the immediate utility of delivering a new document based on the model parameter learned, while the exploration module estimates the future utility of delivering a new document by considering the improvement of the model parameter estimation if we get the user feedback about the document. To trade off exploitation and exploration, the filtering system delivers a document if the combined utility is above zero.

For simplicity, we use Bayesian logistic regression as our learner. We assume the form of the utility function to maximize is:

$$Utility = A_R \cdot R^+ + A_N \cdot N^+ \tag{4.1}$$

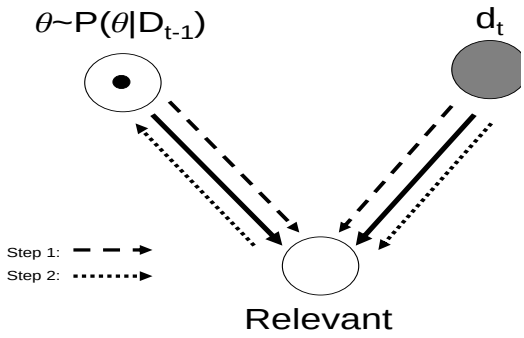


Figure 4.1: Exploitation and exploration for relevance filtering. Step 1: Messages are passed from known nodes "θ" and "d_t" to "relevant" to estimate the probabilistic distribution of "relevant". Then we can estimate the immediate utility. Step 2: Messages are passed from known nodes "d_t" and "relevant" to unknown node "θ" to estimate the probabilistic distribution of "θ", assuming we know the relevance feedback about document "d_t". Then we estimate the future utility gain if d_t is delivered, based on the probabilistic distribution of parameter "θ".

4.1.1 Exploitation using Bayesian inference

As mentioned before, the direct utility gain/loss due to delivering a document can be calculated once we know the probability of relevance of that document. Estimating the probability of relevance of a document based on the model parameter learned corresponds to the first step in Figure 4.1.

In Chapter 3, when a new document arrives, we use the maximum a posteriori MAP estimation of the model parameter θ_{MAP} to estimate the probability of relevance. We can also use the exact inference algorithm as described in Section 2.3.4. Suppose we have a model parameterized as θ to estimate the probability of the relevance of a given document. The prior distribution of the model parameters is $p(\theta)$. After seeing data $D = \{(x_1, y_1), \cdots, (x_k, y_k)\}$, the posterior distribution $p(\theta|D)$ is:

$$p(\theta|D) = \frac{P(D|\theta)p(\theta)}{\int P(D|\theta)p(\theta)d\theta} \tag{4.2}$$

where $P(D|\theta)$ is the likelihood of the user feedback given delivered documents and θ.

$$P(D|\theta) = \prod_i P(y_i|x_i, \theta) \tag{4.3}$$

The exact Bayesian average of the immediate utility gain of delivering a document is:

$$U_1(x|D) = \int_\theta \sum_y A_y P(y|x, \theta)P(\theta|D)d\theta \tag{4.4}$$

where A_y is the utility of delivering a document x if the true label of x is y. According to Table 2.1, $A_y = A_R$ if the true label is "relevant", and $A_y = A_N$ if the true label is "non-relevant".

4.1.2 Exploration using Bayesian active learning

For exploration, we need to measure the improvement on the learned model if we deliver the document. This corresponds to the second step in Figure 4.1. *

In order to quantify the improvement, a measure of the quality of the learned model is needed. It will enable us to estimate the improvement of a model once we know the label of a document compared to the model learned before delivering the document. The goal of estimating a model is to help the system make future decisions, and the object of the system is the utility function. Thus a reasonable measure for the model quality should be based on the utility function.

*We assume the "relevant" node is known in Step 2 because we have an estimate of the distribution of this node as a result of step 1.

In the active learning framework proposed by [145], if we choose to use model $\tilde{\theta}$ and the true model is θ, we incur some loss $Loss(\theta||\tilde{\theta})$. Although we do not know the exact value of θ, $p(\theta|D)$ represents our beliefs about the distribution of θ given the evidence. Thus the expected loss of using model $\tilde{\theta}$ is given by:

$$\begin{aligned} Loss(D,\tilde{\theta}) &= E_D(Loss(\theta,\tilde{\theta})) \\ &= \int_\theta p(\theta|D)Loss(\theta||\tilde{\theta})d\theta \end{aligned} \tag{4.5}$$

where $p(\theta|D)$ is the posterior distribution of different model parameters. The quality of a model after we have seen data set D is:

$$Loss(D) = Loss(D,\theta^*_D) \tag{4.6}$$

where $\theta^*_D = arg\min_{\tilde{\theta}} Loss(D,\tilde{\theta})$ if the system makes decisions using the model that minimizes the lose. [†]

Smaller $Loss(D)$ means a better model. For active learning, $Loss(\theta,\theta^*_D)$ needs to capture the notion of uncertainty of the model parameters. One commonly chosen metric is Kullback-Leibler divergence (KL-divergence) [145]:

$$KL(\theta||\theta^*_D) = \int p(x)\sum_y p(y|x,\theta)\log\frac{P(y|x,\theta)}{P(y|x,\theta^*_D)}dx$$

where $p(x)$ is the distribution of input x, which is independent of θ and is usually given or learned from unlabeled data.

The usefulness of knowing the label of a document is measured by its potential to lower $Loss(D)$. However, in information filtering the ultimate goal is to optimize some utility function in the long run. It is unclear how a smaller KL-divergence relates to higher utility. It is also unnatural to combine KL-divergence with the expected immediate utility credit/loss to get a single quantity on which the decision of whether to deliver a document can be made. So, instead of using KL-divergence, we propose to use the difference between the best possible utility and the actual utility, which we call *utility divergence*, as the function $Loss(\theta,\tilde{\theta})$ to measure the model quality:

$$UD(\theta||\tilde{\theta}) = U(\theta,\theta) - U(\theta,\tilde{\theta}) \tag{4.7}$$

where $U(\theta',\theta'')$ is the expected utility if we choose to use model θ'' and the true model is θ'. A well-defined $U(\theta',\theta'')$ should have the following property

$$\forall\theta',\theta'', U(\theta',\theta') \geq U(\theta',\theta'') \tag{4.8}$$

[†]If the system makes decisions differently, we need to change it accordingly.

which essentially says that the expected utility of an incorrect model cannot exceed the expected utility of the correct model. It is worth noting that KL-divergence proposed by [144] is a special case of *utility divergence*. If we choose to use log-likelihood as utility, then $U(\theta', \theta'')$ is:

$$U(\theta', \theta'') = \int p(x) \sum_y p(y|x, \theta') \log P(y|x, \theta'') dx$$

which shows that when using log-likelihood as utility, $UD(\theta||\tilde{\theta}) = KL(\theta||\tilde{\theta})$.

Using utility divergence as the loss function, $Loss(D)$ can be rewritten as shown below.

$$\begin{aligned} Loss(D) = & \quad Loss(D, \theta^*_D) \\ = & \int p(\theta|D)(U(\theta, \theta) - U(\theta, \theta^*_D))d\theta \end{aligned} \tag{4.9}$$

For information filtering, the goal is to maximize the utility (Equation 4.1), so we define:

$$U(\theta', \theta'') = \int_{S(\theta'')} p(x) \sum A_y P(y|x, \theta') dx \tag{4.10}$$

where $S(\theta'') = \{x| \sum_y A_y P(y|x, \theta'') > 0\}$ is the space of x where model θ'' "thinks" delivering x has immediate positive utility.

The expected reduction of utility divergence due to knowing the label of a document x for the next immediate future (the document right after the current one) is:

$$U_2(x|D) = \sum_y P(y|x, D) Loss(D \cup (x, y)) - Loss(D) \tag{4.11}$$

If there are N_{future} (discounted) future documents, then the expected utility of delivering document x is: [‡]:

$$U(x|D) = U_1(x|D) + N_{future} U_2(x|D) \tag{4.12}$$

We deliver a document x if and only if $U(x|D) \geq 0$.

The whole process from a Bayesian graphical modeling point of view is summarized in Figure 4.1. The system first treats node "relevant" as unknown, and estimates its distribution based on the known nodes "document" and "θ". This estimation is used to calculate the immediate utility gain of delivering the document (Equation 4.4. Then, the system treats the nodes "relevant" and "document" as known, and

[‡]This assumes that the system does not change its model while filtering the following N_{future} documents, and the assumption makes the computation less complex.

estimates the probability distribution of the parameter node "θ". The Utility Divergence derived based on the probability distribution of value of the parameter node is then used to measure the quality of the new model if we know the label of "relevant" node. The quality of the new model minus the quality of the old model is the expected reduction of the expected loss of utility, and this is used as the measure of the future utility gain of delivering the document. When it is combined with the immediate utility, we get a complete estimation of the utility gain (Equation 4.12).

4.1.3 Determining the dissemination threshold based on logistic regression

The proposed algorithm can be applied to a high dimensional space for learning term weights with statistical based profile learning methods, such as the LR_Rocchio algorithm we proposed before. However, the computational complexity of using the proposed algorithm with LR_Rocchio can be very expensive, considering the integration in Equation 4.4 and 4.11. It may takes months to process the standard evaluation data, such as 4 years of US National Library of Medicine's bibliographic database 2.1.2, using a single PC. Although this may be practical in real scenario, we choose not to design an evaluation experiment that takes so long.

Instead, we demonstrate the effect of the proposed algorithm with a smaller problem in one dimensional space: to learn the dissemination threshold while filtering. This is an very important problem in the information filtering community because the threshold affects the filtering system's performance a lot, and much of the filtering research in the last few years were focused on solving the threshold problem [155][123][12][164]. We work with the traditional "retrieval + thresholding" approach described in Section 2.2.2 and assume we already have a separate module that can compute the score of a document. The Rocchio algorithm is used for learning the term weights and query expansion in our experiments [125]. Documents with scores above a profile-specific dissemination threshold are delivered the corresponding user. The input to the algorithm is the score x of a document; the problem is to determine whether to deliver the document given its score. We choose the Rocchio algorithm because 1) it is simple; 2) it is widely used in the TREC adaptive filtering community; 3) the distribution of the Rocchio score can be modeled using simple distributions, which makes it easy to specify the functional form of $P(x)$ to be used Equation 4.7.

We use logistic regression to model the conditional probability of user feedback y given the document score x:

$$P(y = 1|x, \theta) = \frac{1}{1 + \exp(-w_0 - w_1 x)} \tag{4.13}$$

where the prior distribution $p(w)$ equals a Gaussian distribution $N(w; m_0, v_0)$. m_0 is the mean of the Gaussian and v_0^{-1} is the covariance of the Gaussian.

Our task is to find a decision boundary, the dissemination threshold t, to optimize the linear utility function. t corresponds to the boundary of $S(\theta'')$ in Equation 4.10. Thus the quality of the model should be quantified by the expected utility of using $t_{\theta^*_D}$ as the decision boundary that defines $S(\theta'')$ in Equation 4.10:

$$S(\theta'') = [t_{\theta''}, \infty) \tag{4.14}$$

where $t_{\theta''}$ is the threshold that θ'' "thinks" is the best.

$$\begin{aligned} U(\theta', \theta'') &= U(\theta', t_{\theta''}) \\ &= \int_{t_{\theta''}}^{\infty} \left(A_N + \frac{A_R - A_N}{1 + \exp(-w'_0 - w'_1 x)} \right) p(x) dx \\ Loss(D, \tilde{\theta}) &= Loss(D, t_{\tilde{\theta}}) \\ &= \int p(\theta|D)(U(\theta, t_\theta) - U(\theta, t_{\tilde{\theta}}))d\theta \end{aligned}$$

To calculate $Loss(D)$, we can find $t_{\theta^*_D}$ by solving

$$\frac{dLoss(D, t_{\theta^*_D})}{dt_{\theta^*_D}} = 0 \tag{4.15}$$

4.1.4 Computational issues

Computation of U_1 in Equation 4.4 and $Loss(D)$ in Equation 4.9 involve integrating over the posterior distribution of θ. However, the posterior distribution $p(w|D)$ for logistic regression is not simple and the integration cannot be calculated in closed form. Our strategy is to use a Monte Carlo method to get an approximate solution (Section 2.3.4).

We generate K random samples θ_i using the Metropolis-Hastings algorithm [142]. Then U_1 and $Loss(D)$ can be approximated as shown below.

$$U_1(x|D) \approx \frac{1}{K} \sum_{i=1}^{K} \sum_{y} A_y P(y|x, \theta_i) \tag{4.16}$$

$$Loss(D, t_{\tilde{\theta}}) \approx \frac{1}{K} \sum_{i=1}^{K} (U(\theta_i, t_\theta) - U(\theta_i, t_{\tilde{\theta}})) \tag{4.17}$$

In order to generate the random samples from the posterior $p(\theta|D)$ efficiently, we apply Laplace's method to use a Gaussian distribution $N(w; \theta_{MAP}, v)$ to approximate the posterior, where θ_{MAP} is the maximum a posteriori estimation of θ and v is the Hessian matrix of the loglikelihood of training data $\log(P(D|\theta)p(\theta))$ at

Table 4.1: Pseudo code for determining a threshold.

FUNCTION : Calculate dissemination threshold
INPUT : $D = (x_1, x_2), \cdots, (x_k, y_k)$
OUTPUT : Dissemination threshold
LOOP binary search for x such that :
  $U(x|D) = U_1(x|D) + n_{future} \cdot U_2(x|D) \approx 0$
  where
    U_1 is computed using Equation 4.16
    U_2 is computed using Equation 4.11
return threshold=x

FUNCTION : Calculate $Loss(D)$
INPUT : $D = (x_1, x_2), \cdots, (x_k, y_k)$
OUTPUT : $Loss(D)$
Calculate the MAP estimation θ_{MP}
Calculate the Gaussian approximation of $P(\theta|D)$
Generate K samples using Metropolis Algorithm
Calculate $t_{\theta^*_D}$ using Equation 4.15 and Equation 4.17
Return $Loss(D) = Loss(D, t_{\theta^*_D})$
Computational Complexity: O(K)

θ_{MAP}. Then we use this Gaussian approximation to generate candidate values for the Metropolis-Hastings method.

We summarize the computational procedures for determining the dissemination threshold in Table 4.1. A document is delivered when its score is above the threshold. When a document is delivered, the dissemination threshold is recomputed based on the scores and labels of *all* of the delivered documents.

Note that in the previous section, we used the most likely configuration for inference, which is more computationally efficient. In this section, we are using a sampling based algorithm for inference, which is computationally expensive but more appropriate for exploration. The computational complexity of using this active learning based algorithm to determine threshold is $O(K * s)$, where K is the number of Metropolis samples and s is the number of loops while searching for the threshold. K and s can be preset as constant to give a guaranteed response time, which is often preferable in filtering system. [§]

[§]If we use do exploration with LR_Rocchio algorithm in high dimensional space, the computational complexity becomes O(K*s*N), which N is the number of dimensions. Additionally, K needs to be extremely large in order to approximate a high dimension integration well. Thus the computation of exploration with LR_Rocchio in high dimensional space will be much more complex.

4.2 Experimental methodology

The algorithm described in Table 4.1 is evaluated on two text corpora were used in the experiments: the OHSUMED data set used in the TREC-9 Filtering Track (Section 2.1.2) and the Reuter's 2001 data set used in the TREC-10 Filtering Track (Section 2.1.2). The two data sets have rather different properties, as described in Section 2.1.2 and Section 2.1.2.

Utility is measured by the macro average of $T11U = 2 \cdot R^+ - N^+$ and the normalized version $T11SU$ (Section 2.1.1, Equation 2.4 and Equation 2.6).

The "Normal-Exponential" threshold setting algorithm described in [12] is used as a baseline. It uses a normal distribution to fit the relevant documents' scores and an exponential distribution to fit the non-relevant documents. This algorithm was a component of the most effective system tested in the TREC-9 Filtering Track [119]. ¶ One problem with using generative models such as the Normal-Exponential model for learning adaptive filtering thresholds is that although the training data is assumed to be representative, it is in fact biased because the system only gets relevance feedback for documents it delivers (i.e., documents with scores above the dissemination threshold). In [164], we proposed a maximum likelihood normal-exponential (ML N-E) algorithm to explicitly compensate for this sampling bias. This algorithm is used as a second experimental baseline. A straightforward Bayesian approach without active learning ("Bayesian Immediate Learning"), which corresponds to $N_{future} = 0$, is also implemented as a third experimental baseline.

The algorithms cannot learn when the threshold is too high to let any documents be delivered, so the filtering system gradually decreases the threshold in such cases.

The filtering system creates initial profiles using terms from the TREC topic title and description fields (Section 2.1.2). Because the first two relevant documents are sampled according to $P(x|y = 1)$ instead of $P(x)$, we cannot use them for training the discriminative model. So we set the initial threshold to allow the highest-scoring documents (top 1%) in the training data to pass. Once the system has at least 1 positive and 1 negative feedback in the testing document stream, the proposed algorithm is used to set dissemination thresholds.

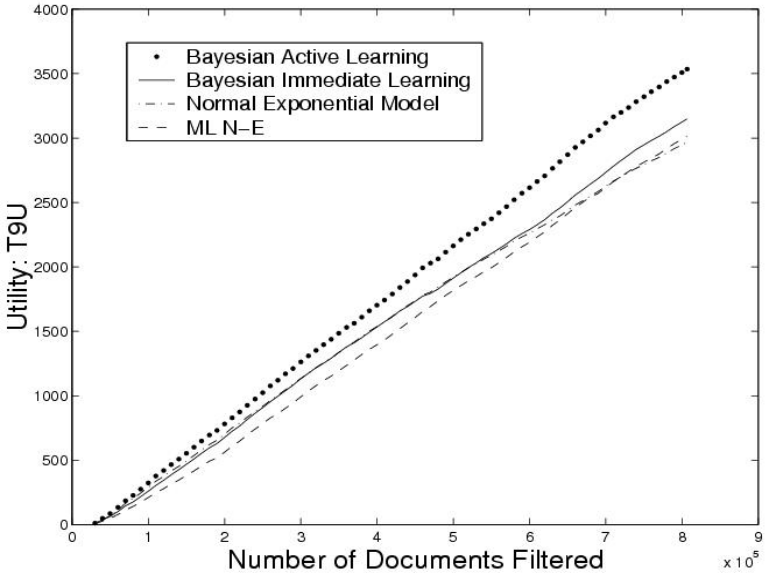
Our algorithm also needs to model $P(x)$, the distribution of document scores. We use a simple exponential model to fit $P(x)$ in our experiments. We set the number of documents in the future $N_{future} = \alpha \cdot \frac{R^+ \cdot N_{new}}{N_{old}}$, where R^+ is the number of relevant documents delivered, N_{new} is the number of expected documents in the future, N_{old} is the number of filtered documents, and $\alpha \cdot \frac{R^+}{N_{old}}$ controls the exploration rate. α is set arbitrarily to 200 in our experiments and is much lower that $\frac{R^+}{N_{old}}$. This is a conservative estimate, and is

¶Experimental results for the Normal-Exponential algorithm are not directly comparable to the prior results, because the profile-learning (term and term weight) algorithms are different.

Table 4.2: Comparison of four threshold-learning algorithms on the TREC-10 filtering data (Reuter's data set).

Metrics	Bayesian Active	Bayesian Immediate	Norm. Exp.	ML N-E
T11U	3,534	3,149	2,969	3,015
T11SU	0.448	0.445	0.436	0.439
Precision	0.463	0.481	0.464	0.496
Recall	0.251	0.234	0.227	0.212
Ave. Doc. Delivered Per Profile	4,527	3,895	2,792	3,380

Figure 4.2: Comparison of the performance of threshold-learning algorithms over time on the TREC-10 filtering data.



similar to the discounted future rewards used in reinforcement learning.

4.3 Experimental results

Our first experiment compares the threshold setting algorithms on the TREC-10 Reuter's corpus. This is considered a relatively difficult corpus because the initial training data is very limited and not particularly representative of the variety in the large number of relevant documents in the test data. Table 4.2 and Figure 4.2 summarize the experimental results.

Active learning is very effective compared to the baseline methods: T11U utility is higher, T11SU utility is slightly higher, precision and Recall are comparable, and many more documents are delivered without hurting

Table 4.3: Comparison of Bayesian active learning and Bayesian immediate learning on one user profile.

Metrics	Bayesian Active	Bayesian Immediate
T11U	10,488	8,712
T11SU	0.296	0.246
Precision	0.682	0.644
Recall	0.578	0.509
Ave. Doc. Delivered Per Profile	10,017	9,342

Table 4.4: Comparison of the threshold learning algorithms on the TREC-9 filtering data set (OHSUMED data, OHSU topics).

Metrics	Bayesian Active	Bayesian Immediate	Norm. Exp.	ML NE
T11U	11.32	11.54	6.59	11.79
T11SU	0.353	0.360	0.329	0.362
Precision	0.300	0.325	0.256	0.339
Recall	0.231	0.203	0.264	0.177
Ave. Doc. Delivered Per Profile	31	25	46	20

utility. As expected, the maximum likelihood normal-exponential method, which compensates for sampling bias, outperforms the basic Normal-Exponential method. Sampling bias is not a problem for discriminative models, such as the Bayesian active and Bayesian immediate methods. Bayesian active learning outperforms the other models at all times during the experiment (Figure 4.2).

Comparing the performance of Bayesian active and immediate learning on profiles where active learning significantly improved performance, we find that active learning increases both recall and precision (e.g., Table 4.3). This improvement is partly due to the profile (term and term weight) learning algorithm, which also benefits from the additional training data generated by the active learner. Our thresholding algorithm does not consider the benefit of an improving profile, so it is suboptimal (although effective). For simplicity we have focused only on threshold learning in this section, however the active learning algorithm (Section 4.1) is not restricted to problems of low dimensionality; a higher dimensionality version of the algorithm could also incorporate profile learning.

The threshold-setting algorithms are also tested on the TREC-9 data set, which contains a relatively small percentage of relevant documents (0.016%); the test data consists of more than 300,000 documents, but only an average of 51 documents per profile are relevant. The OHSUMED topic descriptions are well-written, which provides relatively accurate initial profiles. One might expect that on this data set exploitation would be much more important than exploration, thus active learning might be detrimental. If the threshold is set

too low, the system delivers thousands of non-relevant documents, hurting utility. In the TREC-9 Filtering Track evaluations some participants reported negative $T11U$ utility on this data set [119].

The experimental results are summarized in Table 4.4. As expected, active learning does not improve utility on this data set. More importantly, it does not hurt the utility. Consequently these results rank in the top 2 when compared with results from the 9 systems that participated in the TREC-9 adaptive filtering task. ‖

Bayesian immediate learning can be viewed as an active learner that only selects documents on the positive side of the decision boundary for exploration; Bayesian active learning also samples on the negative side of the decision boundary. The comparable performance of the Bayesian active and Bayesian immediate learners indicates that the active learner recognized that the relatively good initial profiles, the limited number of relevant documents in the stream, and the penalty for delivering non-relevant documents collectively made exploring the negative side of the decision boundary a poor choice. Active learning does not hurt accuracy, even in a test where exploration is a risky choice.

4.4 Related work and our contributions

There has been much work on active learning in the machine learning and IR research communities [70, 87, 54, 99]. An active learner selects data to add to its training set so as to learn more about the world with small amounts of training data. The following three major approaches have used by previous researchers related to active learning.

Uncertainty of data The uncertainty of the data label($P(relevant|D)$), is the focus in this approach. A filtering systems tends to deliver the documents whose labels the system is most uncertain about. For example, the "Query by Committee" algorithm selects the next query according to the principle of maximal disagreement between a committee of classifiers [54]. [99] modified the "Query by Committee" algorithm with a Naive Bayes model, together with unlabeled data for active learning. [87] introduced "uncertainty sampling" to choose the instance that current classifiers are most uncertain about. The underlying assumption of this approach is that the user feedback about the data that the existing model is most uncertain about can usually help to reduce the uncertainty of the model parameters.

Uncertainty of model The uncertainty of the parameter distribution $P(\theta|D)$ is used to measure the quality of a model, either explicitly or implicitly. A model with less uncertainty is usually better, and

‖This comparison is intended to be descriptive only, because the research community now has greater experience with this data set than TREC-9 participants had.

the system usually delivers the document that will produce the best model. [145] provided a theoretical framework that uses KL divergence to measure the uncertainty of the model parameters for active learning and applied it to Support Vector Machine classifiers. [38] used variance of the model parameters to estimate the uncertainty of the statistical model parameters.

Utility of a model The average utility based on the model parameter distribution ($E(U(P(\theta|D)))$) is used to measure the quality of a model. A model with a larger expected utility is usually better, and the system usually delivers the documents that will result the best model. Most of the work in Bayesian experimental design falls into this category. How to define the utility function is a major research topic in this area [34], and it is not necessarily the same as the global utility the system wants to optimize.

Unfortunately, most of the prior active learning research, especially that of the first two categories, focused on interactive retrieval tasks. Thus it often only considered the exploration aspect of the problem, and did not address the trade-off between exploitation and exploration. These algorithms cannot be applied easily to adaptive filtering, where the system is evaluated based on utilities such as $T11U$, and the direct cost/reward of delivering the document (exploitation) is as important as the improvement in model estimation (exploration). Especially in the early stage of filtering, if a lot of non-relevant documents are delivered to the user because the system wants to explore, the user may feel unsatisfied and stop using the system.

There is also much prior research on adaptive filtering and recommender systems. In order to succeed in practice, most of the prior work focused on exploitation, and little of it addressed the trade-off between exploration and exploitation. The adaptive filtering community has developed various algorithms for setting dissemination thresholds, which is vital for the system's performance. Some researchers also consider the long term effect of each recommendation. [134] and [26] proposed to use Markov Decision Processes to model the sequential decision problem in a recommendation system for e-commerce sites. However, a lot of training is needed to learn their model, thus the approach is more appropriate for collaborative filtering. [33] used the information gain between a document and the model to select documents, however the task was batch filtering instead of adaptive filtering, and their approach for combining information gain with the immediate cost/reward is very heuristic.

Prior research in related areas influenced our work. The Bayesian framework, on which our algorithm is based, was widely used by Bayesian statisticians [34]. It has been used by computer scientists for active learning in text classification [145][99]. Our approach falls into the third category listed above, and the main focus of our work is to derive a utility function: Utility Divergence. Our approach also matches the Risk Minimization framework described in [78]. The work described in this dissertation differs from prior work in two major aspects.

- This research uses *utility divergence* to measure the quality of the model for exploration. *Utility divergence* generalizes some already existing measures used for active learning. For example, if the objective function for a classification system is to maximize the likelihood of the data, *utility divergence* becomes KL divergence, which is used to measure the quality of a model in [144]. However, in adaptive filtering user satisfaction is usually modeled by utility (e.g., Table 2.1), and the system is evaluated using linear utility. Our algorithm uses *utility divergence* to measure the quality of the model, thus it optimizes utility directly, based on the Bayesian framework.

- This research considers the direct and indirect cost/reward for delivering a document. An adaptive filtering system must consider the immediate cost/credit for a request, that is, it gets credit A_R for delivering a relevant document and penalty A_N for delivering a non-relevant document. Previous work in active learning did not consider this cost/credit, which affects the system performance significantly. Most of the previous work in adaptive filtering were focused entirely on this cost/credit, disregarding the future benefit.

To summarize, exploitation and exploration are combined in a single, unified framework based on utility divergence.

4.5 Summary

A filtering system that tries to explore what users like may be too aggressive and deliver too many non-relevant documents to the user, while a system that does not explore may be too conservative and perform poorly in the long run. The filtering solution described in this chapter is developed to avoid both problem. Based on Bayesian theory, we model the trade-off between exploitation and exploration in adaptive information filtering. We view it as a two step message passing process in Figure 4.1. In order to optimize a global utility function, we have derived a quantitative measure of the immediate cost/reward and future reward of delivering a document. We believe that this is the first work to study the trade-off between exploration and exploitation in adaptive information filtering.

The experimental results have demonstrated that Bayesian active learning by combination of exploration and exploitation can improve results on favorable data set, for example, when the initial profiles are poor and the document stream contains many relevant documents. The results have also demonstrated that it can have little effect on unfavorable data set, for example, when the initial profiles are good and the document stream contains few relevant documents. Bayesian active learning handles both of these situations well,

exploring only when it is useful to do so. When the algorithm does not explore, it is as good as three competing methods.

This chapter also answers a common question when people use the Bayesian approach: is it worth modeling the uncertainty of the parameters? Since integration as in Equation 2.12 can be computationally expensive, maximum a posteriori MAP estimation (MAP) or maximum likelihood estimation (ML) algorithms (Section 2.3.4) are probably preferable to Bayesian averaging if their performance is comparable. In fact some researchers do think ML or MAP is enough, considering that in some classification tasks, people do observe comparable performance between these approaches. This chapter has demonstrated that active learning is one of the problem where modeling the uncertainty of parameters explicitly is *necessary* for a principled solution. Existing algorithms that consider exploration benefit while filtering without explicitly modeling the model uncertainty are heuristic and have to do exploration and exploitation trade-off in an ad hoc way [33].

There are several directions for further research following the work described in this chapter. The utility used in this chapter is based on TREC relevancy linear utility evaluation measure, and one future direction is to use different utility functions, such as a utility measure with discounted future relevant documents or other criteria beyond relevancy. The research reported here only applied the new framework to setting dissemination thresholds, however the basic principle of combining expected immediate utility and utility divergence gain is also applicable to problems of higher dimensionality, for example learning the importance of features such as words or phrases. The computational method used in this chapter (i.e. approximation based on sampling using Metropolis algorithm) is tailored for low dimensionality problems. For high dimensionality problems, approximation based algorithms might be necessary for efficiency concerns. Our model of $P(x)$ and how the expected number of future documents is estimated are far from optimal, and additional research in this direction is needed. Utility divergence, the model quality measure derived in this chapter, is very general and can also be used in many other active learning tasks besides filtering, such as the interactive retrieval task [136].

Chapter 5

User Study

Traditional adaptive filtering data sets consist of documents, user queries, and assessments of whether a document is relevant to a user query or not. On the other hand, some prior research work suggests that more forms of evidence, such as novelty or readability, about the user's interests and the document content may be useful [166][39][60][131]. However, the traditional datasets introduced in Section 2.1.2 and used in the previous chapters don't support such research. This chapter investigates how to acquire a more detailed adaptive filtering dataset with multiple forms of evidence. The next chapter explores how Bayesian graphical models can be used for adaptive filtering research when rich user information is available.

The following sections describe our efforts towards collecting the new adaptive filtering data set. Section 5.1 describes the adaptive filtering system we developed for the user study and Section 5.2 introduces the subjects participated the study. Section 5.3 describes the data collected, followed by basic statistical analysis of the data in Section 5.4. Section 5.5 summarizes.

5.1 System description

There were two major goals of the user study. The first goal was to collect an adaptive filtering data set from a variety of users with explicit feedback, implicit feedback, a wider range of information about documents and topics, and a heterogeneous set of documents. The second goal was to explore a realistic and relatively low-cost method of collecting detailed data for adaptive filtering research.

To achieve these goals, we developed a web based news story filtering system (Figure 5.1) located at www.yow-now.com. This system constantly gathers and recommends information to the users. The system has six major components: a news crawler, a text indexer, a database server, an adaptive filtering system, a web server, and a browser. The crawler has about 8000 candidate RSS news feeds to crawl frequently. RSS is a format for syndicating news and the content of news-like sites [113]. The adaptive filtering system learns from users' explicit feedback and recommends documents to the users. An indexer [43] parses each incoming news story and incrementally builds a text index of documents to facilitate the computation of

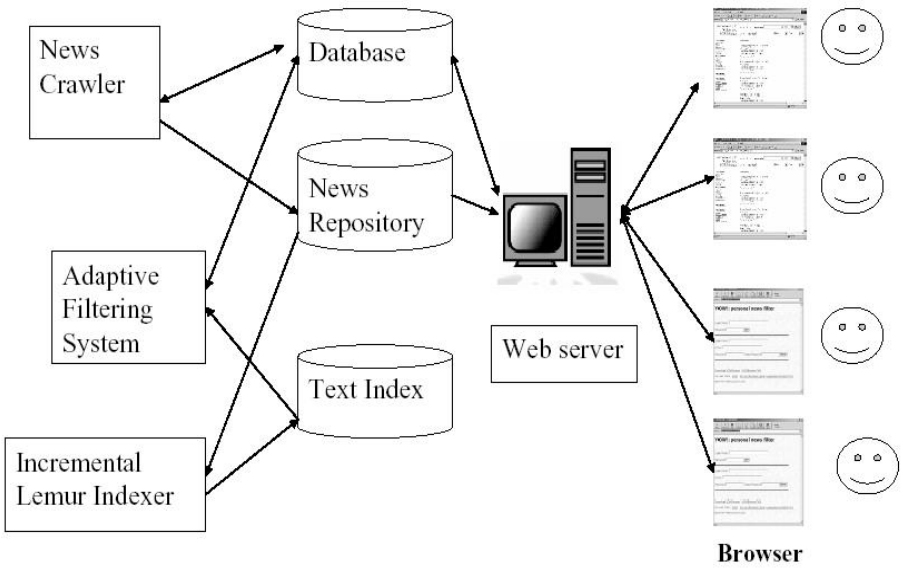


Figure 5.1: The user study system structure. The structured information, such as user feedback and crawler statistics, is kept in the database. The content of each web page crawled is saved in the news repository.

the filtering system. Users use a special browser modified based on the Curious Browser [37] and log into the system daily to read and evaluate what the system has delivered to them. The special browser captures the implicit and explicit user feedback from a user and sends the information to the web server at real time. The information is saved in a central database and used by the filtering system to learn user preferences.

An example of the web interface after a user logs in is in Figure 5.2. The news on the left column are the same for all users, while the news on the right column are user specific. The user specific news the system recommends usually have a long delay, and the user independent news are almost real time with a few minutes delay. The delay of recommendation may be an issue in a real news filtering system if the goal is to evaluate the recommendation accuracy of the filtering system, because the value of information drops quickly over time. However, it is not a serious problem for our task, because the major goal of the study is to collect data.

The interface also provides some simple search functionalities so that the users can search the articles in Yow-now's news archive using keywords and get a list of news, or search the news sources using keywords and get a list of RSS feeds.

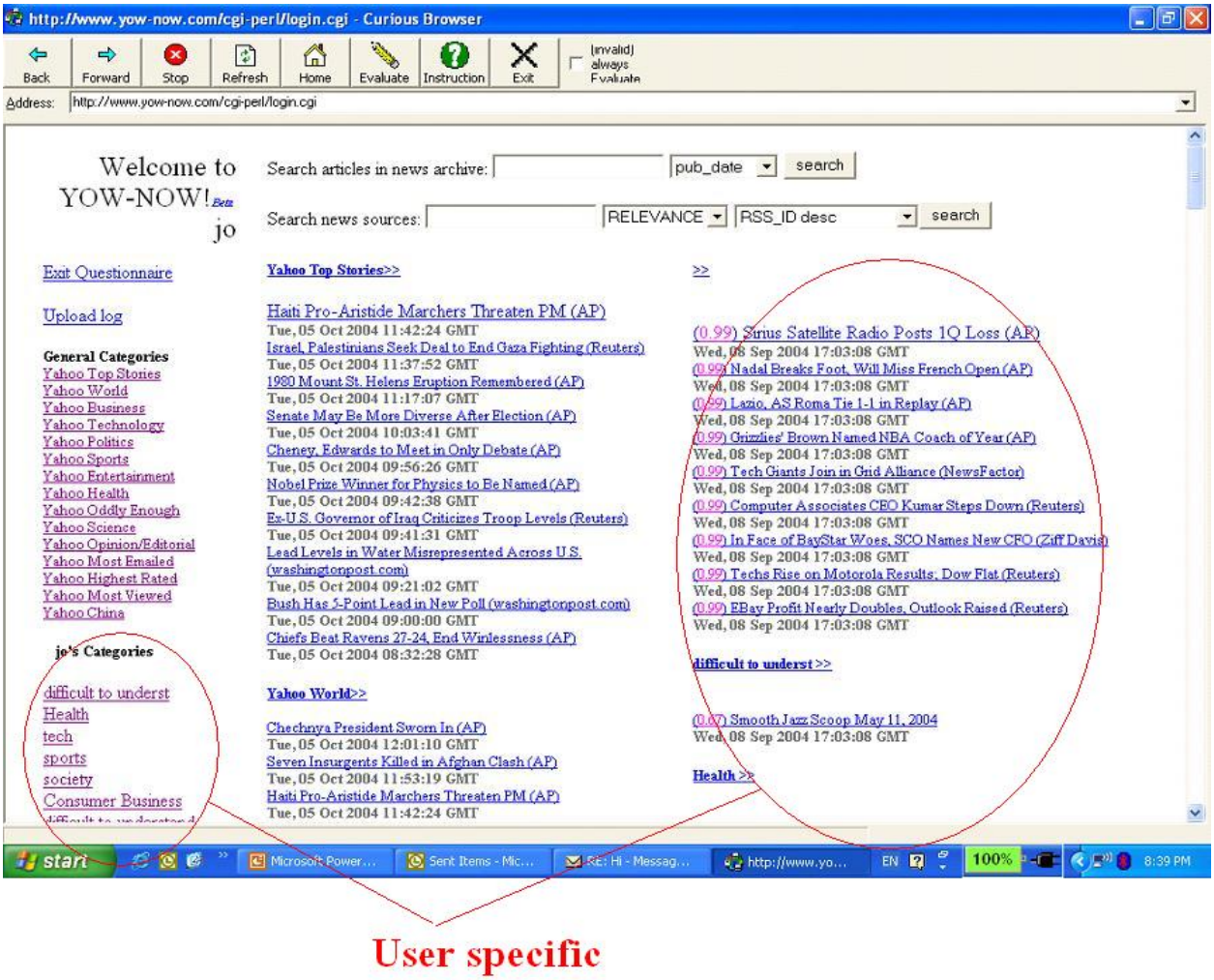


Figure 5.2: Web interface after a user logs in.

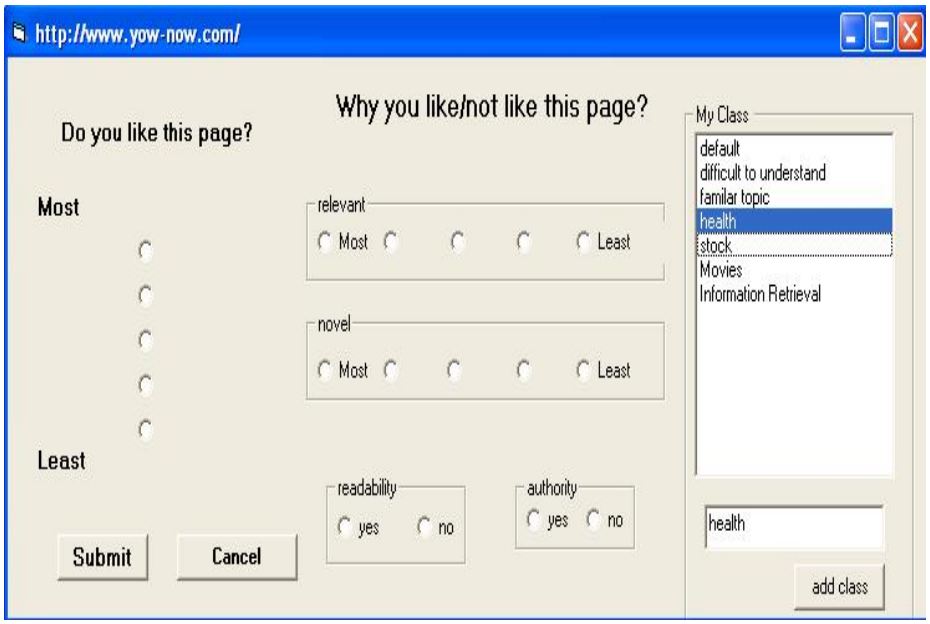


Figure 5.3: The interface for users to provide explicit feedback on the current news story.

5.2 Subjects

We posted several advertisements about the paid study on the campus of Carnegie Mellon University, and subjects were chosen based on first come first serve criteria. They are from a variety of programs at Carnegie Mellon University: Information Systems Management, Business, Electrical and Computer Engineering, Psychology, Art, Mathematics, Professional Writing, Ethics, History and Public Policy, Management, Civil Engineering, Biological Science, Economics, MBA, Clinical Psychology, Industrial Design, Chemical Engineering, Business and Social History, Computational Finance, and Communication Design. The subjects are not affiliated with our research otherwise.

A four week time period was selected for this study since it fit the schedule and funding constraints of the author and also fit the schedule of the participants, who would leave for summer vacation right after the study. We expected to collect enough data for evaluation over this period of time.

The subjects were required to read the news for about 1 hour on www.yow-now.com web site every day and provide explicit feedback for each page they visited. In the last week of the study, some subjects read 2 hours per day, although they were encouraged but not required to do so. Subjects were informed during the recruitment and at the beginning of the study that 1) the study would last for 1 month; 2) they were required to provide user feedback during the study and the feedback would be logged and made publicly

available for the research community after anonymizing their identity; 3) each of them would be paid on hourly basis; and 4) subjects who were unable to finish the first 2 weeks of the study would be paid with state minimum salary. We considered 15 a reasonable subject number that would generate a significant amount of data over 4 weeks. We accepted more than 20 subjects initially, considering the possibility of dropout and our budget constraint. Several subjects dropped out at the first 2 to 3 days without requesting for any salary, one subject dropped out right after the second week, and 20 subjects finished the study in 4 weeks. In general, 28 users, including the author and some other researchers interested in the research, tried this system. However, only 21 users were paid subjects in the user study, including the one who worked only for 2 weeks.

5.3 Data collected

We collected 7881 feedback entries from all 28 users, among which 7839 were from the 21 official participants. Each entry contains several different forms of evidence about a news story a user clicked and assigned to a specific topic. *

Our intention to collect these forms of evidence is not to be exhaustive, but representative. These forms of evidence were saved in several tables inside a database or in text files on the server. They can be roughly classified into the following five categories listed in Table 5.2 to 5.6.

5.3.1 Explicit user feedbacks

The users were required to use a special browser we modified. The browser is based on the CuriousBrowser developed by [37]. After finishing reading a news story, a user was required to click a button on the toolbar of the browser to bring up an evaluation interface as shown in Figure 5.3. † Through this interface, the user provided the explicit feedback about the current story, including the topics the news story belongs to (*classes*), how the user likes this news story (*user likes*), how relevant the news is related to the class(es) (*relevant*), how novel the news story is (*novel*), whether the news story matches the readability level of the user (*readable*), and whether the news story is authoritative (*authoritative*).

The questions were designed to keep the feedback interface easy to understand and reasonably small. We chose to ask about *user likes* because it is the most important reason for why a filtering system should or

*Each entry is for a <document, user topic, time> tuple. Topic usually refers to a class about a specific subject, however we use topic interchangeably with "class" in this chapter.

†The lists of candidate classes on the interface varies for different users. Because users use the system at their own place, we didn't get a snapshot of their remote machine or regenerate the exact interface. This is a snapshot of the author's interface.

shouldn't deliver a document to the user. We chose to ask about *relevant*, *novel*, *readable*, and *authoritative* because them are possible factor that may influence a user's rating of the document according to our previous experience and existing literature ([166][39][76]). The *user likes*, *relevant* and *novel* are recorded as integers ranging from 1 (least) to 5 (most). *readable* and *authoritative* are recorded as 0 or 1. The candidate answers are more detailed for *relevant* and *novel* because of the author's research focus.

A user has the option to provide partial instead of all explicit feedback because the system is designed to give them the flexibility, although formal participants were asked to provide all explicit feedback for the user study. A user can create new classes, and choose multiple classes for one documents. We encouraged the users to create classes about topics they are interested in, however we also let the users put non-topic tags, such as "weird story", using the evaluation interface.

5.3.2 User actions (Implicit feedback)

The browser used was originally designed by [37]. It records some user actions, such as a user's mouse activities, scroll bar activities, and keyboard activities (Table 5.3). It sends a record of these actions in addition to the explicit user feedback to the web server as soon as a user finishes rating a piece of news. The definition of some of the actions are:

TimeOnMouse how many milliseconds the user spent on moving the mouse

TimeOnPage how many milliseconds the user spent on a page

EventOnScroll the number of clicks on the vertical and horizontal scroll bars

ClickOnWindow the number of clicks inside the browser window but not on the scroll bars

If the left mouse button is pressed down, the browser counts that as one click. When the mouse is out of the browser window or when the browser window is not focused, the browser does not capture any activities. More details about the actions are in [84]. These actions are easy to get as implicit feedback from the user.

5.3.3 Topic information

Each participant filled out an exit questionnaire at the end of the user study and answered several topic specific questions for each of his/her most popular 10 topics and topics with more than 20 evaluated documents each (Table 5.4, Section 8.2). The questions include how familiar the user is with the topic before participating in the study (*familiar_topic_before*), how much the user likes this topic (*topic_like*), and how

confident the user is with respect to the answers he/she provided (*topic_confidence*). We include these topic specific information as evidence, because they may be collected when a topic is created and used while filtering. Whether collecting them in exit questionnaire affects the answer needs further investigation. More information about the exit questionnaire is in Section 8.2.

5.3.4 News Source Information

The news stories were crawled from news sources through the RSS. For each RSS feed, we also collected the number of web pages that link to it (*RSS_LINK*), the number of pages that link to the server of it (*HOST_LINK*), and the speed of the server that hosts it. We collected this information because we felt it may be related to the authority of a news story.

5.3.5 Content of each document

One very important information source for the filtering system is the content of each document. Our approach to use the text content is to calculate some representative numbers that characterize the document and use these numbers as evidence while filtering. For example, the relevance score,[‡] readability score, authority score, and novelty score of a document can be estimated based on user history and the content of the document. The scores are very different from the explicit feedback (*relevant*, *novel*, *authoritative*, *readable*), because the scores can be estimated before delivering a document to a user, while explicit feedback can only be collected after a user reads a document.

We collected three pieces of evidence to represent the content of each document: the *relevance score*, the *readability score* and the number of words in the document (*doc_len*) (Table 5.6). To estimate the relevance score of the documents, the system processes all of the documents a user put into a class. These documents were ordered by the feedback time. The system adaptively learns a *LR_Rocchio* relevance model for each class using the relevance feedback each user provided [§]. The relevance score of a document is estimated using the *LR_Rocchio* model learned from all feedback before the document. The LR_Rocchio algorithm requires Boolean user feedback, while the value of the explicit feedback for the relevance in the user study ranges from 1 to 5. To train the model, we consider a rating higher than 2.5 as positive, otherwise negative. A document rated x is considered to be $\beta = |x - 2.5|$ document(s) during learning. Thus a document with a extreme rating, such as 5, has a bigger influence on the relevance model.

[‡]In this user study, this score is intended to be a measure of the topical relevance instead of a more general relevance, which we refer to as "user likes".

[§]User also put non-relevant documents in a class and gave them low relevance score.

To estimate the *readability score* of a document, the system process all of the documents in all users' classes ordered by the feedback time and adaptively learns a user independent readability model using a logistic regression algorithm. The readability model is a high dimensional vector of term weights. The *readability score* of each <document, user class, time> is estimated using the readability model learned from all users' readability feedback before it. It's worth mentioning that the readability model can be user dependent in a filtering system. For example, the system may build different readability model for kids in grade one and college students, because their vocabulary differs a lot [39]. We learned a user independent readability model in this dissertation because all users were undergraduate or graduate students.

5.4 Preliminary data analysis

This section reports some preliminary statistical analysis on the data collected. The analysis is designed to address the following questions.

What are the basic characteristics of each variable? We calculate the mean, standard deviation, max and min, percentage of missing data of each variable. We also plot the histogram and exact value of some variables.

How informative is one type of evidence if other forms of evidence are not available? We calculate the correlation coefficient between each form of evidence and the *user likes* feedback.

Is the evidence person/class specific? We compare person/class specific measures of some variables.

Are the data collected reasonable? We compare the measures of some forms of evidence with those reported by other researchers.

5.4.1 Basic statistics

The basic descriptive statistics of all variables collected are in Tables 5.2 to Table 5.6. The statistics are calculated over 7881 feedback entries from all 28 users, among which 7839 were from the 21 official participants. The minimum values, maximum values, means and variances of the different variables are very different. For example, the mean and variance of *TimeOnPages* are very large ($7.2 \times 10^4, 1.3 \times 10^5$, in milliseconds), while the means and variances of explicit feedback are much smaller, ranging from 0 to 5.

The values of some evidence may be missing, except for the user actions and news source information that the system can always collect. Out of the 7991 entries, only 4522 (57%) entries contain no missing value. The

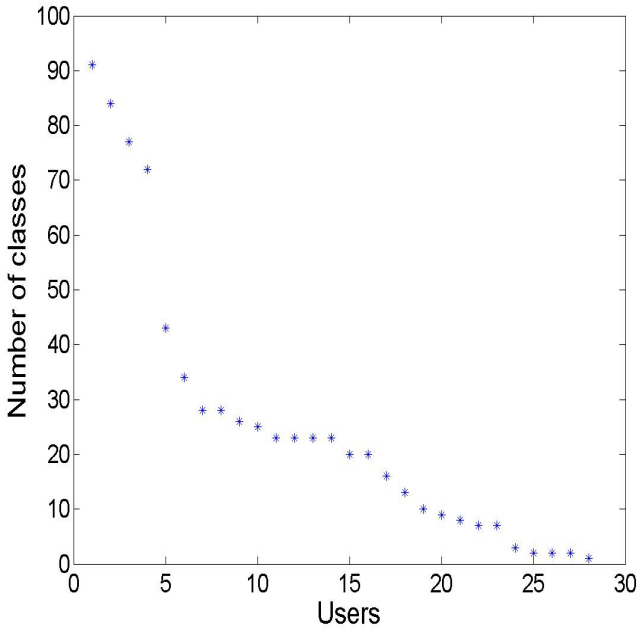


Figure 5.4: The number of classes each user has created.

missing rate of each form of evidence is also reported in the tables. There are several reasons why the evidence is missing. For example, the explicit feedback may be missing because users didn't always follow instructions, a relevance score may be missing for the first several stories in a class, or the $topic\_familiar\_before$ value for a topic may be missing because of the experimental design (Section 8.2). We think it is common to have missing data in an operational environment.

More than 700 classes were created by all 28 users. The 21 official participants, one of which quit after 2 weeks, created 680+ classes during the study. Figure 5.4 shows the number of classes created by each user. On average, each user created 32.5 classes (standard deviation $\approx$ 26). Some users created a large number of classes. Further investigation of user profiles shows that a single user may have created duplicate classes such as "Carnegie Mellon Univ" and "Carnegie Mellon University". There are three possible reasons for this:

1. The data used to generate candidate classes in user feedback interface in Figure 5.3 were saved on user's local machine.[¶] A user didn't follow the instruction to migrate class information from one machine to another when he/she changed machines;

[¶]The server also keeps a copy of the classes created by the user, but the browser uses local data to generate the user interface.

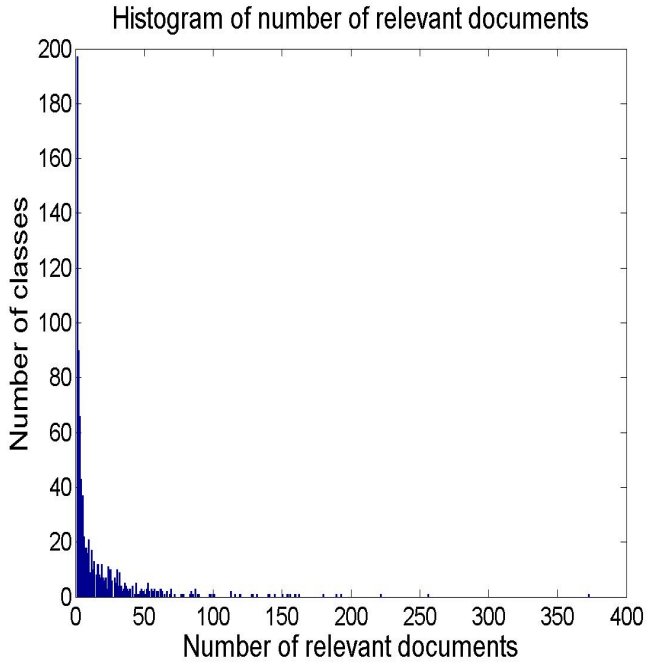


Figure 5.5: The histogram of the number of documents the 28 users clicked and evaluated for each class.

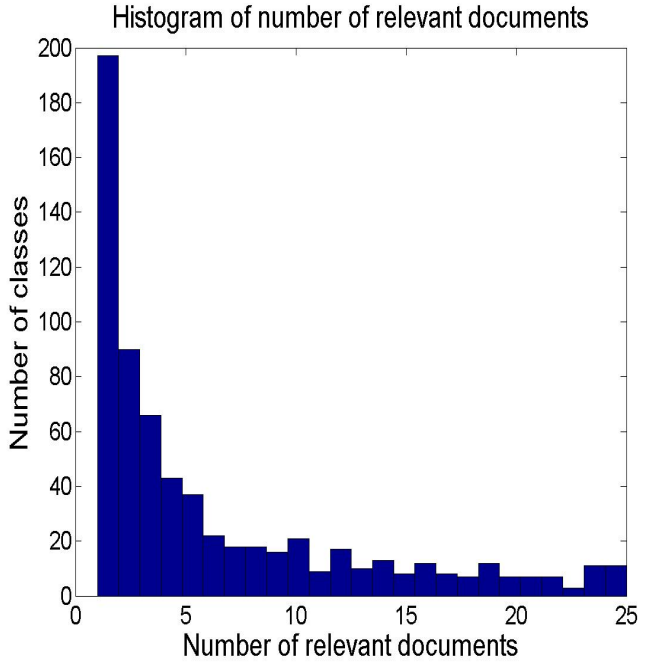


Figure 5.6: The histogram of the number of documents user clicked and evaluated for each class: X truncated to 25.

class label	Count	class label	Count	class label	Count
default	373	experiential	20	Charity	1
familiar topic	256	college	20	court	1
U.S.	222	studies conducted	20	Hong Kong	1
world news	180	diet	20	stupid	1
science	162	presidential	20	offended	1
USA	156	ebay	20	Bangladesh	1
technology	154	SUBJECT Market	19	Food news	1
business	150	entertainment	19	Odd stories	1
politics	145	design	19	Not so interested	2

Table 5.1: Samples of class labels provided by the users and the number of documents put in each class.

2. When the number of classes is large, the class name list on the explicit feedback interface (Figure 5.3) is long. Thus the user typed in a class name instead of taking time to find the existing class using the scroll bar;

3. The user created a class with a typo and then recreated a new one.

Thus we have a comparatively large number of classes per user and a small number of documents per class. Retrospective analysis suggests that GUI and system design changes could reduce the amount of cases, but it is unlikely that they could be entirely eliminated from an operational system used by ordinary people. Systems will always have errors, and people will always make mistakes.

The histogram of the number of documents user clicked and evaluated for each class is in Figure 5.5. To get greater details on the majority of classes, we truncate the X axis to 25 in Figure 5.6. It shows that about 200 classes have only one document. For these classes, learning class specific models is almost impossible. Some classes contain more documents. Class specific models, such as a relevance model, for these larger classes will be more accurate.

Some samples of large, middle and small size classes are listed in Table 5.1. It shows that the classes are very diverse and of very different granularity. Besides using class labels to represent topics, the users also used the class labels as comments for documents, such as "not so interested" or "odd stories". The set of class is very different from one would normally seen in TREC data, because we have given users a great deal of freedom to create classes they want to have in their profile online, and we didn't given them a strict definition of a class. This suggests that in a real scenario, users may not make interpretations and create consistent classes on the fly. Although it poses a challenge to a filtering system to learn classifiers with such diversity, this represents a realistic user scenario.

The label of a large class, such as "USA", suggests a big universe of relevant documents. However, the label may not be an accurate description of a user's information need. As a user's interest is related to the

user's domain beliefs, context and goal, it is not easy for a user to describe what he or she wants exactly using labels. For example "world news" does not mean that the user wants to read all off the world news, since there are thousands documents exist on this topic. Users are rather selective and only read a very small amount of stories every day. The histogram of the variable *user likes* (Figure 5.9) shows that even for the stories a user has read, the user may not like it and rates it 1 or 2.

We plot the histogram of some other variables, such as *relevant* (Figure 5.7), *novel* (Figure 5.7), *readable* (Figure 5.7), *authoritative* (Figure 5.7), the time spent on a page (Figure 5.8) and how much a user likes a topic (*topic_like* Figure 5.9). The figures show that the density distribution of these variables are very different. The distributions of the explicit feedback look like Gaussian distributions, while that of *TimeOnpage* looks like an exponential function. This information may be useful for us to find a better functional forms of the conditional probability or potential functions while developing a graphical models.

5.4.2 Correlation analysis

In order to understand how useful each individual form of evidence is if other forms of evidence are not available, we calculate the correlation between each form of evidence and the explicit feedback *user likes*. The correlations between *user likes* and other forms of explicit feedback are very high (Table 5.2). However, we can only get implicit feedback after a user reads the document, thus the high correlations do not provide much information for the system to make a decision before delivering a document.

The correlations between *user likes* and other forms of evidence are more interesting and useful. The correlation coefficient between the system's topical *relevance score* and *user likes* is 0.37, the highest among all types of evidence that the system can get before delivering a document. This is not surprising since system generated topical relevance score has been used by many filtering systems. However, 0.37 is much lower than 0.73, the correlation between *relevant* and *user likes*. Further analysis indicates that the correlation between *relevance score* and *relevant* is 0.45.

The correlations between *user likes* and the topic information (Table 5.4) are relatively high. This suggests collecting *familiar_topic_before* or *topic_like* in a real filtering system, since they are informative and collecting them requires little user effort (a user only needs to provide information on the class level instead of document level). Section 6.2 will show how to use this information with other forms of evidence in a filtering system.

The correlations between the news source information and *user likes* are weaker(Table 5.5). The success of using link based algorithms for authority analysis in the web community ([76][27]) suggests the number of in-links to a news source *RSS_LINK* may be informative if one wants to predict the authority of a news

story. However, the correlation coefficient between *RSS_LINK* and *authoritative* is only 0.1589. We find that a user may identify a page as not authoritative even when it is from a highly authoritative source, such as from Yahoo News, although the user also identifies other pages from the same news source as authoritative. This suggests that some successful web page authority algorithms using hyper links may not be as successful or sufficient in the news domain.

The correlations between *user likes* and the user actions (Table 5.3) are even lower (Table 5.2). Some actions, such as *TimeOnPage*, are more correlated with *user likes* than other refined actions, such as *NumOfPageDown*. This finding agrees with [37].

5.4.3 User specific analysis

So far, the basic statistics and correlation analysis are user independent. However, users are different. Do the user actions and ratings differ significantly between different subjects? To answer this question, we carried out a multiple comparison using one way ANOVA test for each variable to see whether the means of each variable are the same for different users. Only 17 users with more than 200 feedback entries are included, and other users are excluded. The visualized result for four representative variables are shown in Figure 5.10 to Figure 5.13. In these figures, each line corresponds to the first 200 entries of the corresponding user. For any two users, if their projections on the horizontal axis do not overlap, the means are statistically significantly different. We can see that the means of the same type of evidence can be very different for different users. However, the means are not randomly distributed, and some users have similar mean.

5.4.4 Comparison with Claypool's user study

Did the design of the user study affect the user actions significantly? How would the results vary on different experimental settings? Will other researchers get similar results in a similar experimental setting with a different group of users? It is hard to give good answers to all these questions. Fortunately, the data collected in the user study described in [37] is publicly available. That data set shares some forms of evidence with our data set. We calculate the basic statistics of the shared evidence on their data set (Table 5.7). Comparing Table 5.7 with Table 5.3, we can see that the basic statistics of our data are not very different from data set used in [37]. Comparing the "corr" column and "corrYow" column, we find that the correlation coefficients between each individual action and users' explicit rating are on similar scale for both data sets. Other forms of evidence, such as *relevant*, *novel*, *authoritative* and *readable* were not collected by [37], thus we can't compare with.

Table 5.2: Basic descriptive statistics about explicit feedbacks. RLO and RUP are the lower and upper bounds for a 95% confidence interval for each coefficient.

Variable	min	max	Mean	variance	corr	RLO	RUP	missing
user likes	1	5	3.5	1.2	1	1	1	0.05
relevant	1	5	3.5	1.3	0.73	0.72	0.74	0.005
novel	1	5	3.6	1.33	0.70	0.68	0.70	0.008
authoritative	0	1	0.88	0.32	0.50	0.48	0.52	0.065
readable	0	1	0.90	0.30	0.54	0.53	0.56	0.012

Table 5.3: Basic descriptive statistics about user actions. The unit for *TimeOnPage* and *TimeOnMouse* is millisecond.

Variable	min	max	Mean	variance	corr	RLO	RUP
TimeOnPage	1×10^4	5^6	7.2×10^4	1.3×10^5	0.14	0.11	0.16
EventOnScroll	0	93	1	3.6	0.1	0.08	0.12
ClickOnWindow	0	81	0.93	2.5	0.05	0.03	0.07
TimeOnMouse	0	3.2×10^5	2×10^3	5.8×10^3	0.02	0.002	0.05
MSecForDownArrow	0	1.8^4	211	882	0.08	0.06	0.10
NumOfDownArrow	0	91	1.1	4.7	0.09	0.06	0.10
MSecForUpArrow	0	7×10^3	29	240	0.03	0.004	0.05
NumOfUpArrow	0	23	0.10	0.8	0.04	0.01	0.06
NumOfPageUp	0	19	0.12	0.9	$\simeq 0$	$\simeq 0$	v
NumOfPageDown	0	19	0.14	1	$\simeq 0$	$\simeq 0$	$\simeq 0$
MSecForPageUp	0	6×10^4	22	202	$\simeq 0$	$\simeq 0$	$\simeq 0$
MSecForPageDown	0	7×10^3	28	251	$\simeq 0$	$\simeq 0$	$\simeq 0$

Table 5.4: Basic descriptive statistics about topics.

variable	min	max	Mean	variance	corr	RLO	RUP	missing
topic_familiar_before	0	7	3.6	1.9	0.30	0.28	0.32	0.27
topic_like	0	7	4.9	2.0	0.30	0.28	0.32	0.27
topic_confidence	0	7	4.7	2.0	0.34	0.31	0.36	0.27

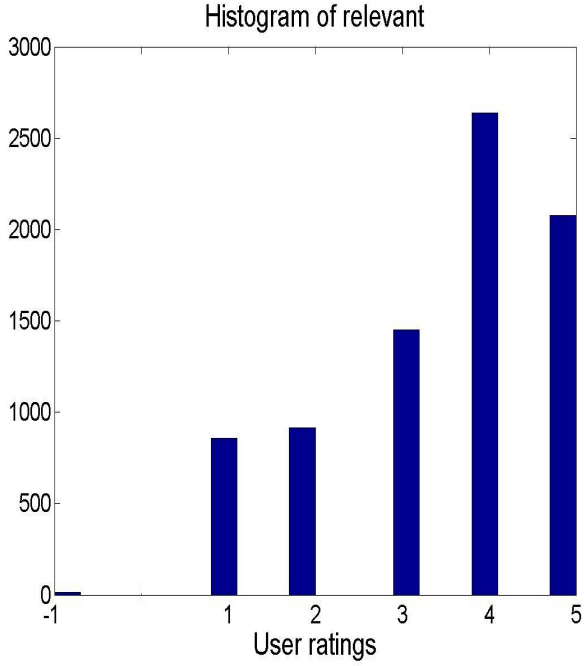
Table 5.5: Basic descriptive statistics about news sources. RSS_LINK is the number of web pages that link to the RSS source. HOST_LINK is the number of pages that link to the server of the RSS source.

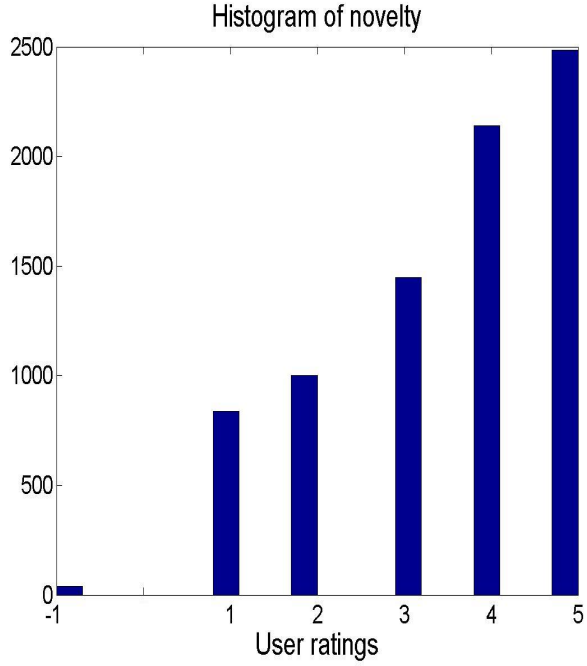
variable	min	max	Mean	variance	corr	RLO	RUP
RSS_LINK	0	1350	90.35	4.89	0.14	0.12	0.17
HOST_LINK	0	4.69×10^5	4.41×10^4	7.5×10^7	0.08	0.06	0.10
RSS_SPEED	0	4.88×10^7	3.92×10^5	3.7×10^9	-0.08	-0.10	-0.06

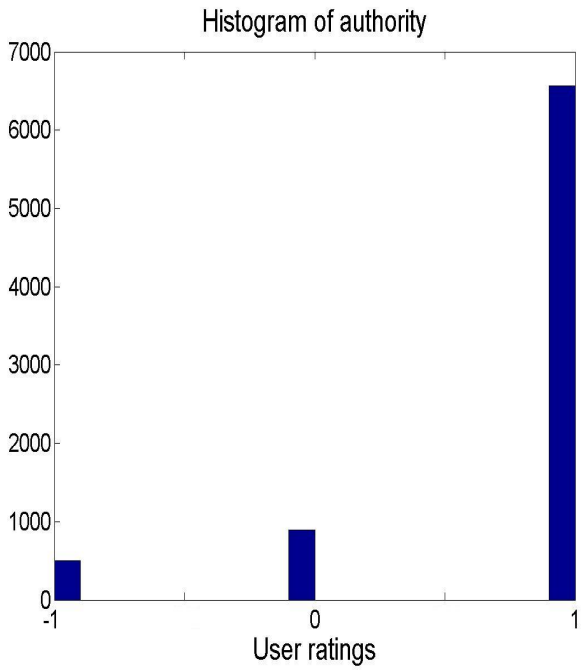
Table 5.6: Basic descriptive statistics about documents. The length of the document does not include HTML tags.

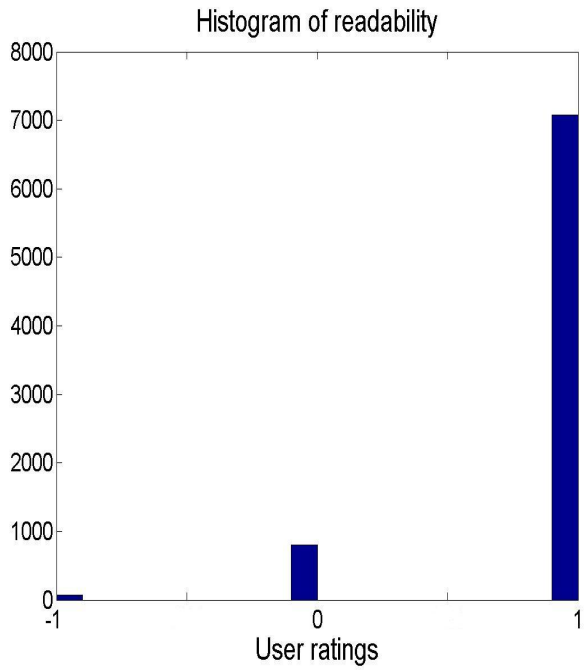
variable	min	max	mean	variance	corr	RLO	RUP	missing
doc_length	1	4^4	837	1.2×10^3	0.04	0.02	0.06	0.05
relevant_score	0	1	0.49	0.42	0.37	0.34	0.39	0.18
readability_score	0.15	1	0.52	0.16	0.25	0.23	0.28	0.11

Figure 5.7: The histogram of four different explicit user feedback. -1 means the user didn't provide the feedback. *relevant* and *novel* are recorded as integers ranging from 1 (least) to 5 (most). *readable* and *authoritative* are recorded as 0(negative) or 1(positive).









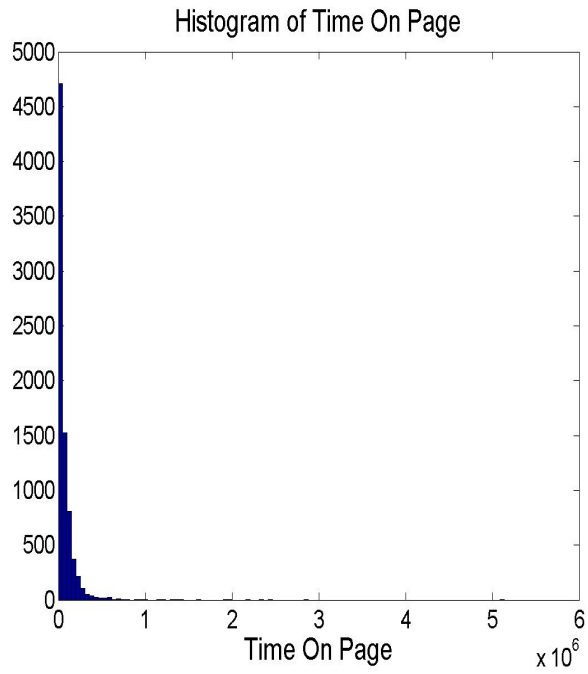


Figure 5.8: The histogram of milliseconds spent on a page.

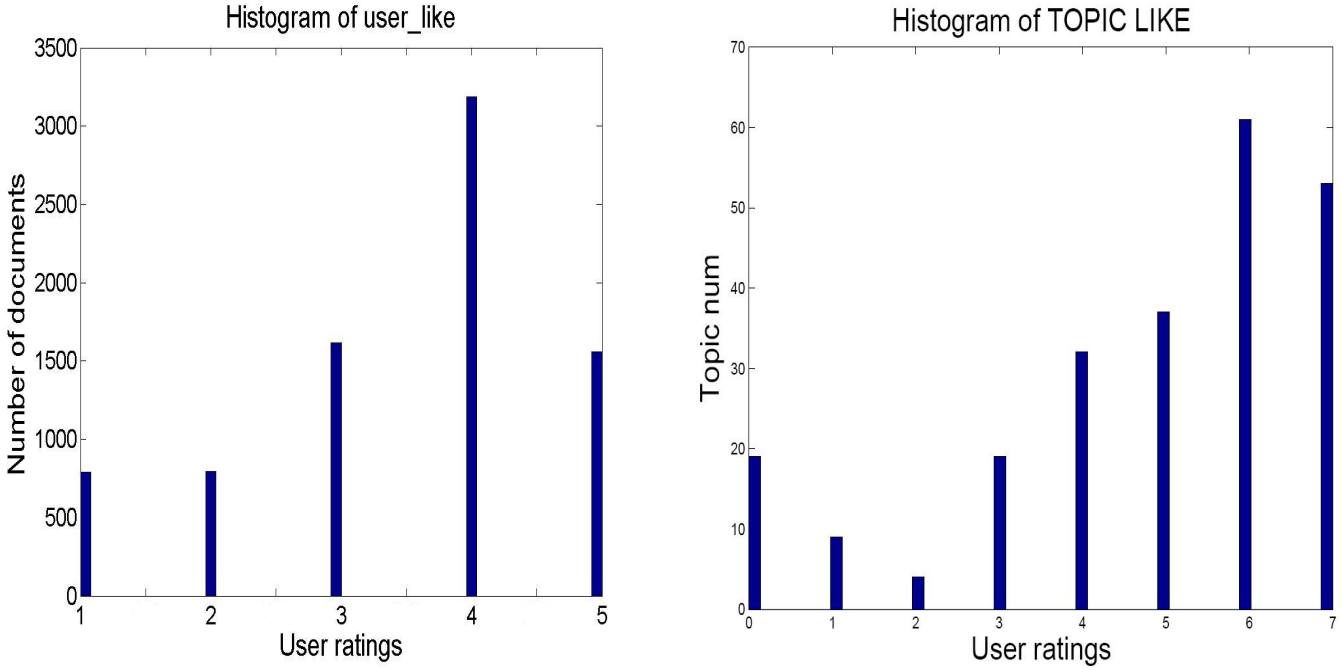


Figure 5.9: The histogram of more variables: *user likes*, and *topic_like*.

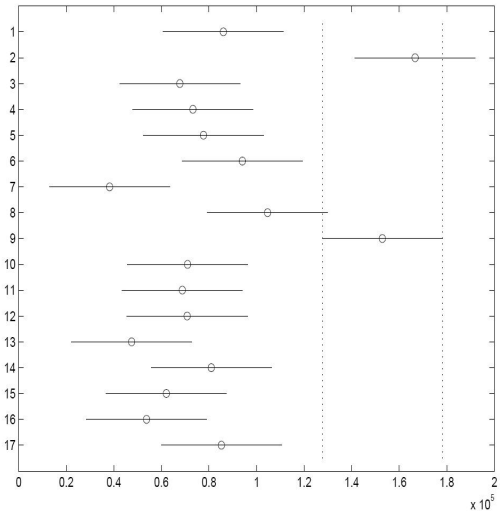


Figure 5.10: Multiple comparison of the average time (in milliseconds) spent on a page for different users. Only 17 users with more than 200 feedback entries are included. Most of the users spent less than 100 seconds/page on average.

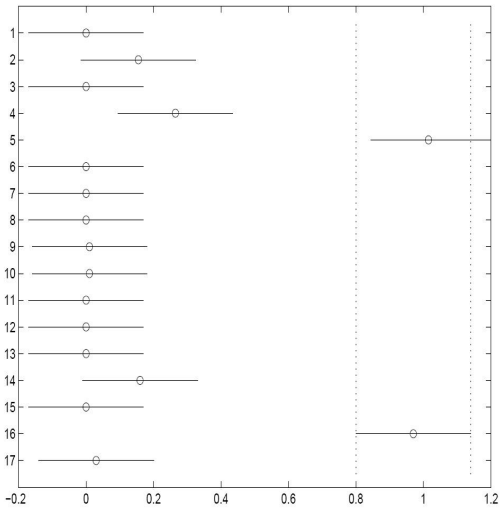


Figure 5.11: Multiple comparison of the average number of up arrow (↑) usage on a page for different users. Only 17 users with more than 200 feedback entries are included.

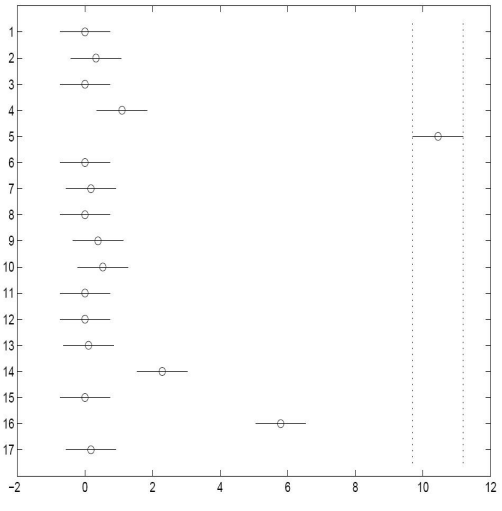


Figure 5.12: Multiple comparison of the average number of down arrow (↓) on a page for different users. Only 17 users with more than 200 feedback entries are included.

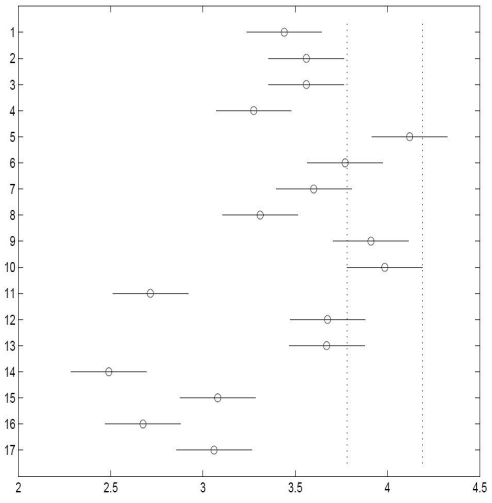


Figure 5.13: Multiple comparison of the average *user likes* rating for different users. Only 17 users with more than 200 feedback entries are included.

Table 5.7: Basic descriptive statistics about user actions collected by the system used in [37]. *corr* is the correlation coefficient between each form of evidence and the explicit feedback on [37]'s data. *corrYow* is the correlation coefficient between each form of evidence and the explicit feedback *user likes* on our user study data.

Variable	min	max	Mean	variance	corr	corrYow
TimeOnPage	0	9.6×10^6	4.2×10^4	2.1×10^5	0.1025	0.136
EventOnScroll	0	151	1.22	7.38	0.0800	0.103
ClickOnWindow	0	297	2.13	9.96	0.1082	0.054
TimeOnMouse	0	7×10^5	6.35×10^3	2.5×10^4	0.1098	0.024
MSecForDownArrow	0	9.4×10^4	347.75	3.1^3	0.0645	0.080
NumOfDownArrow	0	213	1.1337	8.18	0.0887	0.085
MSecForUpArrow	0	4.4×10^4	82.39	1.2×10^3	0.0356	0.026
NumOfUpArrow	0	72	0.17	1.8	0.074	0.037
NumOnPageUp	0	12	0.045	0.51	0.05	$\simeq 0$
NumOfPageDown	0	15	0.06	0.67	0.045	$\simeq 0$
MSecForPageUp	0	2.5×10^4	143.72	1.0×10^3	0.0873	$\simeq 0$
MSecForPageDown	0	4.0×10^4	227.8	1.6×10^3	0.0714	$\simeq 0$
UserRating	0	5	2.29	1.85	1	1

5.5 Summary

This chapter describes a user study to collect an evaluation data for further research on combining multiple forms of evidence. It demonstrates that we can build a longer-term learning environment and collect a significant amount of data about a user's interests with a reasonably small effort. [‖]

We have collected a new evaluation data set that contains thousands of extensive implicit user feedback (such as a user's mouse usage, key board usage, document length), explicit user feedback (such as novel, relevant, readable, authoritative, and whether a user likes a document or not), and other forms of evidence (such as news source information). The basic characteristics, such as the means, for the multiple forms of evidence collected are very diverse. Most forms of evidence are correlated with *user likes*. The correlation between implicit feedback and *user likes* is much weaker than that between explicit feedback and *user likes*. Compared with data collected by other researchers, this data set looks reasonable.

In general, the user study represents a real world task with a more realistic setting, where users choose to create their own classes and read news using their own computers at the time and place they want. This realistic setting enables us to collect a very detailed filtering data set with ordinary people and relatively available tools. The data is very different and possibly more power than existing filtering data sets created by NIST for TREC.

[‖]It used a small budget of about $6000, not including the author's own stipend covered by a fellowship. The author spent about 1 month on designing the user study, 1-2 months on implementing and testing the whole system, and 1 month on running the user study with the real users.

The data set is noisy, with many missing entries, and without thorough evaluation for all <document, user class, time> tuples. It would be relatively easy to create a cleaner data set later, but some of the characteristics, such as missing entries and diversity of variables, are common in the real world and unlikely to be eliminated entirely from operational system used by ordinary people.

Because we only collected data for documents a user clicked, the analysis in this section and later sections only applies to such kind of data. The general statistics and correlation coefficients may be very different for un-clicked documents. Further study, such as treating un-clicked data entries as entries with missing value or forcing users to provide feedback for some un-clicked data, is needed to study this problem.

Chapter 6

Combining Multiple Forms of Evidence Using Graphical Models

We have collected thousands of cases, each of which contains multiple forms of evidence for a <document, user class, time> tuple. Combining the evidence while filtering is a challenging task, and we need to handle the diversity of the evidence and various missing data situations.

Researchers have identified three major advantages of the graphical modeling approach: 1) it can naturally handle situations of missing data based on the conditional dependencies encoded in the graph structure; 2) it can learn causal relationships in the domain, thus help us to understand the problem and to predict the consequences of intervention; and 3) it can easily combine prior knowledge, such as partial information about the causal relationship, with data for learning.

Because of these advantages, we hypothesize: the Bayesian graphical modeling approach is a useful framework to combine multiple forms of evidence for filtering.

One natural approach is representing the filtering system's belief about the user based on multiple forms of evidence as graphical models. The belief can be used in two ways: guiding the system designer's future actions (such as deciding whether to collect certain evidence), or directly used in the choice of a system action (such as deciding whether to deliver a document to the user). To test the hypothesis and explore the graphical models' effectiveness in both directions, we carry out several experiments with the data collected in the user study described in Chapter 5. The experiments were designed to answer the following two specific questions.

- Can the graphical modeling approach help us to better understand the domain? For example, can the algorithm tell us what the relationships are between user actions and relevance of a document, how authority relates to the user preference for the page, whether the usage of a specific keyboard key is informative, are users differ from each other, and so on. This information may guide us design a better filtering system.

- Can the graphical modeling approach help us to improve the performance of an adaptive information

filtering system? For example, when a document arrives, can we predict a user's preference for the document better than using only a topical relevance model? This prediction will be used directly in deciding whether to deliver the document to the user.

To answer the above questions, we study the three advantages of graphical models in the experiments. More specifically, to see whether the proposed solution can help us to understand the domain better, we use the causal graph structure learning algorithms (GM advantage 2), together with some prior knowledge of the domain (GM advantage 3), to derive the causal relationships between different user feedback, actions and user context. To see whether the proposed solution can help us to improve an existing filtering system, especially in the situation of missing data, we use statistical inference tools to predict how much a user likes a document under different evidence missing conditions (GM advantage 1). Different graphical models are developed and evaluated for different purposes, either to understand the domain or to improve the prediction accuracy. Linear regression algorithm with two ways to handle the missing evidence situations are also tried as alternative approaches to combine multiple forms of evidence.

The following sections describe our efforts toward evaluating graphical models for the task of combining multiple forms of evidence for filtering. Section 6.1 describes how we use existing graphical structure learning tools to understand the relationships between various forms of evidence from the data. Section 6.2 explores how to improve the system performance using multiple forms evidence and various models. Section 6.3 discusses related work. Section 6.4 discusses the limitations of our work and proposes future work. Section 6.5 concludes this chapter.

6.1 Understanding the domain using causal structure learning

The correlation analysis in Section 5.4 is useful and has helped us to get a brief idea about the data collected. However, in order to better understand the underlying truth of the domain, we need to go beyond correlation and investigate the potential causal relationships between different variables.

To do that, we first specify N nodes, one for each kind of evidence. The graph structure learning algorithms introduced in Section 2.3.3 are used to explore the causal relationships between multiple forms of evidence from the data collected. Causal discovery is hard, or even impossible due to the possibility of uncollected hidden variables or the inadequacy of the data. Some prior domain knowledge, such as forbidden edges, required edges or temporal tiers, may help to find the causal structure. To demonstrate how to use prior knowledge to help structure learning, we specify the prior knowledge developed by the author as temporal-tier constraints of variables before automatic structure learning.

To generate the temporal tier, we first organize the variables into six tiers manually.

Level 1 topic information ($topic\ info$ =<*familiar_topic_before*>), news source information ($RSS\ info$ =<*RSS_link, host_link*>) and document length (*doc len*);

level 2 hidden variables, such as *relevant novel authoritative* and *readable*, that may affect a user's preference for a document;

Level 3 system generated scores, such as topical *relevance score* and *readability score*;

Level 4 user explicit feedback on *relevant*, *novel*, *authoritative*, and *readable*;

Level 5 user judgment of *user likes*;

Level 6 user actions, such as milliseconds spent on a page (*TimeOnPage*) or the number of clicks on the ↓ key (*NumOfDownArrow*).

We assume users provided accurate judgment about the hidden variables as explicit feedback, thus a user explicit feedback is always the same as the corresponding hidden variable on level 2. Based on this assumption, we merge the corresponding nodes on level 2 and level 4 to form a 5-tier as shown in Figure 6.1. This informs the learning algorithm that a causation (indicated by →) from a higher level to lower level is prohibited.* Although the prior knowledge is engineered by the author and is not guaranteed to be true, it may help the structure learning algorithms by using the constraints to make the search space smaller.

We also tried a different prior by organizing the variables into 2 tiers, with *user likes* on level two, while the other forms of evidence on level one. Moving from a 5-tier prior to a 2-tier prior, we are changing our prior constraints and making different assumptions about the true causal relationships between these variables. This helps us to see what the algorithm can learn from a different prior and what kind of causal relationships are less sensitive to the choice of priors.

There are many graph structure learning packages to generate the graph topology from data [36][133] [107] [46][4][112]. This section reports the results generated by the PC and FCI algorithms implemented in Tetrad [133]. We chose these algorithms because they are basic algorithms for causal discovery that work well with a comparatively small number of nodes and the Tetrad package provides the functionality that enables us to specify prior knowledge/constraints as a temporal order.

It is very encouraging to see that the structure learned automatically using PC algorithm looks reasonable (Figure 6.2). According to Figure 6.2, whether a document is *novel*, *relevant*, *authoritative*, *readable* and

*$X \rightarrow Y$ means X is a direct cause of Y.

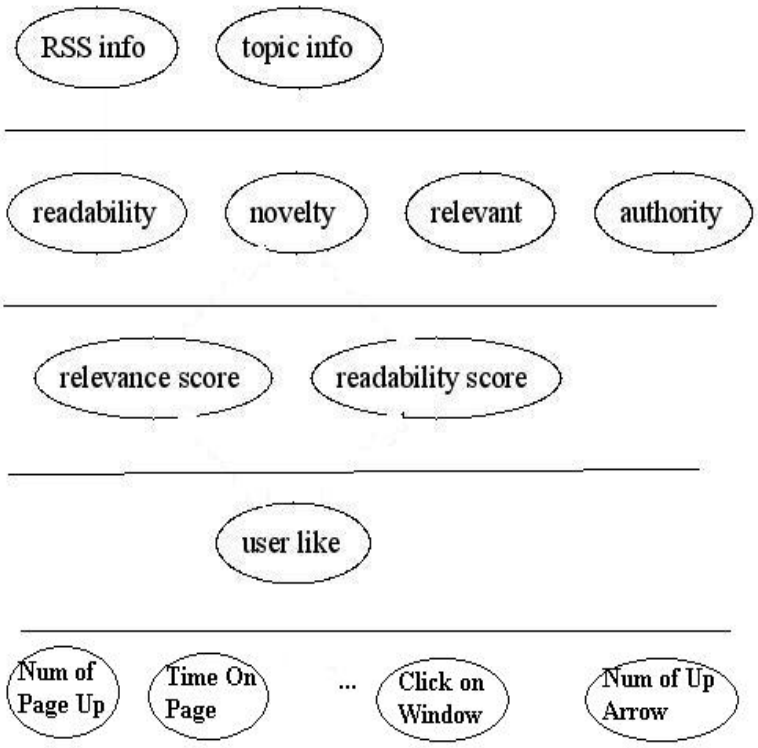


Figure 6.1: Prior knowledge as temporal tier of variables before automatic structure learning. This prior knowledge informs the learning algorithm that a causation (indicated by $\rightarrow$) from a higher level to lower level, such as *relevant* is a direct or indirect cause of *RSS info* ($relevant \rightarrow RSSInfo$), is prohibited.

Figure 6.2: A user independent causal graphical structure learned using PC algorithm. The learning algorithm begins with the 5 tier prior knowledge. In the causal graph, $X - Y$ means the algorithm cannot tell if X causes Y or if Y causes X. $X \longleftrightarrow Y$ means the algorithm found some problem. The problem may happen because of a latent common cause of X and Y, a chance pattern in a sample, or other violations of assumptions.

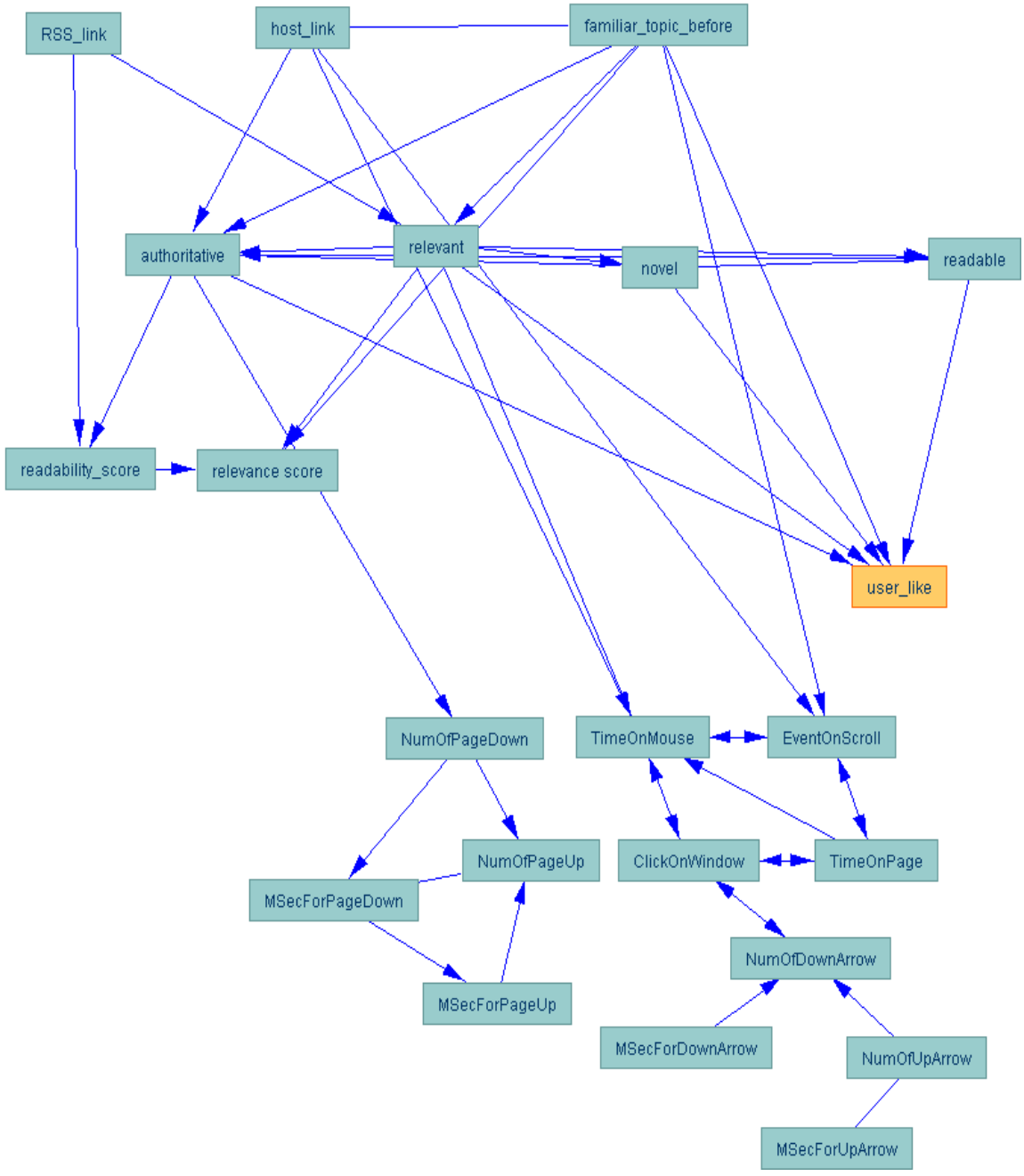


Figure 6.3: A user independent causal graphical structure learned using PC algorithm. The learning algorithm begins with the 2 tier prior knowledge.

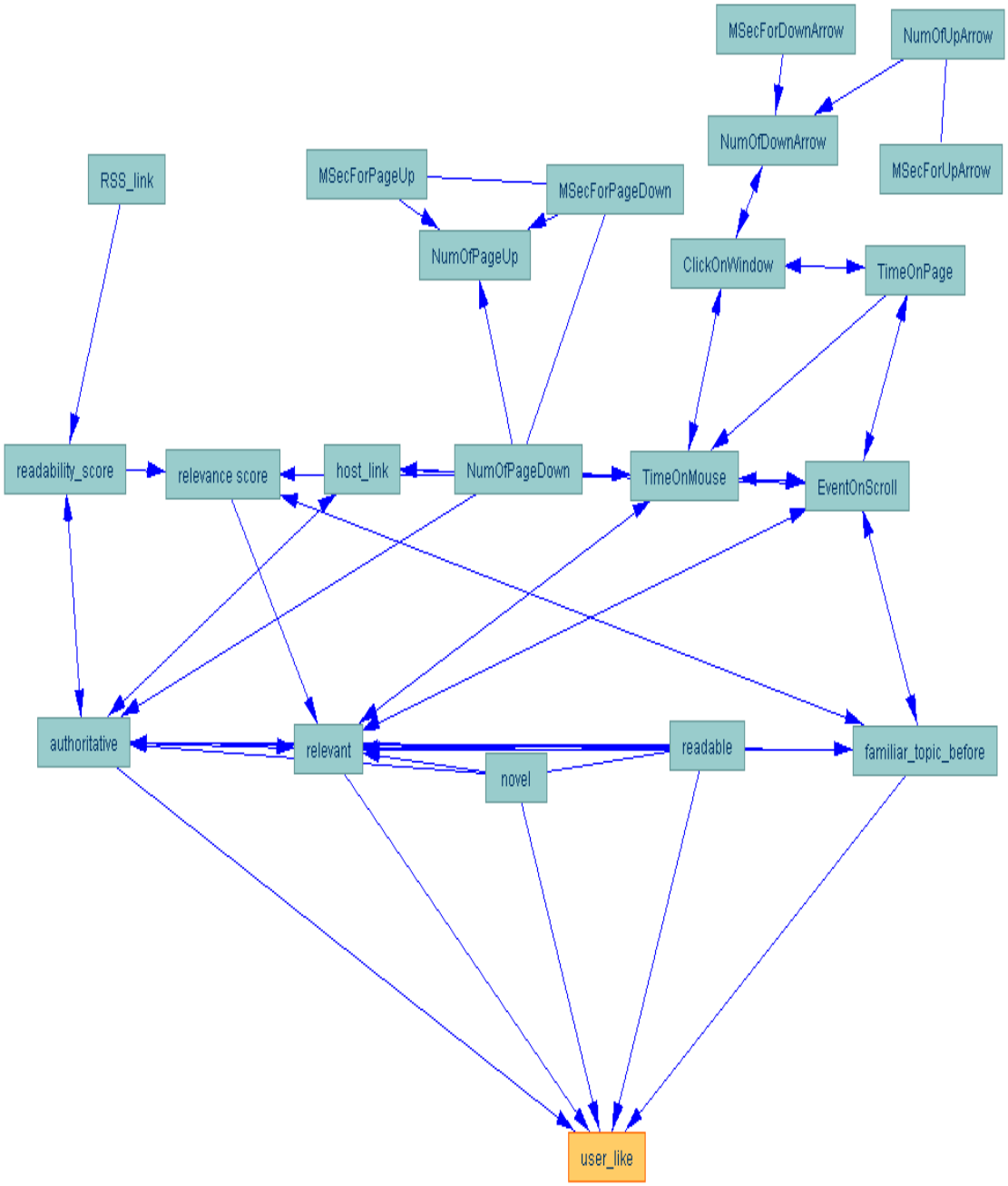
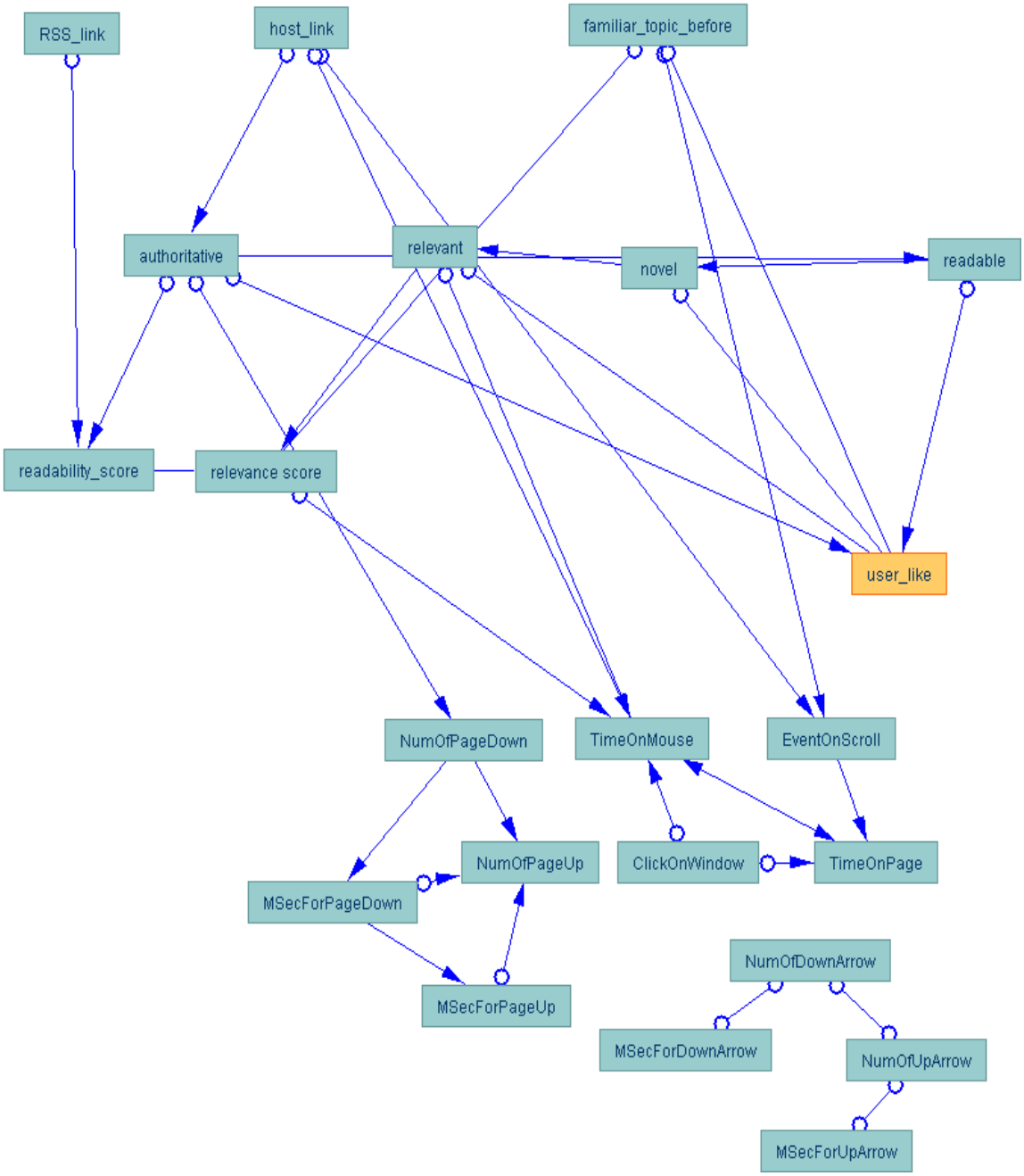


Figure 6.4: A user independent causal graphical structure learned using FCI algorithm. The learning algorithm begins with the 5 tier prior knowledge. $X \rightarrow Y$ means X is a direct or indirect cause of Y. $X \leftrightarrow Y$ means there is an unrecorded common cause of X and Y. "o" means the algorithm cannot determine whether there should or should not be an arrowhead at that edge end. An edge from X to Y that has an arrowhead directed into Y means Y is not a direct or undirect cause of X.



whether a user is familiar with the topic before using the system (*familiar_topic_before*) are direct causes of the user's preference for a document (*user likes*). How familiar with this topic a user is before participating the user study (*familiar_topic_before*) and the number of web links to the news source (*RSS_LINK*) or host (*host_linke*) indirectly affect the user's preference for a page through *relevant* and *authoritative*. *relevant*, *authoritative*, *familiar_topic_before* and *host_link* influence a user's actions, such as the number of events on scroll bars (*EventOnScroll*).

Comparing Tables 5.3 to 5.6 with Figure 6.2, one may ask why some variables are correlated with *user likes* although there are no direct links between them and *user likes*. For example, why is the correlation between *relevance score* and *user likes* 0.39, while there is no direct link between them? Does Figure 6.2 contradict Table 5.6? The answer is "no". As no direct link means *relevance score* is not a *direct* cause/result of *user likes*. The subgraph *user likes* $\leftarrow$ *relevant* $\rightarrow$ *relevance score* means *relevance score* and *user likes* share a common cause of *relevant*. The correlation between *relevance score* and *user likes* is due to the indirect causal relationship between them. Similarly, several variables are correlated with *user likes* but have no direct link to the node *user likes* (Section 5.4.2).

Although we are using different structure learning algorithms (PC vs. FCI) and different priors (2-tier vs. 5-tier), the structures learned share some common properties (Figure 6.2, Figure 6.3 and Figure 6.4). For most variables, except the refined actions about specific keys on the keyboard, the length of the shortest path from the same variable to the *user likes* node in different structures are similar. For example, on all figures, the node *user likes* is directly linked to or from *authoritative*, *relevant*, *novel*, *readable* and *familiar_topic_before*.

Most of the refined actions, such as the number of times the page up key was pressed (*NumOfPageUp*), are several steps away from *user likes*. In Figure 6.4, there is no path from some refined action nodes to *user likes*. This implies that these refined actions are less informative if we want to use the learned model to predict whether a user likes a document or not. This finding agrees with [37] and Table 5.3.

The node *authoritative* is directly linked to *readability score* and *host link*. The link between *host link* and *authoritative* confirms the existing approaches that use the web link structure to estimate the authority of a page [76]. The links between *readability score*, *readable* and *authoritative* are very interesting. They suggest the difficulty to understand a page may make the user feel it is not authoritative. Further investigation shows that although the percentage of un-authoritative news is less than 15% in general, among the 187 news stories some users identified as "difficult" using class labels, 73% were also rated not authoritative. Besides some successful web page authority algorithms that only use hyperlinks, the estimation of authority may be further improved using the content of a page.

variable	relevant	novel	authoritative	readable
relevant	1	0.69	0.4328	0.48
novel	0.69	1	0.4381	0.49
authoritative	0.43	0.44	1	0.61
readable	0.48	0.49	0.61	1

Table 6.1: The correlation coefficient between explicit feedback.

All figures contain links among the four nodes *relevant*, *novel*, *readable* and *authoritative*. Further analysis show that the correlation between each pair is high (Table 6.1). Although the algorithms failed to tell the causal directions between some pairs of variables and disagree with each other about the directions of certain links, they suggest that the four variables influence each other one way or another. For example, the readability of a document may influence the user's evaluation of authority, while whether a document is relevant or not may influence a user's evaluation of novelty. There are two possible explanations: 1) this is an inherent property of the document; or 2) a user is likely to rate one aspect of the document higher than he should if the other aspects are good.

One may ask why the structure in Figure 6.2 contains no link between *readable* and *readability score*, since there is a causal relationship between the two intuitively. To answer this question, one needs to understand that the causal relationships learned automatically are what the algorithm "believes" based on the evidence of the data, the assumptions it makes, and the prior constraints we engineered. The relationships learned may contain error, because the data are noisy, or the assumptions and the prior constraints may be wrong. For example, the PC and FCI algorithms do statistical test about the independence relationships among variables using the data and the final results are subject to the error of the statistical test. The PC algorithm assumes no hidden variables. However, in additional to *relevant, novel, authoritative, and readable*, other hidden variables, such as *whether a document is up-to-date, interesting, misleading, etc.* [131], may exist and influence a user's preference for a document. Thus it is not surprising that some of the causal relationship, such as the link between *readable* and *readability score* is missed in the final graph because of the limitation of the learning algorithms. The models learned merely shed some light on the relationships between the variables instead of uncovering the whole truth. It only serves as a starting point for us. To further understand the domain, we may want to break down some variables in the current graph further and relate them to either the user or document properties. In general, causal discovery is inherently difficult and far from solved.

6.2 Improving system performance using inference algorithms

In the previous section, graphical model structure learning algorithms helped us to understand the relationships between variables in the domain better. However, improving system performance to serve the user better is the primary goal. This section explores how to do that using graphical models. More specifically, we focus on addressing the following questions.

1. Can the graphical model combine multiple forms of evidence and handle missing data scenario?
2. How well does the graphical modeling approach work compared to some other straightforward approaches, such as linear regression?
3. Is going beyond topical relevance to combine multiple forms of evidence better than the traditional relevance filtering?
4. Can we develop a filtering system that works reasonably well with limited user supervision?
5. Are user actions useful for the system given other information?

6.2.1 Experimental Design

Comparison of Graphical models

To answer these questions, several graphical models are created to combine multiple forms of evidence to predict user preference (*user likes*). Each graphical model is uniquely defined by the graph structure and a set of local conditional probability functions or potential functions, both of which can be specified manually or learned from the data.

To derive the graph structure, we may want to use the causal structures learned in the previous section. However, using these structures for inference directly is hard because of the circles and a mixture of directed and undirected links on the graph. Instead, we tried the following directed acyclic graphical models:

GM_complete, an almost complete Bayesian network: In this graph, we order the nodes from top to bottom, and the parents of a node are all the nodes above it, such as in Figure 6.5. For this structure, the order of the nodes is not very important when using Gaussian distributions.

GM_causal, a graphical model inspired by causal models: We manually modify the causal structure in Figure 6.2 to make it a directed acyclic graph. This gives us the *causal* graph structure in Figure 6.6.

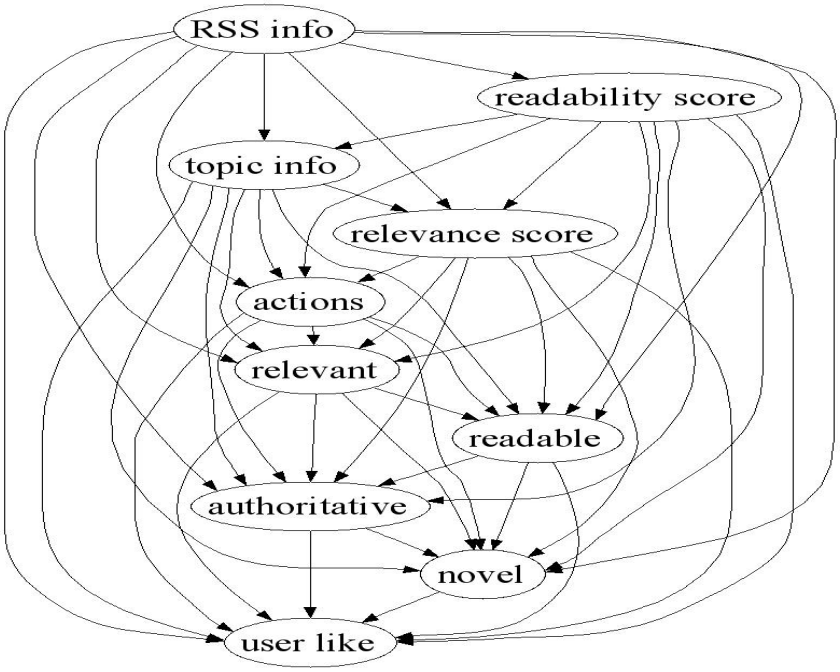


Figure 6.5: Graph structure for GM_complete. In these graphs, *RSS info*={*RSS link, host link*} and *Topic info*={*familiar_topic_before, topic_like*} are 2 dimensional vectors representing the information about the news source and the topic in Table 5.5 and Table 5.4. *actions*=<*TimeOnPage,...*> is a 12 dimensional vector representing the user actions in Table 5.2. *user likes* is the target variable the system predicts.

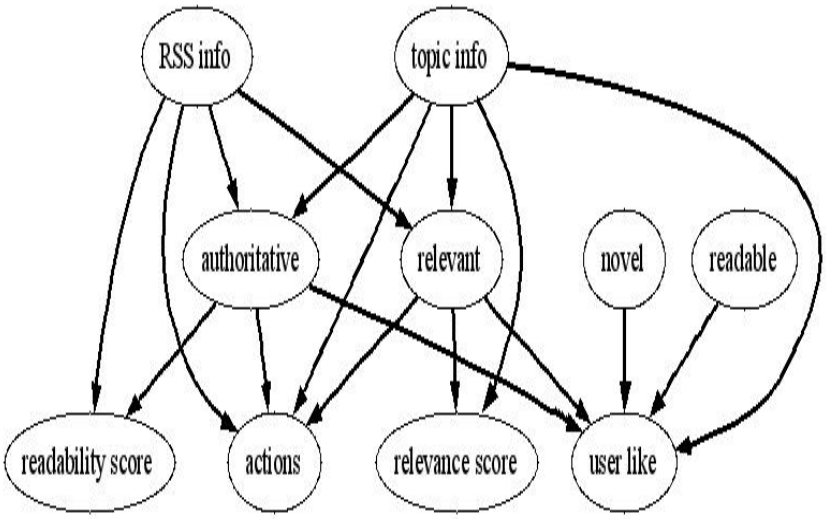


Figure 6.6: Graph structure for GM_causal.

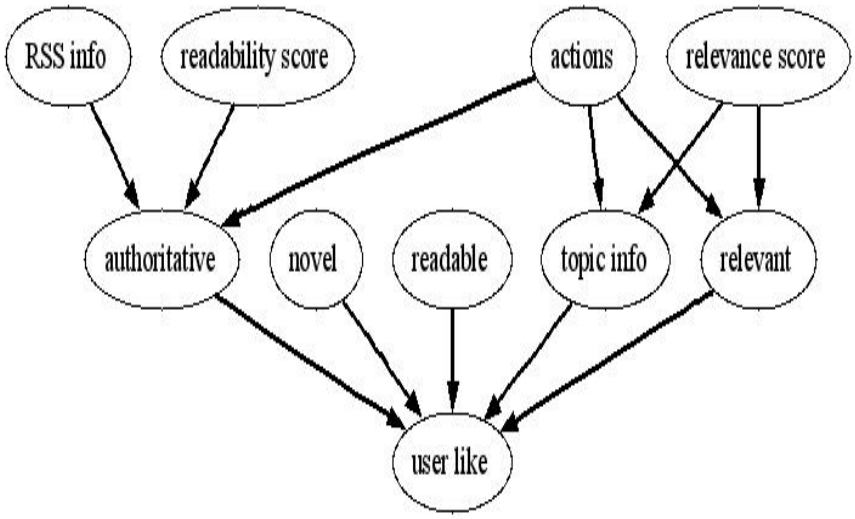


Figure 6.7: Graph structure for GM_inference.

GM_inference We manually modify the structure in Figure 6.3 to make it a directed acyclic graph, and result in Figure 6.7. We call it $GM\_inference$ because the structure looks like an inference graph.

To derive the local conditional probability functions, we need to choose a specific form of the conditional probability function associated with each node. However, it is very difficult to find a good form that is close to the real distribution and mathematically tractable while doing inference. For simplicity, we use Gaussian distributions. If the parents of node X are nodes $Y = (Y_1, Y_2, ...)$, then $P(X|Y) = N(m + W \times Y, \Sigma)$, where $N(\mu, \Sigma)$ is a gaussian distribution with mean μ and covariance Σ. This is a commonly used distribution for continuous valued nodes. We choose it because of the mathematical convenience, the existence of efficient learning and inference algorithms for Gaussian networks, and the availability of modeling tools.

Given a graph structure and a specific form for each conditional probability function, the learning algorithm learn the parameters of the functions from the training data.

Baseline algorithms

To answer the second question and tell how well the graphical modeling approach works compared to some straightforward approaches, we tried an alternative approach to combine multiple forms of evidence: using linear regression. Linear regression models can't handle missing values, so we tried two special methods to solve this problem: 1) building a model that does not use the evidence that is missing for each missing situation ($LR\_different$); or 2) *mean substitution*: replacing each missing value for an evidence with the average of the observed evidence (LR_mean). For K different forms of evidence, the system may need to handle 2^K different evidence missing situations. A large number of linear regression models need to be learned if we use the first approach, considering that K is higher than 15 in some of our experiments. Building 2^{15} models is almost impossible for us, so a heuristic approach, which is discussed later, is used to make the experiments possible.

We chose this algorithm because the linear regression assumes that the conditional probability distribution $P(y|X)$ is a Gaussian distribution, where $y = user\ likes$ and X is a vector with each dimension for a form of evidence. This assumption matches that of the Gaussian network. Thus the major difference between LR models and graphical models is due to the structure instead of the functional form.

Different evidence missing situations for testing

Each algorithm is tested at various evidence missing situations. It is difficult to evaluate algorithms under 2^K different evidence missing situations. Instead we design the experiments as follows to analyze several situations of interest.

Depending on the property of the multiple forms of evidence, we first manually grouped them into seven sets: *relevance score, readability score, topic info, RSS info, user actions, explicit feedback,* and *user likes*. The first four categories may be available before delivering a document to the user, thus can be used by the system to predict user preference for a document while making filtering decisions.

To answer the third question and tell whether going beyond topical relevance to combine multiple forms of evidence is better than the traditional relevance filtering, we rank the first 4 sets of evidence according to the max correlation coefficient between the variables in a category and the *user likes*. The order is: *relevance score, readability score, topic info, RSS info*. A model first predicts the value of *user likes* given only the value of the first evidence (*relevance score*) at testing time. Then more forms of evidence are added in order to see whether the prediction performance increases.

To answer the fourth question and tell whether we can develop a filtering system that works reasonably well with limited user supervision, we manually rank the first 4 sets of evidence according to how easy it is to collect the evidence. The order is: *RSS info, readability score, topic info, relevance score*. A model first predicts the value of *user likes* given only the value of the first evidence (*RSS info*) at testing time. Then more forms of evidence are added in order to see whether the prediction performance increases as more "costly" evidence is available.

To answer the fifth question and tell whether user actions are useful for the system given other information, we compare each model under two conditions:

without actions a model predicts the value of *user likes* given the values of the first four sets of evidence

with actions a model predicts the value of *user like* given the first five sets of evidence, including user actions.

Implementation issues

We develop the experiments with the BNT Toolbox [107]. The maximum likelihood estimations of the parameters (m, W, Σ) are learned from training data using EM algorithm and junction tree inference engine [42] over the graphical models.

In this task, the value of each variable is continuous and normalized to variance one. Each model is learned using all information available on the first 2/3 of the cases, and tested on the remaining 1/3 of the cases.

Not all 7991 cases collected in the user study are used in the experiments. We conducted two sets of experiments. For the first set of experiments, we use 7952 cases where the value of *user likes* is not missing.

For the other set of experiments, we only use 4522 cases where none of the evidence is missing. The results on the first set of runs are analyzed first, followed by a briefly discuss of the results of the second set of runs.

All graphical models and LR_mean model are trained with all types of evidence/features, and the learned models are independent of the testing conditions. For $LR\_different$, we build one model per testing condition and only use features available under the testing condition. However, on the first set of runs using 7952 cases, the training data and testing data contain cases where a piece of evidence that is supposed to be available is missing. These cases in training data are ignored by $LR\_different$ and not used to learn the linear model. However, ignoring these cases in testing data makes cross comparison of testing conditions difficult, because ignored cases depend on the testing condition. So we use mean substitution approach to fill the required missing features in testing data while using $LR\_different$.

Evaluation measures

The correlation coefficient between the predicted value of *user likes* and the users' explicit *user likes* feedback is used as an evaluation measure. The baseline method is using *relevance score* alone.

A linear utility measure is also used. However, the commonly used TREC style linear utility measure (Equation 2.3) can't be used here directly, because it focuses only on topical relevance and is defined over Boolean user feedback. We also consider other aspects of a document now, such as novelty, readability and authority. The system should get a credit for delivering a document that the "user likes" a lot, and get a penalty for delivering a document that the "user dislikes", such as a relevant but redundant document. Furthermore, how much a user likes a document is represented as a number from 1 to 5 instead of a binary value. Thus we modify the TREC style linear utility to get a new evaluation measure for user satisfaction as follows:

$$Utility_{user\ likes} = \sum_{i=1}^{5} A_i C_i \tag{6.1}$$

This measure is very similar to the linear utility measure defined in Equation 2.3 . It corresponds to assigning a positive or negative value to each element in the categories of Table 6.2. In our experiments, we set $(C_1, C_2, C_3, C_4, C_5) = (-1.5, -0.5, 0.5, 1.5, 2.5)$. If a filtering system delivers a document to a user and the user feedback of *user likes* is x, the system receives a value that equals to (x-2.5).

6.2.2 Experimental results and discussions

Figure 6.8 shows the performance of three algorithms on all 7952 cases. The horizontal axis indicates different testing conditions. The vertical axis is the correlation coefficient between the predicted value of *user likes*

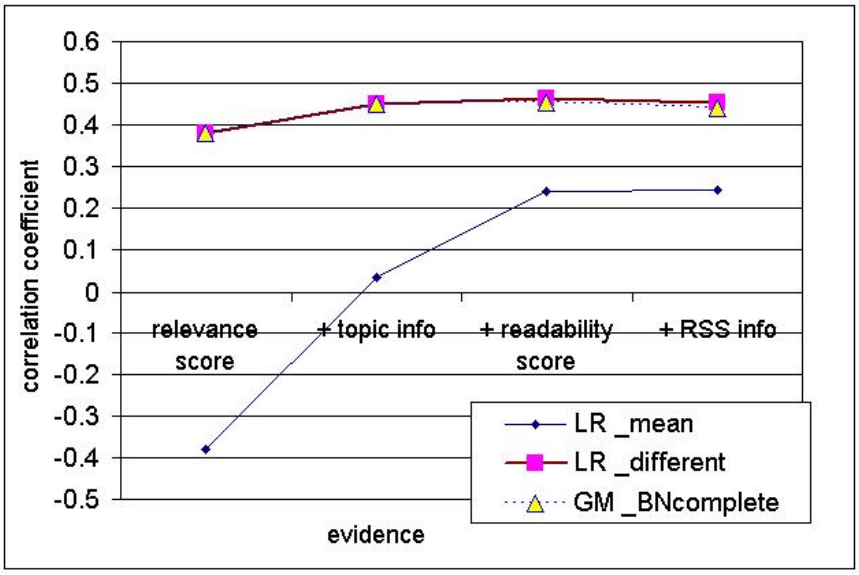


Figure 6.8: Comparison of the prediction power of different models: forms of evidence ordered by correlation coefficient. From left to right, additional sources of evidence are given when testing. "+RSS info" means the values of news source information (RSS info) are given besides the value of *relevance score*, *Topic Info*, and *readability score*.

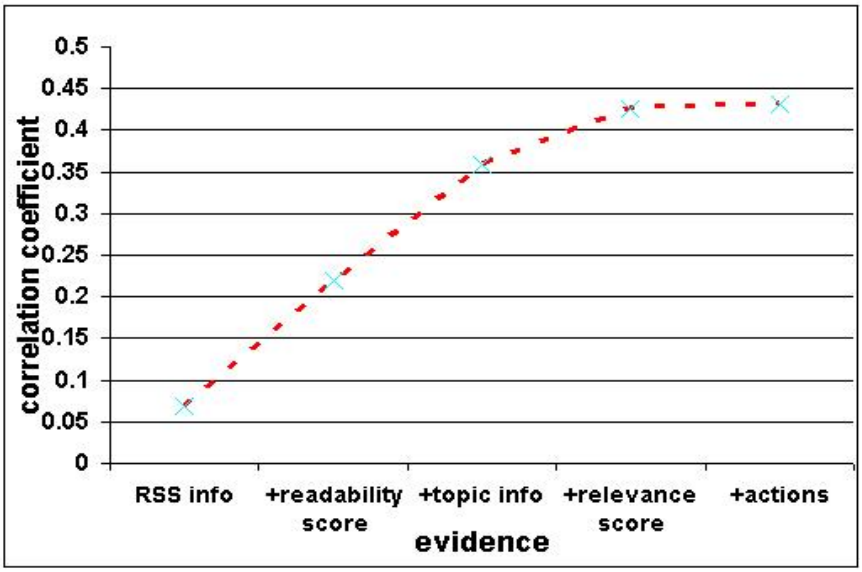


Figure 6.9: Comparison of the prediction power of GM_complete at different missing evidence conditions: forms of evidence ordered by user effort involved.

User like rating	*1*	*2*	*3*	*4*	*5*
Delivered	A_1, C_1	A_2, C_2	A_3, C_3	A_4, C_4	A_5, C_5
Not Delivered	0	0	0	0	0

Table 6.2: The values assigned to documents with different *user likes* ratings. A_1, A_2, A_3, A_4, and A_5 correspond to the number of documents that fall into the corresponding category. C_1, C_2, C_3, C_4 and C_5 correspond to the credit/penalty for each element in the category.

using the model and the users' explicit feedback provided by the users.

The results show that *GM_complete* performs similarly to $LR\_different$. This is not surprising. Theoretically, if there is no missing entries in training data, *GM_complete*'s estimation of the conditional distribution of $P(user\ likes|available\ evidence)$ would be the same as that of $LR\_different$ on a testing case with missing evidence.

$LR\_different$ and *GM_complete* performs reasonably well given only *relevance score*. This is not surprising, since it is well known in the filtering community that the system can improve its performance on future documents with explicit feedback from users on old documents, and existing filtering systems usually use some measure of topical relevance to make decision. It is encouraging to see that as we go beyond topical relevance by adding *topic info*, and *readability score*, the system keeps improving, and the improvement is statistically significant. However, there is no obvious improvement after adding *RSS info*.

One may feel surprised that the correlation coefficient is negative while using *LR_mean* under the "relevance score" condition. Further analysis shows that this evidence is considered unimportant given explicit feedback, thus the learning algorithm assigns a near zero weight, which by chance is negative, to "relevance score". In other words, *LR_mean* gave *explicit feedback* too much weight and overlooked other evidence. Let $user\ likes = a + bX + e$, where the X is other evidence except "relevance score", a and b are the regression weights, and e is the regression "residual". Further investigation show that the 95% confidence interval of the correlation coefficient between e and "relevance score" is [-0.045 0.008]. Thus it is not surprising that "relevance score" has a small negative weight. At testing time, it did not handle the problem of missing *explicit feedback* well and the negative weight of "relevance score" dominates. Although *GM_complete* also gave very high weights to *explicit feedback*, it could infer the missing values based on other available evidence at testing time, and thus it performed better than *LR_mean*. $LR\_different$ does not consider *explicit feedback* for training, thus it overlooks other evidence and suffered less from the problem. *LR_mean* may improve if explicit variables are not included, however it is not a good algorithm to combine multiple forms of evidence if there is a large variance on how informative each evidence is, since it will suffer from a similar problem if some strong evidence is missing due to the same reason. *GM_complete* builds a single model to handle

various evidence missing situations, while $LR\_different$ builds several models, one for each situation. As we mentioned before, there are 2^K different possible evidence missing combinations, and 2^K linear regression models are needed in order to handle all these situations using $LR\_different$ approach. When K is big, $GM\_complete$ may be preferable because it requires less computation and space while performs equally well.

When we order the evidence by the user efforts involved (Figure 6.9), we find that 1) adding "RSS info", "readability score" and topic info improves the performance of the system; and 2) the performance under the "+topic info" condition in Figure 6.9 is close to the "relevance score" condition in Figure 6.8. This experiment was conducted over documents that the user had clicked after seeing their titles. Because most of the clicked documents were somewhat relevant (Figure 5.5), the effect of relevance score is not strong in this experiment. However, this experiment demonstrates the impact and the relative impact of other forms of evidence, such as "RSS info". It's interesting to see that topic familiarity is a factor that influences the user's rating of a document. The fact that adding "RSS info", "readability score" and "topic info" improves the performance may be extended to un-clicked documents and help the system make better recommendations than without using the information. However, the degree of the improvement on un-clicked documents may be different. This result demonstrates how "cheap" information can help to predict whether a user likes a document he/she clicked. This will directly benefit systems for personal information retrieval and re-use[48], since little user supervision is needed to train a model to work under the "+topic info" condition in Figure 6.9.

So far, the only graphical model that has been evaluated is $GM\_complete$. How about other graphical models? Will a model with different structure perform differently? Figure 6.10 compares several graphical models. GM_causal and $GM\_inference$ perform worse than the simple $GM\_complete$. Why do structures that look more causally reasonable not perform as well as the simple $GM\_complete$ on this data set? $GM\_complete$ only assumes the joint distribution of all variables is multivariate Gaussian. GM_causal and $GM\_inference$ make much stronger assumptions by removing some links between variables, thus putting independence constraints while learning the models. As we discussed before, the causal relationships learned automatically are not perfect, thus the constraints imposed by $GM\_inference$ and GM_causal may be wrong. As a result, they performed worse than a $GM\_complete$.

Are user actions useful for the system given other information? We compared each model under two conditions: with and without user actions (Table 6.3). For each model, there is no statistically significant difference after *actions* are added. This means that given other forms of evidence (*RSS info*, *topic info*, *relevance score* and *readability score*), the system didn't improve its prediction much by observing actions after a user reads the document. However, it does not mean the actions are useless if we learn user specific

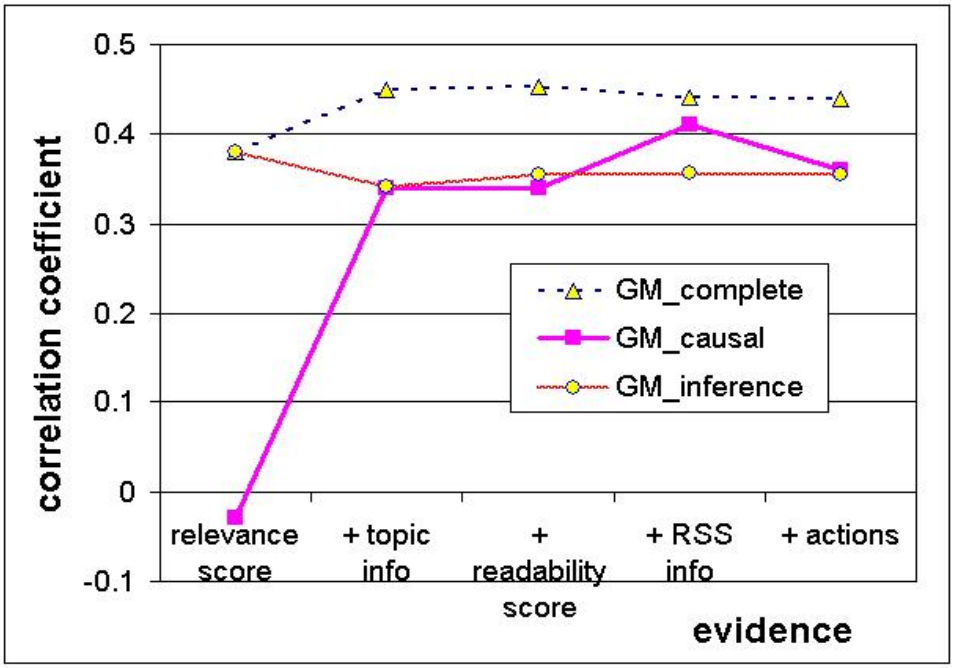


Figure 6.10: Comparison of the prediction power of different graphical models: forms of evidence ordered by correlation coefficient.

Model	Actions added	corr	RLow	RUp
LR_mean	no	0.278	0.243	0.313
LR_mean	yes	0.265	0.229	0.300
LR_different	no	0.437	0.406	0.468
LR_different	yes	0.438	0.406	0.468
GM_simple	no	0.289	0.253	0.323
GM_simple	yes	0.270	0.234	0.305
GM_complete	no	0.425	0.393	0.456
GM_complete	yes	0.432	0.400	0.462
GM_causal	no	0.308	0.273	0.342
GM_causal	yes	0.309	0.274	0.343
GM_inference	no	0.343	0.309	0.376
GM_inference	yes	0.343	0.308	0.376

Table 6.3: A comparison of effect of adding user actions. "relevance score", "readability score", "RSS info" and "topic info" are given before actions where added. The data entries with missing value are also used for training and testing. *corr* is the correlation coefficient between the predicted value of *user likes* using the model and the true explicit feedback provided by the users. RLO and RUP are the lower and upper bounds for a 95% confidence interval for each coefficient.

model, or if other forms of evidence (such as *relevance score*) are not available.

So far, all results are based on 7952 cases where some evidence may be missing. Table 6.4 reports the results on a second set of runs with 4522 cases where no evidence is missing. The results show the performance of *GM_causal* and *GM_inference* changes a lot using this new evaluation data, significantly better than before (Table 6.3). This suggests that we need to be very careful with the structures while using the graphical modeling approach, since a structure that looks more reasonable may work poorly on the inference task. However, we couldn't draw any conclusion on whether *GM_complete* is better in general, because the answer may be different with different conditional probability distributions, different data sets, or a better structure learning algorithm.

Will a filtering system that combines multiple forms of evidence using graphical models help us to build a better practical filtering system that serves the user better? Does a higher correlation between the user's explicit feedback on "user likes" and the predicted values mean higher utility?

To answer these questions, we also use the linear utility measure (Equation 6.1) to evaluate the proposed solution. Ideally, we need to have a thorough evaluation data similar to TREC filtering data, but with multiple forms of evidence. Unfortunately, it is extremely hard to collect such kind of data. Instead, we use all <document, user class, time> tuples with user feedback. The first 2/3 of the cases are used as training data, and the remaining 1/3 of the cases are testing data. The system processes each tuple <document d, class c, time t> in the testing set ordered by time, and decides whether the document d should be delivered to the user class c at time t. Delivering all documents in the testing data to the user gives a utility of 2881.5, which is very high. It is not surprising considering this is a very biased evaluation data set and all testing data are documents already clicked by the user. The highest possible utility on the testing data is 3300.

We compare three approaches.

LR_Rocchio The system delivers the documents to the user if and only if the estimated *relevance score* is higher than 0.5. The relevance score is the same as used before (Section 5.3.5). For a <document, user class, time> tuple missing *relevance score*, the system does not deliver it.

LR_Rocchio + linear regression The system corrects the bias caused by the difference between "user likes" and "relevance score". It uses either linear regression to predict "user likes" using "relevance score", and delivers the documents to the user if and only if the estimated *user likes* is higher than 2.5.

GM_complete + multiple forms of evidence For each incoming document in the test stream, the system uses *GM_complete* to predict *user likes* given *RSS info*, *readability score*, *topic info* and *relevance score*. Then the system delivers the document to the user if and only if the estimated *user likes* value

Model	Condition	corr	RLow	RUp
LR_mean	RSS info	0.0316	-0.0192	0.0822
LR_different	RSS info	0.0316	-0.0192	0.0822
GM_complete	RSS info	0.0316	-0.0192	0.0822
GM_causal	RSS info	0.0316	-0.0192	0.0822
GM_inference	RSS info	0.0316	-0.0192	0.0822
LR_mean	+readability score	0.1467	0.0967	0.196
LR_different	+readability score	0.1365	0.0864	0.1859
GM_complete	+readability score	0.1365	0.0864	0.1859
GM_causal	+readability score	0.0648	0.0141	0.1151
GM_inference	+readability score	0.146	0.0959	0.1953
LR_mean	+topic info	0.2435	0.1952	0.2906
LR_different	+topic info	0.2875	0.2402	0.3333
GM_complete	+topic info	0.2875	0.2402	0.3333
GM_causal	+topic info	0.2572	0.2092	0.304
GM_inference	+topic info	0.2303	0.1817	0.2778
LR_mean	+relevance score	0.1284	0.0782	0.178
LR_different	+relevance score	0.4109	0.3679	0.4522
GM_complete	+relevance score	0.4109	0.3679	0.4522
GM_causal	+relevance score	0.4106	0.3675	0.4519
GM_inference	+relevance score	0.4189	0.3762	0.4599
LR_mean	+actions	0.1075	0.0571	0.1574
LR_different	+actions	0.4184	0.3756	0.4594
GM_complete	+actions	0.4184	0.3756	0.4594
GM_causal	+actions	0.3789	0.3346	0.4215
GM_inference	+actions	0.4424	0.4006	0.4823
LR_mean	+explicit feedback	0.7396	0.7157	0.7617
LR_different	+explicit feedback	0.7396	0.7157	0.7617
GM_complete	+explicit feedback	0.7396	0.7157	0.7617
GM_causal	+explicit feedback	0.7449	0.7214	0.7666
GM_inference	+explicit feedback	0.7449	0.7214	0.7666

Table 6.4: A comparison of different models: no missing value cases, coefficient measure. RLO and RUP are the lower and upper bounds for a 95% confidence interval for each coefficient.

Table 6.5: A comparison of different models: all cases, utility measure. If we deliver all documents in the testing data to the user, the utility is 2881.5. The highest possible utility on the testing data is 3300.

model	evidence	utility
LR_Rocchio	relevance score	2036
LR_Rocchio + linear regression	relevance score	2750
GM_complete	multiple forms of evidence	2953.5

is higher than 2.5.

Table 6.5 shows that combining multiple forms of evidence achieved a much higher utility using relevance score only. Although the experimental setting is far from real because the evaluation data are biased, the graphical model with multiple forms of evidence is more likely to perform better than using relevance information alone in a real scenario.

It is encouraging to see that *GM_complete* performs better than delivering all documents the users clicked. One may feel a little surprised to see that the relevance model performs even worse than delivering all documents to the user, considering relevance models usually perform much better than delivering everything on TREC data. There are two reasons: 1) delivering everything is already a very high baseline because the evaluation data only includes documents clicked by the users; 2) the system could not estimate the relevance score for all <document, user class, time> tuples, especially for the first one or two documents in a user profile .

It is worth mentioning that all the inference tasks only considered <document, user class, time> tuples that corresponds to documents users clicked and assigned class labels. The performance may be different on arbitrary tuples in a real system. A practical filtering system may ask users to create classes manually, or automatically create user classes and assign documents to classes.

6.3 Related work and further discussion

There is much related work on using implicit feedback in the information retrieval community and user modeling community. [75] provides a review and classification of works in these areas according to the behavior category and minimum scope. The prior work suggested many possible behaviors (view, listen, scroll, find, query, print, copy, paste, quote, mark up, type and edit) on different scope (segment, object and class) for system designers to choose from. The user actions we collected are based on [37].

There is some early work on news filtering [81][13][47][62]. [32][79][104]. [24] build a personal news agent that used time-coded feedback from the user to learn a user profile, however their way of integrating

time as feedback is rather heuristic. [106] investigated implicit feedback for filtering news group articles. They discovered that articles readers spent viewing more than 20 seconds as positive feedback can produce better recall and precision in filtering than user's explicit rating. [152] observed incompatible context, noisy context and incomplete query problems in contextual retrieval applications and developed specific models to solve these problems. The approach described in this chapter can handle these problems in a unified framework. There is also much related work on using implicit feedback to improve web retrieval performance [153][9][141]. We notice a recent independent work using a different kind of graphical modeling approach, dependency networks, to discover the relationships between implicit measures and explicit satisfaction, and using decision tree for prediction ([53]). They were focusing on predicting user satisfaction with web search results based on implicit measures gathered while users were conducting their searches and viewing results. Their findings justify the graphical modeling approach's effectiveness in web search task, a task close to filtering. Our work differs from the previous work in the goal of the task, the range of evidence considered, the modeling approach we took, and the findings reached.

Different graphical models, such as Bayesian networks, dependency networks, inference networks, and causal models, have been used to model computer software users [64], car drivers [114], students [41], and other social phenomena [101]. Choosing graphical modeling as a unified framework to combine multiple forms of evidence is motivated by these prior work. Our work differs from the previous work because we are working on filtering, a different task. Moving to the specific domain of information filtering, we have performed a detailed user study with human subjects at the early stage of the research. In the later stages of this research, we have used basic statistical analysis techniques and existing graphical modeling algorithms to understand the data collected and explore how to improve the system performance. More specifically, we have focused on the missing data problem, which becomes more important as more forms of evidence are added.

There is much work about how to handle missing data [89]. [129] gives an overview of the state of art. The approaches to handle missing data can be classified into four categories:

case deletion This approach is the simplest approach and is used by default in many statistical programs. It can be further divided into two categories: 1)complete case analysis that only uses cases that have observed values; 2)available case analysis that estimates different parameters using different sets of samples.

dummy variable coding When the variable is a categorical value, this algorithm creates a new class "not available" and assign this class label to a missing entry. For a learning algorithm, missing data cases no longer exist.

maximum likelihood estimation The algorithm fills in the missing entry using the maximum likelihood estimation of that value. Although the principle of this approach is very simple, but the actual solutions can be very different and computationally expensive, depending on the models the system use to model the variables. Except for some special models, there is no closed form solution for ML estimation and EM algorithm is often used [49].

multiple imputation The algorithm generates multiple imputed values for a single missing entry on the basis of existing data and using those "imputed" values in the solution [130].

In this dissertation, *LR_mean* models the missing variable as a Gaussian distribution and uses the maximum likelihood estimation, the unconditional mean of the variable, to replace the missing value. $LR\_different$ and *GM_complete* model the joint distribution of all variables as Gaussian distribution and uses the maximum likelihood estimation, the conditional mean of the variable, to replace the missing value. Besides the algorithms we tried in this dissertation, other approaches exist to handle the missing value. For example, regression trees can use "surrogate splitters" to split data if a primary splitter is missing. This allows cases with different data patterns, including missing pattern, be handled differently. *GM_complete* may not be the best approach for the task, but it is a rather natural solution under the Bayesian graphical modeling framework and works reasonably well compared to $LR\_different$ and *LR_mean*. Although we have studied the missing value problem, the solutions we tried assume the data are missing at random. We haven't investigate whether the distribution of missingness depends on the value missed, observed data, or any hidden variable. Different missing data situations require different approaches to handle the problem. Further analysis about why data become missing may help us to find a better solution and improve the system's performance further. One possible future direction is to model the missingness explicitly as a random variable in the graphical model.

There exists some work studying criteria beyond topical relevance. [31] studied combining query-relevance with information-novelty for retrieval and summarization and proposed Maximal Marginal Relevance (MMR) criterion to reduce redundancy. [148] considered the incremental value of a piece of information and argued that the standard "present documents in order of estimated relevance" is not appropriate. [166] proposed a two stage filtering system to filter out relevant but redundant documents. [160] went beyond independent relevance and models dependent relevance to retrieve documents that cover as many different subtopics as possible. [150] asked users to read aloud and think aloud while doing hard copy documents selection, audio-taped and analyzed the whole process, and proposed a relevance model based multiple criteria, such as personal knowledge, topicality, quality, novelty, recency, authority and author qualitatively. [131] identified criteria underlying users' relevance judgments and explored how users employed the criteria in making

evaluations by asking users to interpret and sort criteria independent of document manually. In previous work the word "relevant" was used ambiguously, either as a narrow definition of "related to the matter at hand (aboutness)" or a broader definition of "having the ability to satisfy the needs of the user". When it is used by the second definition, such as in [131], researchers were usually studying what this dissertation refers to as *user likes*. In this dissertation, we use "relevant" as is defined in the first definition and use the phrase "user likes" for the second definition. Despite the vocabulary difference, the work in this chapter is motivated by these early works focused on "user likes". The major contributions of our work in this area are: 1) we model the *user likes* and other criteria as hidden variables; 2) we have demonstrated how to quantify the importance of various criteria based on utility optimization and probabilistic reasoning; and 3) we have explored the new methodology for combining these criteria with implicit and explicit user feedback.

6.4 Future work

This is the first step towards combining multiple forms of evidence for filtering using the graphical modeling approach. The experiments are rather simple and further work is needed to fully explore the potential of using graphical models to combine multiple forms of evidence. What follows are several future research directions:

6.4.1 User specific models for inference

We only built user independent graphical models in this chapter. The preliminary data analysis in Section 5.4 shows that users are different. This suggests possible improvement if we build user specific graphical models and possibly combine them with user independent models. We have carried out a preliminary study to compare the user specific model with the user independent model of four arbitrarily selected users. In this study, we deleted all information in the first 4000 entries of a user to simulate the scenario that the user starts using the filtering system later than other users. The information in the first 4000 entries from other users and the first 10% of the data for that user are used to learn a user independent *GM_complete* model for that user. The first 10% of the data from that user are used to learn a user specific *GM_complete* model. Then the learned models are used to predict *user likes* on the remaining 90% of the data on the user given *RSS info*, *relevance score*, *readability score*, *topic info* and *actions* for each case. Compared with user independent model, the user specific modeling approach has both negative and positive results: it works better on users A and B, but worse on users C and D (Table 6.6).

The result does not tell us whether user specific model will help or not. Instead, it suggests much future

userId	user independent	trainNum	testNum	corr	RLO	RUP
A	Yes	1839	55	0.18	-0.09	0.43
A	No	6	55	0.56	0.34	0.71
B	Yes	1969	523	0.28	0.20	0.36
B	No	58	523	0.39	0.32	0.46
C	Yes	2170	420	0.77	0.73	0.81
C	No	46	420	0.60	0.54	0.66
D	Yes	2545	278	0.28	0.17	0.39
D	No	30	278	0.14	0.03	0.25

Table 6.6: Comparing user specific models with user independent model for some users. "corr" is the correlation coefficient between the predicted value of *user likes* using the model and the true explicit feedback provided by the users. "Train No." is the number of training documents used to learn each model. RLO and RUP are the lower and upper bounds for a 95% confidence interval for each coefficient.

work is needed to explore how to build a better user specific model and that results may be fruitful. In general, a user specific model has its pros and cons. In the real world, users are different. However, a filtering system has significantly more training data to learn a user independent model than a user specific model. For a given amount of training data from a user, a user specific model learned only from these data has low bias but high variance. User specific models may work better than a user independent model asymptotically as the amount of training data goes to infinity, and a user independent model may work better initially.

Instead of choosing between a user specific model and a user independent model, an alternative approach is to combine both models using Bayesian priors. Human learners do that implicitly by assuming an unfamiliar person as similar to the "general public". After interacting with the person and knowing more about him/her, a human adapts the stereotypical image about the general public to this specific person. The whole adaptation process can be modeled nicely using the Bayesian approach. We can use the *Bayesian prior* to encode the *user independent* model about the general public, and use the *posterior* to encode the *user specific* model adapted to the specific person. This is one possible direction for future work.

6.4.2 Better models for inference

Further research is needed to explore more structures and functional forms for inference.

How can we use the structure learned to improve the system's inference accuracy? The poor prediction power of *GM_causal* does not mean the structured learned is not useful for inference task. In practical settings, choosing the right feature set is very important for good performance. [5] suggests using causal interpretation for feature selection, because there is a formal connection between causal graph and feature selection: the Markov blanket of "user likes" may be a good feature set. The causal based feature selection

may help to improve the performance of classifier, or help us to decide which evidence should be collected. For example, to predict *user likes* node, we only need to collect variables/features/nodes/evidence that are part of the Markov blanket of the *user likes* node. According to Figure 6.2, *MSecForPageDown*, *MSecForPageUp*, and *NumOfPageUp* are not useful since they are separated from the *user likes* node by *NumOfPageDown*. In other words, the *user likes* variable is conditionally independent of these variables given the Markov blanket of *user likes*. One future direction is to see whether we can improve the prediction accuracy or avoid collecting useless information using causal based feature selection.

GM_causal and $GM\_inference$ performs worse than $GM\_complete$ in our experiments, even though $GM\_complete$ is rather simple and may not be the best for the prediction task. There is much work on alternative graph model structure learning algorithms, such as [35][77][94]. A Bayesian approach is to treat the structure learning as a model selection problem and do model averaging. Alternatively, we can try undirected graphs and graphs with parameter nodes (similar to what we did in the Section 4.1).

When we choose the structures and functional form in Section 6.2.1, the mathematical convenience is a major concern. The conditional probability function Gaussian distribution by no means is the universally best choice. It assumes the joint distribution of these variables is multivariate Gaussian. According to this assumption, the marginal distribution of each variable should be Gaussian. The histograms of some variables contradict the assumption (Figure 5.8), although the distributions of some other variables agree with the assumption (Figure 5.7, Figure 5.9). So the assumption seems wrong. A future direction is to find better structures and functional forms. This may lead to better inference performance.

6.4.3 Integrating novelty/redundancy and authority estimations into graphical models

In this chapter, the system only estimated the *relevance score* and *readability score* of a document and integrated them into the models. Other factors that may affect the user's preference for a document, such as a novelty score or authority score, could be estimated and integrated as well.

The decision about whether a document is novel depends on user's prior knowledge and whether the relevant information in a document is covered by information in the documents delivered previously. Compared to the topical relevancy of a document, which is independent of where the document appears in the stream of documents, the decisions about redundancy and novelty depend very much on when a document appears. This makes novelty/redundancy score estimation a very interesting and challenging topic that we should view from a very different perspective from relevance score estimation. We designed a task and created an evaluation data set that contains known novel/redundant documents in another user study [166]. To make

the user study feasible, we made the following assumptions:

- The user only reads related documents through the filtering system;
- The redundancy/novelty of a new document d_t only depends on the documents the user saw before d_t;
- The redundancy of a document d_t only depends on all the relevant documents the user has seen when d_t arrives;
- For two documents set A and B, if $B \subseteq A$ and B makes d_t redundant, then A also makes d_t redundant.

Based on these assumptions, we hired undergraduate assessors to read relevant documents in chronological order and asked them to identify each document as redundant or not with respect to documents before it. Under this well controlled user study, we collected a clean evaluation data set. We compared several novelty/redundancy measures and found some effective measures for novelty/redundancy score estimation.

The above assumptions and the well controlled user study have made the study of novelty feasible. However, in the loosely controlled user study described in this chapter, the assumptions do not hold because the history of the user is incomplete. Before the users participated in the yow-now study and during the user study, they read news elsewhere. If a document is redundant with respect to a document the user read elsewhere, the current yow-now system may not give the document a low novelty score because the system is not keeping track of the user's other activities. Thus we didn't estimate the novelty score of a document in the study reported in this dissertation, although the approaches proposed in [166] can be used to do that.

However, this is not the fundamental problem of the proposed Bayesian graphical modeling approach. Future work can be done to estimate the novelty score and combine it with other forms of evidence. Although this score would be very unreliable under a loosely controlled experimental setting as described in this chapter, it may be very informative under other environment where the assumptions are more likely to be true, such as a filtering system that monitors all of a user's information seeking activities. From the Bayesian Graphical Modeling point of view, combining novelty score with other aspects while filtering is straightforward. We would also need to compare the Bayesian graphical approach with an existing approach, such as the two stage model [166] and MMR (Maximal Marginal Relevance) model [31].

6.5 Summary

We have explored how to combine different forms of evidence using the graphical modeling approach. We have developed probabilistic user models with *user likes* and other criteria as hidden variables. We have

demonstrated how to quantify the importance of various criteria and combine these criteria with implicit and explicit user feedback based on utility optimization and probabilistic reasoning. The work enables the system to go beyond relevance and develop more interesting and detailed data driven user models than prior research. This is partly because the framework has better theory, and partly because the advantages of the proposed framework matches the task, where it is practical to collect enough training data to learn over a period of time.

We have analyzed the user study data using graphical models, as well as linear regression algorithms. The experimental results show that the graphical modeling approach can help us to understand the causal relationships between multiple forms of evidence in the domain and explain the real world scenario better. It can also help the filtering system to predict user preferences more accurately with multiple forms of evidence than by a relevance model only.

Using more forms of evidence improves the system performance. However, as more forms of evidence are added, missing data is a common problem because of system glitches or because users will not behave as desired. A real system needs to handle various missing data by either ignoring it or by estimating it based on what is known. The graphical modeling approach addresses this problem naturally. Simpler approaches, such as linear regression, were not designed to handle missing values. In order to use them to combine multiple forms of evidence, extra handling of missing data is needed. $LR\_different$ handles the problem by building many different models to be used at different data missing conditions. $LR\_different$ and $GM\_complete$ perform similarly. When there are few types of evidence, $LR\_different$ probably is preferable because of the simplicity. However, as more forms of evidence are added, a more powerful model, such as $GM\_complete$, may be preferable because of the computation and space efficiency.

If the system uses a user independent model to combine multiple forms of evidence and learns user dependent models to calculate some types of evidence, such as relevance scores, the major computation of the system is to learn user specific models, such as a relevance model. This means the computational complexity of using graphical models can be similar to that of traditional filtering system. However, if we need to learn a user specific graphical model for inference (Section 6.4.1), the complexity would be higher.

We only collected data for documents clicked. Further investigation is needed to look at un-clicked data, which is a critical step to see whether the improvement on prediction accuracy of user preferences and utility under the experimental setting described in this chapter will help the system serve the user better in a real filtering environment.

This is the first step towards using graphical models to combine multiple forms of evidence while filtering. The proposed solution, especially the data analyzing methodology used in this chapter, can also be used in

other IR tasks besides filtering, such as context-based retrieval.

Chapter 7

Conclusion and future work

In this chapter, we conclude the dissertation by summarizing our contributions, clarifying the limitations of our work, and proposing several directions for future work.

7.1 Contributions

Information filtering is an important research topic with ever increasing information available in electronic form. Standard ad hoc retrieval systems, such as search engines, let a user use short queries to pull out information. The standard retrieval systems also treat users the same given the query words. However, users are different and are not good at describing their information needs using ad hoc queries. Traditional adaptive information filtering systems try to solve this problem by letting the user tell the system whether a document is relevant or not, and the system learns from this user feedback. This is very convenient for the user since a user can tell whether a document is relevant or not more easily and accurately than describing his/her information needs. It is also a good environment for the filtering system to learn a user profile, since it can accumulate a fair amount of user feedback over time. However, a real user doesn't want to provide a large amount of feedback, especially at the initial stage of filtering. He/she would rather issue a short query or identify a few (one or two) good documents initially, then begin using the system and provide feedback over time. How to develop a filtering system that can work well with limited user supervision is a major challenge for the filtering research community.

On the other hand, because of the possibility of large amount of user interactions over a long period of time, the filtering environment offers rich opportunities for the research community. The interesting and challenging research topics are: how to let systems learn sophisticated user models over time; how to develop a robust learning algorithm that works reasonably well when the amount of training data is small and become more effective with more training data; how to trade off immediate gain vs. long-term gain; how to use multiple forms of evidence, such as user context and implicit feedback from the user, while interacting with a user; and how to handle various problems like missing data in an operational environment robustly.

Solutions to these problems will also help us to solve the limited user supervision problem. Unfortunately, existing filtering research has mostly stayed with simple bag-of-word models and has not studied these topics adequately.

The major contributions of this dissertation are proposing and exploring Bayesian graphical models as a unified framework for filtering and solving the limited training data problem based on utility optimization and probabilistic reasoning. This work is significant because it addresses some long-standing issues in the adaptive information filtering community: the combination of heuristics and statistical learning algorithms, exploitation and exploration trade-offs while actively learning, the integration of a wider range of user-specific and user-independent evidence, and handling situations like missing data that occur in operational environments.

The contributions of the thesis can be summarized in the following three sections:

7.1.1 General contribution: A theoretical framework

The general contribution is introducing an existing general framework to guide the algorithm design of a filtering system and demonstrating how to adapt it to the specific filtering problem. This framework contains three major components:

Representation tools: The framework provides a set of representation tools that enable researchers to build a personalized information filtering system that can combine many aspects such as topical relevance, novelty, readability, authority, and explicit and implicit feedback;

Bayesian axiom: In this framework, maximizing the expectation of a user defined utility function, such as Equation 6.1, is the only decision criterion; and

Inference tools: Statistical inference algorithms introduced in Section 2.3.4 are tools that enable us to estimate probability distributions that can be used to achieve the goal of maximizing the utility.

The framework provides guidance about how to build the next generation of adaptive filtering systems, which will consider a broader range of information and be more sophisticated than existing filtering systems. Compared with other commonly used text classification algorithms, it has five major advantages. First, the goal of the system is clearly stated in a broader way expressed as a utility function defined over whether a user likes a document or not, which depends on several criteria such as the topical relevance, novelty, authority and readability of a document. Second, the system models the uncertainty explicitly using probabilities, which provides a principled way to do active learning. Third, the framework can help us to understand the

causal relationships in the domain and combine multiple forms of evidence to further improve the design of the system. Fourth, the framework enables us to combine prior domain knowledge or heuristics with the training data. Fifth, the framework uses the conditional dependencies encoded in the graph structure to handle things like missing data, which occur in operational environments.

Now researchers are better empowered with the set of modeling tools provide by BGM and a clear goal expressed quantitatively as utility. Furthermore, they benefit from the five advantages of the BGM framework.

7.1.2 Specific contributions

In particular, we have developed specific techniques arising from the Bayesian graphical modelling framework to build a filtering system with desired characteristics. The second contribution of the dissertation is these techniques.

We have implemented and evaluated these techniques on several standard and new data sets. The dissertation has demonstrated that these techniques help filtering systems learn efficiently and work robustly with limited user supervision. More specifically, the key techniques and findings can be summarized as follows.

- We have developed a novel algorithm to combine simple models proposed by an IR expert with complex models using a Bayesian prior. The new algorithm uses the IR expert's heuristic algorithm to learn user interests when the amount of training data is small, and later gradually switches to a more complex learning algorithm to update its beliefs about user interests as more training data are available. This work is important because it shows how to satisfy conflicting user requirements, i.e., work robustly with initial heuristics, and continue to improve over time with training data. Previous solutions required users to choose between heuristic approaches that work with little training data or probabilistic models that offer longer-term accuracy; now they can have both. The filtering system using this algorithm works well: comparable to the best in the TREC-9 adaptive filtering task, much better than the best in the TREC-11 adaptive filtering task, and one of the best in the supervised tracking task at TDT5.

- We have derived a novel model quality measure, *Utility Divergence*, based on Bayesian decision theory. This enables us to measure the utility gain of delivering a document to the user. Most of the previous work in adaptive filtering focused entirely on the immediate cost/credit of delivering a document, disregarding the future benefit. Some prior work considered the future benefit heuristically [33]. Now exploitation (making the user happy right now) and exploration (asking for user feedback) are combined

in a unified framework to optimize a user utility function. This led to a filtering learning system with an active learning capacity that can choose to deliver a document the user may not like because the system believes it can learn a lot from the user feedback and work better in the long run. We believe this is the first non-heuristic approach on the trade-off between exploration and exploitation in information filtering. The experimental results demonstrate the technique works well on favorable data sets where it worth exploring, and has little effect on unfavorable data sets.

- We have demonstrated how to use existing graphical modeling algorithms to combine multiple forms of evidence in a filtering system. We have carried out a user study and collected an extensive data set of various explicit feedback and implicit feedback from the users, together with other evidence. We have shown that causal structure learning algorithm can help understanding the domain, although the causal relationships learned automatically are not perfect. We have developed probabilistic user models with *user likes* and other criteria as hidden variables. We have demonstrated that inference algorithms can predict user preference better with multiple forms of evidence than with the topical relevance information alone. While interacting with the user, the system may fail to collect all forms of evidence for each individual case because of system glitches or because users will not behave as desired. We have demonstrated that the graphical modeling algorithms handle the problem of missing data naturally and efficiently.

Evaluation and explanations of existing techniques similar to ours, the difference between our techniques and existing ones, and why our solutions are important, are discussed in more detail separately in each chapter (Chapters 3 to 6). In general, existing filtering solutions were proposed separately and are ad hoc. There was no principled way to model different aspects (active learning, using prior knowledge or heuristics, combining multiple forms of evidence) and combine them together in the filtering literature. Now we are empowered with BGM, and these specific techniques demonstrate the power of the proposed framework to guide us building a filtering system with the desired characteristics.

It is worth mentioning that the Bayesian graphical modeling framework is a more general and scientific way to develop filtering solutions with the desired characteristics. It provides guidance but does not give "always better" algorithms, and each technique developed under the framework is not guaranteed to be the best.

7.1.3 Contribution beyond filtering

Although the solutions developed in this dissertation are motivated by the filtering problem, the contributions and potential applications of the thesis work go beyond filtering. We summarizes these contributions in the following aspects:

Contribution to user modeling First, we have built a longer-term learning environment for the study and demonstrated that we can collect a significant amount of data about a user's interests. Second, we have built user independent and user specific models from the data. We have modeled the information need of a user as a utility function based on a set of broader, realistic and more distinct criteria, such as topical relevance, novelty, readability and authority. There is much prior work talking about modeling users and going beyond topical relevance. However, the prior works usually come down to a weighted bag of words. Explicitly modeling different criteria and learning the importance of each criterion using probabilistic inference algorithm from the data, the filtering system goes beyond the bag of words approach and combines multiple forms of evidence. This broader, sophisticated, realistic, and data-driven user modeling approach may lead to a system that serves the user better.

Contribution to machine learning An online learning system usually needs to consider the immediate cost/credit as well as longer term rewards. The *utility divergence* we derived in Chapter 4 is a new model quality measure that generalizes some existing ones used for active learning. The exploration and exploitation trade-off solution based on that measure combines the direct and indirect cost/reward under a unified framework to optimizes for utility explicitly, thus enabling a learning algorithm to do active learning without being too conservative or too aggressive.

The three specific techniques developed are not restricted to the filtering domain. In many other tasks, where domain expert's knowledge or heuristics are provided, active learning may help, or multiple forms of evidence are available, these techniques can be applied.

7.2 Limitation and future directions

Although the dissertation has demonstrated the effectiveness of using Bayesian graphical models to building an intelligent filtering system with some desired characteristics, the filtering problem is far from solved. We have already discussed some open questions and future work of the specific techniques developed in relevant chapters, and we highlight several important limitations and future directions below.

7.2.1 Computationally efficient techniques

We have demonstrated that the Bayesian graphical modelling approach enables us to go beyond relevance and build more complex user models. However, more complex models may lead to higher computational cost, and the computational complexity is a major limitation of the proposed framework. Not surprisingly, this limitation is reflected in the solutions we developed.

For example, in Chapter 4, we only applied the active learning technique to solve the one dimensional problem of setting dissemination thresholds, although it can also be used with LR_Rocchio in high dimensional space to learn the term weights of keywords or phrases. What stops us from going from low dimensional active learning to high dimensional active learning is the computational complexity of estimating the integration in Equation 4.4 and 4.11. The Metropolis sampling algorithm used in Chapter 4 works fine in low dimensional spaces, but it is not practical in high dimensional space.

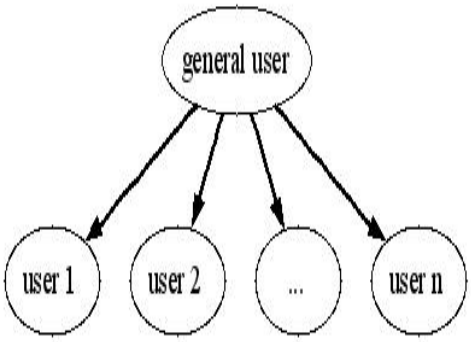
In Section 6.2, we chose the directed acyclic graphs (DAG) as the structures and the Gaussian distributions as the conditional probability functions associated with each node. However, the causal structure (Figure 6.2) and the distributions of some variables (Figure 5.8) learned from the data show that the DAG and Gaussian distributions are far from the optimal. The existence of efficient learning and inference algorithms for Gaussian networks and the availability of modeling tools are the major reasons for our choice.

However, we believe the computational complexity of Bayesian graphical models is not an unsolvable problem. Besides the exact algorithms (Section 6.2) and sampling based algorithms (Section 2.3.4) used in this dissertation, researchers in Bayesian theory and graphical modeling area have developed other inference algorithms, such as variational algorithms ([67][74]) and parametric approximations ([105][159]), that are computationally efficient in certain situations. These inference algorithms have been used with more complex models in other domains. One possible future direction is to use these algorithms for inference while filtering. This will enable us to use more complex graph structure and more general conditional probability functional forms for user modeling. It will also enable us to do active learning in high dimensional space.

7.2.2 User independent, user specific, and cluster specific models

To build a user model while filtering, the first problem that needs to be solved is to decide whether the system should learn a user specific or user independent model. It was handled manually in this dissertation. In Section 6.2, the system learned the user specific relevance models to estimate the *relevance score* of each document, learned a user independent readability model to estimate the *readability score* of each document, and learned user independent graphical models to combine multiple forms of evidence to predict

Figure 7.1: User specific and user independent models



user preferences. These choices are far from optimal. Intuitively, the answer depends on the model type: a relevance model is more likely to be user specific than the readability model. Our preliminary study also suggests that the answer depends on the specific user (Table 6.6).

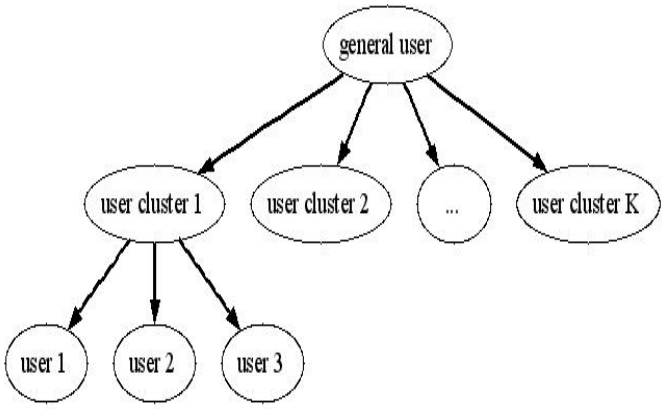
Although the problem has not been answered in this dissertation, it is an outstanding problem instead of a fundamental limitation of the proposed framework. In fact the Bayesian graphical modeling approach provides several possible solutions: to combine both models using the graphical models as shown in Figure 7.1, or to group similar users together and learn a general user model, several user cluster models and user specific models together (Figure 7.2) from the data. When the system initially knows little about a specific user, the user model for that user will be very similar to its parent model, thus system will treat it like a general user. While interacting with the user, the system learns from user feedback and gradually the user specific model is more personalized.

The challenge here is that each user model (a node in Figure 7.2) to be learned can be very complex, including both structure and parameters. How to develop efficient and robust algorithm to learn such a complex hierarchical user model is a future research direction.

7.2.3 Temporal property of adaptive filtering

We haven't considered much of the temporal property of the filtering task, such as the drifting of user interests, the change of how much a user likes a topic (*topic_like*), the evolutionary pattern of the document stream [103], or a utility function defined over time. For example, further analysis of the evidence indicates that the distribution of the data changes over time: the means of some forms of evidence on the testing data, such as *RSS link* and *relevance score*, are different from those of the training data. All models in this dissertation assume the underlying statistical distributions do not change over time, thus may suffer from

Figure 7.2: Cluster based user models.



the problem of trying to learn a static model from data generated by a dynamic model. A future direction is to explore whether dynamic graphical models can be used to solve this problem.

7.2.4 Automatically testing of assumptions

We have made several assumptions in this dissertation. A future direction is to test these assumptions automatically and handle situations where the assumptions do not hold automatically or semi-automatically.

For example, we assume a Rocchio algorithm works better than logistic regression at the early stage of filtering with limited training data when there is an initial query. However, this assumption may not hold, because the Rocchio algorithm may be implemented and perform differently depending on how the dissemination threshold is set, how the term weights are set, and other aspects of the filtering system. In the TREC adaptive filtering tracks, the Rocchio algorithm has been implemented in the worst system as well as among the best systems [119], because other components that would affect the final performance are required while using Rocchio algorithm for filtering but the Rocchio algorithm itself does not tell how to do that. Similarly, the logistic regression algorithm may perform differently depending on how the prior of the algorithm is set and how the user query is used for logistic regression.

We have assumed all variables have a normal distribution, a form of a symmetric bell-shaped curve. One future direction is to test the normality by measuring the skewness (tilt) and the kurtosis (peakedness) of the distribution, or using statistical tests, such as Shapiro-Wilks W test [135] or Kolmogorov-Smirnov D test [97], to test whether the assumption is true. If not, we can use various normalizing transformation to correct the skew [14], or use other distributions when normalizing does not make theoretical sense, such as binary variables. Under the Bayesian framework, a principled approach is to make a less strong assumption instead

of the normality assumption. For example, we can assume the distribution falls into the exponential family, and then let the system to learn the appropriate functional form from the data.

Chapter 8

Appendix

8.1 Appendix 1: Terminologies

1. ***Class*** is a group of documents sharing some common attributes. For example: a set of documents about "presidential election", or a set of documents a user considered "weird stories".

2. ***Profile*** refers to 1) the systems's current representation of a user's information need or things related to a user's information needs (e.g., a query, a threshold, keywords vector); 2) all information the system has acquired about the user's information needs. A user's information needs may be represented by several classes, thus a user profile contains one or more classes. In TREC data set, a user profile contains one class (Section 2.1.2). In the new Yow-now data set, a user profile contains several classes (Chapter 6).

3. ***Topic*** is a class about a specific subject. For example, one topic may be about "presidential election". In the Topic Detection and Tracking task, a topic is defined as an event or activity, along with all directly related events and activities. In the yow-now user study exit questionnaire, "topic" is used to refer to a class a user created, since these questions were designed for classes with subjects.

4. ***Event*** is a specific thing that happens at a specific time and place along with all necessary preconditions and unavoidable consequences.

5. ***Mean average precision (MAP)*** is a standard evaluation measure for ranked retrieval results used in the information retrieval community. $MAP = \frac{1}{R}\sum_{d_i} pr(d_i)$ where d_j is a retrieved relevant document, $pr(d_j) = \frac{r_{n_j}}{n_j}$, n_j is the rank of document d_j, and r_{n_j} is the number of relevant documents ranked higher than document d_j.

6. ***Ad hoc retrieval*** is a retrieval process where a user inputs a query and receives a ranking list of results. The query is usually formed for an immediate problem or information needs and won't be saved and reused.

7. ***Prior*** refers to any information beyond the data. The prior information may be from domain experts, knowledge about the data collection process, model developer's intuition, or whatever heuristics. Priors can be used together with data for parameter learning or structure learning in graphical models. In Bayesian theory, a Bayesian prior is a way to express a modeler's beliefs about a parameter before seeing any data.

8. ***Relevant*** is used ambiguously in literature, either as a narrow definition of "related to the matter at hand (aboutness)" or a broader definition of "has the ability to satisfy the needs of the user". In this dissertation, we use its first definition and use the term "user likes" to meaning described in the second definition.

8.2 Appendix 2: Exit Questionnaire

When each subject applied for the work, he/she filled out an entry questionnaire on paper. When the study finished, he/she filled out an exit questionnaire online. The entry questionnaire was designed based on TREC interactive track. It collected some background information about each subject. It is only for documentation purposes and were not analyzed in this dissertation.

The exit questionnaire was used to collect user topic specific information, as well as the users' feedback on the study. Users answered topic specific questions for his/her largest 10 topics or topics with more than 20 explicit feedbacks. The questions in the exit questionnaire are listed in this section.

The exit questionnaire includes several questions. Some questions were designed for other research related to filtering and they are beyond the scope of this thesis, thus the answers of them won't be analyzed later in this dissertation. The questions analyzed in this dissertation and used by the filtering system are:

topic_like How do you like this topic (whether you want to read news about this topic)?

familiar_topic_before How familiar you are with this topic before participating in the study?

topic_confidence Your confidence with respect to the above questions related to this topic.

Class specific questions

The following questions were asked per topic. The user needs to choose an answer from 0 to 7, and the default answer is 0. Depending on the question, the meanings of the answers are:
Type A: 0 Don't want to answer 1 Not at all 2 3 4 Somewhat 5 6 7 Extremely

Type B: 0 Don't want to answer 1 None 2 3 4 Some 5 6 7 A great deal

The questions and the corresponding answer types are listed here:*

- How do you like this topic (whether you want to read news about this topic)? [Type A]
- How familiar you are with this topic before participating in the study? [Type A]
- How familiar you are with this topic after participating in the study? [Type A]
- How much good information you have read everyday on www.yow-now.com (on this topic)? [Type B]
- How much good information you have read everyday from other web sites (on this topic)? [Type B]
- How much information did you see every day on yow-now that you had read from yow-now before? (on this topic)? [Type B]
- How much information did you see every day on yow-now that you had read somewhere else (not including yow-now) before? (on this topic)? [Type B]
- How much information did you see every day on other web site(s) that you had read on that web site(s) before? (on this topic)? [Type B]
- How much information did you see every day on other web site(s) that you had read somewhere else before? (on this topic)? [Type B]
- You think(guess) how much good information is newly available somewhere on the web everyday (on this topic)? [Type B]
- Your confidence with respect to your response to the above questions related to this topic? [Type A]

User specific questions

The following questions were answered by each user:

- Usually, you can decide whether a document is relevant or not: 0 Don't want to answer
  After reading the title
  After following the link and read the whole article

*Each question is listed as it is in the original questionnaire.

- Usually, you can decide whether a document is redundant or not:
  0 Don't want to answer After reading the title
  After following the link and read the whole article

- Usually, you can decide whether a document is readable:
  0 Don't want to answer
  After reading the title and source
  After following the link and read the whole article

- Usually, you can decide whether a document is authoritive:
  0 Don't want to answer
  1 After reading the title and source
  2 After following the link and read the whole article

- If the system could provide good documents for you every day, you would like to (press Ctrl key while using mouse for multiple choices):
  0 Use a special browser such as Yow-now
  1 Install an internet tool bar
  2 I don't want to change my browser at all, even if changing browser will help
  3 I am not sure.

- If your evaluations will help the system to find good documents for you every day, you would like to (the more you provide, the better the system works)(press Ctrl key while using mouse for multiple choices):
  0 Provide 1-2 evaluations per day if useful;
  1 Provide 3-4 evaluations per day if useful;
  2 Provide 5-6 evaluations per day if useful;
  3 Provide 7-8 evaluations per day if useful;
  4 Provide 9-10 evaluations per day if useful;
  5 Provide $>$ 10 evaluations per day if useful;
  6 Provide $<$ 5 evaluations per week if useful;

7 Provide 5-10 evaluations per week if useful;

8 Provide > 10 evaluations per week if useful;

9 Provide ¡5 evaluations per month if useful;

10 Provide 5-10 evaluations per month if useful;

11 Provide > 10 evaluations per month if useful;

12 I don't want to provide any evaluations, although I want the system to find good documents for me;

13 No, I hate personalization because of privacy concerns;

14 No, I hate personalization because of other reasons

- Please let us know whether you read news from other web sites besides Yow-now during the study:
  0 Don't want to answer;
  1 Not at all 2 3 4 Some 5 6 7 A lot

- During the study, you usually first went to which web site for news every day (press Ctrl key while using mouse for multiple choices):
  Yow-now;
  Yahoo news;
  Google news;
  WSJ;
  CNN;
  BBC;
  USA Today;
  Post Gazette;
  New York Times;
  News Straits;
  Emails;
  Other

- Tell us what do you like about the system?

- Tell us what do you not like about the system?

- Please tell us your overall comments:

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