Exploration and Exploitation in Adaptive Filtering Based on Bayesian Active Learning

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Abstract

In the task of adaptive information filtering, a system receives a stream of documents but delivers only those that match a person's information need. As the system filters it also refines its knowledge about the user's information needs based on relevance feedback from the user. Delivering a document thus has two effects: i) it satisfies the user's information need immediately, and ii) it helps the system better satisfy the user in the future by improving its model of the user's information need. The traditional approach to adaptive information filtering fails to recognize and model this second effect.

This paper proposes *utility divergence* as the measure of model quality. Unlike the model quality measures used in most active learning methods, utility divergence is represented on the same scale as the filtering system's target utility function. Thus it is meaningful to combine the expected immediate utility with the model quality, and to quantitatively manage the trade-off between exploitation and exploration. The proposed algorithm is implemented for setting the filtering system's dissemination threshold, a major problem for adaptive filtering systems. Experiments with TREC-9 and TREC-10 filtering data demonstrate that the proposed method is effective.

1. Introduction

An information filtering system monitors a document stream to find the documents that match information needs specified by user profiles. One of the most difficult task for filtering is on-line time-critical filtering,

Table 1. The values assigned to relevant and non-relevant documents that the filtering system did and did not deliver.

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

where the value of a document decays rapidly with time. In this case the potentially relevant documents must be delivered immediately, thus the system has no time to accumulate and rank a set of documents. *Adaptive information filtering* systems receive periodic feedback from the user about which delivered documents were relevant, which provides training data for learning.[1]

User satisfaction is typically modeled with a linear utility function. The function used in recent TREC Filtering track evaluations is shown below (Robertson & Hull, 2001).

$$Utility = A_R \cdot R^+ + A_N \cdot N^+ + B_R \cdot R^- + B_N \cdot N^- \quad (1)$$

This model corresponds to assigning a positive or negative value to each element in the categories of Table 1, where R^-, R^+, N^-, and N^+ correspond to the number of documents that fall into the corresponding category, and A_R, A_N, B_R and B_N correspond to the credit/penalty for each element in the category. B_R and B_N are usually set to zero because i) user satisfaction is mostly influenced by what has been seen, and ii) N^+ and N^- are usually too big. For example, the TREC-9 Filtering Track Utility was $T9U = 2R^+ - N^+$.

The traditional methods of deciding whether to deliver a document try to maximize the estimated immediate utility of the decision. That is, a document

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[1]In most prior research the feedback is received immediately after the document is delivered.

is delivered 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 functions used by the TREC-9, TREC-10 and TREC-11 Filtering tracks, participants usually set the threshold where $P(relevant|document) = 1/3$ because the expected utility at that point is 0 (Arampatzis & Hameren, 2001; Zhang & Callan, 2001). In fact, delivering a document iff $P(relevant|document) >= 1/3$ was written explicitly in the guidelines of some recent TREC adaptive filtering tracks (Robertson & Hull, 2001).

The delivery criterion above tries to optimize the immediate satisfaction of the user. It does 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.

The work described in this paper is based on considering the value of longer-term exploration along with the immediate reward of delivering a document when setting decision boundaries. We propose to use utility divergence, which is defined in Section 2.2, as the measure of the model quality. 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 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 sections describe our research on exploration and exploitation while filtering based on Bayesian theory. Section 2 describes the general framework of optimizing the utility based on the trade-off between exploration and exploitation using Bayesian active learning. Sections 3 and 4 describe our experimental methodology and results. Section 5 discusses related work and Section 6 concludes.

2. Exploration vs. Exploitation Based on Bayesian Theory

In order to maximize the overall utility of the system we propose to have two modules for the system: The exploitation module and the exploration module. We also propose to use utility as the measure for both modules: U_1, the direct utility gain of delivering a document for the exploitation module, and U_2, the expected utility gain of knowing the document label for the exploration module. Thus we have unified control of the exploration and exploitation trade-off, and deliver a document if the combined utility is above 0.

For simplicity we use Bayesian logistic regression as our learner, and the objective function to maximize is:[2]

$$Utility = A_R \cdot R^+ + A_N \cdot N^+ \qquad (2)$$

2.1. Exploitation Using Bayesian Inference

As mentioned in Section 1, the direct gain/loss in utility due to delivering a document can be estimated based on the probability of relevance for that document. 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:

$$p(\theta|D) = \frac{P(D|\theta)p(\theta)}{\int P(D|\theta)p(\theta)d\theta} \qquad (3)$$

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

$$P(D|\theta) = \prod_i P(y_i|x_i, \theta) \qquad (4)$$

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

$$U_1(x|D) = \int_\theta \sum_y A_y P(y|x, \theta) P(\theta|D) d\theta \qquad (5)$$

where A_y is the utility of delivering a document with the true label y. According to Table 1, $A_y = A_R$ if the true label is "relevant", and $A_y = A_N$ if the true label is "non-relevant".

2.2. Exploration Using Bayesian Active Learning

For exploration we need to define the quality of the learned model. In the active learning framework proposed by (Tong & Koller, 2000), 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

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[2]Most prior adaptive filtering research assumed user satisfaction is influenced only by what is seen, so $B_R = B_N = 0$ (Equation 1). We make the same assumption.

using model $\tilde{\theta}$ is given by:

$$
\begin{aligned}
Loss(D, \tilde{\theta}) &= E_D(Loss(\theta, \tilde{\theta})) \\
&= \int_{\theta} p(\theta|D) Loss(\theta||\tilde{\theta}) d\theta \quad (6)
\end{aligned}
$$

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:

$$
Loss(D) = Loss(D, \theta_D^*) \quad (7)
$$

where $\theta_D^* = arg\min_{\tilde{\theta}} Loss(D, \tilde{\theta})$.

Smaller $Loss(D)$ means a better model. For active learning, $Loss(\theta, \theta_D^*)$ needs to capture the notion of uncertainty of the model. One commonly chosen metric is Kullback-Leibler divergence (KL-divergence) (Tong & Koller, 2000):

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

where $p(x)$ is the distribution of input x, which is independent of θ and is usually given or learned from unlabelled 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 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. It is also unclear how a smaller KL-divergence relates to higher utility. In stead 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:

$$
UD(\theta||\tilde{\theta}) = U(\theta, \theta) - U(\theta, \tilde{\theta}) \quad (8)
$$

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

$$
\forall \theta', \theta'', U(\theta', \theta') \geq U(\theta', \theta'') \quad (9)
$$

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 is a special case of *utility divergence*. If we choose to use loglikelihood 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 loglikelihood 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.

$$
\begin{aligned}
Loss(D) &= Loss(D, \theta_D^*) \\
&= \int p(\theta|D)(U(\theta, \theta) - U(\theta, \theta_D^*)) d\theta \quad (10)
\end{aligned}
$$

For information filtering, the goal is to maximize the utility (Equation 2), so we use the following as utility:

$$
U(\theta', \theta'') = \int_{S(\theta'')} p(x) \sum A_y P(y|x, \theta') dx \quad (11)
$$

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 is:

$$
\begin{aligned}
U_2(x|D) = \\
\sum_y P(y|x, D) Loss(D \cup (x, y)) - Loss(D) \quad (12)
\end{aligned}
$$

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

$$
U(x|D) = U_1(x|D) + N_{future} U_2(x|D) \quad (13)
$$

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

2.3. Logistic Regression to Determine the Dissemination Threshold

Information filtering systems usually compute numeric scores that indicate how well each document matches each profile. For example, one approach used widely in the TREC adaptive filtering community for learning what the user is interested in is based on incremental Rocchio (Rocchio, 1971). Documents with scores above profile-specific dissemination thresholds are delivered. Since the dissemination decision cannot be delayed, it is necessary to find a dissemination threshold for each profile. Optimal dissemination thresholds are difficult to determine a priori unless the relevance score is a good probability measure, which is not true for many profile learning algorithm (e.g., Rocchio, statistical language modeling, and Naive Bayes). Learning optimal dissemination thresholds adaptively is a very important adaptive filtering problem (Arampatzis & Hameren, 2001; Robertson & Walker, 2000; Zhang & Callan, 2001). In this section we apply the theory discussed above to the problem of determining the dissemination threshold. We assume we already have a

separate module that can compute the score of document. 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 use logistic regression to model the conditional probability of user feedback y given the document score x:

$$P(y = 1|x, \theta) = \frac{1}{1 + \exp(-w_0 - w_1 x)} \qquad (14)$$

where the prior distribution $p(w)$ equals the 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.

In information filtering the explicit goal is to find a decision boundary, in this case the dissemination threshold t, to optimize the linear utility function. t corresponds to the boundary of $S(\theta'')$ in Equation 11. 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 11:

$$S(\theta'') = [t_{\theta''}, \infty) \qquad (15)$$

where $t_{\theta''}$ is the threshold model 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

$$\frac{dLoss(D, t_{\theta_D^*})}{dt_{\theta_D^*}} = 0 \qquad (16)$$

2.4. Computational Issues

Computation of U_1 in Equation 5 and $Loss(D)$ in Equation 10 involve integration over posterior $p(\theta|D)$. However, the posterior distribution $p(w|D)$ for logistic regression is quite complicated and the integration cannot be calculated in closed form. Our strategy is to use a Monte Carlo method to get an approximate solution. We generate K random samples θ_i using the Metropolis-Hastings algorithm (Tanner, 1996). Then U_1 and $Loss(D)$ can be approximated as shown below.

$$U_1(x|D) \approx \frac{1}{K} \sum_{i=1}^{K} \sum_{y} A_y P(y|x, \theta_i) \qquad (17)$$

Table 2. Pseudo code for determining a threshold.

```
FUNCTION : Calculate dissemination threshold
INPUT : D = (x_1, x_2), ⋯, (x_k, y_k)
OUTPUT : dissemination threshold
LOOP binary search for x such that :
    U(x|D) = U_1(x|D) + n_future · U_2(x|D) = 0
  where
      U_1 is computed using Equation 17
      U_2 is computed using Equation 12
return x

FUNCTION : Calculate Loss(D)
INPUT : D = (x_1, x_2), ⋯, (x_k, y_k)
OUTPUT : Loss(D)
Calculate the MAP estimation θ_MP
Calculate the Gaussian approximation of P(θ|D)
Generate K samples using Metropolis Algorithm
Calculate t_{θ_D^*} using Equation 16 and Equation 18
Return Loss(D) = Loss(D, t_{θ_D^*})
```

$$Loss(D, t_{\tilde{\theta}}) \approx \frac{1}{K} \sum_{i=1}^{K} (U(\theta_i, t_\theta) - U(\theta_i, t_{\tilde{\theta}})) \quad (18)$$

In order to generate random samples from the posterior $p(\theta|D)$ efficiently, we apply Laplace's method to use a Gaussian distribution $N(w; \theta_{MP}, v)$ to approximate the posterior, where θ_{MP} is the maximum a posteriori estimation of θ and v is the Hessian matrix of the loglikelihood $\log(P(D|\theta)p(\theta))$ at θ_{MP}. Then we use this Gaussian approximation to generate candidate values for the Metropolis-Hastings method.

We summarize the computational procedure for determining the dissemination threshold in Table 2. 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.

3. Experimental Methodology

The algorithm described in Table 2 was tested experimentally using the methodology described below.

3.1. Datasets

Two text corpora were used in the experiments: the OHSUMED dataset used in the TREC-9 Filtering Track, and the Reuters 2001 dataset used in the TREC-10 Filtering Track. As required by the TREC adaptive filtering track, for each user profile, the system begins with two identified relevant documents and

a natural language description of the information need, which is the title and the description field of the corresponding topics provided by NIST. The two datasets have rather different properties, as described below.

3.1.1. OHSUMED Data

The OHSUMED dataset contains 348,566 medical abstracts published from 1987 to 1991 (Hersh et al., 1994). It was used by the TREC-9 Filtering Track (Robertson & Hull, 2001). 63 OHSUMED queries were used to simulate user profiles. The relevance judgments were made by medical librarians and physicians based on the results of interactive searches. In the TREC-9 Filtering Track it is assumed that the user profile descriptions arrived at the beginning of 1988, so the 54,709 articles from 1987 can be used to learn word occurrence (e.g., idf) and corpus (e.g., average document length) statistics. The average number of relevant articles per profile in the testing data is 51.

3.1.2. Reuters 2001 Data

The Reuters 2001 data is a collection of about 810,000 Reuters English News stories from August 20, 1996 to August 19, 1997. It was used by the TREC-10 Filtering Tracks (Robertson & Soboroff, 2002). In TREC-10, 84 Reuters categories were used to simulate user profiles. The average number of relevant articles in the testing data is about 9,795 documents per profile, which is much larger than in the OHSUMED dataset. However, the filtering system only begins with 2 positive and zero negative training data, thus this is considered a very difficult dataset.

3.2. Evaluation Methodology

Utility was measured by the macro average of $T9U = 2 \cdot R^+ - N^+$ and a normalized version of $T11SU$.[3]

The "Normal-Exponential" threshold setting algorithm described in (Arampatzis & Hameren, 2001) was 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 (Robertson & Hull, 2001).[4] One problem with using generative models such as the Normal-Exponential model for

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[3]$T11SU = \frac{max(\frac{T11U}{MaxU}, MinNU)}{1 - MinNU}$, where $MaxU = 2 * (R^+ + R^-), MinNU = -0.5$.

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

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). (Zhang & Callan, 2001) proposed a Maximum Likelihood Normal-Exponential (ML N-E) algorithm to explicitly compensate for this sampling bias. This algorithm was used as a second experimental baseline. For the Bayesian approach we also did some experiments without active learning, which we call "Bayesian Immediate Learning". It was used 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 decreased the threshold in such cases.

3.3. Filtering Environment

An adaptive information filtering system developed by us was used for our experiments. Documents were processed by removing symbols such as punctuation and special characters, excluding stopwords, and stemming terms with the Porter stemmer. Processed documents were compared to each profile using a variant of the BM25 tf.idf formula (Callan, 1996) to measure the similarity of the document and user profile. The Rocchio algorithm was used for updating user profiles. The Bayesian active learner's input was the score that indicates the similarity; its output was a threshold. Documents with similarity scores above the threshold were delivered. Relevance judgements were provided immediately for delivered documents, which enabled the system to update user profiles.
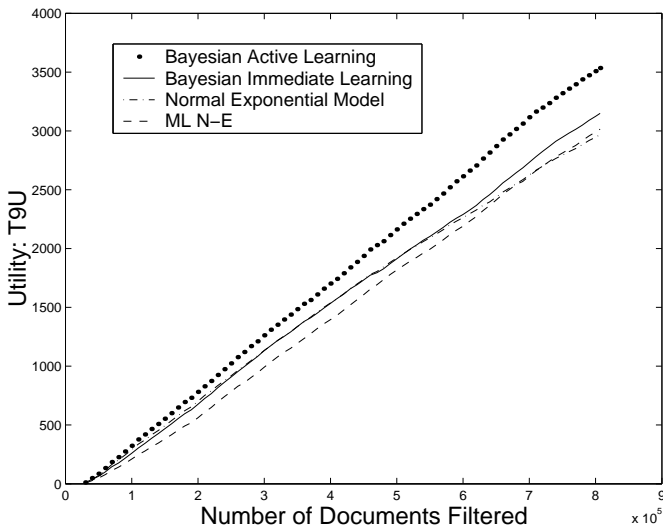
For each topic, the filtering system created initial profiles using terms from the TREC topic Title and Description fields. Because the first two relevant documents were sampled according to $P(x|y = 1)$ instead of $P(x)$, we cannot use it for training the discriminative model. A heuristic set the initial threshold to allow the highest-scoring documents (top 1%) in the training data to pass. Once the system had at least 1 positive and 1 negative feedback in the testing document stream, the proposed algorithm was used to set dissemination thresholds.

Our algorithm also needs to model $P(x)$, the distribution of document scores. We used 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 document delivered, N_{new} is the number of expected documents in the future, N_{old} is the number of filtered documents, and

Table 3. Comparison of four threshold-learning algorithms on the TREC-10 Filtering data. Reuters dataset.

Metrics	Bayesian Active	Bayesian Immediate	Norm. Exp.	ML N-E
T9U	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
Docs/Prof	4,527	3,895	2,792	3,380

Figure 1. Comparison of threshold-learning algorithms on the TREC-10 Filtering data over time. Reuters dataset.

Table 4. Comparison of Bayesian active learning and Bayesian immediate learning on Profile 83.

Metrics	Bayesian Active	Bayesian Immediate
T9U	10,488	8,712
T11SU	0.296	0.246
Precision	0.682	0.644
Recall	0.578	0.509
Docs/Prof	10,017	9,342

Table 5. Comparison of threshold-learning algorithms on TREC-9 Filtering data. OHSUMED data, OHSU topics.

Metrics	Bayesian Active	Bayesian Immediate	Norm. Exp.	ML NE
T9U	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
Docs/Prof	31	25	46	20

α is a constant that controls the exploration rate. α was set arbitrarily to 200 in our experiments. This is a conservative estimate, and is similar to the discounted future rewards used in reinforcement learning.

4. Experimental Results

Our first experiment compared the threshold setting algorithms on the TREC-10 Reuters 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 3 and Figure 1 summarize the experimental results.

Active learning was very effective compared to the baseline methods. T9U utility was higher, T11SU utility was slightly higher, Precision and Recall were comparable, and many more documents were delivered without hurting utility. As expected, the Maximum Likelihood Normal-Exponential method, which compensates for sampling bias, outperformed 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 outperformed the other models at all times during the experiment (Figure 1).

When we compared the performance of Bayesian active and immediate learning on profiles where active learning significantly improved performance we found that active learning increased both Recall and Precision (e.g., Table 4). 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 did not consider the benefit of an improving profile, so it was suboptimal (although effective). For simplicity we have focused only on threshold learning in this paper, however the active learning algorithm (Section 2) is not restricted to problems of low dimensionality; a higher dimensionality version of the algorithm could also incorporate profile learning.

The threshold-setting algorithms were also tested on the TREC-9 dataset, which contains a relatively small percentage of relevant documents (0.016%); the test data consists of more than 300,000 documents, but only 51 documents per profile are relevant, on average. The OHSUMED topic descriptions are well-written, which provides relatively accurate initial profiles. One might expect that on this dataset 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 TREC-9 Filtering Track evaluations some participants reported negative $T9U$ utility on this dataset (Robertson & Hull, 2001).

The experimental results are summarized in Table 5. As expected, active learning did not improve utility on this dataset. More importantly, it did not hurt utility, either. Consequently these results rank in the top 2 when compared with results from the 9 systems that participated in the TREC-9 Adaptive Filtering track.[5]

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 did not hurt accuracy, even in a test where exploration was a risky choice.

5. Related Work

There has been much work on active learning in the machine learning and IR research communities (Joachims, 1998; Lewis & Catlett, 1998; Freund et al., 1997; McCallum & Nigam, 1998). For example, the "Query by Committee" algorithm selects the next query according to the principle of maximal disagreement between a committee of classifiers (Freund et al., 1997). (McCallum & Nigam, 1998) modified the "Query by Committee" algorithm with a Naive Bayes model, together with unlabelled data for active learning. (Lewis & Catlett, 1998) introduced "uncertainty sampling" to choose the instance that current classifiers are most uncertain about. (Tong & Koller, 2000) provided a theoretical framework for active learning and applied it to Support Vector Machine classifiers.

Unfortunately, most of the prior active learning research focused on interactive retrieval tasks, thus it did not address the trade-off between exploitation and exploration. It cannot be applied easily to adaptive filtering, where the system is evaluated based on utilities such as $T9U$, and the direct cost/reward of delivering the document (exploitation) is as important as the improvement in model estimation (exploration).

There is also much prior research on adaptive filtering,

especially on setting dissemination thresholds. However, as discussed in Section 1, none of the previous research addressed the trade-off between exploration and exploitation. The common approach is to consider only exploitation. (Chai et al., 2002) used the information gain between a document and the model to select documents, however the task was batch filtering instead of adaptive filtering, and the method did not provide a framework for combining information gain with the immediate cost/reward.

Prior research in related areas influenced our work. The Bayesian framework, on which our algorithm is based, was used for active learning by (Tong & Koller, 2000) and (McCallum & Nigam, 1998). Our approach also matches the risk minimization model described in (Lafferty & Zhai, 2001). The work described in this paper differs from prior work in two major aspects.

- This research uses *utility divergence* to measure the quality of the model for exploration. If the objective function for a classification system is to maximize the likelihood of the data, KL divergence can be used to measure the quality of a model. However, in adaptive filtering user satisfaction is usually modelled by utility (e.g., Table 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. Previous work in adaptive filtering is 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.

6. Conclusion

This paper provides a framework, based on Bayesian active learning, for modeling the trade-off between exploitation and exploration in adaptive information filtering. It provides a quantitative measure of the immediate cost/reward and future reward of delivering a document when the objective is maximizing a user-

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[5]This comparison is intended to be descriptive only, because the research community now has greater experience with this dataset than TREC-9 participants had.

defined utility measure. We believe that this is the first work to study the trade-off between exploration and exploitation in adaptive information filtering.

The experimental results demonstrate that a combination of exploration and exploitation can improve results, for example, when the initial profiles are poor and the document stream contains many relevant documents. The results also demonstrate that it can have little effect, 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.

There are several directions for future work. 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 methods described in this paper (i.e. approximation based on sampling using Metropolis algorithm) are tailored for low dimensionality problems. For high dimensionality problems, different methods, such as variational methods or Gibbs sampling, might be necessary in order to get the approximation efficiently. Our model of $P(x)$ and the way we calculate the expected number of future documents is also weak; additional research in this direction is needed.

Acknowledgements

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