Incremental Learning for Interactive E-Mail Filtering

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ABSTRACT

In this article, we propose a framework, namely, Prediction-Learning-Distillation (PLD) for interactive document classification and distilling misclassified documents. Whenever a user points out misclassified documents, the PLD learns from the mistakes and identifies the same mistakes from all other classified documents. The PLD then enforces this learning for future classifications. If the classifier fails to accept relevant documents or reject irrelevant documents on certain categories, then PLD will assign those documents as new positive/negative training instances. The classifier can then strengthen its weakness by learning from these new training instances. Our experiments' results have demonstrated that the proposed algorithm can learn from user-identified misclassified documents, and then distil the rest successfully.

Keywords: information filtering; text management

INTRODUCTION

Even after the dot-com bubble, the growth of the Internet does not stop. For example, according to the Australian Bureau of Statistics (2005), at the end of September 2004, total Internet subscribers in Australia numbered more than 5.7 million. This was an increase of more than 520,000 (10%) from the end of March 2004, and data downloaded by subscribers during the September quarter 2004 increased significantly (72%) to 11,004 million megabytes (MBs) from the 6,409 million MBs downloaded during the March quarter 2004. This data indicates that more and more people are joining the Internet, and they were using the Internet as one of the primary sources to gain information.

One of the main reasons people want to be connected is the ability to use e-mail. E-mail was originally designed for asynchronous communication, the same as traditional post mail. However, since e-mail service is useful, easy to use and cheap to send and receive, a great number of applications have been built upon the e-mail ser-
vice, such as document delivery and archiving, work task delegation and task tracking. It is also used for storing personal names and addresses, for sending reminders, handling customer services, scheduling appointments and handling technical support queries (Whittaker & Sidner, 1996). E-mail has become an essential field in contact address books.

As a low-cost, commonly used contact method, there is always a drawback. Many e-mail users start to realize that they have been overloaded by information from e-mail. If the amount of e-mail documents received each day by a user exceeds around 50, the time spent analyzing what is important and what is not, then replying to important ones, can take a considerable amount of daily working hours. To many university academic staffs, a 2-hour session of processing e-mail has become a routine of a normal workday. The time wasted sifting through daily e-mail is a time-consuming, yet extremely important task. Consequently, document classifiers, especially e-mail filters, are put into practice to ensure that a user is not inundated with useless information, which in turn causes them to miss a critical e-mail, file or announcement.

Problems with E-Mail Filtering

Before applying filtering techniques, people would like to ask following questions:

- Can the filter guarantee effectiveness?
- Is the filter easy to use?
- Is the filter really a time saver?

An important assessment for the e-mail filter is how many correct decisions the filter makes. People neither want junk mail to appear in their in-box folder, nor are they happy to see their legitimate mail dumped to the junk folder. Table 1 shows four filter decision types used to measure the quality of filter decision making (Sebastiani, 2002).

Positive means the e-mail item is spam, while negative means the e-mail is not spam. True positives (TP) and true negatives (TN) are right decisions, as user and filter agree each other; however, false negatives (FN) indicate that the filter considers the spam mail item is a legitimate mail item, while false positives (FP) denote that the filter considers the legitimate mail as junk.

If e-mail filter users share the same preference, and they stick to their choice, then a fully automatic filter can be constructed by a knowledge engineering expert system, such as the TCS system (Hayes, Andersen, Nirenburg, & Schmandt, 1990). However, this is usually not the case. This general rule does not always apply to everyone. That is why people do not put much credit on fully automatic filters, because users doubt whether the general filtering rules can com-

### Table 1. The contingency table of user judgements and filter decisions

<table>
<thead>
<tr>
<th>Classifier Decisions</th>
<th>User Judgments</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Positive</td>
</tr>
<tr>
<td>Positive</td>
<td>True Positive</td>
</tr>
<tr>
<td>Negative</td>
<td>False Negative</td>
</tr>
</tbody>
</table>

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