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"MAY I BORROW YOUR FILTER?" EXCHANGING FILTERS TO COMBAT SPAM IN A COMMUNITY

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"May I borrow Your Filter?" Exchanging Filters to Combat Spam in a Community*

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Abstract

Leveraging social networks in computer systems can be effective in dealing with a number of trust and security issues. Spam is one such issue where the "wisdom of crowds" can be harnessed by mining the collective knowledge of ordinary individuals. In this paper, we present a mechanism through which members of a virtual community can exchange information to combat spam.

Previous attempts at collaborative spam filtering have concentrated on digest-based indexing techniques to share digests or fingerprints of emails that are known to be spam. We take a different approach and allow users to share their spam filters instead, thus dramatically reducing the amount of traffic generated in the network. The resultant diversity in the filters and cooperation in a community allows it to respond to spam in an autonomic fashion. As a test case for exchanging filters we use the popular SpamAssassin spam filtering software and show that exchanging spam filters provides an alternative method to improve spam filtering performance.

Keywords: Email filters, spam messages, collaborative recommendation systems, collaborative networks, trust, autonomic communication.

1 Introduction

An estimated 60% to 90% of email traffic on the Internet today can be called "spam". The problem of spam shows no signs of abating with every new popular spam filtering

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solution quickly being breached by new spam methods. Clearly, any static spam solution is doomed to failure.

In the past few years several proposals for filtering spam from *ham* (wanted mail) have emerged. As our brief overview in the following section shows, these proposals vary in their scope, application and effectiveness. While early efforts at spam control concentrated on one-size-fits-all solutions that were situated at the Mail Transfer Agent (MTA), newer solutions recognize that what is spam for one person may in fact be ham for another. This has led to an emergence of personalized filters that can be customized by the user.

However, personalized filters often suffer from a lack of sufficient training data which reduces their effectiveness at least during the initial training period. Most ordinary users do not have the time or the skill required to train their filters properly. This often leads them to forgo personalized solutions and abandon themselves to the mercy of a third-party that decides for them what is spam and what is not. While this may not be such a bad solution for naive users, it raises concerns of censorship, as blacklists may be used to keep out dissent, and lack of diversity. As we explain later, having a set of diverse filters in a community is also very important when combining filters.

Autonomic computing offers a solution through the construction of a community that responds autonomically to spam by using collaborative spam filters that use machine learning. Decentralizing the filter exchange process gives the community a mechanism for self-management. Spamming is a volume business and a single spam email must be sent to hundreds or thousands of users to be economically profitable. If the first user who sees a spam email can share this information with others, they can automatically delete the email from their inboxes. This approach exploits the fact that the more the pairs of eyes that check for spam, the better the results should be.

Damiani et al. presented a solution in [9] where users' opinions are collected on what messages are spam and this collective judgment is used to block propagation of spam to other users. This requires identifying similarity among spam emails as spammers often introduce random content in spam emails to increase their chances of getting through filters.

In this paper, we present an alternative to collecting user opinions that use digest-based indexing techniques. We present a framework that allows individuals in a community to exchange personalized filters instead of information about every spam email. As example of possible usage, two filters may be combined for increased effectiveness. A new user may "borrow" a filter from an existing community member to get him started. Thus a user may exchange a naive Bayesian filter for a rule-based filter by using our mechanism.

Individual filters may be trained using machine learning techniques [13]. A user may decide to give different weights to the acquired filters. She may decide that the filter received from a more technically savvy friend or from a friend who shares her interest more closely or that a filter that has been trained on more data deserves to be given a higher weight. Filter weights may also be adaptive and change according to the performance of individual filters.

Our second contribution is a general framework that can be used to combine the filters ob-

tained by different users based on the trustworthiness and reputation of the filter provider. The remainder of this paper is organized as follows. In Section 2 we discuss previous work and provide a brief overview of existing solutions. In Section 3 we discuss our core idea of exchanging filters instead of spam emails or their digests. This is followed by a brief discussion on the use of reputation to weight filters from users within the community. In Section 5 we present our experimental results and we conclude in Section 6.

2 Related Work

A number of different spam filtering techniques have emerged in the last few years. They include:

1. **List-based filtering** relies on white-lists (set of email address of users whose messages are allowed) and/or blacklists (email or IP addresses known to be used spammers). Lists are vulnerable to address spoofing and may also exclude receiving legitimate messages from users who are not in a white-list or who are present in a blacklist by mistake.

2. **Bayesian classifiers** classify email messages based on features extracted from the message. The features can be the words in a message or subsequences of words or characters [14].

3. **Rule-based filtering** defines a set of rules and corresponding weights (usually assigned through machine learning). Each email is checked against each rule to see if the rule is activated. In this case the rule weight is added to the message score. A message whose score exceeds a threshold is labeled as spam. Rules may include processing of email headers to check for abnormalities such as malformed headers or invalid return addresses and word or feature tests.

4. **Spam traps** publicize fake email addresses that do not belong to any user or group. Any message whose recipient list includes a spam trap address is discarded as spam.

5. **Sender authentication** verifies the identity of the sender before accepting an email. It can be performed by a challenge-response mechanism where the recipient sends a challenge to the sender which must be answered before the email is accepted.The challenge-response technique requires synchrony (it requires the sender and recipient to act within the specified time limit), thus negating a major advantage of email, and is vulnerable to address spoofing which can be used to launch a denial-of-service attack.

6. **Distributed spam identification** such as Vipul's Razor [2], SpamWatch [4], etc. Users detect spam messages and send periodically their reports to a central database so that subsequent arrivals of the same spam can be detected.

7. **Social email networks** exploit the already existing social structure in email networks to prevent spam. This approach is based on the assumption that users who exchange e-mail messages are connected in a social trusted network [7].

Combining and correlating classifiers has been used effectively in many fields such as document classification, speech recognition, optical character recognition (OCR) etc. A combination of classifiers can yield better results than those obtainable by the individual classifiers. Battiti and Colla [6] studied combining classifiers for OCR and found that teams work better than individual classifiers. They also studied the rejection/accuracy compromise: cases where the classification is dubious (e.g., the different classifiers disagree) are "rejected" and directly presented to the user who takes the final decision. In spam filtering, the rejection of classification a few emails (which can be placed in a specific folder) can be acceptable to the user if this strategy manages to reduce costly false positives. In general, a combination works only when classification errors are not completely correlated. This makes diversity in spam filters desirable because diverse filters tend to have uncorrelated classification errors.
In the field of spam recognition, Sakkis et al. [15] and Hershkop and Stolfo [11] have proposed combining spam classifiers. In particular, Hershkop and Stolfo combine classifier confidence factors instead of just a binary output and show that the latter strategy performs better.

3 Advantages of Exchanging Spam Filters

There are several reasons why it is preferable for users in a community to exchange spam filters rather than exchanging opinions about which messages are spam. Filter exchange and combination is an example of trusted community knowledge exchange that allows a community to respond to spam collectively and in an autonomic fashion. Using an already existing overlay network to exchange filters allows building email communities that span multiple administrative domains on the basis of shared email preferences. Further, situating filters at the individual user harnesses the computational power of user machines that far exceeds the power of a centralized spam filter.
Existing collaborative spam filtering mechanisms collect user opinions on whether a message is spam or not. Whenever a user detects a spam message she creates a hash digest of that email. The digest can be made resilient to common word-based attacks [8]. Digest information can either be collected at a central point [1, 2] or be shared among the members of a community using an overlay network [16]. In either case, the amount of traffic generated depends on the number of spam messages received by community members. A solution based on exchanging filters obviates the need for exchanging messages every time a spam message is received. Filters will be exchanged relatively rarely and the frequency of filter exchanges will be independent of the number of spam messages received.
Combining filters can be very useful in the case of multi-lingual users. Let us take the case of an individual from Italy who moves to the United Kingdom. This individual will

now receive all work-related emails in English while still receiving personal emails in Italian. Such a user could easily retain the old "Italian spam filter" that he was using and simply combine it with an "English spam filter" borrowed from a co-worker or friend who receives her email in English.
Another important reason to prefer filter exchange is that of diversity. We know that in nature a population with a gene pool that is diverse has a greater chance of surviving a disease. Similarly, a community of users with a diverse set of filters is likely to be more robust against any one kind of spam. The diversity ensures that it will be highly unlikely that a particular spam is able to get through all the different filter combinations. A spammer would not be able to use a single set of tricks to defeat all filters.
This diversity and flexibility can also be related to the level of sophistication of the user. A naive user may simple "borrow" a filter from a user he trusts or an expert user who is known and trusted in the community. A more sophisticated new user may decide to combine filters from a number of different users. She may also decide to monitor the performance of the filter and tune the filter combination adaptively.
In order to allow users to exchange filters without compromising privacy it is important to separate the public and private parts of each filter (e.g., the white or black lists are in some cases private). We expect that users will not wish to exchange some personalized aspects of their filters. If these can be separated and only the public part of a filter is exchanged, any privacy concerns are adequately addressed. This separation must also be easily understandable by the user.

4 A Language for Describing Spam Filters

Filter exchange rises several issues concerning the compatibility of the filters and their combination. The solution that we propose is a standardized language for filter description. The language enables the specification of functionalities and properties of each filter so that the portability is guaranteed. A standardized language represents the first step toward the combination of the exchanged filters in an easy and autonomic way, without manual intervention of the users, as described in section 4.2
The language describes in a document the number of inputs and outputs of a specific filter and its operation. The document is written in *XML* and is derived from the Web Service Description Language[1] (WSDL) framework. The actions represents the operation of the filter while the location of the service is intended as the creator (or the last modifier) of the filter itself. This last information is essential to build up a trusted network as described in previous section. The description language facilitates more complex definitions of the filter itself by assigning attributes such as weights to the operations and inputs.

[1] http://www.w3.org/TR/wsdl

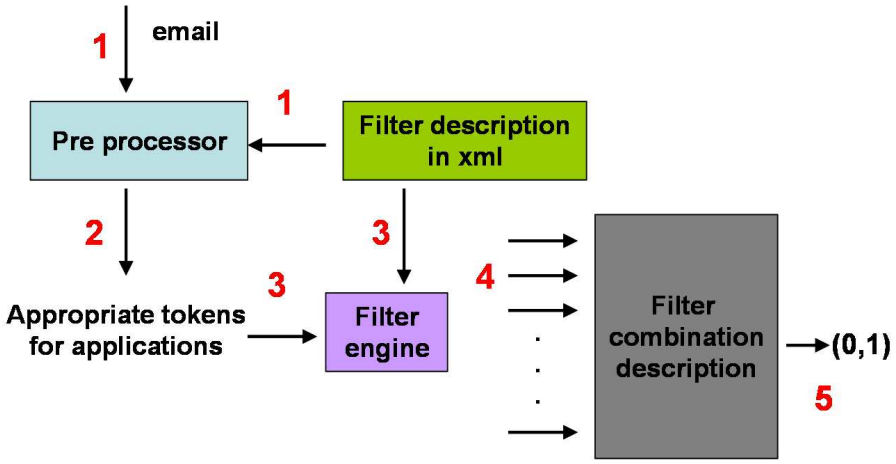

Figure 1: Filter Engine and Pre-processor

4.1 Using Trust for Effective Filter Exchange

Kong et al. [12] have proposed using a collaborative filtering approach within a social e-mail network for weighing reports of spam. Users have a trust value based on the strength of their ties to the network and the correctness of the spam report is weighted according to this trust value. They call their mechanism MailTrust and use an algorithm similar to the one used in PageRank.
We use the reputation of a user to weight a filter received. While the social email network can be used for the initial weights for the exchanged filters, our algorithm goes further and uses filter performance to modify the trust values of users in the community. It is possible to use a reputation management algorithm such as ROCQ [10] that allows users to rate the filters they send to other members of the community and the filter recipients to rate filter performance in turn and thus the trust value of users that send them the filters. In this manner, the community is made robust against malicious users (such as spammers) who may join the community and exchange filters that actually allow spam instead of blocking it.

4.2 Filter Engine for Combination

The description of the filter
The client engine is depicted in figure 1. It is composed of a pre-processor component and a main engine component which are implemented in software and which **are not specific** to any kind of filter. Our main idea is to characterize the output of the pre-processor and the engine output by plugging in the filter description which is expressed in a standardized language.
The steps are performed as follows, where steps 1,2 and 3 are repeated for the number of filters the user has:

1. The filter description is plugged in the pre-processor. The email is given as input to

the pre-processor.

2. Based on the filter specification and on the email, the pre-processor generates a set of "appropriate tokens for the applications". These tokens are filter specific and they are derived from the email (it can be the header, the content - body and subject - or both). This action is referred to "features extraction".

3. These generated tokens (also called features) constitute the input of the engine. The engine loads the appropriate module that contains the filter definition.

4. The output of the filters is redirect to the "Filter Combination Description" component which combines the output received based on internal rules generated by the user. These internal rules represent the **personalized** part of the filter and they are **user-specific**.

5. The output of the "Filter Combination Description" component specifies whether the message should be classified as spam or ham message.

As described above, we have separated the entire system in a common part, the pre-processor and the engine, and the filter specification that is shared among users and that can be plugged into the pre-processor and the engine as module. This choice has been made in order to enable exchange of filters in an easy and compact way.
Another important aspect of the proposed solution is the separation of the filter definition (functionalities) and the personalized part that is represented by the "Filter Combination Description" component. This component is user specific and it loads all the specific settings of the user. We do not require users to share this component since it can disclose personal information.

4.3 Privacy Issues in Filter Exchange

In order to allow users to exchange filters without compromising privacy it is important to separate the public and private parts of each filter (e.g., the white or black lists are in some cases private). We expect that users will not wish to exchange some personalized aspects of their filters. If these can be separated and only the public part of a filter is exchanged, any privacy concerns are adequately addressed. This separation must also be easily understandable by the user.
For privacy purposes we do not want to include in rule specification any sensible information, thus, we have thought of a definition of the rules by using hash values to protect the content. For the sake of clarity we define an example. We have a object named "String" and value "Viagra". The filter must assign a probability of 0.99 to the email to be classified as spam if the "String" is present. To protect the privacy of the content of an email we consider the hash value for Viagra. Thus the object will became - if String MD5 hash of 45FA2B is equal to "String input" MD5 hash value then $P = 0.99$.

5 Experimental Results

In this section we demonstrate a prototype filter exchange mechanism by combining rule-based filters. Due to space constraints we present results from our experiments with exchanging filters based on SpamAssassin only. SpamAssassin [3] is one of the most widely-deployed spam filtering solutions. It is also relatively flexible and combines many different kinds of spam filters such as header-processing, white-lists and blacklists and Bayesian techniques. SpamAssassin's rule-set is manually generated and it uses a simple neural network (perceptron). Each email is tested against the rules to determine the relative score. Messages that score above a fixed threshold are marked as spam.
To validate the claim that the combination of individual filters improves the classification of spam messages, two distinct filters are defined to simulate filters produced by different users and then combined to produce a unique filter that is characterized by the union of both feature sets. The validation is given by testing the three filters on the same set of messages.
For our tests we randomly sort the set of rules available in SpamAssassin 3.1.0 into two buckets so that each bucket characterizes a separate filter. The division is not completely random as it takes the in-built dependencies of the rules into account. The combined filter is constructed by merging the set of rules of each individual filter.

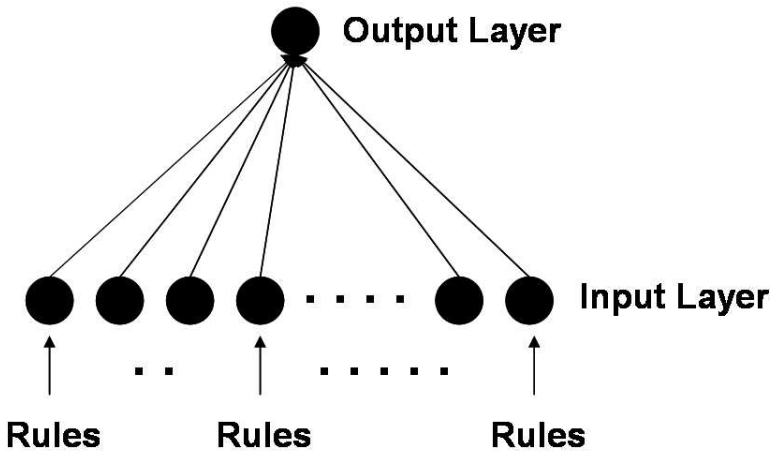

Figure 2: An example of simple neural network (perceptron)

Our email workload consists of 4870 spam messages, downloaded from *http://www.spamarchive.org/* and of 4837 personal ham messages received by the authors. The combined workload is processed using the two filters individually and the filter derived by their combination. The output of the pre-processing stage for each of the three filters consists of a vector of 0s and 1s that indicates whether a specific rule has been activated in the email message (1 if the rule is activated 0 otherwise). This vector is the input for a *neural network* that uses a supervised learning strategy.
The neural network is trained over pre-classified messages so that the relationship between the input (vector of rules) and the output (classification of the message: spam or ham)

is determined. Incoming messages are then classified based on the constructed neural network.

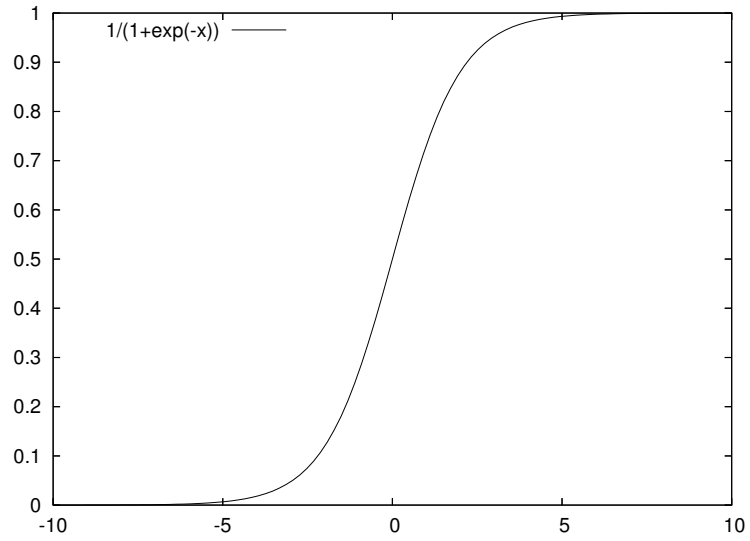

Figure 3: Sigmoid function

We consider the simplest form of neural network, the single-layer perceptron, as depicted in Figure 2, with weights (w_i) associated to the links connecting the input to the output. The output is calculated as the scalar product of the vector of weights and the vector of inputs. A non-linear sigmoidal transfer function ($f(x) = 1/(1 + e^{-x})$) is applied to the result to constrain the output between 0 and 1: 0 for ham messages and 1 for spam messages. A message is classified spam if the output is greater than a fixed threshold (thr). The output of the neural network is continuous and may be interpreted as the degree of belief that a message is spam or ham.

The neural network is trained using information on second derivatives to determine the weight of each input. Details of the method used, *one-step-secant* (OSS), can be found in [5]. The error is represented by the energy function that is calculated as the sum-of-squared-differences between expected and evaluated values. The total energy, $E(w)$ for an iteration is:

$$E(w) = \frac{1}{2}\sum_{p=1}^{|P|} E_p = \frac{1}{2}\sum_{p=1}^{|P|}(t_p - o_p(w))^2 \quad (1)$$

where the expected (target) value for pattern p is t_p and the computed value is o_p. The latter is a function of the weights,which are adjusted through an iterative minimization of the energy function. The number of iterations executed is determined in order to optimize validation performance.

The individual filters and the combined filter are tested on the same set of messages. We divided the collected messages in two sets, one for the training stage and one for validation stage. The training set consists of 5000 messages, with both spam and ham in

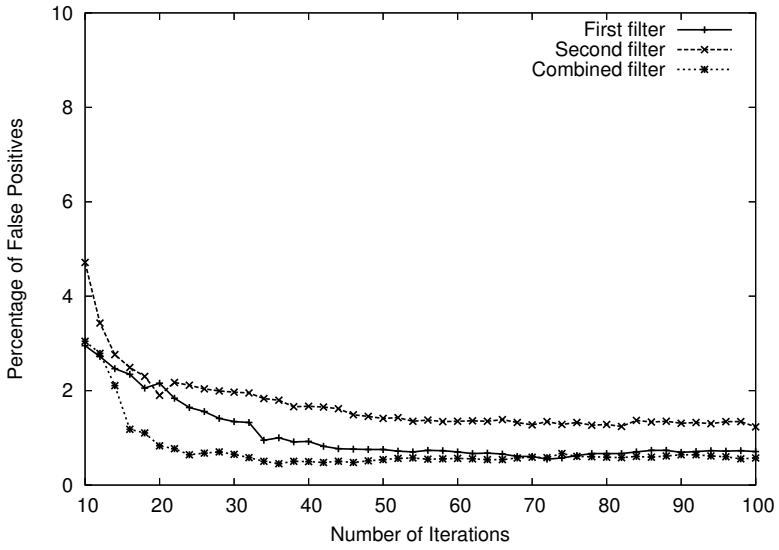

Figure 4: False positive rate - percentage of ham messages classified as spam messages with a classification threshold of 0.7.

equal proportion. The validation set consists of 4707 messages of which 2370 are spam messages and 2337 are ham messages.
The experiments are performed using different classification threshold thr values that vary from 0 to 1 with a step of 0.1. The percentage of false positives, i.e., ham messages that have been wrongly classified as spam messages and the resultant classification energy are evaluated for each of the three classifiers.
Figure 4 shows how the false positive rate for the three filters varies with the number of iterations run on the training set. We see that the combined filter performs better than both individual filters and the percentage of false positive decreases as the number of the iteration increases. The sharp drop in the percentage of false positives during the initial phase (when the number of iterations is low) indicates incomplete classifier training.

		Real	
Predicted		Spam	Ham
	Spam	TP rate	FP rate
	Ham	FN rate	TN rate

Table 1: Confusion Matrix for a general classifier

Table 2 shows a snapshot of the performance of the classifiers at iteration 50. Table 1 explains the confusion matrix in more detail in order to give a better understanding of how the messages have been classified by the filters:

$$TPRate = \frac{Numberofrealspammessagescorrectlypredicted}{Totalnumberofspammessages}$$

$$FPRate = \frac{Numberofrealhammessagesclassifiedasspam}{Totalnumberofhammessages}$$

The True Negative and False Negative rates are correspondingly defined. The combined filter performs better than the two individual filters since the false positive rate is the lowest and the true positive (detection) rate is the highest.

Classification	Classif. 1	Classif. 2	Combined
Spam as Spam (TP)	94.31%	96.30%	97.81%
Spam as Ham (FN)	5.69%	3.70%	2.19%
Ham as Spam (FP)	1.76%	2.74%	1.43%
Ham as Ham (TN)	98.24%	97.26%	98.57%

Table 2: Performance of the three classifiers

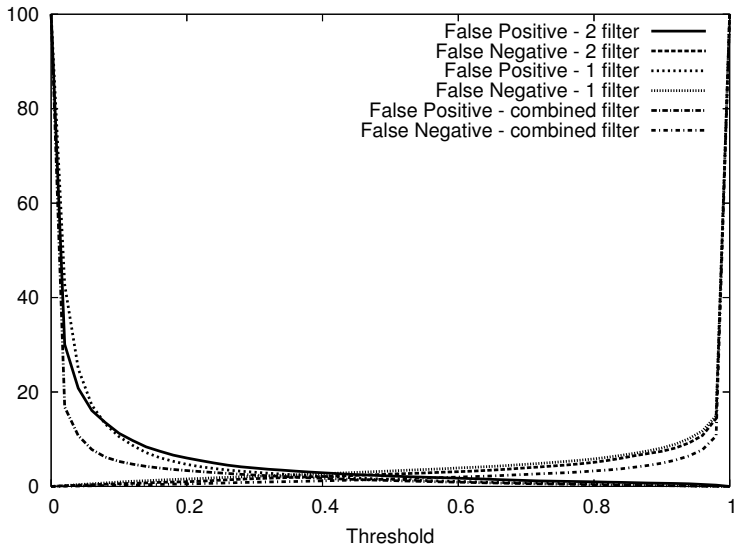

Figure 5: Percentage of False Positives and False Negatives vs. Decision Threshold.

Figure 5 shows how the false positive and false negative rates for each of the three filters varies as the classification threshold varies. As expected the percentage of false positives is very high when the classification threshold is very low and quickly drops to almost zero as the threshold increases. The reverse is true for the percentage of false negatives. We decided to use a threshold of 0.7 for further experiments as in spam filtering the cost of a false positive is much higher than the cost of a false negative.

Figure 6 displays another metric that is useful in evaluating the performance of a filter. A Receiver Operating Characteristic (ROC) curve shows how the percentage of false positives varies with the percentage of true positives. The idea here is to find the appropriate cut-off point where the percentage of false positives is tolerable while ensuring a high proportion of true positives.

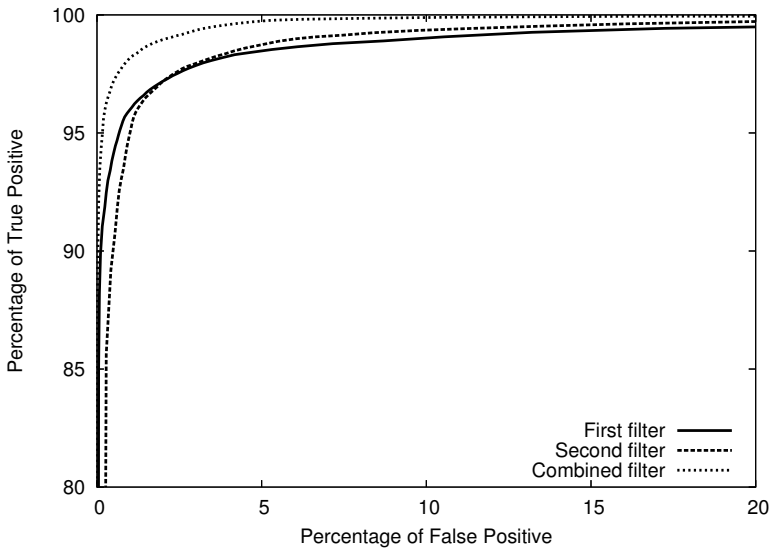

Figure 6: Receiver Operating Characteristic

As defined in Eq. 1, the energy function depends on the classification error. Figure 7 plots the average energy per pattern for each classification or $\frac{E(w)}{|P|}$. Again, the average energy for the combined filter is lower than that for both filters. Thus, we can conclude that combining the two filters gives us better performance.
Our experiments do not attempt at measuring the goodness of a specific filter, i.e. at evaluating the absolute performance of a designed filter, but they do indicate that the combination of general filters performs better than the filters individually.

6 Conclusions

We have presented a new approach to collaborative filtering of email messages based on the exchange of filters developed by different members of the community.
Sharing and exchanging filters instead of emails or digests has many potential advantages ranging from a much lower required communication cost (e.g., in neural networks, a filter built from millions of messages can be described with some hundreds of byte to describe the network weights), a potential large diversity, a much greater flexibility in using and combining different filters. Preliminary experimental results have been provided to motivate the validity of the approach.

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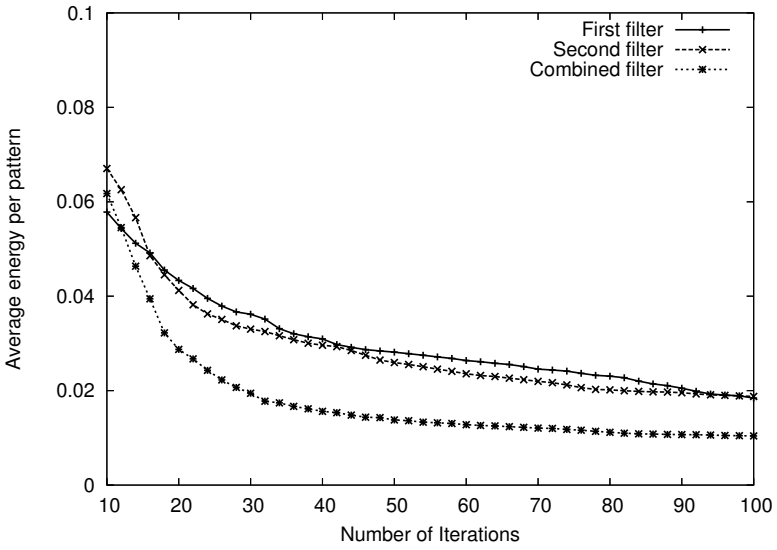

Figure 7: Energy function value per pattern for the classification.

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