SpamCop: A Spam Classification & Organization Program

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Abstract

We present a simple, yet highly accurate, spam filtering program, called SpamCop, which is able to identify about 92% of the spams while misclassifying only about 1.16% of the nonspam e-mails. SpamCop treats an e-mail message as a multiset of words and employs a naïve Bayes algorithm to determine whether or not a message is likely to be a spam. Compared with keyword-spotting rules, the probabilistic approach taken in SpamCop not only offers high accuracy, but also overcomes the brittleness suffered by the keyword spotting approach.

Introduction

With the explosive growth of the Internet, so too comes the proliferation of spams. Spammers collect a plethora of e-mail addresses without the consent of the owners of these addresses. Then, unsolicited advertising or even offensive messages are sent to them in mass-mailings. As a result, many individuals suffer from mailboxes flooded with spams. Many e-mail packages contain mechanisms that attempt to filter out spams by comparing the sender address of the e-mails to predefined lists of known spammers. Such programs have had limited success since spammers often change their address and new spammers continuously appear. Furthermore, spammers have found ways to send messages with forged headers. For example, the sender address can be made the same as the receiver address. A more general and effective approach is obviously needed.

In (Cohen 1996a), Cohen presented an approach to e-mail classification in which a learning program, called RIPPER (Cohen 1995; 1996b), was used to obtain a set of keyword-spotting rules. If all the keywords in a rule are found in a message, the conclusion in the rule is drawn. For example, RIPPER created the following set of rules to recognize talk announcements:

A message is a talk announcement if it contains one of the following:

- 'talk' and 'talk' in 'Subject:' field;
- '2d416' and 'the';
- 'applications' and 'comma' in 'Subject:' field;
- 'visual';
- 'design' and 'transfer';
- 'place' and 'colon' and 'comma' in 'To:' field;
- 'doug' in 'From:' field and 'specification';
- 'presentation'

Otherwise, the message is not a talk announcement.

Cohen reported that the rules generated by RIPPER have similar accuracy as manually generated rules.

Spams form a semantically much broader class than the categories in Cohen's experiments. Their subjects often range from advertising products to "make money fast" schemes to WEB site for "fun-loving adults". The keyword-spotting rules appear to be too brittle for this purpose. The inadequacy of this method for spam filtering is also evidenced by the fact that even experienced computational linguists are not able to come up with a good set of keyword combinations for this purpose.

In this paper, we present a spam-filtering program, called SpamCop, which employs a naïve Bayes algorithm to detect spams. The remainder of this paper is organized as follows. The next section describes the SpamCop program. We then present some experimental results and a comparison with RIPPER.

Description of SpamCop

SpamCop uses a naïve Bayes algorithm to classify messages as regular spam or as nonspam. A message M is classified as a spam if $P(Spam|M)$ is greater than $P(NonSpam|M)$. In most probabilistic approaches to text classification, the attributes of a message are defined as the set or the multiset of words in the message. However, this is not the only viable alternative. For instance, one can also define all the three consecutive letter sequences (trigrams) as the attributes. Once M is represented as a set of attributes $(a_1, \dots, a_n)$, the classification problem becomes that of finding the larger one of $P(Spam|a_1, ..., a_n)$ and $P(NonSpam|a_1, ..., a_n)$. Since

$$P(Spam|a_1, ..., a_n) = \frac{P(Spam, a_1, ..., a_n)}{P(a_1, ..., a_n)}$$

$$P(NonSpam|a_1, ..., a_n) = \frac{P(NonSpam, a_1, ..., a_n)}{P(a_1, ..., a_n)}$$

the problem becomes determining which is the larger one between
$P(Spam, a_1, ..., a_n)$ and $P(NonSpam, a_1, ..., a_n)$, which can be rewritten as:

$$P(Spam, a_1, ..., a_n) = P(a_1, ..., a_n|Spam)P(Spam)$$

$$P(NonSpam, a_1, ..., a_n) = P(a_1, ..., a_n|NonSpam)P(NonSpam)$$

If we further assume that the attributes in a message are conditionally independent given the class of the message, the right hand side of the above equations become:

$$P(Spam, a_1, ..., a_n) = P(a_1|Spam) \dots P(a_n|Spam)P(Spam)$$

$$P(NonSpam, a_1, ..., a_n) = P(a_1|NonSpam) \dots P(a_n|NonSpam)P(NonSpam)$$

We now describe how to estimate the probabilities $P(a_i|Spam)$, $P(a_i|NonSpam)$, $P(Spam)$, $P(NonSpam)$. Once these probabilities become available, the above formulas will allow us to determine which class has the higher conditional probability.

We first tokenize the message. A token is either a consecutive sequence of letters or digits, or a consecutive sequence of non-space, non-letter and non-digit characters (we limit the length of the second kind of token to be at most three characters long). The spaces are ignored. We then remove the suffixes from the tokens using an implementation of the Porter stemmer (Porter 1980) by Frakes and Cox. The frequency counts of the suffix-removed tokens are then accumulated in a frequency count table. For each word W in the training messages, the frequency table contains the count $N(W, Spam)$, and $N(W, NonSpam)$, which is the number of times the word W occurred in the documents that belong to class C. The frequency table also records the total number of words (not necessarily unique) in the spam and nonspam messages: $N(Spam)$ and $N(NonSpam)$. Table 1 illustrates a subset of the frequency table.

Once the frequency table is created, we use the m-estimate method (Mitchell 1997) to estimate the conditional and prior probabilities of the words. M-estimate can be viewed as mixing the sample population in the frequency table with m uniformly distributed virtual examples. In our experiments, we used m=1 and the probability of a word in the virtual example is $\frac{1}{K}$ where K is the number of unique words in the training messages. In other words,

Table 1: Sample entries from the frequency table

word	spam	non-spam	word	spam	non-spam
___	2183	703	report	215	64
|||	60	0	mail	358	167
$	716	295	ship	36	0
adult	52	0	:___	36	0
000	178	26	you	1165	1210
million	69	2	///	251	103
order	253	60	email	212	77
###	44	0	address	239	99
bulk	43	0	your	581	458
monei	127	19	busi	122	30

$$P(W|C) = \frac{N(W, C) + \frac{1}{K}}{N(C) + 1}$$

where C is $Spam$ or $NonSpam$ and W ranges over the set words in the training messages.

Some words are not good indicators of the classification of the message in which they occur. We employed a feature selection algorithm to remove such words from the frequency table so that the classification of a message will not be affected by the accumulation of noise. A word W is removed from the frequency table if one of the following conditions are met:

- $N(W, Spam) + N(W, NonSpam) < 4$; or
- $\frac{P(W|Spam)}{P(W|Spam)+P(W|NonSpam)} \in [0.45, 0.55]$.

Experimental Results

Setup

Our training data consists of 160 spams that were sent to one of the authors (DL) and 466 nonspam messages in DL's mailbox. The testing messages consist of 277 spams obtained from the Internet[1] and 346 NonSpam e-mails in DL's mailbox from a different (but adjacent) time period. The header information is removed from the messages. The classification is completely based on the body of the messages.

There are a total of 230449 words in the training messages with 60434 in spams and 170015 in nonspams. There

[1] http://pantheon.cis.yale.edu/jgfoot/junk.html

are 12228 entries in the frequency table. Applying the feature selection rules from the previous section reduces the number of entries to 3848.

Evaluation Measures

Let

- $TrueCount(Spam)$ and $TrueCount(NonSpam)$ denote the number of spam and nonspam messages in the testing data.
- $CorCount(Spam)$ and $CorCount(NonSpam)$ denote the number of messages that are correctly classified as Spam and NonSpam by SpamCop.

We use three measures to evaluate the performance of SpamCop: false positive rate R_{fp}, false negative rate R_{fn}, and error rate R_e:

$$R_{fp} = 1 - \frac{CorCount(NonSpam)}{TrueCount(NonSpam)}$$

$$R_{fn} = 1 - \frac{CorCount(Spam)}{TrueCount(Spam)}$$

$$R_e = 1 - \frac{CorCount(Spam) + CorCount(NonSpam)}{TrueCount(Spam) + TrueCount(NonSpam)}$$

The false positive rate is the percentage of nonspam messages that are incorrectly classified as spam. It measures how safe the filter is. The false negative rate is the percentage of spam messages that pass through the filter as nonspams. It measures how effective the filter is. The error rate measures the overall performance.

Results

Table 2 summarizes our results. It can be seen that although naïve Bayes algorithm is extremely simple, it achieved very high accuracy, especially with respect to the nonspam messages. Feature selection reduced the frequency table to 1/3 of its original size and resulted in a slightly higher false positive rate, a much lower false negative rate and a lower overall error rate.

Table 2: Testing results with 277 spams and 346 nonspams

Feature Selection	R_{fp}	R_{fn}	R_e
yes	1.16%	8.30%	4.33%
no	0.58%	13.36%	6.26%

We also investigated the effects of the size of the training data on the performance of SpamCop. We divided the training data into 5 even partitions. Each partition has the same spam/nonspam ratio as the whole set. The results are presented in Table 3. The first column is the data size in terms of the number of partitions. For each data size we randomly selected 5 configurations. The average rates of the 5 configurations are shown in last three columns in Table 3. The second column indicates whether the feature selection algorithm was used or not.

Table 3: Effects of the number of training examples

Size	Feature Selection	R_{fp}	R_{fn}	R_e
1/5	yes	1.68%	12.35%	6.42%
1/5	no	1.33%	14.08%	7.00%
2/5	yes	1.68%	10.97%	5.81%
2/5	no	1.10%	12.64%	6.23%
3/5	yes	1.21%	8.66%	4.53%
3/5	no	0.92%	11.84%	5.78%
4/5	yes	1.01%	8.94%	4.53%
4/5	no	0.79%	11.64%	5.62%

SpamCop achieves good performance with as few as 32 spam messages and 91 nonspam messages as training examples. Applying feature selection consistently produced the same effect: slight increase of false positives, a decrease of false negatives, and a moderate decrease of the error rate.

We also experimented with varying the ratios between the number of spam and nonspam messages. The first two columns in Table 4 represent the number of spams and nonspams used in training. Compared with the results in Table 2, it appears that a higher ratio of training examples in a category increases the performance in that category. However, it significantly decreases the performance of the other category.

Table 4: Effects of varying ratios of spam and nonspams

spams	nonspams	R_{fp}	R_{fn}	R_e
32	466	0.06%	53.07%	23.63%
160	91	12.60%	1.44%	7.64%

Using trigrams

Instead of suffix-stripped words, we also used trigrams extracted from words as features. A trigram in a word is a consecutive sequence of three letters in the word. Table 5 illustrates the results of the use of trigram in spam-filtering, using the same training and testing data as the experiment described in Table 2. Considering the amount information that gets lost when using trigrams over words, the values in Table 5 are remarkably close to the values in Table 2. This might be attributed to the fact that since there are much fewer unique trigrams than unique words, the probability estimations for trigrams are more accurate.

Table 5: SpamCop performance using trigrams

Feature Selection	R_{fp}	R_{fn}	R_e
yes	4.91%	6.50%	5.62%
no	2.89%	9.03%	5.61%

Comparison with RIPPER

RIPPER is a rare symbolic learning program that is able to deal with texts. We ran RIPPER with the same training and testing data as used in testing SpamCop. We used the Porter stemmer and treated all the suffix-stripped roots as the features. RIPPER generated 9 rules with 24 conditions and achieved an error rate of 8.67% on the 623 testing messages. The use of the stemmer significantly influenced the performance. Without the stemmer, RIPPER generated 19 rules with 50 conditions and achieved an error rate of 13.64% on the 623 testing messages.

The top ranked rule in RIPPER is that "if a message contains both the dollar sign and the exclaimation mark then it is classified as spam." This rule correctly classified 54 spams and misclassified 5 out of 466 nonspams in the training messages. Although this rule performed very well, it will misclassify long nonspams which happen to contain these two words. In contrast, our probabilistic algorithm is much more robust.

Another example that demonstrates the advantage of a probabilistic classification over a rule-based classification is the word "you". The word "you" has one of the highest ratio between its conditional probability in spam and nonspam messages. In an extreme case, one of the spams in the training example contained 99 occurrences of "you" or "your" in 112 lines of text. Therefore, a high frequency of "you" is a definitely good indicator of spams. However, "you" is also a common word in nonspams. A keyword-spotting rule will not be able to use this in classification.

Conclusion

We presented a simple, yet highly accurate, spam-filtering program, called SpamCop. It treats an e-mail message as a multiset of words and employs a naïve Bayes algorithm to determine whether or not a message is likely to be a spam. Our experiments show that SpamCop is able to identify about 92% of the spams while misclassifying only about 1.16% of the nonspam e-mails. Our experiments also show that high classification accuracy can be achieved with as few as 32 spam examples. Compared with symbolic learning programs such as RIPPER, SpamCop produced higher accuracy and does not suffer from the brittleness associated with keyword-spotting rules.

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