Bayesian Spam Filtering

St. John’s Linux Users’ Group

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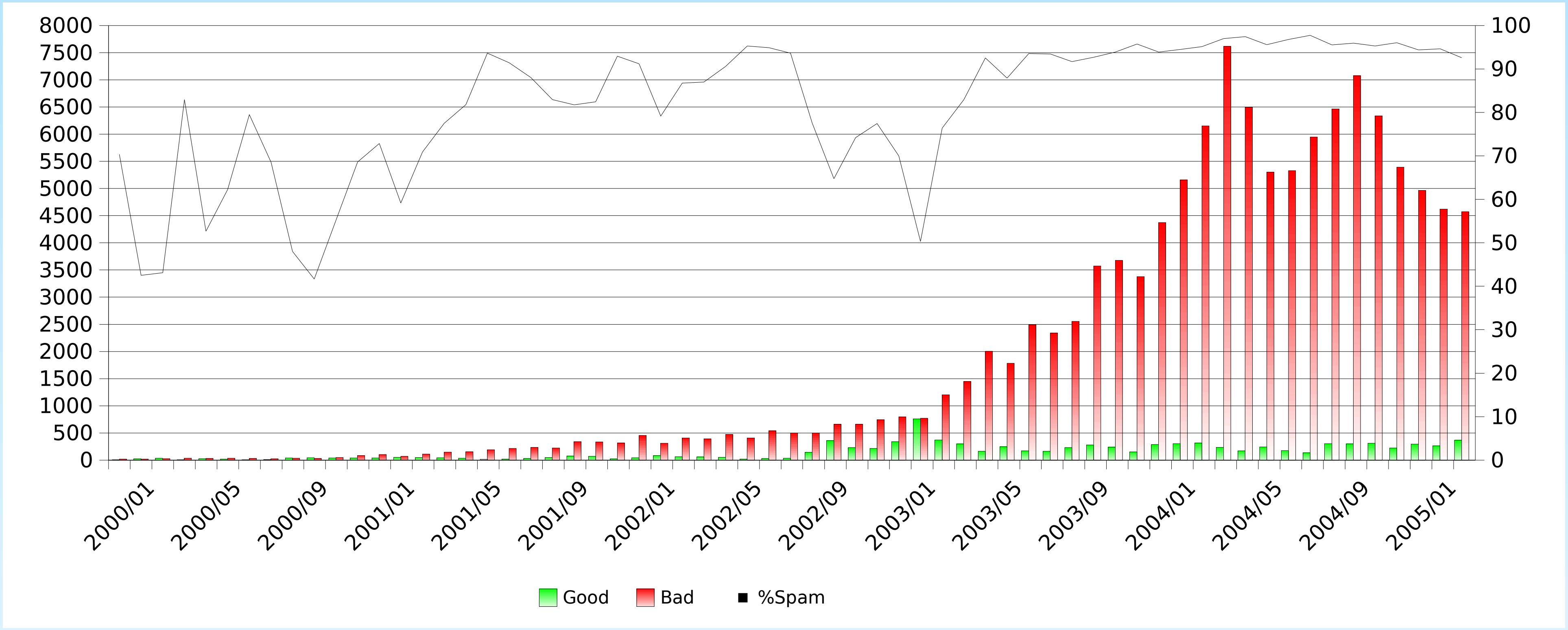
In the beginning...

```
From uunet.uu.net!national-alliance.org!Crusader Sat Sep 30 17:26:42 1995
Received: from asso.nis.garr.it (@asso.nis.garr.it [192.12.192.10]) by
        garfield.cs.mun.ca with SMTP id <102189>; Sat, 30 Sep 1995 17:26:31 -0230
Received: by asso.nis.garr.it (4.1/1.34/ABB950929)
        id AA18937; Sat, 30 Sep 95 19:03:23 +0100
Received: by mercury.sfsu.edu (5.0/SMI-SVR4)
        id AA21676; Sat, 30 Sep 95 11:03:27 -0700
Date:   Sat, 30 Sep 1995 15:33:27 -0230
From:   Crusader@national-alliance.org
Message-Id: <913247217488@National-Alliance.org>
To:     <donald@cs.mun.ca>
To:     <XXXXXX@cs.mun.ca>
Subject: Piranhas
Apparently-To: Crusader@National-Alliance.org



What would you say if a Liberal "social scientist" told you to
jump into a pool filled with five hundred ravenous piranhas?

If you valued your life, you'd certainly refuse the invitation.

But what if the Liberal "social scientist" tried to convince you
to go ahead and jump in, with the argument that "not all of the
piranhas are aggressive.  Some of them probably just want to make
friends with you, and really aren't hungry either.  To say that a
```

... blah, blah, blah...

Ouch!



- The volume of spam was increasing exponentially.
- Currently, about 95% of my e-mail is spam.
- I currently receive about 100 to 150 spam messages per day, over 5MB a week (down from about 200 to 250 per day).

Filtering Attempt

- An early attempt to identify spam was to use **`procmail`**.
- This involved storing regular expressions in one's **`.procmailrc`** which would match phrases that occurred frequently in spam messages. *e.g.*

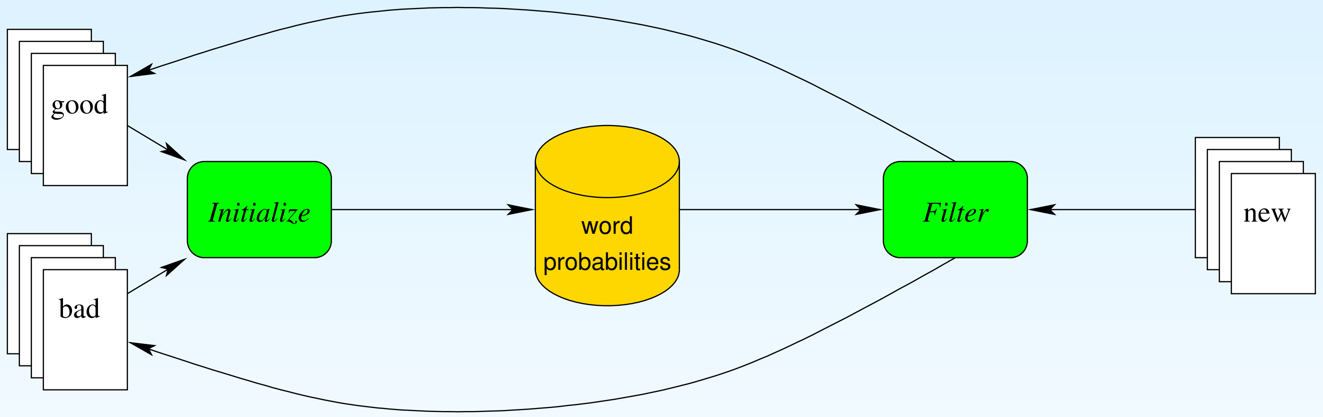
```
:0B:
* (mailto:|subject=(3D)?)(abuse|nosale|(un)?sub|delete|remov(e|al)|exclude|discontinue|nomore|
(additional|more)[-_.]info)|annuler=|(reply|yes|subscribe|remove)["']? (yourself|instructions|
.*from .*mailing|.*(in|as).*subject)|To remove.*(e-?mail|message)|to.* be .*(r.?e.?m.?o.?v.?e.?d?|
taken (from|off)|extracted)|for removal|removal instructions|remove:mailto|to (be taken out|
get off|opt out|remove from|unsubscribe)|remove (requests|me)|(do not|don.t) respond|(global|
no need to) remove|remove[a-z0-9]*@|cancel subscription|remove(me|you|\.(php|html?))|opt.?out|
perman(ent|tently) remov(ed?|al)|remov(ed?|al) (notification|requests|administrator)|$removal:|
remove in the|if you wish to receive|(/|mail)-?(refuse|remove|unsu(b|s))|["']remove["']|off.?list|
reject.?mail
junk/junk.a
```

- Problems
  - Its binary nature could very easily generate false positives.
  - Spam kept changing too rapidly for this strategy to be effective.
  - As a result, the **`.procmailrc`** file became very large and cumbersome to change.

A Better Solution

- In August 2002, Paul Graham advocated Bayesian filtering as an effective means of combatting the spam problem. He didn't actually discover the technique, but he did help popularize it.
- Accuracy rate was claimed to be in excess of 99%.
- The technique has two distinct phases:

A collection of good and bad messages are examined and statistical probabilities for all words is dervied based upon the relative frequencies of each word in the two collection of messages.



The filter uses these statistical probabilities during its analysis of incoming messages to classify them as spam or non-spam.

The Initializing Phase

If we know:

msg_b = total number of bad messages,
msg_g = total number of good messages,
w_b = occurrences of word w in bad messages and
w_g = occurrences of word w in good messages,

then we can assign a probability to each word w based upon the relative frequencies that w occurred in all the bad and good messages.

$$P(w) = \max\left(\min\left(\frac{r_b}{r_g + r_b}, 0.99\right), 0.01\right)$$

where:

$$r_b = \min\left(\frac{w_b}{msg_b}, 1.0\right), \qquad r_g = \min\left(\frac{2w_g}{msg_g}, 1.0\right)$$

The further away $P(w)$ is from 0.5 (neutral), the more useful the word w is in determining whether or not the message is spam.

Initializing Examples

$$msg_b = 69,449 \qquad msg_g = 9,580$$

$w = \text{buy}:$

$w_b = 4,434 \qquad w_g = 171$

$$\begin{aligned} r_b &= \frac{4{,}434}{69{,}449} & r_g &= \frac{2\times171}{9{,}580} & P(w) &= \frac{0.063845}{0.035699+0.063845} \\ &= 0.063845 & &= 0.035699 & &= 0.641374 \end{aligned}$$

$w = \text{university}:$

$w_b = 198 \qquad w_g = 1,243$

$$\begin{aligned} r_b &= \frac{198}{69{,}449} & r_g &= \frac{2\times1243}{9{,}580} & P(w) &= \frac{0.002851}{0.002851+0.259499} \\ &= 0.002851 & &= 0.259499 & &= 0.0108672 \end{aligned}$$

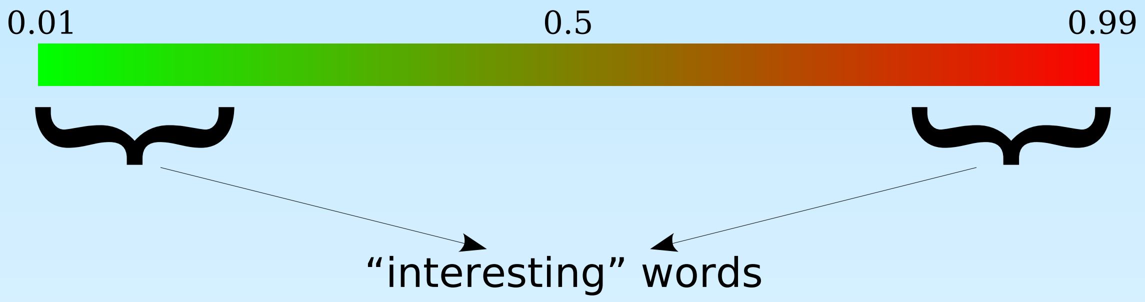
$w = \text{and}:$

$w_b = 158,729 \qquad w_g = 70,828$

$$\begin{aligned} r_b &= \min\left(\frac{158{,}729}{69{,}449}, 1.0\right) & r_g &= \min\left(\frac{2\times70{,}828}{9{,}580}, 1.0\right) & P(w) &= \frac{1}{1+1} \\ &= 1 & &= 1 & &= 0.5 \end{aligned}$$

The Filtering Phase

Once we have generated a database of words and their corresponding probabilities, we can start to filter incoming messages. When we receive a message, we identify the n most *interesting* words, w_i (Graham's algorithm sets $n = 15$). These are the words whose probabilities are furthest away from neutral.



We then apply the following formula:

$$p = \frac{prod_1}{prod_1 + prod_2}$$

where:

$$prod_1 = \prod_{i=1}^{n} P(w_i), \qquad prod_2 = \prod_{i=1}^{n} (1 - P(w_i))$$

The closer that p is to one, the more likely the message is spam.

Filtering Example #1

```
From: Michael Rayment
To: Donald Craig, Geoff Holden
Organization: Memorial University
Subject: Abstract for talk

            What's with Python Anyway?
      A Look at Why Python is so Popular
                   by
              Michael Rayment

This talk will look at how the designers of Python
got it right when they designed the language and wrote
the Python interpreter.  A quick tour of the language
will reveal a symmetric object oriented data
structure model at the heart of the language along
with a rich set of program constructs that allow the
programmer to manipulate the data easily.  All data
are dynamically typed objects that can be assigned
to variables without worrying about type declarations.
Python "does the right thing" according to the context
in which the data is used.  The variable name is
simply a handle.  Among other things this talk will
describe some of the salient features of the language
such as list manipulation, creating classes, handling
exceptions, scope of variables and most importantly
the rich set of predefined module libraries.
```

Filtering Example #1 (Cont'd)

$$
\begin{aligned}
P(\text{variables}) &= 0.01\\
P(\text{Memorial}) &= 0.01\\
P(\text{declarations}) &= 0.01\\
P(\text{Craig}) &= 0.01\\
P(\text{wrote}) &= 0.01\\
P(\text{Geoff}) &= 0.01\\
P(\text{Abstract}) &= 0.01\\
P(\text{Python}) &= 0.01\\
P(\text{dynamically}) &= 0.0104355365\\
P(\text{University}) &= 0.0108397943\\
P(\text{Rayment}) &= 0.0108484296\\
P(\text{Rayment}) &= 0.0108484296\\
P(\text{exceptions}) &= 0.0132622019\\
P(\text{typed}) &= 0.0139836777\\
P(\text{Anyway}) &= 0.0198030382
\end{aligned}
$$

$$
\begin{aligned}
prod_1 &= 4.88921 \times 10^{-30}\\
prod_2 &= 0.842786\\
p &= \frac{4.88921 \times 10^{-30}}{4.88921 \times 10^{-30} + 0.842786}\\
&= 5.80125 \times 10^{-30}
\end{aligned}
$$

Message is not spam!

Filtering Example #2

```
From cubitus@realtywebsites.com  Tue Mar 22 02:16:29 2005
Return-Path: <cubitus@realtywebsites.com>
Received: from realtywebsites.com (unknown [218.85.167.135])
        by mercury.cs.mun.ca (Postfix) with SMTP id 0D3DB18B6E3
        for <donald@garfield.cs.mun.ca>; Tue, 22 Mar 2005 02:16:18 -0330 (NST)
From: <cubitus@realtywebsites.com>
To: <donald@cs.mun.ca>
Subject: At your service, online pharm
Date: Tue, 22 Mar 2005 13:50:20 -0500
Mime-Version: 1.0
Content-Type: text/plain; charset=us-ascii
Message-Id: <20050322054619.0D3DB18B6E3@mercury.cs.mun.ca>
X-Virus-Scanned: by amavisd-new at cs.mun.ca

If you need high quality medication and
would love to save on outrageous retail pricing,
then OnlinePharmacy is for you.

Shopping online for your drug needs saves you the hassle of going to the
doctor,  answering embarassing questions and waiting in line to receive
good treatment?  OnlinePharmacy has been dedicated to serving its online
clientel since 2001.

Try us to find out why ordering your medications online has never been easier.

http://www.fastmail336.com/rx/?76
```

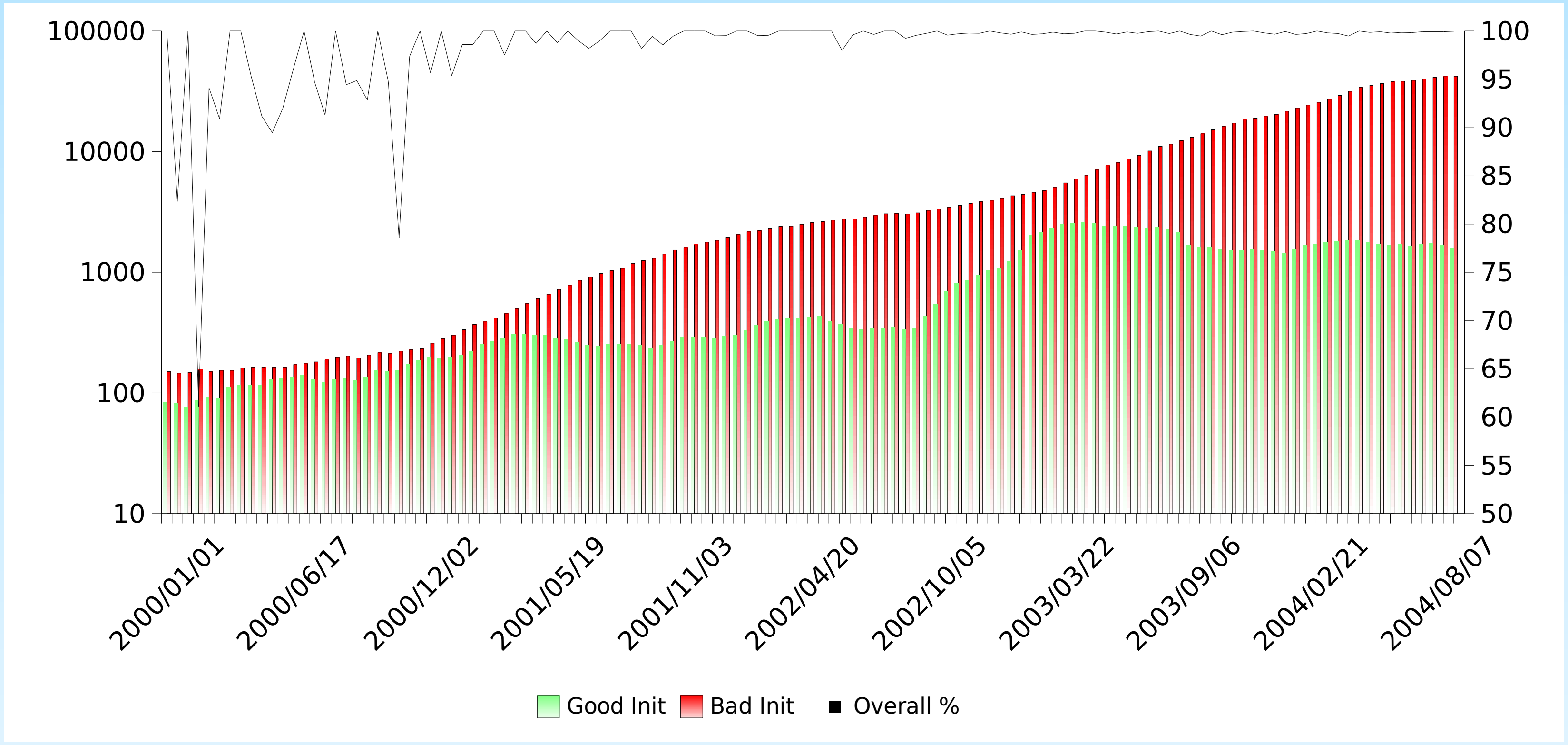
Filtering Example #2 (cont'd)

$$
\begin{aligned}
P(\text{OnlinePharmacy}) &= 0.99 \\
P([218) &= 0.99 \\
P(\text{pharm}) &= 0.0420049316 \\
P(\text{answering}) &= 0.0459504311 \\
P(\text{unknown}) &= 0.9534104082 \\
P(\text{retail}) &= 0.9132323275 \\
P(\text{medications}) &= 0.9128298221 \\
P(\text{medication}) &= 0.9104607169 \\
P(\text{would}) &= 0.0919725162 \\
P(\text{doctor}) &= 0.9036781616 \\
P(\text{questions}) &= 0.1016689722 \\
P(\text{serving}) &= 0.1121766169 \\
P(\text{dedicated}) &= 0.1185694551 \\
P(\text{easier}) &= 0.1433214124 \\
P(\text{going}) &= 0.1536839685
\end{aligned}
$$

$$
\begin{aligned}
prod_1 &= 3.38881 \times 10^{-9} \\
prod_2 &= 1.28555 \times 10^{-10} \\
p &= \frac{3.38881 \times 10^{-9}}{3.38881 \times 10^{-9} + 1.28555 \times 10^{-10}} \\
&= 0.963451
\end{aligned}
$$

Message is spam!

Performance



- Initially, the filter performs very poorly, sometimes misclassifying upto one-third of all messages.

- After being initialized with about 2000 bad messages and 200 good messages, the filter hits very close to 100% effectiveness.

`buryspam.rb`

- Script written in **`ruby`**. An earlier version was written in **`perl`**.

- It has two primary modes (amongst others):
  - Initialization with **`buryspam.rb --init`** (done manually)
  - Filtering with **`buryspam.rb --filter`**. By default, the script takes input from standing input and is typically called automatically by **`procmail`** on each new mail received.

- Script handles multipart messages (MIME attachments).

- Decodes base64, quoted-printable encodings.

- Tries to "intelligently" process HTML messages.

- Confusingly configurable.

- Can do other things as well (generate rudimentary stats, grepping, auto testing, etc.)

buryspam.rb Usage

Setting up **buryspam.rb** can be a bit of a pain. The configuration can be summarized as follows:

- Separate your good and bad mail into two separate directories.
- Create a **.buryspamrc** file which indicates the location of your good and bad mail (as well as the location of your word probabilities file).
- Initialize the filter with **buryspam.rb --init**.
- Modify your **.procmailrc** file (add **buryspam.rb --filter** and deposit messages designated as spam to to a spam folder).

Or

Better yet, rather than **buryspam.rb**, just use the *Thunderbird* e-mail client which already has a Bayesian filter built in. Add-on software exists for other e-mail clients, as well (*e.g.* **spambayes**).

Modifications to Graham's Algorithm

- Slight modifications to the characters that comprise a word. *e.g.* **[** is considered a word character. This helps pick up the first octet of IP addresses that spam a lot, such as **[212**

- During the identification of *interesting* words:
  - a weighted selection of good/bad words is performed in the event of ties. *i.e.* for every extremely bad word that is used in the interesting word list, select two extremely good words.
    This appears to reduce the number of false positives.
  - duplicate interesting words in the body of the messages are not used in the calculation of the final Bayesian value. Duplicate words in the header are retained.
    This seems to reduce the number of false negatives.

- If Bayesian classification considers the message non-spam, then calculate a ratio of extremely bad words to extremely good words. If this ratio is high, then the message is likely spam. This helps reduce false negatives caused by spammers poisoning their messages with random words.

Advantages/Disadvantages of Bayesian filtering

- Advantages
  - Conceptually very easy to understand.
  - Very effective (filters more than 99.691% of my spam)
  - Everyone's filter is essentially customized, making it very difficult for spammers to defeat everyone's filter with a single message.
  - Many e-mail clients now either directly or indirectly support Bayesian filtering.

- Disadvantages
  - You need to have a corpus of good and bad messages to initialize the filter.
  - Initialization is a bit time consuming (but this can be made quicker by caching word counts for each mail folder).
  - On each message, a user-specific database of word probabilities has to be consulted. This makes Bayesian filtering somewhat resource intensive and probably not ideal for sites with large user bases.
  - False positives do happen (but are rare).

Conclusions

- Spam — bad
- Bayesian filtering — good.

Resources

- <**http://www.cs.mun.ca/˜donald/buryspam/**>
  extensive documenation on my **buryspam.rb** script.
- <**http://www.paulgraham.com/spam/**>:
  Paul Graham's spam proposal.
- <**http://www.mozilla.org/**>:
  Free Mozilla Thunderbird e-mail client.
- <**http://spambayes.sourceforge.net/**>:
  Plugins for other e-mail clients.
- <**http://spamassassin.sourceforge.net/doc/sa-learn.html**>:
  SpamAssassin's Bayesian classifier