Email Classification

BEREND TOBER & MATTHEW BUHLER

Email Classification

How do traditional spam filters work?

Our Basic Approach

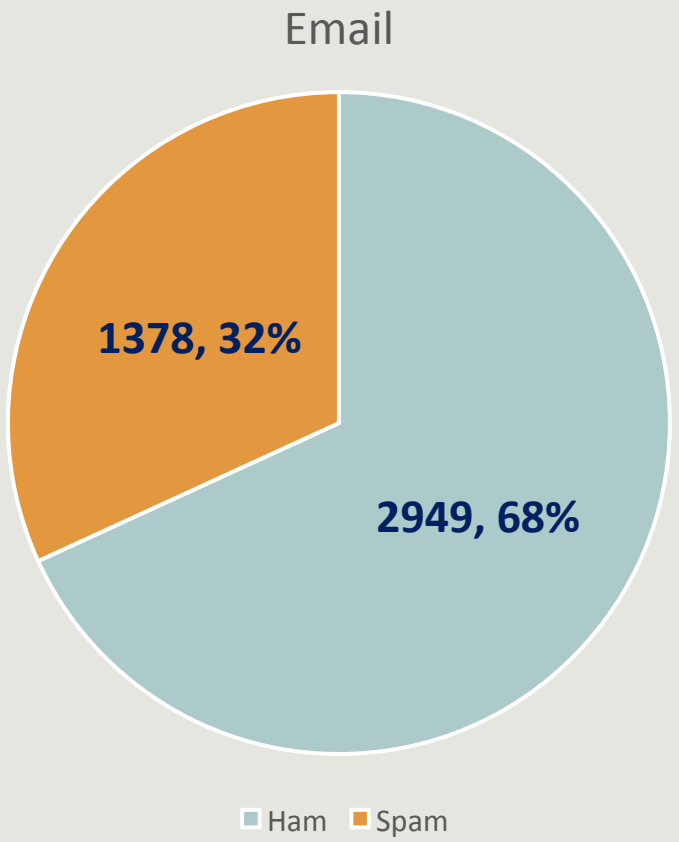
Tools:

- Python
- bash/sed/awk
- Spam Assassin
- Postfix

Raw Data

4,327 Emails

- 1,378 Spam Messages
- 2,949 Ham Messages



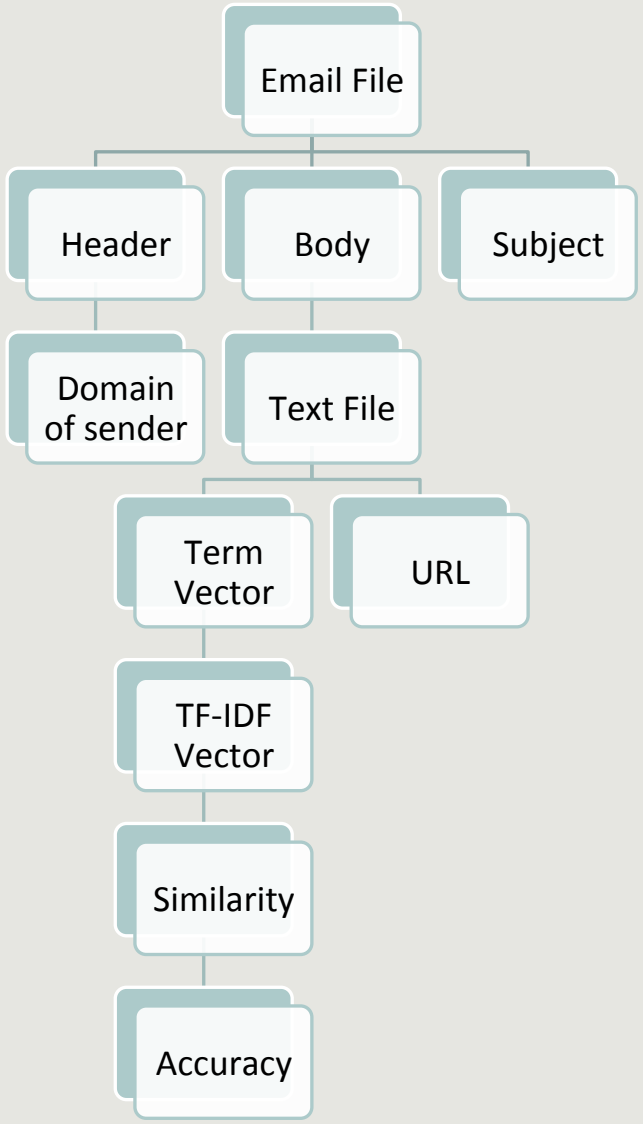
What does our data look like?

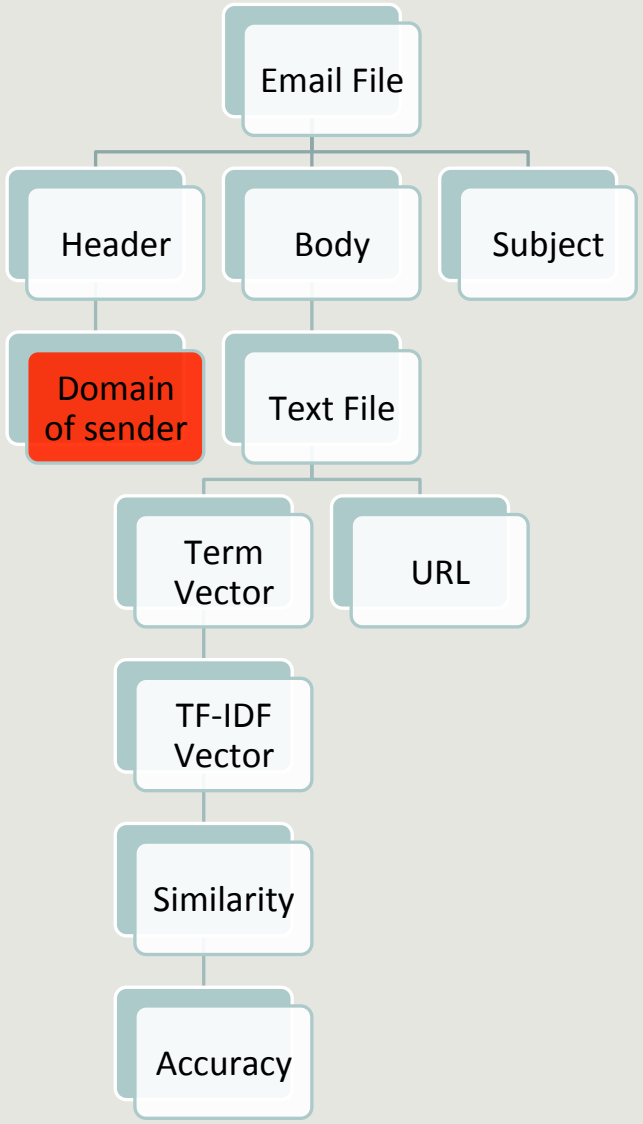
From - Fri Apr 16 10:29:33 2010
Return-Path: dapotor4203@mtnl.net.in
X-Original-To: m0620212@mail.csmining.org
Delivered-To: m0620212@mail.csmining.org
Received: from mail3.csmining.org (localhost [127.0.0.1])
by mail3.csmining.org (csminingorg Mail) with ESMTP id C7C9B16B91
for <m0620212@mail.csmining.org>; Thu, 15 Apr 2010 21:14:12 +0900 (JST)
Received: from spamgw.csmining.org (spamgw.csmining.org [192.168.18.120])
by mail3.csmining.org (csminingorg Mail) with ESMTP id C3FC816B43
for <m0620212@mail.csmining.org>; Thu, 15 Apr 2010 21:14:12 +0900 (JST)
Date: Thu, 15 Apr 2010 21:14:10 +0900 (JST)
Message-Id: 201004151214.o3FCEAR7008043@gw1.csmining.org
Received: from mtnl.net.in (triband-mum-120.60.8.28.mtnl.net.in [120.60.8.28])
by mx2.csmining.org (csminingorg MX Server2) with ESMTP id 421E96D
for <hibody@csmining.org>; Thu, 15 Apr 2010 21:14:10 +0900 (JST)
From: "Medicines from Pfizer" dapotor4203@mtnl.net.in
To: hibody@csmining.org
Subject: Enter now, hibody, 75% off

What does our data look like?

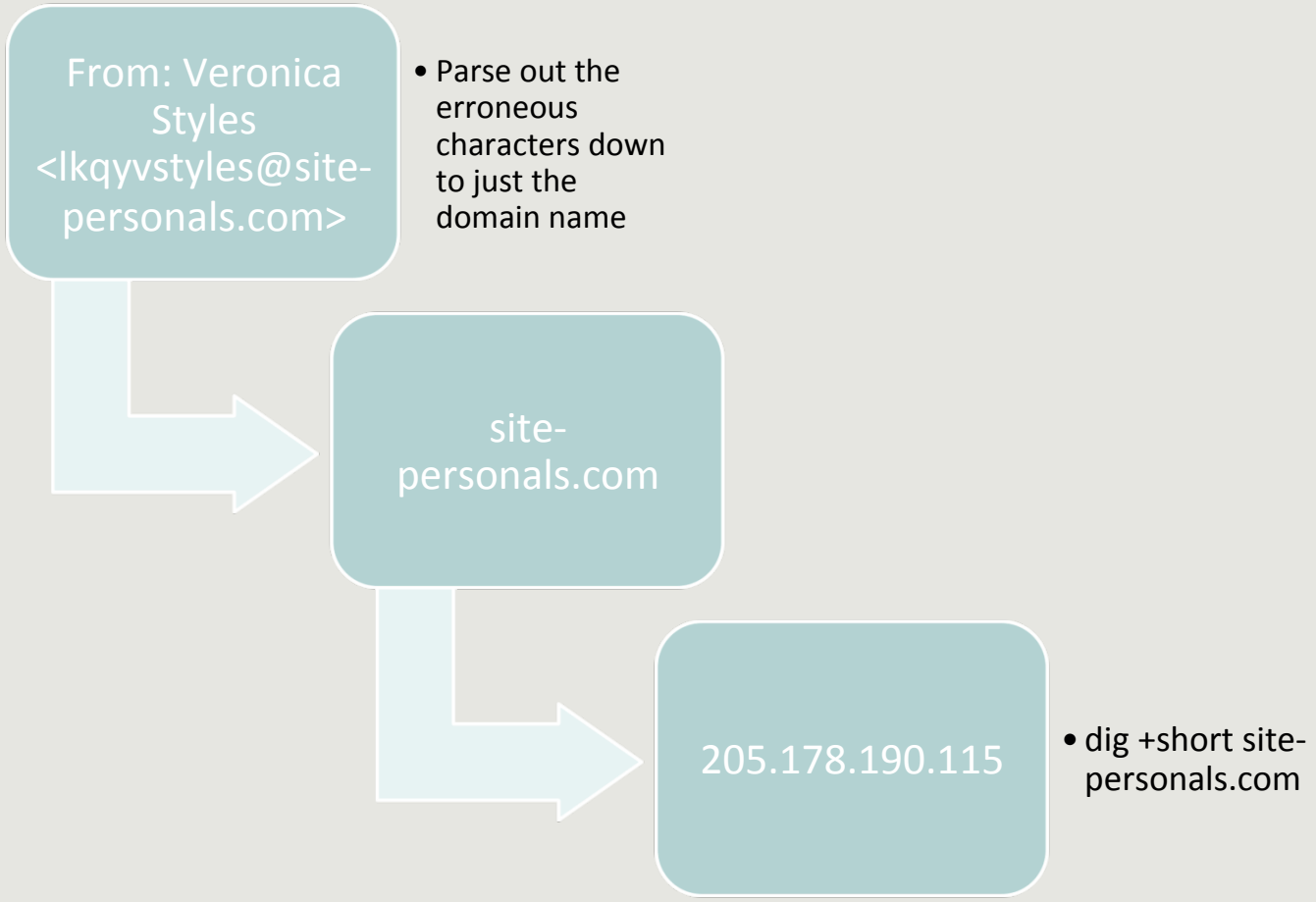
```
<!DOCTYPE html PUBLIC "-//W3C//DTD XHTML 1.0 Transitional//EN" "http://www.w3.org/TR/xhtml1/DTD/xhtml1-transitional.dtd">
<html xmlns="http://www.w3.org/1999/xhtml">
<head>
 <meta http-equiv="Content-Type" content="text/html; charset=utf-8" />
<title>
having National frequently would view</title>
</head>
<body link="#003366" alink="#003366" vlink="#003366">
<div align="center">
<table border="0" cellpadding="0" cellspacing="0" width="728">
<tbody>
<tr>
<td align="center" width="730">
<div style="padding: 5px; font-family: Arial,Helvetica,sans-serif; font-size: 11px; margin-top: 10px; background-color: rgb(239, 239, 239); color: rgb(102, 102, 102); margin-
bottom: 3px;">
To view this email as a web page, <a href="http://f5.pharmlalo.ru/?seufyenow=d87b2b17dd">click here.</a>
</div>
<table bgcolor="#ffffff" border="0" cellpadding="0" width="730">
<tbody>
<tr>
<td align="left" valign="top" width="420">
<div style="font-size: 13px; font-family: arial,helvetica,sans-serif;">
<div style="color: rgb(51, 51, 51); font-size: 16px; font-weight: 700;">
Thu, April 15, 2010</div>
</div>
</td>
<td width="10"> </td>
</tr>
</tbody>
```

Preprocessing Data:



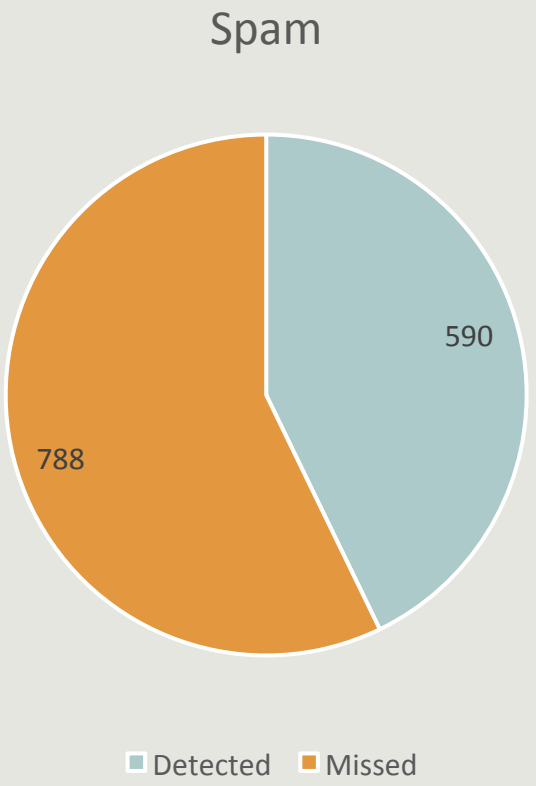

Email File
Header
Body
Subject
Domain of sender
Text File
Term Vector
URL
TF-IDF Vector
Similarity
Accuracy

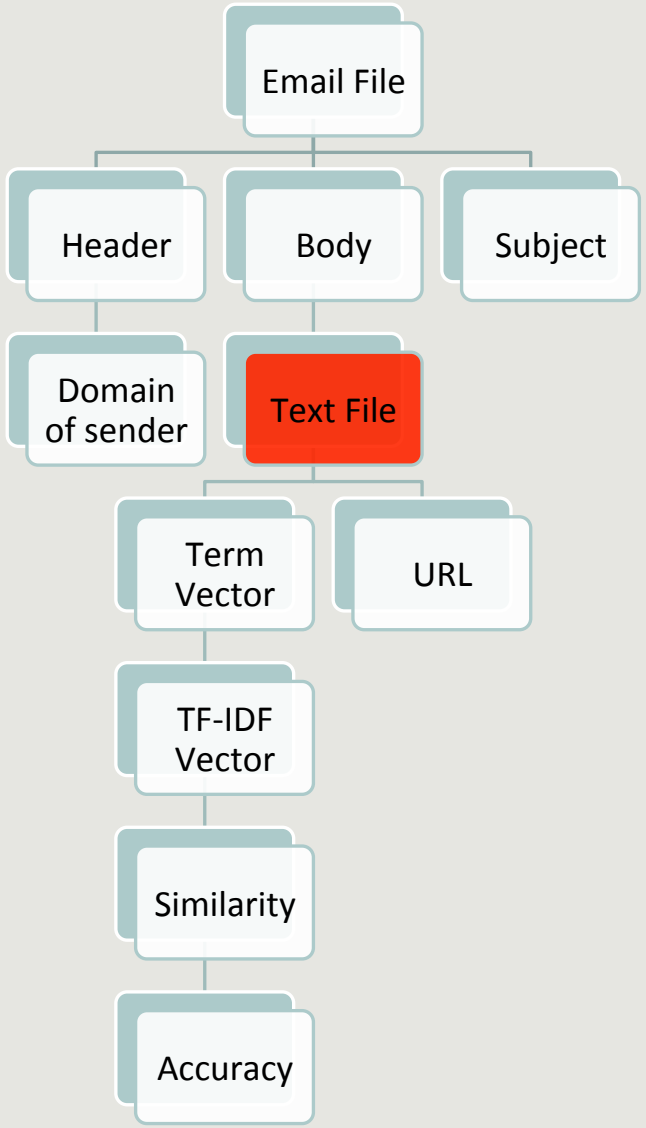
Sender Reputation



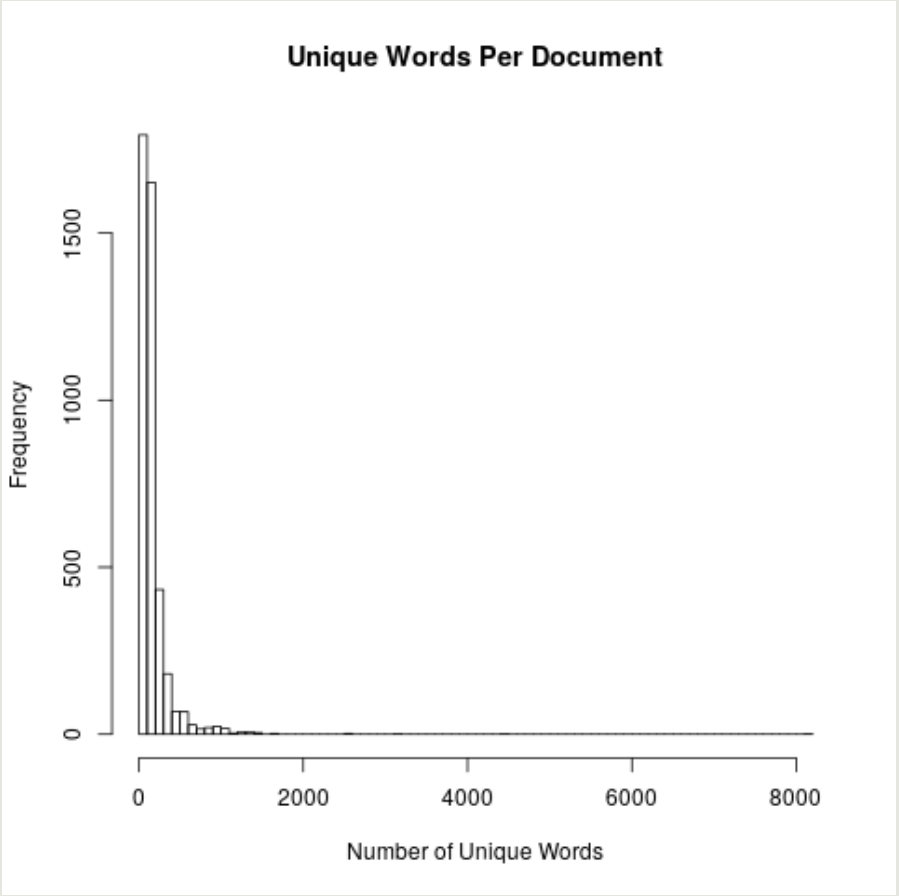
Results

42.8% of Spam messages were successfully identified based solely on the networks.

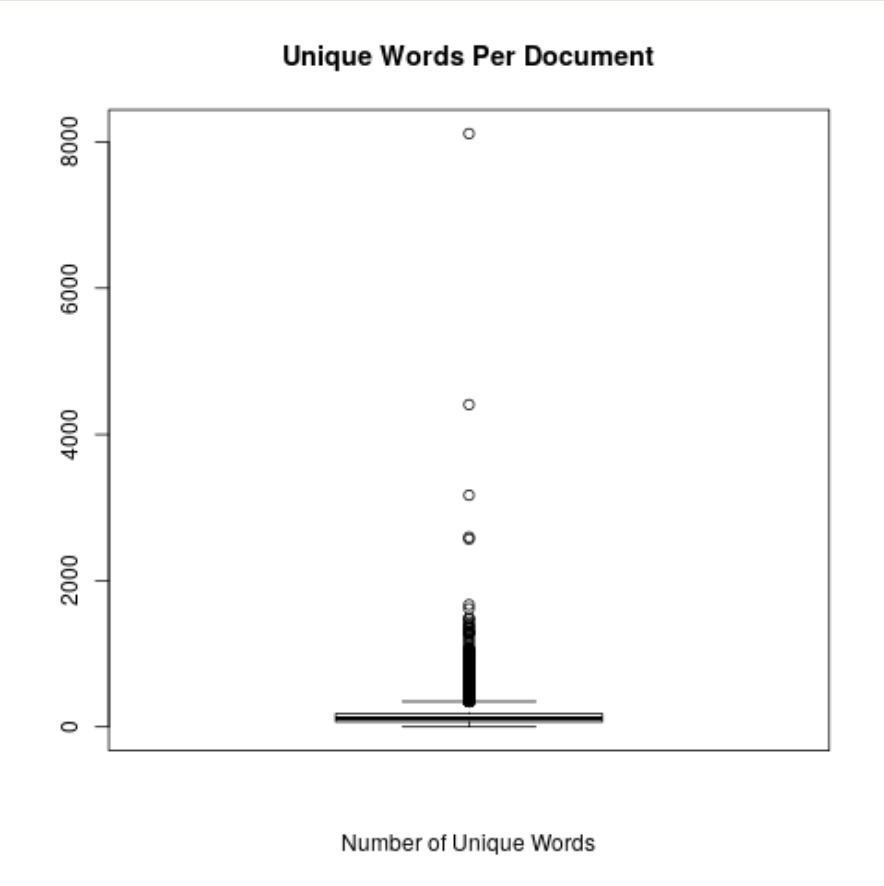



Email File
Header
Body
Subject
Domain of sender
Text File
Term Vector
URL
TF-IDF Vector
Similarity
Accuracy

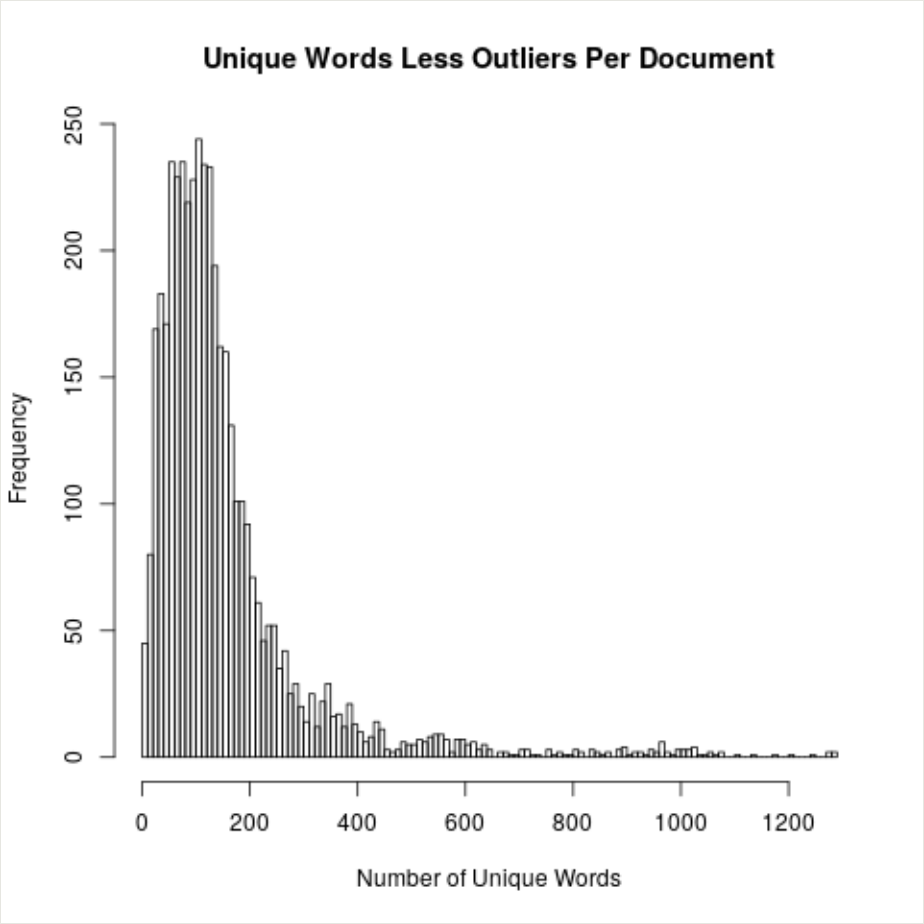
Data


Unique Words Per Document
Frequency
0
500
1000
1500
0
2000
4000
6000
8000
Number of Unique Words

Data


Unique Words Per Document
0
2000
4000
6000
8000
Number of Unique Words

Data with Outliers Removed



Four Contrived Sample Documents

==> examples/poem.eml <==
From: noone@example.com
Subject: A poem about foxes

The nimble brown and white fox jumped over the sleeping dog.

The brown and black dog awoke, looked up at the fox and said, "Woof!"

Four Contrived Sample Documents

==> examples/song.eml <==
From: noone@example.com
Subject: A song about foxes

What does the fox say?
Ding ding ding da ding da ding ding.

Four Contrived Sample Documents

==> examples/skit.eml <==
From: noone@example.com
Subject: A skit about spam

Man: You sit here, dear.
Wife: All right.
Man: Morning!
Waitress: Morning!
Man: Well, what've you got?
Waitress: Well, there's egg and bacon; egg sausage and bacon; egg and spam; egg bacon and spam; egg bacon sausage and spam; spam bacon sausage and spam; spam egg spam spam bacon and spam; spam sausage spam spam bacon spam tomato and spam;
Vikings: Spam spam spam spam...
Waitress: ...spam spam spam egg and spam; spam spam spam spam spam spam baked beans spam spam spam...
Vikings: Spam! Lovely spam! Lovely spam!
Waitress: ...or Lobster Thermidor a Crevette with a mornay sauce served in a Provencale manner with shallots and aubergines garnished with truffle pate, brandy and with a fried egg on top and spam.
Wife: Have you got anything without spam?
Waitress: Well, there's spam egg sausage and spam, that's not got much spam in it.
Wife: I don't want ANY spam!

Four Contrived Sample Documents

Man: Why can't she have egg bacon spam and sausage?
Wife: THAT'S got spam in it!
Man: Hasn't got as much spam in it as spam egg sausage and spam, has it?
Vikings: Spam spam spam spam... (Crescendo through next few lines...)
Wife: Could you do the egg bacon spam and sausage without the spam then?
Waitress: Urgghh! Wife: What do you mean 'Urgghh'? I don't like spam!
Vikings: Lovely spam! Wonderful spam!
Waitress: Shut up! Vikings: Lovely spam! Wonderful spam!
Waitress: Shut up! (Vikings stop) Bloody Vikings! You can't have egg bacon spam and sausage without the spam.
Wife: I don't like spam!
Man: Sshh, dear, don't cause a fuss. I'll have your spam. I love it. I'm having spam spam spam spam spam spam spam beaked beans spam spam spam and spam!
Vikings: Spam spam spam spam. Lovely spam! Wonderful spam!
Waitress: Shut up!! Baked beans are off.
Man: Well could I have her spam instead of the baked beans then?
Waitress: You mean spam spam spam spam spam spam... (but it is too late and the Vikings drown her words)
Vikings: (Singing elaborately...) Spam spam spam spam. Lovely spam! Wonderful spam! Spam spa-a-a-a-a-am spam spa-a-a-a-a-am spam. Lovely spam! Lovely spam! Lovely spam!

Four Contrived Sample Documents

==> examples/spam.eml <==
From: noone@example.com
Subject: A word about Spam

Spam

Term Vectors

==>> examples/poem.term <<==
3 and
2 the
2 fox
2 dog
2 brown
2 The
1 white
1 up
1 sleeping
1 said
1 over
1 nimble
1 looked
1 jumped
1 black
1 awoke
1 at
1 Woof

Term Vectors

==>> examples/song.term <<==
5 ding
2 da
1 the
1 say
1 fox
1 does
1 What
1 Ding

Term Vectors

==> spam.term <==

1 Spam

Term Vectors

==> skit.term <==
95 spam
19 and
13 egg
13 a
11 Lovely
10 bacon
10 Waitress
10 Vikings
9 sausage
7 t
7 Wife
7 Spam
7 Man
7 I
6 it
5 the
5 got
4 you
4 with
4 in
4 have
4 don
4 beans
4 Wonderful
4 Well
3 without
3 up
3 s
3 You
3 Shut
2 there . . .

Term-Frequency/Inverse Document Frequency

$$tf - idf(t,d,D) = tf(t,d) * \log(\frac{M}{df(t,D)})$$

where

tf(t,d) is the number of times term t occurs in document d

df(t,D) is the number of documents term t occurs in across the entire corpus D

M is the number of documents.

Document Frequency

==> examples/document_frequency <==
3 the
2 up
2 fox
2 and
2 What
2 Spam
1 your
1 you
1 words
1 without
1 with
1 white
1 what
1 want
1 ve
1 truffle
1 top
1 too
1 tomato
1 through . . .

Term Vectors vs TF-IDF Vectors

==>> examples/poem.term <<==
3 and
2 the
2 fox
2 dog
2 brown
2 The
1 white
1 up
1 sleeping
1 said
1 over
1 nimble
1 looked
1 jumped
1 black
1 awoke
1 at
1 Woof

==>> examples/poem.tfidf <<==
2.772589 dog
2.772589 brown
2.772589 The
2.079442 and
1.386294 white
1.386294 sleeping
1.386294 said
1.386294 over
1.386294 nimble
1.386294 looked
1.386294 jumped
1.386294 fox
1.386294 black
1.386294 awoke
1.386294 at
1.386294 Woof
0.693147 up
0.575364 the

Term Vectors vs TF-IDF Vectors

==>> examples/song.term <<==
5 ding
2 da
1 the
1 say
1 fox
1 does
1 What
1 Ding

==>> examples/song.tfidf <<==
6.931472 ding
2.772589 da
1.386294 say
1.386294 does
1.386294 Ding
0.693147 fox
0.693147 What
0.287682 the

Term Vectors vs TF-IDF Vectors

==>> examples/skit.term <<==
95 spam
19 and
13 egg
13 a
11 Lovely
10 bacon
10 Waitress
10 Vikings
9 sausage
7 t
7 Wife
7 Spam
7 Man
7 I
6 it
5 the
5 got
4 you
4 with
4 in
4 have
4 don
4 beans
4 Wonderful
4 Well
3 without
3 up
3 s
3 You
3 Shut
2 there
2 then
2 spa
2 much
2 mean
2 like
2 her
2 do
2 dear
2 can

==>> examples/skit.tfidf <<==
131.697964 spam
18.021827 egg
18.021827 a
15.249238 Lovely
13.862944 bacon
13.862944 Waitress
13.862944 Vikings
13.169796 and
12.476649 sausage
9.704061 t
9.704061 Wife
9.704061 Man
9.704061 I
8.317766 it
6.931472 got
5.545177 you
5.545177 with
5.545177 in
5.545177 have
5.545177 don
5.545177 beans
5.545177 Wonderful
5.545177 Well
4.852030 Spam
4.158883 without
4.158883 s
4.158883 You
4.158883 Shut
2.772589 there
2.772589 then
2.772589 spa
2.772589 much
2.772589 mean
2.772589 like
2.772589 her
2.772589 do
2.772589 dear
2.772589 can
2.772589 baked
2.772589 as

Term Vectors vs TF-IDF Vectors

==>> examples/spam.term <<==
1 Spam

==>> examples/spam.tfidf <<==
0.693147 Spam

Cosine Similarity

$$\cos(x, y) = \frac{x \cdot y}{|x||y|}$$

Between vectors x and y

Cosine Similarity

$$\cos(song, poem) = \frac{2\times1 + 2\times1}{\sqrt{41}\sqrt{35}} = 0.105593$$

==>> examples/poem.term <<==

3 and
2 the
2 fox
2 dog
2 brown
2 The
1 white
1 up
1 sleeping
1 said
1 over
1 nimble
1 looked
1 jumped
1 black
1 awoke
1 at
1 Woof

==>> examples/song.term <<==

5 ding
2 da
1 the
1 say
1 fox
1 does
1 What
1 Ding

Document Similarity

$$s_h = \cos(v_{tfidf}, e_h)$$ = "hamminess“

$$s_s = \cos(v_{tfidf}, e_s)$$ = "spamminess"

Threshold

$$s_h s_s \geq t \Rightarrow \text{"ham"}$$

Where

$s_h = \cos(v_{tfidf}, e_h)$ = "hamminess"

$s_s = \cos(v_{tfidf}, e_s)$ = "spamminess"

Scenarios

Document Frequency

tf-idf vectors compared to the document frequency vector

Average Term Frequency

tf-idf vectors compared average of term vectors

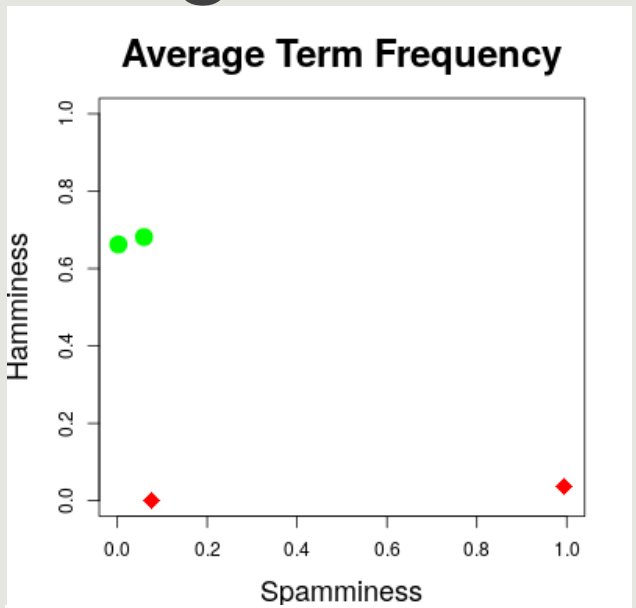
Top-10

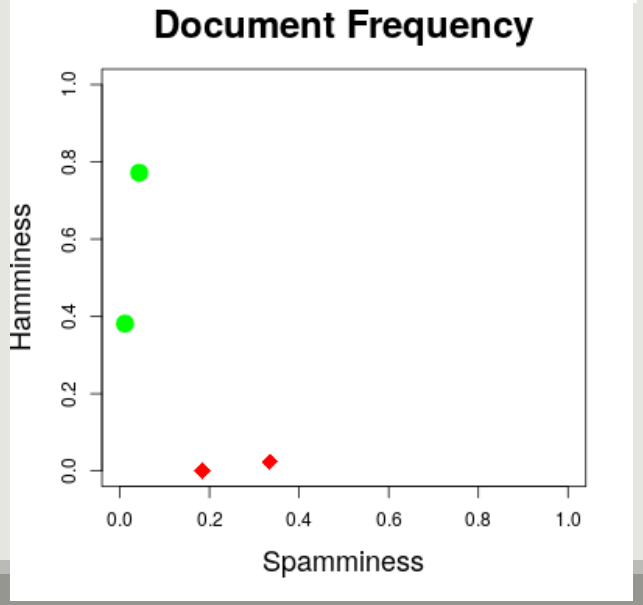
tf-idf vectors truncated to the top-ten scoring words in the document

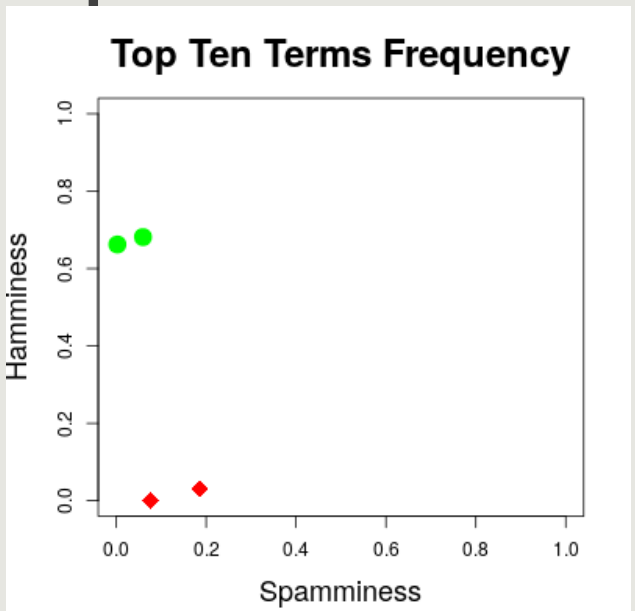
Average TF-IDF

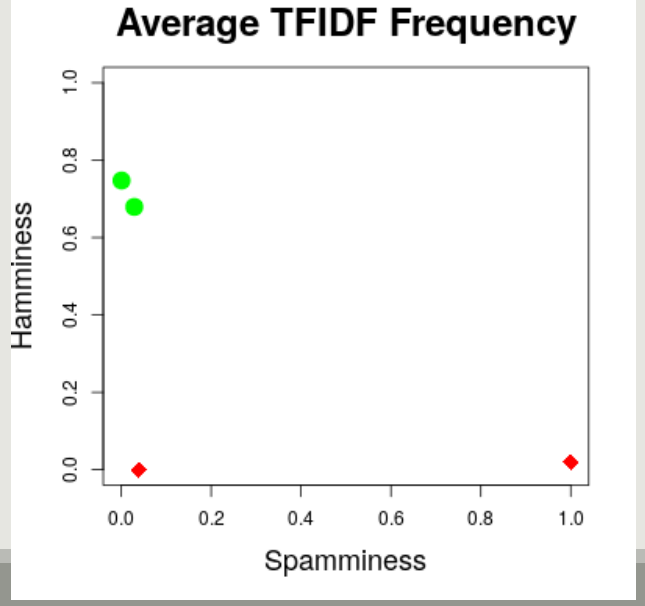
tf-idf vectors compared to the average of tf-idf vectors

Discriminating Between Ham & Spam

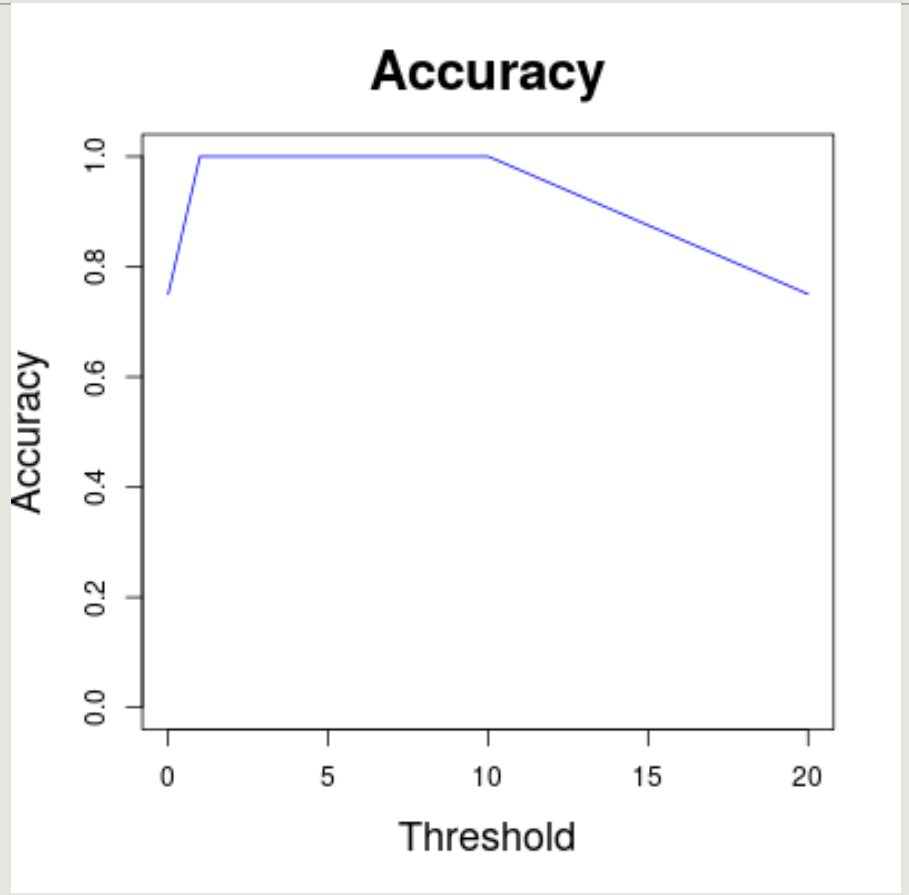








Accuracy



Accuracy

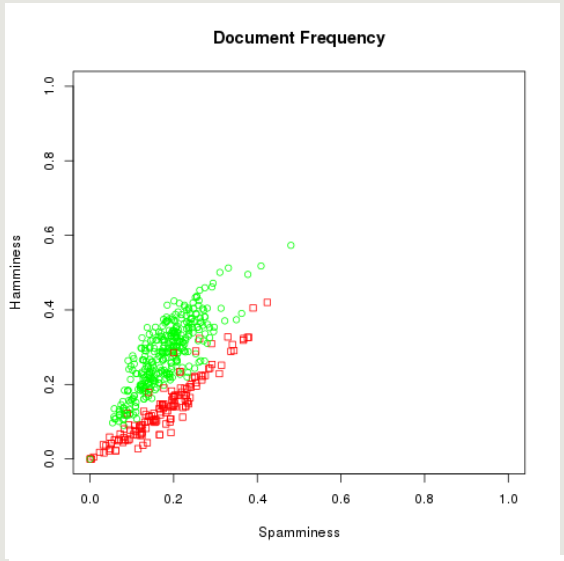
$$A(t) = \frac{m_{00}(t) + m_{11}(t)}{m_{00}(t) + m_{01}(t) + m_{10}(t) + m_{11}(t)}$$

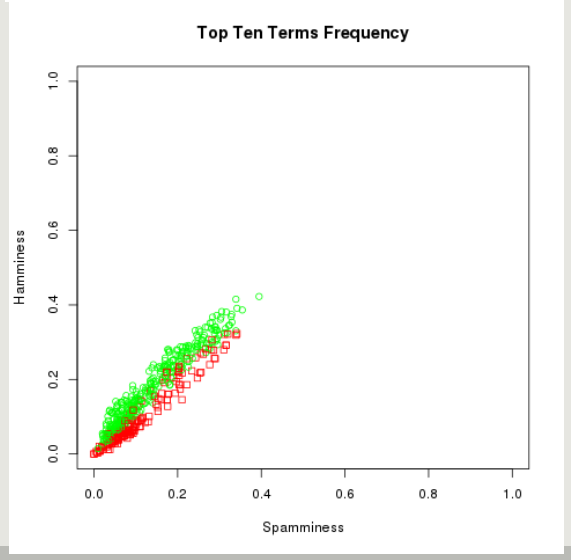
where
$m_{ij}(t)$ is the number of messages actually in class i and identified as class j.

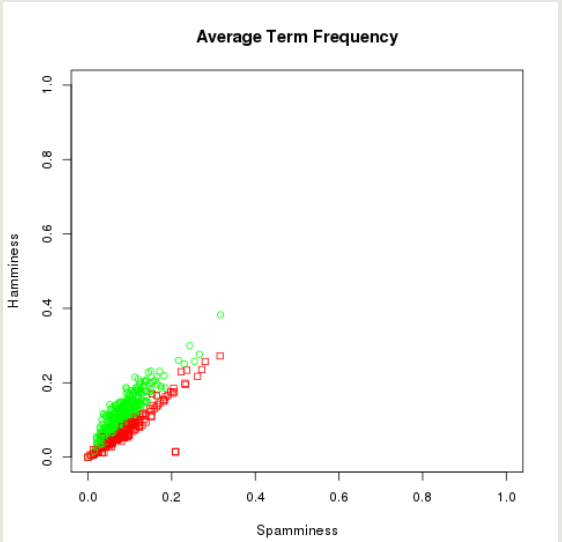
		Predicted Class	
		Spam	Ham
Actual Class	Spam	$m_{oo}(t)$	$m_{01}(t)$
	Ham	$m_{10}(t)$	$m_{11}(t)$

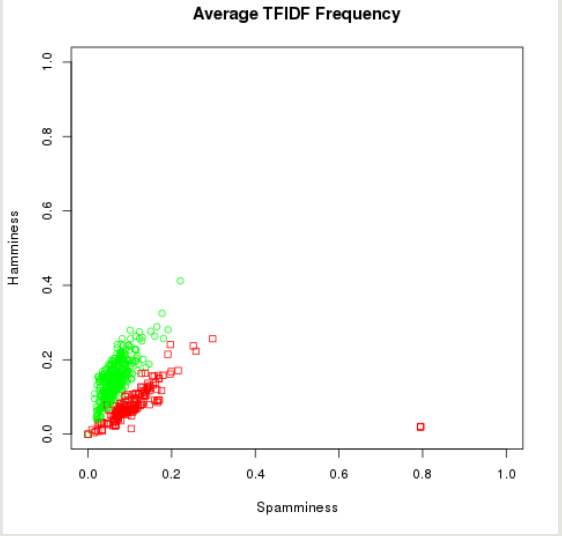
Note
i=j implies correct classification
i≠j implies incorrect classification

Results

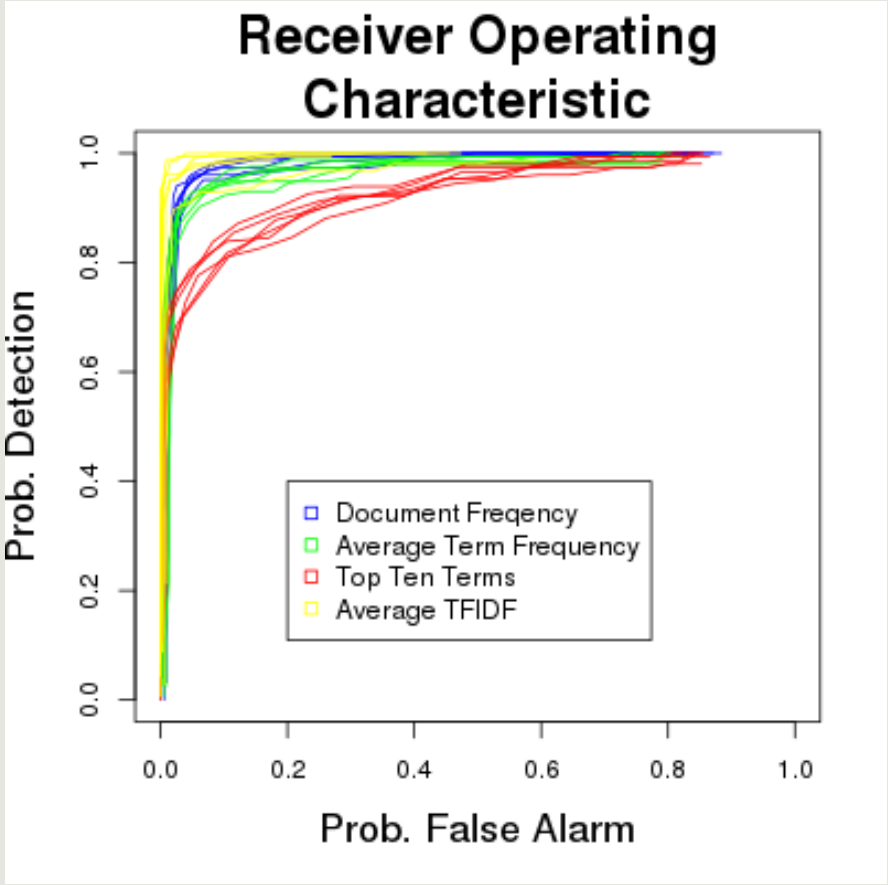

Document Frequency
Hamminess
Spamminess
0.0
0.2
0.4
0.6
0.8
1.0


Top Ten Terms Frequency
Hamminess
Spamminess
0.0
0.2
0.4
0.6
0.8
1.0


Average Term Frequency
Hamminess
Spamminess
0.0
0.2
0.4
0.6
0.8
1.0


Average TFIDF Frequency
Hamminess
Spamminess
0.0
0.2
0.4
0.6
0.8
1.0

Receiver Operating Characteristics

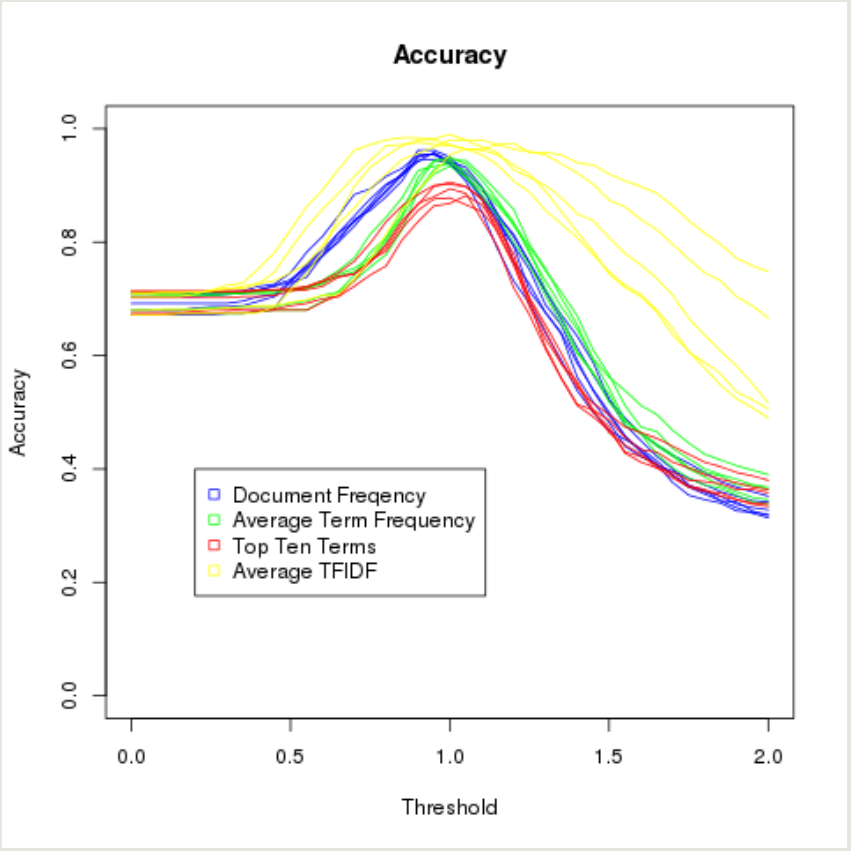


Receiver Operating Characteristics

$$P_D(t) = \frac{m_{00}(t)}{m_{00}(t) + m_{01}(t)}$$

$$P_{FA}(t) = \frac{m_{10}(t)}{m_{10}(t) + m_{11}(t)}$$

Accuracy


Accuracy
Accuracy
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.5
1.0
1.5
2.0
Threshold
Document Freqency
Average Term Frequency
Top Ten Terms
Average TFIDF

Amateurs vs Pros

How does a commercial spam filter stack up using the same dataset?

- Postfix Server
- Dovecot as mail delivery agent
- Spam Assassin as the filter

Accuracy: 93.8%

Average Maximum Accuracy:

Document Similarity – 95.53%

Average Term Similarity – 94.23%

Top-Ten Term Similarity – 89.2%

Average TFIDF Similarity – 95.8%