On Attacking Statistical Spam Filters

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Paper review by Deepak Chinavle

What is Spam

- unsolicited commercial email from someone without a pre-existing business relationship or, in practice, whatever email you don’t want
- Types
  - unsolicited mail containing adult content
  - unsolicited financial offers, etc.
  - unsolicited political or religious mail
  - consider unsolicited commercial email to be spam, even if it came from a sender with whom they’ve “already done business

Bayesian Classifier for Spam Detection (not part of the paper)

- Given – training set of messages with label as spam or no-spam.
- Message is broken into tokens
- Each token's probability given a class is calculated from from it's frequency in that class from the training data set.
- From Bayes theorem, we calculate the class having higher probability.
- Class with higher probability is considered to be the class of the message.

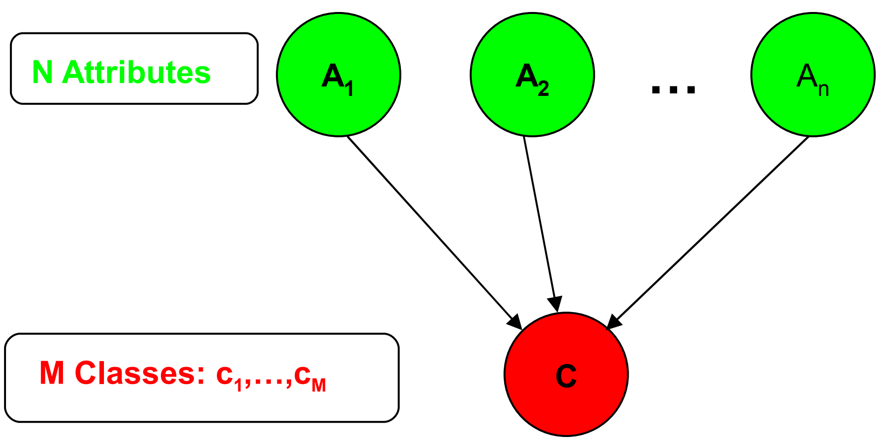
The probabilistic model of Naive Bayes classifier (not part of the paper)

- Assume attributes are independent for a given class
  - A **naïve** assumption

$P(c_k \mid a_1, a_2, \dots, a_n) = ?$ **for every k**

$$P(c_k \mid a_1, a_2, \dots, a_n) = \frac{P(c_k) * \boxed{P(a_1, a_2, \dots, a_n \mid c_k)}}{P(a_1, a_2, \dots, a_n)}$$

$$\boxed{P(a_1, a_2, \dots, a_n \mid c_k) = P(a_1 \mid c_k) * P(a_2 \mid c_k) * \dots * P(a_n \mid c_k)}$$



$P(C = c_1), \dots, P(C = c_k)$: known

Each $P(a_i \mid c_k)$ is easily to compute based on counts

Document classification using Naïve Bayes classifier (not part of the paper)

- The word "discount" appears really often in spam emails (i.e. 99%), but seldom see it in non-spam email (i.e. 1%)

- We need to train the *spam filter* these probabilities
  - We manually indicate whether a new email is spam or not → training set
  - P(discount | spam) = 0.99 , P(University | spam) = 0.05 , …

- After training, the *spam filter* has P(word | spam), for every word

- Filtering a new email consisting of *n* words

$$P(spam \mid words) = \frac{P(words \mid spam) * P(spam)}{P(words)} = \frac{\boxed{P(word_1 \mid spam) * \ldots * P(word_n \mid spam)} * P(spam)}{P(words)}$$

For example "If P(spam | words) > 0.95" → "Junk folder"

Ref: Wikipedia

Content-based Spam Filtering (Quick example of basic attack)

1. From: spammer@example.com
Cheap mortgage now!!!

Feature Weights

2. cheap = 1.0
mortgage = 1.5

3. Total score = 2.5 > 1.0 (threshold)

Spam

Good Word Attacks (quick example of basic attack)

1. From: spammer@example.com
Cheap mortgage now!!!

Corvallis OSU

Feature Weights

2. cheap = 1.0
mortgage = 1.5
Corvallis = -1.0
OSU = -1.0

3. Total score = 0.5 < 1.0 (threshold)

OK

Breaking filters – Attack types

- Tokenization :- Exploit the way features are extracted from messages ex. Putting extra spaces in words.
- Obfuscation :- obscure message contents using encoding ex. URL encoding.
- Weak statistical :- good word attacks with random words.
- Strong statistical :- good word attacks with educated guess of good words to use.

Breaking filters – Challenges faced by both the players

- Developers
  - Need to build accurate filters and at the same time consider possibility of attacks
  - Which training set to use ? This turns out to be very crucial in long run of the filter.
  - What if the training set used itself is erroneous ? This calls for trouble.
  - Lot of spam collections available publicly, what about ham collections ?
  - System wide Vs end user wise configuration of the filter.

Breaking filters – Challenges faced by both the players

- Spammers
  - Need to preserve the original message while still trying to make it look ham.
  - maximize audience size while keeping effort minimal.
  - Key is to find out the filter configuration or to find vulnerabilities in the training set of the filter.

Attack Methodology

- Simple attacks won't work, need to design advanced attacks.
- Designing repeatable attacks (which are missed and not caught subsequently)
- Getting feedback Ex. Yahoo mail.

Example Attack

- Spam example

  1 From: Kelsey Stone <bouhooh@entitlement.com>

  2 Subject: Erase hidden Spies or Trojan Horses from your computer

  3 Erase E-Spyware from your computer

  4 http://boozofoof.spywiper.biz

- To transform this spam, following two methods are used
  - Dictionary attack (random word from dictionary)
  - Common word attack (random words again but which are chosen from list of good words)

- The attacks were carried out against two types of filters
  - SpamBayes version 1.0a9
  - CRM114 release 20040312

- Data: 3000 spams from SpamArchive.org and 3000 hams from SpamAssassin

- n random words were added (n = 10, 25, 50, 100, 200, 300, 400) and for each n experiment repeated 1000 times

Results - SpamBayes

Words	Spam	Ham	Unsure
10	999 / 1000	0 / 0	1 / 0
25	937 / 772	0 / 0	63 / 228
50	484 / 16	0 / 0	516 / 984
100	22 / 0	0 / 943	978 / 57
200	0 / 0	269 / 1000	731 / 0
300	0 / 0	829 / 1000	171 / 0
400	0 / 0	858 / 1000	142 / 0

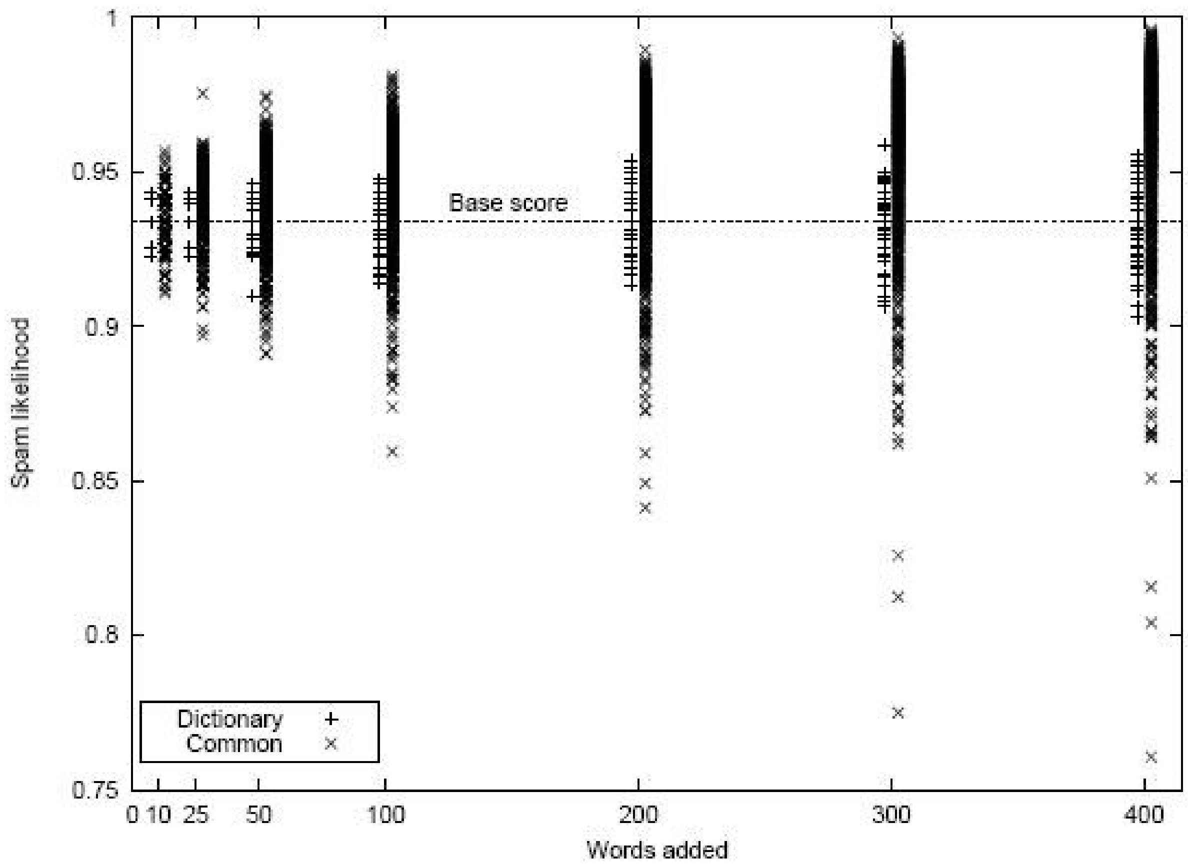
(a) Before training.

Words	Spam	Ham	Unsure
10	1000 / 1000	0 / 0	0 / 0
25	967 / 872	0 / 0	33 / 125
50	601 / 56	0 / 0	399 / 944
100	37 / 0	0 / 735	963 / 265
200	0 / 0	78 / 1000	922 / 0
300	0 / 0	625 / 1000	375 / 0
400	0 / 0	695 / 1000	305 / 0

(b) After training on source picospam.

More susceptible to good word attacks and when number of words added becomes more then 100.

Results - CRM114



- More robust to dictionary and good word attacks.
- Dictionary word attacks more confined (less spread out) compared to common work attacks.
- Bulk of common word attacks shift towards high spam score may be because of sequences of “bad” words.

Conclusion

- Most attacks still don't attack the statistical nature of the filter.
- Spammers modify spam only if they gain more then the effort required.
- Even the good word attacks failed with one of the filters tested.
- Effect of retraining with against attack messaged need to be studied.
- Need to look beyond statistical attacks like application of natural language processing to spam.
- Spam is a never ending game between spammers and anti-spammers.

Some comments

- Cross fold validation not done before giving the results (or at least not mentioned in the paper). Usually results are given after 10- fold cross validation.
- Only two filters used for testing, would have been interesting if filters using different algorithms for document classification were used like naïve bayes, support vector machines, maximum entropy etc.
- Spam and ham emails used were taken only form one source. By taking test data from various sources better models the real world situation.
- The results will be more interesting if the proportion of spam and ham emails is varied for training. For example, instead of using 50-50% ratio, use something like 60-40%. This tells us the bias used by the filter.