Filtering Spam by Using Factors Hyperbolic Trees

Hailong Hou*, Yan Chen, Raheem Beyah, Yan-Qing Zhang
Department of Computer science
Georgia State University
P.O. Box 3994
Atlanta, GA 30302-3994, USA
*Contact author: hhou2@student.gsu.edu, ychen44@student.gsu.edu, rbeyah@cs.gsu.edu, yzhang@cs.gsu.edu

***Abstract*— Most of current anti-spam techniques, like the Bayesian anti-spam algorithm, primarily use lexical matching for filtering unsolicited bulk E-mails (UBE) and unsolicited commercial E-mails (UCE). However, precision of spam filtering is usually low when the lexical matching algorithms are used in real dynamic environments. For example, an E-mail of refrigerator advertisements is useful for most families, but it is useless for Eskimos. The lexical matching anti-spam algorithms cannot distinguish such processed E-mails that are junk to most people but are useful for others. We propose a Factors Hyperbolic Tree (FHT) based algorithm that, unlike the lexical matching algorithms, handles spam filtering in a dynamic environment by considering various relevant factors. The new Ranked Term Frequency (RTF) algorithm is proposed to extract indicators from E-mails that are related to environmental factors. Type-1 and Type-2 fuzzy logic systems are used to evaluate the indicators and determine whether E-mails are spam based on the environmental factors. Additionally, weights of factors in a FHT database are continuously updated according to dynamic conditional factors in a real environment. Simulation results show that the FHT algorithm filters out spam with high precision. Furthermore, the FHT algorithm is more efficient than other methods when it filters E-mails with complex influencing factors. The main contribution of this paper is that the FHT based algorithm can filter E-mails based on influencing factors instead of matched words to allow dynamic filtering of spam E-mails.**

Index Terms—spam; Bayesian algorithm; Ranked Term Frequency; fuzzy logic; factors hyperbolic trees.

I. Introduction

E-mail spam, also known as "bulk E-mail" or "junk E-mail”, has existed since the beginning of the Internet. The basic idea is that nearly identical messages are sent to numerous recipients by E-mail [1]. Spam can be described as unsolicited bulk E-mail (UBE) where *unsolicited* means that the recipient has not granted verifiable permission for the message to be sent and *bulk* means that the message is sent as part of a larger collection of messages, all having substantively identical content [2]. Unsolicited commercial E-mail (UCE) is the most common type of spam. UCE seeks to engage a potential consumer in order to exchange goods or services for money. Spam has become a significant problem and has grown to about 90 billion messages a day. Botnets and virus infected computers, account for about 80% of spam. Symantec [3] recently reported that they detected a 30% increase in phishing attempts from Jan 2006 to the end of the year. Statistics from the Distributed Checksum Clearinghouse (DCC) project [4] show that 51% of the E-mail messages checked by the DCC network in 2007 were likely to be bulk E-mail. About 85.65% threats were checked by MX Logic [5] came from spammers in Jan 2008. Laws to prevent certain types of spam have been enacted in many countries. For example, in the United States, spam is legally permissible according to the CAN-SPAM Act of 2003 provided it follows certain criteria; the European Union (EU) Directive on Privacy and Electronic Communications (2002/58/EC) provides that the EU member states shall take appropriate measures to ensure that unsolicited communications are prevented; also, in Australia, the relevant legislation is the Spam Act 2003 which covers certain types of E-mail and phone spam (which took effect on 11 April 2004). However, good-faith compliance with anti-spam laws is not always enough to keep a legitimate Internet or wireless marketer out of trouble because of the considerable cost to analyze the relevance between the spam messages and the law. This is heightened by the lack of concern of the laws by malicious spammers. We propose the use of the FHT and RTF algorithms that allow spam to be filtered dynamically as some bulk E-mail may be of interest to certain users. This technique assists the users as they will receive E-mail that matches their interests and unsolicited E-mail will be filtered.

The rest of this paper is organized as follows. Section II presents the related work. Section III introduces the FHT and shows how it works. Section IV describes mining data by the RTF algorithm. Section V depicts computation model based on the FHT and fuzzy logic. Section VI evaluates the performance of our model by comparing simulation results of the Bayesian algorithm and the FHT algorithm. Section VII concludes our work and presents future work.

II. Related work

Some popular methods for filtering spam have been deployed by Internet Service Providers (ISPs), like DNS-based blackhole lists (DNSBL), greylisting, spamtraps, enforcing technical requirements, checksumming systems to detect bulk E-mail, and by putting some sort of cost on the sender via a Proof-of-work system or a micropayment. However, each method has strengths and weaknesses and each is controversial due to its weaknesses. Thus, new methods have been developed to replace many of the aforementioned techniques for handling E-mail spam. Among these methods,

978-1-4244-2324-8/08/$25.00 © 2008 IEEE.

This full text paper was peer reviewed at the direction of IEEE Communications Society subject matter experts for publication in the IEEE "GLOBECOM" 2008 proceedings.

Bayesian filtering is probably one of the most widely used to identify spam E-mail, and is therefore integrated in many popular E-mail clients [6, 7]. Algorithms based on Bayes theorem extract keywords and other indicators from E-mail messages, and determine whether the messages are spam using statistical or heuristic schemes. However, spammers nowadays are using sophisticated techniques to trick content based filters by clever manipulation of the spam content [8]. A learning approach to spam sender detection based on features extracted from social networks constructed from E-mail exchange logs was proposed in [9]. The approach extracts several features from E-mail social networks for each sender. Based on these features, a supervised model is used to learn the behaviors of spammers and legitimate senders and then assign a legitimacy score to each sender. Scores are made available in a database where online mitigation methods can query for the score of a particular sender. In [10], the method Spam Filtering Model Based on Support Vector Machine (SVM) is proposed. A SVM is a new learning algorithm which has some attractive features such as eliminating the need for feature selections, which enables easier spam classification. Producing a high dimensional feature space is vital for getting better performance from SVM for filtering spam. However, neither Social Network nor SVM considers dynamic factors in a real environment. The changes of factors indubitably alter E-mail's property so that a useful E-mail may become useless.

In this paper, we propose the FHT based fuzzy decision algorithm for spam detection, which considers dynamic factors and does not require the maintenance of blacklists and white lists. Specifically, the proposed framework extracts several dynamic features from E-mail. A FHT model is used to learn and periodically update the factors' values of features relied on these dynamic features. The fuzzy logic is then used to compute the score of the E-mail. The score is compared to a criterion score λ. If the score is greater than λ, it is considered useful E-mail; otherwise, it is considered spam.

III. FACTORS HYPERBOLIC TREE

A decision is made normally by considering a certain amount of factors along with specific reasoning. For example, determining whether air conditioning (AC) is useful depends on two factors: temperature and zone. Considering another example, the distance required and potential terrain would determine what kind of vehicle needed for an expedition. Thus, an object's (e.g., AC use, vehicle type) value can be influenced by certain types of factors (e.g., temperature, distance, etc.), with the factors relevant at specific times. To express the relationship among decisions, factors, and objects, we propose a FHT which can describe every object of interest with related factors, and the values of factors can be constantly updated, adapting over time.

To implement a FHT based system, a large database needs be formed with objects, factors, and the relationships between them. The records in the database include all the information around us such as products, weather, human, earth, society, country, culture, zone etc. In fact, the relationship between objects and factors is very easily digitized by fuzzy logic systems so that they may be computed by other methods. Moreover, because a database will be used to depict the FHT system, the data structure and the method for obtaining these data are important issues that will be discussed later in the paper.

A. *Classification of factors*

The factors can be classified into two categories: normal and abnormal.

Normal factors: factors that change with time naturally or periodically, such as weather, age, etc.

Abnormal factors: factors that happen suddenly and affect the object immediately, such as disasters and popularity degree, etc.

B. *Expression of normal factors by fuzzy logic system*

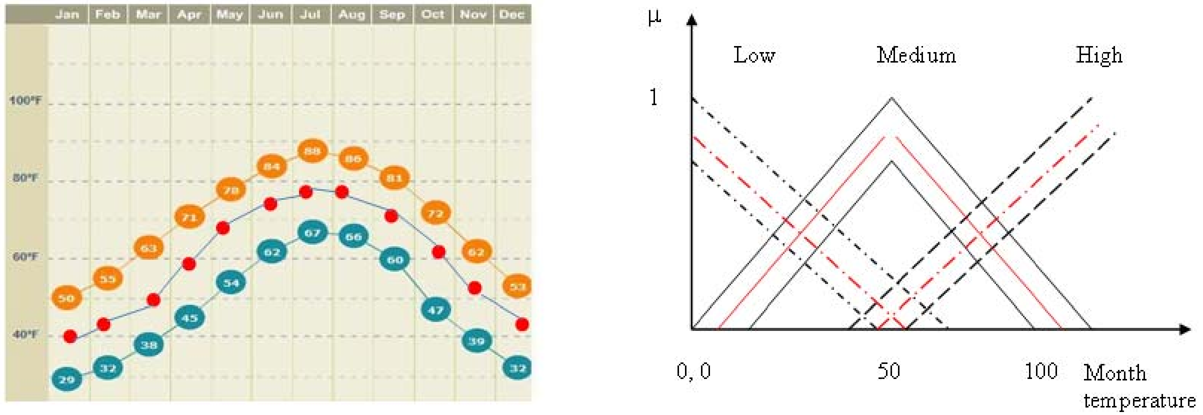
To simplify conditional factors, normal factors are standardized to a number ranging between 0 and 1 by a type-2 fuzzy set, which achieves a more accurate expression. Type-2 fuzzy sets are an extension of type-1 fuzzy sets in which uncertainty is represented by an additional dimension. The Type-2 fuzzy sets are used to normalize factors because: (1) the variation of normal factors obey natural rules, which means the value of normal factor at certain time must fluctuate in a range; and (2) a range of values will be generated if periodic values of normal factors are selected.

Figure 1(a) shows the temperature curve of one year. The value of every month fluctuates in a range (the blue dots indicate lowest temperature, orange dots indicate highest temperature, and the red dots indicate average value). Thus, the type-2 membership function of a specific month's temperature is given in figure 1(b) where each uncertainty temperature value is represented by an additional dimension (the red line indicates the defuzzied membership function).

Overall, in a FHT based system, all the initial weights between factors and object are set to 0; type-2 fuzzy logic is used to compute the weights between normal factors and objects w_{ni} (*i* is the index normal factor) .

C. *Data structure of FHT*

Every object has its own attributes, which are the influencing factors in the FHT algorithm. The database plays a crucial role in the FHT algorithm and stores all the relationships and objects, which should be represented precisely by the data structure of records in the database. In this paper, the FHT is proposed to express our algorithm. Figure 2(a) depicts the data structure of the FHT. In the figure, the decision node is the root and it will organize sub trees; every other node is composed of objects and their related factors. The relationship between object and factors is shown in figure 2(b), specifically, objects can share more than one factors in order to avoid factor redundancy. In the FHT, the object is represented by a factor set, and the values of factor in the set will be updated corresponding to changing environmental factors.



(a) Temperature line

(b) Fuzzy 2 membership function

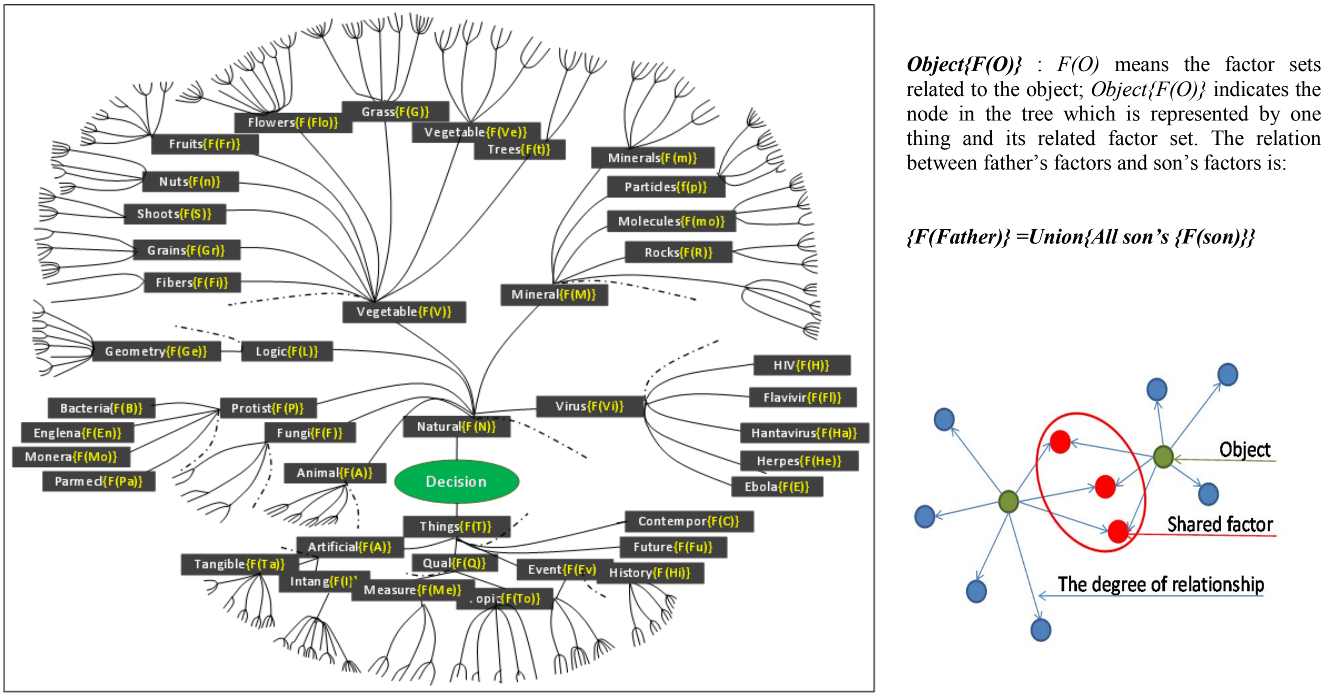
Fig 1. Type-2 fuzzy logic membership function.

D. *Data mining of influencing factors*

To avoid confusion of the relationship between object and factors, relationships must be predefined and initialized in the database.

Once an event triggers input, the weights of the FHT will be updated. However, obtaining data corresponding to the factors is challenging because the database will be large. Data mining for such a huge database is very difficult and optimal algorithms must be used. The Internet is a good way to obtain information to populate the database, although not all websites provide correct information.

Accordingly, authority websites are the best options for extracting information to populate the database. For instance, weather information can be obtained from weather.com; information about the law can be mined from government websites; sports information can be obtained from TNT or ESPN websites, etc. An efficient classification algorithm for distinguishing authority websites and non-authority websites must be designed to facilitate the website selecting process.



Object{F(O)} : *F(O)* means the factor sets related to the object; *Object{F(O)}* indicates the node in the tree which is represented by one thing and its related factor set. The relation between father's factors and son's factors is:

{F(Father)} =Union{All son's {F(son)}}

(a) Factors hyperbolic tree

(b) Relationship between object and factors

Fig 2. Structure of the Factors Hyperbolic Tree.

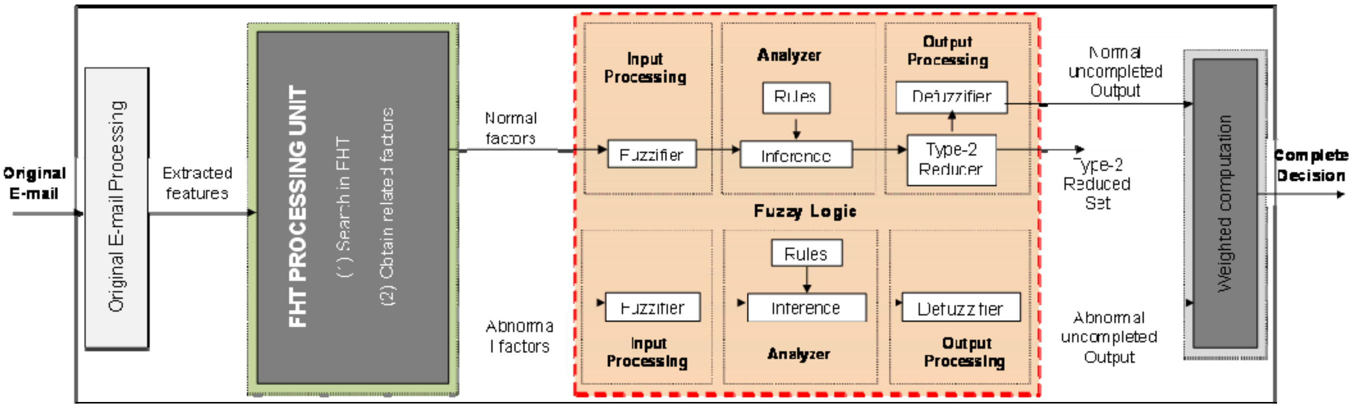


Fig 3. Computation model based on Factors Hyperbolic Tree and fuzzy logic.

IV. RANKED TERM FREQUENCY(RTF)

Key words are used to extract the features of E-mails because words are basic units of languages. RTF is proposed in this section to perform the extraction.

The Term Frequency Inverse Document Frequency (TF-IDF) weight is an algorithm often used in information retrieval and text mining. This weight is a statistical measure used to evaluate how important a word is for a document in a collection or corpus. We propose a RTF algorithm to mine nouns in the document, while the IDF concept is ignored because more accurate features are expected to be obtained only from the single E-mail, but not the entire corpus.

The RTF in the given document is simply the ranked number of times that a given term appears in that document. This count is usually normalized to prevent bias towards longer documents (which may have a higher term frequency regardless of the actual importance of that term in the document) to give a measure of the importance of the term t_i within the particular document d_j.

$$tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \qquad \textit{(1)}$$

Where $n_{i,j}$ is the number of occurrences of the considered term in document d_j, and the denominator is the number of occurrences of all terms in document d_j.

The RTF result will be shown after all $\mathrm{tf}_{i,j}$ have been ranked. A high weight in RTF is reached by a high term frequency (in the given document); hence the weights tend to filter out important noun terms in d_i. To catch the main meaning of documents, we select the first m (3≤m≤8) nouns with the highest weights to process in the FHT algorithm.

V. DECISION COMPUTATION MODEL

The decision is the result of analyzing activities of conditional factors, which will be obtained by searching in FHT. To make a decision, a computation model based on FHT and fuzzy logic is shown in figure 3. The algorithm is described as:

```
FHT based Algorithm
 Start:
     Step 1. Extract features by using RTF and input to FHT .
     Step 2. Search related factors to the features in FHT and
     output factors to Fuzzy Logic Unit in two types: normal
     factors and abnormal factors.
     Step 3. Fuzzy Logic Unit will compute normal factors to
     obtain an incomplete result; then abnormal factors will be
     processed to obtain another incomplete result.
     Step 4. Weighted Computation Unit will calculate two
     incomplete results with predefined weights to obtain a final
     decision.
 End
```

During the step 3, factorial analysis is applied to optimally setting up a rulebase. That is, the factorial analysis algorithm can be used to obtain the affection degree of normal factors by analyzing historical data. The values of these degrees are represented by 1*n matrix:

$$\boldsymbol{Degree= \{d_1, d_2\ldots\ d_n\}}$$

Then the rules can be computed by equation (2):

$$\boldsymbol{Rule_i = 1-(1-a_1{*}d_1)(\ 1-a_2{*}d_2)\ \ldots\ldots(\ 1-a_n{*}d_n)} \qquad \textbf{(2)}$$

(α: the parameter computed from membership function.)

Moreover, for the abnormal factors, the type-1 fuzzy system is applied to compute an incomplete output. Finally, equation (3) is used in step 4 to compute the complete output.

$$\boldsymbol{\lambda = w_1{*}output_{-normal}+w_2{*}output_{-abnormal}} \qquad \textbf{(3)}$$

$w_1$and w_2 are predefined weights.

To identify the spam E-mail by FHT, we test the final output λ compared to prior known spam and get the criterion value by averaging λs. Then E-mail is distinguished by the FHT - if the output is smaller than λ, it is considered spam; otherwise, it is considered not.

VI. PERFORMANCE AND EVALUATION

In this section, we set up experiments to evaluate the performance of the FHT based algorithm and compare it to Bayesian algorithm.

A. *Experiment setup*

Experiment environment: Windows XP professional

Development tools: VS2005, Microsoft Access 2003.

B. *Results and evaluation*

The E-mail filtering result of the FHT depends on the weights of normal and abnormal factors. Different ratios of

978-1-4244-2324-8/08/$25.00 © 2008 IEEE.

these two weights yield different crisp outputs λ. In our experiment, the ratio is set to a fixed value 1 so that we can test several groups of E-mails conveniently. Furthermore, the criterion λ = 0.55 is obtained by averaging all outputs after 100 spam were entered into the FHT based software. Therefore, if the final result of FHT system is greater than 0.55, it should be white E-mail; otherwise, it is spam.

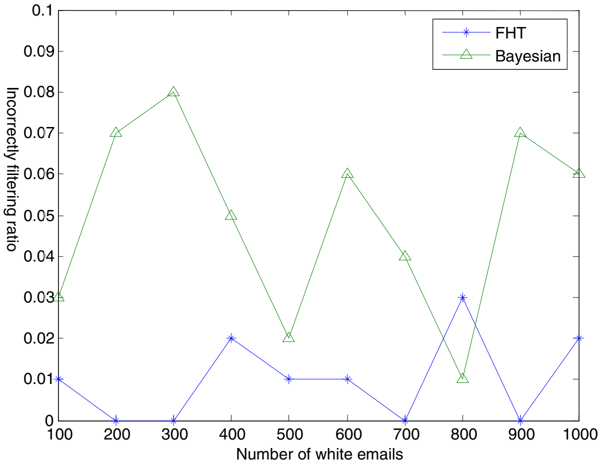


Fig 4. Incorrect classification of Spams.

Two different groups of E-mails were analyzed in the experiment: 1000 spam and 1000 white E-mails. For each group, the 1000 E-mails were divided into 10 sub groups with same size and were filtered by the FHT algorithm and the Bayesian algorithm.

Figure 4 shows the incorrectly filtered result of the FHT algorithm and Bayesian algorithm where E-mails are 100% white E-mails. The FHT algorithm expresses a lower incorrect filtering percentage than the Bayesian algorithm, which indicates that more white E-mails were classified into spam by the Bayesian algorithm than by the FHT algorithm.

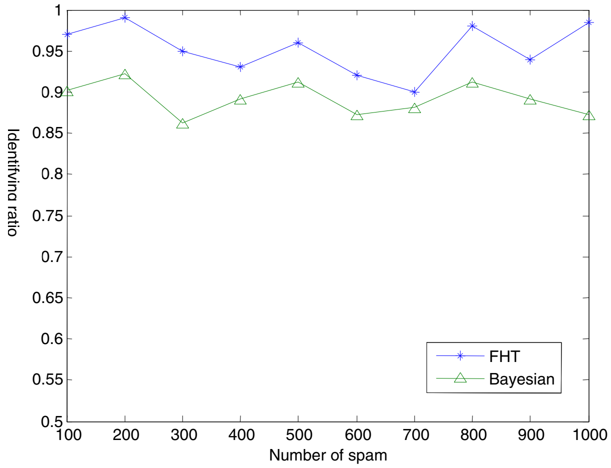


Fig 5. Accurate classification of Spams.

Figure 5 shows the ratio of accurate classification of spam of both algorithms. The FHT algorithm also presents a higher filtering percentage than the Bayesian algorithm, which indicates that FHT algorithm is more efficient for filtering spam than the Bayesian algorithm in our experiment.

VII. Conclusion

In this paper, we proposed the FHT algorithm which filters E-mail by conditional factors instead of word matching. The results of the experiments show this technique can efficiently filter E-mail, and also improve the filtering degree of precision. Experimentally, FHT is a feasible technique to apply to anti-spam filters, especially in the case where information related to current environment factors is not accurately represented by lexical matching algorithms.

In our future work, more spam will be added into our experiment to better compare the filtering efficiency of the FHT and the Bayesian algorithm. We will also complete the factors hyperbolic trees and build a complete system. Then we will apply it to semantic analysis and decision supporting field.

Acknowledgement: We would like to thank Yuchun Tang for providing the spam set to test our algorithm.

References

[1] Wikipedia. Spam (electronic), Jan. 2007. Retrieved: Jan. 2007 http://en.wikipedia.org/wiki/E-mail_spam

[2] Spamhaus. The definition of spam, Jan. 2007. Retrieved: Jan 2007 http://www.spamhaus.org/definition.html.

[3] ZuCFikar Ramzan, Candid W¨uest, “Phishing Attacks: Analyzing Trends in 2006”, CEAS 2007 Fourth Conference on E-mail and AntiSpam, August 23, 2007,

[4] http://www.rhyolite.com/anti-spam/dcc/graphs/?BIG=1&resol=2y#graph1

[5] http://www.mxlogic.com/threat_center/

[6] Sahami, S. Dumais, D. Heckerman, E. Horvitz (1998). “A Bayesian approach to filtering junk E-mail.” AAAI'98 Workshop on Learning for Text Categorization.

[7] Graham, Paul (2002). “A Plan for Spam.”

[8] J. Graham-Cumming. The spammers’ compendium, Jun.2006. Retrieved: Jun. 2006 http://www.jgc.org/tsc/.

[9] HoYu Lam, DitYan Yeung, “a learning approach to spam sender detection based on social networks”, CEAS 2007 Fourth Conference on E-mail and AntiSpam, August 23, 2007,

[10] Islam,Md.R.;Chowdhury,M.U.;Wanlei Zhou. “An Innovative Spam Filtering Model Based on Support Vector Machine”, Proceedings of the 2005 International Conference on Computational Intelligence for Modelling, Control and Automation, and International Conference Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC’05)