Self-Organizing Maps in the Design of Anti-spam Filters
A Proposal based on Thematic Categories

Ylermi Cabrera-León[1], Patricio García Báez[2] and Carmen Paz Suárez-Araujo[3]
[1]*Universidad de Las Palmas de Gran Canaria (ULPGC), Canary Islands, Las Palmas de Gran Canaria, Spain*
[2]*Departamento de Ingeniería Informática y de Sistemas, Universidad de La Laguna, Canary Islands, San Cristóbal de La Laguna, Spain*
[3]*Instituto Universitario de Ciencias y Tecnologías Cibernéticas, ULPGC, Canary Islands, Las Palmas de Gran Canaria, Spain*

Keywords: Anti-spam, Spam, Ham, Artificial Neural Networks, Self-Organizing Maps (SOMs), Thematic Category, Term Frequency, Inverse Category or Class Frequency.

Abstract: Spam, or unsolicited messages sent massively, is one of the threats that affects email and other media. Its high volume generates substantial time and economic losses. A solution to this problem is presented: a hybrid anti-spam filter based on unsupervised Artificial Neural Networks (ANNs). It consists of two steps, preprocessing and processing, both based on different computation models: programmed and neural (using Kohonen SOM). This system has been optimized using, as a data corpus, ham from "Enron Email" and spam from two different sources: traditional (user's inbox) and spamtrap-honeypot. It has been proved that thematic categories can be found both in spam and ham words. 1260 system configurations were analyzed, comparing their quality and performance with the most used metrics. All of them achieved AUC > 0.90 and the best 204 AUC > 0.95, despite just using 13 attributes for the input vectors of the SOM, one for each thematic category. Results were similar to other researchers' over the same corpus, though they make use of different Machine Learning (ML) methods and a number of attributes several orders of magnitude greater. It was further tested with datasets not utilized during design, obtaining $0.77 <$ AUC < 0.96 with normalized data.

1 INTRODUCTION AND BACKGROUND

Nowadays, the use and importance of telecommunication has increased, primarily due to the rise of Information and Communications Technology (ICT). Among the multiple ways to make such communication, email can be highlighted, mainly because it has been used extensively for decades. Unfortunately, this popularity has brought with it the appearance of threats such as hoaxes, cyber-attacks, computer viruses and, to a greater extent, spam.

Although there are many different ways of defining the word "spam" (Subramaniam et al., 2010), in this paper spam refers to any message, mostly email but other media are affected too, sent massively without the recipients having requested or desired it. The characteristic of "massive" must be highlighted because, for years, both spam volume and overall spam rate (in other words, the quantity of spam and the percentage of spam relative to all messages, respectively) have been extremely high: in 2008 about 62 trillion unwanted messages (McAfee and ICF International, 2009) and less than 1 out of 10 emails could be considered as ham (legitimate or desired messages), fortunately improving to 4 out of 10 in 2014 (Statista, 2016).

Considering that, in most cases, their content is offensive or questionable - *e.g.* scam, phishing, illegal drugs, pornography, replicas… (Cabrera León et al., 2015) - it can be asserted that spam is a great scourge, creating quite substantial, both temporary and economic, losses: annually, American firms and consumers experience costs of near \$20 billion due to spam whereas spammers (people or companies that send spam) and spam-advertised firms collect \$200 million worldwide (Rao and Reiley, 2012). This occurs, mainly, due to sending spam being easy and having low cost, and that the recipient carries the bulk of the cost, in contrast to what happens with more traditional or off-line unsolicited marketing methods (Lieb, 2002).

There have been a wide variety of proposals to solve the problem of email spam detection so far, and

Cabrera-León, Y., Báez, P. and Suárez-Araujo, C.
Self-Organizing Maps in the Design of Anti-spam Filters - A Proposal based on Thematic Categories.
DOI: 10.5220/0006041400210032
In *Proceedings of the 8th International Joint Conference on Computational Intelligence (IJCCI 2016) - Volume 3: NCTA*, pages 21-32
ISBN: 978-989-758-201-1

therefore there is a huge proliferation of papers in this regard, as it will be discussed in Subsection 1.1. In this paper another solution to this problem is presented: a hybrid spam filtering system. It can be considered hybrid not only because its two main stages, preprocessing and processing, are based on different computing models - programmed and neural computation, respectively - but also because in the processing one the SOM, an unsupervised ANN, is followed by a non-neural supervised labeling part.

This system has been optimized using, as a data body, ham from "Enron Email" (Cohen, 2004) and spam from two different sources: obtained through traditional ways (user's inbox), or through spamtraps and honeypots. Its quality and performance have been analyzed on several different datasets with both Kohonen maps' most used quality measures, Mean Quantization Error (MQE) and Topographic Error (TE), and the most common performance metrics for classifiers such as Receiver Operating Characteristic (ROC) curves and AUC, among others.

The remainder of this paper is organized as follows. In Subsection 1.1 some of the numerous related works developed throughout the last decades are described. Through Section 2 the dataset and methods are explained. Section 3 shows the experimental results, followed by a discussion of them. Finally, the conclusions can be found in Section 4.

1.1 Related Works

As it is common to defensive and security systems in all areas (such as pathogenic diseases, armament, crime and predation), attackers (spammers in our case) are always one step ahead of defenders (Postini, Inc, 2004), therefore, in this area, the latter need to continuously face new threats and counter shortcomings, weaknesses and security flaws that the former have found, and later exploited, in anti-spam filters, other software or hardware (Spammer-X et al., 2004). Actually, this evolution explains the proliferation of multiple anti-spam techniques developed over the past decades (Wang et al., 2013).

Anti-spam methods may filter during any of the network hierarchical levels (mostly in the Application, Transport and Network layers of the TCP/IP model), *i.e.* in any of the steps involved with sending emails: in the sender device, *en route* and in the recipient. Alongside this manner, spam classifiers can also be grouped by these two ways: based on the design method, and based on the source of information. This section's scope has been reduced by just choosing user-level and administrator-level filters, whose techniques belong to any of the two previous groups, due to the fact that a user-level filtering system was developed here.

1.1.1 Based on the Design Method

There are two subgroups in this group, the latter being the most popular one:

Manual: easier to implement and more useful for email administrators. Despite their slow adaptation to changes in spam, whitelists and blacklists (respectively, lists of good and bad mail servers and ISPs) achieve just 1% of False Positives (FP) and False Negatives (FN) (Erickson et al., 2008). Furthermore, greylisting blocks email delivery temporarily with unrecognized senders, forcing resending, something not usually done by spammers (Kucherawy and Crocker, 2012). It reduces bandwidth waste at the expense of delaying ham too (Harris, 2003).

Based on ML: it is the largest subgroup (Guzella and Caminhas, 2009), where filters can be classified, at the same time, depending on the kind of architecture used (neural or not), or the quantity of human interaction required (supervised, semi-supervised or unsupervised). Making use of the latter, we could classify some anti-spam techniques as follows:

- Supervised: the most popular non-neural one is the Bayesian (Meyer and Whateley, 2004; Sahami et al., 1998), and, therefore, the most attacked by spammers through Bayesian poisoning (Lowd and Meek, 2005; Sprengers and Heskes, 2009; Wittel and Wu, 2004).
  (Metsis et al., 2006) must be described separately from other Bayesian filters because this paper's dataset was built from theirs and later compared with, as explained in Section 2. Their system performs very well (with average sensitivity of 0.9753 and specificity of 0.9726, and quite-near-perfection ROC curves) when 3000 attributes, the greatest number they tested, are used.
  Nowadays, other popular non-neural one, due to its performance, is the Support Vector Machine (SVM) (Drucker et al., 1999; Xie et al., 2009), which is greatly kernel-dependent (Chhabra et al., 2010) and offers better results when several are combined with a voting strategy (Blanco et al., 2007).
  On the other hand, for a long time, the perceptron, neural, has dominated as anti-spam (Kufandirimbwa and Gotora, 2012; Sculley et al., 2006) but the raise of Bayesian and SVM changed this.
  Other supervised ANN is the Learning Vector Quantization (LVQ) with whom (Chuan

et al., 2005) built a quite good filter (96.20% F-measure, 98.97% precision and 93.58% sensitivity) if enough iterations, at least 1500, were made.

- Unsupervised: because no previous data labeling process is needed, emails should occupy less disk space and be more recent (Cabrera León and Acosta Padrón, 2011). Among non-neural filters, we could find: the SpamCampaignAssassin (Qian et al., 2010) based on the detection of spam campaigns, one based on the alienness or searching of similarities in substrings (Narisawa et al., 2007), and other which uses suffix trees (Uemura et al., 2008).
On the other hand, there are also unsupervised neural techniques. The SOM Based Sequence Analysis (Luo and Zincir-Heywood, 2005) makes use of a double hierarchical-leveled SOM, where the second SOM is connected *a posteriori* with a k-Nearest Neighbors (k-NN) for categorization and sequence analysis.
(Vrusias and Golledge, 2009a; Vrusias and Golledge, 2009b) should be introduced separately from others due to their importance for this paper's research. They compare their SOM-based system with what they consider to be the best spam classifiers: the Multinomial Naïve Bayes Boolean, SVM and Boosted Decision Trees. It is a 10x10 SOM, sequentially trained for 1000 cycles, whose input vectors have 26 or 500 attributes, and where keywords were grouped (just when 26 attributes were used) and identified with Term Frequency·Inverse Document Frequency (TF·IDF) and weirdness. The main differences between their filters and this paper's are: larger SOM, smaller input vectors, other learning algorithm and a similar way of identifying keywords were used here, as described in Section 2. They also used datasets based on the "Enron-Spam" corpus from (Metsis et al., 2006).
- Semi-supervised: not many labeled data, due to high costs (Chapelle et al., 2006), with a lot of unlabeled examples. Regularized Discriminant Expectation-Maximization (Gao et al., 2009) combine both transductive (for labeling unlabeled data) with inductive (to make a model in order to classify new data) methods, obtaining 91.66% detection rate and 2.96% FP.
Learning with Local and Global Consistency, of which there is a variant proposed by (Pfahringer, 2006), obtains better results than with k-NN and SVM (Santos et al., 2011; Zhou et al., 2004).
Although SpamAssassin (Mason, 2009) is generally considered supervised, it can also utilize a semi-supervised learning rule (Xu et al., 2009). A semi-supervised version of SVM also exists, Transductive Support Vector Machine (Shunli and Qingshuang, 2010; Zhou et al., 2007), which sometimes performs worse than SVM as an anti-spam (Mojdeh and Cormack, 2008).

1.1.2 Based on the Source of Information

These methods, which use any part of an email *i.e.* envelope, header and body (P. Resnick, 2008), can also be subdivided in the next three assortments:

Content of the Email: the most prevalent way, either using the whole message (Cormack and Mojdeh, 2009) or just selecting parts with different methods: rules (Malathi, 2011), detecting anchored parts (Pitsillidis et al., 2010) or spam campaigns (Qian et al., 2010), signatures of messages (Kolcz et al., 2004), or combining several techniques, such as in SpamAssassin (Mason, 2009; The Apache SpamAssassin Project, 2014) and CRM114 (Yerazunis et al., 2010) popular anti-spam filters.

User Feedback: in spite of users being considered the most reliable and robust anti-spam method, specially against content obfuscation made by spammers, (Graham-Cumming, 2006) find out that they have up to 2% of classification errors, due to ham being very similar to spam - a.k.a. "hard ham" (Feroze et al., 2015) - or the presence of "grey cases" (Bruce, 2012), where categorization has an important subjective factor.

Information Relative to the System: they frequently take the advantage on the inherent difficulty for spammers to change the message headers and produce valid ones (Ramachandran and Feamster, 2006). This can be detected by checking fields of some network protocols, specially the ones which contain the sender's IP and port, and the local sending time (countless emails sent during sender's sleeping time may indicate that sender's device belongs to a botnet). On the other hand, they can also detect the presence or absence of specific characteristics in the message, such as only images (usually no text at all, hence called "image spam") (Fumera et al., 2006; Gao et al., 2009), and attached files, prone to be malware-infected.

Table 1: Original email corpus. In bold our datasets.

FOLDER	HAM–SPAM ORIGINS	NO. OF HAM-SPAM	HAM DATES	SPAM DATES
E1	**farmer-d – GP**	**3672 - 1500**	**12/1999 - 01/2002**	**12/2003 - 09/2005**
E2	**kaminski-v – SH**	**4361 - 1496**	**12/1999 - 05/2001**	**05/2001 - 07/2005**
E3	kitchen-l – BG	4012 - 1500	02/2001 - 02/2002	08/2004 - 07/2005
E4	**williams-w3 – GP**	**1500 - 4500**	**04/2001 - 02/2002**	**12/2003 - 09/2005**
E5	**beck-s – SH**	**1500 - 3675**	**01/2000 - 05/2001**	**05/2001 - 07/2005**
E6	lokay-m – BG	1500 - 4500	06/2000 - 03/2002	08/2004 - 07/2005
SA2	**easy_ham_2 – spam_2**	**1400 - 1397**	**02/2003**	**02/2003**

2 DATASET AND METHODS

2.1 Dataset

In order to work with ANNs effectively, it is crucial to have a broad and representative dataset, *i.e.* a set of emails where both spam and ham are widely represented (Borovicka et al., 2012). Most email corpus are both restricted and costly in order to keep their users' privacy and obstruct spammers' countermeasures. In spite of this, several corpus are freely available nowadays (Cabrera León et al., 2015; Guzella and Caminhas, 2009).

The proposed system has been developed using a free and gratis one: a subset of emails from a corpus created by (Metsis et al., 2006) known as "Enron-Spam". Our dataset was built using only "Enron1" (E1) and "Enron5" (E5) folders, Table 1. By doing this, we have worked with a balanced dataset (5172 ham and 5175 spam) from the preprocessed version of their corpus, wherein:

- Ham belonged to the "Enron Email Corpus", which has been widely used with different preprocessing techniques applied on it (Cohen, 2004; Skillicorn, 2013; Styler, 2011). In fact, (Metsis et al., 2006) use ham from 6 out of 7 Enron users' inboxes from the preprocessed version of (Bekkerman et al., 2004), as seen in the column with the ham origin in Table 1.
- Spam came from two different sources: received in a traditional way by one of the authors of the mentioned corpus, Georgios Paliouras (GP); and through spamtraps (The Apache SpamAssassin Project, 2013) and honeypots (SH), which are anti-spam techniques intended, respectively, to lure spam, and to bait, investigate and punish spammers. Unwanted messages from Bruce Guenter's "Spam Archive" (BG) (Guenter, 1998) were not used in our case, unlike (Metsis et al., 2006).

Our dataset was subsequently partitioned in the following balanced sets: 80% for training-validation the ANN and 20% for testing the system over data never seen before.

Apart from E1 and E5 (E1E5) used during the design of the system, other datasets which came from different email corpora were utilized to test the design more independently, in order to evaluate in a more realistic way the methodology of the system: both preprocessing and processing stages. Thus, the system was further tested on two additional balanced datasets, Table 1: the "Enron2" (E2) and "Enron4" (E4) combination, E2E4 hereafter, which is similar to E1E5 but with ham from other Enron users and different quantities of spam from same sources, and "SpamAssassin_2" (SA2), built choosing the newest ham and spam folders from the SpamAssassin dataset, which differ considerably from our previous datasets in terms of content, topics, origins and dates (The Apache SpamAssassin Project, 2013).

2.2 Methods

The proposed intelligent anti-spam system consisted of two different computing stages or modules, Figure 1, and it can be considered hybrid because each of them was based on a different computing scheme. The first one was the preprocessing stage, Subsection 2.2.1, which was based on programmed computation (*i.e.* digital electronic computing together with stored programs) whereas the second one, the processing stage, Subsection 2.2.2, made use of a neural computing scheme. The preprocessing module was responsible for obtaining a semantic and compact representation of the information environment, a set of feature vectors for emails to analyze. These vectors were the input data for the subsequent hybrid processing module, where the detection of spam by a SOM-based, unsupervised ANN, system was performed, followed by a non-neural supervised labeling method which worked with the outputs of the SOM.

2.2.1 Preprocessing Module

The preprocessing stage is quite important (Hovold, 2005; Zhang, 2012), especially with unsupervised

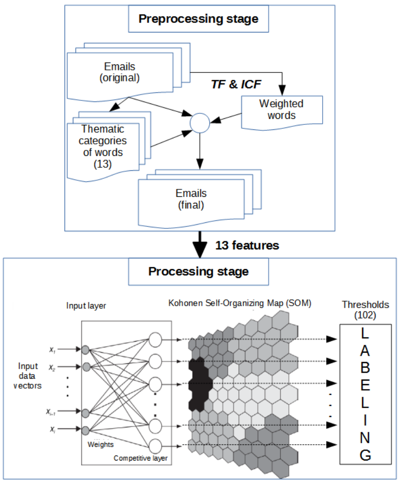


Figure 1: Anti-spam filtering system scheme.

methods due to the fact that no kind of corrective signals nor correct outputs are provided. The main purposes of this stage were: reducing the dimensionality of the vocabulary, and only making use of the most relevant words. Three key concepts - thematic categories, Inverse Category or Class Frequency (ICF) and Top $k\%$ of words - were used, which will be explained in the next paragraphs.

This preprocessing is founded on the premise that there are several spam thematic categories (Cabrera León et al., 2015; Wang et al., 2013), *ergo*, based on this, detection and differentiation from ham would be feasible. The most common thematic categories frequently found in spam and ham, which were expected to exist within our dataset, have been encountered and the most similar ones were lumped together in only 13 thematic categories, Table 2. Email words can belong to more than one category at the same time (*e.g.*: obfuscation & medicine, links & trading…). Initially, our words categorization in thematic categories was made manually, keeping in mind the word's use and context. Later and based on this, this process was automatized. Manual words categorization brought with it two useful advantages:

- No lemmatization nor stemming were required (Porter, 1980), common in many anti-spam filters.
- Robust against words deliberately obfuscated, a countermeasure frequently applied by spammers to deceive or defeat anti-spam techniques (Freschi et al., 2006; Liu and Stamm, 2007).

The existence of the aforementioned thematic categories directed this research to the usage of ICF, which is recommended by some authors when categories or classes exist in the data (Wang and Zhang, 2013), rather than using Inverse Document Frequency (IDF). Both ICF and IDF are used for similar purposes: reduce the importance/weight given by Term Frequency (TF) to "stop words" *i.e.* extremely common words in categories or documents, respectively. The three different variants of ICF described by (Lertnattee and Theeramunkong, 2004) have been checked, which are defined by Equations 1, 2 and 3, where C is the total number of categories, and f_t is the number of categories where token t happens.

$$ICF_{\ Log} = \log(\frac{|C|}{f_t}) \tag{1}$$

$$ICF_{\ Linear} = \frac{|C|}{f_t} \tag{2}$$

$$ICF_{\ Sqrt} = \sqrt{(\frac{|C|}{f_t})} \tag{3}$$

Another interesting aspect in this process was to know if using all the words within a thematic category was better than using less, so the system was tested with different number of words in each one. This number is given by some percentage, k, which means that we chose the $k\%$ of the words with greater $TF_{category} \cdot ICF$, that is, the Top $k\%$ of words.

Our preprocessing stage could be divided in four phases, executed in the indicated sequential order as they are interdependent:

Phase 0: batch extraction of subject line and body of all emails-files in a path. Also, non alphanumeric characters were inserted between blank spaces to ease next phases.

Phase 1: only keeping *selected words*, that is, with length > 2, not very rare and also not too frequent as they might be "stop words" (Zeimpekis et al., 2011). Each email was reduced to a text line, following the bag-of-words model *i.e.* several pairs of selected word next to its raw TF in this document: TF_{document}. At the end of each line two labels were added: spam/ham (not used during training) and the original, alphanumeric, email ID.

Phase 2: previously making the described manual words categorization. Building a 13-dimensional, integer, array where each element, accumulator, represents the sum of the raw TF_{document} of all the words belonging to a thematic category, by looking up the word in every category. At the end of each line the same two labels were inserted.

Phase 3: automatizing words categorization (email words are counted using accumulators as in Phase 2 and associated to, by default 1, the winner thematic category) and weighting words with $TF_{\text{category}} \cdot ICF$ so extremely common words were given less importance. Ordering categories using those values permitted the obtainment of several Top $k\%$ of words to be tested. Building a

Table 2: Description of the 13 thematic categories within our spam and ham words.

THEMATIC CATEGORY	DESCRIPTION
Sex & Relationships	Mostly pornography, casual sex and dating websites
Medicine, Drugs & Body	Selling medicines or illegal drugs. Includes words related with body parts, and surgical procedures and tools
Betting, Gambling & Divination	Includes lotto, sports betting, casino, tarot, etc.
Banking, Investment, Insurance & Trading	Commerce, offers, funds, stock markets...
Links & Email addresses	Parts of links to websites and emails, mainly web extensions and domains
Other languages	Most of the emails were written in English but some were in Spanish, German, French, Dutch and Turkish, among others
Obfuscation	Very common. Words badly written *on purpose* by spammers to interfere with most content-based anti-spam filters
Business, Companies & Government	Name of firms, governmental agencies and analogous
Internet & Technology	ICT vocabulary
Documents & Paperwork	CV, diplomas, business documents, etc.
Names & Family	Names and surnames, also family members
Tourism & Regions	Countries, cities, holidays...
Attached files	Several file extensions and words related with “attach”

13-dimensional, floating point, array where each element represented the sum of the $TF_{\text{document}} \cdot ICF$, similar to Phase 2 but now weighted, of all words belonging to certain thematic category. Same two labels at the end of each line-email.

2.2.2 Processing Module

The system's processing stage has as its information environment the feature vectors obtained in the preprocessing stage. It is hybrid as the first part was based on a type of ANNs, the well known Kohonen Self-Organizing Maps (Kohonen, 2001), whereas the second one was non-neural. Both parts will be explained below.

SOM, as an unsupervised neural architecture, is a very appropriate method for facing the problem to be solved. It quantifies the input space in different regions represented by a specific number of output neurons, a.k.a. detectors. In our case, there are two types of detectors: spam detectors and ham detectors.

Moreover, SOMs might be used as a visualization tool of high-dimensional data by projections over lower-dimensional maps (Rojas, 1996). During this projection process akin to multidimensional scaling, it is easily seen that SOMs try to extract the features of the input space in order to preserve its topological properties, similar to the idea of topographic maps that exist in the brains of highly developed animals (Haykin, 1999).

Its structure is made of an input layer fully interconnected, by excitatory connections, with the neurons in the output layer. The latter is organized in a m-dimensional space, the most common being the 2D matrix. Within this matrix there is a neighborhood relationship between its nodes that is usually defined by an hexagonal or rectangular lattice. Also, the matrix shape can vary, the sheet one being the most common. All neurons within the output layer simultaneously present inhibitory lateral connections among neural neighbors as well as excitatory self-connections. Their neurodynamic is simplified by computing the least (more frequently Euclidean and hence used in this work) distance between the inputs and a model (Kohonen, 2001), which is a parametric real vector, that can be considered as the weight vector in the neural architecture. The winning neuron, a.k.a. Best Matching Unit (BMU), will be the one with the minimum distance value.

The learning process belongs to a winner-take-all, unsupervised and competitive training paradigm. The main variations are seen in the modification of the synaptic weights, which not only affects the winning neuron but also, to a lesser extent, the set of neurons in the winners' neighborhood N (thus, SOM training can be considered cooperative too), and consequently being able to generate topological relations, Equation 4. During the training period, the neighborhood relationship between nodes h_{ji} decreases both in time and distance (commonly a Gaussian function), affecting only the BMU during the final phase. The learning rate α normally decreases with time, usually beginning near the unity and finishing close to zero during the fine tuning done in the last training cycles, although a fixed value may be utilized but not recommended (Tan and George, 2004).

$$\Delta w_{li} = \begin{cases} \alpha(x_i - w_{li}) & \text{if } i \in N = \underset{k}{argmin}\,\{net_k(x)\} \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

SOMs can use two different learning methods: sequential and batch, Equation 5, where $\bar{x}_j$ is the mean of the elements in a list of weights updates; h_{ji}, the neighborhood function; and n_i, the number of elements in that list. Batch learning method, which can be better and converges faster (Kohonen, 2013), has been employed in this article.

$$w_j(n+1) = \frac{\sum_i n_i \cdot h_{ji} \cdot \bar{x}_j}{\sum_i n_i \cdot h_{ji}} \quad (5)$$

The second part of the processing stage was a non-neural supervised classification method, which was appended after the SOM, Figure 1. Its main aim was to label the results obtained by the SOM, that way classifying in spam or ham the emails inputted into the anti-spam filter. It was based on confidence thresholds, which are based on the minimum percentage from which consider an email as spam. These confidence thresholds, which were empirically chosen, will allow us to adjust the system relative to the FP, an important factor in this kind of filters. In a nutshell, an email was labeled as ham if the spam ratio $\frac{\#spam}{\#spam+\#ham}$ was lesser than this threshold, or as spam otherwise, Equation 6.

$$label_{email} = \begin{cases} spam & \text{if } \frac{\#spam}{\#spam+\#ham} \geq \text{threshold} \\ ham & \text{otherwise} \end{cases} \quad (6)$$

3 RESULTS AND DISCUSSION

MATLAB was the main development environment for our anti-spam filter, using the SOM Toolbox (Vesanto et al., 2000) for the SOM architecture and visualization tools, and the Parallel Computing Toolbox (MathWorks, 2014) to reduce the high computational costs of the experiments.

Table 3: Modified characteristics and their tested values for all the 1260 configurations.

CHARACTERISTIC	TESTED VALUES
Normalization	Scenario 1 (None) or Scenario 2 (Variance is normalized to one, linear operation)
ICF	log, linear & sqrt
Top k% of words	100, 95, 90, 75, 50, 25, 10
SOM size	13x13, 20x20, 25x25, 40x40 & 50x50
SOM training algorithm	batch
Number of epochs	100, 500, 1000, 3000, 5000 & 8000
Neighborhood function	gaussian
SOM shape	sheet
Lattice	hexagonal
Weight initialization	linear

The experiments have been performed using original (non-normalized) and normalized data, which are indicated as Scenario 1 and Scenario 2 respectively. 1260 different system configurations were developed, which differed between them by varying several characteristics related to the information environment and the SOM structure, Table 3.

The efficiency and quality of the proposed anti-spam system were determined through the usage of two different families of metrics:

- Quality of the SOM map (Tan and George, 2004): MQE and TE, which measure the map resolution (how accurately the inputs are reflected in the output space) and the topology preservation (the order of the map), respectively.
- On-use performance measures such as F-score, accuracy, precision, specificity, sensitivity, ROC curve and AUC. All of them can be expressed in term of the elements of the confusion matrix: True Positives (TP), FP, True Negatives (TN) and FN. Also, it might be included in this group one simple and low cost metric found out during this research that measures the least Euclidean distance between the ROC curve and the point of perfect classification in (0, 1).
  For evaluation purposes and comparison with other researchers', the best considered performance measures are ROC curves[1] and AUC (Fawcett, 2004; Metz, 1978; Slaby, 2007).

Relative to E1E5 dataset, results obtained with all metrics were quite positive. All the 1260 analyzed configurations obtained $AUC > 0.90$, and even 204 got $AUC > 0.95$ which can be described as "excellent" classifiers in the anti-spam context. Additionally, most metrics's results were quite similar between configurations, even more if comparing same scenario. It has been observed that all pairs Top 100% and Top 95% configurations, with identical rest of parameters, shared the same results. Consequently, Top 95% ones were preferred because of their faster learning due to using a smaller vocabulary. Furthermore, none of the best classifiers for each scenario used the biggest SOM sizes, 50x50, but smaller-sized ones. Besides, it was found out that normalized data behaved better, which usually happens with Kohonen networks. Obtained MQE and TE with normalized data are on the same range of values as other authors' (Cabrera León et al., 2015).

Comparing our results in Table 4 with other researchers' in Table 5, the proposed system achieves worse than desired FP and FN (around 7% and 3%,

[1]Each ROC curve was drawn with 102 specificity and sensitivity values, given by the same number of confidence thresholds, for enhanced ROC curve detail.

Table 5: Results obtained by some researchers, indicating dataset, methodology and metric utilized.

RESEARCH	DATASET	METHOD	BEST RESULTS
(Metsis et al., 2006)	Enron-Spam	Bayesian (several)	Sensitivity = [0.9232 - 0.9753]
(Vrusias and Golledge, 2009b)	Enron-Spam	SOM	Precision = 0.992867 Sensitivity = 0.920067
(Chuan et al., 2005)	SpamAssassin	LVQ	Precision = 0.9897 Sensitivity = 0.9358
(Holden, 2004)	SpamAssassin	Bayesian (several, commercial)	Precision = [0.328 - 1] Sensitivity = [0.837 - 0.988]
(Kufandirimbwa and Gotora, 2012)	SpamAssassin	Perceptron algorithm	Precision = 0.97149 Sensitivity = 0.77859
(Luo and Zincir-Heywood, 2005)	Ling-Spam	Two-level SOMs + k-NN	Precision = [0.933 - 1] Sensitivity = [0.675 - 0.975]
(Shunli and Qingshuang, 2010)	ECML-PKDD 2006	Transductive SVM	AUC = 0.9321
(Xie et al., 2009)	PU1 & PU2	SVM (several)	Accuracy (PU1) = [0.926 - 0.941] Accuracy (PU2) = [0.932 - 0.945]

Table 4: Results of the anti-spam filter for each scenario (testing phase) with E1E5 (20%, 2069 emails) dataset.

	E1E5 (20%)	
PERFORMANCE MEASUREMENTS	Scenario 1	**Scenario 2**
AUC	0.970809	**0.977740**
Discrete AUC (threshold)	0.924172 (38)	**0.944499 (37)**
Accuracy	0.924595	**0.944726**
Precision	0.898782	**0.928571**
F-score	0.927915	**0.946385**
Specificity	0.889344	**0.924103**
Sensitivity	0.959000	**0.964895**
TP	959	**962**
FP	108	**74**
TN	868	**901**
FN	41	**35**
% FP	10.44%	**7.15%**
% FN	3.96%	**3.38%**
Distance to (0, 1)	0.118007	**0.083623**
SOM MAP QUALITY	Scenario 1	**Scenario 2**
MQE	39.592070	**0.452661**
TE	0.118567	**0.078204**

respectively), which should be the correction priority in future works, while good and comparable values with performance metrics. Still, it should be noted that this comparison would have been more realistic if exactly the same emails and preprocessing methods had been tested with other processing techniques. This is expected to be done in future works, together with a more advanced system.

The optimal system configuration used normalized data (Scenario 2), Top 95% of words, ICF sqrt, gaussian neighborhood, hexagonal lattice, 20x20 sheet-shaped map, and trained for 8000 epochs [with the batch algorithm]. It overcame the Scenario 1's opponent that used data without any kind of normalization applied to it, Top 25% of words, ICF log, gaussian neighborhood, hexagonal lattice, 20x20 sheet-shaped map, and was trained for 100 epochs, Table 4 and Figure 2(a)).

The proposed anti-spam filter was further tested with other datasets, which are different from the one used during the design of the anti-spam (E1E5). Indeed, the datasets were mixed in order to analyze both best configurations in a more realistic situation (*i.e.* with emails from diverse origins and in different proportions):

- E2E4: from different folders of the same email corpus, "Enron-Spam".
- E2E4 + SA2: a mix of emails from "Enron-Spam" and "SpamAssassin_2".
- E1E5 + E2E4 + SA2: an even more realistic mix of the three datasets used, including unseen emails from the dataset utilized during the design (E1E5), and without taking into account the mail distribution among them, using the whole set of emails.

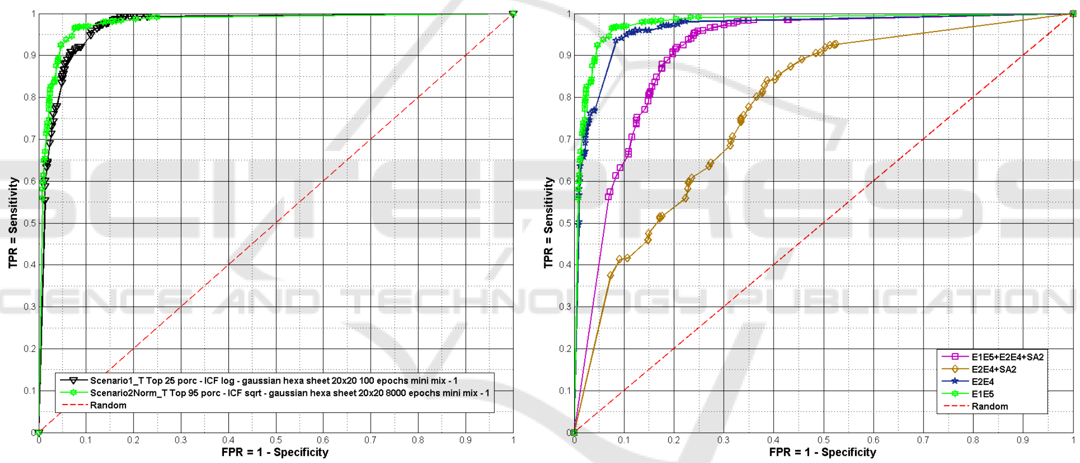
Regarding to Scenario 2 as it has been the one that achieved better performance, obtained results for the previous dataset mixtures vary from having an excellent performance - AUC over 0.964 and 0.906, respectively - with E2E4 and E1E5 + E2E4 + SA2 to a satisfactory one - AUC > 0.778 - with E2E4 + SA2, as seen in Table 6 and Figure 2(b)). These values reflect a coherent behavior and a good performance of the proposed system.

When the analyzed emails share similar characteristics (*e.g.* content, topics and origins) with the dataset used for design, training, performance is excellent. But the system is still able to have good and very good performance with new received emails, whose attributes are highly dissimilar. These differences fully justify the results in each case, Tables 4 and 6. At the same time, results are quite promising and indicative of the goodness of the proposed methods.

Still, a generalization of thematic categories, of the words inside them or a mix of both might be one of the potential solutions in order to improve even

Table 6: Results of the anti-spam filter for each scenario (testing phase) with E2E4 (2000 random emails), E2E4 + SA2 (2000 random, 50% each) and E1E5 + E2E4 + SA2 (20% of E1E5, all E2E4 and SA2, 16719 emails) datasets.

	E2E4		E2E4 + SA2		E1E5 + E2E4 + SA2	
PERFORMANCE MEASUREMENTS	Scenario 1	Scenario 2	Scenario 1	Scenario 2	Scenario 1	Scenario 2
AUC	0.951306	0.964116	0.730900	0.778584	0.886687	0.906290
Discrete AUC (threshold)	0.890036 (71)	0.925391 (48)	0.709345 (71)	0.726712 (27)	0.835745 (71)	0.856466 (48)
Accuracy	0.889952	0.925509	0.707214	0.724960	0.835752	0.856403
Precision	0.897137	0.918835	0.646072	0.677951	0.802223	0.816712
F-score	0.890995	0.927034	0.752889	0.750601	0.844410	0.864702
Specificity	0.895135	0.915401	0.516667	0.612735	0.780211	0.794249
Sensitivity	0.884937	0.935381	0.902023	0.840689	0.891279	0.918684
TP	846	883	847	781	7001	7174
FP	97	78	464	371	1726	1610
TN	828	844	496	587	6127	6215
FN	110	61	92	148	854	635
% FP	9.97%	8.01%	46.44%	37.13%	20.80%	19.11%
% FN	10.71%	5.94%	9.19%	14.78%	10.13%	7.53%
Distance to (0, 1)	0.155679	0.106454	0.493164	0.418753	0.245208	0.221237



(a) (b)

Figure 2: a) ROC curve of the anti-spam filter for each scenario (testing phase - “E1E5” dataset). b) Comparison of the ROC curves obtained by the proposed system for Scenario 2 with several datasets.

more the performance of the proposed system when dealing with any email type. Another solution might be updating the filter periodically with new messages (*i.e.* providing it with online-learning capabilities) to both counteract the evolution of spam and ham content and topics. The latter phenomenon is known as “topic drift” (Wang et al., 2013) and it is related with the general problem of “concept drift” in ML: unexpected variations of the statistical properties of the target variable over time, which usually imply increasingly inaccurate predictions over the course of time (Gama et al., 2014; [Pleaseinsertintopreamble]liobait[Pleaseinsertintopreamble] et al., 2015).

Comparing with the anti-spam filters proposed by (Metsis et al., 2006), from whom most of the datasets used in this paper were obtained, our results in Table 4 are comparable to theirs, Table 5, and our ROC curves in Figure 2(a)) are similar to their separated curves for “Enron1” and “Enron5” folders: specificity = 0.94433 and sensitivity = 0.96436 (average and for only those two folders). The main difference is that their filters make use of a non-neural methodology with supervised learning strategy and up to 3000 attributes while our proposal is a SOM-based system which used only 13 for analogous results. Consequently, we could infer that we utilized both appropriate preprocessing methods, that let us obtain smaller yet more informative input vectors, and a powerful processing tool, which is able to work with such unlabeled vectors.

4 CONCLUSIONS

In this paper a hybrid and modular anti-spam filtering system based on Kohonen Self-Organizing Maps and supervised non-neural computing has been presented. It has been proved that thematic categories can be found in spam and ham so, accordingly, both spam and ham words have been classified in the 13 categories found. The proposed system is robust to word obfuscation, quite frequent in spam, and it is also independent of the need to use stemming or lemmatization algorithms, unlike other anti-spam filters.

All the studied configurations obtained good results with all metrics with E1E5, the dataset used during the design of the system. Results were identical when using the whole set, Top 100%, of keywords from each of the 13 categories or just the Top 95%, something that also brought lower runtime along. Our optimal configuration was attained with normalized data, which is usual with Kohonen SOMs. Obtained results were similar to other researchers' over the same corpus (Metsis et al., 2006), though they use input vectors with a dimensionality several orders of magnitude greater than ours, up to 3000, and a number of Bayesian methods.

The developed anti-spam filter was additionally tested with data that were completely different from the ones used during its design, achieving important findings. Results with E2E4 dataset were similar but worse with the non-Enron SA2. Testing with a mix of the previous three datasets in different number and proportion confirmed that the filter's detection power got affected when newer and off-topic spam and ham were encountered. This is common to other offline-training anti-spam solutions because topics drift along the time as both spam and spammers' techniques evolve (Wang et al., 2013). This situation can be solved with periodic retraining (as in online-training filters) or, on the other hand, improving the generalization of the system or the thematic categories.

Obtained results confirmed the goodness and high quality of the proposed system. The usage of computational intelligence methods and hybrid schemes for designing anti-spam filtering systems were quite beneficial. Both facts encourage us to continue research over these topics. A big upgrading step might be the use of some powerful hybrid neural architectures such as the Counterpropagation network or the Hybrid Unsupervised Modular Adaptive Neural Network (Suárez Araujo et al., 2010).

ACKNOWLEDGEMENTS

The authors would like to thank all six reviewers for their valuable commentaries, which led to the improvement of this article.

REFERENCES

Bekkerman, R., McCallum, A., and Huang, G. (2004). Automatic categorization of email into folders: Benchmark experiments on Enron and SRI corpora. Technical Report IR-418, Center for Intelligent Information Retrieval - University of Massachusetts Amherst.

Blanco, Á., Ricket, A. M., and Martín-Merino, M. (2007). Combining SVM classifiers for email anti-spam filtering. In Sandoval, F., Prieto, A., Cabestany, J., and Graña, M., editors, *Computational and Ambient Intelligence*, volume 4507 of *Lecture Notes in Computer Science. 9th International Work-Conference on Artificial Neural Networks, IWANN 2007*, pages 903–910. Springer Berlin Heidelberg, San Sebastián, Spain.

Borovicka, T., Jirina Jr., M., Kordik, P., and Jirina, M. (2012). Selecting Representative Data Sets. In Karahoca, A., editor, *Advances in Data Mining Knowledge Discovery and Applications*. InTech.

Bruce, J. (2012). Grey Mail: The New Email Nuisance To Hit Your Inbox.

Cabrera León, Y. and Acosta Padrón, O. (2011). Spam: Definition, statistics, anti-spam methods and legislation. Course project, Politechnika Wroclawska, Wroclaw, Poland.

Cabrera León, Y., Suárez Araujo, C. P., and García Báez, P. (2015). *Análisis del Uso de las Redes Neuronales Artificiales en el Diseño de Filtros Antispam: una Propuesta Basada en Arquitecturas Neuronales No Supervisadas*. Final project, Universidad de Las Palmas de Gran Canaria, Las Palmas de Gran Canaria.

Chapelle, O., Schölkopf, B., and Zien, A. (2006). *Semi-Supervised Learning*, volume 2. MIT Press, Cambridge, MA, USA.

Chhabra, P., Wadhvani, R., and Shukla, S. (2010). Spam Filtering using Support Vector Machine. In *Special Issue of IJCCT Vol.1 Issue 2, 3, 4; 2010 for International Conference [ACCTA-2010]*, pages 166–171.

Chuan, Z., Xianliang, L., Mengshu, H., and Xu, Z. (2005). A LVQ-based neural network anti-spam email approach. *ACM SIGOPS Operating Systems Review*, 39(1):34–39 (6).

Cohen, W. W. (2004). Enron Email Dataset.

Cormack, G. V. and Mojdeh, M. (2009). Machine learning for information retrieval: TREC 2009 web, relevance feedback and legal tracks. In *The Eighteenth Text REtrieval Conference Proceedings (TREC 2009)*, pages 1–9, Gaithersburg, MD, USA.

Drucker, H., Wu, D., and Vapnik, V. N. (1999). Support Vector Machines for spam categorization. *IEEE Transactions on Neural Networks*, 10(5):1048–1054.

Erickson, D., Casado, M., and McKeown, N. (2008). The Effectiveness of Whitelisting: A User-Study. In *Proc. of Conference on Email and Anti-Spam*, pages 1–10.

Fawcett, T. (2004). ROC graphs: Notes and practical considerations for researchers. *Machine Learning*, 31(1):1–38.

Feroze, M. A., Baig, Z. A., and Johnstone, M. N. (2015). A Two-Tiered User Feedback-based Approach for Spam Detection. In Becker Westphall, C., Borcoci, E., and Manoharan, S., editors, *ICSNC 2015: The Tenth International Conference on Systems and Networks Communications, November 15-20, 2015, Barcelona, Spain*, pages 12–17. Curran Associates, Inc, Red Hook, NY.

Freschi, V., Seraghiti, A., and Bogliolo, A. (2006). Filtering obfuscated email spam by means of phonetic string matching. In *Advances in Information Retrieval*, pages 505–509. Springer.

Fumera, G., Pillai, I., and Roli, F. (2006). Spam filtering based on the analysis of text information embedded into images. *The Journal of Machine Learning Research*, 7:2699–2720.

Gama, J., Žliobaitė, I., Bifet, A., Pechenizkiy, M., and Bouchachia, A. (2014). A Survey on Concept Drift Adaptation. *ACM Computing Surveys (CSUR)*, 46(4):1–37.

Gao, Y., Yan, M., and Choudhary, A. (2009). Semi Supervised Image Spam Hunter: A Regularized Discriminant EM Approach. In *International Conference on Advanced Data Mining and Applications*, pages 152–164. Springer Berlin Heidelberg.

Graham-Cumming, J. (2006). SpamOrHam. *Virus Bulletin*, pages 22–24.

Guenter, B. (1998). SPAM Archive: Email spam received yearly, since early 1998.

Guzella, T. S. and Caminhas, W. M. (2009). A review of machine learning approaches to Spam filtering. *Expert Systems with Applications*, 36(7):10206–10222.

Harris, E. (2003). The Next Step in the Spam Control War: Greylisting.

Haykin, S. S. (1999). *Neural Networks. A Comprehensive Foundation*. Prentice-Hall International, Ontario, Canada, 2nd edition.

Holden, S. (2004). Spam Filtering II: Comparison of a number of Bayesian anti-spam filters over different email corpora.

Hovold, J. (2005). Naive Bayes Spam Filtering Using Word-Position-Based Attributes. In *CEAS*.

Kohonen, T. (2001). *Self-Organizing Maps*. Springer-Verlag New York, Secaucus, NJ, USA, 3 edition.

Kohonen, T. (2013). Essentials of the self-organizing map. *Neural Networks*, 37:52–65.

Kolcz, A., Chowdhury, A., and Alspector, J. (2004). The impact of feature selection on signature-driven spam detection. In *Proceedings of the 1st Conference on Email and Anti-Spam (CEAS-2004)*, pages 1–8.

Kucherawy, M. and Crocker, D. (2012). RFC 6647 - Email Greylisting: An Applicability Statement for SMTP. Proposed standard.

Kufandirimbwa, O. and Gotora, R. (2012). Spam Detection Using Artificial Neural Networks (Perceptron Learning Rule). *Online Journal of Physical and Environmental Science Research*, 1(2):22–29.

Lertnattee, V. and Theeramunkong, T. (2004). Analysis of inverse class frequency in centroid-based text classification. volume 2, pages 1171–1176. IEEE.

Lieb, R. (2002). Make Spammers Pay Before You Do.

Liu, C. and Stamm, S. (2007). Fighting Unicode-obfuscated spam. In *Proceedings of the Anti-Phishing Working Groups 2nd Annual eCrime Researchers Summit*, pages 45–59. ACM.

Lowd, D. and Meek, C. (2005). Good Word Attacks on Statistical Spam Filters. In *Proceedings of the Second Conference on Email and Anti-Spam (CEAS)*, pages 1–8.

Luo, X. and Zincir-Heywood, N. (2005). Comparison of a SOM based sequence analysis system and naive Bayesian classifier for spam filtering. In *Neural Networks, 2005. IJCNN'05. Proceedings. 2005 IEEE International Joint Conference on*, volume 4, pages 2571–2576.

Malathi, R. (2011). Email Spam Filter using Supervised Learning with Bayesian Neural Network. *Computer Science, HH The Rajah's College, Pudukkottai-622*, 1:89–100.

Mason, J. (2009). Filtering Spam With SpamAssassin.

MathWorks (2014). Parallel Computing Toolbox for Matlab R2014a - User's Guide.

McAfee and ICF International (2009). The Carbon Footprint of Email Spam Report. Technical report.

Metsis, V., Androutsopoulos, I., and Paliouras, G. (2006). Spam Filtering with Naive Bayes - Which Naive Bayes? In *CEAS 2006 - Third Conference on Email and Anti-Spam*, pages 27–28, Mountain View, California, USA.

Metz, C. E. (1978). Basic principles of ROC analysis. In *Seminars in Nuclear Medicine*, volume 8, pages 283–298. Elsevier.

Meyer, T. A. and Whateley, B. (2004). SpamBayes: Effective open-source, Bayesian based, email classification system. In *CEAS*. Citeseer.

Mojdeh, M. and Cormack, G. V. (2008). Semi-supervised spam filtering: Does it work? In *Proceedings of the 31st Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, pages 745–746, Singapore. ACM.

Narisawa, K., Bannai, H., Hatano, K., and Takeda, M. (2007). Unsupervised spam detection based on string alienness measures. In *Discovery Science*, pages 161–172. Springer-Verlag Berlin Heidelberg.

P. Resnick, E. (2008). RFC 5322 - Internet Message Format. Draft standard.

Pfahringer, B. (2006). A semi-supervised spam mail detector. pages 1–5, Berlin, Germany.

Pitsillidis, A., Levchenko, K., Kreibich, C., Kanich, C., Voelker, G. M., Paxson, V., Weaver, N., and Savage, S. (2010). Botnet judo: Fighting spam with itself. In *Symposium on Network and Distributed System Security (NDSS)*, pages 1–19.

Porter, M. F. (1980). An algorithm for suffix stripping. *Program*, 14(3):130–137.

Postini, Inc (2004). The shifting tactics of spammers: What you need to know about new email threats. White paper.

Qian, F., Pathak, A., Hu, Y. C., Mao, Z. M., and Xie, Y. (2010). A Case for Unsupervised-Learning-based Spam Filtering. volume 38, pages 367–368. ACM.

Ramachandran, A. and Feamster, N. (2006). Understanding the network-level behavior of spammers. In *ACM SIGCOMM Computer Communication Review*, volume 36, pages 291–302.

Rao, J. M. and Reiley, D. H. (2012). The Economics of Spam. *Journal of Economic Perspectives*, 26(3):87–110.

Rojas, R. (1996). Kohonen Networks. In *Neural Networks: A Systematic Introduction*, pages 391–412. Springer-Verlag, Berlin.

Sahami, M., Dumais, S., Heckerman, D., and Horvitz, E. (1998). A Bayesian Approach to Filtering Junk E-mail. AAAI Technical Report WS-98-05, Madison, Wisconsin.

Santos, I., Sanz, B., Laorden, C., Brezo, F., and Bringas, P. G. (2011). *Computational Intelligence in Security for Information Systems: 4th International Conference, CISIS 2011, Held at IWANN 2011*. Torremolinos-Málaga, Spain.

Sculley, D., Wachman, G., and Brodley, C. E. (2006). Spam Filtering Using Inexact String Matching in Explicit Feature Space with On-Line Linear Classifiers. In *TREC*.

Shunli, Z. and Qingshuang, Y. (2010). Personal Spam Filter by Semi-supervised Learning. In *Proceedings of the Third International Symposium on Com Puter Science and Computational Technology (ISCSCT '10)*, pages 171–174, Jiaozuo, P. R. China.

Skillicorn, D. (2013). Other versions of the Enron data (preprocessed).

Slaby, A. (2007). ROC Analysis with Matlab. In *Information Technology Interfaces, 2007. ITI 2007. 29th International Conference on*, pages 191–196. IEEE.

Spammer-X, Posluns, J., and Sjouwerman, S. (2004). *Inside the SPAM Cartel*. Syngress - Elsevier, 1 edition.

Sprengers, M. and Heskes, T. T. (2009). *The Effects of Different Bayesian Poison Methods on the Quality of the Bayesian Spam Filter 'SpamBayes'*. Bachelor thesis, Radboud University Nijmegen.

Statista (2016). Global spam volume as percentage of total e-mail traffic from 2007 to 2014.

Styler, W. (2011). The EnronSent Corpus. Technical Report 01-2011, University of Colorado at Boulder Institute of Cognitive Science.

Suárez Araujo, C. P., García Báez, P., and Hernández Trujillo, Y. (2010). Neural Computation Methods in the Determination of Fungicides. In *Fungicides*. INTECH Open Access Publisher, odile carisse edition.

Subramaniam, T., Jalab, H. A., and Taqa, A. Y. (2010). Overview of textual anti-spam filtering techniques. *International Journal of the Physical Science*, 5(12):1869–1882.

Tan, H. S. and George, S. E. (2004). Investigating Learning Parameters in a Standard 2-D SOM Model to Select Good Maps and Avoid Poor Ones. In *Australasian Joint Conference on Artificial Intelligence*, pages 425–437. Springer.

The Apache SpamAssassin Project (2013). Index of the SpamAssassin's Public Corpus.

The Apache SpamAssassin Project (2014). SpamAssassin v3.3.x: Tests Performed to Determine Spaminess and Haminess of a Message.

Uemura, T., Ikeda, D., and Arimura, H. (2008). Unsupervised spam detection by document complexity estimation. In *Discovery Science*, pages 319–331.

Vesanto, J., Himberg, J., Alhoniemi, E., and Parhankangas, J. (2000). SOM Toolbox for Matlab 5. Technical Report Report A57, Helsinki University of Technology.

Vrusias, B. L. and Golledge, I. (2009a). Adaptable Text Filters and Unsupervised Neural Classifiers for Spam Detection. In *Proceedings of the International Workshop on Computational Intelligence in Security for Information Systems CISIS'08*, volume 53 of *Advances in Soft Computing*, pages 195–202. Springer Berlin Heidelberg.

Vrusias, B. L. and Golledge, I. (2009b). Online Self-Organised Map Classifiers as Text Filters for Spam Email Detection. *Journal of Information Assurance and Security (JIAS)*, 4(2):151–160.

Wang, D., Irani, D., and Pu, C. (2013). A Study on Evolution of Email Spam Over Fifteen Years. pages 1–10, Atlanta, Georgia (USA). IEEE.

Wang, D. and Zhang, H. (2013). Inverse-Category-Frequency Based Supervised Term Weighting Schemes for Text Categorization. *Journal of Information Science & Engineering*, 29(2):209–225.

Wittel, G. L. and Wu, S. F. (2004). On Attacking Statistical Spam Filters. In *CEAS*.

Xie, C., Ding, L., and Du, X. (2009). Anti-spam Filters Based on Support Vector Machines. In *Advances in Computation and Intelligence. 4th International Symposium, ISICA 2009*, volume 5821 of *Lecture Notes in Computer Science*, pages 349–357. Springer Berlin Heidelberg, Huangshi, China.

Xu, J.-M., Fumera, G., Roli, F., and Zhou, Z.-H. (2009). Training SpamAssassin with Active Semi-supervised Learning. In *Proceedings of the 6th Conference on Email and Anti-Spam (CEAS'09)*, pages 1–8. Citeseer.

Yerazunis, W., Kato, M., Kori,, M., Shibata, H., and Hackenberg, K. (2010). Keeping the Good Stuff In: Confidential Information Firewalling with the CRM114 Spam Filter & Text Classifier. *White Paper for Black Hat USA*, pages 1–18.

Zeimpekis, D., Kontopoulou, E. M., and Gallopoulos, E. (2011). Text to Matrix Generator (TMG).

Zhang, Y. (2012). Lecture for Chapter 2 - Data Preprocessing.

Zhou, D., Bousquet, O., Lal, T. N., Weston, J., and Schölkopf, B. (2004). Learning with local and global consistency. *Advances in neural information processing systems*, 16:321–328.

Zhou, D., Burges, C. J. C., and Tao, T. (2007). Transductive link spam detection. In *Proceedings of the 3rd International Workshop on Adversarial Information Retrieval on the Web*, pages 21–28.

Žliobaitė, I., Pechenizky, M., and Gama, J. (2015). An overview of concept drift applications. In Japkowicz, N. and Stefanowski, J., editors, *Big Data Analysis: New Algorithms for a New Society*, volume 16 of *Studies in Big Data*, pages 91–114. Springer International Publishing.