

A Result on Spam Email Detection Using Fuzzy C-Mean with Machine Learning

Gauri Katyarmal¹, Dr.G.R.Bamnote²

¹Dept of CSE

²Professor, Dept of CSE

^{1,2}PRMIT&R Badnera , Amravati, India

Abstract- Today, most Internet users use email to communicate electronically. They depend on the Internet to deliver their important emails safely and to the right recipients. However, the fast growth of Internet users and their use of email together with the exponential increase of unsolicited users sending spam have made the email system less reliable. An email can falsely be marked by a spam filter on its way to the recipient or even get buried among junk mail in the recipient's inbox. There are several intelligent anti-spam filters which use different methods to detect spam including and fuzzy logic systems. Fuzzy set is an effective technique for spam detection and email classification. The proposed system enables the user to have more control over the various categories of spam and allows for filter personalization. This proposed work applied fuzzy logic to classify spam. This work used a fuzzy inference system to classify spam mails. This work has a list of spam words and spammer's email addresses in the database. This method extracts features from the email which, this work compares them against a list of spam features stored in the database ranked with its values and categorize the words and addresses in accordance to the ranking. Fuzzy inference system finally classified the spam mails as least dangerous or moderate or most dangerous spam mail.

Keywords- Email, spam, fuzzy logic, filter.

I. INTRODUCTION

E-mail is daily used by millions of people to communicate around the globe and is a mission-critical application for many businesses. With the rapid adaption of Internet as an easy way to communicate, the amount of solicited e-mails, known as spam e-mails, is growing rapidly. There are some unwanted emails that are called "Spam". Today, spam refers to junk, trash or unwanted email. There are many different reasons for sending spam such as selling a product, acquiring personal information from users, spreading viruses and worms, advertising, political advocacy, etc. The opposite of spam, which is a genuine or desirable email, is referred to as "Ham". [7]

E-mail users spend time in deleting the spam message which occupies large storage space in server side and utilizes more network bandwidth and also degrades the effective transmission speed in the network. Spams are denoted as the unwanted e-mails Unsolicited Bulk Mail (UBE), junk emails, un-solicited commercial e-mails, telephone short message service and unwanted instant messenger. Spam prevents e-mail from well-known source even for good content. Trojan virus, e-mail virus and some malware are not considered as spam, even though they share some common characters with spam. Email which is not considered as spam mail is mentioned as ham mail. E-mail spam more commonly involves sending similar messages to millions of recipient.

Spamming started its origin in 1978 by sending spam manually to the limited number of user. In 1994, Canter and Siegel posted a spam "green and lottery" and also some programmers were hired for writing spam programs in the same year. In 1995, it became more popular business and the lists of two million addresses were sold. In 1997, receiving of spam mail to the user became very large and it became out of control. Spam mail has become a very serious issue among the internet users, when the internet initially comes into operation for the use of public in the mid-1990s. There are millions of emails sent and received every day. Many researchers developed filtering techniques to filter spam from ham but the main objective of this research is to detect and classify the spam email a new fuzzy rule based method to classify

II. RELATED WORK

Many studies conducted to detect email spam. Mostly used machine learning classifier as main algorithm and combine it with parameter optimization attribute selection and threshold scheme that commonly used to improve the detection result. To date, the detection accuracy is still challenging; since the best accuracy that fully accepted from all evaluation is still not reached.

Biju Issac and Wedy J Jap have proposed cost-sensitive three-way (Bayesian, thresholds, probability) to

filtering spam emails which can reduce the error rate of miss classifying a legitimate email for spam and show better performance for aspects of cost-sensitive. They split the dataset into 2 parts, training part and testing part with composition 80% and 20% respectively. The dataset used is composed of three different datasets, spam base from the UCI Machine Learning Repository, PU1 corpus and Ling-Spam corpus with accuracy 89.8 and 93.94% respectively.

Combination of Negative Selection Algorithm (NSA) with the differential evolution (DE) has been proposed by George Giannakopoulos. DE implemented the random generation phase detector distance NSA and the results can be maximized and overlapping of the detector can be minimized. DE implemented to improve the generation of detectors at the stage of the NSA, while local outlier factor (LOF) is used as a fitness function. The proposed method using spam base dataset from the UCI machine learning repository and the results yield accuracy about 83.06%. [6]

R Kishore Kumar, G Poonkuzhali and P Sudhakar propose binary search strategy subset by particle swarm optimization with mutation operator (MBPSO) that begins on a wrapper-based feature selection to extract features with the basic decision tree classifier (C4.5) and weighting parameters. The proposed method used different data value or instances with spambase but using the same spam base dataset standard format. They collect 6000 email during year 2012 and accuracy gained by 94.27%. [9]

A novel model proposed by YiShan Gong and Qiang Chen that improves the random generation of a detector in NSA with the use of stochastic distribution to model the data point using particle swarm optimization (PSO) was implemented. Local outlier factor is introduced as the fitness function to determine the local best (Pbest) of the candidate detector that gives the optimum solution. Spambase dataset from the UCI machine learning repository is used as dataset. The proposed method, NSA-PSO produces a level of accuracy of 91.22%. [7]

Another PSO was implemented to improve the random detector generation in the NSA proposed by Biju Issac. The algorithm generates detectors in the random detector generation phase of the negative selection algorithm. The combination of NSA-PSO uses a local outlier factor (LOF) as the fitness function for the detector generation. A distance measure and a threshold value are employed to raise up the distinctiveness between the non-spam and spam detectors after the detector generation. Spam base dataset is used and the proposed method yield accuracy about 83.20%. Classification techniques have been applied in textual

and image spam filtering process. During literature survey, we can see a proposed method, where variant of Naïve Bayes classifier have been applied for spam detection [7]. A Compared classification strategy including Naive Bayes, Neural Network, Decision Tree and SVM were tested on different dataset on emails [9]. In which J48 and NB classifier provides better results compare to NN and SVM. A textual classification method defined by K-NN and Genetic Algorithm for solving clustering problem [2]. A suggestion to combine cluster analysis based on sparse representation with clustering algorithm also provide spam detection.

Today's internet is suffering from major problem known as Email spam .It annoys users and make financial damage to companies. So far developed techniques to stop spam are filtering methods .Spam emails are UBE also known as junk emails, that are send to many recipients who have not requested or subscribe to this. Spam filter removes spam or un-required messages from email inbox. It also has Phishing URLs which redirects users to phishing websites and seeking personal credentials like username and password for financial purpose. The existing work by Rasim M Alguliev, Ramiz M Aliguliyev , did implementation on malicious URL detection in Email. Lexical features, page rank, host information are taken into consideration to classify URLs. Phishtank corpora has been used and Bayesian classification is done to improve the performance of system [1].

T.A.Almeida and A. Yamakami, have presented learning method to filter spam email. The two machine learning algorithm are considered for anti-spam filtering such as Naïve Bayesian and Memory based learning approach and they are compared concerning performance. So, that in both methods spam filtering accuracy has improved and keyword based filter are used widely for email [2].

Jiansheng Wu and Tao Deng, have shown that phishing websites are hacked as soon as they are identified as phishing campaigns have two hours of average life. So to block and identify such phishing URLs they have extracted features like suspicious characters, number of dots, ip address, hexa decimal character [13]. Seongwook Youn and Dennis McLeod, discovered malicious URLs by enhancing blacklisting. One conflict with this method is that their updating process is fast so they failed to identify phishing URLs in early hours of a phishing attack[14]. YiShan Gong and Qiang Chen, endeavor for a survey to recognize the essential features which can develop accuracy and precision for malicious URLs detection [7]. Fumera, Giorgia, Ignazio Pillai, did a feature extraction on Base64 encoding of image with n-gram technique. A SVM needs to be trained for efficiently detecting spam images from legitimate images. Its

seen from experiment that it has improved the performance in terms of Accuracy, Precision and Recall [15].

III. PROPOSED WORK

In the proposed methodology to detect an email as spam or legitimate mail on the basis of text categorization. Various techniques for pre-processing of email format are applied such as applying stop words removing, stemming, feature reduction and feature selection techniques to fetch the keywords from all the attributes and finally using different classifiers to segregate mail as spam or ham. We have used numeric feature representation technique for feature extraction and fuzzy c-mean algorithm for clustering feature vectors, in various clusters and machine learning technique to make predictive analysis of mail filtering, this will be decision making step.

1. Pre-processing

Frequently the texts we have are not those we want to analyse. Having a single file containing the collected works of an author although we are only interested in a single work. Or we may be given a large work broken up into volumes where the division into volumes is not important to us. If we want to break up a long text (such as a book-length work) into smaller chunks so we can get a sense of the variability in an author's writing. If we are comparing one group of writers to a second group, we may wish to aggregate information about writers belonging to the same group. This will require merging documents or other information that were separated initially. This section illustrates these two common pre-processing step: splitting long texts into smaller "chunks" and aggregating texts together. Another important pre-processing step is tokenization.

2. Tokenizing

Tokenization is a critical activity in any information retrieval model, which simply segregates all the words, numbers, and their characters etc. from given document and these identified words, numbers, and other characters are called tokens. Along with token generation this process also evaluates the frequency value of all these tokens present in the input documents.

3. Stemming

Stemming phase is used to extract the sub-part i.e. called as stem/root of a given word. For example, the words continue, continuously, continued all can be rooted to the word continue. The main role of stemming is to remove

various suffixes as result in the reduction of number of words, to have exactly matching stems, to minimize storage requirement and maximize the efficiency of model.

4. Chunking

Chunking is a term referring to the process of taking individual pieces of information and grouping them into larger units. By grouping each piece into a larger whole, you can improve the amount of information you can remember. By separating disparate individual elements into larger blocks, information becomes easier to retain and recall.

5. Stopping

Removal of stop words – Stop words like "and", "the", "of" are very common in all English sentences and are not very meaningful in deciding spam or legitimate status, so these words have been taken away from the emails. For example stop words include "the, as, of, and, or, to etc. this phase is very essential in the tokenization because it has some advantages: It reduces the size of indexing file and it also improve the overall efficiency and make effectiveness.

6. Feature extraction process

Once the dictionary is ready, we can separate word count vector (our feature here) of 3000 dimensions for each email of preparing set. Each word count vector contains the frequency of 3000 words in the training file. Of course you might have guessed by now that most of them will be zero. Let us take an example. Suppose we have 600 words in our dictionary. Each word count vector contains the frequency of 600 dictionary words in the training file. The python code will generate a feature vector matrix whose rows denote 800 files of training set and columns denote 4000 words of dictionary. The incentive at record "ij" will be the quantity of events of jth expression of word reference in ith document.

7. Fuzzy c-means clustering

Fuzzy logic principles can be utilize to cluster multidimensional data, assigning each point a *participation* in each cluster centre from 0 to 100 percent. This can be very powerful compared to traditional hard-threshold clustering where every point is assigned a crisp, exact label. Fuzzy c-means clustering is accomplished via sk fuzzy, c means, and the output from this function can be repurposed to classify new data according to the calculated clusters (also known as *prediction*) via sk fuzzy c means predict Fuzzy clustering (also referred to as soft clustering) is a form of clustering in which each [data point](#) can belong to more than one cluster. Cluster

analysis or clustering involves assigning data points to clusters such that items in the same cluster are as similar as possible, while items belonging to different clusters are as dissimilar as possible. Clusters are identified via similarity measures. These similarity measures include distance, connectivity, and intensity. Different similarity measures may be chosen based on the data or the application. In non-fuzzy clustering (also known as hard clustering), data is divided into different clusters, where each data point can only belong to exactly one cluster. In fuzzy clustering, data points can possibly belong to multiple clusters.

8. Training the classifiers

In the proposed system Support Vector Machines (SVM).SVMs are supervised binary classifiers which are extremely viable when you have higher number of features. The objective of SVM is to separate some subset of preparing data from rest called the support vectors. The decision function of SVM model that predicts the class of the test data is based on support vectors and makes use of a kernel trick. Once the classifiers are trained, we can check the performance of the models on test-set. We separate word count vector for each mail in test-set and anticipate its class with the prepared SVM model.

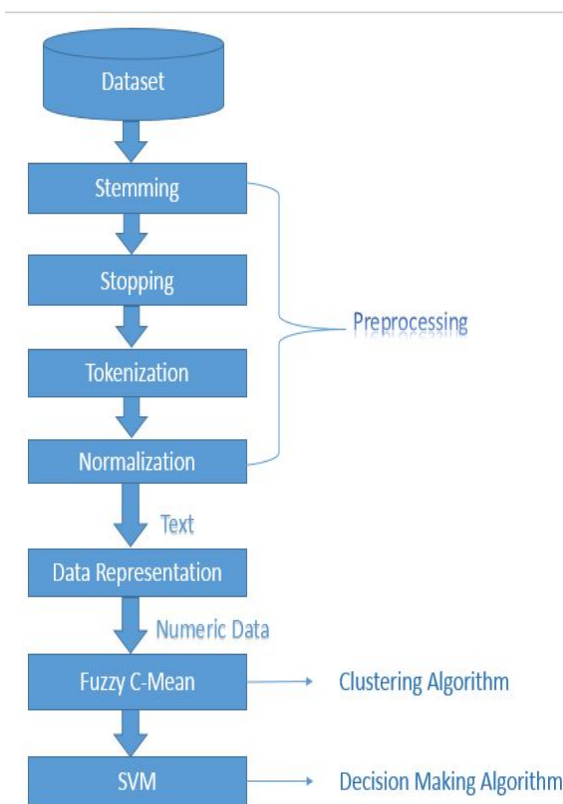


Fig 1. Proposed System Flow Diagram

IV. RESULTS

Experiment were carried out on dataset, which is publicly available. We made different set of files that has equal ham and spam files.

True Positive (TP): Correctly ham and spam detected rate that is actual ham and spam emails.

False Positive (FP): Incorrectly ham and spam detected rate that is not ham and spam emails.

Precision (A): Number of correctly classified instances of class A / number of instances classified as belonging to class A. $P = TP/TP+FP$

Accuracy = (Correctly Classified Emails/Total Emails) * 100
 Proposed scheme was applied on different no of set of datasets and calculated correctly and incorrectly classified instances.

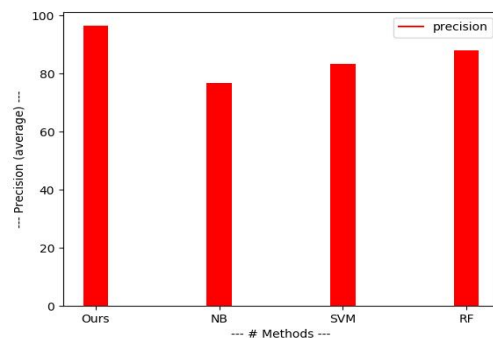


Fig 2. Average spam precision

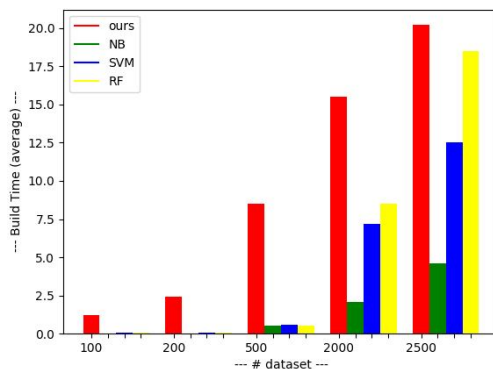


Fig 3. Average build time

In this experiment we apply different classifier and gain more accurate classified instances by using the combination of clustering and classification algorithm. We produced more than 95% accurate result by implementing our proposed method.

V.CONCLUSION

In proposed procedure a comprehensive experiment on spam categorization is performed. The results imply that support vector machine with fuzzy clustering technique is an efficient technique for detecting and categorizing spam compared to the existing methods. Thus the accuracy of spam filtering is improved and spam misclassification is reduced.

Future researches need to consideration on co-evolutionary problem of the spam filtering at server level, because while the spam filter tries to develop its prediction capacity, the spammer try to develop their spam messages in order to overreach the classifiers.

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