

A Back Propagation and Gini’s Index Based Approach for Mobile Spam Classification

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Abstract—With increased internet usage, one of the most prevalent problems faced is constant spamming. While web applications and mailing services are heavily spammed, the upsurge of handheld mobile devices has led to an outburst of heavy mobile spamming. The matter is more severe in mobile devices due to lesser sophisticated filtering mechanisms in built in mobile operating systems. Spam detection is challenging due to the need for semantic analysis of the mobile spam messages, which generally tend to have overlapping polarities. In this paper, a mobile spam classification technique is developed based on Gini’s index and Back-propagation in machine learning. The approach uses the Gini’s splitting criteria for the data sets and backpropagation based neural network as the machine learning classifier. The probabilistic classifier is well suited for datasets of texts messages with overlapping boundaries. The evaluation of the proposed system is based on the accuracy of classification and number of iterations. The results obtained in the proposed work are compared with existing techniques and it is shown that the proposed technique outperforms them in terms of accuracy of classification.

Keywords—Mobile Spam Classification, Gini’s Index, Neural Networks, Back Propagation, Training Iterations, Classification Accuracy.

I.INTRODUCTION

Mobile spamming has become one of the most common techniques for promotions, customer churning and potential attacks targeting the frequently used handheld mobile devices which are more prone to such attacks. The ease of collecting mobile contacts, connected data bases and relatively lesser sophisticated filtering mechanisms for the mobile spam filtering makes its extremely challenging to thwart spamming attacks. A numeric estimation of the rising spamming attacks has been depicted in figure 1, for the 3rd quarter of 2020 citing an increasing trend.

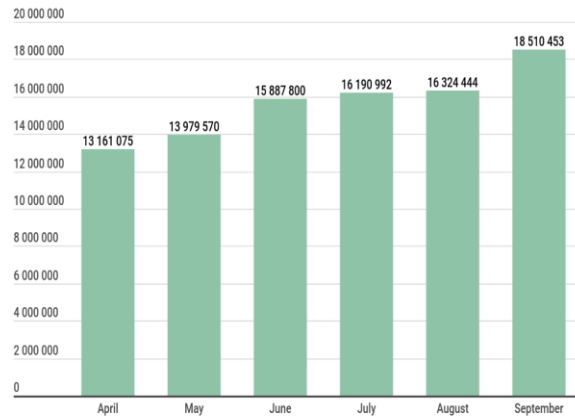


Fig.1 Number of Mobile Spams for Quarter-3, 2020
Courtesy: Kaspersky Labs Security Report

Some of the spamming attacks may be benign while others may be malignant trying to redirect mobile users to malicious websites where user security may be compromised. Since the amount of data is staggering large and complex, off late machine learning based approaches are becoming common to filter out spams. One of the challenges which machine learning based approaches face for mobile spamming platforms is the limited computational and processing capabilities of hand held mobile devices. This makes it necessary to design and test algorithms which are compatible with various versions of mobile operating systems and also supported by limited memory and processing hardware as there exists a lot of diversity in the mobile hardware of different devices. This paper is organized as:

Section I introduces the basic concepts pertaining to mobile spam classification and its necessities. Section II briefly summarizes the work done in the domain. Section III discusses the proposed approach. Section IV illustrates the obtained results. The findings of the paper are concluded in the conclusion.

II. RELATED WORK

Various approaches have been devised for mobile spam classification.

A spam classification mechanism based on text normalization and back propagation based neural network has been proposed by Jain et al. in [1]. The approach also compares the findings of the work with conventionally existing algorithms. Adewole et al. in [2] proposed a bio-inspired evolutionary machine learning based approach for the detection of spam. Different spamming features and sources are analyzed using standard machine learning algorithms using the Weka machine learning tools. The approaches used are the support vector machine (SVM), Ada-Boost, Random Forests, Multi-Layer Perceptron (MLP) Bayes' net. Barushka et al. in [3] proposed the use of regularized deep neural nets for the classification of spams. Sedhai et al. in [4] proposed a semi-supervised approach for spam classification. The data set used was that of Twitter. A similar approach was used by Chao et al. in [5] which aimed at analyzing drifted Twitter spam. Mirza et al. in [6] analyzed the effect of feature selection on spam filtering. A comparative analysis of addition and removal of features from the training data set was done. Afzal et al. in [7] proposed a techniques based on machine learning for bi-lingual data classification. Xu et al. in [8] developed an efficient machine learning based classifier for classification of multiple data sets corresponding to different social media platforms. Elssied et al. in [9] used a dual approach comprising of K-means clustering and support vector machine for spam classification. The clustering based approach was primarily used for data preparation and structuring while the multi-dimensional hyperplane based Support Vector Machine was used for the final classification. Vyas et al. in [10] presented a comprehensive review on the various supervised machine learning based approaches for email spam classification. The concepts of feed forward nets, convolutional nets, back propagation and recurrent nets were discussed in the context of spam filtering. Jatana et al. in [11] proposed a Bayesian classifier based approach for spam filtering. Kandasamy et al. in [12] proposed a natural language processing (NLP) based approach for spam classification using social media data. Prasad et al. in [13] compared the performance of Back Propagation and Resilient Propagation based machine learning approaches for spam classification. Indyk et al. in [14]

proposed a Map Reduce based approach for collective spam classification.

III. PROPOSED SYSTEM MODEL

A. Data processing and normalization:

Since neural nets directly process numeric data sets, the processing of data is done prior to training a neural network. The texts are first split into training and testing data samples in the ratio of 70:30 for training and testing. Further, a data vector containing known and commonly repeated spam and ham words is prepared. The SMS spam collection v.1 dataset is used as a dataset for the proposed work. Text normalization is followed by removal of special characters and punctuation marks.

Subsequently the data set structuring and preparation is performed based on the feature selection. The features selected are:

- 1) Spam words
- 2) Ham Words
- 3) URLs in the message
- 4) Lengthy numerical strings which can be contact numbers
- 5) Character length
- 6) Special symbols
- 7) Presence of currency values
- 8) Self-answering texts

The feature vectors along with the list of commonly accepted spam and ham lists of words comprises of the training vector. A similar process is done for both the training and testing datasets.

B. Neural Network Training

The neural network training model used in the proposed work is the Gini's Index and Back Propagation based neural net. The Gini's index is especially useful for overlapping data sets since it can split data sets with overlapping classes based on conditional probability. The Gini's index for splitting is defined as:

$$GI = 1 - \sum_{i=1}^n p_i^2 \quad (1)$$

Here,

GI represents the Gini's Index

P is the probability of a class

The next step is the design of the neural network for classification. The neural network has the property of

being able to process large data streams in parallel and adapting as per obtained outcomes. The fundamental model of a neural net is depicted in figure 2.

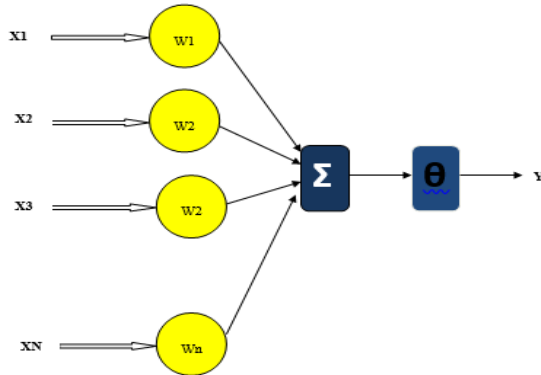


Fig.2 Mathematical Model of ANN

Here,

X represents the parallel input vector.

Y represents the output

Θ represents the bias.

W represents the weights.

The prepared data vector for training is used for training wherein the weights are initialized randomly. A stepwise implementation is done as:

1. Prepare two arrays, one is input and hidden unit and the second is output unit.

Here, a two dimensional array W_{ij} is used as the weight updating vector and output is a one dimensional array Y_i .

3. Original weights are random values put inside the arrays after that the output.

$$x_j = \sum_{i=0} y_i W_{ij} \quad (2)$$

Where,

y_i is the activity level of the j^{th} unit in the previous layer and

W_{ij} is the weight of the connection between the i^{th} and the j^{th} unit.

4. Next, activation is invoked by the sigmoid function applied to the total weighted input.

$$y_i = \left[\frac{e^x - e^{-x}}{e^x + e^{-x}} \right] \quad (3)$$

Summing all the output units have been determined, the network calculates the error (E).

$$E = \frac{1}{2} \sum_i (y_i - d_i)^2 \quad (4)$$

Where, y_i is the event level of the j^{th} unit in the top layer and d_i is the preferred output of the j_i unit.

C. Implementing Back Prop:

Calculation of error for the back propagation algorithm is as follows:

Error Derivative (EA_j) is the modification among the real and desired target:

$$EA_j = \frac{\partial E}{\partial y_j} = y_j - d_j \quad (5)$$

Here,

E represents the error

y represents the Target vector

d represents the predicted output

Error Variations is total input received by an output changed given by:

$$EI_j = \frac{\partial E}{\partial x_j} = \frac{\partial E}{\partial y_j} X \frac{dy_j}{dx_j} = EA_j y_j (1 - y_j) \quad (6)$$

Here,

E is the error vector

X is the input vector for training the neural network

In Error Fluctuations calculation connection into output unit is computed as:

$$EW_{ij} = \frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial x_j} = \frac{\partial x_j}{\partial w_{ij}} = EI_j y_i \quad (7)$$

Here,

W represents the weights

I represents the Identity matrix

I and j represent the two dimensional weight vector indices

Overall Influence of the error:

$$EA_i = \frac{\partial E}{\partial y_i} = \sum_j \frac{\partial E}{\partial x_j} X \frac{\partial x_j}{\partial y_i} = \sum_j EI_j W_{ij} \quad (8)$$

The partial derivative of the Error with respect to the weight represents the error swing for the system while training. The gradient is computed as:

$$g = \frac{\partial e}{\partial w} \quad (9)$$

Here,

g represents the gradient

e represents the error of each iteration

w represents the weights.

The gradient is considered as the objective function to be reduced in each iteration. A probabilistic classification using the Bayes theorem of conditional probability is given by:

$$P\left(\frac{H}{X}\right) = \frac{P\left(\frac{X}{H}\right)P(H)}{P(X)} \quad (10)$$

Here,

Posterior Probability [P (H/X)] is the probability of occurrence of event H when X has already occurred

Prior Probability [P (H)] is the individual probability of event H

X is termed as the tuple and H is is termed as the hypothesis.

Here, [P (H/X)] denotes the probability of occurrence of event X when H has already occurred.

The final classification accuracy is computed as:

$$Ac = \frac{TP+TN}{TP+TN+FP+FN} \quad (11)$$

Here.

TP represents true positive

TN represents true negative

FP represents false positive

FN represents false negative

IV.RESULT

The system is implemented on Matlab. The results obtained on implementing the proposed system is discussed in this section.

	A	B	C	D	E	F
1	v1	spam/ham	Message	Total Characters	mber of numeric dig	Number of upper case
2	ham	0	Available only in bugs n great world la e buffet...	111	0	3
3	ham	0	Ok lar... Joking wif u onit...	29	0	2
4	spam	1	1st May 2005. Text FA to 871211 to receive entry gu...	155	25	10
5	ham	0	U dun say so early hor... U c already then say...	49	0	2
6	ham	0	I don't think he goes to usf, he lives around here th	61	0	2
7	spam	1	FALSE	149	4	7
8	ham	0	ther is not like to speak with me. They treat me like	77	0	2
9	ham	0	Nurungu Vettam) has been set as your callertune	160	1	10
10	spam	1	FALSE	158	19	12
11	spam	1	xdate to the latest colour mobiles with camera for	154	13	14
12	ham	0	i don't want to talk about this stuff anymore tonig)	109	0	2
13	spam	1	pounds txt> CSH11 and send to 87575. Cost 150p/	136	22	17
14	spam	1	FALSE	156	20	40
15	ham	0	promise i wont take your help for granted and will	196	0	3
16	ham	0	I HAVE A DATE ON SUNDAY WITH WILL!!	35	0	26
17	spam	1	AP link in the text txt message or click here>> http	149	0	23
18	ham	0	Oh k...i'm watching here)	26	0	1
19	ham	0	how 2 spell his name... Yes i did. He v naughty ma	81	1	3
20	ham	0	FALSE	58	0	2
21	spam	1	ir national team to 87077 eg ENGLAND to 87077 Ti	156	23	32
22	ham	0	Is that seriously how you spell his name?	41	0	1
23	ham	0	FALSE	49	1	1
24	ham	0	FALSE	53	0	2
25	ham	0	ch then i go str down lor. And 3 smth lor. U finish t	88	1	3
26	ham	0	FFFFH. Alright no way i can meet up with you soon	57	0	3
27	ham	0	st hungry tho. This sucks. Mark is getting worried. f	144	0	8
28	ham	0	Lol your always so convincing.	30	0	1

Fig.3 Raw data samples

The raw data samples are collected after which it is imported to the Matlab workspace.

	1	2	3	4	5	6	7
1	ham	0	Go until jurong point, 111	0	3	free	
2	ham	0	Ok lar... Joking wif u onit...	0	2	wm	
3	spam	1	Free entry in 2 a.m., 155	25	10	cash	
4	ham	0	U dun say so early hor... U c already then say...	0	2	urgent	
5	ham	0	Nah I don't think it, 61	0	2	prize	
6	spam	1	0	149	4	7	jackpot
7	ham	0	Ever my brother is, 77	0	2	subscri	
8	ham	0	As per your request, 160	1	10	congrat	
9	spam	1	0	158	19	12	bonus
10	spam	1	Had your mobile 1, 154	13	14	won	
11	ham	0	I'm gonna be home, 109	0	2	http	
12	spam	1	SIX chances to win, 136	22	17	credit	
13	spam	1	0	156	20	40	www
14	ham	0	I've been searchin, 196	0	3	subscrip	
15	ham	0	I HAVE A DATE O, 35	0	26	call	
16	spam	1	0000MovieC, 149	0	23	lucky	

Fig.4 Conversion of Data into string

Subsequently, the data is converted into strings for ease of analysis of textural data. The data is split into training and testing data samples in the ratio of 70:30. While other data division ratios could have been uses, but in this work, the standard 70:30 ratio is adhered to.

The next process is invoking the Gini's split criteria.

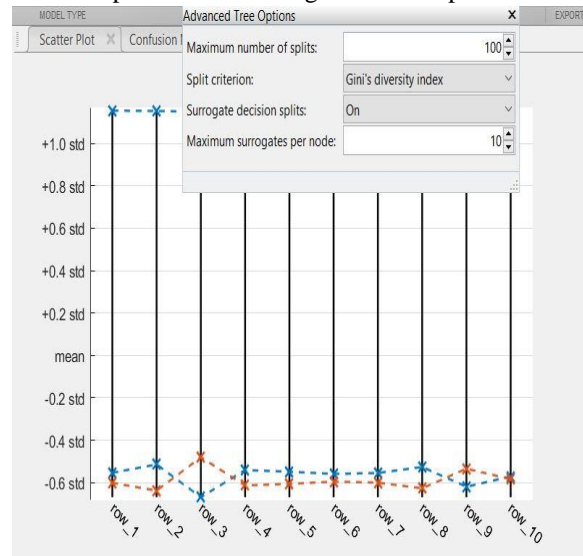


Fig.5 Invoking the Gini's Split criteria

The Gini's split criteria is the precursor to the training of the system.

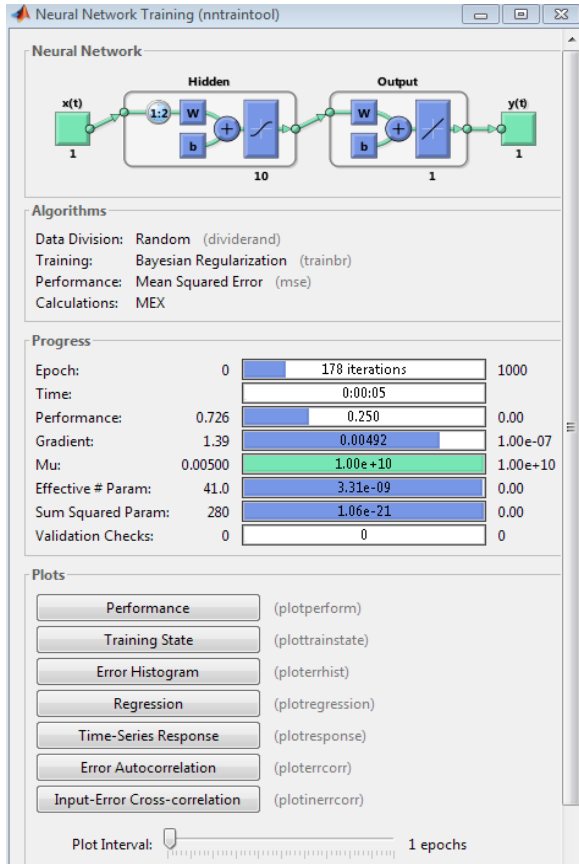


Fig.6 Training Performance

Figure 6 depicts the training parameters of the proposed system which consumes 5 seconds to run 378 iterations of the back propagation algorithm. A 20 neuron hidden layer is designed for the system.

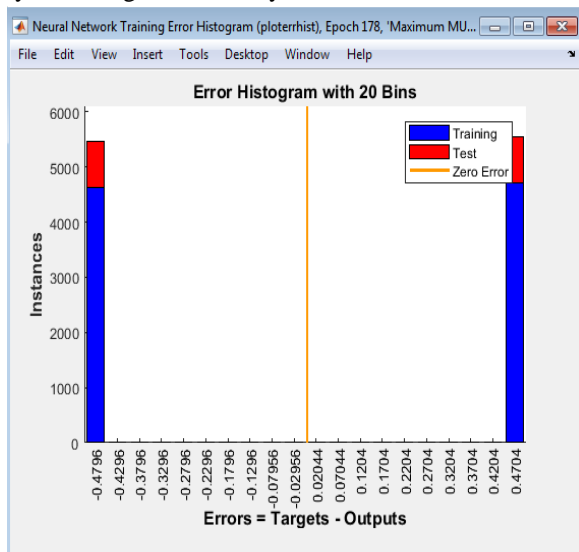


Fig.7 Training Error Histogram

The training error histogram is depicted in figure 7 which is an indicator of the errors occurring during the training process.

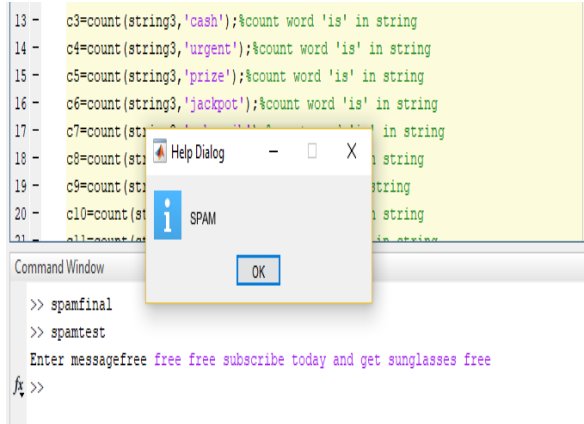


Fig.8 GUI for detection

Figure 8 depicts the GUI for spam detection. A similar GUI represents that of the non-spam or ham case. A comparative analysis with existing approaches is tabulated in table I.

Table I: Comparative Accuracy Analysis of Proposed and Existing Algorithms

S.No.	Technique	Accuracy (%)
1.	SNAP	83.9
2.	AIR SENTI	80.5
3.	Naïve Baye's	64
4.	Random Forests	63
5.	ANN with BackProp	95.81
6.	Proposed Approach: Gradient Descent with BackProp and Gini-Index	99.75

It can be observed from the tabulated results, that the proposed work outperforms the existing algorithms such as SNAPM AIR SENTI, Naïve Gayes', Random Forests and ANN with Back Prop.

V.CONCLUSION

It can be concluded from the aforesaid arguments that mobile spam classification is extremely challenging and non-trivial due to the constraints of computational power and memory at our disposal. Moreover, easier access to handheld devices makes systems more prone to spamming attacks. Text spam classification is non trivial in the sense that it generally belongs to non-clear or fuzzy boundary datasets. The proposed approach

presents a mobile spam classification mechanism Using Gini's Index and Back Propagation. It has been shown that the proposed approach outperforms the existing techniques in terms of classification accuracy. Additionally, the technique consumes moderate number of iterations and low execution time which are critical considerations for mobile devices.

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