

NAÏVE BAYES ALGORITHM FOR DOCUMENT CLASSIFICATION

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ABSTRACT. Classification or document categorization is a problem in library science, information science and computer science. This paper presents an automatic document classification system based on their content using the prior choice in classifying similar document. The classification algorithm is based on the Bayes' theorem from probability theory. In this paper the focus is on the Naive Bayes' method of predicting posterior choice based on the prior or previous classification of similar document. The documents used for this study are digital document in the form of emails. A sample of 5000 random emails were collected from different sources on the internet, these emails are saved as text documents separated in two categories; spam and ham to represent two distinct features. An algorithm is developed into a python code that automatically classify a new email in the form of text document into either category: spam or ham. Any of the two features represents a category in which a document can be grouped. The result output of this research is an algorithm which has 82.88% efficiency. This is better than the average efficiency percentage of other spam filters which use other methods. It was observed from the performance of the algorithm that the use of the Naive Bayes classification method performed better than the average spam filter algorithm.

1. INTRODUCTION

Electronic documents are well accepted and preferred to printed documents. These electronic documents are made easy to receive through the internet networks and made to be easier to distribute compared to printed ones. However, this creates a problem of multiple classification or wrong classification, in that it becomes more difficult to assign a document into which category it might belong. Anyone with access to electronic devices (such as PC, mobile phones, tablets etc.) can have access to tons of documents on such device but would lack the time or effective method of categorizing these documents. Thus this presents the need for an automated system of classifying such documents. This paper presents a way of automatic classifying digital documents with machine learning using a statistical method known as the naive Bayes' classifier, an example of one of the many application of the Bayes' theorem. Naïve Bayes Classifier have been found

Date: Received: Mar 8, 2022; Accepted: Jul 6, 2022.

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Key words and phrases. document classification, Bayesian classification, algorithm, Naïve Bayes' method, Python, posterior probability.

applicable in Credit Scoring, Medical Data Classification, Real-Time Predictions, Text Classification such as Spam Filtering and Sentiment Analysis. It is mainly used in text classification that includes a high-dimensional training dataset. This employs the use of probability to predict the class or category a document belongs. This may be done manually/intellectually or algorithmically (Baharudin, et al., 2010) [2], (Phil Spector, 2005) [11].

The intellectual classification of documents has mostly been the products of library science, while the algorithmic classification of documents is mainly in information science and computer science. The problems are overlapping, resulting into interdisciplinary research on document classification.

Thanuja Nishadi, (2019) [13] discussed about emails and how spammers evade detection and rule based filter algorithm in his work: Text Analysis. Dagobert. S (1985) [6] classified documents as either by content or request. Louridas and Ebert, (2016) [7] discussed automatic classification compared to human classification. Zhang, (2005) [15] presented the methods and perspective Bayesian inference on the classification of documents. Ma, et al., (2020) [8] proposed two popular machine learning methods: Naïve Bayes Classifier and Support Vector Machine for email spam classification. Peng, et al., (2018) [9] implemented an algorithm for enhancing the accuracy of the Naive Bayes Spam Filter. Thabtah and Kamalov, (2017) [12] critically experimentally evaluated and compared four different rule-based classifiers.

However, there is paucity of research on the statistical methodology upon which the algorithm relies.

This research is carried out in designing a document classification system and the use of emails as document of interest is considered. These emails are classified into two distinct categories, Spam and Ham. Spam email is unsolicited and unwanted junk email sent out in bulk to an indiscriminate recipient list. Typically, spam is sent for commercial purposes. It can be sent in massive volume by bot-nets, networks of infected computers. While, Ham is e-mail that is not Spam, i.e. non-spam, or good mail, that is, a synonym for non-spam.

The rest of the research is organized into three sections. Section 2 examines the materials and method applied in this research, mainly, Naive Bayes classification algorithm. Section 3 comprises the results and discussion of findings based on the data collected and the models developed. The conclusion and recommendation are contained in Section 4.

2. METHODOLOGY

2.1. Document Classification Procedure. Firstly, words in the documents are assigned a probability value. Each word has a particular probability of occurring in spam email and in legitimate email. For instance, most email users will frequently encounter the word "Viagra" in spam email, but will seldom see it in other emails. The filter doesn't know these probabilities in advance, and must first be trained so it can build them up. To train the filter, the user must manually indicate whether a new email is spam or not. For all words in each

training email, the filter will adjust the probabilities that each word will appear in spam or legitimate email in its database. For instance, Bayesian spam filters will typically have learned a very high spam probability for the words "Viagra" and "refinance", but a very low spam probability for words seen only in legitimate email, such as the names of friends and family members. To train the algorithm the word probabilities (also known as likelihood functions) are used to compute the probability that an email with a particular set of words in it belongs to either category. Each word in the email contributes to the email's spam probability, or only the most interesting words. This contribution is called the posterior probability and is computed using Bayes' theorem. Then, the email's spam probability is computed over all words in the email, and if the total exceeds a certain threshold (say 95%), the filter will mark the email as a spam. As in any other spam filtering technique, email marked as spam can then be automatically moved to a "Junk" email folder, or even deleted out rightly. The spam filters herein combine the results of both Bayesian spam filtering and other heuristics (predefined rules about the contents, looking at the message's envelope, etc.), resulting in even higher filtering accuracy, sometimes at the cost of adaptiveness (Calders and Verwer, 2010) [5].

2.2. Training the Classifier. The classifiers discussed in this research work learn how to classify a document by being trained. The more examples of documents and their correct classifications it sees, the better the classifier will get at making predictions. The classifier is also specifically designed to start off with the very uncertain and increase in certainty as it learns which features are important for making a distinction. The first thing needed is a class to represent the classifier. This class will encapsulate what the classifier has learned so far. The advantage of structuring the module this way is that it can instantiate multiple classifiers for different users, groups, or queries, and train them differently to respond to a particular group needs. Create a class called classifier in the doc-class.

2.3. Naive Bayes classification algorithm. The Naive Bayes method is a simple Bayesian classifier based on Bayes' theorem from probability theory. In the spam filter system, the stem forms of words occurring in the training documents were used as the features to represent each document. The basic steps in the naive Bayes method are as follows (Vembandasamy,et al., 2015) [14]; (Budiyanto,et al., 2019) [4]:

- i Identify the individual stem words occurring in all the training documents in the training set.
- ii Generate the feature vector for each document in the training document set and store it along with the correct indexes in the knowledge base.

- iii Calculate the probability for each index testing.
- iv Identify the individual stem words occurring in a given test document.
- v Generate the feature vector for this document.
- vi Calculate the probability for this document given each index.
- vii Calculate the probability for each index in the set of indexes for this document and normalize it with Bayes' theorem, this value is the weight of this index.

To compute the probability that a message is spam, taking into consideration all of its words (or a relevant subset of them) sometimes a third time, to deal with rare words. Computing the probability that a message containing a given word is spam.

Suppose the suspected message propose to sell counterfeit copies of well-known brands of watches. The spam detection software, however, does not "know" such facts; all it can do is compute probabilities.

The formula used by the software to determine that, is derived from Bayes' theorem:

$$P(S|W) = \frac{P(W|S).P(S)}{P(W|S)..P(S) + P(W|H)..P(H)} \quad (2.1)$$

where:

$P(S|W)$ is the probability that a message is a spam, knowing that the word "replica" is in it;

$P(S)$ is the overall probability that any given message is spam;

$P(W|S)$ is the probability that the word "replica" appears in spam messages;

$P(H)$ is the overall probability that any given message is not spam (i.e. "ham");

$P(W|H)$ is the probability that the word "replica" appears in ham messages.

Statistics show that the current probability of any message being spam is 80%, at the very least:

$$P(S)=0.8 \quad P(H)=0.2$$

However, Bayesian spam detection algorithm makes the assumption that there is no prior reason for any incoming message to be spam rather than ham, and considers both cases to have equal probabilities of 50%

$$P(S) = 0.5; \quad P(H) = 0.5.$$

The method that employs this hypothesis is said to be "unbiased", meaning that no prejudice regarding the incoming email is presumed. Reducing the general formula to:

$$P(S|W) = \frac{P(W|S)}{P(W|S) + P(W|H)} \quad (2.2)$$

The number $P(W|S)$ used in this formula is approximated to the frequency of messages containing "replica" in the messages identified as spam during the learning phase. Similarly, $P(W|H)$ is approximated to the frequency of messages containing "replica" in the messages identified as ham during the learning phase. For these approximations to make sense, the set of learned messages needs to be big and representative enough. It is also advisable that the learned set of messages conforms to the 50% hypothesis about re-partitioning between spam and ham, i.e. that the datasets of spam and ham are of same size. Of course, determining whether a message is spam or ham based only on the presence of the word "replica" is error-prone, which is why the Bayesian spam software tries to consider every words and combine their spamicities to determine a message's overall probability of being spam (Priya, et al.,2020) [10].

2.3.1. Combining Probabilities for Decision. Most Bayesian spam filtering algorithms are based on formulas that are strictly valid (from a probabilistic standpoint) only if the words present in the message are independent events. On this basis, one can derive the following formula from Bayes' theorem (Aryal and Bhat-tarai, 2021) [1]:

$$P = \frac{P_1 P_2 \dots P_N}{P_1 P_2 \dots P_N + (1 - P_1)(1 - P_2) \dots (1 - P_N)} \quad (2.3)$$

Where: P is the probability that the suspect message is spam;

P_1 is the probability $P(S|W_1)$ that it is a spam knowing it contains a first word (for example "replica");

P_2 is the probability $P(S|W_2)$ that it is a spam knowing it contains a second word (for example "watches"); etc.

P_N is the probability $P(S|W_N)$ that it is a spam knowing it contains nth word (for example "home").

Spam filtering software based on this formula is sometimes referred to as a naive Bayes classifier, as "naive" refers to the strong independence assumptions between the features. The resulting P is typically compared to a given threshold to decide whether the message is spam or not. If P is lower than the threshold, the message is considered as likely ham, otherwise it is considered as likely spam.

2.3.2. Other Expression of the Formula for Combining Individual Probabilities. Usually P is not directly computed using the above formula due to floating-point underflow. Instead, P can be computed in the log domain by rewriting the original equation as follows (Calders and Verwer 2010) [5]:

$$\frac{1}{P} - 1 = \frac{(1 - P_1)(1 - P_2) \dots (1 - P_N)}{P_1 P_2 \dots P_N} \quad (2.4)$$

Taking logs on both sides:

$$\ln\left(\frac{1}{P} - 1\right) = \sum_{i=1}^N (\ln(1 - P_i) - \ln P_i) \quad (2.5)$$

Let

$$\omega = \sum_{i=1}^N (\ln(1 - P_i) - \ln P_i) \quad (2.6)$$

Therefore:

$$\frac{1}{P} - 1 = e^{\omega} \quad (2.7)$$

Hence the alternate formula for computing the combined probability:

$$P = \frac{1}{1 + e^{\omega}} \quad (2.8)$$

Table 1 shows the formula for computing the performance of algorithm where accuracy, recall, precision, F-measure, FP, FN, TP and TN are defined as follows:

TABLE 1. Evaluation Measures for Spam Filters

<i>Evaluation Measure</i>	<i>Evaluation Function</i>
<i>Accuracy</i>	$Acc = \frac{TN + TP}{TP + FN + FP + TN}$
<i>Recall</i>	$r = \frac{TP}{TP + FN}$
<i>Precision</i>	$p = \frac{TP}{TP + FP}$
<i>F - Measure</i>	$F = \frac{2pr}{p + r}$

Source: Berrar, D. (2017) [3].

Accuracy: Percentage of correctly identified spam and ham message.

Recall: Percentage spam message classified.

Precision: Percentage of correct message for spam e-mail.

F-measure: Weighted average comparison of precision and recall.

False Positive Rate (FP): The number of misclassified non spam emails.

False Negative Rate (FN): The number of misclassified spam emails.

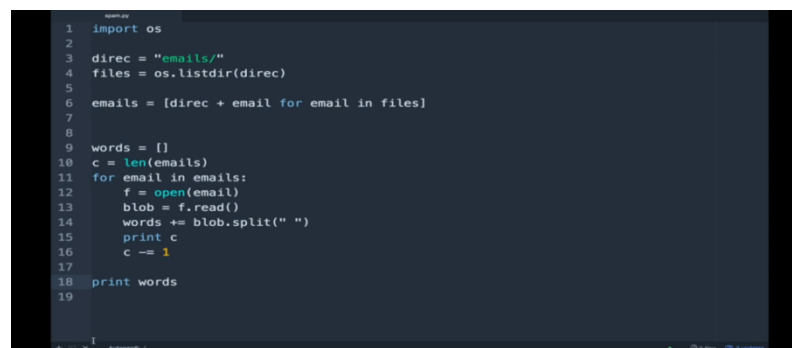
True Positive (TP): The number of spam messages are correctly classified as spam.

True Negative (TN): The number of non-spam e-mail that is correctly classified as non-spam.

3. RESULTS

This section discussed the experimental result by utilizing PyPlot and NumPy tool to implement the Naive Bayes algorithm. The two datasets used to test the algorithm comprises of 1500 Ham messages and 3672 spam messages making a total of 5172 messages.

The two datasets are compared based on the percentage of correctly identified spam and ham message, percentage of spam messages identified, percentage of correct message for spam e-mail and weighted average of precision and recall. For each datasets, 10 run of experiments were conducted using PyPlot and NumPy library in python. The following snippets explain the steps alongside with the codes and the appropriate output upon running of the code in python terminal. The codes in *Figure1* saved the words variable email saved as .csv into the python native and data type which was later used for the further algorithm. It split each words into separate index for calculating the probability values for each words. This part of the code below imports the saved emails document, assigns all the words into a list and names the list 'words' It takes the length of all the words i.e. makes a word count of all the number of words and assigned it to a variable named 'c' this will be used in calculating the probability for each words. These words are then printed out to also indicate the number of times they showed up.



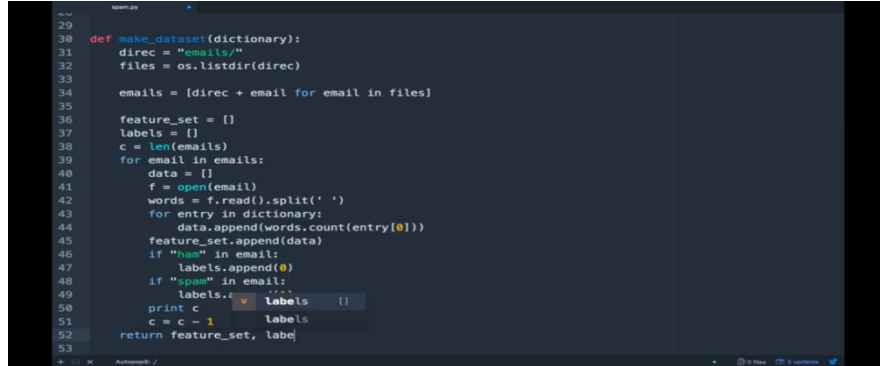
```

1 import os
2
3 direc = "emails/"
4 files = os.listdir(direc)
5
6 emails = [direc + email for email in files]
7
8
9 words = []
10 c = len(emails)
11 for email in emails:
12     f = open(email)
13     blob = f.read()
14     words += blob.split(" ")
15     print c
16     c -= 1
17
18 print words
19

```

Figure 1.0: Email saved as .csv into the python.

In Figure 2, the function below breaks up the text into words by dividing the text on any character that is not a letter, leaving behind the actual words in lowercase. By doing so, it reduces the total number of features.



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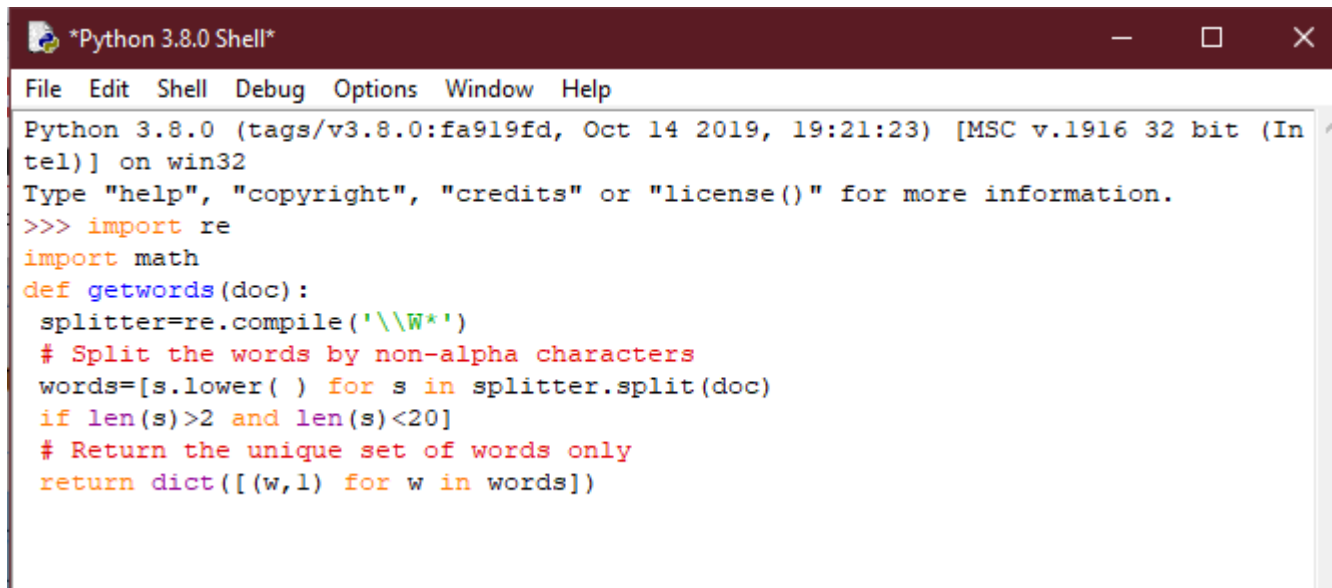
28
29
30 def make_dataset(dictionary):
31     direc = "emails/"
32     files = os.listdir(direc)
33
34     emails = [direc + email for email in files]
35
36     feature_set = []
37     labels = []
38     c = len(emails)
39     for email in emails:
40         data = []
41         f = open(email)
42         words = f.read().split(' ')
43         for entry in dictionary:
44             data.append(words.count(entry[0]))
45         feature_set.append(data)
46         if "ham" in email:
47             labels.append(0)
48         if "spam" in email:
49             labels.append(1)
50     print c, labels
51     c = c - 1
52     return feature_set, labels
53

```

Figure 2.0: Email import into dictionary data structure.

In figure 3, the code takes in the word and divides the number of times it appears by the total number of words and return the unique probability values in a vectored format indexing their word frequency counts, using:

$$P(S|W) = \frac{P(W|S)}{P(W/S) + P(W/H)} \quad (3.1)$$



```

Python 3.8.0 (tags/v3.8.0:fa919fd, Oct 14 2019, 19:21:23) [MSC v.1916 32 bit (Intel)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>>> import re
import math
def getwords(doc):
    splitter=re.compile('\W+')
    # Split the words by non-alpha characters
    words=[s.lower() for s in splitter.split(doc)
    if len(s)>2 and len(s)<20]
    # Return the unique set of words only
    return dict([(w,1) for w in words])

```

Figure 3.0: words split into letters or non-letter characters.

Figure 4 shows spam filtration with machine learning. The code was particularly used to separate the words with the aim of frequency of the set of data needed for interpretation.

```

6 emails = [direc + email for email in files]
7
8
9 words = []
10 c = len(emails)
11
12 for email in emails:
13     f = open(email)
14     blob = f.read()
15     words += blob.split(" ")
16     print c
17     c -= 1
18
19 ren', '"', 't', 'for', 'this', 'amazing', 'new', 'cosmetic', 'cream', 'called', '"', 'decep
20 tion', '"', '\r\n', 'would', 'lose', 'hundreds', 'of', 'modeling', 'assignments', '.', '.',
21 '.', 'because', '.', '.', 'there', 'is', 'no\r\nway', 'i', 'could', 'pass', 'myself
22 ', 'off', 'as', 'a', 'teenager', '.', '\r\nlearn', 'more', 'about', 'this', 'amazing', 'ne
23 w', 'product', '.', '.', '\r\nplease', 'refer', 'all', 'questions', '.', 'opinions', 'or',
24 'additional', 'feedback', 'to', '\r\nservice', 'dept\r\n9420', 'reseda', 'blvd', '#', '13
25 3\r\nnorthridge', '.', 'ca', '91324\r\n']
Souravs-MacBook-Pro:2. Spam filtration with Machine Learning souravjohar$

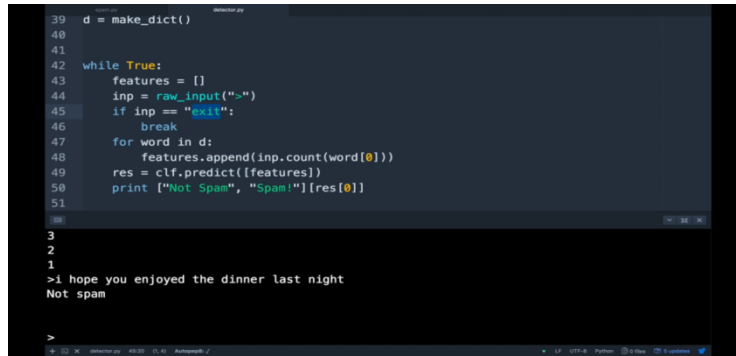
```

Figure 4.0: words separated to be used to get frequency

Figure 5 shows the probability output of the training accuracy. The training algorithm return a probability of 0.9352 value of correctly predicting spam which is a threshold value for our accuracy level using the document data we provided in the training. This serve as a basis of knowing the chances of committing a type II error.

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65 return feature_set, labels
66
67
68 d = make_dict()
69 features, labels = make_dataset(d)
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39 d = make_dict()
40
41
42 while True:
43     features = []
44     inp = raw_input(">")
45     if inp == "exit":
46         break
47     for word in d:
48         features.append(inp.count(word[0]))
49     res = clf.predict([features])
50     print ["Not Spam", "Spam!"][res[0]]
51
52
53 3
54 2
55 1
56 >I hope you enjoyed the dinner last night
57 Not spam
58
59 >

```

Figure 7.0: Test output identifying email as not spam

3.1. Summary of Results. For FP, FN, TP and TN, the average for each dataset are as follows:

- i FP: Total 315 number of misclassified ham emails.
- ii FN: Total 628.65 number of misclassified spam emails.
- iii TP: Total 3043 number of spam messages are correctly classified as spam.
- iv TN: Total 1185 number of ham e-mail that is correctly classified as ham.

Applying the formula in Table 1, we obtain the following results and it shall be interpreted while presenting the results of the analysis.

Percentage accuracy for spam data: 82.88%.
 Percentage for misclassified spam data: 17.12%.
 Percentage accuracy for ham data: 79%.
 Percentage for misclassified ham data: 21%.
 For F-Measure (percentage average measure of accurate spam and ham data classified): 80.1%.

3.2. Interpretation of Results. From Table 1 showing the evaluation measures and functions of the spam filter. The percentage accuracy for both spam data and ham data was calculated as well as their respective misclassified data. On the one hand, the percentage accuracy for spam data and misclassified spam are 82.88% and 17.12% respectively. On the other hand, the percentage accuracy for ham data and misclassified ham data are 79% and 21% respectively. The F-Measure (percentage average measure of accurate spam and ham data classified gives 80.1% From the above, it can be easily inferred that 82.88% of the time, a given spam message will be correctly classified, while 17.12% of the spam message will be misclassified as ham.

Generally, 80.1% of the time, the algorithm will correctly classify a new message as either spam or ham giving a good reliability. The standard average percentage

of known spam filters is given as 80.05% while the algorithm designed in this project surpass it, with the output of 82.88%. Surpassing the average of 80.05% by a margin of 2.83%. This is a lot in computer resources terms.

4. CONCLUSION

Naïve Bayes algorithm is a supervised learning algorithm, which is based on Bayes theorem and used for solving classification problems. In particularly, this paper has shown that the performance of the algorithm that make use of the Naive Bayes classification method performed better than the average spam filter algorithm. For instance, there is a discrepancy of 2.83% between the research result and that of an average spam filtering algorithm. Thus, results shows that Naïve Bayes Classification is a better algorithm for spam classification. The results also showed that percentage accuracy for spam data and ham data in each cases exceed their respective misclassified data which implies a better reliability on the results of the research. Further researches can be done on multinomial algorithm and sentiment analysis so as to determine more features of text classification.

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