

Machine Learning to Detect Spam Emails



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Spam emails have been increasing at a rapid rate since the early 1990's and accounts for 77.2% of all the worlds email traffic (Insu Park, 2016). As a result the there has been a need for constant development of spam email development software.

Spam email classification is a traditional problem in Nature Language Process (NLP). This dissertation contains extensive research to gain an understanding of machine learning algorithms, modern techniques and tools available. While providing a solution to the problem using the Naïve Baye approach and numerous pre-processing methods to develop a model capable of accurately predicting spam emails. Ultimately showing the feasibility of using Naïve Baye classification.

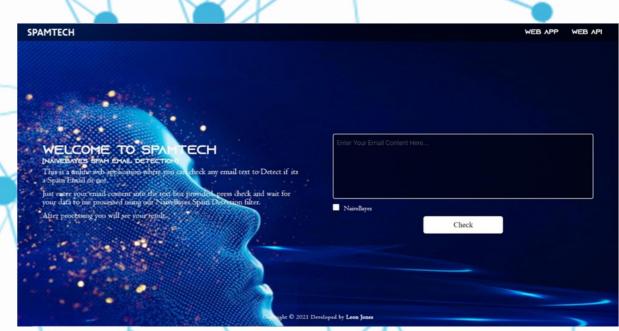


Figure 1. Final Spam Detection Prototype

Introduction & Research

Spam email detection is the process of detecting unwanted and malicious junk emails (spam) to prevent them getting into the users email inbox. Although spam email detection software are not 100% accurate they are the only solution to solve this rapidly growing problem. A 2012 report by Kaspersky found that 2.2% of all emails contained malicious files and email attacks such as Identity theft, Phishing Attacks and Viruses (Namestnikova, 2012).

There are many different spam detection algorithms all using different machine learning techniques to provide accurate predictions. This dissertation outlines five machine learning algorithms as shown below.

- Naïve Bayes Classifier Naïve Bayes is a probabilistic machine learning model base from figure 2. Bayes theorem of probability Wei, 2018).
- Decision Tree Decision tree classifier is a machine learning algorithm that follows a tree like structure to create a model that can decide the value of the sample based on attributes from existing data (Kiamarzpour, 2013).
- Clustering Clustering method is a way to divide a group of objects into similar groups of objects known as clusters (a group of patterns).
- Support Vector Machines Supervised machine learning algorithm that is used for classification and regression.
- Artificial Neural Network Machine learning algorithm that are design to mimic the way that a human's brain works to recognize relationships between sets of data (Berndt Müller, 1995).

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

Figure 2. Theorem of Probability

Implementation

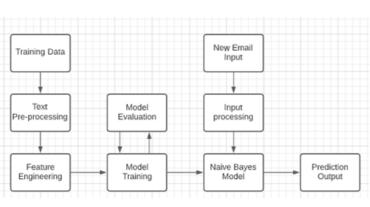


Figure 3. Final Prototype Flow Diagram

The dissertation used the Naïve Bayes classification approach to spam email filtering as from analysis of the research Naïve Bayes offered the best prediction accurately. The implementation was split into two prototypes, the first prototype was the creation of the machine learning spam email detection model. The machine learning model was supplied with a training dataset, this dataset was cleaned and the data visualised ensuring the model was supplied accurate training data. The text processing and vectorization was done using CountVectorizer, bag of words and TF-IDF to assign the weighting of each unique word. The vectorised data could then be used to train the Naive Bayes model. The model was tested using a 80/20 training test split and produced 97% accurate spam email predictions.

Figure 3 is a flow diagram representing each process within the final prototype. The final prototype was the implementation of the Naïve Bayes prediction model created into a django web framework allowing for the model to make prediction on individual emails entered and to be displayed in a more user friendly manner. This involve the designing and creation of the web interface and the retrieval of information entered for the model to make a prediction. Figure 1 shows the final prototype after all development was completed.

Testing & Review

After the successful creation of the final prototype extensive testing was conducted to ensure the functionality and prediction accuracy. The testing was split into 3 testing section. The first section contain 3 email messages used to test the accuracy of the predictions produced, this was a success as all prediction were accurate, showing the model prediction power within a controlled environment. Section 2 was a testing plan



containing 10 tests to test each feature of both the model and interface this was also successful as all tested were passed. The last section was user feedback, 5 peers were given the final prototype and asked to test the accuracy of the model, the result were recorded using questionnaire which could be used to for future development of the project.

Conclusion

The main goal of this dissertation project was to create a machine learning model for spam email detection. This goal was met, as the spam filtering model developed can accurately predict spam emails successfully and was integrated into a Django web framework for individual email predictions. The Naïve Baye classification approach was chosen as extensive research was carried out indicating that this was the most efficient and accurate algorithm giving the small dataset used for training. The biggest issue was the limited data contained within the dataset if the dataset was large this would drastically improve the prediction power of the model. If future development of the project was to continue a number a factures would be added such as the ability to make predation for a dataset of emails, option to use other algorithms to compare their accuracy and further development of normalisation techniques such as stemming.

References

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Figure 4. Spam Collection Dataset