LEV ACADEMIC CENTER

AI Corse Final Project - Email Spam Detection with Machine Learning

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1 Introduction

This project is part of the assignments required in the "Artificial Intelligence" course as part of the master's degree studies in data mining at the Lev Academic Center.

In this project, I use the knowledge I gained during the course to perform a text classification task, using machine learning algorithms. The mission was described in the project requirements as follows:

> ***Email Segregation such as spam and phishing filters*** *– One of the latest trends in the cybersecurity market is email segregation using the AI for detecting, tracking, and analyzing the keywords in the emails to filter the emails for spam and phishing emails. The spam emails are dangerous because if they are not controlled, it occupies the space, delivers the malicious payload, and can cause security vulnerabilities. Similarly, the spear-phishing or the targeted phishing emails are malicious and can collect personal information about an individual for malicious intents such as stealing the data or stealing the money from the bank accounts, etext classification.*

The goal is to create a simple system that will receive from the user as input - the text of an email and classify the email as spam or not spam. The system will do this through preliminary training that will be performed on a data set of emails that are classified as spam or not. During the preliminary training stage, the system will compare the accuracy of 5 Machine Learning classifiers – Decision Tree, Random Forest, Support Vector Machine, Logistic Regression, K Nearest Neighbors, and another Deep Learning classifier - Multi-Layer Perceptron.

The features for the model will be the most significant words that appear in the emails dataset. Words will be determined as most significant using the TF-IDF rating. Also, during the training phase, there will be comparisons between different amounts of features to find the amount that will allow the most accurate prediction, as well as a comparison between types of features - will each feature be one, two, or three words - i.e. unigram, bigram or trigram.

I would like to take this opportunity to thank you for the significant learning in the course. This is a fascinating, modern, and rapidly developing field, and entering the world with the help of this course in particular and the data mining degree, in general, is significant in my professional development.

2 Theoretical Review

2.1 Text Classification

Automatic text classification aims to automatically categorize natural language text into predefined categories or classes. Text classification has a wide range of applications in fields such as information retrieval, content filtering, and email classification. One important area of text classification is topic classification, which involves assigning a topic or theme to a piece of text. Another area of text classification is document classification, which involves categorizing documents based on their content. Many studies in text classification have addressed tasks such as topic identification in news articles, classification of research articles into domains, and email filtering

In text classification, a main technique has been proposed: machine learning (ML). The ML approach is composed of two general steps: (1) learn the model from a training corpus, and (2) classify a test corpus based on the trained model (Pang et al. 2002 and Jeonghee et al. 2003). Various ML methods have been applied for sentiment classification. For instance, Pang and Lee (2005) applied three ML methods: Naive Bayes (NB), Maximum Entropy (ME), and Support Vector Machines (SVM), and combined SVM and regression (SVR) modes, with metric labeling.

2.2 Email Spam Detection

Email spam detection can be approached as a text classification problem, where the goal is to classify emails into two categories: spam and non-spam (also known as "ham"). The classification model is trained on a dataset of labeled emails, where each email is labeled as either spam or ham. The model then learns to associate certain words or patterns of words with either spam or ham and uses this knowledge to predict the label of new emails.

Text classification for email spam detection typically involves the following steps:

a) Data preprocessing: The emails are preprocessed to remove stop words (common words such as "the" and "and" that do not carry much meaning), punctuation, and other noise. The remaining words are then transformed into a numerical representation, such as bag-of-words or term frequency-inverse document frequency (TF-IDF), which can be used as input features for the classification model.
b) Feature selection: Not all words are equally informative for spam detection, so feature selection is used to identify the most relevant words or n-grams (sequences of words) for the classification model.
c) Model training: A classification model is trained on the labeled dataset using a supervised learning algorithm such as Naive Bayes, Support Vector Machines, or Logistic Regression. The model is trained to predict the label (spam or ham) of new emails based on the input features.

d) Model evaluation: The performance of the classification model is evaluated using metrics such as accuracy, precision, recall, and F1-score. The model may also be evaluated on a separate test set to assess its generalization ability.

Several studies were done along the second in favor of identifying spam in emails with the help of ML. Olatunji (2017) created a model based on SVM to classify spam emails and reached an accuracy level of 94%. Another study (Agarwal & Kumar, 2018) built a model based on Naive Bayes and reached an accuracy level of 95.5%. Kumar & Sanket (2020) compared Various methods of machine learning, such as SVM, KNN, RF, DT, NB, and more, and achieved a high accuracy of 98% with the help of Naive Bayes.

2.3 Text Preprocessing

Text preprocessing is crucial in NLP fields such as ML, sentiment analysis, text mining, and text classification. In both general and social text documents, noise such as typos, emojis, slang, HTML tags, spelling mistakes, and repetitive letters often appear. Improperly preprocessed text can result in an incorrect analysis of text classification. In some cases preprocessing methods are considered effective for text classification tasks. For instance, HaCohen-Kerner et al. (2008) demonstrated that using word unigrams including stop words leads to improved results compared to the results obtained using word unigrams excluding stop words.

HaCohen-Kerner et al. (2019) investigated the impact of all possible combinations of six preprocessing methods (punctuation mark removal, reduction of repeated characters, spelling correction, HTML tag removal, converting uppercase letters into lowercase letters, and stopword removal) on text classification in three datasets. In another study, HaCohen-Kerner et al. (2020) explored the influence of combinations of the sentiment analysis of six basic preprocessing methods mentioned in the previous paragraph on text classification in four general benchmark text corpora using a bag-of-words representation. The main conclusion recommended is always to perform an extensive and systematic variety of preprocessing methods, combined with many ML methods to improve the accuracy of text classification.

2.4 Datasets Description

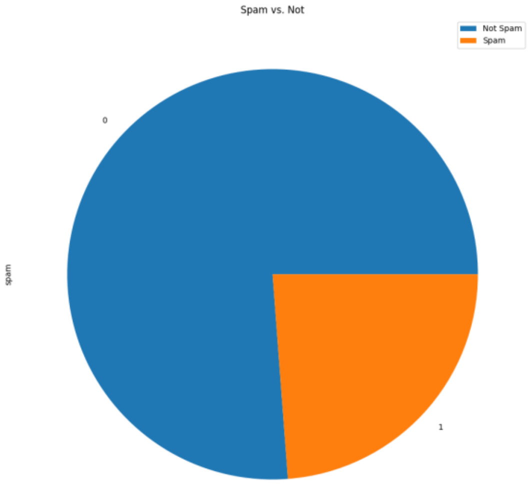
The system is based on a collection of 2 Email datasets in English. The dataset involves texts labeled with two classes (1 for spam, and 0 for not spam).

The first dataset contains 5708 emails and was retrieved from: https://www.kaggle.com/datasets/ozlerhakan/spam-or-not-spam-dataset?resource=download

Some statistics regarding the dataset:

	spam	email_length	email_words	email_unique_words
count	5708	5708	5708	5708

mean	0.238086896	1541.859145	323.9922915	137.1135249
std	0.425949893	1884.805797	390.9019613	107.5285745
min	0	13	2	2
25%	0	508	101	70
50%	0	979	210	109
75%	0	1892.5	401	174
max	1	31055	6348	1357

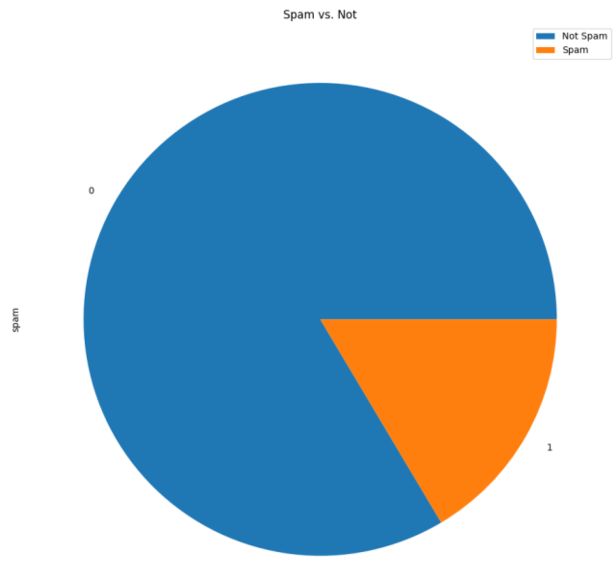


The second dataset contains 2984 emails and was retrieved from:

https://github.com/amankharwal/Email-spam-detection.

Some statistics regarding the dataset:

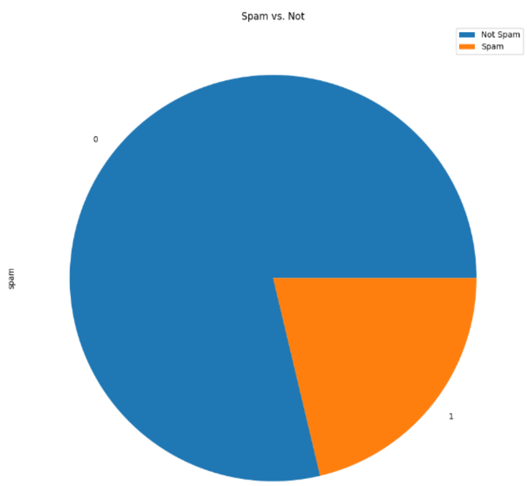
	spam	**email_length**	**email_words**	**email_unique_words**
count	2983	2983	2983	2983
mean	0.1645994	1240.067382	216.0831378	115.1830372
std	0.37088077	1897.926253	324.5735774	112.4566271
min	0	1	0	0
25%	0	387	67	51
50%	0	756	133	89
75%	0	1347	235	140
max	1	22067	3489	1039



I Built a third dataset as a union of the first 2 datasets.

Some statistics:

	spam	email_length	email_words	email_unique_words
count	8691	8691	8691	8691
mean	0.212863882	1438.275572	286.9547808	129.5863537
std	0.409355751	1894.636813	372.997566	109.7337881
min	0	1	0	0
25%	0	467	89	63
50%	0	896	176	101
75%	0	1690.5	346	162
max	1	31055	6348	1357



2.5 Classifiers Description

I applied 6 supervised ML methods on the training datasets' feature matrices: Random Forest (RF), Support Vector Classifier (SVC), Logistic regression (LR), Decision Tree (DT), K Nearest Neighbors (KNN), and Multinomial Naive Bayes (MNB). I also applied a supervised DL method: Multi-layer Perceptron (MLP).

RF is an ensemble learning algorithm that is used for classification and regression problems. (Breiman, 2001). Ensemble methods use multiple learning algorithms to obtain improved predictive performance compared to what can be obtained from any of the constituent learning algorithms. RF combines multiple decision trees to form a forest of trees, and the final prediction is made by taking a majority vote of the trees. RF combines Breiman's "bagging" (Bootstrap aggregating) idea in Breiman (1996) and a random selection of features introduced by Ho (1995) to construct a forest of decision trees

SVC is a variant of the SVM ML method (Cortes and Vapnik, 1995) implemented in SkLearn. SVC uses LibSVM (Chang & Lin, 2011), which is a fast implementation of the SVM method. SVM is a supervised learning algorithm that is used for classification and regression analysis. It works by finding the hyperplane that maximally separates the data into classes. SVM is known for its good generalization ability and its ability to handle non-linearly separable data using the kernel trick.

LR (Cox, 1958; Hosmer et al., 2013)is a supervised learning algorithm that is used for binary and multiclass classification problems. It models the relationship between the dependent variable and the independent variables using a logistic function. It is known also as maximum entropy regression (MaxEnt), logit regression, and the log-linear classifier.

Decision Tree DT (Song and Ying, 2015) is a flowchart-like structure method in which each internal node represents a "test" on an attribute (e.g. whether a coin flip comes up heads or tails), each branch represents the outcome of the test, and each leaf node represents a class label (decision taken after computing all attributes).

KNN stands for K-Nearest Neighbors and is a supervised learning algorithm used for classification and regression analysis (Guo et al., 2003). It works by finding the K closest points (i.e. neighbors) to a given data point in the training set and then classifying the data point based on the class labels of its nearest neighbors. The value of K in KNN is usually chosen by the user and determines how many neighbors to consider when classifying a data point. A smaller value of K (e.g. K=1) can result in a more flexible and potentially more accurate model, but can also be more prone to overfitting. Conversely, a larger value of K can result in a more stable and robust model, but may not be as accurate. KNN is based on the assumption that data points that are close to each other in the feature space are likely to belong to the same class. This makes KNN a useful algorithm for classification tasks where the decision boundary between classes is highly non-linear or difficult to model using other algorithms.

Multinomial Naive Bayes (MNB) is a statistical machine learning algorithm based on the Bayes theorem (Kim et al., 2006). MNB assumes that features are conditionally independent given the target class, estimates the probabilities of each class and the probabilities of each feature given the class, and uses these probabilities to make predictions.

A Multilayer Perceptron (MLP) is a type of artificial neural network (ANN) that is used for a variety of tasks, including classification and regression. An MLP consists of an input layer, one or more hidden layers, and an output layer. The input layer receives the inputs to the network, which are then processed and transformed by the hidden layers. The output layer produces the final output of the network (Hassan et al. 2016).

These ML methods were applied using the following tools and information sources:

- The Python 3.8 programming language. (Van Rossum & Drake, 2009).
- Sklearn – a Python library for ML methods. (Buitinck et al., 2013).
- Pandas – a Python library for data analysis. It provides data structures for efficiently storing large datasets and tools for working with them (McKinney, 2010).
- Thinker – a library to create a simple python GUI application.

I created feature matrices from the datasets, while the features were terms from the dataset with the highest TF-IDF grade.

TF-IDF (Term Frequency-Inverse Document Frequency) is a statistical measure used in information retrieval and natural language processing (Ramos, 2003). It reflects the importance of a word in a document within a corpus of documents. The main idea behind TF-IDF is that a word that occurs frequently in a document but not in many other documents across the corpus is likely to be more important to that document than a word that occurs frequently across many documents. The term frequency (TF) of a word in a document is the number of times it appears in the document. The inverse document frequency (IDF) of a word is the logarithm of the number of documents in the corpus divided by the number of documents in which the word appears. The TF-IDF score for a word in a document is the product of its term frequency and inverse document frequency. I calculated TF-IDF values for word n-grams and char Ngrams in ranges 1-3.

3 Methodology

My way of working was based on the 3 datasets I described. The goal was to train different models on the training dataset and select the best models according to the accuracy score.

For classic ML models, I worked as follows:

- In the first step, for each language, I created a TF-IDF table for all the n-grams in the language and tried to identify how many grams should be selected as model features. I chose the [1,2,3] word n-grams.
- I ran 7 classic classifiers - LR, MNB, KNN, RF, SVM, DT, MLP with varying amounts of features - 500, 1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000, 9000, 10000 and saw which amount of features gets the highest score for each model.
- I applied different pre-processing methods to the data - each method separately as well as the combinations of the methods and examined the level of improvement in each model and the effect of each pre-processing method. The best combination I found was lowercase the text, removing punctuation marks, and removing the phrase "subject: "at beginning of every mail in the first dataset. Removing the stopwords lead to lower accuracy. Lemmatization and stemming took a lot of time so I didn't check it for the whole dataset.
- The best models for each dataset were saved to the file system.
- I created a basic GUI for the system that allows entering an email, choosing a classifier and the model on which it is trained, and trying to classify the email using the trained model that will predict its labeling as spam or not. The GUI allows you to see the email after preprocessing as well as the score of each model to choose the desired one.

The project is built from the following files:

- data_exploration.py - code that goes through the datasets and produces various charts to describe the information.
- data_preperation.py - code that goes over the raw data, and performs various pre-processing functions according to the requirement and more DataFrame is ready for learning.
- train_models.py - the code that runs all the models and trains them, and saves the results to the file system.
- gui.py - this code must be run. Creates the system's GUI and goes behind the scenes to the various functions to pull trained models and try and classify an email entered as input.
- verification.py – the code that runs all models to classify the dev set spam classification and then prints the accuracy of each dataset model.
- data - a folder that contains all the different datasets. There are 2 datasets in Basis numbered 1,2, and there is a combined dataset of both called 1+2. Also, I removed

from each dataset about 20 emails that Model did not train on, which can be used to try the system.

- data_exploration - a folder that contains all the figures and tables describing the different datasets
- trained_models - a folder that contains all the trained models, the feature matrices built based on tf-idf, and CSV files containing the results of all the models as well as the outstanding models with accuracy, precision, recall, f1 indicators.

It is important to note that all the files are documented in a very thorough way, you can understand what the role of each function is and what the main lines do in each function.

4 Program Verification

As explained above, I used 2 basic datasets and a third united dataset. Before I started training the models, I created 2 small datasets called "dev" that contain some emails from the original datasets that the models were not trained on, and in this way, I can check if the models were able to learn.

To validate the model, I created an automated code that pulls the best models from each dataset type and size, i.e. emails1 in trained sizes - 100, 500, and 1000 words in the trained model.

For each word in the dev database, I found its classification by each of the outstanding models and chose the most common classification among all, and compared the original classification of the word against the classification it received in each of the databases - emails1, emails2, emails1+2

The results I received can be seen in the next table:

text id	spam	source	emails1 classification	emails2 classification	emails12 classification
1	0	emails1	0	0	0
2	1	emails1	1	1	1
3	1	emails1	0	1	1
4	1	emails1	1	1	1
5	1	emails1	1	0	1
6	0	emails1	0	0	0
7	0	emails1	0	1	0
8	0	emails1	0	1	0
9	0	emails1	0	1	0
10	1	emails1	1	1	1
11	1	emails1	1	1	1
12	1	emails1	1	1	1
13	1	emails1	1	1	1
14	1	emails1	1	1	1
15	0	emails1	0	1	0
16	0	emails1	0	0	0
17	0	emails1	0	0	0
18	0	emails1	0	0	0
19	0	emails2	1	0	0
20	0	emails2	0	0	0
21	1	emails2	1	1	1
22	1	emails2	1	1	1
23	1	emails2	0	0	0
24	0	emails2	0	0	0
25	1	emails2	1	1	1
26	1	emails2	1	1	1
27	0	emails2	1	0	0
28	0	emails2	1	0	0
29	1	emails2	1	1	1
30	0	emails2	0	0	0

31	0	emails2	1	0	0
32	0	emails2	1	0	0
33	1	emails2	1	1	1
34	1	emails2	1	1	1

The accuracy reflected in the table is as follows:

- emails1 accuracy: 0.7941176470588235
- emails2 accuracy: 0.8235294117647058
- emails12 accuracy: 0.9705882352941176

As can be seen from these results, models trained on dataset emails1 classified spam emails that came from datasets 1 and 2, with a success rate of about 79%. Dataset emails2 was slightly better and the models trained on it classified the same emails with 82% success. It can be seen that the majority of the errors of the models trained on dataset #1 are on emails that came from dataset #2 and vice versa. That means clearly, each database excels at classifying emails that are similar to the emails it was trained on. Therefore, the significant improvement at the level of 97% comes precisely in the models that were adjusted on the 2 reservoirs together. This is a very significant success rate. This illustrates the power and needs for diverse repositories that enable a more general model.

Examples of email classification from the dev database by the system can be seen in detail in Appendix A at the end of this report.

5 Results

An example of classification results can be seen in the previous chapter. In this chapter, I will present the results of the best models in each dataset and the score they received. For each model I trained, I took 75% of the dataset as training data, and 25% as test data with which I evaluated the accuracy of the model.

- The results of the best models of each classifier, for a dataset based on the emails1 pool of 100 emails:

f1_score	recall	precision	accuracy	feature_matrix	model
0.95522388	1	0.91428571	0.94	word_1_2000	Decision Tree
0.96774194	0.9375	1	0.96	word_1_1000	KNN
0.95081967	0.90625	1	0.94	word_1_500	Logistic Regression
0.98412698	0.96875	1	0.98	word_1_2000	Multi-layer Perceptron
0.96774194	0.9375	1	0.96	word_1_500	Multinomial Naive Bayes
0.98461538	1	0.96969697	0.98	word_1_5000	Random Forest
0.96774194	0.9375	1	0.96	word_1_500	Support Vector Machine

- The results of the best models of each classifier, for a dataset based on the emails2 pool of 100 emails:

f1_score	recall	precision	accuracy	feature_matrix	model
0.89361702	0.84	0.95454545	0.9	word_2_100	Decision Tree
0.90566038	0.96	0.85714286	0.9	word_1_100	KNN
0.97959184	0.96	1	0.98	word_1_1000	Logistic Regression
0.97959184	0.96	1	0.98	word_1_500	Multi-layer Perceptron
0.97959184	0.96	1	0.98	word_1_500	Multinomial Naive Bayes
0.97959184	0.96	1	0.98	word_1_500	Random Forest
0.97959184	0.96	1	0.98	word_1_100	Support Vector Machine

- The results of the best models of each classifier, for a dataset based on the emails1+2 pool of 100 emails:

f1_score	recall	precision	accuracy	feature_matrix	model
0.96551724	0.96551724	0.96551724	0.96	word_1_8000	Decision Tree
0.94736842	0.93103448	0.96428571	0.94	word_1_500	KNN
0.94736842	0.93103448	0.96428571	0.94	word_1_500	Logistic Regression
0.96551724	0.96551724	0.96551724	0.96	word_1_3000	Multi-layer Perceptron
0.98245614	0.96551724	1	0.98	word_1_2000	Multinomial Naive Bayes
0.91525424	0.93103448	0.9	0.9	word_1_8000	Random Forest
0.92857142	0.89655172	0.96296296	0.92	word_1_2000	Support Vector Machine

- The results of the best models of each classifier, for a dataset based on the emails1 pool of 500 emails:

f1_score	recall	precision	accuracy	feature_matrix	model
0.94736842	0.96694215	0.92857143	0.948	word_1_500	Decision Tree
0.92063492	0.95867769	0.88549618	0.92	word_1_1000	KNN
0.97540983	0.98347107	0.96747967	0.976	word_1_1000	Logistic Regression

0.98755187	0.98347107	0.99166667	0.988	word_1_2000	Multi-layer Perceptron
0.97925311	0.97520661	0.98333333	0.98	word_1_2000	Multinomial Naive Bayes
0.96774194	0.99173554	0.94488189	0.968	word_1_500	Random Forest
0.98360656	0.99173554	0.97560976	0.984	word_1_500	Support Vector Machine

- The results of the best models of each classifier, for a dataset based on the emails2 pool of 500 emails:

f1_score	recall	precision	accuracy	feature_matrix	model
0.97014925	0.99236641	0.94890511	0.968	word_1_500	Decision Tree
0.93680297	0.96183206	0.91304348	0.932	word_1_500	KNN
0.98461539	0.97709924	0.99224806	0.984	word_1_2000	Logistic Regression
0.99619772	1	0.99242424	0.996	word_1_3000	Multi-layer Perceptron
0.98841699	0.97709924	1	0.988	word_1_2000	Multinomial Naive Bayes
0.98850574	0.98473282	0.99230769	0.988	word_1_500	Random Forest
0.99230769	0.98473282	1	0.992	word_1_1000	Support Vector Machine

- The results of the best models of each classifier, for a dataset based on the emails1+2 pool of 500 emails:

f1_score	recall	precision	accuracy	feature_matrix	model
0.93927125	0.94308943	0.93548387	0.94	word_1_3000	Decision Tree
0.94023904	0.95934959	0.921875	0.94	word_1_1000	KNN
0.98387097	0.99186992	0.976	0.984	word_1_2000	Logistic Regression
0.99193548	1	0.984	0.992	word_2_10000	Multi-layer Perceptron
0.98795181	1	0.97619048	0.988	word_1_4000	Multinomial Naive Bayes
0.98007968	1	0.9609375	0.98	word_1_6000	Random Forest
0.9877551	0.98373984	0.99180328	0.988	word_1_1000	Support Vector Machine

- The results of the best models of each classifier, for a dataset based on the emails1 pool of 1000 emails:

f1_score	recall	precision	accuracy	feature_matrix	model
0.976	0.99186992	0.96062992	0.976	word_1_1000	Decision Tree
0.96047431	0.98780488	0.93461538	0.96	word_1_2000	KNN
0.9939394	1	0.98795181	0.994	word_1_2000	Logistic Regression
1	1	1	1	word_1_2000	Multi-layer Perceptron
0.99593496	0.99593496	0.99593496	0.996	word_1_6000	Multinomial Naive Bayes
0.98790323	0.99593496	0.98	0.988	word_1_6000	Random Forest
0.9979716	1	0.99595142	0.998	word_1_2000	Support Vector Machine

- The results of the best models of each classifier, for a dataset based on the emails2 pool of 1000 emails:

f1_score	recall	precision	accuracy	feature_matrix	model
0.9778672	0.99590164	0.96047431	0.978	word_1_1000	Decision Tree
0.94779116	0.96721311	0.92913386	0.948	word_1_100	KNN
0.98969072	0.98360656	0.99585062	0.99	word_1_3000	Logistic Regression
0.99795501	1	0.99591837	0.998	word_1_4000	Multi-layer Perceptron
0.99590164	0.99590164	0.99590164	0.996	word_1_4000	Multinomial Naive Bayes

0.99794661	0.99590164	1	0.998	word_1_100	Random Forest
0.99588477	0.99180328	1	0.996	word_1_2000	Support Vector Machine

- The results of the best models of each classifier, for a dataset based on the emails1+2 pool of 1000 emails:

f1_score	recall	precision	accuracy	feature_matrix	model
0.93927126	0.93172691	0.94693878	0.94	word_1_2000	Decision Tree
0.93333333	0.92771084	0.93902439	0.934	word_1_500	KNN
0.97975708	0.97188755	0.9877551	0.98	word_1_6000	Logistic Regression
0.98989899	0.98393574	0.99593496	0.99	word_1_6000	Multi-layer Perceptron
0.98174442	0.97188755	0.99180328	0.982	word_1_6000	Multinomial Naive Bayes
0.98196393	0.98393574	0.98	0.982	word_1_2000	Random Forest
0.98380566	0.97590361	0.99183673	0.984	word_1_2000	Support Vector Machine

An example of a full results table can be seen in appendix B. all the full results tables are available in my GitHub account, in the project repository[1] in the directory "trained models". Or can be received by running "train_models.py".

https://github.com/Ronke21?tab=repositories [1]

6 Discussion

Further to all the data presented in the last 2 chapters, some important conclusions can be distinguished:

- It seems that emails that came from emails1 and were not trained on - are correctly classified by a model trained on emails1 because the writing style is probably the same as the entire dataset and there is an overlap between key features in the emails. And the evidence is that I achieved very high classification percentages in each of the datasets separately. The difficulty starts when you take an email in a different writing style and then it seems that sometimes one database does not correctly classify emails that came from another database.
- The idea of combining the 2 datasets and creating a third dataset did create a general model that was able to correctly classify emails from each of the databases. And even handled well with new emails - for example, an email I wrote myself, or an email I received and Gmail classified as spam.
- As part of the test sample I conducted, it seems that the errors between the datasets are more common in non-spam mail, but the model is classified as spam. It could be that keywords that indicate spam in one database indicate ham in another database.
- In the 100-sized datasets, it seems that the models trained on emails2 were better, reaching an accuracy of 0.98-0.9 in each classifier. Emails1 models receive between 0.94-0.98 of this size, and correspondingly also the combined dataset emails1+2. It seems that emails2 is built in a way that makes it easier for the models.
- At a 500-sized dataset, emails1 gets slightly better results than the smaller dataset emails1 sized 100. But dataset 2 increases in the level of accuracy except for KNN which probably multi-neighbors harms its accuracy (too general). The integrated dataset improves and I guess more records allow it to learn the complex pattern better, and a few emails are not enough.
- In the 1000-sized dataset, all the datasets seem to achieve the best results among the many models (except KNN). Multiple examples allow better quality learning of this task.
- Among the classifier types, overwhelmingly, MLP achieves the highest accuracy. In each table you can see another outstanding model - sometimes RF, sometimes MNB, and sometimes SVM. The DT and KNN models are the weakest and this is not surprising. It is known that deep learning models have been a breakthrough when it comes to text classification, and even a basic and outdated model like MLP shows a good job.
- Concerning the number of features - the larger the dataset, the more features are needed because more types of emails need to be known. For example, in datasets of size 100, it can be seen that the outstanding models range from 500 to 2000 features. In datasets of 500 mails, there is an increase to 3000, 4000, and even 10000 features in the integrated dataset. And in the large datasets of 1000 words in the dataset, you can see

large quantities of features but not very much, a maximum of 6000, and there are also quite a few models that excelled in low quantities of features of 1000-2000. It is not possible to point to one trend in the number of features in a relation to the size of the dataset.

7 Conclusions and Future Work

In this paper, I describe my final project in the AI course – a system for Email spam detection.

I applied feature creation of word Ngrams based on tf-idf, 6 supervised machine learning methods and 1 deep learning method. Through various classification methods, I built a relatively strong system for assessing the spam classification of emails in English.

There are various ideas for future research regarding email spam detection:

- Additional repositories can be found and the accuracy of the model can be extended by making it more general.
- It is possible to improve existing ML models by performing parameter tuning, that is, choosing different parameters and comparing them to each model, rather than using the default Python setting.
- Features can be added using dictionaries containing words identified with spam.
- Advanced deep learning models can be trained - such as RNN, and LSTM networks that are particularly suitable for texts.
- It is possible to combine word embedding methods that were a breakthrough in the NLP world such as word2vec, BERT, and more.
- Oversampling methods can be used to increase the email pool. datasets 1-2 are originally unbalanced and contain much more non-spam emails. By oversampling, I can create a balanced pool by creating new spam samples and possibly improve the accuracy of the models.
- A combination of reinforcement learning tools allows the user to teach the system about an email that has been classified - whether it was successful or not. And it can improve the existing models.
- Using better computational resources to train much larger models.

In conclusion, I enjoyed doing the project. I learned a lot about the world of text classification and ended up with good and successful results. In recent years I have experienced the great benefits of automatically classifying emails as spam. I have a lot of emails classified as spam and do not litter the inbox. It seems that this type of model was significant in the past and will continue to be significant for improving the quality of life and use of emails in the modern world.

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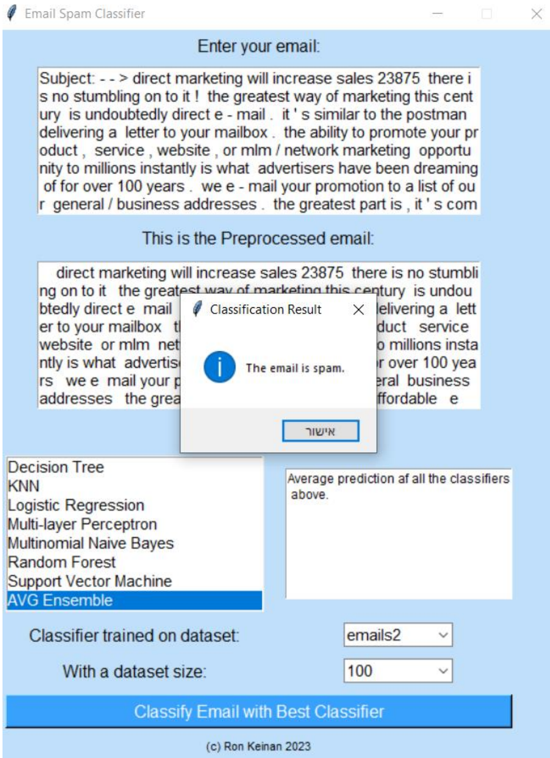
9 Appendices

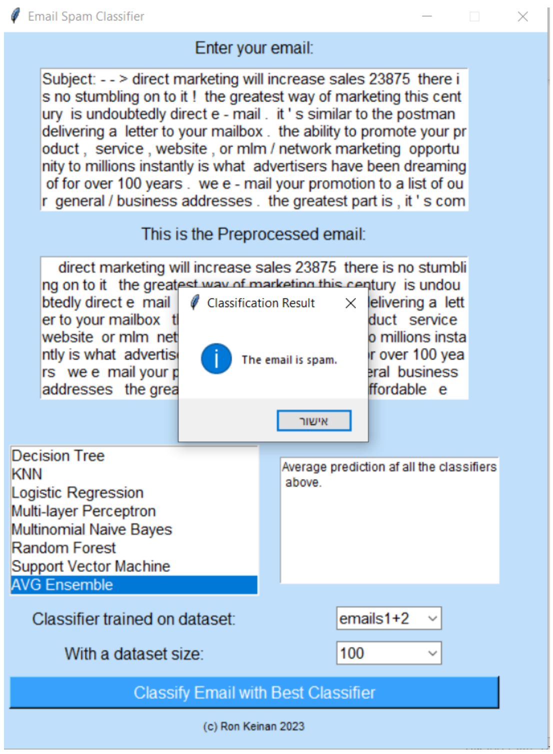
A Examples of dev classifications with the GUI

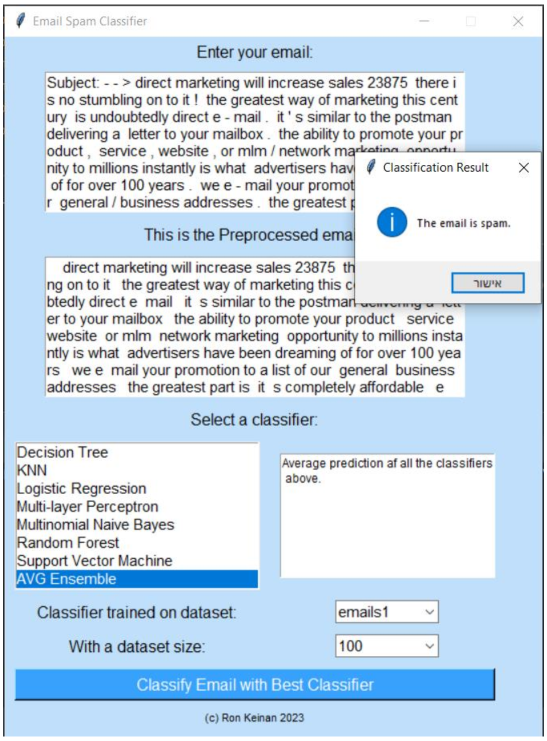
- First email - email that came from database #1 and the models were not trained on it. The email is classified as 1, which means spam:

  The classifications of chosen models were as follows -

Data	data size	classifier	classification
Emails1	100	AVG ensemble	spam
Emails2	100	AVG ensemble	spam
Emails1+2	100	AVG ensemble	spam

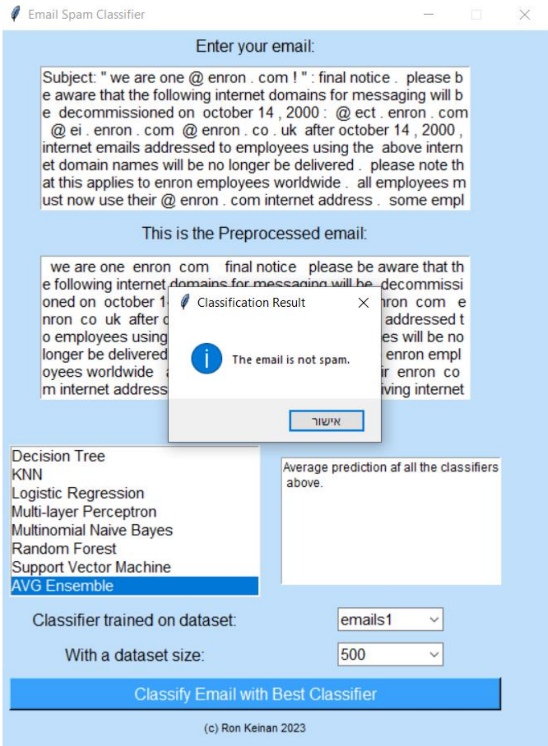

Email Spam Classifier
Enter your email:
Subject: - - > direct marketing will increase sales 23875 there i s no stumbling on to it ! the greatest way of marketing this cent ury is undoubtedly direct e - mail . it ' s similar to the postman delivering a letter to your mailbox . the ability to promote your pr oduct , service , website , or mlm / network marketing opportu nity to millions instantly is what advertisers have been dreaming of for over 100 years . we e - mail your promotion to a list of ou r general / business addresses . the greatest part is , it ' s com
This is the Preprocessed email:
Classification Result
The email is spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails2
With a dataset size:
100
Classify Email with Best Classifier
(c) Ron Keinan 2023

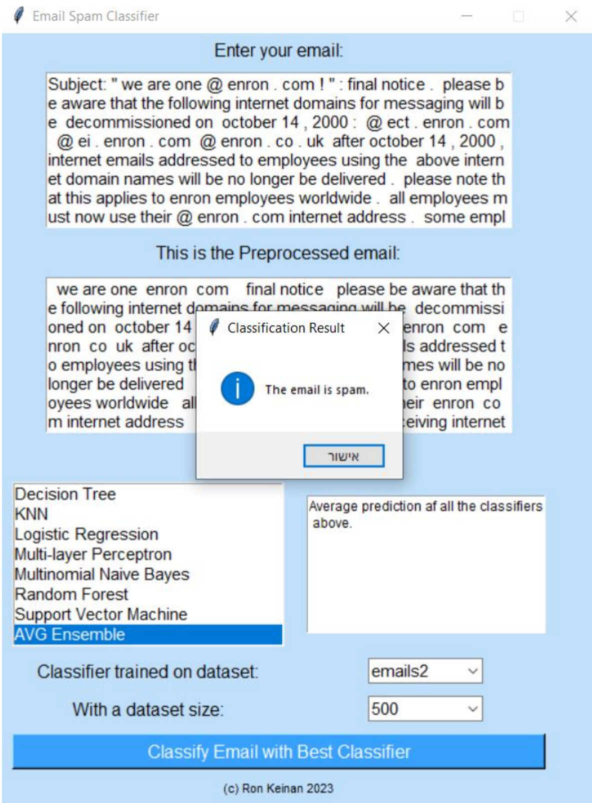

Email Spam Classifier
Enter your email:
Subject: - - > direct marketing will increase sales 23875 there i s no stumbling on to it ! the greatest way of marketing this cent ury is undoubtedly direct e - mail . it ' s similar to the postman delivering a letter to your mailbox . the ability to promote your pr oduct , service , website , or mlm / network marketing opportu nity to millions instantly is what advertisers have been dreaming of for over 100 years . we e - mail your promotion to a list of ou r general / business addresses . the greatest part is , it ' s com
This is the Preprocessed email:
Classification Result
The email is spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails1+2
With a dataset size:
100
Classify Email with Best Classifier
(c) Ron Keinan 2023

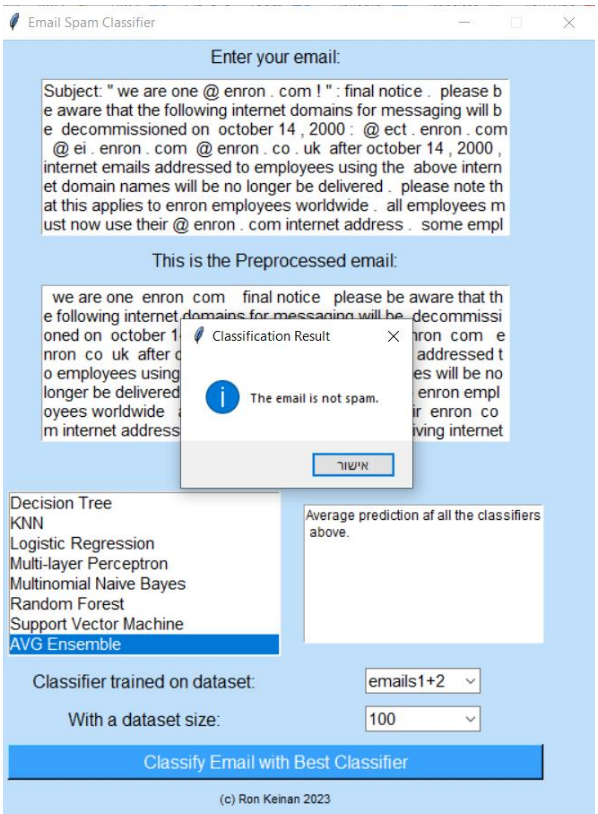


- Second email - email that came from database #1 and the models were not trained on it. The email is classified as 0, meaning not spam:
  The classifications of chosen models were as follows -

Data	data size	classifier	classification
Emails1	500	AVG ensemble	Not spam
Emails2	500	AVG ensemble	Spam
Emails1+2	100	AVG ensemble	Not spam

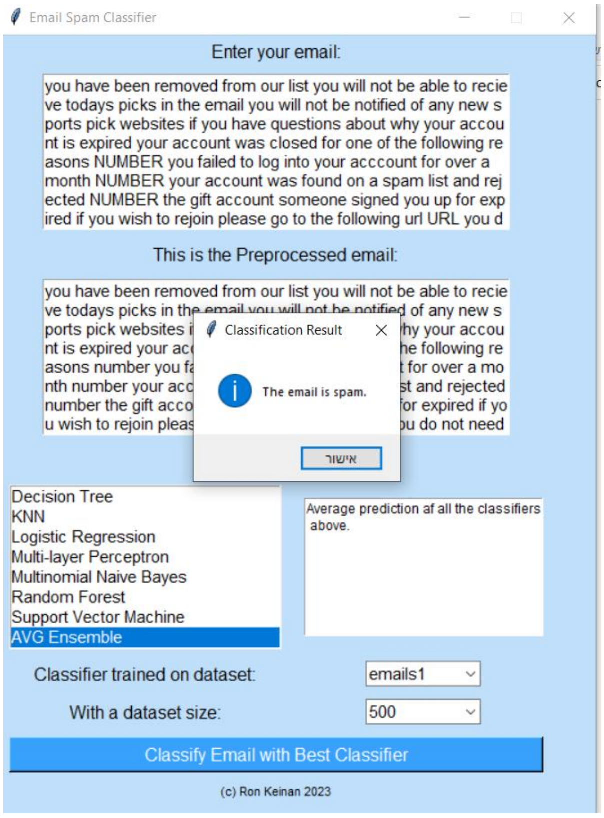

Email Spam Classifier
Enter your email:
Subject: " we are one @ enron . com ! " : final notice . please b
e aware that the following internet domains for messaging will b
e decommissioned on october 14 , 2000 : @ ect . enron . com
@ ei . enron . com @ enron . co . uk after october 14 , 2000 ,
internet emails addressed to employees using the above intern
et domain names will be no longer be delivered . please note th
at this applies to enron employees worldwide . all employees m
ust now use their @ enron . com internet address . some empl
This is the Preprocessed email:
Classification Result
The email is not spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails1
With a dataset size:
500
Classify Email with Best Classifier
(c) Ron Keinan 2023

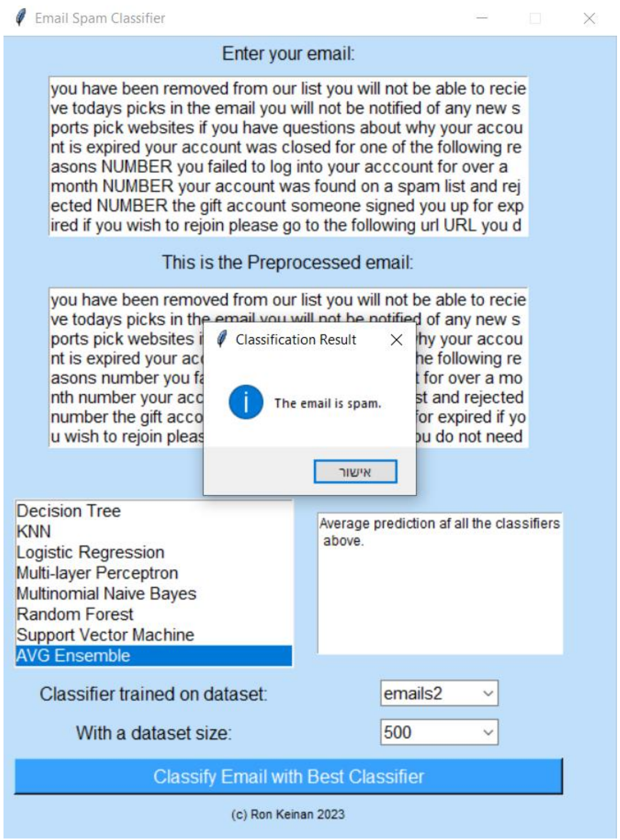

Email Spam Classifier
Enter your email:
Subject: " we are one @ enron . com ! " : final notice . please b
e aware that the following internet domains for messaging will b
e decommissioned on october 14 , 2000 : @ ect . enron . com
@ ei . enron . com @ enron . co . uk after october 14 , 2000 ,
internet emails addressed to employees using the above intern
et domain names will be no longer be delivered . please note th
at this applies to enron employees worldwide . all employees m
ust now use their @ enron . com internet address . some empl
This is the Preprocessed email:
Classification Result
The email is spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails2
With a dataset size:
500
Classify Email with Best Classifier
(c) Ron Keinan 2023

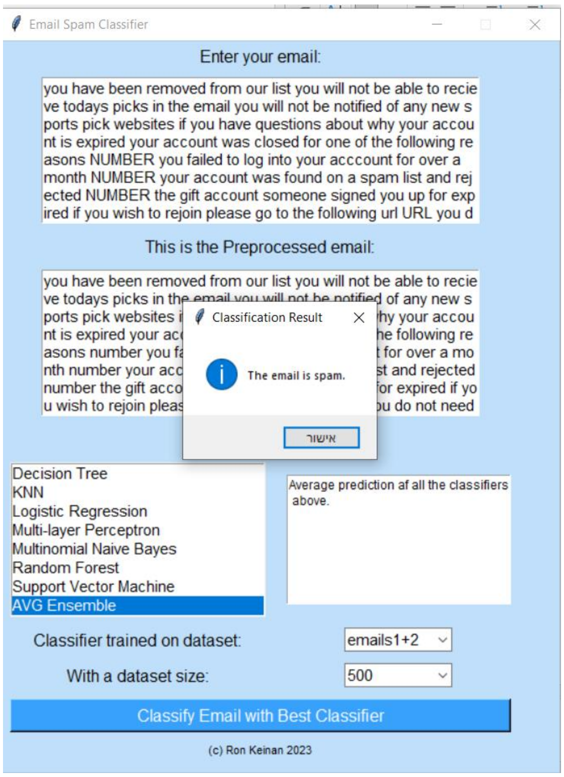


- Third email - email that came from database #2 and the models were not trained on it. The email is classified as 1, which means spam:
  The classifications of chosen models were as follows -

Data	**data size**	**classifier**	**classification**
Emails1	500	AVG ensemble	spam
Emails2	500	AVG ensemble	spam
Emails1+2	500	AVG ensemble	spam

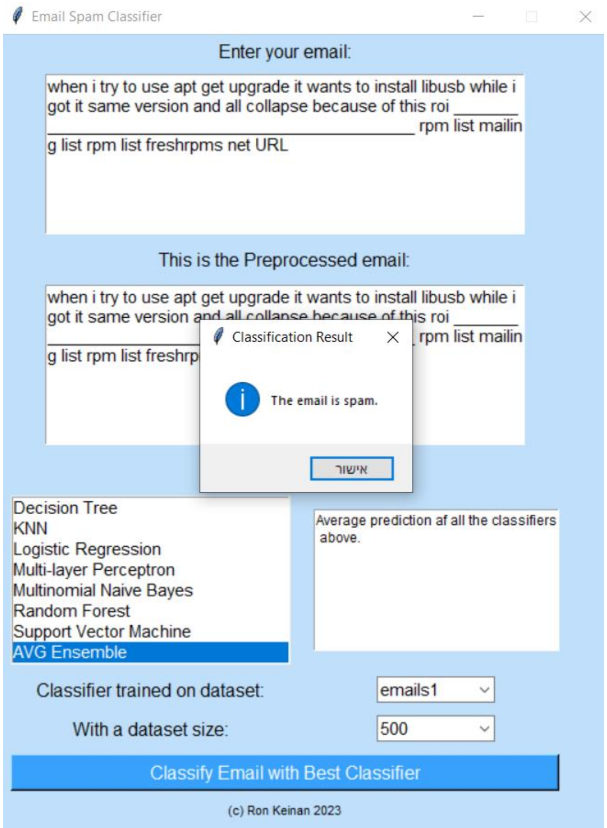

Email Spam Classifier
Enter your email:
you have been removed from our list you will not be able to recieve todays picks in the email you will not be notified of any new sports pick websites if you have questions about why your account is expired your account was closed for one of the following reasons NUMBER you failed to log into your acccount for over a month NUMBER your account was found on a spam list and rejected NUMBER the gift account someone signed you up for expired if you wish to rejoin please go to the following url URL you d
This is the Preprocessed email:
Classification Result
The email is spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails1
With a dataset size:
500
Classify Email with Best Classifier
(c) Ron Keinan 2023

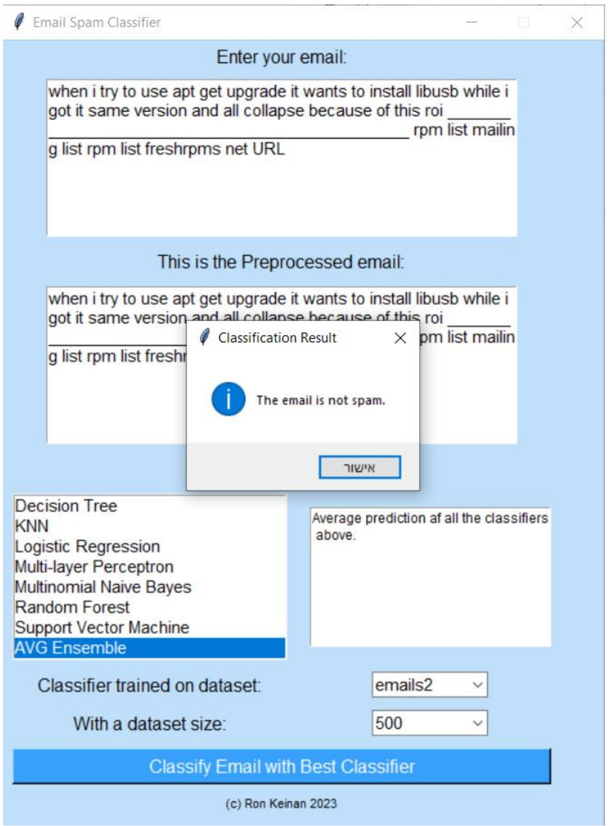

Email Spam Classifier
Enter your email:
you have been removed from our list you will not be able to recieve todays picks in the email you will not be notified of any new sports pick websites if you have questions about why your account is expired your account was closed for one of the following reasons NUMBER you failed to log into your acccount for over a month NUMBER your account was found on a spam list and rejected NUMBER the gift account someone signed you up for expired if you wish to rejoin please go to the following url URL you d
This is the Preprocessed email:
Classification Result
The email is spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails2
With a dataset size:
500
Classify Email with Best Classifier
(c) Ron Keinan 2023

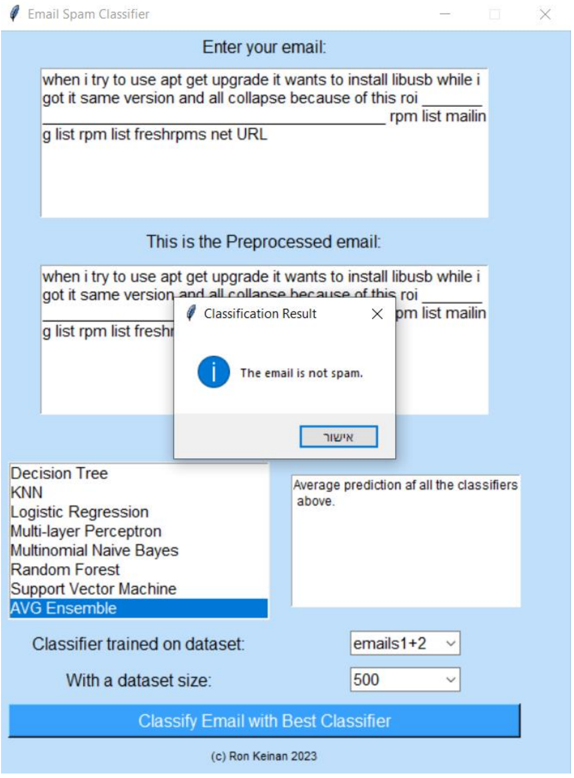


- Fourth email - email that came from database #2 and the models were not trained on it. The email is classified as 0, meaning not spam:
  The classifications of chosen models were as follows -

Data	data size	classifier	classification
Emails1	500	AVG ensemble	Spam
Emails2	500	AVG ensemble	Not spam
Emails1+2	500	AVG ensemble	Not spam

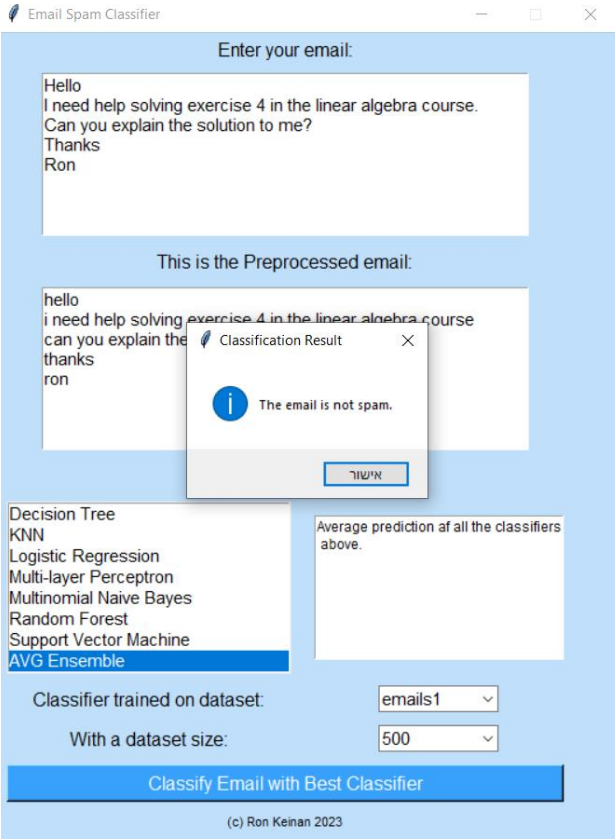

Email Spam Classifier
Enter your email:
when i try to use apt get upgrade it wants to install libusb while i got it same version and all collapse because of this roi ________ rpm list mailin g list rpm list freshrpms net URL
This is the Preprocessed email:
Classification Result
The email is spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails1
With a dataset size:
500
Classify Email with Best Classifier
(c) Ron Keinan 2023

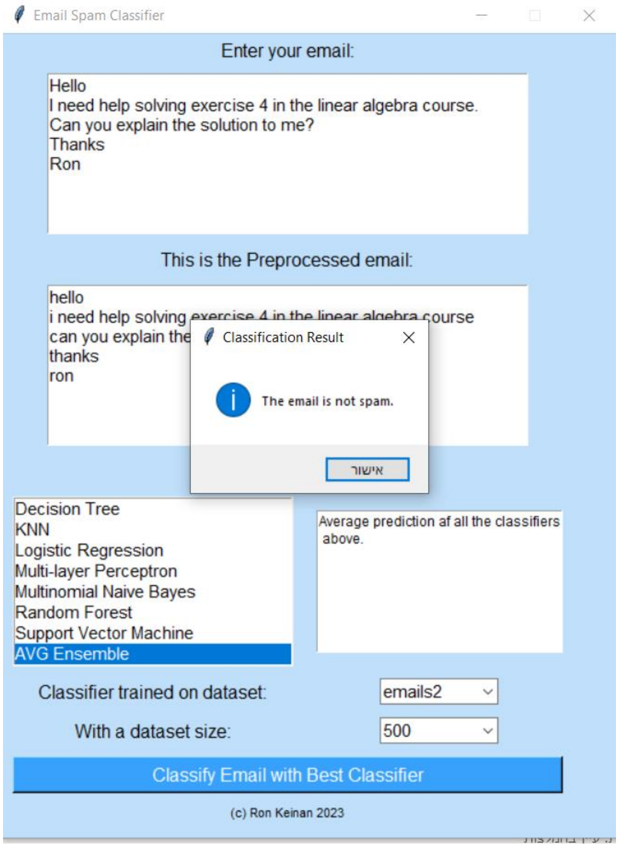

Email Spam Classifier
Enter your email:
when i try to use apt get upgrade it wants to install libusb while i got it same version and all collapse because of this roi ________ rpm list mailin g list rpm list freshrpms net URL
This is the Preprocessed email:
Classification Result
The email is not spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails2
With a dataset size:
500
Classify Email with Best Classifier
(c) Ron Keinan 2023

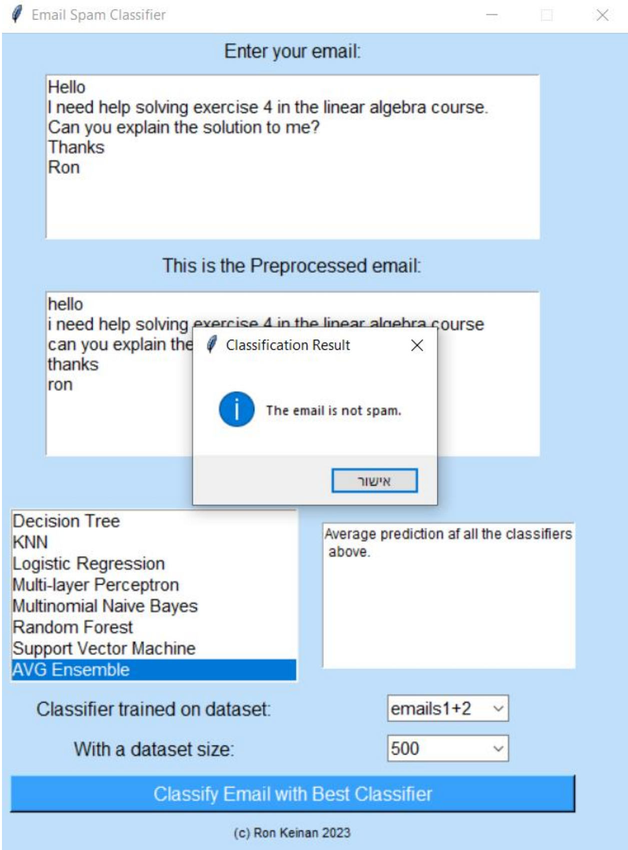


- Fifth email - just an email I made up and is not spam:
  The classifications of chosen models were as follows -

Data	**data size**	**classifier**	**classification**
Emails1	500	AVG ensemble	Not spam
Emails2	500	AVG ensemble	Not spam
Emails1+2	500	AVG ensemble	Not spam

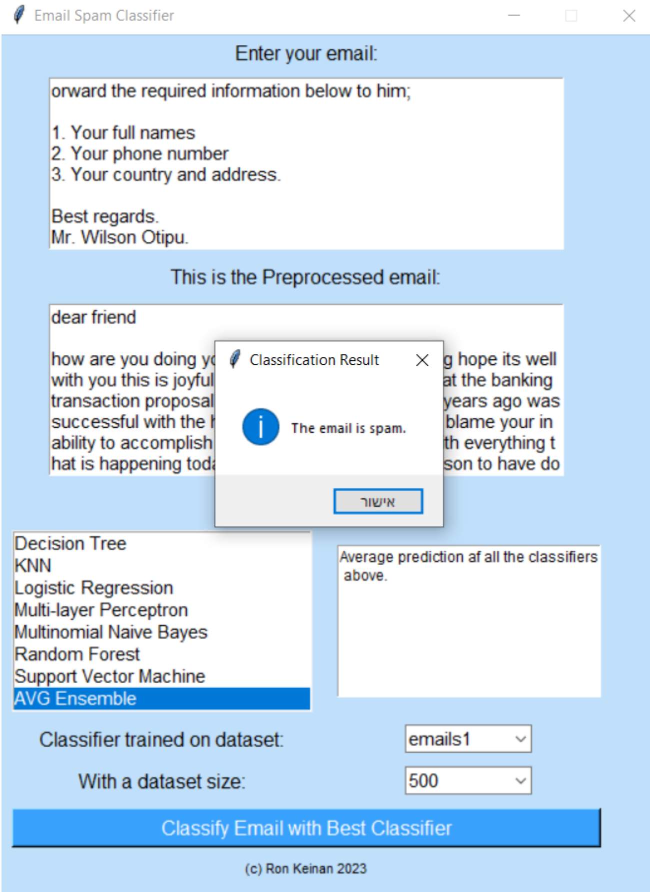

Email Spam Classifier
Enter your email:
Hello
I need help solving exercise 4 in the linear algebra course.
Can you explain the solution to me?
Thanks
Ron
This is the Preprocessed email:
hello
i need help solving
can you explain the
thanks
ron
Classification Result
The email is not spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails1
With a dataset size:
500
Classify Email with Best Classifier
(c) Ron Keinan 2023

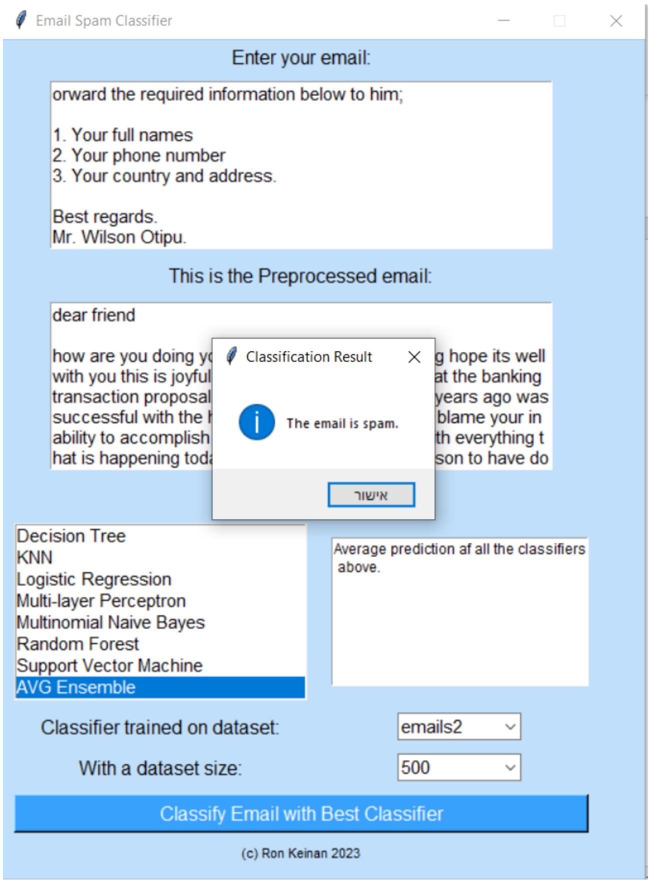

Email Spam Classifier
Enter your email:
Hello
I need help solving exercise 4 in the linear algebra course.
Can you explain the solution to me?
Thanks
Ron
This is the Preprocessed email:
hello
i need help solving
can you explain the
thanks
ron
Classification Result
The email is not spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails2
With a dataset size:
500
Classify Email with Best Classifier
(c) Ron Keinan 2023

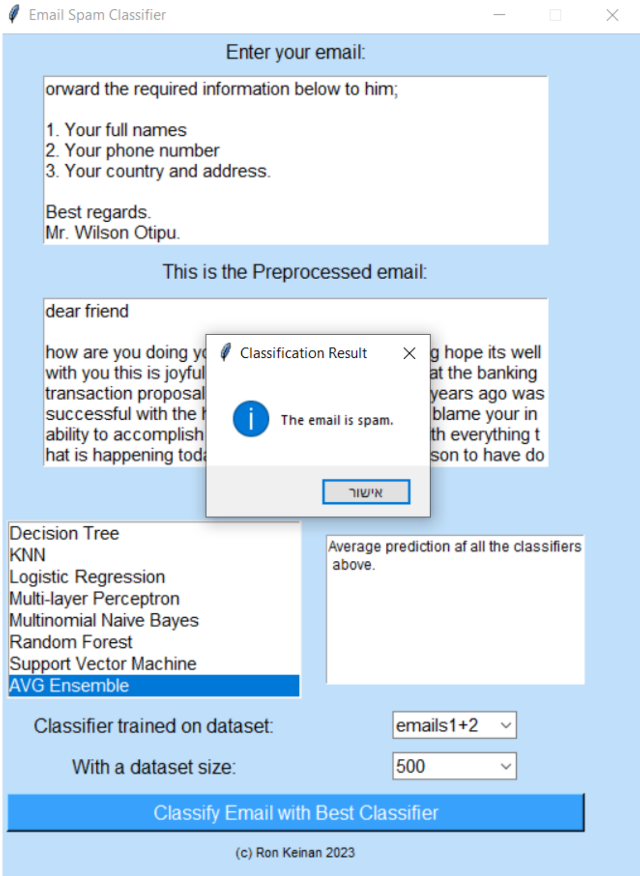


- Sixth email - an email I took from my inbox and which Gmail classified as spam:
  The classifications of chosen models were as follows -

Data	**data size**	**classifier**	**classification**
Emails1	500	AVG ensemble	Spam
Emails2	500	AVG ensemble	Spam
Emails1+2	500	AVG ensemble	Spam


Email Spam Classifier
Enter your email:
orward the required information below to him;
1. Your full names
2. Your phone number
3. Your country and address.
Best regards.
Mr. Wilson Otipu.
This is the Preprocessed email:
dear friend
Classification Result
The email is spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails1
With a dataset size:
500
Classify Email with Best Classifier
(c) Ron Keinan 2023


Email Spam Classifier
Enter your email:
orward the required information below to him;
1. Your full names
2. Your phone number
3. Your country and address.
Best regards.
Mr. Wilson Otipu.
This is the Preprocessed email:
dear friend
Classification Result
The email is spam.
אישור
Decision Tree
KNN
Logistic Regression
Multi-layer Perceptron
Multinomial Naive Bayes
Random Forest
Support Vector Machine
AVG Ensemble
Average prediction af all the classifiers above.
Classifier trained on dataset:
emails2
With a dataset size:
500
Classify Email with Best Classifier
(c) Ron Keinan 2023



B Results of all models scores

Models results in example – training on dataset emails1, size 100:

model	feature_matrix	accuracy	precision	recall	f1_score
KNN	word_1_100	0.84	0.9	0.84375	0.87096774
KNN	word_2_100	0.78	0.76923077	0.9375	0.84507042
KNN	word_3_100	0.48	0.65	0.40625	0.5
KNN	word_1_500	0.92	0.9375	0.9375	0.9375
KNN	word_2_500	0.66	0.65306122	1	0.79012345
KNN	word_3_500	0.66	0.65957447	0.96875	0.78481013
KNN	word_1_1000	0.96	1	0.9375	0.96774194
KNN	word_2_1000	0.86	0.93103448	0.84375	0.8852459
KNN	word_3_1000	0.76	0.77777778	0.875	0.82352941
KNN	word_1_2000	0.9	0.93548387	0.90625	0.92063492
KNN	word_2_2000	0.88	0.96428571	0.84375	0.9
KNN	word_3_2000	0.76	0.77777778	0.875	0.82352941
KNN	word_1_3000	0.9	0.93548387	0.90625	0.92063492
KNN	word_2_3000	0.88	0.96428571	0.84375	0.9
KNN	word_3_3000	0.76	0.77777778	0.875	0.82352941
KNN	word_1_4000	0.9	0.93548387	0.90625	0.92063492
KNN	word_2_4000	0.88	0.96428571	0.84375	0.9
KNN	word_3_4000	0.76	0.77777778	0.875	0.82352941
KNN	word_1_5000	0.9	0.93548387	0.90625	0.92063492

KNN	word_2_5000	0.88	0.96428571	0.84375	0.9
KNN	word_3_5000	0.76	0.77777778	0.875	0.82352941
KNN	word_1_6000	0.9	0.93548387	0.90625	0.92063492
KNN	word_2_6000	0.88	0.96428571	0.84375	0.9
KNN	word_3_6000	0.76	0.77777778	0.875	0.82352941
KNN	word_1_7000	0.9	0.93548387	0.90625	0.92063492
KNN	word_2_7000	0.88	0.96428571	0.84375	0.9
KNN	word_3_7000	0.76	0.77777778	0.875	0.82352941
KNN	word_1_8000	0.9	0.93548387	0.90625	0.92063492
KNN	word_2_8000	0.88	0.96428571	0.84375	0.9
KNN	word_3_8000	0.76	0.77777778	0.875	0.82352941
KNN	word_1_9000	0.9	0.93548387	0.90625	0.92063492
KNN	word_2_9000	0.88	0.96428571	0.84375	0.9
KNN	word_3_9000	0.76	0.77777778	0.875	0.82352941
KNN	word_1_10000	0.9	0.93548387	0.90625	0.92063492
KNN	word_2_10000	0.88	0.96428571	0.84375	0.9
KNN	word_3_10000	0.76	0.77777778	0.875	0.82352941
Logistic Regression	word_1_100	0.9	0.96551724	0.875	0.91803279
Logistic Regression	word_2_100	0.86	0.90322581	0.875	0.88888889
Logistic Regression	word_3_100	0.92	0.88888889	1	0.94117647
Logistic Regression	word_1_500	0.94	1	0.90625	0.95081967
Logistic Regression	word_2_500	0.9	0.96551724	0.875	0.91803279
Logistic Regression	word_3_500	0.92	0.9375	0.9375	0.9375
Logistic Regression	word_1_1000	0.92	1	0.875	0.93333333
Logistic Regression	word_2_1000	0.86	1	0.78125	0.87719298
Logistic Regression	word_3_1000	0.78	0.95652174	0.6875	0.8
Logistic Regression	word_1_2000	0.92	1	0.875	0.93333333
Logistic Regression	word_2_2000	0.84	1	0.75	0.85714286
Logistic Regression	word_3_2000	0.78	0.95652174	0.6875	0.8
Logistic Regression	word_1_3000	0.92	1	0.875	0.93333333
Logistic Regression	word_2_3000	0.84	1	0.75	0.85714286
Logistic Regression	word_3_3000	0.78	0.95652174	0.6875	0.8
Logistic Regression	word_1_4000	0.92	1	0.875	0.93333333
Logistic Regression	word_2_4000	0.84	1	0.75	0.85714286
Logistic Regression	word_3_4000	0.78	0.95652174	0.6875	0.8
Logistic Regression	word_1_5000	0.92	1	0.875	0.93333333
Logistic Regression	word_2_5000	0.84	1	0.75	0.85714286
Logistic Regression	word_3_5000	0.78	0.95652174	0.6875	0.8
Logistic Regression	word_1_6000	0.92	1	0.875	0.93333333
Logistic Regression	word_2_6000	0.84	1	0.75	0.85714286
Logistic Regression	word_3_6000	0.78	0.95652174	0.6875	0.8
Logistic Regression	word_1_7000	0.92	1	0.875	0.93333333
Logistic Regression	word_2_7000	0.84	1	0.75	0.85714286
Logistic Regression	word_3_7000	0.78	0.95652174	0.6875	0.8
Logistic Regression	word_1_8000	0.92	1	0.875	0.93333333
Logistic Regression	word_2_8000	0.84	1	0.75	0.85714286
Logistic Regression	word_3_8000	0.78	0.95652174	0.6875	0.8
Logistic Regression	word_1_9000	0.92	1	0.875	0.93333333

Logistic Regression	word_2_9000	0.84	1	0.75	0.85714286
Logistic Regression	word_3_9000	0.78	0.95652174	0.6875	0.8
Logistic Regression	word_1_10000	0.92	1	0.875	0.93333333
Logistic Regression	word_2_10000	0.84	1	0.75	0.85714286
Logistic Regression	word_3_10000	0.78	0.95652174	0.6875	0.8
Multinomial Naive Bayes	word_1_100	0.94	0.96774194	0.9375	0.95238095
Multinomial Naive Bayes	word_2_100	0.78	0.86206897	0.78125	0.81967213
Multinomial Naive Bayes	word_3_100	0.66	0.94117647	0.5	0.65306122
Multinomial Naive Bayes	word_1_500	0.96	1	0.9375	0.96774194
Multinomial Naive Bayes	word_2_500	0.82	1	0.71875	0.83636364
Multinomial Naive Bayes	word_3_500	0.7	1	0.53125	0.69387755
Multinomial Naive Bayes	word_1_1000	0.86	1	0.78125	0.87719298
Multinomial Naive Bayes	word_2_1000	0.82	1	0.71875	0.83636364
Multinomial Naive Bayes	word_3_1000	0.68	0.94444444	0.53125	0.68
Multinomial Naive Bayes	word_1_2000	0.84	1	0.75	0.85714286
Multinomial Naive Bayes	word_2_2000	0.8	1	0.6875	0.81481481
Multinomial Naive Bayes	word_3_2000	0.68	0.94444444	0.53125	0.68
Multinomial Naive Bayes	word_1_3000	0.84	1	0.75	0.85714286
Multinomial Naive Bayes	word_2_3000	0.8	1	0.6875	0.81481481
Multinomial Naive Bayes	word_3_3000	0.68	0.94444444	0.53125	0.68
Multinomial Naive Bayes	word_1_4000	0.84	1	0.75	0.85714286
Multinomial Naive Bayes	word_2_4000	0.8	1	0.6875	0.81481481
Multinomial Naive Bayes	word_3_4000	0.68	0.94444444	0.53125	0.68
Multinomial Naive Bayes	word_1_5000	0.84	1	0.75	0.85714286
Multinomial Naive Bayes	word_2_5000	0.8	1	0.6875	0.81481481
Multinomial Naive Bayes	word_3_5000	0.68	0.94444444	0.53125	0.68
Multinomial Naive Bayes	word_1_6000	0.84	1	0.75	0.85714286
Multinomial Naive Bayes	word_2_6000	0.8	1	0.6875	0.81481481
Multinomial Naive Bayes	word_3_6000	0.68	0.94444444	0.53125	0.68
Multinomial Naive Bayes	word_1_7000	0.84	1	0.75	0.85714286
Multinomial Naive Bayes	word_2_7000	0.8	1	0.6875	0.81481481
Multinomial Naive Bayes	word_3_7000	0.68	0.94444444	0.53125	0.68
Multinomial Naive Bayes	word_1_8000	0.84	1	0.75	0.85714286
Multinomial Naive Bayes	word_2_8000	0.8	1	0.6875	0.81481481
Multinomial Naive Bayes	word_3_8000	0.68	0.94444444	0.53125	0.68
Multinomial Naive Bayes	word_1_9000	0.84	1	0.75	0.85714286
Multinomial Naive Bayes	word_2_9000	0.8	1	0.6875	0.81481481
Multinomial Naive Bayes	word_3_9000	0.68	0.94444444	0.53125	0.68
Multinomial Naive Bayes	word_1_10000	0.84	1	0.75	0.85714286
Multinomial Naive Bayes	word_2_10000	0.8	1	0.6875	0.81481481
Multinomial Naive Bayes	word_3_10000	0.68	0.94444444	0.53125	0.68
Support Vector Machine	word_1_100	0.9	0.96551724	0.875	0.91803279
Support Vector Machine	word_2_100	0.86	0.90322581	0.875	0.88888889
Support Vector Machine	word_3_100	0.9	0.90909091	0.9375	0.92307692
Support Vector Machine	word_1_500	0.96	1	0.9375	0.96774194
Support Vector Machine	word_2_500	0.84	1	0.75	0.85714286
Support Vector Machine	word_3_500	0.82	0.89655172	0.8125	0.85245901
Support Vector Machine	word_1_1000	0.92	1	0.875	0.93333333

Support Vector Machine	word_2_1000	0.82	1	0.71875	0.83636364
Support Vector Machine	word_3_1000	0.8	0.89285714	0.78125	0.83333333
Support Vector Machine	word_1_2000	0.94	1	0.90625	0.95081967
Support Vector Machine	word_2_2000	0.84	1	0.75	0.85714286
Support Vector Machine	word_3_2000	0.8	0.89285714	0.78125	0.83333333
Support Vector Machine	word_1_3000	0.94	1	0.90625	0.95081967
Support Vector Machine	word_2_3000	0.84	1	0.75	0.85714286
Support Vector Machine	word_3_3000	0.8	0.89285714	0.78125	0.83333333
Support Vector Machine	word_1_4000	0.94	1	0.90625	0.95081967
Support Vector Machine	word_2_4000	0.84	1	0.75	0.85714286
Support Vector Machine	word_3_4000	0.8	0.89285714	0.78125	0.83333333
Support Vector Machine	word_1_5000	0.94	1	0.90625	0.95081967
Support Vector Machine	word_2_5000	0.84	1	0.75	0.85714286
Support Vector Machine	word_3_5000	0.8	0.89285714	0.78125	0.83333333
Support Vector Machine	word_1_6000	0.94	1	0.90625	0.95081967
Support Vector Machine	word_2_6000	0.84	1	0.75	0.85714286
Support Vector Machine	word_3_6000	0.8	0.89285714	0.78125	0.83333333
Support Vector Machine	word_1_7000	0.94	1	0.90625	0.95081967
Support Vector Machine	word_2_7000	0.84	1	0.75	0.85714286
Support Vector Machine	word_3_7000	0.8	0.89285714	0.78125	0.83333333
Support Vector Machine	word_1_8000	0.94	1	0.90625	0.95081967
Support Vector Machine	word_2_8000	0.84	1	0.75	0.85714286
Support Vector Machine	word_3_8000	0.8	0.89285714	0.78125	0.83333333
Support Vector Machine	word_1_9000	0.94	1	0.90625	0.95081967
Support Vector Machine	word_2_9000	0.84	1	0.75	0.85714286
Support Vector Machine	word_3_9000	0.8	0.89285714	0.78125	0.83333333
Support Vector Machine	word_1_10000	0.94	1	0.90625	0.95081967
Support Vector Machine	word_2_10000	0.84	1	0.75	0.85714286
Support Vector Machine	word_3_10000	0.8	0.89285714	0.78125	0.83333333
Decision Tree	word_1_100	0.84	0.9	0.84375	0.87096774
Decision Tree	word_2_100	0.8	0.86666667	0.8125	0.83870968
Decision Tree	word_3_100	0.88	0.84210526	1	0.91428571
Decision Tree	word_1_500	0.84	0.9	0.84375	0.87096774
Decision Tree	word_2_500	0.74	0.88	0.6875	0.77192982
Decision Tree	word_3_500	0.88	0.86111111	0.96875	0.91176471
Decision Tree	word_1_1000	0.92	0.91176471	0.96875	0.93939394
Decision Tree	word_2_1000	0.74	0.82758621	0.75	0.78688525
Decision Tree	word_3_1000	0.9	0.88571429	0.96875	0.92537314
Decision Tree	word_1_2000	0.94	0.91428571	1	0.95522388
Decision Tree	word_2_2000	0.78	0.86206897	0.78125	0.81967213
Decision Tree	word_3_2000	0.88	0.90625	0.90625	0.90625
Decision Tree	word_1_3000	0.9	0.90909091	0.9375	0.92307692
Decision Tree	word_2_3000	0.76	0.85714286	0.75	0.8
Decision Tree	word_3_3000	0.84	0.85294118	0.90625	0.87878788
Decision Tree	word_1_4000	0.94	0.91428571	1	0.95522388
Decision Tree	word_2_4000	0.8	0.86666667	0.8125	0.83870968
Decision Tree	word_3_4000	0.88	0.86111111	0.96875	0.91176471
Decision Tree	word_1_5000	0.86	0.90322581	0.875	0.88888889

Decision Tree	word_2_5000	0.82	0.89655172	0.8125	0.85245901
Decision Tree	word_3_5000	0.88	0.86111111	0.96875	0.91176471
Decision Tree	word_1_6000	0.94	0.91428571	1	0.95522388
Decision Tree	word_2_6000	0.76	0.88461538	0.71875	0.79310345
Decision Tree	word_3_6000	0.88	0.86111111	0.96875	0.91176471
Decision Tree	word_1_7000	0.9	0.90909091	0.9375	0.92307692
Decision Tree	word_2_7000	0.8	0.89285714	0.78125	0.83333333
Decision Tree	word_3_7000	0.82	0.82857143	0.90625	0.86567164
Decision Tree	word_1_8000	0.88	0.90625	0.90625	0.90625
Decision Tree	word_2_8000	0.76	0.83333333	0.78125	0.80645161
Decision Tree	word_3_8000	0.86	0.83783784	0.96875	0.89855073
Decision Tree	word_1_9000	0.88	0.90625	0.90625	0.90625
Decision Tree	word_2_9000	0.76	0.85714286	0.75	0.8
Decision Tree	word_3_9000	0.86	0.83783784	0.96875	0.89855073
Decision Tree	word_1_10000	0.86	0.90322581	0.875	0.88888889
Decision Tree	word_2_10000	0.78	0.88888889	0.75	0.81355932
Decision Tree	word_3_10000	0.86	0.87878788	0.90625	0.89230769
Random Forest	word_1_100	0.94	0.93939394	0.96875	0.95384615
Random Forest	word_2_100	0.82	0.89655172	0.8125	0.85245901
Random Forest	word_3_100	0.92	0.88888889	1	0.94117647
Random Forest	word_1_500	0.96	0.96875	0.96875	0.96875
Random Forest	word_2_500	0.82	0.87096774	0.84375	0.85714286
Random Forest	word_3_500	0.92	0.88888889	1	0.94117647
Random Forest	word_1_1000	0.92	0.9375	0.9375	0.9375
Random Forest	word_2_1000	0.86	0.87878788	0.90625	0.89230769
Random Forest	word_3_1000	0.92	0.91176471	0.96875	0.93939394
Random Forest	word_1_2000	0.96	0.96875	0.96875	0.96875
Random Forest	word_2_2000	0.88	0.86111111	0.96875	0.91176471
Random Forest	word_3_2000	0.92	0.91176471	0.96875	0.93939394
Random Forest	word_1_3000	0.96	0.94117647	1	0.96969697
Random Forest	word_2_3000	0.88	0.90625	0.90625	0.90625
Random Forest	word_3_3000	0.92	0.91176471	0.96875	0.93939394
Random Forest	word_1_4000	0.94	0.93939394	0.96875	0.95384615
Random Forest	word_2_4000	0.88	0.88235294	0.9375	0.90909091
Random Forest	word_3_4000	0.9	0.88571429	0.96875	0.92537314
Random Forest	word_1_5000	0.98	0.96969697	1	0.98461538
Random Forest	word_2_5000	0.86	0.85714286	0.9375	0.89552239
Random Forest	word_3_5000	0.92	0.91176471	0.96875	0.93939394
Random Forest	word_1_6000	0.96	0.96875	0.96875	0.96875
Random Forest	word_2_6000	0.88	0.88235294	0.9375	0.90909091
Random Forest	word_3_6000	0.92	0.91176471	0.96875	0.93939394
Random Forest	word_1_7000	0.96	0.96875	0.96875	0.96875
Random Forest	word_2_7000	0.9	0.90909091	0.9375	0.92307692
Random Forest	word_3_7000	0.94	0.91428571	1	0.95522388
Random Forest	word_1_8000	0.98	0.96969697	1	0.98461538
Random Forest	word_2_8000	0.86	0.87878788	0.90625	0.89230769
Random Forest	word_3_8000	0.92	0.91176471	0.96875	0.93939394
Random Forest	word_1_9000	0.96	0.96875	0.96875	0.96875

Random Forest	word_2_9000	0.9	0.90909091	0.9375	0.92307692
Random Forest	word_3_9000	0.94	0.91428571	1	0.95522388
Random Forest	word_1_10000	0.94	0.96774194	0.9375	0.95238095
Random Forest	word_2_10000	0.88	0.90625	0.90625	0.90625
Random Forest	word_3_10000	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_100	0.9	1	0.84375	0.91525424
Multi-layer Perceptron	word_2_100	0.86	0.93103448	0.84375	0.8852459
Multi-layer Perceptron	word_3_100	0.92	0.88888889	1	0.94117647
Multi-layer Perceptron	word_1_500	0.94	1	0.90625	0.95081967
Multi-layer Perceptron	word_2_500	0.88	1	0.8125	0.89655172
Multi-layer Perceptron	word_3_500	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_1000	0.96	1	0.9375	0.96774194
Multi-layer Perceptron	word_2_1000	0.84	0.96153846	0.78125	0.86206896
Multi-layer Perceptron	word_3_1000	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_2000	0.98	1	0.96875	0.98412698
Multi-layer Perceptron	word_2_2000	0.9	0.96551724	0.875	0.91803279
Multi-layer Perceptron	word_3_2000	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_3000	0.98	1	0.96875	0.98412698
Multi-layer Perceptron	word_2_3000	0.92	1	0.875	0.93333333
Multi-layer Perceptron	word_3_3000	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_4000	0.98	1	0.96875	0.98412698
Multi-layer Perceptron	word_2_4000	0.9	0.96551724	0.875	0.91803279
Multi-layer Perceptron	word_3_4000	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_5000	0.98	1	0.96875	0.98412698
Multi-layer Perceptron	word_2_5000	0.92	1	0.875	0.93333333
Multi-layer Perceptron	word_3_5000	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_6000	0.98	1	0.96875	0.98412698
Multi-layer Perceptron	word_2_6000	0.92	1	0.875	0.93333333
Multi-layer Perceptron	word_3_6000	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_7000	0.98	1	0.96875	0.98412698
Multi-layer Perceptron	word_2_7000	0.9	0.96551724	0.875	0.91803279
Multi-layer Perceptron	word_3_7000	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_8000	0.98	1	0.96875	0.98412698
Multi-layer Perceptron	word_2_8000	0.92	1	0.875	0.93333333
Multi-layer Perceptron	word_3_8000	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_9000	0.98	1	0.96875	0.98412698
Multi-layer Perceptron	word_2_9000	0.9	0.96551724	0.875	0.91803279
Multi-layer Perceptron	word_3_9000	0.92	0.91176471	0.96875	0.93939394
Multi-layer Perceptron	word_1_10000	0.98	1	0.96875	0.98412698
Multi-layer Perceptron	word_2_10000	0.9	0.96551724	0.875	0.91803279
Multi-layer Perceptron	word_3_10000	0.92	0.91176471	0.96875	0.93939394