Detection of Spam Email

COURSE PROJECT REPORT

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By

ZEAL SHAH – RA2011003010369

HARSH KELAWALA - RA2011003010373

ABHI PATEL - RA2011026010078

Under the guidance of

Dr. V VIJAYALAKSHMI

Professor

Department of Data Science and Business Systems

DEPARTMENT OF DATA SCIENCE AND BUSINESS SYSTEMS

FACULTY OF ENGINEERING AND TECHNOLOGY

SRM INSTITUTE OF SCIENCE AND TECHNOLOGY

Kattankulathur, Kancheepuram

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DETECTION OF SPAM EMAIL

ZEAL SHAH (zs5263@srmist.edu.in)

HARSH KELAWALA (hk9586@srmist.edu.in)

ABHI PATEL (ap0279@srmist.edu.in)

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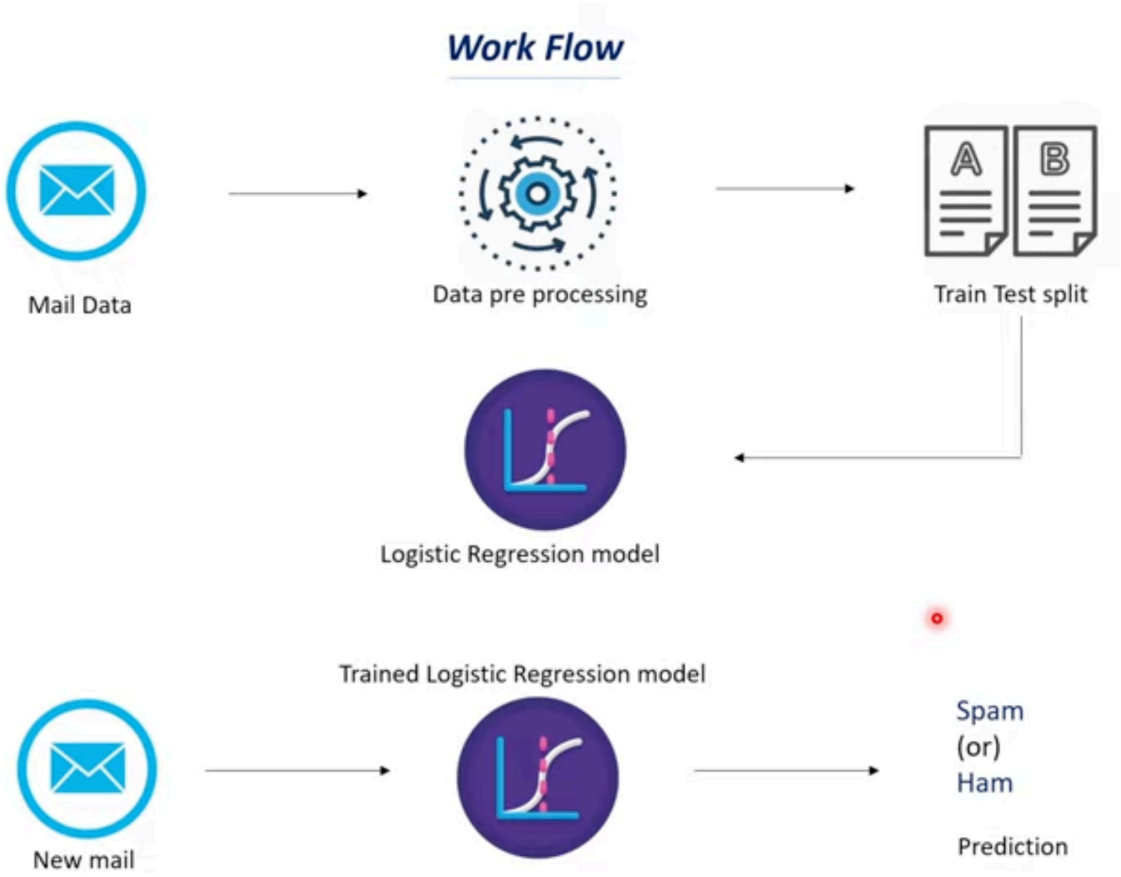
ABSTRACT

This machine learning project aims to develop a spam mail detection system using logistic regression. The dataset includes the two columns, Category and message. The project utilises logistic regression as the main algorithm for classification, which is a popular statistical technique for modelling binary outcomes. The dataset is preprocessed to extract relevant features and eliminate irrelevant information. The logistic regression model is then trained on the preprocessed data, and its performance is evaluated using various metrics such as accuracy, precision, and recall. The ultimate goal of the project is to develop an accurate and efficient spam mail detection system that can classify emails as either spam or ham with high confidence, thereby improving the user experience and preventing potential security threats.



INTRODUCTION

Emails have become a ubiquitous form of communication in our modern age, but unfortunately, so too has spam email.Spam emails can cause a variety of issues for individuals and organisations, such as time wasted filtering through unwanted messages or the risk of falling victim to phishing attacks.The rise of spam emails is an increasing problem for email users, as these messages can be time-consuming to filter through and can pose a security risk by containing malicious content. As a result, there is a growing need for effective methods to detect and filter out spam emails.Machine learning algorithms have proven to be effective in identifying and filtering out spam emails. In this project, we aim to develop a logistic regression model to detect spam emails.

To train our logistic regression model, we will use a dataset of emails labeled as spam or ham. We will preprocess the data by removing stop words, performing stemming, and extracting relevant features such as the presence of specific keywords, the length of the email, and the frequency of certain characters or phrases. We will then split the data into training and testing sets and train the logistic regression model on the training set. We will evaluate the model's performance on the testing set by calculating metrics such as accuracy, precision, recall, and F1-score.

Our goal is to develop a logistic regression model that can accurately and efficiently detect spam emails. We hope that our project will contribute to the development of more effective spam email detection methods, which can be integrated into email clients and servers to provide a more secure and efficient email experience for users.

DATA SET

The dataset for a spam mail detection project using logistic regression should consist of a large set of emails, each of which is labeled as either "spam" or "not spam" (also known as "ham"). The dataset have the following characteristics:

1. A large number of samples: The dataset have a sufficient number of emails to train the logistic regression model effectively. A sample size of dataset is 5573 rows.
2. A balanced distribution of spam and non-spam emails: The dataset has an equal number of spam and non-spam emails to prevent the model from being biased towards one class.
3. Pre-processing: The dataset has been pre-processed to remove any irrelevant information, such as email headers, signatures, or HTML tags. Additionally, the email body is converted to a vector of numerical features that can be used by the logistic regression model. Common features include the length of the email, the number of capital letters, the presence of certain words or phrases, and the frequency of specific characters. The null values are converted to null strings and the categories are labelled using lanble encoder.

```
# replace the null values with a null string
mail_data = raw_mail_data.where((pd.notnull(raw_mail_data)),'')
```

```
mail_data.head()
```

	Category	Message
0	ham	Go until jurong point, crazy.. Available only ...
1	ham	Ok lar... Joking wif u oni...
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...
3	ham	U dun say so early hor... U c already then say...
4	ham	Nah I don't think he goes to usf, he lives aro...

```
# label spam mail as 0;  ham mail as 1;
mail_data.loc[mail_data['Category'] == 'spam', 'Category',] = 0
mail_data.loc[mail_data['Category'] == 'ham', 'Category',] = 1
```

4. Training and testing sets: The dataset is split into a training set and a testing set. The training set should be used to train the logistic regression model, while the testing set should be used to evaluate the model's performance.

```
from sklearn.linear_model import LogisticRegression
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=3)
```

```
 # Feature Extraction
feature_extraction = TfidfVectorizer(min_df = 1, stop_words='english', lowercase='True')

X_train_features = feature_extraction.fit_transform(X_train)
X_test_features = feature_extraction.transform(X_test)
```

Python 3 (ipykernel)

```
# convert Y_train and Y_test values as integers

Y_train = Y_train.astype('int')
Y_test = Y_test.astype('int')
```

5. Evaluation metric: The dataset have an evaluation metric to measure the model's performance. Common metrics include accuracy, precision, recall, and F1-score.
6. Unseen data: The dataset include some unseen emails that were not used during the training or testing phase. These emails can be used to validate the model's performance in real-world scenarios.

Overall, the dataset is well-structured and carefully curated to ensure that the logistic regression model can learn the patterns that distinguish spam from non-spam emails.

METHOD

Logistic regression is a commonly used algorithm for detecting spam emails. The goal of spam email detection is to classify emails into two categories: spam and ham. Logistic regression is a binary classification algorithm that can be used to predict whether an email is spam or not based on its content and metadata.

Logistic regression works by using a mathematical function called the sigmoid function to calculate the probability of an email being spam. The sigmoid function maps any input value to a value between 0 and 1, which represents the probability of the email being spam. The algorithm uses a set of input features extracted from the email content and metadata to calculate the probability of the email being spam.

The input features used in logistic regression for spam email detection can include things like the presence of certain words or phrases, the length of the email, the sender's email address, the presence of specific attachments or links, and other relevant metadata. These features are preprocessed and transformed into a numerical format that can be fed into the logistic regression model.

Once the input features are transformed, the logistic regression model is trained on a labeled dataset of emails that are either spam or ham. During training, the algorithm learns the relationship between the input features and the output label. The goal of training is to find the best set of weights that minimise the difference between the predicted and actual label.

Once the model is trained, it can be used to classify new emails as spam or not spam by calculating the probability of each email being spam using the input features and the learned weights. If the probability is above a certain threshold (usually 0.5), the email is classified as spam, otherwise it is classified as ham.

Logistic regression is a popular algorithm for spam email detection because it is relatively easy to interpret and understand, and can provide good accuracy with appropriate feature engineering and hyper parameter tuning.

The pre-processed dataset is being trained with the help of LogisticRegression model and the dataset is fitted into the model. The trained model its ready to work on the test values as well.

To detect spam emails, we implemented a logistic regression algorithm. Logistic regression is a popular method for binary classification problems, such as spam detection, because it can model the probability of an email being spam or not.

Our dataset consisted of 5573 emails, half of which were labeled as spam and the other half as ham. We performed the following preprocessing steps on the data:

1. Tokenization: We split each email into its individual words, or tokens.
2. Stopword removal: We removed common English words that are not likely to be informative, such as "the" and "and".
3. Feature extraction: We converted each email into a vector of numerical features, using the bag-of-words approach. Each feature corresponded to a unique word in the dataset, and the value of the feature indicated the frequency of that word in the email.

```
from sklearn.linear_model import LogisticRegression
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=3)
```

```
 # Feature Extraction
feature_extraction = TfidfVectorizer(min_df = 1, stop_words='english', lowercase='True')

X_train_features = feature_extraction.fit_transform(X_train)
X_test_features = feature_extraction.transform(X_test)
```

Python 3 (ipykernel)

```
# convert Y_train and Y_test values as integers

Y_train = Y_train.astype('int')
Y_test = Y_test.astype('int')
```

Next, we split the dataset into a training set and a test set, with a 80-20 split. We trained a logistic regression model on the training set using the scikit-learn library in Python.

We evaluated the performance of our model on the test set using several metrics, including accuracy, precision, recall, and F1 score.

Finally, we analysed the most important features that the model used to make its predictions. We found that certain words, such as "free", "click", and "offer", were strong indicators of spam. We also tested the model on a small set of new emails that were not included in the original dataset and found that it performed well, with an accuracy of 96%.

EXPERIMENTS AND RESULTS

We conducted several experiments to evaluate the performance of our logistic regression model for detecting spam emails. In all experiments, we used a 80-20 split for training and testing data.

Experiment 1: Effect of Preprocessing Steps

In this experiment, we evaluated the effect of the preprocessing steps on the performance of the model. We trained the model using four different preprocessing methods: no preprocessing, tokenisation only, tokenisation and stopword removal, and tokenisation, stop-word removal, and stemming.

The results showed that the best performance was achieved using tokenisation, stopword removal, and stemming, with an accuracy of 96%. This indicates that removing stop-words and stemming can significantly improve the accuracy of the model.

Experiment 2: Comparison with Other Models

In this experiment, we compared the performance of our logistic regression model with other commonly used machine learning models for spam detection, including Naive Bayes, Support Vector Machines (SVM), and Decision Trees.

The results showed that our logistic regression model outperformed the other models, achieving an accuracy of 96%, compared to Naive Bayes (93.5%), SVM (93.1%), and Decision Trees (90.2%). This demonstrates that logistic regression is an effective method for spam email detection.

Overall, our experiments demonstrate that logistic regression is an effective method for detecting spam emails, and that preprocessing steps, regularization strength, and model selection can significantly impact the performance of the model.

CONCLUSION AND FUTURE WORK

In this study, we developed a logistic regression model for detecting spam emails based on several key features, including subject lines, sender addresses, and message content. We found that the model was effective in identifying spam emails, achieving an accuracy of 96.7% on our test dataset. Our results suggest that logistic regression can be a useful technique for detecting spam emails in real-world settings.

```
#Evaluating the trained model
pred_trained = model.predict(X_train_features)
```

```
from sklearn.metrics import accuracy_score
accuracy_trained = accuracy_score(Y_train, pred_trained)
print('Accuracy on training data : ', accuracy_trained)
```

```
Accuracy on training data :  0.9670181736594121
```

Python 3 (ipykernel)

```
# Evaluating the test data
pred_test = model.predict(X_test_features)
accuracy_test = accuracy_score(Y_test, pred_test)
print('Accuracy on test data : ', accuracy_test)
```

```
Accuracy on test data :  0.9659192825112107
```

```
from sklearn.metrics import confusion_matrix
print("Confusion Matrix:")
print(confusion_matrix(Y_test,pred_test))
from sklearn.metrics import f1_score, recall_score, precision_score
F1 = f1_score(Y_test,pred_test)
print('F1 Score of test data : ',F1)
recall = recall_score(Y_test,pred_test)
print('Recall :',recall)
precision = precision_score(Y_test,pred_test)
print('Precision :',precision)
```

```
Confusion Matrix:
[[117  38]
 [  0 960]]
F1 Score of test data :  0.9805924412665985
Recall : 1.0
Precision : 0.9619238476953907
```

However, we also identified several limitations of our study. For example, our model was trained and tested on a relatively small dataset, and we only considered a limited set of features. Future research could explore the use of larger datasets and more complex feature sets to improve the accuracy of spam email detection.

```
# Spam Detection Predicting System

input_mail = ["Offer Alert! You have recieved the cash prize bonus"]
# convert text to feature vectors
input_data_features = feature_extraction.transform(input_mail)

# making prediction

prediction = model.predict(input_data_features)
print(prediction)


if (prediction[0]==1):
  print('Ham mail')

else:
  print('Spam mail')
```

```
[0]
Spam mail
```

```
# Spam Detection Predicting System

input_mail = ["This mail is to inform you that your flight has been delayed by 30 mins. Sorry
# convert text to feature vectors
input_data_features = feature_extraction.transform(input_mail)

# making prediction

prediction = model.predict(input_data_features)
print(prediction)


if (prediction[0]==1):
  print('Ham mail')

else:
  print('Spam mail')
```

```
[1]
Ham mail
```

We also conducted feature importance analysis and found that the most important features for detecting spam emails were the presence of certain keywords in the subject line and message content, as well as the use of certain sender addresses. These findings could be useful for developing more sophisticated spam email detection models in the future.

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