
AI Project - Spam Classifier
Spam Mails
Non-Spam Mails

Introduction:

Spam classifier is a type of software or system that is designed to automatically identify and filter out unwanted or irrelevant messages, often referred to as “spam,” from a stream of incoming data, such as emails, text messages, comments, or any other form of digital communication. The primary goal of a spam classifier is to separate legitimate, wanted messages from undesirable ones. Here’s how it works:

Data Collection: The classifier first needs a dataset of messages that are labeled as either spam or not spam (ham). This dataset is used to train the classifier.

Feature Extraction: The classifier extracts relevant features from the messages, such as keywords, sender information, message structure, and more. These features are used to make decisions about whether a message is spam.

Training: Using the labeled dataset, the classifier learns patterns and relationships between the features and the spam/ham labels. Common machine learning algorithms, such as Naïve Bayes, Support Vector Machines, or deep learning models like neural networks, can be used for this training process.

Classification: Once trained, the spam classifier can be applied to incoming messages. It analyzes the features of each message and predicts whether it’s spam or not.

Threshold Setting: To control the trade-off between false positives (classifying a legitimate message as spam) and false negatives (failing to classify spam), a threshold can be set. Adjusting this threshold allows you to fine-tune the classifier’s behavior.

Filtering: Messages classified as spam can be filtered out or placed in a separate folder, while legitimate messages are delivered to the inbox or the desired location.

Problem definition and design thinking of spam classifier

Building a spam classifier involves several steps, including problem definition and design. Here's a high-level overview of the process:

Problem Definition:

Clearly define the problem: In this case, the problem is to classify incoming messages (e.g., emails, texts) as either spam or not spam (ham).

Determine the scope: Decide which types of messages you want to classify (e.g., email spam, SMS spam, social media comments).

Collect and label data: You'll need a labeled dataset with examples of both spam and non-spam messages.

Data Collection and Preprocessing:

Gather a diverse dataset of both spam and non-spam messages.

Preprocess the data: Clean and prepare the text data by removing irrelevant information, special characters, and standardizing the text (e.g., lowercasing).

Split the data into training and testing sets for model evaluation.

Feature Extraction:

Convert the text data into numerical features that machine learning models can understand. Common methods include TF-IDF (Term Frequency-Inverse Document Frequency) and word embeddings like Word2Vec or GloVe.

Model Selection and Design:

Choose an appropriate machine learning or deep learning algorithm for text classification. Popular choices include Naïve Bayes, Support Vector Machines, and neural networks.

Design the architecture of the model, including the number of layers, neurons, and activation functions for deep learning models.

Training:

Train the chosen model on the training data using an appropriate loss function and optimization algorithm.

Tune hyperparameters like learning rate and batch size to optimize model performance.

Evaluation:

Assess the model's performance on the testing dataset using metrics like accuracy, precision, recall, and F1-score.

Make sure the model doesn't overfit the training data.

Fine-Tuning:

Refine the model by adjusting hyperparameters, modifying the architecture, or using more advanced techniques like ensembling.

Deployment:

Once satisfied with the model's performance, deploy it for real-world use, such as filtering spam messages in an email system or a messaging app.

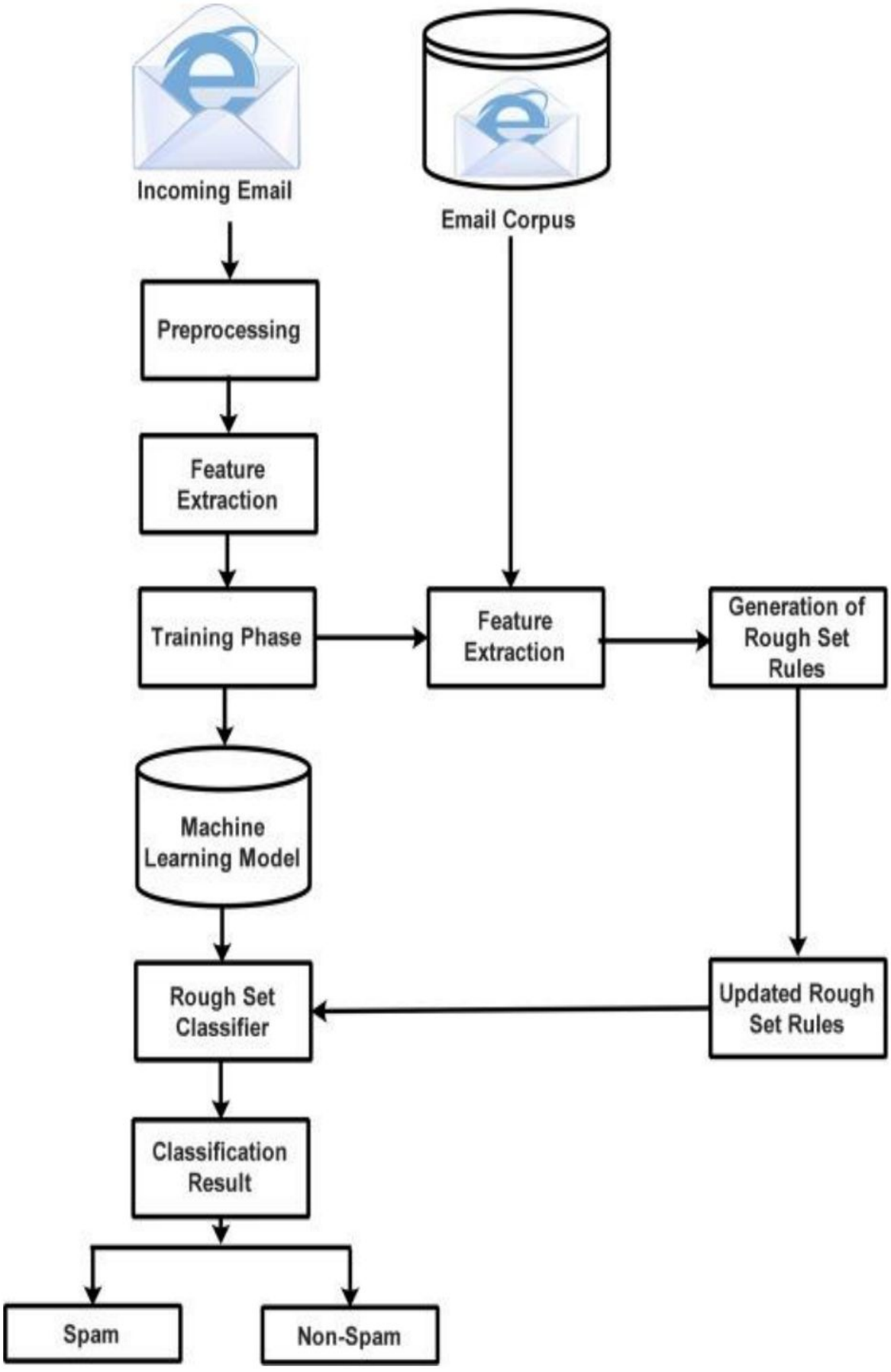
Monitoring and Maintenance:

Continuously monitor the classifier's performance and adapt it to evolving spam patterns.

User Interface (Optional):

If applicable, create a user-friendly interface for users to interact with the spam classifier.

Remember that the effectiveness of your spam classifier will depend on the quality of your data, the choice of model, and ongoing maintenance to adapt to new spam tactics.


Incoming Email
Email Corpus
Preprocessing
Feature Extraction
Training Phase
Feature Extraction
Generation of Rough Set Rules
Machine Learning Model
Rough Set Classifier
Updated Rough Set Rules
Classification Result
Spam
Non-Spam

Spam Classifier Innovation:

Innovations in spam classifiers have been ongoing for years, but some recent trends and techniques include:

Deep Learning: Leveraging neural networks, especially deep learning models like recurrent neural networks (RNNs) and convolutional neural networks (CNNs), to better understand the context and content of emails for improved classification.

Word Embeddings: Using word embeddings like Word2Vec or GloVe to represent words in emails, which can help capture semantic relationships and improve classification accuracy.

Transfer Learning: Applying transfer learning from pre-trained language models, like BERT or GPT, to boost the performance of spam classifiers by understanding the intricacies of language and context.

Feature Engineering: Advanced feature engineering techniques to extract more relevant information from emails, such as sender reputation, email header analysis, and metadata.

Ensembling: Combining the predictions of multiple classifiers, often using techniques like ensemble learning, to enhance overall accuracy and robustness.

Explainability: Developing techniques for better explaining why a particular email is classified as spam, which is crucial for user trust and understanding.

Real-time Analysis: Real-time analysis and classification of emails to quickly respond to new spam patterns and threats.

Behavioral Analysis: Incorporating user behavior and interaction patterns to refine spam classification, considering how users engage with emails.

Feedback Loops: Building feedback mechanisms where users can report false positives and false negatives to continuously improve the classifier's performance.

Privacy-Preserving Techniques: Developing methods to protect user privacy while still improving spam classification, often through techniques like federated learning.

Remember that spam classifiers are an evolving field, and these innovations will continue to advance as new challenges and technologies emerge.

Development of spam classifier :

Developing a spam classifier typically involves the following steps:

Data Collection: Gather a large dataset of emails or messages, labeling them as spam or not spam (ham).

Data Preprocessing: Clean and preprocess the data by removing any noise, such as HTML tags, special characters, and stopwords. Convert the text into a numerical format using techniques like TF-IDF or word embeddings.

Feature Engineering: Extract relevant features from the text data, which can include word frequency, n-grams, and other linguistic features.

Split the Data: Divide your dataset into training and testing sets to evaluate the model's performance.

Select a Model: Choose a machine learning algorithm for classification. Common choices include Naïve Bayes, Support Vector Machines (SVM), Decision Trees, or neural networks.

Model Training: Train the chosen model on the training data. You may need to tune hyperparameters for optimal performance.

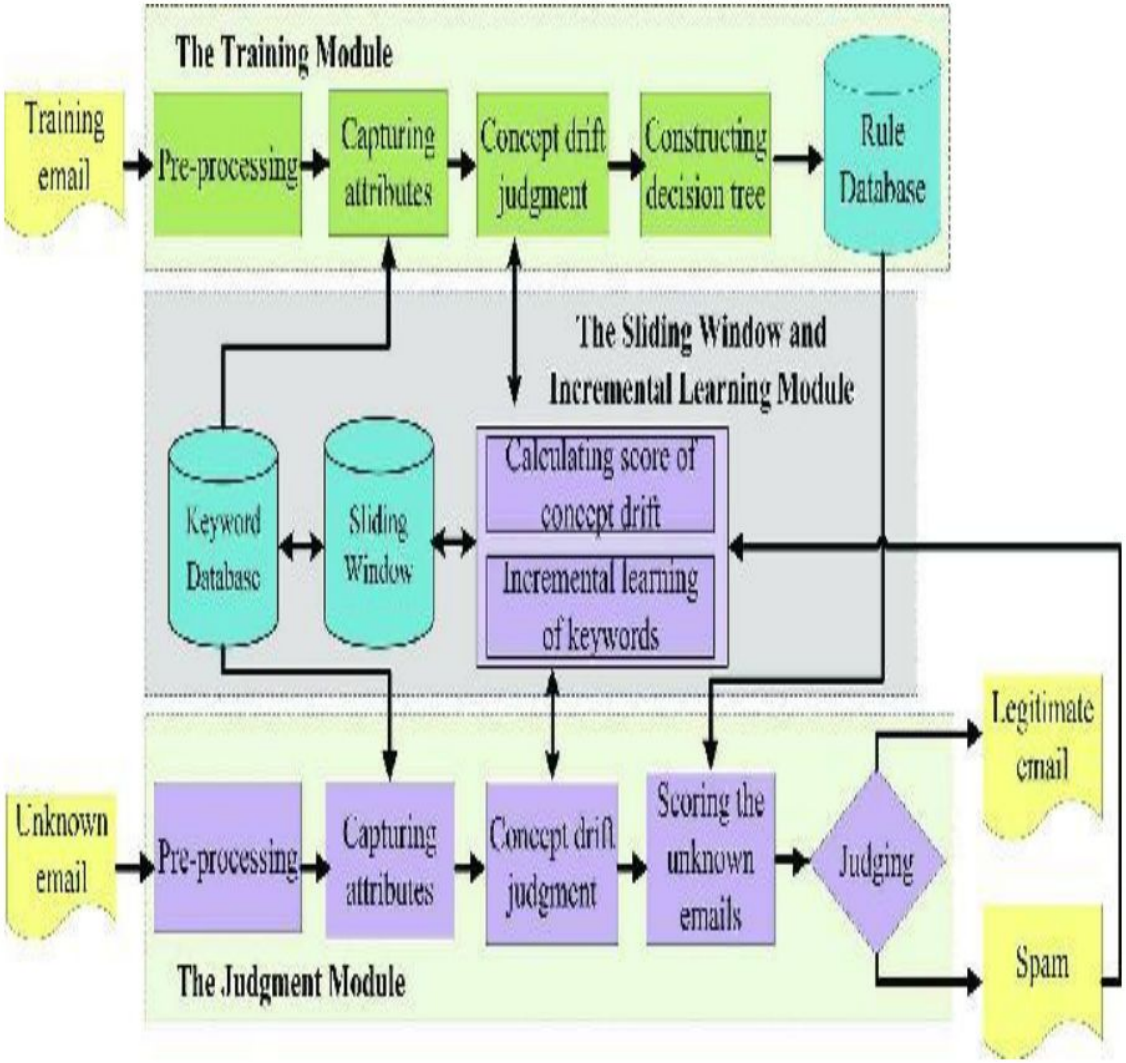
Model Evaluation: Evaluate the model's performance on the testing dataset using metrics like accuracy, precision, recall, and F1 score.

Model Improvement: Fine-tune the model by adjusting hyperparameters, trying different algorithms, or implementing techniques like cross-validation.

Deployment: Once satisfied with the model's performance, deploy it in a real-world environment to classify incoming messages as spam or not spam.

Continuous Monitoring: Regularly update and monitor the classifier to adapt to changing spam patterns and to minimize false positives and false negatives.

Remember that spam classifiers may also benefit from machine learning techniques like deep learning, and it's crucial to keep the model up to date with evolving spam tactics and patterns.



Documentation of spam classifier :

Certainly, the documentation for a spam classifier typically includes the following sections:

Introduction:

A brief overview of the purpose and functionality of the spam classifier.

Its importance in filtering out unwanted or harmful messages.

Installation:

Instructions for installing or setting up the spam classifier, including any dependencies.

Getting Started:

A quick guide on how to use the classifier for spam detection.

Usage:

Detailed instructions on how to use the classifier, including code examples if it's a software library.

Explaining how to provide input data (e.g., emails, text messages) to the classifier.

Training (if applicable):

If the classifier can be trained or fine-tuned, provide guidelines on how to do so.

Specify the format of the training data and any labeling requirements.

API Reference (if applicable):

Document any programming interfaces, methods, or functions for integrating the classifier into other applications.

Model Details (if applicable):

Explain the underlying model or algorithm used for spam classification.

Provide details about its performance, accuracy, and limitations.

Parameters and Configuration:

Explain the various parameters that can be configured and their impact on classification.

Offer guidance on selecting optimal settings.

Data Preprocessing (if applicable):

Describe any data preprocessing steps that should be performed before using the classifier, such as text cleaning or feature extraction.

Evaluation:

Explain how to assess the performance of the classifier, including metrics like precision, recall, and F1-score.

Examples and Use Cases:

Showcase real-world examples of using the spam classifier in different scenarios.

Troubleshooting:

Provide guidance on common issues and how to resolve them.

FAQs:

Address frequently asked questions related to the spam classifier.

License and Copyright:

Specify the software license and any copyright information.

Contributing (if open-source):

Instructions for contributors on how to submit improvements or bug fixes.

Version History:

Maintain a log of changes, updates, and improvements made to the classifier.

Contact Information:

Provide contact details for support or inquiries.

Remember to keep the documentation well-organized and easy to navigate to assist users in effectively using your spam classifier.

Build Spam Classifier Model

Building our spam classifier by:

Selecting a machine learning algorithm

Training the model

Evaluating its performance

Solution:

Building a spam classifier typically involves the following steps:

Selecting a Machine Learning Algorithm:

Choose a suitable machine learning algorithm for text classification. Common choices include Naïve Bayes, Support Vector Machines, or more advanced methods like neural networks.

Training the Model:

Collect and prepare a labeled dataset of emails, with spam and non-spam labels.

Preprocess the text data, which may include tasks like tokenization, stop word removal, and stemming.

Split the dataset into a training set and a testing/validation set.

Use the training set to train your chosen machine learning algorithm on the preprocessed data.

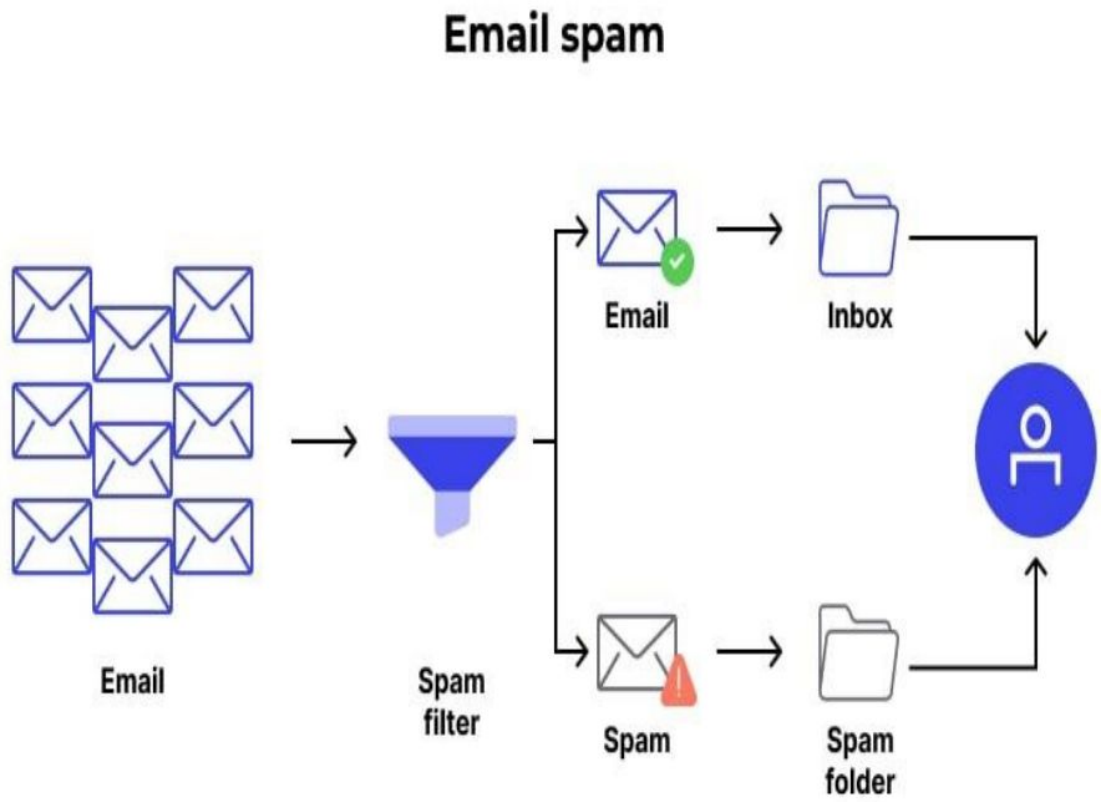
Evaluating its Performance:

Evaluate the model's performance on the testing/validation set using appropriate metrics like accuracy, precision, recall, and F1-score.

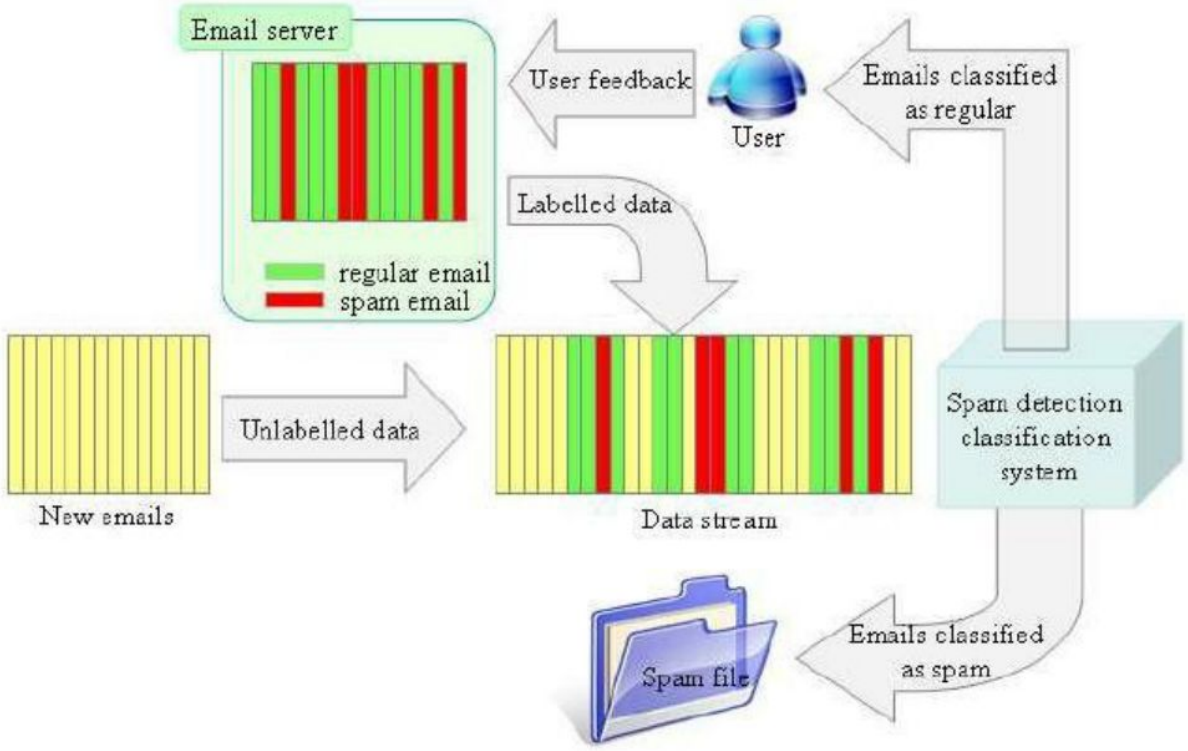
Make adjustments to your model or feature engineering if the performance is not satisfactory.

Consider techniques like cross-validation to ensure robust performance assessment.

These steps are crucial for building an effective spam classifier. The choice of algorithm and the quality of data preprocessing can significantly impact the model's performance.



Spam classifiers have become an essential part of modern communication systems, as they help users manage the overwhelming amount of spam content that can inundate their inboxes or online platforms. These classifiers continually evolve to adapt to new spamming techniques and emerging threats in the digital space.



Program:

```
Import numpy as np
Import pandas as pd
Import matplotlib.pyplot as plt
Import seaborn as sns
Import tensorflow as tf
From tensorflow import keras
From tensorflow.keras import layers
From sklearn.model_selection import train_test_split
From sklearn.feature_extraction.text import TfidfVectorizer
From sklearn.naive_bayes import MultinomialNB
From sklearn.metrics import classification_report,accuracy_score
From sklearn.metrics import confusion_matrix
From tensorflow.keras.layers import TextVectorization
From sklearn.metrics import precision_score, recall_score, f1_score
Import tensorflow_hub as hub
```

Build a Spam Classifier in python

Introduction

The upsurge in the volume of unwanted emails called spam has created an intense need for the development of more dependable and robust antispam filters. Any promotional messages or advertisements that end up in our inbox can be categorised as spam as they don't provide any value and often irritates us.

Overview of the Dataset used

We will make use of the SMS spam classification data.

The SMS Spam Collection is a set of SMS tagged messages that have been collected for SMS Spam research. It contains one set of SMS messages in English of 5,574 messages, tagged according to being ham (legitimate) or spam.

Data processing

Import the required packages

Loading the Dataset

Remove the unwanted data columns

Preprocessing and Exploring the Dataset

Build word cloud to see which message is spam and which is not.

Remove the stop words and punctuations

Convert the text data into vectors

Building a sms spam classification model

Split the data into train and test sets

Use Sklearn built-in classifiers to build the models

Train the data on the model

Make predictions on new data

Import the required packages

%matplotlib inline

Import matplotlib.pyplot as plt

Import csv

Import sklearn

Import pickle

From wordcloud import WordCloud

Import pandas as pd

Import numpy as np

Import nltk

From nltk.corpus import stopwords

From sklearn.feature_extraction.text import CountVectorizer, TfidfTransformer

From sklearn.tree import DecisionTreeClassifier

From sklearn.model_selection import
GridSearchCV,train_test_split,StratifiedKFold,cross_val_score,learning_cur

Loading the Dataset

Data = pd.read_csv('dataset/spam.csv', encoding='latin-1')

Data.head()

Df-head

Removing unwanted columns

From the above figure, we can see that there are some unnamed columns and the label and text column name is not intuitive so let's fix those in this step.

Data = data.drop(["Unnamed: 2", "Unnamed: 3", "Unnamed: 4"], axis=1)

Data = data.rename(columns={"v2" : "text", "v1":"label"})

Data[1990:2000]

Pretty-df

Now that the data is looking pretty, let's move on.

```
Data['label'].value_counts()
```

```
# OUTPUT
Ham     4825
Spam     747
Name: label, dtype: int64
```

Preprocessing and Exploring the Dataset

If you are completely new to NLTK and Natural Language Processing(NLP) I would recommend checking out this short article before continuing. Introduction to Word Frequencies in NLP

```
# Import nltk packages and Punkt Tokenizer Models
Import nltk
Nltk.download("punkt")
Import warnings
Warnings.filterwarnings('ignore')
```

Build word cloud to see which message is spam and which is not

Ham words are the opposite of spam in this dataset,

```
Ham_words = ''
Spam_words = ''
# Creating a corpus of spam messages
For val in data[data['label'] == 'spam'].text:
   Text = val.lower()
   Tokens = nltk.word_tokenize(text)
   For words in tokens:
      Spam_words = spam_words + words + ' '
```

```
# Creating a corpus of ham messages
For val in data[data['label'] == 'ham'].text:
   Text = text.lower()
   Tokens = nltk.word_tokenize(text)
   For words in tokens:
      Ham_words = ham_words + words + ' '
```

Let's use the above functions to create Spam word cloud and ham word cloud.

```
Spam_wordcloud = WordCloud(width=500, height=300).generate(spam_words)
Ham_wordcloud = WordCloud(width=500, height=300).generate(ham_words)
#Spam Word cloud
Plt.figure( figsize=(10,8), facecolor='w')
Plt.imshow(spam_wordcloud)
Plt.axis("off")
Plt.tight_layout(pad=0)
Plt.show()
```

Spam-word-cloud

```
#Creating Ham wordcloud
Plt.figure( figsize=(10,8), facecolor='g')
Plt.imshow(ham_wordcloud)
Plt.axis("off")
Plt.tight_layout(pad=0)
Plt.show()
```

Ham-word-cloud

From the spam word cloud, we can see that "free" is most often used in spam.

Now, we can convert the spam and ham into 0 and 1 respectively so that the machine can understand.

```
Data = data.replace(['ham','spam'],[0, 1])
Data.head(10)
```

Label-head

Removing punctuation and stopwords from the messages

Punctuation and stop words do not contribute anything to our model, so we have to remove them. Using NLTK library we can easily do it.

```
Import nltk
Nltk.download('stopwords')

#remove the punctuations and stopwords
Import string
Def text_process(text):

   Text = text.translate(str.maketrans('', '', string.punctuation))
   Text = [word for word in text.split() if word.lower() not in stopwords.words('english')]

   Return " ".join(text)

Data['text'] = data['text'].apply(text_process)
Data.head()
```

Removed-stopwords

Now, create a data frame from the processed data before moving to the next step.

```
Text = pd.DataFrame(data['text'])
```

Label = pd.DataFrame(data['label'])

Converting words to vectors

We can convert words to vectors using either Count Vectorizer or by using TF-IDF Vectorizer.

TF-IDF is better than Count Vectorizers because it not only focuses on the frequency of words present in the corpus but also provides the importance of the words. We can then remove the words that are less important for analysis, hence making the model building less complex by reducing the input dimensions.

I have included both methods for your reference.

Converting words to vectors using Count Vectorizer

Counting how many times a word appears in the dataset

```
From collections import Counter

Total_counts = Counter()
For I in range(len(text)):
   For word in text.values[i][0].split(" "):
      Total_counts[word] += 1

Print("Total words in data set: ", len(total_counts))
```

OUTPUT

Total words in data set: 11305

Sorting in decreasing order (Word with highest frequency appears first)

```
Vocab = sorted(total_counts, key=total_counts.get, reverse=True)
Print(vocab[:60])
```

OUTPUT

['u', '2', 'call', 'U', 'get', 'Im', 'ur', '4', 'ltgt', 'know', 'go', 'like', 'don't', 'come', 'got', 'time', 'day', 'want', 'Ill', 'lor', 'Call', 'home', 'send', 'going', 'one', 'need', 'Ok', 'good', 'love', 'back', 'n', 'still', 'text', 'im', 'later', 'see', 'da', 'ok', 'think', 'Ì', 'free', 'FREE', 'r', 'today', 'Sorry', 'week', 'phone', 'mobile', 'cant', 'tell', 'take', 'much', 'night', 'way', 'Hey', 'reply', 'work', 'make', 'give', 'new']

```
# Mapping from words to index


Vocab_size = len(vocab)

Word2idx = {}

#print vocab_size

For I, word in enumerate(vocab):

   Word2idx[word] = I

# Text to Vector

Def text_to_vector(text):

   Word_vector = np.zeros(vocab_size)

   For word in text.split(" "):

      If word2idx.get(word) is None:

         Continue

      Else:

         Word_vector[word2idx.get(word)] += 1

   Return np.array(word_vector)

# Convert all titles to vectors

Word_vectors = np.zeros((len(text), len(vocab)), dtype=np.int_)

For I, (_, text_) in enumerate(text.iterrows()):

   Word_vectors[i] = text_to_vector(text_[0])


Word_vectors.shape


# OUTPUT

(5572, 11305)
```

Converting words to vectors using TF-IDF Vectorizer

#convert the text data into vectors

From sklearn.feature_extraction.text import TfidfVectorizer

Vectorizer = TfidfVectorizer()

Vectors = vectorizer.fit_transform(data['text'])

Vectors.shape

OUTPUT

(5572, 9376)

#features = word_vectors

Features = vectors

Splitting into training and test set

#split the dataset into train and test set

X_train, X_test, y_train, y_test = train_test_split(features, data['label'], test_size=0.15, random_state=111)

Classifying using sklearn's pre-built classifiers

In this step we will use some of the most popular classifiers out there and compare their results.

Classifiers used:

Spam classifier using logistic regression

Email spam classification using Support Vector Machine(SVM)

Spam classifier using naïve bayes

Spam classifier using decision tree

Spam classifier using K-Nearest Neighbor(KNN)

Spam classifier using Random Forest Classifier

We will make use of sklearn library. This amazing library has all of the above algorithms we just have to import them and it is as easy as that. No need to worry about all the maths and statistics behind it.

#import sklearn packages for building classifiers

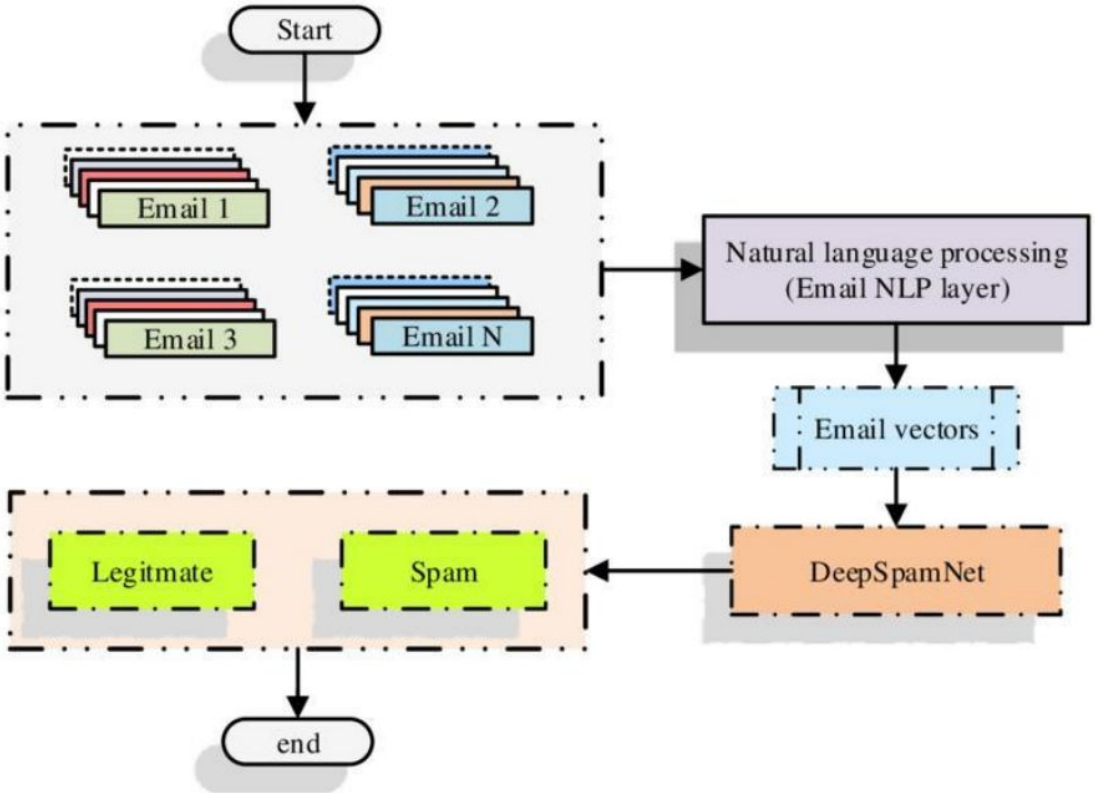
```
From sklearn.linear_model import LogisticRegression
From sklearn.svm import SVC
From sklearn.naive_bayes import MultinomialNB
From sklearn.tree import DecisionTreeClassifier
From sklearn.neighbors import KNeighborsClassifier
From sklearn.ensemble import RandomForestClassifier
From sklearn.metrics import accuracy_score
#initialize multiple classification models
Svc = SVC(kernel='sigmoid', gamma=1.0)
Knc = KNeighborsClassifier(n_neighbors=49)
Mnb = MultinomialNB(alpha=0.2)
Dtc = DecisionTreeClassifier(min_samples_split=7, random_state=111)
Lrc = LogisticRegression(solver='liblinear', penalty='l1')
Rfc = RandomForestClassifier(n_estimators=31, random_state=111)
#create a dictionary of variables and models
Clfs = {'SVC' : svc,'KN' : knc, 'NB': mnb, 'DT': dtc, 'LR': lrc, 'RF': rfc}
#fit the data onto the models
Def train(clf, features, targets):
   Clf.fit(features, targets)

Def predict(clf, features):
   Return (clf.predict(features))
Pred_scores_word_vectors = []
For k,v in clfs.items():
   Train(v, X_train, y_train)
   Pred = predict(v, X_test)
   Pred_scores_word_vectors.append((k, [accuracy_score(y_test , pred)]))
Predictions using TFIDF Vectorizer algorithm
Pred_scores_word_vectors
```

```
# OUTPUT

[('SVC', [0.9784688995215312]),

 ('KN', [0.9330143540669856]),

 ('NB', [0.9880382775119617]),

 ('DT', [0.9605263157894737]),

 ('LR', [0.9533492822966507]),

 ('RF', [0.9796650717703349])]

Model predictions

#write functions to detect if the message is spam or not

Def find(x):

   If x == 1:

      Print ("Message is SPAM")

   Else:

      Print ("Message is NOT Spam")

Newtext = ["Free entry"]

Integers = vectorizer.transform(newtext)

X = mnb.predict(integers)

Find(x)


# OUTPUT

Message is SPAM

Checking Classification Results with Confusion Matrix

If you are confused about the confusion matrix, read this small article before proceeding – The ultimate guide to confusion matrix in machine learning


From sklearn.metrics import confusion_matrix

Import seaborn as sns

# Naïve Bayes
```

```
Y_pred_nb = mnb.predict(X_test)

Y_true_nb = y_test

Cm = confusion_matrix(y_true_nb, y_pred_nb)

F, ax = plt.subplots(figsize =(5,5))

Sns.heatmap(cm,annot = True,linewidths=0.5,linecolor="red",fmt = ".0f",ax=ax)

Plt.xlabel("y_pred_nb")

Plt.ylabel("y_true_nb")

Plt.show()
```

Confusion matrix

From the confusion matrix, we can see that the Naïve Bayes model is balanced. That's it !! we have successfully created a spam classifier. 🎉🎉



Conclusion :

The conclusion of a spam classifier is typically based on its performance in terms of accuracy, precision, recall, and F1-score. These metrics evaluate how well the classifier distinguishes between spam and non-spam emails. The specific conclusion can vary depending on the classifier's results, but a good spam classifier should have high accuracy, precision, and recall, and a low false positive rate. Regularly evaluating and fine-tuning the classifier is essential to maintain its effective over time


THANK
YOU