

## CS5691: Pattern Recognition and Machine Learning

### Assignment-3

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## OBJECTIVE:

To build a spam classifier from scratch

For classification of spam and ham mails I used Naive Bayes Classifier. The dataset has been taken from the following given source

[http://nlp.cs.aueb.gr/software\\_and\\_datasets/Enron-Spam/index.html](http://nlp.cs.aueb.gr/software_and_datasets/Enron-Spam/index.html).

## APPROACH

Data modeling algorithm used-

Naive Bayes is a classification algorithm which is based on generative modeling and works on the principle of Bayes Theorem. Here we make an assumption such that our features are independent of each other.

## Cleaning

After extracting the dataset I *preprocessed* my data by

1. Replaced '\n' to " " and changed the words to lowercase alphabets..
2. Considering only the alphanumeric words.

## Training

After that I maintained a count of each word/feature in a dictionary for each spam and ham mail named as spam\_words and ham\_words. Then we will do *feature extraction* by selecting the top 2000 most occurred set of words in main dictionary named main\_dict

### *Modeling our data by applying Naive Bayes*

Now we have to check the probability of each word given label-y indicating test mail is spam or not spam.

Which can be termed as  $P(\text{Spam} | \text{Mail})$  and  $P(\text{Ham} | \text{Mail})$

Where,  $P(\text{Mail} | \text{Spam}) = P(\text{word1} | \text{Spam}) * P(\text{word2} | \text{Spam}) \dots P(\text{word-n} | \text{Spam})$ , where word-1, word-2 ... word-n is the set of words in the given test mail

$P(\text{Spam})$  - Prior we calculated Spam mail

$P(\text{Mail})$  - Evidence

The same is calculated for ham mail also.

### Testing

Now we have  $P(\text{Spam} | \text{Mail})$  and  $P(\text{Ham} | \text{Mail})$

If  $P(\text{Spam} | \text{Mail}) > P(\text{Ham} | \text{Mail})$ : Mail will be predicted as Spam

else the mail will be predicted as Ham

It is observed that after training with the below-mentioned, we get an accuracy of 90% approx depending on the dataset given.

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