

# Assignment Machine Learning

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**Dataset file name:** category(1).csv

**Data Collection:** For obtaining a variety of data, we had collected data from more than one email ID's including the personal and Bits mail id. We have used Subject, Body and sender as three of the mail for classification into labels. We had chosen six labels to distribute the collected data. Steps followed for data collection are as follows

Step1 - Created six labels in gmail labels.

Step2 - Classified mails under the selected labels manually

Step3 - Created python code to extract subject, body, sender's address into a CSV file from the mails.

Step4 - We used Gmail API to access the emails and extracted it by using a python script.

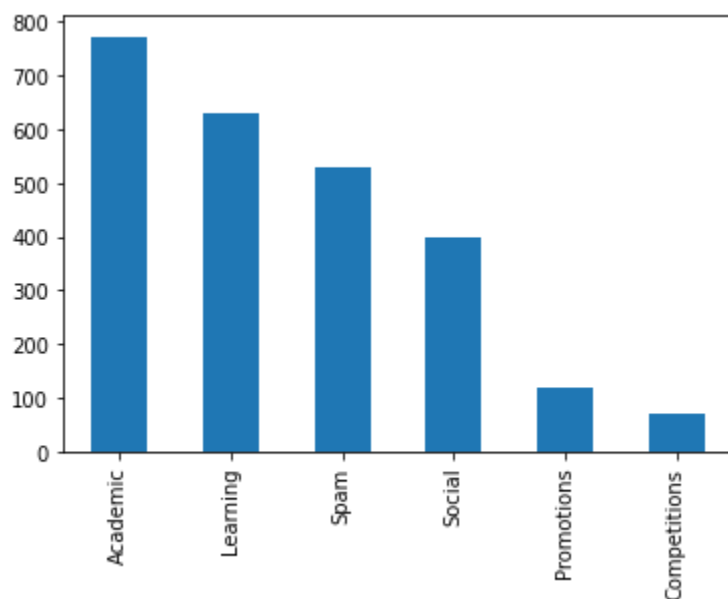
## Data Cleaning:

We cleaned data at several layers

- 1) Removed html tags
- 2) Removed emojis
- 3) Removed characters excluding A-Z and 1-9
- 4) Lemmatized text of the mails
- 5) Removed stop words and converted everything to lower case.

## Exploratory Data Analysis

- Value counts of different categories



**-We used Word clouds to depict key senders, words and body in different label emails**

[illegible][illegible]

### 3) Learning





## Feature Extraction

We concatenated cleaned Senders address, Subject and Body columns of the CSV file to a single column. We splitted data into training and testing data in the ratio of 0.75 and 0.25 respectively.

We used Term Frequency Document-Inverse Frequency (Tf Dif) to extract features from the mails using n-gram range 2,3. We didn't used CountVectorizer to extract features as it doesn't account for relative importance of words. As there were a very high number of features, we selected the top 10% of the features using **sklearn's select percentile** function. It gave us a feature in the form of a numpy array with each element ranging from 0-1.

## Models Used to Classify

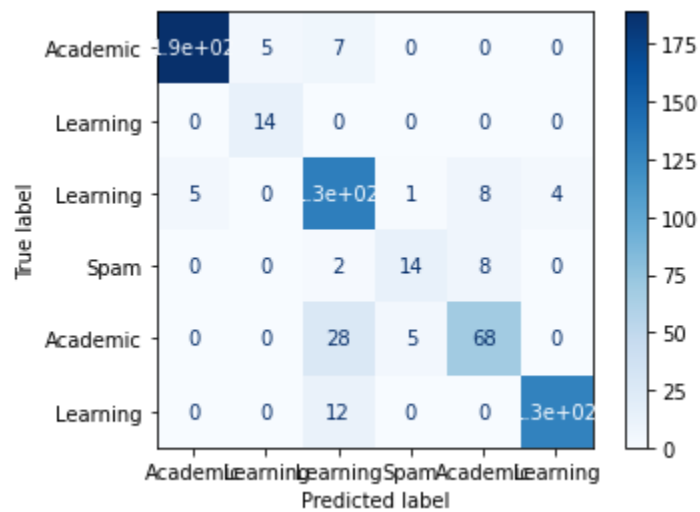
**1)Decision trees :-** After a few iterations, min\_samples\_split =20 , max\_depth = 50 was chosen to save computation time and also preserve accuracy.

Obtained decision tree :

```
import matplotlib.pyplot as plt
fig = plt.figure(figsize=(25,20))
_ = tree.plot_tree(clf, feature_names=feature_names,
                  filled=True)
```





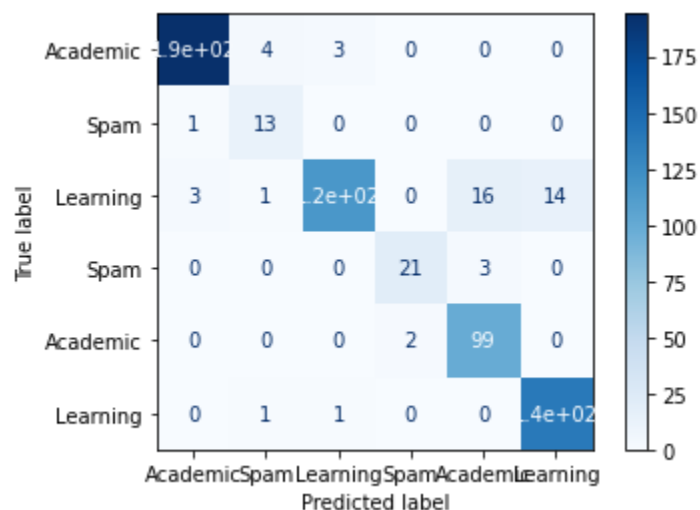


## 2) Gaussian Naive bayes

### a) Classification Report

Other Metrics:				
	precision	recall	f1-score	support
Academic	0.98	0.97	0.97	201
Competitions	0.68	0.93	0.79	14
Learning	0.97	0.77	0.86	150
Promotions	0.91	0.88	0.89	24
Social	0.84	0.98	0.90	101
Spam	0.91	0.99	0.95	141
accuracy			0.92	631
macro avg	0.88	0.92	0.89	631
weighted avg	0.93	0.92	0.92	631

### b) Confusion Matrix



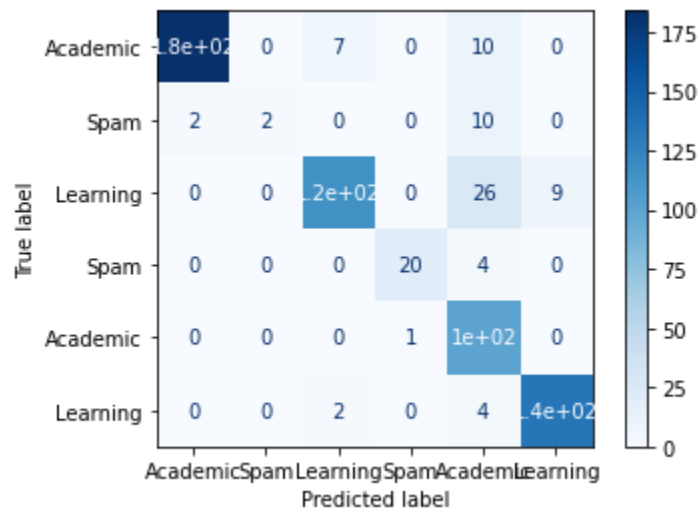


### 3)SVC

#### a) Classification Report

Other Metrics:				
	precision	recall	f1-score	support
Academic	0.99	0.92	0.95	201
Competitions	1.00	0.14	0.25	14
Learning	0.93	0.77	0.84	150
Promotions	0.95	0.83	0.89	24
Social	0.65	0.99	0.78	101
Spam	0.94	0.96	0.95	141
accuracy			0.88	631
macro avg	0.91	0.77	0.78	631
weighted avg	0.91	0.88	0.88	631
0.8811410459587956				

#### b) Confusion Matrix

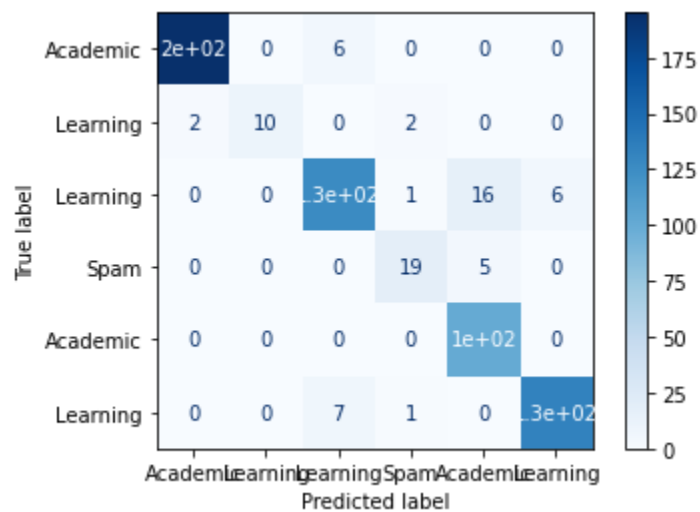


### 4)Random Forest

#### a) Classification Report

Other Metrics:				
	precision	recall	f1-score	support
Academic	0.99	0.97	0.98	201
Competitions	1.00	0.71	0.83	14
Learning	0.91	0.85	0.88	150
Promotions	0.83	0.79	0.81	24
Social	0.83	1.00	0.91	101
Spam	0.96	0.94	0.95	141
accuracy			0.93	631
macro avg	0.92	0.88	0.89	631
weighted avg	0.93	0.93	0.93	631
0.9270998415213946				

## b) Confusion Matrix



## Accuracy model wise

Models	Accuracy (in %)
SVC	88.11
Gaussian NB	92.23
Decision Tree	86.53
Random Forest	92.71

