



विद्या तत्व ज्योतिसमः

ML and NLP PBL 2023

**DEPRESSION DETECTION ANALYSIS IN TWEETS USING  
NAÏVE BAYES**

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## **Problem Statement:**

- In our project, we're working on a special task, finding out if people are feeling sad or dealing with depression based on what they say in their tweets.
- We're using machine learning (ML) and natural language processing (NLP), to teach our system to understand the language in tweets.
- The goal is to detect and analyse a large number of tweets and tell us if there's a possibility that someone might be going through a tough time.
- This could be really helpful for supporting people online and connecting them with the right resources when they need it most.

## **Model:**

### ➤ **Naïve Bayes**

Naive Bayes is a classification algorithm based on Bayes' theorem. It is considered "naive" because it makes an assumption that the features used to describe an observation are conditionally independent, given the class label.

### ➤ **Bayes' Theorem**

The Naive Bayes algorithm relies on Bayes' theorem, which is a mathematical formula that calculates the probability of an event based on prior knowledge of conditions that might be related to the event. The formula is as follows:

$$P(A|B) = P(B|A) \times P(A) / P(B)$$

- $P(A|B)$  is the probability of event A occurring given that event B has occurred.
- $P(B|A)$  is the probability of event B occurring given that event A has occurred.
- $P(A)$  is the prior probability of event A.
- $P(B)$  is the prior probability of event B.

### ➤ **Naïve Bayes Classification**

The Naive Bayes algorithm calculates the probability of each class given the observation and assigns the class with the highest probability to the observation.

$$P(C_i | X) = P(X | C_i) \times P(C_i) / P(X)$$

- **Prior Probability P(C<sub>i</sub>):** This is the probability of **observing class C<sub>i</sub>** without considering any features. It represents our belief about the likelihood of each class before observing the data.
- **Likelihood P (X | C<sub>i</sub>):** This term represents the probability of observing the **features X** given that the **class is C<sub>i</sub>**. The likelihood is often estimated from the training data.
- **Evidence P(X):** This term is the probability of observing the features X across all possible classes. It acts as a normalizing factor and ensures that the sum of posterior probabilities over all classes is equal to 1.
- **Posterior Probability P (C<sub>i</sub> | X):** This is the probability of class C<sub>i</sub> given the observed features X. It's what we're trying to calculate.
- **Decision Rule:** In practical terms, the decision rule for classification often involves selecting the class with the highest posterior probability

$$\text{argmax}_{c_i} \{P(C_i) \times P(X | C_i)\}$$

$$\hat{P}(c_j) = \frac{\text{doccount}(C = c_j)}{N_{\text{doc}}}$$

$$\hat{P}(w_i | c_j) = \frac{\text{count}(w_i, c_j)}{\sum_{w \in V} \text{count}(w, c_j)}$$

fraction of times word  $w_i$  appears among all words in documents of topic  $c_j$

## ➤ Laplace smoothing

Laplace smoothing is a way to prevent these zero probabilities. It involves adding a small constant (usually 1) to the count of each word in each class. This "smoothing" ensures that no word has a zero probability of occurrence in any class, even if it didn't appear in the training data.

$$\begin{aligned}\hat{P}(w_i | c) &= \frac{\text{count}(w_i, c) + 1}{\sum_{w \in V} (\text{count}(w, c) + 1)} \\ &= \frac{\text{count}(w_i, c) + 1}{\left( \sum_{w \in V} \text{count}(w, c) \right) + |V|}\end{aligned}$$

## ➤ Process

### Data Collection

We gathered tweets from Kaggle that were classified as showing moderate, severe, or no depression. Divided dataset into train and test and saved into csv files.

### Data Cleaning

We used stopwords from NLTK library to remove useless words and converted words to lowercase, removed special characters using regular expression library.

### Data Preprocessing

Used Lemmatization to convert words to meaningful base form

### Fit Data using Naïve Bayes Classifier

Build Naïve Bayes classifier from scratch, used dictionaries to store Likelihood of each word with respect to each class.

### Predict Test Data using Naïve Bayes Classifier

Detected tweets in Test dataset as moderate, sever or no depression

### Data Visualization

Used Matplotlib to show percentage of each class in test data set.

## ➤ Tech Stack

- ✓ Python

**Pandas Library** : for making dataframe

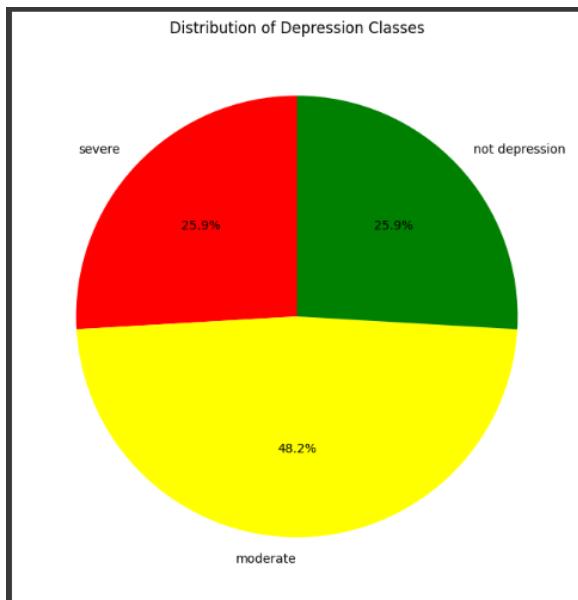
**NLTK (Natural Language ToolKit) Library** : lemmatization , removing stop words

**Regular Expression Library** : removing special characters

**Matplotlib Library** : showing pie chart for percentage of people present in each class

## ➤ Results

48.2% were in moderate depression, 25.9% were in severe depression and remaining were in no depression.



A screenshot of a Google Colab notebook titled "ml\_nlp\_pbl\_sem7". The code cell contains the following Python code for a Naive Bayes classifier:

```
File Edit View Insert Runtime Tools Help
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class Naive_Bayes_Classifier:
    # Constructor
    def __init__(self):
        self.class_prob = {} # P(class)
        self.word_prob = {} # P(word | class)
        self.total_classes = len(y)
        self.vocabulary = set()

    # Fit data Function
    def fit_data(self,X,y):
        count_of_class = {}
        class_samples = len(y)
        for label in y:
            if label in count_of_class:
                count_of_class[label] += 1 #for duplicates
            else:
                count_of_class[label] = 1 # whenever new word comes
```

➤ Link: [https://github.com/aditimahabole/ML\\_NLP\\_Depression\\_Prediction\\_Tweets](https://github.com/aditimahabole/ML_NLP_Depression_Prediction_Tweets)

## ➤ References

- 1.<https://www.analyticsvidhya.com/blog/2022/03/building-naive-bayes-classifier-from-scratch-to-perform-sentiment-analysis/>
- 2.Class teacher Notes