IDENTIFICATION AND DETECTION OF LIKELIHOOD CASES OF DEPRESSION USING TWITTER DATA: A PRESPECTIVE TO DATA SCIENCE

UNDER THE GUIDANCE,

Dr. JITENDHRA KUMAR

SHEETHAL JOSEPH(21MDT0078)

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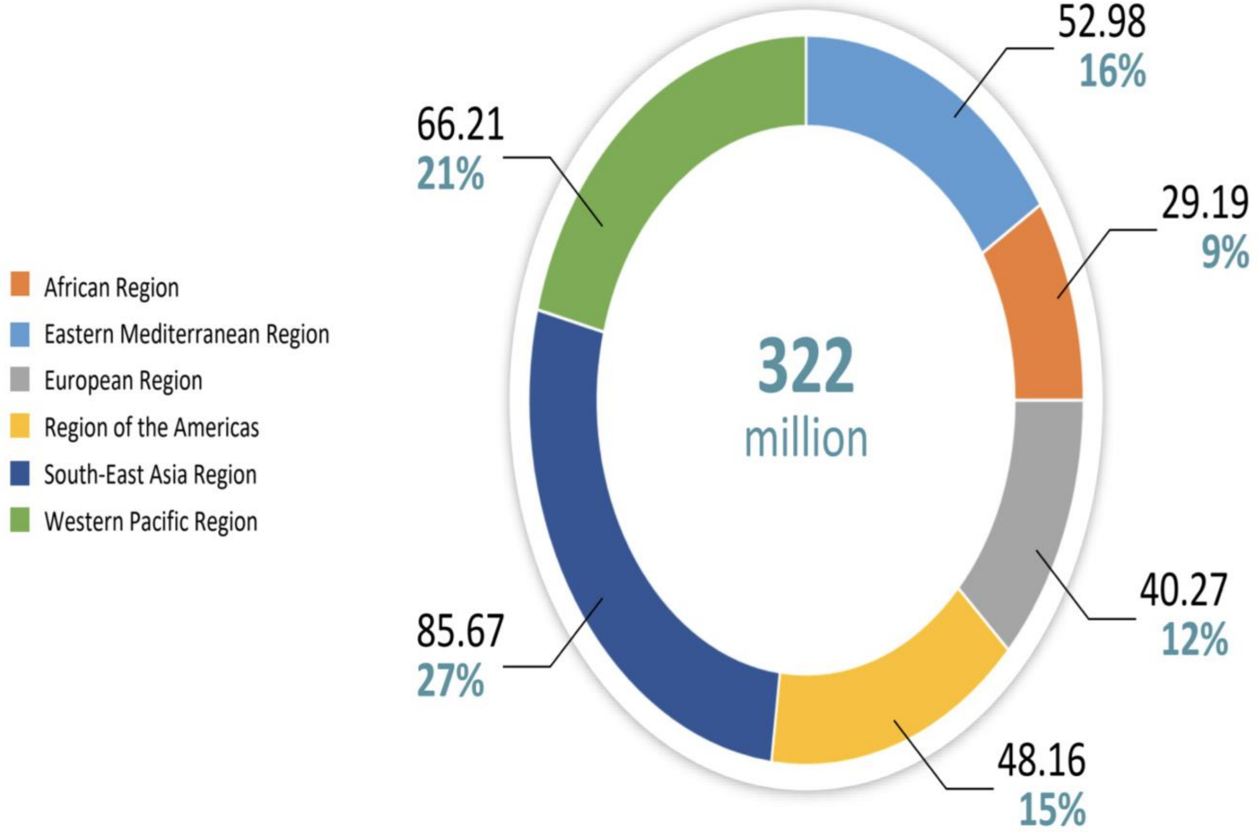
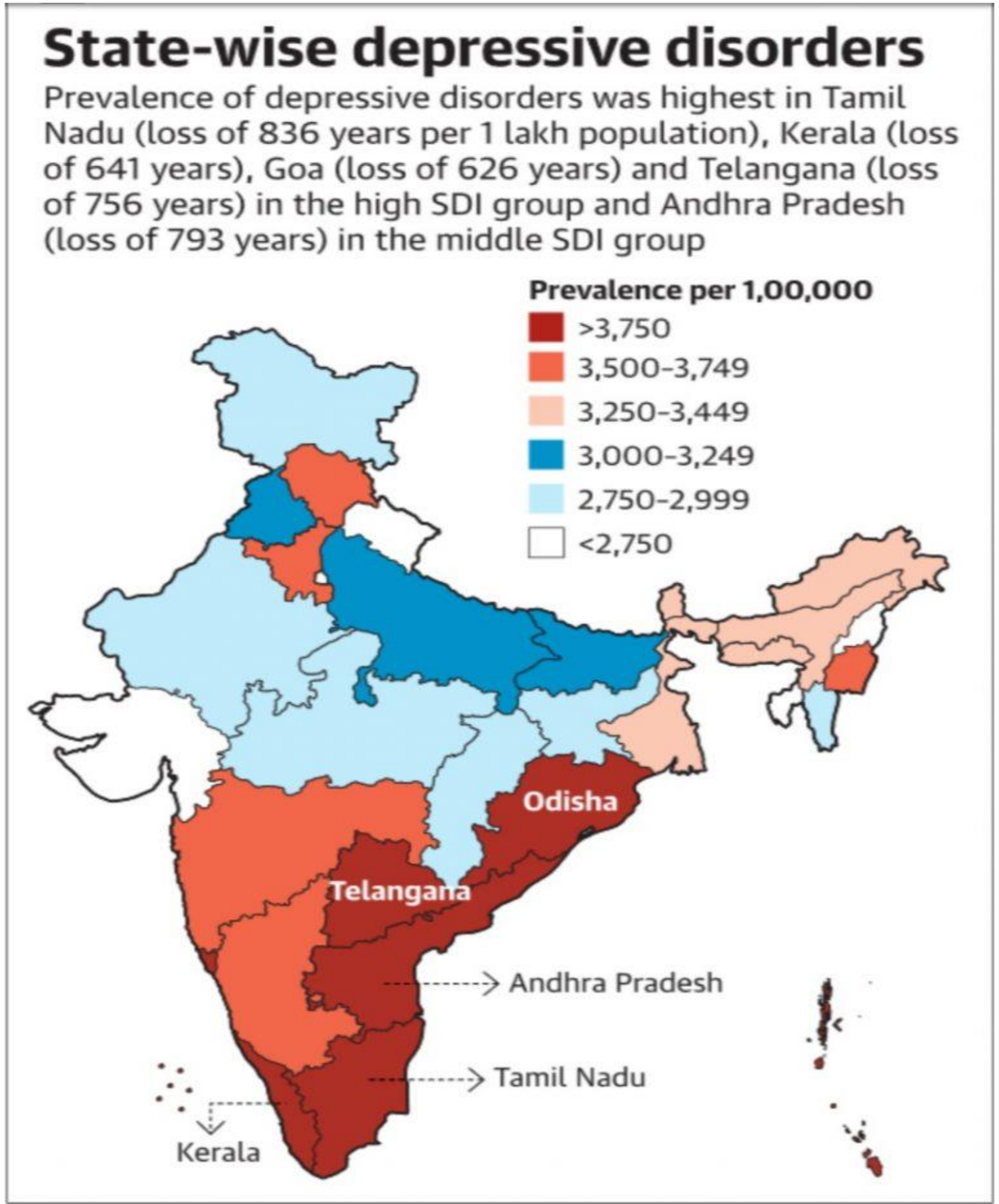
DEPRESSION:A WORLDWIDE ILLNESS

Depression is the leading cause of disability worldwide. Almost 75% of people with mental disorders remain untreated in developing countries with almost 1 million people taking their lives each year. In addition, according to the World Health Organization (WHO), 1 in 13 globally suffers from anxiety. The WHO reports that anxiety disorders are the most common mental disorders worldwide with specific phobia, major depressive disorder and social phobia being the most common anxiety disorders.



DEPRESSION IN INDIA

- In India, approximately 56 million people suffer from depression.
- According to a report in year 2022, the rate of depression in India is 4.50%.
- Every year, about 2 lakhs people commit suicides in India.



PROBLEM OVERVIEW

Depression (major depressive disorder) is a common and serious medical illness that negatively affects how you feel, the way you think and how you act. There are many experiences that can cause us depression, such losing a loved one, losing a job, getting a divorce and other tough situations can lead a person to feel blue, lonely and overwhelmed. Social media platforms are becoming an integral part of people’s life. They reflect user’s personal life. People likes to share happiness, joy and sadness on social media. All forms of depressive disorder experience some of the following symptoms:

(a) reduced concentration and attention

(b) reduced self-esteem and self-confidence

(c) ideas of guilt and unworthiness (even in a mild type of episode)

(d) bleak and pessimistic views of the future

(e) ideas or acts of self-harm or suicide

(f) disturbed sleep

(g) diminished appetite

ABSTRACT

Clinical Depression is a mental disorder involving one or more events of psychological actions that causes persistent feeling of sadness and loss of interest. Tens of millions of people each year suffer from depression and only a fraction receives adequate treatment. In recent years, the continuous increase in popularity of social media platforms has become an integral part of people's life. Previous studies show that these platforms are indeed increasingly used by depressed individuals to reflect on the user's personal life on many levels. The goal of this project is to examine automatically analyzing the social media textual data (Twitter) using Natural Language Processing (NLP) Machine learning (ML) techniques and a deep learning model to detect signs of depression. Feature extraction is done using term frequency inverse document frequency (TF-IDF), and Bag of words (BoW) model. Since the neural networks cannot deal with tweets directly, we used a well-known word embedding techniques called Word2vec by Google for the vector representation. In this project, several supervised machine learning algorithms (such as NB, SVM, RF) with feature engineering techniques are used and compare their performance with those of a transformer based deep learning pre-trained model (distilBERT).

LITERATURE SURVEY

Serial no.	Author name	Year published	Inference
1.	N. Masuda, I. Kurahashi	2016	They carried out the logistic regression to identify users' characteristics, both related and unrelated to social networks, which contribute to suicide ideation. They defined suicide ideation of a user as the membership to at least one active user-defined community related to suicide.
2.	E. Durkheim and A. Suicide	2020	Emile Durkheim's Suicide addresses the phenomenon of suicide and its social causes. Written by one of the world's most influential sociologists, this classic argues that suicide primarily results from a lack of integration of the individual into society.
3.	J. C. Eichstaedt	2018	Here, they used language from Facebook posts of consenting individuals to predict depression in electronic medical records. They accessed the history of Facebook statuses posted by 683 patients visiting a large urban academic emergency department, 114 of whom had a diagnosis of depression in their medical records.

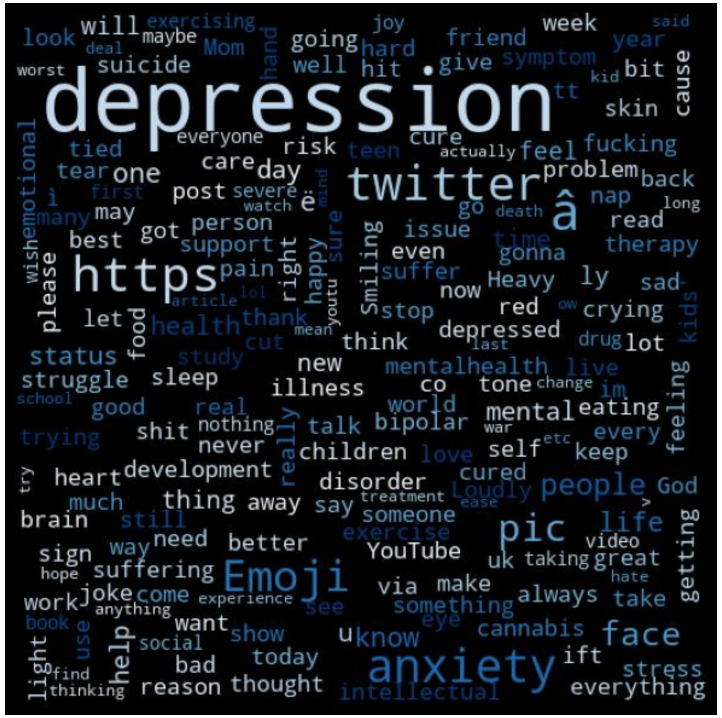
Serial no.	Author name	Year published	Inferences
4.	H. A. Schwartz	2014	In this paper they used survey responses and status updates from 28,749 Facebook users to develop a regression model that predicts users’ degree of depression based on their Facebook status updates. Their user-level predictive accuracy was modest, significantly outperforming a baseline of average user sentiment
5.	Tsugawa	2018	In this paper, they extensively evaluated the effectiveness of using a user’s social media activities for estimating degree of depression. They showed that features obtained from user activities can be used to predict depression of users with an accuracy of 69%.
6.	Nguyen	2015	This paper aims to study the characteristics of online depression communities (CLINICAL) in comparison with those joining other online communities (CONTROL). They used machine learning and statistical methods to discriminate online messages between depression and control communities using mood, psycholinguistic processes and content topics extracted from the posts generated by members of these communities.

METHODOLOGY

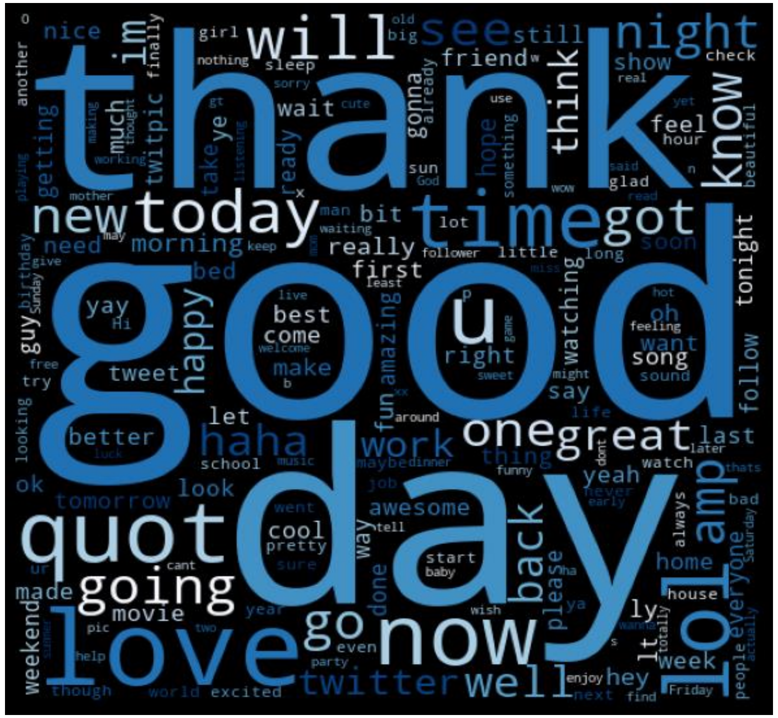
- **STEP 1: DATA COLLECTION**: The dataset has been generated by combining part of the Sentiment140 (8,000 positive tweets), and another one for depressive tweets (2,314 tweets), with a total of 10,314 tweets. Each data in the dataset consists of the tweet and label 0 or 1. 1 denotes that the individual who submitted the tweet exhibits symptoms of depression, while 0 denotes that the user does not.
- **STEP 2: DATA PREPROCESSING**: This process is the NLP technique which can be implemented using the nltk library in python. This is done by removing
  - links, @, and hashtags and emojis. As an example, #sadness" is converted to "sadness."."
  - Expanding contracted text- The word "can't" is changed to "cannot". The phrase "hungryyy" is changed to “hungry.”
  - punctuations and stopwords- stop words are a group of words that don't convey a lot of meaningful information. Example, The letters "a," "the," "is," "are".
  - Stemming- It is a NLP technique in which words can be condensed to their base form. For example, ‘connected’, ‘connection’ and ‘connecting’ can be reduced to the stem ‘connect’.

- **STEP 3: DATA VISUALIZATION-** After cleaning the data, the number of occurrence for each type column 'label' is visualized by the technique called Wordcloud. Word clouds are a type of data visualization where the magnitude of each word represents its frequency or relevance in a textual representation.

For label=1



For label=0



- **STEP 4: FEATURE EXTRACTION-** Feature extraction refers to the process of transforming raw data into numerical features that can be processed while preserving the information in the original data set. The different methods of feature extraction used in this project are:
  - **Bag of Words (BoW)** : Without taking into account the document's word order or structure, the BoW model seeks to describe a document as a collection of its individual words.
  - **TF-IDF Vectorizer**: Using TF-IDF, each word in a text is given a weighted significance score depending on how frequently it appears in the document and how uncommon it is within the corpus of documents.
  - **Word Embeddings (Word2Vec):** represent words as vectors of real numbers in a high dimensional space, with words that have similar meanings or uses being closer to one another than words with unrelated uses.

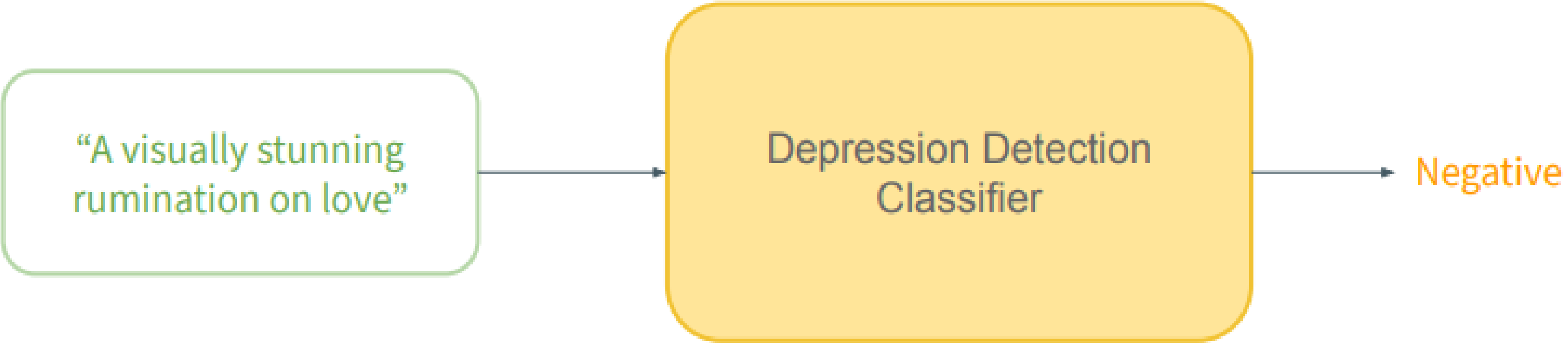
- **STEP 5: MODEL TRAINING**- In this stage, the preprocessed and engineered features that were retrieved from the text input are used to train the machine learning model or the deep learning model. Each feature extraction is trained on each model because different feature extraction techniques are employed. The models used are Naïve Bayes, Random Forest, and Support Vector Machine and also a deep learning approach distilBERT.
- **STEP 6: EVALUATION METRICS**- A machine learning model's performance on a particular task is measured using evaluation metrics. The different metrics used in the project are Accuracy, Precision, Recall and F score.

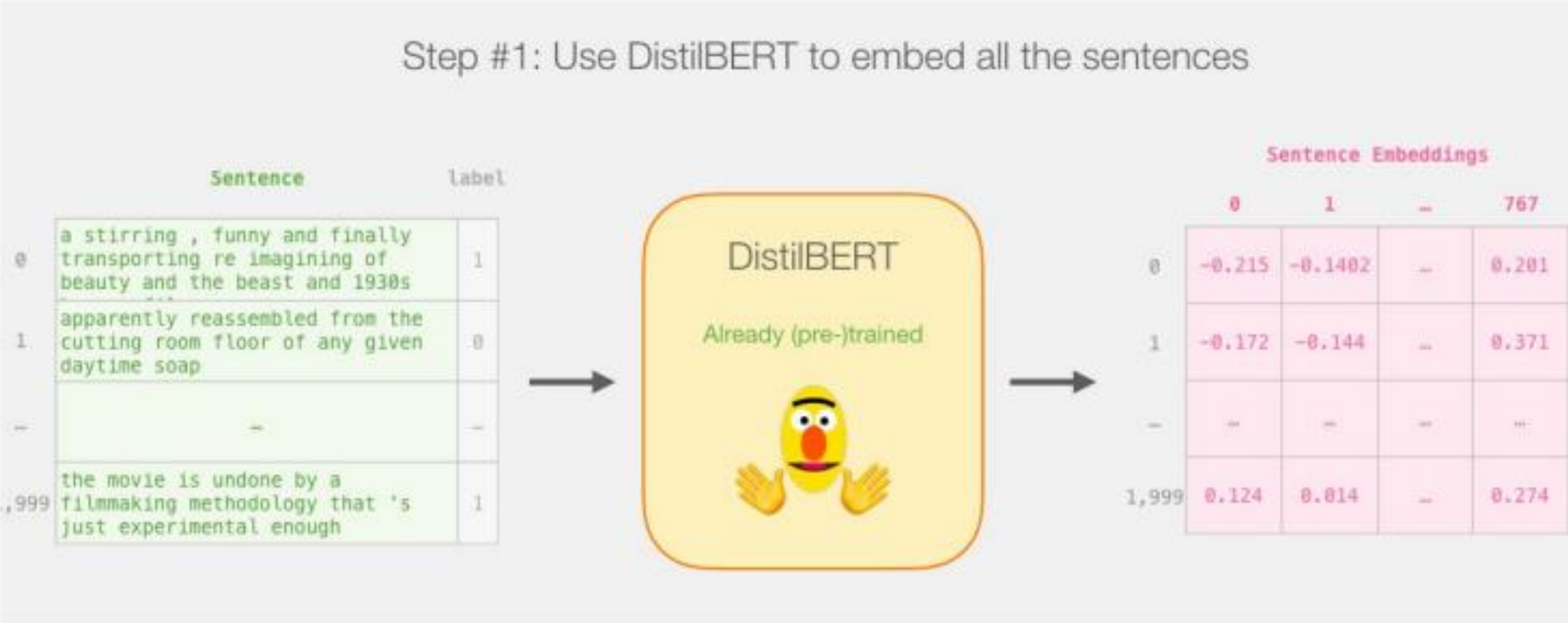
WHY TWEETS

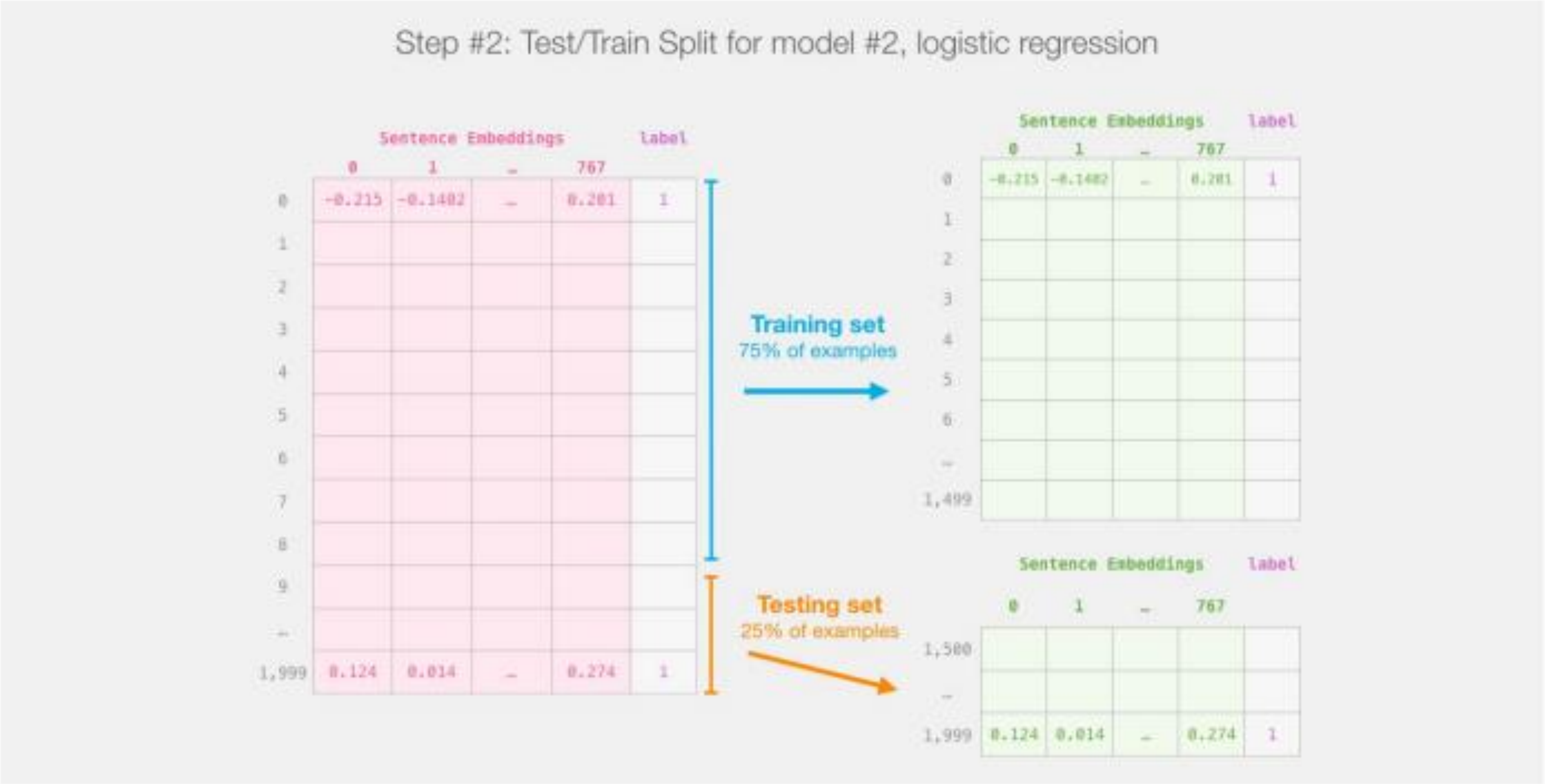
- Twitter currently ranks as one of the world's leading social networks based on active users.
- Tweets are mostly accessible to the public and can be obtained and analyzed, unless flagged by the user as "private".
- Tweets can be collected using Twitter API by searching the tweets for specific keywords, hashtags, or any defined query and can be limited to locations, hashtags and time periods.

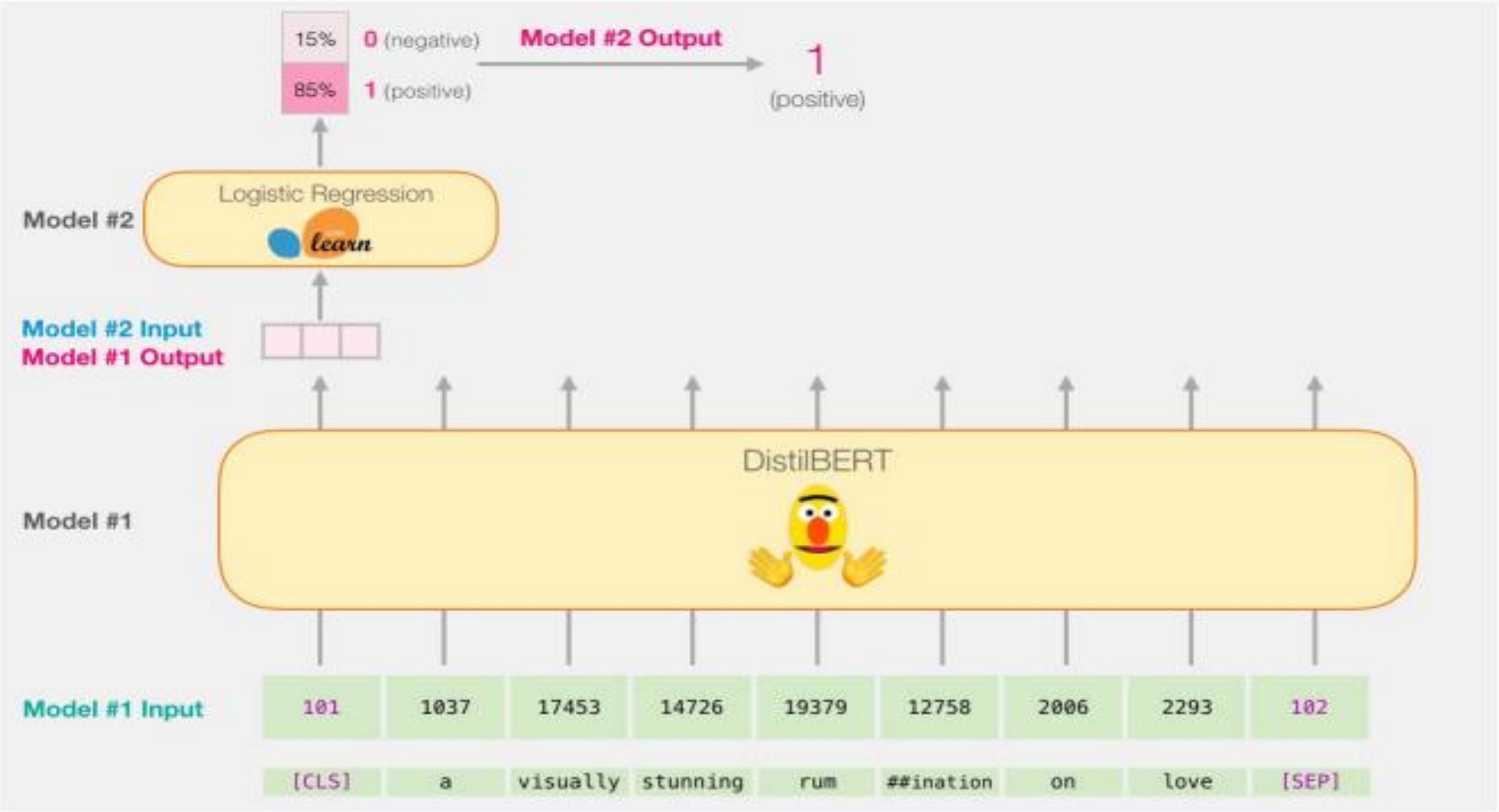
Deep Learning Pre-trained models

Goal: To create a model that produces either 1 (indicating the sentence carries a non-depressive) or a 0 (indicating the sentence carries a depressive sentiment). While we'll be using two models, we will only train the logistic regression model. For DistillBERT, we'll use a model that's already pre-trained and has a grasp on the English language. Think of it as looking like this:




Step #1: Use DistilBERT to embed all the sentences
Sentence
label
0
a stirring , funny and finally transporting re imagining of beauty and the beast and 1930s
1
1
apparently reassembled from the cutting room floor of any given daytime soap
0
…
…
…
1,999
the movie is undone by a filmmaking methodology that 's just experimental enough
1
DistilBERT
Already (pre-)trained
Sentence Embeddings
0
1
…
767
0
-0.215
-0.1402
…
0.201
1
-0.172
-0.144
…
0.371
…
…
…
…
…
1,999
0.124
0.014
…
0.274


Step #2: Test/Train Split for model #2, logistic regression
Sentence Embeddings
label
0
1
…
767
-0.215
-0.1402
0.201
1
1,999
0.124
0.014
0.274
Training set
75% of examples
Testing set
25% of examples
1,499
1,500


15%
0 (negative)
85%
1 (positive)
Model #2 Output
1
(positive)
Logistic Regression
learn
Model #2
Model #2 Input
Model #1 Output
DistilBERT
Model #1
Model #1 Input
101
1037
17453
14726
19379
12758
2006
2293
102
[CLS]
a
visually
stunning
rum
##ination
on
love
[SEP]

WORK PLAN

Sl. No	MONTH-WEEK	PLAN
1.	JANUARY-WEEK 1	Identification of the problem.
2.	JANUARY- WEEK 2,3	Literature review on the decided problem.
3.	JANUARY- WEEK 4	Formation of the abstract.
4.	FEBRUARY- WEEK 1,2	Discussion on the title.
5.	FEBRUARY- WEEK 3	Discussion on the aims, objectives and outcomes of the problem.
6.	FEBRUARY- WEEK 4	Collection of the data.
7.	MARCH- WEEK 1	Methodology: Adaptation of the appropriate methods for the gathered data.
8.	MARCH- WEEK 2	Appropriate analysis, relevant discussion and valid conclusions.
9.	MARCH- WEEK 3	Feedback from guide.
10.	MARCH- WEEK 4	Final documentation and report writing.
11.	APRIL- WEEK 1	Report review.
12	APRIL- WEEK 2 (11 April)	Final review.

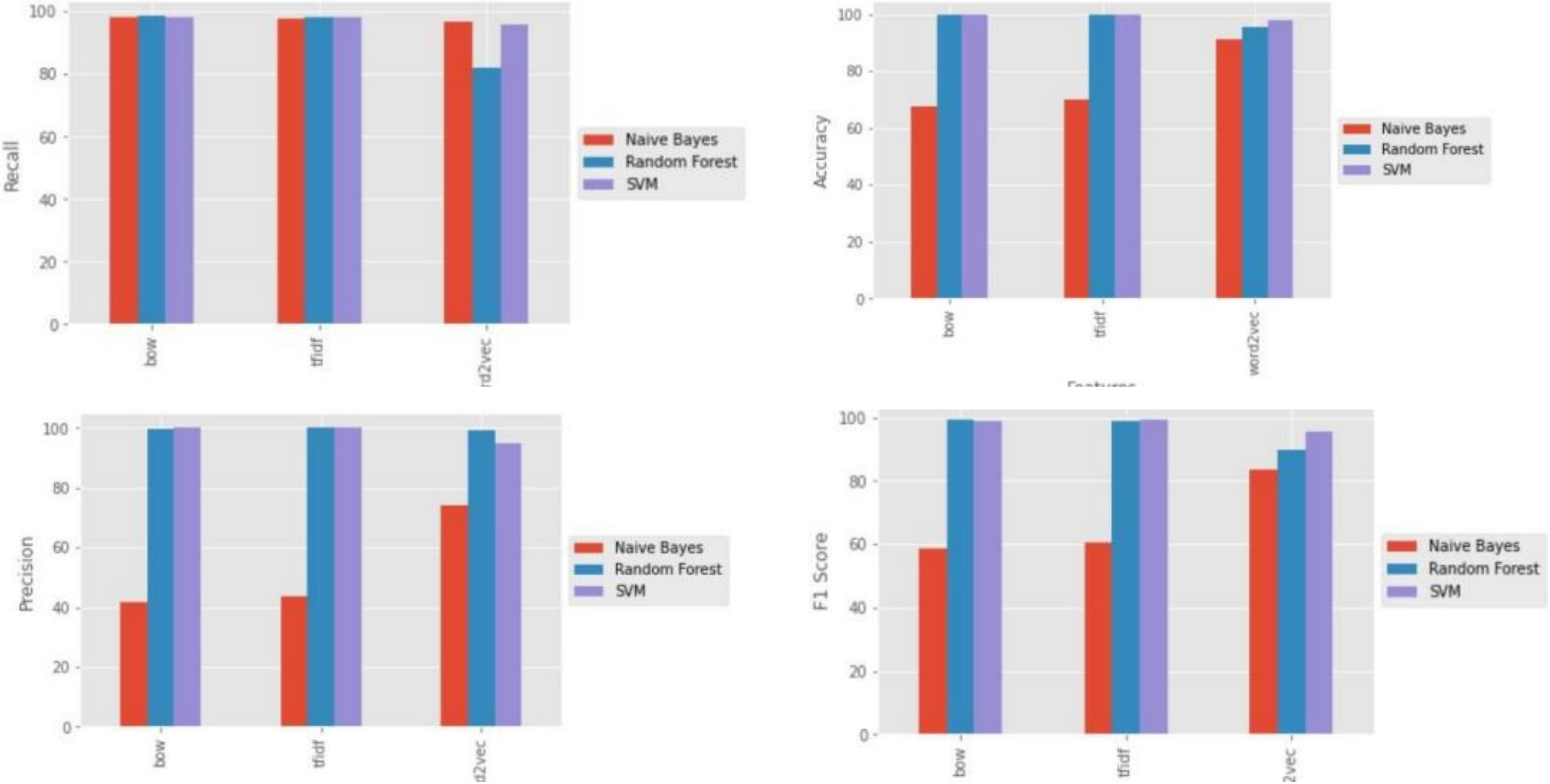
RESULTS

```
Precision:  0.96
Recall:  0.95
F-score:  0.95
Accuracy:  0.98
```

Fig 21: Evaluation metrics of distilBERT model.

	Features		
Model	BOWs	TF-IDF	Word2Vec
Naive Bayes	0.58	0.60	0.83
Random Forest	0.99	0.99	0.89
Kernel SVM	0.99	0.99	0.95

Table 3: F score distribution of the model



Recall
Accuracy
Precision
F1 Score
Naive Bayes
Random Forest
SVM
bow
tfidf
word2vec
0
20
40
60
80
100

CONCLUSION

From the figures and table, we draw the conclusion that the distilBert model, Random Forest model, and SVM model are the best-performing models after comparing the f scores of the suggested models. When compared to the Random Forest and SVM models, the distillBERT model has 0.95 f scores. The Naive Bayes model does not provide the expected prediction since the f scores for each feature are relatively low. Besides the foregoing findings, the language model distil BERT based on transformers performs better than the above traditional models. Compared to conventional machine learning algorithms, BERT is better able to understand the relationships and trends between words and phrases since it is trained on a vast corpus of text data. In order to capture the features necessary for the work at hand, BERT also has the ability to dynamically alter its attention to various areas of the input text.

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