Lexicon-Based Approach to Sentiment Analysis of Bilingual Tweets

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OBJECTIVE

- We aim to implement a Twitter sentiment analysis model that helps to overcome the challenges of identifying the sentiments of bilingual tweets (Tamil and English).
- Classify the tweets present in the dataset into positive and negative.
- Implement the model for different classifiers and evaluate their performance based on accuracy and F1 scores.

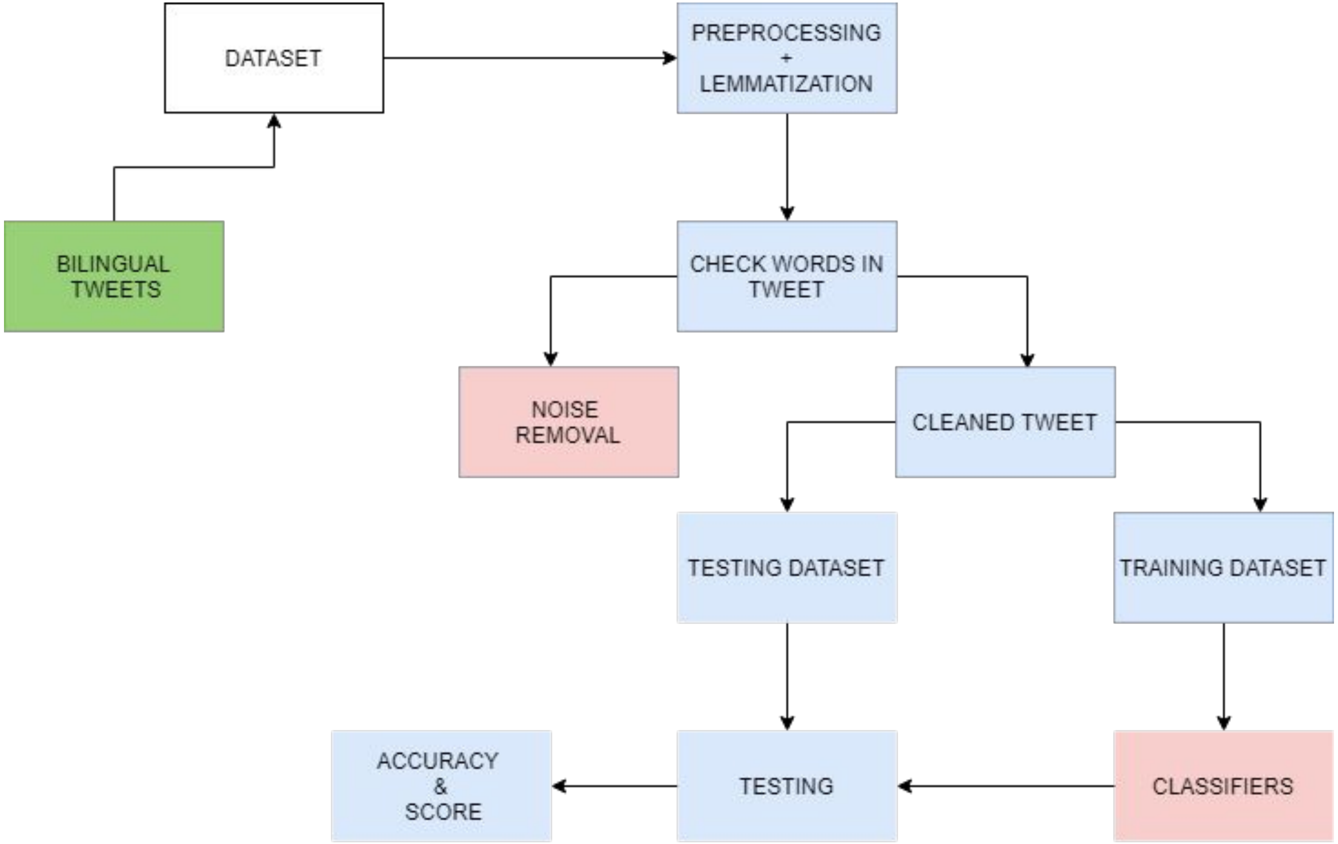
Literature Survey

SNO	TITLE , AUTHOR ,YEAR	PROPOSED METHOD	DATASET	METRICS	MERITS AND DEMERITS	IDEAS FOR ADOPTION
1	Lexicon-Based Approach to Sentiment Analysis of Tweets Using R Language: Second International Conference,Nitika Nigam, Divakar Yadav, ICACDS 2018, Dehradun, India, April 20-21, 2018,	To classify the given set of tweets into two classes: Positive and Negative by extracting the semantics from the tweets and calculating polarity score.	Dataset of PM Modi's Tweets	The final table consists of positive, negative and score values which is represented in the form of a histogram.	Result given conclusive enough for the dataset . The range is small as they've taken smaller dataset. Some of parameters are not taken into consideration like the hybrid languages.	Leveraging the score calculation mechanism used here. Also adopting same style of lexicon based dictionary creation.
2	Tools and Techniques for Lexicon Driven Sentiment Analysis: A Review, Munir Ahmad Shabib Aftab, Syed Shah Muhammad Usman waheed Waheed	Different tools and methods analysed for lexicon based analysis and their accuracy rates compared.	Twitter Data, DIGG, BBC Dataset.	Accuracies of different methods on datasets varying from 95.33 to 66.56 percent.	Different methods explored paving way for understanding the various nuances of analysis. Analysed for 3 datasets hence giving varying pictures. Proposed tools/methods have individual drawbacks.	Adopting the proposed methods for positive, negation, blind negation and split words.

SNO	TITLE , AUTHOR ,YEAR	PROPOSED METHOD	DATASET	METRICS	MERITS AND DEMERITS	IDEAS FOR ADOPTION
3	DepecheMood++: a Bilingual Emotion Lexicon Built Through Simple Yet Powerful Techniques Oscar Araque Lorenzo Gatti2 , Jacopo Staiano3 , Marco Guerini4,5 1Grupo de Sistemas Inteligentes, 2015	An extension of an existing and widely used emotion lexicon for English and creation of emotion lexica for Italian and English through increasing embedding, regression experiments and other techniques.	From Rappler and Corriere and (Guerini and Staiano)	Measured via average correlation of emotions and words mentioned.	The different methods mentioned have their own effect on accuracy for eg adding a word frequency cutoff parameter leads to a benefit in the performance of the generated lexicon; in our experiments we find an optimal value of 10.	The methods mentioned to remove random subsets, of decreasing size, from the original lexicon vocabulary
4	Predicting Tamil Movies Sentimental Reviews Using Tamil Tweets- Vallikannu Ramanathan, T. Meyyappan and S.M. Thamarai- 2019	Sentiment-bearing terms and its neighbouring terms in Tamil tweets are evaluated using contextual semantic sentiment analysis to get more accurate result for the movie sentimental classification	Petra Movie review.	TF-IDF method is used to find the accuracy based on keywords. As well as TF-IDF+ DSO +CSSA	It deals negation problem and Tamil SentiWordNet with adjectives to classify the sentiment. However adverbs not dealt with and dataset is limited. Doesn’t account for tamil words typed in english.	To analyze the semantic meaning between the words contextual semantic sentiment analysis is applied.

SNO	TITLE , AUTHOR ,YEAR	PROPOSED METHOD	DATASET	METRICS	MERITS AND DEMERITS	IDEAS FOR ADOPTION
5	Expressively vulgar: The socio-dynamics of vulgarity and its effects on sentiment analysis in social media Isabel Cachola∗‡ Eric Holgate∗† Daniel Preoţiuc-Pietro ♦ Junyi Jessy Li† 2018	This study performs a large-scale, data-driven empirical analysis of vulgar words using social media data	200 dimensional embeddings trained on a corpus of 50 million tweets (Astudillo et al., 2015).	Mean absolute error (MAE), which asserts more penalty when the predicted label is further away from the true label, i.e., if the system predicts 1, and the true label is -2, the error will be 3 (instead of just “incorrect”).	Introduced a new data set of 6.8K vulgar tweets labeled for sentiment on a five-point scale by nine annotators Token insertion and concatenation improves the prediction of negative tweets, and the prediction of non-negative tweets remain stable. Across sentiment labels, masking improves the prediction of positive tweets; however, the prediction of negative tweets suffer. With masking, the actual vulgar word is replaced by a special token, stripping its meaning.	Masking, Token Insertion and concatenation for analysing vulgar tweets.

DETAILED ARCHITECTURE



LIST OF MODULES

1. Collection of dataset
2. Data Preprocessing
   a. Dataset Cleaning
   b. Add Cleaned tweet to dataset
3. Feature Extraction
4. Training & Testing
5. Performance Evaluations
6. Bilingual Tweets

Module 1: Dataset

- The dataset that was used was obtained from "Kaggle" called the *Sentiment140* dataset.
- It contains 16 Million tweets extracted using the twitter API. The tweets have been annotated (0 = Negative, 1 = Positive) and they can be used to detect sentiment.
- The two columns that we will be needing are:
  - Label
  - Tweet

	Label	number	date	no_query	name	Tweet
0	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...
1	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...
2	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire
3	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....
4	0	1467811372	Mon Apr 06 22:20:00 PDT 2009	NO_QUERY	joy_wolf	@Kwesidei not the whole crew
...	...	...	...	...	...	...
1048570	4	1960186342	Fri May 29 07:33:44 PDT 2009	NO_QUERY	Madelinedugganx	My GrandMa is making Dinenr with my Mum
1048571	4	1960186409	Fri May 29 07:33:43 PDT 2009	NO_QUERY	OffRoad_Dude	Mid-morning snack time... A bowl of cheese noo...
1048572	4	1960186429	Fri May 29 07:33:44 PDT 2009	NO_QUERY	Falchion	@ShaDeLa same here say it like from the Termi...
1048573	4	1960186445	Fri May 29 07:33:44 PDT 2009	NO_QUERY	jonasobsessedx	@DestinyHope92 im great thaanks wbuu?
1048574	4	1960186607	Fri May 29 07:33:45 PDT 2009	NO_QUERY	sugababez	cant wait til her date this weekend

1048575 rows × 6 columns

Module 2: Data Preprocessing

- **Data Cleaning**
  - Changing Labels
  - Dropping unwanted columns
  - Removing Emoticons
  - Replace contraction
  - Lemmatization
  - Removal of Noise

- **Add Cleaned tweet to dataset**
  - Writing Cleaned Tweets to a file
  - Adding Cleaned Tweets as a column to data
  - Display preprocessed data

1. Changing Labels

Pseudo Code:

For every label:

If label is 0 then replace as negative

Else replace as positive

```
#0 to negative and 4 to positive
l=[]
for i in data["Label"]:
  if(i==0):
    l.append("negative")
  else:
    l.append("positive")
data['Comment']=l

data
```

2. Dropping unwanted columns

Pseudo Code:

Data = data.drop(<list of columns to be dropped>)

```
data=data.drop(columns=['number', 'date','name','no_query','Label'])
data
```

	Tweet	Comment
0	is upset that he can't update his Facebook by ...	negative
1	@Kenichan I dived many times for the ball. Man...	negative
2	my whole body feels itchy and like its on fire	negative
3	@nationwideclass no, it's not behaving at all....	negative
4	@Kwesidei not the whole crew	negative
...	...	...
4995	@radcs when are you putting a photo up?	positive
4996	oh wait, thunderstorms tomorrow?! ohSHIT, then...	positive
4997	@gwane and I'd go with either a nose ring or a...	positive
4998	what that - dissertation script is finished an...	positive
4999	@SITSGirls it does indeed. hope you are well t...	positive

5000 rows × 2 columns

3. Removing Emoticons

Pseudo Code:

For *emojis use inputString.encode() to convert to ascii value.*

For keyboard typed emoticons use dictionary to replace equivalent text.

```
[19] def deEmojify(inputString):
       return inputString.encode('ascii', 'ignore').decode('ascii')
```

```
def emoticons():
    return {
        ":)":"smiley",
        ":-)":"smiley",
        ":-]":"smiley",
        ":-3":"smiley",
        ":->":"smiley",
        "8-)":"smiley",
        ":-}":"smiley",
        ":)":"smiley",
        ":]":"smiley",
        ":3":"smiley",
        ":>":"smiley",
        "8)":"smiley",
        ":}":"smiley",
        ":o)":"smiley",
        ":c)":"smiley",
        ":^)":"smiley",
        "=]":"smiley",
```

4. Replace contraction

Pseudo Code:

For contractions use defined dictionary to replace equivalent text.

```
def contractions():
  return {
    "ain't":"is not",
    "amn't":"am not",
    "aren't":"are not",
    "can't":"cannot",
    "'cause":"because",
    "couldn't":"could not",
    "couldn't've":"could not have",
    "could've":"could have",
    "daren't":"dare not",
    "daresn't":"dare not",
    "dasn't":"dare not",
    "didn't":"did not",
    "doesn't":"does not",
    "don't":"do not",
    "e'er":"ever",
    "em":"them",
    "everyone's":"everyone is",
    "finna":"fixing to",
    "gimme":"give me",
    "gonna":"going to",
    "gon't":"go not",
    "gotta":"got to",
    "hadn't":"had not",
    "hasn't":"has not",
```

5. Lemmatization

Pseudo Code:

for word in sentence:

lemm = Lemmatize(word)

return lemm

Input: Eat played slept

Output: eat play sleep

```python
#Lemmatization : Root form of words in tweet

def lemmatization(sent):
  lemmatize=WordNetLemmatizer()
  sentence_after_lemmatization=[]
  for word,tag in pos_tag(word_tokenize(sent)):
    if(tag[0:2]=="NN"):
      pos='n'
    elif(tag[0:2]=="VB"):
      pos='v'
    else:
      pos='a'
    lem=lemmatize.lemmatize(word,pos)
    sentence_after_lemmatization.append(lem)

  st=""

  for i in sentence_after_lemmatization:
    if(i!="be" and i!="is" and len(i)!=1):
      st=st+" "+i

  c=0
  list_text=st.split()
  flag=0
  new_st=""
  for i in list_text:
    temp=i
    if(flag==1):
      flag=0
      continue
    if(i=="not" and (c+1)<len(list_text)):
      for syn in wordnet.synsets(list_text[c+1]):
        antonyms=[]
        for l in syn.lemmas():
          if l.antonyms():
            antonyms.append(l.antonyms()[0].name())
            temp=antonyms[0]
            flag=1
            break
        if(flag==1):
          break
    new_st=new_st+" "+temp
    c+=1
  return new_st
```

6. Removal of Noise

Pseudo Code:

For each word in tweet:

- *Removal of url*
- *Removal handles @*
- *Replacing emoticons with their respective words*
- *Replacing short form words with their full form*

```python
def removal_of_noise(sent):
    clean_sent=[]
    temp_st=""
    list_sent=sent.split(" ")
    c=0
    d=contractions()
    emoji=emoticons()
    for word in list_sent:
        #removal of url
        word = re.sub(r"http\S+", "", word)
        word = re.sub(r"[www.][a-zA-Z0-9_]+[.com]", "", word)
        #removal of account handles '@'
        word = re.sub("(@[A-Za-z0-9_]+)","", word)

        #replacing emoticons with their respective words
        if(word in emoji.keys()):
            word=emoji[word]
        #replacing short form words with their full form
        if(word.lower() in d.keys()):
            word=d[word.lower()]
        if(c==0):
            temp_st=word
        else:
            temp_st=temp_st+" "+word
        c=c+1
    sent=temp_st
    stop_words = set(stopwords.words('english'))
    stop_words.add('is')
    stop_words.remove('not')
    for word in word_tokenize(sent):
        if(word.lower() not in stop_words and word.lower() not in string.punctuation and word!="''" and word!="``" ):
            #print(word)
            word=spell.correction(word.lower())
            word=re.sub("[0-9]+","",word)
            word=re.sub("[.]+"," ",word)
            word=re.sub("[-]+"," ",word)
            word=re.sub("[_]+"," ",word)
            word = re.sub("~"," ", word)
            if(len(word)!=1):
                clean_sent.append(word.lower())
    cleaned_st=""
    for i in clean_sent:
        cleaned_st=cleaned_st+" "+i
    #print(cleaned_st)
    return lemmatization(cleaned_st)
```

7. Preproc() calls all other preprocessing functions

Pseudo Code:

prepoc():

deEmojify()

removal_of_noise()

```
def preproc(text):
 #HTML tags are removed below
 text =BeautifulSoup(text).get_text()
 text =text.replace("’","'")
 new_text=sent_tokenize(text)
 result=0
 new_str=""
 #Emoticons removal + Noise Removal
 for i in new_text:
  j=deEmojify(i)
  res=removal_of_noise(j)
  new_str=new_str+" "+res
 return new_str
```

8. Display Cleaned Tweets

```
clean_list=[]
for i in data["Tweet"]:
  print()
  print(i)
  x=preproc(i)
  clean_list.append(x)
  print()
  print(x)
  print("------------------------")
```

```
 enjoy nice weather
------------------------

@trendhunter Very nice pics! Thanks for sharing it

 nice pic  thanks share
------------------------

@Hollywood_Trey


------------------------

is so anxious for thursday! I can't wait to see mike its been 3 and a half months!

 anxious thursday  not wait see mike half month
------------------------

@FinancegradTH Some days I have too much to say. Not a bad thing to be at a loss for words, you use your brain for much greater things.

 day much say  good thing loss word use brain much great thing
------------------------
```

9. Writing Cleaned Tweets to a file

```
[31]  with open('cleaned_tweet.txt', 'w') as f:
        for item in clean_list:
          f.write("%s\n" % item)
```

10. Adding Cleaned Tweets as a column to data

```
[91]  #reading from file cleaned tweets and storing in a cleaned tweets column in the dataframe
      filename = "cleaned_tweet.txt"
      with open(filename) as f:
        lines = f.read().splitlines()
      lines
      data["cleaned_tweets"]=lines
```

11. PreProcessed Data

```
data
```

	Label	number	date	no_query	name	Tweet	Comment	cleaned_tweets
0	0	1467810672	Mon Apr 06 22:19:49 PDT 2009	NO_QUERY	scotthamilton	is upset that he can't update his Facebook by ...	negative	upset not
1	0	1467810917	Mon Apr 06 22:19:53 PDT 2009	NO_QUERY	mattycus	@Kenichan I dived many times for the ball. Man...	negative	
2	0	1467811184	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	ElleCTF	my whole body feels itchy and like its on fire	negative	itchy
3	0	1467811193	Mon Apr 06 22:19:57 PDT 2009	NO_QUERY	Karoli	@nationwideclass no, it's not behaving at all....	negative	mad not
4	0	1467811372	Mon Apr 06 22:20:00 PDT 2009	NO_QUERY	joy_wolf	@Kwesidei not the whole crew	negative	not
...	...	...	...	...	...	...	...	...
4995	4	1468239135	Tue Apr 07 00:28:57 PDT 2009	NO_QUERY	Radt	@radcs when are you putting a photo up?	positive	
4996	4	1468239145	Tue Apr 07 00:28:57 PDT 2009	NO_QUERY	Disaster08	oh wait, thunderstorms tomorrow?! ohSHIT, then...	positive	love love love
4997	4	1468239164	Tue Apr 07 00:28:58 PDT 2009	NO_QUERY	lilac_dreamer	@gwane and I'd go with either a nose ring or a...	positive	
4998	4	1468239307	Tue Apr 07 00:29:01 PDT 2009	NO_QUERY	TButt1983	what that - dissertation script is finished an...	positive	
4999	4	1468239336	Tue Apr 07 00:29:01 PDT 2009	NO_QUERY	designmama	@SITSGirls it does indeed. hope you are well t...	positive	well

5000 rows × 8 columns

Module 3: Feature Extraction

- Reading adjective file
- Extracting adjectives from the tweets
- Create frequency adjective distribution
- Replacing each cleaned tweet with features
- Display data with their features

1. Reading adjective file

```
[93] filename = "drive/MyDrive/CD PROJECT/english_adjectives.txt"
     with open(filename) as f:
        lines = f.read().splitlines()
     lines
     adjectives=lines
```

2. Extracting adjectives from the tweets

```
all_words=[]
negative=["not"]
for i in data["cleaned_tweets"]:
   for word in word_tokenize(i):
      if(word in adjectives or word in negative):
        all_words.append(word)
```

3. Create frequency adjective distribution

```
[95] import nltk
     BagOfWords = nltk.FreqDist(all_words)
     #BagOfWords
     #len(BagOfWords)
     word_features = list(BagOfWords.keys())[:5000]
     #len(word_features)
     #word_features
```

4. Replacing each cleaned tweet with features

```
new_list=[]
for i in data["cleaned_tweets"]:
    st=""
    for j in i.split():
        if(j in word_features):
            st=st+" "+j
    new_list.append(st)

data["cleaned_tweets"]=new_list
```

5. Display data with their features

```
data
```

	Tweet	Comment	cleaned_tweets
0	is upset that he can't update his Facebook by ...	negative	upset not
1	@Kenichan I dived many times for the ball. Man...	negative	
2	my whole body feels itchy and like its on fire	negative	itchy
3	@nationwideclass no, it's not behaving at all....	negative	mad not
4	@Kwesidei not the whole crew	negative	not
...	...	...	...
4995	@radcs when are you putting a photo up?	positive	
4996	oh wait, thunderstorms tomorrow?! ohSHIT, then...	positive	love love love
4997	@gwane and I'd go with either a nose ring or a...	positive	
4998	what that - dissertation script is finished an...	positive	
4999	@SITSGirls it does indeed. hope you are well t...	positive	well

5000 rows × 3 columns

Module 4: TRAINING & TESTING

- Training and Testing Dataframes

```
[39]  y=data["Comment"]
      x=data.drop('Comment',axis=1)
      x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.15)
```

```
[97]  X_train = pd.DataFrame(columns=['Tweet','cleaned_tweets'])
      X_test = pd.DataFrame(columns=['Tweet','cleaned_tweets'])
      Y_train = []
      Y_test = []
      X_train = X_train.append(x_train)
      for i in y_test:
         Y_test.append(i)
      for i in y_train:
          Y_train.append(i)
      X_test = X_test.append(x_test)
```

- Training sets

```
training_set=[]
count=0
for i in (X_train["cleaned_tweets"]):
  training_set.append((i.split(),Y_train[count]))
  count+=1

def list_to_dict(words_list):
  return dict([(word, True) for word in words_list])

training_set_formatted = [(list_to_dict(element[0]), element[1]) for element in training_set]
#training_set_formatted
```

- Testing Sets

```
test_set=[]
count=0
for i in (X_test["cleaned_tweets"]):
  test_set.append((i.split(),Y_test[count]))
  count+=1

def list_to_dict(words_list):
  return dict([(word, True) for word in words_list])

test_set_formatted= [(list_to_dict(element[0]), element[1]) for element in test_set]
```

CLASSIFIER ALGORITHMS TO TRAIN MODEL

Naive Bayes Algorithm

It is a classification technique based on Bayes' Theorem with an assumption of independence among predictors. A Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature.
Bayes theorem provides a way of calculating posterior probability P(c|x) from P(c), P(x) and P(x|c).

Likelihood   Class Prior Probability

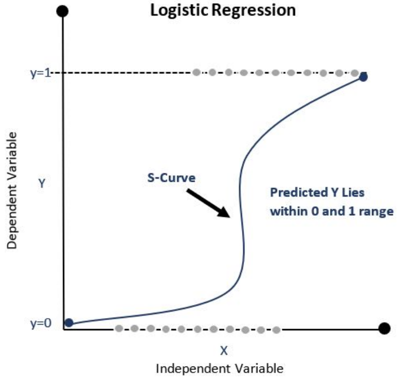
$$P(c \mid x) = \frac{P(x \mid c)P(c)}{P(x)}$$

Posterior Probability   Predictor Prior Probability

$$P(c \mid X) = P(x_1 \mid c) \times P(x_2 \mid c) \times \cdots \times P(x_n \mid c) \times P(c)$$

Logistic Regression Algorithm

Logistic regression is basically a supervised classification algorithm. In a classification problem, the target variable(or output), y, can take only discrete values for a given set of features(or inputs), X.



Naive Bayes Algorithm

```
print("NAIVE BAYES\n")
classifier = nltk.NaiveBayesClassifier.train(training_set_formatted)
print("Accuracy Percentage = ", (nltk.classify.accuracy(classifier, test_set_formatted))*100)
classifiers.append([classifier,"NaiveBayes"])
accuracy.append([(nltk.classify.accuracy(classifier, test_set_formatted))*100,"NB"])
target_names = [ 'positive','negative']
print("\nClassifiaction Report\n")
print(classification_report(Y_test, preds, target_names=target_names))
```

```
NAIVE BAYES

Accuracy Percentage =  60.4

Classifiaction Report

              precision    recall  f1-score   support

    positive       0.56      0.79      0.65       357
    negative       0.69      0.44      0.54       393

    accuracy                           0.60       750
   macro avg       0.63      0.61      0.60       750
weighted avg       0.63      0.60      0.59       750
```

Logistic Regression Algorithm

```
print("LOGISTIC REGRESSION\n")
LogReg_clf = SklearnClassifier(LogisticRegression())
LogReg_clf.train(training_set_formatted)
print("Acuracy Percentage = ", (nltk.classify.accuracy(LogReg_clf, test_set_formatted))*100)
accuracy.append([(nltk.classify.accuracy(LogReg_clf, test_set_formatted))*100,"LogReg"])
classifiers.append([LogReg_clf,"LogisticRegression"])
target_names = [ 'positive','negative']
print("\nClassifiaction Report\n")
print(classification_report(Y_test, preds, target_names=target_names))
```

```
LOGISTIC REGRESSION

Acuracy Percentage =  60.8

Classifiaction Report

              precision    recall  f1-score   support

    positive       0.56      0.79      0.65       357
    negative       0.69      0.44      0.54       393

    accuracy                           0.60       750
   macro avg       0.63      0.61      0.60       750
weighted avg       0.63      0.60      0.59       750
```

MODULE 5: Performance Evaluations

CONFUSION MATRIX

		true class: EFR	true class: LFR	total
predicted class	EFR	True Positives (TP)	False Positives (FP)	predicted EFR
predicted class	LFR	False Negatives (FN)	True Negatives (TN)	predicted LFR
		true EFR	true LFR	

$$\mathrm{PR} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}}$$

$$\mathrm{RE} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}}$$

$$\mathrm{CA} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}}$$

$$\mathrm{F}_1 = \frac{2\mathrm{TP}}{2\mathrm{TP}+\mathrm{FP}+\mathrm{FN}}$$

ACCURACY

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

PRECISION

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

RECALL

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

F1 SCORE

$$\text{F1 Score} = \frac{2 \times (\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$$

Naive Bayes Algorithm

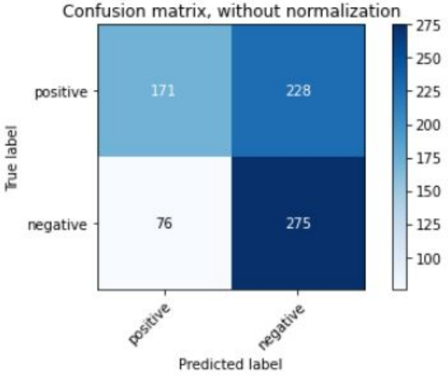
NAIVE BAYES

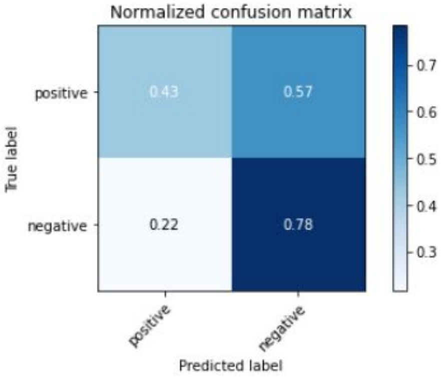
Accuracy Percentage = 59.46666666666667

Classifiaction Report

	precision	recall	f1-score	support
positive	0.69	0.43	0.53	399
negative	0.55	0.78	0.64	351
accuracy			0.59	750
macro avg	0.62	0.61	0.59	750
weighted avg	0.62	0.59	0.58	750

Confusion matrix, without normalization
[[171 228]
 [76 275]]
Normalized confusion matrix
[[0.43 0.57]
 [0.22 0.78]]





Logistic Regression Algorithm

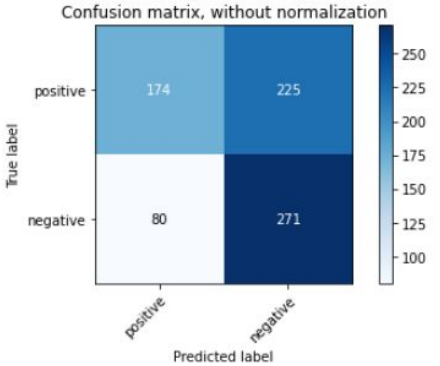
LOGISTIC REGRESSION

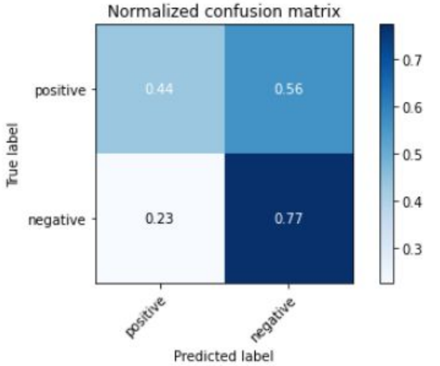
Acuracy Percentage = 59.333333333333336

Classifiaction Report

	precision	recall	f1-score	support
positive	0.69	0.44	0.53	399
negative	0.55	0.77	0.64	351
accuracy			0.59	750
macro avg	0.62	0.60	0.59	750
weighted avg	0.62	0.59	0.58	750

Confusion matrix, without normalization
[[174 225]
 [80 271]]
Normalized confusion matrix
[[0.44 0.56]
 [0.23 0.77]]





MODULE 6: BILINGUAL TWEETS

1. Import libraries

```
from googletrans import Translator
translator = Translator(service_urls=['translate.googleapis.com'])
```

2. Function to create List of Features

```
[69] def features(text):
       new_list=[]
       for i in text.split():
         if(i in adjectives):
           new_list.append(i)
       return new_list
```

3. Classify Function

1. PreProcessing
2. Extract Features
3. Test Data using Classifiers
4. Print Result

[114]
```
def text_classify(text):
  cleaned_text=preproc(text)
  temp=features(cleaned_text)
  test_data=list_to_dict(temp)
  print(temp)
  print("Tweet given by user : ",text)
  for i in classifiers:
    print(i[1])
    determined_label=i[0].classify(test_data)
    print("This Tweet is ",determined_label)
    print("\n\n")
  c=0
```

4. Translating users input to english

[66]
```
#input from the user which will be used to classify
def tanglish(input_text):
  translator = Translator(service_urls=['translate.google.co.in'])
  x=translator.translate(input_text,src="ta",dest="en")
  text_classify(x.text)
```

[67]
```
#input from the user which will be used to classify
from textblob import TextBlob
def tanglish2(input_text):
  l=input_text.split()
  st=""
  for i in l:
    word=TextBlob(i)
    if(word.detect_language()=="ta"):
      translator = Translator(service_urls=['translate.google.co.in'])
      x=translator.translate(i,src="ta",dest="en")
      st=st+" "+x.text
    else:
      st=st+" "+i
  text_classify(st)
```

```python
def func(input_text):
    l=input_text.split()
    flag=0
    for i in l:
        k=len(i)
        if(k<3):
            flag=1
            tanglish(input_text)
    if(not(flag)):
        tanglish2(input_text)
```

Test Cases

```
func("saapadu is bad")
```

```
['bad']
Tweet given by user :  Meals Is Bad
LogisticRegression
This Tweet is  negative
------------------------------
NaiveBayes
This Tweet is  negative
------------------------------
```

```
func("Today is a gud day")
```

```
['good']
Tweet given by user :  Today Is a Good Day
LogisticRegression
This Tweet is  positive
------------------------------
NaiveBayes
This Tweet is  positive
------------------------------
```

```
func("appa is angry")
```

```
['angry']
Tweet given by user :  Dad Is Annry
LogisticRegression
This Tweet is  negative
------------------------------
NaiveBayes
This Tweet is  negative
------------------------------
```

```
func("it is a big veedu")
```

```
['big']
Tweet given by user :  It's A Big House
LogisticRegression
This Tweet is  positive
------------------------------
NaiveBayes
This Tweet is  positive
------------------------------
```

```
func("saapudu is mosam")
```

```
['bad']
Tweet given by user :  Eatty is bad
LogisticRegression
This Tweet is  negative
------------------------------
NaiveBayes
This Tweet is  negative
------------------------------
```

References

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2. Nigam, Nitika & Yadav, Divakar. (2018). Lexicon-Based Approach to Sentiment Analysis of Tweets Using R Language: Second International Conference, ICACDS 2018, Dehradun, India, April 20-21, 2018, Revised Selected Papers, Part I. 10.1007/978-981-13-1810-8_16.
3. Expressively vulgar: The socio-dynamics of vulgarity and its effects on sentiment analysis in social media Isabel Cachola∗‡ Eric Holgate∗† Daniel Preoţiuc-Pietro♦ Junyi Jessy Li†‡Department of Mathematics, †Department of Linguistics,The University of Texas at Austin
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Extracted tweets (10) about Prime Minister Modi. | Download Scientific Diagram (researchgate.net)