Brand Sentiment Analysis using Twitter Mentions

J COMPONENT PROJECT REPORT

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Submitted by

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1. PROBLEM STATEMENT:

In today's world consumers love to compare online and this extends to their and other consumers' opinion, not only on price or product features, When comparing one brand with another, people will often express something along the lines of 'I love company X but hate company Y' or 'company X's blue widget is so much better than company Y's'.

Under analysis, this could produce a neutral result as the negative sentiment cancels out the positive, when in fact there was a clear expression of positive sentiment about company X and negative sentiment about the other. Being able to spot and disentangle these kinds of issues at the data processing stage is important to establish a robust foundation for the sentiment analysis.

Brands use sentiment analysis to find and measure customer opinions and attitudes towards their brand, products, services, campaigns. Analyzing sentiment on social media provides an excellent source of data and will provide digital consumer insights that can:

- Determine brand reputation
- Improve customer experience
- Stop issues becoming a crisis
- Determine future marketing strategies
- Improve marketing campaigns and product messaging
- Identify brand influencers
- Test business KPIs
- Generate leads
- Understand how your brand reputation evolves over time
- Research your competition and understand how their reputation also evolves over time.

2. LINK TO THE PROJECT GITHUB REPOSITORY:

https://github.com/kanikanarayan8/NLP-PROJECT.git

3. TEAM DETAILS:

- 1) KANIKA NARAYAN (17BCE0090)
- 2) AKSHATA CHOUDHARY (17BCE0149)

4. DATASET SOURCE WITH LINK:

The dataset collected by us here is of the analysis of the brand "bmw" starting from date "2019-05-01" until "2020-03-03". It is set for the geological location "New York" so that all the tweets obtained are in the English language. Also, the number of tweets is restricted to 100 in order to save time and reduce computational power. The dataset obtained from this is:

https://docs.google.com/spreadsheets/d/e/2PACX-1vTYEgrqC5VlVtOtDRx7jboJvTRMWQc8Gp4X3TkIgSj_dJ05UGjxDLk3wuob9MjL 7KelHweG3N 1yX/pub?gid=0&single=true&output=csv

For training the model, we have imported the movie review dataset from NLTK for training our model. The NLTK Corpus has a Movie Reviews Corpus with reviews categorized into pos and neg categories, and a number of trainable <u>classifiers</u>, that is each review is categorized as positive or negative.

5. MODULES:

5.1 Modules of the project:

• Get the tweets from the twitter API by running the GetTweetFinal.py script. This script has the GetOldTweets3 module which fetches tweets based on the input parameters.

In this module, we have downloaded the tweets based on the parameters that we have mentioned. The parameters used are: the brand name, the start and end date between which the tweets were done, and the geometric location from where the tweet was done. Adding geometric location will provide us with the tweets of one similar language. We have also set the number of tweets that we need to process on.

All the tweets are saved in a CSV file in the working directory.

• Import the training dataset from NLTK

For training the NLTK model, we have used an already existing dataset: movie reviews. We have used NLTK to download the movie reviews dataset.

• Preprocess data and set parameters for training the model

Divide the dataset into training and testing dataset (80% dataset is kept for training and 20% is kept for testing).

• Train and test model on training set

Train the model using training dataset and testing the model using the testing dataset. We are using Naive Bayes Classifier to classify the tweets into positive or negative emotion based on the positive or negative words obtained from the training dataset. Bayes theorem provides a way of calculating posterior probability P(c|x) from P(c), P(x) and P(x|c). The Naive Bayes Classifier converts data into a frequency table and then fills in a Likelihood Table. Now, it uses the Naive Bayesian equation to calculate the posterior probability for each class. The class with the highest posterior probability is the outcome of prediction.

• Run the saved model on the tweets which we got from Twitter

The model that is trained, is used to find the sentiment of the tweets that were collected in the previous module.

5.2 Code:

• <u>GetTweetFinal.py:</u> For downloading the tweets based on our parameters for sentimental analysis.

tweet = got.manager.TweetManager.getTweets(tweetCriteria)[0]

```
#opening csv file to store tweets

#tweets stored in tweets.csv file
outputFileName = "tweets.csv"
outputFile = codecs.open(outputFileName, "w+", "utf-8")

print('Searching...\n')

#writing the tweets in csv file
def receiveBuffer(tweets):
    for t in tweets:
        outputFile.write(t.text + "\n")

#clear the internal buffer of the file
outputFile.flush()
print('More %d saved on file...\n' % len(tweets))

got.manager.TweetManager.getTweets(tweetCriteria, receiveBuffer)

outputFile.close()
print('Done. Output file generated "%s".' % outputFileName)
```

• <u>NaiveBayesClassifier.py:</u> For training and testing the model and using it for sentimental analysis.

```
import nltk
#training dataset is imported from NLTK
nltk.download('movie_reviews')
import re
import nltk.classify.util
from nltk.classify import NaiveBayesClassifier
from nltk.corpus import movie reviews
#function to create dictionary of positive and negative words
# we use bag of words model where every word is feature name with a value of true
def extract features(word list):
  return dict([(word, True) for word in word_list])
# Load positive and negative reviews using the tags mentioned in the training dataset
positive fileids = movie reviews.fileids('pos')
negative_fileids = movie_reviews.fileids('neg')
# Gathering Positive and negative key words in a dictionary by calling the function
features_positive = [(extract_features(movie_reviews.words(fileids=[f])),'Positive')
for f in positive_fileids]
features_negative = [(extract_features(movie_reviews.words(fileids=[f])),'Negative')
for f in negative_fileids]
# Split the data into train and test (80/20)
```

```
#threshold set to 0.8 to split the data into 80% training dataset and 20% testing dataset
threshold\_factor = 0.8
threshold_positive = int(threshold_factor * len(features_positive)) #length of 80%
positive words+ length of 80% of the negative words for training dataset
threshold_negative = int(threshold_factor * len(features_negative)) #remaining length
of 20% each positive and negative words for testing dataset
#80% of positive words+80% of the negative words as training dataset
features train
                                   features_positive[:threshold_positive]
                                                                                   +
features negative[:threshold negative]
#remaining 20% each positive and negative words as testing dataset
                                  features_positive[threshold_positive:]
features test
                                                                                   +
features_negative[threshold_negative:]
print("\nNumber of training datapoints:", len(features_train))
print("Number of test datapoints:", len(features_test))
# Training the model using Naive Bayes classifier
classifier = NaiveBayesClassifier.train(features_train)
       ("\nAccuracy of the classifier:",
                                                 nltk.classify.util.accuracy(classifier,
features test))
#Sample input reviews for checking the sentimental analysis given by the model
input_reviews = [
   "i dont like the upholstry in this car",
# Saved model is run on the tweets which we got from Twitter
#for counting number of positive reviews.
#for counting number of negative reviews.
n = 0
with open('tweets.csv',encoding="utf-8") as f:
  #checking sentimental for the first 10 tweets collected
  for i in range (10):
     Review = f.readline()
     print("\nReview:", Review)
     #calculating probability distribution
     probdist = classifier.prob_classify(extract_features(Review.split()))
     pred\_sentiment = probdist.max()
     print("Predicted sentiment:", pred_sentiment)
     print("Probability:", round(probdist.prob(pred_sentiment), 2))
     if pred sentiment=="Positive":
       p+=1
     elif pred_sentiment=="Negative":
       n+=1
  print("Overall response average:", (p/(p+n)))
i = 0
```

```
input_reviews = [
  "i dont like the upholstry in this car",
p = 0
n = 0
i = 0
#checking sentimental analysis for the given input
for review in input_reviews:
 print("\nReview:", review)
 probdist = classifier.prob_classify(extract_features(review.split()))
 pred\_sentiment = probdist.max()
 print("Predicted sentiment:", pred_sentiment)
 print("Probability:", round(probdist.prob(pred_sentiment), 2))
```

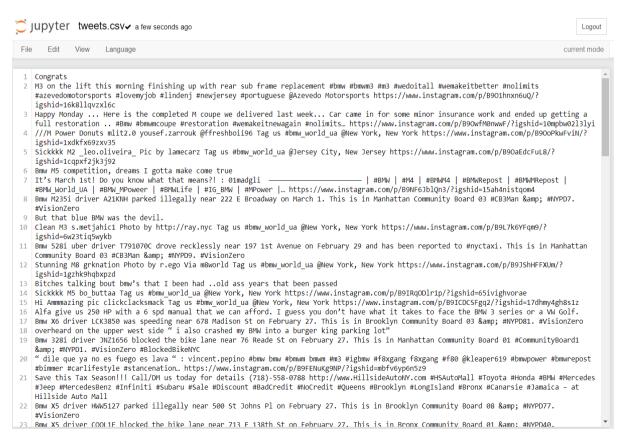
5.3 Snapshots of output:

GetTweetFinal.py:

```
In [1]: pip install GetOldTweets3
        Collecting GetOldTweets3
          Downloading https://files.pythonhosted.org/packages/ed/f4/a00c2a7c90801abc875325bb5416ce9090ac86d06a00cc887131bd73ba45/Get0ld
        Tweets3-0.0.11-py3-none-any.whl
        Requirement already satisfied: lxml>=3.5.0 in c:\users\dell\anaconda3\lib\site-packages (from GetOldTweets3) (4.3.4)
        Collecting pyquery>=1.2.10 (from GetOldTweets3)
          Downloading https://files.pythonhosted.org/packages/78/43/95d42e386c61cb639d1a0b94f0c0b9f0b7d6b981ad3c043a836c8b5bc68b/pyquer
        y-1.4.1-py2.py3-none-any.whl
        Collecting cssselect>0.7.9 (from pyquery>=1.2.10->GetOldTweets3)
          Downloading https://files.pythonhosted.org/packages/3b/d4/3b5c17f00cce85b9a1e6f91096e1cc8e8ede2e1be8e96b87ce1ed09e92c5/csssel
        ect-1.1.0-py2.py3-none-any.whl
        Installing collected packages: cssselect, pyquery, GetOldTweets3
        Successfully installed GetOldTweets3-0.0.11 cssselect-1.1.0 pyquery-1.4.1
        Note: you may need to restart the kernel to use updated packages.
```

```
In [2]: #using twitter API to collect dataset
          import GetOldTweets3 as got
          import sys,getopt,datetime,codecs
         tweets are extracted based on certain criterias: brand name, start and end date between which tweet was done and the geometric tweetCriteria = got.manager.TweetCriteria().setQuerySearch('bmw')\
                                                           .setSince("2019-05-01")\
.setUntil("2020-03-03")\
                                                           .setNear("New York")\
                                                            .setMaxTweets(100)
          #set geometric location as New York to collect all the tweets in english language
          tweet = got.manager.TweetManager.getTweets(tweetCriteria)[0]
          #opening csv file to store tweets
         #tweets stored in tweets.csv file
outputFileName = "tweets.csv"
          outputFile = codecs.open(outputFileName, "w+", "utf-8")
          print('Searching...\n')
         #writing the tweets in csv file def receiveBuffer(tweets):
              for t in tweets:
                  outputFile.write(t.text + "\n")
              #clear the internal buffer of the file
              outputFile.flush()
              print('More %d saved on file...\n' % len(tweets))
          got.manager.TweetManager.getTweets(tweetCriteria, receiveBuffer)
         outputFile.close()
          print('Done. Output file generated "%s".' % outputFileName)
          Searching...
          More 100 saved on file...
         Done. Output file generated "tweets.csv".
```

Tweets.csv where we collected all the tweets



• NaiveBayesClassifier.py:

```
In [1]: import nltk
             #training dataset is imported from NLTK
             nltk.download('movie reviews')
             import nltk.classify.util
             from nltk.classify import NaiveBayesClassifier
             from nltk.corpus import movie reviews
             [nltk_data] Downloading package movie_reviews to
             [nltk data]
                                  C:\Users\dell\AppData\Roaming\nltk data...
             [nltk data]
                               Package movie_reviews is already up-to-date!
In [2]: #function to create dictionary of positive and negative words
def extract_features(word_list):
                 return dict([(word, True) for word in word_list])
            # Load positive and negative reviews using the tags mentioned in the training dataset
positive_fileids = movie_reviews.fileids('pos')
negative_fileids = movie_reviews.fileids('neg')
            # Gathering Positive and negative key words in a dictionary by calling the function features_positive = [(extract_features(movie_reviews.words(fileids=[f])),'Positive') for f in positive_fileids] features_negative = [(extract_features(movie_reviews.words(fileids=[f])),'Negative') for f in negative_fileids]
             # Split the data into train and test (80/20)
             #threshold set to 0.8 to split the data into 80% training dataset and 20% testing dataset threshold_factor = 0.8
             threshold_positive = int(threshold_factor * len(features_positive)) #length of 80% positive words+ length of 80% of the negative threshold_negative = int(threshold_factor * len(features_negative)) #remaining length of 20% each positive and negative words for
            #80% of positive words+80% of the negative words as training dataset
features_train = features_positive[:threshold_positive] + features_negative[:threshold_negative]
#remaining 20% each positive and negative words as testing dataset
features_test = features_positive[threshold_positive:] + features_negative[threshold_negative:]
            print ("\nNumber of training datapoints:", len(features_train))
print ("Number of test datapoints:", len(features_test))
             # Training the model using Naive Bayes classifier
            classifier = NaiveBayesClassifier.train(features_train)
print ("\nAccuracy of the classifier:", nltk.classify.util.accuracy(classifier, features test))
                 ample input reviews for checking the sentimental analysis given by the model
            input_reviews = [
    "i dont like the upholstry in this car",
             # Saved model is run on the tweets which we got from Twitter
       #for counting number of positive reviews.
       #for counting number of negative reviews.
       with open('tweets.csv',encoding="utf-8") as f:
    #checking sentimental for the first 10 tweets collected
             for i in range(10):
                   Review = f.readline()
print ("\nReview:", Review)
#calculating probability distribution
probdist = classifier.prob_classify(extract_features(Review.split()))
                   pred_sentiment = probdist.max()
                   print ("Predicted sentiment:", pred_sentiment )
print ("Probability:", round(probdist.prob(pred_sentiment), 2))
if pred_sentiment=="Positive":
                         p+=1
                   elif pred_sentiment=="Negative":
             print("Overall response average:", (p/(p+n)))
       Number of training datapoints: 1600
       Number of test datapoints: 400
       Accuracy of the classifier: 0.735
       Review: Congrats
       Predicted sentiment: Positive
       Probability: 0.5
       Review: M3 on the lift this morning finishing up with rear sub frame replacement #bmw #bmwm3 #m3 #wedoitall #wemakeitbetter #no
       limits #azevedomotorsports #lovemyjob #lindenj #newjersey #portuguese @Azevedo Motorsports https://www.instagram.com/p/B901hnxn
       6uQ/?igshid=16k8llqvzxl6c
```

```
Probability: 0.53
Review: Happy Monday ... Here is the completed M coupe we delivered last week... Car came in for some minor insurance work and
ended up getting a full restoration .. #Bmw #bmwmcoupe #restoration #wemakeitnewagain #nolimits... https://www.instagram.com/p/B9
OwfM@nwwF/?igshid=1@mpbw@213lvi
Predicted sentiment: Positive
Probability: 0.88
Review: ///M Power Donuts mlit2.0 yousef.zarrouk @ffreshboii96 Tag us #bmw_world_ua @New York, New York https://www.instagram.c
om/p/B90oPkwFviN/?igshid=1xdkfx69zxv35
Predicted sentiment: Positive
Probability: 0.52
Review: Sickkkk M2 _leo.oliveira_ Pic by lamecarz Tag us #bmw_world_ua @Jersey City, New Jersey https://www.instagram.com/p/B90
aEdcFuL8/?igshid=1cqpxf2jk3j92
Predicted sentiment: Positive
Probability: 0.52
Review: Bmw M5 competition, dreams I gotta make come true
Predicted sentiment: Positive
Probability: 0.7
Review: It's March 1st! Do you know what that means?! : 01madgli _____ | #BMW | #M4 | #BMWM4 | #BMWRepost | #BMW_Morld_UA | #BMW_MPoweer | #BMWLife | #IG_BMW | #MPower |... https://www.instagram.com/p/B9NF6JblQn3/?igshid=15
ah4nistgom4
Predicted sentiment: Positive
Probability: 0.81
Review: Bmw M235i driver A21KNH parked illegally near 222 E Broadway on March 1. This is in Manhattan Community Board 03 #CB3Ma
n &amp: #NYPD7. #VisionZero
In [7]: # Sample input reviews
        input_reviews = [
    "i dont like the upholstry in this car",
        1
        p = 0
        n = 0
        #checking sentimental analysis for the given input
        for review in input reviews:
           print ("\nReview:", review)
           probdist = classifier.prob_classify(extract_features(review.split()))
           pred_sentiment = probdist.max()
           print ("Predicted sentiment:", pred sentiment )
           print ("Probability:", round(probdist.prob(pred_sentiment), 2))
        Review: i dont like the upholstry in this car
        Predicted sentiment: Negative
        Probability: 0.84
In [4]: # Sample input reviews
        input_reviews = [
    "This car is amazing",
        ]
         p = 0
        n = 0
```

```
In [4]: # Sample input reviews
input_reviews = [
    "This car is amazing",
]

p = 0
n = 0
i = 0

for review in input_reviews:

print ("\nReview:", review)
probdist = classifier.prob_classify(extract_features(review.split()))
pred_sentiment = probdist.max()

print ("Predicted sentiment:", pred_sentiment )
print ("Probability:", round(probdist.prob(pred_sentiment), 2))
```

Review: This car is amazing Predicted sentiment: Positive Probability: 0.52

Predicted sentiment: Positive

Review: the car has a gay color Predicted sentiment: Positive Probability: 0.69

```
In [6]: # Sample input reviews
input_reviews = [
    "This car is not good",
]

p = 0
n = 0
i = 0

for review in input_reviews:

    print ("\nReview:", review)
    probdist = classifier.prob_classify(extract_features(review.split()))
    pred_sentiment = probdist.max()

    print ("Predicted sentiment:", pred_sentiment )
    print ("Probability:", round(probdist.prob(pred_sentiment), 2))
```

Review: This car is not good Predicted sentiment: Negative Probability: 0.61

6. <u>LIST OF CHALLENGES FACED:</u>

The challenges faced while doing the sentimental analysis of the tweets for the brands mentioned was:

- For a word that is positive, when negative words are added before it then the overall polarity of the word still remains positive.
- In the movie review dataset that we imported from NLTK, each word has a polarity as positive or negative. Whenever a negative word is detected, all the words from a negation cue to the next punctuation token are negated. So, the positive word following it, gets the negative polarity.

7. SNAPSHOTS OF ERRORS AND FIXES:

Error: Whenever there was a negation word like 'not', the sentiment was not predicted correctly.

```
In [4]: # Sample input reviews
input_reviews = [
    "This car is not bad",
]

p = 0
n = 0
i = 0

for review in input_reviews:

    print ("\nReview:", review)
    probdist = classifier.prob_classify(extract_features(review.split()))
    pred_sentiment = probdist.max()

    print ("Predicted sentiment:", pred_sentiment )
    print ("Probability:", round(probdist.prob(pred_sentiment), 2))

Review: This car is not bad
    Predicted sentiment: Negative
    Probability: 0.75
```

Fixing the error: We set the polarity of each word as positive or negative. When we come across a negation word, negate the polarity of all the words encountered as that till the next punctuation.

```
In [6]: # Sample input reviews
input_reviews = [
    "This car is not good",
]

p = 0
n = 0
i = 0

for review in input_reviews:

    print ("\nReview:", review)
    probdist = classifier.prob_classify(extract_features(review.split()))
    pred_sentiment = probdist.max()

    print ("Predicted sentiment:", pred_sentiment )
    print ("Probability:", round(probdist.prob(pred_sentiment), 2))

Review: This car is not good
    Predicted sentiment: Negative
    Probability: 0.61
```

8. REFERENCES:

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