SENTIMENT ANALYSIS OF GLOBAL WARMING USING TWITTER DATA

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MASTER OF SCIENCE

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ABSTRACT

Global warming or climate change is one of the most discussed topics of the decade. Some people think global warming is a severe threat to the planet whereas some people think, it is a hoax. The goal of this paper is to analyze how people's perceptions have changed over the years for past decade using sentiment analysis on Twitter data. Twitter is a social networking platform with 320 million monthly active users. I have captured tweets with words such as "Global warming", "Climate Change" etc. and applied sentiment analysis to classify them as positive, negative or neutral tweets. I have trained Naïve Bayes Classifier, Multinomial Naïve Bayes Classifier and SVM classifiers on several training datasets to optimize for best accuracy. The methodology with best accuracy rate has been used to find out people's perception of global warming over the years using Twitter data.

ACKNOWLEDGEMENTS

I would like to thank Dr. Kendall Nygard for immense support and encouragement during my time at NDSU. I am very grateful for all the support and guidance I have received during the research process.

I would also like to thank my Family for their wonderful support me throughout the entire time.

DEDICATION

I would like to dedicate this research paper to my Family and Dr. Kendall Nygard. This paper would not have been possible without you all. Thank you for your support and I am really grateful for all the faith you have put in me.

THANK YOU.

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1. INTRODUCTION

Global warming is also referred to as climate change and the greenhouse effect. When CO2 and other pollutant gases produced by several sources such as automobiles and industries are released into earth's atmosphere, they eventually flow into space. However, as the production of these gases raises, they get trapped on the earth surface. While on the earth surface, gases like CO2 absorb sun's radiation. Thus, the temperature of the earth has been increasing in the past several decades. This phenomenon is called global warming. Over the years earth's average temperatures have been increased and gradually ocean levels are rising due to melting glacial polar caps. Most of the scientists believe in global warming whereas few scientists believe global warming is a hoax and it's a natural process. The split of the general population who believe in global warming vs those who don't have been changing throughout the years.

Extreme weather conditions like frequent hurricanes, floods, drought and long heatwaves are developing in recent years. Frozen lakes are melting earlier than expected due to warmer winters. According to scientists, 2000-2009 is the hottest decade than any other decade in past 1300 years. The dry places are becoming dryer and wet places are becoming wetter. Earth's geography and climate systems have been changing in an irreparable way. According to scientific studies, earth's temperatures will rise by 8 degrees by 2100[1][2][3].

Twitter is a social media platform with 328 million monthly active users [6]. Since its advent, it has been the best platform to collect people's opinions about various topics like games, politics, entertainment, social causes, global warming etc. In this paper, I used Twitter data to understand the trends of user's opinions about global warming and climate change using sentiment analysis. I have trained various classification algorithms and tested on generic Twitter datasets as well as climate change specific datasets to find a methodology with the best accuracy. Finally, I have captured 5000 tweets for each year in the last decade and used the best classifier to classify tweets into positive, negative and neutral classes. The goal of this paper is to find out how people's perception of global warming has changed over last 10 years. Positive, neutral classes are defined as below.

- Positive = People who think global warming is true
- Negative = People who think global warming is hoax
- Neutral = Neither positive nor negative

Rest of the paper has been arranged as follows. In the subsequent sections, we discuss classifiers such as Naïve Bayes from NLTK platform, Multinomial Naïve Bayes Classifier, Support Vector Machines (SVM) and different types of SVM from the Scikit platform. We look into parameters like TF-IDF, N-gram, stop words and tools like Tweepy. I have explained data capturing and data processing steps in section three. Test methodology has been explained in the fourth section. I have listed test results for NLTK Naïve Bayes classifier with graphs in the fifth section. Sixth section and seventh section describe Scikit Multinomial Naïve Bayes and SVM classifier test results respectively. The eighth section is the comparison of all the classifiers and test results and summarizing the best classification method from all the experimentation done in previous sections. The ninth section contains classification results for twitter data from past ten years pertaining to climate change using the classifier with best accuracy rate. The tenth section refers to the conclusion and future work.

2. LITERATURE REVIEW

This section outlines the technologies and methodologies used in this study in detail. It also dwells on the Algorithms and their parameters used in related contemporary studies.

2.1. Tweepy

Tweepy is an open source python library as mentioned in [4], which enables python to communicate with Twitter and access its Application Programming Interface (API). Capturing real time as well as historic Twitter data is easier using Tweepy. Tweepy along with other libraries developed by developers are used towards performing various services on Twitter [6].

2.2. Naïve Bayes Classifier

Naïve Bayes Classifier is a basic classifier in machine learning. It is an efficient classification method in NLTK (Natural Language Processing Tool Kit) [5]. This classifier works better with Textual contents.

During training, the classifier goes through all text documents and defines the probability of the words being positive, negative and neutral and then compares it to the label of the tweet which is the sentiment in this case. It is based on Bayes theory assuming all variables are independent. I.e. Every feature being classified are independent of the value of other features in the document. This is very efficient classifier and suitable for very large data sets classification. Naïve Bayes classifier is also good with real-time and multi-class classification. Naïve Bayes classifier works efficiently for sentiment analysis on social media like twitter. So, I have chosen Naïve Bayes classifier as one of the classifiers for Global warming Twitter sentiment analysis.

According to Bayes theorem [16][19]

$$P(A \mid B) = \frac{P(B \mid A)P(A)}{P(B)}$$

The terms above are defined as follows:

- P(A/B) = Probability of A given B
- P(B/A) =Probability of B given A
- P(A) = Probability of A
- P(B) = Probability of B

2.3. Multinomial Naïve Bayes Classifier

Multinomial Naïve Bayes classifier is one of the classifiers in SciKit-learn library. It is an enhancement compared to the Naïve Bayes classifier and also is a very efficient classifier. Multinomial Naïve Bayes classifier is the probabilistic classification method where Probability of a class given in a document depends on the prior probability of features appeared in the class whereas in Naïve Bayes classifier each feature is treated as independent of one another. This is the main difference between Naïve Bayes classifier and Multinomial Naïve Bayes classifier [17][14][13].

In this paper, I have used multinomial Naïve Bayes classifier with stop words, multiple n-gram iterations and also with smoothing factor alpha. Results are explained clearly in section 6.

In Multinomial Naïve Bayes classifier [17]

$$\mathrm{P(C/D)}\ \alpha\ \mathrm{P(C)} \prod_{1\le k\le n_k} P(\frac{t_k}{c})$$

The terms above are defined as

- P(C/D) = Probability of class C given document D
- P(C) = Prior Probability of a tweet/text document occurring in class C
- n_k= Number of words
- $P(\frac{t_k}{c})$ = Conditional Probability of term t_k given class C

2.4. Support Vector Machines

Support Vector Machines is an effective machine learning algorithm used for classification and regression use cases. Most of the times SVM is used for classification. It segregates classes by finding the best hyperplane between different classes. Support Vector Machines has different kernel functions which can be used towards creating the best model to find the hyperplane. The kernel functions are Poly, Sigmoid, Linear, and rbf. For this paper, I have used all kernel functions to find the best classification hyperplane. C-support vector classification and Linear Support vector classification have been used as well in this paper. Linear support vector classification is similar to Support Vector classification using the linear algorithm. However, Linear Support Vector machines are more flexible in penalties and losses. So Linear Support Vector classification works efficiently for larger data sets as mentioned in [18][20][28]

2.5. Parameters

Below parameters are used along with Naïve Bayes classifier, Multinomial Naïve Bayes classifier, and Support vector machines classifiers. Using the parameters like stop words, n-gram and TF-IDF, additive smoothing has notable impacts on the experiment results.

2.5.1. N-gram

Language modeling is a probability distribution of a combination of the words. N-gram is one of the methods in language modeling where text documents can be divided into a combination of sequential words. Data from the text document can be divided into n-grams and combination of N-grams. This set of n-grams will be used towards training the algorithms. [0][12]

2.5.1.1. Unigram

Text document can be divided into single words. In n-gram, n refers to the number of words. If the size of the gram is 1, it is called unigram. [0][12]

Ex: Climate change is causing a rise in ocean temperatures.

Using unigram, the above sentence can be divided into the following (Climate, change, is, causing, rise, in, ocean, temperatures)

Stop words such as “is”, “in”, “are” etc. do not contribute to the probability distributions of sentiment analysis. To get a better range of feature vectors, bigram and trigram are better suited.

2.5.1.2. Bigram

If the size of n is equal to two, it is called bigram. [0][12]

Ex**:** Climate change is causing a rise in ocean temperatures.

In bigram above sentence can be divided into ((Climate, change), (Change, is), (is, causing), (causing, rise), (rise, in), (in, ocean), (ocean, temperatures))

2.5.1.3. Trigram

If the size of n is equal to three, it is called trigram. [0][12]

Ex: Climate change is causing a rise in ocean temperatures.

Above sentence in trigrams ((climate, change, is), (change, is, causing), (is, causing, rise), (causing, rise, in), (rise, in, ocean), (in, ocean, temperatures))

2.5.1.4. Four-gram

If the size of n is equal to four, it is called four-gram. [0][12]

Ex: Climate change is causing a rise in ocean temperatures.

Above sentence in four-grams ((climate, change, is, causing), (change, is, causing, rise), (is, causing, rise, in), (causing, rise, in, ocean), (rise, in, ocean, temperatures))

2.5.1.5. Five-gram

If size of n is equal to five, it is called five-gram. [0][12]

Ex: Climate change is causing rise in ocean temperatures.

Above sentence in five-grams ((climate, change, is, causing, rise), (change, is, causing, rise, in), (is, causing, rise, in, ocean), (causing, rise, in, ocean, temperatures))

2.5.2. TF-IDF

TF-IDF stands for term frequency Inverse document frequency. It is a basic classification method to determine the weight of the terms in the given document. Stop words such as “is, it, that, them” etc. which don’t add much in terms of sentiment analysis of the tweet will be neglected in this classification to determine accurate term weight. In this paper, I have used TF-IDF with Multinomial Naïve Bayes classifier. Accuracy has not improved much when minimum term frequency or document frequency are set in this case since we are dealing with Twitter data which consists of a few words per instance rather than a corpus which consists of several large documents. We iteratively experimented with minimum term frequencies and document frequencies set to various values ranging from 5 to 2000 without much significant change in accuracy. TF- IDF gives good results with larger text documents where chances of word repetitions are frequent. [7]

TF(term)= Number of time term appeared in the document/Number of total terms in the document and IDF(term)= Log_e (total number of documents/Number of times term in it)

2.5.3. Stopwords

Stop words are the words which don’t add much weight to the sentence and don’t have much significance. During the classification, removing stop words will save a significant amount of time in terms of computation. Usually, stop words add a lot of unnecessary weight during the classification process. Removing them from tweets will improve the accuracy. [29]

2.5.4. Additive Smoothing

Additive smoothing or Laplace and Lid stone smoothing are introduced to avoid overfitting during the classification process. When algorithm has to classify a new word, which is not in the training dataset, it may not be able to classify the word efficiently on real-time or testing/validation datasets. So, a smoothing parameter alpha is introduced to the equation to account for the missing data. The value of alpha depends on the completeness of the data set and scope of the dataset covering all possible features.

$$P_{Lap}= \frac{x_{i+\propto}}{N+\propto d}$$

If α value is less than 1, it is called lid stone smoothing, and if α value is greater than or equal to 1, it is called Laplace smoothing [30]

3. DATA CAPTURING AND PROCESSING

3.1. Data Capturing Process

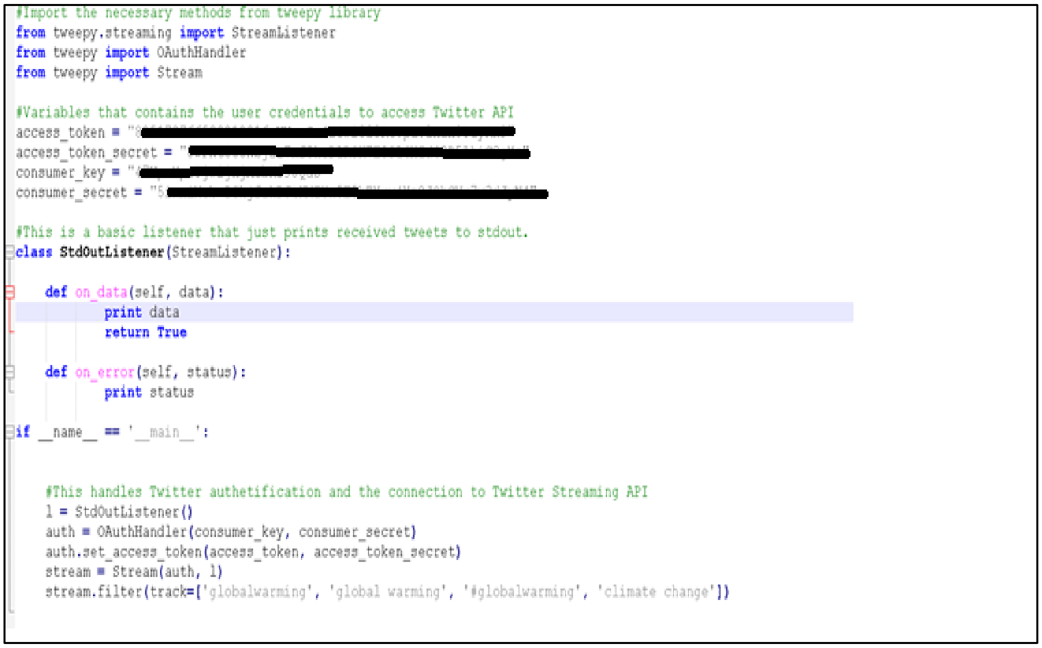
Twitter streaming API is used to capture the data. Twitter streaming API helps to make connection between computer programs and web services. For accessing Twitter streaming API we need four keys called API Key, API Secret, Access Token, and Access Token Secret.

Steps to retrieve four keys

- Create a Twitter account
- Open page https://apps.twitter.com/ and login with twitter credentials
- Try creating a new app
- Fill the form and ‘Create twitter new application’
- Retrieve API keys and API secret
- Retrieve access token and Access token secret.

Once all four keys are retrieved, I have used a python library called Tweepy to download the tweets. Tweepy is connected to Twitter streaming API to retrieve global warming tweets from twitter. I have used the following four terms to gather tweets specific to global warming and climate change for this experiment. ‘Global warming’, ‘Climate Change’, ‘climatechange’, ‘globalwarming’.

Here is the example code used to retrieve global warming tweets from Twitter. [6] [24]



```
#Import the necessary methods from tweepy library
from tweepy.streaming import StreamListener
from tweepy import OAuthHandler
from tweepy import Stream

#Variables that contains the user credentials to access Twitter API
access_token = "[redacted]
access_token_secret = "[redacted]
consumer_key = "[redacted]
consumer_secret = "[redacted]

#This is a basic listener that just prints received tweets to stdout.
class StdOutListener(StreamListener):

    def on_data(self, data):
            print data
            return True

    def on_error(self, status):
            print status

if __name__ == '__main__':


    #This handles Twitter authetification and the connection to Twitter Streaming API
    l = StdOutListener()
    auth = OAuthHandler(consumer_key, consumer_secret)
    auth.set_access_token(access_token, access_token_secret)
    stream = Stream(auth, l)
    stream.filter(track=['globalwarming', 'global warming', '#globalwarming', 'climate change'])
```

Figure 1.   Example Code Tweet Retrieval

3.2. Data Processing

Tweets are captured in a CSV file. Tweets are classified into 3 classes. Positive, negative and neutral as mention before. Table 1 shows some examples of how tweets would be classified in these categories.

Table 1.   Tweets Classification Example

Tweet	Sentiment
climate change is not real you idiot democrats	Negative
How climate change will affect the quality of our water https://t.co/z7AJ0apltF #itstimetochange #climatechange Join @ZEROCO2	Positive
Weather Channel Founder Says Climate Change is not real	Negative
But, but climate change is a hoax. Nothing's changing!	Negative

Table 1. Tweets Classification Example (continued)

Tweet	Sentiment
He could now pass laws to provide health coverage for all, reform immigration, slow global warming	Positive
California Hopes 'Healthy Soil' Will Fight Climate Change	Positive
YOU have been LIED to about #climate change &amp; \"Extreme Weather\". See data here for 100% proof... https://t.co/kWaCLwMZ4e via @J\u2026	Neutral
To all constituents in #Ogmore interested in funding for #environmental #climatechange &amp; #countryside projects	Positive
Solar eclipse: Why the sun is not responsible for recent climate change	Neutral
India loses $10 billion every year to climate change:	Positive
Berlin\u2019s infrastructure is being redesigned to solve drainage and heat problems as #climatechange accelerates	Positive
Loss of Arctic Sea Ice Causes Earliest Pacific Walrus Haul Out Ever https://t.co/RzvS6eQdvV #itstimetochange #climatechange Join @ZEROCO2_	Positive
Women may bear the brunt of #climatechange impacts. #ActOnClimate #KeepItInTheGround https://t.co/1Itnmp6fSy	Positive

3.2.1. Pre-Processing

Every tweet undergoes the following pre-processing steps:

1. All words are changed into lower case

Ex: ***#Climate Change***: ***The Challenge*** may be huge, but a ***Better World*** is 100% ***POSSIBLE***.

Outcome: climate change the challenge may be huge but a better world is 100% possible

2. http or https links are removed and replaced with LINK

   Ex: Allowing #climatechange to continue is unfathomable. Here are some facts: *https://t.co/L0WW9xWT7K*

   Outcome: allowing climatechange to continue is unfathomable here are some facts LINK

3. @Usernames are removed and replaced with USER_REF

   Ex: ***@LamarSmithTX21*** Allowing #climatechange to continue is unfathomable. Here are some facts https://t.co/L0WW9xWT7K

   Outcome: USER_REF allowing climatechange to continue is unfathomable here are some facts LINK

4. Removed all white spaces from tweets

   Ex: @LamarSmithTX21 Allowing #climatechange to continue is unfathomable. Here are some facts https://t.co/L0WW9xWT7K

   Outcome: USER_REF allowing climatechange to continue is unfathomable here are some facts LINK

5. Removed all hashtags from the tweets

   Ex: Allowing ***#climatechange*** to continue is unfathomable. Here are some facts: https://t.co/L0WW9xWT7K

   Outcome: USER_REF allowing climatechange to continue is unfathomable here are some facts LINK

6. Stripped all punctuations from the tweets

Ex: #ClimateChange**:** The Challenge may be huge, but a Better World is 100% POSSIBLE.

Outcome: Climatechange the challenge may be huge but a better world is possible.

Tweets were converted to lower case using python's string class and lower() method. The sub() method from python's regular expression class was used to substitute URLs, usernames, white spaces, hashtags with the relevant values as explained above. The strip() method from string class is used to strip the remaining words of any punctuation.

3.2.2. Obtaining Stop Words List

Stop words are obtained from NLTK and Scikit libraries. I have also added USER_REF and LINK to stop words list. To use custom stop words, all the stop words are listed one per line in a text file. We read the file and each line in the file is appended to a stopwords list data structure to be iterated over in later phases.

3.2.3. Stemming

Stemming is the process of identifying derived words and assigning a word to all the derived words. This will reduce the size of index files. The initial tweet which is in the string format is converted into a python list of substrings which can be used to obtain all the words and punctuation in the tweet. The NLTK Tokenizer Package is used for this purpose. The initial string is decoded to utf8 to avoid working on encoded strings. NLTK library already provides an implementation of the porter stemmer algorithm in the nltk.stem.porter module. The tokenized string is used as input to the porter stemmer.

Tokenizers divide strings into lists of substrings. For example, tokenizers can be used to find the words and punctuation in a string:

Ex: A stemmer of the following words Beautiful, Beautifully, Beauty, Beauties can be Beauty.

I have used Porter stemming algorithm for stemming the tweets. [32]

3.2.4. Big Picture

All the tweets are in a text file in the format of "sentiment, text". We use python's pandas library (read_cvs method) (python data analysis library) to iterate over this file by mentioning the separator as well as the file format. We use SCIKIT's feature extraction module to extract features from these text files. The count vectorizer method (feature_extraction.text. Count Vectorizer) is used to convert these tweets into a matrix of token counts. This method uses the previously described methods for preprocessing, tokenizing, stemming, stop word elimination, n-gram generation, min_df selection to build the respective analyzers, preprocessors etc. The tfidftransformer method in the same feature extraction module listed above operates on the count matrix generated by count vectorizer to generate a normalized tf or tf-idf representation. The classification algorithm works on this representation of the tweet along with the respective sentiment to train the model.

4. TEST METHODOLOGY

The goal of this paper is to perform sentiment analysis on Global warming using twitter data. I have used Naïve Bayes classifier, Multinomial Naïve Bayes Classifier and Support vector machines combined with parameters like stop words, TF-IDF, N-gram. All classifiers are trained with two datasets from twitter and accuracy test was performed on testing data set. Once the algorithm is trained, to understand the perceptions of people over the years on global warming, I have collected 5000 tweets each year for the past 10 years. After training the algorithms and running through several optimization parameter tunings, the best classifier is used to work on the historic climate change data to obtain the sentiment analysis.

4.1. Training Data

There are two datasets used in this study. The first is a 20K tweet dataset which is a conglomerate of multiple publicly available datasets as pointed in [23, 24, 25]. Out of which 18K are training tweets. The second is a 10K tweets climate change dataset, which I have captured from twitter, processed and labeled sentiments. Out of which 8K comprise of the training set. The first dataset comprises of general purpose labeled tweets whereas the second dataset is specific to tweets related to global warming and climate change. Training data set is labeled with positive, negative and neutral sentiments.

4.2. Testing Data

Once algorithms are trained on training set, test data set is used to perform experiments. Both datasets mentioned in 4.1 have 2K testing and validation datasets.

4.3. Randomness

There is an aspect of randomness to the way training and test datasets are picked. For instance, in the non-climate change dataset there are 18K tweets in the training set and 2K tweets in the testing set. I used python’s random module to sample (random.sample(xrange(1, 20000), 18000) the required training dataset and the remaining 2k constitute the testing dataset. Each iteration of the algorithm is trained over three randomly generated unique training and test datasets sampled over the 20k tweets to obtain best performance. The same procedure is followed with general purpose tweets as well as the climate change specific tweets.

5. RESULTS: NAÏVE BAYES CLASSIFICATION

I have used Naïve Bayes classifier on Twitter sentiment analysis dataset.

5.1. Unigram Implementation

I removed stop words and implemented unigram for training and testing data sets. Accuracy percentage is 54.1% and Training time is 869 seconds.

5.2. Bigram Implementation

I have removed stop words and implemented bigram for training and testing data sets. Accuracy percentage is 66.9 and Training time is 6687 seconds.

5.3. Test Accuracy

Removing stop words and using unigram with Naïve Bayes classifier gave 54.1% accuracy and Bigram returned 66.9% accuracy

Table 2. Unigram vs. Bigram NLTK

NLTK	**Accuracy**	**Training time(Sec)**
Unigram + Stop words	54.1	869
Bigram + stop words	66.9	6687

As seen in table 2, using bigrams take close to 8 times longer than using unigram implementation. Since machine learning is an iterative process, long run time would be a hurdle for obtaining optimal time to results.

Table 3. Best Case Summary Step 1

Accuracy	66.9 (Naïve Bayes + Bigram)
Training Time	6687 Seconds

6. RESULTS: MULTINOMIAL NAÏVE BAYES CLASSIFIER

I have used Multinomial Naïve Bayes classifier on Twitter sentiment analysis dataset. This dataset consists of 20k tweets. The results provided here are the best of the 3 runs, where the training set is of 18k randomly picked tweets from the data set of 20k tweets. Rest of the 2k tweets have been used as test data set.

I have trained scikit-Multinomial Naïve Bayes algorithm with 18000 tweets and tested on test data set of 2000 tweets. I have used unigram, bigram, trigram, four-gram, five-gram and different combinations of n-grams. Accuracy rates varied from 21.24% to 55.5%. From all the attempts unigram returns best results with 55.5%. Unigram and bigram combination returns 50.25%.

6.1. N-gram Iterations

Table 4. Index Description

n-gram	**Description**
1	Unigram
2	Bigram
3	Trigram
4	Four-gram
5	Five-gram
1,2	Unigram+ Bigram
1,2,3	Unigram+ Bigram+ Trigram
1,2,3,4	Unigram+ Bigram+ Trigram+ Four-gram

Table 4. Index Description (continued)

n-gram	**Description**
1,2,3,4,5	Unigram+ Bigram+ Trigram+ Four-gram+ Five-gram
2,3,4,5	Bigram+ Trigram+ Four-gram+ Five-gram
3,4,5	Trigram+ Four-gram+ Five-gram
4,5	Four-gram+ Five-gram

Figure 2 below depicts the results from all selected combinations of multinomial Naïve Bayes algorithm results using n-gram.

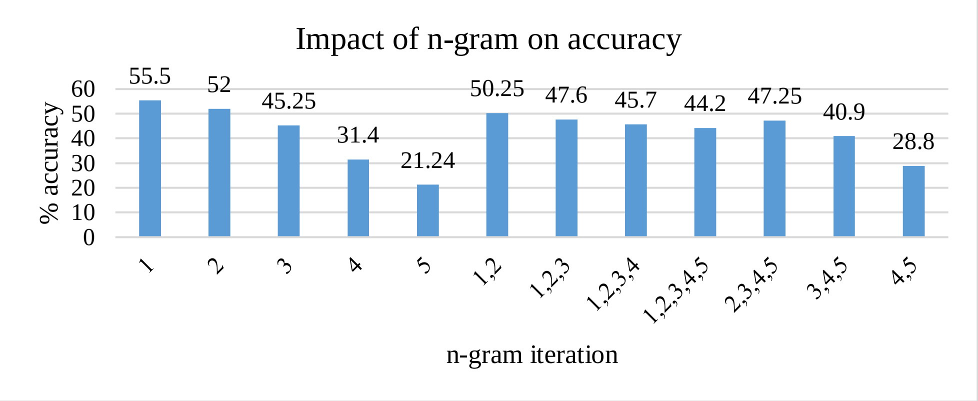


Figure 2. Impact of n-gram on Accuracy with Multinomial NB

Table 5. Best Case Summary Step 2

Accuracy	55.5%
Algorithm	Multinomial Naïve Bayes + unigram

6.2. N-gram Iterations

Introducing smoothing factor α= 0.05 along with removing Stop words from training data set returns 67.1% accuracy. I have taken a custom stop words list and also stop words list from NLTK & Scikit corpus. In both the cases there is no difference in the results. In this test case, unigram and bigram combination returned best results. Accuracy rate is 67.1% which is a huge jump from the 55.5% in the previous test case. Figure 3 graph shows accuracy results of all selected combinations using smoothing factor. Figure 3 points out that there is not much difference in accuracy levels using either custom stop words or using the stop words from NLTK or SCIKIT platforms.

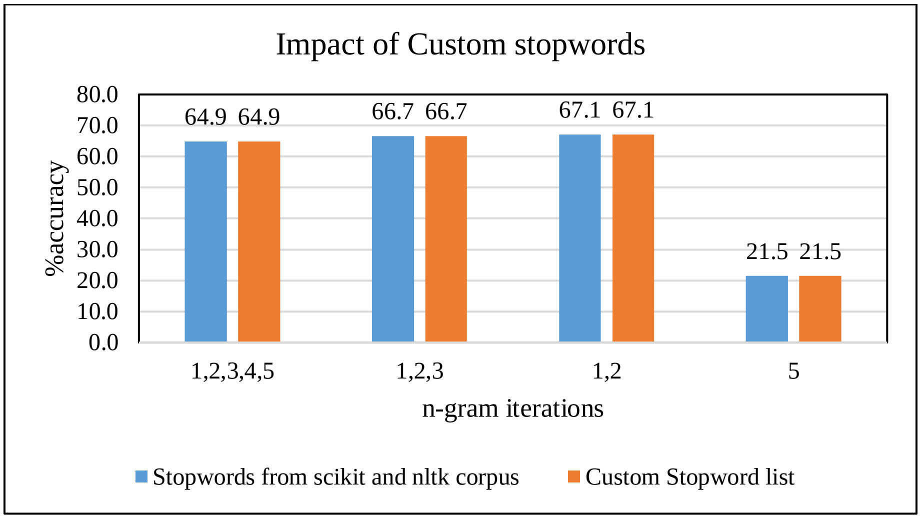


Figure 3. Custom Stopwords vs. NLTK Corpus Stopwords

Table 6. Best Case Summary Step 3

Accuracy	66.7
Algorithm	MNB+ Custom stop words, MNB+ stop words from NLTK & Scikit

6.3. N-gram Iterations with TF-IDF and Alpha Smoothing Parameter

I have introduced smoothing factor alpha to the Multinomial Naïve Bayes algorithm. After going through multiple iterations of unigram, bigram, trigram, four-gram, five-gram and combination of n-grams. The combination of Unigram and Bigram returned 67.05 accurate results.

I have used Laplace smoothing factor with alpha (α) value = 0.04. All tested combinations and results are listed in below graph**.**

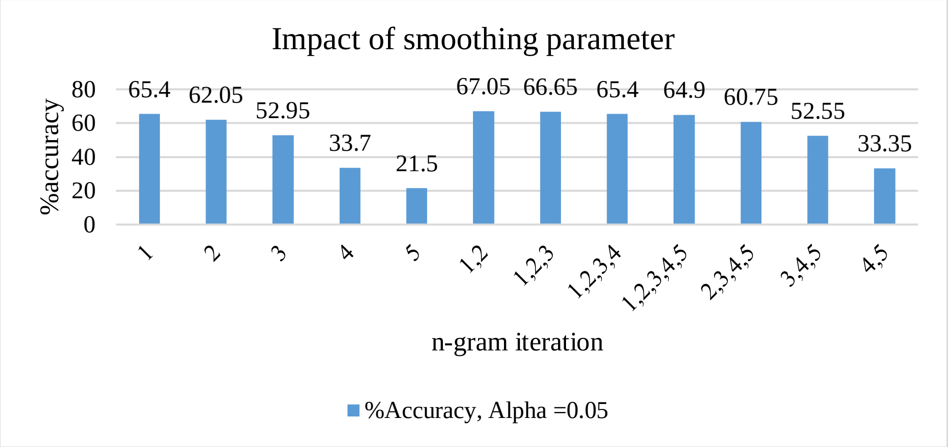


Figure 4. Impact of Smoothing Parameter (alpha) on Accuracy

Table 7. Best Case Summary Step 4

Accuracy	67.05
Algorithm	MNB+ stop words+ TF-IDF+ Unigram+ Bigram + alpha = 0.05

6.4. Tuning Alpha Parameter Value

Removing stop words and tuning alpha value from 0.01 to 1 has improved accuracy. α = 0.04 retuned 67.3. Accuracy levels have been decreased as α value from 0.04 to 1. Figure 5 below shows accuracy rates for different alpha values.

Table 8. Best Case Summary Step 5

Accuracy	67.3
Algorithm	MNB with Unigram+ Bigram; α = 0.04

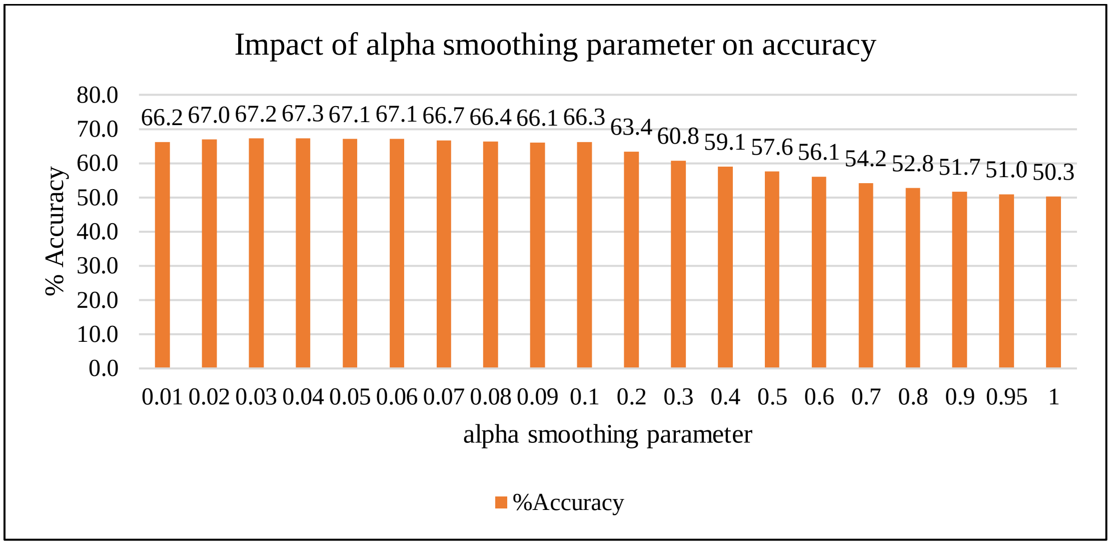


Figure 5. Tuning Smoothing Parameter

7. SUPPORT VECTOR MACHINES

I have performed this experiment on Twitter sentiment analysis dataset. This dataset consists of 20k tweets. The results provided here are the best of the 3 runs, where the training set is of 18k randomly picked tweets from the data set of 20k tweets. Rest of the 2k tweets have been used as test data set.

In this section, I have used two types of Support Vector Machines algorithms.

- Support Vector Classification (SVC) which has four different Kernel algorithms
    - Linear
    - Polynomial
    - Rbf
    - Sigmoid
- Linear Support Vector Classification(Linear-SVC)

7.1. Support Vector Classification -Linear Classifier

Performing multiple iterations with SVC (Linear kernel) has returned below results. SVC combined with unigram, bigram combination returned best accuracy percentage of 70. 5 as shown in Figure 6.

Table 9. Best Case Summary Step 6

Accuracy	70.5
Algorithm	SVC + Stop words+ Algorithm Linear+ Unigram+ Bigram
Training Time	587 seconds
Testing Time	4.973 seconds

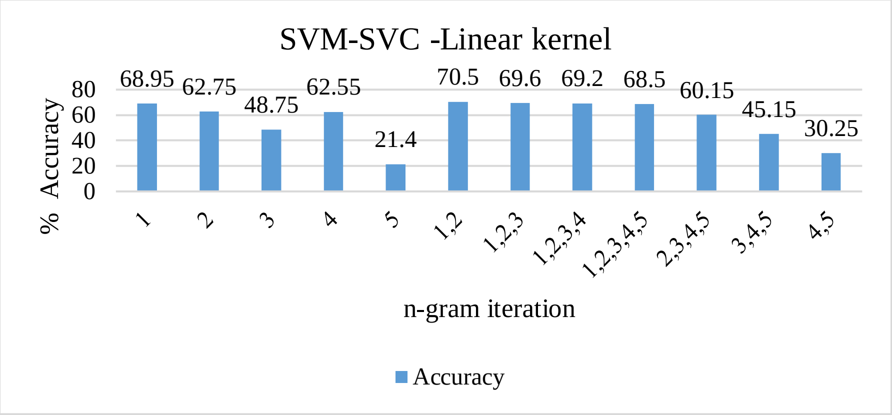


Figure 6. Impact of N-gram on Accuracy with SVM-SVC-Linear kernel

As seen in Table 9, the run time here has reduced by more than 10x when compared to a NLTK Naïve Bayes and bigram case as shown in Table 4. As Unigram and bigram combination returned best results with Linear, So I have tried same combination with polynomial, sigmoid and rbf algorithms. Results are listed in below table 10. The linear kernel still provides the best performance compared to all the other kernels.

Table 10. Effect of Various Kernels in SVC on Accuracy

n-gram iteration	**Accuracy**	**Kernels**
1,2	16.6	poly
1,2	16.6	sigmoid
1,2	16.6	rbf

7.2. Linear Support Vector Classification

Linear SVM is similar to SVC with a linear kernel but Liner SVC is more flexible to penalty and loss. It is also efficient with larger samples compared to SVC Linear as mentioned previously. Linear with Unigram and Bigram combination has returned best accuracy percentages of 71%.

Table 11. Best Case Summary Step 7

Accuracy	71
Algorithm	Linear SVC + Unigram+ Bigram
Training Time	0.387 Sec
Testing Time	0.003 Sec

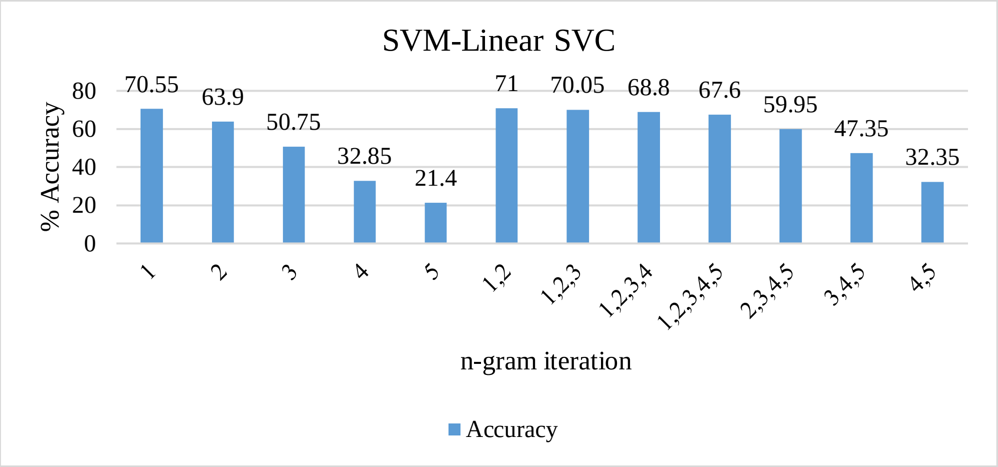


Figure 7. Impact of N-gram on Linear SVC

As seen in Table 11. The time taken has reduced significantly compared to previously tested use cases. After all the experiments, this is the best accuracy rate I have got. So, I have used Linear SVC algorithm along with unigram and bigram combination on climate change data set.

7.3. Linear Support Vector Classification

I have performed this experiment on climate change dataset. This dataset consists of 10k tweets. The results provided here are the best of the 3 runs, where the training set is of 8k randomly picked tweets from the data set of 10k tweets. Rest of the 2k tweets have been used as test data set.

I have used Linear SVC on Climate change data set. Linear SVC and unigram, bigram combination returned 61.67%. From Figure 8, Table 11 and table 12, traditional datasets provide better training accuracy compared to climate change specific datasets. This may be attributed to the fact that a general twitter dataset from multiple sources will have more coverage in terms of bag of words implementations compared to a specific climate change dataset where the algorithm is limited to a smaller bag of words because of the scope of the smaller climate change dataset.

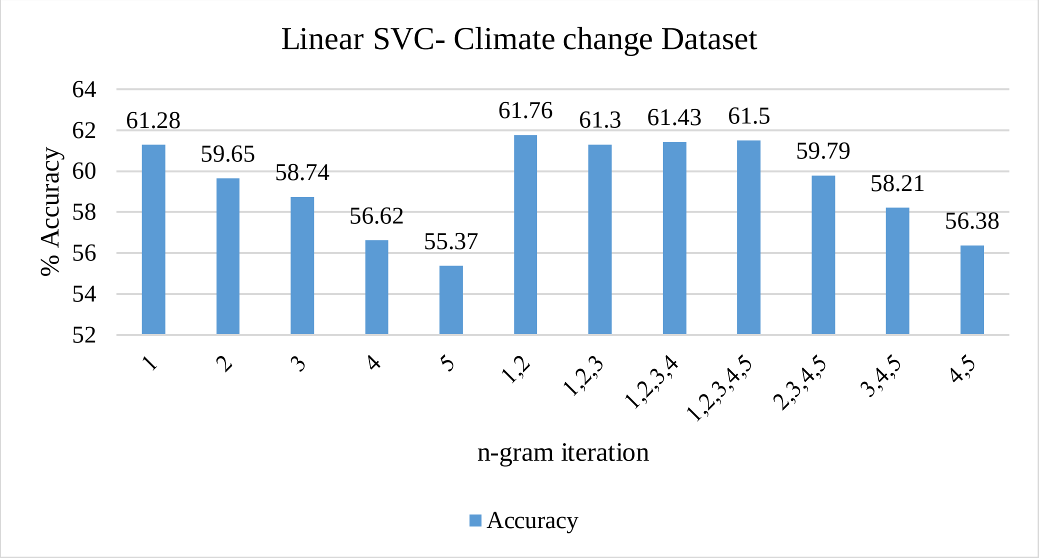


Figure 8. Using Climate Change Specific Dataset with Linear SVC

Table 12. Best Case Summary Step 8

Accuracy	61.76
Algorithm	Linear SVC + (Unigram Bigram)
Training Time	0.144 Sec
Testing Time	0.001 Sec

8. SUMMARY OF TEST CASES

Naïve Bayes Classifier: I have experimented with Unigram and stop words, Bigram and stop words. Unigram and stop words combination has returned best results in this case. In Multinomial Naïve Bayes classifier, I have introduced smoothing parameter alpha, multiple n-gram iterations with stop words has returned better accuracy results than Naïve Bayes classifier. Using Multinomial *Naïve Bayes classifier along with unigram, bigram combination, alpha value as 0.04 has returned* ***67.3 %*** *accuracy.*

Support Vector Machines: I have used Support Vector Classification(SVC) algorithm and Linear Support Vector Classification algorithms. After experimenting with multiple n-gram iterations with different types of SVC algorithms and Linear SVC algorithm, *Linear SVC has returned best accuracy percentage with* ***71%.***

Hence, the algorithm which will be used going forward to operate on historical climate change dataset to understand year over year sentiments for global warming would be Linear SVC as mentioned in Table 11.

9. TREND OF GLOBAL WARMING OVER THE YEARS

From all the tests, Linear SVC algorithm has given more accurate results. So, I have used Linear SVC algorithm to find out year over year perceptions of global warming. I have collected 5000 tweets from each year and classified tweets using SVM- Linear SVC algorithm. Here are the results.

Table 13. Global Warming Sentiment Analysis per year

	2017	**2016**	**2015**	**2014**	**2013**	**2012**	**2011**	**2010**	**2009**	**2008**	**2007**
Positive	2655	2953	2635	3434	2631	2641	2943	2284	2265	637	32
Negative	2037	1777	2007	1129	2207	2157	1844	2383	2297	389	16
Neutral	310	273	359	435	170	199	218	331	437	4	0

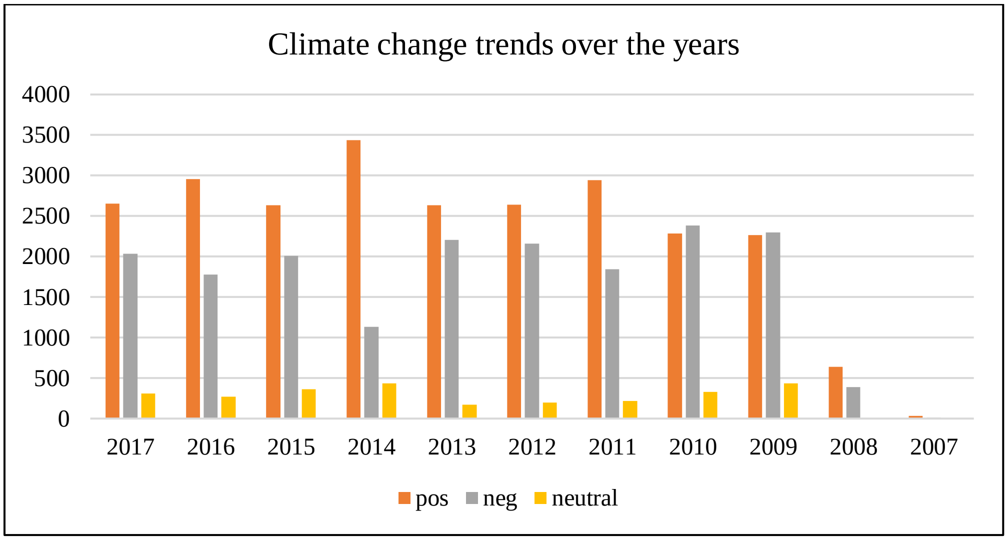


Figure 9. Climate Change Trends over the Years

According to the data there are only 48 tweets related to Global warming in the year 2007. Trend has started since then and the number of people tweeting about Global warming has increased. Until 2010, the number of people who believed in global warming were almost equivalent to the people who thought it was a hoax. Since 2011 trend has changed and more people started believing in global warming.

10. CONCLUSION AND FUTURE WORK

The overall summary of this paper is listed in this section. The aim of this paper to perform sentiment analysis of global warming using Twitter data worth of ten years. To achieve this, I have used Naïve Bayes classifier, Multinomial Naïve Bayes Classifier and Support Vector classification and Linear Support Vector classification algorithms to perform the classification using n-gram iterations, TF-IDF and additive smoothing and removing stop words. Over all Linear SVC with unigram, bigram combination has returned best accuracy with 71%. Hence, I have used Linear SVC to analyze Global warming tweets worth of past 10 years. I have captured 5000 tweets related to Global warming each year for past 10 years and used Linear SVC algorithm to analysis the sentiment. Results returned that trend of tweeting about Global warming started increasing since 2008. In 2009 and 2010 percentage of people used to think Global warming is real is almost equal to number percentage of people think Global warming is a hoax. However, trend has changed. In year 2014 percentage of positive tweets is way more than percentage of negative tweets. When compared to 2014 percentages of positive tweets are higher than negative tweets but percentage of positive tweets has started depreciating. Overall statistics says number of people believe in Global warming are more than people who think Global warming is a hoax in the given sample set.

Future work is to explore and venture into deep learning by evaluating Neural Networks such as LSTM (Long Short-Term Memory) Networks for textual sentiment analysis.

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