Detecting Climate Change Deniers on Twitter Using a Deep Neural Network

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ABSTRACT

Climate change or global warming is a global threat to both human communities and natural systems. In recent years, there is an increasingly public debate on the existence of climate change or global warming, but data describing such discussions are difficult to access. Social media provide a new data source to survey public perceptions and attitudes toward such topics. However, enabling computers to automatically determine users' attitudes towards climate change based on social media contents is still challenging. Taking Twitter data as an example, this study analyzed public discussions about climate change and global warming in year 2016. The objectives are: (1) to develop an optimized Deep Neural Network (DNN) classifier to identify users who are climate change deniers based on tweet contents; (2) to examine the temporal patterns of climate change discussions on Twitter and its driving factors. Results demonstrate that the developed DNN model successfully identified climate change deniers based on tweet contents with an overall accuracy of 88%. There are more climate change discussions during September to December 2016, whereas the percentages of climate change deniers were lower in the same period. Public interests and attitudes on climate change were driven by extreme weather events and environmental policy changes. The developed methodology will shed lights on the utility of deep learning in natural language processing, while the results provide improved understanding of factors affecting public attitudes on climate change.

CCS Concepts

• Computing methodologies →Neural networks

Keywords

Climate change; deep neural network; social media; Twitter.

1. INTRODUCTION

Climate change indicates the abnormal changes of weather conditions or extreme weather events which last for at least decades on planet earth. It could be caused by factors such as variations in solar radiation, volcano eruptions, plate tectonics, biotic processes, and certain human activities [1]. Climate change has a wide range of crucial global impacts, including sea level rise, fluctuations in the number of plants and animals, and more frequent extreme weather events. These changes in the natural environment may affect human health and even bring inevitable crisis and disasters to mankind. Therefore, public recognition on the existence of climate change and its importance has increasingly emerged in contemporary society.

Traditionally, researchers use questionnaire surveys to understand public attitudes on climate change. For example, the climate change communication research team from Yale University initiated a program to evaluate public attitudes on climate change in the United States through questionnaire surveys [2]. However, collecting data through surveys is very time-consuming and expensive. Questionnaire teams are often consisted of a group of psychologists, geographers, political scientists, statisticians, pollsters, and communication scientists to identify key audiences requiring tailored communications and develop strategies to engage these audiences in the research. In addition, people will not think about surveying questions until being asked. Last but not the least, people are more likely to participate in surveys of their interests and neglect others, which will lead to inaccurate investigation results.

With the advent of Big Data era, new data sources such as social media data provide an innovative approach to analyze public attitudes on certain topics, including climate change. There are numerous advantages of using social media data instead of traditional data sources. First, researchers can easily obtain social media users' real-time responses and behaviors on any topics or during any events, which are rarely captured in surveys. Second, unlike traditional surveys, people post their opinions or share their feelings on certain events spontaneously through social media platforms. Therefore, their opinions or feelings would not be misled by designated survey questions. However, enabling computers to understand human languages on social media and automatically detect the underlying emotions are challenging. Users may utilize different set of words or satire to express their perspectives on different topics. Building a designated classifier for each given topic is necessary. Specifically, when analyzing climate change discussions on social media, one critical research question needs to be addressed: how to automatically determine whether one post believes climate change is happening or not?

To solve the research challenge, this study aims to utilize deep neural network, a popular deep learning algorithm, to detect twitter users who are climate change deniers based on their

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tweeting contents related to climate change. Twitter data were collected through Internet Archive, a free online library providing about 1% random Twitter data of the full database. Specifically, there are two objectives: (1) developing an attitude classifier through a Deep Neural Network model; (2) analyzing the temporal trend of climate change deniers on Twitter and its driven factors. In addition to developing a reliable attitude classifier on climate change, this study elucidated the practical methodology of applying deep learning algorithms in natural language processing.

2. LITERATURE REVIEW

Social media, such as Facebook and Twitter, are computer-mediated technologies, which can promote the creation and spread of information, opinions, thoughts and various kinds of expression through virtual communities and networks [3]. Users can express their opinions in the areas of their interests without any restrictions and exchange information anytime at any places via social media platforms. Unlike traditional data, social media data could be collected at an unparalleled scale and reflect public behaviors during different events. Twitter, for instance, is featured by fast information dissemination worldwide as well as convenient access to users' geographic and personal information [4].

Since social media data such as Twitter are always noisy and difficult to analyze, previous studies have developed many frameworks to collect and extract useful information from social media for environmental studies. Twitter data were usually collected through Twitter Application Programming Interface (API) and a set of pre-defined search phrases [5]. One study on Twitter responses to Hurricane Sandy compared data collection methods between using the hashtag '#Sandy' and a set of key words, including 'sandy', 'storm', 'flooding' and 'hurricane' [4]. Their results indicated that Twitter data could be utilized to monitor disaster impacts as well as evaluating disaster damages. Since the number of tweets with x-y coordinate pairs accounted for just 1 to 4 percent of the total amount, Kirilenko (2015) explored a geolocation resolving algorithm of the locational information according to the description included in the user profiles [5]. For each tweet, geographical locations in user's profile were parsed and geocoded to a pair of coordinates though searching geographic information databases, such as the U.S. Census Bureau Topologically Integrated Geographic Encoding and Referencing (TIGER) database [4]. Previous researches demonstrated that about 55 percent of all tweets could be precisely associated to a city through Google geocoding API [6]. To compare Twitter activities in different locations with different user compositions, Zou and others developed a framework with three indexes, Ratio, Normalized Ratio and Sentiment, to represent three dimensions of normalized Twitter responses to disasters and its utility in emergency management. The results explained that there are significant geographical and social disparities in the levels of disaster-related Twitter activity at different emergency phases. They drew a conclusion that social media data can help improve post-disaster damage assessment [7,8].

Due to the popularity of social media used in environmental studies, many scholars have attempted to use social media data, especially Twitter data, to understand public attitudes towards climate change [9]. Williams (2015) collected tweets with 27 hashtags related to climate change and his result indicated that #climate, #climatechange, #globalwarming were the most typical hashtags regarding to climate change discussion on Twitter [10]. The spatial pattern of climate change discussion was significantly uneven, with most of the discussion were generated from Western Europe and coastal regions of United States [4]. Estimating the geographical detail of a tweet made it possible to bridge twitter activities with perceived local climate changes or extreme weather events [9]. Kirilenko also explored Twitter activities related to climate change and its relationship with two factors, temperature anomalies and media coverage. He found that recent news, local weather, and their combinations significantly affected the temporal pattern of public awareness of climate change on Twitter [9]. The more media coverage of climate change or more frequent extreme weather conditions, the greater the public concerns on climate change [9]. In addition, opinions of journalists, celebrities and organizations occupied a large proportion of climate change discussion on Twitter.

Despite the successful examples above, previous studies have also pointed out the limitation of current methods in understanding public discussion on climate change through social media data. First, researchers cannot avoid uncertainty or errors in their findings when applying data processing algorithms [7]. Second, due to the lack of computing capability to collect, process and analyze substantial tweets, previous research collected data for a limited time period and only focused on tweets posted in English [11]. Third, it is difficult to automatically interpret humorous or sarcastic emotions in tweet contents in sentiment analysis. As the amount of crowdsourced data created by social media grows, building a classifier to analyze social media discussion on climate change and identifying climate change deniers is needed.

3. DATA AND METHODS

This study chose Twitter as an example of social media to analyze public attitudes towards climate change. The workflow of Twitter data collection and processing, as well as the implementation of training the classifier using deep neural networks are displayed in Figure 1.

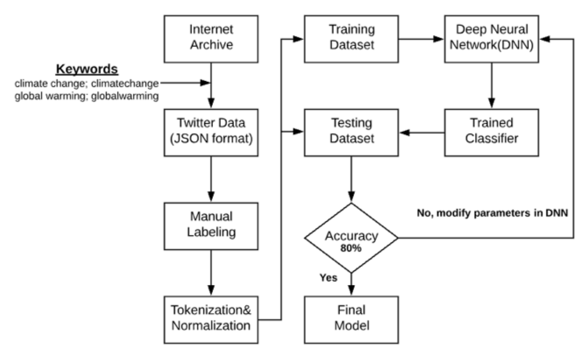

Figure 1. The workflow of data collection and processing, and model training

3.1 Twitter Data Collection and Processing

The first step is data collection. Twitter data were collected from Internet Archive (https://archive.org/), which is a non-profit library providing millions of digital books, software, and websites. In this study, four keywords were used to identify target tweets, including 'climate change', 'climatechange', 'global warming', and 'globalwarming'. To ensure tweets discussing climate change in different regions using different languages would be collected, we translated the four keywords into 34 languages supported by Twitter and added them into the keyword list. Any tweet containing one of the four keywords in any of the 34 languages was identified as climate change related tweets and collected in the target database.

The second step is data pre-processing. Collected Twitter data were stored in JavaScript Object Notation (JSON) format. Each tweet contains information such as tweet content, time when the tweet was created, and information in the user profile, including time when the account was created, tweeting history, and follower/following statuses. This study only used text contents and time when the tweet was created in each record for the subsequent analysis. Once a tweet was identified as a target tweet, it was translated into English for content analysis.

The third step is manual labeling. We randomly selected 2000 sample tweets from the target tweets database and manually assigned them into one of the two categories, climate change deniers and non-deniers. Deniers and non-deniers stand for tweets against and hold the positive or neutral opinions that climate change is happening, respectively. The purpose of manual labeling is to prepare the training and testing datasets, which were used to train and validate the developed attitude classifier. Table 1 exemplifies tweets labeled as climate change deniers and non-deniers. The contents of example tweets classified as deniers showed users' opinions directly through some keywords, for instance, "isn't real" and "hoax". However, tweets created by non-deniers contain users' concerns on the adverse impact of climate change.

Table 1. Sample tweets of climate change deniers and non-deniers

Tweet ID	Tweet Content	Category
1	Global warming isn't real because it was cold today!	Denier
2	Climate change is a hoax…	Denier
3	I watch even less of the global warming alarmists and just live my life.	Denier
4	Urgent action needed on climate change	Non-denier
5	The five stages of global warming: 1. denial 2. guilt 3. depression 4. acceptance 5. drowning	Non-denier
6	Polar bears can grow up to 1,600 pounds ... this polar bear was 245 pounds. do you believe in climate change now ...	Non-denier

Fourth, we used the continuous bag-of-words (CBOW) model, a typical word2vec architecture, to convert tweeting contents to vectors. CBOW model takes two steps: dictionary creation and dataset encoding. To convert tweets to binary vectors with the same length, it is necessary to build a customized dictionary and then encoding each tweet according to the dictionary. First, each tweet content was tokenized into a list of words. Second, each word in the list was lemmatized to its prototype to avoid duplicate counting of the same word in variant forms. Third, the prototype of each word in each tweet was appended to a word list for frequency analysis. Finally, rare noisy and frequent stop words were excluded from the dictionary through customized minimum and maximum thresholds.

Figure 2 gives an example of the CBOW model. After creating a dictionary, each tweet i was initiated as a vector of n zeroes Vi = (0, 0 … 0), where n represents the length of the dictionary and each 0 stands for a word collected in the dictionary. Then tweet i was tokenized and lemmatized into a list prototypes of words. If any word in the dictionary appeared in tweet i, then the 0 at the location of the word in Vi was replaced with 1. This step converted each tweet into a unique binary vector to train the attitude classifier.

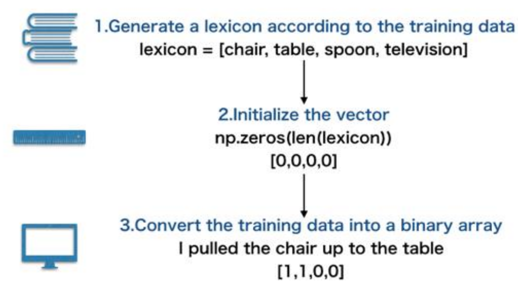

Figure 2. An example of the continuous bag-of-words (CBOW) model

A python script has been developed to collect Twitter data though Twitter streaming API, extracting the text contents, translating non-English tweets into English, creating the dictionary, and converting each tweet to a binary vector of the same length. The translation was realized through Google translation API, while the dictionary creation and vectorization were accomplished using a natural language processing toolkit module (NLTK) for Python. Among the 2000 sample tweets, 80% (1600) were used to train the deep neural network classifier, while the other 20% (400) were used to validate the trained model.

3.2 Deep Neural Network (DNN)

Neural network is a supervised machine learning algorithm that simulates human brains to develop models from the training dataset and uses the trained models to make decisions with new input data. A neural network consists of an input layer, an output layer, and at least one hidden layer with each layer contains several nodes. The number of nodes in the input layer and output layer in a neural network is usually pre-defined, while the depth of hidden layers and the number of nodes in each hidden layer could be customized. Each node is calculated as the weighted sum of all activated nodes from its previous layer.

A neural network with more than two hidden layers can be defined as a deep neural network (DNN), which is one of the most commonly used Deep Learning algorithms. On one hand, the development of advanced computation powers, for instances, graphic processing unit (GPU) and high-performance computers (HPC), allows us to increase the number of hidden layers and nodes to build a large-scale DNN and simulate complex processes. On the other hand, with the amount of data soar significantly in this Big Data era, the performance of DNN could be improved continuously, while the performances of traditional machine learning algorithms may reach an upper limit. The purpose of training the deep neural network is to identify the optimal weights and biases that make the predicted results more accurate. Training a deep neural network includes seven steps:

(1) Initialize the weight and bias of each node in all layers of the deep neural network;

(2) Input the formatted training data;

(3) Calculate the value of each node in each layer with initialized or updated weights and biases;

(4) Output the result;

(5) Compare the modeled output with the expected training dataset to evaluate the model accuracy;

(6) Optimize the weights with the Adam optimizer and back propagation;

(7) Return to step (2) and iterate the optimizing until meeting the required accuracy.

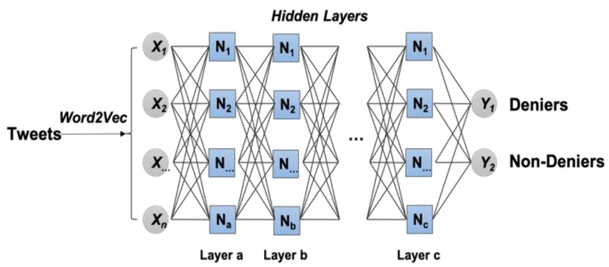

Figure 3. The principle of deep neural networks in this study

The input data were encoded tweets derived from section 3.1. There are two outputs categories: climate change deniers and non-deniers.

Sample tweets were first categorized into deniers and non-deniers and stored into text files respectively. After creating sentiment features, the number of input nodes can be estimated. The longer dictionary length leads to more input nodes. Then we trained and compared model accuracies based on different parameters, including the number of hidden layers, nodes in each hidden layer, the threshold for the frequency of occurrence of the words in the dictionary, and the epoch used to train the DNN. Table 1 below shows the experimental parameters used in this study.

The training and testing datasets were generated randomly, which might cause bias and affect the accuracy for each test run. Therefore, for each set of parameters, the model was tested 10 times, and the averaged accuracy is assigned as the final accuracy for this set of parameters. Using the average accuracy of ten test runs instead of a single test can increase the reliability of experimental results.

Table 2. Configuration of experimental parameters

Parameters	Configurations
Dictionary	[5, 500], [10, 500], [15, 500], [20, 500], [25, 500]
Layers	3, 4
Nodes	500, 600, 700
Epochs	30, 40, 50

4. RESULTS AND DISCUSSION

4.1 Optimized Deep Neural Network

Among the 2,000 sample tweets, 224 (11.2%) tweets denied that climate change is happening, while 1,759 (88%) users were non-deniers (positive or neutral). A total of 17 tweets were unrelated to climate change, since these tweets only attached a few hashtags related to climate change or global warming and did not express any opinions.

Figure 4 shows the accuracies of neural networks with different parameters configuration, ordered according to the overall accuracy. Three main phenomena could be observed from the results. First, the accuracies of neural networks with four hidden layers are generally higher than accuracies of neural networks with three hidden layers, indicating that more hidden layers could improve the model accuracy. Second, for a group of neural networks with four hidden layers and a fixed dictionary derived from thresholds of 25-500 words, the accuracy of the model rises from 85.3% to 85.9% and eventually reaches the best model accuracy in this research at 88.1% as the number of nodes increases. It demonstrates that neural networks with more nodes in hidden layers have higher overall accuracies. Third, changing the number of epochs in training neural networks does not necessarily lead to model improvement. Accuracies of neural networks with four hidden layers and trained in 40 epochs were listed in table 3 and used for the subsequent analysis.

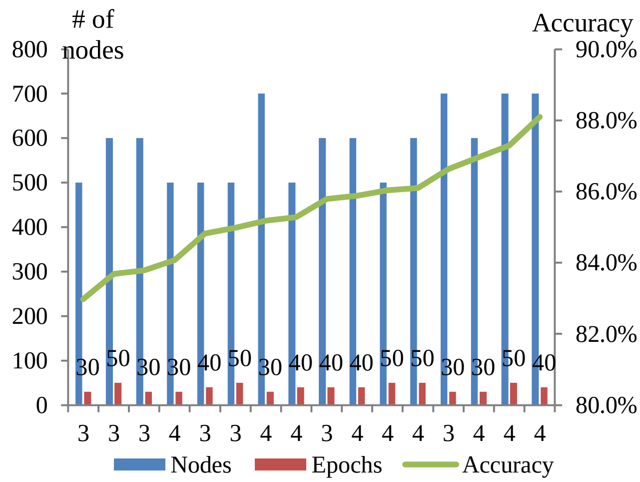

Figure 4. Comparison of neural networks with different parameters configuration

Table 3. Training results with four hidden layers

ID	Dictionary	Nodes	Input nodes	Accuracy
1	5-500	500	690	85.7%
2	5-500	600	690	84.5%
3	5-500	700	690	86.8%
4	10-500	500	344	81.2%
5	10-500	600	344	82.8%
6	10-500	700	344	83.4%

7	15-500	500	221	82.7%
8	15-500	600	221	84.3%
9	15-500	700	221	84.2%
10	20-500	500	162	83.8%
11	20-500	600	162	86.0%
12	20-500	700	162	85.4%
13	25-500	500	132	85.3%
14	25-500	600	132	85.9%
15	25-500	700	132	88.1%

Figure 5 further exhibits how dictionary lengths and numbers of epochs affect model accuracies. The number of hidden layers is 4 in each layer. Five thresholds were used to create dictionaries, include 5-500, 10-500, 15-500, 20-500 and 25-500. Table 3 and Figure 5 indicate that the dictionary of 25-500, 4 hidden layers, 700 nodes and 40 epochs trained the model with the highest accuracy of 88.1%. It is worth noticing that the results of DNN trained models with the same parameters have biases, because the training and testing datasets were generated randomly in each experiment. Using the average accuracy of ten experiments with the same set of parameters could significantly reduce the uncertainty caused by training and testing datasets generation.

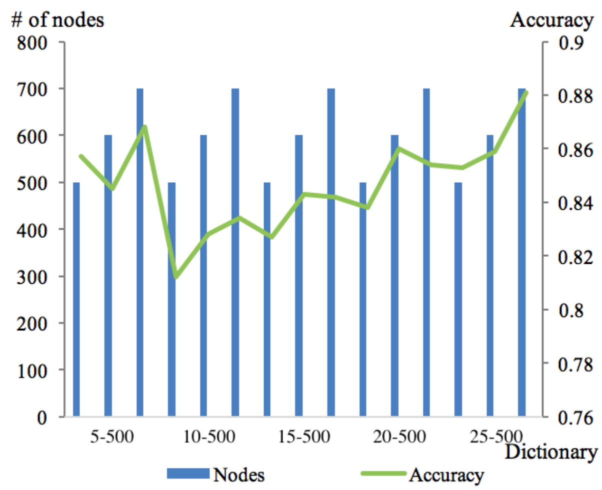

Figure 5. Comparison of neural networks with different nodes and dictionaries configuration

Table 4 summarized the confusion matrix by applying the optimized DNN model to the whole sample dataset. The overall classification accuracy (ACC) is 92.5%, indicating that 92.5% of the tweets are correctly classified. The true positive rate (TPR) and true negative rate (TNR) are 79.02% and 94.26%. The positive predictive rate (PPR) and negative predictive rate (NPR) are 63.67% and 97.24%. In general, the trained model could accurately categorize climate change deniers and non-deniers based on tweet contents. The training model mistakenly classify 47 (false negative rate, FNR = 20.98%) deniers as non-deniers and 101 (false positive rate, FPR = 5.74%) non-deniers as deniers respectively. The DNN model is more likely to falsely recognize non-deniers as deniers since the false discovery rate (FDR) 36.33% is much higher than the false omission rate (FOR) 2.76%. Tweets including double negation might be categorized as deniers by the trained model. Tweets containing political backgrounds and news were also likely to be falsely classified as deniers.

Table 4. Confusion matrix of the optimized modeled and observed deniers and non-deniers

N = 1983	Deniers (Actual)	Non-denier (Actual)	Total
Deniers (Predicted)	**177** **TPR = 79.02%** **PPV = 63.67%**	101 FPR = 5.74% FDR = 36.33%	278
Non-denier (Predicted)	47 FNR = 20.98% FOR = 2.76%	**1658** **TNR = 94.26%** **NPV = 97.24%**	1705
Total	224	1759	**ACC = 92.5%**

4.2 Temporal Trends of Climate Change Deniers

We applied the trained DNN model to climate change tweets collected in 2016 and analyzed the temporal trends of public discussion on climate change. There are 107,453 climate change related tweets collected in 2016. The DNN model classified 9,112 (8.48%) as climate change deniers, and the rest 98,342 (91.52%) as non-deniers.

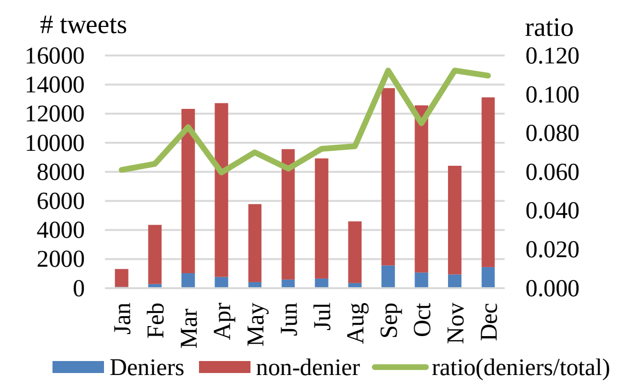

Figure 6. Temporal trends of climate change deniers and non-deniers on Twitter in 2016

Figure 6 displays the monthly temporal trend of climate change deniers in 2016. High climate change discussions were found in March, April, September, October and December. The number of monthly tweets in each of these five months were more than 12,000. The total discussion on climate change and the percentages of deniers are ascending from January to December 2016. This phenomenon could be explained by the following reasons. First, extreme weather events triggered public discussion about climate change. For example, Moscow suffered the biggest blizzard in March during the past 80 years. At the same period, severe drought occurred in Southeast Asia. For instance, Thailand experienced the worst drought during the past half century in 59% regions of the country. In early June, the Seine River in Paris was overloaded by heavy rains, and the water level rose to the highest level in 30 years. In October, the concentration of PM2.5 in New Delhi, India exceeded 10 times the safety standards set by the

World Health Organization. Second, since most twitter users are in the United States, climatic events happened in U.S. may cause more climate change discussions on Twitter. For instance, the 2016 Louisiana Flood was the worst natural disaster in U.S. history since Hurricane Sandy in 2012 and aroused huge discussion about climate change on Twitter. Furthermore, according to a monthly analysis of global temperatures by NASA's Goddard Institute for Space Studies (GISS) in New York, September in 2016 was the warmest September in 136 years. Third, international climate change related events, such as the Paris Agreement in November, may also affect public discussions on Twitter. This global event laid a solid foundation for the future sustainability development and possibly lowered the number of climate change deniers.

Figure 7 is a word cloud generated from collected climate change tweets in 2016 using word art (https://wordart.com/create). The top 15 keywords used in climate change discussion on Twitter were listed in table 5. Climate change and global warming, which were used to collect tweets were not listed in the word cloud and the table. Both the Figure 7 and Table 5 reveal popular topics in climate change discussion as well as validate the underlying factors affecting public recognition on climate change. First, Twitter users tended to quote celebrities' comments, such as Donald Trump, Barack Hussein Obama or climate change scientists, to express their opinions on climate change. Second, users preferred using examples rather than directly expressing personal attitudes on Twitter. For instance, some users introduced the concept of energy crisis, which elucidates that global warming is happening. Third, global events such as climate change summit in Paris also arose public attention on climate change discussion, as explained above.

Figure 7. A word cloud generated from climate change related tweets in 2016

Table 5. Top 15 keywords used in climate change related tweets

Rank	Keyword	Frequency
1	Trump	4745
2	fight	2442
3	world	2376
4	people	2364
5	believe	2360
6	real	2273
7	stop	1881
8	scientists	1811
9	major	1790
10	energy	1759
11	time	1543
12	earth	1538
13	action	1426
14	hoax	1253
15	help	1236

4.3 Limitations and Future Research

Despite the success completion of this research, there are some limitations and potentials for improvement. First, the size of labelled data is small, with only a total of 2,000 sample tweets utilized to train and test the attitude classifier. A larger volume of training data is needed in order to ameliorate the accuracy of the DNN model and increase persuasiveness of this research.

Second, collecting data from Internet Archive is inefficient. In this study, we downloaded, extracted, and analyzed a large number of archive files which requires a large amount of space and time to collect climate change related tweets. Alternatively, Twitter data can be collected directly from Twitter streaming API, which returns around 1% of the full Twitter dataset based on user defined keywords and is more efficient for researchers to obtain huge amounts of real-time target data in a short time period.

Third, the result of manual labeling varies from person to person. This process may introduce human bias in preparing the training and testing dataset. There are inevitably some subjective inferences in manual labeling if users do not clearly express their attitudes in tweets, which is more likely to cause human bias. One tweet being considered by some researcher to be negative might be categorized into the opposite group by other researchers.

Furthermore, identifying sarcasm is extremely challenging for computational algorithms. Specifically, it is also hard for machines to recognize sentences with double negation. Table 6 exemplifies sarcasm and double negation used in climate change discussion on Twitter. Although humans can easily categorize the second tweet as non-deniers, it is difficult for machines to conclude the same results. Since the word "not" and "fools" are negative words, DNN will simply learn that this is a more negative emotion rather than a non-denier.

Table 6. Examples of sarcasm or double negative attitude of climate change on Twitter

Tweet ID	Tweet Content
1	whoops! #algore & #globalwarming alarmists don't want anyone to think about their profound "predictions" of years…
2	People who do not believe that global climate change is happening are real fools.

There are some approaches to alleviate the above limitations. First, we can enlarge the training dataset by employing workforce from designated marketplace, such as Amazon Turk (MTurk). MTurk is a platform offering services of data verification, data cleaning, data processing, etc. It can categorize a variety of information to match a given schema or taxonomy, which could significantly increase working efficiency and achieve better research results.

Second, researchers can survey with certain hashtags to collect training dataset instead of manually labeled tweets, for example, #climatechangeistrue and #climatechangedenier. These hashtags can help easily label users' attitudes when collecting related tweets. It is beneficial for eliminating errors and bias in manual labeling, which is a time-consuming task with many uncertainties involved.

5. CONCLUSION

This study analyzed Twitter data obtaining from Internet Archive (IA) about climate change or global warming by using Deep Neural Network. First, a total of 2,000 tweets relating to climate change were manually labeled into two categories based on tweet contents: deniers and non-deniers. Second, each tweet was tokenized, normalized, and vectorized into a fixed length list. Third, the 2000 coded tweets were divided into training and testing datasets, which were utilized to train and validate a deep neural network with different parameter configurations. Using an optimized DNN model, we examined the temporal changes of public attitudes on climate change during year 2016. Results show that the optimized DNN model can successfully classify 92.5% of the training and testing tweets. High climate change discussion was found during September to December 2016, while the percentages of climate change deniers were also higher during the same period. Local extreme weather events, celebrities' opinions, and global climate change events significantly affected public interests and attitudes towards climate change.

There are some important implications of the findings in this research. Deep Neutral Network is a powerful technique that allows machines to analyze human language in a short time and then make predictions through natural language processing. This study provides a success example using DNN in building a natural language classifier. In addition, the classifier could be used to automatically classify tweets related to climate change. Although the data set is really limited, the model of DNN still can be used for data analysis with a high accuracy.

Although this study has achieved our objectives, there is still space for improvement in further researches. First, a large amount of training dataset is necessary to build a more accurate model. In addition, detailed spatial-temporal analysis during climate change related environmental events might lead to more findings. For example, researchers can analyze climate change discussions on Twitter during some major climate events such as hurricanes, sandstorms, etc. Future investigations could also target on vulnerable areas where people are more likely to talk about climate change and make comparisons with areas that are less likely being affected by global warming. Moreover, other machine learning algorithms of neural networks such as Convolutional Neural Network (CNN) can be applied to build a more accurate attitude classifier.

6. ACKNOWLEDGEMENTS

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