Deciphering Public Opinion of Nuclear Energy on Twitter

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***Abstract*—This paper explores nuclear energy-related Twitter discussions as a response to the 2011 Fukushima Nuclear Disaster and the 2017 Nobel Peace Prize won by the International Campaign to Abolish Nuclear Weapons. We have considered a total of 2 million tweets for these two events. In particular, we employed CNN, LSTM, and Bi-LSTM to investigate whether social media users are supportive or cynical about nuclear energy. Our AI algorithms have performed better for polarity detection (accuracy in the range of 90%) with respect to subjectivity detection (accuracy in the range of 75%). We also note that dominant aspects of supporting tweets revolve around concepts like clean energy, lower CO2 emission, and sustainable future. On the contrary, cynical users see nuclear energy as a threat to the environment, human life, and safety.**

Keywords—nuclear energy, public opinion mining, artificial intelligence

I. INTRODUCTION

User-generated contents such as event-specific online discussions and debates on social network platforms contribute to opinion formations even in the absence of a structured communication system. All such contents are a new source of real-time information during crisis [2], [5], [8], [19], [20], [22], [27], [30]. The automatic detection of relevant and useful information from these social media platforms can be a useful source of information for policymakers, media and communication practitioners, and government agencies as well as for information science researchers who can retrieve information for a particular topic [45].

Information retrieval researchers have explored text content for more than three decades [7], [9], [11], [24]. So far, however, there has been little work on nuclear energy-related information retrieval from social media content – except a few like [45]. Therefore, we explore public opinion of nuclear energy as a reaction to two events: Fukushima Daiichi nuclear disaster in 2011 and the Nobel Peace Prize to the International Campaign to Abolish Nuclear Weapons (ICAN). ICAN has received the award for its work "to draw attention to the catastrophic humanitarian consequences of any use of nuclear weapons and for its ground-breaking efforts to achieve a treaty-based prohibition on such weapons." In particular, we are using artificial intelligence (AI) for domain-specific information retrieval from Twitter data.

Twitter, a micro-blogging platform, allows it users to post a short public message. In other words, Twitter allows social media participants to express their opinion from multiple platforms like mobile and Web. From the perspective of natural language processing (NLP), text classification of social media content is complicated due to several reasons [9], [32], [33], [43]. For instance, text classification cannot be reduced to a word-level analysis to detect the opinion about a complex and sensitive topic like nuclear energy [45]. Bag-of-words models fail to capture the underlying essence of a text [6], [29], [37]. Hence, assessing whether a text contains subjective thoughts about nuclear energy semantically will give better performance [45].

We incorporate a two-step classification process for nuclear energy opinion mining. First, we try to find out whether a tweet is subjective or not. If the tweet is subjective, we then employ sentiment analysis to judge the polarity of that particular tweet. For this two-step classification, we are employing supervised neural network-based learning. Our work is attempting not only to address issues such as positive or negative opinions on social media platforms but also to extract the crucial aspects and concerns such as safety, cost sustainability-related comments on a social media platform. To the best of our knowledge, none of the prior studies has addressed this diverse range of issues in the context of nuclear disaster and energy.

II. RELATED WORKS

A. Public Opinion of Nuclear Energy on Social Media

Researchers have demonstrated the power of social media in real-time information propagation from one corner of the world to another without any structured network. During disasters, social media users generate a considerable number of messages with disaster-related information [26]. Recently, researchers are exploring the usage of microblogging platform at the time of natural disaster or humanmade crisis [45].

Such studies analyzed different types of events like terror attacks [27], flood and tsunami [5], [10], earthquakes [4], [5], [30], cyclones [2], [8], nuclear disaster [45] and epidemics [19], [20]. For instance, [27] explored the capability of social media messages during a social crisis like a terror attack, shooting in a public place and car recall by the motor company due to a manufacturing fault. They also explored the rumor theory at the time of social unrest.

Similarly, [5] considered different features like emoticons frequency, subjectivity, URL information frequency and three lexica (SentiWordNet, Hu-Lin, and AFINN) to detect the polarity of a tweet. Interestingly, they found negative tweets to be more critical than positive tweets during the disaster. Table I provides a summary of these studies. We have reported the event and types of disasters, size, and source of the dataset, as well as the core findings of these studies (refer to Table I).

TABLE I. PRIOR WORKS ON DISASTER USING TWITTER DATA

Disaster (Data)	Core Finding(s)
Earthquake at islands of American Samoa in Sep 2009 (23,354 tweets) & *Tsunami* at Padang, Indonesia in Sep 2009 (19,829 tweets)	[22] explored usages of tweet feed for information dissemination using LDA topic modeling at the time of earthquake and tsunami in the Asia Pacific area. New dynamic corpus refinement method proposed in this paper for the domain/event-specific model training task. The evaluation technique of this paper is quite simple.
Mumbai Terror Attack in Nov 2008 (20,920 tweets); Toyota recall in Mar 2011 (37,323 tweets) & Seattle café shooting May 2012 (9,104 tweets)	[27] explored the applicability of rumor theory during a crisis in the context of social media and community intelligence. They have explored the rumor model as a summation of four inputs: anxiety, source ambiguity, personal involvement, and direct message. Tested their hypothesis in three different contexts and observed that anxiety level was high during the Mumbai terror attack and Seattle shooting in comparison to Toyota recall.
Hurricane Sandy in Oct 2012 (12,933,053 tweets from Oct 26 to Nov 12, 2012)	[8] visualized the sentiment on a geographical map around the disaster. They argue social media data is not trustworthy due to the credibility of the sender and in most cases, the location of the sender is not traceable. This study integrated the actual physical disaster information and the spikes of the emotional activity near the disaster location with accurate longitude and latitude.
Genoa Flood at Italy in Oct 2014 (13,530 tweets)	[5] performed sentiment Analysis using three methods: SentiWordNet, Hu-Liu Lexicon, and AFINN Lexicon. Subjectivity detection accuracy was up to 70%. They observed that positive tweets were not useful at the time of disaster. However, fine granular text classification of negative tweets helps to extract emergency disaster-related information.
Ebola virus outbreak at African countries in Sep 2014 (600,000 tweets) & Zika virus outbreak in Brazil in Feb 2016 (970,000 tweets)	[20] applied word2vec for the text classification task. Demonstrated context/domain-specific word2vec (contrived from a relatively small corpus) can outperform generic corpus (contrived from the voluminous corpus). They also showed that word2vec contrived from scholarly abstract from bio-medical literature can match the performance of tweet corpus.
Nepal Earthquake in Apr 2015 (1,074,864 tweets)	[30] proposed a classifying scheme for disaster-related tweets into eight different classes. These classes are mostly related to humanitarian relief related topics like Monetary support, Water, Airport, Health, and Rumour. They also explored the subtopics of these eight classes in detail with their tweets distribution during the crisis.
Zika virus outbreak in Brazil in Feb 2016 (970,000 tweets)	[19] explored Zika virus-related discussion on the Twitter platform and observed that Twitter users were more concerned about the long term of the Zika virus on pregnant women than the immediate short term effect such as fever and headache.
Hurricane Harvey in Aug 2017 (6732546 tweets); Hurricane Irma in Sept 2017 (1,207,272 tweets) & Hurricane Maria in Oct 2017 (1096335 tweets)	[2] demonstrated the usefulness of textual data as well as image data at the time of disaster. They used machine learning techniques to extract the disaster-related information from multimedia tweet data. They compared their proposed methods for three similar disasters. According to their study, most tweets reported about individual suffering, infrastructure damage, injuries, death, donation, and sympathy. However, all these techniques include humans-in-loop for training data set creation, which is the main obstacle for real-life execution at the time of disaster.

B. Sentiment Analysis Research

In recent years, sentiment analysis has become increasingly popular for processing social media data on online communities, blogs, wikis, microblogging platforms, and other online collaborative media [35]. Sentiment analysis is a branch of affective computing research that aims to mine opinions from the text (but sometimes also images [36] and videos [37]).

Most of the literature is on the English language, but recently, an increasing number of works are tackling the multilingual issue [38], especially in booming online languages such as Chinese [39] and Spanish [40]. Sentiment analysis techniques can be broadly categorized into symbolic and sub-symbolic approaches: the former includes the use of lexicons [41] to encode the polarity associated with words and multiword expressions; the latter consists of unsupervised [42], semi-supervised [43] and supervised [44] machine learning techniques that perform sentiment classification based on word co-occurrence frequencies. Among the supervised techniques, the most popular are those based on deep neural networks, e.g., convolutional neural network (CNN) and recurrent neural network (RNN).

Most of the recent studies on word embedding for text classifications have attempted to capture the syntactic relations between words through vectors (refer to Table II). However, these studies have ignored the sentiment of text to build such word vectors. These studies used context information of words which fails to distinguish words with similar context but the opposite sentiment like ‘good’ and ‘bad’. However, [32] proposed a new method that has used word embedding specifically for sentiment classification, where they incorporated sentiment-specific word embedding (SSWE). They also integrated distant-supervised tweets with positive and negative emoticons to create a large text corpus for the training purpose. Their proposed system ‘Coooolll’ outperformed other hand-crafted feature-based modelings and secured a good rank at Semeval 2013 task.

Recently, CNN has gained enormous success for image-related tasks, but at the same time, many NLP works also used CNN for different learning tasks. [31] used CNN for Twitter sentiment analysis. In their study, they showed a single layer convolution feature map followed by a non-linear, max pooling and softmax classification layer-based sentiment classification model that could compete with the computational dense multi-layer network. Most of the studies before this one used a multi-layer network for language modeling like [18], which were resource-hungry.

This model was also one of the best-performing models in Semeval-2015 for subtask A (among 11 teams) and subtask b (among 40 teams). [14] showed the advantage of the adaptive recursive neural network (AdaRNN) for target-dependent sentiment analysis over the other methods like SVM and RNN without adaptive composition selection. If the sentence is ‘windows is better than ios’, then there are two targets: one is ‘windows’ and another one is ‘ios.’ For the first target ‘windows’, the sentiment is positive, but for the ‘ios’, the sentiment is negative. They converted this sentence into two different dependency trees for two different targets. AdaRNN employed the linguistic and semantic categories at the same time to capture the sentiment of the text. In short, deep learning-based algorithms are very efficient for polarity detection.

TABLE II. PRIOR WORKS ON DISASTER USING SOCIAL MEDIA DATA

Methods	Data	Core Finding(s)
Sentiment-specific word embedding (SSWE) features and state-of-the-art hand-crafted features [32]	SemEval 2013 Twitter sentiment classification dataset	SSWE is trained from 10M tweets collected by positive and negative emotions, without any manual annotation and it performs better than other benchmark methods like SVM, GBM, NeuralNet and many other standard methods.
Deep Convolutional Neural Networks [31]	Semeval-2015 Task 10: phrase-level (subtask A) and message-level (subtask B)	Demonstrate the deep learning approach for sentiment analysis of tweets for predicting polarities at both message and phrase levels. Their network initialization process includes the use of distant supervised to adjust the weights of the network.
Dynamic Convolutional Neural Network (DCNN) [18]	The sentiment of movie reviews in the Stanford Sentiment Treebank	Authors have used Dynamic k-Max Pooling - a global pooling operation over linear sequences. The network handles input sentences of varying lengths and induces a feature graph over the sentence that is capable of explicitly capturing short and long-Range relations. The network does not rely on a parse tree and is readily applicable to any language.

III. MOTIVATIONS

Nowadays, governments include social media as an active communication channel to pass the informational and actionable messages to their citizen. [18] showed how local government in England used Twitter to control the 2011 riot in England. In this study, they explored a small dataset of 1,746 tweets from their 81 local government Twitter accounts. They also found the government primarily used this channel to promote the government's thoughts as well as the government's praise of the actions which were initiated by citizens to control the riot. These studies also ensure citizen engagement in challenging and collaborative actions like service delivery, planning and public management can be overcome much more efficiently by incorporating the citizen in the decision making the process by social media [18]. In the Australian context, [2] studied the use of Twitter by six government departments. In their study, they analyzed different categories of tweets like 'News and Update,' 'External Event Announcement,' 'Asking a Question' and so on. They also probed the distribution of these categories across these various agencies/organizations. This study noted that 'agencies are primarily using Twitter to disperse information, particularly links to news articles about themselves, and to report on their activities'.

[2] also noted that citizen interactions, using the Twitter platform, are mostly in the form of positive and negative feedback to the concerned authority. Moreover, this study noted that the presence of government-to-citizen (G2C) and government-to-government (G2G) tweets in their sample, but there are no tweets in the government-to-business (G2B) category. Similarly, in the context of South Korea, [15] explored the government's Twitter-based networking strategies for both government-to-citizen (G2C) and government-to-government (G2G) communication. Interestingly, their findings suggest that the government's direct networking strategies with citizens (G2C) are not working correctly, but it plays a crucial role in G2G relationships.

In another study, [25] argued that the hybrid communication model of old centralized bureaucratic communication and modern social media-based less bureaucratic communication is the future for government communication. To verify this argument, the authors rely on the usage of Twitter by Dutch police departments for communication purposes. According to their findings, Twitter is mostly used for external communication; however, they used it also for their mutual communication in a substantial way. This study also reported how each police officer became a "hub" in a Twitter Communication network of internal and external communication and the way they used it for both formal and informal communication. Another study in the Indian context probed public opinion regarding changes in transportation policies to control pollution [47].

To sum up, these studies suggest that Twitter-based communication strategies by government agencies can be an option to understand public concerns and opinions. Thus, effective use of Twitter-based communication channels can help government agencies in implementing public policies. Nuclear policy is also an essential area from the policy perspective. Understanding public opinions and sentiments about nuclear energy will help government agencies to design the nuclear policy efficiently. To the best of our knowledge, rarely any studies have probed this issue.

IV. METHODOLOGY

A. *Research Context and Data*

To understand public opinion about nuclear energy, we study public perception about nuclear energy in the context of the Fukushima Nuclear Disaster in 2011 and the Nobel Peace Prize announcement in 2017. Public concerns about nuclear disasters are mostly negative. Social media users think that we can generate energy for our daily living or industrial development without using nuclear energy and at the same time, we will be able to avoid the risk of a nuclear disaster like Fukushima. The nuclear disaster was a consequence of the Tohoku earthquake that happened on 11th March 2011. Due to this earthquake, a massive tsunami hit Japan, and a series of destruction happened in Okuma, Fukushima. One of the largest of them happened at the Fukushima Daiichi Nuclear Power Plant accident. This 2011 disaster was described as "the toughest and the most difficult crisis for Japan" by the Japanese Prime Minister, according to a CNN report.

However, public opinions about the Nobel Peace Prize are mostly positive. This school of thought believes that the nuclear-based energy solution is necessary for the development and one of the best energy source for clean and green energy. To understand the public reaction or opinion about both the events, we use social media data, namely Twitter, in this study. We have considered Twitter data in two phases: from March 2011 to July 2011 immediately after the Fukushima nuclear disaster (procured from GNIP, a subsidiary of Twitter) and from August 2017 to December 2017 after the announcement of the Nobel Peace Prize using the Twitter API. We have considered the following keywords for our data: #fukushima, #Nuclear, #Nuclear Energy, #Disaster, #Nuclear power plant, #Radioactive waste, and #nucleardisaster. The resulting corpus has a total of 3 million tweets (related to the 2011 nuclear disaster) and 3.5 million tweets (after the 2017 Nobel Peace Prize announcement).

B. Classification and Preparation of Gold Standard

At the time of the nuclear disaster, many types of information appeared on the social media, such as facts about nuclear power, pros and cons about nuclear energy, fears of civilian, government warning, rumor, etc. Some of this information was factual, which did not carry any subjective information. However, subjectivity comes from different people, different sources and that is the reason behind the different opinions on the same issue. Based on subjectivity, we can classify opinions into two classes, namely subjective opinion and fact-implied opinion [6]. A subjective opinion is a regular or comparative opinion given in a subjective statement, "Coke tastes great."

A fact implied opinion is a regular or comparative opinion implied in an objective or factual statement, like "My dad bought the car yesterday, and it broke today" [6]. Subjectivity detection is a task of NLP, which helps us to filter out non-a-subjective or neutral text for efficient polarity detection [11]. From extant literature, it can be argued that subjectivity detection before polarity detection will allow a better foundation for the overall sentiment analysis process. In our study, we will confine ourselves to public opinion about nuclear energy. Therefore, we initially selected around 3,500 tweets (after removing retweets, concise text, near similar text) related to nuclear energy. We obtained unanimous agreement (i.e., all three volunteers assigned the same label to a tweet) for 2,308 tweets. Three human annotators independently read the tweets, deciding whether these tweets are subjective. In the same way, we also annotated the tweets for polarity detection means positive or negative. Table III shows the number of tweets in the gold standard finally created.

TABLE III. SAMPLE ANNOTATED TWEETS

Theme & Class		**# of Tweets**	**Sample Tweets**
Subjectivity Detection	***Subjective***	1529	***1.*** It amazes me that people still don't realize how much nuclear would affect our economy for the good and decrease the price of fuel, etc. ***2.*** I am starting to get angry about how someone was stupid enough to build nuclear power plants on/near earthquake zones!
	Objective	779	***1.*** Japan's nuclear safety agency says pressure inside the reactor has risen 1.5%. reports of radiation levels 1000x more inside control room. ***2.*** Following the shutdown of Kashiwazaki-kariwa nuclear power plant in 2007, price of the nuclear fuel collapsed 60% from record levels of $136.
Total		***2308***	
Polarity Detection	***Postive***	772	***1.*** Highly recommend this to anyone interested in energy innovation. Reinventing nuclear is key to achieving a low-carbon energy ***2.*** Hopefully the reactor problems that Japan is having in the aftermath doesn't lead to fear of using nuclear power across the world.
	Negative	757	***1.*** I sure hope that nuclear reactor in Japan doesn't meltdown. What a tragedy they're going through already, even without radiation worries. ***2.*** Wow, an 8.9 earthquake? And I head they had some trouble with nuclear plant and they evacuated 3k people. hope everyones alright in Japan.
Total		***1529***	

C. Our Approach

With the recent development of deep learning, research in AI has gained new vigor and prominence. Machine learning, however, suffers from three big issues, namely: dependency (as it requires training data and is domain-dependent), consistency (as different training or tweaking leads to different results), and transparency (as the reasoning process is uninterpretable).

We address such issues in the context of NLP through a multi-disciplinary approach that aims to bridge the gap between statistical NLP and many other disciplines that are necessary for understanding human languages, such as linguistics, commonsense reasoning, and affective computing.

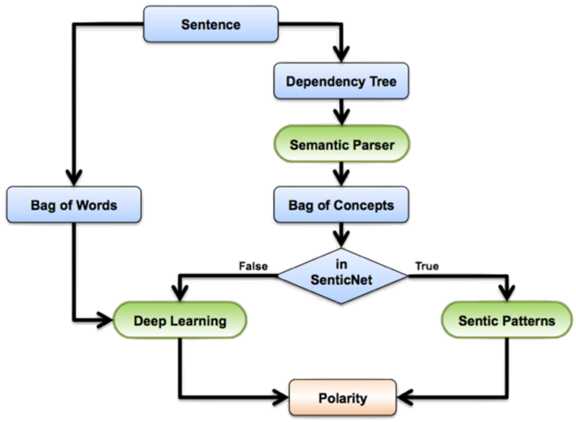

Fig. 1. Proposed Architecture

This is possible thanks to an approach to NLP that is both top-down and bottom-up: top-down for the fact that we leverage symbolic models such as semantic networks and conceptual dependency representations to encode meaning; bottom-up because we use sub-symbolic methods such as deep neural networks and multiple kernels learning to infer syntactic patterns from data. Coupling symbolic and sub-symbolic AI is key for stepping forward in the path from NLP to natural language understanding. Relying solely on machine learning is simply useful to make a 'good guess' based on past experience because sub-symbolic methods only encode correlation and their decision-making process is merely probabilistic. In this work, apply an ensemble of symbolic AI, namely SenticNet and Sentic Patterns, and subsymbolic AI, i.e., deep learning to categorize public opinions about nuclear energy better. Deep learning is also used for subjectivity detection, i.e., for filtering out neutral content.

D. SenticNet

SenticNet [7] is a concept-level knowledge base that provides a set of semantics, sentics, and polarity associated with 100,000 natural language words and multi-word expressions. In particular, semantics are concepts that are most semantically-related to the input concept (i.e., the five concepts that share more semantic features with the input concept), sentics are emotion categorization values expressed in terms of four affective dimensions (Pleasantness, Attention, Sensitivity, and Aptitude) and polarity is floating number between -1 and +1 (where -1 is extreme negativity and +1 is extreme positivity). The knowledge base is downloadable for free as a standalone XML file (http://sentic.net/downloads) and its latest version (released every two years) is also accessible as an API (http://sentic.net/api).

Unlike many other sentiment analysis resources, SenticNet is not built by manually labeling pieces of knowledge coming from general NLP resources such as WordNet or DBPedia. Instead, it is automatically constructed by applying graph-mining and multi-dimensional scaling techniques on the affective commonsense knowledge collected from three different sources, namely: WordNet-Affect, Open Mind Common Sense and GECKA.

SenticNet encodes the denotative and connotative information commonly associated with real-world objects, actions, events, and people. It steps away from blindly using keywords and word co-occurrence counts, and instead relies on the implicit meaning associated with commonsense concepts. Superior to purely syntactic techniques, SenticNet can detect subtly expressed sentiments by enabling the analysis of multiword expressions that do not explicitly convey emotion, but are instead related to concepts that do so.

E. *Sentic Patterns*

SenticNet can be used for different sentiment analysis tasks, including polarity detection, which is performed through sentic patterns [9]. Sentic patterns are linguistic patterns for concept-level sentiment analysis, which allow sentiments to flow from concept to concept based on the dependency relation of the input sentence and, hence, to generate a binary (positive or negative) polarity value reflecting the feeling of the speaker.

Applying SenticNet without these patterns would be a mistake as the knowledge base alone can only provide the polarity associated to concepts but not of the overall sentence. To this end, sentic patterns are applied to the dependency syntactic tree of each sentence. The tree can be re-interpreted in the form of a ‘circuit’ where the ‘signal’ flows from one element (or subtree) to another. After removing the words not used for polarity calculation, a circuit with elements resembling electronic amplifiers, logical complements, and resistors is obtained.

F. *Deep Learning*

Recently, researchers are using deep learning-based methods in areas like medical image processing, stock market prediction, social media analysis and heavy manufacturing industry to explore the unknown business insights from the domain-specific large amount of data [23], [24], [33]. The development of NLP in the last few decades mostly relied on statistical learning and the syntactic nature of text data. Statistical learning helps us to capture the syntactic relation within the text data, but nowadays, we cannot rely only on syntactic knowledge to capture the underlying theme of social media discussion. Hence, in the last couple of years, NLP has changed its focus from syntactic to a semantic understanding of the text data. For instance, in the domain of text classification, researchers are using a deep neural network to classify the text according to their content. In this study, we consider three deep neural network-based classification models like CNN, long short-term memory (LSTM) and bi-directional LSTM (Bi-LSTM) for classifying the nuclear energy-related social media discussion.

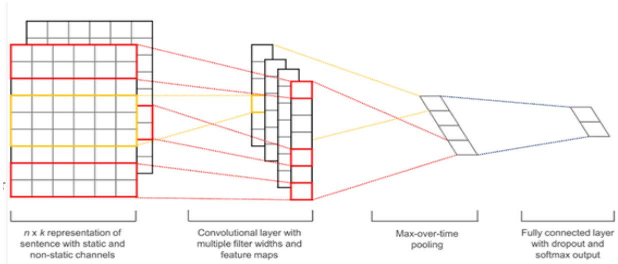

Fig. 2. A Conceptual Architecture of CNN

CNN is predominantly used in computer vision-related tasks. Recently, however, CNNs are also becoming popular for different NLP related tasks. A simple CNN with a single layer of convolution is used for feature engineering. The CNN network is also used for different types of sentence classification tasks such as sentiment analysis, text classification, dialogue generation, machine translation, summarization and question answering (QA). For example, [18] used a dynamic CNN for sentence classification and showed significant improvements over traditional tasks such as sentiment and question type (raw texts) classification. Similarly, [21] applied a much simpler CNN to sentences classification and garnered competitive results. Other studies, such as [13] and [34], also considered a character-level CNN with very deep architecture to compete with traditional BOW or n-gram models.

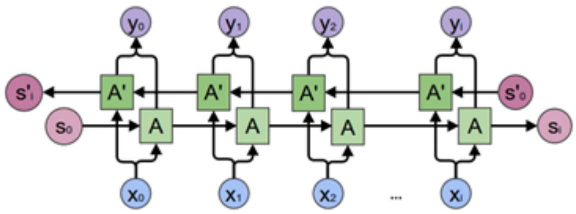

Fig. 3. A Conceptual Architecture of Bi-LSTM

The first layer of CNN embeds words into low-dimensional vectors. For embedding purposes, some models used pre-trained word vectors, whereas other approaches considered self-defined word vectors contrived from scratch. The next convolution layer performs convolutions over the embedded word vectors using multiple filter sizes. These convolutional filters are also called kernels of different sizes, which slides over the word embedding matrix.

The next layer consists of max-pooling for providing a fixed dimension output for the desired classification task. In CNN, a dropout layer is a popular approach to stochastically discard a fraction of neurons in the network to prevent over-fitting. Otherwise, there is always a chance to develop co-dependency between neurons in a fully connected layer during the training process, which leads to over-fitting of the result. In this context, averaging the output using the dropout layer helps us to prevent over-fitting of the training data.

As we discussed in the previous section, one of the main advantages of RNN is that it can use the previous information during the processing of the present computational task. In other words, it predicts the next word in NLP using the sequence of previous words (which it has learned during the past information processing). For instance, an RNN can predict the last part of the text “I grew up in France. So, I speak fluent _____”. RNN will be capable of suggesting that ‘the next word is probably the name of a language.’ However, to narrow down the prediction of which language, RNN considers the context of 'France' from the previous part of the text and predicts "French" (Source: Colah blogs). It is worth noting that if there is a long text data between the two sentences "I grew up in France" and "So, I speak fluent _____," then RNN fails to predict 'French.'

In the deep-learning domain, this shortcoming of RNN gets addressed by the LSTM model. LSTM has an additional forget gate over the simple RNN model [16], [17], [33]. Thus, the LSTM model consists of three gates as following: input gate, forget gate, and the output gate. LSTM model calculates the hidden state by taking a combination of these three gates as per equation below:

$$x = \begin{bmatrix} h_{t-1} \\ x_t \end{bmatrix}$$
$$f_t = \sigma(W_f . x + b_f)$$
$$i_t = \sigma(W_i . x + b_i)$$
$$o_t = \sigma(W_o . x + b_o)$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tanh(W_c . x + b_c)$$
$$h_t = o_t \odot \tanh(c_t)$$

Bidirectional LSTM is an extension of traditional LSTM models. Prior studies have noted that bidirectional LSTM can improve model performance in the context of the sequence classification problem. Hence, in some particular domains, Bi-LSTM is better than classical LSTM. In an LSTM model, the input sequence feed in the network is only in the forward direction. However, a bidirectional LSTM feeds the same input sequence on a reversed copy of the original one. This bidirectional setup helps the network to learn a better context for classification problems. Unidirectional LSTM retrieves the information from past sequences only, but bidirectional will run inputs from two directions, and this preserves the information not only from the past sequence but also from the future sequence, which is most appropriate for the highly complex sequence.

V. FINDINGS

This section reports the accuracy of our different models, which are used to detect subjectivity and polarity. For training the classifier, we consider 80% of these annotated tweets, which includes 20% data for validation and the remaining unexposed 20% data were considered for testing the model accuracy. Our settings for the dropout layer are 0.5 and 0.2 for BI-LSTM and CNN, respectively. We have considered softmax activation in our final classification layer to predict the final class. Results were similar across different batch sizes, epochs, dropout rates, embedding dimensions, and different kernel sizes for CNN. Thus, for the sake of brevity, we report the best results. We use 'rmsprop' as our optimizer. We have performed training in batch sizes of 32 for all four models.

CNN is our best performing model for subjectivity detection, and it has an overall accuracy of 80.7%, followed by Bi-LSTM 77.2% and LSTM 56.7% (see Tables IV, V, & VI). CNN also performed well for polarity detection in concomitance with SenticNet, reaching 92.4% accuracy (see Tables VII, VIII, & IX). Following [46], we have also reported some wrongly annotated tweets and probable reasons for misclassification in Table X.

TABLE IV. SUBJECTIVITY-OBJECTIVITY ANALYSIS USING CNN

Model	**CNN**	**Actual Label**	
Accuracy	***80.7%***	***Subjective***	***Objective***
Predicted Label	***Subjective***	91	33
	Objective	55	278

TABLE V. SUBJECTIVITY-OBJECTIVITY ANALYSIS USING LSTM

Model	**LSTM**	**Actual Label**	
Accuracy	***56.7%***	***Subjective***	***Objective***
Predicted Label	***Subjective***	70	122
	Objective	76	189

TABLE VI. SUBJECTIVITY-OBJECTIVITY ANALYSIS USING BI-LSTM

Model	**Bi-LSTM**	**Actual Label**	
Accuracy	***77.2%***	***Subjective***	***Objective***
Predicted Label	***Subjective***	94	52
	Objective	52	259

TABLE VII. POLARITY ANALYSIS USING SENTICNET & CNN

Model	**SenticNet + CNN**	**Actual Label**	
Accuracy	***92.4%***	***Subjective***	***Objective***
Predicted Label	***Subjective***	144	13
	Objective	10	136

TABLE VIII. POLARITY ANALYSIS USING SENTICNET & LSTM

Model	**SenticNet + LSTM**	**Actual Label**	
Accuracy	***92.1%***	***Subjective***	***Objective***
Predicted Label	***Subjective***	139	9
	Objective	15	140

TABLE IX. POLARITY ANALYSIS USING SENTICNET & BI-LSTM

Model	**SenticNet + Bi-LSTM**	**Actual Label**	
Accuracy	***92.1%***	***Subjective***	***Objective***
Predicted Label	***Subjective***	142	12
	Objective	12	137

TABLE X. ANALYSIS OF WRONGLY CLASSIFIED TWEETS

Sample Tweets	**Actual Label**	**Probable Reasons**
Physical Science We have a guest speaker to discuss alternative energy sources and hopefully give you a new perspective on nuclear energy	Objective	Annotators felt that this tweet is objective information about the talk
Renewable energy is more scalable and a better fit to address global warming than nuclear because it costs much less	Subjective	Subjective view about nuclear, in comparison to renewable energy, is implicit, not explicit
Doesn't hide the fact that nuclear power is not the green and safe way why not hydroelectric power we're surrounded by water	Negative	The tweet is positive about hydroelectric but not nuclear
yeah the nuclear plants are a definite hazard if something happens there but from what I've heard sounds like its low risk	Positive	Tweet mentions both the views

VI. DISCUSSION

To understand the public perception of any social media discussion, we can employ different types of NLP tools. Researchers have proposed different methods with a certain amount of granularity to extract the required information from a particular text document [29]. Most of the social issues create public opinion in a fractured manner as there can be so many views on a particular topic. To capture the detailed view and subline issues, we have applied aspect extraction from tweets. Aspect-based opinion mining is an effective tool and an essential module in NLP. Aspect-based opinion analysis consists of two subtasks - one is aspect extraction, and the second is grouping the different aspects into a broad category for that particular domain. For example, a sentence like "The screen of this mobile phone is bright, but the music quality is not good" contains two aspects, namely screen and music player of the mobile phone.

Aspects can be divided into two groups one is called explicit aspect, and another is called implicit aspects. In the above-mentioned example, the screen and the music player are explicit aspects. Sometimes this implicit aspect is not clear or directly available as an entity; instead, it presents in such an underline structure which is difficult to extract. To capture these different aspects, we have used Sentic LSTM [29] on Nuclear energy-related tweets. We have classified our data into two groups one is in favor of nuclear energy, and another one is opposing nuclear energy. We have identified the different concerns about nuclear disaster and energy using aspect extraction from tweets.

TABLE XI. EXTRACTED ASPECTS & CORRESPONDING TWEETS

Sample Tweets	Aspects
Want renewable energy by the way? Stop voting for Democrats who keep blocking attempts to make nuclear energy more competitive.	Renewable energy
Oil-rich Saudi Arabia wants nuclear power to diversify its energy supply, so it can export more crude rather than burn it.	Energy supply, export
Good luck to Germany lowering its CO2 emissions with energy production like that. They need to double their nuclear.	Energy production
When we talk about energy policy, someone waving a sign and shouting "no nukes!" without understanding nuclear energy.	Energy policy
RT @XYZ: 320 000 tonnes of coal would be needed to supply your lifetime energy demands - compared to nuclear fuel the size of an egg	Coal, supply, Size
Threats of nuclear escalation, backward steps on energy policy have pushed scientists to now move the "Doomsday Clock" closer to "midnight."	Energy policy

Table XI reports the findings of aspect extraction. As mentioned earlier, we have pulled out the aspects by employing Sentic LSTM. We have not reported the exhaustive set of aspects, but just reported a few dominant aspects and their corresponding tweet. The dominant aspects of supporting tweets revolve around the theme of 'renewable energy' and 'energy production.' Twitter users have perceived that nuclear energy is required for development and this energy is also a sustainable solution for the future world.

Interestingly, the opposition camp viewed nuclear energy as unsafe, and that it is harmful to the environment. We also note that some tweets are comparing nuclear energy with other sources of energy, such as solar energy, wind energy, coal energy, hydro energy, and others (see Table XI for a few examples). This aspect extraction analysis helps us to understand public opinion about nuclear energy better.

VII. CONCLUSION

This paper explored Twitter deliberation to understand public sentiment about nuclear-related issues. We have used an ensemble of symbolic and subsymbolic AI for subjectivity and polarity classification, and we have observed that the linguistic content of nuclear energy-related tweets is ambiguous. Hence, we have also tried to study when AI fails to classify a tweet correctly. Overall, our approach has achieved relatively high accuracy for the sentiment classification task. We observed that immediately after the 2011 Fukushima disaster, only 19% of tweets about nuclear power were positive. Interestingly, around 32% of tweets were positive when we considered the period immediately after the Nobel Peace Prize announcement in 2017. Hence, public opinions and awareness are dynamic. However, a significant portion of users is skeptical about nuclear power even today [1].

Our aspect-based analysis will help the government agencies to understand why social media users are apprehensive about nuclear energy. Users perceive nuclear energy as a threat to the environment, human life, and safety. Hence, the government should take appropriate measures to address these issues through various communication channels. Many of these concerns are due to a lack of awareness. A small portion of users is supportive because they think nuclear energy is a source of clean energy. They also associate nuclear energy with lower CO2 emissions and a sustainable future. Hence, we recommend that government agencies should emphasize these brighter sides of nuclear energy to increase awareness among the public. Also, the government has to take proactive steps to address nuclear energy-related myths and misconceptions. One potential drawback of our study is that - social media users may not represent the entire society.

Thus, Twitter users might be a biased sample because prior studies have observed that younger generations are more active on social media platforms. Possibly, the younger generation might support pro-nuclear policy in the future but not the older generation who had experienced disasters like the Fukushima accident in the past. Hence, future studies might consider other data sources to probe this further.

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