Research Paper

JIS

Journal of Information Science
1–15

DOI: 10.1177/01655515211007724
journals.sagepub.com/home/jis
SAGE

A guided latent Dirichlet allocation approach to investigate real-time latent topics of Twitter data during Hurricane Laura

Sulong Zhou
Nelson Institute for Environmental Studies, University of Wisconsin–Madison, USA; Department of Computer Sciences, University of Wisconsin–Madison, USA

Pengyu Kan
Department of Computer Sciences, University of Wisconsin–Madison, USA

Qunying Huang
Department of Geography, University of Wisconsin–Madison, USA

Janet Silbernagel
Nelson Institute for Environmental Studies, University of Wisconsin–Madison, USA; Department of Planning and Landscape Architecture, University of Wisconsin–Madison, USA

Abstract
Natural disasters cause significant damage, casualties and economical losses. Twitter has been used to support prompt disaster response and management because people tend to communicate and spread information on public social media platforms during disaster events. To retrieve real-time situational awareness (SA) information from tweets, the most effective way to mine text is using natural language processing (NLP). Among the advanced NLP models, the supervised approach can classify tweets into different categories to gain insight and leverage useful SA information from social media data. However, high-performing supervised models require domain knowledge to specify categories and involve costly labelling tasks. This research proposes a guided latent Dirichlet allocation (LDA) workflow to investigate temporal latent topics from tweets during a recent disaster event, the 2020 Hurricane Laura. With integration of prior knowledge, a coherence model, LDA topics visualisation and validation from official reports, our guided approach reveals that most tweets contain several latent topics during the 10-day period of Hurricane Laura. This result indicates that state-of-the-art supervised models have not fully utilised tweet information because they only assign each tweet a single label. In contrast, our model can not only identify emerging topics during different disaster events but also provides multilabel references to the classification schema. In addition, our results can help to quickly identify and extract SA information to responders, stakeholders and the general public so that they can adopt timely responsive strategies and wisely allocate resource during Hurricane events.

Keywords
Hurricane Laura; latent topics; natural disaster; situational awareness; Twitter

1. Introduction

Formed on 20 August and dissipated by 29 August 2020, Hurricane Laura was a deadly and destructive Category 4 Atlantic hurricane [1]. The storm killed 31 people in Haiti [2], three in the Dominican Republic [3] and prompted the

Corresponding author:
Qunying Huang, Department of Geography, University of Wisconsin–Madison, Madison, WI 53706, USA.
Email: qhuang46@wisc.edu

evacuation of more than 160,000 people in Cuba [4]. Early on 27 August, Laura made landfall near peak intensity at Cameron, Louisiana [5]. It ranked with several other landfall hurricanes in a tie for fifth place by wind speed (150 mph) on record [6]. At least 14 people died in the United States [7], and it inflicted significant damage to southwestern Louisiana and southeastern Texas with insured damage estimated at close to $9 billion [8].

A key premise of making decisions for disaster response is having prompt, available and accurate situational awareness (SA) [9]. SA is 'all knowledge that is accessible and can be integrated into a coherent picture, when required, to assess and cope with a situation' [10]. Retrieval of SA can help society and decision makers understand the current situation and potential hazards and forecast the ensuing risks and repercussions for the affected community [9,10]. Since relevant and timely information are necessary to inform SA, and for effective and rapid decision-making to direct response and recovery activities, the growth of sharing in-time messages through social media has contributed to production of SA [11,12].

Ranked as one of the top 10 popular social media websites, Twitter has 400 million registered users and over 500 million tweets generated every day [13]. With the capability of real-time feedback and time stamps to provide conversation updates to users, Twitter data have been used for a broad range of applications in natural disasters including fire [14], flood [15], earthquake [16] and hurricane [17]. Natural language processing (NLP) has been known as the most effective technology to mine tweets without fatigue and in a consistent, unbiased manner [18]. During the last decade, variant approaches for detecting the topics in a corpus of tweets have been proposed based on rapid development of neural network (NN) in NLP. Regarding topic classification task, convolutional neural network (CNN) and recurrent neural network (RNN) strongly outperform traditional machine learning models such as logistic regression (LR) and support vector machine (SVM) [19,20]. However, the models based on NNs are costly and time-consuming because they require extensive training data. In addition, they are prone to underfit and overfit problems [21,22]. In particular, the pre-training step requires that millions of tweets must be labelled in advance [23,24], which impedes processing real-time tweets and thus obstructs retrieving SA information. Moreover, as high imbalance is naturally inherent in tweets of different topics [25], regular network models have not shown significant performance and extra complicated strategies are in demand to address the imbalanced data problem [26].

Latent Dirichlet allocation (LDA) model was introduced to reduce the workload and handle imbalanced data [27,28] with a bonus to investigate latent topics of a corpus [29]. In general, LDA models assume that documents consist of a distribution of topics and that topics are made up of a semantically coherent distribution of words. It is an unsupervised algorithm that models each document as a mixture of topics in order to generate automatic summaries of topics in terms of a discrete probability distribution over words for each topic, and further infers per-document discrete distributions over topics [30]. As such, this work intends to leverage LDA models to rapidly assist in disaster response and inform SA, and provide reusable code for future implementation.

Specifically, the objectives of the present work are as follows:

1. Propose a guided LDA approach that integrates domain knowledge, coherence models, latent topics visualisation and validation from official reports;
2. Mine tweets to reveal common classification schema for future use in supervised models;
3. Investigate temporal latent topics to further inform SA for decision makers and local citizens during the Hurricane Laura.

2. Related work

Previous research has proposed different topics classification schema for different disaster events. Vieweg et al. [31] proposed 12 general topics schema for fire and flooding events including warning, preparatory activity, hazard location, flood level, weather, wind visibility, road conditions, advice, evacuation information, volunteer information, animal management and damage/injury reports. Imran et al. [32] proposed five general topics schema for Tornado Joplin and Hurricane Sandy including caution and advice, information source, donation, casualties and damages, and unknown. Huang and Xiao [33] proposed a 47 topics schema based on different disaster stages, including preparedness, emergency response and recovery. In fact, existing studies indicated that the design of the coding schema and associated message classification methods are highly varying and depend on different disaster event types, the analysis purpose or classification purpose of the event and the social media platforms [12]. Since the classification schema varies across research studies and disaster events, it is necessary to identify our own topics schema for Hurricane Laura.

Supervised learning has been used for extracting information from social media for disaster management and response. Habdank et al. [34] collected 3785 tweets during a pipeline explosion accident in Ludwigshafen, Germany and applied supervised learning algorithms, including naive Bayes, decision trees, random forests, SVMs and NNs, to classify whether a tweet was relevant to this accident. Pouyanfar et al. [35] analysed the audio and visual content from more than 1000 video clips from Hurricane Harvey and over 450 video clips from Hurricane Irma on YouTube, using NNs to classify these videos into seven different semantic classes. In these studies, large sets of pre-labelled data were required for the training and validation process, and the label task was extremely time consuming. Also, each piece of data was only assigned to a single label. However, a social media message can often contain multiple semantic meanings. For example, a message 'winds are still 65 mph … over 10 people killed and avoid the flooding area' contains information on 'Information Source', 'Advisory' and 'Casualty' categories. Furthermore, the categories and the criterion of each category defined in these studies are event dependent, which potentially limits their applications across different events.

LDA has been applied to several fields such as software engineering, political science, medical science and geography. More than 200 related scholarly articles from 2003 to 2016 have been fully discussed and reviewed to discover the development, trends and intellectual structure of topic modelling based on LDA [36]. The prominence of LDA model application continues on research regarding natural disasters. Sit et al. [37] proposed a NLP model with LDA to extract detailed information such as affected individuals, donations and support, caution and advice from tweet content for Hurricane Irma. Karami et al. [38] proposed a Twitter SA framework with LDA model to track the negative concerns of people during the 2015 South Carolina flood. Alam et al. [39] proposed an unified framework including LDA to help humanitarian organisations in their relief efforts during Hurricanes Harvey, Irma and Maria. However, there remain two major problems. First, these studies lack a quantitative validation to evaluate the coherence of topic clusters derived from the LDA model. Second, regular LDA models are limited to short tweet text because frequent words are shared between topics and sometimes distinct topics cannot be tagged for each group of words [40].

Evaluation of LDA models is notoriously challenging due to its unsupervised training process. Based on different metrics and purposes, the common evaluation methods include human judgement (eye balling), intrinsic evaluation (perplexity and coherence) and extrinsic evaluation [41]. In the original LDA paper, Blei et al. [30] recommended the perplexity metric as an intrinsic evaluation to justify the selected LDA model. However, subsequent studies have revealed that perplexity is not correlated to, and is even sometimes slightly negatively correlated to human judgement. Sievert and Shirley [42] developed LDAvis, a web-based interactive visualisation python package, to flexibly conclude a fitted LDA model. It allowed for a deep inspection of the keywords most highly associated with each individual topic but without showing specific quantified values as validation. Röder et al. [43] proposed the concept of six-topic coherence metrics by measuring the degree of semantic similarity between high scoring words in the topic. However, the score only reflects the quantified results but does not demonstrate human interpretable content for each topic.

To solve above problems, we proposed a guided LDA approach with pre-defined topic candidates based on domain knowledge, the most effective coherence metric and topic visualisation tool. This approach allows us to select optimal topic numbers and validate the results with both intrinsic evaluation and human judgements. Furthermore, to our knowledge, no other research has used the LDA model with our guided approach to inform SA for the latest Hurricane Laura.

3. Methods

Our framework is mainly comprised of four steps: data collection, data pre-processing, guided LDA and latent topic clusters selection (Figure 1).

3.1. Data collection

Twitter API, despite being free, is limited as users can only retrieve a small portion of relevant tweets. Twint [44] is an advanced Twitter scraping tool written in Python that allows for scraping tweets from Twitter profiles without using Twitter's API. Twint utilises Twitter's search operators to let you scrape tweets from specific users, scrape tweets relating to certain topics, hashtags and trends, or sort out sensitive information from tweets.

3.2. Data pre-processing

Pre-processing is a requisite to convert tweets into a form that is predictable and analyzable for our task. Here are some of the approaches we used in this project:

- *Lowercasing*: removes duplicate words and significantly helps with consistency of expected output, for example, Hurricane → hurricane.

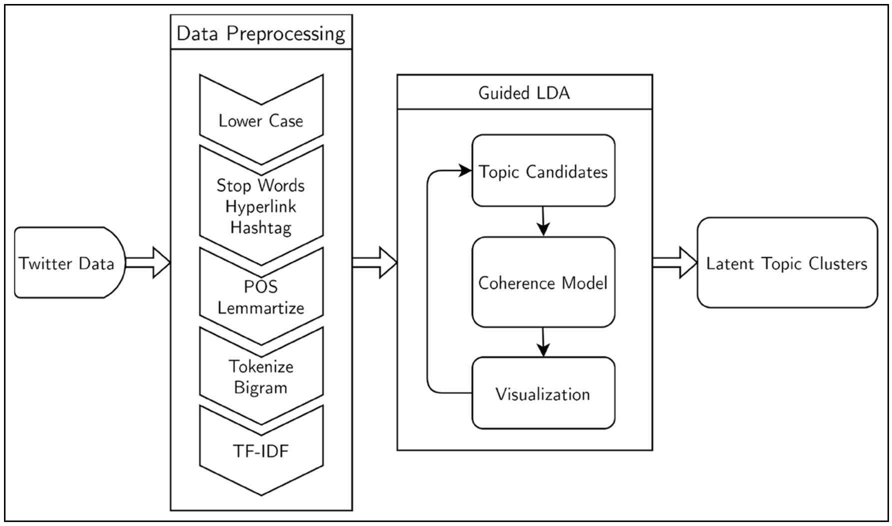

Figure 1. Overview of the proposed workflow of Guided LDA model.

- *Part of speech (POS) tagging*: assigns a POS tag, such as noun, verb and adjective, to each token depending on its usage in the sentence. It is essential for building lemmatisers, for example, storm → noun, and kill → verb.
- *Lemmatisation*: removes inflections and maps a word to its root form without changing its POS, for example, worse → bad, and damaging → damage.
- *Stopword removal*: stop words are a set of commonly used words in a language and across tweets, for example, ‘a’, ‘the’, ‘is’, ‘are’ and ‘hurricane’. By removing low information words from text, we can focus on the important words instead.
- *Noise removal*: removes characters, digits, hashtags, hyperlinks and pieces of text that can interfere with our text analysis.
- *Tokenisation*: separates a piece of tweets into smaller units such as words, or a pair of words (2-gram), for example, ‘Mass destruction in one Lake Charles neighborhood’ → ‘Mass’, ‘destruction’, ‘in’, ‘one’, ‘Lake_Charles’ and ‘neighborhood’.
- *Term frequency–inverse document frequency (TF-IDF)*: assigns a weight to each word based on word frequency which balances the importance of the word in the tweets and corpus.

3.3. Topic model analysis

3.3.1. Regular LDA. LDA is a generative probabilistic model. We assume the total amount of topics as k. The probability of a generated collection D of tweets d is expressed as [30]

$$p(D|\alpha, \beta) = \prod_{d=1}^{M} \int p(\theta_d|\alpha) \cdot \left(\prod_{n=1}^{N_d} \sum_{z_{dn}} p(z_{dn}|\theta_d) p(w_{dn}|z_{dn}, \beta) \right) d\theta_d \tag{1}$$

where D is the collection of tweets d and composed of M tweets, $d = 1, \ldots, M$. θ_d is the distribution of the k topics for a tweet d, where θ_d is a k dimensional vector and $\sum_{i=1,\ldots,k} \theta_d^i = 1$. Specifically, θ_d^i means the probability for tweet d to have the topic i. Furthermore, θ_d is selected through a topic-tweet distribution $p(\theta_d|\alpha)$, which has a prior Dirichlet distribution with parameter α, that is, $\theta_d \sim p(\theta_d|\alpha) = Dir(\alpha)$. For the tweet d, it has N_d amount of words. For the nth word w_{dn} in the tweet d, where $n = 1, \ldots, N_d$, it has possible topic z_{dn}. The probability or word-topic distribution for the word w_{dn} given the topic z_{dn} is described with parameter β, that is, $p(w_{dn} = j|z_{dn} = i, \beta) = \beta_{ij}$. The conditional probability for topic z_{dn} to be i, given the topic distribution θ_d, is $p(z_{dn} = i|\theta_d) = \theta_d^i$.

The prior distribution for the topic-tweet distribution and the word-topic distribution α and β, are initialised as hyperparameters. During the training process, the goal is to train the posterior distribution of these two distributions based on the observed collection of tweets D, such that we can maximise the generative probability for $p(D|\alpha, \beta)$.

At the end of training, the semantic meaning of each topic i is represented by the word-topic distribution associated with topic i, that is, the ith row β_i of the matrix β. The conditional probability β_{ij} for word j based on the topic i is the semantic weight for this word j under this topic i. The higher weight of a word means that this word is more representative for the topic. Therefore, we can select the top 10 words with the highest weights in the row β_i to describe the semantic meaning for this topic i.

3.3.2. Coherence model. The coherence value for a single topic measures how the top scoring words in this topic are semantically similar to each other. As compared with the conventional topic perplexity measurement, which measures how well a trained model can fit or represent the distribution for an unseen tweet [45], coherence measurement focuses more on the interpretative aspect of a topic and has a high correlation to the human scoring of topics [43], whereas the perplexity measurement is sometimes not related to and may even be negatively related to human judgement and interpretation [46]. Therefore, coherence value can provide a better measurement on the semantic performance of the LDA model and the selected topics. Furthermore, due to the correlation between the coherence measurement and human judgement, the higher coherence value indicates that the topic is more interpretive and meaningful for human interpretation. Thus, we adopt the coherence measure during the process of hyper-parameter tuning and select the hyper-parameter k, α and β at which the highest coherence value is reached. In this way, the selected hyper-parameters k, α and β can provide a more meaningful topic selection for tweets along with the LDA model, compared with a random selected hyper-parameters.

3.3.3. Topic visualisation. pyLDAvis is designed to help users interpret the topics in a topic model that has been fit to a corpus of text data [42]. The package extracts information from a fitted LDA topic model to inform an interactive web-based visualisation.

Since each topic is embedded in a high-dimensional space, the pyLDAvis applies the mutidimensional scaling and dimensionality reduction techniques to project each topic's high-dimensional embedding onto the 2D space for visualisation purposes [42]. Specifically, we use the t-distributed stochastic neighbourhood embedding (t-SNE) method in the pyLDAvis package, which is a non-linear dimensionality reduction method. As compared with pyLDAvis' default principal component analysis (PCA) method, which maximises the variance of each topic's projection along the new axis [47], the t-SNE method considers the relative similarity between each topic in the high-dimensional embedding and preserves this similarity after the projection [48]. Therefore, the t-SNE method outperforms the PCA method for visualising the relative relationships between each topic in the projected 2D space and provides a better measurement for the quality of the selected topics.

Compared with traditional clustering techniques where each tweet can only belong to a single topic, an advantage of pyLDAvis is that a word can be clustered to different topics [39,42]. For example, the word 'hit' can appear in a context regarding to information source or damage, and the word 'evacuate' can appear in a context regarding to advisory or relief. In this case, it can better present the nature of language.

3.3.4. LDA with guided approach. The guided approach initially defines topic candidates based on previous research and domain knowledge. The topic candidates provide a specified direction for the word-topic distribution and the topic-tweet distribution to converge towards during the training of the LDA model.

In the regular LDA model, the model is purely trained with a probability-based target function in equation (1). It captures the relationships between words based on the frequency. Therefore, this model may only capture the superficial relationships between the words, which are the most frequent and apparent in the collected tweets [49]. However, this probability-based model performs badly for those less frequently appearing patterns of tweets, because lower frequency means that these patterns contribute less to the target function and thus become less important to be considered by the model. This model will merge these less frequent topics together into a larger topic group instead. Even though this merging process benefits a higher value for the probability-based target function, it harms the coherence and semantic of the topics, as two semantically disparate topics are merged together. Especially in the tweet data, the distribution of different topics is imbalanced and the regular LDA model will generate less interpretative topics.

Thus, we used a guided approach to solve this problem with human intervention. The potential range of numbers and contents of topic were estimated by integrating quantitative (coherence value) and qualitative evaluation (topic

Table 1. Examples of irrelevant tweets.

175,000 dead from the virus, over 1 million unemployed, no money, losing homes. California is on fire. Louisiana-Texas are preparing to be hit with double hurricanes and here you are once again pretending nothings going on and you, going to have a good old time at a party. Again WTF. (8.23)
Texas is facing a double hurricane, while California faces wildfires yet again. What is the republican plan to combat climate change? That what I like to hear. (8.25)
As if the US does not have enough to deal with now we have the consequences of climate change, Horrific wildfires and a Cat 5 unsurvivorable Hurricane and surge heights, during a pandemic. We must come together despite ethnicities, skin color and politics to survive. (8.26)

Table 2. Summary of tweets before and after pre-processing per day during Hurricane Laura.

Date	No. of tweets before pre-processing	No. of tweets after pre-processing	Effective percentage
8.21	2972	1184	39.84%
8.22	28,359	12,779	45.06%
8.23	35,911	16,867	46.97%
8.24	25,842	12,363	47.84%
8.25	48,794	32,697	67.01%
8.26	128,292	59,921	51.57%
8.27	61,339	27,466	44.78%
8.28	15,582	6910	44.35%
8.29	9821	5114	52.07%
8.30	6631	3026	45.63%
Total	363,542	184,564	50.76%

visualisation). Then, the event-specific SA categories and corresponding dominated words were manually summarised with minimal efforts.

4. Results and discussion

4.1. Effective tweets count and rate

We collected the tweets with removing duplicate retweets and searching criterion: 'Hurricane Laura OR Hurricane OR Laura' across 10 days between 21 and 30 August 2020. This time frame was selected based on the landing and duration of Hurricane Laura from 25 to 29 August 2020. After data pre-processing, some irrelevant tweets were filtered out (Table 1) and the number of tweets highly related to Hurricane Laura per day ranged from 1184 to 59,921 (Table 2). On average, 50.85% tweets per day were filtered out for the input for our LDA model.

As shown in Figure 2, the temporal pattern of tweet frequency closely corresponded to the temporal pattern of Hurricane Laura. As soon as Hurricane Laura intensified into a tropical storm on 21 August, 1184 highly related tweets emerged. With a rapid intensification of Hurricane Laura on 26 August [5], the amount of tweets rapidly increased to 59,921 in the same day (around 2.8 times than amount of tweets in previous day). During the 10-day period of Hurricane Laura, Twitter contributed 184,850 related unique tweets in total. However, the average effective rate of tweets was around 51%, which meant only half of the tweets truly contributed to related topics on SA after data pre-processing. The lowest percentage was 39% (1184 out of 2972) on 21 August, while the highest percentage was 67% (32,697 out of 48,794) on 25 August. Since tweets contained a significant amount of noise comprised of fake news, robot messages, advertisements and irrelevant cross-event topics [50,51], pre-processing data prior to topics analysis were necessary and crucial to retrieving precise situational information.

Similarly, in a previous research, 217,074 negative tweets, or 25% of original data, were filtered to showcase helping effective disaster response during the 2015 South Carolina flood because of the Hurricane Joaquin [38], and 20% of over millions of tweets with downloadable images were used as complementary information to improve SA with case studies of Hurricanes Harvey, Irma and Maria [39]. The large amount of data, yet with low percent effectiveness, can illustrate the temporal evolution of hurricane events, thereby informing SA and assisting in disaster response.

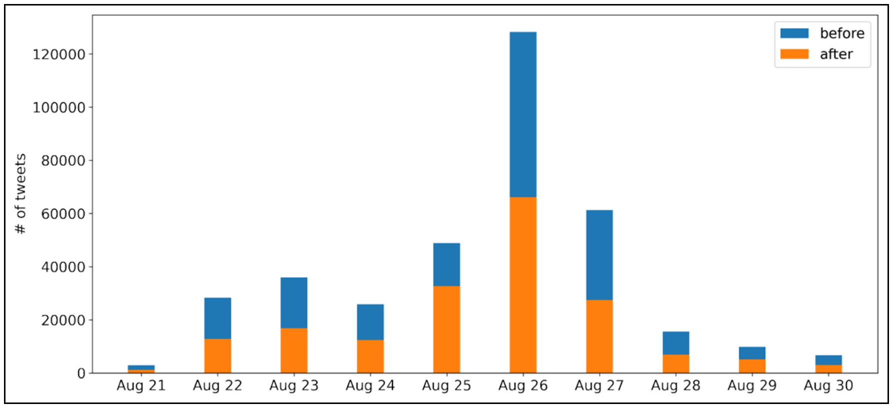

Figure 2. Histogram of tweet count before and after pre-processing per day during Hurricane Laura.

Table 3. Topic candidates referenced from previous research and supplemented from our model.

Candidates	Stage	Description
Advisory	Pre and during	Cautions, advices, warnings, alerts and preparedness
Casualty	During and post	Missing, injured and/or dead people
Damage	During and post	Impacts, damages and affected industries and areas
Relief	During and post	Services, donations and fundraisers to disaster response
Information source	Pre, during and post	Messages from an official news source, media
Emotion	Pre, during and post	Public concerns and feelings
Animal	During	Pet and wildlife protection

Table 4. Tuned hyper-parameters (α, β, k) per day during Hurricane Laura.

Date	α	β	Range of topics with coherence value	No. of topics with pyLDAvis
8.21	0.1	0.6	[3,4]	3
8.22	0.1	0.6	[4,5,6]	4
8.23	0.1	0.6	[5,6,7,8]	6
8.24	0.1	0.6	[6,7,8]	6
8.25	0.1	0.6	[6,7,8]	6
8.26	0.1	0.9	[5,6,7,8]	8
8.27	0.1	0.3	[6,7,8]	6
8.28	0.1	0.6	[3,4,5,6,7]	6
8.29	0.1	0.6	[5,6,7,8]	5
8.30	0.1	0.6	[2,3,4]	3

4.2. Optimal daily K topics

We designed a four-step workflow to estimate the optimal K latent topics for each day. In the first step, we summarised the five most common SA topics including 'Advisory', 'Casualty', 'Damage', 'Relief' and 'Information source' (Table 3) from previous hurricane-related research [31–33,38,39]. In our second step, we set different hyper-parameters in a regular LDA model, and then evaluated each model based on coherence value. The hyper-parameters included topic numbers k, α and β in the LDA equation (1). For each combination of them, we trained with 100 iterations to generate the coherence values and repeated this training process with 10 trials to calculate the average of coherence values (Figure 3). Based on the coherence value across the 10 trials, we selected the pair of (k, α, β) corresponding to the first peak on the graph (Table 4). However, for certain days, there might not exist a clear peak on the graph, as shown in Figure 3. In this case, instead of choosing a specific value for the number of topics k, we chose a range from 5 to 8 for k. In the third step,

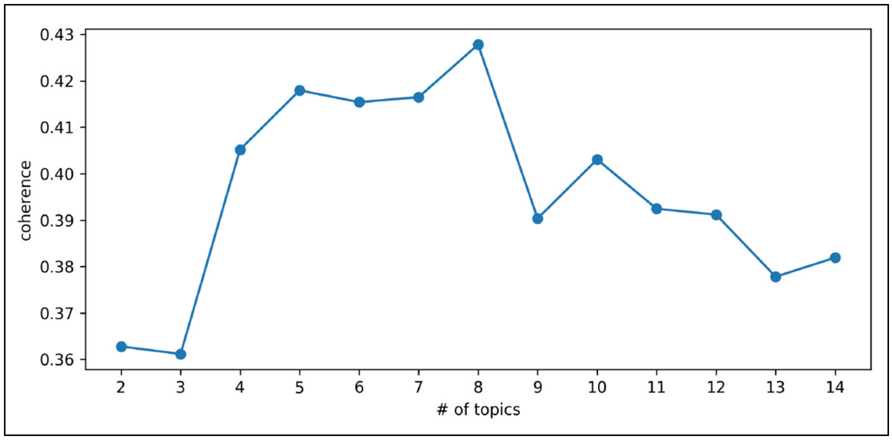

Figure 3. Coherence values of different K selected topics on 26 August.

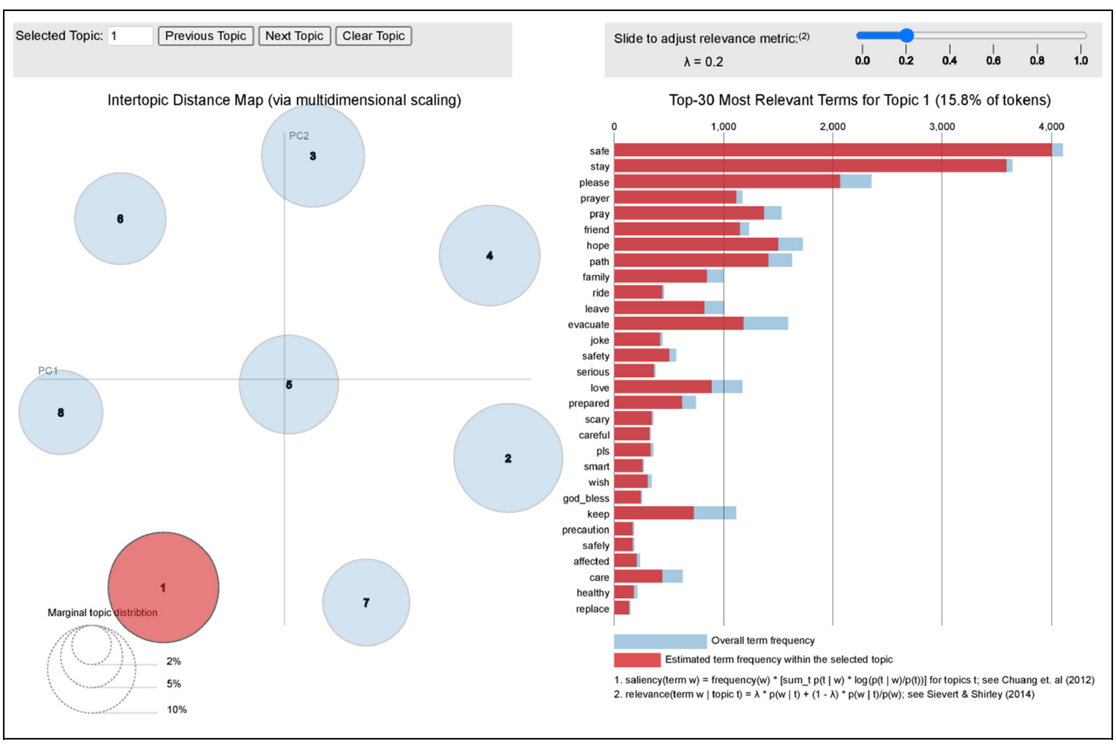

Figure 4. An example to visualise topic clusters and Top-30 dominant words for Topic 1 on 26 August.

using the selected hyper-parameters from the second step, we visualised the generated topics with pyLDAvis (Figure 4), evaluated if the current topics were humanly interpretable, and added two additional category candidates: ‘Emotion’ and ‘Animal’. Finally, we manually selected key words from the top 30 words visualised from pyLDAvis and matched them with the candidates category in Table 3. The final optimal topic number is shown in Figure 5, and corresponding key words for each day are shown in Table 5.

In the second step, the coherence value (Figure 3) and the optimal amount of topics were influenced by the value of α and β, where α was related to the distribution of topics given tweets and β was related to the distribution of words given topics. Empirically, a larger value of α represents more topics that a tweet can contain and it is usually initialised with the value of $1/k$, where k is the total amount of potential topics. In our model, we observed the optimal value of α was 0.1. On the other hand, a larger value of β showed that a topic consisted of more words. Based on the observation

Table 5. Final topic categories and corresponding keywords per day during Hurricane Laura.

Date	Advisory	Casualty	Damage	Relief	Information source	Emotion	Animal
8.21	warn, stock, stay safe, preparedness			shelter, help, protect, evacuate	eye, rain, flood, fema, youtube	scream, worried	
8.22	plan, warning, stay safe, prepared, public advisory, local statement			help, give, supply	cone, shear, tornado, flood, update, intensity, category, twitter	worry, surprised	
8.23	prep, advisory, stay safe, warning issue	die	power, collide, knock utility, terrebonne, lafourche, bernard	service, supply, evacuate, ascension	mph, surge, tornado, heavy rain, weather channel, weather authority, twitter	god, hope, care, pray, bless, scary	
8.24	tip, prep, stock, warning, checklist, stay safe	kill, die, deadly	ruin, wipe	evacuation, responder, supply, amazon	wind, heavy rainfall, cancel class, nhc, twitter, free fl511	god, pray, hope, scary	
8.25	stay, safe, prepare, plan, ready	kill, death	loss, devastate, break, affected	food, money, evacuate	flood, tornado, school close, nhc, news, popular google	hope, pray, care	
8.26	stay, safe, careful, prepare, precaution, public advisory	die, kill, dead, death	lng, oil price, power, trap, slam, house, catastrophic, sink entire, lake charles, beaumont	map, money, resource, recovery, evacuate, evacuation order, maximum sustain	gust, typhoon, 115 mph, forecast, emergency, flash flood, rapidly intensify, fox news, weather channel	cry, amen, hate, hope, pray, stress, terrify, love, peace, god bless	mare
8.27	warn, calm, careful, stay safe	death, kill, unsurvivable	slam, beast, outage, devastate, catastrophic, sulphur	map, radar, rescue, shelter, donate, protect, community	eyewall, gust, nhc, noaa, twitter, youtube, fox news abc news	hope, amen, jesus, mercy, peace, prayer, god bless	pet, mare, animal
8.28	safety, advisory, prepare, poison, carbon monoxide	victim, survivor, death toll	oil, batter, topple, refining, pollutant, gas industry, chemical plant, mississippi river, flow backward, destructive path	fund, donate, rebuild, support, response, recovery, voluntary, 90999 food, aerial picture	150 mph, emergency, flash flood, npr, nyt, wnt, fema, abc news, washington post	hope, pray, relief	
8.29	safety, poison, prepare, generator, carbon monoxide	death toll, woman dead	topples	fund, service, donation, recovery, cleanup start	rain, tornado, remnant, nyt, twitter, youtube	care, pray	
8.30		victim, death toll, family perish	power, loss value, devastate, destruction	donate, pledge, support, sell ebay, recovery			

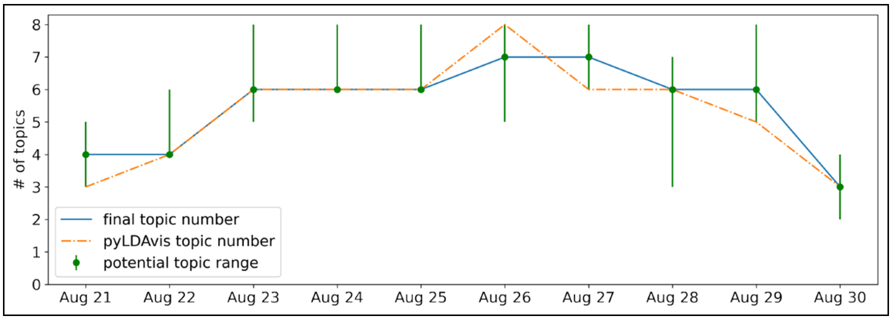

Figure 5. Potential topic range, pyLDAvis topic numbers and final topic numbers per day.

of coherence value across different pairs of hyper-parameters, we mainly selected the value of 0.6 for β on most of days, except for the value of 0.9 on 26 August and 0.3 on 27 August (Table 4).

In the third step, not all the visualisations of k topics for each day were presented because of space limitations. Instead, we used the visualisation for 26 August as an example (Figure 4). On the left, the inter-topic distance map depicts the relative position between each topic under this 2D projection space, which was also the relative position of these topics in their original high dimensional embedding space, under the t-SNE method. Specifically, the closer positions of two topics under this 2D space meant the more similarity of these two topics and the farther positions represented the more exclusiveness of these two topics. On the right, the bars demonstrated the top 30 most relevant words (i.e. words with a high probability of being associated to a topic) for the most prevalent topic among eight topics. The red bars showed word/term frequency for a specific topic while the blue bars indicated the term frequency for all the topics. Figure 4 depicts that 'safe', 'stay', 'please', 'hope' and 'pray' were dominant words for this topic (long red bars) while they were not dominant words for other topics (short blue bars). λ determined the weight given to the probability of a word under a topic relative to its lift[1] (measuring both on the log scale). Setting $\lambda = 1$ resulted in the familiar ranking of words in decreasing order of their topic-specific probability, and setting $\lambda = 0$ ranked terms solely by their lift [42].

As shown in Figure 5, the temporal pattern of topic numbers per day increased for the first 7 days while it dropped for the last 3 days. The greatest number of topics is discussed on 26 and 27 August. Specifically, the topics of 'Advisory', 'Relief', 'Information source' and 'Emotion' were mainly discussed in the pre-landfall stage of Hurricane Laura. Starting from 23 August, the topic of 'Casualty' and 'Damage' appeared in the tweet. On 26 and 27 August, the topic of 'Animal' was also discussed along with all other topics. In the post stage of Hurricane Laura, the discussion about 'Advisory' decreased and focused more on 'Casualty', 'Damage', 'Relief', 'Information source' and 'Emotion' (Table 5).

4.3. Temporal topic content

To verify how efficiently and precisely our models reflected the real-time latent topics during Hurricane Laura, we designed a two-step verification. First, we retrieved 2–5 representative tweets for each topic. Second, we compared the tweets with official reports published by government, authoritative organisation and news media. As shown in Tables 6–10, the contents of tweets regarding advisory, casualty, damage, relief and information source were verified by public announcements from Department of Energy (https://www.energy.gov/), Natural Hurricane Center (https://www.nhc.noaa.gov/), Federal Emergency Management Agency (https://www.fema.gov/), Louisiana Department of Health (https://ldh.la.gov/), American Red Cross (https://www.redcross.org/) and so on. Tables 11 and 12 show the contents of tweets regarding 'Emotion' and 'Animal', respectively.

The authoritative evidence not only showed the credibility but also indicated the timeliness of the tweets that we filtered out. Among these temporal topic contents, we verified some common SA information for hurricane events such as stay safe advisories, death tolls, power outages, wind speed, donation and volunteer topics. In addition, we discovered specific SA information during Hurricane Laura, for instance, the warning that using a generator can cause carbon monoxide poisoning were posted on 28 August, the same day when the FEMA provided the same advisory (Table 6); death toll numbers were posted on 28 August, two days earlier than the official report from Louisiana Department of Health (Table 7); and an update of outage information in Lake Charles was posted on 26 August, closely following the situational report of Department of Energy (Table 8).

Table 6. Tweets example of topic 'Advisory' and official reports.

Tweets	1. Hope everyone whose getting hit by the hurricanes stay safe!!! Stock up on the important things and charge your phones. (8.21) 2. Important PSA but PLEASE DO NOT RUN A GENERATOR INSIDE EVER!! OR IN ANY ENCLOSED SPACES!!! YOU WILL DIE FROM CARBON MONOXIDE POISONING. About half of the confirmed deaths so far from hurricane laura were bc of improper generator usage!! PLEASE DO NOT RUN GENERATORS INDOORS. (8.28)
Report	Department of Energy posted a public advisory regarding to 'Using Portable/Emergency Generators Safely' and warned that using the generator incorrectly can cause carbon monoxide poisoning [52].

Table 7. Tweets example of topic 'Casualty' and official reports.

Tweets	1. BBC News – Hurricane Laura death toll climbs to 14 in the US. (8.28) 2. Hurricane Laura victims may go weeks without power, deaths climb to 14 via @ABCNews (8.28)
Report	Louisiana Department of Health verified 14 deaths tied to Hurricane Laura on 30 August [53].

Table 8. Tweets example of topic 'Damage' and official reports.

Tweets	1. Keeping an eye on the city camera from our sister station KPLC in Lake Charles, you can see lights going out, outages spreading as Hurricane #Laura pushes into southwest Louisiana. Nearly 20,000 without power now, and that number will only grow tonight. (8.26) 2. Updated at 11:45 a.m. Hurricane Laura tore through a region that is home to dozens of major oil refineries, petrochemical plants and plastics facilities. #atx #austin #all512 (8.28)
Report	1. As of 8:30 AM EDT, 25 September, there were approximately 15,000 customer outages reported across Louisiana and Alabama [54]. 2. Hurricane Laura caused significant damage to transmission infrastructure in portions of Louisiana and Texas [54]. 3. National Public Radio (NPR) reported that millions of pounds of extra pollution were released because Hurricane Laura shut down dozens of oil refineries, petrochemical plants and plastics facilities [55].

Table 9. Tweets example of topic 'Relief' and official reports.

Tweets	1. Today, Red Cross Health Services volunteer, Karen Watt, set off for Baton Rouge, LA to support families impacted by hurricanes Marco & Laura. Karen is one of a dozen volunteers from North Texas who has left the region to assist. Learn how you can help (8.25) 2. We committing a $1M donation to relief efforts across Louisiana & Texas for those affected by #HurricaneLaura. If YOU want to help, text LAURA to 90999 for @RedCross, or FOOD to 80100 for @WCKitchen, and $10 will be added to your Verizon Wireless … (8.28) 3. Residents in southwestern Louisiana embarked Saturday on the epic task of cleaning up after Hurricane Laura tore through parts of the state. (8.29)
Report	1. The American Red Cross announced the relief information including food, water and other volunteer assistance and Red Cross Annual Disaster Giving Program (ADGP) members, such as Amazon and American Airlines [56]. 2. Verizon Foundation commits $1 million to Hurricane Laura relief efforts [57].

The results of our work from sections 4.1, 4.2 and 4.3 had twofold benefits. First, it provided a unique classification schema of specific events for hurricane and disaster related research. Second, it supplemented SA for practitioners who were affected during the disaster events, including federal and local agencies and public citizens.

From a research perspective, our study provided the numbers and keywords of latent topics during the Hurricane Laura. The state-of-the-art work using tweets for retrieving SA to support disaster response with supervised models mostly assigned each tweet a single label [63,64]. Among these tweets, however, most actually contained information across multiple topics. For example, the first tweet in Table 6 contained both topics of 'Advisory' and 'Emotion'; the third tweet in Table 10 involved topics of 'Information Source', 'Damage' and 'Advisory'. To fully utilise information

Table 10. Tweets example of topic 'Information source' and official reports.

Tweets	1.	FL511 reminds motorists to create a hurricane preparedness plan that includes recommendations in the event of an evacuation during COVID-19. Download the free FL511 Mobile App to know before you go. #FL511 (8.24)
	2.	Hurricane Laura reaches extremely dangerous Cat 4 strength, NHC warns of unsurvivable storm surge. (8.26)
	3.	An extreme wind warning is continues for Beaumont TX, Lake Charles LA, Port Arthur TX until 1:00 AM CDT for extremely dangerous hurricane winds. Treat these imminent extreme winds as if a tornado was approaching and move immediately to an interior room or shelter NOW!. (8.26)
	4.	Hurricane Laura is appraoching the southwest LA with 150 mph winds and an expected storm surge of 20 ft. Laura will move quickly north after landfall and decrease in strength significantly. (8.26)
	5.	New imagery from @NOAA reveals devastation wrought by Hurricane #Laura 1/ Grand Chenier, Louisiana, near where the highest surge was recorded. (8.28)
Report	1.	National Hurricane Center posted daily update on wind speed of Hurricane Laura since 21 August. On 25 August, it announced that maximum sustained winds have increased to near 90 mph (150 km/h) with higher gusts [58].
	2.	From 27 to 31 August, the National Geodetic Survey (NGS) collected aerial damage assessment images in the aftermath of Hurricane Laura. Imagery was collected in specific areas identified by NOAA in coordination with FEMA and other state and federal partners [59].

Table 11. Tweets example of topic 'Emotion' and official reports.

Tweets	1.	Taking a break from the RNC to get in my car to go to the grocery store for the first time in 7 months because I been too scared of being killed by a mundane daily task, but now two hurricanes are coming and I more scared of running out of water and food than the virus. (8.24)
	2.	my first hurricane in Houston & I, scared after the email I got from the apartment office I just hope water doesn't get into my car. (8.25)
	3.	Pray for the people of Southwestern Louisiana and eastern Texas Gulf coast who are desvated by the aftermath of Hurricane Laura and for those who died. (8.27)
Report		Intercessors for America started a survey to ask for payer for Hurricane Laura. The comments indicated most of the people were worried about the 'unsurvivable' storm and prayed day and night [60].

Table 12. Tweets example of topic 'Animal' and official reports.

Tweets	1.	FREE LARGE ANIMAL STALLS AVAILABLE at Mississippi Fairgrounds as temporary shelter for evacuated horses and livestock affected by #HurricaneLaura. Call 601-961-4000 for more info. @MSDeptofAg @MSEMA @CommAndyGipson @GregMichelMSEMA @WJTV @halterproject #DisasterAnimals (8.27)
	2.	The North Shore Animal League in Port Washington is accepting donations for food and supplies to help pets displaced by Hurricane Laura. (8.27)
Report	1.	On 9 September, it was reported that the state fair was cancelled this year, but livestock barns and horse stalls at the Oregon State Fairgrounds got some use after all. Volunteers remained at the fairgrounds helping care for displaced animals. There were photos of rabbits, horses and goats attached in the news [61].
	2.	North Shore Animal League wrote a blog about 'Supplies Needed for Partner Shelter in Path of Hurricane Laura' to ask for donations by 5 pm Friday, 28 August [62].

and further inform precise SA, our model could serve to generate reasonable classification schema and assign each tweets multiple labels in a supervised model.

From the practitioner perspective, the emerging topics captured by our model can assist the state and federal agencies in casualty and damage estimation with low-cost and wise resource allocation. For example, agencies can prioritise tasks in different ways.

5. Conclusion

Retrieving real-time SA information from big data of tweets is state-of-the-art methodology to aid disaster response and management. However, there remain several quantitative and qualitative challenges to understand and summarise first-hand tweets during disaster events.

One of the challenges to analyse tweets during new hurricane events with a supervised model is to first determine the classification schema into which the tweets should be classified. These categories should ideally be representative of the potential topics in the sense that they reflect the public concerns and issues caused by the event. To address this problem, we applied an LDA topic model on the pre-processed 10-day tweets collected during Hurricane Laura. Then, human experts observed the automatically generated topics and manually assigned and organised category labels for them. Our tested LDA model with a guided approach can make topics more humanly interpretable and determine classification schema for further analysis.

The other challenge is to rapidly and precisely update and extract SA information to government agencies and public citizens. Our study combines a sequence model and topic visualisation to investigate the daily latent topics during Hurricane Laura, and evaluates the representative tweets for each topic by comparing with authoritative announcements and reports. The results suggest that agencies should adopt and adapt strategies day-by-day and wisely allocate resources based on affected areas and population because the number and content of SA topics vary across different stages of disaster events.

Nevertheless, there are still some potential limitations in our current work. First, due to the co-occurrence of several events including COVID-19, wildfires in California, the presidential election and other hurricane events, most tweets were hybrids, containing information across events so that it is difficult to independently analyse the topics solely for Hurricane Laura. Second, our LDA model not only reveals potential categories but also assigns labels to each tweet data. In the future, it is worth applying an advanced attention model to experiment with multilabels generated from our study and thus further inform SA.

Acknowledgements

The authors would like to thank the support from the University of Wisconsin, Madison through the Vilas Associates Competition Award.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship and/or publication of this article.

ORCID iD

Sulong Zhou https://orcid.org/0000-0002-3376-7350

Note

1. $lift = P(topic \wedge word)/(P(topic) \cdot P(word)) = P(word|topic)/P(word)$

References

[1] NASA. Aug. 28, 2020 – Terra Misr Used to Visualize Cloud-top Heights from Hurricane Laura in 3D, 2020, https://blogs.nasa.gov/hurricanes/tag/laura-2020/ (accessed 28 September 2020).
[2] teleSUR. Haiti: Tropical storm Laura death toll now 31, 2020, https://www.telesurenglish.net/news/haiti-tropical-storm-laura-death-toll-now-31-20200829-0006.html (accessed 28 September 2020).
[3] NY Daily News. Hurricane Laura fatally strikes Dominican Republic, Haiti, makes landfall in the U.S., 2020, https://www.nydailynews.com/photos/ny-tropical-storm-laura-marco-20200824-2saekhf5vrhfjneoxrcpyhckpu-photogallery.html (accessed 28 September 2020).
[4] BBC News. Thousands told to evacuate gulf coast as Hurricane Laura nears, 2020, https://www.bbc.com/news/world-us-canada-53885242 (accessed 25 September 2020).
[5] The Washington Post. Hurricane Laura by the numbers: Winds to 154 mph, a 15-foot surge and yet another category 4+ on U.S. *Soil*, 2020, https://www.washingtonpost.com/weather/2020/08/28/hurricane-laura-peak-winds-surge/ (accessed 26 September 2020).
[6] Livingston I and Freedman A. Hurricane Laura makes landfall as category 4 in Louisiana with 'life-threatening' surge, https://www.washingtonpost.com/weather/2020/08/26/hurricane-laura-updates-texas-louisiana/ (accessed 26 September 2020).
[7] BBC News. Hurricane Laura death toll climbs to 14 in the US, 2020, https://www.bbc.com/news/world-us-canada-53955186 (accessed 29 August 2020).
[8] Evans S. Hurricane Laura onshore insured property loss close to $9 BN: KCC, 2020, https://www.reinsurancene.ws/hurricane-laura-onshore-insured-property-loss-close-to-9bn-kcc/ (accessed 31 August 2020).
[9] Ashish N, Eguchi R, Hegde R et al. Situational awareness technologies for disaster response. In: Chen H, Reid E, Senai J et al. (eds) *Terrorism informatics*. New York: Springer, 2008, pp. 517–544.
[10] Sarter NB and Woods DD. Situation awareness: a critical but ill-defined phenomenon. *Int J Aviation Psychol* 1991; 1(1): 45–57.
[11] Goswami S, Chakraborty S, Ghosh S et al. A review on application of data mining techniques to combat natural disasters. *Ain Shams Eng J* 2018; 9(3): 365–378.

[12] Vongkusolkit J and Huang Q. Situational awareness extraction: a comprehensive review of social media data classification during natural hazards. *Ann GIS* 2020 27: 5–28.
[13] Morstatter F, Pfeffer J, Liu H et al. Is the sample good enough? *Comparing data from Twitter's streaming API with Twitter's firehose*, 2013, https://arxiv.org/abs/1306.5204
[14] Mills A, Chen R, Lee J et al. Web 2.0 emergency applications: How useful can twitter be for emergency response? *J Inform Privacy Secur* 2009; 5(3): 3–26.
[15] Palen L, Starbird K, Vieweg S et al. Twitter-based information distribution during the 2009 red river valley flood threat. *Bullet Am Soc Inform Sci Tech* 2010; 36(5): 13–17.
[16] Sakaki T, Okazaki M and Matsuo Y. Earthquake shakes twitter users: real-time event detection by social sensors. In: *Proceedings of the 19th international conference on World Wide Web*, Raleigh, 26–30 April 2010, pp. 851–860. New York: ACM.
[17] Gupta A, Lamba H, Kumaraguru P et al. Faking sandy: characterizing and identifying fake images on twitter during hurricane sandy. In: *Proceedings of the 22nd international conference on World Wide Web*, Florence, 18–22 May 2003, pp. 729–736. New York: ACM.
[18] Imran M, Mitra P and Castillo C. Twitter as a lifeline: Human-annotated twitter corpora for NLP of crisis-related messages, 2016, https://arxiv.org/abs/1605.05894
[19] Stowe K, Anderson J, Palmer M et al. Improving classification of twitter behavior during hurricane events. In: *Proceedings of the sixth international workshop on natural language processing for Social Media*, Melbourne, VIC, Australia, 20 July 2018, pp. 67–75. Stroudsburg PA: ACL.
[20] Alshemali B and Kalita J. Improving the reliability of deep neural networks in NLP: a review. *Knowl Based Syst* 2020; 191: 105210.
[21] Mohammadi M, Al-Fuqaha A, Sorour S et al. Deep learning for IoT big data and streaming analytics: a survey. *IEEE Commun Surv Tutor* 2018; 20(4): 2923–2960.
[22] Erhan D, Courville A, Bengio Y et al. Why does unsupervised pre-training help deep learning? In: *Proceedings of the thirteenth international conference on artificial intelligence and statistics*, Sardinia, 13–15 May 2010.
[23] Severyn A and Moschitti A. Twitter sentiment analysis with deep convolutional neural networks. In: *Proceedings of the 38th international ACM SIGIR conference on research and development in information retrieval*, Santiago, Chile, 9–13 August 2015, pp. 959–962. New York: ACM.
[24] Kapoor A, Horvitz E and Basu S. Selective supervision: Guiding supervised learning with decision-theoretic active learning. *Int Joint Conf Artif Intell* 2007 7: 877–882.
[25] Prusa J, Khoshgoftaar TM, Dittman DJ et al. Using random undersampling to alleviate class imbalance on tweet sentiment data. In: *2015 IEEE international conference on information reuse and integration*, San Francisco, CA, 13–15 August 2015, pp. 197–202. New York: IEEE.
[26] Johnson JM and Khoshgoftaar TM. Survey on deep learning with class imbalance. *J Big Data* 2019; 6(1): 27.
[27] Miwa M, Thomas JO, Mara-Eves A et al. Reducing systematic review workload through certainty-based screening. *J Biomed Inform* 2014; 51: 242–253.
[28] Tahvili S, Hatvani L, Ramentol E et al. A novel methodology to classify test cases using natural language processing and imbalanced learning. *Eng Appl Artif Intel* 2020; 95: 103878.
[29] Andrzejewski D and Zhu X. Latent Dirichlet allocation with topic-in-set knowledge. In: *Proceedings of the NAACL HLT 2009 workshop on semi-supervised learning for natural language processing*, Boulder, CO, 4 June 2009, pp. 43–48. Stroudsburg PA: ACL.
[30] Blei DM, Ng AY and Jordan MI. Latent Dirichlet allocation. In: *Proceedings of the 14th international conference on neural information processing systems*, Vancouver, BC, Canada, 3–8 December 2001, pp. 601–608. New York: ACM.
[31] Vieweg S, Hughes AL, Starbird K et al. Microblogging during two natural hazards events: what twitter may contribute to situational awareness. In: *Proceedings of the SIGCHI conference on human factors in computing systems*, Atlanta, GA, 10–15 April 2010, pp. 1079–1088. New York: ACM.
[32] Imran M, Elbassuoni S, Castillo C et al. Extracting information nuggets from disaster-related messages in social media, https://mimran.me/papers/imran_shady_carlos_fernando_patrick_iscram2013.pdf
[33] Huang Q and Xiao Y. Geographic situational awareness: mining tweets for disaster preparedness, emergency response, impact, and recovery. *ISPRS Int J Geo Inform* 2015; 4(3): 1549–1568.
[34] Habdank M, Rodehutskors N and Koch R. Relevancy assessment of tweets using supervised learning techniques: Mining emergency related tweets for automated relevancy classification. In: *2017 4th international conference on information and communication technologies for disaster management (ICT-DM)*, Manchester, 11–13 December 2017, pp. 1–8. New York: IEEE.
[35] Pouyanfar S, Tao Y, Tian H et al. Multimodal deep learning based on multiple correspondence analysis for disaster management. *World Wide Web* 2019; 22(5): 1893–1911.
[36] Jelodar H, Wang Y, Yuan C et al. Latent Dirichlet allocation (LDA) and topic modeling: models, applications, a survey. *Multimedia Tool Appl* 2019; 78(11): 15169–15211.

[37] Sit MA, Koylu C and Demir I. Identifying disaster-related tweets and their semantic, spatial and temporal context using deep learning, natural language processing and spatial analysis: a case study of hurricane Irma. *Int J Digital Earth* 2019; 12(11): 1205–1229.
[38] Karami A, Shah V, Vaezi R et al. Twitter speaks: a case of national disaster situational awareness. *J Inform Sci* 2020; 46(3): 313–324.
[39] Alam F, Ofli F and Imran M. Descriptive and visual summaries of disaster events using artificial intelligence techniques: case studies of hurricanes Harvey, Irma, and Maria. *Behav Inform Tech* 2020; 39(3): 288–318.
[40] Wang D, Thint M and Al- Rubaie A. Semi-supervised latent Dirichlet allocation and its application for document classification. In: *2012 IEEE/WIC/ACM international conferences on web intelligence and intelligent agent technology*, vol. 3, Macau, China, 4–7 December 2012, pp. 306–310. New York: IEEE
[41] Resnik P, Niv M, Nossal M et al. Using intrinsic and extrinsic metrics to evaluate accuracy and facilitation in computer-assisted coding. In: *Perspectives in health information management computer assisted coding conference proceedings*, Turku, 23–25 August 2006.
[42] Sievert C and Shirley K. LDAvis: A method for visualizing and interpreting topics. In: *Proceedings of the workshop on interactive language learning, visualization, and interfaces*, Baltimore, MD, 27 June 2014, pp. 63–70. Reston, VA: ACL.
[43] Röder M, Both A et al. Exploring the space of topic coherence measures. In: *Proceedings of the eighth ACM international conference on web search and data mining*, 2–6 February 2015, Shanghai, China, pp. 399–408. New York: ACM.
[44] Poldi F. Twint-twitter intelligence tool, 2019, https://github.com/twintproject/twint (accessed 20 August 2018).
[45] Klakow D and Peters J. Testing the correlation of word error rate and perplexity. *Speech Communication* 2002; 38(1–2): 19–28.
[46] Jacobi C, Van Atteveldt W and Welbers K. Quantitative analysis of large amounts of journalistic texts using topic modelling. *Digital J* 2016; 4(1): 89–106.
[47] Wold S, Esbensen K and Geladi P. Principal component analysis. *Chemometr Intel Labor Syst* 1987; 2(1-3): 37–52.
[48] Maaten Lvd Hinton G. Visualizing data using t-SNE. *J Mach Learn Res* 2008; 9: 2579–2605.
[49] Jagarlamudi J, Daum é IIIH and Udupa R. Incorporating lexical priors into topic models. In: *Proceedings of the 13th Conference of the European chapter of the association for computational linguistics*, Avignon, 23–27 April 2012, pp. 204–213. New York: ACM.
[50] Martinez-Rojas M, del Carmen Pardo-Ferreira M and Rubio-Romero JC. Twitter as a tool for the management and analysis of emergency situations: a systematic literature review. *Int J Inform Manag* 2018; 43: 196–208.
[51] Yang J, Yu M, Qin H et al. A twitter data credibility framework – hurricane Harvey as a use case. *ISPRS Int J Geo-Inform* 2019; 8(3): 111.
[52] FEMA. Hurricane Laura, 2020, https://www.fema.gov/disasters/hurricane-laura (accessed 7 October 2020).
[53] LDH. Louisiana department of health verifies two additional hurricane-related deaths, 2020, https://ldh.la.gov/index.ofm/newsroom/detail/5738 (accessed 7 October 2020).
[54] DOE. Hurricane Laura situation reports, 2020, https://www.energy.gov/ceser/listings/hurricane-laura-situation-reports (accessed 7 October 2020).
[55] NPR. Millions of pounds of extra pollution were released before Hurricane Laura's landfall, 2020, https://www.npr.org/sections/health-shots/2020/08/28/906822940/millions-of-pounds-of-extra-pollution-were-released-before-laura-made-landfall (accessed 7 October 2020).
[56] ARC. Thousands still need red cross help weeks after Hurricane Laura landfall, 2020, https://www.redcross.org/about-us/news-and-events/news/2020/red-cross-response-to-hurricane-laura.html (accessed 7 October 2020).
[57] Jay K and Brijlall B. Verizon foundation commits $1 million to Hurricane Laura relief efforts, 2020, https://www.redcross.org/about-us/news-and-events/news/2020/red-cross-response-to-hurricane-laura.html (accessed 7 October 2020).
[58] NOAA. Hurricane Laura advisory archive, 2020, https://www.nhc.noaa.gov/archive/2020/LAURA.shtml (accessed 7 October 2020).
[59] NOAA. August 2020: Hurricane Laura. *National Geodetic Survey Damage Assessment Imagery*, 2020, https://oceanservice.noaa.gov/news/aug20/ngs-storm-imagery-laura.html (accessed 7 October 2020).
[60] Ifapray. Will Hurricane Laura be an 'unsurvivable' storm? *Our Prayers May Make the Difference*, 2020, https://ifapray.org/blog/will-hurricane-laura-be-an-unsurvivable-storm-our-prayers-may-make-the-differenc (accessed 7 October 2020).
[61] Loman A. Photos: Goats, rabbits and horses fleeing fire find shelter at Oregon state fairgrounds, 2020, https://www.salemreporter.com/posts/2912/photos-goats-rabbits-and-horses-fleeing-fire-find-shelter-at-oregon-state-fairgr (accessed 7 October 2020).
[62] Animalleague. Supplies needed for partner shelter in path of Hurricane Laura, 2020, https://www.animalleague.org/blog/spotlight-stories/hurricane-laura-relief-collection/ (accessed 7 October 2020).
[63] Ajao O, Bhowmik D and Zargari S. Fake news identification on twitter with hybrid CNN and RNN models. In: *Proceedings of the 9th international conference on social media and society*, Copenhagen, 18–20 July 2018, pp. 226–230. New York: ACM.
[64] Neppalli VK, Caragea C, Squicciarini A et al. Sentiment analysis during hurricane sandy in emergency response. *Int J Disaster Risk Reduct* 2017; 21: 213–222.