Disentangling the Lexicons of Disaster Response in Twitter

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ABSTRACT

People around the world use social media platforms such as Twitter to express their opinion about various aspects of daily life. In the same way social media changes communication in daily life, it also is transforming the way individuals communicate during disasters and emergencies. Emergency officials have come to rely on social media to communicate alerts and updates. How do users communicate risk on social media? We used a novel information-theoretic unsupervised learning tool, CorEx, to extract and classify highly relevant words used by the public on Twitter during known emergencies, such as fires, explosions, and hurricanes. By utilizing the resulting classification strategy, authorities may be able to use the derived language to craft more relevant risk communication to maximize the propagation of short-message broadcasts such as the Wireless Emergency Alerts (WEA) service.

Categories and Subject Descriptors

J.4 [**Social and Behavioral Sciences**]: Sociology; H.3.3 [**Information Search and Retrieval**]: Information Filtering; K.4.1 [**Computers and Society**]: Public Policy Issues—*Human Safety*

Keywords

Mutual Information, Clustering, Disaster Response, Twitter, Lexicon, Risk

1. INTRODUCTION

The ability to clearly communicate between the public and those responsible for assessing, minimizing, and regulating risks is critical for successful resolution of a public emergency. Strong safety concerns cause the public to develop symptoms of emotional and behavioral distress that adversely affect the perception of risk during a crisis through the evocation of strong emotions such as fear, anxiety, distrust, anger, outrage, helplessness, and frustration[6]. Understanding the dynamics of risk perception during a crisis is crucial for successful emergency response because ultimately people act on the basis of what they believe to be true. Perceived risk is known to have a stronger impact on disaster recovery and preparedness than actual risk as communicated by emergency public information officers. For example, a recent study on risk communication shows households in America are more strongly motivated to prepare for terrorism and other hazards by observing preparations taken by others than they are by information received from preparedness information providers[16]. Although public officials depend on precision and clarity, how do they properly tailor their communication for a public using a different lexicon? The present work presents automated content analysis methods to analyze social media to provide tools to study language used during emergencies, helping to ensure effective communication of risk and of how to mitigate danger in emergencies.

The adoption of risk communication strategies that promote trust, credibility, effectiveness, abidance of moral and ethical values, respect, and timeliness can greatly minimize risk perception biases by reducing public emotional and behavioral distress, whether the emergency concerns disease control[15, 14, 1], natural/manmade disasters (for example, [7]), or terrorism ([5, 4]). Because risk perception is also regulated by social identity factors[8, 11, 10], adopting effective risk communication strategies that promote trust, credibility, etc. requires due attention to cultural differences that characterize diverse populations including persons with functional and access needs, transients/tourists, elderly/older adults, isolated/rural populations, institutional populations, and non-English speaking people.

Over the past few years, short messages have been used in various forms for disaster-related risk communication. The multistage developmental process for risk communication that is discussed by Fischhoff[9] is still relevant to short messages and the new generation of communication media. One notable instance was the use of social media to communicate warning messages during the 2008 terror attack in Mumbai,

India. The consensus of review articles is that social media is not just a new means to carry out an old risk communication strategy[3, 4, 12, 18, 17]. However, language use varies widely, depending on proximity to the disaster, both geographic and experiential[13]. Here, we present a new strategy for analyzing tweets during an emergency to understand how language is being used and which words help communicate latent factors. By analyzing the mutual information between words within a tweet and the extracted latent variables, we show that each type of disaster has a characteristic lexicon which is often surprisingly different from how the same words are used in typical tweets outside of emergencies.

2. METHODS

2.1 Data

Social media is understood as an information propagation tool for reporting on and responding to natural disasters. Emergency management services use social media to issue alerts and warnings, look for reports of emergencies, and understand public response to emergencies. Social media is used to share information leading up to, during, and after the disasters[2]. For the purposes of this study, tweets around a set of well-known and documented disasters were gathered for examination.

To collect pertinent disaster-related tweets, we used 203 U.S. Federal Emergency Management Agency (FEMA) declared disasters in the United States from 2012 and 2013 (http://www.fema.gov/disasters). Historical Twitter data was obtained from Gnip, a provider of the Twitter firehose, using their historical data request API. Each query was composed of curated keyword lists, primarily named entities related to a particular disaster and informal language describing the nature of the event. Queries were further filtered both by geo-tagged location and date range. A date range for the historical query was selected by taking a range of ± 5 days from the event date itself, except for the (non-weather-related) Alamo, Calif., gas leak, where a date range of $+5$ days and -1 day around the event date was used. Example keywords used for the Alamo, Calif., gas leak included the following: leak, gas, evacuation, pg&e, pge, pg+e, alamo, danville, and shelter. Geographical filters for the query were established using the area of impact of the emergency declaration, such as a single 25-mile radius around a defined point, or entire regions were selected when more than a single point of impact exists. For example, Southern California flooding and wildfires searched within California, Hurricane Sandy covered multiple states, and the Alamo gas leak was a single point centered on Alamo, Calif.

Upon acquisition of this data, it was ingested into Elasticsearch, a Lucene based search engine architecture. Messages matching specific query parameters are marked by the vendor as belonging to a specific query set, allowing the messages for all disasters to be stored in a single index and simply filtered for content. A sample of the queries are listed in Table 1, and the complete list is available on request. It is important to note that the nature of collecting only geo-tagged tweets means that we did not collect the subsequent retweets, but many people retweeted non-geocoded tweets and embedded their own geocode.

To generate a control group, we also randomly selected 50,000 tweets with geo-tags collected from the Twitter sprinkler between April and May 2014. This control group, which may or may not contain any disaster-specific tweets, allow us to compare how the risk corpus is used outside of emergency scenarios.

2.2 Risk Corpus

To analyze how people communicate during crises, we hand-curated a list of words based on how users actually communicated on Twitter. The relevant geocoded tweets for each disaster were obtained as described in the data section. This collection of tweets was then used to curate a "risk corpus" of 292 words or expressions identified to be (at least partially) relevant to any of the disaster responses. This particular risk corpus was not meant to be definitive, and future work will focus on optimizing the breadth of the corpus and refining feature selection. Although many of the words may not be specific to commonly held notions of risk, we designed the corpus to encompass many of the ways users communicate fear, intent, targets, and the issues inducing the risk (i.e., the emergency events themselves).

2.3 Clustering

Each item of the corpus was converted into a regular expression to capture common variants and avoid ambiguity. For example, the words smolder and smoldering were represented as smold. Variants of "fire" can be expressed as fire(?!(work|fi)), to avoid tagging fireworks or firefighters as variant of fire, which were searched for separately. The complete list is shown in Appendix A. The resulting crisis related world list alone does not capture how risk is communicated by the public. One would have to identify informative subsets of these words to make sense of the general structure of the risk context conveyed by the public in the tweets. In order to obtain more relevant semantic clustering, we employed Correlation Explanation (CorEx)[20]. CorEx searches for latent variables that explain correlation between the usages of different terms.

A reduced subset of 50,000 tweets was randomly sampled for each disaster type for the final analysis. Some disasters had less than 50,000 tweets, and as many as possible were selected. Each tweet was converted into a vector, X, where X_i is the presence (or absence) of regular expression i in the tweet. For each type of disaster, we used CorEx to generate a tree of latent variables where each variable is constructed to maximally explain the correlations in its children. That is, we simultaneously search over latent variables, $Y_j, j = 1, \ldots, m$, and clusters of words G_j so that $\sum_j TC(X_{G_j}; Y_j)$ is maximized. TC represents the amount of correlation in a group of variables, X_{G_j}, that is explained by Y_j, and is specified by $TC(X_{G_j}; Y_j) = \sum_{i \in G_j} MI(X_i; Y_j) - MI(X_{G_j}; Y_j)$, where $MI(X; Y)$ is the mutual information between X and Y. For a group of uncorrelated X_i's, for instance, this expression would give zero, while it would be maximized if all the variables were identical copies. To construct a tree, we take the $Y^{(n-1)}$'s learned on one level and apply CorEx again to learn a representation, $Y^{(n)}$ [20]. A detail of a sample tree is shown in Figure 1.

The CorEx algorithm provides a tree of latent variables explaining correlation in the data, but it does not provide explicit labels for the latent variables. To label the latent variable nodes of the tree, we propagated up the tree the corpus entries with the highest weight according to the mutual information between the label and the latent variable to be labeled. Results for the Hurricane disaster are shown in Fig-

Table 1: Sample Query Definitions and Volume of Return

Disaster Name	Date Range	Captured Tweets	Query Terms
Alamo, California, Gas Leak	7/23-29/2013	120	leak, gas, evacuation, pg&e, pge, pg+e, alamo, danville, shelter
El Reno, Oklahoma, Tornado	5/25 - 6/6/2013	1145	tornado, wind, shelter, evacuation, storm, chaser, funnel, EF, hail, moore, noise, warning, samaras, el reno, rotating, debris, disaster, twister, siren
Hurricane Sandy	10/10 - 10/25/2012	208,574	storm, hurricane, sandy, frankenstorm, flood, danger
South Dakota Blizzard	9/28 - 10/11/2013	761	cattle, blizzard, storm, atlas, south dakota, snow, freeze, frozen, cold, windy, travel restriction, whiteout

ure 2. To better understand our CorEx results and to test the robustness of our methods, we also applied CorEx to an entirely random sample from our control group, containing no explicitly selected emergency-related tweets.

3. DISCUSSION

The CorEx technique succeeds at identifying both disaster-specific themes as well as how word usage changes during emergencies. As we see in Figures 1 and 2, the resulting trees are largely dominated by terms commonly used in disaster alerts. For the control tweets, the CorEx analysis produces very different clustering, implying different latent variables underlie the use of risk-related terms outside of emergency situations. For example, during fire events, the words "fire" and "firework" are closely associated, but this is not true outside of fire events. Similarly, outside of disaster events, the CorEx generates labels such as "hot/cold", "hours/minutes", "rain/sunny", and "char/destroy," as in Figure 1(c). During disasters, CorEx tends to identify combinations which are more mutually predictive, such as "power/loss", "evacuation/county", and "issued/until." Thus, we conclude that the resulting lexical analysis is specific to how users respond to disasters and not simply generic relations resulting from artifacts of the hand-curated corpus.

Our results show that tweets tend to focus on announcing the emergency, advising others, or describing the damage. Other obvious clusters include expressions of anxiety, frustration, and expletives. The CorEx results enable us to show which words in the corpus are most predictive of the latent feature, and thus may communicate the intent of the latent feature most clearly. For each type of disaster, we have produced a list of words that best communicate the latent variables. That is, for each feature X_i, there is a mutual information with each latent variable Y_j. High mutual information implies high explanatory power, and for each type of disasters we present a list of words that have the most explanatory power in each scenario. Because Y_i represent the latent variable which explains the co-occurence of words below it in the tree, having high $MI(X_i; Y_j)$ means that feature X_i also helps explain why other words are used in combination with it in that disaster scenario. We present a brief list of the most and least informative words for each type of disaster in Table 2.

3.1 Most Informative and Surprising Tweets

The present CorEx technique enables us to analyze each

tweet to determine how it is using words from the corpus of risk words. We score each tweet by summing its total correlation with respect to each latent variable for that disaster type. Low-scoring tweets utilize combinations of words in unexpected ways and often do a poor job at communicating intent. Words that are highly predictive of particular latent variables (and therefore other words), will generally produce "unsurprising" tweets. That is, although the content may refer to a surprising event (tornado, explosion, etc.), the reader should be able to easily interpret how all the terms come together to communicate the inferred latent variable. For example, emergency alerts or discussions of the consequences of disasters tend to be highly informative and unsurprising, while passing comments or references tend to be uninformative and surprising, from our current total-correlation perspective. As a control group, we analyzed random geocoded tweets, and we observe the risk corpus flags official National Weather Service (NWS) alerts as highly relevant outside of emergencies, but during emergencies, the most informative tweets tend to less formal and more emotional than random sample.

3.1.1 Randomly Sampled Tweets

Most Information/Least Surprising

- 50560: severe thunderstorm warning issued may 08 at 2:03pm cdt until may 08 at 2:30pm cdt by nws desmoines http://t.co/...
- 56065: severe thunderstorm warning issued may 07 at 9:20pm cdt until may 07 at 10:15pm cdt by nws minneapolis http://t.co/...
- 65326: flash flood warning issued april 03 at 4:01pm cdt until april 03 at 10:00pm cdt by nws springfield http://t.co/...
- 09:26 bst: temperature: 10.1°c, wind: ssw, 0 mph (ave), 2 mph (gust), humidity: 89%, rain (hourly) 0.0 mm, pressure: 1015 hpa, rising slowly
- 00:33 bst: temperature: 10.2°c, wind: s, 0 mph (ave), 0 mph (gust), humidity: 82%, rain (hourly) 0.0 mm, pressure: 1004 hpa, rising slowly

Least Information/Most Surprising

- "@googlefacts: in a tropical climate, oranges are green. in a temperate climate, oranges are orange." that's why our oranges are green!
- cups that change color with temperature are pretty much the reason i still get out of bed most mornings

(A) Hurricanes

(B) Fires

(C) Random Control
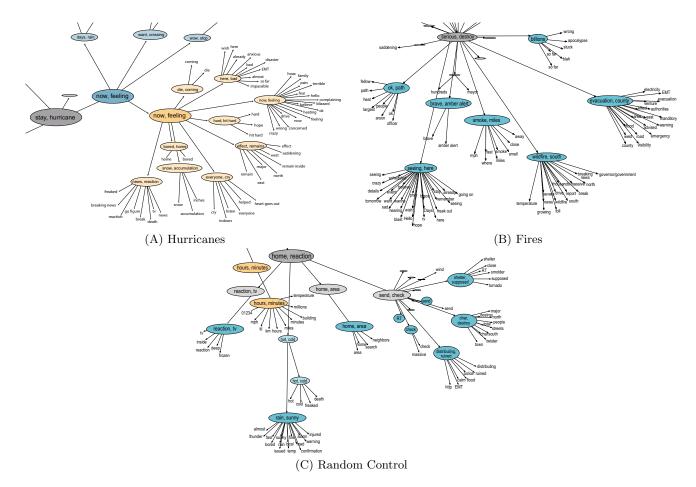
Figure 1: Sample section of CorEx dendrogram for the different disasters and a random sample of tweets from the control group. The inferred latent variable labels are inside the ovals, and the terms are on the leaves of the trees. Colors are solely for clarity.

Table 2: Informative Words and Phrases. We exclude trivial disaster labels, e.g. "hurricane". (01234 indicates numbers)

Disaster Type	Most Informative	Least Informative
Random	love, 01234, want, now, day	mangled, fire dept, funnel, national guard, hoax
Hurricane	01234, house, power, flood, listen	false alarm, mangled, impassible, wind, fire fighters
Fire	01234, burn, smoke, police, firework	doozy, struggle, ice, blah, arson
Explosion	01234, scared, house, expletive, bomb	mph, temperature, anxious, remain inside, hoax
Tornado	01234, until, issued, mph, severe	accumulation, wind, impassible, go figure, remain inside

destroy,people

electricity,area   f@!#,s@!#

f@!#,s@!#

emergency,governor/government

flood   gas,neighbors

mph,hours

hurricane,flood
distributing,streets

snow,accumulation

news,reaction   die,coming

now,feeling   bored,home   everyone,cry

effect,remain

now,feeling

hard,hit hard

here,bad

power,losses

stay,supposed   stay,hurricane

hurricane,storm   now,feeling

Wow,stop

stay,hurricane

Wow,stop

severe,thunder

stay,issued

evacuation,report

want,crossing   days,rain

RT

issued,warning

want,crossing

serious,real deal

days,rain

house,worst

house,worst   away,blowing

house,worst
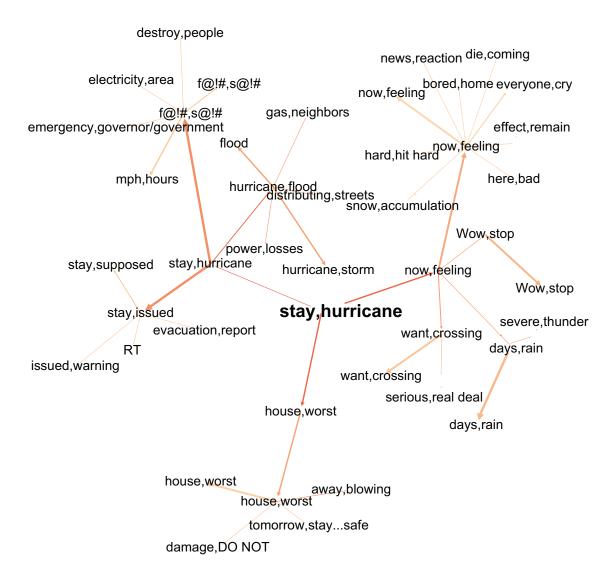
tomorrow,stay...safe

damage,DO NOT

Figure 2: We assign labels to the latent variable tree by propagating highly informative words up the tree. The thickness of an arrow represents the mutual information between a node and its parent. "Stay, Hurricane" is the root node.

- @locallink57 exactly! seems everyone selling them tho?!? crazy ! lol
- @hiramboyd carrasco has the same issue, always loved his velocity but his past two starts haven't convinced me to keep him in rotation
- "solidskathniels: kathniel status: exclusively dating Âľ yes magazine, feb issue." omg omg omg

3.1.2 Hurricanes
Most Information/Least Surprising

- nws bmx has issued a severe thunderstorm warning for pickens county until 1030pm. #alwx
- "@wsvn: flash flood warning issued for eastern broward county and eastern palm beach county until 4:30 p.m."
- there's a flash flood watch in effect for bay county until 7 p.m. we've had reports of water on several roads. be careful out there!
- just what we (in pb county) need - more rain. rt@wptv severe thunderstorm warning for sw palm beach co until 4:15 p.m. #westpalmbeach
- weather gettin crazy sandy is gonna hit hard..god bless everybody stay safe!!

Least Information/Most Surprising

- finally #sandy. i can finally go play waterworld for real! everyone not on my team is a smoker #gonnagetcha
- @jetsgirl15 so far it's a flood watch where i am no wind advisory
- frankenstorm + canadian earthquake + tsunami advisory for hawaii/alaska/western canada.... aks;fkld apocalypse day after tomorrow
- this wind needs to calm the f**k down! #sandy #wind #noclasses #apocalypse #needfood #thankyousandy
- this storm obviously means a zombie apocalypse is coming. if you don't watch the #walkingdead you're screwed. #rickgrimesforpresident

3.1.3 Fires
Most Information/Least Surprising

- bless the 19 fire fighters that have died today protecting us. sending prayers out to all of the families for their loss
- 02:41pm cdt other<-spotr 1 miles ese of lawrence creek, ok-fire storm many homes on fire winds west gust 20-30 mph temp 130 near fire...
- fires and evacuations really freak me out. almost as much as hairless bears, but differently.
- the fire iss like 2 miles aways from where im at & all the smoke is blowing towards palmsprings
- "@nbcbayarea: just in: statewide amber alert issued after deadly house fire in san diego county http://t.co/..." shutup

Least Information/Most Surprising

- " my world falls apart when i see the words 'amber alert' thinking it could be one of my family members or friends out there damn..."
- watching tv and an amber alert came on... remember that movie @hayleyburnsy @krista_odonnell #sketch
- mayor said today is "a bittersweet day." finally seeing progress with the fire, but hundreds will hear that their homes were destroyed.

- amber alert issued for two children after remains of mother found in suspect's burned home: san diego... http://t.co/...
- it's weird/sad to hear the street you grew up on & where your mom still lives is under mandatory evac. #mojavescenic #sharpfire #wrightwood

3.1.4 Tornados
Most Information/Least Surprising

- streets are flooded all over, debris all over and sad to hear about the trailer park 7 miles away, totally destroyed. crazy to think...
- watching news of storm damage from the mcdonalds in chandlerok. carney hit hard. thk u 4 prayers 4 @wsbr #okwx http://t.co/...
- 37 dead & death toll is rising. same path as 1999 where winds reached 300mph and 44 casualties. news says this is worse #prayersforoklahoma
- 08:08pm cdt tor<-spotr 4 miles w of hesston, ks-large tornado spotted five minutes ago, a few miles to our north...
- please b in prayer 4 those here in st louis who lost homes, injuries & damage 2property in last nites tornado. many r still w/out power.

Least Information/Most Surprising

- #gasland2 tom ridge wasn't lying until he said "no methane in water has ever been connected to fracking." bulls***. much bigger issue now.
- other issues the fire study found was water supply is a primary concern for #adamscounty and #hunterstown is one of several "coverage gaps"
- rt @kfdinews: a significant weather advisory has been issued for butler and sedgwick counties. 50 mph winds are possible. #kswx
- boil water advisory in lyon county. any businesses or homeowners in neosho rapids seeing any issues with this? let me know. #kfn
- severe wether storm in kansas. i am staying in a freaking trailer. 60 mph winds.i'm gonna cry. i am so scared. #tornado #prayforme

3.1.5 Freeze
Most Information/Least Surprising

- woman dead after being stranded overnight in snowstorm in local stories, outdoors, staying safe, utah at december 20th, 2012
- ice cycles have taken the place of tornados when it comes to my biggest fear. if one dropped on you, #dead
- our heater stopped working, and it's literally freezing, and i don't want to crawl under the house to fix it. so i'll just stay in bed #dumb
- #very cold deep freeze cover plants pipes bring in kids and animals. do not leave any outside. be sure to pay attention to weather.
- uh question. were we supposed to pick up our schedules sometime during winter break? or do we get them tomorrow. #clueless #senoritis

Least Information/Most Surprising

- ahhhh. almost 5 hours in a wait list line, 2.5 in the ice and cold - and we made it! @sundancefest is intense. @jonathangroff #cog #sendance
- @wx5em: winter weather advisory issued by nws: #sky-warn"where??? what state(s)??? please add "??wx" thank you!
- winter weather advisory issued for tempe, az http://t.co1...
- winter weather advisory issued for tempe, az http://t.co2...
- winter weather advisory issued for tempe, az http://t.co3...

3.1.6 Explosion

Most Information/Least Surprising

- "rt 70 people confirmed dead, including 5 firefighters & 1 police officer. hundreds of others injured in explosion" donde fue el vergazo?
- 70 people confirmed dead, including 5 firefighters & 1 police officer. hundreds of others injured in explosion http://t.co/...
- rt "@breakingnews: texas authorities advise west, texas, residences to leave town immediately following explosion - @westisd"
- more sad news. rt @abc: #westtx fertilizer plant explosion update: mayor says 13 confirmed dead. 5 firefighters, 4 emts and 4 civilians.
- a fertilizer plant in west, tx exploded and 60+ people were killed (hundreds injured). sending thoughts and prayers that way. #prayforwest

Least Information/Most Surprising

- boston bombing suspect caught, b1g ten getting rid of legends/leaders to switch to east-west & kim kardashian's divorce is final. a good day
- my first hard run after the bombings felt perfect and i might finally feel ready for westford in two... http://t.co...
- why do i see muslims terrorists & the westboro church being compared on my tl ; the westboro church are assholes but they're not bombing ppl
- ban the westboro baptist church from entering boston and picketing the funerals of those who died during the bombing http://t.co/...
- @espn they talk about they bombing in boston, where is the coverage of the mass explosion in west texas which took many lives?

4. CONCLUSIONS

The CorEx analysis provides us a tool to extract useful ways to communicate with the public based on a risk corpus, using language already being used on social networks today. By extracting latent variables, we are revealing how words are used together to communicate coherent messages, and we are able to quantify the latent content of each tweet. That is, each latent variable we identify helps to explain the mutual occurrence of words from the corpus in each tweet. In addition to being a useful clustering tool, the CorEx analysis provides us with a dimensionality reduction by mapping each tweet into a vector of probabilities for representing each of the latent variables. Although we applied the same risk corpus to analyze many types of disasters, words and phrases convey information specific to each type of emergency event.

Thus, CorEx and similar analysis can be used to characterize tweet construction, which may help for constructing emergency announcements. Tan et al. have shown that

messages that conform to the community norm have greater propagation through a network [19]. Given this, our work proposes a method for measuring lexical choices against conformity to a norm. In a larger context, one can imagine a scenario where a candidate population is selected; communication in that community is encoded, and then that measurement is used to inform your word selection to increase information propagation.

Future work will quantitatively relate the techniques presented here to observed disaster responses, both in the real world and in controlled experiments. By relating CorEx classification to social media penetration (for example, retweets), we can examine how much fear/doubt exists, compare word-of-mouth advice to official notices, and track if any "bad advice" is spreading.

5. ACKNOWLEDGMENTS

6. REFERENCES

[1] Crisis and emergency risk communication, basic: Quick guide. Report, Centers for Disease Control and Prevention, 2008.

[2] J. P. Bagrow, D. Wang, and A.-L. Barabasi. Collective response of human populations to large-scale emergencies. *PloS one*, 6(3):e17680, 2011.

[3] Booz-Allen-Hamilton. Crisis communications social media round table special report. Report, 2009.

[4] W. J. Burns. Risk perception: a review. Report, USC, 2007.

[5] W. J. Burns and P. Slovic. The diffusion of fear: Modeling community response to a terrorist strike. *The Journal of Defense Modeling and Simulation: Applications, Methodology, Technology*, 4(4):298–317, 2007.

[6] V. Covello and P. M. Sandman. Risk communication: evolution and revolution. *Solutions to an Environment in Peril*, pages 164–178, 2001.

[7] V. T. Covello, R. G. Peters, J. G. Wojtecki, and R. C. Hyde. Risk communication, the west nile virus epidemic, and bioterrorism: responding to the commnication challenges posed by the intentional or unintentional release of a pathogen in an urban setting. *Journal of Urban Health*, 78(2):382–391, 2001.

[8] M. Douglas and A. Wildavsky. Risk and culture: an essay on the selection of technical and environmental dangers. *Berkeley: University of California Press*, 1982.

[9] B. Fischhoff. Risk perception and communication unplugged: Twenty years of process1. *Risk analysis*, 15(2):137–145, 1995.

[10] D. Kahan. Cultural cognition as a conception of the cultural theory of risk. In S. Roeser, R. Hillerbrand, P. Sandin, and M. Peterson, editors, *Handbook of Risk Theory*, pages 725–759. Springer Netherlands, 2012.

[11] J. X. Kasperson, R. E. Kasperson, N. Pidgeon, and P. Slovic. *The social amplification of risk: Assessing fifteen years of research and theory.* The social amplification of risk, 2003.

[12] R. E. Kasperson. Six propositions on public participation and their relevance for risk communication. *Risk analysis*, 6(3):275–281, 1986.

[13] Y. R. Lin. The ripples of fear, comfort and community identity during the boston bombings. In *iConference 2014 Proceedings*, pages 708–720, 2014.

[14] B. Reynolds. Crisis and emergency risk communication by leaders for leaders. centers for disease control and prevention. Report, 2004.

[15] B. Reynolds, J. Hunter-Galdo, and L. Solker. Crisis and emergency risk communication. centers for disease control and prevention. 2002.

[16] P. M. Sandman. Hazard versus outrage in the public perception of risk. *Effective risk communication*, pages 45–49, 1989.

[17] P. Slovic. *The feeling of risk: New perspectives on risk perception.* Routledge, 2010.

[18] P. Slovic, B. Fischhoff, and S. Lichtenstein. Why study risk perception? *Risk analysis*, 2(2):83–93, 1982.

[19] C. Tan, L. Lee, and B. Pang. The effect of wording on message propagation: Topic-and author-controlled natural experiments on twitter. *http://arxiv.org/abs/1405.1438.*

[20] G. Ver Steeg and A. Galstyan. Discovering structure in high-dimensional data through correlation explanation. *http://arxiv.org/abs/1406.1222.*

APPENDIX

A. REGULAR EXPRESSIONS FOR RISK CORPUS FEATURES

```
emergen                                              evacuat       leave
run\S*(\s\S*\s|\s)around                             news          water
everybod                                             terror        fear
omg.*                                                flee          apocalyp
die                                                  pray          fast
drive                                                possible      electric
freak\S*(\s\S*\s|\s)out                              death         cry
confirm                                              rescue        search
com(e|es|ing)                                        struggle      real deal
stay(?! safe)                                        suffer        cause
serious                                              people        destr
break(?!ing news)                                    intense       total
hit\S*(\s\S*\s|\s)hard                               damage        power
glas+\s                                              cnn           \bsad[\b,\s]
tomorrow                                             so far        goin\S*\son
minute                                               hour          day
hear(d|ing|\s|$)                                     feel          official
pain(\s|f|$)                                         authorit      officer
national g                                           mayor         gover
remember                                             impassible    street
hundred                                              thousand      million
dooz\S*                                              almost        examin
go\S*(\s\S*\s|\s)figure                              middle        exact
tv\b                                                 guy\b         ok\b
schedul                                              annoy         punch
stuck                                                send          want
knock                                                mangl         bullsh
(?<!ll)shit                                          fuck you      badass
(?<!hot )messag                                      wrong         stup
(lie[d,\b]|lying)                                    north         south
feet                                                 miles         mph
(?<!false )alarm                                     terribl       fellow
cousin                                               grow          worker
concern                                              nervo         anxio
now[\b,\s]                                           adventure     check
avoid                                                area\b        local
remain\S*(\s\S*\s|\s)inside                          detail        insid
ventur                                               fatal         hurt
media\b                                              tornado       twister
(?<!wild)fire(?! (work|dep|figh))                    storm         firework
wind(s\b,y,ie,\b)                                    rain          windsp
ic[e,y][d,\b]                                        smok          fog+
wildfire                                             paths*\b      blow(s|ing|\b)
boom                                                 blast         bomb
depth                                                cold          hot\b
sear(?!ch)                                           hoax          blah
thund                                                lightn        http?url
(no|not|never|isn't|isnt)\S*(\s\S*\s|\s)fun          one           two
heart\S*(\s\S*\s|\s)go\S*(\s\S*\s|\s)out             six           seven
(no|not|never|isn't|isnt)\S*(\s\S*\s|\s)jok          eleven        twelve
(no|not|never|isn't|isnt)\S*(\s\S*\s|\s)cool         twenty        thirty
(is|are|am)(\s\S*\s|\s)fine                          #\w+
```