Modeling Behavioral Changes, Geospatial Impact and Recovery Timelines from Volumetric Proxies on Twitter

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Abstract

Twitter has been used as a key social networking platform to observe and analyze user behavior. In this paper, we extend the capabilities of Twitter to examine whether these behaviors can be effective in modelling changes associated with a disaster. We examine tweets relating to the Nepal Earthquake of 2015 to determine whether there are observable behavioral changes before and after the earthquake. Next, we attempt to find correlations between volumetric changes and measures of impact of the earthquake on different areas. Finally, we assess the feasibility of using behavioral proxies to compare and model recovery and resilience timelines. We also propose a methodology to assign geo-located tweets to bins based on fixed-intervals of radii, and identify stronger measures of impact that are associated with volumetric changes.

Introduction

Social networking sites have been gaining tremendous popularity since their inception and have become a major tool for mass information sharing online. The usage of social media has largely changed over the years. It is no longer used as just a medium for networking but has evolved into an information bank and propagation tool. Twitter ranks as one of the leading social networks and recorded an average of 313 million monthly active users as of the second quarter of 2016 (Vieweg et al. 2010).

This paper focuses on analysis of twitter data related to the 2015 Nepal Earthquakes. The earthquake that hit Nepal in April 2015 caused major wreckage and left the country in ruins. More than 8,000 people were killed and more than two million were left homeless by the 7.8 magnitude earthquake that shook the nation. Millions of people turned to social media to gain information about the quake and to connect with friends and family. A large volume of tweets were aimed at gaining support and aid to the affected regions. There was an estimated count of 0.2 million tweets on Twitter related to the Nepal earthquake. Such a wide scale usage of Twitter during the disaster opened up new possibilities to use this data for conducting behavioral analysis of tweets.

Information flow during times of crisis and in an environment recovering from natural disasters is different from normal behavior. However, tracking human's behavioral changes at the geographical area that has suffered from a disaster and drawing a picture of the time taken for humans to return back to their normal state is not an easy task. In this paper, we model changes in behavior associated with the volumetric measures of Twitter features such as number of tweets, retweets, favorite count, and the net reach of tweets before, during and after the Nepal earthquake. These changes are measured with respect to two earthquakes in a closed geographic space that have occurred within a span of three weeks. Furthermore, we identify indicators to assess the impact of an earthquake and evaluate these indicators against the volumetric variance of tweet volumes to identify stronger ties. Finally, we estimate whether the behavioral changes show signs and patterns of resilience and recovery after the earthquake.

Background

Social media has been active for many years and the uses of it are growing exponentially. A number of researchers have analyzed the role played by social media during times of disasters. This section provides review of literature on related works such as use of twitter to find behavioral changes during an event.

In earlier works (Mendoza, Poblete, and Castillo 2010), Twitter usage was analyzed in the context of an earthquake which occurred in Chile. The authors observed that after the event people tweeted about alerts, missing and deceased people. They also surveyed the trustworthiness of tweets and verified the false rumors were much more often questioned then confirmed truth. In the research by Vieweg et al. (2010), the authors evaluated the significance of

Twitter as a contribution to the situational awareness picture of two natural disasters. A new framework to predict behavioral changes after disaster occurrence was developed, using cell data record. Information was also generated in understanding displacement patterns and for evaluating communication changes. In the research conducted by Vemparala and Yasin (2014), the impact on Twitter during and after the earthquake at Africa have been evaluated. The authors showed that Twitter was used by citizens and news media organizations during the time of the incident to propagate information.

Another important characteristic is the assessment of disaster damage using social media activities. Kryvasheyeu et al.(2016) used social media data to analyse disaster response and damage assessment. A multiscale analysis of twitter activity before, during and after a disaster was examined to inspect real and perceived threats together with physical disaster effect measured through intensity and damage. In the research by Sakaki, Okazaki, and Matsuo (2010), the authors integrated semantic analysis and real-time nature of Twitter to present potential uses of Twitter data. They also presented innovative social approach models to assess the responses of twitter users to the damages caused by the natural disaster.

Research Questions

In this paper we examine the significance of volumetric changes in predicting recovery and resilience timelines. Moreover, we attempt to find correlations between these changes and the impact of the earthquake at a given area. Specifically, we delve into the following questions in the remainder of this paper:

- *Are there any observable changes in behavior on Twitter usage before and after a disaster?*

Our hypothesis stems from the insight that a crisis or disaster is accompanied by change in behavior of the affected parties, and this behavior manifests itself at large through social media. Instead of granular analysis of individual users, our hypothesis deals with aggregated patterns of users before, during, and after the earthquake.

- *Are volumetric changes in tweets with correlated to how affected an area is by an earthquake?*

We aim to identify how volumes of tweets change in an area subjected to natural disaster in both affected, and unaffected but geographically related regions.

- *Can behavioral changes be used as a proxy for modeling disaster recovery timelines and predicting time to obtain resilience?*

Our aim is to establish a baseline for tweeting behaviour and observe variance from the baseline over the time of the disaster. Volumetric measures are observed in the time that follows the disaster, to project when the original tweeting behaviour can be reinstated.

Methodology

This section provides a detailed description of our method of leveraging the Nepal Earthquake data gathered by the United Nations Global Polls (UNGP). We begin by describing our data collection system, then turn to our active data sampling based on geo located tweets and finally concentrate on dividing the sampled data into different bins.

Data Collection and Sampling

A database containing all tweet IDs associated with the 2015 Nepal Earthquakes (created an account using GMT +5:45) was provided by the United Nations Global Pulse. The database was further sampled to only extract tweets between February and August 2015 resulting in a total of 0.9 million tweet IDs. Twitter Streaming API was used to extract data for these IDs in JSON object format. These objects were further flattened and filtered to include only records that contained tweets geo-located in Nepal. The resulting data contained over 0.2 million geo-located tweets from Nepal. However, users who did not share location information were not considered as they could not be assigned to a specific location.

A set of important features were chosen and extracted from the twitter files for performing volumetric analysis. These features include ‘id_str’ which is a unique representation of a tweet, ‘retweet_count’ that determines the number of times a tweet is been retweeted, ‘user.freinds_count’ and ‘user.follower_count’ that establishes the total number of friends, followers respectively, ‘geo_lat’ and ‘geo_long’ that geotags a tweet. The significance of each of these features were examined over different time zones and regions.

Data Analysis

An important segment of our analysis was associated with grouping data into bins based on the distance from the earthquake. The relative tweet location from the epicenter of the earthquake was calculated for each inspection record by computing the difference in the latitude, longitude value. The data was categorized into different bins based on the distance from the epicenters (major earthquake and two highest aftershocks). Each of these categories differed by a 30 mile radius as shown in figure for one of the 3 regions. While we also evaluated the same for a 15 mile radius, we did not find significant changes in behavior since the bin sizes were too small. All the points that occurred within a 30 mile radius of any epicenter were aggregated into one bin. A similar pattern was used to group data for all bins.

For the purpose of our analysis we considered 4 important measures of behavior - the number of tweets, retweets, favourite count, and friends and followers. Using these features we conducted volumetric analysis per day to understand the mass behavioural changes. To measure the intensity of the disaster effect, each of 75 districts of Nepal were given a rank where 5 being severely affected and 0 being not affected at all. There were several districts overlapping in severely affected as well as moderately affected, hence accordingly ranks were associated to them.

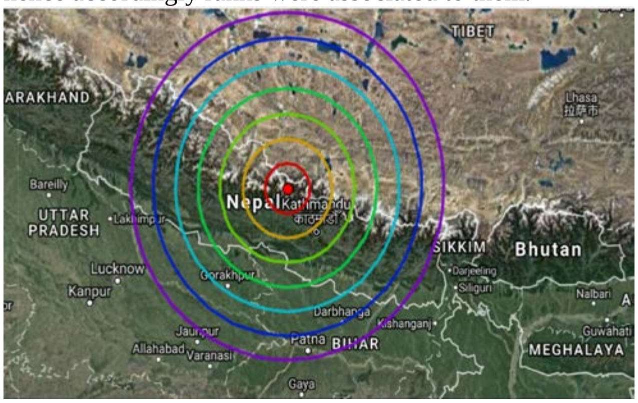

Figure 1: Effect zones for the epicenter with the highest magnitude - Gorkha district

For example, Gorkha being the epicenter was majorly affected had a rank of 5 while Kathmandu lying majorly in severely affected area (innermost dark orange boundary) along with areas of light orange boundary was given a rank of 4.75. Considering this methodology, districts like Parsa, Dhanusa, Kaski were given rank 3 while Accham, Baitadi, and Bajura received 0 being not affected at all. These ranks were called as disaster_magnitude for analysis.

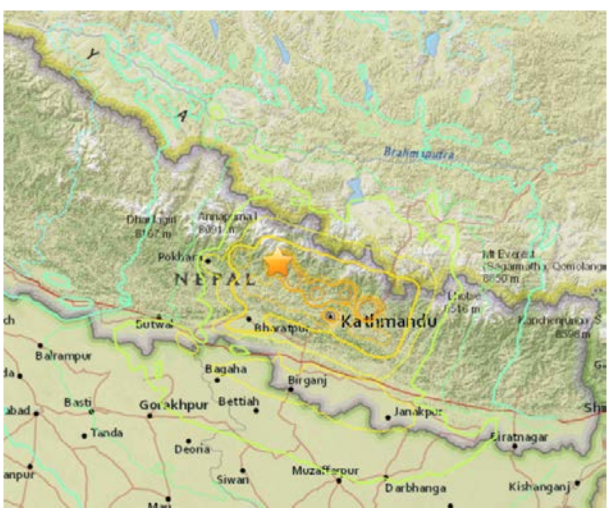

Figure 2: Map of Nepal showing Epicentre, effect and direction of earthquake of Earthquake 25th April, 2015.

In the about figure, the star marks the epicenter (Gorkha District) of Nepal earthquake that happened on 25th April 2015. The above map was secured from United States Global Survey (USGS) which explains the severely affected areas marked by innermost dark orange boundary. The severity decreases as we move outwards marked by dark yellow. The moderately affected areas are shown by light yellow and light green while the mildly affected are shown in blue. The districts which lie outside the blue boundary are marked as not affected areas. This map marks the severity by considering various factors which includes magnitude, direction, aftershocks, and slip velocity.

To measure how affected an area in Nepal was, various factors including death_ratio, injured_ratio, total_buidlings_damaged_ratio, partial_buildings_damage _ratio and disaster_magnitude were considered. The data extracted consisted of fields like number of people dead, people injured, buildings totally damaged, buildings partially damaged, population, and total households of each district. As each district had a different population and area, the fields were normalized before calculating the ratios.

The population density was calculated by finding the ratio of number of people in district X/ total households in district X. After calculating population density, total_buildings_damage_ratio for district X was calculated by number of buildings totally damaged in district X/ Population Density in district X. Similarly, partial_buildings_damage_ratio for district X was calculated by number of buildings partially damaged in district X/ Population Density in district X. Death ratio was calculated by total number of people dead in district X / total population in district X. Similarly, injured ratio was calculated by total number of people injured in district X / total population in district X.

Results

This section presents results that were obtained through our research. Findings relate to behavioral pattern changes, correlation between volumetric changes and impact, and resilience pattern estimation.

Evaluating the Presence of Behavioral Changes

In this section we describe our findings related to the behavioral changes in volumetric features before and after both the earthquakes. First, we observed the frequency of all tweets before the earthquake that occurred before April 25. Next, we observed the frequency of all tweets related to the earthquake that occurred on April 25. We compared tweet frequency pattern between the normal situation and on the day of the attack. We also extended our study to find patterns in the tweet frequency after the first earthquake till the occurrence of the second earthquake followed by the time after the earthquakes.

To obtain a statistically significant difference at each radius bin depicting the distance from earthquake, we conducted an ANOVA test [4] where we notice a significant p-value for features like total number of tweets, net reach and favorite count for all the bins considered. The retweet count did not show significant change. Bins were also considered with a 15 mile radius distance but no significant change in pattern were noticed, hence a 30-mile radius was our choice for further analysis.

Measuring Behavioral Changes in Tweet Frequency

We investigated tweet frequency from February 2015 to a few days after the first earthquake followed by the second earthquake up to a few days after the second earthquake and extract anomalous patterns. Figure 2 presents the patterns of the total number of the tweets before and during the Earthquake - 1 for different bins.

From the figure 3, it can be noticed that the number of tweets shot up on the day of the earthquakes (April 25 and May 12 2015). We also observed a considerable dip in the volume of tweets after the Earthquakes. The variability of tweet volumes at a 30-mile radius distance showed the most significant change in the tweet volume.

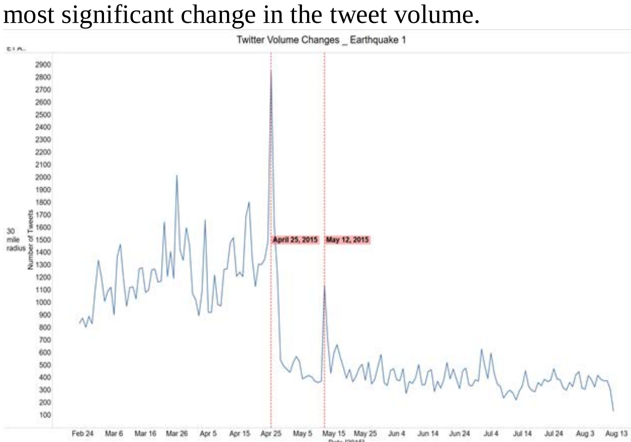

Figure 3: Changes in tweet volumes before and after Earthquake 1 for the bin with 30 mile radius

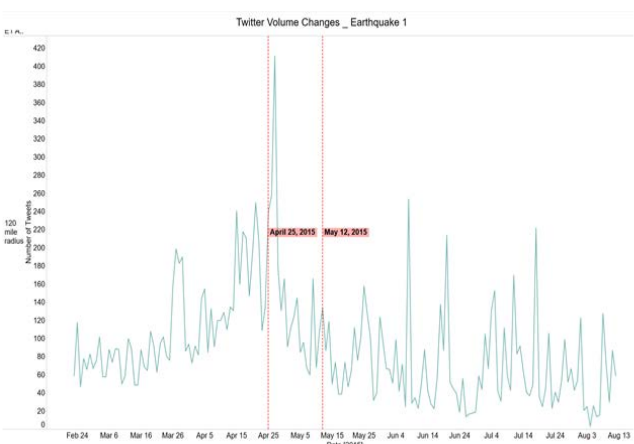

Figure 4: Changes in tweet volumes before and after Earthquake 1 for the bin with 120 mile radius

We noticed that the number of tweets on weekdays and weekends before and after the earthquakes. From these figures we observe there is a noticeable behavioural change in the tweet volume in the 30 and 120 mile radius. The other regions also show a change in tweet volume but due to limitations in the number of tweets available, a significant change is not noticed. Judging from these analyses, the number of tweets on the day of the earthquake increased significantly increased around the 30 and 60 miles region. It can also be inferred that frequent users post a certain amount of tweets that is steadily flowing and that features regular patterns. Further we conducted the ANOVA test to establish statistical significance. We found highly significant p-value, which suggest that there is a significant change in the volume of tweets before and after the earthquakes.

Measuring Behavioral Changes in Retweet Frequency

In case of the retweet volume, we noticed a change in the quantity of tweets before and after the earthquake but a statistically significant change is not noticed. There are occasional peaks in the retweet values especially in the 30 and 60 mile radius, but the other regions do not show significant change in the values. We also noticed that the retweet count after the earthquake comes back to the normal quickly. We notice that the p-value obtained in the ANOVA test are greater than 0.05. Due to this p-value we fail to reject the null hypothesis which states that there is no change in the retweet volume before and after the earthquakes. Further investigating the p-values for each bin we observe that the 60 mile radius bin shows a p-value lesser than 0.05. From this we can conclude that there is statistically significant change in the 60 mile radius distance. All other bins show a p-value greater than 0.05. This leads us to accept the null hypothesis that states that there is no change in the volume of retweets count before and after the earthquake.

Measuring Changes in Favourites and Net Reach

Favourite is calculated by calculating the total number of ‘Likes’ clicked by a user while Net Reach is calculated by cumulating the friends and followers of a user. Net reach value gives us an estimate of the information spread. We noticed a significant peak in the favourite value on the days of the earthquake followed by a steep dip following the earthquake. Occasional increase in the favourite value is noticed in the 30 mile radius but no statistically significant patterns are noticed in other regions. We also noticed that net reach also displays similar patterns - increase on the day the earthquakes followed by steady dips following the earthquakes. We notice highly significant p-values. All the bins also illustrated highly significant values. This formulated us to reject the null hypothesis which states that there is no difference between the patterns before and after the earthquake. The results are summarized in Table 1, and 2.

Behaviour	Statistics For Before And After Earthquake		P-Value For Before And After Earthquake		Mean Before Earthquake		Mean After Earthquake	
	Earthquake 1	Earthquake 2	Earthquake 1	Earthquake 2	Earthquake 1	Earthquake 2	Earthquake1	Earthquake2
Total Tweet	17.7431	15.0141	2.3348e-40	7.3309e-33	1810.7540	1713.4871	836.2568	765.9239
Retweet	-1.6772	1.7392	0.0953	0.0838	726.5573	1084.9358	963.1376	768.5652
Favourite	7.8574	7.5321	4.4609e-13	2.9263e-12	2759.2131	2717.3974	1802.2293	1710.7391
Net Reach	7.1595	7.4090	2.4090e-11	5.9046e-12	1.3047e+07	1.2972e+07	7.2979e+06	6.5924e+06

Table 1: Aggregated statistical values

Behaviour	Bin	ANOVA P-value before and after Earthquake		Mean Before Earthquake		Mean After Earthquake	
		Earthquake 1	Earthquake 2	Earthquake 1	Earthquake 2	Earthquake 1	Earthquake 2
Total Tweet	30	1.8631e-55	0.2762	1222.2121	29.4788	429.3486	19.6941
	60	4.7375e-07	1.5787e-37	263.4754	1070.3205	182.3027	365.0108
	90	0.0017	0.032	124.0163	58.6153	96.6972	40.0652
	120	0.0006	8.6915e-11	110.9344	215.4230	79.0825	120.8043
	150	0.0002	0.0006	41.0983	151.7435	25.9814	116.2934
Retweet	30	0.7226	0.6712	530.4590	63.9718	571.0825	50.5176
	60	0.0001	0.0065	96.7868	685.7179	187.5229	371.4239
	90	0.0110	0.1753	45.6393	57.5897	117.5412	18.5869
	120	0.1800	0.0426	31.6229	111.1923	52.788	75.1630
	150	0.2211	0.0011	14.4262	104.8974	26.3518	184.5978
Favourite Count	30	3.0346e-28	0.0811	1853.4262	81.8591	767.1192	47.1882
	60	0.0006	4.365e-21	486.2950	1627.1794	674.9266	660.9565
	90	0.4159	0.0123	179.1311	86.2307	159.0917	47.9239
	120	0.7734	0.2731	126.7213	408.5897	121.8807	365.1739
	150	0.6807	0.0013	65.1803	284.2435	58.7592	401.5217
Net Reach	30	3.8646e-15	0.2494	9.118203e+06	5.1201e+05	3.4809e+06	2.6033e+05
	60	0.9971	9.7435e-15	2.1243e+06	7.9133e+06	2.1253e+06	2.7503e+06
	90	0.3767	0.0447	9.4277e+05	4.1228e+05	8.4021e+05	1.9762e+05
	120	0.0454	0.1525	3.5170	1.9180e+06	5.4820	1.5426e+06
	150	0.0001	0.5105	2.2808e+05	1.1910e+06	1.0587e+05	1.2950e+06

Table 2: Bin level statistical analysis

Volumetric Changes and Impact

To answer this question, only the earthquake on April 25th is considered. This is because, while judging the absolute effect of an earthquake, recurrent damages to life and property can be hard to isolate. Property damage because of recurrent earthquakes are often exponentially lower than first occurrences. Loss to life also cannot be justified as an absolute measure in the context of recurrent earthquakes because of various activities that change the population density in a disaster affected region.

Establishing a baseline to measure change

To judge volumetric changes in an attribute, it is vital to set an appropriate baseline to measure it against. With hundreds of thousand records in consideration we checked to verify differences in weekday and weekend tweeting patterns as the earthquake happened on a Saturday. Weekday and weekend tweet volumes were found to be significantly different.

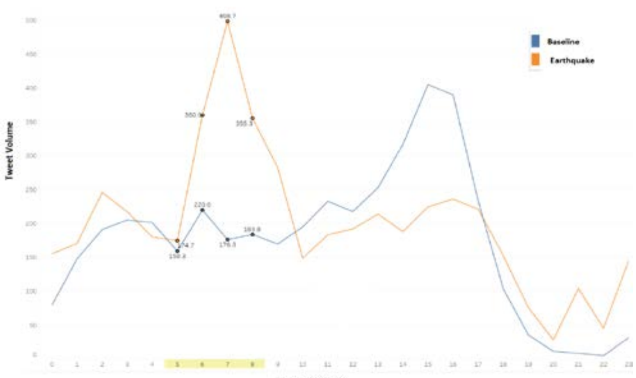

Figure 4: Trend in tweet volumes, during Earthquake and baseline period

The average weekday tweet volume was 1892 and the average weekend tweet volume was 2987. We chose to consider only weekend tweet volumes to constitute the baseline. When we measured the average tweet volume during the earthquake, the volume peaks three times as much as usual during the baseline period in the hour following the earthquake (6-7), as opposed to every other hour that complies with normal weekend trends (peak during the afternoon). Also the volume of tweets increased even during late nights during the earthquake phase showing irregular behaviour.

Correlation between Impact and Volume

The research question focused upon finding a relation between the change in volume of tweets and the severity by which an area is affected. To conduct our analysis, we performed correlation using Pearson's coefficient for change in volume of tweets against each of the measures to determine severity. The measures to determine severity consisted of five different variables which included death_ratio, inured_ratio_ partial_damage, total_damage and disaster_magnitude. Hence, five different test were ran against each of these variables to test correlation with change in volume of tweets.

Unsurprisingly, highest correlation was found with total_buildings_damage_Ratio with an r value of 0.6967 followed by death_ratio with an r-value of 0.4629. The third highest correlation with r-value 0.4433 was found between disaster_magnitude and change in volume of tweets followed by injured ratio with r-value of 0.3675. The least correlation was found between patrial_damage_ratio and change in volume of tweets with r-value of 0.1582. The results show the huge change in volume of tweets in the areas which suffered huge property damage.

We used Linear Regression to know how each variable individually affected the tweet difference. For this analysis we considered the tweet difference to be the output variable.

Variable	*P - value*	*Coefficient*
Partial_Damage_Ratio	0.000000000003864	0.15821
Total_Damage_Ratio	0.0000020754777	0.6967
Death_Ratio	0.0001416295664	0.4629
Injured_Ratio	0.0000678961852	0.3675
Disaster_Magnitude	0.0486568695392	0.4433

Table 3: Linear Regression results

From the p-value we found that Death Ratio, Disaster Magnitude, Injured_Ratio and Total Damage ratio were significant and that Death Ratio was the best predictor for estimating the variance in the tweet difference by explaining about 25% of the variability. Further, we performed multiple regression find the best fit model and their weights showing how important each feature is to the model. From the regression analysis we found the equation for the regression curve to be:

*Tweet Difference = 1.733 * Death_Ratio + 3.47*Disaster_Magnitude - 1.25 * Injured_Ratio + 0.014* Total_Damage_Ratio + 3.382*

The regression curve explains about 61.4 % of the variability in the tweet difference. Overall, there was an increase in tweet volume in the districts affected by the earthquake. Sindhupalchok, Kathmandu & Gorkha have shown a significant increase in the tweet volume even though they are in the affected zone for the earthquake on April 25th.

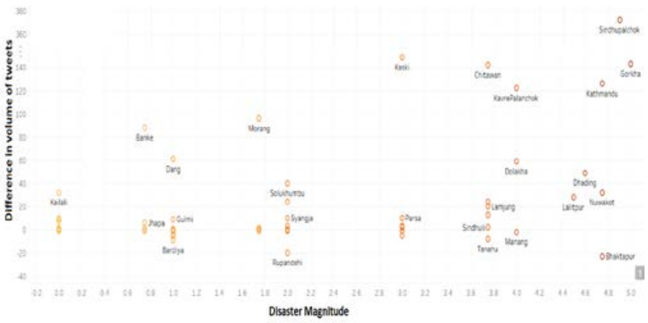

Figure 5: Variance in tweet volumes per district with respect to newly defined disaster magnitude.

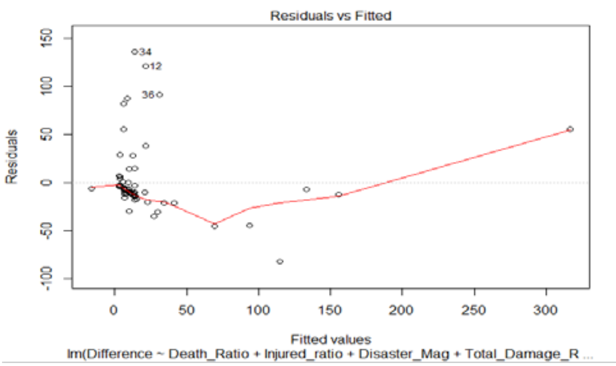

Figure 6: Graph showing many fitted points at the lower end of the scale that have high residual values.

Modelling Resilience Timelines

To answer the final aspect of our research, we considered modelling resilience timelines for each behavior that we had examined a change in with regards to volume before and after the earthquake. To establish a baseline, we used a Recurrent Neural Network that performed a lookback of one day to model the time series associated with the duration before the earthquake that occurred on April 25th, 2015. The tweets relating to that time were aggregated and 4 different statistics were computed for each day - total number of tweets, total number of retweets, total number of tweets that were favorite, and the net reach of the tweets for the given day. Once these measures were aggregated, an LSTM for time-series prediction (Ger, Eck, and Schmidhuber 2001) was trained with one hidden layer comprising of 4 neurons. This model was used to predict the expected volumes for each of these features for the test set - tweets beginning from April 25th.

The model that we constructed was not a strong predictor, but nevertheless, established a baseline to indicate the direction of change in volume and understand behavior of tweets. While in RQ1, we were able to identify that there was indeed a significant difference in behaviors, establishing a baseline to measure direction of change provided a stronger understanding of the impact of the earthquake on the behavior of Twitter users.

Figure 7 illustrates the comparison between the predicted and actual volumes of tweets observed. While the model by itself needs improvement, it serves as a base for comparison of tweets. As can be seen, before the earthquake, expected behavior had regular points of overlap with the observed behavior. Post-earthquake measures indicate that the observed behavior is nowhere in the range of the predicted behavior, and this significant deviance is an indicator that over the next 3 months, there has been no indication of resilience, and this behavior does not seem to be approaching closer to its normal state.

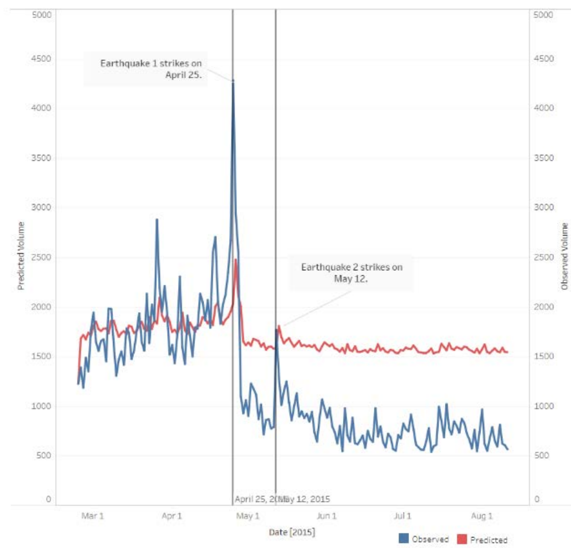

Figure 7: Tweet volumes before, during and after Earthquake

The above graph depicts the predicted and observed tweet volumes before, during, and after the occurrence of the earthquake. The red line indicates values predicted by the LSTM, while the blue line marks points that depict observed volume of tweets during this period.

In order to understand the deviation of the observed behavior from the behavior that was predicted, we computed the difference between observed and expected behavior as outlined in Figures 8, 9, 10 and 11. The blue region indicates that the observed behavior was higher than the expected behavior, while the red region indicates that the observed behavior was lower than the expected behavior, with 0 being the baseline of no difference.

In the case of tweet volumes (Figure 8), there is a noticeable dip in the difference, and it is worth mentioning the direction of effect, where, not only has the difference reduced, but is consistently accumulated a negative difference. Based on this graph, it can be concluded that tweet volumes do not attempt to recover or progress towards recovery, at least beyond the next three months.

As was reported in the first segment of our results section, retweet volumes were found to be different before and after the earthquake, however, the result was validated at a p-value of <0.05. Hence, our research was not able to identify and evidently noticeable changes in behavior before and after the earthquake, as was noted in Figure 9.

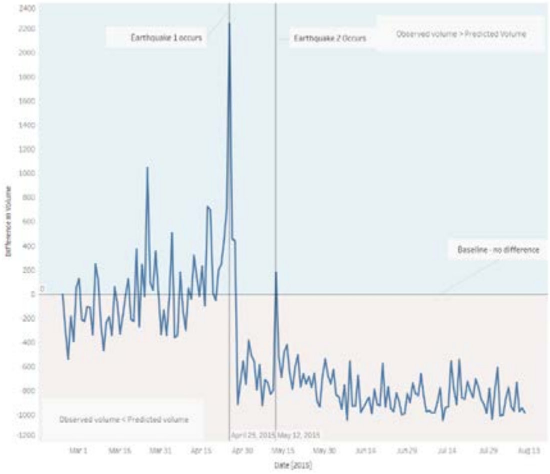

Figure 8: A graph depicting the difference between predicted and observed tweet volumes, with 2 vertical bars corresponding to the date of occurrence of the earthquakes.

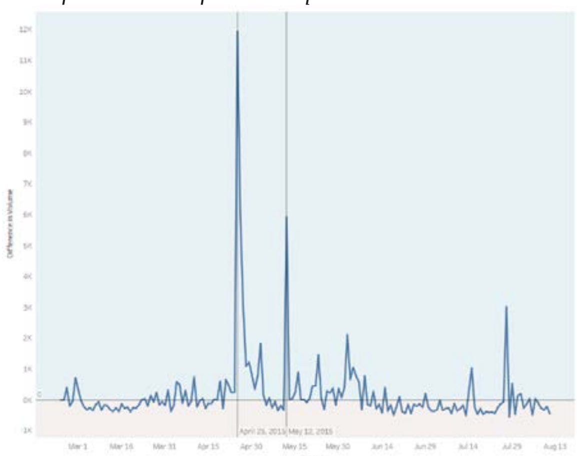

Figure 9: A graph depicting the difference between predicted and observed retweet volumes, with 2 vertical bars corresponding to the date of occurrence of the earthquakes.

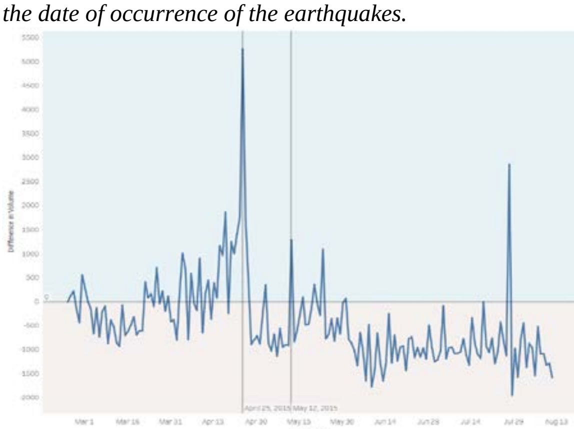

Figure 10: A graph depicting the difference between predicted and observed favourite count, with 2 vertical bars corresponding to the date of occurrence of the earthquakes.

An evident dip in the difference was observed in Figure 10, which indicates that there was a dip in the number of tweets that received a favourite sign after the earthquake. This dip also has some peaks, but these are conclusively caused by external triggers not related to or affected by the earthquake. So ignoring the rapid rise, the overall trend of the curve indicates a decline in this behavior.

An interesting observation was the drastic difference in net reach before and after the earthquake. From the graph, it is evident that before the earthquake, there were a significant number of tweets that were originating from users who had a larger follower and friend count. This means that news, in the form of tweets, had the potential to reach over 35 million people on the day that the earthquake struck. But post the earthquake, the potential number of people the tweets could have reached out to on any particular day dropped drastically. This could mean that information propagation to a larger audience is curtailed after the earthquake and shows no signs of recovery, as can be noted in Figure 11.

These findings indicate that there are no observable signs of recovery or resilience that can establish trends of normal behavior on Twitter.

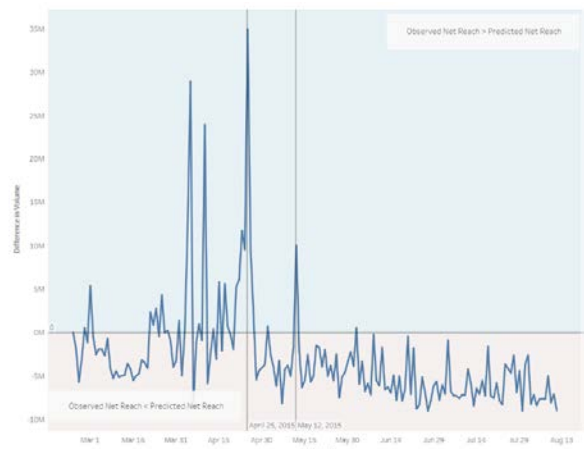

Figure 11: A graph depicting the difference between predicted and observed net reach, with 2 vertical bars corresponding to the date of occurrence of the earthquakes.

Discussion

Our findings entail a few implications that are discussed in this section that relate to the evidence of behavioral changes being effective measures during crisis analysis.

Volumetric Proxies for Behavior Detection

Our findings indicate that volumetric changes provide significant insights about the information-seeking patterns of groups and masses of people. This stands true particularly in times of crisis, when all individuals in a given area are impacted alike, thereby providing a common source of intersection to compare similarities and differences in behavior.

For instance, the volume of tweets reduced over time after the earthquake, as did the favourite count volumes. However, retweet behavior was more or less similar to the pattern observed before the earthquake, indicating that more users were invested in sharing information than creating new information or liking or appreciating the information that is being shared. If after an earthquake, the news being relayed is based on existing tweets, and not necessarily new content, then the chances of misinformation and stale information being spread are massive and compounded after every subsequent earthquake during that time period.

Change and Distance from Crisis

The first segment of our research was aimed at examining whether there was a difference in behavior before and after an earthquake. We found that there was a significant change in behavior, and this was backed by statistical tests that validated these results. The implication of this finding relates to an overall summary. However, different regions were affected differently.

We were able to detect distinguishable behavioral patterns at distances that differed by a 30 mile radii. This meant that the patterns observed at a 30-mile radius were significantly different from those observed at a 120-mile radius. While no absolute conclusion can be made about the direction of change in these areas, the extent of generalizability obtained from this analysis is that there is an observed change in behavior based on distance from the points of crises.

Variance and Direction of Impact

The second aspect of the research touches upon how we can best define the impact of an earthquake and know how volumes of tweets changes during an earthquake in an affected region and in unaffected but geographically related areas. On analysis, we find that there is a significant deviation on a very deep level of granularity. The hour after the earthquake shows very high deviation from baseline. By evaluating the various features we used to define impact we find that damage in property and loss of life best explains the observed variance in tweet volumes.

Magnitude of the earthquake did not prove to be the most significant factor (although significant) in explaining variance, we can see a clear pattern in districts closer to the epicenter and which lie in the direction of the earthquake, showing higher variance in tweet volumes. Therefore, loss of life, property destruction and magnitude rank attributes correlate and best explain change of volume in tweets, as compared to injury caused and partial damage to property.

Recovery and Resilience on Twitter

The third aspect of our research delved into examining whether behavioral changes can be used as proxies to measure recovery and resilience patterns. We found that these changes are effective in establishing a primitive baseline for comparison. Social networking data, in itself, is skewed due to various events. Hence it has been a challenge to model a baseline with less error rate. Our research found that even while the baseline does not mirror the actual volumes, it provides a sense of understanding about the direction of change, and computes the lower threshold to compare the shift in behavior.

We also found that there was no noticeable improvement in the volumetric measures of activity on Twitter that directs the affected areas towards resilience. After the disaster, the volume of tweets, favourite count and net reach decreased sharply, and have not progressed in the direction of bridging that gap over the subsequent 3 months. It is safe for us to assume that there is no observable resilience or progress towards resilience during the 3 months post-earthquake. What is even more interesting is the sharp decrease in net reach, which never recovers fully. Particularly, it appears to be that not many users with a wider audience are using the capabilities of social media to spread information post the earthquake.

Conclusion

The environment and the situation alters information flow patterns and volumes. Through this research, we were able to establish that volumetric changes in twitter can be used as an effective proxy to model behavioural change, in times of crisis. Also, in a geographic area that has suffered an earthquake, loss of life and property destruction can best explain variance in volumes of tweets during earthquake. The places that lie in the direction of earthquake traversal and lie closer to the epicenter tend to show irregular peaking in tweet volumes. With the establishment of the correlation between imp and change, we also examine direction of change before and after the earthquake and successfully conclude that resilience on twitter is not attainable within three months past the earthquake.

Limitations and Future Scope

The first and foremost limitation is the fact that we were only able to examine selective tweets that had a geolocation associated with it. Next, we did not assess the volume of tweets to find relevance. We have also not considered hashtags or other attributes to help distinguish tweeting abnormality due to other major events in the given geographic boundary. Future directions for this research can include, examination of social interaction and impact of active users on information propagation. Ensuring relevance of tweets to the natural disaster considered would further strengthen the research and findings.

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