#NeverAgain

Measuring apathy toward mass shootings by analyzing Twitter sentiment

Lara Bagdasarian
lbagdas@stanford.edu
Meilinda Sun
meilinda@stanford.edu

Stanford University

Introduction

- Mass shootings have been occurring more frequently in recent years
- We hypothesize that Americans are growing more apathetic to such incidents
- Social media, particularly Twitter, functions as an outlet for reflection on current events

We propose to track patterns in the percentage of daily tweets expressing negativity in the aftermath of several mass shooting events and identify features indicative of reactional sensitivity to such events.

Hypothesis

As more mass shootings occur over time, people have a less angry immediate response.

As more mass shootings occur over time, collective anger diffuses more quickly.

Dataset

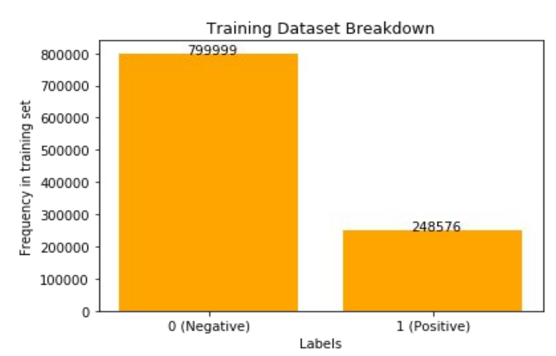
Training Dataset:

- sentiment140 dataset containing 1.6 million general tweets of varying topic
- Hand-labelled for positive and negative sentiment

Experimental Dataset:

- Extracted 300 tweets per day, before and after five major shootings
- Filtered tweets by hashtag corresponding to city of shooting
- Used LDA to filter out tweets addressing topics unrelated to shooting; e.g., Tom Petty's death in the case of the 2017 Vegas shooting

Sandy Hook	2012
San Bernardino	2015
Orlando (Pulse Nightclub)	2016
Las Vegas	2017
Parkland (Stoneman Douglas)	2018



Algorithms and Methods

Data preprocessing & feature representation	Tokenization and lemmatization of tweets; Obtained **GLOVE** vector embedding per word
Sentiment classification	**Logistic Regression** Take mean GLOVE embedding for training and testing data. Train and test logistic regression classifier. / **LSTM (Long Short-term Memory)** Utilize positional information of words by training and testing multi-layer LSTM classifier.
Data representation	Represent percentage of tweets per two-day interval classified as negative.
Understanding nature of negative tweets	Fit data aggregated from each shooting to **LDA (Latent Dirichlet Allocation)** model for unsupervised topic detection and collected human feedback to identify emotional implications of identified topics; tested model on negative tweets
Sentiment graph features	Identify features to represent nature of response to shootings in order to compare progression over time

Sentiment Classification Model Architecture

Logistic Regression:

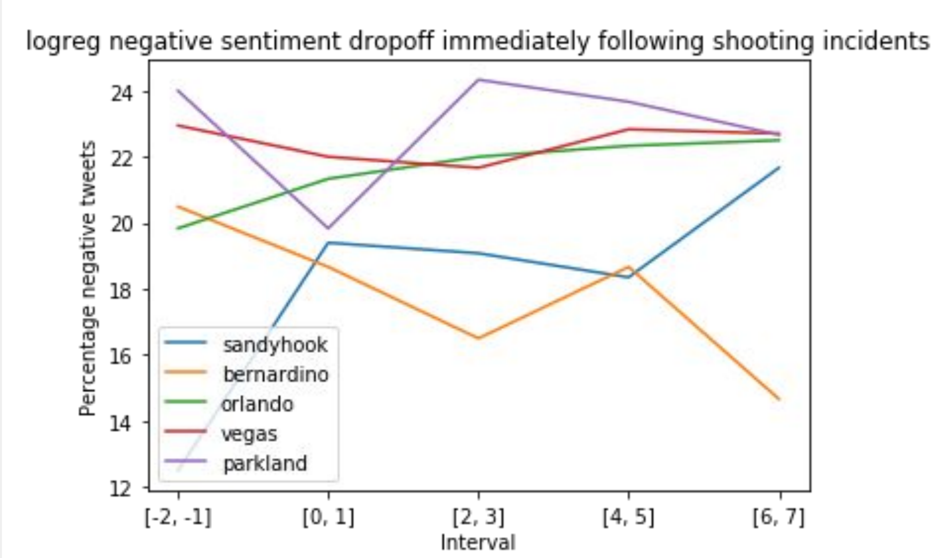
Tokenized tweet → Glove embedding → Average Glove embeddings → Logistic regression

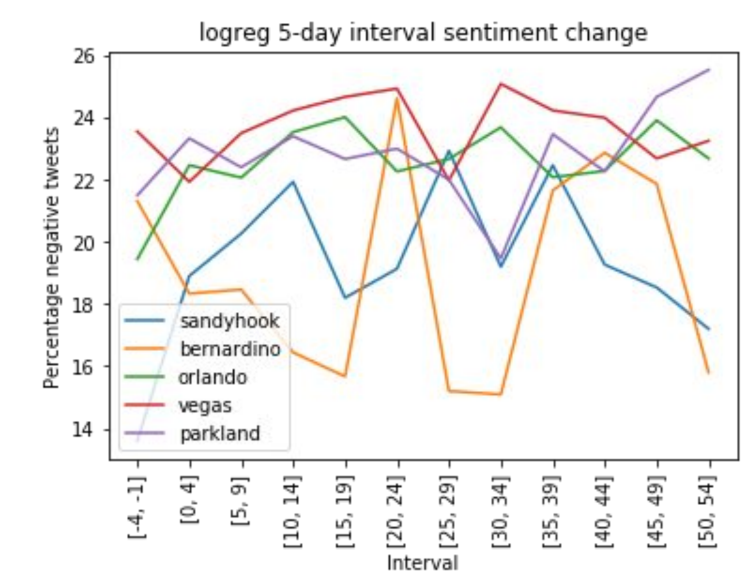
LSTM:

Tokenized tweet → Glove embedding → Dropout → Convolutional 1D → Max Pooling → LSTM → Dense

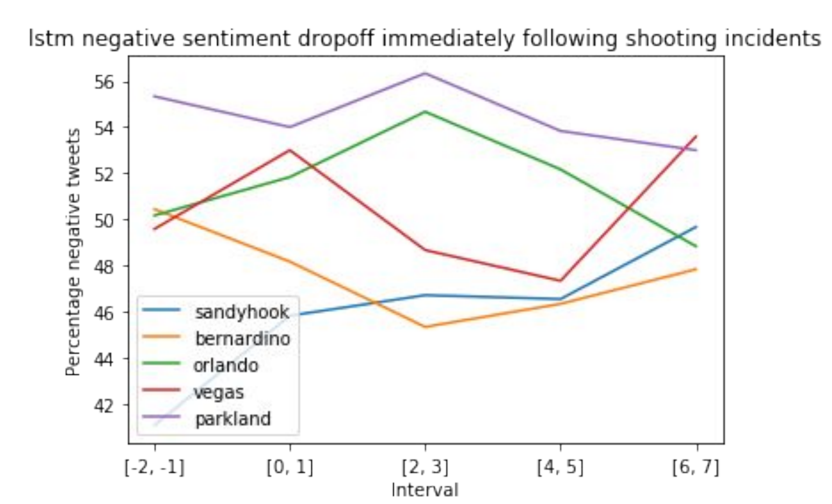
Results

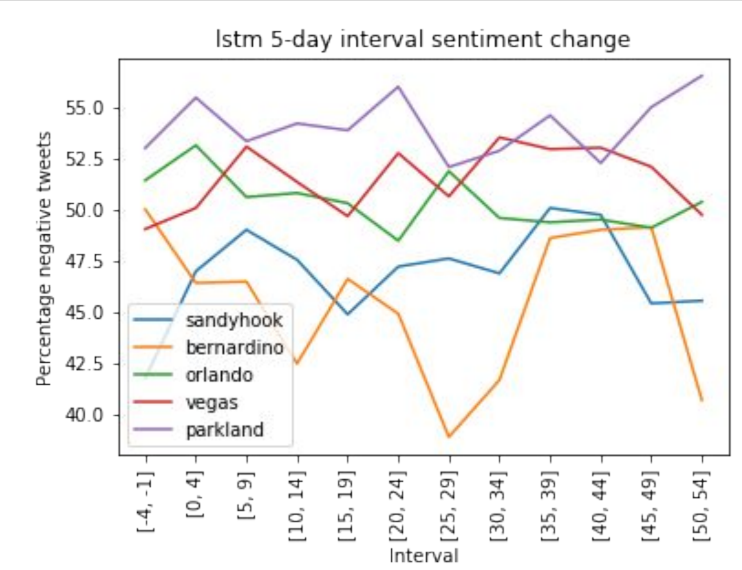
Logistic Regression on GLOVE Embeddings



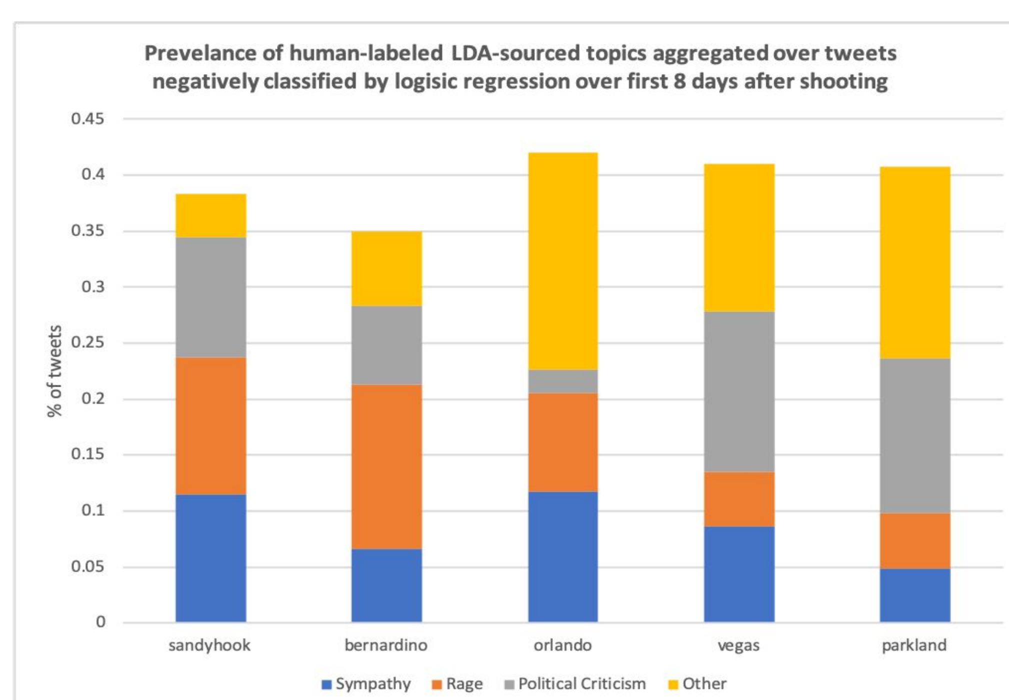


LSTM on GLOVE Embeddings





LDA Representation of Negative Tweets



Sentiment-Shift Graph Features

Initial drop-off: Percentage difference of negative tweets between initial time interval and the time interval immediately following the shooting
How significantly does sentiment change due in response to shooting?

Length of tail: Time taken to return for the percent negative tweets to return to within 5% of the pre-shooting levels
How sustained was negativity after a shooting?

Initial drop-off slope magnitude: Magnitude of slope over first four time intervals subsequent to shooting.
How quickly did negative sentiment subside after the shooting occured?

Analysis using Logistic Regression on GLOVE Embeddings for Sentiment Classification

	Sandy Hook (2012)	San Bernardino (2016)	Orlando (2017)	Las Vegas (2018)	Parkland (2019)
Initial drop-off	-0.728	-2.167	0.667	-0.333	-0.667
Length of tail	None	5	4	2	1
Initial drop-off slope magnitude	0.776	0.0833	-0.375	1.220	0.167

Discussion

- Magnitude of initial drop-off slope appears to decrease, indicating less immediate sensitivity to a mass-shooting event
- No meaningful results could be derived from initial drop-off
- Length of tail decreased over successive shootings indicating a less sustained response to shootings
- Negative tweets appeared to be increasingly comprised of political criticism and less comprised of rage and sympathy (which represent more emotional reactions)

References

Ahamed, Sabber. "Text Classification Using CNN, LSTM and Pre-Trained Glove Word Embeddings: Part-3." Medium, Medium, 13 Jan. 2018, https://medium.com/@sabber/classifying-yelp-review-comments-using-cnn-lstm-and-pre-trained-glove-word-embeddings-part-3-53fcea9a17fa.

Demszky, Dorottya, Nikhil Garg, Rob Voigt, James Zou, Matthew Gentzkow, Jesse Shapiro, and Dan Jurafsky, April 4, 2019. https://arxiv.org/abs/1904.01596.

Jefferson, Henrique. https://github.com/Jefferson-Henrique/GetOldTweets-python.

Pennington, J., Socher, R., & Manning, C. (n.d.). Stanford NLP. Stanford NLP. Retrieved from https://nlp.stanford.edu/projects/glove/

Ma, Edward. "Combing LDA and Word Embeddings for Topic Modeling." Medium, Towards Data Science, 15 Sept. 2018, https://towardsdatascience.com/combing-lda-and-word-embeddings-for-topic-modeling-fe4a1315a5b4.