

An aerial photograph of a rocky coastline. The water is shallow and clear, revealing numerous dark, smooth rocks of various sizes scattered across the seabed. The water's surface is covered in gentle ripples, creating a textured, greenish-blue appearance. The horizon is visible in the distance under a pale sky.

**Language is  
fluid...  
Feeling is static**

Verghese Samuel  
2020

# Problem Statement

People share their opinions on the social media. These opinions have sentiments of positive, neutral, or negative experience.

Given the time and frequency of the user driven content sharing, it is humanly not possible to evaluate the sentiments of each of the content.

How do organizations understand which of these expressed sentiments impact their brand?



An aerial photograph showing the aftermath of a hurricane. The landscape is covered in a thick layer of debris, including wood, metal, and other building materials. Several houses are visible, many of which are severely damaged or completely destroyed. A bridge is visible on the left side of the image, and a body of water is on the right. The text "Hurricane Hit..." is overlaid in the center of the image.

# Hurricane Hit...



| Search Posts             |                                                                                                                                                                                                                                                                                                                                                                       | united states | Q             | SENTIMENT   | EXCLUDE RETWEETS | RESET |  |  |
|--------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------------|---------------|-------------|------------------|-------|--|--|
| USER                     | POST                                                                                                                                                                                                                                                                                                                                                                  | REGION        | COUNTRY       | ENGAGEMENTS |                  |       |  |  |
| <input type="checkbox"/> | <div><div><div><div><div></div><div></div><div></div><div></div><div></div></div></div><div>After one of the worst disasters in U.S. history, we're demanding answers. America deserves to know the truth about the Trump administration's inadequate preparedness and response to Hurricanes Irma and Maria so we can ensure it does not happen...</div></div></div> | NY            | United States | 4,716       |                  |       |  |  |
| <input type="checkbox"/> | <div><div><div><div></div><div><div>SteelerNation</div><div>@SteelerNation</div></div></div><div>People died and lost their homes in that hurricane and Eagles fans think making a meme out of that is okay. Saints by a million</div></div></div>                                                                                                                    | PA            | United States | 2,238       |                  |       |  |  |
| <input type="checkbox"/> | <div><div><div><div></div><div><div>Joy Reid</div><div>@JoyAnnReid</div></div></div><div>California, Texas, Florida and Puerto Rico hurricane victims will pay for the wall?</div></div></div>                                                                                                                                                                        | NY            | United States | 2,130       |                  |       |  |  |
| <input type="checkbox"/> | <div><div><div><div></div><div><div>The Dodo</div><div>@dodo</div></div></div><div>This baby cow was rescued from a hurricane and became best friends with a little boy 🐮❤️ <a href="https://t.co/NAsgrtZxgd">https://t.co/NAsgrtZxgd</a></div></div></div>                                                                                                           | NY            | United States | 1,961       |                  |       |  |  |
| <input type="checkbox"/> | <div><div><div><div></div><div><div>Adam Best</div></div></div><div>This right-wing smear is getting out of hand. Democrats were in Puerto Rico to meet with the governor about post-</div></div></div>                                                                                                                                                               |               |               |             |                  |       |  |  |

# Real-time Tracker: **hurricane**



**120,052**

POSTS

**84,231**

USERS

**125,480**

ENGAGEMENT

**551,327,342**

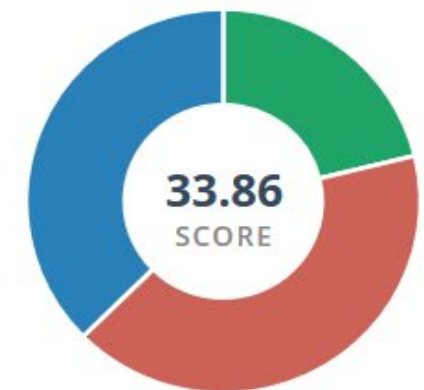
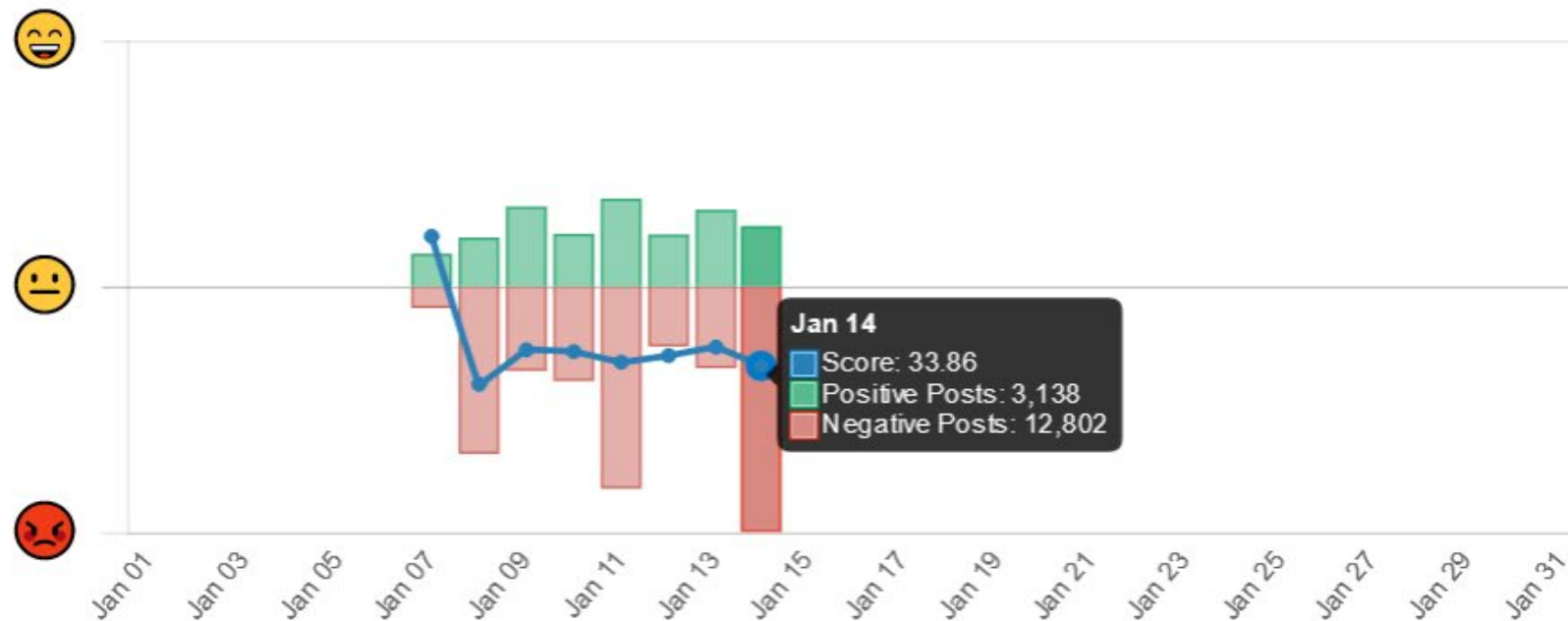
REACH

**995,381,460**

IMPRESSIONS

## Sentiment Timeline

hurricane



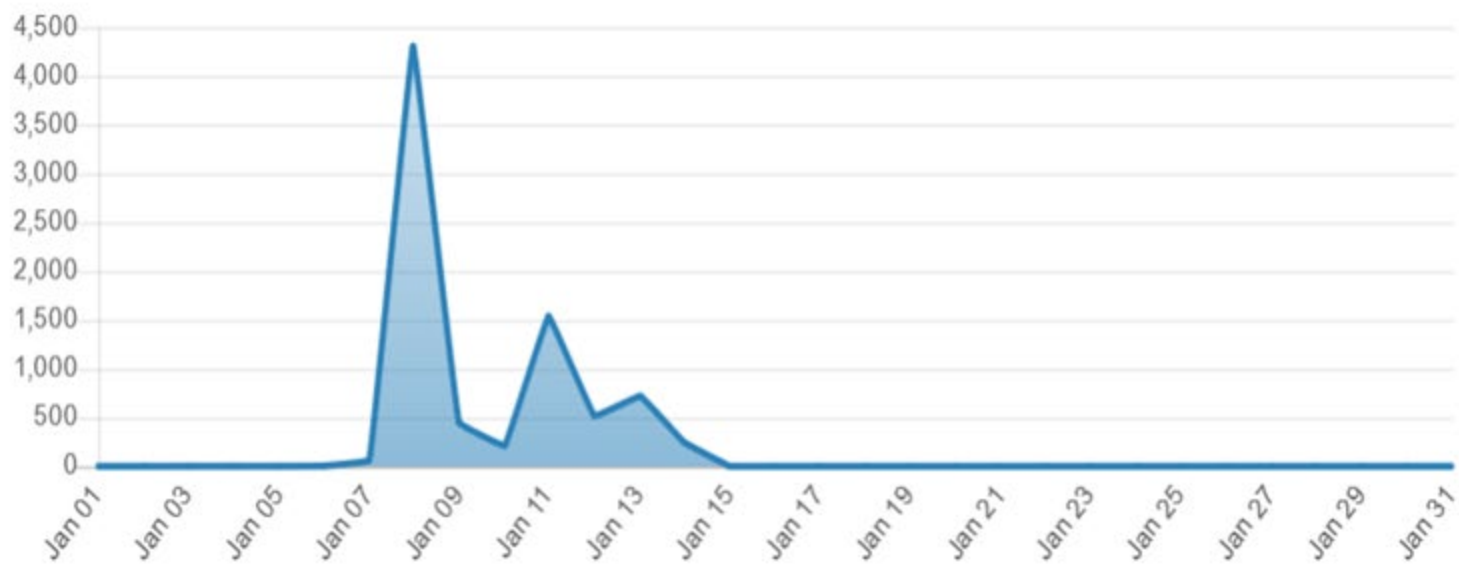
# Trending Topics: Insights into conversations around this tracker

TOPICS ? + Add Subtopic

Top Rising

|            |        |
|------------|--------|
| ▲ puerto   | 17,574 |
| ▲ rico     | 16,482 |
| ▲ wall     | 14,832 |
| ▲ trump    | 12,159 |
| ▲ pay      | 11,394 |
| ▲ america  | 9,658  |
| ▼ like     | 8,370  |
| ▼ disaster | 8,056  |
| ▲ build    | 7,771  |

## Mentions Over Time: disaster



DATES & TIMES ARE BASED ON YOUR LOCAL TIMEZONE: (GMT-0800 | PACIFIC STANDARD TIME)

# Framework for Solution



DATA



MODEL  
(PROBABILISTIC &  
CATEGORICAL)



INTERFERENCE  
ELEMENTS



OUTCOME & TUNING

# Markov Model Structure for Information

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ct techniques, while well  
ch recognition, are just  
e information extraction  
f hidden Markov models  
ks, specifically focusing  
ure from data and how  
ed and unlabeled data.  
ructured model that con-  
tion field outperforms a  
and discuss strategies for  
automatically from data.  
use of distantly-labeled  
provides a significant im-  
acy. Our models are ap-  
distantly-labeled data consistently  
tion accuracy.  
Hidden Markov models, while rela-  
mation extraction, have enjoyed suc-  
ural language tasks. They have be-  
part-of-speech tagging (Kupiec 1999)  
recently been applied to topic dete-  
(Yamron *et al.* 1998) and dialog act  
Shriberg, & others 1998). Other sys-  
for information extraction include th-  
who extracts gene names and locat-  
abstracts, and the Nymble system  
for named-entity extraction. Unlike  
tems do not consider automatically

## A Universal Part-of-Speech Tagset

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### Abstract

To facilitate future research in unsupervised induction of syntactic structure and to standardize best-practices, we propose a tagset that consists of twelve universal part-of-speech categories. In addition to the tagset, we develop a mapping from 25 different treebank tagsets to this universal set. As a result, when combined with the original treebank data, this universal tagset and mapping produce a dataset consisting of common parts-of-speech for 22 different languages. We highlight the use of this resource via two experiments, including one that reports competitive accuracies for unsupervised grammar induction without gold standard part-of-speech tags.

forms across languages. These categories are often called *universals* to represent their cross-lingual nature (Carnie, 2002; Newmeyer, 2005). For example, Naseem et al. (2009) used the Multext-East (Erjavec, 2004) corpus to evaluate their multi-lingual POS induction system, because it uses the same tagset for multiple languages. When corpora with common tagsets are unavailable, a standard approach is to manually define a mapping from language and treebank specific fine-grained tagsets to a predefined universal set. This was the approach taken by Das and Petrov (2011) to evaluate their cross-lingual POS projection system for six different languages.

To facilitate future research and to standardize best-practices, we propose a tagset that consists

## Twitter Sentiment Classification using Distant Supervision

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### ABSTRACT

We introduce a novel approach for automatically classifying the sentiment of Twitter messages. These messages are classified as either positive or negative with respect to a query term. This is useful for consumers who want to research the sentiment of products before purchase, or companies that want to monitor the public sentiment of their brands. There is no previous research on classifying sentiment of messages on microblogging services like Twitter. We present the results of machine learning algorithms for classifying the sentiment of Twitter messages using distant supervision. Our training data consists of Twitter messages with emoticons, which are used as noisy labels. This type of

Consumers can use sentiment analysis to research products or services before making a purchase. Marketers can use this to research public opinion of their company and products, or to analyze customer satisfaction. Organizations can also use this to gather critical feedback about problems in newly released products.

There has been a large amount of research in the area of sentiment classification. Traditionally most of it has focused on classifying larger pieces of text, like reviews [9]. Tweets (and microblogs in general) are different from reviews primarily because of their purpose: while reviews represent summarized thoughts of authors, tweets are more casual and lim-

# Model Foundation