
Language is fluid…
Feeling is static
Verghese Samuel
2020

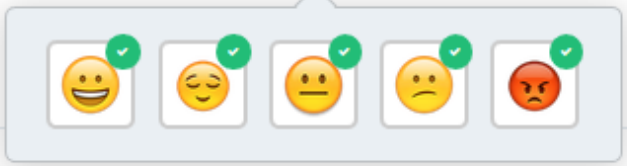
# Problem Statement

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 the content.

How do Organizations understand which of these sentiments impact their brand?


Hurricane Hit...

Search Posts | united states | SENTIMENT | EXCLUDE RETWEETS | RESET



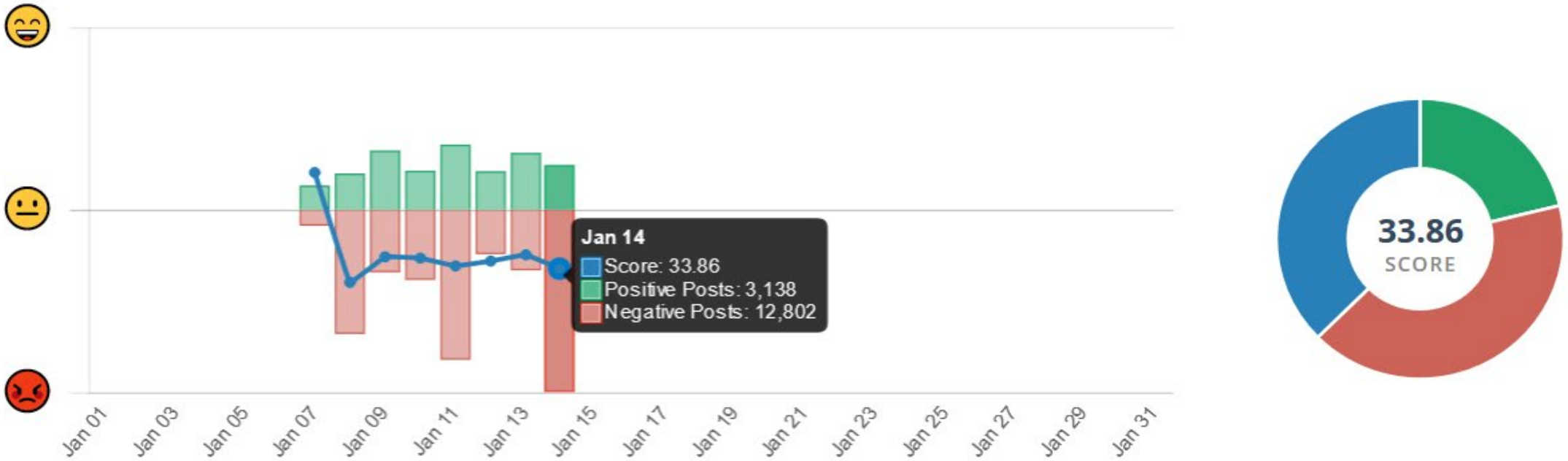
| USER | POST | REGION | COUNTRY | ENGAGEMENTS |
|---|---|---|---|---|
| **Chuck Schumer** @SenSchumer | After one of the worst disasters in U.S. history, we're demanding answers. America deserves to know the truth about the Trump administration's inadequate preparedness and response to Hurricanes Irma and Maria so we can ensure it does not happen... | NY | United States | 4,716 |
| **SteelerNation** @SteelerNation | 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 | PA | United States | 2,238 |
| **Joy Reid** @JoyAnnReid | California, Texas, Florida and Puerto Rico hurricane victims will pay for the wall? | NY | United States | 2,130 |
| **The Dodo** @dodo | This baby cow was rescued from a hurricane and became best friends with a little boy 🐄❤️ **https://t.co/NAsgrtZxgd** | NY | United States | 1,961 |
| **Adam Best** | This right-wing smear is getting out of hand. Democrats were in Puerto Rico to meet with the governor about post- | | | |

# Real-time Tracker: **hurricane**

| 120,052 | 84,231 | 125,480 | 551,327,342 | 995,381,46 |
|---|---|---|---|---|
| POSTS | USERS | ENGAGEMENT | REACH | IMPRESSIONS |

## Sentiment Timeline

hurricane



Real-time Tracker: hurricane

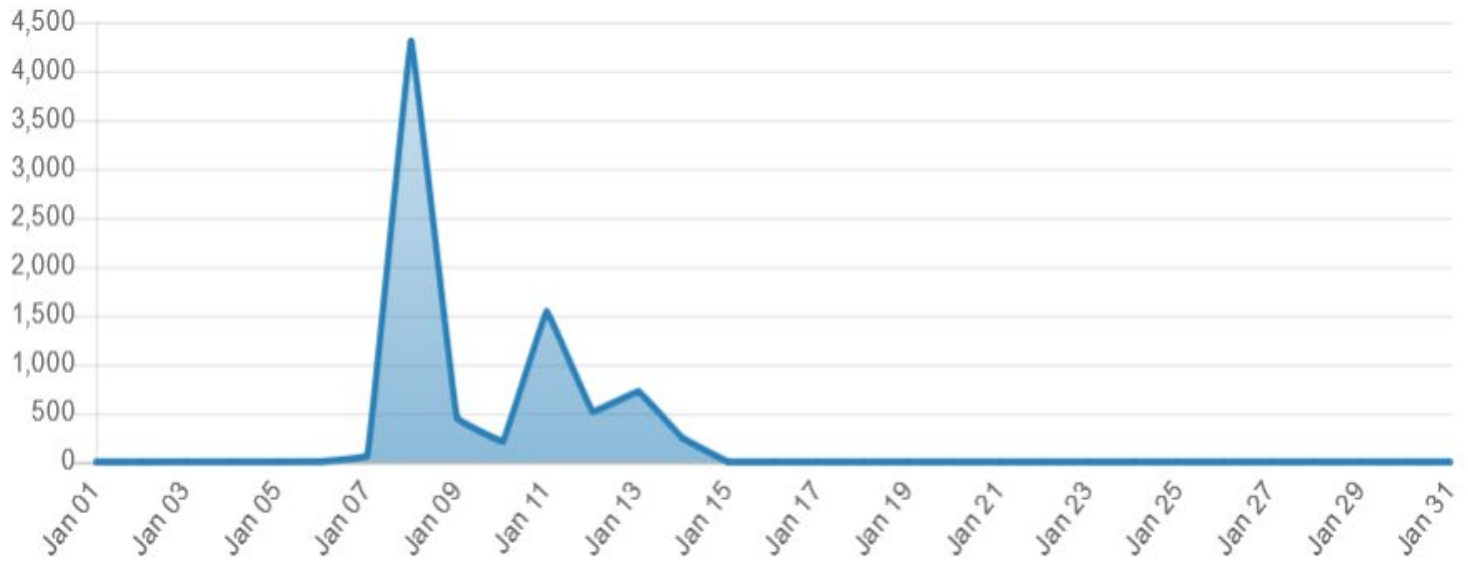
# Trending Topics: Insights into conversations around this tracker

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 |
| know | 7,637 |

## Mentions Over Time: disaster




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

Autonomous Dynamics

# Framework for Solution

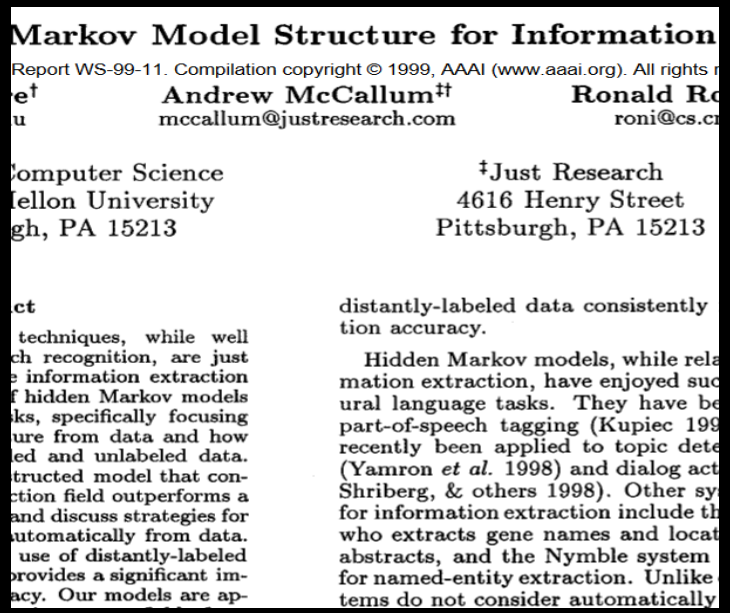
DATA

MODEL

(PROBABILISTIC & CATEGORICAL)

INTERFERENCE ELEMENTS

OUTCOME & TUNING



Markov Model Structure for Information

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Andrew McCallum[†‡] mccallum@justresearch.com

Ronald Ro roni@cs.cr

Computer Science Mellon University gh, PA 15213

[‡]Just Research 4616 Henry Street Pittsburgh, PA 15213

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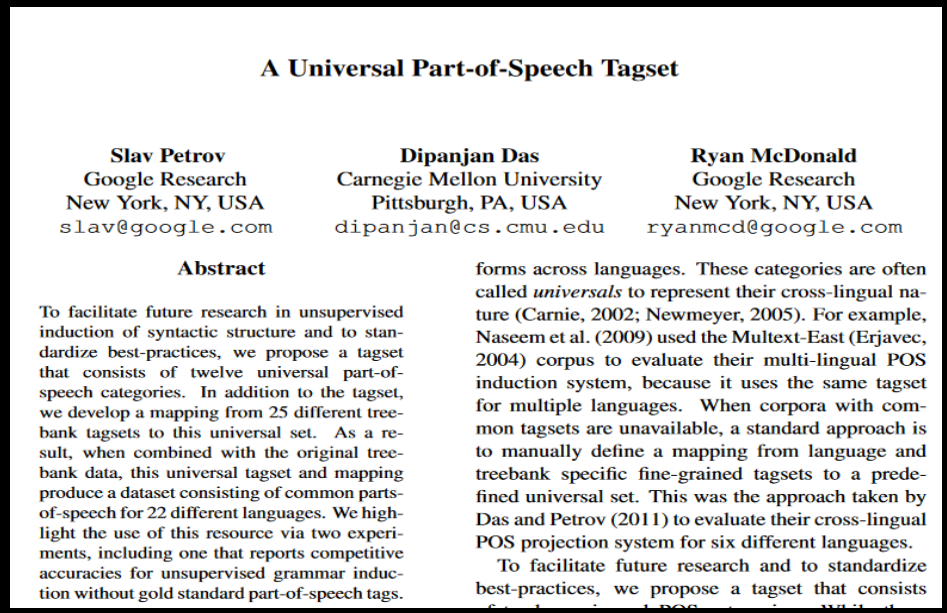
techniques, while well ch recognition, are just information extraction f hidden Markov models ks, specifically focusing ure from data and how ed and unlabeled data. tructed model that con- ction field outperforms a and discuss strategies for utomatically from data. use of distantly-labeled rovides a 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 199 recently been applied to topic dete (Yamron *et al.* 1998) and dialog act Shriberg, & others 1998). Other sy 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

**Slav Petrov** Google Research New York, NY, USA slav@google.com

**Dipanjan Das** Carnegie Mellon University Pittsburgh, PA, USA dipanjan@cs.cmu.edu

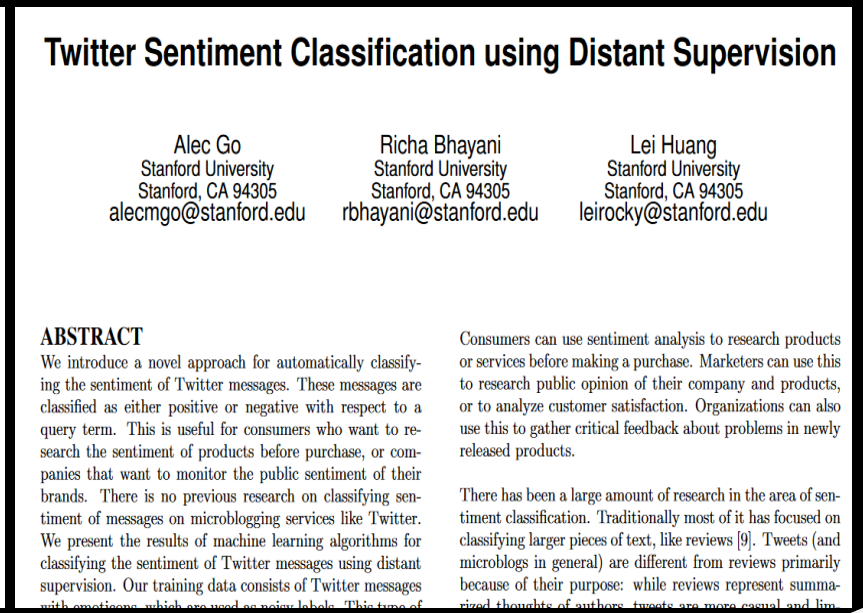
**Ryan McDonald** Google Research New York, NY, USA ryanmcd@google.com

**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

Alec Go Stanford University Stanford, CA 94305 alecmgo@stanford.edu

Richa Bhayani Stanford University Stanford, CA 94305 rbhayani@stanford.edu

Lei Huang Stanford University Stanford, CA 94305 leirocky@stanford.edu

**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

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 summa-

# Model Foundation