# Tweet Analysis: 2018 Camp Fire

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# Agenda

- Context
- Problem statement
- Data collection and feature engineering
- Modeling and analysis
- Challenges and constraints
- Recommendations and next steps

# Context

# Background on project

- Work should focus on:
  - preparing for emergencies
  - o rapidly responding to emergencies, and/or
  - estimating the economic impact of disasters
- Our topic selection criteria:
  - Pulling data from social media
  - Relatively recent disaster
  - End result something that can be generalized to other disasters
  - Unsupervised learning
  - Sentiment analysis

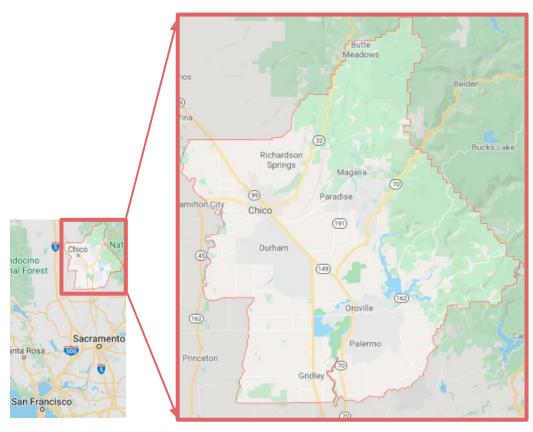
# Case Study

#### Camp Fire

- Paradise, CA (Butte County)
- November 8-25, 2018
- 85 fatalities
- o 17 non-fatal injuries
- o 52,000 evacuated
- o 153,336 acres
- \$16.5 billion worth of damages

#### Reasons for selection

- Timing
- o In US
- Media coverage
- Footprint of impact
- o "Slow" disaster



# Problem Statement

# Refining our problem statement

Problem statement v1

Can we use location-based social media data and a mapping API to map the 2018 California wildfire?

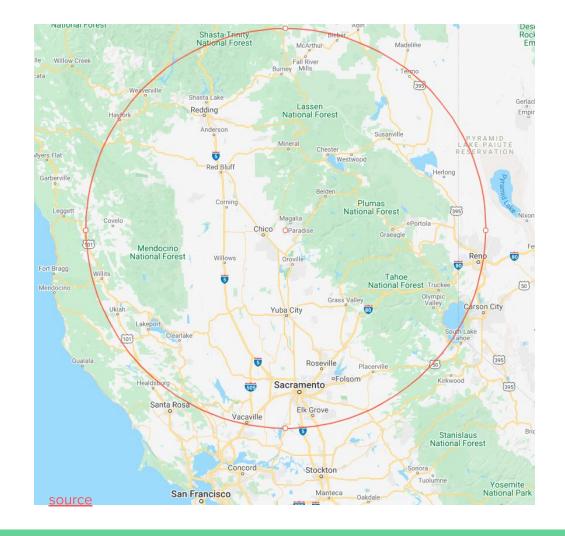
Problem statement v2

Can we build a list of keywords to help detect that an event is happening from social media posts?

Data Collection and Feature Engineering

#### **Data Collection**

- GetOldTweets3 (API)
- Cities of interest
  - Butte County
  - Paradise
  - Chico
  - Magalia
  - Oroville
- Date range: 11/1 11/26
- Pull all tweets within
  100 mile radius
  - Remove duplicates



# Feature Engineering

- key\_score
  - **0** 656; **1** 353; **2** 84; **3** 19; **4** 11; **5** 7
- from\_locations
  - o 32 unique locations
  - o 95% from Butte County
  - o 80% from Chico and Paradise alone
- is-fire-related
  - 46/54 split between is not/is
- during\_fire
  - 20/80 split between is not/is
- sentiment
  - o 65/35 split between positive/negative

#### keywords

- o fire
- o evac
- o smok
- o burn
- o wild
- o blaz
- o hell
- department
- o inferno
- help
- o alone

### Sample tweets



key score: 1

from\_location: Paradise, CA

is-fire-related: 1 during\_fire: 0 sentiment: 1

ource

no words #paradise #paradiseca #paradisecalifornia #campfire #survivor #ilovecalifornia #californiafires #campfireparadise #californiawildfires #californiafirefighter #californiafire... instagram.com/p/BqYzuuggBLs/...

key\_score: 5

from\_location: Paradise, CA

8:48 PM · Nov 19, 2018 from Paradise, CA · Instagram

is-fire-related: 1 during\_fire: 1 sentiment: 1

source

Modeling & Analysis

#### Overview

#### k-Means clustering

- What types of things people are tweeting about during the fire?
- Fire-related tweets only (612)
- Tested to find optimal amount of clusters
- Balance interpretability with granularity of clusters

#### Sentiment analysis

- How does tweet sentiment change over the course of the fire?
- Library: Twitter NLP Toolkit
- Module: Tweet Sentiment Classifier

#### Key score analysis

 How is the key score of a tweet affected by factors such as sentiment, location, and time horizon of the fire?

# k-Means Clustering

#### 3 clusters

- 1: Traffic and road related
- 2: Emotional
- 3: California

#### 5 clusters

- 1: Traffic
- 2: Emotional
  - negative sentiment
- 3: California
- 4: Traffic
- 5: Informational

#### 7 clusters

- 1: Photo
- 2: Fire
- 3: Emotional
  - positive sentiment
- 4: Informational
- 5: Emotional
  - negative sentiment
- 6: California
- 7: Traffic

## k-Means Clustering

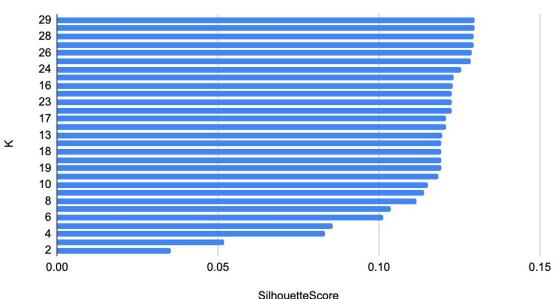
#### Cluster evaluation

- Surprised at the amount of traffic-related tweets
- Emotional nuance clearer with more tweets
- 5 clusters as sweet spot between interpretability and granularity

#### Silhouette scores

- Poor silhouette scores
- Largest increase from 4 to
  5 clusters





## Sentiment Analysis

Positive / negative split

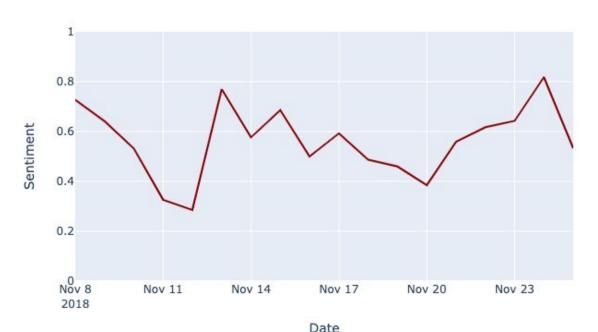
o Pre-fire: 86/14

o During fire: 60/40

o Total: 65/35

- Lowest 4 days after fire started
- Not all tweets negatively classified actually were
  - "Even in the tragic moments of life there are reasons to celebrate...#HappyBirthday #IggyPup. We <3 you!! @Chico, California" (source)

#### Average Sentiment by Day during the 2018 Camp Fire



# Sentiment by Key Score

Average Sentiment by Key Score



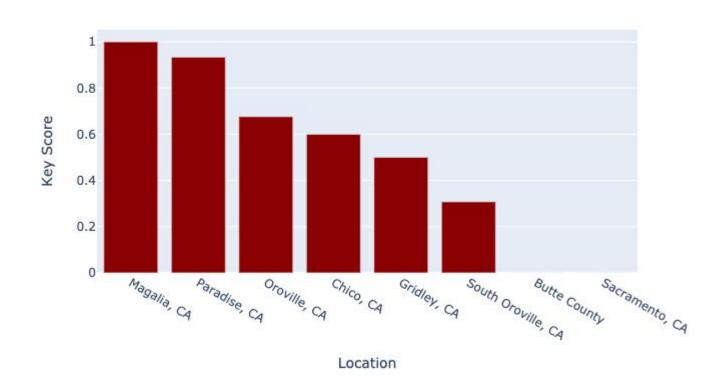
# Key Score by Date

#### Average Key Score by Day



# Key Score by Location

Average Key Score by Location during the Camp Fire



# Challenges & Constraints

# Challenges & Constraints

- Pulling a sufficient amount of data
- Data from single social media source
- Only text data analyzed
- Not all tweets within 100 mile radius captured
  - Only those with location tag

# A question of ethics

• Where is the line between the right to data privacy on using media and using social media data in times of disasters to potentially help save lives?

# Recommendations and Next Steps

#### Whats next?

- Pull in additional Twitter Camp Fire data
- Aggregate data from additional social media sources
  - e.g., 880 of the 1,130 tweets analyzed were originally posted to Instagram
- Improve keyword list
- Try other models
  - o e.g., integrate image recognition
- Test and improve on other disasters
  - o "Slow" disasters (e.g., fires, floods, hurricanes)
  - o "Fast" disasters (e.g., tornados, shootings)
- Develop proof of concept
- Ideal state: deploy product that agencies can implement to monitor social media data

# QUESTIONS?