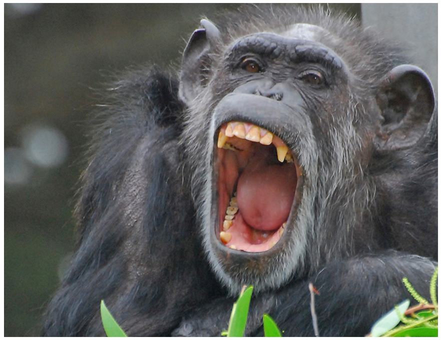
Module 3: GATE and Social Media

Part 1: Introduction

Intro



Functional utterances

Vowels

<u>Velar closure</u>: consonants

Speech

<u>New modality</u>: writing

Digital text

E-mail

Social media

Increased

machine-readable

information

Intro

The end result: a digital sample of all human discourse

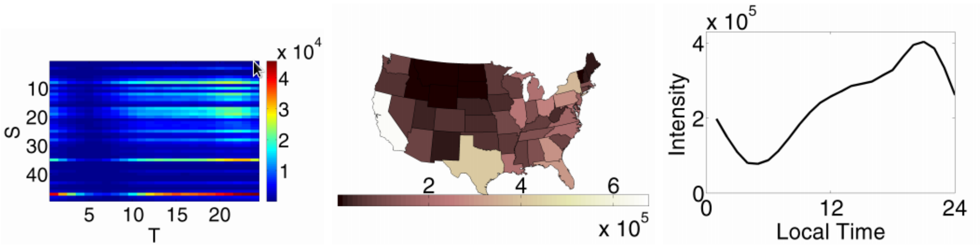
What could we do with that?

What are we *already* doing with it?

Media monitoring and visualisation

Socioscope (Xu 2012) builds realtime maps of roadkill

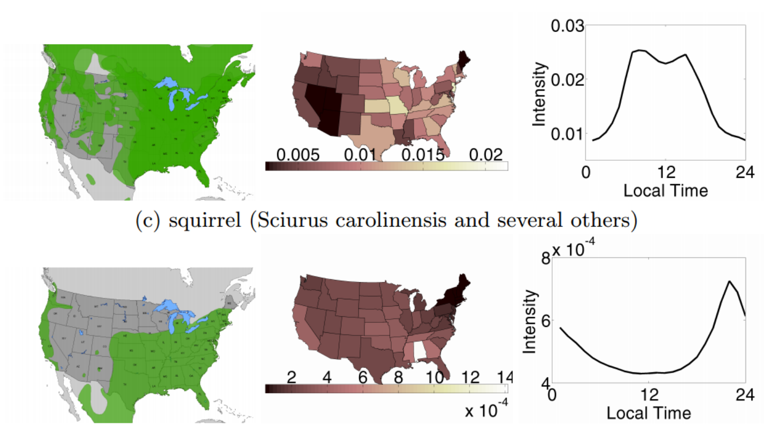
- Treats tweets as observations, roadkill events as latent variables
- Normalisation for spatio-temporal reporting rates, human activity, animal activity



(a) $\widehat{\mathbf{g}}$ (b) spatial (c) temporal

Fig. 2. Human population intensity $\widehat{\mathbf{g}}$.

- Evaluated against government cleanup figures



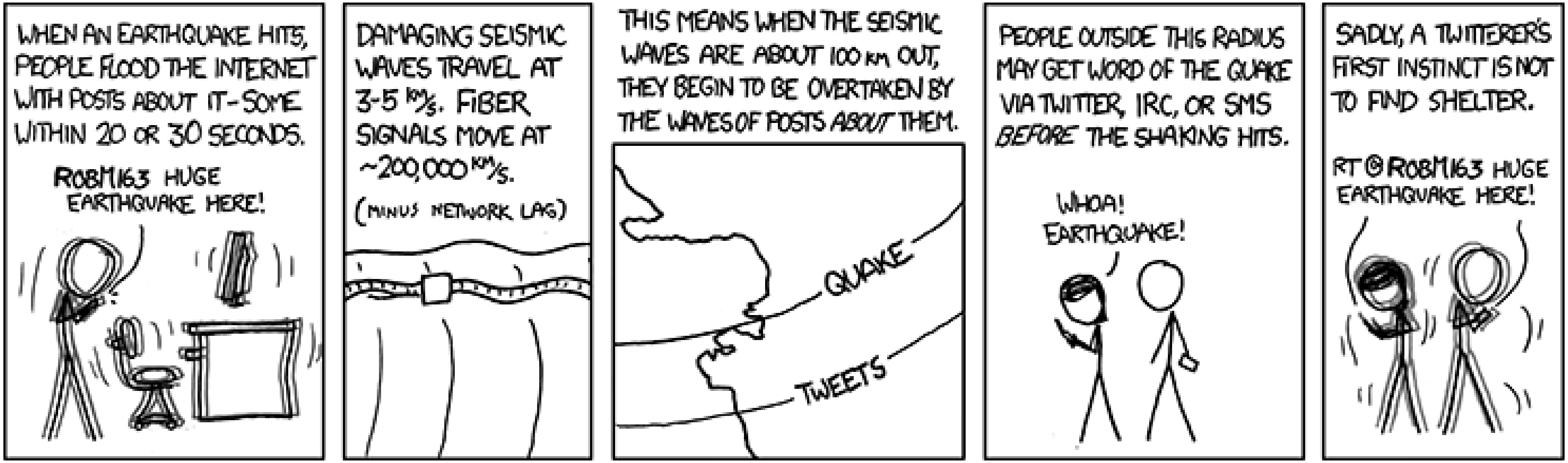
(c) squirrel (Sciurus carolinensis and several others)

(d) opossum (Didelphis virginiana)

Fig. 3. Socioscope estimates match animal habits well. (Left) range map from Nature-

Media monitoring and visualisation

Disaster response (earthquake)

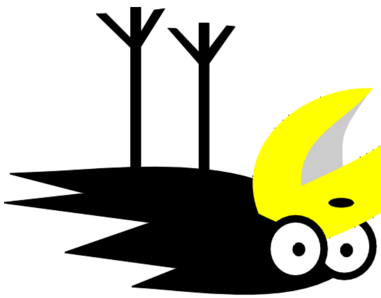


Later research led to improved earthquake alerting systems

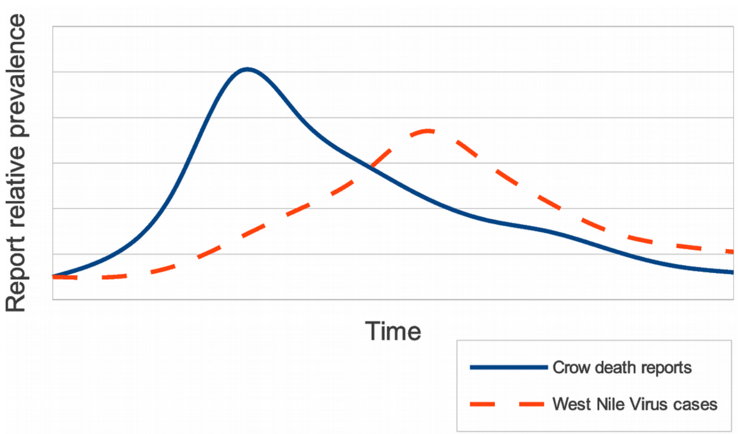
"We consider each Twitter user as a sensor and apply Kalman filtering and particle filtering, which are widely used for location estimation in ubiquitous/pervasive computing. The particle filter works *better* than other comparable methods for estimating the centers of earthquakes and the trajectories of typhoons." - Sakaki 2010

"these feeds represent a hybrid form of a sensor system that allows for the identification and localization of the impact area of the event" (USGS) – Crooks 2012

Social media analysis



-> "There's a <u>dead crow</u> in my garden" ->



Media monitoring and visualisation

Epidemic prediction (flu)

Sadilek (2012) monitored geolocated tweets in greater NY area

- Built classifier for detecting whether a twitterer is unwell
- Monitor friends and collocated twitterers
- See if people become ill based on their social network and movement path

@mari: i think im sick ugh..

Result: predict whether an individual will become ill in the next week with 80% accuracy

Media monitoring and visualisation

Disaster response (fires)

Bushfires regular, dangerous occurrence in Australia

Large region makes it difficult to collect data

Further, difficult problem of distinguishing reports of fires from other fire mentions

Filtering false reports most useful outside of peak season

Uses transductive learning to bypass problem of generalising from noisy data

First deployed in Nov '14

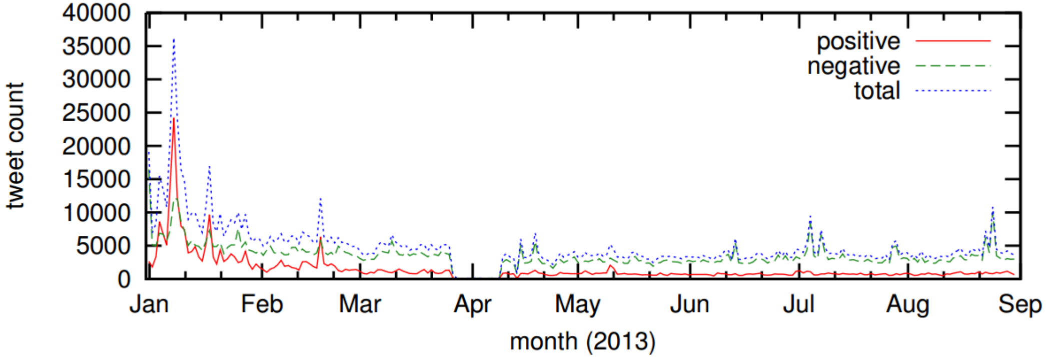


Figure 2: Daily 'fire' Tweet counts.

Social media analysis

Ability to extract sequences of events

Retrieve information on:

- Lifecycle of socially connected groups
- Analyse precursors to events, post-hoc

* Weikum et al. 2011: "Longitudinal analytics on web archive data: It’s about time", *Proc. CIDR*

Intro

Gartner "3V" definition:

1. **Volume**

2. **Velocity**

3. **Variety**

High volume & velocity of messages:

Twitter has ~20 000 000 users per month
They write ~500 000 000 messages per day

Massive variety:
Stock markets;
Earthquakes;
Social arrangements;

Social media sites

Twitter, LinkedIn, Facebook

Twitter has varied uptake per country:

- Low in Denmark, Germany (Facebook is preferred)
- Medium in UK, though often complementary to Facebook
- High in USA

Networks have common themes:

- Individuals as nodes in a common graph
- Relations between people
- Sharing and privacy restrictions
- No curation of content
- Multimedia posting and re-posting

Other features: topics, liking, media, groups, person discovery ..

How can we get information out of these discussions, into a discrete machine-readable format?

NLP on social media text

Multiple sources & definitions of “social media” and “social network site”
Which to choose?

Twitter as the D. Melanogaster
of social media

Newswire: regulated

- “our most frequently-used corpora [..] written and edited predominantly by working-age white men”

Twitter: wild; many styles

- Headlines
- Conversations
- Colloquial
- Just “noise” (hashtags, URLs, mentions)

General challenges

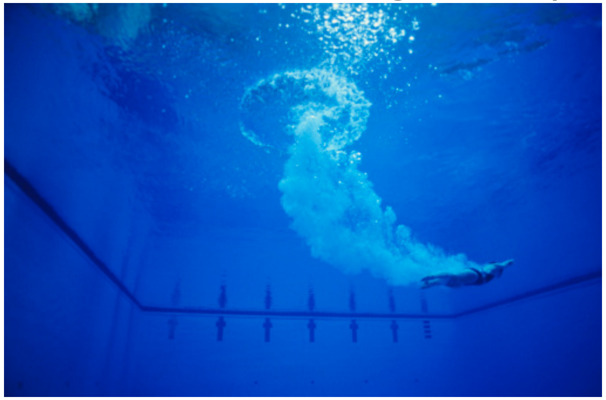
Common complaints we have about social media text:

- Documents are short;
- Language is different to standard prose;
- Words are ambiguous;
- Nonstandard / new lexical items;
- New syntactic patterns.
- Memes

The impact (or the cause?) of these complaints: Low performance of existing systems.

Maybe we need to re-train?

- Shortage of training data;
- Many different sub-domains
- Low-performance of existing techniques.



How can we characterise social media text?

What new techniques can help us process it?

Let's start at the deep end: Twitter text.*

* also – it's public and plentiful

Qualitative genre description

Great diversity in social media users, but they're not illiterate

- People want to represent their own dialects and accents (Jones 2010)
- They pick and choose from the entire stylistic repertoire of language (Tagliamonte 2008)
- Same literacy scores in standard and non-standard vocabulary users (Drouin 2009)

Emoji have more than just an expressive function

- Pragmatic function, e.g. demonstrating a less stressed stance (Dresner 2010)
- Not just pictograms: phrasal abbreviations are also included – *smh*, *lol*
- Lexical items are made nonstandard through lengthening – *coooolll* (Brody 2011)

Qualitative genre description

Social variables associated with certain transformations

- Slang is less inhibited in informal settings (Labov 1972)
- G-dropping mapped from speech to writing (Eisenstein 2010)

    they see me rollin
    they hatin
    patrollin
    tryna to catch me ridin dirty

- Lexemes can have a spatial association within a language (Eisenstein 2011)

This socio-linguistic variation in social media highlights bias in existing resources

- Most text authors from narrow demographic (Eisenstein 2013)
- Social media is not curated, so has different biases
- We have little data that is free from this demographic bias

Quantitative genre description

General style

- Twitter is
- **formal** and **conservative**
- **less conversational** than SMS and online chat;

- It still has a similar brevity to these mediums, but word choice is careful, with high density of lexical words (Halliday 2004);
- Tweets are used for sharing news or broadcasting personal status

Quantitative genre description

Individual style:

- Is style individualistic, or address a large audience? (Yates 1996)
- Users develop linguistically unique styles compared to other mediums;
- For example, both 1st and 3rd person pronouns are common, where other genres tend to stick to just one.
- Intensifier use indicates a younger audience - “really” vs. “very” (Ito 2003).
- Orthographic errors are often intentional (“smoll been” vs “small bean”) (Stewart 2014)

Temporal reference

- Are authors concerned with a certain timeframe? (past, present, future relative to timestamp)
- Temporal references are similar to SMS and online chat: no particular focus

Hands-on: Examining social media data

Let's compare ANNIE's ability to process news with processing tweets

In GATE, create a new corpus called “News” or similar

Create a datastore somewhere and save the corpus there

Load the XML news articles from the hands-on folder into this corpus (in corpora/news-texts)

Load ANNIE and run it over the corpus

Look at the Token annotations, and the Persons, Locations and Organisations

Create another new corpus, called “Tweets” or similar, in the DS

Load the documents from the corpora/tweet-texts subdirectory

Run ANNIE on this corpus

How are the annotations in the tweets? Text.category, entities, names