



















Automatic Detection of Rumours in Social Media: Methods and Challenges

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Veracity: the 4th V of Big Data



PHEME focuses on a fourth crucial, but hitherto largely unstudied, challenge: veracity

- We coined the term phemes
 - memes are thematic motifs that spread through social media in ways analogous to genetic traits
 - phemes add truthfulness and deception to the mix
 - named after ancient Greek Pheme, "embodiment of fame and notoriety, her favour being notability, her wrath being scandalous rumours"





What is a Rumour?

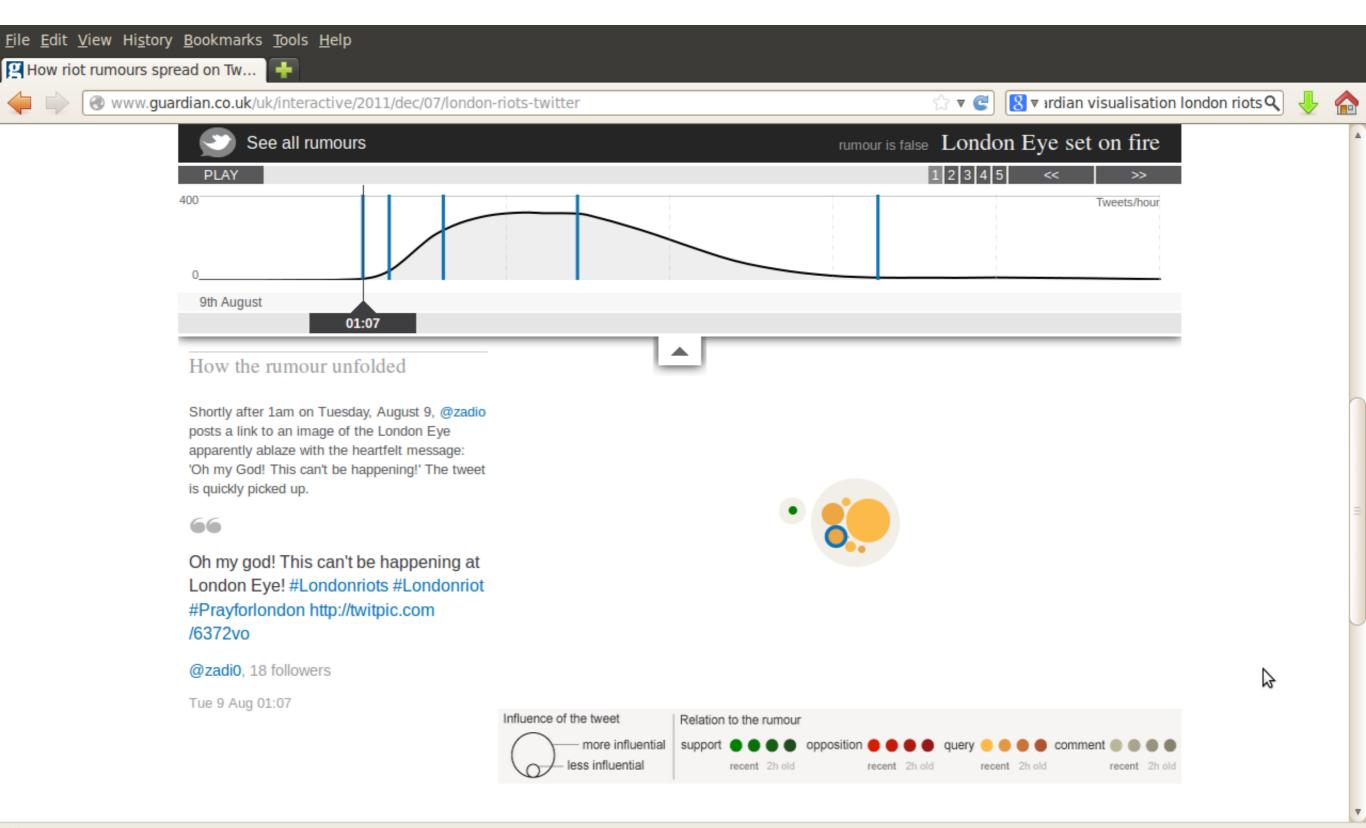


Our definition

"a circulating story of questionable veracity, which is apparently credible but hard to verify, and produces sufficient skepticism and/or anxiety"

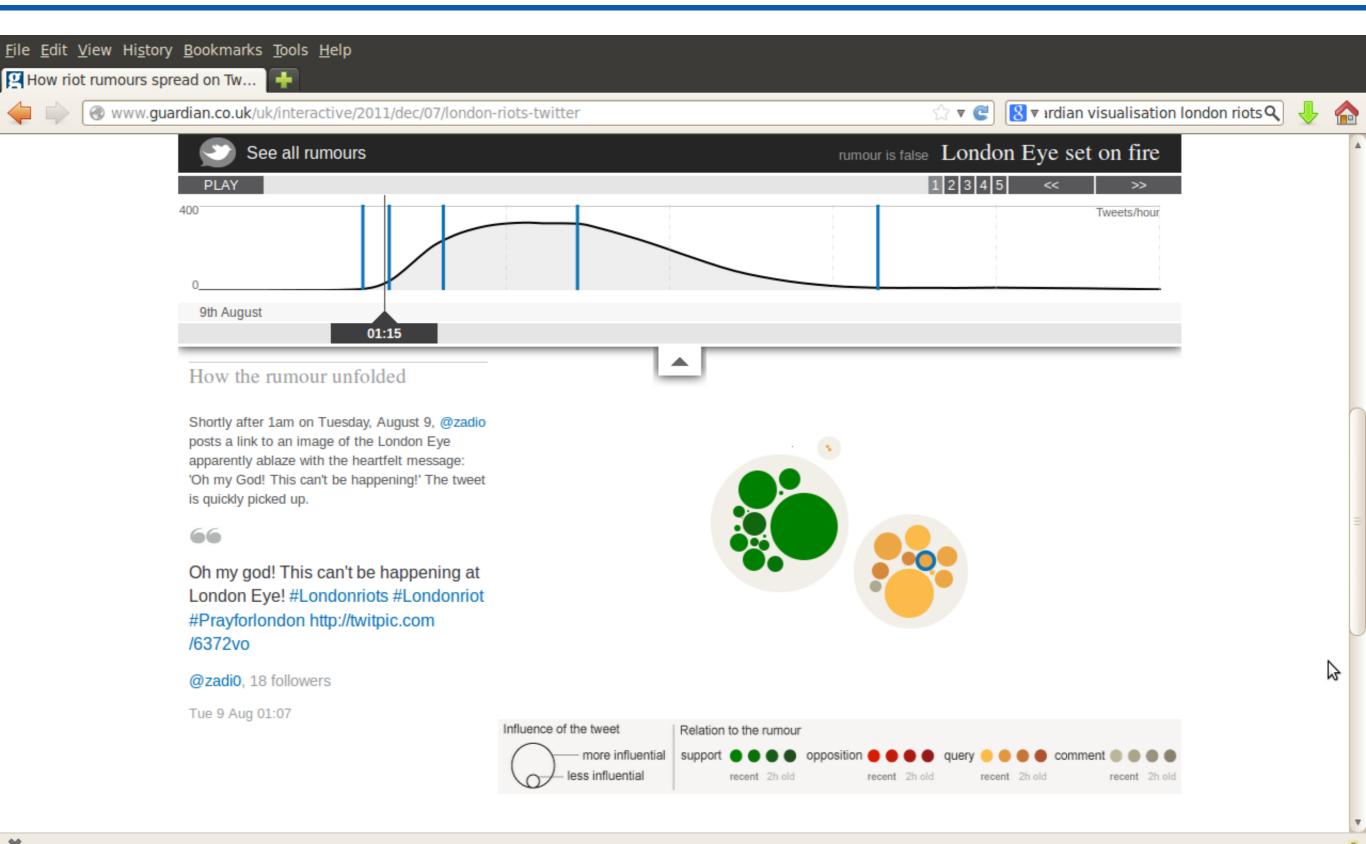
Social Media is Rife with Phemes





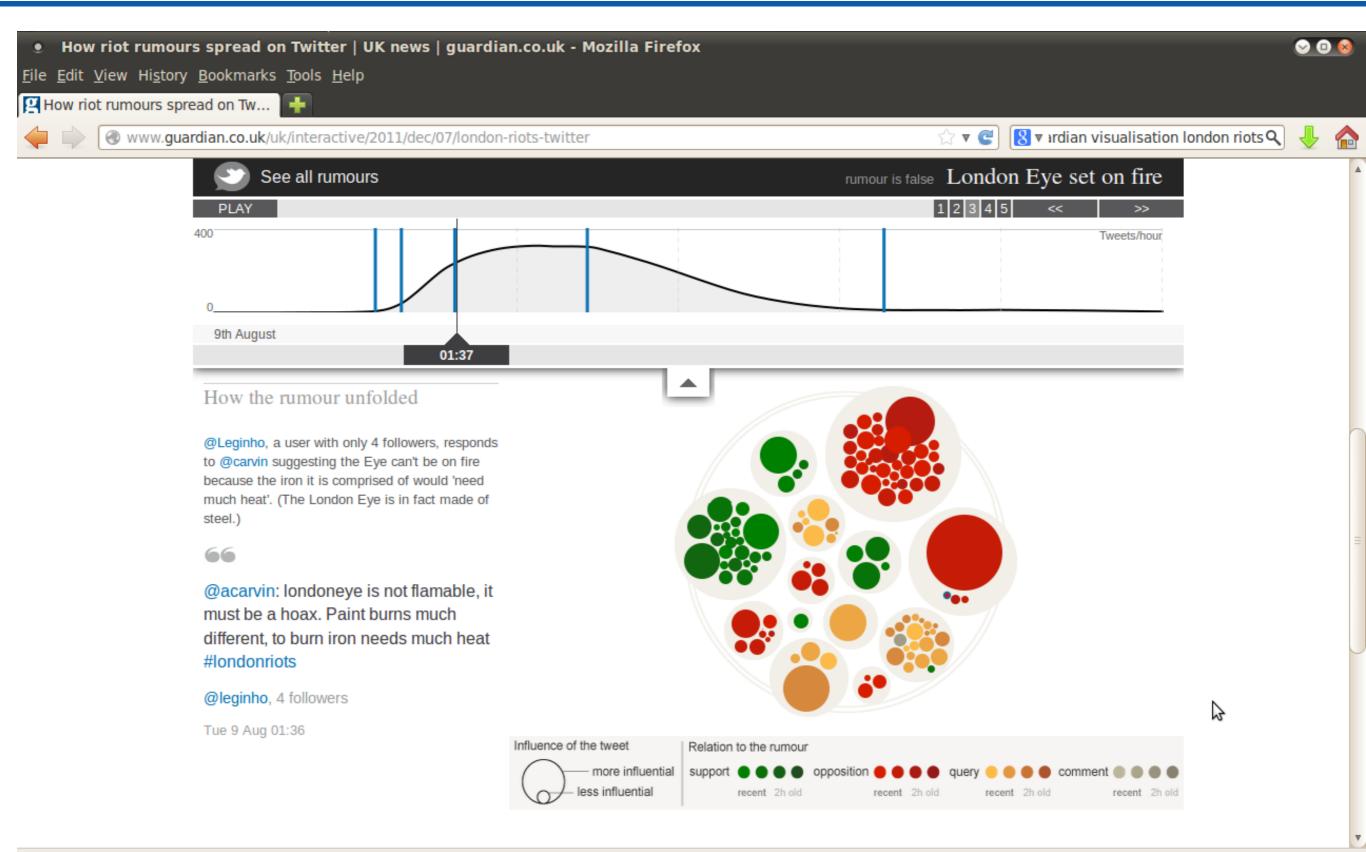
Social Media is Rife with Phemes (2)





Social Media is Rife with Phemes (3)





Rumour analysis: The Challenges



- Journalists do it mostly manually
- Rumour analysis is challenging
 - Some rumours could take days, weeks or even months to die out
 - Ill-meaning humans can currently outsmart computers (and humans) and appear genuine
 - Role of conversational threads in rumour analysis
 - Tweet-rot and deletions
 - Real-time analysis of temporally dynamic phemes



What: High Level Goal



Create a computational framework for automatic discovery and verification of rumours, at scale and fast

- Draw on:
 - NLP: what's said
 - web science: a priori knowledge from Linked Data
 - social science: who spread it, why and how
 - information visualisation: visual analytics



Content verification



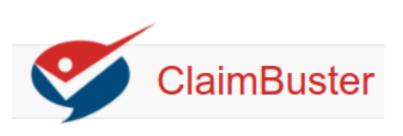
- A number of projects focussed on detecting inaccurate reports, which has recently been relabelled as "fake news".
- Most projects deal with what is known as "fact-checking", comparing sources to validate reports, with an assumption that other sources exist.



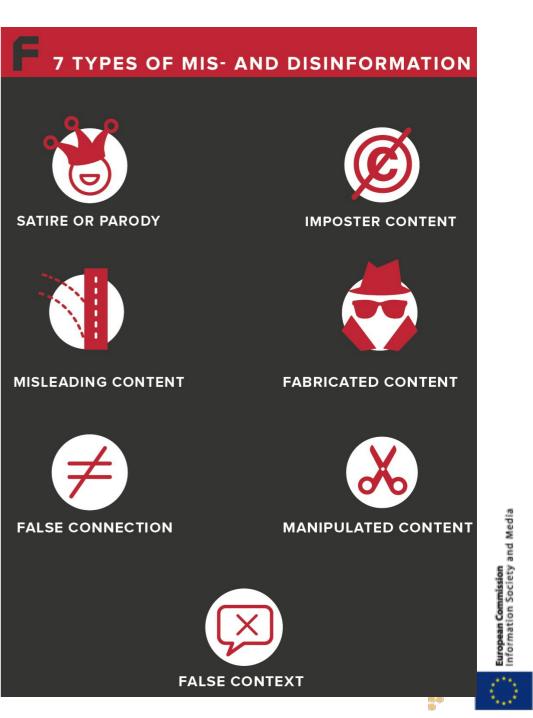












Working with rumours



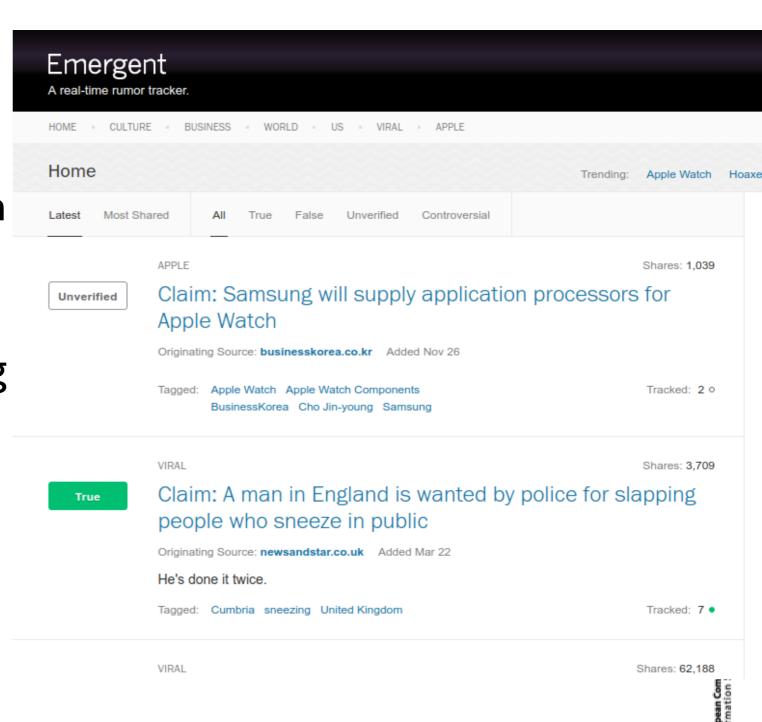
- Rumours spawn and circulate as plausible pieces of information that are unverifiable when they emerge.
- One needs to further explore information to find sources that may not have yet been identified and often wait for new evidence to be released.
- A rumour detection system has to:
 - Identify pieces of information that are unverified and require corroboration.
 - Track what different sources are saying about the rumour.
 - The system progressively updates likely veracity of a rumour, ideally identifying supporting evidence.



Work by others on rumours



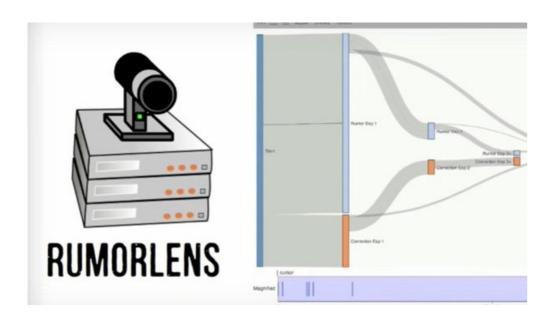
- Emergent.info the most similar project to PHEME tracking unverified reports for debunking/confirmation
- The project has however been discontinued
- Owing to the project being totally manual and lacking automation, maintenance was not viable

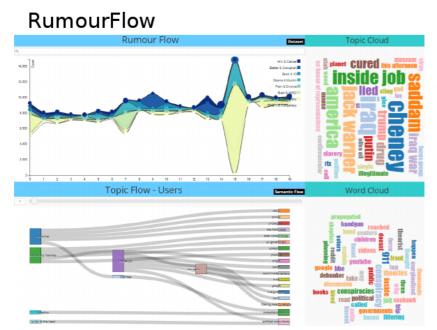


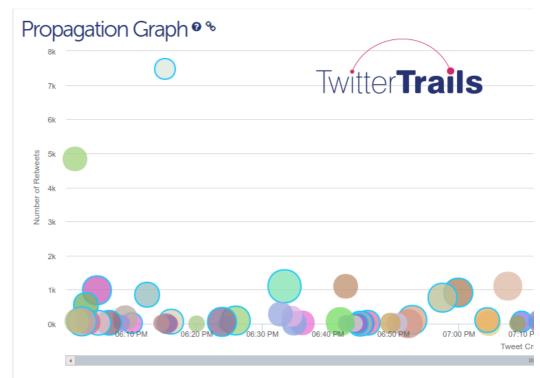
Work by others on rumours



 Other projects on rumours largely focussed on visualisation, tracking rumours input by the user:











PHEME Rumour Datasets



Events:

- Ferguson unrest
- Ottawa shooting
- Sydney seige
- Charlie Hebdo shooting
- German Wings crash

Specific rumours:

- Putin missing
- Prince concert
- Michael Essien
- Gurlit collection

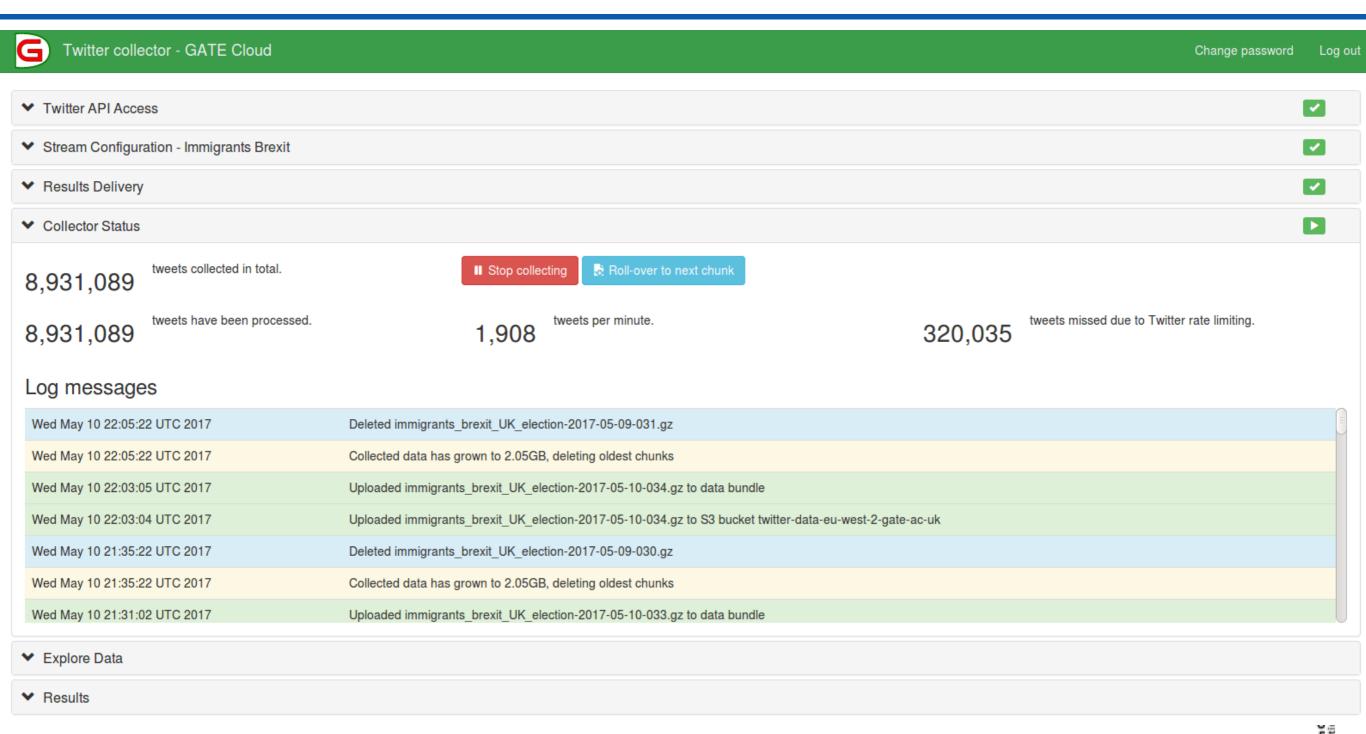


Collect Tweet Datasets



Twitter Collector as a Service





Docs & YouTube videos:

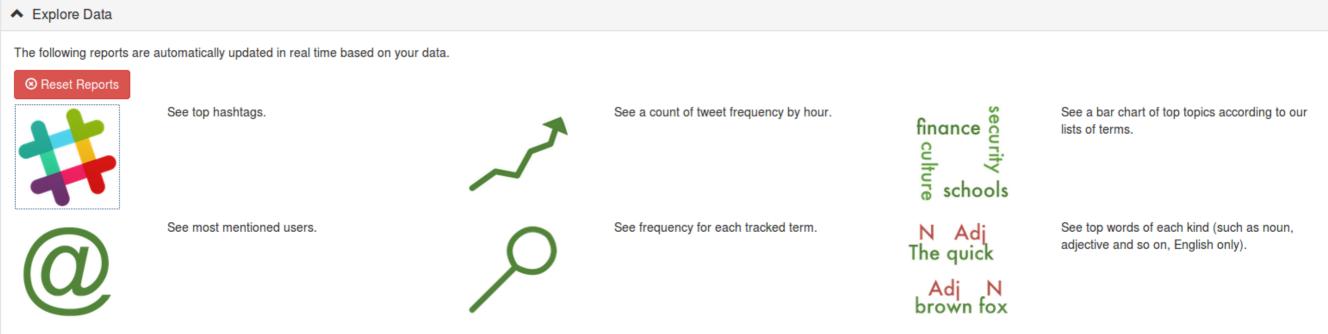
https://cloud.gate.ac.uk/info/help/twitter-collector.html

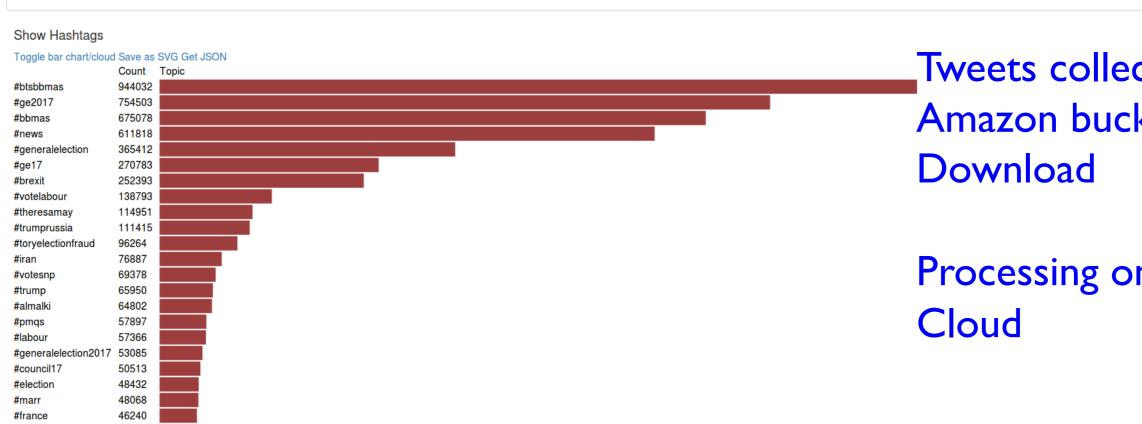




Live Stats and Fine Tuning







Tweets collected in Amazon buckets for

Processing on GATE







45903

#maga

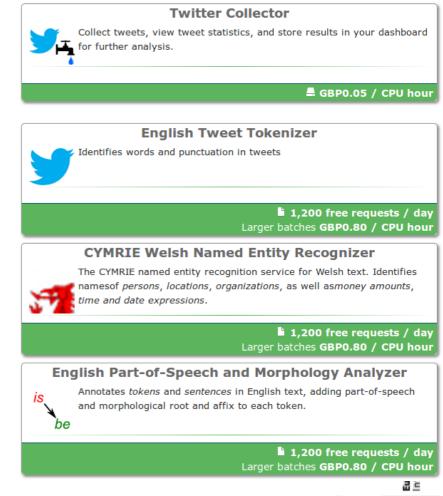
GATE Cloud services



24 services, multiple languages



Home Services **Dashboard** Show only items tagged: Chunker (1) Custom (1) Dutch (1) English (13) Environment (2) French (2) Morphology (1) Named Entity (15) OpenNLP (3) Opinion Mining (4) Part-of-Speech (1) Politics (1) Server (2) SoBigData (1) Spanish (1) Summarization (2) Term Recognition (2) Twitter (11) Welsh (1) **English Named Entity Recognizer English Named Entity Recognizer for Tweets Twitter Collector** Identify names of persons, locations, organizations, as well as money Analyse tweets for names of persons, locations, organizations and other Collect tweets, view tweet statistics, and store results in your dashboard for further analysis. amounts, time and date expressions in English texts automatically. entities. Also performs normalization of abbreviations and common shorthands ("brb", "gr8", "2day", etc.). ■ GBP0.05 / CPU hour 1,200 free requests / day 1,200 free requests / day Larger batches GBP0.80 / CPU hour Larger batches GBP0.80 / CPU hour German Named Entity Recognizer Language Identification for Tweets **English Tweet Tokenizer** A named entity recognition service for documents in German. Based on Service to identify the languages of tweets.a. Identifies words and punctuation in tweets ANNIE, it identifies names of persons, locations, and organizations. 1,200 free requests / day 1,200 free requests / day 1,200 free requests / day Larger batches GBP0.80 / CPU hour Larger batches GBP0.80 / CPU hour Larger batches GBP0.80 / CPU hour French Named Entity Recognizer **CYMRIE Welsh Named Entity Recognizer** Part-of-Speech Tagger for Tweets A named entity recognition service for documents in French. Based on A service that tags tweets with part-of-speech information, e.g. nouns, The CYMRIE named entity recognition service for Welsh text. Identifies ANNIE, it identifies names of persons, locations, and organizations. namesof persons, locations, organizations, as well asmoney amounts, time and date expressions. 1,200 free requests / day 1,200 free requests / day 1,200 free requests / day Larger batches GBP0.80 / CPU hour Larger batches GBP0.80 / CPU hour Larger batches GBP0.80 / CPU hour French Named Entity Recognizer for Tweets **German Named Entity Recognizer for Tweets** English Part-of-Speech and Morphology Analyzer Analyse French tweets for names of persons, locations and organizations. Analyse German tweets for names of persons, locations and Annotates tokens and sentences in English text, adding part-of-speech Also performs normalization of abbreviations and common Twitter slang. organizations. Also performs normalization of abbreviations and common and morphological root and affix to each token. Twitter slang. 1,200 free requests / day 1,200 free requests / day 1,200 free requests / day Larger batches GBP0.80 / CPU hour Larger batches GBP0.80 / CPU hour Larger batches GBP0.80 / CPU hour







Rumour Annotation



Dataset Overview



Data collection and sampling

- Twitter public stream
- Retweet threshold to establish salience
- SWI identified rumourous source tweets and grouped them into stories

Event name	Rumour stories	Annotated threads	Rumour threads	Non-rumour threads
Sydney Siege	61	1321	535	786
Ottawa Shooting	51	901	475	426
Charlie Hebdo	61	2169	474	1695
Germanwings	19	1022	332	690
Ferguson	42	1183	291	892
Prince to play in Toronto	6	241	237	4
Gurlitt	3	386	190	196
Putin missing	6	266	143	123
Essien has Ebola	1	18	18	0
TOTAL	250	7507	2695	4812

en-charliehebdo-553558982476828674

[go back to rumours by accuracy] [go back to rumours by acceptability]

Links to Other Media

[news-media] [for] http://jpupdates.com/2015/01/09/breaking-gunman-takes-hostage-kosher-gocery-store-paris/

Social Media Conversation



@AvitalLeibovich [FR: 2, verified, journalist]

On Israeli TV, an Israeli woman speaks of her nephew, a mother with 6 month old baby, held hostage in the supermarket in Paris, #JeSuisJuif

Annotation: certainty: certain, support: supporting, evidentiality: witnessed,



@talziv [FR: 1, verified, journalist]

@AvitalLeibovich link?

Annotation: certainty: uncertain, evidentiality: unverifiable-source-quoted, responsetype-vs-source: appeal-for-more-information,



@AvitalLeibovich [FR: 2, verified, journalist]

@talziv @Channel2News

Annotation: certainty: underspecified, responsetype-vs-source: comment, responsetype-vs-previous: agreed, evidentiality: url-given,



@talziv [FR: 1, verified, journalist]

@AvitalLeibovich @Channel2News actually, mako.co.il/news

Annotation: responsetype-vs-source: comment, responsetype-vs-previous: comment,



@jessicaelgot [FR: 1, verified, journalist]

@AvitalLeibovich do you have a link?

Annotation: certainty: uncertain, evidentiality: no-evidence, responsetype-vs-source: appeal-for-more-information,

Rumour Analysis



Analysis Stages



1) Rumour detection: identify pieces of information that need to be verified.

2) Rumour stance classification: classify public stance towards the rumour.

3) Veracity classification: determine if a rumour is true, false, or remains unverified.



Rumour detection



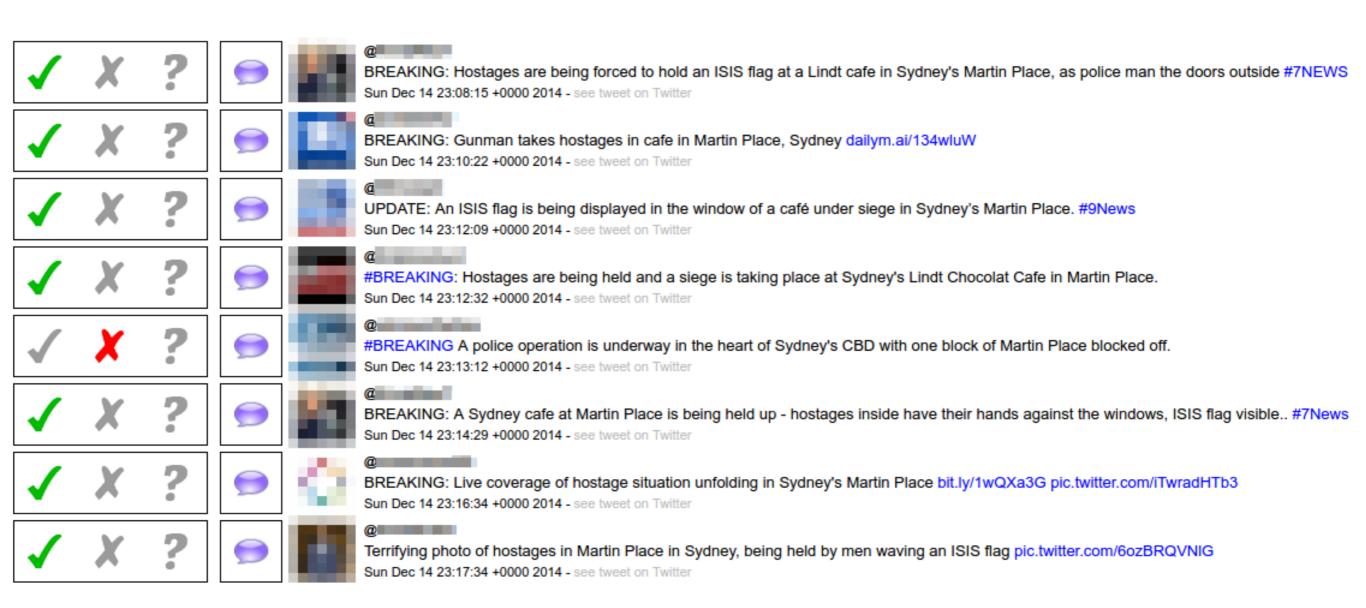
- Classification problem
 - Tweet level
 - Classes: rumour or non-rumour
- Why
 - Identify tweets reporting unverified information.
 - Necessary for subsequent stance and veracity classification.
 - "Michael Brown was involved in a robbery before being shot by police" -> needs context



Rumour detection (2)



Can we then leverage context accumulated throughout the event?



Rumour detection (3)



Conditional Random Fields.

- Comparison vs:
 - -Baseline by Zhao et al. (2015) at WWW.
 - Maximum Entropy.
 - -SVM, Random Forest, NB.
- Features:
 - Content and social



A. Zubiaga, M. Liakata, R. Procter . Exploiting Context for Rumour Detection in Social Media. International Conference on Social Informatics, 109-123. 2017.

Rumour detection (4)



- Experiment methodolgy:
 - Leave-one-event-out: train on n-l event, and test on the n-th event. Cross-validation

-P/R/FI evaluation.



Rumour detection: Results



Classifier	Р	R	F1	
SVM	0.337	0.483	0.397	
Random Forest	0.275	0.099	0.145	
Naive Bayes	0.310	0.723	0.434	
Maximum Entropy	0.338	0.442	0.383	
CRF	0.667	0.556	0.607	
State-of-th	ne-art Ba	aseline		
Classifier	Р	R	F1	
(Zhao et al., 2015)	0.410	0.065	0.113	

European

Rumour Stance classification



- Classification Problem
 - Tweet level
 - Classes: support, deny, question, comment
- Why
 - Show journalists the unfolding online debates on a given pheme
 - Aid veracity classification



Stance classification



```
[depth=0] u1: These are not timid colours; soldiers back guarding Tomb of Unknown Soldier after today's shooting #StandforCanada –PICTURE– [support]

[depth=1] u2: @u1 Apparently a hoax. Best to take Tweet down. [deny]

[depth=1] u3: @u1 This photo was taken this morning, before the shooting. [deny]

[depth=1] u4: @u1 I don't believe there are soldiers guarding this area right now. [deny]

[depth=2] u5: @u4 wondered as well. I've reached out to someone who would know just to confirm that. Hopefully get response soon. [comment]

[depth=3] u4: @u5 ok, thanks. [comment]
```

Rumour Stance & Veracity



- Manual Analysis [Mendoza et al. 2010]
- True rumours: 95% "support", 4% "questioning" and only 0.4% were "denies"
 - → True rumours are largely supported by other Twitter users
- False rumours: 38% "denies" and 17% "questioning"
 - → Stance is an important factor for verification step

Rumour Stance Data



Dataset	Rumours	Supporting	Denying	Questioning	Commenting	Large
Ottawa shooting	58	161	76	64	481	✓
Ferguson riots	46	192	83	94	685	\checkmark
Prince in Toronto	12	19	7	11	59	×
Charlie Hebdo	74	236	56	51	710	\checkmark
Ebola Essien	2	6	6	1	21	×
Germanwings crash	68	177	12	28	169	\checkmark
Putin missing	9	17	7	5	33	×
Sydney siege	71	89	4	99	713	\checkmark





RumourEval



SemEval-2017 Task 8

RumourEval: Determining rumour veracity and support for rumours

RumourEval: Determining rumour veracity and support for rumours





LSTM won RumourEval



Team	Score
DFKI DKT	0.635
ECNU	0.778
IITP	0.641
IKM	0.701
Mama Edha	0.749
NileTMRG	0.709
Turing	0.784
Uwaterloo	0.780



Features: Stance Classification



- Syntactic: #negations, POS
- Lexical: e.g. bag of words, key words
- Lexicon: word embeddings, brown clusters
- Indicator: e.g. "this is nonsense", "is a hoax"
- User metadata: e.g. verified, #followers/followees
- Semantic: e.g. emoticons, sentiment, NEs
- Message metadata: e.g. length of the post, URL
- Content formatting: e.g. capital words ratio
- Punctuation: e.g. ?, ..., !



A. Aker, L. Derczynski, K. Bontcheva. Simple Open Stance Classification for Rumour Analysis. Recent Advances in Natural Language Processing, 2017.

USFD on RumourEval Data



- Applying traditional ML
- Focus on "problem specific" features
 - Capturing Surprise, Doubt, Certainty and Support towards rumourous tweets
 - Similarity to initial tweet
- Random Forest (best performing traditional ML) with features reported by related work yields to 76.54 accuracy
- Adding "problem specific" features yields 79.02 accuracy (LSTM 78.4).



A. Aker, L. Derczynski, K. Bontcheva. Simple Open Stance Classification for Rumour Analysis. Recent Advances in Natural Language Processing, 2017.

Stance Classification: Findings



- Supporting tweets are more likely to include links.
 - i.e. provide evidence
- Looking at the temporal dimension, S/D/Q tend to occur in early stages of a rumour, and then mostly comments later
- We've looked at persistence, finding that supporting users tend to post more tweets, i.e., further insisting



Veracity classification



- Classification Problem
 - Rumour level
 - Classes: true, false or unverified
- Why
 - Help journalists and the public determine if report is accurate.
 - Flagging false rumours to warn users.



Features



- Features similar to stance classification
- NB: those features need to be computed for the entire rumour instead of individual posts
 - E.g. adding feature values over all posts within the rumour and performing normalisation.
- Stance of individual posts is an important feature



Veracity classification



Evaluation: determine, after each tweet, ability to classify veracity of rumour.

Classifier	Without Stance	With stance over time
J48	64.6 I	69.84
Random Forest	<u>68.20</u>	70.76
K-NN	63.69	69.84

PHEME's impact



 Fake News Challenge adopted PHEME's methodology, i.e., a 4-way typology akin to {support, deny, query, comment}

FAKE NEWS CHALLENGE STAGE 1 (FNC-I): STANCE DETECTION

Input

A headline and a body text - either from the same news article or from two different articles.

Output

Classify the stance of the body text relative to the claim made in the headline into one of four categories:

- Agrees: The body text agrees with the headline.
- 2. Disagrees: The body text disagrees with the headline.
- 3. Discusses: The body text discuss the same topic as the headline, but does not take a position
- 4. Unrelated: The body text discusses a different topic than the headline





Journalism dashboard



? Brexit vote may have been hacked. If Russia hacked Brexit, safe to assume they hacked vote totals in other elections.?

Topic: UK triggers Article 50

Number of images: 0 Number of URLs: 4

Verified authors: No

Controversiality score: Low

Veracity: 8 False (100% confidence)

ACTIVITY

Size: 132 tweets

Average activity: 0.16 tweets/second

Oldest tweet: 5:35 AM - 12 Apr

2017

Last activity: 5:48 AM - 12 Apr

EXAMPLE TWEET



@DustinGiebel

"Brexit vote site may have been hacked, MPs say in report" I know some people they should look at.? https://t.co/EWp4HeEDyg

3:22 AM - 12 Apr 2017 open in twitter

NATO to reschedule meeting to accommodate Tillerson

2017

OVERVIEW

ACTIVITY

Size: 71 tweets

Oldest tweet: 4:44 AM - 23 Mar

Last activity: 5:11 AM - 23 Mar

Topic: Nato

Number of images: 1 Average activity: 0.04 tweets/second Number of URLs: 4

Verified authors: Yes

Controversiality score: Low

Veracity:

True (100%)

confidence)

MOST SHARED IMAGE



EXAMPLE TWEET



@thehill 📀

NATO to reschedule meeting to accommodate Tillerson https://t.co/DGrYB6t5nz https://t.co /xuga5LUIr7

2:49 AM - 23 Mar 2017 open in twitter

#WillLondonFall FALL?!?? I AIN'T A SEASON - LONDON. #brexit #NYTimes **#UKParliament #sixwordstory**

OVERVIEW

ACTIVITY

Topic: UK triggers Article 50

Average activity: 2.30 Number of images: 0

Number of URLs: 1

Verified authors: No

Controversiality score: Low

Veracity:

False (100%)

confidence)

Size: 122 tweets

tweets/second

Oldest tweet: 9:19 AM - 12 Apr

Last activity: 9:20 AM - 12 Apr

EXAMPLE TWEET



@michelepaschal1

RT @SixWrd: #WillLondonFall FALL?!?? I AIN'T A SEASON - LONDON. #brexit #NYTimes #UKParliament #sixwordstory https://t.co/R7bOGPBxr1 https?

7:19 AM - 12 Apr 2017 open in twitter

By the time Germany was admitted into NATO the world had literally changed. Germany was no longer a military threat to France, UK, or the US because a

OVERVIEW

ACTIVITY Size: 70 tweets

Topic: Nato

Number of images: 0 Average activity: 0.00 tweets/second

Number of URLs: 0

Verified authors: Yes

Oldest tweet: 6:24 PM - 19 Mar

2017

Controversiality score: High

Last activity: 6:45 PM - 20 Mar

EXAMPLE TWEET

Veracity: uncertain



@Bazuka125 🗸

There's a difference between "they should pay fair share to NATO" and "They should pay us"

4:24 PM - 19 Mar 2017





Tweet Mapping

? Brexit vote may have been hacked. If Russia hacked Brexit, safe to assume they hacked vote totals in other elections.?

For geo-tagged tweets in cluster, map their origin

Discussions Linked URLs Images Places

TOPIC

UK triggers Article 50

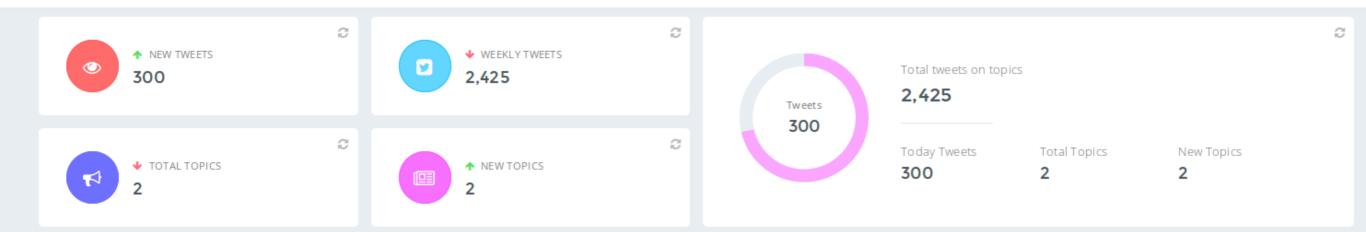
OVERVIEW ACTIVITY Number of images: 0 Size: 132 tweets Number of URLs: 4 Average activity: 0.16 tweets/second Verified authors: No Oldest tweet: 5:35 Controversiality AM - 12 Apr 2017 score: Low Last activity: 5:48 Veracity: False AM - 12 Apr 2017 (100% confidence)

PLACES



Hercule: Fact Checking Dashboard





Recent Viewed Topics

C

Most Popular Topics Topic Title KeyWords Clusters Check Worthy Donald Trump, Immigration ban, court ruling, Super bow, Betsy DeVos, Secretary of Education, Steve Bannon, National Security Council, Chief Donald Strategist, Director of ...**...** 30 Trump National Intelligence, Joint Chiefs of Staff, Science March, March for Science, Kristen Stewart, Russia, Vladimir Putin, Melania, Trump, First Lady Brexit, white paper, Brexit ...l 50 plan View Most Popular Topics

opic Title	KeyWords	Clusters	Check Worthy
Do nal d Trump	Donald Trump, Immigration ban, court ruling, Super bow, Betsy DeVos, Secretary of Education, Steve Bannon, National Security Council, Chief Strategist, Director of National Intelligence, Joint Chiefs of Staff, Science March, March for Science, Kristen Stewart, Russia, Vladimir Putin, Melania, Trump, First Lady	8	.al 30
Brexit	Brexit, white paper,	4	.al 50

opic Title	KeyWords	Clusters	Check Worthy
Donald Trump	Donald Trump, Immigration ban, court ruling, Super bow, Betsy DeVos, Secretary of Education, Steve Bannon, National Security Council, Chief Strategist, Director of National Intelligence, Joint Chiefs of Staff, Science March, March for Science, Kristen Stewart, Russia, Vladimir Putin, Melania, Trump, First Lady	8	il 30
Brexit	Brexit, white paper, plan	4	.all 50

Emerging Topics

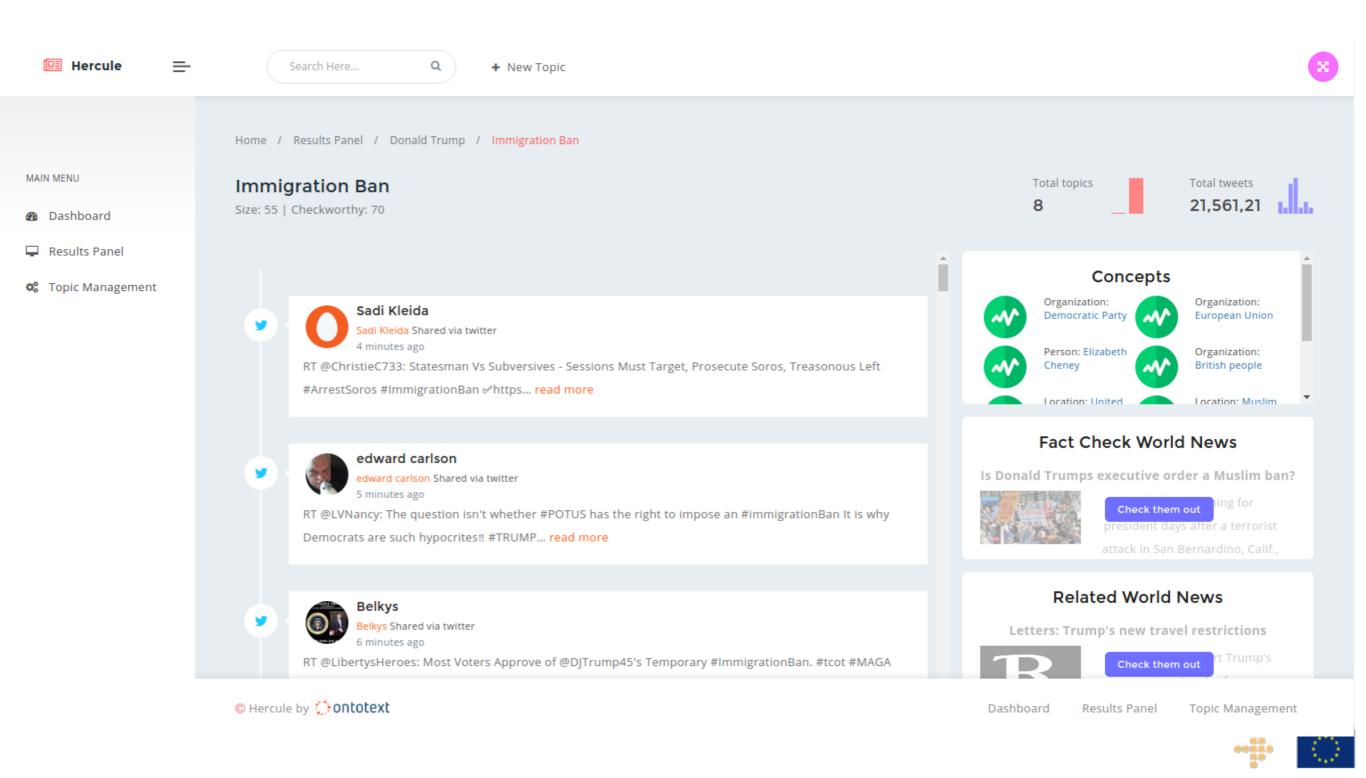


View Emerging Topics



Hercule: Fact Checking UI





Challenges



- Capturing temporal, streaming dynamics
- Improving further:
 - Rumour detection F1 of 60.7% still too low to be useful in practice
 - Rumour stance overall accuracy, but especially on the deny class, needs further improvement
 - Veracity needs significant improvement, for journalists to find it reliable in practical settings
- Provide journalists with the reasons behind a given classification decision



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