



Pacific Northwest
NATIONAL LABORATORY

*Proudly Operated by **Battelle** Since 1965*

Social Data Research at a National Laboratory

Eric Bell













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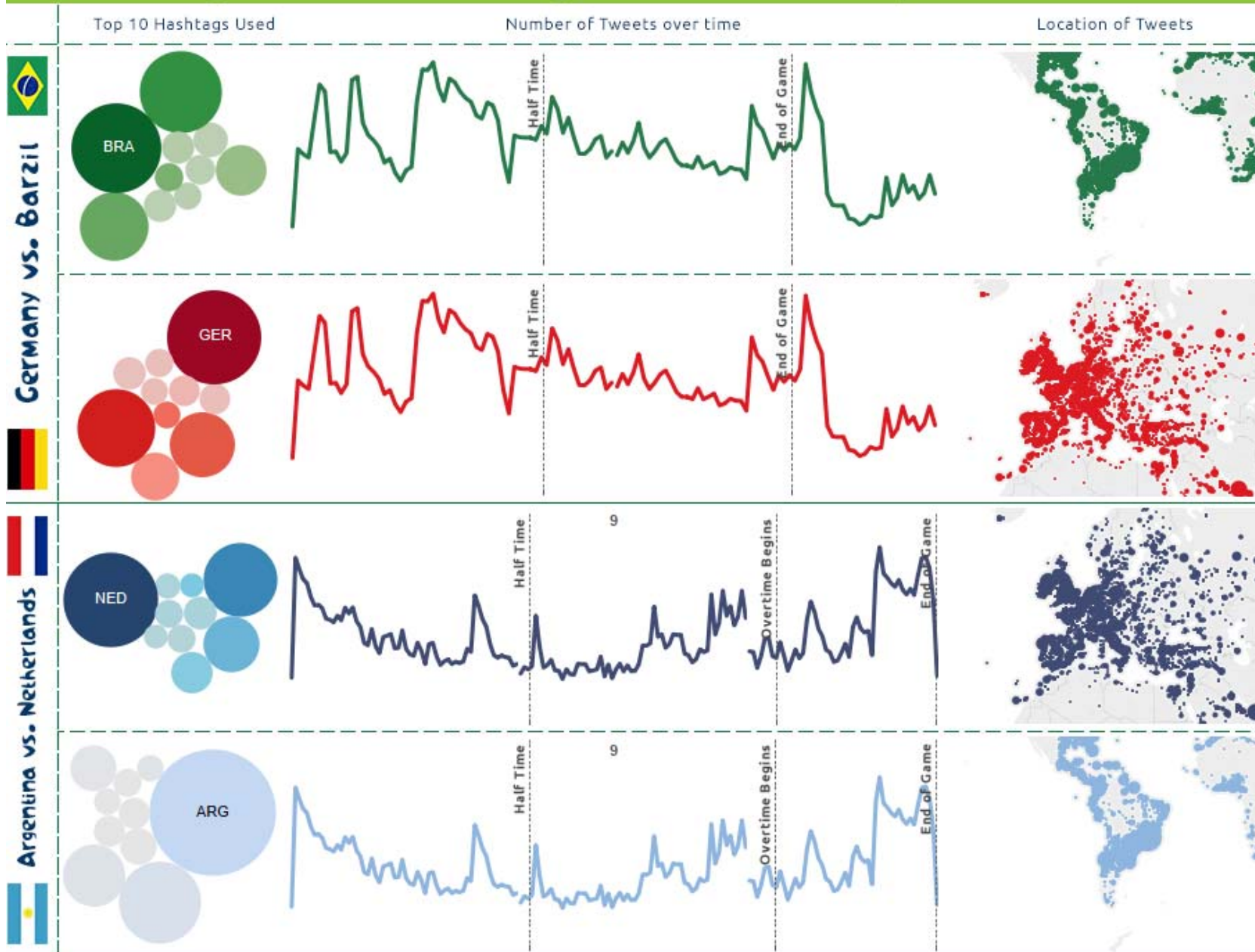


Eric Bell @chsbellboy · now

Happy Purrrthday: bit.ly/25L6dnM (A first cat photo tweet for me) Find out why at [#BigBoulder](#)

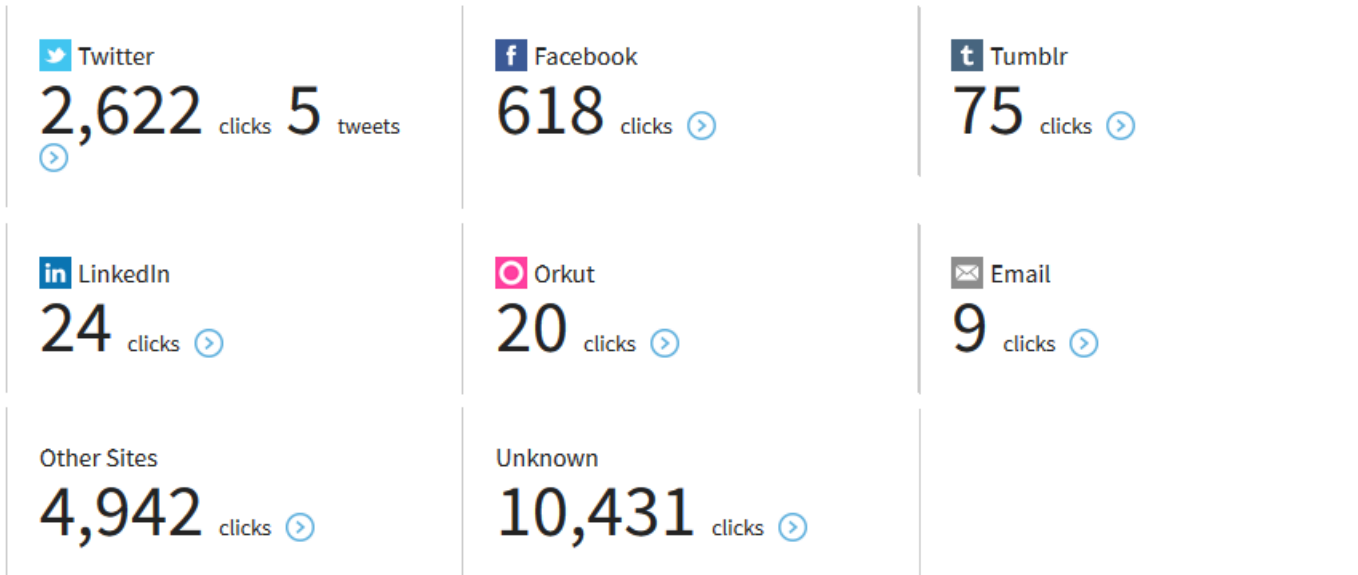


Twitter Activity for the Finals teams during their Semi-Final matches | Total Tweets: 49.8 million

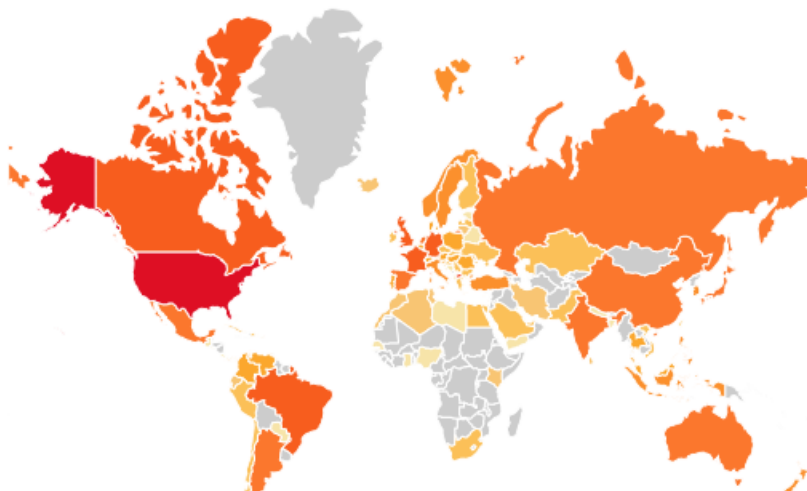


Lancet is not responsible for the accuracy of the data sources and is only displaying a subset of Tweets sent during the Semi-Final games.

WHERE THIS BITLINK WAS SHARED

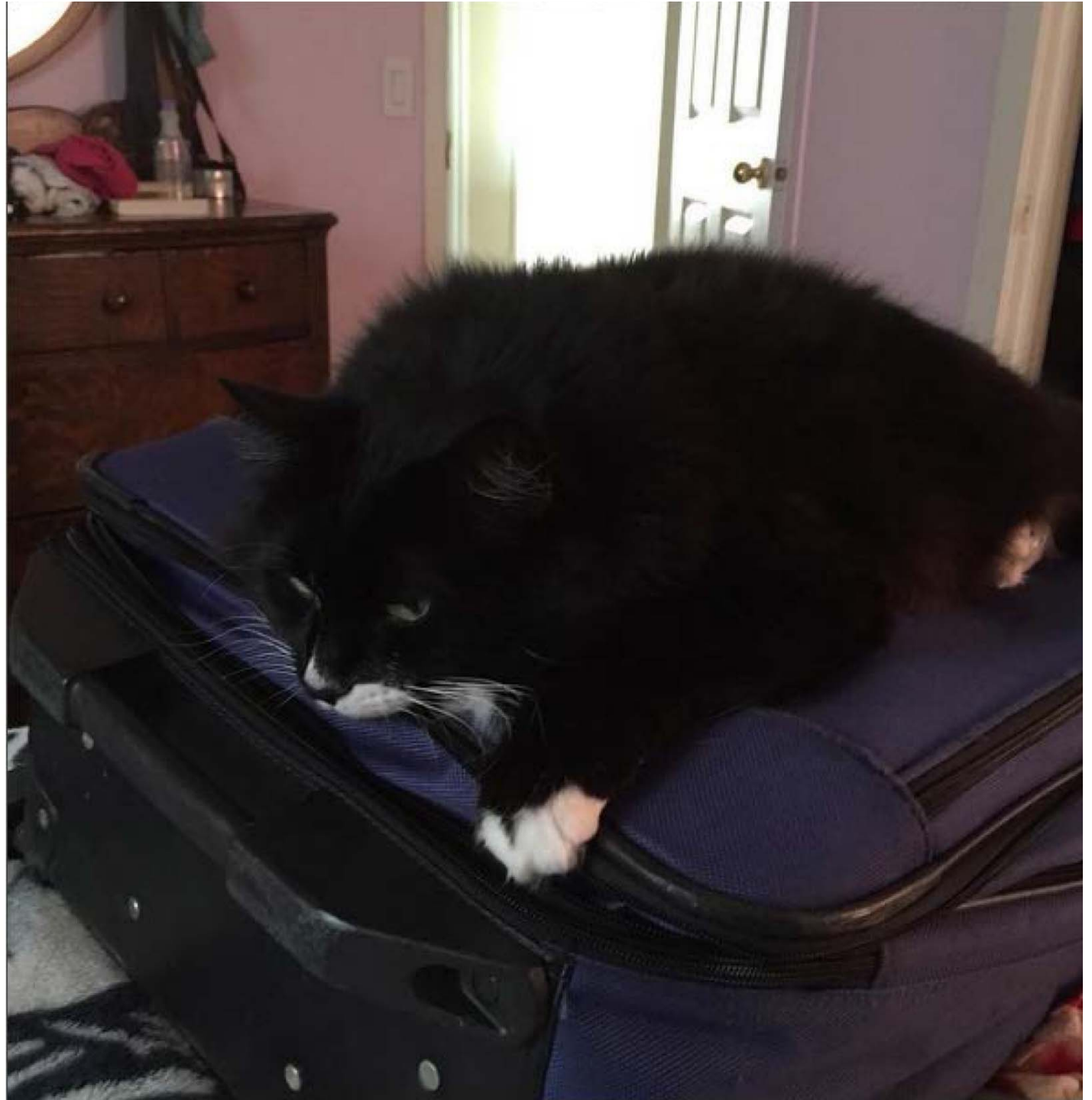
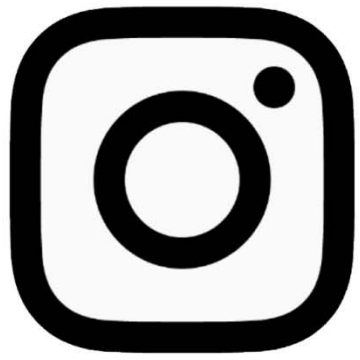


GEOGRAPHIC DISTRIBUTION OF CLICKS



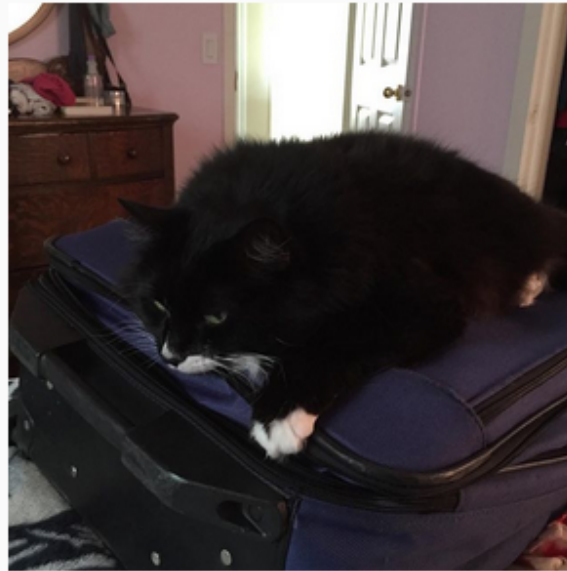
Top Countries (clicks / % of total)

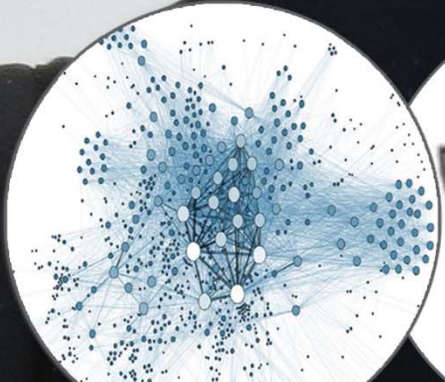
United States	6,984	37%
Macedonia, The For...	1,306	7%
France	824	4%
United Kingdom	810	4%
Canada	713	4%
Germany	589	3%
Brazil	584	3%
Japan	497	3%
Argentina	404	2%
Mexico	373	2%
+90 more		



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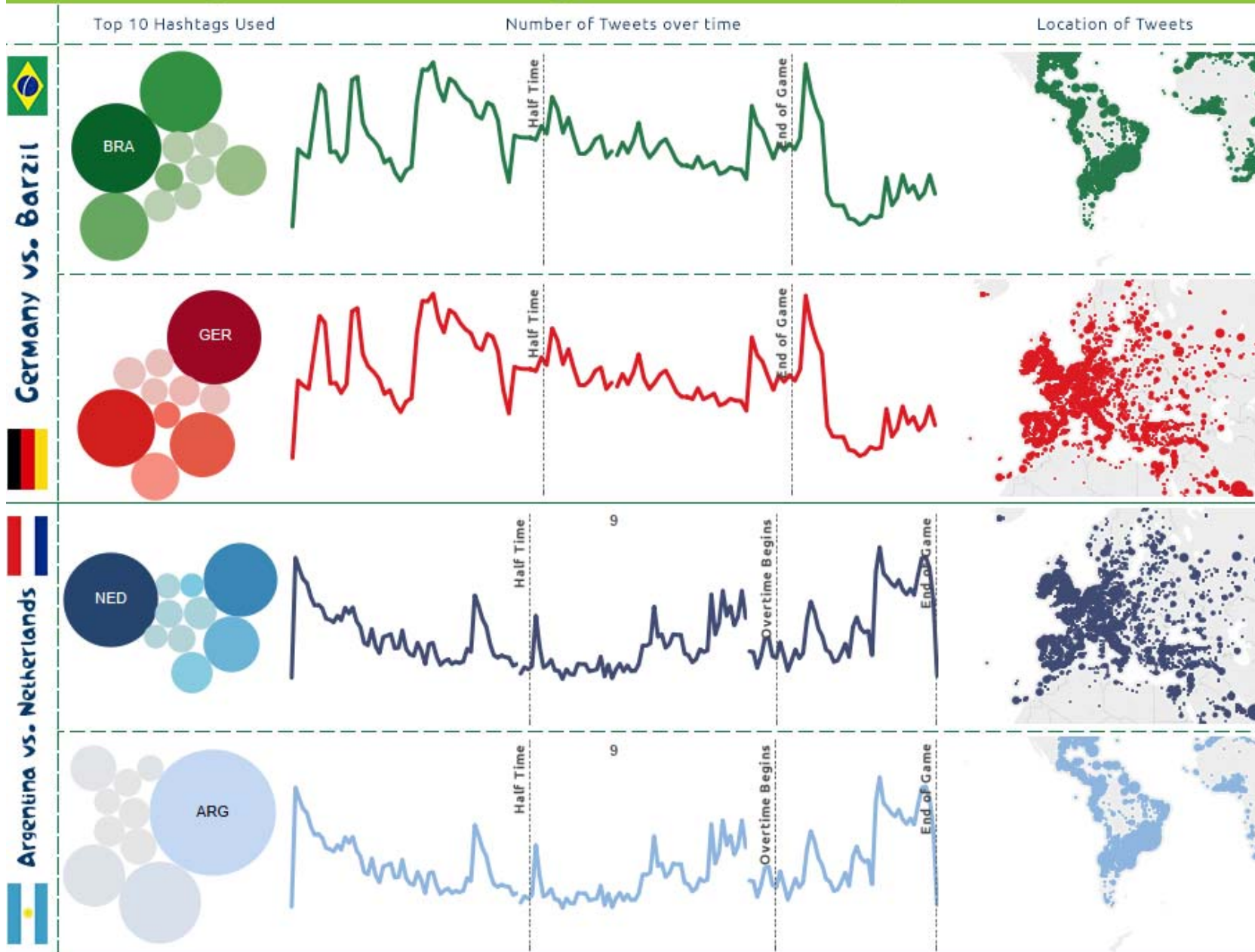






“Think, think, think.”

Twitter Activity for the Finals teams during their Semi-Final matches | Total Tweets: 49.8 million



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Twitter Analysis

- Example Twitter Analysis Problems (Vetted Use Cases)
 - Studying cross-linguistic transfer- the influence of non-English language on various levels of linguistic performance in English.
 - Using twitter data linked across hashtags, authors, geography, or time to learn synonyms for newly emerging words used in social media.
 - Concept drift/relatedness. Using word embeddings, we're building representations of topics or concepts. However, these topics/concepts being discussed change over time. We're exploring the representation necessary for following a fixed topic of conversation over time as the discussion and vocabulary evolves.
 - Studying the share of voice for mentions and references to national laboratories
 - We're interested in understanding the degree to which language sophistication varies on a topic or over time.

Motivation



Positive

- Connect
- Communicate
- Spread information
- Share interests

- Disaster responses
- Crisis events
- Situational awareness



Negative

- Social bots
- Spammers
- Trolls

- Misinformation
- Deceptive content
- Propaganda
- Manipulative campaigns

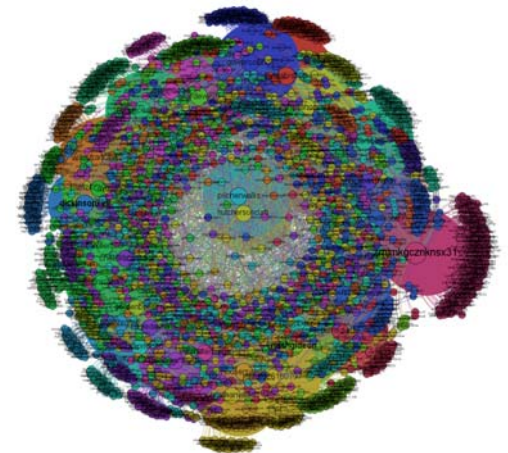
Detection of suspicious accounts = more replicable dataset

Related Work

- ▶ Social bot prediction (Ferrara et al., 2014)
- ▶ Suspended account analysis (Thomas et al., 2011)
- ▶ Non-personal and spam user detection (Guo and Chen, 2014; Lin and Huang, 2013)



- ▶ Troll detection (Mihaylov et al., 2015):
 - Accused trolls, small data (< 1K trolls)
- ▶ Analysis of 20K pro-Kremlin Twitter accounts
 - tweet similar statements during/around breaking news



Who are the trolls?



look like real users (avatars)

similar followers and friends

similar tweeting behavior

Web slang meaning for the word **TROLL** =

A **MESSAGE** OR A **PERSON**, whose primary objective is to

- ANNOY AND PROVOKE PEOPLE
- CAUSE CONTROVERSY
- WRITE POINTLESS COMMENTS

No or limited annotations exist

"PPC-RUSSIA TROLLING"

usually refers to **aggressive and anonymous web communication supporting the agenda of the Russian leadership.**

A stylized illustration of a hand typing on a keyboard, set against a blue circular background. The hand is black and the keyboard keys are white with black dots.

Dataset Creation

Twitter Suspension Policy

- ▶ Spam: invitation spam, selling, phishing
- ▶ Account security at risk: compromised
- ▶ Abusive behavior: violent threats, harassment, hateful conduct, multiple account abuse, impersonation, self-harm



RU-UA Crisis Twitter Dataset:

- ▶ Crisis-relevant keywords in RU/UA
- ▶ Rounds of querying API: March, June, and Dec 2015
- ▶ Balanced set of 188K accounts, 20 tweets per account
- ▶ **Active vs. Non-active: 85% suspended and 15% deleted**

junta
 ceasefire donetsk
 punishers cyborgs dpr fire
 quiet-period pravosekidonbass
 novorossiya negotiations
 national-army cease-fire
 ukrops humanitarian-aid
 battle-of-debaltseve
 mariupol ukrofashysty rebels
 krim-nash pravy-sektor huilo
 debaltsevecheckpoint lpr
 pravosek ilovaisk
 krimnash

Features

Profile	days since account creation, # followers, friends, favorites, tweets, friend-to-follow ratio, name, bio, screen name length in chars/words, number of tweets per hour
Visual	profile background, link, text, sidebar color, background tile, sidebar border color, default profile image
Syntactic	tweet length in words/chars, RT, uppercase, elongated, repeated mixed punctuation, mention, hashtag, link rate, prop. of tweets with links, RTs, mentions, hashtags, punctuation, emoticons
Network	mentions, hashtags, LSA on mentions/hashtags
Text	tweet ngrams (1–3grams, binary vs. frequency), LSA on tweets, LDA topics (50–1K), word2vec embeddings (30–2K)
Affect	number of emoticons, prop. of six emotions, mean scores, prop. of tweets with sentiments (Volkova et al., 2015)

Classification Results

Features	D-S-ND	DS-ND	D-S
Profile	0.78	0.85	0.86
Style + Syntax	0.72	0.81	0.86
Language			
Tweets	0.82	0.87	0.83
Tweets + LSA	0.79	0.84	0.85
Topics	0.77	0.81	0.83
Embeddings	0.72	0.76	0.94
Network			
Hashtags	0.67	0.76	0.84
Mentions	0.69	0.78	0.85
Hashtags + LSA	0.63	0.73	0.84
Mentions + LSA	0.64	0.72	0.85
Affect			
Sentiment + Emotion	0.62	0.72	0.83

Key Findings

Tasks: D – S > DS – ND > D – S – ND

Text: Tweet ngrams and embeddings are the most predictive

Network: Mentions are more predictive than hashtags

Frequency vs. Binary:

- ▶ **Tweet ngrams:** It is not only important what the users say but how much they say it
- ▶ **Mentions and hashtags:** It is not important how much the users use some hashtags or mentions, but whether they use them or not

Analysis: Verbal and Nonverbal Behavior Differences

Verbal Behavior

Deleted and suspended users generate:

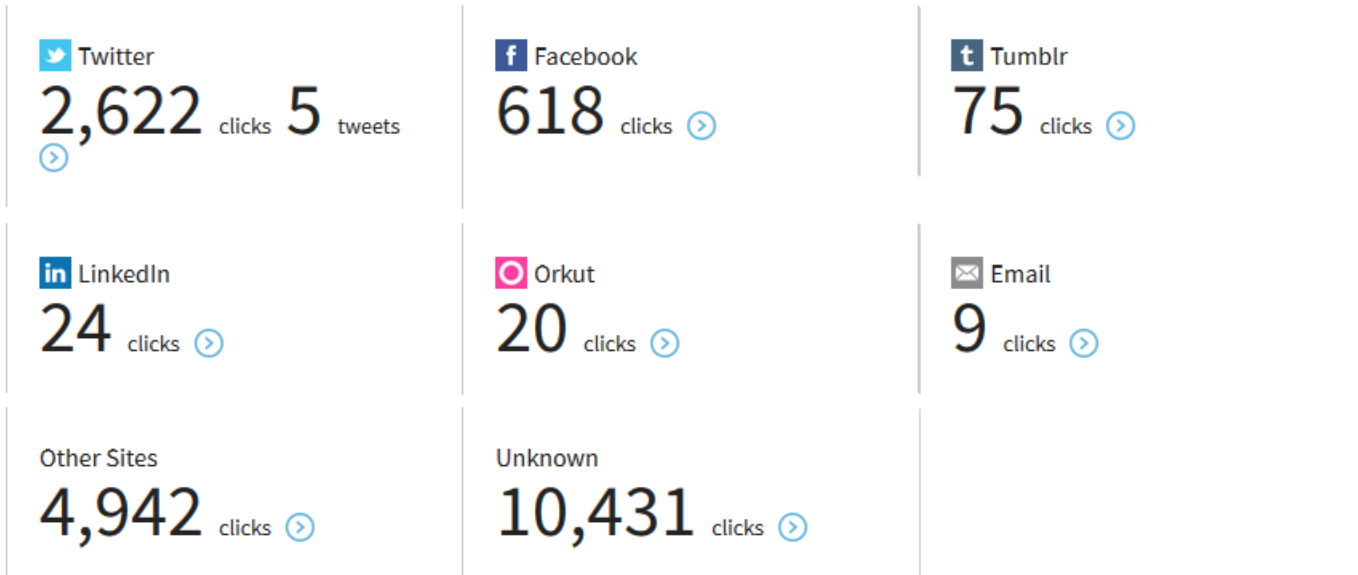
- ▶ Shorter tweets
- ▶ Less elongated capitalized words and repeated punctuation
- ▶ Lower hashtag, mention and URL per word ratios
- ▶ Less RTs, tweets with hashtags, URL and mentions
- ▶ Less tweets with punctuations and emoticons

Nonverbal Behavior

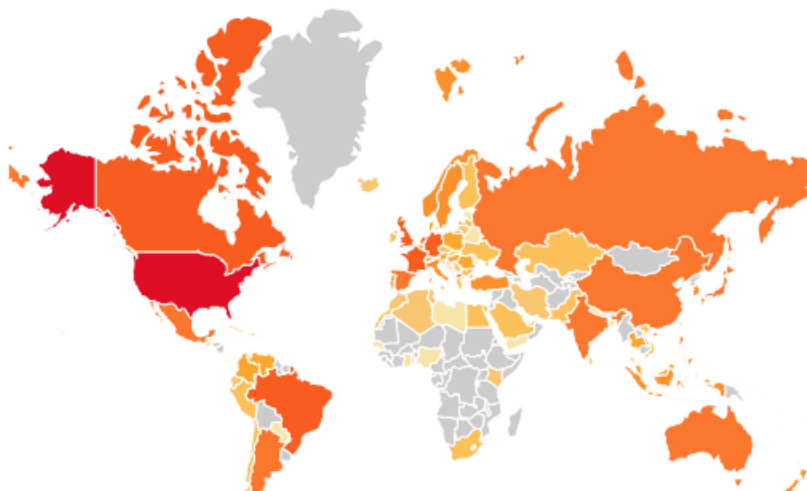
Deleted and suspended users have:

- ▶ More friends
- ▶ Less followers and tweets
- ▶ Lower friend-to-follower ratio
- ▶ Shorter bios
- ▶ Longer user names

WHERE THIS BITLINK WAS SHARED



GEOGRAPHIC DISTRIBUTION OF CLICKS



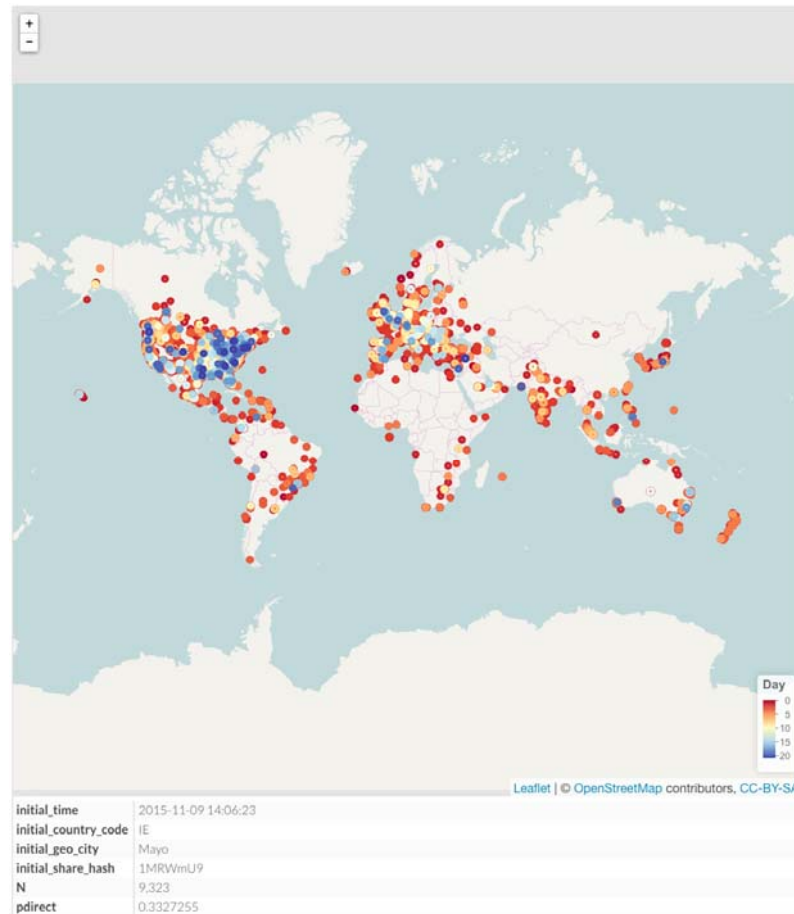
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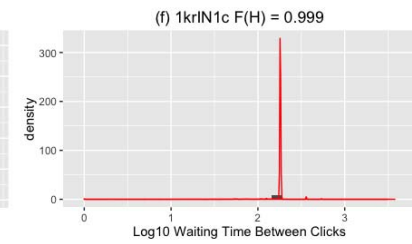
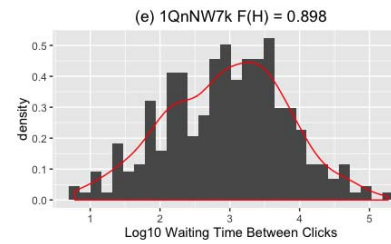
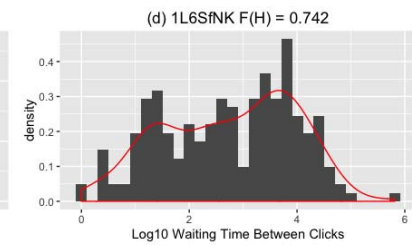
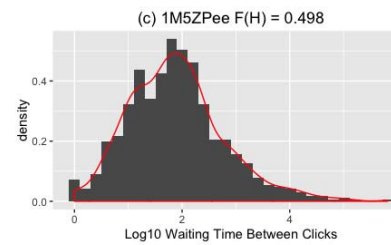
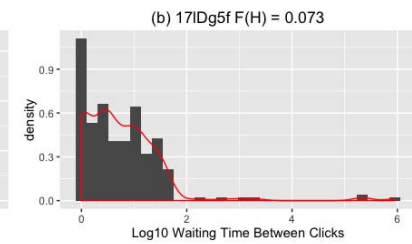
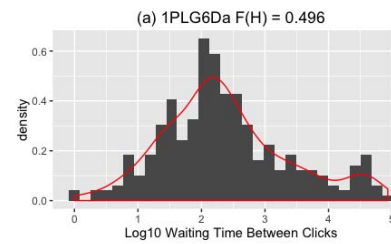
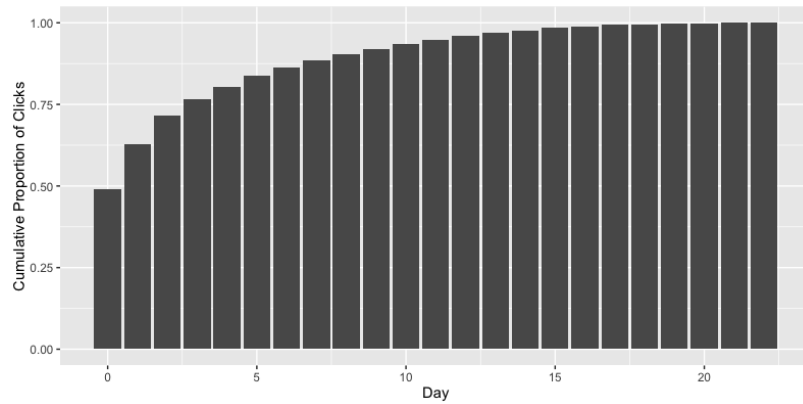
Bitly Research Overview

- How does the design of the UI on various social media platforms manifest different styles of interaction propagation?
- Classic definitions of virality are based on large frequencies or potential reach, we're instead looking to understand a model that lets us find events that are hyperlocally viral. This involves correlation of multiple data types
- Characterize URL types
- What do links look like as they move through time and spread geographically?

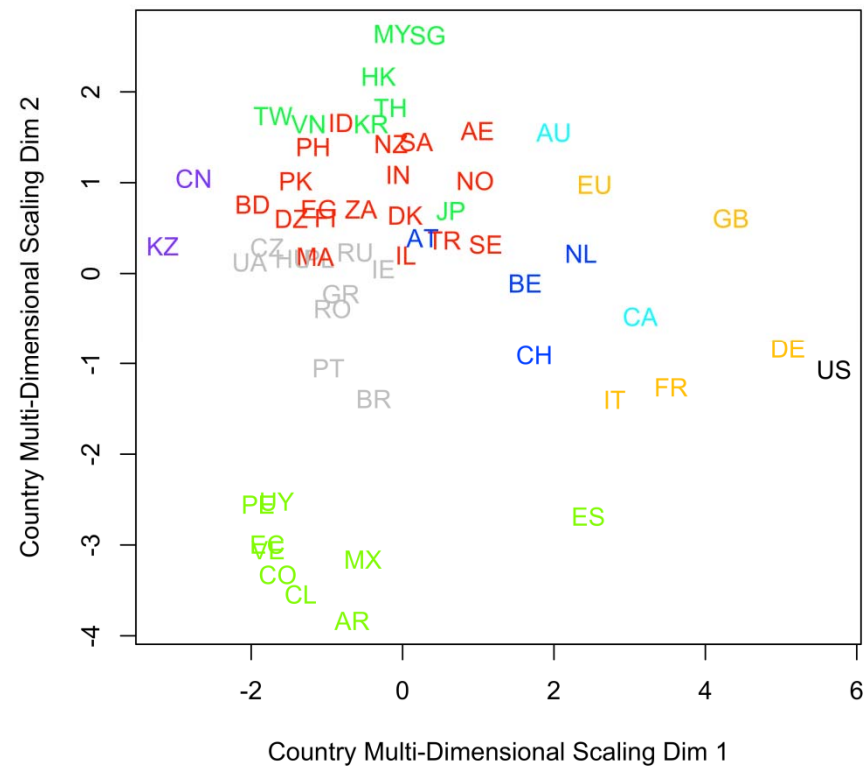
How do you think about Bitly clicks?

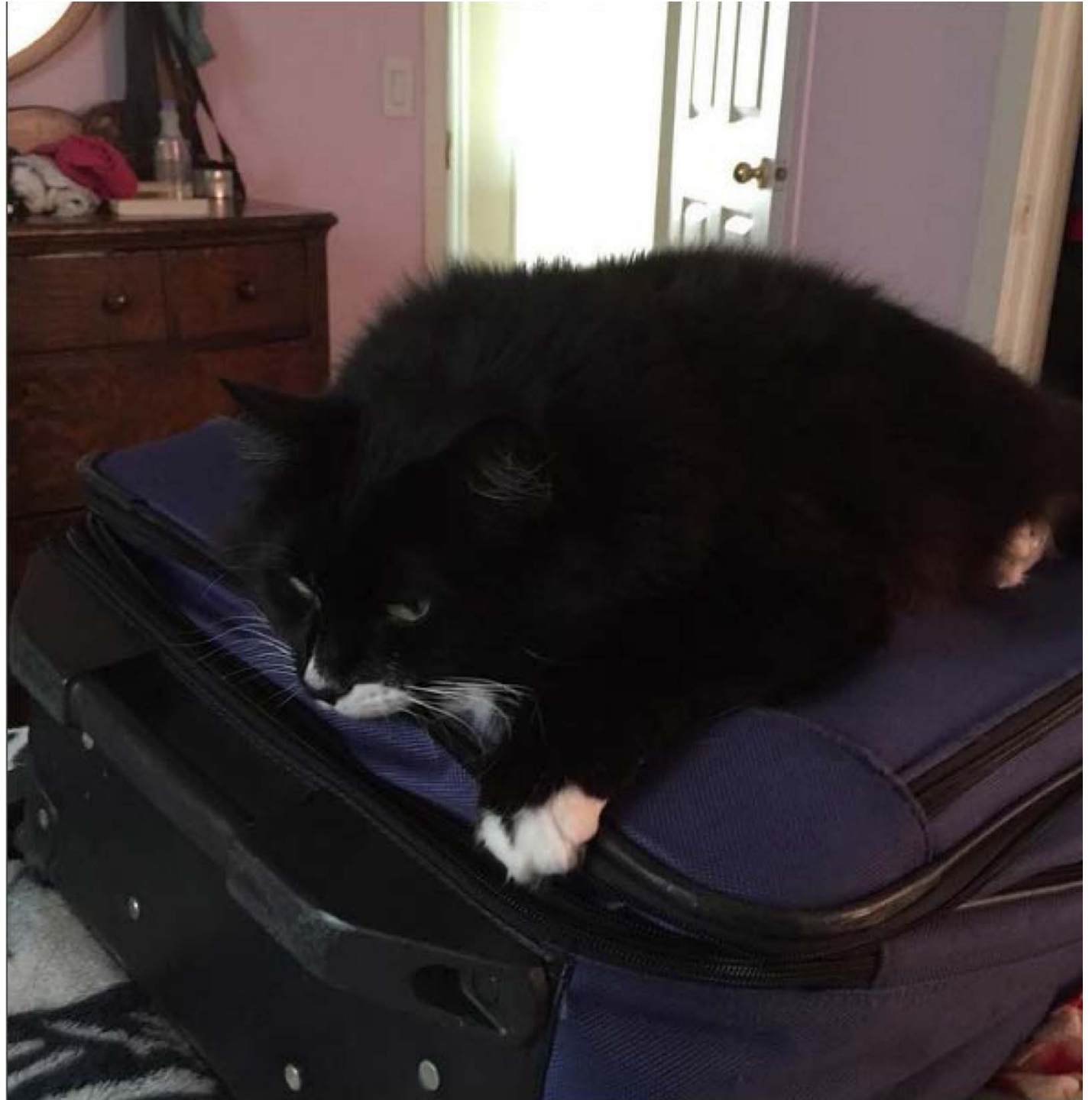
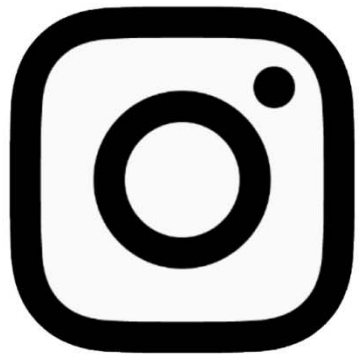


What does it mean to be viral?



Bitly Behavior By Country





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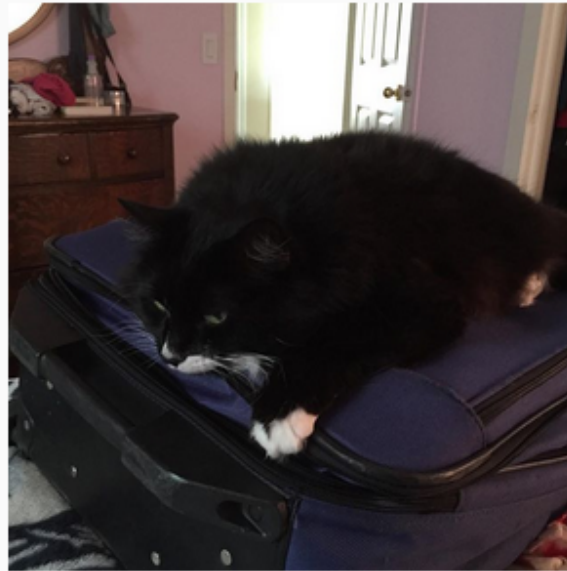
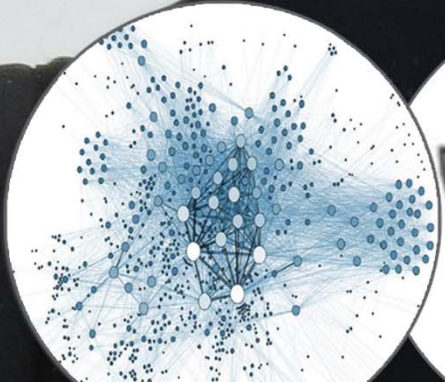


Image Research Overview

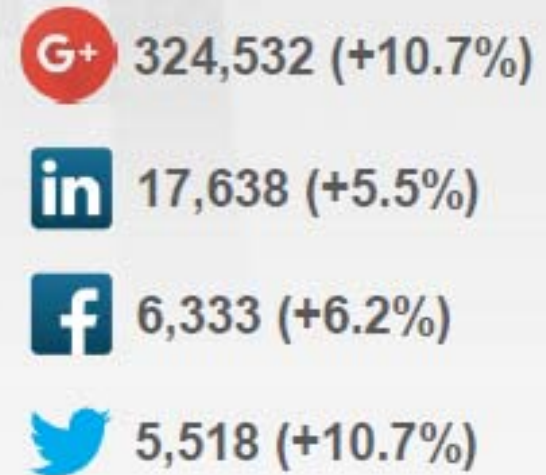
- Image classification and multi-modal embeddings. Using convolutional neural networks, we're building representations of objects and themes within images linked within social media data.
- Using language and visual embeddings, we're exploring models for sense-making across data types for understanding how different data modalities are used to communicate ideas within a social context



Second Quarter Highlights

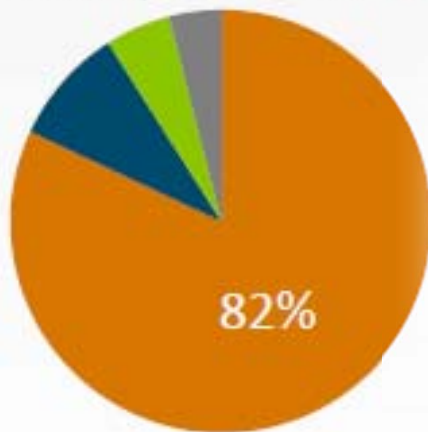
- ▶ **Google+:** More than 24,000 new followers; content viewed 1.63 million times
- ▶ **LinkedIn:** An average of 64.6 engagements by unique users per day
- ▶ **Facebook:** Second among national labs in daily audience engagement
- ▶ **Twitter:** Highest audience engagement among national labs

Second Quarter Growth



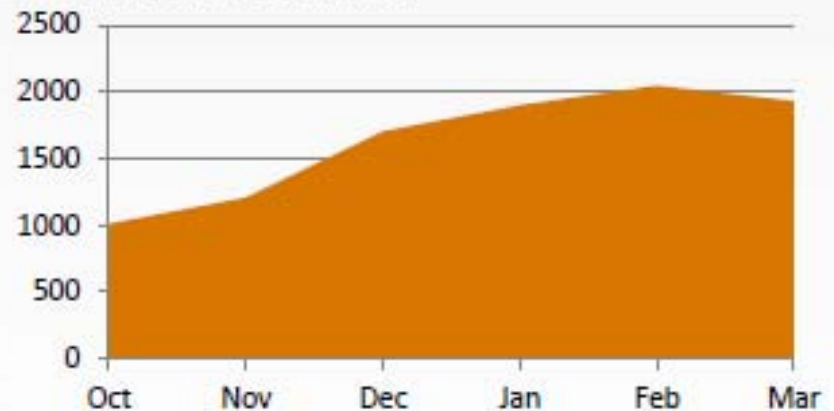
Google+: FYTD Audience Share of Voice

benchmark: as %, actual PNNL content views during period



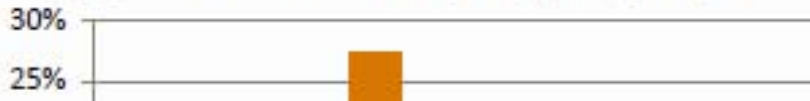
LinkedIn: FYTD Audience Engagement

by month, number of times unique users engaged with PNNL content (clicked, liked, shared or commented)



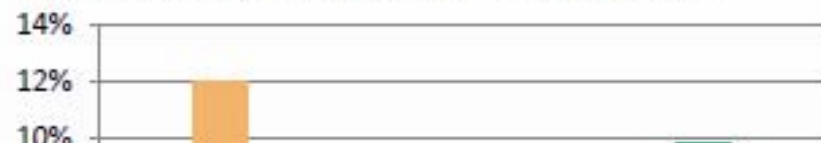
Twitter: FYTD Audience Engagement

*benchmark: unique users engaging in content [unique users engaging / total followers at end of the reporting period] * 100.)*

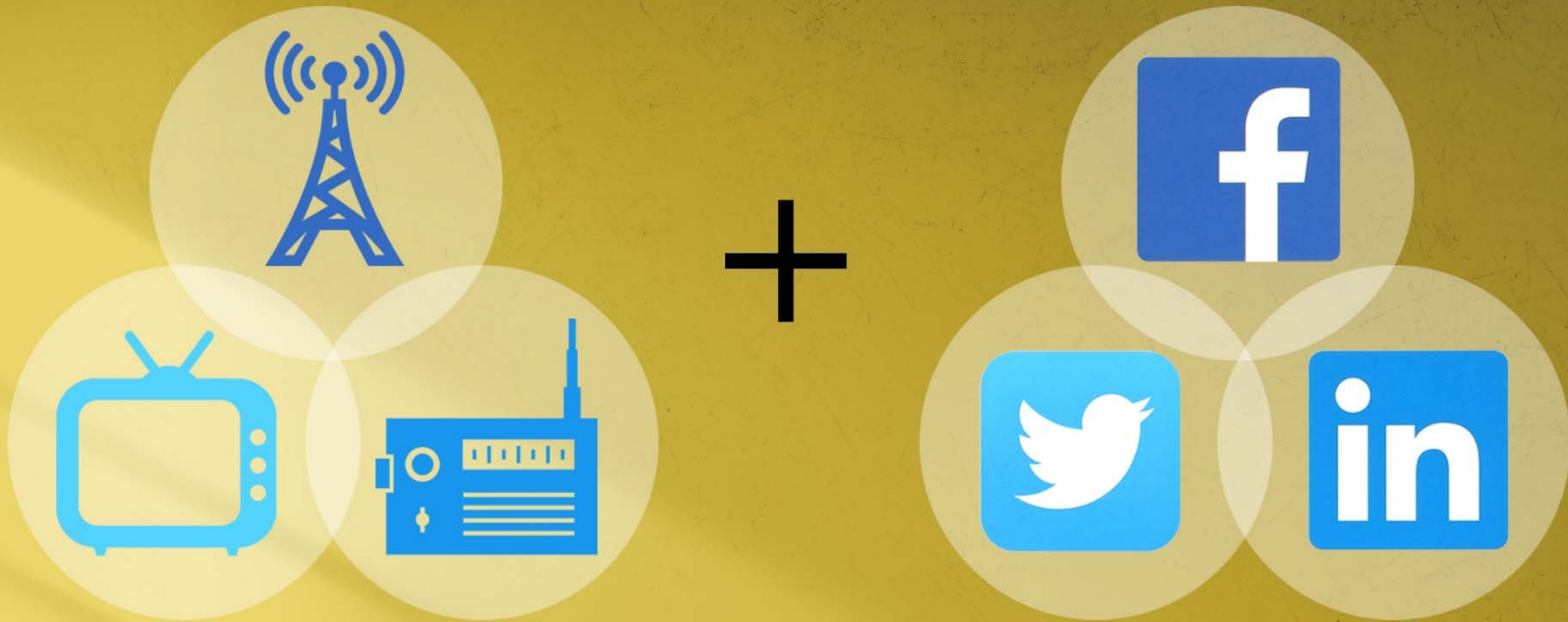


Facebook: FYTD Audience Engagement

benchmark: daily audience engagement per 1000 page likes









ACCEPT

REJECT



NEWSPAPER

NAM REM HARLUNT ETUR MIN PEDIS VEL MAGNATI SIMUS 500,0



world economic

03

ET QUIAM
VELLA
VOLLCAE NIS
ESTEN OLIAE
NULPARI,
QUASPI MO
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QUASPI MO
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EXPLABORERIAM SUMQUIAM VOLEST
VOLORRO IS UT HARZDSCZX VX

Loremp laum ligitaq
quis enim volupta esse
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Obsequatibus voluptas
sunt que et hassam?

Amoribus, adularum
voluptas in voluptas enim

PLabla - Amorem

A green rectangular sign with rounded corners is mounted on two wooden posts. The sign features the text "Silver Bullet" in large white letters, "not" in smaller yellow letters, and "Just Ahead" in white letters below it. The background is a bright blue sky filled with white, fluffy clouds. A faint rainbow is visible in the upper left portion of the sky, and a bright light source, likely the sun, is positioned behind the clouds on the right side, creating a lens flare effect.

Silver Bullet
not Just Ahead

