Social Data Science

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April 24, 2014

Social Data

Where Does Social Data Come From?

Community of Users	Platform	Social Data Analysts
• Common interests • Cultural commonalities • Topic interest/focus • Common assumption about sharing/privacy interaction • Contemporaries/peers	• Interaction modes • Habits • Connections • Recommendations • Engagement • Storage/Structure	• Privacy • T.O.S. • Enablers of advertising network analysis

Common Social Data Sources

- APIs
- scraping
- firehose

Firehose

Continuous stream
of activities
in near-real time

Firehose volumes

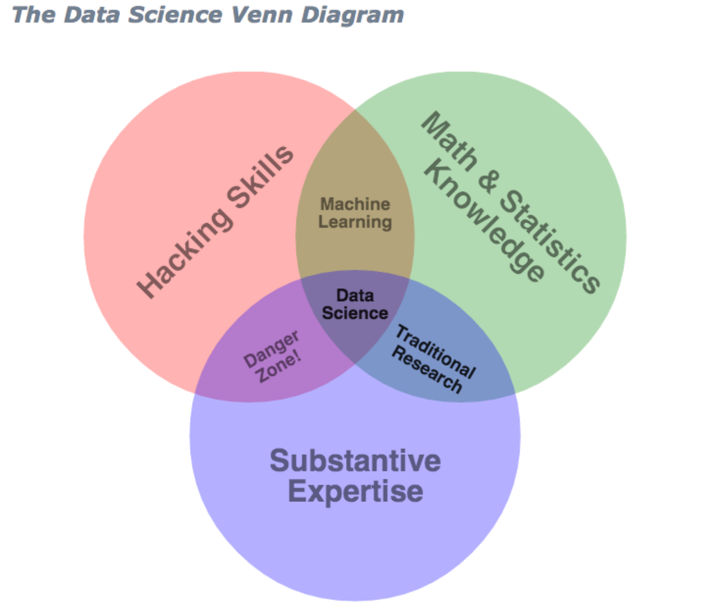
Publisher	Daily Activity
Twitter	520M
Tumblr	110M
Foursquare	4.2M
Wordpress Posts	1M
Wordpress Comments	1.7M
Disqus	1.9M
Engagement (likes, votes)	>60M

Every day @Gnip

$\frac{3}{4}$ Billion IN

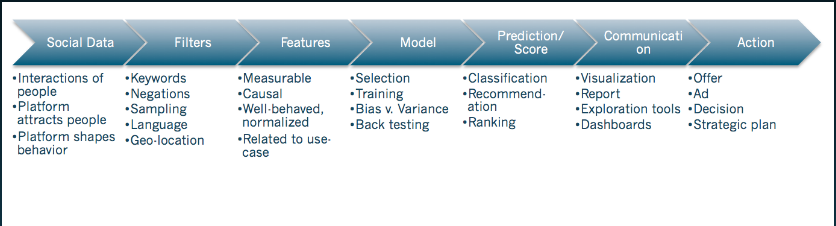
4 Billion + OUT

Data Science



https://s3.amazonaws.com/aws.drewconway.com/latexviz/venn_diagram/data_science.html

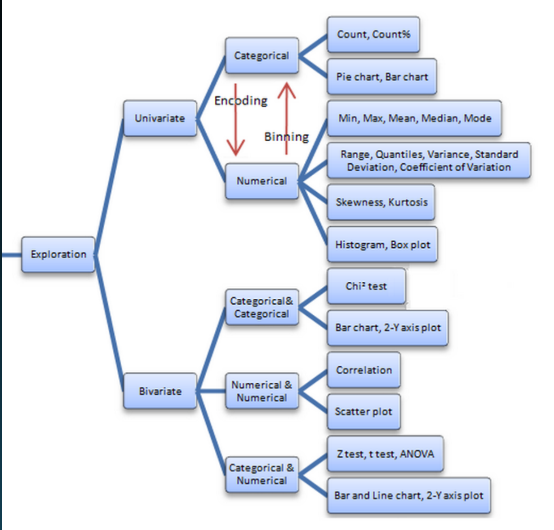
Social Data Processing Pipeline



Three Kinds of Research Projects

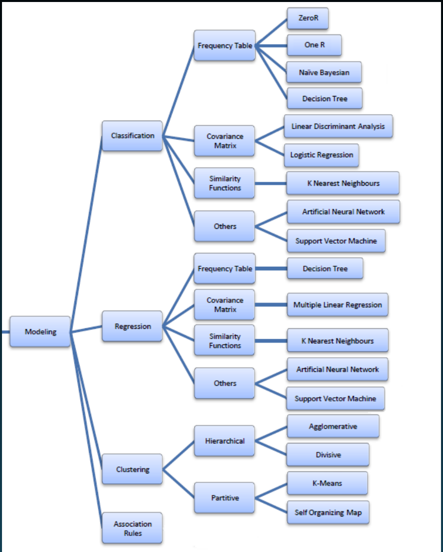
- Descriptive
  - Provides systematic information about a social data set
  - May not begin with hypotheses, but to develop one as you go
  - Detect anomalies
- Exploration
  - Explores a social phenomena
  - Provides background information needed to plan descriptive or explanatory research
  - Trial and error or hypothesis driven
- Explanation
  - 3 Levels: Relationship, Models, Prediction
  - Ideas about the possible causes of a social phenomenon
  - Plan a study that can provide systematic evidence for/against ideas about cause

Data Exploration



http://saedsayad.com/data_mining_map.htm

Data Modeling



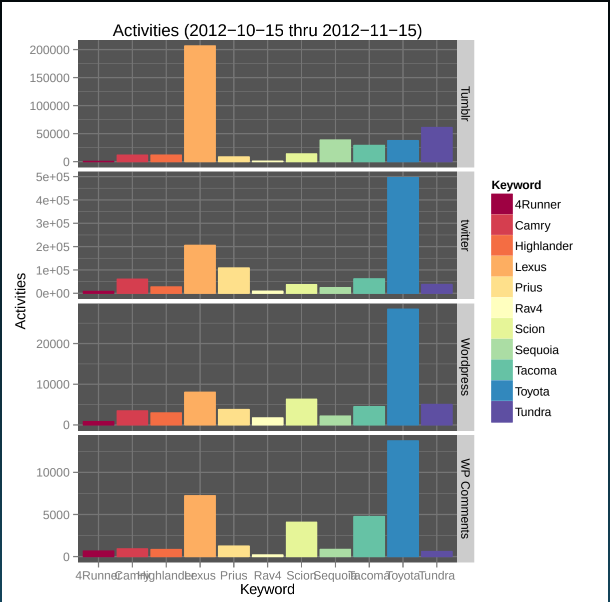
http://saedsayad.com/data_mining_map.htm

Fundamental Processes

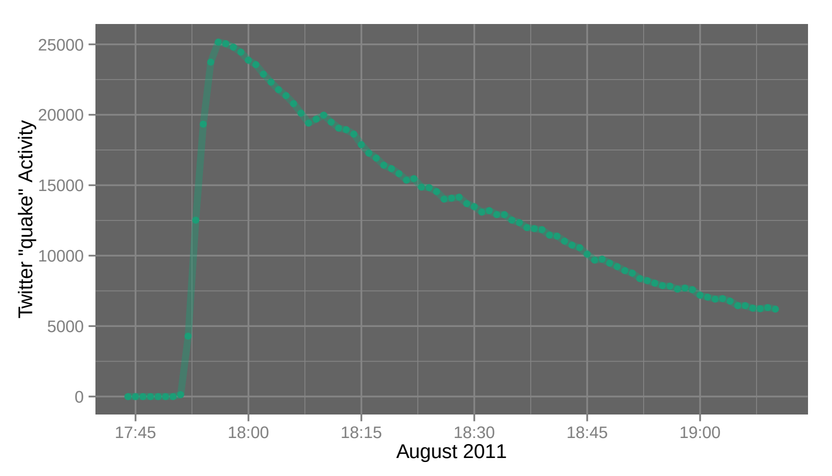
- Networks - e.g. 6-degrees, percolation
- Agent models
- Time series - e.g. “Social Media Pulse”

Time Series: Social Media Pulse

Simple Mention Counts



Unexpected: earthquake



Mentions and time series

We start by bucketing our mention counts by time periods, the activity rate is:

$$\bar{r} = \frac{N}{T},$$

General model for activity rates:

$$p_{activity}(t) = re^{-rt}.$$

give Poisson distribution:

$$P(n) = \frac{e^{-rt}(rt)^n}{n!}.$$

Confidence intervals

Confidence intervals for the Poisson distribution with confidence level equal to $100\%(1-\alpha)$ are given by,

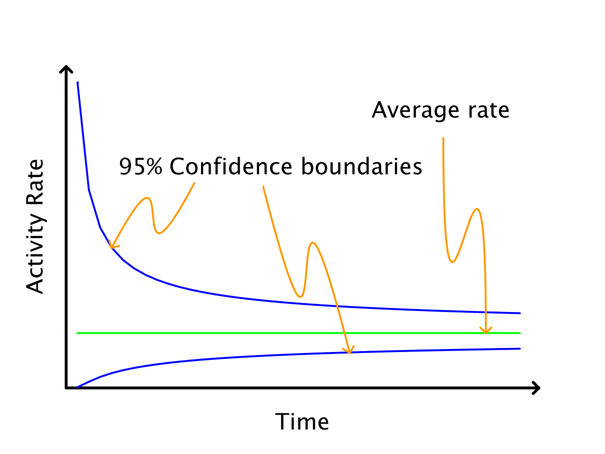
$$\frac{1}{2T}\chi^2(\alpha/2; 2n) \leq r \leq \frac{1}{2T}\chi^2(1-\alpha/2; 2n+2) \qquad (1)$$

where χ^2 is the inverse cumulative distribution function, $CDF^{-1}(p; n)$, of the χ^2 distribution.

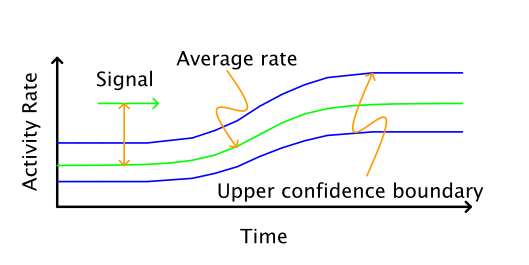
90% confidence intervals?

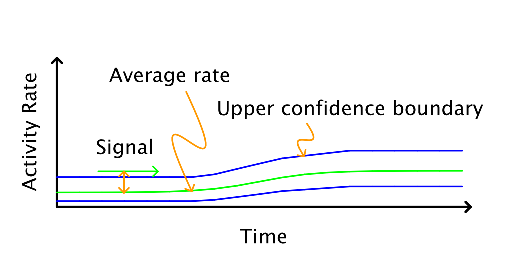
n	Interval Bounds	Interval Size (δn)	Relative Interval
1	0.0513, 4.744	4.693	4.693
2	0.3554, 6.296	5.940	2.970
3	0.8177, 7.754	6.936	2.312
4	1.366, 9.154	7.787	1.947
5	1.970, 10.51	8.543	1.709
10	5.426, 16.96	11.54	1.154
30	21.59, 40.69	19.10	0.6366
40	30.20, 52.07	21.87	0.5468
50	38.96, 63.29	24.32	0.4864
500	463.8, 538.4	74.58	0.1492
750	705.5, 796.6	91.11	0.1215
1000	948.6, 1054.	105.0	0.1050

Make the buckets bigger?



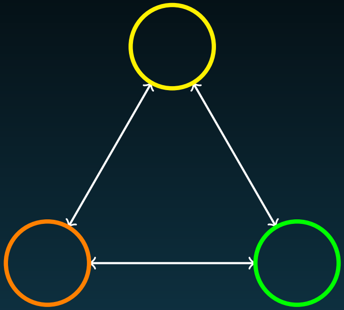
Ignore smaller signals?





signal

$(\Delta r = |rate_f - rate_i|)$



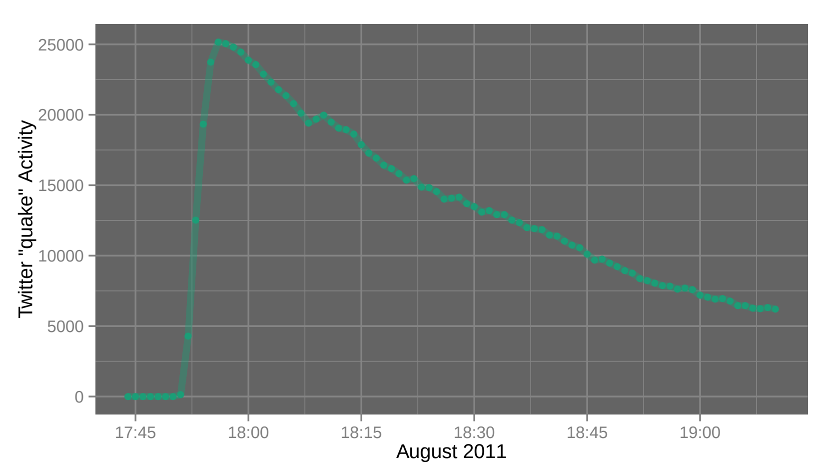
activities

$(N = rate \times time)$

confidence

$(\delta_{rate,N})$

Unexpected: earthquake



Classifying events

Type	Response	Examples
Expected	Build-up/Decay	Hurricane Sandy Olympics
Unexpected (many obs.)	Social Media Pulse	Beyoncé VMAs Mexico earthquake Steve Jobs
Unexpected (network spread)	Network Models	Osama bin Laden Whitney Houston Syrian dissidents

Social media pulse

Given an event, the probability of an activity from one person,

$$f(t) = \lambda \exp(-\lambda(t - t_0)), \text{ for } t \geq 0.$$

Many people posting on same cue; so sum of random variables

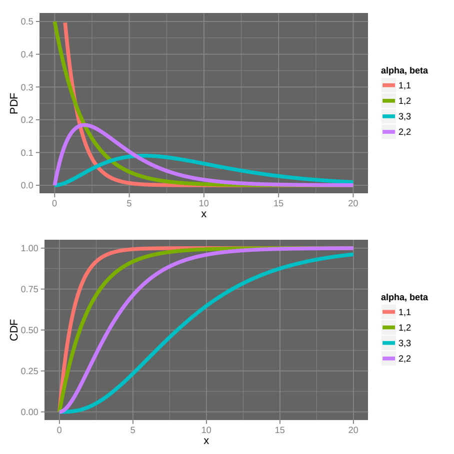
$$S = X_1 + X_2 + \ldots + X_{n \text{ posters}}$$

Gamma probability distribution function,

$$f_S(t) = \frac{\beta^{-\alpha}(t - t_0)^{\alpha - 1} \exp(\frac{-(t - t_0)}{\beta})}{\Gamma(\alpha)}$$

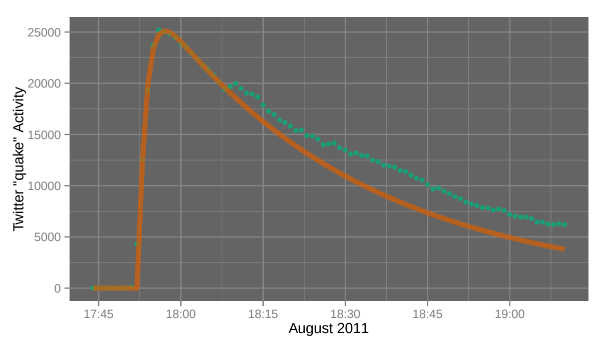
Cumulative distribution is the "generalized regularized incomplete gamma function",

$$F_S(t) = Q(\alpha, 0, \frac{(t - t_0)}{\beta})$$


0.5
0.4
0.3
0.2
0.1
0.0
PDF
0
5
10
15
20
x
alpha, beta
1,1
1,2
3,3
2,2
1.00
0.75
0.50
0.25
0.00
CDF
0
5
10
15
20
x
alpha, beta
1,1
1,2
3,3
2,2

Why model half-life?

- predict total story volume
- compare half-lives
- anomalous story evolution


25000
20000
15000
10000
5000
0
Twitter "quake" Activity
17:45
18:00
18:15
18:30
18:45
19:00
August 2011

Compare events

We start with a least-squares fit of points up to the $2-3\times$ time-to-peak.

$$t_{time-to-peak} = \beta(\alpha - 1)$$

Average event response time,

$$t_{avg} = \alpha\beta$$

Half-life (time to see half of the activities),

$$t_{\frac{1}{2}life} = F_S^{-1}(\frac{1}{2}).$$

Story size,

$$F_S(t) = Q(\alpha, 0, \frac{t-t_0}{\beta}) \tag{2}$$

in terms of the incomplete gamma functions,

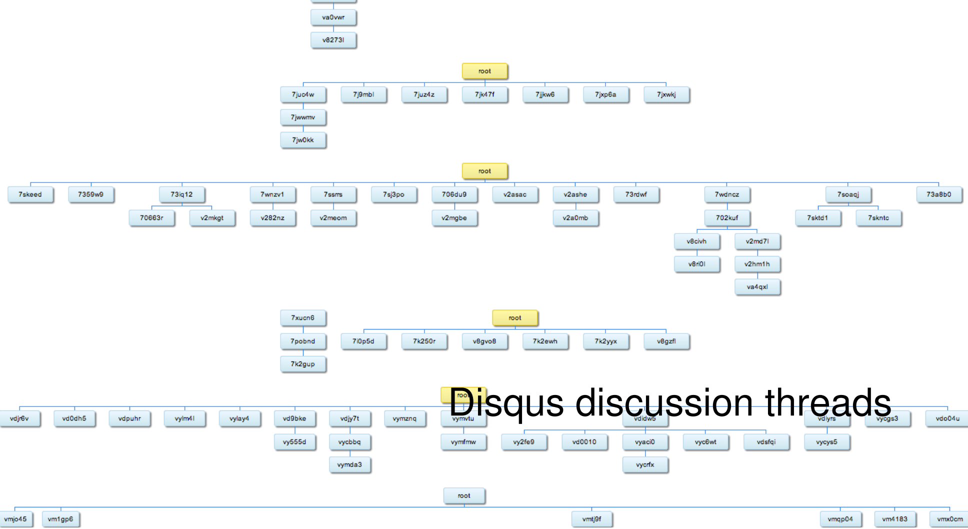
$$S_{vol} = \int_0^\infty r(t)dt = N_{activities} F_S(t), \tag{3}$$

Topic Modeling – Latent Semantic Indexing

What do we talk about when they talk about X?

Apologies: Raymond Carver

Disqus discussion threads



Disqus Threads

- 7 weeks of Disqus comments data
- Key words: “texting,” “driving” and variants
- Select top threads based on mentions
- 61,406 comments from 365 threads

Disqus Topic Model Approach

- Find comments that mention key words
- Corpus of comments (across many threads)
- tf-idf matrix: terms $\times$ comments
- LSI (rotate space to align with "important" dimensions, reduce dimensions)
- K-means (quick-and-dirty clustering in reduced dimensional space)
- …rinse and repeat (looking for distinction and cohesion)

tf-idf and LSI in one page ...

- tf: term frequency
- idf: inverse document frequency

LSI uses singular value decomposition to rotate document matrix from tf-idf to reduce dimensionality in a controlled way. SVD lets us write the document matrix as,

$$D = V \Sigma U^T$$

where Σ is a diagonal matrix and the with values satisfying,

$$\Sigma_{1,1} > \Sigma_{2,2} > \Sigma_{3,3} > \Sigma_{4,4} > \dots$$

To reduce dimensions, truncate the Σ matrix smallest values first.

$$D' \approx V \Sigma' U^T$$

where D' has fewer columns according to how we trimmed Σ.

Disqus Topic Model

- Same 7 weeks; same keywords
- 32,856 comments from 16,886 threads
- LSI: 500 features $\rightarrow$ 80 features
- K-means: 80 clusters as topics (?!)

Topic 46 - Traffic Signals

46

count	frac_gram	act_count	act_frac	n_gram
576	0.031167	254	0.885017	light 1grams
459	0.024836	236	0.822300	red 1grams
167	0.009036	110	0.383275	driver 1grams
160	0.008658	91	0.317073	people 1grams
158	0.008549	100	0.348432	drivers 1grams
136	0.007359	94	0.327526	one 1grams
115	0.006223	69	0.240418	more 1grams
110	0.005952	72	0.250871	traffic 1grams
100	0.005411	75	0.261324	stop 1grams
99	0.005357	63	0.219512	lights 1grams

Topic 46 continued …top 2-grams

293	0.016104	177	0.616725	red light 2grams
52	0.002858	40	0.139373	red lights 2grams
47	0.002583	20	0.069686	light cameras 2grams
39	0.002144	35	0.121951	run red 2grams
35	0.001924	27	0.094077	running red 2grams
29	0.001594	19	0.066202	light camera 2grams
28	0.001539	12	0.041812	yellow light 2grams
28	0.001539	24	0.083624	green light 2grams
22	0.001209	21	0.073171	ran red 2grams
22	0.001209	18	0.062718	through red 2grams

Topic 46 continued …simple sentiment

Words 18718

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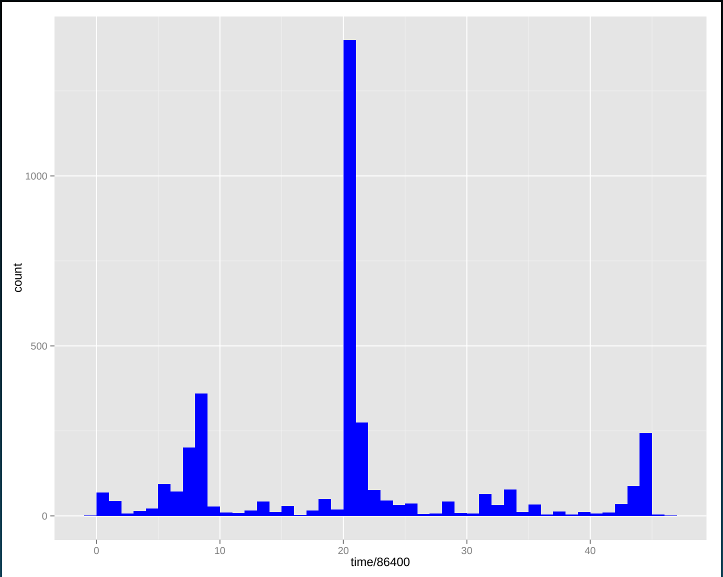
positive ... (0.0389) 728
negative ... (0.0652) 1220
neutral .... (0.8959) 16770
Score .... -0.25257

Topic 46 continued …top +/- sentiment

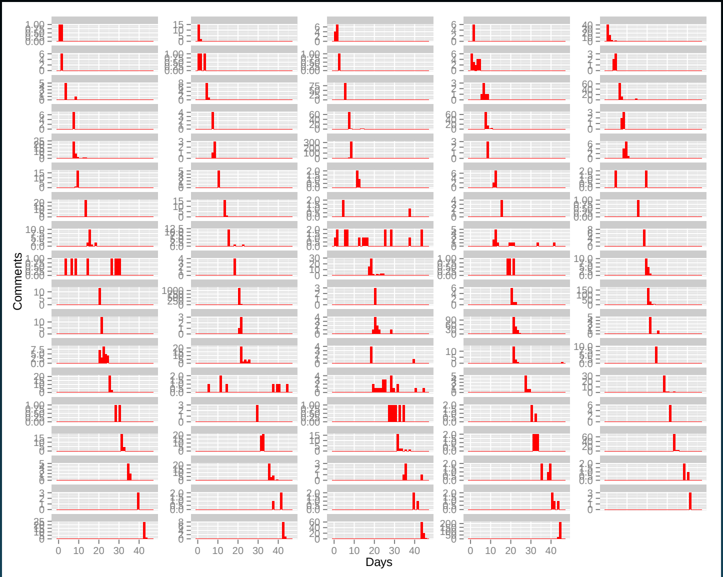
0.000	right	0.003 740	problem	0.001 656
1.000	well	0.002 190	dangerous	0.001 336
2.000	good	0.001 710	killed	0.001 229
3.000	enough	0.001 442	crashes	0.001 122
4.000	safe	0.001 229	bad	0.001 015
5.000	better	0.000 854 8	fault	0.001 015
6.000	work	0.000 854 8	issue	0.000 801 4
7.000	top	0.000 801 4	slow	0.000 801 4
8.000	free	0.000 747 9	problems	0.000 801 4
9.000	pretty	0.000 694 5	limit	0.000 747 9

Focus on the intersection of Thread and Topic models

Comments with key words over time

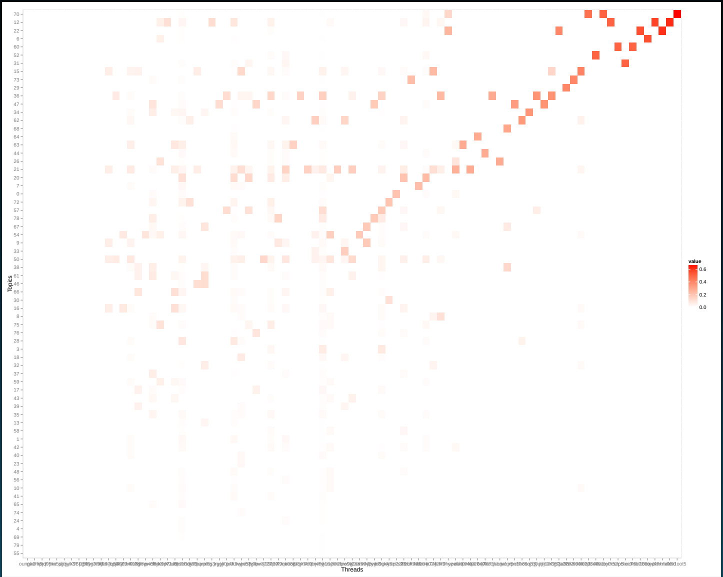


Disqus Thread Activity over Time



Disqus Topics Activity over Time

Dominant Topics × Threads?



When we talk about texting and driving, we talk about …

- Topic 12: poor graphic design
- Topic 50: fake ids and fake drivers licenses
- Topic 58: health/accident insurance
- Topic 62: drunk drivers
- Topic 64: buses and bus drivers
- Topic 67: bikes, bike lanes
- Topic 68: trucks and truck drivers

Thank you!

- Presentation, data, vis. code at:
  http://github.com/DrSkippy27/CU_2014-04