

A Day in the Life of a Data Scientist

Brian Eoff (@bde)
Lead Scientist at Spring

SPRING

What is data science?



Jake Vanderplas

@jakevdp

 Follow

Best thing about being a data scientist:
nobody actually knows what data science
is, so you can pretty much do whatever you
want.



RETWEETS

65

FAVORITES

72



9:28 AM - 17 Oct 2014

Data Science Conference Bingo Card

In-Memory	Unstructured Data	"We're Hiring"	Predictive Analytics	Streaming
Iris Data Set	Machine Learning	Real Time	Datafication	Facebook and Twitter
NoSQL	Mobile	Free Space!!	Internet of Things	Reuters-21578
Visualization	Hadoop	Social Graph	@BigDataBorat quote	Wordcount Demo
Sentiment Analysis	NCDC GSOD	Business Intelligence	Someone who thinks R doesn't suck	"Data Is The New Oil"

Vinod Khosla: In The Next 10 Years, Data Science Will Do More For Medicine Than All Biological Sciences Combined



FREDERIC LARDINOIS 

Wednesday, September 11th, 2013

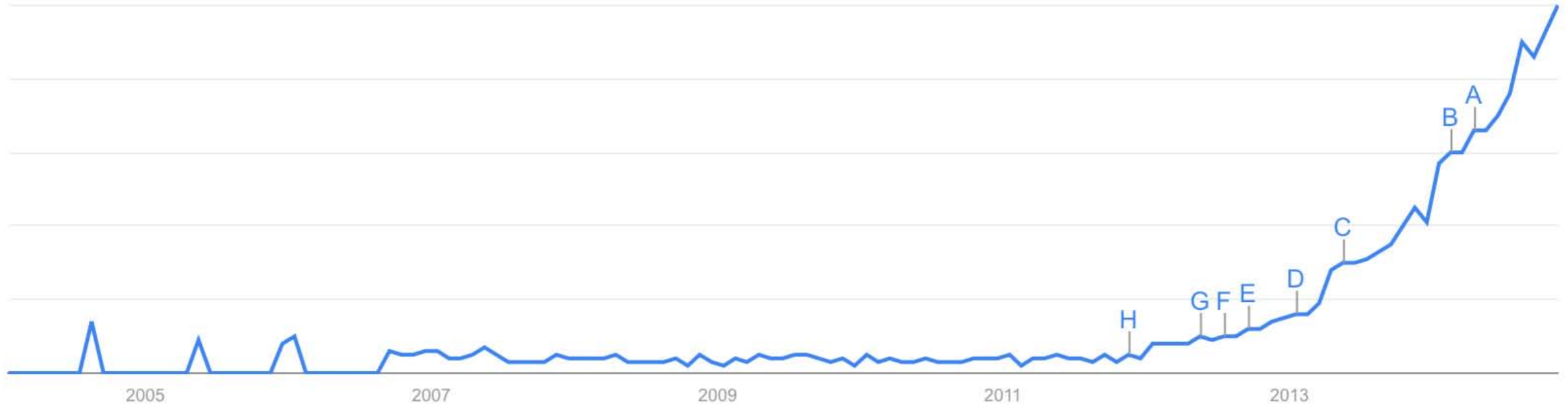
[Comments](#)

Data Scientist: The Sexiest Job of the 21st Century

by Thomas H. Davenport and D.J. Patil

Interest over time ?

News headlines Forecast ?



2011 May - Join Bitly as Data Scientist

2013 August - Lead Data Scientist at Bitly

2014 June - Lead Data Scientist at Spring





Real-Time Media Map

1. Select a media type

Newspapers

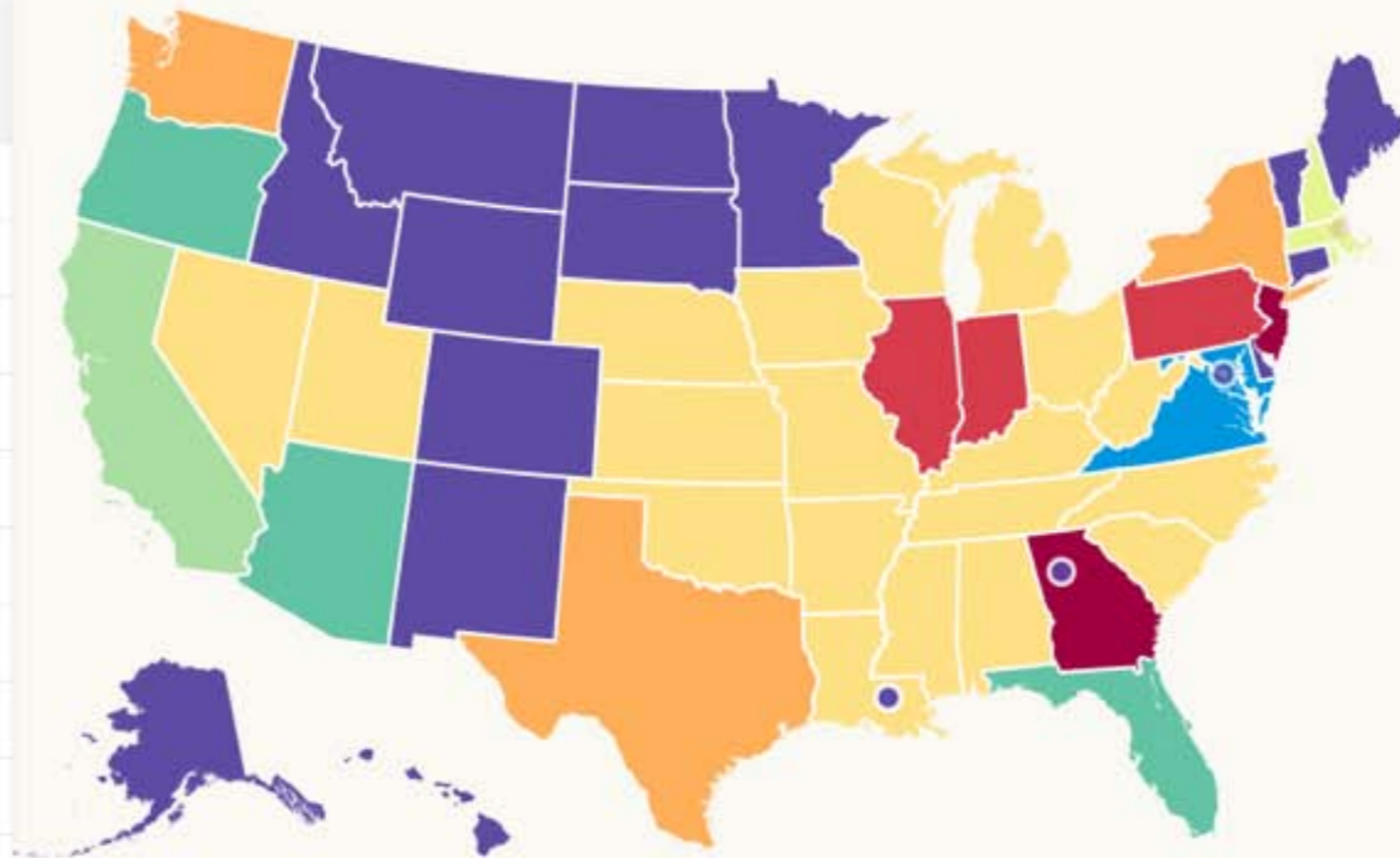
2. Select your view

Real-time traffic Winners by state Both

Media Properties Legend

(click to view by property)

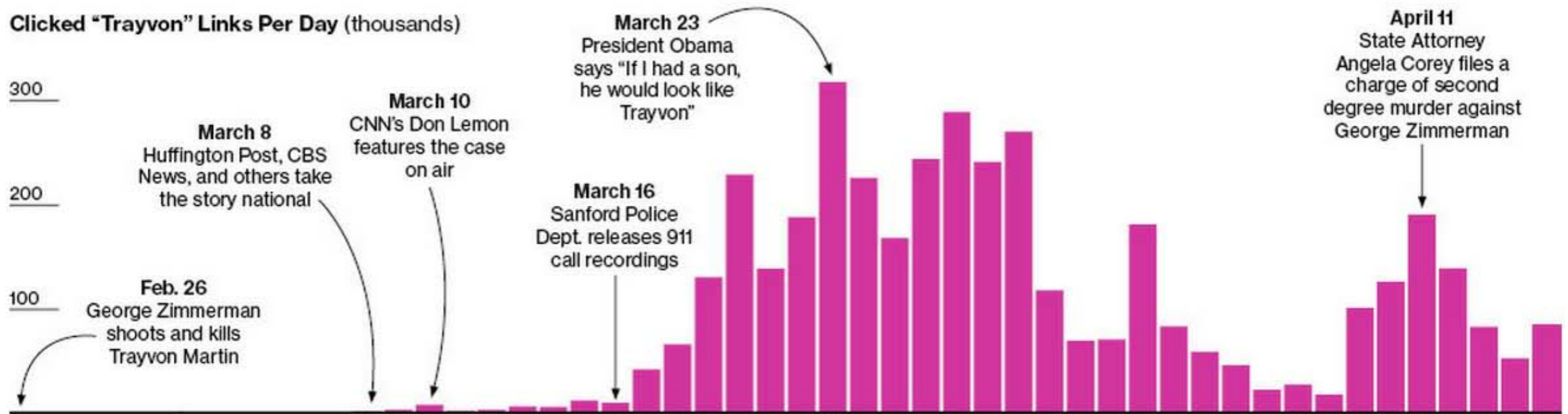
- The New York Times
- Washington Post
- Wall Street Journal
- Chicago Tribune
- Los Angeles Times
- SF Gate
- Boston Globe
- USA Today
- The Guardian
- San Jose Mercury



Interested in what Bitly can do with your link click data? Please reach out to us at community@bitly.com

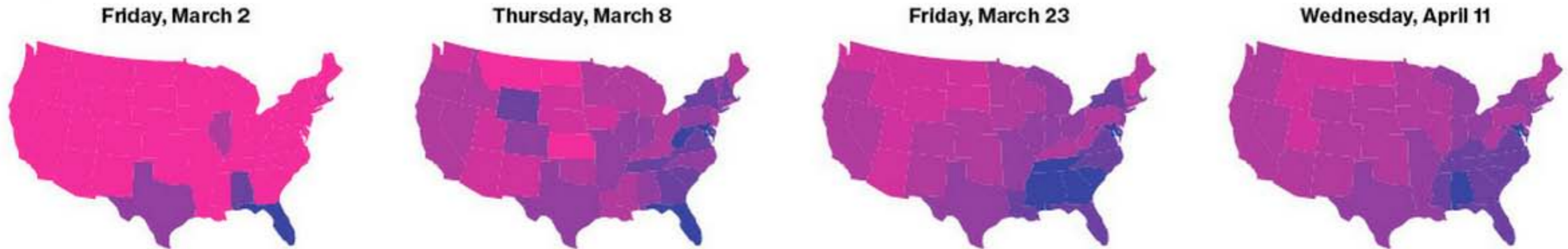


Clicked "Trayvon" Links Per Day (thousands)

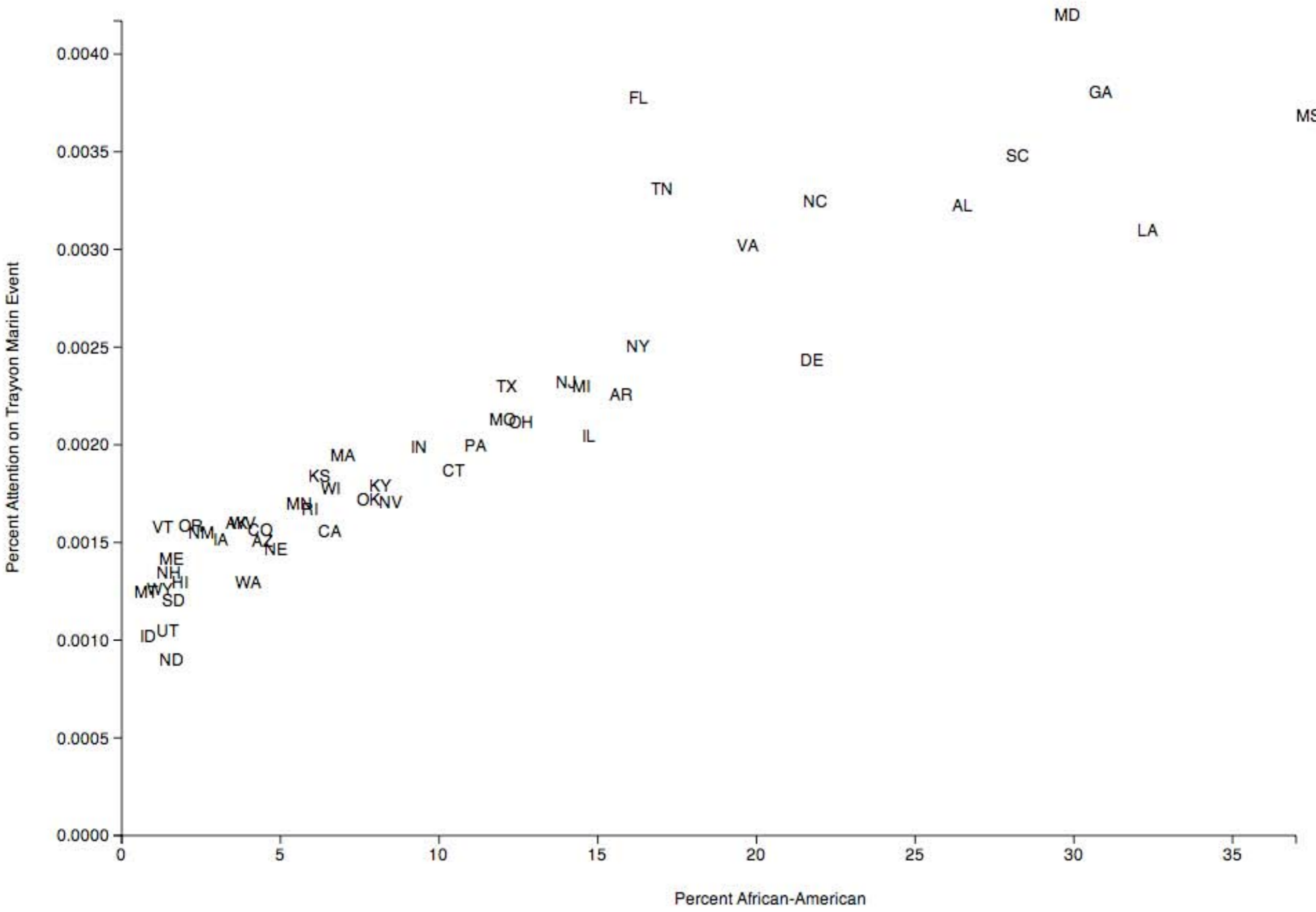


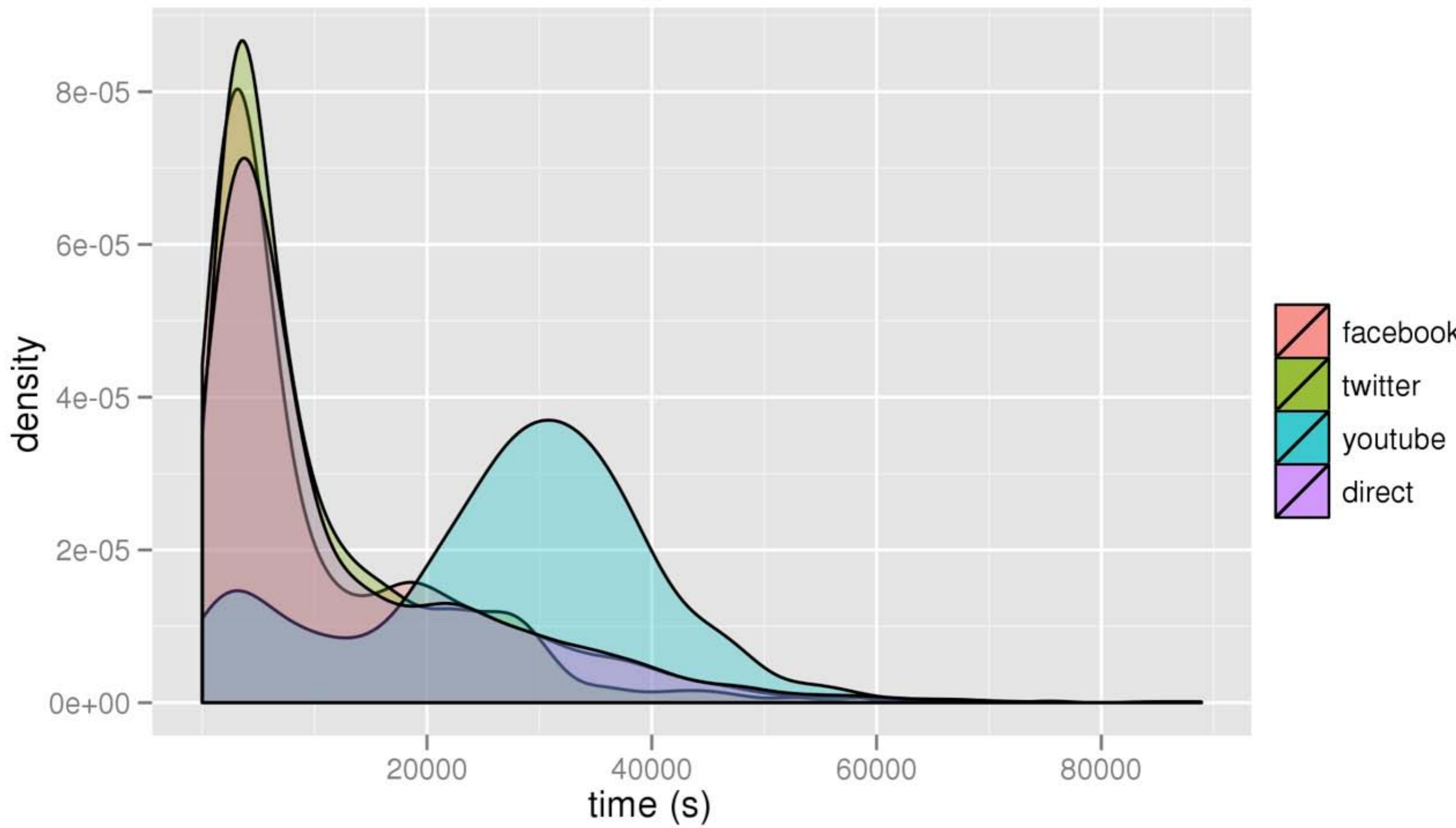
State Interest*

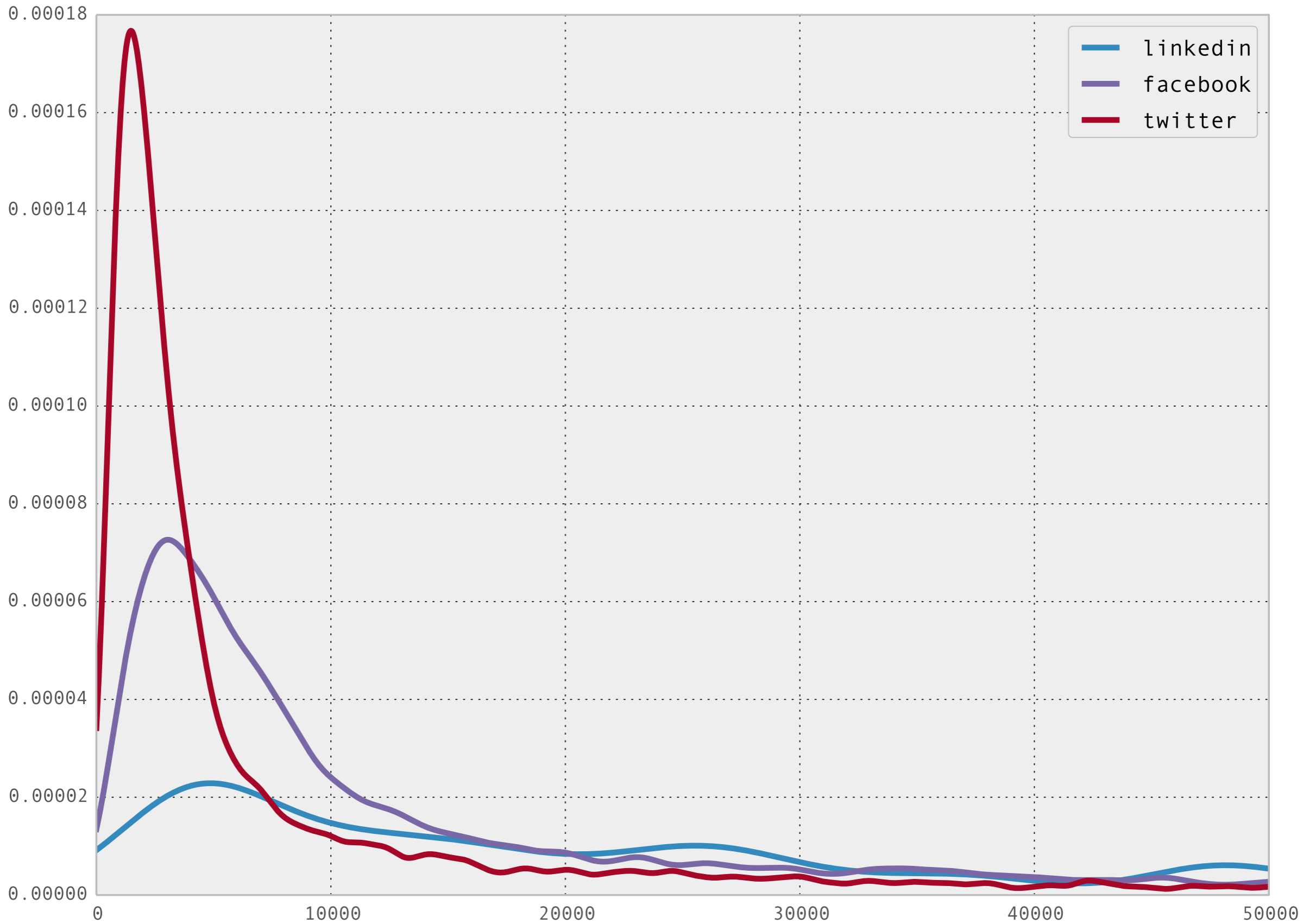
LESS MORE

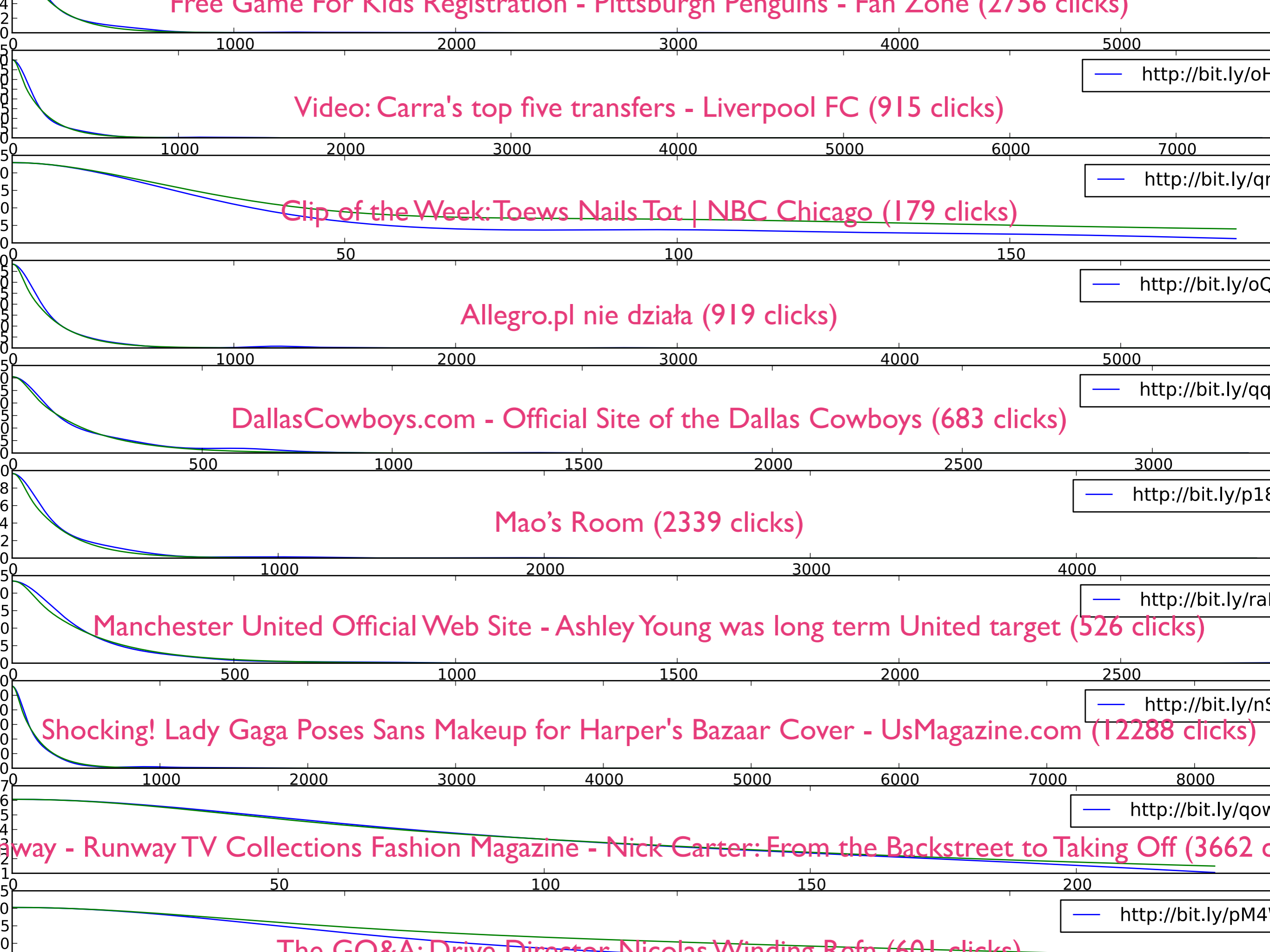


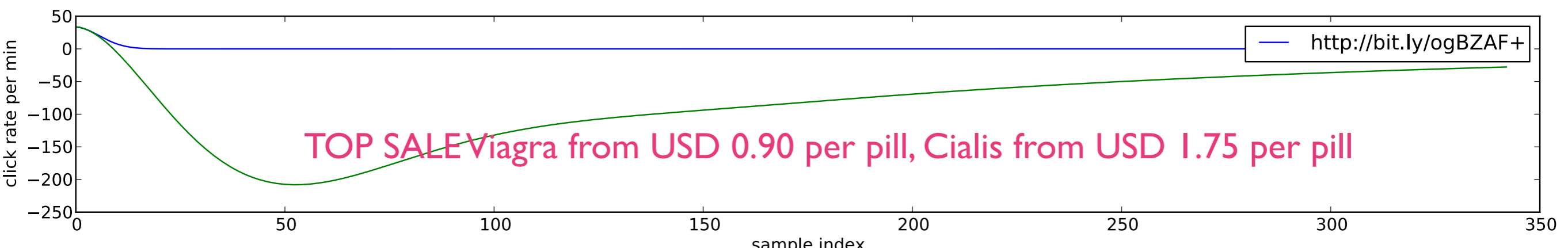
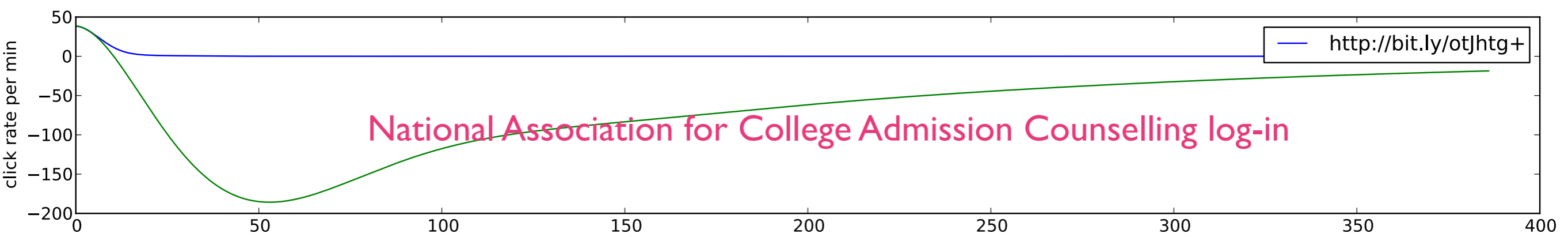
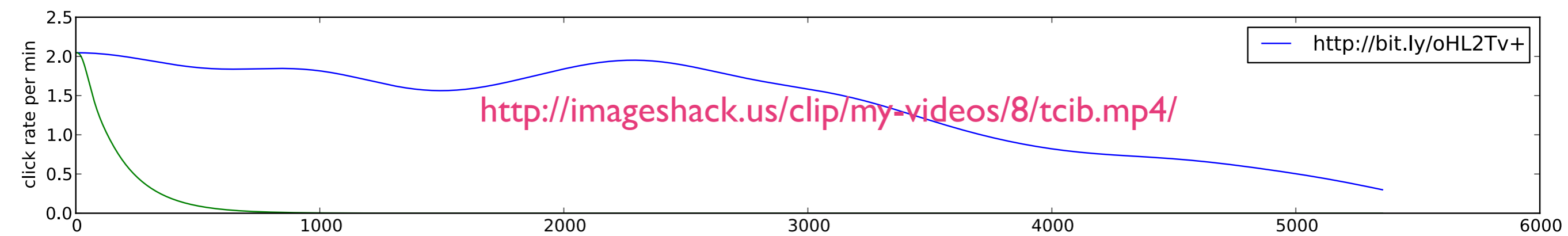
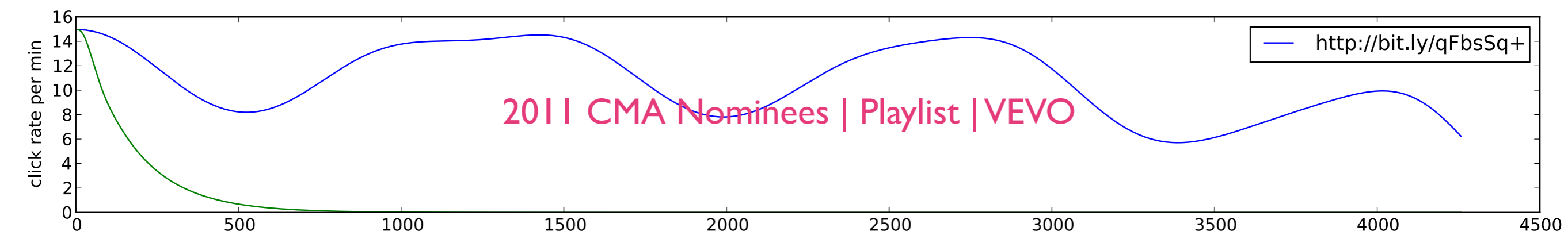
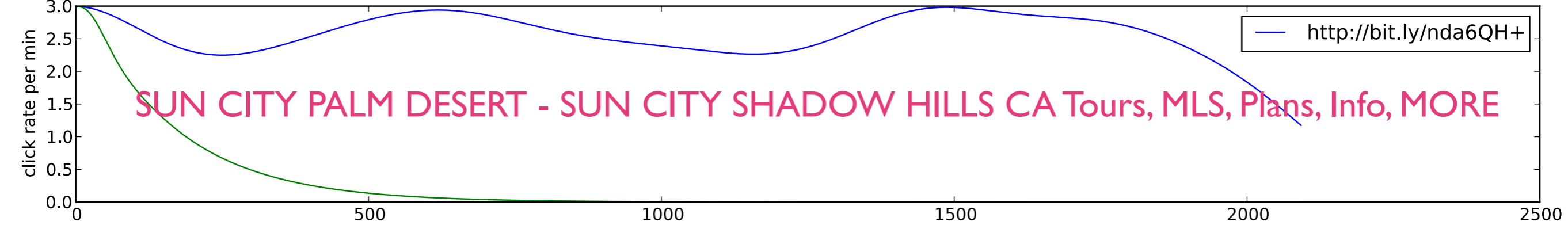
*STATE INTEREST IS THE PORTION OF CLICKED LINKS THAT RELATE TO TRAYVON MARTIN COMPARED WITH OTHER STATES IN ONE DAY. GRAPHIC BY BLOOMBERG BUSINESSWEEK; DATA: BITLY







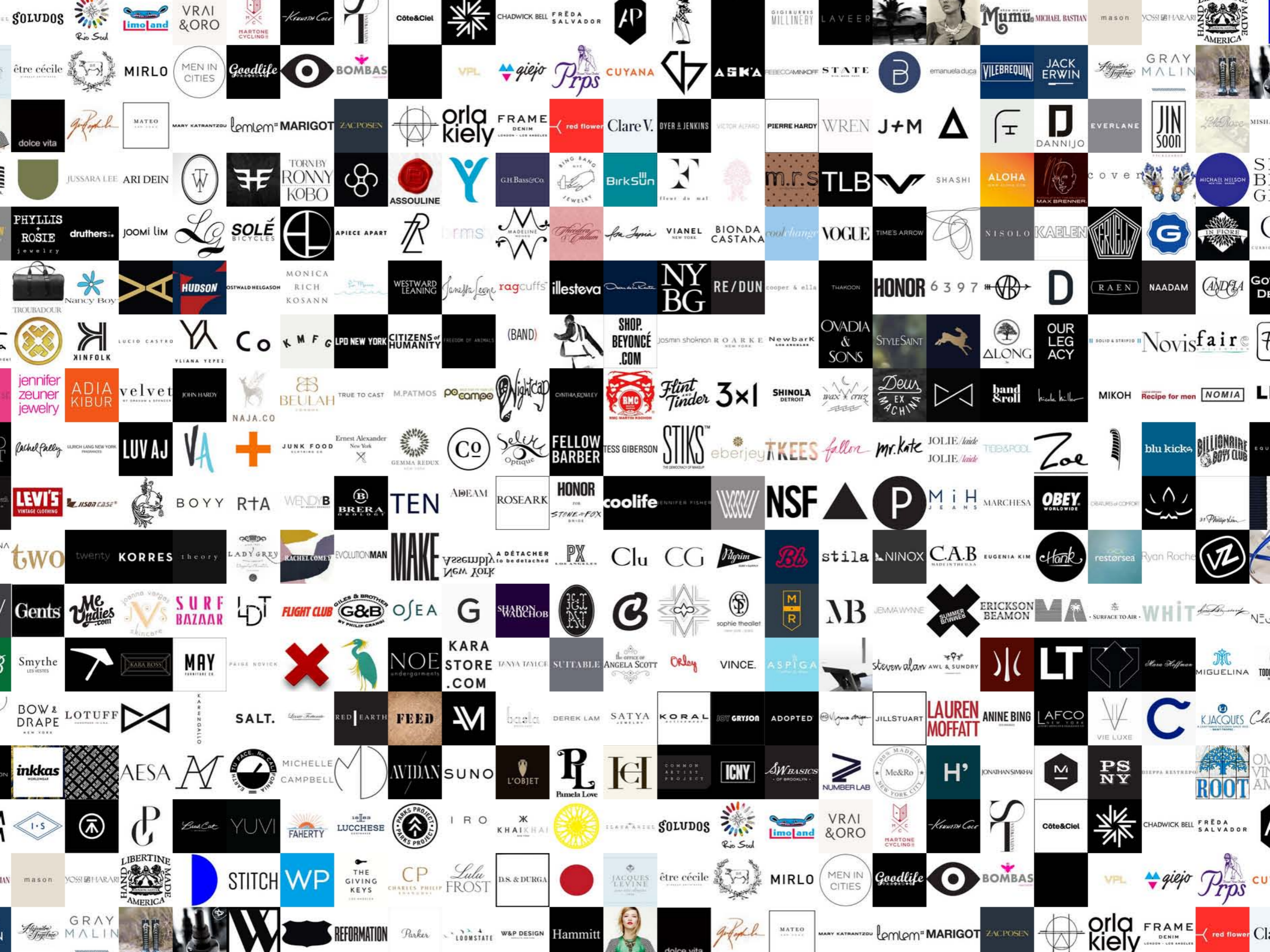


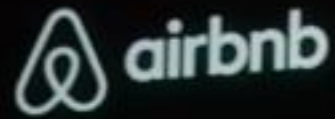




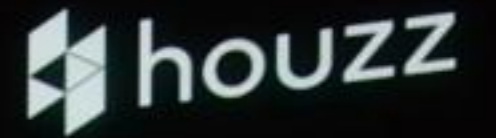
SPRING
EST 2013 NYC

Big-Data
to
No-Data



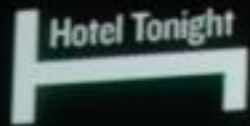


UBER



SEPHORA

STARBUCKS



Jackthreads

Instacart

GROUPON



Eventbrite

FANCY

TICKETS.COM

SPRING
EST 2013 NYC

Panera
BREAD

Chairish

STAPLES



StubHub!

OpenTable



Three Areas of Data Science

Data Engineering



Brian David Eoff @bde · Jun 11

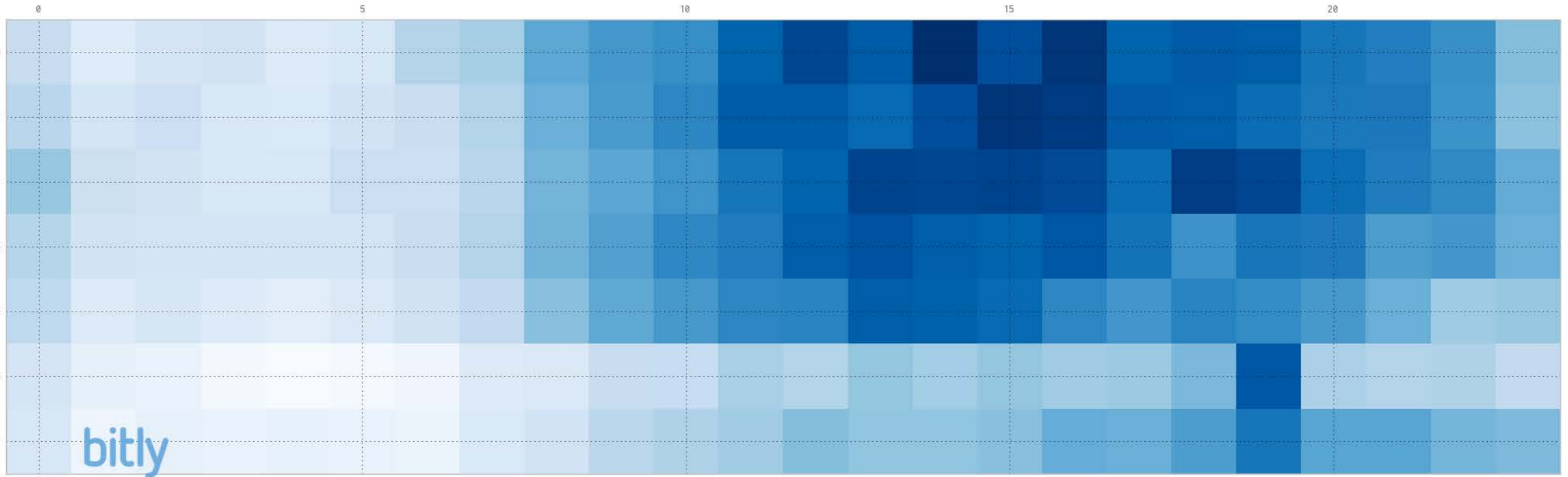
Not so much a data scientist as a data plumber. Conceiving of the flow, pipes and stores necessary to accomplish our goals.

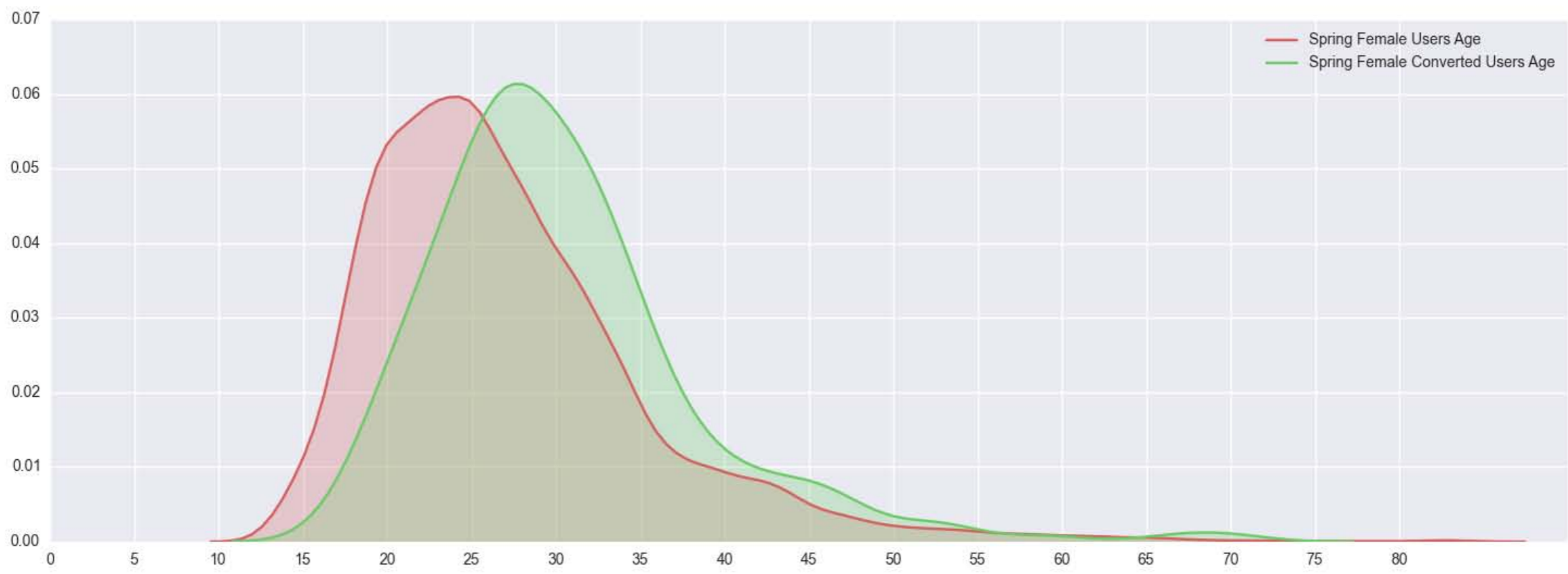
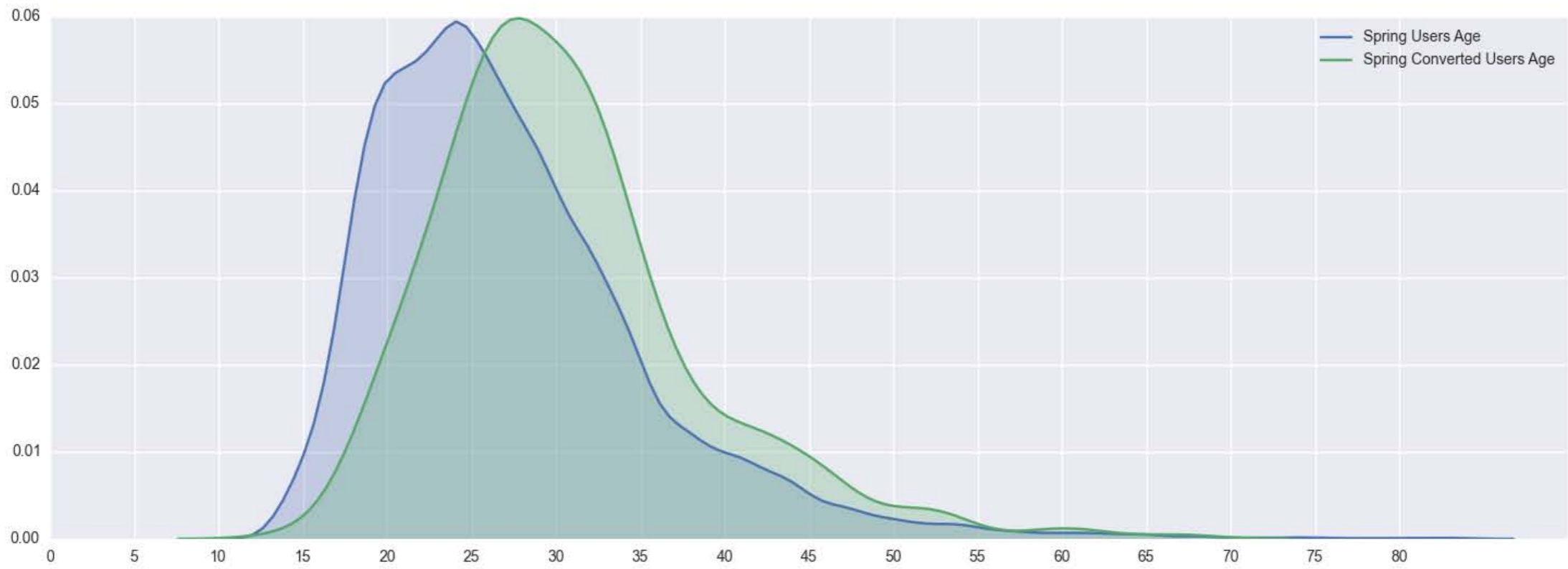
More than...

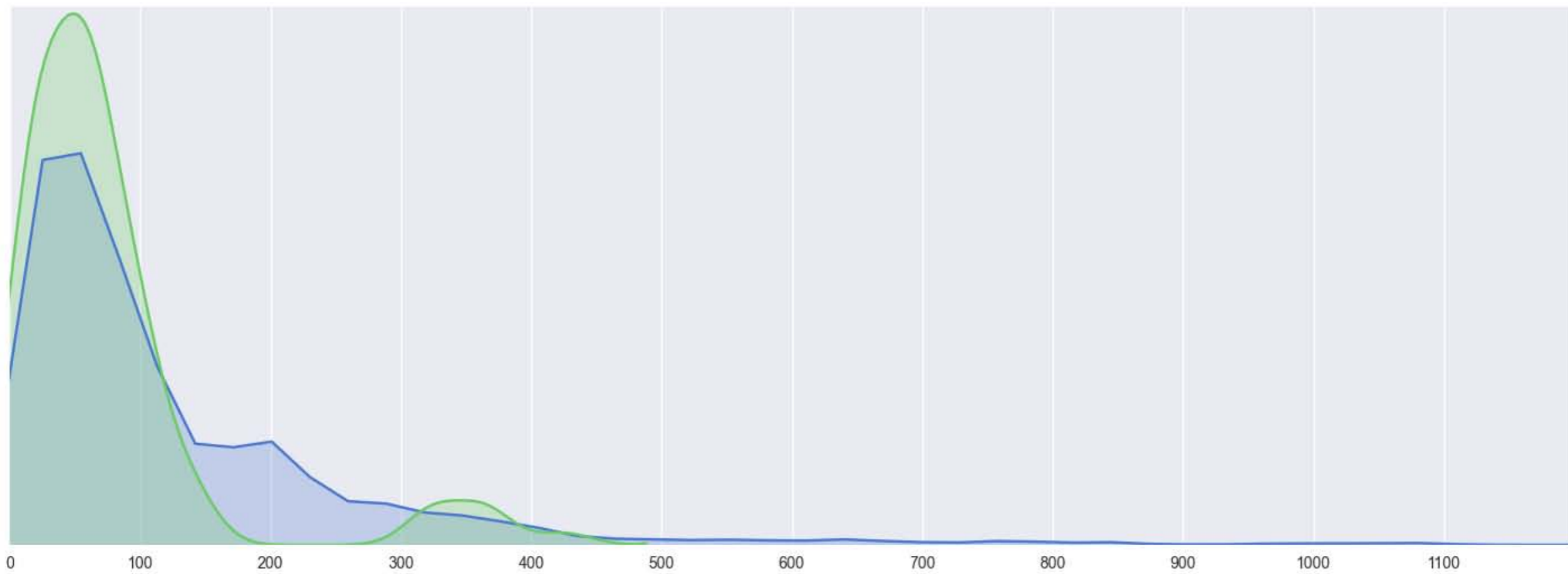


Everything in UTC

Data Analysis







Reproducibility,
Automation,
Version Control

Data Modeling

Discovery

Collaborative Filtering for Implicit Feedback Datasets

Yifan Hu

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Yahoo! Research
Haifa 31905, Israel

Chris Volinsky

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Florham Park, NJ 07932

Abstract

A common task of recommender systems is to improve customer experience through personalized recommendations based on prior implicit feedback. These systems passively track different sorts of user behavior, such as purchase history, watching habits and browsing activity, in order to model user preferences. Unlike the much more extensively researched explicit feedback, we do not have any direct input from the users regarding their preferences. In particular, we lack substantial evidence on which products consumer dislike. In this work we identify unique properties of implicit feedback datasets. We propose treating the data as indication of positive and negative preference associated with vastly varying confidence levels. This leads to a factor model which is especially tailored for implicit feedback recommenders. We also suggest a scalable optimization procedure, which scales linearly with the data size. The algorithm is used successfully within a recommender system for television shows. It compares favorably with well tuned implementations of other known methods. In addition, we offer a novel way to give explanations to recommendations given by this factor model.

Content based approach creates a profile for each user or product to characterize its nature. As an example, a movie profile could include attributes regarding its genre, the participating actors, its box office popularity, etc. User profiles might include demographic information or answers to a suitable questionnaire. The resulting profiles allow programs to associate users with matching products. However, content based strategies require gathering external information that might not be available or easy to collect.

An alternative strategy, our focus in this work, relies only on past user behavior without requiring the creation of explicit profiles. This approach is known as *Collaborative Filtering* (CF), a term coined by the developers of the first recommender system - Tapestry [8]. CF analyzes relationships between users and interdependencies among products, in order to identify new user-item associations. For example, some CF systems identify pairs of items that tend to be rated similarly or like-minded users with similar history of rating or purchasing to deduce unknown relationships between users and items. The only required information is the past behavior of users, which might be their previous transactions or the way they rate products. A major appeal of CF is that it is domain free, yet it can address aspects of the data that are often elusive and very difficult to profile using con-

Popularity

Tools

Caverlee's Rule

How to become a data
scientist?

CONFESSSION

I never took a data
science class.

What do I look for
when I hire?

Questions?

Descriptive, Prescriptive, Predictive

Data Engineering, Data Analysis, Machine Learning/Model Building/Algorithms

ETL, or never underestimate the benefit of a good plumber.

AB Test. Multi-Armed Bandit Testing.
Optimization. Retention

Bitly: 200 Million Events per Day
Spring: 0

Data Science (Inductive Reasoning), obtaining data, cleaning munging data, exploring data, modeling data interpreting data

Data Engineering

ETL

Redshift

Event Streams
Kafka, Kinesis, NSQ

Tools, Process, Recruiting,
Communication, Ethics

Test- Driven Data Science

Learn from software development.

Version Control, Automated Testing

Analysis

Price Points

Conversion

Metric Aggregation

etc.

Matrix Factorization

Recommendation

Popularity