Insights into Social Media Data:
a new formalism inspired in Thermodynamics

Agenda


WHY?
Background

Social Media Usage

- Of the world's ~4.5 billion internet users, almost 3.5 billion use social media[1]
- From 2005-2015 social media usage rose tenfold in the United States alone[2]
- Hundreds of platforms, growing by the year[3], most use two or more[4]
- Many count users in the millions, with some reaching over a billion users[2]
- Social media usage spans demographics[5]; includes individuals, groups and businesses of all sizes[6]
- Critical to maintaining a competitive edge in business[7]
- Has fundamentally changed the way humanity communicates[8]

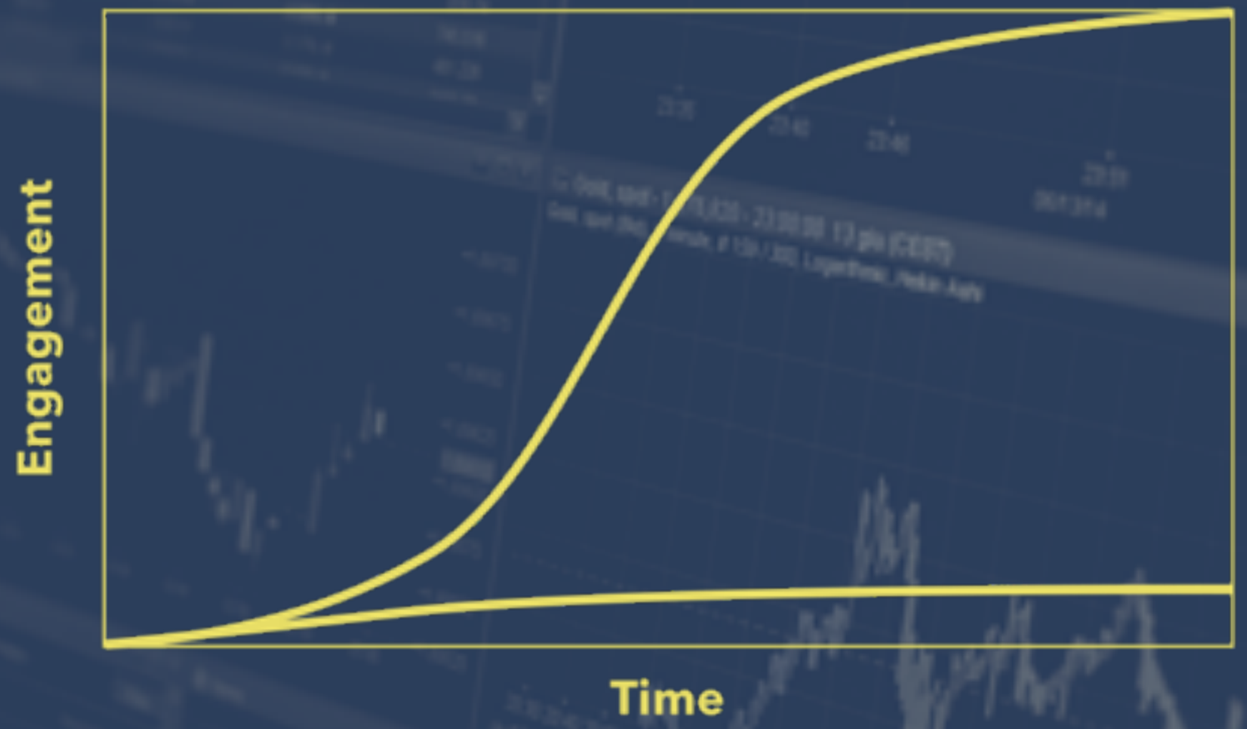
Social Media Analysis

- Understand the network structure of platforms, how people connect (**social network analysis**, **behavioural research**)
- Understand the content being generated and shared among platforms, how people react to and propagate it (**content and sentiment analysis**, **information diffusion theories**)
- Understand where particular interest comes from, the determinants and effects of popular topics (**topic analysis**, **trend analysis**)

Challenges

- Social media generates content of **enormous quantity** at speed[10]
- **Semi-structured** data with **mixed media** necessary to context[11]
- Metadata is sparse + **not always accurate**[12]
- Hardest of **NLP**—jargon, context- + culturally-specific terms[13]
- **Data is harder to get** over time due to platforms commoditising data[14] + increasing privacy controls[15]

Trend Analysis & Prediction



Why?

- Optimise marketing and outreach campaigns
- Understand content consumption
- Observe cultural change over time
- Jump on bandwagons
- Prevent impending harmful content trends

Challenges

- Subjectivity of viewing, sharing content
- False positives in anomaly detection-based methods[16]
- Reliance on other information sources in alternative methods[17]
- Timeliness requirements for analysis and detection[18]
- Topic evolution over time[19]
- Predicting the future? 🤔

Multidisciplinary challenges

- Very human data; erratic behaviours (**behavioural science**)
- Sharing between non-fully-connected graph structure... (**graph theory**)
- ...of nodes with varying levels of transmissiveness (**social contagion**)
- Different content and sentiments get shared in different ways (**information diffusion**)

Analogous Application

Social media analysis requires some new ways of thinking!*

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* see 15, 20-22

Novel cross-disciplinary applications

- Social media trends as contagion theory from **Virology** in Medicine[23 - 25]
- Social media trends as the **Technology Adoption** curve from Information Diffusion Theory[26]
- Social media behaviours observed as sound (**Data Sonification**) to aid in anomaly detection[27]
- Social media network interactions as **Evolutionary Game Theory** from Evolutionary Biology[28]

Entropy Theory

Boltzmann's $S = k \ln(N)$

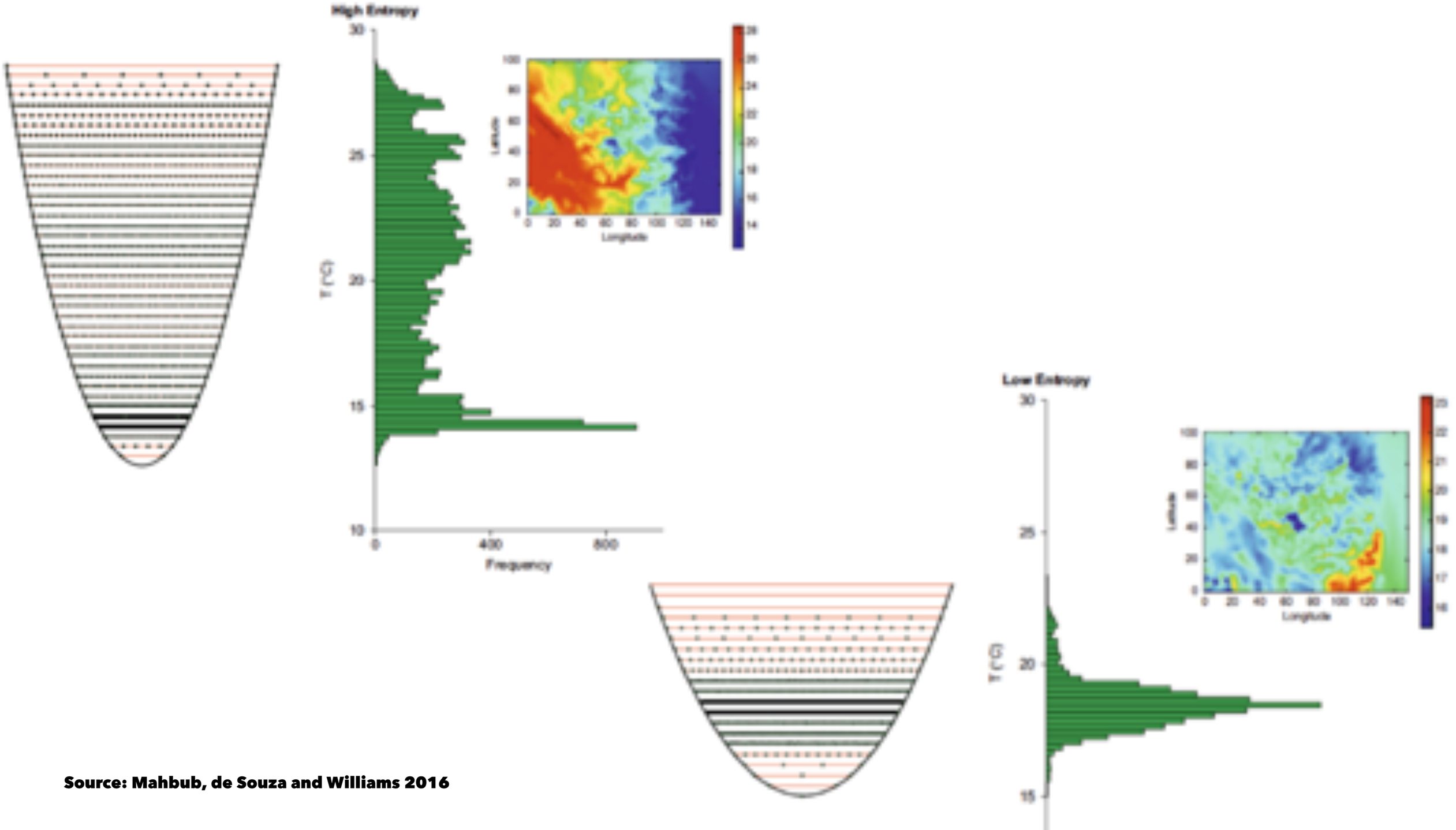
Upper bound of entropy in closed system at equilibrium

Gibb's $S = -k \sum_i P_i \ln P_i$

Upper bound of entropy in closed system not at equilibrium

Shannon's $S = -\sum_i P_i \ln P_i$

Average rate at which information is produced by a stochastic source of data



Source: Mahbub, de Souza and Williams 2016

Entropy over time

- Reveals descriptive statistical measures about a set of data
- But also measures internal diversity and inconsistency
- Takes focus away from upper and lower bounds—or even ranges—in favour of changes in internal distribution that may be more informative
- Is in some cases sufficient to adapt analysis into Markov-model-based prediction

Aims & Objectives

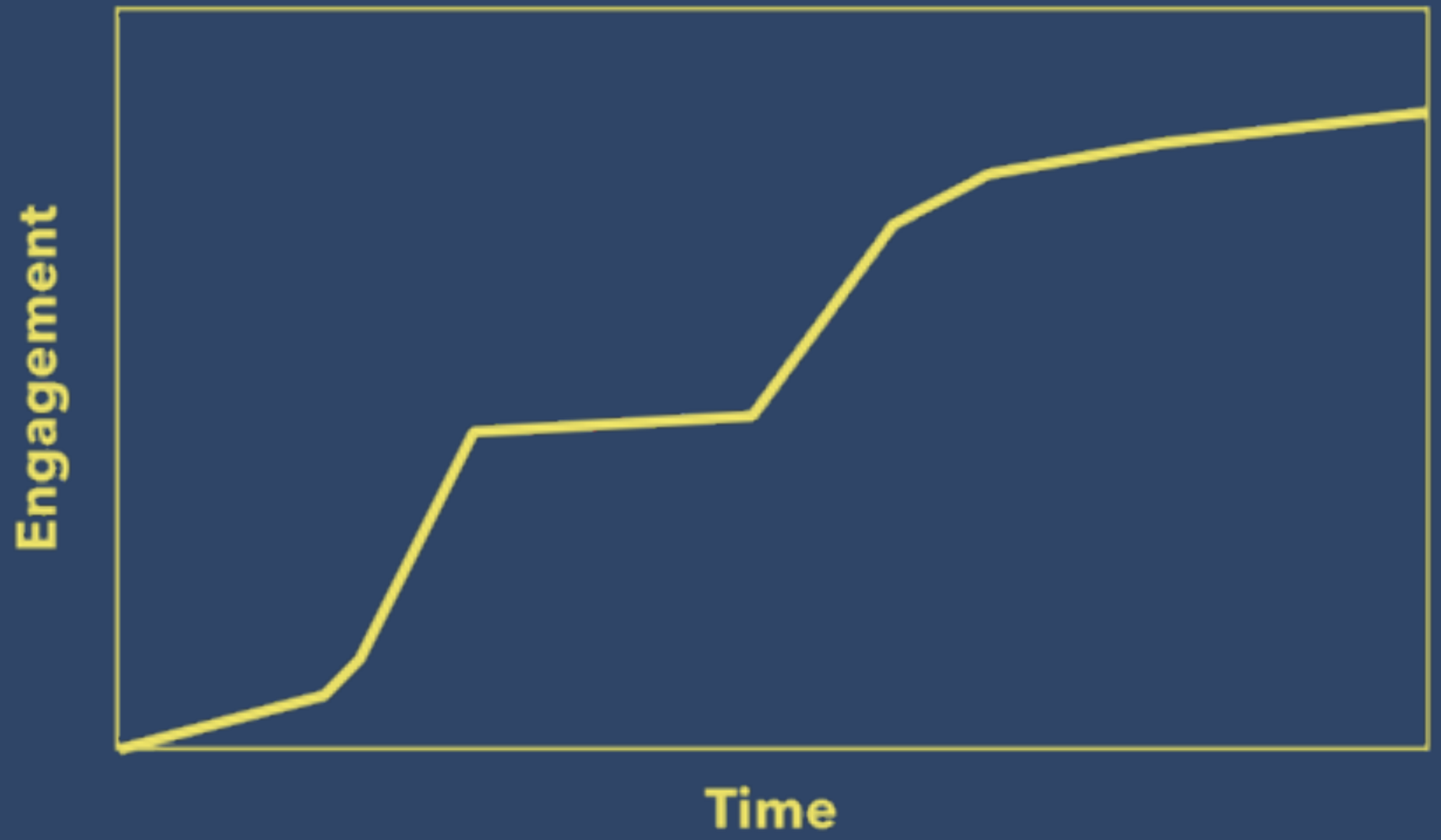
Broadly

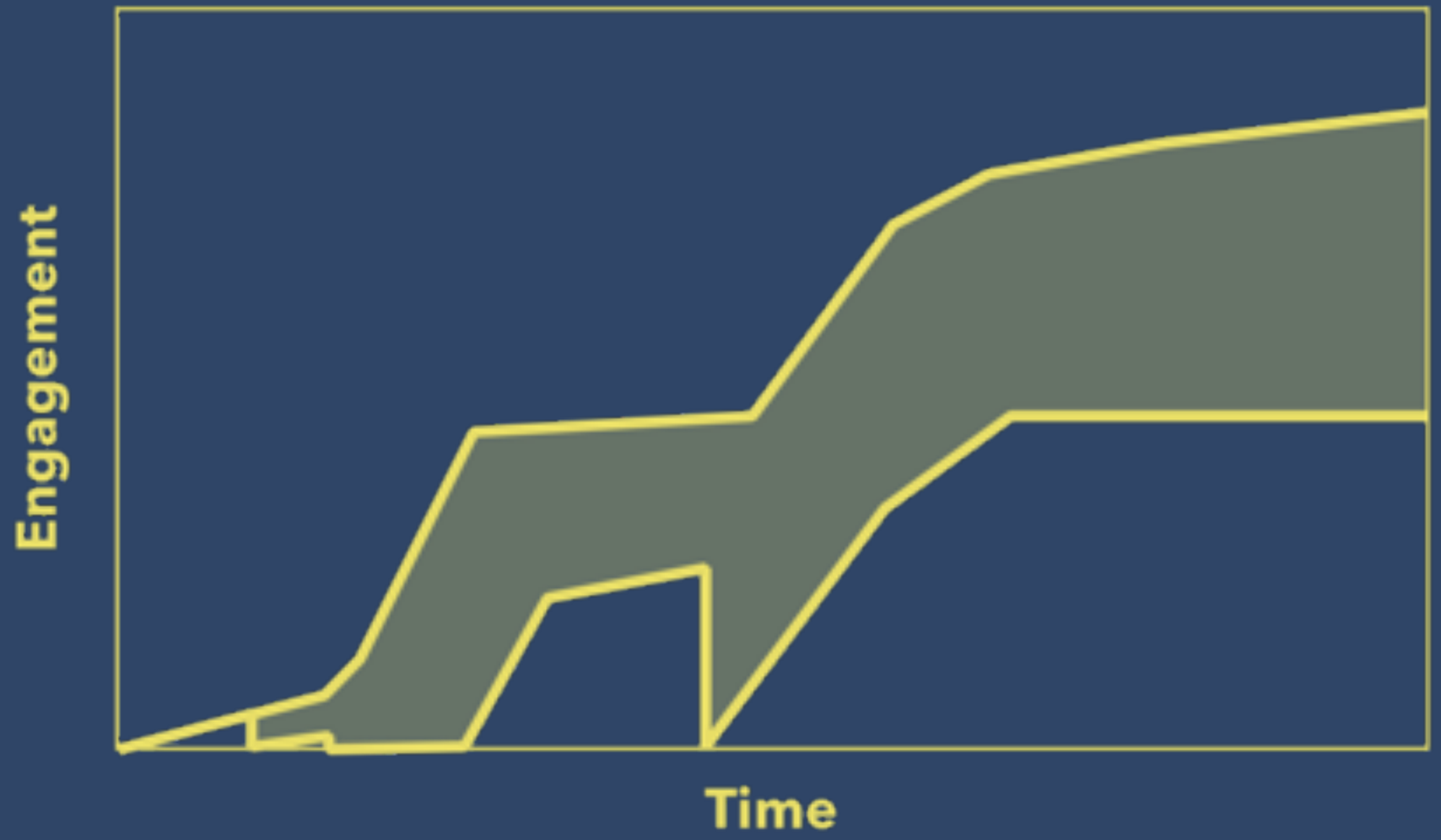
1. Can the analogous application of **Entropy Theory** present useful information about the lifetime of a trend or topic on a Social Media platform?
2. Is there indication that the method could be applied more broadly, or adapted to be **predictive**?

In this study

Experimentation aims to confirm the dual hypotheses as follows:

1. **increasing entropy over time** may suggest impending critical interest preceding a trend developing to significance, and
2. **decreasing rate of entropy increase over time** after a high entropy or engagement level has occurred may suggest new evolution in the topic.


Engagement
Time


Engagement
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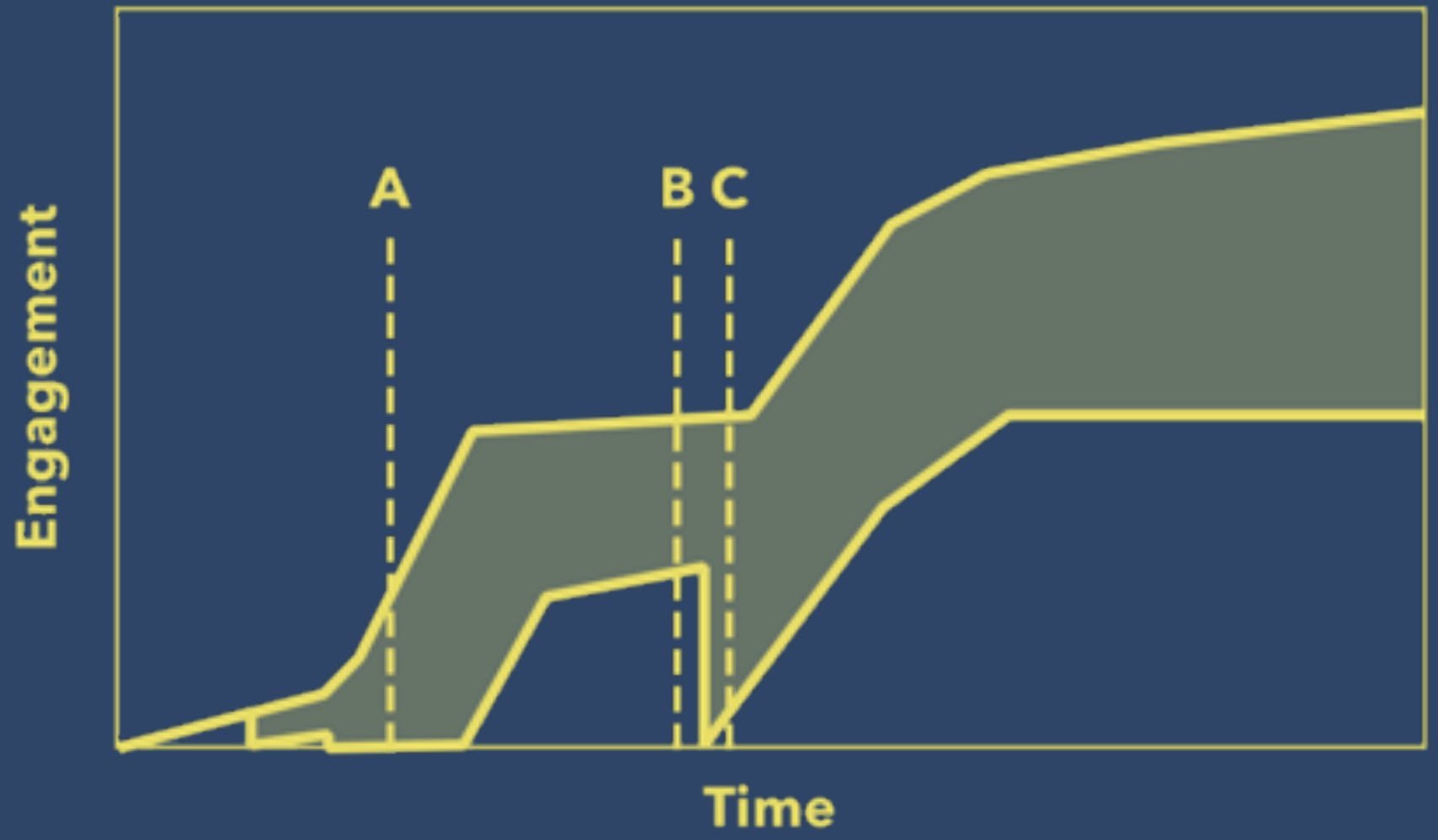
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Engagement
Time

Potential commercial value

If we can predict changes in topic growth over time, this may aid in early **detection of trends**.

This may allow parties to release information at points of predicted **optimal reach** or **engagement potential**.

Potential social research value

Assuming we can predict trend decay over time if no new stimulus is received, we can identify points where new external stimulus probably was received, even where it is not evident in the platform content.

This can help identify new context or **anomalous trends**.

HOW?

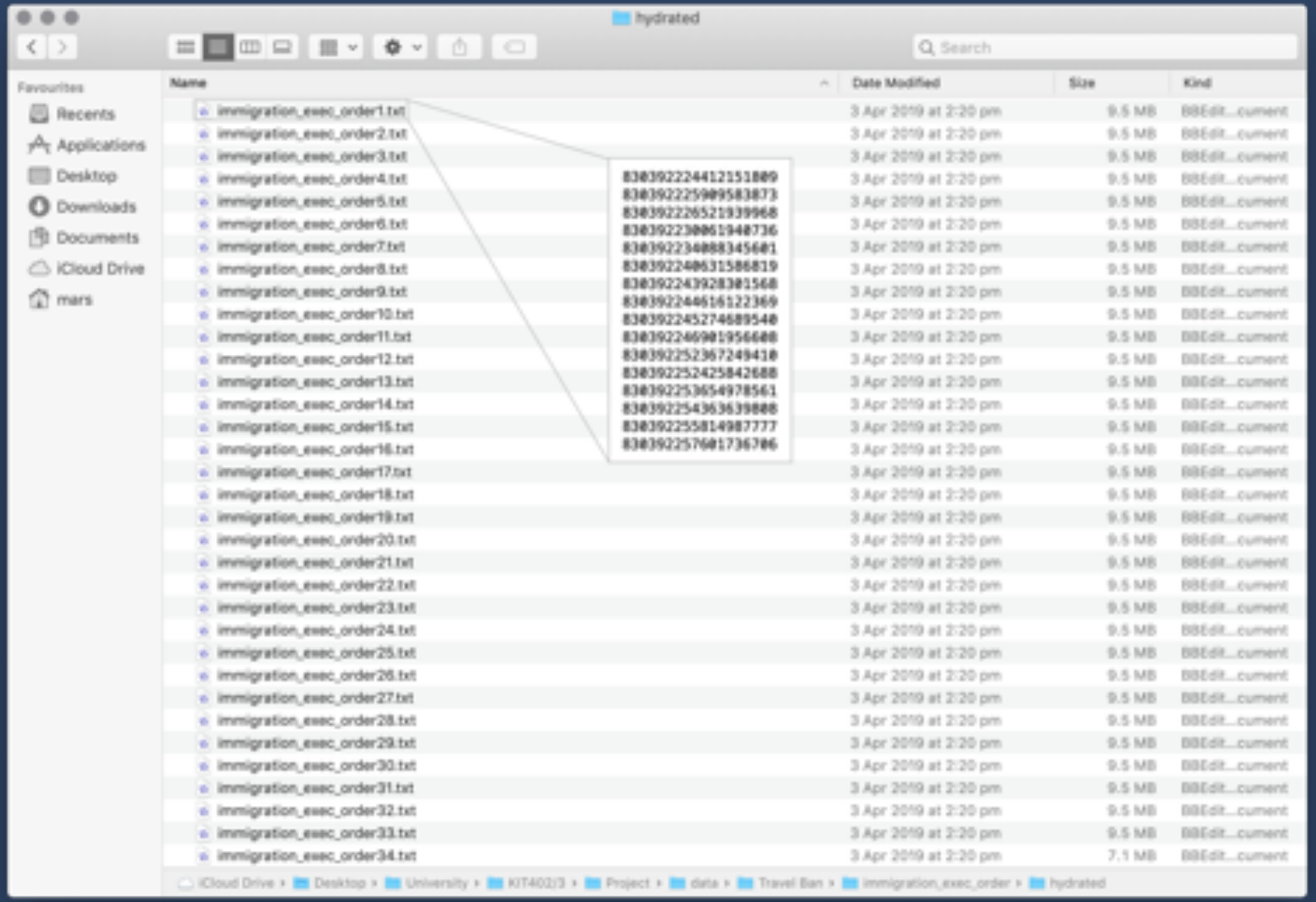
Research Design

Datasets needed for this study

1. Representing a **single** cohesive topic growing over time
2. Representing a higher-level topic with **multiple** sub-topics or evolution over time

Why Twitter?

- Rapid generation of content, rapid decline in interest[17] => *easily observable trends*
- Discrete content size easier to analyse[29] => *more easily verifiable datasets*
- Breadth of functionality in API, well-established tools for research[30] => *easier to get data, perform and recreate studies*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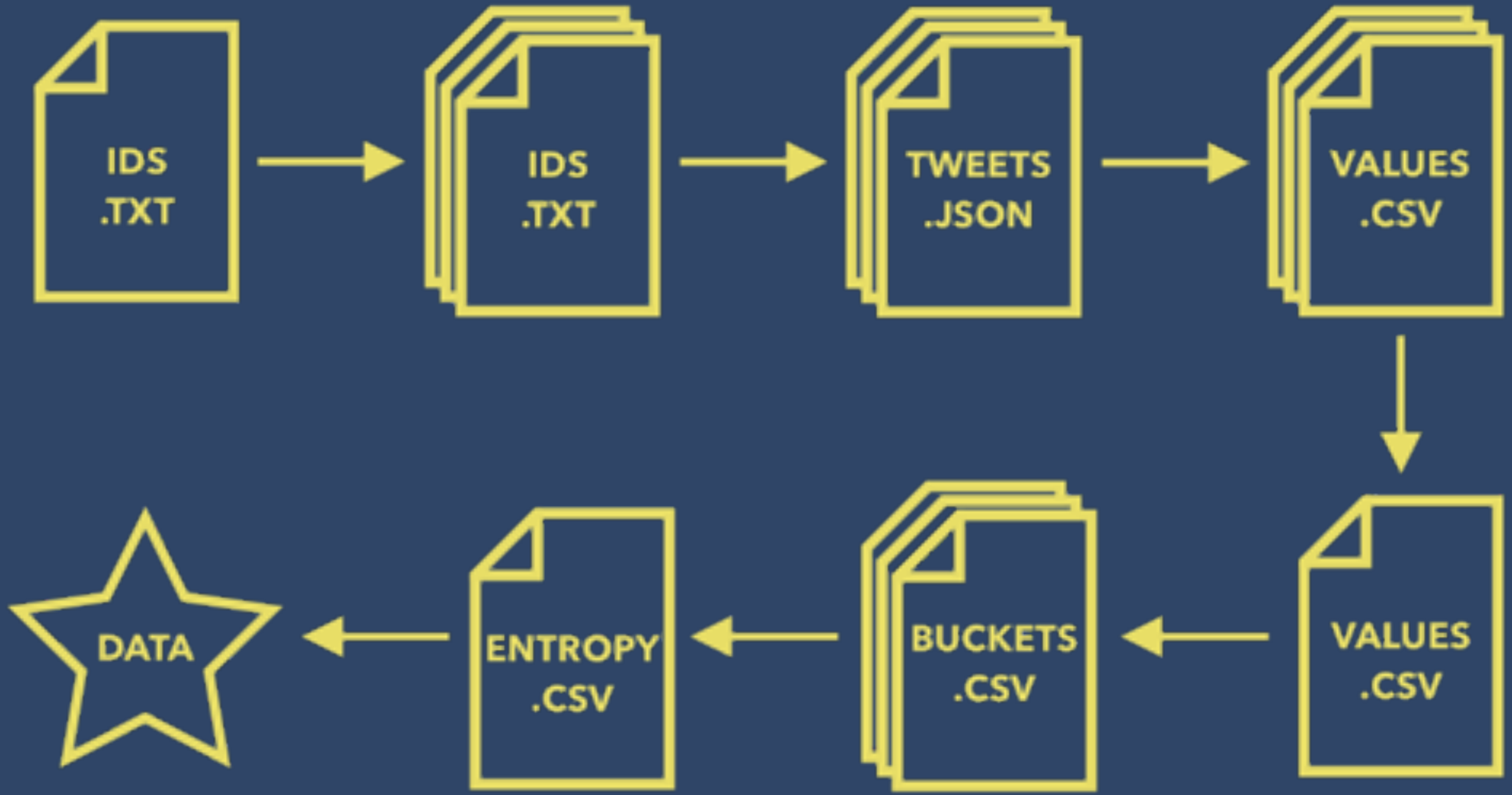
Tweet JSON


```
{
   "created_at":"Fri Feb 10 10:05:45 2017",
   "id_str":"829994567841062 4",
   "full_text": "This is a fake Tweet.",
   "user":{
      "id_str": "972937630",
      "name": "John Doe",
      "screen_name": "johndoe",
      "protected": false,
      "verified": false,
   },
   "retweet_count": 167,
   "favorite_count": 50
}
```


"Hydrating" Tweets: Twarc

- made by researchers (from the *Documenting the Now* project)
- many researchers have used it for studies before, establishing its robustness as a tool[31 - 38]
- lots of visualisation and analysis tools that work with it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File	IDs	Hydrated	Lost
immigration-exec-order1	500,000	342,551	157,449
immigration-exec-order2	500,000	341,873	158,127
immigration-exec-order3	500,000	344,425	155,575
immigration-exec-order4	500,000	375,875	124,125
immigration-exec-order5	500,000	364,173	135,827
immigration-exec-order6	500,000	364,605	135,395
immigration-exec-order7	500,000	332,024	167,976
...	...	...	...
Total	16,875,766	11,776,307	5,099,459

seemingly random yet consistent distribution of missing datapoints

=

suitably random self-selecting population sample 👍

Analysis Phase 1: Exploration

- Establish "ground truth" of trend behaviour over time portrayed in each dataset
- Decide on appropriate granularity for discretisation of data (or justify use of full range of values)
- Explore descriptive statistics to establish theoretical bounds
- Develop strategies for dealing with missing data and edge cases

⚠️ Issues with historical data

1. Shared tweets show no information about whether likes were given to original or share
2. Engagement metrics are associated with time of posting, even though they would have occurred later and over time

It is assumed that the presence of both effects in **both the test and comparison data** will nullify the effect.

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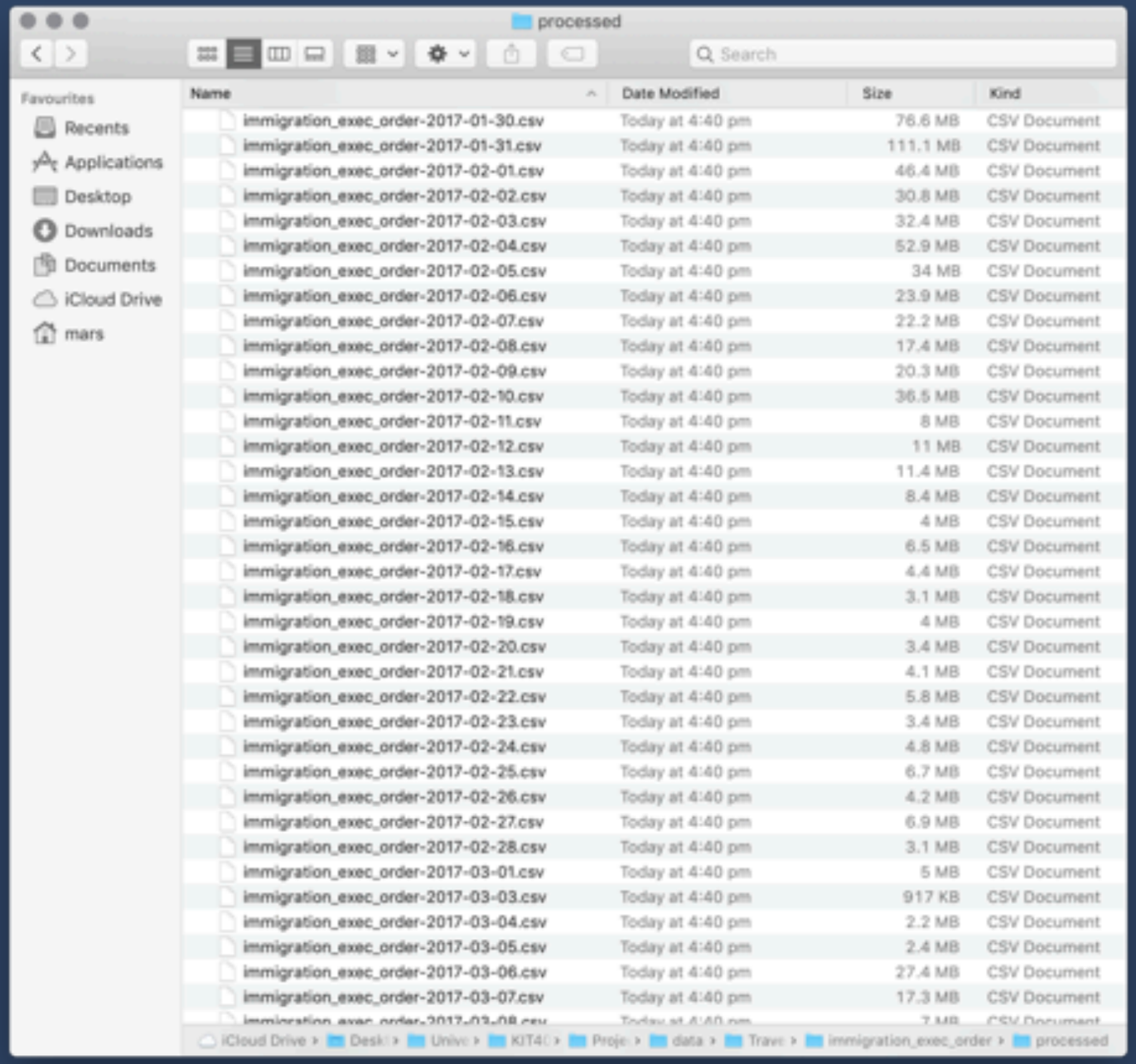
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immigration_exec_order-2017-02-21.csv Today at 4:40 pm 4.1 MB CSV Document
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immigration_exec_order-2017-02-23.csv Today at 4:40 pm 3.4 MB CSV Document
immigration_exec_order-2017-02-24.csv Today at 4:40 pm 4.8 MB CSV Document
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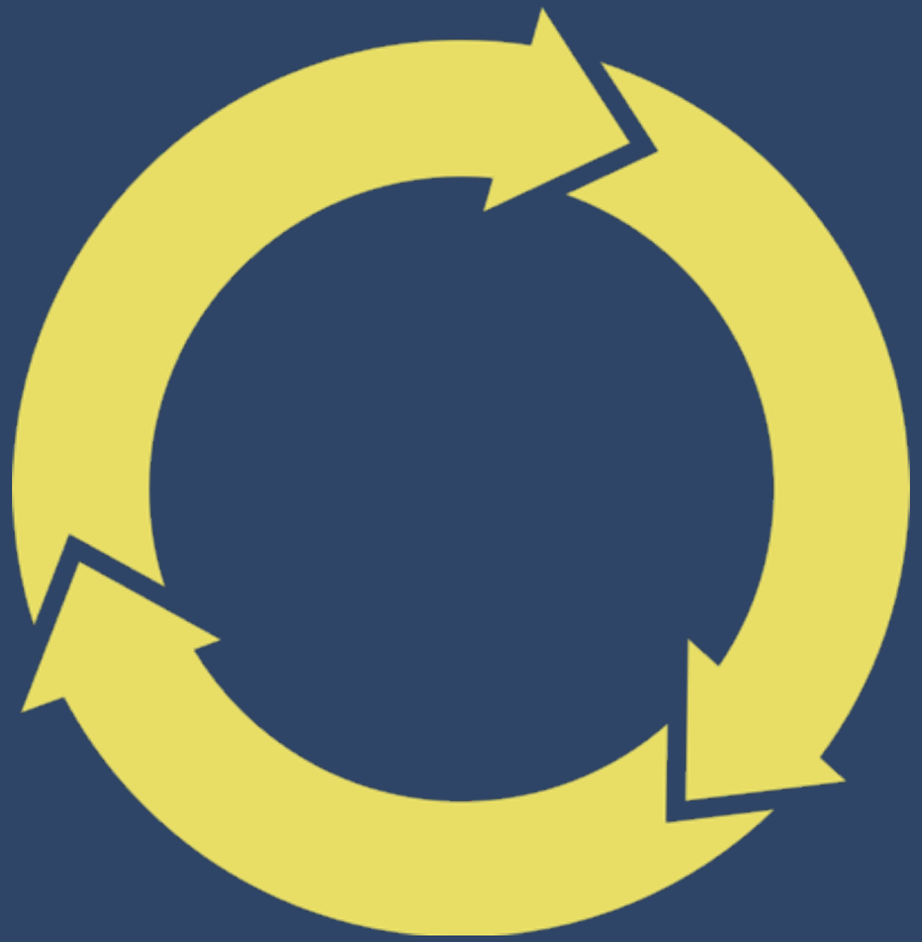
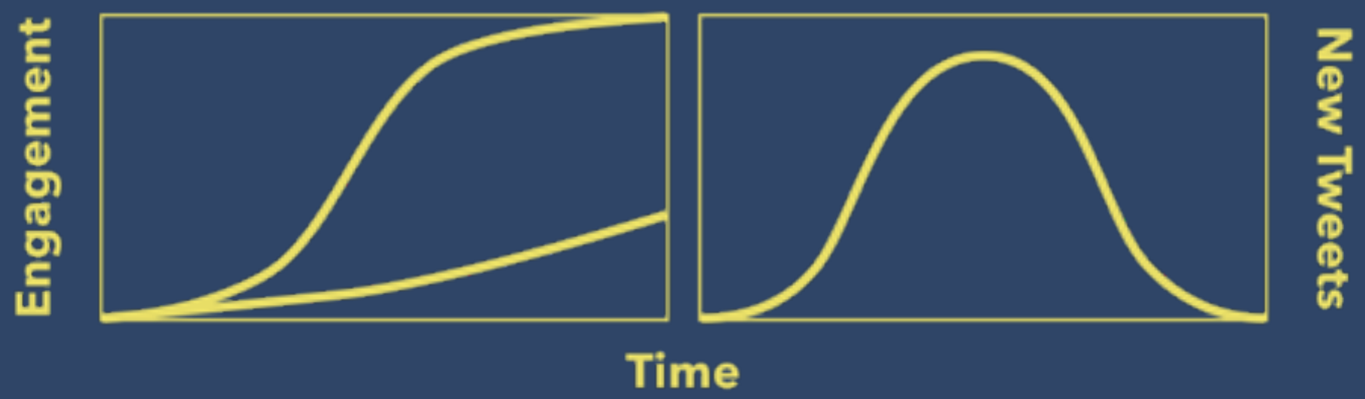
More Analysis!
Phase 2: Discrete topic
&
Phase 3: Evolving topic

Iterative experimentation



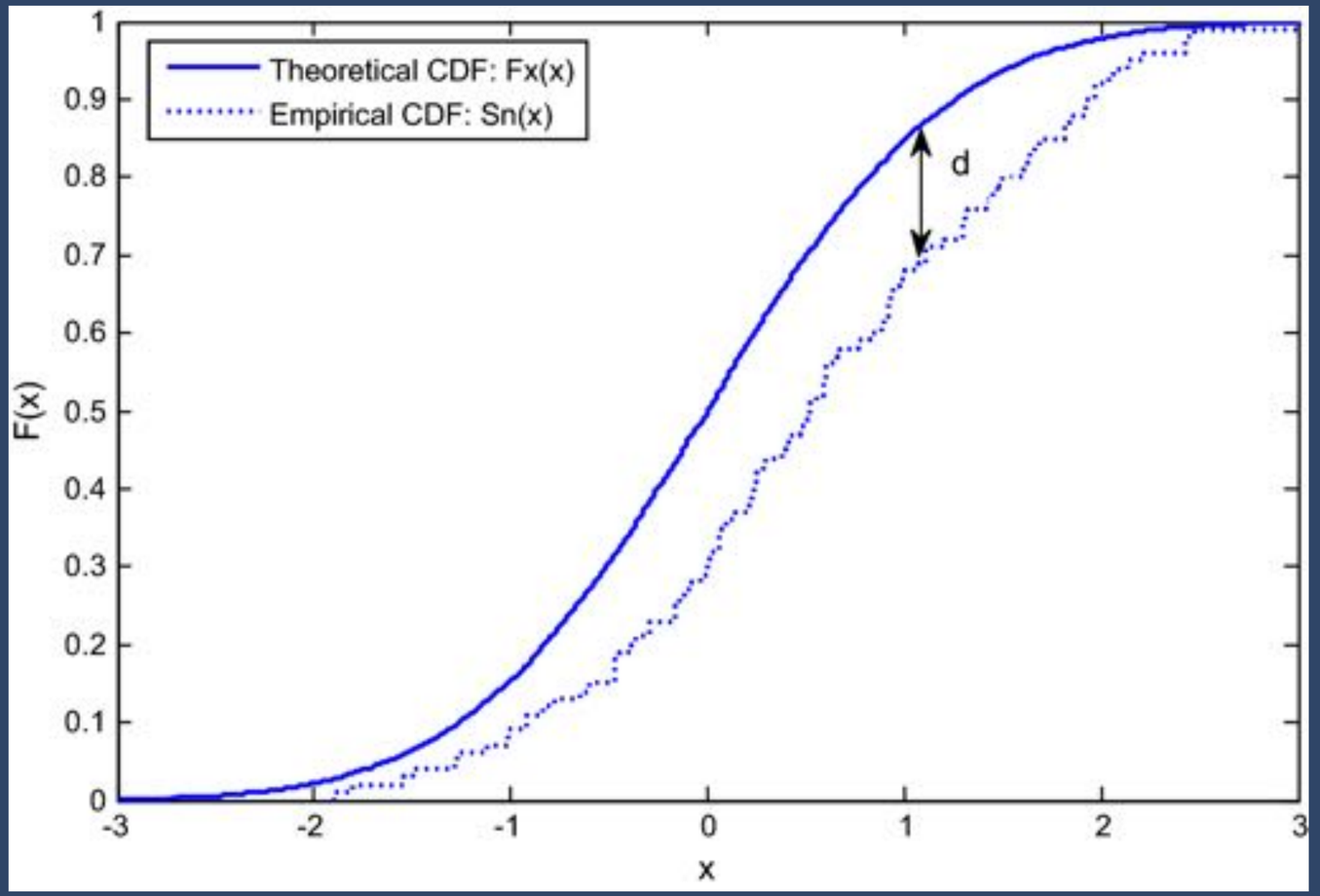

Inferential analysis =
dynamic + reponsive

Predictions

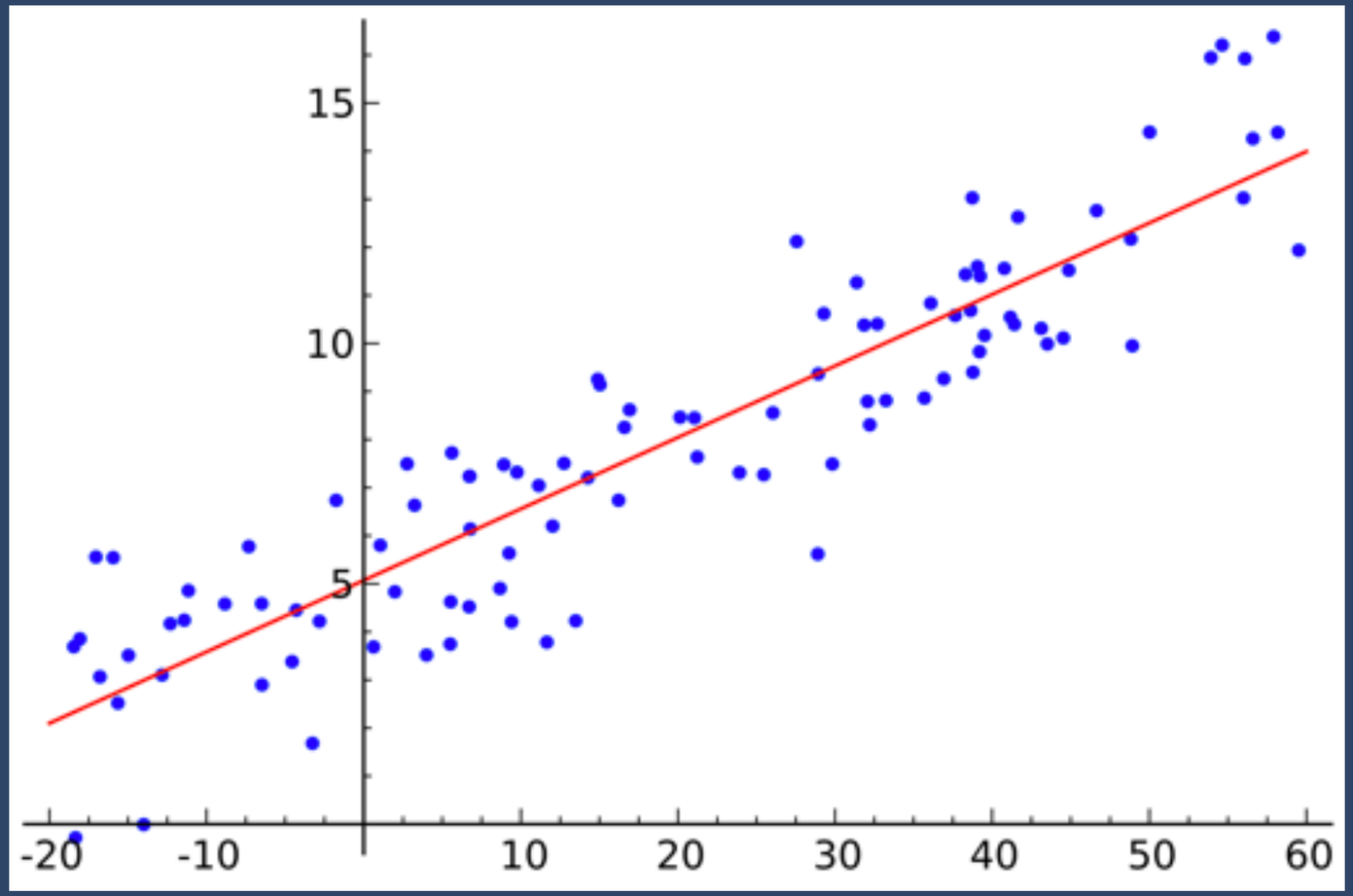


- Normal-ish distribution of new tweets
- Varying loglinear to exponential growth rates in engagement
- Engagements between 0 and ~500,000
- Clear topic plateau point towards end

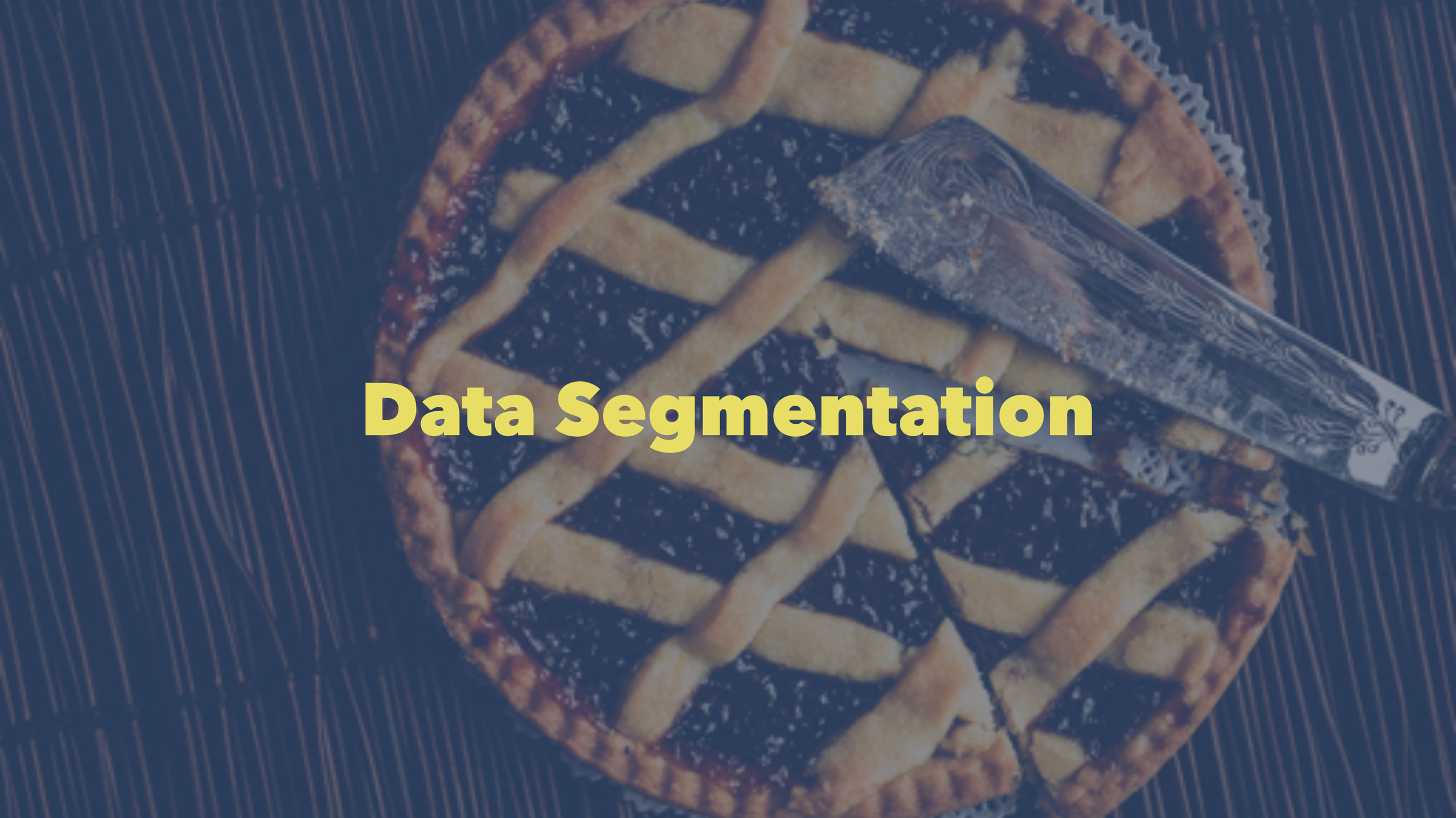
The Kolmogorov-Smirnov & Cucconi Tests



Regression analysis

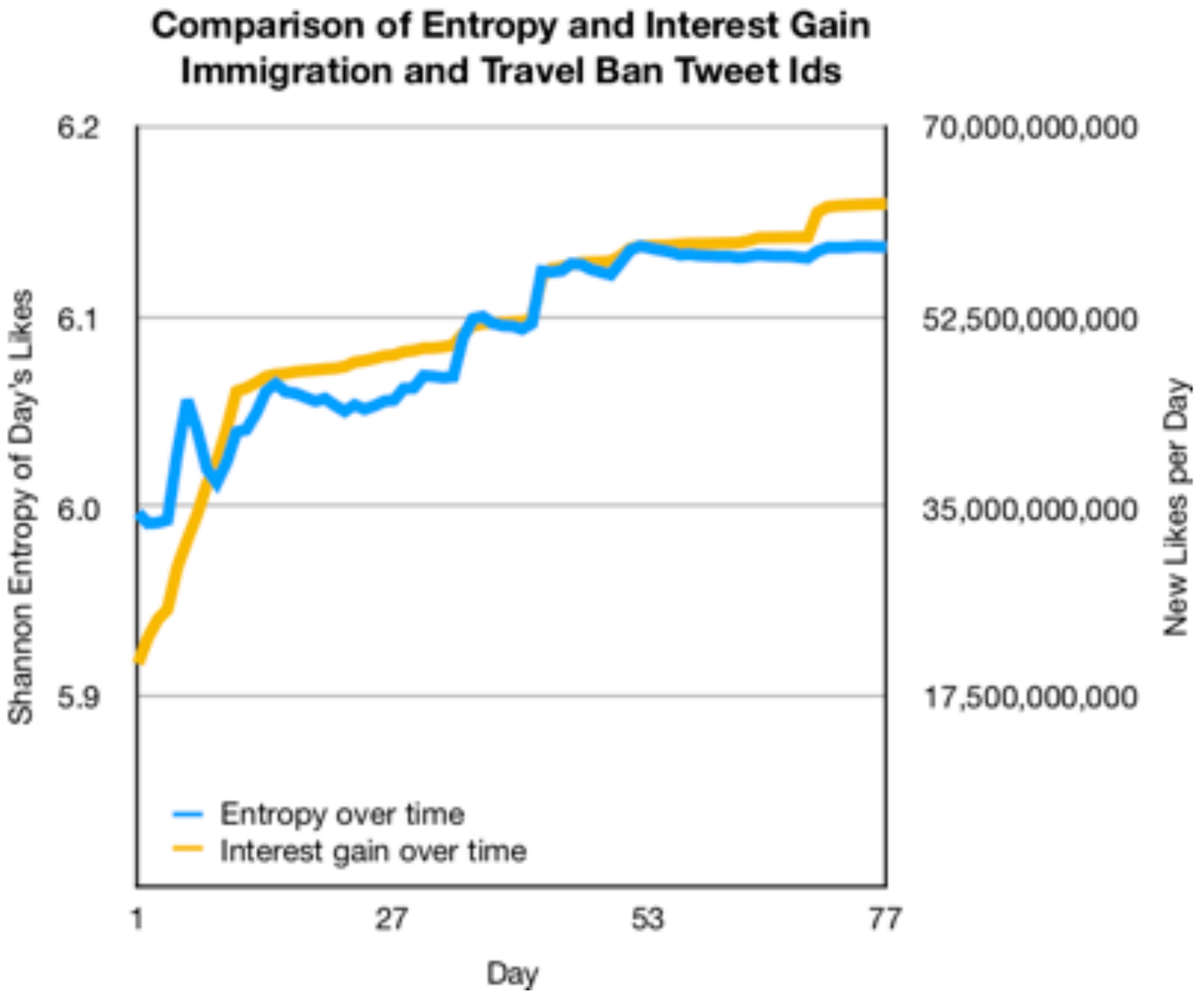


Scaling + Transforming


Data Segmentation

Preliminary Findings

(*very* preliminary, I only just managed to hydrate a complete dataset on Sunday)


Comparison of Entropy and Interest Gain
Immigration and Travel Ban Tweet Ids
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New Likes per Day
Entropy over time
Interest gain over time
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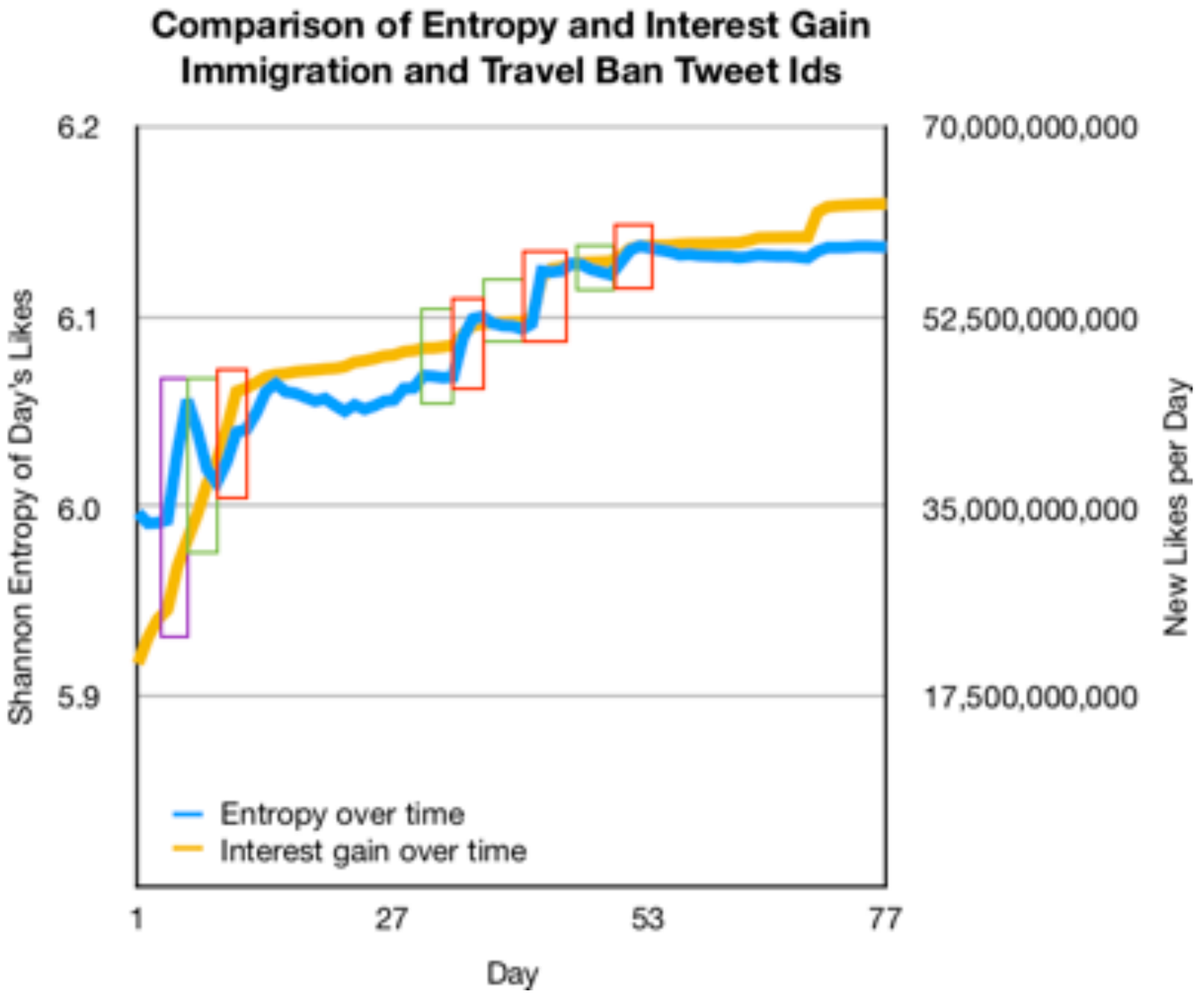
Revisiting hypotheses

I theorised that the patterns to emerge would be two-fold:

1. **increasing** entropy over time **preceding a trend** developing to significance, and
2. **decreasing** rate of entropy increase over time after a high entropy or engagement level **preceding changes in behaviour**.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52,500,000,000
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17,500,000,000
New Likes per Day
Entropy over time
Interest gain over time
1
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Day

...maybe that was too easy? 🤔

Where to go next?

1. **Verify and quantify** the appearance of correlation from initial data
2. **Test bounds** of correlation, extensively
3. **Experiment** with different bucketing values, differently weighted engagement metrics
4. **Observe and record** which factors increase or decrease correlation
5. **Repeat** all of the above with another dataset

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Thank you!

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