Entropy and Information-Theoretic Methods for Text Analysis

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How do we quantify the diversity of language and topics expressed in #BlackLivesMatter and #AllLivesMatter tweets?

Entropy 😱

How do we measure to what extent an individual has adopted the language of a subreddit like r/TheRedPill?

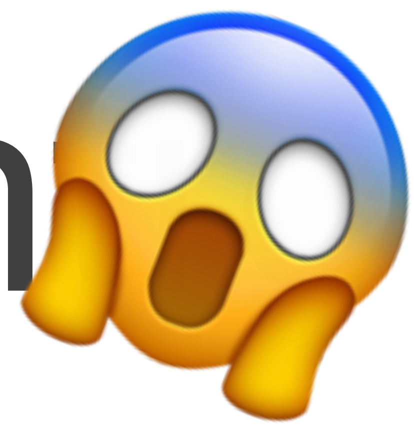
😱 Entropy 😱

How do we measure how particular words and phrases drove the divergence in language between #BlackLivesMatter and #AllLivesMatter?

Entropy

How do we extract topical frames around a particular word or set of words with no assumptions on how those frames were generated?

Entropy

Enpy

What is entropy?

If we wanted to measure surprise, what properties would we want from that measure?

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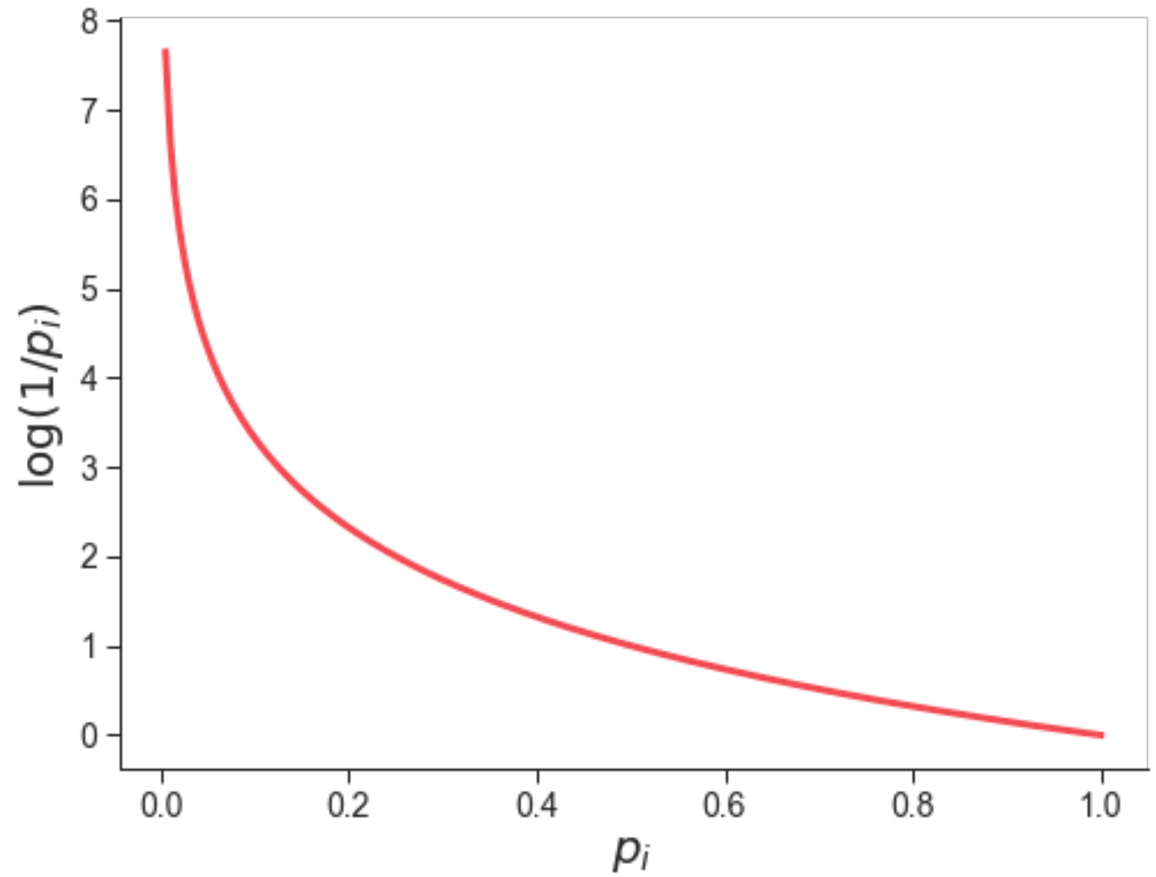
5. **Minimal:** we want the surprise of a collection of events to be at its minimum when only one event can occur ☝🏼

What is entropy?

There is only one function that satisfies all of these properties:

$$\log \frac{1}{p_i}$$



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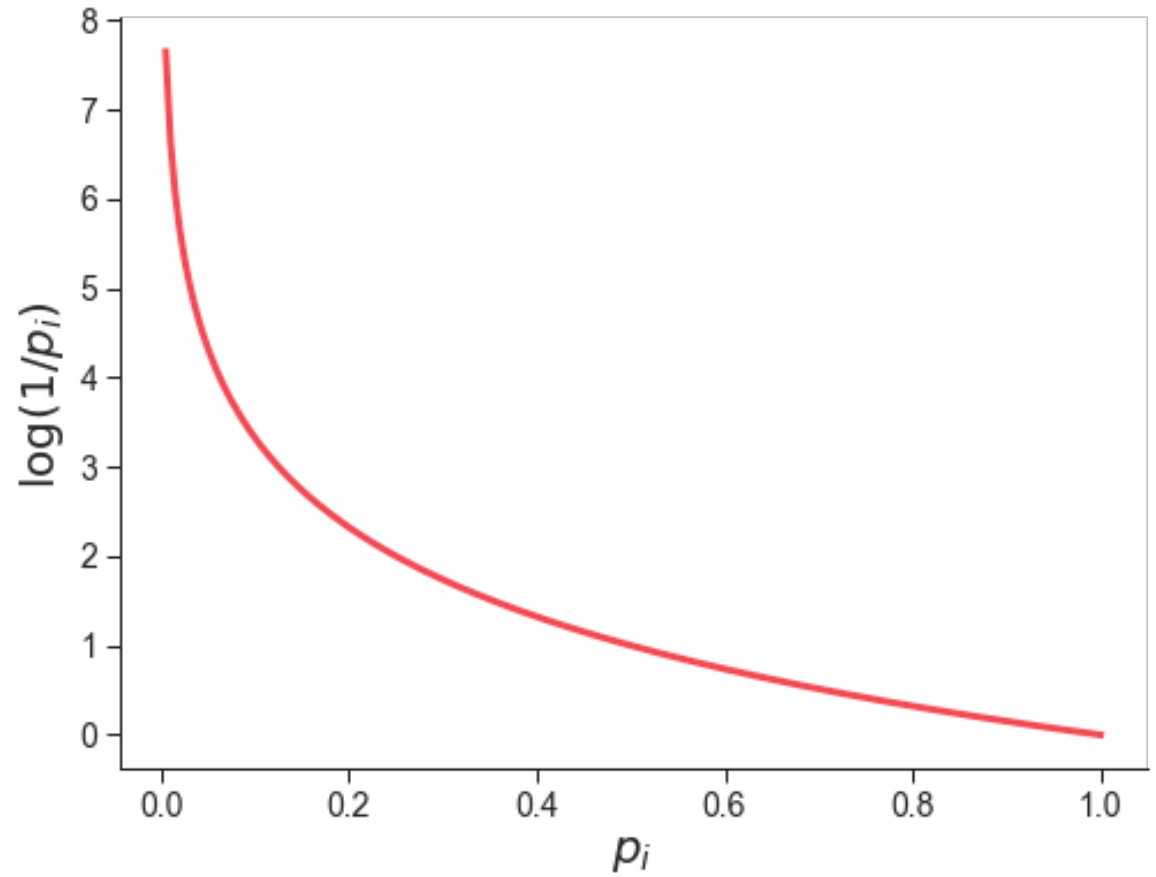


Entropy is the average surprise across a collection of events

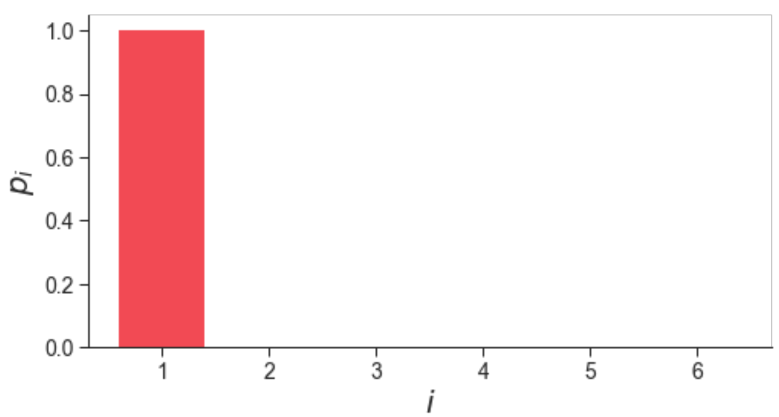
$$H(P) = -\sum_{i=1}^{n} p_i \log p_i$$

😱

Entropy as Diversity

Entropy is at its minimum if the same event is always guaranteed to occur

$$H(P) = 1 \cdot \log 1 = 0$$



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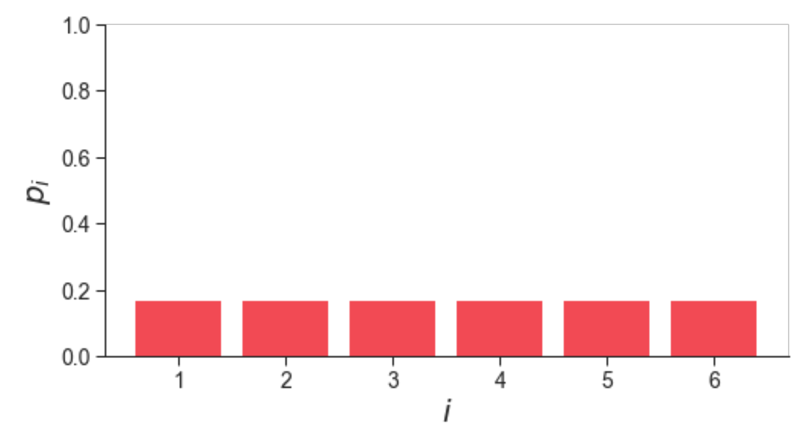

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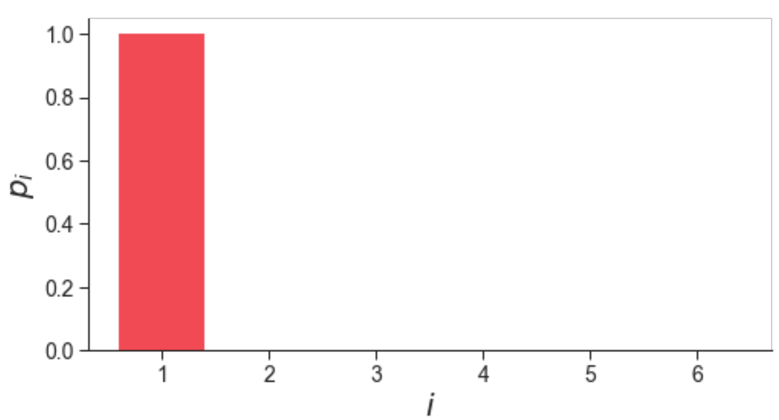

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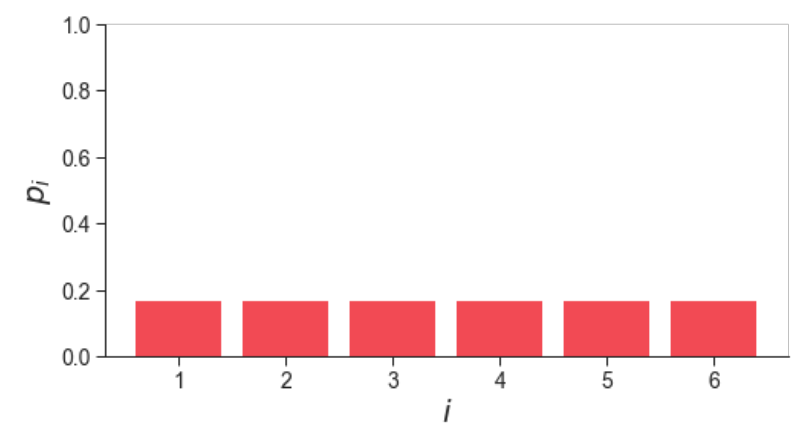
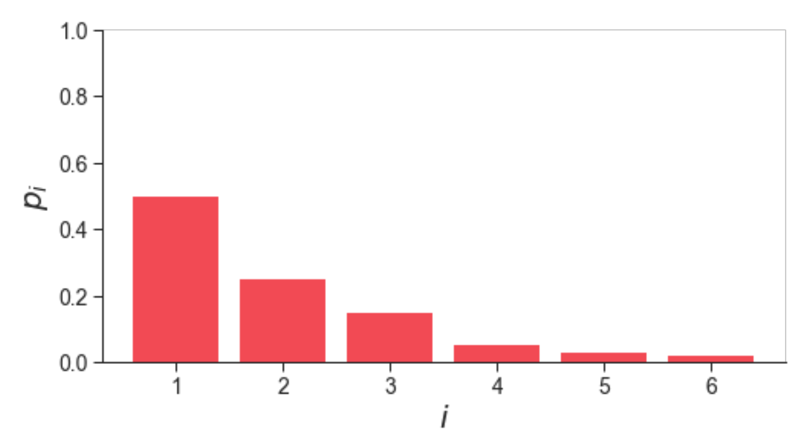


We can think of entropy as the “skew” or “diversity” of a system



Entropy as Diversity

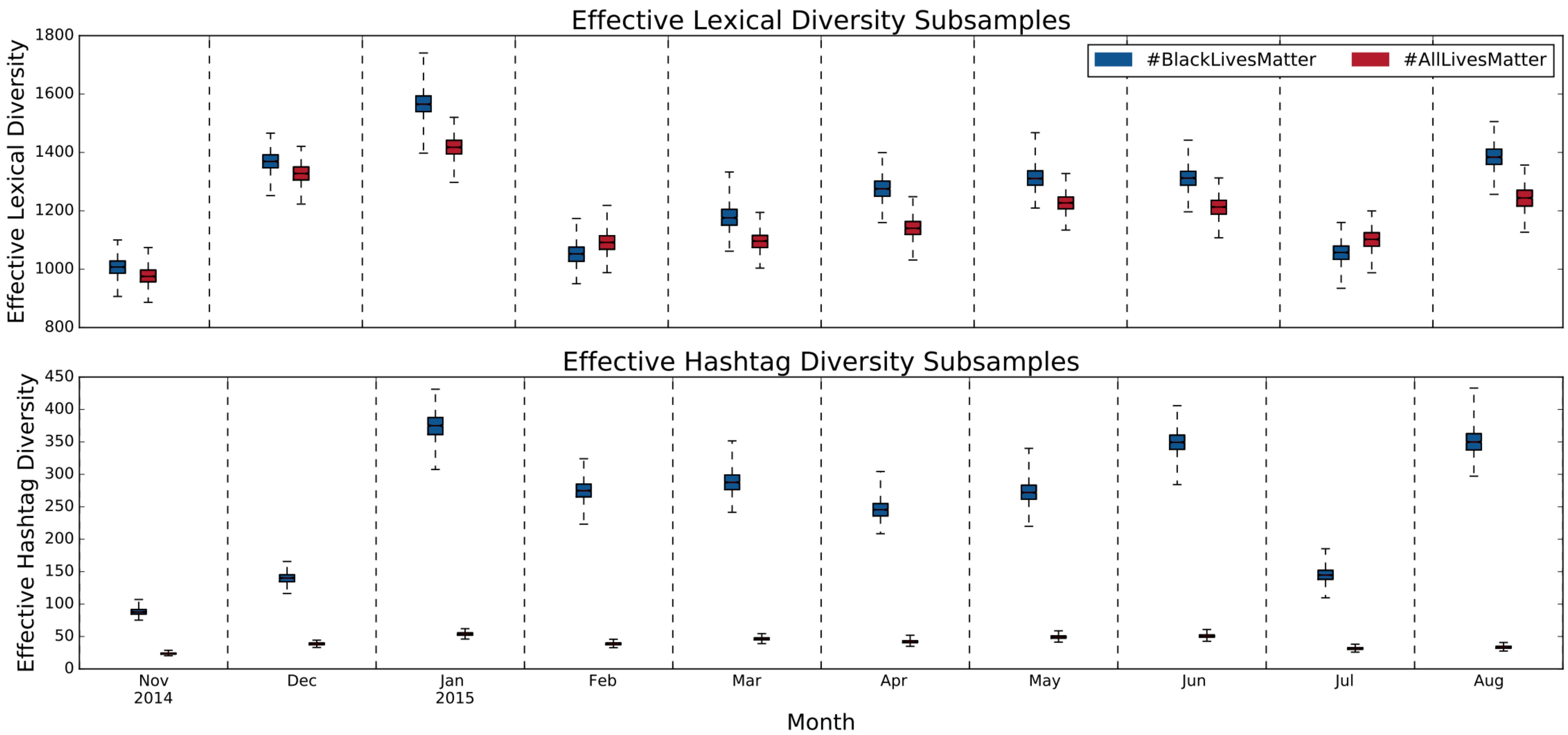
Suppose we have #BlackLivesMatter and #AllLivesMatter tweets and we are interested in understanding how diverse the language is within each hashtag, controlling for the number of tweets in each hashtag

1. Subsample the same number of tweets from both hashtags

2. Calculate the probability distribution over words and hashtags

3. Calculate the entropy of the distributions

4. Repeat steps 1—3 to bootstrap a distribution of language diversities



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Divergence of Distributions

We can also compare two distributions by looking at their *divergence*

$$D_{KL}(P\,||\,Q) = \sum_{i=1}^{n} p_i \left(\log \frac{1}{q_i} - \log \frac{1}{p_i} \right)$$

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Kullback-Leibler 🧐

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Divergence of distribution Q from distribution P

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For example, *i* could represent the *i*th word in a corpus, where q_i is the probability of seeing that word in text *Q* and p_i is the probability of seeing that word in text *P*

Divergence of Language

Suppose we have an online community and we are interested in how the language of users varies over time with respect to the community

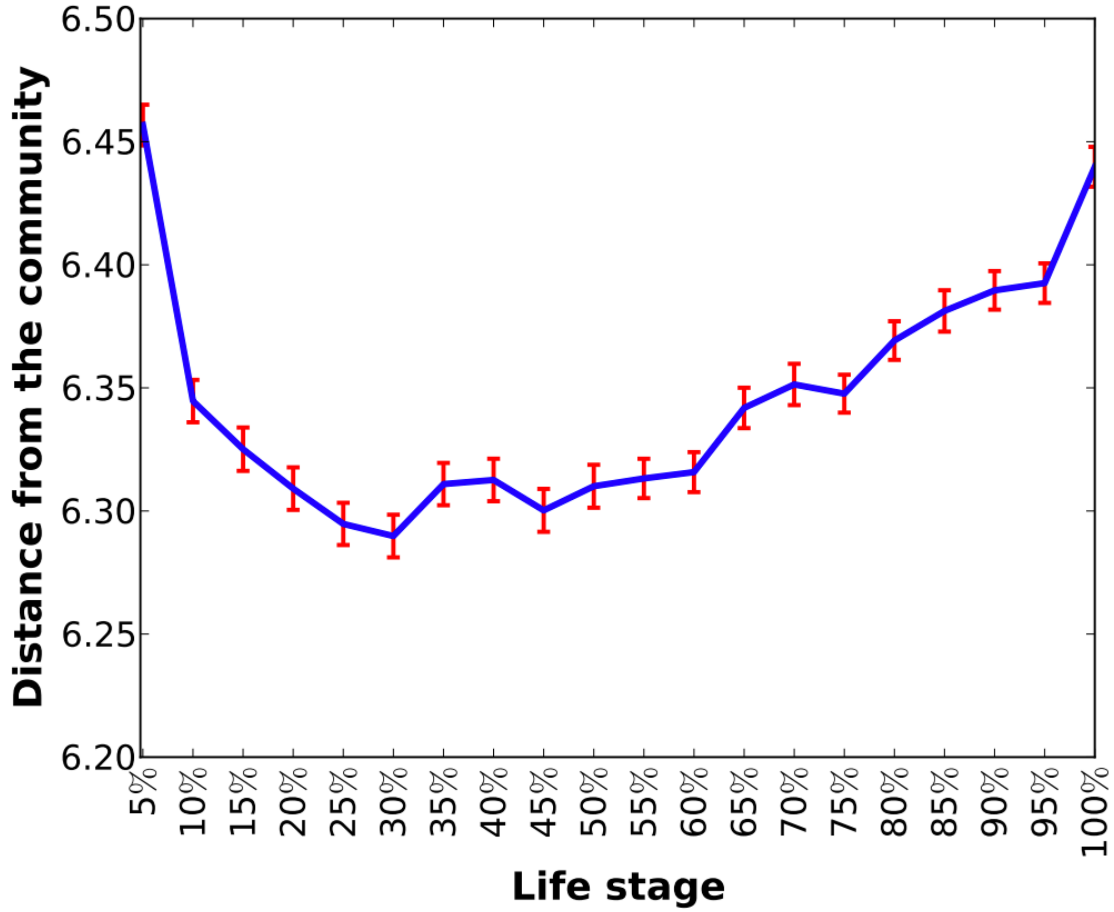
1. Calculate the distribution of language of the community

2. Build a language model over the community, which assigns a probability to seeing a given word or phrase

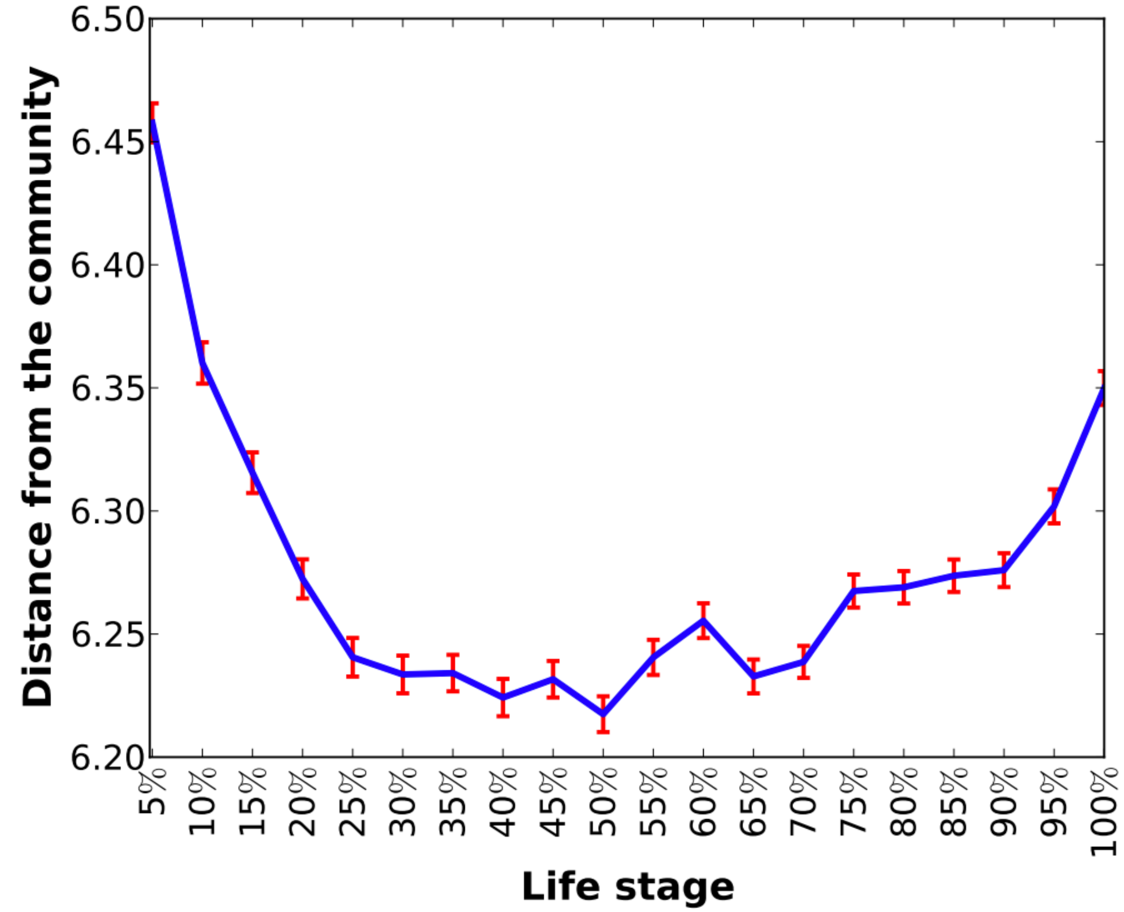
3. Apply the language model to a user's language to calculate their distribution of language

4. Calculate the KL divergence of the user's language from the community's language

5. Average this divergence across users as a function of user "lifetime"



(a) BeerAdvocate



(b) RateBeer

“No Country for Old Members: User Lifecycle and Linguistic Change in Online Communities.” Danescu-Niculescu-Mizil et al. *WWW*, 2013.

Jensen-Shannon Divergence

The Kullback-Leibler divergence is not an ideal measure for text analysis

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Instead, we can look at the Jensen-Shannon divergence

$$D_{JS}(P\,||\,Q) = \frac{1}{2} D_{KL}(P\,||\,M) + \frac{1}{2} D_{KL}(Q\,||\,M)$$

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Mixed distribution
$M = 1/2\, P + 1/2\, Q$

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Advantages:

1. Does not explode (unlike KL divergence)

2. Symmetric (unlike KL divergence)

3. 0 if both texts are exactly the same, 1 if they have no words in common

Interpretability of JSD

The Jensen-Shannon divergence is interpretable at the word level

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Contribution of each word to the divergence

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This means that we can not only measure *how much* two texts diverge,
but also *why* two texts diverge

Interpretability of JSD

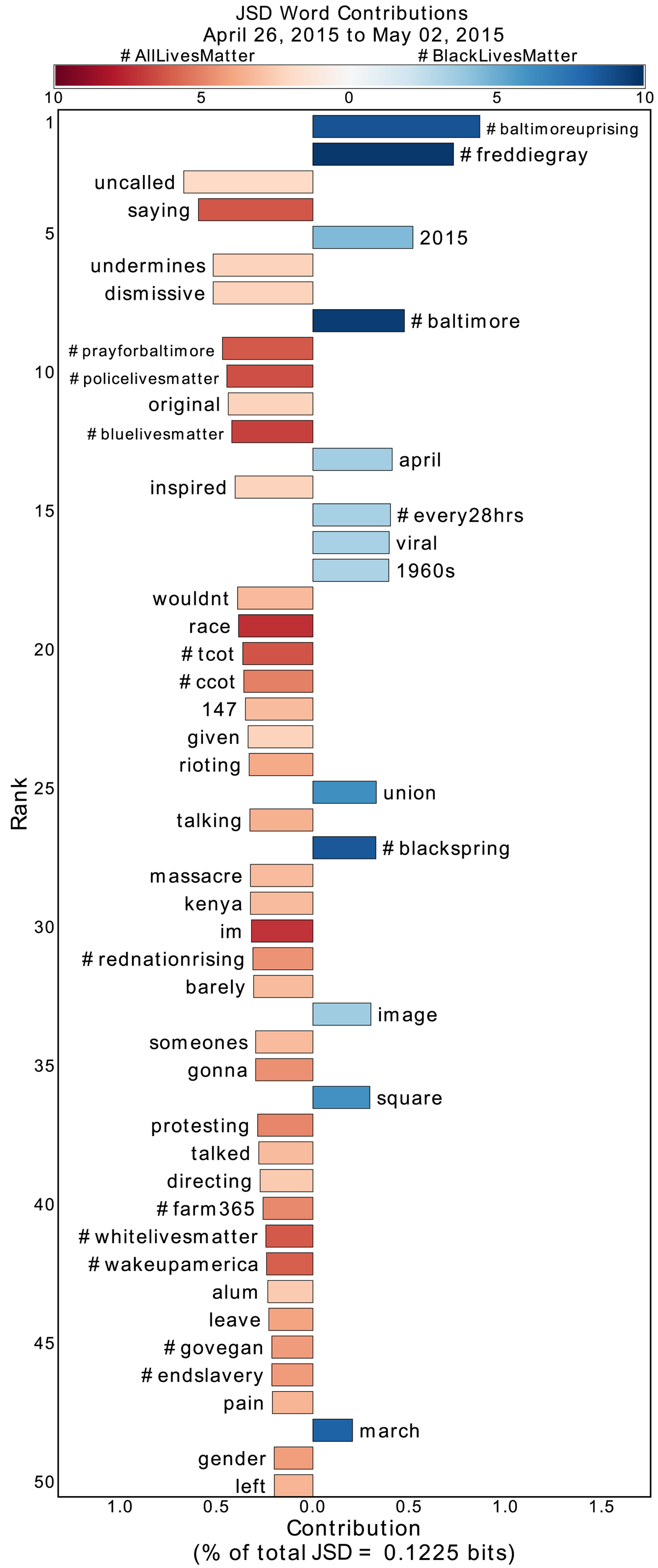
Suppose we want to understand in what ways #BlackLivesMatter and #AllLivesMatter diverged in terms of their language during the Baltimore protests following the death of Freddie Gray

1. Calculate the word distributions of #BlackLivesMatter and #AllLivesMatter

2. Calculate the Jensen-Shannon divergence between the distributions

3. Calculate and attribute each word's contribution to the divergence

4. Provide context to the contribution by calculating the diversity of language around each word



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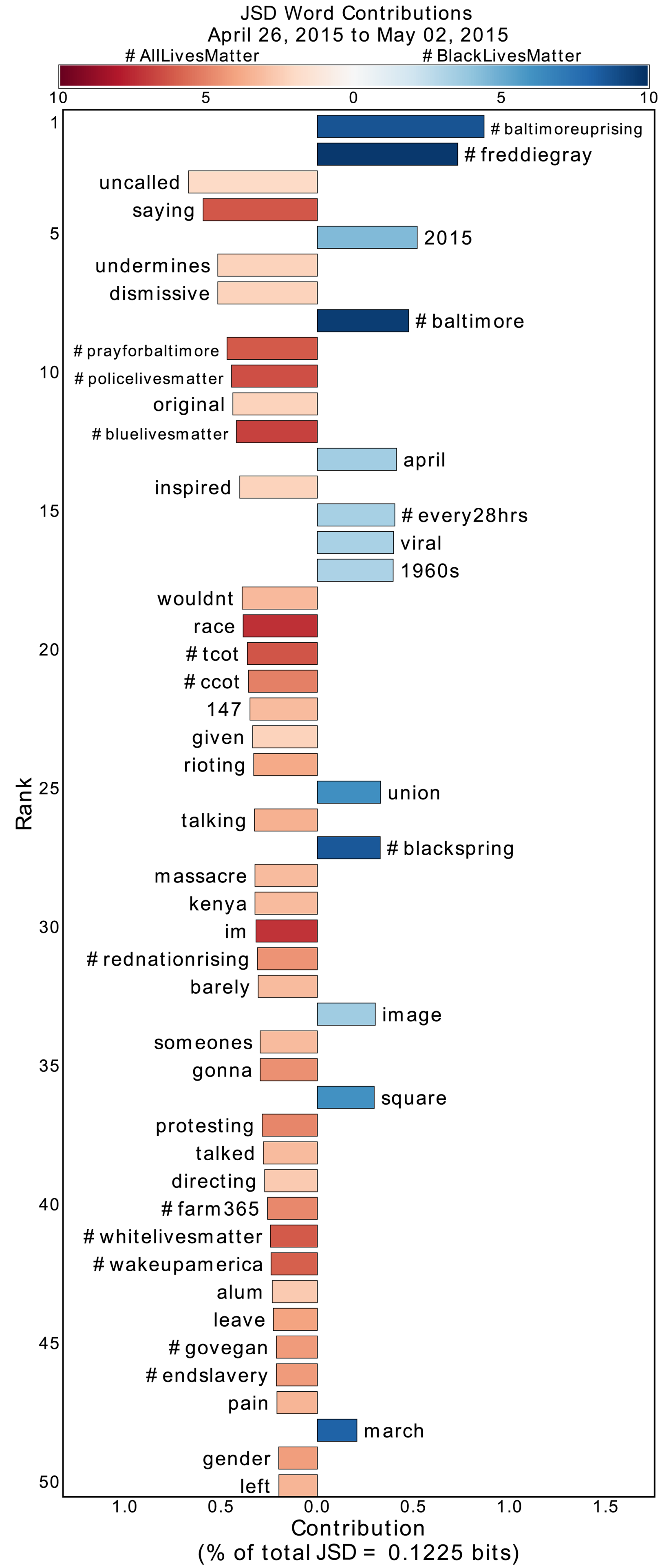
Length of bar indicates the contribution to the divergence



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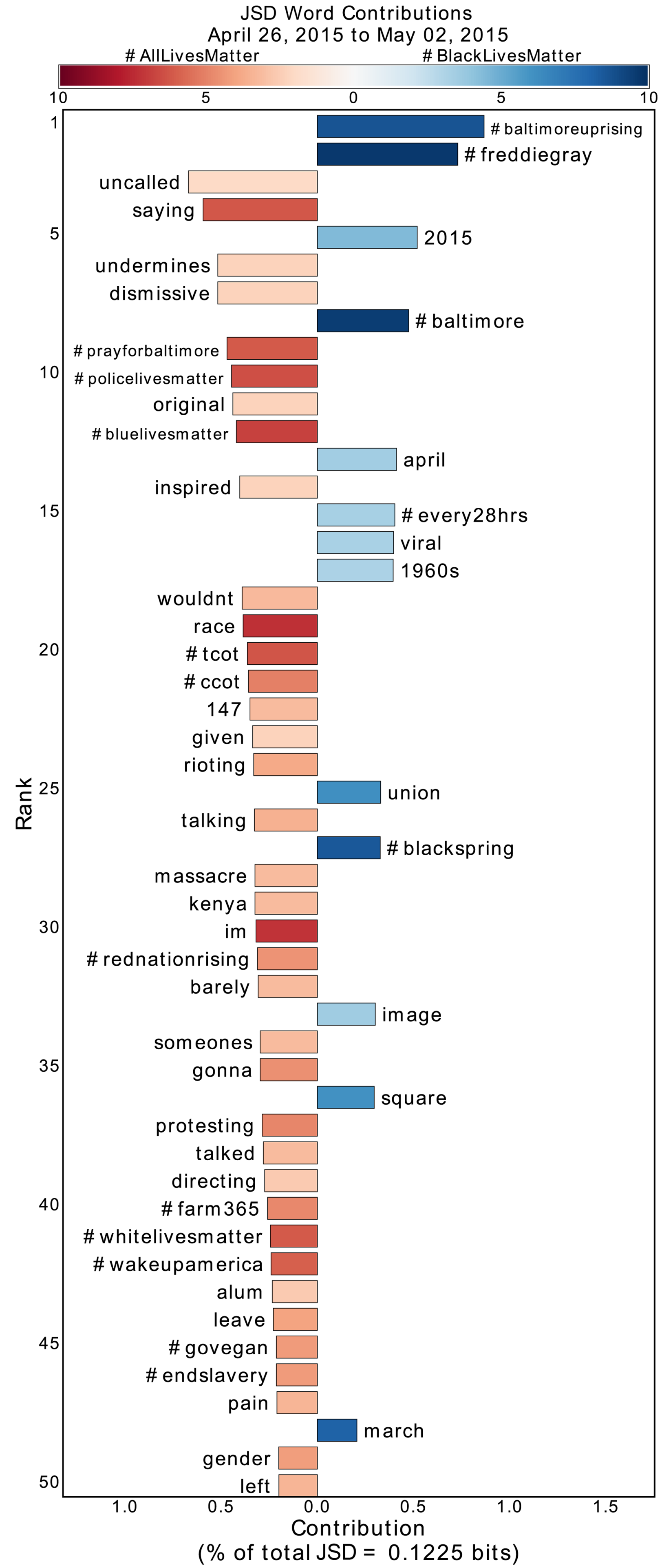
Word is more frequent in #AllLivesMatter



Word is more frequent in #BlackLivesMatter

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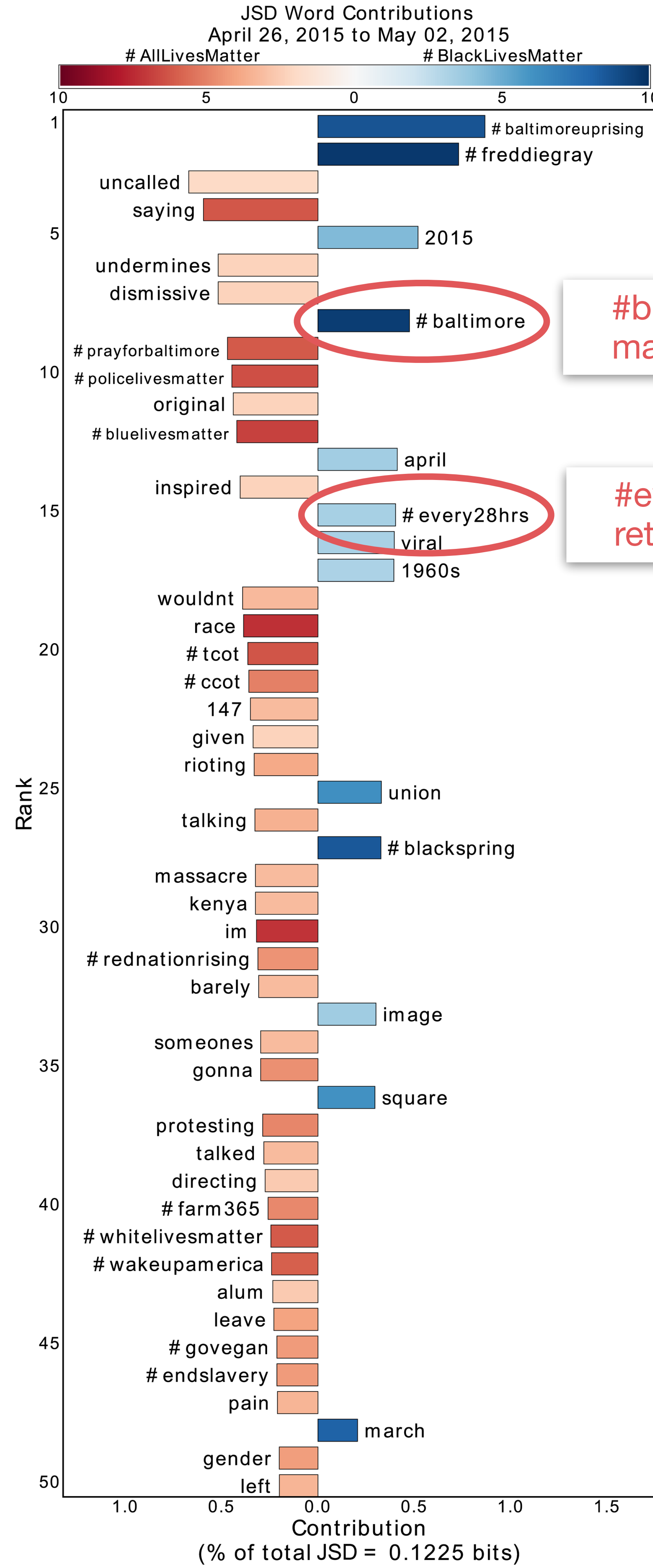
Color indicates the diversity of language used around a particular word (darker = more diversity)

Word is more frequent in #AllLivesMatter



#baltimore was used in many different tweets

#every28hours was primarily used in retweets of a single tweet

Word is more frequent in #BlackLivesMatter

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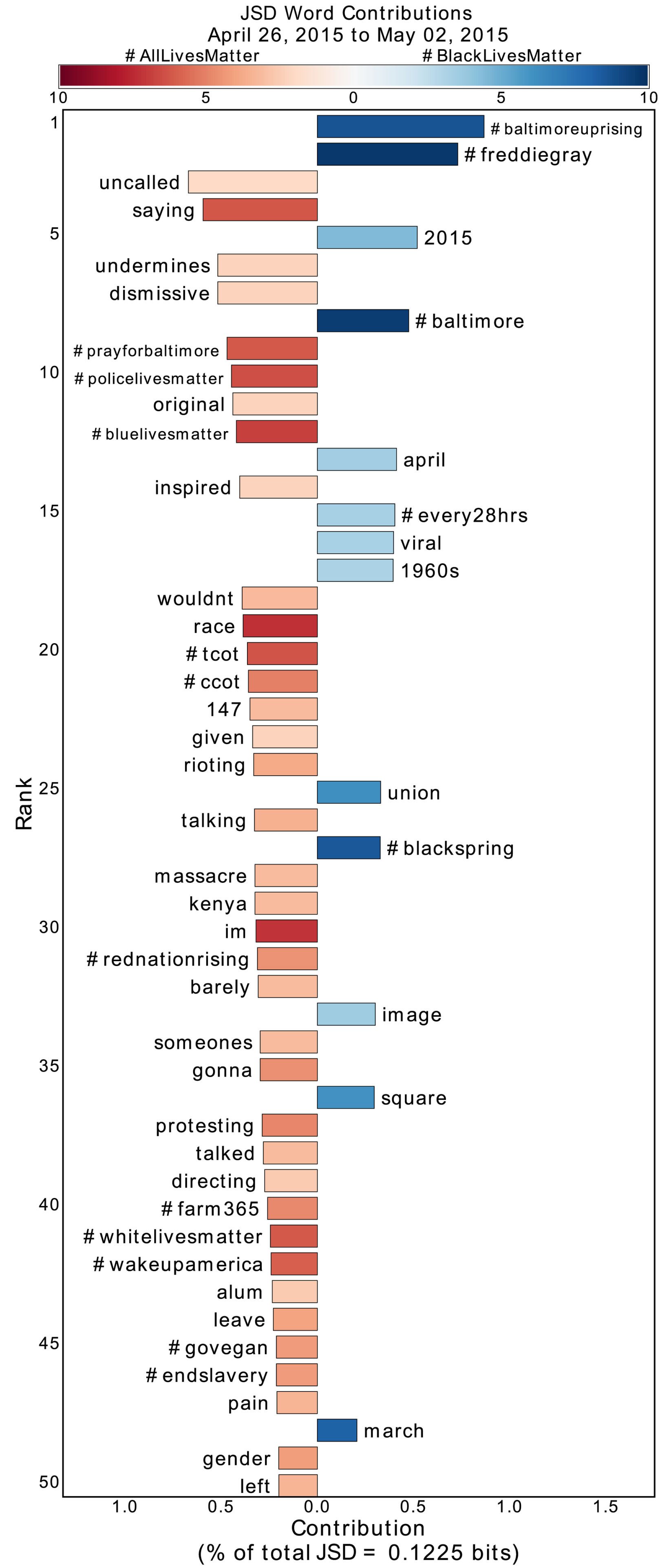

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Information-Theoretic Topics (example)

Documents

$$d_1 \quad \boxed{x_1 \quad x_2} \quad (1,1,0,0,0)$$

$$d_2 \quad \boxed{x_3 \quad x_4} \quad (0,0,1,1,0)$$

Probability table

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Words 1 and 2 are related:

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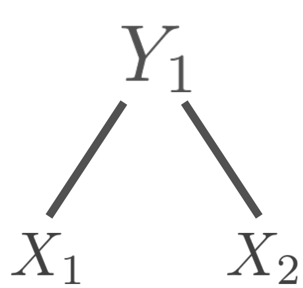

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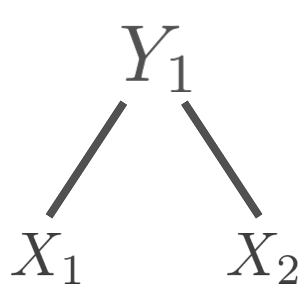

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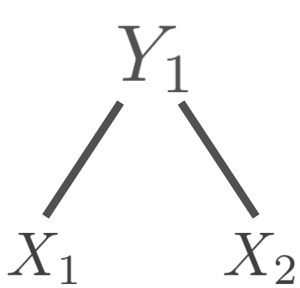

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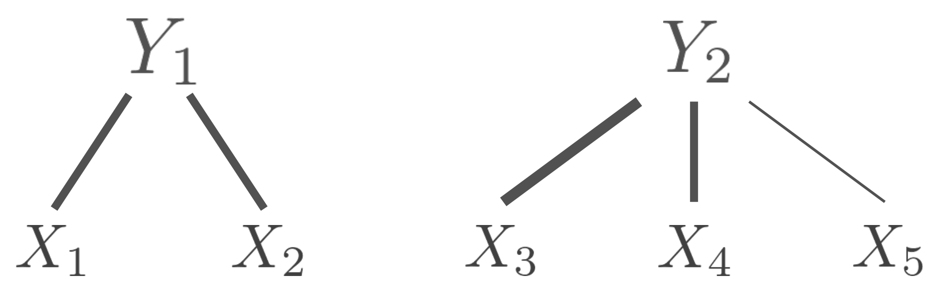

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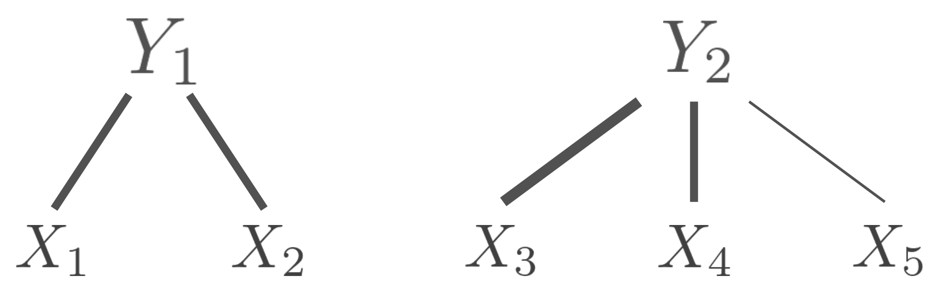

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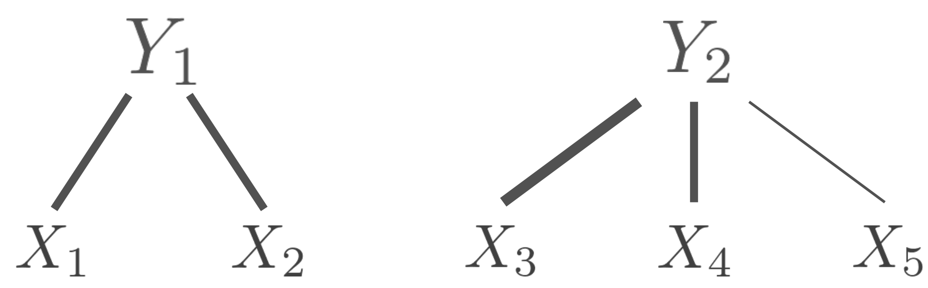

$$\min_{Y} D_{KL}\left(p(x_1, x_2, \dots x_n \mid y) \,||\, \prod_i p(x_i \mid y) \right) = \min_{Y} TC(X_1, X_2, \dots, X_N \mid Y)$$

$TC(X \mid Y) = 0$ if and only if the topic “explains” all the dependencies (total correlation)

Hence, “Total **Cor**relation **Ex**planation” (CorEx)

“Anchored Correlation Explanation: Topic Modeling with Minimal Domain Knowledge.” Gallagher et al. *TACL*, 2017.

Why CorEx?

As a computational social scientist, why might you use CorEx instead of LDA?

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And for many other fun reasons under the hood that I can't fit in a 15 minute talk

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Anchoring Strategies

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Anchoring to unveil topics that do not naturally emerge

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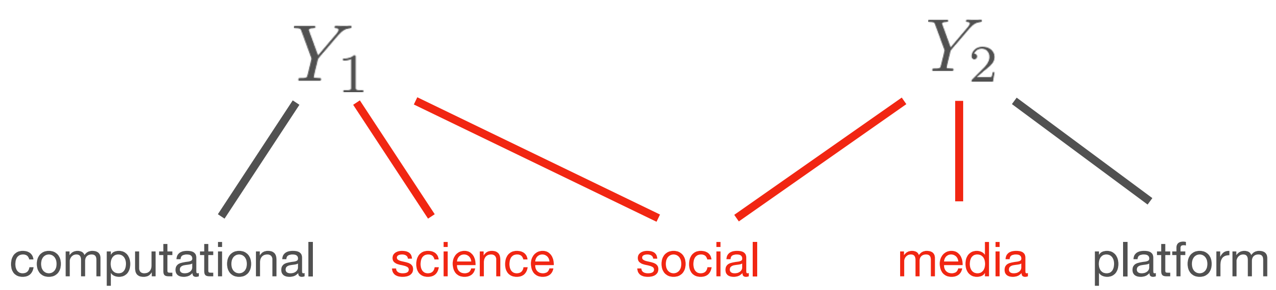
Anchoring to help enforce separation between topics



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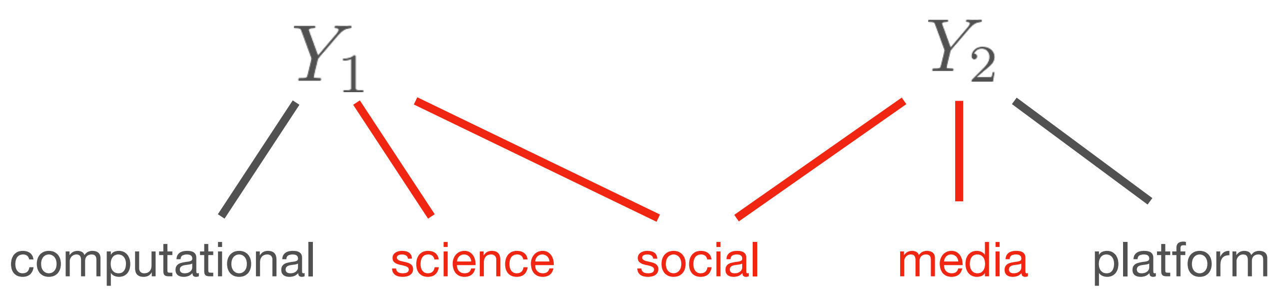
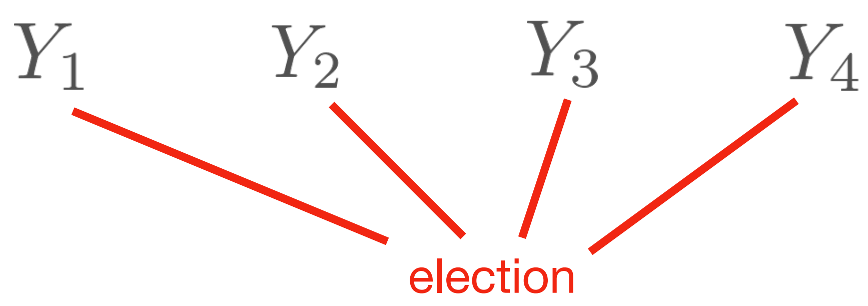
Topic Separability
Anchoring to help enforce separation between topics

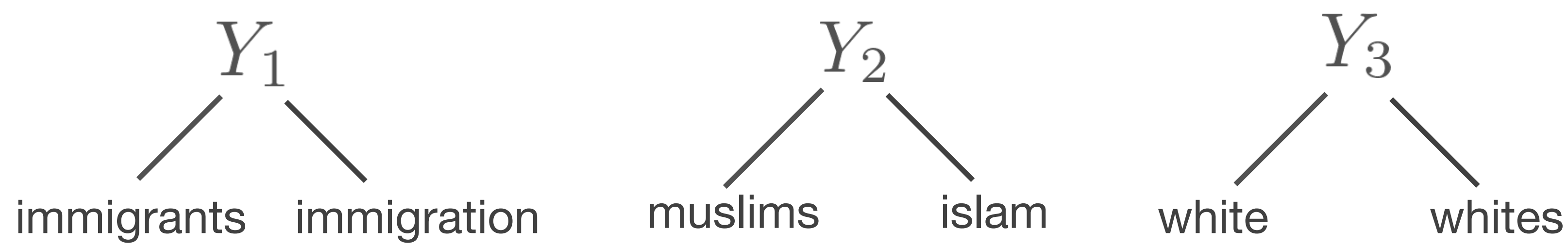


Topic Frames
Anchoring to disambiguate different frames around a word



Anchoring for Topic Representation

Data: news articles about the campaigns of Clinton and Trump, up to August 2016
Method: train one CorEx topic model for each corpus, anchor words for comparison



Work by Abigail Ross and the Computational Story Lab, University of Vermont

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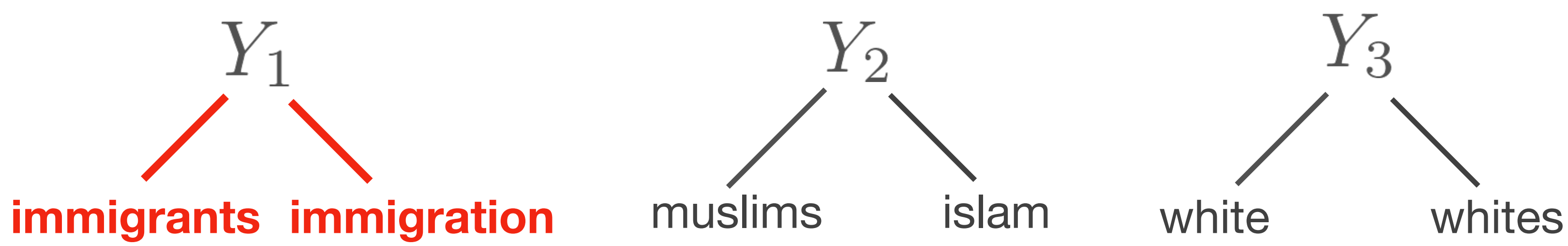

Clinton Topic

1: **immigration**, **immigrants**, jobs, economic, trade, health, tax, wall, care, economy

Trump Topic

1: **immigration**, **immigrants**, illegal, border, mexican, undocumented, rapists, mexico, wall, illegally

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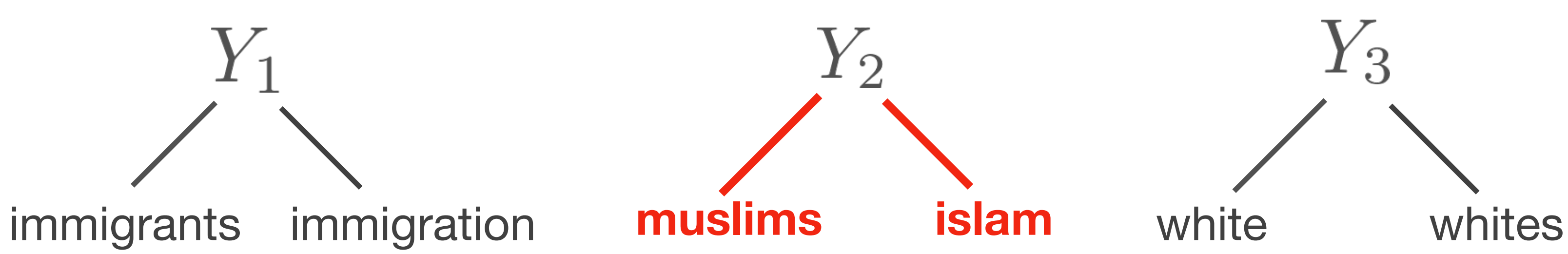

Clinton Topic

2: muslims, **islam**, islamic, gun, terrorism, war, military, iraq, terrorist, syria

Trump Topic

2: muslims, **islam**, united, ban, entering, islamic, muslim, terrorism, terrorist, terrorists

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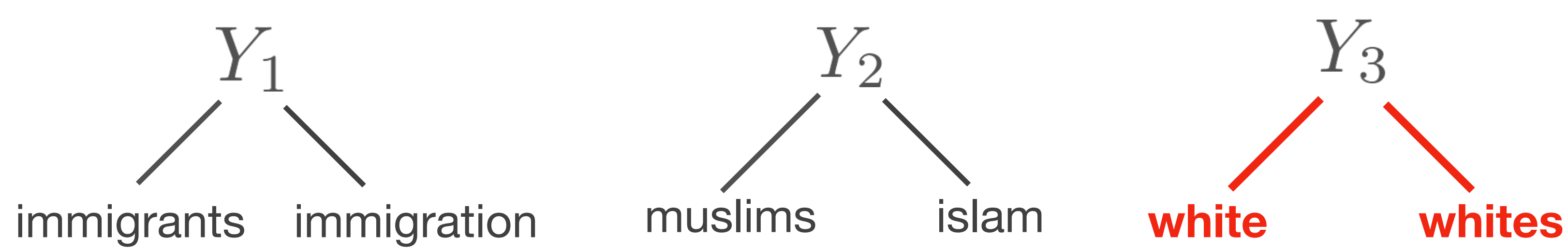


Clinton Topic

3: **white**, i, you, what, do, if, we, it’s, like, people

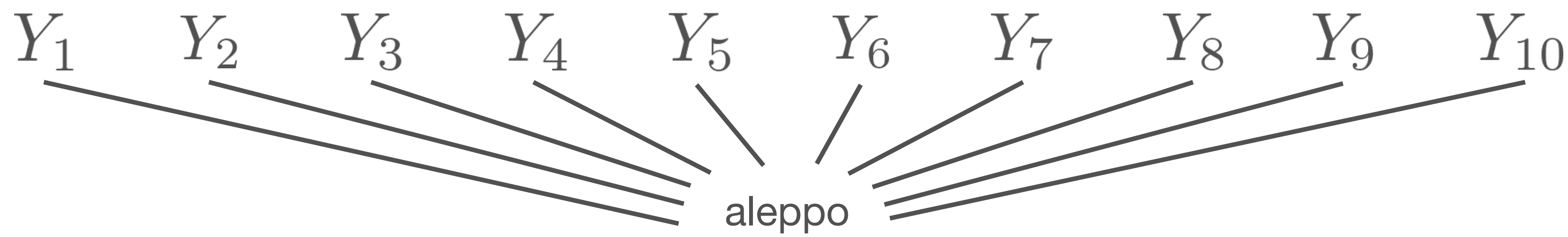
Trump Topic

3: **white**, house, **whites**, supremacists, supremacist, duke, klan, klux, ku, supremacy

Work by Abigail Ross and the Computational Story Lab, University of Vermont

Anchoring for Topic Frames

Data: ~1 million English newswire articles since June 2015 from countries in the Middle East



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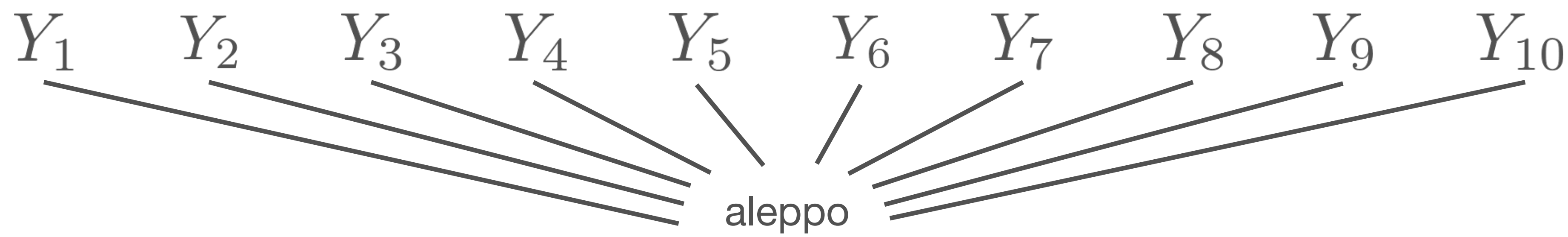

Note: this data broadly covers the Middle East and a priori we do not expect 10 topics to emerge about Aleppo

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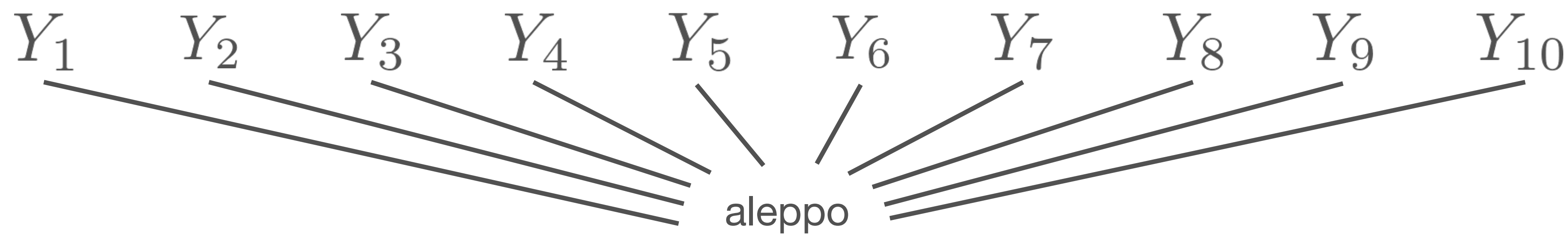

1: **aleppo**, killed, police, security, attack, state, arrested, authorities

2: **aleppo**, forces, syria, military, war, army, civilians, iraq, militants

3: **aleppo**, health, medical, food, care, water, small, conditions, treatment, patients

4: country, **aleppo**, east, across, group, region, middle

5: two, **aleppo**, took, another, place, taking, leaders

6: **aleppo**, russia, iran, barack, obama, moscow, washington, putin

7: **aleppo**, political, court, part, accused, opposition, called, saying, parliament, democratic

8: government, **aleppo**, minister, foreign, states, united, prime, UN, law, nations

9: **aleppo**, city, area, near, air, northern, least, town, eastern, injured

10: **aleppo**, people, children, human, rights, women, social, school, society, lives

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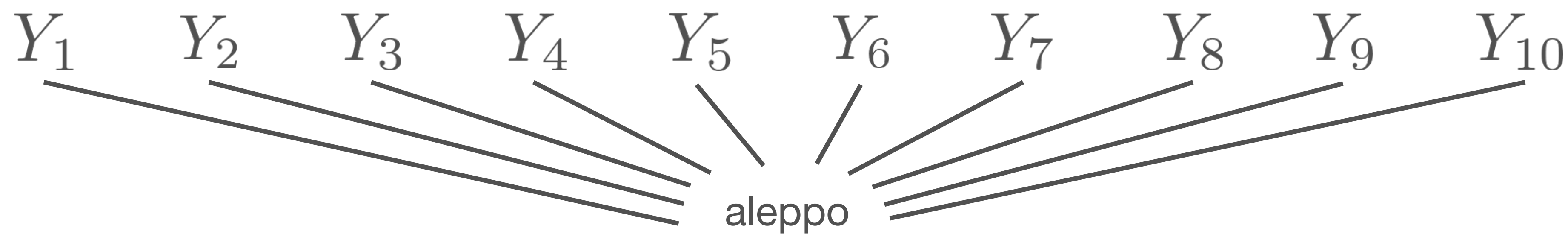

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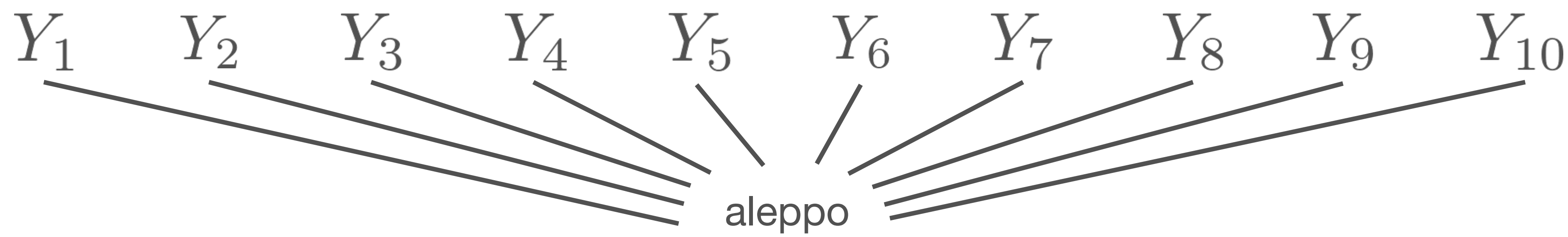

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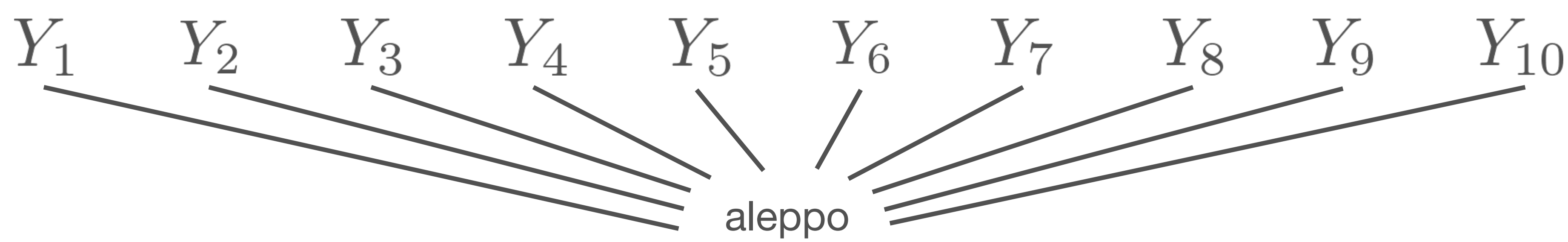

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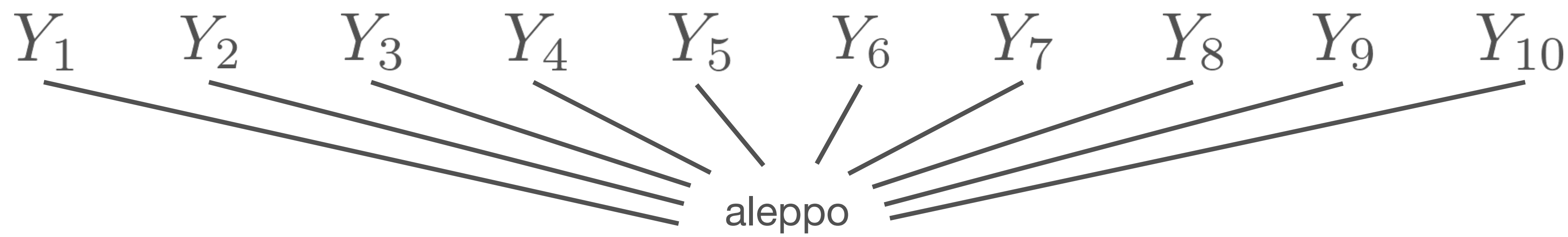

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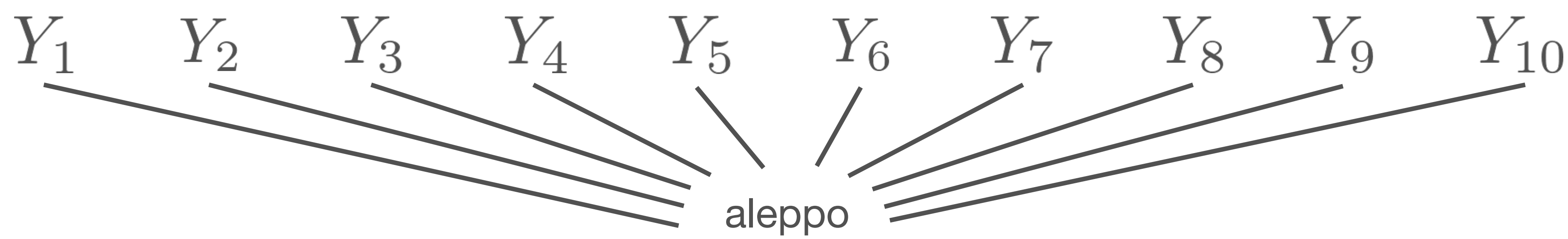

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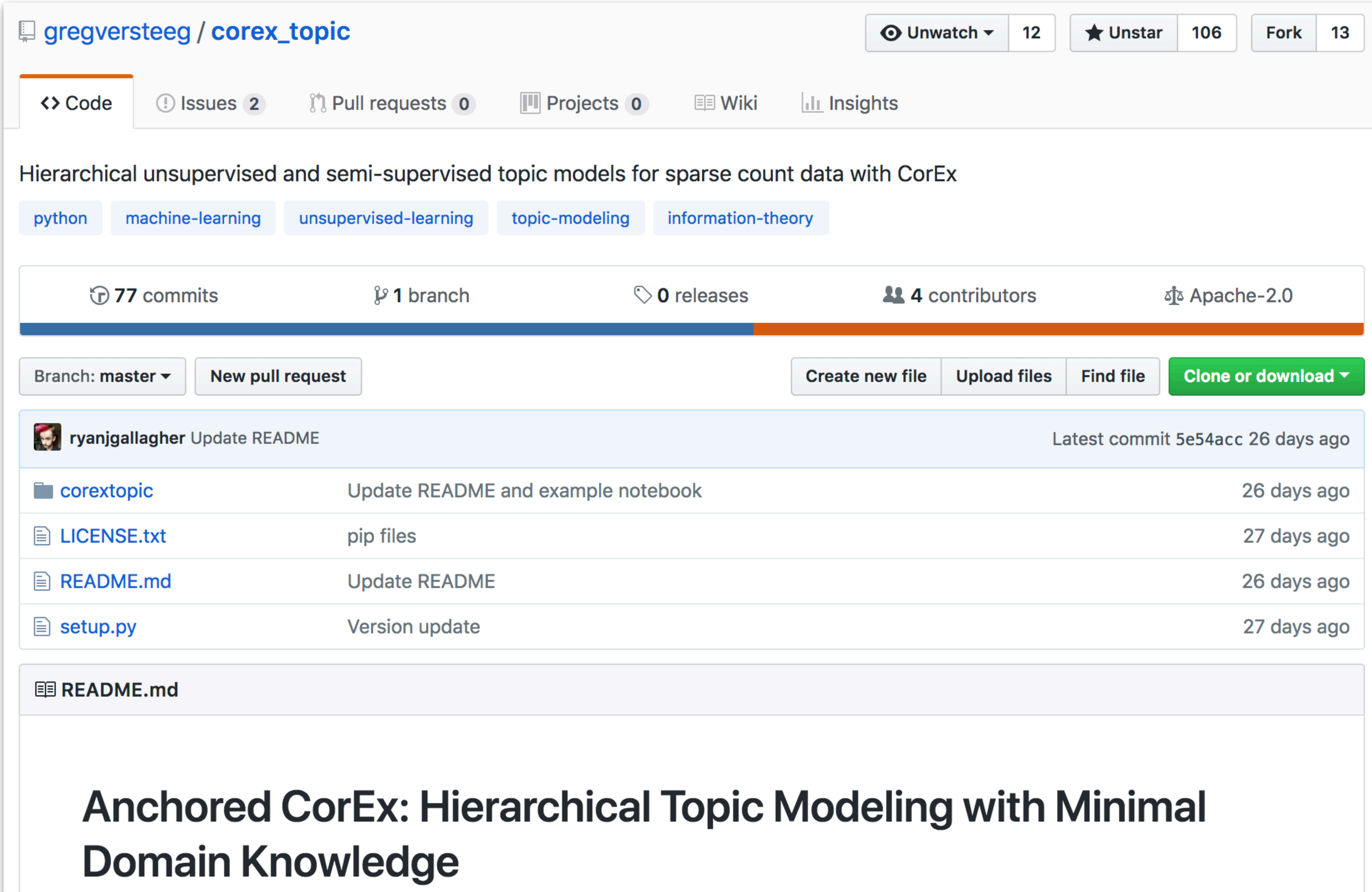
Code is open source and documented

github.com/gregversteeg/corex_topic



Detailed Jupyter notebook working through how to use and understand the CorEx topic model

Anchoring for Semi-Supervised Topic Modeling

Anchored CorEx is an extension of CorEx that allows the "anchoring" of words to topics. When anchoring a word to a topic, CorEx is trying to maximize the mutual information between that word and the anchored topic. So, anchoring provides a way to guide the topic model towards specific subsets of words that the user would like to explore.

The anchoring mechanism is flexible, and so there are many possibilities of anchoring. We explored the following types of anchoring in our TACL paper:

1. Anchoring a single set of words to a single topic. This can help promote a topic that did not naturally emerge when running an unsupervised instance of the CorEx topic model. For example, one might anchor words like "snow," "cold," and "avalanche" to a topic if one suspects there should be a snow avalanche topic within a set of disaster relief articles.
2. Anchoring single sets of words to multiple topics. This can help find different aspects of a topic that may be discussed in several different contexts. For example, one might anchor "protest" to three topics and "riot" to three other topics to understand different framings that arise from tweets about political protests.
3. Anchoring different sets of words to multiple topics. This can help enforce topic separability if there appear to be chimera topics. For example, one might anchor "mountain," "Bernese," and "dog" to one topic and "mountain," "rocky," and "colorado" to another topic to help separate topics that merge discussion of Bernese Mountain Dogs and the Rocky Mountains.

We'll demonstrate how to anchor words to the the CorEx topic model and how to develop other anchoring strategies.

]:
```
# Anchor one word to the first topic
anchor_words = ['nasa']
```

]:
```
# Anchor the word 'nasa' to the first topic
anchored_topic_model = ct.Corex(n_hidden=50, seed=2)
anchored_topic_model.fit(doc_word, words=words, anchors=anchor_words, anchor_strength=6);
```

This anchors the single word "nasa" to the first topic.

]:
```
topic_words,_ = zip(*anchored_topic_model.get_topics(topic=0))
print('0: ' + ','.join(topic_words))
```

```
0: nasa,gov,ames,institute,jpl,station,propulsion,jsc,arc,shafer
```

We can anchor multiple groups of words to multiple topics as well.

Information Theory for Text Analysis

1. We can measure the diversity of language through application of entropy

2. We can quantify *how much* texts diverge from one another

3. We can quantify *why* texts diverge from one another

4. We can learn topics with more control and less assumptions than LDA

Thank you for your time!

@ryanjgallag
ryanjgallag@gmail.com

github.com/gregversteeg/corex_topic