Collecting and Analyzing Social Media Data

Montreal Methods Workshop

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- Elites, everyday citizens, extremists, media etc. on same platform

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- Elites, everyday citizens, extremists, media etc. on same platform
- Access to politically sensitive content and hard to reach populations


You
Tube

What types of data can we collect?

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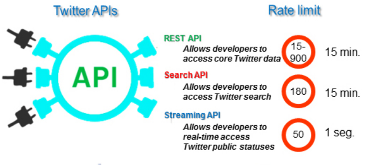
- Static vs. Ongoing collections

Twitter: Social Scientists' Favorite Platform

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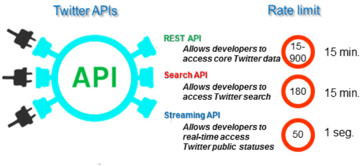


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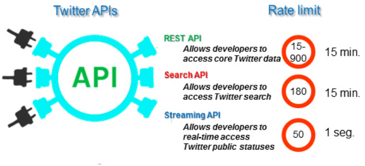


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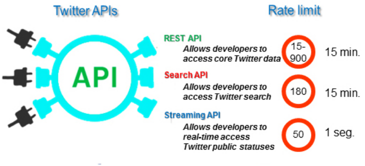


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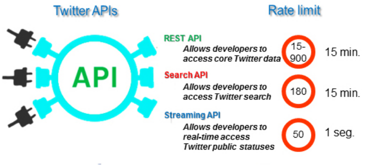


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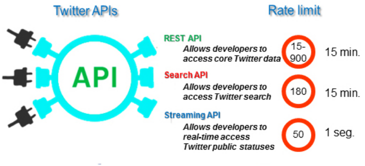


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- Scraping Tweets ▸ Link

Facebook: Challenges and Opportunities for Research

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- Collecting Public Page Data with Crowdtangle Link

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- Using Facebook Ads for Academic Research Link

```
type     by       post_id post_link       post_message    picture full_picture    link
link_domain       post_published  post_published_unix     post_published_sql
likes_count_fb    comments_count_fb       reactions_count_fb      shares_count_fb
engagement_fb     comments_retrieved      comments_base   comments_replies
comment_likes_count       rea_LOVE        rea_WOW rea_HAHA        rea_SAD rea_ANGRY
rea_THANKFUL
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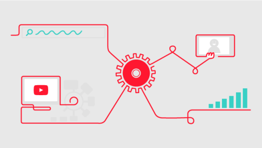
Youtube: An Underutilized Resource

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{
  "kind": "youtube#caption",
  "etag": etag,
  "id": string,
  "snippet": {
    "videoId": string,
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    "trackKind": string,
    "language": string,
    "name": string,
    "audioTrackType": string,
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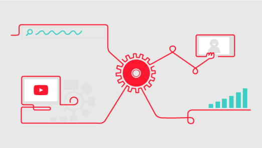


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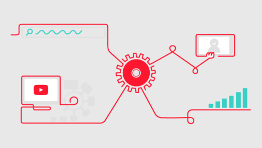

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  ▸ Link
- Channel, Video, Metadata (including comments) & a computer generated TRANSCRIPT (!) in any language

Instagram: There's politics here too!

```
Default: {urlname}
Options:
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{urlname}: Original file name from url.
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{date}: Date of upload. (Format: 20180101)
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- BUT we can data from public accounts ▸ Link

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- Can query by subreddit, time, keywords etc.

TikTok:

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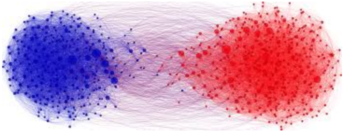
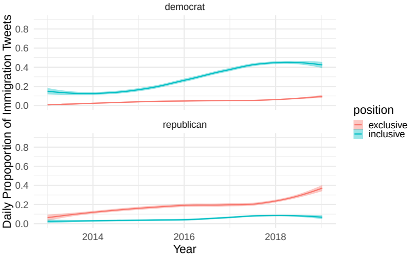
What can we do with social media data?





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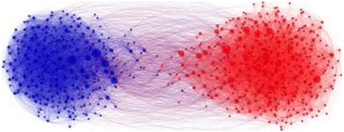

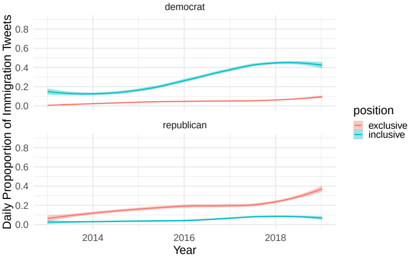

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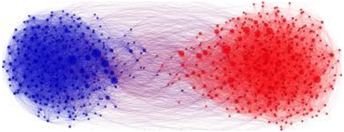

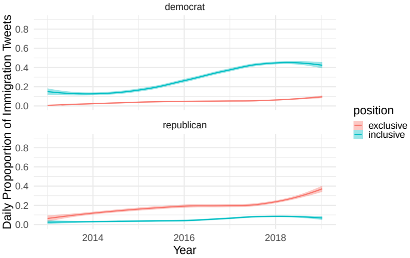

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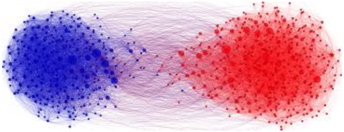

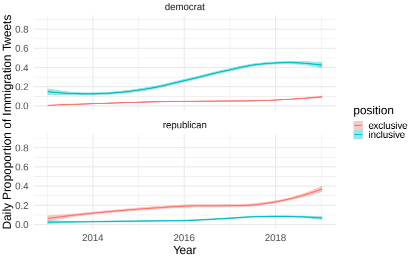

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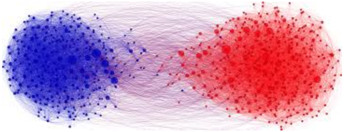

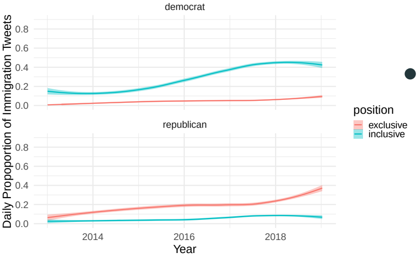

- Text/Image/Video as data
- Network analysis
- Spatial analysis
- Time series analysis

Supervised Approaches

Popular Approaches to Text Analysis for Social Media Data

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- Dictionary-based methods

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Unsupervised Approaches

- LDA & Structural topic models (but watch out for short texts!)
- Neural networks (including word2vec)

Illustration: Was there a “Trump effect” on Twitter?

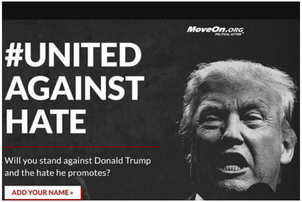
POLITICS SPECIAL REPORTS | Mon Nov 7, 2016 | 10:46pm EST

Hate speech seeps into U.S. mainstream amid bitter campaign

NEWS DESK

HATE ON THE RISE AFTER TRUMP’S ELECTION

By Alexis Okeowo November 17, 2016



DEMOCRACY & GOVERNMENT

Donald Trump and the Escalation of Hate

A number of civil-rights organizations have spoken out about the rise of hate speech and violent threats by groups and individuals who support the presumptive Republican presidential nominee.

BY KARIN KAMP | JUNE 15, 2016

'Massive rise' in hate speech on Twitter during presidential election

Jessica Guynn , USA TODAY Published 5:00 p.m. ET Oct. 21, 2016 | Updated 7:00 p.m. ET Oct. 23, 2016

How do we measure online hate speech?

HATEBASE

reddit

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- Political Datasets & Random Sample of American Twitter Users (June 2015 - June 2017)

Dictionary-based Hate Speech Detection on Twitter

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- Examples of Anti-Hate Speech that include dictionary terms:

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2. Remove terms that are primarily not used as hate speech in a random sample of our Political Twitter dataset. → (e.g. pizza, newspaper, soak, taco)→ (538 terms)
3. Add common Twitter specific terms using word2vec dictionary → (+ 500 terms)

Problems with Dictionary Methods:

- Term can be part of a Twitter handle: @angrybitch
- Dictionary terms can be parts of other words: spicy
- Dictionary terms can be homonyms: "a chink in his armor"
- Examples of Anti-Hate Speech that include dictionary terms:
  - Already been flicked off and called a wetback and it's only been 3 days... thanks Donald trump

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- Examples of Anti-Hate Speech that include dictionary terms:
  - Already been flicked off and called a wetback and it's only been 3 days... thanks Donald trump
  - RT @ShaunKing: This just happened in Indiana. "F*** you n**** bitch. Trump is going to deport you back to Africa." Day 1 of Donald

Supervised Classification (Dictionary-based Method):

- Trained undergraduates and crowd-sourced coders on Crowdflower coded a random sample of 25,000 tweets (each tweet coded by 3 people) containing hate speech OR white nationalist rhetoric terms identified using our dictionary method.

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    - Does this tweet contain hate speech? (yes or no)
    - Does this tweet contain white nationalist rhetoric? (yes or no)
    - Instructions contained detailed definitions and examples.
    - Test questions were used to weed out ineffective coders.

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- Trained two Naive Bayes classifiers (a hate speech and a white nationalist rhetoric classifier).
- We measure the popularity of hate speech and white nationalist rhetoric (WNR) as:
  - The daily proportion of tweets containing hate speech or WNR in each of our datasets.
  - The daily proportion of unique users tweeting hate speech or WNR in each of our datasets.

Method II: Bag of Communities Approach

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- Idea: Find a place with known hate speech, then compare daily tweets with that speech
- Concept: Measure the average predicted probability that tweets are classified as belonging to a corpus of real-world hate speech.

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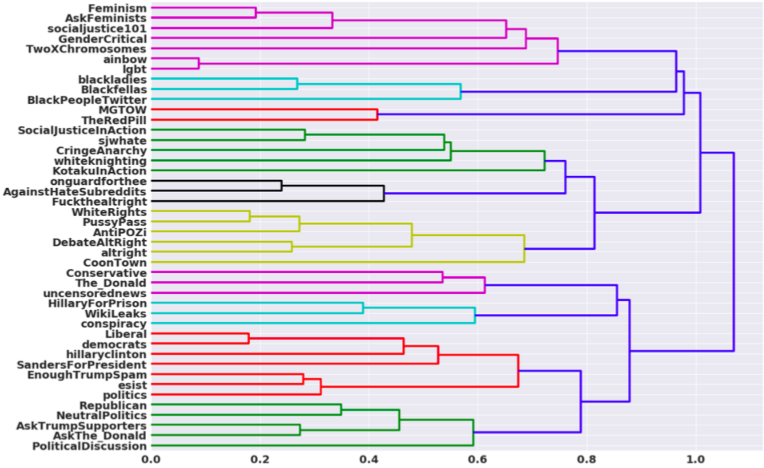
- 5) Apply trained classifier from Step 4 on Twitter data.
- 6) Calculate daily average predicted probability that tweets are classified as belonging to a group of alt-right subreddits.

Validation of Method II: Hierarchical Clustering

Figure 1: Validity Check: Hierarchical Clustering of Subreddits



Validation of Method II: Classifying Twitter Accounts

Accounts classified as **Sport**:

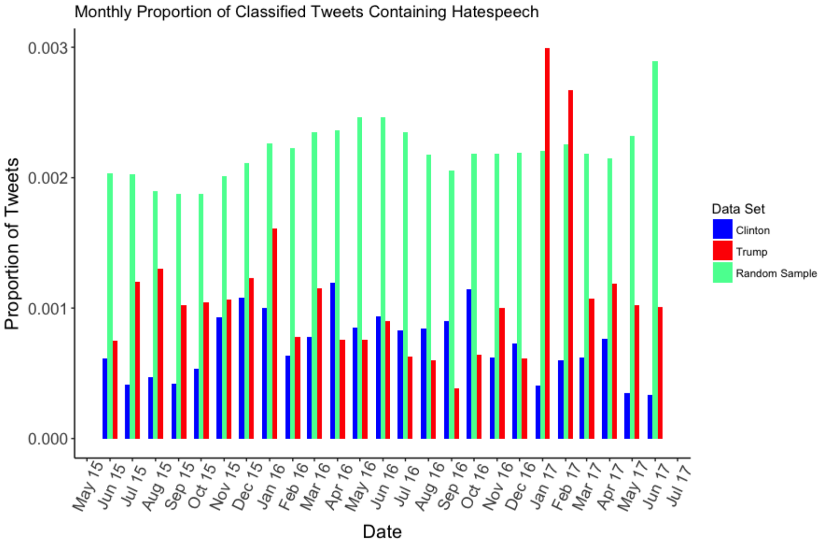
Validation of Method II: Classifying Twitter Accounts

Examples of accounts classified as **Anti-Trump**:

Validation of Method II: Classifying Twitter Accounts

Accounts classified as **Alt-right**:

What can we learn from Twitter data?



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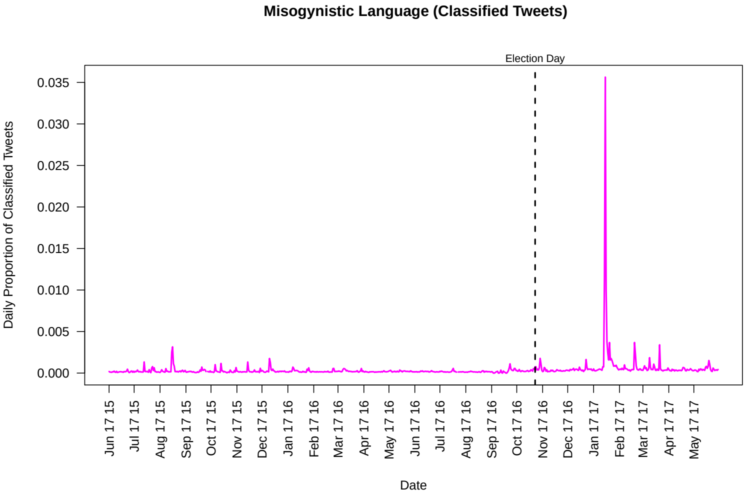

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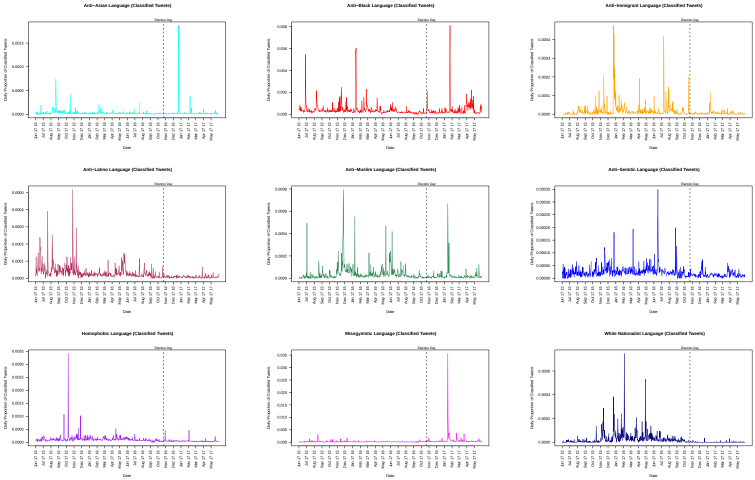

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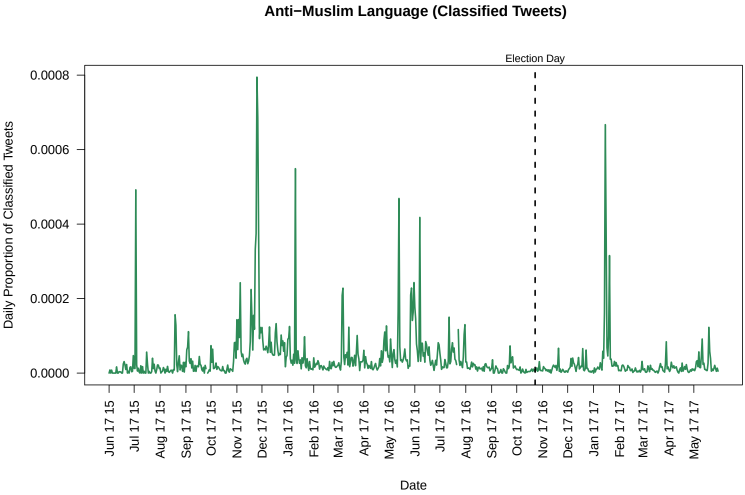

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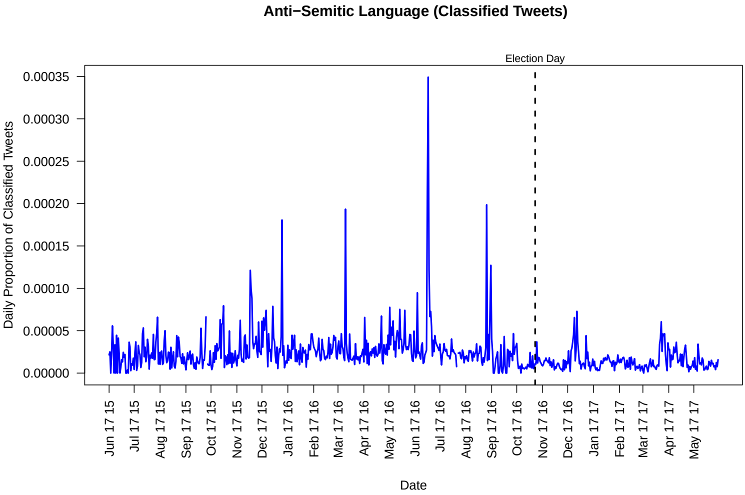
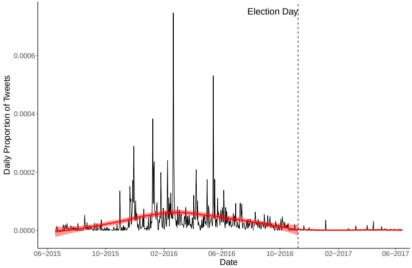
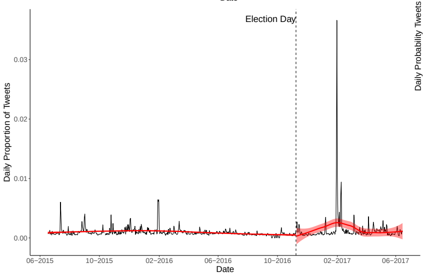
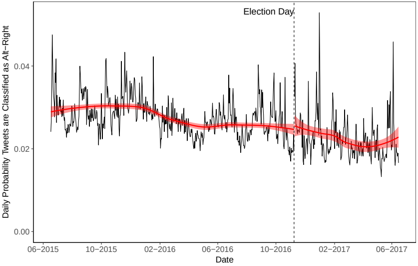


Dictionary vs. Subreddit Analysis







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- Multiple methods & data sources & iterative validation increase our confidence that we're measuring what we think we are
- Even better, combine offline and online measures!

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- But key challenges remain:
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    - Temporal Validity
    - Researchers are at the mercy of the platforms
- Like any data source there are pros and cons and approaches are constantly evolving...

Thank You!

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