social data collaboratory

Social Media and Public Opinion Research: A Road Map for Rigor, Transparency & Replicability

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AAPOR Webinar
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Outline

- Why social media data? How does this relate to Public Opinion Research?
- How social media data are **collected, filtered**, and **reported** can vary widely
- How to collect the data?
  - ➜ Use "search filter"
- How good are your data?
  - ➜ Assess the quality of search filter
- How to report about the data?
  - ➜ Reporting standard

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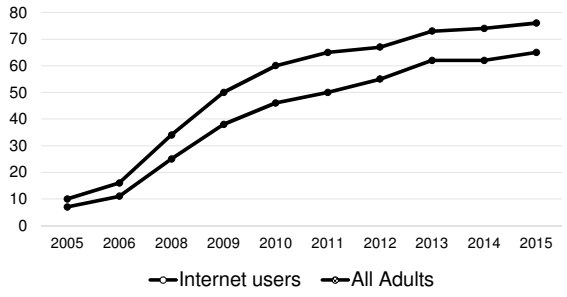
Why Social Media

- Sources of observing health attitude, intention, and behavior
- The real world for youth and young adults[1]
- Data dimensions to consider
  - Amount
  - Content
  - Source
  - Diffusion & network

% of all American adults and internet-using adults who use at least one SNS[2]



1. 90% of US 18-29 year olds use social media; 2. Source: Pew Research Center surveys

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Social Media Data 101

- Social media data Rule 1
  - Analysis is "easy"
  - Data collection and management represent at least 90% of the work
- Social media data Rule 2
  - How you collect (and report) the data WILL influence inferences/conclusions

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About Rule 1:
Anatomy of a Tweet (json format) (for example)


```
"id":"tag:search.twitter.com,2005:472724530994356224",
"objectType":"activity",
"actor":
    {
        "objectType":"person",
        "id":"id:twitter.com:22866991",
        "link":"http://www.twitter.com/joyoushealth",
        "displayName":"Joy McCarthy",
        "postedTime":"2009-03-05T02:32:24.000Z",
        "image":"https://pbs.twimg.com/profile_images/3588771321/0ffc5055c0dda79e7c32c86dea3edb83_normal.png",
        "summary":"Holistic Nutritionist CNP/RNCP, Author of JOYOUS HEALTH: Eat & Live Well Without Dieting. Natural Health expert for the Morning Show & Steven and Chris.",
        "links":
            [
                {
                    "href":"http://www.joyoushealth.ca","rel":"me"
                }
            ],
        "friendsCount":5828,
        "followersCount":18290,
        "listedCount":707,
        "statusesCount":32438,
        "twitterTimeZone":"Central Time (US & Canada)",
        "verified":false,
        "utcOffset":"-18000",
        "preferredUsername":"joyoushealth",
        "languages":
            [
                "en"
            ],
        "location":
            {
                "objectType":"place",
                "displayName":"Toronto, Canada"
            },
        "favoritesCount":324
    },
"verb":"post",
"postedTime":"2014-05-31T13:01:25.000Z",
"generator":
    {
        "displayName":"HootSuite",
        "link":"http://www.hootsuite.com"
    },
"provider":
    {
        "objectType":"service",
        "displayName":"Twitter",
        "link":"http://www.twitter.com"
    },
"link":"http://twitter.com/joyoushealth/statuses/472724530994356224",
"body":"Today is World No Tobacco Day! Check out these tips for breaking bad habits, whatever they may be, from @bitewithlove http://t.co/87vItPLtUl",
```


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More About Rule 1: Example of SDC Workflow

Operationalize	Data Collection	Data Coding	Classification	Reporting
• Data viability • Key search rule generation • Refine search rule	• Estimate/download • Data ingestion • Language filter	• Exploration • Sampling • Human labeling • Reliability	• Classifier training • Classifier testing/tuning • Classifier validation	• Data export • Results exploration • Visualization

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How to Collect Social Media Data?

- Use search filter
- **Search Filter =** Keyword + Search Rule

  Keyword selection is not simple
  - Language and culture vary and change
  - Different language norms, tech constraints, and social functions across platforms

  Search rules for more focused search

Stryker, Wray, Hornik, & Yanovitzky. Journalism & Mass Communication Quarterly 2006 Jun 01;83(2):413-430.

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Not All Data Are Good Data!

- "SMOKING" is an important keyword in tobacco research

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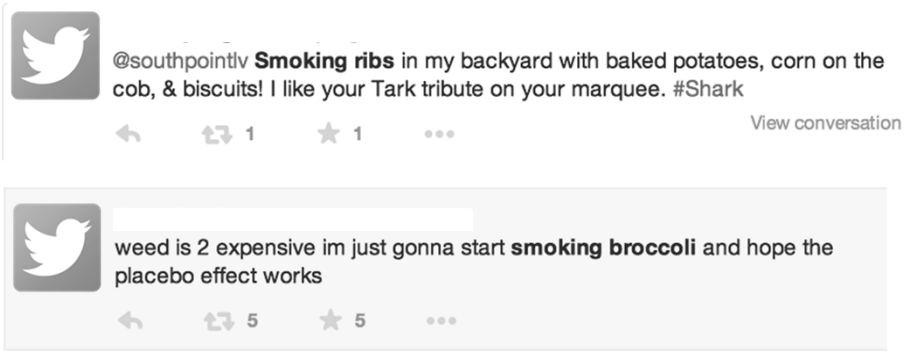

Need filter out irrelevant contents!
Otherwise biased inference

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Not All Data Are Good Data!

- Smoking cigarettes vs. marijuana ⇨ Different sentiment
- Quality of search filter ⇨ Validity of inference

- Mixture of good and bad data in massive quantity
- Use search filter to filter out irrelevant contents
- The search filter affects the amount and content of data

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Search Filter Development

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Search Filter Development

1. Build a list of **search keywords** (Stryker et al. 2006)
   - **I. Generate a list of candidate keywords** based on expert knowledge, systematic search of topic-related language, and other resources.
   - **II. Screen the keywords** by examining relevance and frequency.
   - **III. Discard keywords** that return posts with high proportion of irrelevant contents or relatively low frequency.
   - **IV. Add and screen new keywords** when new relevant terms and phrases emerge.

     Repeat II to IV until no more new relevant terms
2. Integrate keywords with **search rules**

   e.g., “atomizer” NOT “perfume”

Stryker, Wray, Hornik, & Yanovitzky. Journalism & Mass Communication Quarterly 2006 Jun 01;83(2):413-430.

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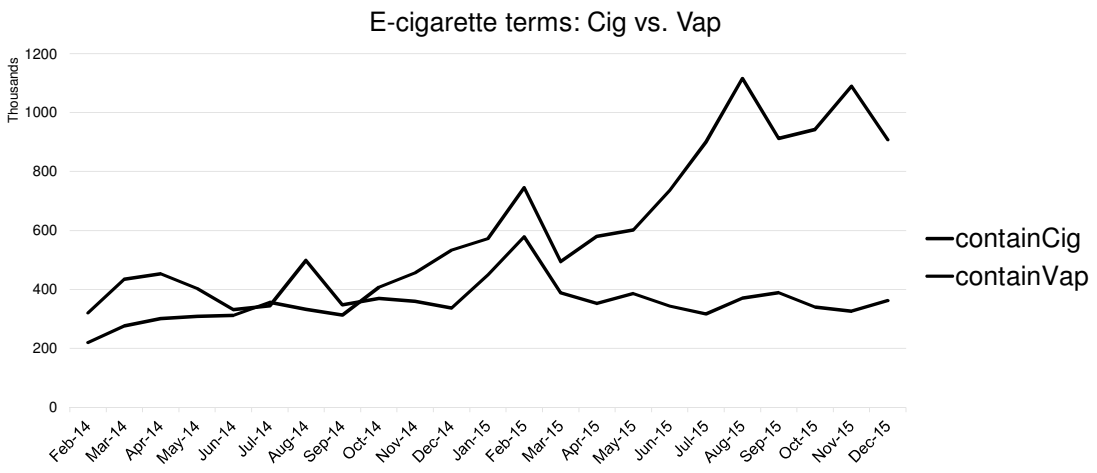
Language changes! Stream vs. Historic



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Language (English) Filter

- Language filter affects amount and content of the data
- Metadata: Twitter as an example
  - Actor's language: User's default language (if user provides)
  - Lang[3]: Machine-detected language[1] of the tweet text.
  - Gnip's language value[3]: Gnip's language detection. Language detection 1.0.
  - Twitter_lang: Language detection 2.0
- Machine learning algorithm
  - Language detection libraries of python
  - e.g. langid (Lui and Baldwin 2012), langdetect, pycld2 (Dick Sites[2])

1. BCP 47 language identifier ; 2. CLD: compact language detection; 3. Not provided from Gnip 2.0

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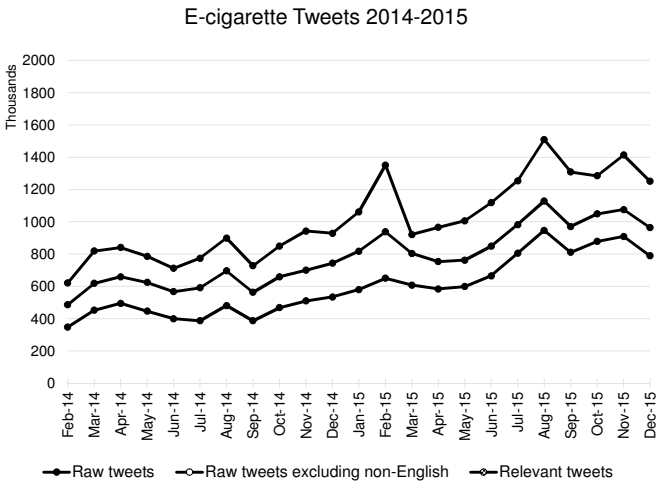
Language (English) Filter



- Example:
  - E-cigarette tweets
  - Filter on actor's language, lang, Gnip's language value – English if 50% or more of available language fields indicates English
- Different filters
  - Change amount and content
  - Affect classifier training
- Report
  - whether language filter is used
  - how it is carried out.

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Search Filter Assessment

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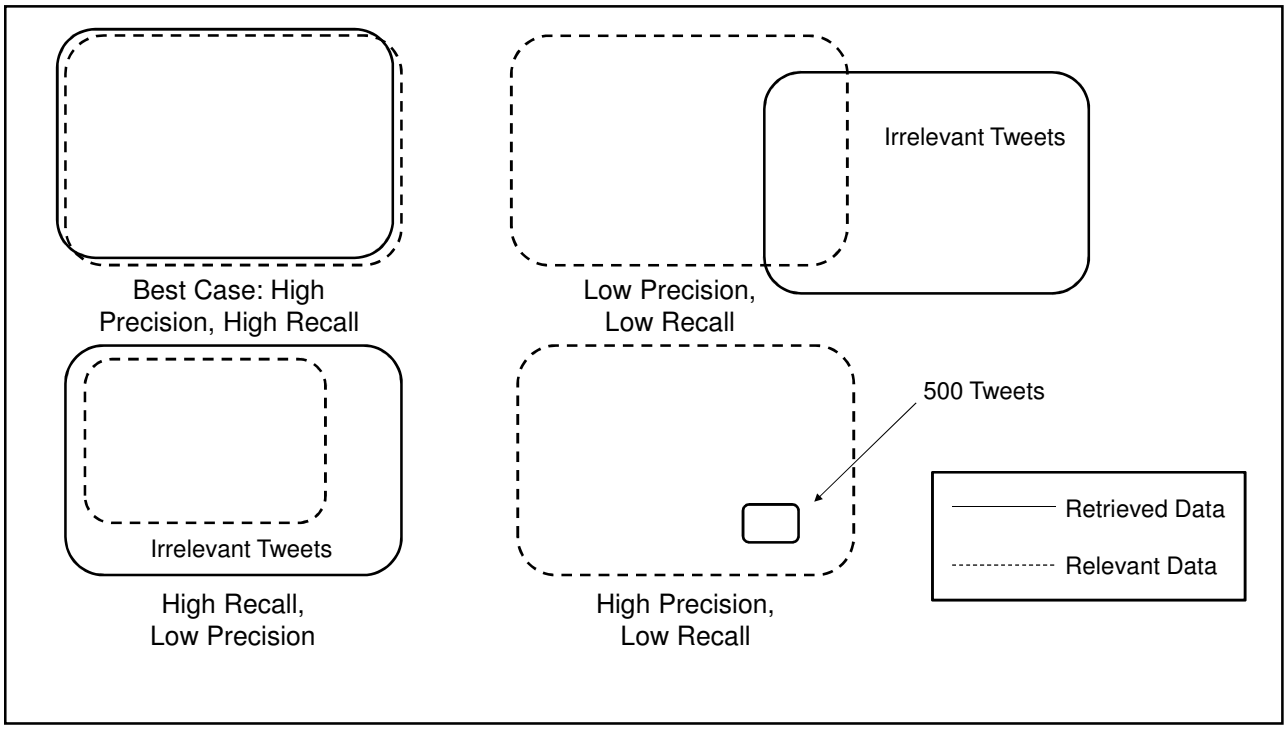
Garbage In, Garbage Out



Retrieval Data Quality Measures

- **Recall = a/(a+c)**
  How much of the relevant messages is retrieved?
- **Precision = a/(a+b)**
  How much of the retrieved messages is relevant?
- F-Score
- Specificity = d/(b+d)
- Negative predictive value = d/(c+d)

	Human Coding	
Search Filter	Coded Relevant	Coded Not Relevant
Retrieved	a (TP)	b (FP)
Not Retrieved	c (FN)	d (TN)

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Retrieval Data Quality Measures

$$Recall = \frac{(precision)P(retrieved)}{(precision)P(retrieved) + P(relevant|unretr)[1 - P(retrieved)]}$$

Retrieval recall and precision ≠ **Classifier** recall and precision

Trade-off between recall and precision

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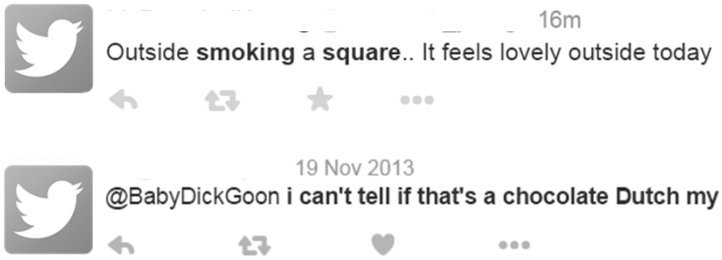
Humans Can Make Errors



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Humans Can Make Errors

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Humans Can Make Errors: Subject Matter Expertise is Necessary

Human coding may not be a gold standard

- Ambiguous language
- Short messages
- Creative terms, unknown acronyms, slang, and colloquial
- Misspelling
- Fatigue

- Human coding has <100% recall, <100% specificity
  - ➜ Biased assessment of search filter quality (Staquet et al. 1981)

Staquet et al. Methodology for the assessment of new dichotomous diagnostic tests. J Chronic Dis 1981;34(12):599-610.

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Concrete Examples: E-Cigarette Messages on Twitter

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E-Cigarette Search Filter: depends on your RQ

Category	Keywords and Rules
Variations and alternative terms of e-cigarettes	ecig(s), "e cig(s)", e-cig(s), ecigarette(s), e-cigarette(s), ehokah, e-hookah, ejuice(s), e-juice(s), eliquid(s), e-liquid(s), esmokes, e-smoke(s), lavatube(s), smokestik(s)
E-cigarette device parts	cartomizer(s), atomizer(s), NOT perfume
Specific brand of e-cigarettes	@blucig, from:blucig, blu cig, blu cigarette, njoy cig, njoy cigarette, "green smoke" "south beach smoke", eversmoke, "Joye 510", joye510, joyetech, logicecig, logicecigs, smartsmoker, "v2 cig(s), v2cig(s), zerocig(s)
Behavior	vaper(s), vaping

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Data Collection Experiment: How You Get Data Matters

- Tweets posted from Jan 15 – Jun 15, 2015 via 3 APIs
- Consistent keywords across the APIs
- Keywords for the three topics

Tobacco	E-Cigarettes	Anti-Smoking
cig hookah(s) tobacco shisha rello(s) cigarillo(s) skoal snus Marlboros	ecig vaper(s) Vaping eliquid(s) e-liquid(s) cartomizer	@drfriedencdc smokefree secondhand smoke quitline(s) #quitnow

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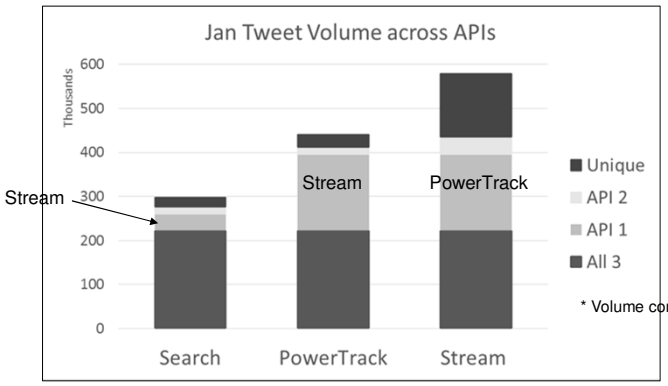
Tweet Volume

- The tweets largely overlapped between the 3 APIs.
- But, each API retrieved unique tweets too.
- Unique tweets may result in different research conclusion.



* Volume combining all three topics

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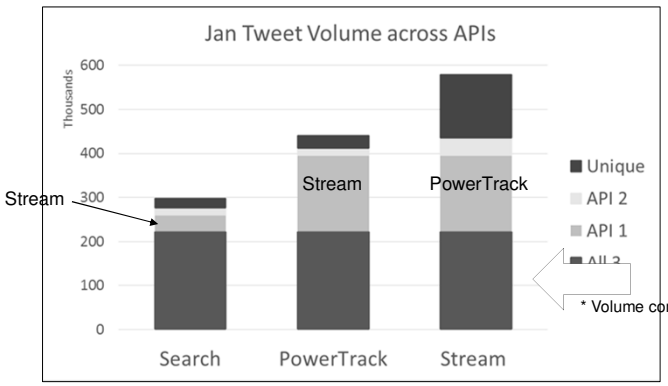

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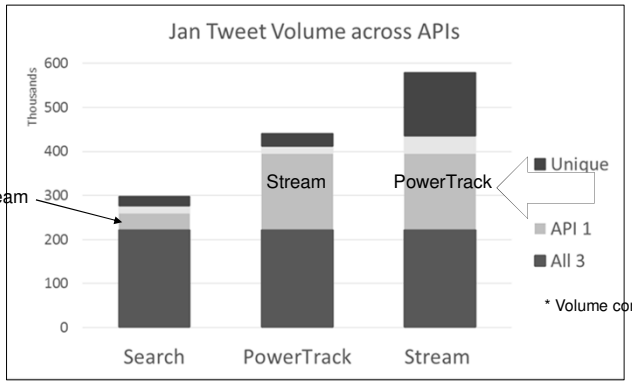

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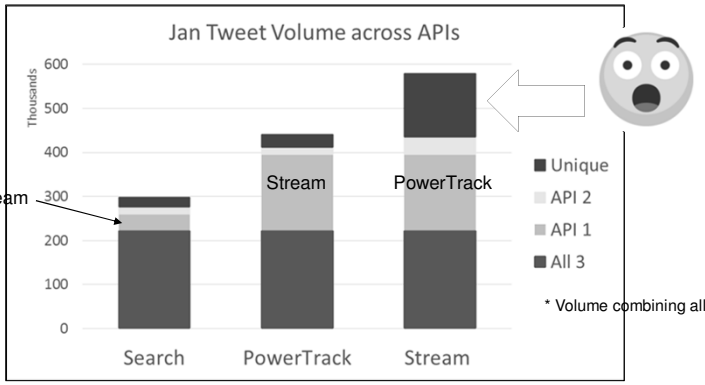

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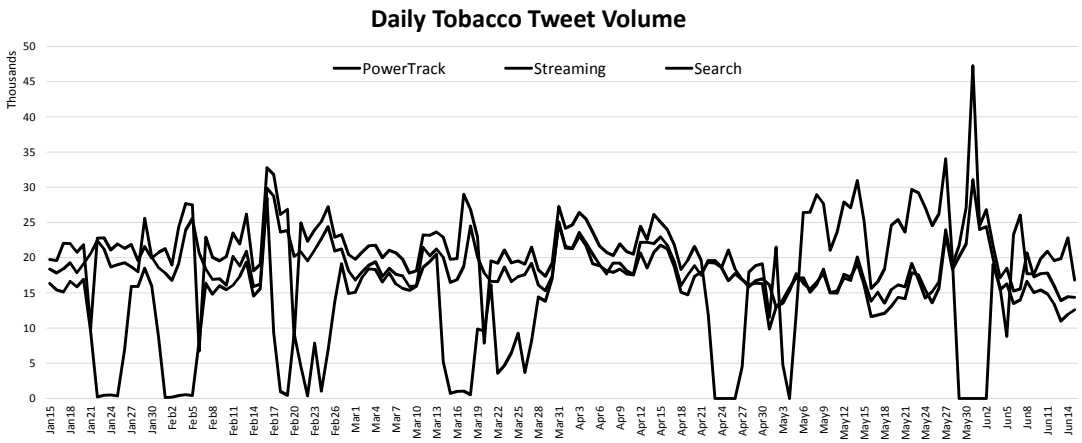
Tobacco Volume



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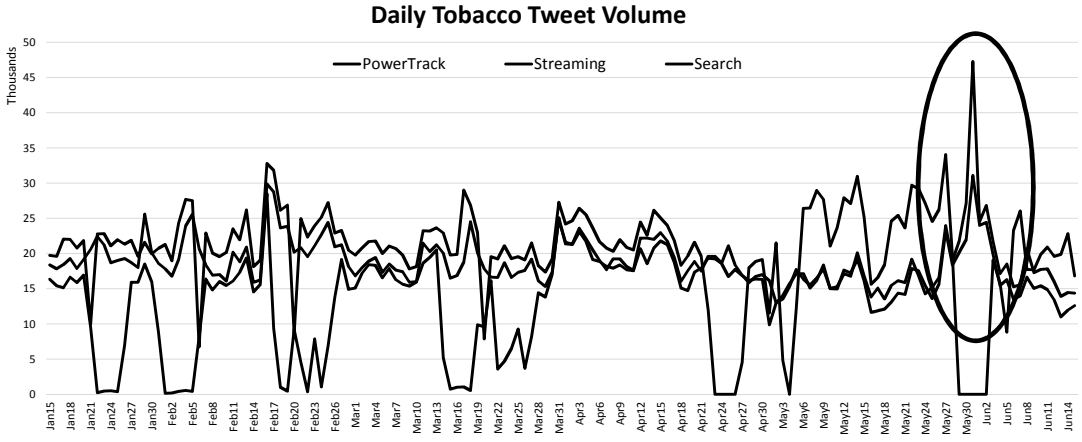
Tobacco Volume



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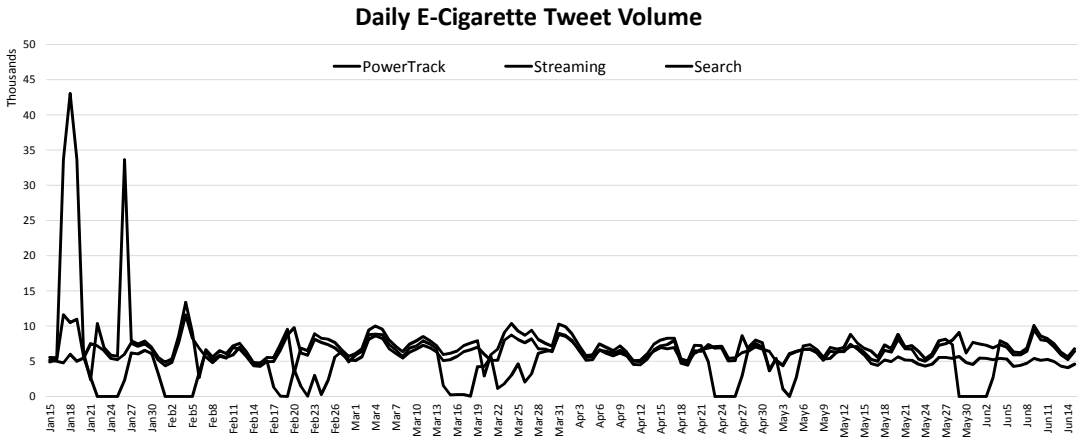
E-cigarette



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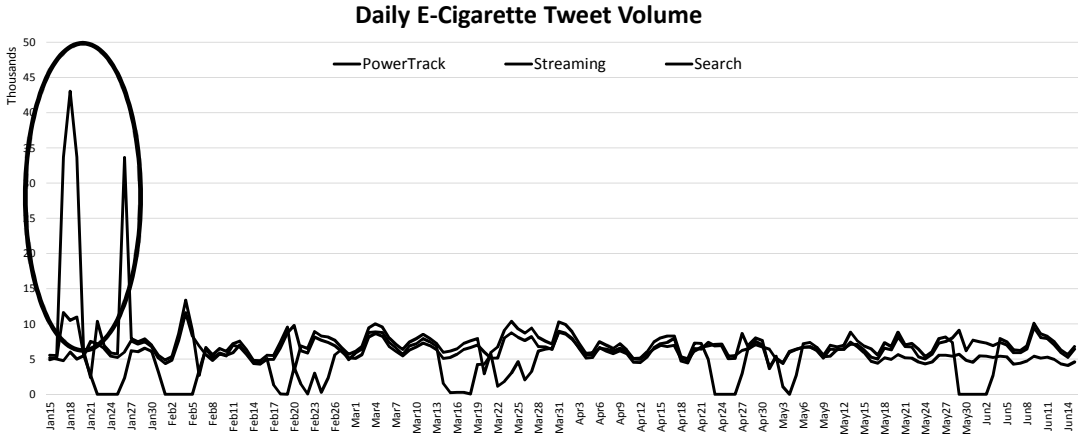
E-cigarette



What are the **sources** and **content** of these tweets?

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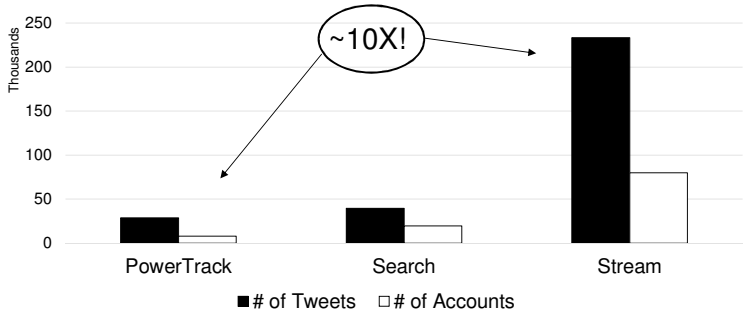
E-Cigarette Tweets & Accounts

- Jan e-cigarette tweets

	PowerTrack	Search	Stream
# of Tweets	28,785	39,569	233,372
# of Accounts	8,130	19,568	80,037
Avg # of Tweets / Account	3	2	3



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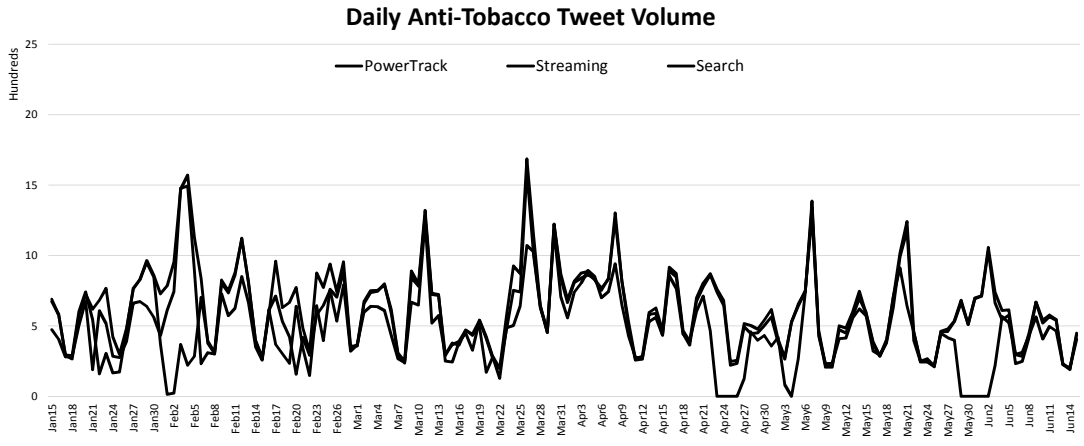
Anti-smoking



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Reporting Standard For Social Media Data Use

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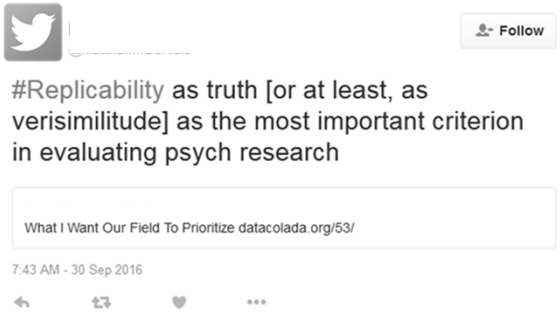
Minimum Disclosure

- **Data**
- **Development of search filter**
- **Assessment of search filter**



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Minimum Disclosure

- **Data**
  - Scope of the study
    - Definition of e-cigarette posts
  - Platform, time frame
    - Twitter, Oct 1-Oct 31 2015
  - Source or method used to access data
    - Twitter Streaming API
- **Development of search filter**
  - Keywords generation and refinement
    - Criteria to drop or add keywords
    - Precision and frequency of keywords.
  - List of final keywords and search rules
    - Acceptable signal-to-noise ratio
    - Research topic determines the definition of “noise”

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Minimum Disclosure

- **Assessment of search filter**
  - Assumption about human coding
    - Human coding as gold standard
  - Sampling frame and size for human coding
    - Proportionate stratified sampling, oversample of certain keywords, etc.
  - Quality measures
    - Inter-coder reliability
    - Retrieval precision & recall
  - Classifier training, if used to retrieve relevant data
    - Classifier precision & recall

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Preferred Disclosure

- Source code
- Model equations
- Coding/labeling instructions manual
- Ethical concerns/need for IRB review
- Data decay assessment

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Summary & Discussion

- Social media are valuable and alternative or complementary data sources for public opinion and behavioral research
- Collecting social media data that are both **precise** and **accurate** is critical to reaching correct research conclusions
- Need a standard of reporting social media data collection, filtering and quality, so that quality of data retrieved and analyses may be compared across different studies
- Our method to develop search filter and assess its quality can be adapted to other text-based social media data
- Future research: semi-automation of keyword selection

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Thank You!