

Vaccine (Dis)information on Twitter

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Introduction

Online social networks (OSNs) are today a primary way to spread and consume information.







- ❖ OSNs are open: users can post anything → proliferation of information with various degrees of truthfulness.
- Fake news articles are created and distributed for various purposes, and their use and availability have become mainstream.
- Goal: analyze if characteristic patterns exits in fake news spreading; use to identify and stop.
- Start by analyzing spreading pattern of pro vs. con vaccine-related tweets.

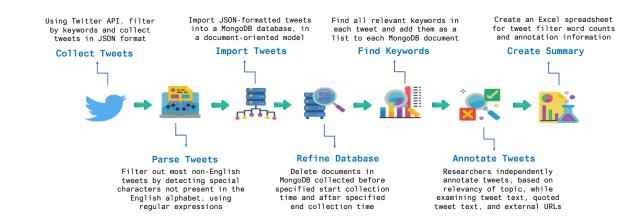
Experiments

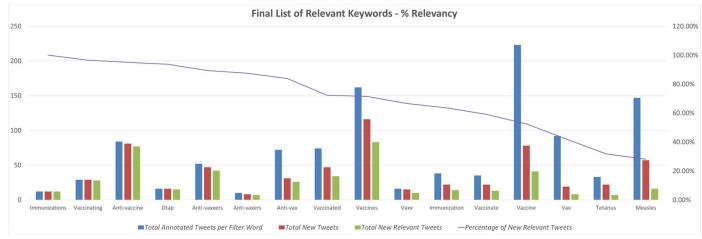
Goal: Find a comprehensive list of highly relevant keywords to create the best sample representing the diverse opinions of the public on vaccines.

Procedure:

- Collected tweets for 60 minutes filtering by a set K_{initial} of 83 keywords (such as "vaccine", "immunize", " MMR")
- The 60 minute collection yielded 7316 tweets, each containing one or more keywords.
- Each of 4 researchers analyzed the first 50 tweets for each keyword, annotating them as relevant or irrelevant to the topic of vaccines.
- All keywords which yielded less than 10 relevant tweets are discarded from the list of candidate relevant keywords:
 - $K = K_{initial} \{keyword with < 10 relevant tweets\}$
- Retain in K only keywords with 25%+ relevancy ratio, within the collection of tweets with full-agreement (either relevant or irrelevant) among all 4 annotators:
 - $K = K \{\text{keyword with } < 25\% \text{ relevant tweets} \}$
- Order remaining keywords by percent relevancy: K = (k₁, k₂, ..., k_n) ordered set.
- For each keyword k_i ∈ K, discard the tweets that were already relevant for any words k_i ∈ K, j<i.</p>
- This process gives the final relevancy ratio values and the final list of relevant keywords K_{final} (16 keywords).

Experiments Workflow





Future Work

- Upon completion of comprehensive list of most relevant keywords, collect new dataset and use it to build classification model to automatically assign tweets to one of 4 classes pro-vaccines, anti-vaccines, neutral, or irrelevant.
- ❖ Analyze spreading patterns of pro-/anti- vaccine tweets.

References

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