Tracking Social Media Movements with Dynamic Keyword Algorithm

Maya Srikanth[1,4], Nicholas Adams-Cohen[3,5], Anqi Liu[1,4], Jian Cao[2,4], Anima Anandkumar[1,4], R. Michael Alvarez[2,4]
Computing and Mathematical Sciences[1], Social Sciences[2], Immigration Policy Lab[3]
California Institute of Technology[4], Stanford[5]

Problem

- Social media debates are long term and dynamic
- Data collection methods relying on static keyword sets to pull data are quickly outpaced by conversation
- **We propose an algorithm** to track fast-changing social media discussions and **demonstrate** performance and results on #MeToo & Election Fraud data

Data and Method

- **2017 #MeToo:** historical data curated by Twitter using Boolean filtering
  - **Goal:** discover trending hashtags in monthly dynamic analysis and evaluate performance
- **2020 Election Fraud:** streaming API
  - **Goal:** discover relevant keywords in real time to include in streaming monitor

Dynamic Algorithm

- *Begin with initial keyword set s_0 at $t = 0$.*
- *Repeat until $t = T$:*
  - *Use keyword set s_t to stream dataset K_t.*
  - *Train GloVe on K_t to produce G_t, the embedding space of all dialogue.*
  - *For each word $s \in s_t$, find n closest neighbors via cosine distance.*
  - *Extract relevant terms from neighbors and filter outdated terms to produce s_{t+1}.*
  - *Set $s \leftarrow s_{t+1}$ and $t \leftarrow t + 1$.*

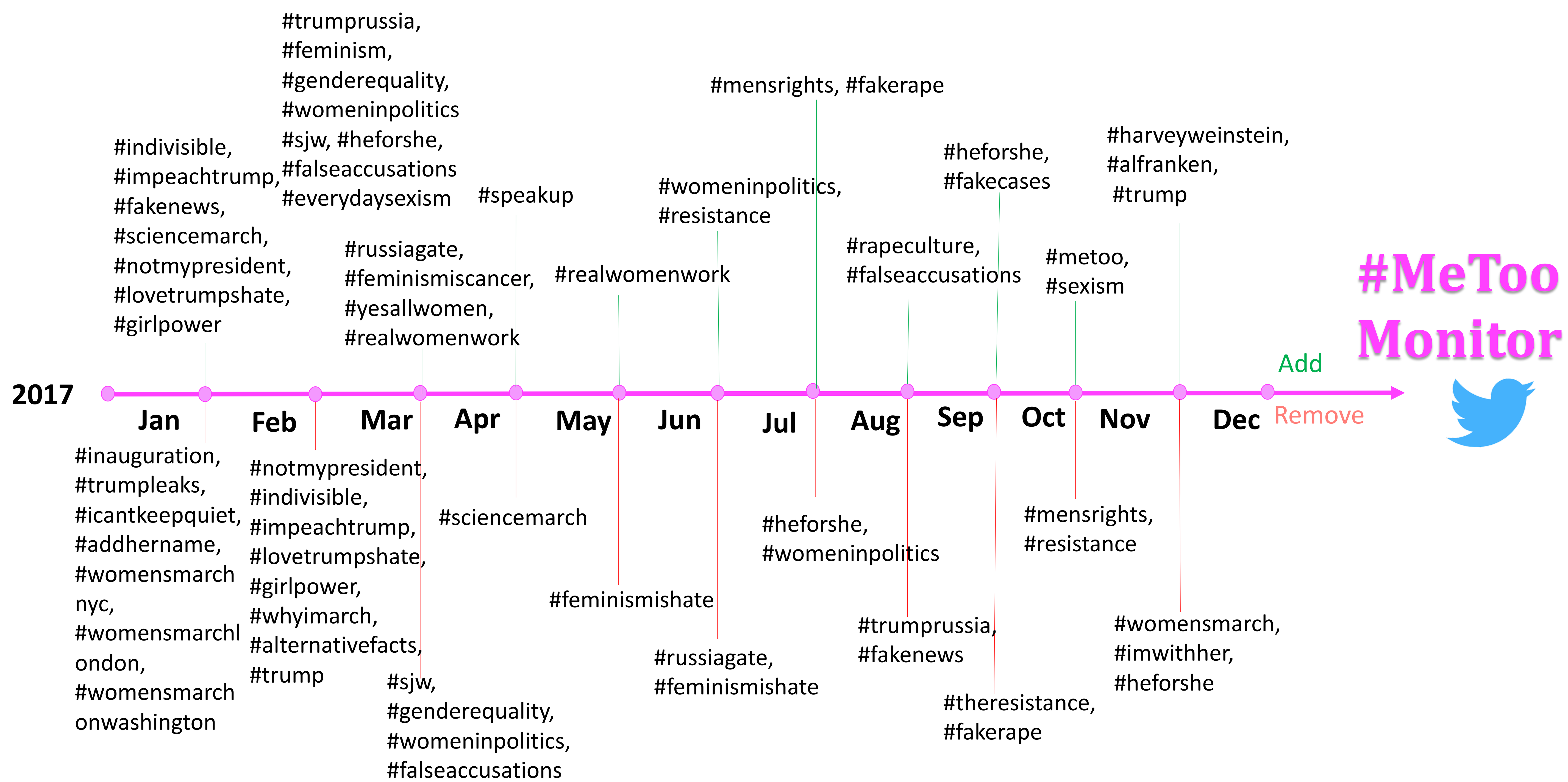

Figure 1. #MeToo Keyword Evolution. Evolution of keyword set (restricted to 15 keywords) in a simulation of the algorithm on historical 2017 #MeToo data. Choice of which terms to add or remove each month is based on an analysis of corpus frequency and cosine similarity as presented in Figure 2 below.

#MeToo Interface

Corpus Frequency	Cosine Distance	Neighbors
0.000040	0.259658	#theresistance
0.000391	0.259966	@potus
0.000013	0.282956	#potus
0.000137	0.296841	#maga
0.001361	0.305750	@realdonaldtrump
0.000063	0.309266	#resist
0.000000	0.324266	ityi
0.000010	0.328069	#alternativefacts
0.000021	0.334142	#resistance
0.000014	0.338640	#notmypresident
0.000002	0.340954	#trumpleaks
0.000007	0.359081	#inauguration
0.000015	0.373553	#womansmarch
0.000003	0.379256	#nodapl
0.000021	0.379575	#womensmarchonwashington
0.000000	0.386028	gnrtc

Figure 2. Interface for choosing neighbors in Dynamic Algorithm. Shown are the 15 closest words to "#trump" in Jan 2017 #MeToo data. "Corpus Frequency" is the proportion of corpus that contains the keyword.

Election Fraud Monitor

- **Noncitizen:** (@gatewaypundit, #stopthesteal)
- **Voting**: (mail, pandemic)
- **Rigged**: (scandal)
- **Voter**: (suppression, gerrymandering)
- **Voter intimidation**: (lynching, segregation, #antifathugs)
- **Voter Suppression:** (gerrymandering, racist)
- **Alien voting**: (#trumpisa, illegal, #unsc)

Figure 3. Election Fraud Discovered Keywords. Bolded words are original keywords, and words in parentheses are close neighbors discovered by the dynamic algorithm over a week's worth of data.

Performance of Dynamic Algorithm on Historical #MeToo Data

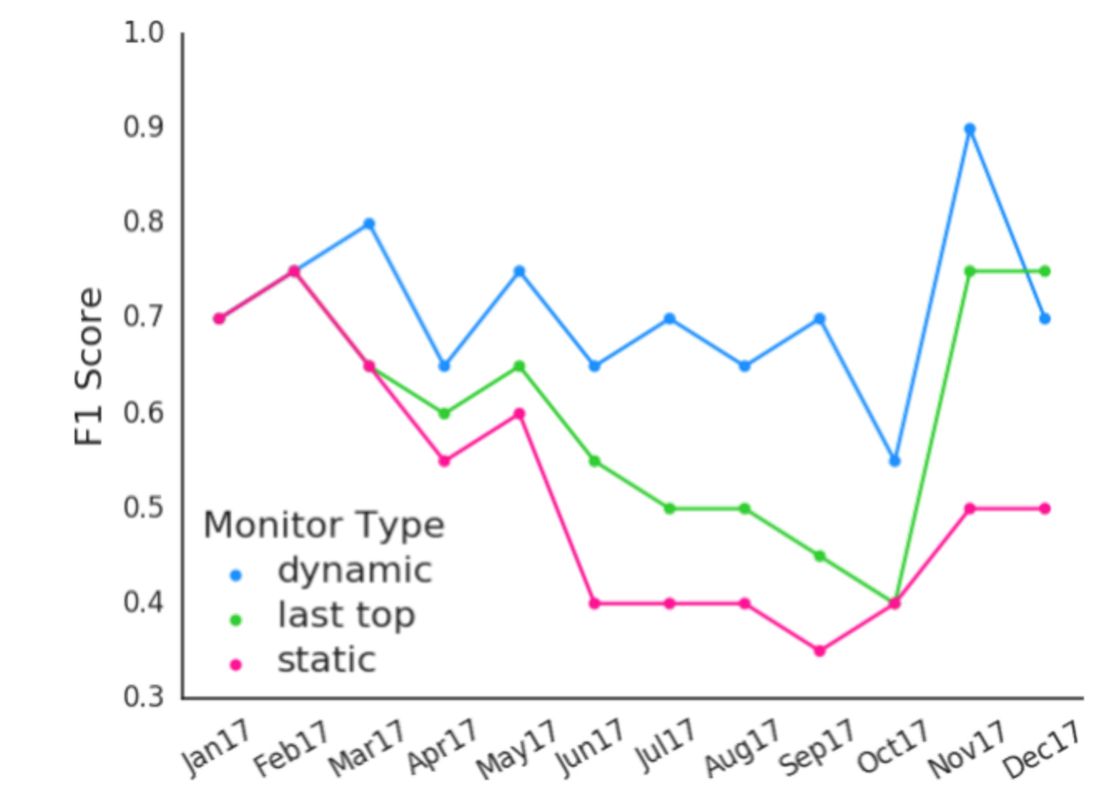

Figure 4. Performance of various monitors (including dynamic algorithm) on historical #MeToo data show in terms of F1 score with respect to target set of top 20 hashtags per month.

Figure 4 Monitor Types:

- **Dynamic** (see Dynamic Algorithm)
- **Last-top**: uses top 15 most frequent hashtags in previous month to pull data
- **Static:** uses top 15 hashtags in January to pull data throughout all months

Conclusion & Discussion

- Algorithm offers **12.5% improvement in F1 score** over conventional static data collection methods.
- Algorithm in the wild has the potential to uncover **new & meaningful** terms
- Working on ML-driven forecasting of trending hashtags for keyword selection.

Acknowledgements

- Special thanks to Oracle Cloud!