Dynamic topic modeling of the COVID-19 Twitter narrative among U.S. governors and cabinet executives

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Abstract
A combination of federal and state-level decision making has shaped the response to COVID-19 in the United States. In this paper we analyze the Twitter narratives around this decision making by applying a dynamic topic model to COVID-19 related tweets by U.S. Governors and Presidential cabinet members. We use a network Hawkes binomial topic model to track evolving sub-topics around risk, testing and treatment. We also construct influence networks amongst government officials using Granger causality inferred from the network Hawkes process.

Introduction
By mid-April 2020, the number of active COVID-19 cases has reached over 2 million and the number of deaths is over 140,000 world-wide. The United States has the largest share of confirmed cases (over 670,000) and confirmed deaths (over 27,000). Without a vaccine yet available, states throughout the U.S. are attempting to control transmission and reduce strain on the healthcare system through school and business closings, along with shelter-in-place orders. Careful planning and coordination is needed both to minimize risk from the disease, and to minimize the long-term economic impact.

In the U.S., a combination of federal and state-level decision making has shaped the country’s response to COVID-19. The response is quickly evolving, making it difficult to understand how decision makers have influenced each other, and whom among the decision makers have emerged as leaders on different topics. To overcome this difficulty, we analyze the Twitter narrative of various decision makers through dynamic topic modeling. Specifically, we analyze a dataset of all COVID-19 related tweets by U.S. Governors, the President, and his cabinet members between January 1st 2020 and April 7th 2020. We use a Hawkes binomial topic model (HBTM) (Mohler et al. 2016) to track evolving sub-topics around risk, testing and vaccination/treatment. The model also allows for estimation of Granger causality inferred from the network Hawkes process.

Hawkes Binomial Topic Model
We analyze COVID-19 related tweets by U.S. governors and cabinet members using a network Hawkes binomial topic model\(^1\) (HBTM) (Mohler et al. 2016) with intensity \(\lambda_s(t, \bar{m})\) at node \(s\) in the network determined by,

\[
\lambda_s(t, \bar{m}) = \mu_s(t)J_0(\bar{m}|p_0^s) + \sum_{t>t_i} \theta_{ss}, \omega_{ss}, e^{-\omega_{ss}(t-t_i)}J_i(\bar{m}, \bar{m}_s)p_{s, sf}^s p_{ss}^s.
\]

A Hawkes process is a model for contagion in social media where the occurrence of a post increases the likelihood of more posts in the near future. In the HBTM, tweets are represented as bags of words following a Binomial distribution. When viewed as a branching process, the daughter event bag of words is generated by randomly turning on/off parent words through independent Bernoulli random variables.

In Equation 1 events at time \(t_i\) are associated with a mark \(\bar{m}_i\), a vector of size \(W\), the number of words in the overall dictionary across events. The binary variables indicate whether each word is present or absent in the event at time \(t_i\). Spontaneous events occur according to a Poisson process with rate \(\mu_s(t)\) at node \(s\) in the network (here a node is either a governor or cabinet member). Unlike in (Mohler et al. 2016), we let the spontaneous rate vary in time to reflect the exponential increase in overall COVID-19 related Twitter activity (for estimation we use a non-parametric histogram). The mark vector of spontaneous events is determined by,

\[
J_0(\bar{m}|p_0^s) = p_0^s \sum_{j=1}^W m_j (1 - p_0^s)^{W-\sum_{j=1}^W m_j},
\]
which is the product of $W$ independent Bernoulli random variables with parameters $p^s_i$.

The parameter $\theta_{s_s'}$ determines the expected number of tweets by individual $s$ triggered by a tweet by individual $s'$ and can be viewed as a measure of influence. The expected waiting time between a parent-daughter event pair is given by $\omega_{s_s'}$. The mark of a daughter event is determined by two independent Bernoulli processes. Each word absent, or “turned off,” in the parent bag of words is added to the bag of words of the child event with probability $p^s_{on}$. Each word present in the parent bag of words is deleted with probability $p^s_{off}$. Thus $J_3$ is given by,

$$J_3(\vec{m}, \vec{m_i}|p^s_{off}, p^s_{on}) =$$

$$J_1(\vec{m}, \vec{m_i}|p^s_{off}, p^s_{on}) =$$

$$J_2(\vec{m}, \vec{m_i}|p^s_{off}, p^s_{on}) =$$

$$J_3(\vec{m}, \vec{m_i}|p^s_{off}, p^s_{on}) =$$

$$J_4(\vec{m}, \vec{m_i}|p^s_{off}, p^s_{on}) =$$

where $W_{1}^{\vec{m}, \vec{m_i}}$ is the number of words present in the child vector and absent in the parent vector, $W_{2}^{\vec{m}, \vec{m_i}}$ is the number of words absent in both vectors, $W_{3}^{\vec{m}, \vec{m_i}}$ is the number of words in the parent vector absent in the child vector, and $W_{4}^{\vec{m}, \vec{m_i}}$ is the number of words present in both vectors.

After removing stop words we restrict the dictionary to the $W$ most frequent words, on the order of several hundred most frequent words across tweets. The Model given by Eq. 1 can be viewed as a branching process and is estimated using Expectation-Maximization (EM) (Mohler et al. 2016). Using the EM algorithm for estimation has the added benefit that branching probabilities, estimates of the likelihood that tweet $i$ was triggered by tweet $j$, are jointly estimated with the model:

$$q_{ij} =$$

$$q_{ij} =$$

$$q_{ij} =$$

$$q_{ij} =$$

$$q_{ij} =$$

These branching probabilities can then be clustered to generate families of dynamic topics over time (Mohler et al. 2016).

**Related work**

We note that Hawkes branching point processes in general are a popular model for mimicking viral processes on social media. Previous studies have utilized temporal point processes to model Twitter (Zhao et al. 2015; Simma and Jordan 2012), Dirichlet Hawkes processes (Du et al. 2015; Xu and Zha 2017; Lai et al. 2014), joint models of information diffusion and evolving networks (Farajtabar et al. 2017), Hawkes topic modeling for detecting fake retweeters (Dutta et al. 2020), and Latent influencers are modeled in (Tan, Rao, and Neville 2018) using an Indian buffet Hawkes process. For a review of point process modeling of social media data see (Kim, Paini, and Jurdak 2020).

Compared to standard LDA-type Hawkes processes, the HBTM has the advantage that it jointly estimates a network that can be used to measure influence; additionally, HBTM automatically detects the number of clusters. The temporal aspect of HBTM-like dynamic topic models tend to improve topic coherence in relation to LDA (see Figure 2).

![Figure 1: In the HTBM, spontaneous events occur with marks generated by a binomial random variable over the dictionary of keywords contained in the data set. Events then trigger offspring events whose marks are generated by switching parent event words off (white circle) with probability $p_{off}$ and on (black circle) with probability $p_{on}$. Unique events are delineated with dashed lines. Clusters are groups of parent daughter events connected by triggering.](image)

![Figure 2: UCI coherence of HBTM vs. LDA when applied to COVID-19 related tweets by governors and cabinet members.](image)
assign tweets to the same group when a link between tweet $i$ and tweet $j$ is sampled. In Fig. 3, we show topic clusters over time consisting of more than 10 tweets. Each marker height represents the size of the cluster and the most frequent keywords per marker indicate the topics of the clusters.

The clusters show roughly four phases in time, with a significant gap between the first phase and the rest. In the first phase (early February), the federal government (most frequent handle @SecAzar, Alex Azar, Sec. of Health) informed the public of the outbreak in China and claimed to closely monitor the situation. Also in this phase several state governors (most frequent handle @NYGovCuomo, Andrew Cuomo, Gov. of New York) started reporting confirmed cases, but stated that the risk was low, as the number of cases was limited.

The second and the third phases (early March) appeared almost a month later. From the keywords in these two phases, we can see that the government started to take action to protect the American citizens (possibly overseas in the regions of the outbreak). We can also see that live updates and press conferences were given to brief the public. Keywords like spread and emergency indicate that the outbreak was getting worse in the U.S. Meanwhile, the keyword test was mentioned frequently alongside laboratory, as limitations in U.S. testing was driving some of the narrative.

The fourth phase starts around mid-March, when clusters became larger and denser. In this phase, live updates were held by many governors on a regular basis (the highest peak in Fig. 3). We also see the separation between the federal and state governments, as the clusters divided into government, administration, america and the various states (maryland, ohio, louisiana, arizona, indiana). The Louisiana governor John Bel Edwards (@LouisianaGov) and the Ohio governor Mike DeWine (@GovMikeDeWine) were among the most active on Twitter sending information to the people in their respective states.

The topic of risk appears in this phase, and the message is that risk remains low. New topics also emerged on social distancing policies such as school close, stay home, and work (from) home. During the third phase the government began addressing problems like healthcare for workers and families, and loan(s) for small businesses due to the impact of the pandemic. The slogan socialdistancing was widely adopted in this phase.

In the most recent phase, a cluster with frequent words live update, press conference, and briefing is the largest, alongside a narrative around the number of tested, confirmed positive and death cases in different states. The Louisiana and Ohio governors continued to be the most active. Also small businesses remained a concern during this phase and the keyword disaster indicates the negative impact of COVID-19. Meanwhile, quarantine and stay home were encouraged and reiterated on Twitter. The sacrifices of health workers were acknowledged (thank).

In Figure 4, we show inferred influence among governors and cabinet members by plotting a network where each edge weight from $i \rightarrow j$ is determined by the total estimated number of tweets triggered at node $j$ by tweets from node $i$. 
Figure 5: Spontaneous vs. triggering effects of politicians on Twitter. Vertical axis: base intensities (spontaneous) and effective influences (triggering) are normalized over politicians; horizontal axis: Twitter handles of politicians. To save space, vertical axis is truncated at 0.08, rendering President Trump’s spontaneous rate off the chart (~ 0.16).

The network shows influence across party lines, with Democrat governors GovNedLamont, GovernorTomWolf, GovMurphy and LouisianaGov highly connected with Republican governors GovRicketts, GovLarryHogan and GovParsonMO. We caution that this network captures Granger causality (Xu, Farajtabar, and Zha 2016), and does not control for confounding effects. In Figure 5, we plot the estimated baseline rate of spontaneous tweets per governor and cabinet member (i.e. $\mu_s(t)$ averaged across time), along with each individual’s estimated influence (average number of subsequent tweets in the network directly triggered by a Tweet, i.e. $\theta_{ss}'$ summed over $s'$ and scaled by the number of tweets by $s$). Here we observe that President Trump has the highest rate of spontaneous tweets, followed by the Governor of Hawaii and Secretary Azar. Governors Ducey, Wolf and Lamont are the largest estimated influencers.

Risk, treatment and testing sub-topics
In addition to applying the HBTM to all COVID-19 related tweets, we also apply the model separately to three sub-categories. We first apply HBTM to tweets containing the word “risk”. A sequence of clusters are illustrated in the top row of Fig. 6. The emergence of this sub-category coincides with the start of the second phase of the general timeline, and it appears that the CDC was among the first to mention how serious the risk was and asked for immediate actions. However, the subsequent clusters in early March indicate that both state and federal governments (Republicans and Democrats) were telling the public that the risk remains low. Also in this period, we observe calls for washing hands to reduce risk, and that seniors were identified to be the most vulnerable. After March 15, the narrative changes and the high risk to the general population is acknowledged. Keywords like age and adult indicate the high risk across age groups, even for young adults. The word high frequently co-occurs with test and quarantine; due to the high risk of transmission, state governments increased testing and enforced quarantine(s). Overall, from left to right, the sequence of clusters show a clear trend in the narrative from low risk in late February to high risk in April.

Next, we apply HBTM to tweets containing the words “vaccine” and “treatment”. The resulting clusters are illustrated in the middle row of Fig. 6. In mid-March, keywords launch, trial, clinicaltrial, phase, and candidate indicate that vaccine candidates were identified and entered the clinical trial phase. We can also see the National Institute of Health (NIH) partner with the pharmaceutical industry in developing the vaccine. Later in March, we start to see clusters where state governors (mainly Democrats) commented on the lack of resources, equipment, ventilators, and hospital beds. We also see cabinet members (specifically Sec. of Health @SecAzar) giving updates about vaccine development (genetic sequence and clinical trial). Another narrative is around an agreement (agree) with insurance companies to ease the burden of the pandemic on their customers. Additionally, we see the request to create global researcher team in developing a vaccine. In general, the clusters here suggest that the search for a vaccine has been a collective effort that crosses political parties and national boundaries.

In the bottom row of Fig. 6, we show clusters found by applying HBTM after filtering the dataset on the keyword “test”. In early March, we see that new test kits were available. Tweets mention (negative) test results of some individuals by the Democrat governors and cabinet members. Concern about the capacity of testing facilities and hospitals is also discussed in early March. In mid-March, testing is ex-
Figure 6: Timeline of sub-topics on risk, treatment and testing. Clusters with size at least 2 are pinned. Keywords indicate the topic of the clusters. The marker color indicates the dominant component of the cluster.

Table 1: Officials ranked by in-degree (most influenced) and out-degree (most influential) in influence networks.

| Topic   | In-degree             | Out-degree                     |
|---------|-----------------------|--------------------------------|
| all     | GovMurphy, GovRicketts, LouisianaGov | GovNedLamont, GovMurphy, GovMLG |
| risk    | GovMikeDeWine, NYGovCuomo, GovMLG | GovMikeDeWine, GovPritzker, SecAzar |
| treatment | SecAzar, GovNedLamont, GovofCO | GovofCO, GovChrisSununu, GovNedLamont |
| test    | GovNedLamont, GovMikeDeWine, LouisianaGov | NYGovCuomo, GovHerbert, GovKemp |

In Figure 7, we plot Granger causality influence networks for the risk, treatment and testing sub-topics. Again we see connections crossing party lines. In the case of testing, the network is characterized by a dense set of connections between a select set of governors. The risk and treatment networks are characterized by more active nodes with fewer connections. In Table 1 we also list the most influential officials by sub-topic along with those officials most influenced.

**Conclusion**

We analyzed the COVID-19 Twitter narrative among U.S. governors and presidential cabinet members using a Hawkes binomial topic model. We observed several narratives between January 1st and early April 2020, including a shift in the assessment of risk from low to high, discussion of a lack of testing resources which later subsided, and sub-topics around the impact of COVID-19 on businesses, efforts to create treatments and a vaccine, and calls for social distancing and staying at home. We also constructed influence networks amongst government officials using Granger causality inferred from the network Hawkes process. President Trump stands out for spontaneity, yet appears to have little influence with respect to network cross-excitation. Polarization is not obvious in the Granger influence networks; we observe a high level of cross party event triggering and influence seems more geographically clustered and related to state size.

We see several potential directions for future work. Here we limited the analysis to only COVID-19 related tweets among U.S. government officials. The HBTM can be used to
explore the COVID-19 narrative among the general population and may highlight issues around trust in institutions, adherence to social distancing, and economic impacts. Furthermore, analyzing non-COVID related tweets by government officials prior to the pandemic and constructing an evolving influence network may provide insights into how bi-partisan cooperation changes during national emergencies.

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References
Buntain, C.; McGrath, E.; and Behlendorf, B. 2018. Sampling social media: Supporting information retrieval from microblog data resellers with text, network, and spatial analysis. In Proc. of the Hawaii Intl. Conf. on System Sciences.

Cinelli, M. e. a. 2020. The covid-19 social media infodemic. arXiv:2003.05004.

Du, N.; Farajtabar, M.; Ahmed, A.; Smola, A. J.; and Song, L. 2015. Dirichlet-hawkes processes with applications to clustering continuous-time document streams. In Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 219–228. ACM.

Dutta, H. S.; Dutta, V. R.; Adhikary, A.; and Chakraborty, T. 2020. Hawkseye: Detecting fake retweeters using hawkes process and topic modeling. IEEE Transactions on Information Forensics and Security.

Farajtabar, M.; Wang, Y.; Gomez-Rodriguez, M.; Li, S.; Zha, H.; and Song, L. 2017. Coevolve: A joint point process model for information diffusion and network evolution. The Journal of Machine Learning Research 18(1):1305–1353.

Kim, M.; Paining, D.; and Jurdak, R. 2020. Real-world diffusion dynamics based on point process approaches: A review. Artificial Intelligence Review 53(1):321–350.

Lai, E.; Moyer, D.; Yuan, B.; Fox, E.; Hunter, B.; Bertozzi, A. L.; and Brantingham, J. 2014. Topic time series analysis of microblogs. Technical report, DTIC Document.

Mohler, G.; Buntain, C.; McGrath, E.; and LaFree, G. 2016. Hawkes binomial topic model with applications to coupled conflict-twitter data. DOI: 10.13140/RG.2.2.13638.83527.

Simma, A., and Jordan, M. I. 2012. Modeling events with cascades of poisson processes. arXiv preprint arXiv:1203.3516.

Tan, X.; Rao, V.; and Neville, J. 2018. The indian buffet hawkes process to model evolving latent influences. In UAI, 795–804.

Thelwall, M., and Thelwall, S. 2020a. Covid-19 tweeting in english: Gender differences. arXiv:2003.11090.

Thelwall, M., and Thelwall, S. 2020b. Retweeting for covid-19: Consensus building, information sharing, dissent, and lockdown life. arXiv:2004.02793.

Xu, H., and Zha, H. 2017. A dirichlet mixture model of hawkes processes for event sequence clustering. In Advances in Neural Info. Processing Systems, 1354–1363.

Xu, P.; Dredze, M.; and Broniatowski, D. A. 2020. The twitter social mobility index: Measuring social distancing practices from geolocated tweets. arXiv:2004.02397.

Xu, H.; Farajtabar, M.; and Zha, H. 2016. Learning granger causality for hawkes processes. In International Conference on Machine Learning, 1717–1726.

Yin, F.; Lv, J.; Zhang, X.; Xia, X.; and Wu, J. 2020. Covid-19 information propagation dynamics in the chinese sina-microblog. Math. Biosciences and Eng. 17(3):2676.

Zhao, Q.; Erdogdu, M. A.; He, H. Y.; Rajaraman, A.; and Leskovec, J. 2015. Seismic: A self-exciting point process model for predicting tweet popularity. In Proceedings of the 21th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 1513–1522. ACM.