Influence Dynamics Among Narratives: A Case Study of the Venezuelan Presidential Crisis

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Influence Dynamics Among Narratives

Motivation

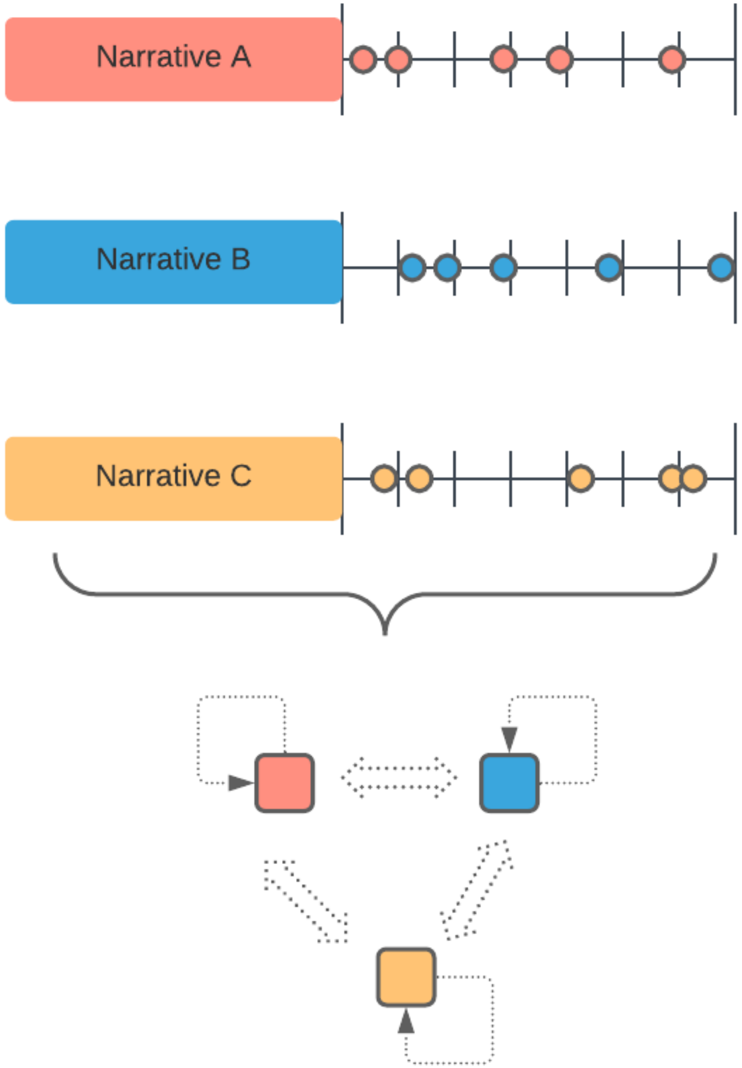
- Given the evident importance of social media on the Venezuelan Presidential crisis [1], we want to characterize how narratives influence each other through Twitter discussions.

Outcomes

- Provided an interpretable and unambiguous representation of these influences via Process Influence Measures (PIMs) by modelling data with a multi-variate point process.
- Interpreted co-evolving influences among narratives under the prism of Granger Causality.

Conclusions

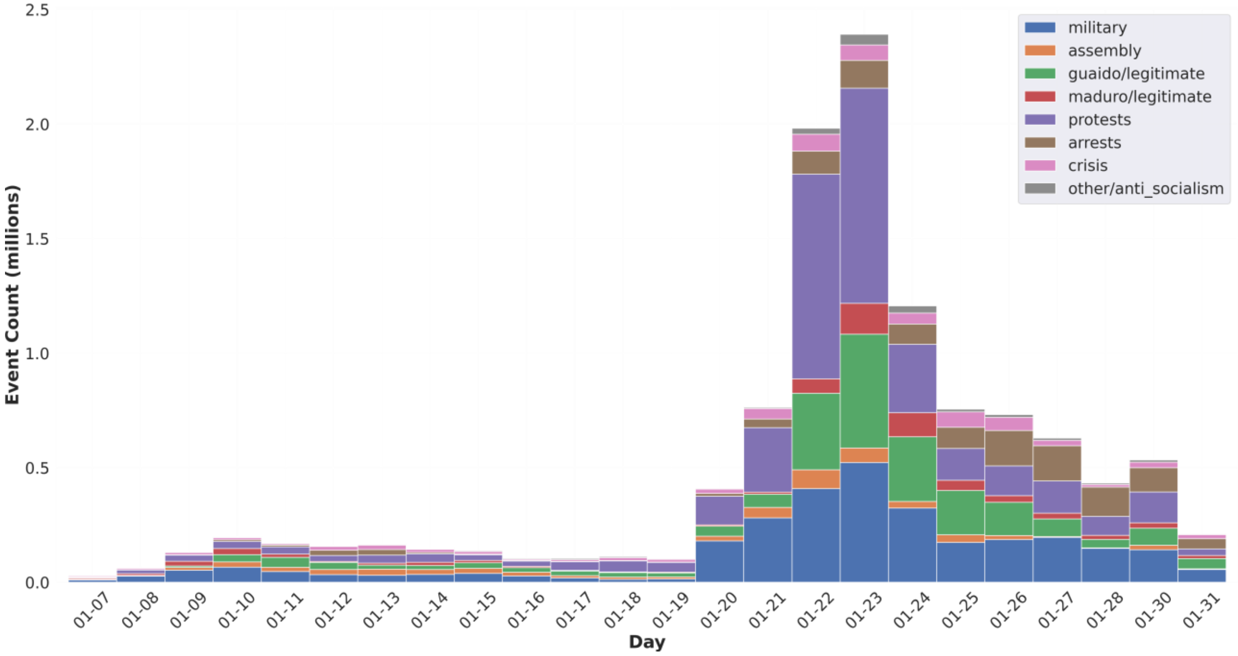
- Strong influences attributed to landmark events.
- Causal influences, if they exist, can be determined.
- We can provide social scientists and analysts with a tool to better understand socio-political phenomena.



Data

- Venezuelan Presidential Crisis
  - Began January 10th after inauguration of Nicolás Maduro following a widely disputed election on May 2018.
  - Escalation after Juan Guaidó declared himself interim president on January 23rd .
  - There was participation both by domestic and international parties.

- Data provided by Leidos.
  - **Over 7 million tweets** from December 25th to February 1st.
  - Over 1 million unique users.
  - Each tweet labelled with possibly multiple narratives.
  - Only considered narratives present in at least 100k tweets, 8 narratives.



Narrative Annotation

Annotation Strategy

- Non-Negative Matrix Factorization (NNMF) to obtain narratives [2].These narratives were then refined and formalized by Subject Matter Experts (SME) [3].
- A subset of the tweet were manually annotated with narratives by SME.
- These manually annotated tweets were used to train a BERT-based multilingual cased multi-label classification model [4].
- Narrative based model produced an aggregate light's kappa score of 0.64.

High level observations

- Tweets about Protest and Military dominate.
- Assembly, arrests and protests are strongly anti-maduro.

Table 1. Stance distribution per narrative of the Venezuela Twitter data.

Narrative	Total Tweets	% anti-Maduro	% pro-Maduro
military	1,534,242	67.38	21.87
assembly	252,448	95.79	1.82
guaido/legitimate	1,014,726	95.43	3.02
maduro/legitimate	304,127	2.92	96.72
protests	1,746,615	85.87	2.42
arrests	570,574	97.73	0.74
crisis	305,291	73.25	3.58
anti-socialism	101,716	78.04	14.77

Methodology: Process Dynamics

- Dynamics of tweets are modelled as a Multi-Variate Hawkes Process (MVHPs) [5]
  - A system of univariate Hawkes processes with a process per narrative.
  - The process is uniquely identified by its conditional intensity function $\lambda_i(t \mid \mathcal{H}_{t^-})$.

$$\lambda_i(t \mid \mathcal{H}_{t-}) = \lim_{h \to 0} \frac{\mathbb{E}\{N(t+h) - N(t) \mid \mathcal{H}_{t-}\}}{h}$$

- **Constructing the intensity function**
  - Base intensity --- background influences
  - Self-excitation --- narratives influencing themselves
  - Mutual-excitation --- narratives influenced by other narratives

$$\lambda_i(t \mid \mathcal{H}_{t-}) = \boxed{b_i(t)} + \boxed{a_{i,i} \sum_{t_k^i \in \mathcal{H}_{t-}^i} \phi_{i,i}(t - t_k^i)} + \boxed{\sum_{\substack{j \in \mathcal{P} \\ j \neq i}} \alpha_{i,j} \sum_{t_k^j \in \mathcal{H}_{t-}^j} \phi_{i,j}(t - t_k^j)}$$

- Key assumption
  - Each event generated is attributed to a single cause.

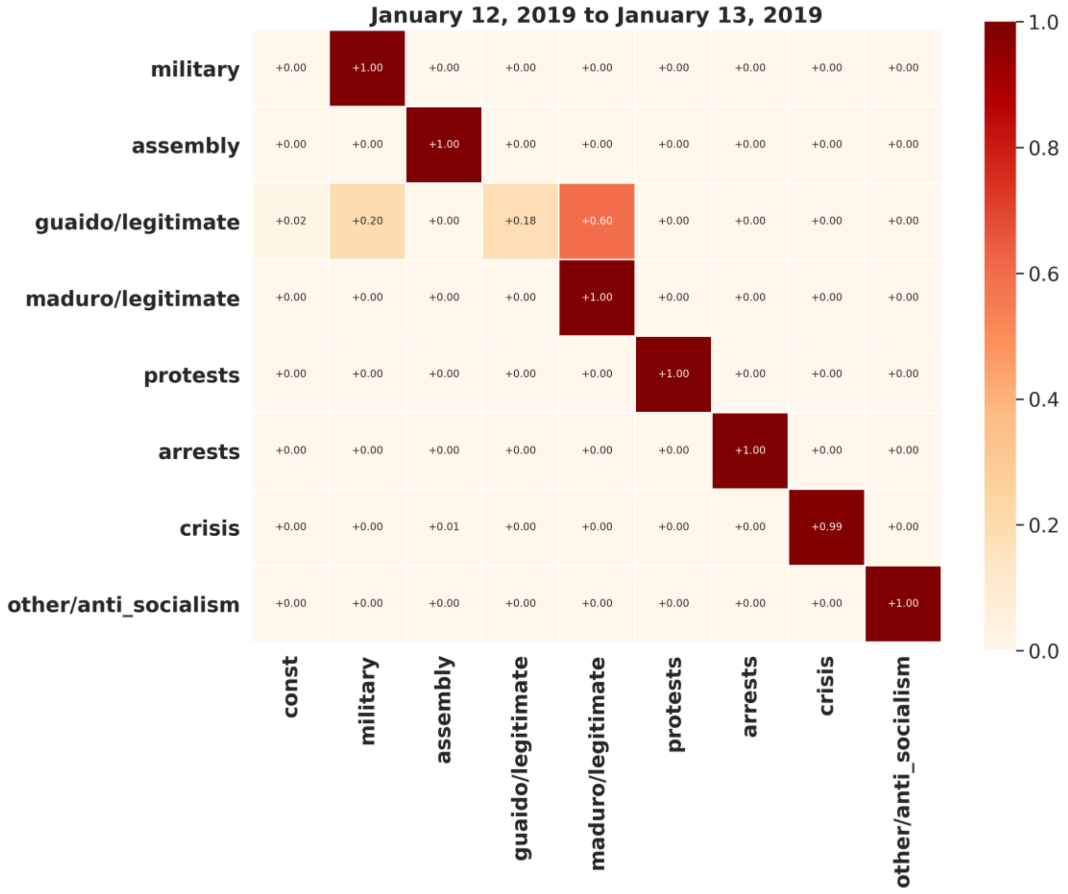
Methodology: Granger Causality for point processes

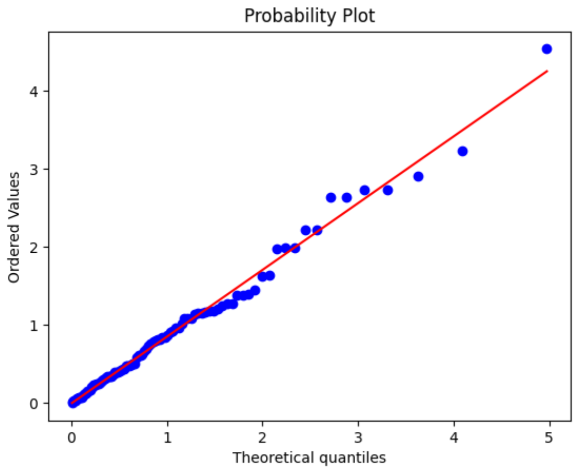
- Granger Causality is established for point processes if $\alpha_{i,j} > 0, a_{i,i} > 0$.
- Alpha values by themselves are devoid of meaning, since their nature of influence depends on
  - Memory kernel choices.
  - Timestamps and volume of events.
- **Process Influence Measures (PIMs):**
  - Provide an un-ambiguous and interpretable representation of intra & inter-narrative influence.
  - Identify, for each event, the narrative that is the **most likely theorized** cause.
  - Estimate probability that event of narrative j influences events of narrative i.
  - Obtained via frequency counts of probabilities for each potential parent j.

$$\mathbb{P}\left\{E_k^i \text{ was caused by any earlier event in } \mathcal{E}^j\right\} = \frac{a_{i,j} \sum_{t_\ell^j \in \mathcal{H}^j_{t_k^i -}} \phi_{i,j}(t_k^i - t_\ell^j)}{\lambda_i(t_k^i \mid \mathcal{H}^i_{t_k^i -})}$$

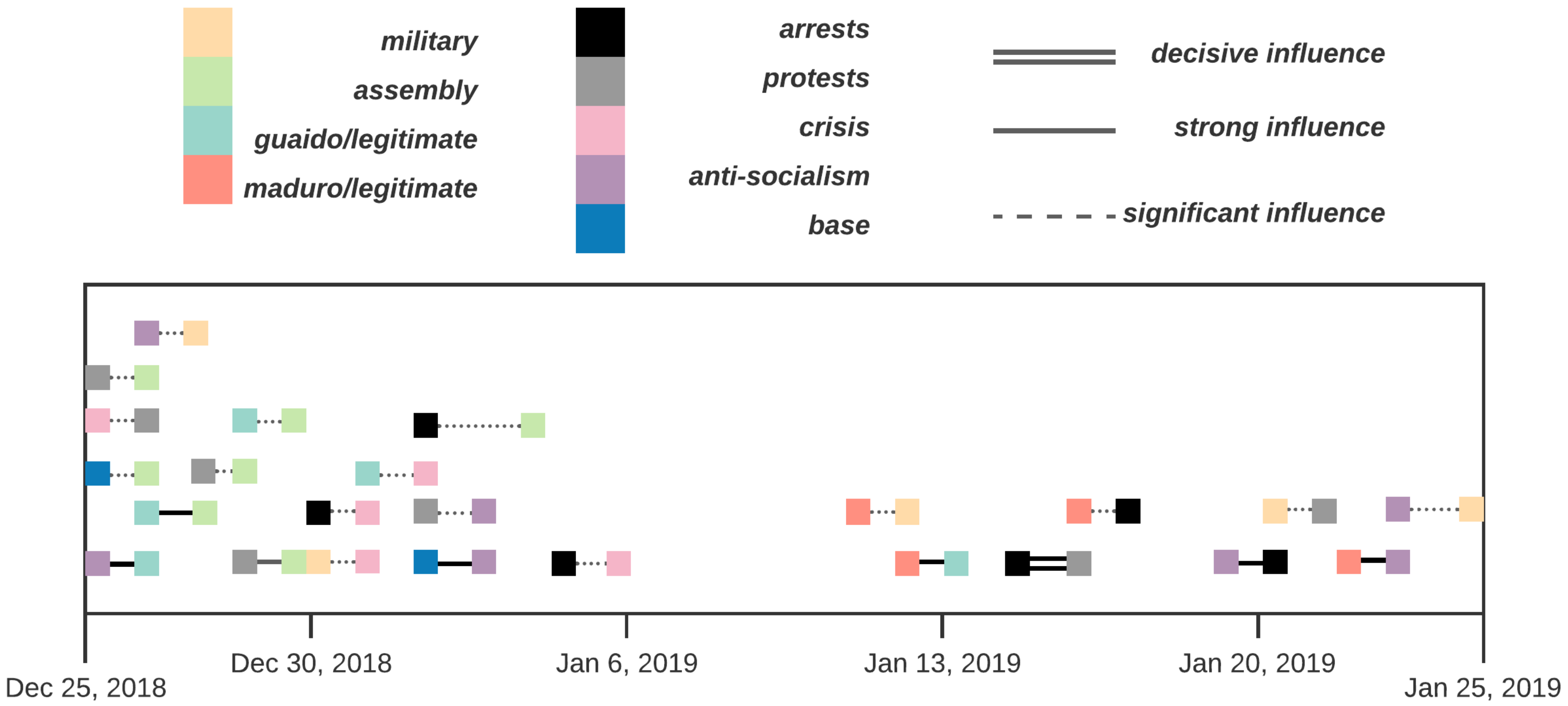
Case Study: Venezuelan Presidential Crisis

- We trained a MVHP on overlapping 2-day windows across the time period of interest until a reasonably good fit was attained.
- Each window produced a trained model with parameters, which were then used to build PIM heatmaps.
- For ease of interpretation, we associated PIM values with keywords: significant – (0.2, 0.6] , strong – (0.6, 0.99] and decisive (.99,1].
- The overarching trend was self-excitation, with some notable exceptions.
- *Maduro/legitimate* is never influenced by any other narrative.





Case Study: Venezuelan Presidential Crisis



Results: Venezuelan Presidential Crisis

Some observations from PIMs

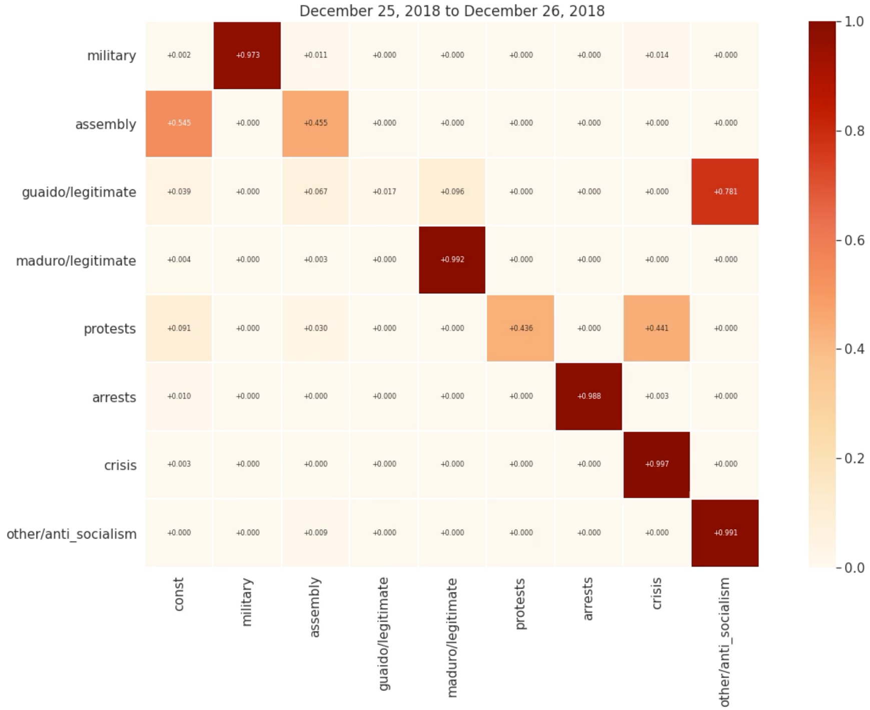
- 25th – 26th December, *anti-socialism* strongly influences *guaido/legitimate;* before the crisis began.
- 11th – 12th January, *maduro/legitimate* significantly influences *military;* after the first open cabildo.

VENEZUELA

Asamblea Nacional se declaró en emergencia y convocó a cabildo abierto

Directiva de la AN se pronunció este jueves tras juramentación de Maduro / Foto: Twitter

Video



Results: Venezuelan Presidential Crisis

- 12th – 13th January, *maduro/legitimate* significantly influences *guaido/legitimate;* coincides with Guaidó's arrest.
- 14th – 15th January, arrests decisively influence protests.

The New York Times

Venezuela Opposition Leader Is Arrested After Proposing to Take Power

- 20th – 21st January, *military* significantly influences *protests;* overlaps with when military members rose against Maduro, followed by widespread protests.
- 24th – 25th January, *anti-socialism* significantly affect *military;* wake of protests calling for military to relinquish allegiance to Maduro.

Venezuela protests: thousands march as military faces call to abandon Maduro

Tens of thousands protest against Nicolás Maduro after disputed elections, bolstered by support from international governments

▲ Juan Guaido declares himself "acting president" during a rally against leader Nicolas Maduro. Photograph: Federico Parra/AFP/Getty Images

Tens of thousands of Venezuelans have taken to the streets of the country's capital in what opponents of Nicolás Maduro hope will prove a turning point for the country's slide into authoritarianism and economic ruin.

Contributions

- We presented a tool for **exploratory analysis** of **inter-/intra-narrative influences** using point processes.
- We proposed **Process Influence Measures** (PIMs) as an **interpretable representation of influences** for point processes.
- Regarding the **Venezuelan Presidential Crisis**.
  - We illustrated the utility of PIM evolution in understanding inter-narrative influence.
  - Landmark events during the Venezuelan Presidential crisis potentially trigger cross-narrative influences of interest, warranting further investigation.

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Thank you for your time

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- Contact: aaravamudan2014@my.fit.edu

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BACKUP SLIDES

Backup: Training

- Assumptions
  - Memory kernel function $\phi_{i,j}$ (t) --- Exponential kernel. i.e., each event's influence decays exponentially.
  - Additive influences from base, self-excitation and mutual excitation.
  - $\alpha_{i,j} \geq 0, a_{i,i} \geq 0.$

Granger Causality

- **Definition:**

  Granger causality is a predictive causality; if history of process A is useful in predicting process B, then A Granger causes B.

- Basic principles:
  - The cause happens prior to effect,.
  - The cause has unique information to contribute to the effect.

- Autoregressive models for example can also be used to infer Granger Causality.

"A better term might be *temporally related*, but since cause is such a simple term, we shall continue to use it "

- Clive Granger

Backup: Going from Granger Causality to Causality

- Such claims concerning Granger causality can guide analysts establish causality.
- Human-in-the-loop is <u>essential</u> to validate claims of causality.
  - Subject Matter Experts (SMEs) can decide to include other potential exogenous influence to verify causality and to put in context.
- If there exists overwhelming causal links (or lack thereof), this model can find them.
- It is up to the SME to discard links (or explain it’s presence) based on real-world evidence and update the model.
- This model does not intend to replace the social scientist or analyst, rather aid them.

Future Work

Future Work

- Incorporate
  - Exogenous events of potential relevance (e.g., oil prices and news articles)
  - User stances (e.g., pro- or anti-Maduro)
- Investigate coordinated inauthentic behavior and evaluate influence of Information Operations (IO) and platform manipulation
  - Can we disentangle inauthentic behavior from these messages ?
  - Are there consistent messages that can be captured by language models ?