Describing information influence in social media with coupling inference methods

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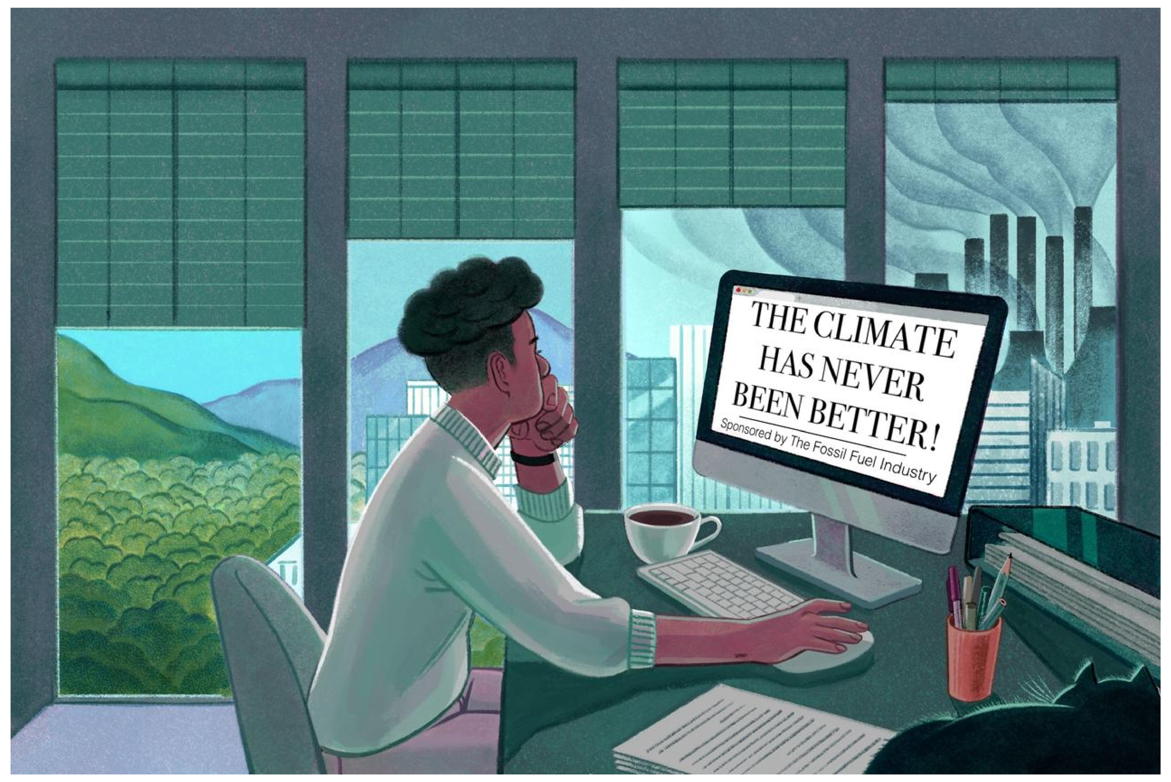
Abstract

Based on the news sources shared on Twitter, this work focuses on leveraging coupling inference methods between time series of user activity to understand the dynamics of influence on social media. We build graphs representing different influence relationships between users and define influence measures relating to new and existing concepts in social media influence from those. We find that our methods allow us to detect users who spread more disinformation than average. We compare several influence measures and discover that they are only weakly correlated, implying that they do not capture the same influence types, but are complimentary.

Introduction

- Quantifying influence between users on social media is an inherently difficult task, but essential in order to detect and counter disinformation.
- Disinformation/misinformation (about climate change) is very frequent on social media. Malicious governments/companies/institutions/individuals use such platforms to spread their message.
- An increasing number of people tend to rely almost exclusively on social media for getting news [5, 7].
- Misinformation about climate change has confused the public, led to political inaction, and stalled support for or led to rejection of mitigation policies [3].
- Recommender systems used in social media platforms further help the propagation of misinformation [2] and the creation of echo chambers.



Motivation

- Create a system able to capture influence attempts relating to (climate change) disinformation between users on Twitter.
- Derive new influence measures describing the amount of disinformation shared by the users on Twitter.

Methodology

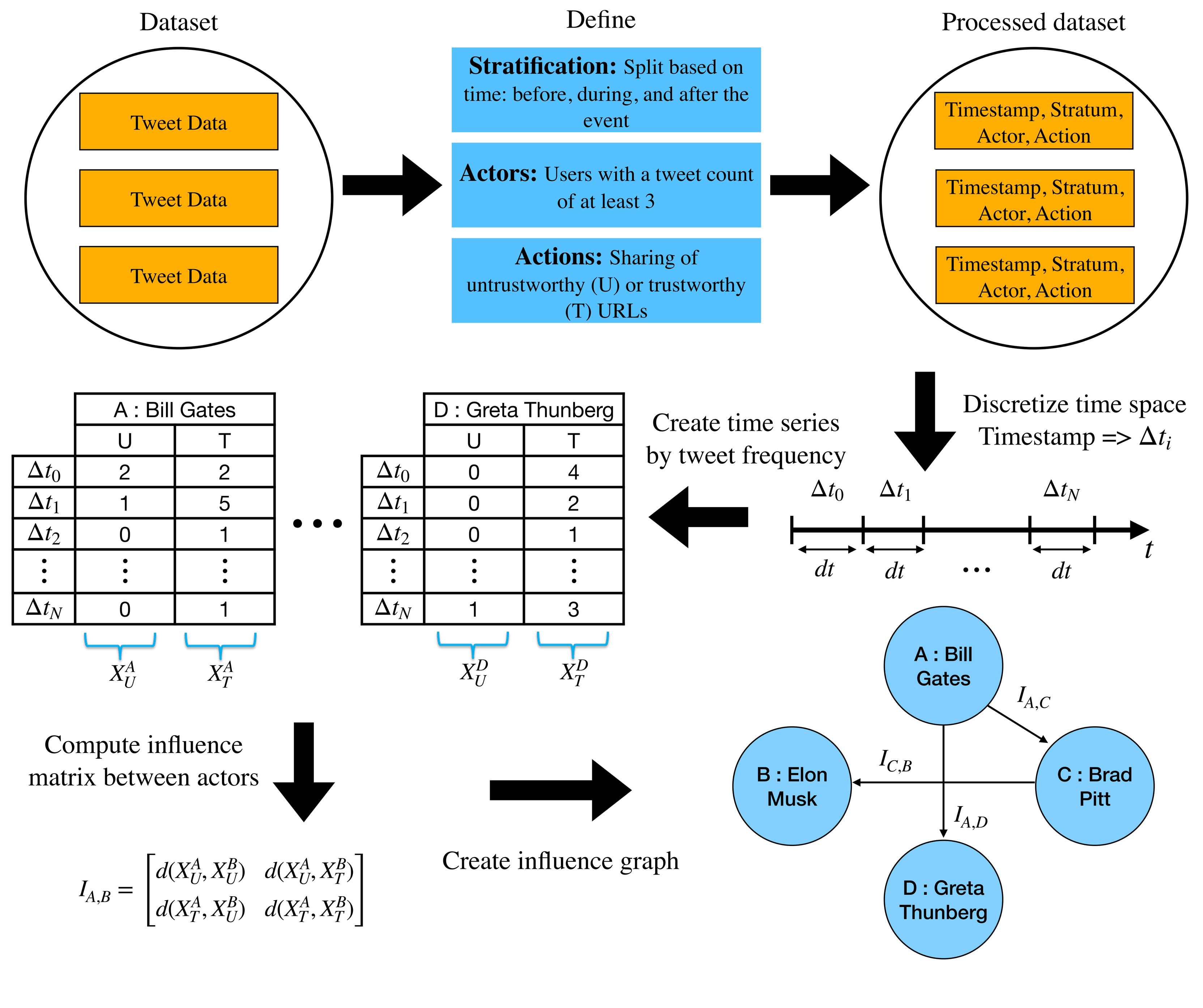


Fig. 2: Influence graph creation pipeline from a dataset of tweets.

Figure 2 presents our method to derive influence graphs. We consider 2 coupling inference methods (function $d(\cdot, \cdot)$ in the pipeline flow chart): **Transfer Entropy** (TE) [6] and **Joint Distance Distribution** (JDD) [1].

Influence measures and datasets

From the influence graphs, we derive influence measures based on topology:

- **outdegree**: for each node (actor) in the influence graph, outdegree directly indicates how many other actors this actor influenced.
- **betweenness**: the betweenness centrality measures how important a node is in the graph, in the sense of shortest path to every other node. In our case, it is an indication of how well one actor serves as a bridge to influence many other users.

These measures can be fine-grained and derived for each edge type in the graph (**Trustworthy** (T) or **Untrustworthy** (U) action combinations).

We use our methods on the following datasets:

- **COP26:** all climate related tweets containing a URL around COP26.
- **COP27:** all climate related tweets containing a URL around COP27.
- **Skripal:** all tweets related to the Skripal poisoning in 2018. It is a well known case of disinformation campaign. Used for comparison to a known case.

Results

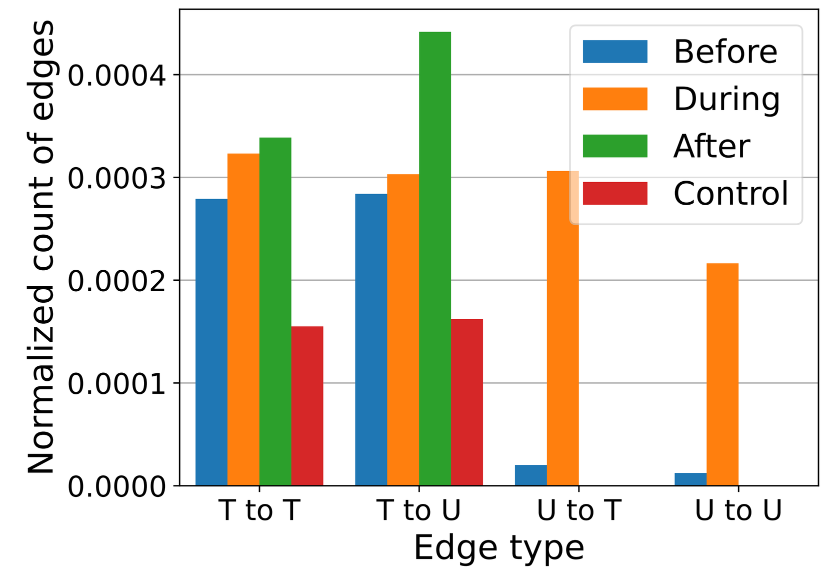


Fig. 3: Normalized count of each edge type for the COP26 dataset.

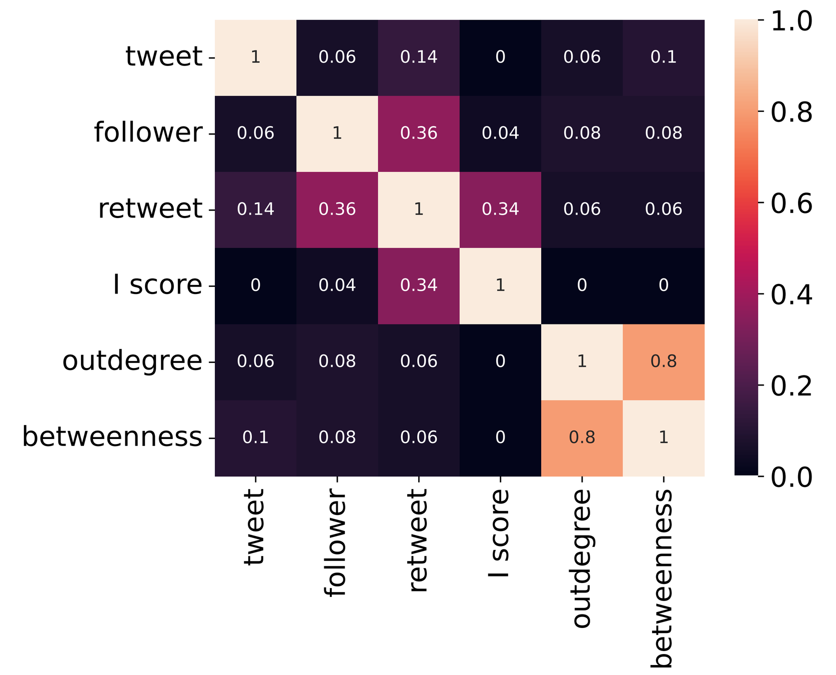


Fig. 4: Correlation matrix for all influence measures (for the COP26 dataset).

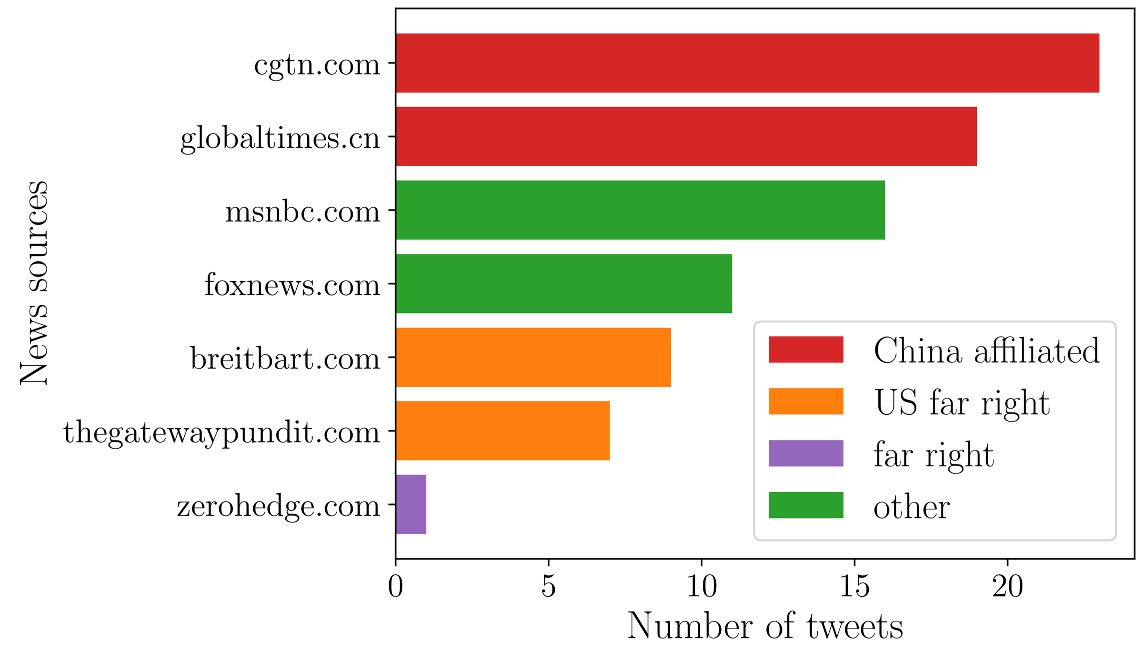


Fig. 5: URL domains shared by the 5 most influential users according to our new influence measures (COP26 dataset).

Conclusion

- Large spikes of influence of the untrustworthy-untrustworthy type during COP26. This provides potential evidence of a disinformation campaign.
- Influence measures are weakly correlated between themselves. Only outdegree and betweenness exhibit relatively high correlation.
- Our method detects users influencing others by posting large amounts of content from China-affiliated or far-right-affiliated news outlets.

References

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