Master in Computational Science and Engineering
Mathematics Section, EPFL

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Describing information influence in social media with coupling inference methods

Master Thesis Defense

March 6th, 2023

Ecole Polytechnique Fédérale de Lausanne,
Massachusetts Institute of Technology

STUDENT

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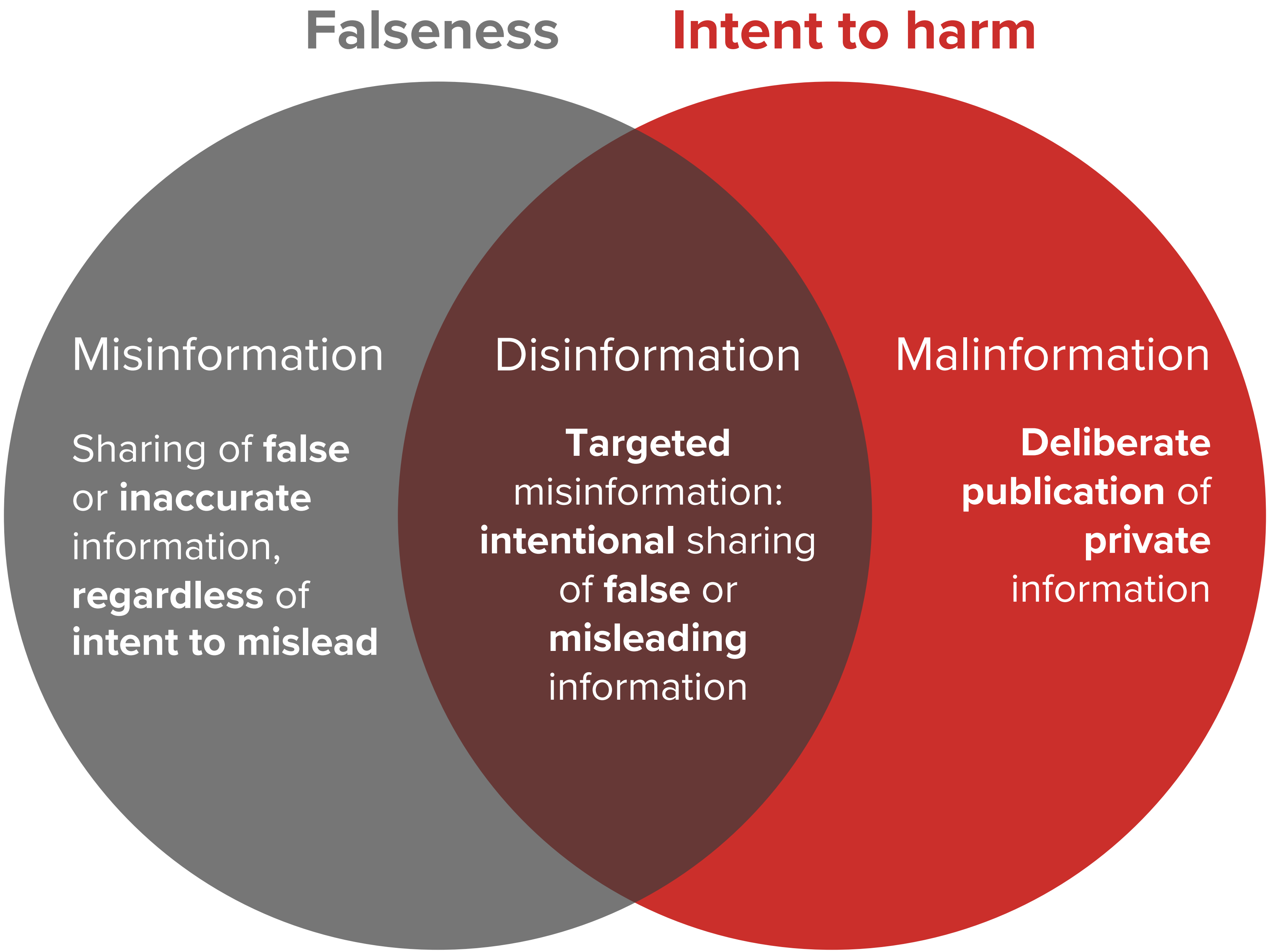
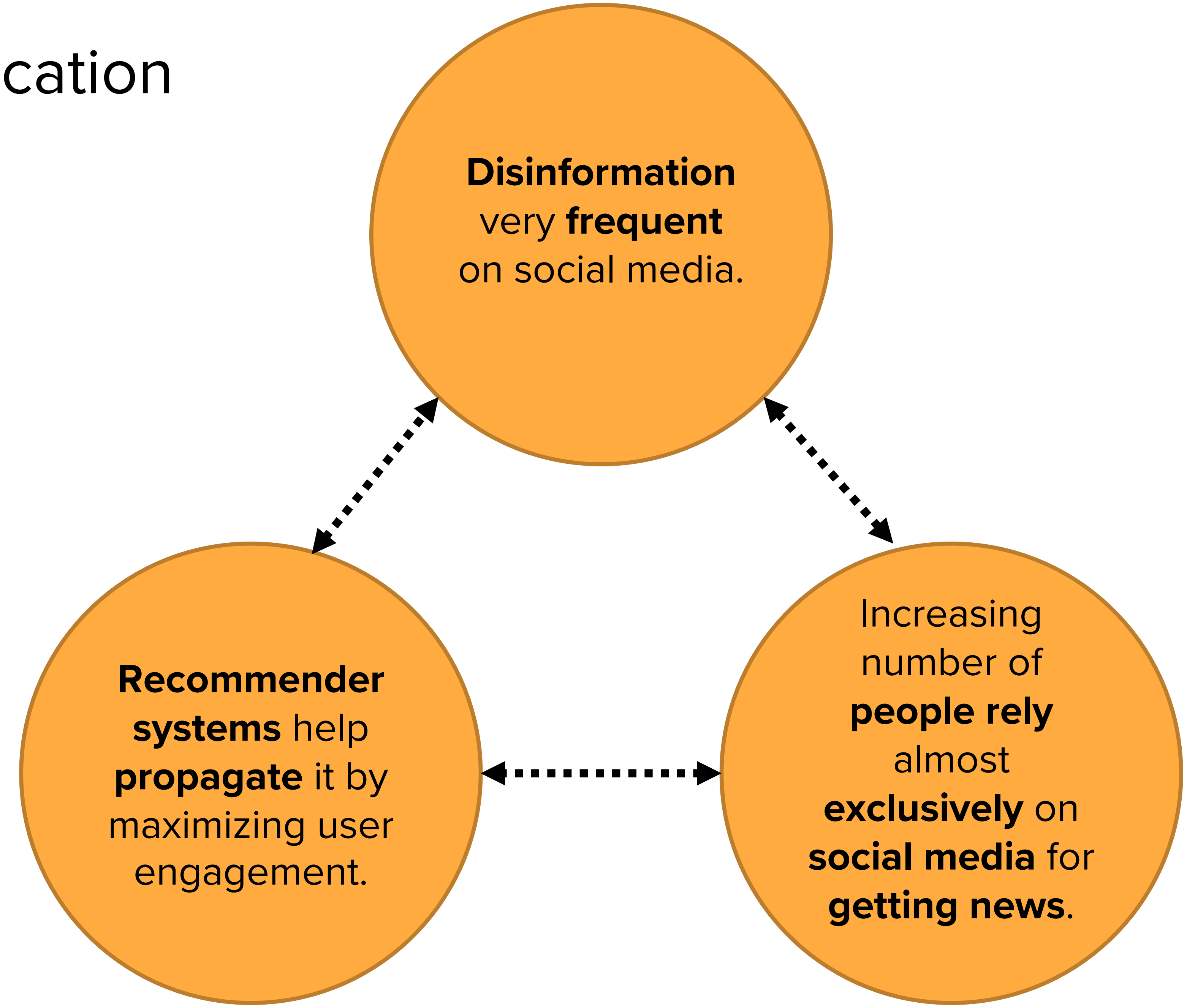
Introduction

Terminology



Circle of amplification



Impact of disinformation

- Confused the public, led to **political inaction**, and to the **rejection** of mitigation **policies**

- **Lost of trust** in government, scientific community, medicine...

- **Polarization** and **social fracture**

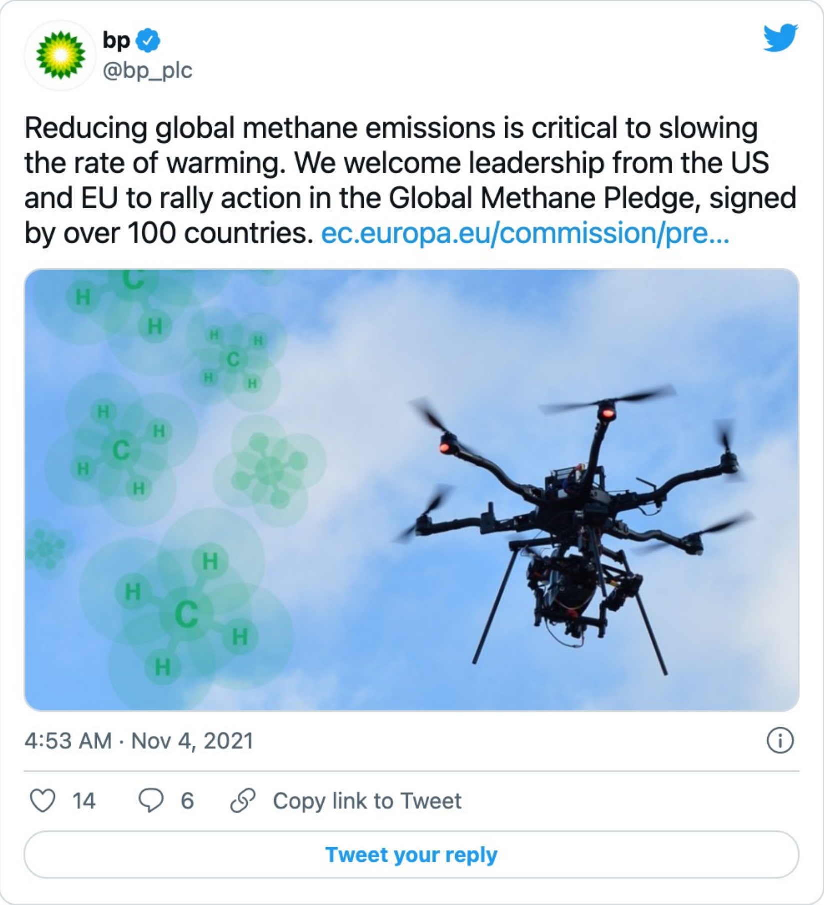
Image from nrdc.org

From Whom?

- Individuals

From Whom?

- Individuals
- Companies



From Whom?

- Individuals
- Companies
- Institutions

American Petroleum Institute
@APIenergy

We will continue to focus on industry actions and innovations that will help reduce emissions, while producing reliable, affordable natural gas and oil.

3:10 PM · Nov 8, 2021

8 3 Copy link to Tweet

Tweet your reply

From Whom?

- Individuals
- Companies
- Institutions
- States

Global Times

OPINION / EDITORIAL

China keeps its promises on climate, so should the US: Global Times editorial

By Global Times

Published: Nov 11, 2021 10:26 PM

CGTN See the difference

Home China World Politics Business Opinions Tech & Sci Culture Sports Travel Nature Picture Video Live TV Specials Learn Chinese

China 22:35, 03-Nov-2021 Translate

China tells U.S. to take actions, not empty words on climate change

CGTN

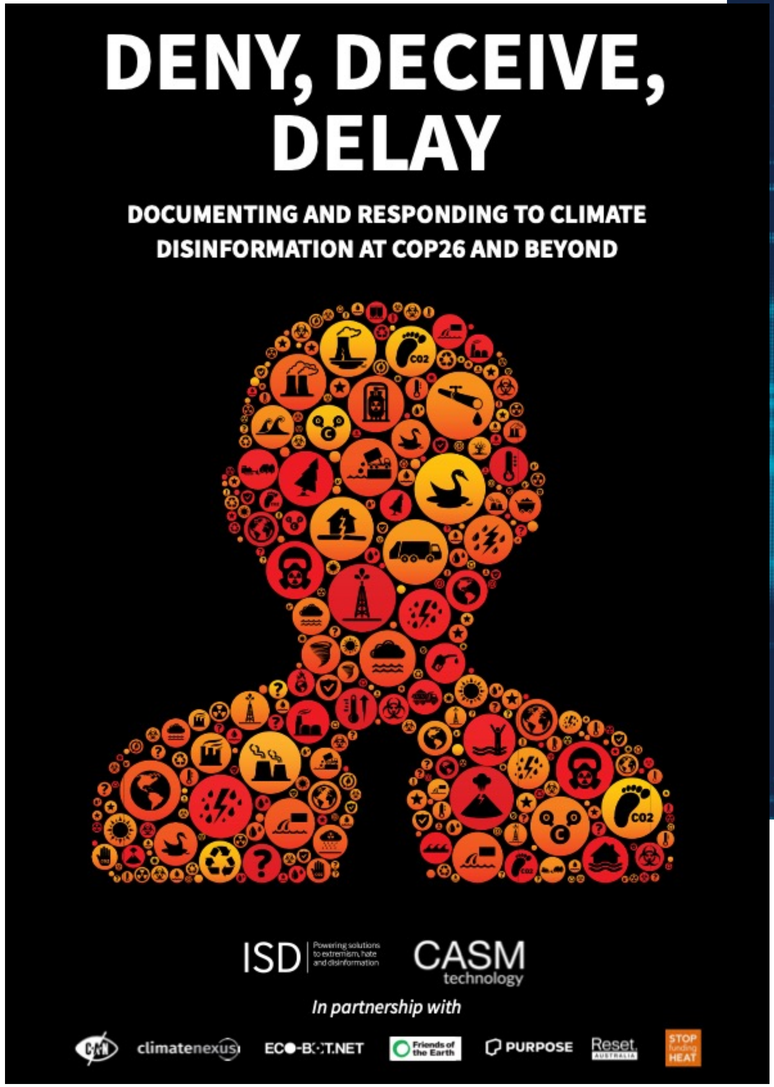
Share

China-controlled media

Goal & Motivation

Disinformation campaigns

- **Virulent, organized, large scale disinformation operation** by coordinated actors
- **Flooding the zone**
- **Deny responsibility** in assassination, **opposition** to climate **regulations**



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-
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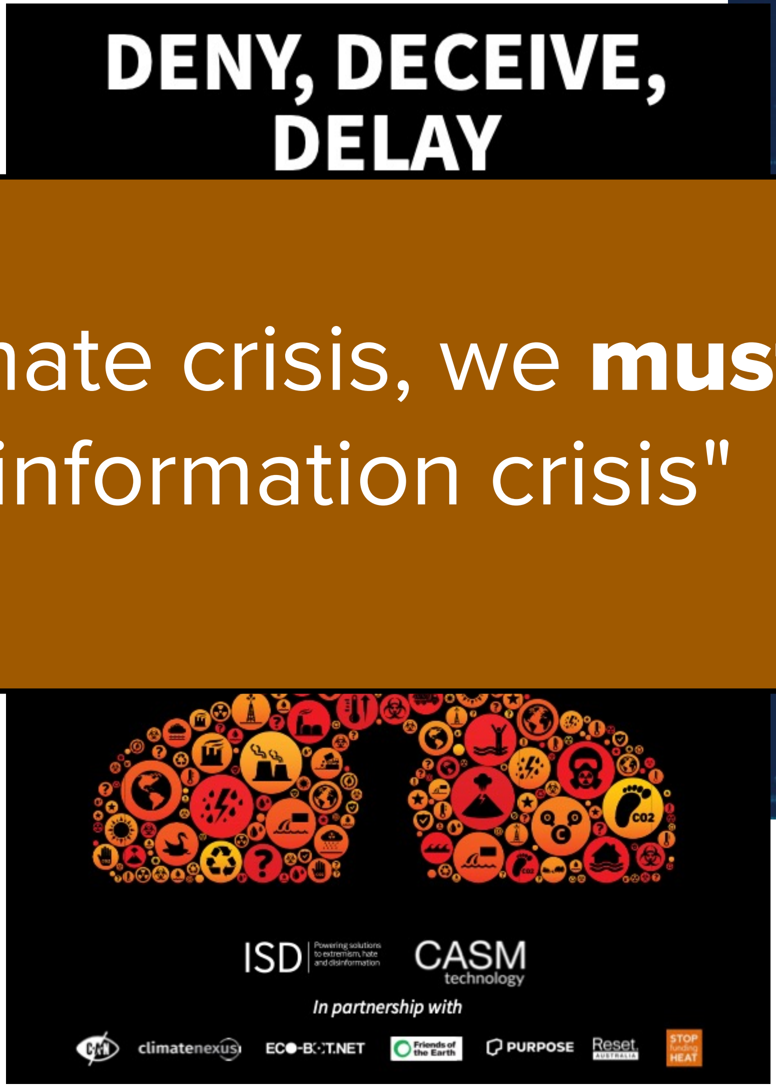

"To solve the climate crisis, we **must** also tackle the information crisis"

Modeling influence

- Create a **system** able to **capture influence attempts** relating to (climate change) **disinformation** between users on **Twitter**.

- **Quantify** the **influence** between users on **Twitter**

- Derive **new influence measures** describing the amount of **disinformation** shared by the users on **Twitter**.

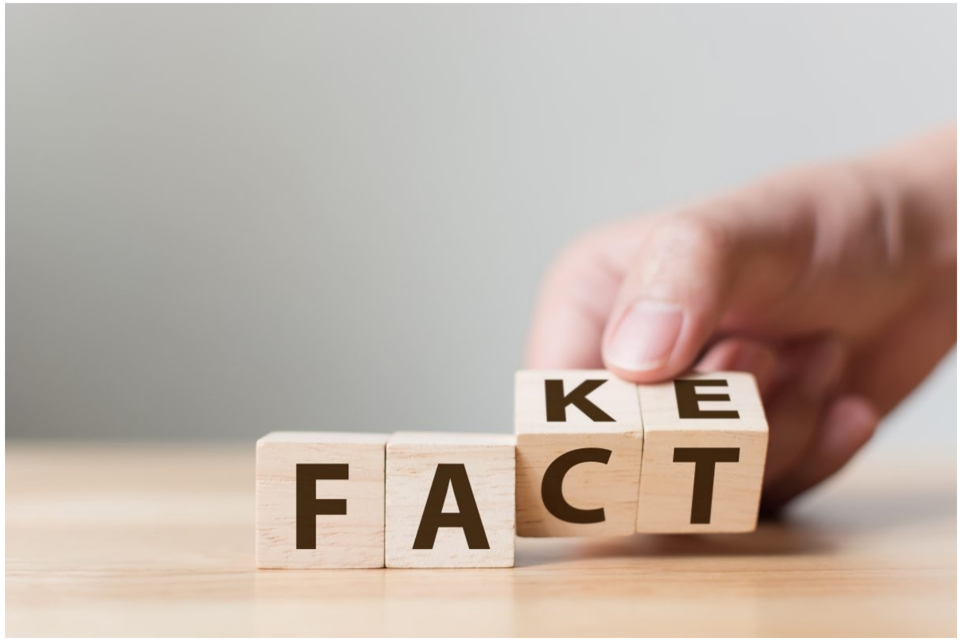

Image from commonexperience.edu

Contribution

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- **Create** and curate **2 new datasets** of tweets around **COP26** and **COP27**
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- **Sensitivity** analysis of **key-components** of the framework

Contribution

- **Create** and curate **2 new datasets** of tweets around **COP26** and **COP27**
- **Derive** new **influence measures**
- **Study** existing and new **influence measures** and how they are **correlated**
- **Sensitivity** analysis of **key-components** of the framework
- **Generalize** on different **types** of **events**

Methodology

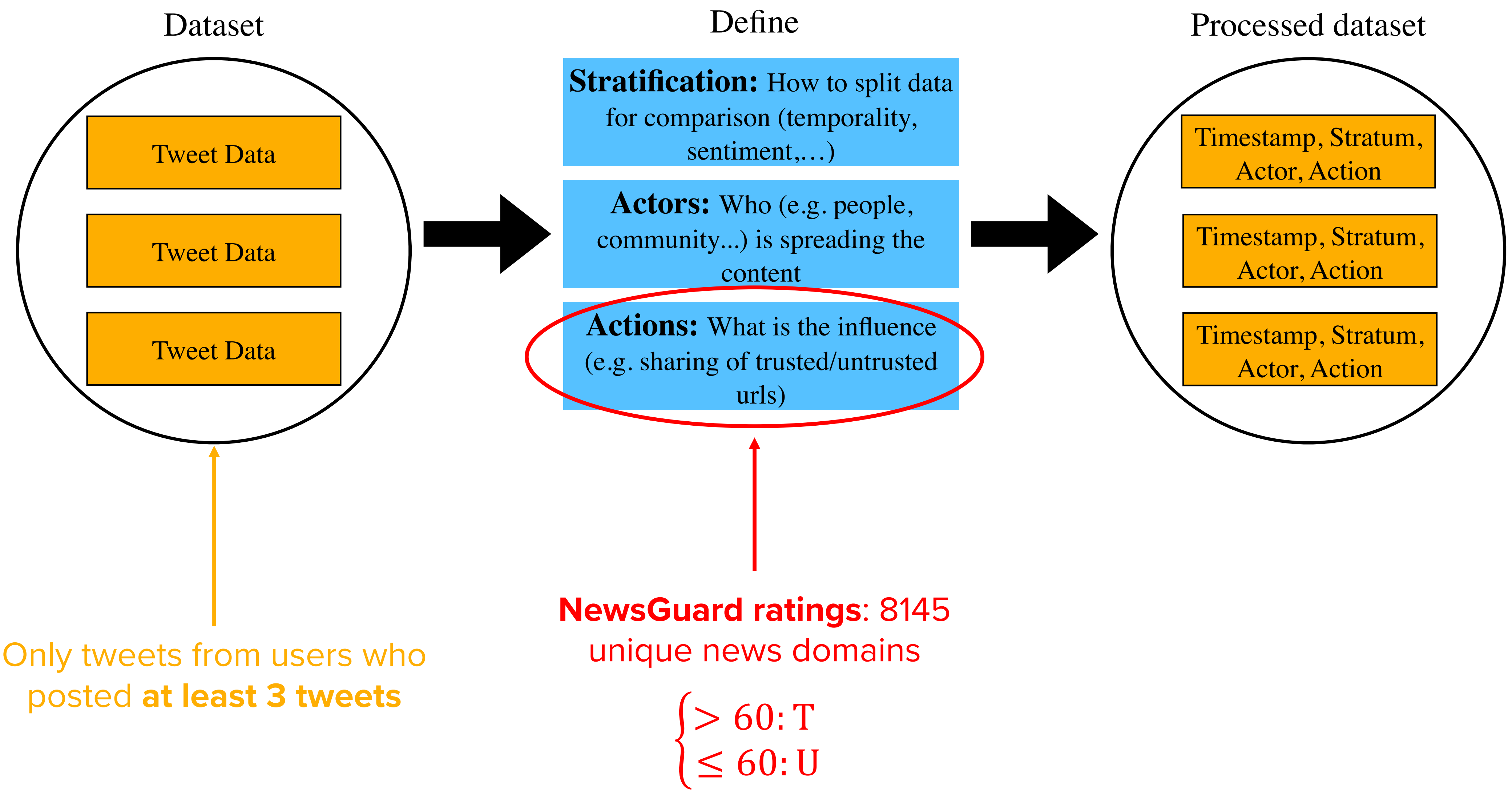
Datasets

- **COP26:** all **climate-related** tweets containing a **URL** around COP26 (2021).
- **COP27:** all **climate-related** tweets containing a **URL** around COP27 (2022).
- **Control:** all **climate-related** tweets containing a **URL** at random dates.
- **Skripal:** all tweets related to the **Skripal poisoning** in 2018 and containing a **URL**.

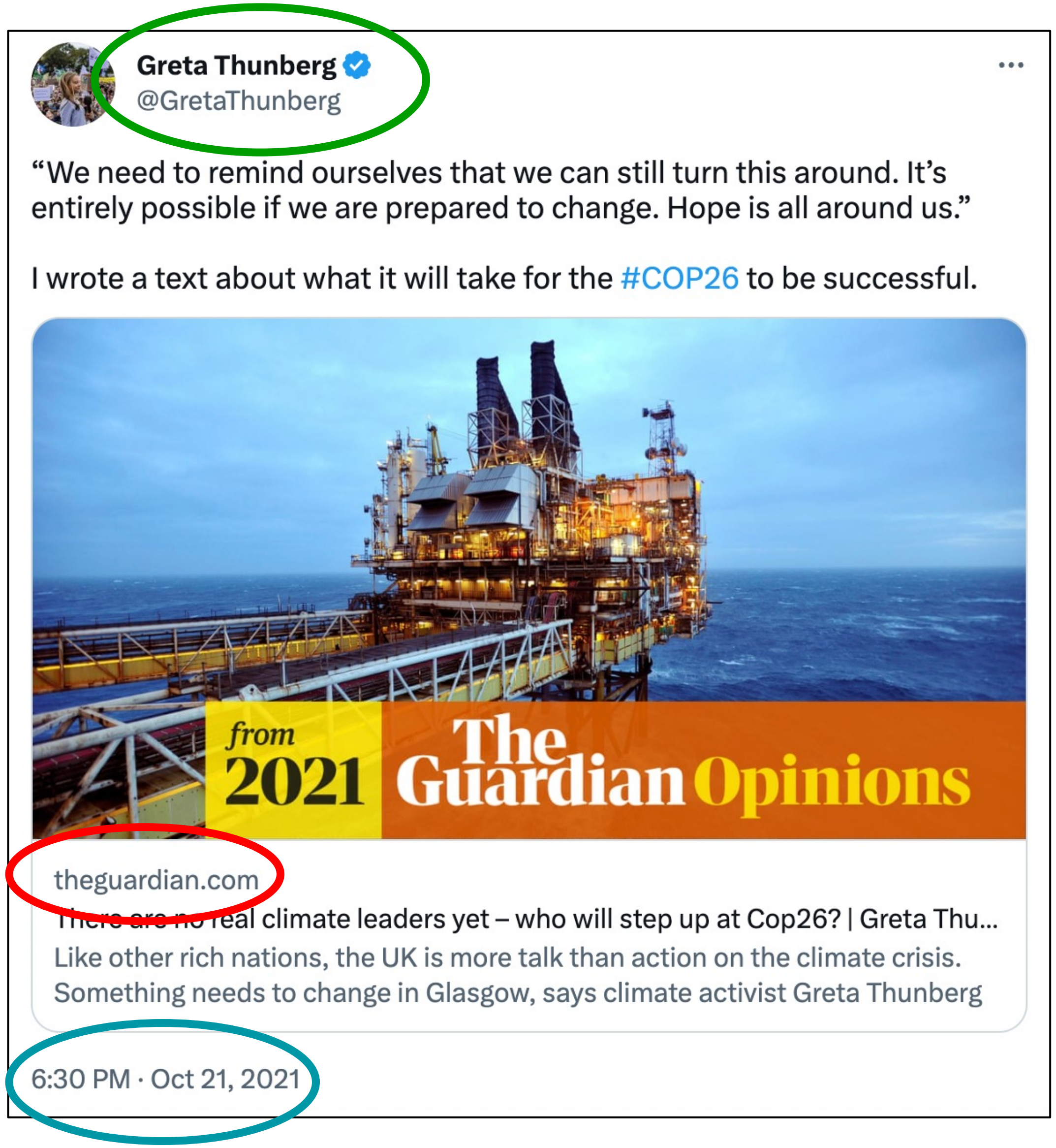
```
("climate change" OR #climatechange OR #climate_change OR "climate crisis" OR #climatecrisis OR
#climate_crisis OR "climate emergency" OR #climateemergency OR #climate_emergency OR "global warming"
OR #globalwarming OR #global_warming OR "climate action" OR #climateaction OR #climate_action)
has:links lang:en
```

Twitter API query to obtain climate-related tweets

Data processing

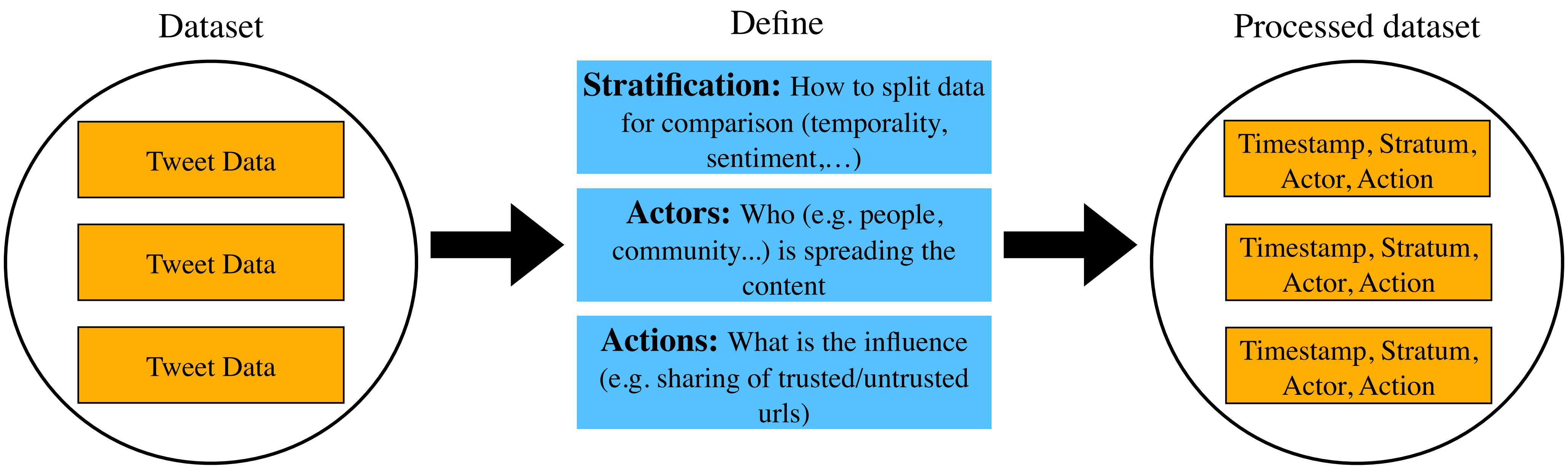


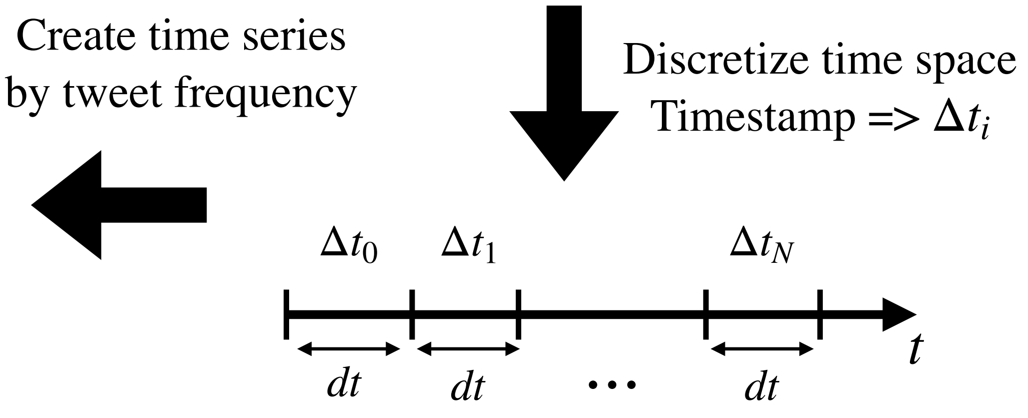
Data processing (example)



- **Timestamp:** 2021-10-21 at 18:30
- **Stratification:** Before COP26 (based on timestamp)
- **Actor:** Greta Thunberg
- **Action:** sharing of **T**rustworthy (**T**) news (NewsGuard score for *theguardian.com* is 100)

Time series creation





	Bill Gates	
	U	T
Δt_0	2	2
Δt_1	1	5
Δt_2	0	1
$\vdots$	$\vdots$	$\vdots$
Δt_N	0	1

	Greta Thunberg	
	U	T
Δt_0	0	4
Δt_1	0	2
Δt_2	0	1
$\vdots$	$\vdots$	$\vdots$
Δt_N	1	3

Influence graphs

	A : Bill Gates	
	U	T
Δt_0	2	2
Δt_1	1	5
Δt_2	0	1
$\vdots$	$\vdots$	$\vdots$
Δt_N	0	1
	X_U^A	X_T^A

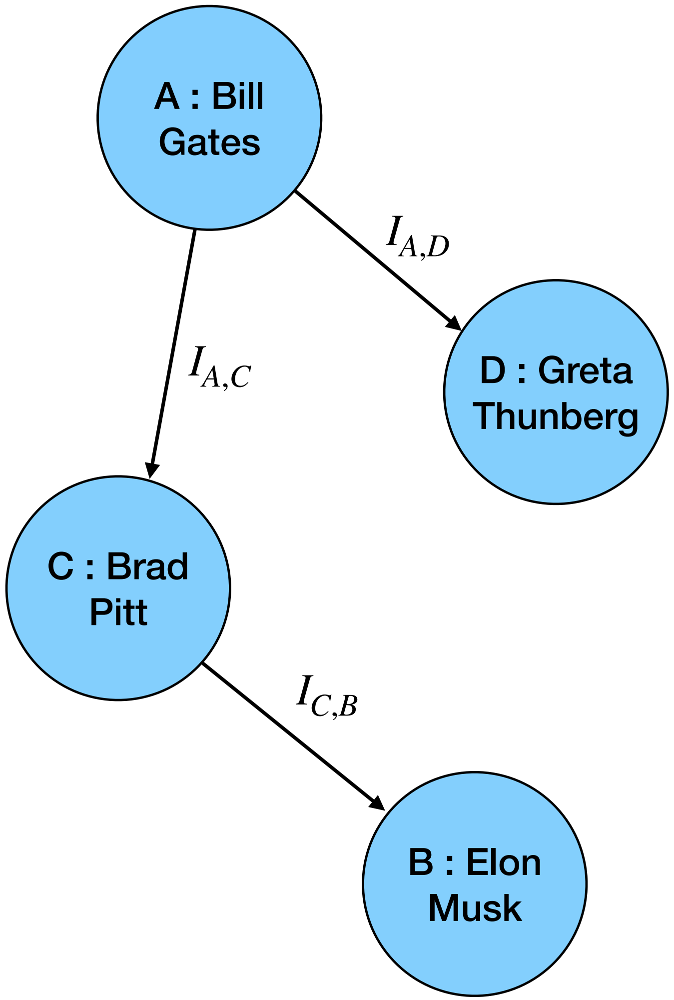
$\cdots$

	D : Greta Thunberg	
	U	T
Δt_0	0	4
Δt_1	0	2
Δt_2	0	1
$\vdots$	$\vdots$	$\vdots$
Δt_N	1	3
	X_U^D	X_T^D

Compute influence matrix between actors

$$I_{A,B} = \begin{bmatrix} d(X_U^A, X_U^B) & d(X_U^A, X_T^B) \\ d(X_T^A, X_U^B) & d(X_T^A, X_T^B) \end{bmatrix}$$

Create influence graph



Coupling Inference Methods

Key component: Coupling Inference Methods

Transfer Entropy (TE)

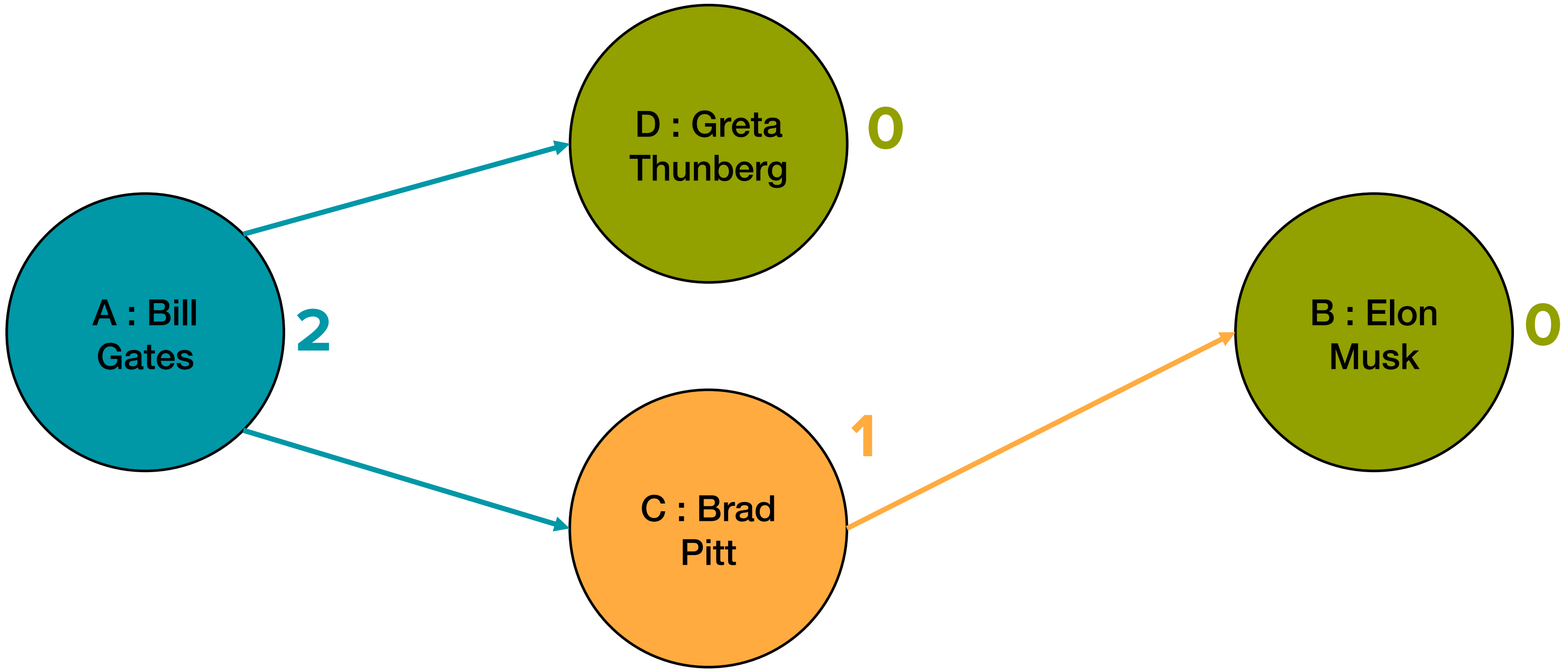
- Need to **binarize** the time series
- **Naive estimation** of state probabilities
- Need an **arbitrary threshold**
- Well-known and **less** subject to **noise**

Joint Distance Distribution (JDD)

- Use **original** (standardized) **values**
- Based on **distances**
- Formulated as **hypothesis testing**
- **More** subject to **noise**

Influence measures

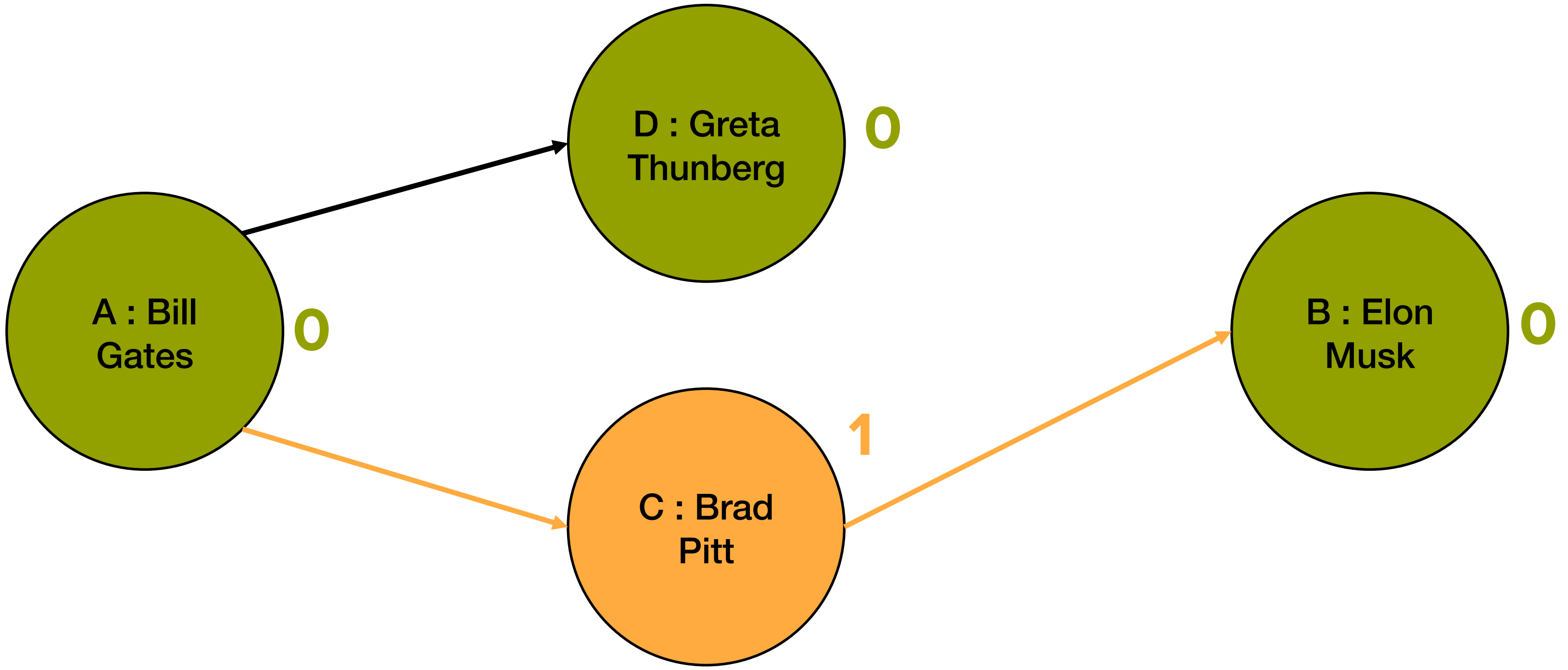
- ***Outdegree:*** for each node (actor) in the influence graph, outdegree directly **indicates how many other actors this actor influenced.**



Influence measures

- ***Outdegree:*** for each node (actor) in the influence graph, outdegree directly **indicates how many other actors this actor influenced.**

- ***Betweenness:*** indication of **how well one actor serves as a bridge to influence many other users.**



Influence measures

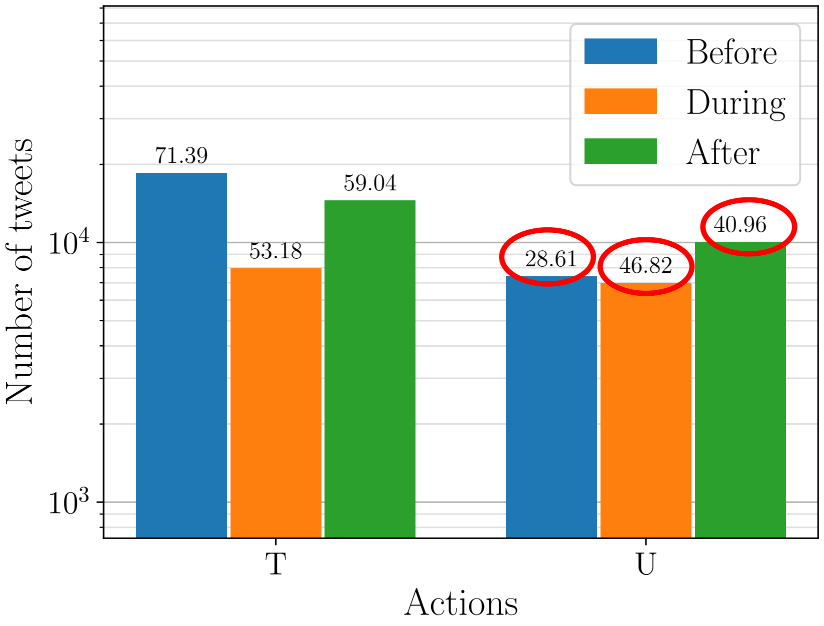
These measures can be fine-grained and derived for each edge type in the graph:

- T-T: **echo chamber** of trustworthy news sharing.
- T-U: **credibility cross-over** of trustworthy to untrustworthy news sharing
- U-T: **credibility cross-over** of untrustworthy to trustworthy news sharing
- U-U: **echo chamber** of untrustworthy news sharing.

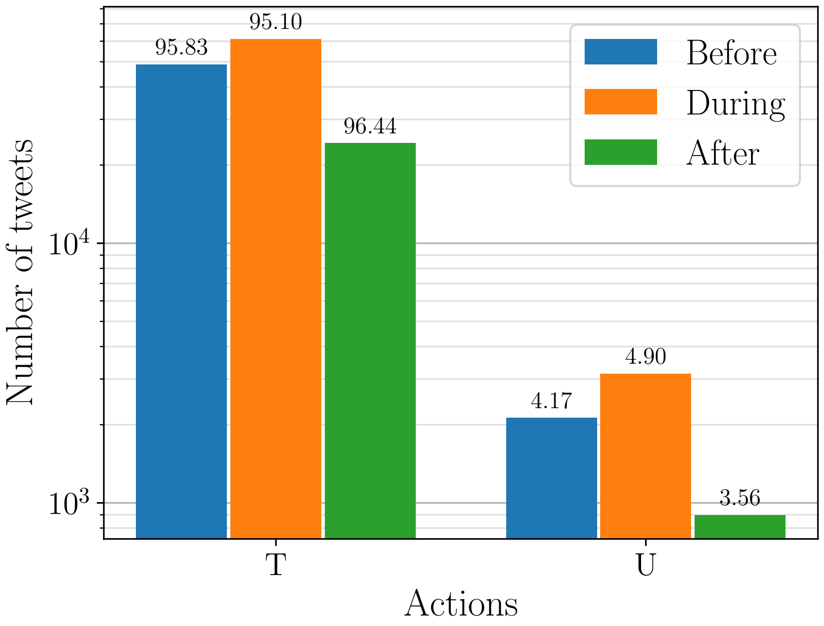
Results

Action distributions

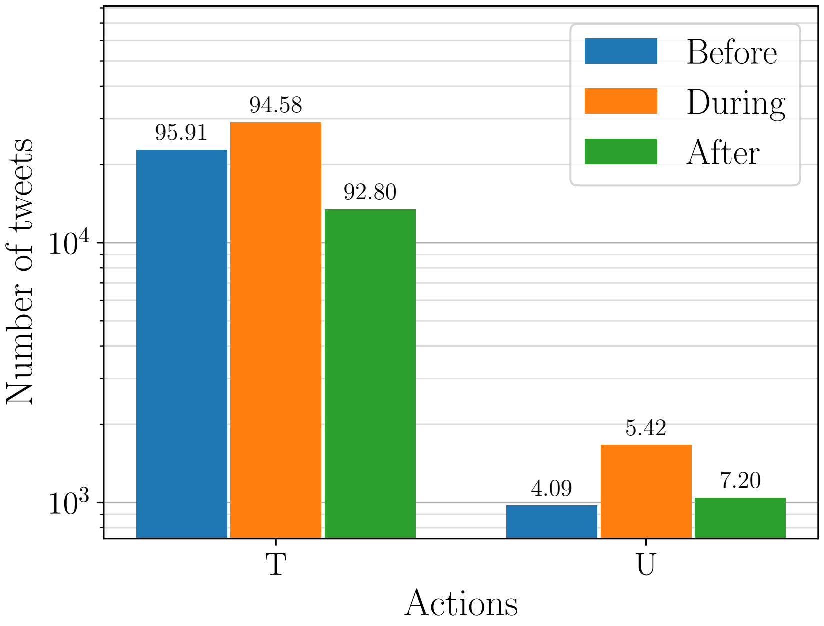
- Proportion of **untrustworthy news** sharing **larger** during **Skripal**
- May be a **hint** of **underlying disinformation campaign**



Skripal dataset



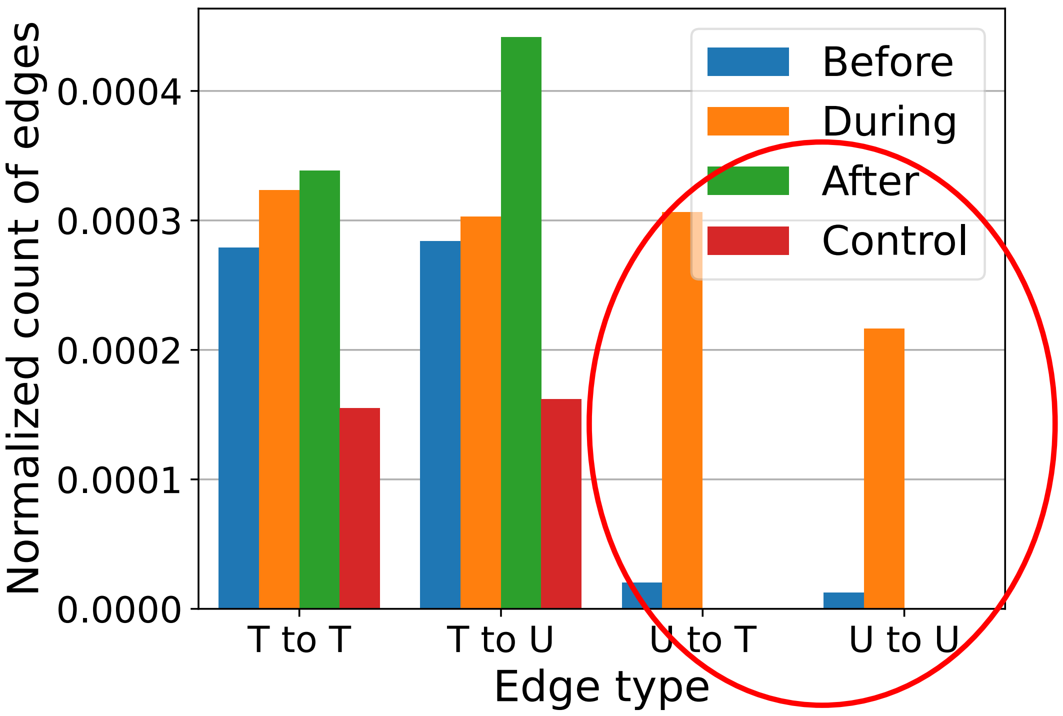
COP26 dataset



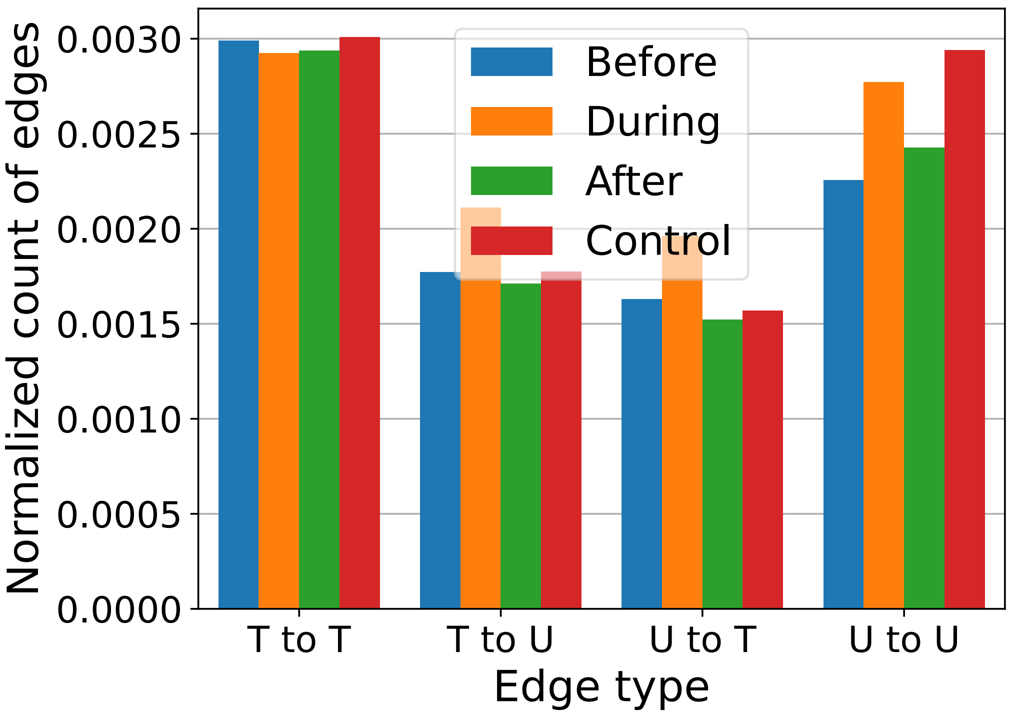
COP27 dataset

Comparison JDD-TE influence graphs

- JDD detects **large spikes** of influence of the **untrustworthy** types during COP26.
- **No difference** with the **control** for **TE**.



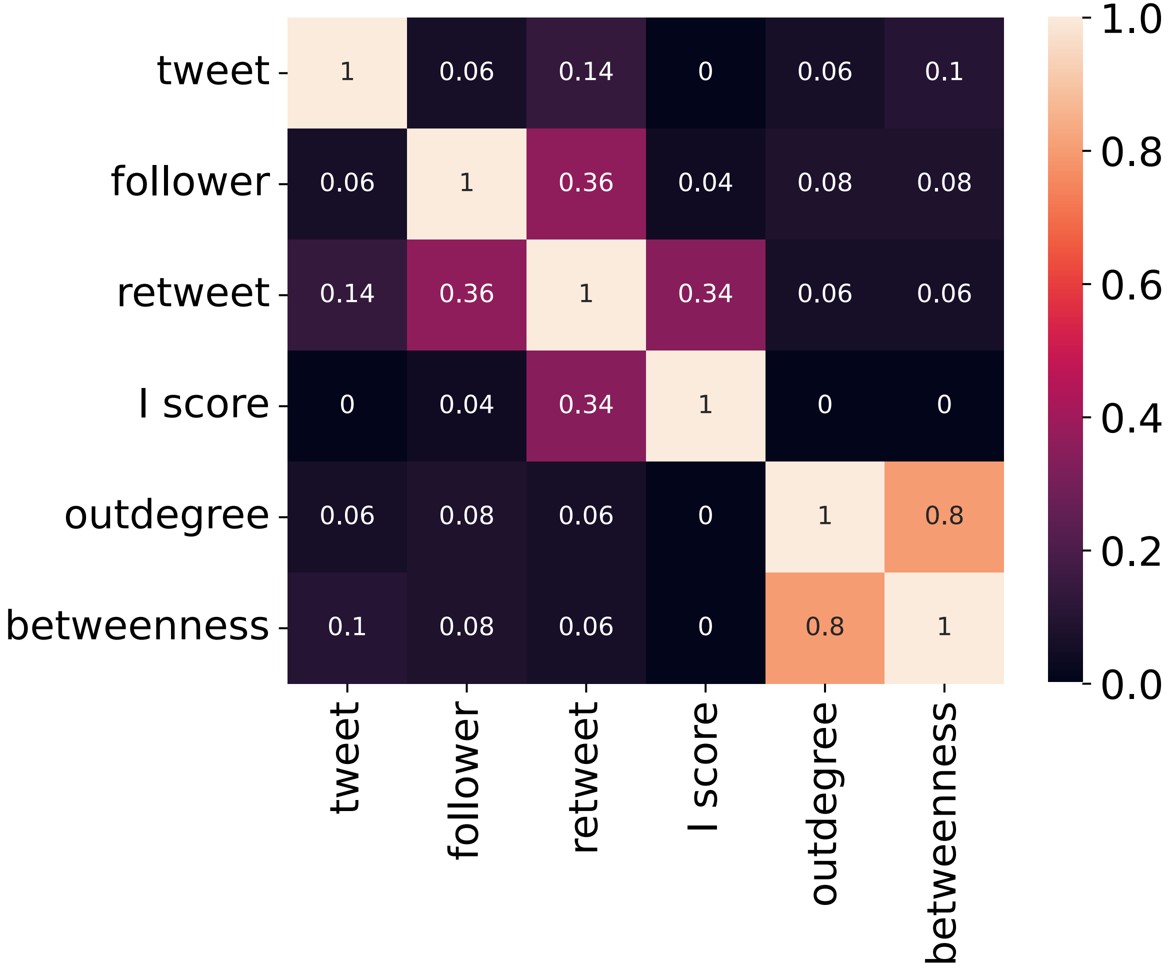
JDD on the COP26 dataset



TE on the COP26 dataset

One influence measure to rule them all?

- **Weak** overall **correlations**
- Only **outdegree** and **betweenness** exhibit relatively **high correlation**.
- **Each measure** is in fact capturing **different types of information**, and influence definitions.



Correlation matrix between influence measures for JDD on the COP26 dataset

What do influential people share? -- Skripal

	Skripal dataset	Top 10 JDD	Top 10 TE
Before	4.8	-	32.9
During	3.9	33.6	15.1
After	6.3	20.7	10.9

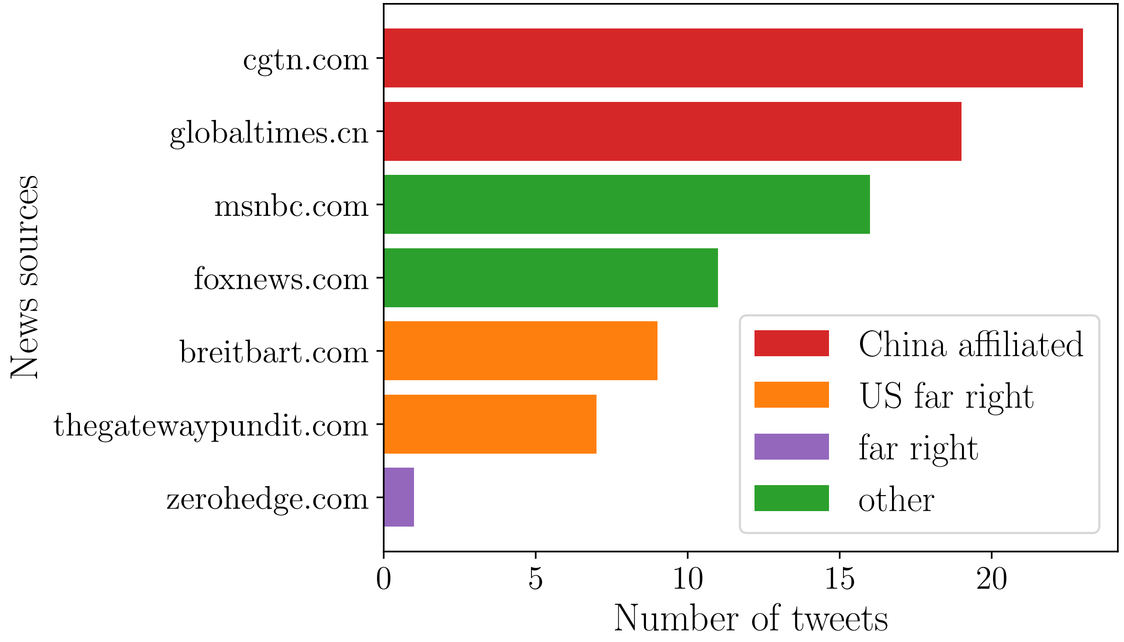
Mean number of mentions of “rt.com”

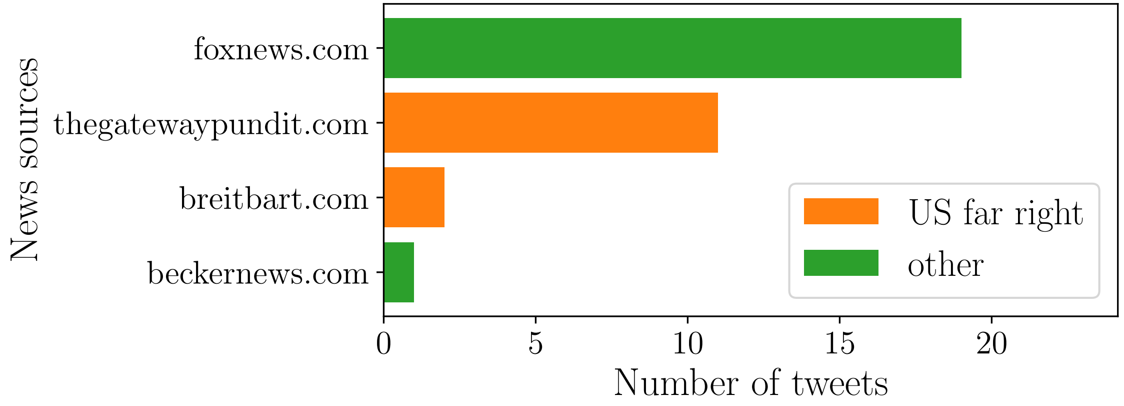
	Skripal dataset	Top 10 JDD	Top 10 TE
Before	1.1	-	4.0
During	1.9	28.7	19.5
After	1.4	11.5	0

Mean number of mentions of “sputniknews.com”

- **RT** and **Sputnik** vectors of Russian **disinformation** campaign during Skripal
- **Significantly more sharing** of these websites by the most **influential** users **we detected**
- Even **more sharings** by users detected by **JDD compared to TE**

What do influential people share? -- COP26





- **Most influential users** share articles from **China-controlled** or **far-right-affiliated** media
- **JDD** detects **more** content directly related to **disinformation than TE**
- **China-affiliated** news outlets share **anti-US** and **anti-Western** climate **narratives**.
- **Far-right US** outlets share **counter narrative** and narrative **against Biden**'s climate awareness

Conclusion

Conclusion

- **Quantifying influence** between users on social media is **difficult**, but **essential** to detect and **counter disinformation**.
- **Derived** and **explored** a **novel method** to **measure influence** and **detect disinformation** on social media.
- **Compared** two **coupling inference methods** to derive the influence graphs.
- **Influence measures** have relatively **low correlation** between themselves, showcasing that they **do not capture the same types of influence**.
- **JDD** results in **sparser influence graphs**, but finds individuals who seem **more active** in spreading **disinformation** than when using **TE**.

Future work

- **Explore** other **action** definitions
- Incorporate **content analysis**
- Further **validate** on other **known cases** of **disinformation campaigns**

Thank you!