UTS

Behavioral Data Science

Breaking free of the arms race

Slipping to the Extreme: A Mixed Method to Explain How Extreme Opinions Infiltrate Online Discussions

Data Science Institute

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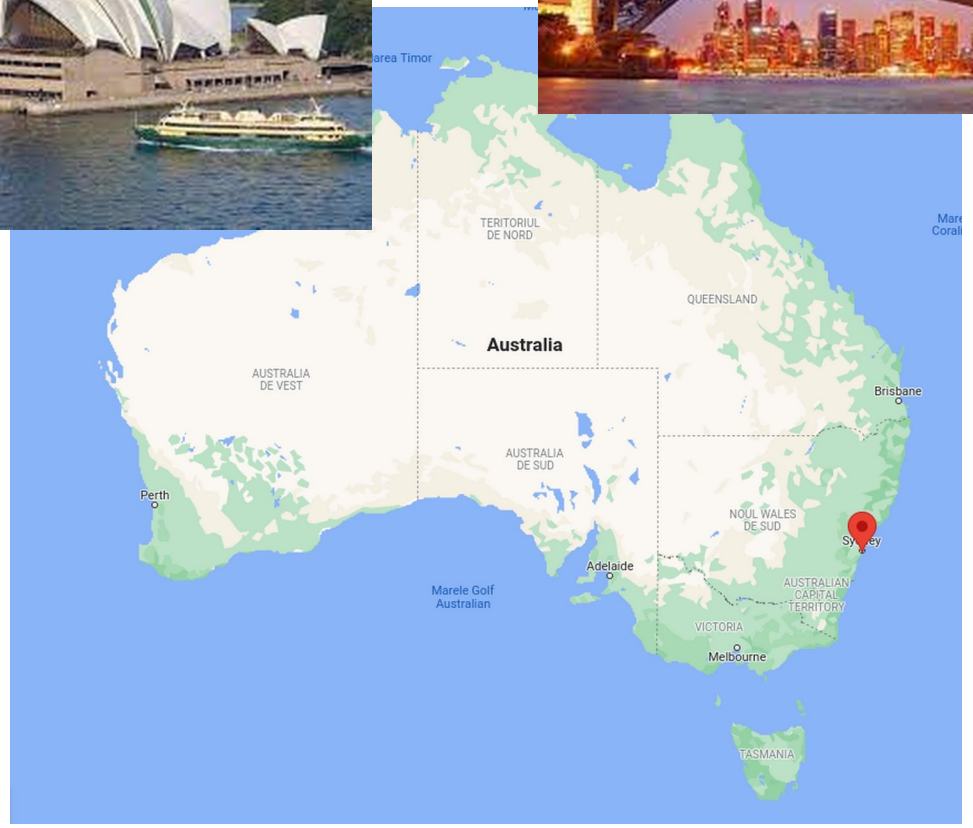
https://www.behavioral-ds.science



Located in Sydney, Australia

A city campus, iconic brutalist style blended with modern buildings

The research group

Behavioral Data Science

2 PostDocs, 7 PhD, 1 Masters, 1 assistant prof.





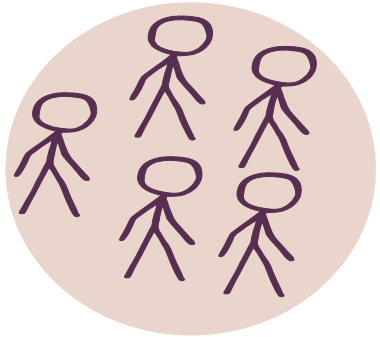




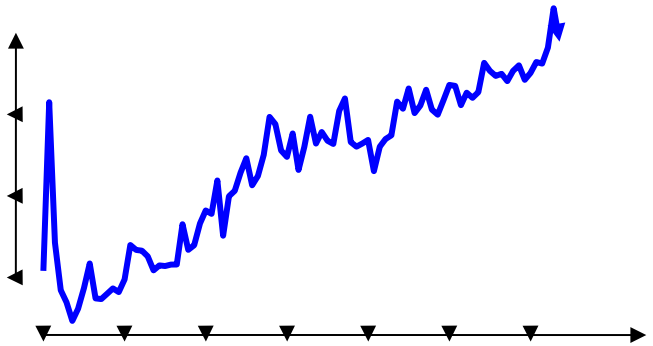


The Behavioral Data Science

1.



information diffusion
epidemics spreading
behavioral modeling



The Behavioral Data Science

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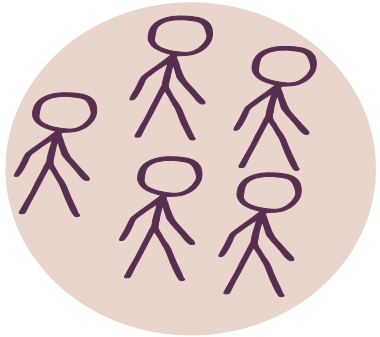

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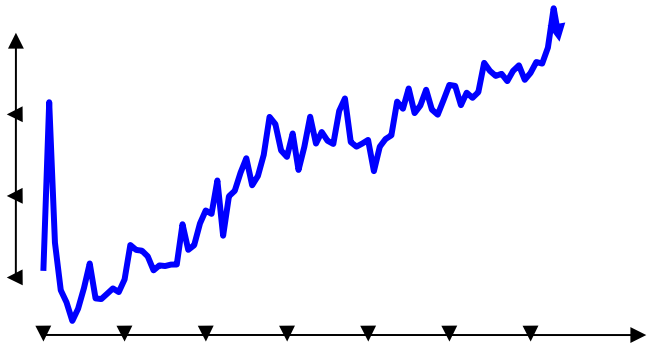

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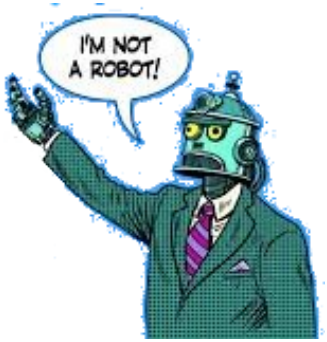

[Rizoiu et al ICWSM'18]

[Kim et al Journ.Comp.SocSci'19]

The Behavioral Data Science

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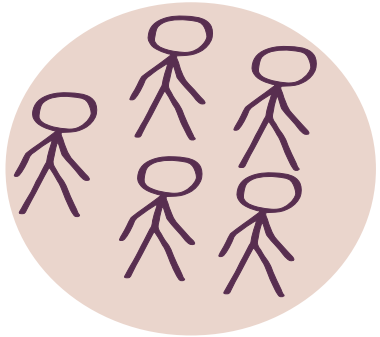

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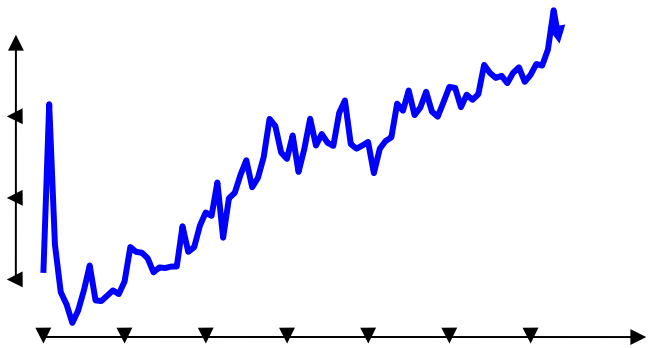

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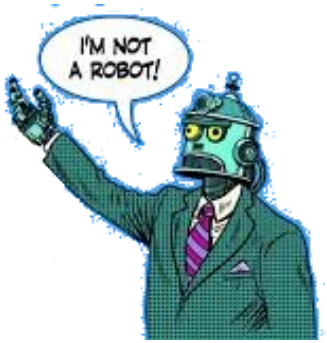


[Rizoiu et al ICWSM'18]

[Kim et al Journ.Comp.SocSci'19]

Our founders & collaborators around Information Disorder

Information integrity initiative:
fighting misinformation in Australia

Real-time detection of
disinformation campaigns

Hate Speech propagation
on Social Media

Expert roundtable for
Defamation law reform

Tracking Disinformation
Campaigns across terrain

Detection and debunking
for online misinformation

Presentation plan

The grand vision:
Breaking free of the arms race – an end-to-end solution to information disorder

The research:
Slipping to the extremes: combining qualitative research and computer science to fight problematic speech

FIRSTDRAFT

7 COMMON FORMS OF INFORMATION DISORDER

SATIRE OR PARODY

No intention to cause harm but has potential to fool

MISLEADING CONTENT

Misleading use of information to frame an issue or individual

IMPOSTER CONTENT

When genuine sources are impersonated

FABRICATED CONTENT

New content is 100% false, designed to deceive and do harm

FALSE CONNECTION

When headlines, visuals or captions don't support the content

FALSE CONTEXT

When genuine content is shared with false contextual information

MANIPULATED CONTENT

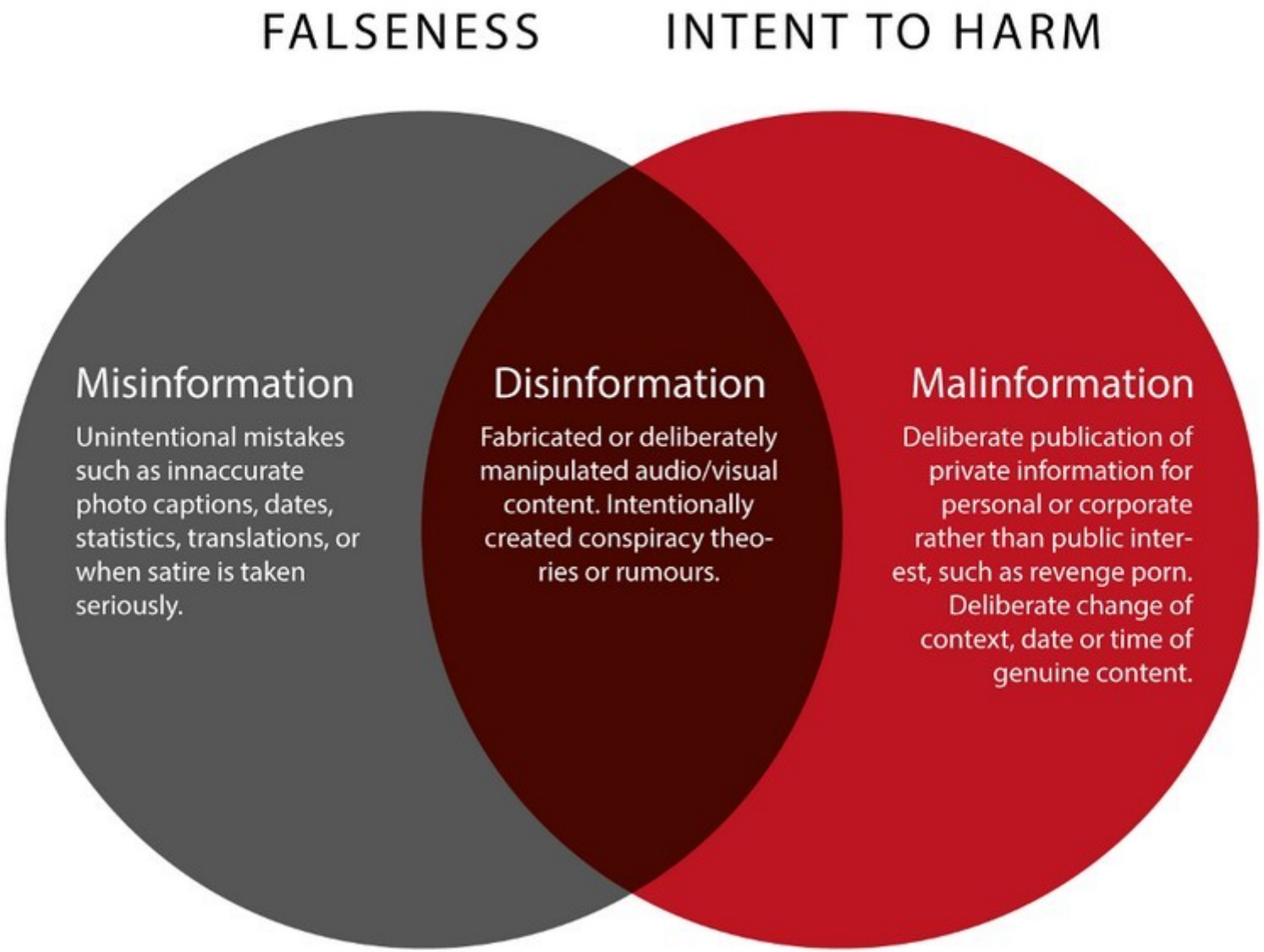
When genuine information or imagery is manipulated to deceive

Problematic speech

Problematic speech is online interactions, speech, and artefacts that are inaccurate, misleading, inappropriately attributed, or altogether fabricated (Jack 2017).

- misinformation
- disinformation
- hate speech

Mis- vs Dis-information



Red Queen effect

Content-based detectors are sensitive to adversarial training attacks – simply use the detector to train the attacker.

"Now, here, you see, it takes all the running you can do just to keep in the same place. If you want to get somewhere else, you must run at least twice as fast!"

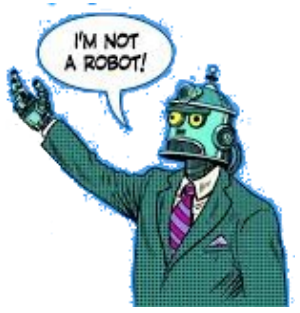
- Red Queen from *Through the Looking Glass*

Our detection approach in a nutshell

Build social sensors – the reaction of the social system cannot be faked

Early detection systems – information spread patterns within the user population

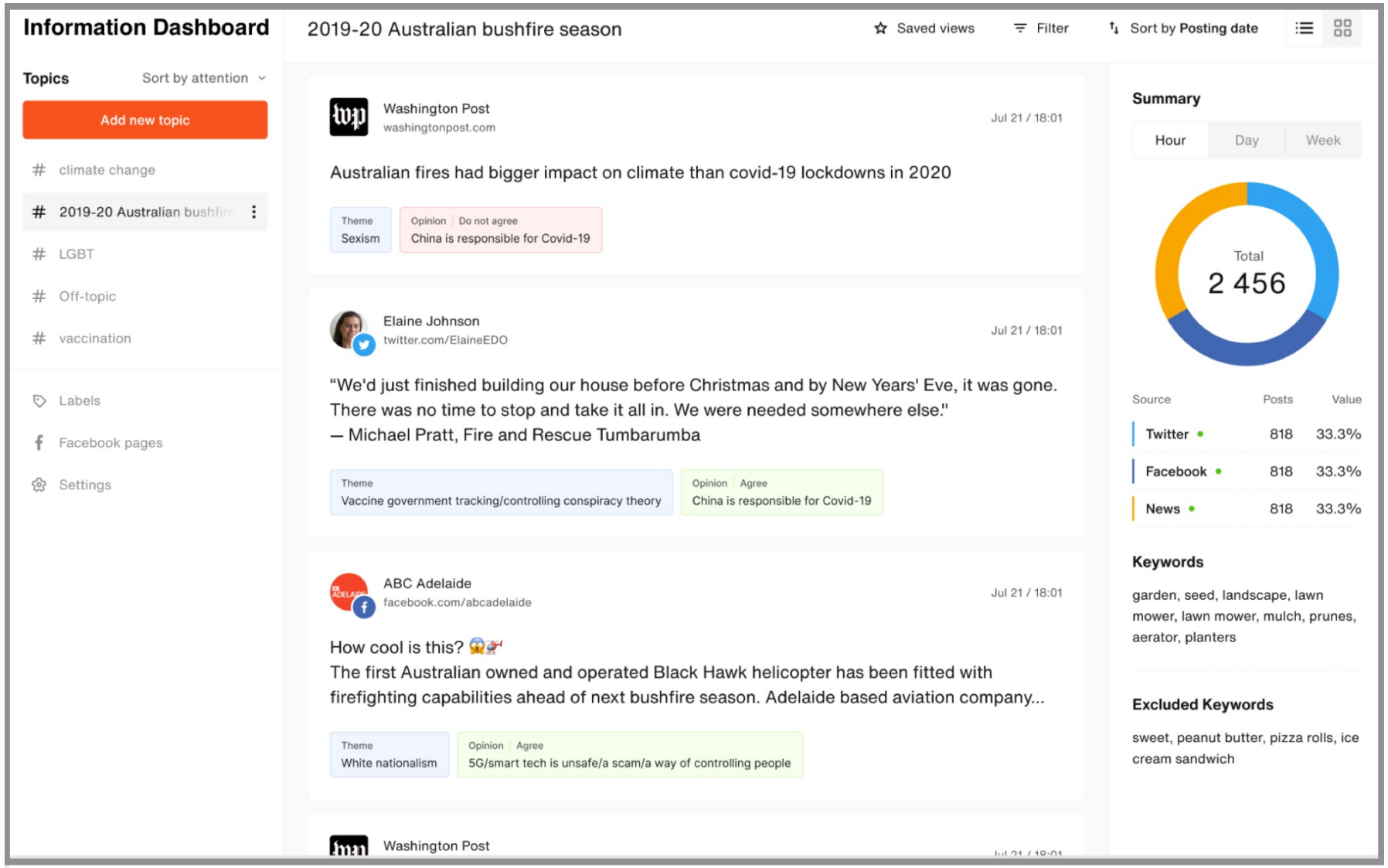
Distinguish content types and user actions – how online social systems react to them.



UTS capabilities in Influence Operations space

	Monitor	Detect	Predict	Mitigate
Response level				
Objective	How can we develop and deploy dashboards to monitor discussion on both the social media and traditional media outlets, in which the adversaries are most likely to deploy the influence operations?	How do we most effectively identify and triage information campaigns based on the characteristics of the message, how it spreads, who is communicating it, and where it is being communicated?	What factors accelerate and intensify the communication and reach of weaponized messages within and across online environments, and which factors lead to the most significant real-world harms?	What are practical approaches that allow us to both pro-actively and re-actively limit the harms of problematic messaging, including identifying where, when and how counter-messaging should be deployed?
	Monitor discussions on social and traditional media	Detect adversarial information campaigns	Estimate the effectiveness of influence operations	Design and apply countermeasures
Approach	Characterising the dynamic interaction between traditional and social media ecosystems in the flow and spread of disinformation and problematic content.	Utilise information diffusion techniques to identify problematic content based on the way it moves through and across online channels	Model the impact of networks and influencers on the virality and reach of problematic messages	Use natural language processing to automatically generate counter-messaging that is tuned for the platform and target group of interest
	Develop and deploy a "mission control" dashboard to retrieve content from a constantly updating list of traditional media and Internet sources.	Deploy natural language processing techniques to automate the detection of problematic online messages based on the structure and content of the message	Track the spread of problematic messages across and between online platforms and into the real-world	Identify key message inoculation points in social networks based on how information flows and gains velocity

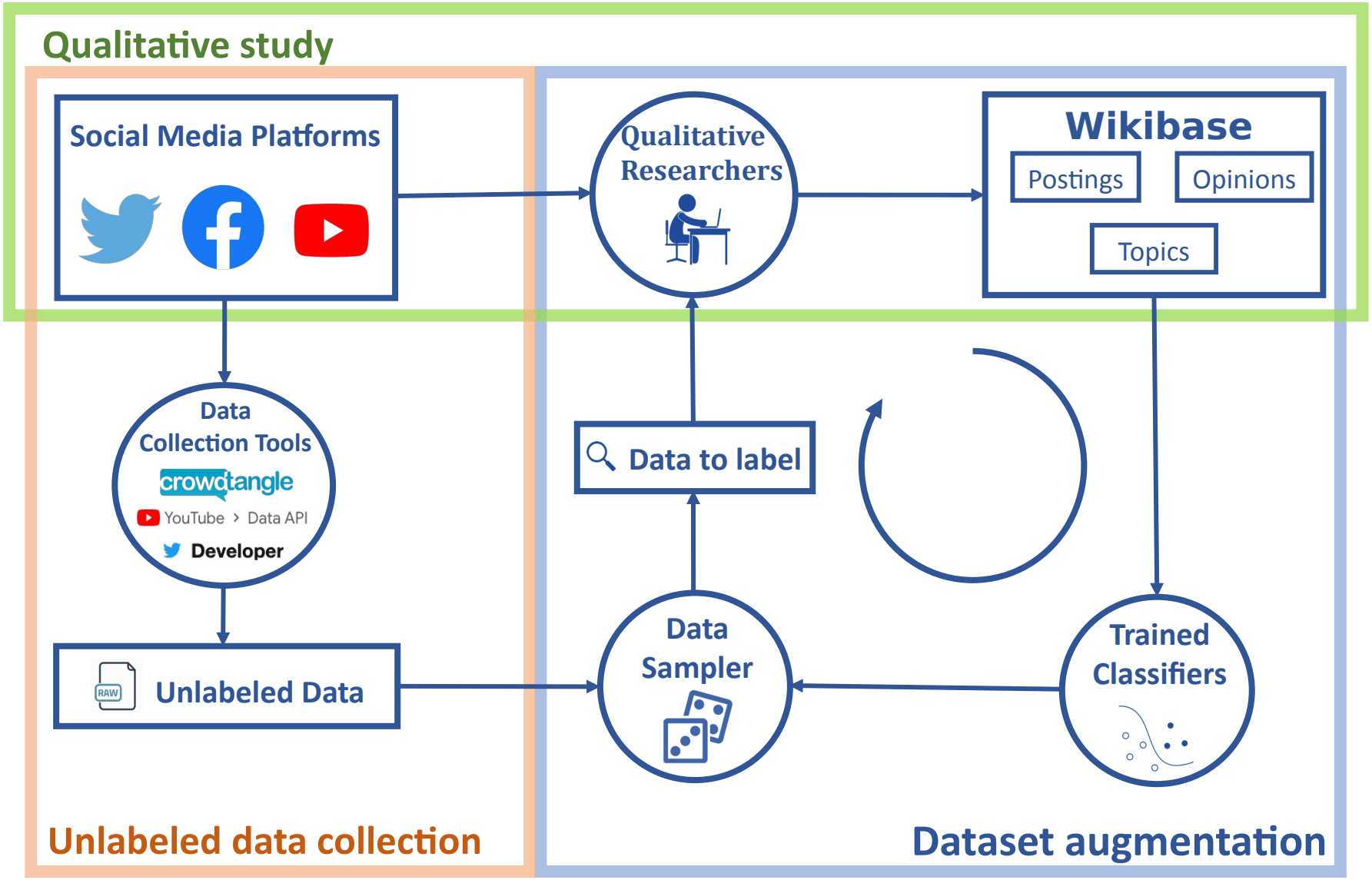
Monitor: Monitoring discussion spaces (1) (TRL: 4)



Graphical interface of the Information Dashboard

Monitor: Monitoring discussion spaces (2)

[Kong et al 2022]



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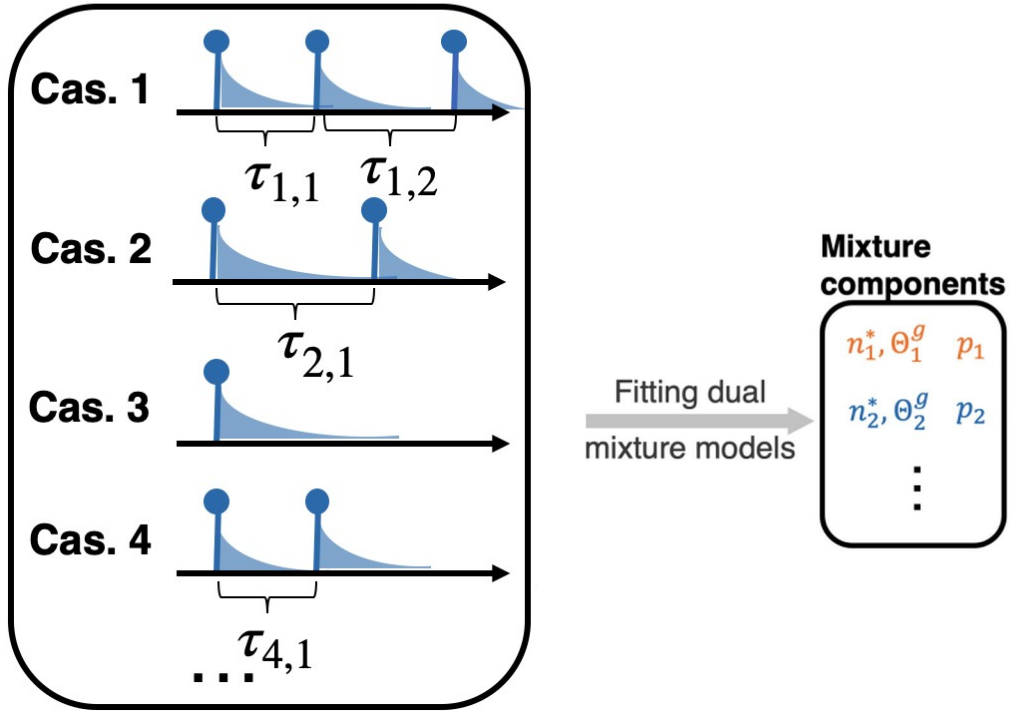
Detect: Build publisher embeddings from mixture models

[Kong et al 2020]



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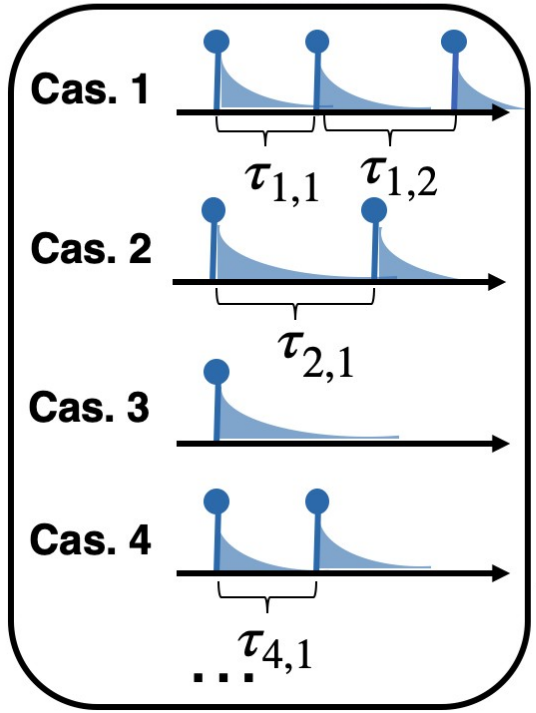

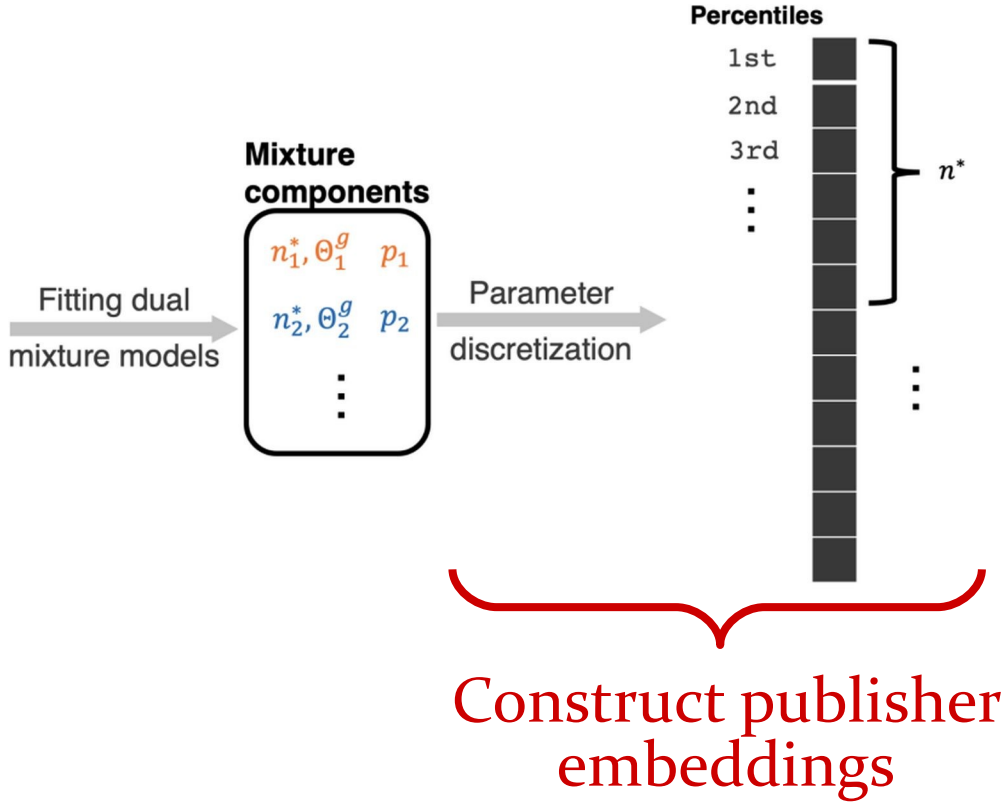

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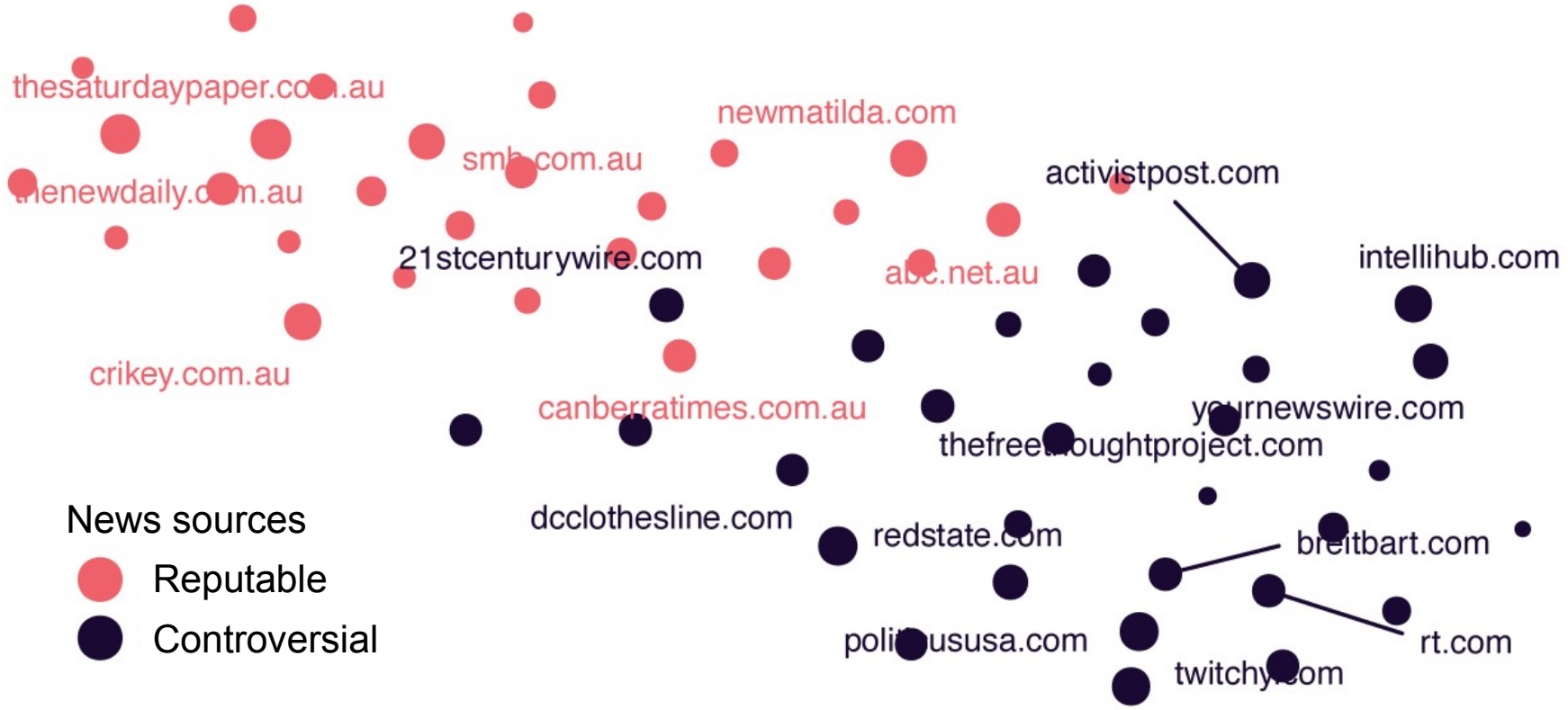
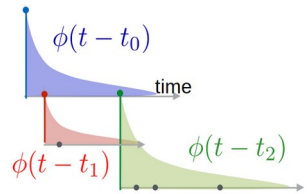
Detect: separating controversial from reputable (TRL: 5)



Reputable and controversial sources are separable based solely on how their information spreads

Detect controversial news without content analysis



The technical detail:

Mathematical generative modelling; Hawkes processes; joint modelling

evently

https://www.behavioral-ds.science/theme1_content/evently/

Mitigate: Identify influential inauthentic users (TRL: 5)

Identify users engaged in influence operations

Estimate their impact on the wider community

The technical detail:

Influence estimation using stochastic modelling; content-free analysis

birdspotter

https://www.behavioral-ds.science/theme2_content/birdspotter/

Presentation plan

The grand vision:
Breaking free of the arms race – an end-to-end solution to information disorder

The research:
Slipping to the extremes: combining qualitative research and computer science to fight problematic speech

Slipping to the Extreme: A Mixed Method to Explain How Extreme Opinions Infiltrate Online Discussions

Quyu Kong,[1,2] Emily Booth,[2] Francesco Bailo,[2] Amelia Johns,[2] Marian-Andrei Rizoiu[1,2]

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[2] University of Technology Sydney

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Abstract

Qualitative research provides methodological guidelines for observing and studying communities and cultures on online social media platforms. However, such methods demand considerable manual effort from researchers and may be overly focused and narrowed to certain online groups. In this work, we propose a complete solution to accelerate qualitative analysis of problematic online speech — with a specific focus on opinions emerging from online communities — by leveraging machine learning algorithms. First, we employ qualitative methods of deep observation for understanding problematic online speech. This initial qualitative study constructs an ontology of problematic speech, which contains social media postings annotated with their underlying opinions. The qualitative study also dynamically constructs the set of opinions, simultaneous with labeling the postings. Next, we collect a large dataset from three online social media platforms (Facebook, Twitter and Youtube) using keywords. Finally, we introduce an iterative data exploration procedure to augment the dataset. It alternates between a data sampler, which balances exploration and exploitation of unlabeled data, the automatic labeling of the sampled data, the manual inspection by the qualitative mapping team and, finally, the retraining of the automatic opinion classifier. We present both qualitative and quantitative results. First, we present detailed case studies of the dynamics of problematic speech in a far-right Facebook group, exemplifying its mutation from conservative to extreme. Next, we show that our method succesfully learns from

and Vraga 2018) being recorded in the literature. To date, there exist three primary types of methods for addressing problematic information. The first type concentrated on large-scale monitoring of social media datasets to detect inauthentic accounts (bots and trolls) (Ram, Kong, and Rizoiu 2021) and coordinated disinformation campaigns (Rizoiu et al. 2018). The second group aims to understand which platforms, users, and networks contribute to the "infodemic" (Smith and Graham 2019; Bruns, Harrington, and Hurcombe 2020; Colley and Moore 2020). The third group uses computational modeling to predict future pathways and how the information will spread (Molina et al. 2019). These studies provide valuable insights into understanding how problematic information spreads and detecting which sources are reshared frequently and by which accounts. Though the first and third research approaches offer breadth of knowledge and understanding, there are limitations — they often have less to say about why certain accounts and views gain traction with vulnerable groups and online communities.

Qualitative research methods are well placed to address this gap. They provide rich, contextual insights into the social beliefs, values, and practices of online communities, which shape how information is shared and how opinions are formed (Glaeser and Sunstein 2009; Boyd 2010; Baym 2015; Johns 2020). This is also fundamental to un-

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The gap of methods

Computational and quantitative

Large-scale monitoring of social media datasets [Kong et al, CIKM'20] [Ram et al, WSDM'21]

Identify platforms, users, and networks that contribute to the "infodemic" [Smith and Graham 2019] [Bruns et al 2020]

Future information spread [Molina et al. 2019]

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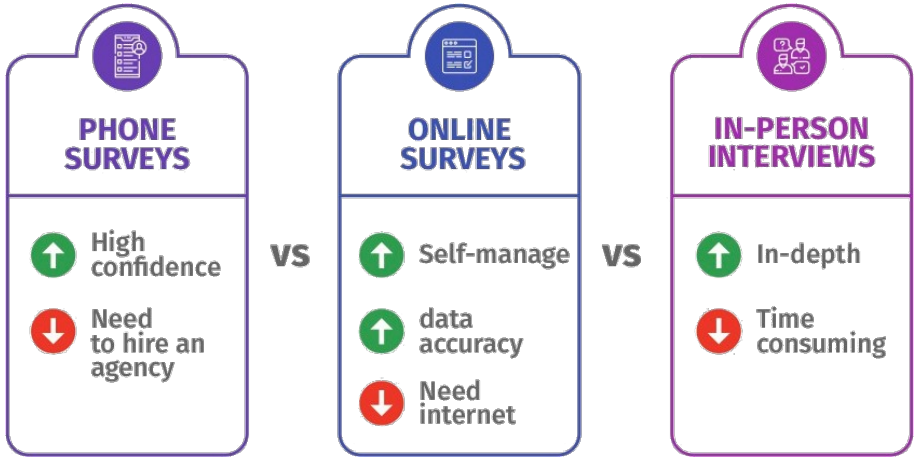


Qualitative and ethnographic

Large-scale monitoring of social media datasets [Kong et al, CIKM'20] [Ram et al, WSDM'21]

Identify platforms, users, and networks that contribute to the "infodemic" [Smith and Graham 2019] [Bruns et al 2020]

Future information spread [Molina et al. 2019]

How information is shared and how opinions are formed [Boyd 2010] [Baym 2015]

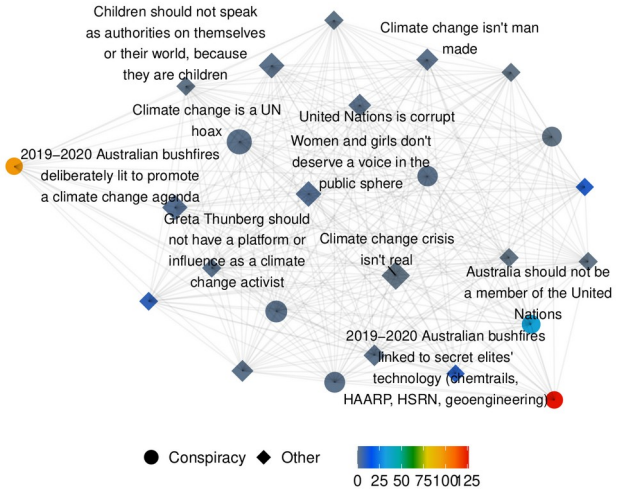
Why opinions and information sources scale to encompass large segments of the online society [Bailo 2020] [Bruns et al 2020]

Research questions

Can we leverage both qualitative and quantitative analysis for studying problematic online speech?

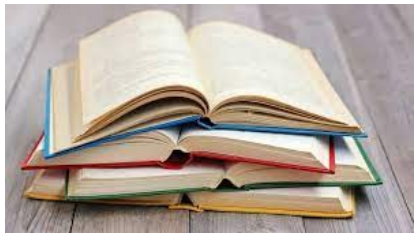
Can we accelerate qualitative research and observations of online behavior with machine learning algorithms?

Can we track the dynamics of problematic opinions from online discussions using unlabeled data?



Interdisciplinary approach and team

Communication science



Literature

Computer science

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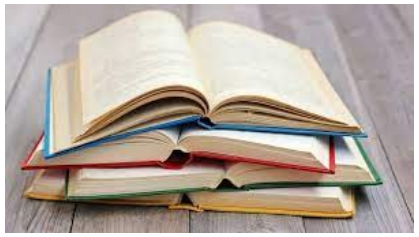
Francesco Bailo

Amelia Johns



Literature

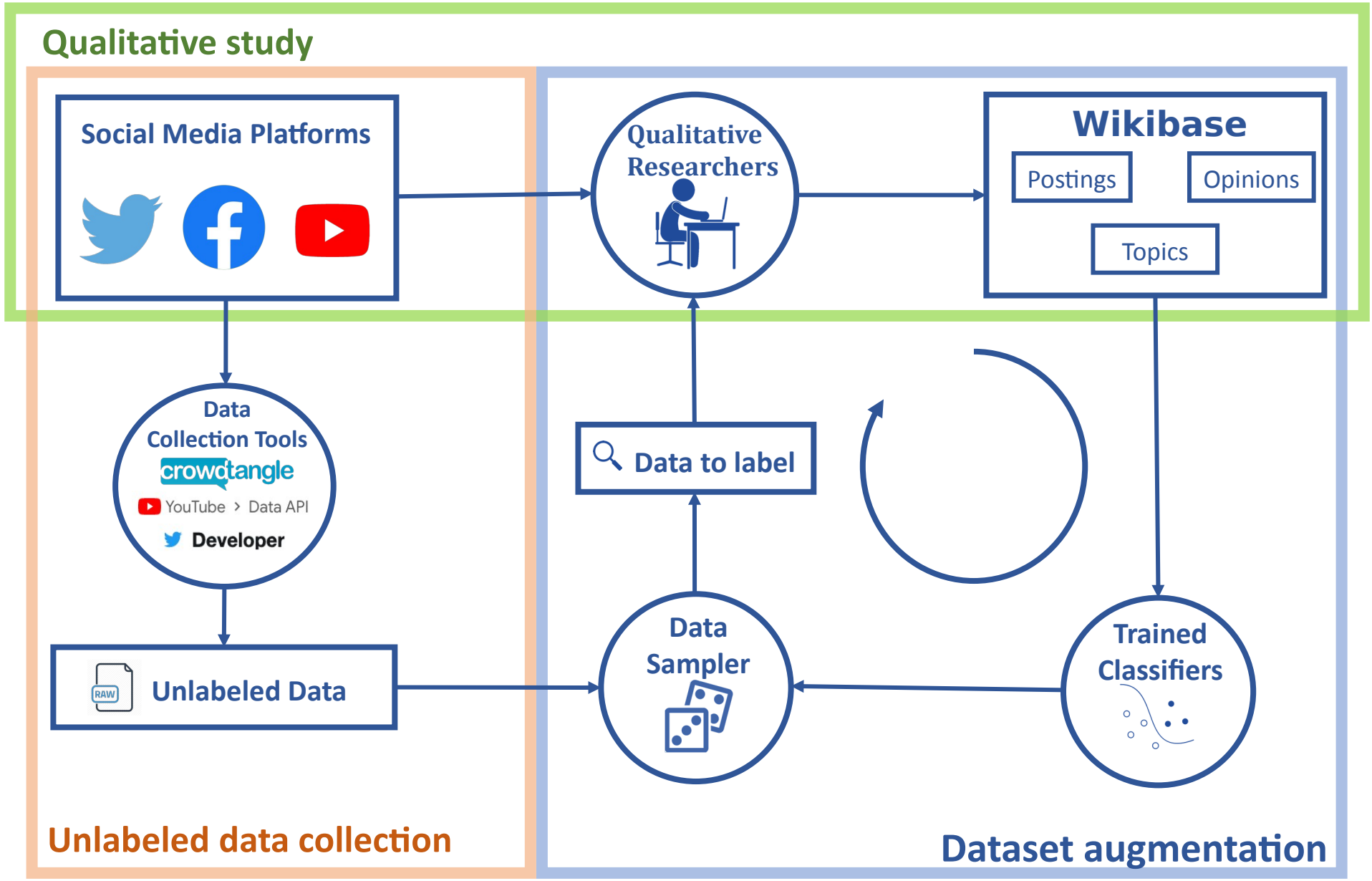
Emily Booth

Computer science

Marian-Andrei Rizoiu

Quyu Kong

Overall Approach



1. Qualitative Study

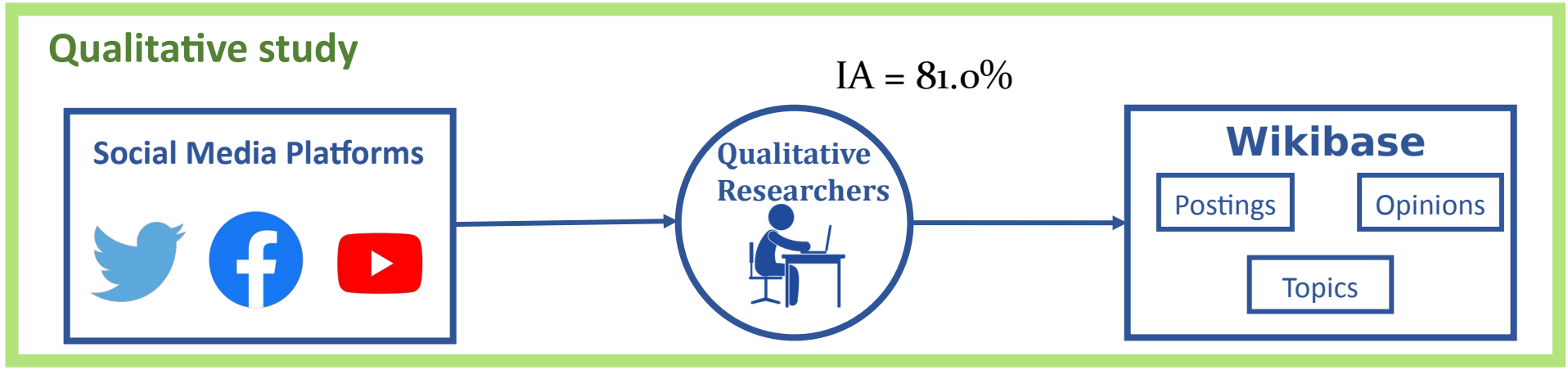
Four topics:

- 2019-20 Australian bushfire season
- Climate change
- COVID-19
- Vaccination

Dec 2019 – Jan 2021

Internet places:

- News stories
- Facebook page monitoring
- Cross-page link tracking
- Platform recommender systems

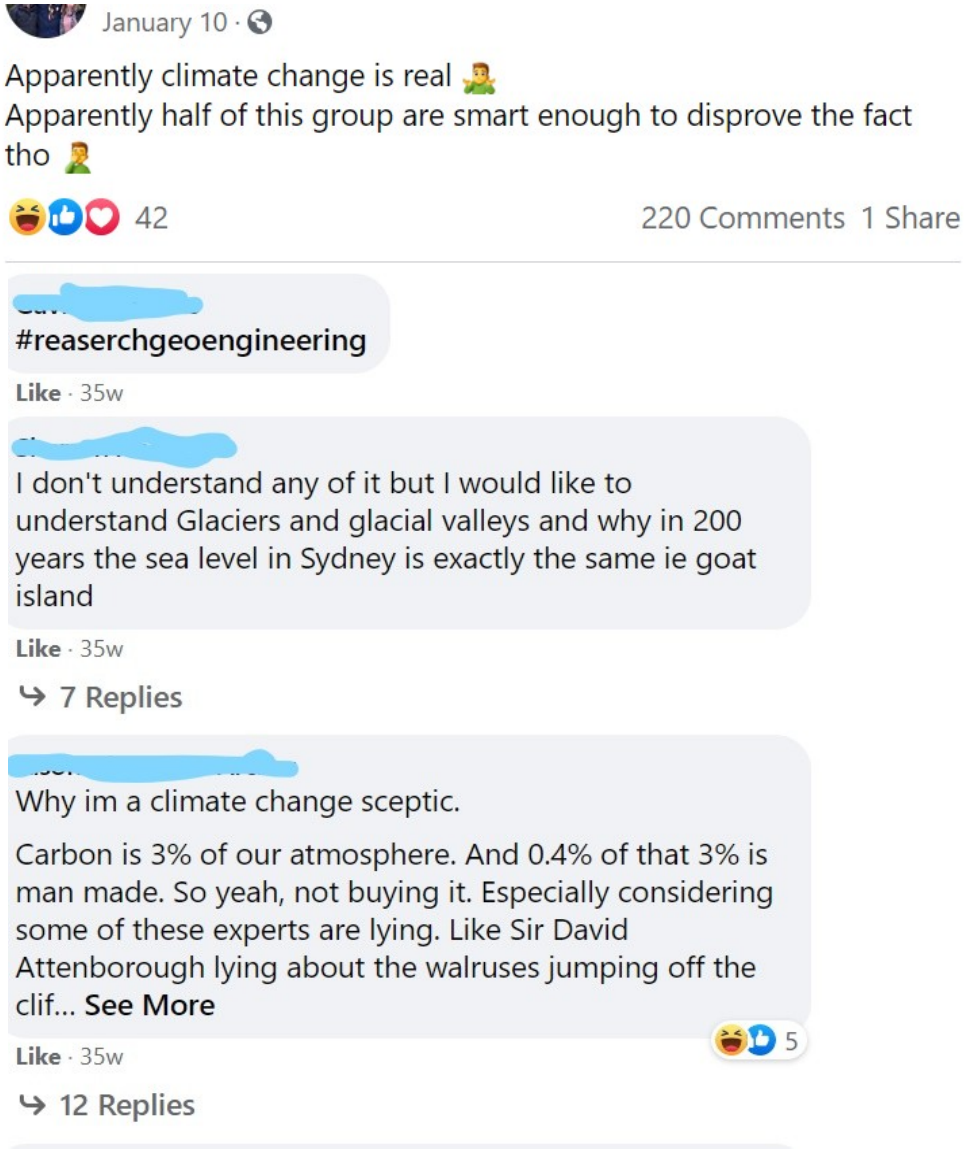


614 postings and 65 opinions:

- Climate change crisis isn't real
- United Nations is corrupt
- Climate change is a UN hoax
- United Nations want to be the global ruling government
- Experts manipulate data for private or corporate agendas
- Vaccines cause Autism
- The World Health Organization is corrupt
- Men are being chemically emasculated by the government/science/elites
- Covid-19 is the Chinese government's bioweapon

Take Australia Back - Public Facebook group, 11.2K members.

Sample post and comments 1: Jan 10 2020



January 10 ·

Apparently climate change is real 🤦
Apparently half of this group are smart enough to disprove the fact tho 🤦

42 220 Comments 1 Share

[redacted]
#reaserchgeoengineering

Like · 35w

[redacted]
I don't understand any of it but I would like to understand Glaciers and glacial valleys and why in 200 years the sea level in Sydney is exactly the same ie goat island

Like · 35w

↳ 7 Replies

[redacted]
Why im a climate change sceptic.

Carbon is 3% of our atmosphere. And 0.4% of that 3% is man made. So yeah, not buying it. Especially considering some of these experts are lying. Like Sir David Attenborough lying about the walruses jumping off the clif... See More

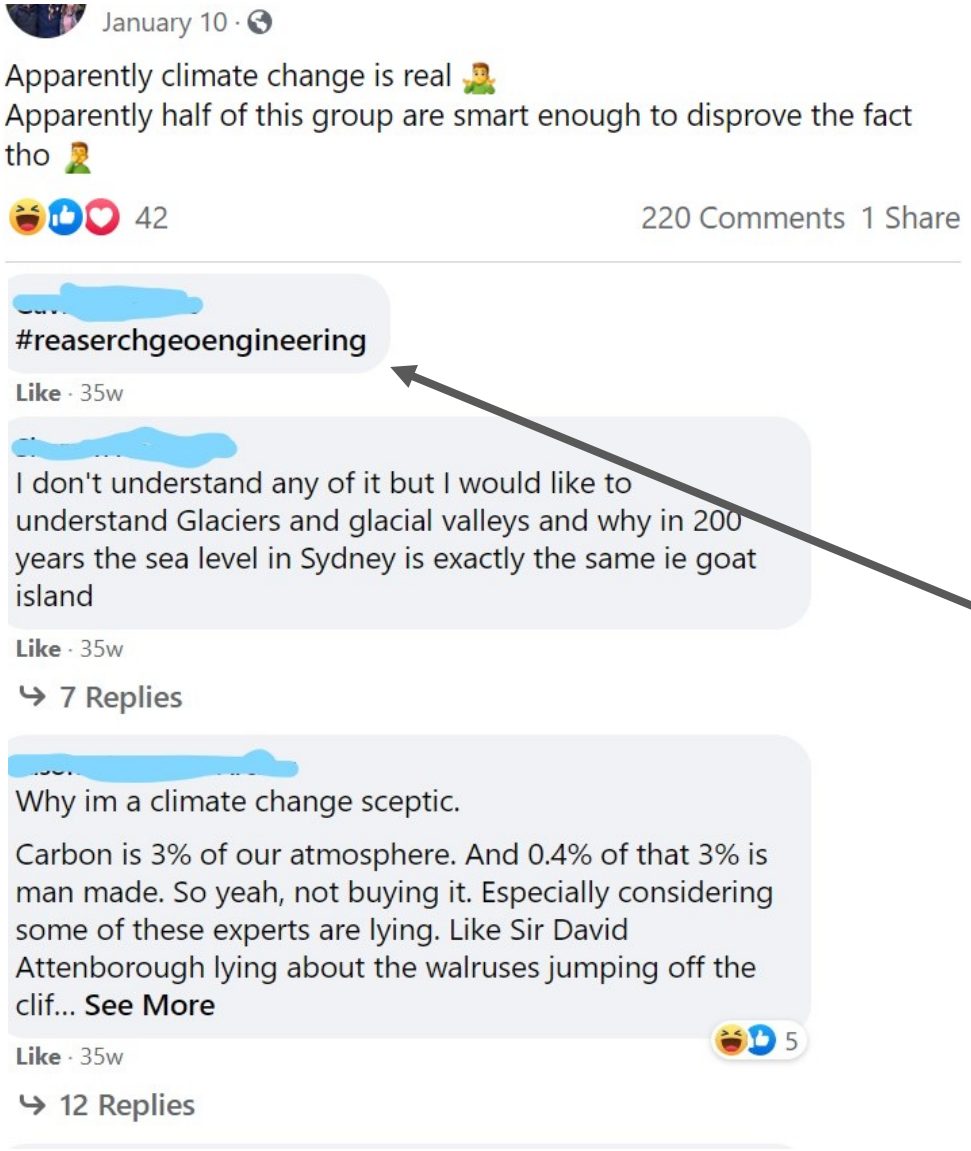
5

Like · 35w

↳ 12 Replies

Take Australia Back - Public Facebook group, 11.2K members.

Sample post and comments 1: Jan 10 2020



- 50/50 climate change denial and support
- Some respectful debate but mainly polarising contest and troll-like social practices
- Use of misogynistic and ableist abuse to inflame/polarise/derail opposing opinion
- Small number of conspiracy theories (e.g. chemtrails)
- 40-60+ user group
- Text based comments, few links out, more comments than shares

Sample post and comments 2: 16 September 2020

84 9 Comments 58 Shares

Like Share

1

Like · 5h

Yeah, you can just remove the cloth masks anytime you want. And also they don't silence you as much as muffle your voice.

Like · 5h · Edited

But it covers so much of your emotion and power. There is a reason men do this to women in Islam.

Like · 5h

Like · 1h

how true

I joined this group when we were fighting against scomo cause he's a dick head, now this group is full of dickheads

Like · 1h · Edited 3

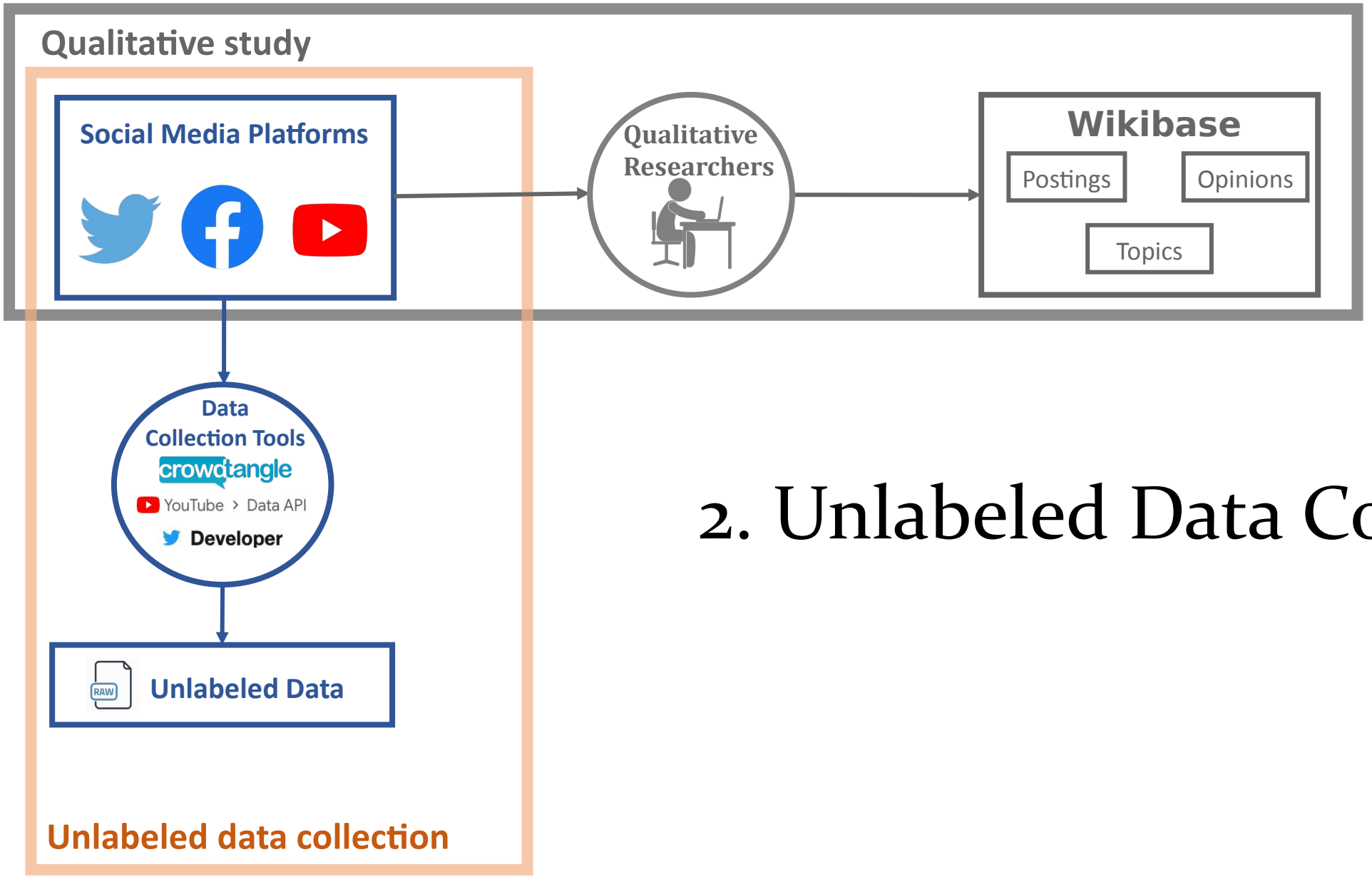
Not too mention most of those iron masks had fukn locks on them

Like · 1h 3

its one of the first thing you learn on your road of indoctrination you mean. 😉

Like · 1h

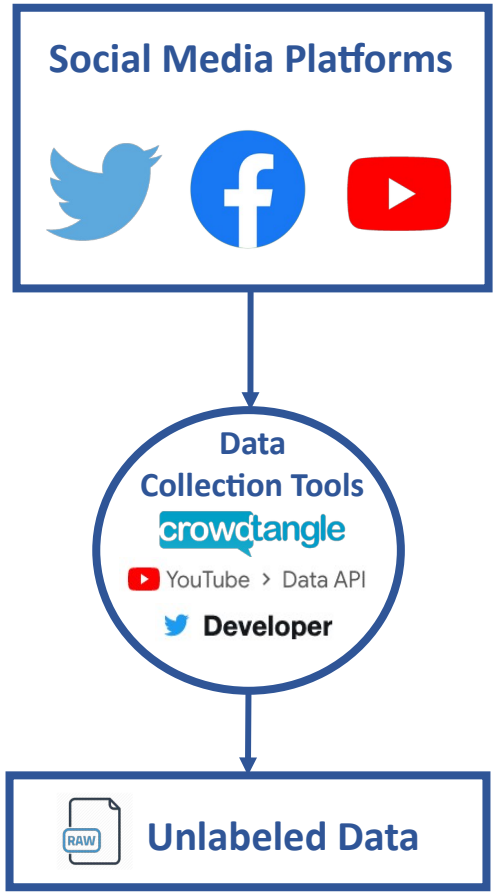
realise who controls the puppets first.



2. Unlabeled Data Collection

2. Unlabeled Data Collection

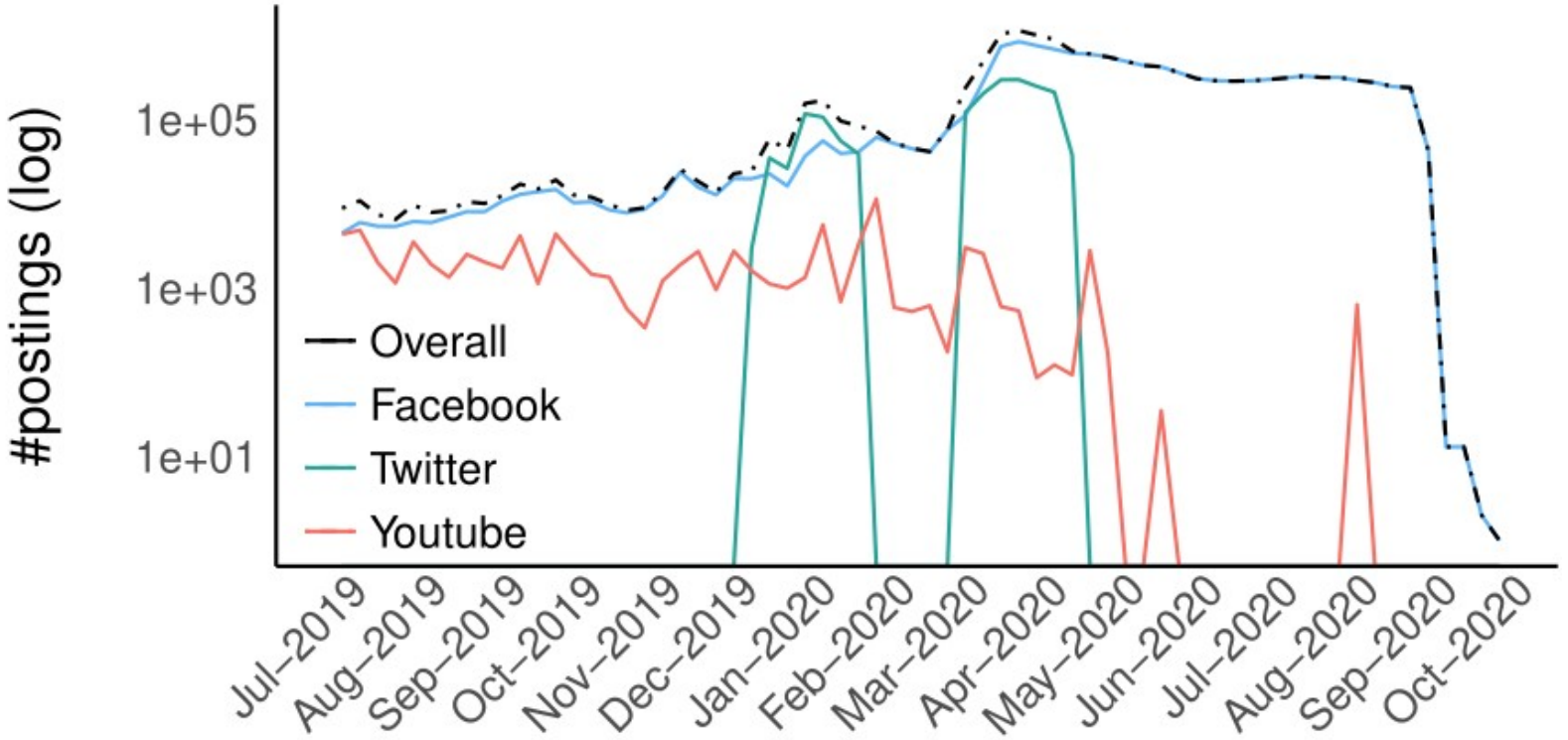
Topics	Selected keywords
2019-20 Australian bushfire season, Climate change	bushfire, australian fires, arson, scottyfrommarketing, liarfromtheshiar, australiaburns, australiaburning, itsthegreensfault, backburning, back burning, climate change, climate mergency, climate hoax, climate crisis, climate action now
Covid-19, Vaccination	covid, coronavirus, covid-19, pandemic, world health organization, vaccine, social distancing, quarantine, plandemic, chinavirus, wuhan, stayhome, MadeinChina, ChinaLiedPeopleDied, 5G, chinacentric

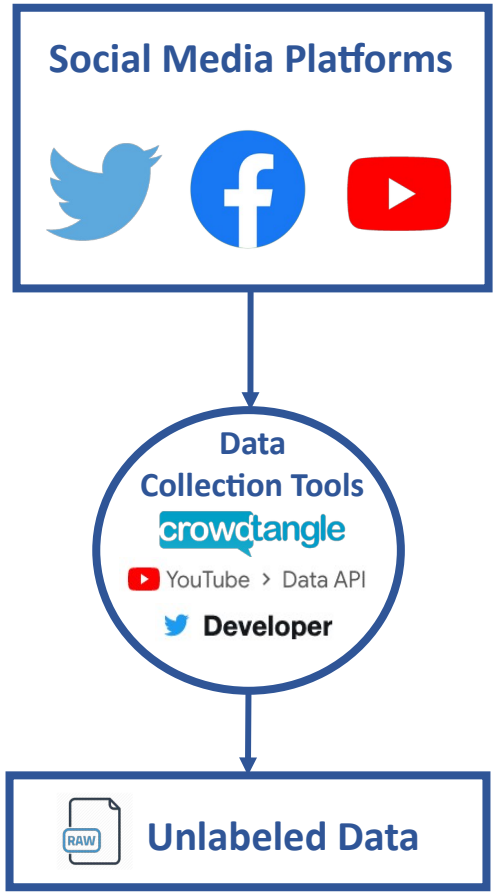


13.3M postings:

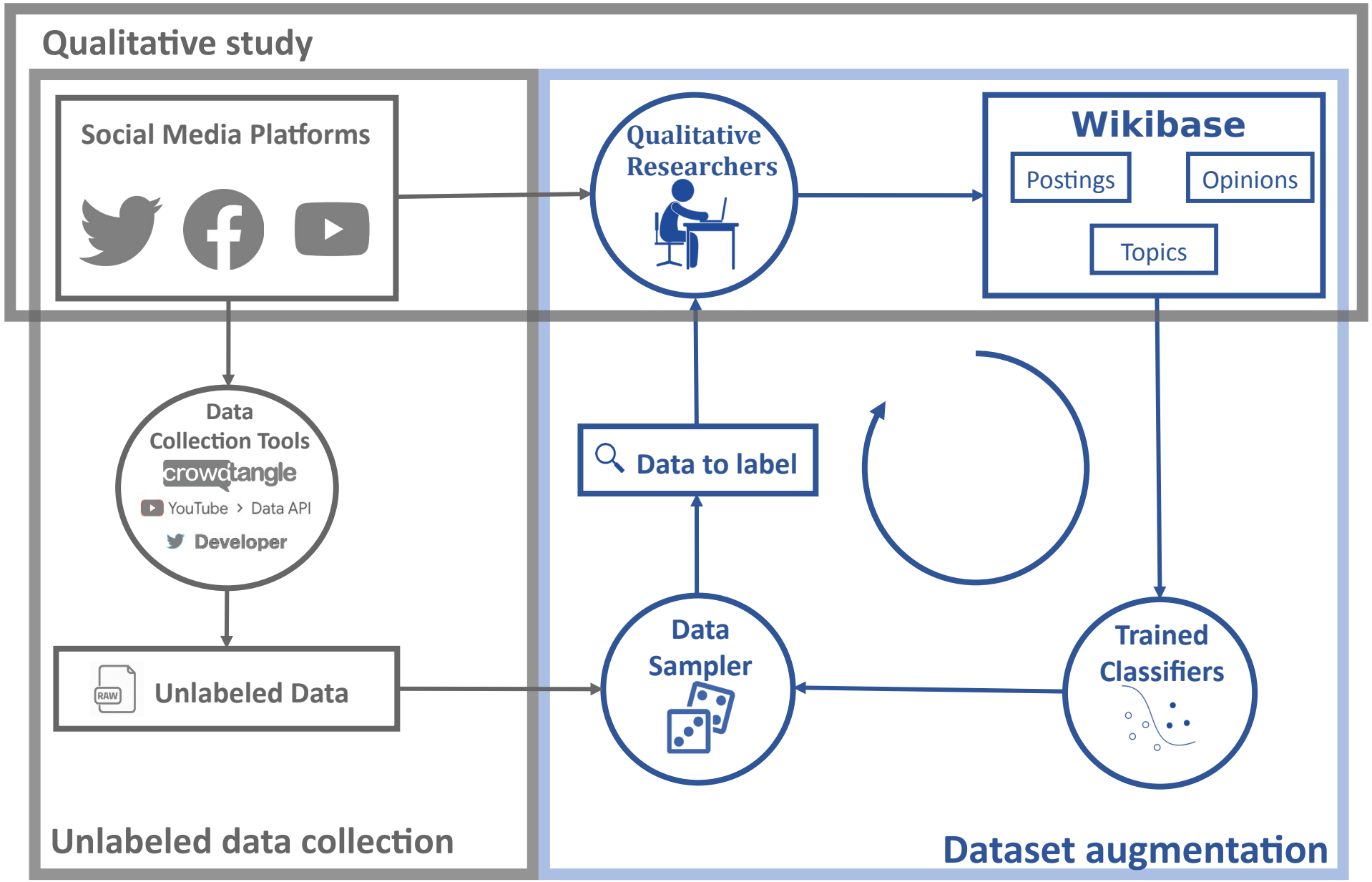
- 11.4M Facebook
- 1.8M Twitter
- 91K YouTube comments

2. Unlabeled Data Collection



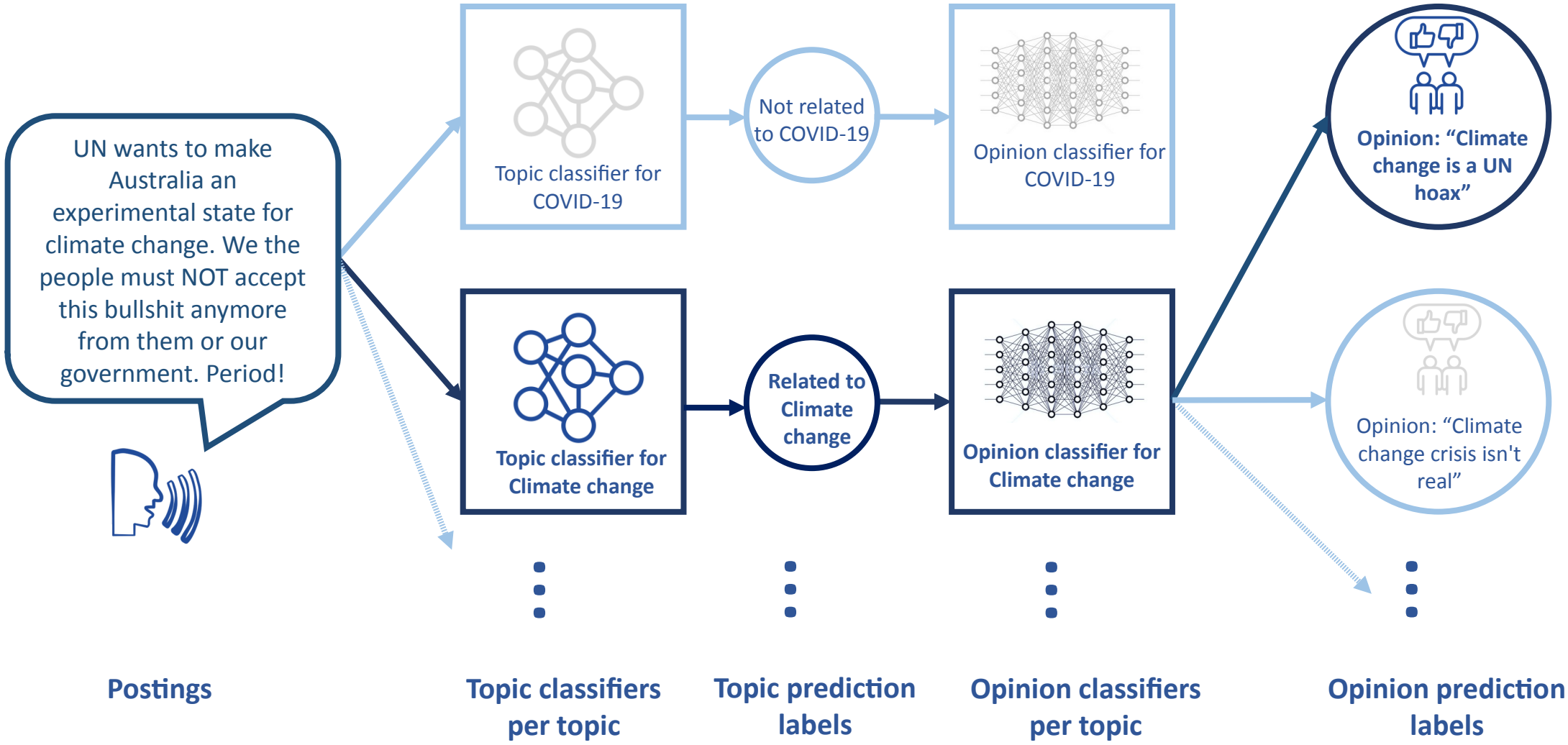


3. Dataset Augmentation



Two levels of classifiers

	RF	SVM	XGBoost	RoBERTa
Macro Accuracy	0.791	0.775	0.779	**0.800**
Macro F1	0.782	0.768	0.768	**0.800**

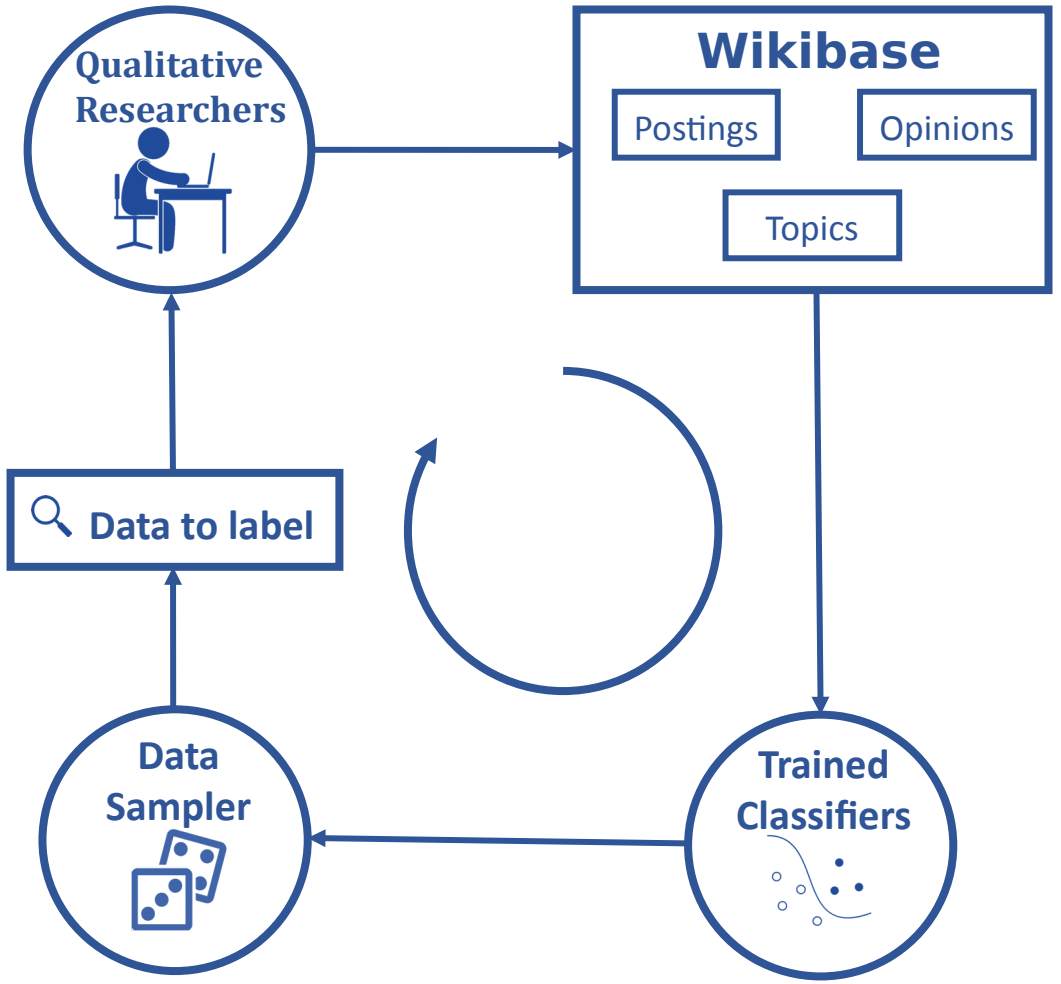


3. Dataset Augmentation

- Human-in-the-loop Machine Learning

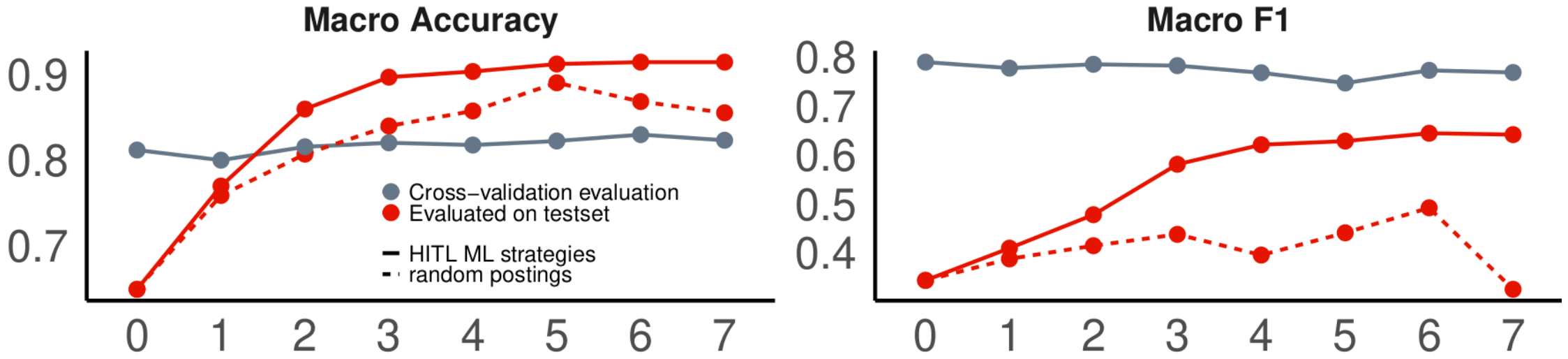
- Three strategies for data sampling:
  - Active learning
    10 posts / iteration / topic
    $u(\boldsymbol{x}) = 1 - p(\hat{y} \mid \boldsymbol{x}; f_{t,i})$
  - Top confidence
    10 posts / iteration / topic
  - Random sampling
    5 posts / iteration / topic

- Iterated until convergence
  - cross-validation error VS test set error
  - gain on test set between two iterations



Results

Human-in-the-loop performance



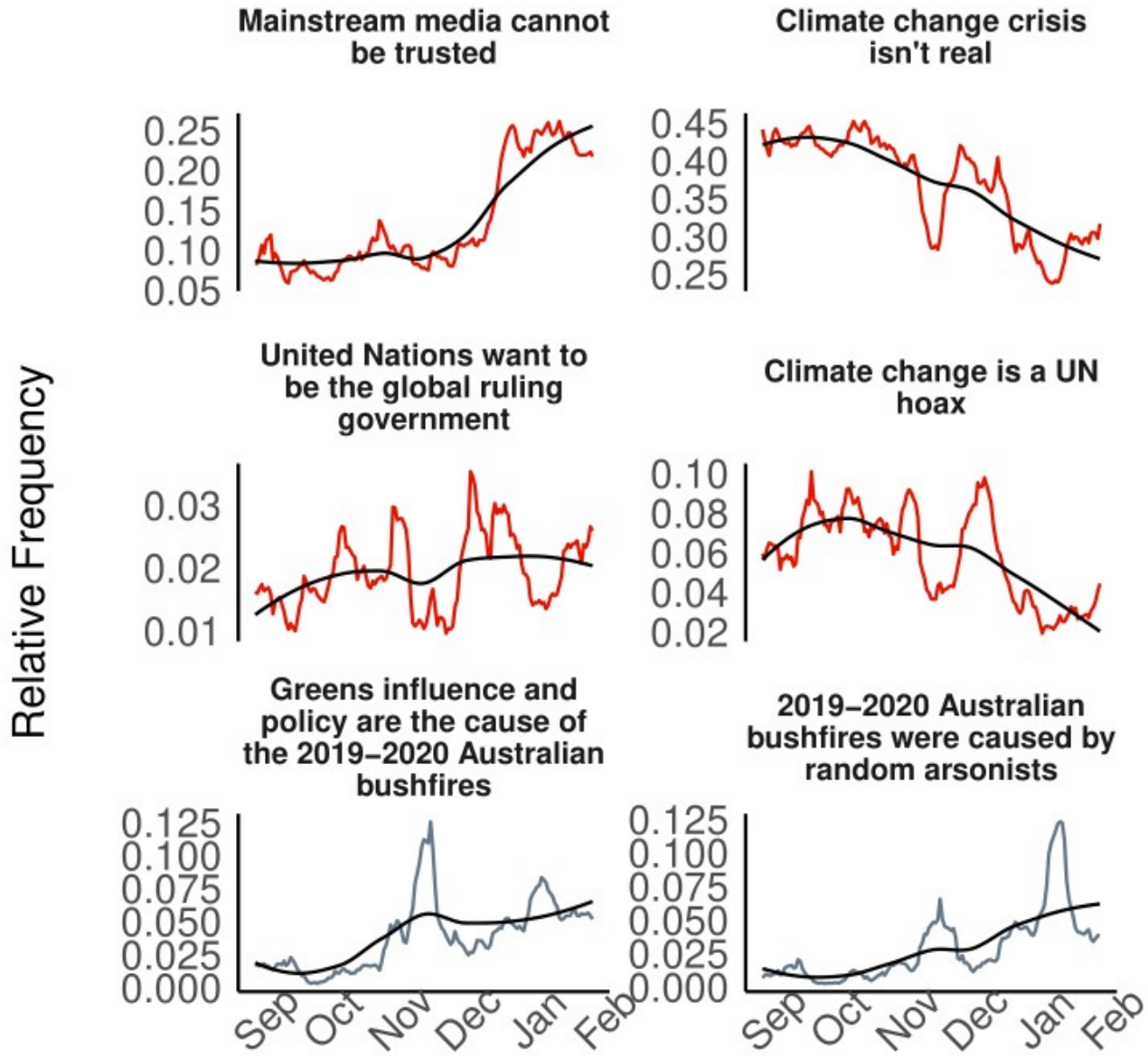
- Performances improve as more batches are performed
- Gap between generalization and test set error reduces
- Improvement plateaus as the process converges
- Human-in-the-Loop outperforms static random selection of samples

	L0	L7
#posts	614	1381
#opinions	65	71

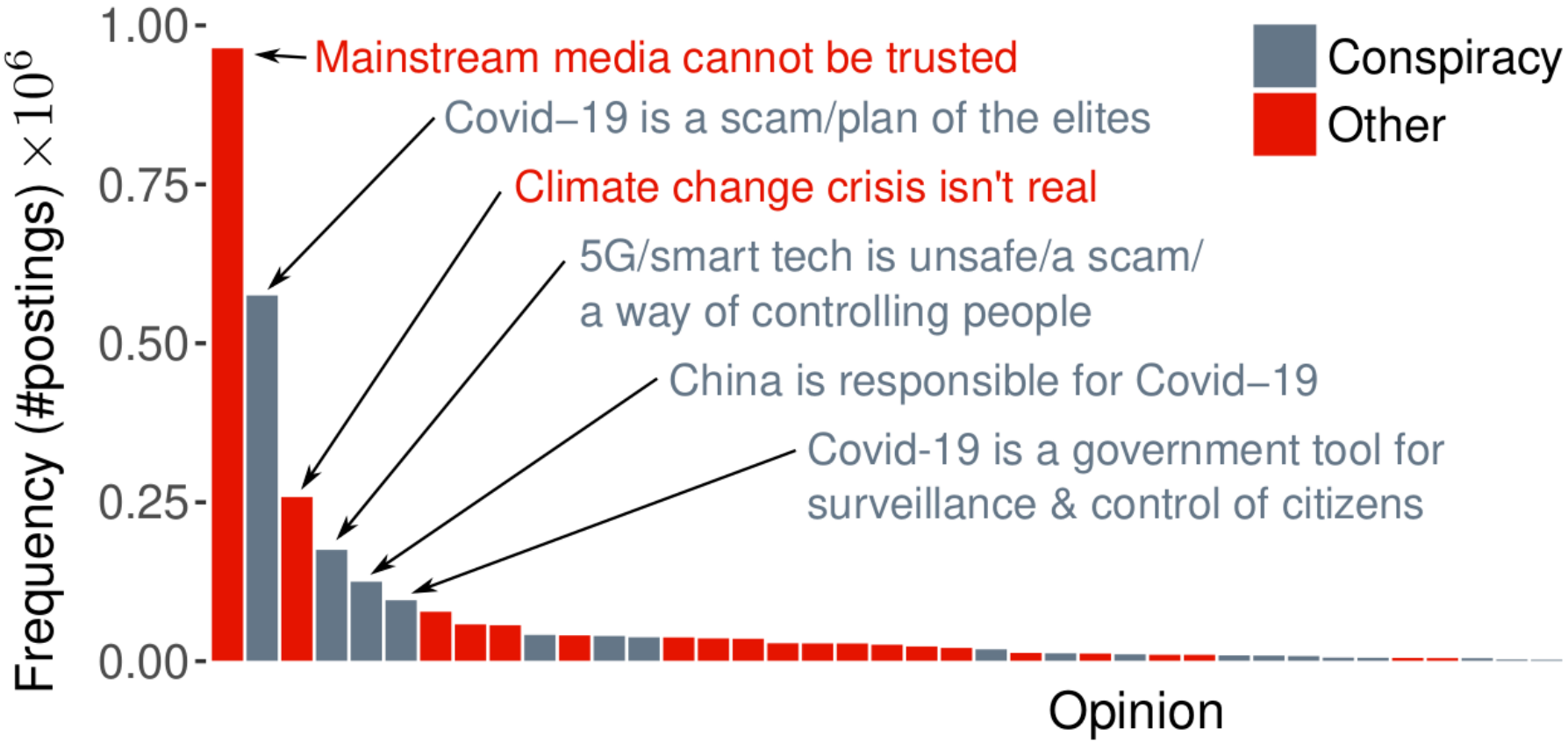
Opinion analysis at scale

Fully labeled dataset stats

- 1.7M postings with at least one opinion
- 314K postings with 2 or more opinions
- 21.26M off-topic postings
- **Total**: 22.96M postings

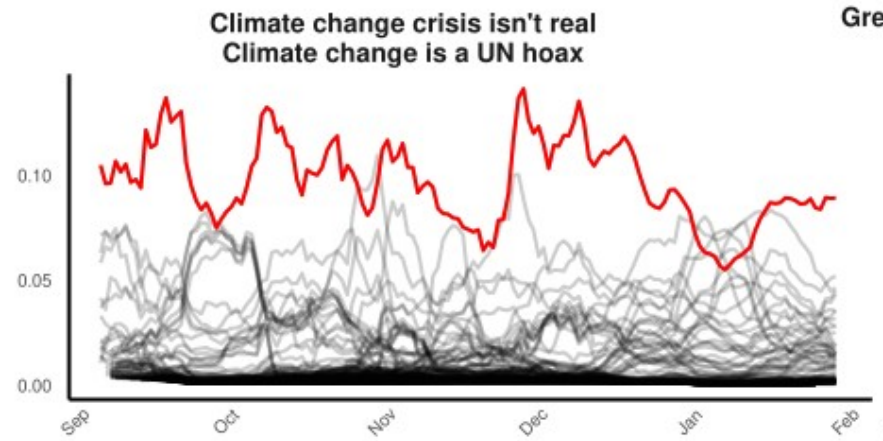


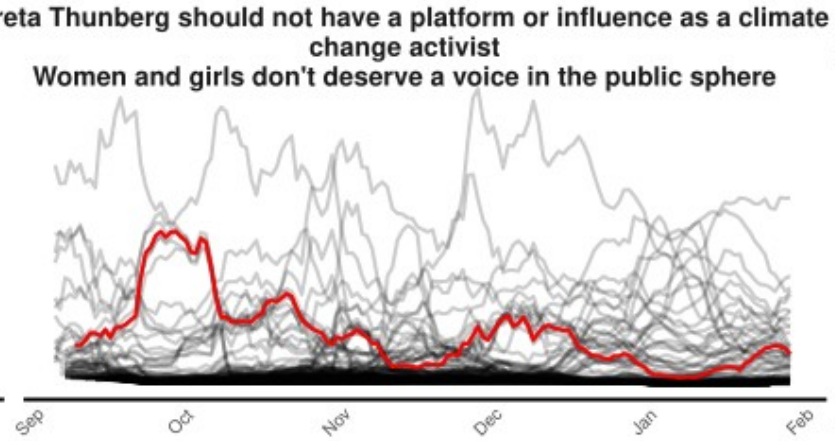
Opinion analysis at scale

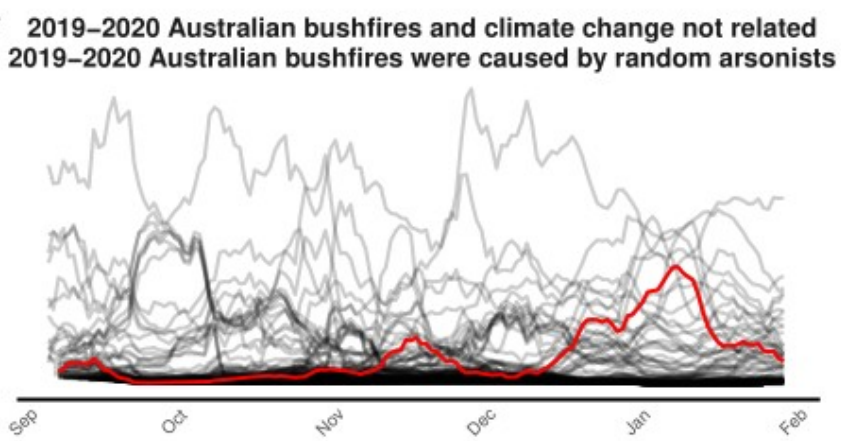


- Opinion usage frequency is longtail distributed
- Four of the top six opinions endorse conspiracy theories

Opinion co-occurrence network







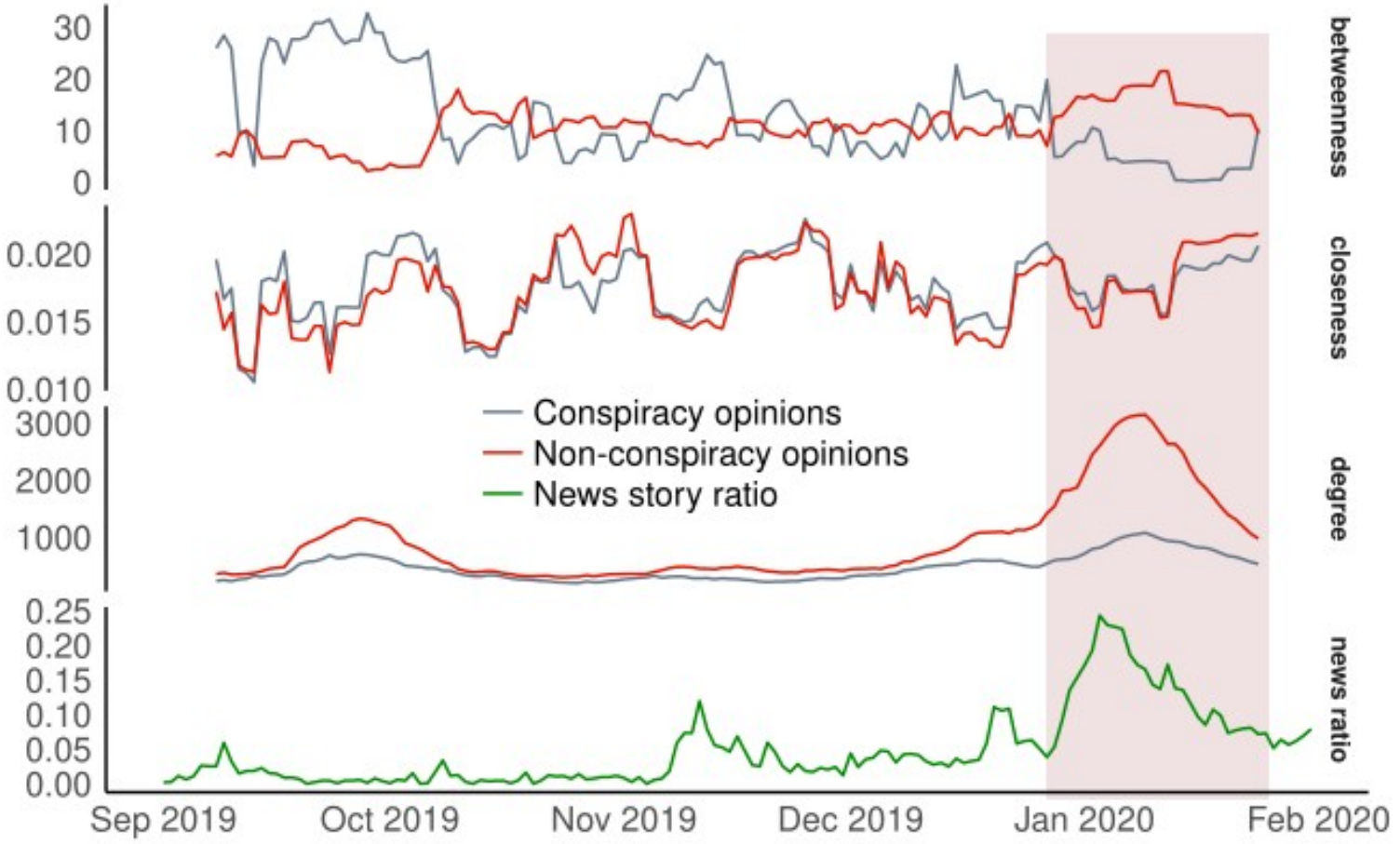
A continuous and relatively strong association between prevalent opinions

Associations with declining relative frequencies

Rising associations – early warnings for their adoption (and possibly normalization) by participants

Centrality of conspiracy opinions and news ratio

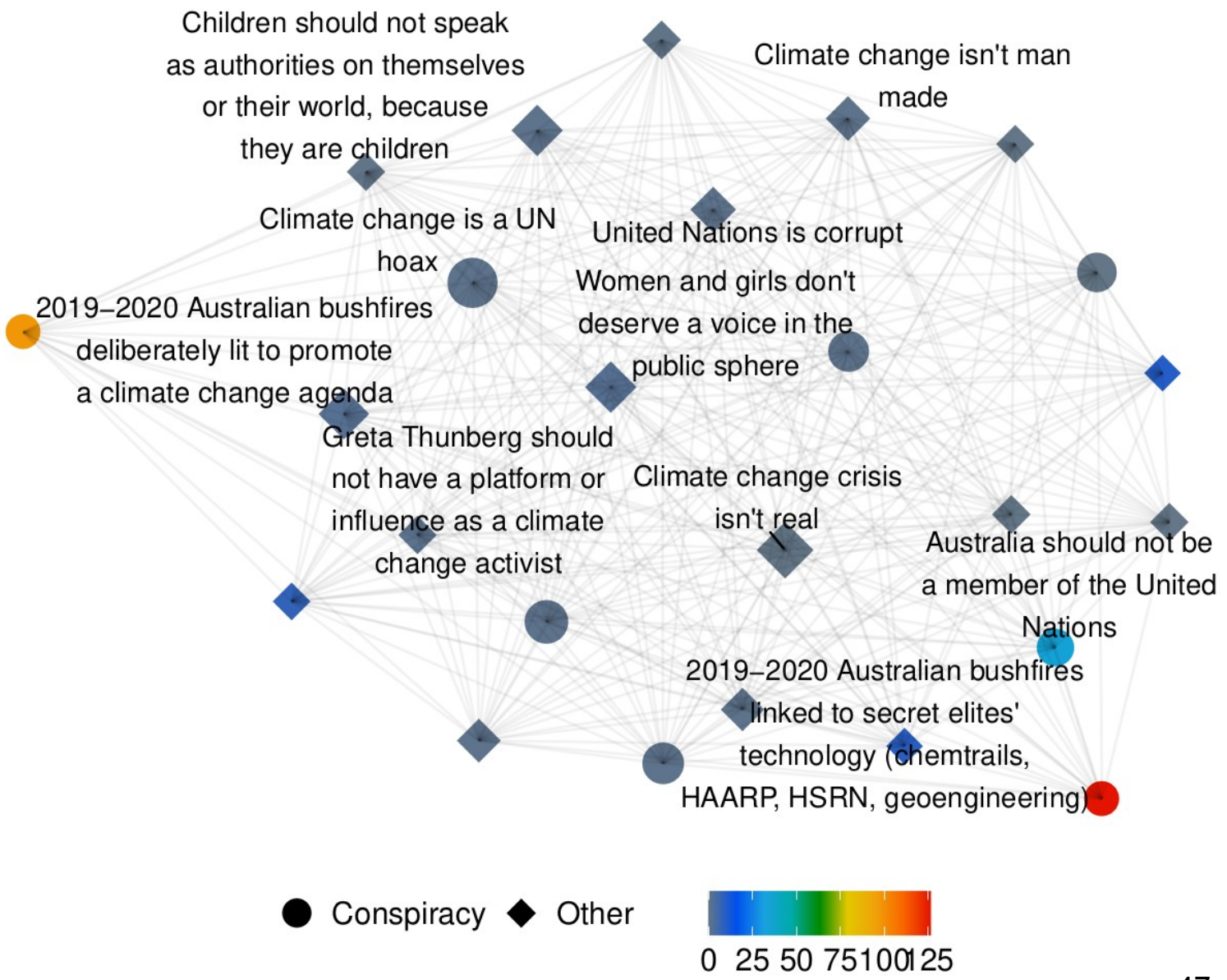
Higher coverage from news media reduces centrality of conspiracy opinions.



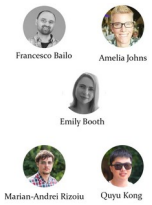
coverage ratios from Media Cloud (Roberts et al. 2021)

Opinion co-occurrence network

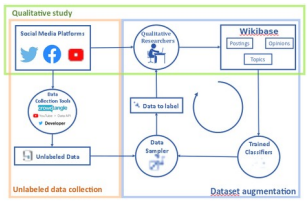
- High betweenness centrality of conspiracy opinions → selectively used in conjunction with many other opinions
- 14 days in late September 2019 – peak betweeness
- Conspiracy opinions are used together with mainstream opinions – rationalize and popularize them



Summary

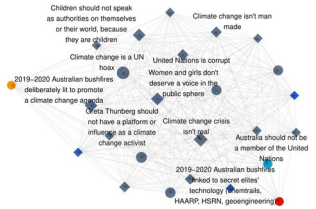


An inter-disciplinary team and methods to solve a difficult task: detecting and mapping the impact of online problematic content



A mixed qualitative and human-in-the-loop Machine Learning approach for detecting problematic content

A representative annotated dataset of online problematic content, qualitative and quantitative analyses



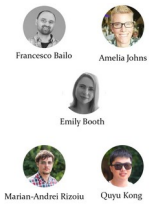
A hypothesis of how fringe opinions infiltrate mainstream discourse via co-occurrence with established opinions

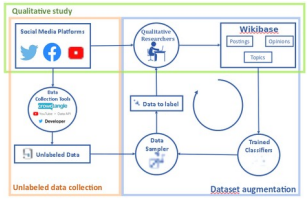
Behavioral Data Science

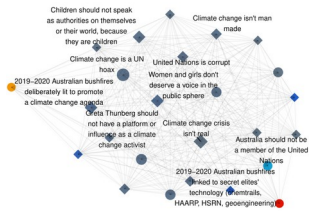
Thank you!

UTS Data Science

UTS UNIVERSITY OF TECHNOLOGY SYDNEY







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