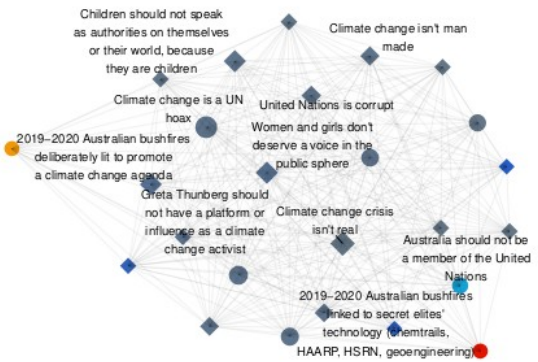
Behavioral Data Science

UTS Data Science

UTS UNIVERSITY OF TECHNOLOGY SYDNEY

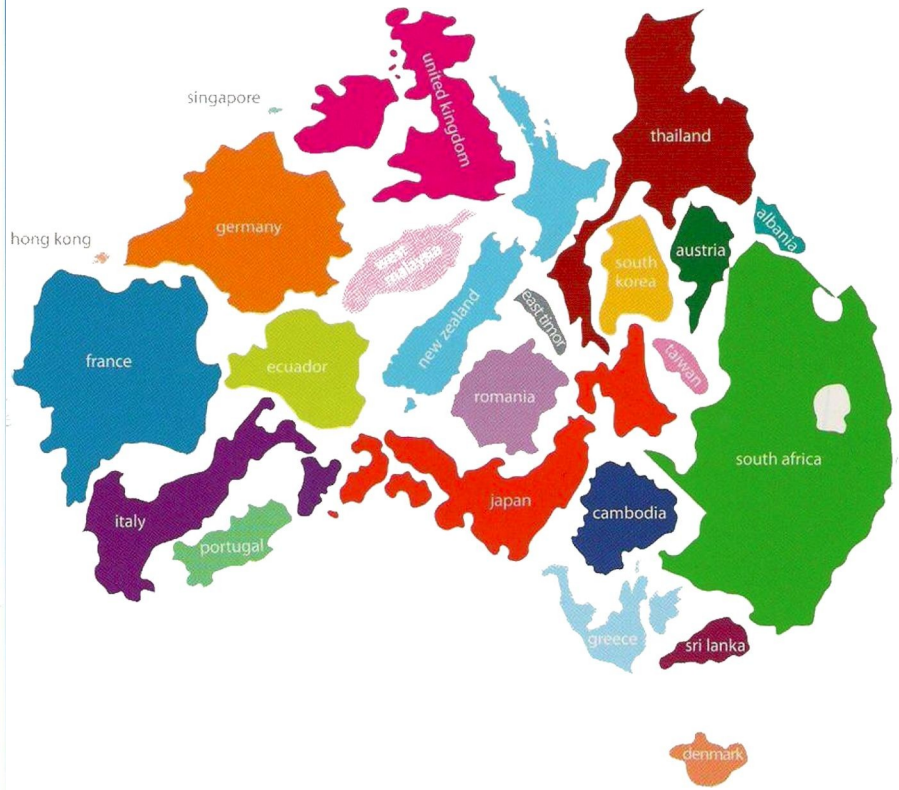


Mapping Online Problematic Content: Mixing Qualitative Approaches with State-of-the-art Machine Learning

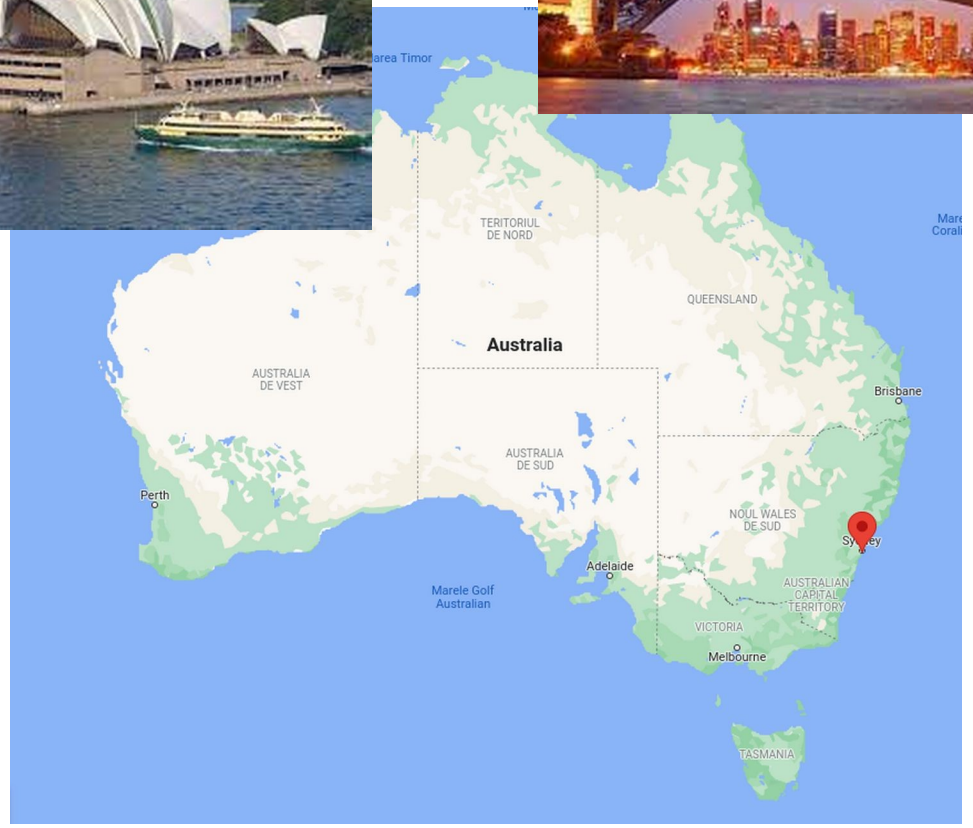
Marian-Andrei Rizoiu | Behavioural Data Science
Marian-Andrei.Rizoiu@uts.edu.au
https://www.behavioral-ds.ml

Australia

The world map, according to Australians



Australia is a big BIG place



Located in Sydney, Australia

A city campus, iconic brutalist style blended with modern buildings

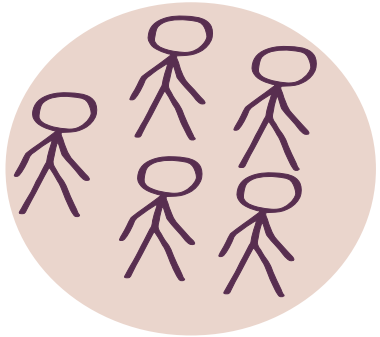
The research group

Behavioral Data Science

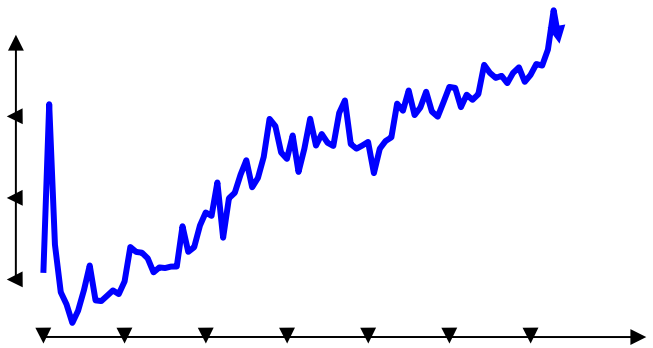
1 PostDoc, 6 PhD, 3 Masters, 1 assistant prof.

The Behavioral Data Science

1.



information diffusion
epidemics spreading
behavioral modeling



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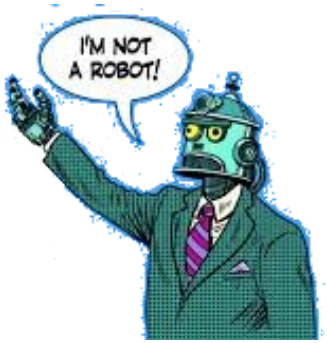

[Rizoiu et al ICWSM'18]

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

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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francesco.bailo@uts.edu.au, marian-andrei.rizoiu@uts.edu.au

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 opinions 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-

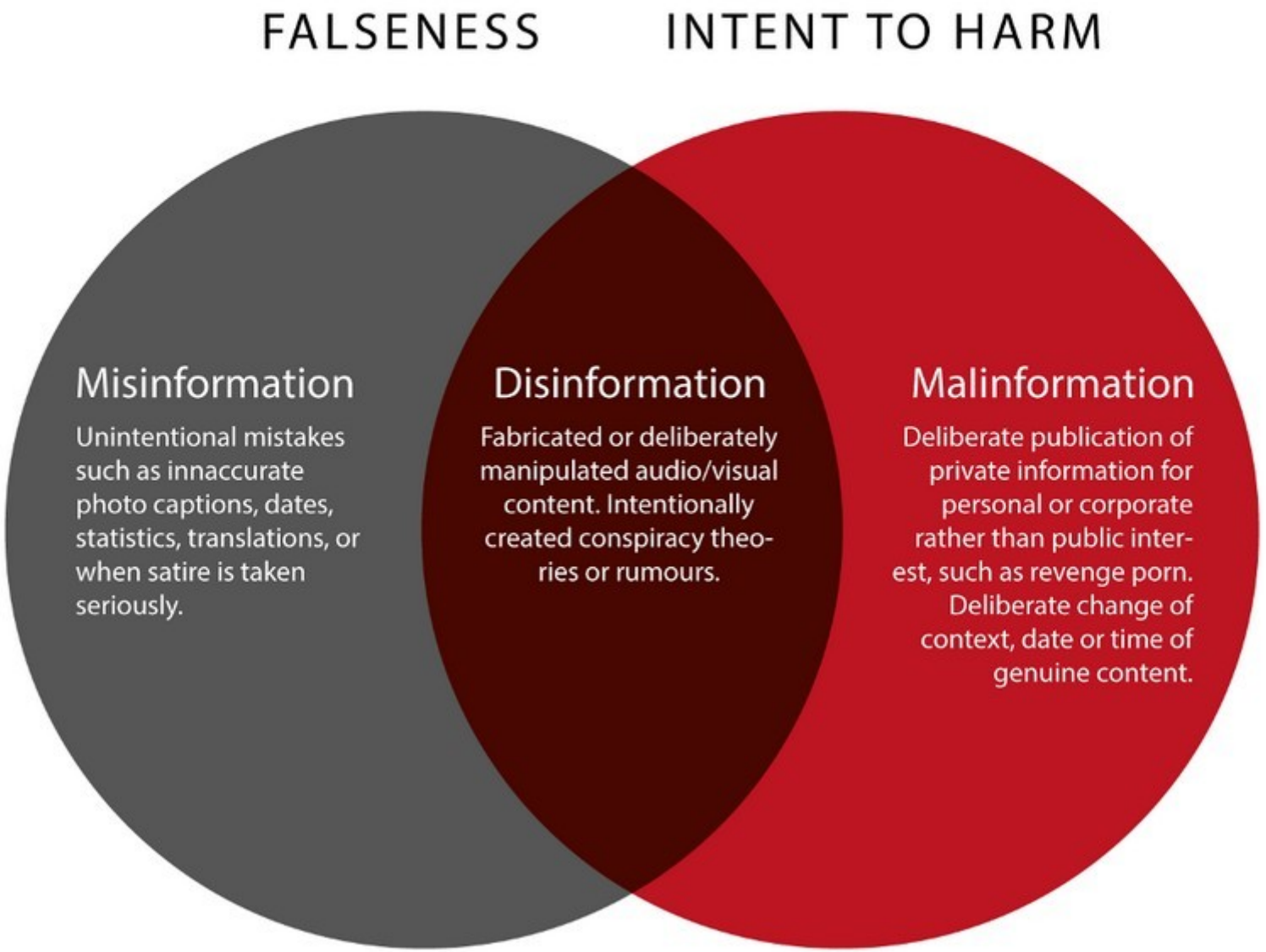
Kong, Q., Booth, E., Bailo, F., Johns, A., & Rizoiu, M.-A. (2022). Slipping to the Extreme: A Mixed Method to Explain How Extreme Opinions Infiltrate Online Discussions. In AAAI International Conference on Web and Social Media. Retrieved from http://arxiv.org/abs/2109.00302

Motivation

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

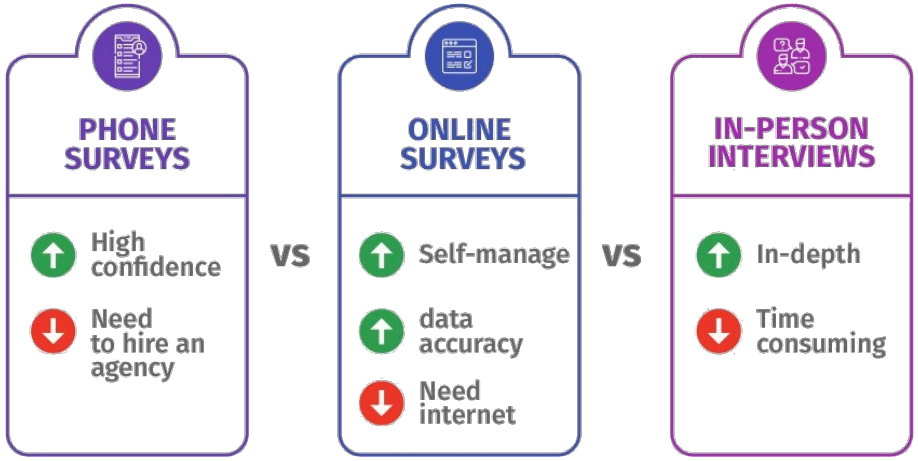
- misinformation
- disinformation
- hate speech

Types of information disorder



The gap of methods

Computational and quantitative



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]

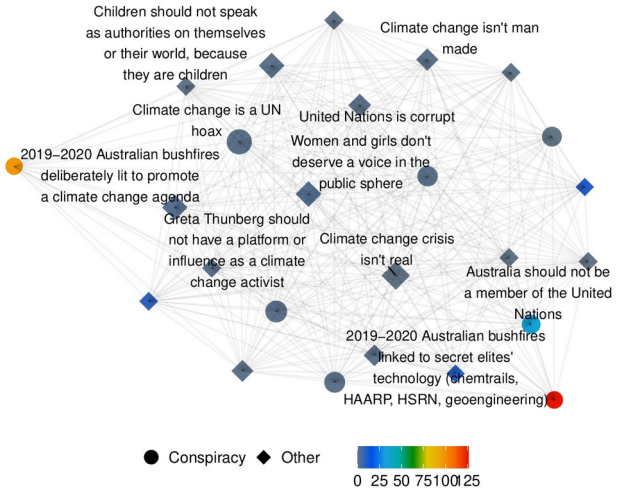
Why opinions and information sources scale to encompass large segments of the online society [Bailo 2020] [Bruns et al 2020]

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?

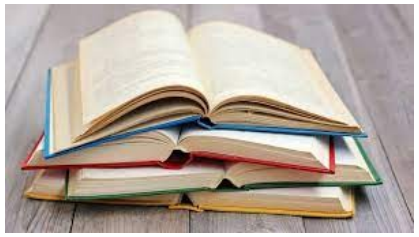


Interdisciplinary approach and team

Communication science

Francesco Bailo

Amelia Johns



Literature

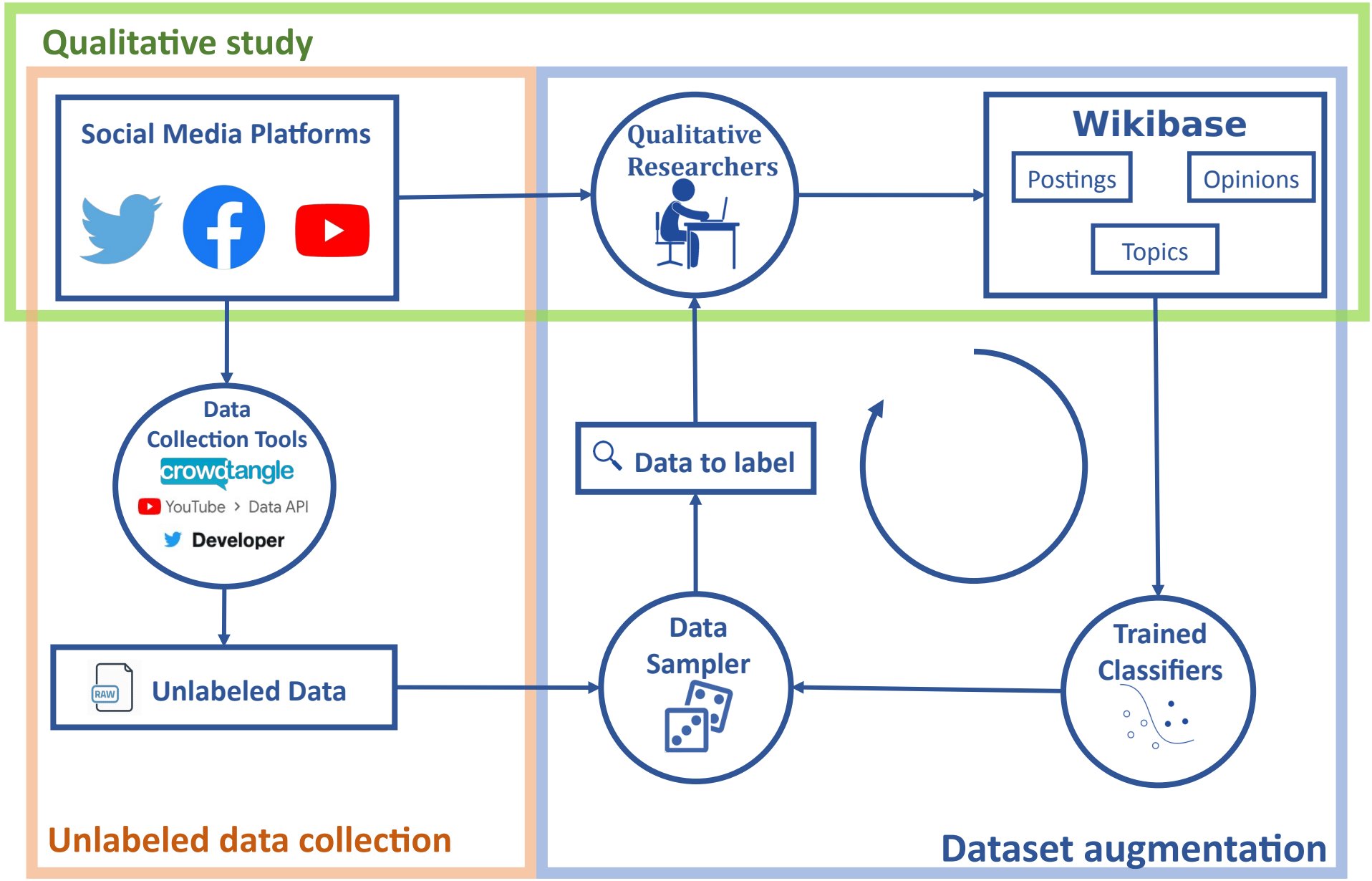
Emily Booth

Computer science

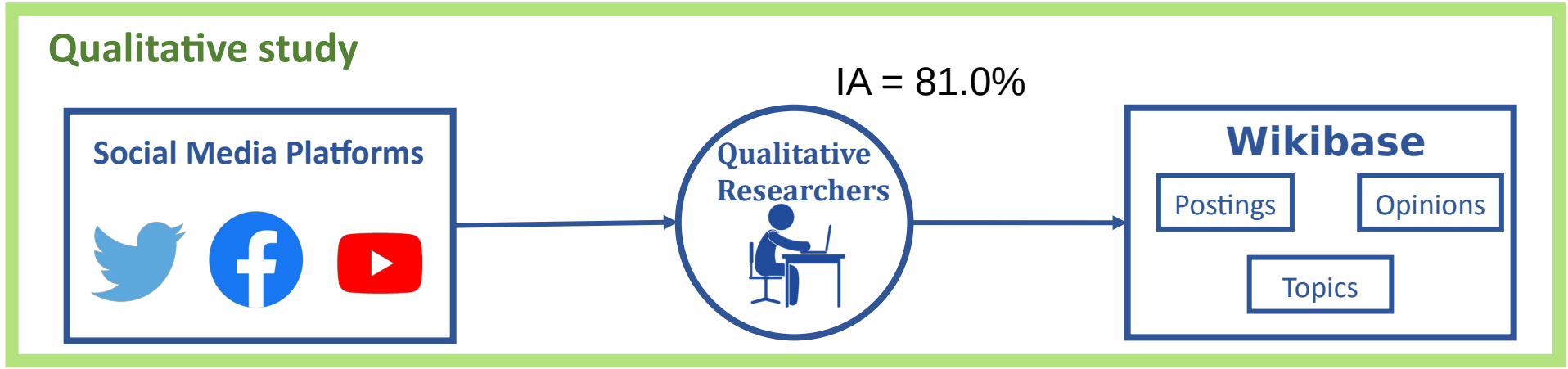
Marian-Andrei Rizoiu

Quyu Kong

Presentation Plan / Overall Approach



1. Qualitative Study



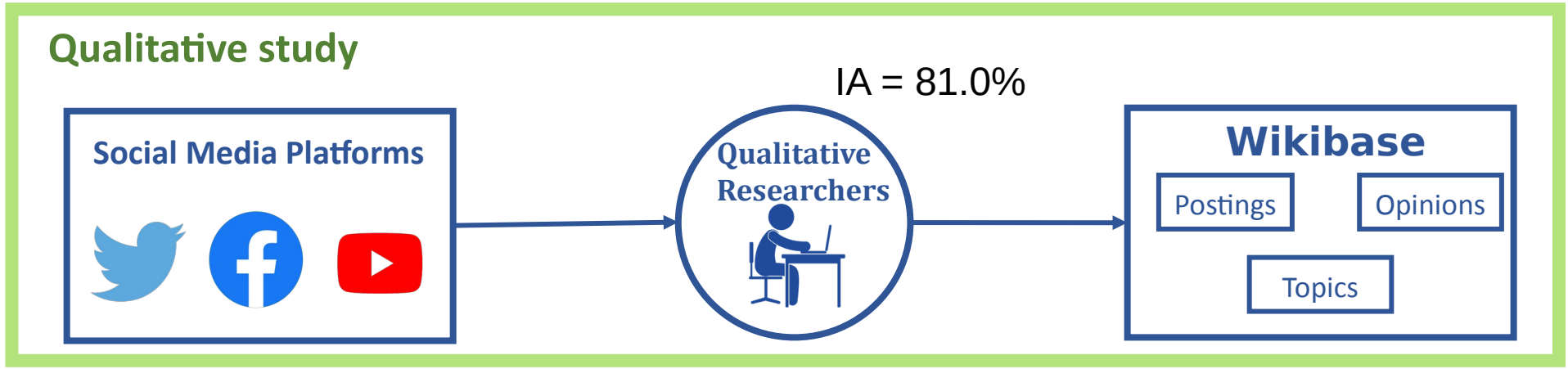
Four topics:

- 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]

- 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

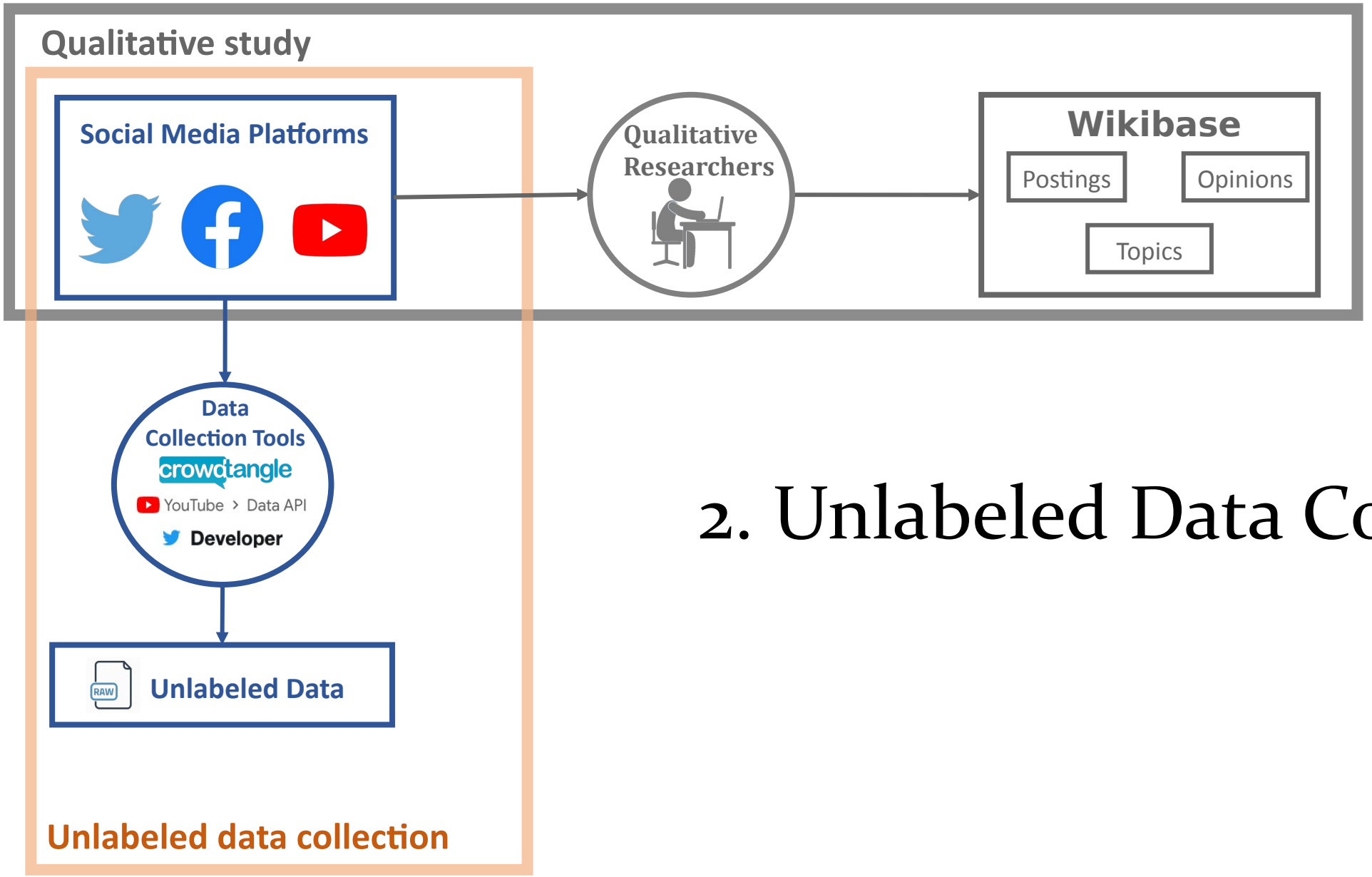
Not too mention most of those iron masks had fukn locks on them

Like · 1h 3

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

Like · 1h

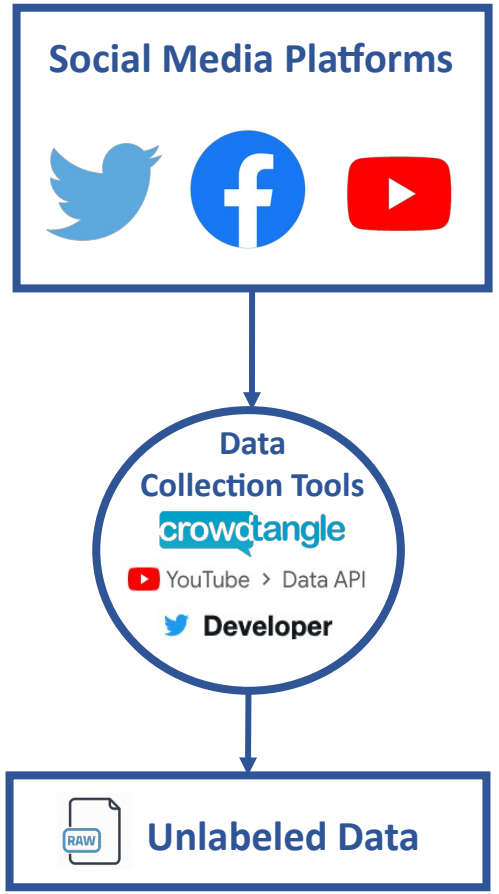
realise who controls the puppets first.



2. Unlabeled Data Collection

2. Unlabeled Data Collection

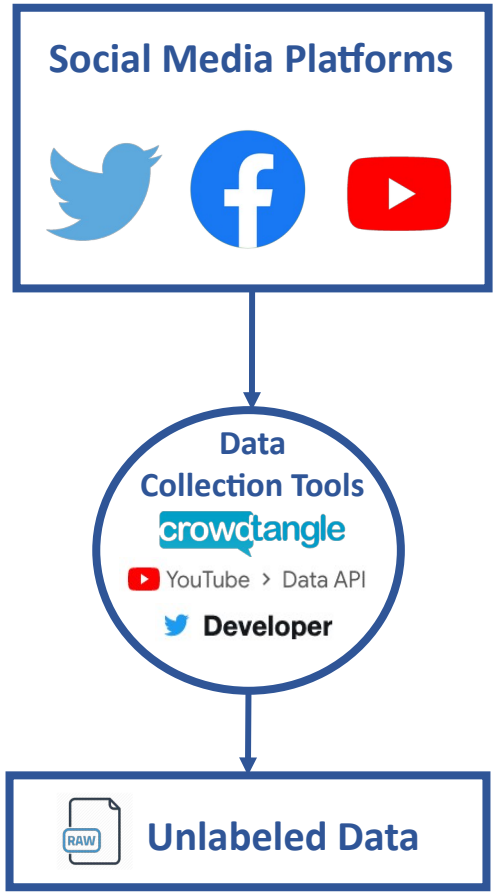
Topics	Selected keywords
2019-20 Australian bushfire season, Climate change	bushfire, australian fires, arson, scottyfrommarketing, liarfromtheshiar, australiaburns, australiaburning, itsthegreensfault, backburning, back burning, climate change, climate mergency, climate hoax, climate crisis, climate 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



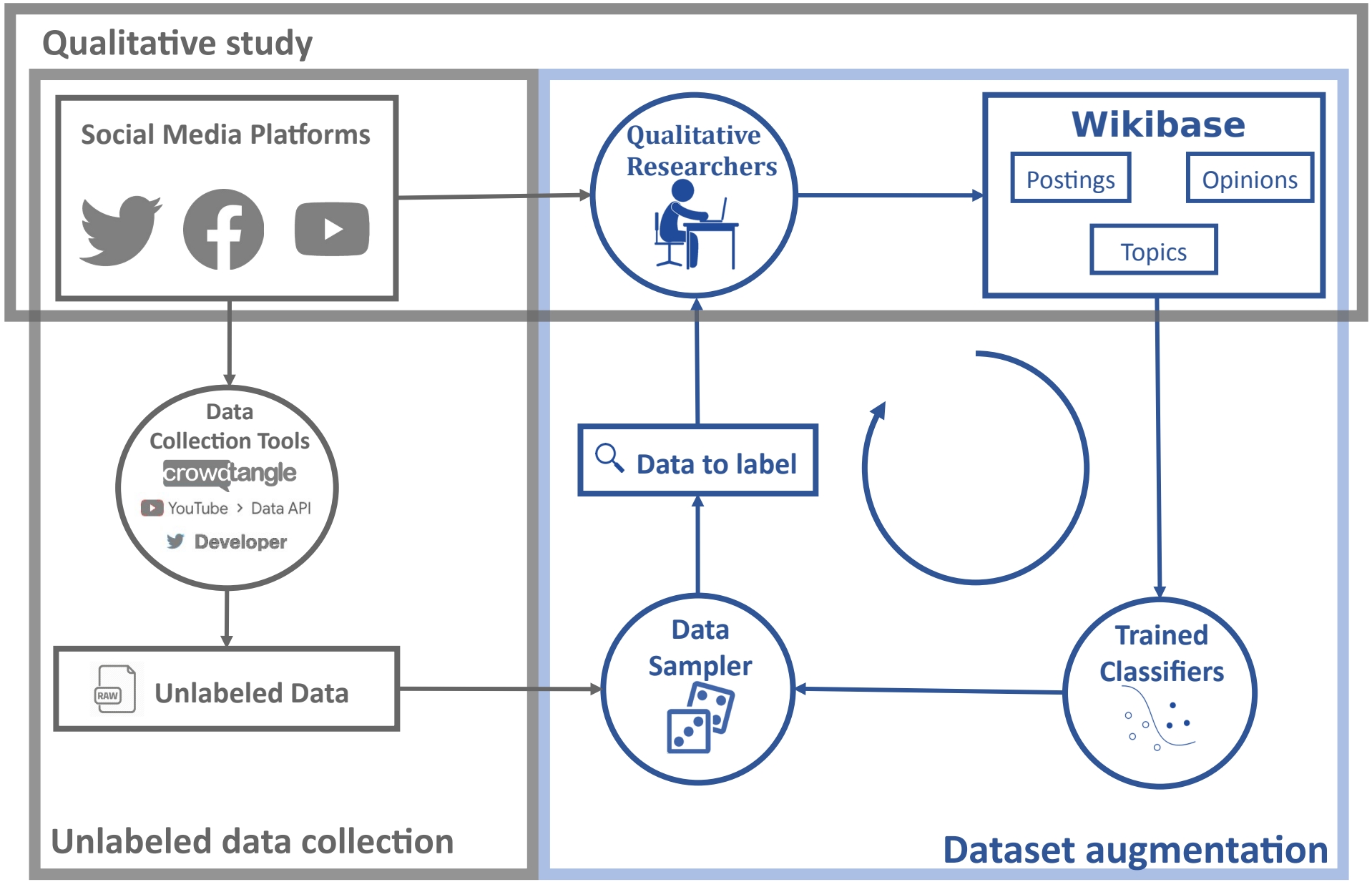
13.3M postings:

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

2. Unlabeled Data Collection

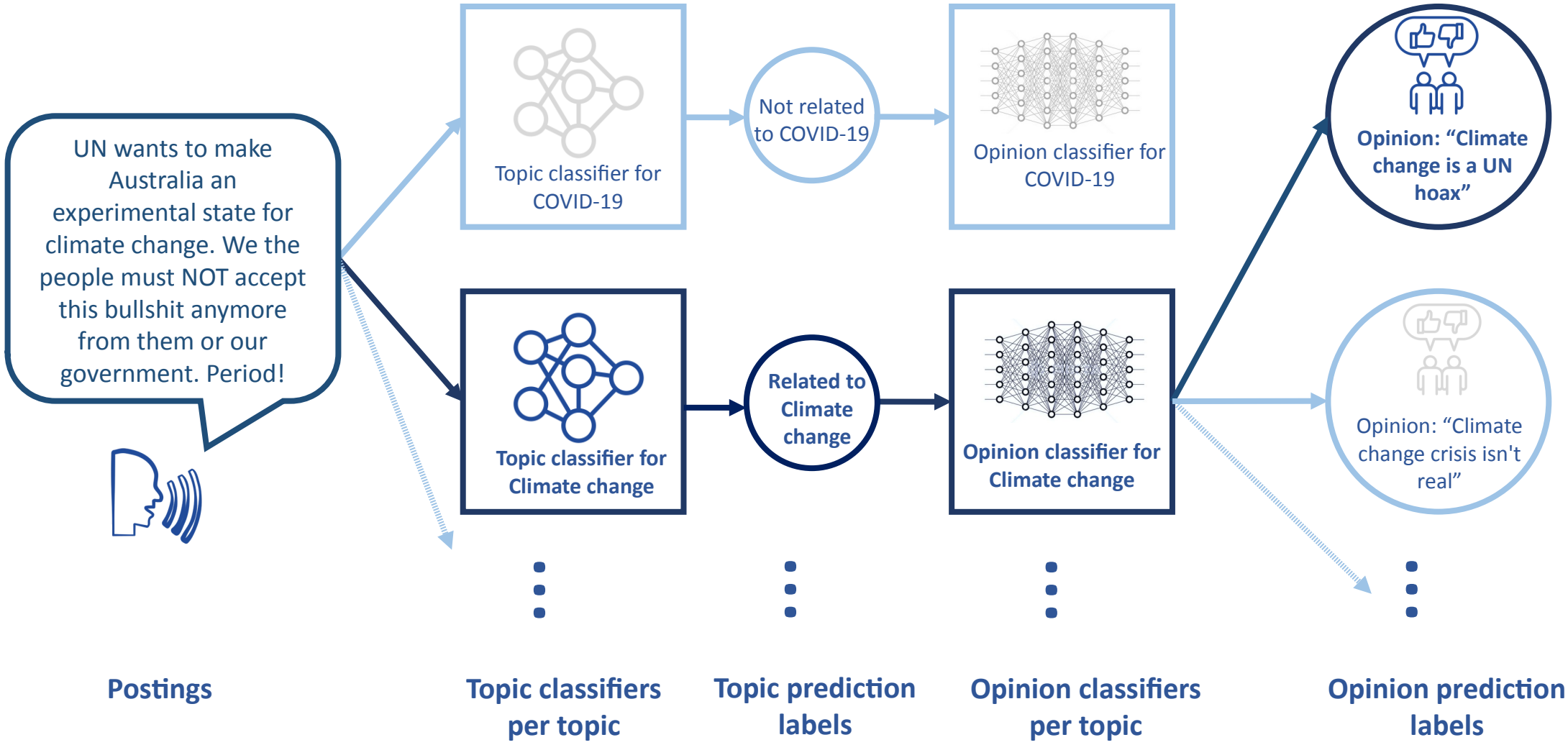


3. Dataset Augmentation



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**

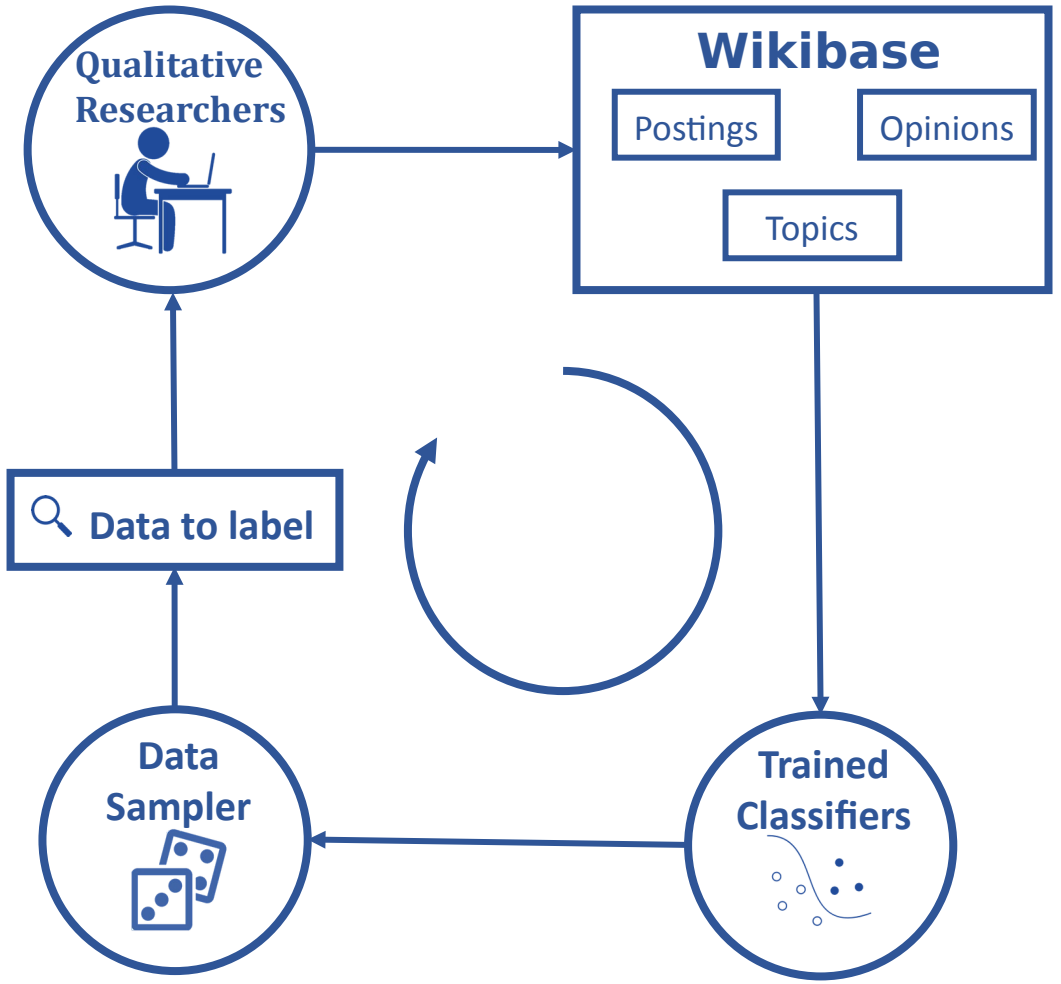


3. Dataset Augmentation

- Human-in-the-loop Machine Learning

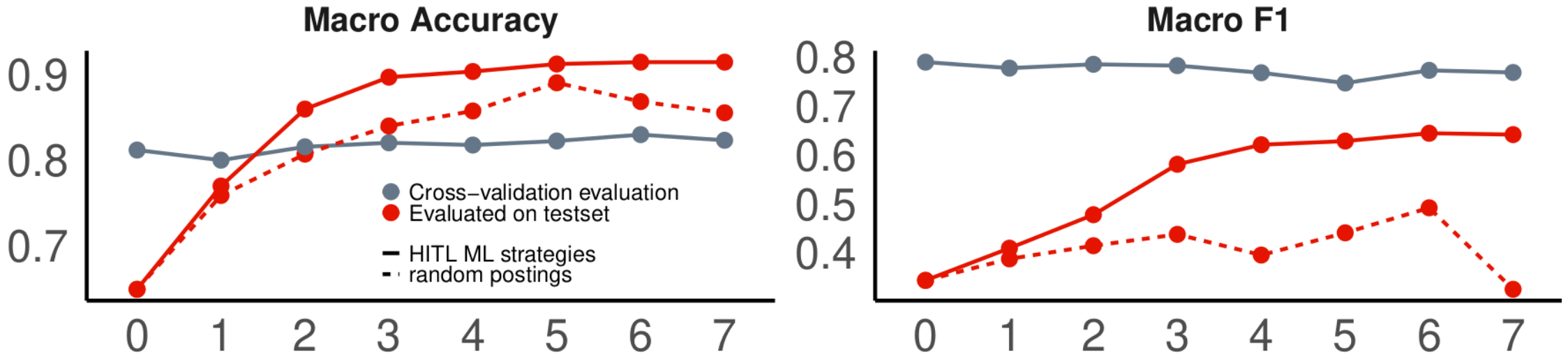
- Three strategies for data sampling:
  - Active learning
    10 posts / iteration / topic
    $u(\boldsymbol{x}) = 1 - p(\hat{y} \mid \boldsymbol{x}; f_{t,i})$
  - Top confidence
    10 posts / iteration / topic
  - Random sampling
    5 posts / iteration / topic

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



Results

Human-in-the-loop performance



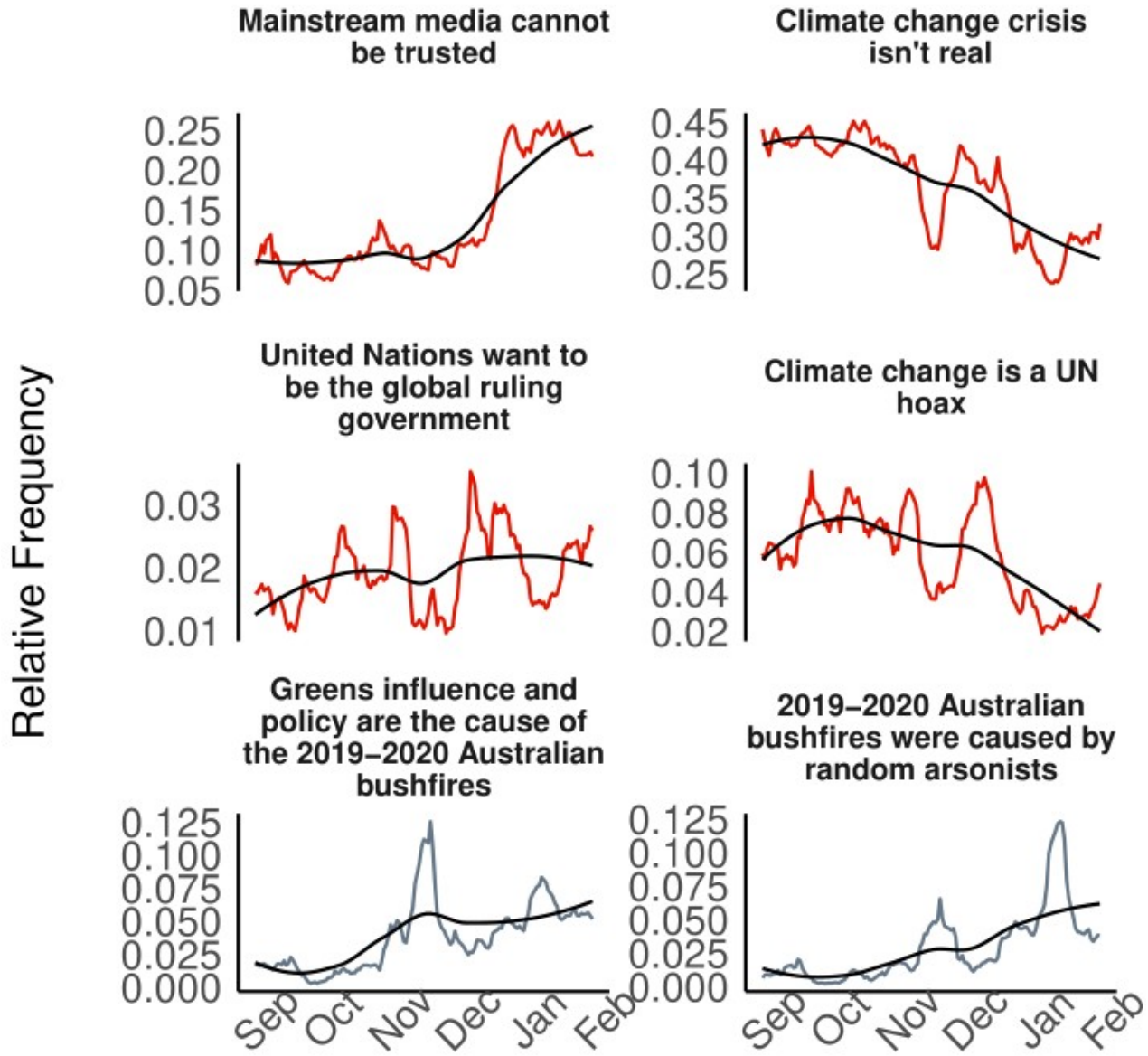
- Performances improve as more batches are performed
- Gap between generalization and test set error reduces
- Improvement plateaus as the process converges
- Human-in-the-Loop outperforms static random selection of samples

	L0	L7
#posts	614	1381
#opinions	65	71

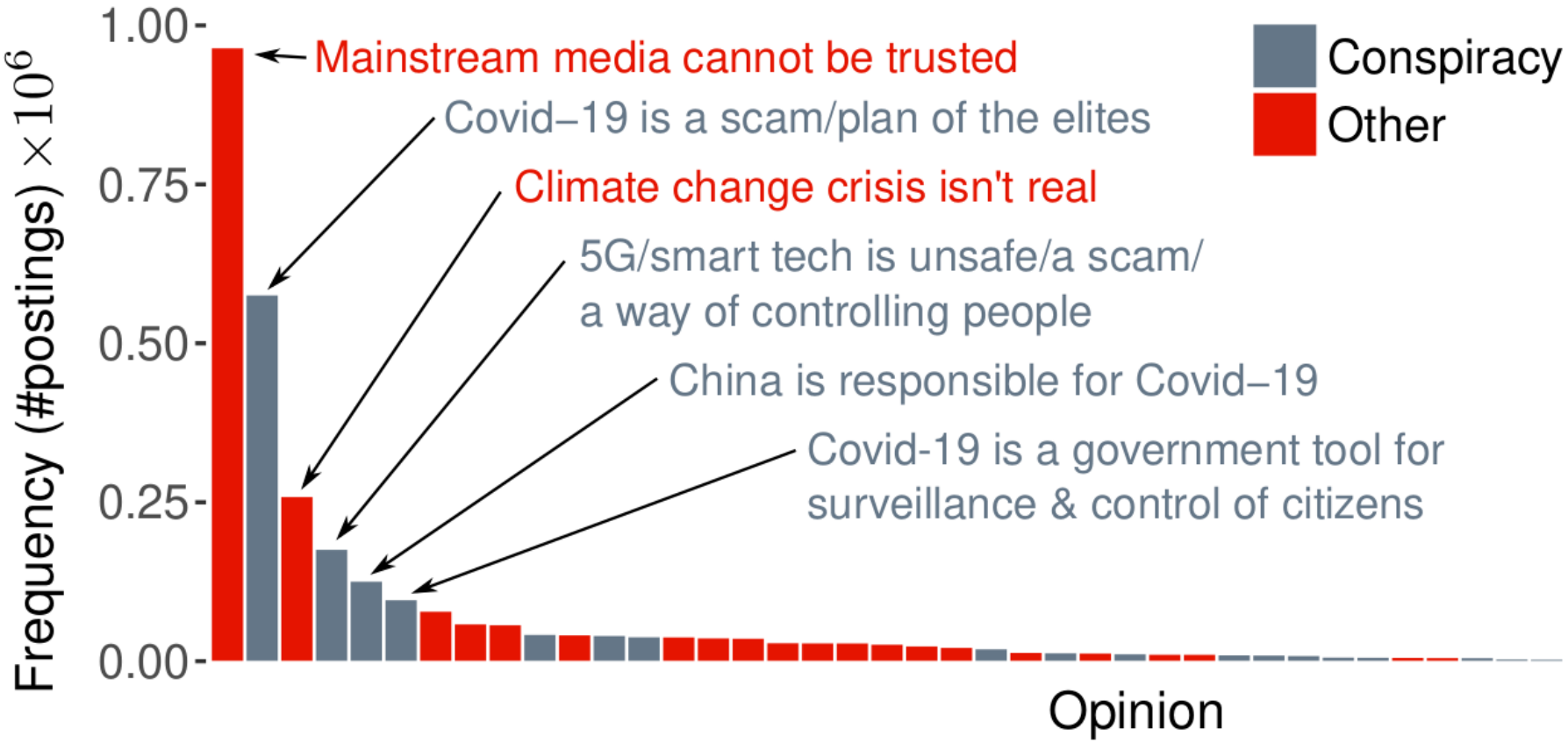
Opinion analysis at scale

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

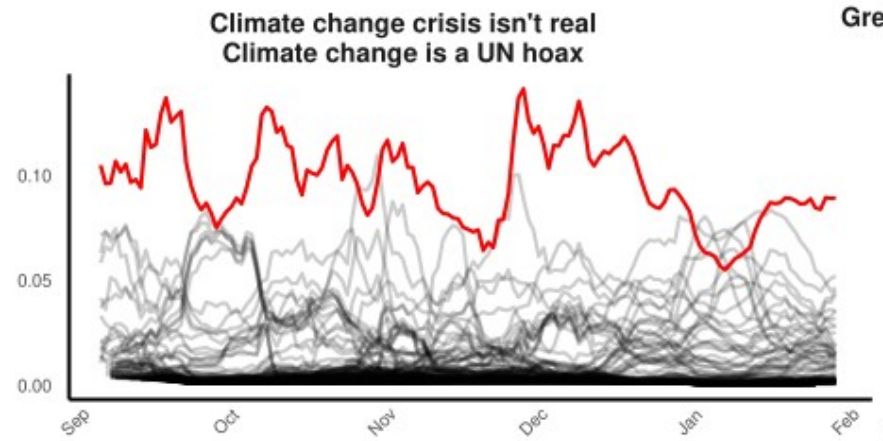


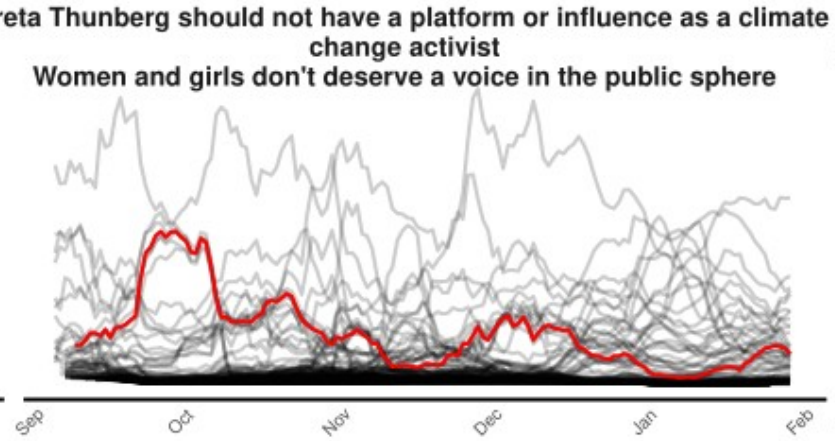
Opinion analysis at scale

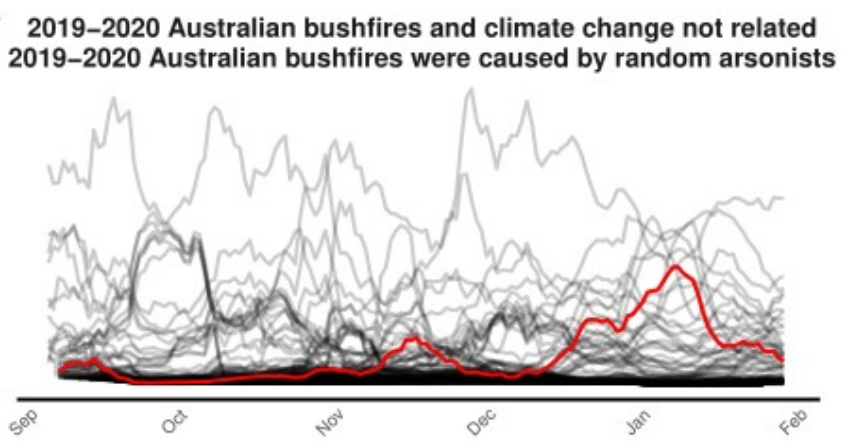


- Opinion usage frequency is longtail distributed
- Four of the top six opinions endorse conspiracy theories

Opinion co-occurrence network







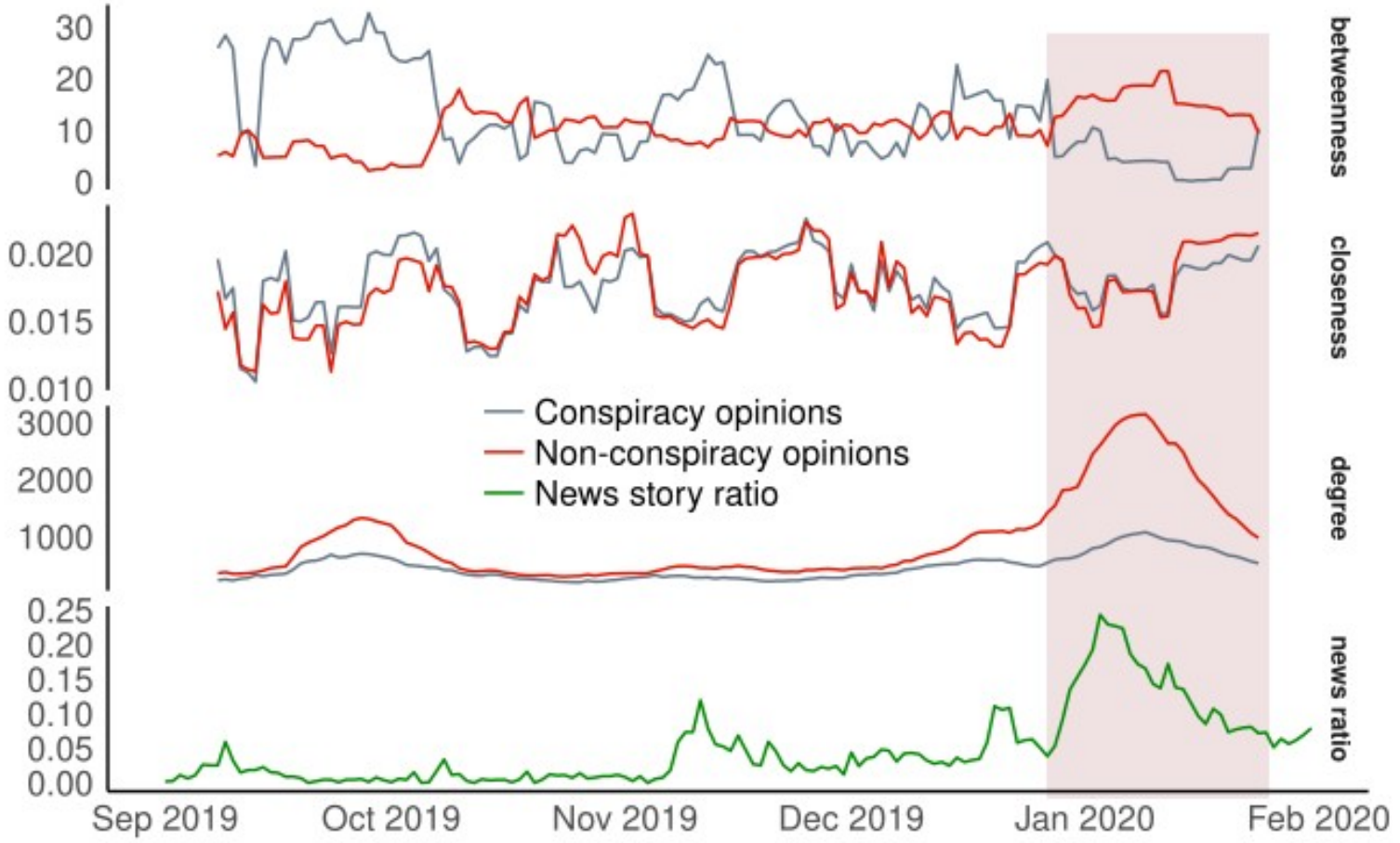
A continuous and relatively strong association between prevalent opinions

Associations with declining relative frequencies

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

Centrality of conspiracy opinions and news ratio

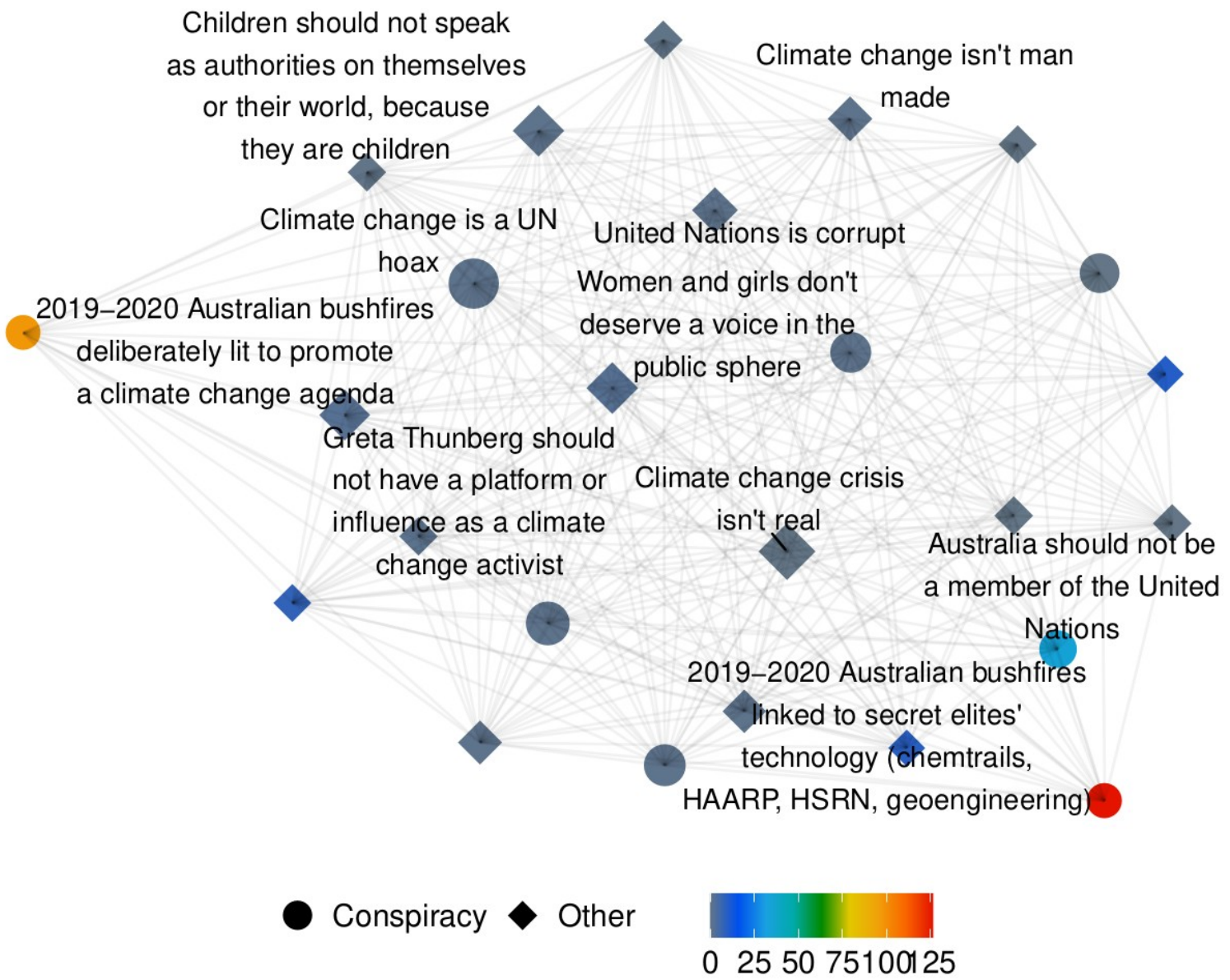
Higher coverage from news media reduces centrality of conspiracy opinions.



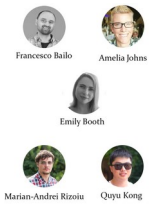
coverage ratios from Media Cloud (Roberts et al. 2021)

Opinion co-occurrence network

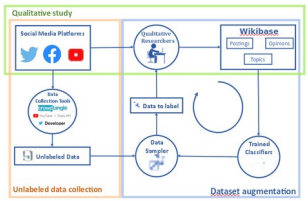
- High betweenness centrality of conspiracy opinions → selectively used in conjunction with many other opinions
- 14 days in late September 2019 – peak betweeness
- Conspiracy opinions are used together with mainstream opinions – rationalize and popularize them



Summary

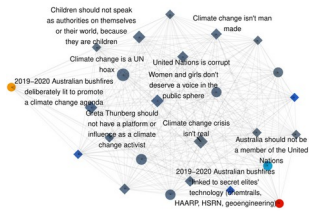


An inter-disciplinary team and methods to solve a difficult task: detecting and mapping the impact of online problematic content



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!

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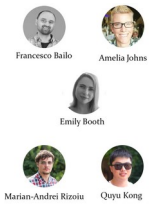

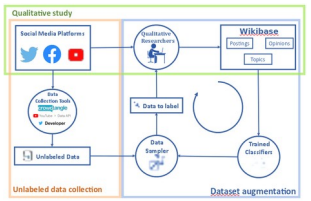

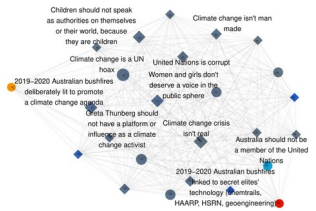

An inter-disciplinary team and methods to solve a difficult task: detecting and mapping the impact of online problematic content

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