

# **Under The Same Flag**

## Exploring Protest Fragmentation With Search Query Data

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APSA,  
Sep 2023

# Motivation

## Why do some protest campaigns succeed while others fail?

Structural factors: Economy, Technology, Regime, Demography

Strategy & Tactics: Mobilization, Violence, Collective Identity

Internal Factors: Leadership, Organization, Agenda, Unity

- Understudied
- Weak results

## Challenges [Quantification]

Access to relevant information: timely events, surveys are costly

Measurement error

Sensitive survey questions ↗ self-selection bias & “dishonesty” bias

Media bias

Misclassify multiple campaigns as a single entity

Comparability: cross-country / cross-campaign is a concern

# This Paper

- Protest Fragmentation**
  - Goals / Motivations Perspective
  - Do scholars mistakenly categorize de-facto separate campaigns as a single entity? [*"Under The Same Flag" Hypothesis*]
- Current Goal:** Method to estimate **campaign fragmentation\***
- Desired Properties**
  - Behavior-based measure:** media reports, surveys, expert opinions
  - Explicit interpretation:** Likert scale, composite measures [*Polity IV*]
  - Comparability:** cross-country / cross-campaign comparison

\* **Campaign Fragmentation** – variation in the goals / motivations of a protest campaign among protesters

# Focus

- **Sub-national differences in the demand for information related to a protest campaign**

**Assumption:** High variation ↗ High protest fragmentation

- **Correlated behaviors**

**Key idea:** Individuals who look for the same information related to a protest campaign share similar views regarding the goals of this campaign

- **Implementation**

**Input data:** Search queries (Google Trends)

**Key feature:** Ability to identify *other* search queries individuals conduct when they seek for protest-campaign information

# How scholars measure protest fragmentation

## Surveys

General Population: Activists underrepresented  
Behavior: Reported ≠ Observed  
Self-selection | 'Dishonesty' bias  
List-experiments are hard | Costs

Protesters: Hard timing (!) | Safety concerns  
Locations underrepresented | Costs



## 1. Identify Protesters

웃웃 웃웃웃  
웃 웃웃 웃

## 2. Identify Differences

웃웃 웃웃웃  
Corruption  
Ethnic Discrimination

# How scholars measure protest fragmentation

## □ Event Cataloging

Documents: Proclaimed goals ≠ Actual goals  
Leadership perspective  
Spontaneous collective action

News: Bias in media reporting  
'Black Box'

Multimedia: Representativeness  
Reporting Bias | Costs  
Leadership perspective

## The New York Times

So Many Faces Make Up One Crowd



A scene from the documentary filmed during protests in Ukraine. Cinema Guild



## 1. Identify Protesters

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## 2. Identify Differences

웃웃 웃웃웃  
Corruption  
Ethnic Discrimination

# How scholars measure protest fragmentation

□ User-generated content

## 1. Identify Protesters

웃웃 웃웃웃  
웃 웃웃 웃

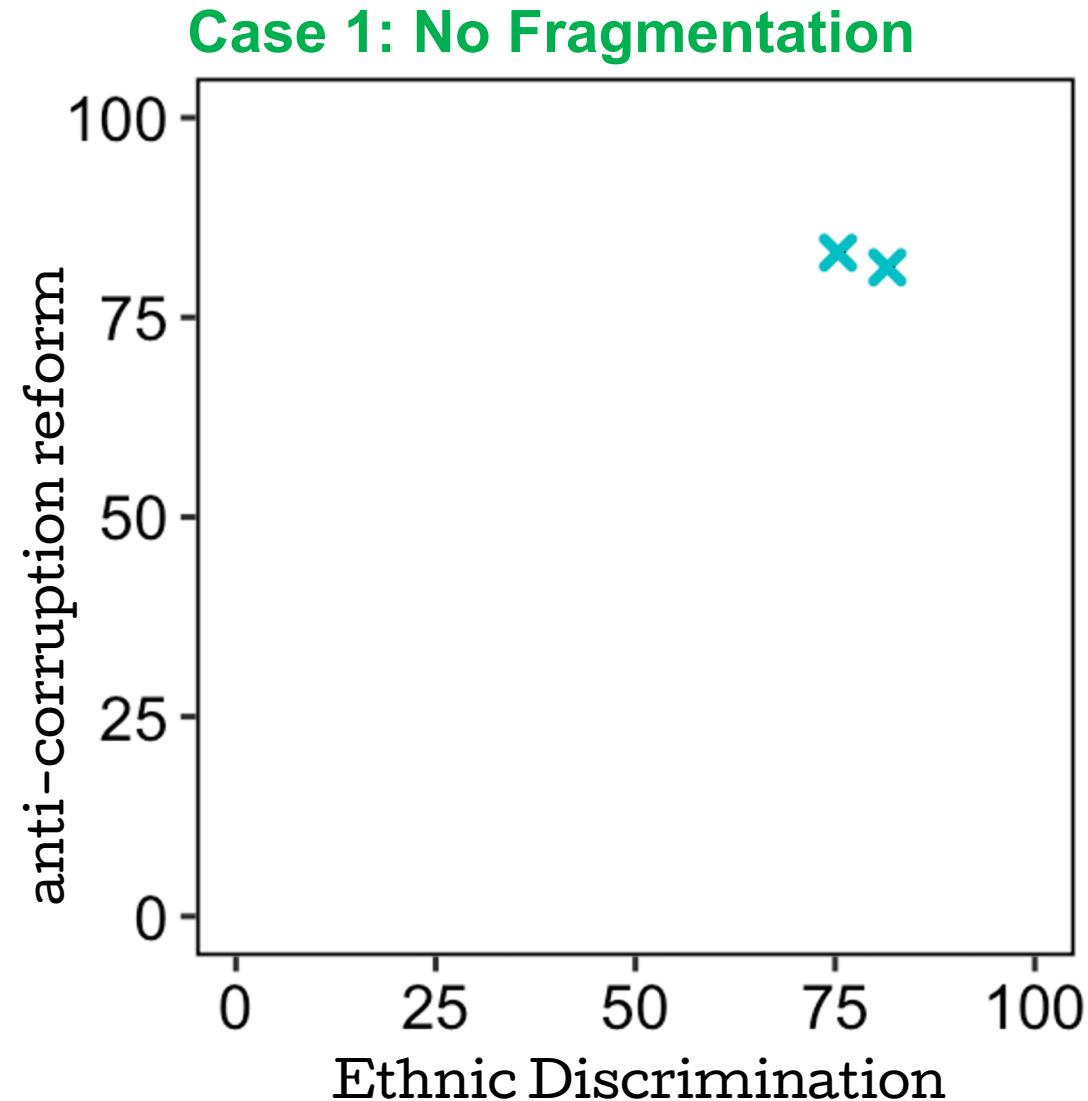
## 2. Identify Differences

웃웃 웃웃웃  
Corruption Ethnic  
Ethnic Discrimination

# Theory

- In location  $x_i$ , individuals who look for
  - └ protest campaign information *also* search:
    - └ “revolution”
    - └ “anti-corruption reform”

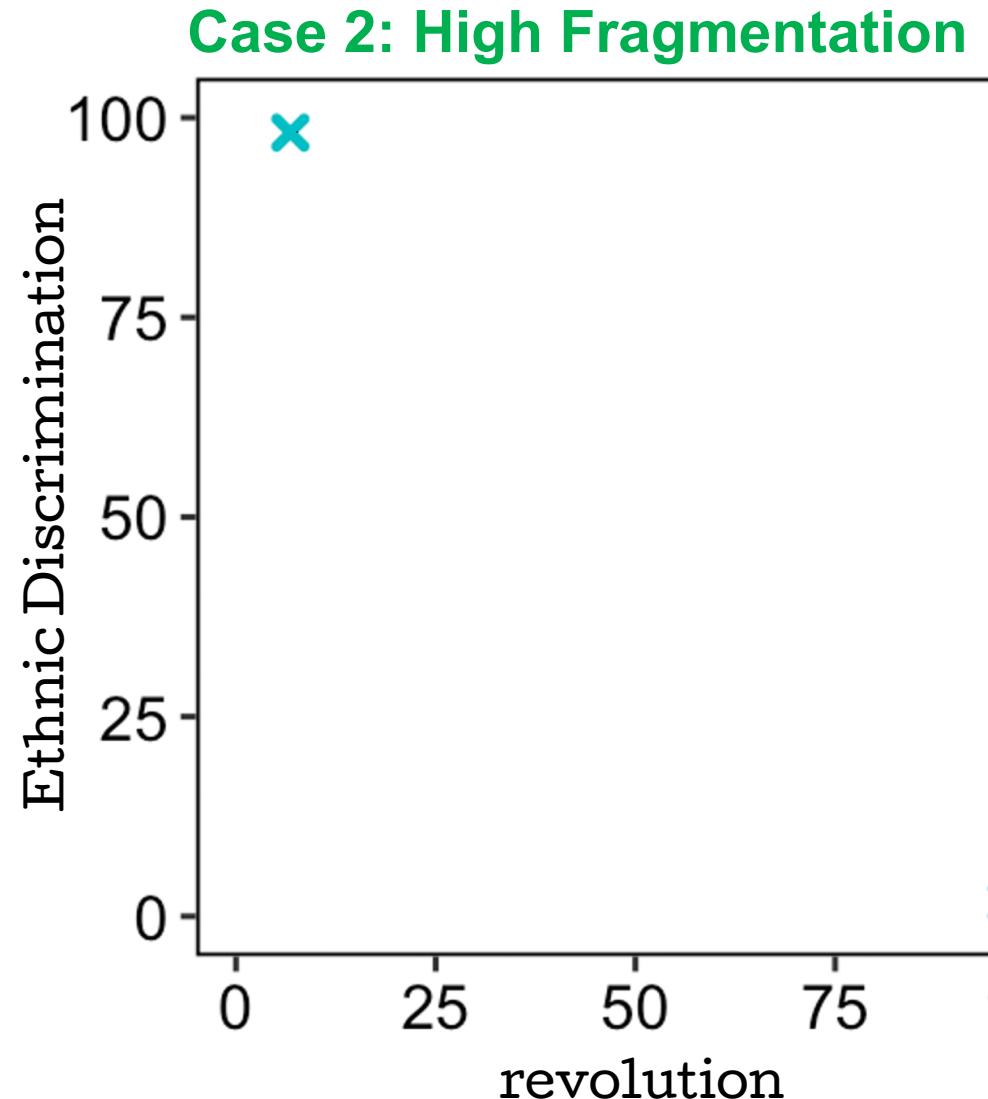
**Similar interest in both topics**  
→ unified protest campaign



# Theory

- In location  $x_i$ , individuals who look for protest campaign information also search:
  - └ “revolution”
  - └ “anti-corruption reform”

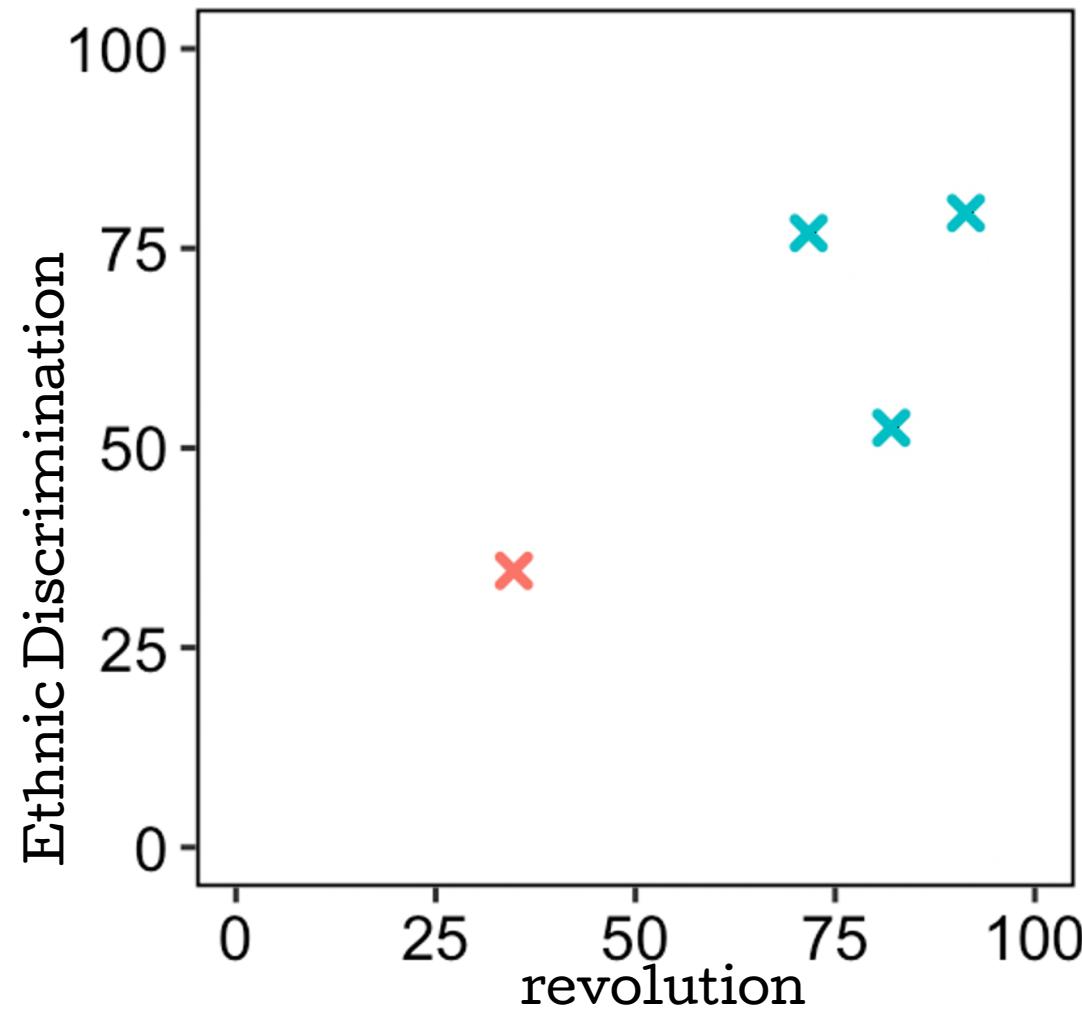
**Dissimilar interest in topics**  
⇒ **High protest campaign fragmentation**



# Theory

- In location  $x_i$ , individuals who look for protest campaign information *also* search:
  - “revolution”
  - “anti-corruption reform”

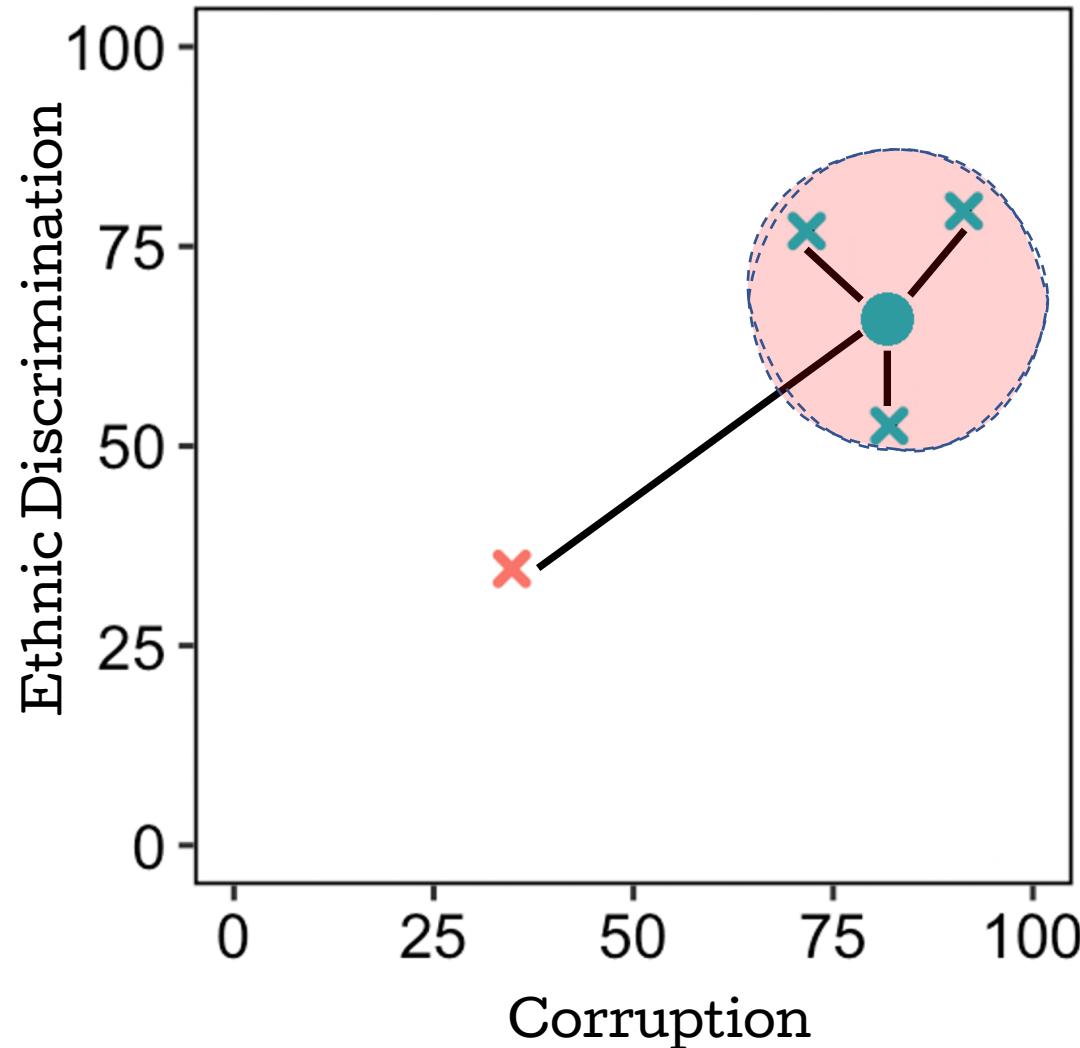
Case 3: Multiple Locations



# Theory

- In location  $x_i$ , individuals who look for protest campaign information *also* search:
  - “revolution”
  - “anti-corruption reform”
  
- Proposed Approach**
  - Identify the largest cluster [robust to outliers]
  - Calculate cluster’s centroid [*n*-dimensional space]
  - Fragmentation Score:** average distance to the centroid [Manhattan distance]

Case 3: Multiple Locations



# Search Queries



**Initial Q:** How do people search for protest-related information?

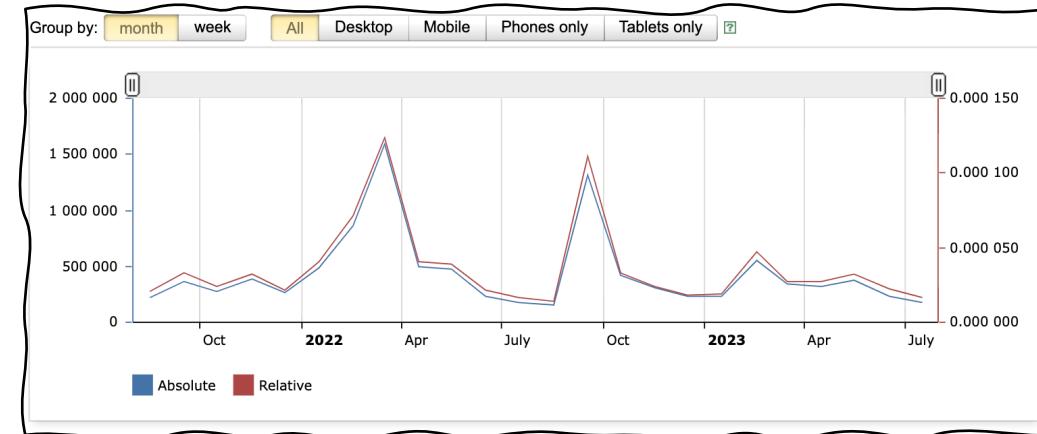
– **Identify:** Search queries by a keyword  
Similar queries

– **Classification method:** Clicking same websites

The screenshot shows the Yandex Keyword statistics interface. The search term entered is 'МИТИНГ'. The results are grouped into two sections: 'Other searches containing the word «МИТИНГ» — 123,966 impressions per month' and 'Requests, similar to «МИТИНГ»'. Both sections provide 'Statistics by keyword' and 'Displays per month' for each entry.

Period	Absolute	Relative
01.08.2021 - 31.08.2021	216 811	0.000 020 736 036
01.09.2021 - 30.09.2021	363 898	0.000 033 018 338
01.10.2021 - 31.10.2021	277 206	0.000 023 673 519
01.11.2021 - 30.11.2021	391 215	0.000 032 698 807
01.12.2021 - 31.12.2021	265 974	0.000 021 635 545
01.01.2022 - 31.01.2022	491 261	0.000 040 198 758
01.02.2022 - 28.02.2022	867 256	0.000 071 654 695
01.03.2022 - 31.03.2022	1 587 907	0.000 123 160 982
01.04.2022 - 30.04.2022	494 952	0.000 040 661 098
01.05.2022 - 31.05.2022	471 760	0.000 039 129 490
01.06.2022 - 30.06.2022	237 453	0.000 021 874 484
01.07.2022 - 31.07.2022	172 360	0.000 016 349 320

Raw volume of search queries containing keyword



Raw data over time

# Search Queries



## G-Trends: **Queries aggregated by topics**

- Identify:
  - “Co-related” queries | topics
  - `Protest topic` ~ `Related topics`

**Classification method:** Wikipedia  
[Reverse Engineering]



Anti-CAA Protests (India, 2019)

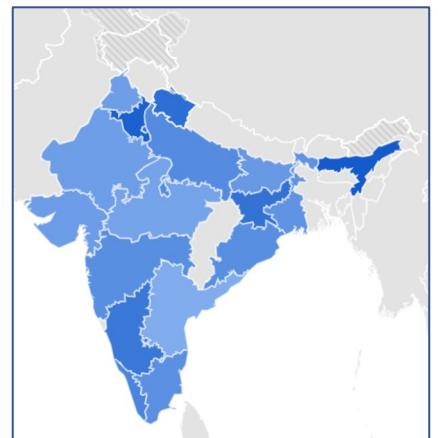
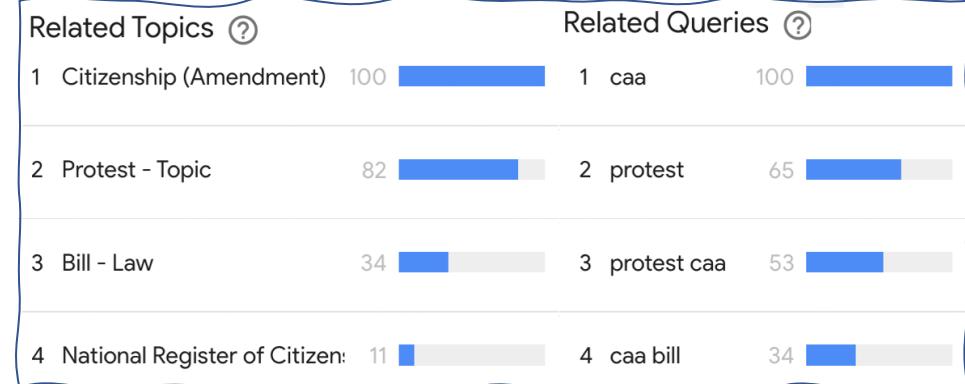
## Citizenship (Amendment) Bill protests

Citizenship (Amendment) Bill protests

Search term

Citizenship (Amendment) Bill protests

Topic



# Implementation with G-Trends

Example: Citizenship Amendment Act protests (India, 2019)

## Google trends

- Score [0-100] based on the volume of search queries
- Provides data for separate queries and queries aggregated into topics
- Identifies queries / topics correlated with the initial query / topic
- Subnational level data

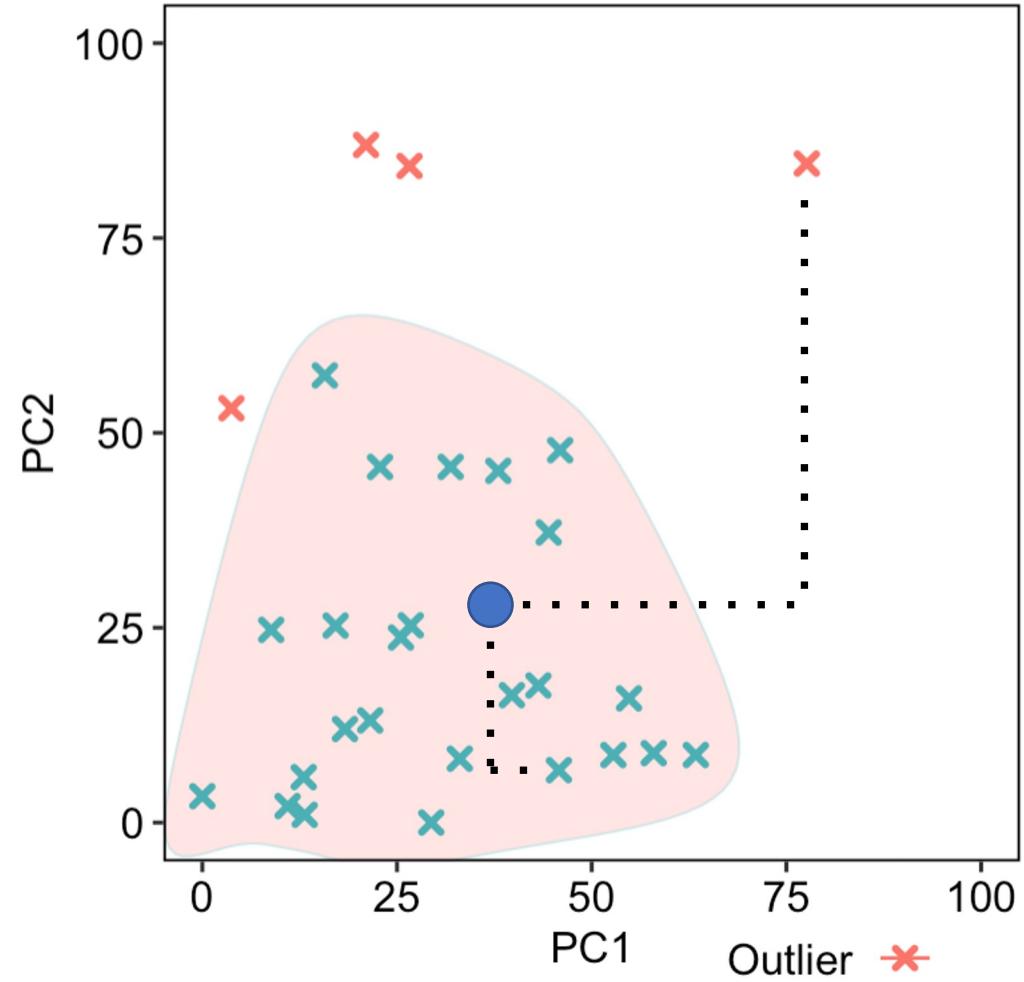
## Fragmentation due geographic variation

# Implementation with G-Trends

Example: Citizenship Amendment Act protests (India, 2019)

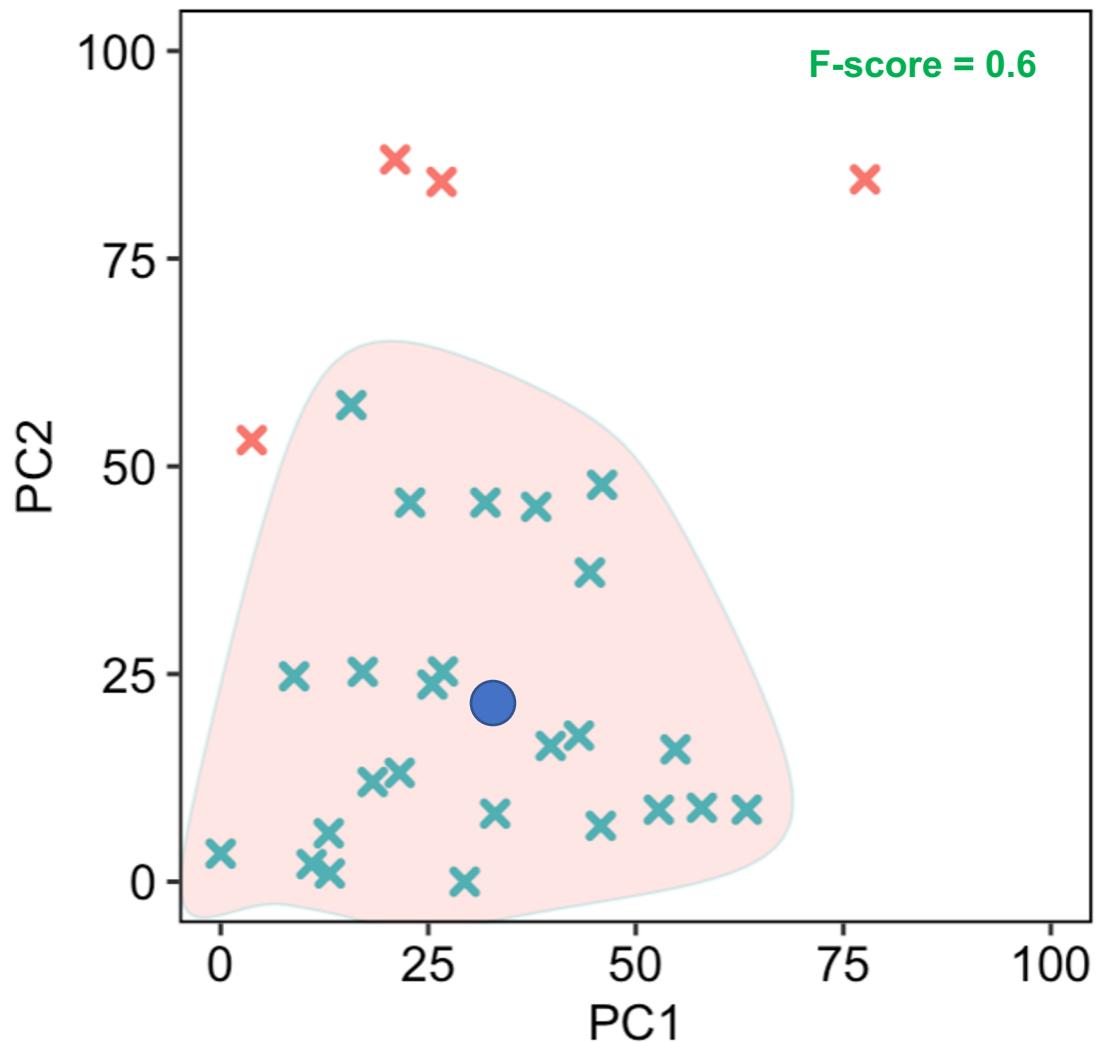
- Citizenship Amendment Act protests (India, 2019)**
  - Identify the protest movement topic
  - Identify first 10 correlated topics
  - Identify largest cluster [via DBSCAN]
  - Calculate centroid
  - Calculate mean distance  $D$  [Manhattan]
  - Adjust  $(100 - \frac{D}{2})/100$

**Fragmentation Score = 0.6**

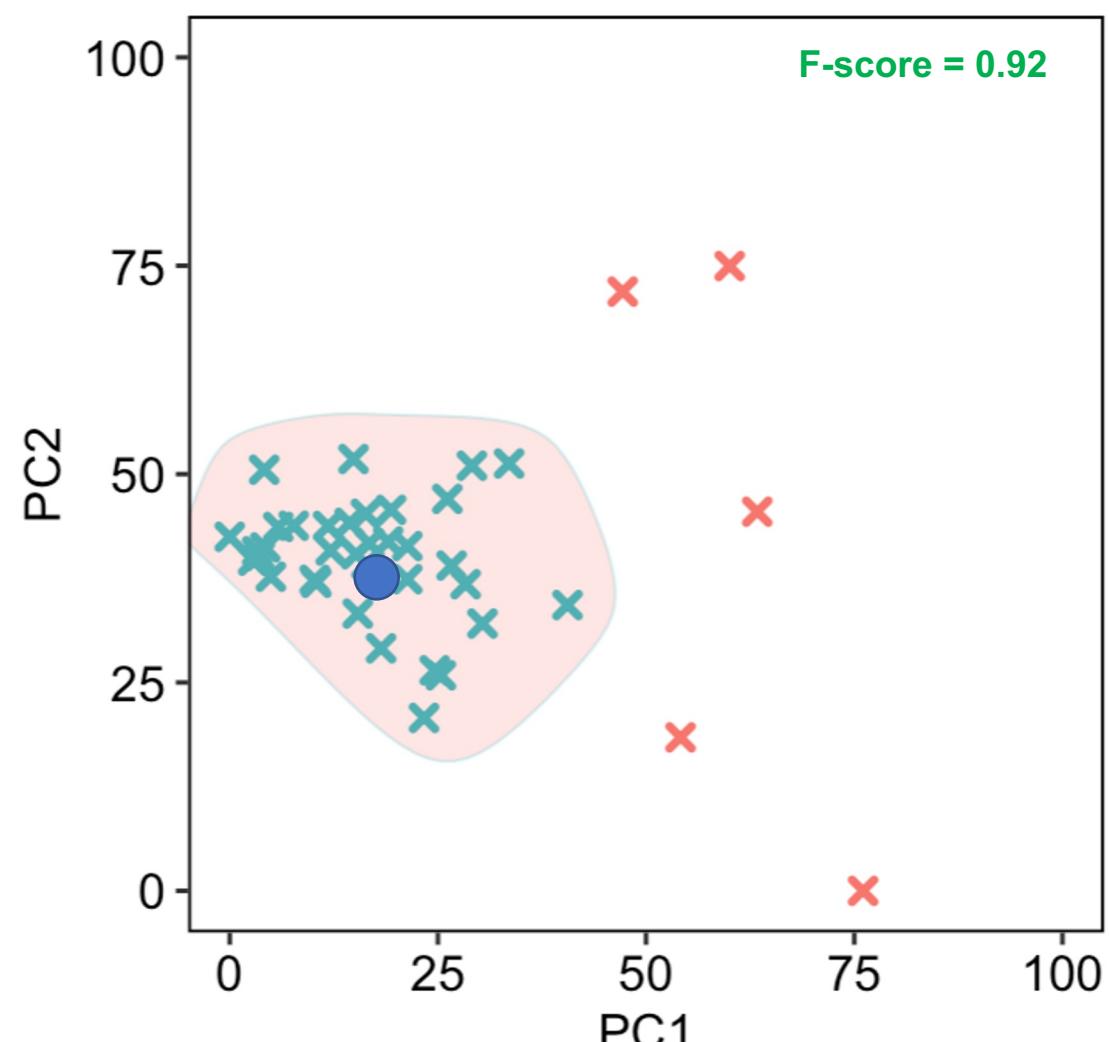


\* Principal Components are used for illustration purposes

# Comparison India-2019 VS US-2017

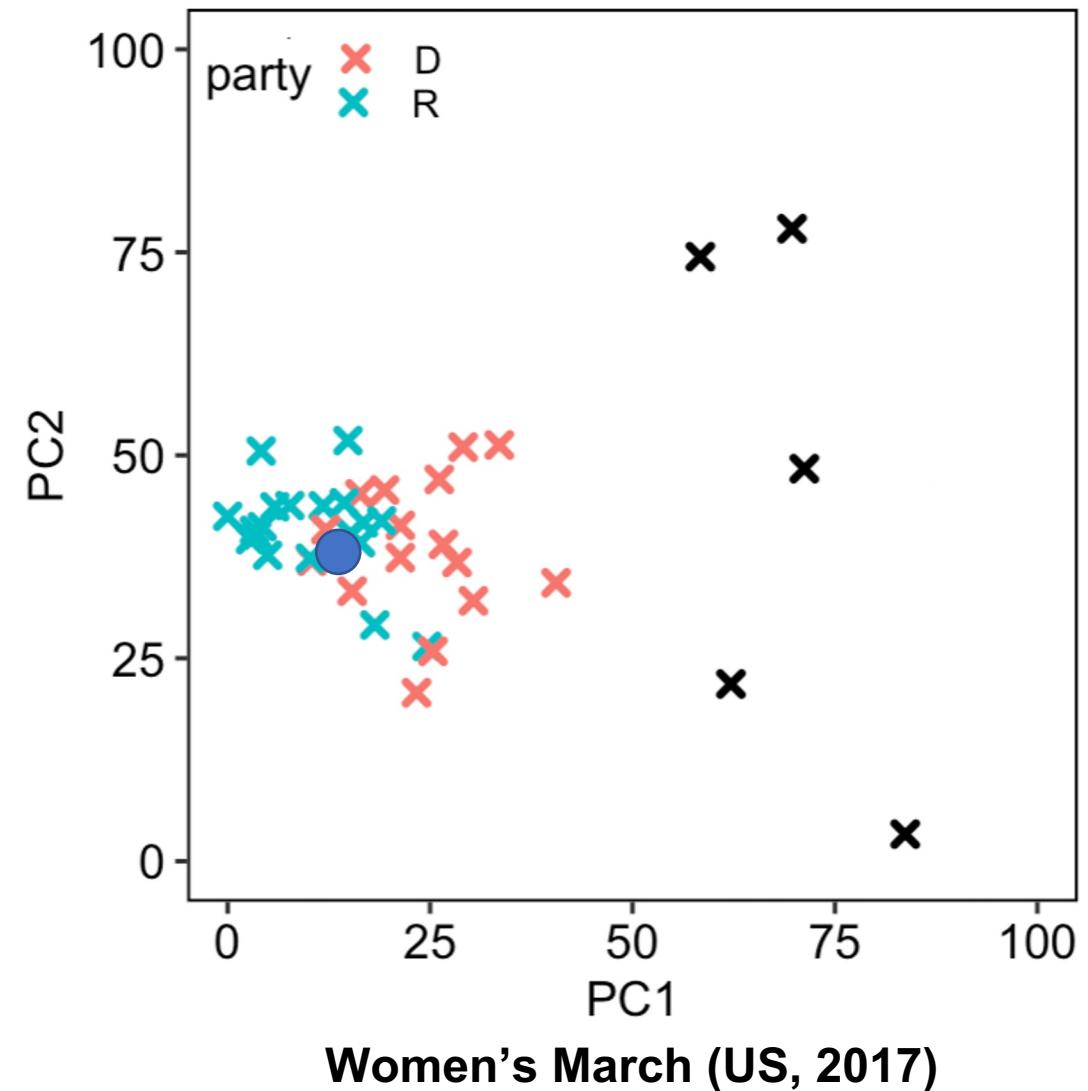
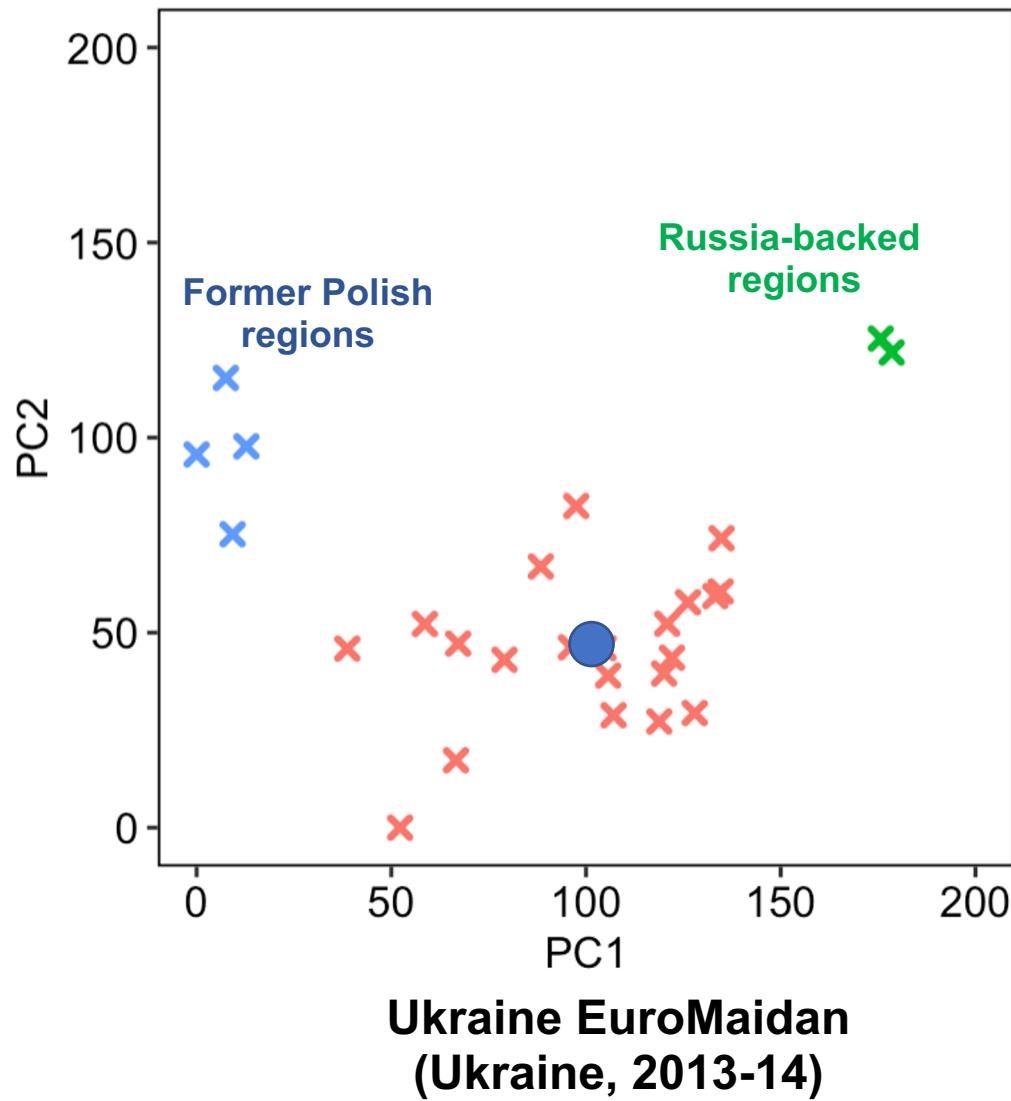


Citizenship Amendment Act  
protests (India, 2019)



Women's March (US, 2017)

# Validity Check Potentially Important Variables



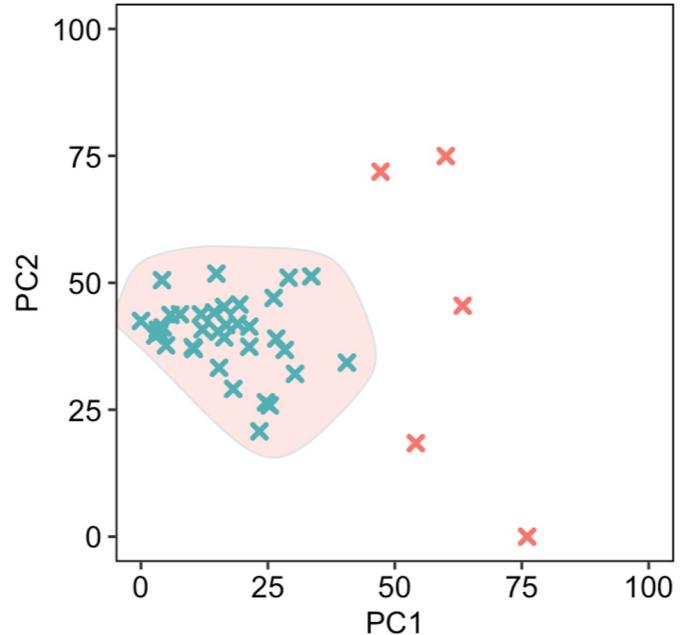
# At the end of the day

## Not an ideal measure

- Benefits:**
  - observed behavior
  - mitigate biases
  - fine-grained data
  - real-time
  - free
- Issues:**
  - cross-location variation is required
  - Inequality in Internet coverage
  - Protesters ≠ Interested in Protest
  - Specific Censorship Regimes

## Applications

- Standardized measure with explicit interpretation**
- Temporal Dynamics**
- Misclassification**



# Concluding thoughts

Thank  
you!

## Not an ideal measure

- └ Benefits:
  - observed behavior
  - comparability
  - fine-grained data

## Applications

- └ Protest Fragmentation snapshot
- └ Solving misclassification issue (single VS multiple campaigns)
- └ Track temporal dynamics

## Issues

- └ **Location-based measure:** cross-location variation is required
- └ **Inequality in Internet coverage:** [fades away with time]
- └ **Protesters ≠ Interested in Protest Information**
- └ **Specific Censorship Regimes:** China [Google Censored]  
Russia [Identity Check]

# Feedback, please



## Next steps



Robustness:  Correlations with other existing measures

Sensitivity to: Alternative clustering / list of topics

Thank  
you!