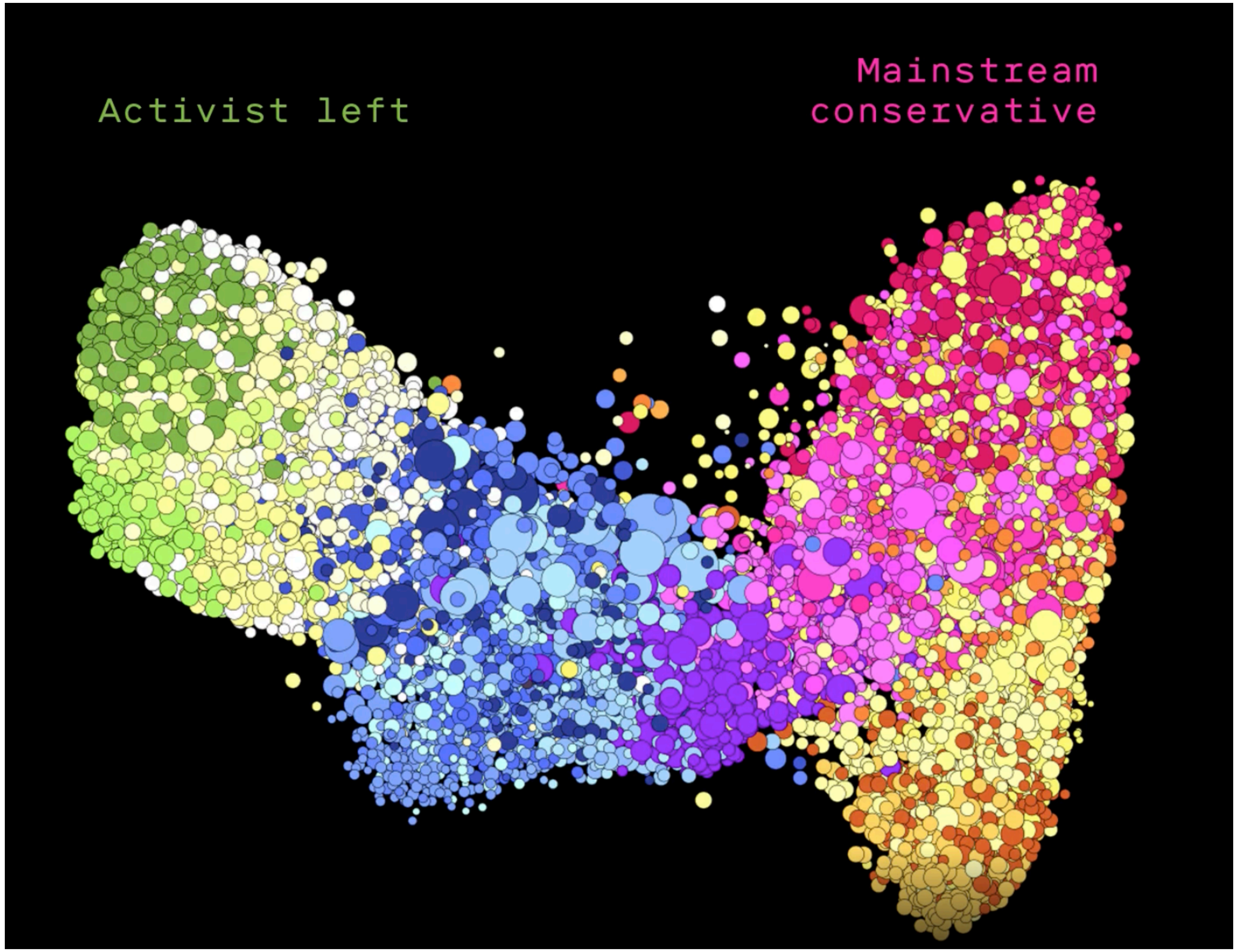
Minimizing Polarization and Disagreement Using Topic-Based Timeline Algorithms

Tianyi Zhou, Stefan Neumann, Kiran Garimella, Aristides Gionis

*This work is under submission

Background: Online media polarization

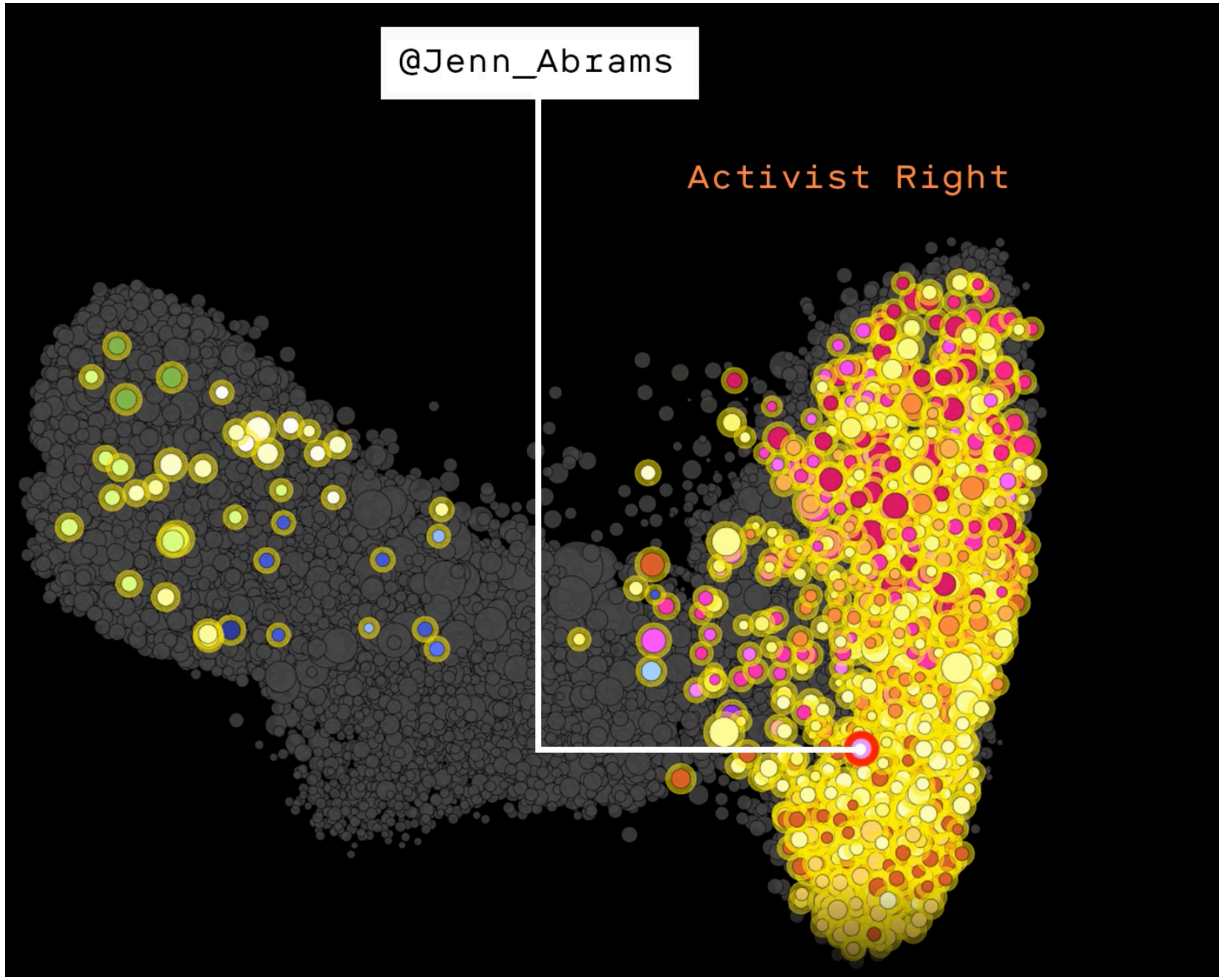
US political spectrum on the eve of the 2016 election.



** By John Kelly and Camille François, MIT Technology Review, 2018*

Background: Online media polarization

This figure highlights the followers of an American woman called Jenna Abrams, a following gained with her viral tweets about slavery, segregation, Donald Trump, and Kim Kardashian. Her far-right views endeared her to conservatives, and her entertaining shock tactics won her attention from several mainstream media outlets.



* *By John Kelly and Camille François, MIT Technology Review, 2018*

Motivation

Online media users show diverse interests

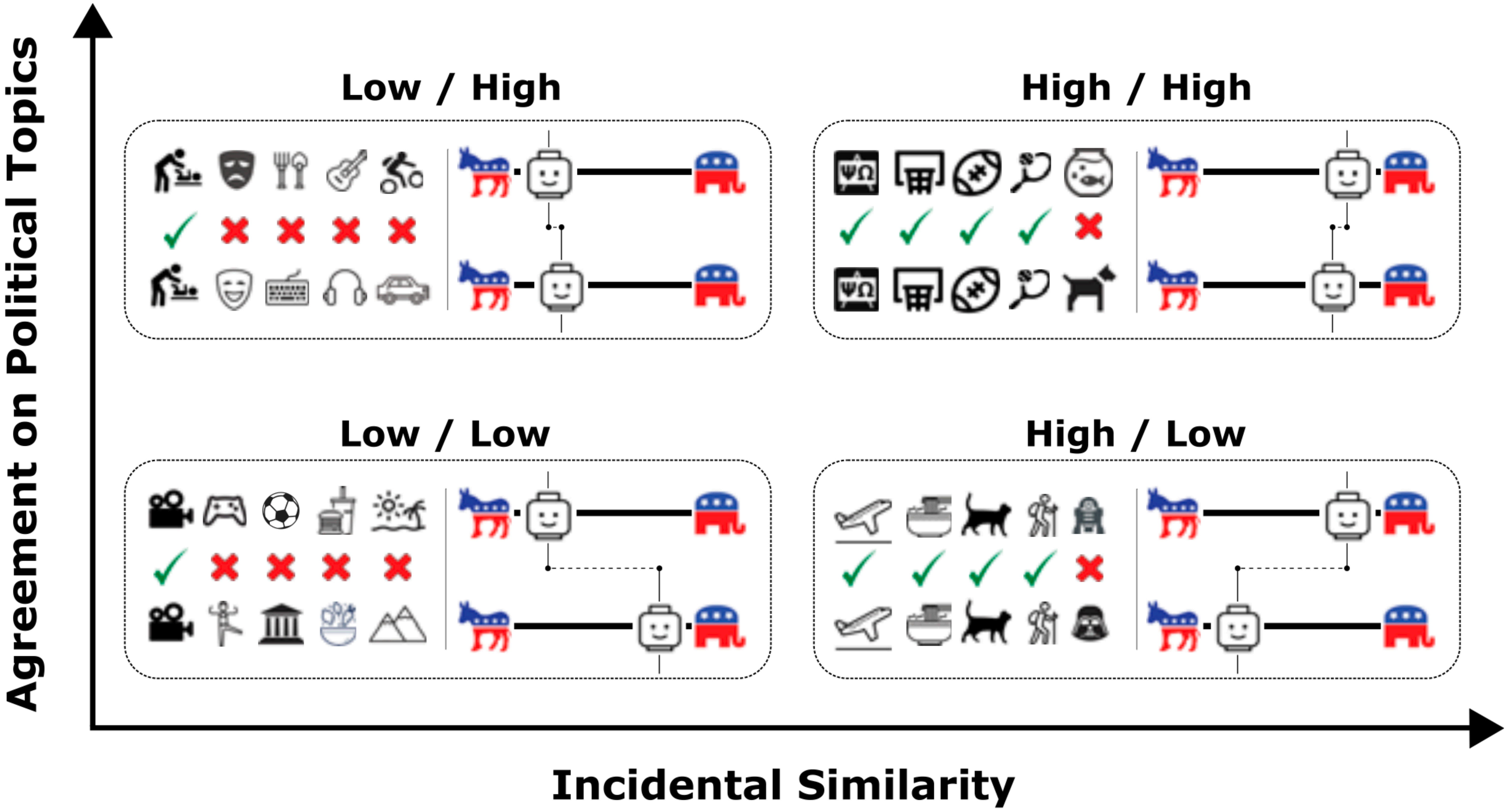
- **Users interests from online tool "Who likes What".**

* *Who likes what: https://twitter-app.mpi-sws.org/who-likes-what*

Motivation

Interests similarity and political preference

- Recent research shows that users with similar interests are more likely to assimilate their political views. [1]



* Incidental similarity: similarity on a number of demographic and biographical features, such as **age**, **gender**, **hometown**, **university**, **sports teams**, **personal interests**, and **idiosyncratic quirks**.

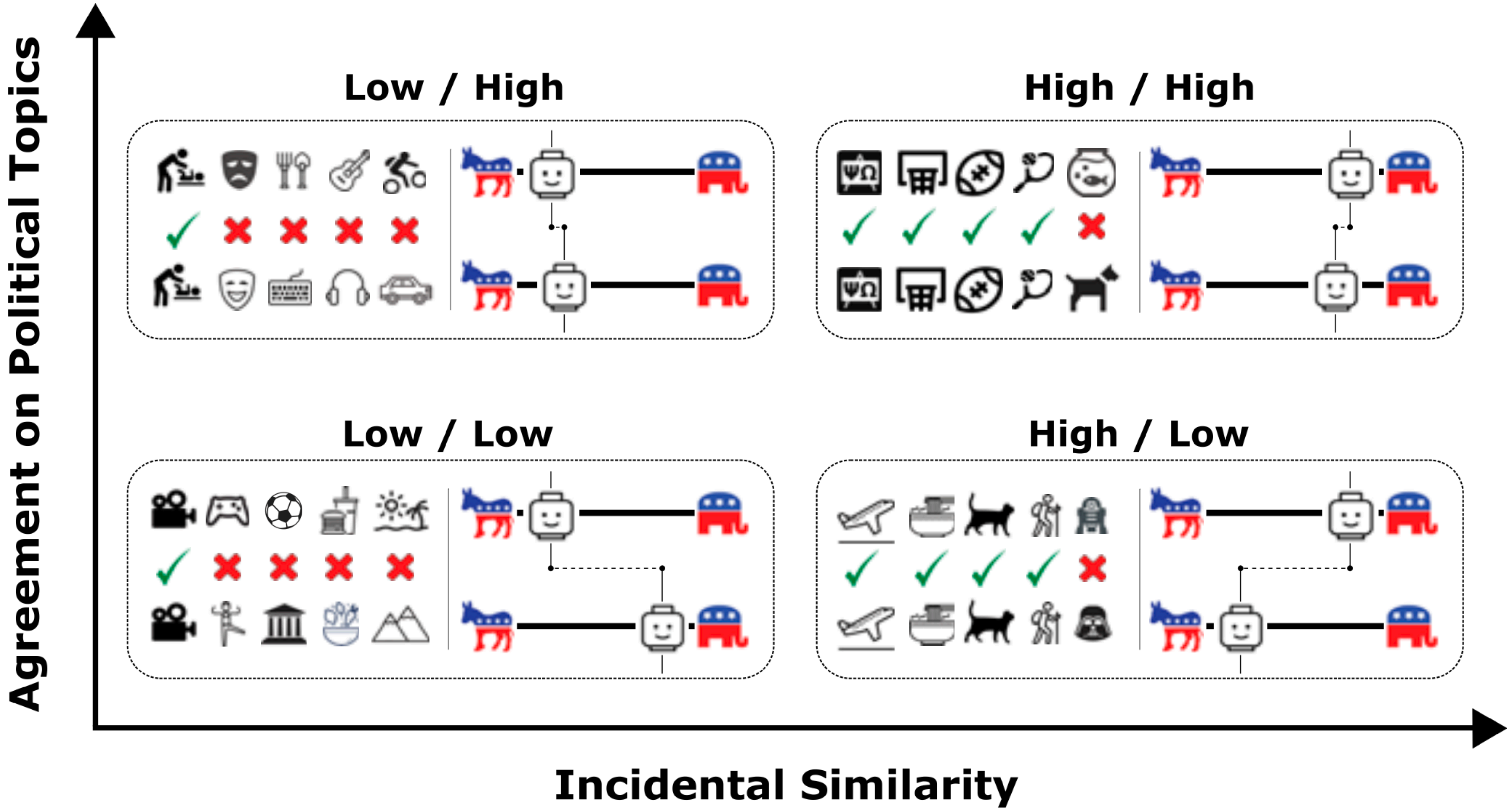
[1] Balietti, Stefano, et al. "Reducing opinion polarization: Effects of exposure to similar people with differing political views." *Proceedings of the National Academy of Sciences* 118.52 (2021): e2112552118.

Motivation

Interests similarity and political preference

- Recent research shows that users with similar interests are more likely to assimilate their political views. [1]

- Fostering consensus: encouraging cross-cutting political communication based on nonpolitical commonalities.



* Incidental similarity: similarity on a number of demographic and biographical features, such as **age**, **gender**, **hometown**, **university**, **sports teams**, **personal interests**, and **idiosyncratic quirks**.

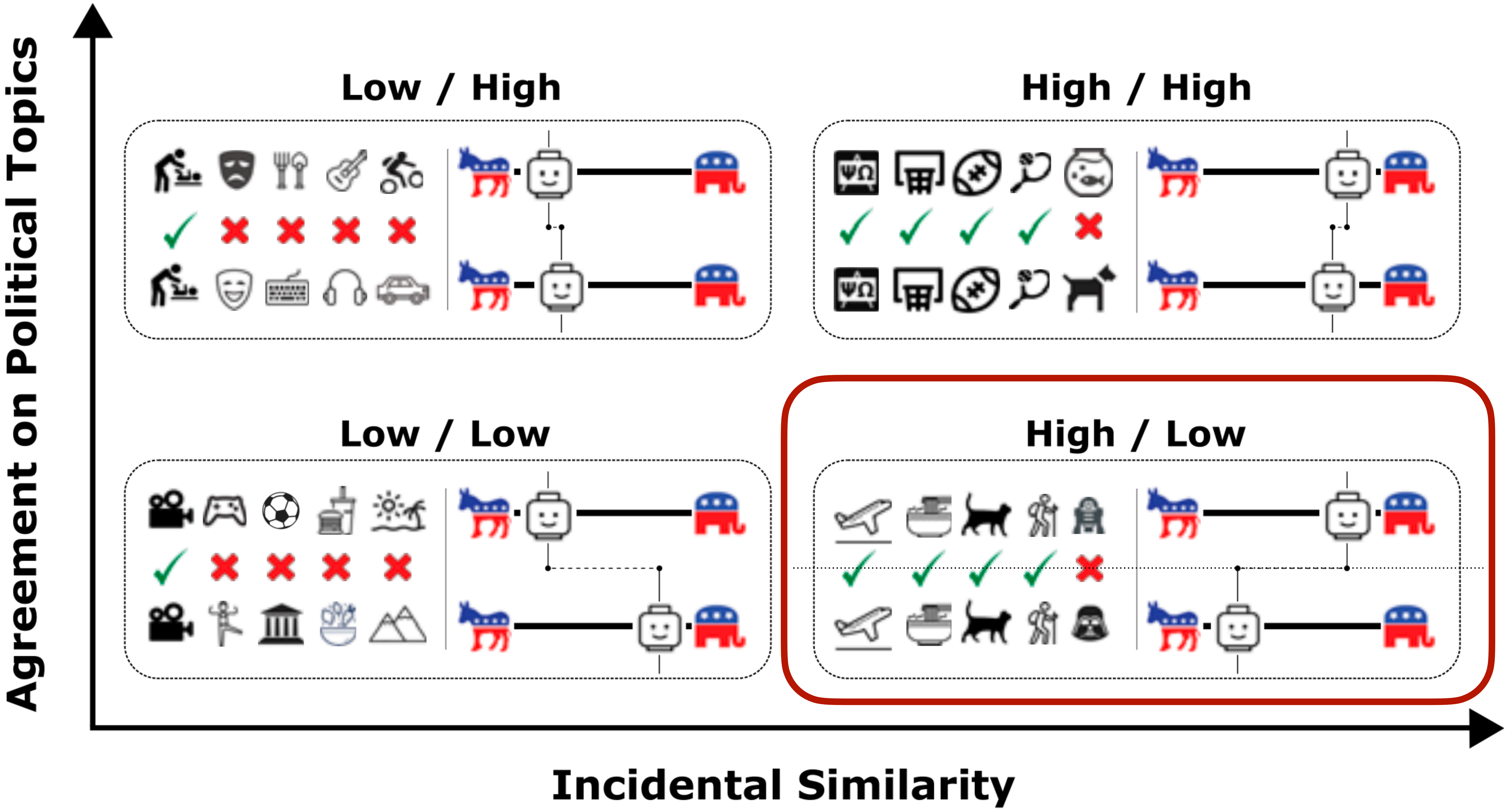
[1] Balietti, Stefano, et al. "Reducing opinion polarization: Effects of exposure to similar people with differing political views." *Proceedings of the National Academy of Sciences* 118.52 (2021): e2112552118.

Motivation

Interests similarity and political preference

- Recent research shows that users with similar interests are more likely to assimilate their political views. [1]

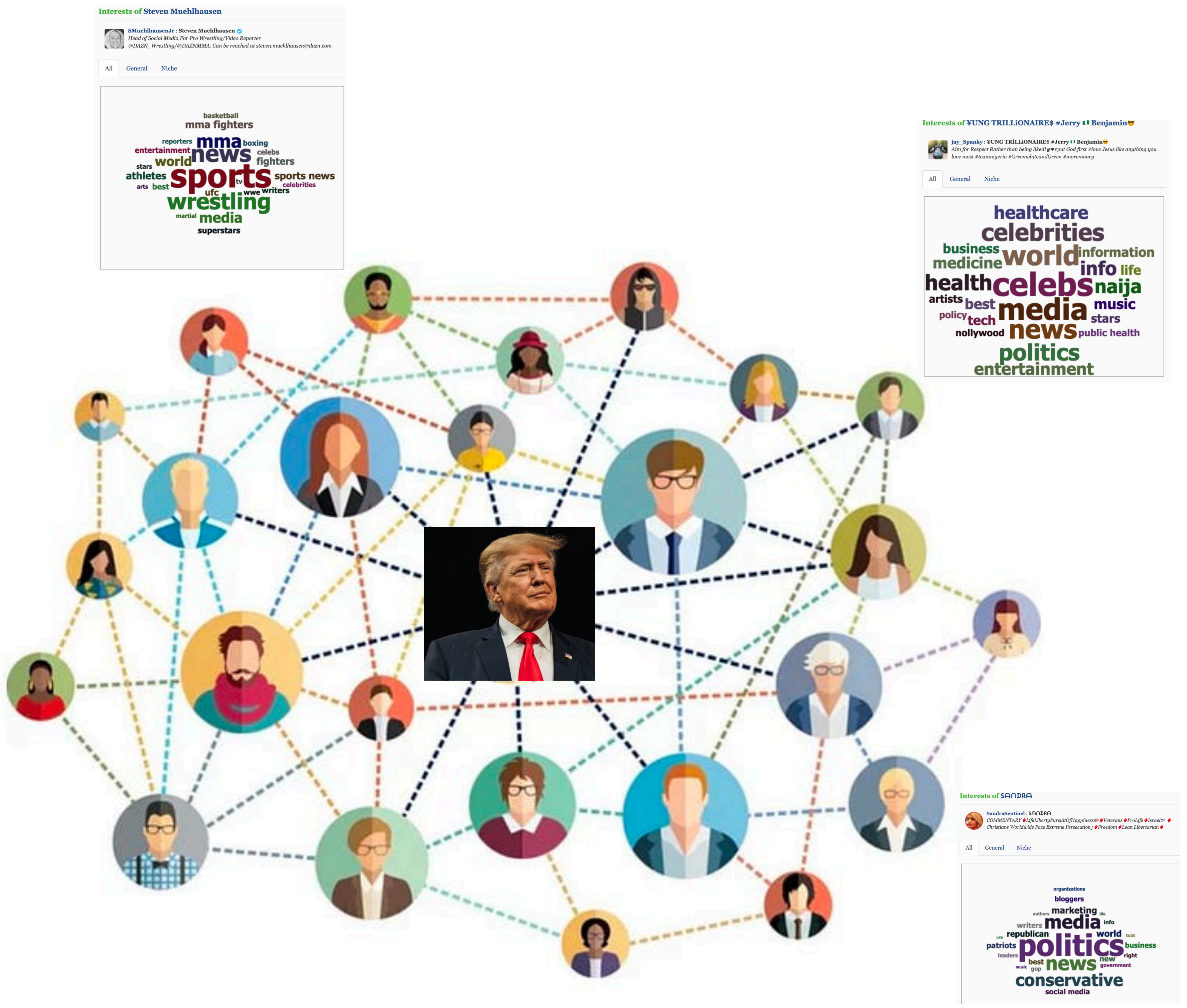
- Fostering consensus: encouraging cross-cutting political communication based on nonpolitical commonalities.



* Incidental similarity: similarity on a number of demographic and biographical features, such as **age**, **gender**, **hometown**, **university**, **sports teams**, **personal interests**, and **idiosyncratic quirks**.

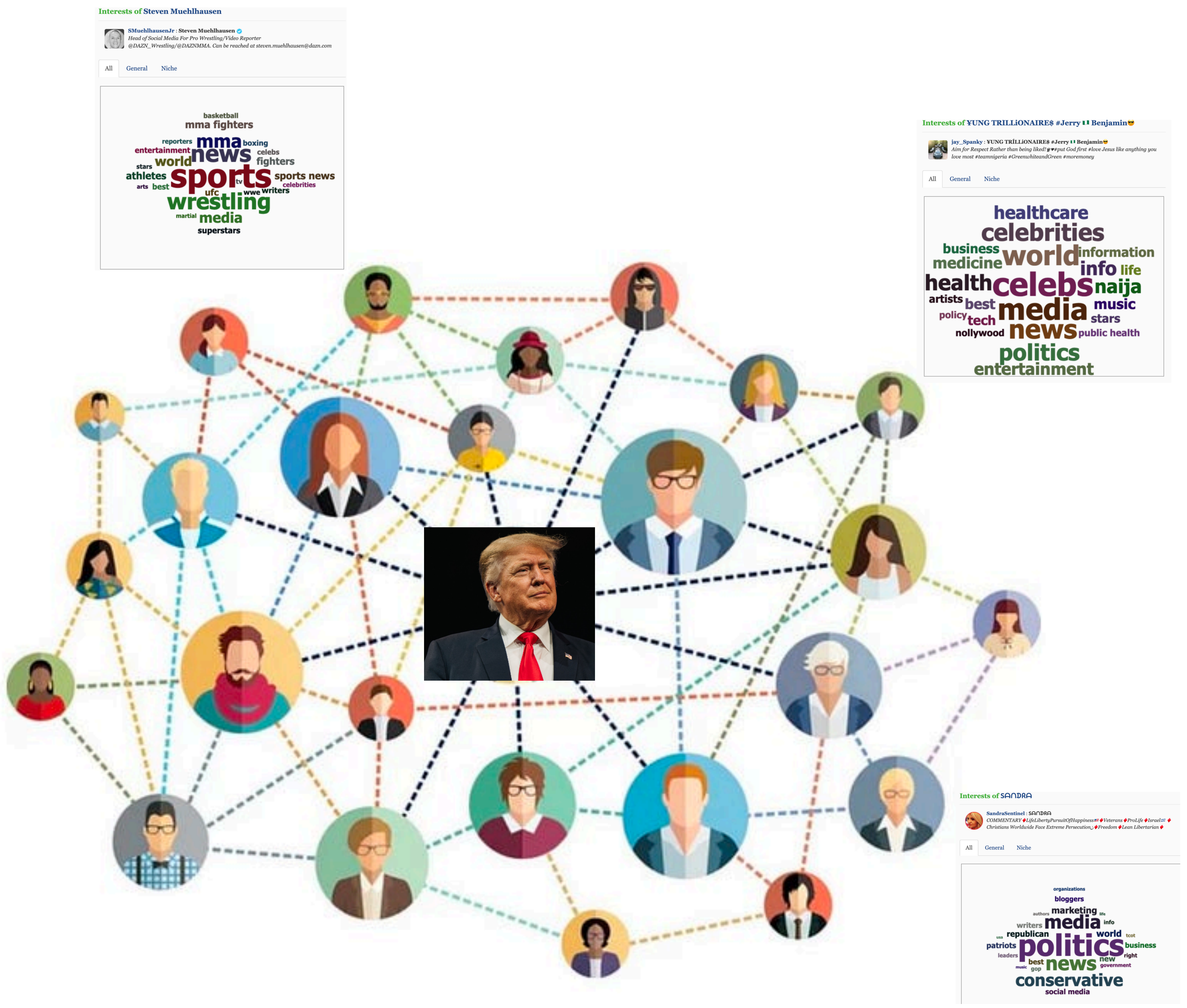
[1] Balietti, Stefano, et al. "Reducing opinion polarization: Effects of exposure to similar people with differing political views." *Proceedings of the National Academy of Sciences* 118.52 (2021): e2112552118.

Problem



- Users form a social network:
  - Nodes represent users
  - Edges represent following relations or interactions
  - Meta information
    - innate opinion on politics
    - personal interests (sports, music, etc)

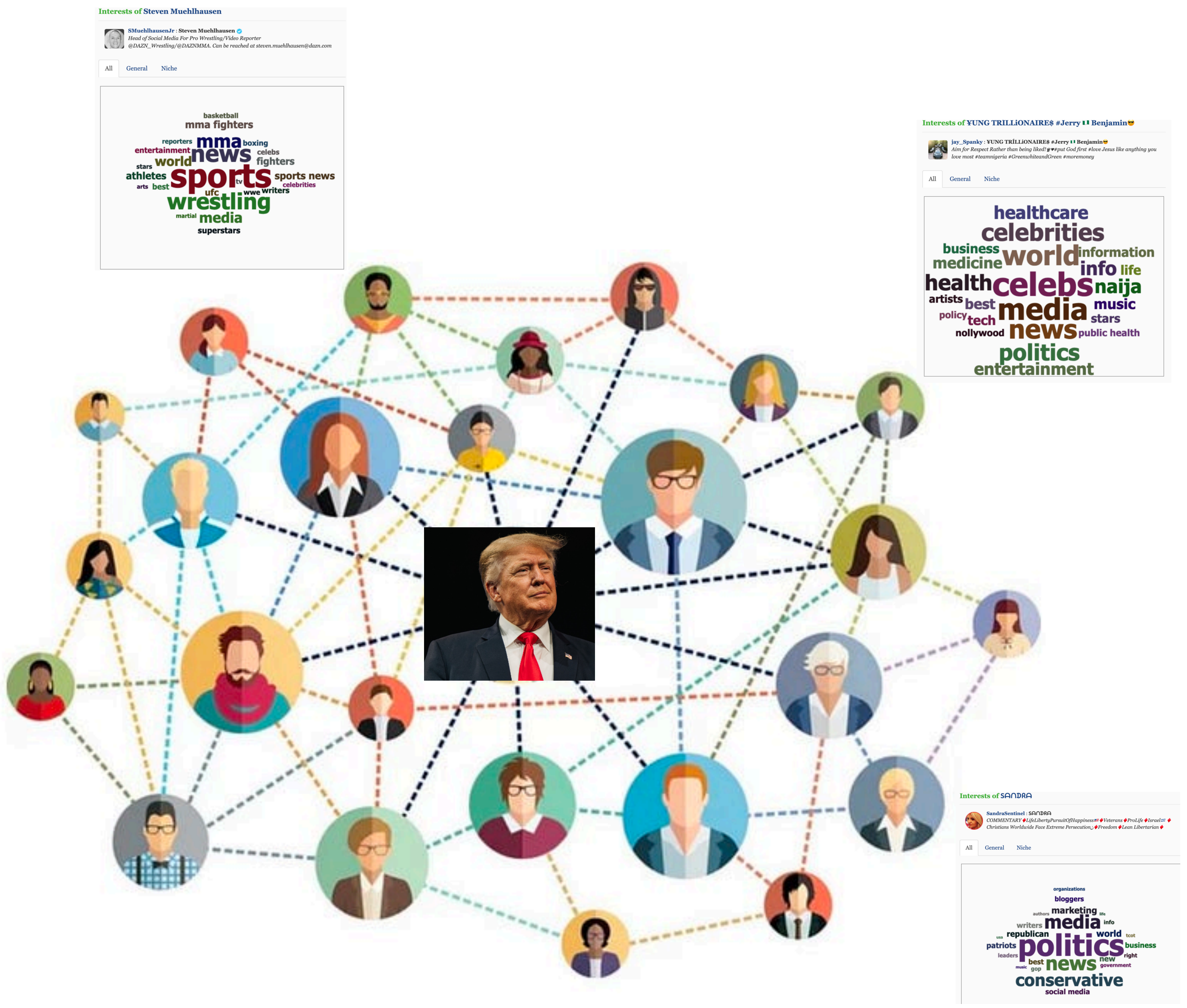
Problem



- Users form a social network:
  - Nodes represent users
  - Edges represent following relations or interactions
  - Meta information
    - innate opinion on politics
    - personal interests (sports, music, etc)

- We measure polarization and disagreement in the social network:
  - Polarization: variance of opinions
  - Disagreement: tension along edges in the network

Problem

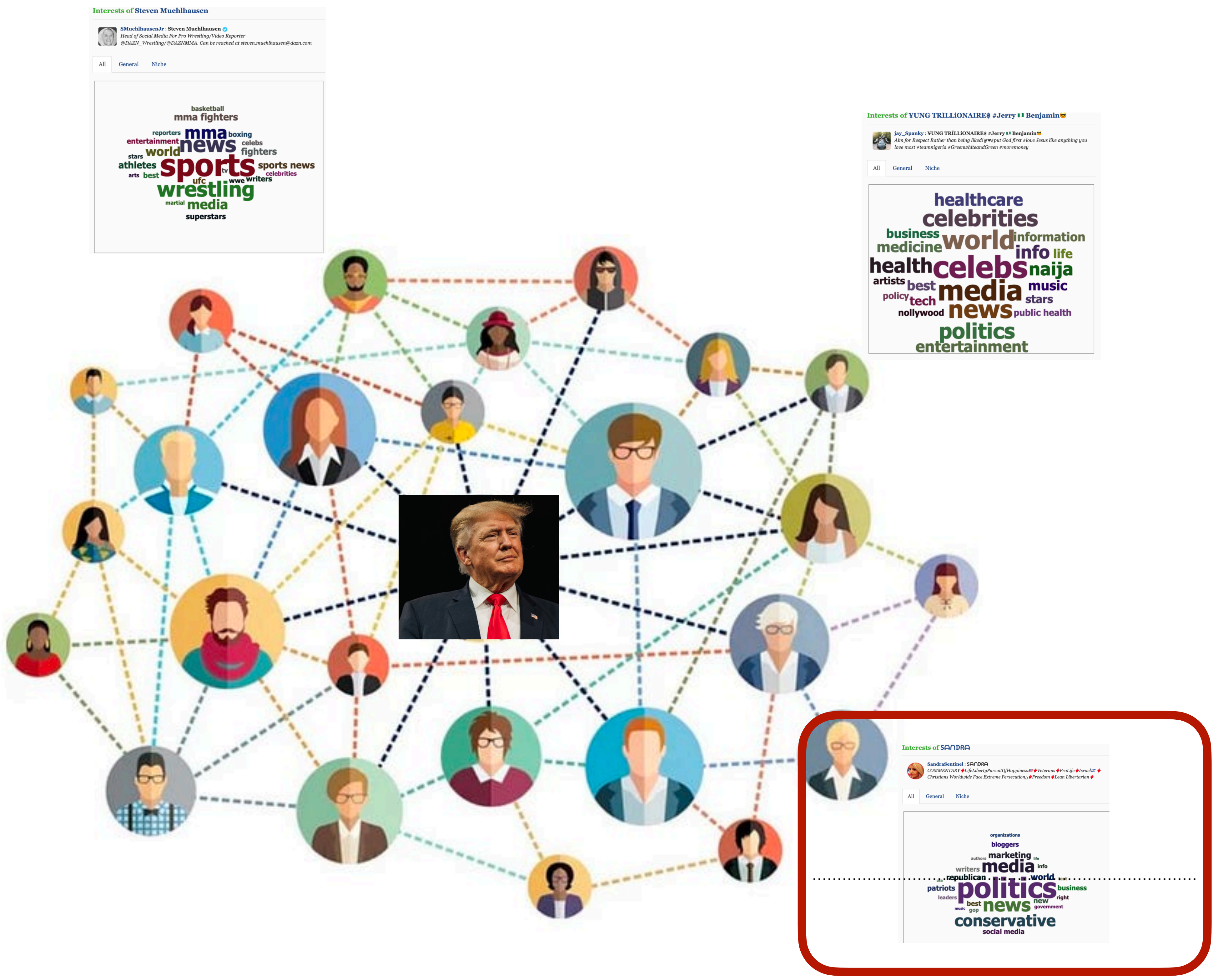


- Users form a social network:
  - Nodes represent users
  - Edges represent following relations or interactions
  - Meta information
    - innate opinion on politics
    - personal interests (sports, music, etc)

- We measure polarization and disagreement in the social network:
  - Polarization: variance of opinions
  - Disagreement: tension along edges in the network

- **Goal: minimizing polarization and disagreement in the network**

Problem



We make recommendations relevant to user interests

- Users form a social network:
  - Nodes represent users
  - Edges represent following relations or interactions
  - Meta information
    - innate opinion on politics
    - personal interests (sports, music, etc)

- We measure polarization and disagreement in the social network:
  - Polarization: variance of opinions
  - Disagreement: tension along edges in the network

- **Goal: minimizing polarization and disagreement in the network**

Problem

We use information about user topical interests, and the influencers on these topics

User-to-topic matrix, X

	Sports	Music	...	Politic
Tom	0.7	0.2	…	0.1
Alice	0.2	0.5	…	0.2
...	…	…	…	…
John	0.3	0.2	…	0.4

Topic-to-influencer matrix, Y

	Tom	Alice	...	John
Sport	0	0.08	…	0
Music	0.05	0.01	…	0.02
...	…	…	…	…
Politic	0.02	0.04	…	0.03

Problem

We use information about user topical interests, and the influencers on these topics

User-to-topic matrix, X

	Sports	Music	...	Politic
Tom	0.7	0.2	…	0.1
Alice	0.2	0.5	…	0.2
...	…	…	…	…
John	0.3	0.2	…	0.4

User interests sum to 1

Topic-to-influencer matrix, Y

	Tom	Alice	...	John
Sport	0	0.08	…	0
Music	0.05	0.01	…	0.02
...	…	…	…	…
Politic	0.02	0.04	…	0.03

Influencer scores on a topic sum to1

Problem

. . .

We use information about user topical interests, and the influencers on these topics

User-to-topic matrix, X

	Sports	Music	...	Politic
Tom	0.7	0.2	…	0.1
Alice	0.2	0.5	…	0.2
...	…	…	…	…
John	0.3	0.2	…	0.4

Topic-to-influencer matrix, Y

	Tom	Alice	...	John
Sport	0	0.08	…	0
Music	0.05	0.01	…	0.02
...	…	…	…	…
Politic	0.02	0.04	…	0.03

Recommendation graph based on user interests, XY

- Nodes represent users
- Edges represent recommendations based on interests

User-to-topic matrix, X

	Sports	Music	...	Politic
Tom	0.7	0.2	…	0.1
Alice	0.2	0.5	…	0.2
...	…	…	…	…
John	0.3	0.2	…	0.4

Topic-to-influencer matrix, Y

	Tom	Alice	...	John
Sport	0	0.08	…	0
Music	0.05	0.01	…	0.02
...	…	…	…	…
Politic	0.02	0.04	…	0.03

Recommendation network based on user interests, M

Original Social network, A

- Social network with interest recommendation, A+M
- Same nodes and denser edges.

User-to-topic matrix, X

Given a budget, how could we redistribute row values to find the optimal solution X that gives the lowest polarization and disagreement?*

	Sports	Music	...	Politic
Tom	0.7	0.2	...	0.1
Alice	0.2	0.5	...	0.2
...	...	...	...	...
John	0.3	0.2	...	0.4

Recommendation network based on user interests, M

Original Social network, A

Topic-to-influencer matrix, Y

	Tom	Alice	...	John
Sport	0	0.08	...	0
Music	0.05	0.01	...	0.02
...	...	...	...	...
Politic	0.02	0.04	...	0.03

- Social network with interest recommendation, A+M
- Same nodes and denser edges.

We present a **gradient descent-based algorithm** for this problem, and show that under realistic parameter settings it computes a $(1+\epsilon)$-**approximate** solution in time $\tilde{O}(m\sqrt{n}\log 1/\epsilon)$ where m is the number of edges in the graph and n is the number of vertices.

Optimal user-to-topic matrix, X^*

	Sports	Music	...	Politic
Tom	0.6	0.3	...	0.1
Alice	0.2	0.7	...	0.1
...	...	...	...	...
John	0.3	0.2	...	0.5

Topic-to-influencer matrix, Y

	Tom	Alice	...	John
Sport	0	0.08	...	0
Music	0.05	0.01	...	0.02
...	...	...	...	...
Politic	0.02	0.04	...	0.03

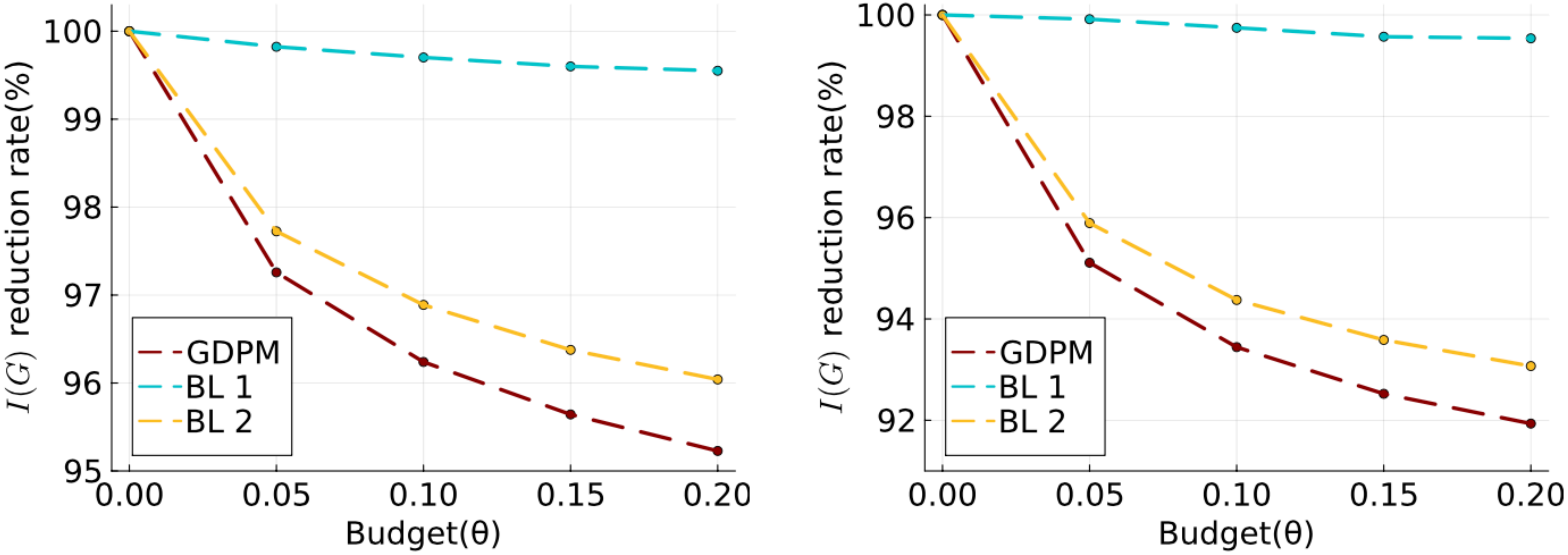
Recommendation network based on user interests, M

+

Original Social network, A

- Social network with interest recommendation, A+M
- Same nodes and denser edges.

Experimental results



(a) TwitterSmall (b) TwitterLarge

Reduction of the polarization and disagreement index on two Twitter dataset for our algorithm GDPM and two baseline algorithms.

Dataset

- **Innate opinion of users**
  - Political polarity score

- **Twitter dataset**
  - A list of Twitter accounts who actively engage in political discussions in the US.
  - For these accounts, we obtain a list of followers for each and corresponding tweets using Twitter API.
  - TwitterSmall: 5,000 seed users.
  - TwitterLarge: 50,000 seed users.

- **Ethical issues of dataset**
  - We anonymize ID and names for each Twitter account.
  - Interest and influence of users are represented in matrix without personal information.
  - We only report aggregated statistical metrics.

Ethical Considerations

- **Intended usage:**
  - Our goal is encouraging cross-cutting political communication based on nonpolitical commonalities, like interests in sports and music.
  - Using small budget to change users interest-based feeds is considered a milder intervention which respects users preference.

- **Abuse**
  - By manipulating budget parameter and topics, the algorithm may be used to guide user to an intended direction in a long term process.
  - Social media platforms can anyway make changes to user timeline with no transparency and with the aim to optimize objectives of their interest, e.g., engagement.
  - Deploying the algorithm in real-world setting may led to unexpected effects.

Thanks