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How Collaboration Patterns Evolve In Crisis Response?

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Collaborations in Volunteer Activities

Emergence Response

Community Bonding

Teamwork

Enhanced collaboration usually leads to **greater retention** and **increased effectiveness**, enabling a swifter response to crises and improved organizational agility.

“Shenzhen Pioneers” Volunteering Platform

Time Period

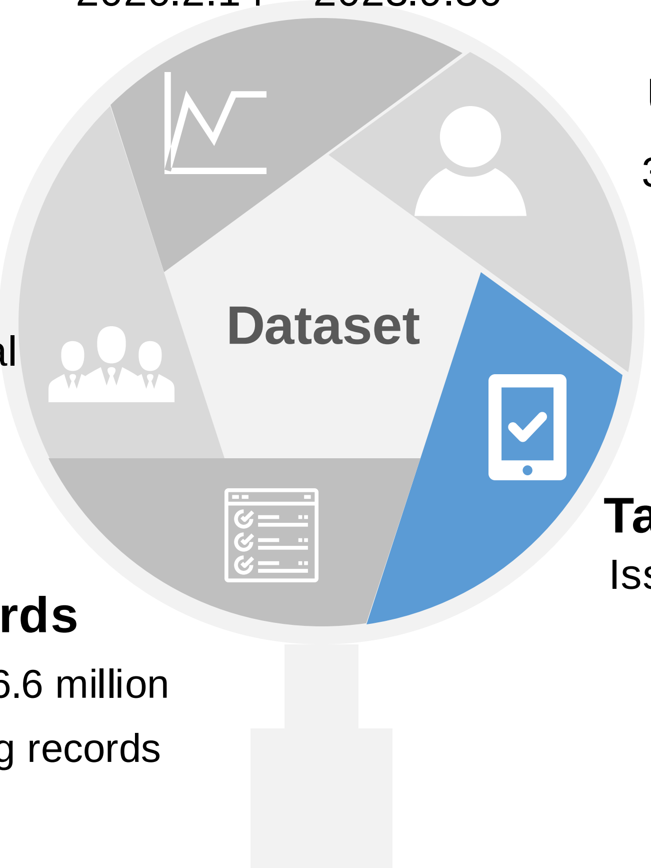
2020.2.14 – 2023.9.30

User ID

361114 Users in Total

Issuer ID

25278 Issuer in Total

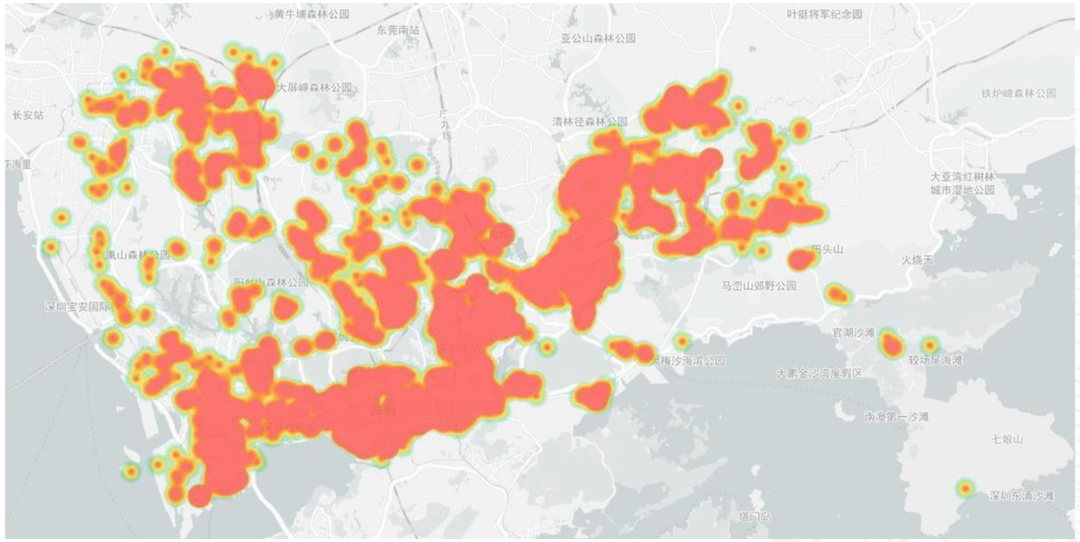


Tasks

Issued 1207304 Tasks

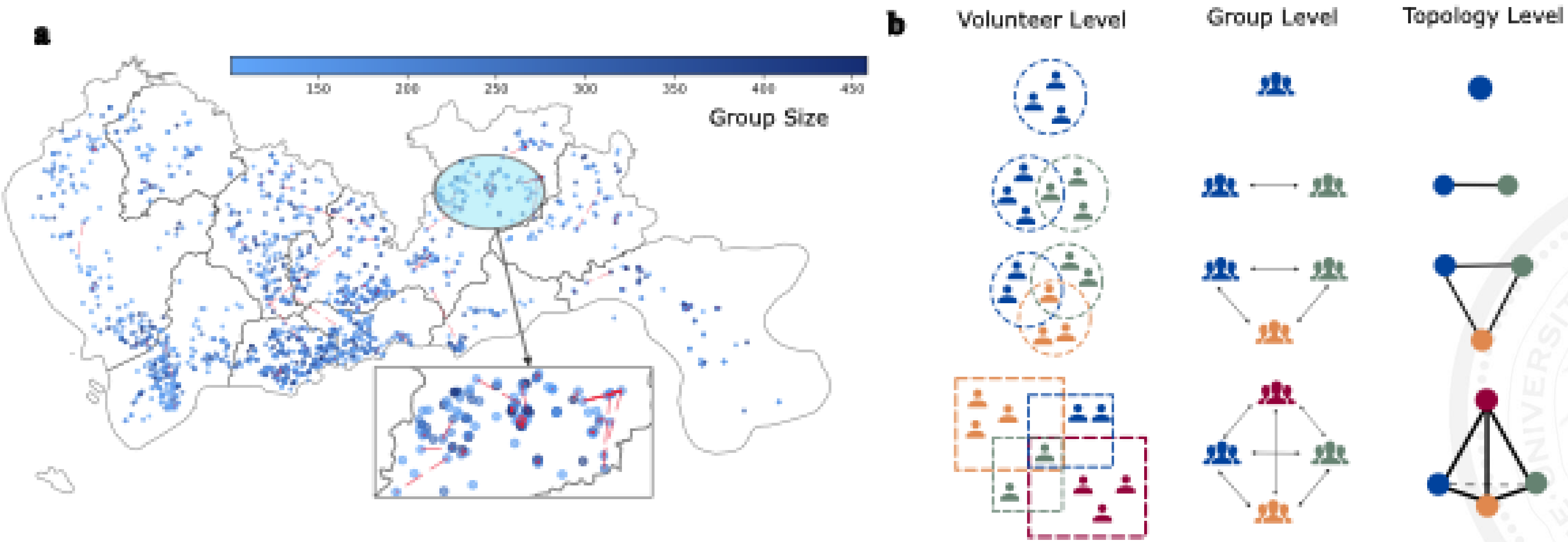
Records

More than 6.6 million volunteering records



Heatmap of volunteer activities

Collaborations Among Volunteer Groups



Spatial-temporal and Non-pairwise

It's effective to present collaboration in terms of topology!

Research Questions

- How to quantify collaboration patterns from a large-scale dynamic volunteering activities?

- What are the (spatial-temporal) factors for collaborations?

- Is the collaboration pattern critical for the collective effectiveness of volunteers?

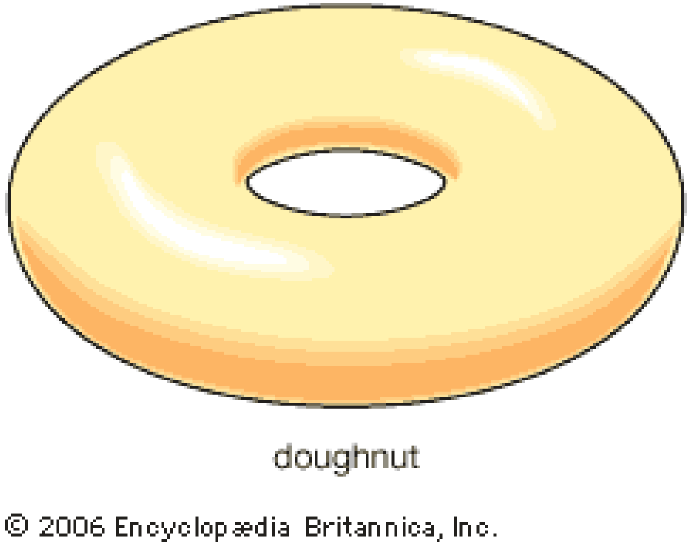
Methodology

Background on topological data analysis

Zigzag Persistence

Topological Data Analysis

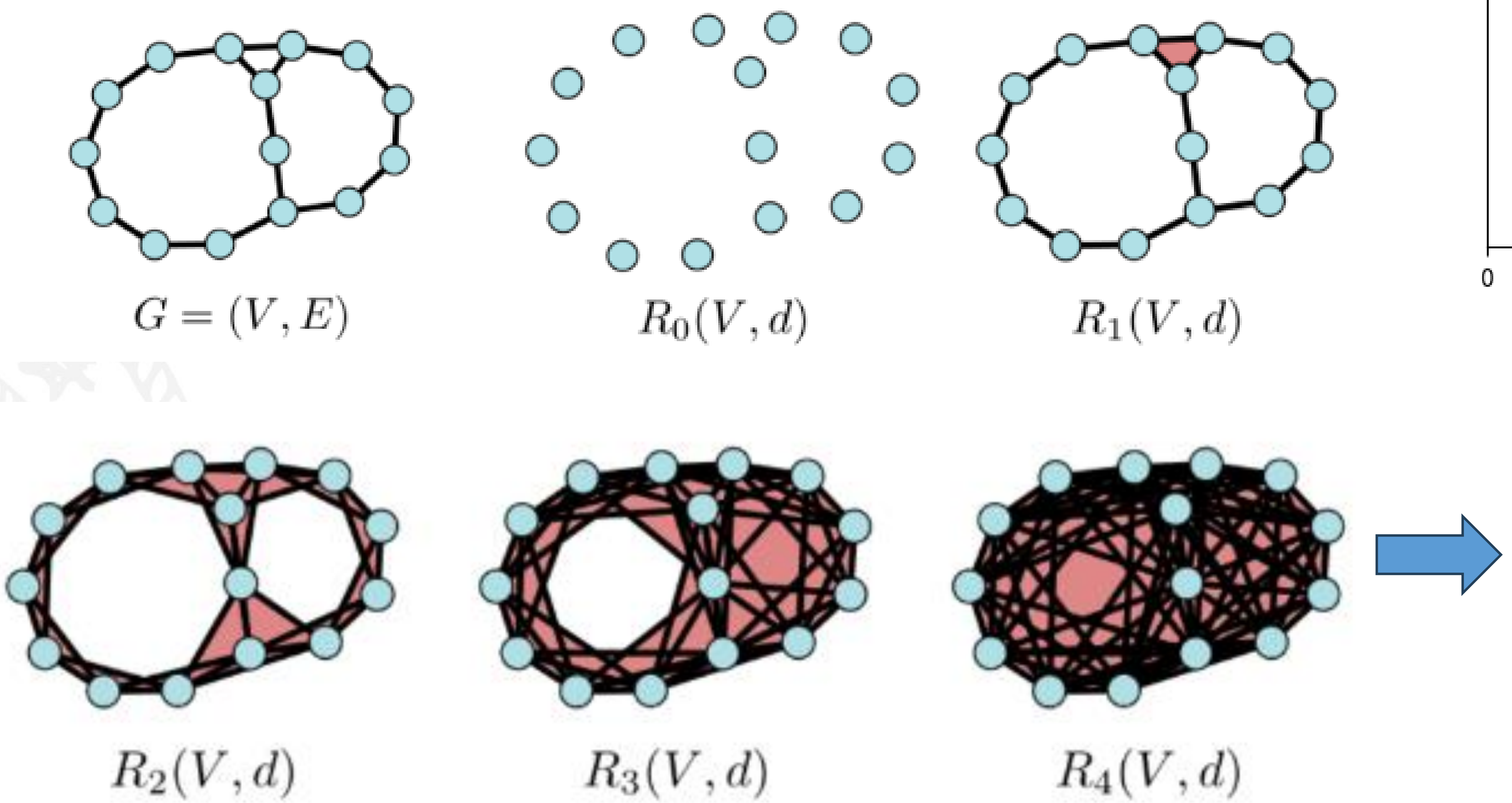
- Topology is…
  - The study of holes
  - The Study of connectivity
  - Could think of it as space bending
- Betti Numbers
  - β_0 = # connected components
  - β_1 = # cycles
  - β_2 = # voids
  - …….

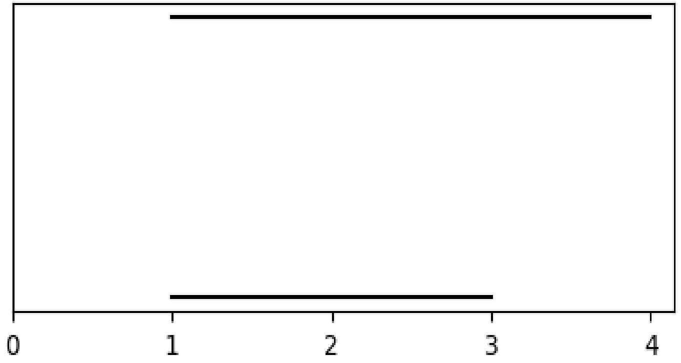


$$\beta_0 = 1$$
$$\beta_1 = 1$$
$$\beta_2 = 0$$

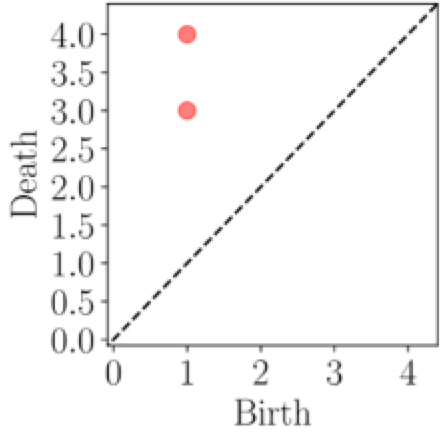
Rips Filtration on Graphs

Pros: inclusions only go one way.





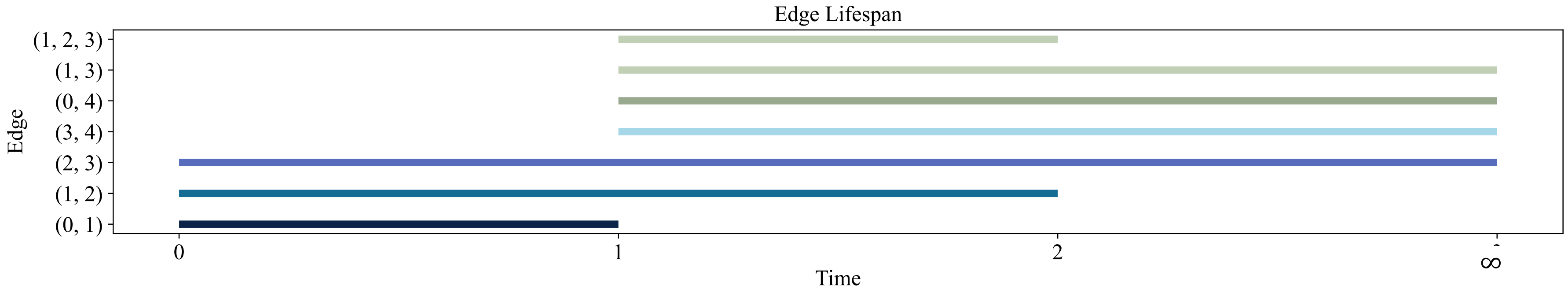
Persistence Barcode

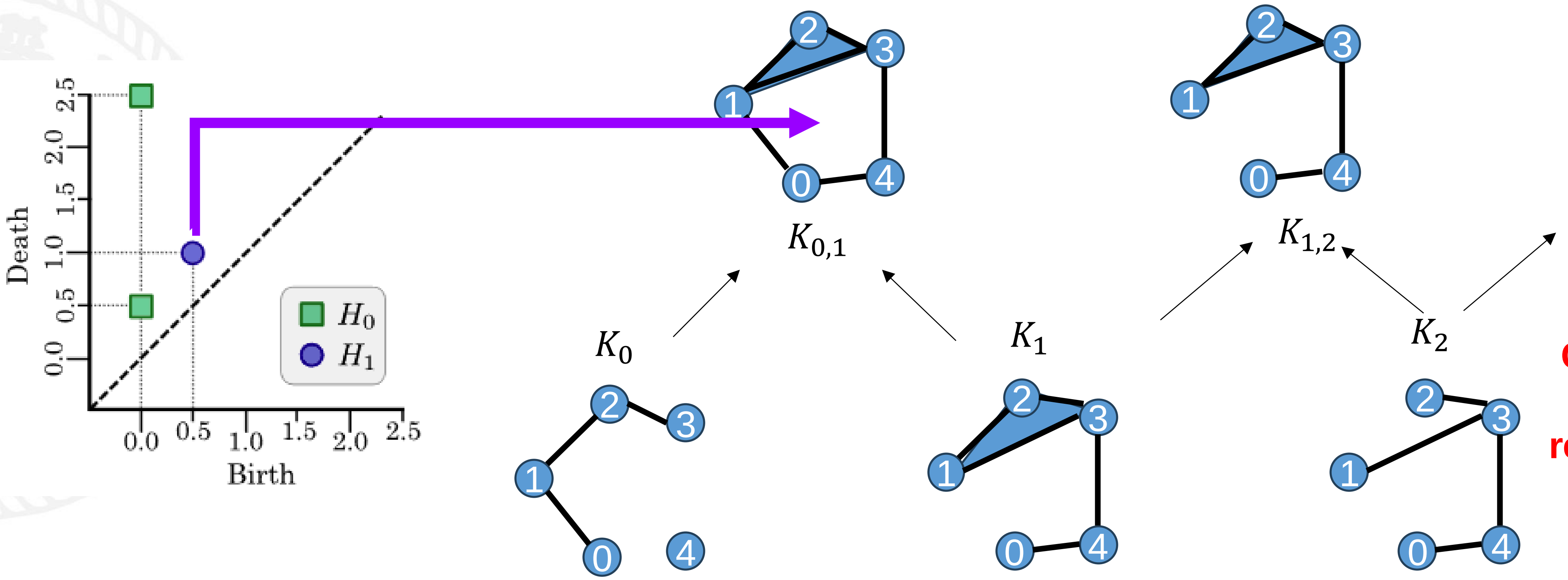


Persistence Diagram

Capture topological features by building simplicial complexes as parameters (shortest path distance) increase.

Zigzag Persistence on Graphs

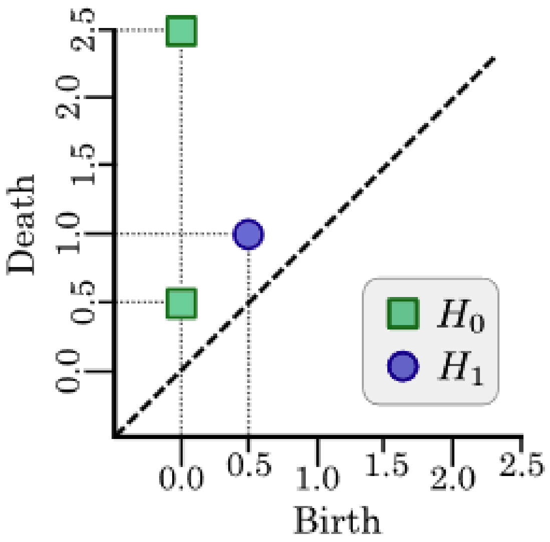




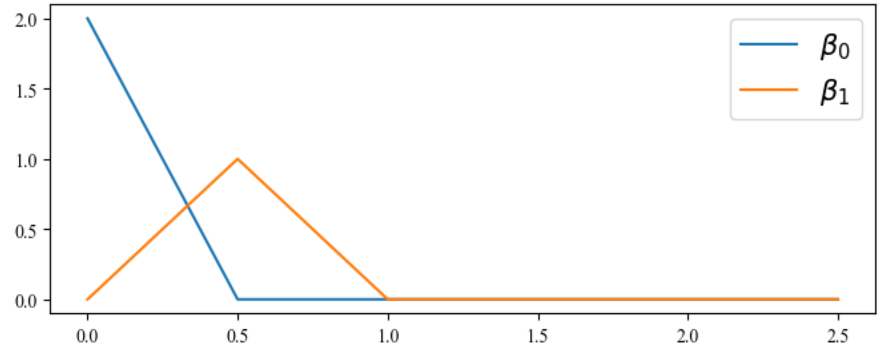
Cons: Able to track edge addition and removal, suitable for temporal graphs!

Feature Vectorization

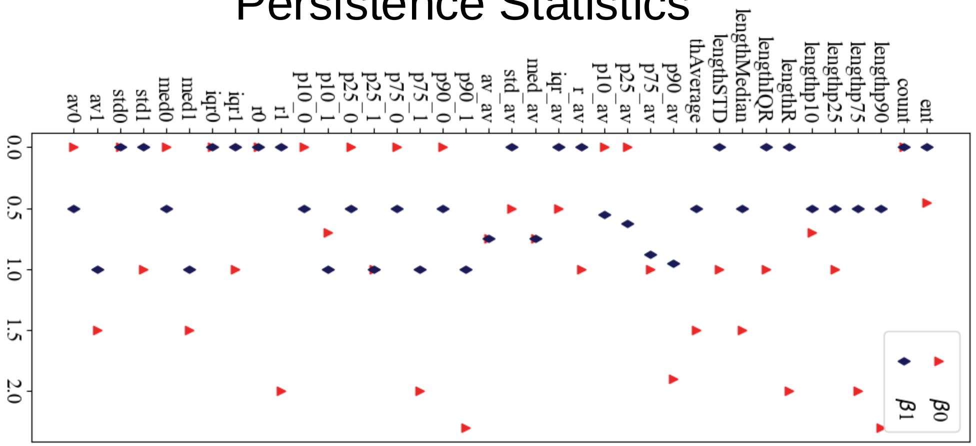
Persistence Diagram



Betti Curve



Persistence Statistics



Definition 3.6. The **Betti curve** of $\mu : B \to \mathbb{Z}_{>0}$ is the curve $\beta_\mu : \mathbb{R} \to \mathbb{R}$ given by

$$\beta_\mu(t) = \sum_{[p,q]\in B} \mathbb{1}_{p\leq t<q} \cdot \mu_{p,q}.$$

Here $\mathbb{1}_\bullet$ is the indicator function as described in Definition 3.2, so this function counts the number of intervals (with multiplicity) in B which contain t. Very similar in spirit (and formula) to the Betti curve is the following vectorization from [20].

Definition 3.1. The **persistence statistics** vector of $\mu : B \to \mathbb{Z}_{>0}$ consists of:

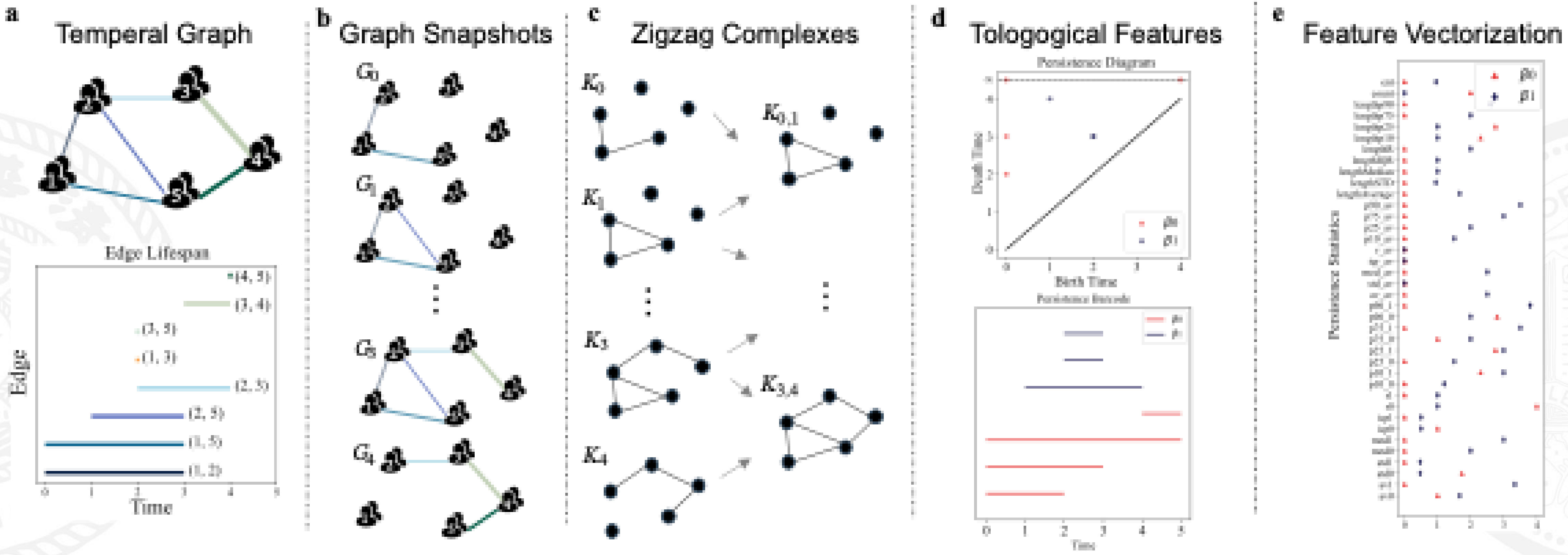
1) the mean, the standard deviation, the median, the interquartile range, the full range, the 10^{th}, 25^{th}, 75^{th} and 90^{th} percentiles of the births p, the deaths q, the midpoints $\frac{p+q}{2}$ and the lifespans $q-p$ for all intervals $[p,q]$ in B counted with multiplicity;
2) the total number of bars (again counted with multiplicity), and
3) the *entropy* of μ, defined as the real number

$$E_\mu := -\sum_{[p,q]\in B} \mu_{p,q} \cdot \left(\frac{q-p}{L_\mu}\right) \cdot \log\left(\frac{q-p}{L_\mu}\right),$$

where L_μ is the weighted sum

$$L_\mu := \sum_{[p,q]\in B} \mu_{p,q} \cdot (q-p). \tag{1}$$

Zigzag Persistence-based Framework

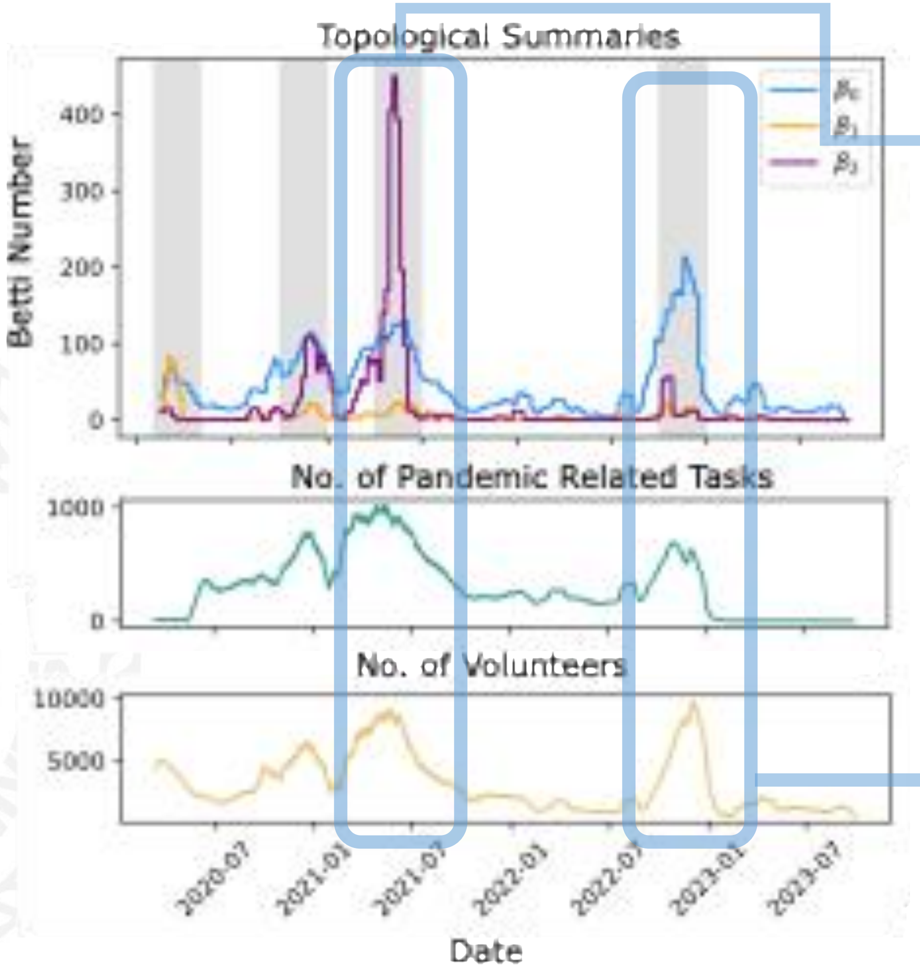


Results

Temporal evolution of volunteer collaboration patterns to the COVID-19 pandemic.
Regional Differences on Volunteer Collaboration Patterns.

Topological patterns can reflect external perturbations.

Pandemic Effects

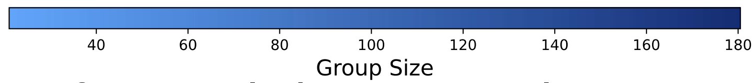


2021 Apr – 2021 Jul

Pandemic Waves In Shenzhen

2022 Oct – 2023 Jan

Nationwide Reopening



During the pandemic, high-dimensional collaborations emerged more frequently between volunteer groups. However, after the pandemic, groups tended to prefer completing tasks individually.

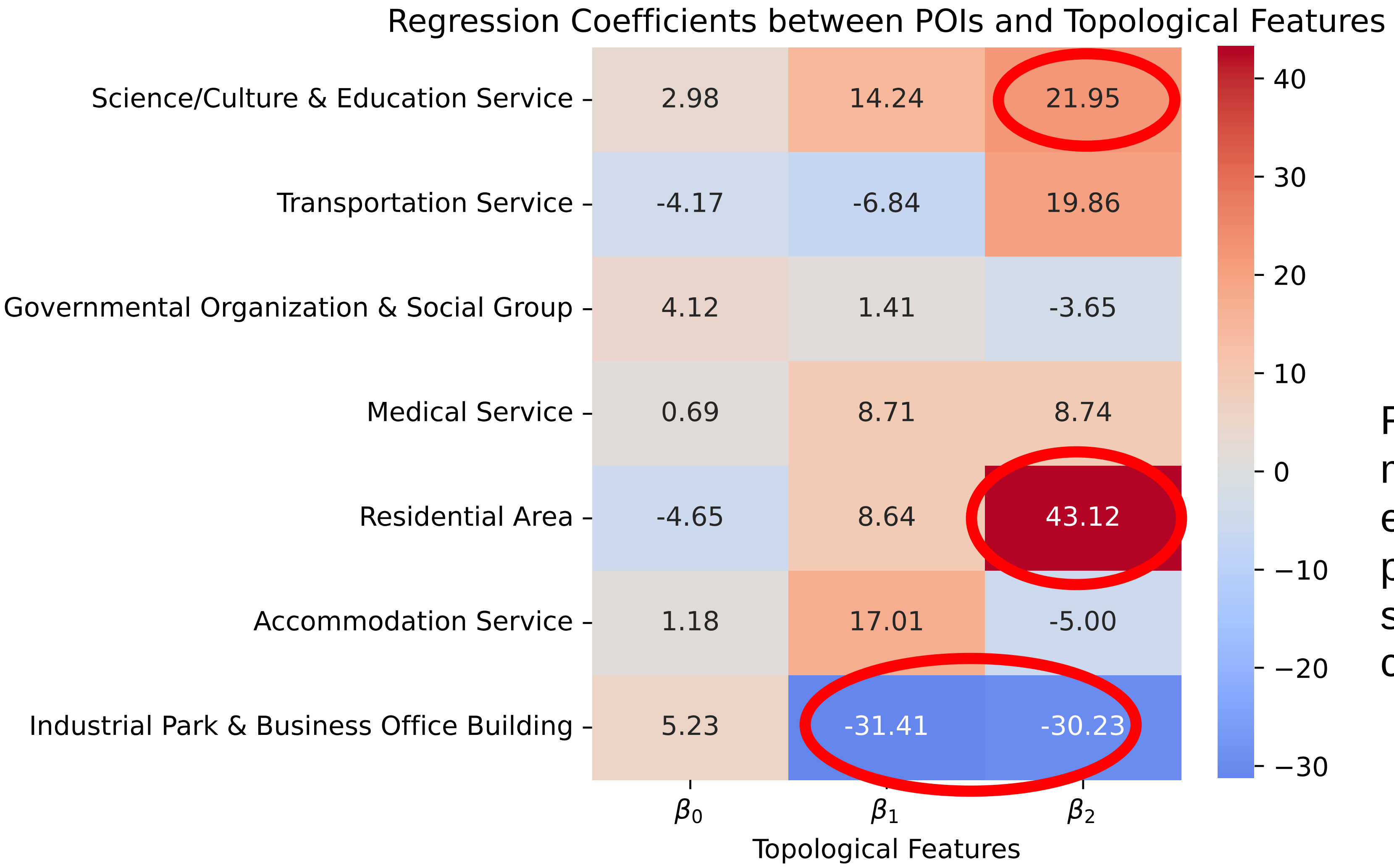
Regional Difference Influence: Point-of-interest Correlation

Point-of-interest of 72 Streets

POI Type	Yuanling Street	Pinghu Street	…
Science/Culture & Education Service	256	662	…
Transportation Service	267	900	…
Governmental Organization & Social Group	103	462	…
Medical Service	90	876	…
Residential Area	25	187	…
Accommodation Service	19	550	…
Industrial Park & Business Office Building	38	339	...

POI Data crawling from GAODE: https://lbs.amap.com/api/webservice/guide/api/search

Point-of-interest Effects



Persistence Feature

POI Matrix

$$\underset{72*38}{Y} = \underset{72*7}{X} * \underset{7*38}{\beta}$$

Residential areas and areas with more educational institutions exhibited tighter collaboration patterns, while industrial regions showed fewer high-dimensional collaborations.

Is the collaboration pattern critical for global/system effectiveness?

Goal: Simulates volunteer collaboration behavior and investigate how cross-community collaboration correlates to the system effectiveness.

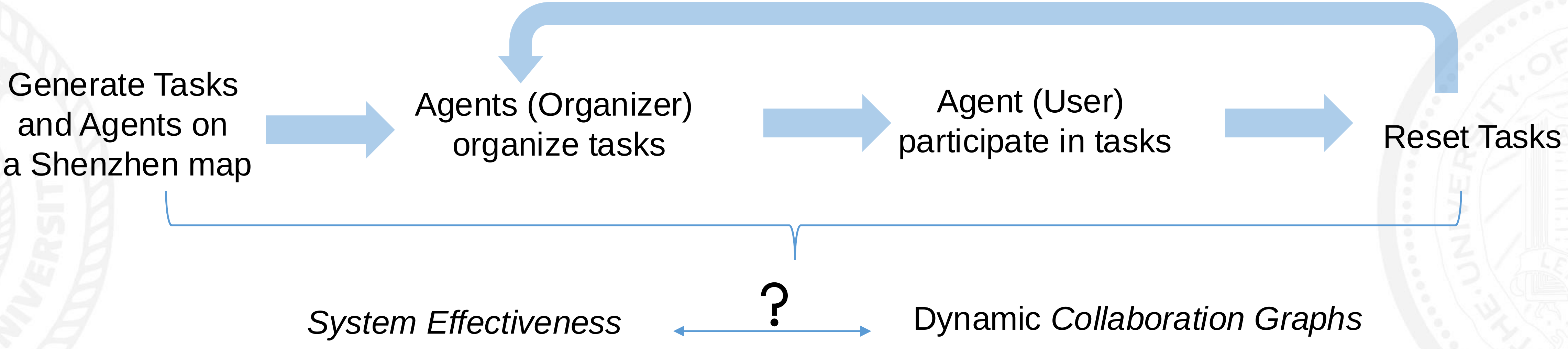


Fig. Simulation Pipeline

Simulation Settings -- Agents

- Parameter
  - home location : agent‘s position (lat, lon)
  - Home street: 72 streets from Pioneers
  - If organizer: percentage p
- Action
  - Organizers’ Action
  - Participants’ Action
- System perturbation settings:
  - Add and remove agents periodic at some timestep

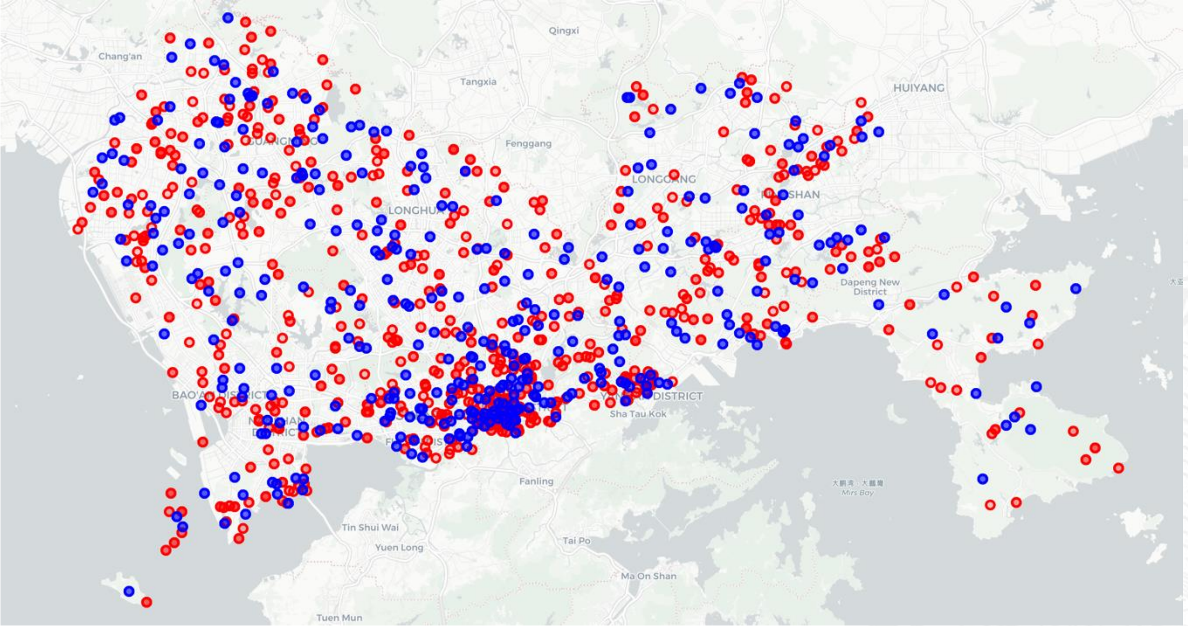


Fig. Generate Agents and tasks (red: agents, blue: tasks)

Simulation Settings – Agents Actions

The probability of organizer o_i to organize a task with task type t located at (lat, lon) is:

$$P\left(T_{lat,lon,t}\middle|o_i\right) = v_4 * \frac{1}{distance} + v_5 \ * task\ affinity$$

$$P\left(T_{lat,lon,t}\middle|u_i\right) = v_1 * \frac{1}{distance} + v_2 \ * task\ affinity + v_3 \ * collaborative\ propensity$$

- Distance: distance between the selected task and agents’ home location
- Task affinity: agents task type preference (sampling task type distribution from real data)
- Collaborative propensity: number of agents already selected tasks that user u_i collaborated before

System Effectiveness (E)

Given a task T with task type t located at (lat,lon), the effectiveness can be computed as follows:

$$E(T_{lat,lon,t}) = team\ size\ * team\ cohesion\ * team\ familiarity$$

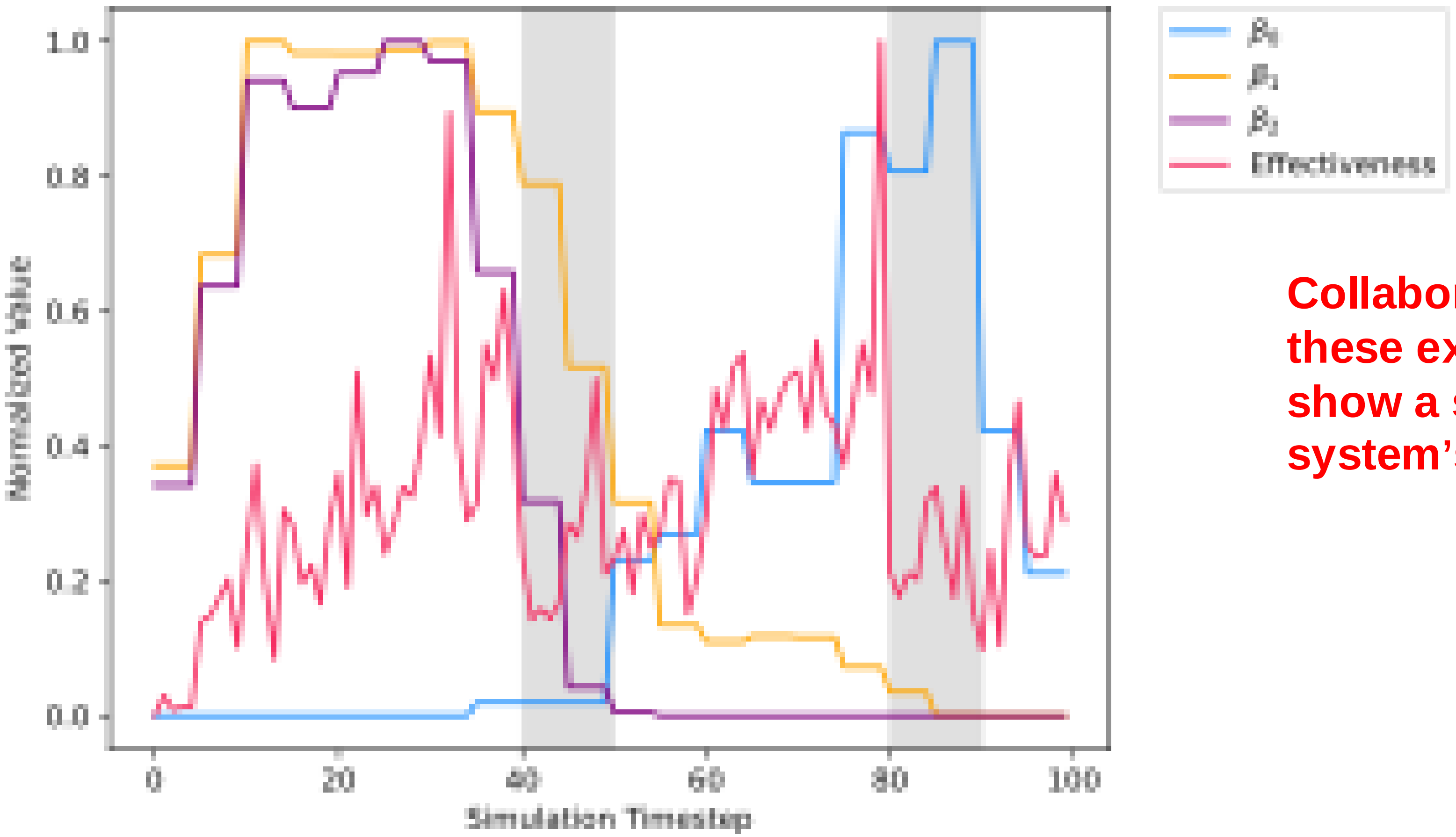
Where:
- Team size (N): the number of agents participate in this task
- Team cohesion: the normalized number of pairwise collaborations within the team before

$$team\ cohesion = \frac{1}{N^2} \sum_{i,j\ \in Agents} if\_collaborate(Agent_i, Agent_j)$$

- Team familiarity: the average number of participation times in the task type t within the group (initialized from real data and increasing with the iteration of the simulation)

Guimera, Roger, et al. "Team assembly mechanisms determine collaboration network structure and team performance." *Science* 308.5722 (2005): 697-702.

Simulation Results



Collaboration patterns respond to these external perturbations and show a strong correlation with the system's overall effectiveness

Conclusion

- We **quantified and analyzed dynamic collaboration networks** in social network via a novel topological data analysis-based framework.
- We demonstrated the existence of higher-order community collaborations in Shenzhen during the COVID-19 pandemic and analyzed the influence of the pandemic and regional factors.
- We discovered pandemic and regional factors **affect** collaboration patterns
- Further simulation results showed that collaboration patterns are correlated with system effectiveness and can reflect external perturbations. **(as a way measure and facilitate system effectiveness)**

Thanks