PrivGraph: Differentially Private Graph Data Publication by Exploiting Community Information

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Outline

- Background
- Problem Definition
- Method
- Evaluation
- Conclusion

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Big Data Era

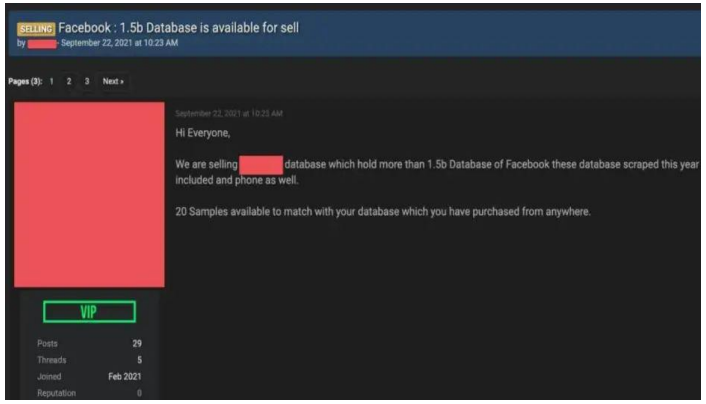
- Data collection
  - Browsing history, communication records, …
- Data analysis
  - Improving user experience, recommendation, …

User Data **Data Collection** **Data Analysis**

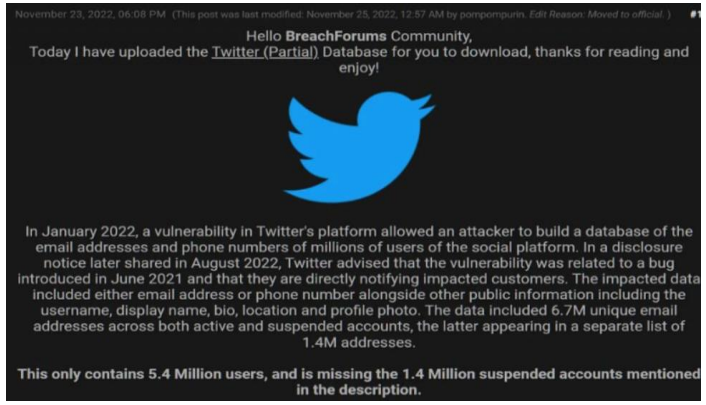
Privacy Accidents

2017, Yahoo
breached 3 billion user data

2020, Microsoft
exposed 250 million records

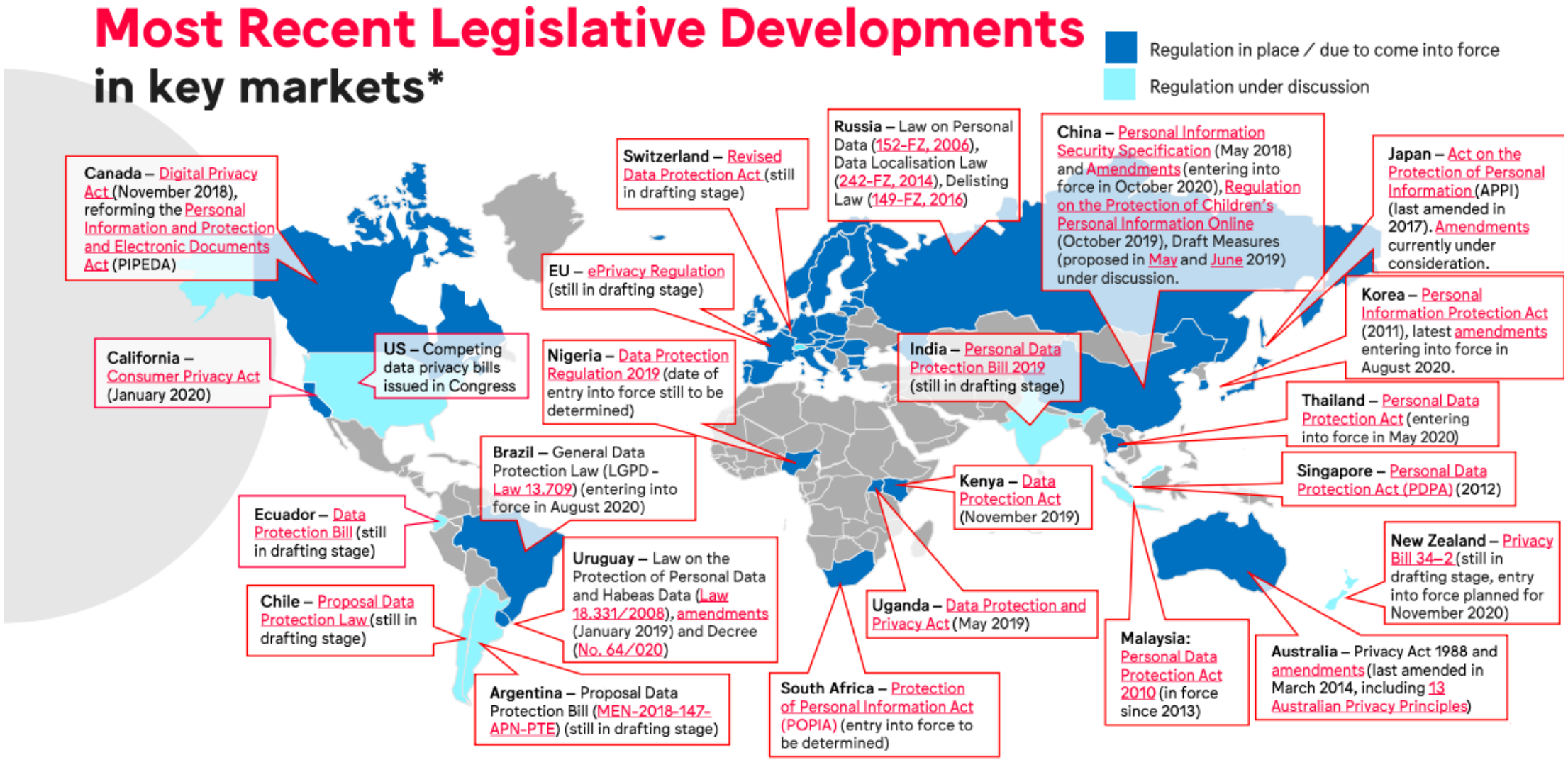


2021, Facebook
1.5 billion user data sold



2022, Twitter
breached 540 million user data

Laws for Privacy Protection



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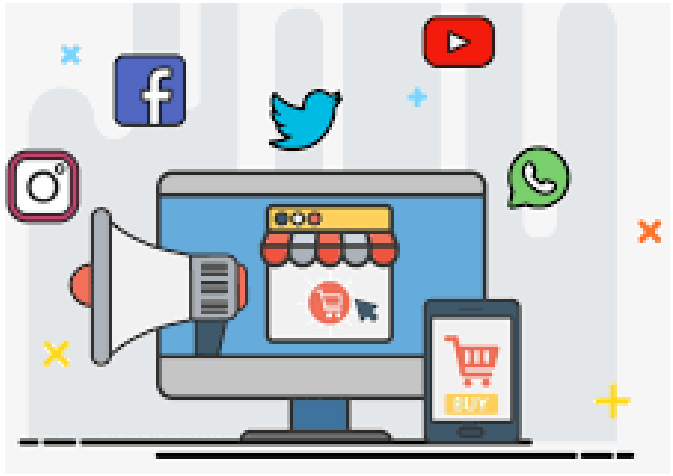
Problem Definition

Social Contacts **Vote Network** **Email Communication**

The edges of a graph may contain users' sensitive information.

Problem Definition

- **Related Tasks**

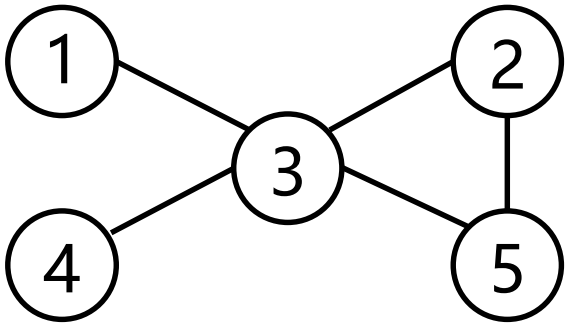


Advertising

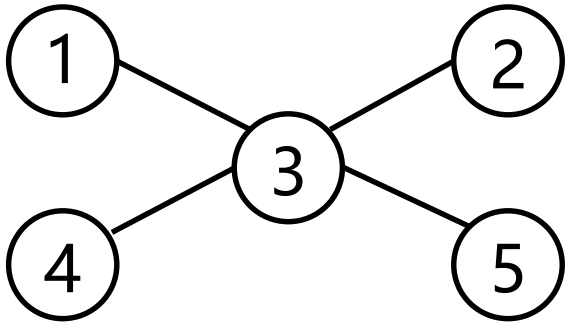
User Protrait

Epidemiological Study

Problem Definition



A graph G



An edge neighboring graph G'

Randomization Algorithm

Statistical result

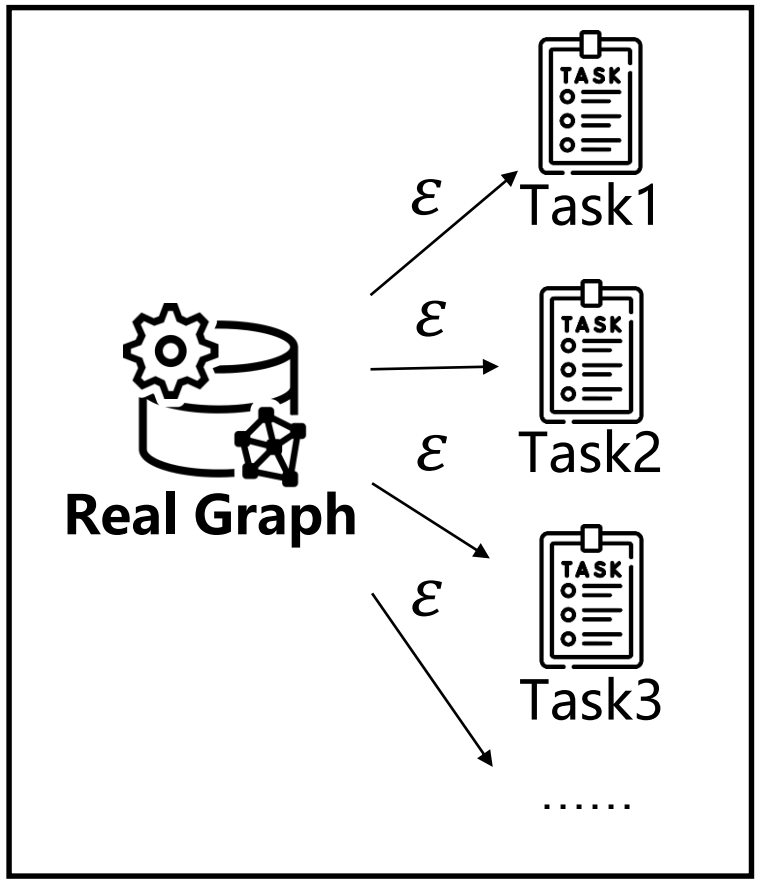
T satisfy

$$\frac{\Pr[A(G) \in T]}{\Pr[A(G') \in T]} \leq e^{\varepsilon}$$

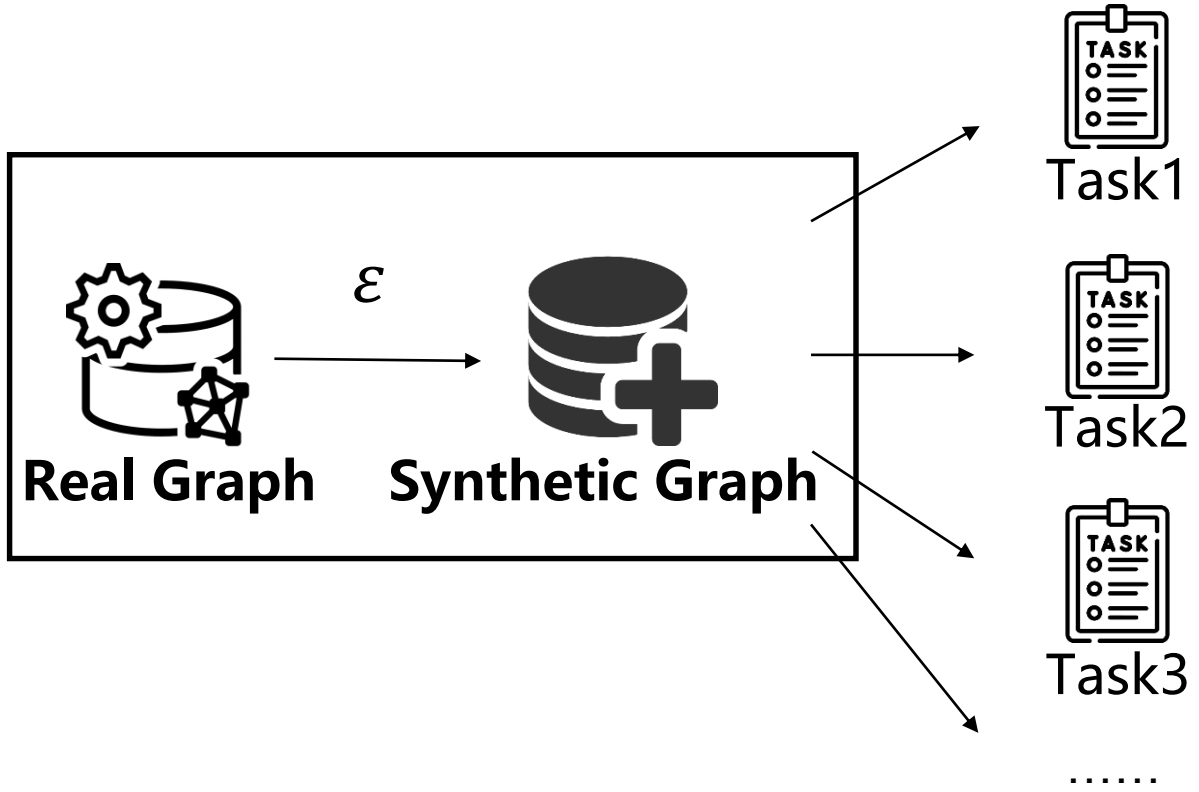
Edge-DP: Limit the impact of any edge in the graph on the output

Problem Definition

Private Tasks



Private Data Synthesis



Our goal: Synthesize a graph under edge-DP while ensuring high utility

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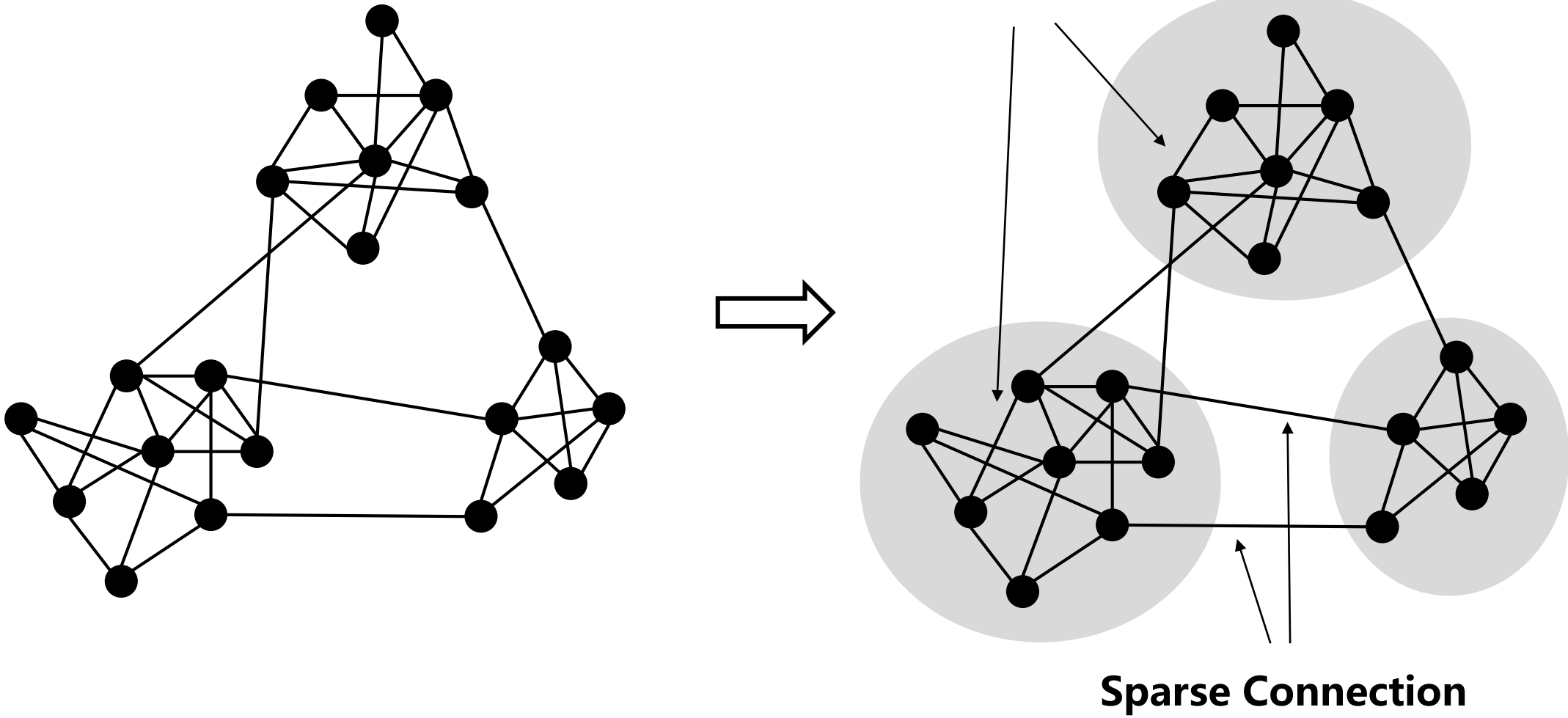
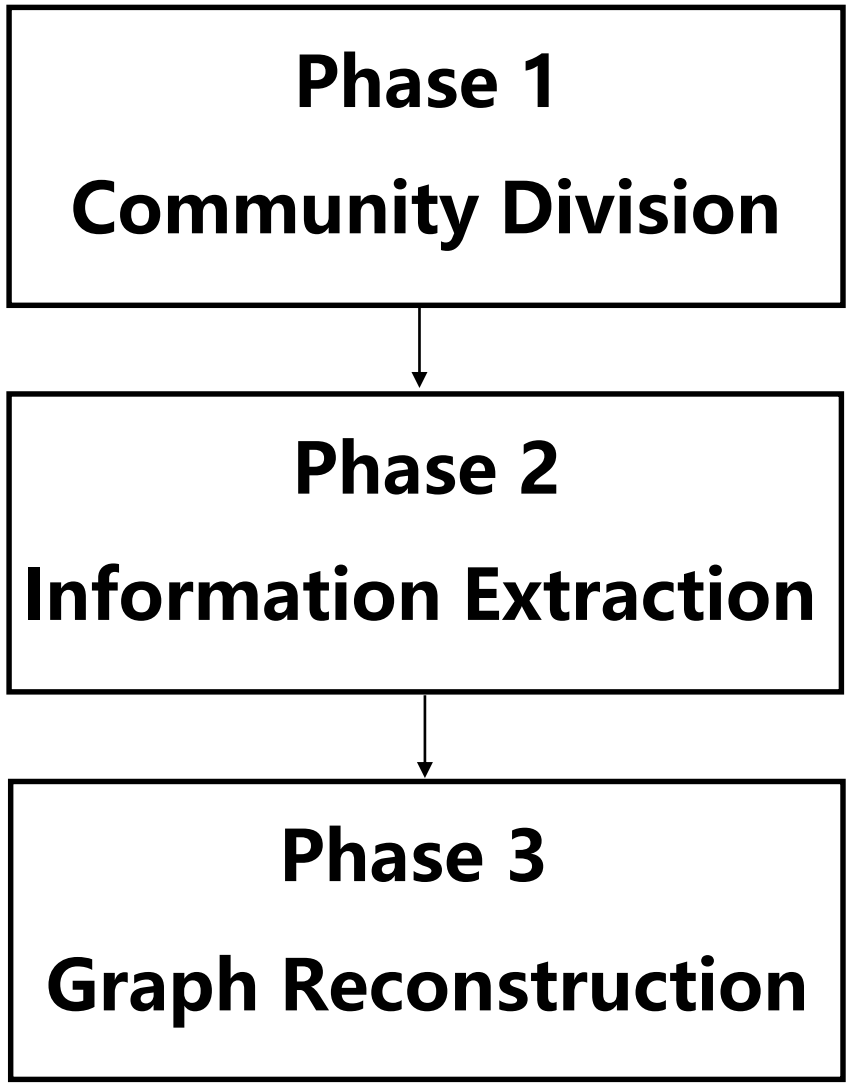
Intuition

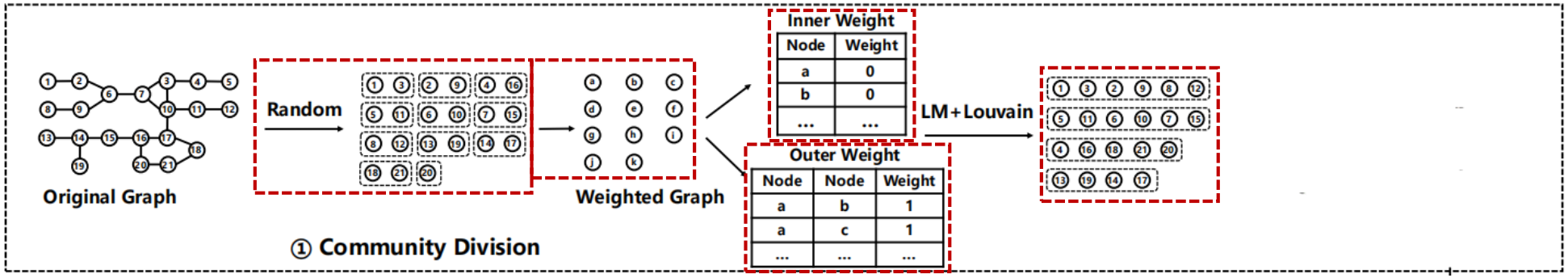


Workflow of PrivGraph



Workflow of PrivGraph

- Phase 1: Community Division (CD)
- Phase 2: Information Extraction (IE)
- Phase 3: Graph Reconstruction (GR)



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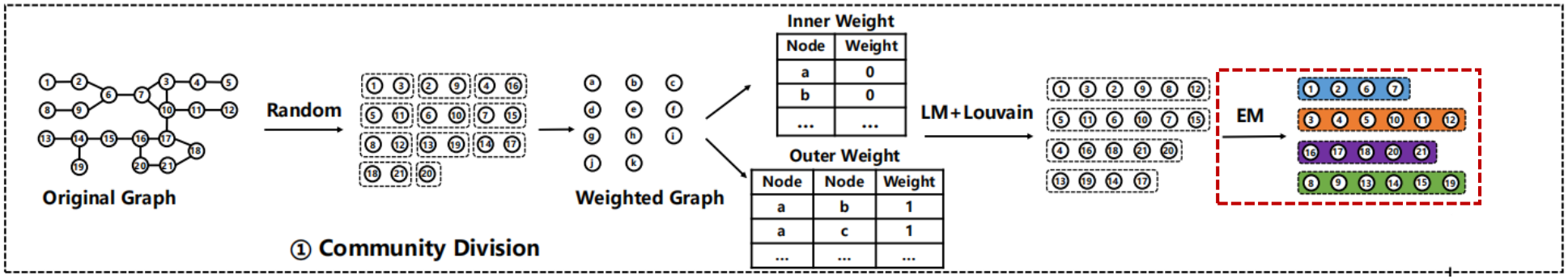

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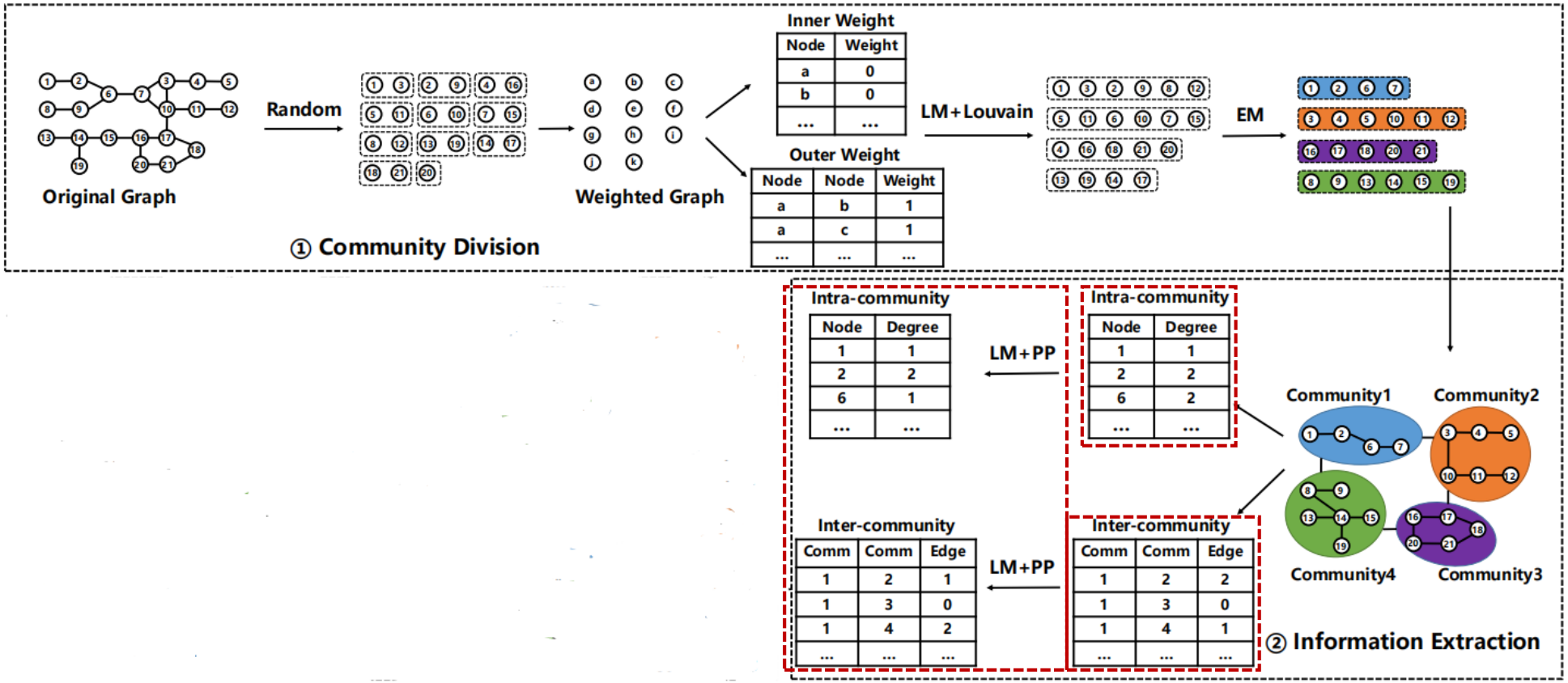

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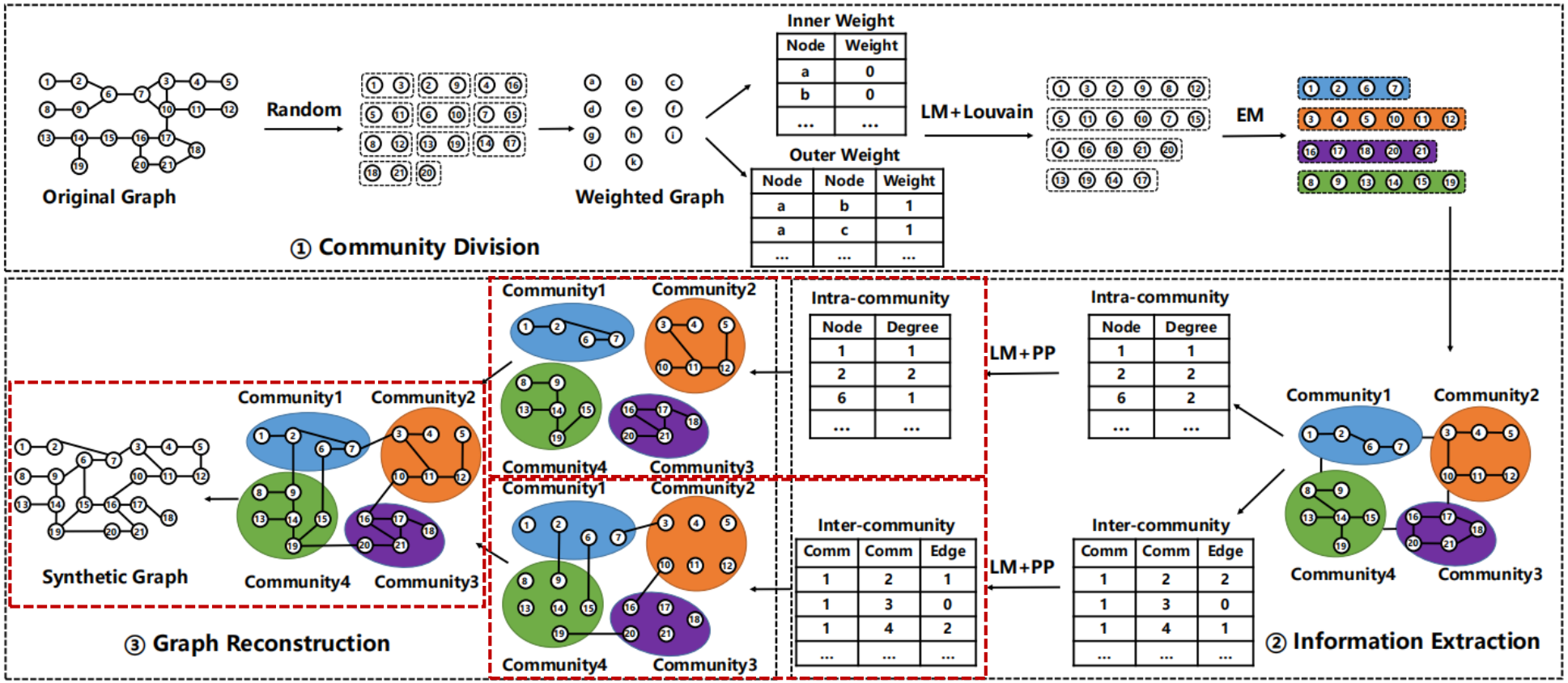

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Experiment Setup

Dataset

- 6 real world datasets

Dataset	Nodes	Edges	Density	Type
Chamelon [65]	2,277	31,421	0.01213	Web page
Facebook [46]	4,039	88,234	0.01082	Social
CA-HepPh [44]	12,008	118,521	0.00164	Collaboration
Enron [63]	33,696	180,811	0.00032	Email
Epinions [62]	75,879	405,740	0.00014	Trust
Gowalla [13]	196,591	950,327	0.00005	Social

Experiment Setup

Metrics

- Community Discovery: Normalized Mutual Information
- Node Information: Eigenvector Centrality Score
- Degree Distribution
- Path Condition: Diameter
- Topology Structure: Clustering Coefficient, Modularity

Competitors

- LDPGen[1]
- TmF[2]
- PrivHRG[3]
- DER[4]

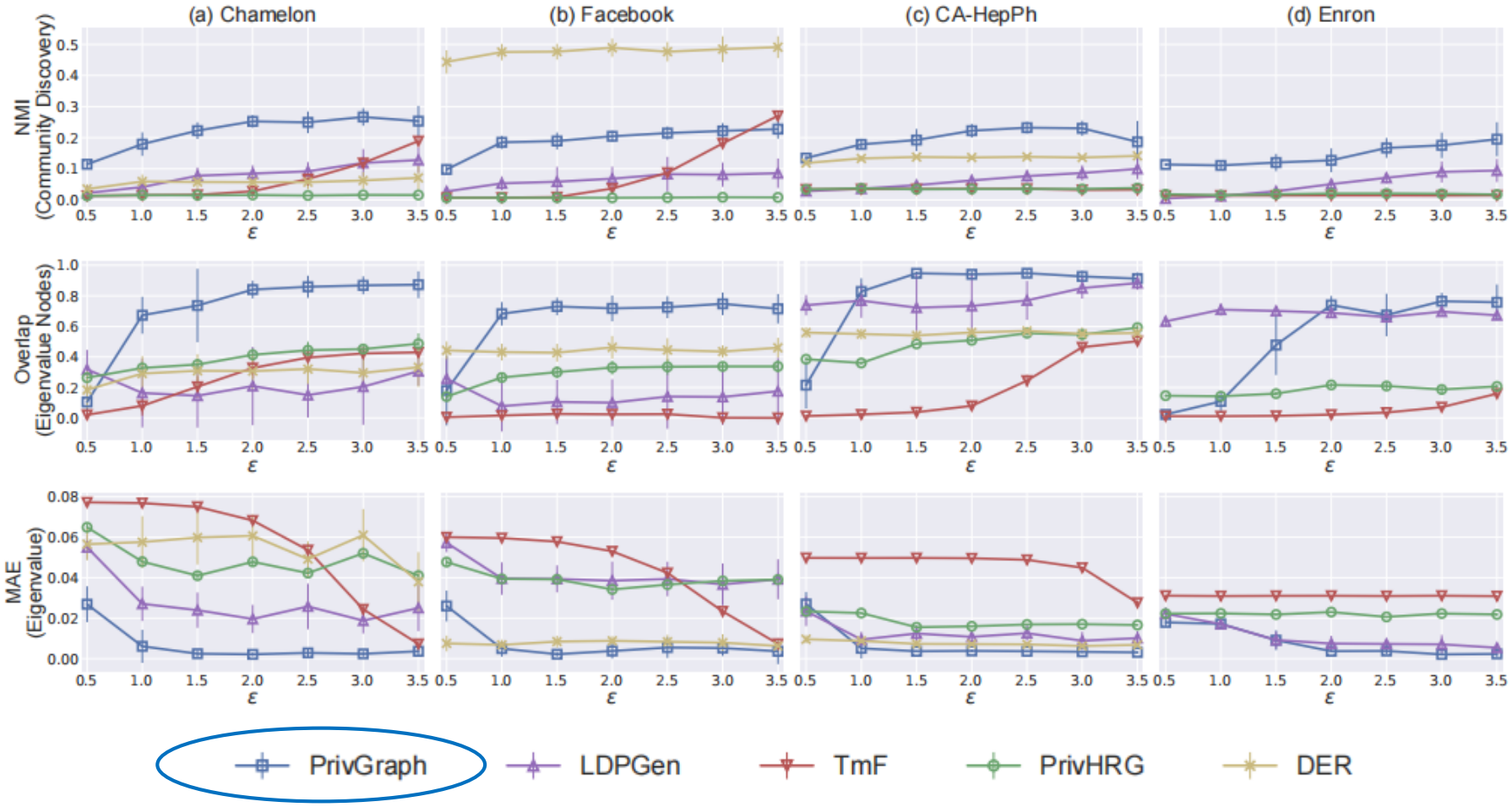
[1] 2017 CCS Generating Synthetic Decentralized Social Graphs with Local Differential Privacy

[2] 2015 ASONAM Differentially Private Publication of Social Graphs at Linear Cost

[3] 2015 SIGKDD Differentially Private Network Data Release via Structural Inference

[4] 2014 VLDBJ Correlated Network Data Publication via Differential Privacy

Performance

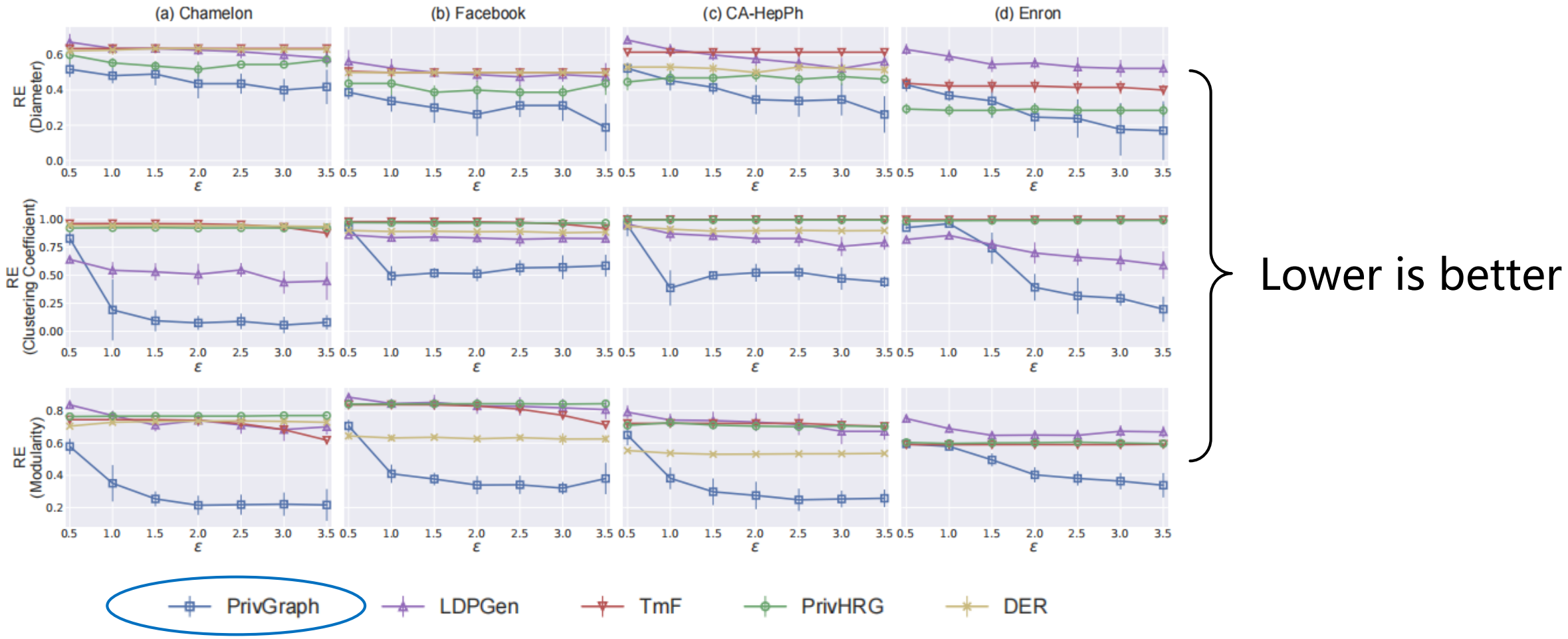


Higher is better

→ Lower is better

PrivGraph outperforms other methods in most cases.

Performance



Lower is better

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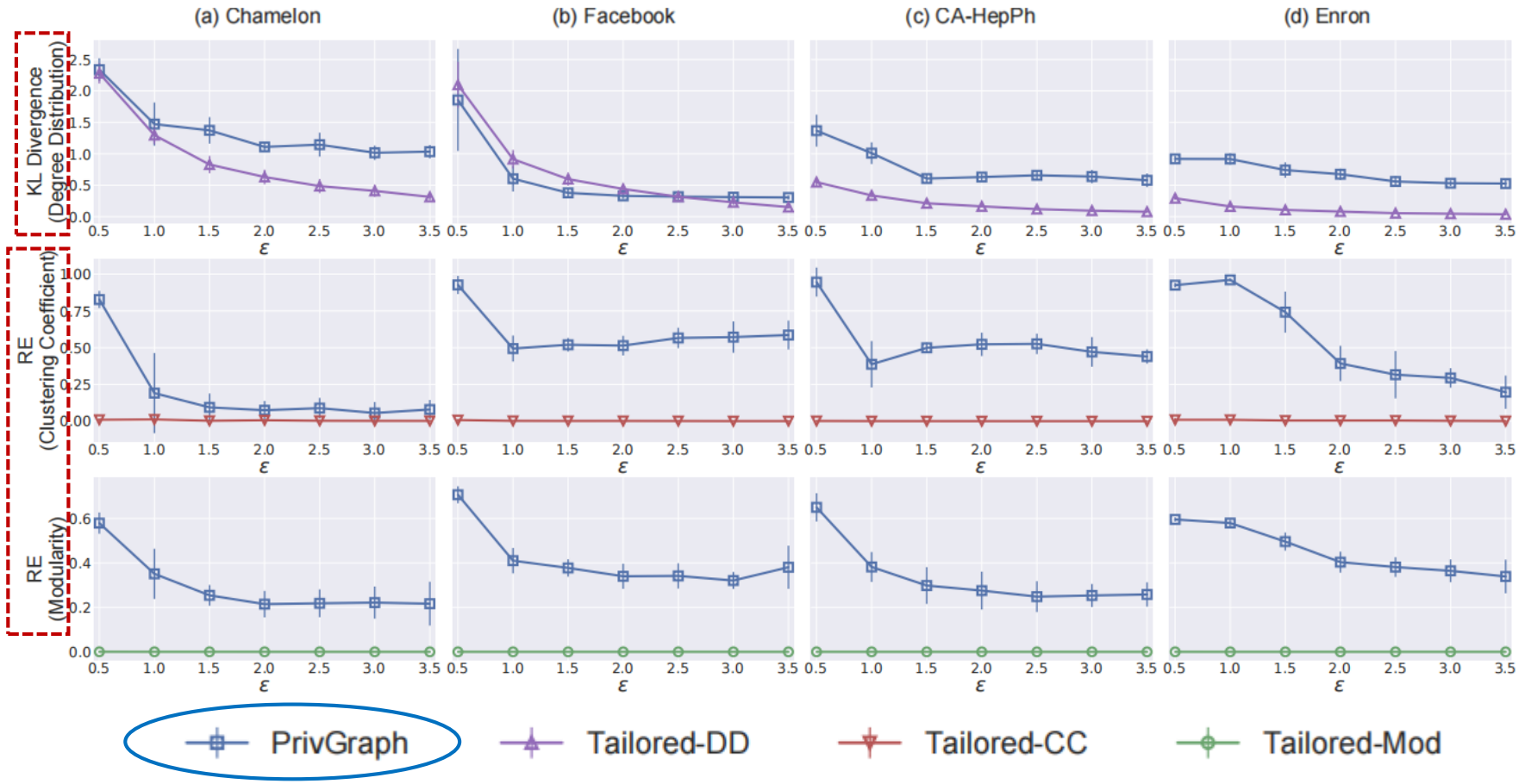
Comparison with Tailored Methods

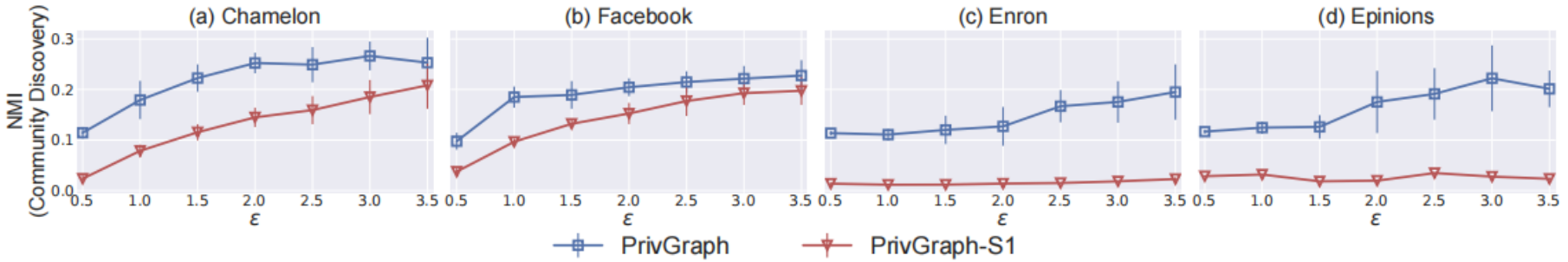


Lower is better

PrivGraph achieves competitive performance on the degree distribution.

Preservation for Small Communities

- Louvain adopted in phase 1 might miss the small communities[1] during the modularity optimization process.



→ Higher is better

PrivGraph can compensate the shortcoming of Louvain since the information extraction and graph reconstruction processes help to recover the small communities.

[1] S. Fortunato and M. Barthelemy. Resolution limit in community detection. PNAS, 104(1):36–41, 2007.

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Conclusion

- A deep analysis of existing solutions on differentially private graph synthesis
- A practical method PrivGraph to generate a synthetic graph under DP
- An extensive evaluation on multiple datasets and metrics to illustrate the superiority of PrivGraph

Thank you for your attention

Q & A

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