dK-Personalization: Publishing Network Statistics with Personalized Differential Privacy

Masooma Iftikhar
Qing Wang
Yang Li

School of Computing
College of Engineering and Computer Science
The Australian National University, Canberra, Australia

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- Sensitivity Analysis

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- Experiments and Results

Introduction

- Network analysis provides unique insights about social network activities, disease transmission, consumer behaviour, communication patterns, and recommendations.

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Motivation

- Network analysis provides unique insights about social network activities, disease transmission, consumer behaviour, communication patterns, and recommendations.
- However, given the private nature of data about individuals stored in networks, releasing network data raises privacy concerns, thereby requiring privacy-preserving mechanisms.
- The current focus of privacy is around differential privacy (DP). However, a uniform privacy level (i.e., ε [1]) is assigned to each individual while guaranteeing DP, which may over or under protect individuals.

[1] Smaller value of ε implies a stronger privacy guarantee.

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- **Key Challenges:**
  - Each individual (node) has its own privacy preference whereas each data point in data distribution reflects information about more than one node.

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- **Key Challenges:**
  - Each individual (node) has its own privacy preference whereas each data point in data distribution reflects information about more than one node.
  - Network data is highly sensitive to structural changes under DP.

Problem Formulation

We define the notion of neighboring graphs ($G \sim G'$) under edge and node-DP.

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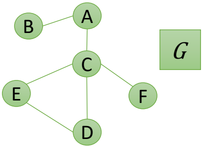
Original-Graph



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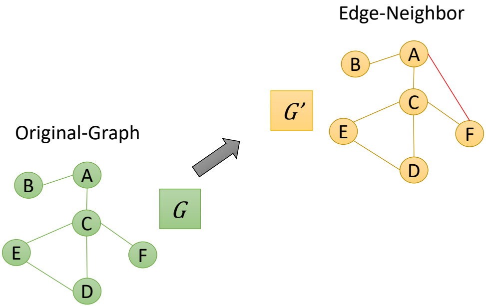

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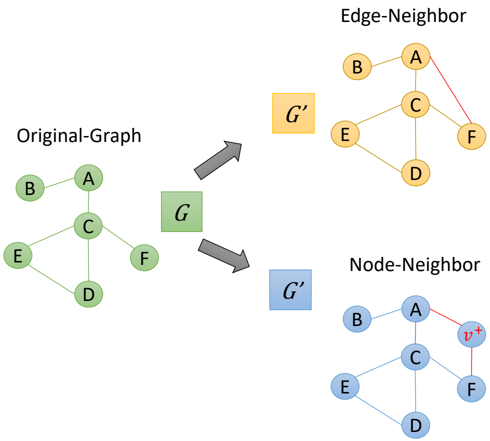

G and *G'* differ in one edge.

G and *G'* differ in one node and the set of edges incident to that node.

The dK-graph model [4] offers a systematized way to extract subgraph degree distributions from a given graph, i.e. dK-distributions.

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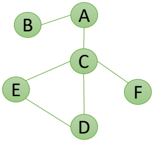
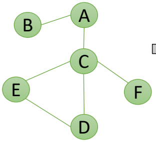
$$G \xrightarrow{1K(G)} \begin{Bmatrix} 1 & 2 \\ 2 & 3 \\ 4 & 1 \end{Bmatrix} \quad \textit{Degree Distribution}$$



DK-DISTRIBUTION

The dK-graph model [4] offers a systematized way to extract sub-graph degree distributions from a given graph, i.e. dK-distributions.

G



$$\xrightarrow{1K(G)} \left\{ \begin{array}{cc} 1 & 2 \\ 2 & 3 \\ 4 & 1 \end{array} \right\} \quad \textit{Degree Distribution}$$

$$\xrightarrow{2K(G)} \left\{ \begin{array}{l} \langle 1,2 \rangle = 1 \ \ \text{(B-A)} \\ \langle 1,4 \rangle = 1 \ \ \text{(F-C)} \\ \langle 2,2 \rangle = 1 \ \ \text{(E-D)} \\ \langle 2,4 \rangle = 3 \ \ \text{(A-C), (D-C), (E-C)} \end{array} \right\} \quad \textit{Joint Degree Distribution}$$

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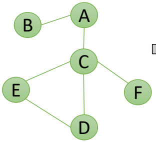

$1K(G)$ → $\left\{ \begin{array}{cc} 1 & 2 \\ 2 & 3 \\ 4 & 1 \end{array} \right\}$ *Degree Distribution*

$2K(G)$ → *Joint Degree Distribution*

<1,2> = 1 (B-A)
<1,4> = 1 (F-C)
<2,2> = 1 (E-D)
<2,4> = 3 (A-C), (D-C), (E-C)

$3K(G)$ → *Clustering Coefficient Distribution*

<1,2,4> = 2 (B-A-C), (F-C-A)
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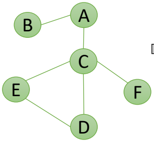

$1K(G)$ → *Degree Distribution*

1	2
2	3
4	1

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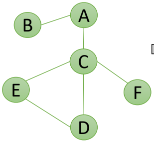

$1K(G)$

$$\begin{Bmatrix} 1 & 2 \\ 2 & 3 \\ 4 & 1 \end{Bmatrix}$$

Degree Distribution

$2K(G)$

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Joint Degree Distribution

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Clustering Coefficient Distribution

- When $d = |V|$, a dK-distribution specifies the entire graph.
- $\gamma^{dK}(G)$ queries the dK-distribution of G.

- Given two (edge or node) neighboring graphs $G \sim G'$ where G' is obtained from G by adding (or deleting) an edge (or node) can affect more than one node.

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- Thus, PDP should be formalized in terms of all affected nodes to guarantee ε-indistinguishability.
- Given a privacy specification $\Phi = \{\varepsilon_1, \dots \varepsilon_n\}$, denote Φ^v the privacy preference ε of a node v

- **Edge Φ-PDP:** For $G \overset{e}{\sim} G'$, adding (or deleting) an edge affects exactly two nodes u and v.

$$Pr[\mathcal{K}(G) \in \mathcal{O}] \leq e^{min\{\Phi^u, \Phi^v\}} \times Pr[\mathcal{K}(G') \in \mathcal{O}].$$

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- **Node Φ-PDP:** For $G \overset{n}{\sim} G'$, adding (or deleting) a node v^+ affects $|E^+|$ nodes incident to v^+ and v^+ itself.

$$Pr[\mathcal{K}(G) \in \mathcal{O}] \leq e^{min\{\Phi^v | (v^+, v) \in E^+\}} \times Pr[\mathcal{K}(G') \in \mathcal{O}] \quad \text{and}$$

$$Pr[\mathcal{K}(G) \in \mathcal{O}] \leq e^{\Phi^{v^+}} \times Pr[\mathcal{K}(G') \in \mathcal{O}]$$

- We want to generate D_Φ that is an anonymized version of D satisfying (edge or node) Φ-PDP.

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- We view the response to γ^{dK} as a collection of responses to degree queries, one for each tuple (entry) in a dK-distribution.

(DEGREE QUERY)

A *degree query* $\gamma_q : \gamma^{dK}(G) \rightarrow \mathbb{N}$ maps a degree tuple $d_t \in \gamma^{dK}(G)$ to a frequency value in $\mathbb{N}$ s.t. $(d_t, \gamma_q(G)) \in \gamma^{dK}(G)$.

Sensitivity Analysis

We analyze the sensitivity (Δ) [2] of a single dK-distribution entry, i.e., degree query γ_q rather than the entire dK-distribution γ^{dK}.

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- $\Delta(\gamma_q)$ of $(deg(G) + 1) \times |E^+|$ over 2K(G) under node-DP.

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- $\Delta(\gamma_q)$ of is 2 over 1K(G) under Edge-DP.

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- $\Delta(\gamma_q)$ of is 2 over 1K(G) under Edge-DP.
- $\Delta(\gamma_q)$ of is $2 \times deg(G) + 1$ over 2K(G) under Edge-DP.

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- $\Delta(\gamma_q)$ of is $2 \times deg(G) + 1$ over 2K(G) under Edge-DP.

We observe that the sensitivity of γ_q is half as compared to γ^{dK}.

[2] The maximum change in γ_q.

Proposed Personalized Approaches

Local Least Based Personalized Perturbation: LL-dK perturbs entries with the strongest local ε.

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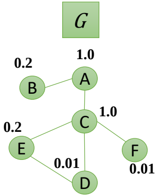

Personalized Approach I

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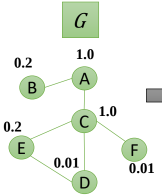
Local Least Based Personalized Perturbation: LL-dK perturbs entries with the strongest local ε.



$\Upsilon^{1K}(G)$ = 1K(G)

1	2	(B,F)
2	3	(A,D,E)
4	1	(C)

1K–distribution of G

$\Upsilon^{2K}(G)$ = 2K(G)

<1,2> = 1	(B-A)
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2K–distribution of G

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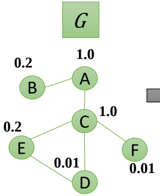

$\Upsilon^{1K}(G) = \text{1K(G)}$

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2	3	(A,D,E)
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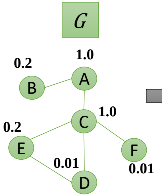

$\Upsilon^{1K}(G) = 1\text{K(G)}$

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2	3	(A,D,E)
4	1	(C)

1K–distribution of G

$\Upsilon^{2K}(G) = 2\text{K(G)}$

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$\langle 1,4 \rangle = 1$	(F-C)
$\langle 2,2 \rangle = 1$	(E-D)
$\langle 2,4 \rangle = 3$	(A-C), (D-C), (E-C)

2K–distribution of G

The frequency value 2 in $1K(G)$, and the frequency value 3 in $2K(G)$ are perturbed with $\varepsilon = min(\Phi^B, \Phi^F)$, and $\varepsilon = min(\Phi^A, \Phi^C, \Phi^D, \Phi^E)$, respectively.

Threshold Projection Based Personalized Perturbation: TP-dK transforms a graph into a θ-bounded graph then removes all nodes with $\varepsilon < \tau$.

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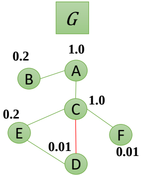

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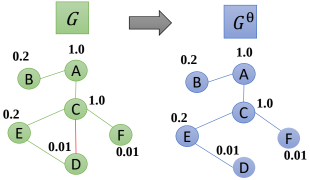

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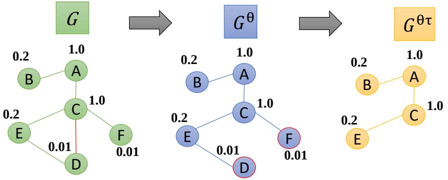
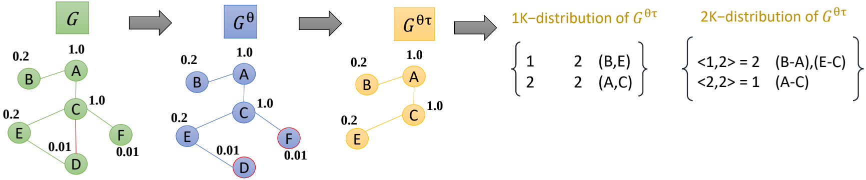


Personalized Approach II

Threshold Projection Based Personalized Perturbation: TP-dK transforms a graph into a θ-bounded graph then removes all nodes with $\varepsilon < \tau$.



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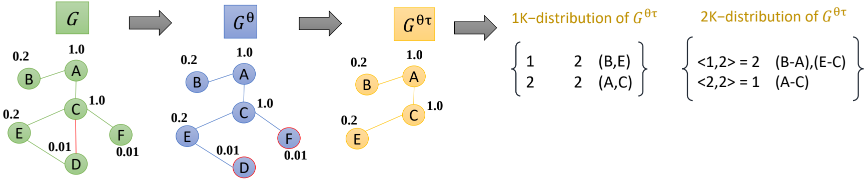

Since $deg(G) \leq \theta$, the sensitivity of γ_q is reduced.

PERSONALIZED APPROACH II

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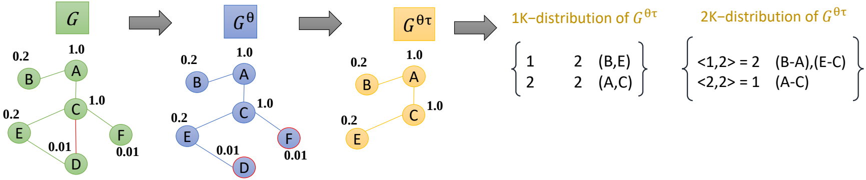

Since $deg(G) \leq \theta$, the sensitivity of γ_q is reduced.

With threshold τ all nodes with high privacy are removed.

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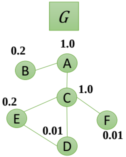

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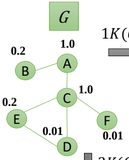

$\Upsilon^{1K}(G) = 1\mathrm{K(G)}$

$1K(G) \Rightarrow$

1	2	(B,F)
2	3	(A,D,E)
4	1	(C)

1K–distribution of G

$\Upsilon^{2K}(G) = 2\mathrm{K(G)}$

$2K(G) \Rightarrow$

<1,2> = 1	(B-A)
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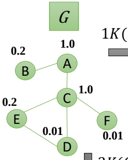
2K–distribution of G

Sampling Based Personalized Perturbation: ST-dK first splits entries, and then samples them with non-uniform probabilities.



$1K(G)$ →

$\Upsilon^{1K}(G) = $ 1K(G)

1	2	(B,F)
2	3	(A,D,E)
4	1	(C)

1K–distribution of G

Split →

1	1	(B)
1	1	(F)
2	1	(A)
2	1	(D)
2	1	(E)
4	1	(C)

$2K(G)$ →

$\Upsilon^{2K}(G) = $ 2K(G)

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2K–distribution of G

Split →

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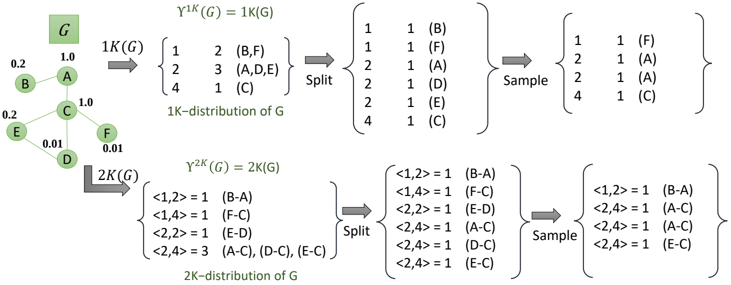
Personalized Approach III

Sampling Based Personalized Perturbation: ST-dK first splits entries, and then samples them with non-uniform probabilities.



Personalized Approach III

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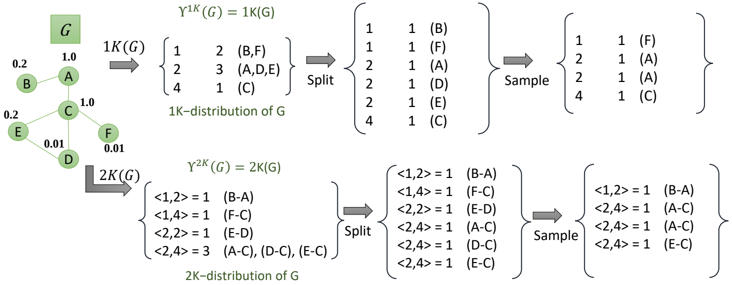
Sampling Based Personalized Perturbation: ST-dK first splits entries, and then samples them with non-uniform probabilities.



Inclusion probability for each entry depends on corresponding ε and global threshold τ.

Personalized Approach III

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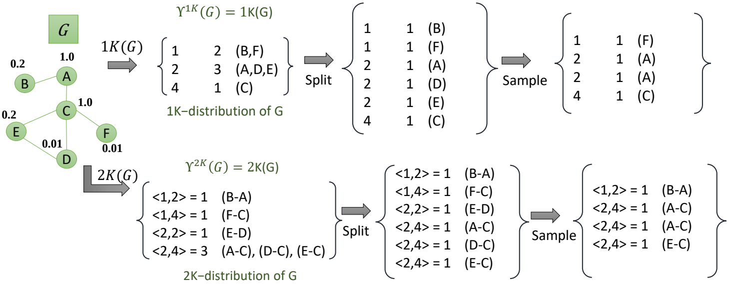

Inclusion probability for each entry depends on corresponding ε and global threshold τ.

Sampled dK-distribution is perturbed with τ.

Aggregation Based Personalized Perturbation: AG-dK computes corresponding ε values to performs aggregation over dK-distribution.

Personalized Approach IV

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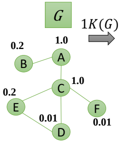

$1K(G)$ → $\Upsilon^{1K}(G) = $ 1K(G)

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1K–distribution of G

$2K(G)$ → $\Upsilon^{2K}(G) = $ 2K(G)

<1,2> = 1	(B-A)
<1,4> = 1	(F-C)
<2,2> = 1	(E-D)
<2,4> = 3	(A-C), (D-C), (E-C)

2K–distribution of G

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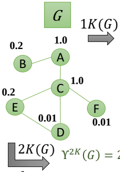
Aggregation Based Personalized Perturbation: AG-dK computes corresponding ε values to performs aggregation over dK-distribution.



$\Upsilon^{1K}(G) = 1K(G)$

1	2	(B,F)
2	3	(A,D,E)
4	1	(C)

1K–distribution of G

0.01	0.2	-
0.01	0.2	1.0
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Corresponding privacy preferences

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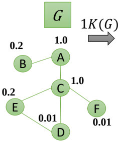

$1K(G)$ → $\Upsilon^{1K}(G) = 1K(G)$

$$\begin{Bmatrix} 1 & 2 & (B,F) \\ 2 & 3 & (A,D,E) \\ 4 & 1 & (C) \end{Bmatrix}$$

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Corresponding privacy preferences

Aggregation →

Partition

$$\begin{Bmatrix} 1 & 2 & (B,F) \\ 2 & 3 & (A,D,E) \\ \text{-----} & & \\ 4 & 1 & (C) \end{Bmatrix}$$

Aggregation

$$\begin{Bmatrix} \begin{Bmatrix} 1 \\ 2 \end{Bmatrix} = 5 \ \ (B,F), (A,D,E) \\ \begin{Bmatrix} 4 \end{Bmatrix} = 1 \ \ (C) \end{Bmatrix}$$

$2K(G)$ → $\Upsilon^{2K}(G) = 2K(G)$

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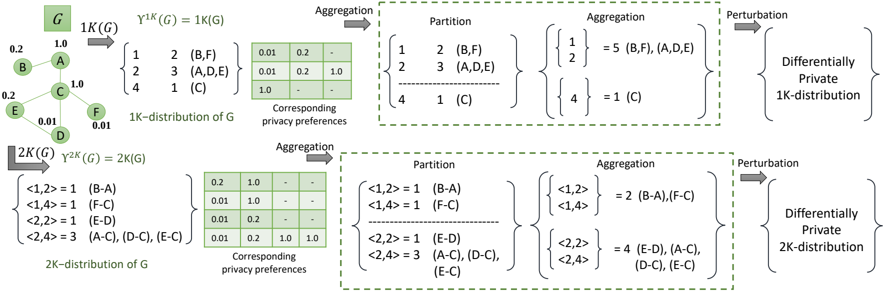

Personalized Approach IV

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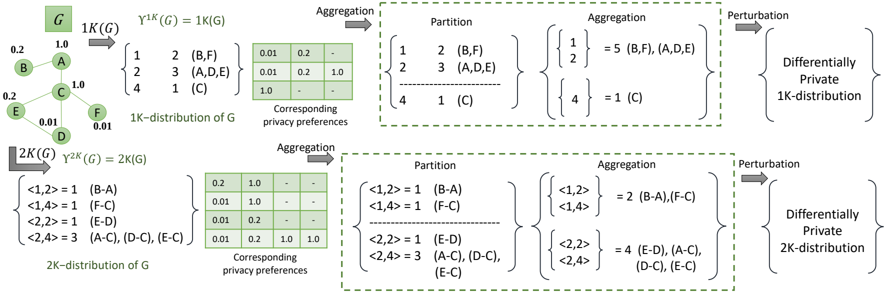
Aggregation Based Personalized Perturbation: AG-dK computes corresponding ε values to performs aggregation over dK-distribution.



Entries are perturbed with the strongest local ε corresponding to each partition.

Personalized Approach IV

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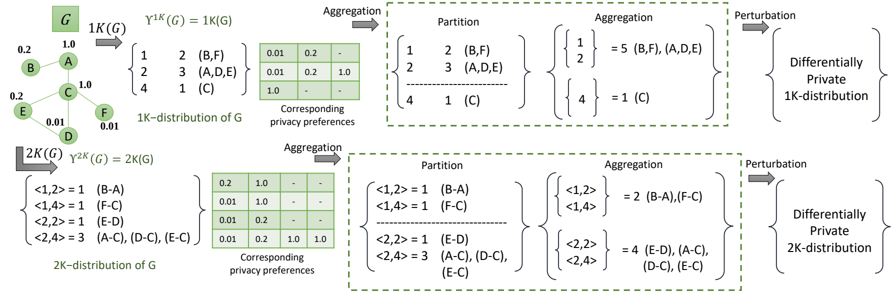

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γ_q is approximated to $\gamma_q \circ \mathcal{M}$.

Experiments and Results

- Four network datasets:

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  (1) *Facebook* contains 4,039 nodes and 88,234 edges.

  (2) *Wiki-Vote* contains 7,115 nodes and 103,689 edges.

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EXPERIMENTS I

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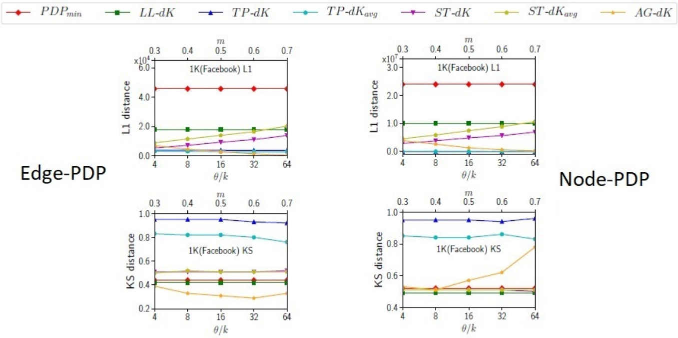

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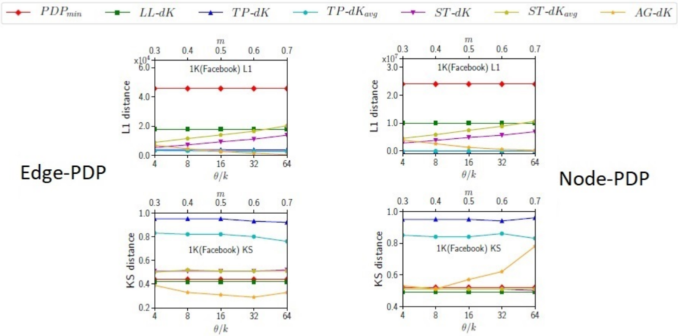

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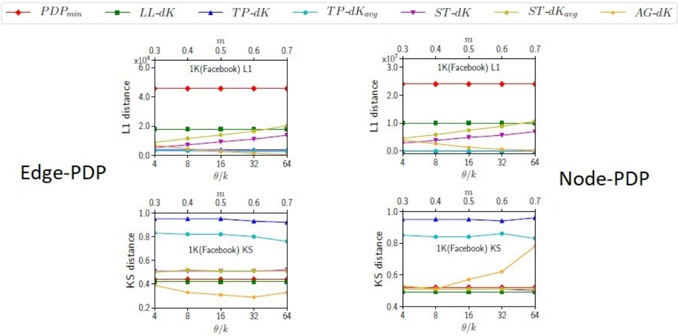

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- AG-dK outperforms under edge-PDP and LL-dK outperforms under node-PDP by generating more similar 1K-distributions.

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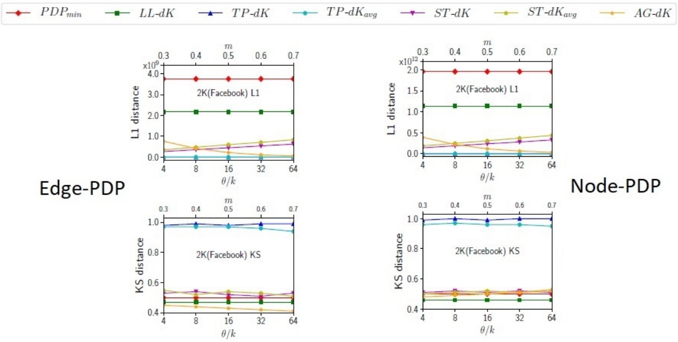

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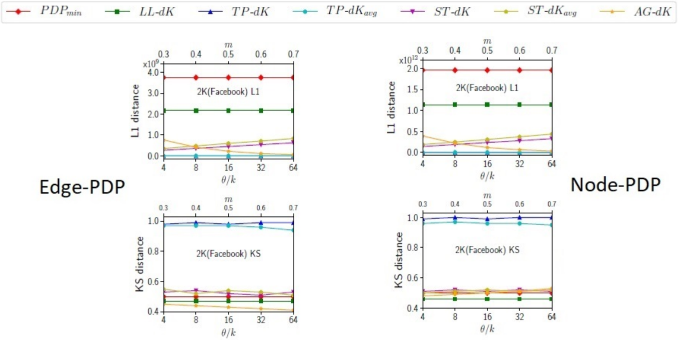

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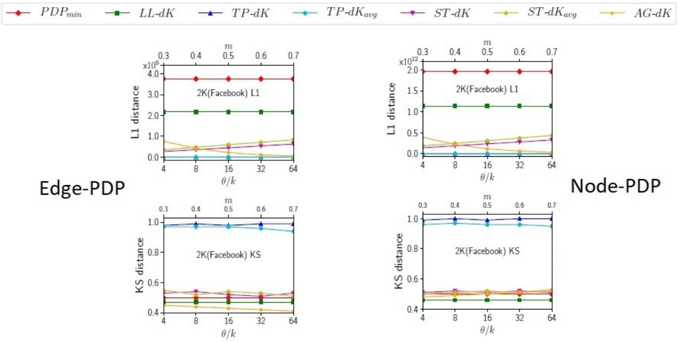

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What kind of trade-off exists between utility and privacy while generating personalized differentially private dK-distributions?

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- The error caused by sensitivity (Δ) and the privacy preference ε dominates the impact on output utility.
- Increasing ε and decreasing Δ can help to reduce error.
- Reducing sensitivity is more challenging under node-PDP than for edge-PDP as graph data is highly sensitive under node-DP.

Conclusion and Future work

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- **Future work:** To this work will consider local differential privacy to release network statistics under personalization.

References

Wei-Yen Day, Ninghui Li, and Min Lyu.
Publishing graph degree distribution with node differential privacy.
In *SIGMOD*, pages 123–138, 2016.

Cynthia Dwork, Frank McSherry, Kobbi Nissim, and Adam Smith.
Calibrating noise to sensitivity in private data analysis.
In *TCC*, pages 265–284, 2006.

Priya Mahadevan, Calvin Hubble, Dmitri Krioukov, Bradley Huffaker, and Amin Vahdat.
Orbis: rescaling degree correlations to generate annotated internet topologies.
In *SIGCOMM*, pages 325–336, 2007.

Priya Mahadevan, Dmitri Krioukov, Kevin Fall, and Amin Vahdat.
Systematic topology analysis and generation using degree correlations.
In *SIGCOMM*, pages 135–146, 2006.

Alessandra Sala, Xiaohan Zhao, Christo Wilson, Haitao Zheng, and Ben Y Zhao.
Sharing graphs using differentially private graph models.
In *SIGCOMM*, pages 81–98, 2011.

William E Yancey, William E Winkler, and Robert H Creecy.
Disclosure risk assessment in perturbative microdata protection.
In *Inference control in statistical databases*, pages 135–152. 2002.

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Thanks for your attention!

Any **Questions**