Supplementary Materials

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1 DETAILED DERIVATIONS OF THEORETICAL ANALYSIS

Since the edge subgraph sampled from the Shadow-Target Bridge Graph contains nodes from both partial target graph and shadow graph, we start with a formal definition of target nodes density:

Definition 1.1. [Density of target nodes in the edge subgraph]

$$D = \frac{1}{|\mathcal{V}_{i,j}^r|} \sum_{v \in \mathcal{V}_{i,j}^r} \frac{|\{u|u \in N_v^t\}|}{|\{u|u \in N_v^t\}| + |\{u|u \in N_v^s\}|} \,, \quad (1)$$

where $\mathcal{V}_{i,j}^r$ is the nodes set of the edge subgraph $\mathcal{G}_{i,j}^r$ of edge (v_i, v_j). For node v, N_v^t is the neighbor set that belong to partial target graph, and N_v^s is the neighbor set that belong to shadow graph. D ranges from 0 to 1, with a larger D indicating a higher proportion of nodes from partial target graph in the edge subgraph.

We define the privacy theft of edge subgraph structure feature extraction process as follows:

Definition 1.2 (Measurement of privacy theft for edge subgraph structure feature extraction). Given the link and its corresponding edge subgraph, the nodes' features and representations after edge subgraph structure feature extraction follow the distributions $\mathbf{P}$ and $\widetilde{\mathbf{P}}$, respectively. Privacy theft for edge subgraph structure feature extraction is measured by the distance between $\mathbf{P}$ and $\widetilde{\mathbf{P}}$.

For the convenience of subsequent analysis, we employ the Wasserstein distance to measure the distance between two multivariate normal distributions $p \sim \mathcal{N}(\mu_p, \Sigma_p)$ and $q \sim \mathcal{N}(\mu_q, \Sigma_q)$:

$$\mathcal{W}[p,q] = (\mu_p - \mu_q)^T(\mu_p - \mu_q) + \text{Tr}(\Sigma_p) + \text{Tr}(\Sigma_q) - 2\text{Tr}((\Sigma_p^{\frac{1}{2}}\Sigma_q\Sigma_p^{\frac{1}{2}})^{\frac{1}{2}}). \quad (2)$$

We employ Contextual Stochastic Block Model for our analysis, treating the edge subgraph with n nodes as a random graph $\mathcal{G}_{i,j}^r \sim (n, p, q, \mu, k\mu, d)$. In the edge subgraph, we use v^t to represent the nodes from the partial target graph and v^s to represent the nodes from the shadow graph. We denote feature vectors of v^t as x^t, where each dimension of x^t follows $\mathcal{N}(\mu, 1)$, whereas those of v^s as x^s, where each dimension of x^s follows $\mathcal{N}(k\mu, 1)$. Thus, x^t follow the normal distribution $\mathcal{N}(\mu_{x^t}, \Sigma_{x^t})$ and x^s follow the normal distribution $\mathcal{N}(\mu_{x^s}, \Sigma_{x^s})$, where

$$\mu_{x^t}[i] = \mu, \ \mu_{x^s}[i] = k\mu, \ \Sigma_{x^t}[i,i] = \Sigma_{x^s}[i,i] = 1 \ (0 \le i < d). \quad (3)$$

Best-case scenario. The representation of node a after propagation can be written as:

$$z_a = \frac{1}{|N_a|}x_a^t + \sum_{b \in N_a^t} \frac{1}{\sqrt{|N_a|\,|N_b|}}x_b^t \,, \quad (4)$$

where N_a denotes the neighbor set of node v_a. Consider the generation process of the synthetic edge subgraph that only includes nodes v^t, which means $N_a = N_a^t$. For each node, the approximate size of its neighbor set can be expressed as np. Thus representations

of nodes in the edge subgraph follow distribution $\mathcal{N}(\mu_z, \Sigma_z)$, where

$$\mu_z[i] = \frac{\mu}{|N_a|} + \sum_{b \in N_a^t} \frac{\mu}{\sqrt{|N_a||N_b|}}$$
$$= \frac{\mu}{np} + np \cdot \frac{\mu}{\sqrt{np}\sqrt{np}} \quad (5)$$
$$= \frac{1+np}{np}\mu,$$

$$\Sigma_z[i,i] = \frac{1}{|N_a|^2} + \sum_{b \in N_a^t} \frac{1}{|N_a|\,|N_b|}$$
$$= \frac{1}{(np)^2} + np \cdot \frac{1}{np \cdot np} \quad (6)$$
$$= \frac{1+np}{n^2p^2} \quad (0 \le i < d).$$

Using Eq.2 and Def.1.2, in the optimal case where the edge subgraph only includes v^t, privacy theft (PT) of edge subgraph structure feature extraction can be quantified as:

$$PT^{opt} = \mathcal{W}[z,x]$$
$$= (\mu_z - \mu_x)^T(\mu_z - \mu_x) + Tr(\Sigma_z) + Tr(\Sigma_x) - 2Tr((\Sigma_z^{\frac{1}{2}}\Sigma_x\Sigma_z^{\frac{1}{2}})^{\frac{1}{2}})$$
$$= \sum_{i=1}^{d}(\frac{1+np}{np}\mu - \mu)^2 + \sum_{i=1}^{d}\frac{1+np}{n^2p^2} + \sum_{i=1}^{d}1 - 2\sum_{i=1}^{d}\sqrt{\frac{1+np}{n^2p^2}}$$
$$= d\mu^2(\frac{1}{np})^2 + d\left(\sqrt{\frac{np+1}{n^2p^2}} - 1\right)^2.$$
$$(7)$$

General-case scenario. The representation of node a after propagation can be written as:

$$z_a = \frac{1}{|N_a|}x_a + \sum_{b \in N_a^t} \frac{1}{\sqrt{|N_a|\,|N_b|}}x_b^t + \sum_{b \in N_a^s} \frac{1}{\sqrt{|N_a|\,|N_b|}}x_b^s, \quad (8)$$

where N_a denotes the neighbor set of node v_a. Each node's neighbors consist of both nodes v^t and v^s, hence $N_a = N_a^t \cup N_a^s$. The size of the neighbor set can be approximately represented as $n(p+q)$. A percentage of $p/(p+q)$ of its neighbors are v^t, whereas a percentage of $q/(p+q)$ of its neighbors are v^s. In the edge subgraph, for the nodes v^t from the partial target graph, their representations z^t follow the distribution $\mathcal{N}(\mu_{z^t}, \Sigma_{z^t})$, while those of v^s from the shadow graph follow the distribution $\mathcal{N}(\mu_{z^s}, \Sigma_{z^s})$, where

$$\mu_{z^t}[i] = \frac{\mu}{|N_a|} + \sum_{b \in N_a^t} \frac{\mu}{\sqrt{|N_a||N_b|}} + \sum_{b \in N_a^s} \frac{k\mu}{\sqrt{|N_a||N_b|}}$$
$$= \frac{\mu}{n(p+q)} + np \cdot \frac{\mu}{n(p+q)} + nq \cdot \frac{k\mu}{n(p+q)} \quad (9)$$
$$= \frac{1+n(p+kq)}{n(p+q)}\mu,$$

$$\mu_{z^s}[i] = \frac{k\mu}{|N_a|} + \sum_{b \in \mathbf{N}_a^t} \frac{\mu}{\sqrt{|N_a||N_b|}} + \sum_{b \in \mathbf{N}_a^s} \frac{k\mu}{\sqrt{|N_a||N_b|}}$$

$$= \frac{k\mu}{n(p+q)} + np \cdot \frac{\mu}{n(p+q)} + nq \cdot \frac{k\mu}{n(p+q)} \quad (10)$$

$$= \frac{k + n(p+kq)}{n(p+q)}\mu,$$

$$\Sigma_{z^s}[i,i] = \Sigma_{z^t}[i,i] = \frac{1}{|N_a|^2} + \sum_{b \in N_a} \frac{1}{|N_a||N_b|}$$

$$= \frac{1}{n^2(p+q)^2} + n(p+q) \cdot \frac{1}{n^2(p+q)^2} \quad (11)$$

$$= \frac{1 + n(p+q)}{n^2(p+q)^2},$$

where $0 \le i < d$. To facilitate analysis, we take the average of z^t and z^s, such that the representations of all nodes in the edge subgraph approximately follow distribution $\mathcal{N}(\mu_z, \Sigma_z) = \mathcal{N}(\frac{\mu_{z^t}+\mu_{z^s}}{2}, \frac{\Sigma_{z^t}+\Sigma_{z^s}}{2})$. Correspondingly, initial feature vectors approximately follow distribution $\mathcal{N}(\mu_x, \Sigma_x) = \mathcal{N}(\frac{\mu_{x^t}+\mu_{x^s}}{2}, \frac{\Sigma_{x^t}+\Sigma_{x^s}}{2})$, where

$$\mu_z[i] = \frac{(k+1) + 2n(p+kq)}{2n(p+q)}\mu, \quad \Sigma_z[i,i] = \frac{n(p+q)+1}{n^2(p+q)^2},$$

$$\mu_x[i] = \frac{(k+1)}{2}\mu, \quad \Sigma_x[i,i] = 1. \quad (12)$$

Similar to the procedure used to compute PT^{opt}, using Eq.2 and Def.1.2, in the general case where the edge subgraph contains both v^t and v^s, privacy theft of edge subgraph structure feature extraction can be quantified as:

$$PT = \mathcal{W}[z, x]$$

$$= (\mu_z - \mu_x)^T(\mu_z - \mu_x) + Tr(\Sigma_z) + Tr(\Sigma_x) - 2Tr((\Sigma_z^{\frac{1}{2}}\Sigma_x\Sigma_z^{\frac{1}{2}})^{\frac{1}{2}})$$

$$= d\mu^2 [\frac{1}{n(p+q)} \frac{1+k}{2} + \frac{p-q}{p+q}\frac{1-k}{2}]^2 + d\left(\sqrt{\frac{n(p+q)+1}{n^2(p+q)^2}} - 1\right)^2. \quad (13)$$

Further analysis. In the above discussion, two distinct scenarios of privacy theft were derived based on both the optimal scenario and the general scenario. To approximate the level of privacy theft in Eq.13 to that of Eq.7, i.e., to make $\Delta PT = PT^{opt} - PT$ approach 0 as much as possible, it can be readily observed that k should equal 1. When $k = 1$, the representation of ΔPT is:

$$\Delta PT = du^2\left[\left(\frac{1}{np}\right)^2 - \left(\frac{1}{n(p+q)}\right)^2\right]$$

$$+ d\left[\left(\sqrt{\frac{np+1}{n^2p^2}} - 1\right)^2 - \left(\sqrt{\frac{n(p+q)+1}{n^2(p+q)^2}} - 1\right)^2\right]. \quad (14)$$

Based on Definition 1.1, we can get

$$D = \frac{1}{|\mathcal{V}_{i,j}^r|} \sum_{v \in \mathcal{V}_{i,j}^r} \left| \frac{|\{u|u \in N_v^{target}\}|}{|\{u|u \in N_v^{target}\}| + |\{u|u \in N_v^{shadow}\}|} \right|$$

$$= \frac{1}{n} \sum_{v \in \mathcal{V}_{i,j}^r} \frac{np}{np+nq} = \frac{p}{p+q}. \quad (15)$$

Then, we substitute Eq.15 into Eq.14. We can transform it into the following form:

$$\Delta PT = d\mu^2 [(\frac{1}{np})^2 - (\frac{D}{np})^2] + d[(\sqrt{\frac{np+1}{n^2p^2}} - 1)^2$$

$$- (\sqrt{\frac{npD+D^2}{n^2p^2}} - 1)^2]$$

$$= d\mu^2 \frac{1-D^2}{n^2p^2} + d[\sqrt{\frac{np+1}{n^2p^2}} - \sqrt{\frac{npD+D^2}{n^2p^2}}]$$

$$\cdot [\sqrt{\frac{np+1}{n^2p^2}} + \sqrt{\frac{npD+D^2}{n^2p^2}} - 2]$$

$$= d\mu^2 \frac{(1-D)(1+D)}{n^2p^2} + d\frac{\sqrt{np+1} - \sqrt{npD+D^2}}{np}$$

$$\cdot \frac{\sqrt{np+1} + \sqrt{npD+D^2} - 2np}{np} \quad (16)$$

$$= d\mu^2 \frac{(1-D)(1+D)}{n^2p^2} + d\frac{np+1-npD-D^2}{np(\sqrt{np+1} + \sqrt{npD+D^2})}$$

$$\cdot \frac{\sqrt{np+1} + \sqrt{npD+D^2} - 2np}{np}$$

$$= d\mu^2 \frac{(1-D)(1+D)}{n^2p^2} + d\frac{(1-D)(np+1+D)}{np(\sqrt{np+1} + \sqrt{npD+D^2})}$$

$$\cdot \frac{\sqrt{np+1} + \sqrt{npD+D^2} - 2np}{np}$$

$$= d[\frac{1+D}{n^2p^2}\mu^2 + \frac{np+1+D}{np(\sqrt{np+1} + \sqrt{npD+D^2})}$$

$$\cdot \frac{\sqrt{np+1} + \sqrt{npD+D^2} - 2np}{np}](1-D)$$

Finally, we obtain the mathematical representation of ΔPT in the main paper.

2 DETAILS OF THE DATASET

We use four real datasets from different multimedia domains including sixteen graphs for evaluation. See Table 1 for the statistics of the dataset

Twitch. The Twitch dataset contains social networks from five regions (ENGB, ES, TW, RU, PTBR) . Nodes represent users within a country, and edges represent mutual friendships. The attributes of each node include the user's game preferences, location, and streaming habits. The task of the GNN model is to predict whether the streamer will use explicit language.

Facebook. The Facebook dataset contains social networks from five US universities (Caltech, Haverford, Reed, Simmons, Swarthmore). Nodes represent students at an American university, and edges represent friendships between two students. The attributes of each node include the student's grade, major, high school, and place of residence. The task of the GNN model is to predict the gender of a user.

ArnetMiner. The ArnetMiner dataset contains citation networks from three academic databases (DBLPv7, Citationv1, and ACMv9).

Table 1: Statistics for datasets.

Dataset		Nodes	Edges	Features	Classes	Density	Avg Degree
ArnetMiner	**Dblpv7**	5484	8130	6775	5	0.0005	1
	Acmv9	9360	15602	6775	5	0.0004	1
	Citationv1	8935	15113	6775	5	0.0004	1
Airport	**Brazil**	131	1134	8	4	0.1332	8
	Europe	399	6392	8	4	0.0805	15
	USA	1190	14789	8	4	0.0209	11
Twitch	**ENGB**	7126	35324	3170	2	0.0014	4
	ES	4648	59382	3170	2	0.0055	12
	PTBR	1912	31299	3170	2	0.0171	16
	RU	4385	37304	3170	2	0.0039	8
	TW	2772	63462	3170	2	0.0165	22
Facebook	**Caltech**	769	16656	3020	3	0.0564	21
	Haverford	1446	59589	3020	3	0.0570	41
	Reed	962	18812	3020	3	0.0407	19
	Simmons	1518	32988	3020	3	0.0287	21
	Swarthmore	1659	61050	3020	3	0.0444	36

Nodes represent papers, and edges represent citation relationships. The attributes of each node consist of sparse bag-of-words features extracted from the paper titles. The task of the GNN model is to predict the related research field of the paper.

Airport. The Airport dataset contains airport networks from three countries or regions (Brazil, USA, and Europe). Nodes represent airports, and edges represent the presence or absence of commercial flights between two airports. We use the one-hot encoding of the node as the node feature. The task of the GNN model is to predict airport activity levels measured by flights or the number of people passing through the airport.

3 MORE EXPERIMENTAL RESULTS

In the main paper, we demonstrate the performance of LinkThief when the link leakage rate of the target graph is 0.3. Next, we will demonstrate how LinkThief performs when the target graph's link leakage rate is 0.1 and 0.2, respectively. As shown in Table 2 ~ 9, We can observe that LinkThief demonstrates superior link stealing performance compared to LSA-3 and LSA-4, regardless of the target graph's link leakage rate.

Table 2: Performance of LinkThief on the Twitch dataset with a target graph leak rate of 0.1.

Target Dataset	Attack Method	ENGB ASR	ENGB AUC	ES ASR	ES AUC	PTBR ASR	PTBR AUC	RU ASR	RU AUC	TW ASR	TW AUC
		Shadow Dataset									
ENGB	LSA-3	-	-	0.5376	0.5612	0.5278	0.5402	0.5346	0.5601	0.5287	0.5398
	LSA-4	-	-	0.4997	0.5352	0.5203	0.5147	0.5134	0.5287	0.5117	0.5108
	Ours	-	-	**0.7542**	**0.8324**	**0.7579**	**0.8257**	**0.7604**	**0.8296**	**0.7519**	**0.8164**
ES	LSA-3	0.5333	0.5724	-	-	0.5437	0.5743	0.5437	0.5732	0.5413	0.5672
	LSA-4	0.5001	0.5021	-	-	0.4986	0.5002	0.4879	0.4823	0.4977	0.4953
	Ours	**0.8142**	**0.8797**	-	-	**0.7984**	**0.8688**	**0.8003**	**0.8744**	**0.8047**	**0.8716**
PTBR	LSA-3	0.5256	0.5787	0.5523	0.5804	-	-	0.5503	0.5804	0.5388	0.5784
	LSA-4	0.5086	0.5189	0.4936	0.5189	-	-	0.5091	0.5008	0.5182	0.5077
	Ours	**0.8003**	**0.8715**	**0.7958**	**0.8649**	-	-	**0.7932**	**0.8687**	**0.7958**	**0.8587**
RU	LSA-3	0.5386	0.5587	0.5301	0.5497	0.5303	0.5518	-	-	0.5238	0.5384
	LSA-4	0.5078	0.5013	0.4991	0.5203	0.4901	0.4992	-	-	0.4903	0.4937
	Ours	**0.8217**	**0.8935**	**0.7844**	**0.8573**	**0.7943**	**0.8627**	-	-	**0.7852**	**0.8678**
TW	LSA-3	0.5198	0.5375	0.5286	0.5387	0.5187	0.5289	0.5183	0.5482	-	-
	LSA-4	0.5089	0.5112	0.4956	0.5006	0.5119	0.5203	0.5101	0.5024	-	-
	Ours	**0.8152**	**0.8887**	**0.8021**	**0.8866**	**0.8018**	**0.8763**	**0.8112**	**0.8832**	-	-

Table 3: Performance of LinkThief on the Twitch dataset with a target graph leak rate of 0.2.

Target Dataset	Attack Method	ENGB ASR	ENGB AUC	ES ASR	ES AUC	PTBR ASR	PTBR AUC	RU ASR	RU AUC	TW ASR	TW AUC
		Shadow Dataset									
ENGB	LSA-3	-	-	0.5401	0.5642	0.5298	0.5443	0.5379	0.5627	0.5302	0.5417
	LSA-4	-	-	0.4982	0.5357	0.5224	0.5187	0.5183	0.5307	0.5197	0.5164
	Ours	-	-	**0.7718**	**0.8468**	**0.7726**	**0.8437**	**0.7732**	**0.8324**	**0.7699**	**0.8349**
ES	LSA-3	0.5342	0.5761	-	-	0.5488	0.5789	0.5526	0.5819	0.5501	0.5786
	LSA-4	0.5009	0.5054	-	-	0.5001	0.5026	0.4902	0.4887	0.4992	0.5001
	Ours	**0.8231**	**0.8903**	-	-	**0.8154**	**0.8852**	**0.8161**	**0.8913**	**0.8263**	**0.8894**
PTBR	LSA-3	0.5497	0.5802	0.5572	0.5849	-	-	0.5541	0.5839	0.5401	0.5802
	LSA-4	0.5102	0.5203	0.4977	0.5258	-	-	0.5107	0.5026	0.5201	0.5126
	Ours	**0.8276**	**0.9048**	**0.8035**	**0.8851**	-	-	**0.8154**	**0.8849**	**0.8143**	**0.8812**
RU	LSA-3	0.5413	0.5602	0.5317	0.5528	0.5342	0.5542	-	-	0.5255	0.5407
	LSA-4	0.5100	0.5038	0.5026	0.5237	0.4921	0.5008	-	-	0.4946	0.5001
	Ours	**0.8127**	**0.8842**	**0.8001**	**0.8712**	**0.8054**	**0.8809**	-	-	**0.8001**	**0.8794**
TW	LSA-3	0.5252	0.5401	0.5302	0.5406	0.5217	0.5303	0.5261	0.5497	-	-
	LSA-4	0.5113	0.5132	0.4987	0.5031	0.5145	0.5237	0.5117	0.5081	-	-
	Ours	**0.8273**	**0.8903**	**0.8217**	**0.8974**	**0.8172**	**0.8955**	**0.8287**	**0.8973**	-	-

Table 4: Performance of LinkThief on the Facebook dataset with a target graph leak rate of 0.1.

Target Dataset	Attack Method	Caltech ASR	Caltech AUC	Haverford ASR	Haverford AUC	Reed ASR	Reed AUC	Simmons ASR	Simmons AUC	Swarthmore ASR	Swarthmore AUC
		Shadow Dataset									
Caltech	LSA-3	-	-	0.5702	0.6125	0.5637	0.6048	0.5713	0.6102	0.5747	0.6173
	LSA-4	-	-	0.4987	0.5289	0.5189	0.5137	0.5117	0.5302	0.5187	0.5189
	Ours	-	-	**0.7348**	**0.8053**	**0.7258**	**0.7940**	**0.7203**	**0.7887**	**0.7253**	**0.8064**
Haverford	LSA-3	0.5543	0.5912	-	-	0.5683	0.6001	0.5623	0.5897	0.5713	0.6002
	LSA-4	0.4921	0.5003	-	-	0.4983	0.5002	0.4831	0.4904	0.5002	0.4988
	Ours	**0.7389**	**0.8187**	-	-	**0.8109**	**0.8176**	**0.7376**	**0.8136**	**0.7256**	**0.8123**
Reed	LSA-3	0.5324	0.5675	0.5381	0.5636	-	-	0.5329	0.5648	0.5376	0.5639
	LSA-4	0.5056	0.5103	0.4931	0.5132	-	-	0.5072	0.5001	0.5103	0.5103
	Ours	**0.7031**	**0.7604**	**0.7165**	**0.7832**	-	-	**0.7067**	**0.7729**	**0.7012**	**0.7698**
Simmons	LSA-3	0.5713	0.6123	0.5621	0.5912	0.5672	0.6058	-	-	0.5641	0.6098
	LSA-4	0.5098	0.5012	0.5008	0.5171	0.4878	0.5001	-	-	0.4923	0.4984
	Ours	**0.7539**	**0.8168**	**0.7483**	**0.8163**	**0.7396**	**0.8031**	-	-	**0.7623**	**0.8016**
Swarthmore	LSA-3	0.5701	0.5981	0.5675	0.5904	0.5647	0.5887	0.5605	0.5809	-	-
	LSA-4	0.5063	0.5032	0.4947	0.5003	0.5036	0.5123	0.5088	0.5039	-	-
	Ours	**0.7341**	**0.7953**	**0.7358**	**0.7983**	**0.7312**	**0.8027**	**0.7011**	**0.7849**	-	-

Table 5: Performance of LinkThief on the Facebook dataset with a target graph leak rate of 0.2.

Target Dataset	Attack Method	Shadow Dataset									
		Caltech		Haverford		Reed		Simmons		Swarthmore	
		ASR	AUC	ASR	AUC	ASR	AUC	ASR	AUC	ASR	AUC
Caltech	LSA-3	-	-	0.5728	0.6164	0.5703	0.6124	0.5742	0.6148	0.5747	0.6173
	LSA-4	-	-	0.4997	0.5328	0.5202	0.5188	0.5200	0.5327	0.5206	0.5203
	Ours	-	-	**0.7687**	**0.8425**	**0.8099**	**0.8834**	**0.8050**	**0.8803**	**0.7589**	**0.8432**
Haverford	LSA-3	0.5627	0.5963	-	-	0.5718	0.6024	0.5698	0.5931	0.5759	0.6034
	LSA-4	0.4978	0.5036	-	-	0.5017	0.5034	0.4968	0.4953	0.5011	0.5001
	Ours	**0.7698**	**0.8564**	-	-	**0.8432**	**0.8572**	**0.8053**	**0.8818**	**0.7672**	**0.8578**
Reed	LSA-3	0.5417	0.5712	0.5434	0.5702	-	-	0.5417	0.5707	0.5402	0.5714
	LSA-4	0.5089	0.5187	0.4968	0.5211	-	-	0.5103	0.5037	0.5167	0.5172
	Ours	**0.7773**	**0.8532**	**0.7531**	**0.8039**	-	-	**0.7482**	**0.8137**	**0.7389**	**0.8023**
Simmons	LSA-3	0.5728	0.6118	0.5688	0.6024	0.5700	0.6103	-	-	0.5753	0.6136
	LSA-4	0.5111	0.5012	0.5017	0.5229	0.4933	0.5074	-	-	0.4964	0.5001
	Ours	**0.7829**	**0.8478**	**0.7831**	**0.8537**	**0.7739**	**0.8439**	-	-	**0.7934**	**0.8439**
Swarthmore	LSA-3	0.5718	0.5984	0.5699	0.5948	0.5689	0.5913	0.5685	0.5903	-	-
	LSA-4	0.5097	0.5113	0.5001	0.5047	0.5116	0.5218	0.5104	0.5059	-	-
	Ours	**0.7837**	**0.8463**	**0.7734**	**0.8463**	**0.7764**	**0.8512**	**0.7598**	**0.8439**	-	-

Table 6: Performance of LinkThief on the ArnetMiner dataset with a target graph leak rate of 0.1.

Target Dataset	Attack Method	Shadow Dataset					
		Dblpv7		Acmv9		Citationv1	
		ASR	AUC	ASR	AUC	ASR	AUC
Dblpv7	LSA-3	-	-	0.8278	0.8864	0.8304	0.8884
	LSA-4	-	-	0.8111	0.8674	0.8051	0.8654
	Ours	-	-	**0.8240**	**0.8915**	**0.8281**	**0.8961**
Acmv9	LSA-3	0.8278	0.8913	-	-	0.8392	0.9096
	LSA-4	0.8066	0.8673	-	-	0.8305	0.9006
	Ours	**0.8257**	**0.8953**	-	-	**0.8331**	**0.9109**
Citationv1	LSA-3	0.8386	0.8951	0.8398	0.9082	-	-
	LSA-4	0.8220	0.8932	0.8334	0.8940	-	-
	Ours	**0.8364**	**0.8998**	**0.8367**	**0.9074**	-	-

Table 7: Performance of LinkThief on the ArnetMiner dataset with a target graph leak rate of 0.2.

Target Dataset	Attack Method	Shadow Dataset					
		Dblpv7		Acmv9		Citationv1	
		ASR	AUC	ASR	AUC	ASR	AUC
Dblpv7	LSA-3	-	-	0.8292	0.8871	0.8302	0.8906
	LSA-4	-	-	0.8112	0.8814	0.8052	0.8769
	Ours	-	-	**0.8311**	**0.8993**	**0.8351**	**0.9043**
Acmv9	LSA-3	0.8261	0.8926	-	-	0.8384	0.9140
	LSA-4	0.8086	0.8773	-	-	0.8269	0.9006
	Ours	**0.8294**	**0.8979**	-	-	**0.8412**	**0.9153**
Citationv1	LSA-3	0.8362	0.8953	0.8422	0.9119	-	-
	LSA-4	0.8322	0.8931	0.8334	0.8944	-	-
	Ours	**0.8425**	**0.9067**	**0.8498**	**0.9145**	-	-

Table 8: Performance of LinkThief on the Airport dataset with a target graph leak rate of 0.1.

Target Dataset	Attack Method	Shadow Dataset					
		Brazil		Europe		USA	
		ASR	AUC	ASR	AUC	ASR	AUC
Brazil	LSA-3	-	-	0.7788	0.8419	0.7948	0.8603
	LSA-4	-	-	0.6801	0.7390	0.5567	0.6468
	Ours	**-**	**-**	**0.7752**	**0.8425**	**0.7924**	**0.8591**
Europe	LSA-3	0.7932	0.8584	-	-	0.8017	0.8850
	LSA-4	0.7853	0.8530	-	-	0.6612	0.8044
	Ours	**0.7974**	**0.8615**	**-**	**-**	**0.8157**	**0.8902**
USA	LSA-3	0.8604	0.9305	0.8678	0.9341	-	-
	LSA-4	0.8496	0.9264	0.8367	0.9132	-	-
	Ours	**0.8637**	**0.9320**	**0.8719**	**0.9358**	**-**	**-**

Table 9: Performance of LinkThief on the Airport dataset with a target graph leak rate of 0.2.

Target Dataset	Attack Method	Shadow Dataset					
		Brazil		Europe		USA	
		ASR	AUC	ASR	AUC	ASR	AUC
Brazil	LSA-3	-	-	0.8097	0.8769	0.7919	0.8803
	LSA-4	-	-	0.6801	0.7390	0.5567	0.6468
	Ours	**-**	**-**	**0.8056**	**0.8792**	**0.8040**	**0.8878**
Europe	LSA-3	0.8248	0.8964	-	-	0.8257	0.8951
	LSA-4	0.7853	0.8730	-	-	0.6612	0.8044
	Ours	**0.8230**	**0.8944**	**-**	**-**	**0.8291**	**0.8995**
USA	LSA-3	0.8704	0.9402	0.8772	0.9387	-	-
	LSA-4	0.8496	0.9264	0.8367	0.9132	-	-
	Ours	**0.8713**	**0.9422**	**0.8783**	**0.9441**	**-**	**-**