

# **Towards Differentially Private Inference on Network Data**

A thesis presented  
by

Alexander Koujianos Goldberg

To  
Applied Mathematics  
in partial fulfillment of the honors requirement  
for the degree of  
Bachelor of Arts

Harvard College  
Cambridge, Massachusetts  
March 30, 2018

## **Abstract**

This is my abstract.

## **Acknowledgements**

Thanks everyone!

# Contents

<b>1</b>	<b>Introduction</b>	<b>1</b>
1.1	Motivation . . . . .	1
1.2	A Road Map . . . . .	5
<b>2</b>	<b>Statistical Modeling of Networks</b>	<b>6</b>
2.1	Exponential Random Graph Models (ERGMs) . . . . .	6
2.2	Sufficient Statistics of ERGMs . . . . .	8
2.3	Bayesian Inference on ERGMs . . . . .	13
<b>3</b>	<b>Differential Privacy for Networks</b>	<b>15</b>
3.1	Basics of Differential Privacy . . . . .	15
3.2	Edge-Level vs. Node-Level Adjacency . . . . .	19
3.3	Restricted Sensitivity . . . . .	20
<b>4</b>	<b>Private Inference on ERGMs</b>	<b>23</b>
4.1	Releasing Private Sufficient Statistics . . . . .	23
4.2	Inference Using Noisy Sufficient Statistics . . . . .	28
4.3	Related Work . . . . .	30
<b>5</b>	<b>Empirical Evaluation of Private Inference</b>	<b>32</b>
5.1	Experimental Setup . . . . .	32
5.2	Edge-Adjacency Model . . . . .	34
5.3	Edge-Adjacency Model with Private Labels . . . . .	42
5.4	Node-Adjacency Model . . . . .	42
<b>6</b>	<b>Conclusion</b>	<b>44</b>
	<b>References</b>	<b>45</b>
<b>A</b>	<b>MCMC Methods for Bayesian Inference over ERGMs</b>	<b>48</b>
A.1	Simulating Networks from an ERGM . . . . .	48
A.2	Population MCMC Version of the Exchange Algorithm . . . . .	49
<b>B</b>	<b>Smooth Projections to <math>\mathcal{H}_k</math></b>	<b>50</b>
B.1	Edge-Adjacency Model . . . . .	50
B.2	Node-Adjacency Model . . . . .	51
<b>C</b>	<b>Additional Empirical Results</b>	<b>54</b>

# Chapter 1: Introduction

## 1.1 Motivation

Networks are ubiquitous both as subjects of scientific study and as fixtures of everyday life. From popular social networks like Facebook to webs of financial transactions, mobile phone call records, and communications via email, rich network data constitutes a popular subject for statistical inquiry in a broad range of disciplines. However, due to the interconnected nature of the data, protecting the privacy of participants in a network while conducting statistical analysis can be difficult. A number of recent examples highlight the challenges of keeping network data private:

**The Cambridge Analytica Case** [RCC18]: In late March 2018, revelations emerged that a political consulting firm, Cambridge Analytica, had harvested over 50 million user profiles off Facebook allowing them to build psychological profiles of a vast portion of the American electorate. Only 270,000 users had actually consented to give Cambridge Analytica access to their profile information via an online survey. However, by leveraging users' friend networks, it was possible for Cambridge Analytica to violate the privacy of a much larger number of people.

**“Gaydar”** [JM09]: Consider an individual on Facebook who does not publicly disclose their sexual orientation, presumably because they wish this data to be kept private. By analyzing the proportion of this user's friends who publicly reveal being gay, it is possible to learn with high accuracy whether this user is gay or straight. In effect, then, a person's relationships along with publicly available data about their acquaintances, friends, and coworkers implicitly disclose private information about the person.

**The Structure of Intimate Relationships** [BK14]: Even with no profile information made public, it is possible to identify the romantic partner of a Facebook user with high accuracy using only the structure of their friend network – an intimate relationship is highly likely between individuals in the network who have many mutual friends, but whose friends have few mutual friends, a phenomenon known as “dispersion”. Therefore, suppressing identities of people in the network does not suffice to protect privacy, as the links within the network alone may reveal potentially sensitive, private, information like a person's romantic partner.

These examples highlight the fundamental difficulty of analyzing relational data while respecting the privacy of data holders – network structure discloses an extensive amount of ostensibly private information about both the identity of participants and the nature of their relationships. Further, distinctive substructures of a network can make it relatively easy to reconstruct a naively anonymized network given auxiliary information: a number

of proposed attacks on networks have demonstrated that an attacker with relatively little additional information may (with high probability) identify participants in any unlabeled network ([BDK11],[NS09]). Thus, statistical analysis of network data, while popular, is also problematic from a privacy standpoint. In response to this issue, a growing body of work seeks to answer the question: is it possible to protect the privacy of individuals included in a network dataset while enabling researchers to conduct useful analysis of network structure?

A promising direction for answering this question involves employing a rigorous and meaningful concept of privacy first proposed for analysis of tabular data: differential privacy [DMNS06]. At a high level, differential privacy promises that the participation of any single individual in a dataset will not noticeably alter the results of an analysis of the dataset. The differential privacy guarantee holds even if an adversary is equipped with arbitrary auxiliary information about the participants in a dataset. Indeed, differential privacy promises that were an adversary to know the data of every other individual in a dataset, she still could not discover the private information of the final unknown participant in the dataset.

Further, differential privacy provides a quantifiable notion of privacy, as it is operationalized by two small, non-negative parameters  $\epsilon$  and  $\delta$ . The parameter  $\epsilon$  captures the amount of privacy leaked by the analysis. As  $\epsilon$  decreases, it becomes more difficult for an adversary to discern the private information of an individual in the dataset. The parameter  $\delta$  specifies the probability of a potentially catastrophic privacy leakage. When  $\delta = 0$ , we speak of  $\epsilon$ -differential privacy. For  $\delta > 0$ , we provide  $(\epsilon, \delta)$ -differential privacy, which promises that an algorithm is  $\epsilon$ -differentially private with probability  $1 - \delta$ , but permits an arbitrarily bad privacy leak with probability  $\delta$ . We may be comfortable with this relaxed concept of privacy, if  $\delta$  is vanishingly small (one in a million, for instance), so that the chance of a privacy leak is low. The quantifiability of differential privacy allows for rigorous study of the trade-off between privacy and utility in data analysis.

Protecting the privacy of individuals included in a network dataset requires identifying what aspects of the network should be considered private. A network abstractly represents relationships between various entities – the entities are referred to as *nodes* in the network (potentially with *labels* specifying nodal attributes) and the links between entities are referred to as *edges*. As the examples of “Gaydar” and romantic relationships on Facebook suggest, even if only node labels are considered private data, treating labels alone as private may not in itself preserve privacy, as the edge structure can reveal sensitive information about the labels. Furthermore, the goal may be to explicitly protect the relationships in a network, not just identities of participants. For instance, in a network of romantic partnerships the identity of participants may be public information, while the relationships could be sensitive. Thus, meaningful notions of privacy should seek to also protect the privacy of edges in a network.

In protecting the privacy of edges in a network there is ambiguity as to what granularity of privacy to provide. Differential privacy specifies that the “participation” of any single individual in a dataset should not alter the result of an analysis significantly. We could take “participation” to mean the inclusion of a single edge in the network and guarantee *edge-level privacy* by protecting the privacy of any sensitive relationship in the network.

Alternatively, we could protect the inclusion of a node and all edges incident to that node in the network, providing a much stronger privacy guarantee known as *node-level privacy*. While node-level privacy offers a strictly stronger privacy guarantee than edge-level privacy, there may be cases where we are only concerned with protecting any single relationship in a network, not all of an individual’s relationships. Further, node-level privacy may have an extensive cost in utility. Therefore, we consider both the notions of edge-level privacy and node-level privacy in our analysis.

The goal of this work is to enable differentially private statistical inference for network data using a general class of models known as exponential random graph models or ERGMs. To this end, we propose new methods for differentially private inference and investigate their performance relative to alternatives and to non-private inference in a series of experiments.

In contrast to simply computing statistics on a network – like degree distributions or clustering coefficients – statistical modeling of a network posits an explicit probability distribution over the space of possible networks, allowing researchers to study the distinctive structural properties of an instantiated network and the processes that gave rise to such structure. ERGMs are one of the most commonly employed statistical models of network data, having been applied to a broad range of problems, including analysis of interactions between proteins in the human body [RAS10], networks of neurons in the brain as people age [SDC+16], corporate management structures at Enron [UHH13], and the demographics of high school friendships [GKM09]. The goal of inference over an ERGM is to estimate parameters of the model that make a real-world network most likely over the modeled probability distribution. Then, there are two natural goals for differentially private inference over ERGMs:

1. Permit researchers to reach valid conclusions about network structure under differential privacy constraints.
2. Learn a model in a differentially private manner that puts high probability on networks with similar structure to the non-private network.

Fulfilling the first goal permits researchers to employ differentially private inference in rigorous study of network data. Meanwhile, the second (related) goal enables the private release of synthetic network data by sampling networks from an ERGM estimated in a differentially private manner. Currently, there exist ad-hoc methods for releasing anonymized data to researchers for statistical analysis. A common approach taken by statistical agencies is to fit an ERGM to a sensitive network dataset and then release a network drawn from the fitted model for use by researchers. [HKB+08]. Our aim is to make rigorous the privacy guarantees of such an approach, by guaranteeing differential privacy.

There is a growing body of research on differentially private release of various statistics of networks, such as degree distributions ([HLMJ09], [DLL16]), clustering coefficients [WWZX12], and counts of small subgraphs like triangles [KRSY14] among many others. In comparison, there has been relatively little study of differentially private inference over network data. Karwa and Slavkovic propose a differentially private inference method for a specific class of ERGM known as the  $\beta$ -model. The  $\beta$ -model uses only the degree distribution as a sufficient statistic [KS16]. While they provide an elegant mathematical

formulation of differentially private inference on this model, the  $\beta$ -model is used relatively infrequently in actual analyses, as it cannot capture many structures of interest in network data. For general ERGMs there exist two proposed methods. Lu and Miklau [LM14] give an  $(\epsilon, \delta)$ -differentially private inference method based on perturbing sufficient statistics of an ERGM while Karwa et. al [KKS17] propose an  $\epsilon$ -differentially private method based on perturbing the underlying network. Both of these approaches work only for edge-level privacy with node labels taken to be public. Additionally, they only allow for accurate inference under large privacy budgets (with  $\epsilon$  taken to be greater than 3 or  $\delta$  taken to be 0.5,) while in practice we want much smaller privacy budgets with  $\epsilon$  less than 1 and  $\delta$  taken to be very small (on the order of one in a million, for instance) [NSW+17].

As we demonstrate through a series of experiments, neither of these approaches allow for private inference in the edge-privacy model with desirable levels of privacy. In contrast, our proposed methods allow for accurate edge-level  $\epsilon$ -differentially private inference with low privacy budgets. Further, we are the first to suggest methods for inference under node-level privacy and for inference which treats labels as private. We provide a comprehensive study of differentially private inference using ERGMs under a number of different granularities of privacy and at more realistic privacy budgets than current work. To summarize, we make three main contributions towards the goal of practical differentially private inference for network data using ERGMS:

- We enable accurate inference *under edge-level privacy at lower, more realistic, privacy budgets* than current methods.
- Unlike previous proposed methods, we permit differentially private inference under edge-level privacy with *private node labels*, rather than treating labels as public.
- We suggest the first (to our knowledge) method for differentially private inference under the stronger notion of *node-level privacy*.

Our methods take advantage of the recently proposed machinery of “restricted sensitivity” ([BBDS13], [KNRS13]) to perturb network data much less dramatically than existing methods for guaranteeing differential privacy. Restricted sensitivity exploits the observation that many real world networks are sparse: individuals in the network tend to have relatively few relationships compared to the size of the network. For instance, Facebook has over 2 billion users, but users have no more than a few thousand friends. While restricted sensitivity was initially proposed for edge-level and node-level differentially private release of statistics of networks, it has not been utilized for statistical inference over networks. We propose employing restricted sensitivity to elegantly leverage the sparsity common in real-world network data to perform useful private inference.

We conduct extensive experimentation on both synthetic network data and a real high school friendship network. We first provide evidence on the improved performance of our approach over existing methods in the edge-level privacy model. Then, we demonstrate the viability of our proposed methods for inference with private labels as well as in the node-level privacy model.

## **1.2 A Road Map**

In **Chapter 2** we...

In **Chapter 3** we...

In **Chapter 4** we...

In **Chapter 5** we...

In **Chapter 6** we...

# Chapter 2: Statistical Modeling of Networks

An increasingly popular approach in quantitative analysis of networks is to fit statistical models to realized network data. Many of these models have generative interpretations, allowing researchers to understand the relative importance of multiple endogenous processes to the resulting structure of the network. The advantage of such an approach is best illustrated in contrast to computing statistics – like degree distributions or clustering coefficients – to describe the network structure, without an explicit model of the network. While such metrics are useful in summarizing the structural properties of a given network, they cannot tease out the underlying processes that may give rise to such structures.

For example, one of the distinguishing characteristics of many real-world social networks is the tendency to have more triangles (sets of three connected nodes) than would be expected by drawing random edges of a graph [GKM09]. There are a number of different processes in the formation of a friend network that could give rise to this outcome. One potential explanation is the notion of “triangle closure,” or the tendency for people to become friends with friends-of-friends, since they are easier to meet. Another subtly different explanation is that triangles arise out of “assortative matching,” the propensity for people with the same attributes to become friends with one another, leading to clustering in the network. Finally, a high number of triangles in a social network could arise for reasons of “sociality,” the presence of only a few highly social individuals in the network, who are mutual friends to many people.

In order to consider what global or local processes best explain particular structures of a network, a statistical model of network data posits a probability distribution over the space of possible networks. The goal of inference is to tune parameters of the distribution, such that the realized network is likely to be observed under the probability distribution.

A simple example of such a model is the Erdős-Rényi Random Graph Model, known as the  $G(n, p)$  model, which proposes that edges are drawn independently with probability  $p$  between any two nodes of a network with  $n$  nodes. While this model has been studied in great depth by graph theorists, it does not capture many important features of real world networks, like the tendency for clustering or the power-law distribution of degrees. In order to model such structures in networks, a more general class of random graph models are Exponential Random Graph Models.

## 2.1 Exponential Random Graph Models (ERGMs)

Formally, a graph  $G = (V, E)$  is defined by a set of nodes (or vertices)  $V$ , with  $|V| = n$  and edges  $E$ , representing the presence or absence of relationships between nodes. We will

use the “adjacency matrix” representation of a graph, which we denote  $x$ , where  $x_{ij} = 1$  if an edge exists between nodes  $i$  and  $j$  and  $x_{ij} = 0$  otherwise. The models we consider are defined over undirected graphs, where all the edges are bidirectional, and the adjacency matrix is therefore symmetric. We refer to the number of edges adjacent to node  $i$  as the *degree* of node  $i$  so  $d_i = \sum_{j=1}^n x_{ij}$ . Then, the *degree distribution* is  $D = (D_0, \dots, D_{n-1})$  where  $D_k = |\{i \in V : d_i = k\}|$ .

**Definition 2.1** (Exponential Random Graph [WP96]). A probability distribution over graphs of  $n$  vertices belongs to the family of *exponential random graph models* (henceforth referred to as ERGMs) if it takes the form:

$$\Pr(x|\theta) = \exp \left\{ \theta^T u(x) - \psi(\theta) \right\}$$

where  $\theta$  is a vector of parameters of the model,  $u(x)$  is a vector of sufficient statistics computed on graph  $x$ , and  $\psi(\theta)$  is a normalization constant needed to ensure a valid probability distribution so:

$$\psi(\theta) = \log \sum_{x'} \exp \left\{ \theta^T u(x') \right\}$$

ERGMs describe a broad class of random graphs, with varying conditional dependence relationships between edges. For instance, the  $G(n, p)$  graph can be viewed as an ERGM:

**Example 2.1** ( $G(n, p)$  graphs). We can represent the Erdős-Rényi Random Graph ( $G(n, p)$ ) model as an ERGM, by taking

$$u(x) = |E|, \quad \theta = \log \frac{p}{1-p}$$

$$\psi(\theta) = - \binom{n}{2} \log(1-p) = - \binom{n}{2} \log \frac{e^{-\theta}}{1+e^{-\theta}}$$

Then,

$$\begin{aligned} \Pr(x|\theta) &= \exp \left\{ |E| \log \frac{p}{1-p} + \binom{n}{2} \log(1-p) \right\} \\ &= p^{|E|} (1-p)^{\binom{n}{2} - |E|} \\ &= \prod_{i < j} p^{x_{ij}} (1-p)^{1-x_{ij}} \end{aligned}$$

so each possible edge is included independently with probability  $p$  as specified by the Erdős-Rényi Model.

In order to model more complex structures in a network, researchers have proposed higher order sufficient statistics of ERGMs that imply more general conditional independence assumptions than the Erdős-Rényi Model. For instance, “Markov” graphs, allow the probabilities of any two possible edges in a graph to be conditionally dependent if the edges share a common endpoint. This dependency allows for node level effects on edge formation. In fact, Markov dependencies are captured by ERGMs of the following form:

**Example 2.2** (Markov graphs [FS86]). Any undirected *Markov graph* has probability distribution:

$$\Pr(x|\theta, \tau) = \exp \left\{ \sum_{k=1}^{n-1} \theta_k S_k(x) + \tau T(x) - \psi(\theta, \tau) \right\}$$

where the sufficient statistics are

number of edges:	$S_1(x) = \sum_{1 \leq i < j \leq n} x_{ij} =  E $
number of $k$ -stars ( $k \geq 2$ ):	$S_k(x) = \sum_{i=1}^{n-1} \binom{i}{k} D_i(x)$
number of triangles:	$T(x) = \sum_{1 \leq h < i < j \leq n} x_{hi}x_{ij}x_{jh}$

and the parameters are  $\{\theta_k\}_{k=1}^n$  and  $\tau$ .<sup>1</sup>

## 2.2 Sufficient Statistics of ERGMs

In practice, due to its simplicity, the  $G(n, p)$  model is used only as a starting point in inference over real-world data, while the full Markov graph model is infrequently used as it suffers from poor statistical properties. In particular, the Markov graph model is degenerate for many parameter configurations, representing only distributions that put all of their probability mass on either nearly-complete graphs (graphs with all edges present) or on  $G(n, p)$  graphs [Jon99]. In response to these problems of degeneracy with Markov graphs, more robust “alternating” sufficient statistics are generally used in ERGMs to capture structural properties of networks. We will first provide definitions of these statistics and then expand on the mathematical motivation behind them.

### 2.2.1 Alternating Sufficient Statistics

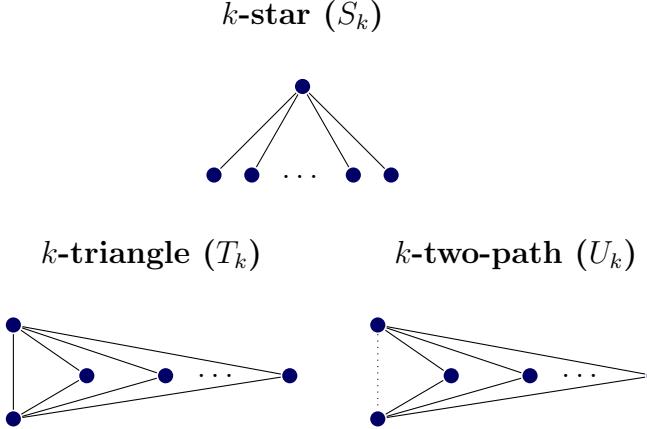
**Definition 2.2** (Alternating  $k$ -star statistic [SPRH06]). The *alternating  $k$ -star* statistic on graph  $x$  with weighting parameter  $\lambda \geq 1$  is defined as

$$\begin{aligned} u_\lambda^{(s)}(x) &= S_2 - \frac{S_3}{\lambda} + \frac{S_4}{\lambda^2} - \cdots + (-1)^{n-2} \frac{S_{n-1}}{\lambda^{n-3}} \\ &= \sum_{k=2}^{n-1} \frac{S_k}{\lambda^{k-2}} \end{aligned}$$

We introduce the notion of “shared partners” of two nodes – the number of common neighbors that two nodes share – which give a clean way to count  $k$ -triangles and  $k$ -two-paths.

---

<sup>1</sup>Note that setting  $\theta_2 = \dots = \theta_k = \tau = 0$  in the Markov model, we recover the  $G(n, p)$  model, which is an instance of a Markov graph since any two edges are conditionally independent in the  $G(n, p)$  model.



**Figure 2.1:** Subgraphs used in sufficient statistics of ERGMs.

**Definition 2.3** (Shared partners). We denote the *shared partner count* of nodes  $i$  and  $j$ :

$$P_{ij}(x) = \sum_{\ell \in V} x_{i\ell} x_{j\ell} \quad (2.1)$$

We define  $k$ -triangles analogously to  $k$ -stars, so that a  $k$ -triangle consists of  $k$  triangles that all share an edge. We can count the total number of  $k$ -triangles in a graph using the number of shared partners:

$$T_k(x) = \sum_{1 \leq i < j \leq n} x_{ij} \binom{P_{ij}}{k} \quad \text{for } (k \geq 2), \quad \text{and } T_1 = \frac{1}{3} \sum_{1 \leq i < j \leq n} x_{ij} P_{ij} \quad (2.2)$$

**Definition 2.4** (Alternating  $k$ -triangle statistic [SPRH06]). The *alternating  $k$ -triangle* statistic on graph  $x$  with weighting parameter  $\gamma \geq 1$  is defined as

$$\begin{aligned} u_\gamma^{(t)}(x) &= 3T_1 - \frac{T_2}{\gamma} + \frac{T_3}{\gamma^2} - \cdots + (-1)^{n-3} \frac{T_{n-2}}{\gamma^{n-3}} \\ &= 3T_1 + \sum_{k=2}^{n-2} \left( \frac{-1}{\gamma} \right)^{k-1} T_k \end{aligned}$$

We define an *independent  $k$ -two-path* as a pair of nodes (possibly connected or unconnected) with  $k$  paths of length 2 connecting them. We can think of a  $k$ -two-path as a precondition for a  $k$ -triangle, since every  $k$ -triangle must contain an independent  $k$ -two-path. In terms of shared partners, independent  $k$ -two-paths can be represented as:

$$U_k(x) = \sum_{1 \leq i < j \leq n} \binom{P_{ij}}{k} \quad \text{for } k \neq 2 \quad \text{and } U_2(x) = \frac{1}{2} \sum_{1 \leq i < j \leq n} \binom{P_{ij}}{2} \quad (2.3)$$

**Definition 2.5** (Alternating  $k$ -two-path statistic [SPRH06]). The *alternating  $k$ -two-path*

statistic on graph  $x$  with weighting parameter  $\gamma \geq 1$  is defined as

$$\begin{aligned} u_\gamma^{(p)}(x) &= U_1 - \frac{2U_2}{\gamma} + \frac{U_3}{\gamma^2} - \cdots + (-1)^{n-3} \frac{U_{n-2}}{\gamma^{n-3}} \\ &= U_1 - \frac{2U_2}{\gamma} + \sum_{k=3}^{n-2} \left( \frac{-1}{\gamma} \right)^{k-1} U_k \end{aligned}$$

Now, having defined the “alternating” sufficient statistics, the proposed model has the form

$$\Pr(x|\theta) = \exp \left\{ \theta_1 E(x) + \theta_2 u_\lambda^{(s)}(x) + \theta_3 u_\gamma^{(t)}(x) + \theta_4 u_\gamma^{(p)}(x) - \psi(\theta) \right\} \quad (2.4)$$

where  $E(x)$  is the number of edges in graph  $x$ , the alternating  $k$ -two-path and  $k$ -triangle statistics generally use the same weighting parameter  $\gamma$ . In practice, a subset of the sufficient statistics can be used in the model, depending on what properties of a graph are pertinent to model for a given network.

The overarching motivation behind introducing “alternating” sufficient statistics of the ERGMs is that these statistics are robust to addition or removal of an edge adjacent to an individual node, alleviating degeneracies in the Markov graph model. For instance, consider adding an edge to a high degree node with degree  $k$ . This new edge contributes one  $(k+1)$ -star,  $\binom{k}{k-1}$   $k$ -stars,  $\binom{k}{k-2}$   $(k-1)$ -stars and so on. Therefore, the total number of additional stars in the graph resulting from adding this edge is  $\sum_{i=0}^k \binom{k}{i} = 2^k$ . For Markov graphs including all stars with arbitrary associated parameters, this could lead to a large increase (or decrease) in the likelihood of the graph making the model degenerate as it places almost all of its probability on either near-complete or near-empty graphs. However, by imposing constraints on the parameters  $\theta_k$ , namely by alternating the signs of the  $k$ -star statistics, the additional  $(k-1)$ -stars and  $k$ -stars balance each-other out. The same general reasoning applies to the use of alternating statistics for  $k$ -triangles and  $k$ -two-paths – alternation prevents the probability distribution from putting all of its mass on graphs with many high degree nodes, preventing degeneracy of the model.

This interpretation of alternating statics as limiting the sensitivity of the likelihood to addition or removal of edges to high degree nodes can be understood by looking at an alternative representation of the statistics in terms of the degree distribution and the number of shared partners for nodes. Below, we present these equivalent representations of the statistics, which will also be helpful in proofs of privacy in Chapter 4.

### Alternating $k$ -star

Note that using the relationship between  $k$ -stars and degrees given in Example 2.2 along with the binomial theorem we can rewrite the *alternating  $k$ -star* statistic as:

$$\begin{aligned}
u_{\lambda}^{(s)}(x) &= \sum_{i=1}^{n-1} D_i(x) \sum_{k=2}^{n-1} \left(\frac{-1}{\lambda}\right)^{k-2} \binom{i}{k} \\
&= \lambda^2 \sum_{i=0}^{n-1} \left(\frac{\lambda-1}{\lambda}\right)^i D_i + 2\lambda|E| - n\lambda^2
\end{aligned} \tag{2.5}$$

The alternating  $k$ -star statistic is thus made up of the number of edges as well as a linear combination of the degree sequence where lower degree nodes are up-weighted exponentially compared to higher degree nodes, reflecting the tendency towards a power law degree distribution. Since a term representing the number of edges in the network is generally included along with this statistic, the model is mathematically equivalent to a model using a geometrically weighted average of the degree sequence. Sociologically, the coefficient of the  $k$ -star statistic can thus be interpreted as the propensity for high degree nodes in the network. If the coefficient of the statistic is positive, then networks with a few high degree “hubs” are observed, while if it is negative, high degree nodes are discouraged and the network consists of mostly low-degree nodes [SPRH06].

### Alternating $k$ -triangle

Similarly, for the alternating  $k$ -triangle statistic, we can gain insight by rewriting in terms of the number of shared partners for pairs of nodes. By using this representation of  $k$ -triangles from Equation (2.2) along with the binomial theorem, we can rewrite the *alternating  $k$ -triangle* statistic as:

$$\begin{aligned}
u_{\gamma}^{(t)}(x) &= \sum_{1 \leq i < j \leq n} x_{ij} \sum_{k=1}^{n-2} \left(\frac{-1}{\gamma}\right)^{k-1} \binom{P_{ij}}{k} \\
&= \gamma \sum_{1 \leq i < j \leq n} x_{ij} \left(1 - \left(\frac{\gamma-1}{\gamma}\right)^{P_{ij}}\right) \\
&= \gamma|E| - \gamma \sum_{1 \leq i < j \leq n} x_{ij} \left(\frac{\gamma-1}{\gamma}\right)^{P_{ij}}
\end{aligned} \tag{2.6}$$

Note, then, that any edge that does not participate in a triangle (so  $x_{ij} = 1$  but  $P_{ij} = 0$ ) does not contribute to the the alternating  $k$ -triangle statistic. On the other hand, as we add additional shared partners to an edge, the second term in (2.6) falls exponentially so the statistic increases, but by less for higher order  $k$ -triangles than for lower-order triangles. Sociologically, this term can be interpreted as the importance of triangle closure in the generation of the graph [GKM09]. In contrast to directly including the number of triangles in the graph, the alternating  $k$ -triangles statistic is more stable, preventing the model degeneracies discussed above.

## Alternating $k$ -two-path

Using the representation of  $k$ -two-paths in terms of shared partners from Equation (2.3) and the binomial theorem, we can rewrite the *alternating  $k$ -two-path* statistic as:

$$\begin{aligned} u_{\gamma}^{(p)}(x) &= \sum_{1 \leq i < j \leq n} \sum_{k=1}^{n-2} \left(\frac{-1}{\gamma}\right)^{k-1} \binom{P_{ij}}{k} \\ &= \gamma \sum_{1 \leq i < j \leq n} \left(1 - \left(\frac{\gamma-1}{\gamma}\right)^{P_{ij}}\right) \\ &= \gamma \binom{n}{2} - \gamma \sum_{1 \leq i < j \leq n} \left(\frac{\gamma-1}{\gamma}\right)^{P_{ij}} \end{aligned} \quad (2.7)$$

Thus, the alternating  $k$ -two-path has an interpretation similar to that of the alternating  $k$ -triangle. As shared partners are added for any two nodes, the second term of the statistic increases, but the increase falls exponentially with additional partners. This term is generally only included in conjunction with the  $k$ -triangle statistic to try to separate out the effects of two-paths forming between unconnected nodes and mutual connections forming between already connected nodes.

### 2.2.2 Sufficient Statistics for Labeled Nodes

The alternating statistics over  $k$ -stars,  $k$ -triangles and  $k$ -two-paths capture structural properties of network data. Frequently, however, there are labels associated with nodes in the network, which are important to model. ERGMs can take into consideration both the structure of the network and the labels associated with nodes, by including sufficient statistics based off of the labels, allowing researchers to capture properties like homophily, the tendency for similar actors to build relationships with one another within a network. Generally, labels are taken to be fixed and exogenous to the edges, so that attributes of the nodes may affect the formation of the network, whereas relationships in the network are not thought of as impacting attributes. This is generally a reasonable assumption, as labels often represent the identity of an individual, containing characteristics like gender, race, or age. As there are many potential ways to incorporate labeled data into an ERGM, we will focus here on three of the most commonly used statistics for discrete nodal attributes, “homophily”, “popularity” and “mixing.”<sup>2</sup>

In particular, letting  $z_i$  be a discrete attribute of node  $i$  (gender, for instance) we introduce the following sufficient statistics to represent different processes of social selection [LKR12]:

---

<sup>2</sup>These have fairly straightforward analogues for continuous nodal attributes, but we focus on the discrete case, as this is applicable to the dataset analyzed.

**Table 2.1:** Common sufficient statistics for discrete nodal attributes.

<i>Parameter</i>	<i>Statistic</i>
Homophily (Uniform)	$\sum_{i < j} x_{ij} \mathbb{I}(z_i = z_j)$
Homophily (Differential)	$\sum_{i < j} x_{ij} \mathbb{I}(z_i = z_j = a)$
Popularity	$\sum_{i < j} x_{ij} (\mathbb{I}(z_i = a) + \mathbb{I}(z_j = a))$
Mixing	$\sum_{i < j} x_{ij} \mathbb{I}(z_i = a) \mathbb{I}(z_j = b)$

Uniform homophily captures the tendency for nodes with the same attribute to share an edge, while differential homophily captures this phenomenon for a specific attribute, which may be useful if, for instance, we thought that men and women have different propensities to become friends with people of the same gender. The popularity parameter is fairly self-explanatory as it measures the number of edges that have nodes with a given attribute as an endpoint and can be thought of as the overall sociability of a group with a specific attribute. Finally, the mixing parameter represents the number of edges between nodes with two different, specific attributes. Including such nodal attribute statistics in conjunction with the alternating sufficient statistics discussed in Section 2.2 allows for specification of ERGMs that separate out social selection effects like homophily from structural effects like triangle closure, making ERGMs a powerful modeling tool.

## 2.3 Bayesian Inference on ERGMs

Having provided an ERGM specification that captures the characteristics of interest in a network, the goal of inference is to find parameters  $\theta$  that describe the realized data well. In the framework of maximum likelihood estimation, this means finding a  $\theta$  that maximizes the probability of drawing observed network  $x_{obs}$  from the distribution  $p(X|\theta)$ . In the Bayesian paradigm, an analyst specifies a prior distribution over  $\theta$  and then wishes to compute a posterior distribution of  $\theta$  given the observed network. Bayesian inference is more general than maximum likelihood inference in the sense that if an analyst chooses a flat prior on  $\theta$  (a uniform prior over the parameter space) and takes the maximum of the posterior as a point estimate, then Bayesian inference reduces to maximum likelihood inference.

In general, exact inference is not feasible for ERGMs due to the presence of the intractable normalizing constant  $\psi(\theta)$  in the likelihood (Definition 2.1), which is a sum over the space of possible graphs on  $n$  nodes of size  $2^{\binom{n}{2}}$ . Therefore, a number of approximate MCMC approaches have been proposed to perform inference. In this work, we focus on Bayesian inference over ERGMs, because it constitutes the state-of-the-art in non-private inference methods and has been shown to be more stable than MCMC-MLE approaches

[CF11]. Additionally, the noise from differentially private mechanisms can be incorporated quite naturally into the Bayesian framework. The non-private Bayesian inference method proposed by Caimo and Friel is based on the Exchange Algorithm[MGM12] and is fairly simple to describe:

---

**Algorithm 1** Non-Private Bayesian Inference for ERGMs (Exchange Algorithm) [CF11]

---

Input: ERGM distribution  $\pi(X|\theta)$ , prior  $p(\theta)$ , observed graph  $x_{obs}$ , number of burn-in draws  $r$ , symmetric proposal distribution  $h(\cdot|\theta)$ .

Output: sequence of draws  $\theta^{(r)}, \dots, \theta^{(T)}$  from posterior distribution  $p(\theta|x_{obs})$ .

For  $t = 1, \dots, T$ :

1. Draw parameter vector  $\theta^* \sim h(\cdot|\theta^{(t-1)})$
2. Sample graph  $x^* \sim \pi(\cdot|\theta^*)$
3. Accept the proposed move with probability  $\min\{1, \alpha\}$ . If the move is accepted, set  $\theta^{(t)} = \theta^*$ . Otherwise, set  $\theta^{(t)} = \theta^{(t-1)}$

where

$$\alpha = \frac{p(\theta^*)}{p(\theta^{(t-1)})} \exp \left\{ (\theta^* - \theta^{(t-1)})^T (u(x_{obs}) - u(x^*)) \right\}$$


---

The algorithm can be justified by considering sampling from an augmented distribution with two auxiliary variables  $x^*, \theta^*$ :

$$p(x^*, \theta^*, \theta|x_{obs}) \propto \pi(x_{obs}|\theta)p(\theta)h(\theta^*|\theta)\pi(x^*|\theta^*)$$

where  $\pi$  refers to the ERGM probability distribution. Marginalizing out  $\theta^*$  and  $x$  from the augmented distribution gives the posterior distribution  $p(\theta|x_{obs})$  of interest. Steps 1 and 2 are Gibbs updates of  $\theta^*$  and  $x^*$ , while step 3 can be justified as the appropriate Metropolis-Hastings acceptance ratio:

$$\begin{aligned} \alpha &= \frac{\pi(x_{obs}|\theta^*)p(\theta^*)h(\theta^{(t-1)}|\theta^*)\pi(x^*|\theta^{(t-1)})}{\pi(x_{obs}|\theta^{(t-1)})p(\theta)h(\theta^*|\theta^{(t-1)})\pi(x^*|\theta^*)} \\ &= \frac{p(\theta^*)}{p(\theta)} \frac{\pi(x_{obs}|\theta^*)\pi(x^*|\theta^{(t-1)})}{\pi(x_{obs}|\theta^{(t-1)})\pi(x^*|\theta^*)} \end{aligned}$$

where we drop the  $h$  transition probabilities by symmetry and the intractable normalizing constants for  $\theta^*$  and  $\theta^{(t-1)}$  cancel, allowing easy computation of  $\alpha$ . Thus, by standard MCMC theory, the draws  $\theta^{(t)}$  come asymptotically from the desired posterior distribution.

In practice, Caimo and Friel advocate the use of a population-MCMC variant of their basic algorithm, in which multiple Markov chains are run in parallel, with the state space defined over the  $\theta$ 's of these multiple chains, as this population MCMC approach tends to converge faster and lead to less temporal dependence in draws from the Markov chain. We use this method, known as Parallel Adaptive Direction Sampling, in our private inference methods and explain it in detail in Appendix A along with a Metropolis-Hastings sampler to simulate networks from an ERGM with specified parameters.

# Chapter 3: Differential Privacy for Networks

We employ the framework of differential privacy to protect individuals' data while analyzing network data. First, we provide the basic definition of differential privacy and mechanisms that meet this definition for general datasets, then explain specific problems that arise in applying these general definitions to network data, and finally detail the machinery of "restricted sensitivity" which we propose to use for differentially private inference over ERGMs.

## 3.1 Basics of Differential Privacy

### Definitions

Let  $\mathcal{D}$  denote the space of all possible datasets. Then:

**Definition 3.1.** Two datasets  $x, x' \in \mathcal{D}$  are *adjacent*, written as  $x \sim x'$ , if they differ in the record of one individual. For tabular data, this means that the datasets differ in a single row.

**Definition 3.2.** The *distance* between two datasets  $x, x' \in \mathcal{D}$ , denoted  $d(x, x')$  is the minimum length of the sequence of datasets beginning with  $x$  and ending with  $x'$  such that every two consecutive datasets on the path are adjacent. So, two datasets are clearly adjacent, or neighboring, if  $d(x, x') = 1$ .

**Definition 3.3** ( $\epsilon$ -differential privacy [DMNS06]). Let  $\mathcal{A}$  be an algorithm over datasets in  $\mathcal{D}$ . Then  $\mathcal{A}$  is  $\epsilon$ -*differentially private* if for all  $S \subseteq \text{Range}(\mathcal{A})$  and for every pair of neighboring datasets  $x, x' \in \mathcal{D}$ ,

$$\Pr[\mathcal{A}(x) \in S] \leq e^\epsilon \Pr[\mathcal{A}(x') \in S]$$

Intuitively, differential privacy promises that the participation of any individual in a dataset does not significantly change the outcome of an analysis run on the dataset, limiting the potential harm (or benefit) to a data provider due to the inclusion of her data. Smaller values of  $\epsilon$  correspond to stronger guarantees of privacy where  $\epsilon = 0$  suggests that the algorithm does not learn anything from the data and therefore the algorithm is useless. Additionally, it is clear that no non-trivial deterministic algorithm satisfies  $\epsilon$ -differential privacy for any value of  $\epsilon$ . If  $\mathcal{A}$  is deterministic and its output differs on at least two datasets, then there must be neighboring datasets such that the probability of a specific output is 0 on one dataset and 1 on the other, preventing the ratio between probabilities on this response from being bounded as required. Therefore, mechanisms that provide differential privacy will have to introduce some randomness, or noise, into their answers.

We can relax the definition of  $\epsilon$ -differential privacy to allow for a small probability of potentially catastrophic privacy leakage:

**Definition 3.4**  $((\epsilon, \delta)$ -differential privacy [DMNS06]).  $\mathcal{A}$  is  $(\epsilon, \delta)$ -differentially private if for all  $S \subseteq \text{Range}(\mathcal{A})$  and for every pair of neighboring datasets  $x, x' \in \mathcal{D}$ ,

$$\Pr[\mathcal{A}(x) \in S] \leq e^\epsilon \Pr[\mathcal{A}(x') \in S] + \delta$$

It is immediate from the definition that  $(\epsilon, \delta)$ -differential privacy is equivalent to  $\epsilon$ -differential privacy when  $\delta = 0$ . For  $\delta > 0$ , however,  $(\epsilon, \delta)$  guarantees that the mechanism is  $\epsilon$ -differentially private with probability  $1 - \delta$ , but makes no promises about the privacy loss that occurs with probability  $\delta$ . Therefore, if  $\delta$  is on the order of  $\frac{1}{n}$  where  $n$  is the size of the dataset, it is possible to satisfy  $(\epsilon, \delta)$ -DP by releasing a row of the data. Further, a mechanism that sometimes releases the entire dataset still satisfies  $(\epsilon, \delta)$ -DP.

**Example 3.1.** An algorithm that selects at random one record in the dataset and exactly releases this record is  $(\epsilon, \frac{1}{n})$ -differentially private for any value of  $\epsilon$ .

**Example 3.2.** An algorithm that releases the entire dataset with probability  $\delta$  and a constant value with probability  $1 - \delta$  is  $(\epsilon, \delta)$ -differentially private for any value of  $\epsilon$ .

As these examples demonstrate,  $(\epsilon, \delta)$ -differential privacy only provides meaningful privacy for values of  $\delta$  much smaller than  $\frac{1}{n}$ . In particular,  $\epsilon$  should be taken to be “cryptographically small” (e.g. take  $\delta = \frac{1}{1,000,000}$  for networks over a few 100 nodes.)

## Properties

One of the desirable properties of differential privacy is its immunity to *post-processing* – armed with the output of a differentially private mechanism, an analyst cannot degrade privacy any further without additional information about the private dataset. In the context of inference over ERGMs, this property suggests that after computing sufficient statistics of a model in a differentially private manner, inference using these sufficient statistics can be thought of as a post-processing step that does not further degrade privacy. Formally:

**Property 1** (Post-processing [DMNS06]). If  $\mathcal{A}$  is an  $(\epsilon, \delta)$ -differentially private algorithm, then for an arbitrary mapping  $f$ ,  $f \circ \mathcal{A}$  is also  $(\epsilon, \delta)$ -differentially private.

A second useful property of differential privacy is that multiple differentially private algorithms compose, so applying many differentially private algorithms to the same dataset still provides privacy, albeit with higher privacy loss. This allows for basic DP algorithms to be used as building blocks in more complicated algorithms and in particular to split a privacy budget across multiple private computations on the data. Specifically, basic composition states that the privacy loss incurred by running multiple DP algorithms on a dataset grows linearly:

**Property 2** (Basic Composition [DMNS06]). Let  $\mathcal{A}_i$  be an  $(\epsilon_i, \delta_i)$ -differentially private algorithm for  $i \in [k]$ . Then, the algorithm releasing the result of running all  $k$  algorithms on the dataset  $\mathcal{A}_{[k]}(x) = (\mathcal{A}_1(x), \dots, \mathcal{A}_k(x))$  is  $(\sum_{i=1}^k \epsilon_i, \sum_{i=1}^k \delta_i)$ -DP.

## Mechanisms

We now describe two simple mechanisms that satisfy differential privacy. First, we describe the Laplace Mechanism, which answers queries on a dataset in a differentially private manner by adding Laplace noise to queries. Then, we introduce Randomized Response, which provides privacy by randomly perturbing the underlying dataset.

### Laplace Mechanism

We define a query to be a function mapping the dataset to a vector of real numbers,  $f : \mathcal{D} \rightarrow \mathbb{R}^m$ . Then the local sensitivity of a query on a dataset  $x$  is the maximum  $\ell_1$ -norm of the difference in the query over neighbors of dataset  $x$ .

**Definition 3.5** (Local sensitivity). The *local sensitivity* of a query  $f$  on a dataset  $x$  is

$$LS_f(x) = \max_{x' \sim x} \|f(x) - f(x')\|_1$$

The global sensitivity is the worst-case local sensitivity over all possible datasets:

**Definition 3.6** (Global sensitivity). The *global sensitivity* of a query  $f$  is

$$GS_f = \max_{x \in \mathcal{D}} LS_f(x)$$

A basic result in differential privacy is that adding Laplace noise scaled to the global sensitivity provides differential privacy:

**Theorem 3.1** (Laplace mechanism [DMNS06]). *Let  $f$  be a query on dataset  $x$  with global sensitivity  $GS_f$  and let  $\text{Lap}$  denote the zero-mean Laplace distribution<sup>1</sup>. Then, the Laplace mechanism  $\mathcal{A}_L$  that outputs*

$$\mathcal{A}_L(x, f, \epsilon) = f(x) + (Y_1, \dots, Y_m)$$

where  $Y_i \stackrel{i.i.d.}{\sim} \text{Lap}\left(\frac{GS_f}{\epsilon}\right)$  is  $\epsilon$ -differentially private.

Note that the Laplace mechanism scales noise to the *global sensitivity*. While it is tempting to calibrate noise to local sensitivity, this does not protect privacy, because the noise level may disclose information about the underlying dataset. However, we can add noise scaled to a smooth upper bound on the local sensitivity, namely a function  $S$  that is larger

---

<sup>1</sup>The Laplace distribution centered at 0 with scale parameter  $b$  has probability density function  $p(x|b) = \frac{1}{2b} e^{-|x|/b}$  and the variance of the distribution is  $\sigma^2 = 2b^2$ .

than the local sensitivity for all datasets and for which  $\ln(S(\cdot))$  is not too sensitive. The smoothness is parameterized by  $\beta$ , where  $\beta$  depends on  $\epsilon$  and  $\delta$ :

**Theorem 3.2** (Calibrating Noise to  $\beta$ -Smooth Upper Bound on Local Sensitivity [NRS07]). *A  $\beta$ -smooth upper bound on the local sensitivity of query  $f$  is a function  $S_{f,\beta}$  that satisfies:*

- (i)  $S_{f,\beta}(x) \geq LS_f(x) \quad \forall x \in \mathcal{D}$
- (ii)  $S_{f,\beta}(x) \leq \exp\{-\beta d(x, x')\} S_{f,\beta}(x') \quad \forall x, x' \in \mathcal{D}$

It is possible to satisfy  $(\epsilon, \delta)$ -differential privacy by adding Laplace noise scaled to  $\frac{2S_{f,\beta}(x)}{\epsilon}$  where  $\beta = -\frac{\epsilon}{2\ln(\delta)}$  and  $S_{f,\beta}$  is a  $\beta$ -smooth upper bound on  $LS_f(x)$ . It is possible to satisfy  $\epsilon$ -differential privacy by adding Cauchy noise<sup>2</sup> scaled to  $\sqrt{2}S_{f,\beta}(x)$  where  $\beta = \epsilon/\sqrt{2}$ .

Then, global sensitivity trivially satisfies the definition of a  $\beta$ -smooth upper bound on local sensitivity, but it is a very conservative bound. The smallest function  $S$  to satisfy the definition of a  $\beta$ -smooth upper bound is known as the *smooth sensitivity*:

**Definition 3.7** (Smooth Sensitivity [NRS07]). For query  $f$  and dataset  $x$ , define the *local sensitivity at distance of  $t$*  to be

$$LS_f^{(t)}(x) = \max_{\substack{x' \in \mathcal{D}: \\ d(x, x') \leq t}} LS_f(x')$$

Then the *smooth sensitivity* is

$$S_{f,\beta}^*(D) = \max_t e^{-t\beta} LS_f^{(t)}(D)$$

The smooth sensitivity is the smallest  $\beta$ -smooth upper bound on the local sensitivity in the sense that for any other  $\beta$ -smooth upper bound  $S$ ,  $S_{f,\beta}^*(D) \leq S(D)$  for all datasets  $D$ . Thus, if we can compute the smooth sensitivity efficiently, then we can potentially add much less noise by calibrating to smooth rather than global sensitivity.

## Randomized Response

In contrast to the Laplace Mechanism, which perturbs the output of a query on a dataset, randomized response perturbs the underlying dataset by randomly introducing spurious data. A typical version of randomized response over binary data proceeds as follows:

For each bit in a dataset consisting of  $\{0, 1\}$  values:

1. Flip a biased coin with probability  $p_1$  of heads.
2. If tails, then record the bit truthfully.

---

<sup>2</sup>The Cauchy distribution with median 0 and scale parameter  $b$  has probability density function  $p(x|b) = 1/(b\pi(1 + (x/b)^2))$ . Roughly, the Cauchy distribution can provide  $\epsilon$ -DP because it has fatter tails than the Laplace distribution.

3. If heads, then flip a second biased coin with probability  $p_2$  of heads and record 1 if heads, 0 if tails.

A benefit of randomized response is that it can be employed while collecting data, by using the coin-flipping procedure to collect responses in a study. The method provides plausible deniability for respondents, so it may incentivize participation in surveys for sensitive information. It is easy to verify that taking  $p_1 = 2p$  and  $p_2 = \frac{1}{2}$  yields the following simpler description:

**Theorem 3.3** (Binary Randomized Response [War65],[KKS17]). *Let  $\mathcal{D} = \{0, 1\}^n$  so  $x \in \mathcal{D}$  consists of binary data. Then, randomized response flips each bit of  $x$  with probability  $p \in (0, \frac{1}{2})$  and releases the resulting noisy bits. This process provides  $\epsilon$ -differential privacy taking  $p \geq \frac{1}{e^\epsilon + 1}$ .*

We may also use a generalized version randomized response for a dataset where each row is drawn from an arbitrary data universe  $\mathcal{U}$ :

**Theorem 3.4** (General Randomized Response). *Consider dataset  $x \in \mathcal{D} = \mathcal{U}^n$  and an algorithm which with probability  $p$  for each row, replaces the row with an entry drawn uniformly at random from  $\mathcal{U}$ . Then, this algorithm is  $\epsilon$ -differentially private, taking  $p \geq \frac{|\mathcal{U}| - 1}{e^\epsilon + |\mathcal{U}| - 1}$ .*

## 3.2 Edge-Level vs. Node-Level Adjacency

We now turn to the question of how to define “adjacency” for graphs, as opposed to tabular data. We will define graphs abstractly in terms of vertex sets and edge sets, rather than as adjacency matrices in this section, as it makes the definitions easier to specify and more intuitive. There are two reasonable and widely used definitions of adjacency, which provide privacy at very different granularities and thus may be appropriate in different circumstances:

**Definition 3.8** (Edge-level adjacency). We define two graphs  $G_1 = (V_1, E_1)$  and  $G_2 = (V_2, E_2)$  to be *edge-adjacent* if they have the same vertex set ( $V_1 = V_2$ ) and they differ in only one edge ( $|E_1 \Delta E_2| = 1$ ).

Differential privacy with respect to edge-adjacency protects the privacy of individual relationships between nodes. Thus, edge-level privacy could protect a Facebook friendship with a controversial political leader. However, privacy at the edge-level could not promise to prevent an adversary from discerning whether an individual has mostly Republican or Democratic friends on Facebook. Such concerns motivate a stronger definition of neighboring graphs:

**Definition 3.9** (Node-level adjacency). We define two graphs  $G_1 = (V_1, E_1)$  and  $G_2 = (V_2, E_2)$  to be *node-adjacent* if  $G_1 - v_i = G_2 - v_i$  for some vertex  $v_i$ , where  $G - v_i$  means deleting edges adjacent to node  $v_i$ .

An additional consideration in defining adjacent graphs is how to account for labeled nodes. In the node-level case, labels are protected since removing a vertex and replacing it with a different vertex suggests changing the labeling on that vertex. For edge-level privacy, labels could be taken to be either public or private information. There may be cases where the only sensitive information is the edges in the graph, not the identities of nodes (for instance, in a public social network, where people's identities may be readily searchable online, while their friendships are kept private.) However, in many settings, it seems preferable to protect the labels in addition to the relationships. Thus, letting there be some labeling function associated with a network that specifies a vector of nodal attributes for each node  $\ell : V \rightarrow \mathbb{R}^m$ , we define edge-level adjacency for labeled networks as follows:

**Definition 3.10** (Edge-level adjacency with private labels). We define two graphs  $G_1 = (V_1, E_1)$  and  $G_2 = (V_2, E_2)$  with labeling functions  $\ell_1$  and  $\ell_2$  to be *edge-adjacent with private labels* if they have the same vertex set ( $V_1 = V_2$ ) and either they differ in only one edge ( $|E_1 \Delta E_2| = 1$ ) or differ in one label ( $\ell_1(v) \neq \ell_2(v)$  for exactly one vertex  $v$ .)

### 3.3 Restricted Sensitivity

Node-level privacy constitutes a strictly stronger guarantee than edge-level privacy, but it is often much more difficult to perform accurate analysis under node-level privacy. For instance, consider computing the degree distribution on an  $n$ -node graph. The global sensitivity under edge-level adjacency is only 2, since the degree of two nodes will change by 1 due to the addition or removal of an edge. However, under node-level adjacency, removing or adding all edges to a node of degree  $n - 1$  would affect  $n$  entries of the degree distribution, so the global sensitivity is  $n$  and naive application of the Laplace mechanism would completely destroy the counts of the degree distribution. Furthermore, even under edge-level adjacency many statistics computed on networks have high global sensitivity. For instance, the count of triangles in a graph (which is used in the alternating  $k$ -triangle sufficient statistic in ERGMs) has global sensitivity  $O(n)$  in the edge-level case, since a single edge could be the base of a triangle with each other node in the graph.

The high global sensitivity of many graph statistics is particularly problematic for sparse graphs, where the noise completely overwhelms the true statistics. This is especially troubling, because sparsity is a characteristic of many real world networks. For instance, Facebook has billions of users, but users tend to have on the order of 1000 friends or fewer. We can formalize the hypothesis that a graph is sparse by considering the *degree* of the graph, the maximum degree of any of its nodes. If we hypothesize that all the graphs under consideration have limited degree, then the global sensitivity might be much lower over these limited-degree graphs than over all graphs on  $n$  nodes. For example, considering the space of graphs with degree of at most  $k \ll n$ , the triangle count would have a much lower global sensitivity of  $O(k)$  rather than  $O(n)$  over the space of all graphs on  $n$  nodes.

If we were certain that the graphs under consideration always had limited degree, we could scale noise to the sensitivity over limited degree graphs. However, our hypothesis might be false, so adding noise assuming that the graph has limited degree would not

protect privacy for an arbitrary graph. Therefore, it is necessary to first project the graph into the space of limited degree graphs. If the limited degree hypothesis is true then the projection will not alter the graph at all, so the analysis is accurate up to the distortion of the noise-adding procedure. We formally define the *limited degree hypothesis*:

**Definition 3.11** (Limited Degree Hypothesis). Let  $\mathcal{G}_n$  be the space of graphs on  $n$  nodes. Then, a graph  $G \in \mathcal{G}_n$  satisfies the *limited degree hypothesis* if it belongs to the class  $\mathcal{H}_k$  where  $\mathcal{H}_k$  is the set of graphs:

$$\mathcal{H}_k = \{G = (V, E) \in \mathcal{G}_n : \deg(v) \leq k, \forall v \in V\}$$

Then, the restricted sensitivity is the global sensitivity of the query restricted to limited degree graphs:

**Definition 3.12** (Restricted sensitivity [BBDS13]). For a given notion of adjacency (either edge or node), we define the *restricted sensitivity* of query  $f$  over hypothesis  $\mathcal{H}_k \in \mathcal{G}_n$  as

$$RS_f(\mathcal{H}) = \max_{\substack{G, G' \in \mathcal{H}_k: \\ G \sim G'}} \|f(G) - f(G')\|_1$$

To protect privacy over arbitrary graphs, while calibrating noise to the restricted sensitivity rather than the global sensitivity, we require a projection  $\mu : \mathcal{G} \rightarrow \mathcal{H}_k$ . We can define the sensitivity of the projection in terms of how much it changes the distance by a multiplicative factor between any two adjacent graphs. In particular:

**Definition 3.13** (Local sensitivity of projection  $\mu$  [KNRS13]). Define the local sensitivity of projection  $\mu : \mathcal{G}_n \rightarrow \mathcal{H}_k$  on graph  $G \in \mathcal{G}_n$  to be:

$$LS_\mu(G) = \max_{G' \sim G} d(\mu(G), \mu(G'))$$

Then, the global sensitivity and smooth sensitivity can be defined as before. Now, if we can find a projection  $\mu$ , where it is possible to bound the global sensitivity by a small constant, so  $\forall G \in \mathcal{G}_n : LS_\mu(G) \leq c$ , then for any two neighboring graphs the effect of first projecting a graph to  $\mathcal{H}_k$  before answering a query only increases global sensitivity by a multiplicative factor of  $c$ :

**Lemma 3.1** (Global Sensitivity on Composed Functions). *For projection  $\mu : \mathcal{G}_n \rightarrow \mathcal{H}_k$  and query  $f : \mathcal{G}_n \rightarrow \mathbb{R}^m$ , define  $f_{\mathcal{H}_k} = f \circ \mu$  to be the query applied to the projection. Then  $GS_{f_{\mathcal{H}_k}} \leq GS_\mu \cdot RS_f(\mathcal{H}_k)$ .*

In particular, this suggests that if we find a projection to  $\mathcal{H}_k$  with low global sensitivity  $c$ , then using  $\epsilon$ -differentially private mechanisms like the Laplace mechanism that calibrate noise to  $c \cdot RS_f(\mathcal{H})$  can give significant accuracy gains over global sensitivity. Blocki et al. give such a projection for the edge-adjacency model with  $GS_\mu = 3$  that is also efficient (linear in the number of edges in the graph.) We give the details of this projection in Appendix B.

In the node level-adjacency model an efficient projection with low global sensitivity is not known [KNRS13]. However, it can be shown that if we use the smooth sensitivity of  $\mu$ , then multiplying this  $\beta$ -smooth upper bound by the restricted sensitivity of  $f$  gives a  $\beta$ -smooth bound on the local sensitivity of the composition  $f_{\mathcal{H}_k}$  as above:

**Lemma 3.2** ( $\beta$ -Smooth Bound on Composed Functions). *Let  $S_\mu(G)$  be a  $\beta$ -smooth upper bound on the local sensitivity of  $\mu$  on graph  $G \in \mathcal{G}_n$ . Then  $S_{f_{\mathcal{H}_k}} = S_\mu(G) \cdot RS_f(\mathcal{H}_k)$  is a  $\beta$ -smooth bound on the local sensitivity of  $f_{\mathcal{H}_k} = f \circ \mu$ .*

We detail two possible projections for the node-adjacency model in Appendix B ([KNRS13], [BBDS13]). The first, which we refer to as  $\mu_{trunc}$  simply removes nodes of high degree and the other,  $\mu_{LP}$  solves a linear program. It is possible to give  $\beta$ -smooth upper bounds on the local sensitivity for each of these projections. Roughly speaking, the benefits of node truncation are that it is more efficient than the LP and has low smooth sensitivity when there are few nodes with degree close to the cutoff  $k$ , which is often applicable since degree distributions frequently follow a power law. However, the smooth sensitivity of  $\mu_{trunc}$  could be high for graphs in  $\mathcal{H}_k$  if the graph does in fact have many nodes with degree close to the cutoff  $k$ . On the other hand, the smooth sensitivity of  $\mu_{LP}$  is always relatively low when the hypothesis  $\mathcal{H}_k$  is true, but the LP is not strictly a projection in that it is guaranteed to project graphs in  $\mathcal{H}_k$  to themselves, but its image is  $\mathcal{H}_{2k}$  not  $\mathcal{H}_k$ . Therefore, we must calibrate noise to the restricted sensitivity over  $\mathcal{H}_{2k}$  when using the LP. Thus, we expect  $\mu_{trunc}$  to have low smooth sensitivity in practice and to give a lower bound on restricted sensitivity than  $\mu_{LP}$  (since node truncation requires calibrating noise to restricted sensitivity over  $\mathcal{H}_k$  rather than  $\mathcal{H}_{2k}$ .) For these reasons, in addition to the greater efficiency of  $\mu_{trunc}$ , we propose using node truncation as a smooth projection for the node-adjacency model.

Then, taking advantage of restricted sensitivity over  $\mathcal{H}_k$  and the appropriate projections, we can perform inference over ERGMs while adding relatively low noise to sufficient statistics that have high global sensitivity. Our primary focus in proving privacy will be bounding the restricted sensitivity of the queries of interest over  $\mathcal{H}_k$  in order to take advantage of this machinery of restricted sensitivity.

# Chapter 4: Private Inference on ERGMs

In this chapter, we propose methods for differentially private inference over ERGMs with the alternating and nodal attribute sufficient statistics defined in Section 2.2. We propose perturbing the sufficient statistics, taking advantage of restricted sensitivity to limit the amount of noise needed to protect privacy. Then, it is possible to perform Bayesian inference taking into account the level of noise added. Since the restricted sensitivity is public, we are able to do principled inference over the posterior incorporating the randomness of the privacy mechanism, which has been shown to lead to more reliable inference in many cases (see [FGWC16], [KS16], [KKS17], [LM14] for instance).

Our primary contribution is the proposal to use the machinery of restricted sensitivity in adding noise to sufficient statistics. The advantages of employing restricted sensitivity for inference over ERGMs are threefold:

- Calibrating noise to restricted sensitivity enables *lower noise in the edge-adjacency model* than current methods, permitting accurate inference at lower privacy budgets.
- Restricted sensitivity permits private release of sufficient statistics under edge level privacy with *private labels*, whereas prior work has treated labels as public.
- By using restricted sensitivity, we suggest the first (to our knowledge) method that performs differentially private inference under the *node-adjacency model*, a strictly stronger notion of privacy than the edge-adjacency model.

Restricted sensitivity relies on the hypothesis that the graph we are analyzing is sparse, namely that its max degree node has degree  $k$ . There are a number of reasons to believe that the limited degree hypothesis  $\mathcal{H}_k$  is a reasonable assumption when modeling real social network data with ERGMs. First, previous empirical analyses of ERGMs have demonstrated that for reasonable parameter values, the distribution tends to put low probability mass on high-degree graphs [SPRH06]. Thus, given that we assume that an observed network is roughly drawn from the probability distribution specified by an ERGM, we believe with high probability that the graph has relatively low degree. Second, many real-world social networks are fairly sparse and have bounded degree. Thus, an analyst is likely to believe that their network data represents a sparse graph and could reasonably choose a degree cutoff based on similar public datasets or domain knowledge.

## 4.1 Releasing Private Sufficient Statistics

In this section, we bound the restricted sensitivity under  $\mathcal{H}_k$  of a number of the most commonly used sufficient statistics in ERGMs. As the following summary shows, in the

edge-adjacency case, restricted sensitivity is much lower than global sensitivity for alt- $k$ -triangle and alt- $k$ -two path, assuming  $k \ll n$ . In the node-level case, adding noise scaled to the global sensitivity overwhelms the computed statistics in most cases, motivating the need for restricted sensitivity. For labeled networks, the global sensitivity is very low if labels are considered public and only edges are taken to be private. However, if labels are private, then the restricted sensitivity is much lower than the global sensitivity.

**Table 4.1:** Restricted Sensitivity on  $\mathcal{H}_k$  for Common Structural Statistics

	Edge-Level		Node-Level	
	$RS_f(\mathcal{H}_k)$	$GS_f$	$RS_f(\mathcal{H}_k)$	$GS_f$
Edges	1	1	$k$	$n - 1$
Alt $k$ -star ( $u_\lambda^{(s)}$ )	$2\lambda$	$2\lambda$	$3\lambda k$	$O(n)$
Alt $k$ -triangle ( $u_\gamma^{(t)}$ )	$2(k - 1) + \gamma$	$O(n)$	$k^2 + (\gamma - 1)k$	$O(n^2)$
Alt $k$ -two-path ( $u_\gamma^{(p)}$ )	$2(k - 1)$	$O(n)$	$k^2$	$O(n^2)$

**Table 4.2:** Restricted Sensitivity on  $\mathcal{H}_k$  for Common Statistics of Labeled Networks

	Public Labels	Private Labels	
	$GS_f$	$RS_f(\mathcal{H}_k)$	$GS_f$
Homophily	1	$k$	$n - 1$
Popularity	2	$2k$	$2n$
Mixing	1	$k$	$n - 1$

Below, we derive the restricted sensitivity of the alternating sufficient statistics of an ERGM under edge level privacy and node level privacy respectively. The “weighting parameters” of the alternating statistics  $\gamma$  and  $\lambda$  are generally set to be small constants between roughly 1 and 5 (most empirical work seems to find that values between 1 and 2 suffice) so the choice of this parameter has a fairly minor effect on the level of noise.

### 4.1.1 Edge Level Privacy

For the alternating  $k$ -star statistic under edge-level privacy, restricted sensitivity does not give any advantage over using global sensitivity, as the global sensitivity of this statistic is quite low:

**Claim 4.1.1** (Global sensitivity of alternating  $k$ -star under edge-level privacy). *The global sensitivity of the alternating  $k$ -star statistic is less than  $2\lambda$ .*

*Proof.* We use the alternative formulation of the statistic given in Equation (2.5):

$$u_\lambda^{(s)}(x) = \lambda^2 \sum_{i=0}^{n-1} \left( \frac{\lambda - 1}{\lambda} \right)^i D_i + 2\lambda|E| - n\lambda^2$$

Then, consider adjacent graphs  $x, x'$  differing in one edge where  $x$  has the additional edge. Then, the first term of the alternating  $k$ -statistic is larger for  $x'$  than for  $x$  and by at most  $2\lambda$  and at least 0, while the second term is larger for  $x$  than for  $x'$  by  $2\lambda$ . Hence, the difference between the alternating  $k$ -star statistic computed on  $x$  and  $x'$  is at most  $|2\lambda - 0| = 2\lambda$ .  $\square$

**Claim 4.1.2** (Restricted sensitivity of alternating  $k$ -triangle under edge-level privacy). *The restricted sensitivity of the alternating  $k$ -triangle statistic under  $\mathcal{H}_k$  is less than  $2(k - 1) + \gamma$ .*

*Proof.* Consider two adjacent graphs  $x, x' \in \mathcal{H}_k$  differing in exactly one edge, so that  $x_{ij} = 1$  and  $x'_{ij} = 0$ . Now, note that for nodes  $i$  and  $j$ , the number of shared partners is the same in  $x$  and  $x'$  since all edges are the same except for the edge between  $i$  and  $j$ . Then, let  $P_{ij} = P'_{ij} = m \leq k - 1$  by the limited degree hypothesis. Note that there are  $2m$  edges for which  $P'_e = P_e - 1$ , since there are two other edges in each triangle. Then, recalling the definition of the alternating  $k$ -triangle statistic in terms of the shared partners of  $i$  and  $j$  given in Equation (2.6):

$$u_\gamma^{(t)}(x) = \gamma|E| - \gamma \sum_{1 \leq i < j \leq n} x_{ij} \left( \frac{\gamma - 1}{\gamma} \right)^{P_{ij}}$$

we have that

$$\begin{aligned} |u_\gamma^{(t)}(x) - u_\gamma^{(t)}(x')| &= \left| \gamma - \gamma \left( \frac{\gamma - 1}{\gamma} \right)^m + \gamma \sum_{e=1}^{2m} \left[ \left( \frac{\gamma - 1}{\gamma} \right)^{P_e-1} - \left( \frac{\gamma - 1}{\gamma} \right)^{P_e} \right] \right| \\ &= \left| \gamma - \gamma \left( \frac{\gamma - 1}{\gamma} \right)^m + \sum_{e=1}^{2m} \left( \frac{\gamma - 1}{\gamma} \right)^{P_e-1} \right| \\ &\leq 2m + \gamma \\ &\leq 2(k - 1) + \gamma \end{aligned}$$

$\square$

Note the usefulness of restricted sensitivity here, in contrast to global sensitivity. The global sensitivity of this statistic is  $O(n)$ , since in the worst case there could be a graph with an  $(n - 1)$ -triangle where removing the base of the triangle leads to the removal of  $O(n)$  triangles. However, if we restrict degrees, we add much less noise.

**Claim 4.1.3** (Restricted sensitivity of alternating  $k$ -two-path under edge-level privacy). *The restricted sensitivity of the alternating  $k$ -two-path statistic under  $\mathcal{H}_k$  is less than  $2(k - 1)$ .*

*Proof.* The proof will proceed in roughly the same way as for  $k$ -triangles. Define  $x$  and  $x'$  in the same way and recall the definition of the alternating  $k$ -two-path statistic in terms of shared partners as given in Equation (2.7):

$$u_\gamma^{(p)}(x) = \gamma \binom{n}{2} - \gamma \sum_{1 \leq i < j \leq n} \left( \frac{\gamma - 1}{\gamma} \right)^{P_{ij}}$$

Then, the change between the statistic on  $x$  and  $x'$  is equal to

$$|u_\gamma^{(p)}(x) - u_\gamma^{(p)}(x')| = \sum_{e=1}^{2m} \left( \frac{\gamma-1}{\gamma} \right)^{P_e-1} \leq 2m \leq 2(k-1)$$

□

### 4.1.2 Node Level Privacy

**Claim 4.1.4** (Restricted sensitivity of alternating  $k$ -star under node-level privacy). *The restricted sensitivity with hypothesis  $\mathcal{H}_k$  of alternating  $k$ -star under node-level differential privacy is less than  $3\lambda k$ .*

*Proof.* We will again use the formulation of the alternating  $k$ -star statistic in terms of degree distribution from Equation (2.5). Now, consider two graphs  $x, x' \in \mathcal{H}_k$  differing in one node  $i$  of degree  $m \leq k$ , with all of its incident edges removed in  $x'$ . Then, the degree of node  $i$  is  $m$  in  $x$  and 0 in  $x'$ , while the degrees of  $m$  other nodes are 1 lower in  $x'$  than in  $x$ , so:

$$\begin{aligned} |u_\lambda^{(s)}(x) - u_\lambda^{(s)}(x')| &= \left| 2\lambda m + \lambda^2 \left( \left( \frac{\lambda-1}{\lambda} \right)^m - 1 \right) + \sum_{j:x_{ij}=1} \lambda \left( \frac{\lambda-1}{\lambda} \right)^{d_j-1} \right| \\ &\leq \left| 3\lambda m + \lambda^2 \left( \left( \frac{\lambda-1}{\lambda} \right)^m - 1 \right) \right| \end{aligned}$$

and note that  $0 \leq \left( \frac{\lambda-1}{\lambda} \right)^m \leq 1$  and that  $|\lambda^2| \leq 3\lambda m$  for reasonable choices of  $k$  and  $\lambda$  (since generally we choose  $1 < \lambda < 5$ , so in order to have the  $\lambda^2$  term dominate the  $3\lambda k$  term we would have to restrict  $k$  to 1, which would not be interesting or realistic). Thus, because  $m \leq k$ , the sensitivity is bounded by  $3\lambda k$ . □

**Claim 4.1.5** (Restricted sensitivity of alternating  $k$ -triangle under node-level privacy). *The restricted sensitivity with hypothesis  $\mathcal{H}_k$  of the alternating  $k$ -triangle statistic under node-level differential privacy is less than  $k^2 + (\gamma-1)k$ .*

*Proof.* Consider two adjacent graphs  $x, x' \in \mathcal{H}_k$  differing in one node  $i$  of degree  $m$ . Now, since each of the  $m$  edges incident to node  $i$  is removed this changes  $m$  edges  $x_{ij} = 1$  to  $x'_{ij} = 0$ , so  $E(x) - E(x') = m$  and for each of these  $m$  edges

$$x_{ij} \left( \frac{\gamma-1}{\gamma} \right)^{P_{ij}} - x'_{ij} \left( \frac{\gamma-1}{\gamma} \right)^{P'_{ij}} = \left( \frac{\gamma-1}{\gamma} \right)^{P_{ij}}$$

so the direct effect of removing the  $x_{ij}$  is that  $u_\gamma^{(t)}(x') - u_\gamma^{(t)}(x) \leq m\gamma - 0$  (ignoring the effect on the shared partners of edges not adjacent to  $i$ .)

Now, we consider edges  $e$  such that the endpoints of  $e$  have  $i$  as a shared partner. Note that there are  $\binom{m}{2} = m^2 - m$  such edges, because we can choose any 2 edges of  $i$  and the

endpoints of these edges have  $i$  as a shared partner. Now, each of these edges still exists in  $x'_{ij}$  but has its number of shared partners decrease by 1. Then, we have

$$\begin{aligned} |u_\gamma^{(t)}(x) - u_\gamma^{(t)}(x')| &= \left| \gamma m - \gamma \sum_{j:x_{ij}=1} \left( \frac{\gamma-1}{\gamma} \right)^{P_{ij}} + \sum_{e=1}^{m^2-m} \left( \frac{\gamma-1}{\gamma} \right)^{P_e-1} \right| \\ &\leq |\gamma m + (m^2 - m)| \\ &\leq k^2 + (\gamma - 1)k \end{aligned}$$

□

**Claim 4.1.6** (Restricted sensitivity of alternating  $k$ -two-path under node-level privacy). *The restricted sensitivity with hypothesis  $\mathcal{H}_k$  of the alternating  $k$ -two-path statistic under node-level differential privacy is less than  $k^2$ .*

*Proof.* As for  $k$ -triangles, consider two adjacent graphs  $x, x' \in \mathcal{H}_k$  differing in node  $i$  of degree  $m$ . Then, the removal of these  $m$  edges impacts the shared partners of  $m^2$  edges, the  $m$  incident to  $i$  and the  $\binom{m}{2} = m^2 - m$  that have  $i$  as a shared partner and the decrease in shared partners for each of these edges can change the statistic by at most 1 so the overall change is at most  $m^2 \leq k^2$ . □

### 4.1.3 Private Labels

If labels are considered public, then the global sensitivity of the sufficient statistics using discrete attributes of nodes given in Table 2.1 have low global sensitivity in the edge-adjacency model, since they are effectively counts of edges for nodes with certain attributes, and adjacent graphs have only a single edge changed and all labels kept the same. However, if labels are considered private then the change in a single label could change the count for all edges incident to that node, leading to very high global sensitivity of  $O(n)$ . By using restricted sensitivity, we can bound the sensitivity to be  $O(k)$ . Additionally, note that differential homophily and popularity are vectors of queries, with dimension the size of the number of attributes under consideration. However, these queries are structurally disjoint as a change in one attribute can only change the counts of two entries of the vector, making it easy to bound the  $\ell_1$ -sensitivity of the entire vector. We give the proof for homophily, while the proofs for popularity and mixing follow from the same argument:

**Claim 4.1.7** (Restricted sensitivity of homophily with private labels.). *Both differential and uniform homophily have  $\ell_1$ -restricted sensitivity  $k$ .*

*Proof.* Recall that for attributes  $a_1, \dots, a_m$  differential homophily is given by

$$\left( \sum_{i<j} x_{ij} \mathbb{I}(z_i = z_j = a_1), \dots, \sum_{i<j} x_{ij} \mathbb{I}(z_i = z_j = a_m) \right)$$

Then, changing nodal attribute  $z_i$  from  $a$  to  $b$  changes the endpoint of at most  $k$  edges. If both endpoints of an edge had endpoint  $a$ , then this reduces the count of entry  $a$  in the

vector by 1, while if the endpoints of the edge were  $a$  and  $b$  to start with, this increases the count in entry  $b$  by 1. These cases are disjoint so the largest  $\ell_1$  difference in the vector is  $k$ . For uniform homophily, it is easy to see that changing one label could change at most  $k$  edges and each edge is counted only once in uniform homophily, so the global sensitivity is 1.  $\square$

## 4.2 Inference Using Noisy Sufficient Statistics

Now, by projecting a network into  $\mathcal{H}_k$  using the projections specified in Appendix B and then applying the Laplace mechanism (3.1), we can release the sufficient statistics of the ERGM in a differentially private manner by calibrating the noise of the Laplace mechanism to the restricted sensitivity. We could now release these sufficient statistics to analysts who wish to study the network, since the likelihood of the ERGM depends on the data only through the sufficient statistics. Using noisy statistics directly for standard inference techniques has been shown to lead to biased estimates, however, as the sufficient statistics may not even be graphical. Therefore, in the framework of Bayesian inference we want to compute the posterior over both the observed network and the privacy mechanism. In particular, letting  $\tilde{y}$  be the “noisy network” defined by the application of our privacy mechanism to the true network we wish to compute the posterior:

$$p(\theta|\tilde{y}) \propto p(\tilde{y}|\theta)p(\theta) = \sum_x p(\tilde{y}|x)p(x|\theta)p(\theta) \quad (4.1)$$

where  $p(\tilde{y}|x)$  is the privacy distribution defined by our mechanism,  $p(x|\theta)$  is the ERGM distribution and  $p(\theta)$  is the prior on  $\theta$  which is specified by the analyst. Then, along the lines of [LM14], it is simple to modify the Exchange Algorithm for non-private inference to draw from the posterior that incorporates the privacy distribution, as shown in Algorithm 2.

As in the non-private case, Algorithm 2 draws samples from the true posterior of interest as  $T \rightarrow \infty$  by MCMC theory. Steps 1 and 2 can be justified as Gibbs updating steps as in the non-private case, while steps 3 and 4 are component-wise Metropolis-Hastings updates, where we update the variables separately rather than in a block, because this tends to lead to higher acceptance ratios and thus faster convergence [GL06], [LM14]. Intuitively,  $x^*$  can be thought of as our best guess of the true underlying network. Then,  $\theta^*$  is replaced in step 3 if it explains this best guess of the network well, while  $x^*$  is updated if the new network is likely to be the true network over the noise of the privacy mechanism. Additionally, we propose using the population MCMC version of the exchange algorithm, as this leads to better convergence in practice and still converges to the correct posterior.

Note that  $\alpha_1$  does not depend on the choice of privacy mechanism, while  $\alpha_2$  is simple to compute under the addition of Laplace noise. In particular, if we add Laplace noise scaled to  $L$  (for instance,  $L = 3 \cdot RS_f(\mathcal{H}_k)$  in the edge-adjacency case) to the sufficient statistics of the network then:

---

**Algorithm 2** Bayesian Inference for ERGMs with Differentially Private Network Data

---

Input: ERGM distribution  $\pi(X|\theta)$ , prior  $p(\theta)$ , noisy network  $\tilde{y}$ , privacy distribution  $\pi_p(\tilde{y}|y)$ , number of burn-in draws  $r$ , symmetric proposal distribution  $h(\cdot|\theta)$ .  
Output: sequence of draws  $\theta^{(r)}, \dots, \theta^{(T)}$  from posterior distribution  $p(\theta|\tilde{y})$ .

For  $t = 1, \dots, T$ :

1. Draw parameter vector  $\theta^* \sim h(\cdot|\theta^{(t-1)})$
2. Sample graph  $x^* \sim \pi(\cdot|\theta^*)$
3. Replace  $\theta^{(t-1)}$  with  $\theta^*$  with probability  $\min\{1, \alpha_1\}$ .
4. Replace  $x^{(t-1)}$  with  $x^*$  with probability  $\min\{1, \alpha_2\}$ .

where

$$\begin{aligned}\alpha_1 &= \frac{p(\theta^*)}{p(\theta^{(t-1)})} \exp \left\{ (\theta^* - \theta^{(t-1)})^T (u(x^{(t-1)}) - u(x^*)) \right\} \\ \alpha_2 &= \frac{\pi_p(\tilde{y}|x^*)}{\pi_p(\tilde{y}|x^{(t-1)})} \exp \left\{ (\theta^* - \theta^{(t-1)})^T (u(x^{(t-1)}) - u(x^*)) \right\}\end{aligned}$$


---

$$\begin{aligned}\log \frac{\pi_p(\tilde{y}|x^*)}{\pi_p(\tilde{y}|x^{(t-1)})} &= \log (Lap(\tilde{y} - x^*|L)) - \log (Lap(\tilde{y} - x^{(t-1)}|L)) \quad (4.2) \\ &= \frac{|\tilde{y} - x^{(t-1)}|}{L} - \frac{|\tilde{y} - x^*|}{L}\end{aligned}$$

In the edge-adjacency model, the restricted sensitivity is public, so we can easily compute the ratio in *eq. (4.2)* using  $L = 3RS_f(\mathcal{H}_k)$  where the factor of 3 comes from the global sensitivity of the projection. In the node-level case, we compute smooth sensitivity of the projection which cannot be publicly released, but we can release the value of the smooth sensitivity assuming the graph belongs to  $\mathcal{H}_k$  as explained in *Appendix B*, so inference is still valid when the analyst's assumptions about the degree of the graph are met.

In general, we assume that the number of nodes in a graph is known and public. For the case where labels are public, sampling a graph in step 2 is straightforward as we sample a graph from the space of all possible graphs with the  $n$  labeled nodes of the original graph. However, if labels are private, then these labels must be privatized as well. This is straightforward to by releasing a noisy histogram of the labels, which has global sensitivity of 1 and therefore is high accuracy assuming that there are a limited number of types of labels [DMNS06]. Then, this noisy histogram can be used as the node-set over which graphs are sampled in step 2 of the algorithm.

## The Full Workflow

Putting together our bounds on restricted sensitivity and inferential procedure the workflow for differentially private inference looks roughly as follows, given hypothesis  $\mathcal{H}_k$ , privacy budget  $\epsilon, \delta$  (where the  $\delta$  is necessary only for the node-level case using Laplace noise) and network data  $y$ :

1. Split privacy budget between sufficient statistics under consideration (and potentially using some of the privacy budget for a histogram of private labels).
2. Project  $y$  to  $\mathcal{H}_k$  using smooth projections  $\mu$  specified for edge and node level privacy respectively in Appendix B.
3. Compute and release restricted sensitivity of sufficient statistics.
4. If labels are considered private, then release noisy histogram of node labels.
5. Draw noise according to restricted sensitivity (Laplace noise scaled to  $3RS_f(\mathcal{H}_k)/\epsilon$  in the edge-level case and  $S_{\mu, -\epsilon/2 \ln \delta} RS_f(\mathcal{H}_k)$  in the node-level case where  $\mu$  is the node-truncating projection. Add this noise to sufficient statistics and release these noisy sufficient statistics.
6. Using the noisy sufficient statistics from step 4 and the restricted sensitivity levels from step 3, perform inference using Algorithm 2.

Then, privacy follows by applying composition in step 1, restricted sensitivity with the Laplace Mechanism in steps 2-5 and post-processing in step 6. Post-processing is particularly useful here, because MCMC methods frequently require tuning of the inference, whereby we run the inferential procedure multiple times and run diagnostics to make sure it converges (for instance, by checking that every 100 samples from the posterior are not highly correlated.) By post-processing, we can run step 6 an arbitrary number of times to tune the inferential procedure because differential privacy is provided by steps 1 to 5.

## 4.3 Related Work

Our work builds on two proposed methods, both of which only consider the edge-adjacency privacy model with labels taken to be public. The method most closely related to our work is that of Lu and Miklau [LM14] who also suggest adding noise to sufficient statistics and then performing Bayesian inference. In order to avoid adding noise scaled to the high global sensitivity of these statistics, they calibrate noise to a private bound on the local sensitivity of the network. In particular, they use an approach suggested in [KRSY14] to compute a differentially private over-estimate on the local sensitivity and scale noise to this estimated local sensitivity, providing  $(\epsilon, \delta)$ -differential privacy and allowing for less noise than calibrating to the global sensitivity when  $GS_{LS_f}$  can be bounded and is small. In particular, in their method, the expected scale of Laplace noise is  $\frac{2LS_f(G)}{\epsilon} + \frac{4GS_{LS_f} \ln(1/\delta)}{\epsilon^2}$  whereas we add noise scaled to  $3RS_f(\mathcal{H}_k)/\epsilon$ . For reasonable choice of  $k$ , the restricted

sensitivity is close to the local sensitivity on graph  $G$ , while the second term can be quite large for small privacy budgets in  $\epsilon$  and  $\delta$ . Miklau and Lu test their approach with  $\delta = 0.1$ , which is an unreasonable choice of this parameter in practice, since a method that released the entire dataset one tenth of the time would satisfy  $(\epsilon, \delta)$ -DP with this parameter (Example 3.2). We find through a battery of tests that our proposed method (which takes  $\delta = 0$ ) adds much less noise than the bounding of local sensitivity approach, especially for small privacy budgets. This difference in the magnitude of noise makes a significant difference in the accuracy of inference, as our method can perform accurate inference for realistic small privacy budgets. The primary drawback of our approach is that it requires a reasonable estimate of the maximum degree of the network, while the private bounding of local sensitivity can calibrate noise to the sparsity of the graph without assumptions on the part of the analyst. However, if the graph is not relatively sparse, bounding local sensitivity may still add significant noise, so this seems like a reasonable assumption for an analyst to be able to make.

Another approach suggested by Karwa et. al. [KKS17], uses randomized response on edges of the network, where the network is thought of as a binary database of 0s and 1s indicating the presence or absence of an edge between any two nodes. Then, they use maximum likelihood estimation on this perturbed network taking into account the flipping of edges. The main benefit of this method is that it potentially permits greater flexibility as the perturbed network can be released for public use and researchers can use any sufficient statistics they like. Our method requires a commitment to use a specific set of sufficient statistics, although we bound restricted sensitivity for a fairly broad range of the most commonly used sufficient statistics in ERGMs. The primary drawback of the randomized response approach is that for low privacy budgets, it leads to extensive distortion of the underlying network. For instance, taking  $\epsilon = 1$  suggests a probability of flipping each edge of around 25%, which for a sparse network in which only 5% of edges are present may completely overwhelm network structure. We test randomized response, using Bayesian inference, as it is straightforward to account for this noise in the Bayesian inferential framework and find, as expected, that their method only works for relatively large privacy budgets, whereas our proposal works for lower, more realistic privacy budgets.

# Chapter 5: Empirical Evaluation of Private Inference

The performance of inference methods for ERGMs is primarily studied via empirical testing. We conduct a series of tests, both on synthetic graphs drawn from a variety of ERGM models and on a high school friend network dataset collected by sociologists. In the edge-level privacy model, we compare the noise-addition of our method against private bounding of local sensitivity. Then, we compare the inference quality of our proposed restricted sensitivity method against both private bounding of local sensitivity and randomized response. We find that our method gives better utility at low privacy budgets of  $\epsilon = 1$  or  $2$  compared to competing methods in the edge-level model which can only provide useful inference for values of  $\epsilon$  of  $3$  or above. Next, we compare the inference quality of our proposed methods against non-private inference for the cases of private labels with edge-level privacy and the case of node-level privacy. We demonstrate the viability of inference for large, highly sparse, networks, under these stronger privacy constraints.

## 5.1 Experimental Setup

### Data

We test our proposed methods on networks drawn from 3 different ERGM models using the alternating structural sufficient statistics introduced in Section 2.2 so the probability distribution has the form:

$$\Pr(x|\theta) \propto \exp \left\{ \theta_1 E(x) + \theta_2 u_{\lambda}^{(s)}(x) + \theta_3 u_{\gamma}^{(t)}(x) + \theta_4 u_{\gamma}^{(p)}(x) \right\}$$

with the following parameters for each model:

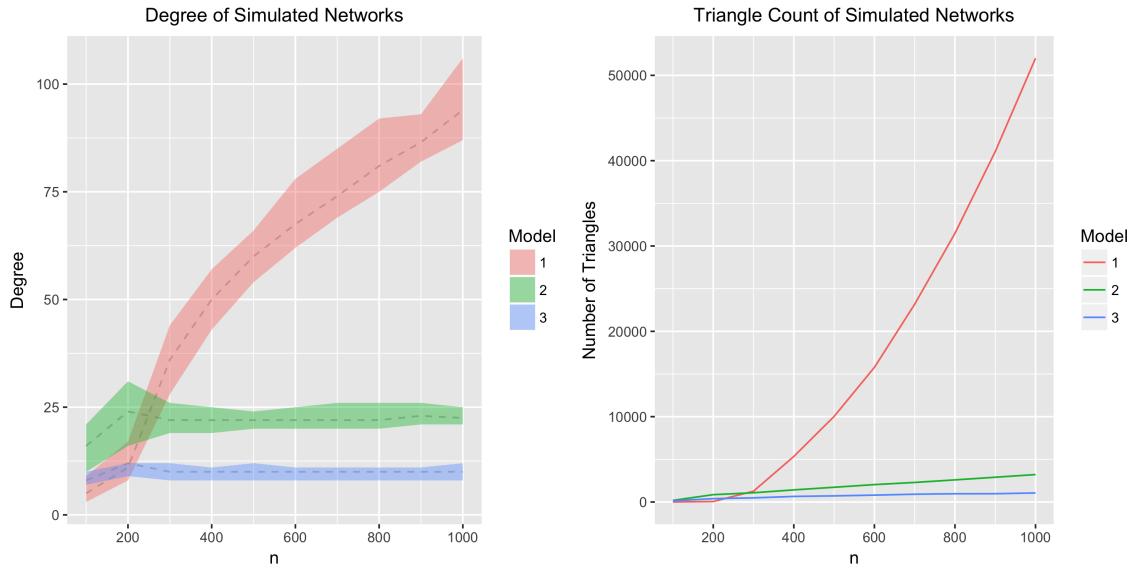
Model	$\theta_1$ (Edges)	$\theta_2$ (Stars)	$\theta_3$ (Triangles)	$\theta_4$ (Two-Paths)
1	-4.6	0.0	1.0	0.0
2	-4.6	0.0	2.0	-0.1
3	-4.6	2.0	2.0	-0.5

**Table 5.1:** Parameters of Synthetic Networks

We fix the edge parameter at  $-4.6$ , because in the absence of any other sufficient statistics this corresponds to a  $G(n, p)$  model with  $p = 1\%$ , leading to sparse networks. Then, the other parameters are chosen based on reasonable choices of these parameters from analyses

of real network data, with Model 1 constituting a simple model introducing only the alternating  $k$ -triangle parameter in addition to edges and Model 3 representing the most complex model, including all four structural parameters. In Model 2, we incorporate a two-path parameter in addition to the triangle parameter, because the small negative parameter encourages sparsity while still leading to a large number of triangles in the network. In all three models we use a positive parameter for triangles, because triangulation is one of the most distinctive structures of networks captured by ERGMs that other stochastic models of networks are unable to describe. Additionally, triangle count is one of the most difficult statistics to compute privately as it has high sensitivity relative to the scale of the statistic.

We simulate networks using the sampling method detailed in Appendix A.1 for graphs on  $n$  nodes with  $n$  ranging from 100 to 1000 in order to study networks with a range of sizes. Current standard inference methods for ERGMs generally can only handle networks of around 1000 nodes at most, hence our choice of this upper limit on the size of the networks. For each  $n$  and each model we draw 50 networks. Looking at the structure of the simulated networks indicates that the 3 models put most of their probability mass on distinctive networks. On average, networks drawn from Model 1 have edge density (proportion of possible edges present) of 6%, networks from Model 2 have average density of 1%, and networks from Model 3 average 0.5%. Further, the max degree and triangle counts of the networks vary highly between the three models:



**Figure 5.1:** Degree of simulated networks (with shading indicating max and min over the 50 samples and dashed line showing median degree) along with the mean triangle count for simulated networks.

Networks drawn from Model 1 have the highest degree and triangle count, while networks simulated from Model 2 have approximately three times as many triangles as networks from Model 3. Additionally, all three models capture more complex structures in networks than the basic  $G(n, p)$  model with  $p = 1\%$ , for which simulated networks tend to have only one tenth the number of triangles as Model 3 despite having higher edge density.

In addition to the simulated networks, we test our methods on a dataset known as the

“Faux Mesa High School Network”, which is a publicly available social network released by sociologists who studied high schools in the Southwestern United States. These researchers surveyed the entire student body of a high school and formulated a social network with 205 nodes corresponding to students (labeled with attributes like Race and Sex) and 203 undirected edges representing reported mutual friendships between students [HHB+08]. The publicly available network on which we test inference was generated by researchers by fitting an ERGM to the dataset and then releasing a network sampled from this distribution. This suggests that privacy was a concern for the underlying network data. Therefore, the synthetic network maintains the interesting structural properties of the underlying dataset. Performing inference over this dataset permits us to ask whether researchers would reach similar conclusions using our proposed differentially private inference methods as using standard non-private inference.

## Implementation

Below, we give a number of important implementation details that apply to all conducted tests:

- Code is written in the R programming language, with the procedure for sampling networks used for inference built on top of the packages `ergm` [HHB+08] and `Bergm` [CF14], which support non-private inference over ERGMS.
- In order to explore a broad parameter space and compare a variety of approaches, the experiments ran in parallel on Harvard’s Odyssey computing cluster. To speed up individual experiments (which was particularly important during initial debugging), the inference step exploited thread level parallelism on the 32-core machines.
- Unless otherwise specified, we give overall privacy budget (in terms of  $\epsilon$  and  $\delta$ ), which is evenly split between sufficient statistics needed for inference, employing the composition property of differential privacy.
- For all parameters, we specify an “uninformative” prior of  $\mathcal{N}(0, 50)$  in inference. Since parameters estimates are generally small compared to the variance of the prior, this prior has little effect on the posterior parameter estimates. It may be possible to improve performance by incorporating simple prior information, like the expected signs of parameters, about which researchers often have beliefs, which may be an interesting notion to investigate in future work.
- To obtain point estimates of fitted parameters, we take the mean of the posterior distribution over parameters, which is standard practice for Bayesian inference on ERGMs [CF11].

## 5.2 Edge-Adjacency Model

For edge-level privacy, we compare our proposed method against two alternative methods, the private bound on local sensitivity approach suggested by Lu and Miklau [LM14] and the randomized response method of Karwa et al. [KKS17], described in Section 4.3.

Since the private local sensitivity method also adds noise to sufficient statistics and then performs inference as our restricted sensitivity-based method does, we first compare the noise addition step between these methods. We find that restricted sensitivity allows for much lower noise addition, measured in terms of root-mean-square error, especially at small values of  $\epsilon$ .

Then, we evaluate how difference in perturbation of the network data impacts quality of inference. We compare the performance of differentially private inference between the three methods by looking at how close parameter estimates are to the “ground-truth” parameters. For the three synthetic networks, we take ground-truth to be the true parameters of the ERGMs from which we drew synthetic data (specified in Table 5.1) while for the Mesa high school data we learn parameters non-privately and take these to be a best guess of true parameters.

### 5.2.1 Noise Addition Comparison

#### Setup

For noise addition comparisons, we test the difference in noise added to sufficient statistics for the three synthetic network models and all values of  $n$ . We compare noise addition under restricted sensitivity with various max degree cutoffs and private local sensitivity. For each of the 50 networks of size  $n$  drawn from a model, we draw noise 50 times for each noise addition method, resulting in 2500 simulated noise draws for each  $n$ . We compute the four sufficient statistics (edges, alt- $k$ -star, alt- $k$ -triangle, and alt- $k$ -two-path) with privacy levels per-statistic of  $\epsilon = 0.025, 0.125$ , and  $0.25$  (so by the composition property of differential privacy, overall privacy budgets using the 4 statistics  $0.1, 0.5$ , and  $1$  respectively) and display results below for the largest per-statistic budget of  $\epsilon = 0.25$ . For the private bounding of local sensitivity, which can only guarantee  $(\epsilon, \delta)$ -DP, we use an overall budget of  $\delta = 10^{-6}$  so that the privacy guarantee is comparable to that of pure  $\epsilon$ -differential privacy.

Further, we test varying degree cutoffs  $k$  of the restricted degree hypothesis. Lower (more aggressive) setting of  $k$  allows for less Laplace noise to be added since the restricted sensitivity is smaller. However, if  $k$  is lower than the true degree of the network, then the projection to the space of networks of degree  $k$  requires removing edges from the network, introducing bias into the released sufficient statistics. Since mean square error is variance plus squared bias, using RMSE captures both the error from projection bias and from Laplace noise addition. Specifically, we test three choices of  $k$ :

1. Take  $k$  equal to the minimum degree over the 50 networks drawn from a given model, which may allow for low Laplace noise, but at the expense of potentially high bias induced by removing many edges.
2. Take  $k$  to be the median degree over the 50 networks, allowing relatively low scale of Laplace noise, while also introducing limited bias since the edge-level projection requires removing edges from nodes that have degree higher than  $k$  of which we expect there to be relatively few.

- Take  $k$  to be a conservative estimate of 1.5 times the maximum degree of the 50 networks drawn from a given model, which guarantees that we never under-estimate the degree of a network.

## Results

As comparison of noise in Figure 5.2 demonstrates, for  $\epsilon = 0.25$  per statistic, our proposal of scaling noise to restricted sensitivity introduces much lower error into sufficient statistics than for private bounding of local sensitivity described in Section 4.3. The difference in noise addition is larger for the sparser networks drawn from Models 2 and 3, than for networks drawn from Model 1, because the degree of these networks is lower, giving a restricted sensitivity bound closer to the local sensitivity of the statistics. Further, the scale of noise added in the private bound on local sensitivity is  $O\left(\frac{LS}{\epsilon} + \frac{\log(1/\delta)}{\epsilon^2}\right)$ , whereas restricted sensitivity adds noise scaled to  $O\left(\frac{RS}{\epsilon}\right)$  so as  $\epsilon$  gets smaller the  $\frac{1}{\epsilon^2}$ . Therefore, for smaller  $\epsilon$  the  $\frac{1}{\epsilon^2}$  term grows faster than the  $\frac{1}{\epsilon}$  term leading to even higher noise addition for private bounding of local sensitivity. Consistent with this observation, for tests run with smaller  $\epsilon$  of 0.025 and 0.125-per statistic, we observed that restricted sensitivity outperforms private local sensitivity in the amount of noise added by an even larger factor. This suggests that for smaller overall privacy budgets than  $\epsilon = 1$  or for cases where we introduce more sufficient statistics (for instance, when we want terms incorporating nodal attributes) so that we must split the privacy budget between more terms, restricted sensitivity will dominate private local sensitivity by an even larger margin.

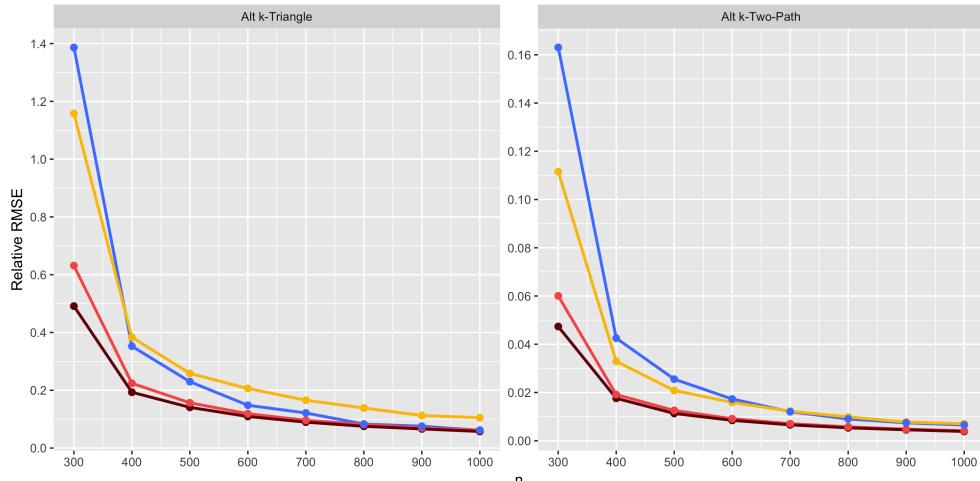
Comparing the RMSE of statistics to the true values, we observe that restricted sensitivity may permit inference in settings where the noise added by private local sensitivity would overwhelm the true statistic value. For instance, for networks with 300 nodes drawn from Model 3, the RMSE of the  $k$ -triangle statistic is over three times the value of the true statistic when noise is scaled to private local sensitivity, while restricted sensitivity adds noise under half the true statistic value. Further, we observe that as networks grow larger the error relative to the size of the network decreases, since the degree of the network remains low, while the magnitude of the sufficient statistics increases, allowing for lower noise addition relative to the magnitude of the statistics.

Comparison of the different thresholds for the degree cutoff  $k$ , suggests that even a conservative cutoff outperforms private local sensitivity. However, choosing a more aggressive cutoff leads to much lower error, indicating that the lowered variance induced by Laplace noise addition has a much larger impact on error than the bias introduced by projecting networks of degree slightly larger than  $k$  to the space of graphs with degree  $k$ . In fact, for the alternating  $k$ -triangle and the alternating  $k$ -two-path statistics, using the aggressive min  $k$  cutoff, such that the degree of all the networks is beneath the cutoff, slightly outperforms restricted median. However, this aggressive setting of the cutoff introduced more bias into the edges and alt  $k$ -star terms. While the median cutoff leads to the removal of less than 0.05% of edges in the network for all  $n$ , the min cutoff leads to the removal of around 0.3% of edges. Additional testing with a highly aggressive cutoff of 0.75(min degree) led to the removal of 7 – 8% of edges highly increasing RMSE of released private statistics. The ability to use cutoffs below the actual degree of networks while adding limited bias to computed statistics most likely arises because ERGMs tend

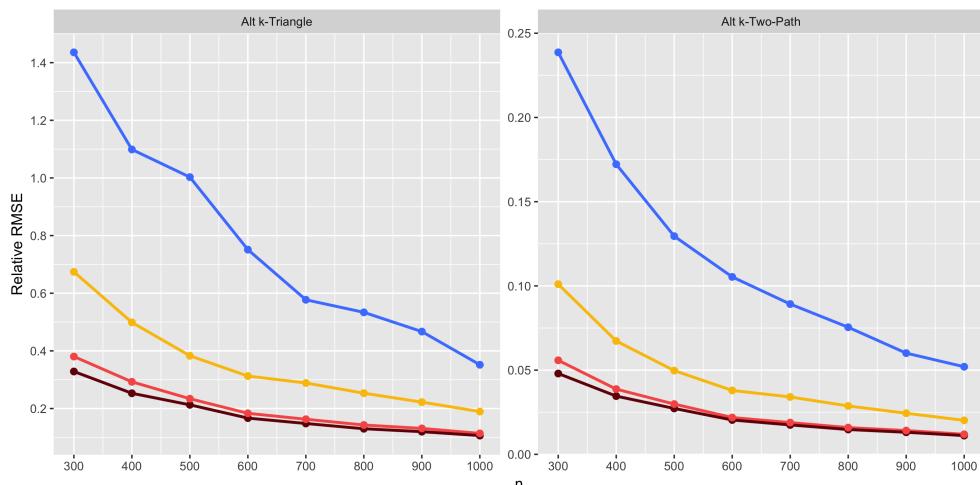
**Figure 5.2:** Comparison of Relative RMSE of edge-DP sufficient statistics released at a privacy level of  $\epsilon = 0.25$ -per statistic. Laplace noise is scaled to either a private bound on local sensitivity or to restricted sensitivity with 3 settings of degree cutoff  $k$ .

Method: ● private local ● restricted conservative ● restricted median ● restricted min

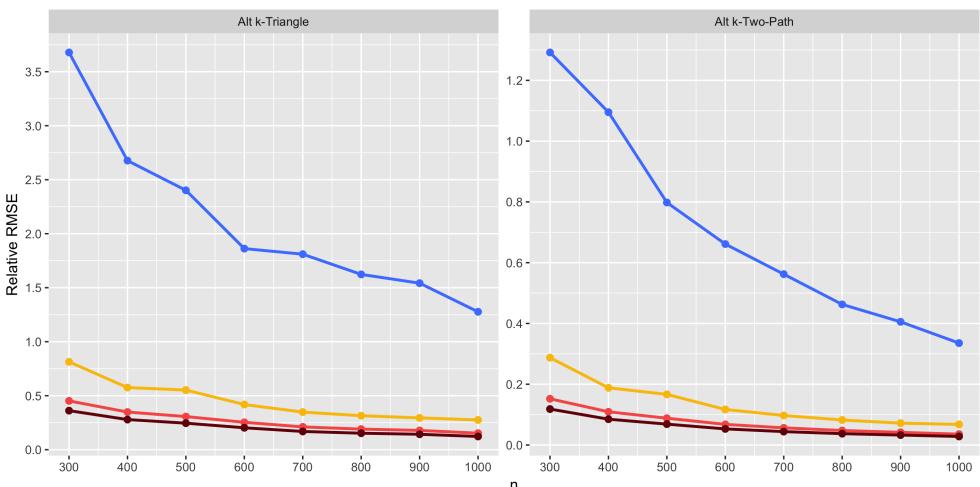
(a) Model 1



(b) Model 2



(c) Model 3



to well-capture power laws of degree distributions, such that there are relatively few nodes with degree close to the max degree. Therefore, choosing a cutoff below the max degree of the cutoff leads to the removal of only a few edges incident to these few nodes, skewing the structure of the network very little. Our comparison indicates that setting  $k$  equal to the median of all max degrees for simulated networks constitutes a good choice of  $k$ , so we use this setting of  $k$  in our inference tests.

Overall, our tests suggest that for reasonable choices of privacy budget  $\epsilon$ , restricted sensitivity introduces much lower error to sufficient statistics than privately bounding local sensitivity. Further, aggressively setting the degree cutoff  $k$  to be beneath the max degree of actual networks can decrease the overall error in privatizing network statistics.

### 5.2.2 Inference Comparison on Synthetic Networks

Next, we test how the differing approaches to perturbing the network data impact the quality of inference. We find that for small privacy budgets our proposed method outperforms randomized response and for either small privacy budgets or the use of many sufficient statistics our method outperforms private bounding of local sensitivity.

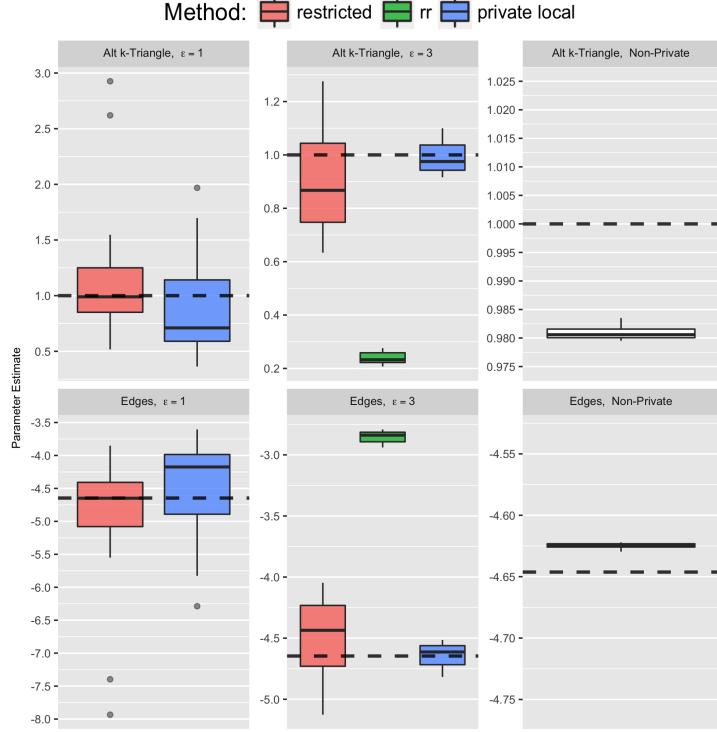
#### Setup

We test the performance of private inference on networks drawn from each of the three models with overall privacy budgets of  $\epsilon = 1$  and  $\epsilon = 3$ . Specifically, for  $N = 25$  tests of inference, we randomly choose one of the 50 networks on 300 nodes drawn from a model and run inference on this model to learn the parameters for which the model was drawn. This implies that Model 1 has the largest privacy budget per-statistics, since we split the fixed privacy budget over only the 2 statistics for Model 1 rather than 3 statistics for Model 2 and 4 statistics for Model 3. We test inference on networks of 300 nodes because private inference is expected to have higher utility on larger networks (as the amount of added noise is lower compared to the value of true statistics as shown in Figure 5.2) but running a relatively large number of tests on networks with more than 300 nodes was computationally infeasible within the scope of this work. For the small privacy budget of  $\epsilon = 1$ , the inference method using randomized response fails to converge (which is unsurprising, because this corresponds to a probability of over 25% of flipping each edge in the network, so the posterior distribution spreads probability mass over a very large range of possible networks.) Therefore, for  $\epsilon = 1$  we only report results for private local sensitivity and restricted sensitivity, while for  $\epsilon = 3$  (corresponding to a flipping probability of 5.6% in randomized response), we report results for all three methods.

#### Results

Model 1 uses only two sufficient statistics, allowing for high values of  $\epsilon$  per statistic, since the privacy budget is split between few statistics. Thus, restricted sensitivity and private local sensitivity give similarly high accuracy for  $\epsilon = 1$  as shown in Figure ???. At the large privacy budget of  $\epsilon = 3$ , private local sensitivity performs better than restricted sensitivity, although both have very low KL-divergence and mean absolute error comparable to

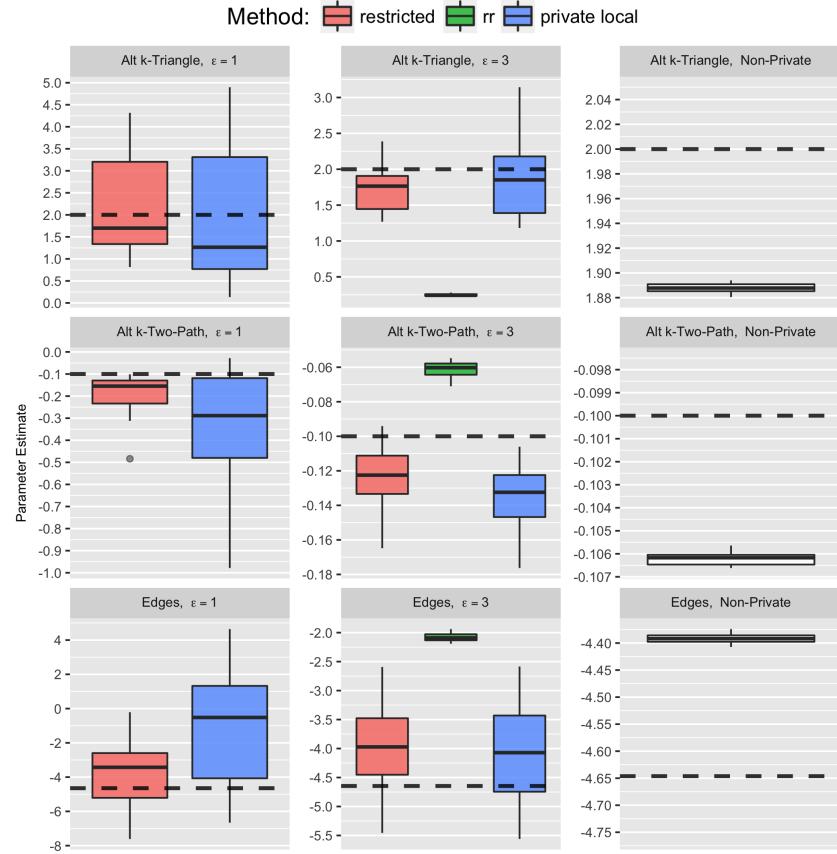
**Figure 5.3:** Differentially private parameter estimates for 300 node synthetic networks drawn from *Model 1*. The dotted black line denotes ground-truth parameter values.



non-private inference. In contrast, randomized response performs much worse than the two other methods, which is not surprising because for  $\epsilon = 3$ , randomized response has a probability of flipping each edge of 4.7%, which may heavily distort network structure considering that networks drawn from model 1 only have edge density of 6%.

For Models 2 and 3, restricted sensitivity outperforms both restricted sensitivity and private local sensitivity. For Model 3, which uses all 4 sufficient statistics, we observe that at  $\epsilon = 1$ , private local sensitivity cannot perform useful inference, as the average bias of parameter estimates is over 2 times the value of the parameters. However, using restricted sensitivity allows for useful parameter estimates, with relative MAEs well under 1. Additionally, as the number of parameters increases (from Model 1 to 3) we can observe that randomized response becomes more competitive with the other approaches. This is due to the fact that randomized response does not require splitting a privacy budget between parameters, so its performance is not strongly affected by the number of parameters in the model. Meanwhile, as noted in Section 4.3 private local sensitivity grows with a factor of  $\frac{1}{\epsilon^2}$  for each statistic so as the privacy budget per-parameter gets smaller, the performance of private bounding of local sensitivity is significantly degraded. In contrast to private local sensitivity, then, our proposed method using restricted sensitivity allows for a larger number of parameters to be utilized in the model, while using small privacy budgets.

**Figure 5.4:** Parameter estimates for 300 node synthetic networks drawn from *Model 2*.



### 5.2.3 Inference Comparison on Mesa High School Network

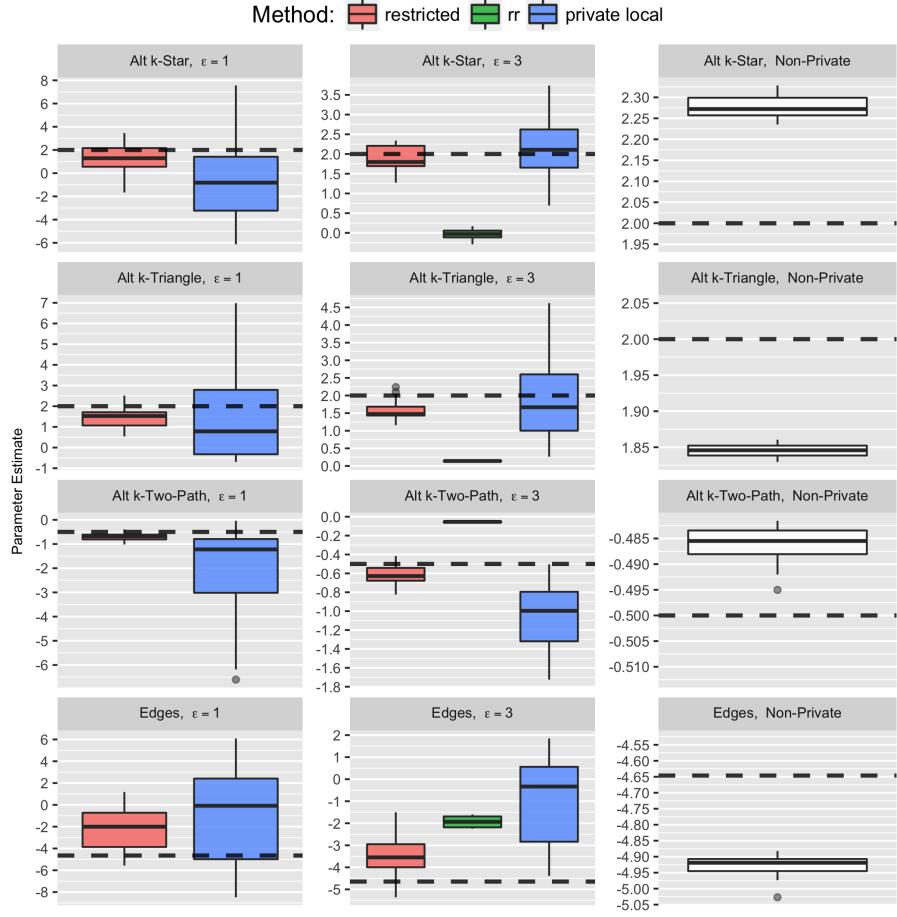
#### Setup

To test the performance of inference on network data representative of datasets analyzed by researchers, we apply the three private inference approaches to the Mesa High School Friend Network. We run 25 tests of inference for each method and  $\epsilon \in \{1, 2, 3, 4\}$ . Based on models used to study high school friendship networks in the published literature on the subject [GKM09] as well as the models used for non-private inference on this particular network [HHB+08] we fit the a model to the data, incorporating ‘Sex’ labels on nodes. In particular, we look at both the four alternating structural statistics as well as measures of popularity by sex and overall homophily by sex. In this section, we consider labels to be public in line with previously proposed methods, so the sufficient statistics using nodal attributes have low global sensitivity as specified in Table 4.2.

#### Results

As shown in Figure ??, by KL-divergence restricted sensitivity strongly outperforms private local sensitivity, with median KL divergence ten times lower than for private local sensitivity at all  $\epsilon$ . The parameter estimates from private local sensitivity tend to be wildly off from the non-private estimates as the amount of added noise is larger than the sufficient

**Figure 5.5:** Parameter estimates for 300 node synthetic networks drawn from *Model 3*.



statistics. This demonstrates one of the major shortcomings of private local sensitivity: it performs poorly for small values of  $\delta$  and  $\epsilon$ , so splitting privacy budget between many sufficient statistics leads to large degradation in utility. Randomized response performs significantly worse than restricted sensitivity in terms of KL-divergence, but has lower variance of KL-divergence. We hypothesize that randomized response is more consistent over many iterations, because the flipping of edges with high probability effectively makes the network resemble a  $G(n, p)$  network by removing triangles and two-paths, such that the networks consistently converge to a similar model, while restricted sensitivity perturbs the sufficient statistics so may sometimes lead to more or fewer triangles or  $k$ -stars in the network.

In Figure 5.2 we display “typical” test runs, by looking at the parameter estimates for the test runs with the median KL divergence among all tests, for restricted sensitivity with  $\epsilon = 2$  and for randomized response with  $\epsilon = 3$ . These results suggests that randomized response may overwhelm interesting structures in the network, while restricted sensitivity preserves the basic conclusions about network structure. Indeed, the parameter estimates for all of the structural parameters using randomized response are not significantly different from 0. In contrast, the alternating sufficient statistics maintain the correct sign and triangulation is statistically significant for non-private inference using restricted sensitivity as it is under non-private inference. In general, standard errors are larger for

**Table 5.2:** Parameter values and standard errors for typical test run (test with median KL divergence) on Mesa High School Friend Network Data.

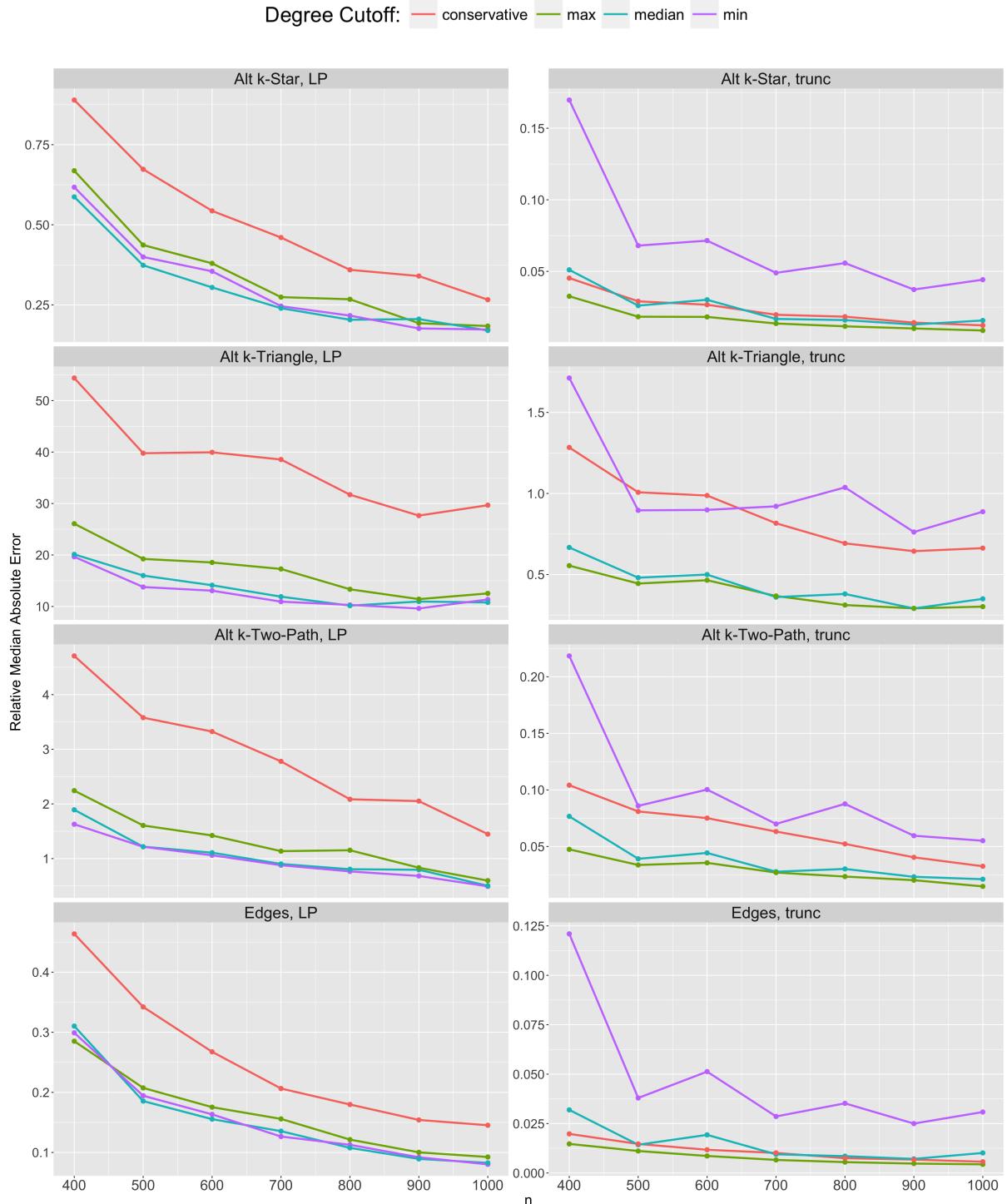
Parameter	Non-Private	Restr. Sensitivity ( $\epsilon = 2$ )	Rand. Response ( $\epsilon = 3$ )
Edges	-4.398 (0.35)	-4.577 (0.95)	-2.213 (2.23)
Popularity (Female)	-0.436 (0.35)	-0.545 (0.98)	-0.708 (1.23)
Popularity (Male)	-0.663 (0.34)	-0.552 (0.74)	-0.789 (1.22)
Homophily (Sex)	0.369 (0.12)	0.677 (0.47)	0.028 (0.07)
Alt $k$ -Star	-0.094 (0.34)	-0.20 (0.48)	-0.094 (1.22)
Alt $k$ -Triangle	1.485 (0.14)	2.532 (0.24)	-0.023 (0.03)
Alt $k$ -Two-Path	-0.036 (0.04)	-0.33 (0.07)	0.046 (0.01)

private inference than for non-private inference, which demonstrates that our inference is accounting for the increased uncertainty in parameter estimates due to the perturbation of the privacy mechanism. Randomized response leads to much higher standard errors than restricted sensitivity, because the high perturbation probability on edges leads to high variance in the potential true network data. Overall, the typical parameter estimates, suggest that restricted sensitivity permits researchers to reach similar conclusions under private and non-private inference, while randomized response for even the large privacy budget of  $\epsilon = 3$  introduces both high bias and high uncertainty in parameter estimates.

### 5.3 Edge-Adjacency Model with Private Labels

### 5.4 Node-Adjacency Model

**Figure 5.6:** Comparison of Relative Median Absolute Error of node-DP sufficient statistics released at a privacy level of  $\epsilon = 0.5$ -per statistic for networks from *Model 1*. Cauchy noise is scaled to the restricted sensitivity times a  $\beta$ -smooth bound on the local sensitivity of projection. Projection using an LP is shown on the left and using node truncation is shown on the right



# Chapter 6: Conclusion

Future Work:

1. Synthetic data??? Low KL-divergence suggests that drawing data using the parameters we learned maintain structure of the original network. Currently, graphs are drawn from non-private learned parameters to provide privacy for network data indicating that this is a promising approach for releasing synthetic networks, but systematic study is needed.
2. Testing node-level privacy on larger networks.
3. Adapting more scalable inference methods to take into account the privacy mechanism. To date, Karwa et. al has proposed MLE estimation and we use Bayesian inference, but there are much more efficient methods based on correcting a pseudo-posterior – could these be used (scalability would be very helpful here)
4. Directed networks.

# References

- [AGZF09] E. M. Airoldi, A. Goldenberg, A. Zheng, and S. Fienberg, “A survey of statistical network models”, eng, *Machine Learning -Boston-*, vol. 2, no. 2, 2009, ISSN: 0885-6125.
- [BDK11] L. Backstrom, C. Dwork, and J. Kleinberg, “Wherefore art thou r3579x?: Anonymized social networks, hidden patterns, and structural steganography”, eng, *Communications of the ACM*, vol. 54, no. 12, pp. 133–141, Dec. 2011, ISSN: 0001-0782.
- [BK14] L. Backstrom and J. Kleinberg, “Romantic partnerships and the dispersion of social ties: A network analysis of relationship status on facebook”, eng, in *Proceedings of the 17th ACM conference on computer supported cooperative work & social computing*, ser. CSCW ’14, ACM, Feb. 2014, pp. 831–841.
- [BBDS13] J. Blocki, A. Blum, A. Datta, and O. Sheffet, “Differentially private data analysis of social networks via restricted sensitivity”, eng, in *Proceedings of the 4th conference on innovations in theoretical computer science*, ser. ITCS ’13, ACM, Jan. 2013, pp. 87–96.
- [BFM17] L. Bouranis, N. Friel, and F. Maire, “Efficient bayesian inference for exponential random graph models by correcting the pseudo-posterior distribution”, *Social Networks*, vol. 50, pp. 98–108, 2017, ISSN: 0378-8733. DOI: <https://doi.org/10.1016/j.socnet.2017.03.013>. [Online]. Available: <http://www.sciencedirect.com/science/article/pii/S0378873315301489>.
- [CF11] A. Caimo and N. Friel, “Bayesian inference for exponential random graph models”, eng, *Social Networks*, vol. 33, no. 1, pp. 41–55, 2011, ISSN: 0378-8733.
- [CF14] ———, “Bergm: Bayesian exponential random graphs in r”, *Journal of Statistical Software*, vol. 61, no. 2, pp. 1–25, 2014. [Online]. Available: <http://www.jstatsoft.org/v61/i02/>.
- [DLL16] W.-Y. Day, N. Li, and M. Lyu, “Publishing graph degree distribution with node differential privacy”, in *SIGMOD Conference*, 2016.
- [DMNS06] C. Dwork, F. Mcsherry, K. Nissim, and A. Smith, “Calibrating noise to sensitivity in private data analysis”, in *Proceedings of the 3rd Theroy of Cryptography Conference*, Springer, 2006, pp. 265–284.
- [FGWC16] J. Foulds, J. Geumlek, M. Welling, and K. Chaudhuri, “On the theory and practice of privacy-preserving bayesian data analysis”, Mar. 2016.
- [FS86] O. Frank and D. Strauss, “Markov graphs”, *Journal of the American Statistical Association*, vol. 81, Sep. 1986, ISSN: 0162-1459.
- [GL06] D. Gamerman and H. Lopes, *Markov chain Monte Carlo: stochastic simulation for Bayesian inference*, eng. Jan. 2006, pp. xvii–xvii.

- [GKM09] S. M. Goodreau, J. A. Kitts, and M. Morris, “Birds of a feather, or friend of a friend?: Using exponential random graph models to investigate adolescent social networks”, *Demography*, vol. 46, no. 1, pp. 103–125, 2009.
- [Han03] M. S. Handcock, “Assessing degeneracy in statistical models of social networks”, Tech. Rep., Dec. 2003, Working Paper no. 39, Center for Statistics and the Social Sciences, University of Washington, Seattle.
- [HG10] M. S. Handcock and K. J. Gile, “Modeling social networks from sampled data”, eng, *Ann. Appl. Stat.*, vol. 4, no. 1, pp. 5–25, Mar. 2010.
- [HLMJ09] M. Hay, C. Li, G. Miklau, and D. Jensen, “Accurate estimation of the degree distribution of private networks”, eng, IEEE Publishing, Dec. 2009, pp. 169–178.
- [HH06] D. R. Hunter and M. S. Handcock, “Inference in curved exponential family models for networks”, eng, *Journal of Computational and Graphical Statistics*, vol. 15, no. 3, pp. 565–583, Sep. 2006.
- [HHB+08] D. R. Hunter, M. S. Handcock, C. T. Butts, S. M. Goodreau, and M. Morris, “Ergm: A package to fit, simulate and diagnose exponential-family models for networks”, *Journal of Statistical Software*, vol. 24, no. 3, pp. 1–29, 2008.
- [JM09] C. Jernigan and B. Mistree, “Gaydar: Facebook friendships expose sexual orientation”, *First Monday*, vol. 14, no. 10, 2009.
- [Jon99] J. Jonasson, “The random triangle model”, eng, *Journal of Applied Probability*, vol. 36, no. 3, pp. 852–867, Sep. 1999.
- [KKS17] V. Karwa, P. N. Krivitsky, and A. B. Slavkovic, “Sharing social network data: Differentially private estimation of exponential family random graph models”, *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, vol. 66, no. 3, pp. 481–500, Apr. 2017.
- [KRSY14] V. Karwa, S. Raskhodnikova, A. Smith, and G. Yaroslavtsev, “Private analysis of graph structure”, eng, *ACM Transactions on Database Systems (TODS)*, vol. 39, no. 3, pp. 1–33, Oct. 2014.
- [KS16] V. Karwa and A. Slavkovic, “Inference using noisy degrees: Differentially private  $\beta$ -model and synthetic graphs”, eng, *Annals of Statistics*, vol. 44, no. 1, Feb. 2016.
- [KNRS13] S. P. Kasiviswanathan, K. Nissim, S. Raskhodnikova, and A. Smith, “Analyzing graphs with node differential privacy”, in *Theory of Cryptography*, A. Sahai, Ed., Berlin, Heidelberg: Springer Berlin Heidelberg, 2013, pp. 457–476.
- [LM14] W. Lu and G. Miklau, “Exponential random graph estimation under differential privacy”, eng, in *Proceedings of the 20th ACM SIGKDD international conference on knowledge discovery and data mining*, ACM, Aug. 2014, pp. 921–930.
- [LKR12] D. Lusher, J. Koskinen, and G. Robins, *Exponential Random Graph Models for Social Networks : Theory, Methods, and Applications*. Cambridge: Cambridge University Press, 2012.
- [MT07] F. Mcsherry and K. Talwar, “Mechanism design via differential privacy”, eng, IEEE, Oct. 2007, pp. 94–103.

- [MW12] D. Mir and R. Wright, “A differentially private estimator for the stochastic kronecker graph model”, eng, in *Proceedings of the 2012 Joint EDBT/ICDT Workshops*, ser. EDBT-ICDT ’12, ACM, Mar. 2012, pp. 167–176.
- [MGM12] I. Murray, Z. Ghahramani, and D. MacKay, “Mcmc for doubly-intractable distributions”, Jun. 2012.
- [NSR11] A. Narayanan, E. Shi, and B. I. P. Rubinstein, “Link prediction by de-anonymization: How we won the kaggle social network challenge”, Feb. 2011.
- [NS09] A. Narayanan and V. Shmatikov, “De-anonymizing social networks”, in *Proceedings of the 2009 30th IEEE Symposium on Security and Privacy*, ser. SP ’09, Washington, DC, USA: IEEE Computer Society, 2009, pp. 173–187.
- [NRS07] K. Nissim, S. Raskhodnikova, and A. Smith, “Smooth sensitivity and sampling in private data analysis”, eng, in *Proceedings of the thirty-ninth annual ACM symposium on theory of computing*, ser. STOC ’07, ACM, Jun. 2007, pp. 75–84.
- [NSW+17] K. Nissim *et al.*, “Differential privacy : A primer for a nontechnical audience”, 2017.
- [RAS10] E. Roland, B. Alla, and B. Svetlana, “Bayesian statistical modelling of human protein interaction network incorporating protein disorder information”, eng, *BMC Bioinformatics*, vol. 11, no. 1, Jan. 2010.
- [RCC18] M. Rosenberg, N. Confessore, and C. Cadwalladr, *How trump consultants exploited the facebook data of millions*, Mar. 2018. [Online]. Available: <https://www.nytimes.com/2018/03/17/us/politics/cambridge-analytica-trump-campaign.html>.
- [SDC+16] M. R. Sinke, R. M. Dijkhuizen, A. Caimo, C. J. Stam, and W. M. Otte, “Bayesian exponential random graph modeling of whole-brain structural networks across lifespan”, eng, *NeuroImage*, vol. 135, pp. 79–91, Jul. 2016.
- [SPRH06] T. Snijders, P. Pattison, G. Robins, and M. Handcock, “New specifications for exponential random graph models”, eng, *Sociological Methodology*, vol. 36, pp. 99–153, Jan. 2006.
- [UHH13] S. Uddin, J. Hamra, and L. Hossain, “Exploring communication networks to understand organizational crisis using exponential random graph models”, eng, *Computational and Mathematical Organization Theory*, vol. 19, no. 1, pp. 25–41, Mar. 2013.
- [WWZX12] Y. Wang, X. Wu, J. Zhu, and Y. Xiang, “On learning cluster coefficient of private networks”, *2012 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining*, pp. 395–402, 2012.
- [War65] S. L. Warner, “Randomized response: A survey technique for eliminating evasive answer bias”, *Journal of the American Statistical Association*, vol. 60, no. 309, pp. 63–69, Mar. 1965.
- [WP96] S. Wasserman and P. Pattison, “Logit models and logistic regressions for social networks”, eng, *Psychometrika*, vol. 61, no. 3, pp. 401–425, Sep. 1996.

# Appendix A: MCMC Methods for Bayesian Inference over ERGMs

## A.1 Simulating Networks from an ERGM

First, we describe a simple MCMC method for simulating networks from an ERGM given parameters of the model. This method is used both to generate synthetic graphs in our experiments and to draw samples needed for inference.

---

**Algorithm 3** Metropolis-Hastings Sampler for ERGMs

---

Input: parameter vector  $\theta$ , initial graph  $x^{(0)}$ , number of iterations  $T$   
Output: sequence of graphs  $x^{(1)}, \dots, x^{(T)}$  such that  $x^{(T)} \sim p(X|\theta)$  as  $T \rightarrow \infty$

For  $t = 1, \dots, T$ :

1. Select nodes  $i$  and  $j$  at random
  2. Propose graph  $x^*$  which is the same as  $x^{(t-1)}$  except that we “toggle” the edge between  $i$  and  $j$  so  $x_{ij}^* = 1 - x_{ij}^{(t-1)}$
  3. Accept the proposed move with probability  $\min\left\{1, \frac{p(x^*|\theta)}{p(x^{(t-1)}|\theta)}\right\}$ . If the move is accepted set  $x^{(t)} = x^*$ . Otherwise, set  $x^{(t)} = x^{(t-1)}$
- 

The acceptance ratio (assuming all pairs of nodes are chosen with equal probability) is just  $\exp\{\theta^T(u(x^*) - u(x^{(t-1)}))\}$ . As the difference in sufficient statistics between two graphs differing in an edge (known as the “change statistic”) is typically a simple function of the nodes participating in that edge, this ratio is easy to compute (for instance, for the edges sufficient statistic, it is always just 1 if adding an edge and  $-1$  if removing).

If an ERGM specification puts most of its probability mass on relatively sparse graphs, the sampler that proposes all pairs of nodes with equal probability in step 1 will reject the addition of an edge in most steps, leading to slow convergence. Therefore, Tie-No-Tie (TNT) sampling is generally used in step 1, where we first select either the set of edges or the set of non-edges with equal probability and then pairs of nodes are selected uniformly at random from within the chosen set, biasing step 1 to consider removing edges more frequently than adding (and accounting for the non-uniform proposal distribution in the acceptance ratio). Therefore, throughout this thesis we use TNT sampling to efficiently draw samples from ERGMs. [LKR12]

## A.2 Population MCMC Version of the Exchange Algorithm

The basic exchange algorithm for Bayesian inference over ERGMs can be easily modified to take advantage of population MCMC methods, which tend to converge faster, since using various chains reduces temporal dependency between time-steps in the Markov Chain. In particular, Caimo and Friel propose using parallel ADS, which maintains a collection of  $H$  chains that interact with one another.

---

**Algorithm 4** Non-Private Bayesian Inference for ERGMs (Parallel ADS) [CF11]

---

Input: ERGM distribution  $\pi(X|\theta)$ , prior  $p(\theta)$ , observed graph  $x_{obs}$ , number of chains to use  $H$ , tuning parameter  $\gamma$ .

Output: sequence of draws  $(\theta_1^{(r)}, \dots, \theta_1^{(T)}), \dots, (\theta_H^{(r)}, \dots, \theta_H^{(T)})$  from posterior distributions  $p(\theta_h|x_{obs})$ .

For  $t = 1, \dots, T$ :

For each chain  $h = 1, \dots, H$ :

1. Select at random two different chains  $h_1$  and  $h_2$  from  $\{1, \dots, H\} \setminus h$
2. Propose  $\theta_h^* = \theta_h^{(t-1)} + \gamma (\theta_{h_1}^{(t-1)} - \theta_{h_2}^{(t-1)}) + \epsilon$   
where  $\epsilon$  is random noise drawn from a symmetric distribution, such as a Normal.
3. Sample graph  $x_h^* \sim \pi(\cdot | \theta_h^*)$
4. Accept the proposed move with probability  $\min\{1, \alpha\}$ . If the move is accepted, set  $\theta_h^{(t)} = \theta_h^*$ . Otherwise, set  $\theta_h^{(t)} = \theta_h^{(t-1)}$

where

$$\alpha = \frac{p(\theta_h^*)}{p(\theta_h^{(t-1)})} \exp \left\{ \left( \theta_h^* - \theta_h^{(t-1)} \right)^T (u(x_{obs}) - u(x_h^*)) \right\}$$


---

The MH acceptance ratio remains the same as in the single-site update, because the proposal distribution is still symmetric – making the reverse jump from  $\theta_h^*$  to  $\theta_h^{(t-1)}$  simply requires reversing  $\epsilon$  and the order of  $h_1$  and  $h_2$ . The tuning parameter  $\gamma$  controls the amount of interaction between chains and is generally taken to be in the range 0.5 and 1 (in this case we take  $\gamma = 0.5$  throughout.) Additionally, the number of chains to use can be tuned in inference, but we choose to use 3 chains throughout as this seems to lead to fast convergence.

## Appendix B: Smooth Projections to $\mathcal{H}_k$

### B.1 Edge-Adjacency Model

Blocki et al. give an efficient projection to  $\mathcal{H}_k$  in the edge-adjacency model with  $GS_\mu = 3$  [BBDS13]:

---

**Algorithm 5** 3-smooth Projection to  $\mathcal{H}_k$  for Edge-Adjacency Model

---

Input: graph  $G$ , cutoff  $k$

Output: graph  $\mu(G)$  with max degree  $k$

1. Fix a canonical ordering over all possible edges in a graph on  $n$  vertices. Let  $e_1^v \dots e_t^v$  denote the edges incident to vertex  $v$  in this canonical ordering.
  2. Delete edge  $e = (u, v)$  if and only if:
    - (i)  $e = e_j^v$  for  $j > k$ , or
    - (ii)  $e = e_j^u$  for  $j > k$
- 

Intuitively, we keep only the first  $k$  edges in the canonical ordering for any node with degree above  $k$ . It is clear, then, that this algorithm results in a graph of max degree  $k$  and that any graph where all nodes have degree less than  $k$  are unchanged. The global sensitivity follows fairly straightforwardly. Consider two graphs  $G_1$  and  $G_2$  that are neighbors differing on a single edge  $e = (x, y)$  where wlog  $G_1$  contains  $e$ . Then, for every vertex that is not  $x$  or  $y$ , exactly the same set of edges is deleted, since  $e$  does not appear in any other nodes' canonical ordering. If  $e$  is deleted, then  $\mu(G_1) = \mu(G_2)$ . However, if  $e$  is not deleted than there may be at most one edge incident to  $x$  and one edge incident to  $y$  that were deleted from  $\mu(G_1)$  but not  $\mu(G_2)$ , so the neighboring graphs differ in 3 edges. In practice, since this algorithm deletes edges from high degree nodes, it may not bias results too extensively to aggressively estimate  $k$  for a graph, as this will only mark edges for deletion on a few nodes that are above the cutoff. However, choosing a cutoff that is too low may remove many edges from many high degree nodes, which will bias not only the number of edges, but also many other sub-graph counts like triangles  $k$ -stars, which we explore in our experimental results.

## B.2 Node-Adjacency Model

### Naive Truncation

The naive truncation projection  $\mu_{trunc} : \mathcal{G}_n \rightarrow \mathcal{H}_k$  proposed by Kasiviswanathan et. al. simply removes all nodes from the graph with degree above the cutoff  $k$  [KNRS13]. It is clear, then, that  $\mu_{trunc}$  maps any graph in  $\mathcal{H}_k$  to itself and that its image is  $\mathcal{H}_k$ . Moreover,  $\mu_{trunc}$  is quite efficient, requiring  $O(n + \binom{n}{2})$  time. It is also fairly simple to characterize the smooth sensitivity of  $\mu_{trunc}$ . First, note that the local sensitivity of  $\mu_{trunc}$  on graph  $G$  is  $1 + D_k(G) + D_{k+1}(G)$  where  $D_i$  is the number of nodes of degree  $i$  in graph  $G$  since rewiring one node in the graph may affect whether all nodes of degree  $k$  or  $k+1$  are truncated by  $\mu_{trunc}$ . We can characterize the smooth sensitivity as follows:

**Proposition B.1** (Smooth Sensitivity of  $\mu_{trunc}$  [KNRS13]). Given graph  $G$  and hypothesis  $\mathcal{H}_k$ , let  $N_t(G)$  denote the number of nodes with degrees in the range  $[k-t, k+t+1]$  and let  $C_t = 1 + t + N_t(G)$ . Then:

1. The local sensitivity of  $\mu_{trunc}$  is  $C_0(G)$ .
2. The local sensitivity at distance  $t$  of  $\mu_{trunc}$  is  $C_{t-1}(G)$ .
3. The  $\beta$ -smooth sensitivity of  $\mu_{trunc}$  is  $\max_{t \geq 0} e^{-\beta t} C_t(G)$ .
4. If  $N_{\ln n/\beta}(G) \leq \ell$ , so there are at most  $\ell$  nodes in  $G$  with degree in range  $k \pm (\ln n/\beta)$ , then

$$S_{\mu,\beta}^*(G) \leq 1 + \ell + \frac{1}{\beta}$$

Thus, we can compute  $\beta$ -smooth sensitivity efficiently using either part 3 or 4 of the above proposition. Notice that even if a graph is in  $\mathcal{H}_k$ , it may have high smooth sensitivity if it has many nodes with degree close to the cutoff  $k$ . However, part 4 gives a guideline for choosing a conservative cutoff  $k$ . In particular, by choosing  $k$  to be  $\ln n/\beta$  above what is thought to be the max degree of the graph, then the smooth sensitivity would simply be 1. This is not an unreasonable quantity to add to the cutoff, if the cutoff is itself  $O(\log n)$ , which is often the case. Further, degree distributions are often thought to fall exponentially, so that it is unlikely that there are very many nodes with degree near the cutoff, especially if a conservative cutoff is chosen, suggesting that  $\ell$  might be quite low, even for cutoffs close to the believed cutoff  $k$ .

### LP-Based Projection

Blocki et al. propose a projection using linear programming. Their method satisfies a relaxed definition of a projection, where  $\mu_{LP} : \mathcal{G}_n \rightarrow \mathcal{H}_{2k}$  and  $\forall G \in \mathcal{H}_k, \mu(G) = G$ , (but graphs in  $\mathcal{H}_k$  are not necessarily mapped to themselves). Because the image is  $\mathcal{H}_{2k}$ , their method requires calibrating the restricted sensitivity to  $\mathcal{H}_{2k}$ . However, in contrast to

naive truncation, their approach guarantees that graphs in  $\mathcal{H}_k$  always have low smooth sensitivity, because their algorithm outputs an estimator of the distance between a graph and its projection, used to compute a  $\beta$ -smooth upper bound, where the distance estimator is always 0 for graphs in  $\mathcal{H}_k$ .

The algorithm is also less efficient than naive truncation as it requires solving a linear program with  $n + \binom{n}{2}$  decision variables: a variable  $x_u$  per node  $u$  representing whether node  $u$  should be removed from the projected graph or not and a variable  $w_{u,v}$  per edge  $(u, v)$  representing whether the edge from  $u$  to  $v$  remains in the projected graph:

---

**Algorithm 6** Projection and 4-Smooth Distance Estimator to  $\mathcal{H}_{2k}$  for Node-Adjacency Model [BBDS13]

---

Input: graph  $G$ , cutoff  $k$

Output: graph  $\mu_{LP}(G)$  with max degree  $2k$ , 4-smooth estimate of distance from graph to its projection  $\hat{d}(G)$

1. Solve the following LP to get fractional solution  $(\bar{x}^*, \bar{w}^*)$ . Let there be  $n$  decision variables  $x_u$ , one for each vertex, and  $\binom{n}{2}$  decision variables  $w_{u,v}$  one for each potential edge. Additionally, let  $a_{uv} = 1$  if the edge  $\{u, v\}$  is in  $G$  and 0 otherwise. Then, solve the following LP:

$$\begin{aligned} \min \sum_{v \in V} x_v \quad & s.t. \\ (1) \quad & \forall v, x_v \geq 0 \\ (2) \quad & \forall u, v, w_{u,v} \geq 0 \\ (3) \quad & \forall u, v, a_{uv} \geq w_{uv} \geq a_{uv} - x_u - x_v \\ (4) \quad & \forall u, \sum_{v \neq u} w_{u,v} \leq k \end{aligned}$$

2. Let  $\mu_{LP}(G)$  be the graph resulting from removing every edge in  $G$  for which either endpoint has weight greater than  $\frac{1}{4}$ , so either  $x_u^* > \frac{1}{4}$  or  $x_v^* > \frac{1}{4}$  for edge  $(u, v)$ .
  3. Define distance estimator to be  $\hat{d}(G) = 4 \sum_u x_u^*$ .
- 

It is clear that if  $G \in \mathcal{H}_k$ , then the algorithm will return a distance estimator of 0 and  $\mu_{LP}(G) = G$ , since we can take all  $x_v$  to be equal to 0,  $w_{uv} = a_{uv}$  so that conditions 1 to 3 of the LP are met and condition 4 is met because all vertices have degree less than  $k$ . Using the distance estimator gives a  $\beta$ -smooth upper bound on the local sensitivity of  $\mu_{LP}$ :

**Proposition B.2** (Smooth Sensitivity of  $\mu_{LP}$  [BBDS13]). The smooth sensitivity of  $\mu_{LP}$  can be bounded by

$$S_{\mu, \beta}(G) \leq \exp \left\{ \frac{\beta}{4} \hat{d}(G) \right\} \cdot g \left( \frac{\beta}{4} \right)$$

where

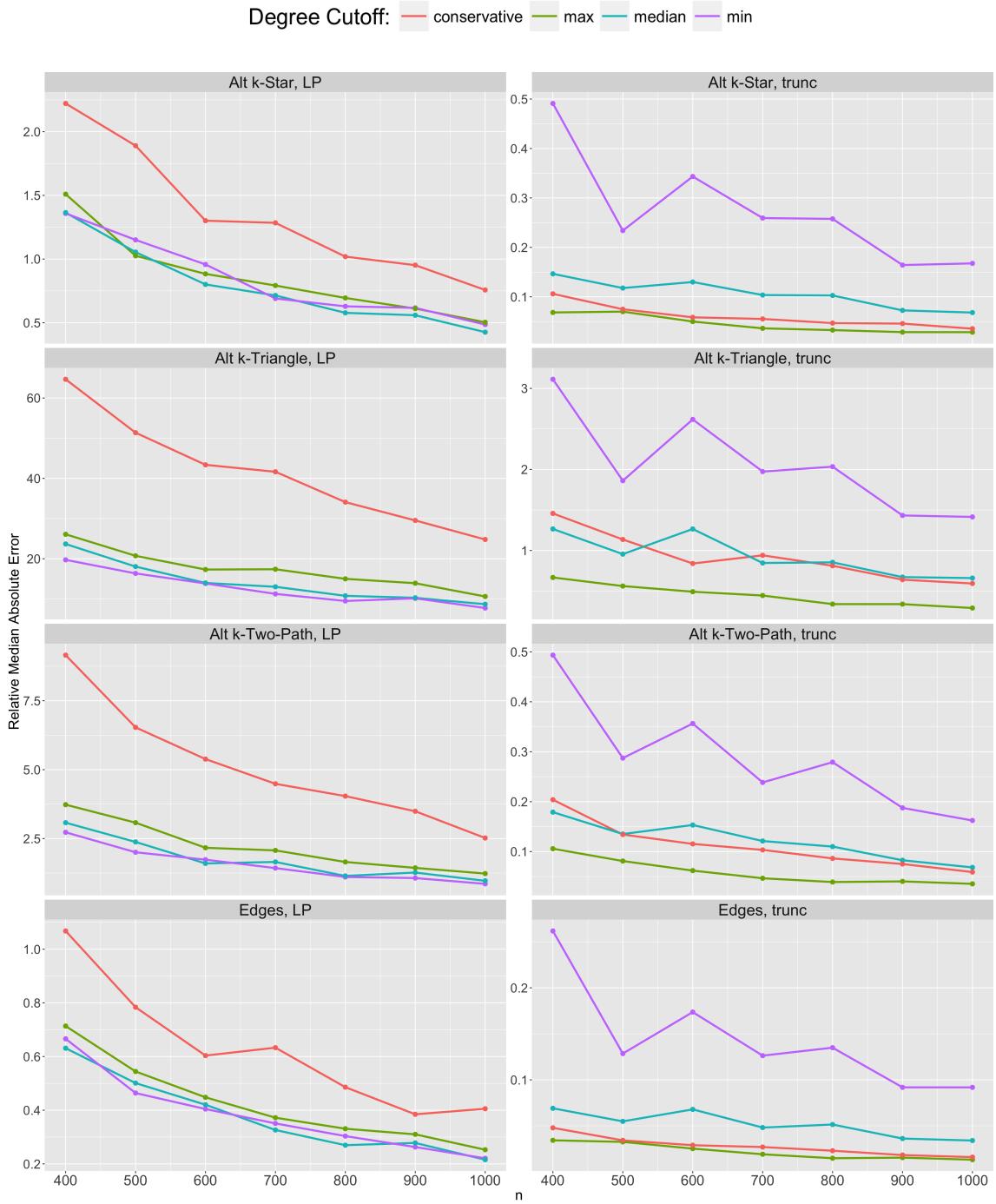
$$g(x) = \begin{cases} \frac{2}{x} e^{-1+\frac{5}{2}x}, & 0 \leq x \leq \frac{2}{5} \\ 5, & x > \frac{2}{5} \end{cases}$$

so  $S_{\mu,\beta}(G)RS_f(\mathcal{H}_{2k})$  is a  $\beta$ -smooth upper bound on the local sensitivity of  $f \circ \mu_{LP}$  on graph  $G$ .

Comparing the two proposed methods, it is preferable to use naive truncation in cases where we believe  $k \geq \ln n/\beta$ , because then setting the cutoff to be  $\hat{k} = k + \ln n/\beta$ , we expect smooth sensitivity of  $\mu_{trunc}$  to be below  $1 + \frac{1}{\beta}$  and the restricted sensitivity will be lower than  $RS_f(\mathcal{H}_{2k})$ . In general, since we believe the graphs under consideration to have very few high degree nodes close to the cutoff, we expect naive truncation to perform quite well, since the smooth sensitivity should be relatively low for the graphs considered, while considering restricted sensitivity on  $\mathcal{H}_{2k}$  may introduce more noise.

## Appendix C: Additional Empirical Results

**Figure C.1:** Comparison of Relative Median Absolute Error of node-DP sufficient statistics released with  $\epsilon = 0.5$ -per statistic and Cauchy noise addition for networks from *Model 2*.



**Figure C.2:** Comparison of Relative Median Absolute Error of node-DP sufficient statistics released with  $\epsilon = 0.5$ -per statistic and Cauchy noise addition for networks from *Model 3*.

