Perils of Location Tracking? Personalized and Interpretable Privacy Preservation in Consumer Mobile Trajectories

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Consumer location tracking is becoming omnipresent on mobile devices, producing vast volumes of behavior-rich location trajectory data. These data have enabled a wide range of opportunities for monetization, such as location-based targeting. An advertiser, however, could either use the acquired location data to play the role of a "butler" who understands consumer needs and provides valuable personalized services, or goes overboard with marketing campaigns and misuses the location data by invading consumer privacy and becoming a real-life "stalker". This calls attention for regulatory bodies and location data collectors, such as mobile app owners or data aggregators, to identify ways to balance the privacy risk to each consumer and value to any advertiser when sharing consumer location data with advertisers. This will curtail the stalker intent while facilitating the butler service. Existing approaches to privacy preservation are unsuited for location data as they are largely not personalized and difficult for data collectors to interpret the trade-off between privacy risks to consumers and values to advertisers. To address this research gap, we propose a personalized and interpretable framework that enables location data collectors to optimize the risk-value trade-off. Validating the framework on nearly one million location trajectories from more than 40,000 individuals, we find that high privacy risks indeed prevail in the absence of data obfuscation. For instance, on average an individual's home address can be accurately predicted within a radius of 2.5 miles and mobile operating system with an 82% success. Moreover, 49% individuals' entire location trajectories can be fully identified by knowing merely two randomly sampled locations visited by the individual. Outperforming multiple baselines, the proposed framework significantly reduces the consumers' privacy risks (e.g., by 15% of inferring home address) with minimal (i.e., $< 1\%$) decrease in the value to an advertiser. As novel and powerful consumer location trajectory data become increasingly available, we demonstrate their value to advertisers and accompanying privacy risks to consumers, and most importantly, propose a personalized and interpretable framework to mitigate their risks while maximizing their values.

Keywords: consumer privacy, GPS tracking, location data, mobile trajectory, machine learning, data obfuscation, mobile advertising

1. Introduction

1.1. Smart Tracking, Targeting, and Privacy

According to the latest Pew Research (Taylor and Silver 2019), 76% and 45% of the current population in the advanced and emerging economies, respectively, own a smartphone. These percentages continue to rise rapidly. Among the U.S. smartphone consumers, over 90% use location services such as Google Maps (Pew 2016). The fast penetration of smartphones, combined with the wide adoption of location services, has produced a vast volume of behavior-rich mobile location data (or location data, trajectory data hereafter). These data represent one of the latest, and most important, information sources available to marketers in the evolution of marketing data, from surveys to online clickstream and social media data (Wedel and Kannan 2016). It has also opened up $21 billion sales opportunities for advertisers, ranging from e-commerce retailers sending discount coupons to individuals in the vicinity of a store, commonly known as geo-fencing, to personal injury lawyers targeting those in emergency rooms (Luo et al. 2014, Andrews et al. 2016, Ghose et al. 2018, Kelsey 2018).

Geo-marketing based on mobile location data is attractive to advertisers for multiple reasons. First, mobile location data are straightforward to collect, an app permission away, tracked in the background in most mobile ecosystems, and readily accessible to advertisers.[1] Second, mobile location data are superior to alternative location data. The built-in sensors of mobile devices can provide continuous tracking of the movement trajectory of an individual (i.e., a sequence of fine-grained location GPS coordinates). Such individual-level location trajectory data are more precise and granular than social media geo-tags and consumer self check-ins. They are also more representative of the population than the less granular taxi and public transportation location data. Third, mobile location data offer an extensive profile of a consumer, whose location are being tracked by a smartphone) for targeting purposes, such as his/her spatial-temporal movements, thus rich contexts of his/her behaviors and brand preferences, broad lifestyle patterns, socioeconomic conditions, and social relationships (Ghose et al. 2018). Such offline data become even more powerful if combined with the consumer's online footprints, such as click stream data or social media data, rendering a holistic online-offline consumer portfolio. Fourth, owing to excellent tracking and targeting of mobile advertising, attributing the success of a location-based ad campaign is simplified.

[1] While both Apple and Android have taken measures to limit the collection of location data, guidelines remain ambiguous about the sales of such data to advertisers (Apple 2014, Verge 2019).

Advertisers have access to a unique device ID associated with each smartphone, thus reducing their overhead to stitch together consumers' location data across sessions or apps when measuring the success of a campaign and gain a holistic view of each consumer (Apple 2012). Fifth, geo-marketing by butler advertisers also benefits consumers (Ghose 2017), such as allowing consumers to receive enhanced services, personalization (Chellappa and Shivendu 2010), and financial benefits such as coupons (Luo et al. 2014, Ghose et al. 2018) or lower insurance premiums (Soleymanian et al. 2019).

Mobile location data not only provide values to advertisers whose butler actions further benefit consumers, but also monetization opportunities to location data collectors who share data with advertisers. Despite of the existence of diverse sources and varieties of mobile location data, the backbone of this rapidly growing mobile location data economy is the huge number of mobile applications (apps hereafter). App owners and location data aggregators serve a two-sided market with consumers on one side and advertisers on the other, collecting location data to offer better services to consumers and to monetize with advertisers. For example, a recent article by the New York Times reported that mobile location data collectors accrue half to two cents per consumer per month from advertisers (Valentino-Devries et al. 2018).

Meanwhile this powerful new form of human location and movement data offer important values to advertisers (and as a result to consumers and data collectors as well), they entail major consumer privacy concerns, such as the inference of home locations. "Privacy" is defined as "the quality or state of being apart from company or observation" in Merriam-Webster. In business contexts, privacy broadly pertains to the protection of individually identifiable information online or offline, and the adoption and implementation of privacy policies and regulations. It is a key driver of online trust (Hoffman et al. 1999). More than three-quarters of consumers believe that online advertisers hold more information about them than they are comfortable with; and approximately half of them believe that websites ignore privacy laws (Dupre 2015). For offline location data, privacy risks are exemplified by identifications of an individual's home address, daily movement trajectories, and broad lifestyle, as vividly depicted by two recent New York Times' articles (Valentino-Devries et al. 2018, Thompson and Warzel 2019). These risks are arguably more concerning than those associated with other forms of consumer data, such as an individual's media habit or social media content.

The discussions so far call for data collectors, before sharing location data with advertisers, to maintain a crucial trade-off between the value to an advertiser and privacy risk to a consumer. This responsibility falls primarily upon data collectors as they are situated right between advertisers and consumers, and hold vested interests in continuously maintaining consumers' trust in order to collect and monetize location data.[2] This notion is also consistent with the extant literature

[2] Cambridge Analytica's misuse of consumer data exemplifies severe backlash on the data collector, Facebook, whose privacy practices resulted in loss of both consumers and advertisers (Pew 2018).

across multiple disciplines on data sharing (Li et al. 2012, Terrovitis et al. 2008, Li and Sarkar 2009, Chen et al. 2013, Yarovoy et al. 2009, Machanavajjhala et al. 2009). The unique properties of, and hence challenges entailed by, the increasingly accessible and important mobile location data to be detailed next, nonetheless, call for novel frameworks to accomplish this trade-off. We thus aim to develop a personalized, privacy-preserving framework that incorporates consumer heterogeneity and optimizes a data collector's trade-off between value to an advertiser and privacy risk to a consumer.

1.2. Research Agenda and Challenges

As discussed earlier, there are three key entities in our business setting.

1. *Consumer:* is an individual who owns a smartphone with one or more of the apps installed that transmit the individual's location data to the data collector. Each consumer has the option to opt out of any app's location tracking, with some potential downsides of restricted use of certain app functions, such as maps or local restaurant finders.

2. *Advertiser:* is a firm that acquires data from a data collector to improve the targetability of their marketing campaigns. A subset of advertisers, or even a third party, with access to the location data, might have a stalker intent (stalkers hereafter) to perform malicious activities on the location data that invade consumer privacy, such as overly aggressive marketing or ignoring privacy concerns.

3. *Data collector:* is an app owner that collects consumers' location data from its mobile app, or a data aggregator that integrates location data from multiple apps. The data are collected in real time and may then be shared with or sold to advertisers interested in targeting the consumers.

In this work, we take a data collector's perspective and propose a framework for the data collector to balance between protecting consumer privacy against any stalker intent of an advertiser and preserving butler advertisers' targeting capabilities via data accessibility, accuracy, and usability (Muralidhar and Sarathy 2006). We aim to answer the following essential questions.

1. *Consumer's privacy risk:* What are some of the key privacy risks of mobile location data to a consumer due to an advertiser's potential stalker intent? Can these risks be quantified at a consumer level? Since a data collector has limited purview of how an advertiser could link the location data to a consumer's private information, understanding and quantifying the risks associated with various types of stalker behaviors (or threats hereafter) is a crucial first step to perform necessary data obfuscations.

2. *Advertiser's utility:* What is the value of raw and obfuscated mobile location data to a butler advertiser's targeting abilities (for simplicity, advertiser's utility hereafter). In specific, what types of key behavioral information can a butler advertiser extract from mobile location data to target consumers in a mutually beneficial way?

3. *Data collector's trade-off between consumers' privacy risks and advertiser's utility:* Is there a reasonable privacy-utility trade-off? If yes, what are the necessary steps that a data collector needs to take?

To accomplish the above, several methodological challenges need to be overcome. Our research questions, from a methodological standpoint, broadly fall under the paradigm of Privacy-Preserving Data Publishing (PPDP) widely studied in the context of relational databases (Fung et al. 2010). Nonetheless, the unique properties of mobile location data, such as high dimensionality (due to a large number of locations visited), sparsity (fewer overlap of locations across consumers), and sequentiality (order of locations visited), pose additional challenges (Chen et al. 2013). For example, traditional k-anonymity, which ensures an individual's record is indistinguishable from at least $k-1$ records, and its extensions face the curse of high dimensionality while dealing with granular, sometimes second-by-second, location data (Aggarwal 2005). $\epsilon-$differential privacy anonymization, which ensures adding or deleting a single consumer record has no significant impact on analysis outcomes, and other randomization-based obfuscation techniques (Machanavajjhala et al. 2006), fail to preserve the truthfulness of location data, rendering obfuscated data less useful for an advertiser's visual data mining tasks. More recent local obfuscation techniques (Chen et al. 2013, Terrovitis et al. 2017) that suppress locations with lower risk-utility trade-off provide a good privacy-utility balance. However, the obfuscation mechanisms are often complex for a data collector to interpret and apply in practice. For instance, the $(K, C)_L$ privacy framework (Chen et al. 2013) requires multiple parameters from a data collector, such as the probability thresholds of a privacy threat to succeed in different types of behaviors. LSup (Terrovitis et al. 2017) requires similar input parameters. Given the complex nature of these approaches, understanding and setting such parameters are non-trivial for a data collector. Hence, a more interpretable framework is needed to assist a data collector. Furthermore, the extant approaches do not tie a butler advertiser's utility to specific business use cases. These approaches, devised mostly from the Computer Science literature, measure an advertiser's utility by simply the number of unique locations or location sequences preserved in the obfuscated data (Chen et al. 2013, Terrovitis et al. 2017). These measures are rather rudimentary and impractical for advertisers to interpret or link to monetary decision-making. This challenge thus needs to be tackled by tying the advertiser's utility to real-world business contexts. We will next overview the proposed framework that intends to address the above challenges.

1.3. Overview of Proposed Framework

We provide a brief overview of the proposed framework that consists of three main components: quantification of a consumer's privacy risk, quantification of an advertiser's utility, and obfuscation scheme for a data collector.

Quantification of Consumer's Privacy Risk. While the proposed framework may accommodate a variety of privacy risks, we illustrate the framework by computing two specific risks of vital concerns to consumers. One is "sensitive attribute inference", where a consumer's sensitive attributes, such as home address, is being inferred (Li et al. 2007, Tucker 2013, Gardete and Bart 2018, Rafieian and Yoganarasimhan 2018). And two is "re-identification threat", where all locations visited by a consumer are being identified based on a subset of the locations visited by the consumer (Samarati 2001, Pellungrini et al. 2018).

Quantification of Advertiser's Utility. While the utility of the mobile location data to an advertiser are multi-faceted, we demonstrate a specific utility related to one arguably most popular and essential business goal examined in the literature – Point-of-Interest (POI hereafter) recommendations in mobile advertising (Ghose et al. 2018). Reliable predictions of a consumer's future locations would enable an advertiser to target the consumer with relevant contextual contents. For instance, if a chain restaurant can accurately predict that a consumer is going to be in the vicinity of one of its outlets, it may target the consumer with a discount coupon of value to the consumer. We hence quantify this utility as the accuracy of a neighborhood-based collaborative filtering recommendation model trained on the location data. The central idea of this recommender is to identify other consumers with similar historical preferences in order to infer the focal consumer's future preferences (Bobadilla et al. 2011)

Obfuscation Scheme for Data Collector. Acknowledging many potential solutions to the privacy-utility trade-off facing a location data collector may emerge, we propose an obfuscation scheme grounded on the idea of suppressing a subset of a consumer's locations, given the consumer's specific privacy risk and the frequency, recency, and time that the consumer spent at each location. We achieve this by introducing consumer-specific parameters that control the number and identity of the locations suppressed for each consumer. The suppression, while reducing each consumer's privacy risk, also adversely impacts an advertiser's utility. Hence, we empirically identify the parameters that balance the privacy-utility trade-off through a structured grid search while leveraging the earlier risk quantification for each consumer.

In summary, Figure 1 illustrates the proposed framework encompassing the three components discussed above. In Part A, we compute each consumer's privacy risk and advertiser's utility associated with the unobfuscated mobile location data (i.e., the full sample). These would also represent the counterfactual case when no privacy protection is performed. We expect the full unobfuscated sample to yield the maximum utility to advertisers and incur maximum privacy risk to consumers if the data were shared as is. In Part B, we perform consumer-level obfuscation by computing the number and identity of locations to be suppressed for each consumer using each consumer's risk scores computed on the full unobfuscated sample, as well as the frequency,

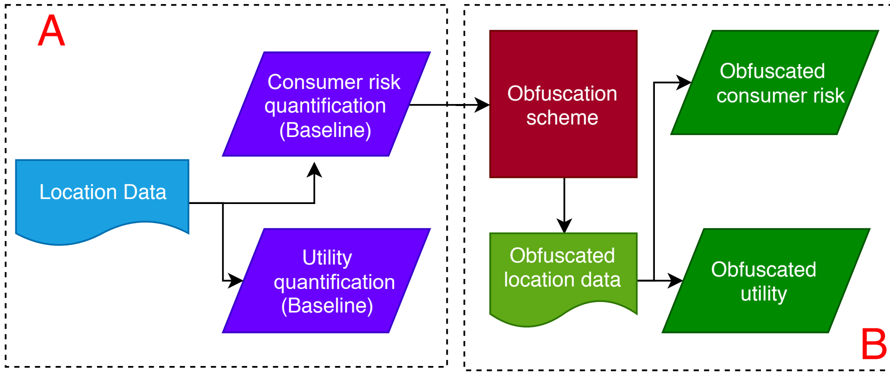


Figure 1 **Overview of the proposed framework**

recency, and time spent by the consumer at each location. We then repeat the above risk and utility computations by varying the parameters to empirically determine the best trade-off.

As alluded to earlier, while we illustrate the power and value of the proposed framework by examining two key types of privacy risks and one key advertiser application, the framework is flexible to accommodate other types of privacy risks, such as the inference of a consumer's location sequence or visit frequency for which the risk may be quantified either analytically or via machine learning heuristics (Pellungrini et al. 2018). It may accommodate other types of advertiser use cases as well, for which the utility may be computed as the predictive accuracy for the business application of interest, such as when a consumer is most likely to convert given the consumer's past location trajectory, or how much is an advertiser's incremental revenue from geo-marketing. The framework is also applicable to other contexts, for instance, when the data collector conducts geo-marketing for itself or for advertisers without sharing location data. We will summarize the key findings next.

1.4. Summary of Key Findings

We validate the proposed framework on a unique data set of nearly one million mobile locations from over 40,000 individuals in a major mid-Atlantic metropolitan area in the U.S. over a period of five weeks in 2018. The main findings are summarized as follows.

First, we find that the absence of an obfuscation scheme, that is, no steps taken by a data collector to ensure consumer privacy, indeed entails high privacy risks to consumers. On average, the success probability of a privacy threat is 83% for inferring a consumer's sensitive information and 49% for re-identifying a consumer's entire location trajectory, respectively. Specifically, on average a customer's home address can be predicted within a radius of 2.5 miles and mobile operating system[3] with an 82% success. Moreover, an individual's entire location trajectories can be fully identified

[3] Previous surveys have shown a strong relationship between mobile operating system and consumer demographics.(eMarketer 2013)

with a 49% success by knowing only two randomly sampled locations visited by a consumer. It is noteworthy that these success probabilities of various privacy threats are all estimated based on machine learning heuristics, which require merely the consumers' locations and corresponding timestamps as the inputs, as we will describe later. Hence, any entities, including advertisers, that have access to the location data could accomplish the same.

Second, we find significant values of the mobile location data to advertisers. An advertiser aiming to target consumers by identifying the next location most likely visited by a consumer would be able to predict it with 25% success. This means that by analyzing the behavioral patterns revealed by the historical location trajectories, for every one out of four customers, advertisers are able to design a highly precise geo-targeting strategy.

Finally, a data collector could curtail the potential invasion of consumer privacy by performing data obfuscation. Using the proposed obfuscation scheme, where we suppress each consumer's locations based on the consumer's privacy risks and frequency, recency, and time spent at each location, a data collector may choose from multiple trade-off options to perform the obfuscation. Moreover, we find that the proposed framework presents a better choice set of trade-offs when compared to eight baselines obfuscation schemes of various types, including the rule based, consumer risk based, and latest suppression techniques such as Terrovitis et al. (2017). For instance, when the privacy threat is to predict a consumer's home address, the proposed obfuscation scheme reduces the risk by 15%, which represents the maximum decrease when compared to the baselines, with a minimum decrease of less than 1% in an advertiser's utility. We will present a more detailed discussion of the empirical findings and comparisons with the baseline obfuscation schemes in Section 5.

1.5. Summary of Key Contributions

We propose an interpretable framework built upon the principle of personalized data obfuscation for the emerging and increasingly critical mobile location data. These data exhibit distinctive properties, such as high dimensionality (resulting from massive numbers of locations visited by consumers), sparsity (with fewer overlaps across visited locations), and sequentiality (with temporal ordering of visited locations), hence imposing unique methodological challenges.

Conceptually, this research demonstrates the importance for location data collectors to preserve both consumer privacy and data utility to advertisers on a two-sided market. It hence presents a systematic framework to accomplish this privacy-utility balance. It also stands among the first research to demonstrate the immense business values of the novel mobile location data that capture granular human movements and are increasingly leveraged by marketers and other entities, such as municipalities (for instance, for smart city planning). This research simultaneously illustrates the significant privacy risks associated with these data if no framework were in place to preserve consumer privacy.

Managerially, this framework tackles three inter-related, critical challenges facing location data collectors: quantification of a consumer's privacy risks, quantification of an advertiser's utility (i.e., value of mobile location data to an advertiser), and design of an intuitive and interpretable obfuscation scheme for a data collector. It offers any data collector multiple, interpretable, and personalized options that require only parsimonious input to protect consumer privacy while preserving an advertiser's utility, hence overall monetization opportunities for the data collector.

Methodologically, this framework (1) quantifies each consumer's privacy risk by extracting a comprehensive set of features from the mobile location data, thus accommodating various types of privacy risks and allowing identifications of which features contribute the most to the privacy risks; (2) measures an advertiser's utility associated with specific, real-world business use cases, such as POI recommendations shown to improve retailers' incremental revenues (Ghose et al. (2018)); (3) proposes an interpretable obfuscation scheme that suppresses locations at each consumer level to facilitate a data collector with multiple intuitive options to maintain the privacy-utility trade-off; (4) demonstrates efficacy by validating the proposed framework on a massive, real-world mobile location data set and comparing the suggested obfuscation scheme with eight benchmarks.

A balance between consumer privacy and geo-marketing constitutes part of a broader debate over tracking and targeting on digital platforms. This debate has resulted in actions from both industries and regulatory bodies. For instance, Apple, with 44.6% US smartphone market share (Statista 2018), introduced limited ad tracking (LAT) in 2016, which allows individuals to opt out of tracking indefinitely (Apple 2016). Following suit, Android, the second most adopted mobile ecosystem rendered more controls to each consumer to limit tracking in its latest software update (Verge 2019). European Union's General Data Protection Regulation (GDPR, Regulation (2016)), effective from May 2018, requires individuals to opt-in (rather than opt out of) behavioral targeting and to give explicit permission for their data to be shared across firms. Balancing the benefit and privacy risk of consumer location data is increasingly becoming a key concern and top priority for firms and regulatory bodies. Besides strengthening privacy regulations, more research is called for to develop privacy-friendly data storage, processing, and analysis technologies (Wedel and Kannan 2016). Against this background, our research provides empirical evidence and practical solutions to inform the ongoing debate over mobile location tracking and location-based targeting. The rest of the manuscript is organized as follows. In Section 2, we review the literatures from various disciplines that are relevant to our research questions. In Section 3, we provide details of our business setting and discuss sampling and summary statistics of the mobile location data under analysis. In Section 4, we introduce the proposed framework (Figure 1). In Section 5, we discuss the empirical results and detail the advantages of the proposed framework. We offer concluding remarks in Section 6.

2. Literature Review

We will concisely review the most relevant Marketing, Management, Information Systems (IS), and Computer Science (CS) literature on consumer privacy, privacy-preserving methodologies, and location-based mobile advertising.

2.1. Literature on Consumer Privacy

The literature, particularly from Marketing, has a historical, and newly revived, interest in consumer privacy. As different forms of consumer data emerge over time, the literature has examined consumer privacy concerns that arise from many business contexts and data forms, such as marketing research like surveys (Mayer and White Jr 1969, De Jong et al. 2010, Acquisti et al. 2012), direct marketing via phones or emails (Hann et al. 2008, Kumar et al. 2014, Goh et al. 2015), offline retail sales (Schneider et al. 2018), subscription services and various customer relationship management (CRM) programs (Conitzer et al. 2012), online personalization services in computers and mobile devices (Chellappa and Shivendu 2010), online search and e-commerce transactions (Bart et al. 2005), online social networks (Adjerid et al. 2018). Prior studies have also examined privacy topics related to finance and healthcare, such as crowd-funding (Burtch et al. 2015), credit transactions, insurance (Garfinkel et al. 2002, Soleymanian et al. 2019), and healthcare (Garfinkel et al. 2002, Miller and Tucker 2009, 2017). As advertisers commonly target consumers by leveraging consumers' private information, the latest research has also investigated online, social media, and mobile advertising (Goldfarb and Tucker 2011a,b,c, Conitzer et al. 2012, Tucker 2013, Gardete and Bart 2018, Rafieian and Yoganarasimhan 2018). Broadly speaking, any circumstances that involve customer databases would entail privacy concerns and needs for privacy protection (Garfinkel et al. 2002, Martin et al. 2017, Muralidhar and Sarathy 2006, Qian and Xie 2015). As a result, even business-to-business (B2B) platforms incur privacy concerns and require effective strategies to address these concerns (Kalvenes and Basu 2006). Nonetheless, as massive amounts of novel mobile location data emerge, which offer unparalleled opportunities to examine large populations' granular lifestyles and generate debatably more severe privacy concerns, more research is needed to quantify consumer privacy risks and devise privacy-preserving strategies.

Marketing research on consumer privacy falls into four main streams: consumer-, firm-, regulation-, and methodology- focused. We will concisely review each. The first stream takes on a consumers' perspective, and as a result, derives implications for firms to design privacy-friendly policies. For instance, a number of studies examine how consumers respond to privacy concerns or make privacy choices about privacy-intruding survey questions (Acquisti et al. 2012), platform provided privacy settings (Burtch et al. 2015, Adjerid et al. 2018), online display ads that match the website contents but with obtrusive format (Goldfarb and Tucker 2011c,b), or opt-in/out options of email marketing programs (Kumar et al. 2014). Other studies explore how normative and heuristic decision processes influence consumers' privacy decision making (Adjerid et al. 2016). Overall, these studies point to the positive effect of granting consumers enhanced controls over their own privacy, such as increasing their likelihood of responding to sensitive survey questions or click on personalized ads (Tucker 2013). Interestingly, this stream of research also reveals that consumers behave in a way that reflects a "privacy paradox": claiming to care about their personal data yet more than willing to exchange the data for concrete benefits, such as convenience, personalization, or discounts (Acquisti and Grossklags 2005, Chellappa and Sin 2005, Awad and Krishnan 2006, Xu et al. 2011, Ghose 2017, Luo et al. 2014, Ghose et al. 2018), lower insurance premiums (Soleymanian et al. 2019), or a wider reach to audiences on social media for information acquisition or propagation (Adjerid et al. 2018). This paradox conversely indicates the potential for butler advertisers to leverage the newest mobile location data for geo-marketing to consumers in a mutually beneficial manner.

The second stream of literature assumes a firms' perspectives, often using a game-theoretic approach to reach normative implications of firms' privacy policies. For instance, Chellappa and Shivendu (2010) derive the optimal design of personalization services for customers with heterogeneous privacy concerns. Gardete and Bart (2018) propose an optimal choice of ad content and communication when the firm withholds the customers' private information. Conitzer et al. (2012) reveal a monopoly's optimal cost of privacy for customers to remain anonymous. Hann et al. (2008) show that consumers' different actions toward preserving their privacy, such as address concealment or deflecting marketing, impact a firm's actions to either shifting marketing toward other consumers or reduce marketing overall. Adding competition to the picture, this stream of research also suggests optimal competitive strategies when profiting from disclosing customer information (Casadesus-Masanell and Hervas-Drane 2015), or designing a B2B market which preserves privacy to incentivize competitor participation (Kalvenes and Basu 2006). Other studies have also conceptualized the differential importance of privacy to different platforms (Bart et al. 2005) and assessed the impact of data breaches on firms financial performances (Martin et al. 2017). Interestingly, this stream of research also demonstrates that firms, such as an ad network, do have innate incentives to preserve customer privacy even without privacy regulations (Rafieian and Yoganarasimhan 2018).

The third stream of research focuses on privacy regulations. For example, these regulations are shown to impact firms' privacy-pertinent practices, technology innovations (Adjerid et al. 2016) and adoptions (Miller and Tucker 2009, 2017), and consumers' responses to e.g. the do-no-call registry (Goh et al. 2015). European Union (EU)'s privacy policy reduces the effectiveness of online display ads (Goldfarb and Tucker 2011a). Different components of a privacy law may also incur different effects, for instance, granting consumers controls over re-disclosure encourages, whereas privacy notification deters, genetic testing (Miller and Tucker 2017).

The fourth stream of research develops methodologies for regulatory bodies and firms to address privacy concerns. These methods fall under two broad categories: without data obfuscation and with as in our research. Without data obfuscation, these methods largely involve firms altering consumers' privacy perceptions, hence alleviating privacy concerns. Examples include altering the order of survey questions (Acquisti et al. 2012), revealing other consumers' attitudes towards privacy (Acquisti et al. 2012), altering the labels of privacy-protecting options (Adjerid et al. 2018), offering opt-in/out options (Kumar et al. 2014), granting enhanced privacy controls over, for instance, personally identifiable information (Tucker 2013), allowing customers to remain anonymous with a cost (Conitzer et al. 2012), or providing only aggregate instead of granular information (Sandıkçı et al. 2013). Consumers themselves may also take actions to preserve privacy, such as declining to answer certain survey questions, concealing addresses, or deflecting marketing solicitations (Hann et al. 2008). Globally, governments are also providing regulatory protections, such as national do-no-call registries (Goh et al. 2015) and state genetic privacy laws (Miller and Tucker 2017). Other methodologies, on the other hand, leverage obfuscation to the original data or query outputs. The premise is that an entity, data collector in our setting, would perform data transformation to preserve consumer privacy before releasing the data to a third party, an advertiser for instance, while ensuring that the data remain usable. Since such research is most related to our work, we will provide a more thorough survey of two sub-streams of this research based on the assumptions made when developing the relevant techniques (Clifton and Tassa 2013).

2.2. Privacy-preserving Methodology: Syntactic Models

The assumption of syntactic models is that the entity performing the transformation knows the type of threat that a stalker or malicious entity is going to perform on the shared data, and accordingly transforms the data to curtail that specific threat. The seminal work in this area was the concept of k-anonymity (Samarati and Sweeney 1998) aimed at columnar data to ensure that given a column, there would be at least k records that take the same columnar value. This would ensure that a consumer is protected from a re-identification threat, that is, his/her record cannot be completely identified even if a stalker has some background knowledge, usually a subset of the consumer's column values.

Studies have shown that k-anonymity is NP hard and suffers from the curse of dimensionality (Meyerson and Williams 2004). Variations of the concept of k-anonymity and heuristics to approximate k-anonymity have hence been proposed (Aggarwal et al. 2005). Since k-anonymity primarily focuses on the re-identification threat, the method is susceptible to sensitive attribute inference when a stalker aims to only infer a particular column of a consumer rather than completely re-identify all the columnar values. ℓ-diversity (Machanavajjhala et al. 2006) and confidence bounding (Wang et al. 2007) are proposed to address these shortcomings. ℓ-diversity accomplishes this by obfuscating data such that sensitive attributes are well represented for each consumer, while confidence bounding limits a stalker's confidence of inferring a sensitive value to a certain threshold. In the context of mobile location data, the above methodologies are shown to suffer from the curse of high dimensionality (*Aggarwal* 2005), reducing an advertiser's utility. To address this, variations of k-anonymity, such as k^m-anonymity (Terrovitis et al. 2008) and complete k-anonymity (Bayardo and Agrawal 2005), have been proposed for high dimensional transaction data. However, these techniques only address re-identification threats and are still vulnerable to sensitive attribute inference. Further, while these techniques work well for high dimensional data, they do not explore obfuscation of temporal information crucial in extracting behavioral information from location data. Next, we will review some of the recent syntactic models proposed to obfuscate location data.

Researchers, primarily from Computer Science, have proposed extensions of the above traditional heuristics to preserve privacy in simulated/synthetic location data (Chen et al. 2013, Terrovitis et al. 2008, Abul et al. 2008, Yarovoy et al. 2009), truck/car movements (Abul et al. 2008, Yarovoy et al. 2009), or social media check-in data (Terrovitis et al. 2017, Yang et al. 2018). The seminal work by (Abul et al. 2008) proposes (k, δ) anonymity to perform space generalization on location data. In other words, the trajectories are transformed so that k of them lie in a cylinder of the radius δ. A variation of k-anonymity is further proposed for moving object databases (MOD) based on the assumption that MODs do not have a fixed set of quasi-identifiers (QIDs) (Yarovoy et al. 2009). The authors define the timestamps of the location as QIDs and propose two obfuscation techniques based on space generalization. These two studies aim at protecting consumers from re-identification and re-identification threat.

More recently, suppression techniques have garnered attention in obfuscating location data (Chen et al. 2013, Terrovitis et al. 2008, 2017). For example, the seminal work by Terrovitis et al. (2008) presents a local suppression obfuscation technique assuming that a stalker has access to partial consumer trajectories, similar to the setting of re-identification threat in our study. Built on this work, Terrovitis et al. (2017) further propose global suppression, separately from local suppression. Providing privacy guarantees against both identity and attribute linkage threats, Chen et al. (2013) develop $(K, C)_L$ privacy framework. The model requires three parameters from a data collector: a stalker's success probability thresholds in both types of threats and a parameter corresponding to a stalker's background knowledge. Instead of measuring the data utility with a rudimentary metric, the number of unique location points or frequent sequences preserved in the obfuscated data, as in Chen et al. (2013) and Terrovitis et al. (2008, 2017), our research captures the data utility by tying it to a popular business objective of advertiser, POI prediction/recommendation.

2.3. Privacy-preserving Methodology: Differentially Private Algorithms

This sub-stream of research is based on the concept of ϵ-differential privacy (Dwork and Lei 2009). Differentially private algorithms guarantee that a stalker would make the same inference from the shared data whether or not the individual is included in the data. Unlike syntactic models, they are not limited to a specific type of threats, thus presenting a much stronger privacy notion. The transformations performed on the data usually involve perturbation, that is, adding a noise to the data before sharing them (Muralidhar and Sarathy 2006). Another related method is data shuffling, which is usually performed across rows or columns, such as replacing a subset of a consumer's record with another consumer's record to minimize privacy risks. Various studies have leveraged perturbation, data shuffling, or a combination of them (Qian and Xie 2015). For instance, Garfinkel et al. (2002) perturb the answer of a database query to generate the correct answer probabilistically or deterministically embedded in the range of the perturbed answers. Muralidhar and Sarathy (2006) employ data shuffling for confidential numerical data where the values of the condential variables are shuffled among observations, while preserving a high level of data utility and minimizing the risk of disclosure. Schneider et al. (2018) develop a Bayesian probability model to produce synthetic data. Besides perturbation and data shuffling, public key encryption, digital certificate, and blinded signatures are also common privacy-friendly tools (Kalvenes and Basu 2006). All of the above methods focus on columnar data.

In the context of location data, the literature is sparse. A few techniques have been developed to generate synthetic trajectories from a series of differentially private queries (He et al. 2015, Chen et al. 2012). The utility of the data preserved while generating these trajectories usually involves summary statistics, such as the number of unique locations or frequent location patterns. Moreover, owing to the stronger theoretical guarantees to be met, these techniques have been empirically shown to not preserve the truthfulness of the location data, hence hindering marketers' abilities to perform sophisticated data mining tasks (Terrovitis et al. 2017).

In our research, the consumers have explicitly opted in to share their location data with the data collector and advertisers in order to reap the benefits of personalized offering. Hence, we take the route of syntactic models, which are more likely to result in a higher data utility for advertisers, and thus consumers. We assume that a data collector has reasonable knowledge about the type of privacy threats that a consumer could be potentially exposed to by sharing the location data. To minimize the privacy threats, we propose an obfuscation scheme based on suppression that also ensures sufficient utility of the obfuscated location data to an advertiser.

Our study distinguishes itself from the prior research along several dimensions. From a methodological perspective, we quantify the privacy risk at a consumer level, instead of an aggregate or location level as in the prior literature (Terrovitis et al. 2008, 2017). Next, we measure the utility of the location data within the contexts of real-world business applications, such as POI recommendation, instead of using the aggregate or rudimentary metrics from the literature, such as the number of unique location points or frequent sequences (He et al. 2015). From the standpoint of practical applicability, the proposed framework requires merely one parsimonious input regarding the cardinality of partial trajectories (see Section 4.1.3 for a more detailed explanation) in order to compute the privacy risks and obfuscate the trajectory data. Therefore, it is intuitive and interpretable to the data collector or any manager. We also introduce a heuristic decision factor to provide a data collector with multiple trade-off options between the consumer's' privacy risk and advertiser's utility. Finally, most prior studies have validated their recommendations only on synthetic data (Chen et al. 2013, Terrovitis et al. 2008, Abul et al. 2008, Yarovoy et al. 2009), vehicle movements (Abul et al. 2008, Yarovoy et al. 2009), or social media check-ins (Terrovitis et al. 2017, Yang et al. 2018) with various data limitations, such as accuracy or representativeness, as described earlier. We in contrast validate the proposed framework on detailed mobile location data from massive numbers of consumers spanning across weeks.

2.4. Location-based Mobile Advertising

Finally, our work is related to the research on mobile marketing and location-based advertising. Using randomized field experiments, researchers have demonstrated that mobile advertisements based on the location and time information can significantly increase consumers' likelihood of redeeming geo-targeted mobile coupons (Fang et al. 2015, Molitor et al. 2019, Fong et al. 2015b, Luo et al. 2014). In our framework, we measure the utility of the location data to an advertiser by considering a popular business application, POI recommendation, as identifying the next location most likely visited by a consumer based on his or her prior trajectories is crucial to perform such behavioral targeting. In a recent paper by Ghose et al. (2018), the authors design a POI-based mobile recommendation based on similarities of consumers' mobile trajectories and demonstrate that such a strategy can lead to a significant improvement in retailer's incremental revenues. Other recent studies have revealed that understanding consumers' hyper-context, for example, the crowdedness of their immediate environment (Andrews et al. 2016), weather (Li et al. 2017), or the competitive choices (Fong et al. 2015a, Dubé et al. 2017), is also critical to marketers' evaluations of the effectiveness of mobile marketing. Another group of studies have further examined consumers' perceptions and attitudes toward mobile location-based advertising (Bruner and Kumar 2007, Xu 2006). In the next section, we will describe the data analyzed.

3. Data

We partner with a leading U.S. data collector that aggregates location data across hundreds of commonly used mobile apps varying from news, weather, map, to fitness and covering one-quarter of the U.S. population across Android and iOS operating systems.

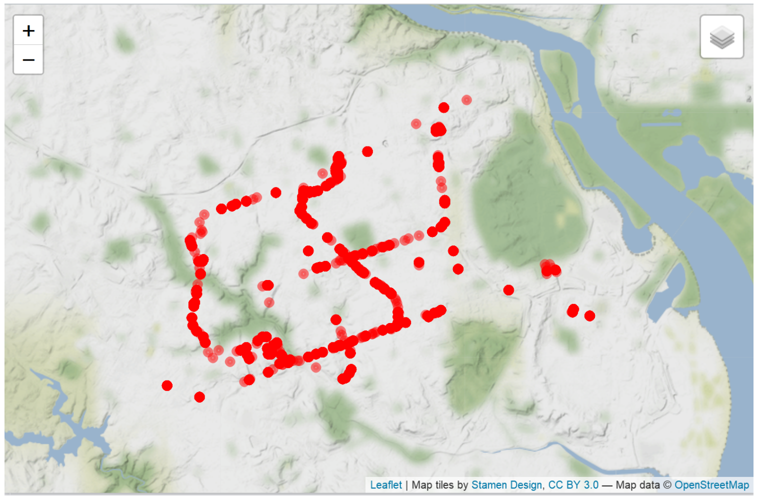


Figure 2 An example of a consumer's footprints with 732 unique locations over the five-week sample period

Description	Mean (S.D.)	Min (Max)
Number of locations per person	23.47 (50.26)	2 (1104)
Number of unique locations per person	14.25 (38.12)	2 (963)
Overall duration (in hours)	272.97 (278.25)	0.05 (759.27)
Duration at each location (minutes)	27.96 (45.99)	1.6 (359.23)
Distance between locations (in km)	1.89 (3.89)	0.02 (75.49)

Table 1 Summary statistics of the location data sample under analysis

The data sample under analysis covers a major mid-Atlantic metropolitan region in the U.S. Figure 2 displays the region's map (blurred on purpose due to a confidentiality agreement) and an example of a consumer's footprints with 732 unique locations visited during our five-week sampling period between September and October, 2018. The entire sample includes 940,000 locations from 40,012 consumers. Each row of the data corresponds to a location recorded for a consumer and also contains information about

- Consumer ID: a unique identifier of each consumer.
- Platform ID: Identifier of the consumer's mobile operating system (Android or iOS).
- Latitude and longitude (i.e., geo-coordinates) of the location.
- Timestamp: the beginning time at the location.
- Time spent: The amount of time spent at the location.

We randomly sample 50% of all consumers in the data (20,000 consumers) and all their location data for training and cross-validating our machine learning models, with details offered in Section 5 and Appendix A. Based on the models and parameters trained, we then conduct the focal analysis using the remaining 50% of the data with 20,012 consumers and their location data. Table 1 displays the summary statistics of the data. On average, a consumer visited from 2 to 963 unique locations tracked by the data. To reduce smartphone battery drainage, data redundancy, and storage cost, each consumer's smartphone is pinged frequently, but only recorded a location when there is a substantial shift in the geo-coordinates. The average duration at each location is 27.96 minutes. And the Euclidean distance between any two consecutively tracked locations is 1.89 km on average after converting the locations' latitudes and longitudes to the Universal Transverse Mercator (UTM) coordinates.

The literature on privacy-preserving sharing of location data, primarily from the Computer Science discipline, has tested the methodologies on either simulated data (Chen et al. 2013, Terrovitis et al. 2008, Abul et al. 2008, Yarovoy et al. 2009), vehicle movements (Abul et al. 2008, Yarovoy et al. 2009), or social media check-ins (Terrovitis et al. 2017, Yang et al. 2018), also merely over a short period such as 24 hours. We make an initial effort to develop a privacy-preserving framework for, and validate it on, a real-world human physical movement data across a large population. Such data are automatically tracked in real time by mobile devices, often via wifi, beacons, and GPS etc. multi-technology multilateration with an accuracy radius of merely 20 meters. They are thus much more precise than cell tower tracking often with an accuracy radius of a few kilometers, social media geo-tags known for its sparsity and inaccuracy, or consumers' self check-ins that rely on consumers' manual labor and willingness to check in at any location. The mobile location data under our study are also more representative of the general population than taxi or public transportation data, hence much more valuable to advertisers and other data consumers. On the other hand, these data's massive scale and high dimensionality, in our case nearly one million mobile location over just five weeks from one metropolitan region, also entail unique challenges, as discussed earlier, hence imminent needs to develop new frameworks to address these challenges.

4. Methodology

The proposed framework aims at enabling a location data collector to share data with advertisers in a privacy preserving manner, while ensuring that the advertiser attains sufficient utility from the published data. Consistent with the premise of syntactic models, a data collector has some knowledge about the types of potential privacy threats (Clifton and Tassa 2013). While the proposed framework accommodates various types of privacy threats, we illustrate it by considering two commonly encountered types - sensitive attribute inference and re-identification threat. We will introduce the notations first and then formulate the privacy preservation in the context of the location data.

Definition 1. *A trajectory T_i of a consumer i is defined as a temporally ordered set of tuples $T_i = \{(l_i^1, t_i^1), ..., (l_i^{n_i}, t_i^{n_i})\}$, where $l_i^j = (x_i^j, y_i^j)$ is a location with geo-coordinates (i.e., a pair of longitude and latitude) x_i^j and y_i^j, t_i^j is the corresponding timestamp, and n_i is the number of locations tracked of consumer i.*

Problem Formulation. We frame the problem of preserving privacy in location data at a consumer level. Let r_i denote a consumer i's privacy risk associated with trajectory T_i for a specific type of privacy threat, and u_i the advertiser's utility from leveraging consumer i's trajectory. A data collector aims to find a transformation $T_i \to \mathcal{P}(T_i)$, where $\mathcal{P}(T_i)$ is consumer i's obfuscated trajectory that the data collector shares with an advertiser by minimizing r_i while maintaining u_i. The transformation is based on suppressing the locations in T_i given two parameters. One parameter is s_i, the suppression weight corresponding to each location in T_i, assigned based on various measures, such as the consumer's frequency, recency, and time spent at each location. The other is z_i, the suppression score for consumer i that is proportional to, and thus controls the number of locations in T_i to be suppressed, assigned based on the consumer's privacy risk. Both parameters contribute to the final suppression probabilities assigned to each location in T_i. In Section 4.3, we will detail a structured grid search to fine-tune these two parameters, which do not need to be input by a data collector. Both parameters contribute to the final suppression probabilities assigned to each location in T_i. Hence, the corresponding obfuscated risk and utility of $\mathcal{P}(T_i; \{\vec{s_i}, z_i\})$ are functions of the two suppression parameters,

$$r_i = \mathcal{PR}(T_i; \{\vec{s_i}, z_i\})$$
$$u_i = \mathcal{U}(T_i; \{\vec{s_i}, z_i\}),$$

where $\mathcal{PR}(.)$ and $\mathcal{U}(.)$ depend on the type of privacy threat and business objective of the advertiser, respectively.

Overall, for a set of N consumers' trajectories $T = \{T_1, ..., T_N\}$, the data collector aims to find a transformation of T, $T \to \mathcal{P}(T; \{\vec{s_i}, z_i\}_{i=1}^N)$, to produce the obfuscated trajectories to be shared with advertisers that minimize the expected privacy risk $E(r_i)$ of consumers while maintaining the expected data utility $E(u_i)$. Consistent with our focal research questions and the overview of the three components in the proposed framework (Fig. 1), we further break down the data collector's problem above into three sub-problems below. The first two pertain to the estimation of u_i and r_i based on $\mathcal{PR}$ and $\mathcal{U}$, respectively; and the third is to identify the suppression parameters $\{\vec{s_i}, z_i\}$.

Research Question 1. ***Quantification of Consumer's Privacy Risk:*** *Given consumer trajectories T and a privacy threat $\mathcal{PR}$, we calculate each consumer's risk $\{r_1, ..., r_N\}$ associated with T, where each $r_i \in [0, 1]$ indicates a stalker's success rate in inferring the private information from consumer i's trajectory T_i.*

Research Question 2. ***Quantification of Advertiser's Utility:*** *Given consumer trajectories T and a business objective $\mathcal{U}$, we quantify the utility of the trajectories to an advertiser $\{u_1, ..., u_N\}$.*

Research Question 3. ***Obfuscation Scheme for Data Collector:*** *Given consumer trajectories T and their corresponding risks, for an advertiser's business objective $\mathcal{U}$, we aim to find $T \rightarrow \mathcal{P}(T; \{\vec{s_i}, z_i\}_{i=1}^{N})$, where $\mathcal{P}(T)$ selects a subset of location tuples from each T_i based on the parameters $\{\vec{s_i}, z_i\}$, balancing r_i and utility u_i.*

Next, we will illustrate the quantification of two classes of privacy risks in Section 4.1 and quantification of the data's utility to an advertiser in one business application of POI recommendation in Section 4.2. Finally, in Section 4.3, we will propose an obfuscation scheme that provides a balance between the privacy risks and data utility.

4.1. Quantification of Consumer's Privacy Risk

The first step of the proposed framework is quantifying consumer's privacy risk. To accomplish this, we simulate a stalker's actions and assign its extent of success in obtaining a consumer's sensitive information as privacy risk. Privacy threats could range from using simple heuristics, such as querying the consumers' trajectories, to leveraging more robust machine learning heuristics to predict a consumer's sensitive attribute (Li et al. 2007, Yang et al. 2018). In our framework, we consider both simple and sophisticated heuristics. Specifically, we will examine two types of the most commonly encountered stalker threats. In the first type, a stalker aims to infer a consumer's complete set of locations T_i from the published trajectories $\mathcal{P}(T)$, orchestrating an "re-identification threat" (Pellungrini et al. 2018). With some background knowledge, such as a subset of consumer's locations $\overline{T_i} \in T_i$, a stalker could query the published trajectories $\mathcal{P}(T)$ to identify a subset of consumer trajectories $\overline{T} = \{T_1, , T_J\}, \overline{T_i} \in \overline{T_j}; \forall j \in [1 : J], J \leq N$, where $\overline{T}$ consists of all the individuals who have visited the locations in $\overline{T_i}$. The success of the stalker in obtaining T_i would depend on the value of J - lower the value of J, higher the success. Next, exploiting the obtained complete trajectory, T_i, a stalker could employ a robust machine learning heuristic and extract spatial and temporal information to further infer other sensitive information, such as home and work addresses of the consumer(Yang et al. 2018). This class of privacy threat is termed "sensitive attribute inference". In the following sub-sections, we first discuss the information that an stalker could extract from the published trajectories and then quantify each of these two classes of privacy risks.

4.1.1. Trajectory Feature Extraction. To replicate a stalker's adversarial actions and assess each consumer's privacy risks, we extract a comprehensive set of features from the trajectories examined by the literature, $\mathcal{F}(T)$ (Gonzalez et al. 2008, Eagle and Pentland 2009, Williams et al. 2015, Pappalardo et al. 2016, Ashbrook and Starner 2003, Zheng et al. 2010, Wang et al.

2011). These extracted features, as we will see later in Section 5.1, will also help a data collector interpret which features contribute to the privacy risks, gain insights on possible obfuscation schemes, and quantify and interpret the data utility to an advertiser. We will categorize these features as below.

1. **Consumer Mobility**: This set of features captures a consumer's aggregate mobility patterns based on the locations visited in T_i, including the consumer's frequency to, time spent at (Pappalardo et al. 2016), and distance traveled to a location (Williams et al. 2015). We also compute other richer mobility features, such as entropy (Eagle and Pentland 2009) and radius of gyration (Gonzalez et al. 2008). A detailed description of these features is listed in Table 2.

2. **Consumer-Location Affinity**: Leveraging the literature on learning significant locations from predicting movement across consumer trajectories (Ashbrook and Starner 2003, Zheng et al. 2010), we build three consumer-location tensors: the frequency to, time spent at, and total distance traveled from the immediate prior location to each location by a consumer at a weekly level. Each of these three tensors is of order three—consumer by unique location by week. We then extract consumer specific, lower dimensional representations by performing a higher order singular value decomposition (HOSVD) on the three tensors separately (De Lathauwer et al. 2000). HOSVD is usually applied to extract features from multivariate data with temporal and spatial dimensions similar to ours (Fanaee-T and Gama 2015). Since the tensors are populated over the locations visited by these consumers, the extracted features would effectively capture the affinity of the consumers to significant locations.

3. **Consumer-Consumer Affinity**: Prior studies have also predicted consumer network or social links based on trajectories (Wang et al. 2011). We thus quantify the consumers' co-location behaviors by building consumer-consumer affinity tensors based on the locations that the consumers share at a weekly level. Each tensor would be third order —consumer by consumer by week. We populate three such tensors with the average frequency to, total time spent at, and distance traveled to each co-visited location within a week, respectively. Next, we perform a HOSVD on these three tensors to extract the consumer specific low dimensional representations indicative of the affinity to other consumers. The incremental benefit of the affinity features is discussed in Appendix B.

Stylized Example. We illustrate the above consumer-location and consumer-consumer affinity features using a stylized example. Consider three consumer trajectories as defined in Definition 1: $T_1 = \{(A,1),(B,1),(A,2),(A,2)\}$, $T_2 = \{(C,1),(A,1),(A,1)\}$, $T_3 = \{(D,1),(B,1),(C,2)\}$, where A,B,C,D are location identifiers and the granularity of the timestamps is at a weekly level. That is, $T = \{T_1,T_2,T_3\}$ reveals that these three consumers visited four unique locations over a period of two weeks. Each of the three consumer-location tensors discussed above would be of size $[3\times4\times2]$ for the 3 consumers, 4 unique locations, and 2 weeks For instance, the frequency matrix of the

Feature	Description
`average_locations`	Number of locations in T_i averaged weekly.
`average_ulocations`	Number of unique locations in T_i averaged weekly.
`average_distance`	Distance travelled by a consumer to visit locations in T_i, averaged weekly.
`average_dwell`	Time spent at locations in T_i averaged weekly.
`avg_max_distance` (Williams et al. 2015)	Average of the maximum distance travelled by a consumer each week.
`freq_rog`, `time_rog`, `dist_rog` (Gonzalez et al. 2008)	Radius of gyrations is the characteristic distance traveled by an individual. $rog_i = \sqrt{\frac{1}{\lvert T_i\rvert}\sum_{j=1}^{\lvert T_i\rvert} w_{ij}(l_{ij} - l^i_{cm})^2}$ $l^i_{cm} = \frac{1}{\lvert T_i\rvert}\sum_{j=1}^{j=\lvert T_i\rvert} l_{ij}$, l_{ij} are the geographical coordinates l^i_{cm} is the center of mass of the consumer w_{ij} are weights obtained based on frequency, time & distance w.r.t to l_{ij}
`freq_entropy`, `time_entropy`, `dist_entropy` (Eagle and Pentland 2009)	Mobility entropy measures the predictability of consumer trajectory. $E_i = -\sum_{j=1}^{\lvert T_i\rvert} p_{ij} log_2 p_{ij}$, p_{ij} computed from w_{ij} for time, frequency & distance.

Table 2 Description of consumer mobility features

first consumer with T_1 is $\begin{pmatrix} 1 & 1 & 0 & 0 \\ 2 & 0 & 0 & 0 \end{pmatrix}$, where the rows and columns correspond to the 2 weeks and 4 unique locations, respectively, and each entry in the matrix captures the number of times that each of the four locations was visited by this consumer during that week. Each of the three consumer-consumer location tensors described above would be of size $[3 \times 3 \times 2]$ for the 3 consumers by 3 consumers by 2 weeks. For instance, the frequency matrix for the first consumer with T_1 would be $\begin{pmatrix} 1 & \frac{(1+2)}{2} & \frac{(1+1)}{2} \\ 1 & 0 & 0 \end{pmatrix}$, where the rows and columns correspond to weeks and the consumer pairs 1-1, 1-2, and 1-3, and each entry in the matrix is the average frequency of the co-visited locations within each consumer pair (e.g., during week 1, $(A, 1)$ co-visited between consumers 1 and 2, and $(B, 1)$ co-visited between consumers 1 and 3). The time and distance tensors are similarly constructed. We then perform a HOSVD on these tensors separately and use the first five principal components that capture a majority of the variance. Hence, for each consumer and tensor, we have five lower dimensional representations that capture the corresponding consumer-location and consumer-consumer affinities. Next, we imitate how a stalker would use the extracted features from the published trajectories to orchestrate privacy threats.

4.1.2. Sensitive Attribute Inference. Leveraging the published trajectories $\mathcal{P}(T)$ and the extracted features, a stalker could infer various sensitive attributes, such as age and gender, thus posing a privacy threat (Li et al. 2007). The stalker is assumed to use a model $\mathcal{M}$ to infer these sensitive attributes (Yang et al. 2018). Intuitively, the more certain a stalker is about a consumer's sensitive attributes based on $\mathcal{M}$, the higher is the consumer's privacy risk. To replicate the stalker's actions, we train a supervised model, $\mathcal{M}_{proxy}$, with the extracted features. This acts as a proxy for the stalker's model $\mathcal{M}$. To quantify each consumer's risk, we assign the certainty of identifying a sensitive attribute from the consumer's published trajectory using $\mathcal{M}_{proxy}$. In this research, we illustrate the method by inferring two sensitive attributes, home address and mobile operating system.

Proxy stalker model ($\mathcal{M}_{proxy}$). We enlist Random Forest as $\mathcal{M}_{proxy}$ in light of its flexibility in handling regression and classification tasks, and its competitive performance across a wide range of supervised learning algorithms (Breiman 2001, Liaw et al. 2002). For each sensitive attribute, we learn a Random Forest using the extracted features[4]. The risk is then calculated as the certainty of $\mathcal{M}_{proxy}$ in identifying the corresponding sensitive attribute, that is, the probability of correct identifying the attribute in classification, or negative root-mean-square error in regression. We also perform a 0-1 normalization in case of regression, such that $r_i \in [0,1]$.

4.1.3. Re-identification Threat. Adapting the notion of risk that a stalker is able to identify a consumer and associate the consumer with a record in the published data (Samarati 2001, Samarati and Sweeney 1998), we define re-identification threat in the context of location data. Here, a stalker tries to re-identify all locations visited by a consumer based on some prior knowledge of an (often small) subset of locations visited by the consumer, such as employer address from a membership registration form. Formally, this problem can be defined as follows:

Definition 2. *Given the published trajectories $\mathcal{P}(T)$ and a subset of consumer i's trajectory under threat $\bar{T}_i \subseteq T_i$, where $|\bar{T}_i| = r$, the stalker aims to identify T_i from $\mathcal{P}(T)$.*

Since a data collector does not know consumer i under threat or the subset locations $\bar{T}_i$ a-priori, to quantify the consumer's risk r_i, one would need to account for all $\binom{|T_i|}{r}$ possible subsets of T_i for all N consumers. For each such subset, $\bar{T}_i$, the probability of a consumer being identified completely (i.e., to infer T_i) is $\frac{1}{J}$, where J denotes number of consumers in N who have visited all the locations in $\bar{T}_i$. If no other consumer has visited any of the locations in $\bar{T}_i$, the probability of identification of i's trajectory would be 1 for the subset considered. We quantify a consumer's re-identification risk as the maximum of these probabilities over all such subsets.

[4] We have also compared Random Forest with a number of tree-based and boosting classification methods – xGBoost (Chen and Guestrin 2016), Conditional inference trees (Hothorn et al. 2015), Adaboost (Hastie et al. 2009); and found that Random Forest provids the best out-of-sample performance.

A Stylized Example. Let $T_1 = \{(A,1),(B,1),(C,2),(C,2)\}$, $T_2 = \{(A,1),(B,1),(A,2)\}$, $T_3 = \{(A,1),(B,1),(C,2)\}$. Assume $|\bar{T}_i| = 2$. To compute the risk for consumer 1 across both weeks, we consider the subset $\{(A,B),(B,C),(A,C)\}$. Then the corresponding probabilities of consumer 1's identification are $\{\frac{1}{3},\frac{1}{2},\frac{1}{2}\}$, since across these two weeks, 3 consumers have visited (A,B), 2 visited (B,C), and 2 visited (A,C). Thus, consumer 1's re-identification risk is $max(\frac{1}{3},\frac{1}{2},\frac{1}{2}) = \frac{1}{2}$.

Speed-up Heuristic. While the re-identification risk can be exactly computed for a given r, it is computationally inefficient with a complexity of $O(\binom{|T_i|}{r}\times N)$ where $|T_i|$ is the total number of unique locations visited by a consumer i. To speed up the computation, we leverage a recent work (Pellungrini et al. 2018) that empirically shows the predictability of the re-identification risk for a given k using mobility features. The main idea is to learn a supervised algorithm, Random Forest, by building a set of mobility features similar to $\mathcal{F}(T)$ discussed in Section 4.1.1. We adopt this idea by further augmenting the mobility features with our consumer-consumer and consumer-location affinity features. We then analytically compute the risks for a subset of the consumers and use the trained model to approximate the risks for the rest of the consumers (see Appendix A for the technical details).

4.2. Quantification of Advertiser's Utility

Having quantified each consumer's privacy risk associated with two commonly encountered privacy threats on location data (our research question 1), we next examine the utility that an advertiser would derive from the published trajectories (research question 2). The behaviorally rich nature of location data enables advertisers to derive insights and perform various targeted marketing activities leading to monetary benefits. In this work, we consider a popular business application, POI recommendation (Ashbrook and Starner 2003). The underlying idea is to leverage the historical consumer preferences revealed in the trajectories to predict the locations that a consumer is most likely to visit in the future. Accurate prediction of a consumers future locations would enable an advertiser to target the consumer with relevant, contextualized marketing campaigns (Ghose et al. 2018). To this end, we quantify an advertiser's utility by learning a recommender model. Intuitively, more accurate POI predictions will render better targeting, leading to a higher utility for the advertiser. Hence, we quantify the utility of consumer $i's$ data u_i as the accuracy of the future predictions made by the recommendation model.

Most recommendation models leverage collaborative filtering to identify other consumers with similar historical preferences to infer the focal consumer's future (Bobadilla et al. 2011). This idea is consistent with human social behavior: people tend to account for their acquaitances' tastes, opinions, and experiences when making own decisions. We thus imitate an advertiser's use of the location data for POI recommendation and compare a number of recommendation models examined in the literature (Appendix A). We focus the ensuing discussion on the best performing nearest neighborhood (NN) based learning technique. Simply put, the main idea of NN is to identify the m consumers most similar to the focal consumer, namely m neighbors, and utilize their locations to predict the focal consumers future preferences. The similarity is computed based on the visited locations that reveal each consumer's preferences by leveraging the set of features extracted from the published trajectories described earlier in Section 4.1.1, $\mathcal{F}(T)$. To find the m most similar consumers, we compute the cosine similarity between two consumers i and j with the extracted features $\mathcal{F}(T_i)$ and $\mathcal{F}(T_j)$, respectively:

$$sim(\mathcal{F}(T_i),\mathcal{F}(T_j)) = \frac{\mathcal{F}(T_i)\cdot\mathcal{F}(T_j)}{||\mathcal{F}(T_i)||||\mathcal{F}(T_j)||} \tag{1}$$

After identifying the m most similar consumers to a consumer i, denoted by M_i, we aggregate and rank the unique locations visited by M_i based on a combination of visit frequency and these m consumers' similarities to consumer i. Specifically, for each consumer $j \in M_i$, location $l \in T_j$, let f_j^l denote the number of times that consumer j visited location l, then the rank of a location l for consumer j is determined by:

$$o_{ij}^l = \sum_{l=1}^{|T_j|} \frac{f_j^l}{\sum_l f_j^l} sim(\mathcal{F}(T_i),\mathcal{F}(T_j)) \tag{2}$$

In the above equation, $\frac{f_j^l}{\sum_l f_j^l}$ is the normalized visit frequency at a consumer level for a location. Intuitively, Equation 2 ensures that an individual i is most likely to visit the most frequently visited location of the most similar consumer. We further aggregate o_{ij}^l across all the consumers who visited the location l in M_i by computing the mean of o_{ij}^l:

$$o_i^l = \frac{1}{\sum_{j=1}^{|M_i|} 1(l \in T_j)} \sum_{j=1}^{|M_i|} 1(l \in T_j)\cdot o_{ij}^l \tag{3}$$

where $1(j \in T_j) = 1$ if consumer j has visited location l and zero otherwise. Higher the value of o_i^l, more likely that an individual i visits location l in the future. The next k locations an individual i is most likely to visit correspond to the top k ranked locations in M_i. The utility of an advertiser for consumer i's location trajectory T_i is measured as the accuracy of the predictions made by the recommender for the different values of k. This is computed by the widely used information retrieval metrics that assess the quality of the recommendations - Average Precision at k ($AP@k$) (Equation 4) and Average Recall at k ($AR@k$) (Equation 5) (Yang et al. 2018). These are further aggregated to compute the expected advertiser utility $E(u_i)$ by averaging across all consumers' $MAP@k$ and $MAR@k$.

More specifically, let $L_i = \{l_i^1, l_i^2, , l_i^{k'}\}$ be the actual next k' locations visited by consumer i and $\overline{L_i} = \{\overline{l_i^1}, \overline{l_i^2}, ..., \overline{l_i^k}\}$ be the predictions made by the NN recommender ordered by the ranking based on Equation 3. First, the average precision AP_i^k and average recall AR_i^k for consumer i with top k recommended locations are given by

$$AP_i^k = \frac{1}{|L_i \cap \overline{L}_i|)} \sum_{j=1}^{k} \frac{|L_{1:j} \cap \overline{L}_{1:j}|}{|L_{1:j}|)} \tag{4}$$

$$AR_i^k = \frac{1}{|L_i \cap \overline{L}_i|)} \sum_{j=1}^{k} \frac{|L_{1:j} \cap \overline{L}_{1:j}|}{|L_i|)} \tag{5}$$

The intuition is that AP_i^k measures the proportion of the recommended locations that are relevant, while AR_i^k measures the proportion of relevant locations that are recommended. Then, $MAP@k$ and $MAR@k$ are computed by averaging AP_i^k and AR_i^k across all the consumers. Also, the parameter m, number of the most similar neighbors used for location predictions, is selected by performing a five-fold cross-validation aimed at maximizing the accuracy of the recommendations. This is a technique commonly used in the statistical learning literature to ensure a good out-of-sample performance (Friedman et al. 2001). We will detail how we empirically select the number of the most similar neighbors in Section 5.2.

4.3. Obfuscation Scheme

The last step in our framework is to address the third research question – devising an obfuscation scheme for the data collector that would balance the privacy risks to the consumers and the utility of the published trajectories to the advertiser. As discussed earlier, given the unique properties of trajectory data, such as high dimensionality, sparsity, and sequentiality, employing the traditional obfuscation techniques proposed for relational data, such as k-anonymity (Samarati and Sweeney 1998), ℓ-diversity (Machanavajjhala et al. 2006), and confidence-bounding (Wang et al. 2007) would be computationally prohibitive and significantly reduce the utility of the resulting obfuscated data (Aggarwal 2005). On the other hand, those techniques devised specifically for trajectory data are often complex for a data collector to interpret and apply in practice. For instance, the $(K,C)_L$ privacy framework (Chen et al. 2013) requires multiple parameter inputs from a data collector, including the threshold of the stalker's success probability and the stalker's background knowledge in each type of threat. LSup (Terrovitis et al. 2017) requires similar inputs. Given the complex nature of such heuristics, setting these parameters and interpreting the resulting obfuscations for practical purposes is non-trivial. Moreover, the current techniques do not provide the flexibility for a data collector to choose among multiple obfuscation schemes.

Addressing these critical challenges, we develop $T \rightarrow P(T, \{\vec{s}_i, z_i\}_{i=1}^N))$, a personalized consumer-specific suppression technique that is interpretable to the data collector. It requires merely a single parameter input that corresponds to a stalker's background knowledge for re-identification threat – the number of a consumer's locations already known to the stalker (i.e., the cardinality of the set $\overline{T_i}$ as defined in Definition 2). Also, the suppression technique requires no input parameters for the sensitive attribute threat. Furthermore, the data collector will enjoy the flexibility of choosing among multiple interpretable obfuscations for each type of privacy threat by performing a structured grid search on the two consumer.

In our obfuscation scheme, a consumer's location trajectory T_i is suppressed based on two consumer specific parameters $\{\vec{s_i}, z_i\}$. As described earlier, z_i is proportional to, and controls the number of locations to be suppressed for a consumer's trajectory T_i. Further, within T_i, $\vec{s_i}$ are the weights assigned to denote the likelihood for each location to be suppressed. By definition, $\vec{s_i} \in \mathbb{R}^+$ and $z_i \in \mathbb{R}^+$. To identify $\{\vec{s_i}, z_i\}$ that reduce each consumer's risk r_i while maintaining u_i, the data collector could perform a search over a random grid of positive values of $\vec{s_i}$ and z_i, and assess r_i and u_i for each parameter specification. However, this naive search would be computationally inefficient and depending on the grid of values chosen, there may not be a set of parameters $\{\vec{s_i}, z_i\}$ that could satisfactorily balance the risk-utility trade-off. Hence, a sophisticated grid search is needed.

A more structured approach to identify $\{\vec{s_i}, z_i\}$ would be to consider a grid that ensures a reduction in consumer's risk and then assess u_i to select a specification that balances the risk-utility trade-off. Intuitively, more the number of locations suppressed in T_i, the less trajectories $\mathcal{P}(T_i)$ are published, offering a stalker less data to infer private information. For instance, in the extreme scenario when no trajectories are published, both re-identification and sensitive attribute risks would be zero. Further, to ensure similar risk reduction for a high-risk and a low-risk consumer, the number of locations suppressed would need to be proportional to the corresponding consumer's privacy risk r_i. Factoring these observations, in our search strategy, we assign the grid for z_i, the suppression score for a consumer that controls the number of locations suppressed for each consumer as $z_i = r_i \times p$, where p is a positive grid parameter.

While z_i ensures that consumer's locations are suppressed proportionally based on the risk score, to further limit the information available to perform a stalker threat, the more informative locations within T_i would need to be suppressed with a higher probability. Since the informativeness is related to the possible features that can be extracted by a stalker from T_i (Section 4.1.1), we assign the weights $\vec{s_i} = \{w_i^1, w_i^2, ..., w_i^{|T_i|}\}$ based on either of the three qualitative measures - frequency, recency, and time spent at each location. To exemplify, let $L_i = \{l_i^1, l_i^2, ..., l_i^{k_i}\}$, be the unique locations in $T_i = \{(l_i^1, t_i^1), ..., (l_i^{n_i}, t_i^{n_i})\}$, $k_i \leq n_i$. Then the weights $\vec{s_i}$ assigned based on the corresponding frequencies $L_i = \{f_i^1, f_i^2, ..., f_i^{k_i}\}$ of L_i are given by $\vec{s_i} = \{\frac{f_i^1}{\sum_{j=1}^{k_i} f_i^j}, \frac{f_i^2}{\sum_{j=1}^{k_i} f_i^j}, ..., \frac{f_i^{k_i}}{\sum_{j=1}^{k_i} f_i^j}\}$. Combining the search strategies of the two parameters $\{\vec{s_i}, z_i\}$, we assign the suppression probabilities for each location in T_i

In our obfuscation scheme $P(T, \{\vec{s_i}, z_i\}_{i=1}^{N})$), the unique locations are independently suppressed with probabilities

$$z_i + z_i \times w_i^1, z_i + z_i \times w_i^2, ..., z_i + z_i \times w_i^{k_i}, w_i \in \vec{s_i} \tag{6}$$

Note that with the proposed search strategy since r_i and w_i can be computed apriori[5], the suppression probabilities for each location in T_i depend only on the grid parameter p. For a value of p, the probabilities would ensure that users at higher risk have more informative locations suppressed in their published trajectories compared to lower risk users.

Suppressing the location data to limit a stalker's ability to invade private information would also adversely affect a butler advertiser's utility derived from $\mathcal{P}(T)$. For instance, in the extreme scenario when each consumer's risk $r_i = 1$ and p is reasonably high, all locations would be suppressed (i.e., complete suppression[6]: $\{\mathcal{P}(T_i)\} = \mathcal{P}(T) = \emptyset$), resulting in no utility to the advertiser, nor threat to consumer privacy. A similar inference can be made when $p = 0$ (i.e., no suppression: $\mathcal{P}(T) = T$), resulting in high data utility and also high privacy risk. Noting these two extreme scenarios, we empirically determine the specification of suppression parameters $\{\vec{s_i}, z_i\}$ by varying the grid parameter p and the corresponding published trajectories $\mathcal{P}(T)$ that provide a utility-risk balance.

In a nutshell, the proposed obfuscation scheme has two main advantages. First, the structured grid search by varying the grid parameter p provides the data collector with multiple trade-off choices. Second, the two identified parameters $\{\vec{s_i}, z_i\}$ provide the data collector with consumer level interpretability of the obfuscation of T_i. By fine-tuning $\{\vec{s_i}, z_i\}$, our ultimate goal is to understand, quantify, and optimize the trade-off between the data utility ($\mathcal{U}$) and privacy risk ($\mathcal{PR}$) in a meaningful way.

5. Empirical Study

Consistent with the overview of the proposed framework (Part A of Figure 1), prior to obfuscation, we first compute each consumer i's suppression score z_i based on the calculated risk r_i (Section 4.1) and compute each consumer's suppression weight $\vec{s_i}$ based on the frequency, recency, and time spent at each location (Section 4.3). We also compute the data utility $MAP@k$ and $MAR@k$ (Section 4.2) on the unobfuscated data. Next, we obfuscate each consumer's trajectory based on the suppression probability of each location computed from combining the above computed z_i and s_i (Equation 6) by varying $p \in \mathcal{G}_p = \{0, 0.1, ..., 1\}$ (Part B of Figure 1). We will discuss each of the above steps in detail below.

[5] r_i estimated as detailed in Section 4.1 and w_i from the data depending on frequency, recency or time spent at each location

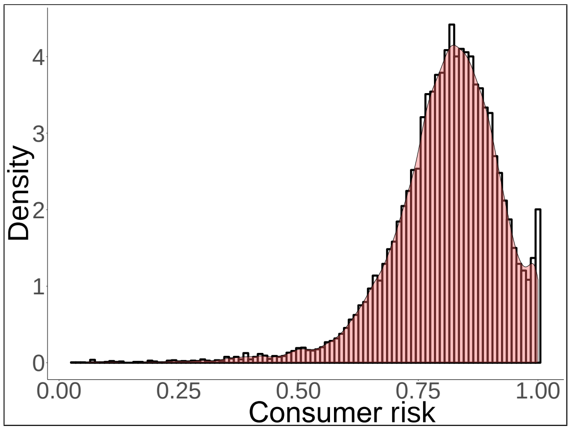
[6] Note that $r_i \in [0, 1]$ and $w_i^j \in [0, 1]$ by construction. In our empirical study, whenever $(z_i + z_i \times w_i^j)p > 1$, we suppress the location j with probability 1

5.1. Quantification of Consumer's Privacy Risk

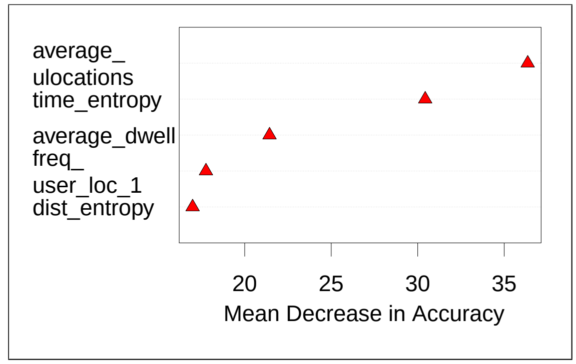
We estimate the overall consumer risk for various levels of obfuscations $p \in \mathcal{G}_p$. For each type of threat, we first quantify the consumer risk by extracting features $\mathcal{F}(T)$, learning the machine learning heuristics to predict consumer risk for the entire sample ($p = 0$) without any obfuscation. These risks are baseline individual risks when the location data are shared with an advertiser as is (Part A in Figure 1). Based on these baseline risks, we perform consumer-level obfuscation by varying $p \in \mathcal{G}_p$ (Part B in 1). Note that each value of p would result in a new specification of the suppression parameters $\{\vec{s_i}, z_i\}_{i=1}^N$, assignment of suppression probabilities to trajectories in T, resulting in varied obfuscations $P(T)$. We then repeat the process extracting features and re-calculating the consumer risks on each obfuscated trajectory $P(T)$. Finally, we compute the overall privacy risk $E(r_i)$ by averaging the risks across all consumers. To obtain a consistent estimate, we use bootstrapping with 20 trials for each $p \in \mathcal{G}_p$.

In the sensitive attribute threat, we consider two sensitive attributes of home address and mobile operating system. To train the predictive model, we mimic a stalker with access to a training sample of known trajectories and sensitive attributes. We split the data into two random samples: 50% training set (T_{train}) with 20,000 consumers to train the predictive model, and 50% test set (T_{test}) with 20,012 consumers. Recall that in risk quantification (Section 4.1), we use Random Forest regressor to predict the risk of home locations and use Random Forest classifier to predict mobile operating system and re-identification risks. To avoid over-fitting, we perform a five-fold cross-validation on T_{train} and pick two optimal hyper-parameters specific to the Random Forest – the maximum number of features in the tree and the number of trees (see the Appendix A for more details). Cross-validation ensures that the model produces better out-of-sample predictions (Friedman et al. 2001). Once the model is trained, we apply it to estimate the risk on T_{test} in each privacy threat. In Figure 4, we report the average risk computed for each p across all consumers in T_{test}. To compute the privacy risk of the re-identification threat, we assume the number of locations in each consumer's trajectory already known to a stalker is 2, that is, $|\bar{T}_i| = 2$ in Definition 2 to illustrate our approach.

A data collector can gain a host of insights from the initial step of quantifying consumers' privacy risks prior to obfuscation, such as which consumers are at the greatest risk, what is the severity of each privacy risk, which feature is most informative to a stalker and hence should be suppressed. For example, Figure 3a offers the data collector a visual of the distribution of the consumers' risks if a stalker were to infer their operating systems from the unobfuscated trajectory data. It shows that the majority of the consumers carry a relatively high risk (≥ 0.75 chance of success for a stalker) of their sensitive attribute of operating system being inferred if no obfuscation were performed. Also, the average risk of home address inference is 0.84. By assessing the error of the



(a) Consumer risk density - OS inference threat



(b) Feature importance, OS inference model

Figure 3 Personalized Risk Management Insights

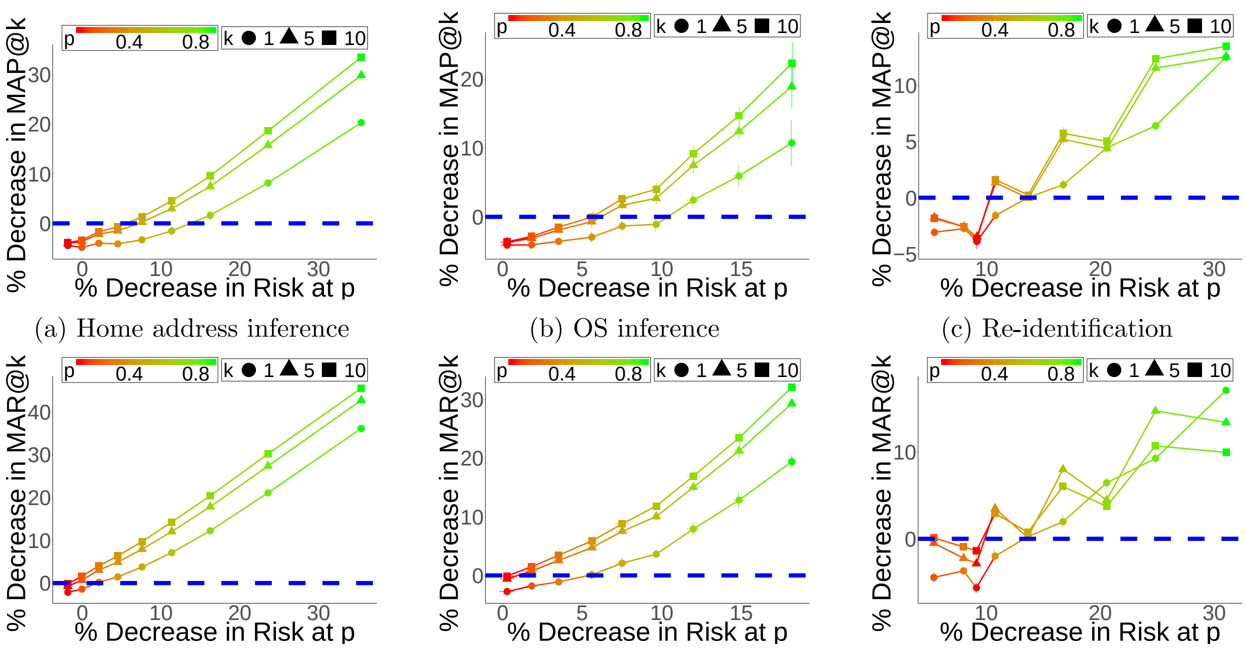
Random Forest regressor learned to predict the home address, we find that on average a stalker could successfully identify a consumer's home address within a radius of 2.5 miles (Appendix A). Further, the average risk of re-identifying an individual's entire trajectory by knowing merely two randomly sampled locations is 0.49, that is, a 49% chance of success for a stalker. In addition, the data collector can assess the worst cases associated with the top-risk consumers in each of the above threats.

Despite these paramount privacy risks arising from unobfuscated location data, they can be curtailed by a data collector using the proposed framework. For instance, the risk associated with the operating system inference could be reduced by 10% (Figures 4b, 4e, $p = 0.6$) while fully preserving the data utility on the POI@1 performance. As a follow-up step, by implementing the POI recommendation strategy in the real world, a data collector can also measure the monetary value of an individual trajectory, and compare it with the user-specific privacy risk to better understand customer lifetime value (Berger and Nasr 1998) and personalize customer relationship management.

In addition, a data collector may look at the feature importance prior to obfuscation. For instance, Figure 3b displays the top five most important features of the Random Forest trained to compute the consumers' risks in Figure 4b. A data collector can infer that the temporal information of the trajectories (`time_entropy` and `average_dwell`) contributes most to the model's predictive performance. Hence, a possible obfuscation scheme that removes (even partially) the timestamps in the trajectories would prevent the stalker from constructing the temporal features and hence considerably reduce the consumers' risks. Similar insights can be gained by analyzing the risk scores related to other stalker threats - home address inference and re-identification threat considered in the work.

5.2. Quantification of Advertiser's Utility

Next, we compute the data utility to a butler advertiser by leveraging a collaborative filtering recommendation heuristic to predict each consumer's future locations. To assess the predictive accuracy, we use the locations actually visited by each consumer in the fifth week as the ground truth and train the recommender model to predict the locations. Based on each consumer's risk level calculated earlier, we perform varying levels of obfuscation, $p \in \mathcal{G}_p$. A neighborhood-based recommender (Bobadilla et al. 2011) is learned on a grid of $\{5, 10, 25, 50, 100, 200\}$ to tune the number of neighbors via a five-fold cross-validation on the obfuscated data. The model ranks the locations that a consumer is likely to visit in the fifth week of the observation period. That is, we build the features (discussed in Section. 4.1.1) on the first four weeks of the obfuscated data and tune the number of neighbors to maximize the prediction accuracy. Then, we compute the average utility for the advertiser across all consumers, $MAP@k$ and $MAR@k$, for $k = \{1, 5, 10\}$ to illustrate the method's efficacy. The model can also be used to compute $MAP@k$ and $MAR@k$ for other values of k. We perform 20 trials for each p and report the mean and 95% confidence intervals of the utility (Figure 4). A more detailed explanation of the utility computation is available in the Appendix B.



(a) Home address inference (b) OS inference (c) Re-identification

(d) Home address inference (e) OS inference (f) Re-identification

Figure 4 Proposed framework - $MAP@k$ **and** $MAR@k$ **for varying** p

5.3. Obfuscation Scheme for Data Collector

In Figures 4a, 4b, and 4c, we visualize the trade-off between data utility and privacy risk. The locations are suppressed based on the suppression probabilities assigned to each T_i that depend on the single parameter p, and derived from the two parameters $\{\vec{s_i}, z_i\}_{i=1}^{N}$ in our obfuscation scheme (Eq 6, Section 4.3). We will focus on discussing the results where the suppression weights $\vec{s_i}$ are assigned based on the frequency to each location, although we have also assigned $\vec{s_i}$ based on recency and time spent at each location (Appendix D). In Figures 4a, 4b, and 4c, the X and Y axes display the percentage decrease in the aggregate risk and $MAP@k$ from the original sample ($p = 0$) with no obfuscation for each $p \in \mathcal{G}_p$ respectively. We plot these for $k = \{1, 5, 10\}$. Intuitively, the higher the value of X-axis, the more the decrease in the overall risk and hence better preservation of privacy. On the other hand, the lower values of Y-axis correspond to a lesser decrease in the utility of the obfuscated data compared to the original data, suggesting a similar utility for the advertiser even after obfuscation. A data collector who aims to trade off between utility and privacy is thus presented with multiple choices in our framework. Ideally, a good choice for obfuscation would be the values of p that correspond to a higher value along the X-axis and a lower value along the Y-axis. In the figures, the horizontal blue line, with no decrease in data utility from obfuscation indicates these choices. Similar insights can be drawn from figures 4d, 4e, and 4f where we compare the percentage decreases in $MAR@k$ to the percentage decreases in the aggregate risk.

In all graphs in Figure 4, we observe that as we increase p, both the quantities decrease in the aggregate risk (X-axis) and decrease in the performance measures (Y-axis) increase. This is expected since an increase in p, for the same consumer risk scores, more locations get suppressed, meaning more information loss to an advertiser's utility as well as a privacy threat. For a given percentage decrease in risk, we observe a lesser corresponding percentage decrease in performance. This can be explained by the framework's obfuscation parameters $\{\vec{s_i}, z_i\}_{i=1}^{N}$ which are varied based on the consumer risk scores that capture the success of a privacy threat. This risk-based obfuscation would penalize and cause more information loss to the stalker's adversarial intent compared to the utility. The figures also emphasize the proposed framework's flexibility to provide a data collector with several interpretable choices for obfuscation. Further, since our obfuscation scheme works by suppressing a set of location tuples instead of randomization (Yang et al. 2018) or splitting (Terrovitis et al. 2017), this would also have potential benefits to the server costs incurred by an advertiser in storing and analyzing the location data.

5.4. Model Comparisons

We compare our framework's obfuscation scheme with eight different baselines corresponding to three types of obfuscation schemes – obfuscation rules derived from timestamps of consumer locations, alternate suppression schemes based on consumer risk and the most recent work in syntactic models LSup and GSup (Terrovitis et al. 2017).

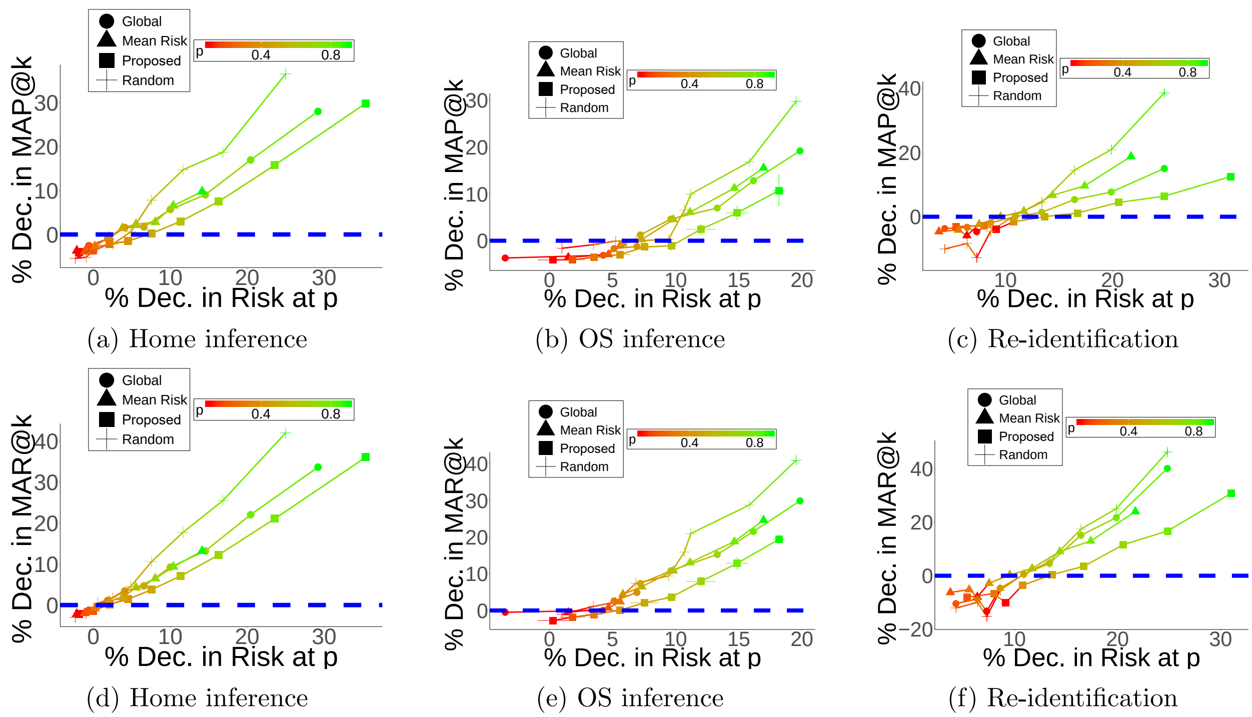
Obfuscation rule	% Decrease Home address risk	% Decrease Operating system risk	% Decrease Re-identification risk	% Decrease Utility (MAP@1)	% Decrease Utility (MAR@1)
Remove Sleep hours	2.43	12.51	1.41	11.83	12.69
Remove Sleep and working hours	10.72	21.84	21.49	34.45	23.72
Remove time stamps	13.45	25.49	0	33.16	32.97

Table 3 Alternative Schemes: Rule-based Obfuscation

5.4.1. Comparisons to Rule-based Obfuscations. We derive a few practical rules for obfuscation based on the timestamps of consumer locations in the location data. In the absence of a privacy-friendly framework, a data collector could perform obfuscation by choosing to 1) Remove all the locations during the usual sleeping hours (10 PM - 7 AM) on all days, 2) Remove locations in sleeping hours and working hours (9 AM - 6 PM) on weekdays, or 3) Remove timestamps of locations entirely before sharing the data. The three time-based rule obfuscations would reduce the amount of information that can be extracted from the shared location data and hence would adversely affect the advertiser's utility and adversarial intent to invade consumer's privacy. For instance, if the timestamps of the location data were to be removed both mobility features (refer Table 2) – `time_entropy`, `time_rog`, `average_dwell` and the consumer-consumer, consumer-Location affinity features (refer Section 4.1.1 based on time spent by a consumer at a location cannot be computed.

The decrease in risks for the two threats and decrease in utility for each of these obfuscations are presented in Table 3. As expected, there is a decrease in both risk and utility. In the home address inference threat (Figure 4a, $p = 0.7$, $k = 1$), we find that a risk to consumer privacy can be reduced by 15% (maximum decrease when compared to rule-based heuristics) with less than 1% decrease in $MAP@1$ (minimum decrease). A similar trend is observed in re-identification threat (Figures 4c, 4f). In the operating system inference (Figure 4a, $p = 0.9$, $k = 1$), we observe that risk is reduced by $\approx$ 18% compared to 25.49% when timestamps are removed. However, this is achieved with a lesser decrease in utility $\approx$ 10% using the proposed framework when compared to the 33%. Overall, we find a better choice set for the trade-off justifying a need for a privacy-friendly framework to assist a data collector to share location data in a privacy-friendly way.

5.4.2. Comparisons to Risk-based Obfuscations. We compare the proposed obfuscation framework to three alternate suppression baselines. These are devised to show the efficacy of consumer risk quantification and personalized local suppression (achieved by introducing and identifying consumer-specific parameters $\{\vec{s_i}, z_i\}$) of trajectories performed in our framework.



(a) Home inference (b) OS inference (c) Re-identification

(d) Home inference (e) OS inference (f) Re-identification

Figure 5 Proposed framework vs risk-based obfuscations - $MAP@1$ **and** $MAR@1$

1. **Random** - In this baseline, we do not perform suppression of locations at a consumer level. Instead of hiding location tuples in T_i based on $z_i = r_i \times p$ and suppression weights $\vec{s_i}$, we randomly suppress locations in T. We suppress the same number of location tuples as in our framework's obfuscation scheme to make it comparable.

2. **Mean Risk** - Here, we perform a consumer-specific suppression without any variation across consumers here. We replace the consumer risk score r_i with the mean $\bar{r} = \frac{1}{N}\sum_i r_i$ as r_i and hide locations using $z = \bar{r} \times p$ and suppression weights $\vec{s_i}$ as described in Section 4.3 for each T_i.

3. **Global** - In this baseline, we suppress a location tuple globally. That is, a tuple in any T has the same chance of being suppressed irrespective of a different consumer risk threat. This is different from our obfuscation scheme where a tuple may not be suppressed for a less risky but has been suppressed for a high risk consumer. For each tuple, we assign the mean of consumer risk scores as tuple risk score, vary p and perform suppression.

We empirically compare the proposed obfuscation scheme to the baselines listed and visualize $MAP@1$ and $MAR@1$ in Figure 5. We observe that, for a given decrease in risk, our framework's obfuscation has the least decrease in utility gain across all three threats. Random baseline, which is an ablation of our obfuscation scheme without the risk quantification step performs the worst among competing models. This justifies a need for threat quantification either at a consumer-level (Mean Risk and proposed obfuscation) or at a location tuple level (Global). Better performance than Mean Risk baseline shows that a personalized level of obfuscation for each consumer is necessary. Finally, a higher utility gain over Global baseline emphasizes the need for quantifying and suppressing locations at a consumer level compared to a tuple level.

5.4.3. Comparisons to Prior Suppression Models. Finally, we compare the proposed framework to the most recent suppression based syntactic models LSup and GSup proposed by Terrovitis et al. (2017). We observe that in a majority (10 out of 12) of the cases, the proposed framework provides a better trade-off (denoted by green color in Table 4) compared to both LSup and GSup. This improved trade-off come with an added benefit that the obfuscation scheme of the proposed framework only requires one input parameter corresponding to the number of locations of a stalker in the re-identification threat compared to the various parameters required for LSup and GSup. Due to space limitations, we discuss the details of the comparison in Appendix C.

6. Conclusion

Smartphone location tracking has created a wide range of opportunities for data collectors to monetize location data (Valentino-Devries et al. 2018). Leveraging the behavior-rich location data for targeting is proven to be an effective mobile marketing strategy to increase advertisers' revenues (Ghose et al. 2018). However, these monetary gains come at the cost of potential invasion of consumer privacy. In this research, we tackle this important and under-studied topic from a data collector's perspective. We identify the key challenges faced by a data collector and propose an end-to-end framework to enable a data collector to leverage location data while preserving consumer privacy.

The existing literature on privacy preservation, primarily from the Computer Science discipline, are either unsuited for this new type of data with distinct challenges, or not interpretable or personalized to an individual level. Our research fills this gap. Specifically, we propose a framework of three components, each addressing a key topic facing a data collector. First, we quantify each consumer's risks, exemplified by two common types of stalker behaviours – sensitive attribute threat and re-identification threat. These risks are intuitively modeled as the stalker's success probabilities in inferring the consumer's private information. Second, we measure the utility of the location trajectory data to an advertiser by considering a popular business use case - POI recommendations. The utility is estimated by the accuracy of using the location data to infer a consumer's future locations. Finally, to enable a data collector to trade off between consumer risk and advertiser utility, we propose an obfuscation scheme suppressing consumers' trajectories based on their individual risks associated with each privacy threat and informativeness of each location in their trajectories. The proposed obfuscation scheme provides multiple options for the data collector to choose from based on specific business contexts.

We validate the proposed framework on a unique data set containing nearly a million mobile locations tracked from over 40,000 individuals over a period of five weeks in 2018. To our best knowledge, this research reflects an initial effort to analyze such a rich, granular, newly available human trajectory data; and for the purpose of privacy preservation. We find that there exists a high risk of invasion of privacy in the location data if a data collector does not obfuscate the data. On average, a stalker could accurately predict an individuals home address within a radius of 2.5 miles and mobile operating system with an 82% success. The proposed risk quantification enables a data collector to identify high risk individuals and those features contributing to the risk associated with each privacy threat. Furthermore, using the proposed obfuscation scheme, a data collector can achieve better trade-off between consumer privacy and advertiser utility when compared to several alternative rule-based and risk-based obfuscations. For instance, in the home address inference threat, we find that a risk to consumer privacy can be reduced by 15%, a maximum decrease when compared to rule-based heuristics, with less than 1% decrease in utility, a minimum decrease. Further, we compare our proposed framework to eight baselines and exemplify the performance gains in balancing the privacy-utility trade-off. In summary, this study presents conceptual, managerial, and methodological contributions to the literature and business practice, as summarized in the Introduction. Besides offering a powerful tool to data collectors to preserve consumer privacy while maintaining the usability of the increasingly accessible form of rich and highly valuable location data, this research also informs the ongoing debate of consumer privacy and data sharing regulations.

Despite the contributions, there are limitations of this research, thus calling for continued explorations of this rich and promising domain. For example, our data contain device IDs, but no detailed demographics, associated with each consumer. When such data become available, one may, for instance, develop deeper insights into which demographic sub-populations are most vulnerable to privacy risks. Also, our analysis considered the locations' longitudes and latitudes, but not names (such as Starbucks) or types (such as hospital). Hence future research may further distinguish varied sensitivity levels across locations in privacy preservation. Furthermore, as other data, such as the same consumers' online clickstreams or social media comments, become linked to their mobile location data, more sophisticated privacy preservation methodologies may be developed.

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Appendix A: Model choices in proposed framework

We empirically justify the model choices made in our methodology. All the choices were made based by assessing the performance of different machine learning heuristics used in our framework on unobfuscated data. First, in Figures 6a, 6b we show the incremental benefit of the affinity features discussed in the feature extraction $\mathcal{F}(T)$. Figure 6a shows the accuracy of the Random Forest classifier to predict the operating system of a consumer. The model was regularized by performing a grid search on the maximum number of features and trees [7] via five-fold cross-validation. The best performing model has an accuracy of 82% which indicates the success a stalker would have in inferring the unpublished operating system of a consumer from trajectory data. In Figure 6b, we plot the RMSE of the Random Forest regressor trained to predict the home address of a consumer.[8]

Next, we learn two regression models to predict the Universal Transverse Mercator (UTM) transformed latitude and longitude of the home location with similar hyperparameter tuning as earlier. The error estimate is the Euclidean distance between the estimated and assigned home UTM coordinates. From the box plots of the re-sampled performance measures (Figures 6a, 6b), we notice that the consumer-consumer and consumer-Location affinity features incrementally improve the performance of both the proxy models learned. In Figures 6c, 6d, we visualize the $MAP@k$ and $MAR@k$ of the neighborhood-based recommendation model learned by tuning the number of neighbors.

We compare the performance with several baselines - recommendations based on the most popular locations (Most Popular), based on the locations that the consumer spent the most time in (Most Dwell (consumer)), visited most frequently (Most Frequent (consumer)) and an SVD on the consumer-location matrix populated with frequency. We observe that the NN based model performs better in both the metrics compared to the baselines justifying the choice. The RMSE, 3,900 meters $\approx$ 2.46 miles indicates the success a stalker would have in identifying the home location of a consumer from non-obufuscated data. Further, we also notice the incremental benefit (See NN consumer Mobility vs NN consumer Mobility + affinities in Figures 6c, 6d) of the affinity features in the recommendation performance.

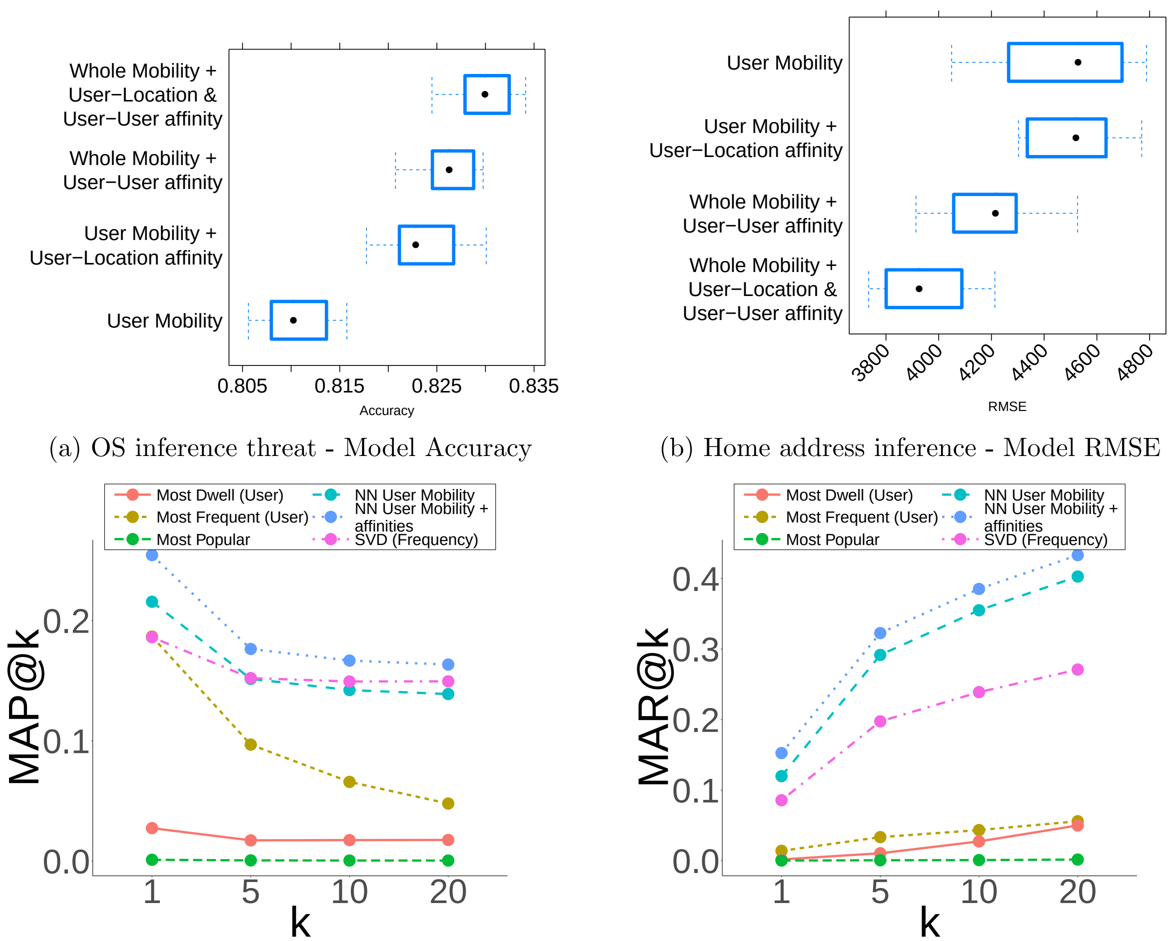
Appendix B: Utility measurement

We compute the data utility under different obfuscations. We estimate this by computing the performance of a neighborhood-based collaborative filtering recommendation heuristic to accurately predict future consumer locations. To assess the accuracy of predictions made, we treat the locations visited by each consumer in the fifth week as ground truth and train the recommender model to predict these locations.

Based on the consumer risks, we obfuscate T_{train} by varying $p \in \mathcal{G}_p$. We learn a neighborhood-based recommender (Bobadilla et al. 2011) tuning number of neighbors by five-fold cross-validation on the obfuscated training sample $\mathcal{P}(T_{train})$. The model is learned to rank locations a consumer is likely to visit in the fifth

[7] Grid for fraction of features - $\{.25, .5, .75, 1\}$, trees - $\{50, 100, 200\}$

[8] We infer the ground truth of home location in our data by assigning this to be the most frequently visited location during 10 PM - 6 AM for each consumer. We have already tested alternative time periods such as 11 PM - 5 AM, and the results remain robust. We also delete the inferred home location from all consumer trajectories for our experiments.



(a) OS inference threat - Model Accuracy

(b) Home address inference - Model RMSE

(c) $MAP@k$ POI Recommendation model

(d) $MAR@k$ POI Recommendation model

Figure 6 Proposed framework model choices

week of the observation period. That is, we build features, $\mathcal{F}(P(T_{train}))$ on first four weeks and tune number of neighbors[9] to maximize prediction accuracy. Then, we compute utility —$MAP@k$, $MAR@k$ on T_{test} for $k = \{1, 5, 10\}$[10]. Intuitively, $MAP@1$ and $MAR@1$, for example, represent advertiser's utility to predict next location a consumer is most likely to visit in the fifth week based of the recommender model that was learned on the obfuscated data. A key detail in the utility estimation is that we do not perform any obfuscation on T_{test} for any value of p since our aim is to quantify the ability of obfuscated data, $\mathcal{P}(T_{train})$ to learn true preferences of a consumer, which are revealed in the unobfuscated test sample. Similar to risk, we perform twenty trials for each p and report mean and 95% confidence intervals of utility metrics in Figure 4.

Appendix C: Comparison to LSup and GSup

Continuing our comparison to different types of baselines from Section 5.4, here, we compare the proposed framework to the most recent syntactic models LSup and GSup proposed by (Terrovitis et al. 2017). Both

[9] Grid for number of neighbors - $\{5, 10, 25, 50, 100, 200\}$

[10] The learned recommender model can be used to compute $MAP@k$, $MAR@k$ for other values of k as well. We consider $k = \{1, 5, 10\}$ for illustration of the method's efficacy.

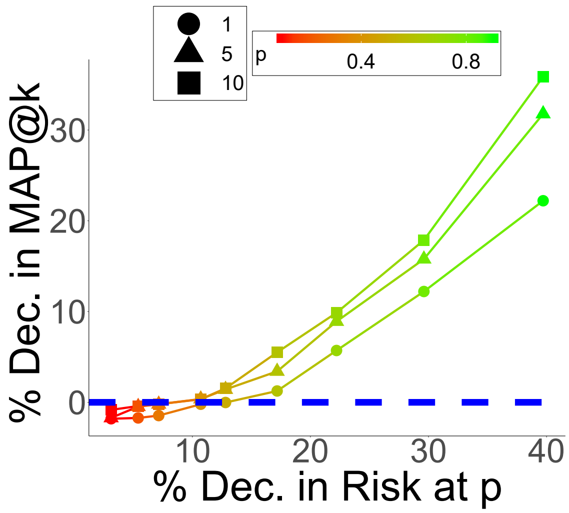
the models obfuscate the location data to reduce the re-identification threat by maintaining utility. Methodologically, these models differ from the proposed framework (Section 4.3) in two ways. First, in both LSup and GSup, the consumer risk is only quantified for one threat (re-identification) whereas our framework additionally considers sensitive attribute inference. Second, the suppression is either performed globally, that is a location is suppressed across all the consumers(GSup) or locally (LSup), location suppressed for a subset of the consumers. In our suppression scheme, thanks to the introduction of the two consumer specific parameters $\{\vec{s_i}, z_i\}$, suppression occurs at a consumer level with varying suppression probabilities assigned to each location a consumer has visited. In addition, compared to the parsimonious inputs that our proposed framework requires, both the models in consideration require multiple input parameters P_{br}, number of adversaries $\mathcal{A}$ and background knowledge of each adversary in $\mathcal{A}$. P_{br} controls the number of locations suppressed either locally (LSup) or globally (GSup). Higher the value of P_{br}, lower the number of location suppressed. In our comparison, we follow the empirical evaluation framework of the authors to set the number of adversaries $\mathcal{A}$ and background knowledge of each adversary in $\mathcal{A}$ and vary P_{br}.

Obfuscation Method	% Decrease Home address risk	% Decrease Operating system risk	% Decrease Re-identification risk	% Decrease Utility (MAP@1)	% Decrease Utility (MAR@1)
GSup ($P_{br} = 0.2$)	18.12	9.26	14.52	7.74	8.31
GSup ($P_{br} = 0.5$)	7.25	3.11	7.29	4.49	3.42
LSup ($P_{br} = 0.2$)	22.16	14.56	31.56	5.31	7.12
LSup ($P_{br} = 0.5$)	9.15	4.01	10.91	-1.65	0.86

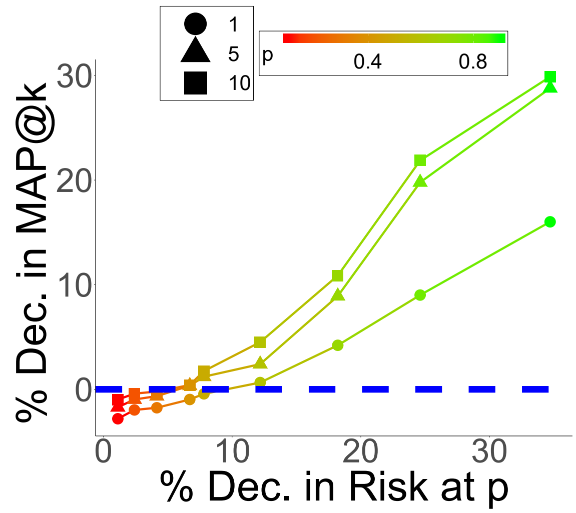
Table 4 LSup **and** GSup **comparison. (Green/Red indicate proposed framework provides a better/worse trade-off)**

In Table 4, we present the the decrease in consumer risk from the unobfuscated trajectories for the two types of privacy threats - re-identification and sensitive attribute inference[11] (operating system and home address inference) and the corresponding measures of advertiser's utility as $MAP@1$, $MAR@1$. To identify the obfuscation scheme that provides the better/worse trade-off, we compute the slope ($\frac{Y}{X}$ in Figure 4 —% Decrease in utility divided by % Decrease in risk) for different decreases in utility ($MAP@1$) of LSup and GSup. We observe that in a majority (10 out of 12) of the cases, the proposed framework provides a better trade-off (denoted by green color in Table 4) compared to both LSup and GSup. This improved trade-off come with an added benefit that the proposed framework only requires one input parameter corresponding to the number of locations of a stalker in the re-identification threat compared to the various parameters required for LSup and GSup.

[11] Since the considered models do not handle sensitive attribute inference, we obfuscated the data to reduce re-identification threat and use the same obfuscated data to quantify the reduce in consumer risk for the two types of attacks.



(a) Suppression based on time spent



(b) Suppression based on recency

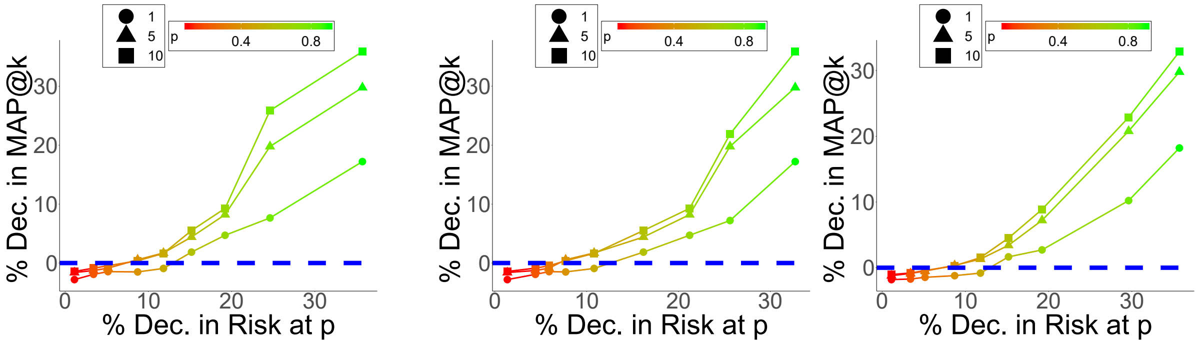
Figure 7 Proposed framework : Home address inference, suppression by recency and time spent.

Appendix D: Suppression based on recency and time spent

In our suppression scheme detailed in Section 4.3, we introduce and provide a structured grid search by varying the grid parameter p to identify two consumer specific parameters $\{\vec{s_i}, z_i\}$, where z_i captures the number of locations to be suppressed for a given consumer trajectory T_i and within T_i, we assign weights to each tracked location through $\vec{s_i}$ to denote the likelihood of a specific location being suppressed. In our empirical study detailed in Section 5, in Figure 4, we assign $\vec{s_i}$ based on the frequency of the location visited in T_i. Here, we augment the empirical study and showcase the flexibility of the proposed suppression scheme by assigning the $\vec{s_i}$ based on time spent by a consumer at each location in T_i and the recency of the locations in T_i. For brevity, we only consider the sensitive attribute threat where a stalker aims to infer the home address of a consumer and visualize the privacy-utility trade-off in figures 7b,7a. Similar to Figure 4, we observe that for a given percentage decrease in risk, there is a lesser corresponding percentage decrease in performance in both the figures.

Appendix E: Varying sample sizes

To test for the robustness of the results discussed in Figure 4, we repeat our empirical exercise on three random samples - 25%, 50% and 75% of the full 40,000 consumer trajectory data. For brevity and to avoid repetition of similar plots, the suppression is performed based on the frequency of location visited by a consumer (similar to Figure 4) for the home address inference threat. The resulting plots comparing the percentage decreases in consumer risk and advertiser's utility from the baselines (unobfuscated data) are visualized in Figures 8a,8b,8c. We note that even at smaller samples, the slope (% Decrease in utility divided by % Decrease in risk) at different values of p is similar to the full sample (Figure 4a).



(a) 25% of data sample (b) 50% of data sample (c) 75% of data sample

Figure 8 Proposed framework : Home address inference, varying sample sizes