Privacy-preserving publication of complex data

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Big Data and complex data

- **Characteristics of Big Data**
  - Volume, Velocity, **Variety**, Veracity, **Value**
- **Big Data in data mining**
  - Explores complex, evolving relationships among data (HACE Theorem [Wu et al. TKDE'13])
- **Complex data**
  - Movement data (sensors, social-network checkins)
  - Marketing data (purchases over time)
  - Health data (activities, diagnoses)

Complex data publishing

Goal: Share individuals' data for analysis and mining

- **Utility**
  - Location-based services with movement data
  - Personalized services, advertising with marketing data
  - Medical services (ADL) with health data
- **Privacy**
  - Prevent re-identification and/or sensitive location inference
  - Prevent mining of sensitive knowledge
  - Prevent inference of health profile
- **Maximize utility subject to privacy. But,**
  - Data are high dimensional (classic distance becomes meaningless)
  - Data are large (need efficient processing)
  - Problems are difficult (computationally hard and inapproximable)

Focus of the presentation

- **Trajectory data anonymization**[1,2]
- **Event sequence sanitization**[3]
- **IoT data privacy monitoring**

[1] https://doi.org/10.1109/ICDMW.2013.136
[2] http://dl.acm.org/citation.cfm?id=2870625
[3] https://doi.org/10.1137/1.9781611974010.87

Trajectory data anonymization: Setting (1/2)

- **Trajectory dataset**
  - sequence of locations per user, thousands of users
  - collected from sensors, phones, social apps
  - shared for analysis (queries, mining, visualization)

Trajectory dataset

Id	Name	trajectory
t_1	*Mary*	(d, a, c, e)
t_2	*Jim*	(b, a, e, c)
t_3	*Anne*	(a, d, e, f)
t_4	*Nick*	(b, d, e, c)
t_5	*Mark*	(d, g, c)
t_6	*Helen*	(d, e)

Trajectory data anonymization: Setting (2/2)

- **Privacy threats**
  - Re-identification: users linked to their anonymous profiles
  - Inference of sensitive locations
    - Revealing health issues, religion & political orientation

- **Example**

Trajectory dataset

Id	Name	trajectory
t_1	*Mary*	(d, a, c, e)
t_2	*Jim*	(b, a, e, c)
t_3	*Anne*	(a, d, e, f)
t_4	*Nick*	(b, d, e, c)
t_5	*Mark*	(d, g, c)
t_6	*Helen*	(d, e)

- John knows that Anne visited a cinema (a) and then a restaurant (d)
- Anne linked to t_3 and visited clinic (f) with prob. 1

Trajectory data anonymization: Goal

Problem (at a very high level)

Given a trajectory dataset, set of sensitive locations, and a distortion measure, transform the trajectory dataset, so that

- sufficiently low re-identification probability
- sufficiently low prob. of inferring any subsequence of sensitive locations
- minimum distortion (maximum usefulness)

Original dataset $\mathcal{T}$

Id	trajectory
t_1	(d, a, c, e)
t_2	(b, a, e, c)
t_3	(a, d, e, f)
t_4	(b, d, e, c)
t_5	(d, g, c)
t_6	(d, e)

Anonymized dataset

Id	trajectory
t'_6	$(\{d, a, c, e\}, \{d, a, c, e\})$
t'_3	$(\{d, a, c, e\}, \{d, a, c, e\}, \{d, a, c, e\}, f)$
t'_1	$(\{d, a, c, e\}, \{d, a, c, e\}, \{d, a, c, e\}, \{d, a, c, e\})$
t'_4	$(\{a, b, d\}, \{a, b, d\}, e, c)$
t'_2	$(\{a, b, d\}, \{a, b, d\}, e, c)$
t'_5	$(\{a, b, d\}, g, c)$

Trajectory data anonymization: Contributions (1/2)

- **Transformation operation**
  - Replace a location with a set of locations
    $a \rightarrow \{a, b, c\}$ (interpreted as any of the locations)
- **Utility measures**
  - Based on geographical and/or semantic distance, to find similar trajectories

Trajectory data anonymization: Contributions (2/2)

- **Privacy principle**

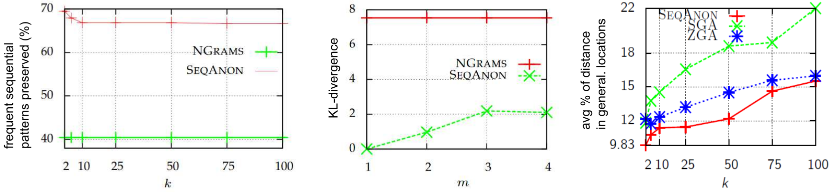
$(k, \ell)^m$-anonymous set of trajectories

- Prob. of re-identification using any sequence s of at most m nonsensitive locations bound by $\frac{1}{k}$
- Prob. of inferring any sequence of sensitive locations s', given s, bound by $\frac{1}{\ell}$

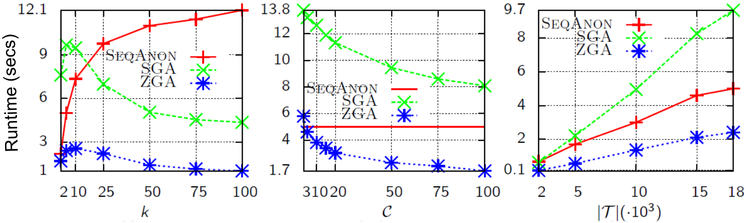
- **Efficient algorithms:** Select similar trajectories, group them together, anonymize them
    - ZGA: Z-order space filling curves
    - SGA: Projection on frequent sequential patterns
    - SeqAnon: Lattice-based search

Trajectory data anonymization: Results

- **Utility: Gowalla dataset**



- **Runtime (secs): Oldenburg dataset**



Data stream sanitization: Setting

- **Data stream: event sequence**
  - thousands of time points and a segmental structure
  - featured in applications such as marketing, web analysis, and medicine

$$(\{\mathtt{a}.1, \mathtt{b}.4, \mathtt{c}.5\}, \mathtt{t}_1) \quad (\{\mathtt{a}.2, \mathtt{b}.4, \mathtt{c}.7, \mathtt{d}.7\}, \mathtt{t}_2) \quad (\{\mathtt{a}.8, \mathtt{b}.7, \mathtt{c}.1, \mathtt{d}.4\}, \mathtt{t}_3) \quad \ldots$$

- **Frequent event mining**
  - find events with relative frequency $\geq \delta$ in any sequence prefix
  - fundamental for analyzing event sequences

  - may expose sensitive events that represent confidential knowledge

Data stream sanitization: Example

BigMart

Collects purchases from customers
Transforms them into event sequence

$(\{a.1, b.4, c.5\}, t_1) \quad (\{a.2, b.4, c.7, d.7\}, t_2) \quad (\{a.8, b.7, c.1, d.4\}, t_3) \quad \ldots$

MarketResearch

customer profiling
fraud or change analysis
trend analysis

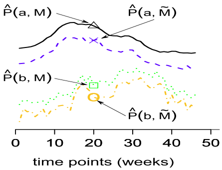
mines frequent events that
give competitive advantage
and sells it to BigMart's competitors

- Financial and reputational loss to organizations & unwarranted public concern

Data stream sanitization: Contributions

The first approach to sanitizing event sequences.

- **Utility model** for sanitized event sequences
  - Impact of deletion on the probability distribution of events



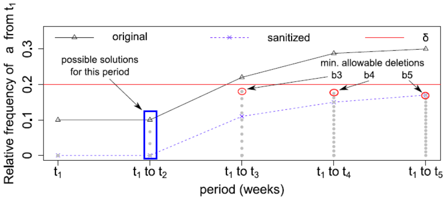
- **Definition** of the *Event Sequence Sanitization* (ESS) problem

> **Event Sequence Sanitization**
>
> Given an event sequence, a set of sensitive events, and threshold δ, construct a sanitized event sequence D' s.t.:
>
> (I) no sensitive event has relative frequency $\geq \delta$, in *any prefix*
>
> (II) D' has optimal utility, according to the model.

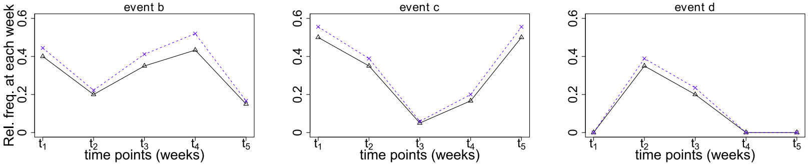
- **Optimal algorithms** for the ESS problem: *ODESA* and *ESSA*

Data stream sanitization: Overview

- **Dynamic programming:** for selecting occurrences to delete



- **Optimal error:** accurate frequent event mining



IoT data privacy monitoring (1/2)

Privacy evaluation of IoT devices and applications

- **Alarming findings:** out of 314 IoT devices [4]
  - 59% didn't explain how personal inf. was collected, used, disclosed
  - 68% didn't explain how user information was stored
  - 72% didn't explain how users can delete their information off the device
- **Standards and guides** (OWASP, GSM, OneM2M)
  - How much personal information is collected?
  - Are personal data encrypted at rest and/oir in transit?
  - Has data been de-identified and/or anonymized?
  - Could user opt-out from the collection of unnecessary data for the device's operation?

[4] GPEN privacy sweep 2016 https://www.privacyenforcement.net/node/717

IoT data privacy monitoring (2/2)

- **Different from the standard data publishing setting**
  - Data of different formats and come as streams
  - Privacy threats need to be discovered, explained, prevented
- **Research issues**
  - How to discover privacy issues on the fly from Big Data Streams?
  - How to do that without breaching the privacy of IoT device users?
  - How to involve users in the loop?
- **How to deal with the issues?**
  - Project starts in August

Conclusions

- **Big Data are often complex and high-dimensional**
  - trajectories
  - event sequences
  - combinations of them (demographics and sequential data)
  - graphs
- **Protecting the privacy of complex data is not easy**
- **Overview of some of our current and future work in the area**