



EuroDW2017

Toward Privacy-Preserving IoT Data Publishing

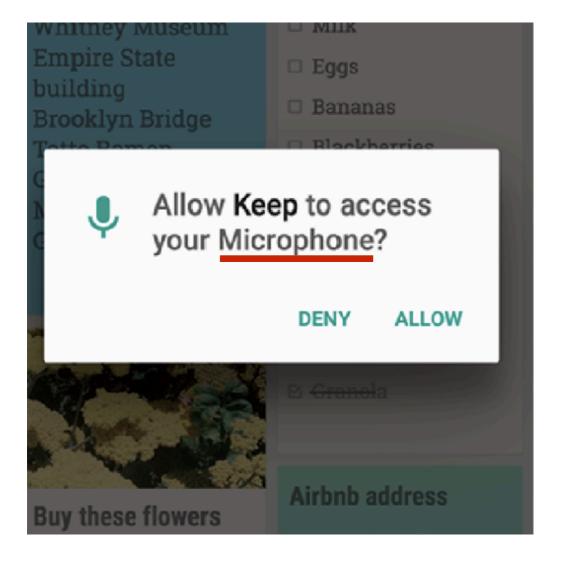
by Mohammad Malekzadeh

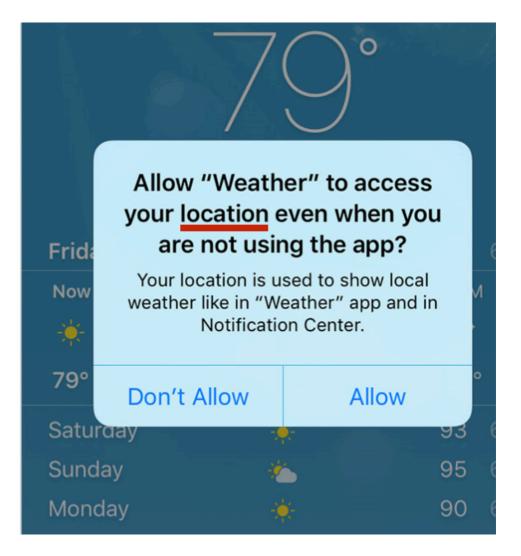
m.malekzadeh@qmul.ac.uk

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To begin with

User permission dialogs for Android and iOS^[1]





Two valuable sources of information Audio Signal and Location



BACKGROUND & PROBLEM DEFINITION

Dichotomy

- Personal time-series often contains
 precious information and individual
 behaviour can be inferred from them.
- Publishing/Mining such time-series immediately can violates individual privacy.
- But, users benefit from sharing and mining their data by external entities.
 - healthcare home security traffic controlling lifestyle improvement ...

Disclosure



There are two types of **disclosure risk**:

1) Identity disclosure:

• The association of a user's identity with a disseminated data containing confidential information

2) Attribute disclosure:

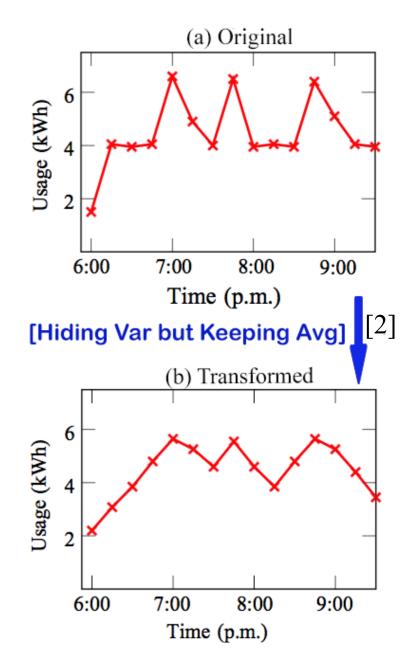
• The association of an attribute value based on the disseminated data with the user

BACKGROUND & PROBLEM DEFINITION

Problem Definition

- By sharing personal IoT data:
- original time-series mustn't be accurately reconstructed; also, sensitive information shouldn't be inferred;
- 2. yet, some **agreed statistics** should be accurately **estimated** despite the transformation

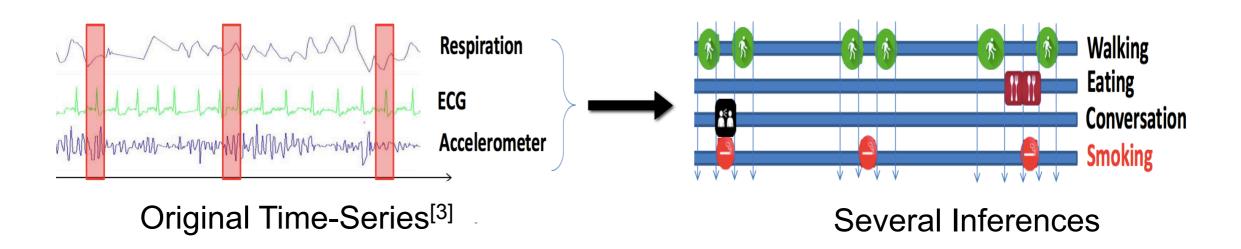




Privacy vs. Utility



- i. A privacy breach will occur when user's sensitive information can be inferred from published data.
- ii. A **utility loss** will happen when **user-aware insensitive information** cannot be inferred by third parties' application.



Techniques and Threats



Mathematical Second Se

O Threat is linkage attack using other auxiliary data sources to infer the sensitive attributes of individuals within the same dataset.

Randomisation: protecting the sensitive information contained in real data by adding some noise

Threat is removing the noise in the data in such a way that it fits the aggregate structure of the data.

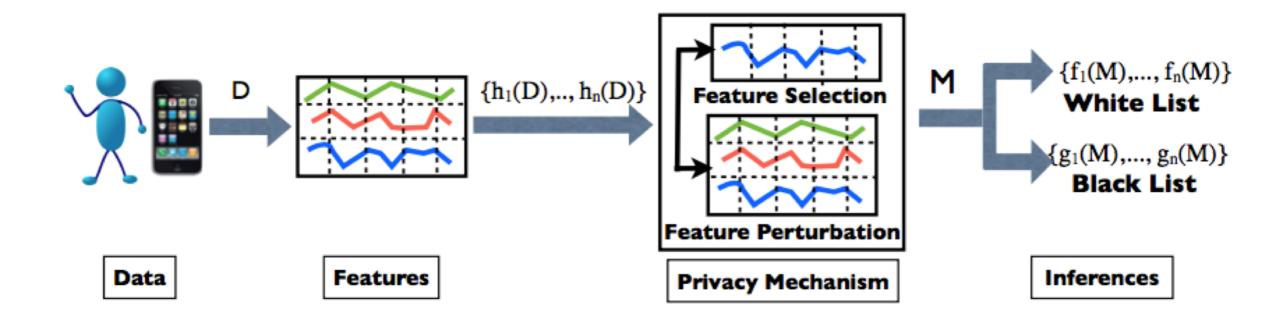
Data Synthesis: protect privacy and confidentiality of authentic data

Threat is trying to separate real data from synthetic ones.

TECHNIQUES & RELATED WORK



White & Black List

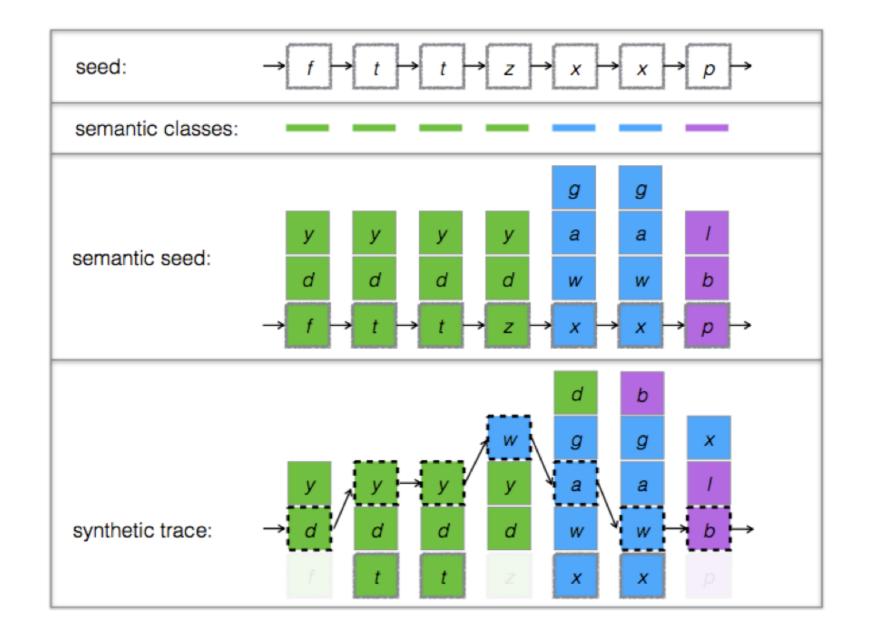


Feature Selection and Perturbation in Time-Series^[4]

TECHNIQUES & RELATED WORK

Location Obfuscation





Generating Fake Time-Series from Original One^[5]

Degree of Perturbation



- current approaches devised more for the static datasets; for dynamic cases of time-series data, scalability challenges are very crucial
 - need to **further perturbation** for coping with the correlation across time-series
 - privacy-utility trade-off over time is often obtained through **optimisations**

Privacy Measure



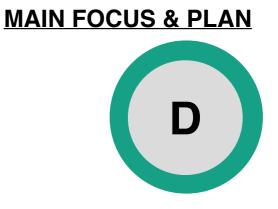
- Definition of proper measures that can truly assess the privacy of the protection
 - some measures focus on protecting the identity of a participant
 - other measures focus on the amount of sensitive information that is contained in the noisy data.
- An efficient privacy measure is more applicationspecific

Variability in Sensitivity

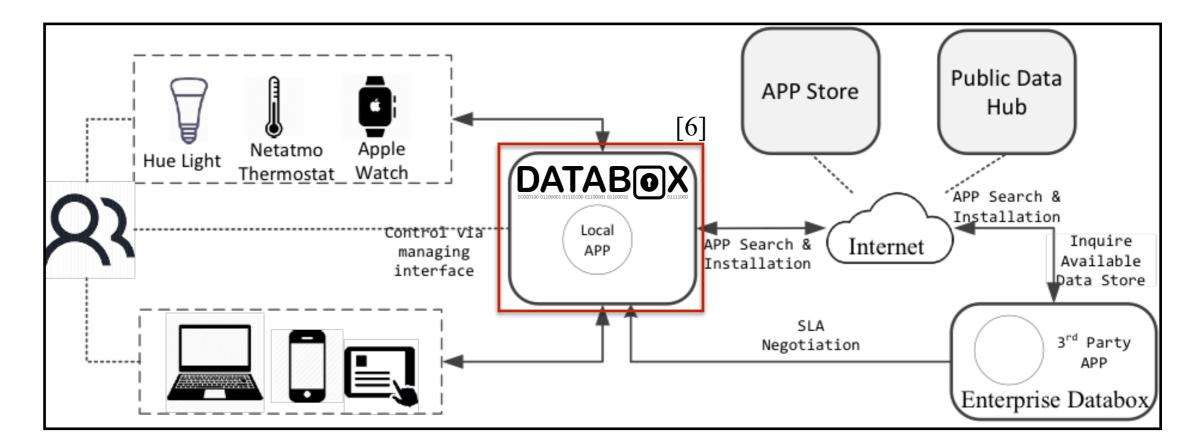


- Some applications must protect aggregate secrets while others must protect secrets about individuals
- In some cases, only certain attributes need to be protected, and certain individuals may require more privacy protection than others
- Some time-series data carries disparate information about various user behaviours

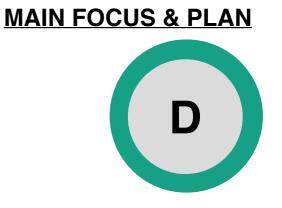
Databox



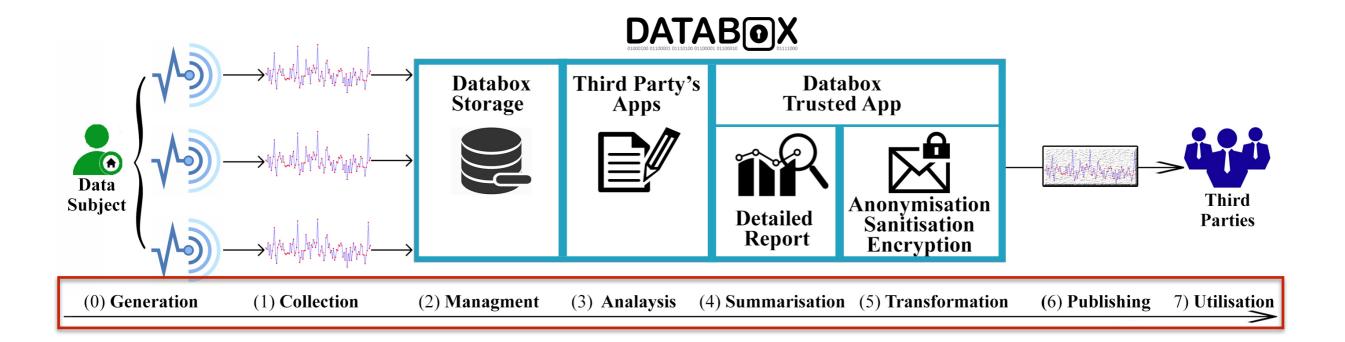
- Solution Enforcing accountability and control by design at the users' end.
- Processing of personal data can be done locally
- Publishing IoT time-series data as a part of Databox.



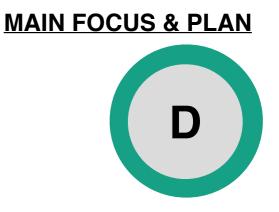
IoT Data Flow



* Third parties' apps installed on Databox are able to request for several data from different sources and perform desired analytics on the large quantity of data.

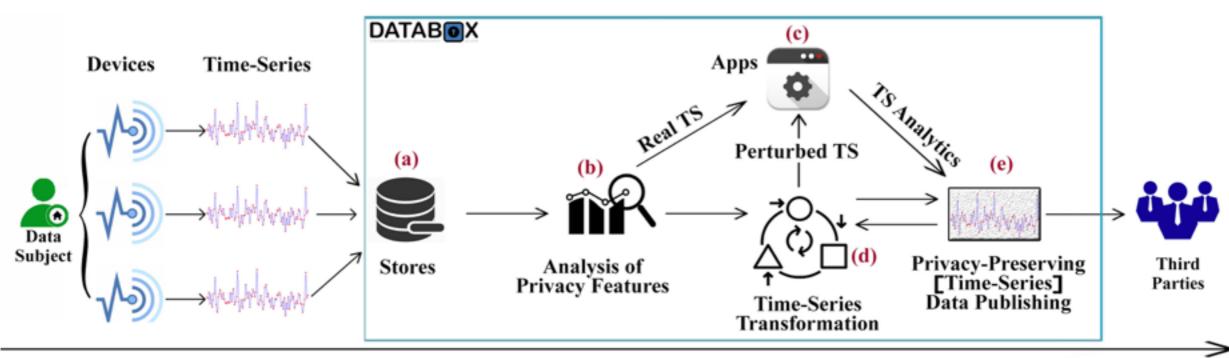


Approach

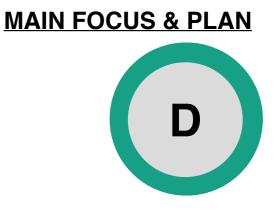


* Awareness of threats on collected time-series that can jeopardise user privacy, will help users to choose whether to provide apps their raw data or applying some transformation before granting access to them.

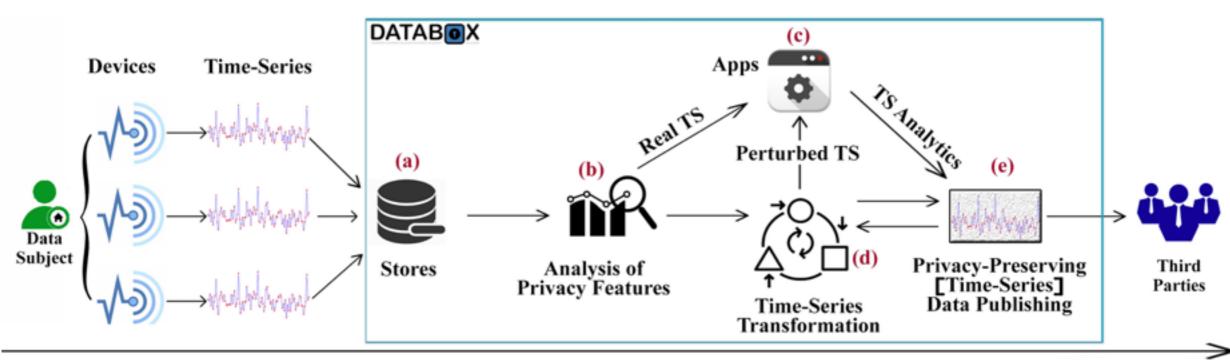
* When the processing of users' data is completed, users can allow their apps to send the results back to their providers via a privacy-preserving data publishing method.



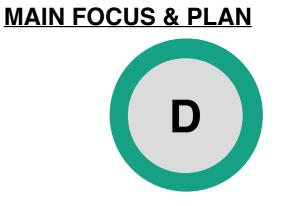
Goals



- A. Extraction of the meaningful statistics and characteristics of time series which are pertinent to user privacy.
- B. Transformation of the time-series to prevent third parties from **inferring user-specified sensitive information** while being able to accurately **achieve the agreed information**.



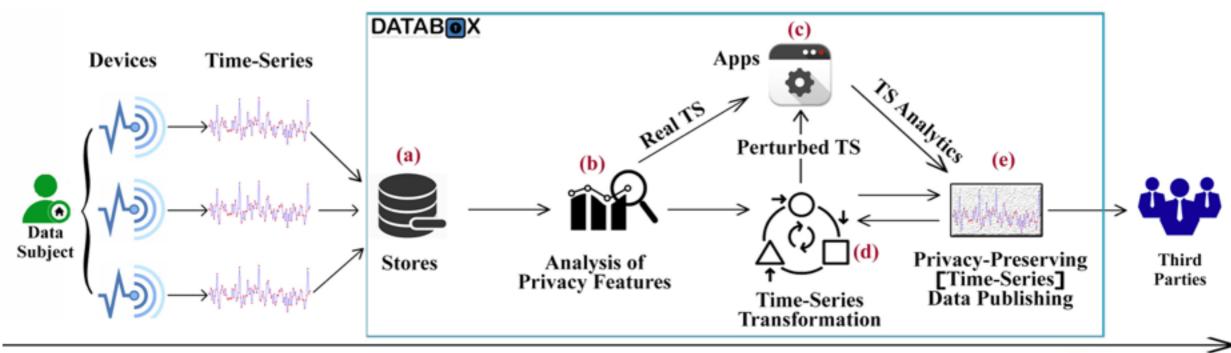
Future Direction



1) Suitable **measures** for evaluation of privacy-preserving IoT data publishing should be defined.

2) Real-world time-series **data** from IoT sensors (for a few specific sensor types) should be collected through development of specific apps for Databox.

3) We will consider **privacy leakage** in time-series data produced by multiple sensors for specific applications.



References

[1] Spensky, Chad, et al. "SoK: Privacy on Mobile Devices-It's Complicated." *Proceedings on Privacy Enhancing Technologies* 2016.3 (2016): 96-116.

[2] Laforet, Fabian, et al. "Individual privacy constraints on time-series data." Information Systems 54 (2015): 74-91.

[3] Saleheen, Nazir, et al. "mSieve: differential behavioral privacy in time series of mobile sensor data." *Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 2016.

[4] Chakraborty, Supriyo, et al. "Balancing behavioral privacy and information utility in sensory data flows." Pervasive and Mobile Computing 8.3 (2012): 331-345.

[5] Bindschaedler, Vincent, et al. "Synthesizing plausible privacy-preserving location traces." *Security and Privacy (SP), 2016 IEEE Symposium on*. IEEE, 2016.

[6] Haddadi, Hamed, et al. "Personal data: Thinking inside the box." arXiv preprint arXiv:1501.04737 (2015). Proceedings of The Fifth Decennial Aarhus Conference on Critical Alternatives. Aarhus University Press, 2015.

Thanks for your attention

