

KNOW Center





## Privately Connecting Mobility to Infectious Diseases via Applied Cryptography

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What It Is, and What It Is Not

	Contact Tracing Apps	Our Approach
Feature phones	×	✓
Data available	×/√	<ul> <li>Image: A second s</li></ul>
Contact tracing	$\checkmark$	×

#### Human mobility is a critical factor in infectious disease

- Increased contacts between susceptible and infected individuals.
- Introduction of pathogens into new geographical regions.

understanding human mobility ↓ understanding dynamic of pandemic



#### Connecting mobile phone data to infectious diseases



Fig.: Quantifying the Impact of Human Mobility on Malaria [WET<sup>+</sup>12], Science Magazine 2012

#### Go one step further

So far:

• Aggregated mobility data of all subscribers

→ issues when relatively few cases or mass-gatherings.

Our proposition:

Aggregated mobility data of infected individuals
 ~> likely more accurate epidemiological models, BUT

# Why was this not done so far?

#### Privacy?!

Two options:

- Sending mobile operator patients' identifiers
- Researchers get access to non-anonymized data records



#### Solution: Cryptography



- Homomorphic encryption protects patients' identifiers
- Zero-knowledge proof techniques ensure minimum cardinality of identifiers' set.
- Differential privacy protects highly sensitive output.



Data Aggregation

$$\begin{array}{ccccc} ct_1 & ct_2 & ct_3 \\ id_1 & id_2 & id_3 \\ (1 & 0 & 1 \end{array} ) \times \begin{pmatrix} 2 & 0 & 3 \\ 3 & 1 & 1 \\ 1 & 4 & 3 \end{pmatrix} \begin{array}{c} id_1 & ct_1 & ct_2 & ct_3 \\ id_2 & = \begin{pmatrix} 3 & 4 & 6 \end{pmatrix} \\ id_3 & & & \end{array}$$

Matrix-vector multiplication: Baby-Step Giant-Step algorithm

#### Validation of Request

$$(3 \ 4 \ 6) + mask$$
, where  $mask = \begin{cases} 0 & \text{if honest} \\ random & \text{else} \end{cases}$ 

 $\begin{aligned} mask_{\text{bin}} \leftarrow \langle \boldsymbol{c}, \boldsymbol{c} - \boldsymbol{1} \rangle \\ mask_{\text{HW}} \leftarrow \langle \boldsymbol{c}, \boldsymbol{1} \rangle - w \\ mask \leftarrow \mu_{\text{bin}} + \mu_{\text{HW}} \end{aligned}$ 

Adding Noise (Differential Privacy)

# 

Producing noise: Laplace distribution with privacy parameter  $\epsilon$ 

Larger  $\epsilon \rightsquigarrow \text{less noise} \rightsquigarrow \text{less privacy}$ 

#### **Differential Privacy Experiments**



#### Legal Analysis

Patients' ids:

### Encryption → Anonymization (when decryption key is not given away) ⇒ not personal data (GDPR)

Mobility data:

DP and orthogonal technical measures ~ risk of de-identification highly unlikely

#### Is this feasible/affordable in practice for whole countries?

 $< 2h \stackrel{\wedge}{=} 10$ \$ (e.g. Austria, Singapore, NY City)

- Optimized C++ implementation using SEAL
- 96 Threads
- IGiB data



#### Security

Homomorphic encryption  $\Rightarrow$  semi-honest security.

Is semi-honest security enough for medical records and location data?

#### NO

- Medical records: Private against malicious adversaries.
- Location data: DP protection against malicious researchers.

Even in times of crisis where it is tempting to (temporarily) lower data protection standards for purposes of big data analytics, there are technical methods to keep data protection standards high. And those technical methods are practical and available.

> https://covid-heatmap.iaik.tugraz.at/en/ https://eprint.iacr.org/2020/522

#### **References I**

[WET<sup>+</sup>12] Amy Wesolowski, Nathan Eagle, Andrew J Tatem, David L Smith, Abdisalan M Noor, Robert W Snow, and Caroline O Buckee.

#### Quantifying the impact of human mobility on malaria.

Science, 338(6104):267–270, 2012.