

# On Privacy and Intersections

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## Scope of this talk

Discuss about the problems of **Private Equality Testing**, **Private Set Intersection** and **Private Set Similarity**.

# Private Equality Testing

## PET

Let us assume that we have Alice and Bob who have a value and are willing to share **only one bit of information** whether their values are the same or not.

# Private Proximity Testing

## PPT

Alice and Bob want to test whether they are in proximity or not.

# Private Set Intersection

## PSI

Let us assume that we have Alice and Bob who are willing to share their common elements, but **nothing** more with each other.

# Private Set Similarity

## PSS

Let us assume that we have Alice and Bob are willing to share how many common elements they do have but **nothing** more with each other.

# Excessive use of PSI/S

## What happens after many queries?

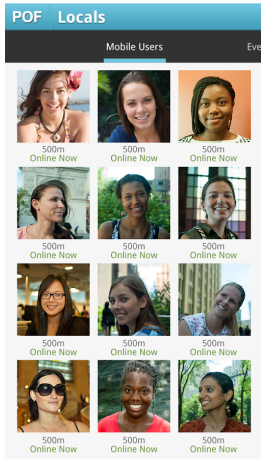
Alice may start comparisons with  $000\dots 0$  and  $100\dots 0$  to find Bob's set using PSS

# What can we do with them?

- Determine if two people are in the same area or in proximity (more on this next).
- Determine if two people know each other in a OSN.
- Determine if Alice has a bank account in Bank ABC.
- Determine if a suspect is in a flight.
- Determine if a person is in two suspect lists.
- Document similarity
- Biometric authentication (more on this next)
- DNA similarity/queries
- Private distributed Uber-like services (under development)





















# Location-awareness of OSNs



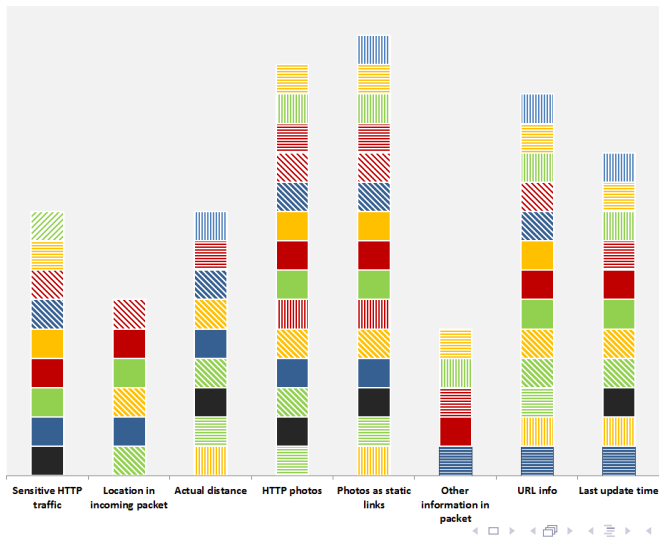
# Questions

- How accurate are these distances?
- Do these applications allow location-based attacks?
- Could we locate people from the reported distances? If so, with what accuracy?
- What kind of data are they sending?
- How do they send this data?
- What others can infer?

# Numbers...

| Application | Version | Installations | Code  | Application       | Version | Installations | Code  |
|-------------|---------|---------------|---|-------------------|---------|---------------|---|
| ChatOn      | 3.0.2   | 100m-500m     |  | Singles around me | 3.3.1   | 500K-1m       |  |
| Grindr      | 2.0.24  | 5m-10m        |  | SKOUT             | 4.4.2   | 10m-50m       |  |
| Hornet      | 2.0.14  | 1m-5m         |  | Tagged            | 7.3.0   | 10m-50m       |  |
| I-Am        | 3.2     | 500K-1m       |  | Tango             | 5.8     | 100m-500m     |  |
| LOVOO       | 2.5.6   | 10m-50m       |  | Tinder            | 4.0.9   | 10m-50m       |  |
| MeetMe      | 9.2.0   | 10m-50m       |  | Tingle            | 1.12    | -             |  |
| MoMo        | 5.4     | 1m-5m         |  | Waplog            | 3.0.3   | 5m-10m        |  |
| POF         | 2.40    | 10m-50m       |  | WeChat            | 6.0.1   | 100m-500m     |  |
| SayHi       | 3.6     | 10m-50m       |  | Zoosk             | 8.6.21  | 10m-50m       |  |

# Vulnerabilities



# Authentication

With passwords we authenticate users using something that they *know*. Another approach is to authenticate users by something that they *are*, something that cannot be forgotten or forged.

# Biometric authentication

- Iris
- Retina
- Fingerprint
- Face
- Vains
- Gait
- Ear
- Palm
- ...

# Drawbacks

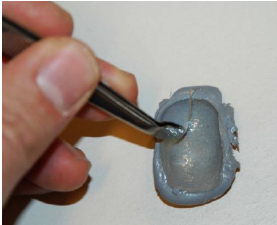
## They are not exact

Regardless of the underlying data, every measurement is not exactly the same as the one registered.

## They are permanent

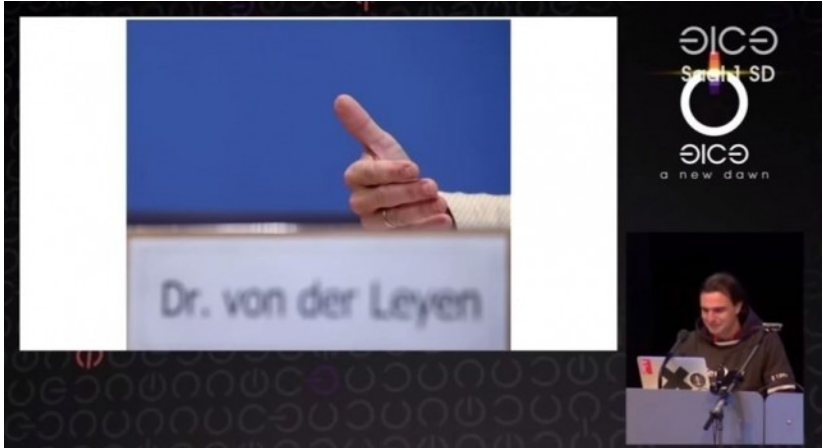
While one could easily pick another password if it has been compromised, what should a user do if her biometrics are lost?

# Copy+Paste





# Copy+Paste



## Copy+Paste

*“Research is needed in order to explore whether it is possible to use other biometric data (potentially already used in another context and in another domain) than fingerprint, iris or facial picture to store in the e-Passport chip, which would guarantee the same or higher level of security, but would be more accurate and could be retrieved in a more efficient manner than in the case of the conventionally used biometric data types.”*

From BES-06-2015 H2020 Border crossing points topic 2:  
Exploring new modalities in biometric-based border checks

# The need

We need protocols which do *not* leak any information about the biometrics, or at least minimize the exposure.

## The need – refined

We need protocols which do *not* leak any information when exchanging sensitive information about individuals, or at least minimize the exposure.

## Related work

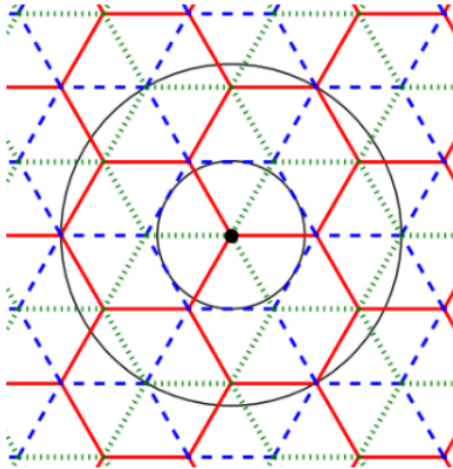
The PET problem was first introduced by Huberman, Franklin, and Hogg in 1999. Their proposed solution used the DH key agreement scheme.

**Why don't you simply use hashes?**

## Related work (cont)

The PSI problem was introduced by Freedman, Nissim, and Pinkas in 2004. The proposed solution used polynomial interpolation. Currently, there are many approaches using e.g. Yao's garbled circuits, Bloom filters and Oblivious Transfer. However, one work that must be mentioned is the work of De Cristofaro who reduced the complexity of the problem to linear.

# The Narayanan et al. grid



# Narayanan et al. protocol

Alice picks a random  $r$  and calculates  $C_A = (g_r, h^{a+r})$  and sends it to Bob. On receiving  $C_A = (g_1, g_2)$ , Bob picks two random numbers  $s$  and  $t$  and computes:  $C_B = (g_1^s g^t, g_2^s h^{(t-sb)})$  and sends it to Alice. When Alice receives  $C_B = (u_1, u_2)$ , she computes  $m = u_2 u_1^{-x}$ . If  $m = 1$ , Alice knows that she is in proximity to Bob, otherwise, she cannot deduce anything more about Bob's whereabouts.



# NTRU

A lattice-based encryption algorithm, very good homomorphic properties (Semi Homomorphic Encryption), extremely fast and secure, even from quantum attacks.

# NTRU: Setup

We then select two random polynomials  $f$  and  $g$  with small coefficients (-1, 0 and 1). We also require  $f$  to be invertible in  $\mathbb{Z}_q[x]/(x^N - 1)$  and  $\mathbb{Z}_p[x]/(x^N - 1)$ , and we denote these inverses  $f_q$  and  $f_p$  respectively. The public key  $h$  is defined as  $h = pgf_q$ , while  $f$  and  $f_p$  are the private key.

# NTRU: parameters

| Level(bits) | $p$ | $q$  | $n$ | $D_1$ | $D_2$ | $D_3$ | $D_g$ | $D_m$ |
|-------------|-----|------|-----|-------|-------|-------|-------|-------|
| 128         | 3   | 2048 | 439 | 9     | 8     | 5     | 146   | 112   |
| 192         | 3   | 2048 | 593 | 10    | 10    | 8     | 197   | 158   |
| 256         | 3   | 2048 | 743 | 11    | 11    | 15    | 247   | 204   |

# NTRU: Encrypt/Decrypt

## Encrypt

We map the message to a polynomial  $m$  with small coefficients and pick a random “small” polynomial  $r$ , and send the message  $c = hr + m \in \mathbb{Z}_q[x]/(x^N - 1)$ .

## Decrypt

The recipient multiplies it with  $f$  and rearranges the coefficients to reside within  $[-q/2, q/2]$  and reduces it modulo  $p$ . Finally, she multiplies the result with  $f_p$ .

# Privacy-Preserving Biometric Authentication

Many approaches such as:

- Blanton et al. [1] exploit the homomorphic properties of the encryption method of Damgard et al. [2].
- Shahandashti et al. [3] the Paillier homomorphic scheme for private fingerprint matching.

These methods are too slow and consume a lot of bandwidth.

## Blundo et al. sampling

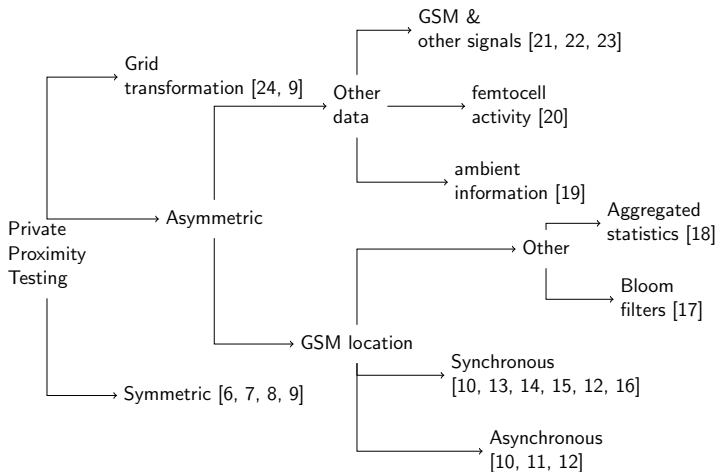
Blundo et al. [4] proposed a probabilistic protocol for the privacy-preserving evaluation of “sample set similarity”. They use MinHash to sample each set, and perform the protocol of De Cristofaro et al. [5] to determine the *cardinality* of the common elements of both sets.

# From PET to PPT

## Private Equality Testing (PET)

- Alice and Bob that want to reveal **only a single** bit of information: whether they have the same secret value or not.
- PET is a potential building block for a PPT protocol. Locations are represented by geographical cells.
- Then each cell is mapped to a unique value in a finite set (a unique id for each “cell”).
- Problem: What happens if users **are in proximity** but they reside at the edges of **neighboring cells**?

# A roadmap of PPT protocols





# Setup

- We use the idea of overlapping grids of Narayanan et al. [10], to reduce PPT to PET.
- For simplicity we describe the procedure in one grid. In each grid, each cell is marked as  $\ell_j$ .
- The scope of the protocol is to determine whether two users, Alice and Bob are in the same cell or not.
- The set of all possible cells is denoted as  $\mathcal{L}$ , so  $\mathcal{L} = \{\ell_1, \ell_2, \dots, \ell_k\}$  where  $|\mathcal{L}| \leq \mathcal{O}(2^{32})$ .

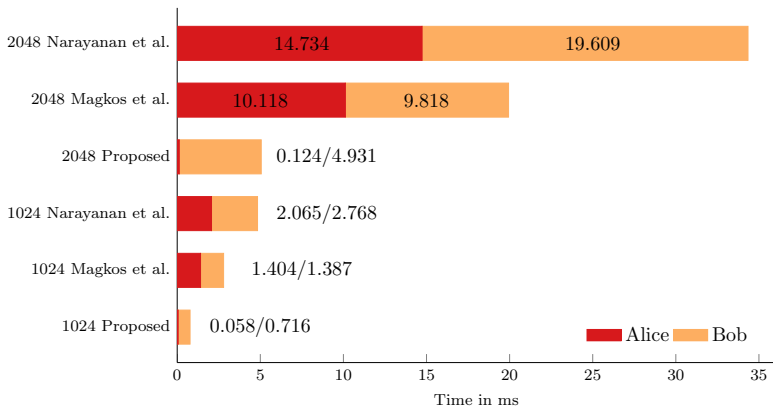
# A factoring based protocol

Alice (the initiator of the protocol) has published  $n_A = p_A \cdot q_A$  (where  $p_A, q_A$  are kept private) and she currently uses the private key pair  $d_A(\equiv l_A)$  and  $e_A$ . In the same way, Bob has published  $n_B = p_B \cdot q_B$  and he currently uses the private key pair  $d_B(\equiv l_B)$  and  $e_B$ .

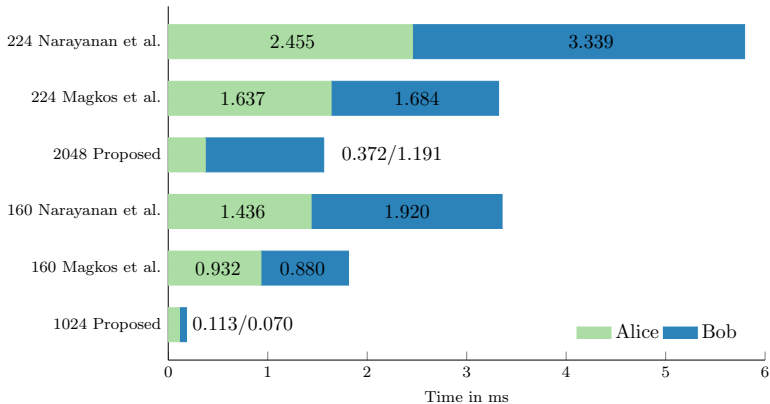
## A factoring based protocol (cont.)

- Step 1:** Alice picks a random integer  $r_A$  of high entropy (say, 1024 bit) and computes:  $c_A = (r_A^{l_A} \bmod n_B)^{e_A} \bmod n_A$  and sends it to Bob.
- Step 2:** Bob computes  $x = (c_A^{l_B} \bmod n_A)^{e_B} \bmod n_B$  and  $c_B = H(x)$  and sends  $c_B$  to Alice.
- Step 3:** Alice checks whether  $c_B \stackrel{?}{=} H(r_A \bmod n_B \bmod n_A)$ . If the equality holds, Alice is convinced that  $l_A = l_B$ . If not, Alice learns nothing about Bob's private input.

# Efficiency



# Efficiency with EC



# Communication cost

|                   | Alice | Bob  |
|-------------------|-------|------|
| Narayanan et al.  | 1024  | 2048 |
| Magkos et al.     | 1024  | 1280 |
| Proposed protocol | 1024  | 256  |

## Description

Let Alice be located in  $\ell_A$  and Bob in  $\ell_B$ .

**Step 1:** Alice sends the message  $c_A = rh + \ell_A$  to Bob, where  $r$  is a random invertible polynomial in  $\mathbb{Z}_q[x]/(x^N - 1)$ .

**Step 2:** Bob picks a random polynomial  $\rho$  with small coefficients and sends Alice  $c_B = \rho(c_A - \ell_B)$ .

**Step 3:** Alice receives it and checks whether  $r^{-1}c_B$  decrypts to zero.

# Correctness

Assume that  $l_A = l_B$ . Let  $m$  denote the expected encrypted message.

- In step 2, Bob computes:

$$c_B \equiv \rho(c_A - \ell_B) \equiv rh\rho$$

that he will sent to Alice.

- When Alice in step 3 decrypts:

$$r^{-1}c_B = r^{-1}rh\rho \equiv h\rho$$

the result will be 0, otherwise it will be a random polynomial.



# Protocol implementation

- We compare our protocol with the Narayanan et al. in an Intel Core i3-2100 CPU(3.1GHz) with 6GB of RAM, running on 64-bit linux using Sage<sup>1</sup>.
- The protocol of Narayanan et al. has been implemented over elliptic curves, using Curve25519 [25] for 128-bits of security, and for 192 and 256 bits security we used the curves M-383 and M-511 respectively [26].
- For NTRU we have used the latest parameters proposed by SecurityInnovation [27].

**Table:** NTRU parameters for different security levels

| Level(bits) | p | q    | n   | $D_1$ | $D_2$ | $D_3$ | $D_g$ | $D_m$ |
|-------------|---|------|-----|-------|-------|-------|-------|-------|
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# Computation and communication costs

| Security | Narayanan et al. |         |         | Proposed |       |        | R  |
|----------|------------------|---------|---------|----------|-------|--------|----|
|          | Alice            | Bob     | Total   | Alice    | Bob   | Total  |    |
| 128      | 80.718           | 99.194  | 179.912 | 7.362    | 1.051 | 8.413  | 21 |
| 192      | 102.267          | 133.873 | 236.140 | 10.527   | 1.518 | 12.045 | 19 |
| 256      | 155.329          | 193.887 | 349.216 | 12.733   | 1.745 | 14.478 | 24 |

**Table:** Time in ms and Security in bits.

| Security | Narayanan et al. | Proposed |
|----------|------------------|----------|
| 128      | 128              | 1208     |
| 192      | 192              | 1630     |
| 256      | 256              | 2044     |

# Setup

We assume that Alice has created an NTRU key pair, so  $h$  is her public key and  $f, f_p$  her private.

Both parties split their feature vectors in blocks of length  $\lambda$ , creating  $k$  blocks.

Moreover, we assume that both of them know a function  $\chi : \{0, 1\}^\lambda \rightarrow \mathbb{D}$ , where  $\mathbb{D}$  contains the polynomials of  $\mathbb{Z}_q[x]/(x^N - 1)$  with coefficients -1, 0 and 1. For the sake of simplicity instead of  $\chi(m)$  we will write  $m$ .

## Description

Let  $\alpha_i$  and  $\beta_i, i \in [1, k]$  denote the blocks of Alice and Bob respectively.

**Step 1:** Alice sends Bob the message

$$M_A = \{hs_i + \alpha_i\}, \forall i \in [1, k]$$

where  $s_i$  are random polynomials in  $\mathbb{D}$ .

**Step 2:** Bob computes the vector

$$M_B = \{M_{A_i} - (hs'_i + \beta_i)\}, \forall i \in [1, k]$$

where  $s'_i$  are random polynomials in  $\mathbb{D}$ .

Bob picks a random permutation  $\pi$  and sends Alice

$$M'_B = \pi(M_B).$$

**Step 3:** Alice decrypts each  $M_{B'_i}$  and computes the weight  $w_i$  of each recovered message. If  $\sum_{i=1}^k w_i < \tau$  then Alice deduces that  $d_H(\mathcal{A}, \mathcal{B}) < \tau$ .

# Protocol implementation

- We compare our protocol with the Narayanan et al. in an Intel Core i3-2100 CPU(3.1GHz) with 6GB of RAM, running on 64-bit linux using Sage<sup>2</sup>.
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# Parameters

| Security Level | RSA   | NTRU |      |     |                   |
|----------------|-------|------|------|-----|-------------------|
|                |       | p    | q    | n   | Public key (bits) |
| 128            | 3072  | 3    | 2048 | 439 | 4829              |
| 192            | 7680  | 3    | 2048 | 593 | 6523              |
| 256            | 15360 | 3    | 2048 | 743 | 8173              |

Parameters for the most popular security levels (in bits). For RSA the numbers denote the length (in bits) of the underlying modulo field according to NIST [28]. For NTRU, the numbers are precise and recommended by SecurityInnovation (<https://github.com/NTRUOpenSourceProject/ntru-crypto/blob/master/doc/NewParameters.pdf>).

# Computation cost

| Security | Blundo et al. |        |        | Proposed |       |       |
|----------|---------------|--------|--------|----------|-------|-------|
|          | Alice         | Bob    | Total  | Alice    | Bob   | Total |
| 128      | 0.024         | 2.227  | 2.251  | 0.187    | 0.115 | 0.302 |
| 192      | 0.066         | 12.352 | 12.418 | 0.250    | 0.153 | 0.403 |
| 256      | 0.183         | 59.421 | 59.605 | 0.299    | 0.220 | 0.519 |

# Communication cost

| Security | Blundo et al. | Proposed |
|----------|---------------|----------|
| 128      | 78.125        | 75.453   |
| 192      | 190.625       | 101.922  |
| 256      | 378.125       | 127.703  |

Approximate communication cost in KB. Security in bits.



# A generic attack

Alice performs one execution of the protocol with Bob using firstly the sequence  $00 \dots 000$  and then  $10 \dots 000$ . She can tell which one is closest...

## A patch

Let  $\mathcal{F}(k, x)$  denote a Pseudo Random Function (PRF), where  $k$  is the PRF key and  $x$  is the point at which the function is evaluated. Bob proposes a random seed  $s$  so Alice and Bob compute the following for their sequences:  $\mathcal{F}(s, m_i || i) \bmod 2, i \in \{1, 2, \dots, k\}$ .

## Where to find these results

- C. Patsakis, J. van Rest, M. Choras and M. Bouroche  
Privacy-Preserving Biometric Authentication and Matching  
via Lattice-Based Encryption 10th International Workshop on  
Data Privacy Management (DPM 2015), Vienna, Austria -  
September 21-22, 2015.
- C. Patsakis, P. Kotzanikolaou and M. Bouroche, Private  
Proximity Testing on Steroids: An NTRU-based protocol”,  
11th International Workshop on Security and Trust  
Management (STM 2015), 21-22 September 2015, Vienna,  
Austria.
- C. Patsakis, A. Zigomitros, A. Solanas, “Analysis of Privacy  
and Security Exposure in Mobile Dating Applications”,  
International Conference on Mobile, Secure and  
Programmable Networking (MSPN'2015), Paris, France, June  
15-17. 2015.

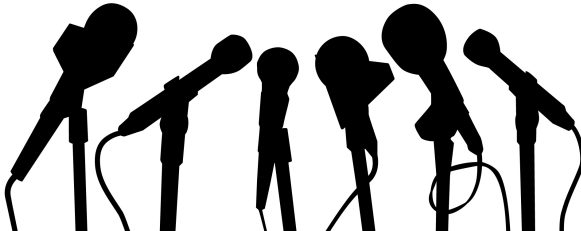
## Where to find these results(cont)

- C. Patsakis, A. Zigomitros, A. Solanas, “Analysis of Privacy and Security Exposure in Mobile Dating Applications”, International Conference on Mobile, Secure and Programmable Networking (MSPN’2015), Paris, France, June 15-17, 2015.
- C. Patsakis, A. Zigomitros, A. Solanas, Privacy-Aware Genome Mining: Server-Assisted Protocols for Private Set Intersection and Pattern Matching”, 28th International Conference on Computer-Based Medical Systems, CBMS 2015, 22-25 June, Sao Paulo, Brazil.
- P. Kotzanikolaou, C. Patsakis, E. Magkos, M. Korakakis, “Lightweight Private Proximity Testing for Geospatial Social Networks”, Computer Communications, Special Issue on Online Social Networks (Imprint)

Thank you!

# Q&A

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