

# Multi-Key Homomorphic Encryption for Collaborative Camera Attribution

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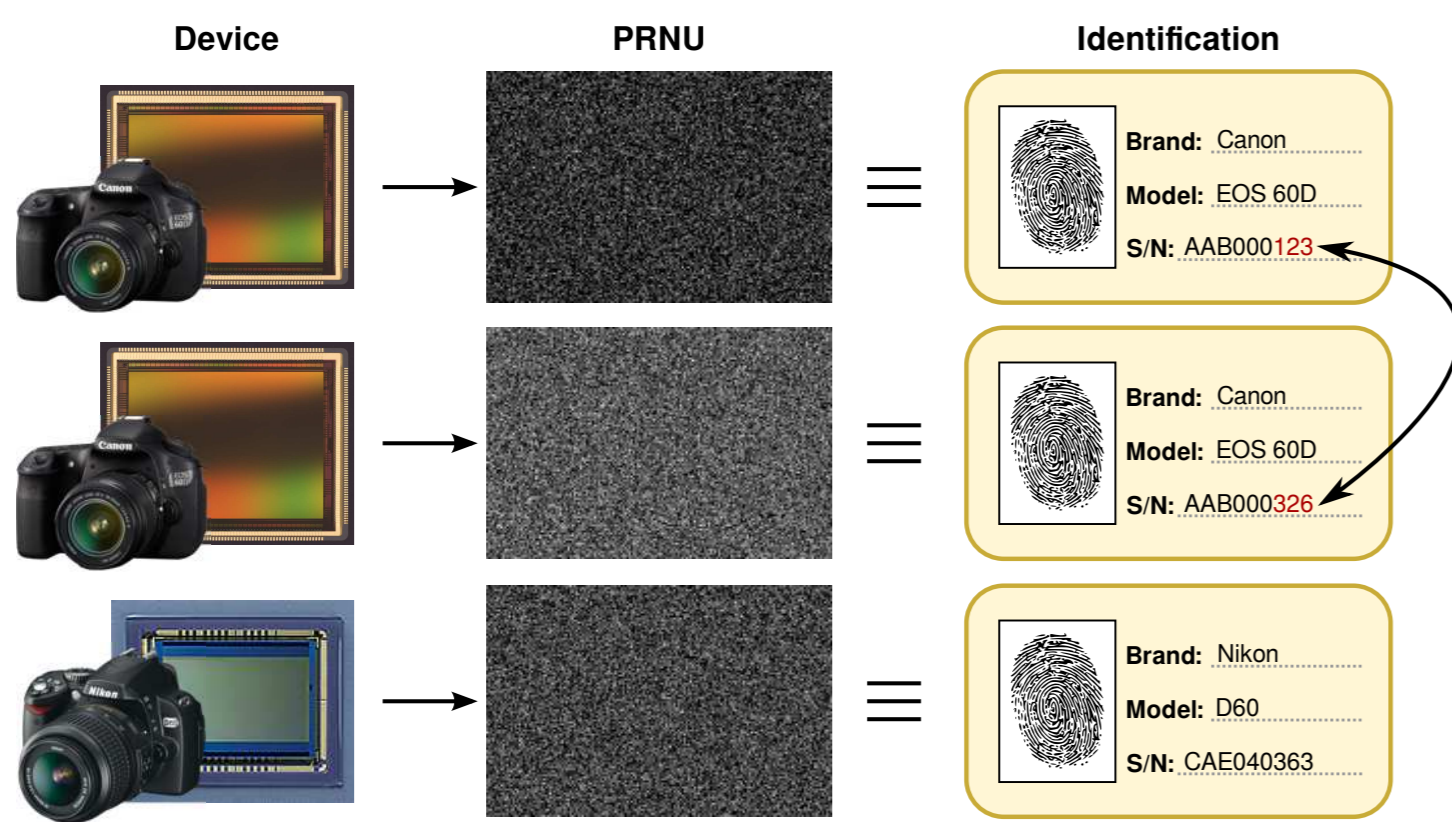
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## Camera attribution problem

- The amount of multimedia content that law enforcement agencies (LEAs) must deal with in their investigations is ballooning.
- Collaboration between LEAs is becoming essential in a growing number of cases.
- The exchange of multimedia is strongly limited by privacy and data-protection laws.
- One relevant scenario within image forensics is the case of camera attribution.



## Privacy-sensitive information

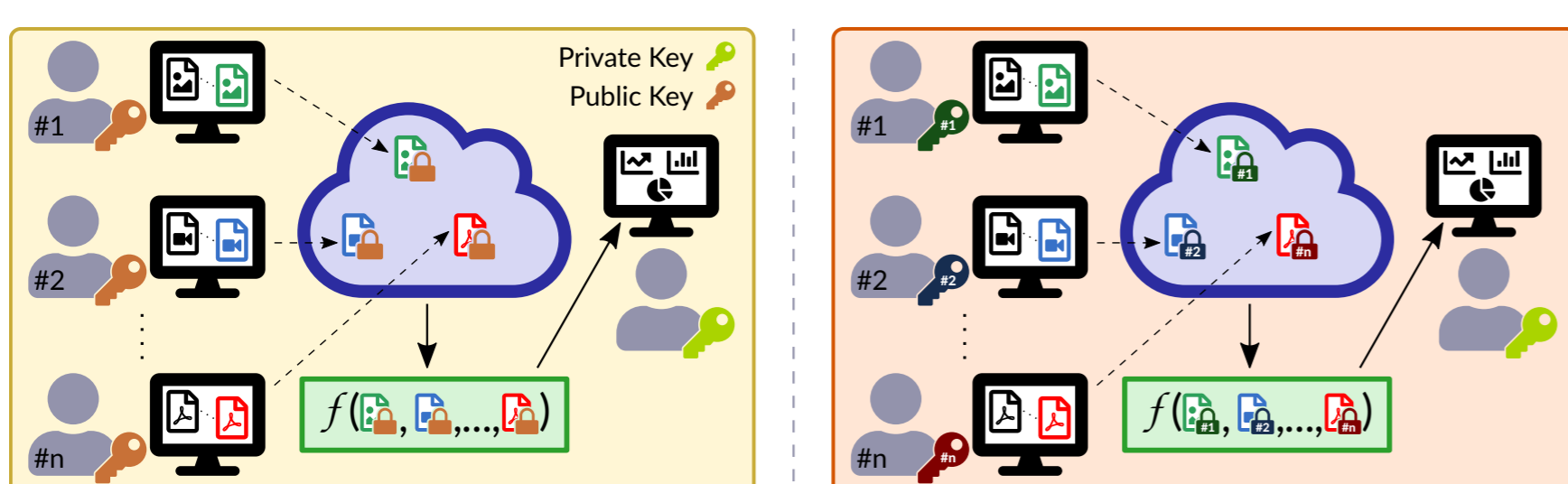
- A number of images from the same device or camera model must be pooled together in order to extract fingerprints reliably.
- The images used to extract the fingerprints may be very sensitive (e.g., in child abuse cases).
- Recent works have shown that camera fingerprints estimates can leak a considerable amount of information from the images used for extraction [1]



## Secure Camera Attribution

- Several works have addressed the mentioned privacy risks with different tools:
  - A fully unattended solution based on the use of lattice-based cryptosystems [2].
  - A combination of trusted hardware and HE (Homomorphic Encryption) [3].
  - The use of Shamir's secret sharing [4].
- These methods assume an outsourcing scenario, and focus in fingerprint detection.
- To the best of our knowledge, our recent work in secure camera attribution [5] is the first to propose a federated framework for fingerprint extraction/detection.

## Collaborative Forensic Scenario

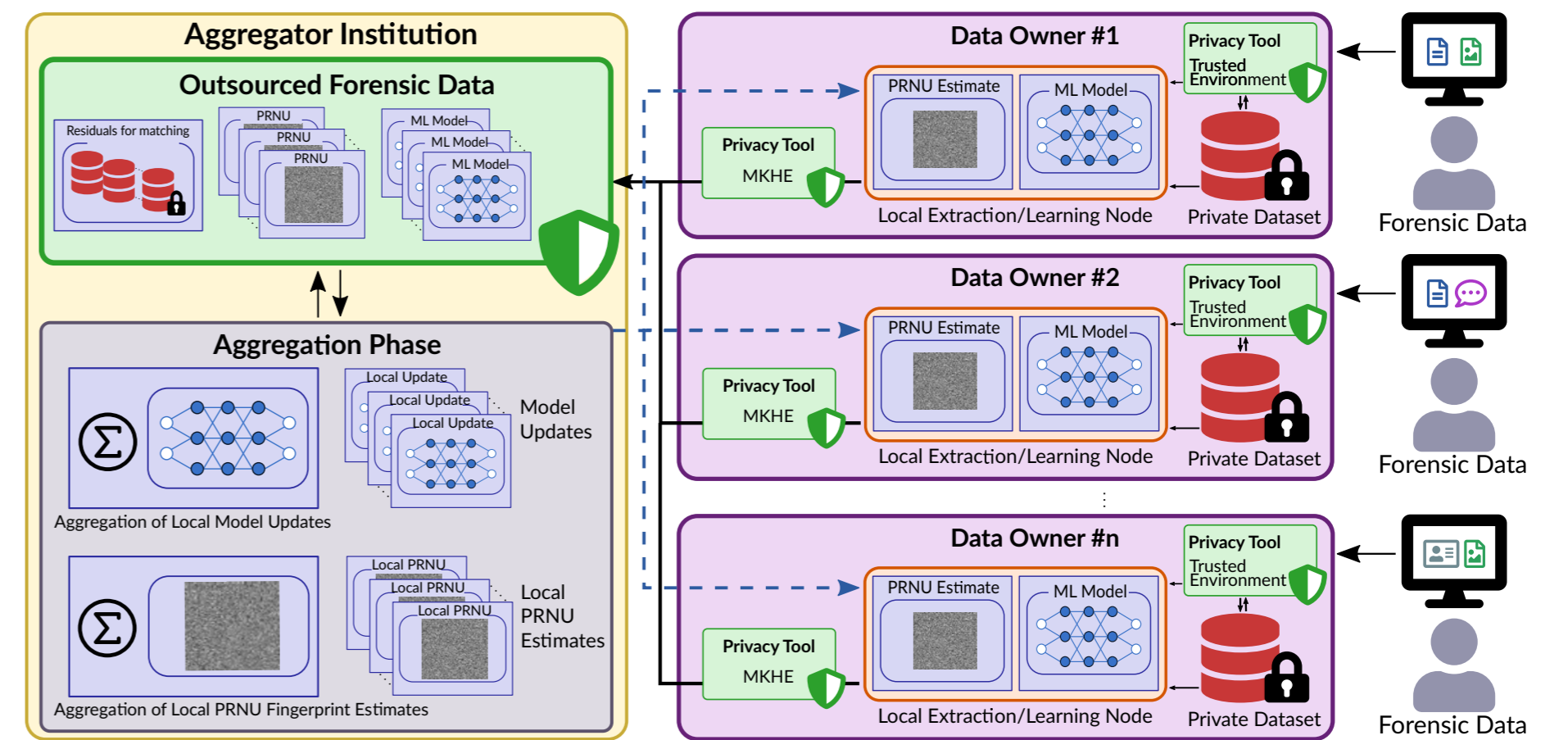


- Data Owners are LEAs or Forensic Institutions aiming at camera fingerprint extraction through collectively trained models.
- The aggregator can be a Data Owner, or a larger organization like Europol or Interpol.
- The end users would be the participating or other LEAs or Forensic institutions.
- MKHE (Multi-Key Homomorphic Encryption) tools, instead of single-key HE, fit better the needs of our collaborative scenario [6].

## Proposed Collaborative Framework

Our federated framework builds upon two key concepts [5]:

- Unprotected local data is isolated in different silos.
- All information leaving a silo is previously encrypted with MKHE [6].



### Workflow with MKHE

- All involved Data Owners generate their own individual secret key and also a collective public key.
- Each Data Owner encrypts its data to be outsourced under a collective public key.
- One of the entities will be in charge of computing a particular functionality  $f$ .
- All involved parties collaboratively decrypt the output.

## Example functionalities inside the framework

- Training of ML models for noiseprint extraction.
  - The functionality  $f$  is the aggregation of local models.
- Aggregation of local fingerprint estimates (e.g., PRNU or noiseprint).
  - The functionality  $f$  is implemented with a homomorphic addition, followed by a division after decryption.
- Fingerprint matching.
  - The functionality  $f$  corresponds with a set of homomorphic scalar products among encrypted fingerprint estimates.
- Residuals matching and/or fingerprint/residual matching.
  - The functionality  $f$  corresponds to a set of homomorphic scalar products with encrypted fingerprints/residuals.

## Implementation runtimes

- Aggregation and matching functionalities implemented with Lattigo v3.0.4 [7]. Parameters:  $\{T = 2^{16} + 1, \text{bfv.PN12QP109}\}$  and  $\{T = 3 \cdot 2^{30} + 1, \text{bfv.PN13QP218}\}$ .
- Evaluation runtimes were conducted multi-threaded on an Intel Core i7-4510U @ 2.00GHz x 4 with 7.7GB. The rest of primitives were conducted singled-threaded.

| 64 parties + Cloud fingerprint 1024 X 1024 | CKG + RKG + RTG (Cloud + Parties) | Encryption | Evaluation | CKS (cloud + Parties) | Decryption |
|--|-----------------------------------|------------|------------|-----------------------|------------|
| Aggregation                                | 2 ms + 716 us                     | 826 ms     | 689 ms     | 594 ms + 735 ms       | 173 ms     |
| Matching                                   | 227 ms + 98 ms                    | 1.13 s     | 65 s       | 775 ms + 483 ms       | 166 ms     |

## References

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