

Privacy and Integrity Preserving Computations with CRISP

S. Chatel, A. Pyrgelis, J.R. Troncoso-Pastoriza, J-P. Hubaux
Laboratory for Data Security, EPFL

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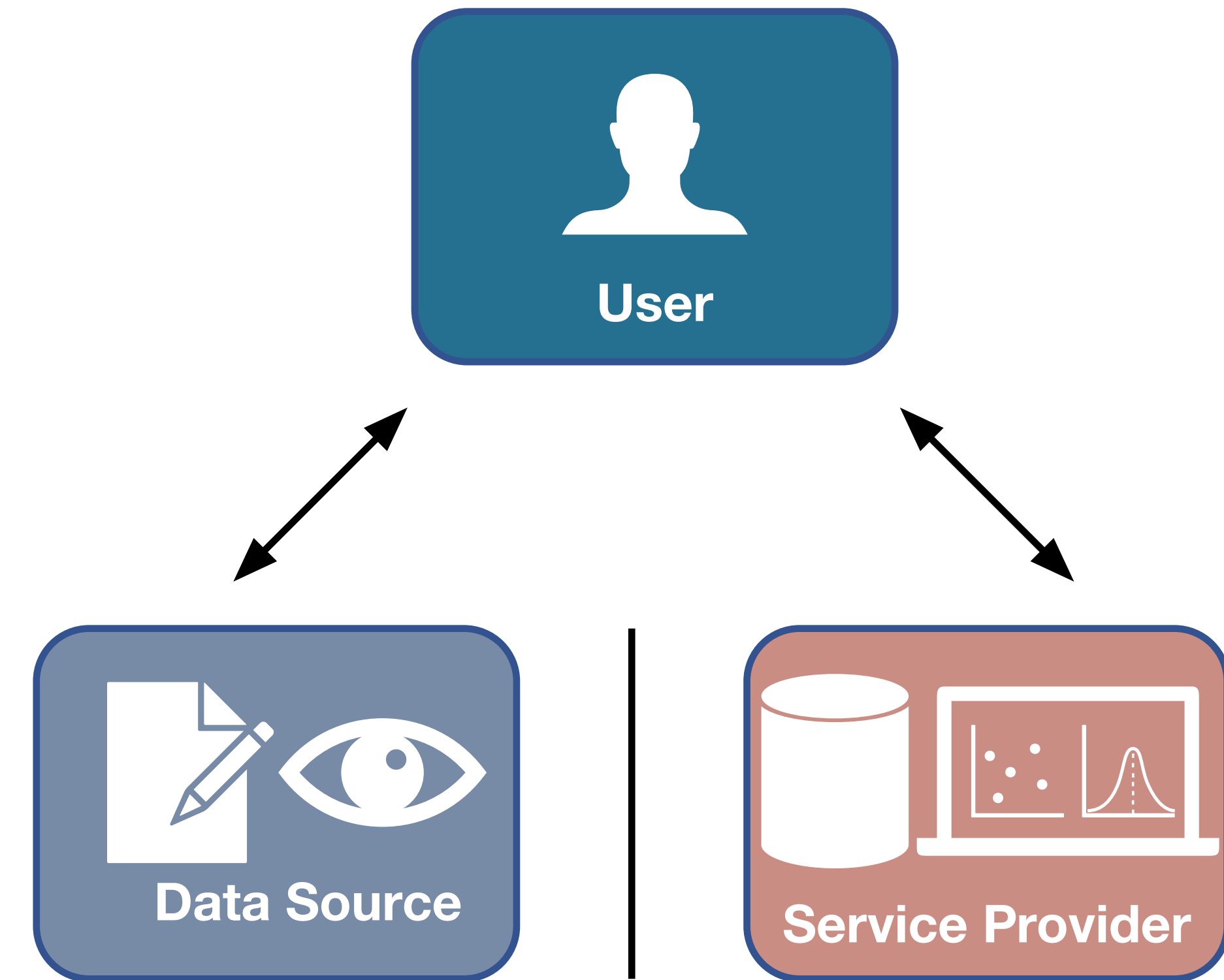
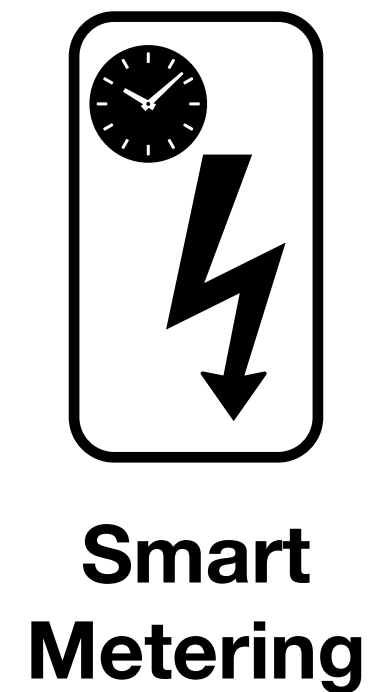
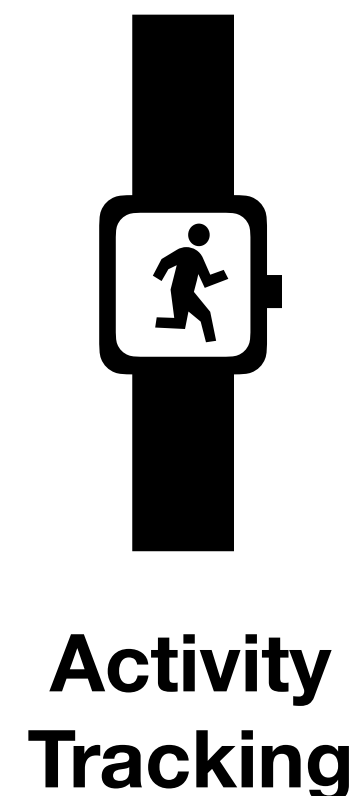
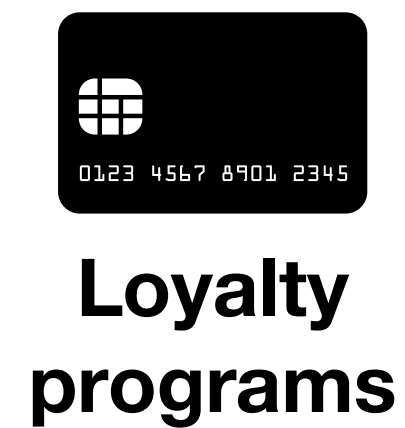
Data Analysis Cycle

Data source creates data about a user

The **user** wishes to obtain a service from a provider

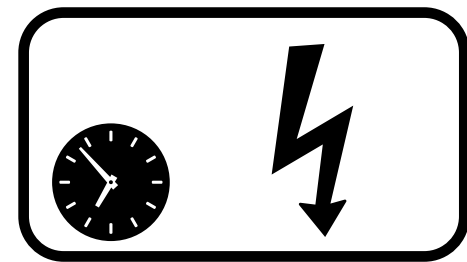
A **provider** is interested in gaining some information

This data flow models several real-life use case:



Motivation

Real-world data flows are vulnerable to attacks on privacy and authenticity e.g.:



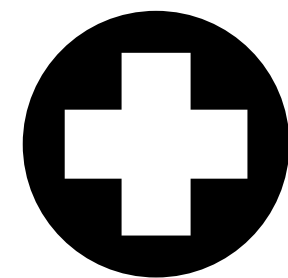
Smart Metering

Load balancing, forecast, energy savings
Inference on user's behavior
Protection required to avoid disruption



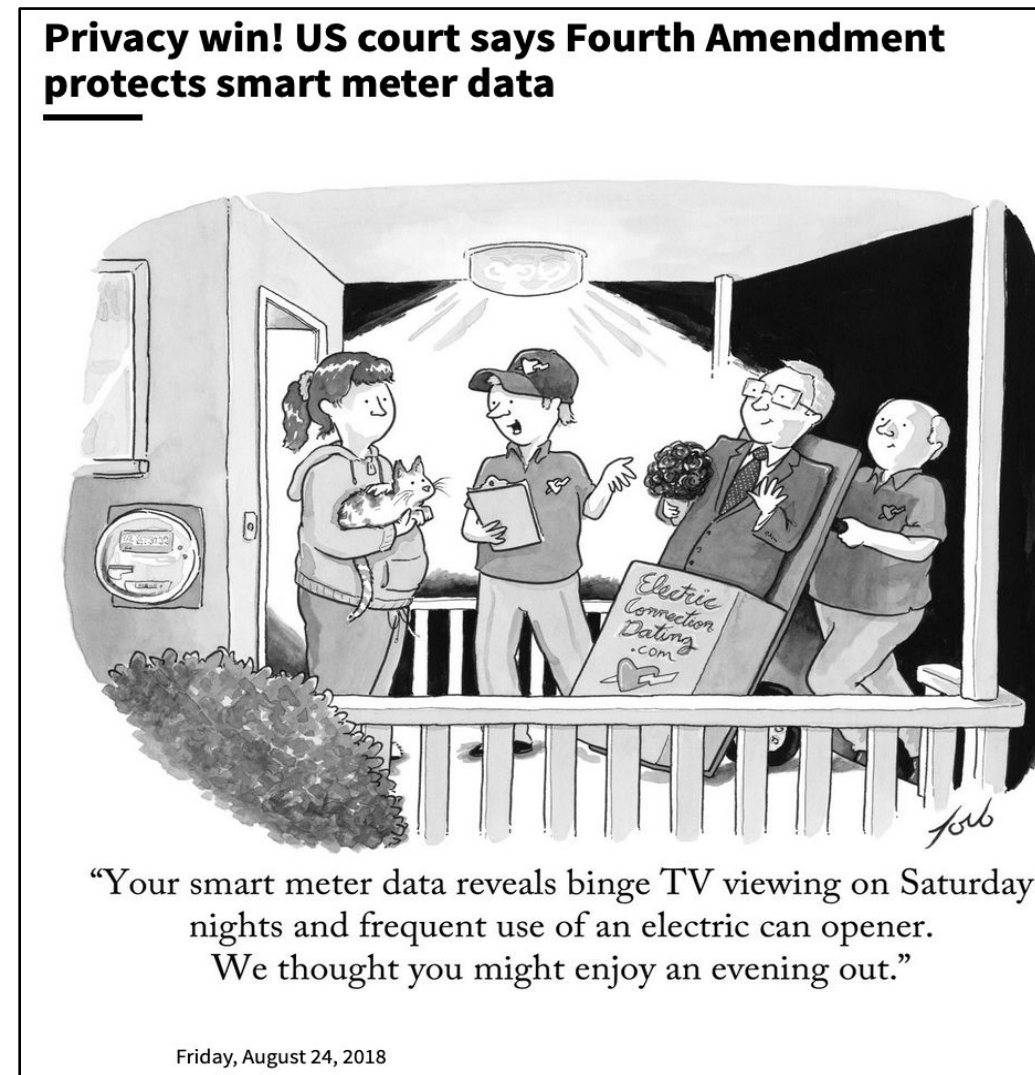
Personal Tracking

Location-based activity tracking
Privacy breach about user's behaviour or even national security interests
Protection required for insurance fraud

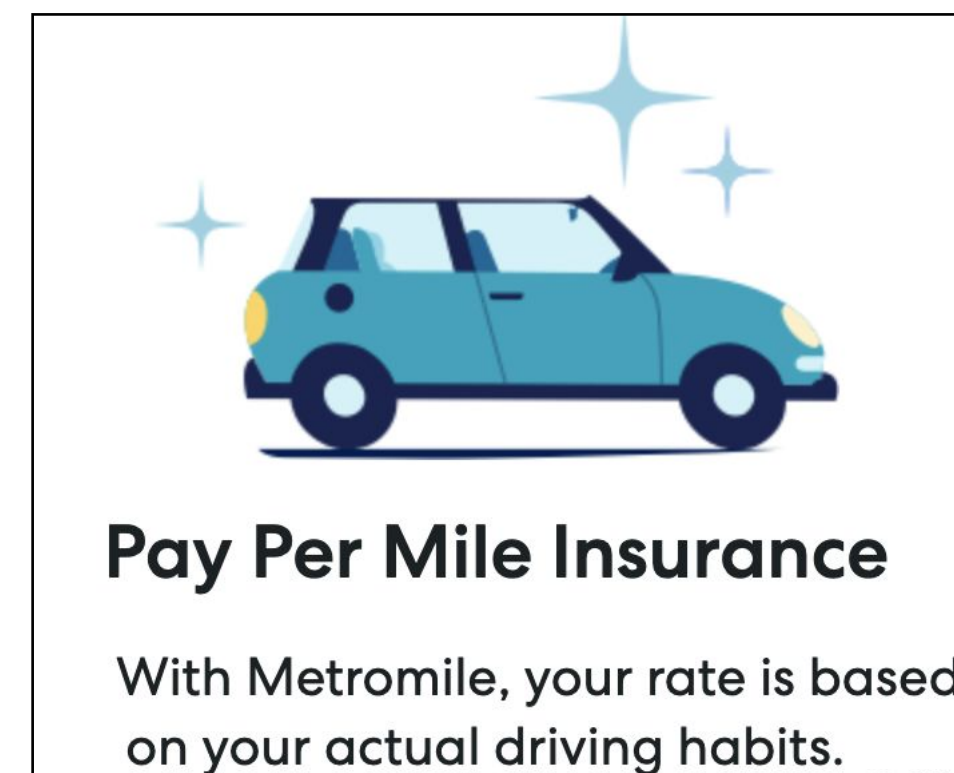


Medical Monitoring

Genomic Data Analysis
Privacy breach for user and relatives
Protection required to avoid misdiagnosis



Naperville Smart Meter Awareness v. City of Naperville, No. 16-3766 (7th Cir. 2018)



Pay Per Mile Insurance

With Metromile, your rate is based on your actual driving habits.



Hubaux et al., Genomic Data Privacy and Security: Where We Stand and Where We Are Heading
IEEE Security & Privacy 2017

Objectives of CRISP

We design and implement CRISP, a solution to compute securely on authenticated data at an acceptable cost in utility, without compromising privacy

Privacy

Prevent the service provider from gaining more information than required

Integrity

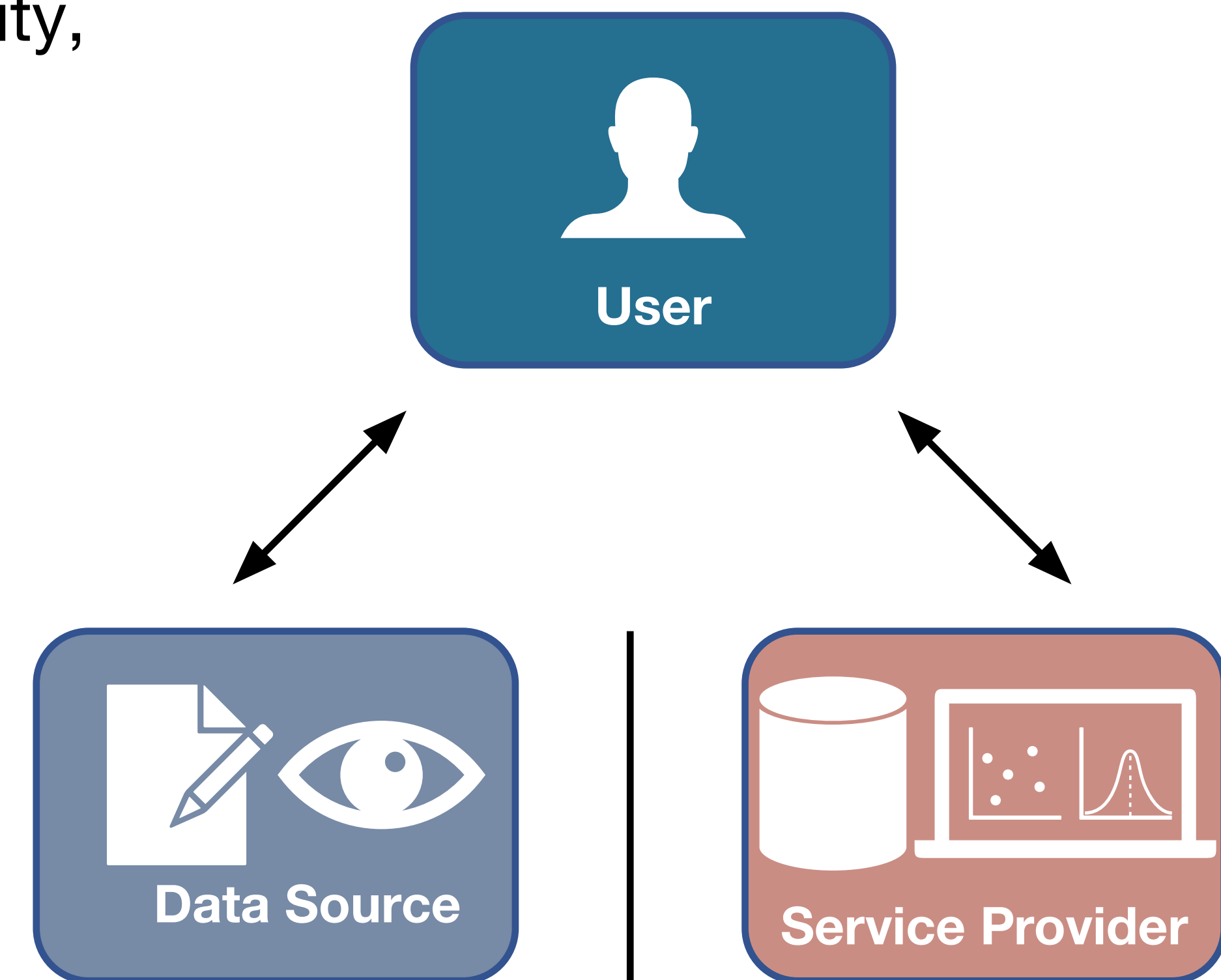
Prevent the user from cheating the service provider

Utility

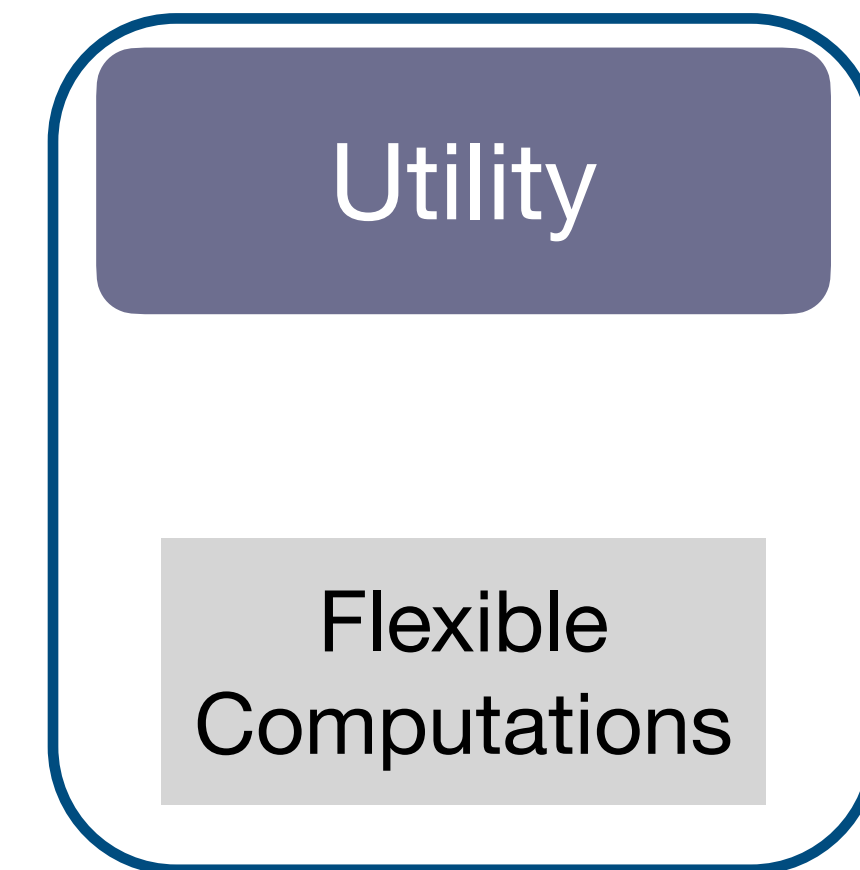
Ensure good quality of service for both user and service provider

Deployability

Ensure smooth deployment with existing software and hardware infrastructure

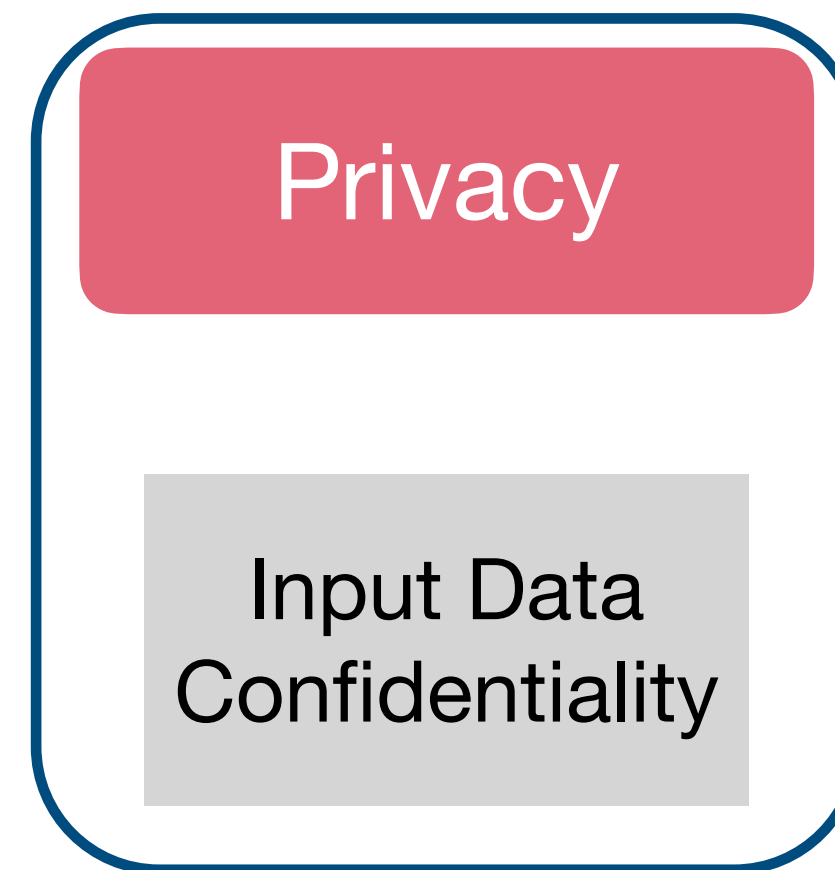


CRISP Overview



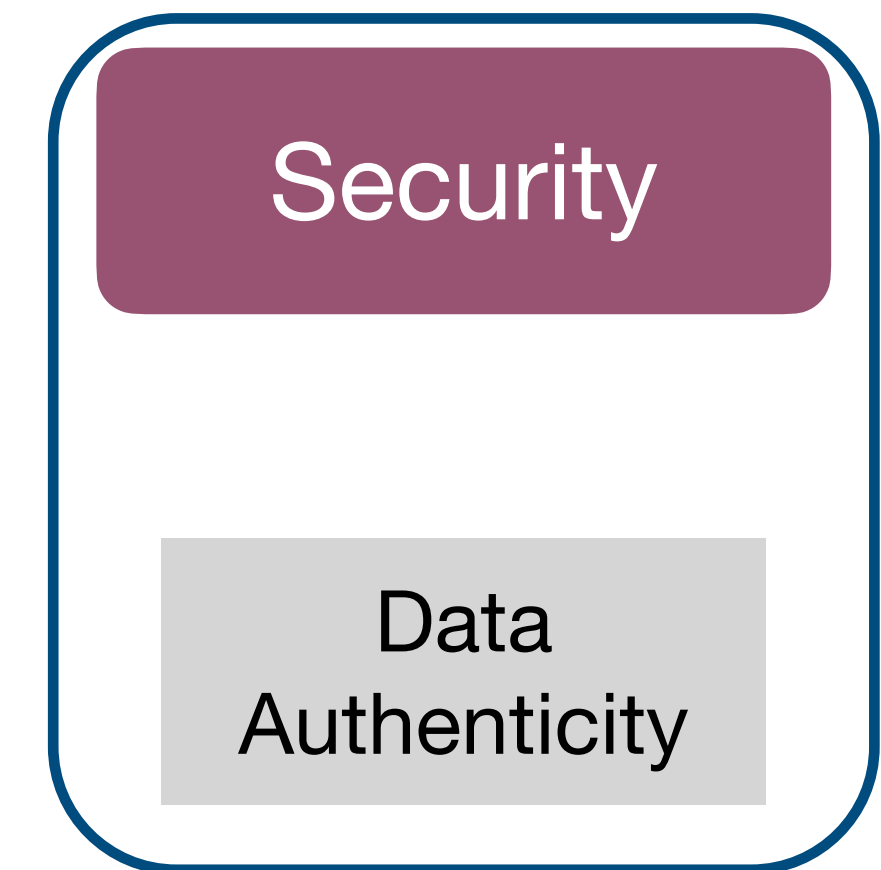
Fully Homomorphic Encryption ^(a)

Enable polynomial computations on the encrypted data without decryption



Commitments and Blindings ^(c)

Reveal only the result of the computation and prevent cheating



Zero-Knowledge Circuit Evaluation ^(b)

Evaluate a tailored circuit checking the encryption and hash of the data

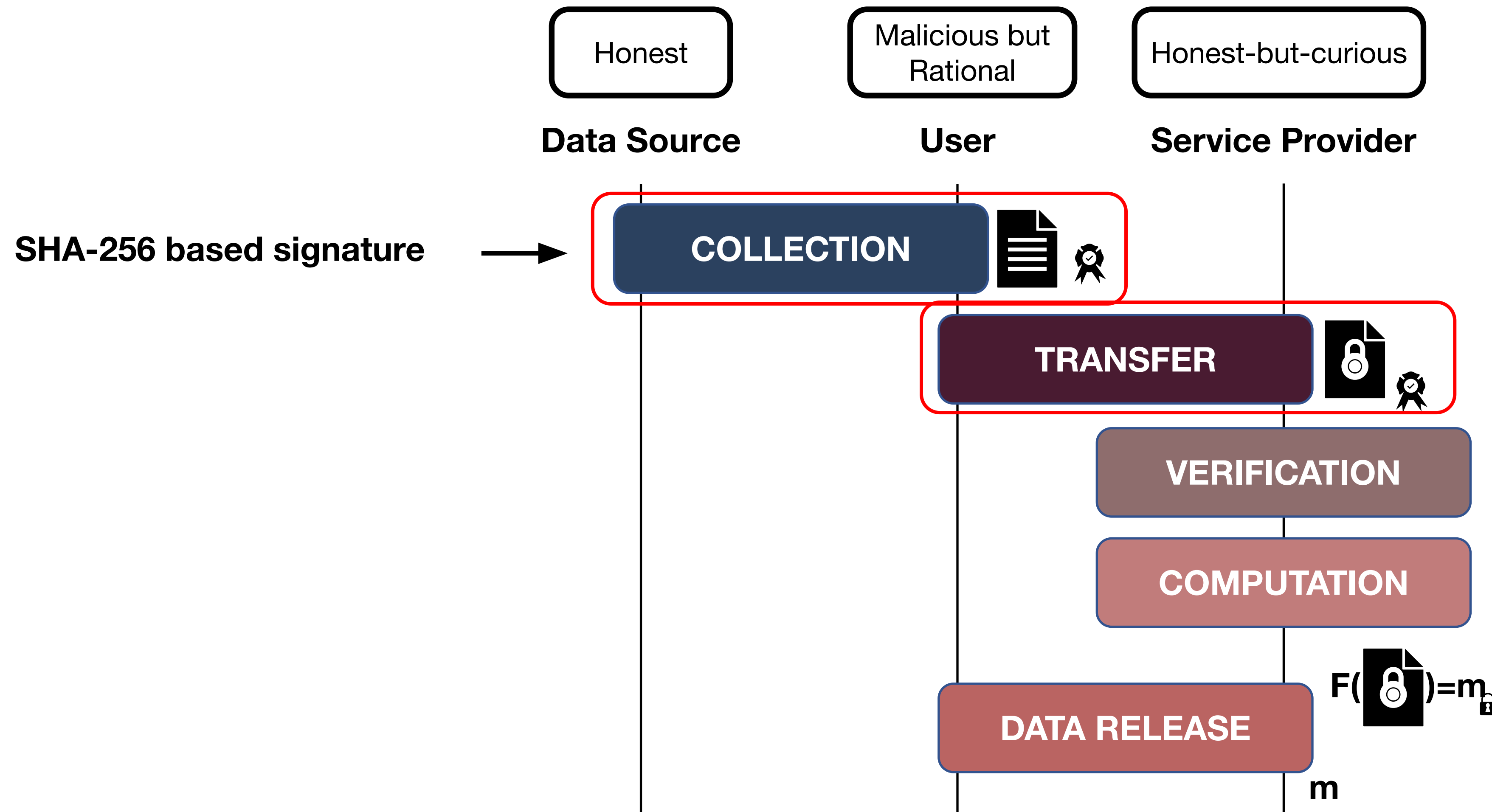
(a) Cheon et al., "Homomorphic Encryption for Arithmetic of Approximate Numbers", ASIACRYPT 2017

(b1) Giacomelli et al., "ZKBoo: Faster Zero-Knowledge for Boolean Circuits", USENIX Security 2016

(b2) Chase et al., "Post-Quantum Zero-Knowledge and Signatures from Symmetric-Key Primitives", CCS 2017

(c) Baum et al., "More Efficient Commitments from Structured Lattice Assumptions", ePrint 2016

CRISP Model



Transfer Phase

The user generates a proof guaranteeing

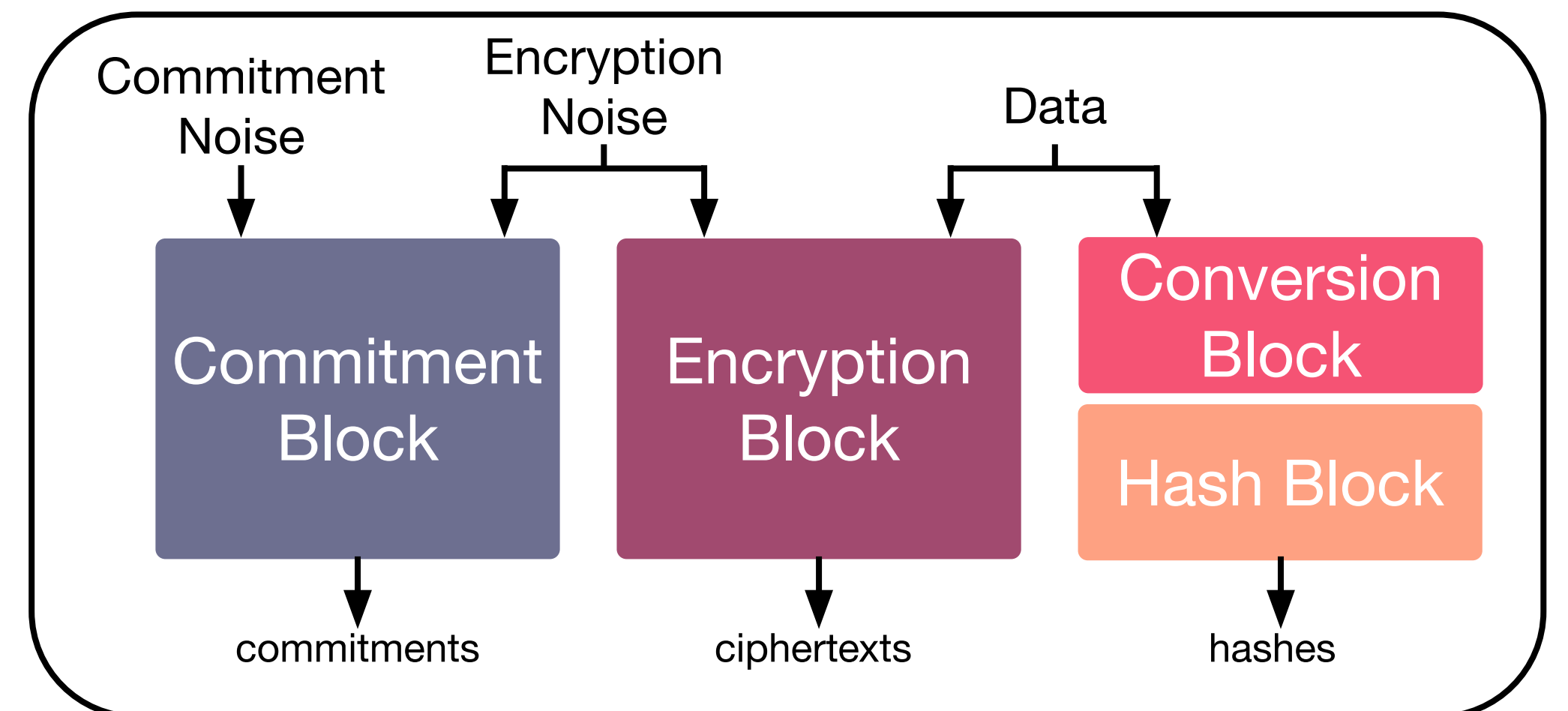
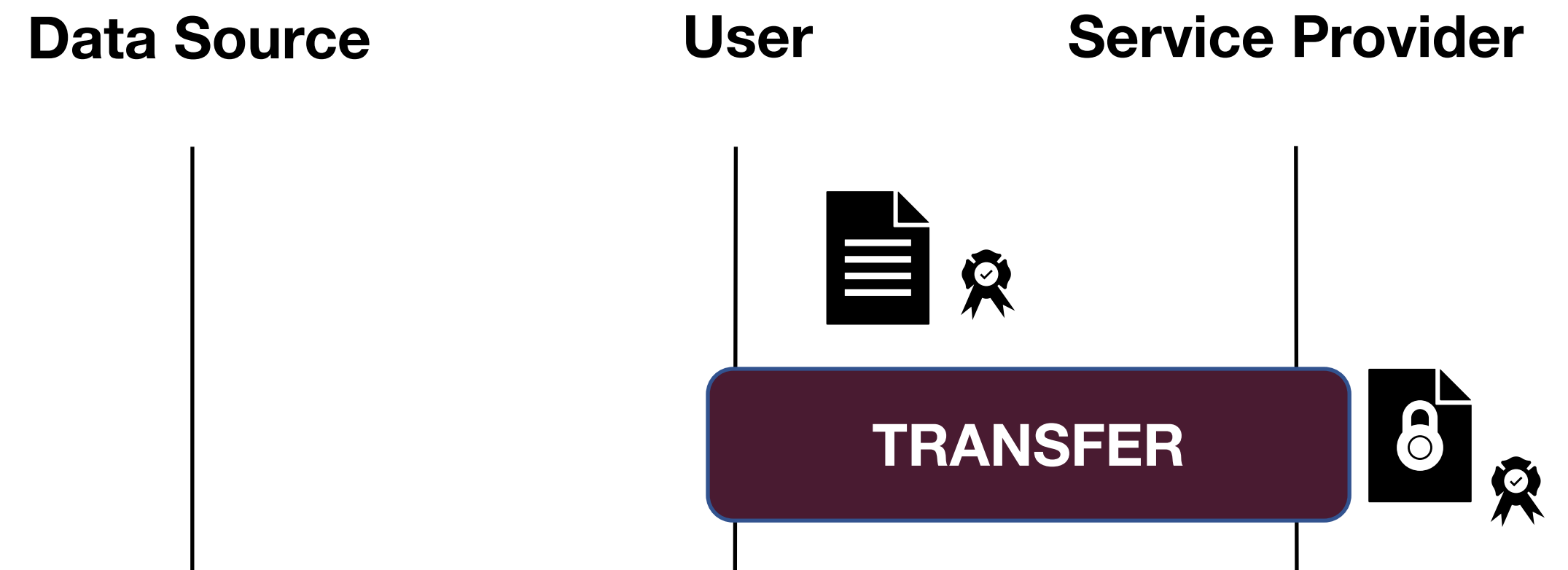
- Correct encryption
- Integrity of the data

We designed a custom circuit to check simultaneously

- The hash of the data
- The norm of the encryption noises
- The encryption of the data

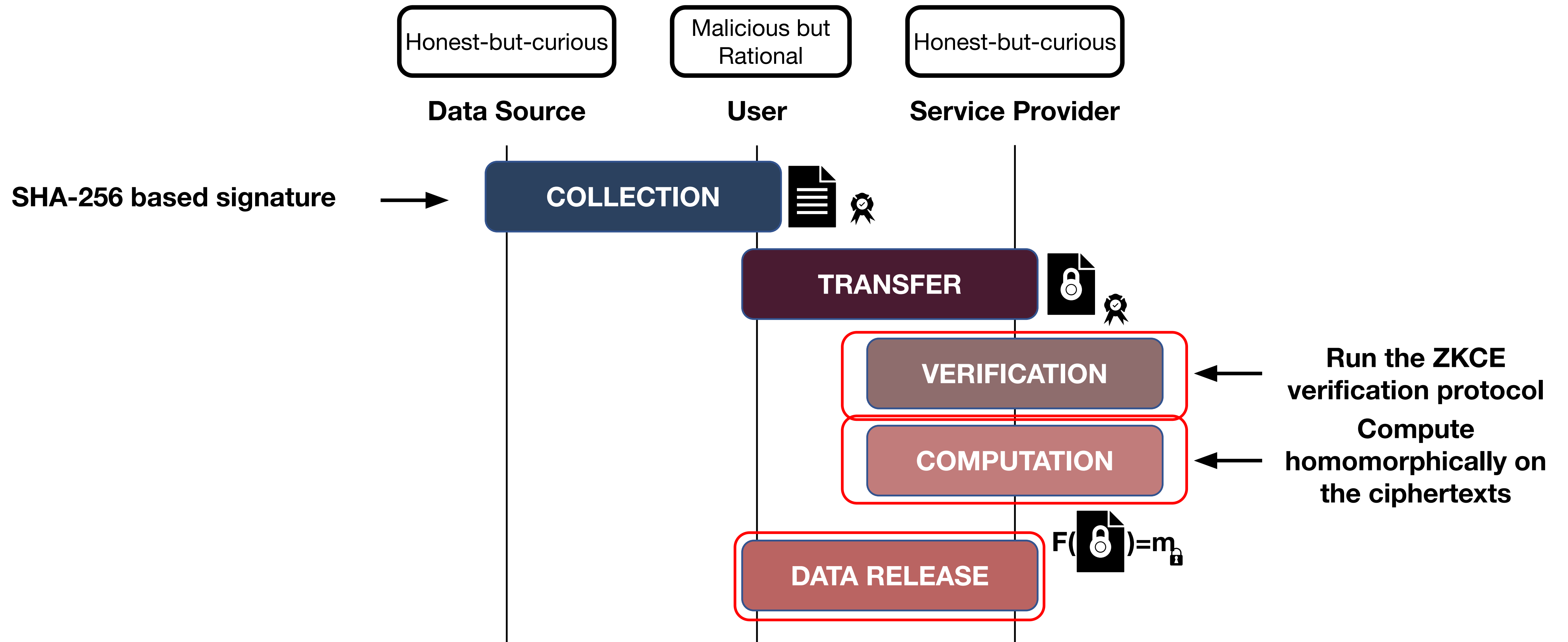
CRISP relies on a Zero-Knowledge Circuit Evaluation and Lattice-Based Commitments

Eventually, the user sends the message
 $M = \{\text{ciphertexts, commitments, proof, hashes, signatures}\}$



Tailored circuit used in the Zero-Knowledge Circuit Evaluation

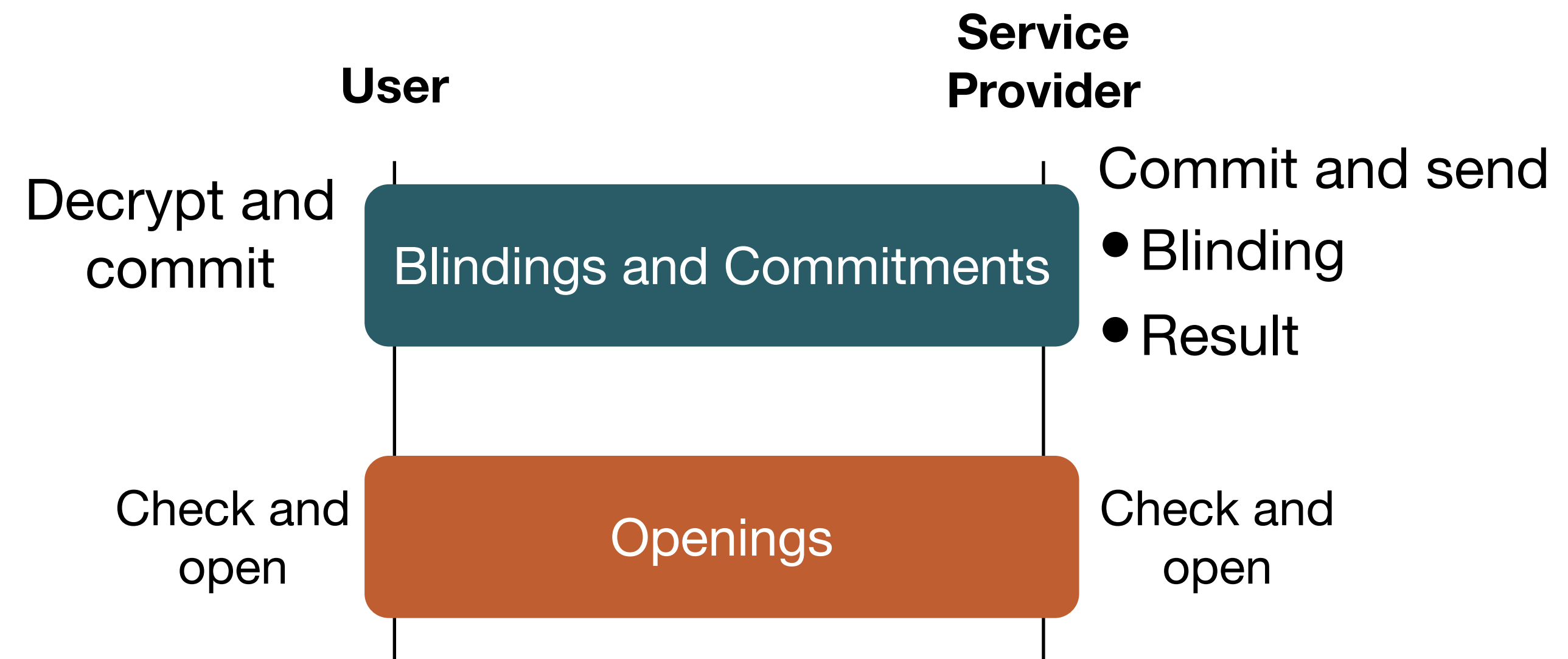
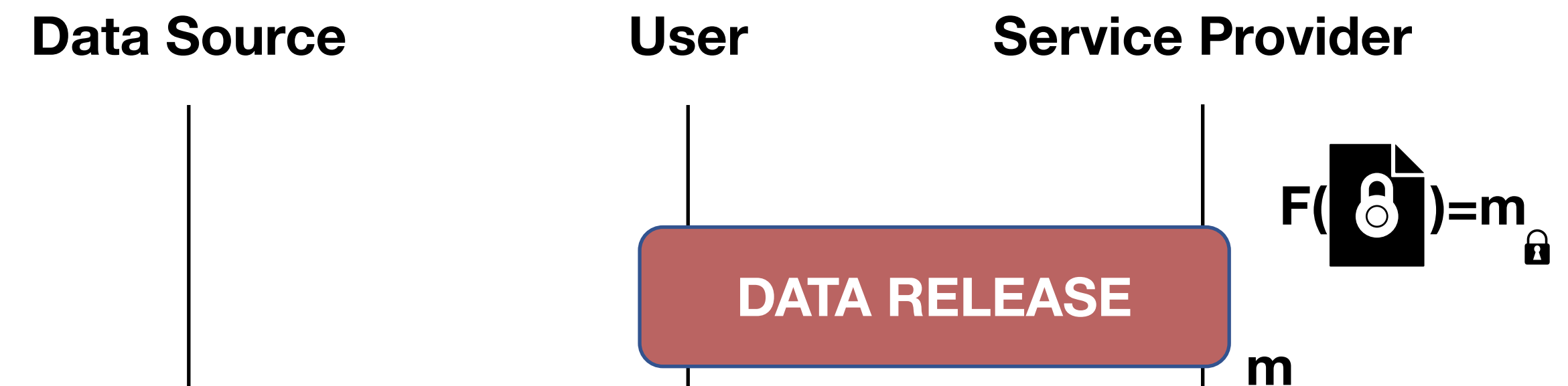
Verification and Computation Phase



Release Phase

The **user** and **service provider** engage in an interactive protocol to reveal only the result of the computation in a tamper-proof manner

Two-round protocol the security of which relies on the security of the underlying commitment scheme



Evaluation: Overhead

We evaluated the communication and computation overhead.

Overall, we achieve:

- One-shot generation and offloading of the proof for multiple computations
- Packing of numerous data points into one ciphertext
- Support for several subsequent operations at no additional proof cost

Use Case	t_{PROVE} (s)	t_{VERIFY} (s)	Proof Size (MB)
Smart Metering	200 ± 10	82 ± 5	650
Disease Susceptibility based on Genomic Data	26 ± 4	13 ± 2	54
Location-Based Activity-Tracking	470 ± 40	210 ± 10	1,603

Acceptable overhead, considering:

- Possibility to offload the proof to a public billboard
- Several optimisations can reduce the overhead

Optimizations

Several optimizations are possible to reduce the proof size:

- Zero-Knowledge Circuit Evaluator

Preprocessing^(d)

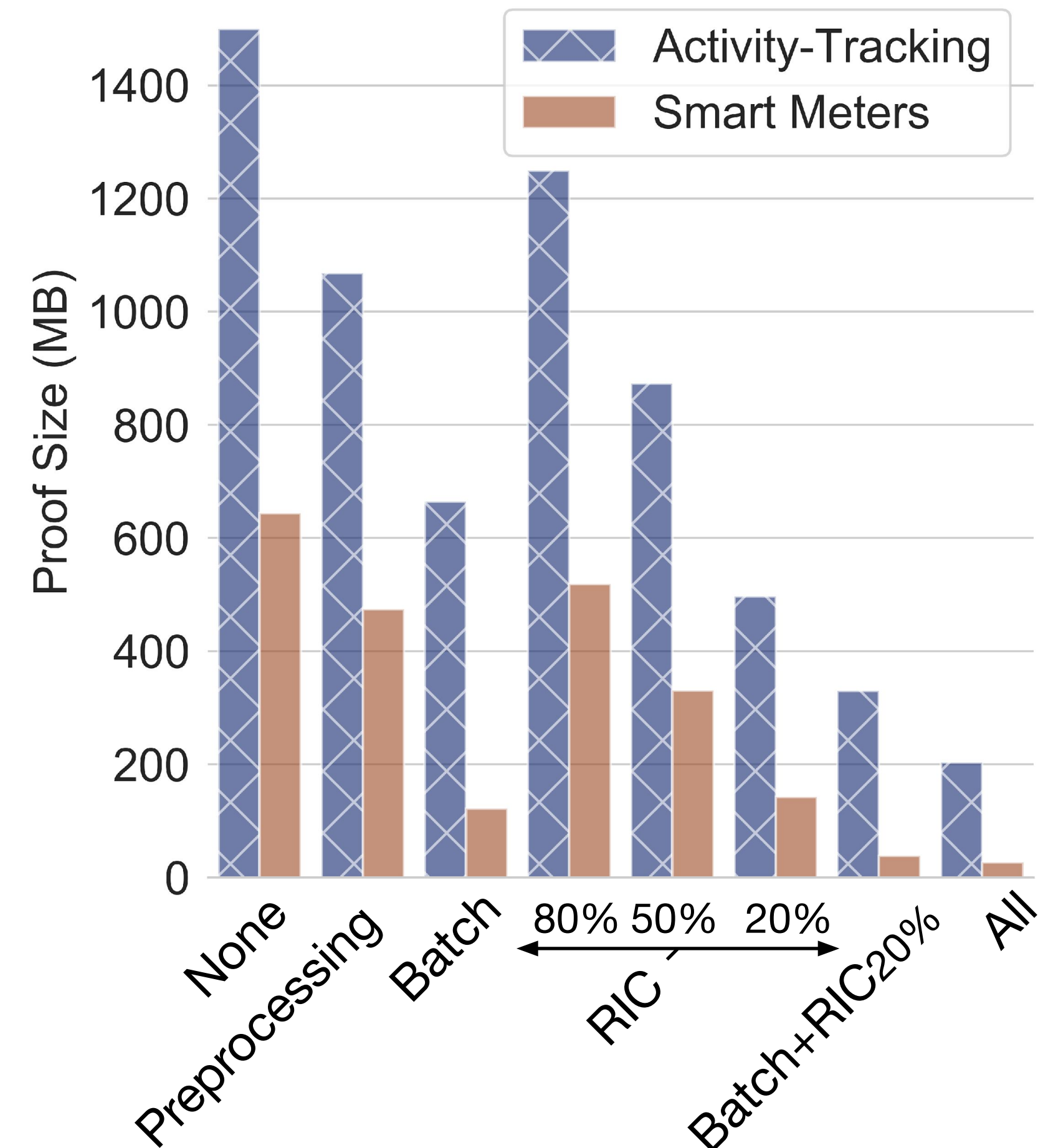
Rely on an offline phase to reduce the number of required online interactions

- Batching

Use the signature to its full extent to pack as many data points as possible (data source modification required)

- Random Integrity Checks (RIC)

The verifier picks at random a subset of data points which authenticity is checked



Conclusion on CRISP

Reconciles **security**, **privacy**, and **utility** using zero-knowledge proofs and homomorphic encryption:

- Ensures **computations on authenticated data**
- Preserves privacy of the data
- Does not affect accuracy more than the FHE scheme
- **One-time communication** overhead for the prover

Future work

- Malicious Service Provider
- Further reduce the proof size relying on alternative zero-knowledge proofs or increasing the number of parties

Thank you

`sylvain.chatel@epfl.ch`

`https://github.com/ldsec/CRISP`