

### Privacy-Preserving Data Aggregation with Public Verifiability Against Internal Adversaries

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### Data aggregation Examples

- Process and summarize data to extract insights from it
- Examples
  - Censuses
  - COVID-19
  - Smart grids
- Medical data



https://www.economist.com/books-and-arts/2020/04/16/a-lively-and-enlightening-history-of-the-census

# **Privacy concerns**

Medical data

• Fines

T Delft

- Lack of trust leads to harmful behaviours
  - Not disclosing "embarrassing" conditions
  - Self-treating

![](_page_2_Picture_6.jpeg)

# Why we need verifiability

- Intermediate stations in smart grids may be hacked
- Reporters are not trusted
- Incorrect medical data may lead to wrong diagnoses

![](_page_3_Picture_4.jpeg)

### Verifiable privacy-preserving data aggregation

- Compute a statistic from a set of private inputs
- No unauthorized party learns the individual inputs
- Only the final result is revealed
- The correctness of the result can be verified

![](_page_4_Picture_5.jpeg)

![](_page_4_Figure_6.jpeg)

# **Related work**

#### **Malicious aggregator**

The aggregator must provide an aggregate signature of the summation, which can be verified by anyone holding the verification key.

The aggregator cannot produce the signature by itself.

![](_page_5_Figure_4.jpeg)

![](_page_5_Picture_5.jpeg)

 Iraklis Leontiadis, Kaoutar Elkhiyaoui, Melek Önen, and Refik Molva. PUDA - privacy and unforgeability for data aggregation. In Michael K. Reiter and David Naccache, editors, Cryptology and Network Security 14th International Conference, CANS 2015, Marrakesh, Morocco, December 10-12, 2015, Proceedings, volume 9476 of Lecture Notes in Computer Science, pages 3–18. Springer, 2015. doi:10.1007/978-3-319-26823-1\_1.

 Bence Gabor Bakondi, Andreas Peter, Maarten H. Everts, Pieter H. Hartel, and Willem Jonker. Publicly verifiable private aggregation of time-series data. In 10th International Conference on Availability, Reliability and Security, ARES 2015, Toulouse, France, August 24-27, 2015, pages 50–59. IEEE Computer Society, 2015. doi:10.1109/ARES.2015.82.

![](_page_5_Picture_8.jpeg)

## **Related work**

#### Malicious aggregator and users

![](_page_6_Figure_2.jpeg)

If the aggregator is allowed to collude with at least 1 user, these schemes cannot guarantee the integrity of the aggregation anymore

![](_page_6_Picture_4.jpeg)

![](_page_6_Picture_5.jpeg)

 Iraklis Leontiadis, Kaoutar Elkhiyaoui, Melek Önen, and Refik Molva. PUDA - privacy and unforgeability for data aggregation. In Michael K. Reiter and David Naccache, editors, Cryptology and Network Security 14th International Conference, CANS 2015, Marrakesh, Morocco, December 10-12, 2015, Proceedings, volume 9476 of Lecture Notes in Computer Science, pages 3–18. Springer, 2015. doi:10.1007/978-3-319-26823-1\_1.

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## **Related work**

#### Malicious aggregator and users

![](_page_7_Picture_2.jpeg)

Fully Trusted
 Honest-but-Curious
 Malicious
 Collusion

- LL21 introduces an additional honest-butcurious party called the Converter to help with the construction of the signatures.
- The verifier must be a fully-trusted external party.
- Only pairwise collusions between each party are permitted. However, a flaw in the protocol may allow an aggregator that colludes with 1 user to forge arbitrary signatures.

![](_page_7_Picture_7.jpeg)

Leontiadis, Iraklis, and Ming Li. "Secure and Collusion-Resistant Data Aggregation from Convertible Tags." International Journal of Information Security 20, no. 1 (February 2021): 1–20. https://doi.org/10.1007/s10207-019-00485-4.

# Our goal

- A privacy-preserving data aggregation scheme with **public verifiability** achieve
  - Confidentiality of the private inputs
  - Integrity and Authenticity of the aggregate statistic (the sum)
- with
  - a malicious aggregator
  - multiple malicious users
- without relying on additional semi-trusted parties during execution.

![](_page_8_Picture_8.jpeg)

## **Adversarial model**

System model and assumptions

![](_page_9_Figure_2.jpeg)

Fully Trusted
 Honest-but-Curious
 Malicious
 Collusion

- There can be multiple verifiers
- Anyone can be a verifier, including the users and the aggregator
- · The trusted authority T leaves after the setup
- The aggregator and a subset of users of size *k* are actively malicious and can collude with each other. They attempt to learn the private inputs of other users and to affect the correctness of the aggregation
- Availability attacks are out of scope for now. They are addressed with the mPVAS-IV extension

# **Our contribution**

- mPAS: Publicly Verifiable Aggregate Signatures with Malicious Participants
- mPAS+: Reduced communication cost by grouping users.
- mPAS-IV: Detection and removal of malicious users.
- mPAS-UD: Exit strategy without restarting the protocol.

![](_page_10_Picture_5.jpeg)

# Publicly Verifiable Aggregate Signatures with Malicious Participants (mPVAS)

![](_page_11_Picture_1.jpeg)

Goal

• Each user starts from a commitment of this form (initial signature)

![](_page_12_Figure_3.jpeg)

Goal

• The goal is to aggregate all submitted signatures

 $(H(t))^{\sum sk_i} \cdot (g_1)^{\sum x_{i,t}}$ 

![](_page_13_Picture_4.jpeg)

Goal

- Since the generators are public, the input value can easily be modified by multiplying the signature by  $g_1^{\chi\prime}$
- To prevent this, we can wrap the signature under an additional exponent s that must not be disclosed to the aggregator

![](_page_14_Picture_4.jpeg)

![](_page_14_Picture_5.jpeg)

Goal

- mPVAS can be run in parallel to another privacy-preserving data summation scheme
  - mPVAS computes the aggregate signature, the data summation protocol computes the sum of the inputs
- The sum can also be extracted from the signature if the input space is small enough

![](_page_15_Picture_5.jpeg)

1. Setup phase

![](_page_16_Picture_2.jpeg)

![](_page_16_Picture_3.jpeg)

The trusted dealer chooses a random secret  $s \in \mathbb{Z}_p$ 

![](_page_16_Picture_5.jpeg)

- Users can collude with the aggregator, so we must also protect s from them
- Assume at most k malicious users, then we can split the secret into k+1 shares

![](_page_17_Picture_4.jpeg)

![](_page_18_Figure_2.jpeg)

![](_page_18_Picture_3.jpeg)

![](_page_19_Picture_0.jpeg)

![](_page_19_Figure_2.jpeg)

![](_page_19_Picture_3.jpeg)

![](_page_20_Picture_2.jpeg)

![](_page_20_Picture_3.jpeg)

![](_page_21_Picture_0.jpeg)

![](_page_21_Figure_2.jpeg)

![](_page_21_Picture_3.jpeg)

![](_page_22_Figure_2.jpeg)

![](_page_22_Picture_3.jpeg)

### 1. Setup phase

![](_page_23_Figure_2.jpeg)

Dealer generates k + 1 random keys  $ek_{j,i} \in \mathbb{Z}_p$  for each user such that

$$\sum_{j=1}^{n} \sum_{i=1}^{k+1} ek_{j,i} = 0$$

# **″**UDelft

![](_page_24_Picture_0.jpeg)

![](_page_24_Picture_2.jpeg)

![](_page_24_Picture_3.jpeg)

![](_page_25_Figure_2.jpeg)

![](_page_25_Picture_3.jpeg)

![](_page_26_Figure_2.jpeg)

![](_page_27_Figure_2.jpeg)

![](_page_28_Figure_2.jpeg)

![](_page_28_Picture_3.jpeg)

### 2. Signing phase

Each user in the signing set adds its share  $[s]_j$  of s in the exponent and adds one masking factor  $H_1(t)^{ek_{j,1}}$  to the signature

![](_page_29_Figure_3.jpeg)

![](_page_30_Picture_0.jpeg)

![](_page_30_Figure_2.jpeg)

![](_page_30_Picture_3.jpeg)

![](_page_31_Picture_0.jpeg)

![](_page_31_Figure_2.jpeg)

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![](_page_32_Figure_2.jpeg)

![](_page_33_Figure_2.jpeg)

![](_page_34_Figure_2.jpeg)

![](_page_35_Picture_0.jpeg)

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![](_page_37_Picture_2.jpeg)

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![](_page_38_Picture_2.jpeg)

![](_page_38_Picture_3.jpeg)

![](_page_38_Picture_4.jpeg)

![](_page_39_Picture_2.jpeg)

![](_page_39_Figure_3.jpeg)

![](_page_39_Picture_4.jpeg)

![](_page_40_Figure_2.jpeg)

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![](_page_41_Figure_1.jpeg)

![](_page_41_Picture_2.jpeg)

## **Extensions**

- mPAS: Publicly Verifiable Aggregate Signatures with Malicious Participants
- mPAS+: Reduced communication cost by grouping users.
- mPAS-IV: Detection and removal of malicious users.
- mPAS-UD: Exit strategy without restarting the protocol.

![](_page_42_Picture_5.jpeg)

# **Evaluation**

### Setup

- Threadripper 7970X CPU... on a single core
- Python, with CHARM for pairing cryptography
- MNT224 as type-3 elliptic curve (112 bits of security)
- Basic implementation, no specific optimizations

![](_page_43_Picture_6.jpeg)

## **Evaluation**

#### mPVAS – Empirical runtime

![](_page_44_Figure_2.jpeg)

**TU**Delft

## **Evaluation**

### **Communication complexity**

Dealer	Agg.	User	Verifier	Ledge
O(n)	<i>O</i> (1)	<i>O</i> (1)	-	no
O(1)	O(1)	O(1)	-	O(n)
O(n)	$O(n^2)$	O(n)	-	no
O(n)	O(kn)	O(k)	-	no
O(n)	O(cn)	O(c)	-	no
O(n)	O(kn)	O(k)	-	no
O(n)	O(kn)	O(k)	-	no
	$\begin{array}{c} \textbf{Dealer} \\ O(n) \\ O(1) \\ O(n) \end{array}$	DealerAgg. $O(n)$ $O(1)$ $O(1)$ $O(1)$ $O(n)$ $O(n^2)$ $O(n)$ $O(kn)$ $O(n)$ $O(kn)$ $O(n)$ $O(kn)$ $O(n)$ $O(kn)$ $O(n)$ $O(kn)$ $O(n)$ $O(kn)$	DealerAgg.User $O(n)$ $O(1)$ $O(1)$ $O(1)$ $O(1)$ $O(1)$ $O(n)$ $O(n^2)$ $O(n)$ $O(n)$ $O(kn)$ $O(k)$ $O(n)$ $O(cn)$ $O(c)$ $O(n)$ $O(kn)$ $O(k)$ $O(n)$ $O(kn)$ $O(k)$ $O(n)$ $O(kn)$ $O(k)$ $O(n)$ $O(kn)$ $O(k)$	DealerAgg.UserVerifier $O(n)$ $O(1)$ $O(1)$ - $O(1)$ $O(1)$ $O(1)$ - $O(n)$ $O(n^2)$ $O(n)$ - $O(n)$ $O(kn)$ $O(k)$ - $O(n)$ $O(cn)$ $O(c)$ - $O(n)$ $O(kn)$ $O(k)$ - $O(n)$ $O(kn)$ $O(k)$ - $O(n)$ $O(kn)$ $O(k)$ - $O(n)$ $O(kn)$ $O(k)$ -

![](_page_45_Picture_3.jpeg)

[29] Iraklis Leontiadis and Ming Li. Secure and collusion-resistant data aggregation from convertible tags. Int. J. Inf. Sec., 20(1):1–20, 2021. doi:10.1007/s10207-019-00485-4.

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[37] Yanli Ren, Yerong Li, Guorui Feng, and Xinpeng Zhang. Privacy-enhanced and verification-traceable aggregation for federated learning. IEEE Internet Things J., 9(24):24933–24948, 2022. doi:10.1109/JIOT.2022.3194930.

# Conclusion

Recap

- Publicly verifiable summation with input confidentiality and output integrity
- First scheme against collusion of aggregator and multiple malicious users
- Three extensions: improved communication, input validation, and availability
- Fast for practical applications (even without any optimisations)

![](_page_46_Picture_6.jpeg)

### Thank you very much for your time!

### Special thanks to the anonymous reviewers.

![](_page_47_Picture_2.jpeg)

![](_page_47_Picture_3.jpeg)

![](_page_47_Picture_4.jpeg)