

Packed Multiplication: How to Amortize the Cost of Side-channel Masking ?

Extended version

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Abstract. Higher-order masking countermeasures provide strong provable security against side-channel attacks at the cost of incurring significant overheads, which largely hinders its applicability. Previous works towards remedying cost mostly concentrated on “local” calculations, i.e., optimizing the cost of computation units such as a single AND gate or a field multiplication. This paper explores a complementary “global” approach, i.e., considering multiple operations in the masked domain as a batch and reducing randomness and computational cost via amortization. In particular, we focus on the amortization of ℓ parallel field multiplications for appropriate integer $\ell > 1$, and design a kit named *packed multiplication* for implementing such a batch. For $\ell + d \leq 2^m$, when ℓ parallel multiplications over \mathbb{F}_{2^m} with d -th order probing security are implemented, packed multiplication consumes $d^2 + 2\ell d + \ell$ bilinear multiplications and $2d^2 + d(d+1)/2$ random field variables, outperforming the state-of-the-art results with $O(\ell d^2)$ multiplications and $\ell \lfloor d^2/4 \rfloor + \ell d$ randomness. To prove d -probing security for packed multiplications, we introduce some weaker security notions for multiple-inputs-multiple-outputs gadgets and use them as intermediate steps, which may be of independent interest. As parallel field multiplications exist almost everywhere in symmetric cryptography, lifting optimizations from “local” to “global” substantially enlarges the space of improvements. To demonstrate, we showcase the method on the AES Subbytes step, GCM and TET (a popular disk encryption). Notably, when $d = 8$, our implementation of AES Subbytes in ARM Cortex M architecture achieves a gain of up to 33% in total speeds and saves up to 68% random bits than the state-of-the-art bitsliced implementation reported at ASIACRYPT 2018.

1 Introduction

Side-channel attacks that exploit leakage emitting from devices pose an important threat for cryptographic implementations. Masking [14, 26] is one of the most investigated protection techniques. The core idea is to randomly split each secret-dependent variable into a vector of $d + 1$ shares called *sharing*, and then implements the cryptographic algorithm over sharings instead of the raw secrets. This ensures that the initial secret cannot be rebuilt from any less than d intermediate variables in the implementation, which is called *d-private security* (a.k.a. *d-probing security*).⁷

To have secure functionalities over sharings, a masking scheme, or a *private circuit*, firstly constructs *gadgets* for various elementary calculations over sharings, and then compose the gadgets to reach the desired functionality. Obviously, to improve efficiency, it is crucial to have better gadgets (particularly for multiplications). This has motivated plenty of works concentrating on e.g., reducing the randomness complexity [5, 6, 28, 12], and securing processing dependent inputs [20, 12].

⁷ While the leakages of all the $d + 1$ shares enable reconstruction of information theoretically, the intrinsic noise in the leakages renders secret recovery infeasible in practice [14, 17, 21, 33].

Recently proposed masking schemes are typically accomplished by *formal proofs* of the aforementioned *d-private security* notion. To establish this notion, the naive method is to show that the possible tuples of intermediate variables are all independent of the secret by enumeration. Though, such an enumeration becomes intricate as the size of function grows, and it is only feasible for small circuits such as a single multiplication gadget. This naturally motivates the composition approach, i.e., proving that under certain conditions, a large circuit built upon *d-private* gadgets is *d-private*. In this respect, several composable security notions have been introduced, such as the notions of *d-Non-Inference* (NI) and *d-Strong Non-Inference* (SNI) [2]. Thanks to those security notions, a composition of gadgets with some refreshing added in-between, can be proved to be globally *d-private* secure.

Besides the above foundational advances, the past two decades have also witnessed the rapid efficiency improvement of masking schemes. Despite these, higher-order masking with many shares remains of limited use due to the overhead, especially in the resource-constraint environment [27, 19]. *It is still compelling and challenging to decrease the complexity of masking schemes.*

Local versus Global efficiency optimization. As discussed before, the community has devoted to designing better gadgets [5, 6, 28, 12] due to their fundamental influences on the high-level circuits. In fact, to our knowledge, modulo a few exceptions that will be discussed later, most of the prior works only concentrated on “local” optimizations, i.e., on reducing the complexity of individual elementary calculation such as an S-box or even a single AND gate. This “local” approach considerably simplifies the situation and enables pushing the limits of gadgets. At the same time, by the aforementioned composition framework, this naturally results in high-level circuits with better performance and provable security.

On the other hand, note that cryptographic algorithms typically consist of executing a basic function for many times in parallel. For example, the AES (more generally, virtually all the block ciphers except for the so-called ARX designs) evaluates an S-box for 16 times within each round. And, at a higher level, many modes of operations are explicitly designed to support running several primitives in parallel. For instance, the Counter (CTR) mode encrypts several blocks in parallel, and the Galois/Counter Mode (GCM) combines the CTR mode with a structure consisting of several field multiplications in parallel.

Facing this situation, this paper takes a complementary “global” view, considers multiple such parallel functions as a batch, and seeks for optimizations within such batches. This switch enables many possibilities of improvements that used to be excluded in the classical “local” optimizations. In particular, the presence of multiple calculations naturally motivates using the *amortization* technique, which aims at *reducing the averaged complexity for the masking of several operations.*

While the idea of “global” optimization via amortizing appears natural, the technique of security proof is quite non-trivial. Particularly, due to amortization, various operations in the same batch now share randomness or intermediate variables, and thus cannot be analyzed independently. To cope with this difficulty, in our security analysis, we will treat parallel operations in the same batch as a whole, and consider the corresponding *gadgets with multiple input and output sharings (shorted as MIMO gadgets in the rest of the paper)*. This shift of viewpoint clearly excludes NI/SNI as the security goal. Informally speaking, any composition of *d-NI* and *d-SNI* gadgets is still *d-SNI* if each sharing is used at most once as input of any *d-NI* gadget and the input sharings of a gadget come from different gadgets. Designing secure circuits under this condition may requires many refresh gadgets, which are expensive. Therefore, new security notions for MIMO gadgets are required.

1.1 Our Contributions

We investigate global optimizations within batches of several field multiplications.⁸ The concrete technique is to amortize the randomness and computational costs of several parallel masked multiplications. As a result, we propose a new construction named *packed multiplication*, which computes ℓ masked multiplications in parallel for any integer $\ell \geq 1$. Then, in order to prove security for our scheme, we introduce a new set of security notions for MIMO gadgets. We finally demonstrate potential applications and showcase the packed multiplication method on AES, Galois/Counter Mode (GCM) [30], and a popular disk encryption scheme TET (which is short for linear-Transformation; ECB; linear-Transformation) [23]. We details these contributions below.

Packed Multiplication. To maximize the efficiency of linear gadgets, this paper concentrates on Boolean sharings (a.k.a. additive sharings) over the finite field \mathbb{F}_q of characteristic 2, meaning that the XOR of

⁸ Note that the AND gate can be viewed as the field multiplication in \mathbb{F}_2 .

the shares equals the initial secret. In this setting, a packed multiplication scheme takes two vectors of ℓ Boolean sharings as inputs, which encode the 2ℓ inputs of the ℓ field multiplications, and gives ℓ Boolean sharings as outputs encoding the ℓ multiplication results, as depicted in Figure 1 (right). Packed multiplication proceeds in two steps. First, each input vector is (re)encoded as a “packed” sharing using a randomized linear code. When the field size $q \geq \ell+d$, each resulted “packed” sharing consists of only $\ell+d$ shares in total, meaning that the size of data is compressed from $\ell(d+1)$ to $\ell+d$. Second, a multiplication over the packed sharings is calculated, resulting in Boolean sharings (the number of result shares is $\ell(d+1)$). This step can be seen as a batch of ℓ masked local multiplications *sharing* some randomness and intermediate results. Besides, our scheme is compatible even when the field size $q \leq \ell+d$, at the cost of raising the number of shares, say n , to $n > d + 1$ with security order d , as long as the linear codes of length $\ell+n-1$ with dual distance $d + 1$ exist.

In contrast, following the classical “local” approach, the two input vectors are viewed as ℓ pairs of sharings, and each of the ℓ pairs is processed independently, as shown in Figure 1 (left). As mentioned before, such independence simplifies security analysis at the expense of limiting optimizations to local. For a more complete comparison, we consider the setting of masking ℓ parallel multiplications, and list the complexities of packed multiplication and some other popular schemes in Table 1, where the complexity of our scheme is typical estimated when the field size $q \geq \ell + d$. In the comparison, we regard the number of bilinear multiplications (i.e., of general multiplications of two non-constant variables in the finite field) and the number of random elements as the metrics for computational [6] and randomness complexities respectively.

Towards Provable Security. Packed multiplication schemes produce MIMO gadgets. For their provable security, Cassiers et al. introduced a stronger variant of SNI named Multiple-Inputs / Multiple-Outputs Strong Non-Inference (MIMO-SNI) [13]. They also introduced Probe Isolating Non-Interference (PINI) [13] notion that enables the building of more efficient gadgets. Unfortunately, both MIMO-SNI and PINI are too strong and could not be achieved by ours. To rescue, we identify a set of intermediate composable security notions for MIMO gadgets that interpolates between the stronger MIMO-SNI and the weaker (S)NI. In addition, ours are orthogonal to PINI. We refer to Figure 2 for an illustration. With the new notions, our gadgets can be securely composed with each other, either by satisfying our specialized composition theorem, or through direct proof in the probe propagation framework introduced in [5, 11].

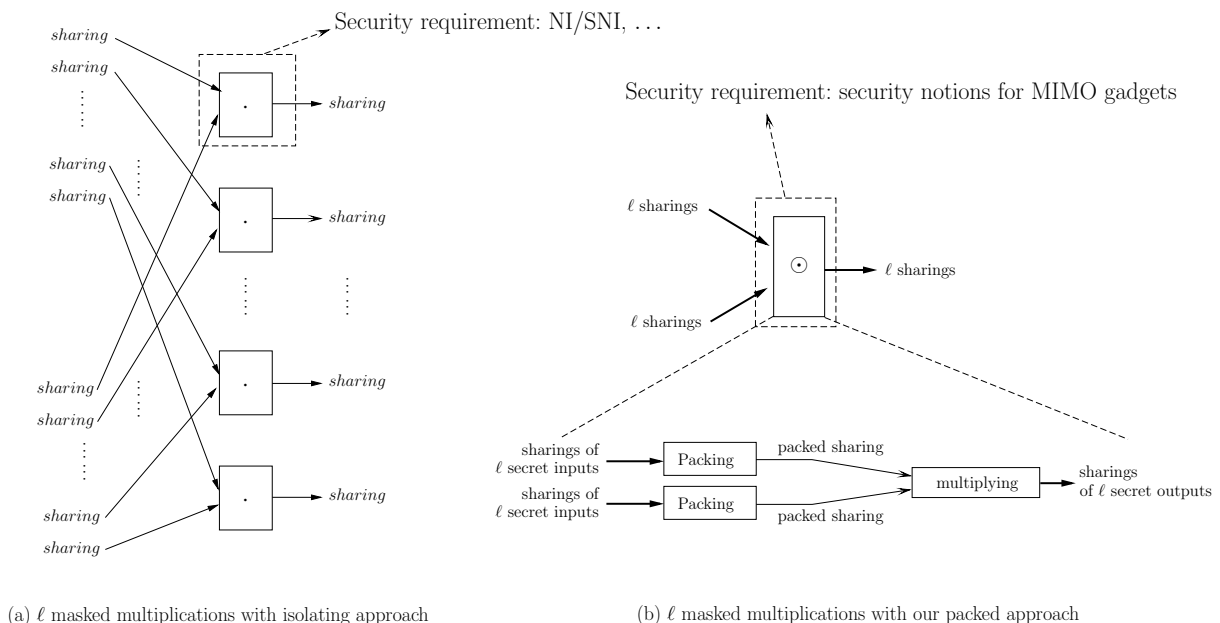


Fig. 1. Packed multiplication in general (right) and the comparison with classical isolating approach (left).

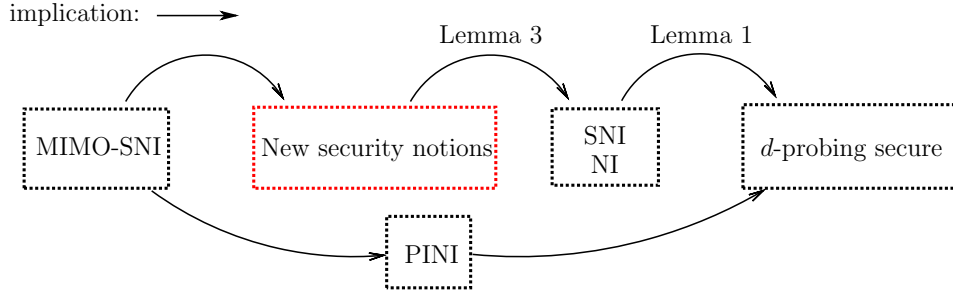


Fig. 2. Relations among different security notions.

Table 1. Complexities of ℓ parallel multiplications with security order d

| | | Computational complexity ¹ | Randomness complexity ² |
|-------------------------------------|--------------------|---------------------------------------|------------------------------------|
| Our Scheme | Packing | 0 | d^2 |
| | Multiplying | $d^2 + 2\ell d + \ell$ | $d(d+1)/2$ |
| | Total | $d^2 + 2\ell d + \ell$ | $2d^2 + d(d+1)/2$ |
| Tight private circuits [26] | | $\ell d^2 + 2\ell d + \ell$ | $\ell d(d+1)/2$ |
| Masking with reduced randomness [5] | | $\ell d^2 + 2\ell d + \ell$ | $\ell(d + \lfloor d^2/4 \rfloor)$ |
| Multiplication over finite fields * | [6, Algorithm 4] | $2\ell d + \ell$ | $\ell(2d^2 + d(d+1)/2)$ |
| | [6, Algorithm 5] | $\ell d^2 + 2\ell d + \ell$ | ℓd |
| Code-based masking [38] | | $d^2 + 2\ell d + \ell^2$ | $2d(d+\ell)$ |

* Despite the small instantiations for $d \leq 4$ [28], it requires large enough finite fields, e.g., the field size $q > d(d+1)(12d)^d$ [6, Theorem 5.4].

Applications. As parallel multiplications exist almost everywhere in symmetric cryptography, our packed multiplication has potentially broad applicability and deep impact. To demonstrate, we showcase the method on the *AES Subbytes step* and the *polynomial-evaluation hash*.

The AES Subbytes step consists of parallel S-boxes evaluations. Based on the ARM Cortex M architecture, we implement 16 AES S-boxes by applying the packed multiplication and report the performance results. Notably, when the security order is of $d = 8$, our implementation achieves a gain of up to 33% in speeds and saves up to 68% random bits compared with the state-of-the-art bitsliced implementation [9].

The polynomial-evaluation hash involves a structure of several multiplications in parallel, and thus our packed multiplication is well suited. This benefits the SCA resilience for two scenarios: GCM and TET.

1.2 Related works

Previous amortization. As mentioned before, global view and amortization were only considered in very few early works. Roughly, they fall into three concrete approaches, i.e., randomness re-use, masking with robust Pseudorandom Generator (PRG) and the code-based masking. The former two approaches aim at amortization of randomness rather than reducing computational cost, while the last addresses both.

Randomness re-use. This approach aims at re-using random bits in different gadgets. Faust et al. [18] introduce a security model allowing multiple gadgets to securely re-use randomness, and proposed threshold implementation-based gadgets in their model. This method provides a quite efficient scheme for small values of security order.

Masking with robust PRGs. Ishai et al. proposed to expand the randomness using the so-called robust PRG [25] in the private circuits, where the number of True Random Number Generator (TRNG) calls for seeds is independent of the circuit size. A recent work of Coron et al. describes a quite practical construction in this direction [15], where the number of random bits is only $\tilde{O}(t^2)$ for security against t probes. This strategy can be regarded as a certain form of amortization (of TRNG calls), but it is a bit of orthogonal to ours. In contrast, we consider the amortization of both randomness and computational costs.

Code-based masking. It was recently shown by Wang et al. [38] that the general type of masking called code-based masking is able to encode multiple secrets together into one codeword and calculate parallel operations over these secrets together in the masked domain. Admittedly, the packed multiplication proposed in this paper shares some ideas with the code-based masking. But we give a practical and much more efficient scheme. Notably, our scheme generally works with Boolean sharings, which enables more efficient masked linear operations. In contrast, the code-based masking proposed in [38] was a generic scheme, whose further specification and optimization were left as an open problem. We give a complexity comparison in Table 1 to highlight the improvement of our scheme.

Polynomial masking with packed secret sharing technique [22] can be regarded as a variant of the code-based masking, and its multiplications are performed based on the MPC protocol of Damgård et al. [16]. This scheme however requires a heavy random generation process that becomes an efficiency bottleneck.

Security notions for MIMO gadgets. Cassiers et al. introduced a stronger variant of SNI named Multiple-Inputs / Multiple-Outputs Strong Non-Inference (MIMO-SNI) [13].⁹ Though, MIMO-SNI gadget comes at a higher complexity compared to the SNI ones. They also introduced the Probe Isolating Non-Interference (PINI) [13] notion that enables the building of more efficient gadgets. Informally speaking, a composition of multiple gadgets is d -PINI (resp., d -MIMO-SNI) if every gadget is d -PINI (resp., d -MIMO-SNI). In addition, d -PINI (resp., d -MIMO-SNI) alone implies the d -private security. Unfortunately, these two notions are both too strong for our new multiplication gadget. For this reason, we will propose in Section 3 a set of new security notions that bridge our new gadgets to the probing security.

⁹ The notion of MIMO gadgets shall be distinguished from MIMO-SNI: the former are gadgets with multiple input and output sharings, while the latter is a security model for MIMO gadgets.

1.3 Organization

In the remainder of this paper, we present notations and necessary notions in Section 2. We then introduce our new security notions in Section 3. We propose the packed multiplication in Section 4, and in Section 5 propose a construction of the linear operations that complies with the new security notions. Section 7 illustrates the applications.

2 Preliminary

2.1 Notations

In the following, we denote by \mathbb{F}_q a characteristic 2 finite field, where $q = 2^m$ for any $m \geq 1$, and denote field elements by lower-case letters. We use \oplus to denote plus over the finite field. For simplicity, we use \sum for the summation over any fields or rings. For a natural number n we denote by $[n]$ the set of integers from 1 to n both included. Let calligraphies (e.g., \mathcal{I}) be sets, and $|\mathcal{I}|$ denote the length of the set \mathcal{I} . Let bold lower cases (e.g., \mathbf{x}) be the vectors over $\mathbb{F}_q^{|\mathbf{x}|}$, where $|\mathbf{x}|$ denotes the length of the vector, $\mathbf{x}[i]$ denotes the i^{th} element of vector \mathbf{x} , and $\mathbf{x}[i:j]$ denotes the vector made up of i^{th} to j^{th} elements of vector \mathbf{x} . Unless otherwise noted, we assume the vectors are row vectors in this paper, and the column vectors are denoted as \mathbf{x}^T .

Let bold capital letters (e.g., \mathbf{A}) be the matrices in $\mathbb{F}_q^{r \times c}$ (or $r \times c$ matrix), for row and column counts being r and c respectively. $\mathbf{A}[i, j]$ denotes the element of \mathbf{A} at i^{th} row and j^{th} column, $\mathbf{A}[i, \cdot]$ (resp., $\mathbf{A}[\cdot, i]$) denotes the i^{th} row (resp., column) of matrix \mathbf{A} , and $\mathbf{A}[i:j, \cdot]$ denotes the matrix made up of i^{th} to j^{th} rows of \mathbf{A} . Let \mathbf{A}^T denote the transpose of the matrix \mathbf{A} . For a $r \times c$ matrix \mathbf{A} and a set $\mathcal{I} \subseteq [r]$ (resp., $\mathcal{J} \subseteq [c]$), $\mathbf{A}[\mathcal{I}, \cdot]$ (resp., $\mathbf{A}[\cdot, \mathcal{J}]$) denotes the submatrix of \mathbf{A} made up of the rows (resp., columns) indexed by \mathcal{I} (resp., \mathcal{J}). For matrices \mathbf{A} and \mathbf{B} , we denote their product as $\mathbf{A} \times \mathbf{B}$, or in short \mathbf{AB} in non-ambiguous cases. Specifically, we use $\mathbf{O}^{r \times c}$ to denote the zero matrix in $\mathbb{F}_q^{r \times c}$ and \mathbf{I}^n the identity matrix in $\mathbb{F}_q^{n \times n}$; to ease understanding, when there is no ambiguity, their superscripts will be omitted. For two matrices \mathbf{A} and \mathbf{B} , $[\mathbf{A}, \mathbf{B}]$ is the concatenation of \mathbf{A} and \mathbf{B} by columns, and $[\mathbf{A}; \mathbf{B}]$ is the concatenation of \mathbf{A} and \mathbf{B} by rows. A set of n variables can be represented as $\{x_i\}_{i=1}^n \stackrel{\text{def}}{=} \{x_1, \dots, x_n\}$, and this representation can be adopted for a set of vectors or matrices.

2.2 Private Circuits

We view a circuit C as a directed acyclic graph with gates and wires being vertices and edges respectively. We assume that the wires carry variables in \mathbb{F}_q and the gates are elementary calculations over \mathbb{F}_q . A randomized circuit is a circuit augmented with random gates. A random gate is a gate that puts a random variable in its output wire. Variables carried in the wires of a circuit C are called intermediate variables of C . A probe to a circuit is an intermediate variable whose value is assumed to be revealed to the adversary. For a circuit C with input $\mathbf{x} \in \mathbb{F}_q^\ell$, $C(\mathbf{x})$ produces the output $\mathbf{y} \in \mathbb{F}_q^{\ell'}$ that we denote $C(\mathbf{x}) \stackrel{\text{def}}{=} \mathbf{y}$. And for a set \mathcal{P} of probes, $C_{\mathcal{P}}(\mathbf{x})$ returns the values of the probes by feeding \mathbf{x} as the input of C . We call a set (or vector) of variables (say, \mathbf{x}) over \mathbb{F}_q independent of the other vector of variables \mathbf{y} if $\Pr(\mathbf{x} = \alpha \mid \mathbf{y} = \beta) = \Pr(\mathbf{x} = \alpha)$ for any value α of \mathbf{x} and any value β of \mathbf{y} , where the probability is taken over the random coins used to generate these vectors.

We begin by recalling the notion of sharings, the basis of masking. We also provide our new notion of *packed sharing*. It should be noted that, for the notion of sharing, we let the number of shares be n (rather than $d + 1$) for compatibility (of any field sizes) reason. As mentioned in the introduction, our scheme is also compatible with a small field size (i.e., $q < \ell + d$ with ℓ parallel multiplications), at the cost of raising the number of shares in a sharing to $n > d + 1$ with security order d .

Definition 1 (Sharing and packed sharing) For a variable $x \in \mathbb{F}_q$, we say $\hat{\mathbf{x}} \in \mathbb{F}_q^n$ is a sharing of x if there exists an encoder $\text{Enc} : (\mathbb{F}_q, \mathbb{F}_q^{n-1}) \rightarrow \mathbb{F}_q^n$, a decoder $\text{Dec} : \mathbb{F}_q^n \rightarrow \mathbb{F}_q$ and $\mathbf{r} \in \mathbb{F}_q^{n-1}$ such that $\hat{\mathbf{x}} = \text{Enc}(x, \mathbf{r})$ and $x = \text{Dec}(\hat{\mathbf{x}})$. Particularly, a sharing $\hat{\mathbf{x}}$ of x is called a Boolean sharing, if $x = \text{Dec}(\hat{\mathbf{x}}) = \sum_{i=1}^n \hat{\mathbf{x}}[i]$.

For $\ell > 1$ and a vector of variables $\mathbf{x} \in \mathbb{F}_q^\ell$, we say $(\tilde{\mathbf{x}}, \hat{\mathbf{u}}) \in (\mathbb{F}_q^\ell, \mathbb{F}_q^{n-1})$ is a packed sharing of \mathbf{x} if there exists an encoder $\text{Enc} : (\mathbb{F}_q^\ell, \mathbb{F}_q^{n-1}) \rightarrow (\mathbb{F}_q^\ell, \mathbb{F}_q^{n-1})$, a decoder $\text{Dec} : (\mathbb{F}_q^\ell, \mathbb{F}_q^{n-1}) \rightarrow \mathbb{F}_q^\ell$ and $\mathbf{r} \in \mathbb{F}_q^{n-1}$ such that

$(\tilde{\mathbf{x}}, \hat{\mathbf{u}}) = \text{Enc}(\mathbf{x}, \mathbf{r})$ and $\mathbf{x} = \text{Dec}(\tilde{\mathbf{x}}, \hat{\mathbf{u}})$. Moreover, an element of a packed sharing $(\tilde{\mathbf{x}}, \hat{\mathbf{u}})$ is an element of either $\tilde{\mathbf{x}}$ or $\hat{\mathbf{u}}$.

Elements of a sharing or packed sharing are called shares.

In the rest of the paper, unless explicitly stated, all sharings are Boolean sharings. We next recall the notion of private circuit compiler [26] as follows.

Definition 2 (Private circuit compiler [26]) A private circuit compiler for a circuit C with input in \mathbb{F}_q^ℓ and output in $\mathbb{F}_q^{\ell'}$ is defined by a triple $(\mathsf{I}, \mathsf{T}, \mathsf{O})$ where

- $\mathsf{I} : \mathbb{F}_q \rightarrow \mathbb{F}_q^n$, is an encoder that randomly maps each input $x \in \mathbb{F}_q$ to a sharing.
- T is a circuit transformation whose input is circuit C , and output is a randomized circuit C' with ℓ sharings as the input, and ℓ' sharings as the output.
- $\mathsf{O} : \mathbb{F}_q^n \rightarrow \mathbb{F}_q$ is a decoder that maps each output sharing $\hat{\mathbf{z}} \in \mathbb{F}_q^n$ to the corresponding output $z \in \mathbb{F}_q$.

We say that $(\mathsf{I}, \mathsf{T}, \mathsf{O})$ is a private circuit compiler and C' is a d -private circuit (or d -probing secure) if the following requirements hold:

- *Correctness*: for any input $\mathbf{x} \in \mathbb{F}_q^\ell$, $\Pr \left(\mathsf{O}^\circ(C'(\mathsf{I}^\circ(\mathbf{x}))) = C(\mathbf{x}) \right) = 1$, where I° (resp., O°) is a canonical encoder (resp., decoder) that encodes (resp., decodes) each element of input secrets \mathbf{x} (resp., each sharing of output sharings) by repeatedly calling I (resp., O).
- *Privacy*: for any input $\mathbf{x} \in \mathbb{F}_q^\ell$ and any set of probes \mathcal{P} such that $|\mathcal{P}| \leq d$, $C'_{\mathcal{P}}(\mathsf{I}(\mathbf{x}))$ are independent of the input \mathbf{x} , where d is called the security order.

We consider the circuit transformation T realized by the composition of gadgets. An *gadget* is a randomized circuit whose inputs (resp., outputs) are either sharings or packed sharings. We say that a gadget G implements a function $f : \mathbb{F}_q^\ell \rightarrow \mathbb{F}_q^{\ell'}$, if and only if $\mathsf{O}^\circ(G(\mathsf{I}^\circ(\mathbf{x}))) = f(\mathbf{x})$ for any $\mathbf{x} \in \mathbb{F}_q^\ell$, where I° (resp., O°) encodes (resp., decodes) each input (resp., output). Gadget composition builds bigger circuits from a number of gadgets, by connecting the output wires of some gadgets to the input wires of the others. To cleanly pinpoint the “pattern” of a composition, we appeal to an acyclic graph C . I.e., the resulted bigger circuit is obtained by replacing the vertices of C with the gadgets. In such a graph, the involved gadgets are called *sub-gadgets*, and the edges carry sharings or packed sharings. An *MIMO gadget* is a gadget with multiple input sharings or output sharings. Note that the composed gadget C' is a gadget, and thus a recursive composition of gadgets is also a gadget.

2.3 Composable security notions

While the notion of d -private security nicely protects against side-channel attacks, it is not trivial to prove that large circuits such the AES fulfill it. The difficulty stems from enumerating the probes within the circuit, the complexity of which increases exponentially with the circuit size. The natural solution is to use the composition method, so that one can focus on each individual gadget, while the global d -private security is ensured by composition. Barthe et al. introduced first composable security notions [2] for (small) gadgets that are sufficient to result in provable probing security.

Simulatability. We first recall the definition of simulatability introduced in [5]:

Definition 3 (Simulatability [5]) Let $\mathcal{P} = \{p_1, \dots, p_d\}$ be a set of d probes of a gadget G with input shares \mathcal{X} . Let $\mathcal{S} \subseteq \mathcal{X}$ be a subset of input shares. A simulator is a randomized function $S : \mathbb{F}_q^{|\mathcal{X}|} \rightarrow \mathbb{F}_q^d$. A distinguisher is a randomized function $D : (\mathbb{F}_q^d, \mathbb{F}_q^{|\mathcal{X}|}) \rightarrow \{0, 1\}$. The set of probes \mathcal{P} can be simulated with shares in \mathcal{S} if and only if there exists a simulator S such that for any distinguisher D and any inputs shares \mathcal{X} , we have:

$$\Pr \left[D(G_{\mathcal{P}}(\mathcal{X}), \mathcal{X}) = 1 \right] = \Pr \left[D(S(\mathcal{S}), \mathcal{X}) = 1 \right] ,$$

where the probability is over the random coins in G , S and D .

(Strong) Non-Inference. We then recall the first set of composable security notions introduced in [2]. The probes of a gadget are separated as follows:

- Output probes: output variables.
- Internal probes: variables except for the output probes.

Definition 4 (d -(Strong) Non-Inference ((S)NI)[2]) Let G be a gadget with sharings as inputs and outputs. G is d -NI (resp., d -SNI), if any probes consisting of t_{int} internal probes and t_{out} outputs probes with $t_{int} + t_{out} \leq d$ can be simulated with $t_{int} + t_{out}$ (resp., t_{int}) shares of each input sharing.

As shown in Lemma 1, both d -NI and d -SNI imply the d -private security.

Lemma 1 (NI/SNI implies probing security [2]) If a gadget G is d -SNI or d -NI, then G is a d -private circuit if any d shares in each input sharing are independent of the secrets and all input sharings are independently encoded.

More importantly, in the proof of probing security, NI and SNI can reduce the elaboration from trying all tuples of probes of a full circuit to only verifying each small gadget. Informally speaking, any composition of d -NI and d -SNI gadgets is still d -NI if each sharing is used at most once as input of any d -NI gadget and the input sharings of a gadget come from different gadgets.

2.4 Different types of gadgets

As gadgets can be used as building blocks of private circuits, it is necessary to specify types of gadgets that are required for protecting cryptographic algorithms.

The first type of gadgets is linear gadgets that implement linear functions. As the encoder is usually homomorphic (for example, the encoder of the Boolean sharing) over linear functions, linear gadgets can be correctly constructed by applying linear functions on the shares of the same index, which we will denote as *the trivial implementation of a linear function*. It becomes more difficult for (nonlinear) gadgets implementing nonlinear functions such as multiplication, since the encoder is usually not homomorphic over nonlinear functions. The last type of gadgets is the refresh gadget (a.k.a, the refreshing) that re-randomizes a sharing, which is usually needed for the composition of gadgets. Existing works (e.g., [4, 3, 1]) have provided different refresh gadgets that are asymptotically more efficient than multiplication gadgets. In the rest of the paper, we mainly focus on a typical nonlinear gadget: multiplication gadget that implements the multiplication over \mathbb{F}_q in the masked domain.

3 New security notions for MIMO gadgets

To motivate, this section begins by recalling the limitation of NI/SNI with MIMO gadgets. Then, to ease understanding, we serve intuition for our new security notions in sub-section 3.2. The core concept will be the notion of t -chunk that describes a set of shares from the input or output sharings of a gadget. The formal definitions are finally given in sub-section 3.3.

3.1 Limitation of NI/SNI with MIMO gadgets

The notions of NI and SNI are not perfectly suitable for MIMO gadgets. To see this, let's consider, for example, the compositions of two gadgets, as illustrated in Figure 3. In Figure 3-(a), the composition of G_1 and G_2 subjects to the rule in Lemma 1, and thus is 3-SNI. Figure 3-(b) shows an improper composition, where two probes (one internal and one output) of G_2 requires 4 input variables to simulate, which cannot be further simulate with the input of G_1 since G_1 is 3-SNI. Figure 3-(c) fixes the issue of Figure 3-(b) by adding SNI refreshings, which however comes at huge overheads. Note that a similar illustration can be found in [13, Figure 5], where the authors considered a linear operation between two outputs of a nonlinear gadget.

In the rest of this section, we investigate more suitable security notions for gadgets with multiple input and output. In Appendix A, we recall two other such candidates named MIMO-SNI and PINI [13]. However, for example, the packed multiplication that we will introduce in Section 4 is neither d -MIMO-SNI nor d -PINI, but is d -SNI. It indicates that there should exist some security notions between MIMO-SNI and SNI (stronger than SNI and weaker than MIMO-SNI) and more suitable to the packed multiplication. In this respect, we put forward a set of new security notions.

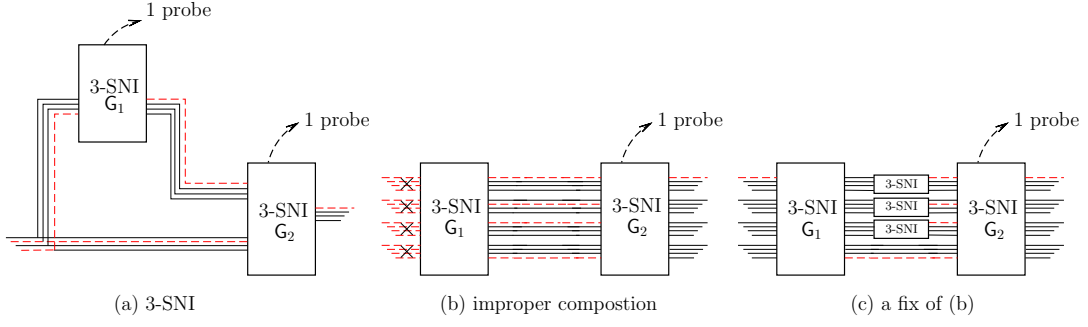


Fig. 3. Limitation of (S)NI.

3.2 Intuition behind the new security notions

The notion of simulatability captures that a set of output shares and t_{int} internal shares can be simulated with some input shares called *propagated shares*. In this respect, how to define the output shares and the propagated shares is critical in different security notions. Let $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$ be ℓ sharings that can be either input sharings or output sharings of a gadget. For an integer t , we define the types of set \mathcal{X} consisting of some shares in $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$ as follows:

- i.* $|\mathcal{X}| = t$, i.e., \mathcal{X} consists of t shares in $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$.
- ii.* $|\mathcal{X}| = \ell t$, and \mathcal{X} consists of t shares in each sharing of $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$.

It can be seen that, in (S)NI, output and propagated shares relate to types *i* and *ii* respectively. The only difference between SNI and NI is the values of the parameters t for output and propagated shares. And in MIMO-SNI, output and propagated shares relate to types *ii* and *i* respectively, which makes it a stronger property than (S)NI. It is because, compared with (S)NI, MIMO-SNI allows that a larger set of output shares can be simulated with a smaller set of propagated shares. Examples can be found in Figures 5-(a) (b) and (c).

For our new security notions, we introduce a new type of set \mathcal{X} as follows:

- iii.* \mathcal{X} consists of a t -chunk of $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$, where the t -chunk is defined below, and we also depict an example in Figure 4.

Definition 5 A t -chunk of sharings $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell \in \mathbb{F}_q^n, \dots, \mathbb{F}_q^n$ is a subset of a set made up of the following two parts:

1. (α part) $\{\hat{\mathbf{x}}_k[i] \mid k \in \mathcal{K}, i \in \mathcal{I}\}$ for $\mathcal{K} \subseteq [\ell]$, $\mathcal{I} \subseteq [n]$ and $|\mathcal{K}| + |\mathcal{I}| = t_\alpha$.
2. (β part) t_β shares from $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$.

such that $t \geq t_\alpha + t_\beta$.

It should be noted that the t -chunk is only defined with sharings, rather than the packed sharings.

The rationale of the t -chunk definition. The t -chunk is defined in accordance with the formalism of packed multiplication given latter in Section 4. We will mostly consider an abstract computation that takes sharings $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell \in \mathbb{F}_q^n, \dots, \mathbb{F}_q^n$ as inputs and sums (XOR) the rows of $\mathbf{X} \stackrel{\text{def}}{=} \hat{\mathbf{X}} \oplus \hat{\mathbf{Q}}$, resulting in $\tilde{\mathbf{x}} \in \mathbb{F}_q^\ell$, where $\hat{\mathbf{X}}[k] \stackrel{\text{def}}{=} \hat{\mathbf{x}}_k$ for $k \in [\ell]$ and $\hat{\mathbf{Q}} \in \mathbb{F}_q^{n \times \ell}$ is a random matrix. During the process, there also exist variables $f(\hat{\mathbf{Q}}[i, \cdot])$ for any function $f: \mathbb{F}_q^\ell \rightarrow \mathbb{F}_q$ and any $i \in [n]$. A specification of such abstract algorithm is the packing in Gadget 1-P, and an example will be depicted in Figure 6. In this case, a certain amount of probes to $f(\hat{\mathbf{Q}}[i, \cdot])$, $\hat{\mathbf{X}}$, \mathbf{X} and $\tilde{\mathbf{x}}$ can be simulated with a t -chunk of $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$ for some $t \geq 0$. More concretely (but informally),

- Let $\mathcal{I} \subseteq [n]$ and $\mathcal{K} \subseteq [\ell]$, the probes to $f(\hat{\mathbf{Q}}[i, \cdot])$ for $i \in \mathcal{I}$ can be simulated by sampling the corresponding random distribution, and probes to $\tilde{\mathbf{x}}[k]$ for $k \in \mathcal{K}$ can be simulated with the α part of $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$ corresponding to \mathcal{I} and \mathcal{K} . In the example of Figure 4, the probes of this type relate to $\mathcal{I} = \{2, 3, 4\}$ and $\mathcal{K} = \{5, 6\}$.

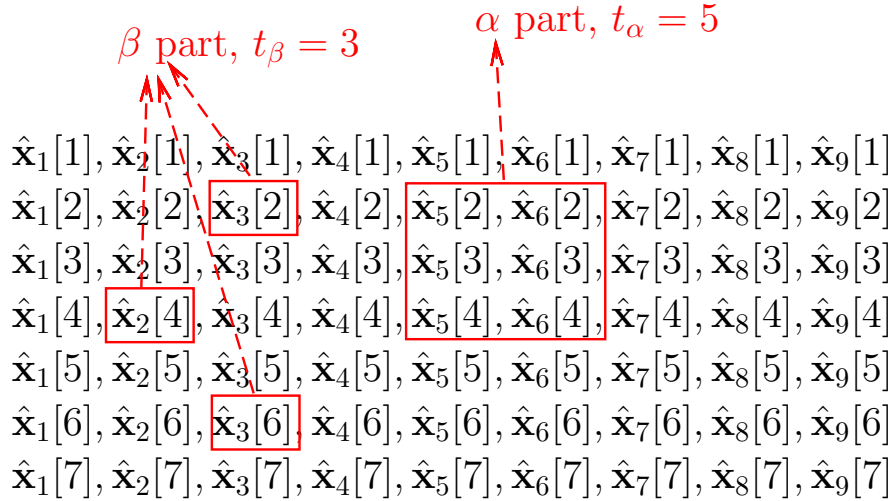


Fig. 4. An examples of an 8-chunk of sharings $\hat{x}_1, \dots, \hat{x}_7$, where $t_\alpha = 5$ and $t_\beta = 3$. Each column of the matrix corresponds to a distinct sharing.

- The probes to $\hat{\mathbf{X}}$ can be simulated with the β part of sharings $\hat{x}_1, \dots, \hat{x}_\ell$. In the example of Figure 4, the probes of this type are $\hat{\mathbf{X}}[3,2]$, $\hat{\mathbf{X}}[2,4]$ and $\hat{\mathbf{X}}[3,6]$.

Below in Lemma 2, we show that the union of two t -chunks is a $2t$ -chunk. Its proof is in Appendix B.1. This property enables merging several t -chunk probes.

Lemma 2 (Closure of t -chunk under union) *If \mathcal{S}_1 and \mathcal{S}_2 are t_1 -chunk and t_2 -chunk of sharings $\hat{x}_1, \dots, \hat{x}_\ell$ respectively, then $\mathcal{S}_1 \cup \mathcal{S}_2$ is a $(t_1 + t_2)$ -chunk of $\hat{x}_1, \dots, \hat{x}_\ell$.*

Cautionary note. By definition, a subset of a t -chunk is also a t -chunk. Thus, a t -chunk should also be a t' -chunk for any $t' > t$. Moreover, the partition of \mathcal{S} (into α and β parts) is not unique. For example, the set of share highlighted in Figure 4 can also be 9-chunk, if it is partitioned in a way that β part contains all the highlighted shares and α part is empty. Also note that, there always exists a minimum value of t for any set of shares. For example, the set of share highlighted in Figure 4 can not be t -chunk for any $t < 8$.

3.3 New security notion for MIMO gadgets

In this sub-section, we formally introduce the new security notions. We begin with the first one:

1. d -Chunk Strong Non-Inference and d -Chunk Non-Inference, abbreviated as d -CNI and d -CSNI respectively.

They share a similar structure with NI/SNI, but output and propagated shares are replaced with a t -chunk of the output and input sharings respectively, making them to be positioned in-between d -(S)NI and d -MIMO-SNI. The formal definition of d -C(S)NI is as follows.

Definition 6 (d -C(S)NI) *Let \mathcal{G} be a gadget with sharings as inputs and outputs. \mathcal{G} is d -CNI (resp., d -CSNI), if any probes consisting of t_{int} internal probes and a t_{out} -chunk of output sharings with $t_{int} + t_{out} \leq d$ can be simulated with a $(t_{int} + t_{out})$ -chunk (resp., t_{int} -chunk) of input sharings.*

In Figure 5-(a)(b)(c)(d), we give examples to illustrate the differences of the d -C(S)NI, (S)NI and MIMO-SNI. Also note that type iii shares cover type i shares with the same value of t , and thus, as shown in Lemma 3, d -C(S)NI implies the (S)NI security. The full proof is given in Appendix B.2.

Lemma 3 d -CNI \Rightarrow d -NI, d -CSNI \Rightarrow d -SNI and d -CSNI \Rightarrow d -CNI.

3.4 New security notion for gadgets with packed sharings

While the d -C(S)NI meets the minimal requirement for protecting any cryptographic algorithm, it is (by definition) only for gadgets with sharings as inputs and outputs, and thus incompatible with packed sharings. Such compatibility has the (obvious) advantage of enabling extension to any gadgets that are composed of packing, multiplying and linear gadgets. For example the masked AES S-box that we will present later in Figure 9, Section 6. The security proof of such composition can be much simplified if there exist secure notions particularly for packing and multiplying gadgets, more generally, for gadgets with packed sharings as inputs or outputs.

Therefore, to facilitate the compositions for gadgets with packed sharings, two other new notions are necessary:

2. For the gadgets with input sharings and output packed sharings, we propose d -Input-Chunk Non-Inference and d -Input-Chunk Strong Non-Inference, abbreviated as d -ICNI and d -ICSNI respectively.
3. For the gadgets with input packed sharings and output sharings, we propose d -Output-Chunk Non-Inference and d -Output-Chunk Strong Non-Inference, abbreviated as d -OCNI and d -OCSNI respectively.

The formal definitions are in Definitions 7 and 8. Also see Figure 5-(e)(f) for the corresponding illustrations.

Definition 7 (d -IC(S)NI) Let G be a gadget with sharings as inputs and packed sharings as outputs. G is d -ICNI (resp., d -ICSNI), if any probes consisting of t_{int} internal probes and t_{out} shares from output packed sharings with $t_{int} + t_{out} \leq d$ can be simulated with a $(t_{int} + t_{out})$ -chunk (resp., t_{int} -chunk) of input sharings.

Definition 8 (d -OC(S)NI) Let G be a gadget with packed sharings as inputs and sharings as outputs. G is d -OCNI (resp., d -OCSNI), if any probes consisting of d_{int} internal probes and a d_{out} -chunk of output sharings with $t_{int} + t_{out} \leq d$ can be simulated with $t_{int} + t_{out}$ (resp., t_{int}) shares of each input packed sharing.

In Sections 4 and 5, we will propose constructions for d -CSNI and d -CNI packed gadgets that we will use in tailored analyzes of some relevant circuits in Sections 6 and 7.1. We leave the proposition and proof of more generic composition rules as an important goal for further research and present in Appendix E first steps in this direction.

Composability of all the new notions (i.e., d -C(S)NI, d -IC(S)NI and d -OC(S)NI) can be proved by using the probe propagation framework introduced in [11, 3] (see a description in Appendix C). Based on the new security notions, in Appendix D we give three examples to illustrate the composition of the gadgets in the probe propagation framework.

4 Packed multiplication gadget

4.1 Construction

We consider the element-wise product (a.k.a., the entrywise product or the Hadamard product) of two secret vectors. That is, for $\mathbf{x} \stackrel{\text{def}}{=} (\mathbf{x}[1], \dots, \mathbf{x}[\ell])$ and $\mathbf{y} \stackrel{\text{def}}{=} (\mathbf{y}[1], \dots, \mathbf{y}[\ell])$, we consider computing $\mathbf{z} = \mathbf{x} \odot \mathbf{y} \stackrel{\text{def}}{=} (\mathbf{x}[1]\mathbf{y}[1], \dots, \mathbf{x}[\ell]\mathbf{y}[\ell])$ in the masked domain, where \odot denotes the element-wise multiplication over \mathbb{F}_q^ℓ . The inputs of the packed multiplication gadget are $\ell \times 2$ Boolean sharings:

$$\{\hat{\mathbf{x}}_i\}_{i=1}^\ell \stackrel{\text{def}}{=} \{(\hat{\mathbf{x}}_i[1], \dots, \hat{\mathbf{x}}_i[n])\}_{i=1}^\ell \quad \text{and} \quad \{\hat{\mathbf{y}}_i\}_{i=1}^\ell \stackrel{\text{def}}{=} \{(\hat{\mathbf{y}}_i[1], \dots, \hat{\mathbf{y}}_i[n])\}_{i=1}^\ell$$

And the outputs should also be ℓ Boolean sharings $\{\hat{\mathbf{z}}_i\}_{i=1}^\ell$ such that:

$$\sum_{i=1}^n \hat{\mathbf{z}}_k[i] = \left(\sum_{i=1}^n \hat{\mathbf{x}}_k[i] \right) \left(\sum_{i=1}^n \hat{\mathbf{y}}_k[i] \right), \quad \text{for any } k \in [\ell].$$

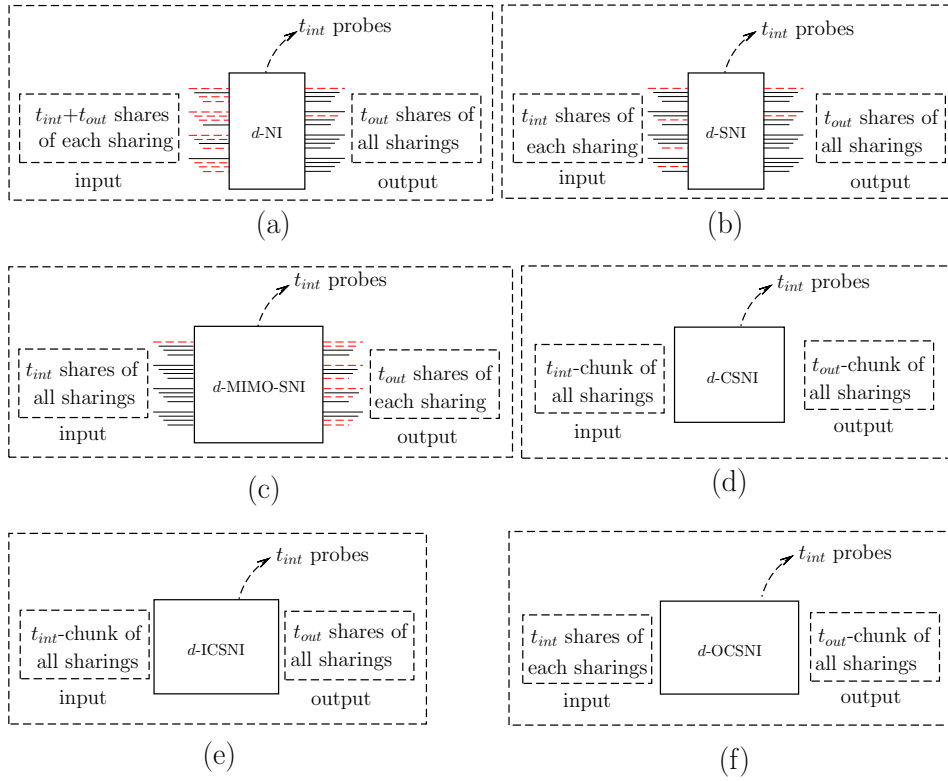


Fig. 5. Difference between the security notions.

- (a) d -NI: t_{out} output probes and t_{int} internal probes can be simulated with propagated shares that consist of $t_{int} + t_{out}$ shares of each input sharing.
- (b) d -SNI: output probes are the same as d -NI case, and the propagated shares consist of t_{int} shares of each input sharing.
- (c) d -MIMO-SNI: the output probes consist of t_{out} shares of each output sharing, and the propagated share is only t_{int} input share of all input sharings.
- (d) d -CSNI: output probes consists of a t_{out} -chunk of output sharings, and the propagated shares consist of a t_{int} -chunk of output sharings.
- (e) d -ICSNI: output probes are shares from packed sharings, and the propagated shares are the same as d -CSNI case.
- (f) d -OCSNI: output probes are the same as d -CSNI case, and the propagated shares are shares from packed sharings.

The gadget requires an $(n-1) \times \ell$ matrix \mathbf{A} such that any $d < n$ columns of $[\mathbf{I}, \mathbf{A}]$ are independent. In other words, $[\mathbf{I}, \mathbf{A}]$ is the generating matrix (with the size $(n-1) \times (\ell+n-1)$) of a linear code with dual distance $d+1$. A typical example of \mathbf{A} is an $(n-1) \times \ell$ MDS matrix, and in this case, $d = n-1$.

The packed multiplication can be divided into two sub-gadgets: *Packing* and *Multiplying*. Generally speaking, the first gadget manipulates $\{\hat{\mathbf{x}}_i\}_{i=1}^\ell$ and $\{\hat{\mathbf{y}}_i\}_{i=1}^\ell$ separately to compute the packed sharings $(\tilde{\mathbf{x}}, \hat{\mathbf{u}}) \in (\mathbb{F}_q^\ell, \mathbb{F}_q^{n-1})$ and $(\tilde{\mathbf{y}}, \hat{\mathbf{v}}) \in (\mathbb{F}_q^\ell, \mathbb{F}_q^{n-1})$, and the second gadget computes the result from the packed sharings. More details are elaborated as follows:

- *Packing*: This sub-gadget packs the sharings $\{\hat{\mathbf{x}}_i\}_{i=1}^\ell$ into a packed sharing that is a tuple $(\tilde{\mathbf{x}}, \hat{\mathbf{u}}) \in (\mathbb{F}_q^\ell, \mathbb{F}_q^{n-1})$, such that for any $k \in [\ell]$, x_k can be reconstructed from $\tilde{\mathbf{x}}[k]$ and $\hat{\mathbf{u}}$ via $x_k = \tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{u}}\mathbf{A}[k]$. The packed sharings should also meet the requirement of security, that is, any d elements of $(\tilde{\mathbf{x}}, \hat{\mathbf{u}})$ are independent of the secret variables \mathbf{x} . Similarly, $\{\hat{\mathbf{y}}_i\}_{i=1}^\ell$ are also packed into a packed sharings $(\tilde{\mathbf{y}}, \hat{\mathbf{v}})$ in the same vein.
- *Multiplying*: This sub-gadget computes the sharings of $\mathbf{x} \odot \mathbf{y}$ from the packed sharings $(\tilde{\mathbf{x}}, \hat{\mathbf{u}})$ and $(\tilde{\mathbf{y}}, \hat{\mathbf{v}})$. At a high level, for each $k \in [\ell]$, this sub-gadget perform a calculation with two-stages that first calculates outer product of the input shares $(\tilde{\mathbf{x}}[k], \hat{\mathbf{v}})^T \times (\tilde{\mathbf{y}}[k], \hat{\mathbf{u}})$, and then compresses the results

with some randomness. More importantly, the random matrix \mathbf{R} and the calculation of \mathbf{S} are shared (amortized) for different values of k .

We give the packed multiplication gadget in Gadget 1, which is made up of Gadget 1-P and Gadget 1-M for packing and multiplying respectively. We also present examples of Gadget 1-P and Gadget 1-M in Figures 6 and 7 respectively.

Gadget 1 Packed Multiplication

Input: Boolean sharings $\{\hat{\mathbf{x}}_i\}_{i=1}^\ell \in (\mathbb{F}_q^n, \dots, \mathbb{F}_q^n)$ and $\{\hat{\mathbf{y}}_i\}_{i=1}^\ell \in (\mathbb{F}_q^n, \dots, \mathbb{F}_q^n)$.

Output: Boolean sharings $\{\hat{\mathbf{z}}_i\}_{i=1}^\ell \in (\mathbb{F}_q^n, \dots, \mathbb{F}_q^n)$.

1: The gadget ensures that:

$$\hat{\mathbf{z}}_k[1] \oplus \dots \oplus \hat{\mathbf{z}}_k[n] = \left(\sum_{i=1}^n \hat{\mathbf{x}}_k[i] \right) \left(\sum_{i=1}^n \hat{\mathbf{y}}_k[i] \right), \text{ for any } k \in [\ell].$$

2: \mathbf{A} is an $(n-1) \times \ell$ matrix over \mathbb{F}_q such that any d columns of $[\mathbf{I}, \mathbf{A}]$ are independent.

Gadget 1-P: Packing

Input: Boolean sharings $\{\hat{\mathbf{x}}_i\}_{i=1}^\ell$

Output: Packed sharings $(\tilde{\mathbf{x}}, \hat{\mathbf{u}}) \in (\mathbb{F}_q^\ell, \mathbb{F}_q^{n-1})$

The gadget ensures that: $\mathbf{x}_k = \tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{u}}\mathbf{A}[k]$, for any $k \in [\ell]$.

1: Randomly generate a matrix $\mathbf{Q} \in \mathbb{F}_q^{(n-1) \times (n-1)}$

▷ **Amortization:** The size of \mathbf{Q} is independent of ℓ

2: $\hat{\mathbf{Q}} := \mathbf{Q}\mathbf{A}$

3: $\mathbf{X} := [\hat{\mathbf{x}}_1^\top, \dots, \hat{\mathbf{x}}_\ell^\top] \oplus [\hat{\mathbf{Q}}; \mathbf{0}^\ell]$

▷ $\mathbf{0}^\ell$ denotes an ℓ -length zero vector.

4: $\hat{\mathbf{u}} := \sum_{i=1}^{n-1} \mathbf{Q}[i, \cdot]$ and $\tilde{\mathbf{x}} := \sum_{i=1}^n \mathbf{X}[i, \cdot]$

For the packing from $\{\hat{\mathbf{y}}_i\}_{i=1}^\ell$ to $(\tilde{\mathbf{y}}, \hat{\mathbf{v}})$: Repeat Gadget 1-P with input $\{\hat{\mathbf{y}}_i\}_{i=1}^\ell$. It ensures that: $\mathbf{y}_k = \tilde{\mathbf{y}}[k] \oplus \hat{\mathbf{v}}\mathbf{A}[k]$, for any $k \in [\ell]$.

Gadget 1-M: Multiplying

Input: Packed sharings $(\tilde{\mathbf{x}}, \hat{\mathbf{u}})$ and $(\tilde{\mathbf{y}}, \hat{\mathbf{v}})$.

Output: Boolean sharings $\{\hat{\mathbf{z}}_k\}_{k=1}^\ell$.

The gadget ensures that $\sum_{i=1}^n \hat{\mathbf{z}}_k[i] = (\tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{u}}\mathbf{A}[k]) (\tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{v}}\mathbf{A}[k])$, for any $k \in [\ell]$.

1: Randomly generate a symmetric matrix $\mathbf{R} \in \mathbb{F}_q^{(n-1) \times (n-1)}$

2: Let \mathbf{R}_{diag} be the diagonal matrix such that $\mathbf{R}_{\text{diag}}[i, i] = \mathbf{R}[i, i]$ for $i \in [n-1]$

3: **for** $k = 1; k \leq \ell; k++$ **do**

4: Let $\mathbf{a}_k^\top = \mathbf{A}[k]$

5: $e_k := \tilde{\mathbf{x}}[k]\tilde{\mathbf{y}}[k], \mathbf{k}_k := \tilde{\mathbf{x}}[k]\hat{\mathbf{v}}, \mathbf{w}_k^\top := \hat{\mathbf{u}}^\top\tilde{\mathbf{y}}[k], \mathbf{S} := \hat{\mathbf{u}}^\top\hat{\mathbf{v}}$

▷ Compute the outer product: $\begin{bmatrix} e_k, & \mathbf{k}_k \\ \mathbf{w}_k^\top, & \mathbf{S} \end{bmatrix} = [\tilde{\mathbf{x}}[k], \hat{\mathbf{u}}]^\top \times [\tilde{\mathbf{y}}[k], \hat{\mathbf{v}}]$

▷ **Amortization:** \mathbf{S} only need to be computed once for different values of k

6: $\hat{\mathbf{t}}_k^\top := \begin{bmatrix} e_k, & 0 \\ \mathbf{w}_k^\top, & (\mathbf{S} \oplus \mathbf{R}) \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{a}_k^\top \end{bmatrix} \oplus \begin{bmatrix} \mathbf{a}_k \mathbf{R}_{\text{diag}} \mathbf{a}_k^\top \\ \mathbf{k}_k^\top \end{bmatrix}$

▷ **Amortization:** \mathbf{R} and \mathbf{R}_{diag} are re-used for different values of k

7: $\hat{\mathbf{z}}_k := \hat{\mathbf{t}}_k \odot [1, \mathbf{a}_k]$

8: **end for**

4.2 Correctness of Gadget 1

In the following, we claim the correctness of Gadget 1, and the full proof is given in Appendix F.

Theorem 1 *The correctness of Gadget 1-P and Gadget 1-M are ensured, i.e., for any $k \in [\ell]$, $\mathbf{x}_k = \tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{u}}\mathbf{A}[k]$, $\mathbf{y}_k = \tilde{\mathbf{y}}[k] \oplus \hat{\mathbf{v}}\mathbf{A}[k]$, and $\sum_{i=1}^n \hat{\mathbf{z}}_k[i] = (\tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{u}}\mathbf{A}[k]) (\tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{v}}\mathbf{A}[k])$.*

4.3 Security of Gadget 1

We first describe some intuitions behind the construction with respect to the security. Then, we give the security claim of Gadget 1 in Theorem 2, where the full proof will be given in Appendix G.

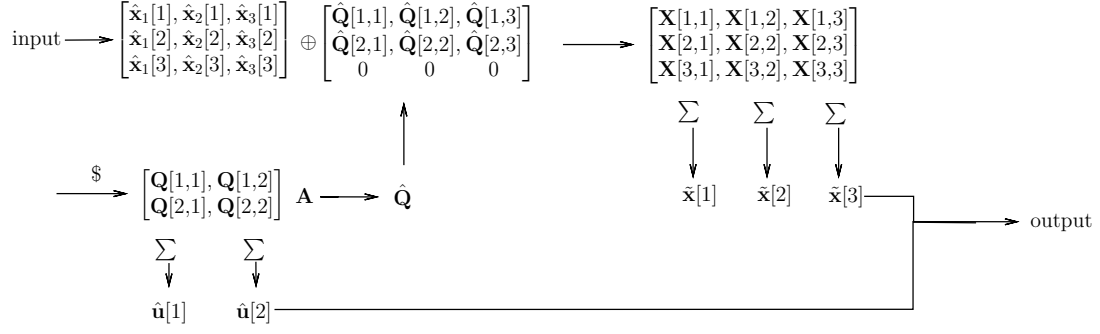


Fig. 6. Illustration of Gadget 1-P for $n = 3$ and $\ell = 3$

$\mathbf{a}_k^T = \mathbf{A}[, k]$ for $k \in [\ell]$
 \mathbf{R} is a 2×2 symmetric random matrix
 \mathbf{R}_{diag} is the diagonal matrix of \mathbf{R}

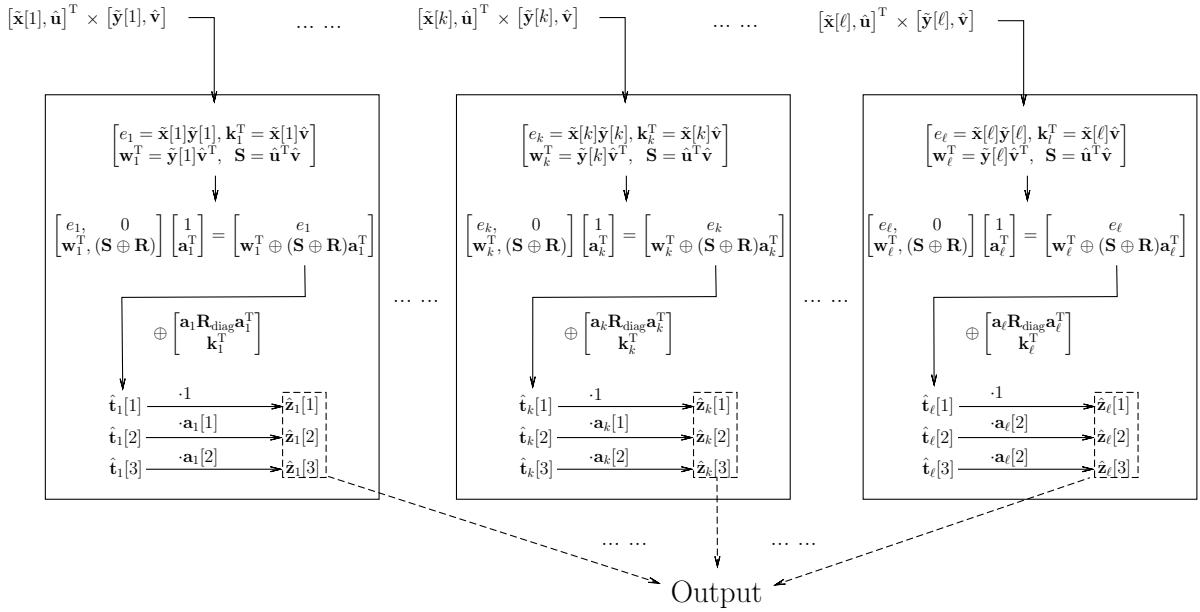


Fig. 7. Illustration of Gadget 1-M for $n = 3$

Gadget 1-P first generates a uniformly distributed matrix \mathbf{Q} , which is then multiplied by \mathbf{A} . And, the result is used to mask the input sharings, resulting in \mathbf{X} . As any d columns of $[\mathbf{I}, \mathbf{A}]$ are independent, any d columns of $[\mathbf{Q}, \mathbf{QA}]$ are uniformly distributed. We can see that all probes (at most d) to Gadget 1-P should relate to no more than d columns of $[\mathbf{Q}, \mathbf{QA}]$. To ease the analysis, we can consider a simple case that the entries of \mathbf{Q} are unknown (and there is no probe to the calculation of \mathbf{QA}), the process of summing the rows of $[\mathbf{Q}, \mathbf{X}]$ should be randomized by uniform random elements, preventing the leaks of inputs. Then, regarding the case that \mathbf{Q} leaks, one can refer to the rationale of the t -chunk definition in Section 3.2.

The intuition behind the construction of Gadget 1-M is similar, but analysis will be more scrupulous, since the random matrix \mathbf{R} is symmetric.

Theorem 2 *Gadget 1-P is d -ICSNI, Gadget 1-M is d -OCNI, and Gadget 1 is d -CSNI.*

5 Linear gadgets

In this section, we discuss how to implement a linear transformation $L : \mathbb{F}_q^\ell \rightarrow \mathbb{F}_q^{\ell'}$ with sharings. First, sub-section 5.1 shows that the trivial implementation of a linear function is d -NI. Though, such a trivial implementation suffers from limitations in the composition with d -CSNI gadgets (e.g., the packed multiplication), which is shown in sub-section 5.2. This motivates the construction of a more secure d -CNI linear gadget in sub-section 5.3.

5.1 Trivial implementation

Gadget 2 shows the trivial implementation of a linear operation with Boolean sharings $\{\hat{\mathbf{x}}_i\}_{i=1}^\ell$. The gadget manipulates shares with different indices separately. Each internal probe relates to at most one index of $\{\hat{\mathbf{x}}_i\}_{i=1}^\ell$, and any t_{out} shares of $\{\hat{\mathbf{z}}_i\}_{i=1}^{\ell'}$ relates to at most t_{out} indices of $\{\hat{\mathbf{x}}_i\}_{i=1}^\ell$, and in total any t_{int} internal probes and t_{out} shares of $\{\hat{\mathbf{z}}_i\}_{i=1}^{\ell'}$ can be simulated with at most $(t_{int} + t_{out})$ shares of $\{\hat{\mathbf{x}}_i\}_{i=1}^\ell$. Thus, Gadget 2 is d -NI for any $d \leq n$.

Gadget 2 Trivial linear operation

Input: Boolean sharings $\{\hat{\mathbf{x}}_i\}_{i=1}^\ell \in (\mathbb{F}_q^n, \dots, \mathbb{F}_q^n)$

Output: Boolean sharings $\{\hat{\mathbf{z}}_i\}_{i=1}^{\ell'} \in (\mathbb{F}_q^n, \dots, \mathbb{F}_q^n)$

- 1: **for** $i = 1; i \leq n; i++$ **do**
 - 2: $\hat{\mathbf{z}}_1[i], \dots, \hat{\mathbf{z}}_{\ell'}[i] = L(\hat{\mathbf{x}}_1[i], \dots, \hat{\mathbf{x}}_\ell[i])$
 - 3: **end for**
-

However, Gadget 2 is not d -CNI. For example, if $L(\{\hat{\mathbf{x}}_k[i]\}_{k=1}^\ell) = \sum_{k=1}^\ell \hat{\mathbf{x}}_k[i]$ for $i \in [n]$, then for $t \leq d$, any t shares of $\hat{\mathbf{z}}$ depend on t shares of each of $\hat{\mathbf{x}}_k[i]$ for $i \in [n]$, rather than a t -chunk of input sharings. An exception is when shares of input sharings are operated separately, which is shown in Lemma 4, and the full proof is given in Appendix I.1.

Lemma 4 *Any gadget that manipulates the shares of input sharings separately (i.e., there is no single variable related to more than one input shares), is d -CNI for any $d \geq 0$.*

5.2 Why a d -CNI linear gadget is necessary?

While trivially implemented linear gadgets are quite efficient, its composition with the d -CSNI packed multiplication gadget (described in Section 4) is not. Below we elaborate with an example.

Figure 8-(a) shows an improper composition: G_1 and G_2 are 3-CSNI and 3-NI respectively, and one probe of G_2 can be simulated with one share of each G_2 's input sharing, which however cannot be simulated with the input of G_2 . To fix this issue, one can rely on the strategy of adding refreshings between the two gadgets in the same way as Figure 3-(c) in Section 2.3. Note that a d -SNI refresh gadget for one sharing of size n asymptotically requires up to $O(n \log n)$ random elements [4, 1], and with all the sharings, it

leads to an inefficient composition. Figure 3-(b) shows a more efficient solution, where G_2 is changed with a 3-CNI gadget to make the composition work. The latter solution (of Figure 3-(b)) raises the following question:

Can a d -CNI linear gadget be more efficient than the strategy of combining a trivial linear gadget with d -SNI refreshings?

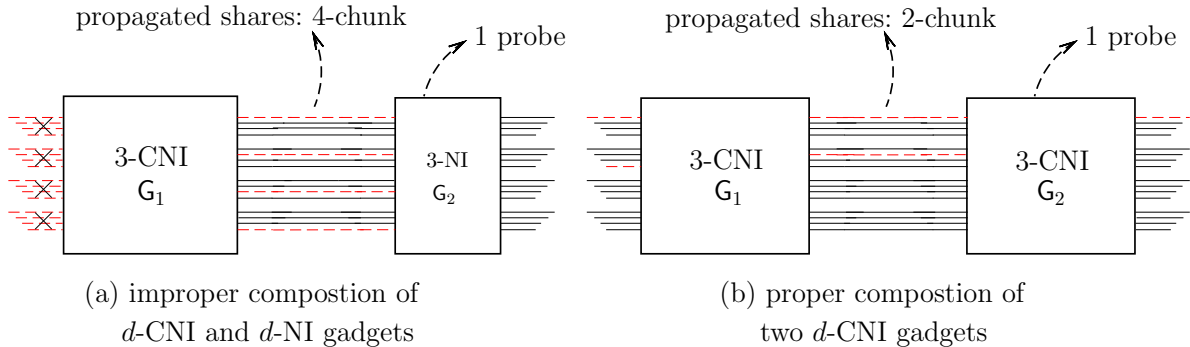


Fig. 8. An example to show the necessity of d -CNI linear gadget

5.3 New construction of linear operation

We answer the question affirmatively. In Gadget 3, we give a new construction of linear operation for Boolean sharings. It first refreshes each input sharing by using the so-called locality refreshing [25, 15], which requires $n - 1$ random elements. Then, it performs the linear operation on the refreshed sharings. In total, Gadget 3 uses $\ell(n-1)$ random elements for ℓ input sharings. In Theorem 3, we claim the security of Gadget 3, and the full proof is given in Appendix I.2.

Gadget 3 d -CNI Linear operation

Input: Boolean sharings $\{\hat{\mathbf{x}}_i\}_{i=1}^{\ell} \in (\mathbb{F}_q^n, \dots, \mathbb{F}_q^n)$

Output: Boolean sharings $\{\hat{\mathbf{z}}_i\}_{i=1}^{\ell'} \in (\mathbb{F}_q^n, \dots, \mathbb{F}_q^n)$

- 1: **for** $k = 1; k \leq \ell; k++$ **do**
 - 2: Generate a uniformly distributed vector $\mathbf{r}_k \in \mathbb{F}_q^{n-1}$
 - 3: $\hat{\mathbf{y}}_k[1:n-1] = \hat{\mathbf{x}}_k[1:n-1] \oplus \mathbf{r}_k$
 - 4: $\hat{\mathbf{y}}_k[n] = \hat{\mathbf{x}}_k[n] \oplus \sum_{i=1}^{n-1} \mathbf{r}_k[i]$
 - 5: **end for**
 - 6: Call Gadget 2 with input sharings $\{\hat{\mathbf{y}}_i\}_{i=1}^{\ell}$ and output sharings $\{\hat{\mathbf{z}}_i\}_{i=1}^{\ell'}$
-

Theorem 3 *Gadget 3 is d -CNI for any d such that $d \leq n$.*

5.4 Linear gadgets for packed sharings

The linear gadget investigated above only considers (Boolean) sharings, which is already sufficient to protect the cryptographic algorithms. For the packed sharings, the linear gadget are more complicated and may come at high overhead. The main reason is that, the trivial implementation of linear transformation gadget is based on the premise that Boolean sharings encode each secret independently, which however is not standing for the packed sharings. Besides, the code-based masking also face this issue, and a similar reasoning can be found in [38, Section 5.2].

An exception is that the addition over packed sharings can be trivially implemented by manipulating shares with different indices separately. That is, for input packed sharings $(\tilde{\mathbf{x}}, \hat{\mathbf{u}})$ and $(\tilde{\mathbf{y}}, \hat{\mathbf{v}})$, the trivial addition is $(\tilde{\mathbf{x}} \oplus \tilde{\mathbf{y}}, \hat{\mathbf{u}} \oplus \hat{\mathbf{v}})$. In Lemma 5, we give the security of this trivial addition, which can be regarded as a variant of d -NI for the packed sharings (note that the d -NI is defined only for gadgets with input and output sharings). The proof will be given in Appendix I.3.

Lemma 5 *For a trivial addition gadget with two input packed sharings, any t_{out} shares of output packed sharings and t_{int} internal probes can be simulated with $t_{int} + t_{out}$ shares of each of input packed sharings.*

6 Application to AES SubBytes

6.1 Implementation approach using the tower field method

AES-128, the internal states, including the round keys, are viewed as a set of 16 variables (say, $\{x_1, \dots, x_{16}\}$) in \mathbb{F}_{2^8} . In its SubBytes step, an S-box is computed over each of the 16 states. The S-box is a nonlinear function $\mathbb{F}_{2^8} \rightarrow \mathbb{F}_{2^8}$ that consists of the inverse in \mathbb{F}_{2^8} and an affine transformation. In the field inversion can be decomposed into several multiplications in \mathbb{F}_{2^4} (that can be fully tabulated) and linear operations using the tower field method [29]:

1. $(a_h, a_l) := \delta(x) \in (\mathbb{F}_{2^4}, \mathbb{F}_{2^4})$
2. $a := \lambda a_h^2 \oplus a_l(a_h \oplus a_l) \in \mathbb{F}_{2^4}$
3. $a' := (a^2 a)^4 a^2 \in \mathbb{F}_{2^4}$
4. $a'_h := a' a_h \in \mathbb{F}_{2^4}$
5. $a'_l := a'(a_h + a_l) \in \mathbb{F}_{2^4}$
6. $S(x) := \text{Aff}(\delta^{-1}((a'_h, a'_l))) \in \mathbb{F}_{2^8}$

In detail, the input $x \in \mathbb{F}_{2^8}$ is mapped to $a_h, a_l \in \mathbb{F}_{2^4}$ using a linear isomorphism mapping $\delta : \mathbb{F}_{2^8} \rightarrow (\mathbb{F}_{2^4}, \mathbb{F}_{2^4})$, and λ is a constant in \mathbb{F}_{2^4} . After computations over \mathbb{F}_{2^4} in steps 2 to 5, the inverse isomorphism mapping $\delta^{-1} : (\mathbb{F}_{2^4}, \mathbb{F}_{2^4}) \rightarrow \mathbb{F}_{2^8}$ maps (a'_h, a'_l) back to an element in field \mathbb{F}_{2^8} , and finally, an affine transformation $\text{Aff} : \mathbb{F}_{2^8} \rightarrow \mathbb{F}_{2^8}$ yields the S-box output.

We use MDS matrices from the Reed-Solomon code [34], and thus $n = d + 1$. By the MDS conjecture [36], $d \times \ell$ MDS matrix over \mathbb{F}_{2^4} shall satisfy $\ell + d \leq |\mathbb{F}_{2^4}| = 16$. Thus, we set $\ell = 8$ and implement 8 S-boxes together by using the packed multiplication (16 S-boxes can be achieved by invoking this implementation twice). The input and output of masked S-boxes are 8 sharings. The implementation is optimized by separating the packing and multiplying gadgets to reduce the number of calls to packing, as well as to re-use the packed sharings to the largest extent. The process is shown in Figure 9, in which P and M denote the packing and multiplying of Gadget 1-P and Gadget 1-M with $\ell = 8$ respectively. The $()^2$, $()^4$, δ , λa^2 and \oplus are trivial implementations of the corresponding linear operations, and the last gadget that is a combination of inverse isomorphism and affine is implemented by Gadget 3.

In the security analysis, to be strictly consistent with the definition of circuits, where all variables are in the same finite field, we map each variables (say a) in \mathbb{F}_{2^4} to a variable (say b) in \mathbb{F}_{2^8} , such that the most significant 4 bits of b are identical to the 4 bits of a , and the least significant 4 bits of b are zeros. Then, each function over \mathbb{F}_{2^4} is isomorphically mapped to a gate over \mathbb{F}_{2^8} by which the function is performed only over the most significant 4 bits of the variables. The function $\delta : \mathbb{F}_{2^8} \rightarrow (\mathbb{F}_{2^4}, \mathbb{F}_{2^4})$ (resp., $\delta^{-1} : (\mathbb{F}_{2^4}, \mathbb{F}_{2^4}) \rightarrow \mathbb{F}_{2^8}$) is isomorphically mapped to a gate $\mathbb{F}_{2^8} \rightarrow (\mathbb{F}_{2^8}, \mathbb{F}_{2^8})$ (resp., $\mathbb{F}_{2^8} \rightarrow (\mathbb{F}_{2^8}, \mathbb{F}_{2^8})$) by which each output (resp., input) is mapped to a variable in \mathbb{F}_{2^8} by the same vein as before. Note that these mappings are only for the security analysis and do not impact the efficiency of the implementation.

Proposition 1 (The SubBytes implementation is d -CSNI) *The composed gadget in Figure 9 is d -CSNI.*

The full proof is given in Appendix K.

Though we adopt the tower field method [29] and separate the packing and multiplying gadgets for the sake of reducing the cost to the utmost. We believe a simpler implementation using the multiplication chain [35] in a larger field \mathbb{F}_{2^8} will be interesting as well. In this respect, we describe such a masked AES implementation in Appendix J.

6.2 Implementation results

It can be seen that, the implementation of 8 S-boxes contains 6 instances of Gadget 1-P and 5 instances of Gadget 1-M. The random requirements of Gadget 1-P and Gadget 1-M are d^2 and $d(d + 1)/2$ 4-bit

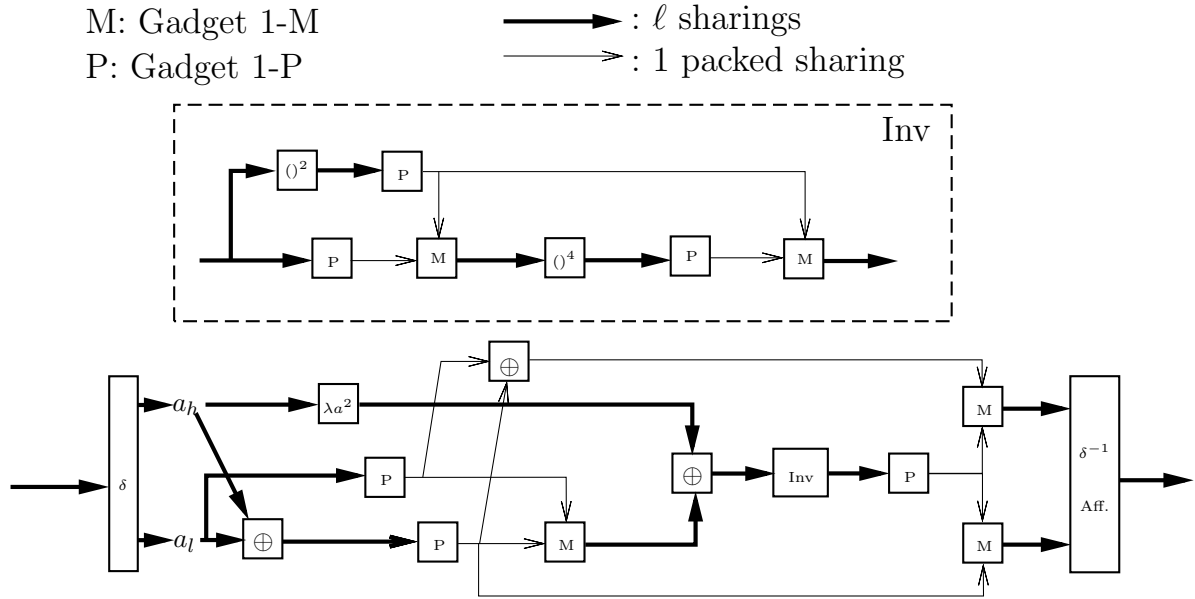


Fig. 9. Masked AES S-box with packed multiplication.

variables respectively. The δ^{-1} and affine operation are implemented together by Gadget 3, which requires $8dl$ bytes of randomness. At last, the total random bits for 16 AES S-boxes is

$$\left((d^2 \times 6 + (d(d+1)/2) \times 5) \times 4 + dl \times 8 \right) \times 2 = 68d^2 + 20d + 16dl.$$

For $\ell = 8$, the above result is $68d^2 + 148d$.

The S-boxes are implemented with security orders $d = 4, 8$ based on the ARM Cortex M architecture. The multiplication by matrix \mathbf{A} at line 2 of Gadget 1-P and line 6 of Gadget 1-M are tabulated, which in total requires $16dl$ bytes of memory. For the consistency with the state-of-the-art results, the randomness in our implementations can be obtained from a constrained TRNG that outputs 32-bit of fresh randomness every 80 clock cycles, which is also used in [9] and recommended in [27]. For the comparison with the state-of-the-art implementations, we consider the implementations of bitslice AES S-boxes reported in [19, 9] as the benchmarks.

The performance results are summarized in Table 2. Compared with the work of [9], our implementation saves 55% and 68% cycles for the generation of randomness for $d = 4$ and 8 respectively. The code sizes of our implementations are larger, which is due to the loop unrolling of our implementation. Indeed, our implementations are slightly slower than the bitsliced methods in computation, which is because that bitsliced methods perfectly fit the bitwise AND and XOR instructions. By contrast, our implementations are based on the multiplication in $\text{GF}(2^4)$, which is not directly supported in microprocessors and can only rely on pre-computed tables. Nevertheless, we emphasize that this computational loss could be mitigated or eliminated via the following two approaches:

1. One can optimize the matrix \mathbf{A} to make the corresponding multiplication more efficient. Sometimes an MDS matrix is not needed: even though $d < n - 1$, the ratio of cost to security order may be better (than using the MDS matrix).
2. One can implement the masked AES on hardware, where the field multiplication and linear transformation can be optimized in bit-level.

We refer to them as future works. Finally, despite the computational loss, our implementation still achieves a gain of up to 33% in total speed when $d = 8$.

Regarding computational cost, the issue of field multiplication in software indicates that bitsliced implementations may be more efficient. However, the bitsliced consumes more randomness. With same value of security order d and the number of parallel multiplications (say, ℓ), larger field (say, \mathbb{F}_{2^4} or \mathbb{F}_{2^8}) may give a smaller number of shares n for a packed sharing. Generally, if $\ell + d \leq |\mathbb{F}_q|$, we can choose

\mathbf{A} in Gadget 1 an MDS matrix, and then we have $n = \ell + d$. But for bitsliced case, $|\mathbb{F}_q| = 2$, and thus $n > \ell + d$. Therefore, the situation of combining bitsliced implementation with the packed multiplication is more complicated: operation can be more efficient (with the bitwise AND instruction) at the cost of more randomness bits. We refer to this investigation as a future work.

Last but not least, we make the source codes of our AES-Sboxes implementation available on https://github.com/wjwangcrypto/Packed_mul.

Table 2. Summary of performances for 16 AES S-boxes

| | Cycles for Computation | Cycles for Generating Randomness | Total Cycles | Code size | RAM size |
|---------------------------------|------------------------|----------------------------------|---------------|------------|------------|
| [19, R.-P. method], $d = 4$ | 19 232 | 34 944 | 54 176 | 4KB | unreported |
| [19, Bitsliced method], $d = 4$ | 11 502 | 17 472 | 28 974 | 3.1KB | unreported |
| [9, Bitsliced method], $d = 4$ | 9 222 | 9 282 | 18 504 | unreported | unreported |
| Our work, $d = 4$ | 15 998 | 4 200 | 20 198 | 9.8KB | 10.9KB |
| [19, R.-P. method], $d = 8$ | 70 840 | 163, 072 | 233 912 | 4KB | unreported |
| [19, Bitsliced method], $d = 8$ | 34 798 | 81 536 | 116 334 | 3.1KB | unreported |
| [9, Bitsliced method], $d = 8$ | 27 028 | 43 316 | 70 344 | unreported | unreported |
| Our work, $d = 8$ | 33 142 | 13 840 | 46 982 | 17KB | 11.8KB |

7 Application to GHASH, AES-GCM, and more

7.1 A brief description of GHASH and AES-GCM

Authenticated encryption aims at ensuring both confidentiality and integrity simultaneously [10], and has become the de facto standard for secure data transferring. The authenticated encryption algorithm AES-GCM was proposed by McGrew and Viega in [30] and standardized by NIST since 2007. It combines an encryption based on the widely used AES algorithm in counter mode and an authenticator based on the GHASH function involving multiplications in $\mathbb{F}_{2^{128}}$. The authenticator mixes ciphertexts, potential associated data and a secret parameter derived from the encryption key to produce a tag. See Appendix L for a graphic description.

It is compulsory to seek for side-channel secure implementations for such a standard. A crucial step is to secure the GHASH function, which is essentially a *polynomial-evaluation hash*. Its takes $\iota + 1$ variables s_0, \dots, s_ι in $\mathbb{F}_{2^{128}}$ as well as an authentication key $h \in \mathbb{F}_{2^{128}}$ as inputs, and evaluates Equation 2 below.

$$\text{tag} = h^\iota s_0 \oplus h^{\iota-1} s_1 \oplus \dots \oplus h s_\iota . \quad (1)$$

A sequential calculation of the polynomial-evaluation hash can be built by the Horner’s rule [24]:

$$x_i = \begin{cases} 0 & \text{for } i = 0 \\ (x_{i-1} \oplus s_i)h & \text{for } i = 1, \dots, \iota \end{cases} , \quad (2)$$

where the output $\text{tag} = x_\iota$.

For the underlying block cipher AES, the implementation approach has been discussed in Section 6. Here we concentrate on the other main indigent GHASH. Note that various SCAs against GHASH have been reported in e.g., [8, 7], which enable recovering the key h and creating forgeries. It is thus unsurprising that masking GHASH has received quite a lot attention, see e.g., [32, 37]. However, existing masked implementations of GHASH only considered protecting against known SCAs, leaving out *provable security*. Here we will fill in the gap. In detail, we study the case that h and s_0, \dots, s_ι are encoded into sharings: $\hat{\mathbf{h}}$ and $\hat{\mathbf{s}}_0, \dots, \hat{\mathbf{s}}_\iota$, and the masked GHASH outputs the sharing of the tag. The crux is to masking the polynomial-evaluation hash (Equation 2), on which we will elaborate in the next sub-section.

7.2 Provably secure masked implementation of polynomial-evaluation hash

To mask the polynomial-evaluation hash, the most straightforward approach is to apply ISW multiplication (more concretely, the generalized version for finite field in [35]) in the sequential calculation of Equation 2. This approach consumes $\iota + 1$ ISW multiplications, each of which consists of $(d + 1)^2$ bilinear multiplications and requires $64(d + 1)d$ random bits. Based on the above, the cost of this approach is estimated and summarized in Table 3.

Note that the computation of polynomial-evaluation hash can be parallelized. In detail, assuming $\ell \mid \iota$, the parallelized version computes $\{x_1^{(i)}, \dots, x_\ell^{(i)}\}$ from $i = 0$ to $i = \frac{\iota}{\ell}$ as follows:

$$x_k^{(i)} = \begin{cases} s_k h^k & \text{for } i = 0 \\ (x_k^{(i-1)} \oplus s_{k+i} h^k) & \text{for } i = 1, \dots, \frac{\iota}{\ell}, \text{ for } k \in [\ell] \end{cases} \quad (3)$$

Finally, the summation $\sum_{k=1}^{\ell} x_k^{(\frac{\iota}{\ell})}$ is taken as the tag. The computation of $\{x_1^{(i)}, \dots, x_\ell^{(i)}\}$ for $i \in [\frac{\iota}{\ell}]$ can be parallelized and thus fits our packed multiplication of Gadget 1. In Figure 10, we present our new approach based on packed multiplication.

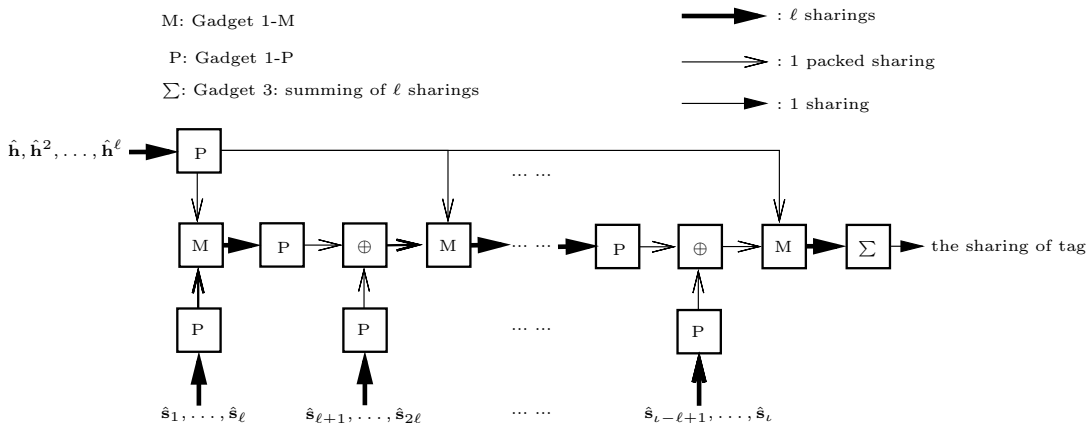


Fig. 10. Masked polynomial-evaluation hash with packed multiplication.

Based on the probing propagation framework, it is easy to see that the composed gadget in Figure 10 is d -CSNI. To estimate the cost, we use the MDS matrix from the Reed-Solomon code for the matrix \mathbf{A} of our packed multiplication gadgets, and thus $n = d + 1$. By the MDS conjecture [36], ℓ and d can be arbitrarily large as long as $\ell + d \leq |\mathbb{F}_{2^{128}}| = 2^{128}$. The estimated cost of this approach is also given in Table 3. It can be seen that, asymptotically, the new scheme with packed multiplication achieves a gain of cost up to ℓ times from the straightforward approach.

Table 3. Estimated costs of the masked polynomial-evaluation hash over $\mathbb{F}_{2^{128}}$

| | Sequential Implementation with ISW multiplication | Figure 10 with Packed multiplication |
|---------------------------------|---|--|
| Randomness complexity (in bits) | $64(\iota + 1)d(d + 1)$ | $\frac{64(\iota+1)d(d+1)+128(\iota+1)d^2}{\ell}$ |
| Computational complexity * | $(\iota + 1)(d + 1)^2$ | $\frac{(\iota+1)(d+1)^2}{\ell}$ |

* Metric: the number of bilinear multiplications.

7.3 More applications of the masked polynomial-evaluation hash

Besides the GCM, polynomial-evaluation hashes have wide applications, see [39, 31]. We thus believe our approach have a great impact. To demonstrate, we take disk encryption as another example. For this pur-

pose, Halevi proposed a mode named TET (short for linear-Transformation; ECB; linear-Transformation) [23]. The mode can be seen as the ECB encryption sandwiched between two layers of “blockwise-universal hash”. An instance of such hashes proposed in [23] was named Blockwise Polynomial-Evaluation (BPE). With inputs $x_1, \dots, x_\tau \in \mathbb{F}_{2^p}^\ell$ and key $(\beta, \tau) \in (\mathbb{F}_{2^p}, \mathbb{F}_{2^p})$, BPE firstly computes

$$s = x_1\tau \oplus x_2\tau^2 \oplus \dots \oplus x_\ell\tau^\ell. \quad (4)$$

Then, the result is obtained by

$$y_i = x_i \oplus s \oplus \alpha^{i-1}\beta, \text{ for } i \in [\ell],$$

where $\alpha \in \mathbb{F}_{2^p}$ is a constant. It is clear that BPE is essentially a polynomial-evaluation hash following Equation 1, and thus it can also be parallelized and implemented in the same vein as that of Figure 10.

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A Probing-Isolating Non-Inference (PINI) and Multiple-Input-Multiple-Output Strong Non-Inference (MIMO-SNI)

Definition 9 (*d*-PINI [13]) Let G be a gadget with sharings as inputs and outputs. G is *d*-PINI if any t_{int} internal probes and output shares indexed by \mathcal{O} with $t_{int} + |\mathcal{O}| \leq d$ can be simulated with inputs shares indexed by \mathcal{I} for $|\mathcal{I}| \leq t_{int} + |\mathcal{O}|$ and $\mathcal{O} \subseteq \mathcal{I}$.

Definition 10 (*d*-MIMO-SNI [13]) Let G be a gadget with ℓ sharings as inputs and ℓ' sharings as outputs. G is *d*-MIMO-SNI, if any t_{int} internal probes and output shares indexed by $\mathcal{O}_1, \dots, \mathcal{O}_{\ell'}$ respectively with $|\mathcal{O}_1| + t_{int} \leq d, \dots, |\mathcal{O}_{\ell'}| + t_{int} \leq d$ can be simulated with t_{int} inputs shares.

B Proofs regarding composable security notions

B.1 Proof of Lemma 2

Let \mathcal{S}_1 (resp., \mathcal{S}_2) consist of

1. $\{\hat{\mathbf{x}}_k[i] \mid k \in \mathcal{K}_1, i \in \mathcal{I}_1\}$ (resp., $\{\hat{\mathbf{x}}_k[i] \mid k \in \mathcal{K}_2, i \in \mathcal{I}_2\}$) with $|\mathcal{K}_1| + |\mathcal{I}_1| = t_{\alpha,1}$ (resp., $|\mathcal{K}_2| + |\mathcal{I}_2| = t_{\alpha,2}$).
2. $t_{\beta,1}$ (resp., $t_{\beta,2}$) shares from $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_{\ell}$.

such that $t_{\alpha,1} + t_{\beta,1} = t_1$ (resp., $t_{\alpha,2} + t_{\beta,2} = t_2$).

Then, $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2$ consists of

1. $\{\hat{\mathbf{x}}_k[i] \mid k \in \mathcal{K}_1, i \in \mathcal{I}_1\} \cup \{\hat{\mathbf{x}}_k[i] \mid k \in \mathcal{K}_2, i \in \mathcal{I}_2\} \subseteq \{\hat{\mathbf{x}}_k[i] \mid k \in \mathcal{K}, i \in \mathcal{I}\}$ with $t_{\alpha} = |\mathcal{K}| + |\mathcal{I}| = t_{\alpha,1} + t_{\alpha,2}$.
2. $t_{\beta} = t_{\beta,1} + t_{\beta,2}$ shares from $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_{\ell}$.

We can see that $t_{\alpha} + t_{\beta} = t_1 + t_2$, giving that \mathcal{S} is a $(t_1 + t_2)$ -chunk of $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_{\ell}$.

B.2 Proof of Lemma 3

By definition, *d*-NI (resp., *d*-SNI) ensures that any t_{out} output probes and t_{int} internal probes such that $t_{out} + t_{int} \leq d$ can be simulated with $t_{out} + t_{int}$ (resp., t_{int}) shares of each input sharing. The differences between *d*-C(S)NI and *d*-(S)NI are the output probes (needed to be simulated) and propagated probes. More precisely, *d*-(S)NI considers t_{out} output shares (denoted as \mathcal{P}_O) as output shares and a set consisting of t shares of each input sharing as propagation shares. In contrast, the *d*-C(S)NI replaces them with a t -chunk of input and output sharings respectively.

Clearly, \mathcal{P}_O is a specific t_O -chunk of output sharings by setting $t_{\alpha} = 0$. At the same time, by the definition of t -chunk, any t -chunk of input sharings relates to at most t shares of each input sharing. Thus, *d*-CNI implies *d*-NI and *d*-CSNI implies *d*-SNI.

Beside, by definition, we can directly see that is a gadget is *d*-CSNI, then it is *d*-CNI.

C Probe propagation framework

In this section, we describe the probe propagation framework introduced in [11, 3] that is an intuitive interpretation of the simulatability definition, based on which the composability of the new security notions can be realized.

Let a composed gadget be G . For a set of probes \mathcal{P} , the goal of probe propagation framework is to analyze how \mathcal{P} are simulated with a set of input shares \mathcal{S} . A composition of gadgets can be seen as a directed acyclic graph whose vertices are gadgets and edges transfer sharings or packed sharings. Let the number of gadgets be p and the composed gadget be G , as every directed acyclic graph has a topological ordering, we can order the gadgets as G_1, \dots, G_p , such that G_i is positioned before G_j for any $i < j$. We then show that \mathcal{P} can be divided into different subsets $\mathcal{P}_1, \dots, \mathcal{P}_p$ and \mathcal{P}_O such that the internal probes of G_i are in \mathcal{P}_i for $i = [p]$ and the output probes of the G are in \mathcal{P}_O . Each probe that transfers between gadgets (say, the former gadget G_i and the latter ones $\{G_j\}_{j \in \mathcal{J}}$ for $\mathcal{J} \subseteq \{i+1, \dots, p\}$) can be regarded as either the internal probe of each of $\{G_j\}_{j \in \mathcal{J}}$ or the output probe of G_i . Without loss of generality, we regard each of such probes as the internal probes of the latter gadgets, which ensures that $\bigcup_{i=1}^p \mathcal{P}_i \cup \mathcal{P}_O = \mathcal{P}$. The probe propagation framework analyzes the gadgets one by one from G_p to G_1 :

- Initiate a set \mathcal{S} to be empty. After the iteration, \mathcal{S} should be a subset of the shares in the input sharings of the composed gadget, and expected to be the propagated shares of all the probes.
- Let $\mathcal{P}_{O_p} \subseteq \mathcal{P}_O$ be the set of probes both in \mathcal{P}_O and in output of G_p , i.e., $\mathcal{P}_{O_p} \stackrel{\text{def}}{=} \mathcal{P}_O \cap \mathcal{O}_{G_p}$, where \mathcal{O}_{G_p} consists of the output variables of G_p . The framework checks if $\mathcal{P}_p \cup \mathcal{P}_{O_p}$ can be simulated with the input shares \mathcal{S}_p of G_p :
 - If so, then we call the shares \mathcal{S}_p as the *propagated shares* of G_p . To this point, if \mathcal{S}_p can be further simulated with input shares of G , then $\mathcal{P}_p \cup \mathcal{P}_{O_p}$ can be as well. Thus, in the rest of the analysis, we replace the probes related to $\mathcal{P}_p \cup \mathcal{P}_{O_p}$ with \mathcal{S}_p and continue to check the probes in G_{p-1} . Additionally, we put G 's input shares that appeared in \mathcal{S}_p into \mathcal{S} .
 - If $\mathcal{P}_p \cup \mathcal{P}_{O_p}$ cannot be simulated with the input shares of G_i , then the analysis stops.
- Then, the framework iteratively checks G_i and constructs \mathcal{S}_i from $i = p - 1$ until $i = 1$. In each step, it puts the G 's input shares appeared in \mathcal{S}_i into \mathcal{S} . Note that for any $i < p$, the probes of G_i is made up of two parts: \mathcal{P}_i and the propagated shares that are connected to outputs of G_i .

At last, If the analysis process does not stop until $i = 1$, we can figure out the security notion of the composed gadget by the shares in \mathcal{S} .

In the next section, we exemplify the framework by proving three examples.

D Examples For the compatibility of the new gadget in the probe propagation framework

The first example is shown in Figure 11-(a): G_1 and G_2 are d -CSNI gadgets with ℓ input and output sharings, and they connect to a d -CNI gadget G_3 . The second example is shown in Figure 11-(b): a d -OCNI gadget G_3 connects to the outputs of two d -ICSNI gadgets (G_1 and G_2), and packed sharings are transferred between them. The third example is more complicated and shown in Figure 11-(c). As shown in Proposition 2, those three composed gadgets are all d -CSNI.

Proposition 2 *The three composed gadgets in Figure 11 are all d -CSNI.*

We next give proofs for the three examples.

D.1 Proof of the first example

Let the composed gadget be G . Without loss of generality, assume that the probes of G consist of t_{int} internal probes and a t_{out} -chunk of output sharings such that $t_{int} + t_{out} \leq d$. We divide the probes of G into different subsets $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ and \mathcal{P}_O such that all the internal probes of G_i are in \mathcal{P}_i for $i \in \{1, 2, 3\}$ and all the output probes are in \mathcal{P}_O . The probe propagation framework then analyzes the gadgets one by one from G_3 to G_1 . A set \mathcal{S} is initiated to empty. For $i \in \{1, 2, 3\}$, let \mathcal{S}_i be propagated share corresponding to G_i . The details of the checking process are shown below:

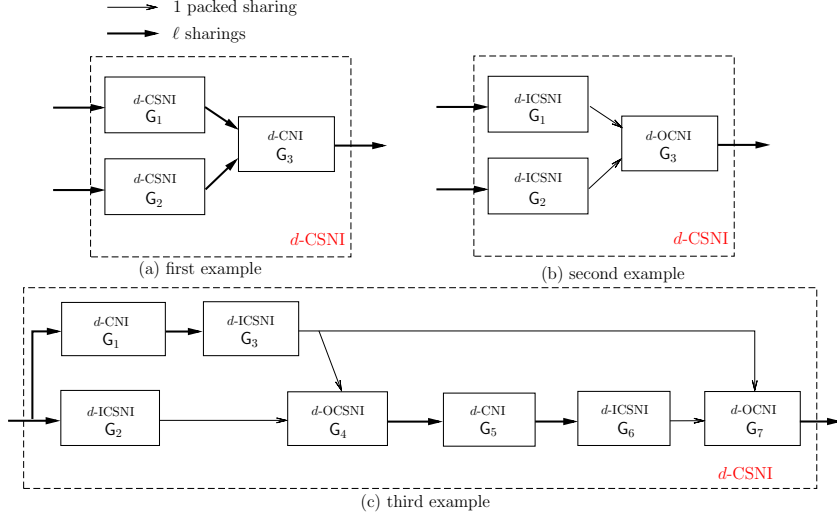


Fig. 11. Examples to illustrate the composition of gadgets with packed sharings transferred between them.

1. The probes in G_3 are $\mathcal{P}_3 \cup \mathcal{P}_O$. As G_3 is d -CNI, $\mathcal{P}_3 \cup \mathcal{P}_O$ can be simulated with G_3 's propagated shares \mathcal{S}_3 that is a t_3 -chunk of G_3 's input sharings with $t_3 = t_{out} + |\mathcal{P}_3|$. Let $\mathcal{S}_{3,1}$ and $\mathcal{S}_{3,2}$ be the sets of sharings that from outputs of G_1 and G_2 , and they are t_3 -chunk of output sharings of G_2 and G_3 respectively, since a subset of a t -chunk is also a t -chunk.
2. The probes in G_2 are a subset of $\mathcal{P}_2 \cup \mathcal{S}_3$. As G_2 is d -CSNI and $t_3 + |\mathcal{P}_2| \leq d$, any subset of $\mathcal{P}_2 \cup \mathcal{S}_3$ can be simulated with G_2 's propagated shares \mathcal{S}_2 that is a t_2 -chunk of G_2 's input sharings with $t_2 = |\mathcal{P}_2|$. As G_2 's input sharings are a subset of G 's input sharings, probes in \mathcal{S}_2 are put into \mathcal{S} .
3. The probes in G_1 are a subset of $\mathcal{P}_1 \cup \mathcal{S}_3$. As G_1 is d -CSNI and $t_3 + |\mathcal{P}_1| \leq d$, any subset of $\mathcal{P}_1 \cup \mathcal{P}_O$ can be simulated with G_2 's propagated shares \mathcal{S}_1 that is a t_1 -chunk of G_1 's input sharings with $t_1 = |\mathcal{P}_1|$. As G_1 's input sharings are a subset of G 's input sharings, probes in \mathcal{S}_1 are put into \mathcal{S} .

Moreover, the above two steps can be summarized in a short form in Table 4.

Table 4. Proof of the first example based on the probe propagation framework

| Gadgets | Security notion | Probes | Propagated shares \mathcal{S}_i | \mathcal{S} |
|---------|-----------------|------------------------------------|--|------------------------------------|
| G_2 | d -CNI | $\mathcal{P}_2 \cup \mathcal{P}_O$ | t_3 -chunk of G_3 's input sharings, for $t_3 = \mathcal{P}_3 + t_{out}$ | \emptyset |
| G_2 | d -CSNI | $\mathcal{P}_2 \cup \mathcal{P}_O$ | t_2 -chunk of G_2 's input sharings, for $t_2 = \mathcal{P}_2 $ | \mathcal{S}_1 |
| G_1 | d -CSNI | $\mathcal{P}_1 \cup \mathcal{S}_1$ | t_1 -chunk of G_1 's input sharings, for $t_1 = \mathcal{P}_1 $ | $\mathcal{S}_1 \cup \mathcal{S}_2$ |

At last, the set of propagated shares $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2$, which is a t -chunk of G 's input sharings with $t \leq |\mathcal{S}_1| + |\mathcal{S}_2| \leq t_{int}$. Therefore, all the probes in G can be simulated with a t -chunk of input sharings of G , where $t \leq t_{int}$, which by definition, gives that G is d -CSNI. \square

D.2 Proof of the second example

Proof. Let the composed gadget be G . Without loss of generality, assume that the probes of G consist of t_{int} internal probes and t_{out} -chunk of output sharings such that $t_{int} + t_{out} \leq t$. We divide the probes of G into different subsets $\mathcal{P}_1, \mathcal{P}_2, \mathcal{P}_3$ and \mathcal{P}_O such that all the internal probes of G_i are in \mathcal{P}_i for $i = \{1, 2, 3\}$ and all the output probes are in \mathcal{P}_O . The probe propagation framework then analyzes the gadgets one

by one from G_3 to G_1 . A set \mathcal{S} is initiated to be empty. For $i \in \{1, 2, 3\}$, let \mathcal{S}_i be propagated shares corresponding to G_i . We summarize the analysis in Table 5.

Table 5. Proof of the security of the second example

| Gadgets | Security notion | Probes | \mathcal{S}_i | \mathcal{S} |
|---------|-----------------|--|---|------------------------------------|
| G_3 | d -OCNI | $\mathcal{P}_3 \cup \mathcal{P}_O$ | $\hat{\mathbf{x}}[\mathcal{I}] \cup \hat{\mathbf{y}}[\mathcal{J}]$ | \emptyset |
| G_2 | d -ICSNI | $\mathcal{P}_2 \cup \hat{\mathbf{y}}[\mathcal{J}]$ | t_2 -chunk of G_2 's input sharings, for $t_2 = \mathcal{P}_2 $ | \mathcal{S}_2 |
| G_1 | d -ICSNI | $\mathcal{P}_1 \cup \hat{\mathbf{x}}[\mathcal{I}]$ | t_1 -chunk of G_1 's input sharings, for $t_1 = \mathcal{P}_1 $ | $\mathcal{S}_1 \cup \mathcal{S}_2$ |

At last, the set of propagated shares $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2$, which is a $(t_1 + t_2)$ -chunk of G 's input sharings, where $t_1 + t_2 \leq t_{int}$. Therefore, all the probes in G can be simulated with a t -chunk of input sharings of G with $t \leq t_{int}$, which by definition, gives that G is d -CSNI. \square

Remark. Due to the similarity of the proofs using the framework, in the rest of the appendix, we will short such proofs in a form of only providing the tables shown above and necessary explanations.

D.3 Proof of the third example

Let the composed gadget be G . Without loss of generality, assume that the probes of G consist of t_{int} internal probes and t_{out} -chunk of output sharings such that $t_{int} + t_{out} \leq d$. We divide the probes of G into different subsets $\mathcal{P}_1, \dots, \mathcal{P}_7$ and \mathcal{P}_O such that all the internal probes of G_i are in \mathcal{P}_i for $i \in [7]$ and all the internal probes are in \mathcal{P}_O . Let $t_i = |\mathcal{P}_i|$ for $i \in [7]$. The probe propagation framework then analyzes the gadgets one by one from G_7 to G_1 . A set \mathcal{S} is initiated to empty. For $i \in [7]$, let \mathcal{S}_i be propagated shares of G_i . We summarize the analysis in Table 6.

Table 6. Proof of the third example based on the probe propagation framework

| Gadgets | Security notion | Probes | Propagated shares \mathcal{S}_i | \mathcal{S} |
|---------|-----------------|---|--|------------------------------------|
| G_7 | d -OCNI | $\mathcal{P}_7 \cup \mathcal{P}_O$ | $\hat{\mathbf{x}}[\mathcal{I}] \cup \hat{\mathbf{y}}[\mathcal{J}]$, $ \mathcal{I} = \mathcal{P}_7 + \mathcal{P}_O $ and $ \mathcal{J} = \mathcal{P}_7 + \mathcal{P}_O $ | \emptyset |
| G_6 | d -ICSNI | $\mathcal{P}_6 \cup \hat{\mathbf{y}}[\mathcal{J}]$ | t_6 -chunk of G_6 's input sharings, for $t_6 = \mathcal{P}_6 $ | \emptyset |
| G_5 | d -CNI | $\mathcal{P}_5 \cup \mathcal{S}_6$ | t_5 -chunk of G_5 's input sharings, for $t_5 = \mathcal{P}_5 + t_6 = \mathcal{P}_5 + \mathcal{P}_6 $ | \emptyset |
| G_4 | d -OCNI | $\mathcal{P}_4 \cup \mathcal{S}_5$ | $\hat{\mathbf{x}}'[\mathcal{I}'] \cup \hat{\mathbf{y}}'[\mathcal{J}']$, $ \mathcal{I}' = \mathcal{P}_4 + t_5 = \mathcal{P}_4 + \mathcal{P}_5 + \mathcal{P}_6 $ and $ \mathcal{J}' = \mathcal{P}_4 + t_5 = \mathcal{P}_4 + \mathcal{P}_5 + \mathcal{P}_6 $ | \emptyset |
| G_3 | d -ICSNI | $\mathcal{P}_3 \cup \hat{\mathbf{x}}[\mathcal{I}] \cup \hat{\mathbf{x}}'[\mathcal{I}']$ | t_3 -chunk of G_6 's input sharings, for $t_3 = \mathcal{P}_3 $ | \emptyset |
| G_2 | d -ICSNI | $\mathcal{P}_2 \cup \hat{\mathbf{y}}'[\mathcal{J}']$ | t_2 -chunk of G_2 's input sharings, for $t_2 = \mathcal{P}_2 $ | \mathcal{S}_2 |
| G_1 | d -CNI | $\mathcal{P}_1 \cup \mathcal{S}_3$ | t_1 -chunk of G_1 's input sharings, for $t_1 = \mathcal{P}_1 + t_3 = \mathcal{P}_1 + \mathcal{P}_3 $ | $\mathcal{S}_1 \cup \mathcal{S}_2$ |

At last, the set of propagated shares $\mathcal{S} = \mathcal{S}_1 \cup \mathcal{S}_2$, which is a $(t_1 + t_2)$ -chunk of G 's input sharings, where $t_1 + t_2 = |\mathcal{P}_2| + |\mathcal{P}_1| + t_3 \leq t_{int}$. Therefore, all the probes in G can be simulated with a t_{int} -chunk of input sharings of G , which by definition, gives that G is t -CSNI. \square

E First steps to the generic composition rules of new security notions

The d -C(S)NI supports the following composition Lemmas 6 and 7.

Lemma 6 *A composite gadget G made of a d -CNI gadget G_1 and a d -CNI gadget G_2 is d -CNI if the inputs (and resp. the outputs) of G are the inputs of G_1 (resp. outputs of G_2).*

If additionally either G_1 or G_2 is d -CSNI, then G is d -CSNI.

Proof. Let us first observe that all the inputs of G_2 are outputs of G_1 , and reciprocally.

Next, the set of probes \mathcal{P} in G can be partitioned into \mathcal{P}_1 the probes on G_1 , \mathcal{P}_2 the probes on G_2 and \mathcal{P}_{O_2} the output probes of G_2 , such that $|\mathcal{P}_1 \cup \mathcal{P}_2| = t \leq d$. By definition of d -CNI, \mathcal{P}_2 can be simulated with a t_2 -chunk of G_2 's input for $t_2 = |\mathcal{P}_2|$, which is also t_2 -chunk of G_1 's output. Then, a t_2 -chunk of G_1 's output and \mathcal{P}_1 can be further simulated with a t -chunk of G_1 's input, since $t \leq |\mathcal{P}_1| + t_2$. This shows that G is d -C-NI.

If G_1 is d -C-SNI, then a t_2 -chunk of G_1 's output and \mathcal{P}_1 can be simulated with a t_1 -chunk of G_1 's input, where $t_1 = |\mathcal{P}_1|$. Let \mathcal{P}_{int} be the internal probes in G and $t_{int} = |\mathcal{P}_{int}|$, we have $\mathcal{P}_1 \subset \mathcal{P}_{int}$, which implies $t_1 \leq t_{int}$. G is therefore d -C-SNI.

If G_2 is d -C-SNI, then let $\mathcal{P}_{2,int}, \mathcal{P}_O$ be a partition of \mathcal{P}_2 such that \mathcal{P}_O is the set of output probes on G_2 (which are also the output probes of G). The probes \mathcal{P}_2 can be simulated with a $t_{2,int}$ -chunk of its input, where $t_{2,int} = |\mathcal{P}_{2,int}|$. Using the same argument as previously, we conclude that \mathcal{P} can be simulated with a t_{int} -chunk of its inputs, where $t_{int} = |\mathcal{P}_1 \cup \mathcal{P}_{2,int}|$ is the number of internal probes. \square

In Appendix E.1, we exemplify the general composition of d -C(S)NI gadgets with Lemma 6. In the following, we present the most natural composition rule in Lemma 7 with only d -CSNI gadget.

Lemma 7 *Any composition of d -CSNI gadgets is d -CSNI.*

Proof. The proof is based on the probe propagation framework introduced in Appendix C. Let G be a gadget composed of d -C-SNI gadgets G_1, \dots, G_p . Let \mathcal{P} be a set of at most d probes in G , partitioned in sets $\mathcal{P}_1, \dots, \mathcal{P}_p$ and \mathcal{P}_O such that each \mathcal{P}_i contains the probes in G_i and \mathcal{P}_O contains the probes on the outputs of G . Since the gadget composition graph is a directed acyclic graph, we assume wlog that the gadgets G_i are sorted according to the reverse topological ordering (i.e., G_1 is the "last" gadget in the composition).

By induction, we prove that there exists a set of propagated shares \mathcal{S}_i that is $|\mathcal{P}_i|$ -chunk and that enables to simulate the outputs of G_i that are in any \mathcal{S}_j with $j < i$ or in \mathcal{P}_O . All those sets are resp. $|\mathcal{P}_j|$ -chunk or $|\mathcal{P}_O|$ -chunk, hence their union is $(\sum_{j < i} |\mathcal{P}_j| + |\mathcal{P}_O|)$ -chunk. Since $\sum_{j \leq i} |\mathcal{P}_j| + |\mathcal{P}_O| \leq d$, the d -C-SNI gadget G_i can be simulated with the $|\mathcal{P}_i|$ -chunk \mathcal{S}_i .

Finally, we observe that the inputs of G required for the simulation are a subset of the union of the \mathcal{S}_i 's. This union is t_{int} -chunk, where $t_{int} = \sum_i |\mathcal{P}_i|$. \square

One of the most direct applications of the above rules is that the composition of Figure 3-(b) in Section 3.1 works without any refreshing, if G_1 and G_2 are both d -C-SNI.

The above rules do not cover every case of secure composition. Further works may want to generalize furthermore the composition results (similarly to the results for (S)NI in [11]), or use directly the probe propagation framework.

E.1 Examples for the compatibility of the new gadget with the general composition rule

In Figure 12, we exemplify the general composition of d -C(S)NI gadgets with Lemma 6. Assuming we aim at composing three gadgets G_1, G_2 and G_3 . Figure 12-(a) shows an improper composition where the input sharings of d -CNI G_2 connect to outputs of G_1 whose outputs are also used as the input of G_3 (G_1 is not exclusively connected to G_2). Figure 12-(b) fixes the issue by moving the direct connection between G_1 and G_3 to between G_2 and G_3 , resulting a d -CSNI composed gadget (by Lemma 6, the composition of G_2 and G_3 is d -CSNI, and then the composition of G_1, G_2 and G_3 is d -CSNI).

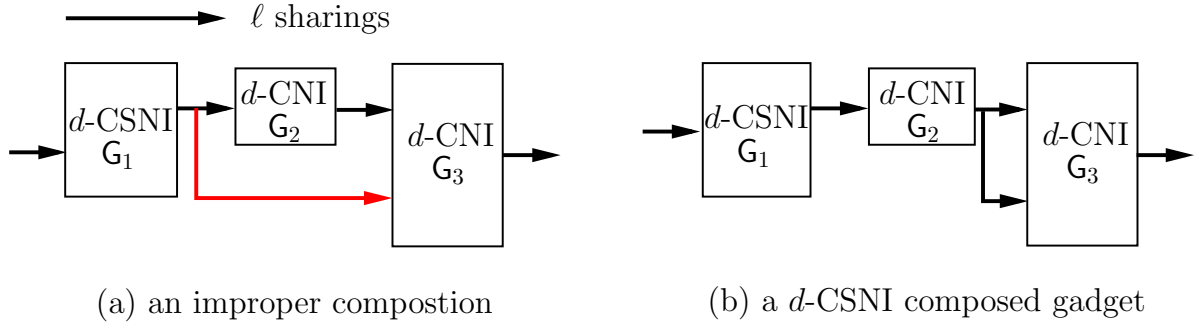


Fig. 12. Simple examples to illustrate the composability.

F Proof of Theorem 1

For any $k \in [\ell]$, we have

$$\begin{aligned}
\tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{u}}\mathbf{A}[k] &= \tilde{\mathbf{x}}[k] \oplus \left(\sum_{i=1}^{n-1} \mathbf{Q}[i, \cdot] \right) \mathbf{A}[k] \\
&= \sum_{i=1}^{\ell} \mathbf{X}[i, k] \oplus \left(\sum_{i=1}^{n-1} \mathbf{Q}[i, \cdot] \right) \mathbf{A}[k] \\
&= \sum_{i=1}^{\ell} (\tilde{\mathbf{x}}_k[i] \oplus \mathbf{Q}[i, \cdot] \mathbf{A}[k]) \oplus \left(\sum_{i=1}^{n-1} \mathbf{Q}[i, \cdot] \mathbf{A}[k] \right) \\
&= x_k .
\end{aligned}$$

Thus, we have

$$\mathbf{x} = \tilde{\mathbf{x}} \oplus \hat{\mathbf{u}}\mathbf{A} . \quad (5)$$

Similarly, for the packed sharing $(\tilde{\mathbf{y}}, \hat{\mathbf{v}})$, we also have

$$\mathbf{y} = \tilde{\mathbf{y}} \oplus \hat{\mathbf{v}}\mathbf{A} . \quad (6)$$

Equations 5 and 6 gives that for any $k \in [\ell]$. We then prove the rest part of Theorem 1. $\mathbf{x}_k = \tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{u}}\mathbf{A}[k]$ and $\mathbf{y}_k = \tilde{\mathbf{y}}[k] \oplus \hat{\mathbf{v}}\mathbf{A}[k]$.

In Gadget 1-M, let \mathbf{R}_L and \mathbf{R}_R be the left and right triangular matrix of \mathbf{R} excluding the diagonal. Obviously, $\mathbf{R}_L = \mathbf{R}_R^T$, since \mathbf{R} is a symmetric matrix. For the rest of proof, let k be any integer in $[\ell]$. We have

$$\begin{aligned}
\mathbf{a}_k \mathbf{R}^T \mathbf{a}_k^T &= \mathbf{a}_k (\mathbf{R}_L \oplus \mathbf{R}_R \oplus \mathbf{R}_{\text{diag}})^T \mathbf{a}_k^T \\
&= \mathbf{a}_k \mathbf{R}_L \mathbf{a}_k^T \oplus \mathbf{a}_k \mathbf{R}_R \mathbf{a}_k^T \oplus \mathbf{a}_k \mathbf{R}_{\text{diag}} \mathbf{a}_k^T .
\end{aligned}$$

As $\mathbf{a}_k \mathbf{R}_L \mathbf{a}_k^T$ is a 1×1 matrix,

$$(\mathbf{a}_k \mathbf{R}_L \mathbf{a}_k^T)^T = \mathbf{a}_k \mathbf{R}_R \mathbf{a}_k^T = \mathbf{a}_k \mathbf{R}_L \mathbf{a}_k^T ,$$

then

$$\mathbf{a}_k \mathbf{R}^T \mathbf{a}_k^T = \mathbf{a}_k \mathbf{R}_{\text{diag}} \mathbf{a}_k^T . \quad (7)$$

By the instructions of Gadget 1-M, we have

$$\hat{\mathbf{z}}_k[1] \oplus \dots \oplus \hat{\mathbf{z}}_k[n] = \left(\begin{bmatrix} \tilde{\mathbf{x}}[k] \tilde{\mathbf{y}}[k], & 0 \\ \mathbf{w}_k^T, & \mathbf{S} \oplus \mathbf{R} \end{bmatrix} \begin{bmatrix} 1 \\ \mathbf{a}_k^T \end{bmatrix} \oplus \begin{bmatrix} \mathbf{a}_k \mathbf{R}_{\text{diag}} \mathbf{a}_k^T \\ \mathbf{k}_k^T \end{bmatrix} \right)^T \begin{bmatrix} 1 \\ \mathbf{a}_k^T \end{bmatrix}$$

By expanding the matrix addition and multiplication, we have

$$\begin{aligned}
&\hat{\mathbf{z}}_k[1] \oplus \dots \oplus \hat{\mathbf{z}}_k[n] \\
&= \tilde{\mathbf{x}}[k] \tilde{\mathbf{y}}[k] \oplus \mathbf{a}_k \mathbf{R}_{\text{diag}} \mathbf{a}_k^T \oplus \\
&\quad \mathbf{w}_k \mathbf{a}_k^T \oplus \mathbf{a}_k \mathbf{S}^T \mathbf{a}_k^T \oplus \mathbf{a}_k \mathbf{R}^T \mathbf{a}_k^T \oplus \mathbf{k}_k \mathbf{a}_k^T .
\end{aligned}$$

By Equation 7, $\mathbf{a}_k \mathbf{R}_{\text{diag}} \mathbf{a}_k^T \oplus \mathbf{a}_k \mathbf{R} \mathbf{a}_k^T = 0$, and by the instruction of Gadget 1-M, $\mathbf{w}_k = \tilde{\mathbf{x}}[k] \hat{\mathbf{v}}$ and $\mathbf{k}_k = \tilde{\mathbf{y}}[k] \hat{\mathbf{u}}$, we then have

$$\begin{aligned} \hat{\mathbf{z}}_k[1] \oplus \dots \oplus \hat{\mathbf{z}}_k[n] &= \tilde{\mathbf{x}}[k] \tilde{\mathbf{y}}[k] \oplus \mathbf{w}_k \mathbf{A}[k] \oplus \mathbf{k}_k \mathbf{A}[k] \oplus \mathbf{a}_k \mathbf{S}^T \mathbf{a}_k^T \\ &= \tilde{\mathbf{x}}[k] \tilde{\mathbf{y}}[k] \oplus \tilde{\mathbf{x}}[k] \hat{\mathbf{v}} \mathbf{A}[k] \oplus \tilde{\mathbf{y}}[k] \hat{\mathbf{u}} \mathbf{A}[k] \oplus \mathbf{a}_k \mathbf{S}^T \mathbf{a}_k^T. \end{aligned}$$

\mathbf{S}^T can be rewritten as $\mathbf{S}^T = \hat{\mathbf{y}}^T \hat{\mathbf{x}}$, then

$$\mathbf{a}_k \mathbf{S}^T \mathbf{a}_k^T = (\hat{\mathbf{u}} \mathbf{a}_k^T) (\hat{\mathbf{v}} \mathbf{a}_k^T).$$

Thus, we have

$$\begin{aligned} &\hat{\mathbf{z}}_k[1] \oplus \dots \oplus \hat{\mathbf{z}}_k[n] \\ &= \tilde{\mathbf{x}}[k] \tilde{\mathbf{y}}[k] \oplus \tilde{\mathbf{x}}[k] \hat{\mathbf{v}} \mathbf{a}_k^T \oplus \tilde{\mathbf{y}}[k] \hat{\mathbf{u}} \mathbf{a}_k^T \oplus (\hat{\mathbf{u}} \mathbf{a}_k^T) (\hat{\mathbf{v}} \mathbf{a}_k^T) \\ &= (\tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{u}} \mathbf{a}_k^T) (\tilde{\mathbf{y}}[k] \oplus \hat{\mathbf{v}} \mathbf{a}_k^T). \end{aligned}$$

By Equations 5 and 6, $\tilde{\mathbf{x}}[k] \oplus \hat{\mathbf{u}} \mathbf{a}_k^T$ and $\tilde{\mathbf{y}}[k] \oplus \hat{\mathbf{v}} \mathbf{a}_k^T$ can be replaced with $\mathbf{x}[k]$ and $\mathbf{y}[k]$ respectively, we finally have

$$\hat{\mathbf{z}}_k[1] \oplus \dots \oplus \hat{\mathbf{z}}_k[n] = x_k y_k,$$

which completes the proof. \square

G Proof of Theorem 2

We focus on the the first two parts, which we give in Lemmas 8 and 9 respectively, whose proofs are given latter in Appendix H.

Lemma 8 *Gadget 1-P is d-ICSNI.*

Lemma 9 *Gadget 1-M is d-OCNI.*

Note that Gadget 1 has the same composition structure as the example show in Figure 11-(b). Then, by Propostion 2, Gadget 1 is d-CSNI. \square

H Proofs of Lemmas 8 and 9

We begin this section with some Lemmas showing properties related to the matrix \mathbf{A} used in Gadget 1 and the t -chunk. Based on those properties, we then give the proofs of Lemmas 8 and 9.

H.1 Necessary lemmas

Lemma 10 *Let \mathbf{A} be an $(n-1) \times \ell$ matrix such that any $d < n$ columns of $[\mathbf{I}, \mathbf{A}]$ are independent, and let \mathbf{B} be a $r \times (n-1)$ random matrix over \mathbb{F}_q . Then any d columns of $[\mathbf{B}, \mathbf{B}\mathbf{A}]$ are uniformly distributed.*

Proof. Let $\tilde{\mathbf{B}} = [\mathbf{B}, \mathbf{B}\mathbf{A}]$, and let $\tilde{\mathbf{A}} = [\mathbf{I}, \mathbf{A}]$. For a set $\mathcal{J} \subseteq [r + n - 1]$ such that $|\mathcal{J}| = d$, $\tilde{\mathbf{B}}[\cdot, \mathcal{J}]$ can be represented as $\mathbf{B}\tilde{\mathbf{A}}[\cdot, \mathcal{J}]$. As any $d < n$ columns of $\tilde{\mathbf{A}}$ are independent, $\tilde{\mathbf{A}}[\cdot, \mathcal{J}]$ has full column rank, then $\tilde{\mathbf{B}}[\cdot, \mathcal{J}] = \mathbf{B}\tilde{\mathbf{A}}[\cdot, \mathcal{J}]$ is uniformly distributed, completing the proof. \square

Lemma 11 *Let \mathbf{A} be an $(n-1) \times \ell$ matrix such that any $d < n$ columns of $[\mathbf{I}^{n-1}, \mathbf{A}]$ are independent. For any $\mathcal{I} \subseteq [n-1]$ such that $n-1-d \leq |\mathcal{I}| \leq n-1$, any $d-(n-1-|\mathcal{I}|)$ columns of $[\mathbf{I}^{|\mathcal{I}|}, \mathbf{A}[\mathcal{I}, \cdot]]$ are independent.*

Proof. Let \mathcal{C} be a linear code corresponding to the generating matrix $[\mathbf{I}^{n-1}, \mathbf{A}]$, and the generating matrix of its dual code \mathcal{C}^\perp is $[\mathbf{A}^T, \mathbf{I}^\ell]$. As any d columns of $[\mathbf{I}^{n-1}, \mathbf{A}]$ are independent, the distance of \mathcal{C}^\perp is then $d + 1$. And by the definition of the distance of a linear code, the distance of a code $\mathcal{C}_\mathcal{I}^\perp$ with generating matrix $[\mathbf{A}[\mathcal{I}, \cdot]^T, \mathbf{I}^\ell]$ such that $\mathcal{I} \subseteq [n-1]$ and $n-1-d \leq |\mathcal{I}| \leq n-1$, is $d + 1 - (n-1-|\mathcal{I}|)$. It is because, deleting $n-1-|\mathcal{I}|$ rows of \mathbf{A} associates to deleting $n-1-|\mathcal{I}|$ columns of $[\mathbf{A}^T, \mathbf{I}^\ell]$, which gives that the distance of $\mathcal{C}_\mathcal{I}^\perp$ is decreased from that of \mathcal{C}^\perp by $n-1-|\mathcal{I}|$. Therefore, as the generating matrix of the dual code of $\mathcal{C}_\mathcal{I}^\perp$ is $[\mathbf{I}^{n-1-|\mathcal{I}|}, \mathbf{A}[\mathcal{I}, \cdot]]$, any $d-(n-1-|\mathcal{I}|)$ columns of $[\mathbf{I}^{|\mathcal{I}|}, \mathbf{A}[\mathcal{I}, \cdot]]$ are independent. \square

We give the definition of t -chunk of a *matrix* in below.

Definition 11 Let \mathbf{X} be an $\ell \times n$ matrix. A t -chunk of \mathbf{X} is a subset of a set consisting of the following two parts

1. (α part) $\{\mathbf{X}[k, i] \mid k \in \mathcal{K}, i \in \mathcal{I}\}$ for $\mathcal{K} \subset [\ell]$, $\mathcal{I} \subset [n]$ and $|\mathcal{K}| + |\mathcal{I}| = t_\alpha$,
2. (β part) t_β entries of \mathbf{X} ,

such that $t \geq t_\alpha + t_\beta$.

Based on this definition, we have the following properties.

Lemma 12 (Properties of t -chunk) Let \mathcal{S} be a t -chunk of an $\ell \times n$ matrix \mathbf{X} , the following properties are fulfilled.

- (1) (equivalence between a t -chunk of a matrix and a t -chunk of sharings) \mathcal{S} is also a t -chunk of $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$, where $\hat{\mathbf{x}}_k \stackrel{\text{def}}{=} \mathbf{X}[k, \cdot]$ for $k \in [\ell]$.
- (2) \mathcal{S} is also a t -chunk of \mathbf{X}^\top .
- (3) Given that \mathcal{S} associates to t_{row} rows and at most t_{maxel} entries of each row of \mathbf{X} , we have $t_{\text{row}} + t_{\text{maxel}} \leq t$.

Proof. Lemma 12-(1)(2) can be achieved directly from the Definitions 5 and 11. In the following, we focus on the third property. We aim at proving that \mathcal{S} relates to at most t_{maxel} entries of each of t_{row} rows of \mathbf{X} , such that $t_{\text{row}} + t_{\text{maxel}} \leq t$. We partition \mathcal{S} into \mathcal{S}_α and \mathcal{S}_β such that \mathcal{S}_α is the α part of \mathcal{S} and \mathcal{S}_β is the β part of \mathcal{S} .

- \mathcal{S}_α relates to at most $t_{\text{maxel}, \alpha}$ entries of each of $t_{\text{row}, \alpha}$ rows of \mathbf{X} , such that $t_{\text{row}, \alpha} + t_{\text{maxel}, \alpha} \leq t_\alpha$.
- \mathcal{S}_β relates to at most $t_{\text{maxel}, \beta}$ entries of each of $t_{\text{row}, \beta}$ rows of \mathbf{X} , such that $t_{\text{row}, \beta} + t_{\text{maxel}, \beta} \leq t_\beta$.

Therefore, $\mathcal{S} = \mathcal{S}_\alpha \cup \mathcal{S}_\beta$ relates to at most t_{maxel} entries of each of t_{row} rows of \mathbf{X} , such that $t_{\text{row}} + t_{\text{maxel}} \leq t_\alpha + t_\beta = t$. \square

Remark. The above lemmas are sufficient to prove the security of Gadget 1-P. While below we give another lemma on the symmetric random matrix \mathbf{R} that particularly will facilitate the security proof of the Gadget 1-M.

Lemma 13 Let \mathbf{A} be an $(n-1) \times \ell$ matrix such that any $d < n$ columns of $[\mathbf{I}, \mathbf{A}]$ are independent. Let \mathbf{R} be an $(n-1) \times (n-1)$ symmetric random matrix, and let \mathbf{R}_{diag} be the diagonal matrix such that $\mathbf{R}_{\text{diag}}[i, i] = \mathbf{R}[i, i]$ for $i \in [n-1]$. Then for any $\mathcal{I} \subseteq [n-1]$ and $\bar{\mathcal{I}} \stackrel{\text{def}}{=} [n-1] \setminus \mathcal{I}$

1. Any $(d - |\mathcal{I}| - 1)$ -chunk of $\mathbf{R}[\bar{\mathcal{I}}, \cdot] \mathbf{A}$ is uniformly distributed and independent of both \mathbf{R}_{diag} and $\mathbf{R}[\mathcal{I}, \cdot]$;
2. Any $(d - |\mathcal{I}|)$ -chunk of $\mathbf{R}[\bar{\mathcal{I}}, \cdot] \mathbf{A}$ is uniformly distributed and independent of $\mathbf{R}[\mathcal{I}, \cdot]$.

Proof (proof of item (1)). For any \mathcal{S} a $(d - |\mathcal{I}| - 1)$ -chunk of $\mathbf{R}[\bar{\mathcal{I}}, \cdot] \mathbf{A}$, there exists a set $\mathcal{I}' \subseteq \bar{\mathcal{I}}$, such that \mathcal{S} is a $(d - |\mathcal{I}| - 1)$ -chunk of $\mathbf{R}[\mathcal{I}', \cdot] \mathbf{A}$. We first aim at proving that, for any $i \in \mathcal{I}'$, any $d - |\mathcal{I}| - |\mathcal{I}'|$ elements of $\mathbf{R}[i, \cdot] \mathbf{A}$ are uniformly distributed and independent of \mathbf{R}_{diag} , $\mathbf{R}[\mathcal{I}, \cdot]$ and $\mathbf{R}[\mathcal{I}' \setminus \{i\}, \mathcal{J}']$.

Let a set $\mathcal{J}' = [n-1] \setminus (\mathcal{I}' \cup \mathcal{I})$, then we have $|\mathcal{J}'| = n - 1 - |\mathcal{I}'| - |\mathcal{I}|$. By Lemma 11, any $d - (n - 1 - |\mathcal{J}'|) = d - (|\mathcal{I}| + |\mathcal{I}'|)$ columns of $\mathbf{A}[\mathcal{J}', \cdot]$ are independent. As \mathbf{R} is a symmetric random matrix, $\mathbf{R}[\mathcal{I}', \mathcal{J}']$ is uniformly distributed and independent of both \mathbf{R}_{diag} and $\mathbf{R}[\mathcal{I}, \cdot]$. Clearly, $|\mathcal{J}'| \geq d - (n - 1 - |\mathcal{J}'|)$, then any $d - (n - 1 - |\mathcal{J}'|) = d - (|\mathcal{I}| + |\mathcal{I}'|)$ elements of $\mathbf{R}[i, \mathcal{J}'] \mathbf{A}[\mathcal{J}', \cdot]$ are uniformly distributed and independent of \mathbf{R}_{diag} , $\mathbf{R}[\mathcal{I}, \cdot]$ and other rows of $\mathbf{R}[\mathcal{I}', \mathcal{J}'] \mathbf{A}[\mathcal{J}', \cdot]$. For any $i \in \mathcal{I}'$, $\mathbf{R}[i, \cdot] \mathbf{A}$ can be represented as

$$\mathbf{R}[i, \cdot] \mathbf{A} = \mathbf{R}[i, \mathcal{J}'] \mathbf{A}[\mathcal{J}', \cdot] \oplus \mathbf{R}[i, \mathcal{I}' \cup \mathcal{I}] \mathbf{A}[\mathcal{I}' \cup \mathcal{I}, \cdot].$$

Then, any $d - (|\mathcal{I}| + |\mathcal{I}'|)$ elements of $\mathbf{R}[i, \cdot] \mathbf{A}$ are uniformly distributed and independent of \mathbf{R}_{diag} , $\mathbf{R}[\mathcal{I}, \cdot]$ and $\mathbf{R}[\mathcal{I}' \setminus \{i\}, \mathcal{J}']$.

We then consider the set \mathcal{S} . For $i \in \mathcal{I}'$, let $\mathcal{S}_i = \mathcal{S} \cap \mathbf{R}[i, \cdot] \mathbf{A}$. By Lemma 12, \mathcal{S} relates to at most t_1 entries of each row of $\mathbf{R}[\mathcal{I}', \cdot] \mathbf{A}$, for $t_1 + |\mathcal{I}'| \leq d - |\mathcal{I}|$, and thus

$$|\mathcal{S}_i| \leq t_1 \leq d - |\mathcal{I}| - |\mathcal{I}'|.$$

Thus, \mathcal{S}_i is masked by $d - |\mathcal{I}| - |\mathcal{I}'|$ elements of $\mathbf{R}[i, \cdot] \mathbf{A}$, which are uniformly distributed and independent of \mathbf{R}_{diag} , $\mathbf{R}[\mathcal{I}, \cdot]$ and $\mathbf{R}[\mathcal{I}' \setminus \{i\}, \mathcal{J}']$, and the random coins comes from $\mathbf{R}[i, \mathcal{J}']$. We can see that all the corresponding random coins of \mathcal{S}_i for all $i \in \mathcal{I}'$ are uniform distributed and independent of \mathbf{R}_{diag} and $\mathbf{R}[\mathcal{I}, \cdot]$, giving that \mathcal{S} is uniformly distributed and independent of \mathbf{R}_{diag} and $\mathbf{R}[\mathcal{I}, \cdot]$. \square

Proof (proof of item (2)). The proof is similar to that of item (1). For any \mathcal{S} a $(d-|\mathcal{I}|)$ -chunk of $\mathbf{R}[\bar{\mathcal{I}},]\mathbf{A}$, there exists a set $\mathcal{I}' \subseteq \bar{\mathcal{I}}$, such that \mathcal{S} is a $(d-|\mathcal{I}|)$ -chunk of $\mathbf{R}[\mathcal{I}',]\mathbf{A}$. We first aim at proving that, for any $i \in \mathcal{I}'$, any $d - |\mathcal{I}| - |\mathcal{I}'| + 1$ elements of $\mathbf{R}[i,]\mathbf{A}$ are uniformly distributed and independent of $\mathbf{R}[\mathcal{I},]$ and $[\mathbf{R}[\mathcal{I}'/\{1\}, \mathcal{J}'], \mathbf{R}_{\text{diag}}[\mathcal{I}'/\{1\},]]$.

Let a set $\mathcal{J}' = [n-1]/(\mathcal{I}' \cup \mathcal{I})$, then we have $|\mathcal{J}'| = n - 1 - |\mathcal{I}'| - |\mathcal{I}|$. By Lemma 11, for $i \in \mathcal{I}'$, any $d - (n-1-|\mathcal{J}'|) + 1 = d - (|\mathcal{I}| + |\mathcal{I}'|) + 1$ columns of $[\mathbf{A}[\mathcal{J}',]; \mathbf{A}[i,]]$ are independent. As \mathbf{R} is a symmetric random matrix, for $i \in \mathcal{I}'$, $[\mathbf{R}[\mathcal{I}', \mathcal{J}'], \mathbf{R}_{\text{diag}}[i, i]]$ is uniformly distributed and independent of $\mathbf{R}[\mathcal{I},]$. Clearly, $|\mathcal{J}'| + 1 \geq d - (n-1-|\mathcal{J}'|) + 1$, then any $d - (n-1-|\mathcal{J}'|) + 1 = d - |\mathcal{I}| - |\mathcal{I}'| + 1$ elements of $\mathbf{R}[i, \mathcal{J}']\mathbf{A}[\mathcal{J}',]$ are uniformly distributed and independent of $\mathbf{R}[\mathcal{I},]$ and other rows of $[\mathbf{R}[\mathcal{I}', \mathcal{J}'], \mathbf{R}_{\text{diag}}[\mathcal{I}',]]$. For $i \in \mathcal{I}'$, $\mathbf{R}[i,]\mathbf{A}$ can be represented as

$$\mathbf{R}[i,]\mathbf{A} = \mathbf{R}[i, \mathcal{J}']\mathbf{A}[\mathcal{J}',] \oplus \mathbf{R}[i, i]\mathbf{A}[i,] \oplus \mathbf{R}[i, \mathcal{I}' \cup \mathcal{I}]\mathbf{A}[\mathcal{I}' \cup \mathcal{I},].$$

Then, any $d - |\mathcal{I}| - |\mathcal{I}'| + 1$ elements of $\mathbf{R}[i,]\mathbf{A}$ are uniformly distributed and independent of $\mathbf{R}[\mathcal{I},]$ and $[\mathbf{R}[\mathcal{I}'/\{1\}, \mathcal{J}'], \mathbf{R}_{\text{diag}}[\mathcal{I}'/\{1\},]]$.

We then consider the set \mathcal{S} . For $i \in \mathcal{I}$, let $\mathcal{S}_i = \mathcal{S} \cap \mathbf{R}[i,]$. By Lemma 12, \mathcal{S} relates to at most t_1 entries of each row of $\mathbf{R}[\mathcal{I}',]\mathbf{A}$, for $t_1 + |\mathcal{I}'| \leq d - |\mathcal{I}| + 1$, and thus

$$|\mathcal{S}_i| \leq t_1 \leq d - |\mathcal{I}| - |\mathcal{I}'| + 1.$$

Thus, \mathcal{S}_i is masked by $d - |\mathcal{I}| - |\mathcal{I}'| + 1$ elements of $\mathbf{R}[i,]\mathbf{A}$, which are uniformly distributed and independent of $\mathbf{R}[\mathcal{I},]$ and $\mathbf{R}[\mathcal{I}'/\{i\}, \mathcal{J}']$, and the random coins comes from $\mathbf{R}[i, \mathcal{J}']$. We can see that all the corresponding random coins of \mathcal{S}_i for all $i \in \mathcal{I}'$ are uniform distributed and independent of $\mathbf{R}[\mathcal{I},]$, giving that \mathcal{S} is uniformly distributed and independent of \mathbf{R}_{diag} and $\mathbf{R}[\mathcal{I},]$. \square

H.2 Proofs of Lemmas 8 and 9

Proof of Lemma 8 The probes are divided into different subsets based on the types of variables:

- The probes in the input shares: $\mathcal{P}_{\text{input}}$.
- The probes in the random variables: $\mathcal{P}_{\text{rand}}$, which consist of the following variables: entries in $\hat{\mathbf{Q}}$ and \mathbf{Q} , and variables in the computation of $\hat{\mathbf{Q}} = \mathbf{Q}\mathbf{A}$. In the computation of $\mathbf{Q}\mathbf{A}$, each row of \mathbf{Q} is linearly transformed to a distinct column of $\hat{\mathbf{Q}}$. Thus, for each probe p in $\mathcal{P}_{\text{rand}}$, there exists a function $f : \mathbb{F}_q^{n-1} \rightarrow \mathbb{F}_q$ and an index $i \in [n-1]$, such that $p = f(\hat{\mathbf{Q}}[i, 1], \dots, \hat{\mathbf{Q}}[i, n-1])$.
- The probes in the computation of the function from the concatenated matrix $[\mathbf{X}, \mathbf{Q}]$ to $(\tilde{\mathbf{x}}, \hat{\mathbf{u}})$ (also including the output probes): \mathcal{P}_{sum} , in which $\mathbf{X}[, j]$ and $\mathbf{Q}[, j]$ are separately summed up to $\tilde{\mathbf{x}}[j]$ and $\hat{\mathbf{u}}[j]$. Thus, each probe p in \mathcal{P}_{sum} can be represented as $p = \sum_{i \in \mathcal{I}'} \mathbf{X}[\mathcal{I}', j]$ for $j \in [\ell]$ and $\mathcal{I}' \subseteq [n]$, or $p = \sum_{i \in \mathcal{I}'} \mathbf{Q}[\mathcal{I}', j]$ for $j \in [n-1]$ and $\mathcal{I}' \subseteq [n-1]$.

We build the sets $\mathcal{I}_1, \dots, \mathcal{I}_\ell$ and a temporary set $\mathcal{I}_{\text{rand}}$ and run a simulator as following steps

1. Initiate set \mathcal{I}_k to be empty for any $k \in [\ell]$, and initiate a set $\mathcal{I}_{\text{rand}}$ to be empty.
2. For each probe in $\mathcal{P}_{\text{input}}$, say $\hat{\mathbf{x}}_k[i]$ for $k \in [\ell]$ and $i \in [n]$, put the corresponding index i into \mathcal{I}_k . Then, p is a function of $\hat{\mathbf{x}}_1[\mathcal{I}_1], \dots, \hat{\mathbf{x}}_\ell[\mathcal{I}_\ell]$, and thus can be simulated. This step puts at most $|\mathcal{P}_{\text{input}}|$ indices into $\bigcup_{k \in [\ell]} \mathcal{I}_k$, which corresponds to a $|\mathcal{P}_{\text{input}}|$ -chunk of input sharings.
3. The probes in $\mathcal{P}_{\text{rand}}$ can be simulated by sampling uniform distribution. Moreover, for each probe in $\mathcal{P}_{\text{rand}}$, say $p = f(\hat{\mathbf{Q}}[i, 1], \dots, \hat{\mathbf{Q}}[i, n-1])$, we put the corresponding index i to the set $\mathcal{I}_{\text{rand}}$, which is useful in the latter process of simulation. In this step, there are at most $|\mathcal{P}_{\text{rand}}|$ indices put into $\mathcal{I}_{\text{rand}}$.
4. For each probe in \mathcal{P}_{sum} , there exists a set $\mathcal{I}' \subseteq [n-1]$, and the probe can be represented as $p = \sum_{i \in \mathcal{I}'} \mathbf{X}[\mathcal{I}', j]$ or $p = \sum_{i \in \mathcal{I}'} \mathbf{X}[\mathcal{I}', j] \oplus \mathbf{X}[n, j]$ for $j \in [\ell]$, or $p = \sum_{i \in \mathcal{I}'} \mathbf{Q}[\mathcal{I}', j]$ for $j \in [n-1]$, then \mathcal{I}' can be divided into two parts: $\mathcal{I}'_1 \subseteq \mathcal{I}_{\text{rand}}$ and $\mathcal{I}'_2 \subseteq [n-1]/\mathcal{I}_{\text{rand}}$. We separate the analysis into following cases
 - If the term $\mathbf{X}[n, j]$ is in p , then put n into \mathcal{I}_j , and thus this term can be simulated.
 - Put \mathcal{I}'_1 into \mathcal{I}_j , and thus the terms in $\mathbf{X}[\mathcal{I}'_1, j]$ or $\mathbf{Q}[\mathcal{I}'_1, j]$ can be simulated.

- Finally, we consider the terms in $\mathbf{X}[\mathcal{I}'_2, j]$ or $\mathbf{Q}[\mathcal{I}'_2, j]$. From the instruction of Gadget 1-P, $[\mathbf{X}, \mathbf{Q}] = [[\hat{\mathbf{x}}_1; \dots; \hat{\mathbf{x}}_\ell]^\top, \mathbf{O}^{(n-1) \times (n-1)}] \oplus [\hat{\mathbf{Q}}, \mathbf{Q}]$, and thus we first analysis the matrix $[\hat{\mathbf{Q}}, \mathbf{Q}][\mathcal{I}'_2, j]$, which can be represented as $\mathbf{Q}[\mathcal{I}'_2, j][\mathbf{A}, \mathbf{I}^{n-1}]$. By Lemma 10, any d columns of $\mathbf{Q}[\mathcal{I}'_2, j][\mathbf{A}, \mathbf{I}^{n-1}]$ are uniformly distributed, and the random coins comes from the random variables in $\mathbf{Q}[\mathcal{I}'_2, j]$, which are independent of other rows of \mathbf{Q} . Since all the probes only relate to at most d columns of $[\mathbf{X}, \mathbf{Q}]$, then the terms in $\mathbf{X}[\mathcal{I}'_2, j]$ or $\mathbf{Q}[\mathcal{I}'_2, j]$ can be simulated by sampling from uniform distribution.

In this step, a subset of \mathcal{I}_{rand} is put into \mathcal{I}_k for $k \in \mathcal{K}$ and $|\mathcal{K}| \leq |\mathcal{P}_{sum}|$, which corresponds to a $\frac{(|\mathcal{P}_{sum}| + |\mathcal{P}_{rand}|)}{(|\mathcal{P}_{sum}| + |\mathcal{P}_{rand}|)}$ -chunk of input sharings.

Now, all the probes are simulated, and $\{\hat{\mathbf{x}}_k[\mathcal{I}_k]\}_{k \in [\ell]}$ corresponds to a $(|\mathcal{P}_{sum}| + |\mathcal{P}_{rand}| + |\mathcal{P}_{input}|)$ -chunk of $\{\hat{\mathbf{x}}_k\}_{k \in [\ell]}$. Therefore, for any t_{out} output probes and internal probes \mathcal{P}_{int} such that $|\mathcal{P}_{int}| + t_{out} \leq d$, there exists a $|\mathcal{P}_{int}|$ -chunk of input sharings \mathcal{S} , and a simulator \mathbf{S} such that

$$\Pr \left[\mathbf{D} \left(\mathbf{G}_{\mathcal{P}} \left(\{\hat{\mathbf{x}}_i\}_{i=1}^\ell, \{\hat{\mathbf{x}}_i\}_{i=1}^\ell \right) = 1 \right) = 1 \right] = \Pr \left[\mathbf{D} \left(\mathbf{S}(\mathcal{S}), \{\hat{\mathbf{x}}_i\}_{i=1}^\ell \right) = 1 \right],$$

where \mathcal{P} is the set of all probes. □

Proof of Lemma 9 For the convenience, we short some intermediate variables as

$$\begin{aligned} \mathbf{W} &\stackrel{\text{def}}{=} [\mathbf{w}_1^\top, \dots, \mathbf{w}_\ell^\top] = \hat{\mathbf{u}}^\top \times \tilde{\mathbf{y}}, \\ \mathbf{K} &\stackrel{\text{def}}{=} [\mathbf{k}_1^\top, \dots, \mathbf{k}_\ell^\top] = \hat{\mathbf{v}}^\top \times \tilde{\mathbf{x}}, \\ \hat{\mathbf{S}} &\stackrel{\text{def}}{=} \mathbf{S} \oplus \mathbf{R} = \hat{\mathbf{u}}^\top \times \hat{\mathbf{v}} \oplus \mathbf{R}, \text{ and} \\ \mathbf{e} &= [e_1, \dots, e_\ell] = [\tilde{\mathbf{x}}[1]\tilde{\mathbf{y}}[1], \dots, \tilde{\mathbf{x}}[\ell]\tilde{\mathbf{y}}[\ell]]. \end{aligned}$$

The output of Gadget 1-M can be regarded as a matrix $[\mathbf{z}_1^\top, \dots, \mathbf{z}_\ell^\top]$. Then, by the instruction of Gadget 1-M, the process of computation can be rewritten as

$$\begin{aligned} [\hat{\mathbf{z}}_1^\top, \dots, \hat{\mathbf{z}}_\ell^\top] &= [\hat{\mathbf{t}}_1^\top \odot [1; \mathbf{a}_1^\top], \dots, \mathbf{z}_\ell^\top \odot [1; \hat{\mathbf{t}}_1^\top]] \\ &= [\hat{\mathbf{t}}_1^\top, \dots, \mathbf{z}_\ell^\top] \odot [1; \mathbf{A}], \end{aligned}$$

and

$$\begin{aligned} [\hat{\mathbf{t}}_1^\top, \dots, \hat{\mathbf{t}}_\ell^\top] &= \left[\begin{array}{c} e_1 \oplus \mathbf{a}_1 \mathbf{R}_{\text{diag}} \mathbf{a}_1^\top \\ (\hat{\mathbf{S}} \mathbf{a}_1^\top \oplus \mathbf{w}_1^\top) \oplus \mathbf{k}_1^\top \end{array} \right], \dots, \left[\begin{array}{c} e_\ell \oplus \mathbf{a}_\ell \mathbf{R}_{\text{diag}} \mathbf{a}_\ell^\top \\ (\hat{\mathbf{S}} \mathbf{a}_\ell^\top \oplus \mathbf{w}_\ell^\top) \oplus \mathbf{k}_\ell^\top \end{array} \right] \\ &= \left[\begin{array}{c} \mathbf{e} \oplus \mathbf{A}^\top \mathbf{R}_{\text{diag}} \mathbf{A} \\ (\hat{\mathbf{S}} \mathbf{A} \oplus \mathbf{W}) \oplus \mathbf{K} \end{array} \right], \end{aligned}$$

where the order of the operation is consistent with the operators' priorities.

The probes are divided into different subsets based on the types of variables

- The probes in the input shares: \mathcal{P}_{input} .
- The probes in the outer product of the input shares: \mathcal{P}_\times , which include the variables in \mathbf{S} , \mathbf{W} and \mathbf{K} .
- The probes in the random variables: \mathcal{P}_{rand} .
- The probes to the calculation from \mathbf{R}_{diag} to $\mathbf{A}^\top \mathbf{R}_{\text{diag}} \mathbf{A}$: \mathcal{P}_{diag} . Note that there may exist overlaps between \mathcal{P}_{rand} and \mathcal{P}_{diag} , which are entries on the diagonal of \mathbf{R} , and we count them as in \mathcal{P}_{rand} .
- The probes in the calculation from $\hat{\mathbf{S}}$ to $\hat{\mathbf{S}} \mathbf{A}$: \mathcal{P}_{mul} . For each probe p in \mathcal{P}_{mul} , there exists a function $f : \mathbb{F}_q^n \rightarrow \mathbb{F}_q$ and indices $i \in [n-1]$ and $k \in [\ell]$, such that p can be represented as $p = f(\hat{\mathbf{S}}[i, 1], \dots, \hat{\mathbf{S}}[i, n-1])$.
- The probes in $\hat{\mathbf{S}} \mathbf{A} \oplus \mathbf{W}$: \mathcal{P}_\oplus
- The probes in the output $\hat{\mathbf{z}}_1, \dots, \hat{\mathbf{z}}_\ell$ or $\hat{\mathbf{t}}_1, \dots, \hat{\mathbf{t}}_\ell$: \mathcal{P}_O . Note that shares of $\hat{\mathbf{t}}_1, \dots, \hat{\mathbf{t}}_\ell$ are manipulated separately to calculate the output sharings, and thus we don't distinguish the probes $\hat{\mathbf{t}}_k[i]$ and $\hat{\mathbf{z}}_k[i]$ for $k \in [\ell]$ and $i \in [n]$, and regard both of them as the probes to $\hat{\mathbf{z}}_k[i]$. Also note that \mathcal{P}_O is a t_O -chunk of output sharings.

We build the sets $\mathcal{I}_{\hat{\mathbf{u}}}, \mathcal{I}_{\tilde{\mathbf{x}}}, \mathcal{I}_{\hat{\mathbf{v}}}, \mathcal{I}_{\tilde{\mathbf{y}}}$ and a temporary set \mathcal{I}_{mr} and run a simulator as following steps

1. Initiate $\mathcal{I}_{\hat{\mathbf{u}}}, \mathcal{I}_{\tilde{\mathbf{x}}}, \mathcal{I}_{\hat{\mathbf{v}}}, \mathcal{I}_{\tilde{\mathbf{y}}}$ and \mathcal{I}_{mr} to be empty.

2. For each probe in \mathcal{P}_{input} or \mathcal{P}_\times , put corresponding indices into $\mathcal{I}_{\hat{\mathbf{u}}}$, $\mathcal{I}_{\hat{\mathbf{x}}}$, $\mathcal{I}_{\hat{\mathbf{v}}}$ and $\mathcal{I}_{\hat{\mathbf{y}}}$, then the probe can be simulated with $\hat{\mathbf{u}}[\mathcal{I}_{\hat{\mathbf{u}}}]$, $\hat{\mathbf{v}}[\mathcal{I}_{\hat{\mathbf{v}}}]$, $\hat{\mathbf{x}}[\mathcal{I}_{\hat{\mathbf{x}}}]$ and $\hat{\mathbf{y}}[\mathcal{I}_{\hat{\mathbf{y}}}]$. This step puts at most $|\mathcal{P}_{input}| + |\mathcal{P}_\times|$ indices into both $(\mathcal{I}_{\hat{\mathbf{x}}}, \mathcal{I}_{\hat{\mathbf{u}}})$ and $(\mathcal{I}_{\hat{\mathbf{y}}}, \mathcal{I}_{\hat{\mathbf{v}}})$.
3. For each probe in \mathcal{P}_{rand} , say $\mathbf{R}[i, j]$, put i into \mathcal{I}_{mr} , $\mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{\hat{\mathbf{v}}}$, and this probe can be simulated by randomly sampling from uniform distribution. This step puts at most $|\mathcal{P}_{rand}|$ indexes into \mathcal{I}_{mr} , $\mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{\hat{\mathbf{v}}}$. Note that, although the simulation of probes in \mathcal{P}_{rand} can be done without the sets \mathcal{I}_{mr} , $\mathcal{I}_{\hat{\mathbf{u}}}$ or $\mathcal{I}_{\hat{\mathbf{v}}}$, the set \mathcal{I}_{mr} is quite important in the simulation of latter steps, and putting the indexes into $\mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{\hat{\mathbf{v}}}$ is to ensure $\mathcal{I}_{mr} \subseteq \mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{mr} \subseteq \mathcal{I}_{\hat{\mathbf{v}}}$.
4. For each probe $p = f(\hat{\mathbf{S}}[i, 1], \dots, \hat{\mathbf{S}}[i, n-1])$ in \mathcal{P}_{mul} , if $i \notin \mathcal{I}_{mr}$, put i into all of \mathcal{I}_{mr} , $\mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{\hat{\mathbf{v}}}$. Then, this probe can be represented as $p = f(\mathbf{S}[i, 1] \oplus \mathbf{R}[i, 1], \dots, \mathbf{S}[i, d] \oplus \mathbf{R}[i, d])$. For each term in p (say, $\hat{\mathbf{S}}[i, j]$), consider the following conditions (where if needed, $\mathbf{S}[i, j]$ can be simulated with $\hat{\mathbf{u}}[i]$ and $\hat{\mathbf{v}}[j]$).
 - If $\hat{\mathbf{S}}[j, i]$ is also included as a term in at least one probe in \mathcal{P}_{mul} , then $\mathbf{S}[i, j]$ need to be simulated. As j should be included into $\mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{\hat{\mathbf{v}}}$ when considering the probe $p = f(\hat{\mathbf{S}}[j, 1], \dots, \hat{\mathbf{S}}[j, n-1])$, so $\mathbf{S}[i, j]$ can be simulated after putting all the i -indexes.
 - If $\mathbf{R}[i, j] \in \mathcal{P}_{rand}$. We need to put j into $\mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{\hat{\mathbf{v}}}$ to simulate $\mathbf{S}[j, i]$. Note that, as $i \in \mathcal{I}_{mr}$, we don't need to add it twice.
 - If $\mathbf{R}[j, i] \in \mathcal{P}_{rand}$, then j is in $\mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{\hat{\mathbf{v}}}$, and thus we can simulate $\mathbf{S}[j, i]$.
 - If none of the above conditions are fulfilled, $\hat{\mathbf{S}}[j, i]$ can be simulated by sampling from uniform distributions, as $\mathbf{R}[i, j]$ is uniformly distributed and independent of probes analyzed in former steps.

Then, p can be simulated with $\hat{\mathbf{u}}[\mathcal{I}_{\hat{\mathbf{u}}}]$ and $\hat{\mathbf{v}}[\mathcal{I}_{\hat{\mathbf{v}}}]$. This step puts at most $|\mathcal{P}_{mul}|$ indices into $\mathcal{I}_{\hat{\mathbf{u}}}$, $\mathcal{I}_{\hat{\mathbf{v}}}$ and indices into \mathcal{I}_{mr} . To this step, the building of temporary set \mathcal{I}_{mr} is complete, which will be used in the next steps. Now we can see that $\mathcal{I}_{mr} \subseteq \mathcal{P}_{mul} \cup \mathcal{P}_{rand}$, $|\mathcal{P}_{mul}| + |\mathcal{P}_{rand}| \geq |\mathcal{I}_{mr}|$, $\mathcal{I}_{mr} \subseteq \mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{mr} \subseteq \mathcal{I}_{\hat{\mathbf{v}}}$. Note that in this step, the simulation works for any function $f : \mathbb{F}_q^{n-1} \rightarrow \mathbb{F}_q$.

5. The probes in \mathcal{P}_{diag} can be simulated by randomly sampling all the entries in \mathbf{R}_{diag} from uniform distribution.
6. We finally consider the probes in \mathcal{P}_\oplus and \mathcal{P}_O , each of which can be represented as one of the following forms
 - $(\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W})[i, k] \in \mathcal{P}_\oplus$ for $i \in [n-1]$ and $k \in [\ell]$;
 - $(\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W} \oplus \mathbf{K})[i, k] \in \mathcal{P}_O$;
 - $e_k \oplus \mathbf{a}_k \mathbf{R}_{diag} \mathbf{a}_k^T \in \mathcal{P}_O$ for $i \in [n-1]$ and $k \in [\ell]$.

We further partition the probes in \mathcal{P}_\oplus and \mathcal{P}_O into several parts as follows and build a set \mathcal{M} .

- $\mathcal{P}_1: e_k \oplus \mathbf{a}_k \mathbf{R}_{diag} \mathbf{a}_k^T \in \mathcal{P}_O$.
- $\mathcal{P}_2: (\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W} \oplus \mathbf{K})[i, k] \in \mathcal{P}_O$ for $i \in \mathcal{I}_{mr}$ and $k \in [\ell]$.
- $\mathcal{P}_3: (\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W})[i, k] \in \mathcal{P}_\oplus$ for $i \in \mathcal{I}_{mr}$ and $k \in [\ell]$.
- $\mathcal{P}_4: (\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W} \oplus \mathbf{K})[i, k] \in \mathcal{P}_O$ for $i \in \bar{\mathcal{I}}_{mr}$ and $k \in [\ell]$. Moreover, we put all the tuples of (i, k) appeared in \mathcal{P}_4 into a set \mathcal{M} .
- $\mathcal{P}_5: (\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W})[i, k] \in \mathcal{P}_\oplus$ for $i \in \bar{\mathcal{I}}_{mr}$ and $(i, k) \notin \mathcal{M}$.
- $\mathcal{P}_6: (\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W})[i, k] \in \mathcal{P}_\oplus$ for $i \in \bar{\mathcal{I}}_{mr}$ and $(i, k) \in \mathcal{M}$.

We put the all the values of k appeared in above sets (i.e., from \mathcal{P}_1 to \mathcal{P}_6) into $\mathcal{I}_{\hat{\mathbf{x}}}$ and $\mathcal{I}_{\hat{\mathbf{y}}}$. By Lemma 12-(3), the number of k values appeared in \mathcal{P}_1 , \mathcal{P}_2 and \mathcal{P}_4 is at most t_{out} . As the corresponding tuples of (i, k) of \mathcal{P}_6 and \mathcal{P}_4 are overlapped, the k values appeared in \mathcal{P}_6 are also appeared in \mathcal{P}_4 , and they should not be added in twice. Thus, the number of k values appeared in all above sets is at most $t_{out} + |\mathcal{P}_3| + |\mathcal{P}_5|$, which are added into $\mathcal{I}_{\hat{\mathbf{x}}}$ and $\mathcal{I}_{\hat{\mathbf{y}}}$. Then, we simulate above parts one by one:

- (a) Each probe in \mathcal{P}_1 (say, $e_k \oplus \mathbf{a}_k \mathbf{R}_{diag} \mathbf{a}_k^T$) can be simulated, since $e_k = \hat{\mathbf{x}}[k] \hat{\mathbf{y}}[k]$ and k is in $\mathcal{I}_{\hat{\mathbf{x}}}$ and $\mathcal{I}_{\hat{\mathbf{y}}}$.
- (b) We then consider the probes in \mathcal{P}_2 and \mathcal{P}_3 . As $i \in \mathcal{I}_{mr} \subseteq \mathcal{I}_{\hat{\mathbf{u}}}$ and $i \in \mathcal{I}_{mr} \subseteq \mathcal{I}_{\hat{\mathbf{v}}}$, i is already in $\mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{\hat{\mathbf{v}}}$. Each of those probes is a sum of the following two variables
 - $(\hat{\mathbf{S}}\mathbf{A})[i, k]$: this variable can be simulated in step 4, where the simulation works with any function $f : \mathbb{F}_q^{n-1} \rightarrow \mathbb{F}_q$.
 - $\mathbf{W}[i, k]$ or $(\mathbf{W} \oplus \mathbf{K})[i, k]$: this variable can be simulated since k is in $\mathcal{I}_{\hat{\mathbf{x}}}$ and $\mathcal{I}_{\hat{\mathbf{y}}}$, and i is in $\mathcal{I}_{\hat{\mathbf{u}}}$ and $\mathcal{I}_{\hat{\mathbf{v}}}$.

Then, the probes in $\mathcal{P}_2 \cup \mathcal{P}_3$ can be simulated.

(c) For probes in \mathcal{P}_4 and \mathcal{P}_5 , each of them is masked by an entry in \mathbf{RA} , and can be represented as

$$(\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W} \oplus b\mathbf{K})[i, k] = (\mathbf{RA} \oplus \mathbf{SA} \oplus \mathbf{W} \oplus b\mathbf{K})[i, k]$$

for $i \in \bar{\mathcal{I}}_{mr}$, $k \in [\ell]$ and $b \in \{0, 1\}$. The probes in \mathcal{P}_4 corresponds to at most $|\mathcal{P}_4|$ elements in $\mathbf{R}[\bar{\mathcal{I}}_{mr}, \mathbf{A}]$, and the probes in \mathcal{P}_5 correspond to a t_{out} -chunk of elements in $\mathbf{R}[\bar{\mathcal{I}}_{mr}, \mathbf{A}]$. Let $\mathcal{P}' \stackrel{\text{def}}{=} \mathcal{P}_1 \cup \mathcal{P}_{diag}$, we separate the analysis into two cases:

- i. If $\mathcal{P}' \neq \emptyset$, then Lemma 13-(1) can be applied: any $(d - |\mathcal{I}_{mr}| - 1)$ -chunk of $\mathbf{R}[\bar{\mathcal{I}}_{mr}, \mathbf{A}]$ are uniformly distributed and independent of other probes, and $|\mathcal{P}_4| + t_{out} \leq d - |\mathcal{P}_{mul}| - |\mathcal{P}_{rand}| - |\mathcal{P}_1| \leq d - |\mathcal{I}_{mr}| - 1$.
- ii. If $\mathcal{P}' = \emptyset$, then Lemma 13-(2) can be applied: any $(d - |\mathcal{I}_{mr}|)$ -chunk of $\mathbf{R}[\bar{\mathcal{I}}_{mr}, \mathbf{A}]$ are uniformly distributed and independent of other probes, and $|\mathcal{P}_4| + t_{\mathcal{P}_5} \leq d - |\mathcal{P}_{mul}| - |\mathcal{P}_{rand}| \leq d - |\mathcal{I}_{mr}|$.

Thus, the entries in $\mathbf{R}[\bar{\mathcal{I}}_{mr}, \mathbf{A}]$ corresponding to probes in \mathcal{P}_4 and \mathcal{P}_5 are uniformly distributed and independent of other probes. Then, probes in \mathcal{P}_4 and \mathcal{P}_5 can be simulated by randomly sampling from uniform distribution.

- (d) To simulate each probe $(\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W} \oplus \mathbf{K})[i, k]$ in \mathcal{P}_6 , we can simulate $\mathbf{K}[i, k]$, since $(\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W} \oplus \mathbf{K})[i, k]$ in \mathcal{P}_6 and have been simulated. Thus, for each probe $(\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W} \oplus \mathbf{K})[i, k]$ in \mathcal{P}_6 , k and i need to be in $\mathcal{I}_{\tilde{\mathbf{x}}}$ and $\mathcal{I}_{\tilde{\mathbf{v}}}$ respectively (to simulate the $\mathbf{K}[i, k]$), making at most $|\mathcal{P}_6|$ indices to be added in $\mathcal{I}_{\tilde{\mathbf{v}}}$ (and k is already in $\mathcal{I}_{\tilde{\mathbf{x}}}$). Then, each probe in \mathcal{P}_6 can be simulated with knowing $(\hat{\mathbf{S}}\mathbf{A} \oplus \mathbf{W})[i, k]$ and $\mathbf{K}[i, k]$.

In summary, this step puts at most $|\mathcal{P}_3| + |\mathcal{P}_5| + t_{out}$ indices into $\mathcal{I}_{\tilde{\mathbf{x}}}$, at most $|\mathcal{P}_3| + |\mathcal{P}_5| + t_{out}$ indices into $\mathcal{I}_{\tilde{\mathbf{y}}}$, and at most $|\mathcal{P}_6|$ indices into $\mathcal{I}_{\tilde{\mathbf{v}}}$.

Now, all of probes are simulated and the analysis is completed. In total, there are at most

$$|\mathcal{P}_{input}| + |\mathcal{P}_x| + |\mathcal{P}_{rand}| + |\mathcal{P}_{mul}| + |\mathcal{P}_3| + |\mathcal{P}_5| + t_{out} \leq d$$

indices in $(\mathcal{I}_{\tilde{\mathbf{x}}}, \mathcal{I}_{\tilde{\mathbf{u}}})$, and at most

$$|\mathcal{P}_{input}| + |\mathcal{P}_x| + |\mathcal{P}_{rand}| + |\mathcal{P}_{mul}| + |\mathcal{P}_3| + |\mathcal{P}_5| + |\mathcal{P}_6| + t_{out} \leq d$$

indices in $(\mathcal{I}_{\tilde{\mathbf{y}}}, \mathcal{I}_{\tilde{\mathbf{v}}})$. Therefore, for any internal probes \mathcal{P}_{int} and t_O -chunk of output sharings such that $t_O + |\mathcal{P}_{int}| \leq d$, we can build the sets $\mathcal{I}_{\tilde{\mathbf{u}}}$, $\mathcal{I}_{\tilde{\mathbf{x}}}$, $\mathcal{I}_{\tilde{\mathbf{v}}}$ and $\mathcal{I}_{\tilde{\mathbf{y}}}$ such that $|\mathcal{I}_{\tilde{\mathbf{u}}}| + |\mathcal{I}_{\tilde{\mathbf{x}}}| \leq d$ and $|\mathcal{I}_{\tilde{\mathbf{v}}}| + |\mathcal{I}_{\tilde{\mathbf{y}}}| \leq d$, and a simulator \mathbf{S} such that

$$\begin{aligned} & \Pr[\mathbf{D}(\mathbf{G}_{\mathcal{P}}(\hat{\mathbf{u}}, \tilde{\mathbf{x}}, \hat{\mathbf{v}}, \tilde{\mathbf{y}}), \hat{\mathbf{u}}, \tilde{\mathbf{x}}, \hat{\mathbf{v}}, \tilde{\mathbf{y}}) = 1] \\ &= \Pr[\mathbf{D}(\mathbf{S}(\hat{\mathbf{u}}[\mathcal{I}_{\tilde{\mathbf{u}}}], \tilde{\mathbf{x}}[\mathcal{I}_{\tilde{\mathbf{x}}}], \hat{\mathbf{v}}[\mathcal{I}_{\tilde{\mathbf{v}}}], \tilde{\mathbf{y}}[\mathcal{I}_{\tilde{\mathbf{y}}}], \hat{\mathbf{u}}, \tilde{\mathbf{x}}, \hat{\mathbf{v}}, \tilde{\mathbf{y}}) = 1], \end{aligned}$$

where \mathcal{P} is the set of all probes. □

I Proofs in Section 5

I.1 Proof of Lemma 4

Let the input sharings be $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$. As the gadget operates the shares of input sharings separately, then every probe depends on at most one input share. We build the sets $\mathcal{I}_1, \dots, \mathcal{I}_\ell$ and run a simulator as following steps

1. Initiate set \mathcal{I}_k to be empty for any $k \in [\ell]$.
2. For each probe, if it depends on one input share, say $\hat{\mathbf{x}}_k[i]$, put i into \mathcal{I}_k . Then, this probe can be simulated with $\hat{\mathbf{x}}_1[\mathcal{I}_1], \dots, \hat{\mathbf{x}}_\ell[\mathcal{I}_\ell]$.

Now, all the probes are simulated, and we can see that $\{\hat{\mathbf{x}}_k[\mathcal{I}_k]\}_{k \in [\ell]}$ corresponds to a $(t_{out} + t_{int})$ -chunk of $\{\hat{\mathbf{x}}_k\}_{k \in [\ell]}$. □

I.2 Proof of Theorem 3

The probes are divided into different subsets based on the types of variables

- The probes to the input shares: \mathcal{P}_{input} .
- The probes to the random variables: \mathcal{P}_{rand} .
- The probes to $L(\hat{\mathbf{y}}_1[i], \dots, \hat{\mathbf{y}}_\ell[i])$ for any $i \in [n]$: \mathcal{P}_L .
- The probes to the output shares: \mathcal{P}_O .

We build the sets $\mathcal{I}_1, \dots, \mathcal{I}_\ell$ and a temporary set \mathcal{I}_{rand} and run a simulator as following steps

1. Initiate set \mathcal{I}_k to be an empty set for any $k \in [\ell]$.
2. For each probe in \mathcal{P}_{input} , then put the corresponding index into $\mathcal{I}_1, \dots, \mathcal{I}_\ell$. Then, p is a function of $\hat{\mathbf{x}}_1[\mathcal{I}_1], \dots, \hat{\mathbf{x}}_\ell[\mathcal{I}_\ell]$, and thus can be simulated. Moreover, we put the corresponding i -index to a set \mathcal{I}_{input} . This step puts at most $|\mathcal{P}_{input}|$ indices into $(\mathcal{I}_1, \dots, \mathcal{I}_\ell)$.
3. The probes in \mathcal{P}_{rand} can be simulated by sampling uniform distribution. Moreover, for each probe in \mathcal{P}_{rand} , we put the corresponding k -index to a set \mathcal{I}_{rand} .
4. For each probe in \mathcal{P}_L or \mathcal{P}_O , the probe can be represented as $p = g(\{\hat{\mathbf{y}}_k[i] \mid k \in \mathcal{I}'\})$, where $\mathcal{I}' \subseteq [\ell]$, then we partition \mathcal{I}' into \mathcal{I}'_1 and \mathcal{I}'_2 such that $\mathcal{I}'_2 \subseteq \mathcal{I}_{rand}$ and $\mathcal{I}'_1 \subseteq [\ell] \setminus \mathcal{I}_{rand}$. We separate our discussion into two cases:
 - \mathcal{I}'_1 are put i into \mathcal{I}_k , and thus $\{\hat{\mathbf{y}}_k[i] \mid k \in \mathcal{I}'_1\}$ can be simulated.
 - As long as the random variables masked to $\{\hat{\mathbf{y}}_k[i] \mid k \in \mathcal{I}'_2\}$ are unknown, $\{\hat{\mathbf{y}}_k[i] \mid k \in \mathcal{I}'_2\}$ can be simulated by sampling uniform distribution.

Then, $p = g(\{\hat{\mathbf{y}}_k[i] \mid k \in \mathcal{I}'\})$ can be simulated with $\{\hat{\mathbf{x}}_k[\mathcal{I}_k]\}_{k=1}^\ell$. This step puts at most $|\mathcal{I}_{rand}|$ indices into each of $\{\mathcal{I}_k\}_{k \in \mathcal{K}}$ for $|\mathcal{K}| = |\mathcal{P}_L| + |\mathcal{P}_O|$, corresponding to a $(|\mathcal{P}_L| + |\mathcal{I}_{rand}|)$ -chunk of $\{\hat{\mathbf{x}}\}_{k=1}^\ell$.

Now, all the probes are simulated, and $\{\hat{\mathbf{x}}_k[\mathcal{I}_k]\}_{k \in [\ell]}$ corresponds to a $(|\mathcal{P}_L| + |\mathcal{P}_{rand}| + |\mathcal{P}_{input}|)$ -chunk of $\{\hat{\mathbf{x}}_k\}_{k \in [\ell]}$. Therefore, for any t_{out} -chunk of output sharings and internal probes \mathcal{P}_{int} such that $|\mathcal{P}_{int}| + t_{out} \leq d$, there exists a $(t_{out} + |\mathcal{P}_{int}|)$ -chunk of input sharings, and a simulator S such that

$$\Pr \left[D \left(G_{\mathcal{P}} \left(\{\hat{\mathbf{x}}_k\}_{k=1}^\ell \right), \{\hat{\mathbf{x}}_k\}_{k=1}^\ell \right) = 1 \right] = \Pr \left[D \left(S(\mathcal{S}), \{\hat{\mathbf{x}}_k\}_{k=1}^\ell \right) = 1 \right],$$

where \mathcal{P} is the set of probes. □

I.3 Proof of Lemma 5

As trivial addition over packed sharings manipulates shares with different indices separately. Each internal or output probe relates to at most one index of input packed sharings, and thus any t_{int} internal probes and t_{out} output probes can be simulated with at most shares with $t_{int} + t_{out}$ indices of each of input packed sharings, which completes the proof.

J An implementation approach using multiplication chain

To implement the SubBytes step of AES-128, Rivain et al. proposed to represent the inverse by a power function $\mathbb{F}_{2^8} \rightarrow \mathbb{F}_{2^8}$, which can be further decomposed into a chain of several multiplications and squaring functions [35]. We use MDS matrices from the Reed-Solomon code [34], and thus $n = d + 1$. By the MDS conjecture [36], $d \times \ell$ MDS matrix over \mathbb{F}_{2^8} shall satisfy $\ell + d \leq |\mathbb{F}_{2^8}| = 256$. Thus, we set $\ell = 16$ and implement 16 S-boxes together by using the packed multiplication. The inputs and outputs of masked S-boxes are 16 sharings. The process is shown in Figure 13. PC denotes the packed multiplication in Gadget 1 with $\ell = 16$ (and, by Theorem 2, is d -CSNI). The $(\cdot)^2$, $(\cdot)^4$, $(\cdot)^{16}$ and Aff are implemented by Gadget 3 (and, by Theorem 3, are d -CNI). The R is a d -CSNI refreshing with identical input / output secrets by calling the packed multiplication with the input sharings and sharings of $(1, \dots, 1)$, and, by Theorem 2, is d -CSNI. We can confirm from the figure that the composition follows the composition rules in Lemmas 6 and 7, and thus the composed gadget is d -CSNI.

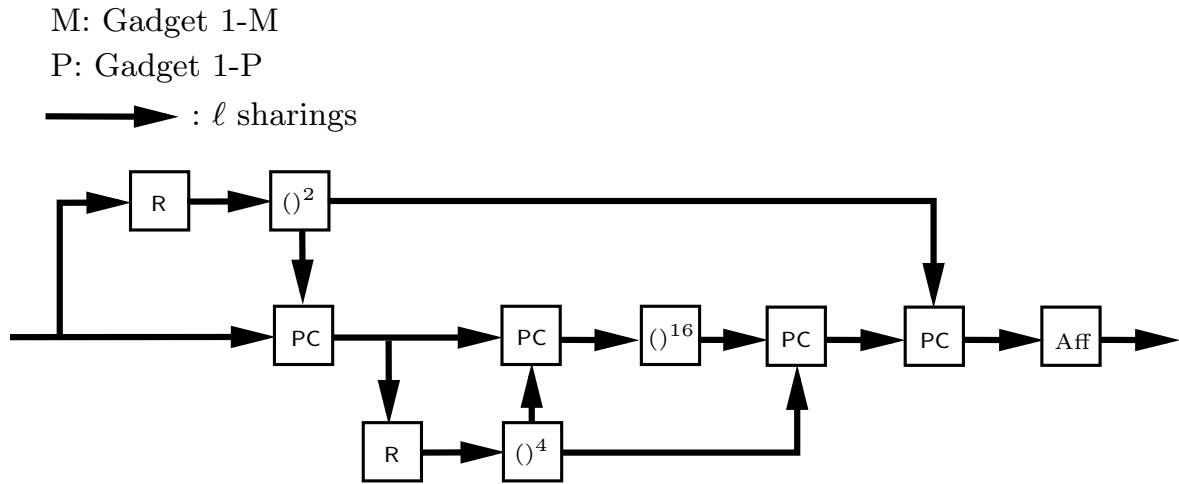


Fig. 13. Masked AES S-box with packed multiplication using multiplication chain.

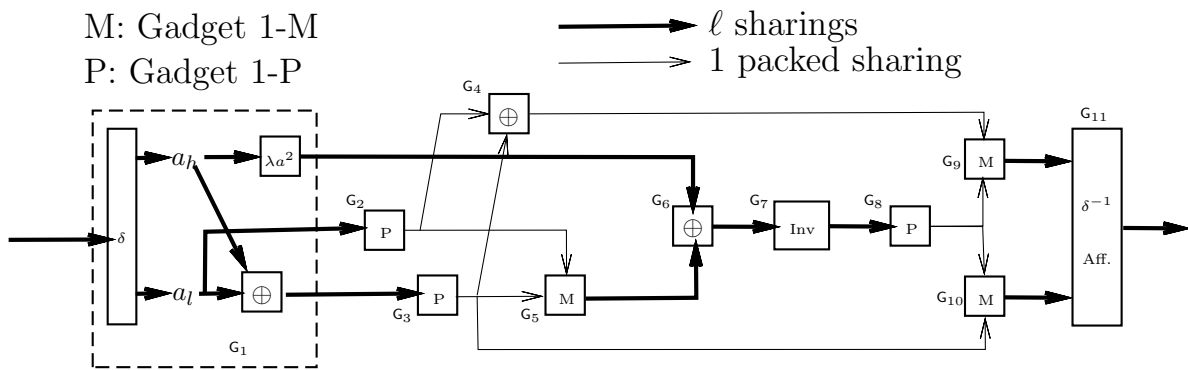


Fig. 14. AES S-box

K Proof of Proposition 1

Let the composed gadget be \mathbf{G} . Assume that the probes of \mathbf{G} consists of t_{int} internal probes and t_{out} -chunk of output sharings such that $t_{int} + t_{out} \leq d$. As shown in Figure 14, the gadgets of δ , λa^2 and first \oplus can be regarded as a whole gadget \mathbf{G}_1 , then we can order the gadgets as $\mathbf{G}_1, \dots, \mathbf{G}_{11}$, such that \mathbf{G}_i comes before \mathbf{G}_j for $i < j$. we divide the probes of \mathbf{G} into different subsets $\mathcal{P}_1, \dots, \mathcal{P}_{11}$ and \mathcal{P}_O such that all the internal probes of \mathbf{G}_i are in \mathcal{P}_i for $i = [11]$ and all the internal probes are in \mathcal{P}_O . First of all, Lemma 14 provide a stronger security claim (than the NI) for the trivial addition gadget \mathbf{G}_6 . \square

Lemma 14 *For a trivial addition gadget with input sharings $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell \in \mathbb{F}_q^n, \dots, \mathbb{F}_q^n$ and $\hat{\mathbf{y}}_1, \dots, \hat{\mathbf{y}}_\ell \in \mathbb{F}_q^n, \dots, \mathbb{F}_q^n$, any t_{out} -chunk of output sharings and t_{int} internal probes such that $t_{out} + t_{int} \leq t < n$ can be simulated with a t -chunk of $\hat{\mathbf{x}}_1, \dots, \hat{\mathbf{x}}_\ell$ and a t -chunk of $\hat{\mathbf{y}}_1, \dots, \hat{\mathbf{y}}_\ell$.*

Proof. The probes are either input variables (denoted as \mathcal{P}_{int}), or output shares (denoted as \mathcal{P}_{out}). We have that $|\mathcal{P}_{int}| = t_{int}$, and \mathcal{P}_{int} is t_{out} -chunk of output sharings. We build the sets \mathcal{I} and \mathcal{J} and run a simulator as following steps

- Initiate sets \mathcal{I} and \mathcal{K} to be empty sets.
- For each probe in \mathcal{P}_{input} , say $\hat{\mathbf{x}}_k[i]$ or $\hat{\mathbf{y}}_k[i]$, then put i and k into \mathcal{I} and \mathcal{K} . Then, this probe is a function of $\{\hat{\mathbf{x}}_k[\mathcal{I}]\}_{k \in \mathcal{K}}$ and $\{\hat{\mathbf{y}}_1[\mathcal{I}]\}_{k \in \mathcal{K}}$, and thus can be simulated.
- For each probe in \mathcal{P}_O , say $\hat{\mathbf{x}}_k[i] \oplus \hat{\mathbf{y}}_k[i]$, then put i and k into \mathcal{I} and \mathcal{K} . Then, this probe is a function of $\{\hat{\mathbf{x}}_k[\mathcal{I}]\}_{k \in \mathcal{K}}$ and $\{\hat{\mathbf{y}}_1[\mathcal{I}]\}_{k \in \mathcal{K}}$, and thus can be simulated.

Therefor, for any t_{out} -chunk of output sharings and internal probes \mathcal{P}_{int} such that $|\mathcal{P}_{int}| + t_{out} \leq t$, there exists sets \mathcal{I} and \mathcal{K} such that $|\mathcal{I}| + |\mathcal{K}| \leq t$, and a simulator \mathbf{S} such that

$$\begin{aligned} & \Pr [\mathbf{D}(\mathbf{G}_{\mathcal{P}}(\{\hat{\mathbf{x}}_k, \hat{\mathbf{y}}_k\}_{k \in [\ell]}), \{\hat{\mathbf{x}}_k, \hat{\mathbf{y}}_k\}_{k \in [\ell]}) = 1] \\ &= \Pr [\mathbf{D}(\mathbf{S}(\{\hat{\mathbf{x}}_k[\mathcal{I}], \hat{\mathbf{y}}_k[\mathcal{I}]\}_{k \in \mathcal{K}}), \{\hat{\mathbf{x}}_k, \hat{\mathbf{y}}_k\}_{k \in [\ell]}) = 1], \end{aligned}$$

where $\mathcal{P} = \mathcal{P}_{int} \cup \mathcal{P}_O$. \square

Besides, we can see that gadget \mathbf{G}_1 operates the input shares separately, and thus by Lemma 4, it is d -CNI. The probe propagation framework then analysis the gadgets one by one from \mathbf{G}_{11} to \mathbf{G}_1 . A set \mathcal{S} is initiated to empty. For $i \in [11]$, let \mathcal{S}_i be propagated shares of \mathbf{G}_i . We summarize the analysis based on the probe propagation framework in Table 7.

L An illustration of GCM

Table 7. Proof of AES S-box based on the probe propagation framework

| Gadgets | Security notion | Probes | Propagated shares \mathcal{S}_i | \mathcal{S} |
|----------|-----------------|--|--|-----------------|
| G_{11} | d -CNI | $\mathcal{P}_{11} \cup \mathcal{P}_O$, where \mathcal{P}_O is t_{out} -chunk of G 's output sharings | t_{11} -chunk of G_{11} 's input sharings, for $t_{11} = \mathcal{P}_{11} + t_{out}$ | \emptyset |
| G_{10} | d -OCNI | $\mathcal{P}_{10} \cup \mathcal{S}_{11}^{(1)}$, where $\mathcal{S}_{11}^{(1)}$ is $t_{11}^{(1)}$ -chunk of G_{11} 's input sharings | $\hat{\mathbf{x}}_{G_{10}}[\mathcal{I}_{G_{10}}] \cup \hat{\mathbf{y}}_{G_{10}}[\mathcal{J}_{G_{10}}]$, $ \mathcal{I}_{G_{10}} = \mathcal{P}_{10} + t_{11}^{(1)}$ and $ \mathcal{J}_{G_{10}} = \mathcal{P}_{10} + t_{11}^{(1)}$ | \emptyset |
| G_9 | d -OCNI | $\mathcal{P}_9 \cup \mathcal{S}_{11}^{(2)}$, where $\mathcal{S}_{11}^{(2)}$ is $t_{11}^{(2)}$ -chunk of G_{11} 's input sharings | $\hat{\mathbf{x}}_{G_9}[\mathcal{I}_{G_9}] \cup \hat{\mathbf{y}}_{G_9}[\mathcal{J}_{G_9}]$, $ \mathcal{I}_{G_9} = \mathcal{P}_9 + t_{11}^{(2)}$ and $ \mathcal{J}_{G_9} = \mathcal{P}_9 + t_{11}^{(2)}$ | \emptyset |
| G_8 | d -ICSNI | $\mathcal{P}_8 \cup \hat{\mathbf{y}}_{G_{10}}[\mathcal{J}_{G_{10}}] \cup \hat{\mathbf{x}}_{G_9}[\mathcal{I}_{G_9}]$ | t_8 -chunk of G_8 's input sharings, for $t_8 = \mathcal{P}_8 $ | \emptyset |
| G_7 | d -CSNI | $\mathcal{P}_7 \cup \mathcal{S}_8$ | t_7 -chunk of G_7 's input sharings, for $t_7 = \mathcal{P}_7 $ | \emptyset |
| G_6 | Lemma 14 | $\mathcal{P}_6 \cup \mathcal{S}_7$ | t_6 -chunk of G_6 's input sharings, for $t_6 = \mathcal{P}_6 + t_7 = \mathcal{P}_6 + \mathcal{P}_7 $ | \emptyset |
| G_5 | d -OCNI | $\mathcal{P}_5 \cup \mathcal{S}_6^{(1)}$, where $\mathcal{S}_6^{(1)}$ is $t_6^{(1)}$ -chunk of G_6 's input sharings | t_6 -chunk of G_6 's input sharings, for $t_6 = \mathcal{P}_6 + t_7 = \mathcal{P}_6 + \mathcal{P}_7 $ | \emptyset |
| G_4 | Lemma 5 | $\mathcal{P}_4 \cup \hat{\mathbf{y}}_{G_9}[\mathcal{J}_{G_9}]$ | $\hat{\mathbf{x}}_{G_4}[\mathcal{I}_{G_4}] \cup \hat{\mathbf{y}}_{G_4}[\mathcal{J}_{G_4}]$, $ \mathcal{I}_{G_4} = \mathcal{P}_4 + \mathcal{J}_{G_9} $ and $ \mathcal{J}_{G_4} = \mathcal{P}_4 + \mathcal{J}_{G_9} $ | \emptyset |
| G_3 | d -ICSNI | $\mathcal{P}_3 \cup \hat{\mathbf{x}}_{G_5}[\mathcal{I}_{G_5}] \cup \hat{\mathbf{x}}_{G_4}[\mathcal{I}_{G_4}] \cup \hat{\mathbf{x}}_{G_{10}}[\mathcal{I}_{G_{10}}]$ | t_3 -chunk of G_3 's input sharings, for $t_3 = \mathcal{P}_3 $ | \emptyset |
| G_2 | d -ICSNI | $\mathcal{P}_2 \cup \hat{\mathbf{y}}_{G_5}[\mathcal{J}_{G_5}] \cup \hat{\mathbf{y}}_{G_4}[\mathcal{J}_{G_4}]$ | t_2 -chunk of G_2 's input sharings, for $t_2 = \mathcal{P}_2 $ | \emptyset |
| G_1 | d -CNI | $\mathcal{P}_1 \cup \mathcal{S}_6^{(2)} \cup \mathcal{S}_2 \cup \mathcal{S}_3$ | t_1 -chunk of G_1 's input sharings, for $t_1 = \mathcal{P}_1 + t_6^{(2)} + t_2 + t_3$, and thus $t_1 = \mathcal{P}_1 + \mathcal{P}_6 + \mathcal{P}_7 + \mathcal{P}_1 + \mathcal{P}_2 $ | \mathcal{S}_1 |

* $\mathcal{S}_6 = \mathcal{S}_6^{(1)} \cup \mathcal{S}_6^{(2)}$ and $t_6 = t_6^{(1)} + t_6^{(2)}$.
 * $\mathcal{S}_{11} = \mathcal{S}_{11}^{(1)} \cup \mathcal{S}_{11}^{(2)}$ and $t_{11} = t_{11}^{(1)} + t_{11}^{(2)}$.

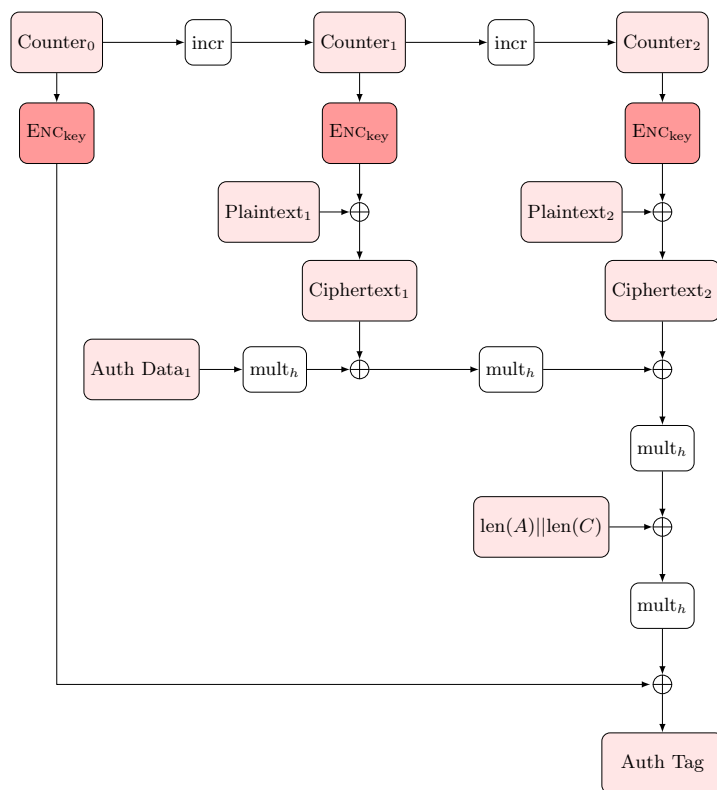


Fig. 15. An Illustration of GCM.