

# Multi-Input Functional Encryption: Efficient Applications From Symmetric Primitives (extended version)

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**Abstract.** Functional Encryption (FE) allows users who hold a specific secret key (known as the functional key) to learn a specific function of encrypted data whilst learning nothing about the content of the underlying data. Considering this functionality and the fact that the field of FE is still in its infancy, we sought a route to apply this potent tool to design efficient applications. To this end, we first built a symmetric FE scheme for the  $\ell_1$  norm of a vector space, which allows us to compute the sum of the components of an encrypted vector. Then, we utilized our construction, to design an Order-Revealing Encryption (ORE) scheme and a privately encrypted database. While there is room for improvement in our schemes, this work is among the first attempts that seek to utilize FE for the solution of practical problems that can have a tangible effect on people’s daily lives.

**Keywords:** Differential Privacy · Functional Encryption · Order Revealing Encryption

## 1 Introduction

Functional Encryption (FE) is an emerging cryptographic technique that allows selective computations over encrypted data. FE schemes provide a key generation algorithm that outputs decryption keys with remarkable capabilities. More precisely, each decryption key  $\text{sk}_f$  is associated with a function  $f$ . In contrast to traditional cryptographic techniques, using  $\text{sk}_f$  on a ciphertext  $\text{Enc}(x)$  does *not* recover  $x$  but a function  $f(x)$  – thus keeping the actual value  $x$  private. While the first constructions of FE allowed the computation of a function over a *single* ciphertext, more recent works [24] introduced the more general notion of multi-input FE (MIFE). In a MIFE scheme, given ciphertexts  $\text{Enc}(x_1), \dots, \text{Enc}(x_n)$ , a user can use  $\text{sk}_f$  to recover  $f(x_1, \dots, x_n)$ . The function  $f$  can allow only highly processed forms of data to be learned by the functional key holder. Unfortunately, while MIFE seems to be a perfect fit for many real-life applications – especially cloud-based ones where multiple users store large volumes of data in remote and

possibly corrupted entities [33,34] – most of the works in the field revolve around constructing *generic* schemes that do not support specific functions. Hence, while the concept of FE has the potential to unleash new, creative, useful and emerging applications, it still holds a promise that remains *largely untapped* from a practical perspective. Having identified the importance of FE and believing that it is a family of modern encryption schemes that can push us into an uncharted technological terrain, we try to make a first attempt to smooth out the identified asymmetries between theory and practice. To do so, we first design a MIFE scheme for the  $\ell_1$  norm of a vector space based on [1]. Then, using our MIFE scheme we attempt a first approach in embedding FE into the problems of Order-Revealing-Encryption (ORE) [11] and Differentially Private Databases [32].

An ORE scheme simply requires that there exists a publicly computable function that compares two ciphertexts. ORE is an important cryptographic primitive in the study of symmetric searchable encryption because it allows for efficient range queries, sorting, and threshold filtering on encrypted data. An encryption scheme is called order-revealing if the comparison of two ciphertexts leaks *only* the ordering of the corresponding plaintexts and nothing else. Approaching the problem of ORE using MIFE is *not* a novel idea. In [11], authors proposed a MIFE-based ORE construction. However, their scheme relies on multi-linear maps [12] and thus, is impractical for real-life applications. While subsequent designs in the field of ORE [28] are significantly more efficient, they do not rely on functional encryption. With this in mind, we sought to design the first order-revealing encryption scheme based solely on MIFE from symmetric primitives. Continuing our research into proving that FE can be a fundamental tool for a slew of applications, we turned our attention to the important problem of differential privacy [19]. While cryptography ensures the confidentiality of the data stored in a database, it does not ensure the privacy of the users. This is one of the big hurdles that security researchers as well as big industrial players have wrestled with for decades [5,26]. While there are numerous works that deal with either the problem of private databases [21], or that of encrypted databases [20], there are only a handful [3] that focus on combining differential privacy with cryptography to construct privately encrypted databases. This fact motivated us to attempt a first approach towards a multi-input functionally encrypted private database. In particular, we design an application in which a data owner (curator) encrypts her data locally using MIFE, before outsourcing them to the cloud. Then, we allow a *possibly malicious* analyst to query the database for various functions of her choice (i.e. sum of the entries, averages, etc.). To make our construction private, we use the well-studied *Laplace Mechanism* [22].

## 1.1 Contribution

The contribution of this paper is twofold: (1) First, we design a MIFE scheme in the symmetric key setting for the  $\ell_1$  norm of a vector, based on the single-client MIFE for inner products presented in [1]. Then, we show how our scheme can be transformed from the single-client to the multi-client setting. This transformation requires the users to perform a Multi-Party Computation (MPC). More

precisely, each user generates their own symmetric keys independently and then they collaborate to calculate a functional decryption key  $sk_f$  that is derived from a combination of all the generated symmetric keys. This result is quite remarkable since users generate their private keys locally and independently. As a result, their symmetric keys are never exposed to unauthorized parties, and thus no private information about the content of the underlying ciphertexts is revealed. At the same time, sufficient information to generate the functional decryption key is provided. (2) Our second contribution derives from the identified need to create a dialogue between the theoretical concept of FE and real life applications. As a result, we tried to provide a pathway towards new prospects that show the direct and realistic applicability of this promising encryption technique when applied to concrete obstacles. To this end, we showed how our MIFE scheme can be used to provide a solution to two disjointed but important problems. More precisely, we show how our scheme can be used to provide realistic solutions to the problems of Order-Revealing-Encryption [11] and Differentially Private Databases [3].

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**Order Revealing Encryption:** ORE [11] is an encryption technique that allows direct comparison of two ciphertexts, yielding the ordering of the corresponding plaintexts. This is done by using a comparison function CMP. This is done with the help of a comparison function CMP defined as follows:

$$\text{CMP}(x_i, x_j) = \begin{cases} 1 & \text{if } x_i > x_j \\ 0 & \text{if } x_i = x_j \\ -1 & \text{if } x_i < x_j \end{cases}$$

In our case, the CMP function takes as input two ciphertexts encrypted under our MIFE scheme and, with the help of a secret functional key  $\text{sk}_f$ , outputs the result  $r \in \{-1, 0, 1\}$  depending on the ordering of the corresponding plaintexts. Our first ORE scheme, MORE, makes direct use of our MIFE scheme for the  $\ell_1$  norm resulting to a very efficient and straight forward solution. However, MORE is susceptible to the inference attacks presented in [32]. To this end, we also present TWOMORE – a two-layered encryption ordering revealing scheme that is based on MORE and is susceptible to the attacks presented in [32]. More precisely, we prove that TWOMORE satisfies the *best-possible* security for an ORE scheme as defined in [9] which states that the ciphertexts do not leak any information beyond the ordering of the plaintexts.

***Privately Encrypted Databases:*** We design a Privately Encrypted Database similar to the one presented in [3]. The main difference between the two works, is that in [3], authors use as a basis Structured Encryption [15], which can be seen as a generalization of Symmetric Searchable Encryption [37] while we solely base our construction on our MIFE scheme for the  $\ell_1$  norm. Moreover, we choose to use the Laplace Mechanism [22] as a privacy mechanism. The reason for choosing the Laplace Mechanism is that it is defined using the  $\ell_1$  norm of a database (i.e. the sum of all entries) and thus, along with our MIFE scheme, they compliment each other very well. Finally, we prove the security of our construction assuming the existence of a *statistical* adversary.

## 1.2 Organization

In Section 2, we present well-established works in the area of Functional Encryption and Multi-Input Functional Encryption. In Section 3 we provide the basic notation and definitions that are used throughout the paper. In Section 4, we present the first result of this paper, a multi-client MIFE scheme for the  $\ell_1$  norm in the symmetric key setting. Then, we show how our MIFE scheme can be leveraged to design an order revealing encryption scheme (Section 5) and a privately encrypted database (Section 6) In Section 7 we discuss future directions for the applications presented in this paper and finally, Section 8 concludes the paper.

## 2 Related Work

While numerous studies with general definitions and generic constructions of FE have been proposed [35,27,38,25,14] there is a clear lack of work proposing FE schemes supporting specific functions – a necessary step that would allow

FE to transcend its limitations and provide the foundations for reaching its full potential. To the best of our knowledge, the only works that have shown how to efficiently run specific functions on ciphertexts is [1,2] which calculates inner-product and [36] which successfully executes computations with quadratic polynomials. While [1] and [14] are symmetric FE schemes (i.e. efficient), their actual application in real-life scenarios can be considered as limited since both are limited to supporting the single-client model. Our work is heavily influenced by the symmetric key MIFE scheme for inner products presented in [1] where authors designed a scheme that can be regarded as the FE equivalent of the one-time-pad. More precisely, using [1] as a basis, we constructed a symmetric key MIFE scheme for the  $\ell_1$  norm of an arbitrary vector space. Most importantly, we show that our construction can also support the multi-client model while preserving exactly the same security properties as the MIFE for inner-product in [1]. This is a significant result as it proves that functional encryption can be efficiently applied to solve more complex problems.

### 3 Preliminaries

**Notation** If  $\mathcal{Y}$  is a set, we use  $y \xleftarrow{\$} \mathcal{Y}$  if  $y$  is chosen uniformly at random from  $\mathcal{Y}$ . The cardinality of a set  $\mathcal{Y}$  is denoted by  $|\mathcal{Y}|$ . If  $\mathcal{X}$  and  $\mathcal{Y}$  are two sets, we denote by  $[\mathcal{X}, \mathcal{Y}]$  all the functions from  $\mathcal{X}$  to  $\mathcal{Y}$  and by  $\overline{[\mathcal{X}, \mathcal{Y}]}$  all the injective functions from  $\mathcal{X}$  to  $\mathcal{Y}$ . For a positive integer  $m$ ,  $[m]$  denotes the set  $\{1, \dots, m\}$ . If  $m \in \mathbb{Z}$ , we denote by  $m[i]$  the digit in the  $i$ -th position of  $m$  where  $m[0]$  is the rightmost digit. The number of digits of  $m$  in base  $n$  is  $\lfloor \log_n m \rfloor + 1$ . Vectors are denoted in bold as  $\mathbf{x} = [x_1, \dots, x_n]$ . A probabilistic polynomial time (PPT) adversary  $\mathcal{ADV}$  is a randomized algorithm for which there exists a polynomial  $p(z)$  such that for all input  $z$ , the running time of  $\mathcal{ADV}(z)$  is bounded by  $p(|z|)$ . A database is denoted by DB, an encrypted database by EDB and a private encrypted database by PEDB. An invertible pseudorandom function (IPRF) [10] is defined as follows:

**Definition 1 (Invertible Pseudorandom Function (IPRF)).** *An IRPF with key-space  $\mathcal{K}$ , domain of definition  $\mathcal{X}$  and range  $\mathcal{Y}$  consists of two functions  $G : (\mathcal{K} \times \mathcal{X}) \rightarrow \mathcal{Y}$  and  $G^{-1} : (\mathcal{K} \times \mathcal{Y}) \rightarrow \mathcal{X} \cup \{\perp\}$ . Moreover, let  $\mathbf{G.Gen}(1^\lambda)$  be an algorithm that given the security parameter  $\lambda$ , outputs  $k \in \mathcal{K}$ . The functions  $G$  and  $G^{-1}$  satisfy the following properties:*

1.  $G^{-1}(k, G(k, x)) = x, \forall x \in \mathcal{X}$ .
2.  $G^{-1}(k, y) = \perp$  if  $y$  is not an image of  $G$ .
3.  $G$  and  $G^{-1}$  can be efficiently computed by deterministic polynomial algorithms.
4.  $G(k, \cdot) \in \overline{[\mathcal{X}, \mathcal{Y}]}, G^{-1}(k, \cdot) \in \overline{[\mathcal{Y}, \mathcal{X}]}$

The function  $G : (\mathcal{K} \times \mathcal{X}) \rightarrow \mathcal{Y}$  is an IPRF if  $\forall$  PPT adversary  $\mathcal{A}$ :

$$\begin{aligned} & |Pr[k \leftarrow \mathbf{G.Gen}(1^\lambda) : \mathcal{A}^{G(k, \cdot), G^{-1}(k, \cdot)}(1^\lambda) = 1] - \\ & Pr[k' \xleftarrow{\$} \overline{[\mathcal{X}, \mathcal{Y}]} : \mathcal{A}^{R(\cdot), R^{-1}(\cdot)}(1^\lambda) = 1] = \text{negl}(\lambda) \end{aligned} \quad (1)$$

**Definition 2 ( $\ell_1$  norm).** The  $\ell_1$  norm of  $\mathbb{Z}^n$  is a function  $\|\cdot\|_1$  defined by:

$$f(x) = \|\mathbf{x}\|_1 = \sum_{i=1}^{i=n} x_i = x_1 + \dots + x_n, \text{ for } \mathbf{x} = [x_1, \dots, x_n] \in \mathbb{Z}^n$$

### 3.1 Multi-Input Functional Encryption

**Definition 3 (Multi-Input Functional Encryption in the Symmetric Key Setting).** Let  $\mathcal{F} = \{f_1, \dots, f_n\}$  be a family of  $n$ -ary functions where each  $f_i$  is defined as follows:  $f_i : \mathbb{Z}^n \rightarrow \mathbb{Z}$ . A multi-input functional encryption scheme for  $\mathcal{F}$  consists of the following algorithms:

- $\text{Setup}(1^\lambda)$  : Takes as input a security parameter  $\lambda$  and outputs a secret key  $\mathbf{K} = [k_1, \dots, k_n] \in \mathbb{Z}^n$ .
- $\text{Enc}(\mathbf{K}, i, x_i)$  : Takes as input  $\mathbf{K}$ , an index  $i \in [n]$  and a message  $x_i \in \mathbb{Z}$  and outputs a ciphertext  $ct_i$ .
- $\text{KeyGen}(\mathbf{K}, f)$  : Takes as input  $\mathbf{K}$  and a description of a function  $f_i$  and outputs a functional decryption key  $\text{sk}_{f_i}$ .
- $\text{Dec}(\text{sk}_{f_i}, ct_1, \dots, ct_n)$  : Takes as input a decryption key  $\text{sk}_{f_i}$  for a function  $f_i$  and  $n$  ciphertexts and outputs a value  $y \in \mathbb{Z}$ .

For the needs of our work, we will draw on the one-adaptive (one-AD) and one-selective (one-SEL) security definitions from [1] that were first formalized in [4]. Informally, in the one-AD-IND security game, the adversary  $\mathcal{ADV}$  receives the encryption key of the MIFE scheme and then adaptively queries the corresponding oracle for functional decryption keys of her choice. Furthermore,  $\mathcal{ADV}$  outputs two messages  $x_0$  and  $x_1$  to the encryption oracle, who flips a random coin and outputs an encryption of  $x_\beta, \beta \in \{0, 1\}$ . If the functional keys are associated with functions that do not distinguish between the messages (i.e.  $f(x_0) = f(x_1)$ ) then  $\mathcal{ADV}$  should *not* be able to distinguish between the encryptions of  $x_0$  and  $x_1$ . In the case of the one-SEL-IND security, the game is identical to the one-AD-IND case, with the only difference being that  $\mathcal{ADV}$  needs to decide on the  $x_0$  and  $x_1$  messages *before* seeing the encryption key. The “one” in both security games determines that the encryption oracle can only be queried once for each slot  $i$  (i.e. the adversary is not allowed to issue multiple queries to the encryption oracle for the same  $x_i$ ).

**Definition 4 (one-AD-IND-secure MIFE).**

For every MIFE scheme for  $\mathcal{F}$ , every PPT adversary  $\mathcal{ADV}$ , every security parameter  $\lambda \in \mathbb{N}$  we define the following experiment for  $\beta \in \{0, 1\}$ :

*Adaptive Security*

one-AD-IND $_{\beta}^{\text{MIFE}}$ ( $1^\lambda, \mathcal{ADV}$ ):  
 $\mathbf{K} \leftarrow \text{Setup}(1^\lambda)$   
 $\alpha \leftarrow \mathcal{ADV}^{\text{KeyGen}(\mathbf{K}), \text{Enc}(\cdot, \cdot)}$   
 Output  $\alpha$

Where  $\text{Enc}(\cdot, \cdot, \cdot)$  is an oracle that on input  $(i, x_i^0, x_i^1)$ , flips a random coin  $\beta$  and outputs  $\text{Enc}(\mathbf{K}, i, x_i^\beta)$ ,  $\beta \in \{0, 1\}$ . Moreover,  $\mathcal{ADV}$  is restricted to only make queries to the  $\text{KeyGen}$  oracle satisfying  $f(x_1^0, \dots, x_n^0) = f(x_1^1, \dots, x_n^1)$ . A MIFE scheme is said to be one-AD-IND secure if for all PPT adversaries  $\mathcal{ADV}$ , their advantage is negligible in  $\lambda$  where the advantage is defined as:

$$\begin{aligned} \text{Adv}^{\text{one-AD-IND}}(\lambda, \mathcal{ADV}) &= |\text{Pr}[\text{one-AD-IND}_0^{\text{MIFE}}(1^\lambda, \mathcal{ADV}) = 1] \\ &\quad - \text{Pr}[\text{one-AD-IND}_1^{\text{MIFE}}(1^\lambda, \mathcal{ADV}) = 1]| \end{aligned}$$

**Definition 5 (one-SEL-IND-secure MIFE).**

For every MIFE scheme for  $\mathcal{F}$ , every PPT adversary  $\mathcal{ADV}$ , and every security parameter  $\lambda \in \mathbb{N}$  we define the following experiment for  $\beta \in \{0, 1\}$ :

*Selective Security*

$\text{one-SEL-IND}_\beta^{\text{MIFE}}(1^\lambda, \mathcal{ADV})$ :  
 $\{x_i^b\}_{i \in [n], b \in \{0, 1\}} \leftarrow \mathcal{ADV}(1^\lambda, f_i)$   
 $\mathbf{K} \leftarrow \text{Setup}(1^\lambda)$   
 $ct_i = \text{Enc}(\mathbf{K}, x_i^\beta)$   
 $\alpha \leftarrow \mathcal{ADV}^{\text{KeyGen}(\mathbf{K})}(\{ct_i\})$   
 Output  $\alpha$

$\mathcal{ADV}$  is restricted to only make queries to the  $\text{KeyGen}$  oracle satisfying  $f(x_1^0, \dots, x_n^0) = f(x_1^1, \dots, x_n^1)$ . A MIFE scheme is said to be one-SEL-IND secure if for all PPT adversaries  $\mathcal{ADV}$ , their advantage is negligible in  $\lambda$  where the advantage is defined as:

$$\begin{aligned} \text{Adv}^{\text{one-SEL-IND}}(\lambda, \mathcal{ADV}) &= |\text{Pr}[\text{one-SEL-IND}_0^{\text{MIFE}}(1^\lambda, \mathcal{ADV}) = 1] \\ &\quad - \text{Pr}[\text{one-SEL-IND}_1^{\text{MIFE}}(1^\lambda, \mathcal{ADV}) = 1]| \end{aligned}$$

## 4 Multi-Input Functional Encryption for the $\ell_1$ Norm

In this section, we present the first result and an important contribution of our work. In particular, in the first part of this section, we show how the one-AD-IND-secure MIFE scheme for inner-products from [1], can be transformed to a one-AD-IND-secure MIFE scheme for the  $\ell_1$  norm ( $\text{MIFE}_{\ell_1}$ ), while preserving exactly the same security properties. Then, we show how we can transform our construction from the single-client model to the multi-client one. For purposes of completeness, we briefly recall the one-AD-IND-secure MIFE scheme for inner-products in Figure 1. The security of both MIFE schemes (inner products and  $\ell_1$  norm), is derived from the fact that they behave as the functional encryption equivalent of the one-time-pad. Note that, just like in the case of the one-time-pad, to achieve perfect secrecy, we require that  $|k_i| \geq |x_i|$ , where  $k_i$  is the encryption key and  $x_i$ , the message to be encrypted.

$\text{Setup}(1^\lambda) :$ $\forall i \in [n], k_i \xleftarrow{\$} \mathbb{Z}$ Return $\mathbf{K} = \{k_1, \dots, k_n\} \in \mathbb{Z}^n$	$\text{KeyGen}(\mathbf{K}, y_1    \dots    y_n) :$ Return $\text{sk}_f = \sum_{i \in [n]} \langle k_i, y_i \rangle$
$\text{Enc}(\mathbf{K}, i, x_i) :$ Return $ct_i = x_i + k_i$	$\text{Dec}(\text{sk}_f, ct_1, \dots, ct_n) :$ Return $\sum_{i=1}^n \langle ct_i, y_i \rangle - \text{sk}_f$

Fig. 1: one-AD-IND-secure MIFE for inner products.

In the previous scheme, by fixing  $\mathbf{y}$  to be  $\mathbf{y} = [1, \dots, 1]$ , we compute  $\langle \mathbf{x}, 1 \rangle = \|\mathbf{x}\|_1$  for  $\mathbf{x} \in \mathbb{Z}^n$ . By doing so, we manage to transform the original inner products MIFE to a new construct that successfully computes the  $\ell_1$  norm. Our construction is illustrated in Figure 2. Our construction, illustrated in Figure 2 is a special case of the scheme presented in [1] and hence, it is straight forward that the security proofs of the two schemes will be similar. By fixing  $y$  to be  $y = [1, \dots, 1]$ , we compute  $\langle x, 1 \rangle = \|x\|_1$  for  $x \in \mathbb{Z}^n$  and thus, transform the MIFE for inner products to MIFE for the  $\ell_1$  norm. Our construction is illustrated in Figure 2. Since our construction is a special case of the scheme in Figure 1, it is straight forward that the security proof of our scheme will be very similar to the one presented in [1].

$\text{Setup}(1^\lambda) :$ $\forall i \in [n], k_i \xleftarrow{\$} \mathbb{Z}$ Return $\mathbf{K} = [k_1, \dots, k_n] \in \mathbb{Z}^n$	$\text{KeyGen}(\mathbf{K}) :$ Return $\text{sk}_f = \ \mathbf{K}\ _1 = \sum_i^n k_i$
$\text{Enc}(\mathbf{K}, i, x_i) :$ Return $ct_i = x_i + k_i$	$\text{Dec}(\text{sk}_f, ct_1, \dots, ct_n) :$ Return $\sum_{i=1}^n ct_i - \text{sk}_f$

Fig. 2: one-AD-IND-secure MIFE for the  $\ell_1$  norm (MIFE $_{\ell_1}$ ).

**Theorem 1.** *The MIFE scheme for the  $\ell_1$  norm (described in Figure 2) is one-AD-IND-secure. That is, for all PPT adversaries  $\mathcal{ADV}$  :*

$$\text{Adv}_{\mathcal{ADV}}^{\text{one-AD-IND}}(\lambda) = 0$$

*Proof.* The proof consists of two parts. First we construct a selective distinguisher  $\mathcal{B}$  whose advantage for the one-SEL-IND experiment is an upper bound for the advantage of any adaptive distinguisher  $\mathcal{ADV}$ . Then, using the fact that the MIFE for the  $\ell_1$  norm behaves like the one-time-pad, we prove that the advantage of  $\mathcal{B}$  is zero.

For the first part of the proof we will use a complexity argument. In particular, let  $\mathcal{B}$  be an adversary that guesses the challenge  $\{x_i^b\}$  and then simulates

the one-AD-IND experiment of  $\mathcal{ADV}$ . If  $\mathcal{B}$  successfully guesses  $\mathcal{ADV}$ 's challenge then she can simulate  $\mathcal{ADV}$ 's view. Otherwise it outputs  $\perp$ . Hence,  $\mathcal{ADV}$ 's advantage maximizes when  $\mathcal{B}$  guesses correctly the challenge. If the input space is  $\mathcal{X}$ , then  $\mathcal{B}$  can guess successfully with probability exactly  $|\mathcal{X}|^{-1}$ . Hence:

$$Adv_{\mathcal{ADV}}^{one-AD-IND} \leq |\mathcal{X}|^{-1} Adv_{\mathcal{B}}^{one-SEL-IND}$$

From the above, it can be seen that if the input space  $\mathcal{X}$  is very large, the advantage of  $\mathcal{ADV}$  tends to zero independently of the value of  $Adv_{\mathcal{B}}^{one-SEL-IND}$  (i.e.  $|\mathcal{X}| \rightarrow \infty \Rightarrow Adv_{\mathcal{ADV}}^{one-AD-IND} \rightarrow 0$ ). We will still show that no matter the cardinality of  $\mathcal{X}$ ,  $Adv_{\mathcal{ADV}}^{one-AD-IND} = 0$ . To do so, we first need to prove that the advantage of the selective adversary is zero, or  $Adv_{\mathcal{B}}^{one-SEL-IND} = 0$ . This will directly imply that  $Adv_{\mathcal{ADV}}^{one-AD-IND} = 0$ , since we already know that  $Adv_{\mathcal{ADV}}^{one-AD-IND} \leq Adv_{\mathcal{B}}^{one-SEL-IND}$ . In Figure 3 we present a hybrid game that is identical to the one-SEL-IND security game. This is derived from the fact that if  $u \stackrel{\$}{\leftarrow} \mathbb{Z}$ , then  $\{u_i\}$  and  $\{u_i - x_i^\beta\}$  are identical distributions. It is easy to see that the only information leaking about  $\beta$ , is  $\|\mathbf{r} - \mathbf{x}^\beta\|$ , which is independent of  $\beta$  according to the definition of the security game and the restrictions of the adversary.

$\text{Hybrid}_\beta(\lambda, \mathcal{B}):$ $\{x_i^b\}_{b \in \{0,1\}} \leftarrow \mathcal{B}(1^\lambda, \mathcal{F})$ $\forall i \in [n]:$ $r_i \stackrel{\$}{\leftarrow} \mathbb{Z}$ $ct_i \leftarrow r_i$ $\alpha \leftarrow \mathcal{B}^{\mathcal{O}_{gen}(\cdot)}(ct_i)$ $\text{Output } \alpha$	$\mathcal{O}_{gen}(\mathbf{r}):$ $\forall i \in [n]:$ $\mathbf{sk}_f = \ \mathbf{r} - \mathbf{x}^\beta\ _1 =$ $\sum_{i=1}^n (r_i - x_i^\beta)$ $\text{Return } \mathbf{sk}_f$
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Fig. 3: Hybrid games for the proof of Theorem 1

While we showed that a MIFE scheme for inner products can be transformed to a MIFE scheme for the  $\ell_1$  norm, our construction is still inadequate for an e-voting protocol. This is due to the fact that our construction only supports the single-client model. In Section 4.1, we show how our single client MIFE can be extended to support the multi-client model.

#### 4.1 From Single-Client to Multi-Client MIFE

We are now ready to describe how we can transform our single-user  $\text{MIFE}_{\ell_1}$  to the multi-user MIFE for the  $\ell_1$  norm ( $\text{MUMIFE}_{\ell_1}$ ). The idea is the following: Each user generates a symmetric key  $k_i \in \mathbb{Z}$  which uses it to encrypt a plaintext  $x_i$  as  $ct_i = k_i + x_i$ . All the generated symmetric keys, form a vector

$\mathbf{K} = [k_1, \dots, k_n] \in \mathbb{Z}^n$ , where  $n$  is the number of users. The functional decryption key  $\mathbf{sk}_f$  is then  $\|\mathbf{K}\|_1$  and decryption works as follows:

$$\sum_{i=1}^n ct_i - \mathbf{sk}_f = \sum_{i=1}^n (k_i + x_i) - \sum_{i=1}^n k_i = \sum_{i=1}^n x_i = \|\mathbf{x}\|_1$$

A third party decryptor who would get access to  $\mathbf{sk}_f$  should only learn  $\|\mathbf{x}\|_1$  and *not* each individual  $x_i$ . In addition to that, the users should never reveal their symmetric keys. To achieve this, we assume the existence of a trusted authority that will allow users to perform an MPC in order to jointly compute a masked version of  $\mathbf{sk}_f$  without revealing each distinct  $k_i$ . Our construction is presented in Figure 4.

In our system model, we assume the existence of a Trusted Execution Environment (TEE) that will allow the TA to run in a trusted state. Hence, the existence of a trusted entity relies on more realistic assumptions.

**Trusted Execution Environments:** A TEE is a secure, integrity-protected environment, with processing, memory and storage capabilities, isolated from an untrusted, Rich Execution Environment that comprises the OS and installed applications. While there are several different TEEs in our work we rely on the use of Intel SGX whose main functionalities are (1) Isolation, (2) Sealing and (3) Attestation. Due to space constraints, we omit their formal description (more details can be found in [17]).

*Trusted Authority (TA)* TA is running in an enclave and is responsible for generating and distributing a unique random number  $s_i$  to each user  $u_i$ . The users will use the received random values to mask their symmetric keys. By doing so, and considering the fact that TA is running in an enclave and thus it is trusted, they will be able to jointly compute a masked version of the functional decryption key  $\mathbf{sk}_f$  which will be used by the evaluator to calculate  $\mathbf{sk}_f$ .

*Evaluator (EV)* EV is an untrusted entity responsible for collecting users' ciphertexts  $\{ct_1, \dots, ct_n\}$ , generating the functional decryption key  $\mathbf{sk}_f$  based on the masked value that will receive from users and finally, calculate  $f(x_1, \dots, x_n)$  without learning any information about each individual  $x_i$ .

<u>MUMIFE<math>_{\ell_1}</math>.Setup(<math>1^\lambda</math>) :</u> - $TA : \forall i \in [n], s_i \leftarrow \mathbb{Z}$ - $TA : s_i \rightarrow u_i$ - $TA : S = \ \mathbf{s}\ _1 = \sum_{i=1}^n s_i \rightarrow EV$ - $u_i : \text{Generates } k_i \in \mathbb{Z}$	<u>MUMIFE<math>_{\ell_1}</math>.Enc(<math>k_i, x_i, s_i</math>)</u> $T = 0$ <b>for</b> $i = 1$ <b>to</b> $n$ : - $u_i : ct_i = k_i + x_i$ - $u_i : T = T + k_i + s_i$ - $u_i : ct_i \rightarrow EV$ - <b>if</b> ( $i == n$ ): $u_i : T \rightarrow EV$ - <b>else</b> $u_i : T \rightarrow u_{i+1}$
<u>MUMIFE<math>_{\ell_1}</math>.KeyGen(<math>T, S</math>)</u> $EV : sk_f = T - S$	<u>MUMIFE<math>_{\ell_1}</math>.Dec(<math>sk_f, ct_1, \dots, ct_n</math>)</u> $EV : \sum_{i=1}^n ct_i - sk_f$

Fig. 4: Multi-Input MIFE for the  $\ell_1$  norm (MUMIFE $_{\ell_1}$ )

**Correctness:** The correctness of the MUMIFE $_{\ell_1}$  scheme presented in Figure 4 follows directly since:

$$\begin{aligned} \sum_{i=1}^n ct_i - sk_f &= \sum_{i=1}^n ct_i - T + S = \\ &= \sum_{i=1}^n k_i + \sum_{i=1}^n x_i - \sum_{i=1}^n (k_i + s_i) + \sum_{i=1}^n s_i = \|\mathbf{x}\|_1 \end{aligned}$$

**Theorem 2.** *The Multi-User Multi-Input Functional Encryption scheme for the  $\ell_1$  norm (described in Figure 4) is one-AD-IND-secure. That is, for all PPT adversaries  $\mathcal{ADV}$  :*

$$Adv_{\mathcal{ADV}}^{one-AD-IND}(\lambda) = 0$$

*Proof (Proof Sketch).* The proof is omitted since it is a direct result from Theorem 1. This can be seen by the fact that the Encryption and KeyGen oracles are identical to the ones described in Figure 3. The only difference is that in the case of MUMIFE $_{\ell_1}$ , the Setup algorithm is executed by multiple users instead of one, since each user generates a distinct symmetric key. Without loss of generality, we can assume that this is exactly the same procedure since in the case of MIFE $_{\ell_1}$ , one user samples  $n$  random numbers from  $\mathbb{Z}$  resulting to a vector  $\mathbf{K} = [k_1, \dots, k_n]$ , and in case of MUMIFE $_{\ell_1}$ ,  $n$  users sample one random number from  $\mathbb{Z}$  each, resulting to a vector  $\mathbf{K}' = [k'_1, \dots, k'_n]$ . However, the distributions  $\{k_i\}$  and  $\{k'_i\}$  are identical and thus we conclude that we can use exactly the same Hybrid game as the one in Figure 3.

## 5 Order Revealing Encryption

We now show how our MIFE $_{\ell_1}$  scheme can be utilized to perform Order Revealing Encryption (ORE). Informally, ORE is an encryption technique that allows

direct comparison of two ciphertexts yielding the order of the plaintexts. The notion was first introduced in [11] where a construction based on multi-linear maps was presented. However fascinating, such an approach is impractical for realistic scenarios. An improved ORE scheme was presented in [28] where each query requires time linear to the total number of ciphertexts. Our MORE scheme is formally presented in Figure 5.

In this section, we present MORE – a Multi-Input Functional Order Revealing Encryption scheme that takes as input two encrypted numbers and returns their ordering. MORE is solely based on the  $\text{MIFE}_{\ell_1}$  presented in Section 4.

**Definition 6 (MORE).** *MORE is a two party scheme between a curator (data owner) and a CSP that consists of three polynomial-time protocols that work as follows:*

- $EDB \leftarrow \text{Setup}(1^\lambda, DB)$ : *The Data Owner (or Curator) gives as input the security parameter  $\lambda$  and a sequence of plaintexts. The CSP receives a sequence of ciphertexts.*
- $\text{sk}_f \leftarrow \text{KeyGen}(k_i, k_j)$ : *The curator gives as input two encryption keys  $k_i$  and  $k_j$  and receives  $\text{sk}_f$ .*
- $(r \in \{-1, 0, 1\}) \leftarrow \text{Query}(ct_i, ct_j, \text{sk}_f)$ : *The curator gives as input two ciphertexts and a functional key  $\text{sk}_f$ . The server performs the comparison of the ciphertexts and returns 1 if  $c_i > c_j$ , -1 if  $c_i < c_j$  and 0 if  $c_i = c_j$ .*

Our MORE scheme is formally presented in Figure 5.

<p><u>MORE.Setup(<math>1^\lambda, DB</math>) :</u> Curator: <math>\forall x_i \in DB</math> Run:</p> <ul style="list-style-type: none"> <li>- <math>\text{MIFE}_{\ell_1}.\text{Setup}(1^\lambda)</math></li> <li>- <math>\text{MIFE}_{\ell_1}.\text{Enc}(\mathbf{K}, i, x_i)</math></li> </ul>	<p><u>MORE.Query(<math>\text{sk}_f, ct_i, ct_j</math>)</u> Curator:</p> <ul style="list-style-type: none"> <li>- Send <math>(\text{sk}_f, ct_i, ct_j)</math> to the CSP.</li> </ul>
<p><u>MORE.KeyGen(<math>ct_i, ct_j</math>)</u> Curator:</p> <ul style="list-style-type: none"> <li>- Run <math>\text{MIFE}.\text{KeyGen}(ct_i, ct_j)</math></li> <li>- Return <math>\text{sk}_f = k_j - k_i</math></li> </ul>	<p>CSP:</p> <ul style="list-style-type: none"> <li>- Run <math>\text{MIFE}.\text{Dec}(\text{sk}_f, ct_i, ct_j)</math></li> <li>- Return <math>r \in \{-1, 0, 1\}</math></li> </ul>

Fig. 5: Order Revealing Encryption based on  $\text{MIFE}_{\ell_1}$

**Correctness:** The correctness MORE scheme follows since:

$$\begin{aligned}
 ct_i - ct_j + \text{sk}_f &= (x_i + k_i) - (x_j + k_j) + \text{sk}_f \\
 &= x_i + \cancel{k_i} - x_j - \cancel{k_j} + \cancel{k_j} - \cancel{k_i} \\
 &= x_i - x_j
 \end{aligned} \tag{2}$$

**Theorem 3.** *The MORE scheme described in Figure 5 is one-AD-IND-secure.*

Proof is omitted as it is a direct result of Theorem 1.

While our construction may be simplistic, it is susceptible to the inference attacks presented by Naveed et al. in [32]. These attacks rely heavily on the fact that Order Preserving encrypted ciphertexts enable equality comparisons by design. In the next subsection, we present an extension of the MORE scheme that is secure against these attacks.

### 5.1 Two-Layered Encryption

We start by describing the core security properties that our enhanced scheme has to fulfil. First we give the definition of *best-possible* security for an ORE scheme [9].

**Definition 7 (Best-Possible Security).** *An ORE scheme satisfies the notion of best-possible security with respect to a leakage function  $\mathcal{L}_{CMP}$ , if  $\mathcal{L}_{CMP}$  only reveals the ordering of the plaintexts and nothing else. In particular:*

$$\mathcal{L}_{CMP}(ct_1, \dots, ct_n) = \{i, j, \text{CMP}(x_i, x_j)\} \quad (3)$$

Where  $\text{CMP}(x_i, x_j)$  is a comparison function defined as:

$$\text{CMP}(x_i, x_j) = \begin{cases} 1 & \text{if } x_i > x_j \\ 0 & \text{if } x_i = x_j \\ -1 & \text{if } x_i < x_j \end{cases}$$

**Definition 8 (TWOMORE with Leakage).**

Let  $\text{TWOMORE} = (\text{IPRFSetup}, \text{Setup}, \text{KeyGen}, \text{Query})$  be an ORE scheme, and let  $\mathcal{A}_q$  be an adversary for some  $q = \text{poly}(n)$ . Moreover, let  $\mathcal{S}$  be a simulator and  $\mathcal{L}(\cdot)$  a leakage function. We define the following experiments:

*Real Experiment*

$K_G \leftarrow \text{TWOMORE.IPRFSetup}(1^\lambda)$   
 $(i, j) \leftarrow \mathcal{A}_1(1^\lambda)$   
 $r \leftarrow \text{TWOMORE}(\text{sk}_f, ct_i^{(2)}, ct_j^{(2)})$   
 Output a bit  $b$  indicating whether this is the real or the ideal experiment

*Ideal Experiment*

$st_{\mathcal{S}} \leftarrow \mathcal{S}(1^\lambda)$   
 $(i, j) \leftarrow \mathbb{A}_1(1^\lambda)$   
 $r \leftarrow \text{TWOMORE}(st_{\mathcal{S}}, \mathcal{L}_{CMP}(ct_1^{(2)}, \dots, ct_N^{(2)}))$   
 Output a bit  $b$  indicating whether this is the real or the ideal experiment

We say that the ORE scheme is secure with respect to the best-possible leakage function  $\mathcal{L}_{CMP}$  if and only if no PPT adversary  $\mathcal{ADV}$  can distinguish between the real and ideal experiments.

**Definition 9 (TWOMORE).** *TWOMORE* is a two party protocol between a curator and a CSP that consists of four polynomial-time protocols that work as follows:

- $K_G \leftarrow \text{IPRFSetup}(1^\lambda)$ : The Curator gives as input a security parameter  $\lambda$  and receives a key  $K_G$  for an IPRF  $G$ .
- $E_{DB} \leftarrow \text{Setup}(1^\lambda, DB)$ : The curator gives as input the security parameter  $\lambda$  and a sequence of plaintexts. The CSP receives a sequence of ciphertexts.
- $\text{sk}_f \leftarrow \text{KeyGen}(k_i, k_j)$ : The curator gives as input two encryption keys  $k_i$  and  $k_j$  and receives a functional key  $\text{sk}_f$ .
- $(r \in \mathbb{Z}) \leftarrow \text{Query}(ct_i, ct_j, \text{sk}_f)$ : The curator gives as input two ciphertexts and a functional key  $\text{sk}_f$ . The server performs the comparison of the ciphertexts and returns  $r = c_j - c_i$ .

A TWOMORE scheme is used as follows. First the curator generates a key  $K_G$  for the IPRF  $G$ . Then she runs the  $\text{MIFE}_{\ell_1}.\text{Enc}$  for all  $x_i \in DB$  to get the first layer ciphertexts  $ct_i^{(1)}$ . After she receives the corresponding ciphertexts, she applies  $G$  on each  $ct_i^{(1)}$  to get the second level ciphertexts  $ct_i^{(2)}$ . Finally, she sends the encrypted database  $E_{DB}$  to the CSP. To hide the exact difference of the two compared numbers, the curator can simply send a functional key  $\text{sk}_f$  that is off by a certain value. Then, after she receives  $r$  from the CSP, she can add that value to  $r$  to find the correct result. A detailed construction is illustrated in Figure 6.

**Correctness:** The correctness of the MORE scheme follows from the fact that:

$$G^{-1} \left( K_G, G \left( K_G, ct_i^{(1)} \right), G \left( K_G, ct_j^{(1)} \right) \right) = \left( ct_i^{(1)}, ct_j^{(2)} \right)$$

And then directly from the correctness of the MORE construction.

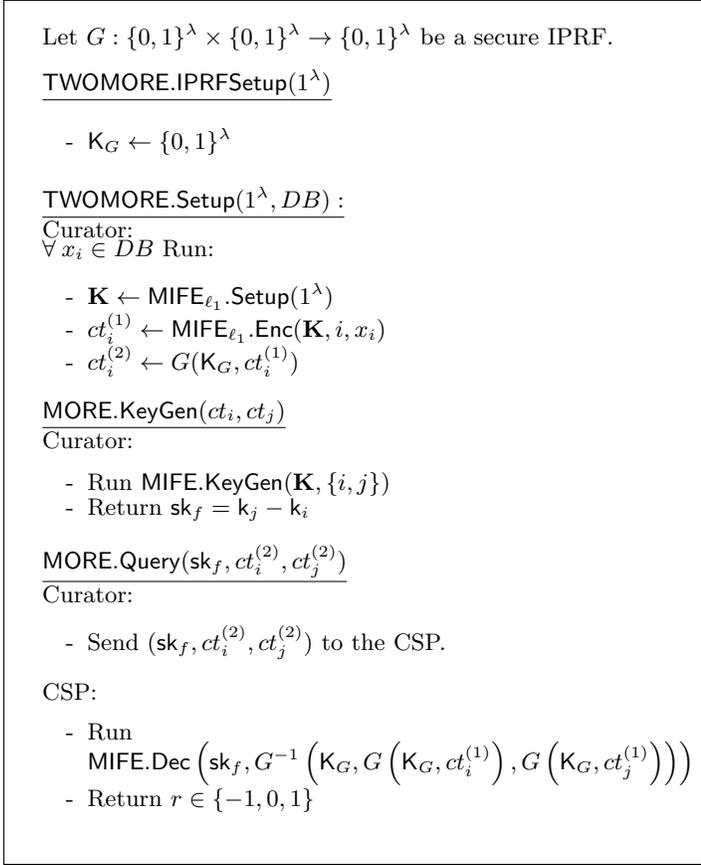
## 5.2 Security Analysis

We will now prove that our TWOMORE satisfies the *best-possible* security property. Like in similar works [28,16,11], we assume that the CSP is honest but curious. In particular, we will show that we can build a simulator  $\mathcal{S}$  which given as input only the leakage function  $\mathcal{L}_{CMP}$ , it can simulate the real functionalities of TWOMORE.

**Theorem 4.** *TWOMORE is secure with the best-possible leakage function  $\mathcal{L}_{CMP}$  assuming that  $G$  is a secure IPRF - modelled as a truly random function.*

We start by describing the simulator  $\mathcal{S}$ . Since  $\mathcal{S}$  has access to  $\mathcal{L}_{CMP}$ , it knows the ordering of the plaintexts. To reply consistently to  $\mathcal{A}$ 's queries,  $\mathcal{S}$  maintains a dictionary  $\text{Dict}$ , where it stores the functional keys  $\text{sk}_f$  for each  $\{i, j\}$  pair that  $\mathcal{A}$  queries, along with the  $\{i, j\}$  pair.

To prove Theorem 4 we make use of a Hybrid Argument. **Hybrid 0:** This is the real experiment.

Fig. 6: Two-Layered Order Revealing Encryption based on  $\text{MIFE}_{\ell_1}$

**Hybrid 1:** Like Hybrid 0 but instead of an IPRF,  $\mathcal{S}$  uses a truly random function. The indistinguishability of Hybrids 0 and 1 follows directly from the security of the IPRF.

**Hybrid 2:** This is the ideal experiment.

**Lemma 1.** *Hybrid 2 is indistinguishable from Hybrid 1*

*Proof.* On each query that includes  $(\text{sk}_f, ct_i^{(2)}, ct_j^{(2)})$ ,  $\mathcal{S}$  stores the functional key along with the indices of the ciphertexts in Dict. This does not affect  $\mathcal{A}$ 's point of view. As a next step,  $\mathcal{S}$  invokes  $\mathcal{L}_{CMP}(i, j)$  and sends back to  $\mathcal{A}$  a response  $r \in \{-1, 0, 1\}$ .

## 6 Functionally Encrypted Private Databases

In this section, we extend the MIFE-ORE construction presented in Section 5 to also ensure the privacy of the users instead of only protecting the confidentiality of their data. In particular, we assume that a curator encrypts her data locally before outsourcing them to the cloud, using our MIFE scheme for the  $\ell_1$  norm. Then, we allow an analyst to perform different kinds of queries (i.e. ORE queries, sums, averages) on the curator's encrypted data. To achieve our goal we describe a new primitive called *Multi-Input Functionally Encrypted Private Databases* (MIFE-PDB).

### 6.1 Background

We proceed by providing the main definitions of  $\epsilon$ -differential privacy ( $\epsilon$ -DP) and the main properties of the Laplace mechanism.

**Definition 10 ( $\ell_1$ -distance).** *The  $\ell_1$ -distance between two databases  $DB$  and  $DB'$  is given by:*

$$\| \|DB - DB'\| \|_1 \quad (4)$$

*The  $\ell_1$ -distance counts the number of entries on which the two databases differ.*

**Definition 11.** *Two databases  $DB$  and  $DB'$  are neighbouring if:*

$$\| \|DB - DB'\| \|_1 \leq 1 \quad (5)$$

**Definition 12 ( $\epsilon$ -DP).** *A privacy mechanism  $\mathcal{M} : \mathbb{N}^{\mathcal{D}} \rightarrow \text{Im}(\mathcal{M})$  is  $\epsilon$ -DP if  $\forall \mathcal{S} \subset \text{Im}(\mathcal{M})$  and  $\forall$  neighboring databases  $DB, DB' \in \mathbb{N}^{|\mathcal{D}|}$ :*

$$\Pr[\mathcal{M}(DB) \in \mathcal{S}] \leq e^\epsilon \Pr[\mathcal{M}(DB') \in \mathcal{S}]$$

**Definition 13 ( $\ell_1$  sensitivity).** *The  $\ell_1$  sensitivity of a query  $q : \mathbb{N}^{|\mathcal{D}|} \rightarrow \mathbb{R}$  is:*

$$\Delta q = \max_{d(DB, DB') \leq 1} \|q(DB) - q(DB')\|_1$$

**Definition 14 (Laplace distribution).** *The Laplace distribution centered at 0 and with scale parameter  $b$  is given by:*

$$\text{Lap}(z) = \frac{1}{2b} e^{-\frac{|z|}{b}}$$

where the mean is 0 and the variance is  $2b^2$ .

We are now ready to proceed with the definition of the Laplace Mechanism [22].

**Definition 15 (Laplace Mechanism).** *Given a query  $q : \mathbb{N}^{|\mathcal{D}|} \rightarrow \mathbb{R}$ , the Laplace Mechanism is:*

$$M_L(DB, q, \epsilon) = q(DB) + Y_i,$$

where  $Y_i \sim \text{Lap}(b)$

A proof showing that the Laplace Mechanism is  $\epsilon$ -differentially private can be found in [22].

## 6.2 A Multi-Input Functionally Encrypted Database

We now proceed with the definition and construction of our Multi-Input Functionally Encrypted Database (MIFE-PDB).

**Definition 16 (MIFE-PDB).** *A MIFE-PDB scheme consists of four polynomial-time protocols Setup, KeyGen, Query and PQuery that work as follows:*

- $PEDB \leftarrow \text{Setup}(1^\lambda, DB)$ : *The curator gives as input the security parameter  $\lambda$  and a sequence of plaintexts. The CSP receives a sequence of ciphertexts.*
- $\text{sk}_f \leftarrow \text{KeyGen}(\mathbf{K}, f)$ : *The curator gives as input two encryption keys  $k_i$  and  $k_j$  and receives a functional key  $\text{sk}_f$ .*
- $r \leftarrow \text{Query}(\text{sk}_f)$ : *The curator a functional key  $\text{sk}_f$  for a function of her choice. The server replies with a result  $r$ .*
- $r \leftarrow \text{PQuery}(\text{sk}_f)$ : *This is a three party protocol between the Analyst, the Curator and the CSP. The Analyst requests a functional key  $\text{sk}_f$  for a function  $f$  of her choice. The Curator generates the key and sends it back to the Analyst. The Analyst then performs a private query to the CSP and receives back a result  $r$ .*

The MIFE-PDB scheme works as follows: The Setup, KeyGen and Query protocols, have the same flow as in the MIFE-ORE construction described in Section 5. For the analyst to perform a private query, she first contacts the curator providing her with a description of the function  $f$  for which she wants a functional key  $\text{sk}_f$ . The curator generates the corresponding samples  $\gamma \xleftarrow{\$} \text{Lap}(\frac{\Delta q}{\epsilon})$  and adds it to the key. Finally, the curator sends back  $\text{sk}'_f = \text{sk}_f + \gamma$ . The analyst can now contact the CSP to perform her private query. The MIFE-PDB scheme is presented in Figure 7.

<p><u>MIFE – PDB.Setup(<math>1^\lambda, DB</math>) :</u>  Curator:  <math>\forall x_i \in DB</math> Run:</p> <ul style="list-style-type: none"> <li>- MIFE<math>_{\ell_1}</math>.Setup(<math>1^\lambda</math>)</li> <li>- MIFE<math>_{\ell_1}</math>.Enc(<math>\mathbf{K}, i, x_i</math>)</li> </ul> <p><u>MIFE – PDB.KeyGen(<math>f</math>)</u>  Curator:</p> <ul style="list-style-type: none"> <li>- Run MIFE.KeyGen(<math>f</math>)</li> <li>- Return <math>\mathbf{sk}_f</math></li> </ul> <p><u>MIFE – PDB.Query(<math>\mathbf{sk}_f, f</math>)</u>  Curator:</p> <ul style="list-style-type: none"> <li>- Send <math>(\mathbf{sk}_f, f)</math> to the CSP.</li> </ul> <p>CSP:</p> <ul style="list-style-type: none"> <li>- Run MIFE.Dec(<math>\mathbf{sk}_f, PEDB</math>)</li> <li>- Return a result <math>r</math></li> </ul>	<p><u>MIFE – PDB.PQuery(<math>\mathbf{sk}_f</math>)</u>  Analyst:</p> <ul style="list-style-type: none"> <li>- Request a functional key for a function <math>f</math> from the curator.</li> </ul> <p>Curator:</p> <ul style="list-style-type: none"> <li>- Run <math>\mathbf{sk}_f \leftarrow</math> MIFE – PDB.KeyGen(<math>f</math>)</li> <li>- Sample noise <math>\gamma \xleftarrow{\\$} \text{Lap}(\frac{\Delta q}{\epsilon})</math></li> <li>- Send <math>\mathbf{sk}'_f = \mathbf{sk}_f + \gamma</math> back to the analyst.</li> </ul> <p>Analyst:</p> <ul style="list-style-type: none"> <li>- Send a query to the the CSP.</li> </ul> <p>CSP:</p> <ul style="list-style-type: none"> <li>- Run MIFE.Dec(<math>\mathbf{sk}_f, PEDB</math>)</li> <li>- Return a result <math>r</math> to the analyst</li> </ul>
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Fig. 7: Multi-Input Functionally Encrypted Private Database

**Threat Model:** For this application of our MIFE scheme, we need to revisit our threat model as we do not longer face an adversary that aims at breaking the cryptography. More specifically, we prove that our construction is differentially private by assuming the existence of a statistical adversary that corrupts the analyst. The statistical adversary can see the responses to the private queries but does not have access to the encrypted database nor to the queries of the curator.

**Theorem 5.** *Let  $PDB, PDB' \in \mathbb{N}^{|\mathcal{D}|}$  be arbitrary neighbouring databases, let  $q : \mathbb{N}^{|\mathcal{D}|} \rightarrow \mathbb{R}$  be an arbitrary query and let  $r, r' \in \mathbb{R}$ . Moreover, let  $M_L$  be the Laplace Mechanism. Then, the PQuery protocol in MIFE-PDB is  $\epsilon$ -differentially private as per Definition 12.*

*Proof.* Our goal is to prove that issuing a private query  $q$  to PDB reveals no more information than what is allowed by the privacy factor  $\epsilon$ . In our construction, we have that a query to the database returns a result  $r'$ . In other words,  $q(PDB) = r'$ . However, the query contains the secret functional key  $\mathbf{sk}'_f = \mathbf{sk}_f + \gamma$ , where  $\gamma \leftarrow \text{Lap}(\frac{\Delta q}{\epsilon})$ . Hence when the Laplace Mechanism is applied on the query we get

$$\begin{aligned}
M_L(q, PDB, \epsilon) &= r = r' + \gamma \Rightarrow \\
\gamma &= r - r' \Rightarrow \\
\gamma &= r - q(PDB).
\end{aligned}$$

However, since  $\gamma$  is arbitrarily chosen from the Laplace distribution ( $\gamma \stackrel{\$}{\leftarrow} \text{Lap}(\frac{\Delta q}{\epsilon})$ ), then, without loss of generality, we can replace  $\gamma$  with  $\text{Lap}(\frac{\Delta q}{\epsilon})$ . Hence, we get:

$$\begin{aligned} \frac{\Pr[M_L(PDB, q, \epsilon) = r]}{\Pr[M_L(PDB', q, \epsilon) = r]} &= \frac{\Pr[\text{Lap}(\frac{\Delta q}{\epsilon}) = r - q(PDB)]}{\Pr[\text{Lap}(\frac{\Delta q}{\epsilon}) = r - q(PDB')]} \\ &= \frac{\frac{\epsilon}{2\Delta q} \exp(-\frac{|r - q(PDB)|}{\Delta q})}{\frac{\epsilon}{2\Delta q} \exp(-\frac{|r - q(PDB')|}{\Delta q})} \\ &= \exp\left(-\frac{\epsilon|r - q(PDB')| - |r - q(PDB)|}{\Delta q}\right) \\ &= \exp\left(\frac{\epsilon|q(PDB') - q(PDB)|}{\Delta q}\right) \leq e^\epsilon \end{aligned}$$

## 7 Future Directions

While this work is amongst the first that utilize FE to address real-life problems, we acknowledge that it faces certain limitations. However, it is our firm belief that our schemes can serve as the basis for more advanced applications.

**Range Queries** Our TWOMORE scheme is a good candidate for a Range Queries scheme. In such a scheme, a user is enabled to issue encrypted search queries of the form "Find all values in the range  $[a, b]$ ". Achieving such a scheme from an ORE scheme is not trivial since the contents of the query must also be protected like in the case of SSE schemes. Moreover, we plan to further enhance our construction with the important properties of forward and backward privacy [13] to ensure that updates on the database leak as little information as possible.

**Functionally Encrypted Dynamic Private Databases** Our main goal for this application is to make our database dynamic so that it would support cloud storage designs like the ones presented in [30,31,7,29]. A good first step towards such a database is to try modifying the differential privacy definitions accordingly. In particular, we would need to prove that our construction satisfies the following definition of differential privacy under continual observations [23]:

**Definition 17.** Let  $M$  be a privacy mechanism, let  $S \subset \text{Im}(M^\lambda)$  and let  $DB_0$  be the starting database.  $M$  is said to be differentially private over continual observations if for all neighboring sequences of curator operations  $\sigma = (\sigma_1, \dots, \sigma_\lambda)$  and  $\sigma' = (\sigma'_1, \dots, \sigma'_\lambda)$ :

$$\frac{\Pr[(M(DB_1), \dots, M(DB_\lambda)) \in S]}{e^\epsilon \Pr[(M(DB'_1), \dots, M(DB'_\lambda)) \in S]} \leq 1$$

Where  $DB_i$  results from applying the update operation  $\sigma_i$  to  $DB_{i-1}$  and  $DB'_i$  from applying  $\sigma'_i$  to  $DB'_{i-1}$ .

With this in mind, we hope that the scheme presented in this work can be regarded as a first step towards the first Dynamic Functionally Encrypted Private Database.

## 8 Conclusion

The future will inevitably bring to the fore the need to exploit the power and applicability of FE. In addition to that, we strongly believe that cloud-based services will rely less on traditional decryption of information, and more on computations over encrypted data. We hope that this work will kick-start a period of greater research in the area of privacy-preserving computations in untrusted clouds and will allow us to see things concealed beneath the surface of the theoretical concepts of FE.

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