

CoVault: Secure Selective Analytics of Sensitive Data for the Public Good

Abstract—In a *secure selective analytics platform*, data sources consent to the *exclusive use* of their data for a pre-defined set of analytics queries performed by a specific group of analysts, and for a limited period. If the platform is secure under a sufficiently strong threat model, it can provide the missing link to enabling powerful analytics of sensitive personal data, by alleviating data subjects’ concerns about leakage and misuse of data. For instance, many types of powerful analytics that benefit public health, mobility, infrastructure, finance, or sustainable energy can be made differentially private, thus alleviating concerns about *privacy*. However, no platform currently exists that can technically prevent *data leakage and misuse* under a sufficiently strong threat model; as a result, analytics that would be in the public interest are not done.

CoVault uses a new minimal trust implementation of functional encryption (FE) for secure analytics, which relies on a unique combination of secret sharing, multi-party secure computation (MPC), and different trusted execution environments (TEEs). CoVault is secure under a very strong threat model that tolerates compromise and side-channel attacks on any one TEE implementation. Despite the cost of MPC, we show that CoVault scales to very large databases using map-reduce based query parallelization. For example, we show that CoVault can perform epidemic analytics queries at scale.

1. Introduction

Certain forms of privacy-preserving analytics on high-resolution personal data could be of significant benefit to society. Examples of such data include individuals’ education, health, nutrition, activity, mobility, social contacts, income, and finances. Such data is already being captured with high resolution and velocity by individuals’ smart devices and apps, by online services, and when citizens use offline services that involve digital record-keeping. Large-scale analytics of this data could benefit (i) public health, e.g., by studying epidemics with high spatio-temporal resolution, or new and rare diseases; (ii) sustainability, e.g., by informing transportation, energy, and urban planning; (iii) social welfare, e.g., by uncovering disparities in income and access to education / services; and (iv) economic stability, e.g., by providing insight into markets and consumer behavior.

We note that these analytics produce statistical results that do not inherently violate the privacy of individuals reflected in the data. Indeed, techniques like differential privacy (DP) can formally guarantee individuals’ privacy. Despite the benefits and the availability of privacy-preserving techniques like DP, however, many societies forego such

analytics out of concern that sensitive personal data, once collected and aggregated, could be leaked to unauthorized parties or misused for undesired purposes. Potential misuse could range from the controversial (e.g., for law enforcement) to the outright undemocratic (e.g., surveillance and discrimination of certain individuals and groups). Instead, the prevailing approach has been to minimize data collection and aggregation to ensure individuals’ privacy and prevent data misuse, unauthorized commercial data exploitation, and government overreach. Indeed, existing public sector data is either carefully limited in scope and collected infrequently, e.g., census data, or exists in silos like local government agencies and is unavailable for aggregation and analytics. Data collected by the private sector also tends to be unavailable for analytics in the public interest, partly due to data protection laws (e.g., GDPR, HIPAA) and partly due to commercial interests.

There is a growing realization, however, that this conservative approach conflicts with urgent societal challenges like public health and sustainability. For instance, the European Parliament recently approved the Data Governance Act (DGA) [3], which aims to promote the availability of protected public sector data and a trustworthy environment to facilitate its use for research. We note that part of this environment could be a technical platform for performing analytics on protected data securely.

The key challenge in enabling secure analytics of personal data is an analytics platform that prevents misuse and leakage of user data using technical means under a suitably strong threat model. In this setting, which we call *secure selective analytics (SSA)*, there are multiple *data sources*, who contribute data for a specific purpose and for a limited period. A small number of independent operators jointly provide the analytics platform, which aggregates and stores encrypted data, and performs queries on the data. Finally, there are *analysts* who wish to obtain query results on contributed data.

Key requirements. In order to enable selective analytics on aggregated sensitive data, the SSA platform should meet the following key requirements:

(1) *Selective forward consent*: Data sources consent *a priori* to a defined set of analytics queries performed on their data on behalf of a defined set of analysts, for a limited period of time.

(2) *Minimal trust*: Given the sensitivity of the raw data and the potential for data leakage and misuse, the platform’s security must not rely on trust in any single party (platform operator, analyst, software developer, hardware vendor) or

software/hardware component. Also, the platform must tolerate side channels.

(3) *Scalability*: To be of practical use, the platform should be able to perform common analytics queries on large-scale datasets collected from many data sources.

The SSA requirements apply whenever multiple data sources wish to make their sensitive data available to third-party analysts for a specific purpose. However, this paper focuses on the emerging application area of analytics for the *public good*. Studies indicate that individuals are willing to contribute their data for causes that demonstrably benefit the public good, making this a scenario with high potential impact [46], [74], [73], [5], [56]. Regardless of who benefits from the analytics, however, an SSA platform ensures that data sources retain complete control over who gets to use their data for what specific purpose and for how long; it can therefore support analytics in broader scenarios.

Prior work. *Conventional* analytics platforms operate on unencrypted, raw data. Therefore, data sources must trust the platform and its operator not to leak raw data, execute queries that data sources have not consented to, or let unauthorized parties execute queries. *Hardware-secured platforms* rely on a Trusted Execution Environment (TEE) [54], [77], [12], [10], [17], [70], [39], [66], [52], [53] to execute queries on otherwise encrypted data within a secure hardware compartment. While more secure than conventional platforms, they are vulnerable to compromise of the TEE or its vendor. Moreover, unless oblivious algorithms are used in the TEEs [85], they are vulnerable to side channels (many such attacks have been reported [58]). Neither approach meets the minimal trust requirement.

Federated analytics systems support differentially private analytics queries over distributed data [16], [68], [69], [67], leaving data sources in control of their data. However, network limitations (delay, bandwidth), availability of data stores, and the overhead of cryptographic primitives, which need to be borne in large part by data sources, limit the expressiveness of queries that can be practically executed at scale. Other systems compute aggregates on *homomorphically encrypted (HE) data* [20], [24], [65], [21], [62]. Full HE is very expensive [76], while partial HE restricts query expressiveness. Also, decrypting query results requires a trusted party or MPC among a set of non-colluding parties [67]. Neither type of system supports selective forward consent or protects against side channels.

CoVault. CoVault uses a different design in order to meet the specific requirements of SSA. It achieves the selective forward consent requirement using a form of functional encryption (FE). FE is a generalization of public-key encryption where possessing a secret key allows one to learn a pre-defined set F of functions of the encrypted cleartext m , but nothing else about m . We observe that FE provides the essential functionality of selective forward consent: Data sources can encrypt their data using the public key, and F forms the set of queries allowed on the data. Only the results of pre-approved queries can be obtained from the encrypted data. Moreover, the variant of FE used in CoVault

goes beyond conventional FE by limiting, in addition to the queries, the set of decryptors (analysts) and the period during which decryption (queries) can be performed.

To meet the minimal trust requirement, CoVault relies on a multi-party FE construction that combines secret sharing, multi-party secure computation (MPC), and multiple TEE implementations. The construction is secure under a threat model that tolerates side channels as well as compromise of any t of n TEE implementations, where t and n depend on the specific MPC protocol used (1 of 2 in our prototype). Data is *encrypted* by secret-sharing it to a small set of n independent parties that obtain and store one share each, and jointly implement *decryption* using MPC. To minimize trust in the parties and enable software attestation, each party executes inside a TEE. To raise the bar for collusion and correlated failure of TEEs, each party uses a TEE of a different implementation and vendor. To render TEE side channels ineffective, we use oblivious MPC. Finally, the parties in CoVault can be hosted in a co-location center, thereby achieving both physical isolation as well as efficient communication and data access.

CoVault achieves scalability as follows. The dominant cost of executing queries in CoVault is MPC and oblivious data access to prevent side channels. To enable scale-out with cores and servers, CoVault relies on a form of oblivious map-reduce, where each mapper and reducer is implemented as an instance of oblivious MPC. For queries that access data based on private attributes, CoVault uses an efficient private information retrieval (PIR) protocol. Finally, CoVault can produce materialized views to avoid expensive operations like joins during interactive query processing.

To the best of our knowledge, CoVault is the first analytics platform that meets the SSA requirements. Thus, CoVault can enable selective analytics on sensitive data with minimal trust assumptions, and it scales out to large datasets and complex queries using map-reduce parallelism. For instance, § 7 shows that CoVault can perform epidemic analytics on personal mobility and contact data at scale.

Contributions. (1) Motivation and requirements for a secure selective analytics (SSA) platform. (2) The design, implementation, and evaluation of an SSA platform. (3) A multi-party functional encryption construction in a strong threat model that tolerates side channels and compromise of any t of n TEE implementations. (4) Several additional technical components of possibly independent interest: A provably secure secret-sharing scheme with built-in MACs (§ 4.4), a modified 2-party MPC (2PC) protocol that produces asymmetric outputs (§ 4.3), and a simple PIR scheme that supports fetches in constant time (§ 6). (5) A data-oblivious map-reduce in 2PC for scalable query processing (§ 6.1).

2. CoVault Overview

2.1. Requirements

We mentioned the key requirements of secure selective analytics in § 1, namely selective forward consent, minimal

trust, and scalability. For completeness, we list here additional requirements that are not unique to SSA and may apply more generally to other secure analytics platforms.

Transparency To justify the public’s trust, the system is fully transparent in its design, implementation (source code), configuration, and operation, including what queries are performed by whom at what time.

Confidentiality Subject to a strong threat model (§ 3.2), it is impossible to extract information from the database except through the approved analytics query interface, and only approved analysts can obtain query results.

Integrity Data and query results cannot be altered by the platform or by third parties without detection.

Privacy While privacy requires query-specific mechanisms and cannot be provided by the analytics platform itself, the platform is compatible with strong privacy-preserving mechanisms like differential privacy.

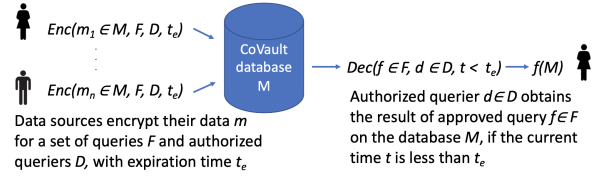
2.2. Building blocks used in CoVault

Secret sharing is a method for sharing a secret value among multiple parties, such that the value can be obtained only if a sufficient fraction of shares (possibly all) are combined. CoVault uses secret sharing to tolerate the compromise of one party’s TEE implementation without risking data disclosure.

Secure multi-party computation (MPC) allows several parties to jointly compute a function without revealing their respective inputs. MPC protocols are secure in either a semi-honest [83], [48] or a malicious [81] threat model. To evaluate queries on secret-shared data, CoVault uses oblivious MPC in the t -of- n malicious threat model, where up to t of the n parties may be malicious. The value of the maliciousness threshold t varies from $n/3$ to $n-1$ depending on the protocol. Garbled circuits (GCs) are a specific 2PC technique ($n = 2, t = 1$) [64]. GCs are inherently oblivious as circuits have no control flow constructs. The CoVault prototype uses GCs to execute queries.

Trusted execution environments (TEEs) are supported by many recent general-purpose CPUs, e.g., Intel SGX, AMD SEV, and the upcoming Intel TDX and ARM CCA [28], [6], [72], [71]. TEEs provide confidentiality and integrity of data and computation under a threat model that tolerates compromised operating systems, hypervisors, and even some physical attacks [22], [28]. Unlike the first-generation SGX, the newer SEV-SNP, TDX, and CCA encapsulate an entire VM, providing a familiar, general programming model and a large memory space. An attestation protocol generates a cryptographic proof that a VM executes in an authentic TEE of a given type and that its initial memory state matches the expected secure hash value (measurement). Given this proof, the VM is provided with cryptographic material needed to authenticate itself to remote parties and to access data sealed for it. CoVault uses TEEs to encapsulate each party’s computation. The security guarantees of a TEE depend on the integrity of its vendor’s certificate chain, proprietary hardware, and firmware. To minimize the chance

Figure 1: CoVault: Using FE for secure analytics



of correlated compromises, CoVault relies on independent TEE implementations, one for each party.

Functional Encryption (FE) is a generalization of public-key encryption, which enables the holder of a private key to learn a pre-defined function of what the ciphertext is encrypting, but nothing else [19]. Iron [37] implements FE using a TEE; this construction is efficient but vulnerable to side channels, and its security relies on the integrity of the (one) TEE’s hardware implementation and its vendor. CoVault relies on a new FE-like construction, which extends Iron to be secure without placing trust in any single TEE implementation or vendor, and tolerates side channels.

Private Information Retrieval (PIR) techniques allow a client to fetch data from a database without disclosing *which* data is fetched [27]. CoVault uses PIR to fetch data from materialized views when executing data-dependent queries.

2.3. Approach and roadmap

In CoVault, data sources encrypt their data using a variant of FE, such that only the results of a pre-defined set of queries F can be obtained from the encrypted data, and only by a pre-defined set of authorized queriers D , before expiration time t_e (Figure 1). At the heart of CoVault is a multi-party FE-like construction, which we develop through successive refinement of strawman designs in § 3 and fully describe in § 4. In § 5, we describe the design of the CoVault analytics platform based on this FE-like construction, and in § 6 we show how to execute general analytic queries in an efficient and scalable manner. In § 7 we evaluate CoVault in the context of epidemic analytics as an example application scenario. The appendix describes ingress processing (§ B) and offers further details about the epidemic analytics scenario (§ C). Also, we describe the algorithm used to estimate end-to-end query latency in § D, and provide proofs of CoVault’s FE-like construction (§ E) and end-to-end security (§ F).

3. CoVault’s FE-like construction

In this section, we present the high-level API of CoVault’s FE-like construction, and present the construction by incrementally refining a series of strawman designs.

3.1. API

FE allows a party with access to only a ciphertext and an appropriate decryption key to compute a specific function of

the cleartext. More precisely, given a set X (plaintext space) and a set \mathcal{F} of functions over X (function space), a FE scheme over (X, \mathcal{F}) enables one to evaluate $f(x)$ given the encryption of $x \in X$ and a decryption key sk_f for $f \in \mathcal{F}$ [19]. One cannot learn anything about x other than $f(x)$ using the decryption key sk_f .

We use a variant of FE that allows encryptors to specify which functions from the function space can be run on their data, which decryptors can request the evaluation of these functions, and when their data expires. We reflect this variation in the $(Setup, KeyGen, Enc, Dec)$ API, which defines a FE scheme in the literature.

$mpk[F, D, t_e], msk[F, D, t_e] \leftarrow Setup(1^\kappa, F, D, t_e)$ This operation takes as input a security parameter κ , a set of functions F , a set of authorized decryptors D and an expiration time t_e . It outputs a master public-private keypair constrained to F , D and t_e . The public key, $mpk[F, D, t_e]$, is published for use by encryptors, while the private key, $msk[F, D, t_e]$, is held secret by a trusted party.

$sk_f \leftarrow KeyGen(msk[F, D, t_e], f, d)$ This operation takes as input a constrained master secret key $msk[F, D, t_e]$, a specific function f , and a decryptor d . It outputs a function secret key sk_f if $f \in F$ and $d \in D$. Otherwise, it fails and outputs \perp . sk_f can be used to obtain $f(m)$ for any m encrypted using $mpk[F, D, t_e]$ (see $Dec()$ below). $KeyGen()$ is executed by the trusted party on behalf of a decryptor d . The decryptor provides f , while the trusted party provides $msk[F, D, t_e]$.

$c \leftarrow Enc(mpk[F, D, t_e], m)$ This operation takes as input a constrained master public key $mpk[F, D, t_e]$ and a message m . It outputs a ciphertext c .

$f(m) \leftarrow Dec(sk_f, c)$ This operation takes as input a function secret key sk_f and a ciphertext c . It outputs $f(m)$ if $sk_f \neq \perp$, c was generated using $Enc(mpk[F, D, t_e], m)$, sk_f was generated using $KeyGen(msk[F, D, t_e], f, d)$ with the same F , D and t_e , and the current time is less than the expiration time t_e . Otherwise, it fails and outputs \perp .

3.2. Desired properties and threat model

Properties. We are interested in two security properties:

- **(Data) Confidentiality.** Plaintexts remain confidential, except that authorized decryptors (in the set D) may learn authorized functions (from the set F) of the plaintexts if they execute $Dec()$ before the expiration time t_e . No other entity learns anything about plaintexts.
- **(Result) Integrity.** The decryptor receives the correct value of the its provided function, f , applied to the encrypted plaintext, m . An adversary cannot modify f , m , or the result $f(m)$ without detection.

Threat model. We aim to provide confidentiality and integrity in the presence of active attacks that may exploit software or hardware vulnerabilities, including side channels. Denial-of-service attacks are out of scope; they can be addressed with orthogonal techniques. We do not trust any

single technology or vendor to produce hardware resilient to strong attacks and, therefore, divide trust among multiple parties and hardware technologies. Specifically, both our FE-like construction and the CoVault design (which builds on this construction) secret-share data among n independent parties for confidentiality, and use n -party MPC in the t -of- n malicious model to answer queries. To raise the bar for compromise or malice, we encapsulate each party in an independent TEE implementation from a different vendor and the code of the parties running in the TEEs is attested to be correct. Moreover, we assume that no more than t parties collude to subject their TEEs to *simultaneous* physical attacks [58].

Our precise assumption is that at least $n-t$ of the parties' TEEs remain uncompromised and free from side-channel exploits. The remaining t TEEs may be arbitrarily malicious: they may be subject to software or hardware attacks (even in collusion with a hardware vendor) and may run the wrong code (different from what was attested). Our design provides confidentiality and integrity in this very strong threat model.

We note that the use of diverse TEEs significantly reduces the threat of collusion attacks: Even a malicious alliance of more than t parties would face the technical difficulty of having to simultaneously compromise their respective, different TEE implementations for a successful attack. This fact significantly reduces the burden of having to choose non-colluding parties. While details depend on the specific deployment scenario, choosing independent commercial providers—ideally subject to different jurisdictions—should suffice in most cases.

The prototype implementation of our FE-like construction (§ 4) uses two parties ($n = 2$) of which one may be compromised ($t = 1$). As the 2PC protocol, we rely on DualEx [49]. Compared to other maliciously-secure 2PC protocols, DualEx is more efficient but may leak one bit of information if the protocol aborts due to an active attack on one of the two parties. This leak cannot be amplified by repetition: DualEx informs the honest party of the attack, so the honest party refuses to interact further with the malicious party. We admit this 1-bit leak tacitly as it provides significant performance gains in return.

Next, we describe three strawman designs that attain confidentiality and integrity under progressively weaker assumptions. The last design matches our threat model and is the basis of our actual FE-like construction (§ 4). Figure 2 summarizes the assumptions of the three designs.

3.3. Strawman 1 (S1): n -party FE construction

Our first strawman design, S1, implements the FE API of § 3.1 by combining secret sharing and n -party MPC. Specifically, n independent parties ¹ *jointly* implement the trusted party of FE that holds the master secret key, $msk[F, D, t_e]$.

In S1, confidentiality relies on at least $n-t$ parties being honest and free of side-channel exploits.

1. We do not use the terms “party” or “parties” to refer to other actors in the system like encryptors and decryptors.

	Confidentiality if:	Integrity if:
S1	At least $n - t$ parties trusted and free of side-channel exploits	All parties semi-honest (no active attacks)
S2	At least $n - t$ parties with uncompromised TEEs and free of side-channel exploits	All parties semi-honest (no active attacks)
S3	At least $n - t$ parties with uncompromised TEEs and free of side-channel exploits. (Same as our threat model.)	

Figure 2: Assumptions needed to attain confidentiality and integrity in our Strawman designs.

Components. Encryptors encode data using a n -of- n *secret-sharing scheme*, such that the cleartext cannot be recovered unless all of the n shares are available; then, they entrust each data share to a different one of n parties. To decrypt data, the parties run n -party MPC on their shares to produce the result $f(m)$. The chosen MPC scheme is secure in the t -of- n malicious model: no party learns anything about m other than $f(m)$ as long as at least $n - t$ parties are honest (i.e., they follow the protocol, do not disclose any information not required by the protocol to any other party, and are not subject to any successful hardware or software attack). Furthermore, the chosen MPC scheme is data oblivious, i.e., without any control flow. A simple way to attain data obliviousness is to use a circuit-based MPC scheme.

Implementation. Next, we sketch how S1 implements the operations in § 3.1, which can be run after the n parties are initialized. In contrast with the standard FE API, some elements, which we denote with capital letters, are vectors.

$MPK[F, D, t_e], MSK[F, D, t_e] \leftarrow Setup(1^\kappa, F, D, t_e)$

Each party runs this function locally to produce its own key pair and link it to F , D and t_e . The output values MPK and MSK are n -element vectors, one for each party/share. Each party keeps its *secret* key locally.

$SK_f \leftarrow KeyGen(MSK[F, D, t_e], f, d)$ The decryptor d calls this function on each party and provides the parameter f . Regarding the first parameter, $MSK[F, D, t_e]$, each party provides its own secret key. Each party runs the function locally, and independently produces a cryptographic authorization token sk_f , linked to f and t_e if $f \in F$ and the caller $d \in D$. Each party returns its sk_f to the decryptor: the return parameter SK_f represents an n -element vector with one authorization token per party.

$C \leftarrow Enc(MPK[F, D, t_e], m)$ Every encryptor runs this function locally. The encryptor secret-shares m into n shares, and encrypts each share with the corresponding party's public key in the vector $MPK[F, D, t_e]$. C represents the vector of encrypted shares returned to the encryptor who may then transmit it to decryptors over any channel.

$f(m) \leftarrow Dec(SK_f, C)$ The decryptor d calls this function on each party, providing the authorization token

(previously received from a *KeyGen* call) and the share encrypted with that party's public key. If each party accepts its authorization token as valid and each party's current clock time is less than t_e (which each party linked with its token), then the parties decrypt their shares using their corresponding secret key of $MSK[F, D, t_e]$, and perform MPC to compute the result $f(m)$ encrypted with the caller's (decryptor's) public key. If any party rejects its authorization token from SK_f or believes t_e is past, the result is \perp .

Properties. The S1 FE construction provides confidentiality as long as at least $n - t$ parties are honest and free of side-channel exploits (all others may be arbitrarily malicious). Since S1 does not run parties in TEEs (that is covered in S2 below), honesty of the $n - t$ parties assumes the absence of malicious intent as well as hardware and software attacks against those parties. Simultaneous side-channel attacks on all but the $n - t$ honest parties do not violate confidentiality, since such attacks reveal at most $n - t$ of the n shares outside MPC, and nothing from within the MPC (as the MPC scheme is data oblivious). Furthermore, the integrity of $f(m)$ holds as long as all parties are semi-honest and do not manipulate their shares.

3.4. Strawman 2 (S2): S1 + TEE encapsulation

Our next strawman design, S2, weakens the assumption of at least $n - t$ honest parties for the *confidentiality* of S1 to the assumption of at least $n - t$ *uncompromised TEE implementations*.

Components. S2 additionally executes each of the n parties inside a TEE of a different and independent implementation. The code of every party is attested to be correct.

Implementation. The system initialization involves starting and attesting the TEEs encapsulating each of the n parties. Once the TEEs are started, all communication among and with the TEEs occurs via secure channels tied to the attestation. The API functions are implemented as in S1, but the n parties run in their respective TEEs.

Properties. S2 improves S1 by providing confidentiality as long as at least $n - t$ TEEs are uncompromised and free of side-channel exploits. The remaining t parties and their underlying TEEs may be arbitrarily compromised or subject to side-channel exploits. Furthermore, the integrity of $f(m)$ holds as long as all parties are semi-honest and, in particular, do not manipulate their input shares (as in S1).

3.5. Strawman 3 (S3): S2 + MACs

Strawman S3 weakens the assumption needed for the *integrity* of $f(m)$ to at least $n - t$ *uncompromised TEE implementations*.

Components. S3 is like S2, but adds message authentication codes (MACs) to data shares.

Implementation. Same as S2, except that $Enc()$ adds a MAC to each encrypted share. The MPC within a $Dec()$

operation checks these MACs, and produces a MAC on the result $f(m)$, which the caller (decryptor) should check.

Properties. Differently from S2, in S3 the integrity of $f(m)$ holds under the same assumption as for confidentiality: At least $n - t$ parties’ TEEs must be uncompromised and free of side-channel exploits. Hence, S3 attains confidentiality and integrity in our desired threat model (§ 3.2).

4. Details of the FE construction

CoVault’s full FE-like construction follows the S3 design. The construction uses two parties, 2PC, and two independent TEE implementations ($n = 2$ and $t = 1$). The S3 strawman omits many details, which we describe in this section. First, we discuss the mechanisms behind the attestation of TEEs. Then, we present our secret-sharing scheme, and discuss how we implement 2PC using garbled circuits in the malicious threat model by adapting the existing DualEx protocol [49] and adding output integrity guarantees.

4.1. TEE attestation

Background. The parties use different, independent TEE implementations. A party runs each component of its processing pipeline in a separate TEE of its given implementation. Each party’s processing pipeline consists of two kinds of components: a single provisioning service (PS) and one or more data processors (DPs). The PSs perform actions on behalf of their party, and also attest and provision the DPs in their pipeline with the keypair necessary to decrypt shares. The DPs of a party are the entities that jointly perform 2PC with the DPs of the other party: each party’s DP represents a *party* in S3, in the sense of 2PC. Each pair of DPs (i.e., one per party) is specific to a pre-determined set of functions F , a set of decryptors D , and an expiration time t_e .

Assumptions. A trusted process separately attests the PSs and signs their public keys, verifies that the DPs correctly authorize decryptors in D , and verifies that the specification of F matches the source code of the DPs. In § 5, we describe how we implement this trusted process in CoVault in a decentralized fashion using community approval.

System initialization.

- 1) Each party instantiates its PS; then, each PS generates its party’s private-public keypair.
- 2) Each party starts its DPs; then, each DP is remotely attested and provisioned by its PS with cryptographic keys, including the key to decrypt its share of data (in the sense of standard asymmetric cryptography).
- 3) Each PS holds information on the set of triples $[F, D, t_e]$. For each triple, this information consists of the specification of each function in F , the public keys of the authorized decryptors in D , the data expiration date t_e , and the public keys of both DPs that implement that $[F, D, t_e]$.
- 4) The PSs and DPs can be safely shut down and restarted from their sealed state [25] without requiring re-attestation.

4.2. Secret-sharing and encryption

An encryptor wishing to encrypt a cleartext data item m first generates a single-use random value r . The shares of m are then r and $m \oplus r$, where \oplus is bitwise exclusive-or (XOR). Encryptors can contact the PSs to retrieve information on the set of $[F, D, t_e]$ they can consent to, as well as the public keys of the DPs that implement them. If an encryptor consents to a particular $[F, D, t_e]$, they secret-share their data, encrypt each share with the appropriate public key, and send the encrypted share to the respective DP. Secret sharing ensures data confidentiality, while subsequently encrypting the shares prevents data misuse: Only correctly attested TEEs (i.e., provisioned with the corresponding decryption keys) can decrypt the shares.

4.3. Garbled circuits in the malicious model

The DPs run 2PC using Yao’s garbled circuits [83] (GCs) in the *malicious* threat model. Yao’s original GC protocol is secure only in the *semi-honest* threat model: One party (the *generator*) generates a garbled circuit representing the computation, and the other party (the *evaluator*) blindly evaluates the circuit, using oblivious transfer (OT) to ask the generator for the garbling of the evaluator’s inputs. A malicious generator can generate an incorrect circuit and thereby compromise data confidentiality and result integrity.

Extensions of Yao’s protocol to the malicious setting are usually very expensive [81], but one recent extension—the DualEx protocol [49]—is reasonably efficient. DualEx runs *two* instances of a semi-honest GC protocol concurrently on separate core pairs, with the roles of the generator and evaluator swapped. Both runs use a maliciously-secure OT protocol [82]. Each run reveals the computation result to the respective evaluator, so both parties learn the result. A final maliciously-secure circuit [81] checks that the results match. The 1-bit result of this check is revealed to both parties. A malicious party can use this check to learn any one bit of the other party’s input. However, if the result is false, the honest party refuses to communicate further with the other party, so this leak cannot be amplified by repetition. Hence, DualEx is maliciously secure *except* for a 1-bit leak in the information-theoretic sense. This relaxation enables better runtime efficiency compared to other maliciously-secure GC protocols, which is why we build on DualEx.

Our extension to DualEx. We design a modified DualEx protocol that does not reveal the output of the computation to the two parties, but instead to the decryptor, in order to match the needs of our FE design (strawmen S1–S3). Specifically, our *modified DualEx* reveals different *shares* of the output to the two parties. The two parties send these shares to the decryptor, who reconstructs the output. (Note that this is security-equivalent to, but more efficient than, encrypting the output with the decryptor’s public key within 2PC, as in strawmen S1–S3.)

Our modified DualEx works as follows. Let y be the actual computation output. The two parties first run standard

DualEx to compute $y \oplus r_1 \oplus r_2$, where y is the actual computation output, and r_1 and r_2 are random values respectively provided by each party as additional inputs to the circuit, and \oplus is bitwise exclusive-or (XOR) (the XOR operation can be implemented very efficiently in garbled circuits [51]). The computed value $y \oplus r_1 \oplus r_2$ is returned to the two parties by the standard DualEx. Then, the parties recover shares of y as follows: Party 1 computes the XOR of its random input r_1 and the output $y \oplus r_1 \oplus r_2$, while Party 2 ignores the output and uses r_2 as its share. These resulting values, namely $y \oplus r_2$ and r_2 , are the shares of y .

For integrity, the shares r_2 and $y \oplus r_2$ are also MAC'd within 2PC, using the protocol in § 4.4. The two parties eventually send their MAC'd shares to the decryptor, who checks the MACs and reconstructs the output. We prove the security of our modified DualEx protocol in § E.4.

4.4. Secret-sharing with MACs

Following strawman S3, our design uses MACs over input and output shares for integrity. First, encryptors locally compute MACs on their data shares, before encrypting and uploading them to the DPs; the DPs check the MACs on input shares within 2PC before computing any function. Second, the DPs compute MACs on the shares of the function's output in 2PC, as described in the previous subsection.

To this end, we extend the secret-sharing scheme of § 4.2 with MACs as follows: To securely share x , generate a random key k , compute $t \leftarrow \text{HMAC}_k(x)$, secret-share k into k_1, k_2 and x into x_1, x_2 using the scheme of § 4.2. Output (x_i, k_i, t) to party i for $i = 1, 2$. The two parties can jointly verify the MAC later, but neither party can manipulate its share x_i or k_i without failing subsequent verification. Our implementation uses a SHA-3 HMAC. We formally prove the security of this construction in § E.3.

5. CoVault's design

Next, we show how CoVault uses the FE-like construction from § 3.5 and § 4 in a secure selective analytics platform.

Roadmap. A data source (encryptor) consents to having its data used for queries (functions) in F by queriers in D for a period ending at time t_e ; we call the triple $[F, D, t_e]$ a *query class*. A query class is the unit of consent: Data sources decide on the query class(es) they wish to consent to, and encrypt their data accordingly. Once time t_e has passed, the DPs that implement the associated class cease to decrypt/query the data, effectively making the data in the query class inaccessible. Authorized queriers can request a given query to be run on the data contributed to a query class by contacting the DPs implementing that query class. Next, we sketch how operations in CoVault are mapped to the operations of the FE-like construction defined in § 3.1.

Defining a query class. To define a new query class, an interested analyst calls the *Setup* operation of both PSs, passing the appropriate F, D, t_e as arguments. The PSs

update their configuration state accordingly and publish the vector of public keys $MPK[F, D, t_e]$ and the public keys of the DPs associated with the new query class.

Contributing data. Data sources choose a query class to which they wish to contribute their data. Then, they perform the *Enc* operation locally using the vector of public keys associated with the chosen query class to produce the encrypted and MAC'd shares of their data, which they then send to the DPs associated with the query class.

Querying the database. To run a query f , a querier connects via secure channels to the two DPs that implement the appropriate query class. The querier first performs a *KeyGen* operation on both DPs to obtain SK_f and then performs a *Dec* operation on both DPs to obtain the shares of the desired query result. These two operations check that the function and the decryptor are in the query class, and that the expiration time of the query class has not passed.

Community approval process. CoVault relies on a community approval process to justify trust in its software. In principle, each data source could inspect the source code of the PSs, the DPs of relevant query classes, as well as the build chain used to compile the system, in order to verify that all components are correctly implemented according to their specification, and then remotely attest the PSs—which form the system's technical root of trust—to make sure their initial measurement hash is as expected. However, this approach is impractical, because most data sources lack the technical expertise and resources to perform these actions. The community approval process provides a level of indirection. Interested community experts inspect the system components and publish signed statements that a PS or DP with a given measurement hash correctly implements a specification. Separately, community members may remotely attest the PSs and sign their public keys if their measurement hashes are as expected. Data sources can rely on the assessments of community experts they trust. We describe community approval in more detail in § A.

Privacy from authorized queriers. To ensure that authorized queriers cannot infer private data from the results of authorized queries, query implementations should provide strong privacy guarantees, ideally differential privacy. Queries with weak privacy should not be approved by community experts. Auxiliary state needed for enforcing privacy, such as residual privacy budgets in the case of differential privacy, can be stored in CoVault's database itself (secret-shared, MAC'd and encrypted like other data), and the enforcement of the privacy policy, such as updates to residual privacy budgets, can be done in 2PC. The DPs can also maintain a log of executed queries for later audit.

5.1. Security Analysis and Proofs

CoVault attains the confidentiality and integrity properties stated in our threat model (§ 3.2), which assumes that at least $n - t$ of the parties' TEEs are uncompromised and free of side-channel exploits. This assumption, together with our community approval process, implies that at least $n - t$ of the

DPs to which a data source provides shares are completely honest, i.e., they follow prescribed protocols and do not leak additional information, even under active attacks (side-channel or other). Hence, the security of CoVault’s design reduces to proving that the MPC scheme we use is actually t -of- n secure in the malicious model. The design uses $n = 2$, $t = 1$, and relies on a combination of our modified DualEx protocol for maliciously-secure 2PC (§ 4.3) and our secret-sharing with MACs (§ 4.4). We formally define and prove the security of these constructions, CoVault’s FE-like construction and its end-to-end design in § E.

6. Data processing

Each of the two parties has access to its own data store, which contains that party’s shares. For simplicity, we refer to both data stores as CoVault’s db (database), but we note that any fetch operation on this db consists of two independent, parallel fetches, one per party. In this section, we discuss the general structure of CoVault’s db and how we run queries on large datasets *scalably*. Due to space constraints, we defer a description of data ingress processing to § B.

Database. CoVault’s (encrypted, MAC’d) data shares can be stored in any untrusted database. In general, the db access pattern during a query can leak secrets. A general solution is ORAM [40]; however, ORAM – even a read-only variant – is expensive and does not naturally permit concurrent access. Therefore, CoVault relies on the private information retrieval (PIR) scheme described in the next paragraph. Queries that access rows in a manner that does not reveal secrets (e.g., perform a full scan or use a public index) can be optimized and do not use PIR (§ 6.2).

Oblivious database access. CoVault uses a simple random shuffling scheme to shuffle tables that are accessed with non-public keys. The shuffling hides which records are accessed and forms a simple PIR scheme with no query-time overhead. Shuffling is implemented by a pair of DPs, DP_1 and DP_2 , without 2PC. DP_1 locally shuffles the rows of a table using a randomly generated permutation ρ_1 that it keeps secret. The shuffling is implemented obliviously but locally on DP_1 ; whenever two rows are read to potentially be swapped, they are re-encrypted within DP_1 , so an outside observer cannot determine whether they were actually swapped. DP_1 then passes the shuffled table to DP_2 , which re-shuffles once more with a permutation ρ_2 , that it (DP_2) generates uniformly at random and keeps secret. The resulting overall permutation $\rho_1 \circ \rho_2$ remains unknown to either DP alone and is uniformly random as long as one DP is honest, so this scheme is robust to one malicious party per our threat model. During query execution, the DPs provide ρ_1 and ρ_2 as private inputs to 2PC. Using this information, $\rho_1 \circ \rho_2$ is computed *within* 2PC, and the indices of rows in the end-to-end shuffle are calculated.

Shuffling cannot hide whether two lookups access the same row. Therefore, to avoid frequency attacks, a shuffled table is used for one query only, and a query never fetches the same row twice. Reshuffling can be done ahead of time, so that freshly shuffled tables are readily available to queries.

6.1. Query processing

The unit of querying in CoVault is a SQL filter-groupby-aggregate (FGA) query, which we call a *basic* query. In general, a querier may make a series of *data-dependent* basic queries with query parameters of later queries depending on the results of earlier queries. In the following, we first describe how CoVault executes basic queries, and then how it handles data-dependent series of basic queries.

FGA or basic queries. A FGA/basic query has the form:

```
SELECT aggregate([DISTINCT] column1), ...
FROM T WHERE condition GROUP BY column2
```

Here, *aggregate* is an aggregation operator like SUM or COUNT. The query can be executed as follows: (i) filter (select) from table *T* the rows that satisfy *condition*, (ii) group the selected rows by *column2*, and (iii) compute the required *aggregate* in each group. A straightforward way of implementing a FGA query is to build a *single* garbled circuit that takes as input the two shares of the entire table *T* and implements steps (i)–(iii). However, this approach does not take advantage of *core parallelism* to reduce query latency. Moreover, the size of this circuit grows super-linearly with the size of *T* and the circuit may become too large to fit in the memory available on any one machine. To exploit core parallelism and to make circuit size manageable, CoVault relies on the observation that FGA queries can be implemented using map-reduce [32]. We first explain how this works in general (without 2PC) and then explain how CoVault does this in 2PC.

Background: FGA queries with map-reduce. Suppose we have m cores available. The records of table *T* are split evenly among the m cores.

Step (i): Each core splits its allocated records into more manageable *chunks* and applies a **map** operation to each chunk; this operation linearly scans the chunk and filters only the records that satisfy the **WHERE condition**.

Steps (ii) and (iii): These steps are implemented using a tree-shaped **reduce** phase. The 1st stage of this phase uses half the number of reducers as the map phase. Each **1st-stage reducer** consumes the (filtered) records output by two mappers, sorts the records by the grouping column *column2*, and then performs a linear scan to compute an aggregate for each value of *column2*. The output is a sorted list of *column2* values with corresponding aggregates. Each subsequent stage of reduce uses half the number of reducers of the previous stage: Every **subsequent-stage reducer** merges the sorted lists output by two previous-stage reducers adding their corresponding aggregates and producing another sorted list. The last stage, which is a single reducer, produces a single list of *column2* values with their aggregates.

CoVault: FGA queries with map-reduce in 2PC. CoVault executes FGA queries by implementing the mappers and reducers described above as *separate* garbled circuits and evaluating the circuits in 2PC. Thus, CoVault inherits scaling with cores from the map-reduce paradigm.

The *challenge* here is that circuits can implement only a limited class of algorithms. In particular, a circuit is data-oblivious—it lacks control flow—and the length of the output of a circuit cannot depend on its inputs. However, common algorithms for sorting rely on control flow (they branch based on the result of integer comparison), and standard algorithms for filtering and merging lists produce outputs whose lengths are dependent on the values in the input lists. Hence, to implement mappers and reducers in circuits, we have to use specific algorithms that are data oblivious and pad output to a size that is independent of the inputs (this padded output size, denoted d below, is an additional parameter of the algorithm; it should be an upper bound on the possible output sizes). In the following, we explain basic data-oblivious algorithms that CoVault relies on, and then explain how it combines them with padding when needed to implement mappers and reducers in circuits.

CoVault relies on the following standard data-oblivious algorithms implemented in circuits:

- A *linear scan* passes once over a list performing some operation (e.g., marking) on each element, or computing a running total.
- *Oblivious sort* on a list. While oblivious sort has a theoretical complexity $O(n \log(n))$, all practical algorithms are in $O(n(\log(n))^2)$. CoVault uses bitonic sort [14].
- *Oblivious sorted merge* merges two sorted lists into a longer sorted list. It retains duplicates. CoVault uses bitonic merge, which is in $O(n \log(n))$ [14].
- *Oblivious compact* moves marked records to the end of a list, compacting the remaining records at the beginning of the list in order. For this, CoVault uses an $O(n \log(n))$ butterfly circuit algorithm [41, Section 3].

CoVault uses these algorithms to implement mappers and reducers as follows. A CoVault **mapper** uses a *linear scan* to only mark records that do *not* satisfy the `WHERE` condition with a discard bit; it does not actually drop them, else the size of the output list might leak secrets. A **1st-stage reducer** *obliviously sorts* the outputs of two mappers, ordering first by the discard bit, and then by the `GROUP BY` criterion, `column2`. This pushes all records marked as discard by the mappers to the end of the list, and groups the rest in sorted order of `column2`. Records with the same value of `column2` belong to the same group, so the reducer must consider them just once when computing the aggregate. To this end, it performs a *linear scan* to (a) compute a running aggregate for each unique group, and (b) mark all but one record in each group to be discarded. Finally, it does an *oblivious compact* to push all records marked as discard to the end of the list. The unmarked records contain *unique*, sorted values of `column2` paired with corresponding aggregates. This output is truncated or padded to a fixed length d , which, as mentioned earlier, is an additional query parameter that should be an upper bound on the possible number of unique groups in `column2`. **Subsequent-stage reducers** are similar to the 1st-stage reducers, except that they receive two already sorted lists as input, so they use *oblivious sorted merge* instead of the

more expensive oblivious sort.

The theoretical complexities of a mapper, 1st-stage reducer, and subsequent-stage reducer are $O(c)$ where c is the chunk size, $O(c(\log(c))^2)$ and $O(d \log(d))$, respectively. The chunk size c has a non-trivial effect on query latency: Larger chunks result in more expensive mappers and 1st-stage reducers, but fewer total number of mappers and reducers. In practice, we determine the chunk size empirically to minimize query latency; our experiments use $c = 10k$.

Running a series of data-dependent FGA queries. If the data rows accessed by a FGA query *depend* on the output of an earlier query, information about database contents may leak via the db access pattern. To avoid such leaks, a data-dependent series of FGA queries uses previously shuffled tables only (§ 6). Also, the number of records read must not depend on previous query results; to this end, 2PC adds dummy record reads.

6.2. Optimizations

Indexing by public attributes. If a table contains a non-sensitive, public attribute, we can speed up queries that filter on this attribute by creating *public indexes* on this attribute and fetching only filtered data, thus not needing to filter within 2PC. In this case, CoVault does not MAC each record individually, but computes MACs (one per column) on all records with the same public attribute value, as they would be fetched together. Of course, each data source must consent for a given attribute to be public: CoVault’s public configuration contains the public attributes for each query class. In § 7.1, we show examples of tables (views) and queries that exploit such indexes on public attributes.

Joins. Join operations are very expensive when done obliviously [85], and even more expensive in 2PC. For instance, consider a self-join: each row of a table is compared to every other row of the same table. To hide access patterns, an oblivious self-join scans the whole table for each row in the table. However, if the access pattern reveals *only* public information, we can speed up joins. In fact, the access pattern is *not* sensitive if the data is joined on a public attribute. In these cases, CoVault performs joins outside 2PC. We describe an example of this optimization in § C.

Materialized views. A materialized view is a stored query result, maintained to speed up future queries that contain the same subquery. CoVault supports materialized views, including those on pre-joined data. If a public attribute exists, CoVault stores materialized views with a public primary index. If no public attribute exists, or if a query requires secret-dependent data access to a view, CoVault stores shuffled copies of the view, suitable for PIR (§ 6).

Keeping data in garbled form. Data passed between data sources and DPs, between pairs of DPs along the map-reduce pipeline, and between DPs and queriers must be MAC’d to prevent either party from modifying its shares. MAC computation in garbled circuits is expensive to the point that it can be the dominant cost of 2PC (see § C.3).

While the use of MACs to protect data between data sources and DPs, and between DPs and queriers is unavoidable, we can eliminate MACs between DPs along the map-reduce pipeline by passing values between DPs of consecutive stages in garbled form (i.e., their in-circuit representation). This eliminates the need for the MACs within map-reduce. We use this optimization in our prototype implementation.

7. Evaluation

We implemented CoVault using EMP-toolkit [80], a library that compiles and executes C/C++ programs in garbled circuits-based 2PC, using recent optimizations such as Half Gates [84] and FreeXOR [51]. We use bitonic sort and bitonic merge from the EMP library, and implement our own primitives for compaction, linear scan, and the MAC of §4.4 (based on a SHA-3 HMAC, using a pre-existing circuit for the core SHA-3 loop). We compose these to implement microbenchmarks and queries. Redis (v5.0.3, non-persistent mode) is used as the db, and we use the optimizations mentioned in §6.2. We implemented the two-party shuffle operation from §6 and we hold shuffled views in memory on a DP (rather than in Redis) for efficient re-shuffling.

We run 2PC between two parties on Intel and AMD CPUs, respectively. We use 7 machines with Intel®Xeon®Gold 6244 3.60GHz 16-core processors (2 sockets, 8 cores/socket, 1 thread/core) and 495GB RAM each, and 7 machines with AMD EPYC 7543 2.8GHz 32-core processors (2 sockets, 16 cores/socket, 1 thread/core) and 525 GB RAM each. All machines run Debian 10 and are connected via two 1/10GB Broadcom NICs to a Cisco Nexus 7000 series switch. In addition, each pair of Intel and AMD machines is directly connected via two 25Gbps links over Mellanox NICs; these are used for 2PC. Frequency scaling is disabled on the Intel machines, where the CPU governor is set to performance mode; this feature is not available on the AMD machines, which only have the nominal frequency option.

On both types of machines, we run computations on Linux Debian 10, hosted inside VMs managed using libvirt 5.0 libraries, the QEMU API v5.0.0, and the QEMU hypervisor v3.1.0. On the AMD machines we run the VMs in SEV-SNP TEEs provided in the sev-snp-devel branch of the AMDSEV repo [1], along with their patched Qemu fork. On the Intel machines, we run the VMs without a TEE, because CPUs with TDX are not yet available and SGX has very stringent memory limits. We believe the resulting performance of 2PC is nevertheless representative, because it is limited by the slower AMD CPUs, which do use TEEs. We use at most 16 cores in the AMD SNP-SEV VMs to match the cores available on the Intel machines (as cores are used in pairs).

7.1. Example scenario: Epidemic analytics

We evaluate CoVault in the context of epidemic analytics. We note that epidemic analytics is only an example

Figure 3: Schemas of two materialized views used for epidemic analytics. The first column in *italics* is a public index, while the rest of the record is confidential. (The full schemas are shown in Figure 7).

T_E	<i>space-time-region</i>	eid	did1	did2	...
T_P	<i>epoch</i>	did1, time	did2	duration	prev next ...

scenario: CoVault’s query processing overhead is independent of the data semantics, which impacts at the most the choice of the upper bound on the possible output sizes (see §6.1). Hence, this evaluation applies to any other application scenario implementing queries with the same sequence of FGA operations and similar input and output sizes.

We use synthetic data representing time series of GPS locations and pairwise Bluetooth radio encounters reported by smartphones [55], [75]. Real data of this sort would be sensitive, and we assume that users would provide such data for the purpose of privacy-preserving epidemic analytics only to a secure selective analytics platform like CoVault.

We detail the data upload process and CoVault’s data pre-processing steps in §C.2. The pre-processing results in two materialized views T_E and T_P , whose schemas are shown in Figure 3. Each view has a *public*, coarse-grained index, which is shown in *italics* font. T_E is a list of pairwise encounters with an encounter id (eid), anonymous ids of the two devices (did1, did2) and additional information about the encounter (indicated by dots ... in the table). Its public index is a coarse-grained *space-time-region*, which generally is of the order of several km²h. Records within the same space-time-region are stored together in CoVault’s db. The resolution of space-time regions depends on public information and is chosen so as to achieve an approximately even number of records per space-time region. The exact number of records in each space-time region is obfuscated by padding all regions to the same length (§C.1).

The second view T_P contains encounters privately indexed by individual device ids and the times of the encounter reports (did1, time). A record also contains pointers to the previous and next encounter of the same device. These pointers are used to traverse the timeline of a given device. The public index is a coarse-grained interval of time (~1h) in which the encounter occurred. We call this interval an *epoch*. T_P is used by data-dependent queries as explained later, so this view is randomly shuffled (§6).

Our evaluation uses the three queries q1–q3 shown in Figure 4, which we developed in consultation with an epidemiologist. Queries q1 and q2 are histogram queries on frequencies of encounters. They bin devices in a given set A by the number of total encounters and the number of unique encounters with distinct devices they had in a given, arbitrary space-time region R. Such queries can be used to understand the impact of contact restrictions (such as closure of large events) on the frequency of contacts between people. These queries run on T_E . Query q3 asks how many devices from set B encountered a device from the set A within a given time interval. This query can be used to determine

Figure 4: Queries used in the evaluation. The selections on the public attributes space-time-region and epoch are done outside 2PC using the public indexes of T_E and T_P . R is a set of space-time-regions.

<p>(q1) Histogram of #encounters, in space-time regions R, of devices in set A</p> <pre>SELECT HISTO(COUNT(*)) FROM T_E WHERE did1 ∈ A AND space-time-region ∈ R</pre>
<p>(q2) Histogram of #unique devices met, in space-time regions R, by each device in set A</p> <pre>SELECT HISTO(COUNT(DISTINCT(did2))) FROM T_E WHERE did1 ∈ A AND space-time-region ∈ R</pre>
<p>(q3) Count #devices in set B that encountered a device in set A in the time interval [start, end]</p> <pre>WITH TT AS (SELECT * FROM T_P WHERE start < epoch < end) SELECT COUNT(DISTINCT(did2)) FROM TT WHERE did1 ∈ A AND did2 ∈ B AND start < time < end</pre>

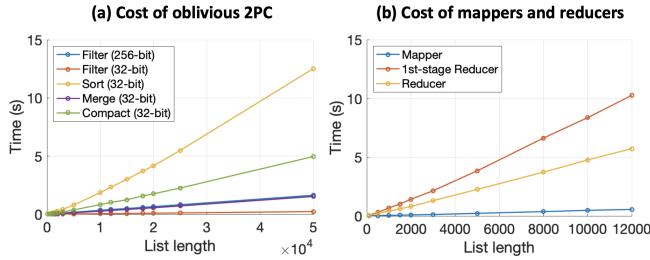


Figure 5: Processing time vs. workload size

if two outbreaks of an epidemic (corresponding to the sets of devices A and B) are directly connected. A related query, discussed in §C.4, extends q3 to indirect encounters between A and B via a third device.

7.2. Microbenchmarks

We first report the costs of basic 2PC primitives (§ 6.1), individual mappers and reducers (§ 6.1), and random shuffling (§ 6). All experiments reported here are on a single pair of cores, one Intel and one AMD. We measure the cost of only one of the two executions of DualEx since the two executions are completely independent everywhere in CoVault, execute in parallel, and synchronize only once at the end of every query for DualEx’s equality check (which is performed only at the last reducer stage). The reported experiments ran the 2PC generator on an Intel core and the evaluator on an AMD core, but we have tried the opposite configuration and the results are similar.

Primitives. Figure 5a shows the time taken to execute the basic oblivious 2PC primitives from § 6.1—linear scans on 32-bit and 256-bit records, sort, sorted merge, and compact on 32-bit records—as a function of the number of records. Each reported number is an average of 100 measurements.

The coefficient of variation for input size 100 elements is 17% on average and at least 8% for each operation. For other input sizes, it is below 4% on average and at most 5% across all operations.

The trends are as expected: The cost of linear scans grows linearly in the input size, while the costs of sort, sorted merge and compact are slightly super-linear. In particular, the cost of sorting is significantly higher than that of compaction, which is why our reduce trees sort only in the first stage and then use compact only (§ 6.1).

Map and reduce. The basic units of query processing are map and reduce operations. Figure 5b shows the average time taken to execute specific but representative map, 1st-stage reduce, and subsequent-stage reduce operations as a function of the number of input records on a single core pair. The specific operations are from query q2 in Figure 4. The map operation takes records from T_E , pre-filtered to a given space-time region. It linearly scans the records to mark those whose did1 matches a given device id and projects every marked record to just a 32-bit fingerprint of did2, in effect finding all devices (did2s) that met the given device id. The 1st-stage reduce takes the outputs of two maps, sorts and merges them, marks duplicate fingerprints for deletion, and compacts, in effect *counting* the number of unique devices. The subsequent-stage reduce does the same, but on the output of the 1st-stage reduce, so it does not have to sort. The results are as expected: map is linear in the number of input records, while reduce is slightly super-linear.

Shuffling. Next, we evaluate the cost of random shuffling to produce shuffled encounters views (§ 6). First, random shuffling requires a *one-time* pre-processing step to MAC and encrypt every record separately. A basic unit (2 AMD + 2 Intel cores) in our setup pre-processes records of schema T_P in 17.8ms per record, with standard deviation < 0.9ms (6%). A country with population 80M produces 11.85B encounters/day, assuming conservatively 100 encounters/person/day in rural areas and 200 encounters/person/day in urban areas; pre-processing all encounters in a day requires 2,441 basic units, or 4,882 core pairs. An urban town with population 200k would produce 40M encounters/day and similarly require 8 basic units, or 16 core pairs.

Each shuffle itself requires two *sequential* oblivious sorts on CPUs of different types (outside 2PC). Shuffling a view of 617M records—a conservative upper bound on the number of encounters generated in 1h in a urban city with population 3M—takes about 56min in our setup. Shuffling one-tenth the number, 61M records, takes 4min. Variances are negligible. The scaling is super-linear because oblivious sort (even outside 2PC) runs in $O(n(\log(n))^2)$ steps.

Queries use a shuffle only once, but shuffles can be generated ahead of time in parallel. Because sorting takes place on one machine at a time, a single pair of cores can, in less than 1h, produce 2 different shuffles for encounters generated in 1h. Therefore, we can prepare shuffles for q queries using $q/2$ pairs of cores continuously.

Bandwidth. 2PC streams large garbled circuits from the generator to the evaluator, and the generator also transmits

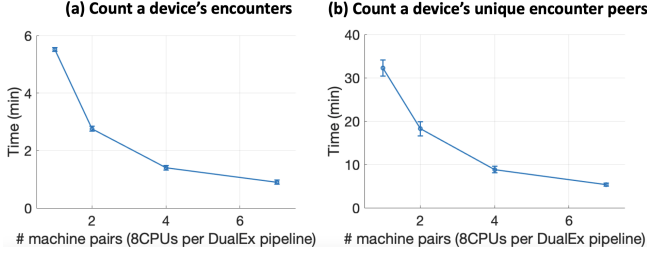


Figure 6: Query latency vs. available core pairs for the basic query of queries (q1) and (q2) from Figure 4.

the garbling of the evaluator’s inputs. During a series of sort and scan operations, the average bandwidth from the generator to the evaluator, measured with NetHogs [2], is ~ 2.72 Gbps. The bandwidth from the evaluator to the generator is negligible in comparison (0.11Gbps). With DualEx, the average bandwidth would be 2.72Gbps in each direction. Thus, 16 active cores on each machine need a bandwidth of 22.64Gbps in each direction, which our 2x25Gbps links can easily support.

Storage overhead. When storing dbs in non-garbled form (i.e., without the optimization of § 6.2), CoVault imposes slightly more than 2x storage overhead on the db. The 2x comes from the need to store two shares per value, and there is slightly more storage for MACs depending on the size of the space-time region or epoch (one MAC per column per region or epoch). When storing in garbled form, as we actually do, the overhead is 512x: Each bit of data expands to 128 bits due to garbling, which doubles due to secret sharing, and further doubles due to the two parallel garbled circuits of DualEx. Based on the conservative calculation above, a country with population 80M generates 11.85B encounters/day, which amounts to at most 2.40 TB (non-garbled) and 618.78 TB (garbled) of added storage per day for our largest view T_E .

7.3. Query latency

We empirically evaluate end-to-end query latency, a key performance metric, for the queries q1–q3 of Figure 4.

Queries q1 and q2. Queries q1 and q2 run on the view T_E . The queries fetch only the records that are in the space-time region R , using the public index on T_E . This significantly reduces the size of the input table and the query latency. In both queries, we iterate over devices in the given set A . For each device a in A we issue a basic FGA query. For q1, this basic query counts the number of encounters of device a in T . For q2, this basic query counts the number of unique devices that device a met. Note that basic queries for all devices in A can be done in parallel, independently. We empirically evaluate the latency-resource trade-off for the basic queries of q1 and q2 by varying the number of available machine pairs from 1 to 7. The experiments here are end-to-end and perform both runs of DualEx (in parallel, on two pairs of cores).

Figure 6a shows the latency of q1’s basic query against the number of available machines. All points are averages of 10 runs (std. dev. $< 4.7\%$). As input, we use a table with 28M encounter records (corresponding to a conservative upper bound on encounters generated in a space-time region with 10k data sources reporting 200 encounters/day over 14 days). We process these records in chunks of size 10k, which minimizes the latency empirically. Mappers filter input encounters to those involving the specific user, and reducers just aggregate the number of encounters. The latency is almost inversely proportional to the number of core pairs available, since the bulk of the work is map-reduce locally on each machine (cross-machine reduce is done only once at the end).

Figure 6b shows the latency of q2’s basic query in the same setup. The map phase is unchanged, but each reduce now combines and removes duplicates from two lists of encountered devices. As explained in § 6.1, we need to specify an upper bound on the size of each reducer’s output. Here, we fix this to 500 (i.e., we assume that a person will encounter at most 500 unique devices in 14 days). Numbers are averages of 10 runs each, and coefficients of variation are below 9.1%. Again, the query latency varies almost inversely with the number of machines, but the costs are higher than those of q1 since reducers do more work.

Scaling. From measurements of individual mappers and reducers in queries, we can extrapolate the number of machines needed to attain a certain query latency with a given number of input records. For example, if the input was 10 times larger (280M records), answering q2’s basic query in 10min needs 736 core pairs (i.e., 46 8-CPU machines). The details of our extrapolation algorithm are in § D.

Query q3. This query asks for the number of devices in B that directly encountered a device in A in the time interval $[start, end]$. To implement q3, we traverse the trajectories of devices in B backwards in time, by iterating over *epochs*, from the epoch that contains *end* to the epoch that contains *start*. This iteration over epochs is done outside 2PC since epochs are public. The data for each epoch is successively loaded into a temporary table, called TT in the query, and this table is then processed via a query in 2PC. The 2PC query traverses the trajectory of each device in B from the device’s last encounter in the epoch to their earliest encounter, by following encounter pointers. For this traversal, 2PC makes data-dependent queries to the epoch’s records in TT but since the records in each epoch are randomly shuffled per our PIR scheme, this does not reveal any secrets. To ensure that no secrets leak via the *number* of lookups in an epoch, we use a fixed, conservative number of lookups per device (in B) per epoch, fetching dummies when needed (the size of B is part of the query, hence, public). Every other device encountered by a device (in B) during the traversal is checked for membership in A , via a Bloom filter initialized with devices in A (the Bloom filter is implemented in 2PC). Whenever the membership test succeeds, we mark the device in B as having encountered someone in A . At the end, we simply count the number of marked devices.

In our experiments, it took (in 2PC) a constant 52ms to initialize the Bloom filter for $A = 10$, 27ms (std. dev. 2ms) to fetch an encounter from a shuffled view, 43ms (std. dev. 5ms) to check membership in the Bloom filter, and 10ms (std. dev. 2ms) to check that an encounter’s time is between `start` and `end`. Assuming $B = 10$, a total of $e = 336$ epochs (corresponding to a period of 14 days with 1h epochs), and at most $n = 30$ encounters/person/h, the total query latency comes to $52 + (27 + 10 + 43) \cdot e \cdot n \cdot |B| = 2.24$ hours.

Note that our PIR scheme improves query latency significantly by enabling data-dependent accesses. Without PIR, we would have to scan *all* encounters in the time interval `[start, end]`. Assuming, as before, that 11.85B encounters are generated in a country every day, and the interval `[start, end]` is 14 days long, this data-independent approach would have to process nearly $11.85B \cdot 14 = 165.9B$ encounter records in 2PC. By contrast, the data-dependent approach above processes a total of $336 \cdot 30 \cdot 10 = 100,800$ records in 2PC, which is over 6 orders of magnitude fewer records fetched and processed in 2PC.

Summary We conclude our evaluation with a list of key takeaways. First, CoVault’s combination of garbled circuits and map-reduce scales well: CoVault can analyze large datasets with reasonable latency using proportionally more cores. Second, the core requirements are moderate even for country-scale datasets if query latencies of the order of hours are acceptable. For example, for a mid-sized country with 80M people, we estimate that continuously ingesting all incoming encounter records (11.85B records/day) requires 1,660 core pairs on a continuous basis (see § C.3), shuffling incoming records continuously – if needed for data-dependent queries – needs another 4,882 core pairs on a continuous basis (§ 7.2), and running an epidemic analytics query like `q2` on 14 days of such records (165.9B records) within 10h requires an additional 5,600 core pairs engaged for the 10h of the query’s execution. Although high in absolute number, these core requirements correspond to mid-sized datacenters operated by individual organizations today, and we believe that such an investment is justifiable when the analytics has a sufficiently high socio-economic benefit. The core requirements are proportional to the size of the datasets. For example, for a urban town with 200k people recording 200 encounters/day each (a total of 40M encounters/day), the core requirements for continuous data ingestion, continuous shuffling and answering `q2` on 14 days of records within 10h would be 6, 16 and 20 core pairs, respectively.

8. Related work

We discussed prior work on hardware-secured, federated, and homomorphic encryption-based analytics platforms in § 1. Here, we discuss other related work.

Encrypted databases. Early encrypted databases like CryptDB [65] used weak forms of encryption like deterministic or order-preserving encryption, which are insecure

in practice [44], [18]. Blind Seer [63] uses strong encryption combined with 2PC to traverse a specialized index, but leaks information by exposing its search tree traversal and supports only a limited set of search queries.

Data-oblivious analytics. Data analytics can be implemented using data-oblivious algorithms to prevent information leaks through memory access patterns. Cipherbase’s oblivious extension [11] proposes optimized, oblivious implementations of query operators but, to the best of our knowledge, this extension was not implemented. Ohrimenko, Schuster et al. [60], Ohrimenko, Costa et al. [59], and M^2R [33] use similar techniques to mitigate side channels in map-reduce and machine-learning queries. Opaque [85], OCQ [31], and StealthDB [43] are secure analytics platforms that run encapsulated in a (single) TEE but, additionally, implement query operators using oblivious algorithms. OblIDB [36] extends Opaque and Cipherbase with optimized operators that do not need to scan the whole table for every query. Although CoVault also relies on oblivious algorithms, its threat model is stronger: it does *not* rely on the honesty of any single party or TEE implementation.

ORAM [40], [79], [34] is a general technique for hiding the memory access pattern of any computation. However, ORAM is costly compared to custom oblivious query operations. For read-only queries, private information retrieval (PIR) offers a more efficient alternative [26], [29], [61], [78]. CoVault avoids the costs of ORAM and PIR for queries whose access patterns reveal no secrets. For other queries, CoVault uses a new PIR scheme based on ahead-of-time random shuffling (§ 6).

Analytics using secret sharing. Like CoVault, Obsecure [45], SMCQL [15], Cryptε [24], and GraphSC [57] use secret sharing to distribute trust over multiple parties, and MPC or partially homomorphic encryption to process queries. Waldo [30] uses secret sharing and 3PC, relying on distributed trust in 2 out of 3 servers. Unlike CoVault, Waldo is focused on analytics of time-series data from a single source, and aims to keep queries confidential. All these systems rely on an undischarged assumption about the non-collusion of parties. In CoVault, the parties execute in different TEE implementations to reduce this assumption to the security of $n - t$ TEE implementations. Moreover, none of the prior platforms support selective consent.

9. Conclusion

CoVault is a secure selective analytics platform based on a new FE-like construction. The platform supports selective forward consent and is secure under a strong threat model that tolerates compromise and side-channel attacks against any one TEE implementation, and thereby enables analytics on sensitive data for the public good. Experimental results show that CoVault can perform powerful analytics, while scaling out to large databases using map-reduce parallelism.

CoVault’s efficiency can be further improved using techniques that we plan to explore in future work: (i) opportunistic use of partially-homomorphic secret sharing to

compute certain operations locally outside MPC, (ii) use of a combination of arithmetic and boolean circuits for MPC, and (iii) use of more than 2 parties, since MPC over 3 or more parties can be significantly cheaper than 2PC [23], [9] (this requires more than two TEE implementations, which will likely be available in the near future).

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Appendix A.

Community approval process

As discussed in § 5, CoVault relies on a community approval process to justify trust in the system. Specifically, CoVault relies on community approval for two purposes: (i) to justify the trust in the PSs, which form CoVault’s root of trust by attesting and provisioning DPs; (ii) to justify data sources’ trust that the query classes to which they contribute their data do what their specification says it does. In both cases, data sources and users can rely on experts they trust who have attested the PSs or reviewed the implementation of PSs and DPs.

Any interested community member can inspect the source code of each system component, verify their measurement hashes, remotely attest the PSs, and publish a signed statement of their opinion. To do so, a witness performs the following operations: 1) Check if another witness it trusts has already verified and attested the PSs (it would not scale to have *every* witness remotely attesting the PSs); if not, inspect the source code of the PSs and the build chain used to compile all system components, make sure they correctly implement the system’s specification, and verify that the measurement hash recorded in the system configuration matches the source code, and remotely attest the PSs accordingly; 2) Obtain the current system configuration from the PSs; 3) Review the specification and source code of each query in a given class, and verify the measurement hash of the class’s DPs recorded in the configuration; 4) Publish a signed statement of their (the witness’s) assessment.

We note that attackers could remove or suppress witness statements, and false witnesses could post false statements about PS attestations or PS and DP (query class) reviews. However, this amounts at most to denial-of-service (DoS) as long as data sources are not distracted by reviews (positive or negative) from witnesses they do not fully trust. Furthermore, we note that the state of the PSs could be rolled back by deleting their sealed states or replacing the sealed states with an earlier version. However, this also amounts to DoS, as it would merely have the effect of making inaccessible some recently defined query classes and their data.

Appendix B.

Ingress processing with public attributes

Many analytics applications like epidemic or financial transaction analytics rely on (spatio-)temporal data. In these applications, it is likely that the queries analyse data in a given (space-)time region. If the (spatio-)time attribute reveals no sensitive information, we can exploit data locality: grouping and storing together data according to *public* (spatio-)temporal information speeds up the queries fetching a whole group for processing. To exploit data locality, CoVault creates a materialized view(s) indexed by a public attribute(s), e.g., coarse-grained (space-)time information. Thus, CoVault is a read-only platform but supports db appends in order of public attributes: CoVault’s ingress processing pipeline allows incremental data upload from several

data sources and produces materialized views securely and efficiently. In this section, we explain CoVault’s ingress processing, which is implemented in 2PC by two dedicated DPs called the two Ingress Processors (IPs).

Batch append Data sources upload new data in batches, which are padded to obfuscate the exact amount of data being uploaded. Data sources may pre-partition data according to public attributes, or locally pre-join or pre-select data prior to upload. Once a batch is uploaded, the batch becomes immutable and queryable. Before appending that batch to CoVault’s db, the IPs may perform pre-processing operations in 2PC; for instance, the IPs can buffer different batches and run group or sort operations (in 2PC) in order to produce or append to materialized views. The actual operations and materialized views are application-specific; in §C, we discuss the example scenario of epidemics analytics. Note that data sources can contribute data to one or more query classes. CoVault’s IP pairs are query-class specific.

Ingress security and integrity Data sources upload batches to IPs using session keys, thus are not identifiable by the IPs. The batches are padded, and the padding is “revealed” only within 2PC: no single IP party can determine the actual amount of data in any batch. For added security, data sources can split a single batch into multiple batches randomly and upload them with different session keys. They may also use VPN/Tor to obfuscate their Internet addresses during upload.

Storing data in garbled form As discussed in § 6.2, computing MACs in 2PC is expensive. So, we eliminate the MACs between IPs and DPs as well, by storing values in CoVault’s db directly in garbled form. Doing so significantly increases the size of stored data: garbling codes each bit in a 128-bit space. However, this choice eliminates the need for the IPs to compute MACs in 2PC, and for the DPs to verify them. (However, recall that IPs need to *verify* in 2PC the MACs added to their shares by the data sources, and this is unavoidable). This optimization of storing garbled values can be generalized to different query classes by using a separate secret to garble circuits for each query class: an IP pair garbles every datum once for the query class it manages, and each DP pair gets access to the secret of its class only.

Appendix C. Epidemics Analytics: Further Details

C.1. Database

Epidemic analytics operates on a time series of individual locations and pairwise contacts among data sources’ devices. Such data may originate, for instance, from smartphone apps that record GPS coordinates and pairwise Bluetooth encounters [55], [75], or from a combination of personal devices and Bluetooth beacons installed in strategic locations [8], [13]. We assume that data sources consent to consider as *public* coarse-grained spatio-temporal information related to the data they upload, as well as the inputs and the results of statistical epidemiological queries.

Figure 7: Materialized views used for epidemic analytics. The first column is a public index. (*s.t.* = *space-time*).

View	Record fields							
T_E	<i>s.-t.-region</i>	<i>eid</i>	<i>did1</i>	<i>did2</i>	<i>t</i>	<i>dur</i>	<i>aux</i>	<i>validity</i>
T_S	<i>s.-t.-region</i>	<i>did1</i>	<i>aux</i>	period of contagion				
T_P	<i>epoch</i>	<i>did1, t</i>	<i>did2</i>	<i>dur</i>	<i>prev</i>	<i>next</i>	<i>aux</i>	<i>validity</i>

Here, we describe the records and materialized views used in our epidemic analytics scenario. Each view consists of a variable number of records of the form described in Figure 7. There is a separate view for every query class. The views include encounters identified by an encounter id (*eid*). If two data sources share an encounter, they report the same *eid* for that encounter, along with their own device id *did*. Only mutually confirmed encounters—encounters reported by both peers with consistent information on the encounter—are used for analytics. For this purpose, the IPs perform a join of the individual encounter reports, and add a *validity* attribute to potentially mark an encounter as confirmed (see § C.2). Additionally, the records may report *t*, a fine-grained temporal information indicating when an encounter begins, *dur*, the encounter duration, and *aux*, any additional information not currently used (e.g., fine-grained location or signal strength). Finally, note that the records in T_P are organized by device trajectories: these records are indexed by *did1* and *t*, and each entry contains the indexes of the previous (*prev*) and next (*next*) encounters of *did1*. This view is used by queries that search trajectories in an encounter graph (q3 in Figure 4 and q4 in Figure 9).

Space-time views These materialized views speed up queries that have no data-dependent flow control. The views are grouped in space-time regions, indexed by a *public*, coarse-grained space-time index. Space-time views contain either encounter records (T_E) or information related to sick people (T_S). When a data source uploads a batch of encounters, it pre-selects the coarse-grained space-time index that batch maps to. The IPs collect batches from different data sources, and generate space-time views grouping data in the same space-time region. Using space-time views accelerates queries whose input parameters specify an arbitrary space-time region in input: prior to run the query in 2PC, the DPs can locally fetch all records whose coarse-grained index falls within the space-time region in input.

The resolution of the space-time regions depends on publicly known population density information and mobility patterns at a given location, day of the week, and time of the day, and is chosen so as to achieve an approximately even number of records per region. Each region is padded to its nominal size to hide the actual number of records it contains. (Note that many shards corresponding to locations at sea, in the wilderness, or night time have a predicted size of zero and therefore do not exist in the views.)

Shuffled encounter views As discussed in § 6.2, space-time views can be used only if the queries do not require any secret-dependent data access. Otherwise, we use shuffled

encounter views, which support our PIR scheme. These views allow running a sequence of basic queries on T_P ; however, CoVault cannot reveal the *sequence* of space-time regions analysed, as such sequence might reveal data sources' movements in time. Thus, the only public attribute is a conservative coarse-grained *time* information, which we call *epoch*. The primary key is encrypted and *the records within each epoch are randomly shuffled*. The mapping between a record, its encrypted key, and its position within the view can be reconstructed only in 2PC. The views are produced by the IPs and the records in an epoch are re-shuffled by the DPs after each use in a query (§ 6).

Risk encounter view This materialized view contains encounters that involve a diagnosed patient and took place during the patient's contagion period. Conceptually, it is the result of a join of T_E and T_S , computed incrementally during ingress processing and in cooperation with data sources. The view supports efficient queries that focus on potential and actual infections.

C.2. Ingress Processing

Next, we discuss CoVault's ingress processing (§ B) specific to epidemic analytics. As mentioned in § C.1, the IPs check whether an encounter is confirmed, and potentially mark it as valid. Here, we give more details about this computation. Before uploading data to a view, the data source partitions its encounters into *per-space-time-region* batches, sorts each batch by *eid*, and *randomly pads* each batch to hide the actual number of encounters in the batch (§ B). Then, the data source secret-shares and MACs the batches following the protocol of § 4.4, and uploads the batches to the two IPs using session keys.

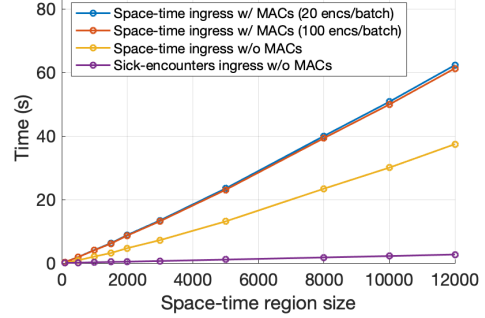
Throughout a day, each IP pair receives batches from data sources and stores them locally (outside 2PC). Periodically, e.g., once per day, each IP pair runs a 2PC, which: (1) consumes all per-device batches for the space-time region; (2) reconstructs the batches from the shares; (3) verifies the per-batch MACs; (4) merges the (sorted) batches into a space-time region buffer using oblivious sorted merge [47]; (5) and truncates or pads the sorted list to the expected space-time region size.

The sorting puts padding uploaded by the data sources at the end of the buffer, so truncating the buffer deletes padding first. Next, the IPs confirm encounters within 2PC. For each *eid*, they check if both peers have uploaded the encounter with consistent locations and times, and set the validity bit of each encounter accordingly. This requires a linear scan of the space-time region. Finally, each IP in the pair appends the space-time region (in garbled form, see § B) to the appropriate tables and materialized views, performing random shuffling when needed.

C.3. Evaluation of Ingress Processing

Ingress processing (§§ B and C.2) converts batches of records uploaded by data sources to tables/views used by

Figure 8: Cost of ingress processing on a single space-time region as a function of the region size.



queries. Again, we report the costs of only one of the two circuits of DualEx because ingress does not perform DualEx's equality check and runs the two circuits completely independently in parallel (the tables/views created by the IPs are stored in their in-circuit, garbled form).

The two highest, nearly overlapping lines of Figure 8 show the average time for ingress processing to generate a single space-time region in T_E , as a function of the region size (x-axis) and the upload batch size (20 encounters/batch or 100 encounters/batch) on a pair of cores (i.e., a pair of IPs). The IPs perform all the (1–5) steps in § C.2. The costs are slightly super-linear because the IPs sort each batch and merge the sorted batches. A significant part of this cost (between 40% and 65% depending on the region size) is the verification of per-batch MACs (*cf.* the 3rd line, which shows the cost without it). This high cost of MAC verification in 2PC is why we store tables/views in garbled form and avoid verifying MACs again in query processing. Note that the cost of ingress processing without MAC verification depends on the region size but not the batch size; in fact, the batch size impacts only the number of batches and the time to upload each batch to the IPs via a different, secure connection. This cost is negligible compared to the costs of 2PC operations. The lowest line of Figure 8 is the cost of ingress operations to populate the table of data sources diagnosed sick (T_S). This cost is much lower than that of generating a space-time region since T_S is not sorted and each record in T_S has fewer bits, which reduces MAC verification time.

Scaling The relevant performance metric for ingress processing is throughput: We want to determine how many core pairs we need to keep up with the data rate generated by a given administrative entity (e.g., country, city). Thus, we run a 5h experiment where m core pairs generate space-time regions of 100 records each from uploads in batches of size 20. We measured the throughput of ingress processing (in encounters processed per hour), varying m from 1 to 8.

As expected, the results show perfect linear scaling with the number of available core pairs, from 584k to 4.75M encounters processed per hour for 1 and 8 core pairs, respectively. From this, we can extrapolate the number of core pairs needed to keep up with all encounters generated in a given world region. For example, conservatively as-

Figure 9: Query q4. The selection on the public attribute epoch is done outside 2PC using T_P 's public index.

```

(q4) Count #devices in B that encountered a de-
      vice which previously encountered a device in
      A, with both encounters in the time interval
      [start,end]
WITH TT AS
  (SELECT * FROM  $T_P$ 
   WHERE start < epoch < end)
SELECT COUNT(DISTINCT(T2.did2))
FROM (TT AS T1) JOIN (TT AS T2)
ON T1.did2 == T2.did1
WHERE T1.did1 ∈ A AND T2.did2 ∈ B AND
start < T1.time < T2.time < end

```

suming 200 encounters/person/day in urban areas and 100 encounters/person/day in rural areas, we estimate that, every 24h: (a) a mid-sized country with population 80M would generate 11.85B encounters; (b) a big metropolitan area with population 8M would generate 1.6B encounters; (c) a urban city with population 3M would generate 600M encounters; (d) a urban town with population 200k would generate 40M encounters.

Extrapolating from the linear scaling above, we estimate that the two runs of DualEx would need a total of 1660, 226, 86, and 6 core pairs, respectively. According to these estimates, the ingress processing of a whole country is well within the means of a small-scale data center, while that of a town would require a single pair of machines.

C.4. Evaluation of an additional query

Here, we describe another data dependent query q4 (Figure 9), which we also evaluate for latency. This query asks how many devices from set B encountered a device from the set A indirectly through an intermediate device (all within a given time interval). This query can be used to determine if two outbreaks of an epidemic (corresponding to the sets A and B) are indirectly connected over 1-hop.

Latency evaluation We implemented and evaluated the latency of q4 in the same setting as q3 (§ 7.3). Unlike q3, which makes one traversal over the trajectories of devices in B, q4 uses *two* traversals. One traversal collects all encounters of devices in A moving forwards in time; the second traversal collects all encounters of devices in B moving backwards in time. We then sort the collected encounters of $A \cup B$ ascending by time, and make a linear pass over them maintaining two Bloom filters, one of all devices that have encountered a device in A and the other of devices in B who have encountered a device *already* in the first Bloom filter. The result of the query is the size of the second filter at the end.

In our experiments, Bloom filter operations take 709ms per encounter and there is a one-time setup cost of 129ms. Sorting the encounter list of $A \cup B$ has negligible cost in comparison. Assuming $e = 336$ epochs, $n = 30$ encounters/person/h, $|A| = 10$ and $|B| = 10$ (the same values

that we assumed for q3), this encounter list has length $m = e \cdot n \cdot (|A| + |B|) = 201,600$. The total query latency is $129 + 27 \cdot e \cdot n \cdot (|A| + |B|) + (10 + 709) \cdot m = 1.74$ days. In this case, the savings over a naive approach of scanning all encounter records are even more pronounced than those in the case of q3, since the naive approach would have to first sort 165.9B records in 2PC and then scan them maintaining the same two Bloom filters.

Appendix D.

Estimation of end-to-end query latency

We describe how we estimate the end-to-end latency of a query executed in 2PC using our map-reduce approach, as a function of the number of available machine pairs. By reversing the estimation function, we can also easily determine the number of machines needed to attain a given query latency.

We start with two basic mathematical facts that we need for our estimates.

Lemma 1. *Given n i.i.d. random variables X_1, \dots, X_n with normal distributions of mean μ and standard deviation σ , let $X = \max(X_1, \dots, X_n)$. Then, $\mathbb{E}[X] \leq \mu + \sigma \sqrt{2 \ln(n)}$.*

Proof. This is a folklore result. We provide a simple proof here. Let $t > 0$ be a parameter. Since e^y is a convex function of y , by Jensen's inequality, $e^{t\mathbb{E}[X]} \leq \mathbb{E}[e^{tX}] = \mathbb{E}[\max_i e^{tX_i}] \leq \mathbb{E}[\sum_{i=1}^n e^{tX_i}] = \sum_{i=1}^n \mathbb{E}[e^{tX_i}]$. From the moment generating function of the normal distribution, $\mathbb{E}[e^{tX_i}] = t\mu + \frac{1}{2}\sigma^2 t^2$. Hence, $e^{t\mathbb{E}[X]} \leq ne^{(t\mu + \frac{1}{2}\sigma^2 t^2)}$, and $\mathbb{E}[X] \leq \frac{\ln(n)}{t} + \mu + \frac{t\sigma^2}{2}$. The function on the right is minimized for $t = \frac{\sqrt{2 \ln(n)}}{\sigma}$, and its minimum value is $\mu + \sigma \sqrt{2 \ln(n)}$, as required. \square

In the sequel, we let $\mathbb{E}[D; n]$ denote the expected value of the maximum of n i.i.d. random variables, each drawn from the normal distribution D . Lemma 1 says that

$$\mathbb{E}[D; n] \leq \mu + \sigma \sqrt{2 \ln(n)}$$

where μ and σ are the mean and standard deviation of D .

Lemma 2. *For any natural number $K \geq 0$,*

$$\sqrt{K} + \sqrt{K-1} + \dots + \sqrt{1} \leq \frac{2}{3}((K+1)^{3/2} - 1)$$

Proof.

$$\begin{aligned}
& \sqrt{K} + \sqrt{K-1} + \dots + \sqrt{1} \\
&= \int_K^{K+1} \sqrt{x} dx + \dots + \int_1^2 \sqrt{x} dx \\
&\leq \int_K^{K+1} \sqrt{x} dx + \dots + \int_1^2 \sqrt{x} dx \\
&= \int_1^{K+1} \sqrt{x} dx \\
&= \frac{2}{3}((K+1)^{3/2} - 1)
\end{aligned}$$

\square

Now we explain our estimation of end-to-end latency. Suppose we have M available machines pairs and each machine has $2C$ available cores. This gives us a total of C units of DualEx execution per machine pair and a total of MC units of DualEx execution. In the sequel, we use the term *unit* to mean “a unit of DualEx execution”.

For a given query, let the queried table have N records. We divide the records of the table into *chunks* of t records each, and then divide the chunks evenly among the MC units. So, each unit starts with N_c chunks, where

$$N_c = \frac{N}{tMC}$$

The best value of t is determined empirically: If t is too small, each mapping and initial reducing circuit does very little work (and setup costs dominate). If t is too high, the state of all parallel cores on a machine may not fit in memory. For tables in our evaluation, we usually pick t to be 10,000 records.

The query actually executes in 4 fine-grained stages. All but the last stage do *not* perform the final equality check of DualEx, but each stage does run the two symmetric DualEx 2PC computations.

- 1) (Unit-level) Each unit (2+2 cores on a machine pair) maps two chunks out of its N_c chunks and then reduces them to an intermediate result. Each unit then alternates mapping a new chunk and reducing the mapped chunk with the intermediate result previously available on the unit, producing a new intermediate result. This second step is repeated $N_c - 2$ times on each unit till all chunks are consumed and one intermediate result is obtained on each unit. All MC units do these computations in parallel. Let D_{mmr} be the latency distribution of the first two maps followed by reduce on a single unit, and let D_{mr} be the latency distribution of each of one subsequent map+reduce on a single unit.
- 2) (Machine-pair-level) All C units on a single machine pair reduce their results to a single result using a balanced reduction tree. All M machine pairs do this independently in parallel. Let D_{mach} be the latency distribution of this on a single machine.
- 3) (Cross-machine) All intermediate results across all machine pairs are reduced using a balanced reduce tree to two final results, which are on a single machine. Only one unit per machine pair is used. At the end, one machine ends up with two results. Let D_{cmr} be the latency distribution of the following cross-machine computation: Two pairs of machines reduce in parallel and one pair sends its result to the other pair at the end. We call this a cross-machine reduction unit (*cmru*).
- 4) (Final reduce) The machine pair getting the last two intermediate results performs one final reduce with the DualEx equality check at the end. Let the latency distribution of this final step be D_{fr} .

We empirically estimate D_{mmr} , D_{mr} , D_{mach} , D_{cmr} , and D_{fr} by observing the means and standard deviations of the corresponding latencies while running a query on a small number of machines. Let μ_{mmr} and σ_{mmr} denote the

mean and standard deviations of D_{mmr} , and similarly for the remaining four distributions. For our end-to-end latency estimate we model each of these distributions as a *normal* distribution with the measured mean and standard deviation.

There is no synchronization at the end of each stage in our implementation, e.g., if all units on a machine pair have finished stage 1, that machine pair goes ahead with stage 2 without waiting for other machine pairs to finish stage 1. However, we estimate the end-to-end query latency *conservatively* by instead calculating the latency of a hypothetical execution model where there is a full, instantaneous synchronization at the end of each of the first three stages. This latter latency is definitely a conservative upper bound on the actual latency, and is much easier to calculate.

Let cost_1 – cost_4 be the expected costs of the four stages above in the conservative (synchronizing) model. We upper-bound each of these separately.

Estimating cost_1 The latency of stage 1 on each unit has a normal distribution given by $D_1 = D_{mmr} + (N_c - 2)D_{mr}$. From standard properties of normal distributions, D_1 has mean and standard deviation μ_1 and σ_1 where

$$\begin{aligned}\mu_1 &= \mu_{mmr} + (N_c - 2)\mu_{mr} \\ \sigma_1 &= \sqrt{\sigma_{mmr}^2 + (N_c - 2)\sigma_{mr}^2}\end{aligned}$$

Then, since stage 1 consists of MC parallel units, we have:

$$\text{cost}_1 = \mathbb{E}[D_1; MC] \leq \mu_1 + \sigma_1 \sqrt{2 \ln(MC)}$$

Estimating cost_2 In stage 2, M machines operate in parallel, each with latency D_{mach} . Thus, we have:

$$\text{cost}_2 = \mathbb{E}[D_{mach}; M] \leq \mu_{mach} + \sigma_{mach} \sqrt{2 \ln(M)}$$

Estimating cost_3 Stage 3 is a tree-shaped cross-machine reduce. The number of levels in this tree is K where:

$$K = \lceil \log_2(M) \rceil$$

At the first level, we have $\lceil M/4 \rceil$ parallel cmrus. At the second level, we have $\lceil M/8 \rceil$ parallel cmrus, and so on, till we have only 1 cmru. Hence, we get:

$$\begin{aligned}\text{cost}_3 &\leq \sum_{i=2}^K \mathbb{E}[D_{cmr}; \lceil M/(2^i) \rceil] \\ &\leq \sum_{i=2}^K \left(\mu_{cmr} + \sigma_{cmr} \sqrt{2 \ln(\lceil M/(2^i) \rceil)} \right) \\ &= (K-1)\mu_{cmr} + \sigma_{cmr} \sqrt{2 \ln 2} \sum_{i=2}^K \sqrt{\lceil M/(2^i) \rceil} \\ &\leq (K-1)\mu_{cmr} + \sigma_{cmr} \sqrt{2 \ln 2} \sum_{i=1}^{K-2} \sqrt{i} \\ &\leq (K-1)\mu_{cmr} + \frac{2}{3}\sigma_{cmr} \sqrt{2 \ln 2} ((K-1)^{3/2} - 1)\end{aligned}$$

Estimating cost_4 This cost is immediate:

$$\text{cost}_4 = \mu_{fr}$$

Our computed upper-bound on the query latency is then $\text{cost}_1 + \text{cost}_2 + \text{cost}_3 + \text{cost}_4$.

Appendix E. Proofs of Security

In this section, we prove the end-to-end security of CoVault and show that it can be used to implement functional encryption (with one-bit leakage). CoVault combines many building blocks and therefore we slowly build up to the security proof in §E.6.1, defining several intermediate building blocks and properties. Figure 10 gives an outline of how these building blocks fit together.

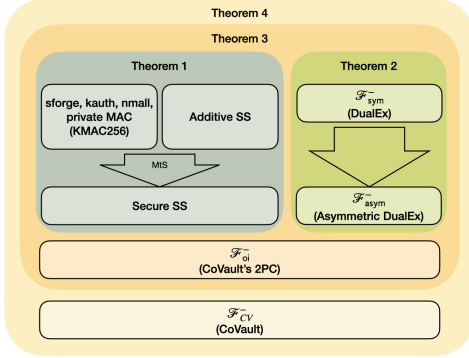


Figure 10: An overview of the proof of security of CoVault.

In §E.1, we introduce notation and the preliminaries necessary for our proofs of security: message authentication codes and their properties (§E.2) and secure secret sharing (§E.2.1). In §E.3, we combine MACs and secret sharing to give a construction of a secure secret sharing scheme and a proof of its security. In §E.4, we modify DualEx, a symmetric 2PC protocol with one-bit leakage, to enable asymmetric outputs, then prove that this modified protocol (asymmetric DualEx) is secure.

Next, we combine these two building blocks and show that the resulting protocol securely computes a function on a reconstructed input while maintaining output integrity. This follows from our proof in §E.5 that a secure secret sharing is secure for computing on authenticated data (Def. 12) even in the presence of one-bit leakage. Finally, in §E.6, we define CoVault's ideal functionality and provide a proof of end-to-end security for the system. We show in §F that this functionality can be used to construct a functional encryption scheme (with one-bit leakage) and also a stronger notion we call *pre-constrained* functional encryption.

E.1. Notation and preliminaries

For any deterministic functionality \mathcal{H} , let \mathcal{H}^- be the functionality that computes \mathcal{H} with one-bit leakage. That is, for a malicious party P_i , the two-party functionality \mathcal{H}^- returns the same output as \mathcal{H} along with some one-bit leakage function ℓ of P_i 's choice applied to the other party's input x ($|\ell(x)| = 1$). For a randomized functionality, ℓ can depend on the other party's input and the randomness used by the functionality.

Throughout this appendix, we assume that some algorithms can output a distinguished symbol \perp . Our security proofs consider PPT (probabilistic polynomial-time) adversaries \mathcal{A} . As is standard in cryptography, the security properties of the schemes we introduce are proven by showing that the *advantage* (defined separately for every property) of a PPT adversary \mathcal{A} is upper-bounded by a *negligible function*:

Definition 1 (negligible function). *A function f is negligible if for all $c \in \mathbb{N}$ there exists an $N \in \mathbb{N}$ such that $f(n) < n^{-c}$ for all $n > N$.*

E.2. Message authentication codes

In CoVault, we use MACs to provide integrity for the data sent by a device to the system. When a device generates data, it secret-shares it before sending one share to each of the two TEEs. Because standard, additive secret sharing schemes are malleable, we utilize message authentication codes (MACs) to add integrity.

Definition 2 (message authentication code (MAC)). *A message authentication code (MAC) is a triple of polynomial-time algorithms $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ such that*

- *KeyGen takes as input a security parameter 1^κ and outputs a random key $k \leftarrow \mathcal{D}_\kappa$*
- *Mac takes as input a key k in some domain \mathcal{D}_κ associated with a security parameter 1^κ and a message m in some domain \mathcal{D}_m and outputs a tag t .*
- *Verify takes as input a key $k \in \mathcal{D}_\kappa$, a message $m \in \mathcal{D}_m$, and a tag t and outputs one of two distinguished symbols \top, \perp .*

For correctness, we require that for all $m \in \mathcal{D}_m$ and $k \in \mathcal{D}_\kappa$, $\text{Verify}(k, m, \text{Mac}(k, m)) = \top$.

Notation. Define $\text{Mac}_k(m) := \text{Mac}(k, m)$ and $\text{Verify}_k(m, t) := \text{Verify}(k, m, t)$.

The security guarantees of MACs span a wide range. We define the relevant notions below.

One-time strong unforgeability. Informally, one-time strong unforgeability says that it is infeasible to forge a tag on a message without knowing the key (including a new tag on a message for which the attacker already knows a tag).

Let $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ be a MAC. For a given PPT adversary \mathcal{A} , we define \mathcal{A} 's advantage with respect to M as $\text{MAC1-sforge-adv}[\mathcal{A}, M] :=$

$$\Pr \left[\begin{array}{l} m \leftarrow \mathcal{A}(1^\kappa); \\ k \leftarrow \text{KeyGen}(1^\kappa); \\ t \leftarrow \text{Mac}_k(m); \\ (m', t') \leftarrow \mathcal{A}(t) \end{array} : \begin{array}{l} (m', t') \neq (m, t) \wedge \\ \text{Verify}_k(m', t') = \top \end{array} \right].$$

Definition 3 (one-time strong unforgeability). *We say a MAC $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ is one-time strongly unforgeable (alternatively, one-time strongly secure) if, for all PPT adversaries \mathcal{A} , there exists a negligible function negl such that $\text{MAC1-sforge-adv}[\mathcal{A}, M] \leq \text{negl}(\kappa)$.*

One-time key authenticity. Standard notions of MAC security deal only with the consequences of an attacker viewing a message-tag pair. In our setting, we introduce a new notion of security for MACs which considers the case in which \mathcal{A} has access to a message-key pair. Informally, a MAC is key authentic if it is difficult to find a new key which still authenticates a given message-tag pair.

Let $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ be a MAC. For a given PPT adversary \mathcal{A} , we define \mathcal{A} 's advantage with respect to M as $\text{MAC1-kauth-adv}[\mathcal{A}, M] :=$

$$\Pr \left[\begin{array}{l} m \leftarrow \mathcal{A}(1^\kappa); \\ k \leftarrow \text{KeyGen}(1^\kappa); \\ t \leftarrow \text{Mac}_k(m); \\ k' \leftarrow \mathcal{A}(k) \end{array} : k' \neq k \wedge \text{Verify}_{k'}(m, t) = \top \right].$$

Definition 4 (one-time key authenticity). We say a MAC $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ is one-time key authentic if, for all PPT adversaries \mathcal{A} , there exists a nonnegligible function negl such that $\text{MAC1-kauth-adv}[\mathcal{A}, M] \leq \text{negl}(\kappa)$.

One-time non-malleability. In this case, we require that an adversary cannot cause a fixed, known tag to verify a message even if it can modify the message and key by some additive shift.

Let $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ be a MAC. For a given PPT adversary \mathcal{A} , we define \mathcal{A} 's advantage with respect to M as $\text{MAC1-nmall-adv}[\mathcal{A}, M] :=$

$$\Pr \left[\begin{array}{l} m \leftarrow \mathcal{A}(1^\kappa); \\ k \leftarrow \text{KeyGen}(1^\kappa); \\ t \leftarrow \text{Mac}_k(m); \\ (\Delta_m, \Delta_k) \leftarrow \mathcal{A}(t) \end{array} : (\Delta_m, \Delta_k) \neq (0, 0) \wedge \text{Verify}_{k+\Delta_k}(m+\Delta_m, t) = \top \right].$$

Definition 5 (one-time non-malleability). We say a MAC $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ is one-time non-malleable if, for all PPT adversaries \mathcal{A} , there exists a nonnegligible function negl such that $\text{MAC1-nmall-adv}[\mathcal{A}, M] \leq \text{negl}(\kappa)$.

Privacy. Let $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ be a MAC. For a given PPT adversary \mathcal{A} , we define \mathcal{A} 's advantage with respect to M as $\text{MAC-priv-adv}[\mathcal{A}, M] :=$

$$\left| \Pr \left[\begin{array}{l} (m_0, m_1) \leftarrow \mathcal{A}(1^\kappa); \\ k \leftarrow \text{KeyGen}(1^\kappa); \\ b \leftarrow_{\$} \{0, 1\}; \\ t_b \leftarrow \text{Mac}_k(m_b) \end{array} : \mathcal{A}(t_b) = b \right] - \frac{1}{2} \right|.$$

Definition 6 (privacy). We say a MAC $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ is private if, for all PPT adversaries \mathcal{A} , there is a negligible function negl such that $\text{MAC-priv-adv}[\mathcal{A}, M] \leq \text{negl}(\kappa)$.

E.2.1. Secure secret-sharing. As mentioned previously, the data sent to CoVault is secret-shared by the source between two TEEs. Basic secret-sharing schemes only deal with privacy of the shared data and do not consider accuracy of reconstruction. In this section, we define (in addition to the notion of privacy) a notion of authenticity which captures the property that the holder of a share of the data cannot, without being detected, change its share in a way that causes

the reconstructed data to be altered. A secret sharing scheme with this additional property is called “secure” and will ultimately be achieved by leveraging MACs (§E.3).

Definition 7 (secret-sharing scheme). A pair of polynomial-time algorithms $\Sigma = (\text{Share}, \text{Rec})$ is a (two-party) secret-sharing scheme if

- Share takes as input a security parameter 1^κ and a value x in the domain \mathcal{D}_κ associated with κ (e.g., $\mathcal{D}_\kappa = \{0, 1\}^\kappa$) and outputs two shares sh_1, sh_2 . We assume κ is implicit in each share.
- Rec takes as input two shares and outputs either a value $y \in \mathcal{D}_\kappa$ or \perp .

For correctness, we require that for all κ and $x \in \mathcal{D}_\kappa$, $\text{Rec}(\text{Share}(1^\kappa, x)) = x$.

Privacy. Informally, privacy says that, given a share of one of two values x_0, x_1 , an adversary \mathcal{A} cannot distinguish whether x_0 or x_1 was shared.

Let $\Sigma = (\text{Share}, \text{Rec})$ be a secret-sharing scheme. For a given PPT adversary \mathcal{A} , we define \mathcal{A} 's advantage with respect to Σ as $\text{SS-priv-adv}[\mathcal{A}, \Sigma] :=$

$$\left| \Pr \left[\begin{array}{l} (x_0, x_1, i) \leftarrow \mathcal{A}(1^\kappa); \\ b \leftarrow_{\$} \{0, 1\}; \\ (\text{sh}_{b,1}, \text{sh}_{b,2}) \leftarrow \text{Share}(1^\kappa, x_b) \end{array} : \mathcal{A}(\text{sh}_{b,i}) = b \right] - \frac{1}{2} \right|.$$

Definition 8 (privacy). We say a secret-sharing scheme $\Sigma = (\text{Share}, \text{Rec})$ is private if, for all PPT adversaries \mathcal{A} , there is a negligible function negl such that $\text{SS-priv-adv}[\mathcal{A}, \Sigma] \leq \text{negl}(\kappa)$.

Authenticity. Informally, authenticity guarantees that any modification to a share will result in Rec returning \perp with high probability.

Let $\Sigma = (\text{Share}, \text{Rec})$ be a secret-sharing scheme. For a given PPT adversary \mathcal{A} , we define \mathcal{A} 's advantage with respect to Σ as $\text{SS-auth-adv}[\mathcal{A}, \Sigma] :=$

$$\Pr \left[\begin{array}{l} (x, i) \leftarrow \mathcal{A}(1^\kappa); \\ (\text{sh}_1, \text{sh}_2) \leftarrow \text{Share}(1^\kappa, x); \\ \text{sh}'_i \leftarrow \mathcal{A}(\text{sh}_i) \end{array} : \text{sh}'_i \neq \text{sh}_i \wedge \text{Rec}(\text{sh}'_i, \text{sh}_{3-i}) \neq \perp \right].$$

Definition 9 (authenticity). We say a secret-sharing scheme $\Sigma = (\text{Share}, \text{Rec})$ is authenticated if, for all PPT adversaries \mathcal{A} , there is a negligible function negl such that $\text{SS-auth-adv}[\mathcal{A}, \Sigma] \leq \text{negl}(\kappa)$.

Definition 10 (security). We say a secret-sharing scheme $\Sigma = (\text{Share}, \text{Rec})$ is secure if it is both private and authenticated.

E.3. Secure secret sharing construction

There are several ways to construct a secure secret-sharing scheme $\Sigma_M = (\text{Share}_M, \text{Rec}_M)$ using a MAC $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ and base (non-authenticated) secret-sharing scheme $\Sigma = (\text{Share}, \text{Rec})$. We introduce MAC-then-Share, the construction used in CoVault, and analyze its security.

Definition 11 (MAC-then-share (MtS)). Let $M = (\text{KeyGen}, \text{Mac}, \text{Verify})$ be a MAC and $\Sigma = (\text{Share}, \text{Rec})$ a secret-sharing scheme. Define $\Sigma_M = (\text{Share}_M, \text{Rec}_M)$, the MtS secret-sharing scheme based on M and Σ , as follows:

- Share_M takes as input a security parameter 1^κ and a value x in the domain \mathcal{D}_κ associated with κ . It generates a single key k using KeyGen and uses it to compute one tag t on the secret value x as $t := \text{Mac}_k(x)$. Now it shares x, k by computing $(x_1, x_2) \leftarrow \text{Share}(x)$ and $(k_1, k_2) \leftarrow \text{Share}(k)$, and outputs two shares sh_1, sh_2 with $\text{sh}_i := (x_i, k_i, t)$.
- Rec_M takes as input two shares. If the tags match, it reconstructs $y := \text{Rec}(x_1, x_2)$ and $k' := \text{Rec}(k_1, k_2)$. Then, if $\text{Verify}_{k'}(y, t) = \top$, it returns y ; otherwise it returns \perp .

What properties are required of the MAC and secret-sharing scheme in order for their composition to be a secure secret-sharing scheme? In Theorem 1, we show that the MAC must meet all four properties presented in Section E.2 in order for the MtS construction to be secure.

Theorem 1. *If M is a one-time strongly unforgeable, key authentic, non-malleable, and private MAC and Σ an additive secret-sharing scheme, then the MtS secret-sharing scheme Σ_M constructed from M and Σ is secure.*

Proof. The privacy of Σ_M follows directly from privacy of M (since $\text{Mac}_k(x)$ reveals nothing about x) and Σ (x_i also reveals nothing about x).

Authenticity of Σ_M is a bit more unwieldy. We prove the contrapositive that if Σ_M is not authenticated, then either (1) M is not strongly secure, (2) M lacks key authenticity, or (3) M is malleable. As before, we do this by reduction of an adversary \mathcal{A} with $\text{SS-auth-adv}[\mathcal{A}, \Sigma_M]$ nonnegligible to three adversaries for each of the three corresponding games, and show that at least one of them has nonnegligible advantage in its game.

First, we construct an adversary $\mathcal{A}_{\text{sforge}}$ for the game $\text{MAC1-sforge}_{\mathcal{A}_{\text{sforge}}, M}$. $\mathcal{A}_{\text{sforge}}$ receives x, i from \mathcal{A} and constructs a MtS triple $\text{sh}_i := (x_i, k_i, t_i)$ as follows: it sends x to its game to get $t := \text{Mac}_k(x)$, picks a random $k_i \in \mathcal{D}_\kappa$, and runs Share on x, t to get x_1, x_2, t_1, t_2 . Now $\mathcal{A}_{\text{sforge}}$ runs \mathcal{A} on sh_i to get $\text{sh}'_i := (x'_i, k'_i, t'_i)$ and returns (x', t') , where $x' \leftarrow \text{Rec}(x'_i, x_{3-i})$ and $t' \leftarrow \text{Rec}(t'_i, t_{3-i})$.

Next, we construct an adversary $\mathcal{A}_{\text{kauth}}$ for the game $\text{MAC-kauth}_{\mathcal{A}_{\text{kauth}}, M}$. $\mathcal{A}_{\text{kauth}}$ is given x, i by \mathcal{A} and sends x to its game, which sends back a key k . It uses this key to construct a MtS triple $\text{sh}_i := (x_i, k_i, t)$, computing $t := \text{Mac}_{k_i}(x)$ and running Share on x, k to get x_1, x_2, k_1, k_2 . Now $\mathcal{A}_{\text{kauth}}$ runs \mathcal{A} on sh_i to get $\text{sh}'_i := (x'_i, k'_i, t')$ and returns $k' \leftarrow \text{Rec}(k'_i, k_{3-i})$.

Third, we construct an adversary $\mathcal{A}_{\text{nmall}_M}$ for the MAC non-malleability game. $\mathcal{A}_{\text{nmall}_M}$ is given x, i by \mathcal{A} and sends x to its game to receive t . It constructs an MtS triple $\text{sh}_i := (x_i, k_i, t_i)$ by choosing a random $k \in \mathcal{D}_\kappa$ and running Share on x, k, t . Now $\mathcal{A}_{\text{nmall}_M}$ runs \mathcal{A} on sh_i to get $\text{sh}'_i := (x'_i, k'_i, t')$. It computes $x' \leftarrow \text{Rec}(x'_i, x_{3-i})$, $k' \leftarrow \text{Rec}(k'_i, k_{3-i})$, and returns (x', k') .

We now analyze the winning probability of each of the three adversaries. By our assumption, \mathcal{A} wins its game with nonnegligible probability, implying $t' = t$. If \mathcal{A} returns sh'_i such that $k'_i = k_i$ with nonnegligible probability, then $\mathcal{A}_{\text{sforge}}$ has nonnegligible advantage and we are done. If not, then with nonnegligible probability, \mathcal{A} returns sh'_i with $k'_i \neq k_i$. If $x'_i = x_i$ a nonnegligible fraction of the time, $\mathcal{A}_{\text{kauth}}$ has nonnegligible advantage in its game, and we are done. Otherwise, $x'_i \neq x_i$ and $\mathcal{A}_{\text{nmall}_M}$ has nonnegligible advantage in the non-malleability game for M : it has a pair $(\Delta_m := x'_i - x_i, \Delta_k := k'_i - k_i)$ such that $\text{Verify}_{k'_i + k_{3-i}}(x'_i + x_{3-i}, t) = \text{Verify}_{(k_i + k_{3-i}) + \Delta_k}((x_i + x_{3-i}) + \Delta_m, t) = \top$.

Thus, if M is authenticated, it is not strongly secure, lacks key authenticity, or is malleable, all of which contradict our assumptions. \square

Note that the proof also holds for the XOR secret sharing scheme by substituting $+, -$ for \oplus .

Concrete Construction. CoVault uses KMAC256[50], a NIST-standardized SHA3-based MAC. It can be abstracted as follows, where \parallel indicates concatenation. (We omit some additional parameters which are constant and public in CoVault; see Appendix A in [50] and Section 6.1 in [35].)

KeyGen: Use SHA3's key generation algorithm.

Mac_k(m): Compute $h := \text{SHA3}(k)$ and announce it publicly. Output $t := \text{SHA3}(k \parallel m)$.

Verify_k(Output): Output \top iff $\text{SHA3}(k) = h \wedge \text{SHA3}(k \parallel m) = t$.

This MAC meets the conditions of Theorem 1 in the random oracle model (ROM):

- **one-time strong unforgeability:** Due to randomness of the output $\text{SHA3}(k \parallel m')$.
- **one-time key authenticity:** Due to collision-resistance, which guarantees that for $k \neq k'$ we have with overwhelming probability that $\text{SHA3}(k \parallel m) \neq \text{SHA3}(k' \parallel m)$.
- **one-time non-malleability:** Again due to collision-resistance, since for $(k, m) \neq (k', m')$ we have with overwhelming probability that $\text{SHA3}(k \parallel m) \neq \text{SHA3}(k' \parallel m')$.
- **privacy:** Due to randomness of the output of SHA3.

Hence, CoVault's MtS construction of Σ_M with Σ as the additive secret sharing scheme and M as KMAC256 is secure. In §E.5, we will show that this means it can safely be used inside a secure computation.

E.4. DualEx functionality with asymmetric outputs

Before turning to the use of our secure secret sharing construction within a secure multi-party (two-party) computation protocol, we must discuss the exact protocol used by CoVault and its non-standard security guarantees.

CoVault uses the DualEx protocol[49] as a building block. DualEx guarantees security against malicious adversaries at almost the cost of semi-honest protocols, but with the following caveats: it can compute any *symmetric*

two-party functionality \mathcal{F}_{sym} , and it does so with one-bit leakage. By symmetric we mean that both parties are required to receive the same output.

In this section, we will address how to modify DualEx to allow for the computation of *asymmetric* functionalities while maintaining the same security guarantees (malicious with one-bit leakage). This modified DualEx, which we dub “asymmetric DualEx”, will be used to implement the core functionality of CoVault, and the one-bit leakage will carry through the remainder of the proofs.

Let $f : \mathcal{X} \times \mathcal{X} \rightarrow \mathcal{Y}$ be some function. In the CoVault setting, we want the output of f to be shared between the parties so that neither learns the output. More specifically, we want to compute the functionality $\mathcal{F}_{\text{asym}}$ that takes as input x_1 from one party and x_2 from the other, and returns a uniformly random r to the first party and $f(x_1, x_2) \oplus r$ to the second party. When P_1 is honest, r is chosen by $\mathcal{F}_{\text{asym}}$; when P_1 is malicious, P_1 chooses r .

To do this, we construct a two-party protocol Π that computes $\mathcal{F}_{\text{asym}}$ via access to the symmetric functionality \mathcal{F}_{sym} that takes inputs $(x_1, r_1), (x_2, r_2) \in \mathcal{X} \times \mathcal{Y}$ from the parties, computes $y := f(x_1, x_2) \oplus r_1 \oplus r_2$, and returns y to both parties. The protocol proceeds as follows:

- Each party P_i holds an input $x_i \in \mathcal{X}$. It additionally samples a uniform blinding value $r_i \in \mathcal{Y}$. The parties then provide their inputs (x_1, r_1) and (x_2, r_2) , respectively, to \mathcal{F}_{sym} .
- Both parties receive in return $y := f(x_1, x_2) \oplus r_1 \oplus r_2$.
- P_1 computes its output as $y_1 := r_1$, while P_2 computes its output as $y_2 := y \oplus r_2$.

Notice that $y \oplus r_2 = f(x_1, x_2) \oplus r_1$, so the protocol outputs $f(x_1, x_2) \oplus r_1$ to the second party and the parties now hold shares of $f(x_1, x_2)$. Below we show that this modified protocol maintains the same security guarantees as the base DualEx.

Theorem 2. Π securely computes $\mathcal{F}_{\text{asym}}^-$ against malicious adversaries in the $\mathcal{F}_{\text{sym}}^-$ -hybrid model.

Proof. Let \mathcal{A} be a PPT adversary corrupting party P_i . To prove the security of Π against malicious adversaries in the $\mathcal{F}_{\text{sym}}^-$ -hybrid world, we give an adversary \mathcal{S}_i in the ideal world that simulates an execution of Π in the hybrid world. We first consider the case of a corrupted P_1 .

Simulator \mathcal{S}_1 : \mathcal{S}_1 has access to the ideal functionality $\mathcal{F}_{\text{asym}}^-$ computing $f(x_1, x_2) \oplus r$ with one-bit leakage. Given f , \mathcal{S}_1 works as follows:

- Receive inputs x'_1, r'_1 , and a leakage function $\ell : \mathcal{X} \times \mathcal{Y} \rightarrow \{0, 1\}$ from P_1 .
- Sample $y^* \leftarrow \mathcal{Y}$. Convert ℓ into a function $\ell^* : \mathcal{X} \rightarrow \{0, 1\}$ by letting $\ell^*(x) = \ell(x, y^* \oplus r'_1 \oplus f(x'_1, x))$ for all $x \in \mathcal{X}$.
- Send (x'_1, r'_1) and ℓ^* to the ideal functionality $\mathcal{F}_{\text{asym}}^-$; the honest party sends x_2 to $\mathcal{F}_{\text{asym}}^-$.
- Receive in return from $\mathcal{F}_{\text{asym}}^-$ r'_1 and some one-bit leakage $b^* := \ell^*(x_2)$. The honest party receives $y_2^* := f(x'_1, x_2) \oplus r'_1$.

- Send y^*, b^* to P_1 .

We prove indistinguishability of the following distribution ensembles.

Ideal experiment. This is defined by the interaction of \mathcal{S}_1 with the ideal functionality $\mathcal{F}_{\text{asym}}^-$. \mathcal{A} outputs an arbitrary function of its view; the honest party outputs what it received from the experiment, namely y_2^* . Let $\text{IDEAL}_{\mathcal{S}_1}(1^\kappa, x_1, x_2, \ell, f)$ be the joint random variable containing the output of the adversary \mathcal{S}_1 and the output of the honest party. Concretely,

$$\text{IDEAL}_{\mathcal{S}_1}(1^\kappa, x_1, x_2, \ell, f) = ((y^*, b^*), y_2^*).$$

Hybrid experiment. let $\text{H}_{\mathcal{A}}(1^\kappa, x_1, x_2, \ell, f)$ be the joint random variable containing the view of the adversary \mathcal{A} and the output of the honest party in the $\mathcal{F}_{\text{sym}}^-$ -hybrid world. Concretely,

$$\text{H}_{\mathcal{A}}(1^\kappa, x_1, x_2, \ell, f) = ((y, b), y_2).$$

\mathcal{S}_1 perfectly simulates the view of a malicious P_1 in the hybrid world. Because r_2 is chosen uniformly at random, both y^* and y are distributed uniformly at random and are thus perfectly indistinguishable. By the definition of ℓ^* , $b^* = \ell(x_2, y^* \oplus f(x'_1, x_2) \oplus r'_1)$. Furthermore, by the definition of y , $r_2 = y \oplus f(x'_1, x_2) \oplus r'_1$, so $b = \ell(x_2, r_2)$ is perfectly indistinguishable from b^* . Hence the joint distributions of (y^*, b^*) and (y, b) are perfectly indistinguishable. Finally, y_2^* and y_2 are identical by the definition of y_2 and thus perfectly indistinguishable.

Next, we give a simulator \mathcal{S}_2 for the case of a corrupted P_2 .

Simulator \mathcal{S}_2 : \mathcal{S}_2 has access to the ideal functionality $\mathcal{F}_{\text{asym}}^-$ computing $f(x_1, x_2) \oplus r$ with one-bit leakage. Given f , \mathcal{S}_2 works as follows:

- Receive inputs x'_2, r'_2 , and a leakage function ℓ from P_2 .
- Forward x'_2 and ℓ to the ideal functionality $\mathcal{F}_{\text{asym}}^-$; the honest party sends x_1 to $\mathcal{F}_{\text{asym}}^-$.
- Receive in return from $\mathcal{F}_{\text{asym}}^-$ the output $z := f(x_1, x'_2) \oplus r_1$ for uniformly random r_1 and some one-bit leakage $b := \ell(x_1)$. The honest party receives r_1 .
- Compute $y^* := z \oplus r'_2$. Send y^*, b to P_2 .

We prove indistinguishability of the following distribution ensembles.

Ideal experiment. This is defined by the interaction of \mathcal{S}_2 with the ideal functionality $\mathcal{F}_{\text{asym}}^-$. \mathcal{A} outputs an arbitrary function of its view; the honest party outputs its honestly computed value of y_1 , namely r_1 . Let $\text{IDEAL}_{\mathcal{S}_2}(1^\kappa, x_1, x_2, \ell, f)$ be the joint random variable containing the output of the honest party and the output of the adversary \mathcal{S}_2 . Concretely,

$$\text{IDEAL}_{\mathcal{S}_2}(\kappa, x_1, x_2, \ell, f) = (r_1, (y^*, b)).$$

Hybrid experiment. let $H_A(1^\kappa, x_1, x_2, \ell, f)$ be the joint random variable containing the the output of the honest party and the view of the adversary \mathcal{A} in the $\mathcal{F}_{\text{sym}}^-$ -hybrid world. Concretely,

$$H_A(1^\kappa, x_1, x_2, \ell, f) = (r_1, (y, b)).$$

S_2 perfectly simulates the view of a malicious P_2 in the hybrid world, since $y^* = z \oplus r'_2 = f(x_1, x'_2) \oplus r_1 \oplus r'_2 = y$.

Therefore, Π is secure (up to 1 bit of leakage) against malicious adversaries in the $\mathcal{F}_{\text{sym}}^-$ -hybrid model. \square

Notice that the DualEx protocol is an instantiation of $\mathcal{F}_{\text{sym}}^-$, so our modified protocol is a real-world protocol with the same security guarantees against malicious parties as the original DualEx: privacy up to one bit of leakage and full correctness of the output.

E.5. Secure computation on shared data

We are now ready to pull together the two branches of CoVault’s approach: secure secret sharing and secure computation with one-bit leakage.

In CoVault, we wish to securely run some function on the data collected from various data sources; as is common, we will achieve this via secure multi-party (two-party) computation. That data is stored in secret-shared form, and must therefore be reconstructed within the secure computation. In this section, we define the desired functionality in this case: one that outputs only either the correct computation $f(x)$ or aborts (\perp) (we call this ideal functionality \mathcal{F}_{oi} , for “output integrity”). A secret sharing scheme which, when used to reconstruct within the secure computation, enables this ideal functionality is called *secure for computing on authenticated data*.

Fix some function f and secret-sharing scheme $\Sigma = (\text{Share}, \text{Rec})$. Define the function f_Σ as

$$f_\Sigma(\text{sh}_1, \text{sh}_2) = \begin{cases} \perp & \text{Rec}(\text{sh}_1, \text{sh}_2) = \perp \\ f(\text{Rec}(\text{sh}_1, \text{sh}_2)) & \text{otherwise.} \end{cases}$$

We consider a hybrid-world execution in which a dealer D shares some value x between two parties P_1 and P_2 . At some later point in time, the parties invoke an ideal functionality \mathcal{F} that computes f_Σ (with abort). In more detail, the hybrid-world execution with some function f using an input x , both potentially chosen by the malicious party, proceeds as follows:

Initial sharing: D runs $(\text{sh}_1, \text{sh}_2) \leftarrow \text{Share}(1^\kappa, x)$ and sends sh_i to P_i .

Parties invoke ideal functionality: Party P_i sends an input sh'_i to the ideal functionality \mathcal{F} computing f_Σ ; an honest party sends the share it received from the dealer. \mathcal{F} computes $y := f_\Sigma(\text{sh}'_1, \text{sh}'_2)$ and sends y to the malicious party.

Output delivery: After receiving y , the malicious party tells the ideal functionality to either continue or abort. In the former case, \mathcal{F} sends y to the honest party;

in the latter case, it sends \perp to the honest party. The honest party outputs whatever it receives from the ideal functionality.

For an adversary \mathcal{A} , let $H_A^\Sigma(1^\kappa, x, f)$ be the joint random variable containing the view of the malicious party and the output of the honest party.

We compare a hybrid-world execution to an *ideal-world* execution in which the parties have access to an ideal functionality \mathcal{F}_{oi} that can (only) return $y = f(x)$ (oi stands for “output integrity”). Concretely, the ideal-world execution proceeds as follows:

Parties invoke ideal functionality: The parties invoke \mathcal{F}_{oi} , which sends $f(x)$ to the malicious party.

Output delivery: After receiving $f(x)$, the malicious party tells \mathcal{F}_{oi} to either continue or abort. In the former case, the ideal functionality sends $f(x)$ to the honest party; in the latter case, it sends \perp to the honest party. The honest party outputs whatever it receives from the ideal functionality; the malicious party can output an arbitrary function of its view.

For an adversary \mathcal{S} , let $\text{IDEAL}_\Sigma(1^\kappa, x, f)$ be the joint random variable containing the output of the adversary and the output of the honest party.

Definition 12. We say Σ is secure for computing on authenticated data if for all PPT \mathcal{A} there exists a PPT \mathcal{S} such that distribution ensembles $\{H_A^\Sigma(1^\kappa, x, f)\}_{\kappa, x, f}$ and $\{\text{IDEAL}_\Sigma(1^\kappa, x, f)\}_{\kappa, x, f}$ are computationally indistinguishable.

However, things are not as simple as that: CoVault uses asymmetric DualEx, so we have one bit of leakage to contend with. Specifically, in our case both functionalities \mathcal{F} and \mathcal{F}_{oi} will leak one bit of information. Next, we will show that this is not a problem and that any secure secret sharing scheme is secure for computing on authenticated data (even when the secure computation leaks one bit of information).

Let \mathcal{F}^- be the ideal two-party functionality that takes as input two secret shares sh_1, sh_2 , computes $y := f_\Sigma(\text{sh}_1, \text{sh}_2)$ (where f_Σ is defined as in Section E.5), and outputs y to both parties with one-bit leakage.

Define the following protocol Π for computing f_Σ with one-bit leakage in the \mathcal{F}^- -hybrid model:

- 1) The dealer D shares some value x as $(\text{sh}_1, \text{sh}_2) \leftarrow \text{Share}(1^\kappa, x)$ and sends sh_i to P_i .
- 2) P_i sends an input sh'_i to \mathcal{F}^- ; the honest party sends the share it received from the dealer. The malicious party additionally sends a leakage function ℓ .
- 3) \mathcal{F}^- computes $y := f_\Sigma(\text{sh}'_1, \text{sh}'_2)$ and sends y and ℓ evaluated on the honest party’s share to the malicious party.
- 4) The malicious party tells \mathcal{F}^- to either continue or abort. In the former case, \mathcal{F}^- sends y to the honest party; in the latter case, it sends \perp . The honest party then outputs whatever it received from the ideal functionality.

Theorem 3. *If Σ is a secure secret-sharing scheme, then it is secure for computing on authenticated data (even in the presence of one-bit leakage).*

Proof. Let \mathcal{A} be a PPT adversary corrupting party P_i and let \mathcal{A} fix x, f . We prove security by simulation: to prove the security of Π against malicious adversaries in the \mathcal{F}^- -hybrid world, we give an adversary \mathcal{S} (the simulator) in the ideal world that interacts with P_i and the ideal functionality computing f with one-bit leakage. \mathcal{S} simulates an execution of Π in the hybrid world.

Simulator \mathcal{S} : Given 1^κ , \mathcal{S} works as follows:

- 1) \mathcal{S} simulates the dealer by choosing a random value \hat{x} and running $(\hat{sh}_1, \hat{sh}_2) \leftarrow \text{Share}(1^\kappa, \hat{x})$. It gives \hat{sh}_i to P_i .
- 2) \mathcal{S} receives \hat{sh}'_i and a leakage function ℓ from P_i .
- 3) If $\hat{sh}'_i \neq \hat{sh}_i$, then \mathcal{S} sends **abort** to the ideal functionality computing f with one-bit leakage, gives \perp to P_i , and halts. Otherwise, \mathcal{S} sends a new leakage function $\ell^* : \mathcal{X} \rightarrow \{0, 1\}$, where $\ell^*(x) := \ell(x \oplus \hat{sh}_1) \forall x \in \mathcal{X}$, and receives $y := f(x)$ and a bit $b^* := \ell^*(x)$. \mathcal{S} forwards both values to P_i .
- 4) If P_i aborts, then \mathcal{S} also aborts; otherwise, it sends **continue** to the ideal functionality.

We prove indistinguishability of the ideal and \mathcal{F}^- -hybrid distribution ensembles using a sequence of experiments.

Ideal experiment. This is defined by the interaction of \mathcal{S} with the ideal functionality computing f with one-bit leakage. \mathcal{A} outputs an arbitrary function of its view; the honest party outputs what it received from the experiment. Let $\text{IDEAL}_\mathcal{S}(1^\kappa, x, \ell, f)$ be the joint random variable containing the output of the adversary \mathcal{S} and the output y_2 of the honest party, which is either y or \perp . Concretely,

$$\text{IDEAL}_\mathcal{S}(1^\kappa, x, \ell, f) = ((\hat{sh}_1, \hat{sh}'_1 \ell, y, b^*, \text{continue/abort}), y_2).$$

Hybrid experiment 1. The first hybrid experiment proceeds in the same way as the ideal world except, instead of \mathcal{S} simulating the dealer, the true dealer D runs $(sh_1, sh_2) \leftarrow \text{Share}(1^\kappa, x)$ and gives sh_i to P_i .

For the adversary \mathcal{A} , let $\text{H1}_\mathcal{A}(1^\kappa, x, f)$ be the joint random variable containing the view of the adversary and the output of the honest party in this hybrid experiment. Concretely,

$$\text{H1}_\mathcal{A}(1^\kappa, x, \ell, f) = ((sh_1, sh'_1 \ell, y, b^*, \text{continue/abort}), y_2).$$

Hybrid experiment 2 (\mathcal{F}^- -hybrid experiment). Next, we define a second hybrid experiment, substituting ideal functionality \mathcal{F}^- computing f_Σ with one-bit leakage for the ideal functionality computing $f(x)$ with one-bit leakage. This experiment proceeds in the same way as hybrid experiment 1, except that, upon receipt of sh'_i and ℓ from P_i , the experiment forwards this value to \mathcal{F}^- (the honest party sends its true share sh_{3-i}) and then returns the output of \mathcal{F}^- , namely $y' := f_\Sigma(sh'_1, sh'_2)$ and $b := \ell(sh_{3-i})$, to \mathcal{A} .

For the adversary \mathcal{A} , let $\text{H2}_\mathcal{A}^{\mathcal{F}^-}(1^\kappa, x, f)$ be the joint random variable containing the view of the adversary and the output of the honest party in this hybrid experiment. Concretely,

$$\text{H2}_\mathcal{A}^{\mathcal{F}^-}(1^\kappa, x, \ell, f) = ((sh_1, sh'_1 \ell, y', b, \text{continue/abort}), y_2).$$

First, we claim the distribution ensembles $\{\text{H1}_\mathcal{A}(1^\kappa, x, f)\}_{\kappa, x, f}$ and $\{\text{IDEAL}_\mathcal{S}(1^\kappa, x, f)\}_{\kappa, x, f}$ are indistinguishable.

Suppose, towards a contradiction, that \mathcal{A} is able to distinguish the ensembles with nonnegligible probability. Then we can construct an adversary \mathcal{A}' with nonnegligible advantage in the privacy game for Σ : \mathcal{A}' chooses two random values x_0, x_1 and a bit i , which it sends to its game to get $sh_{b,i}$ of x_b for unknown b . It now communicates with \mathcal{A} , acting as \mathcal{S} in a run of the ideal experiment with $\hat{x} := x_0$ and $x := x_1$.

At the end of the run, \mathcal{A} guesses whether it participated in an execution of the ideal experiment or hybrid experiment 1. In the former case, \mathcal{A}' returns $b' := 0$; in the latter, it returns $b' := 1$. With nonnegligible probability, the run was an instance in which \mathcal{A} was able to distinguish correctly (without guessing), implying it was able to distinguish between a share of x_0 and a share of x_1 . Thus with nonnegligible probability, $b' = b$ and \mathcal{A}' wins.

This contradicts our assumption that Σ is private, so the ensembles must be indistinguishable.

Next, we show the distribution ensembles $\{\text{H1}_\mathcal{A}(1^\kappa, x, f)\}_{\kappa, x, f}$ and $\{\text{H2}_\mathcal{A}^{\mathcal{F}^-}(1^\kappa, x, f)\}_{\kappa, x, f}$ are indistinguishable.

Note first that, by definition, $b^* = \ell(\hat{sh}'_2)$ and $b = \ell(sh_2)$, with $\text{Rec}(\hat{sh}_1, \hat{sh}'_2) = \text{Rec}(sh_1, sh_2) = x$. Since \hat{sh}'_2 and sh_2 are both distributed uniformly at random, b^* and b are identically distributed.

The only other potentially different component in the two ensembles is y (resp. y'). Suppose towards a contradiction, that \mathcal{A} is able to distinguish the ensembles with nonnegligible probability. Then we can construct an adversary \mathcal{A}' with nonnegligible advantage in the authenticity game for Σ . Given sh_i , \mathcal{A}' chooses a random x and receives a share sh'_i of x from the game. It now communicates with \mathcal{A} in a run of hybrid experiment 2, acting as the simulator \mathcal{S}_2 . When \mathcal{A} sends sh'_i , \mathcal{A}' forwards this value to its game.

At the end of the run, \mathcal{A} guesses which experiment was run. With nonnegligible probability, the run was an instance in which \mathcal{A} was able to distinguish correctly (without guessing), implying $f_\Sigma(sh'_i, sh_{3-i}) \neq \perp$ and $sh'_i \neq sh_i$. So \mathcal{A}' wins with nonnegligible probability. (The other case, in which $f_\Sigma(sh'_i, sh_{3-i}) = \perp$ and $sh'_i = sh_i$, would violate the correctness requirement of Σ .)

This contradicts our assumption that Σ is authenticated, so the ensembles must be indistinguishable.

To conclude, notice that by transitivity, we have computational indistinguishability of $\{\text{IDEAL}_\mathcal{S}(1^\kappa, x, f)\}_{\kappa, x, f}$ and $\{\text{H2}_\mathcal{A}^{\mathcal{F}^-}(1^\kappa, x, f)\}_{\kappa, x, f}$, so Σ is secure for computing on authenticated data in the \mathcal{F}^- -hybrid world. \square

Notably, if Σ is secure for computing on authenticated data, it also guarantees the integrity of the output y , since it guarantees the integrity of \mathcal{A} 's input.

E.6. CoVault security analysis

Finally, we can prove the end-to-end security of the full CoVault protocol. Let Σ_M be a secure secret sharing scheme, and for sets V_1, V_2 , define $\text{Rec}(V_1, V_2)$ as reconstructing each pair of corresponding shares in V_1, V_2 . That is, $\text{Rec}(V_1, V_2) = \{\text{Rec}(\text{sh}_k^1, \text{sh}_k^2)\}_{k=1}^{|V_1|}$ (return \perp if $|V_1| \neq |V_2|$). Define the ideal functionality $\mathcal{F}_{\text{asym}}^-$ as a modified version of the ideal functionality of the same name defined in §E.4: $\mathcal{F}_{\text{asym}}^-$ first takes as input two functions f_1, f_2 . If $f_1 \neq f_2$, the functionality aborts; otherwise, it continues as before, computing $f = f_1 = f_2$. Additionally, when the leakage bit is 1 (without loss of generality), $\mathcal{F}_{\text{asym}}^-$ sends a distinguished message `cheat` to the honest party. This captures the probability that a malicious adversary attempting to learn some leakage bit is caught with probability $1/2$ (derived from the DualEx protocol).

E.6.1. Ideal functionality. Let Q, QP_1, QP_2 be potentially malicious parties; an adversary can corrupt at most the set $\{Q, QP_i\}$ of parties for some $i \in \{1, 2\}$.

The parties interact with the ideal functionality \mathcal{F}_{CV}^- as follows. Q sends two (potentially different) functions f_1, f_2 to QP_1, QP_2 , respectively. The (trusted) dealer D send sets $V_1, V_2 \in \mathcal{X}^m$, respectively, to QP_1, QP_2 . QP_1 and QP_2 send f'_1, f'_2, V'_1, V'_2 to the ideal functionality \mathcal{F}_{CV}^- . At this point a corrupted QP_i can additionally send a leakage function ℓ to \mathcal{F}_{CV}^- .

Upon receiving $f'_1, f'_2, V'_1, V'_2, \ell$, \mathcal{F}_{CV}^- computes an output y and evaluates ℓ on the honest party's input to get a leakage bit b . If $f'_1 \neq f'_2$, $y = \perp$; otherwise, it sets $f = f'_1$ (without loss of generality) and computes $y = f_{\Sigma_M}(V'_1, V'_2)$. The ideal functionality sends y to Q and b to the malicious QP. If $b = 1$, it also alerts the honest QP by sending it a distinguished message `cheat`, in which case that QP aborts.

E.6.2. Full protocol. Let $\Sigma_M = (\text{Share}_M, \text{Rec}_M)$ be a secure secret-sharing scheme. Define the following protocol Π in the $\mathcal{F}_{\text{asym}}^-$ -hybrid model:

- 1) Q sends two (potentially different) functions f_1, f_2 to QP_1, QP_2 , respectively, who send functions f'_1, f'_2 to the ideal functionality $\mathcal{F}_{\text{asym}}^-$; an honest Q sends $f_1 = f_2$, and an honest QP sends the function it received from Q . (Notice that leaking the equality of f'_1, f'_2 does not reveal additional information to the adversary, since it already knows the two functions.)
- 2) D sends V_1, V_2 to QP_1, QP_2 , respectively, who send inputs V'_1, V'_2 to $\mathcal{F}_{\text{asym}}^-$; an honest QP sends the set it received from the dealer. A malicious QP can additionally send a one-bit leakage function ℓ .
- 3) $\mathcal{F}_{\text{asym}}^-$ computes authenticated shares $y_1, y_2 \in \mathcal{Y}$, where $y_1, y_2 := \text{Share}_M(f_{\Sigma_M}(V'_1, V'_2))$ and sends y_i to QP_i . It also computes ℓ evaluated on the honest party's input and sends the leakage bit to the malicious QP.

- 4) If the leakage bit is 1, $\mathcal{F}_{\text{asym}}^-$ alerts the honest QP by sending it a distinguished message `cheat`. Importantly, once cheating is detected, the honest QP completes the current execution but never runs any subsequent iterations of the protocol.
- 5) Each party QP_i sends a value y'_i to Q ; the honest party sends the value y_i it received from the ideal functionality.
- 6) Q recovers $y' = \text{Rec}_M(y'_1, y'_2)$.

E.6.3. Proof of security.

Theorem 4. Π securely computes \mathcal{F}_{CV}^- in the $\mathcal{F}_{\text{asym}}^-$ -hybrid model against malicious adversaries capable of corrupting at most the set $\{Q, QP_i\}$ for $i \in \{1, 2\}$.

Proof. Let \mathcal{A} be a PPT adversary corrupting parties Q, QP_i . To prove the security of Π against malicious adversaries in the $\mathcal{F}_{\text{asym}}^-$ -hybrid world, we give an adversary \mathcal{S} in the ideal world that interacts with Q, QP_i to simulate an execution of Π in the hybrid world.

Simulator \mathcal{S} : \mathcal{S} has access to the ideal functionality \mathcal{F}_{CV}^- . \mathcal{S} works as follows:

- Receive f_{3-i} from Q and f'_i, V'_i, ℓ from QP_i . Forward f_{3-i} to QP_{3-i} .
- Send f'_i, V'_i, ℓ to \mathcal{F}_{CV}^- ; the honest party QP_{3-i} sends f_{3-i}, V_{3-i} .
- Receive $y := f_{\Sigma_M}(V'_i, V_{3-i})$ and some one-bit leakage $b := \ell(V_{3-i})$ from \mathcal{F}_{CV}^- .
- Let $y_i^*, y_{3-i}^* \leftarrow \text{Share}_M(y)$. Send y_i^*, b to QP_i and y_{3-i}^* to Q .

We now prove indistinguishability of the ideal and $\mathcal{F}_{\text{asym}}^-$ -hybrid distribution ensembles.

Ideal experiment. This is defined by the interaction of \mathcal{S} with the ideal functionality \mathcal{F}_{CV}^- . \mathcal{A} outputs an arbitrary function of its view; the honest party outputs nothing. Let $\text{IDEAL}_{\mathcal{S}}(V, \ell, f)$ be the joint random variable containing the transcript of \mathcal{S} in the ideal world. Concretely,

$$\text{IDEAL}_{\mathcal{S}}(V, \ell, f) = (f_{3-i}, f'_i, V'_i, \ell, y_i^*, b, y_{3-i}^*).$$

Hybrid experiment. Let $H_{\mathcal{A}}(V, \ell, f)$ be the joint random variable containing the view of the adversary \mathcal{A} in the $\mathcal{F}_{\text{asym}}^-$ -hybrid world. Concretely,

$$H_{\mathcal{A}}(V, \ell, f) = (f_{3-i}, f'_i, V'_i, \ell, y_i, b, y_{3-i}).$$

\mathcal{S} perfectly simulates the view of the malicious parties in the hybrid world since the joint distributions of (y_i^*, y_{3-i}^*) and (y_i, y_{3-i}) are both distributed uniformly at random conditioned on $\text{Rec}_M(y_i^*, y_{3-i}^*) = \text{Rec}_M(y_i, y_{3-i}) = f_{\Sigma_M}(V_1, V_3)$.

Let p_i be the probability the leakage bit is 0 in iteration i (that is, the attacker is not caught). Without loss of generality, we can assume $p_i \geq 1/2$ (if not, the attacker can flip the leakage and learn the same information while lowering

its probability of being caught). Then the probability that the attacker is never caught is $p^* = \prod_i p_i$. Define the information learned in iteration i as $I_i = \max\{-\log p_i\} = -\log \max\{p_i\}$. Let $I^* = \sum_i I_i$. Then $I^* \geq -\log p^*$. So $I^* \geq \kappa$ implies $p^* \leq 2^{-\kappa}$, i.e., the probability that the attacker learns at least κ bits is at most $2^{-\kappa}$.

Security follows by a hybrid argument and Theorems 1, 2, and 3. \square

Appendix F.

CoVault's functional encryption

Definition 13 (Functional encryption with one-bit leakage). A functional encryption (FE) scheme with one-bit leakage is a tuple of polynomial-time algorithms $\mathcal{FE}^- = (\text{Setup}, \text{KeyGen}, \text{Enc}, \text{Dec})$ with message space \mathcal{M} such that

- $(\text{mpk}, \text{msk}) \leftarrow \text{Setup}(1^\kappa)$ takes as input a security parameter and outputs a master keypair.
- $\text{sk}_f \leftarrow \text{KeyGen}(\text{msk}, f)$ takes as input a master secret key and a function f and outputs a function secret key sk_f .
- $c \leftarrow \text{Enc}(\text{mpk}, m)$ takes as input a master public key and a message m and outputs a ciphertext c .
- $f(m), \ell(m) \leftarrow \text{Dec}(\text{sk}_f, \ell, c)$ takes as input a function secret key for a function f , a one-bit leakage function $\ell : \mathcal{M} \rightarrow \{0, 1\}$, and a ciphertext of m (for some m), and outputs a value y and $\ell(m)$.

For correctness, we require that for all messages m , all master keypairs $\text{mpk}, \text{msk} \leftarrow \text{Setup}(1^\kappa)$, all functions f and corresponding function secret keys $\text{sk}_f \leftarrow \text{KeyGen}(\text{msk}, f)$, we have $\text{Dec}(\text{sk}_f, \text{Enc}(\text{mpk}, m)) = f(m), \ell(m)$.

We adapt the strong definition² of security [42, Def. 3.1] to include one-bit leakage. Following their lead, we call a simulator \mathcal{S} *admissible* if, for each input f , it makes only a single query to $U_m(\cdot)$ and only on the f it received, and additionally allow \mathcal{S} to make a single query to $U_m(\cdot)$ for each decryption call on c and only on the leakage function ℓ used in the decryption.

Definition 14 (security (up to one-bit leakage)). We say an FE scheme with one-bit leakage is secure if for all PPT \mathcal{A} there exists an admissible stateful PPT simulator \mathcal{S} such that the following distribution ensembles are computationally indistinguishable:

$$\begin{array}{ll} \text{REAL}_{\mathcal{A}}^{\mathcal{FE}^-}(1^\kappa) & \text{IDEAL}_{\mathcal{A}, \mathcal{S}}^{\mathcal{FE}^-}(1^\kappa) \\ (\text{mpk}, \text{msk}) \leftarrow \text{Setup}(1^\kappa) & (\text{mpk}, \text{msk}) \leftarrow \text{Setup}(1^\kappa) \\ m \leftarrow \mathcal{A}^{\text{KeyGen}(\text{msk}, \cdot)}(\text{mpk}) & m \leftarrow \mathcal{A}^{\text{KeyGen}(\text{msk}, \cdot)}(\text{mpk}) \\ c \leftarrow \text{Enc}(\text{mpk}, m) & c \leftarrow \mathcal{S}(\text{mpk}, Q, 1^{|m|}) \\ \alpha \leftarrow \mathcal{A}^{\text{KeyGen}(\text{msk}, \cdot)}(c) & \alpha \leftarrow \mathcal{A}^{U_m(\cdot)}(\text{msk}, \cdot)(c) \\ \text{output } (m, \alpha) & \text{output } (m, \alpha) \end{array}$$

where $U_m(f) := f(m)$ is a universal oracle for the message m and Q is the set $\{(f_i, \text{sk}_i, f_i(m))\}_i$ corresponding

2. See [4] for a comparison of several versions of FE security.

to \mathcal{A} 's queries to the key generation oracle (where sk_i is function secret key corresponding to f_i).

A version of FE with one-bit leakage can easily be realized from CoVault and is shown in Construction 1. We note that it meets the definition of FE from the point of view of any one party; of course, if parties collude and share their shares with each other, they can recover m . This case is ruled out by the assumption of our threat model.

Construction 1 (FE from CoVault). Let Σ_M be a secure secret sharing scheme, $\Pi_{\mathcal{E}}$ be a CPA-secure encryption scheme, and \mathcal{F}_{CV}^- be the ideal functionality defined in E.6.1 using Σ_M .

- $\text{Setup}(1^\kappa)$: QP_1, QP_2 each generate a keypair for $\Pi_{\mathcal{E}}$ (a corrupted QP can generate an arbitrary pair (pk_i, sk_i)). Define $\text{mpk} := (pk_1, pk_2)$ and $\text{msk} := (sk_1, sk_2)$.
- $\text{KeyGen}(\text{msk}, f)$: Send f to each QP_i to receive a function-authorization token pair (f_i, auth_i) such that the authorization token is tied to the function (e.g., a signature on the function description); an honest QP sets $f_i := f$, and a corrupted QP outputs an arbitrary pair of bit strings. Output $\text{sk}_f := ((f_1, \text{auth}_1), (f_2, \text{auth}_2))$.
- $\text{Enc}(\text{mpk}, m)$: parse $\text{mpk} = (pk_1, pk_2)$, compute $(\text{sh}_1, \text{sh}_2) \leftarrow \text{Share}_M(m)$, and set $c_i \leftarrow \Pi_{\mathcal{E}}. \text{Enc}(pk_i, \text{sh}_i)$. Output $c := (c_1, c_2)$.
- $\text{Dec}(\text{sk}_f, \ell, c)$: parse $\text{sk}_f = ((f_1, \text{auth}_1), (f_2, \text{auth}_2))$ and $c = (c_1, c_2)$. Send $(f_i, \text{auth}_i), c_i$ to QP_i . An honest QP validates its authorization token auth_i and, if the check passes, computes $\text{sh}_i \leftarrow \Pi_{\mathcal{E}}. \text{Dec}(sk_i, c_i)$ and feeds f_i, sh_i into \mathcal{F}_{CV}^- . A corrupted QP picks its inputs to \mathcal{F}_{CV}^- arbitrarily and also sends a leakage function ℓ' . \mathcal{F}_{CV}^- outputs y to both QPs and additionally sends ℓ' evaluated on the honest QP 's input to the corrupted QP . The algorithm outputs y and the message leakage $\ell(m)$ which is implicitly defined as $\ell(m) := \ell'(m \oplus \text{sh}_i)^3$, where $\text{sh}_i \leftarrow \Pi_{\mathcal{E}}. \text{Dec}(sk_i, c_i)$ and QP_i is the corrupted QP .

Correctness follows from the correctness of $\Sigma_M, \Pi_{\mathcal{E}}$, and \mathcal{F}_{CV}^- : if all parties behave honestly, \mathcal{F}_{CV}^- will output $y = f(\text{Rec}_M(\Pi_{\mathcal{E}}. \text{Dec}(pk_1, c_1), \Pi_{\mathcal{E}}. \text{Dec}(pk_2, c_2))) = f(\text{Rec}_M(\text{sh}_1, \text{sh}_2)) = f(m)$.

Theorem 5. Construction 1 is secure up to one-bit leakage in the \mathcal{F}_{CV}^- -hybrid model.

Proof. Let \mathcal{A} be a PPT adversary corrupting QP_i . We give a simulator \mathcal{S}_i such that the distribution ensembles $\{\text{REAL}_{\mathcal{A}}^{\mathcal{FE}^-}(1^\kappa)\}_\kappa$ and $\{\text{IDEAL}_{\mathcal{A}, \mathcal{S}_i}^{\mathcal{FE}^-}(1^\kappa)\}_\kappa$ are computationally indistinguishable (in fact, they are perfectly indistinguishable). For simplicity of notation, we assume the base secret-sharing scheme Σ of Σ_M is the XOR scheme; our proof generalizes to any other underlying scheme as long as it is possible, given ℓ' and sh_i , to compute a function ℓ such

3. This conversion between ℓ and ℓ' is necessary because we defined \mathcal{F}_{CV}^- as evaluating the leakage function on the other party's input, while here we define it to be evaluated on the message.

that $\ell(x) := \ell'(y)$ for all (x, y) such that $\Sigma.\text{Rec}(y, \text{sh}_i) = x$. We abuse notation slightly by using sh_i to refer both to fully authenticated shares of Σ_M and the underlying shares of Σ without authenticating information.

Simulator \mathcal{S}_i :

- 1) Given mpk, \mathcal{Q} , and $1^{|m|}$, \mathcal{S}_i samples a uniform m^* , and runs Enc honestly: it computes $(\text{sh}_1^*, \text{sh}_2^*) \leftarrow \text{Share}_M(m^*)$ and outputs $c := (\Pi_{\mathcal{E}}.\text{Enc}(pk_1, \text{sh}_1^*), \Pi_{\mathcal{E}}.\text{Enc}(pk_2, \text{sh}_2^*))$.
- 2) After this point, it responds to any key-generation queries f honestly, namely with $\text{sk}_f \leftarrow \text{KeyGen}(\text{msk}, f)$. Whenever \mathcal{A} runs Dec on c , \mathcal{S}_i simulates the underlying ideal functionality \mathcal{F}_{CV}^- , intercepting the inputs sh_i', ℓ' . If $\text{sh}_i' \neq \text{sh}_i^*$, \mathcal{S}_i sets $y^* := \perp$; otherwise $y^* := U_m(f_i)$. It sets $b^* := U_m(\ell)$, where $\ell(m) := \ell'(m \oplus \text{sh}_i^*)$ is the implicit leakage function of Dec . \mathcal{S}_i returns y^*, b^* to \mathcal{A} .

Clearly, \mathcal{S}_i is admissible. We now consider a series of hybrid-world executions to show that the distribution ensembles $\{\text{REAL}_{\mathcal{A}}^{\mathcal{F}_{CV}^-}(1^\kappa)\}_\kappa$ and $\{\text{IDEAL}_{\mathcal{A}, \mathcal{S}_i}^{\mathcal{F}_{CV}^-}(1^\kappa)\}_\kappa$ are indistinguishable.

Hybrid 1 Our first hybrid behaves in the same way as the simulator \mathcal{S}_i except that it also computes a true sharing $(\text{sh}_1, \text{sh}_2) \leftarrow \text{Share}_M(m)$ and computes c as $(\Pi_{\mathcal{E}}.\text{Enc}(pk_i, \text{sh}_i^*), \Pi_{\mathcal{E}}.\text{Enc}(pk_{3-i}, \text{sh}_{3-i}))$.

Hybrid 2 In the next hybrid, we also change the remaining ciphertext component so $c := (\Pi_{\mathcal{E}}.\text{Enc}(pk_i, \text{sh}_i), \Pi_{\mathcal{E}}.\text{Enc}(pk_{3-i}, \text{sh}_{3-i}))$.

Hybrid 3 Finally, instead of simulating \mathcal{F}_{CV}^- during Dec queries, our last hybrid simply participates honestly in the decryption (and thus the evaluation of \mathcal{F}_{CV}^-).

The indistinguishability of $\{\text{IDEAL}_{\mathcal{A}, \mathcal{S}_i}^{\mathcal{F}_{CV}^-}(1^\kappa)\}_\kappa$ and $\{\text{H1}_{\mathcal{A}}^{\mathcal{F}_{CV}^-}(1^\kappa)\}_\kappa$ follows immediately from CPA-security of $\Pi_{\mathcal{E}}$, since \mathcal{A} does not know sk_{3-i} . Hybrid 1 and 2 are indistinguishable by reduction to the privacy of the secret-sharing scheme Σ_M . In more detail, a distinguisher \mathcal{D} between the hybrids could be used to construct an adversary \mathcal{A}' with nonnegligible advantage in the privacy game of Σ_M : \mathcal{A}' simply lets $x_0 := m$ and samples x_1 uniformly at random. Upon receiving a share from the game, it runs \mathcal{D} with c_i set to the encryption under pk_i of the share it received from the game (sh_i or sh_i^*); if \mathcal{D} outputs “real”, it outputs 0, and otherwise it outputs 1.

Next, notice that Hybrid 2’s output y^* equals $f_\Sigma(\text{sh}_i, m \oplus \text{sh}_i)$, which is also the output of \mathcal{F}_{CV}^- in Hybrid 3. Additionally, by definition we have $b^* = \ell'(m \oplus \text{sh}_i^*)$, while in Hybrid 3, \mathcal{F}_{CV}^- outputs $b = \ell'(\text{sh}_{3-i}) = \ell'(m \oplus \text{sh}_i)$. We just argued above that by the privacy of Σ_M , the distributions of sh_i^* and sh_i are indistinguishable, and therefore so are b^* and b . Finally, note that Hybrid 3 is exactly the real-world experiment.

In summary, by the privacy of Σ_M , CPA-security of $\Pi_{\mathcal{E}}$, and the security of \mathcal{F}_{CV}^- , the distribution ensembles

$\{\text{REAL}_{\mathcal{A}}^{\mathcal{F}_{CV}^-}(1^\kappa)\}_\kappa$ and $\{\text{IDEAL}_{\mathcal{A}, \mathcal{S}}^{\mathcal{F}_{CV}^-}(1^\kappa)\}_\kappa$ are (perfectly) indistinguishable. \square

F.1. Pre-constrained functional encryption

In our setting, we want a slightly stronger version of functional encryption: the data sources should be able to fix the functions allowed to run on its data, and by what queriers those functions can be run. We can capture this by modifying the above definition of functional encryption as follows.

We call this *pre-constrained functional encryption* (PCFE), to mirror the recently introduced notion of pre-constrained encryption [7].⁴ Because we believe PCFE to be an independently interesting primitive, below we give a definition without one-bit leakage; it is easy to adapt it to include leakage as in Definition 13 by letting Dec additionally accept an input ℓ and output $\ell(m)$.

Definition 15 (Pre-constrained functional encryption). *A pre-constrained FE scheme is a tuple of polynomial-time algorithms $\text{PCFE} = (\text{Setup}, \text{KeyGen}, \text{Enc}, \text{Dec})$ such that*

- $(\text{mpk}[F, P], \text{msk}[F, P]) \leftarrow \text{Setup}(1^\kappa, F, P)$: the setup algorithm takes as input a security parameter, a function class F , and a set of public keys P representing authorised parties; it outputs a constrained master keypair.
- $\text{sk}_{f, pk} \leftarrow \text{KeyGen}(\text{msk}[F, P], f, pk)$ ⁵: key generation takes as input a constrained master secret key, a function f , and a party’s public key pk . If $f \in F$ and $pk \in P$, it outputs a party-specific function secret key $\text{sk}_{f, pk}$; otherwise it outputs \perp .
- $c \leftarrow \text{Enc}(\text{mpk}[F, P], m)$: encryption takes as input a constrained master public key and a message m and outputs a ciphertext c .
- $f(m) \leftarrow \text{Dec}(\text{sk}_{f, pk}, c)$: decryption takes as input a function secret key for a function f and a ciphertext and outputs $f(m)$ for some message m (if $\text{sk}_f = \perp$ it outputs \perp).

For correctness, we require that for all messages m , all function classes F and sets of parties P , all master keypairs $\text{mpk}[F, P], \text{msk}[F, P] \leftarrow \text{Setup}(1^\kappa, F, P)$, all functions $f \in F$ and parties $pk \in P$, and all function keys $\text{sk}_f \leftarrow \text{KeyGen}(\text{msk}[F, P], f, pk)$, we have $\text{Dec}(\text{sk}_f, \text{Enc}(\text{mpk}[F, P], m)) = f(m)$.

The security definition is a straightforward extension of Definition 14, and we define the class of admissible simulators in the same way. This time, however, our construction will use trusted execution environments (TEEs). We assume the TEEs work perfectly, and leave the question of modelling our TEE architecture as an interesting open

4. Unlike [7], we do not give a full treatment of this primitive but only a definition which is a straightforward extension of existing definitions and a simple construction from strong assumptions. We leave a more thorough exploration of pre-constrained FE and constructions from standard assumptions as an interesting direction for future work.

5. This is intentionally not styled pk to show that pk and sk_f are unrelated; pk is a public key for a completely different (underlying) PKE.

problem. Interested readers may look at [38] for an example of how the TEEs could be modelled.

Definition 16 (security (with one-bit leakage)). *We say a pre-constrained FE scheme with one-bit leakage is secure if for all PPT \mathcal{A} there exists an admissible stateful PPT simulator \mathcal{S} such that the following distribution ensembles are computationally indistinguishable:*

$$\begin{aligned}
& \text{REAL}_{\mathcal{A}}^{\text{PCFE}}(1^\kappa, F, P) \\
& (\text{mpk}[F, P], \text{msk}[F, P]) \leftarrow \text{Setup}(1^\kappa, F, P) \\
& m \leftarrow \mathcal{A}^{\text{KeyGen}(\text{msk}[F, P], \cdot)}(\text{mpk}[F, P]) \\
& c \leftarrow \text{Enc}(\text{mpk}[F, P], m) \\
& \alpha \leftarrow \mathcal{A}^{\text{KeyGen}(\text{msk}[F, P], \cdot)}(c) \\
& \text{output } (m, \alpha) \\
\\
& \text{IDEAL}_{\mathcal{A}, \mathcal{S}}(1^\kappa, F, P) \\
& (\text{mpk}[F, P], \text{msk}[F, P]) \leftarrow \text{Setup}(1^\kappa, F, P) \\
& m \leftarrow \mathcal{A}^{\text{KeyGen}(\text{msk}[F, P], \cdot)}(\text{mpk}[F, P]) \\
& c \leftarrow \mathcal{S}(\text{mpk}[F, P], Q, 1^{|m|}) \\
& \alpha \leftarrow \mathcal{A}^{\mathcal{S}^{U_m(\cdot)}(\text{msk}[F, P], \cdot)}(c) \\
& \text{output } (m, \alpha)
\end{aligned}$$

Again, we give a construction from CoVault, this time augmented with TEEs.

Construction 2 (PCFE from CoVault and TEEs). *Let \mathcal{F}_{CV}^- and Σ_M be defined as in Construction 1. $\text{Enc}(\text{mpk}[F, P], m)$ is defined the same way as before, and the remaining algorithms work as follows:*

- $\text{Setup}(1^\kappa, F, P)$ produces and signs a TEE configuration config identifying F and P and provisions (a set of) TEEs with it; as before, it outputs a garbage mpk,
- $\text{KeyGen}(\text{msk}[F, P] := \text{config}, f, pk)$ checks if $f \in F$ and $pk \in P$, where F, P are defined by config; if so, it outputs a function-authorization token pair (f, auth) , and
- $\text{Dec}(sk_f := (f, \text{auth}), (c_1, c_2))$ validates the authorization token auth. If the check passes, it runs \mathcal{F}_{CV}^- like before; otherwise, it outputs \perp .

In practice, Setup is run by every provisioning service (PS) for the TEEs that act as data processors (DPs) in its own pipeline. (The PSs themselves are attested by community volunteers.) Enc is run locally by the data sources, and the resulting ciphertexts (encrypted shares) are each sent to a different DP via secure point-to-point channels (i.e., using a PKE). KeyGen and Dec are combined and run inside an MPC protocol by the set of DPs provisioned with the configuration produced by the setup, using \mathcal{F}_{CV}^- as before and with the input pk set to the querier's public key.

Correctness holds by the same logic as before. Correctness holds by the same logic as before. Since we assume the TEEs behave as intended, and the checks on f and pk are always computed correctly; therefore, on the set of inputs $f \in F$ and $pk \in P$, this construction is equivalent to Construction 1, and security (with one-bit leakage) follows as before.