Enabling Strong Database Integrity using Trusted Execution Environments

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Abstract

Immutable and consistent sharing of data across organization boundaries enables a new class of applications. Because conventional datastores cannot provide this functionality, blockchains have been proposed as one possible solution. Yet public blockchains are energy inefficient, hard to scale and suffer from limited throughput and high latencies, while permissioned blockchains depend on specially designated nodes, potentially leak meta-information, and also suffer from scale and performance bottlenecks.

This paper presents CreDB, a datastore that provides blockchain-like guarantees of integrity using trusted execution environments. CreDB employs three novel mechanisms to support a new class of applications. First, it creates a permanent record of every transaction, known as a witness, that clients can then use not only to audit the database, but to prove to third parties that desired actions took place. Second, it associates with every object an inseparable and inviolable security policy, which not only performs access control but enables the datastore to implement state machines whose behavior is amenable to analysis. Finally, CreDB provides a protected function evaluation mechanism that allows integrity-protected computation over private data. The paper describes these mechanisms, and the applications they collectively enable, in detail. We have fully implemented CreDB on Intel SGX. Evaluation shows that these new mechanisms do not adversely affect performance.

1 Introduction

Many high-value applications require the reliable and immutable storage of data across multiple distrusting parties [49, 17, 54]. These applications are characterized by integrity requirements wherein each party must abide by pre-defined policies. Conventional databases cannot live up to this challenge, as they require full trust in the database application and host operating system.

Blockchains have recently emerged as a potential platform to address the needs of these applications. Public blockchains [37, 50], based on Nakamoto consensus, maintain an immutable log of events distributed across all participants of the system. As a result, they are energy inefficient, hard to scale, and suffer from limited throughput and high latencies [15]. Further, due to their open and distributed setting, they cannot be used to store private or confidential data. Permissioned blockchains [10, 3, 2] employ a committee consensus protocol [11, 29, 24] to maintain the log and append updates in an orderly fashion. Changes can only be made if a specified quorum of the committee agrees to do so. This approach necessarily requires specially designated committee nodes, exposes at least meta-information to those nodes, and is limited in performance by bottlenecks in the quorum.

These efforts were preceded by earlier work on accountability systems [28, 51], which ensure integrity by allowing clients to audit the log with respect to states they have observed previously. But accountability mechanisms can only enforce fork consistency [34, 19], a weaker security property than strong consistency.

This work presents CreDB, a high-integrity log store (HILS) that provides the integrity guarantees of blockchains, using much more efficient and scalable techniques backed by secure hardware. HILS systems differ significantly from ACID databases, the industry standard for high integrity systems, by providing an immutable history of changes to objects. In a nutshell, a HILS system is an append-only log [13] of partially-ordered states. Past states cannot be changed and new states can only be appended to the log. Building on this foundation, CreDB nodes can operate independently, as a “blockchain of one,” or as part of a network of nodes that can share designated data items and invoke computations on each other. Each node in the system runs in a trusted execution environment (TEE), provided by the system’s hardware. The usage of TEEs enables nodes to trust another participant’s computation without trusting the administrator of that system. Because each service can run their own database node backed by a TEE, the throughput scales with the number of nodes in the system.

CreDB nodes issue witnesses, which are permanent and tamper-proof certificates of the state of the system. Further, they are independently verifiable, i.e. verification should not depend on a specific node in the system. It can be used to establish facts about the datastore, such as the instantaneous contents of objects, the existence of certain data or past transactions, and ordering of transactions. This enables even untrusted applications, backed by CreDB, to provide proofs of their correct operation to third parties. Because witnesses are free-standing, they enable parties who are not direct clients of the database to verify crucial aspects of the database’s operation.

CreDB enables every object to be coupled with an associated semantic security policy. Because policies are enforced by TEE-backed software, they are inseparable from their associated data. And because they are written in a Turing-complete language, they can express rich, object-specific policies. And because the semantic security policies are encoded symbolically as abstract syntax trees, they are amenable to analysis by third parties. Coupled with witnesses, these techniques enable a third party to inspect the policy associated with an object and thus establish trust in the future behavior of that object. These capabilities can be used to build smart contracts on CreDB.
Finally, CreDB provides a protected function evaluation mechanism that enables clients to compute a function over remote private data, which in turn generates a witness carrying the result. For the party issuing the function call, the witness yields a verifiable, portable certificate that the function has been executed, with integrity, on the specified data, with the attached result. The primary use of this functionality is to compute a vetted function over private data without revealing the input data to the remote party. For security purposes, the holder of the data retains full control over what can be done with the data, and both parties, the invoker and the data holder, must agree on which functions can be executed.

While there has been much past work on high-integrity data storage and data processing systems, to our knowledge, no datastores exist that combine these three synergistic features. Ryoan [22] has examined functions can be executed across private data. Guardat [47] reduces the attack surface of a system by enforcing data policies on the storage layer. Further, Cipherbase [4] enforces security properties using trusted hardware modules. Finally, past systems have explored the use of trusted hardware to enhance audit mechanisms [13, 26]. CreDB takes these concepts and provides one holistic approach to secure and tamper-proof data storage, built using modern trusted hardware.

The rest of this paper is structured as follows. The next section provides the overarching data and computation model for CreDB (Section 2). Section 3 details how this model was implemented using Intel SGX. The following two sections evaluate a full prototype of the system. The evaluation contains a qualitative part, explaining how to implement several sample applications (Section 4), and a quantitative part, describing the impact our execution environment has on the performance of the system (Section 5). We show that, depending on the workload, CreDB can process up to 50k operations per second on a single machine. Further, we show that it can process 200 transactions per second on the TPC-C benchmark.

2 The CreDB Data Store

At a high level, every CreDB node implements a secure database using a trusted execution environment (TEE) that clients, as well as other nodes, can connect to. Each database instance has its own timeline, datastore, and set of connected nodes. A node connects to other CreDB nodes to create a network across which data can be shared, and functions can be invoked, securely. Clients connect through one or multiple CreDB nodes and do not need special hardware support. This enables porting legacy database applications to this new abstraction and provide them with stronger integrity guarantees. Nodes and clients rely on a public attestation service to ensure integrity and authenticity of database nodes. Attestation services provide a public-key infrastructure to ensure the authenticity of parties. No private data, not even metadata, is transferred to the attestation service.

Applications are written against the CreDB API, which is a superset of a traditional key-value API. The most notable additions are timeline inspection, secure semantic policies, witness generation, and protected function evaluation, which we discuss below after we provide the basic object and event model on which the system is based.

2.1 Objects and Events

CreDB exposes a flexible object model that accommodates unstructured, as well as structured, data. Objects are collections of attribute-value pairs, where attributes can have types such as lists, dictionaries, binary data, and primitive values, which consist of integers, floating point numbers and strings.

The datastore maintains a partially-ordered log of events, each relating to one or more objects. Events record the creation, update, or deletion of one, or multiple, objects. Events store the new value of all updated objects. In the case of a deletion, the new value is a tombstone entry . Figure 2 gives an example of the lifetime of an object x, where each modification creates a state transition and a new event that holds the most recent value. Events relating to the same object are arranged in a total order to guarantee linearizability [21]. Further, in case events are created by a transaction that spans multiple objects, an event may also capture the dependencies between versions of different objects. For instance, Figure 3 shows an event from a transaction that reads from object “foo” and then writes to object “bar”. Crucially, events that are unrelated are not ordered with respect to each other at all.

Figure 2: The lifetime of an object mapped to a sequence of events. Because CreDB guarantees strong consistency this order must be total. ⊥ represents a deleted object (i.e. "tombstone" entry)
2.2 Timeline Inspection

Unlike a traditional key-value store, CreDB enables historical retrievals from any previous point in time. The desire for such rich semantics has been underscored by the interest in both blockchains and bitemporal databases [42]. CreDB thus implements an edidic database that stores the set of all modifications to all objects, which is essential for analysis and audit, and produces an API for inspecting historical values.

The CreDB API enables clients to retrieve previous versions of an object using the get_version and get_event calls. get_version takes an object key and version id and returns that object's state at that specific point in the timeline. get_event takes an event identifier and returns the values of the objects affected (read or written) by that event, but not other unrelated objects. This enables the datastore to support multiple concurrent updates, and obviates the need to have a single, totally-ordered log, which would hamper performance. This design decision is coupled with our decision to have a partial order between unrelated events. Thus, our API is only guaranteed to answer questions of the form “what was X’s value when I updated Y?” if X was in the read set of the transaction that updated Y. Figure 3 illustrates how a read-dependency is encoded. When inspecting the event that sets “bar” to 47, the API will return a reference to the value of “foo” when it was read by the transaction. A full enumeration of API calls can be found in Appendix A.

The CreDB API also enables applications to replay the timeline of dependent events in order to reason about the order, and causality, of events. This feature is enabled by retrieving, and stepping through, the timeline using the get_history-call. The immutable log ensures that this timeline is final and can be reasoned about safely. The database can then answer questions such as “who has updated X since it was first created?”. This ability to explore object timelines enables applications to implement audits. For instance, an application can check if all previous modifications to an object adhere to a policy after the fact. For example, in supply chain management, once a contaminated resource has been discovered, we can check the various nodes in the supply chain if any of their products contain said contaminated resource.

2.3 Secure Semantic Policies

Secure semantic policies enable applications to associate application-specific constraints with an object. These policies are inseparable from the object to which they belong and inviolable even by the principal controlling the database instance. To access the database, a user must necessarily go through the CreDB secure semantic policy enforcement engine mandated by the TEE. Thus, even an attacker who takes over the database cannot subvert the access policies associated with objects. In case of accessing a previous version of the object, that version’s policy and state will be used to make an access control decision.

Policies use the current state of the object, as well as information about the attempted operation, to make access control decisions. Policies are then represented as functions that take these two entities as inputs and return a boolean. Figure 1 illustrates a simple policy, which restricts an object to only be updated once per principal, while reads are always permitted. The policy execution has access to two sources of information: op_info and op_context. op_info contains information about the operation itself, such as the kind of operation and the proposed change. op_context allows to retrieve information about the issuing party, such as their identity.

Policies are specified at the time of an object’s creation and can be modified after the fact only if the policy permits it. And changes to a policy are stored in the object’s timeline just like changes to all other fields of the object. Accesses to an object’s value in the timeline lead to the evaluation of the object’s policy at that point in time. In order to achieve this, object policies are not allowed to have any side effects, and to avoid having to totally order all events, they also are prohibited from accessing the state of other objects.

Each CreDB node maintains a registry of identities, which can be leveraged by policies to make access decisions. Identities are tuple consisting of a human-readable name and a public key. This registry is used to prevent man-in-the-middle, and other impersonation, attacks. We assume a public key infrastructure (PKI). When a previously unknown party connects to a node, it queries the PKI to gather information about said node.

Identities are inseparable from the associated authenticated communication channel. In particular, nodes cannot change their identity after a connection has been set up. The rather complex and authentication and attestation mechanisms then only has to be done once, when setting up the channel. Policies and stored procedures to rely on the authenticity of the referenced identities.

Semantic security policies can make use of timeline inspection to make access control decisions. In particular, they can examine the object’s timeline, for instance, to determine how often an object has been modified, in total or by a specific client, or check the object’s history against a predicate. A common example is that an application wants to limit the number of updates to an
object that is allowed by a specific user or the number of total updates.

2.4 Witnesses

Witnesses are a permanent, external, and free-standing record of the database state. They encode a set of events with respect to their position in the timeline, and are signed by the private key of the CreDB instance. Because of their free-standing nature, witnesses are useful even beyond the existence of the issuing service.

A witness is comprised of a list of events, as well as their location in the timeline and potential causal dependencies between each other. They are generated automatically in response to every transaction on the database. The set of events inside a witness then corresponds to the state of the object at the time the transaction read or updated them.

Witnesses enable auditing applications that use CreDB as their datastore. Applications generate witnesses by issuing transactions to the datastore, which can then be shown to other parties as a proof of action. For example, witnesses can serve as a payment receipt or a proof of ownership for a certain asset. Further, witnesses can be used to prove that an update was not made using false assumptions by capturing the read set of a transaction at the time of commit. For example, a bank clerk who wants to show that they observed an irregularity in a bank account before declining a credit request can refer to a specific point in an objects timeline by using a witness.

The CreDB API supports three key actions on witnesses: (1) verifying them for authenticity, (2) examining witness contents, and (3) ordering witnesses with respect to each other. Witness verification ensures that a witness is authentic, that it was created by a TEE running CreDB. This can be achieved by checking the witness against the against the public key of the principal provided by the attestation service. Witness verification does not explicitly guarantee freshness, but a witness can include in it a timestamp signed by a trusted time source to indicate the time at which it was signed. In applications where establishing an absolute time is not necessary, a relative order can be established using the timeline inspection primitives described below.

By allowing clients to extract the contents of witnesses, we enable local timeline inspection without the need to access the datastore itself. A local timeline can be generated from a single witness or a set of overlapping witnesses. The clients then have access to a timeline inspection API that provides similar function calls as those when interacting directly with the server.

Local timeline inspection then enables checking the order of events the relative order of two witnesses or specific events contained in the witnesses. A call to check_order can return: Before, After or Incomparable. Incomparable can be returned when the witnesses represent two non-intersecting sets of events. In cases where it should be possible to always order two witnesses, a common object must be included, which will never yield Incomparable. This approach enables CreDB to achieve high performance, as it does not impose a total order on all concurrent transactions, and instead permits the timeline to be structured as a DAG.

Together, these three actions enable application clients to audit application behavior without direct access to the datastore itself. Clients can reason about the correctness and trustworthiness of the application logic by collecting and verifying witnesses that are generated by the datastore and passed on by the application. For example, they can inspect which principals have access to their sensitive data by requesting a witness containing the data’s access policy. A certified access policy can further provide a guarantee that the data is protected from a malicious application.

2.5 Protected Function Evaluation

The key novel primitive supported by CreDB is protected function evaluation (PFE). PFE enables parties to invoke a custom function on a remote node in a secure execution environment guarded by the TEE. This way, data protected by the TEE remains private to the trusted environment, and only the designated result of the function call is revealed to the caller.

Since computations on private data have the intended goal of retrieving some information extracted from that data, they need to be vetted to ensure that this leakage is permissible to all parties. CreDB employs two mechanisms to perform this vetting. First, prior to execution of a function, both the calling and the executing parties must approve the function. The executing party needs to ensure that no private data is leaked and the function execution does not take up an unreasonable amount of resources. This can be done by checking the functions hash against a whitelist or by analyzing the AST of the function. Much past work concerns itself with the analysis of function properties, including for information leakage [16] and information flow techniques [31], and is beyond the scope of our work. In addition, every single object retrieved during the PFE has its semantic security policy checked on every access.

After successful execution, the calling party receives a certificate containing a function identifier and its result. CreDB identifies functions through the hash of their bytecode. The certificate is signed by a persistent key associated with the CreDB instance of the executing party. Chained with a certificate attesting to the
authenticity of that CreDB instance, this certificate can be presented to other clients or systems not connected to CreDB.

This design imposes minimal structure on CreDB certificates. In particular, it deliberately leaves freshness guarantees up to applications – CreDB does not purport to provide a global clock or a total order on events. The critical observations behind this decision are threefold. First, no single notion of time can serve every application. Some applications require sub-microsecond granularity, which could entail inordinate overheads, while others have much coarser grained requirements. Second, even if there was a time granularity that one could pick for most applications, current technologies for providing a trusted time source into a secure execution environment provide much weaker guarantees than the TEE itself, because they rely on additional hardware outside of the CPU die [14]. Finally, it has been our experience that most applications care about establishing simple happens-before relationships between objects.

2.6 Summary

We outlined the four core features provided by CreDB, beyond conventional key-value storage. Together, these synergistic features make CreDB a high-integrity logstore which protects the data from unwanted access and provides strong accountability. Thus, CreDB can be described as a "blockchain of one", a self-standing blockchain that does not rely on expensive data replication or other consensus mechanisms.

3 Implementation

We implemented a fully-functional prototype of the CreDB database. The prototype is built on top of the Intel SGX SDK, which provides a well-documented TEE with certain restrictions. In particular, the memory encryption mechanism that protects TEEs from unwanted access causes a severe limitation on speed memory can be accessed quickly. SGX comes with an encrypted page cache (EPC) that can be accessed quickly through an in-memory encrypted page cache module (EPCM) [14]. As the time of this writing, all SGX-enabled CPUs can handle only an EPC of at most 128MB. This EPC also needs to hold program code and stack, which results in an available heap size of roughly 90MB. While future generations of CPUs might increase the EPC size, it seems unlikely that such a size restriction disappear completely. Not only data that is held in heap memory, but also function arguments need to be encrypted and decrypted when crossing enclave boundaries, for example when a network message is passed from the untrusted part of the database to the enclave.

In order to overcome these performance limitations, our prototype design follows two goals. First, we aim to keep the overall memory consumption low, by using efficient and lightweight data structures. Second, the implementation minimizes the amount of memory that has to be moved in and out of the EPC. The latter is achieved through a custom paging mechanism, which will be described in the next section.

3.1 A concurrent append-only log

Figure 4: Implementation of a CreDB node: The keyspace is broken down into multiple shards. Each shard stores its events in a sequence of blocks.

CreDB nodes achieve high throughput by breaking down their keyspace into \( n \) shards. Consistent hashing is used to assign a key range to each of the shards, where \( n \) is set sufficiently large to exceed the number of hardware threads available. Each node then runs multiple concurrent threads, inside and outside the enclave, to efficiently leverage the shards setup, visualized in Figure 4. The untrusted threads wait on a multi-threaded event loop built on top of epoll. Once an event is dispatched by an untrusted thread it will be forwarded to a trusted thread. Threads then work update the log by working with one or multiple shards. In order to achieve strong consistency, only one thread at a time can update the same shard. This is enforced through a read-write locking mechanism inside the TEE.

In order to enforce the append-only mechanism for the log, the timeline for each shard is sequenced into blocks. Only the newest block is then modified when a new event is inserted into the log, the other blocks are considered sealed. A primary index structure allows retrieving the most recent event associated with an object, without having to perform a linear scan across the log. Further, secondary indexes can be created to quickly react to more complex queries. CreDB’s custom paging mechanism moves blocks in and out of the EPC. Previous work has shown that a reference count based mechanism can achieve a significant performance benefit compared to SGX native paging mechanism [38]. A dedicated, shard aware, and CreDB-specific paging mechanism allows accommodating arbitrarily large data sizes in the enclave’s fixed heap space. Blocks are only evicted if no threads are using them at the current point in time. Eviction is run whenever the number of blocks in memory exceeds a certain size. Besides being stored on the local file system, encrypted blocks are also cached in the untrusted memory to retrieved them more quickly. A similar paging mechanism is also employed for primary and secondary indexes.
3.2 Ensuring Data Freshness

Because paging moves data out of the enclave, CreDB employs mechanisms to avoid stale data from being loaded back into the enclave. The enclave can easily detect corrupt data due to the encryption scheme applied to the data blocks. To prevent an adversary to present the enclave with correct but outdated blocks, CreDB enforces a simple mechanisms. For each shard, only the most recent, i.e. pending, block is considered mutable, the others are marked as sealed. The enclave then always keeps the pending block in memory and only allows to load sealed blocks.

Because index nodes are mutable, a different mechanisms is required to ensure their freshness. To ensure node loaded from disk are fresh, each node holds a version number for itself, and one for each of its children. An update then does not only modify the leaves, but the version numbers in all its ancestors as well. This mechanism is similar to Merkle-trees, however a hash is not required as the data is already encrypted on disk.

3.3 Efficient Transaction Processing and Witness Generation

In order to enable witness generation, we implement serializable transactions using optimistic concurrency control [25], so malicious parties cannot break the liveness of the system. The party initiating the transaction sends a message containing all reads and a set of writes. In the validation phase, the node first checks if the reads are the most recent to the respective objects. If no conflicts are detected, the node proceeds to the write phase, where it issues all updates to the log by creating new events. Further, events are annotated with causal dependencies using the transactions read set. Locks are only acquired during validation and write phase of the transaction, all of which can be executed on the server-side without leaving the trusted environment. Further, locks to shards are always acquired in the same order, to ensure no deadlocks are introduced during concurrent transactions. Finally, to ensure liveness cannot be impacted, transactions can only span a single CreDB node.

We then extended the transaction primitive to enable accountability by generating witnesses after a successful commit. Clients can request the generation of a witness as a result of a transaction. In particular, we add a certification phase after the write phase. This step is optional, in order to allow clients that do not need a self-standing witness to avoid any additional computation. The certification phase takes the read set, as well as the set of events created in the write phase. From these, it generates a digest and signs it using the enclaves private key. This way, only a single asymmetric cryptographic operation per transaction has to be executed by the CreDB node.

3.4 Peering Handshake

All communication, between other CreDB nodes and clients, require a secure, confidential, and authenticated channel in order to uphold all of the datastore’s integrity guarantees. This is achieved by using a remote attestation. Remote attestation consists of a handshake that serves two purposes. First, it sets up an encrypted channel using a Diffie-Hellman Key Exchange (DHKE) rooted in the TEE. Second, it verifies that the TEE is executing a non-modified version of the CreDB implementation. Previous work has described how such attestation channels can be set up, for example to establish a secure payment channel [30].

The attestation process can be broken down into eight steps, which are visualized in Figure 5. (1) The initiating party sends its Group ID (and SGX specific detail), public key (used to verify authenticity), and name (for easy addressing of the node). (2) The other party then responds by also sharing its public key and name. Parties can store known public keys and/or use public key infrastructures to ensure the authenticity of other parties, as described in Section 2.3. This mechanism prevents man-in-the-middle attacks. (3)(4) Once both parties have shared their public keys they can initiate a DHKE to generate a shared secret. (5) The initiating party then sends a quote of their enclave. A quote is generated from a snapshot of the enclaves content, including both data and loaded program code. It can thus be used to reliably identify the code running on the remote party. (6)(7) The other party forwards the quote to an attestation service. Attestation services are Intel-verified entities that can check the enclaves signature for validity. This step is needed to support revocation to keys of malicious CPUs. (8) Once the attestation service has (or has not) verified the quote, the result is sent back to the initiating party. At this point, assuming the quote and signature were valid, a one-sided authenticated channel is setup up.

In order to set up a bidirectional channel between two CreDB nodes, this attestation handshake has to be performed once in each direction. There might be ways to shorten the bidirectional handshake process by avoiding redundant messages. However, a fast attestation process is not necessary for performance as the CreDB model assumes long-running connections between nodes.
3.5 Trusted Program Execution

Efficient program and policy evaluation are enabled by a lightweight Python interpreter that runs inside the TEE. Our implementation aims to find a middle ground between ease of use and efficiency. CreDB clients come with a compiler that can convert a subset of Python to a compressed abstract syntax tree (cAST). The cAST can then be stored as bytecode on a CreDB node. Programs run in isolation, but are able to access other parts of the TEE using Python bindings that are shipped as part of the implementation.

The execution environment further protects nodes from malicious programs exhausting the EPC size. Programs can be executed with a pre-defined execution limits: such as the amount of memory it can use up the most, the number of execution steps it is allowed to take, and the number of remote functions it is permitted to call. The node keeps track of the program memory consumption and amount of execution steps, if execution exceeds either limit, it will be aborted.

Each execution environment is assigned its own userspace thread that can safely be suspended if needed. Programs run non-preemptively and either pause when waiting for a message from another node, or stop when they have exhausted execution limits. This achieves two purposes. First, hardware threads are not occupied by programs that are waiting for an I/O operation to finish. Second, execution of the system will not halt, even if more programs execute than the number of threads supported by the TEE. This overcomes another limitation of the current SGX generation, which is that TEEs can only execute up to a pre-defined limit of hardware threads.

4 Example Applications

CreDB provides a novel programming environment for high-integrity applications in a Byzantine environment. To demonstrate the practicality of this model, this section describes multiple applications built on CreDB.

4.1 Multi-Tenant Datastores

Keeping data secure from unprivileged access is a common problem in enterprise datastores. Often a shared nothing architecture, where each tenant has their own distinct protected storage area, is not feasible as tenants might still want to exchange, or grant temporary access to, privileged data. For example, HIPAA compliant systems have strict rules on who can access the data but need the possibility to grant special rights to users in case of an emergency.

Access Control Lists (ACLs) are the state-of-the-art mechanism to enforce multi-user access rights on a set of objects. Each object in a datastore is associated with its own ACL. And each ACL contains a mapping from user to permissions. A permission can give users different levels of access, such as read-only, read/write, or execute. Permissions can then be dynamically changed.

We demonstrate that an ACL mechanism can be implemented, and enforced, using CreDB’s policy system. To achieve this each holds an acl-field, which contains a mapping from users to permissions. The object’s policy as shown in Listing 2 then inspects the acl-field and decide whether to allow an access or not depending on its value. Further, users with the right privileges can modify the acl-field and, thus, change the permissions during runtime.

Listing 2: An access control policy

```python
import self
from op_context import source_name
from op_info import is_modification
ACL_NONE = 0
ACL_READ = 1
ACL_WRITE = 2
if self.contains("acl." + source_name)
    val = self.get("acl." + source_name)
    if is_modification:
        return val & ACL_WRITE
    else:
        return val & ACL_READ
else:
    # Deny access if no entry in ACL
    return False
```

4.2 Checking Credit History

In order to make a decision on whether or not to grant a new loan, a credit issuer might check the customer’s bank for their credit history. However, the bank might not want to reveal customers’ credit history for both privacy and business reasons. Further, the customer might have multiple bank accounts that need to be checked for credit history. Currently, this problem is addressed through a third party credit score agency that is trusted by all parties. Such an approach might not always be feasible as it requires such a common trusted party to exist and usually creates additional fees and pose additional vulnerabilities.

CreDB’s PFE mechanism natively accommodates such blind checks. The credit issuer can provide a credit score checker and execute it on the bank’s data, without getting access to the credit data itself. Further, it supports nested PFEs, i.e. PFEs invoking other PFEs during their execution. The function can be vetted to ensure that it returns solely the credit score, without leaking any sensitive parts of the client’s credit history. First, the function queries the client’s bank for the credit history. It then runs a credit score calculation on the accumulated credit history. Because the PFE has been vetted by the client a priori, they can ensure that non sensitive part of their credit history is leaked.
4.3 Mandatory Read Logging

CreDB does not log read accesses by default, but applications can enforce such a mechanism. We demonstrate a mechanism similar to one presented by Vahldiek et al. [47], that requires clients to create a log entry before accessing the data. This mechanism cannot track how often an object is read, or whether the read access was successful. However, it requires each read to be preceded by a log entry, which collects information about attempted reads to the data.

Listing 3 illustrates how CreDB can implement this policy. The object consists of the read log, the actual data field, as well as two functions policy and prepare_read. When a client wants to update the value of an object, it can just issue the write directly, as CreDB will take care of creating and logging a new version. However, before the client issues a read, it will need to invoke the prepare_read function, which creates a log entry with the name of the client and the current version number of the object. When the client, then, tries to read the data-field, the policy will check whether a corresponding log entry exists before granting access. The client’s identity is authenticated by the mechanism described in Section 2.3. Note that the policy can be extended to include other access control mechanisms.

4.4 Trusted Email Quotes

“Fake news” and misrepresentation of information has been a constant problem in online communities. Users have no easy way of verifying that statements were actually made by a specific entity or that the statement has not been changed in any way.

We implemented an email service that provides authentic quotes. A quote is considered authentic if, and only if, the quoting client has received the exact quote before composing the message. The email service uses CreDB as its data storage and to enforce two invariants. First, clients can only quote text from messages they have received. Second, quotes cannot be modified in any way.

When clients issue, that is, store, a new email, the server checks that email against a policy. In particular, the policy scans the email for any quotes. Quotes, in our setup, are marked using a pre-defined delimiter. The policy then checks each quote against the two invariants. If either of the invariants is violated it will reject the update. Further, the policy will not allow messages to be changed post-facto.

4.5 Wire Transfers

Banks can perform wire transfers using a network of CreDB nodes. In such setup, each bank maintains its own database instance and connects it to database nodes of banks it co-operates with. The financial sector has already shown a high interest in HILS systems, as it wants to reliably move high-value assets between organization boundaries. Current mechanisms involve trusted third-party banks and human verification, which creates high costs and long transfer times.

Money can then be moved between accounts on the same bank, and accounts on remote banks. Banks track both the value stored by other parties at the local bank as well as a set of remote accounts they maintain at other parties. To move money between two accounts on the same bank we can directly credit and debit the two affected accounts. We call this functionality move_locally.

Moving money between accounts on two different banks needs two steps. To ensure correctness, these two steps are execute in form on a trusted function move_remotely the sender’s bank. First, the function debits money locally by modifying the sender’s accounts balance. Second, it calls move_locally on the receiver’s bank to move money between the sender’s bank’s account to the receivers account.

4.6 Privacy-preserving Age Verification

Services often hold private information about clients that shall only be used for very specific purposes. One common example
for this is age verification, where it usually only necessary to know whether the user’s age is above a certain minimum but the actual date of birth is irrelevant. However, most services require and store the full date of birth of the user. Once such data is stored on a server, the user loses control over what is going to happen to their sensitive private information.

We sketch a system that allows using a client’s birthday only to verify if they are 18 years or older. This mechanism can be used for similar privacy-preserving data items, such as the user’s location. User sensitive information is stored in an object, that only allows access through a set of pre-defined functions. In the case of age verification, this function just returns a boolean value, whether or not the user’s age is above the required minimum.

5 Experimental Evaluation

We evaluate the prototype under both macro and microbenchmarks. For all single server experiments, the server process was hosted on a machine running Ubuntu 17.10. The server machine is equipped with 32GB of RAM and an Intel Core i7 6700K CPU offering 8 logical cores. The current prototype uses version 1.9 of the Intel SGX SDK and is compiled using GNU g++7. The client workload is distributed across multiple machines to make sure only the server’s processing power can be a possible bottleneck. The main takeaway from the result in this section is that the overheads associated with this kind of secure hardware are modest, and likely to yield systems that can rival industry standard datastores, while providing much stronger integrity and confidentiality protections for the data.

5.1 Transactional Performance

We expose CreDB to a TPC-C workload and compare it to MongoDB, a popular key-value store. The experimental setup we chose consists of two warehouses and a 1GB dataset. We use the py-tpcc implementation extended with a CreDB driver. For CreDB, data is stored normalized. In particular, each order is a distinct object and not part of the client’s record. We compare this against MongoDB with normalized data as well as a variant with denormalized data.

Figure 6 visualizes the observed performance of the different systems. We plot the throughput (on the y-axis) against the number of clients (on the x-axis). As expected the version of CreDB that runs without a trusted environment performs significantly better. However, to our surprise, MongoDB only performs about twice as fast as CreDB. Note that, unlike CreDB, MongoDB does not have support for linearizable transactions. CreDB’s throughput reaches its maximum of about 200tx/s within only a few clients, because at this point the size of the EPC is exhausted and the datastore has to start paging.

5.2 Network Scaling

We further evaluate how a network of CreDB nodes scales with the number of servers. Our benchmark is built on top of the wire transfer application sketched in Section 4.5. We allocate ten physical servers to this benchmark: five hosting the clients and five hosting the servers. Because these machines don’t come with the most recent Intel CPU generation, we run the network scaling benchmark in simulation mode. Thus, absolute numbers are not reflective of what is achievable on hardware, but the overall scaling trend is reflective of the system’s behavior.

The benchmark then evaluates a workload, where two hundred clients issue a total of 10,000 requests to a set of banks. These requests consist of transferring money from one to another account. This account can either be located on the same bank as the sender’s account or on any remote bank. In order to support such remote transfers, all banks in this setup are connected to all other banks.

Figure 7: Performance of a network of CreDB nodes: Throughput scales linearly with the number of servers in the network

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1https://github.com/apavlo/py-tpcc
In Figure 7 we gradually increase the number of banks and plot the overall throughput of the system. We observe that the throughput of the system increases with the number of banks. When the number of banks is low, most wire transfers are computationally cheap local money transfers. However, because the set of liabilities and assets can quickly grow large, a single bank can only perform so many operations. When the number of banks is higher, the benefit of having the set of accounts split across multiple servers seems to outweigh the overhead of remote function evaluation.

5.3 Encryption and Paging

Even with the previously described optimizations in the current implementation suffers an order of magnitude loss in performance once we exceed the size of the fast memory. In order to understand the performance impact of the paging and encryption mechanisms, we compare three different versions of CreDB. PlainDB does not use trusted environments or paging at all, PageDB does use paging but does not run in an enclave, and CreDB runs natively in an enclave.

Figure 8a identifies where these limitations come from. For each measurement, we preload the database with 1 million objects of 1024 bytes each. As expected, there is a large performance hit when running inside the enclave. Further, the results also show that under a Zipf workload the hit is not that large. An important observation is that, even in the worst case, the throughput is still sufficient for most applications. In fact, the observed throughput is several orders of magnitude higher than what systems like Bitcoin offer [15].

5.4 Security Policies and Stored Procedures

An important question is how much the execution of security policies harms the performance of the system. To evaluate this we execute a monotonic incremenal, which only allows to read or increment a value by one, on the setup described in Section 5.3. In order to achieve this a policy enforces that the only a pre-defined function increment can modify the value of the counter. Function increment, when called, will increment the value by exactly one and return the most recent value in an atomic fashion. This function was chosen because its minimalist implementation allows the benchmark to spend most of its time on the security policy.

Figure 8b shows that the major overhead is created by SGX and not the policy. Again, we compare two different implementations: one that runs in SGX (CreDB) and one that does not (PlainDB). As expected, PlainDB is faster in both, reading the value of the counter and incrementing the counter’s value. CreDB has roughly a 40% overhead due to encrypting and decrypting data that it writes to disk. Compared to this, the overhead of the policy itself is not really significant. Executing the policy creates an overhead of about 10%. In the case of increment the database executes both, a policy and a custom increment function, without much overhead.

5.5 Overhead of Witness Generation

Creating a signed certificate of a set of events incurs a non-trivial overhead. We evaluate how a get-operation as part of a transaction performs compares to a standalone get. We initialized the database with 10,000 objects and observed how variation in the object size (and, thus, request size) affects the performance of either setup. All get request were sampled from a uniform distribution.

Figure 8c visualizes how the performance of the two set up compares over a varying object size. We observe that the witness generation overhead, independent of the object size, produces roughly the same overhead. We attribute this overhead to the comparatively expensive asymmetric cryptographic operation that is needed to create the witness signature.

6 Discussion and Future Work

More expressive object semantics The evaluated prototype is built to scale with large-scale datasets, but does not accommodate large individual objects. In particular, large objects are not able to fit in enclave memory and cannot be efficiently sharded into multiple blocks. This can either be addressed by transparently splitting larger objects into multiple smaller objects, or by allowing multi-object policies, such that applications can split objects themselves. To make such an implementation efficient, the log would be required to only record the changes made to, and not the full values of, objects in order to keep log size small. The latter approach would also open up the system for applications that require support for nested objects, where each layer has its own associated policy.

Another common problem in databases that is not addressed in this paper is schema consolidation, where different parties may not structure their stored objects in the same manner. We envision a simple type system where objects, both locally and remote, can be checked against a specification. This can then be used to not only check the object for a specific structure, but also to verify its policy. Similarly, specifications can check other functions that are part of the object and speed up PFE, by defining a common protocol between multiple nodes.

Handling Crash Failures Crash failures can be caused by either broken hardware or malicious database operators that terminate the execution of the enclave. While the confidentiality of the hardware enclave cannot be broken this way, it may render the datastore inaccessible. In a realtime system, we assume that database operators are economically incentivized to replicate the encrypted data of the enclave sufficiently. Further, witnesses provide a way to retain facts about the datastore even after it went offline.

While out of the scope of this paper, a logical extension to the CreDB database model is to include replication requirements into the storage policies. For instance, nodes may advertise that they replicate all updates to a set of connected nodes. A write will only be considered successful when the write has been replicated to all members of the replica set. Such successful replica-
(a) The effect of paging on the performance on the system. Current SGX implementations only provide a small fast memory area.

(b) Overhead incurred by (a) SGX encryption and (b) executing security policies on a single object. All workloads fit into the fast memory region.

(c) Comparison of transactions that either yield or don’t yield witnesses. We observe the overhead of witness generation is considerably small.

Figure 8: Microbenchmark results

Enforcement of Retrievability (PoR) [23, 43] allows verifying that the solution could then be certified through a witness similarly to other database operations.

Side-channel Attacks Side-channel attacks, that is attacks that observe the application’s behavior through non-standard communication, such as looking at its CPU or cache usage, are of constant interest in the security community. Thus, several papers have addressed how the confidentiality of trusted hardware enclaves can be broken using such attacks [41]. Most of these attacks benefit from the fact that weak cryptographic code, e.g. where application secrets modify the control flow, is executed inside the enclave. While preventing CreDB nodes from side-channel attacks is beyond the scope of the paper, all cryptographic code in the enclave is implemented using constant-time libraries. We reserve addressing side-channel attacks against protected function evaluation for future work.

Multi-Node Transactions The accountable transactions described in this paper can only be executed on a single node of the system. However, certain operations may require atomicity and/or isolation across multiple CreDB instances. In the current implementation, this must be achieved on the application level. Future versions of CreDB may support multi-node transactions natively. However, this is a non-trivial task, due to the lack of a notion of time in the current version of SGX. This makes it non-trivial to detect failing parties and establish the order between events across node boundaries. Potential avenues for federated transactions could be trusted time source, or a trusted event ordering service [18] running inside a TEE.

7 Related Work

Enforcing Policies on Data TEEs are one specific instance of trusted platform modules (TPMs). The Nexus Operating System and its associated Authorization Logic [44] allow enforcing policies on applications. The Nexus uses a TPM to ensure only an authenticated and trusted kernel can be booted. The resulting operating system can then enforce complex constraints on applications running in its userspace. Traditional TPMS, such as the one used by Nexus, are usually harder to deploy as they require a fully trusted computation stack. TEEs, on the other hand, provide a “reverse sandbox” that shield enclave code from malicious host operating system. Thus, CreDB only requires trust in the trusted hardware and enclave code.

Information flow control is another common technique to enforce the integrity of a program’s execution. SIF [12] and Fabric [45] use a combination of static and dynamic information flow tracking to enforce policies through compiler and runtime. Fabric [32] extend this paradigm to the distributed setting. While such techniques can protect data from malicious code, it cannot protect from other attackers, and is, thus, orthogonal to the mechanisms described in this paper.

In a distributed setting, certain consensus protocols can be used to shield a system from Byzantine principals [11, 9, 35]. In such an environment, the trust lies in the network itself and a large majority of nodes behaving honestly. Thus, they require careful selection of committee members and require a larger number of replicas than the approach described in this paper. Further, they do not shield from data leakage and cannot enforce access controls.

Ensuring Data Integrity Tamper-evident logs allow detecting Byzantine behaviors of storage servers [28, 51] and more complex applications [20]. While most of these mechanisms only provide fork consistency, A2M [13] uses trusted hardware to achieve strong consistency in such a setup. However, even if an audit mechanism provides strong consistency, to ensure detection of misbehavior, it requires that clients are honest and communicate with each other. Further, misbehavior can be detected only after the fact which is not a strong enough guarantee for many applications.

TrInc [26] provides a monotonic incremender implemented in trusted hardware. Systems like CreDB can benefit from TrInc as it helps to protect from staleness attack, for example after an enclave is restarted. TrInc can also be used as a primitive to build byzantine fault-tolerant systems with fewer replicas. However, it cannot be used to enforce access control to data.

Proof of Retrievability (PoR) [23, 43] allows verifying that
a remote service indeed holds a dataset. PoR assumes a single client and thus is not suitable for some of CreDB’s use cases. One possible application for PoR in CreDB would be to verify replication of encrypted data on a third party.

Concerto [5] is a datastore that achieves strong consistency using server-side integrity verification Due to batch verification, this approach achieves much higher performance than other mechanisms [27]. However, Concerto ensures only data integrity and does not guard the data from unwanted accesses.

Guardat [47] shields data from malicious applications by enforcing policies in the storage layer. The high level motivation of Guardat is to reduce the attack surface of a complex system to a single policy-enforcing service. CreDB takes this concept a step further and enforces policies using trusted hardware.

Encrypted Databases If users trust the database application, operating on encrypted data might be sufficient to achieve confidentiality. Maheshwari et al. [33] presented one of the first encrypted databases. Their system stores hashes of the encrypted data in a small trusted hardware module to protect from tampering.

CryptDB [39] and Monomi [46] rely on homomorphic encryption of data. To make such a scheme efficient performance-wise, CryptDB does not encrypt all data and only supports a subset of the SQL language. TrustedDB [7] and Cipherbase [4] overcome this limitation by running queries on encrypted data using a trusted hardware module. All of these systems, to our knowledge, assume a single trusted client, potentially running multiple applications. In contrast, the policy enforcement and accountability features in CreDB are designed with especially multiple distrusting clients in mind.

Protecting Applications and Data using TEEs Previous work demonstrated how to run mostly unmodified applications in trusted virtual machines [8] or containers [6] executing in a TEE. The main difference between these approaches and CreDB is the choice of abstraction. We believe an eidetic datastore with built-in policies provides means for application developers to better leverage the power of trusted hardware enclaves. Further, we provide the witness primitive that can certify facts, even beyond the existence of database instance.

Ryoan [22] explores protecting data that is processed in the cloud using TEEs. This is achieved through a network of enclaves, similar to how CreDB nodes connect to each other. While Ryoan provides a sophisticated protected function evaluation mechanisms, it does not provide a mean for tamper-proof storage of data. Further, Ryoan connects nodes in a topology that is known a priori.

Cryptocurrencies and Blockchains Digital payment systems have been researched for about two decades [40, 48]. However, Bitcoin [37] was the first system that found widespread use and interested outside out the academic community. Recently, the focus has shifted from using blockchains simply to enable digital payment towards more generalized high-integrity storage solutions. Permissioned [10, 3, 2], as well as permissionless [37, 50], blockchains require computationally expensive replication to ensure integrity. CreDB, on the other hand, presents itself as a standalone "blockchain of one" that does not require any form of replication for integrity.

Combining TEEs and Blockchains Permissionless Blockchains are by design public. Trusted execution environments can enhance such blockchains with confidentiality. Town Crier [52] is an authenticated data feed that gives smart contract access to privacy-sensitive data. Further TEEs can be used to build more energy-efficient consensus mechanisms. Proof of Elapsed Time (PoET) [1] uses a trusted hardware enclave to ensure nodes can only forge new blocks once they have waited a certain period of time. Zhang et al. further improve this scheme by using the Proof of Work for useful computation [53]. These approaches are mostly suitable for the permissionless setting, where replicas can join and leave at any time. This is significantly different from the model CreDB provides.

TeeChan [30] implements fast and lightweight payment channels using TEEs. CreDB uses an identical handshake to set up a connection between two nodes as TeeChan. TeeChan, unlike CreDB, is further backed by the Bitcoin blockchain for the case of enclave failures, which allows for straightforward failure recovery. It is, on the other hand, an approach specifically tailored towards Bitcoin payment channels.

8 Conclusion

We presented CreDB, a novel datastore that provides strong integrity guarantees through security policies and witnesses. We classify CreDB as a High Integrity Log Store, and more specific a self-standing "blockchain of one". "Blockchains of one" combine the best of both worlds from conventional datastores and blockchains: they do not rely on massive replication or expensive proof of work, but still enforce high integrity of the stored data.

This paper demonstrated that CreDB allows to build high integrity distributed applications with relatively low effort. Our evaluation shows that this approach can handle hundreds of complex transactions a second, and can scale with the number of nodes in the system. We conclude that CreDB’s design in high performance compared to state-of-the-art systems such as Bitcoin or Hyperledger.

A The CreDB API

The following table shows all operations supported by the CreDB database model. Aside from executing standalone, operations can be executed in the context of a transaction. Until committed, transactions create a locally isolated view of the database and the attempted changes. These changes are only merged if no conflicts are detected on commit. Further, clients can construct, and inspect a local timeline. Only read operations can be per-
formed on such a local timeline, and such reads can only return data that is contained in the witnesses.

### Table 1: List of all CreDB API calls

| Function evaluation                  | Description                                                                 |
|--------------------------------------|-----------------------------------------------------------------------------|
| call(path)                           | Call the function located at path                                           |
| execute(func)                        | Execute `func` on the server side                                            |
| call_on_peer(path)                   | Call function on a remote party                                             |

### Table 2: Python modules available to protected function evaluations

| db                                   | Interact with the database as a client would do                           |
|--------------------------------------|---------------------------------------------------------------------------|
| self                                | If the function is part of an object, this module provides access to that object |
| rand                                | Allows code to access the random number generators provided by the TEE    |
| http                                | Provides a module to access external sources using HTTP(S)                 |

### B Policy and PFE Language

The CreDB database model is intended to be language agnostic. In this section, we present the policy language used in the prototype implementation, which is a subset of Python. In particular, it supports an imperative version of Python, that does not include object-oriented paradigms or functions. The Python code can access a few built-in modules to increase its functionality. The list of currently supported module is show in Table 2. Future versions of CreDB may introduce more modules to allow novel kinds of stored procedures.

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