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FaunaDB: An Architectural Overview

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ORIGINS OF FAUNADB

The history of database management systems is one of increasing abstraction.

Initially, hierarchical and key-value databases abstracted query expression from storage format management, improving performance, reuse, and correctness.

In the business data era, relational systems like SQL abstracted query expression from the underlying data structures and, to a degree, the query execution plan [1].

Today, in the internet era, the typical database user is no longer an analyst sitting at a workstation. From an operational perspective, customers have supplanted data experts as the primary consumers of data. Customers care primarily about what is happening now: which friends are online, the location of their on-route car, or their current account balance.

While customers are served in real time, the underlying data, including historical data, must be made available for analytics and machine learning workloads in a procedural interaction model.

To meet customers' expectations, the software enterprise is tasked with delivering real time access to a highly volatile data set to a large number of end users at high throughput, low latency, and scale. Furthermore, the software enterprise itself must keep pace with new customer requirements and business needs.

Fauna's team encountered this challenge at Twitter as we developed the distributed data systems for the core business objects: statuses, timelines, users, binary assets, the social graph, and the cache.

The NoSQL movement ushered in many systems which attempted to address this problem by jettisoning operational integrity in order to focus on either ease of initial application development, and ease of operations at scale. They sought to compromise avoid the architectural complexities introduced by ACID transactions by opting for an eventually consistent data approach. However, most didn't achieve either. These first generation NoSQL systems can sometimes be productive and scalable, but are extremely complex to operate. And, of course, transactional data consistency is left as an exercise for the application developer to implement in code.

> When data systems do not enable both developer productivity and business scale while guaranteeing operational integrity, business agility is compromised.

In this paper we introduce a FaunaDB, a transactional NoSQL database which delivers on the scale, ease of use, and productivity promise of the NoSQL movement while recovering the safety and correctness lost with the abandonment of ACID transactions.

FOUNDATIONS

FaunaDB's architecture can be thought of as a distributed data operating system. Like an operating system, it is composed of several interrelated subsystems:

- **A NoSQL query language** provides the productivity and flexibility of a general-purpose programming language when working with FaunaDB. Similar to LINQ, it is implemented as an embedded DSL within each client driver's host language, leveraging existing developer tools and increasing ease-of-use and safety.
- **A semi-structured document model** adapts to existing application data as it evolves over time and eliminates the object-relational impedance mismatch typically experienced when working with SQL systems.
- **A distributed ACID transaction engine** backed by a distributed, replicated global log maximizes correctness and ease-of-use without limiting scalability or fault-tolerance.

- **A row-level access control system** enforces security permissions down to granularity of individual records and allows safe direct access from untrusted clients.

- **A policy-based workload resource manager**, similar to an operating system kernel, fairly allocates compute, memory, and IO resources to competing applications and workloads based on operator specified priorities and quotas, and tracks per-tenant resource utilization.

- **A datacenter-aware routing layer**, similar to a software load balancer, minimizes effective latency and maximizes global availability.

- **A temporal storage engine** maintains the entire history of each record and index within a configurable retention window, providing better auditability of writes and efficient snapshot reads of data.

FaunaDB is inspired by technology from Twitter, Facebook, Netflix and others, and is influenced by the database research community. With a design focus on ease of deployment, ease of day-to-day DevOps and ease of use, these foundations permit FaunaDB to scale, perform, and operate without compromising on strong consistency that enterprises need. FaunaDB is implemented in Scala and runs on the JVM on all major operating systems.

DATA MODEL

FaunaDB implements a semi-structured, schema free object-relational data model, a strict superset of the relational, document, object-oriented, and graph paradigms:

- Records are inserted as semi-structured documents called instances, which can include recursively nested objects and arrays as well as scalar types.

- Instances are grouped into classes, which are similar to tables in a relational database. However, like a document database, full or partially shared schema within a class is optional, not mandatory.

- Classes are grouped into databases. Like filesystem directories, databases can recursively contain other databases.

- Database access is controlled by keys. Keys are credentials that identify the application requesting access and close over a specific database context. They can be assigned priorities, resource quotas, and access control roles.

- Derived relations are built with indexes. An index is a transformation of a set of input instances into one or more result sets composed of terms and values. Indexes are expressed as partially applied queries and can transform, cover, order their inputs, and enforce constraints (in FaunaDB, indexes and views are the same).

- Queries can be parameterized as functions, similar to stored procedures in a SQL system, in order to share logic across applications, abstract logic from applications that are difficult to upgrade in place, or create custom security models.

QUERY LANGUAGE

SQL is a poor fit for modern operational workloads, as the proliferation of ORM libraries attempting to hide it has shown. It is not type-safe, leading to frequent security flaws. Its declarative programming model leaves the performance profile of any specific query unknown and unpredictable. It is not extensible in a portable way, and programming complex compute logic within a query is not practical.

In order to conform to modern development practices, FaunaDB implements a new query language that is intuitive, flexible, and type safe. Interaction with the database is mediated by drivers that publish embedded DSLs for popular application languages.

Developers using FaunaDB write application-native code in a familiar style within a transaction context. A single request

can encapsulate a transaction that spans multiple records. The FaunaDB driver reflects on the native expression and serializes it to the wire protocol. The transaction is then transmitted and executed atomically by the database. The experience is similar to working with a tuple space or other distributed computation architecture that moves computation to the data [4].

IMPLEMENTATION

FaunaDB's query language is designed to increase safety, predictability, and performance:

- **Queries are written in the host application language and inherit its safety mechanisms.** There is no additional string evaluation step that can lead to injection attacks.
- **All queries execute autonomically and transactionally.** Session transactions are not supported. Because the database receives the entire transaction before constructing the execution plan, execution can proceed with maximum parallelization and data locality. Optimization opportunities like predicate pushdown apply universally and predictably.
- **Query capabilities that are inherently non-scalable are replaced with semantics that are.** For example, FaunaDB does not allow bulk table scans, but requires non-primary-key access to be backed by an index.
- **Database sessions are stateless.** Every transaction is identified with an access token that closes over the transaction context. Connections are very low overhead and suitable for ephemeral use, making access from serverless applications or embedded devices practical.

These improvements are difficult or impossible in legacy query languages because they require restricting the language, not extending it, damaging standards compatibility.

At the same time, the extensibility of FaunaDB's query language allows the database to incorporate an effectively unlimited number of additional functions common to other data domains such as geographic indexing, full-text search, iterative machine learning, etc., without the burden of grafting custom syntax and extensions onto a closed standard model.

EXAMPLES

This transaction, written in Scala, inserts a blog post with case-insensitive tags:

```
Create(Class("posts"),
  Obj("data" → Obj("title" → "All Aboard",
                   "tags" → Map(Lambda { tag => Casefold(tag) },
                                Arr("Ship", "Travel")))))
```

This read-only transaction looks up posts by the "travel" tag in an index:

```
Paginate(
  Match(Index("posts_by_tags"), "travel")))
```

This read-only transaction perform a relational join of blog posts and inbound references to them by primary key:

```
Paginate(
  Join(Match(Index("posts_by_tags"),"travel"),
     Index("linkbacks_by_post"))))
```

TEMPORALITY

Event sourcing, reactive programming and other audit and stream-oriented data architectures are prevalent in modern applications but are not supported by the underlying data stores. Complex lambda architectures and inconsistent application-managed audit logs are common substitutes for native database support. Typically, historical data cannot be accessed in real time or with the same query capabilities as current data.

In order to support these fundamental interaction patterns with no additional application complexity, all records in FaunaDB (including schema records) are temporal. When instances are changed, their prior contents are not overwritten; instead, a new instance version at the current transaction timestamp is inserted into the instance history, either as a

create, update, or delete event. FaunaDB supports configurable retention policies on a per-class and per-database basis.

All reads—including index reads, joins, or any other query expression in FaunaDB—can be executed consistently at any point in the past or transformed into a change feed of events between any two points in time. This is useful for auditing, rollback, cache coherency, syncing to second systems, and forms a fundamental part of FaunaDB's isolation model. Privileged actors can manipulate historical versions directly to fix data inconsistencies, scrub personally identifiable information, insert data into the future, or perform other maintenance tasks.

SECURITY

Most databases implement schema-level user authentication only, since they were designed for small numbers of internal business users. But modern applications are exposed to millions of untrusted and potentially malicious actors and must implement identity management authentication, and row-level security at a minimum.

FaunaDB internalizes these concerns in order to deliver both administrative and application-level identity and security either through API servers or directly to untrusted clients like mobile, browser, and embedded applications.

Pushing security concerns to the database guarantees that all applications interacting with the same dataset implement the same access control, and dramatically reduces the attack surface, a critical business risk.

IDENTITY

Application actors in FaunaDB (such as users or customers) can be identified either with built-in password authentication or via a trusted service that delegates authentication to some other provider. Once identified, application actors receive a token they can use to perform further requests that closes over their identity and access context, similar to an access token in OAuth2.

This allows untrusted mobile, web, or other fat clients to interact directly with the database and participate in the row-level access control system. Actors identified as instances never have access to administrative controls.

System actors are identified by keys; keys can have a variety of levels of privilege. Keys always close over a specific logical database scope and cannot access parent databases in the recursive hierarchy, although they optionally can access child databases.

ACCESS CONTROL

System actors have roles assigned to their keys which can only be changed by a superior actor. These roles limit activity to administrative access, read/write access to all instance data, or access to public instance data only.

- Row-level security for application access control is managed through assignment of identities and to read, update, create, and delete access control lists on instances, indexes, stored procedures, and classes.
- Data-driven rights decisions, such access groups, can be implemented by assigning access control query expressions to ACLs. These query expressions are parameterized on the object that contains the role, and must return a set of identities allowed to fulfill the role.
- Finally, the identity of the actor performing a transaction can be accessed within the context of a stored procedure in order to implement completely custom access logic within the database.

Like a filesystem, FaunaDB transparently enforces row-level access control at all times; there is no way to circumvent it.

AUDITING AND LOGGING

All administrative and application transactions in FaunaDB can be optionally logged; additionally, the underlying temporal model preserves the previous contents of all records within the configured retention periods.

Although FaunaDB does not natively track data provenance, applications can tag every transaction with actor information and access that data historically as part of the instance versions.

SCALABILITY

FaunaDB is designed to be horizontally and vertically scalable, self-coordinating, and have no single point of failure.

Every node in a FaunaDB cluster performs three roles simultaneously:

- Serving as a **query coordinator**.
- Serving as a **data replica**.
- Serving as a **log replica**.

No operational tasks are required to configure the role of a node.

Every FaunaDB cluster is made up of three or more logical datacenters (a physical datacenter can contain more than one logical datacenter).

ROUTING

Any FaunaDB node in any datacenter can receive a request for any logical database in the cluster. This node will act as query coordinator and begin executing the transaction by pushing read predicates to data replicas that own the underlying data, waiting on the responses, and accumulating a write buffer if the transaction includes writes.

Read predicates may be as simple as row-level lookups, or as complex as partial query subtrees. Multi-level predicate pushdown is supported. This dramatically reduces latency and increases throughput via increased parallelism and data locality.

If the transaction is read-only a response will be returned to the client immediately; if the transaction includes writes, it will be forwarded to the appropriate log replica for transaction resolution. The log replica will forward the transaction to involved data replicas which will definitively resolve the transaction and return a response to the client-connected node, which will then return the response to the client.

DATA PARTITIONING

Within each datacenter, the logical data layout is partitioned across all nodes within the datacenter. Instances, including their history, are partitioned by primary key. Indexes are partitioned by term. Both instances and indexes scale linearly for reads and writes, regardless of their cardinality or the number of nodes in the physical cluster.

Hotspots in indexes are possible if the read or write velocity of a specific index entry exceeds the median size by a substantial margin. In this case FaunaDB can partition the instance or index entry across multiple ranges and perform a partial scatter-gather query on read, similar to a search system.

FAULT TOLERANCE AND CAP

While it is impossible for any distributed system to guarantee both total consistency and total availability at the same time, FaunaDB aims to provide the ideal tradeoff between the two. For most applications, maintaining consistency is optimal. Hence, according to the CAP theorem [5], FaunaDB is a CP system.

Nevertheless, FaunaDB is resilient to many types of faults that would affect availability in a less sophisticated system. In particular, a FaunaDB cluster is not vulnerable to any single point of failure, even at the datacenter level.

Some specific faults that FaunaDB can tolerate are:

- A node is temporarily unavailable (process crash; hardware reboot).
- A node is permanently unavailable (physical hardware failure).
- A node becomes slow (local resource contention or degraded hardware).
- A network partition isolates a datacenter—in this case, the isolated datacenter can continue to serve reads but cannot accept writes.

A FaunaDB cluster maintains availability in the face of faults due to the redundancy inherent in maintaining multiple replicas of the dataset. For example, in a cluster configured with five datacenters, as long as three datacenters remain available, the cluster can respond to all requests.

Although a FaunaDB cluster is capable of responding to transactions despite a partial or total failure in multiple datacenters, it is still in a degraded state. An additional concurrent failure in another datacenter may impact availability.

FaunaDB does not automatically decommission failed nodes or datacenters; this decision is left to the operator to avoid triggering cascading failures.

DURABILITY

FaunaDB's local storage engine is implemented as a compressed log-structured merge tree [6], similar to the primary storage engine in Google Bigtable [7]. LSM storage engines are well-suited to both magnetic drives and SSDs.

WRITES

Transactions are committed in batches to the global transaction log (the equivalent of a distributed write-ahead log, discussed below). Replicas tail the log and apply relevant write effects atomically in bulk. This model maintains very high throughput with log-structured merge trees and avoids the need to accumulate and sort incoming write effects in a memory table. Because FaunaDB's temporal data model is composed of immutable versions, there are no synchronous overwrites.

READS

The on-disk levels act as a series of overlays that logically combine into the local dataset. This means that reads may need to check multiple levels to find the complete result set they are interested in. This degrades read performance compared to a data structure that is modified in place, like a B+ tree.

PERFORMANCE

A variety of other optimizations such as local index structures are kept in memory to minimize the need to seek through each level file itself to find if a data item is present.

The level files themselves are compressed on disk with the LZ4 algorithm to reduce disk and IO usage. This also improves the performance of the filesystem cache. Since level files are immutable, compression only occurs once per level file, minimizing the performance impact.

In order to mitigate the latency impact of multi-level reads, a local background process called compaction is triggered when the number of levels exceeds a fixed size. Compaction performs an incremental merge-sort of the contents of a batch of level files and emits a new combined file. In the process, expired and deleted data is evicted, shrinking the on-disk storage usage.

Compaction can be performed asynchronously, but progress must be guaranteed over time or read performance will degrade. The compaction tasks are managed via the process scheduler in order to balance their resource requirements with the need to prioritize synchronous transactions.

TRANSACTIONAL CONSISTENCY

Strict serializability is widely recognized as the ideal consistency model. Because it:

- is easy for developers to reason about
- minimizes application complexity
- reduces the total amount of data that needs to be stored

However, strict serializability in traditional systems incurs a substantial performance cost, especially in distributed environments.

FaunaDB's consistency model is designed to deliver strict serializability across multi-key transactions in a globally-distributed cluster without compromising scalability, throughput, or read latency.

All read-write transactions are strictly serializable based on their position in a global transaction log. Read-only transactions are serializable. Database drivers maintain a high watermark of the log position of their last request—equivalent to a causal token—guaranteeing a monotonically advancing view of the global transaction order. Additionally, each datacenter uses a synchronization scheme to share the most recently applied log position among all query coordinators, in order to provide a consistent view in the presence of hidden coordination across client.

Finally, write transactions are restricted to a single logical database, but read-only transactions that recursively span multiple logical databases maintain the same serializability guarantee as single database read-only transactions if appropriate permissions have been assigned.

TRADE-OFFS

FaunaDB's primary trade-off is that write latency has a lower bound of the round-trip latency between the originating datacenter and a subset of the other datacenters. The scalability function is logarithmic; as additional datacenters are added to improve availability, the marginal impact of each one on latency decreases.

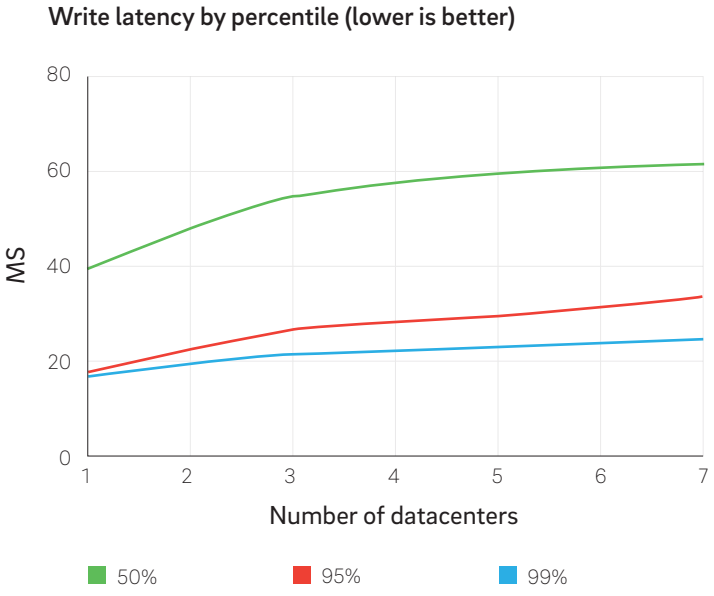


Figure 4: Latency benchmark showing asymptotic scalability of writes as additional datacenters are added

This network latency is strictly worse than the latency exposed by eventually-consistent, distributed key/value stores, which do not attempt to guarantee global durability before acknowledging a commit, or SQL systems which rely on asynchronous replication and cannot serve consistent reads from replicas. Increased application parallelism can compensate for the latency increase on individual writes with no impact on overall throughput.

Additionally, unlike strongly-consistent systems like Google Spanner [8], FaunaDB has no window of ambiguity for which all reads may potentially be delayed—a property that becomes untenable on public networks at global scale.

Finally, session transactions are disallowed in FaunaDB. While session transactions are a convenient feature for some applications, they are also a frequent source of performance problems, and can be simulated via snapshot reads and compare-and-swap functionality if necessary.

IMPLEMENTATION

Transaction resolution in FaunaDB is inspired by the Calvin protocol [2], backed by a highly optimized version of Raft [3]. Raft serves to replicate a distributed transaction log, while Calvin manages transaction resolution across multiple data partitions. The globally replicated transaction log maintains an order of all transactions within a logical database. The log is processed as an ordered series of batches called **epochs**. The typical epoch window in FaunaDB is 10 milliseconds, which allows the cluster to parallelize transaction application with minimal impact on observed latency.

When a transaction is submitted to a **query coordinator**, the coordinator speculatively executes the transaction at the latest known log timestamp to discover read and write intents. If the transaction includes writes, it then is forwarded to the nearest **log replica**, which records it as a part of the next epoch, as agreed upon by consensus with the other replicas.

At this point, all required cross-datacenter communication has occurred. The order of transactions within the epoch and with respect to the transaction log is resolved, the transaction

is stamped with a logical timestamp reflecting its position within the log, and each datacenter proceeds to independently and deterministically resolve transaction effects.

The transaction is then forwarded to each local **data replica**, as determined by its read and write intents. Each data replica receives only the subset of transactions in the epoch that involve reads or writes of data in its **partitions**, and processes them in the pre-determined order. Each data replica will block on reads for values it does not own, and forwards reads to all other involved partitions for those it does. Once it receives all read values for the transaction, it will resolve the transaction and apply any local writes. If any preconditions of the original speculative execution fail (e.g. a read dependent on a value that has changed is no longer covered by the set of read intents), the transaction will be aborted.

Because the transaction log maintains a global order, and data nodes are aware of their own position in the log, reads can be consistently served from the local datacenter at all times, and the causal order of two transactions can always be determined by the ordering of their respective log positions.

Although transaction throughput is theoretically constrained by the degree of contention among the log replicas within each epoch, in FaunaDB resolution context is partitioned by logical database, so aggregate transaction throughput is unbounded. The theoretical upper throughput bound per logical database is approximately one million transactions per second.

RESILIENCY

The transaction processing pipeline is tolerant of node failure and latency at each step.

- If the coordinating node cannot communicate with the local log replica, it may safely forward its transaction to another log replica.
- If a data replica does not receive an epoch batch from the local log replica in a timely manner, it may retrieve the epoch batch from another log replica.
- If, during transaction application a data replica does not receive part of the transaction's reads from other partitions, it may safely read the missing values at the specific log position from other replicas of the failed partition.

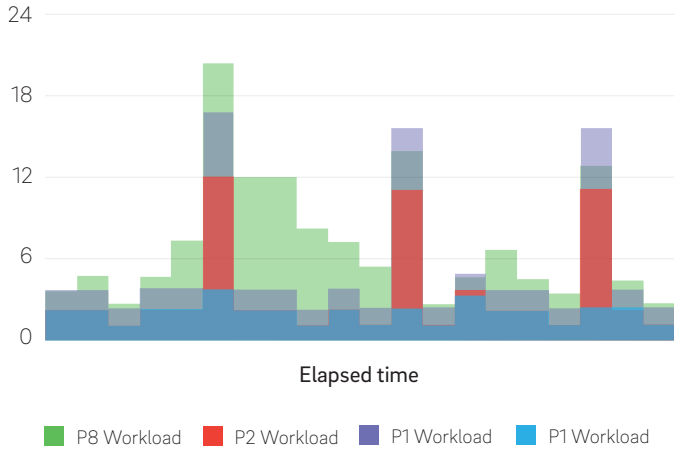
WORKLOAD RESOURCE MANAGEMENT (QOS)

In order to effectively respond to rapidly changing workloads and provide safe access to shared data sets, FaunaDB implements a **policy-based workload resource manager** that dynamically allocates resources and enforces quality of service.

FaunaDB's query planner evaluates transactions as a series of interleaved and potentially parallelizable compute and IO subqueries, and guarantees that execution will always yield at predictable and granular barriers (for example, loop iteration). This restricts the complexity of continuations and lets the executor context switch and re-enter scheduling each time a predictable quantity of resources is consumed from each IO or compute execution thread, without requiring a more complicated pre-emptive multitasking scheme.

Transaction subqueries are slotted into per-resource queues first by their **execution context** (synchronous or asynchronous), and secondarily by their **priority context**, which is either the priority of their logical database, or the priority of their access key if it has one.

Submitted work



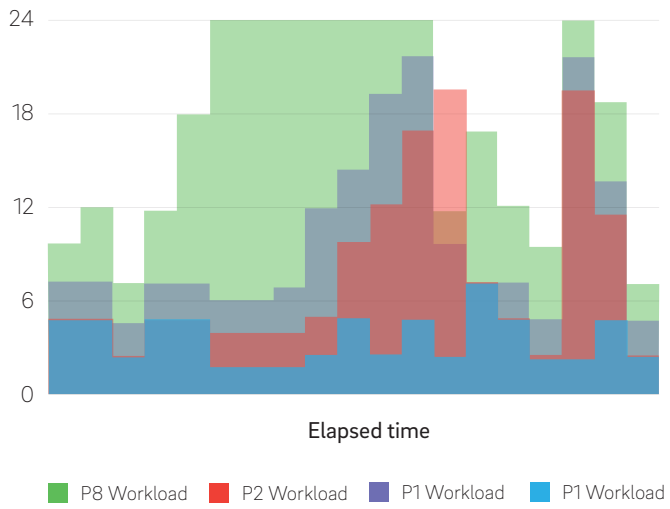


Figure 5: Idealized process scheduler example showing priority-based preemption

Execution proceeds via cooperative multitasking. Subqueries are selected for execution according to a recursive, weighted fair queuing algorithm [9] and scheduled onto native threads.

The overall impact is that workloads can be recursively ordered by business priority, and low priority tasks are time-shifted and consume whatever idle capacity remains. This dramatically improves aggregate utilization. The more diverse applications, datasets, and workloads are hosted in a single FaunaDB cluster, the better the price/performance becomes compared to a statically provisioned data architecture.

BACKGROUND TASKS

Background tasks such index builds are a frequent source of availability problems in legacy database systems.

In order to mitigate this, background work in FaunaDB is managed internally by a journaled, topology-aware **task scheduler**, similar to Apache Hadoop YARN [10].

IMPLEMENTATION

FaunaDB's implementation is general purpose. Tasks may be limited to one instance across a cluster or per database, or be assigned a specific data range (in which case, the executing node will be one that is a data replica for that range). The execution state of each task is persisted in a consistent metadata store, meaning that scheduled tasks may run in a node agnostic manner: If a node fails or leaves the cluster, its tasks are automatically reassigned to other valid nodes and restarted or resumed.

Task execution throughput is controlled by FaunaDB's resource scheduler. General background work not associated with any tenant is run at low priority, allowing the task to proceed as idle resources allow and eliminate the impact of background tasks on synchronous requests.

OPERATIONS

FaunaDB is designed to be extremely straightforward to operate. Our goal is to subsume as much of the complexities of database management, and put the burden of maintaining cluster guarantees on the system itself rather than on the operator. The end result is that daily devops tasks are vastly simplified and are more amenable to automation.

The cluster management infrastructure reuses the consistency mechanism and process scheduler to guarantee that the cluster is always in a coherent state, and that work generated by operational changes does not adversely affect production workloads.

TOPOLOGICAL CHANGES

Cluster topology changes include:

- Adding, removing, or replacing a physical node in the cluster.
- Adding or removing a datacenter.
- Changing the replication configuration of a logical database.

During cluster transition states, node failures and other interruptions do not affect cluster availability. If the node running the supervisor process fails, then its lease on the supervisor role will expire and another node will assume

the role. All incremental steps within each transition process are idempotent and may be safely restarted or reverted.

OTHER MAINTENANCE

Other maintenance tasks include:

- Taking logical and storage-format backups.
- Performing anti-entropy checks.
- Upgrading the on-disk storage format.

These do not require a state machine transition, but still rely on the process scheduler to avoid impacting production traffic.

SUCCESS PATTERNS WITH FAUNADB

FaunaDB has found applications across diverse industry vertical segments, including financial services, e-commerce, and SaaS.

A variety of success patterns with FaunaDB have emerged from customer usage:

- Enterprises that require strong consistency for transactions can use FaunaDB as a distributed ledger.
- Product teams building new applications for mobile, web, or other fat clients can use FaunaDB as a distributed application backend.
- Developers of software-as-a-service products can use FaunaDB's quality-of-service and multi-tenancy capabilities to isolate and improve their customers' experience.
- Enterprises with data in legacy silos can use FaunaDB as a scalable data fabric to integrate them.
- Multi-product enterprises can realize significant utilization improvements by consolidating applications into a shared FaunaDB cluster.
- Companies with data hosted in a single geographic location can use FaunaDB to distribute their data globally in multi-region deployments.
- Enterprises in transition to the cloud can use FaunaDB to unify on-premises and cloud data in hybrid and multi-cloud deployments.
- Operators struggling to manage cross-team/cross-workload access to shared data can use FaunaDB to efficiently allocate resources and improve availability.

As FaunaDB matures we anticipate customers will experience compounding returns on their investment. Unlike multi-system database deployments, each additional FaunaDB feature or client application incurs no additional cost in operational complexity, infrastructure footprint, availability, or scalability.

CONCLUSION

This paper gives an overview of the design and architecture of FaunaDB, a transactional NoSQL database with a tenant-aware resource management system and flexible operational profile.

FaunaDB is our effort to build a database for modern enterprises' mission-critical use cases. Our work is based on the state-of-the-art research and industry progress in databases and operating systems, as well as a wealth of hands-on operational experience.

Although we have attempted to be comprehensive, we have left out many details. We look forward to working with the developer community, academia, and current and future customers to realize a shared vision of what modern operational database management should be.

CONTACT

We're working with developers, customers, and partners at all levels of growth. We'd love to help you get started with FaunaDB as well. For more information and to discuss working together, please email our team at **priority@fauna.com**, or visit us on the web at **fauna.com/request-info**.

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