Search on Secondary Attributes in Geo-Distributed Systems

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In the age of big data, more and more applications need to query and analyse large volumes of continuously updated data in real-time. In response, cloud-scale storage systems can extend their interface that allows fast lookups on the primary key with the ability to retrieve data based on non-primary attributes. However, the need to ingest content rapidly and make it searchable immediately while supporting low-latency, high-throughput query evaluation, as well as the geo-distributed nature and weak consistency guarantees of modern storage systems pose several challenges to the implementation of indexing and search systems. We present our early-stage work on the design and implementation of an indexing and query processing system that enables real-time queries on secondary attributes of data stored in geo-distributed, weakly consistent storage systems.

1 Introduction

Various object storage systems have arisen over the recent years to meet the needs of internet-scale applications. These data stores, including BigTable [1], Amazon’s Dynamo [2], Cassandra [3] and HBase [4] among others, are able of storing large amounts of rapidly evolving data, while maintaining high performance. In order to achieve their scalability, these systems typically expose a simple GET/PUT API which allows access to data only through their primary key. Although key-based access to data is scalable, it is only useful when the keys of objects that need to be located are known. This shifts the responsibilities of representing secondary attributes, one-to-many relationships and many-to-many relationships to application developers, and forces them to either fit their application logic into a key-value model, or maintain data in one system and relationships in another. Furthermore, it makes it difficult to implement applications that need to retrieve data by attributes other than the primary key. As an example of secondary attributes, consider the case of photograph files where secondary attributes may include information such as file-size, creation date, access rights, geolocation information, confidence score for classification classes, and other user-defined attributes. The ability to perform queries on secondary attributes can be a preferred way to access data for these applications, and would be a natural retrieval mechanism that can complement the usual key-based semantics of object storage systems.

Indexing secondary keys has been studied extensively in systems offering strong consistency, especially in the context of traditional database systems. However, modern geo-distributed storage systems present different challenges to the implementation of secondary indexes. These systems replicate data over servers across geo-distributed data centres (DCs). Client operations are served by accessing the local replica without synchronising with other DCs. This ensures minimal latency and enables the system to remain available under network partition (AP). As a result, these systems offer weak consistency guarantees, where reads might return stale values and writes may conflict. In this setting, indexing systems need to ingest updates locally at each DC, propagate index updates in the background, and resolve conflicting in-
Moreover, an increasing number of applications continuously produce large amounts of data at high rates. An example is social media applications, such as Twitter [5], where millions of users continuously post new content. This creates the need for real-time search: secondary attributes of continuously created content need to be searchable within seconds after creation.

1.1 Problem Statement and Challenges

The research problem addressed in this thesis is enabling efficient discovery and retrieval of data stored in large-scale, geo-distributed, weakly consistent object storage systems. Our goal is to extend these systems with an efficient and scalable indexing and query processing system, focused on real-time queries on non-primary attributes.

In this section, we describe the requirements and challenges involved in extending a geo-distributed, weakly consistent storage system to support real-time search on secondary attributes. These challenges guide our design choices for the implementation of our system.

Low-latency, high-throughput query processing. Users and applications expect to receive query results with minimal latency. Moreover, cloud-scale search systems must be able to cope with large query volumes. In other words, the query processing system must achieve both low latency and high throughput. Maintaining high performance is especially challenging for data stores that scale to very large amounts of data.

Evolving dataset. In the setting of real-time search, data may be created and updated at a high rate. Despite that, users and application expect data to be searchable within a short amount of time. The indexing system must therefore ingest and index updates achieving both low latency and high throughput. In addition, index update operations should not occur significant overhead to the latency of source data reads and writes.

Search systems that support real-time queries on evolving datasets, must enable large volumes of concurrent index reads and writes. Index structures must track updates incrementally as they occur while at the same time being accessed to answer queries.

Geo-distributed, AP data stores. Today’s large-scale storage systems replicate data across geo-distributed data centres in order to avoid network latency and tolerate network partitions. They implement weak consistency models, where client operations are served by the local replica, while updates are propagated asynchronously to other replicas. As a result, search systems must be able to ingest concurrent updates and serve queries at multiple DCs without synchronisation across replicas. Moreover, indexing systems must be able to resolve conflicting modifications to index structures caused by concurrent updates at different replicas.

1.2 Data and System Model

In an object storage system, objects are composed of an uninterpreted blob of data (content), accompanied by a set of additional metadata attributes, and are assigned a globally unique identifier (key). We model the secondary attributes as a JSON-like object attached to each data object, consisting of a set key-value pairs of binary (text) or numerical data. Secondary attributes may consist both of system metadata (content size, timestamp of last modification, author, access control lists), as well as custom, user-defined attributes. This representation resembles the model that Amazon’s S3 object storage API [6] implements.

Applications expect to be able to perform both exact match and range queries, using multiple secondary attributes, and express queries as logical expressions using conjunctions and disjunctions.

We model the geo-distributed data store as a set of storage servers grouped in geo-distributed data centres. Data is partitioned among servers within a DC, and fully replicated among DCs. Read and write requests are served from the DC nearest to the client’s
location without contacting remote DCs, while updates are propagated asynchronously among DCs.

2 Problem Analysis & Design Space

In this section we give an overview of the various design questions that affect the design of a system that supports real-time queries on secondary attributes in geo-distributed weakly consistent storage systems.

We perform a detailed analysis of the various aspects of described problem, and discussing how the problem’s requirements affect our design choices.

2.1 Index Organisation

In an object storage system as described in 1.2, clients can perform queries on secondary attributes by translating them to Get operations. However, since there are no index structure to enable fast lookups on secondary attributes, queries will have to scan the entire dataset to select objects that match the given query. Moreover, since data is partitioned among servers using the objects’ primary keys, all servers need to be accessed for each given query, resulting in large network loads.

The above discussion shows the inherent inability of an indexless system to efficiently and scalably process queries on secondary attributes. It is thus evident the need to extend these system with distributed secondary indexes. Secondary indexes allow parallel access to different parts of the index and can improve throughput and scalability.

There are two main approaches to organising a distributed index:

Colocation (Local indexes). One approach is to colocate index structures on the same servers as the source data. Systems using this approach need to query all servers storing index partitions for each index lookup. This allows low latency index updates, as it does not require communication among servers. However, the lookup cost increases linearly with the number of servers in the system, limiting the scalability of the system.

Independent Partitioning (Global Indexes). Another approach is to partition the index independently from the data, so that indexes are not necessarily located on the same servers as the corresponding data. Systems that choose this approach achieve constant index lookup latency, and better scalability as their throughput increases with the addition of servers. However, supporting range queries with an index that uses independent partitioning is challenging. Using the underlying storage to store index entries destroys data locality, as storage systems use hashing to shard their data.

2.2 Inter-DC Index Replication

Extending a geo-distributed data store to support queries on secondary attributes requires distributing secondary indexes in multiple data centres. Same as source data, indexes need to be fully replicated among DCs, so that queries can be evaluated locally without need for communication with remote servers. Geo-replicated indexes can ingest updates locally, and propagate updates among DCs in the background.

There are two design choices for propagating index updates among DCs. One approach is to rely on the underlying data store’s write log. Index replicas at each DC process updates as they are appended to the local write log, either by operation performed locally or by operation propagated from other DCs. When using this approach, indexes need to process each new update that is appended to the log and issue index update operations when required. This may not be efficient for attributes that are not frequently updated, since indexes will waste computations by going through large volumes of updates but rarely updating their indexed values.

A different approach is to use a mechanism that propagates updates directly among indexes, without relying on the propagation of source data writes. This mechanism can be either operation-based, and propagate index update operations among index replicas, or state-based, in which case it will replicate the state of index structures. This approach is more suitable for rarely updated attributes, but incurs increased network traffic in the case of heavily updated indexes.
Another aspect of a geo-replicated indexing system which ingests updates locally at multiple DCs and propagates them at the background, is the fact that concurrent index updates may conflict. As an example of conflicting index updates, consider the case where an object \texttt{Obj} is concurrently updated in DC1, and DC2. In DC1, the attribute \texttt{Attr} is set to the value \texttt{A}, while in DC2 \texttt{Attr} is set to the value \texttt{B}. The index structures of each DC are updated accordingly by adding \texttt{Obj} to the index entries \texttt{Attr:A} and \texttt{Attr:B} respectively. After propagating these updates and merging, index structures should converge to the same state. Furthermore, the merged index state should reflect the conflict resolution performed by the storage system, which will choose either value \texttt{A} or \texttt{B} for \texttt{Attr}, using a strategy such as last-writer-wins.

This issue highlights the need for a conflict resolution mechanism which will ensure that index replicas converge to the same state even in the presence of conflicting updates.

### 2.3 Index Maintenance

In traditional database systems, data are expected to be searchable immediately after being updated, as search queries are a primary mechanism for data retrieval. Additionally, indexes are used internally for other operations such as view maintenance. These systems thus maintain strong consistency between indexes and base tables by updating their indexes synchronously, in the critical path of each update.

On the other hand, in the context of web search, content is not expected to be available for searching immediately. Web crawlers periodically crawl web content and build indexes, using batch operations to achieve high throughput. These are eventually consistent with the source data, and depending on the type of the content indexing delays of minutes, hours of even days might be acceptable.

In the case of secondary indexes in storage systems, these exist a spectrum of design choices for index maintenance. The most write-optimised approach is not to maintain the indexes synchronously, which can have no write overhead but results in stale search results. On the other end, the most read-optimised approach is to synchronously update indexes in place; that is, to keep every index entry up-to-date based on the latest data updates. This may be expensive task in a global index scheme, where the creation of a single new object may involve communication with multiple servers to update indexes for different secondary attributes. There are other design choices that fall in the spectrum between these two approaches, as [9] shows.

#### 2.3.1 Implications of Asynchronous Index Maintenance

Maintaining strong consistency between indexes and source data may be prohibitive for distributed data stores that accept high rates of updates, due to the overhead in write latency caused by the index maintenance task.

Indexing systems may therefore choose to update their indexes asynchronously. This can be implemented by a background task which subscribes to the storage system’s log, receives updates when they are appended to the log, and maintains the indexes.

As result of this approach indexes may lag behind the state of the data store due to message delays or high load, and not contain the effects of recent writes. Moreover, the amount of divergence between index and source data may grow unboundedly depending on the system’s load.

At the same time, applications that perform searches on evolving datasets may require fresh search results, as data is changing quickly and factors such as potential profit may depend on the ability to obtain fresh search results.

Therefore, to address the requirements of different applications, a search system may use an additional mechanism that updates search results with recent - not yet indexed - writes at query time. Since this mechanism would require additional computations, it creates a trade-off between query response time and result freshness. Applications can trade additional computations for results freshness, and obtain stale results with low latency, or more fresh results with slower response time.

Moreover, allowing divergence between the state of indexes and the state of the data store intro-
duces both false-positives; Indexes may contain old entries of objects whose attribute values have been updated. False-positives can be removed at query time by checking query results against the data store.

2.4 Multi-Resolution Indexing

High cardinality attributes that have a large number of distinct values, may have a negative impact on both indexing and query processing. This is especially true for system metadata such as last access timestamp and object size (although object size values can be efficiently represented in an index by their logarithm) which are stored with high precision by the storage system. Storing each distinct value as an index entry greatly increases the size of the index. Moreover, queries often require small precision ("objects with size greater than 1GB", "objects last accessed more than 3 months ago").

An approach that can address this challenge is binning, where each index entry represents a range of values. Binning can reduce the index size and improve performance, but it also introduces false positives, as results of a query may partially belong in a bin. In this case, every object contained in the bin need to be checked in order to remove those that do not satisfy the query condition, a process called candidate check. When a candidate check is needed, it usually dominates the query response time.

The impact of candidate checks can be minimised by an efficient placement of bin boundaries. An adaptive indexing system may dynamically place and adjust bin boundaries based on the number of objects contained in each bin and the resolution at which attributes appear in past queries, with the goal of finding the best trade-off between index size and candidate checks.

3 Literature Review

3.1 Secondary Indexes in Distributed NoSQL Databases

Current NoSQL systems have adopted different strategies to support secondary indexes. The design choices of these approaches depend on the characteristics of each data store and the expected workloads.

SLIK [7] extends RAMCloud [10], a distributed in-memory key-value storage system, to provide secondary indexes. It achieves scalability by partitioning indexes independently of the source data. SLIK deals with potential consistency problems that occur as a result of indexes and source data being stored in different servers by introducing two mechanisms: It (1) uses an ordered write approach which ensures that the lifespan of each index entry spans that of the corresponding object, and (2) uses objects as the ground truth to determine the liveness of index entries, by rechecking index lookup results against the source data. Additionally, SLIK performs long-running bulk operations such as index creation, deletion and migration in the background, without blocking normal operations. The system implements secondary indexes as B+ trees and stores them as regular tables in the underlying key-value store.

Diff-Index [8] and Hindex [9] both extend log-structured key-value stores to support secondary indexes. Both works focus mainly on the scheduling of the index maintenance operations in order to improve performance of write operations. Their design decision are further discussed in Section 3.5. These systems maintain global indexes and store index entries as regular key-value pairs in the underlying data stores. They update their secondary indexes using regular GET/PUT operations offered by the underlying data stores.

Qader et al. [11] study the secondary indexing techniques used in state-of-the-art commercial and research NoSQL databases. More specifically, they categorise secondary indexes in (1) stand-alone indexes, where indexing structures are built and maintained and (2) filter indexes, where there is no separate secondary index structured, but secondary attribute index information is stored inside the original data blocks. Stand-alone indexing techniques are further categorised to those that perform in-place update (i.e. for each write the index structures are accessed, updated and stored back to disk), and those that perform append-only updates. The authors implement a number of different secondary indexing techniques on top of LevelDB [12] and study the
trade-offs between different indexing techniques on various workloads. This work is mainly focused on a single server instance of LevelDB and does not consider a distributed setting.

3.2 Searchable Key-Value Stores

HyperDex \[13\] is a distributed key-value store that provides an interface for retrieving objects based on secondary attributes. It implements this functionality not by using secondary indexes, but through hyperspace hashing. Objects are deterministically mapped to coordinates in a multi-dimensional space in which axes correspond to the objects’ secondary attributes. Each server of the system is responsible for a region of the hyperspace and stores the objects that fall within this region. Using this mapping, each search operation is mapped to the hyperspace and the servers that need to be contacted are determined. Additionally, HyperDex addresses consistency issues that potentially arise from concurrent updates and object relocation due to updates in their secondary attributes by a replication protocol that orders updates by arranging an object’s replicas into a value-depended chain.

Innesto \[14\] is another searchable key-value data store, that supports search on secondary attributes without maintaining indexes. Innesto supports multi-attribute range search on any number of secondary attributes. The system distributes data by spatially partitioning the key space and maintains a hierarchy of partitions to support efficient range search. To provide secondary attribute search on a table, Innesto creates search clones. Each clone is a separate copy of the entire table partitioned differently based on a subset of secondary attributes. Innesto provides a strong data consistency model by using one-round transactions to consistently update data and search clones in parallel.

Replex \[15\] is a multi-key datastore that supports queries against multiple keys. Replex does not maintain secondary indexes but instead uses a replication scheme that makes use of a replication unit, which combines the notion of a replica and an index, called replex. A replex stores a data table and shards the rows across multiple partitions. All replexes store the same data, and each one sorts and partitions data by a different sorting key associated with that replex. The system uses chain replication to replicate a row to a number of replex partitions, each of which sorts the row by the replex’s corresponding index.

3.3 Commercial Distributed NoSQL Databases

Various commercial NoSQL systems support secondary indexes. In this section we describe the design choices that some well known NoSQL system make to implement, distribute and maintain their secondary indexes.

MongoDB \[16\] uses the B-tree data structure to implement secondary indexes, and updates indexes synchronously for each data update. Cassandra \[3\] colocates indexes at the same servers with the source data. Indexes are implemented as hidden tables in the underlying data store, and are maintained by a background process. New index entries are written at the same time as the primary data is updated and old entries are removed lazily at query time.

DynamoDB \[17\] enables users to create multiple secondary indexes on a table, and perform query and scan operations on these indexes. It supports both global and local secondary indexes, and reflects updates to indexes synchronously at write time. A global secondary index allows users to query an entire table across all partitions, while a local secondary indexes allows users to query over a single table partition.

RiakKV \[18\] is another distributed NoSQL database that supports secondary indexing \[19\]. Indexes are stored locally for each partition and updated synchronously at write time. At query time, the system determines the minimum number of partitions that it needs to examine to retrieve a full set of results, broadcasts the query to the selected partitions.

3.4 Range Queries on Distributed Hash Tables

Distributed storage systems often rely on Distributed Hash Tables (DHTs) as building blocks to implement partitioning of their data to multiple servers.
DHTs perform hash partitioning to efficiently map keys to servers. Although hash partitioning achieves load balancing and scalability, it also destroys data locality. It is thus challenging to efficiently extend these systems with global indexes that support range queries.

The problem of supporting range queries on distributed structured overlays has been thoroughly studied in the context of structured Peer-to-Peer (P2P) networks, implemented on top of DHTs. While DHTs are efficient for keyword search which requires point queries \[20, 21\], range queries are more challenging to implement.

**Over-DHT approaches.** A class of solutions aims at building indexing structures using the DHT as a building block. These approaches focus on implementing distributed prefix trees \[22\] and distributed binary trees \[23\]. Distributed prefix trees create data locality over DHTs by partitioning the data domain with the use of prefixes. This strategy provides a global knowledge of the tree structure. Binary trees, on the other hand, provide a flexible way to partition the value space. The space can be partitioned in equal parts to provide random access to tree nodes, or using other schemes in favour of load balancing.

The Prefix Hash Tree (PHT) \[22\] is a distributed data structure that enables one-dimensional range queries over any DHT. PHT creates data locality by using a prefix rule to recursively divide the space of binary keys, forming a binary trie. Tree nodes are mapped to DHT nodes by computing a hash over the PHT node label. The mapping between PHT nodes and DHT nodes is generated by computing a hash over the PHT node label. Looking up a key consists of finding a leaf node whose label is a prefix of that key. A range query consists of contacting all leaf nodes whose label fall within the given range.

Range Search Tree (RST) \[23\] presents an adaptive protocol to support range queries in DHT-based systems. The RST data structure is a complete and balanced binary tree where each node represents a different range. Each non-leaf node corresponds to the union of its two children, while leaf nodes correspond to the smallest sub-ranges. In RST, a set of DHT nodes share the load of each sub-range to improve load balancing. RST uses a dynamic mechanism to apply insertions only to a set of sub-ranges that is needed, based on the query ranges and the load information, instead of applying insertions to every level of the RST. Moreover, RST adaptively uses nodes only if their presence in the RST can lower the overall query cost and optimises itself based on load changes.

**DHT-dependent approaches.** Another class of solutions aims to adapt the DHT to support range queries instead of using it as a building block.

MAAN \[24\] extends Chord with locality preserving hashing to create data locality and support multi-attribute range queries. A range query for the interval starts at the node responsible for the lower bound and traverses successor links until the upper bound is reached. A drawback of this approach is that locality preserving hashing provides poor load balancing under skewed distributions.

Saturn \[25\] uses order preserving functions to support range queries, and focuses on addressing the challenge of load balancing by introducing a mechanism for replica placement under skewed distributions. The system detects overloaded nodes and randomly distributes their load using a multiple ring architecture, where overloaded nodes replicate their data on a new ring, using a multi-ring hash function. Saturn is implemented on top of an order-preserving DHT system such as MAAN.

### 3.5 Consistency between Index and Source Data

Diff-Index \[8\] presents an approach to add secondary indexes in HBase \[4\], a distributed LSM store. The authors show that the characteristics of LSM stores (no in-place update, asymmetric read/write latency) as well as the distributed nature of the system make the task of maintaining a fully consistent index with reasonable update performance particularly challenging. Diff-index offers different levels of consistency between indexes and source data, and makes trade-offs between index update latency and consistency. In particular, the system offers multiple levels of consistency varying from causal to eventual consistency. The consistency level can be chosen per in-
dex depending on the workload and consistency requirements. To implement eventual consistency, Diff-index maintains an in-memory queue which caches all writes that require index processing. Writes are immediately acknowledged to the clients, while the index is maintained by a background process. Additionally, the system implements session consistency by tracking additional state in the client library.

Hindex [9] addresses the problem of supporting secondary indexes on top of log-structured key-value stores with the goal of providing value-based access to data. Hindex uses performance-aware approach which decomposes the task of index maintenance to two sub-tasks, (1) index-insert; inserting new index entries and (2) index-repair; removing old index entries, and executes the inexpensive index-insert task synchronously while deferring the expensive index-repair. The authors propose two scheduling schemes for the index-repair operations; an offline repair that is coupled with the key-value store’s compaction mechanism, and an online repair where index-repair operations are piggybacked in the execution path of value-based read operation.

Earlybird [5] is the retrieval engine that lies at the core of Twitter’s real-time search service. Twitter users collectively post over 250 million tweets per day, and Earlybird achieves to make tweets searchable within 10 seconds after creation. In order to support the demands of real-time search, the system organises inverted indexes in two levels: an read-only optimised index and an active write-friendly, block-allocated index that supports both rapid tweet indexing and query evaluation. Moreover, authors present a single-writer, multiple-reader lock-free algorithm that enforces consistency using a simple memory barrier.

3.6 Multi-Resolution Indexing

Binning approaches have been proposed in the context of bitmap indexing, as a way to reduce storage overhead and improve performance of bitmap indexes on high-cardinality attributes. There are two conventional binning strategies for bitmap indexing, equi-width and equi-depth. Equi-width binning divides the entire dataset value domain into equal intervals, while equi-depth binning ensures that each bin contains approximately an equal number of indexed elements.

A dynamic bin expansion and contraction approach for highly skewed data has been presented in [26]. The proposed approach initially constructs bins using the equi-width method. When a bin grows beyond a threshold, it is expanded into multiple smaller-range bins. The authors show that the performance of dynamic expansion approach is comparable with the optimal partition approach, especially for highly skewed data.

The work in [27] presents a multi-resolution bitmap indexing framework designed for use with scientific data. The authors provide a formal framework for analysing the relationship between storage and performance of multi-resolution bitmap indexes, deciding the number of resolutions and size of bins at each resolution, and provide an algorithm for querying a multi-resolution bitmap index with an arbitrary number of levels.

3.7 MapReduce Indexing

In the context of information retrieval, McCreadie et al. [28] contribute a step towards understanding the benefits of indexing large Web corpora using the MapReduce processing paradigm. The authors describe and evaluate existing methods of performing document indexing in MapReduce, and propose a novel indexing strategy, optimised for large Web corpora. They conclude that early MapReduce indexing techniques, proposed in the original, MapReduce paper generate too much intermediate map data causing overall slowness, and therefore these strategies are impractical for indexing at large scale. On the other side the proposed indexing strategy scales well with both corpus size and horizontal hardware scaling.

While the MapReduce paradigm can be efficiently used for performing batch indexing jobs on large-scale datasets, it is less suitable for incrementally updating indexes in the presence of high rates of updates. However, these techniques can be useful for performing batch index creation on pre-existing datasets, or querying attributes with no existing indexes.
4 Proposed Approach

4.1 Overview

In this section we present our early stage work on the design of a system that extends geo-distributed object stores to support search on secondary attributes. We describe the mechanisms used for various aspects of our system, and discuss how these mechanisms enable our system to efficiently address the challenges discussed so far. Our next steps include defining the algorithms and policies that will make use of these mechanisms to efficiently implement the system’s functionality, implementing a prototype of the system, as well as performing experiments to validate the efficiency of our proposed solution.

Our system enables multi-dimensional queries that use both exact match and range predicates, as well as logical operators. It is able to ingest writes and queries concurrently in multiple data centres, and fully replicates secondary indexes among DCs. Additionally, it allows clients to specify a bound on search result staleness of each query, enabling clients to make a trade-off between query response time and result freshness.

Moreover, our design enables the system to adaptively adjust to the system’s workload. We describe how our system can be extended to dynamically adjust index resolution based on attribute value skewness and query distribution, and how it can adaptively allocate computation resources available for indexing and query processing in order to cope with high loads.

4.2 Index Organisation

We model our system as a network of interconnected logical computation units, called Query Processing Units (QPU). Each QPU is responsible for serving a particular set of queries. Queries posed to the system are processed by being routed through the network of QPUs. Moreover, write operations performed in the storage system are also propagated and indexed using the QPU network.

The network is organised using three types of connections between QPUs, which express different aspects of the described problem:

- Each QPU is responsible for serving queries for a range of values of some secondary attributes. A QPU can be connected with other QPUs that are responsible for sub-ranges of its range of attribute values (Section 4.2.1).

- Each QPU is responsible for responding to queries with results that contain the effects of write operations performed in specified time interval. A QPU can be connected with other QPUs responsible for sub-intervals of its time interval (Section 4.2.2).

- Each QPU is responsible for returning results for data stored in a specified set of data centres. A QPU can be connected with other QPUs responsible for a subset of DCs (Section 4.2.3).

Furthermore, each QPU maintains a multi-level cache of query results that can be used to respond to queries (Section 4.2.4).

4.2.1 Value Space Partitioning

Our system uses a static schema for supporting search on secondary attributes. This schema can be described as set of secondary attributes Attr_1, Attr_2, ..., Attr_N. The values of each attribute Attr_i are ordered and belong in the range [Min_i, Max_i]. Secondary attribute values form a N-dimensional space, where each axis corresponds to an attribute. Objects stored in the data store are logically represented as N-dimensional points in this space, specified by their secondary attribute values.

Each QPU is responsible for a range of values [L_i, U_i] of each attribute Attr_i and acts as a service that processes queries in this region. Both QPUs and queries can be represented as logical N-dimensional rectangles. QPUs serve queries that intersect with their region of the hyperspace.

Using value space partitioning, QPUs are organised hierarchically as a distributed R-tree [29, 30]. A QPU can be connected to other QPUs that cover smaller sub-spaces of its region of the hyperspace. Value space partitioning is not strict, as QPUs with
the same parent can overlap in parts of their regions. Using the hierarchical structure of the R-tree, QPUs can offload parts of their computations to other QPUs and then combine retrieved results.

Figure 1 shows an example of a two dimensional space formed by two indexed attributes, which is partitioned into hierarchy a hierarchy of regions.

### 4.2.2 Freshness Interval Partitioning

An additional, internal, dimension in the indexing schema is formed by write operation timestamps. Each QPU is responsible for returning results that contain effects of write operations performed in the time interval \([T_{start_i}, T_{end_i}]\). Representing result freshness as an additional axis the multi-dimensional space is a generalization of the distributed R-tree structure.

For a given region of the attribute value space, a QPU can be responsible for older, already indexed updates, and another QPU can be responsible for recent updates that have not yet been processed. QPUs responsible for older updates respond to queries by performing index lookups, while QPUs responsible for newer updates need to pull and process updates at query time, or scan the underlying data store. Depending on the freshness requirement of each query, the query is processed by a combination of QPUs with different freshness intervals.

### 4.2.3 Data Centre Partitioning

We further generalise the QPU network by making each QPU responsible for serving queries using data stored in a set of data centres. This mechanism enables the QPU network to index write operations and respond to queries in a geo-distributed multi-DC system. A QPU responsible for multiple DCs can be connected to other QPUs responsible for a single DC, and forward query computation to the corresponding QPUs based on the DC where a given query originates from.

This mechanism enables the geo-distribution of the QPU network, as different QPUs can be located in different DCs, and is complementary to inter-DC index replication. Index updates are propagated among DCs using the mechanism described in Section 4.4.2.

Using DC partitioning, queries can be processed in a geo-distributed system even without the use of inter-DC index replication mechanism or in the case of partial replication, where datasets are not fully replicated among DCs.

Figure 2 depicts an example of a QPU network containing all types of connections between QPUs.

### 4.2.4 Result Caching

QPUs can maintain multiple levels of caches storing query results, in order to enable low latency query processing. Caches can be considered as partial indexes, containing only a selected subset of index entries. Each cache maintains a subset of the index entries stored in lower level caches.

Internal QPUs of the network can respond to
4.3 Query Processing

Our system processes queries by routing them through the distributed QPU network. Using the network structure, a given query is decomposed into more fine-grained sub-queries and their computation is assigned to the corresponding QPUs. Partial results returned from these QPUs are then incrementally combined to calculate the final response the given query.

Query routing is a recursive process. Each QPU processes given sub-queries independently using a greedy algorithm. Given a query, a QPU first determines if it can retrieve the response from its cache hierarchy. If the query response cannot be retrieved by a cache, then the next level cache is visited.

Depending on the type of connections between QPUs, different strategies are used to determining how queries can be processed:

- **Value space partitioning.** For connections that perform value space partitioning, the QPU calculates the mapping of a given query to the N-dimensional space, determines which QPU sub-regions intersect with the mapping of the given query, decomposes it into sub-queries, and forwards these sub-queries to the corresponding QPUs.

- **Freshness Interval Partitioning.** For connections that perform freshness interval partitioning, the QPU determines which QPUs intersect with the staleness requirements of the given query, and forwards it accordingly.

- **Data Centre Partitioning.** For DC partitioning connections, the QPU first determines if index updates are replicated to the DC where the query originated from. If index updates are replicated, then the QPU only forwards the query to QPUs responsible for this DC. Otherwise, the query is forwarded to other QPUs according to which DCs results need to be fetched from.
Figure 3: The process of routing the query "objects where (GPA>2.0 AND GPA<3.0) AND Major=Computer Science" and Result Freshness<\(t_2\) posed in DC1 through the QPU network of the example in Figure 2.

This process is recursively repeated at each QPU, until the given query is answered by QPU caches or QPUs with no further connections are reached (leaf QPUs). Leaf QPUs process sub-queries in parallel, and return lists of objects that satisfy the given sub-queries to the higher levels. QPUs then recursively combine the retrieved partial results to calculate the final query response.

Figure 3 illustrates the process of decomposing and routing a query through the QPU network of Figure 2.

### 4.4 Index Maintenance

Within each data centre, leaf query processing units maintain their indexes structures asynchronously, in a per-operation basis. When a write operation is performed locally, it is processed, a new entry is appended to the storage system’s log, and then it is acknowledged to the client. The log of the data store exposes a publish-subscribe mechanism that allows QPUs to receive and process write operations. Each QPU independently receives all write operations performed in the local DC, filters operations involving secondary attributes for which it is responsible, and inserts new index entries or remove deprecated ones accordingly.

#### 4.4.1 Cache Maintenance

QPUs are maintained using a combination of pull and push strategies. Full indexes keep track of the index entries stored in the lowest level caches. Once an index entry is updated as a result of a write operation, the index pushes this entry to the corresponding caches in order to update their outdated index entries. Each cache then further pushes updated index entries to higher level caches when necessary.

Conversely, caches store results of expected queries by pulling them from lower level caches, and eventually from full indexes.

#### 4.4.2 Inter-DC Index Replication

As discussed in Section 4.2.3, the QPU network is geo-distributed among data centres. QPUs are replicated and different QPUs are responsible for the same regions of the multi-dimensional attribute space in different DCs. Queries can therefore be answered by combining QPUs from each DC. However, this approach incurs additional overhead as it requires communication between DCs. We use an additional mechanism that replicates QPU indexes among DCs and ensures that replicated indexes eventually converge, so that there is no need for inter-DC communication for query processing.

Each QPU is maintained locally, and updates are
asynchronously propagated among DCs. We use two different strategies to manage index replication among DCs, which are illustrated in Figure 4. One strategy is to replicate log entries of source data writes. QPUs receive all local write operations as well as writes propagated from other DCs, and use the information provided by log entries to maintain their indexing structures. The second strategy involves direct communication among QPUs. QPUs receive and process only local writes, and asynchronously propagate index update operations to other DCs. Alternatively, QPUs can be updated by pulling the state of corresponding QPUs from other DCs and merging it with their own.

Each of these strategies is suitable for indexes with different characteristics. When indexing attributes that are rarely updated, processing all write operations, local and remote, is inefficient and may result in waste of computation resources. In these cases, propagating index operations is more efficient. On the other hand, in cases where an indexed attribute is frequently updated, propagating a large volume of index operations may add unnecessary additional network traffic to the system.

Since each query processing unit is maintained independently, the indexing system can dynamically choose which strategy to use for each QPU. QPUs expose an interface that allows corresponding QPU located in other DCs to subscribe to their updates. Each QPU is initially updated by receiving write operations from the storage system’s log. At the same time, it maintains statistics on how frequently write operations result to updates to its region of the space. When the selectivity of write operation for an individual QPU is above a certain threshold, it can subscribe to updates from the corresponding units in the other DCs and switch to the second maintenance strategy. Conversely, when updates from other QPUs are frequent, the QPU can switch again to receiving updates from the write log.

4.5 Query Processing Unit Implementation

Since query processing units operate as services, their internal index implementation may vary as long as they expose the same interface. Different instances of the system may implement different index structures depending on the characteristics of the indexed attributes.

A straightforward implementation is to maintain a simple inverted index for each indexed attribute. Attribute values in each index are sorted, and each value points to a posting list of primary keys of objects that have this value. Given a query, the QPU performs lookups in the corresponding inverted indexes and then calculates the intersection of the retrieved lists of keys.

Since indexes are replicated among DCs, they must be able to converge to a consistent state even when operations are applied in index replicas in a different order. This is accomplished by implementing index structures as a composition of Conflict-Free Replicated Data Types (CRDTs). CRDTs are replicated data types that guarantee convergence of conflicting operations without the need for application conflict handling. The use of CRDTs enables index structures to merge updates originating at different replicas without the need for central synchronisation or explicit conflict resolution, despite messages being duplicated and reordered.

However, this mechanism is not sufficient for maintaining a replicating index. Conflicting concurrent updates to an object’s secondary attributes will re-

![Figure 4: Inter-DC index replication. Replicated QPUs are maintained either by receiving write operations that are propagated through the data store’s log (a) or by directly propagating index update operations among QPUs (b).](image-url)
sult in the introduction of false positives in the index. In the case of the example described in Section 2.2, after propagating updates and merging, the indexes in DC1 and DC2 will contain both entries \texttt{Attr:A} and \texttt{Attr:B}. However, the storage system will choose value A or B based on a strategy such as last-writer wins.

We address this issue by adding a mechanism that checks query results against the source data and removes false positives. Moreover, we use a background task that periodically scans indexes and removes false positives by checking the source data.

4.6 Bounding Search Result Staleness

Query processing units receive updates asynchronously and independently from each other. As a result, QPUs may be updated at different rates and diverge from the state of the storage system and from each other. Search results may therefore be unboundedly stale relatively to the state of the data store.

To address this issue, we design a mechanism that enables clients to bound the staleness of their search results. Using this mechanism, applications can limit the amount of staleness of each query, according to their needs. Since acquiring less stale search results requires additional computations, applications can make a trade-off between query response time (and resource utilisation in general) and query result freshness.

We model the storage system’s log as a list of write operations. Each operation that is appended to the log is assigned with a unique monotonically increasing \texttt{LogID}. QPUs that are responsible for recent updates use vector clocks to maintain information on their divergence from the state of the storage system and from each other. A vector clock \texttt{VC} consists of an entry \texttt{VC}_k for each QPU, indicating that \texttt{QPU}_k has applied all write operations up to \texttt{VC}_k. QPUs periodically exchange vector clocks, by propagating them to QPUs that maintain connections to them, following the inverse path of QPU network connections. When a QPU processes a new write operation, it increments the corresponding vector clock entry.

Using its vector clock, a QPU can determine a \texttt{LogID} so that every QPU in its sub network hierarchy has applied all updates up to that \texttt{LogID}. We call this \texttt{LogID} a stable index snapshot for this set of QPUs. Additionally, cached index entries are stored along with their vector clocks so that QPUs can determine their staleness.

When issuing a query, clients provide an additional argument indicating the desired level of search result staleness. This argument has the form of discrete staleness levels, ranging from strongly consistent to unboundedly stale results.

Given a query and the staleness level attribute, QPUs use vector clock information to compute the stable index snapshot for the entire QPU network; The lowest \texttt{LogID} up to which every QPU has applied all updates. Additionally, the system obtains the \texttt{LogID} of the most recently appended write operation from the log. The difference between these two values represents the maximum amount of staleness for any QPU in the network. Based on this information and the given staleness argument, the system determines a target \texttt{LogID}_t. Any QPU or cache that contributes to the processing of the given query must contain the effects of all write operation at least up to \texttt{LogID}_t. Based on the given \texttt{LogID}_t, QPUs ignore older cached entries and pull write operations from the log, or from QPUs located in other DCs in order to process the required write operations up to the specified limit. As a result, query result staleness is bounded by \texttt{LogID}_t.

4.7 Future Directions

4.7.1 Adaptive Index Construction

Our system design enables the implementation of an additional mechanism that will dynamically construct the distributed QPU network in order to optimise its structure according to query load and attribute value distributions. Initially, a single query processing unit will be responsible for the entire attribute value space. As new objects are stored in the system, when the number of indexed objects in a QPU reaches a threshold, the unit will expand the network by spawning a number of new QPUs and
assigning each one of them with a sub-part of its region of the space. On the other hand, when, due to deletions, the number of objects which a QPU indexes reaches below a threshold, it can be merged with a neighbouring unit, therefore contracting the QPU network. This allows QPUs to manage index sizes and prevent fragmentation.

This mechanism can also allow the QPU network to adaptively adjust to query load. Additional QPUs can be spawned when the query load in a particular region of the space is high, in order to spread the load more evenly between QPUs. Conversely, under-utilised QPUs can be merged to reduce maintenance costs.

Moreover, this mechanism can address the need for multi-resolution indexing. When a part of the value space is queried with higher resolution, a high load is introduced to the QPUs which are responsible for these region of the space. As a result, the QPU network will dynamically expand by spawning more QPUs responsible for these regions. Spawned QPUs will be responsible for a smaller part of the hyperspace, resulting to higher resolution indexing in these regions of the space.

4.7.2 Dynamic Resource Allocation

Query processing units operate as services and are not bound to physical servers in the system. This enables the use of various mechanisms to dynamically adapt the amount of computation resources available to the system.

Multiple QPUs with low indexing and query processing load can be collocated in the same physical servers. At the same time, highly loaded units can migrate to new servers in order to have more computation resources available to them and balance load between servers. Additionally, the system can spawn multiple instances of a QPU, and place each one of them placed in a different server.

Furthermore, the strategy of attribute value space partitioning enables two additional mechanisms for adjusting computation resources available to the system:

- QPUs can cover overlapping regions of the space. This allows the system to perform load balancing by having a choice of multiple QPUs for parts of a given query.
- QPUs can dynamically adjust their boundaries and exchange the regions of space they are responsible for. Dynamic boundary movement allows the system to re-assign a part of the space that is assigned to a highly loaded QPU with limited resources, to another QPU with more available resources.

4.7.3 Network structure caching

The hierarchical structure of the distributed QPU network ensures that only local structure knowledge is required in order to route queries through the network, and no QPU needs to have a view of the entire network structure. Each QPU needs to maintain the boundaries and mapping to physical servers, for the QPUs it is connected to. In order to process a given query, QPUs recursively determine which of the QPUs they are connected to should contribute to the query processing and forward the corresponding sub-queries to them. However, as the network expands and adds more levels, this process can lead to increased network traffic due to messages between QPUs.

To address this problem, each QPU can maintains a cache of the structure of the part of the network that is reachable through it. The QPU’s structure cache stores the boundaries of QPUs as well as their mapping to servers, for a number connection levels. QPUs periodically send their cache to higher to the network hierarchy, so that network structure changes are propagated through the network. Modifications to the network structure, such as additions of new QPUs and boundary adjustment are performed locally and then propagated upwards. Using this mechanism, QPUs can decompose and route queries without the need to go through the entire structure of the network, reducing thus the number of messages needed to sent thought the network to process each query.

However, since caches are updated asynchronously, there may be cache misses when sub-queries are forwarded to units that no longer exist or are not placed
in the destination servers. When a cache miss occurs, QPUs iteratively backtrack and use higher levels of the network hierarchy until the query can be successfully processed.

5 Discussion and Next Steps

We have introduced and analysed the research problem of extending geo-distributed, weakly consistent data stores to provide real-time search on secondary attributes. We have presented our study of the state-of-the-art on various fields related to providing secondary attribute search in distributed systems.

Our literature review shows that secondary indexing systems are commonly designed based on specific system architecture and workload characteristics. This shows that no optimal design exists for an indexing and query processing system, and implementing such systems is based on making trade-offs according to the target use case characteristics. Based on this observation, we have analysed the design space and discussed how various design choices affect the efficiency of the system and address the problem’s requirements.

Moreover, most related works focus more on the low level design of indexing data structures and their maintenance, and less on the distributed nature of the system. To our knowledge, there is no work considering an indexing system that is replicated among multiple data centres. Moreover, most approaches choose to maintain indexes that are strongly consistent with the source data by updating index structures synchronously, in the critical path of write operations. We have introduced and described our approach which focuses on the geo-distributed nature of the system, and explores the space between strong and eventual index consistency.

As a first step, we have proposed the mechanisms that can be used for implementing a system that efficiently addresses our problem statement. At next steps of our work, we intend to define the algorithms and policies that will make use of the described mechanisms to implement the system’s functionality, and implement a prototype of the system.

We plan to use greedy algorithms and heuristics for processing queries using the distributed network of query processing units instead of using query optimization techniques. We believe that applying query optimization techniques in order to find the optimal processing strategy for each query is out of the scope of our approach, and we should instead use best effort techniques which minimize response time. As future work, we intend to apply learning algorithms to tune the parameters of our greedy algorithms and optimise them at runtime.

Furthermore, our model of QPUs that work as services and are not bound to specific system servers enables us to expand the QPU network towards the edge of the network, and place QPUs to client machines. Performing computations at the edge enables the system to reduce the computation load at the code of the system, enable more sophisticated indexing techniques, and improve availability in case of network partitioning.

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