Memcache as a Service

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Goals

Rapid application development ("velocity")

- Speed of adding new features is paramount

Scale

- Billions of users
- Every user on FB all the time

Performance

Low latency for every user everywhere

Fault tolerance

Scale implies failures

Consistency model:

"Best effort eventual consistency"

Facebook's Scaling Problem

- Rapidly increasing user base
 - Small initial user base
 - 2x every 9 months
 - 2013: 1B users globally
- Users read/update many times per day

 Increasingly intensive app logic per user
 2x I/O every 4-6 months
- Infrastructure has to keep pace

Scaling Strategy

Adapt off the shelf components where possible

Fix as you go

- no overarching plan
- Rule of thumb: Every order of magnitude requires a rethink

Three-Tier Web Architecture

Front End Server Front End Server Front End Server Client Front End Server Cache Server Cache Server Cache Server

Storage Server Storage Server Storage Server Storage Server Storage Server

Three-Tier Web Architecture



Storage Server Storage Server Storage Server Storage Server Storage Server

Three-Tier Web Architecture



Facebook Three Layer Architecture

- Application front end
 - Stateless, rapidly changing program logic
 - If app server fails, redirect client to new app server
- Memcache
 - Lookaside key-value cache
 - Keys defined by app logic (can be computed results)
- Fault tolerant storage backend
 - Stateful
 - Careful engineering to provide safety and performance
 - Both SQL and NoSQL

Facebook Workload

Each user's page is unique

draws on events posted by other users

Users not in cliques

– For the most part

User popularity is zipf

- Some user posts affect very large #'s of other pages
- Most affect a much smaller number

Workload

- Many small lookups
- Many dependencies
- App logic: many diffuse, chained reads
 latency of each read is crucial
- Much smaller update rate

still large in absolute terms

Scaling

- A few servers
- Many servers
- An entire data center
- Many data centers

Each step 10-100x previous one

Facebook

- Scale by hashing to partitioned servers
- Scale by caching
- Scale by replicating popular keys
- Scale by replicating clusters
- Scale by replicating data centers

Scale By Consistent Hashing

Hash users to front end web servers Hash keys to memcache servers Hash files to SQL servers

Result of consistent hashing is all to all communication pattern

 Each web server pulls data from all memcache servers and all storage servers

Scale By Caching: Memcache

Sharded in-memory key-value cache

- Key, values assigned by application code
- Values can be data, result of computation
- Independent of backend storage architecture (SQL, noSQL) or format
- Design for high volume, low latency

Lookaside architecture

Lookaside Read

Web Server







Cache



Lookaside Read

Web Server





Lookaside Operation (Read)

- Webserver needs key value
- Webserver requests from memcache
- Memcache: If in cache, return it
- If not in cache:
 - Return error
 - Webserver gets data from storage server
 - Possibly an SQL query or complex computation
 - Webserver stores result back into memcache

Question

What if swarm of users read same key at the same time?

Lookaside Write Web Server 1. update | ok!

Cache



Lookaside Write

Web Server





Lookaside Operation (Write)

- Webserver changes a value that would invalidate a memcache entry
 - Could be an update to a key
 - Could be an update to a table
 - Could be an update to a value used to derive some key value
- Client puts new data on storage server
- Client invalidates entry in memcache

Why Not Delete then Update? Web Server 1. delete k Cache ok!







Memcache Consistency

Is memcache linearizable?

Example

Reader

Writer

Read cache

If missing,

Fetch from database

Store back to cache

Change database Delete cache entry

Interleave any # of readers/writers

Example

- Read cache
- Read database

- change database
- Delete entry

• Store back to cache

Memcache Consistency

Is the lookaside protocol eventually consistent?

Lookaside With Leases

Goals:

- Reduce (not eliminate) per-key inconsistencies
- Reduce cache miss swarms

On a read miss:

- leave a marker in the cache (fetch in progress)
- return timestamp
- check timestamp when filling the cache
- if changed in meantime: don't overwrite
- If another thread read misses:
 - find marker and wait for update (retry later)

Question

What if front end crashes while holding read lease? Would any other front end be able to read the data?

Question

Is FB's version of lookaside with leases linearizable?

Example: Cache data with 1 replica

Reader1 (data cached) Writer

Change database

Read replica1 (old value)

> CRASH! (before Delete cache)

Read replica1 (old value)

Question

Is FB's version of lookaside with leases linearizable?

Note FB allows popular data to be found in multiple cache servers

FB Replicates Popular Data Across Caches



Storage Server Storage Server Storage Server Storage Server Storage Server

Example: Cache data with 2 replicas

Reader1 Reader2 (data cached) (not cached)

Change database

Writer

Read replica1

(old value) Read replica2

Miss CRASH!

Fetch from db (before Delete cache) Read replica1 Write back to replica 2

(old value) (new value)

Latency Optimizations

Concurrent lookups

- Issue many lookups concurrently
- Prioritize those that have chained dependencies
- Batching
 - Batch multiple requests (e.g., for different end users) to the same memcache server

Incast control:

Limit concurrency to avoid collisions among RPC responses

More Optimizations

Return stale data to web server if lease is held

No guarantee that concurrent requests returning stale data will be consistent with each other

Partitioned memory pools

- Infrequently accessed, expensive to recompute
- Frequently accessed, cheap to recompute
- If mixed, frequent accesses will evict all others

Replicate keys if access rate is too high

Gutter Cache

When a memcache server fails, flood of requests to fetch data from storage layer

- Slower for users needing any key on failed server
- Slower for users due to storage server contention

Solution: backup (gutter) cache

- Time-to-live invalidation (ok if clients disagree as to whether memcache server is still alive)
- TTL is eventually consistent

Scaling Within a Cluster

What happens as we increase the number of memcache servers to handle more load?

- Recall: All to all communication pattern
- Less data between any pair of nodes: less batching
- Need even more replication of popular keys
- More failures: need bigger gutter cache

Multi-Cluster Scaling

Multiple independent clusters within data center

- Each with front-ends, memcache servers
- Data replicated in the caches in each partition
- Shared storage backend
- Data is replicated in each cluster (inefficient?)
 - need to invalidate every cluster on every update

Instead:

- invalidate local cluster on update (read my writes)
- background invalidate driven off of database update log
- temporary inconsistency!

Multi-Cluster Scaling

Web Server

get Cache







SC.



Multi-Cluster Scaling



mcsqueal

Web servers talk to local memcache. On update:

- Acquire local lease
- Tell storage layer which keys to invalidate
- Invalidate local memcache

Storage layer sends invalidations to other clusters

- Scan database log for updates/invalidations
- Batch invalidations to each cluster (mcrouter)
- Forward/batch invalidations to remote memcache servers

Per-Cluster vs. Multi-Cluster

Per-cluster memcache servers

- Frequently accessed data
- Inexpensive to compute data
- Lower latency, less efficient use of memory

Shared multi-cluster memcache servers

- infrequently accessed
- hard to compute data
- higher latency, more memory efficient

Cold Start Consistency

During new cluster startup:

- Many cache misses!
- Lots of extra load on SQL servers

Instead of going to SQL server on cache miss:

- Webserver gets data from warm memcache cluster
- Puts data into local cluster
- Subsequent requests hit in local cluster

Multi-Region Scaling

Storage layer consistency

- Storage at one data center designated as primary
- All updates applied at primary
- Updates propagated in background to other data centers

What could go wrong?



Multi-Region Consistency

To perform an update to key:

- put marker into local region
- Send write to primary region
- Delete local copy

On a cache miss:

- Check if local marker
- If so, fetch data from primary region
- Fill local copy

FB: Data Centers without Data

Tradeoff in increasing number of data centers

- Lower latency when data near clients
- More consistency overhead
- More opportunity for inconsistency

Mini-data centers

- Front end web servers
- Memcache servers
- No backend storage: remote access for cache misses

Linearizability?

Is linearizability possible with a memcache layer?

- Needs help from storage layer
- Every cached copy removed before write

What about snapshot reads?

- Needs help from storage layer
- Every copy has version timestamp range
- Multikey query valid if ranges overlap