Basics

30 March 2024 02:07 PM

SHARDING → dividing data into smaller fragments + storing them on different distributed machine

TYPES

- Range Based / Dynamic
  - → Each shard holds a range of values
  - → Ex:- date ranges, time ranges
  - → when ordering + ranges are there in data
- Hash-Based / Algorithmic / key based
  - → use a hash fun^n on data to get which shard
  - → used when there is no natural order (ids)
- Directory Based
  - → you manually maintain a data → shard mapping
- Geo-Based
  - → shard based on geo locations or names to locations

Partitioning → same logic but logically within same system

PROS

- → Faster and efficient queries (given you pick good sharding strategy)
- → eliminate single pt of failure

CONS

- → outage possible as it is distributed
  - soln: master-slave design
    - handles writes
    - handles reads
- → Fixed number of shards · Need rebalancing / resharding
  - soln: Consistent hashing
- → Skewed shards — Better sharding fn approach
- → joins across shards are costly

IMPROVEMENTS

→ SHARD + INDEXING

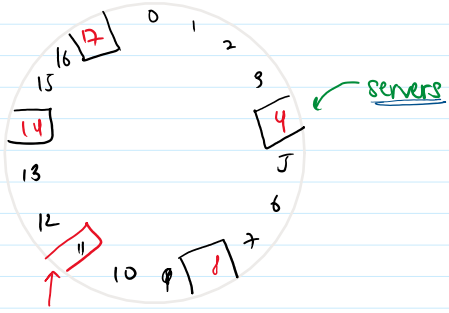
Ex:- shard on CITY + index on AGE

→ here first shard on city + Internally each shard is indexed based on age

Query:- give me all persons in DELHI with age between 20-40

CONSISTENT HASHING

* Normal hashing :- lets say you have (N) servers
  - (h(data) % N)
    - h(data) → hash fn
    - N → no of servers
    - % → you cant change this
  - if done needs rehashing everything
* Consistent Hashing
  - → Consider your slots are in circular form
  - → x → hash fn(n) → (0 - 360°) example
  - → Each result of hash fn will lie on this circle
  - → some of these slots will be servers also



HOW IT WORKS

- → data → hf^n ( ) → slot_no = (3)
- → move clockwise and see next server to (3)
- → (3) gets stored in (4) ie (4)

New server gets added

- → (11) is now made a server
- → New indexing doesn't change (9,10 will go to (11) instead of (14))
  - Rebalancing is minimal
    - → only (9) (10) which was prev sharded to (14) need to be rendered to (11) Now

* LOAD Factor = 1/N (ideal case) equal load to each server
  - → But this isn't possible when you have sparse

soln: **Virtual servers**

- → Add more server slots which brings load factor to 1/N
- → Internally a single sever handles (2+ slots)

Ex:- (11) might be [illegible]

→ Add more server slots which brings load factor to 1/N
→ Internally a single server handles (2+ slots)
Ex:- (8, 11) might be handled by a single physical server

ACID

→ Maintained in Relational DBs → Good at vert scale (Bad at vertical)
→ Fixed schema
→ Generally not distributed

Atomicity

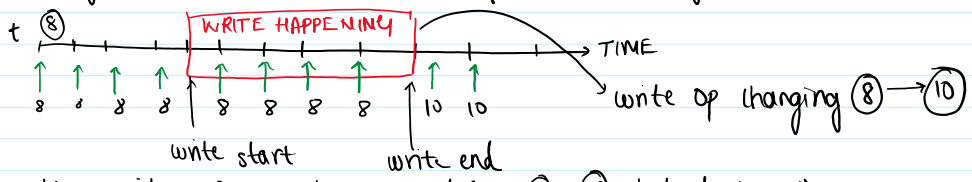
→ A txn can either happen completely or not happen at all
Ex:- Bank amt transfer
① Deduct frm ur acc → ② Add to the desn acnt
Now this shud happen completely. Ex lets say it got deducted from accnt but then failed
→ In such case revert back everything
everything or nothing approach

Consistency

→ multiple reads at same time should give same results
Why easy? since its not distributed no issue of out-of-sync replicas

Isolation

→ Every transactn happens independently without caring abt other parallel transactions



→ Here write opn was changing val frm (8) → (10) but during the process any read doesn't know or care abt this and still reads as (8)
→ Only after write operation is completed and state is updated, Read returns (10)

Durability

Every txn is logged and data is being persisted

BASE

→ shown in NOSQL Databases → No fixed schema
→ vertically scalable
→ Distributed (data stored across machines)

Basically Available

→ Since data is distributed across servers it can handle outages
→ If one server crashes another replica/machine can give u the data

Soft States

→ States/values can auto change without txn or user queries
How? SYNC across replicas
→ since data is stored across machines/replicas it may happen that data copies keep getting updated
dirty data NOT IN SYNC → Latest in-sync data

Eventually Consistent

→ Not immediately consistent → ACID ones are immediate consistent

→ 2 simultaneous reads may give different results sometimes
why? sync might have been happening b/w 2 reads

∴ TXNs are not always consistent due to distributed nature
BUT will become consistent after some time (once sync/updates are completed)

Rate Limiters

06 June 2024 22:10

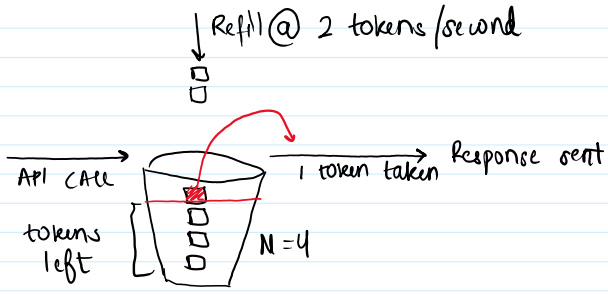
RATE LIMITERS → server side
RATE LIMITERS → client side

TYPES →
- Leaky bucket
- Token Bucket
- Fixed window
- Sliding window
- Counting sliding window

TOKEN BUCKET

→ You have (N) tokens in a Bucket (consider this as a currency)

→ whenever a request comes
① Check if bucket has token
- (NO) → send (429) response code
- (Yes) → Take one token from the bucket



⚠ Refiller :→ Refill the tokens in the bucket at certain rate

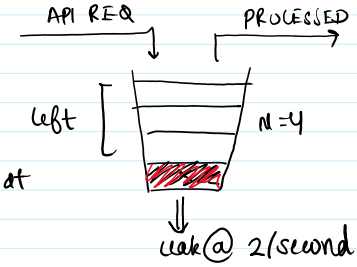
refill_rate ≡ TPS/speed of your api

* Configurations → ① N = Bucket size
② Refill rate

LEAKY BUCKET

→ You have a bucket of size (N)
→ A request comes in, if bucket
- (Full) → 429 code
- (else) → Add 1 token to the bucket

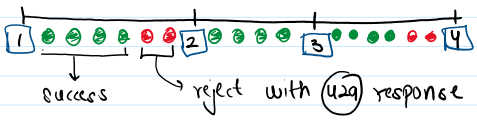
→ Leak rate → You keep on removing tokens at this given rate
↓
Similar to refill rate in token bucket



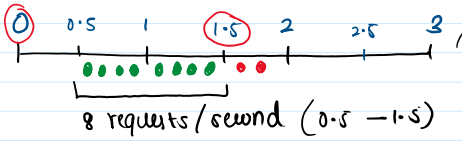
* IDEAL CASE → Rate of API Hits ≤ LEAK RATE

FIXED WINDOW

→ You maintain certain windows (INTERVALS) and each window can only contain (N) items
→ Ex:- Window of 1 min each → N = 4



CON → Doesn't always guarantee rate limit
Ex:- N = 4/sec



→ valid since our windows are 0 – 1 – 2 – 3
But truly not limiting at Boundaries

SLIDING LOG WINDOW

→ Instead of fixed window you use timestamps to dynamically calculate it
→ Rate = 4 req/sec

Ex
→ Request comes at 1.5, you count no of req blw 0.5 ⟷ 1.5
if num < 4
→ Insert this log (timestampt reqid)

* Ensures proper dynamic rate limiting

CONS
→ you store each request as one entry
∴ Space needed = N
→ lets say your Rate is 1000 rps ⟹ you will store 1000 log entries

SOLUTION

SLIDING COUNTER WINDOW

→ Instead of pushing each request as log item maintain a counter
→ Rate = 1000 rps

ts	counter
0.1	1
0.2	100
0.3	200
⋮	⋮
0.9	400

Here instead of 1000 logs you will only have 10 logs

→ space = 1000 → 10
→ No of ts steps

Microservice Architecture

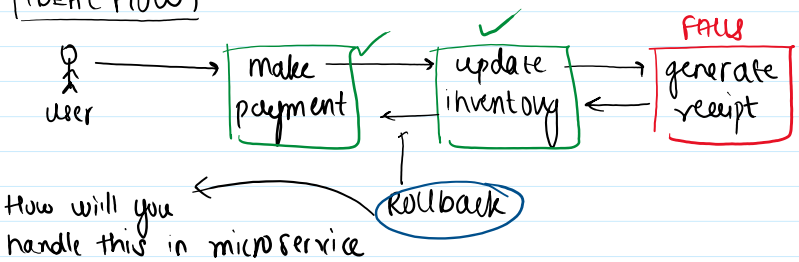
06 June 2024 22:54

DISTRIBUTED TRANSACTIONS

PREMISE → You have 3 services

- PAYMENT → make payment
- INVENTORY → decrease purchased items
- RECEIPTS → generate receipt

IDEAL FLOW



How will you handle this in microservice

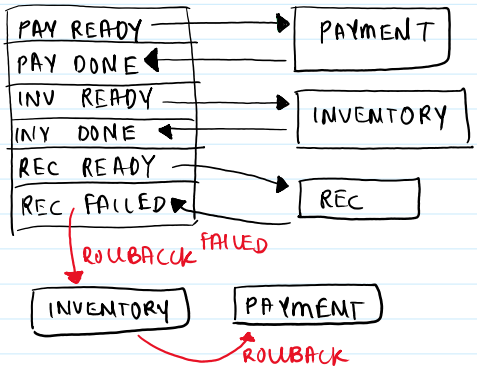
→ ① 2PC [2/3 phase commits] BLOCKING
② 3PC
③ SAGA (ASYNC)

SAGA → Sequence of Local transactions

* Asynchronous and non-blocking but complex to implement

→ Queues are used for Inter Process Communication

STEPS



Implementation

→ 3 microservices

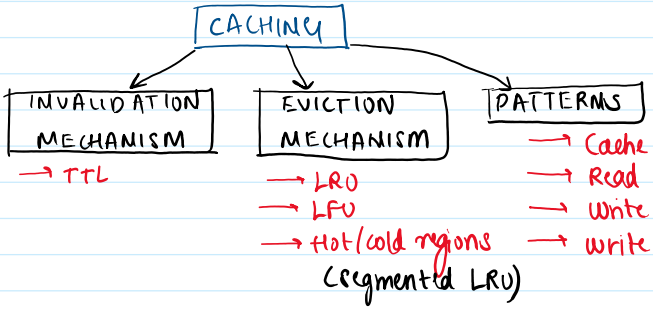
→ (3*2) Queues { 1 success, 1 failure } one b/w each 2 service

→ 2 Queues

① Handles all success (all 4 service listen to this
② Handles all failures OR listen to a specified partition)

Caching

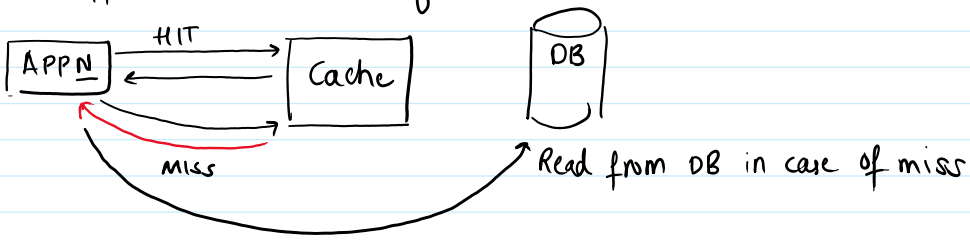
07 June 2024 23:04



PATTERNS

CACHE ASIDE

→ Cache cant communicate directly with DB
Application does that for it



→ Initially data is loaded into the cache by app^n
On every cache miss, the app^n directly fetches data from DB
→ On new data, it will always be MISS
↳ until you update cache

PROS

* Good for HEAVY-READ app^ns like dashboards
* If cache fails → you can directly hit the DB each time down
* Since data stored in cache and DB is different, you can have diferent schemas

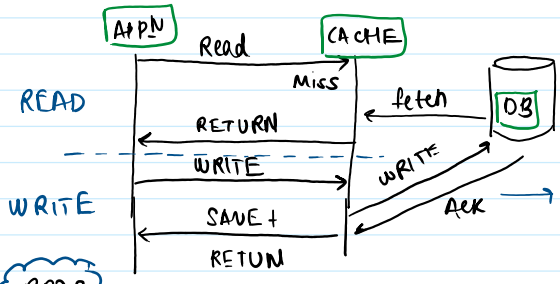
CONS

* New data will be Miss
* Inconsistency in data if it gets updated in DB

READ THROUGH

→ Cache can communicate directly with DB App^n only accesses Cache
→ READ MISS : Cache itself updates value from DB and then returns
↳ New val, update

→ Writing new data :- you will write to cache + cache will write to DB
→ if this was update invalidate cache which will be updated on next miss



* DB schema ≡ Cache schema

WRITE are SYNCHRONOUS

PROS

→ Great for heavy reads why? (On write cache writes to DB, waits for Ack saves it in cache and then sends it back)
→ You dont wanna hit miss

PROS
→ Great for heavy reads · why? (On write cache writes to DB, waits for Ack saves it in cache and then sends it back)
→ You dont worry abt Miss and fetch from DB

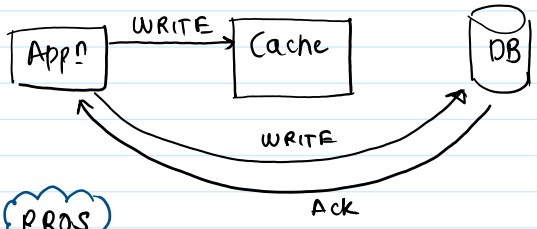
CONS → Cache cant fail
→ Cache miss for new data (PRE-HEATING can solve)
→ Cache schema ≠ DB schema
→ Data inconsistency

WRITE THROUGH → used with READ THROUGH (100% CONSISTENT)
→ Here for writes you directly write to DB and invalidate cache (if updated)
→ Next hit will be cache miss and cache will fetch from DB
(saves latency of app ⟷ cache ⟷ DB for write operations)

WRITE AROUND → You ONLY WRITE TO DB and forget
* when you do a get nxt time: CACHE miss and cache will fetch from DB

WRITE BACK → SYNCHRONOUS — same as write through (BUT cache updates DB → Not app itself)
→ ASYNCHRONOUS — NOT 100% consistent

SYNCHRONOUS
→ App itself writes to both DB and cache whenever a write hapens

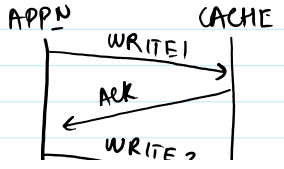


① write to DB
② wait for Ack → use 2PC
③ write to DB

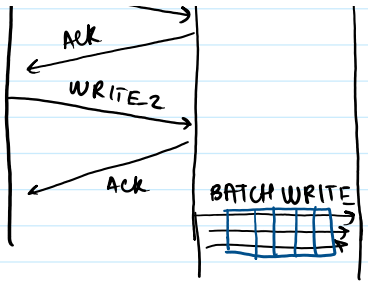
PROS
→ Very high hits and low misses
→ Very rare chance of inconsistency
} you always write to (DB + Cache) each time No lag

CONS
→ High latency due to 2 writes and Ack wait
→ Need 2PC to make sure DB update is ACID

ASYNCHRONOUS
→ App only writes to cache and then forgets
→ Cache then asynchronously writes data into the Database independently
↳ done via QUEUES
→ you can publish 1 event for each write
OR Batch (n) writes and at once write to DB



PROS
→ WRITE HEAVY applications
→ Lesser write latency and lower inconsistency
→ Better performance



→ lesser write latency and lower inconsistency
→ better performance

CONS
→ sync issues if you immediately read again before DB write is done

Best with READ THROUGH CACHE
why? → when write happens u just write to cache and forget
→ Now you can directly read that data from cache (even though its still not in DB)

GLOBALLY DISTRIBUTED CACHE

① There can be (N) different cache servers distributed across clusters
↳ A cache gateway redirects requests to appropriate servers
ⓐ Default uses consistent hashing for allocation
ⓑ Geographically based - route/store in nearest store
ⓒ Identifier based – Ex: Based on country_id group and store in same server
or multiple countries INTO 1 continent server

REDUNDANCY

* use QUORUM u need consensus for both READ + WRITES by setting values of (R), (W)
→ you need values read from atleast (R) copies
→ you need to write data to atleast (W) copies/machines

(R) → Read consensus frm (R) nodes
(W) → write consensus frm (W) nodes
(N) → Replication factor

R + W ≤ N
EVENTUALY CONSISTENT

R + W > N
STRONGLY CONSISTENT

W+Y?
→ R + W ≤ N : assume N = 3
* R = 1, W = 2
WRITE : u write to 2 copies and leave third
READ : needs only 1 copy
↳ if it reads from 3rd then inconsistent
* R = 2 : W = 1
→ WRITE : to any 1 assume (C1)
→ READ : (C1)(C2) valid
(C2)(C3) INCONSISTENT
(C3)(C1) valid

R + W > N
Ensures that there is atleast 1 overlap blw write and read consensus

Isolation Levels

08 June 2024 14:54

DATA CONSISTENCY
- Linearizable
- Eventual
- Casual
- Quorum

LINEARIZABLE

→ single thread sequential execution of Queries
→ No chance of any mismatches
→ PERFECT consistency

EVENTUAL

→ DB might not be always consistent BUT eventually consistent
→ multiple Queries/read/writes can happen of multiple threads/servers
  ↳ parallel process so is faster
* But sync takes some time after transactions

CASUAL

→ Allows parallel transactions BUT operations are linear/serialize in single transaction
→ Consistent within transaction
→ Better than casual but not as good as linear

CONS: Aggregates/joins are inconsistent

QUORUM

↳ Configurable consistency vs performance

R + W > N	Highly consistent
R + W ≤ N	Eventually consistent

TRANSACTION ISOLATION LEVELS

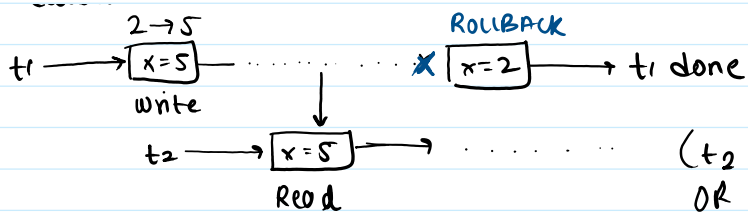
A transaction has three operations

BEGIN TXN → COMMIT TXN → ROLLBACK

- BEGIN TXN: Start ops
- COMMIT TXN: txn done and update res to DB
- ROLLBACK: Rollback commit in case of errors/failure

READ UNCOMMITED

→ Each txn directly writes to DB ≡ No concept of COMMITS (No data replication)
→ Causes DIRTY READS



(t_2 never gets rolled back value of x)
OR some other op? might also have updated it

READ COMMITTED

→ Txn can only read values which are committed by other txns
→ slower since you have commit step (↳ it wont roll back later)
and dont directly update DB

* in both read commited/uncomited you cant ensure REPEATABLE READS
→ if you have 2 reads of same var in the txn
you can get 2 different values (someone else must have updated it)

REPEATABLE READS = SNAPSHOT ISOLATION

→ when any row is read by a transaction
its LOCKED until that transaction ends
→ other txns which update this locked value can locally commit and keep it as new version and update in DB once lock is released

SERIALIZABLE

→ All operations in txn are executed sequentially in order
→ if 2 txns dont have any common ops then they can run in parallel
(common ops → Both writes and reads)
→ use serialized Locks

least isolation most efficient

Least efficiency most isolation

READ UNCOMMITTED	READ COMMITTED	REPEATABLE READS	SERIALIZABLE

← EFFICIENCY →

ISOLATION →

CRDT

19 December 2024 19:34

CONFLICT-FREE REPLICATED DATA TYPE

WHY CRDTS

→ You are in a multi-writer DB duplication setup
→ Now at same time the same key may get updated → WHICH VALUE WILL YOU PICK?

1. Last write wins (very bad)
2. Store all writes and decide which to pick later
3. Let DB take that call = CRDT

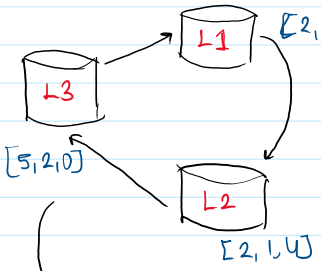
INFO ABOUT CRDTS

→ The conflict merges will happen eventually (NOT immediately)
→ which DB uses CRDTS? → Riak
→ Redis (sets in Redis enterprise)

OPERATIONAL CRDTS

→ You design a distributed counter on a multi-leader/writer setup → INCR(idx) = increments value of `idx` by 1
→ but this can be simultaneously done on separate leaders at a time

VERSION VECTORS



[2,1,0] → version vector → we store one such vector for each index

[2,1,0] → received 2 increments from leader 1, 1 incr from leader 2

value(idx) = sum(version vector of idx)

→ Here instead of passing list of size(N_leaders) we just call incr(si) on the other leaders
→ Ex: – Instead of [5,0,3] being saved you would have just incr(5i)

L3 [5,2,0] → incr(L1,+1) × 5, incr(L2,+1) × 2 → This take O(1) instead of O(n-leaders).

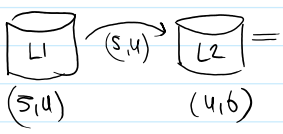
OPERATIONAL CRDT

→ SOME CONS
1. You need to ensure no drops and no duplicates (when incr for example)
2. Need to be casually consistent (same order followed)

(ex: if u make a set using opn CRDT → remove(idx) can be done only a add(idx) has happened)

STATE BASED CRDTS

→ Instead of sending just the increments, SEND ENTIRE CRDT



L2 → merge([5,4],[4,6]) = [5,6] → take max of each server

The merge needs to be → 1. COMMUTATIVE → M(a,b) = M(b,a)

The merge needs to be → (1) COMMUTATIVE → M(a,b) = M(b,a)
(2) ASSOCIATIVE → M(a, M(b,c)) = M(M(a,b), c)
(3) IDEMPOTENT → M(a,b) = M(M(a,b), b)
↳ this handles in case of duplicate msgs received

HOW DO U COMMUNICATE AMONG WRITE-LEADERS
↳ using state CRDT
(1) Dont need order (ASOC+COMM) ⟹ GOSSIP PROTOCOL
(2) duplicates r fine (IDEMP)
→ No extra/special infra needed

TYPES OF CRDTS

NAME	operational CRDT	State-based CRDT	final counts
Counter	incr(leader)	incrs: [0,2,1]	↓
Decreasable Counter	incr(leader), decr(L)	incs: [0,2,1] decs: [0,1,0]	= [0,1,1]
Sets	add(x), remove(x)		

↳ Hard to implement

Which Databases?

22 December 2024 00:11

DB INDEXES

B+ Trees

→ Stored on disk
- → slower writes
- → faster reads
- → NO size issues

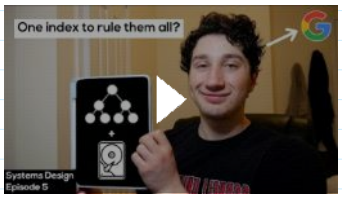
LSM TREE + SS Tables

→ LSM : memory

SS-Tables : disk (only when needed)
- → slower reads (read across SS tables)
- → faster writes (write to memory)
- → delete = writing a tombstone

B+ Trees: How do B-Tree Indexes work? | Systems Design Interview: 0 to 1 with Google Software Engineer

LSM Trees + SS Tables: LSM Tree + SSTable Database Indexes | Systems Design Interview: 0 to 1 with Google Software Engineer



REPLICATION

1. Single leader → 1 Node handles writes / can read from many replicas
2. Multi leader → You can write to multiple nodes + Read multiple
   - → chances of write-merge conflicts
3. Leaderless → you write/read from any node/replica
   - → uses multicast / gossip protocol among nodes

MY-SQL

→ Relational / Normalized data (Uses 2Phase-commits for concurrency)
- CACID + transactional guarantee
- → very slow but surety

→ Uses B+ Trees + Single leader replication

Mongo DB

→ Document based NOSQL DB (data written as large documents)

→ Btrees + transaction support

NOTE Nothing very special but acts like SQLish NOSQL DB → transactional support

APACHE CASSANDRA

→ Wide column DB : has shard key + sort key
- ○ Flexible schemas
- ○ Easy to partition

→ Multi leader / Leaderless replication (configurable using Q worms)
- ○ Super fast writes but uses Last-write-wins for write conflicts

→ Index : LSM Tree + SS Tables
- ○ Fast writes

USE case Apps with high write volume/speed. Consistency is not so important

RIAK

→ key-value based NOSQL DB

→ Multi-leader / leaderless BOT supports CRDTs (Manual code for merge conflict)

→ SStables + LSM trees

USES : High write throughput + controllable write conflicts

HBASE

→ Wide column DB — shard key + sort key

→ Single leader replication
- → Built on top of HDFS : durable and reliable
- → slower for frequent ops

→ LSM Trees + SS tables

→ Colum oriented storage
- → column compression + data locality in column

USES : Large data + fast column reads

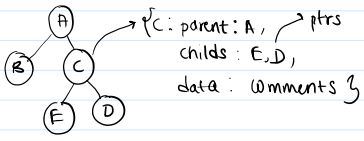
→ colum oriented storage
→ column compression + data locality in column

Uses :- Large data + fast column reads

GRAPH DATABASES

NATIVE GRAPH DB (NEO4J)

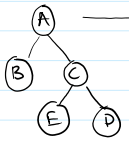
→ you store each node and memory ptrs to its adjacent nodes within the representations



+ Faster lookups since addresses are stored
− Inserts/updates are slower
  ① You need to traverse to insert location
  ② Create node and find nbrs/par/childs
  ③ Create links and store

NON-NATIVE GRAPH DB

→ you store data in some tabular format and later perform joins/ops to get relations



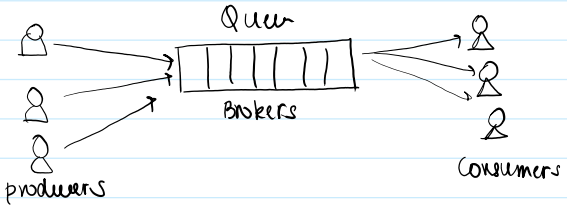
id	par-id	comment
A	–	good post
B	A	agree, +1
C	A	ur joking
E	C	+1
D	C	ur right

+ Insertions are easy → just adding rows
− Queries/getting relations are tough/slower
  → since you dont have addresses you need self joins (in this case)

Streaming

22 December 2024 00:40

- Generally works on concepts of PRODUCERS + CONSUMER



MESSAGE BROKERS

IN-MEMORY (RabbitMQ)

- → stateless + in memory
- → PUSH model
  - → Sends msgs to consumers + waits for ACK
- → At-least once semantics
- → Very low latency

LOG-BASED (kafka)

- → stateful + events written to a log
- → POLL model
  - → Consumers read at their own pace
    - → uses offset-based model
- → at least once, at most once + exactly once semantics
- → High throughput and durable

STREAM PROCESSING

- → joining streams and processing
- → fault tolerance of streams
- → Spark streaming
  - → micro batch processing
- → Flink
  - → realtime on event at a time

CHAINED AFTER MSG BROKERS
acts like consumers

APACHE FLINK

- → Gaurantees that each msg affects state only once
- → Flink checkpoints your state and dumps it to storage (S3)
  - you can replay the events from your log-based queue
  - Done by a job manager / zookeeper