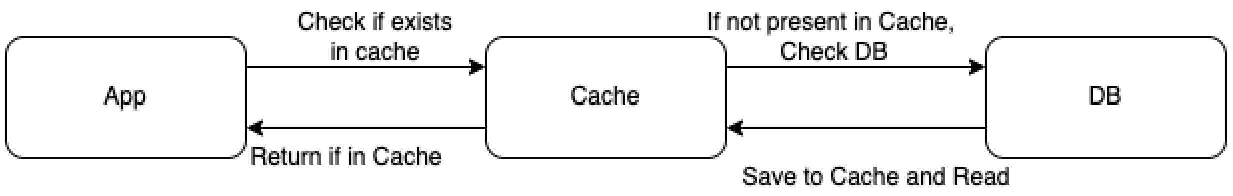
Design Cache



Features:

Amount of Data we will be Caching : Approx. Few TBs

Eviction Strategy:
Few picks : FIFO , LRU (Least Recently Used) , LFU (Least Frequently Used)
Let's pick LRU (default eviction strategy for Cache)

Access Pattern:
Few picks: Write through, Write around and Write back.

Write through Cache: This is a caching system where writes go through the cache and the write is considered success only if the writes to DB and Cache both succeed. Useful in applications which write and reread information quickly. However, write latency is higher as there are writes to 2 separate systems.

Write around cache: This is a caching system where write directly goes into DB. The cache system reads information from DB in case of a miss. While this ensures lower write load to cache and faster writes, this can lead to higher lead latency in case of applications which write and reread information quickly.

Write back cache: Write is done to the caching layer first and the write is confirmed as soon as the write to cache completes. The cache then asynchronously syncs this write to the DB. This ensures quick write but it's an in-memory write / not persistent - there is a chance of loss of data in case of crash/ caching layer dies. We can solve this problem by introducing replicas.

Let's pick the write around cache (more details).

Estimations:

Total Cache: 30 TB
QPS: 10 M QPS
Total Number of Machines: 1 Machin has 72 G RAM, so 30 TB/ 72 G = 30000 G/ 72 G = 400+ Machines

Design Goals:

Latency, Consistency and Availability

We cannot have all 3, so we need to prioritize 2 of them.

Is Latency important ? Yes, the whole point of caching is low latency.

Consistency vs Availability: Unavailability means the caching machine goes down. Since we are thinking of a system like Google/Twitter, when a user views a Timeline , it's okay to miss a few latest tweets, but unavailability could lead to higher latency and load on DB. So, prioritizing availability over consistency. It's okay to have a system which is eventually consistent.

Deep Dive:

LRU Cache

Initially : A Simple HashMap
With eviction strategies: LRU Cache code:

We need a data structure which at any given instance - can give the least recently used object in order. Let's say we maintain a linked list to do it, we try to keep the list ordered by the order in which they are used.
Whenever a get happens, we will need to move the object from a certain position to the front of the list, which means a delete followed by an insert at the beginning. Inserting at the beginning of the list is trivial. How do we achieve erase of an object from a random position at the least amount of time possible ? How about we maintain a map that stores the values corresponding to the linked list node.

Ok, now we know the node, we need to know the previous and next node to enable deletion of the node - easiest way is to use a Doubly Linked list.

```
public class Solution {
```

```java
private Hashtable<Integer, Node> cache = new Hashtable<>();
private int count;
private int capacity;
private Node head, tail;


class Node {
    int key;
    int value;
    Node prev;
    Node next;
}

public Solution(int capacity) {
    this.capacity = capacity;
    this.count = 0;
    head = new Node ();
    tail = new Node ();
    head.prev = null;
    head.next = tail;
    tail.prev = head;
    tail.next = null;
}

public int get(int key) {
    Node node = cache.get(key);
    if ( node == null ){
        return -1;
    }
    this.moveToHead(node);
    return node.value;
}

private void moveToHead(Node node){
    this.removeNode(node);
```

```
        this.addNode(node);
    }

    private void removeNode (Node node){
        Node prev = node.prev;
        Node next = node.next;
        prev.next = next;
        next.prev = prev;
    }

    private void addNode(Node node ){
        node.prev = head;
        node.next = head.next;
        head.next.prev = node;
        head.next = node;
    }

    public void set(int key, int value) {
        Node node = cache.get(key);
        if ( node == null ){
            Node newNode = new Node();
            newNode.key = key;
            newNode.value = value;
            this.cache.put(key, newNode);
            this.addNode(newNode);
            ++count;

            if (count > capacity){
                Node toBeDeleted = this.popTail();
                this.cache.remove(toBeDeleted.key);
                --count;
            }
        } else {
            node.value = value;
            this.moveToHead(node);
        }
    }

    private Node popTail(){
        Node result = tail.prev;
        this.removeNode(result);
        return result;
    }
}
```

GET:

1. Read from HashMap
2. Update DLL

SET:

If the cache is full:

3. Find out the least recently used item
4. Remove it from Cache
5. Remove from the DLL

Then:

6. Insert into hash
7. Insert into linked list

To keep the latency to minimum for our system:

As is the case with most concurrent systems, write competes with reads and other writes. This requires some form of locking when a write is in progress, we can choose to have writes as granular as possible to help with their performance.

Read path is going to be highly frequent , as latency is our design goal, read (operation 1) should be pretty fast and require minimum locking. Operation 2 can happen asynchronously.

HashMap implementation:

Hashmap could be implemented with multiple values. One common way could be hashing with a linked list (Colliding values linked together in a linked list).
HashMap Size = N

```
H =  array of pointers  (size N ) with every element initialized to NULL.
For a give key k , generate g = hash(k) % N
Node newEntry = new Node ( v )
newEntry.next = H[g]
H[g] = newEntry
```

With the above implementation, whenever there is a write, instead of having a lock on HashMap level, we can have it at row level. This way, reading for row i will not affect writing for row j if i != j.

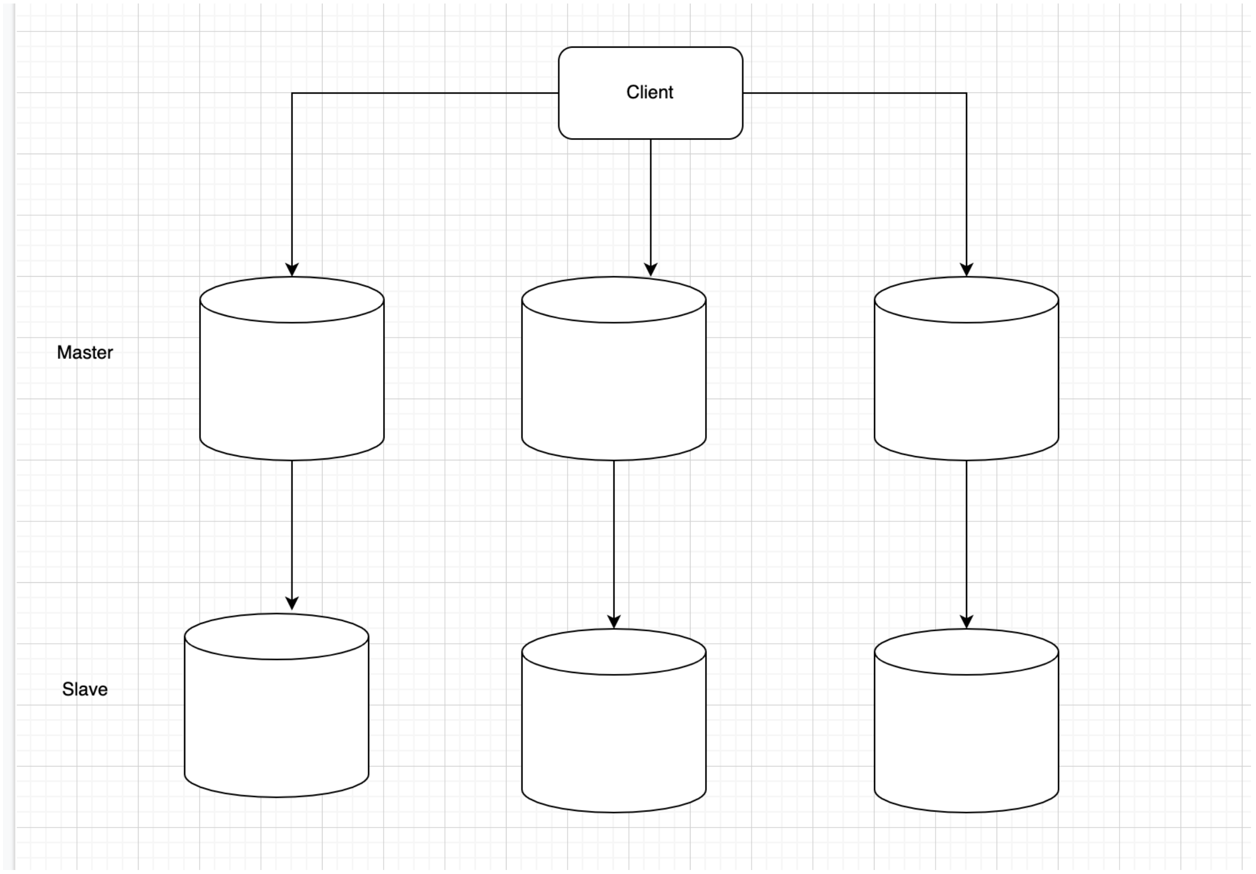
Note that we would also keep N as high as possible for granualrity.

QPS at machine level :

Total Data: 30 TB
Number of Machines: 30 TB/ 72 G = 420
Total QPS: 10 M
QPS per machine = 10 M / 420 = 23000 QPS

What happens when a machine handling a shard goes down?

If only one machine is handling one shard, and if the machine goes down, all the requests start hitting the DB and there will be elevated latency. To avoid this, we can have multiple copies of “shard” that serve as slaves to the master. All the slaves will be eventually consistent with master server.


Client
Master
Slave