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System Design Basics

Whenever we are designing a large system, we need to consider a few things:

1. What are the different architectural pieces that can be used?
2. How do these pieces work with each other?
3. How can we best utilize these pieces: what are the right tradeoffs?

Investing in scaling before it is needed is generally not a smart business proposition; however, some forethought into the design can save valuable time and resources in the future. In the following chapters, we will try to define some of the core building blocks of scalable systems. Familiarizing these concepts would greatly benefit in understanding distributed system concepts. In the next section, we will go through Consistent Hashing, CAP Theorem, Load Balancing, Caching, Data Partitioning, Indexes, Proxies, Queues, Replication, and choosing between SQL vs. NoSQL.

Let's start with the Key Characteristics of Distributed Systems.

Key Characteristics of Distributed Systems

Key characteristics of a distributed system include Scalability, Reliability, Availability, Efficiency, and Manageability. Let's briefly review them:

Scalability

Scalability is the capability of a system, process, or a network to grow and manage increased demand. Any distributed system that can continuously evolve in order to support the growing amount of work is considered to be scalable.

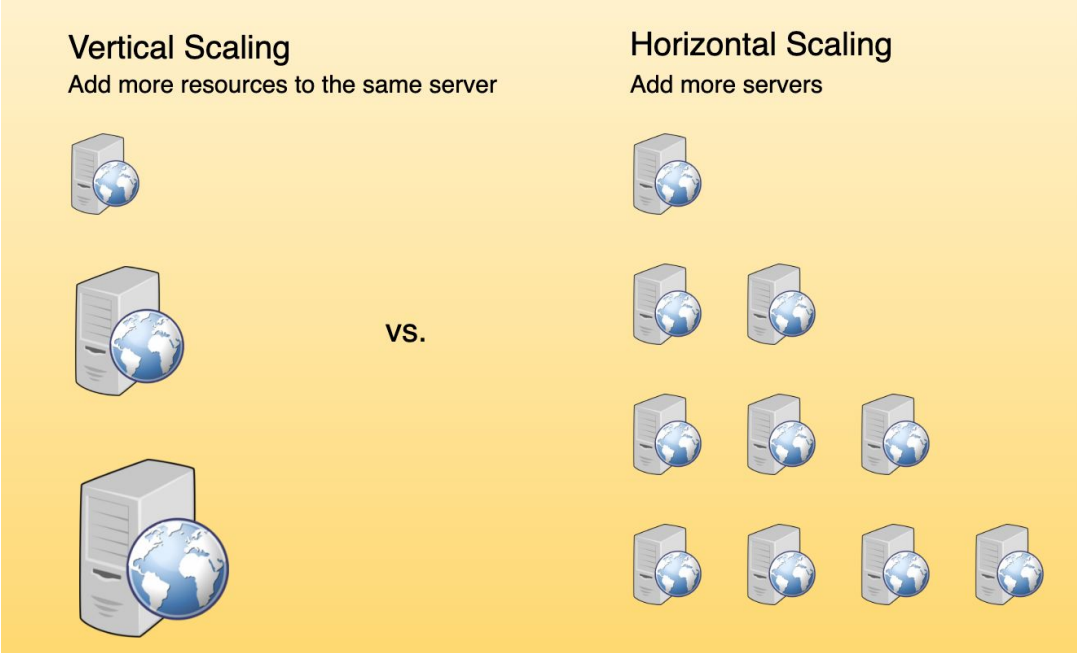
A system may have to scale because of many reasons like increased data volume or increased amount of work, e.g., number of transactions. A scalable system would like to achieve this scaling without performance loss.

Generally, the performance of a system, although designed (or claimed) to be scalable, declines with the system size due to the management or environment cost. For instance, network speed may become slower because machines tend to be far apart from one another. More generally, some tasks may not be distributed, either because of their inherent atomic nature or because of some flaw in the system design. At some point, such tasks would limit the speed-up obtained by distribution. A scalable architecture avoids this situation and attempts to balance the load on all the participating nodes evenly.

Horizontal vs. Vertical Scaling: Horizontal scaling means that you scale by adding more servers into your pool of resources whereas Vertical scaling means that you scale by adding more power (CPU, RAM, Storage, etc.) to an existing server.

With horizontal-scaling it is often easier to scale dynamically by adding more machines into the existing pool; Vertical-scaling is usually limited to the capacity of a single server and scaling beyond that capacity often involves downtime and comes with an upper limit.

Good examples of horizontal scaling are Cassandra and MongoDB as they both provide an easy way to scale horizontally by adding more machines to meet growing needs. Similarly, a good example of vertical scaling is MySQL as it allows for an easy way to scale vertically by switching from smaller to bigger machines. However, this process often involves downtime.



Vertical scaling vs. Horizontal scaling

Reliability

By definition, reliability is the probability a system will fail in a given period. In simple terms, a distributed system is considered reliable if it keeps delivering its services even when one or several of its software or hardware components fail. Reliability represents one of the main characteristics of any distributed system, since in such systems any failing machine can always be replaced by another healthy one, ensuring the completion of the requested task.

Take the example of a large electronic commerce store (like Amazon), where one of the primary requirement is that any user transaction should never be canceled due to a failure of the machine that is running that transaction. For instance, if a user has added an item to their shopping cart, the system is expected not to lose it. A reliable distributed system achieves this through redundancy of both the software components and data. If the server carrying the user's shopping cart fails, another server that has the exact replica of the shopping cart should replace it.

Obviously, redundancy has a cost and a reliable system has to pay that to achieve such resilience for services by eliminating every single point of failure.

Availability

By definition, availability is the time a system remains operational to perform its required function in a specific period. It is a simple measure of the percentage of time that a system, service, or a machine remains operational under normal conditions. An aircraft that can be flown for many hours a month without much downtime can be said to have a high availability. Availability takes into account maintainability, repair time, spares availability, and other logistics considerations. If an aircraft is down for maintenance, it is considered not available during that time.

Reliability is availability over time considering the full range of possible real-world conditions that can occur. An aircraft that can make it through any possible weather safely is more reliable than one that has vulnerabilities to possible conditions.

Reliability Vs. Availability

If a system is reliable, it is available. However, if it is available, it is not necessarily reliable. In other words, high reliability contributes to high availability, but it is possible to achieve a high availability even with an unreliable product by minimizing repair time and ensuring that spares are always available when they are needed. Let's take the example of an online retail store that has 99.99% availability for the first two years after its launch. However, the system was launched without any information security testing. The customers are happy with the system, but they don't realize that it isn't very reliable as it is vulnerable to likely risks. In the third year, the system experiences a series of information security incidents that suddenly result in extremely low availability for extended periods of time. This results in reputational and financial damage to the customers.

Efficiency

To understand how to measure the efficiency of a distributed system, let's assume we have an operation that runs in a distributed manner and delivers a set of items as result. Two standard measures of its efficiency are the response time (or latency) that denotes the delay to obtain the first item and the throughput (or bandwidth) which denotes the number of items delivered in a given time unit (e.g., a second). The two measures correspond to the following unit costs:

- Number of messages globally sent by the nodes of the system regardless of the message size.
- Size of messages representing the volume of data exchanges.

The complexity of operations supported by distributed data structures (e.g., searching for a specific key in a distributed index) can be characterized as a function of one of these cost units. Generally speaking, the analysis of a distributed structure in terms of 'number of messages' is over-simplistic. It ignores the impact of many aspects, including the network topology, the network load, and its variation, the possible heterogeneity of the software and hardware components involved in data processing and routing, etc. However, it is quite difficult to develop a precise cost model that would accurately take into account all these performance factors; therefore, we have to live with rough but robust estimates of the system behavior.

Serviceability or Manageability

Another important consideration while designing a distributed system is how easy it is to operate and maintain. Serviceability or manageability is the simplicity and speed with which a system can be repaired or maintained; if the time to fix a failed system increases, then availability will decrease. Things to consider for manageability are the ease of diagnosing and understanding problems when they occur, ease of making updates or modifications, and how simple the system is to operate (i.e., does it routinely operate without failure or exceptions?).

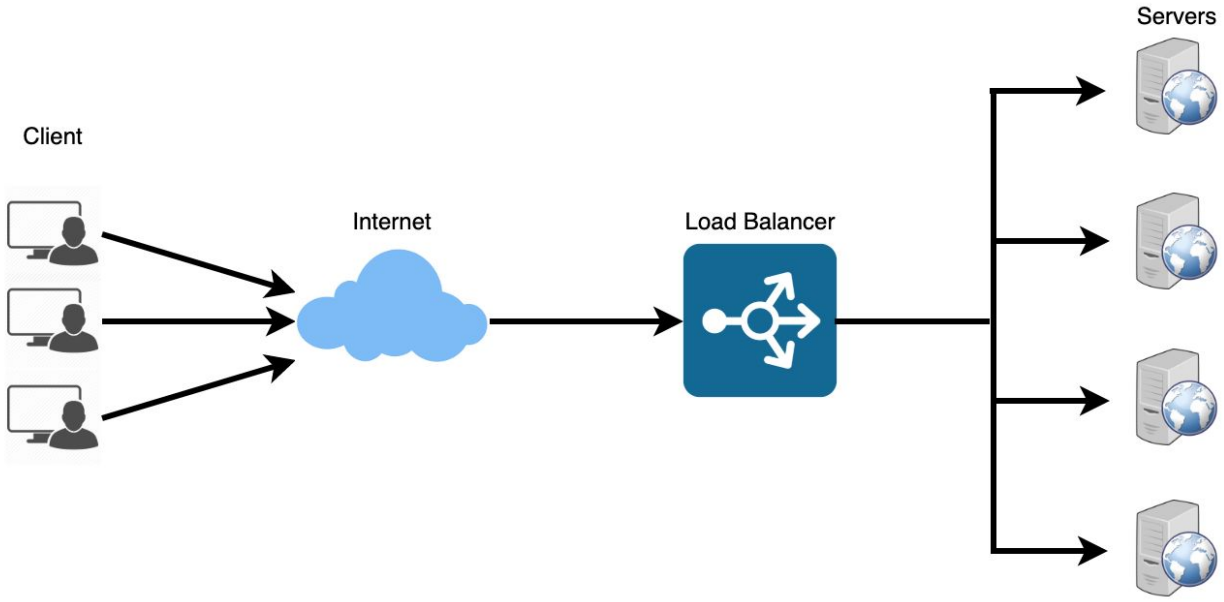
Early detection of faults can decrease or avoid system downtime. For example, some enterprise systems can automatically call a service center (without human intervention) when the system experiences a system fault.

Load Balancing

Load Balancer (LB) is another critical component of any distributed system. It helps to spread the traffic across a cluster of servers to improve responsiveness and availability of applications, websites or databases. LB also keeps track of the status of all the resources while distributing requests. If a server is not available to take new requests or is not responding or has elevated error rate, LB will stop sending traffic to such a server.

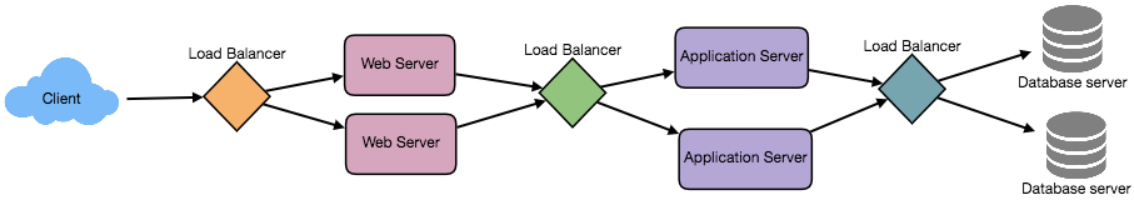
Typically a load balancer sits between the client and the server accepting incoming network and application traffic and distributing the traffic across

multiple backend servers using various algorithms. By balancing application requests across multiple servers, a load balancer reduces individual server load and prevents any one application server from becoming a single point of failure, thus improving overall application availability and responsiveness.



To utilize full scalability and redundancy, we can try to balance the load at each layer of the system. We can add LBs at three places:

- Between the user and the web server
- Between web servers and an internal platform layer, like application servers or cache servers
- Between internal platform layer and database.



Benefits of Load Balancing

- Users experience faster, uninterrupted service. Users won't have to wait for a single struggling server to finish its previous tasks. Instead, their requests are immediately passed on to a more readily available resource.
- Service providers experience less downtime and higher throughput. Even a full server failure won't affect the end user experience as the load balancer will simply route around it to a healthy server.
- Load balancing makes it easier for system administrators to handle incoming requests while decreasing wait time for users.
- Smart load balancers provide benefits like predictive analytics that determine traffic bottlenecks before they happen. As a result, the smart load balancer gives an organization actionable insights. These are key to automation and can help drive business decisions.
- System administrators experience fewer failed or stressed components. Instead of a single device performing a lot of work, load balancing has several devices perform a little bit of work.

Load Balancing Algorithms

How does the load balancer choose the backend server?
Load balancers consider two factors before forwarding a request to a backend server. They will first ensure that the server they choose is actually responding appropriately to requests and then use a pre-configured algorithm to select one from the set of healthy servers. We will discuss these algorithms shortly.

Health Checks - Load balancers should only forward traffic to "healthy" backend servers. To monitor the health of a backend server, "health checks" regularly attempt to connect to backend servers to ensure that servers are listening. If a server fails a health check, it is automatically removed from the pool, and traffic will not be forwarded to it until it responds to the health checks again.

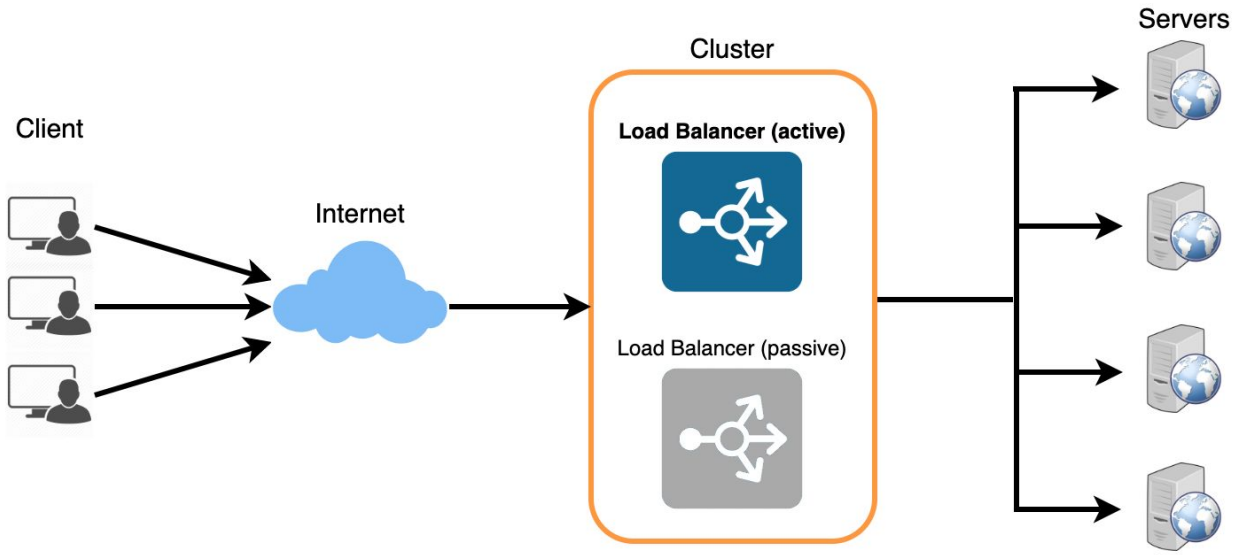
There is a variety of load balancing methods, which use different algorithms for different needs.

- Least Connection Method — This method directs traffic to the server with the fewest active connections. This approach is quite useful when there are a large number of persistent client connections which are unevenly distributed between the servers.

- Least Response Time Method — This algorithm directs traffic to the server with the fewest active connections and the lowest average response time.
- Least Bandwidth Method - This method selects the server that is currently serving the least amount of traffic measured in megabits per second (Mbps).
- Round Robin Method — This method cycles through a list of servers and sends each new request to the next server. When it reaches the end of the list, it starts over at the beginning. It is most useful when the servers are of equal specification and there are not many persistent connections.
- Weighted Round Robin Method — The weighted round-robin scheduling is designed to better handle servers with different processing capacities. Each server is assigned a weight (an integer value that indicates the processing capacity). Servers with higher weights receive new connections before those with less weights and servers with higher weights get more connections than those with less weights.
- IP Hash — Under this method, a hash of the IP address of the client is calculated to redirect the request to a server.

Redundant Load Balancers

The load balancer can be a single point of failure; to overcome this, a second load balancer can be connected to the first to form a cluster. Each LB monitors the health of the other and, since both of them are equally capable of serving traffic and failure detection, in the event the main load balancer fails, the second load balancer takes over.



Following links have some good discussion about load balancers:
[1] What is load balancing
[2] Introduction to architecting systems
[3] Load balancing

Caching

Load balancing helps you scale horizontally across an ever-increasing number of servers, but caching will enable you to make vastly better use of the resources you already have as well as making otherwise unattainable product requirements feasible. Caches take advantage of the locality of reference principle: recently requested data is likely to be requested again. They are used in almost every layer of computing: hardware, operating systems, web browsers, web applications, and more. A cache is like short-term memory: it has a limited amount of space, but is typically faster than the original data source and contains the most recently accessed items. Caches can exist at all levels in architecture, but are often found at the level nearest to the front end where they are implemented to return data quickly without taxing downstream levels.

Application server cache

Placing a cache directly on a request layer node enables the local storage of response data. Each time a request is made to the service, the node will quickly return local cached data if it exists. If it is not in the cache, the requesting node will query the data from disk. The cache on one request layer node could also be located both in memory (which is very fast) and on the node's local disk (faster than going to network storage).

What happens when you expand this to many nodes? If the request layer is expanded to multiple nodes, it's still quite possible to have each node host its own cache. However, if your load balancer randomly distributes requests across the nodes, the same request will go to different nodes, thus increasing cache misses. Two choices for overcoming this hurdle are global caches and distributed caches.

Content Distribution Network (CDN)

CDNs are a kind of cache that comes into play for sites serving large amounts of static media. In a typical CDN setup, a request will first ask the CDN for a piece of static media; the CDN will serve that content if it has it locally available. If it

isn't available, the CDN will query the back-end servers for the file, cache it locally, and serve it to the requesting user.

If the system we are building isn't yet large enough to have its own CDN, we can ease a future transition by serving the static media off a separate subdomain (e.g. static.yourservice.com) using a lightweight HTTP server like Nginx, and cut-over the DNS from your servers to a CDN later.

Cache Invalidation

While caching is fantastic, it does require some maintenance for keeping cache coherent with the source of truth (e.g., database). If the data is modified in the database, it should be invalidated in the cache; if not, this can cause inconsistent application behavior.

Solving this problem is known as cache invalidation; there are three main schemes that are used:

Write-through cache: Under this scheme, data is written into the cache and the corresponding database at the same time. The cached data allows for fast retrieval and, since the same data gets written in the permanent storage, we will have complete data consistency between the cache and the storage. Also, this scheme ensures that nothing will get lost in case of a crash, power failure, or other system disruptions.

Although, write through minimizes the risk of data loss, since every write operation must be done twice before returning success to the client, this scheme has the disadvantage of higher latency for write operations.

Write-around cache: This technique is similar to write through cache, but data is written directly to permanent storage, bypassing the cache. This can reduce the cache being flooded with write operations that will not subsequently be re-read, but has the disadvantage that a read request for recently written data will create a "cache miss" and must be read from slower back-end storage and experience higher latency.

Write-back cache: Under this scheme, data is written to cache alone and completion is immediately confirmed to the client. The write to the permanent storage is done after specified intervals or under certain conditions. This results in low latency and high throughput for write-intensive applications, however, this

speed comes with the risk of data loss in case of a crash or other adverse event because the only copy of the written data is in the cache.

Cache eviction policies

Following are some of the most common cache eviction policies:

1. First In First Out (FIFO): The cache evicts the first block accessed first without any regard to how often or how many times it was accessed before.
2. Last In First Out (LIFO): The cache evicts the block accessed most recently first without any regard to how often or how many times it was accessed before.
3. Least Recently Used (LRU): Discards the least recently used items first.
4. Most Recently Used (MRU): Discards, in contrast to LRU, the most recently used items first.
5. Least Frequently Used (LFU): Counts how often an item is needed. Those that are used least often are discarded first.
6. Random Replacement (RR): Randomly selects a candidate item and discards it to make space when necessary.

Following links have some good discussion about caching:
[1] Cache
[2] Introduction to architecting systems

Data Partitioning

Data partitioning is a technique to break up a big database (DB) into many smaller parts. It is the process of splitting up a DB/table across multiple machines to improve the manageability, performance, availability, and load balancing of an application. The justification for data partitioning is that, after a certain scale point, it is cheaper and more feasible to scale horizontally by adding more machines than to grow it vertically by adding beefier servers.

1. Partitioning Methods

There are many different schemes one could use to decide how to break up an application database into multiple smaller DBs. Below are three of the most popular schemes used by various large scale applications.

a. Horizontal partitioning: In this scheme, we put different rows into different tables. For example, if we are storing different places in a table, we can decide that locations with ZIP codes less than 10000 are stored in one table and places with ZIP codes greater than 10000 are stored in a separate table. This is also called a range based partitioning as we are storing different ranges of data in separate tables. Horizontal partitioning is also called as Data Sharding.

The key problem with this approach is that if the value whose range is used for partitioning isn't chosen carefully, then the partitioning scheme will lead to unbalanced servers. In the previous example, splitting location based on their zip codes assumes that places will be evenly distributed across the different zip codes. This assumption is not valid as there will be a lot of places in a thickly populated area like Manhattan as compared to its suburb cities.

b. Vertical Partitioning: In this scheme, we divide our data to store tables related to a specific feature in their own server. For example, if we are building Instagram like application - where we need to store data related to users, photos they upload, and people they follow - we can decide to place user profile information on one DB server, friend lists on another, and photos on a third server.

Vertical partitioning is straightforward to implement and has a low impact on the application. The main problem with this approach is that if our application experiences additional growth, then it may be necessary to further partition a feature specific DB across various servers (e.g. it would not be possible for a single server to handle all the metadata queries for 10 billion photos by 140 million users).

c. Directory Based Partitioning: A loosely coupled approach to work around issues mentioned in the above schemes is to create a lookup service which knows your current partitioning scheme and abstracts it away from the DB access code. So, to find out where a particular data entity resides, we query the directory server that holds the mapping between each tuple key to its DB server. This loosely coupled approach means we can perform tasks like adding servers to the DB pool or changing our partitioning scheme without having an impact on the application.

2. Partitioning Criteria

a. Key or Hash-based partitioning: Under this scheme, we apply a hash function to some key attributes of the entity we are storing; that yields the partition number. For example, if we have 100 DB servers and our ID is a numeric value

that gets incremented by one each time a new record is inserted. In this example, the hash function could be 'ID % 100', which will give us the server number where we can store/read that record. This approach should ensure a uniform allocation of data among servers. The fundamental problem with this approach is that it effectively fixes the total number of DB servers, since adding new servers means changing the hash function which would require redistribution of data and downtime for the service. A workaround for this problem is to use Consistent Hashing.

b. List partitioning: In this scheme, each partition is assigned a list of values, so whenever we want to insert a new record, we will see which partition contains our key and then store it there. For example, we can decide all users living in Iceland, Norway, Sweden, Finland, or Denmark will be stored in a partition for the Nordic countries.

c. Round-robin partitioning: This is a very simple strategy that ensures uniform data distribution. With 'n' partitions, the 'i' tuple is assigned to partition (i mod n).

d. Composite partitioning: Under this scheme, we combine any of the above partitioning schemes to devise a new scheme. For example, first applying a list partitioning scheme and then a hash based partitioning. Consistent hashing could be considered a composite of hash and list partitioning where the hash reduces the key space to a size that can be listed.

3. Common Problems of Data Partitioning

On a partitioned database, there are certain extra constraints on the different operations that can be performed. Most of these constraints are due to the fact that operations across multiple tables or multiple rows in the same table will no longer run on the same server. Below are some of the constraints and additional complexities introduced by partitioning:

a. Joins and Denormalization: Performing joins on a database which is running on one server is straightforward, but once a database is partitioned and spread across multiple machines it is often not feasible to perform joins that span database partitions. Such joins will not be performance efficient since data has to be compiled from multiple servers. A common workaround for this problem is to denormalize the database so that queries that previously required joins can be performed from a single table. Of course, the service now has to deal with all the perils of denormalization such as data inconsistency.

b. Referential integrity: As we saw that performing a cross-partition query on a partitioned database is not feasible, similarly, trying to enforce data integrity constraints such as foreign keys in a partitioned database can be extremely difficult.

Most of RDBMS do not support foreign keys constraints across databases on different database servers. Which means that applications that require referential integrity on partitioned databases often have to enforce it in application code. Often in such cases, applications have to run regular SQL jobs to clean up dangling references.

c. Rebalancing: There could be many reasons we have to change our partitioning scheme:

1. The data distribution is not uniform, e.g., there are a lot of places for a particular ZIP code that cannot fit into one database partition.
2. There is a lot of load on a partition, e.g., there are too many requests being handled by the DB partition dedicated to user photos.

In such cases, either we have to create more DB partitions or have to rebalance existing partitions, which means the partitioning scheme changed and all existing data moved to new locations. Doing this without incurring downtime is extremely difficult. Using a scheme like directory based partitioning does make rebalancing a more palatable experience at the cost of increasing the complexity of the system and creating a new single point of failure (i.e. the lookup service/database).

Indexes

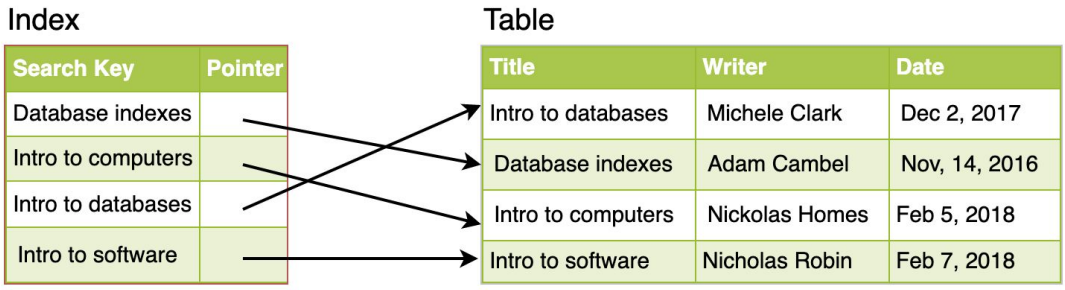
Indexes are well known when it comes to databases. Sooner or later there comes a time when database performance is no longer satisfactory. One of the very first things you should turn to when that happens is database indexing.

The goal of creating an index on a particular table in a database is to make it faster to search through the table and find the row or rows that we want. Indexes can be created using one or more columns of a database table, providing the basis for both rapid random lookups and efficient access of ordered records.

Example: A library catalog

A library catalog is a register that contains the list of books found in a library. The catalog is organized like a database table generally with four columns: book title, writer, subject, and date of publication. There are usually two such catalogs: one sorted by the book title and one sorted by the writer name. That way, you can either think of a writer you want to read and then look through their books or look up a specific book title you know you want to read in case you don't know the writer's name. These catalogs are like indexes for the database of books. They provide a sorted list of data that is easily searchable by relevant information.

Simply saying, an index is a data structure that can be perceived as a table of contents that points us to the location where actual data lives. So when we create an index on a column of a table, we store that column and a pointer to the whole row in the index. Let's assume a table containing a list of books, the following diagram shows how an index on the 'Title' column looks like:



Just like a traditional relational data store, we can also apply this concept to larger datasets. The trick with indexes is that we must carefully consider how users will access the data. In the case of data sets that are many terabytes in size, but have very small payloads (e.g., 1 KB), indexes are a necessity for optimizing data access. Finding a small payload in such a large dataset can be a real challenge, since we can't possibly iterate over that much data in any reasonable time. Furthermore, it is very likely that such a large data set is spread over several physical devices—this means we need some way to find the correct physical location of the desired data. Indexes are the best way to do this.

How do Indexes decrease write performance?

An index can dramatically speed up data retrieval but may itself be large due to the additional keys, which slow down data insertion & update.

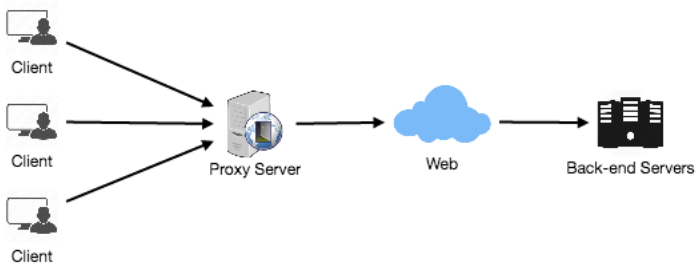
When adding rows or making updates to existing rows for a table with an active index, we not only have to write the data but also have to update the index. This will decrease the write performance. This performance degradation applies to all insert, update, and delete operations for the table. For this reason, adding unnecessary indexes on tables should be avoided and indexes that are no longer used should be removed. To reiterate, adding indexes is about improving the performance of search queries. If the goal of the database is to provide a data store that is often written to and rarely read from, in that case, decreasing the performance of the more common operation, which is writing, is probably not worth the increase in performance we get from reading.

For more details, see Database Indexes.

Proxies

A proxy server is an intermediate server between the client and the back-end server. Clients connect to proxy servers to request for a service like a web page, file, connection, etc. In short, a proxy server is a piece of software or hardware that acts as an intermediary for requests from clients seeking resources from other servers.

Typically, proxies are used to filter requests, log requests, or sometimes transform requests (by adding/removing headers, encrypting/decrypting, or compressing a resource). Another advantage of a proxy server is that its cache can serve a lot of requests. If multiple clients access a particular resource, the proxy server can cache it and serve it to all the clients without going to the remote server.



Proxy Server Types

Proxies can reside on the client's local server or anywhere between the client and the remote servers. Here are a few famous types of proxy servers:

Open Proxy

An open proxy is a proxy server that is accessible by any Internet user. Generally, a proxy server only allows users within a network group (i.e. a closed proxy) to store and forward Internet services such as DNS or web pages to reduce and control the bandwidth used by the group. With an open proxy, however, any user on the Internet is able to use this forwarding service. There two famous open proxy types:

1. Anonymous Proxy - This proxy reveals its identity as a server but does not disclose the initial IP address. Though this proxy server can be discovered easily it can be beneficial for some users as it hides their IP address.
2. Transparent Proxy – This proxy server again identifies itself, and with the support of HTTP headers, the first IP address can be viewed. The main benefit of using this sort of server is its ability to cache the websites.

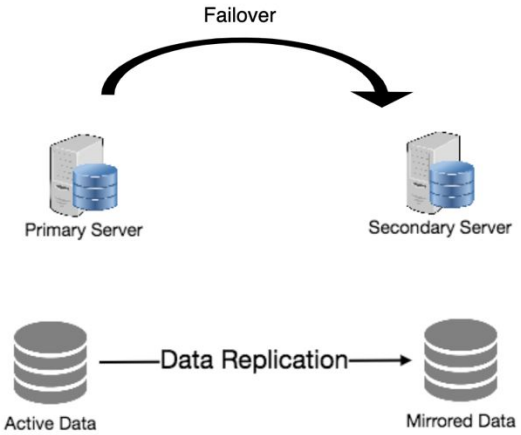
Reverse Proxy

A reverse proxy retrieves resources on behalf of a client from one or more servers. These resources are then returned to the client, appearing as if they originated from the proxy server itself

Redundancy and Replication

Redundancy is the duplication of critical components or functions of a system with the intention of increasing the reliability of the system, usually in the form of a backup or fail-safe, or to improve actual system performance. For example, if there is only one copy of a file stored on a single server, then losing that server means losing the file. Since losing data is seldom a good thing, we can create duplicate or redundant copies of the file to solve this problem.

Redundancy plays a key role in removing the single points of failure in the system and provides backups if needed in a crisis. For example, if we have two instances of a service running in production and one fails, the system can failover to the other one.



Replication means sharing information to ensure consistency between redundant resources, such as software or hardware components, to improve reliability, fault-tolerance, or accessibility.

Replication is widely used in many database management systems (DBMS), usually with a master-slave relationship between the original and the copies. The master gets all the updates, which then ripple through to the slaves. Each slave outputs a message stating that it has received the update successfully, thus allowing the sending of subsequent updates.

SQL vs. NoSQL

In the world of databases, there are two main types of solutions: SQL and NoSQL (or relational databases and non-relational databases). Both of them differ in the way they were built, the kind of information they store, and the storage method they use.

Relational databases are structured and have predefined schemas like phone books that store phone numbers and addresses. Non-relational databases are unstructured, distributed, and have a dynamic schema like file folders that hold everything from a person's address and phone number to their Facebook 'likes' and online shopping preferences.

SQL

Relational databases store data in rows and columns. Each row contains all the information about one entity and each column contains all the separate data

points. Some of the most popular relational databases are MySQL, Oracle, MS SQL Server, SQLite, Postgres, and MariaDB.

NoSQL

Following are the most common types of NoSQL:

Key-Value Stores: Data is stored in an array of key-value pairs. The 'key' is an attribute name which is linked to a 'value'. Well-known key-value stores include Redis, Voldemort, and Dynamo.

Document Databases: In these databases, data is stored in documents (instead of rows and columns in a table) and these documents are grouped together in collections. Each document can have an entirely different structure. Document databases include the CouchDB and MongoDB.

Wide-Column Databases: Instead of 'tables,' in columnar databases we have column families, which are containers for rows. Unlike relational databases, we don't need to know all the columns up front and each row doesn't have to have the same number of columns. Columnar databases are best suited for analyzing large datasets - big names include Cassandra and HBase.

Graph Databases: These databases are used to store data whose relations are best represented in a graph. Data is saved in graph structures with nodes (entities), properties (information about the entities), and lines (connections between the entities). Examples of graph database include Neo4J and InfiniteGraph.

High level differences between SQL and NoSQL

Storage: SQL stores data in tables where each row represents an entity and each column represents a data point about that entity; for example, if we are storing a car entity in a table, different columns could be 'Color', 'Make', 'Model', and so on.

NoSQL databases have different data storage models. The main ones are key-value, document, graph, and columnar. We will discuss differences between these databases below.

Schema: In SQL, each record conforms to a fixed schema, meaning the columns must be decided and chosen before data entry and each row must have data for

each column. The schema can be altered later, but it involves modifying the whole database and going offline.

In NoSQL, schemas are dynamic. Columns can be added on the fly and each 'row' (or equivalent) doesn't have to contain data for each 'column.'

Querying: SQL databases use SQL (structured query language) for defining and manipulating the data, which is very powerful. In a NoSQL database, queries are focused on a collection of documents. Sometimes it is also called UnQL (Unstructured Query Language). Different databases have different syntax for using UnQL.

Scalability: In most common situations, SQL databases are vertically scalable, i.e., by increasing the horsepower (higher Memory, CPU, etc.) of the hardware, which can get very expensive. It is possible to scale a relational database across multiple servers, but this is a challenging and time-consuming process.

On the other hand, NoSQL databases are horizontally scalable, meaning we can add more servers easily in our NoSQL database infrastructure to handle a lot of traffic. Any cheap commodity hardware or cloud instances can host NoSQL databases, thus making it a lot more cost-effective than vertical scaling. A lot of NoSQL technologies also distribute data across servers automatically.

Reliability or ACID Compliancy (Atomicity, Consistency, Isolation, Durability): The vast majority of relational databases are ACID compliant. So, when it comes to data reliability and safe guarantee of performing transactions, SQL databases are still the better bet.

Most of the NoSQL solutions sacrifice ACID compliance for performance and scalability.

SQL VS. NoSQL - Which one to use?

When it comes to database technology, there's no one-size-fits-all solution. That's why many businesses rely on both relational and non-relational databases for different needs. Even as NoSQL databases are gaining popularity for their speed and scalability, there are still situations where a highly structured SQL database may perform better; choosing the right technology hinges on the use case.

Reasons to use SQL database

Here are a few reasons to choose a SQL database:

1. We need to ensure ACID compliance. ACID compliance reduces anomalies and protects the integrity of your database by prescribing exactly how transactions interact with the database. Generally, NoSQL databases sacrifice ACID compliance for scalability and processing speed, but for many e-commerce and financial applications, an ACID-compliant database remains the preferred option.
2. Your data is structured and unchanging. If your business is not experiencing massive growth that would require more servers and if you're only working with data that is consistent, then there may be no reason to use a system designed to support a variety of data types and high traffic volume.

Reasons to use NoSQL database

When all the other components of our application are fast and seamless, NoSQL databases prevent data from being the bottleneck. Big data is contributing to a large success for NoSQL databases, mainly because it handles data differently than the traditional relational databases. A few popular examples of NoSQL databases are MongoDB, CouchDB, Cassandra, and HBase.

1. Storing large volumes of data that often have little to no structure. A NoSQL database sets no limits on the types of data we can store together and allows us to add new types as the need changes. With document-based databases, you can store data in one place without having to define what "types" of data those are in advance.
2. Making the most of cloud computing and storage. Cloud-based storage is an excellent cost-saving solution but requires data to be easily spread across multiple servers to scale up. Using commodity (affordable, smaller) hardware on-site or in the cloud saves you the hassle of additional software and NoSQL databases like Cassandra are designed to be scaled across multiple data centers out of the box, without a lot of headaches.
3. Rapid development. NoSQL is extremely useful for rapid development as it doesn't need to be prepped ahead of time. If you're working on quick iterations of your system which require making frequent updates to the data structure without a lot of downtime between versions, a relational database will slow you down.

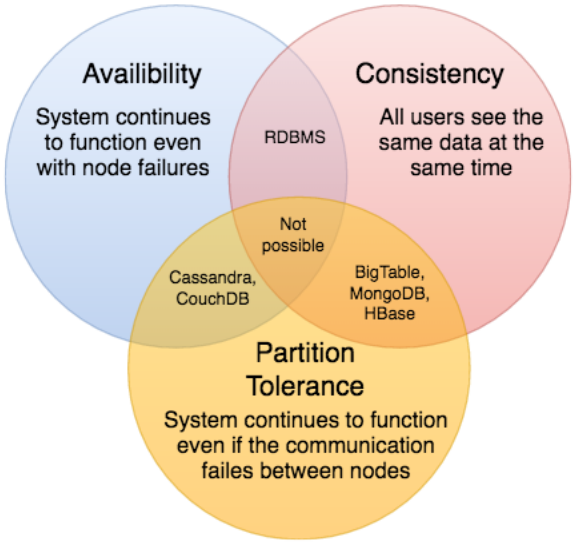
CAP Theorem

CAP theorem states that it is impossible for a distributed software system to simultaneously provide more than two out of three of the following guarantees (CAP): Consistency, Availability, and Partition tolerance. When we design a distributed system, trading off among CAP is almost the first thing we want to consider. CAP theorem says while designing a distributed system we can pick only two of the following three options:

Consistency: All nodes see the same data at the same time. Consistency is achieved by updating several nodes before allowing further reads.

Availability: Every request gets a response on success/failure. Availability is achieved by replicating the data across different servers.

Partition tolerance: The system continues to work despite message loss or partial failure. A system that is partition-tolerant can sustain any amount of network failure that doesn't result in a failure of the entire network. Data is sufficiently replicated across combinations of nodes and networks to keep the system up through intermittent outages.



We cannot build a general data store that is continually available, sequentially consistent, and tolerant to any partition failures. We can only build a system that has any two of these three properties. Because, to be consistent, all nodes should see the same set of updates in the same order. But if the network suffers

a partition, updates in one partition might not make it to the other partitions before a client reads from the out-of-date partition after having read from the up-to-date one. The only thing that can be done to cope with this possibility is to stop serving requests from the out-of-date partition, but then the service is no longer 100% available.

Consistent Hashing

Distributed Hash Table (DHT) is one of the fundamental components used in distributed scalable systems. Hash Tables need a key, a value, and a hash function where hash function maps the key to a location where the value is stored.

```
index = hash_function(key)
```

Suppose we are designing a distributed caching system. Given 'n' cache servers, an intuitive hash function would be 'key % n'. It is simple and commonly used. But it has two major drawbacks:

1. It is NOT horizontally scalable. Whenever a new cache host is added to the system, all existing mappings are broken. It will be a pain point in maintenance if the caching system contains lots of data. Practically, it becomes difficult to schedule a downtime to update all caching mappings.
2. It may NOT be load balanced, especially for non-uniformly distributed data. In practice, it can be easily assumed that the data will not be distributed uniformly. For the caching system, it translates into some caches becoming hot and saturated while the others idle and are almost empty.

In such situations, consistent hashing is a good way to improve the caching system.

What is Consistent Hashing?

Consistent hashing is a very useful strategy for distributed caching system and DHTs. It allows us to distribute data across a cluster in such a way that will minimize reorganization when nodes are added or removed. Hence, the caching system will be easier to scale up or scale down.

In Consistent Hashing, when the hash table is resized (e.g. a new cache host is added to the system), only 'k/n' keys need to be remapped where 'k' is the total number of keys and 'n' is the total number of servers. Recall that in a caching system using the 'mod' as the hash function, all keys need to be remapped.

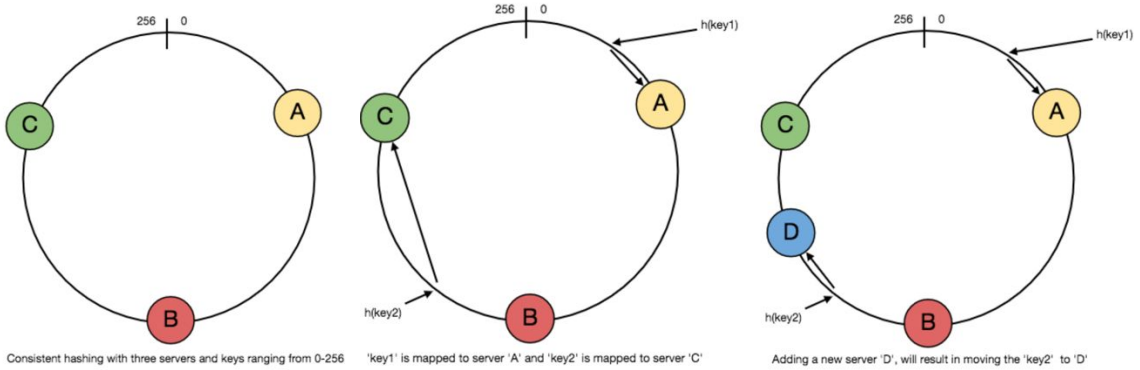
In Consistent Hashing, objects are mapped to the same host if possible. When a host is removed from the system, the objects on that host are shared by other hosts; when a new host is added, it takes its share from a few hosts without touching other's shares.

How does it work?

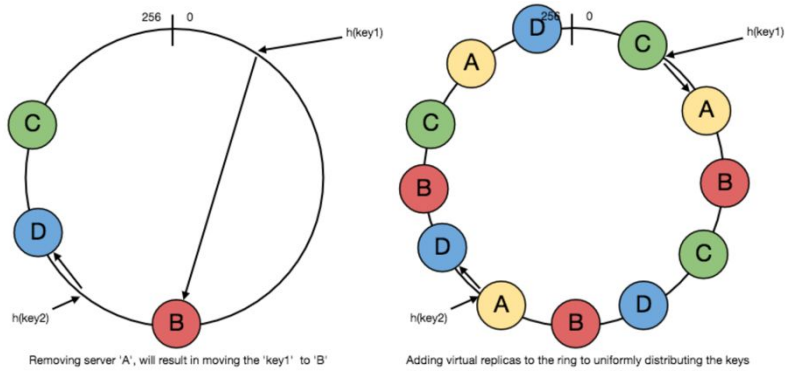
As a typical hash function, consistent hashing maps a key to an integer. Suppose the output of the hash function is in the range of [0, 256). Imagine that the integers in the range are placed on a ring such that the values are wrapped around.

Here's how consistent hashing works:

1. Given a list of cache servers, hash them to integers in the range.
2. To map a key to a server,
    - Hash it to a single integer.
    - Move clockwise on the ring until finding the first cache it encounters.
    - That cache is the one that contains the key. See animation below as an example: key1 maps to cache A; key2 maps to cache C.



Consistent hashing with three servers and keys ranging from 0-256 'key1' is mapped to server 'A' and 'key2' is mapped to server 'C' Adding a new server 'D', will result in moving the 'key2' to 'D'

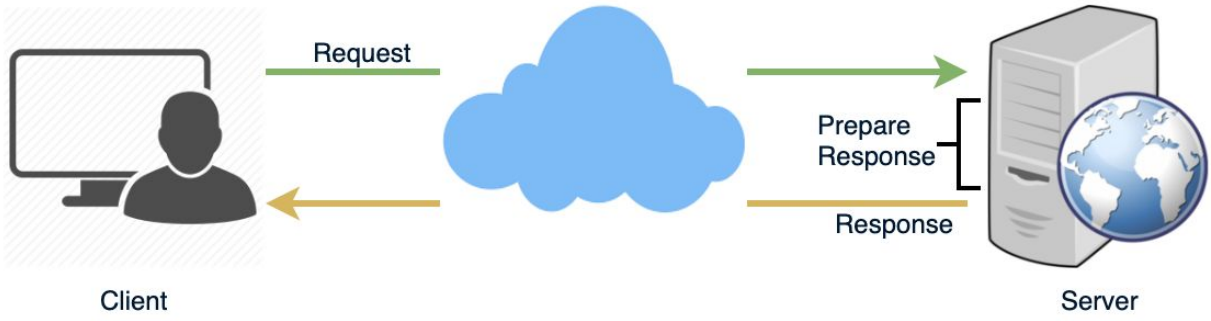


Long-Polling vs WebSockets vs Server-Sent Events

What is the difference between Long-Polling, WebSockets, and Server-Sent Events?

Long-Polling, WebSockets, and Server-Sent Events are popular communication protocols between a client like a web browser and a web server. First, let's start with understanding what a standard HTTP web request looks like. Following are a sequence of events for regular HTTP request:

1. The client opens a connection and requests data from the server.
2. The server calculates the response.
3. The server sends the response back to the client on the opened request.



HTTP Protocol

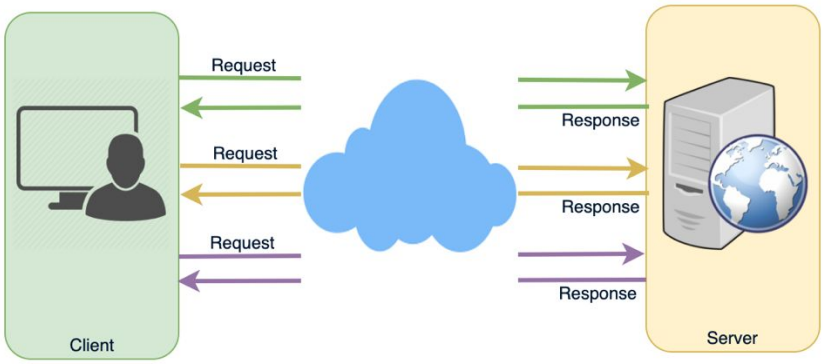
Ajax Polling

Polling is a standard technique used by the vast majority of AJAX applications. The basic idea is that the client repeatedly polls (or requests) a server for data.

The client makes a request and waits for the server to respond with data. If no data is available, an empty response is returned.

1. The client opens a connection and requests data from the server using regular HTTP.
2. The requested webpage sends requests to the server at regular intervals (e.g., 0.5 seconds).
3. The server calculates the response and sends it back, just like regular HTTP traffic.
4. The client repeats the above three steps periodically to get updates from the server.

The problem with Polling is that the client has to keep asking the server for any new data. As a result, a lot of responses are empty, creating HTTP overhead.



Ajax Polling Protocol

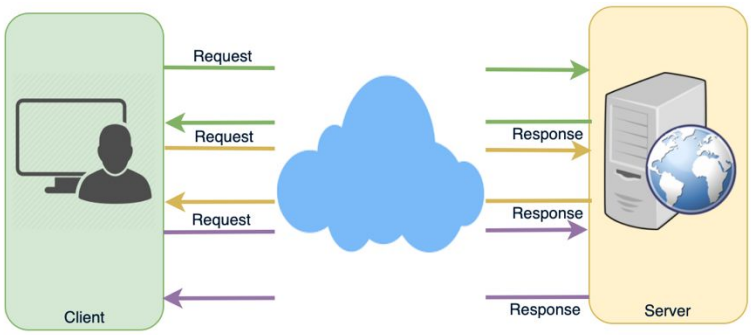
HTTP Long-Polling

This is a variation of the traditional polling technique that allows the server to push information to a client whenever the data is available. With Long-Polling, the client requests information from the server exactly as in normal polling, but with the expectation that the server may not respond immediately. That's why this technique is sometimes referred to as a "Hanging GET".

- If the server does not have any data available for the client, instead of sending an empty response, the server holds the request and waits until some data becomes available.
- Once the data becomes available, a full response is sent to the client. The client then immediately re-request information from the server so that the server will almost always have an available waiting request that it can use to deliver data in response to an event.

The basic life cycle of an application using HTTP Long-Polling is as follows:

1. The client makes an initial request using regular HTTP and then waits for a response.
2. The server delays its response until an update is available or a timeout has occurred.
3. When an update is available, the server sends a full response to the client.
4. The client typically sends a new long-poll request, either immediately upon receiving a response or after a pause to allow an acceptable latency period.
5. Each Long-Poll request has a timeout. The client has to reconnect periodically after the connection is closed due to timeouts.



Long Polling Protocol

WebSockets

WebSocket provides Full duplex communication channels over a single TCP connection. It provides a persistent connection between a client and a server that both parties can use to start sending data at any time. The client establishes a WebSocket connection through a process known as the WebSocket handshake. If the process succeeds, then the server and client can exchange data in both directions at any time. The WebSocket protocol enables communication between a client and a server with lower overheads, facilitating real-time data transfer from and to the server. This is made possible by providing a standardized way for the server to send content to the browser without being asked by the client and allowing for messages to be passed back and forth while keeping the connection open. In this way, a two-way (bi-directional) ongoing conversation can take place between a client and a server.

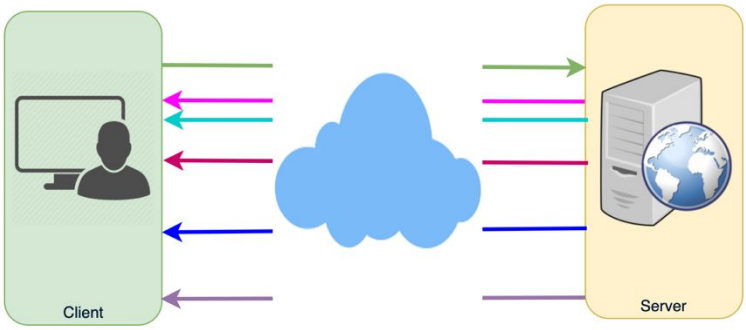
WebSockets Protocol

Server-Sent Events (SSEs)

Under SSEs the client establishes a persistent and long-term connection with the server. The server uses this connection to send data to a client. If the client wants to send data to the server, it would require the use of another technology/protocol to do so.

1. Client requests data from a server using regular HTTP.
2. The requested webpage opens a connection to the server.
3. The server sends the data to the client whenever there's new information available.

SSEs are best when we need real-time traffic from the server to the client or if the server is generating data in a loop and will be sending multiple events to the client.



Server Sent Events Protocol

System Design Interviews: A step by step guide

A lot of software engineers struggle with system design interviews (SDIs) primarily because of three reasons:

- The unstructured nature of SDIs, where they are asked to work on an open-ended design problem that doesn't have a standard answer.
- Their lack of experience in developing large scale systems.
- They did not prepare for SDIs.

Like coding interviews, candidates who haven't put a conscious effort to prepare for SDIs, mostly perform poorly especially at top companies like Google, Facebook, Amazon, Microsoft, etc. In these companies, candidates who don't perform above average, have a limited chance to get an offer. On the other hand, a good performance always results in a better offer (higher position and salary), since it shows the candidate's ability to handle a complex system.

In this course, we'll follow a step by step approach to solve multiple design problems. First, let's go through these steps:

Step 1: Requirements clarifications

It is always a good idea to ask questions about the exact scope of the problem we are solving. Design questions are mostly open-ended, and they don't have ONE correct answer, that's why clarifying ambiguities early in the interview becomes critical. Candidates who spend enough time to define the end goals of the system always have a better chance to be successful in the interview. Also, since we only have 35-40 minutes to design a (supposedly) large system, we should clarify what parts of the system we will be focusing on.

Let's expand this with an actual example of designing a Twitter-like service. Here are some questions for designing Twitter that should be answered before moving on to the next steps:

- Will users of our service be able to post tweets and follow other people?
- Should we also design to create and display the user's timeline?
- Will tweets contain photos and videos?
- Are we focusing on the backend only or are we developing the front-end too?
- Will users be able to search tweets?
- Do we need to display hot trending topics?
- Will there be any push notification for new (or important) tweets?

All such question will determine how our end design will look like.

Step 2: System interface definition

Define what APIs are expected from the system. This will not only establish the exact contract expected from the system, but will also ensure if we haven't gotten any requirements wrong. Some examples for our Twitter-like service will be:

```
postTweet(user_id, tweet_data, tweet_location, user_location, timestamp, …)
generateTimeline(user_id, current_time, user_location, …)
markTweetFavorite(user_id, tweet_id, timestamp, …)
```

Step 3: Back-of-the-envelope estimation

It is always a good idea to estimate the scale of the system we're going to design. This will also help later when we will be focusing on scaling, partitioning, load balancing and caching.

- What scale is expected from the system (e.g., number of new tweets, number of tweet views, number of timeline generations per sec., etc.)?
- How much storage will we need? We will have different numbers if users can have photos and videos in their tweets.
- What network bandwidth usage are we expecting? This will be crucial in deciding how we will manage traffic and balance load between servers.

Step 4: Defining data model

Defining the data model early will clarify how data will flow among different components of the system. Later, it will guide towards data partitioning and management. The candidate should be able to identify various entities of the system, how they will interact with each other, and different aspect of data management like storage, transportation, encryption, etc. Here are some entities for our Twitter-like service:

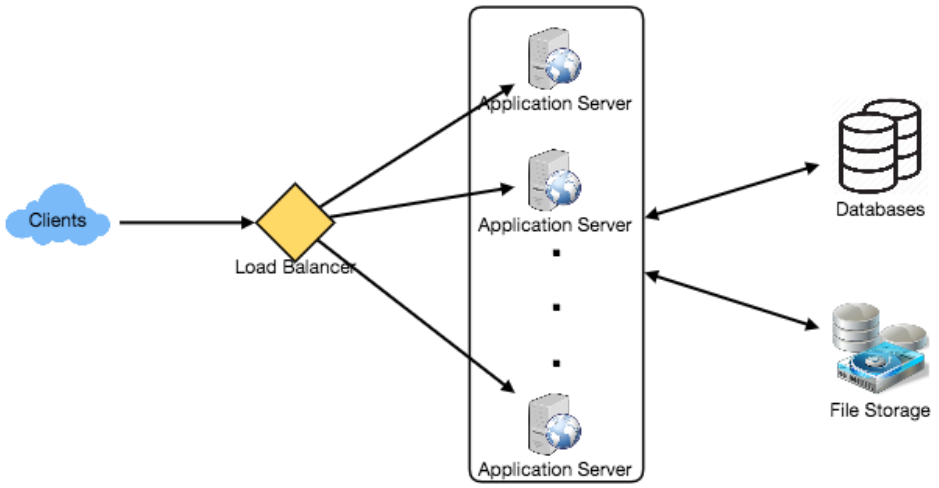
User: UserID, Name, Email, DoB, CreationData, LastLogin, etc.
Tweet: TweetID, Content, TweetLocation, NumberOfLikes, TimeStamp, etc.
UserFollowo: UserdID1, UserID2
FavoriteTweets: UserID, TweetID, TimeStamp

Which database system should we use? Will NoSQL like Cassandra best fit our needs, or should we use a MySQL-like solution? What kind of block storage should we use to store photos and videos?

Step 5: High-level design

Draw a block diagram with 5-6 boxes representing the core components of our system. We should identify enough components that are needed to solve the actual problem from end-to-end.

For Twitter, at a high-level, we will need multiple application servers to serve all the read/write requests with load balancers in front of them for traffic distributions. If we're assuming that we will have a lot more read traffic (as compared to write), we can decide to have separate servers for handling these scenarios. On the backend, we need an efficient database that can store all the tweets and can support a huge number of reads. We will also need a distributed file storage system for storing photos and videos.



Step 6: Detailed design

Dig deeper into two or three components; interviewer's feedback should always guide us what parts of the system need further discussion. We should be able to present different approaches, their pros and cons, and explain why we will prefer one approach on the other. Remember there is no single answer, the only important thing is to consider tradeoffs between different options while keeping system constraints in mind.

- Since we will be storing a massive amount of data, how should we partition our data to distribute it to multiple databases? Should we try to store all the data of a user on the same database? What issue could it cause?
- How will we handle hot users who tweet a lot or follow lots of people?
- Since users' timeline will contain the most recent (and relevant) tweets, should we try to store our data in such a way that is optimized for scanning the latest tweets?
- How much and at which layer should we introduce cache to speed things up?
- What components need better load balancing?

Step 7: Identifying and resolving bottlenecks

Try to discuss as many bottlenecks as possible and different approaches to mitigate them.

- Is there any single point of failure in our system? What are we doing to mitigate it?
- Do we have enough replicas of the data so that if we lose a few servers we can still serve our users?
- Similarly, do we have enough copies of different services running such that a few failures will not cause total system shutdown?
- How are we monitoring the performance of our service? Do we get alerts whenever critical components fail or their performance degrades?

Summary

In short, preparation and being organized during the interview are the keys to be successful in system design interviews. The above-mentioned steps should guide you to remain on track and cover all the different aspects while designing a system.

Let's apply the above guidelines to design a few systems that are asked in SDIs.

Designing a URL Shortening service like TinyURL

Let's design a URL shortening service like TinyURL. This service will provide short aliases redirecting to long URLs. Similar services: bit.ly, goo.gl, qlink.me, etc. Difficulty Level: Easy

1. Why do we need URL shortening?

URL shortening is used to create shorter aliases for long URLs. We call these shortened aliases "short links." Users are redirected to the original URL when they hit these short links. Short links save a lot of space when displayed, printed, messaged, or tweeted. Additionally, users are less likely to mistype shorter URLs.

For example, if we shorten this page through TinyURL:

https://www.educative.io/collection/page/5668639101419520/5649050225344512/5668600916475904/

We would get:

http://tinyurl.com/jlg8zpc

The shortened URL is nearly one-third the size of the actual URL.

URL shortening is used for optimizing links across devices, tracking individual links to analyze audience and campaign performance, and hiding affiliated original URLs.

If you haven't used tinyurl.com before, please try creating a new shortened URL and spend some time going through the various options their service offers. This will help you a lot in understanding this chapter.

2. Requirements and Goals of the System

You should always clarify requirements at the beginning of the interview. Be sure to ask questions to find the exact scope of the system that the interviewer has in mind.

Our URL shortening system should meet the following requirements:

Functional Requirements:

1. Given a URL, our service should generate a shorter and unique alias of it. This is called a short link. This link should be short enough to be easily copied and pasted into applications.
2. When users access a short link, our service should redirect them to the original link.
3. Users should optionally be able to pick a custom short link for their URL.
4. Links will expire after a standard default timespan. Users should be able to specify the expiration time.

Non-Functional Requirements:

1. The system should be highly available. This is required because, if our service is down, all the URL redirections will start failing.
2. URL redirection should happen in real-time with minimal latency.
3. Shortened links should not be guessable (not predictable).

Extended Requirements:

1. Analytics; e.g., how many times a redirection happened?
2. Our service should also be accessible through REST APIs by other services.

3. Capacity Estimation and Constraints

Our system will be read-heavy. There will be lots of redirection requests compared to new URL shortenings. Let's assume 100:1 ratio between read and write.

Traffic estimates: Assuming, we will have 500M new URL shortenings per month, with 100:1 read/write ratio, we can expect 50B redirections during the same period:

100 * 500M => 50B

What would be Queries Per Second (QPS) for our system? New URLs shortenings per second:

500 million / (30 days * 24 hours * 3600 seconds) = ~200 URLs/s

Considering 100:1 read/write ratio, URLs redirections per second will be:

100 * 200 URLs/s = 20K/s

Storage estimates: Let's assume we store every URL shortening request (and associated shortened link) for 5 years. Since we expect to have 500M new URLs every month, the total number of objects we expect to store will be 30 billion:

500 million * 5 years * 12 months = 30 billion

Let's assume that each stored object will be approximately 500 bytes (just a ballpark estimate–we will dig into it later). We will need 15TB of total storage:

30 billion * 500 bytes = 15 TB

Bandwidth estimates: For write requests, since we expect 200 new URLs every second, total incoming data for our service will be 100KB per second:

200 * 500 bytes = 100 KB/s

For read requests, since every second we expect ~20K URLs redirections, total outgoing data for our service would be 10MB per second:

20K * 500 bytes = ~10 MB/s

Memory estimates: If we want to cache some of the hot URLs that are frequently accessed, how much memory will we need to store them? If we follow the 80-20 rule, meaning 20% of URLs generate 80% of traffic, we would like to cache these 20% hot URLs.

Since we have 20K requests per second, we will be getting 1.7 billion requests per day:

20K * 3600 seconds * 24 hours = ~1.7 billion

To cache 20% of these requests, we will need 170GB of memory.

0.2 * 1.7 billion * 500 bytes = ~170GB

One thing to note here is that since there will be a lot of duplicate requests (of the same URL), therefore, our actual memory usage will be less than 170GB.

High level estimates: Assuming 500 million new URLs per month and 100:1 read:write ratio, following is the summary of the high level estimates for our service:

New URLs	200/s
URL redirections	20K/s
Incoming data	100KB/s
Outgoing data	10MB/s
Storage for 5 years	15TB
Memory for cache	170GB

4. System APIs

Once we've finalized the requirements, it's always a good idea to define the system APIs. This should explicitly state what is expected from the system.

We can have SOAP or REST APIs to expose the functionality of our service. Following could be the definitions of APIs for creating and deleting URLs:

```
createURL(api_dev_key, original_url, custom_alias=None, user_name=None, expire_date=None)
```

Parameters:
api_dev_key (string): The API developer key of a registered account. This will be used to, among other things, throttle users based on their allocated quota.
original_url (string): Original URL to be shortened.
custom_alias (string): Optional custom key for the URL.
user_name (string): Optional user name to be used in encoding.
expire_date (string): Optional expiration date for the shortened URL.

Returns: (string)
A successful insertion returns the shortened URL; otherwise, it returns an error code.

```
deleteURL(api_dev_key, url_key)
```

Where "url_key" is a string representing the shortened URL to be retrieved. A successful deletion returns 'URL Removed'.

How do we detect and prevent abuse? A malicious user can put us out of business by consuming all URL keys in the current design. To prevent abuse, we can limit users via their api_dev_key. Each api_dev_key can be limited to a certain number of URL creations and redirections per some time period (which may be set to a different duration per developer key).

5. Database Design

Defining the DB schema in the early stages of the interview would help to understand the data flow among various components and later would guide towards data partitioning.

A few observations about the nature of the data we will store:

1. We need to store billions of records.
2. Each object we store is small (less than 1K).
3. There are no relationships between records—other than storing which user created a URL.
4. Our service is read-heavy.

Database Schema:

We would need two tables: one for storing information about the URL mappings, and one for the user's data who created the short link.

URL	
PK	**Hash: varchar(16)**
	OriginalURL: varchar(512)
	CreationDate: datetime
	ExpirationDate: datatime
	UserID: int

User	
PK	**UserID: int**
	Name: varchar(20)
	Email: varchar(32)
	CreationDate: datetime
	LastLogin: datatime

What kind of database should we use? Since we anticipate storing billions of rows, and we don't need to use relationships between objects – a NoSQL key-value store like DynamoDB, Cassandra or Riak is a better choice. A NoSQL choice would also be easier to scale. Please see SQL vs NoSQL for more details.

6. Basic System Design and Algorithm

The problem we are solving here is, how to generate a short and unique key for a given URL.

In the TinyURL example in Section 1, the shortened URL is "http://tinyurl.com/jlg8zpc". The last six characters of this URL is the short key we want to generate. We'll explore two solutions here:

a. Encoding actual URL

We can compute a unique hash (e.g., MD5 or SHA256, etc.) of the given URL. The hash can then be encoded for displaying. This encoding could be base36 ([a-z ,0-9]) or base62 ([A-Z, a-z, 0-9]) and if we add '+' and '/' we can use base64 encoding. A reasonable question would be, what should be the length of the short key? 6, 8 or 10 characters.

Using base64 encoding, a 6 letter long key would result in 64^6 = ~68.7 billion possible strings
Using base64 encoding, an 8 letter long key would result in 64^8 = ~281 trillion possible strings

With 68.7B unique strings, let's assume six letter keys would suffice for our system.

If we use the MD5 algorithm as our hash function, it'll produce a 128-bit hash value. After base64 encoding, we'll get a string having more than 21 characters (since each base64 character encodes 6 bits of the hash value). Since we only have space for 8 characters per short key, how will we choose our key then? We can take the first 6 (or 8) letters for the key. This could result in key duplication though, upon which we can choose some other characters out of the encoding string or swap some characters.

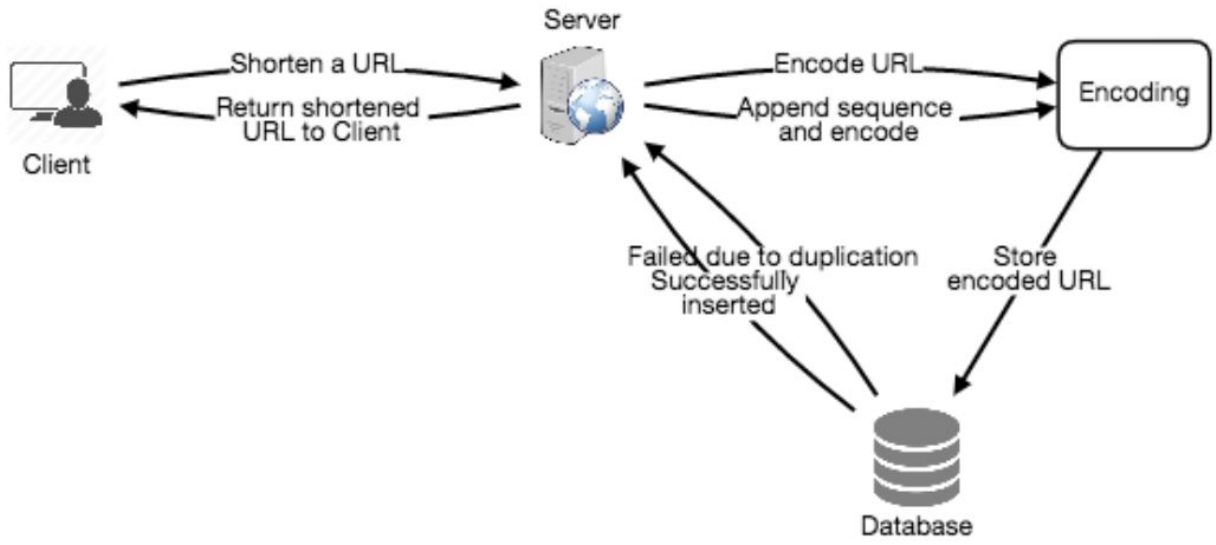
What are different issues with our solution? We have the following couple of problems with our encoding scheme:

1. If multiple users enter the same URL, they can get the same shortened URL, which is not acceptable.
2. What if parts of the URL are URL-encoded?
   e.g., http://www.educative.io/distributed.php?id=design,

and http://www.educative.io/distributed.php%3Fid%3Ddesign are identical except for the URL encoding.

Workaround for the issues: We can append an increasing sequence number to each input URL to make it unique, and then generate a hash of it. We don't need to store this sequence number in the databases, though. Possible problems with this approach could be an ever-increasing sequence number. Can it overflow? Appending an increasing sequence number will also impact the performance of the service.

Another solution could be to append user id (which should be unique) to the input URL. However, if the user has not signed in, we would have to ask the user to choose a uniqueness key. Even after this, if we have a conflict, we have to keep generating a key until we get a unique one.



Designing Pastebin

Let's design a Pastebin like web service, where users can store plain text. Users of the service will enter a piece of text and get a randomly generated URL to access it. Similar Services: pastebin.com, pasted.co, chopapp.com Difficulty Level: Easy

1. What is Pastebin?

Pastebin like services enable users to store plain text or images over the network (typically the Internet) and generate unique URLs to access the uploaded data. Such services are also used to share data over the network quickly, as users would just need to pass the URL to let other users see it.

If you haven't used pastebin.com before, please try creating a new 'Paste' there and spend some time going through the different options their service offers. This will help you a lot in understanding this chapter.

2. Requirements and Goals of the System

Our Pastebin service should meet the following requirements:

Functional Requirements:

1. Users should be able to upload or "paste" their data and get a unique URL to access it.
2. Users will only be able to upload text.
3. Data and links will expire after a specific timespan automatically; users should also be able to specify expiration time.
4. Users should optionally be able to pick a custom alias for their paste.

Non-Functional Requirements:

1. The system should be highly reliable, any data uploaded should not be lost.
2. The system should be highly available. This is required because if our service is down, users will not be able to access their Pastes.
3. Users should be able to access their Pastes in real-time with minimum latency.
4. Paste links should not be guessable (not predictable).

Extended Requirements:

1. Analytics, e.g., how many times a paste was accessed?
2. Our service should also be accessible through REST APIs by other services.

3. Some Design Considerations

Pastebin shares some requirements with URL Shortening service, but there are some additional design considerations we should keep in mind.

What should be the limit on the amount of text user can paste at a time? We can limit users not to have Pastes bigger than 10MB to stop the abuse of the service.

Should we impose size limits on custom URLs? Since our service supports custom URLs, users can pick any URL that they like, but providing a custom URL is not mandatory. However, it is reasonable (and often desirable) to impose a size limit on custom URLs, so that we have a consistent URL database.

4. Capacity Estimation and Constraints

Our services will be read-heavy; there will be more read requests compared to new Pastes creation. We can assume a 5:1 ratio between read and write.

Traffic estimates: Pastebin services are not expected to have traffic similar to Twitter or Facebook, let's assume here that we get one million new pastes added to our system every day. This leaves us with five million reads per day.

New Pastes per second:

1M / (24 hours * 3600 seconds) ~= 12 pastes/sec

Paste reads per second:

5M / (24 hours * 3600 seconds) ~= 58 reads/sec

Storage estimates: Users can upload maximum 10MB of data; commonly Pastebin like services are used to share source code, configs or logs. Such texts are not huge, so let's assume that each paste on average contains 10KB.

At this rate, we will be storing 10GB of data per day.

1M * 10KB => 10 GB/day

If we want to store this data for ten years we would need the total storage capacity of 36TB.

With 1M pastes every day we will have 3.6 billion Pastes in 10 years. We need to generate and store keys to uniquely identify these pastes. If we use base64 encoding ([A-Z, a-z, 0-9, ., -]) we would need six letters strings:

64^6 ~= 68.7 billion unique strings

If it takes one byte to store one character, total size required to store 3.6B keys would be:

3.6B * 6 => 22 GB

22GB is negligible compared to 36TB. To keep some margin, we will assume a 70% capacity model (meaning we don't want to use more than 70% of our total storage capacity at any point), which raises our storage needs to 51.4TB.

Bandwidth estimates: For write requests, we expect 12 new pastes per second, resulting in 120KB of ingress per second.

12 * 10KB => 120 KB/s

As for the read request, we expect 58 requests per second. Therefore, total data egress (sent to users) will be 0.6 MB/s.

58 * 10KB => 0.6 MB/s

Although total ingress and egress are not big, we should keep these numbers in mind while designing our service.

Memory estimates: We can cache some of the hot pastes that are frequently accessed. Following the 80-20 rule, meaning 20% of hot pastes generate 80% of traffic, we would like to cache these 20% pastes

Since we have 5M read requests per day, to cache 20% of these requests, we would need:

0.2 * 5M * 10KB ~= 10 GB

5. System APIs

We can have SOAP or REST APIs to expose the functionality of our service. Following could be the definitions of the APIs to create/retrieve/delete Pastes:

```
addPaste(api_dev_key, paste_data, custom_url=None user_name=None, paste_name=None, expire_date=None)
```

Parameters:
api_dev_key (string): The API developer key of a registered account. This will be used to, among other things, throttle users based on their allocated quota.
paste_data (string): Textual data of the paste.
custom_url (string): Optional custom URL.
user_name (string): Optional user name to be used to generate URL.
paste_name (string): Optional name of the paste
expire_date (string): Optional expiration date for the paste.

Returns: (string)
A successful insertion returns the URL through which the paste can be accessed, otherwise, it will return an error code.

Similarly, we can retrieve and delete Paste APIs:

```
getPaste(api_dev_key, api_paste_key)
```

Where "api_paste_key" is a string representing the Paste Key of the paste to be retrieved. This API will return the textual data of the paste.

```
deletePaste(api_dev_key, api_paste_key)
```

A successful deletion returns 'true', otherwise returns 'false'.

6. Database Design

A few observations about the nature of the data we are storing:

1. We need to store billions of records.
2. Each metadata object we are storing would be small (less than 1KB).
3. Each paste object we are storing can be of medium size (it can be a few MB).
4. There are no relationships between records, except if we want to store which user created what Paste.
5. Our service is read-heavy.

Database Schema:

We would need two tables, one for storing information about the Pastes and the other for users' data.

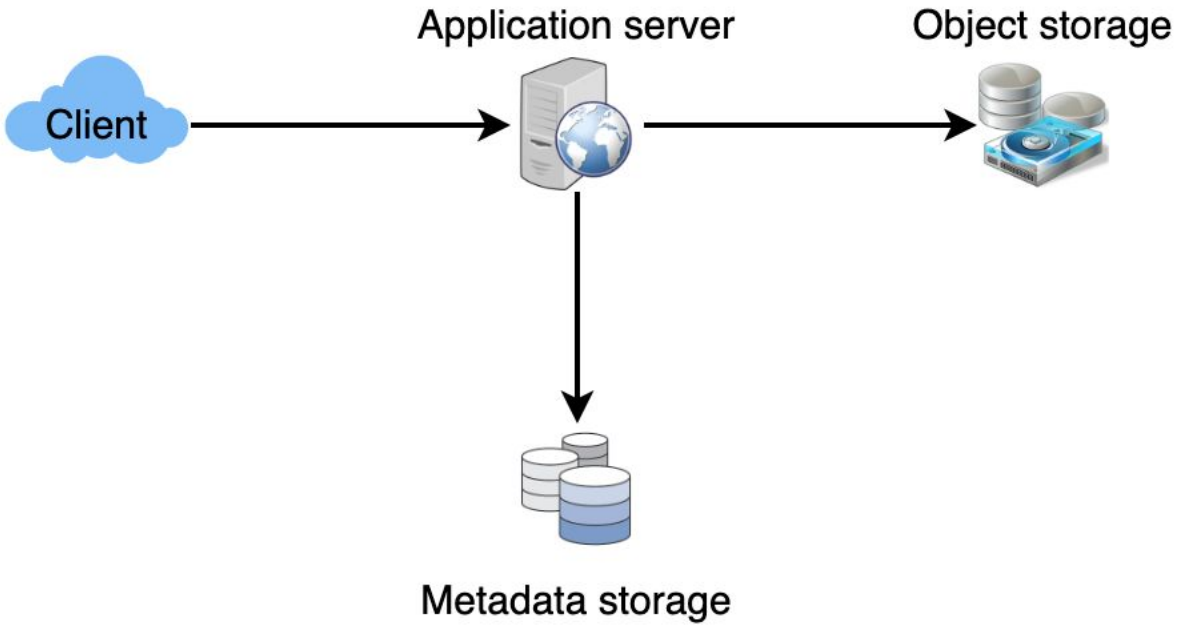
Paste	
PK	**URLHash: varchar(16)**
	ContentKey: varchar(512) ExpirationDate: datatime UserID: int CreationDate: datetime

User	
PK	**UserID: int**
	Name: varchar(20) Email: varchar(32) CreationDate: datetime LastLogin: datatime

Here, 'URlHash' is the URL equivalent of the TinyURL and 'ContentKey' is a reference to an external object storing the contents of the paste; we'll discuss the external storage of the paste contents later in the chapter.

7. High Level Design

At a high level, we need an application layer that will serve all the read and write requests. Application layer will talk to a storage layer to store and retrieve data. We can segregate our storage layer with one database storing metadata related to each paste, users, etc. while the other storing the paste contents in some object storage (like Amazon S3). This division of data will also allow us to scale them individually.



8. Component Design

a. Application layer

Our application layer will process all incoming and outgoing requests. The application servers will be talking to the backend data store components to serve the requests.

How to handle a write request? Upon receiving a write request, our application server will generate a six-letter random string, which would serve as the key of the paste (if the user has not provided a custom key). The application server will then store the contents of the paste and the generated key in the database. After the successful insertion, the server can return the key to the user. One possible problem here could be that the insertion fails because of a duplicate key. Since we are generating a random key, there is a possibility that the newly generated key could match an existing one. In that case, we should regenerate a new key and try again. We should keep retrying until we don't see failure due to the duplicate key. We should return an error to the user if the custom key they have provided is already present in our database.

Another solution of the above problem could be to run a standalone Key Generation Service (KGS) that generates random six letters strings beforehand and stores them in a database (let's call it key-DB). Whenever we want to store a

new paste, we will just take one of the already generated keys and use it. This approach will make things quite simple and fast since we will not be worrying about duplications or collisions. KGS will make sure all the keys inserted in key-DB are unique. KGS can use two tables to store keys, one for keys that are not used yet and one for all the used keys. As soon as KGS gives some keys to an application server, it can move these to the used keys table. KGS can always keep some keys in memory so that whenever a server needs them, it can quickly provide them. As soon as KGS loads some keys in memory, it can move them to the used keys table, this way we can make sure each server gets unique keys. If KGS dies before using all the keys loaded in memory, we will be wasting those keys. We can ignore these keys given that we have a huge number of them.

Isn't KGS a single point of failure? Yes, it is. To solve this, we can have a standby replica of KGS and whenever the primary server dies it can take over to generate and provide keys.

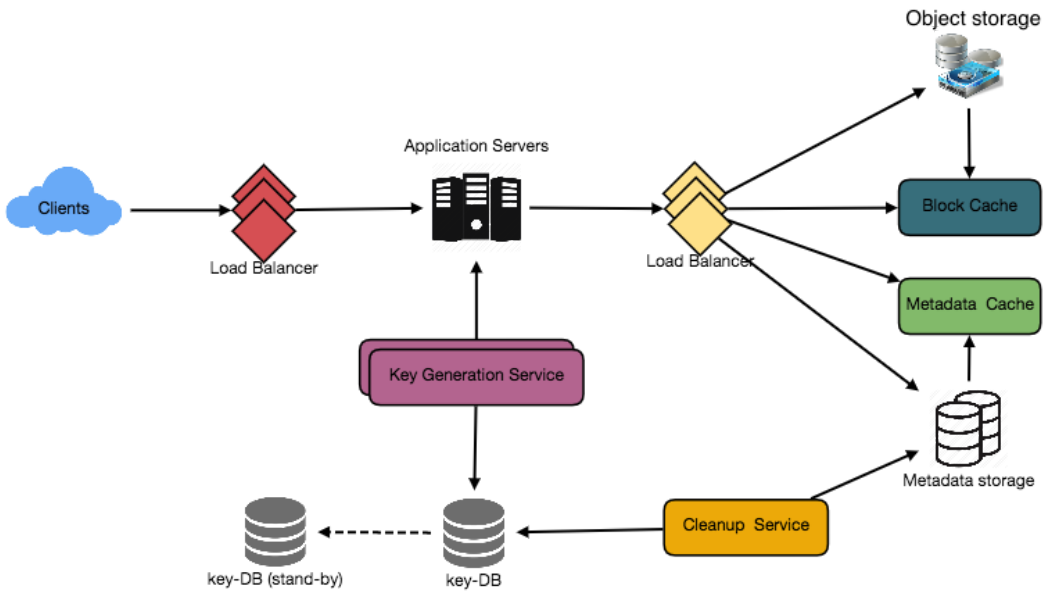
Can each app server cache some keys from key-DB? Yes, this can surely speed things up. Although in this case, if the application server dies before consuming all the keys, we will end up losing those keys. This could be acceptable since we have 68B unique six letters keys, which are a lot more than we require.

How does it handle a paste read request? Upon receiving a read paste request, the application service layer contacts the datastore. The datastore searches for the key, and if it is found, returns the paste's contents. Otherwise, an error code is returned.

b. Datastore layer

We can divide our datastore layer into two:

1. Metadata database: We can use a relational database like MySQL or a Distributed Key-Value store like Dynamo or Cassandra.
2. Object storage: We can store our contents in an Object Storage like Amazon's S3. Whenever we feel like hitting our full capacity on content storage, we can easily increase it by adding more servers.



Detailed component design for Pastebin

9. Purging or DB Cleanup

Please see Designing a URL Shortening service.

10. Data Partitioning and Replication

Please see Designing a URL Shortening service.

11. Cache and Load Balancer

Please see Designing a URL Shortening service.

12. Security and Permissions

Please see Designing a URL Shortening service.

Designing Instagram

Let's design a photo-sharing service like Instagram, where users can upload photos to share them with other users. Similar Services: Flickr, Picasa
Difficulty Level: Medium

1. What is Instagram?

Instagram is a social networking service which enables its users to upload and share their photos and videos with other users. Instagram users can choose to share information either publicly or privately. Anything shared publicly can be seen by any other user, whereas privately shared content can only be accessed by a specified set of people. Instagram also enables its users to share through many other social networking platforms, such as Facebook, Twitter, Flickr, and Tumblr.

For the sake of this exercise, we plan to design a simpler version of Instagram, where a user can share photos and can also follow other users. The 'News Feed' for each user will consist of top photos of all the people the user follows.

2. Requirements and Goals of the System

We'll focus on the following set of requirements while designing the Instagram:

Functional Requirements

1. Users should be able to upload/download/view photos.
2. Users can perform searches based on photo/video titles.
3. Users can follow other users.
4. The system should be able to generate and display a user's News Feed consisting of top photos from all the people the user follows.

Non-functional Requirements

1. Our service needs to be highly available.
2. The acceptable latency of the system is 200ms for News Feed generation.
3. Consistency can take a hit (in the interest of availability), if a user doesn't see a photo for a while; it should be fine.
4. The system should be highly reliable; any uploaded photo or video should never be lost.

Not in scope: Adding tags to photos, searching photos on tags, commenting on photos, tagging users to photos, who to follow, etc.

3. Some Design Considerations

The system would be read-heavy, so we will focus on building a system that can retrieve photos quickly.

1. Practically, users can upload as many photos as they like. Efficient management of storage should be a crucial factor while designing this system.
2. Low latency is expected while viewing photos.
3. Data should be 100% reliable. If a user uploads a photo, the system will guarantee that it will never be lost.

4. Capacity Estimation and Constraints

- Let's assume we have 500M total users, with 1M daily active users.
- 2M new photos every day, 23 new photos every second.
- Average photo file size => 200KB
- Total space required for 1 day of photos

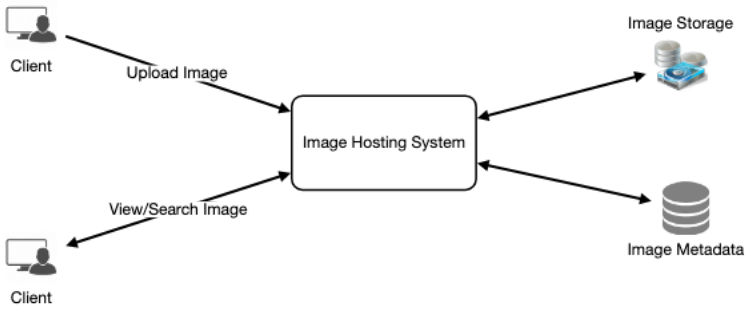
2M * 200KB => 400 GB

- Total space required for 10 years:

400GB * 365 (days a year) * 10 (years) ~= 1425TB

5. High Level System Design

At a high-level, we need to support two scenarios, one to upload photos and the other to view/search photos. Our service would need some object storage servers to store photos and also some database servers to store metadata information about the photos.



6. Database Schema

Defining the DB schema in the early stages of the interview would help to understand the data flow among various components and later would guide towards data partitioning.

We need to store data about users, their uploaded photos, and people they follow. Photo table will store all data related to a photo; we need to have an index on (PhotoID, CreationDate) since we need to fetch recent photos first.

Photo	
PK	**PhotoID: int**
	UserID: int
	PhotoPath: varchar(256)
	PhotoLatitude: int
	PhotoLongitude: int
	UserLatitude: int
	UserLongitude: int
	CreationDate: datetime

User	
PK	**UserID: int**
	Name: varchar(20)
	Email: varchar(32)
	DateOfBirth: datetime
	CreationDate: datetime
	LastLogin: datatime

UserFollow	
PK	**UserID1: int** **UserID2: int**

A straightforward approach for storing the above schema would be to use an RDBMS like MySQL since we require joins. But relational databases come with their challenges, especially when we need to scale them. For details, please take a look at SQL vs. NoSQL.

We can store photos in a distributed file storage like HDFS or S3.

We can store the above schema in a distributed key-value store to enjoy the benefits offered by NoSQL. All the metadata related to photos can go to a table where the 'key' would be the 'PhotoID' and the 'value' would be an object containing PhotoLocation, UserLocation, CreationTimestamp, etc.

We need to store relationships between users and photos, to know who owns which photo. We also need to store the list of people a user follows. For both of these tables, we can use a wide-column datastore like Cassandra. For the 'UserPhoto' table, the 'key' would be 'UserID' and the 'value' would be the list of

'PhotoIDs' the user owns, stored in different columns. We will have a similar scheme for the 'UserFollow' table.

Cassandra or key-value stores in general, always maintain a certain number of replicas to offer reliability. Also, in such data stores, deletes don't get applied instantly, data is retained for certain days (to support undeleting) before getting removed from the system permanently.

7. Data Size Estimation

Let's estimate how much data will be going into each table and how much total storage we will need for 10 years.

User: Assuming each "int" and "dateTime" is four bytes, each row in the User's table will be of 68 bytes:

UserID (4 bytes) + Name (20 bytes) + Email (32 bytes) + DateOfBirth (4 bytes) + CreationDate (4 bytes) + LastLogin (4 bytes) = 68 bytes

If we have 500 million users, we will need 32GB of total storage.

500 million * 68 ~= 32GB

Photo: Each row in Photo's table will be of 284 bytes:

PhotoID (4 bytes) + UserID (4 bytes) + PhotoPath (256 bytes) + PhotoLatitude (4 bytes) + PhotLongitude(4 bytes) + UserLatitude (4 bytes) + UserLongitude (4 bytes) + CreationDate (4 bytes) = 284 bytes

If 2M new photos get uploaded every day, we will need 0.5GB of storage for one day:

2M * 284 bytes ~= 0.5GB per day

For 10 years we will need 1.88TB of storage.

UserFollow: Each row in the UserFollow table will consist of 8 bytes. If we have 500 million users and on average each user follows 500 users. We would need 1.82TB of storage for the UserFollow table:

500 million users * 500 followers * 8 bytes ~= 1.82TB

Total space required for all tables for 10 years will be 3.7TB:

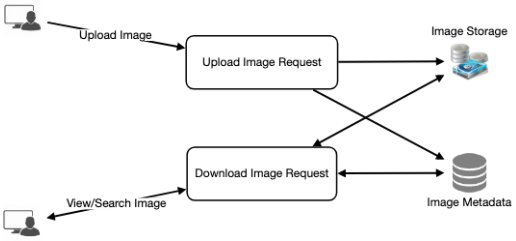
32GB + 1.88TB + 1.82TB ~= 3.7TB

8. Component Design

Photo uploads (or writes) can be slow as they have to go to the disk, whereas reads will be faster, especially if they are being served from cache.

Uploading users can consume all the available connections, as uploading is a slow process. This means that 'reads' cannot be served if the system gets busy with all the write requests. We should keep in mind that web servers have a connection limit before designing our system. If we assume that a web server can have a maximum of 500 connections at any time, then it can't have more than 500 concurrent uploads or reads. To handle this bottleneck we can split reads and writes into separate services. We will have dedicated servers for reads and different servers for writes to ensure that uploads don't hog the system.

Separating photos' read and write requests will also allow us to scale and optimize each of these operations independently.



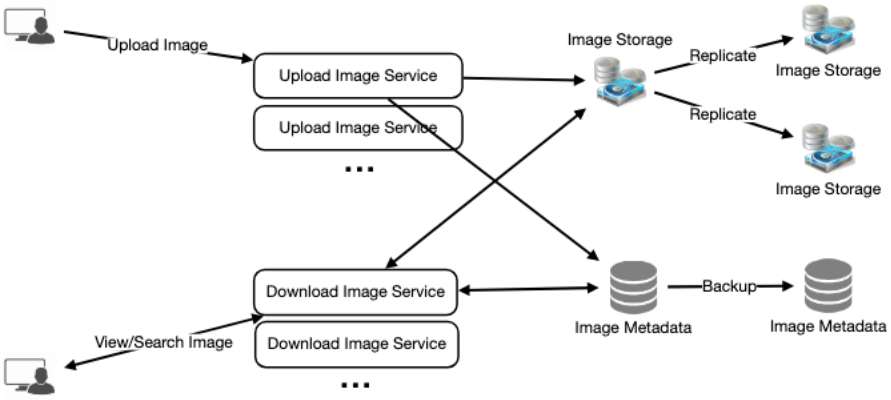
9. Reliability and Redundancy

Losing files is not an option for our service. Therefore, we will store multiple copies of each file so that if one storage server dies we can retrieve the photo from the other copy present on a different storage server.

This same principle also applies to other components of the system. If we want to have high availability of the system, we need to have multiple replicas of services running in the system, so that if a few services die down the system still remains available and running. Redundancy removes the single point of failure in the system.

If only one instance of a service is required to run at any point, we can run a redundant secondary copy of the service that is not serving any traffic, but it can take control after the failover when primary has a problem.

Creating redundancy in a system can remove single points of failure and provide a backup or spare functionality if needed in a crisis. For example, if there are two instances of the same service running in production and one fails or degrades, the system can failover to the healthy copy. Failover can happen automatically or require manual intervention.



10. Data Sharding

Let's discuss different schemes for metadata sharding:

a. Partitioning based on UserID Let's assume we shard based on the 'UserID' so that we can keep all photos of a user on the same shard. If one DB shard is 1TB, we will need four shards to store 3.7TB of data. Let's assume for better performance and scalability we keep 10 shards.

So we'll find the shard number by UserID % 10 and then store the data there. To uniquely identify any photo in our system, we can append shard number with each PhotoID.

How can we generate PhotoIDs? Each DB shard can have its own auto-increment sequence for PhotoIDs and since we will append ShardID with each PhotoID, it will make it unique throughout our system.

What are the different issues with this partitioning scheme?

1. How would we handle hot users? Several people follow such hot users and a lot of other people see any photos they upload.

2. Some users will have a lot of photos compared to others, thus making a non-uniform distribution of storage.
3. What if we cannot store all pictures of a user on one shard? If we distribute photos of a user onto multiple shards will it cause higher latencies?
4. Storing all photos of a user on one shard can cause issues like unavailability of all of the user's data if that shard is down or higher latency if it is serving high load etc.

b. Partitioning based on PhotoID If we can generate unique PhotoIDs first and then find a shard number through "PhotoID % 10", the above problems will have been solved. We would not need to append ShardID with PhotoID in this case as PhotoID will itself be unique throughout the system.

How can we generate PhotoIDs? Here we cannot have an auto-incrementing sequence in each shard to define PhotoID because we need to know PhotoID first to find the shard where it will be stored. One solution could be that we dedicate a separate database instance to generate auto-incrementing IDs. If our PhotoID can fit into 64 bits, we can define a table containing only a 64 bit ID field. So whenever we would like to add a photo in our system, we can insert a new row in this table and take that ID to be our PhotoID of the new photo.

Wouldn't this key generating DB be a single point of failure? Yes, it would be. A workaround for that could be defining two such databases with one generating even numbered IDs and the other odd numbered. For MySQL, the following script can define such sequences:

```
KeyGeneratingServer1:
auto-increment-increment = 2
auto-increment-offset = 1

KeyGeneratingServer2:
auto-increment-increment = 2
auto-increment-offset = 2
```

We can put a load balancer in front of both of these databases to round robin between them and to deal with downtime. Both these servers could be out of sync with one generating more keys than the other, but this will not cause any issue in our system. We can extend this design by defining separate ID tables for Users, Photo-Comments, or other objects present in our system.

Alternately, we can implement a 'key' generation scheme similar to what we have discussed in Designing a URL Shortening service like TinyURL.

How can we plan for the future growth of our system? We can have a large number of logical partitions to accommodate future data growth, such that in the beginning, multiple logical partitions reside on a single physical database server. Since each database server can have multiple database instances on it, we can have separate databases for each logical partition on any server. So whenever we feel that a particular database server has a lot of data, we can migrate some logical partitions from it to another server. We can maintain a config file (or a separate database) that can map our logical partitions to database servers; this will enable us to move partitions around easily. Whenever we want to move a partition, we only have to update the config file to announce the change.

11. Ranking and News Feed Generation

To create the News Feed for any given user, we need to fetch the latest, most popular and relevant photos of the people the user follows.

For simplicity, let's assume we need to fetch top 100 photos for a user's News Feed. Our application server will first get a list of people the user follows and then fetch metadata info of latest 100 photos from each user. In the final step, the server will submit all these photos to our ranking algorithm which will determine the top 100 photos (based on recency, likeness, etc.) and return them to the user. A possible problem with this approach would be higher latency as we have to query multiple tables and perform sorting/merging/ranking on the results. To improve the efficiency, we can pre-generate the News Feed and store it in a separate table.

Pre-generating the News Feed: We can have dedicated servers that are continuously generating users' News Feeds and storing them in a 'UserNewsFeed' table. So whenever any user needs the latest photos for their News Feed, we will simply query this table and return the results to the user.

Whenever these servers need to generate the News Feed of a user, they will first query the UserNewsFeed table to find the last time the News Feed was generated for that user. Then, new News Feed data will be generated from that time onwards (following the steps mentioned above).

What are the different approaches for sending News Feed contents to the users?

1. Pull: Clients can pull the News Feed contents from the server on a regular basis or manually whenever they need it. Possible problems with this approach

are a) New data might not be shown to the users until clients issue a pull request b) Most of the time pull requests will result in an empty response if there is no new data.

2. Push: Servers can push new data to the users as soon as it is available. To efficiently manage this, users have to maintain a Long Poll request with the server for receiving the updates. A possible problem with this approach is, a user who follows a lot of people or a celebrity user who has millions of followers; in this case, the server has to push updates quite frequently.

3. Hybrid: We can adopt a hybrid approach. We can move all the users who have a high number of follows to a pull-based model and only push data to those users who have a few hundred (or thousand) follows. Another approach could be that the server pushes updates to all the users not more than a certain frequency, letting users with a lot of follows/updates to regularly pull data.

For a detailed discussion about News Feed generation, take a look at Designing Facebook's Newsfeed.

12. News Feed Creation with Sharded Data

One of the most important requirements to create the News Feed for any given user is to fetch the latest photos from all people the user follows. For this, we need to have a mechanism to sort photos on their time of creation. To efficiently do this, we can make photo creation time part of the PhotoID. As we will have a primary index on PhotoID, it will be quite quick to find the latest PhotoIDs.

We can use epoch time for this. Let's say our PhotoID will have two parts; the first part will be representing epoch time and the second part will be an auto-incrementing sequence. So to make a new PhotoID, we can take the current epoch time and append an auto-incrementing ID from our key-generating DB. We can figure out shard number from this PhotoID (PhotoID % 10) and store the photo there.

What could be the size of our PhotoID? Let's say our epoch time starts today, how many bits we would need to store the number of seconds for next 50 years?

86400 sec/day * 365 (days a year) * 50 (years) => 1.6 billion seconds

We would need 31 bits to store this number. Since on the average, we are expecting 23 new photos per second; we can allocate 9 bits to store auto

incremented sequence. So every second we can store (2^9 => 512) new photos. We can reset our auto incrementing sequence every second.

We will discuss more details about this technique under 'Data Sharding' in Designing Twitter.

13. Cache and Load balancing

Our service would need a massive-scale photo delivery system to serve the globally distributed users. Our service should push its content closer to the user using a large number of geographically distributed photo cache servers and use CDNs (for details see Caching).

We can introduce a cache for metadata servers to cache hot database rows. We can use Memcache to cache the data and Application servers before hitting database can quickly check if the cache has desired rows. Least Recently Used (LRU) can be a reasonable cache eviction policy for our system. Under this policy, we discard the least recently viewed row first.

How can we build more intelligent cache? If we go with 80-20 rule, i.e., 20% of daily read volume for photos is generating 80% of traffic which means that certain photos are so popular that the majority of people read them. This dictates that we can try caching 20% of daily read volume of photos and metadata.

Designing Dropbox

Let's design a file hosting service like Dropbox or Google Drive. Cloud file storage enables users to store their data on remote servers. Usually, these servers are maintained by cloud storage providers and made available to users over a network (typically through the Internet). Users pay for their cloud data storage on a monthly basis.

Similar Services: OneDrive, Google Drive

Difficulty Level: Medium

1. Why Cloud Storage?

Cloud file storage services have become very popular recently as they simplify the storage and exchange of digital resources among multiple devices. The shift from using single personal computers to using multiple devices with different platforms and operating systems such as smartphones and tablets each with portable access from various geographical locations at any time, is believed to be accountable for the huge popularity of cloud storage services. Following are some of the top benefits of such services:

Availability: The motto座右銘 of cloud storage services is to have data availability anywhere, anytime. Users can access their files/photos from any device whenever and wherever they like.

Reliability and Durability: Another benefit of cloud storage is that it offers 100% reliability and durability of data. Cloud storage ensures that users will never lose their data by keeping multiple copies of the data stored on different geographically located servers.

Scalability: Users will never have to worry about getting out of storage space. With cloud storage you have unlimited storage as long as you are ready to pay for it.

If you haven't used dropbox.com before, we would highly recommend creating an account there and uploading/editing a file and also going through the different options their service offers. This will help you a lot in understanding this chapter.

2. Requirements and Goals of the System

You should always clarify requirements at the beginning of the interview. Be sure to ask questions to find the exact scope of the system that the interviewer has in mind.

What do we wish to achieve from a Cloud Storage system? Here are the top-level requirements for our system:

1. Users should be able to upload and download their files/photos from any device.
2. Users should be able to share files or folders with other users.
3. Our service should support automatic synchronization between devices, i.e., after updating a file on one device, it should get synchronized on all devices.
4. The system should support storing large files up to a GB.
5. ACID-ity is required. Atomicity, Consistency, Isolation and Durability of all file operations should be guaranteed.
6. Our system should support offline editing. Users should be able to add/delete/modify files while offline, and as soon as they come online, all their changes should be synced to the remote servers and other online devices.

Extended Requirements

- The system should support snapshotting of the data, so that users can go back to any version of the files.

3. Some Design Considerations

- We should expect huge read and write volumes.
- Read to write ratio is expected to be nearly the same.
- Internally, files can be stored in small parts or chunks (say 4MB); this can provide a lot of benefits i.e. all failed operations shall only be retried for smaller parts of a file. If a user fails to upload a file, then only the failing chunk will be retried.

- We can reduce the amount of data exchange by transferring updated chunks only.
- By removing duplicate chunks, we can save storage space and bandwidth usage.
- Keeping a local copy of the metadata (file name, size, etc.) with the client can save us a lot of round trips to the server.
- For small changes, clients can intelligently upload the diffs instead of the whole chunk.

4. Capacity Estimation and Constraints

- Let's assume that we have 500M total users, and 100M daily active users (DAU).
- Let's assume that on average each user connects from 3 different devices.
- On average if a user has 200 files/photos, we will have 100 billion total files.
- Let's assume that average file size is 100KB, this would give us ten petabytes of total storage.

100B * 100KB => 10PB

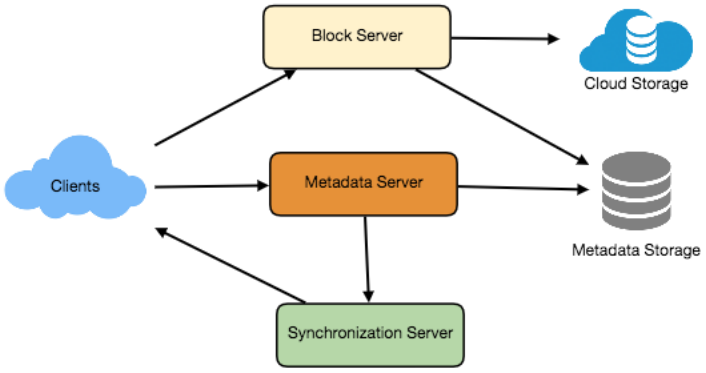
- Let's also assume that we will have 1M active connections per minute.

5. High Level Design

The user will specify a folder as the workspace on their device. Any file/photo/folder placed in this folder will be uploaded to the cloud, and whenever a file is modified or deleted, it will be reflected in the same way in the cloud storage. The user can specify similar workspaces on all their devices and any modification done on one device will be propagated to all other devices to have the same view of the workspace everywhere.

At a high level, we need to store files and their metadata information like File Name, File Size, Directory, etc., and who this file is shared with. So, we need some servers (Block Server) that can help the clients to upload/download files to Cloud Storage and some servers (Metadata Server) that can facilitate updating metadata about files and users. We also need some mechanism (Synchronization Server) to notify all clients whenever an update happens so they can synchronize their files.

As shown in the diagram below, Block servers will work with the clients to upload/download files from cloud storage and Metadata servers will keep metadata of files updated in a SQL or NoSQL database. Synchronization servers will handle the workflow of notifying all clients about different changes for synchronization.



6. Component Design

Let's go through the major components of our system one by one:

a. Client

The Client Application monitors the workspace folder on the user's machine and syncs all files/folders in it with the remote Cloud Storage. The client application will work with the storage servers to upload, download, and modify actual files to backend Cloud Storage. The client also interacts with the remote Synchronization Service to handle any file metadata updates, e.g., change in the file name, size, modification date, etc.

Here are some of the essential operations for the client:

1. Upload and download files.
2. Detect file changes in the workspace folder.
3. Handle conflict due to offline or concurrent updates.

How do we handle file transfer efficiently? As mentioned above, we can break each file into smaller chunks so that we transfer only those chunks that are modified and not the whole file. Let's say we divide each file into fixed sizes of

4MB chunks. We can statically calculate what could be an optimal chunk size based on

1) Storage devices we use in the cloud to optimize space utilization and input/output operations per second (IOPS)

2) Network bandwidth

3) Average file size in the storage etc. In our metadata, we should also keep a record of each file and the chunks that constitute it.

Should we keep a copy of metadata with Client? Keeping a local copy of metadata not only enable us to do offline updates but also saves a lot of round trips to update remote metadata.

How can clients efficiently listen to changes happening with other clients? One solution could be that the clients periodically check with the server if there are any changes. The problem with this approach is that we will have a delay in reflecting changes locally as clients will be checking for changes periodically compared to a server notifying whenever there is some change. If the client frequently checks the server for changes, it will not only be wasting bandwidth, as the server has to return an empty response most of the time, but it will also be keeping the server busy. Pulling information in this manner is not scalable.

A solution to the above problem could be to use HTTP long polling. With long polling the client requests information from the server with the expectation that the server may not respond immediately. If the server has no new data for the client when the poll is received, instead of sending an empty response, the server holds the request open and waits for response information to become available. Once it does have new information, the server immediately sends an HTTP/S response to the client, completing the open HTTP/S Request. Upon receipt of the server response, the client can immediately issue another server request for future updates.

Based on the above considerations, we can divide our client into following four parts:

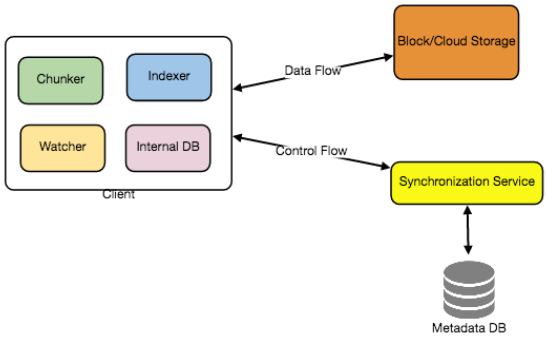
I. Internal Metadata Database will keep track of all the files, chunks, their versions, and their location in the file system.

II. Chunker will split the files into smaller pieces called chunks. It will also be responsible for reconstructing a file from its chunks. Our chunking algorithm will detect the parts of the files that have been modified by the user and only

transfer those parts to the Cloud Storage; this will save us bandwidth and synchronization time.

III. Watcher will monitor the local workspace folders and notify the Indexer (discussed below) of any action performed by the users, e.g. when users create, delete, or update files or folders. Watcher also listens to any changes happening on other clients that are broadcasted by Synchronization service.

IV. Indexer will process the events received from the Watcher and update the internal metadata database with information about the chunks of the modified files. Once the chunks are successfully submitted/downloaded to the Cloud Storage, the Indexer will communicate with the remote Synchronization Service to broadcast changes to other clients and update remote metadata database.



How should clients handle slow servers? Clients should exponentially back-off if the server is busy/not-responding. Meaning, if a server is too slow to respond, clients should delay their retries and this delay should increase exponentially.

Should mobile clients sync remote changes immediately? Unlike desktop or web clients, mobile clients usually sync on demand to save user's bandwidth and space.

b. Metadata Database

The Metadata Database is responsible for maintaining the versioning and metadata information about files/chunks, users, and workspaces. The Metadata Database can be a relational database such as MySQL, or a NoSQL database service such as DynamoDB. Regardless of the type of the database, the Synchronization Service should be able to provide a consistent view of the files using a database, especially if more than one user is working with the same file simultaneously. Since NoSQL data stores do not support ACID properties in favor of scalability and performance, we need to incorporate the support for

ACID properties programmatically in the logic of our Synchronization Service in case we opt for this kind of database. However, using a relational database can simplify the implementation of the Synchronization Service as they natively support ACID properties.

The metadata Database should be storing information about following objects:

1. Chunks
2. Files
3. User
4. Devices
5. Workspace (sync folders)

c. Synchronization Service

The Synchronization Service is the component that processes file updates made by a client and applies these changes to other subscribed clients. It also synchronizes clients' local databases with the information stored in the remote Metadata DB. The Synchronization Service is the most important part of the system architecture due to its critical role in managing the metadata and synchronizing users' files. Desktop clients communicate with the Synchronization Service to either obtain updates from the Cloud Storage or send files and updates to the Cloud Storage and, potentially, other users. If a client was offline for a period, it polls the system for new updates as soon as they come online. When the Synchronization Service receives an update request, it checks with the Metadata Database for consistency and then proceeds with the update. Subsequently, a notification is sent to all subscribed users or devices to report the file update.

The Synchronization Service should be designed in such a way that it transmits less data between clients and the Cloud Storage to achieve a better response time. To meet this design goal, the Synchronization Service can employ a differencing algorithm to reduce the amount of the data that needs to be synchronized. Instead of transmitting entire files from clients to the server or vice versa, we can just transmit the difference between two versions of a file. Therefore, only the part of the file that has been changed is transmitted. This also decreases bandwidth consumption and cloud data storage for the end user. As described above, we will be dividing our files into 4MB chunks and will be transferring modified chunks only. Server and clients can calculate a hash (e.g., SHA-256) to see whether to update the local copy of a chunk or not. On the server, if we already have a chunk with a similar hash (even from another user),

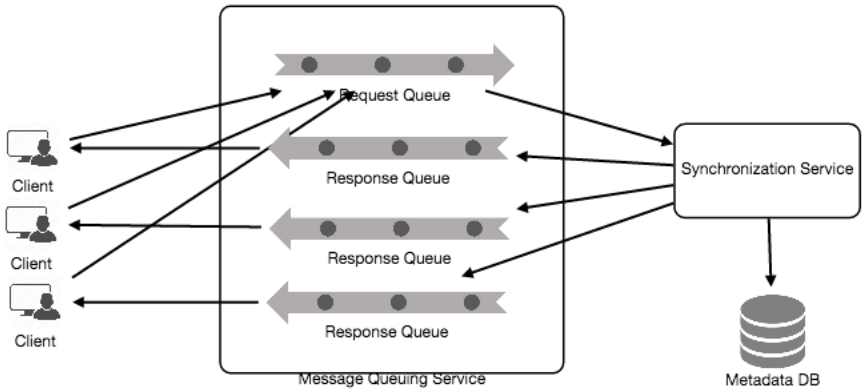
we don't need to create another copy, we can use the same chunk. This is discussed in detail later under Data Deduplication.

To be able to provide an efficient and scalable synchronization protocol we can consider using a communication middleware between clients and the Synchronization Service. The messaging middleware should provide scalable message queuing and change notifications to support a high number of clients using pull or push strategies. This way, multiple Synchronization Service instances can receive requests from a global request Queue, and the communication middleware will be able to balance its load.

d. Message Queuing Service

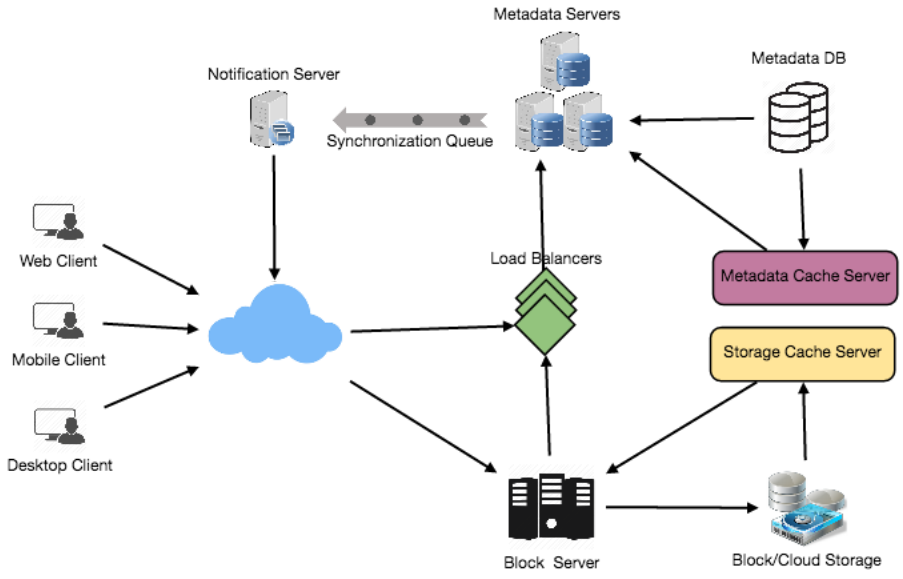
An important part of our architecture is a messaging middleware that should be able to handle a substantial number of requests. A scalable Message Queuing Service that supports asynchronous message-based communication between clients and the Synchronization Service best fits the requirements of our application. The Message Queuing Service supports asynchronous and loosely coupled message-based communication between distributed components of the system. The Message Queuing Service should be able to efficiently store any number of messages in a highly available, reliable and scalable queue.

The Message Queuing Service will implement two types of queues in our system. The Request Queue is a global queue and all clients will share it. Clients' requests to update the Metadata Database will be sent to the Request Queue first, from there the Synchronization Service will take it to update metadata. The Response Queues that correspond to individual subscribed clients are responsible for delivering the update messages to each client. Since a message will be deleted from the queue once received by a client, we need to create separate Response Queues for each subscribed client to share update messages.



e. Cloud/Block Storage

Cloud/Block Storage stores chunks of files uploaded by the users. Clients directly interact with the storage to send and receive objects from it. Separation of the metadata from storage enables us to use any storage either in the cloud or in-house.



7. File Processing Workflow

The sequence below shows the interaction between the components of the application in a scenario when Client A updates a file that is shared with Client B

and C, so they should receive the update too. If the other clients are not online at the time of the update, the Message Queuing Service keeps the update notifications in separate response queues for them until they come online later.

1. Client A uploads chunks to cloud storage.
2. Client A updates metadata and commits changes.
3. Client A gets confirmation and notifications are sent to Clients B and C about the changes.
4. Client B and C receive metadata changes and download updated chunks.

8. Data Deduplication

Data deduplication is a technique used for eliminating duplicate copies of data to improve storage utilization. It can also be applied to network data transfers to reduce the number of bytes that must be sent. For each new incoming chunk, we can calculate a hash of it and compare that hash with all the hashes of the existing chunks to see if we already have the same chunk present in our storage.

We can implement deduplication in two ways in our system:

a. Post-process deduplication
With post-process deduplication, new chunks are first stored on the storage device and later some process analyzes the data looking for duplication. The benefit is that clients will not need to wait for the hash calculation or lookup to complete before storing the data, thereby ensuring that there is no degradation in storage performance. Drawbacks of this approach are

1) We will unnecessarily be storing duplicate data, though for a short time,

2) Duplicate data will be transferred consuming bandwidth.

b. In-line deduplication
Alternatively, deduplication hash calculations can be done in real-time as the clients are entering data on their device. If our system identifies a chunk that it has already stored, only a reference to the existing chunk will be added in the metadata, rather than a full copy of the chunk. This approach will give us optimal network and storage usage.

9. Metadata Partitioning

To scale out metadata DB, we need to partition it so that it can store information about millions of users and billions of files/chunks. We need to come up with a partitioning scheme that would divide and store our data in different DB servers.

1. Vertical Partitioning: We can partition our database in such a way that we store tables related to one particular feature on one server. For example, we can store all the user related tables in one database and all files/chunks related tables in another database. Although this approach is straightforward to implement it has some issues:

1. Will we still have scale issues? What if we have trillions of chunks to be stored and our database cannot support storing such a huge number of records? How would we further partition such tables?
2. Joining two tables in two separate databases can cause performance and consistency issues. How frequently do we have to join user and file tables?

2. Range Based Partitioning: What if we store files/chunks in separate partitions based on the first letter of the File Path? In that case, we save all the files starting with the letter 'A' in one partition and those that start with the letter 'B' into another partition and so on. This approach is called range based partitioning. We can even combine certain less frequently occurring letters into one database partition. We should come up with this partitioning scheme statically so that we can always store/find a file in a predictable manner.

The main problem with this approach is that it can lead to unbalanced servers. For example, if we decide to put all files starting with the letter 'E' into a DB partition, and later we realize that we have too many files that start with the letter 'E', to such an extent that we cannot fit them into one DB partition.

3. Hash-Based Partitioning: In this scheme we take a hash of the object we are storing and based on this hash we figure out the DB partition to which this object should go. In our case, we can take the hash of the 'FileID' of the File object we are storing to determine the partition the file will be stored. Our hashing function will randomly distribute objects into different partitions, e.g., our hashing function can always map any ID to a number between [1…256], and this number would be the partition we will store our object.

This approach can still lead to overloaded partitions, which can be solved by using Consistent Hashing.

10. Caching

We can have two kinds of caches in our system. To deal with hot files/chunks we can introduce a cache for Block storage. We can use an off-the-shelf solution like Memcached that can store whole chunks with its respective IDs/Hashes and Block servers before hitting Block storage can quickly check if the cache has desired chunk. Based on clients' usage pattern we can determine how many cache servers we need. A high-end commercial server can have 144GB of memory; one such server can cache 36K chunks.

Which cache replacement policy would best fit our needs? When the cache is full, and we want to replace a chunk with a newer/hotter chunk, how would we choose? Least Recently Used (LRU) can be a reasonable policy for our system. Under this policy, we discard the least recently used chunk first. Load Similarly, we can have a cache for Metadata DB.

11. Load Balancer (LB)

We can add the Load balancing layer at two places in our system:

1) Between Clients and Block servers and

2) Between Clients and Metadata servers.

Initially, a simple Round Robin approach can be adopted that distributes incoming requests equally among backend servers. This LB is simple to implement and does not introduce any overhead. Another benefit of this approach is if a server is dead, LB will take it out of the rotation and will stop sending any traffic to it. A problem with Round Robin LB is, it won't take server load into consideration. If a server is overloaded or slow, the LB will not stop sending new requests to that server. To handle this, a more intelligent LB solution can be placed that periodically queries backend server about their load and adjusts traffic based on that.

12. Security, Permissions and File Sharing

One of the primary concerns users will have while storing their files in the cloud is the privacy and security of their data, especially since in our system users can share their files with other users or even make them public to share it with

everyone. To handle this, we will be storing the permissions of each file in our metadata DB to reflect what files are visible or modifiable by any user.

Designing Facebook Messenger

Let's design an instant messaging service like Facebook Messenger where users can send text messages to each other through web and mobile interfaces.

1. What is Facebook Messenger?

Facebook Messenger is a software application which provides text-based instant messaging services to its users. Messenger users can chat with their Facebook friends both from cell-phones and Facebook's website.

2. Requirements and Goals of the System

Our Messenger should meet the following requirements:

Functional Requirements:

1. Messenger should support one-on-one conversations between users.
2. Messenger should keep track of the online/offline statuses of its users.
3. Messenger should support the persistent storage of chat history.

Non-functional Requirements:

1. Users should have real-time chat experience with minimum latency.
2. Our system should be highly consistent; users should be able to see the same chat history on all their devices.
3. Messenger's high availability is desirable; we can tolerate lower availability in the interest of consistency.

Extended Requirements:

- Group Chats: Messenger should support multiple people talking to each other in a group.
- Push notifications: Messenger should be able to notify users of new messages when they are offline.

3. Capacity Estimation and Constraints

Let's assume that we have 500 million daily active users and on average each user sends 40 messages daily; this gives us 20 billion messages per day.

Storage Estimation: Let's assume that on average a message is 100 bytes, so to store all the messages for one day we would need 2TB of storage.

20 billion messages * 100 bytes => 2 TB/day

To store five years of chat history, we would need 3.6 petabytes of storage.

2 TB * 365 days * 5 years ~= 3.6 PB

Other than the chat messages, we would also need to store users' information, messages' metadata (ID, Timestamp, etc.). Not to mention, the above calculation doesn't take data compression and replication into consideration.

Bandwidth Estimation: If our service is getting 2TB of data every day, this will give us 25MB of incoming data for each second.

2 TB / 86400 sec ~= 25 MB/s

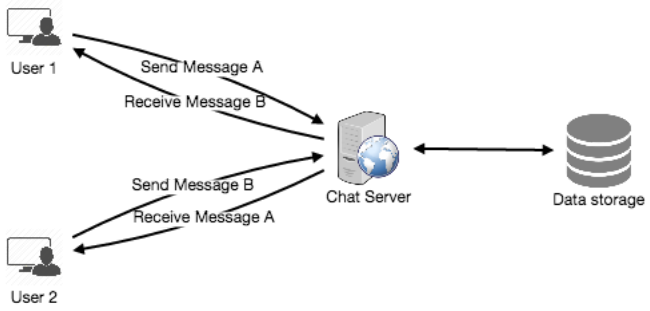
Since each incoming message needs to go out to another user, we will need the same amount of bandwidth 25MB/s for both upload and download.

High level estimates:

Total messages	20 billion per day
Storage for each day	2TB
Storage for 5 years	3.6PB
Incoming data	25MB/s
Outgoing data	25MB/s

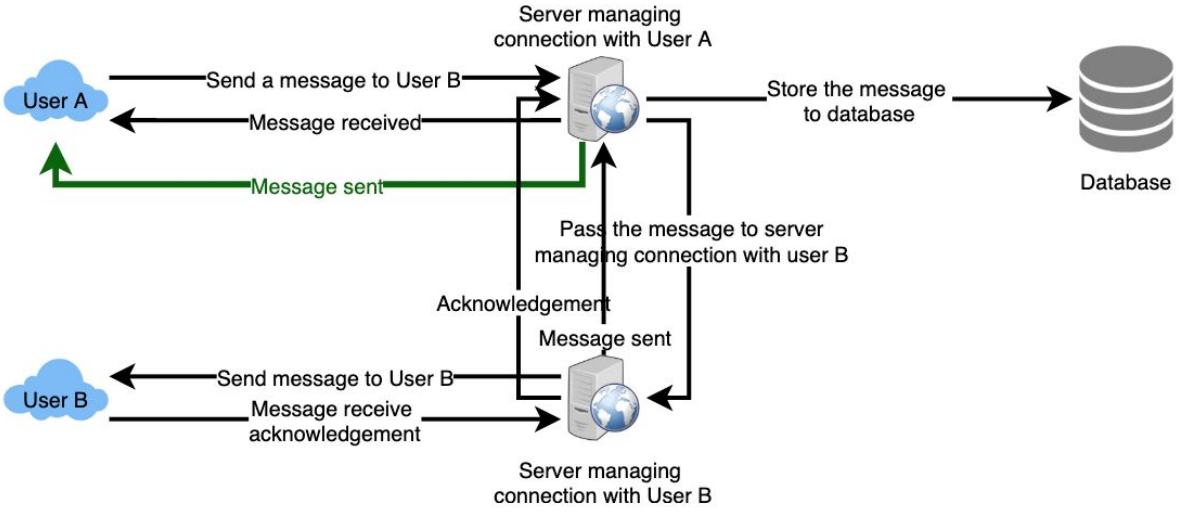
4. High Level Design

At a high-level, we will need a chat server that will be the central piece, orchestrating all the communications between users. When a user wants to send a message to another user, they will connect to the chat server and send the message to the server; the server then passes that message to the other user and also stores it in the database.



The detailed workflow would look like this:

1. User-A sends a message to User-B through the chat server.
2. The server receives the message and sends an acknowledgment to User-A.
3. The server stores the message in its database and sends the message to User-B.
4. User-B receives the message and sends the acknowledgment to the server.
5. The server notifies User-A that the message has been delivered successfully to User-B.



Request flow for sending a message

5. Detailed Component Design

Let's try to build a simple solution first where everything runs on one server. At the high level our system needs to handle the following use cases:

1. Receive incoming messages and deliver outgoing messages.
2. Store and retrieve messages from the database.
3. Keep a record of which user is online or has gone offline, and notify all the relevant users about these status changes.

Let's talk about these scenarios one by one:

a. Messages Handling

How would we efficiently send/receive messages? To send messages, a user needs to connect to the server and post messages for the other users. To get a message from the server, the user has two options:

1. Pull model: Users can periodically ask the server if there are any new messages for them.

2. Push model: Users can keep a connection open with the server and can depend upon the server to notify them whenever there are new messages.

If we go with our first approach, then the server needs to keep track of messages that are still waiting to be delivered, and as soon as the receiving user connects to the server to ask for any new message, the server can return all the pending messages. To minimize latency for the user, they have to check the server quite frequently, and most of the time they will be getting an empty response if there are no pending message. This will waste a lot of resources and does not look like an efficient solution.

If we go with our second approach, where all the active users keep a connection open with the server, then as soon as the server receives a message it can immediately pass the message to the intended user. This way, the server does not need to keep track of the pending messages, and we will have minimum latency, as the messages are delivered instantly on the opened connection.

How will clients maintain an open connection with the server? We can use HTTP Long Polling or WebSockets. In long polling, clients can request information from the server with the expectation that the server may not respond immediately. If the server has no new data for the client when the poll is received, instead of sending an empty response, the server holds the request open and waits for response information to become available. Once it does have new information, the server immediately sends the response to the client, completing the open request. Upon receipt of the server response, the client can immediately issue another server request for future updates. This gives a lot of improvements in latencies, throughputs, and performance. The long polling request can timeout or can receive a disconnect from the server, in that case, the client has to open a new request.

How can the server keep track of all the opened connection to redirect messages to the users efficiently? The server can maintain a hash table, where "key" would be the UserID and "value" would be the connection object. So whenever the server receives a message for a user, it looks up that user in the hash table to find the connection object and sends the message on the open request.

What will happen when the server receives a message for a user who has gone offline? If the receiver has disconnected, the server can notify the sender about the delivery failure. If it is a temporary disconnect, e.g., the receiver's long-poll request just timed out, then we should expect a reconnect from the user. In that

case, we can ask the sender to retry sending the message. This retry could be embedded in the client's logic so that users don't have to retype the message. The server can also store the message for a while and retry sending it once the receiver reconnects.

How many chat servers we need? Let's plan for 500 million connections at any time. Assuming a modern server can handle 50K concurrent connections at any time, we would need 10K such servers.

How do we know which server holds the connection to which user? We can introduce a software load balancer in front of our chat servers; that can map each UserID to a server to redirect the request.

How should the server process a 'deliver message' request? The server needs to do the following things upon receiving a new message:

1) Store the message in the database

2) Send the message to the receiver and

3) Send an acknowledgment to the sender.

The chat server will first find the server that holds the connection for the receiver and pass the message to that server to send it to the receiver. The chat server can then send the acknowledgment to the sender; we don't need to wait for storing the message in the database (this can happen in the background). Storing the message is discussed in the next section.

How does the messenger maintain the sequencing of the messages? We can store a timestamp with each message, which is the time the message is received by the server. This will still not ensure correct ordering of messages for clients. The scenario where the server timestamp cannot determine the exact order of messages would look like this:

1. User-1 sends a message M1 to the server for User-2.
2. The server receives M1 at T1.
3. Meanwhile, User-2 sends a message M2 to the server for User-1.
4. The server receives the message M2 at T2, such that T2 > T1.
5. The server sends message M1 to User-2 and M2 to User-1.

So User-1 will see M1 first and then M2, whereas User-2 will see M2 first and then M1.

To resolve this, we need to keep a sequence number with every message for each client. This sequence number will determine the exact ordering of messages for EACH user. With this solution, both clients will see a different view of the message sequence, but this view will be consistent for them on all devices.

b. Storing and retrieving the messages from the database

Whenever the chat server receives a new message, it needs to store it in the database. To do so, we have two options:

1. Start a separate thread, which will work with the database to store the message.
2. Send an asynchronous request to the database to store the message.

We have to keep certain things in mind while designing our database:

1. How to efficiently work with the database connection pool.
2. How to retry failed requests.
3. Where to log those requests that failed even after some retries.
4. How to retry these logged requests (that failed after the retry) when all the issues have resolved.

Which storage system we should use? We need to have a database that can support a very high rate of small updates and also fetch a range of records quickly. This is required because we have a huge number of small messages that need to be inserted in the database and, while querying, a user is mostly interested in sequentially accessing the messages.

We cannot use RDBMS like MySQL or NoSQL like MongoDB because we cannot afford to read/write a row from the database every time a user receives/sends a message. This will not only make the basic operations of our service run with high latency but also create a huge load on databases.

Both of our requirements can be easily met with a wide-column database solution like HBase. HBase is a column-oriented key-value NoSQL database that can store multiple values against one key into multiple columns. HBase is modeled after Google's BigTable and runs on top of Hadoop Distributed File System (HDFS). HBase groups data together to store new data in a memory buffer and, once the buffer is full, it dumps the data to the disk. This way of storage not only helps to store a lot of small data quickly but also fetching rows

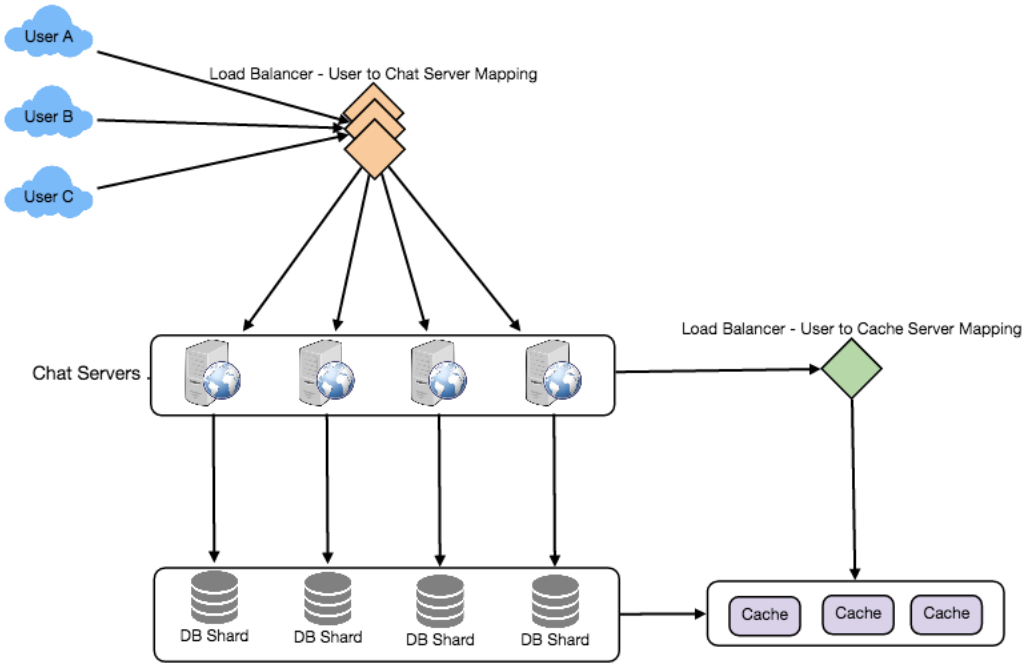
by the key or scanning ranges of rows. HBase is also an efficient database to store variable sized data, which is also required by our service.

How should clients efficiently fetch data from the server? Clients should paginate 分頁 while fetching data from the server. Page size could be different for different clients, e.g., cell phones have smaller screens, so we need a fewer number of message/conversations in the viewport.

c. Managing user's status

We need to keep track of user's online/offline status and notify all the relevant users whenever a status change happens. Since we are maintaining a connection object on the server for all active users, we can easily figure out the user's current status from this. With 500M active users at any time, if we have to broadcast each status change to all the relevant active users, it will consume a lot of resources. We can do the following optimization around this:

1. Whenever a client starts the app, it can pull the current status of all users in their friends' list.
2. Whenever a user sends a message to another user that has gone offline, we can send a failure to the sender and update the status on the client.
3. Whenever a user comes online, the server can always broadcast that status with a delay of a few seconds to see if the user does not go offline immediately.
4. Clients can pull the status from the server about those users that are being shown on the user's viewport. This should not be a frequent operation, as the server is broadcasting the online status of users and we can live with the stale offline status of users for a while.
5. Whenever the client starts a new chat with another user, we can pull the status at that time.



Design Summary: Clients will open a connection to the chat server to send a message; the server will then pass it to the requested user. All the active users will keep a connection open with the server to receive messages. Whenever a new message arrives, the chat server will push it to the receiving user on the long poll request. Messages can be stored in HBase, which supports quick small updates, and range based searches. The servers can broadcast the online status of a user to other relevant users. Clients can pull status updates for users who are visible in the client's viewport on a less frequent basis.

6. Data partitioning

Since we will be storing a lot of data (3.6PB for five years), we need to distribute it onto multiple database servers. What will be our partitioning scheme?

Partitioning based on UserID: Let's assume we partition based on the hash of the UserID so that we can keep all messages of a user on the same database. If one DB shard is 4TB, we will have "3.6PB/4TB ~= 900" shards for five years. For simplicity, let's assume we keep 1K shards. So we will find the shard number by "hash(UserID) % 1000" and then store/retrieve the data from there. This partitioning scheme will also be very quick to fetch chat history for any user.

In the beginning, we can start with fewer database servers with multiple shards residing on one physical server. Since we can have multiple database instances

on a server, we can easily store multiple partitions on a single server. Our hash function needs to understand this logical partitioning scheme so that it can map multiple logical partitions on one physical server.

Since we will store an unlimited history of messages, we can start with a big number of logical partitions, which will be mapped to fewer physical servers, and as our storage demand increases, we can add more physical servers to distribute our logical partitions.

Partitioning based on MessageID: If we store different messages of a user on separate database shards, fetching a range of messages of a chat would be very slow, so we should not adopt this scheme.

7. Cache

We can cache a few recent messages (say last 15) in a few recent conversations that are visible in a user's viewport (say last 5). Since we decided to store all of the user's messages on one shard, the cache for a user should entirely reside on one machine too.

8. Load balancing

We will need a load balancer in front of our chat servers; that can map each UserID to a server that holds the connection for the user and then direct the request to that server. Similarly, we would need a load balancer for our cache servers.

9. Fault tolerance and Replication

What will happen when a chat server fails? Our chat servers are holding connections with the users. If a server goes down, should we devise 制定計劃 a mechanism to transfer those connections to some other server? It's extremely hard to failover TCP connections to other servers; an easier approach can be to have clients automatically reconnect if the connection is lost.

Should we store multiple copies of user messages? We cannot have only one copy of the user's data, because if the server holding the data crashes or is down permanently, we don't have any mechanism to recover that data. For this, either we have to store multiple copies of the data on different servers or use techniques like Reed-Solomon encoding to distribute and replicate it.

10. Extended Requirements

a. Group chat

We can have separate group-chat objects in our system that can be stored on the chat servers. A group-chat object is identified by GroupChatID and will also maintain a list of people who are part of that chat. Our load balancer can direct each group chat message based on GroupChatID and the server handling that group chat can iterate through all the users of the chat to find the server handling the connection of each user to deliver the message.

In databases, we can store all the group chats in a separate table partitioned based on GroupChatID.

b. Push notifications

In our current design, users can only send messages to active users and if the receiving user is offline, we send a failure to the sending user. Push notifications will enable our system to send messages to offline users.

For Push notifications, each user can opt-in from their device (or a web browser) to get notifications whenever there is a new message or event. Each manufacturer maintains a set of servers that handles pushing these notifications to the user.

To have push notifications in our system, we would need to set up a Notification server, which will take the messages for offline users and send them to the manufacture's push notification server, which will then send them to the user's device.

Designing Twitter

Let's design a Twitter-like social networking service. Users of the service will be able to post tweets, follow other people, and favorite tweets.

Difficulty Level: Medium

1. What is Twitter?

Twitter is an online social networking service where users post and read short 140-character messages called "tweets." Registered users can post and read tweets, but those who are not registered can only read them. Users access Twitter through their website interface, SMS, or mobile app.

2. Requirements and Goals of the System

We will be designing a simpler version of Twitter with the following requirements:

Functional Requirements

1. Users should be able to post new tweets.
2. A user should be able to follow other users.
3. Users should be able to mark tweets as favorites.
4. The service should be able to create and display a user's timeline consisting of top tweets from all the people the user follows.
5. Tweets can contain photos and videos.

Non-functional Requirements

1. Our service needs to be highly available.
2. Acceptable latency of the system is 200ms for timeline generation.
3. Consistency can take a hit (in the interest of availability); if a user doesn't see a tweet for a while, it should be fine.

Extended Requirements

1. Searching for tweets.
2. Replying to a tweet.
3. Trending topics – current hot topics/searches.
4. Tagging other users.
5. Tweet Notification.
6. Who to follow? Suggestions?
7. Moments.

3. Capacity Estimation and Constraints

Let's assume we have one billion total users with 200 million daily active users (DAU). Also assume we have 100 million new tweets every day and on average each user follows 200 people.

How many favorites per day? If, on average, each user favorites five tweets per day we will have:

200M users * 5 favorites => 1B favorites

How many total tweet-views will our system generate? Let's assume on average a user visits their timeline two times a day and visits five other people's pages. On each page if a user sees 20 tweets, then our system will generate 28B/day total tweet-views:

200M DAU * ((2 + 5) * 20 tweets) => 28B/day

Storage Estimates Let's say each tweet has 140 characters and we need two bytes to store a character without compression. Let's assume we need 30 bytes to store metadata with each tweet (like ID, timestamp, user ID, etc.). Total storage we would need:

100M * (280 + 30) bytes => 30GB/day

What would our storage needs be for five years? How much storage we would need for users' data, follows, favorites? We will leave this for the exercise.

Not all tweets will have media, let's assume that on average every fifth tweet has a photo and every tenth has a video. Let's also assume on average a photo is 200KB and a video is 2MB. This will lead us to have 24TB of new media every day.

(100M/5 photos * 200KB) + (100M/10 videos * 2MB) ~= 24TB/day

Bandwidth Estimates Since total ingress is 24TB per day, this would translate into 290MB/sec.

Remember that we have 28B tweet views per day. We must show the photo of every tweet (if it has a photo), but let's assume that the users watch every 3rd video they see in their timeline. So, total egress will be:

(28B * 280 bytes) / 86400s of text => 93MB/s
+ (28B/5 * 200KB) / 86400s of photos => 13GB/S
+ (28B/10/3 * 2MB) / 86400s of Videos => 22GB/s

Total ~= 35GB/s

4. System APIs

Once we've finalized the requirements, it's always a good idea to define the system APIs. This should explicitly state what is expected from the system.

We can have SOAP or REST APIs to expose the functionality of our service. Following could be the definition of the API for posting a new tweet:

```
tweet(api_dev_key, tweet_data, tweet_location, user_location, media_ids, maximum_results_to_return)
```

Parameters:
api_dev_key (string): The API developer key of a registered account. This will be used to, among other things, throttle users based on their allocated quota.
tweet_data (string): The text of the tweet, typically up to 140 characters.
tweet_location (string): Optional location (longitude, latitude) this Tweet refers to. user_location (string): Optional location (longitude, latitude) of the user adding the tweet.
media_ids (number[]): Optional list of media_ids to be associated with the Tweet. (All the media photo, video, etc. need to be uploaded separately).

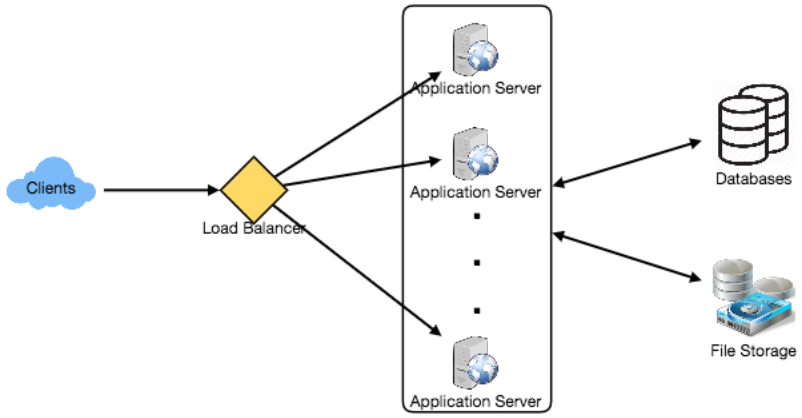
Returns: (string)
A successful post will return the URL to access that tweet. Otherwise, an appropriate HTTP error is returned.

5. High Level System Design

We need a system that can efficiently store all the new tweets, 100M/86400s => 1150 tweets per second and read 28B/86400s => 325K tweets per second. It is clear from the requirements that this will be a read-heavy system.

At a high level, we need multiple application servers to serve all these requests with load balancers in front of them for traffic distributions. On the backend, we

need an efficient database that can store all the new tweets and can support a huge number of reads. We also need some file storage to store photos and videos.



Although our expected daily write load is 100 million and read load is 28 billion tweets. This means on average our system will receive around 1160 new tweets and 325K read requests per second. This traffic will be distributed unevenly throughout the day, though, at peak time we should expect at least a few thousand write requests and around 1M read requests per second. We should keep this in mind while designing the architecture of our system.

6. Database Schema

We need to store data about users, their tweets, their favorite tweets, and people they follow.

Tweet	
PK	**TweetID: int**
	UserID: int
	Content: varchar(140)
	TweetLatitude: int
	TweetLongitude: int
	UserLatitude: int
	UserLongitude: int
	CreationDate: datetime
	NumFavorites: int

User	
PK	**UserID: int**
	Name: varchar(20)
	Email: varchar(32)
	DateOfBirth: datetime
	CreationDate: datetime
	LastLogin: datatime

UserFollow	
PK	**UserID1: int** **UserID2: int**

Favorite	
PK	**TweetID: int** **UserID: int**
	CreationDate: datetime

For choosing between SQL and NoSQL databases to store the above schema, please see 'Database schema' under Designing Instagram.

7. Data Sharding

Since we have a huge number of new tweets every day and our read load is extremely high too, we need to distribute our data onto multiple machines such that we can read/write it efficiently. We have many options to shard our data; let's go through them one by one:

Sharding based on UserID: We can try storing all the data of a user on one server. While storing, we can pass the UserID to our hash function that will map the user to a database server where we will store all of the user's tweets, favorites, follows, etc. While querying for tweets/follows/favorites of a user, we can ask our hash function where we can find the data of a user and then read it from there. This approach has a couple of issues:

1. What if a user becomes hot? There could be a lot of queries on the server holding the user. This high load will affect the performance of our service.
2. Over time some users can end up storing a lot of tweets or having a lot of follows compared to others. Maintaining a uniform distribution of growing user data is quite difficult.

To recover from these situations either we have to repartition/redistribute our data or use consistent hashing.

Sharding based on TweetID: Our hash function will map each TweetID to a random server where we will store that Tweet. To search for tweets, we have to query all servers, and each server will return a set of tweets. A centralized server will aggregate these results to return them to the user. Let's look into timeline generation example; here are the number of steps our system has to perform to generate a user's timeline:

1. Our application (app) server will find all the people the user follows.
2. App server will send the query to all database servers to find tweets from these people.
3. Each database server will find the tweets for each user, sort them by recency and return the top tweets.
4. App server will merge all the results and sort them again to return the top results to the user.

This approach solves the problem of hot users, but, in contrast to sharding by UserID, we have to query all database partitions to find tweets of a user, which can result in higher latencies.

We can further improve our performance by introducing cache to store hot tweets in front of the database servers.

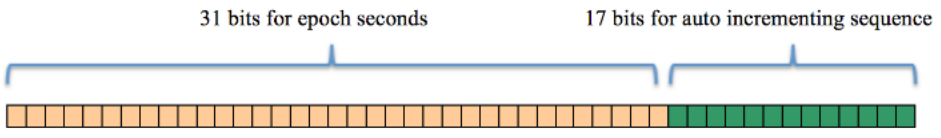
Sharding based on Tweet creation time: Storing tweets based on creation time will give us the advantage of fetching all the top tweets quickly and we only have to query a very small set of servers. The problem here is that the traffic load will not be distributed, e.g., while writing, all new tweets will be going to one server and the remaining servers will be sitting idle. Similarly, while reading, the server holding the latest data will have a very high load as compared to servers holding old data.

What if we can combine sharding by TweetID and Tweet creation time? If we don't store tweet creation time separately and use TweetID to reflect that, we can get benefits of both the approaches. This way it will be quite quick to find the latest Tweets. For this, we must make each TweetID universally unique in our system and each TweetID should contain a timestamp too.

We can use epoch time for this. Let's say our TweetID will have two parts: the first part will be representing epoch seconds and the second part will be an auto-incrementing sequence. So, to make a new TweetID, we can take the current epoch time and append an auto-incrementing number to it. We can figure out the shard number from this TweetID and store it there.

What could be the size of our TweetID? Let's say our epoch time starts today, how many bits we would need to store the number of seconds for the next 50 years?

86400 sec/day * 365 (days a year) * 50 (years) => 1.6B



We would need 31 bits to store this number. Since on average we are expecting 1150 new tweets per second, we can allocate 17 bits to store auto incremented sequence; this will make our TweetID 48 bits long. So, every second we can

store (2^17 => 130K) new tweets. We can reset our auto incrementing sequence every second. For fault tolerance and better performance, we can have two database servers to generate auto-incrementing keys for us, one generating even numbered keys and the other generating odd numbered keys.

If we assume our current epoch seconds are "1483228800," our TweetID will look like this:

1483228800 000001
1483228800 000002
1483228800 000003
1483228800 000004
…

If we make our TweetID 64bits (8 bytes) long, we can easily store tweets for the next 100 years and also store them for mili-seconds granularity.

In the above approach, we still have to query all the servers for timeline generation, but our reads (and writes) will be substantially quicker.

1. Since we don't have any secondary index (on creation time) this will reduce our write latency.
2. While reading, we don't need to filter on creation-time as our primary key has epoch time included in it.

8. Cache

We can introduce a cache for database servers to cache hot tweets and users. We can use an off-the-shelf **現成** solution like Memcache that can store the whole tweet objects. Application servers, before hitting database, can quickly check if the cache has desired tweets. Based on clients' usage patterns we can determine how many cache servers we need.

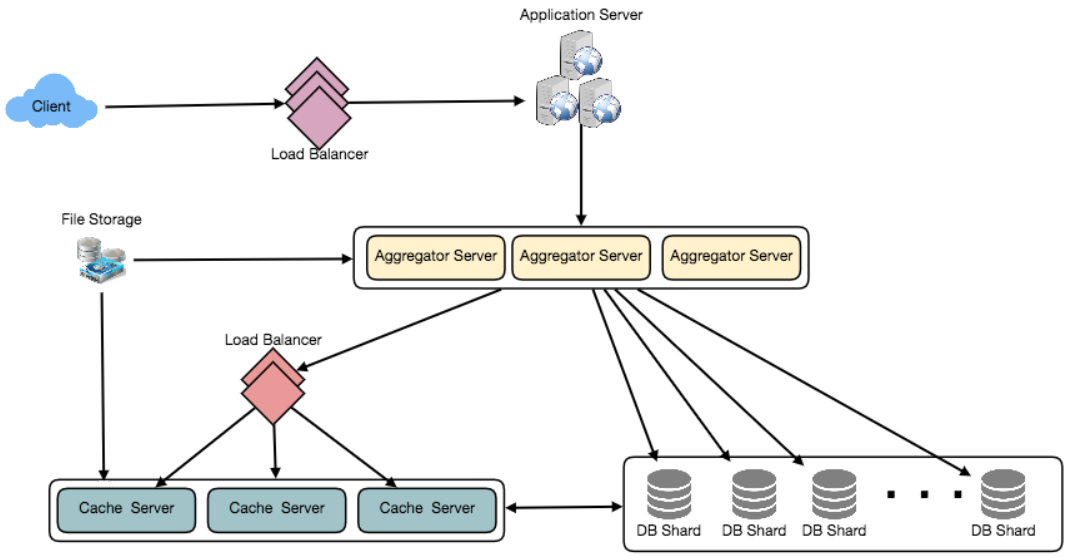
Which cache replacement policy would best fit our needs? When the cache is full and we want to replace a tweet with a newer/hotter tweet, how would we choose? Least Recently Used (LRU) can be a reasonable policy for our system. Under this policy, we discard the least recently viewed tweet first.

How can we have a more intelligent cache? If we go with 80-20 rule, that is 20% of tweets generating 80% of read traffic which means that certain tweets are so

popular that a majority of people read them. This dictates that we can try to cache 20% of daily read volume from each shard.

What if we cache the latest data? Our service can benefit from this approach. Let's say if 80% of our users see tweets from the past three days only; we can try to cache all the tweets from the past three days. Let's say we have dedicated cache servers that cache all the tweets from all the users from the past three days. As estimated above, we are getting 100 million new tweets or 30GB of new data every day (without photos and videos). If we want to store all the tweets from last three days, we will need less than 100GB of memory. This data can easily fit into one server, but we should replicate it onto multiple servers to distribute all the read traffic to reduce the load on cache servers. So whenever we are generating a user's timeline, we can ask the cache servers if they have all the recent tweets for that user. If yes, we can simply return all the data from the cache. If we don't have enough tweets in the cache, we have to query the backend server to fetch that data. On a similar design, we can try caching photos and videos from the last three days.

Our cache would be like a hash table where 'key' would be 'OwnerID' and 'value' would be a doubly linked list containing all the tweets from that user in the past three days. Since we want to retrieve the most recent data first, we can always insert new tweets at the head of the linked list, which means all the older tweets will be near the tail of the linked list. Therefore, we can remove tweets from the tail to make space for newer tweets.



9. Timeline Generation

For a detailed discussion about timeline generation, take a look at Designing Facebook's Newsfeed.

10. Replication and Fault Tolerance

Since our system is read-heavy, we can have multiple secondary database servers for each DB partition. Secondary servers will be used for read traffic only. All writes will first go to the primary server and then will be replicated to secondary servers. This scheme will also give us fault tolerance, since whenever the primary server goes down we can failover to a secondary server.

11. Load Balancing

We can add Load balancing layer at three places in our system

1) Between Clients and Application servers

2) Between Application servers and database replication servers and

3) Between Aggregation servers and Cache server.

Initially, a simple Round Robin approach can be adopted; that distributes incoming requests equally among servers. This LB is simple to implement and does not introduce any overhead. Another benefit of this approach is that if a server is dead, LB will take it out of the rotation and will stop sending any traffic to it. A problem with Round Robin LB is that it won't take servers load into consideration. If a server is overloaded or slow, the LB will not stop sending new requests to that server. To handle this, a more intelligent LB solution can be placed that periodically queries backend server about their load and adjusts traffic based on that.

12. Monitoring

Having the ability to monitor our systems is crucial. We should constantly collect data to get an instant insight into how our system is doing. We can collect following metrics/counters to get an understanding of the performance of our service:

1. New tweets per day/second, what is the daily peak?
2. Timeline delivery stats, how many tweets per day/second our service is delivering.
3. Average latency that is seen by the user to refresh timeline.

By monitoring these counters, we will realize if we need more replication, load balancing, or caching.

13. Extended Requirements

How do we serve feeds? Get all the latest tweets from the people someone follows and merge/sort them by time. Use pagination to fetch/show tweets. Only fetch top N tweets from all the people someone follows. This N will depend on the client's Viewport, since on a mobile we show fewer tweets compared to a Web client. We can also cache next top tweets to speed things up.

Alternately, we can pre-generate the feed to improve efficiency; for details please see 'Ranking and timeline generation' under Designing Instagram.

Retweet: With each Tweet object in the database, we can store the ID of the original Tweet and not store any contents on this retweet object.

Trending Topics: We can cache most frequently occurring hashtags or search queries in the last N seconds and keep updating them after every M second. We can rank trending topics based on the frequency of tweets or search queries or retweets or likes. We can give more weight to topics which are shown to more people.

Who to follow? How to give suggestions? This feature will improve user engagement. We can suggest friends of people someone follows. We can go two or three levels down to find famous people for the suggestions. We can give preference to people with more followers.

As only a few suggestions can be made at any time, use Machine Learning (ML) to shuffle and re-prioritize. ML signals could include people with recently increased follow-ship, common followers if the other person is following this user, common location or interests, etc.

Moments: Get top news for different websites for past 1 or 2 hours, figure out related tweets, prioritize them, categorize them (news, support, financial,

entertainment, etc.) using ML – supervised learning or Clustering. Then we can show these articles as trending topics in Moments.

Search: Search involves Indexing, Ranking, and Retrieval of tweets. A similar solution is discussed in our next problem Design Twitter Search.