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 computing layer: 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 locally cached data if it exists. If it is not in the cache, the requesting node will fetch the data from the 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 Delivery (or 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.

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Cache Invalidation#

While caching is fantastic, it requires some maintenance to keep the 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 simultaneously. 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. Least Frequently Used (LFU): Counts how often an item is needed. Those that are used least often are discarded first.

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.

Key Characteristics of Distributed Systems

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.

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.

Consistent Hashing

Background#

While designing a scalable system, the most important aspect is defining how the data will be partitioned and replicated across servers. Let's first define these terms before moving on:

Data partitioning: It is the process of distributing data across a set of servers. It improves the scalability and performance of the system.

Data replication: It is the process of making multiple copies of data and storing them on different servers. It improves the availability and durability of the data across the system.

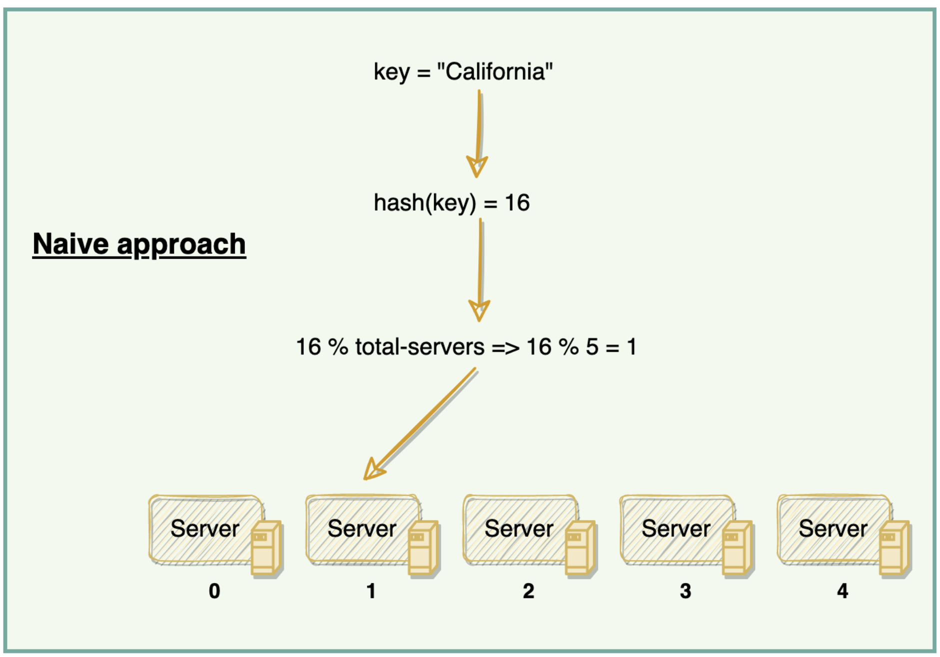
Data partition and replication strategies lie at the core of any distributed system. A carefully designed scheme for partitioning and replicating the data **enhances the performance, availability, and reliability of the system** and also defines how efficiently the system will be scaled and managed.

What is data partitioning?#

As stated above, the act of distributing data across a set of nodes is called data partitioning. There are two challenges when we try to distribute data:

1. How do we know on which node a particular piece of data will be stored?
2. When we add or remove nodes, how do we know what data will be moved from existing nodes to the new nodes? Additionally, how can we minimize data movement when nodes join or leave?

A naive approach will use a suitable hash function to map the data key to a number. Then, find the server by applying modulo on this number and the total number of servers. For example:



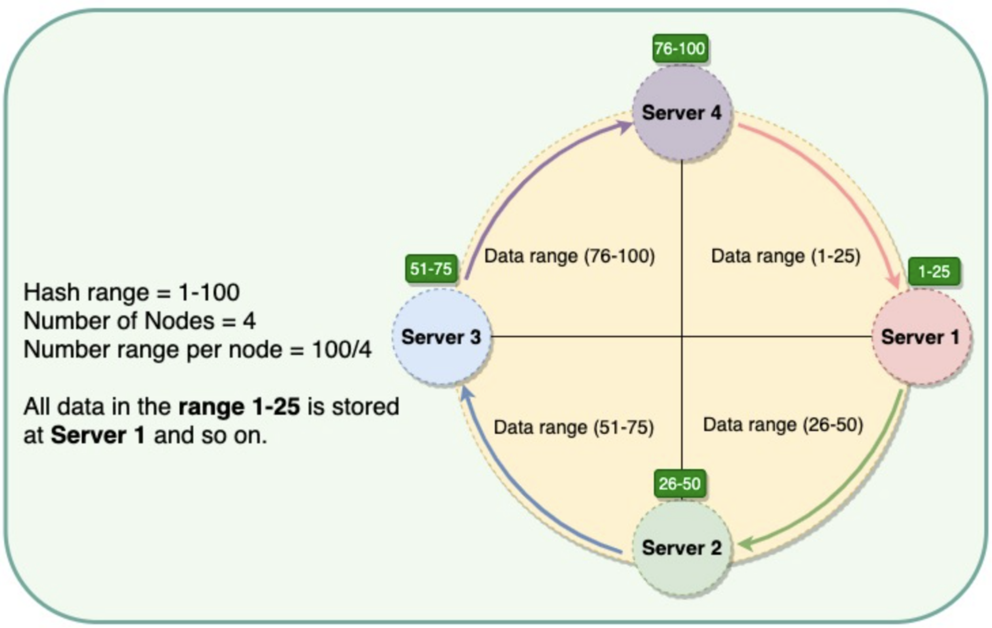
Data partitioning using simple hashing

The scheme described in the above diagram solves the problem of finding a server for storing/retrieving the data. But when we add or remove a server, all our existing mappings will be broken. This is because the total number of servers will be changed, which was used to find the actual server storing the data. So to get things working again, we have to **remap all the keys** and move our data based on the new server count, which will be a **complete mess!**

Consistent Hashing to the rescue#

Distributed systems can use Consistent Hashing to distribute data across nodes. Consistent Hashing maps data to physical nodes and ensures that **only a small set of keys move when servers are added or removed.**

Consistent Hashing stores the data managed by a distributed system in a ring. Each node in the ring is assigned a range of data. Here is an example of the consistent hash ring:



Consistent Hashing ring

With consistent hashing, the ring is divided into smaller, predefined ranges. Each node is assigned one of these ranges. The start of the range is called a **token**. This means that each node will be assigned one token. The range assigned to each node is computed as follows:

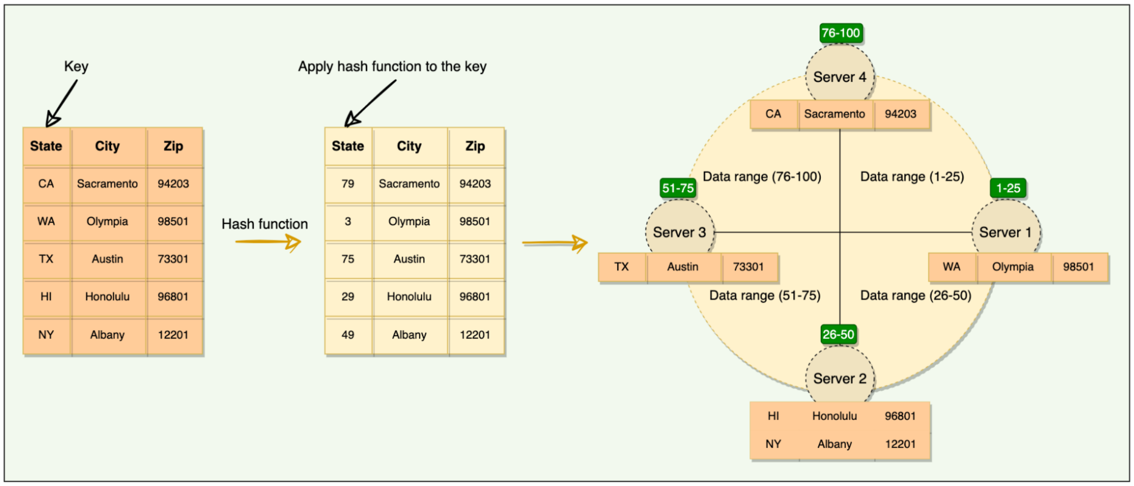
Range start: Token value

Range end: Next token value - 1

Here are the tokens and data ranges of the four nodes described in the above diagram:

Server	Token	Range Start	Range End
Server 1	1	1	25
Server 2	26	26	50
Server 3	51	51	75
Server 4	76	76	100

Whenever the system needs to read or write data, the first step it performs is to apply the MD5 hashing algorithm to the key. The output of this hashing algorithm determines within which range the data lies and hence, on which node the data will be stored. As we saw above, each node is supposed to store data for a fixed range. Thus, the hash generated from the key tells us the node where the data will be stored.



Distributing data on the Consistent Hashing ring

The Consistent Hashing scheme described above works great when a node is added or removed from the ring, as in these cases, since only the next node is affected. For example, when a node is removed, the next node becomes responsible for all of the keys stored on the outgoing node. However, this scheme can **result in non-uniform data and load distribution**. This problem can be solved with the help of Virtual nodes.

Virtual nodes#

Adding and removing nodes in any distributed system is quite common. Existing nodes can die and may need to be decommissioned. Similarly, new nodes may be added to an existing cluster to meet growing demands. To efficiently handle these scenarios, Consistent Hashing makes use of virtual nodes (or Vnodes).

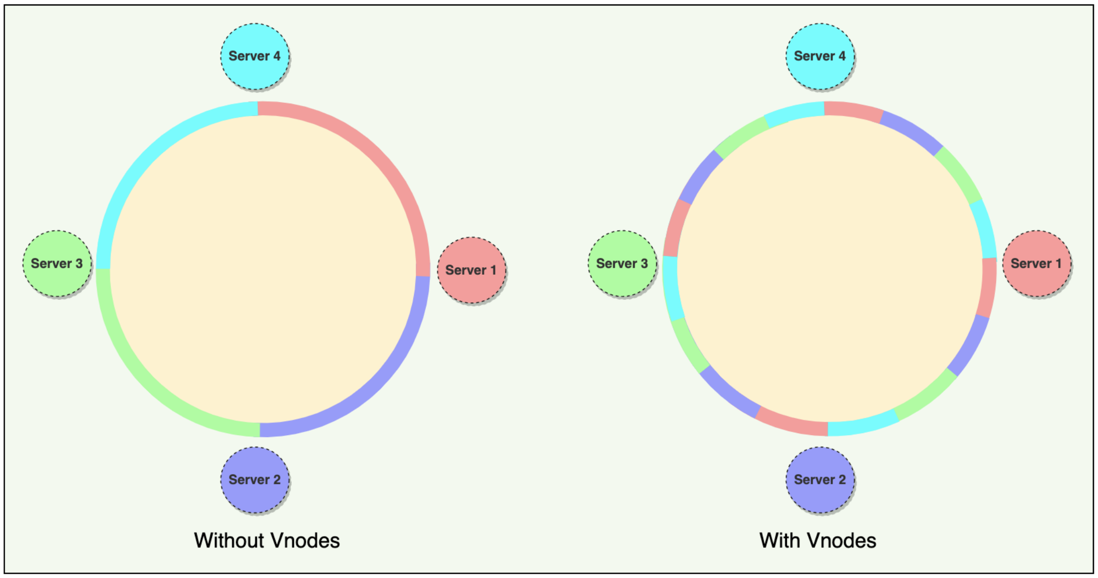
As we saw above, the basic Consistent Hashing algorithm assigns a single token (or a consecutive hash range) to each physical node. This was a static division of ranges that requires calculating tokens based on a given number of nodes. This scheme made adding or replacing a node an expensive operation, as, in this case, we would like to rebalance and distribute the data to all other nodes, resulting in moving a lot of data. Here are a few potential issues associated with a manual and fixed division of the ranges:

- **Adding or removing nodes**: Adding or removing nodes will result in recomputing the tokens causing a significant administrative overhead for a large cluster.
- **Hotspots**: Since each node is assigned one large range, if the data is not evenly distributed, some nodes can become hotspots.

  In a distributed system, any server responsible for a huge partition of data can become a bottleneck for the system. A large share of data storage and retrieval requests will go to that node which can effectively bring the performance of the whole system down. Such loaded servers are called hotspots.

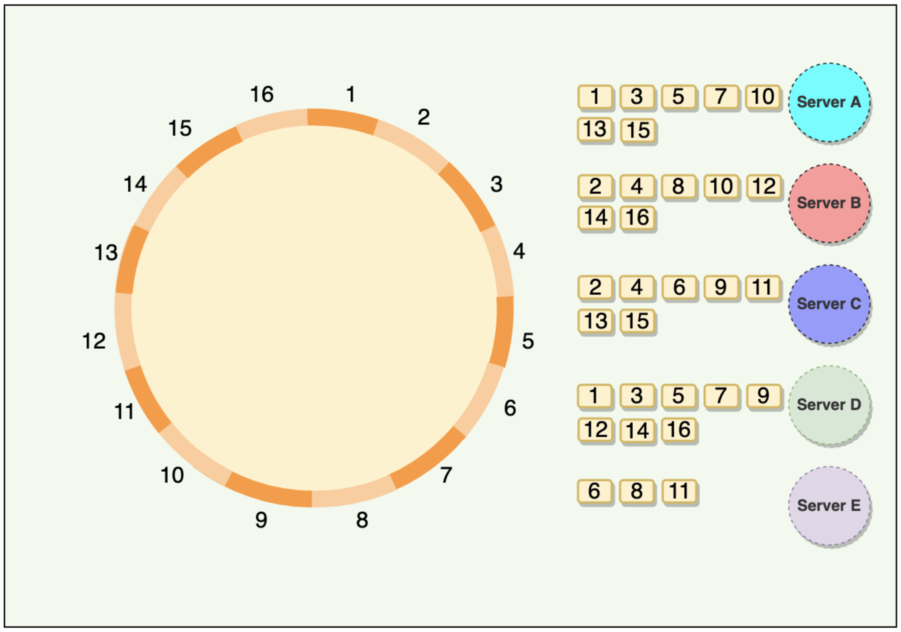
- **Node rebuilding**: Since each node's data might be replicated (for fault-tolerance) on a fixed number of other nodes, when we need to rebuild a node, only its replica nodes can provide the data. This puts a lot of pressure on the replica nodes and can lead to service degradation.

To handle these issues, Consistent Hashing introduces a new scheme of distributing the tokens to physical nodes. Instead of assigning a single token to a node, the hash range is divided into multiple smaller ranges, and each physical node is assigned several of these smaller ranges. Each of these subranges is considered a Vnode. With Vnodes, instead of a node being responsible for just one token, it is responsible for many tokens (or subranges).



Mapping Vnodes to physical nodes on a Consistent Hashing ring

Practically, Vnodes are **randomly distributed** across the cluster and are generally **non-contiguous** so that no two neighboring Vnodes are assigned to the same physical node or rack. Additionally, nodes do carry replicas of other nodes for fault tolerance. Also, since there can be heterogeneous machines in the clusters, some servers might hold more Vnodes than others. The figure below shows how physical nodes A, B, C, D, & E use Vnodes of the Consistent Hash ring. Each physical node is assigned a set of Vnodes and each Vnode is replicated once.



Mapping Vnodes to physical nodes on a Consistent Hashing ring

Advantages of Vnodes#

Vnodes gives the following advantages:

1. As Vnodes help spread the load more evenly across the physical nodes on the cluster by dividing the hash ranges into smaller subranges, this speeds up the rebalancing process after adding or removing nodes. When a new node is added, it receives many Vnodes from the existing nodes to maintain a balanced cluster. Similarly, when a node needs to be rebuilt, instead of getting data from a fixed number of replicas, many nodes participate in the rebuild process.
2. Vnodes make it easier to maintain a cluster containing heterogeneous machines. This means, with Vnodes, we can assign a high number of sub-ranges to a powerful server and a lower number of sub-ranges to a less powerful server.
3. In contrast to one big range, since Vnodes help assign smaller ranges to each physical node, this decreases the probability of hotspots.

Data replication using Consistent Hashing#

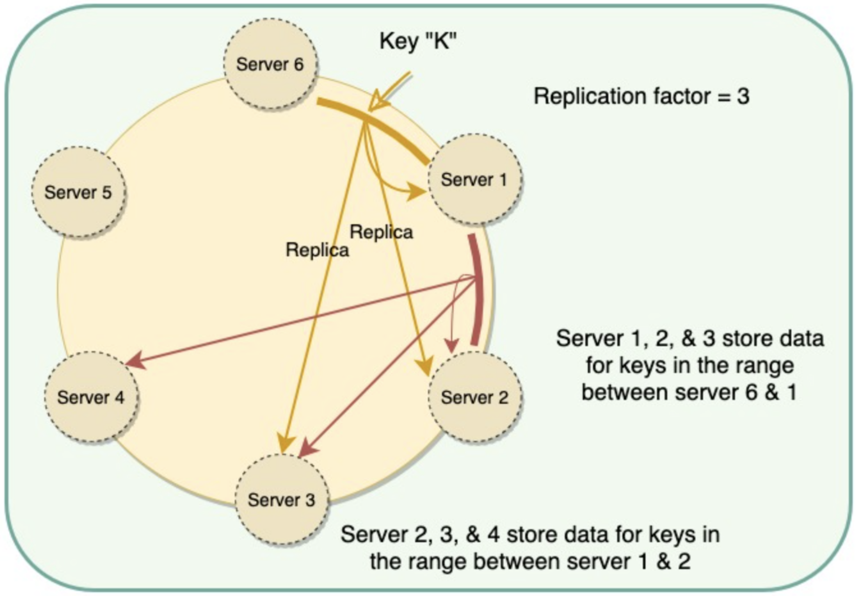
To ensure highly availability and durability, Consistent Hashing replicates each data item on multiple N nodes in the system where the value N is equivalent to the replication factor.

Any system is considered durable if it does not lose the data that was successfully committed to it. In other words, durability guarantees against any data loss due to corruption or a permanent component failure like a storage device or a server.

The replication factor is the number of nodes that will receive the copy of the same data. For example, a replication factor of two means there are two copies of each data item, where each copy is stored on a different node.

Each key is assigned to a **coordinator node** (generally the first node that falls in the hash range), which first stores the data locally and then replicates it to N-1 clockwise successor nodes on the ring. This results in each node owning the region on the ring between it and its Nth predecessor. In an **eventually consistent** system, this replication is done asynchronously (in the background).

In eventually consistent systems, copies of data don't always have to be identical as long as they are designed to eventually become consistent. In distributed systems, eventual consistency is used to achieve high availability.



Replication in Consistent Hashing

Consistent Hashing in System Design Interviews#

As we saw above, Consistent Hashing helps with efficiently partitioning and replicating data; therefore, any distributed system that needs to scale up or down or wants to achieve high availability through data replication can utilize Consistent Hashing. A few such examples could be:

- Any system working with a set of storage (or database) servers and needs to scale up or down based on the usage, e.g., the system could need more storage during Christmas because of high traffic.
- Any distributed system that needs dynamic adjustment of its cache usage by adding or removing cache servers based on the traffic load.
- Any system that wants to replicate its data shards to achieve high availability.

Consistent Hashing use cases#

Amazon’s Dynamo and Apache Cassandra use Consistent Hashing to distribute and replicate data across nodes.