Chapter 7

Consistency and replication

An important issue in distributed systems is the replication of data. Data are generally replicated to enhance reliability or improve performance. One of the major problems is keeping replicas consistent. Informally, this means that when one copy is updated we need to ensure that the other copies are updated as well; otherwise the replicas will no longer be the same. In this chapter, we take a detailed look at what consistency of replicated data actually means and the various ways that consistency can be achieved.

We start with a general introduction discussing why replication is useful and how it relates to scalability. We then continue by focusing on what consistency actually means. An important class of what are known as consistency models assumes that multiple processes simultaneously access shared data. Consistency for these situations can be formulated with respect to what processes can expect when reading and updating the shared data, knowing that others are accessing that data as well.

Consistency models for shared data are often hard to implement efficiently in large-scale distributed systems. Moreover, in many cases simpler models can be used, which are also often easier to implement. One specific class is formed by client-centric consistency models, which concentrate on consistency from the perspective of a single (possibly mobile) client. Client-centric consistency models are discussed in a separate section.

Consistency is only half of the story. We also need to consider how consistency is actually implemented. There are essentially two, more or less independent, issues we need to consider. First of all, we start with concentrating on managing replicas, which takes into account not only the placement of replica servers, but also how content is distributed to these servers.

The second issue is how replicas are kept consistent. In most cases, applications require a strong form of consistency. Informally, this means that updates are to be propagated more or less immediately between replicas. There are various alternatives for implementing strong consistency, which are discussed in a separate section. Also, attention is paid to caching protocols, which form a special case of consistency protocols.

Being arguably the largest distributed system, we pay separate attention to caching and replication in Web-based systems, notably looking at content delivery networks as well as edge-server caching techniques.

7.1 Introduction

In this section, we start with discussing the important reasons for wanting to replicate data in the first place. We concentrate on replication as a technique for achieving scalability, and motivate why reasoning about consistency is so important.

Reasons for replication

There are two primary reasons for replicating data. First, data are replicated to increase the reliability of a system. If a file system has been replicated it may be possible to continue working after one replica crashes by simply switching to one of the other replicas. Also, by maintaining multiple copies, it becomes possible to provide better protection against corrupted data. For example, imagine there are three copies of a file and every read and write operation is performed on each copy. We can safeguard ourselves against a single, failing write operation, by considering the value that is returned by at least two copies as being the correct one.

The other reason for replicating data is performance. Replication for performance is important when a distributed system needs to scale in terms of size or in terms of the geographical area it covers. Scaling with respect to size occurs, for example, when an increasing number of processes needs to access data that are managed by a single server. In that case, performance can be improved by replicating the server and subsequently dividing the workload among the processes accessing the data.

Scaling with respect to a geographical area may also require replication. The basic idea is that by placing a copy of data in proximity of the process using them, the time to access the data decreases. As a consequence, the performance as perceived by that process increases. This example also illustrates that the benefits of replication for performance may be hard to evaluate. Although a client process may perceive better performance, it may also be the case that more network bandwidth is now consumed keeping all replicas up to date.

If replication helps to improve reliability and performance, who could be against it? Unfortunately, there is a price to be paid when data are replicated. The problem with replication is that having multiple copies may lead to consistency problems. Whenever a copy is modified, that copy becomes different from the rest. Consequently, modifications have to be carried out on all copies to ensure consistency. Exactly when and how those modifications need to be carried out determines the price of replication.

To understand the problem, consider improving access times to Web pages. If no special measures are taken, fetching a page from a remote Web server may sometimes even take seconds to complete. To improve performance, Web browsers often locally store a copy of a previously fetched Web page (i.e., they *cache* a Web page). If a user requires that page again, the browser automatically returns the local copy. The access time as perceived by the user is excellent. However, if the user always wants to have the latest version of a page, he may be in for bad luck. The problem is that if the page has been modified in the meantime, modifications will not have been propagated to cached copies, making those copies out-of-date.

One solution to the problem of returning a stale copy to the user is to forbid the browser to keep local copies in the first place, effectively letting the server be fully in charge of replication. However, this solution may still lead to poor access times if no replica is placed near the user. Another solution is to let the Web server invalidate or update each cached copy, but this requires that the server keeps track of all caches and sending them messages. This, in turn, may degrade the overall performance of the server. We return to performance versus scalability issues below.

In the following we will mainly concentrate on replication for performance. Replication for reliability is discussed in Chapter 8.

Replication as scaling technique

Replication and caching for performance are widely applied as scaling techniques. Scalability issues generally appear in the form of performance problems. Placing copies of data close to the processes using them can improve performance through reduction of access time and thus solve scalability problems.

A possible trade-off that needs to be made is that keeping copies up to date may require more network bandwidth. Consider a process P that accesses a local replica N times per second, whereas the replica itself is updated M times per second. Assume that an update completely refreshes the previous version of the local replica. If $N \ll M$, that is, the access-to-update ratio is very low, we have the situation where many updated versions of the local replica will never be accessed by P, rendering the network communication for those versions useless. In this case, it may have been better not to install a local replica close to P, or to apply a different strategy for updating the replica.

A more serious problem, however, is that keeping multiple copies consistent may itself be subject to serious scalability problems. Intuitively, a collection of copies is consistent when the copies are always the same. This means that a read operation performed at any copy will always return the same result. Consequently, when an update operation is performed on one copy, the update should be propagated to all copies before a subsequent operation takes place, no matter at which copy that operation is initiated or performed.

This type of consistency is sometimes informally (and imprecisely) referred to as tight consistency as provided by what is also called synchronous replication. (In Section 7.2, we will provide precise definitions of consistency and introduce a range of consistency models.) The key idea is that an update is performed at all copies as a single atomic operation, or transaction. Unfortunately, implementing atomicity involving a large number of replicas that may be widely dispersed across a large-scale network is inherently difficult when operations are also required to complete quickly.

Difficulties come from the fact that we need to synchronize all replicas. In essence, this means that all replicas first need to reach agreement on when exactly an update is to be performed locally. For example, replicas may need to decide on a global ordering of operations using Lamport timestamps, or let a coordinator assign such an order. Global synchronization simply takes a lot of communication time, especially when replicas are spread across a wide-area network.

We are now faced with a dilemma. On the one hand, scalability problems can be alleviated by applying replication and caching, leading to improved performance. On the other hand, to keep all copies consistent generally requires global synchronization, which is inherently costly in terms of performance. The cure may be worse than the disease.

In many cases, the only real solution is to relax the consistency constraints. In other words, if we can relax the requirement that updates need to be executed as atomic operations, we may be able to avoid (instantaneous) global synchronizations, and may thus gain performance. The price paid is that copies may not always be the same everywhere. As it turns out, to what extent consistency can be relaxed depends highly on the access and update patterns of the replicated data, as well as on the purpose for which those data are used.

There are a range of consistency models and many different ways to implement models through what are called distribution and consistency protocols. Approaches to classifying consistency and replication can be found in [Gray et al., 1996; Wiesmann et al., 2000] and [Aguilera and Terry, 2016].

7.2 Data-centric consistency models

Traditionally, consistency has been discussed in the context of read and write operations on shared data, available by means of (distributed) shared memory, a (distributed) shared database, or a (distributed) file system. Here, we use the broader term **data store**. A data store may be physically distributed across multiple machines. In particular, each process that can access data from the store is assumed to have a local (or nearby) copy available of the entire store. Write operations are propagated to the other copies, as shown in Figure 7.1. A data operation is classified as a write operation when it changes the data, and is otherwise classified as a read operation.

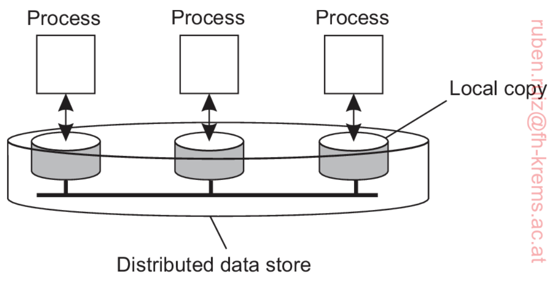


Figure 7.1: The general organization of a logical data store, physically distributed and replicated across multiple processes.

A **consistency model** is essentially a contract between processes and the data store. It says that if processes agree to obey certain rules, the store promises to work correctly. Normally, a process that performs a read operation on a data item, expects the operation to return a value that shows the results of the last write operation on that data.

In the absence of a global clock, it is difficult to define precisely which write operation is the last one. As an alternative, we need to provide other definitions, leading to a range of consistency models. Each model effectively restricts the values that a read operation on a data item can return. As is to be expected, the ones with major restrictions are easy to use, for example when developing applications, whereas those with minor restrictions are generally considered to be difficult to use in practice. The trade-off is, of course, that the easy-to-use models do not perform nearly as well as the difficult ones. Such is life.

Continuous consistency

There is no such thing as a best solution to replicating data. Replicating data poses consistency problems that cannot be solved efficiently in a general way. Only if we loosen consistency can there be hope for attaining efficient solutions. Unfortunately, there are also no general rules for loosening consistency: exactly what can be tolerated is highly dependent on applications.

There are different ways for applications to specify what inconsistencies they can tolerate. Yu and Vahdat [2002] take a general approach by distinguishing three independent axes for defining inconsistencies: deviation in numerical values between replicas, deviation in staleness between replicas, and deviation with respect to the ordering of update operations. They refer to these deviations as forming **continuous consistency** ranges.

Measuring inconsistency in terms of numerical deviations can be used by applications for which the data have numerical semantics. One obvious example is the replication of records containing stock market prices. In this case, an application may specify that two copies should not deviate more than \$0.02, which would be an *absolute numerical deviation*. Alternatively, a *relative numerical deviation* could be specified, stating that two copies should differ by no more than, for example, 0.5%. In both cases, we would see that if a stock goes up (and one of the replicas is immediately updated) without violating the specified numerical deviations, replicas would still be considered to be mutually consistent.

Numerical deviation can also be understood in terms of the number of updates that have been applied to a given replica, but have not yet been seen by others. For example, a Web cache may not have seen a batch of operations carried out by a Web server. In this case, the associated deviation in the *value* is also referred to as its *weight*.

Staleness deviations relate to the last time a replica was updated. For some applications, it can be tolerated that a replica provides old data as long as it is not *too* old. For example, weather reports typically stay reasonably accurate over some time, say a few hours. In such cases, a main server may receive timely updates, but may decide to propagate updates to the replicas only once in a while.

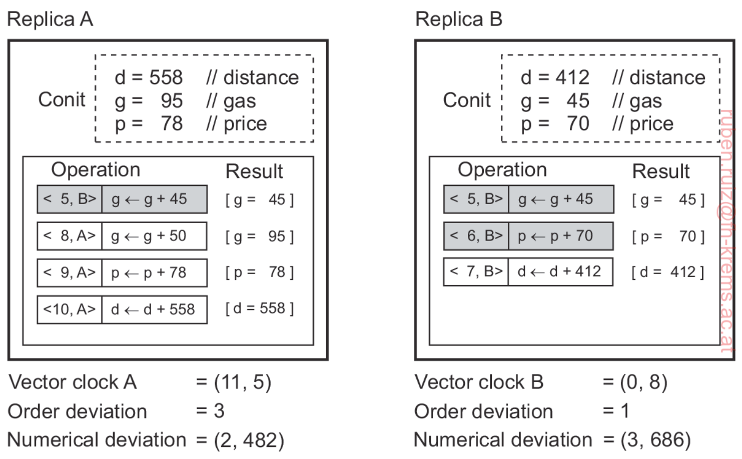
Finally, there are classes of applications in which the ordering of updates are allowed to be different at the various replicas, as long as the differences remain bounded. One way of looking at these updates is that they are applied tentatively to a local copy, awaiting global agreement from all replicas. As a consequence, some updates may need to be rolled back and applied in a different order before becoming permanent. Intuitively, ordering deviations are much harder to grasp than the other two consistency metrics.

The notion of a conit

To define inconsistencies, Yu and Vahdat introduce a **consistency unit**, abbreviated to **conit**. A conit specifies the unit over which consistency is to be measured. For example, in our stock-exchange example, a conit could be defined as a record representing a single stock. Another example is an individual weather report.

To give an example of a conit, and at the same time illustrate numerical and ordering deviations, consider the situation of keeping track of a fleet of cars. In particular, the fleet owner is interested in knowing how much he pays on average for gas. To this end, whenever a driver tanks gasoline, he reports the amount of gasoline that has been tanked (recorded as `g`), the price paid (recorded as `p`), and the total distance since the last time he tanked (recorded by the variable `d`). Technically, the three variables `g`, `p`, and `d` form a conit. This conit is replicated across two servers, as shown in Figure 7.2, and a driver regularly reports his gas usage to one of the servers by separately updating each variable (without further considering the car in question).

The task of the servers is to keep the conit "consistently" replicated. To this end, each replica server maintains a two-dimensional vector clock. We use the notation $\langle T, \mathsf{R} \rangle$ to express an operation that was carried out by replica R at (its) logical time T.



Replica A
Conit
d = 558 // distance
g = 95 // gas
p = 78 // price
Operation
Result
< 5, B> g ← g + 45 [g = 45]
< 8, A> g ← g + 50 [g = 95]
< 9, A> p ← p + 78 [p = 78]
<10, A> d ← d + 558 [d = 558]
Vector clock A = (11, 5)
Order deviation = 3
Numerical deviation = (2, 482)
Replica B
Conit
d = 412 // distance
g = 45 // gas
p = 70 // price
Operation
Result
< 5, B> g ← g + 45 [g = 45]
< 6, B> p ← p + 70 [p = 70]
< 7, B> d ← d + 412 [d = 412]
Vector clock B = (0, 8)
Order deviation = 1
Numerical deviation = (3, 686)

Figure 7.2: An example of keeping track of consistency deviations.

In this example we see two replicas that operate on a conit containing the data items g, p, and d from our example. All variables are assumed to have been initialized to 0. Replica A received the operation

$$\langle 5, \mathsf{B} \rangle : \mathsf{g} \leftarrow \mathsf{g} + 45$$

from replica B. We have shaded this operation gray to indicate that A has *committed* this operation to its local store. In other words, it has been made permanent and cannot be rolled back. Replica A also has three *tentative* update operations listed: $\langle 8, \mathsf{A} \rangle$, $\langle 9, \mathsf{A} \rangle$, and $\langle 10, \mathsf{A} \rangle$, respectively. In terms of continuous consistency, the fact that A has three tentative operations pending to be committed is referred to as an **order deviation** of, in this case, value 3. Analogously, with in total three operations of which two have been committed, B has an order deviation of 1.

From this example, we see that A's logical clock value is now 11. Because the last operation from B that A had received had timestamp 5, the vector clock at A will be $(11, 5)$, where we assume the first component of the vector is used for A and the second for B. Along the same lines, the logical clock at B is $(0, 8)$.

The **numerical deviation** at a replica R consists of two components: the number of operations at all *other* replicas that have not yet been seen by R, along with the sum of corresponding missed values (more sophisticated schemes are, of course, also possible). In our example, A has not yet seen operations $\langle 6, \mathsf{B}\rangle$ and $\langle 7, \mathsf{B}\rangle$ with a total value of 70 + 412 units, leading to a numerical deviation of $(2, 482)$. Likewise, B is still missing the three tentative operations at A, with a total summed value of 686, bringing B's numerical deviation to $(3, 686)$.

Using these notions, it becomes possible to specify specific consistency schemes. For example, we may restrict order deviation by specifying an acceptable maximal value. Likewise, we may want two replicas to never numerically deviate by more than 1000 units. Having such consistency schemes does require that a replica knows how much it is deviating from other replicas, implying that we need separate communication to keep replicas informed. The underlying assumption is that such communication is much less expensive than communication to keep replicas synchronized. Admittedly, it is questionable if this assumption also holds for our example.

Note 7.1 (Advanced: On the granularity of conits)
There is a trade-off between maintaining fine-grained and coarse-grained conits. If a conit represents a lot of data, such as a complete database, then updates are aggregated for all the data in the conit. As a consequence, this may bring replicas sooner in an inconsistent state. For example, assume that in Figure 7.3 two replicas may differ in no more than one outstanding update. In that case, when the data items in Figure 7.3 have each been updated once at the first replica, the second one will need to be updated as well. This is not the case when choosing a smaller conit, as shown in Figure 7.3 There, the replicas are still considered to be up to date. This problem is particularly important when the data items contained in a conit are used completely independently, in which case they are said to **falsely share** the conit.

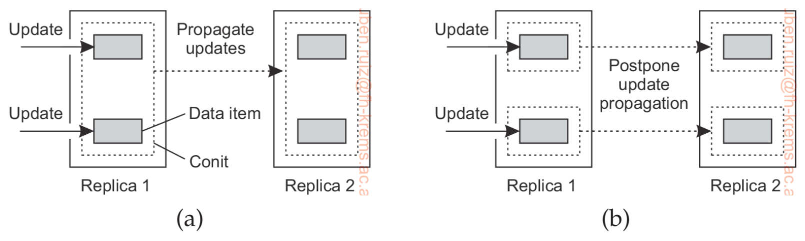


Figure 7.3: Choosing the appropriate granularity for a conit. (a) Two updates lead to update propagation. (b) No update propagation is needed.

Unfortunately, making conits very small is not a good idea, for the simple reason that the total number of conits that need to be managed grows as well. In other words, there is an overhead related to managing the conits that needs to be taken into account. This overhead, in turn, may adversely affect overall performance, which has to be taken into account.

Although from a conceptual point of view conits form an attractive means for capturing consistency requirements, there are two important issues that need to be dealt with before they can be put to practical use. First, in order to enforce consistency we need to have protocols. Protocols for continuous consistency are discussed later in this chapter.

A second issue is that program developers must specify the consistency requirements for their applications. Practice indicates that obtaining such requirements may be extremely difficult. Programmers are generally not used to handling replication, let alone understanding what it means to provide detailed information on consistency. Therefore, it is mandatory that there are simple and easy-to-understand programming interfaces.

Note 7.2 (Advanced: Programming conits)
Continuous consistency can be implemented as a toolkit which appears to programmers as just another library that they link with their applications. A conit is simply declared alongside an update of a data item. For example, the fragment of pseudocode

```
AffectsConit(ConitQ, 1, 1);
append message m to queue Q;
```

states that appending a message to queue `Q` belongs to a conit named `ConitQ`. Likewise, operations may now also be declared as being dependent on conits:

```
DependsOnConit(ConitQ, 4, 0, 60);
read message m from head of queue Q;
```

In this case, the call to `DependsOnConit()` specifies that the numerical deviation, ordering deviation, and staleness should be limited to the values 4, 0, and 60 (seconds), respectively. This can be interpreted as that there should be at most 4 unseen update operations at other replicas, there should be no tentative local updates, and the local copy of `Q` should have been checked for staleness no more than 60 seconds ago. If these requirements are not fulfilled, the underlying middleware will attempt to bring the local copy of `Q` to a state such that the read operation can be carried out.

The question, of course, is how does the system know that `Q` is associated with `ConitQ`? For practical reasons, we can avoid explicit declarations of conits and concentrate only on the grouping of operations. The data to be replicated is collectively considered to belong together. By subsequently associating a write operation with a named conit, and likewise for a read operation, we tell the middleware layer when to start synchronizing the *entire* replica. Indeed, there may be a considerable amount of false sharing in such a case. If false sharing needs to be avoided, we would have to introduce a separate programming construct to explicitly declare conits.

Consistent ordering of operations

There is a huge body of work on data-centric consistency models from the past decades. An important class of models comes from the field of parallel programming. Confronted with the fact that in parallel and distributed computing multiple processes will need to share resources and access these resources simultaneously, researchers have sought to express the semantics of concurrent accesses when shared resources are replicated. The models that we discuss here all deal with consistently ordering operations on shared, replicated data.

In principle, the models augment those of continuous consistency in the sense that when tentative updates at replicas need to be committed, replicas will need to reach agreement on a global, that is, consistent ordering of those updates.

Sequential consistency

In the following, we will use a special notation in which we draw the operations of a process along a time axis. The time axis is always drawn horizontally, with time increasing from left to right. We use the notation $W_i(x)a$ to denote that process P_i writes value a to data item x. Similarly, $R_i(x)b$ represents the fact that process P_i reads x and is returned the value b. We assume that each data item has initial value NIL. When there is no confusion concerning which process is accessing data, we omit the index from the symbols W and R.

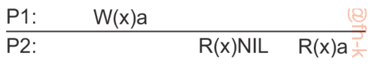


Figure 7.4: Behavior of two processes operating on the same data item. The horizontal axis is time.

As an example, in Figure 7.4 P_1 does a write to a data item x, modifying its value to a. Note that, according to our system model the operation $W_1(x)a$ is first performed on a copy of the data store that is local to P_1, and only then is it propagated to the other local copies. In our example, P_2 later reads the value NIL, and some time after that a (from its local copy of the store). What we are seeing here is that it took some time to propagate the update of x to P_2, which is perfectly acceptable.

Sequential consistency is an important data-centric consistency model, which was first defined by Lamport [1979] in the context of shared memory for multiprocessor systems. A data store is said to be sequentially consistent when it satisfies the following condition:

> *The result of any execution is the same as if the (read and write) operations by all processes on the data store were executed in some sequential order and the operations of each individual process appear in this sequence in the order specified by its program.*

What this definition means is that when processes run concurrently on (possibly) different machines, any valid interleaving of read and write operations is acceptable behavior, but *all processes see the same interleaving of operations*. Note that nothing is said about time; that is, there is no reference to the "most recent" write operation on a data item. Also, a process "sees" the writes from all processes but only through its own reads.

That time does not play a role can be seen from Figure 7.5. Consider four processes operating on the same data item x. In Figure 7.5(a) process P_1 first performs $W_1(x)a$ on x. Later (in absolute time), process P_2 also performs a write operation $W_2(x)b$, by setting the value of x to b. However, both processes P_3 and P_4 *first* read value b, and *later* value a. In other words, the write operation $W_2(x)b$ of process P_2 appears to have taken place before $W_1(x)a$ of P_1.

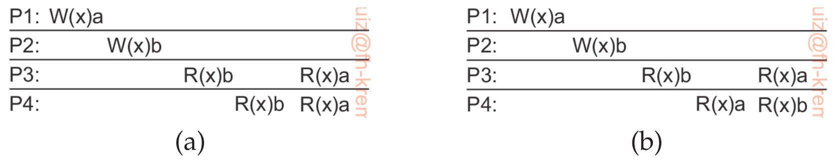


Figure 7.5: (a) A sequentially consistent data store. (b) A data store that is not sequentially consistent.

In contrast, Figure 7.5(b) violates sequential consistency because not all processes see the same interleaving of write operations. In particular, to process P_3, it appears as if the data item has first been changed to b, and later to a. On the other hand, P_4 will conclude that the final value is b.

Process P_1	Process P_2	Process P_3
`x ← 1;`	`y ← 1;`	`z ← 1;`
`print(y,z);`	`print(x,z);`	`print(x,y);`

Figure 7.6: Three concurrently executing processes.

To make the notion of sequential consistency more concrete, consider three concurrently executing processes P_1, P_2, and P_3, shown in Figure 7.6 (taken from [Dubois et al., 1988]). The data items in this example are formed by the three integer variables x, y, and z, which are stored in a (possibly distributed) shared sequentially consistent data store. We assume that each variable is initialized to 0. In this example, an assignment corresponds to a write operation, whereas a print statement corresponds to a simultaneous read operation of its two arguments. All statements are assumed to be indivisible.

Various interleaved execution sequences are possible. With six independent statements, there are potentially 720 (6!) possible execution sequences, although some of these violate program order. Consider the 120 (5!) sequences that begin with `x ← 1`. Half of these have `print(x,z)` before `y ← 1` and thus violate program order. Half also have `print(x,y)` before `z ← 1` and also violate program order. Only 1/4 of the 120 sequences, or 30, are valid. Another 30 valid sequences are possible starting with `y ← 1` and another 30 can begin with `z ← 1`, for a total of 90 valid execution sequences. Four of these are shown in Figure 7.7.

Execution 1	Execution 2	Execution 3	Execution 4
P_1: `x ← 1;`	P_1: `x ← 1;`	P_2: `y ← 1;`	P_2: `y ← 1;`
P_1: `print(y,z);`	P_2: `y ← 1;`	P_3: `z ← 1;`	P_1: `x ← 1;`
P_2: `y ← 1;`	P_2: `print(x,z);`	P_3: `print(x,y);`	P_3: `z ← 1;`
P_2: `print(x,z);`	P_1: `print(y,z);`	P_2: `print(x,z);`	P_2: `print(x,z);`
P_3: `z ← 1;`	P_3: `z ← 1;`	P_1: `x ← 1;`	P_1: `print(y,z);`
P_3: `print(x,y);`	P_3: `print(x,y);`	P_1: `print(y,z);`	P_3: `print(x,y);`
Prints: `001011`	*Prints:* `101011`	*Prints:* `010111`	*Prints:* `111111`
Signature: 00 10 11	*Signature:* 10 10 11	*Signature:* 11 01 01	*Signature:* 11 11 11
(a)	(b)	(c)	(d)

Figure 7.7: Four valid execution sequences for the processes of Figure 7.6. The vertical axis is time.

In Figure 7.7(a) the three processes are run in order, first P_1, then P_2, then P_3. The other three examples demonstrate different, but equally valid, interleavings of the statements in time. Each of the three processes prints two variables. Since the only values each variable can take on are the initial value (0), or the assigned value (1), each process produces a 2-bit string. The numbers after *Prints* are the actual outputs that appear on the output device.

If we concatenate the output of P_1, P_2, and P_3 in that order, we get a 6-bit string that characterizes a particular interleaving of statements. This is the string listed as the *Signature* in Figure 7.7. Below we will characterize each ordering by its signature rather than by its printout.

Not all 64 signature patterns are allowed. As a trivial example, 00 00 00 is not permitted, because that would imply that the print statements ran before the assignment statements, violating the requirement that statements are executed in program order. A more subtle example is 00 10 01. The first two bits, 00, mean that y and z were both 0 when P_1 did its printing. This situation occurs only when P_1 executes both statements before P_2 or P_3 starts. The next two bits, 10, mean that P_2 must run after P_1 has started but before P_3 has started. The last two bits, 01, mean that P_3 must complete before P_1 starts, but we have already seen that P_1 must go first. Therefore, 00 10 01 is not allowed.

In short, the 90 different valid statement orderings produce a variety of different program results (less than 64, though) that are allowed under the assumption of sequential consistency. The contract between the processes and the distributed shared data store is that the processes must accept all of these as valid results. In other words, the processes must accept the four results shown in Figure 7.7 and all the other valid results as proper answers, and must work correctly if any of them occurs. A program that works for some of these results and not for others violates the contract with the data store and is incorrect.

Note 7.3 (Advanced: The importance and intricacies of sequential consistency)
There is no doubt that sequential consistency is an important model. In essence, of all consistency models that exist and have been developed, it is the easiest one to understand when developing concurrent and parallel applications. This is due to the fact that the model matches best our expectations when we let several programs operate on shared data simultaneously. At the same time, implementing sequential consistency is far from trivial [Adve and Boehm, 2010]. To illustrate, consider the example involving two variables x and y, shown in Figure 7.8.

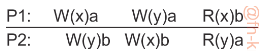


Figure 7.8: Both x and y are each handled in a sequentially consistent manner, but taken together, sequential consistency is violated.

If we just consider the write and read operations on x, the fact that P_1 reads the value a is perfectly consistent. The same holds for the operation $R_2(y)b$ by process P_2. However, when taken together, there is no way that we can order the write operations on x and y such that we can have $R_1(x)a$ and $R_2(y)b$ (note that we need to keep the ordering as executed by each process):

Ordering of operations	Result	
$W_1(x)a; W_1(y)a; W_2(y)b; W_2(x)b$	$R_1(x)b$	$R_2(y)b$
$W_1(x)a; W_2(y)b; W_1(y)a; W_2(x)b$	$R_1(x)b$	$R_2(y)a$
$W_1(x)a; W_2(y)b; W_2(x)b; W_1(y)a$	$R_1(x)b$	$R_2(y)a$
$W_2(y)b; W_1(x)a; W_1(y)a; W_2(x)b$	$R_1(x)b$	$R_2(y)a$
$W_2(y)b; W_1(x)a; W_2(x)b; W_1(y)a$	$R_1(x)b$	$R_2(y)a$
$W_2(y)b; W_2(x)b; W_1(x)a; W_1(y)a$	$R_1(x)a$	$R_2(y)a$

In terms of transactions, the operations carried out by P_1 and P_2 are not **serializable**. Our example shows that sequential consistency is not **compositional**: when having data items that are each kept sequentially consistent, their composition as a set need not be so [Herlihy and Shavit, 2008]. The problem of noncompositional consistency can be solved by assuming **linearizability**. This is best explained by making a distinction between the start and completion of an operation, and assuming that it may take some time. Linearizability [Herlihy and Wing, 1991] states that:

Each operation should appear to take effect instantaneously at some moment between its start and completion.

Returning to our example, Figure 7.9 shows the same set of write operations, but we have now also indicated when they take place: the shaded area designates the time the operation is being executed. Linearizability states that the effect of an operation should take place somewhere during the interval indicated by the shaded area. In principle, this means that at the time of completion of a write operation, the results should be propagated to the other data stores.

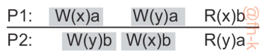


Figure 7.9: An example of taking linearizable sequential consistency into account, with only one possible outcome for x and y.

With that in mind, the possibilities for properly ordering become limited:

Ordering of operations	Result	
$W_1(x)a$; $W_2(y)b$; $W_1(y)a$; $W_2(x)b$	$R_1(x)b$	$R_2(y)a$
$W_1(x)a$; $W_2(y)b$; $W_2(x)b$; $W_1(y)a$	$R_1(x)b$	$R_2(y)a$
$W_2(y)b$; $W_1(x)a$; $W_1(y)a$; $W_2(x)b$	$R_1(x)b$	$R_2(y)a$
$W_2(y)b$; $W_1(x)a$; $W_2(x)b$; $W_1(y)a$	$R_1(x)b$	$R_2(y)a$

In particular, $W_2(y)b$ is completed before $W_1(y)a$ starts, so that y will have the value a. Likewise, $W_1(x)a$ completes before $W_2(x)b$ starts, so that x will have value b. It should not come as a surprise that implementing linearizability on a many-core architecture may impose serious performance problems. Yet at the same time, it eases programmability considerably, so a trade-off needs to be made.

Causal consistency

The **causal consistency** model [Hutto and Ahamad, 1990] represents a weakening of sequential consistency in that it makes a distinction between events that are potentially causally related and those that are not. We already came across causality when discussing vector timestamps in the previous chapter. If event b is caused or influenced by an earlier event a, causality requires that everyone else first see a, then see b.

Consider a simple interaction by means of a distributed shared database. Suppose that process P_1 writes a data item x. Then P_2 reads x and writes y. Here the reading of x and the writing of y are potentially causally related because the computation of y may have depended on the value of x as read by P_2 (i.e., the value written by P_1).

On the other hand, if two processes spontaneously and simultaneously write two different data items, these are not causally related. Operations that are not causally related are said to be **concurrent**.

For a data store to be considered causally consistent, it is necessary that the store obeys the following condition:

Writes that are potentially causally related must be seen by all processes in the same order. Concurrent writes may be seen in a different order on *different machines.*

As an example of causal consistency, consider Figure 7.10. Here we have an event sequence that is allowed with a causally consistent store, but which is forbidden with a sequentially consistent store or a strictly consistent store. The thing to note is that the writes $W_2(x)b$ and $W_1(x)c$ are concurrent, so it is not required that all processes see them in the same order.

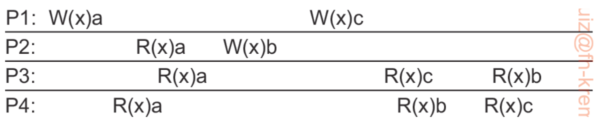


Figure 7.10: This sequence is allowed with a causally-consistent store, but not with a sequentially consistent store.

Now consider a second example. In Figure 7.11(a) we have $W_2(x)b$ potentially depending on $W_1(x)a$ because writing the value b into x may be a result of a computation involving the previously read value by $R_2(x)a$. The two writes are causally related, so all processes must see them in the same order. Therefore, Figure 7.11(a) is incorrect. On the other hand, in Figure 7.11(b) the read has been removed, so $W_1(x)a$ and $W_2(x)b$ are now concurrent writes. A causally consistent store does not require concurrent writes to be globally ordered, so Figure 7.11(b) is correct. Note that Figure 7.11(b) reflects a situation that would not be acceptable for a sequentially consistent store.

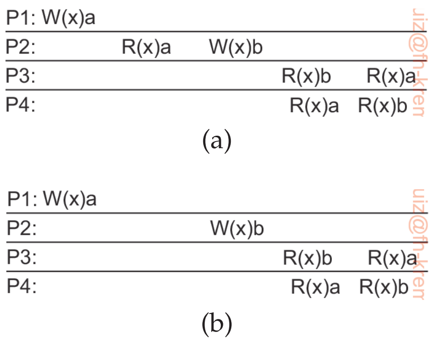


Figure 7.11: (a) A violation of a causally-consistent store. (b) A correct sequence of events in a causally-consistent store.

Implementing causal consistency requires keeping track of which processes have seen which writes. There are many subtle issues to take into account. To illustrate, assume we replace $W_2(x)b$ in Figure 7.11(a) with $W_2(y)b$, and likewise $R_3(x)b$ with $R_3(y)b$, respectively. This situation is shown in Figure 7.12.

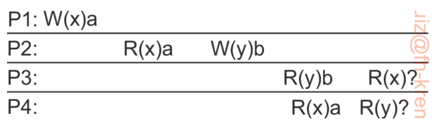


Figure 7.12: A slight modification of Figure 7.11(a). What should $R_3(x)$ or $R_4(y)$ return?

Let us first look at operation $R_3(x)$. Process P_3 executes this operation after $R_3(y)b$. We know at this point for sure that $W(x)a$ *happened before* $W(y)b$. In particular, $W(x)a \rightarrow R(x)a \rightarrow W(y)b$, meaning that if we are to preserve causality, reading x after reading b from y can return only a. If the system would return NIL to P_3 it would violate the preservation of causal relationships.

What about $R_4(y)$? Could it return the initial value of y, namely NIL? The answer is affirmative: although we have the formal *happened-before* relationship $W(x)a \rightarrow W(y)b$, without having read b from y, process P_4 can still justifiably observe that $W(x)a$ took place independently from the initialization of y.

Implementationwise, preserving causality introduces some interesting questions. Consider, for example, the middleware underlying process P_3 from Figure 7.12. At the point that this middleware returns the value b from reading y, it must know about the relationship $W(x)a \rightarrow W(y)b$. In other words, when the most recent value of y was propagated to P_3's middleware, at the very least metadata on y's dependency should have been propagated as well. Alternatively, the propagation may have also been done together with updating x at P_3's node. By-and-large, the bottom line is that we need a dependency graph of which operation is dependent on which other operations. Such a graph may be pruned at the moment that dependent data is also locally stored.

Grouping operations

Many consistency models are defined at the level of elementary read and write operations. This level of granularity is for historical reasons: these models have initially been developed for shared-memory multiprocessor systems and were actually implemented at the hardware level.

The fine granularity of these consistency models in many cases does not match the granularity as provided by applications. What we see there is that concurrency between programs sharing data is generally kept under control through synchronization mechanisms for mutual exclusion and transactions. Effectively, what happens is that at the program level read and write operations are bracketed by the pair of operations ENTER_CS and LEAVE_CS. A process that has successfully executed ENTER_CS will be ensured that all the data in its local store is up to date. At that point, it can safely execute a series of read and write operations on that store, and subsequently wrap things up by calling LEAVE_CS. Data and instructions between ENTER_CS and LEAVE_CS is denoted as a **critical section**.

In essence, what happens is that within a program the data that are operated on by a series of read and write operations are protected against concurrent accesses that would lead to seeing something else than the result of executing the series as a whole. Put differently, the bracketing turns the series of read and write operations into an atomically executed unit, thus raising the level of granularity.

In order to reach this point, we do need to have precise semantics concerning the operations ENTER_CS and LEAVE_CS. These semantics can be formulated in terms of shared **synchronization variables**, or simply **locks**. A lock has shared data items associated with it, and each shared data item is associated with at most one lock. In the case of coarse-grained synchronization, all shared data items would be associated to just a single lock. Fine-grained synchronization is achieved when each shared data item has its own unique lock. Of course, these are just two extremes of associating shared data to a lock. When a process enters a critical section it should *acquire* the relevant locks, and likewise when it leaves the critical section, it *releases* these locks.

Each lock has a current owner, namely, the process that last acquired it. A process not currently owning a lock but wanting to acquire it has to send a message to the current owner asking for ownership and the current values of the data associated with that lock. While having *exclusive access* to a lock, a process is allowed to perform read and write operations. It is also possible for several processes to simultaneously have *nonexclusive access* to a lock, meaning that they can read, but not write, the associated data. Of course, nonexclusive access can be granted if and only if there is no other process having exclusive access.

We now demand that the following criteria are met [Bershad et al., 1993]:

- Acquiring a lock can succeed only when all updates to its associated shared data have completed.
- Exclusive access to a lock can succeed only if no other process has exclusive or nonexclusive access to that lock.
- Nonexclusive access to a lock is allowed only if any previous exclusive access has been completed, including updates on the lock's associated data.

Note that we are effectively demanding that the usage of locks is linearized, adhering to sequential consistency. Figure 7.13 shows an example of what is known as **entry consistency**. We associate a lock with each data item separately. We use the notation L(x) as an abbreviation for acquiring the lock for x, that is, *locking* x. Likewise, U(x) stands for releasing the lock on x, or *unlocking* it. In this case, P_1 locks x, changes x once, after which it locks y.

Process P_2 also acquires the lock for x but not for y, so that it will read value a for x, but may read NIL for y. However, because process P_3 first acquires the lock for y, it will read the value b when y was unlocked by P_1. It is important to note here that each process has a *copy* of a variable, but that this copy need not be instantly or automatically updated. When locking or unlocking a variable, a process is explicitly telling the underlying distributed system that the copies of that variable need to be synchronized. A simple read operation without locking may thus result in reading a local value that is effectively stale.

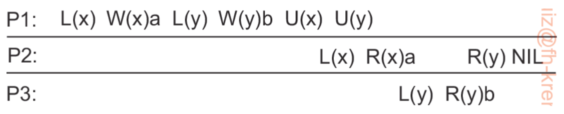


Figure 7.13: A valid event sequence for entry consistency.

One of the programming problems with entry consistency is properly associating data with locks. One straightforward approach is to explicitly tell the middleware which data are going to be accessed, as is generally done by declaring which database tables will be affected by a transaction. In an object-based approach, we could associate a unique lock with each declared object, effectively serializing all invocations to such objects.

Consistency versus coherence

At this point, it is useful to clarify the difference between two closely related concepts. The models we have discussed so far all deal with the fact that a number of processes execute read and write operations on a set of data items. A **consistency model** describes what can be expected with respect to that set when multiple processes concurrently operate on that data. The set is then said to be consistent if it adheres to the rules described by the model.

Where data consistency is concerned with a set of data items, **coherence models** describe what can be expected to hold for only a single data item [Cantin et al., 2005]. In this case, we assume that a data item is replicated; it is said to be coherent when the various copies abide to the rules as defined by its associated consistency model. A popular model is that of sequential consistency, but now applied to only a single data item. In effect, it means that in the case of concurrent writes, all processes will eventually see the same order of updates taking place.

Eventual consistency

To what extent processes actually operate in a concurrent fashion, and to what extent consistency needs to be guaranteed, may vary. There are many examples in which concurrency appears only in a restricted form. For example, in many database systems, most processes hardly ever perform update operations; they mostly read data from the database. Only one, or very few processes perform update operations. The question then is how fast updates should be made available to only-reading processes. In the advent of globally operating content delivery networks, developers often choose to propagate updates slowly, implicitly assuming that most clients are always redirected to the same replica and will therefore never experience inconsistencies.

Another example is the Web. In virtually all cases, Web pages are updated by a single authority, such as a webmaster or the actual owner of the page. There are normally no write-write conflicts to resolve. On the other hand, to improve efficiency, browsers and Web proxies are often configured to keep a fetched page in a local cache and to return that page upon the next request. An important aspect of both types of Web caches is that they may return out-of-date Web pages. In other words, the cached page that is returned to the requesting client is an older version compared to the one available at the actual Web server. As it turns out, many users find this inconsistency acceptable (to a certain degree), as long as they have access only to the same cache. In effect, they remain unaware of the fact that an update had taken place, just as in the previous case of content delivery networks.

Yet another example, is a worldwide naming system such as DNS. The DNS name space is partitioned into domains, where each domain is assigned to a naming authority, which acts as owner of that domain. Only that authority is allowed to update its part of the name space. Consequently, conflicts resulting from two operations that both want to perform an update on the same data (i.e., **write-write conflicts**), never occur. The only situation that needs to be handled are **read-write conflicts**, in which one process wants to update a data item while another is concurrently attempting to read that item. As it turns out, also in this case is it often acceptable to propagate an update in a lazy fashion, meaning that a reading process will see an update only after some time has passed since the update took place.

These examples can be viewed as cases of (large scale) distributed and replicated databases that tolerate a relatively high degree of inconsistency. They have in common that if no updates take place for a long time, all replicas will gradually become consistent, that is, have exactly the same data stored. This form of consistency is called **eventual consistency** [Vogels, 2009].

Data stores that are eventually consistent thus have the property that in the absence of write-write conflicts, all replicas will converge toward identical copies of each other. Eventual consistency essentially requires only that updates are guaranteed to propagate to all replicas. Write-write conflicts are often relatively easy to solve when assuming that only a small group of processes can perform updates. In practice, we often also see that in the case of conflicts, one specific write operation is (globally) declared as "winner," overwriting the effects of any other conflicting write operation. Eventual consistency is therefore often cheap to implement.

Note 7.4 (Advanced: Making eventual consistency stronger)

Eventual consistency is a relatively easy model to understand, but equally important is the fact that it is also relatively easy to implement. Nevertheless, it is a weak-consistency model with its own peculiarities. Consider a calendar shared between Alice, Bob, and Chuck. A meeting M has two attributes: a proposed starting time and a set of people who have confirmed their attendance. When Alice proposes to start meeting M at time T, and assuming no one else has confirmed attendance, she executes the operation $\mathsf{W_A(M)[T,\{A\}]}$. When Bob confirms his attendance, he will have read the tuple $\mathsf{[T,\{A\}]}$ and update M accordingly: $\mathsf{W_B(M)[T,\{A,B\}]}$. In our example two meetings $\mathsf{M_1}$ and $\mathsf{M_2}$ need to be planned.

Assume the sequence of events

$$\mathsf{W_A(M_1)[T_1,\{A\}]} \rightarrow \mathsf{R_B(M_1)[T_1,\{A\}]} \rightarrow$$

$$\mathsf{W_B(M_1)[T_1,\{A,B\}]} \rightarrow \mathsf{W_B(M_2)[T_2,\{B\}]}.$$

In other words, Bob confirms his attendance at $\mathsf{M_1}$ and then immediately proposes to schedule $\mathsf{M_2}$ at $\mathsf{T_2}$. Unfortunately, Chuck *concurrently* proposes to schedule $\mathsf{M_1}$ at $\mathsf{T_3}$ when Bob confirms he can attend $\mathsf{M_1}$ at $\mathsf{T_1}$. Formally, using the symbol "$\|$" to denote concurrent operations, we have,

$$\mathsf{W_B(M_1)[T_1,\{A,B\}]} \parallel \mathsf{W_C(M_1)[T_3,\{C\}]}$$

Using our usual notation, these operations can be illustrated as shown in Figure 7.14.

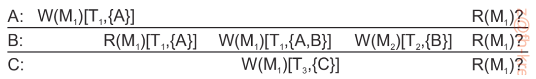


Figure 7.14: The situation of updating two meetings $\mathsf{M_1}$ and $\mathsf{M_2}$.

Eventual consistency may lead to very different scenarios. There is a number of write-write conflicts, but in any case, eventually $\mathsf{[T_2,\{B\}]}$ will be stored for meeting $\mathsf{M_2}$, as the result of the associated write operation by Bob. For the value of meeting $\mathsf{M_1}$ there are different options. In principle, we have *three* possible outcomes: $\mathsf{[T_1,\{A\}]}$, $\mathsf{[T_1,\{A,B\}]}$, and $\mathsf{[T_3,\{C\}]}$. Assuming we can maintain some notion of a global clock, it is not very likely that $\mathsf{W_A(M_1)[T_1,\{A\}]}$ will prevail. However, the two write operations $\mathsf{W_B(M_1)[T_1,\{A,B\}]}$ and $\mathsf{W_C(M_1)[T_1,\{C\}]}$ are truly in conflict. In practice, one of them will win, presumably through a decision by a central coordinator.

Researchers have been seeking to combine eventual consistency with stricter guarantees on ordering. Bailis et al. [2013] propose to use a separate layer that operates on top of an eventually consistent, distributed store. This layer implements causal consistency, of which it has been formerly proven that it is the best attainable consistency in the presence of network partitioning [Mahajan et al., 2011]. In our example, we have only one chain of dependencies:

$$W_A(M_1)[T_1, \{A\}] \rightarrow R_B(M_1)[T_1, \{A\}] \rightarrow$$

$$W_B(M_1)[T_1, \{A, B\}] \rightarrow W_B(M_2)[T_2, \{B\}].$$

An important observation is that with causal consistency in place, once a process reads $[T_2, \{B\}]$ for meeting M_2, obtaining the value for M_1 returns either $[T_1, \{A, B\}]$ or $[T_3, \{C\}]$, but certainly not $[T_1, \{A\}]$. The reason is that $W_B(M_1)[T_1, \{A, B\}]$ immediately precedes $W_B(M_2)[T_2, \{B\}]$, and at worse may have been overwritten by $W_C(M_1)[T_3, \{C\}]$. Causal consistency rules out that the system could return $[T_1, \{A\}]$.

However, eventual consistency may overwrite previously stored data items. In doing so, dependencies may be lost. To make this point clear, it is important to realize that in practice an operation at best keeps track of the immediate preceding operation it depends on. As soon as $W_c(M_1)[T_3, \{C\}]$ *overwrites* $W_B(M_1)[T_1, \{A, B\}]$ (and propagates to all replicas), we also break the chain of dependencies

$$W_A(M_1)[T_1, \{A\}] \rightarrow R_B(M_1)[T_1, \{A\}] \rightarrow \cdots \rightarrow W_B(M_2)[T_2, \{B\}]$$

which would normally prevent $W_A(M_1)[T_1, \{A\}]$ ever overtaking $W_B(M_1)[T_1, \{A, B\}]$ and any operation depending on it. As a consequence, maintaining causal consistency requires that we do maintain a history of dependencies, instead of just keeping track of immediately preceding operations.

7.3 Client-centric consistency models

Data-centric consistency models aim at providing a systemwide consistent view on a data store. An important assumption is that concurrent processes may be simultaneously updating the data store, and that it is necessary to provide consistency in the face of such concurrency. For example, in the case of object-based entry consistency, the data store guarantees that when an object is called, the calling process is provided with a copy of the object that reflects all changes to the object that have been made so far, possibly by other processes. During the call, it is also guaranteed that no other process can interfere, that is, mutual exclusive access is provided to the calling process.

Being able to handle concurrent operations on shared data while maintaining strong consistency is fundamental to distributed systems. For performance reasons, strong consistency may possibly be guaranteed only when processes use mechanisms such as transactions or synchronization variables. Along the same lines, it may be impossible to guarantee strong consistency, and weaker forms need to be accepted, such as causal consistency in combination with eventual consistency.

In this section, we take a look at a special class of distributed data stores. The data stores we consider are characterized by the lack of simultaneous updates, or when such updates happen, it is assumed that they can be relatively easily resolved. Most operations involve reading data. These data stores offer a weak consistency model, such as eventual consistency. By introducing special client-centric consistency models, it turns out that many inconsistencies can be hidden in a relatively cheap way.

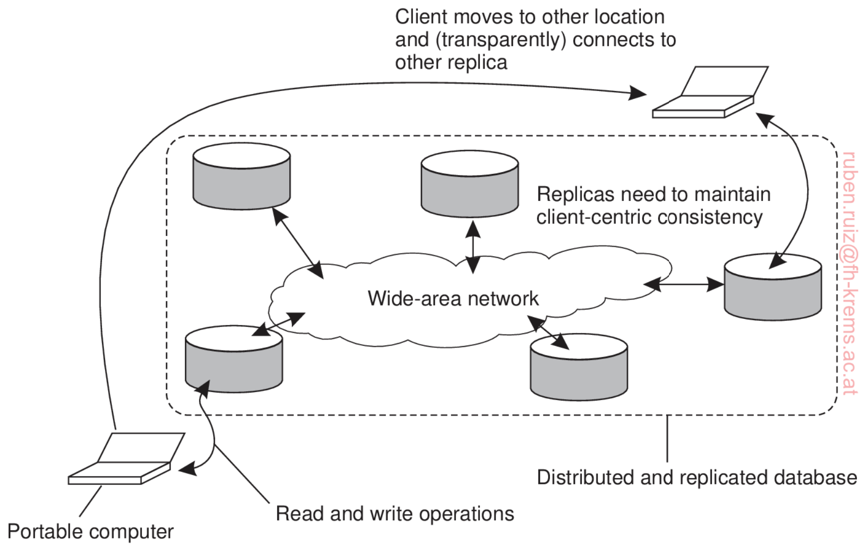

Client moves to other location and (transparently) connects to other replica
Replicas need to maintain client-centric consistency
Wide-area network
Distributed and replicated database
Read and write operations
Portable computer

Figure 7.15: The principle of a mobile user accessing different replicas of a distributed database.

Eventually consistent data stores generally work fine as long as clients always access the same replica. However, problems arise when different replicas are accessed over a short period of time. This is best illustrated by considering a mobile user accessing a distributed database, as shown in Figure 7.15.

The mobile user, say, Alice, accesses the database by connecting to one of the replicas in a transparent way. In other words, the application running on Alice's mobile device is unaware on which replica it is actually operating. Assume Alice performs several update operations and then disconnects again. Later, she accesses the database again, possibly after moving to a different location or by using a different access device. At that point, she may be connected to a different replica than before, as shown in Figure 7.15. However, if the updates performed previously have not yet been propagated, Alice will notice inconsistent behavior. In particular, she would expect to see all previously made changes, but instead, it appears as if nothing at all has happened.

This example is typical for eventually consistent data stores and is caused by the fact that users may sometimes operate on different replicas while updates have not been fully propagated. The problem can be alleviated by introducing **client-centric consistency**. In essence, client-centric consistency provides guarantees *for a single client* concerning the consistency of accesses to a data store by that client. No guarantees are given concerning concurrent accesses by different clients. If Bob modifies data that is shared with Alice but which is stored at a different location, we may easily create write-write conflicts. Moreover, if neither Alice nor Bob access the same location for some time, such conflicts may take a long time before they are discovered.

Client-centric consistency models originate from the work on Bayou and, more general, from mobile-data systems (see, for example, Terry et al. [1994], Terry et al. [1998], or Terry [2008]). Bayou is a database system developed for mobile computing, where it is assumed that network connectivity is unreliable and subject to various performance problems. Wireless networks and networks that span large areas, such as the Internet, fall into this category.

Bayou essentially distinguishes four different consistency models. To explain these models, we again consider a data store that is physically distributed across multiple machines. When a process accesses the data store, it generally connects to the locally (or nearest) available copy, although, in principle, any copy will do just fine. All read and write operations are performed on that local copy. Updates are eventually propagated to the other copies.

Client-centric consistency models are described using the following notations. Let x_i denote the *version* of data item x. Version x_i is the result of a series of write operations that took place since initialization, its **write set** $WS(x_i)$. By appending write operations to that series we obtain another version x_j and say that x_j *follows from* x_i. We use the notation $WS(x_i;x_j)$ to indicate that x_j follows from x_i. If we do not know if x_j follows from x_i, we use the notation $WS(x_i|x_j)$.

Monotonic reads

The first client-centric consistency model is that of monotonic reads. A (distributed) data store is said to provide **monotonic-read consistency** if the following condition holds:

> *If a process reads the value of a data item x, any successive read operation on x by that process will always return that same value or a more recent value.*

In other words, monotonic-read consistency guarantees that once a process has seen a value of x, it will never see an older version of x.

As an example where monotonic reads are useful, consider a distributed e-mail database. In such a database, each user's mailbox may be distributed and replicated across multiple machines. Mail can be inserted in a mailbox at any location. However, updates are propagated in a lazy (i.e., on demand) fashion. Only when a copy needs certain data for consistency are those data propagated to that copy. Suppose a user reads his mail in San Francisco. Assume that only reading mail does not affect the mailbox, that is, messages are not removed, stored in subdirectories, or even tagged as having already been read, and so on. When the user later flies to New York and opens his mailbox again, monotonic-read consistency guarantees that the messages that were in the mailbox in San Francisco will also be in the mailbox when it is opened in New York.

Using a notation similar to that for data-centric consistency models, monotonic-read consistency can be graphically represented as shown in Figure 7.16. Rather than showing *processes* along the vertical axis, we now show *local data stores*, in our example L_1 and L_2. A write or read operation is indexed by the process that executed the operation, that is, $W_1(x)a$ denotes that process P_1 wrote value a to x. As we are not interested in specific values of shared data items, but rather their versions, we use the notation $W_1(x_2)$ to indicate that process P_1 produces version x_2 without knowing anything about other versions. $W_2(x_1;x_2)$ indicates that process P_2 is responsible for producing version x_2 that follows from x_1. Likewise, $W_2(x_1|x_2)$ denotes that process P_2 producing version x_2 *concurrently* to version x_1 (and thus potentially introducing a write-write conflict). $R_1(x_2)$ simply means that P_1 reads version x_2.

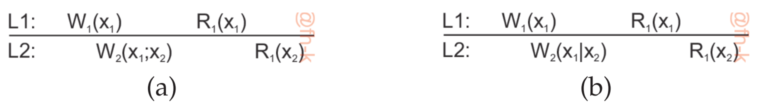


Figure 7.16: The read operations performed by a single process P at two different local copies of the same data store. (a) A monotonic-read consistent data store. (b) A data store that does not provide monotonic reads.

In Figure 7.16(a) process P_1 first performs a write operation on x at L_1, producing version x_1 and later reads this version. At L_2 process P_2 first produces version x_2, following from x_1. When process P_1 moves to L_2 and reads x again, it finds a more recent value, but one that at least took its previous write into account.

Figure 7.16(b) shows a situation in which monotonic-read consistency is violated. After process P_1 has read x_1 at L_1, it later performs the operation $R_1(x_2)$ at L_2. However, the preceding write operation $W_2(x_1|x_2)$ by process P_2 at L_2 is known to produce a version that does not follow from x_1. As a consequence, P_1's read operation at L_2 is known not to include the effect of the write operations when it performed $R_1(x_1)$ at location L_1.

Monotonic writes

In many situations, it is important that write operations are propagated in the correct order to all copies of the data store. This property is expressed in monotonic-write consistency. In a **monotonic-write consistent** store, the following condition holds:

> *A write operation by a process on a data item* x *is completed before any successive write operation on* x *by the same process.*

More formally, if we have two successive operations $W_k(x_i)$ and $W_k(x_j)$ by process P_k, then, regardless where $W_k(x_j)$ takes place, we also have $WS(x_i;x_j)$. Thus, completing a write operation means that the copy on which a successive operation is performed reflects the effect of a previous write operation by the same process, no matter where that operation was initiated. In other words, a write operation on a copy of item x is performed only if that copy has been brought up to date by means of any preceding write operation by that same process, which may have taken place on other copies of x. If need be, the new write must wait for old ones to finish.

Note that monotonic-write consistency resembles data-centric FIFO consistency. The essence of FIFO consistency is that write operations by the same process are performed in the correct order everywhere. This ordering constraint also applies to monotonic writes, except that we are now considering consistency only for a single process instead of for a collection of concurrent processes.

Bringing a copy of x up to date need not be necessary when each write operation completely overwrites the present value of x. However, write operations are often performed on only part of the state of a data item. Consider, for example, a software library. In many cases, updating such a library is done by replacing one or more functions, leading to a next version. With monotonic-write consistency, guarantees are given that if an update is performed on a copy of the library, all preceding updates will be performed first. The resulting library will then indeed become the most recent version and will include all updates that have led to previous versions of the library.

Monotonic-write consistency is shown in Figure 7.17. In Figure 7.17(a) process P_1 performs a write operation on x at L_1, presented as the operation $W_1(x_1)$. Later, P_1 performs another write operation on x, but this time at L_2, shown as $W_1(x_2;x_3)$. The version produced by P_1 at L_2 follows from an update by process P_2, in turn based on version x_1. The latter is expressed by the operation $W_2(x_1;x_2)$. To ensure monotonic-write consistency, it is necessary that the previous write operation at L_1 has already been propagated to L_2, and possibly updated.

In contrast, Figure 7.17(b) shows a situation in which monotonic-write consistency is not guaranteed. Compared to Figure 7.17(a) what is missing is the propagation of x_1 to L_2 before another version of x is produced, expressed

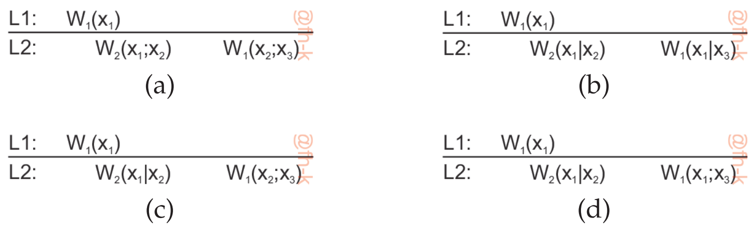


Figure 7.17: The write operations performed at two different local copies of the same data store. (a) A monotonic-write consistent data store. (b) A data store that does not provide monotonic-write consistency. (c) Again, no consistency as $WS(x_1|x2)$ and thus also $WS(x_1|x_3)$. (d) Consistent as $WS(x_1;x_3)$ although x_1 has apparently overwritten x_2.

by the operation $W_2(x_1|x_2)$. In this case, process P_2 produced a concurrent version to x_1, after which process P_1 simply produces version x_3, but again concurrently to x_1. Only slightly more subtle, but still violating monotonic-write consistency, is the situation sketched in Figure 7.17(c). Process P_1 now produces version x_3 which follows from x_2. However, because x_2 does not incorporate the write operations that led to x_1, that is, $WS(x_1|x_2)$, we also have $WS(x_1|x_3)$.

An interesting case is shown in Figure 7.17(d). The operation $W_2(x_1|x_2)$ produces version x_2 concurrently to x_1. However, later process P_1 produces version x_3, but apparently based on the fact that version x_1 had become available at L_2. How and when x_1 was transferred to L_2 is left unspecified, but in any case a write-write conflict was created with version x_2 and resolved in favor of x_1. A consequence is that the situation shown in Figure 7.17(d) follows the rules for monotonic-write consistency. Note, however, that any subsequent write by process P_2 at L_2 (without having read version x_1) will immediately violate consistency again. How such a violation can be prevented is left as an exercise to the reader.

Note that, by the definition of monotonic-write consistency, write operations by the same process are performed in the same order as they are initiated. A somewhat weaker form of monotonic writes is one in which the effects of a write operation are seen only if all preceding writes have been carried out as well, but perhaps not in the order in which they have been originally initiated. This consistency is applicable in those cases in which write operations are commutative, so that ordering is really not necessary. Details are found in [Terry et al., 1994].

Read your writes

A data store is said to provide **read-your-writes consistency**, if the following condition holds:

The effect of a write operation by a process on data item x *will always be seen by a successive read operation on* x *by the same process.*

In other words, a write operation is always completed before a successive read operation by the same process, no matter where that read operation takes place.

The absence of read-your-writes consistency is sometimes experienced when updating Web documents and subsequently viewing the effects. Update operations frequently take place by means of a standard editor or word processor, perhaps embedded as part of a content management system, which then saves the new version on a file system that is shared by the Web server. The user's Web browser accesses that same file, possibly after requesting it from the local Web server. However, once the file has been fetched, either the server or the browser often caches a local copy for subsequent accesses. Consequently, when the Web page is updated, the user will not see the effects if the browser or the server returns the cached copy instead of the original file. Read-your-writes consistency can guarantee that if the editor and browser are integrated into a single program, the cache is invalidated when the page is updated, so that the updated file is fetched and displayed.

Similar effects occur when updating passwords. For example, to enter a digital library on the Web, it is often necessary to have an account with an accompanying password. However, changing a password may take some time to come into effect, with the result that the library may be inaccessible to the user for a few minutes. The delay can be caused because a separate server is used to manage passwords and it may take some time to subsequently propagate (encrypted) passwords to the various servers that constitute the library.

Figure 7.18(a) shows a data store that provides read-your-writes consistency. Note that Figure 7.18(a) is very similar to Figure 7.16(a), except that consistency is now determined by the last write operation by process P_1, instead of its last read.

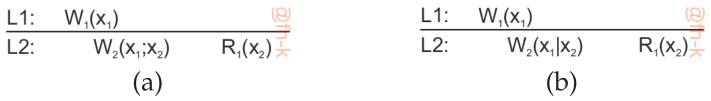


Figure 7.18: (a) A data store that provides read-your-writes consistency. (b) A data store that does not.

In Figure 7.18(a) process P_1 performed a write operation $W_1(x_1)$ and later a read operation at a different local copy. Read-your-writes consistency guarantees that the effects of the write operation can be seen by the succeeding read operation. This is expressed by $W_2(x_1;x_2)$, which states that a process P_2 produced a new version of x, yet one based on x_1. In contrast, in Figure 7.18(b) process P_2 produces a version concurrently to x_1, expressed as $W_2(x_1|x_2)$.

This means that the effects of the previous write operation by process P_1 have not been propagated to L_2 at the time x_2 was produced. When P_1 reads x_2, it will not see the effects of its own write operation at L_1.

Writes follow reads

The last client-centric consistency model is one in which updates are propagated as the result of previous read operations. A data store is said to provide **writes-follow-reads** consistency, if the following holds.

A write operation by a process on a data item x *following a previous read operation on* x *by the same process is guaranteed to take place on the same or a more recent value of* x *that was read.*

In other words, any successive write operation by a process on a data item x will be performed on a copy of x that is up to date with the value most recently read by that process.

Writes-follow-reads consistency can be used to guarantee that users of a network newsgroup see a posting of a reaction to an article only after they have seen the original article [Terry et al., 1994]. To understand the problem, assume that a user first reads an article A. Then, she reacts by posting a response B. By requiring writes-follow-reads consistency, B will be written to any copy of the newsgroup only after A has been written as well. Note that users who only read articles need not require any specific client-centric consistency model. The writes-follows-reads consistency assures that reactions to articles are stored at a local copy only if the original is stored there as well.

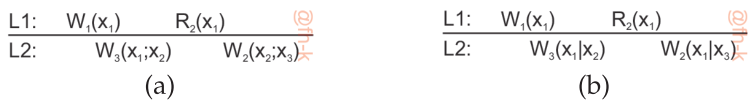

L1: $W_1(x_1)$ $R_2(x_1)$
L2: $W_3(x_1;x_2)$ $W_2(x_2;x_3)$
(a)
L1: $W_1(x_1)$ $R_2(x_1)$
L2: $W_3(x_1|x_2)$ $W_2(x_1|x_3)$
(b)

Figure 7.19: (a) A writes-follow-reads consistent data store. (b) A data store that does not provide writes-follow-reads consistency.

This consistency model is shown in Figure 7.19. In Figure 7.19(a), process P_2 reads version x_1 at local copy L_1. This version of x was previously produced at L_1 by process P_1 through the operation $W_1(x_1)$. That version was subsequently propagated to L_2, and used by another process P_3 to produce a new version x_2, expressed as $W_3(x_1;x_2)$. When process P_2 later updates its version of x after moving to L_2, it is known that it will operate on a version that follows from x_1, expressed as $W_2(x_2;x_3)$. Because we also have $W_3(x_1;x_2)$, we known that $WS(x_1;x_3)$.

The situation shown in Figure 7.19(b) is different. Process P_3 produces a version x_2 concurrently to that of x_1. As a consequence, when P_2 updates x after reading x_1, it will be updating a version it had not read before. Writes-follow-reads consistency is then violated.

7.4 Replica management

A key issue for any distributed system that supports replication is to decide where, when, and by whom replicas should be placed, and subsequently which mechanisms to use for keeping the replicas consistent. The placement problem itself should be split into two subproblems: that of placing *replica servers*, and that of placing *content*. The difference is a subtle one and the two issues are often not clearly separated. Replica-server placement is concerned with finding the best locations to place a server that can host (part of) a data store. Content placement deals with finding the best servers for placing content. Note that this often means that we are looking for the optimal placement of only a single data item. Obviously, before content placement can take place, replica servers will have to be placed first.

Finding the best server location

Where perhaps over a decade ago one could be concerned about where to place an individual server, matters have changed considerably with the advent of the many large-scale data centers located across the Internet. Likewise, connectivity continues to improve, making *precisely* locating servers less critical.

Note 7.5 (Advanced: Replica-server placement)
The placement of replica servers is not an intensively studied problem for the simple reason that it is often more of a management and commercial issue than an optimization problem. Nonetheless, analysis of client and network properties are useful to come to informed decisions.

There are various ways to compute the best placement of replica servers, but all boil down to an optimization problem in which the best K out of N locations need to be selected ($K < N$). These problems are known to be computationally complex and can be solved only through heuristics. Qiu et al. [2001] take the distance between clients and locations as their starting point. Distance can be measured in terms of latency or bandwidth. Their solution selects one server at a time such that the average distance between that server and its clients is minimal given that already k servers have been placed (meaning that there are $N - k$ locations left).

As an alternative, Radoslavov et al. [2001] propose to ignore the position of clients and only take the topology of the Internet as formed by the autonomous systems. An **autonomous system** (**AS**) can best be viewed as a network in which the nodes all run the same routing protocol and which is managed by a single organization. As of 2015, there were some 30,000 ASes. Radoslavov et al. first consider the largest AS and place a server on the router with the largest number of network interfaces (i.e., links). This algorithm is then repeated with the second largest AS, and so on.

As it turns out, client-unaware server placement achieves similar results as client-aware placement, under the assumption that clients are uniformly distributed across the Internet (relative to the existing topology). To what extent this assumption is true is unclear. It has not been well studied.

One problem with these algorithms is that they are computationally expensive. For example, both the previous algorithms have a complexity that is higher than $\mathcal{O}(N^2)$, where N is the number of locations to inspect. In practice, this means that for even a few thousand locations, a computation may need to run for tens of minutes. This may be unacceptable.

Szymaniak et al. [2006] have developed a method by which a region for placing replicas can be quickly identified. A region is identified to be a collection of nodes accessing the same content, but for which the internode latency is low. The goal of the algorithm is first to select the most demanding regions–that is, the one with the most nodes–and then to let one of the nodes in such a region act as replica server.

To this end, nodes are assumed to be positioned in an m-dimensional geometric space, as we discussed in the previous chapter. The basic idea is to identify the K largest clusters and assign a node from each cluster to host replicated content. To identify these clusters, the entire space is partitioned into cells. The K most dense cells are then chosen for placing a replica server. A cell is nothing but an m-dimensional hypercube. For a two-dimensional space, this corresponds to a rectangle.

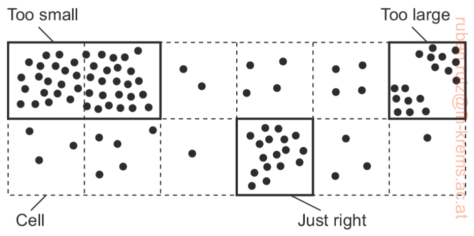


Figure 7.20: Choosing a proper cell size for server placement.

Obviously, the cell size is important, as shown in Figure 7.20. If cells are chosen too large, then multiple clusters of nodes may be contained in the same cell. In that case, too few replica servers for those clusters would be chosen. On the other hand, choosing small cells may lead to the situation that a single cluster is spread across a number of cells, leading to choosing too many replica servers.

As it turns out, an appropriate cell size can be computed as a simple function of the average distance between two nodes and the number of required replicas. With this cell size, it can be shown that the algorithm performs as well as the close-to-optimal one described by Qiu et al. [2001], but having a much lower complexity: $\mathcal{O}(N \times \max\{\log(N), K\})$. To give an impression what this result means: experiments show that computing the 20 best replica locations for a collection of 64,000 nodes is approximately 50,000 times faster. As a consequence, replica-server placement can now be done in real time.

Content replication and placement

When it comes to content replication and placement, three different types of replicas can be distinguished logically organized as shown in Figure 7.21.

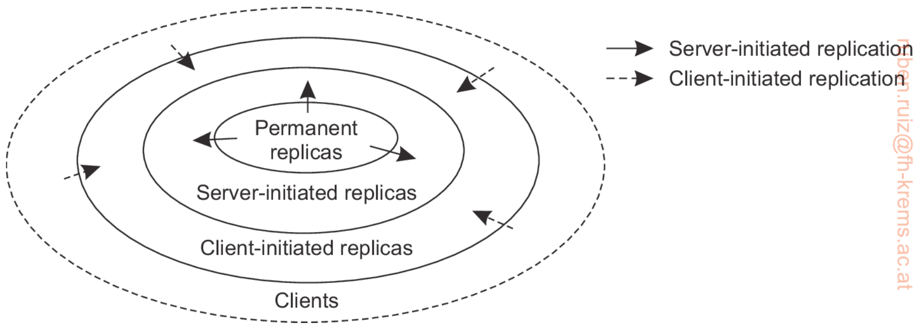

Server-initiated replication
Client-initiated replication
Permanent replicas
Server-initiated replicas
Client-initiated replicas
Clients

Figure 7.21: The logical organization of different kinds of copies of a data store into three concentric rings.

Permanent replicas

Permanent replicas can be considered as the initial set of replicas that constitute a distributed data store. In many cases, the number of permanent replicas is small. Consider, for example, a Web site. Distribution of a Web site generally comes in one of two forms. The first kind of distribution is one in which the files that constitute a site are replicated across a limited number of servers at a single location. Whenever a request comes in, it is forwarded to one of the servers, for instance, using a round-robin strategy.

The second form of distributed Web sites is what is called **mirroring**. In this case, a Web site is copied to a limited number of servers, called **mirror sites**, which are geographically spread across the Internet. In most cases, clients simply choose one of the various mirror sites from a list offered to them. Mirrored Web sites have in common with cluster-based Web sites that there are only a few replicas, which are more or less statically configured.

Similar static organizations also appear with distributed databases [Kemme et al., 2010; Özsu and Valduriez, 2011]. Again, the database can be distributed and replicated across a number of servers that together form a cluster of servers, often referred to as a **shared-nothing architecture**, emphasizing that neither disks nor main memory are shared by processors. Alternatively, a database is distributed and possibly replicated across a number of geographically dispersed sites. This architecture is generally deployed in federated databases [Sheth and Larson, 1990].

Server-initiated replicas

In contrast to permanent replicas, server-initiated replicas are copies of a data store that exist to enhance performance, and created at the initiative of the (owner of the) data store. Consider, for example, a Web server placed in New York. Normally, this server can handle incoming requests quite easily, but it may happen that over a couple of days a sudden burst of requests come in from an unexpected location far from the server. In that case, it may be worthwhile to install a number of temporary replicas in regions where requests are coming from.

Note 7.6 (Advanced: An example of dynamic Web-content placement)
The problem of dynamically placing replicas has since long been addressed in Web hosting services. These services offer an often relatively static collection of servers spread across the Internet that can maintain and provide access to Web files belonging to third parties. To provide optimal facilities such hosting services can dynamically replicate files to servers where those files are needed to enhance performance, that is, close to demanding (groups of) clients.

Given that the replica servers are already in place, deciding where to place content is not that difficult. An early case toward dynamic replication of files in the case of a Web hosting service is described by Rabinovich et al. [1999]. The algorithm is designed to support Web pages for which reason it assumes that updates are relatively rare compared to read requests. Using files as the unit of data, the algorithm works as follows.

The algorithm for dynamic replication takes two issues into account. First, replication can take place to reduce the load on a server. Second, specific files on a server can be migrated or replicated to servers placed in the proximity of clients that issue many requests for those files. In the following, we concentrate only on this second issue. We also leave out a number of details, which can be found in [Rabinovich et al., 1999].

Each server keeps track of access counts per file, and where access requests come from. In particular, when a client C enters the service, it does so through a server close to it. If client C_1 and client C_2 share the same closest server P, all access requests for file F at server Q from C_1 and C_2 are jointly registered at Q as a single access count $\mathsf{cnt}_\mathsf{Q}(\mathsf{P},\mathsf{F})$. This situation is shown in Figure 7.22.

When the number of requests for a specific file F at server S drops below a deletion threshold $\mathsf{del}(\mathsf{S},\mathsf{F})$, that file can be removed from S. As a consequence, the number of replicas of that file is reduced, possibly leading to higher work loads at other servers. Special measures are taken to ensure that at least one copy of each file continues to exist.

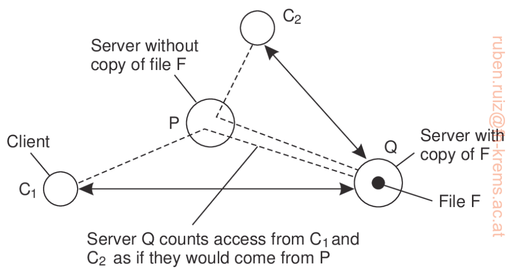

C2
Server without copy of file F
P
Client
Q
Server with copy of F
C1
File F
Server Q counts access from C1 and C2 as if they would come from P

Figure 7.22: Counting access requests from different clients.

A replication threshold rep(S, F), which is always chosen higher than the deletion threshold, indicates that the number of requests for a specific file is so high that it may be worthwhile replicating it on another server. If the number of requests lie somewhere between the deletion and replication threshold, the file is allowed to be only migrated. In other words, in that case it is important to at least keep the number of replicas for that file the same.

When a server Q decides to reevaluate the placement of the files it stores, it checks the access count for each file. If the total number of access requests for F at Q drops below the deletion threshold del(Q, F), it will delete F unless it is the last copy. Furthermore, if for some server P, $\text{cnt}_Q(P, F)$ exceeds more than half of the total requests for F at Q, server P is requested to take over the copy of F. In other words, server Q will attempt to migrate F to P.

Migration of file F to server P may not always succeed, for example, because P is already heavily loaded or is out of disk space. In that case, Q will attempt to replicate F on other servers. Of course, replication can take place only if the total number of access requests for F at Q exceeds the replication threshold rep(Q, F). Server Q checks all other servers in the Web hosting service, starting with the one farthest away. If, for some server R, $\text{cnt}_Q(R, F)$ exceeds a certain fraction of all requests for F at Q, an attempt is made to replicate F to R.

Note that as long as guarantees can be given that each data item is hosted by at least one server, it may suffice to use only server-initiated replication and not have any permanent replicas. However, permanent replicas are often useful as a back-up facility, or to be used as the only replicas that are allowed to be changed to guarantee consistency. Server-initiated replicas are then used for placing read-only copies close to clients.

Client-initiated replicas

An important kind of replica is the one initiated by a client. Client-initiated replicas are more commonly known as (**client**) **caches**. In essence, a cache is a local storage facility that is used by a client to temporarily store a copy of the data it has just requested. In principle, managing the cache is left entirely to the client. The data store from where the data had been fetched has nothing to do with keeping cached data consistent. However, there are many occasions in which the client can rely on participation from the data store to inform it when cached data has become stale.

Client caches are used only to improve access times to data. Normally, when a client wants access to some data, it connects to the nearest copy of the data store from where it fetches the data it wants to read, or to where it stores the data it had just modified. When most operations involve only reading data, performance can be improved by letting the client store requested data in a nearby cache. Such a cache could be located on the client's machine, or on a separate machine in the same local-area network as the client. The next time that same data needs to be read, the client can simply fetch it from this local cache. This scheme works fine as long as the fetched data have not been modified in the meantime.

Data are generally kept in a cache for a limited amount of time, for example, to prevent extremely stale data from being used, or simply to make room for other data. Whenever requested data can be fetched from the local cache, a **cache hit** is said to have occurred. To improve the number of cache hits, caches can be shared between clients. The underlying assumption is that a data request from client C_1 may also be useful for a request from another nearby client C_2.

Whether this assumption is correct depends very much on the type of data store. For example, in traditional file systems, data files are rarely shared at all (see, e.g., Muntz and Honeyman [1992] and Blaze [1993]) rendering a shared cache useless. Likewise, it turns out that using Web caches to share data has been losing ground, partly also because of the improvement in network and server performance. Instead, server-initiated replication schemes are becoming more effective.

Placement of client caches is relatively simple: a cache is normally placed on the same machine as its client, or otherwise on a machine shared by clients on the same local-area network. However, in some cases, extra levels of caching are introduced by system administrators by placing a shared cache between a number of departments or organizations, or even placing a shared cache for an entire region such as a province or country.

Yet another approach is to place (cache) servers at specific points in a wide-area network and let a client locate the nearest server. When the server is located, it can be requested to hold copies of the data the client was previously fetching from somewhere else [Noble et al., 1999].

Content distribution

Replica management also deals with propagation of (updated) content to the relevant replica servers. There are various trade-offs to make.

State versus operations

An important design issue concerns what is actually to be propagated. Basically, there are three possibilities:

- Propagate only a notification of an update.
- Transfer data from one copy to another.
- Propagate the update operation to other copies.

Propagating a notification is what **invalidation protocols** do. In an invalidation protocol, other copies are informed that an update has taken place and that the data they contain are no longer valid. The invalidation may specify which part of the data store has been updated, so that only part of a copy is actually invalidated. The important issue is that no more than a notification is propagated. Whenever an operation on an invalidated copy is requested, that copy generally needs to be updated first, depending on the specific consistency model that is to be supported.

The main advantage of invalidation protocols is that they use little network bandwidth. The only information that needs to be transferred is a specification of which data are no longer valid. Such protocols generally work best when there are many update operations compared to read operations, that is, the read-to-write ratio is relatively small.

Consider, for example, a data store in which updates are propagated by sending the modified data to all replicas. If the size of the modified data is large, and updates occur frequently compared to read operations, we may have the situation that two updates occur after one another without any read operation being performed between them. Consequently, propagation of the first update to all replicas is effectively useless, as it will be overwritten by the second update. Instead, sending a notification that the data have been modified would have been more efficient.

Transferring the modified data among replicas is the second alternative, and is useful when the read-to-write ratio is relatively high. In that case, the probability that an update will be effective in the sense that the modified data will be read before the next update takes place is high. Instead of propagating modified data, it is also possible to log the changes and transfer only those logs to save bandwidth. In addition, transfers are often aggregated in the sense that multiple modifications are packed into a single message, thus saving communication overhead.

The third approach is not to transfer any data modifications at all, but to tell each replica which update operation it should perform (and sending only the parameter values that those operations need). This approach, also referred to as **active replication**, assumes that each replica is represented by a process capable of "actively" keeping its associated data up to date by performing operations [Schneider, 1990]. The main benefit of active replication is that updates can often be propagated at minimal bandwidth costs, provided the size of the parameters associated with an operation are relatively small. Moreover, the operations can be of arbitrary complexity, which may allow further improvements in keeping replicas consistent. On the other hand, more processing power may be required by each replica, especially in those cases when operations are relatively complex.

Pull versus push protocols

Another design issue is whether updates are pulled or pushed. In a **push-based approach**, also referred to as **server-based protocols**, updates are propagated to other replicas without those replicas even asking for the updates. Push-based approaches are often used between permanent and server-initiated replicas, but can also be used to push updates to client caches. Server-based protocols are generally applied when strong consistency is required.

This need for strong consistency is related to the fact that permanent and server-initiated replicas, as well as large shared caches, are often shared by many clients, which, in turn, mainly perform read operations. Consequently, the read-to-update ratio at each replica is relatively high. In these cases, push-based protocols are efficient in the sense that every pushed update can be expected to be of use for at least one, but perhaps more readers. In addition, push-based protocols make consistent data immediately available when asked for.

In contrast, in a **pull-based approach**, a server or client requests another server to send it any updates it has at that moment. Pull-based protocols, also called **client-based protocols**, are often used by client caches. For example, a common strategy applied to Web caches is first to check whether cached data items are still up to date. When a cache receives a request for items that are still locally available, the cache checks with the original Web server whether those data items have been modified since they were cached. In the case of a modification, the modified data are first transferred to the cache, and then returned to the requesting client. If no modifications took place, the cached data are returned. In other words, the client polls the server to see whether an update is needed.

A pull-based approach is efficient when the read-to-update ratio is relatively low. This is often the case with (nonshared) client caches, which have only one client. However, even when a cache is shared by many clients, a pull-based approach may also prove to be efficient when the cached data items are rarely shared. The main drawback of a pull-based strategy in comparison to a push-based approach is that the response time increases in the case of a cache miss.

When comparing push-based and pull-based solutions, there are a number of trade-offs to be made, as shown in Figure 7.23. For simplicity, consider a client-server system consisting of a single, nondistributed server, and a number of client processes, each having their own cache.

Issue	Push-based	Pull-based
State at server	List of client replicas and caches	None
Messages sent	Update (and possibly fetch update later)	Poll and update
Response time at client	Immediate (or fetch-update time)	Fetch-update time

Figure 7.23: A comparison between push-based and pull-based protocols in the case of multiple-client, single-server systems.

An important issue is that in push-based protocols, the server needs to keep track of all client caches. Apart from the fact that stateful servers are often less fault tolerant, keeping track of all client caches may introduce a considerable overhead at the server. For example, in a push-based approach, a Web server may easily need to keep track of tens of thousands of client caches. Each time a Web page is updated, the server will need to go through its list of client caches holding a copy of that page, and subsequently propagate the update. Worse yet, if a client purges a page due to lack of space, it has to inform the server, leading to even more communication.

The messages that need to be sent between a client and the server also differ. In a push-based approach, the only communication is that the server sends updates to each client. When updates are actually only invalidations, additional communication is needed by a client to fetch the modified data. In a pull-based approach, a client will have to poll the server, and, if necessary, fetch the modified data.

Finally, the response time at the client is also different. When a server pushes modified data to the client caches, it is clear that the response time at the client side is zero. When invalidations are pushed, the response time is the same as in the pull-based approach, and is determined by the time it takes to fetch the modified data from the server.

These trade-offs have lead to a hybrid form of update propagation based on leases. In the case of replica management, a **lease** is a promise by the server that it will push updates to the client for a specified time. When a lease expires, the client is forced to poll the server for updates and pull in the modified data if necessary. An alternative is that a client requests a new lease for pushing updates when the previous lease expires.

Leases, originally introduced by Gray and Cheriton [1989], provide a convenient mechanism for dynamically switching between a push-based and pull-based strategy. Consider the following lease system that allows the expiration time to be dynamically adapted depending on different lease criteria, described in [Duvvuri et al., 2003]. We distinguish the following three types of leases. (Note that in all cases, updates are pushed by the server as long as the lease has not expired.)

First, **age-based leases** are given out on data items depending on the last time the item was modified. The underlying assumption is that data that have not been modified for a long time can be expected to remain unmodified for some time yet to come. This assumption has shown to be reasonable in the case of, for example, Web-based data and regular files. By granting long-lasting leases to data items that are expected to remain unmodified, the number of update messages can be strongly reduced compared to the case where all leases have the same expiration time.

Another lease criterion is how often a specific client requests its cached copy to be updated. With **renewal-frequency-based leases**, a server will hand out a long-lasting lease to a client whose cache often needs to be refreshed. On the other hand, a client that asks only occasionally for a specific data item will be handed a short-term lease for that item. The effect of this strategy is that the server essentially keeps track only of those clients where its data are popular; moreover, those clients are offered a high degree of consistency.

The last criterion is that of state-space overhead at the server. When the server realizes that it is gradually becoming overloaded, it lowers the expiration time of new leases it hands out to clients. The effect of this **state-based lease** strategy is that the server needs to keep track of fewer clients as leases expire more quickly. In other words, the server dynamically switches to a more stateless mode of operation, thereby expecting to offload itself so that it can handle requests more efficiently. The obvious drawback is that it may need to do more work when the read-to-update ratio is high.

Unicasting versus multicasting

Related to pushing or pulling updates is deciding whether unicasting or multicasting should be used. In unicast communication, when a server that is part of the data store sends its update to *N* other servers, it does so by sending *N* separate messages, one to each server. With multicasting, the underlying network takes care of sending a message efficiently to multiple receivers.

In many cases, it is cheaper to use available multicasting facilities. An extreme situation is when all replicas are located in the same local-area network and that hardware broadcasting is available. In that case, broadcasting or multicasting a message is no more expensive than a single point-to-point message. Unicasting updates would then be less efficient.

Multicasting can often be efficiently combined with a push-based approach to propagating updates. When the two are carefully integrated, a server that decides to push its updates to a number of other servers simply uses a single multicast group to send its updates. In contrast, with a pull-based approach, it is generally only a single client or server that requests its copy to be updated. In that case, unicasting may be the most efficient solution.

Managing replicated objects

As we mentioned, data-centric consistency for distributed objects comes naturally in the form of entry consistency. Recall that in this case, the goal is to group operations on shared data using synchronization variables (e.g., in the form of locks). As objects naturally combine data and the operations on that data, locking objects during an invocation serializes access and keeps them consistent.

Although conceptually associating a lock with an object is simple, it does not necessarily provide a proper solution when an object is replicated. There are two issues that need to be solved for implementing entry consistency. The first one is that we need a means to prevent concurrent execution of multiple invocations on the same object. In other words, when any method of an object is being executed, no other methods may be executed. This requirement ensures that access to the internal data of an object is indeed serialized. Simply using local locking mechanisms will ensure this serialization.

The second issue is that in the case of a replicated object, we need to ensure that all changes to the replicated state of the object are the same. In other words, we need to make sure that no two independent method invocations take place on different replicas at the same time. This requirement implies that we need to order invocations such that each replica sees all invocations in the same order. We describe a few general solutions in Section 7.5.

In many cases, designing replicated objects is done by first designing a single object, possibly protecting it against concurrent access through local locking, and subsequently replicating it. The role of middleware is to ensure that if a client invokes a replicated object, the invocation is passed to the replicas and handed to the their respective object servers in the same order everywhere. However, we also need to ensure that all threads in those servers process those requests in the correct order as well. The problem is sketched in Figure 7.24.

Multithreaded (object) servers simply pick up an incoming request, pass it on to an available thread, and wait for the next request to come in. The server's thread scheduler subsequently allocates the CPU to runnable threads. Of course, if the middleware has done its best to provide a total ordering for request delivery, the thread schedulers should operate in a deterministic fashion in order not to mix the ordering of method invocations on the same object. In other words, If threads T_1^1 and T_1^2 from Figure 7.24 handle the same incoming (replicated) invocation request, they should both be scheduled before T_2^1 and T_2^2, respectively.

Of course, simply scheduling *all* threads deterministically is not necessary. In principle, if we already have total-ordered request delivery, we need only to ensure that all requests for the same replicated object are handled in the order they were delivered. Such an approach would allow invocations for different objects to be processed concurrently, and without further restrictions

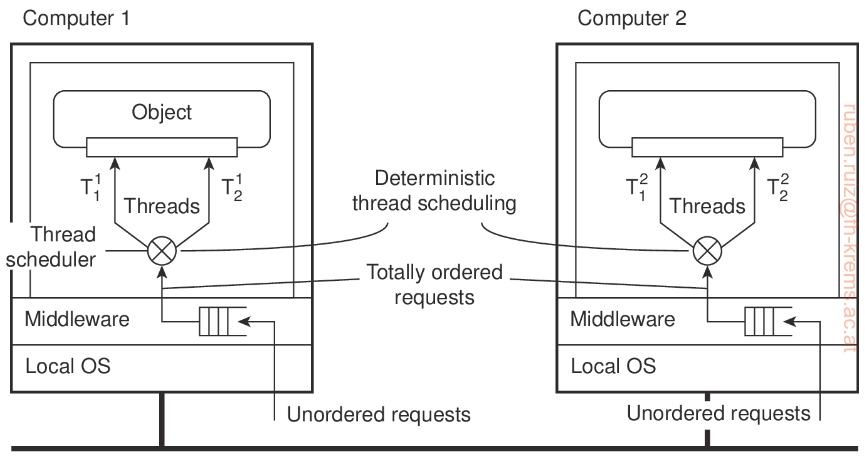


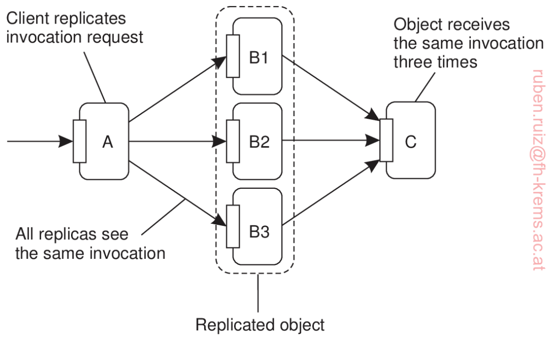
Figure 7.24: Deterministic thread scheduling for replicated object servers.

from the thread scheduler. Unfortunately, only few systems exist that support such concurrency.

One approach, described by Basile et al. [2002], ensures that threads sharing the same (local) lock are scheduled in the same order on every replica. At the basics lies a primary-based scheme in which one of the replica servers takes the lead in determining, for a specific lock, which thread goes first. An improvement that avoids frequent communication between servers is described in [Basile et al., 2003]. Note that threads that do not share a lock can thus operate concurrently on each server.

One drawback of this scheme is that it operates at the level of the underlying operating system, meaning that every lock needs to be managed. By providing application-level information, a huge improvement in performance can be made by identifying only those locks that are needed for serializing access to replicated objects (see Taiani et al. [2005]).

Note 7.7 (Advanced: Replicated invocations)
Another problem that needs to be solved is that of replicated invocations. Consider an object A calling another object B as shown in Figure 7.25. Object B is assumed to call yet another object C. If B is replicated, each replica of B will, in principle, call C independently. The problem is that C is now called multiple times instead of only once. If the called method on C results in the transfer of $100,000, then clearly, someone is going to complain sooner or later.



Client replicates invocation request
A
B1
B2
B3
C
Object receives the same invocation three times
All replicas see the same invocation
Replicated object

Figure 7.25: The problem of replicated method invocations.

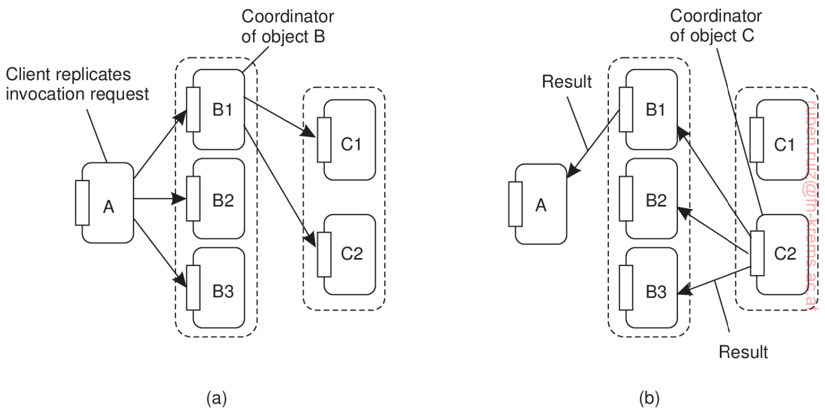


Figure 7.26: (a) Forwarding an invocation request from a replicated object to another replicated object. (b) Returning a reply from one replicated object to another.

There are not many general-purpose solutions to solve the problem of replicated invocations. One solution is to simply forbid it [Maassen et al., 2001], which makes sense when performance is at stake. However, when replicating for fault tolerance, the following solution proposed by Mazouni et al. [1995] may be deployed. Their solution is independent of the replication policy, that is, the exact details of how replicas are kept consistent. The essence is to provide a replication-aware communication layer on top of which (replicated) objects execute. When a replicated object B invokes another replicated object C, the invocation request is first assigned the same, unique identifier by each replica of B. At that point, a coordinator of the replicas of B forwards its request to all the replicas of object C, while the other replicas of B hold back their copy of the invocation request, as shown in Figure 7.26. The result is that only a single request is forwarded to each replica of C.

The same mechanism is used to ensure that only a single reply message is returned to the replicas of B. This situation is shown in Figure 7.26. A coordinator of the replicas of C notices it is dealing with a replicated reply message that has been generated by each replica of C. However, only the coordinator forwards that reply to the replicas of object B, while the other replicas of C hold back their copy of the reply message.

When a replica of B receives a reply message for an invocation request it had either forwarded to C or held back because it was not the coordinator, the reply is then handed to the actual object.

In essence, the scheme just described is based on using multicast communication, but in preventing that the same message is multicast by different replicas. As such, it is essentially a sender-based scheme. An alternative solution is to let a receiving replica detect multiple copies of incoming messages belonging to the same invocation, and to pass only one copy to its associated object. Details of this scheme are left as an exercise.

7.5 Consistency protocols

We now concentrate on the actual implementation of consistency models by taking a look at several consistency protocols. A **consistency protocol** describes an implementation of a specific consistency model. We follow the organization of our discussion on consistency models by first taking a look at data-centric models, followed by protocols for client-centric models.

Continuous consistency

As part of their work on continuous consistency, Yu and Vahdat [2000] have developed a number of protocols to tackle the three forms of consistency. In the following, we briefly consider a number of solutions, omitting details for clarity.

Bounding numerical deviation

We first concentrate on one solution for keeping the numerical deviation within bounds. Again, our purpose is not to go into all the details for each protocol, but rather to give the general idea. Details for bounding numerical deviation can be found in [Yu and Vahdat, 2000].

We concentrate on writes to a single data item x. Each write W(x) has an associated **value** that represents the numerical value by which x is updated, denoted as $val(\mathsf{W}(\mathsf{x}))$, or simply $val(\mathsf{W})$. For simplicity, we assume that $val(\mathsf{W}) > 0$. Each write W is initially submitted to one out of the N available replica servers, in which case that server becomes the write's **origin**, denoted as $origin(\mathsf{W})$. If we consider the system at a specific moment in time we will see several submitted writes that still need to be propagated to all servers.

To this end, each server $\mathsf{S_i}$ will keep track of a **log** $\mathsf{L_i}$ of writes that it has performed on its own local copy of x.

Let $TW[i,j]$ be the effect of performing the writes executed by server $\mathsf{S_i}$ that originated from server $\mathsf{S_j}$:

$$TW[i,j] = \sum\{val(\mathsf{W})|origin(\mathsf{W}) = \mathsf{S_j} \text{ and } \mathsf{W} \in \mathsf{L_i}\}$$

Note that $TW[i,i]$ represents the aggregated writes submitted to $\mathsf{S_i}$. Our goal is for any time t, to let the current value v_i of x at server $\mathsf{S_i}$ deviate within bounds from the actual value v of x. This actual value is completely determined by all submitted writes. That is, if v_0 is the initial value of x, then

$$v = v_0 + \sum_{k=1}^{N} TW[k,k]$$

and

$$v_i = v_0 + \sum_{k=1}^{N} TW[i,k]$$

Note that $v_i \leq v$. Let us concentrate only on absolute deviations. In particular, for every server $\mathsf{S_i}$, we associate an upperbound δ_i such that we need to enforce:

$$v - v_i \leq \delta_i$$

Writes submitted to a server $\mathsf{S_i}$ will need to be propagated to all other servers. There are different ways in which this can be done, but typically an epidemic protocol will allow rapid dissemination of updates. In any case, when a server $\mathsf{S_i}$ propagates a write originating from $\mathsf{S_j}$ to $\mathsf{S_k}$, the latter will be able to learn about the value $TW[i,j]$ at the time the write was sent. In other words, $\mathsf{S_k}$ can maintain a **view** $TW_k[i,j]$ of what it believes $\mathsf{S_i}$ will have as value for $TW[i,j]$. Obviously,

$$0 \leq TW_k[i,j] \leq TW[i,j] \leq TW[j,j]$$

The whole idea is that when server $\mathsf{S_k}$ notices that $\mathsf{S_i}$ has not been staying in the right pace with the updates that have been submitted to $\mathsf{S_k}$, it forwards writes from its log to $\mathsf{S_i}$. This forwarding effectively *advances* the view $TW_k[i,k]$ that $\mathsf{S_k}$ has of $TW[i,k]$, making the deviation $TW[i,k] - TW_k[i,k]$ smaller. In particular, $\mathsf{S_k}$ advances its view on $TW[i,k]$ when an application submits a new write that would increase $TW[k,k] - TW_k[i,k]$ beyond $\delta_i/(N-1)$. We leave it as an exercise to the reader to show that advancement always ensures that $v - v_i \leq \delta_i$.

Bounding staleness deviations

There are many ways to keep the staleness of replicas within specified bounds. One simple approach is to let server $\mathsf{S_k}$ keep a real-time vector clock $\mathsf{RVC_k}$

where $\mathsf{RVC}_\mathsf{k}[i] = t_i$ means that S_k has seen all writes that have been submitted to S_i up to time t_i. In this case, we assume that each submitted write is timestamped by its origin server, and that t_i denotes the time *local to* S_i.

If the clocks between the replica servers are loosely synchronized, then an acceptable protocol for bounding staleness would be the following. Whenever server S_k notes that $t_k - \mathsf{RVC}_\mathsf{k}[i]$ is about to exceed a specified limit, it simply starts pulling in writes that originated from S_i with a timestamp later than $\mathsf{RVC}_\mathsf{k}[i]$.

Note that in this case a replica server is responsible for keeping its copy of x up to date regarding writes that have been issued elsewhere. In contrast, when maintaining numerical bounds, we followed a push approach by letting an origin server keep replicas up to date by forwarding writes. The problem with pushing writes in the case of staleness is that no guarantees can be given for consistency when it is unknown in advance what the maximal propagation time will be. This situation is somewhat improved by pulling in updates, as multiple servers can help to keep a server's copy of x fresh (i.e., up to date).

Bounding ordering deviations

Recall that ordering deviations in continuous consistency are caused by the fact that a replica server tentatively applies updates that have been submitted to it. As a result, each server will have a local queue of tentative writes for which the actual order in which they are to be applied to the local copy of x still needs to be determined. The ordering deviation is bounded by specifying the maximal length of the queue of tentative writes.

As a consequence, detecting when ordering consistency needs to be enforced is simple: when the length of this local queue exceeds a specified maximal length. At that point, a server will no longer accept any newly submitted writes, but will instead attempt to commit tentative writes by negotiating with other servers in which order its writes should be executed. In other words, we need to enforce a globally consistent ordering of tentative writes.

Sequential consistency: Primary-based protocols

In practice, we see that distributed applications generally follow consistency models that are relatively easy to understand. These models include those for bounding staleness deviations, and to a lesser extent also those for bounding numerical deviations. When it comes to models that handle consistent ordering of operations, sequential consistency, notably those in which operations can be grouped through locking or transactions are popular.

As soon as consistency models become slightly difficult to understand for application developers, we see that they are ignored even if performance could be improved. The bottom line is that if the semantics of a consistency model are not intuitively clear, application developers will have a hard time building correct applications. Simplicity is appreciated (and perhaps justifiably so).

In the case of sequential consistency, it turns out that **primary-based protocols** prevail. In these protocols, each data item x in the data store has an associated primary, which is responsible for coordinating write operations on x. A distinction can be made as to whether the primary is fixed at a remote server or if write operations can be carried out locally after moving the primary to the process where the write operation is initiated.

Remote-write protocols

The simplest primary-based protocol that supports replication is the one in which all write operations need to be forwarded to a fixed single server. Read operations can be carried out locally. Such schemes are also known as **primary-backup protocols** [Budhijara et al., 1993]. A primary-backup protocol works as shown in Figure 7.27. A process wanting to perform a write operation on data item x, forwards that operation to the primary server for x. The primary performs the update on its local copy of x, and subsequently forwards the update to the backup servers. Each backup server performs the update as well, and sends an acknowledgment to the primary. When all backups have updated their local copy, the primary sends an acknowledgment to the initial process, which, in turn, informs the client.

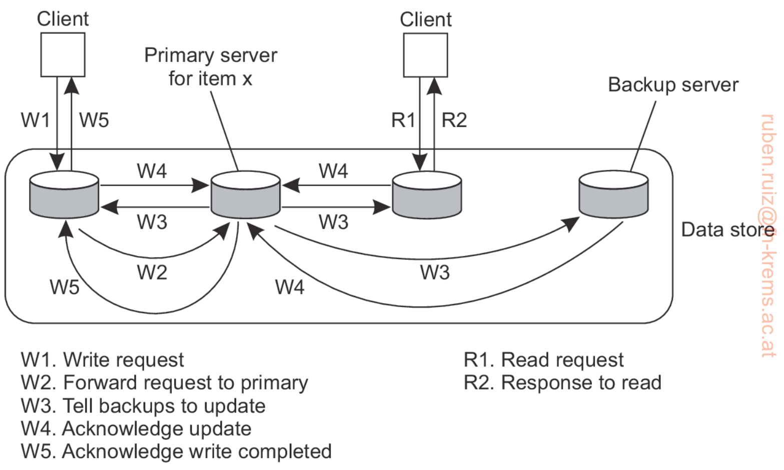


Figure 7.27: The principle of a primary-backup protocol.

A potential performance problem with this scheme is that it may take a relatively long time before the process that initiated the update is allowed to continue. In effect, an update is implemented as a blocking operation. An alternative is to use a nonblocking approach. As soon as the primary has updated its local copy of x, it returns an acknowledgment. After that, it tells the backup servers to perform the update as well. Nonblocking primary-backup protocols are discussed in [Budhiraja and Marzullo, 1992].

The main problem with nonblocking primary-backup protocols has to do with fault tolerance. In a blocking scheme, the client process knows for sure that the update operation is backed up by several other servers. This is not the case with a nonblocking solution. The advantage, of course, is that write operations may speed up considerably.

Primary-backup protocols provide a straightforward implementation of sequential consistency, as the primary can order all incoming writes in a globally unique time order. Evidently, all processes see all write operations in the same order, no matter which backup server they use to perform read operations. Also, with blocking protocols, processes will always see the effects of their most recent write operation (note that this cannot be guaranteed with a nonblocking protocol without taking special measures).

Local-write protocols

A variant of primary-backup protocols is one in which the primary copy migrates between processes that wish to perform a write operation. As before, whenever a process wants to update data item x, it locates the primary copy of x, and subsequently moves it to its own location, as shown in Figure 7.28. The main advantage of this approach is that multiple, successive write operations can be carried out locally, while reading processes can still access their local copy. However, such an improvement can be achieved only if a nonblocking protocol is followed by which updates are propagated to the replicas after the primary has finished with locally performing the updates.

This primary-backup local-write protocol can also be applied to mobile computers that are able to operate in disconnected mode. Before disconnecting, the mobile computer becomes the primary server for each data item it expects to update. While being disconnected, all update operations are carried out locally, while other processes can still perform read operations (but no updates). Later, when connecting again, updates are propagated from the primary to the backups, bringing the data store in a consistent state again.

As a last variant of this scheme, nonblocking local-write primary-based protocols are also used for distributed file systems in general. In this case, there may be a fixed central server through which normally all write operations take place, as in the case of remote-write primary backup. However, the server temporarily allows one of the replicas to perform a series of local updates, as this may considerably speed up performance. When the replica server is done, the updates are propagated to the central server, from where they are then distributed to the other replica servers.

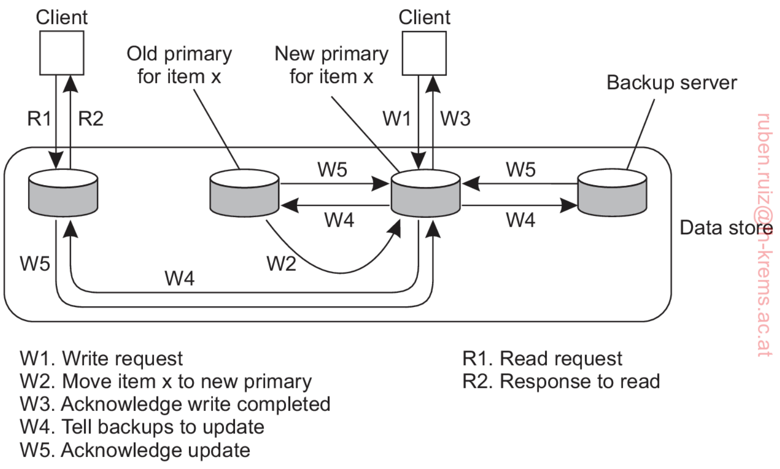


Figure 7.28: Primary-backup protocol in which the primary migrates to the process wanting to perform an update.

Sequential consistency: Replicated-write protocols

In replicated-write protocols, write operations can be carried out at multiple replicas instead of only one, as in the case of primary-based replicas. A distinction can be made between active replication, in which an operation is forwarded to all replicas, and consistency protocols based on majority voting.

Active replication

In active replication, each replica has an associated process that carries out update operations. In contrast to other protocols, updates are generally propagated by means of the write operation that causes the update. In other words, the operation is sent to each replica. However, it is also possible to send the update.

One problem with active replication is that operations need to be carried out in the same order everywhere. Consequently, what is needed is a total-ordered multicast mechanism. A practical approach to accomplish total ordering is by means of a central coordinator, also called a **sequencer**. One approach is to first forward each operation to the sequencer, which assigns it a unique sequence number and subsequently forwards the operation to all replicas. Operations are carried out in the order of their sequence number.

Note 7.8 (Advanced: Achieving scalability)
Note that using a sequencer may easily introduce scalability problems. In fact, if total-ordered multicasting is needed, a combination of symmetric multicasting

using Lamport timestamps [Lamport, 1978] and sequencers may be necessary. Such a solution is described by Rodrigues et al. [1996]. The essence of that solution is to have multiple sequencers multicast update operations to each other and order the updates using Lamport's total-ordering mechanism, as described in Section 6.2. Nonsequencing processes are grouped such that each group uses a single sequencer. Any nonsequencing process sends update requests to its sequencer and waits until it receives an acknowledgment that its request has been processed (i.e., multicast to the other sequencers in a total-ordered fashion). Obviously, there is a trade-off between the number of processes that act as sequencer and those that do not, as well as the choice of processes to act as sequencer. As it turns out, this trade-off depends very much on the application and, in particular, the relative update rate at each process.

Quorum-based protocols

A different approach to supporting replicated writes is to use **voting**, as originally proposed by Thomas [1979] and generalized by Gifford [1979]. The basic idea is to require clients to request and acquire the permission of multiple servers before either reading or writing a replicated data item.

As a simple example of how the algorithm works, consider a distributed file system and suppose that a file is replicated on N servers. We could make a rule stating that to update a file, a client must first contact at least half the servers plus one (a majority) and get them to agree to do the update. Once they have agreed, the file is changed and a new version number is associated with the new file. The version number is used to identify the version of the file and is the same for all the newly updated files.

To read a replicated file, a client must also contact at least half the servers plus one and ask them to send the version numbers associated with the file. If all the version numbers are the same, this must be the most recent version because an attempt to update only the remaining servers would fail because there are not enough of them.

For example, if there are five servers and a client determines that three of them have version 8, it is impossible that the other two have version 9. After all, any successful update from version 8 to version 9 requires getting three servers to agree to it, not just two.

When quorum-based replication was originally introduced, a somewhat more general scheme was proposed. In it, to read a file of which N replicas exist, a client needs to assemble a **read quorum**, an arbitrary collection of any N_R servers, or more. Similarly, to modify a file, a **write quorum** of at least N_W servers is required. The values of N_R and N_W are subject to the following two constraints:

1. $N_R + N_W > N$
2. $N_W > N/2$

The first constraint is used to prevent read-write conflicts, whereas the second prevents write-write conflicts. Only after the appropriate number of servers has agreed to participate can a file be read or written.

To see how this algorithm works, consider Figure 7.29(a) which has $N_R = 3$ and $N_W = 10$. Imagine that the most recent write quorum consisted of the 10 servers C through L. All of these get the new version and the new version number. Any subsequent read quorum of three servers will have to contain at least one member of this set. When the client looks at the version numbers, it will know which is most recent and take that one.

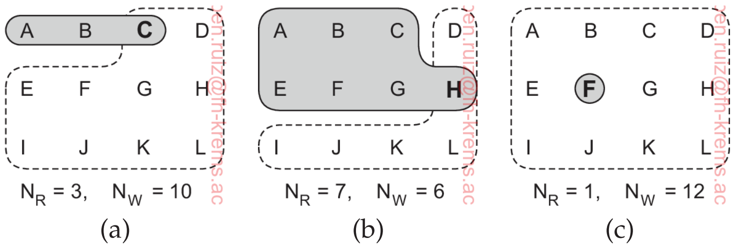


Figure 7.29: Three examples of the voting algorithm. The gray areas denote a read quorum; the white ones a write quorum. Servers in the intersection are denoted in boldface. (a) A correct choice of read and write set. (b) A choice that may lead to write-write conflicts. (c) A correct choice, known as ROWA (read one, write all).

In Figure 7.29 we see two more examples. In Figure 7.29(b) a write-write conflict may occur because $N_W \leq N/2$. In particular, if one client chooses $\{A, B, C, E, F, G\}$ as its write set and another client chooses $\{D, H, I, J, K, L\}$ as its write set, then clearly we will run into trouble as the two updates will both be accepted without detecting that they actually conflict.

The situation shown in Figure 7.29(c) is especially interesting because it sets N_R to one, making it possible to read a replicated file by finding any copy and using it. The price paid for this good read performance, however, is that write updates need to acquire all copies. This scheme is generally referred to as **Read-One, Write-All**, (**ROWA**). There are several variations of quorum-based replication protocols. Jalote [1994] provides a good overview.

Cache-coherence protocols

Caches form a special case of replication, in the sense that they are generally controlled by clients instead of servers. However, cache-coherence protocols, which ensure that a cache is consistent with the server-initiated replicas are, in principle, not very different from the consistency protocols discussed so far.

There has been much research in the design and implementation of caches, especially in the context of shared-memory multiprocessor systems. Many solutions are based on support from the underlying hardware, for example, by assuming that snooping or efficient broadcasting can be done. In the context of middleware-based distributed systems that are built on top of general-purpose operating systems, software-based solutions to caches are more interesting. In this case, two separate criteria are often maintained to classify caching protocols (see also Min and Baer [1992], Lilja [1993], or Tartalja and Milutinovic [1997]).

First, caching solutions may differ in their **coherence detection strategy**, that is, *when* inconsistencies are actually detected. In static solutions, a compiler is assumed to perform the necessary analysis prior to execution, and to determine which data may actually lead to inconsistencies because they may be cached. The compiler simply inserts instructions that avoid inconsistencies. Dynamic solutions are typically applied in the distributed systems studied in this book. In these solutions, inconsistencies are detected at runtime. For example, a check is made with the server to see whether the cached data have been modified since they were cached.

In the case of distributed databases, dynamic detection-based protocols can be further classified by considering exactly when during a transaction the detection is done. Franklin et al. [1997] distinguish the following three cases. First, when during a transaction a cached data item is accessed, the client needs to verify whether that data item is still consistent with the version stored at the (possibly replicated) server. The transaction cannot proceed to use the cached version until its consistency has been definitively validated.

A second, optimistic, approach is to let the transaction proceed while verification is taking place. In this case, it is assumed that the cached data were up to date when the transaction started. If that assumption later proves to be false, the transaction will have to abort.

The third approach is to verify whether the cached data are up to date only when the transaction commits. In effect, the transaction just starts operating on the cached data and hopes for the best. After all the work has been done, accessed data are verified for consistency. When stale data were used, the transaction is aborted.

Another design issue for cache-coherence protocols is the **coherence enforcement strategy**, which determines *how* caches are kept consistent with the copies stored at servers. The simplest solution is to disallow shared data to be cached at all. Instead, shared data are kept only at the servers, which maintain consistency using one of the primary-based or replication-write protocols discussed above. Clients are allowed to cache only private data. Obviously, this solution can offer only limited performance improvements.

When shared data can be cached, there are two approaches to enforce cache coherence. The first is to let a server send an invalidation to all caches whenever a data item is modified. The second is to simply propagate the update. Most caching systems use one of these two schemes. Dynamically choosing between sending invalidations or updates is sometimes supported in client-server databases.

Finally, we also need to consider what happens when a process modifies cached data. When read-only caches are used, update operations can be performed only by servers, which subsequently follow some distribution protocol to ensure that updates are propagated to caches. In many cases, a pull-based approach is followed. In this case, a client detects that its cache is stale, and requests a server for an update.

An alternative approach is to allow clients to directly modify the cached data, and forward the update to the servers. This approach is followed in **write-through caches**, which are often used in distributed file systems. In effect, write-through caching is similar to a primary-based local-write protocol in which the client's cache has become a temporary primary. To guarantee (sequential) consistency, it is necessary that the client has been granted exclusive write permissions, or otherwise write-write conflicts may occur.

Write-through caches potentially offer improved performance over other schemes as all operations can be carried out locally. Further improvements can be made if we delay the propagation of updates by allowing multiple writes to take place before informing the servers. This leads to what is known as a **write-back cache**, which is, again, mainly applied in distributed file systems.

Note 7.9 (Example: Client-side caching in NFS)
As a practical example, consider the general caching model in NFS as shown in Figure 7.30. Each client can have a memory cache that contains data previously read from the server. In addition, there may also be a disk cache that is added as an extension to the memory cache, using the same consistency parameters.

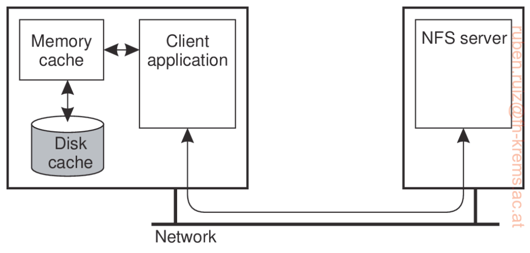


Figure 7.30: Client-side caching in NFS.

Typically, clients cache file data, attributes, file handles, and directories. Different strategies exist to handle consistency of the cached data, cached attributes, and so on. Let us first take a look at caching file data.

NFSv4 supports two different approaches for caching file data. The simplest approach is when a client opens a file and caches the data it obtains from the server as the result of various read operations. In addition, write operations can be carried out in the cache as well. When the client closes the file, NFS requires that if modifications have taken place, the cached data must be flushed back to the server. This approach corresponds to implementing session semantics as discussed earlier.

Once (part of) a file has been cached, a client can keep its data in the cache even after closing the file. Also, several clients on the same machine can share a single cache. NFS requires that whenever a client opens a previously closed file that has been (partly) cached, the client must immediately revalidate the cached data. Revalidation takes place by checking when the file was last modified and invalidating the cache in case it contains stale data.

In NFSv4 a server may delegate some of its rights to a client when a file is opened. **Open delegation** takes place when the client machine is allowed to locally handle open and close operations from other clients on the same machine. Normally, the server is in charge of checking whether opening a file should succeed or not, for example, because share reservations need to be taken into account. With open delegation, the client machine is sometimes allowed to make such decisions, avoiding the need to contact the server.

For example, if a server has delegated the opening of a file to a client that requested write permissions, file locking requests from other clients on the same machine can also be handled locally. The server will still handle locking requests from clients on other machines, by simply denying those clients access to the file. Note that this scheme does not work in the case of delegating a file to a client that requested only read permissions. In that case, whenever another local client wants to have write permissions, it will have to contact the server; it is not possible to handle the request locally.

An important consequence of delegating a file to a client is that the server needs to be able to recall the delegation, for example, when another client on a different machine needs to obtain access rights to the file. Recalling a delegation requires that the server can do a callback to the client, as illustrated in Figure 7.31.

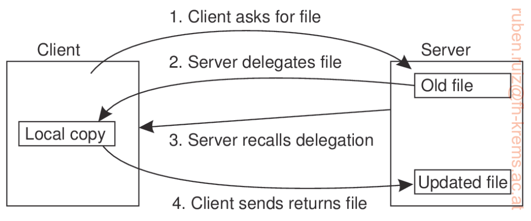


Figure 7.31: Using the NFSv4 callback mechanism to recall file delegation.

A callback is implemented in NFS using its underlying RPC mechanisms. Note, however, that callbacks require that the server keeps track of clients to which it has delegated a file. Here, we see another example where an NFS server can no longer be implemented in a stateless manner. Note, however, that the combination of delegation and stateful servers may lead to various problems in the presence of client and server failures. For example, what should a server do when it had delegated a file to a now unresponsive client?

Clients can also cache attribute values, but are largely left on their own when it comes to keeping cached values consistent. In particular, attribute values of the same file cached by two different clients may be different unless the clients keep these attributes mutually consistent. Modifications to an attribute value should be immediately forwarded to the server, thus following a write-through cache coherence policy.

A similar approach is followed for caching file handles (or rather, the name-to-file handle mapping) and directories. To mitigate the effects of inconsistencies, NFS uses leases on cached attributes, file handles, and directories. After some time has elapsed, cache entries are thus automatically invalidated and revalidation is needed before they are used again.

Implementing client-centric consistency

For our last topic on consistency protocols, let us draw our attention to implementing client-centric consistency. Implementing client-centric consistency is relatively straightforward if performance issues are ignored.

In a naive implementation of client-centric consistency, each write operation W is assigned a globally unique identifier. Such an identifier is assigned by the server to which the write had been submitted. We refer to this server as the **origin** of W. Then, for each client, we keep track of two sets of writes. The read set for a client consists of the writes relevant for the read operations performed by a client. Likewise, the write set consists of the (identifiers of the) writes performed by the client.

Monotonic-read consistency is implemented as follows. When a client wants to perform a read operation at a server, that server is handed the client's read set to check whether all the identified writes have taken place locally. If not, it contacts the other servers to ensure that it is brought up to date before carrying out the read operation. Alternatively, the read operation is forwarded to a server where the write operations have already taken place. After the read operation is performed, the write operations that have taken place at the selected server and which are relevant for the read operation are added to the client's read set.

Note that it should be possible to determine exactly where the write operations identified in the read set have taken place. For example, the write identifier could include the identifier of the server to which the operation was submitted. That server is required to, for example, log the write operation so that it can be replayed at another server. In addition, write operations should be performed in the order they were submitted. Ordering can be achieved by letting the client generate a globally unique sequence number that is included in the write identifier. If each data item can be modified only by its owner, the latter can supply the sequence number.

Monotonic-write consistency is implemented analogous to monotonic reads. Whenever a client initiates a new write operation at a server, the server is handed over the client's write set. (Again, the size of the set may be prohibitively large in the face of performance requirements. An alternative solution is discussed below.) It then ensures that the identified write operations are performed first and in the correct order. After performing the new operation, that operation's write identifier is added to the write set. Note that bringing the current server up to date with the client's write set may introduce a considerable increase in the client's response time since the client then waits for the operation to fully complete.

Likewise, read-your-writes consistency requires that the server where the read operation is is to be performed has seen all the write operations in the client's write set. The writes can simply be fetched from other servers before the read operation is actually executed, although this may lead to a poor response time. Alternatively, the client-side software can search for a server where the identified write operations in the client's write set have already been performed.

Finally, writes-follow-reads consistency can be implemented by first bringing the selected server up to date with the write operations in the client's read set, and then later adding the identifier of the write operation to the write set, along with the identifiers in the read set (which have now become relevant for the write operation just performed).

Note 7.10 (Advanced: Improving efficiency)

It is easy to see that the read set and write set associated with each client can become very large. To keep these sets manageable, a client's read and write operations are grouped into sessions. A **session** is typically associated with an application: it is opened when the application starts and is closed when it exits. However, sessions may also be associated with applications that are temporarily exited, such as user agents for e-mail. Whenever a client closes a session, the sets are simply cleared. Of course, if a client opens a session that it never closes, the associated read and write sets can still become very large.

The main problem with a naive implementation lies in the representation of the read and write sets. Each set consists of a number of identifiers for write operations. Whenever a client forwards a read or write request to a server, a set of identifiers is handed to the server as well to see whether all write operations relevant to the request have been carried out by that server.

This information can be more efficiently represented by means of vector timestamps as follows. First, whenever a server accepts a new write operation W, it assigns that operation a globally unique identifier along with a timestamp $ts(\mathsf{W})$. A subsequent write operation submitted to that server is assigned a higher-valued timestamp. Each server $\mathsf{S_i}$ maintains a vector timestamp $\mathsf{WVC_i}$, where $\mathsf{WVC_i}[j]$ is equal to the timestamp of the most recent write operation originating from S_j that has been processed by S_i.

For clarity, assume that for each server, writes from S_j are processed in the order that they were submitted. Whenever a client issues a request to perform a read or write operation O at a specific server, that server returns its current timestamp along with the results of O. Read and write sets are subsequently represented by vector timestamps. More specifically, for each session A, we construct a vector timestamp SVC_A with $SVC_A[i]$ set equal to the maximum timestamp of all write operations in A that originate from server S_i:

$$SVC_A[j] = \max\{ts(W) | W \in A \text{ and } origin(W) = S_j\}$$

In other words, the timestamp of a session always represents the latest write operations that have been seen by the applications that are being executed as part of that session. The compactness is obtained by representing all observed write operations originating from the same server through a single timestamp.

As an example, suppose a client, as part of session A, logs in at server S_i. To that end, it passes SVC_A to S_i. Assume that $SVC_A[j] > WVC_i[j]$. What this means is that S_i has not yet seen all the writes originating from S_j that the client has seen. Depending on the required consistency, server S_i may now have to fetch these writes before being able to consistently report back to the client. Once the operation has been performed, server S_i will return its current timestamp WVC_i. At that point, SVC_A is adjusted to:

$$SVC_A[j] \leftarrow \max\{SVC_A[j], WVC_i[j]\}$$

Again, we see how vector timestamps can provide an elegant and compact way of representing history in a distributed system.

7.6 Example: Caching and replication in the Web

The Web is arguably the largest distributed system ever built. Originating from a relatively simple client-server architecture, it is now a sophisticated system consisting of many techniques to ensure stringent performance and availability requirements. These requirements have led to numerous proposals for caching and replicating Web content. Where the original schemes (which are still largely deployed) have been targeted toward supporting static content, much effort has also been put into supporting dynamic content, that is, supporting documents that are generated on-the-spot as the result of a request, as well as those containing scripts and such. An overview of traditional Web caching and replication is provided by Rabinovich and Spastscheck [2002].

Client-side caching in the Web generally occurs at two places. In the first place, most browsers are equipped with a relatively simple caching facility. Whenever a document is fetched it is stored in the browser's cache from where it is loaded the next time. In the second place, a client's site often runs a Web proxy. A Web proxy accepts requests from local clients and passes these to Web servers. When a response comes in, the result is passed to the client. The advantage of this approach is that the proxy can cache the result and return that result to another client, if necessary. In other words, a Web proxy can implement a shared cache. With so many documents being generated on the fly, the server generally provides the document in pieces instructing the client to cache only those parts that are not likely to change when the document is requested a next time.

In addition to caching at browsers and proxies, ISPs generally also place caches in their networks. Such schemes are mainly used to reduce network traffic (which is good for the ISP) and to improve performance (which is good for end users). However, with multiple caches along the request path from client to server, there is a risk of increased latencies when caches do not contain the requested information.

Note 7.11 (Advanced: Cooperative caching)
As an alternative to building hierarchical caches, one can also organize caches for cooperative deployment as shown in Figure 7.32. In **cooperative caching** or **distributed caching**, whenever a cache miss occurs at a Web proxy, the proxy first checks a number of neighboring proxies to see if one of them contains the requested document. If such a check fails, the proxy forwards the request to the Web server responsible for the document. In more traditional settings, this scheme is primarily deployed with Web caches belonging to the same organization or institution.

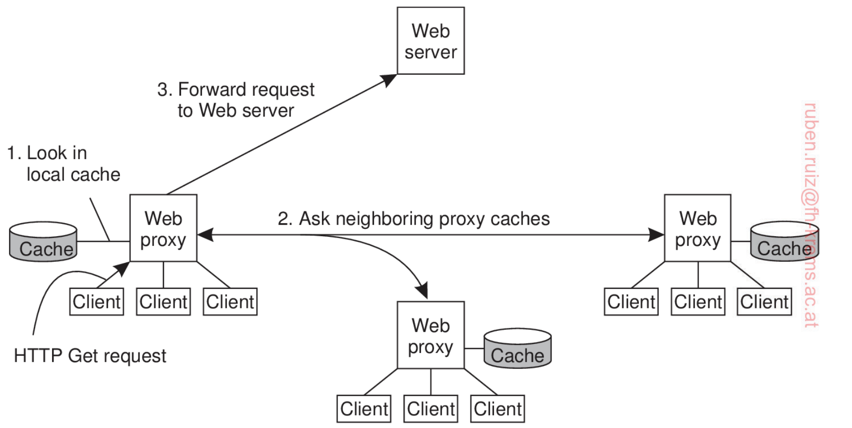


Figure 7.32: The principle of cooperative caching.

A study by Wolman et al. [1999] shows that cooperative caching may be effective for only relatively small groups of clients (in the order of tens of thousands of users). However, such groups can also be serviced by using a single proxy cache, which is much cheaper in terms of communication and resource usage. However, in a study from a decade later, Wendell and Freedman [2011] show that in a highly decentralized system, cooperative caching actually turned out be highly effective. These studies do not necessarily contradict each other: in both cases, the conclusion is that the effect of cooperative caching depends highly on the demands from clients.

A comparison between hierarchical and cooperative caching by Rodriguez et al. [2001] makes clear that there are various trade-offs to make. For example, because cooperative caches are generally connected through high-speed links, the transmission time needed to fetch a document is much lower than for a hierarchical cache. Also, as is to be expected, storage requirements are less strict for cooperative caches than hierarchical ones.

Different cache-consistency protocols have been deployed in the Web. To guarantee that a document returned from the cache is consistent, some Web proxies first send a conditional HTTP get request to the server with an additional If-Modified-Since request header, specifying the last modification time associated with the cached document. Only if the document has been changed since that time, will the server return the entire document. Otherwise, the Web proxy can simply return its cached version to the requesting local client, which corresponds to a pull-based protocol.

Unfortunately, this strategy requires that the proxy contacts a server for each request. To improve performance at the cost of weaker consistency, the widely-used Squid Web proxy [Wessels, 2004] assigns an expiration time T_{expire} that depends on how long ago the document was last modified when it is cached. In particular, if $T_{last\_modified}$ is the last modification time of a document (as recorded by its owner), and T_{cached} is the time it was cached, then

$$T_{expire} = \alpha(T_{cached} - T_{last\_modified}) + T_{cached}$$

with $\alpha = 0.2$ (this value has been derived from practical experience). Until T_{expire}, the document is considered valid and the proxy will not contact the server. After the expiration time, the proxy requests the server to send a fresh copy, unless it had not been modified. We note that Squid also allows the expiration time to be bounded by a minimum and a maximum time.

As an alternative to a pull-based protocol is that the server notifies proxies that a document has been modified by sending an invalidation. The problem with this approach for Web proxies is that the server may need to keep track of a large number of proxies, inevitably leading to a scalability problem. However, by combining leases and invalidations, the state to be maintained at the server can be kept within acceptable bounds. Note that this state is largely dictated by the expiration times set for leases: the lower, the less caches a server needs to keep track of. Nevertheless, invalidation protocols for Web proxy caches are hardly ever applied. A comparison of Web caching consistency policies can be found in [Cao and Ozsu, 2002]. Their conclusion is that letting the server send invalidations can outperform any other method in terms of bandwidth and perceived client latency, while maintaining cached documents consistent with those at the origin server.

Finally, we should also mention that much research has been conducted to find out what the best cache replacement strategies are. Numerous proposals exist, but by-and-large, simple replacement strategies such as evicting the least recently used object work well enough. An in-depth survey of replacement strategies is presented by Podling and Boszormenyi [2003]; Ali et al. [2011] provide a more recent overview which also includes Web prefetching techniques.

As the importance of the Web continues to increase as a vehicle for organizations to present themselves and to directly interact with end users, we see a shift between maintaining the content of a Web site and making sure that the site is easily and continuously accessible. This distinction has paved the way for **content delivery networks** (**CDN**). The main idea underlying these CDNs is that they act as a Web hosting service, providing an infrastructure for distributing and replicating the Web documents of multiple sites across the Internet. The size of the infrastructure can be impressive. For example, as of 2016, Akamai is reported to have over 200,000 servers spread across 120 countries.

The sheer size of a CDN requires that hosted documents are automatically distributed and replicated. In most cases, a large-scale CDN is organized along the lines of a feedback-control loop, as shown in Figure 7.33 and which is described extensively in [Sivasubramanian et al., 2004b].

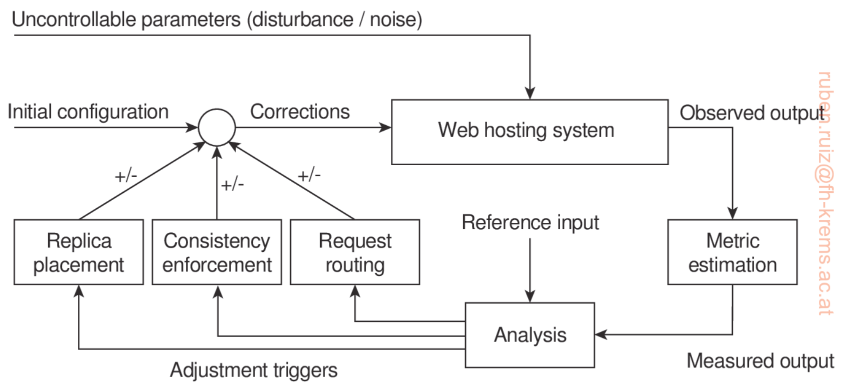


Figure 7.33: The general organization of a CDN as a feedback-control system.

There are essentially three different kinds of aspects related to replication in Web hosting systems: metric estimation, adaptation triggering, and taking appropriate measures. The latter can be subdivided into replica placement decisions, consistency enforcement, and client-request routing. In the following, we briefly pay attention to each these.

An interesting aspect of CDNs is that they need to make a trade-off between many aspects when it comes to hosting replicated content. For example, access times for a document may be optimal if a document is massively replicated, but at the same time this incurs a financial cost, as well as a cost in terms of bandwidth usage for disseminating updates. By and large, there are many proposals for estimating how well a CDN is performing. These proposals can be grouped into several classes.

First, there are *latency metrics*, by which the time is measured for an action, for example, fetching a document, to take place. Trivial as this may seem, estimating latencies becomes difficult when, for example, a process deciding on the placement of replicas needs to know the delay between a client and some remote server. Typically, an algorithm globally positioning nodes as discussed in Chapter 6 will need to be deployed.

Instead of estimating latency, it may be more important to measure the available bandwidth between two nodes. This information is particularly important when large documents need to be transferred, as in that case the responsiveness of the system is largely dictated by the time that a document can be transferred. There are various tools for measuring available bandwidth, but in all cases it turns out that accurate measurements can be difficult to attain (see also Strauss et al. [2003], Shriram and Kaur [2007], Chaudhari and Biradar [2015], and Atxutegi et al. [2016]).

Another class consists of *spatial metrics* which mainly consist of measuring the distance between nodes in terms of the number of network-level routing hops, or hops between autonomous systems. Again, determining the number of hops between two arbitrary nodes can be very difficult, and may also not even correlate with latency [Huffaker et al., 2002]. Moreover, simply looking at routing tables is not going to work when low-level techniques such as **multi-protocol label switching** (**MPLS**) are deployed. MPLS circumvents network-level routing by using virtual-circuit techniques to immediately and efficiently forward packets to their destination (see also Guichard et al. [2005]). Packets may thus follow completely different routes than advertised in the tables of network-level routers.

A third class is formed by *network usage metrics* which most often entails consumed bandwidth. Computing consumed bandwidth in terms of the number of bytes to transfer is generally easy. However, to do this correctly, we need to take into account how often the document is read, how often it is updated, and how often it is replicated.

Consistency metrics tell us to what extent a replica is deviating from its master copy. We already discussed extensively how consistency can be measured in the context of continuous consistency [Yu and Vahdat, 2002].

Finally, *financial metrics* form another class for measuring how well a CDN is doing. Although not technical at all, considering that most CDN operate on a commercial basis, it is clear that in many cases financial metrics will be decisive. Moreover, the financial metrics are closely related to the actual infrastructure of the Internet. For example, most commercial CDNs place servers at the edge of the Internet, meaning that they hire capacity from ISPs directly servicing end users. At this point, business models become intertwined with technological issues, an area that is not at all well understood. There is only few material available on the relation between financial performance and technological issues [Janiga et al., 2001].

From these examples it should become clear that simply measuring the performance of a CDN, or even estimating its performance may by itself be an extremely complex task. In practice, for commercial CDNs the issue that really counts is whether they can meet the service-level agreements that have been made with customers. These agreements are often formulated simply in terms of how quickly customers are to be serviced. It is then up to the CDN to make sure that these agreements are met.

Another question that needs to be addressed is when and how adaptations are to be triggered. A simple model is to periodically estimate metrics and subsequently take measures as needed. This approach is often seen in practice. Special processes located at the servers collect information and periodically check for changes.

Note 7.12 (Advanced: Flash crowds)

A major drawback of periodic evaluation is that sudden changes may be missed. One type of sudden change that has received considerable attention is that of flash crowds. A **flash crowd** is a legitimate sudden burst in requests for a specific Web document. In many cases, these type of bursts can bring down an entire service, in turn causing a cascade of service outages.

Handling flash crowds can be difficult. One solution is to massively replicate a Web site and as soon as request rates start to rapidly increase, requests should be redirected to the replicas to offload the master copy. This type of overprovisioning is obviously not the way to go. Instead, what is needed is to dynamically create replicas when demand goes up, and start redirecting requests when the going gets tough. With cloud computing now properly in place, combined with the fact that cloning virtual machines is relatively simple, reacting to sudden changes in request demands is practically feasible. Also, as we shall discuss below, using techniques for content delivery networks have proven to work well.

However, even better than reacting would be to predict flash crowds, yet this is actually very difficult if not practically impossible. Figure 7.34 shows access traces for three different Web sites that suffered from a flash crowd.

As a point of reference, Figure 7.34(a) shows regular access traces spanning two days. There are also some very strong peaks, but otherwise there is nothing shocking going on. In contrast, Figure 7.34(b) shows a two-day trace with four sudden flash crowds. There is still some regularity, which may be discovered after a while so that measures can be taken. However, the damage may be been done before reaching that point.

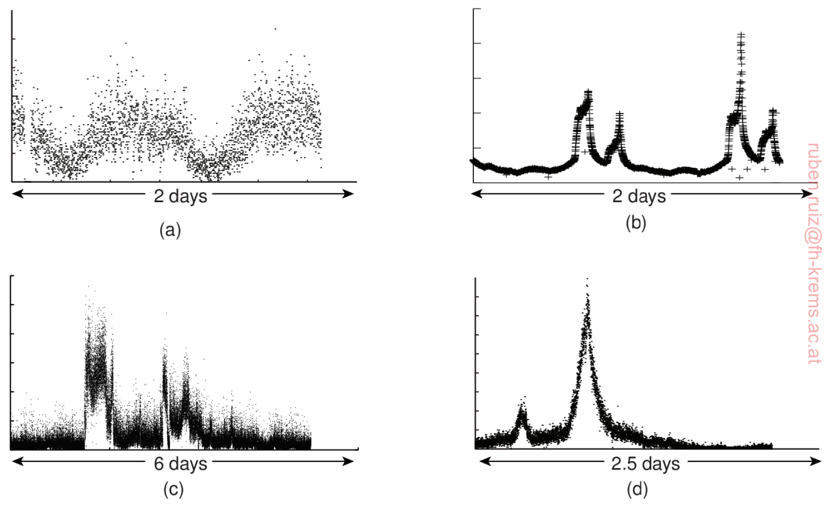


Figure 7.34: One normal and three different access patterns reflecting flash-crowd behavior. Adapted from Baryshnikov et al. [2005].

Figure 7.34(c) shows a trace spanning six days with at least two flash crowds. In this case, any predictor is going to have a serious problem, as it turns out that both increases in request rate are almost instantaneously. Finally, Figure 7.34(d) shows a situation in which the first peak should probably cause no adaptations, but the second obviously should. This situation turns out to be the type of behavior that can be dealt with quite well through runtime analysis.

As mentioned, there are essentially only three (related) measures that can be taken to change the behavior of a Web hosting service: changing the placement of replicas, changing consistency enforcement, and deciding on how and when to redirect client requests. We already discussed the first two measures extensively. Client-request redirection deserves some more attention. Before we discuss some of the trade-offs, let us first consider how consistency and replication are dealt with in a practical setting by considering the Akamai situation [Dilley et al., 2002; Nygren et al., 2010].

The basic idea is that each Web document consists of a main HTML (or XML) page in which several other documents such as images, video, and audio have been embedded. To display the entire document, it is necessary that the embedded documents are fetched by the user's browser as well. The assumption is that these embedded documents rarely change, for which reason it makes sense to cache or replicate them.

Each embedded document is normally referenced through a URL. However, in Akamai's CDN, such a URL is modified such that it refers to a **virtual ghost**, which is a reference to an actual server in the CDN. The URL also contains the host name of the origin server for reasons we explain next. The modified URL is resolved as follows, as is also shown in Figure 7.35.

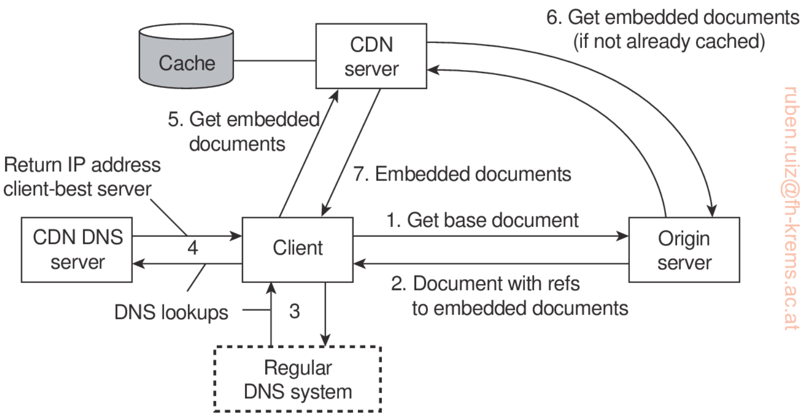

6. Get embedded documents (if not already cached)
Cache
CDN server
5. Get embedded documents
Return IP address client-best server
7. Embedded documents
1. Get base document
CDN DNS server
4
Client
Origin server
2. Document with refs to embedded documents
DNS lookups
3
Regular DNS system

Figure 7.35: The principal working of the Akamai CDN.

The name of the virtual ghost includes a DNS name such as ghosting.com, which is resolved by the regular DNS naming system to a CDN DNS server (the result of step 3). Each such DNS server keeps track of servers close to the client. To this end, any of the proximity metrics we have discussed previously could be used. In effect, the CDN DNS servers redirect the client to a replica server best for that client (step 4), which could mean the closest one, the least-loaded one, or a combination of several such metrics (the actual redirection policy is proprietary).

Finally, the client forwards the request for the embedded document to the selected CDN server. If this server does not yet have the document, it fetches it from the original Web server (shown as step 6), caches it locally, and subsequently passes it to the client. If the document was already in the CDN server's cache, it can be returned forthwith. Note that in order to fetch the embedded document, the replica server must be able to send a request to the origin server, for which reason its host name is also contained in the embedded document's URL.

An interesting aspect of this scheme is the simplicity by which consistency of documents can be enforced. Clearly, whenever a main document is changed, a client will always be able to fetch it from the origin server. In the case of embedded documents, a different approach needs to be followed as these documents are, in principle, fetched from a nearby replica server. To this end, a URL for an embedded document not only refers to a special host name that eventually leads to a CDN DNS server, but also contains a unique identifier that is changed every time the embedded document changes. In effect, this identifier changes the name of the embedded document. As a consequence, when the client is redirected to a specific CDN server, that server will not find the named document in its cache and will thus fetch it from the origin server. The old document will eventually be evicted from the server's cache as it is no longer referenced.

This example already shows the importance of client-request redirection. In principle, by properly redirecting clients, a CDN can stay in control when it comes to client-perceived performance, but also taking into account global system performance by, for example, avoiding that requests are sent to heavily loaded servers. These so-called **adaptive redirection policies** can be applied when information on the system's current behavior is provided to the processes that take redirection decisions. This brings us partly back to the metric estimation techniques discussed previously.

Besides the different policies, an important issue is whether request redirection is transparent to the client or not. In essence, there are only three redirection techniques: TCP handoff, DNS redirection, and HTTP redirection. We already discussed TCP handoff. This technique is applicable only for server clusters and does not scale to wide-area networks.

DNS redirection is a transparent mechanism by which the client can be kept completely unaware of where documents are located. Akamai's two-level redirection is one example of this technique. We can also directly deploy DNS to return one of several addresses as we discussed before. Note, however, that DNS redirection can be applied only to an entire site: the name of individual documents does not fit into the DNS name space.

HTTP redirection, finally, is a nontransparent mechanism. When a client requests a specific document, it may be given an alternative URL as part of an HTTP response message to which it is then redirected. An important observation is that this URL is visible to the client's browser. In fact, the user may decide to bookmark the referral URL, potentially rendering the redirection policy useless.

Up to this point we have mainly concentrated on caching and replicating static Web content. In practice, we see that the Web is increasingly offering more dynamically generated content, but that it is also expanding toward offering services that can be called by remote applications. Also in these situations we see that caching and replication can help considerably in improving the overall performance, although the methods to reach such improvements are more subtle than what we discussed so far (see also Conti et al. [2005]).

When considering improving performance of Web applications through caching and replication, matters are complicated by the fact that several solutions can be deployed, with no single one standing out as the best. Let us consider the edge-server situation as sketched in Figure 7.36 (see also Sivasubramanian et al. [2007]). In this case, we assume a CDN in which each hosted site has an origin server that acts as the authoritative site for all read and update operations. An edge server is used to handle client requests, and has

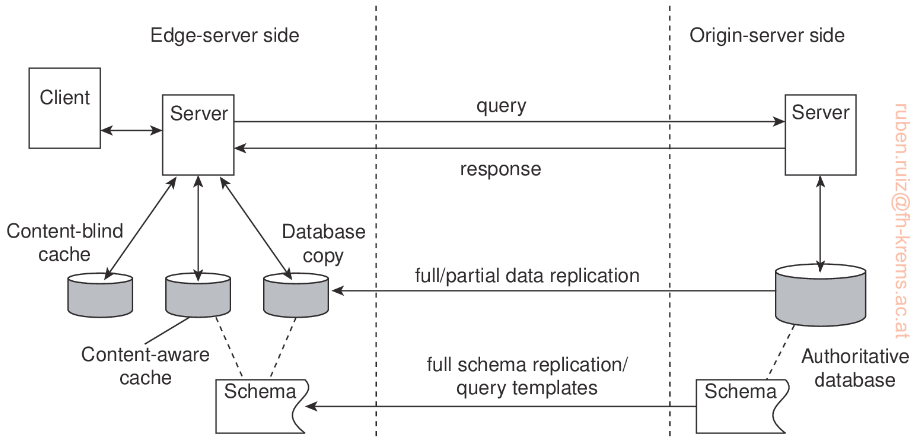


Figure 7.36: Alternatives for caching and replication with Web applications.

the ability to store (partial) information as also kept at an origin server.

Recall that in an edge-server architecture, Web clients request data through an edge server, which, in turn, gets its information from the origin server associated with the specific Web site referred to by the client. As also shown in Figure 7.36 we assume that the origin server consists of a database from which responses are dynamically created. Although we have shown only a single Web server, it is common to organize each server according to a multitiered architecture as we discussed before. An edge server can now be roughly organized along the following lines.

First, to improve performance, we can decide to apply full replication of the data stored at the origin server. This scheme works well whenever the update ratio is low and when queries require an extensive database search. As mentioned above, we assume that all updates are carried out at the origin server, which takes responsibility for keeping the replicas and the edge servers in a consistent state. Read operations can thus take place at the edge servers. Here we see that replicating for performance will fail when the update ratio is high, as each update will incur communication over a wide-area network to bring the replicas into a consistent state. As shown by Sivasubramanian et al. [2004a], the read/update ratio is the determining factor to what extent the origin database in a wide-area setting should be replicated.

Another case for full replication is when queries are generally complex. In the case of a relational database, this means that a query requires that multiple tables need to be searched and processed, as is generally the case with a join operation. Opposed to complex queries are simple ones that generally require access to only a single table in order to produce a response. In the latter case, **partial replication** by which only a subset of the data is stored at the edge server may suffice.

An alternative to partial replication is to make use of **content-aware caches**. The basic idea in this case is that an edge server maintains a local database that is now tailored to the type of queries that can be handled at the origin server. To explain, in a full-fledged database system a query will operate on a database in which the data has been organized into tables such that, for example, redundancy is minimized. Such databases are also said to be **normalized**.

In such databases, any query that adheres to the data schema can, in principle, be processed, although perhaps at considerable costs. With content-aware caches, an edge server maintains a database that is organized according to the structure of queries. What this means is that queries are assumed to adhere to a limited number of templates, effectively meaning that the different kinds of queries that can be processed is restricted. In these cases, whenever a query is received, the edge server matches the query against the available templates, and subsequently looks in its local database to compose a response, if possible. If the requested data is not available, the query is forwarded to the origin server after which the response is cached before returning it to the client.

In effect, what the edge server is doing is checking whether a query can be answered with the data that is stored locally. This is also referred to as a **query containment check**. Note that such data was stored locally as responses to previously issued queries. This approach works best when queries tend to be repeated.

Part of the complexity of content-aware caching comes from the fact that the data at the edge server needs to be kept consistent. To this end, the origin server needs to know which records are associated with which templates, so that any update of a record, or any update of a table, can be properly addressed by, for example, sending an invalidation message to the appropriate edge servers. Another source of complexity comes from the fact that queries still need to be processed at edge servers. In other words, there is nonnegligible computational power needed to handle queries. Considering that databases often form a performance bottleneck in Web servers, alternative solutions may be needed. Finally, caching results from queries that span multiple tables (i.e., when queries are complex) such that a query containment check can be carried out effectively is not trivial. The reason is that the organization of the results may be very different from the organization of the tables on which the query operated.

These observations lead us to a third solution, namely **content-blind caching**. The idea of content-blind caching is extremely simple: when a client submits a query to an edge server, the server first computes a unique hash value for that query. Using this hash value, it subsequently looks in its cache whether it has processed this query before. If not, the query is forwarded to the origin and the result is cached before returning it to the client. If the query had been processed before, the previously cached result is returned to the client.

The main advantage of this scheme is the reduced computational effort that is required from an edge server in comparison to the database approaches described above. However, content-blind caching can be wasteful in terms of storage as the caches may contain much more redundant data in comparison to content-aware caching or database replication. Note that such redundancy also complicates the process of keeping the cache up to date as the origin server may need to keep an accurate account of which updates can potentially affect cached query results. These problems can be alleviated when assuming that queries can match only a limited set of predefined templates as we discussed above.

7.7 Summary

There are primarily two reasons for replicating data: improving the reliability of a distributed system and improving performance. Replication introduces a consistency problem: whenever a replica is updated, that replica becomes different from the others. To keep replicas consistent, we need to propagate updates in such a way that temporary inconsistencies are not noticed. Unfortunately, doing so may severely degrade performance, especially in large-scale distributed systems.

The only solution to this problem is to relax consistency somewhat. Different consistency models exist. For continuous consistency, the goal is to set bounds to numerical deviation between replicas, staleness deviation, and deviations in the ordering of operations.

Numerical deviation refers to the value by which replicas may be different. This type of deviation is highly application dependent, but can, for example, be used in replication of stocks. Staleness deviation refers to the time by which a replica is still considered to be consistent, despite that updates may have taken place some time ago. Staleness deviation is often used for Web caches. Finally, ordering deviation refers to the maximum number of tentative writes that may be outstanding at any server without having synchronized with the other replica servers.

Consistent ordering of operations has since long formed the basis for many consistency models. Many variations exist, but only a few seem to prevail among application developers. Sequential consistency essentially provides the semantics that programmers expect in concurrent programming: all write operations are seen by everyone in the same order. Less used, but still relevant, is causal consistency, which reflects that operations that are potentially dependent on each other are carried out in the order of that dependency.

Weaker consistency models consider series of read and write operations. In particular, they assume that each series is appropriately "bracketed" by accompanying operations on synchronization variables, such as locks. Although this requires explicit effort from programmers, these models are generally easier to implement in an efficient way than, for example, pure sequential consistency.

As opposed to these data-centric models, researchers in the field of distributed databases for mobile users have defined a number of client-centric consistency models. Such models do not consider the fact that data may be shared by several users, but instead, concentrate on the consistency that an individual client should be offered. The underlying assumption is that a client connects to different replicas in the course of time, but that such differences should be made transparent. In essence, client-centric consistency models ensure that whenever a client connects to a new replica, that replica is brought up to date with the data that had been manipulated by that client before, and which may possibly reside at other replica sites.

To propagate updates, different techniques can be applied. A distinction needs to be made concerning *what* is exactly propagated, to *where* updates are propagated, and *by whom* propagation is initiated. We can decide to propagate notifications, operations, or state. Likewise, not every replica always needs to be updated immediately. Which replica is updated at which time depends on the distribution protocol. Finally, a choice can be made whether updates are pushed to other replicas, or that a replica pulls in updates from another replica.

Consistency protocols describe specific implementations of consistency models. With respect to sequential consistency and its variants, a distinction can be made between primary-based protocols and replicated-write protocols. In primary-based protocols, all update operations are forwarded to a primary copy that subsequently ensures the update is properly ordered and forwarded. In replicated-write protocols, an update is forwarded to several replicas at the same time. In that case, correctly ordering operations often becomes more difficult.

We pay separate attention to caching and replication in the Web and, related, content delivery networks. As it turns out, using existing servers and services, much of the techniques discussed before can be readily implemented using appropriate redirection techniques. Particularly challenging is caching content when databases are involved, as in those cases, much of what a Web server returns is dynamically generated. However, even in those cases, by carefully administrating what has already been cached at the edge, it is possible to invent highly efficient and effective caching schemes.